Artificial Intelligence

Deep Learning and Reinforcement Learning

1111AI07
MBA, IM, NTPU (M6132) (Fall 2022)
Wed 2, 3, 4 (9:10-12:00) (B8F40)

https://meet.google.com/miy-fbif-max

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2022-11-09

Syllabus

Week	Date	Subject/Topics
1	2022/09/14	Introduction to Artificial Intelligence
2	2022/09/21	Artificial Intelligence and Intelligent Agents
3	2022/09/28	Problem Solving
4	2022/10/05	Knowledge, Reasoning and Knowledge Representation; Uncertain Knowledge and Reasoning
5	2022/10/12	Case Study on Artificial Intelligence I
6	2022/10/19	Machine Learning: Supervised and Unsupervised Learning

Syllabus

Week Date Subject/Topics

7 2022/10/26 The Theory of Learning and Ensemble Learning

8 2022/11/02 Midterm Project Report

9 2022/11/09 Deep Learning and Reinforcement Learning

10 2022/11/16 Deep Learning for Natural Language Processing

11 2022/11/23 Invited Talk: AI for Information Retrieval

12 2022/11/30 Case Study on Artificial Intelligence II

Syllabus

Week	Date	Subject/Topics
13	2022/12/07	Computer Vision and Robotics
14	2022/12/14	Philosophy and Ethics of AI and the Future of AI
15	2022/12/21	Final Project Report I
16	2022/12/28	Final Project Report II
17	2023/01/04	Self-learning
18	2023/01/11	Self-learning

Deep Learning and Reinforcement Learning

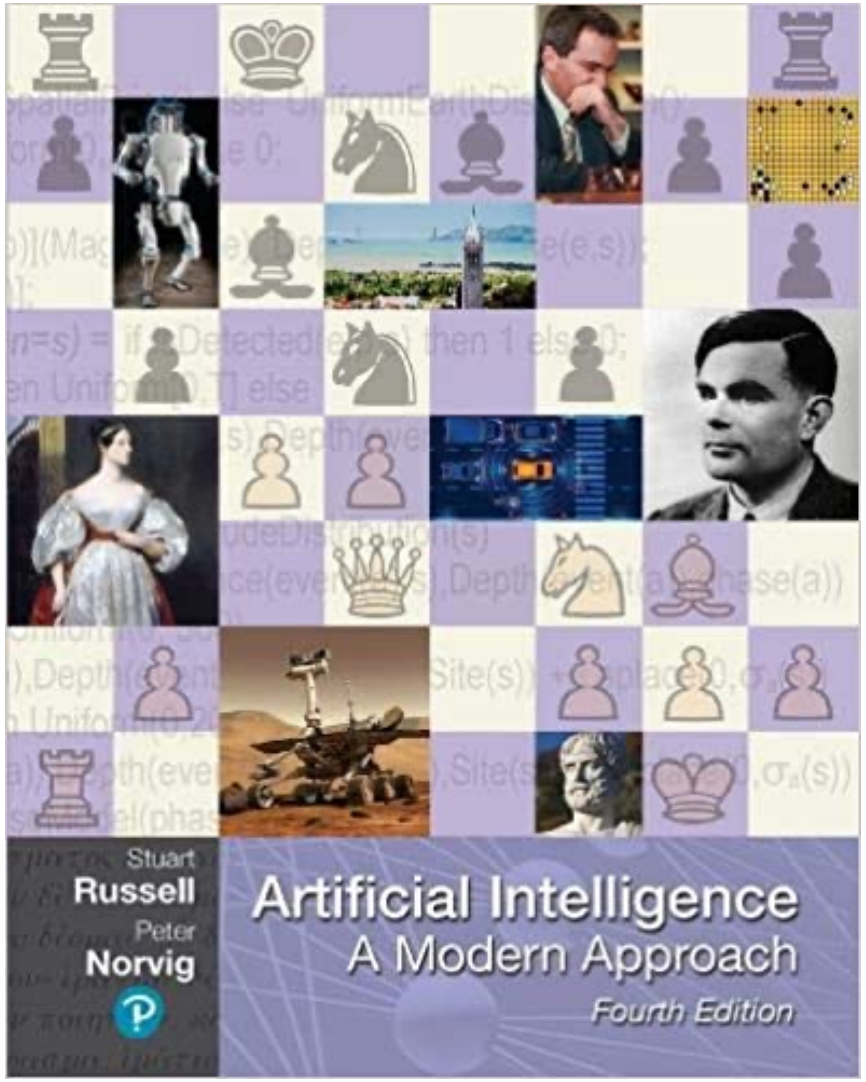
Outline

- Deep Learning
  - Neural Networks (NN)
  - Convolutional Neural Networks (CNN)
  - Recurrent Neural Networks (RNN)
- Reinforcement Learning (RL)
  - Markov Decision Processes (MDP)
- Deep Reinforcement Learning (DRL) Algorithms
  - SARSA
  - Q-Learning
  - DQN
  - A3C
  - Rainbow

Stuart Russell and Peter Norvig (2020),

Artificial Intelligence: A Modern Approach,

4th Edition, Pearson



Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson

https://www.amazon.com/Artificial-Intelligence-A-Modern-Approach/dp/0134610997/

Artificial Intelligence: A Modern Approach

1. Artificial Intelligence
2. Problem Solving
3. Knowledge and Reasoning
4. Uncertain Knowledge and Reasoning
5. Machine Learning
6. Communicating, Perceiving, and Acting
7. Philosophy and Ethics of AI

Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson

Artificial Intelligence:

Machine Learning

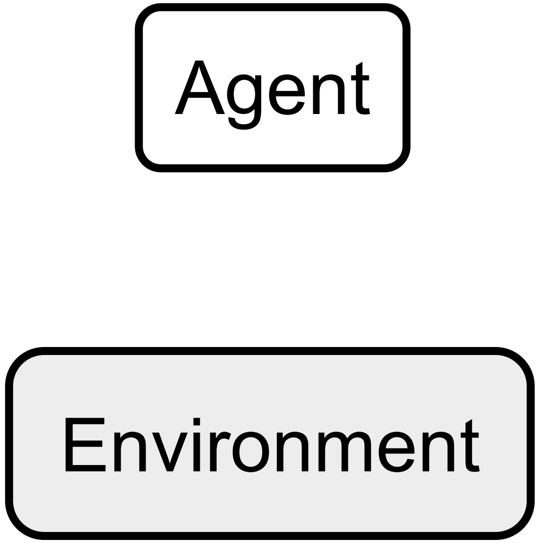
Artificial Intelligence:
5. Machine Learning

- Learning from Examples
- Learning Probabilistic Models
- Deep Learning
- Reinforcement Learning

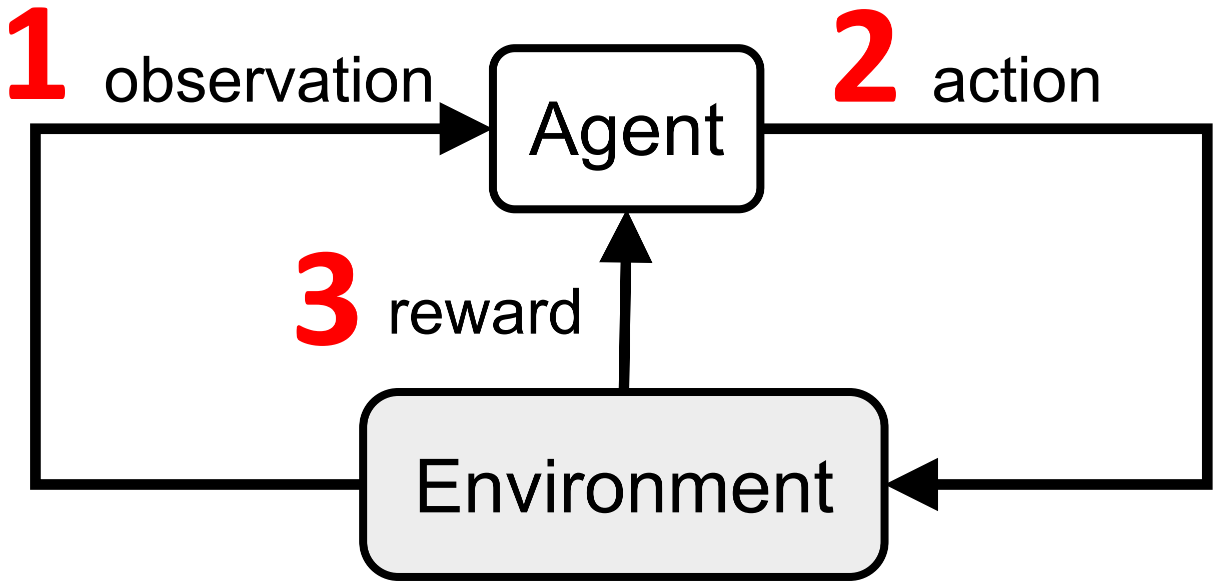
Artificial Intelligence: Reinforcement Learning

- Learning from Rewards
- Passive Reinforcement Learning
- Active Reinforcement Learning
- Generalization in Reinforcement Learning
- Policy Search
- Apprenticeship and Inverse Reinforcement Learning
- Applications of Reinforcement Learning

Reinforcement Learning (DL)

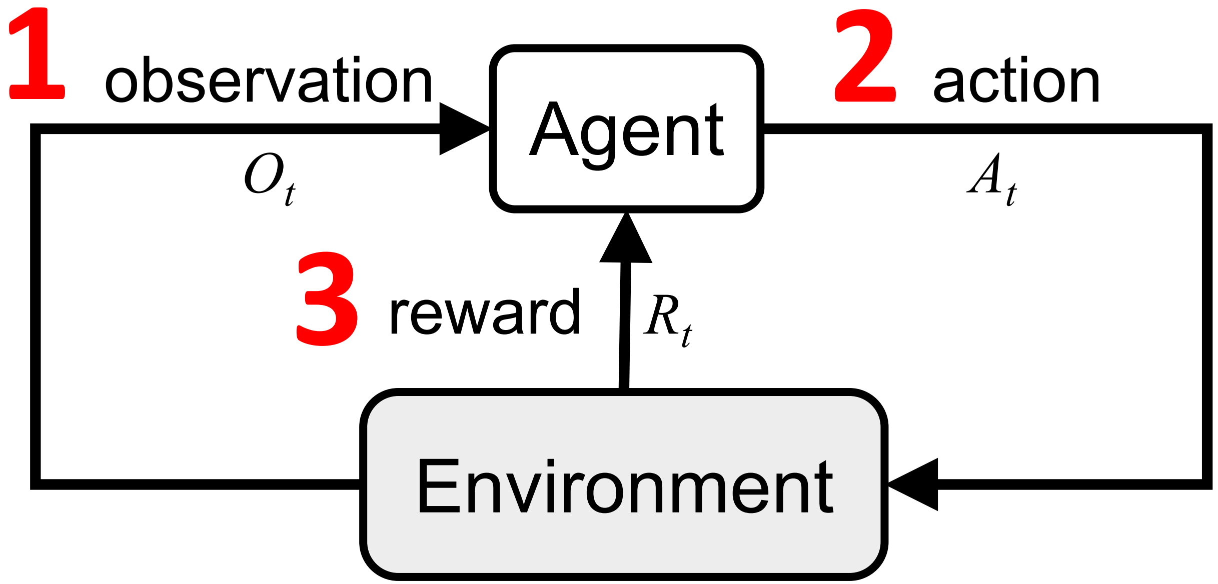


Reinforcement Learning (DL)



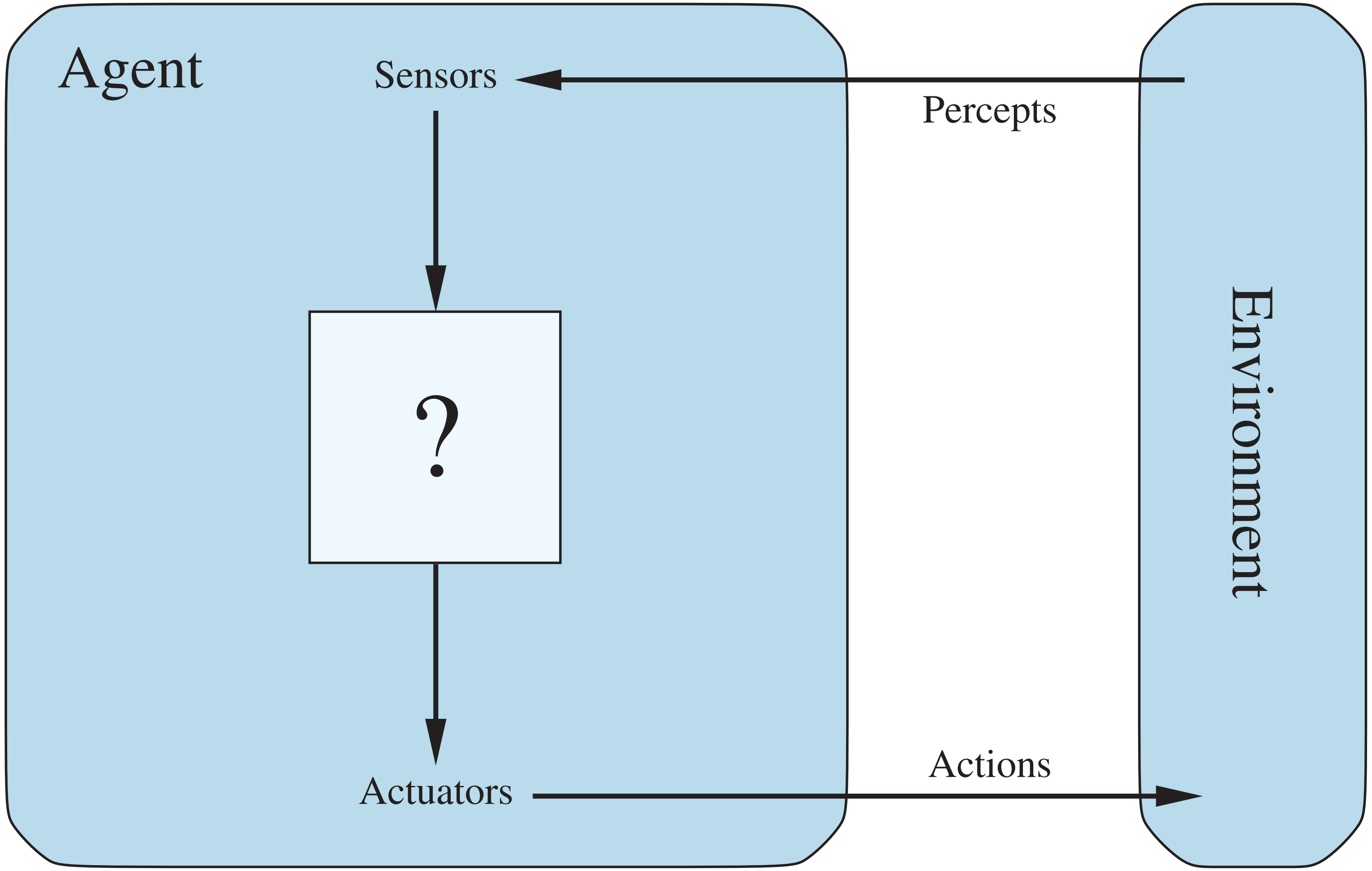
Source: Richard S. Sutton & Andrew G. Barto (2018), Reinforcement Learning: An Introduction, 2nd Edition, A Bradford Book.

Reinforcement Learning (DL)



Source: Richard S. Sutton & Andrew G. Barto (2018), Reinforcement Learning: An Introduction, 2nd Edition, A Bradford Book.

Agents interact with environments through sensors and actuators



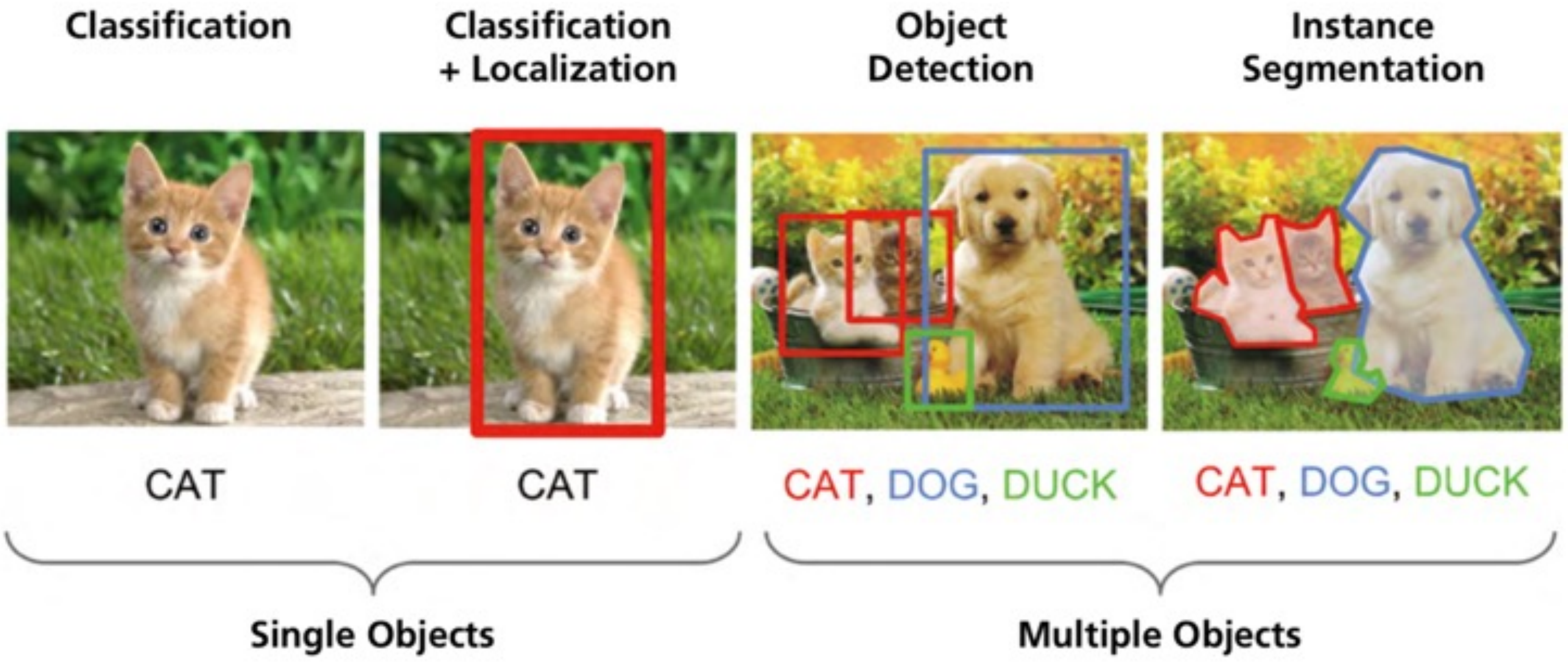
Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson

AI Acting Humanly:
The Turing Test Approach
(Alan Turing, 1950)

- Knowledge Representation
- Automated Reasoning
- Machine Learning (ML)
  - Deep Learning (DL)
- Computer Vision (Image, Video)
- Natural Language Processing (NLP)
- Robotics

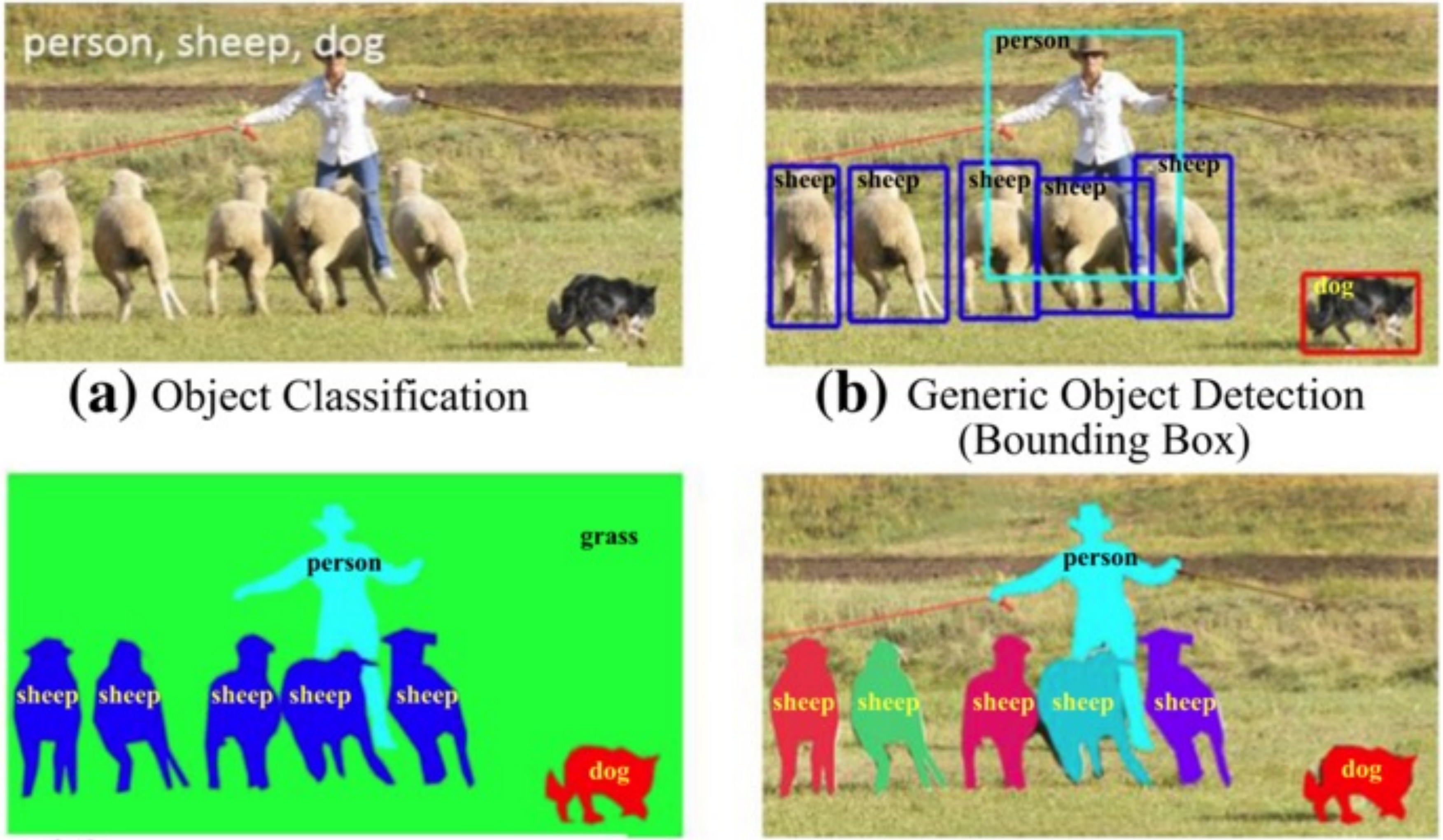
Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson

Computer Vision: Image Classification, Object Detection, Object Instance Segmentation



Source: DHL (2018), Artificial Intelligence in Logistics,
http://www.globalhha.com/doclib/data/upload/doc_con/5e50c53c5bf67.pdf/

Computer Vision: Object Detection



(a) Object Classification

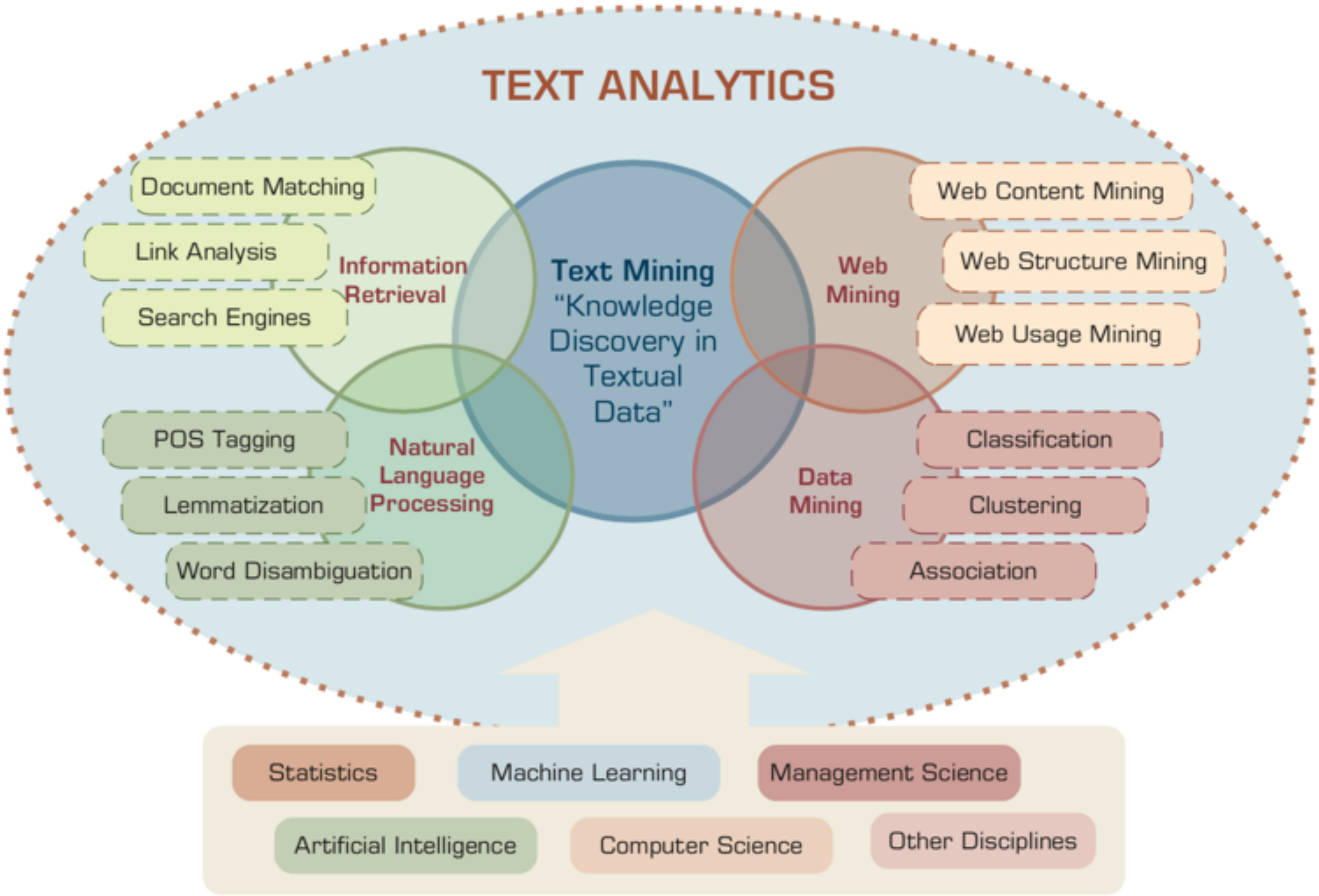
(b) Generic Object Detection (Bounding Box)

(c) Semantic Segmentation

(d) Object Instance Segmetation

Source: Li Liu, Wanli Ouyang, Xiaogang Wang, Paul Fieguth, Jie Chen, Xinwang Liu, and Matti Pietikäinen. "Deep learning for generic object detection: A survey." International journal of computer vision 128, no. 2 (2020): 261-318.

Text Analytics and Text Mining



Source: Ramesh Sharda, Dursun Delen, and Efraim Turban (2017), Business Intelligence, Analytics, and Data Science: A Managerial Perspective, 4th Edition, Pearson

Deep learning for financial applications: A survey

Applied Soft Computing (2020)

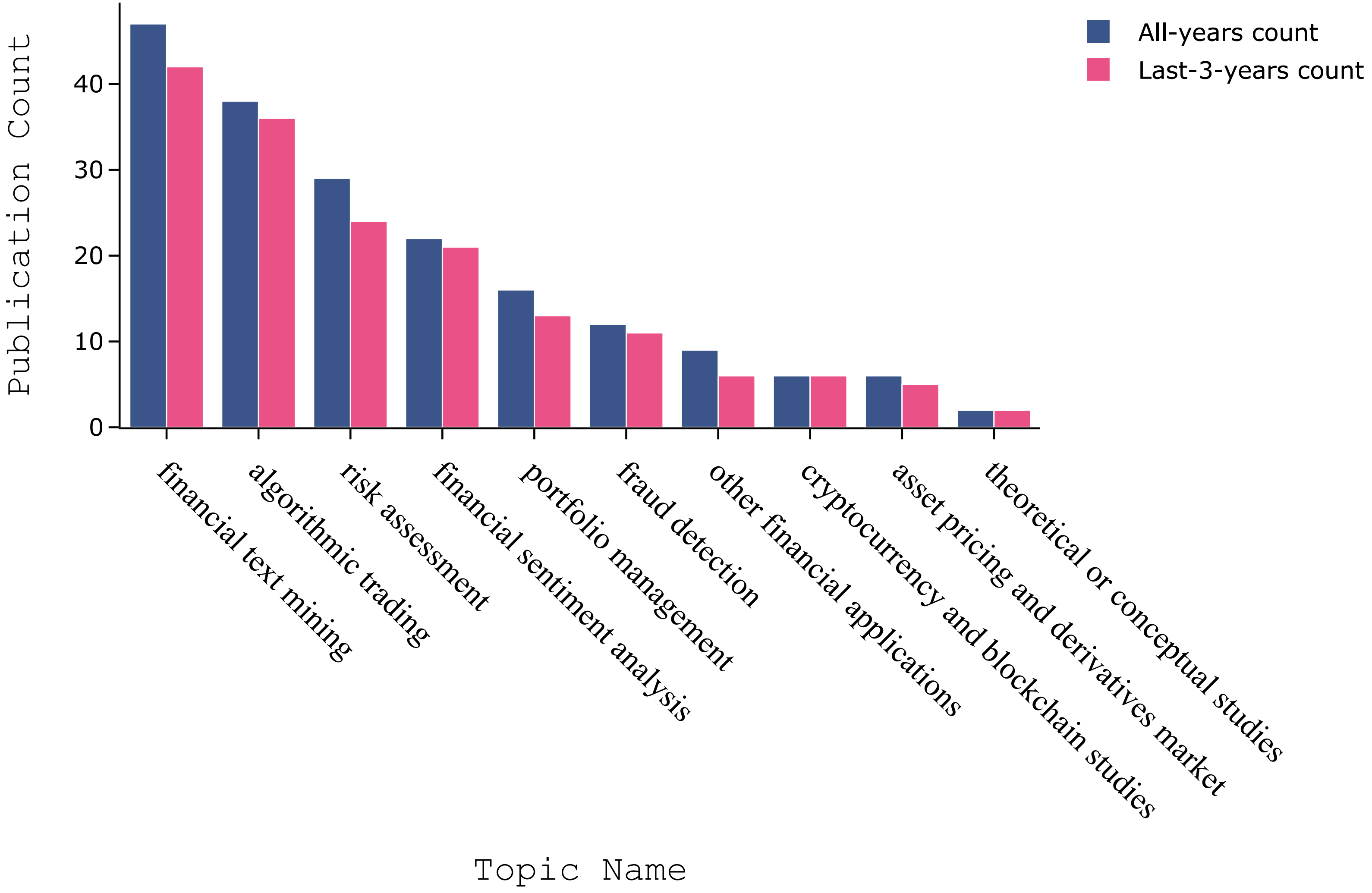
Source:
Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey."
Applied Soft Computing (2020): 106384.

Financial time series forecasting with deep learning: A systematic literature review: 2005–2019

Applied Soft Computing (2020)

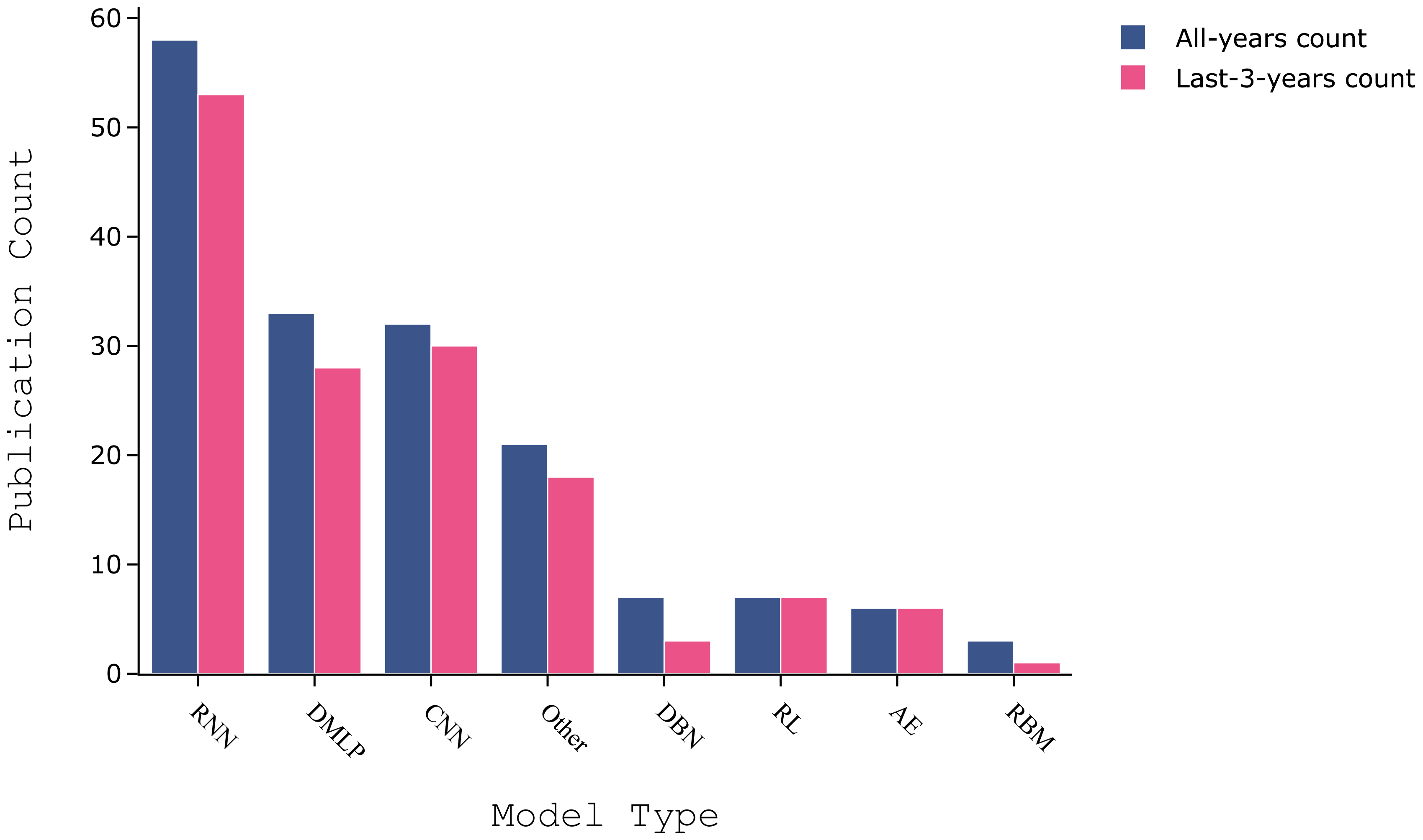
Source:
Omer Berat Sezer, Mehmet Ugur Gudelek, and Ahmet Murat Ozbayoglu (2020), "Financial time series forecasting with deep learning: A systematic literature review: 2005–2019." Applied Soft Computing 90 (2020): 106181.

Deep learning for financial applications: Topics



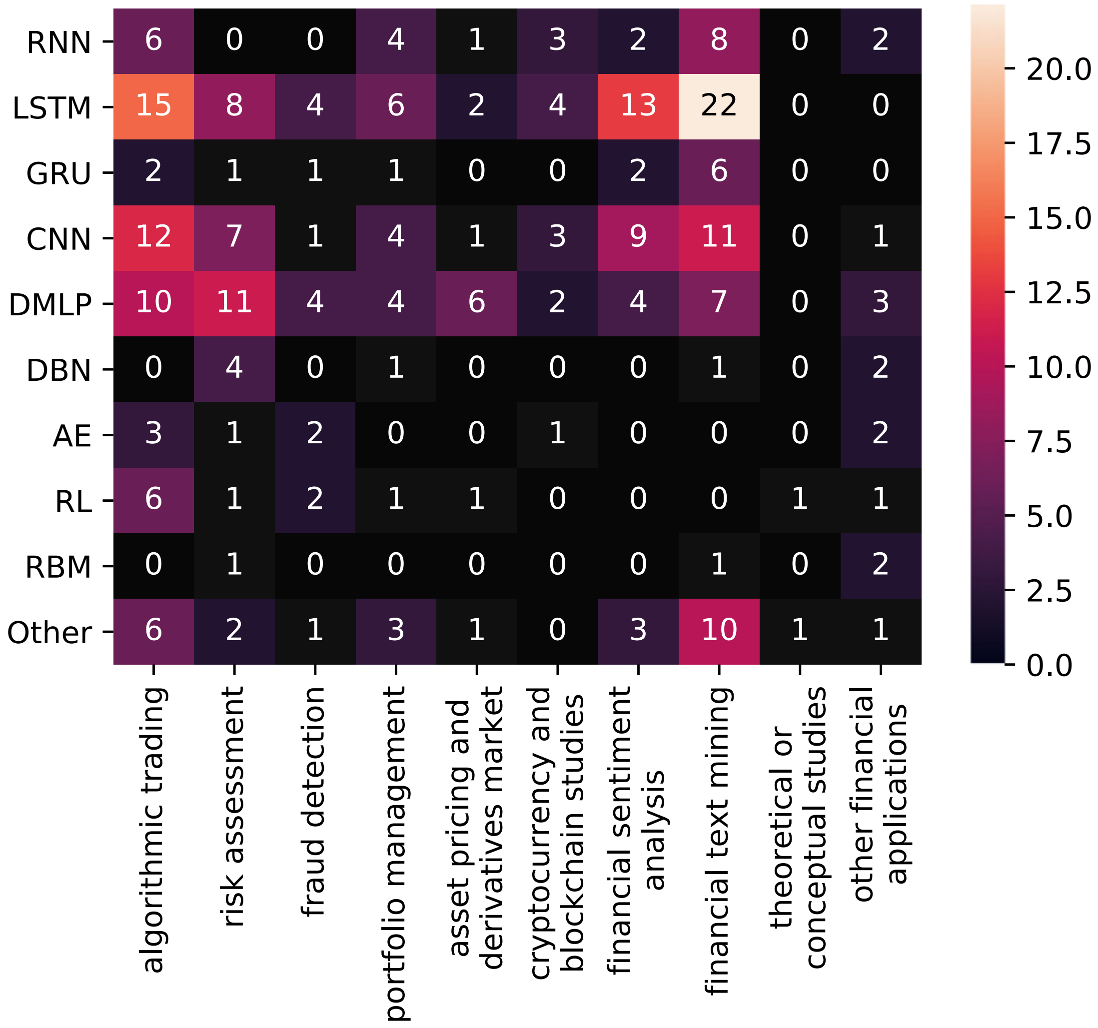
Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

Deep learning for financial applications: Deep Learning Models



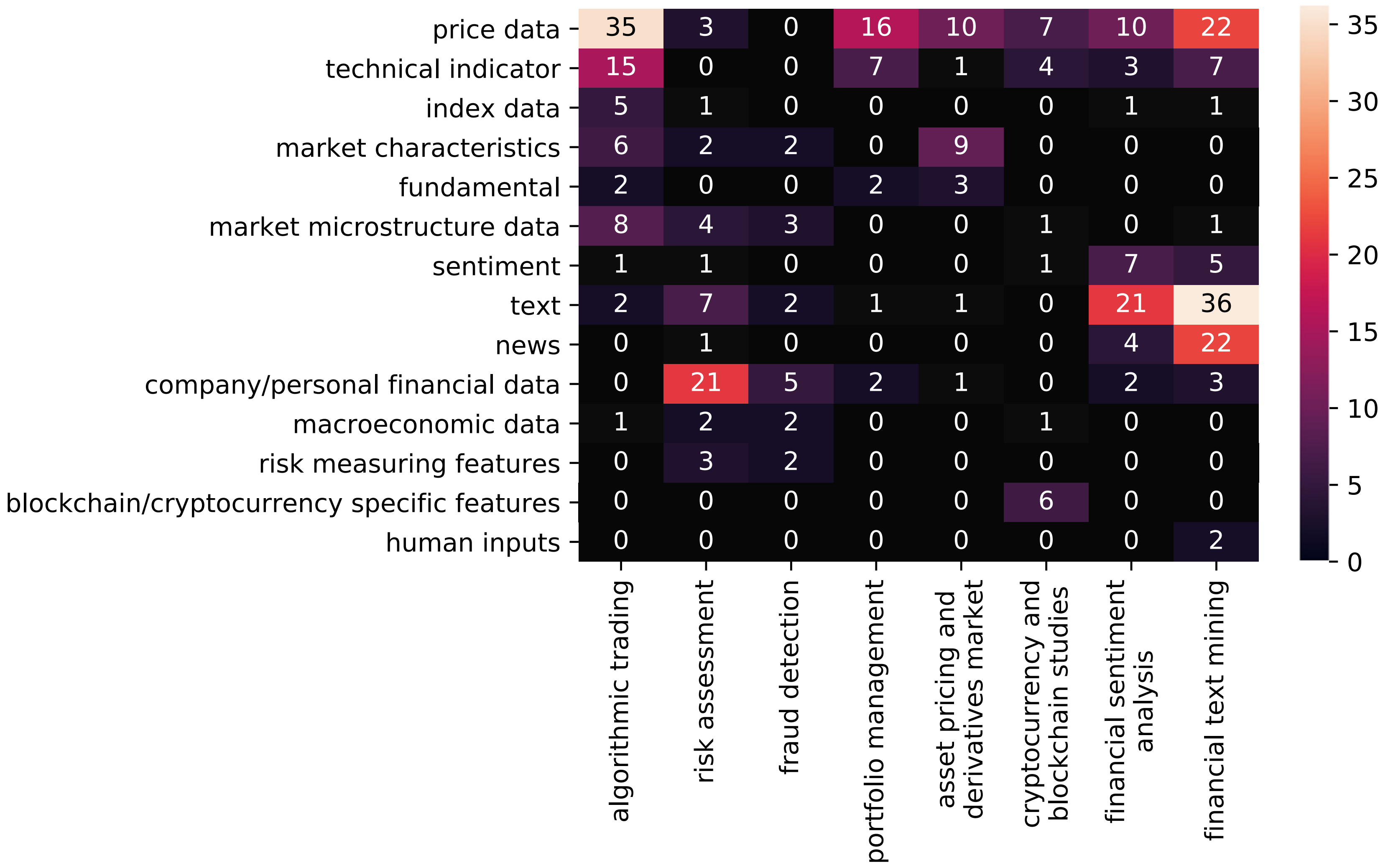
Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

Deep learning for financial applications: Topic-Model Heatmap



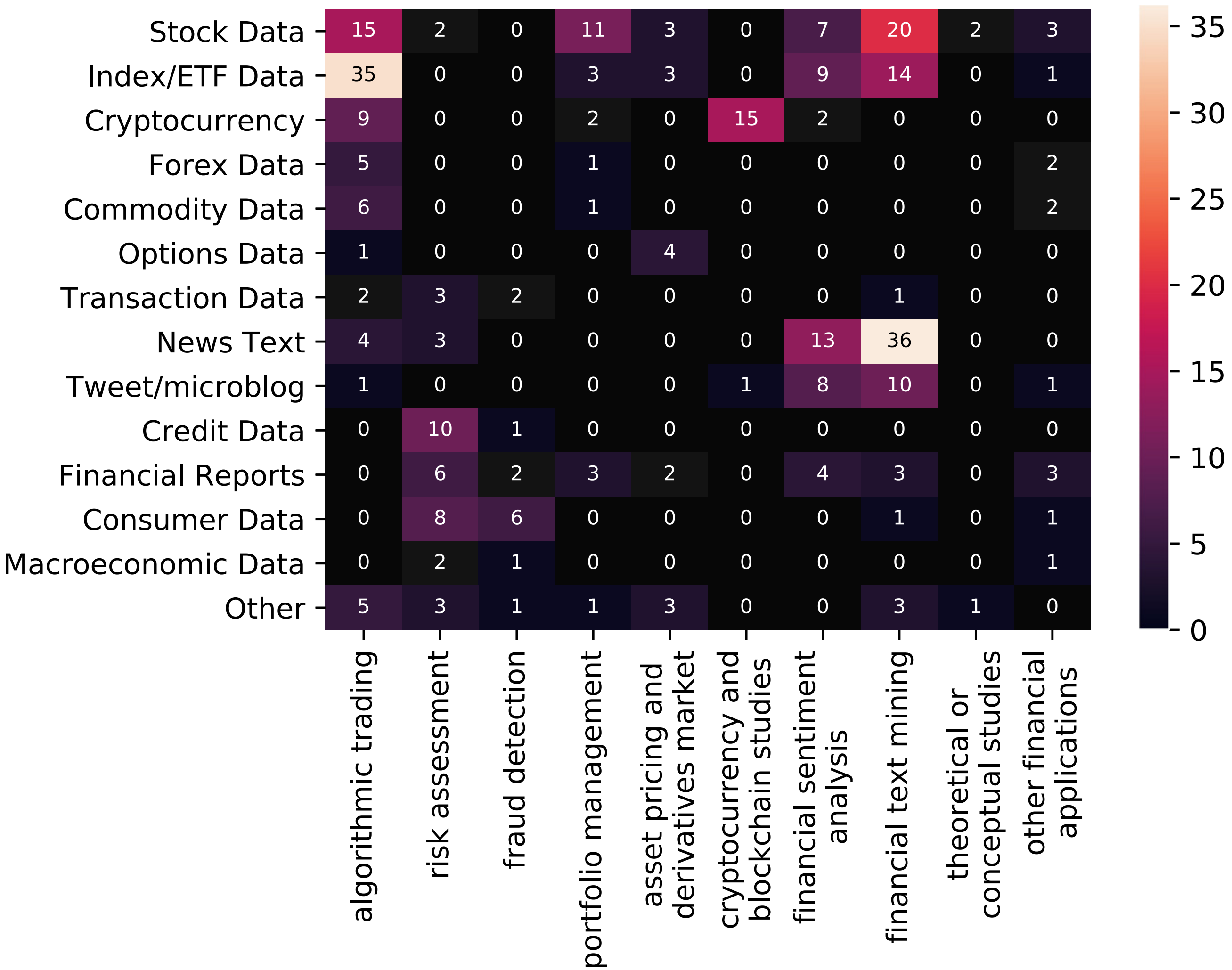
Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

Deep learning for financial applications: Topic-Feature Heatmap



Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

Deep learning for financial applications: Topic-Dataset Heatmap



Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

Deep learning for financial applications:

Algo-trading applications embedded with time series forecasting models

Art.	Data set	Period	Feature set	Method	Performance criteria	Environment
[33]	GarantiBank in BIST, Turkey	2016	OCHLV, Spread, Volatility, Turnover, etc.	PLR, Graves LSTM	MSE, RMSE, MAE, RSE, Correlation R-square	Spark
[34]	CSI300, Nifty50, HSI, Nikkei 225, S&P500, DJIA	2010–2016	OCHLV, Technical Indicators	WT, Stacked autoencoders, LSTM	MAPE, Correlation coefficient, THEIL-U	–
[35]	Chinese Stocks	2007–2017	OCHLV	CNN + LSTM	Annualized Return, Mxm Retracement	Python
[36]	50 stocks from NYSE	2007–2016	Price data	SFM	MSE	–
[37]	The LOB of 5 stocks of Finnish Stock Market	2010	FI-2010 dataset: bid/ask and volume	WMTR, MDA	Accuracy, Precision, Recall, F1-Score	–
[38]	300 stocks from SZSE, Commodity	2014–2015	Price data	FDDR, DMLP+RL	Profit, return, SR, profit-loss curves	Keras
[39]	S&P500 Index	1989–2005	Price data, Volume	LSTM	Return, STD, SR, Accuracy	Python, TensorFlow, Keras, R, H2O
[40]	Stock of National Bank of Greece (ETE).	2009–2014	FTSE100, DJIA, GDAX, NIKKEI225, EUR/USD, Gold	GASVR, LSTM	Return, volatility, SR, Accuracy	Tensorflow
[41]	Chinese stock-IF-IH-IC contract	2016–2017	Decisions for price change	MODRL+LSTM	Profit and loss, SR	–
[42]	Singapore Stock Market Index	2010–2017	OCHL of last 10 days of Index	DMLP	RMSE, MAPE, Profit, SR	–
[43]	GBP/USD	2017	Price data	Reinforcement Learning + LSTM + NES	SR, downside deviation ratio, total profit	Python, Keras, Tensorflow
[44]	Commodity, FX future, ETF	1991–2014	Price Data	DMLP	SR, capability ratio, return	C++, Python
[45]	USD/GBP, S&P500, FTSE100, oil, gold	2016	Price data	AE + CNN	SR, % volatility, avg return/trans, rate of return	H2O

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

Deep learning for financial applications:

Algo-trading applications embedded with time series forecasting models

Art.	Data set	Period	Feature set	Method	Performance criteria	Environment
[46]	Bitcoin, Dash, Ripple, Monero, Litecoin, Dogecoin, Nxt, Namecoin	2014–2017	MA, BOLL, the CRIX returns, Euribor interest rates, OCHLV	LSTM, RNN, DMLP	Accuracy, F1-measure	Python, Tensorflow
[47]	S&P500, KOSPI, HSI, and EuroStoxx50	1987–2017	200-days stock price	Deep Q-Learning, DMLP	Total profit, Correlation	–
[48]	Stocks in the S&P500	1990–2015	Price data	DMLP, GBT, RF	Mean return, MDD, Calmar ratio	H2O
[49]	Fundamental and Technical Data, Economic Data	–	Fundamental , technical and market information	CNN	–	–

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

Deep learning for financial applications:

Classification (buy–sell signal, or trend detection) based algo-trading models

Art.	Data set	Period	Feature set	Method	Performance criteria	Environment
[51]	Stocks in Dow30	1997–2017	RSI	DMLP with genetic algorithm	Annualized return	Spark MLlib, Java
[52]	SPY ETF, 10 stocks from S&P500	2014–2016	Price data	FFNN	Cumulative gain	MatConvNet, Matlab
[53]	Dow30 stocks	2012–2016	Close data and several technical indicators	LSTM	Accuracy	Python, Keras, Tensorflow, TALIB
[54]	High-frequency record of all orders	2014–2017	Price data, record of all orders, transactions	LSTM	Accuracy	–
[55]	Nasdaq Nordic (Kesko Oyj, Outokumpu Oyj, Sampo, Rautaruukki, Wartsila Oyj)	2010	Price and volume data in LOB	LSTM	Precision, Recall, F1-score, Cohen's k	–
[56]	17 ETFs	2000–2016	Price data, technical indicators	CNN	Accuracy, MSE, Profit, AUROC	Keras, Tensorflow
[57]	Stocks in Dow30 and 9 Top Volume ETFs	1997–2017	Price data, technical indicators	CNN with feature imaging	Recall, precision, F1-score, annualized return	Python, Keras, Tensorflow, Java
[58]	FTSE100	2000–2017	Price data	CAE	TR, SR, MDD, mean return	–
[59]	Nasdaq Nordic (Kesko Oyj, Outokumpu Oyj, Sampo, Rautaruukki, Wartsila Oyj)	2010	Price, Volume data, 10 orders of the LOB	CNN	Precision, Recall, F1-score, Cohen's k	Theano, Scikit learn, Python
[60]	Borsa Istanbul 100 Stocks	2011–2015	75 technical indicators and OCHLV	CNN	Accuracy	Keras
[61]	ETFs and Dow30	1997–2007	Price data	CNN with feature imaging	Annualized return	Keras, Tensorflow
[62]	8 experimental assets from bond/derivative market	–	Asset prices data	RL, DMLP, Genetic Algorithm	Learning and genetic algorithm error	–
[63]	10 stocks from S&P500	–	Stock Prices	TDNN, RNN, PNN	Missed opportunities, false alarms ratio	–
[64]	London Stock Exchange	2007–2008	Limit order book state, trades, buy/sell orders, order deletions	CNN	Accuracy, kappa	Caffe
[65]	Cryptocurrencies, Bitcoin	2014–2017	Price data	CNN, RNN, LSTM	Accumulative portfolio value, MDD, SR	–

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Deep learning for financial applications:
Stand-alone and/or other algorithmic models

Art.	Data set	Period	Feature set	Method	Performance criteria	Environment
[66]	DAX, FTSE100, call/put options	1991–1998	Price data	Markov model, RNN	Ewa-measure, iv, daily profits' mean and std	–
[67]	Taiwan Stock Index Futures, Mini Index Futures	2012–2014	Price data to image	Visualization method + CNN	Accumulated profits,accuracy	–
[68]	Energy-Sector/ Company-Centric Tweets in S&P500	2015–2016	Text and Price data	LSTM, RNN, GRU	Return, SR, precision, recall, accuracy	Python, Tweepy API
[69]	CME FIX message	2016	Limit order book, time-stamp, price data	RNN	Precision, recall, F1-measure	Python, TensorFlow, R
[70]	Taiwan stock index futures (TAIFEX)	2017	Price data	Agent based RL with CNN pre-trained	Accuracy	–
[71]	Stocks from S&P500	2010–2016	OCHLV	DCNL	PCC, DTW, VWL	Pytorch
[72]	News from NowNews, AppleDaily, LTN, MoneyDJ for 18 stocks	2013–2014	Text, Sentiment	DMLP	Return	Python, Tensorflow
[73]	489 stocks from S&P500 and NASDAQ-100	2014–2015	Limit Order Book	Spatial neural network	Cross entropy error	NVIDIA's cuDNN
[74]	Experimental dataset	–	Price data	DRL with CNN, LSTM, GRU, DMLP	Mean profit	Python

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Deep learning for financial applications:
Credit scoring or classification studies

Art.	Data set	Period	Feature set	Method	Performance criteria	Env.
[77]	The XR 14 CDS contracts	2016	Recovery rate, spreads, sector and region	DBN+RBM	AUROC, FN, FP, Accuracy	WEKA
[78]	German, Japanese credit datasets	–	Personal financial variables	SVM + DBN	Weighted-accuracy, TP, TN	–
[79]	Credit data from Kaggle	–	Personal financial variables	DMLP	Accuracy, TP, TN, G-mean	–
[80]	Australian, German credit data	–	Personal financial variables	GP + AE as Boosted DMLP	FP	Python, Scikit-learn
[81]	German, Australian credit dataset	–	Personal financial variables	DCNN, DMLP	Accuracy, False/Missed alarm	–
[82]	Consumer credit data from Chinese finance company	–	Relief algorithm chose the 50 most important features	CNN + Relief	AUROC, K-s statistic, Accuracy	Keras
[83]	Credit approval dataset by UCI Machine Learning repo	–	UCI credit approval dataset	Rectifier, Tanh, Maxout DL	–	AWS EC2, H2O, R

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Deep learning for financial applications:

Financial distress, bankruptcy, bank risk, mortgage risk, crisis forecasting studies.

Art.	Data set	Period	Feature set	Method	Performance criteria	Env.
[84]	966 french firms	–	Financial ratios	RBM+SVM	Precision, Recall	–
[85]	883 BHC from EDGAR	2006–2017	Tokens, weighted sentiment polarity, leverage and ROA	CNN, LSTM, SVM, RF	Accuracy, Precision, Recall, F1-score	Keras, Python, Scikit-learn
[86]	The event data set for large European banks, news articles from Reuters	2007–2014	Word, sentence	DMLP +NLP preprocess	Relative usefulness, F1-score	–
[87]	Event dataset on European banks, news from Reuters	2007–2014	Text, sentence	Sentence vector + DFFN	Usefulness, F1-score, AUROC	–
[88]	News from Reuters, fundamental data	2007–2014	Financial ratios and news text	doc2vec + NN	Relative usefulness	Doc2vec
[89]	Macro/Micro economic variables, Bank charac-teristics/performance variables from BHC	1976–2017	Macro economic variables and bank performances	CGAN, MVN, MV-t, LSTM, VAR, FE-QAR	RMSE, Log likelihood, Loan loss rate	–
[90]	Financial statements of French companies	2002–2006	Financial ratios	DBN	Recall, Precision, F1-score, FP, FN	–
[91]	Stock returns of American publicly-traded companies from CRSP	2001–2011	Price data	DBN	Accuracy	Python, Theano
[92]	Financial statements of several companies from Japanese stock market	2002–2016	Financial ratios	CNN	F1-score, AUROC	–
[93]	Mortgage dataset with local and national economic factors	1995–2014	Mortgage related features	DMLP	Negative average log-likelihood	AWS
[94]	Mortgage data from Norwegian financial service group, DNB	2012–2016	Personal financial variables	CNN	Accuracy, Sensitivity, Specificity, AUROC	–
[95]	Private brokerage company's real data of risky transactions	–	250 features: order details, etc.	CNN, LSTM	F1-Score	Keras, Tensorflow
[96]	Several datasets combined to create a new one	1996–2017	Index data, 10-year Bond yield, exchange rates,	Logit, CART, RF, SVM, NN, XGBoost, DMLP	AUROC, KS, G-mean, likelihood ratio, DP, BA, WBA	R

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

Deep learning for financial applications:
Fraud detection studies

Art.	Data set	Period	Feature set	Method	Performance criteria	Env.
[114]	Debit card transactions by a local Indonesia bank	2016–2017	Financial transaction amount on several time periods	CNN, Stacked-LSTM, CNN-LSTM	AUROC	–
[115]	Credit card transactions from retail banking	2017	Transaction variables and several derived features	LSTM, GRU	Accuracy	Keras
[116]	Card purchases' transactions	2014–2015	Probability of fraud per currency/origin country, other fraud related features	DMLP	AUROC	–
[117]	Transactions made with credit cards by European cardholders	2013	Personal financial variables to PCA	DMLP, RF	Recall, Precision, Accuracy	–
[118]	Credit-card transactions	2015	Transaction and bank features	LSTM	AUROC	Keras, Scikit-learn
[119]	Databases of foreign trade of the Secretariat of Federal Revenue of Brazil	2014	8 Features: Foreign Trade, Tax, Transactions, Employees, Invoices, etc	AE	MSE	H2O, R
[120]	Chamber of Deputies open data, Companies data from Secretariat of Federal Revenue of Brazil	2009–2017	21 features: Brazilian State expense, party name, Type of expense, etc.	Deep Autoencoders	MSE, RMSE	H2O, R
[121]	Real-world data for automobile insurance company labeled as fradulent	–	Car, insurance and accident related features	DMLP + LDA	TP, FP, Accuracy, Precision, F1-score	–
[122]	Transactions from a giant online payment platform	2006	Personal financial variables	GBDT+DMLP	AUROC	–
[123]	Financial transactions	–	Transaction data	LSTM	t-SNE	–
[124]	Empirical data from Greek firms	–	–	DQL	Revenue	Torch

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Deep learning for financial applications: Portfolio management studies

Art.	Data set	Period	Feature set	Method	Performance criteria	Env.
[65]	Cryptocurrencies, Bitcoin	2014–2017	Price data	CNN, RNN, LSTM	Accumulative portfolio value, MDD, SR	–
[127]	Stocks from NYSE, AMEX, NASDAQ	1965–2009	Price data	Autoencoder + RBM	Accuracy, confusion matrix	–
[128]	20 stocks from S&P500	2012–2015	Technical indicators	DMLP	Accuracy	Python, Scikit Learn, Keras, Theano
[129]	Chinese stock data	2012–2013	Technical, fundamental data	Logistic Regression, RF, DMLP	AUC, accuracy, precision, recall, f1, tpr, fpr	Keras, Tensorflow, Python, Scikit learn
[130]	Top 5 companies in S&P500	–	Price data and Financial ratios	LSTM, Auto-encoding, Smart indexing	CAGR	–
[131]	IBB biotechnology index, stocks	2012–2016	Price data	Auto-encoding, Calibrating, Validating, Verifying	Returns	–
[132]	Taiwans stock market	–	Price data	Elman RNN	MSE, return	–
[133]	FOREX (EUR/USD, etc.), Gold	2013	Price data	Evolino RNN	Return	Python
[134]	Stocks in NYSE, AMEX, NASDAQ, TAQ intraday trade	1993–2017	Price, 15 firm characteristics	LSTM+DMLP	Monthly return, SR	Python,Keras, Tensorflow in AWS
[135]	S&P500	1985–2006	monthly and daily log-returns	DBN+MLP	Validation, Test Error	Theano, Python, Matlab
[136]	10 stocks in S&P500	1997–2016	OCHLV, Price data	RNN, LSTM, GRU	Accuracy, Monthly return	Keras, Tensorflow
[137]	Analyst reports on the TSE and Osaka Exchange	2016–2018	Text	LSTM, CNN, Bi-LSTM	Accuracy, R^2	R, Python, MeCab
[138]	Stocks from Chinese/American stock market	2015–2018	OCHLV, Fundamental data	DDPG, PPO	SR, MDD	–
[139]	Hedge fund monthly return data	1996–2015	Return, SR, STD, Skewness, Kurtosis, Omega ratio, Fund alpha	DMLP	Sharpe ratio, Annual return, Cum. return	–
[140]	12 most-volumed cryptocurrency	2015–2016	Price data	CNN + RL	SR, portfolio value, MDD	–

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Deep learning for financial applications:
Asset pricing and derivatives market studies

Art.	Der. type	Data set	Period	Feature set	Method	Performance criteria	Env.
[137]	Asset pricing	Analyst reports on the TSE and Osaka Exchange	2016–2018	Text	LSTM, CNN, Bi-LSTM	Accuracy, R^2	R, Python, MeCab
[142]	Options	Simulated a range of call option prices	–	Price data, option strike/maturity, dividend/risk free rates, volatility	DMLP	RMSE, the average percentage pricing error	Tensorflow
[143]	Futures, Options	TAIEX Options	2017	OCHLV, fundamental analysis, option price	DMLP, DMLP with Black scholes	RMSE, MAE, MAPE	–
[144]	Equity returns	Returns in NYSE, AMEX, NASDAQ	1975–2017	57 firm characteristics	Fama–French n-factor model DL	R^2,RMSE	Tensorflow

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Deep learning for financial applications:

Cryptocurrency and blockchain studies

Art.	Data set	Period	Feature set	Method	Performance criteria	Env.
[46]	Bitcoin, Dash, Ripple, Monero, Litecoin, Dogecoin, Nxt, Namecoin	2014–2017	MA, BOLL, the CRIX daily returns, Euribor interest rates, OCHLV of EURO/UK, EURO/USD, US/JPY	LSTM, RNN, DMLP	Accuracy, F1-measure	Python, Tensorflow
[65]	Cryptocurrencies, Bitcoin	2014–2017	Price data	CNN	Accumulative portfolio value, MDD, SR	–
[140]	12 most-volumed cryptocurrency	2015–2016	Price data	CNN + RL	SR, portfolio value, MDD	
[145]	Bitcoin data	2010–2017	Hash value, bitcoin address, public/private key, digital signature, etc.	Takagi–Sugeno Fuzzy cognitive maps	Analytical hierarchy process	–
[146]	Bitcoin data	2012, 2013, 2016	TransactionId, input/output Addresses, timestamp	Graph embedding using heuristic, laplacian eigen-map, deep AE	F1-score	–
[147]	Bitcoin, Litecoin, StockTwits	2015–2018	OCHLV, technical indicators, sentiment analysis	CNN, LSTM, State Frequency Model	MSE	Keras, Tensorflow
[148]	Bitcoin	2013–2016	Price data	Bayesian optimized RNN, LSTM	Sensitivity, specificity, precision, accuracy, RMSE	Keras, Python, Hyperas

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

Deep learning for financial applications:

Financial sentiment studies coupled with text mining for forecasting

Art.	Data set	Period	Feature set	Method	Performance criteria	Env.
[137]	Analyst reports on the TSE and Osaka Exchange	2016–2018	Text	LSTM, CNN, Bi-LSTM	Accuracy, R^2	R, Python, MeCab
[150]	Sina Weibo, Stock market records	2012–2015	Technical indicators, sentences	DRSE	F1-score, precision, recall, accuracy, AUROC	Python
[151]	News from Reuters and Bloomberg for S&P500 stocks	2006–2015	Financial news, price data	DeepClue	Accuracy	Dynet software
[152]	News from Reuters and Bloomberg, Historical stock security data	2006–2013	News, price data	DMLP	Accuracy	–
[153]	SCI prices	2008–2015	OCHL of change rate, price	Emotional Analysis + LSTM	MSE	–
[154]	SCI prices	2013–2016	Text data and Price data	LSTM	Accuracy, F1-Measure	Python, Keras
[155]	Stocks of Google, Microsoft and Apple	2016–2017	Twitter sentiment and stock prices	RNN	–	Spark, Flume,Twitter API,
[156]	30 DJIA stocks, S&P500, DJI, news from Reuters	2002–2016	Price data and features from news articles	LSTM, NN, CNN and word2vec	Accuracy	VADER
[157]	Stocks of CSI300 index, OCHLV of CSI300 index	2009–2014	Sentiment Posts, Price data	Naive Bayes + LSTM	Precision, Recall, F1-score, Accuracy	Python, Keras
[158]	S&P500, NYSE Composite, DJIA, NASDAQ Composite	2009–2011	Twitter moods, index data	DNN, CNN	Error rate	Keras, Theano

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

Deep learning for financial applications:

Text mining studies without sentiment analysis for forecasting

Art.	Data set	Period	Feature set	Method	Performance criteria	Env.
[68]	Energy-Sector/ Company-Centric Tweets in S&P500	2015–2016	Text and Price data	RNN, KNN, SVR, LinR	Return, SR, precision, recall, accuracy	Python, Tweepy API
[165]	News from Reuters, Bloomberg	2006–2013	Financial news, price data	Bi-GRU	Accuracy	Python, Keras
[166]	News from Sina.com, ACE2005 Chinese corpus	2012–2016	A set of news text	Their unique algorithm	Precision, Recall, F1-score	–
[167]	CDAX stock market data	2010–2013	Financial news, stock market data	LSTM	MSE, RMSE, MAE, Accuracy, AUC	TensorFlow, Theano, Python, Scikit-Learn
[168]	Apple, Airbus, Amazon news from Reuters, Bloomberg, S&P500 stock prices	2006–2013	Price data, news, technical indicators	TGRU, stock2vec	Accuracy, precision, AUROC	Keras, Python
[169]	S&P500 Index, 15 stocks in S&P500	2006–2013	News from Reuters and Bloomberg	CNN	Accuracy, MCC	–
[170]	S&P500 index news from Reuters	2006–2013	Financial news titles, Technical indicators	SI-RCNN (LSTM + CNN)	Accuracy	–
[171]	10 stocks in Nikkei 225 and news	2001–2008	Textual information and Stock prices	Paragraph Vector + LSTM	Profit	–
[172]	NIFTY50 Index, NIFTY Bank/Auto/IT/Energy Index, News	2013–2017	Index data, news	LSTM	MCC, Accuracy	–
[173]	Price data, index data, news, social media data	2015	Price data, news from articles and social media	Coupled matrix and tensor	Accuracy, MCC	Jieba
[174]	HS300	2015–2017	Social media news, price data	RNN-Boost with LDA	Accuracy, MAE, MAPE, RMSE	Python, Scikit-learn

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

Deep learning for financial applications:

Text mining studies without sentiment analysis for forecasting

Art.	Data set	Period	Feature set	Method	Performance criteria	Env.
[175]	News and Chinese stock data	2014–2017	Selected words in a news	HAN	Accuracy, Annual return	–
[176]	News, stock prices from Hong Kong Stock Exchange	2001	Price data and TF-IDF from news	ELM, DLR, PCA, BELM, KELM, NN	Accuracy	Matlab
[177]	TWSE index, 4 stocks in TWSE	2001–2017	Technical indicators, Price data, News	CNN + LSTM	RMSE, Profit	Keras, Python, TALIB
[178]	Stock of Tsugami Corporation	2013	Price data	LSTM	RMSE	Keras, Tensorflow
[179]	News, Nikkei Stock Average and 10-Nikkei companies	1999–2008	news, MACD	RNN, RBM+DBN	Accuracy, *P*-value	–
[180]	ISMIS 2017 Data Mining Competition dataset	–	Expert identifier, classes	LSTM + GRU + FFNN	Accuracy	–
[181]	Reuters, Bloomberg News, S&P500 price	2006–2013	News and sentences	LSTM	Accuracy	–
[182]	APPL from S&P500 and news from Reuters	2011–2017	Input news, OCHLV, Technical indicators	CNN + LSTM, CNN+SVM	Accuracy, F1-score	Tensorflow
[183]	Nikkei225, S&P500, news from Reuters and Bloomberg	2001–2013	Stock price data and news	DGM	Accuracy, MCC, %profit	–
[184]	Stocks from S&P500	2006–2013	Text (news) and Price data	LAR+News, RF+News	MAPE, RMSE	–

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

Deep learning for financial applications:

Financial sentiment studies coupled with text mining without forecasting

Art.	Data set	Period	Feature set	Method	Performance criteria	Env.
[85]	883 BHC from EDGAR	2006–2017	Tokens, weighted sentiment polarity, leverage and ROA	CNN, LSTM, SVM, Random Forest	Accuracy, Precision, Recall, F1-score	Keras, Python, Scikit-learn
[185]	SemEval-2017 dataset, financial text, news, stock market data	2017	Sentiments in Tweets, News headlines	Ensemble SVR, CNN, LSTM, GRU	Cosine similarity score, agreement score, class score	Python, Keras, Scikit Learn
[186]	Financial news from Reuters	2006–2015	Word vector, Lexical and Contextual input	Targeted dependency tree LSTM	Cumulative abnormal return	–
[187]	Stock sentiment analysis from StockTwits	2015	StockTwits messages	LSTM, Doc2Vec, CNN	Accuracy, precision, recall, f-measure, AUC	–
[188]	Sina Weibo, Stock market records	2012–2015	Technical indicators, sentences	DRSE	F1-score, precision, recall, accuracy, AUROC	Python
[189]	News from NowNews, AppleDaily, LTN, MoneyDJ for 18 stocks	2013–2014	Text, Sentiment	LSTM, CNN	Return	Python, Tensorflow
[190]	StockTwits	2008–2016	Sentences, StockTwits messages	CNN, LSTM, GRU	MCC, WSURT	Keras, Tensorflow
[191]	Financial statements of Japan companies	–	Sentences, text	DMLP	Precision, recall, f-score	–
[192]	Twitter posts, news headlines	–	Sentences, text	Deep-FASP	Accuracy, MSE, R^2	–
[193]	Forums data	2004–2013	Sentences and keywords	Recursive neural tensor networks	Precision, recall, f-measure	–
[194]	News from Financial Times related US stocks	–	Sentiment of news headlines	SVR, Bidirectional LSTM	Cosine similarity	Python, Scikit Learn, Keras, Tensorflow

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

Deep learning for financial applications: Other text mining studies

Art.	Data set	Period	Feature set	Method	Performance criteria	**Env.**
[72]	News from NowNews, AppleDaily, LTN, MoneyDJ for 18 stocks	2013–2014	Text, Sentiment	DMLP	Return	Python, Tensorflow
[86]	The event data set for large European banks, news articles from Reuters	2007–2014	Word, sentence	DMLP +NLP preprocess	Relative usefulness, F1-score	–
[87]	Event dataset on European banks, news from Reuters	2007–2014	Text, sentence	Sentence vector + DFFN	Usefulness, F1-score, AUROC	–
[88]	News from Reuters, fundamental data	2007–2014	Financial ratios and news text	doc2vec + NN	Relative usefulness	Doc2vec
[121]	Real-world data for automobile insurance company labeled as fradulent	–	Car, insurance and accident related features	DMLP + LDA	TP, FP, Accuracy, Precision, F1-score	–
[123]	Financial transactions	–	Transaction data	LSTM	t-SNE	–
[195]	Taiwan's National Pension Insurance	2008–2014	Insured's id, area-code, gender, etc.	RNN	Accuracy, total error	Python
[196]	StockTwits	2015–2016	Sentences, StockTwits messages	Doc2vec, CNN	Accuracy, precision, recall, f-measure, AUC	Python, Tensorflow

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

Deep learning for financial applications:
Other theoretical or conceptual studies

Art.	SubTopic	IsTimeSeries?	Data set	Period	Feature set	Method
[197]	Analysis of AE, SVD	Yes	Selected stocks from the IBB index and stock of Amgen Inc.	2012–2014	Price data	AE, SVD
[198]	Fraud Detection in Banking	No	Risk Management / Fraud Detection	–	–	DRL

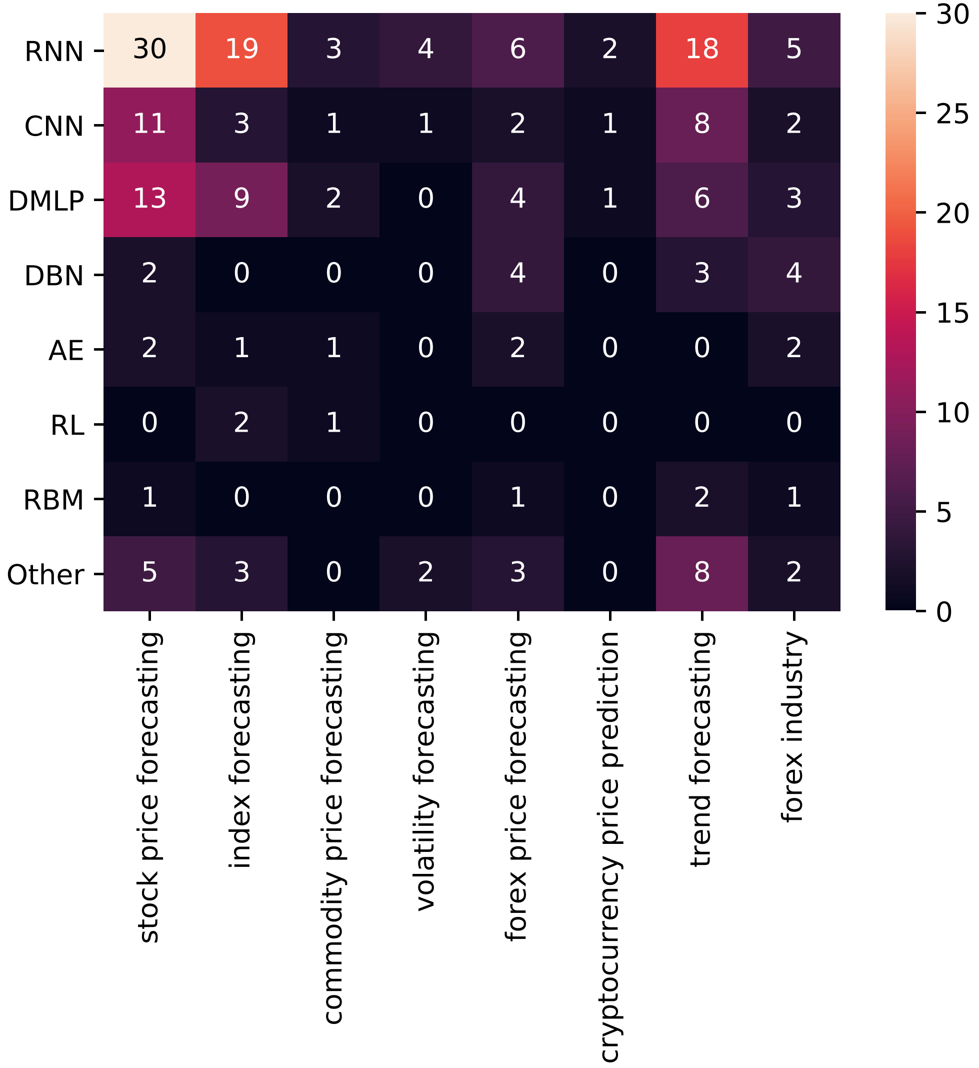
Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

Deep learning for financial applications: Other financial applications

Art.	Subtopic	Data set	Period	Feature set	Method	Performance criteria	Env.
[47]	Improving trading decisions	S&P500, KOSPI, HSI, and EuroStoxx50	1987–2017	200-days stock price	Deep Q-Learning and DMLP	Total profit, Correlation	–
[193]	Identifying Top Sellers In Underground Economy	Forums data	2004–2013	Sentences and keywords	Recursive neural tensor networks	Precision, recall, f-measure	–
[195]	Predicting Social Ins. Payment Behavior	Taiwan's National Pension Insurance	2008–2014	Insured's id, area-code, gender, etc.	RNN	Accuracy, total error	Python
[199]	Speedup	45 CME listed commodity and FX futures	1991–2014	Price data	DNN	–	–
[200]	Forecasting Fundamentals	Stocks in NYSE, NASDAQ or AMEX exchanges	1970–2017	16 fundamental features from balance sheet	DMLP, LFM	MSE, Compound annual return, SR	–
[201]	Predicting Bank Telemarketing	Phone calls of bank marketing data	2008–2010	16 finance-related attributes	CNN	Accuracy	–
[202]	Corporate Performance Prediction	22 pharmaceutical companies data in US stock market	2000–2015	11 financial and 4 patent indicator	RBM, DBN	RMSE, profit	–

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

Financial time series forecasting with deep learning: Topic-model heatmap



Source: Omer Berat Sezer, Mehmet Ugur Gudelek, and Ahmet Murat Ozbayoglu (2020), "Financial time series forecasting with deep learning: A systematic literature review: 2005–2019." Applied Soft Computing 90 (2020): 106181.

Stock price forecasting using only raw time series data

Art.	Data set	Period	Feature set	Lag	Horizon	Method	Performance criteria	Env.
[80]	38 stocks in KOSPI	2010–2014	Lagged stock returns	50 min	5 min	DNN	NMSE, RMSE, MAE, MI	–
[81]	China stock market, 3049 Stocks	1990–2015	OCHLV	30 d	3 d	LSTM	Accuracy	Theano, Keras
[82]	Daily returns of 'BRD' stock in Romanian Market	2001–2016	OCHLV	–	1 d	LSTM	RMSE, MAE	Python, Theano
[83]	297 listed companies of CSE	2012–2013	OCHLV	2 d	1 d	LSTM, SRNN, GRU	MAD, MAPE	Keras
[84]	5 stock in NSE	1997–2016	OCHLV, Price data, turnover and number of trades.	200 d	1..10 d	LSTM, RNN, CNN, MLP	MAPE	–
[85]	Stocks of Infosys, TCS and CIPLA from NSE	2014	Price data	–	–	RNN, LSTM and CNN	Accuracy	–
[86]	10 stocks in S&P500	1997–2016	OCHLV, Price data	36 m	1 m	RNN, LSTM, GRU	Accuracy, Monthly return	Keras, Tensorflow
[87]	Stocks data from S&P500	2011–2016	OCHLV	1 d	1 d	DBN	MSE, norm-RMSE, MAE	–
[88]	High-frequency transaction data of the CSI300 futures	2017	Price data	–	1 min	DNN, ELM, RBF	RMSE, MAPE, Accuracy	Matlab
[89]	Stocks in the S&P500	1990–2015	Price data	240 d	1 d	DNN, GBT, RF	Mean return, MDD, Calmar ratio	H2O
[90]	ACI Worldwide, Staples, and Seagate in NASDAQ	2006–2010	Daily closing prices	17 d	1 d	RNN, ANN	RMSE	–
[91]	Chinese Stocks	2007–2017	OCHLV	30 d	1..5 d	CNN + LSTM	Annualized Return, Mxm Retracement	Python
[92]	20 stocks in S&P500	2010–2015	Price data	–	–	AE + LSTM	Weekly Returns	–
[93]	S&P500	1985–2006	Monthly and daily log-returns	*	1 d	DBN+MLP	Validation, Test Error	Theano, Python, Matlab
[94]	12 stocks from SSE Composite Index	2000–2017	OCHLV	60 d	1..7 d	DWNN	MSE	Tensorflow
[95]	50 stocks from NYSE	2007–2016	Price data	–	1d, 3 d, 5 d	SFM	MSE	–

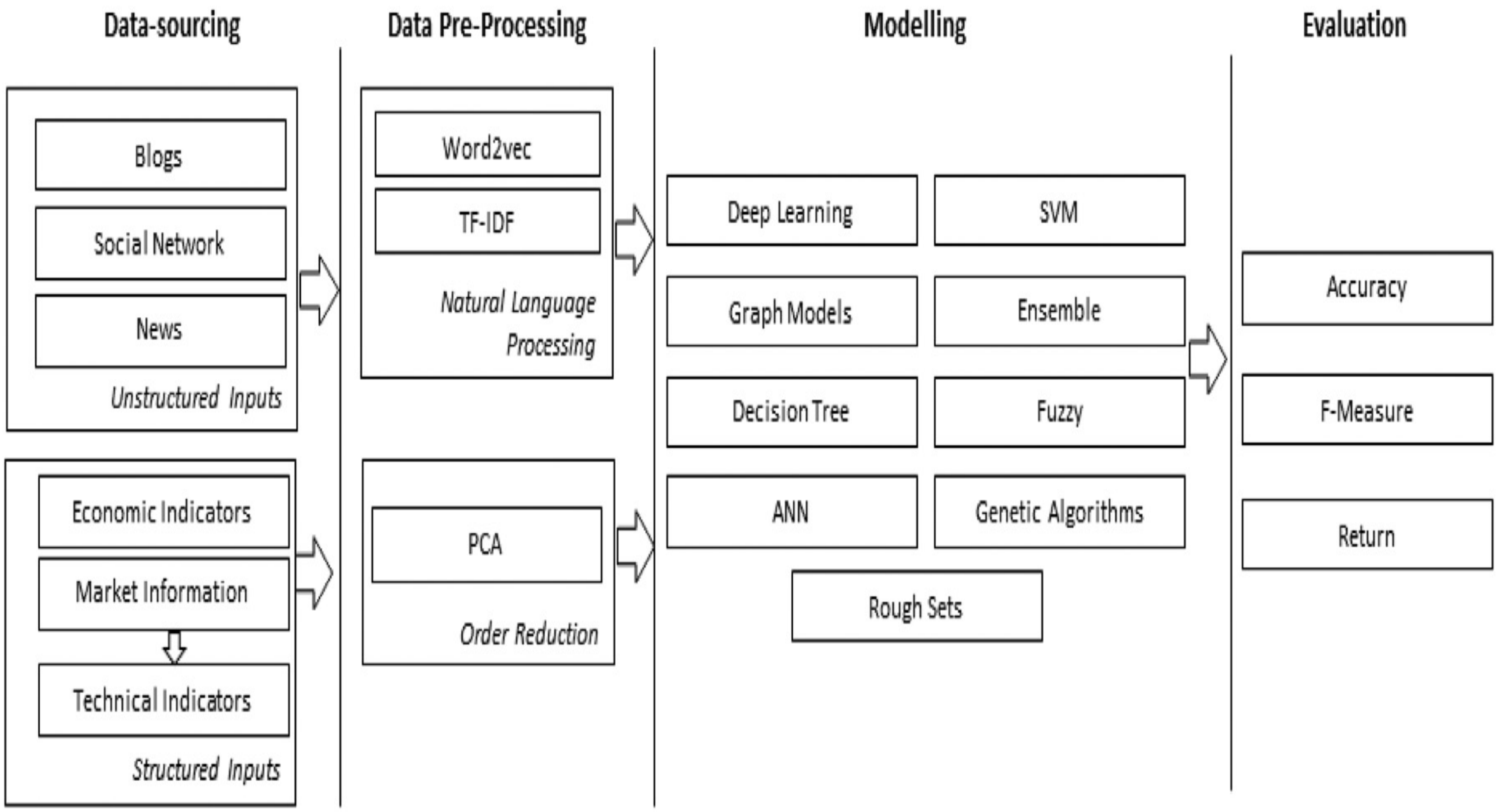
Source: Omer Berat Sezer, Mehmet Ugur Gudelek, and Ahmet Murat Ozbayoglu (2020), "Financial time series forecasting with deep learning: A systematic literature review: 2005–2019." Applied Soft Computing 90 (2020): 106181.

Stock price forecasting using various data

Art.	Data set	Period	Feature set	Lag	Horizon	Method	Performance criteria	Env.
[96]	Japan Index constituents from WorldScope	1990–2016	25 Fundamental Features	10 d	1 d	DNN	Correlation, Accuracy, MSE	Tensorflow
[97]	Return of S&P500	1926–2016	Fundamental Features:	–	1 s	DNN	MSPE	Tensorflow
[98]	U.S. low-level disaggregated macroeconomic time series	1959–2008	GDP, Unemployment rate, Inventories, etc.	–	–	DNN	R^2	–
[99]	CDAX stock market data	2010–2013	Financial news, stock market data	20 d	1 d	LSTM	MSE, RMSE, MAE, Accuracy, AUC	TensorFlow, Theano, Python, Scikit-Learn
[100]	Stock of Tsugami Corporation	2013	Price data	–	–	LSTM	RMSE	Keras, Tensorflow
[101]	Stocks in China's A-share	2006–2007	11 technical indicators	–	1 d	LSTM	AR, IR, IC	–
[102]	SCI prices	2008–2015	OCHL of change rate, price	7 d	–	EmotionalAnalysis + LSTM	MSE	–
[103]	10 stocks in Nikkei 225 and news	2001–2008	Textual information and Stock prices	10 d	–	Paragraph Vector + LSTM	Profit	–
[104]	TKC stock in NYSE and QQQQ ETF	1999–2006	Technical indicators, Price	50 d	1 d	RNN (Jordan–Elman)	Profit, MSE	Java
[105]	10 Stocks in NYSE	–	Price data, Technical indicators	20 min	1 min	LSTM, MLP	RMSE	–
[106]	42 stocks in China's SSE	2016	OCHLV, Technical Indicators	242 min	1 min	GAN (LSTM, CNN)	RMSRE, DPA, GAN-F, GAN-D	–
[107]	Google's daily stock data	2004–2015	OCHLV, Technical indicators	20 d	1 d	$(2D)^2$ PCA + DNN	SMAPE, PCD, MAPE, RMSE, HR, TR, R^2	R, Matlab
[108]	GarantiBank in BIST, Turkey	2016	OCHLV, Volatility, etc.	–	–	PLR, Graves LSTM	MSE, RMSE, MAE, RSE, R^2	Spark
[109]	Stocks in NYSE, AMEX, NASDAQ, TAQ intraday trade	1993–2017	Price, 15 firm characteristics	80 d	1 d	LSTM+MLP	Monthly return, SR	Python,Keras, Tensorflow in AWS
[110]	Private brokerage company's real data of risky transactions	–	250 features: order details, etc.	–	–	CNN, LSTM	F1-Score	Keras, Tensorflow
[111]	Fundamental and Technical Data, Economic Data	–	Fundamental , technical and market information	–	–	CNN	–	–
[112]	The LOB of 5 stocks of Finnish Stock Market	2010	FI-2010 dataset: bid/ask and volume	–	*	WMTR, MDA	Accuracy, Precision, Recall, F1-Score	–
[113]	Returns in NYSE, AMEX, NASDAQ	1975–2017	57 firm characteristics	*	–	Fama–French n-factor model DL	R^2, RMSE	Tensorflow

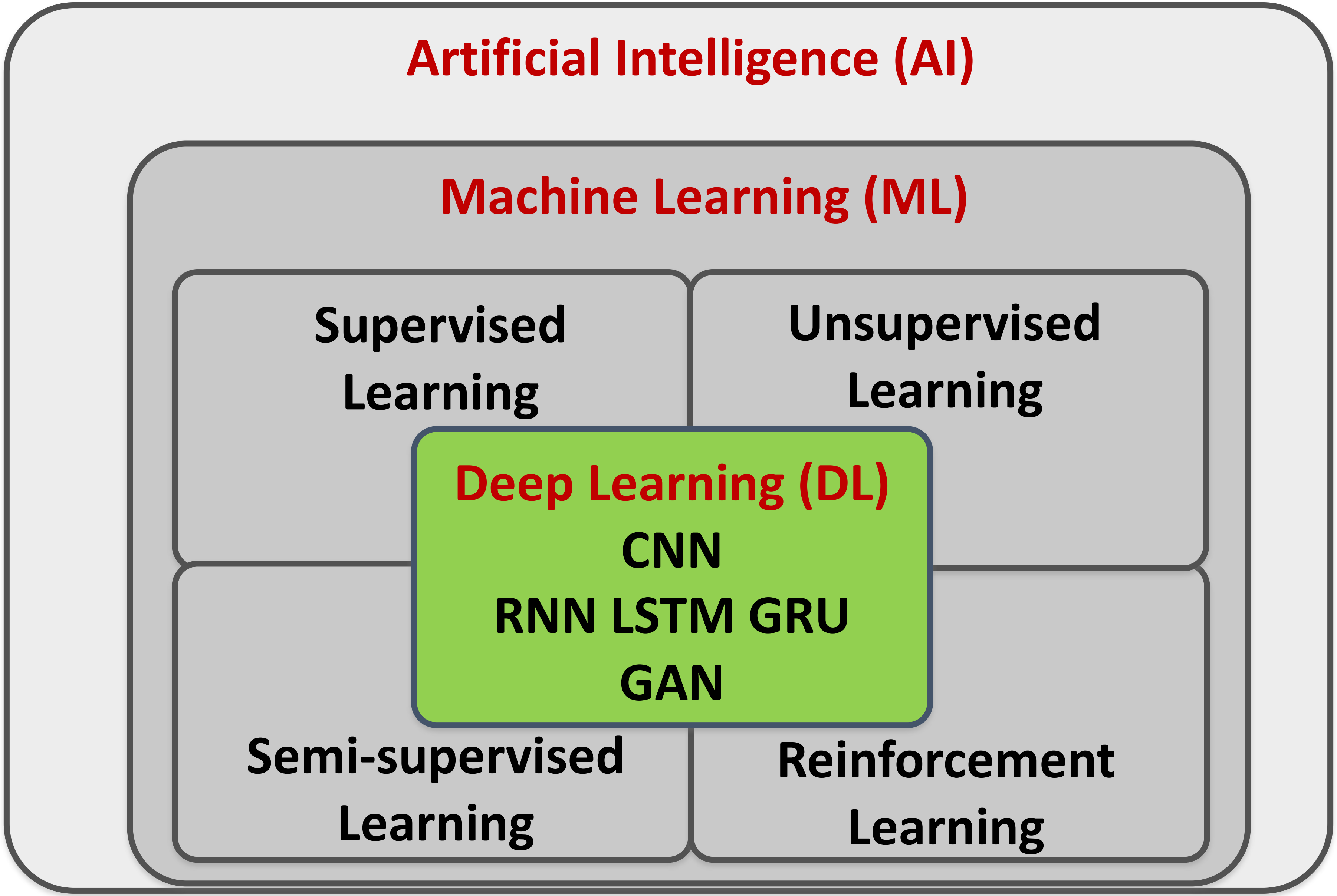
Source: Omer Berat Sezer, Mehmet Ugur Gudelek, and Ahmet Murat Ozbayoglu (2020), "Financial time series forecasting with deep learning: A systematic literature review: 2005–2019." Applied Soft Computing 90 (2020): 106181.

Stock Market Movement Forecast:
Phases of the stock market modeling



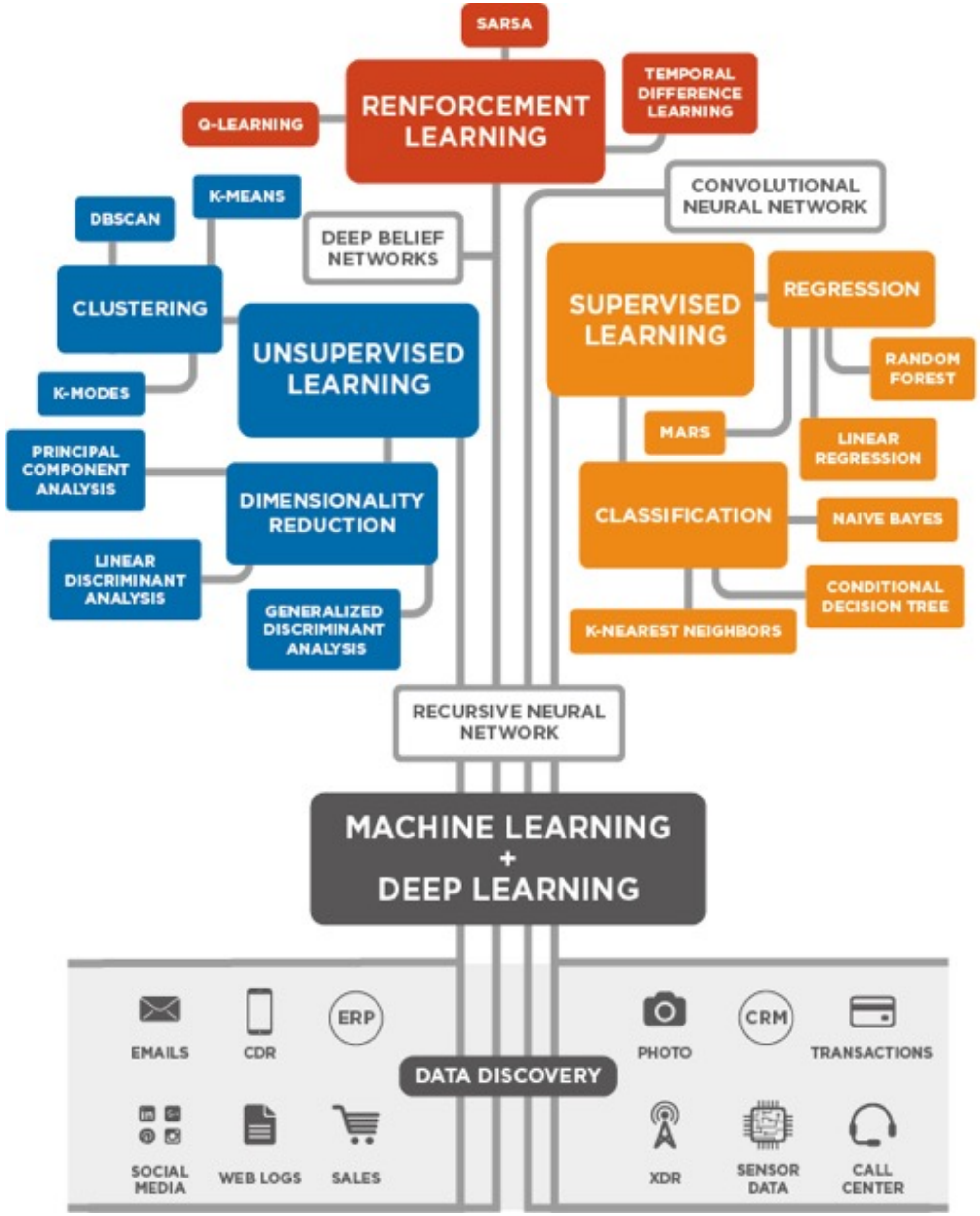
Source: O. Bustos and A. Pomares-Quimbaya (2020), "Stock Market Movement Forecast: A Systematic Review." Expert Systems with Applications (2020): 113464.

AI, ML, DL



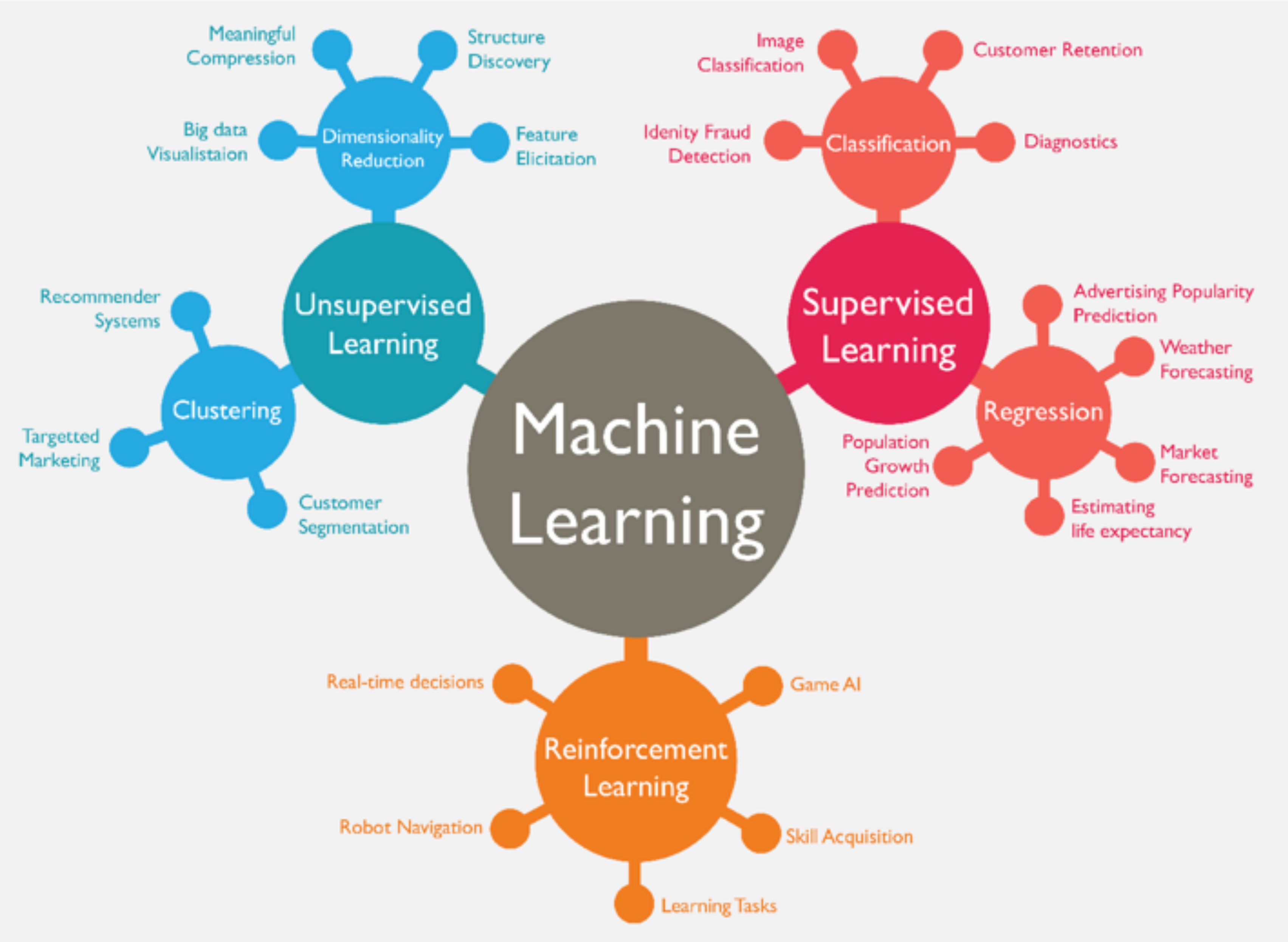
Source: https://leonardoaraujosantos.gitbooks.io/artificial-inteligence/content/deep_learning.html

3 Machine Learning Algorithms



Source: Enrico Galimberti, http://blogs.teradata.com/data-points/tree-machine-learning-algorithms/

Machine Learning (ML)



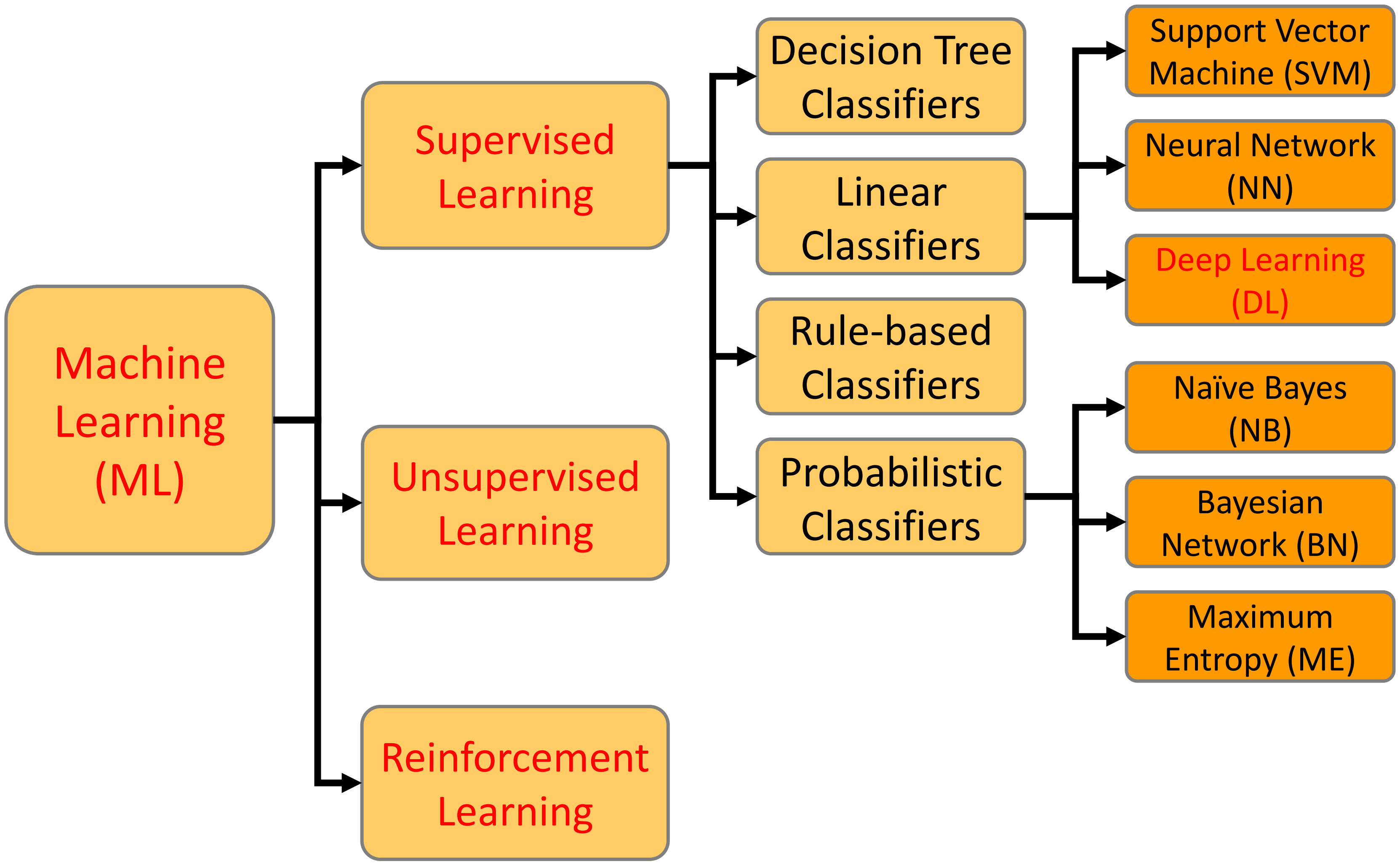
Source: https://www.mactores.com/services/aws-big-data-machine-learning-cognitive-services/

Machine Learning Models

- Deep Learning
- Kernel
- Association rules
- Ensemble
- Decision tree
- Dimensionality reduction
- Clustering
- Regression Analysis
- Bayesian
- Instance based

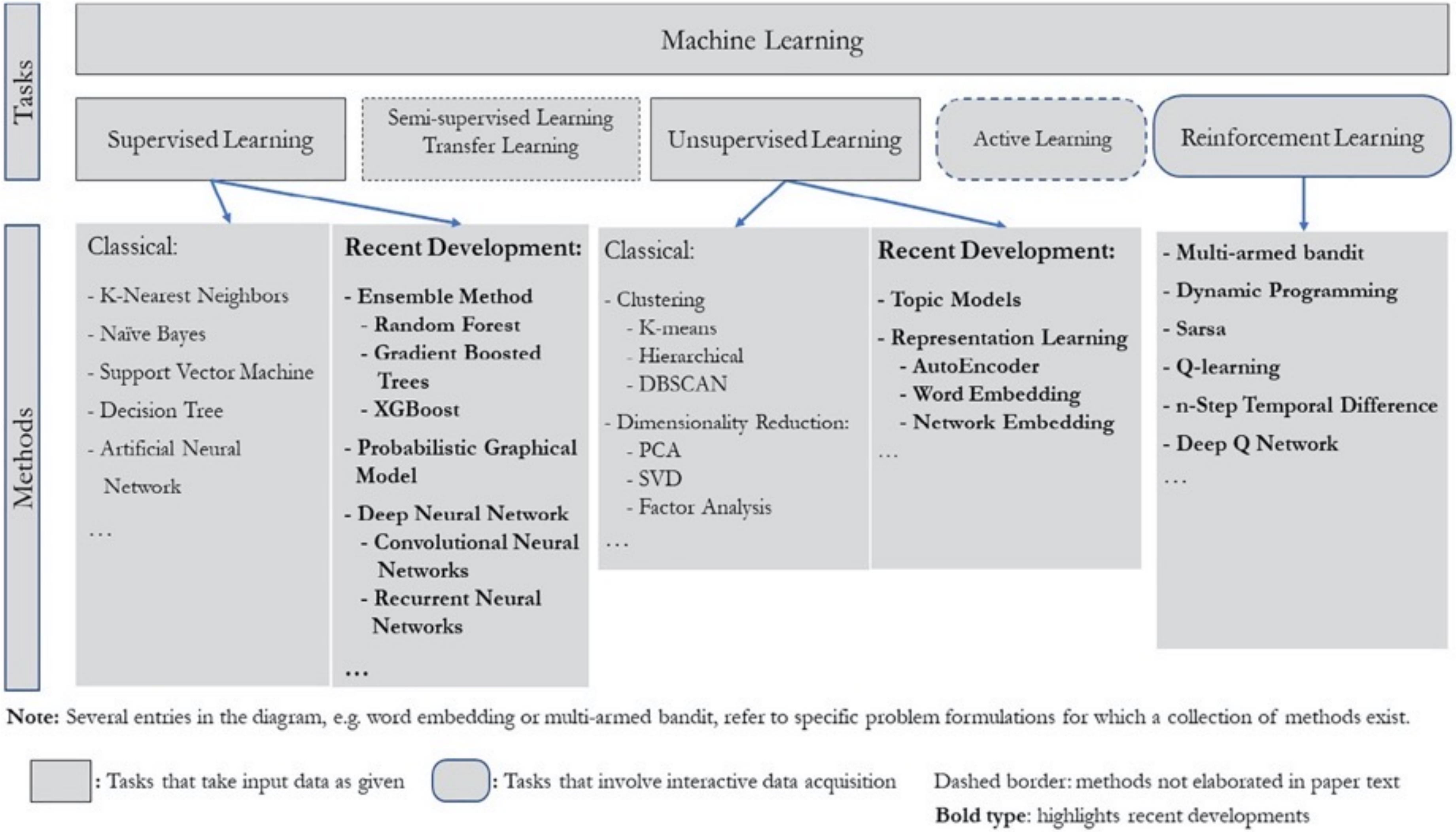
Source: Sunila Gollapudi (2016), Practical Machine Learning, Packt Publishing

Machine Learning (ML) / Deep Learning (DL)



Source: Jesus Serrano-Guerrero, Jose A. Olivas, Francisco P. Romero, and Enrique Herrera-Viedma (2015), "Sentiment analysis: A review and comparative analysis of web services," Information Sciences, 311, pp. 18-38.

Machine Learning Tasks and Methods



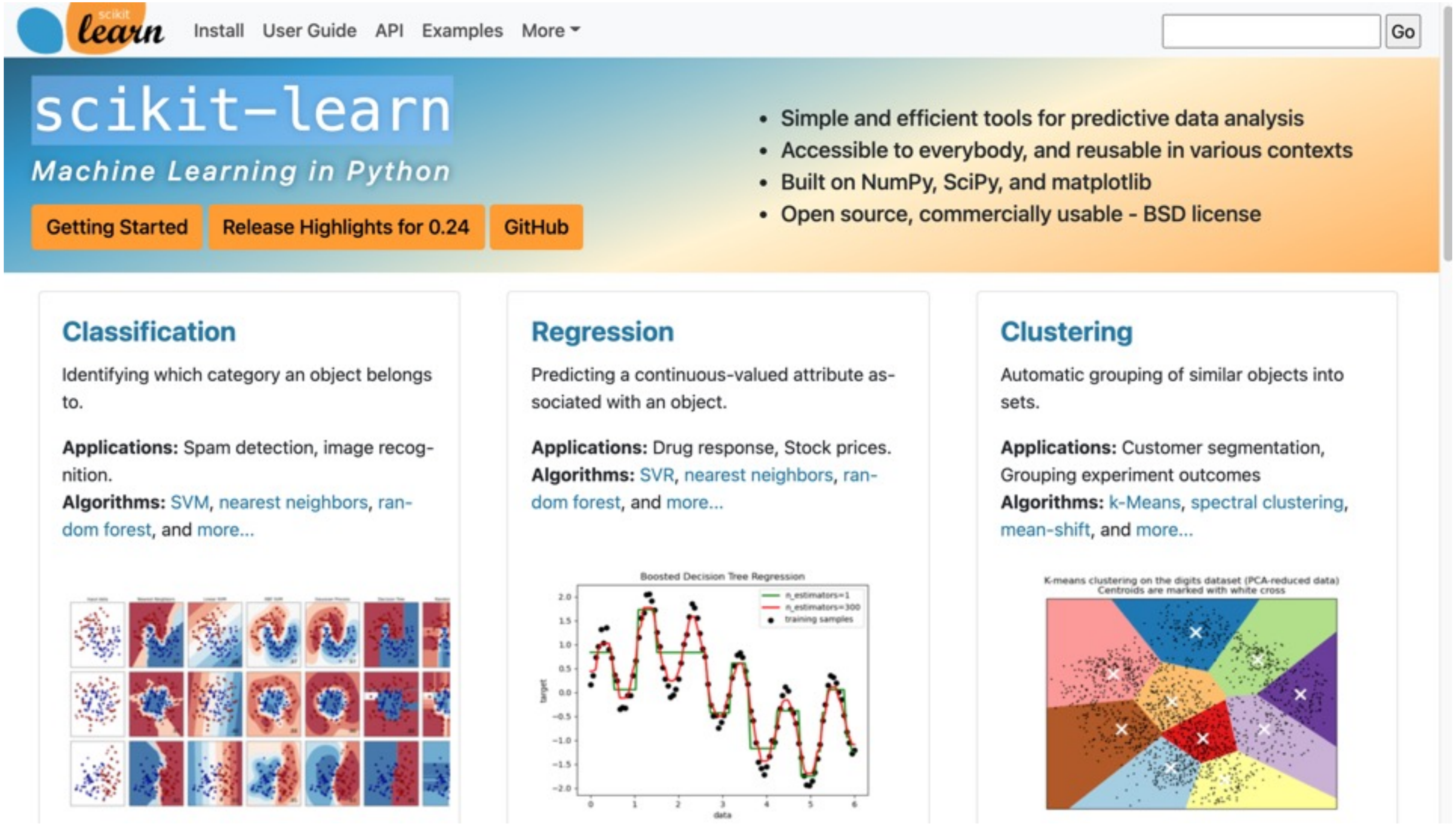
Source: Liye Ma and Baohong Sun (2020), "Machine learning and AI in marketing – Connecting computing power to human insights." International Journal of Research in Marketing, 37, no. 3, 481-504.

Machine Learning

Scikit-Learn

Machine Learning in Python

Scikit-Learn



Source: http://scikit-learn.org/

Machine Learning
Supervised Learning (Classification)
Learning from Examples

$$y = f(x)$$

x	y

Machine Learning
Supervised Learning (Classification)
Learning from Examples

$$y = f(x)$$

x

```
5.1,3.5,1.4,0.2,Iris-setosa
4.9,3.0,1.4,0.2,Iris-setosa
4.7,3.2,1.3,0.2,Iris-setosa
7.0,3.2,4.7,1.4,Iris-versicolor
6.4,3.2,4.5,1.5,Iris-versicolor
6.9,3.1,4.9,1.5,Iris-versicolor
6.3,3.3,6.0,2.5,Iris-virginica
5.8,2.7,5.1,1.9,Iris-virginica
7.1,3.0,5.9,2.1,Iris-virginica
```

y

Linear function

$$y = f(x)$$

$$y = w_1 x + w_0$$

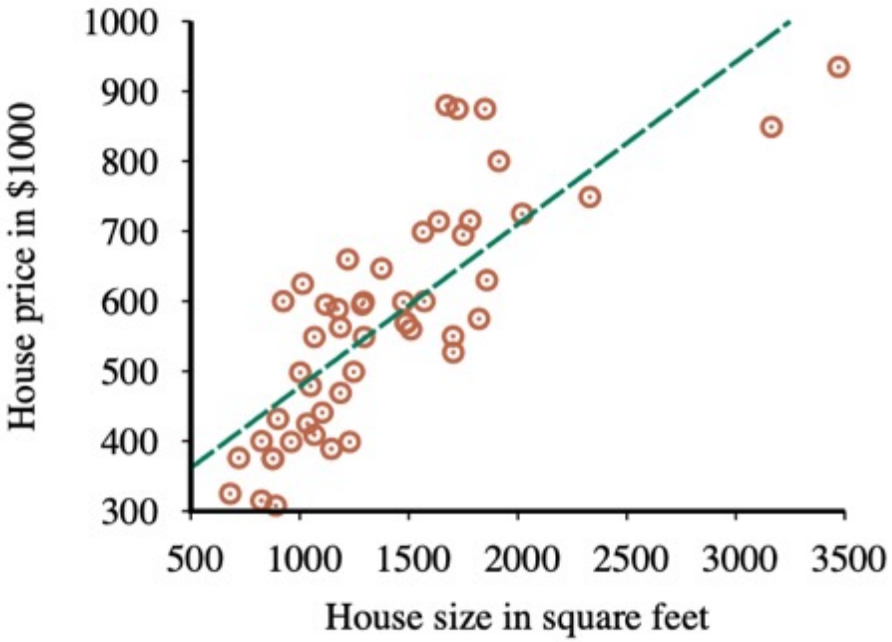
$$h_w(x) = w_1 x + w_0$$

Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson

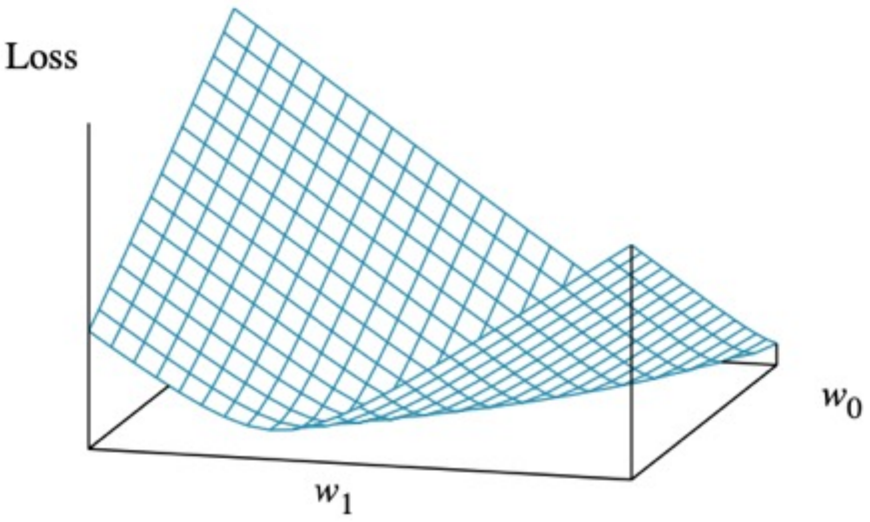
Linear Regression Weight Space

$$h_w(x) = w_1 x + w_0$$

$$w^* = \mathbf{argmin}_w \, Loss(h_w)$$



$y = 0.232\ x + 246$

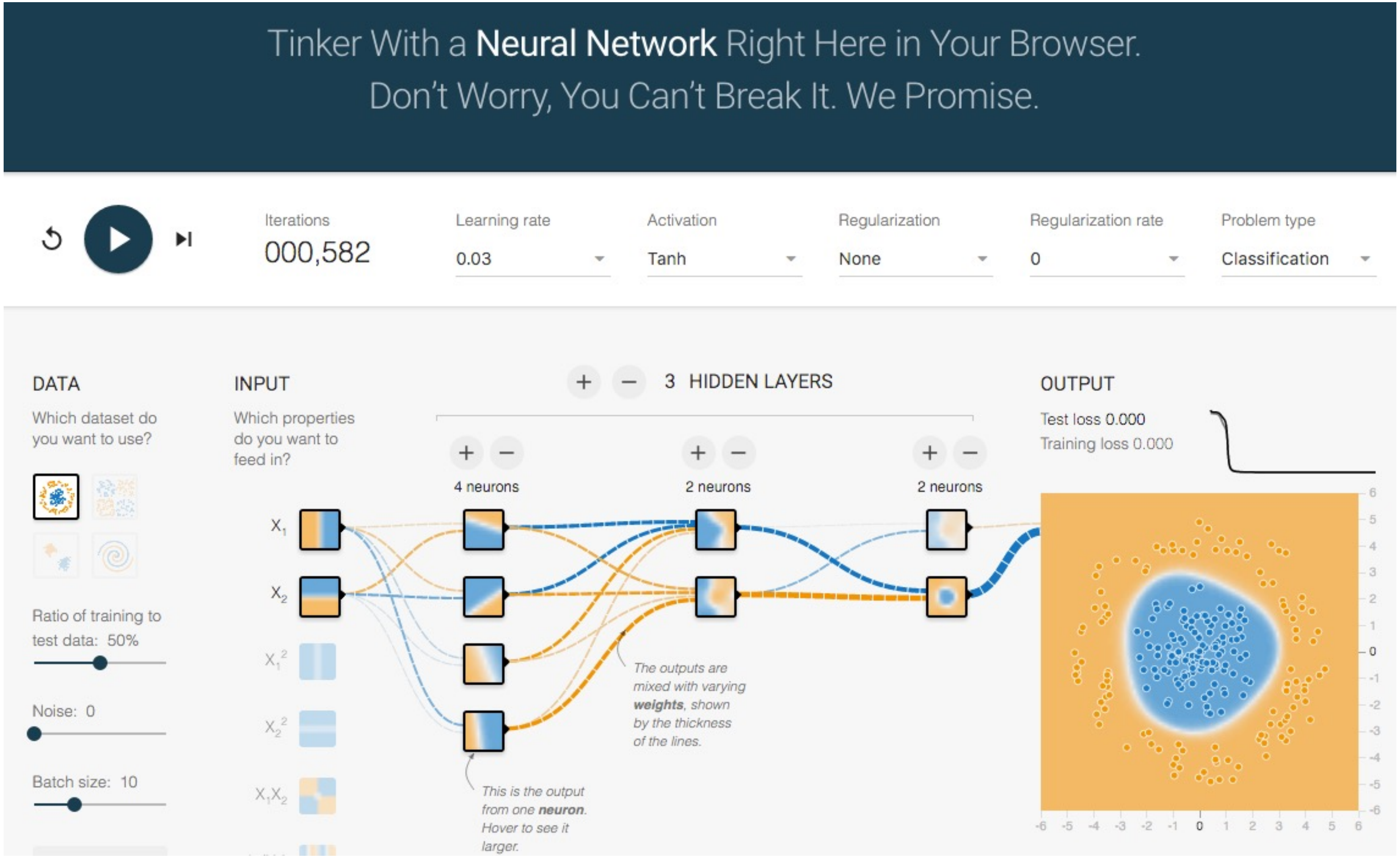


Loss function for Weights (w_1, w_0)

Deep Learning

Deep Learning
and
Neural Networks

TensorFlow Playground



http://playground.tensorflow.org/

Tensor

- 3
  - # a rank 0 tensor; this is a scalar with shape []
- [1. ,2., 3.]
  - # a rank 1 tensor; this is a vector with shape [3]
- [[1., 2., 3.], [4., 5., 6.]]
  - # a rank 2 tensor; a matrix with shape [2, 3]
- [[[1., 2., 3.]], [[7., 8., 9.]]]
  - # a rank 3 tensor with shape [2, 1, 3]

https://www.tensorflow.org/

Scalar 80

Vector [50 60 70]

Matrix

$$\begin{bmatrix} 50 & 60 & 70 \\ 55 & 65 & 75 \end{bmatrix}$$

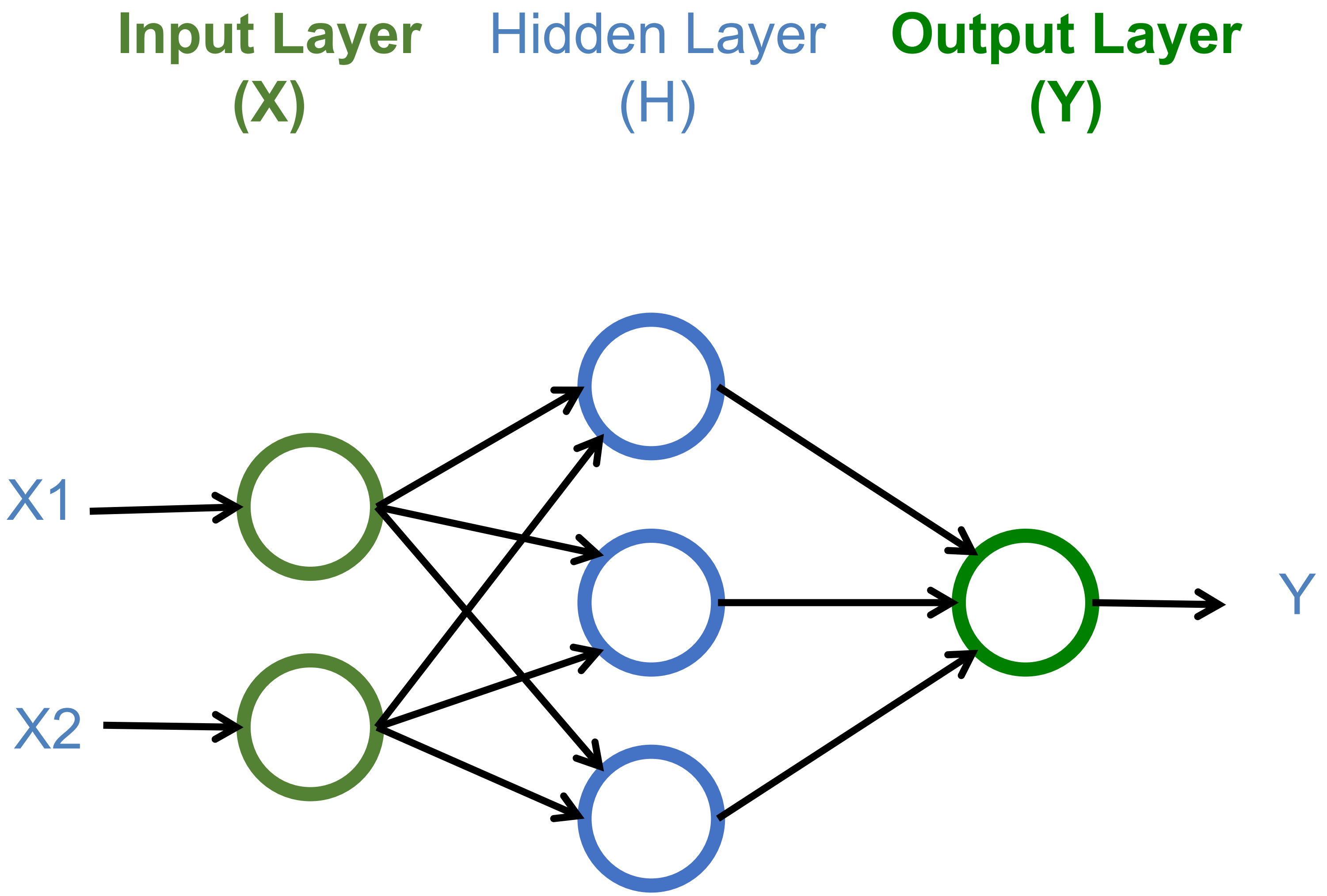
Tensor

$$\begin{bmatrix} [50 & 60 & 70] & [70 & 80 & 90] \\ [55 & 65 & 75] & [75 & 85 & 95] \end{bmatrix}$$

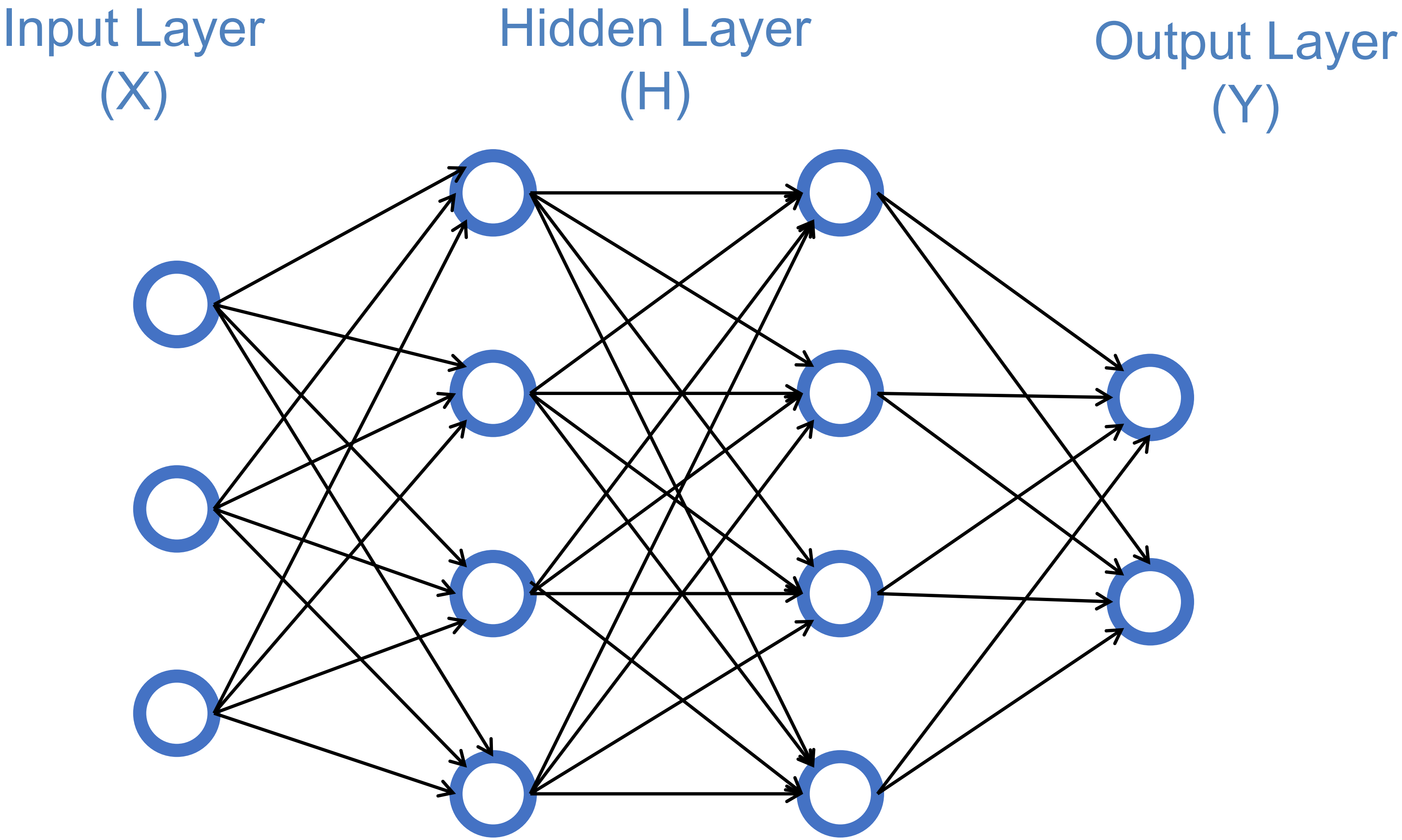
Deep Learning
and
Neural Networks

Deep Learning Foundations: Neural Networks

Deep Learning and Neural Networks



Deep Learning and Neural Networks



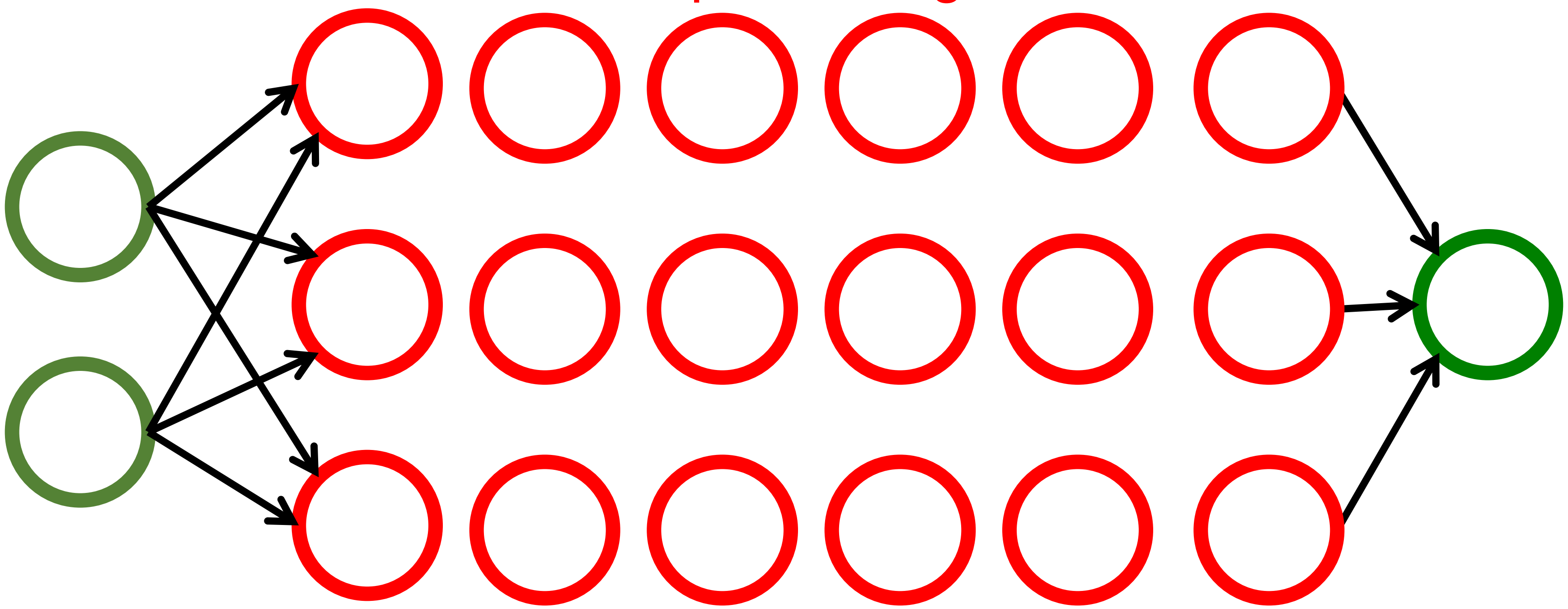
Deep Learning and Neural Networks

Input Layer (X)

Hidden Layers (H)

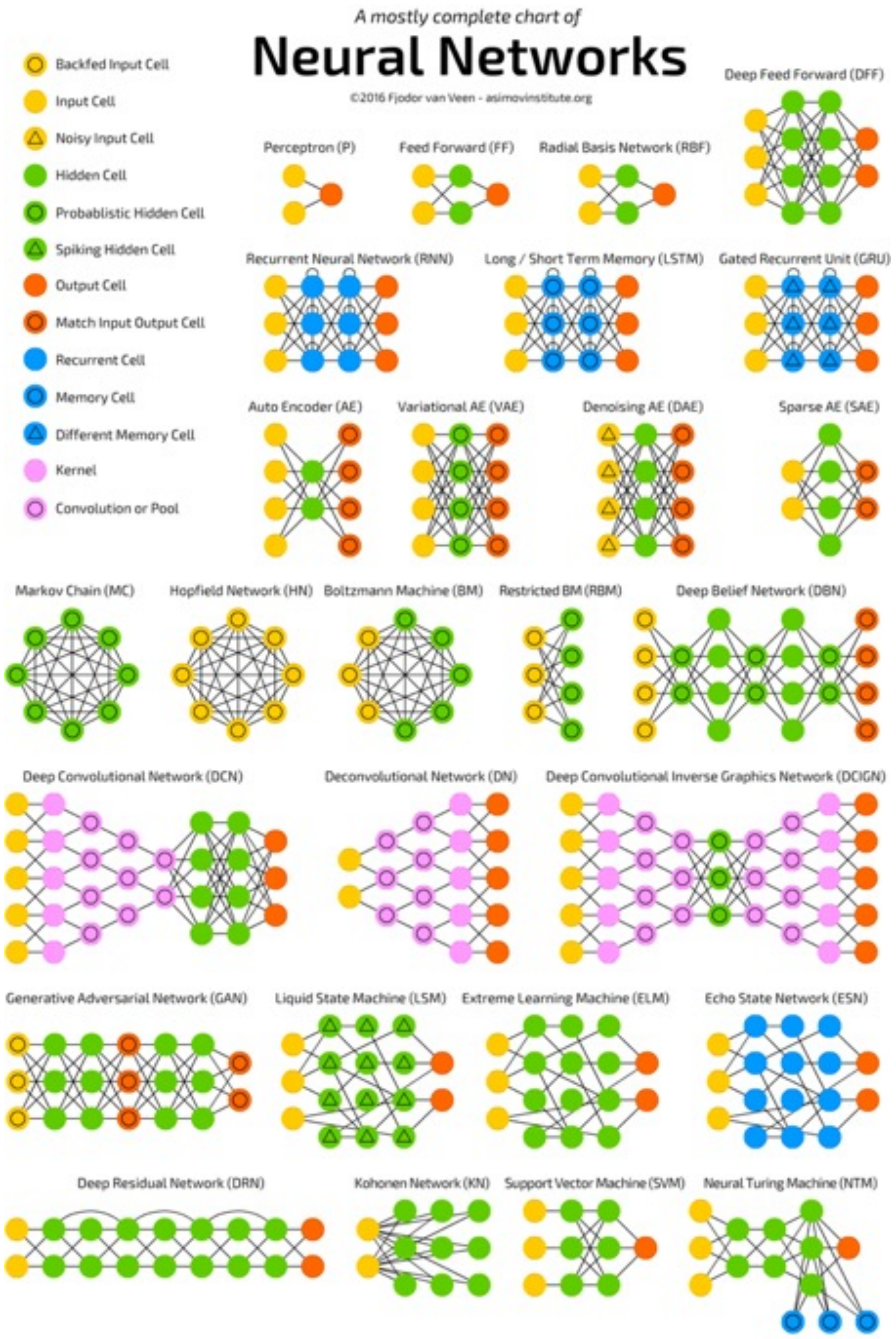
Output Layer (Y)

Deep Neural Networks
Deep Learning

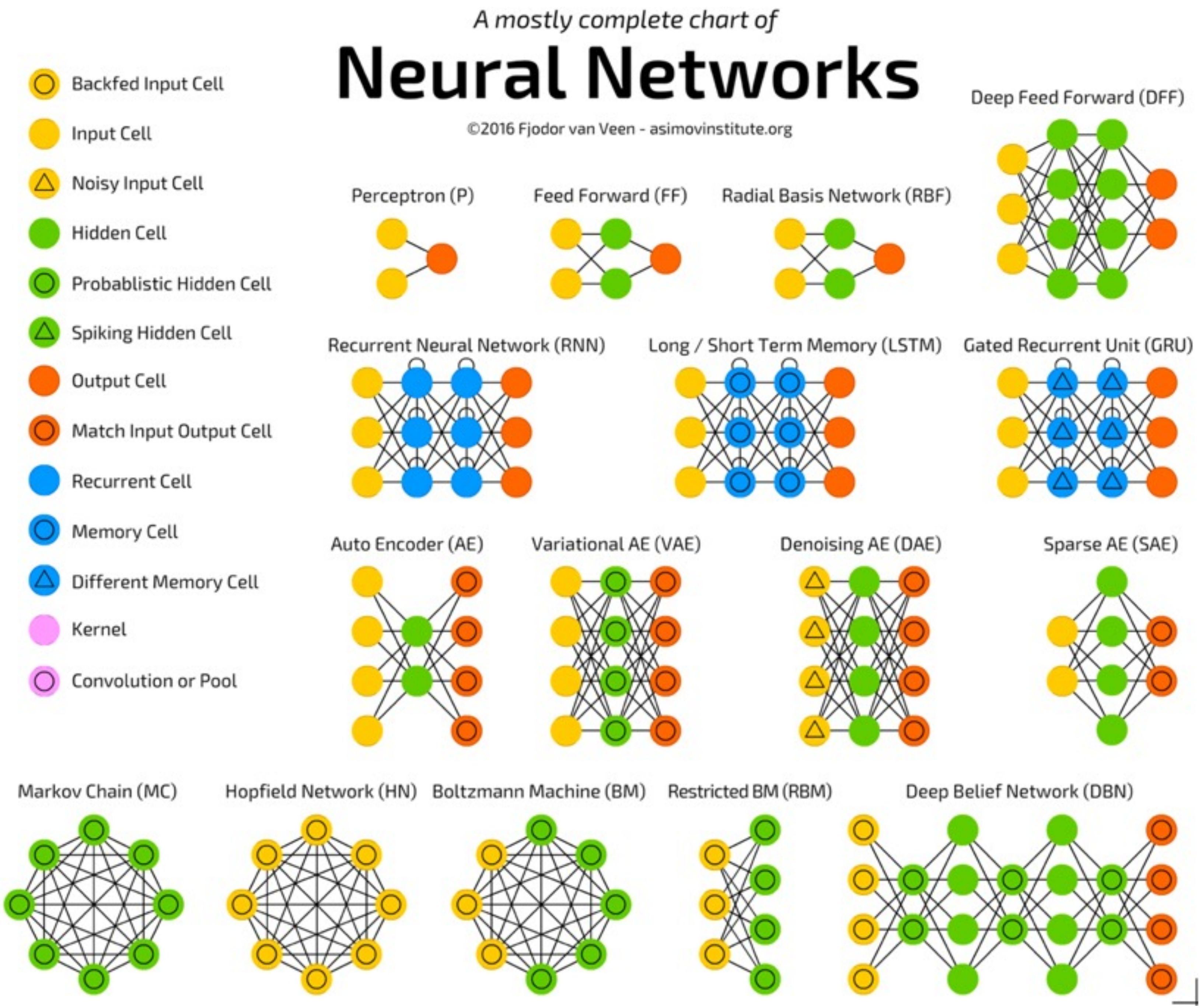


Deep Learning
and
Deep Neural Networks

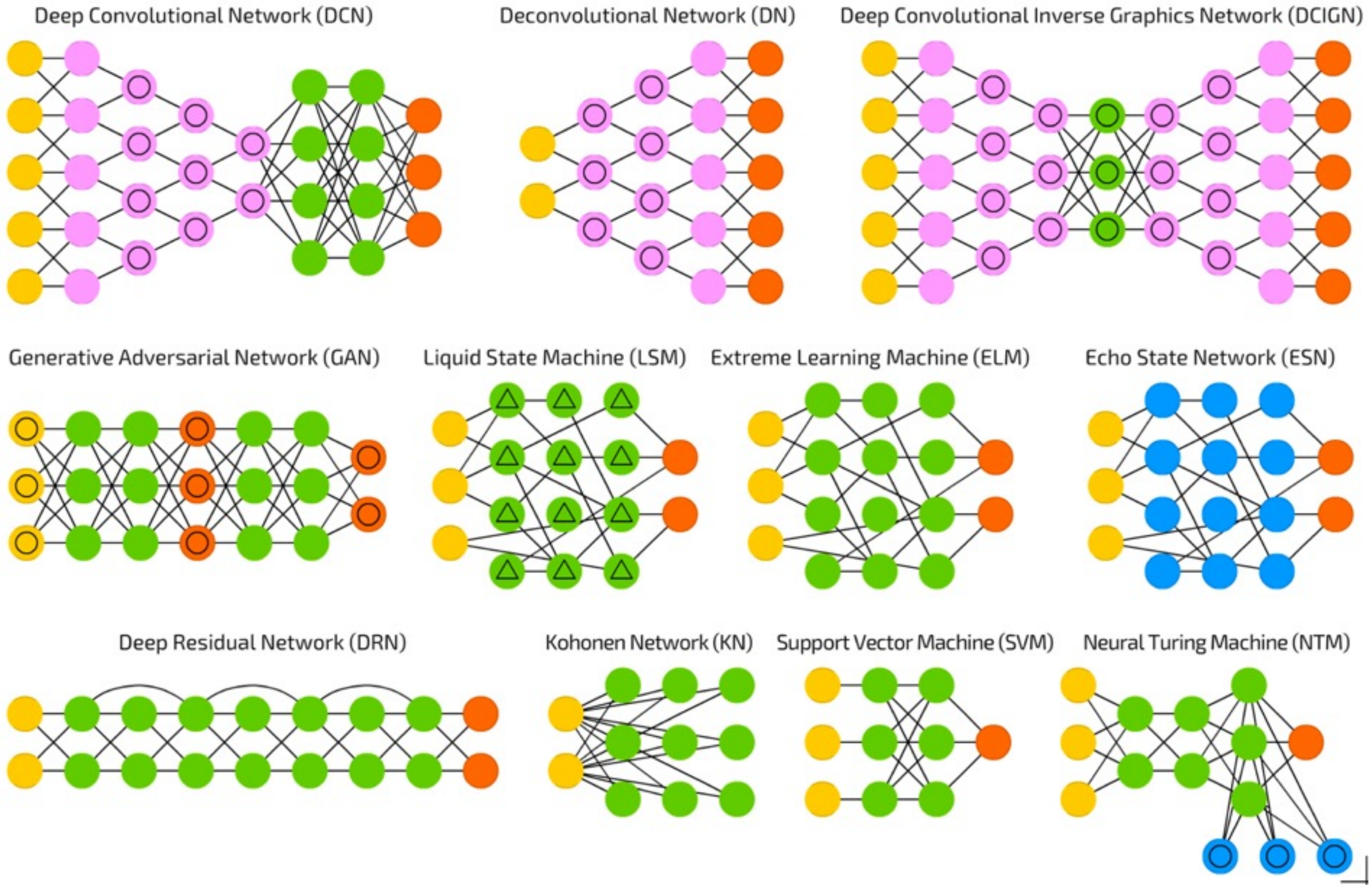
Neural Networks (NN)



Source: http://www.asimovinstitute.org/neural-network-zoo/

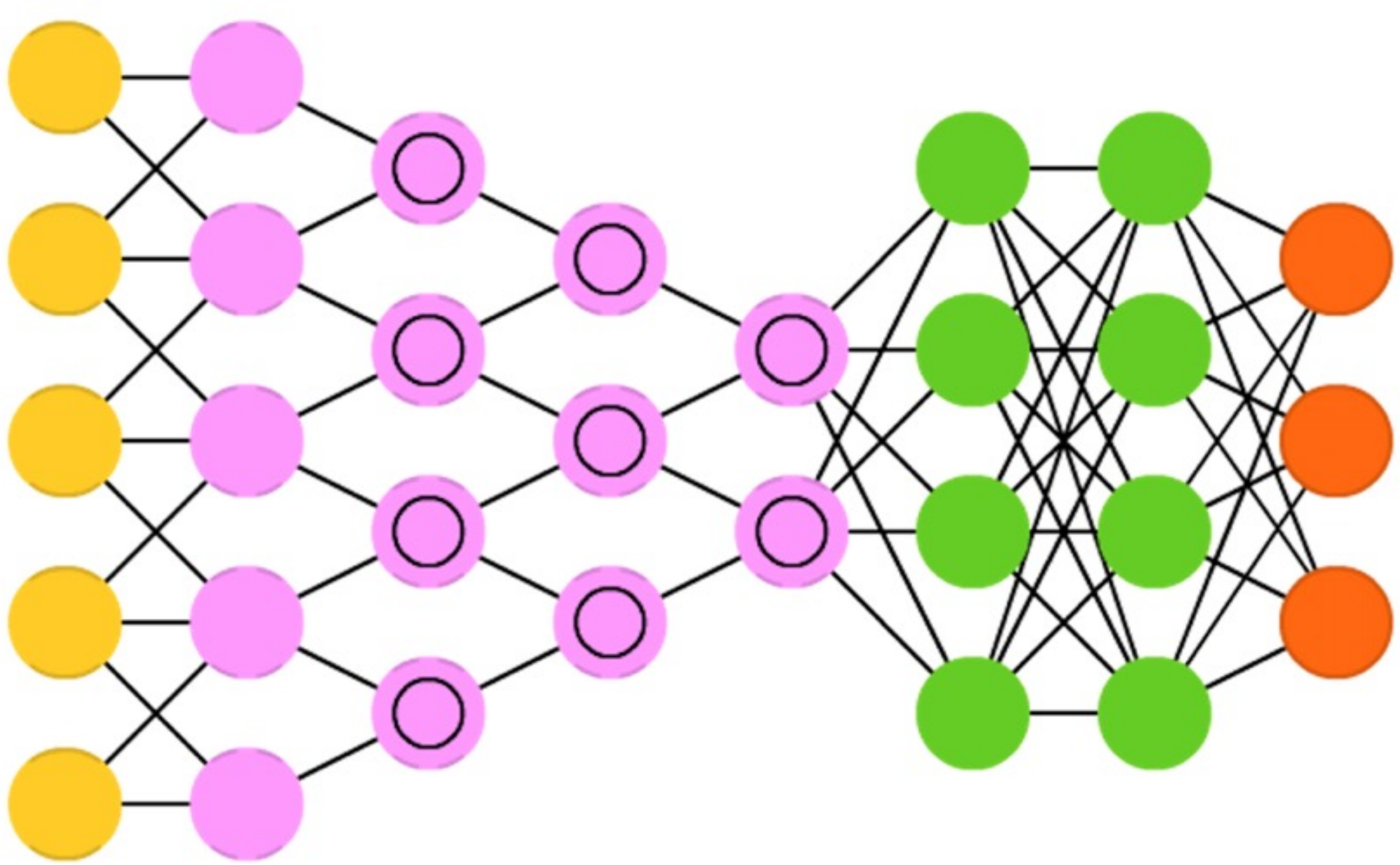


Source: http://www.asimovinstitute.org/neural-network-zoo/



Source: http://www.asimovinstitute.org/neural-network-zoo/

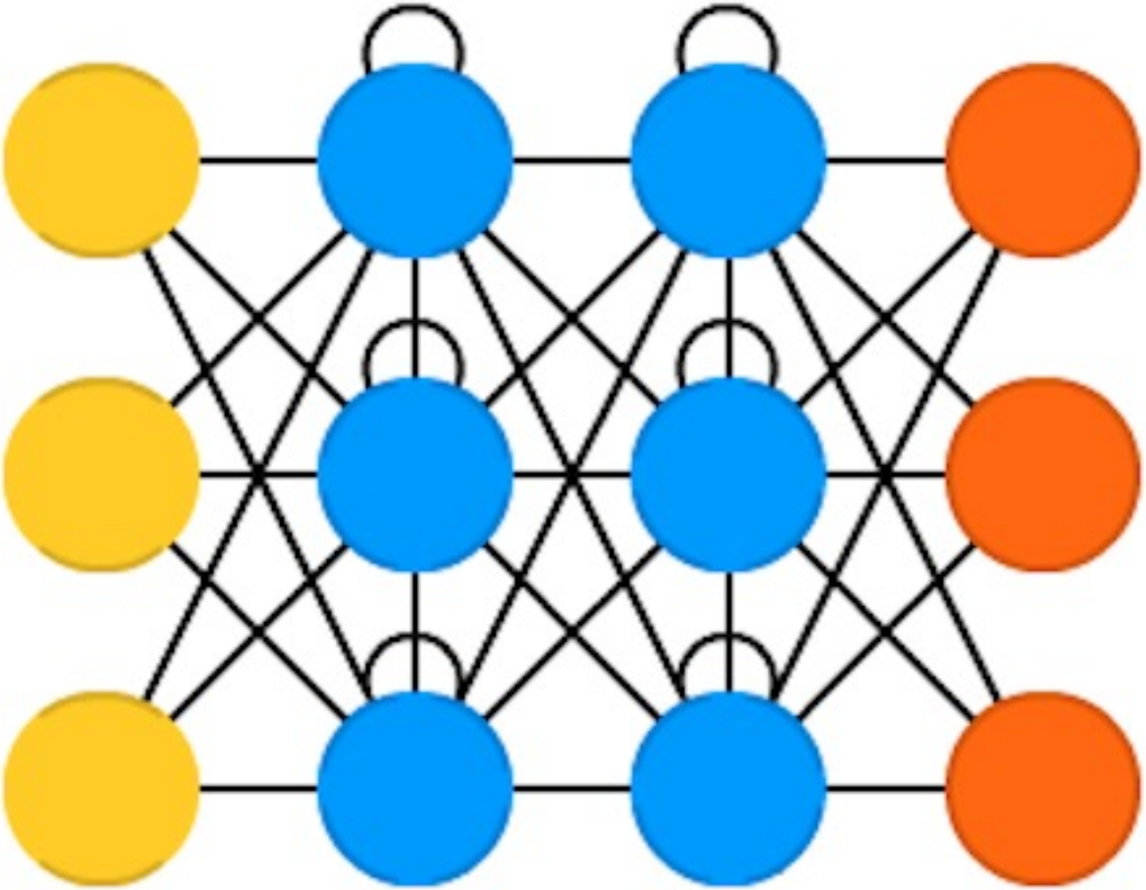
Convolutional Neural Networks (CNN or Deep Convolutional Neural Networks, DCNN)



LeCun, Yann, et al. “Gradient-based learning applied to document recognition.” Proceedings of the IEEE 86.11 (1998): 2278-2324.

Source: http://www.asimovinstitute.org/neural-network-zoo/

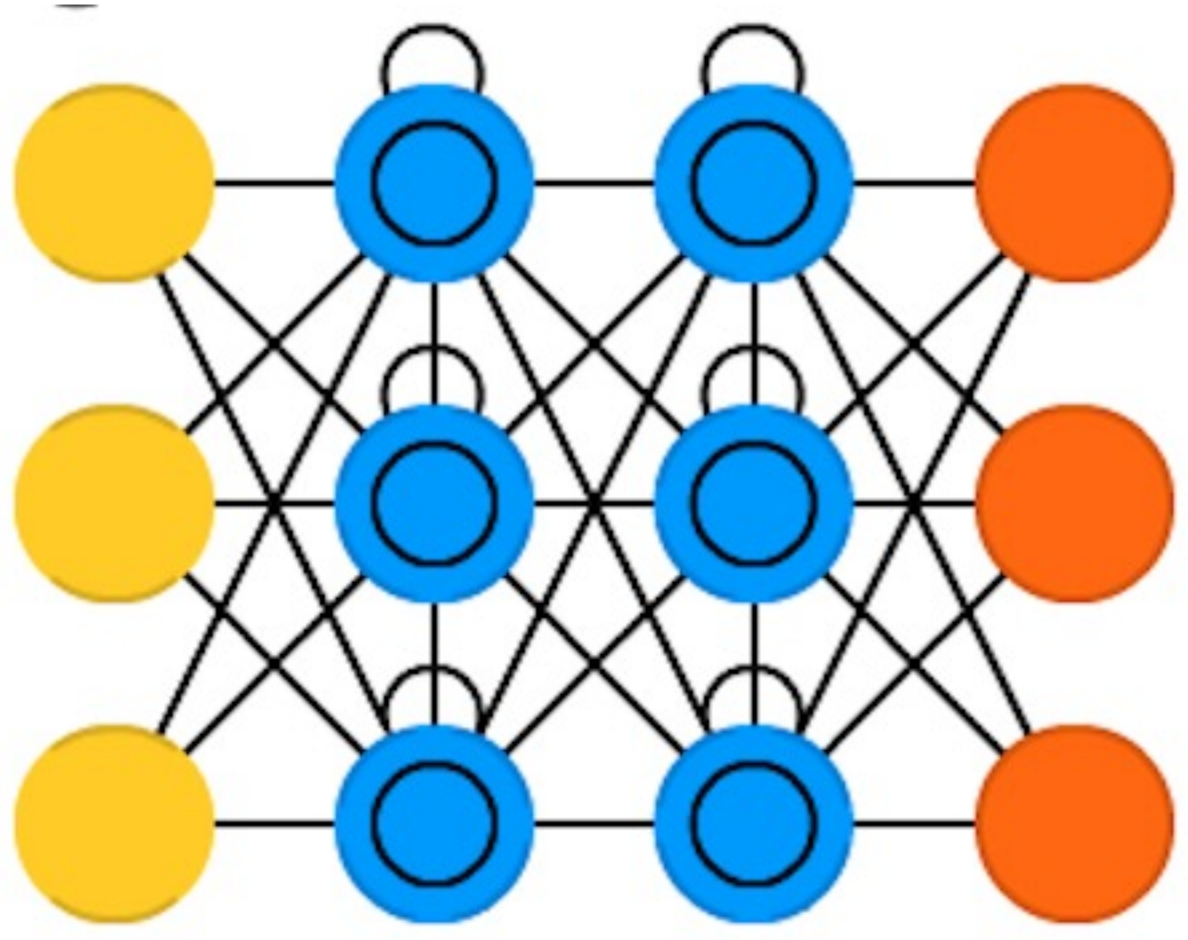
Recurrent Neural Networks (RNN)



Elman, Jeffrey L. "Finding structure in time." Cognitive science 14.2 (1990): 179-211

Source: http://www.asimovinstitute.org/neural-network-zoo/

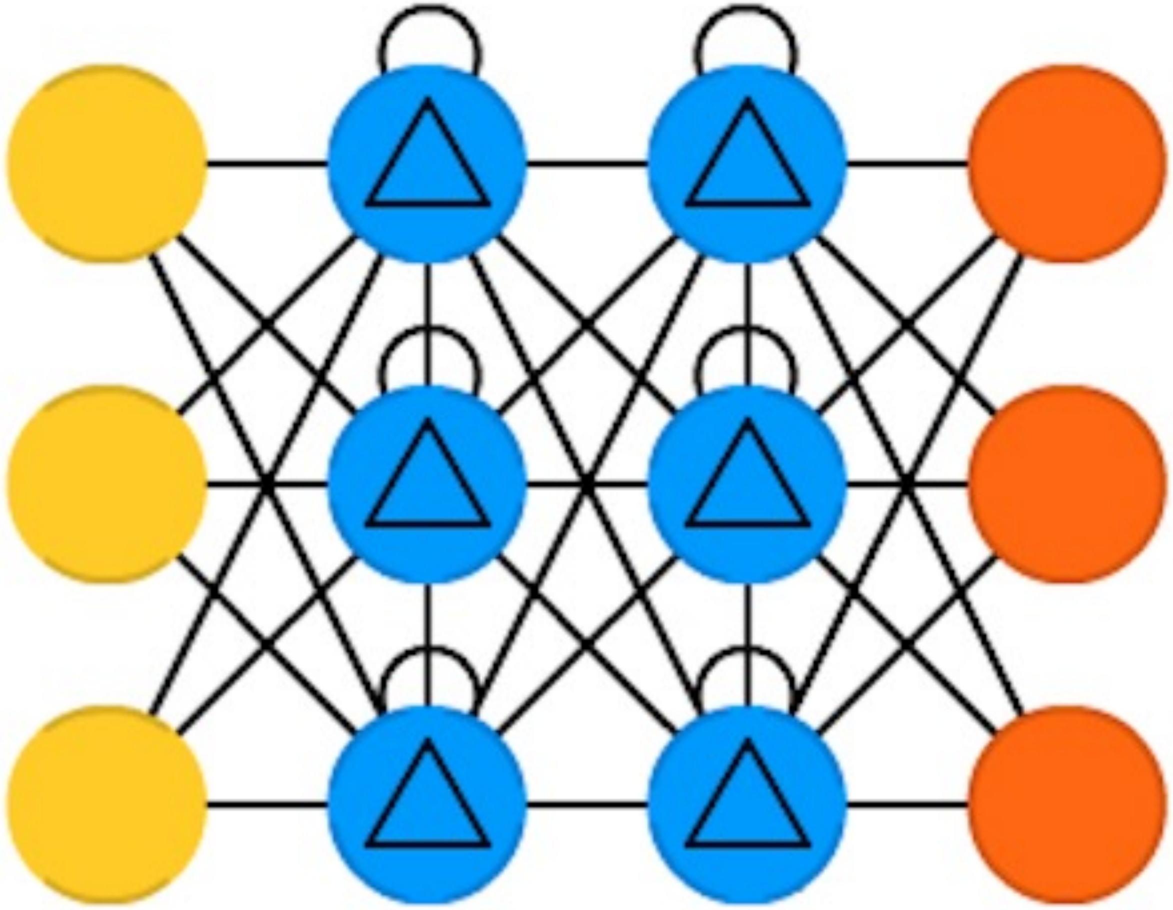
Long / Short Term Memory (LSTM)



Hochreiter, Sepp, and Jürgen Schmidhuber. "Long short-term memory." Neural computation 9.8 (1997): 1735-1780.

Source: http://www.asimovinstitute.org/neural-network-zoo/

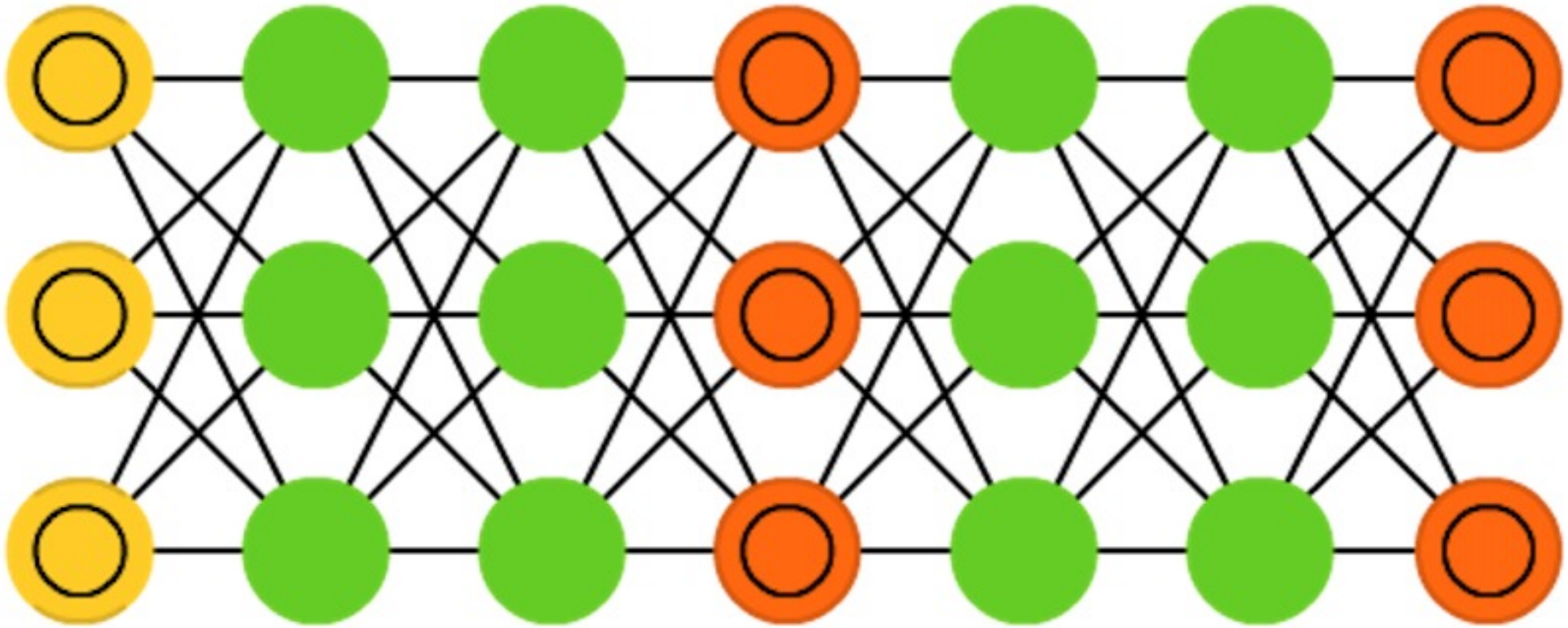
Gated Recurrent Units (GRU)



Chung, Junyoung, et al. "Empirical evaluation of gated recurrent neural networks on sequence modeling." arXiv preprint arXiv:1412.3555 (2014).

Source: http://www.asimovinstitute.org/neural-network-zoo/

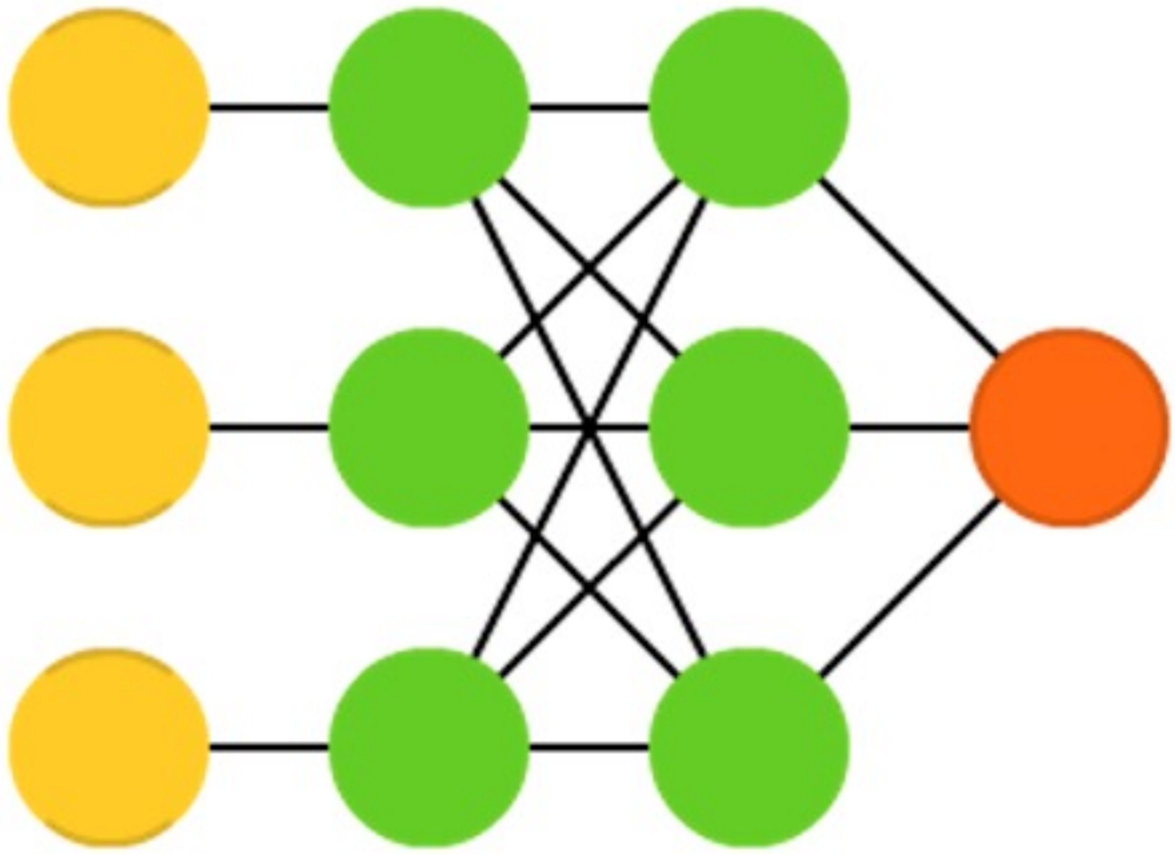
Generative Adversarial Networks (GAN)



Goodfellow, Ian, et al. "Generative adversarial nets." Advances in Neural Information Processing Systems. 2014.

Source: http://www.asimovinstitute.org/neural-network-zoo/

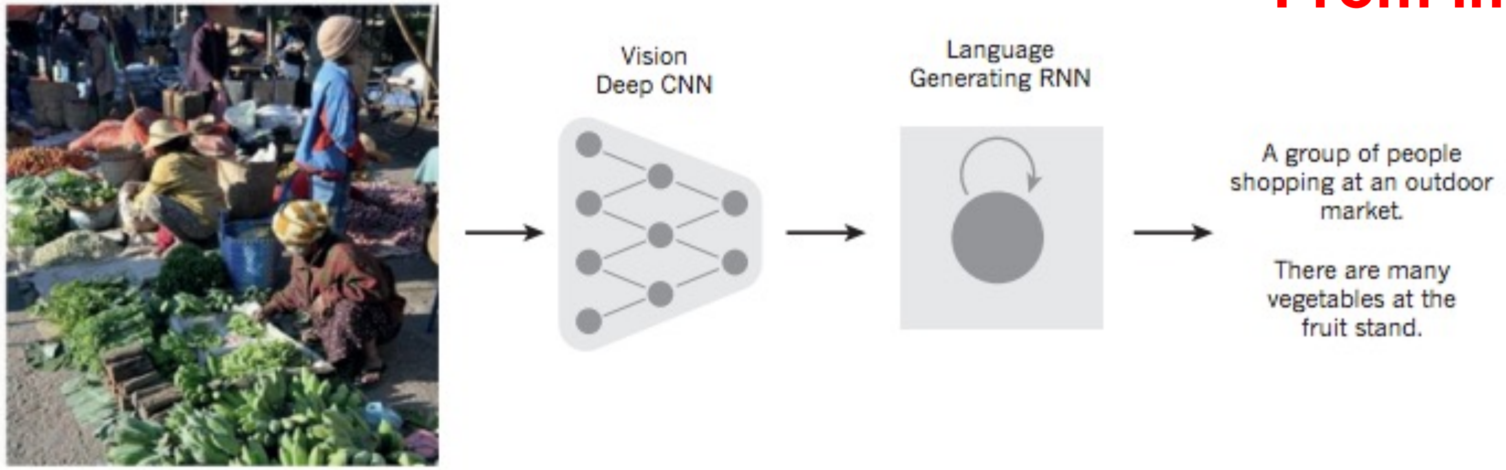
Support Vector Machines (SVM)



Cortes, Corinna, and Vladimir Vapnik. "Support-vector networks." Machine learning 20.3 (1995): 273-297.

Source: http://www.asimovinstitute.org/neural-network-zoo/

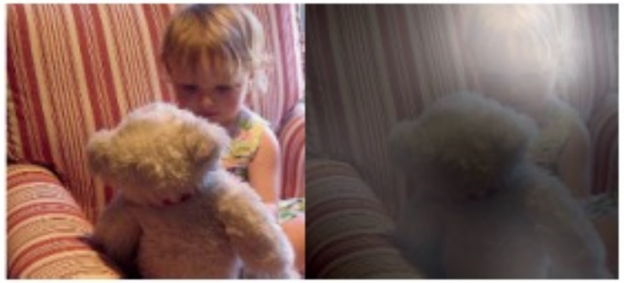
From image to text




A woman is throwing a **frisbee** in a park.


A **dog** is standing on a hardwood floor.

A **stop** sign is on a road with a mountain in the background


A little **girl** sitting on a bed with a teddy bear.


A group of **people** sitting on a boat in the water.


A giraffe standing in a forest with **trees** in the background.

Source: LeCun, Yann, Yoshua Bengio, and Geoffrey Hinton. "Deep learning." Nature 521, no. 7553 (2015): 436-444.

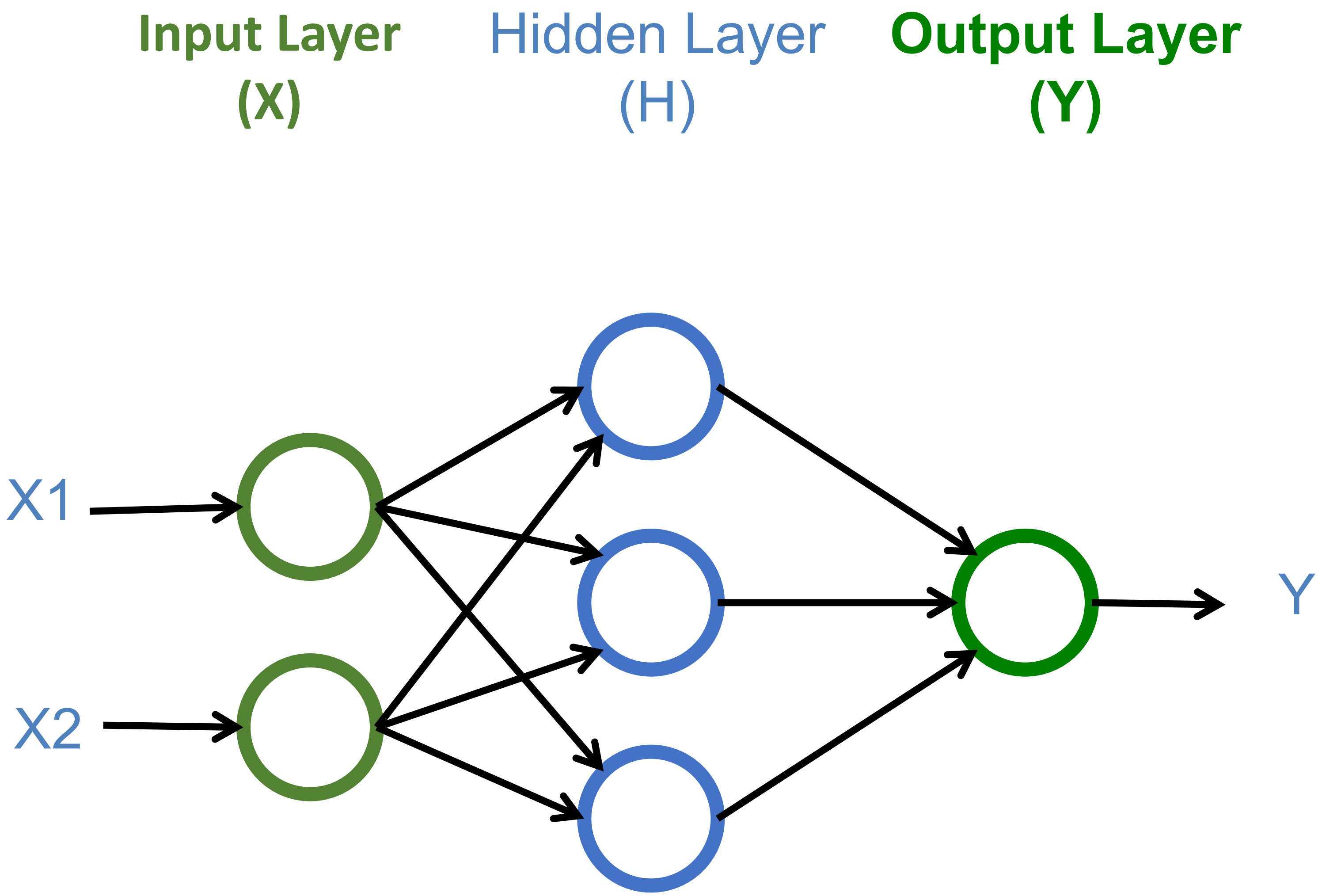
From image to text

Image: deep convolution neural network (CNN)
Text: recurrent neural network (RNN)

A group of **people** sitting on a boat in the water.

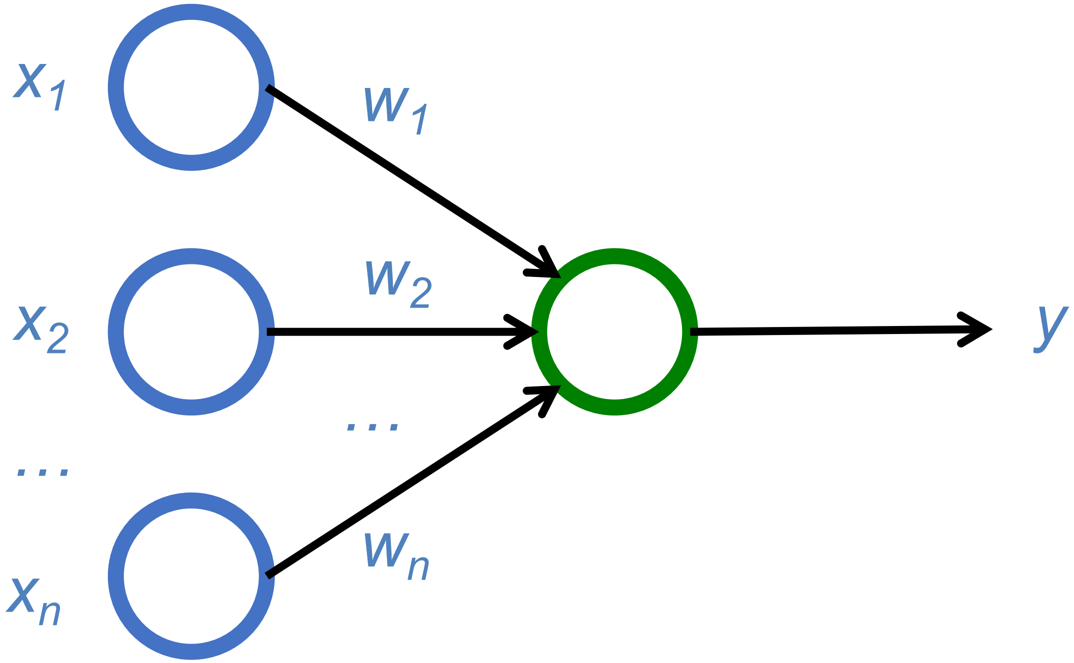
Source: LeCun, Yann, Yoshua Bengio, and Geoffrey Hinton. "Deep learning." Nature 521, no. 7553 (2015): 436-444.

Neural Networks



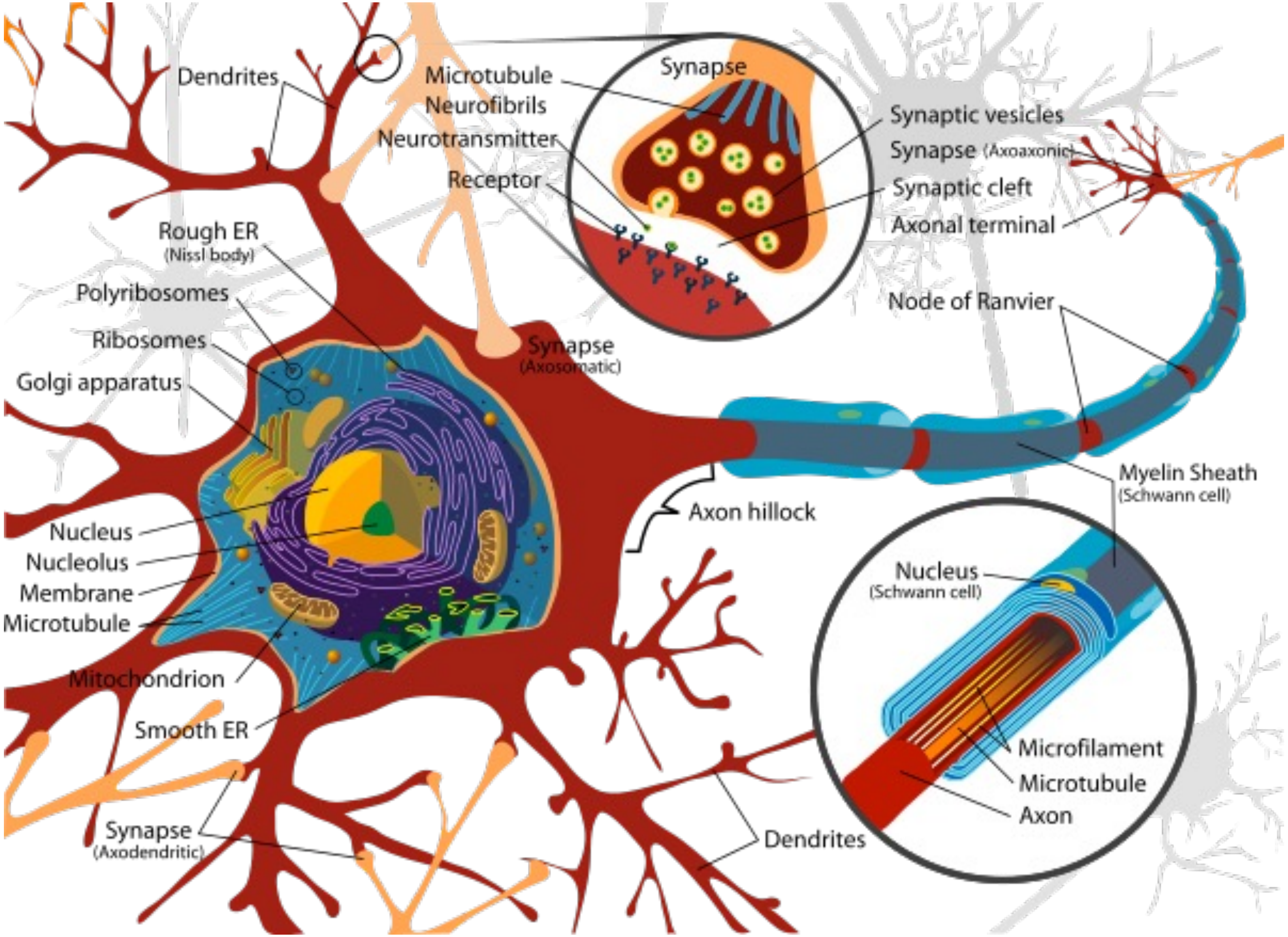
Source: https://www.youtube.com/watch?v=bxe2T-V8XRs&index=1&list=PLiaHhY2iBX9hdHaRr6b7XevZtgZRa1PoU

The Neuron



Source: Jeff Dean (2016), Large-Scale Deep Learning For Building Intelligent Computer Systems, WSDM 2016

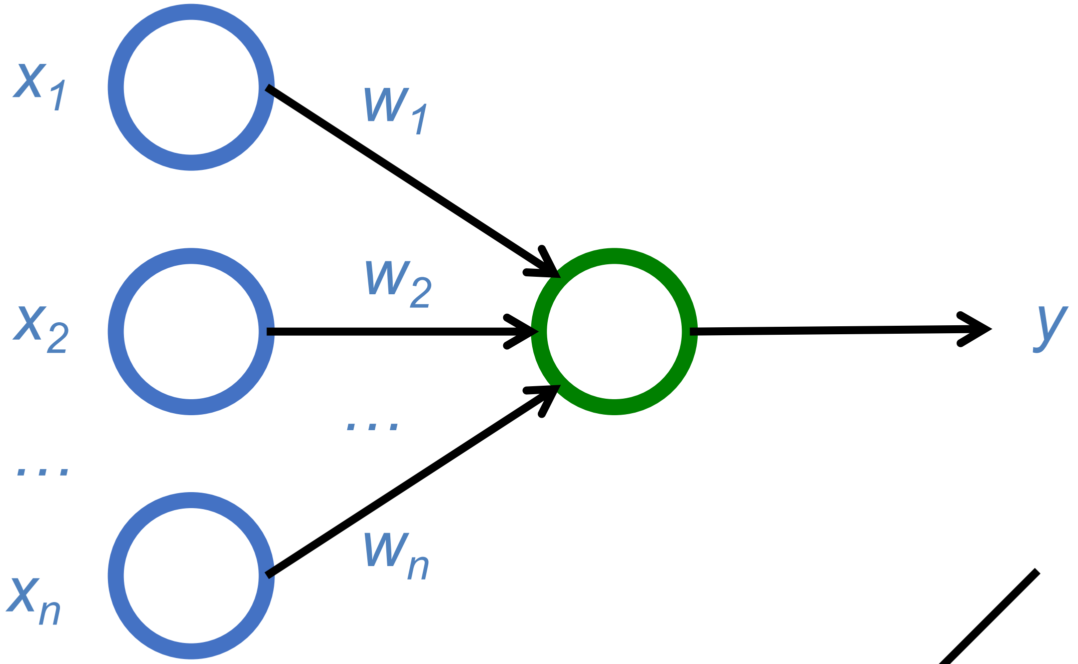
Neuron and Synapse

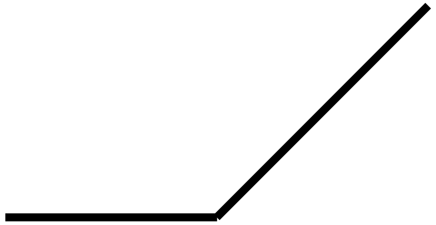


Source: https://en.wikipedia.org/wiki/Neuron

The Neuron

$$y = F\left(\sum_i w_i x_i\right)$$

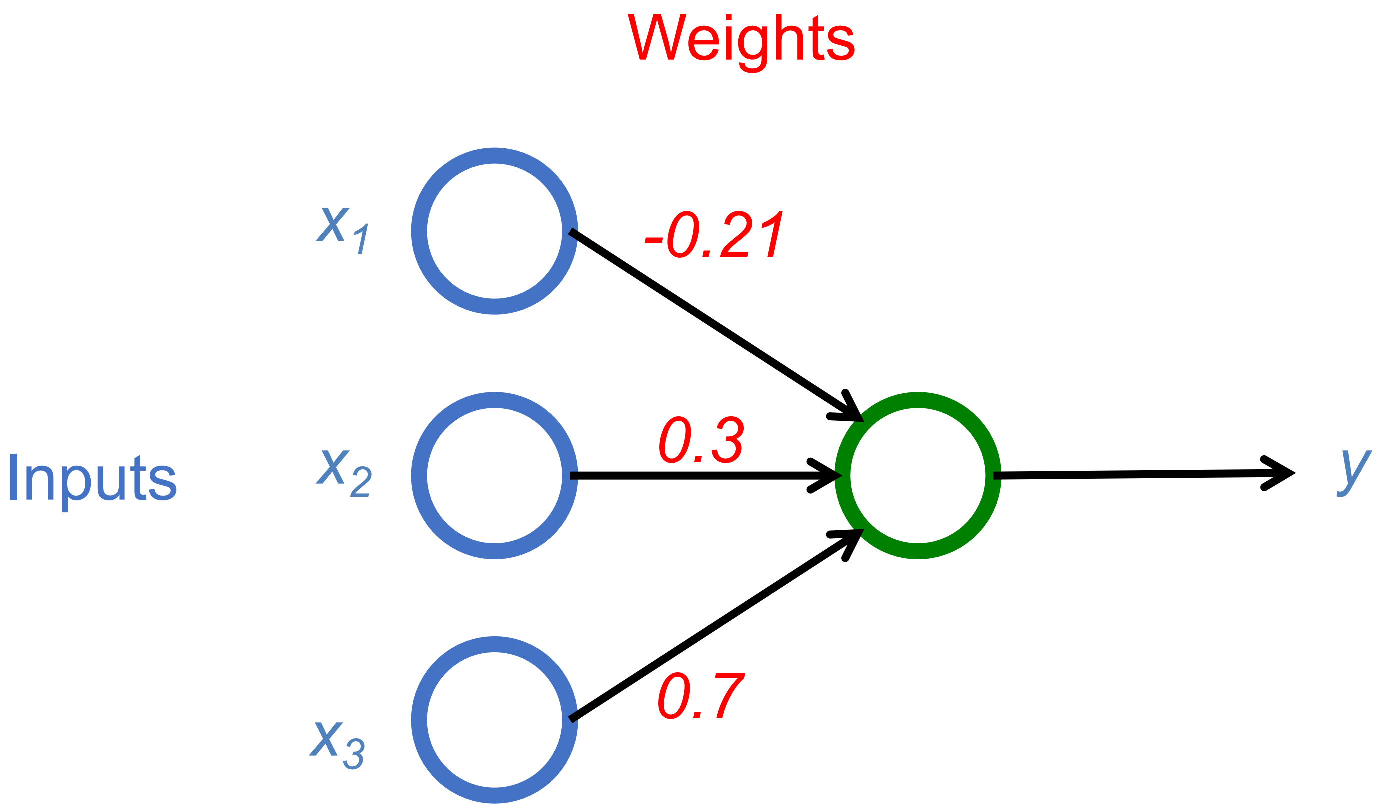




$$F(x) = \max(0, x)$$

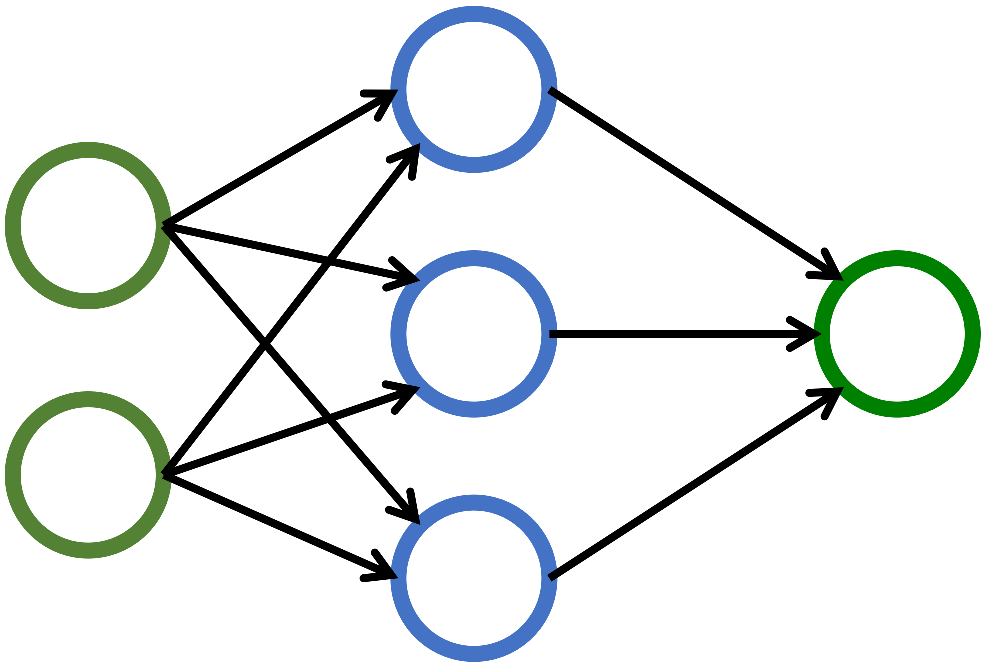
Source: Jeff Dean (2016), Large-Scale Deep Learning For Building Intelligent Computer Systems, WSDM 2016

$$y = max\ (\ 0,\ -0.21\ *\ x_1 + 0.3\ *\ x_2 + 0.7\ *\ x_3\ )$$



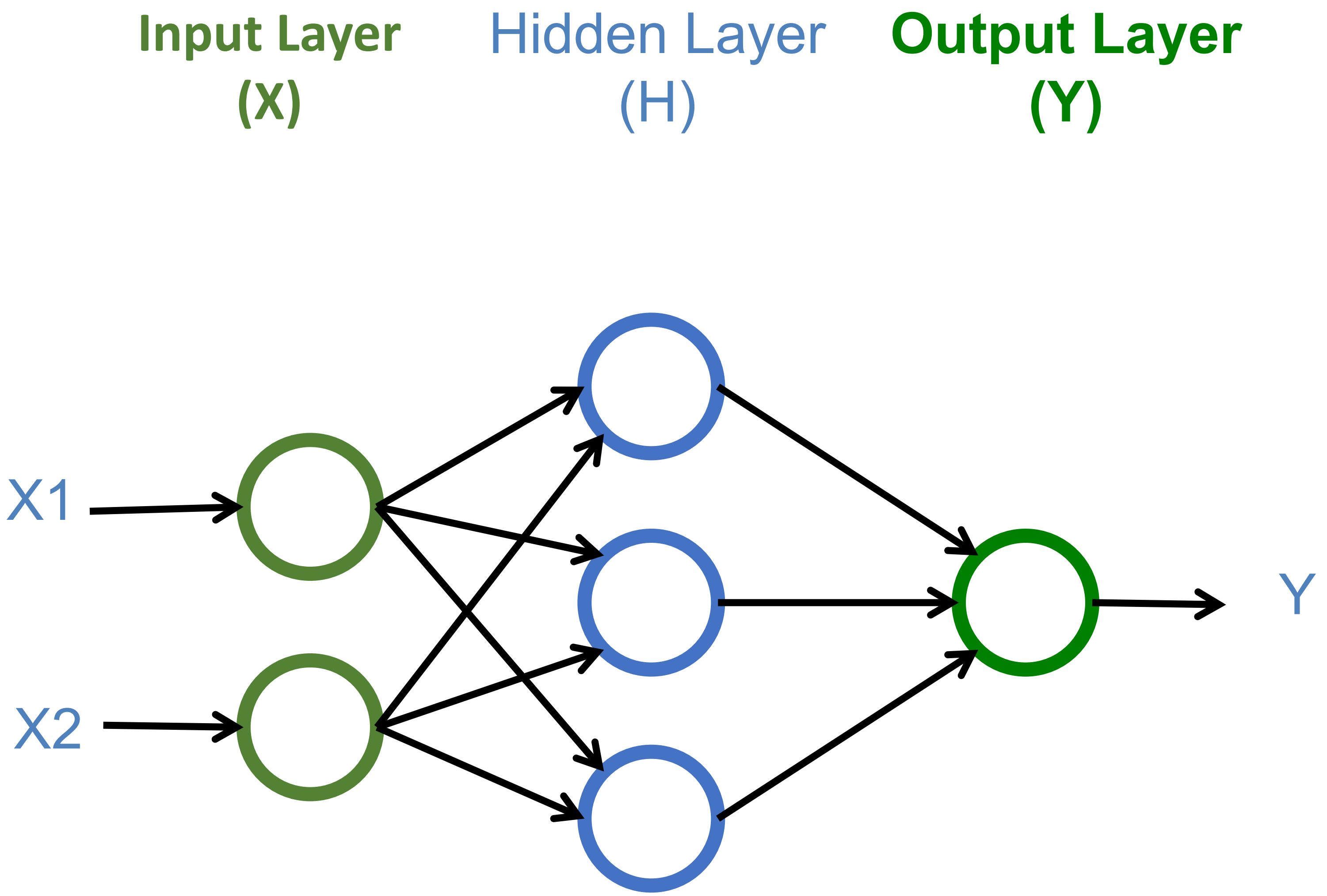
Source: Jeff Dean (2016), Large-Scale Deep Learning For Building Intelligent Computer Systems, WSDM 2016

Neural Networks



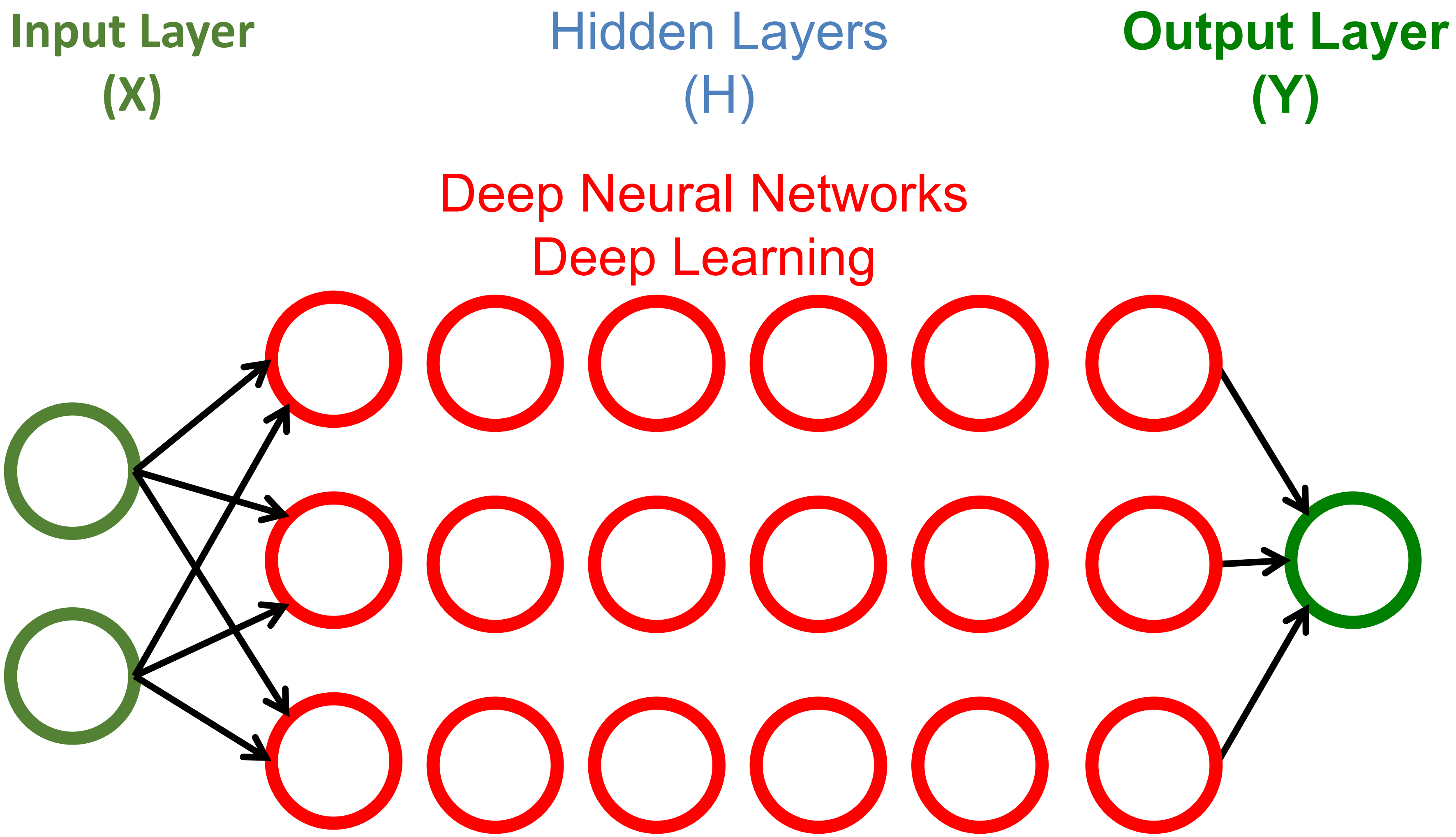
Source: https://www.youtube.com/watch?v=bxe2T-V8XRs&index=1&list=PLiaHhY2iBX9hdHaRr6b7XevZtgZRa1PoU

Neural Networks



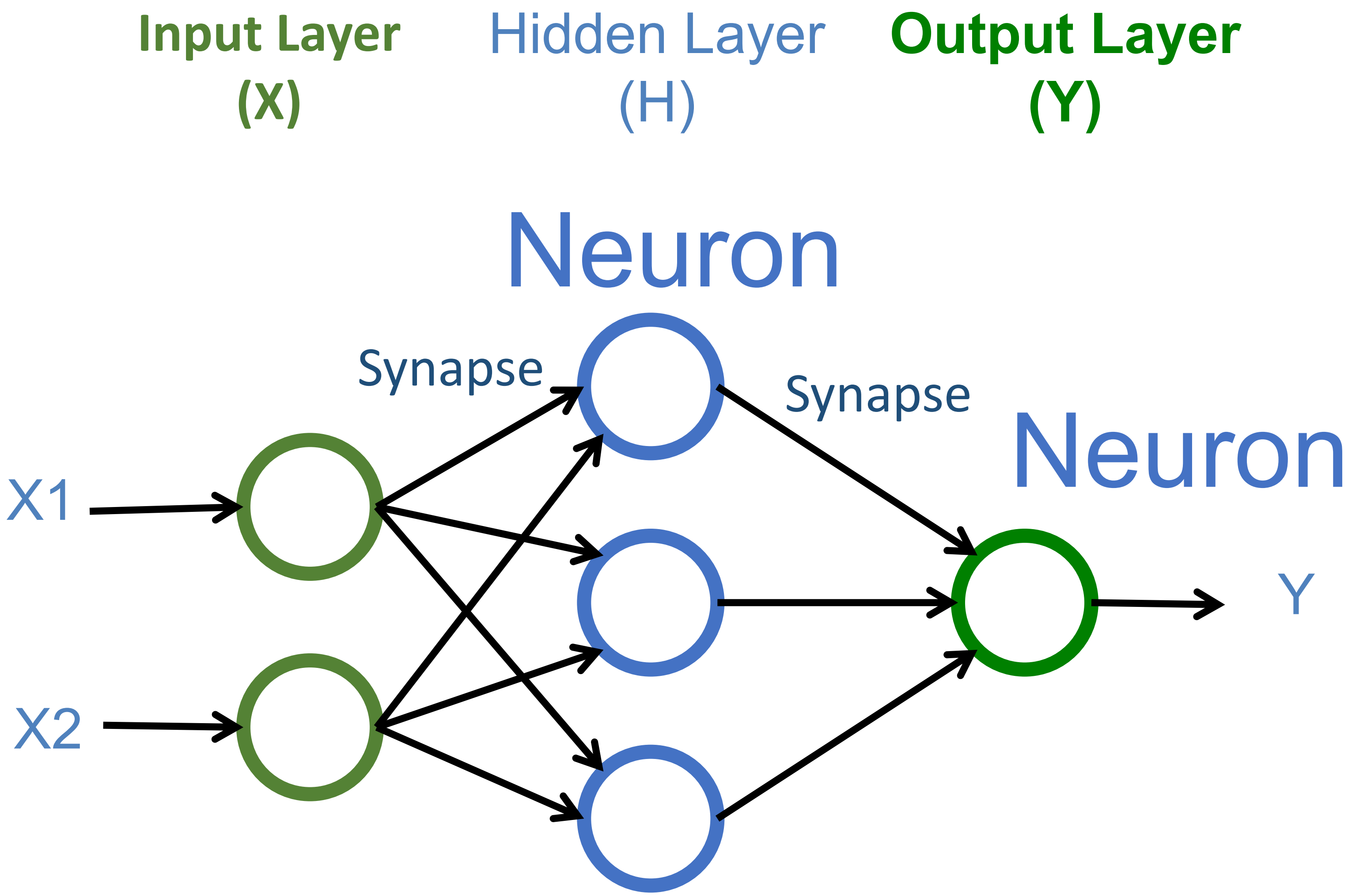
Source: https://www.youtube.com/watch?v=bxe2T-V8XRs&index=1&list=PLiaHhY2iBX9hdHaRr6b7XevZtgZRa1PoU

Neural Networks



Source: https://www.youtube.com/watch?v=bxe2T-V8XRs&index=1&list=PLiaHhY2iBX9hdHaRr6b7XevZtgZRa1PoU

Neural Networks



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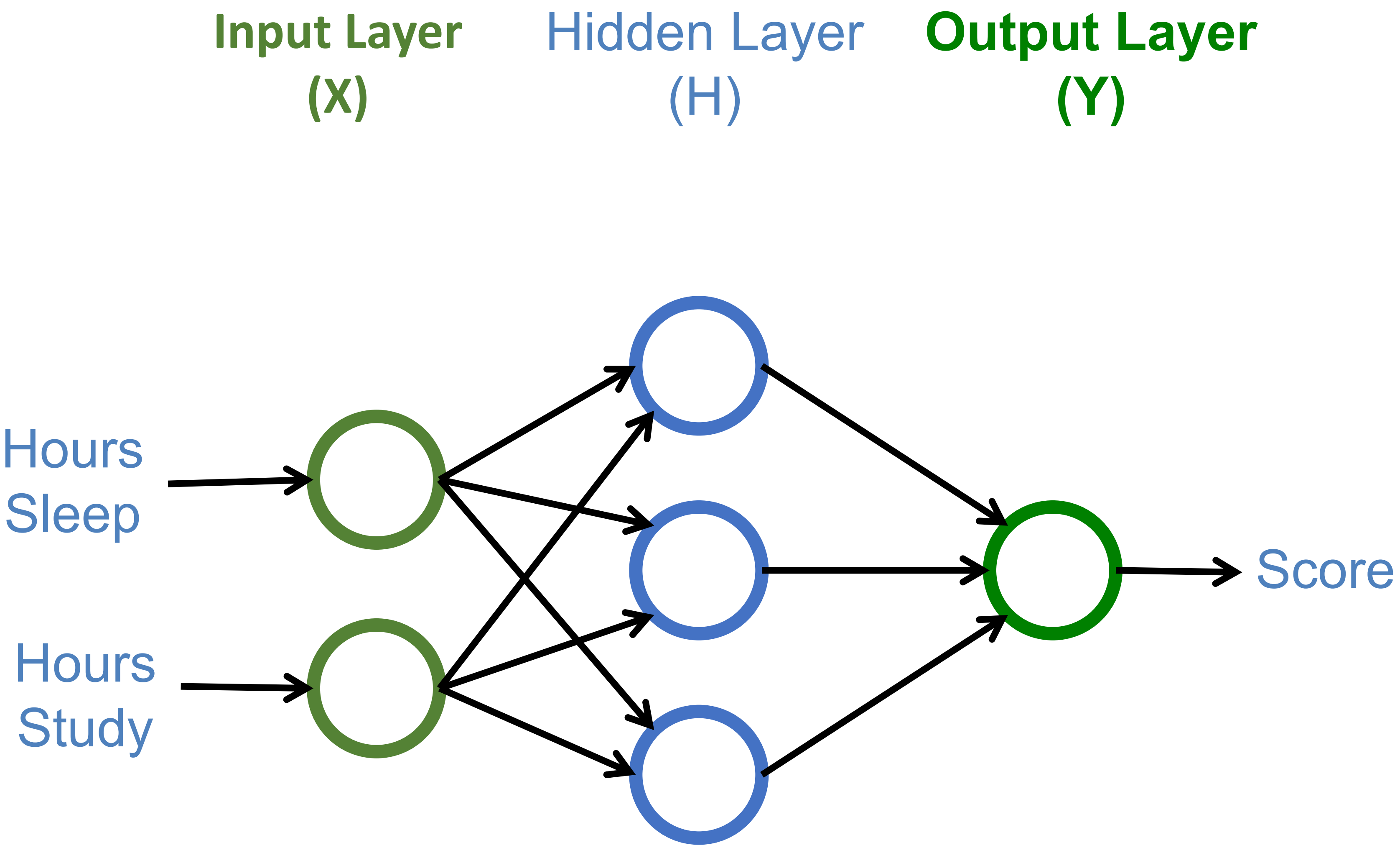
Neural Networks



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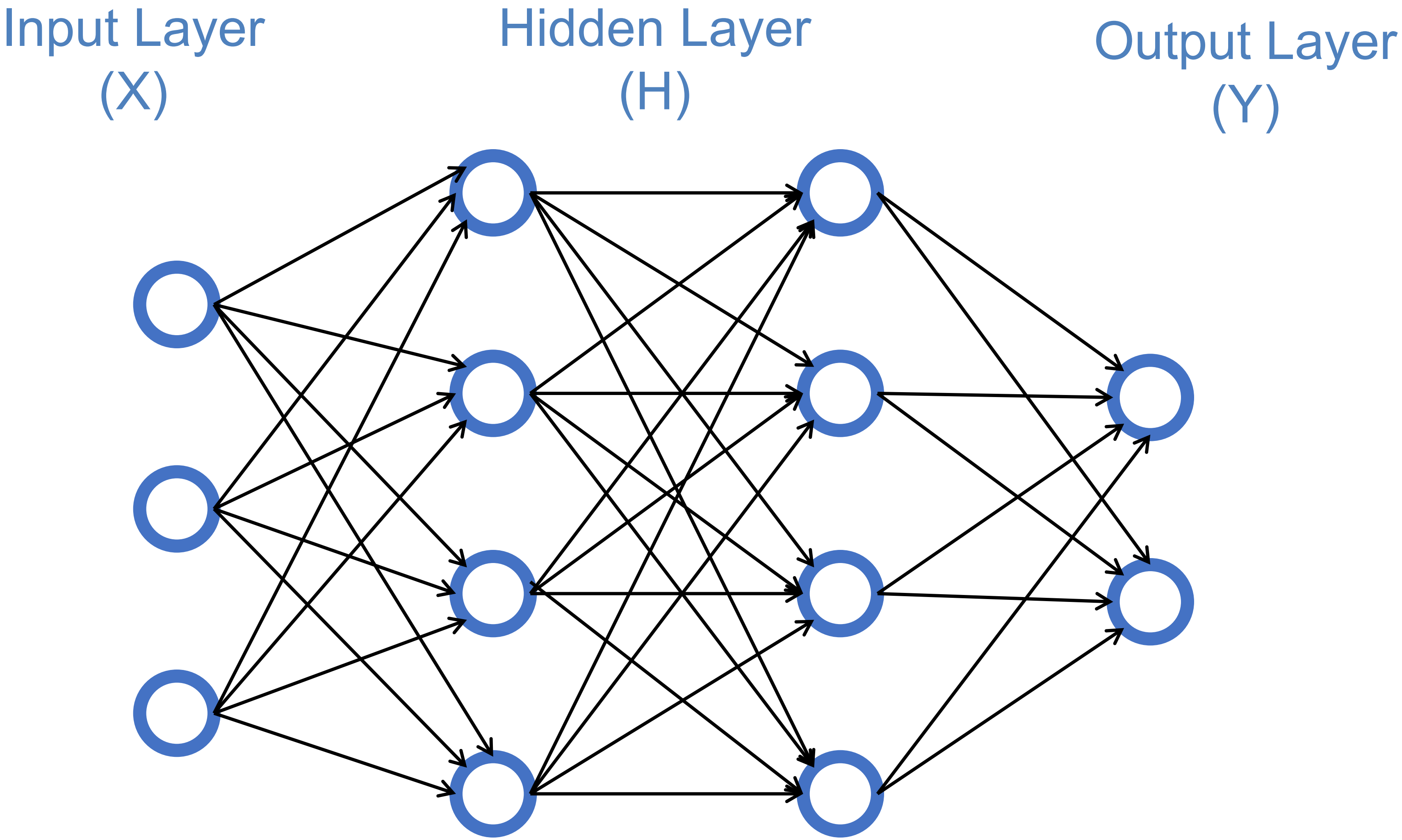
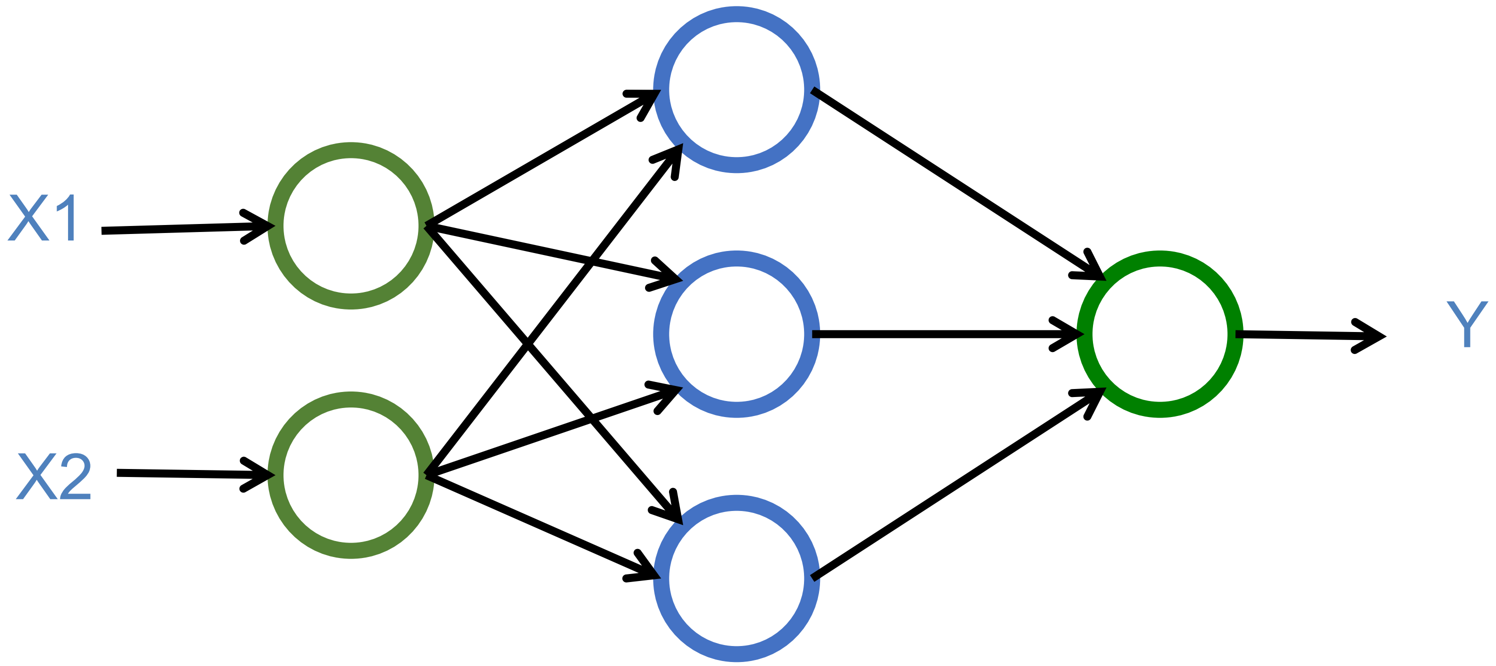
Neural Networks



Source: https://www.youtube.com/watch?v=P2HPcj8lRJE&list=PLjJh1vlSEYgvGod9wWiydumYl8hOXixNu&index=2

Neural Networks

Input Layer (X) | Hidden Layer (H) | **Output Layer (Y)**



Source: https://www.youtube.com/watch?v=bxe2T-V8XRs&index=1&list=PLiaHhY2iBX9hdHaRr6b7XevZtgZRa1PoU

X		Y
Hours Sleep	Hours Study	Score
3	5	75
5	1	82
10	2	93
8	3	?

	X		Y
	Hours Sleep	Hours Study	Score
Training	3	5	75
	5	1	82
	10	2	93
Testing	8	3	?

Source: https://www.youtube.com/watch?v=bxe2T-V8XRs&index=1&list=PLiaHhY2iBX9hdHaRr6b7XevZtgZRa1PoU

$$Y = W X + b$$

Output input

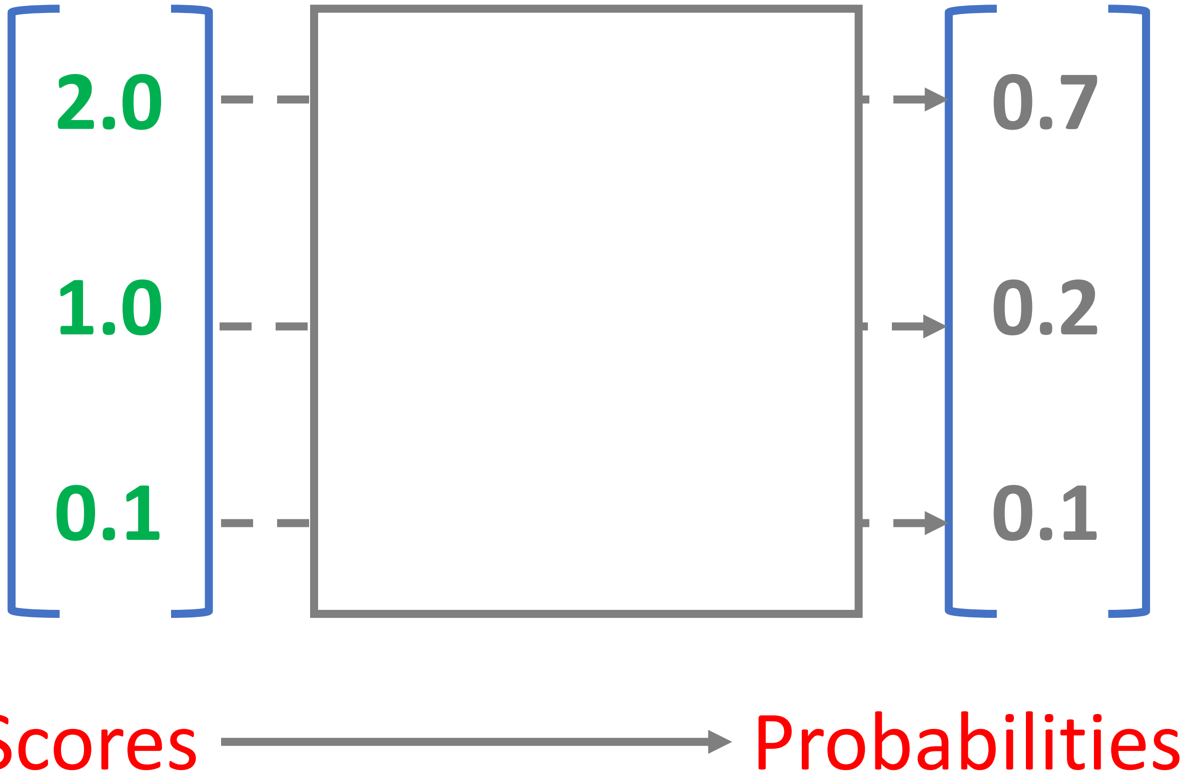
$$Y = W\,X + b$$

Weights bias

Trained

Source: https://www.youtube.com/watch?v=G8eNWzxOgqE

$$WX + b = Y$$



SoftMAX

$$\mathbf{W}\,\mathbf{X} + \mathbf{b} = \mathbf{Y} \quad \begin{bmatrix} 2.0 \\ 1.0 \\ 0.1 \end{bmatrix} \rightarrow \boxed{S(y_i) = \frac{e^{y_i}}{\sum_j e^{y_j}}} \rightarrow \begin{bmatrix} 0.7 \\ 0.2 \\ 0.1 \end{bmatrix}$$

Logits

Scores $\longrightarrow$ Probabilities

Source: https://www.youtube.com/watch?v=G8eNWzxOgqE

$$S(y_i) = \frac{e^{y_i}}{\sum_j e^{y_i}} = \frac{e^{2.0}}{e^{2.0}+e^{1.0}+e^{0.1}} = \frac{2.7182^{2.0}}{2.7182^{2.0}+2.7182^{1.0}+2.7182^{0.1}} = 0.7$$

$$S(y_i) = \frac{e^{y_i}}{\sum_j e^{y_j}} = \frac{e^{1.0}}{e^{2.0}+e^{1.0}+e^{0.1}} = \frac{2.7182^{1.0}}{2.7182^{2.0}+2.7182^{1.0}+2.7182^{0.1}} = 0.2$$

$$S(y_i) = \frac{e^{y_i}}{\sum_j e^{y_j}} = \frac{e^{0.1}}{e^{2.0}+e^{1.0}+e^{0.1}} = \frac{2.7182^{0.1}}{2.7182^{2.0}+2.7182^{1.0}+2.7182^{0.1}} = 0.1$$

W X + b = Y

$$\begin{bmatrix} 2.0 \\ 1.0 \\ 0.1 \end{bmatrix} \rightarrow \boxed{S(y_i) = \frac{e^{y_i}}{\sum_j e^{y_j}}} \rightarrow \begin{bmatrix} 0.7 \\ 0.2 \\ 0.1 \end{bmatrix}$$

Logits

Scores → Probabilities

Source: https://www.youtube.com/watch?v=G8eNWzxOgqE

Training a Network
=
Minimize the Cost Function

Source: https://www.youtube.com/watch?v=bxe2T-V8XRs&index=1&list=PLiaHhY2iBX9hdHaRr6b7XevZtgZRa1PoU

Training a Network

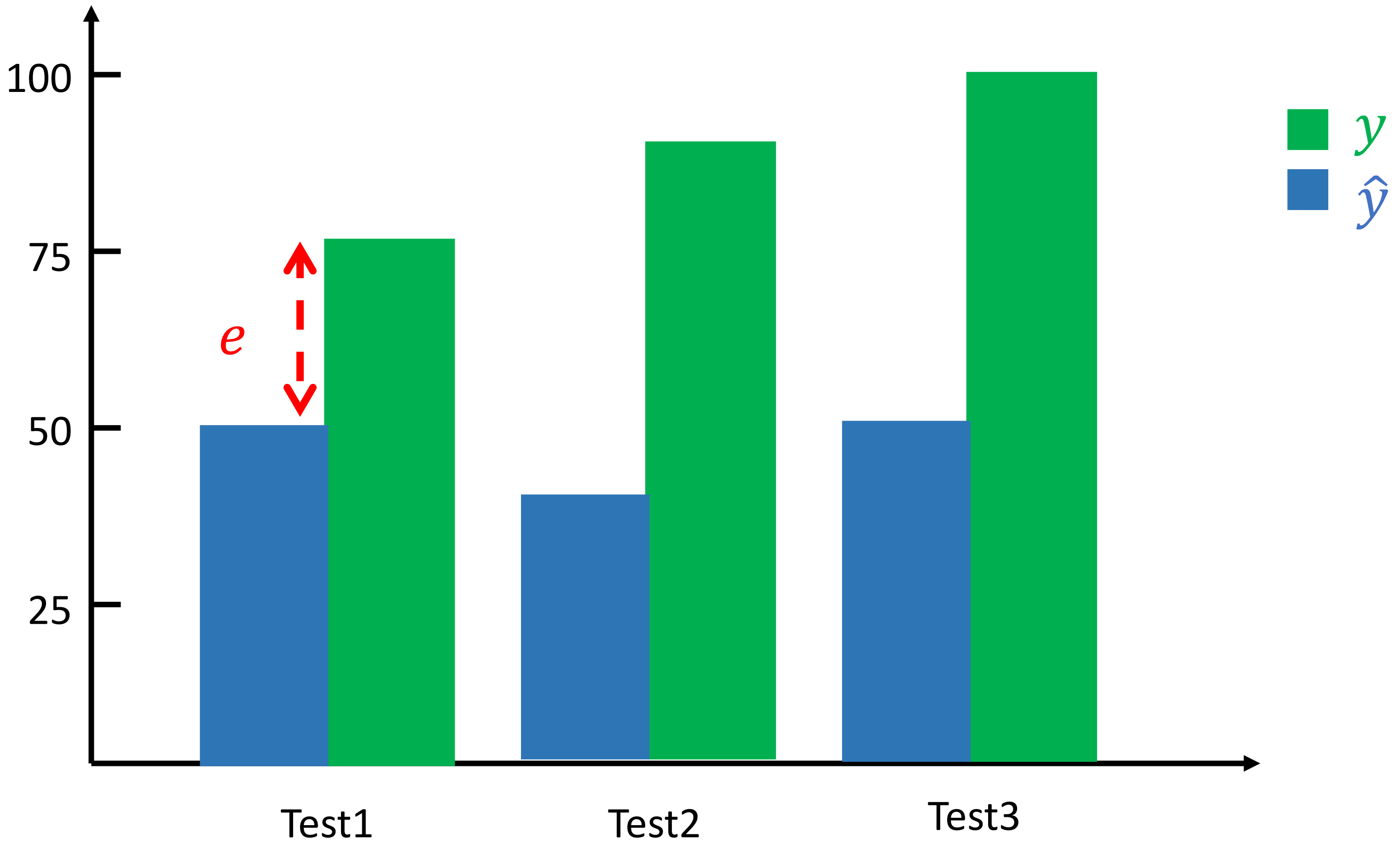
=

Minimize the Cost Function

Minimize the Loss Function

Error = Predict Y - Actual Y

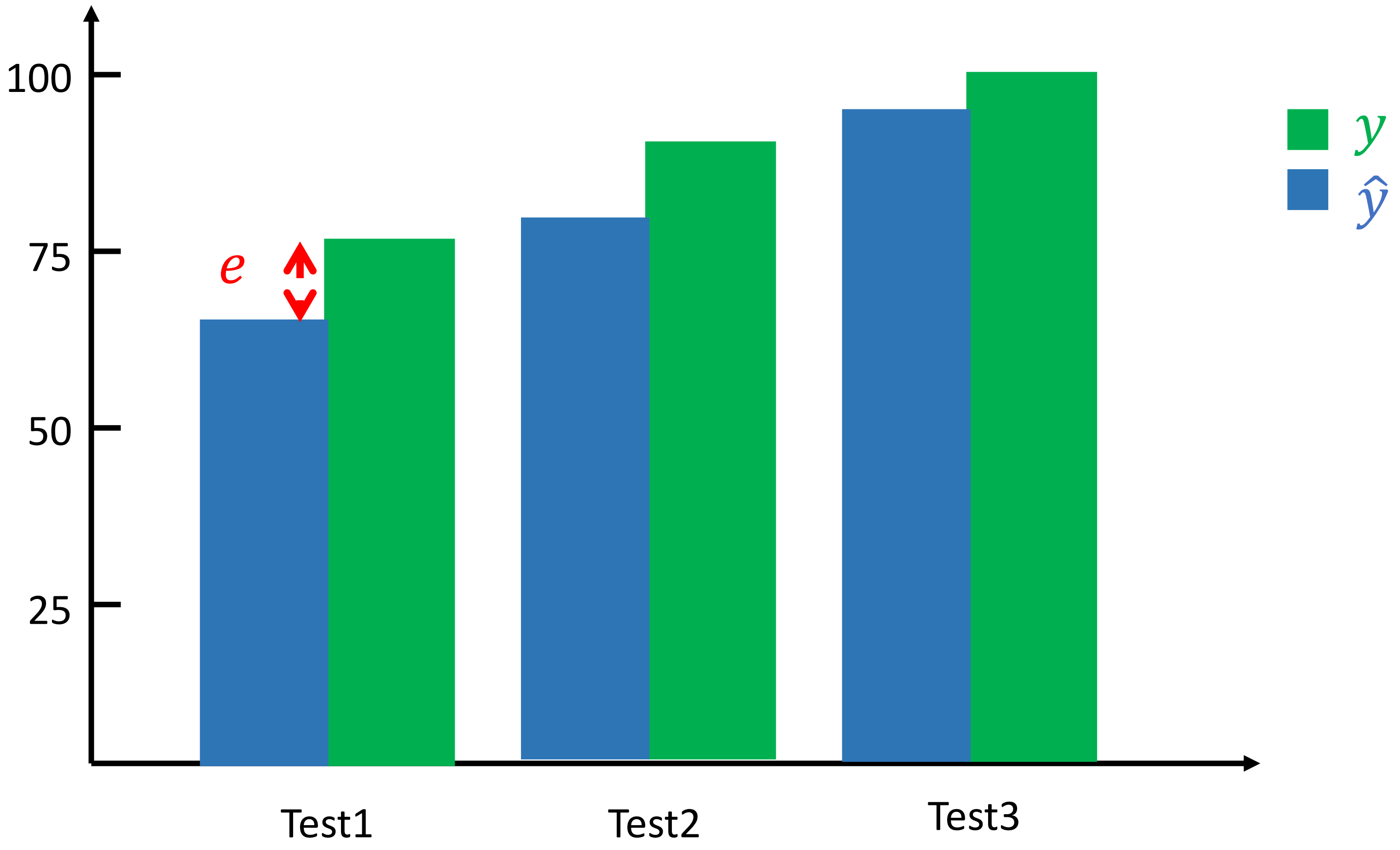
Error : Cost : Loss



Source: https://www.youtube.com/watch?v=bxe2T-V8XRs&index=1&list=PLiaHhY2iBX9hdHaRr6b7XevZtgZRa1PoU

Error = Predict Y - Actual Y

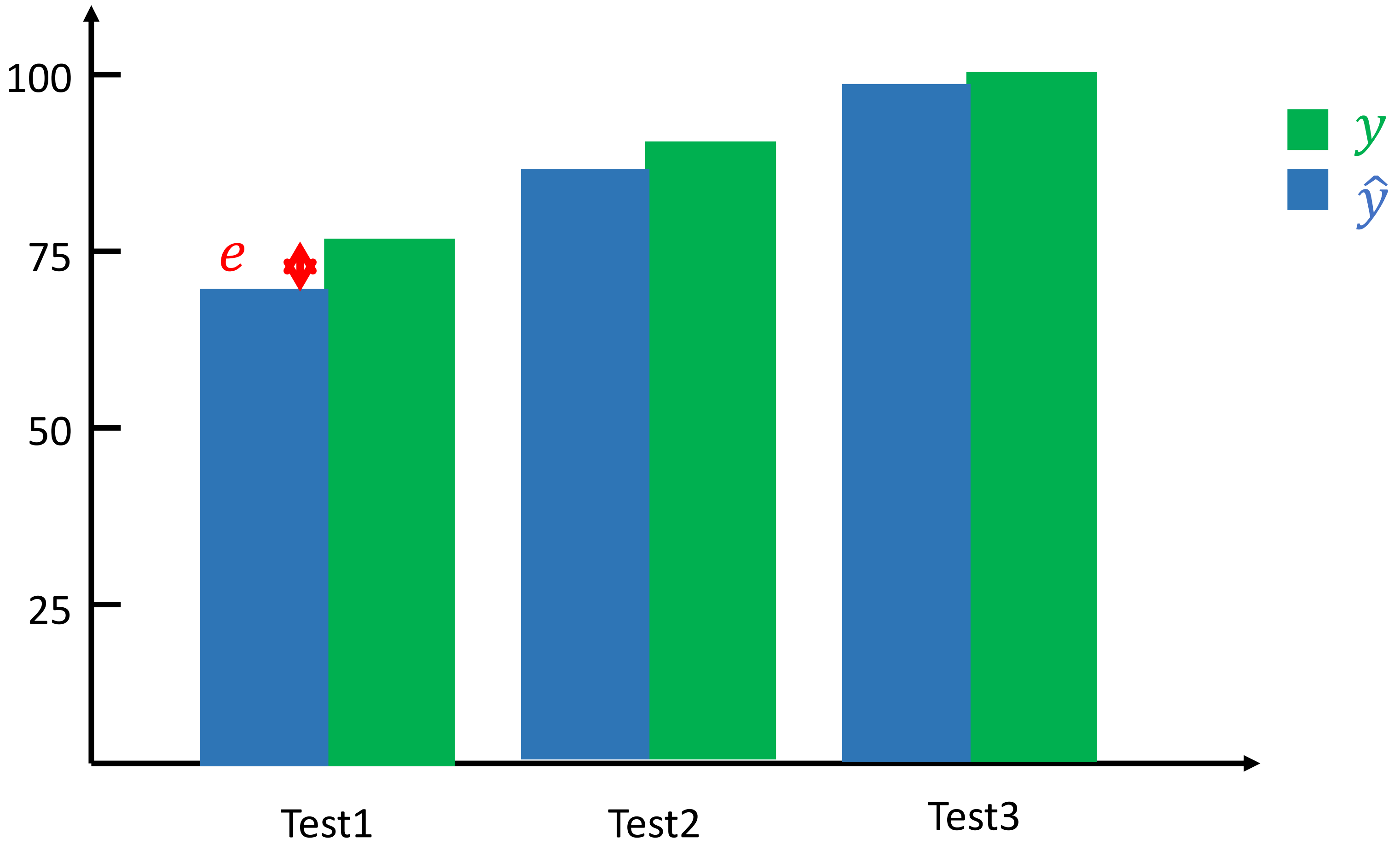
Error : Cost : Loss



Source: https://www.youtube.com/watch?v=bxe2T-V8XRs&index=1&list=PLiaHhY2iBX9hdHaRr6b7XevZtgZRa1PoU

Error = Predict Y - Actual Y

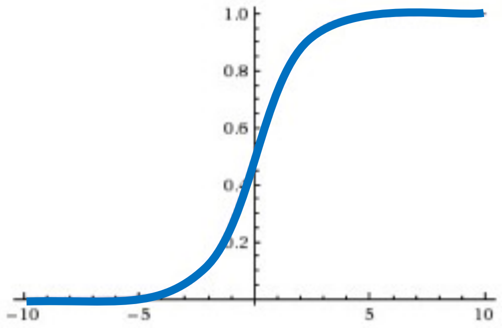
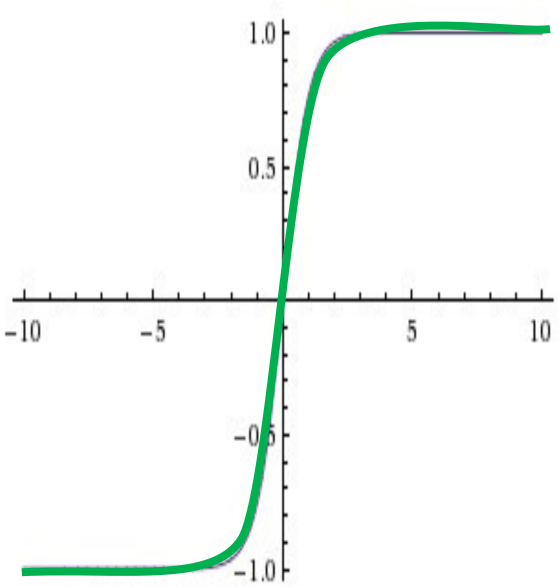
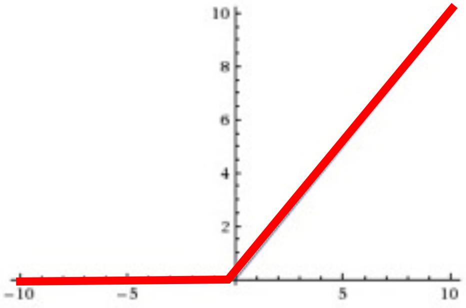
Error : Cost : Loss



Source: https://www.youtube.com/watch?v=bxe2T-V8XRs&index=1&list=PLiaHhY2iBX9hdHaRr6b7XevZtgZRa1PoU

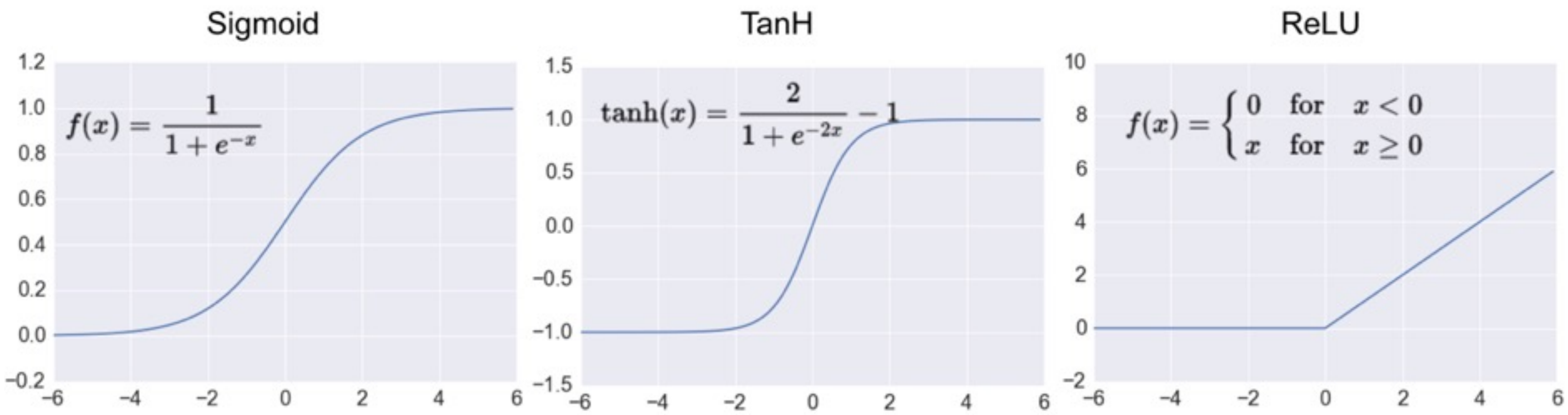
Activation Functions

Activation Functions

Sigmoid	TanH	ReLU (Rectified Linear Unit)
		
[0, 1]	[-1, 1]	$f(x) = max(0, x)$

Source: http://cs231n.github.io/neural-networks-1/

Activation Functions



Source: http://adilmoujahid.com/posts/2016/06/introduction-deep-learning-python-caffe/

Loss Function

Binary Classification: 2 Class

Activation Function:
Sigmoid

Loss Function:
Binary Cross-Entropy

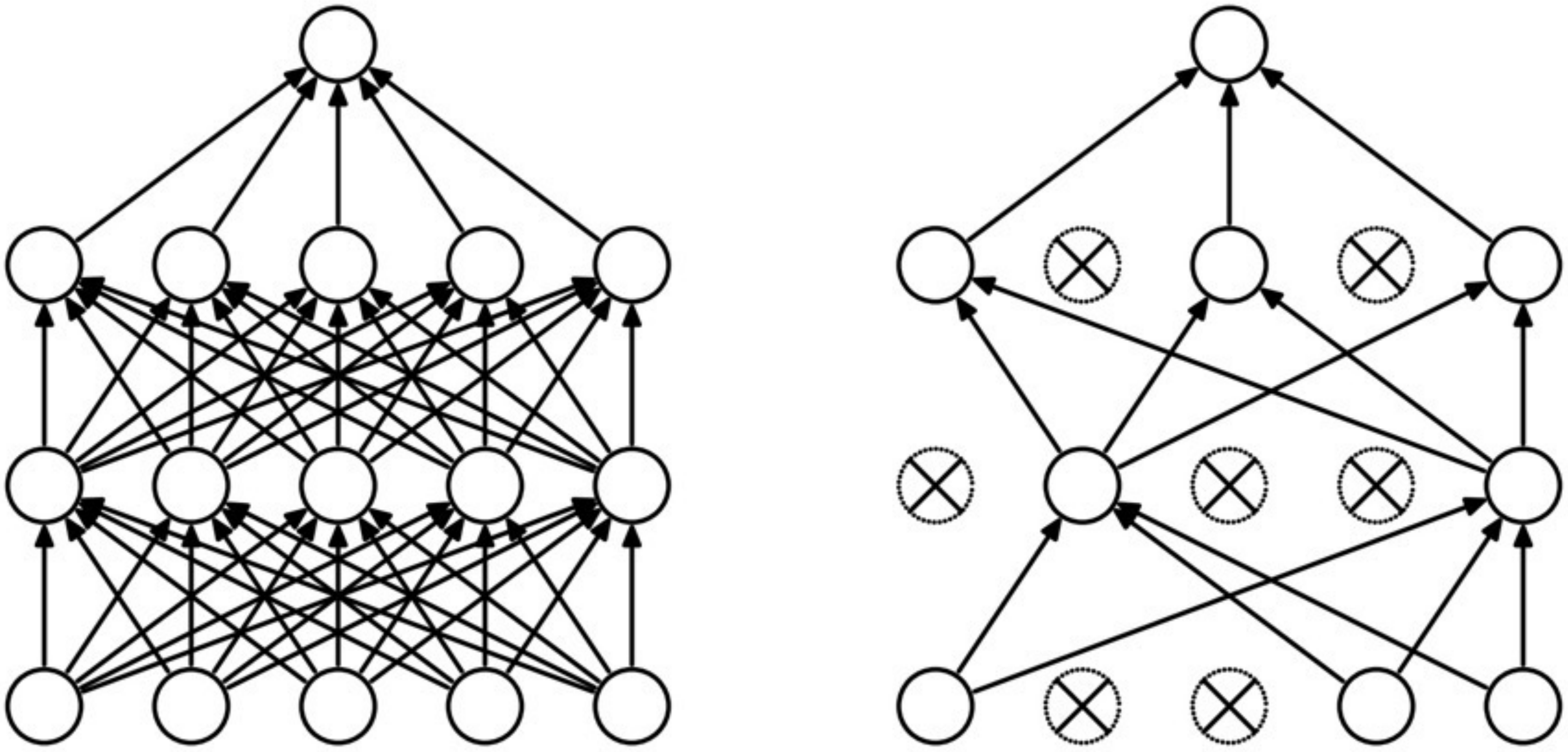
Multiple Classification: 10 Class

Activation Function:
SoftMAX

Loss Function:
Categorical Cross-Entropy

Dropout

Dropout: a simple way to prevent neural networks from overfitting



(a) Standard Neural Net

(b) After applying dropout.

Source: Srivastava, Nitish, Geoffrey E. Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov.
"Dropout: a simple way to prevent neural networks from overfitting." *Journal of machine learning research* 15, no. 1 (2014): 1929-1958.

Learning Algorithm

While not done:

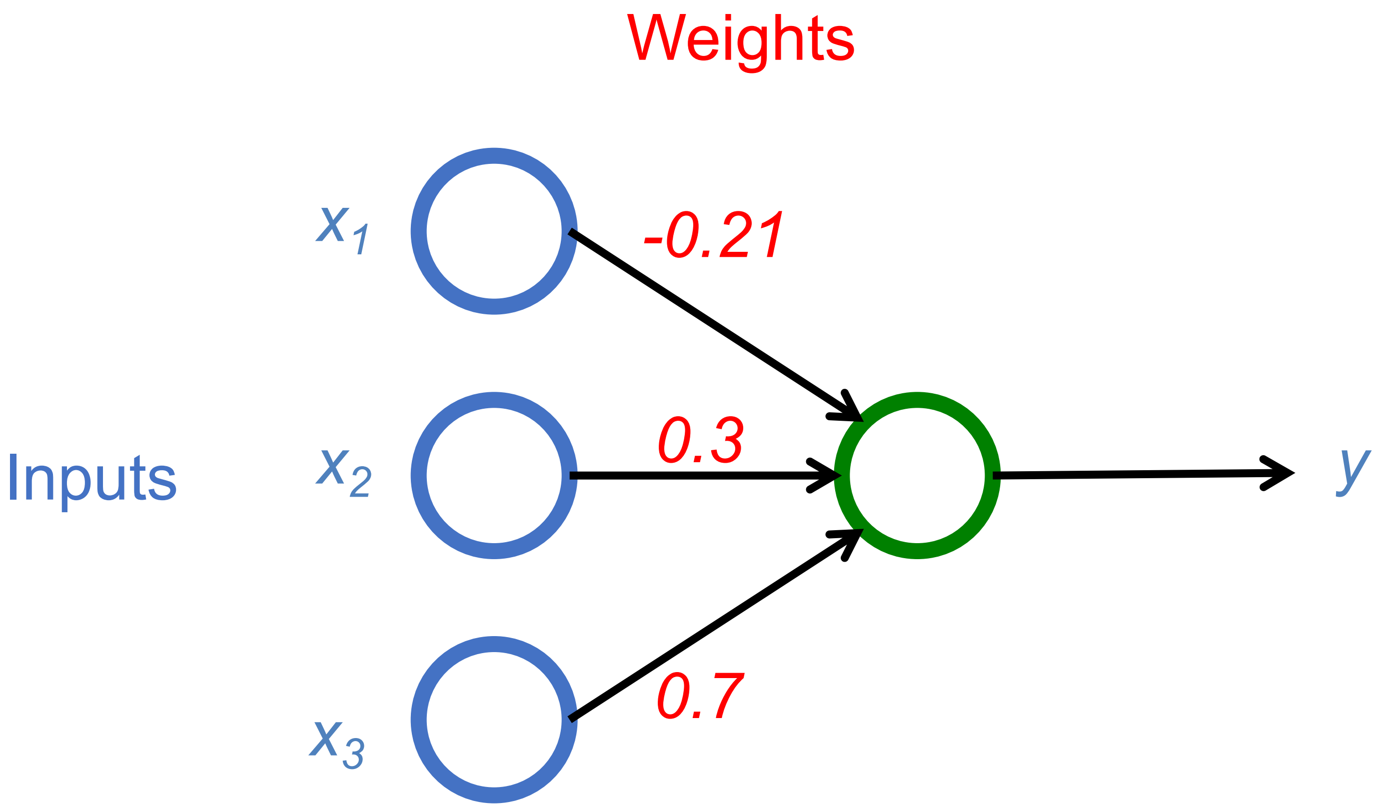
Pick a random training example "(input, label)"

Run neural network on "input"

Adjust weights on edges to make output closer to "label"

Source: Jeff Dean (2016), Large-Scale Deep Learning For Building Intelligent Computer Systems, WSDM 2016

$$y = max\ (\ 0,\ -0.21 * x_1 + 0.3 * x_2 + 0.7 * x_3\ )$$

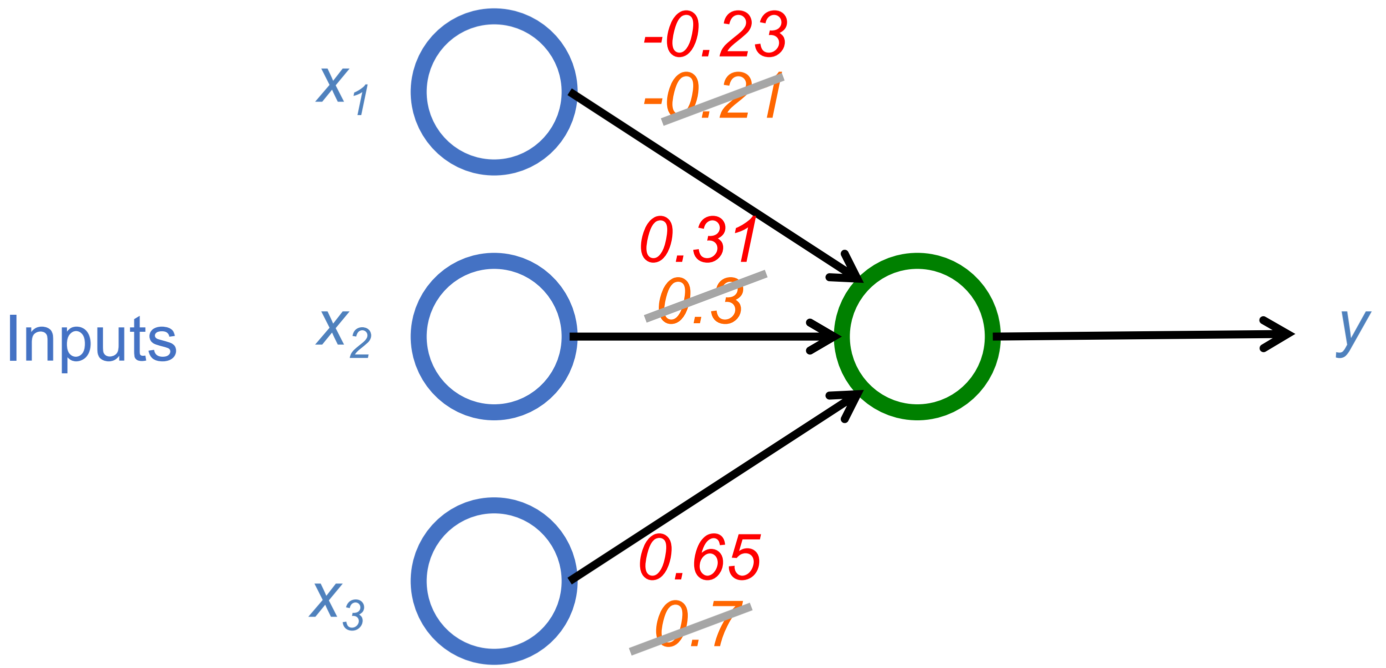


Next time:

$$y = max\ (\ 0,\ -0.23 * x_1 + 0.31 * x_2 + 0.65 * x_3\ )$$

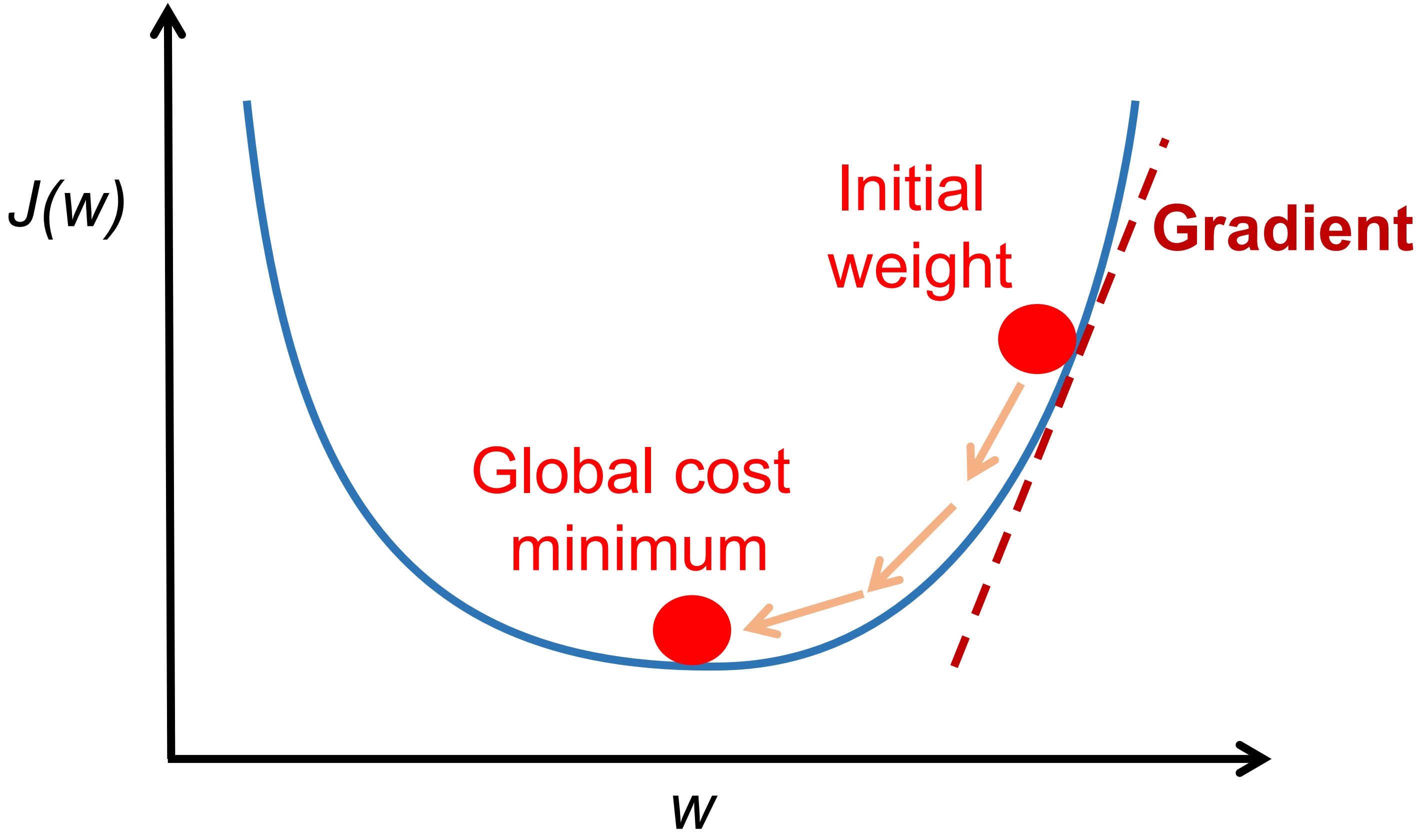
$$\cancel{y = max\ (\ 0,\ -0.21 * x_1 + 0.3 * x_2 + 0.7 * x_3\ )}$$

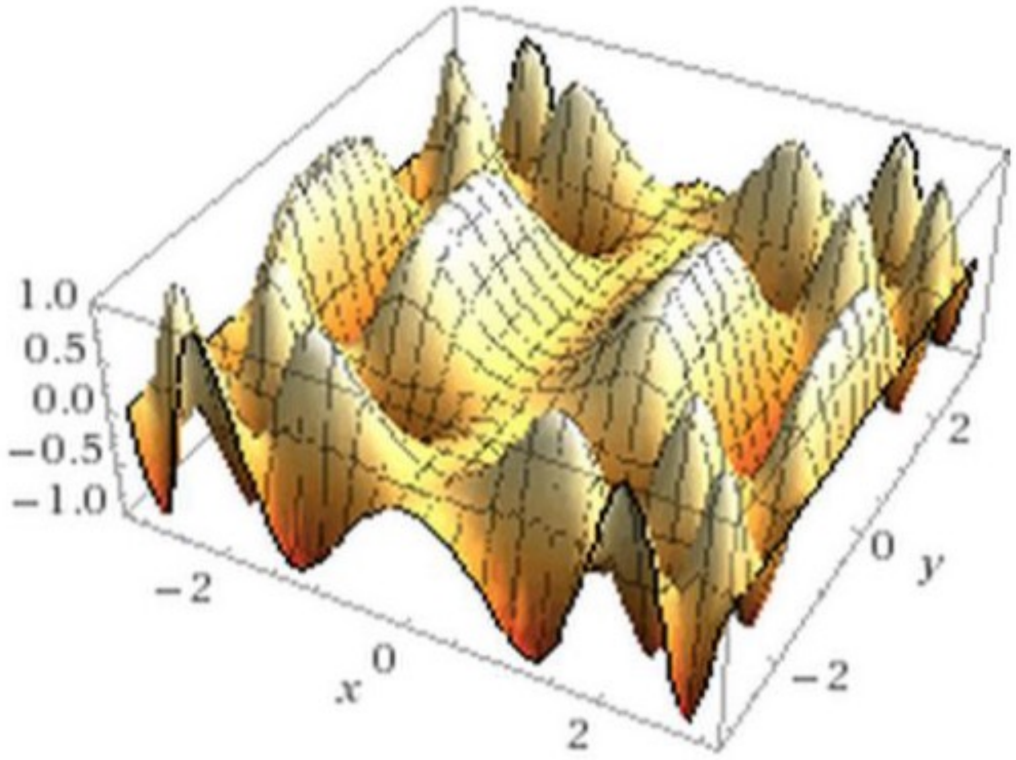
Weights



Optimizer:

Stochastic Gradient Descent (SGD)

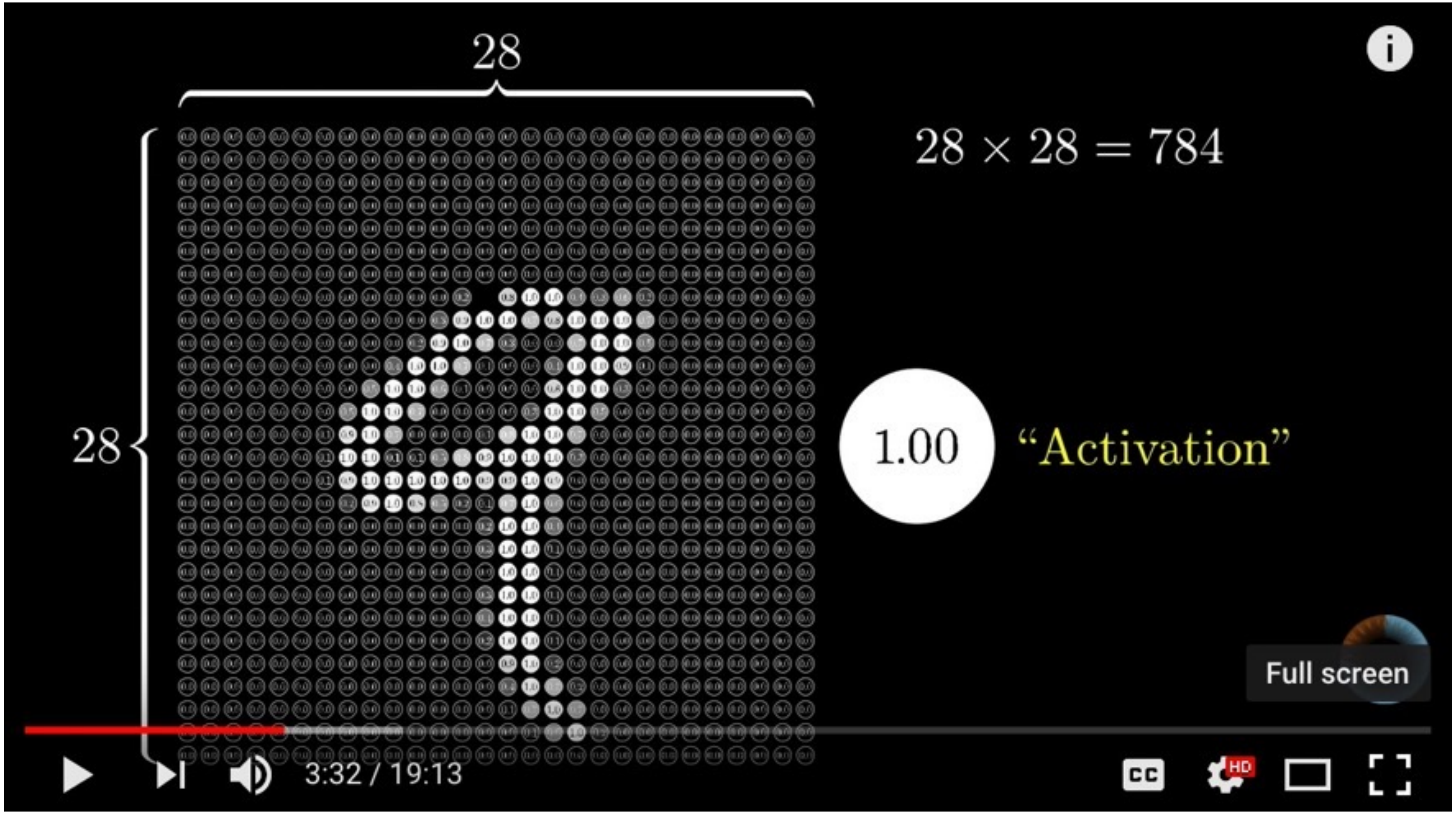




This shows a function of 2 variables: real neural nets are functions of hundreds of millions of variables!

Source: Jeff Dean (2016), Large-Scale Deep Learning For Building Intelligent Computer Systems, WSDM 2016

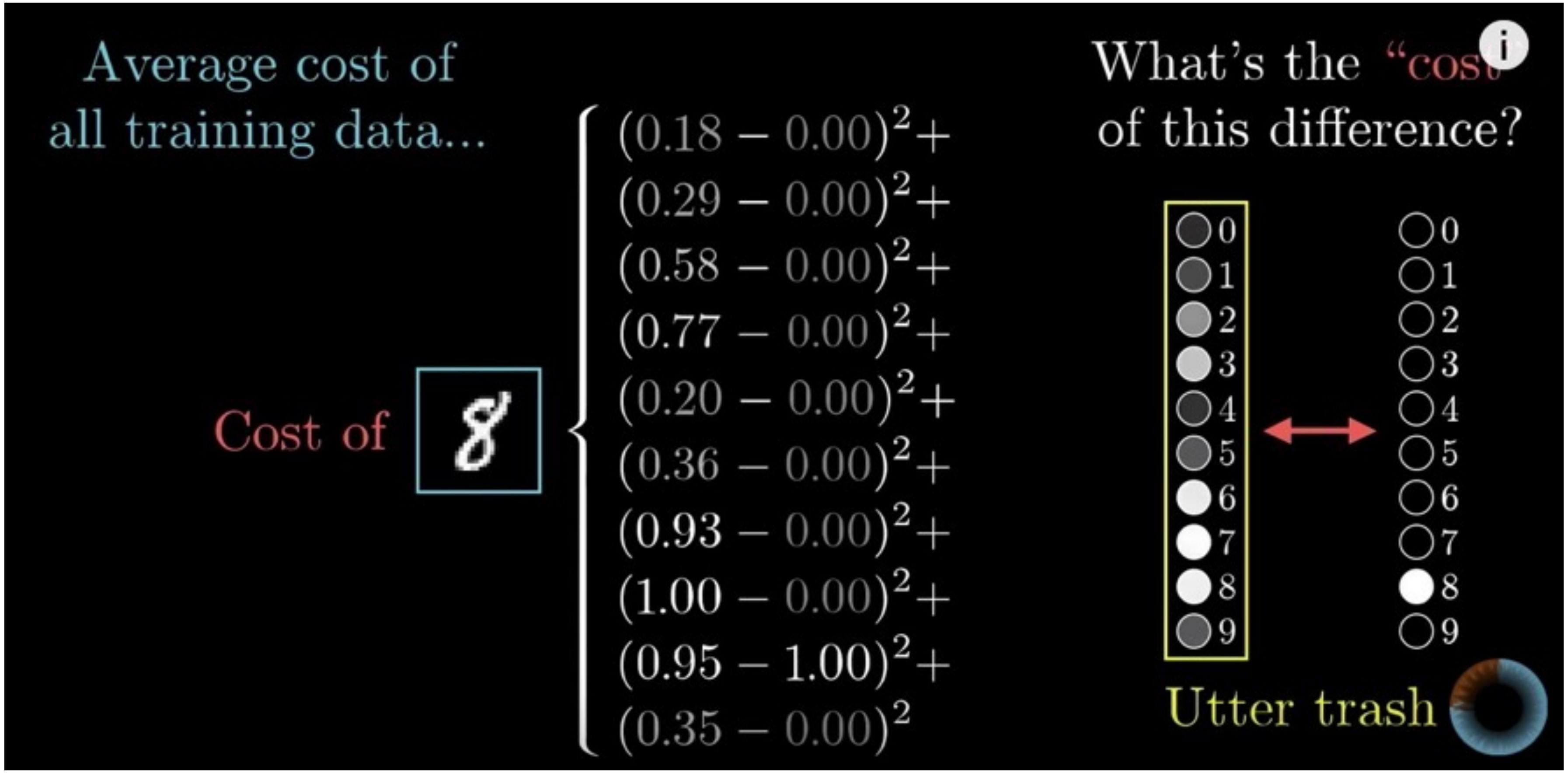
Neural Network and Deep Learning



Source: 3Blue1Brown (2017), But what *is* a Neural Network? | Chapter 1, deep learning, https://www.youtube.com/watch?v=aircAruvnKk

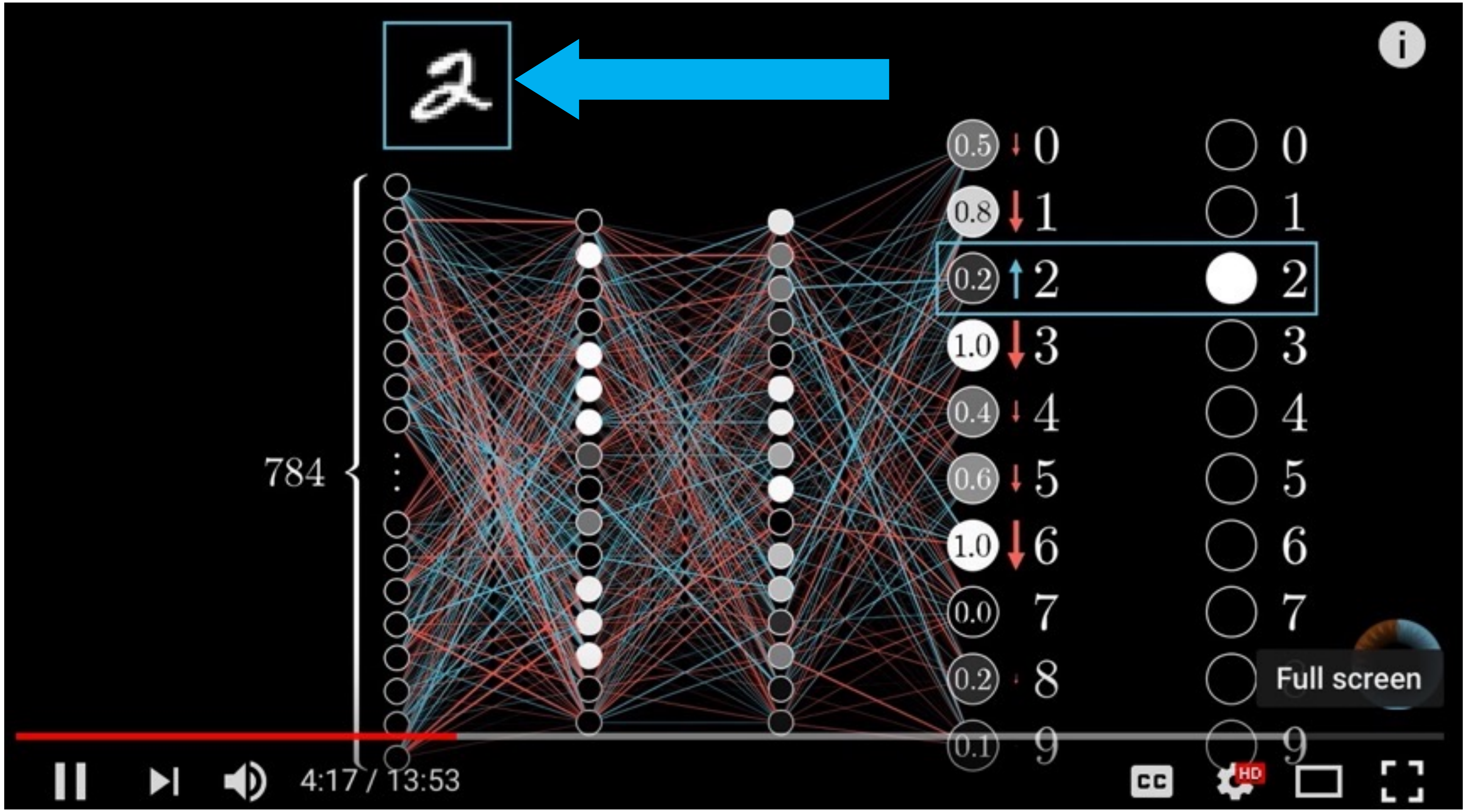
Gradient Descent

how neural networks learn



Source: 3Blue1Brown (2017), Gradient descent, how neural networks learn | Chapter 2, deep learning, https://www.youtube.com/watch?v=IHZwWFHWa-w

Backpropagation



Source: 3Blue1Brown (2017), What is backpropagation really doing? | Chapter 3, deep learning, https://www.youtube.com/watch?v=Ilg3gGewQ5U

Learning Algorithm

While not done:

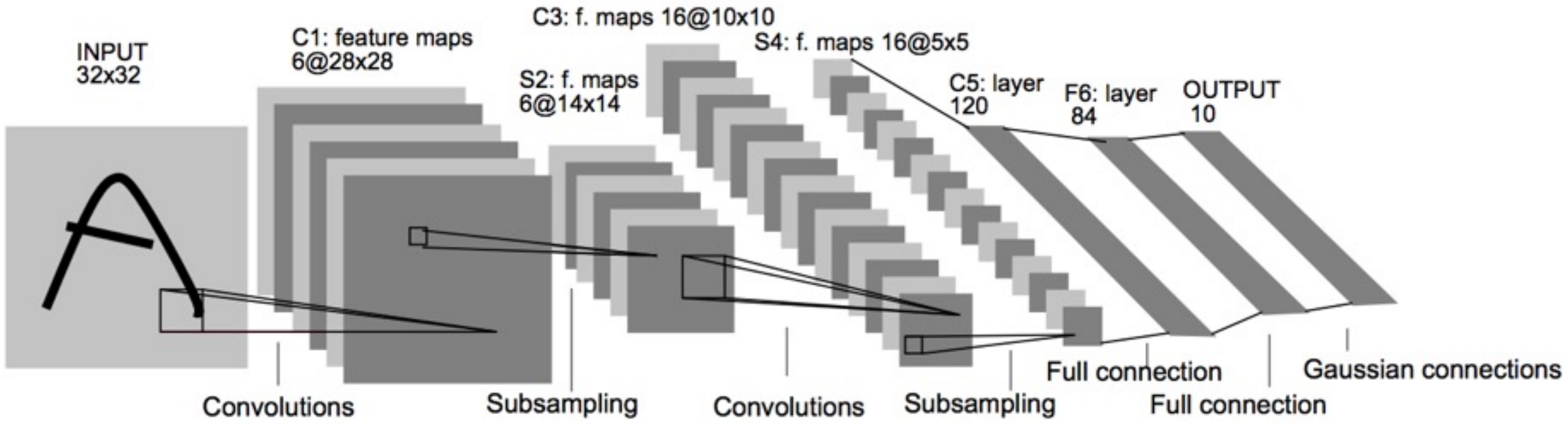
Pick a random training example "(input, label)"

Run neural network on "input"

Adjust weights on edges to make output closer to "label"

Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNN)



Architecture of LeNet-5 (7 Layers) (LeCun et al., 1998)

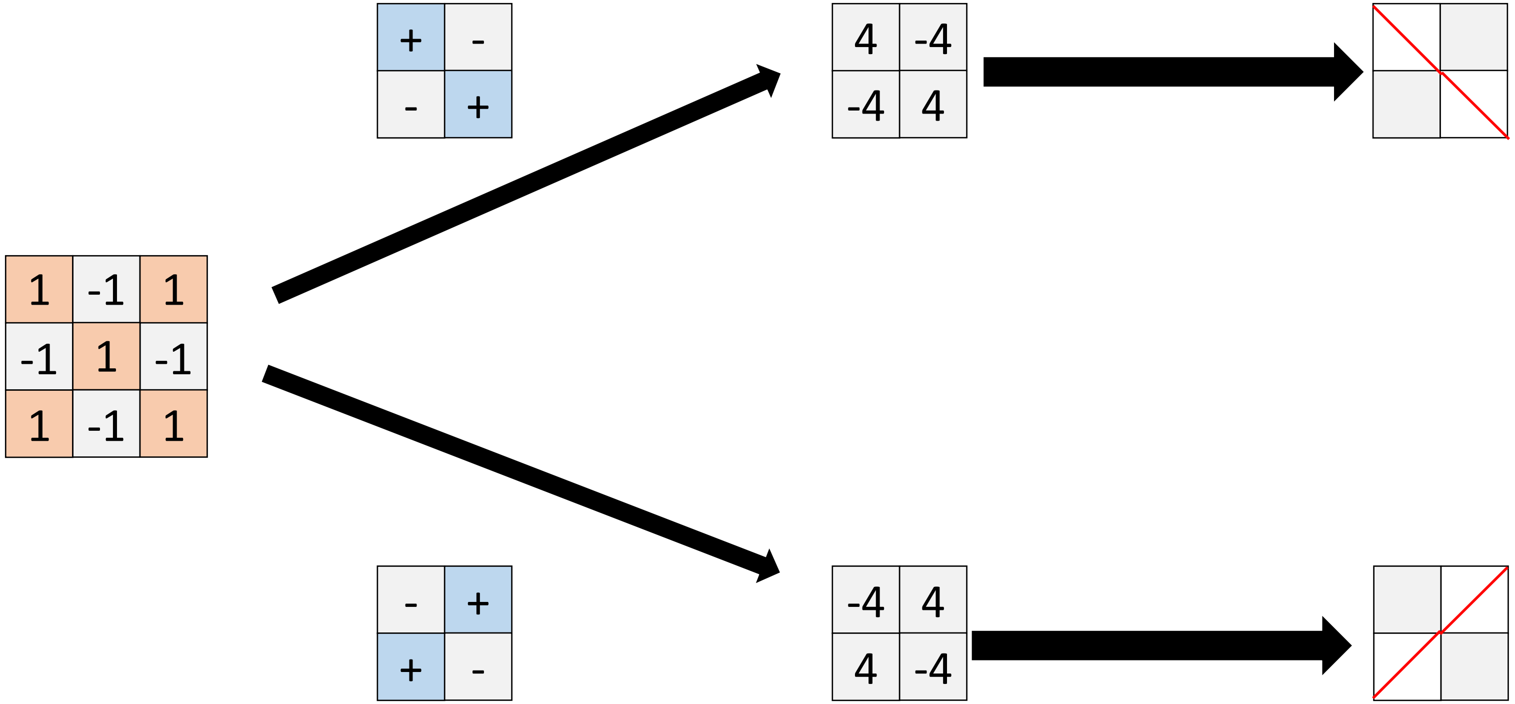
Source: http://yann.lecun.com/exdb/publis/pdf/lecun-01a.pdf

Source: LeCun, Yann, Léon Bottou, Yoshua Bengio, and Patrick Haffner. "Gradient-based learning applied to document recognition." *Proceedings of the IEEE* 86, no. 11 (1998): 2278-2324.

Convolutional Neural Networks (CNN)

- **Convolution**
- **Pooling**
- **Fully Connection (FC) (Flattening)**

A friendly introduction to Convolutional Neural Networks and Image Recognition

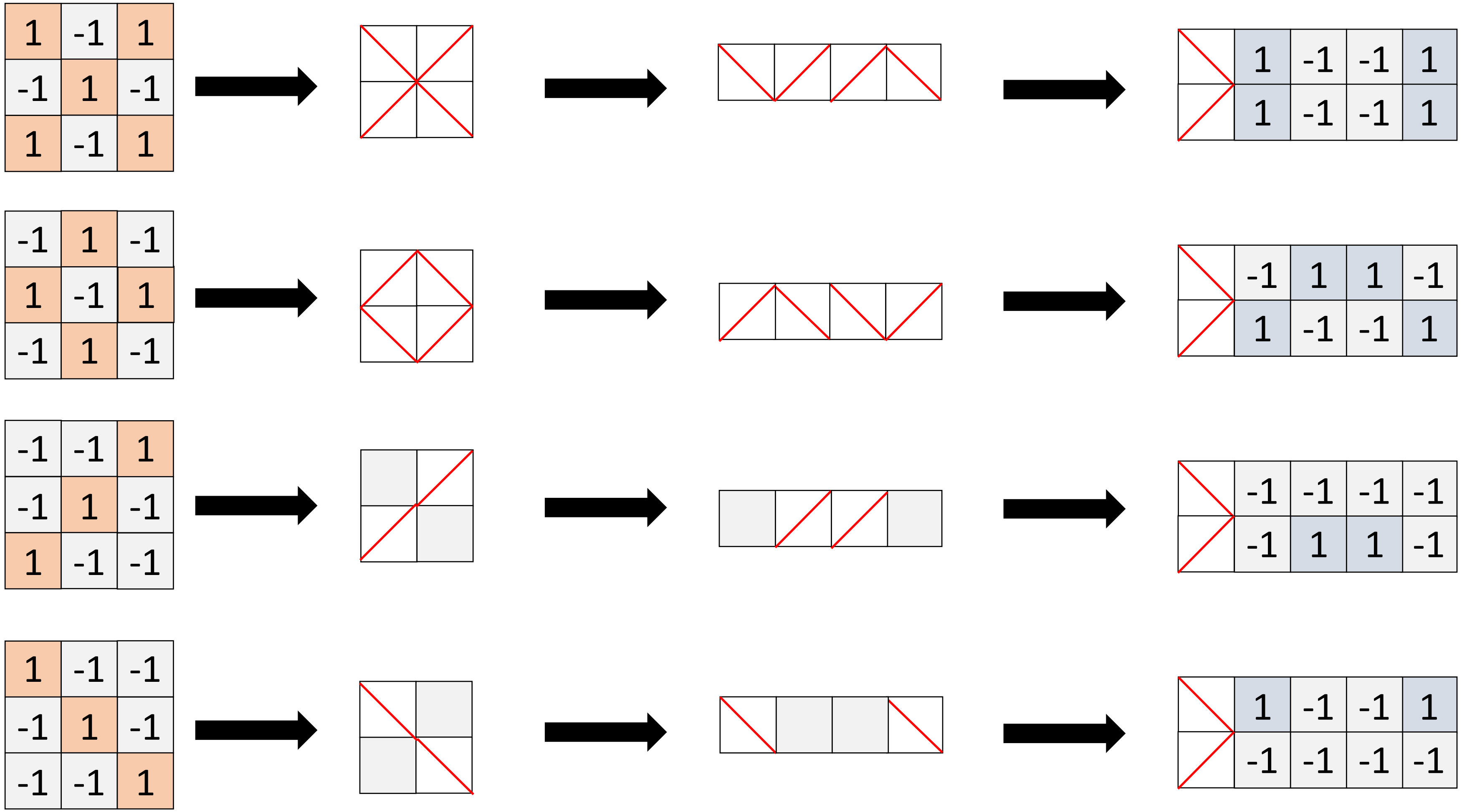


Convolution Layer

Pooling Layer

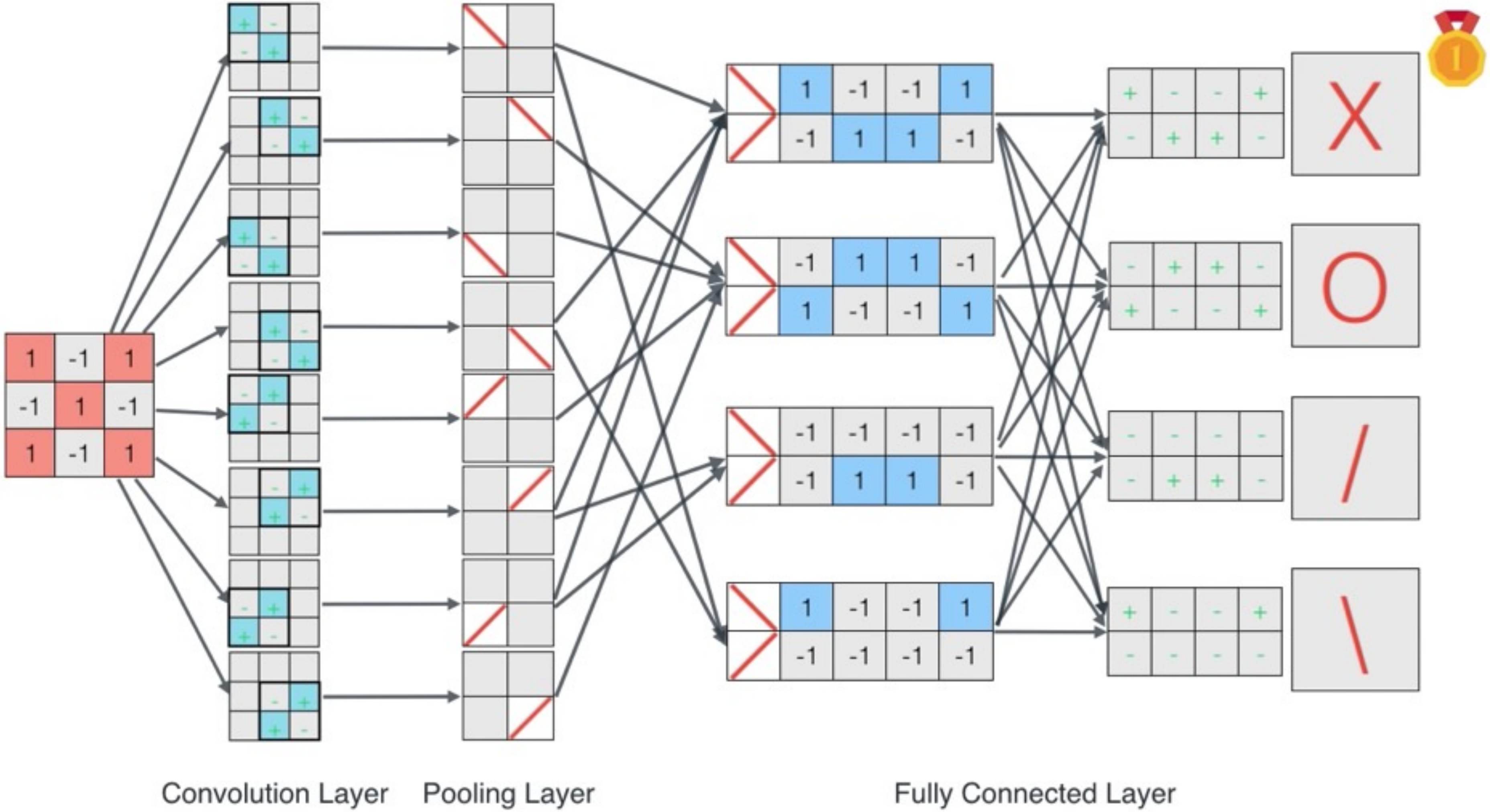
Source: Luis Serrano (2017), A friendly introduction to Convolutional Neural Networks and Image Recognition, https://www.youtube.com/watch?v=2-Ol7ZB0MmU

A friendly introduction to Convolutional Neural Networks and Image Recognition



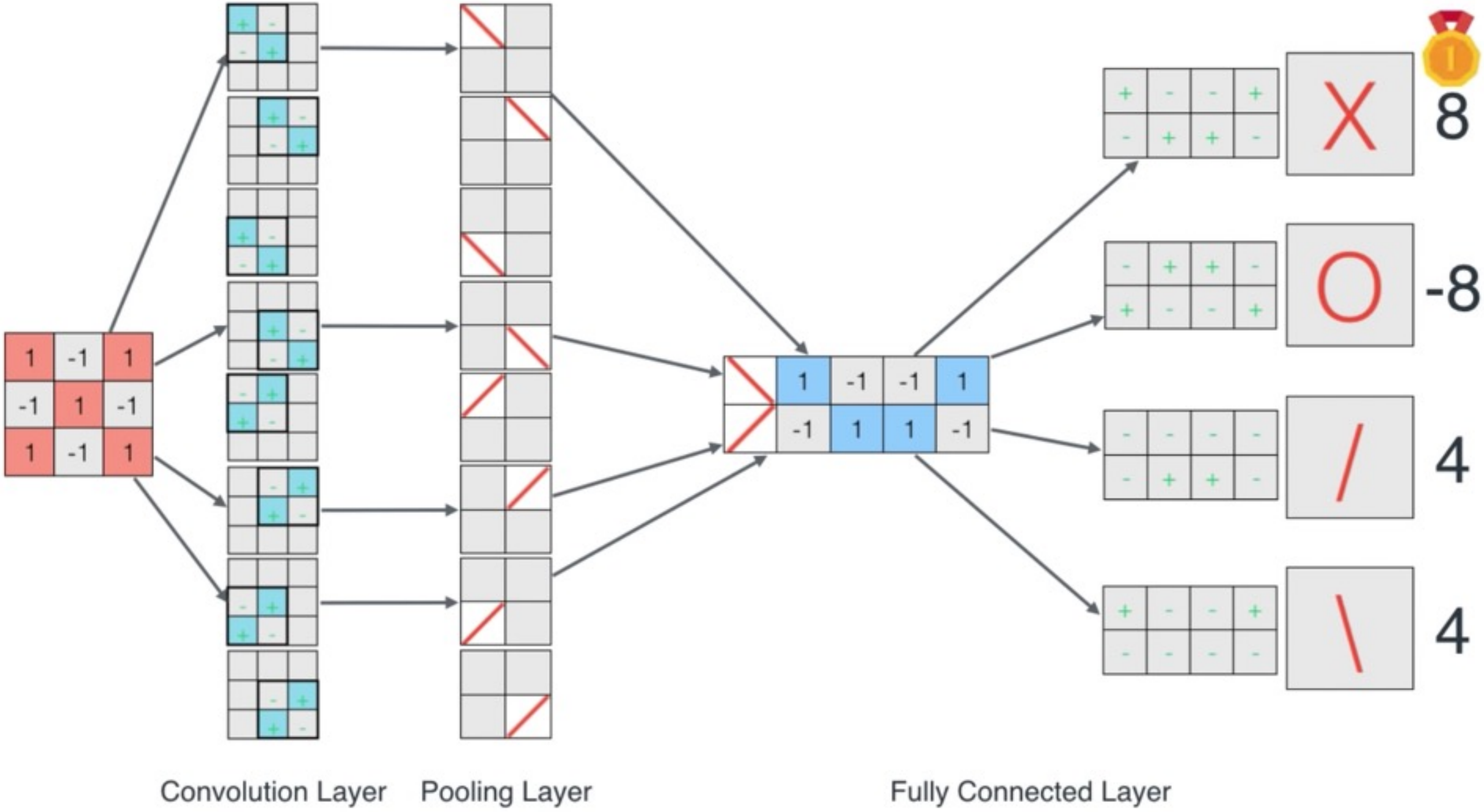
Source: Luis Serrano (2017), A friendly introduction to Convolutional Neural Networks and Image Recognition, https://www.youtube.com/watch?v=2-Ol7ZB0MmU

A friendly introduction to Convolutional Neural Networks and Image Recognition



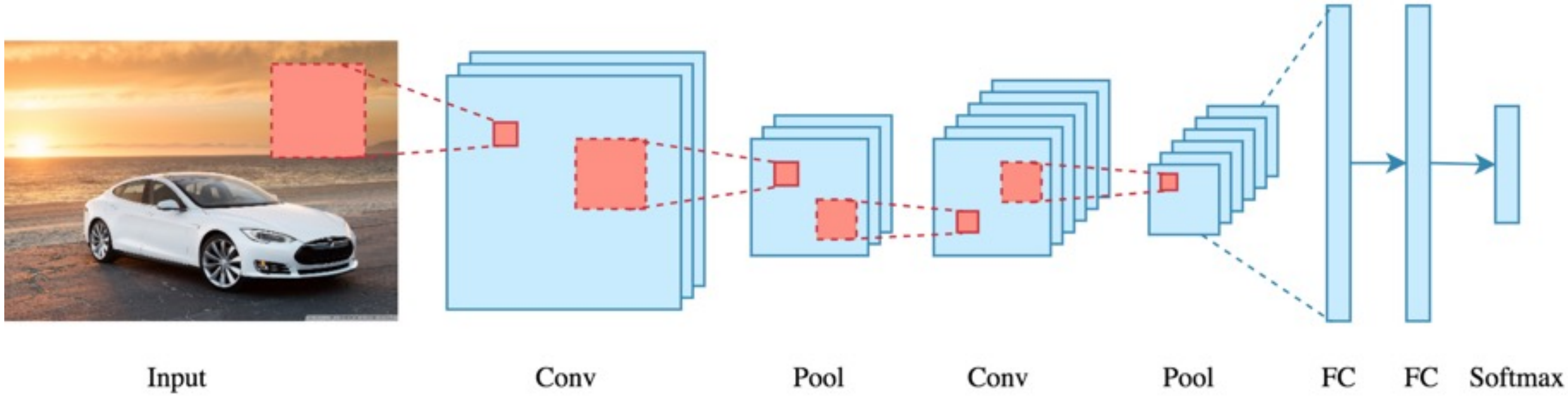
Source: Luis Serrano (2017), A friendly introduction to Convolutional Neural Networks and Image Recognition, https://www.youtube.com/watch?v=2-Ol7ZB0MmU

A friendly introduction to Convolutional Neural Networks and Image Recognition



Source: Luis Serrano (2017), A friendly introduction to Convolutional Neural Networks and Image Recognition, https://www.youtube.com/watch?v=2-Ol7ZB0MmU

CNN Architecture



Source: Arden Dertat (2017), Applied Deep Learning - Part 4: Convolutional Neural Networks, https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

CNN Convolution Layer

Convolution is a **mathematical operation** to **merge two sets** of information

3x3 convolution

1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

Input

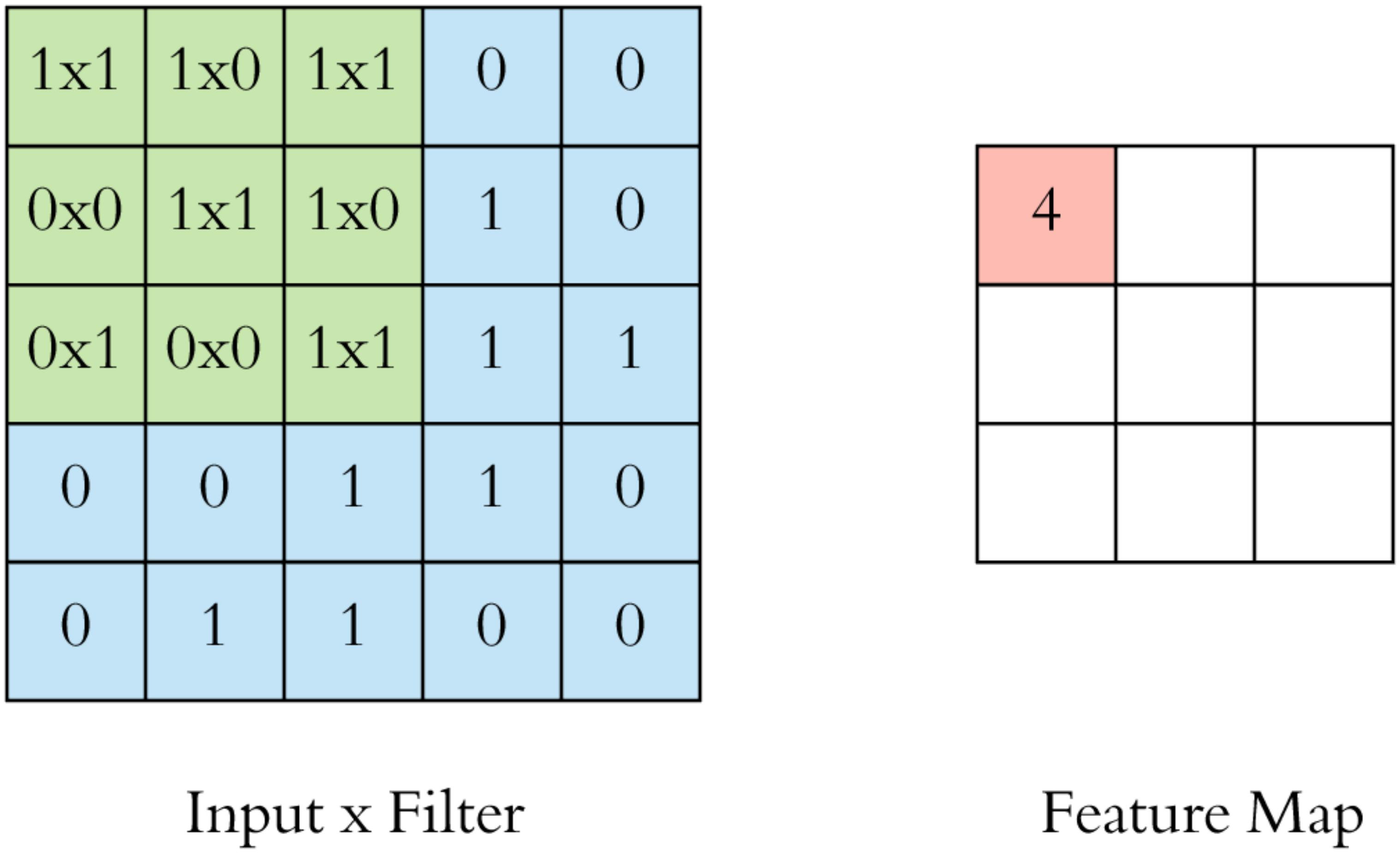
1	0	1
0	1	0
1	0	1

Filter / Kernel

Source: Arden Dertat (2017), Applied Deep Learning - Part 4: Convolutional Neural Networks, https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

CNN Convolution Layer
Input x Filter --> Feature Map

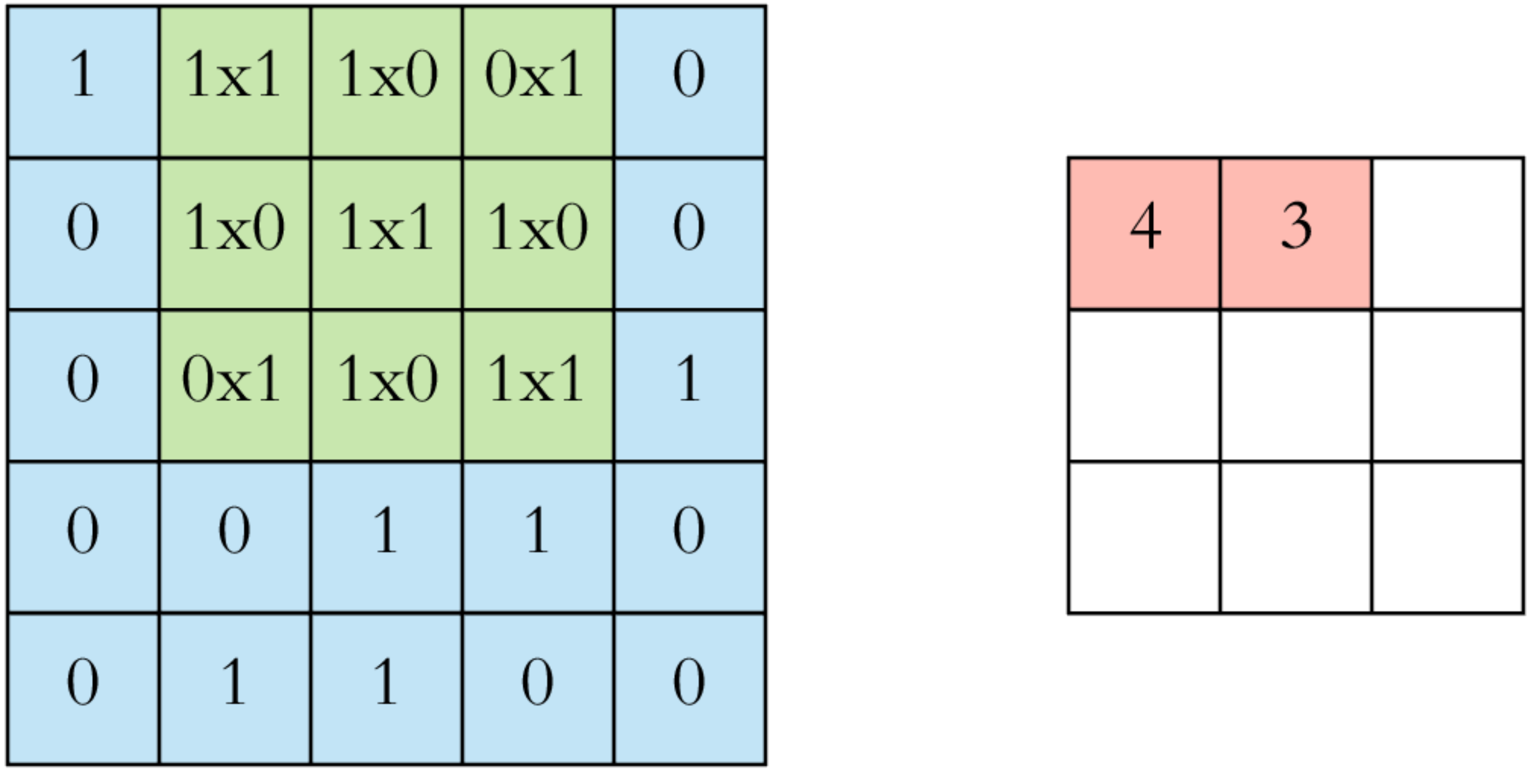
receptive field: 3x3



Source: Arden Dertat (2017), Applied Deep Learning - Part 4: Convolutional Neural Networks,
https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

CNN Convolution Layer
Input x Filter --> Feature Map

receptive field: 3x3

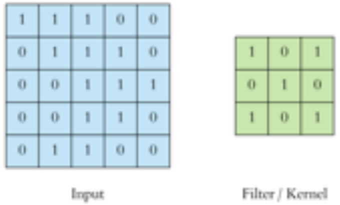


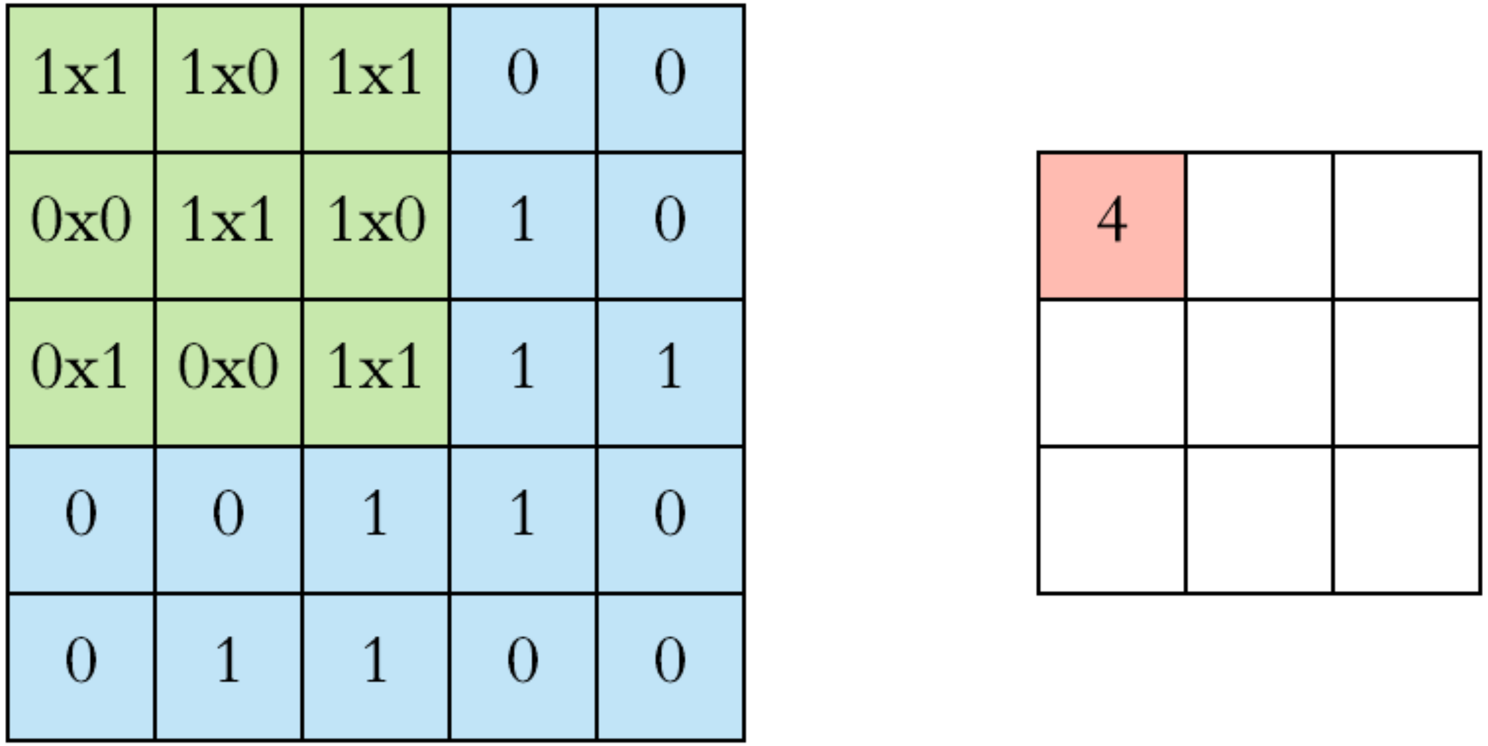
Input x Filter

Feature Map

Source: Arden Dertat (2017), Applied Deep Learning - Part 4: Convolutional Neural Networks, https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

CNN Convolution Layer



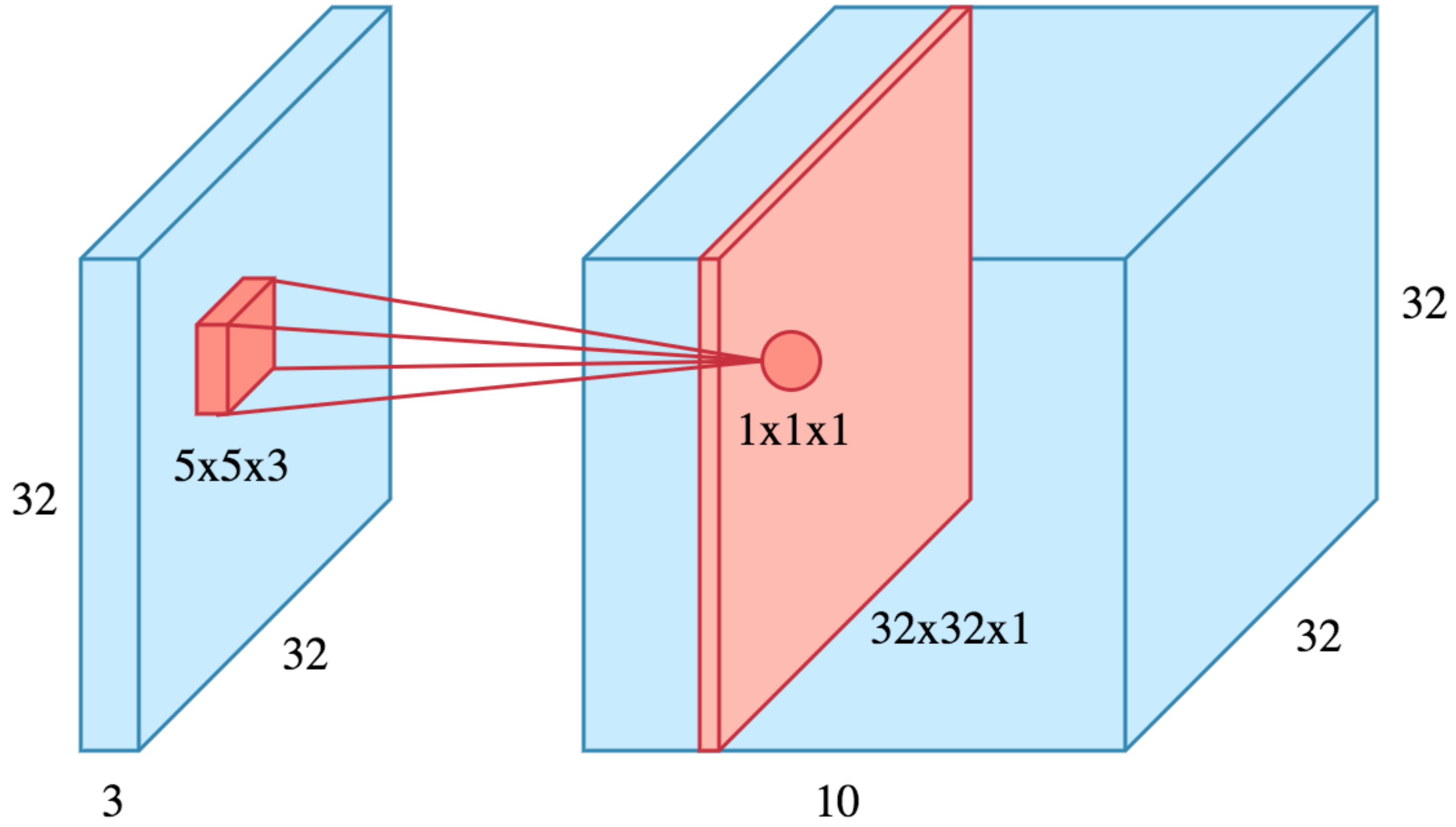


Example convolution operation shown in 2D using a 3x3 filter

Source: Arden Dertat (2017), Applied Deep Learning - Part 4: Convolutional Neural Networks,
https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

CNN Convolution Layer

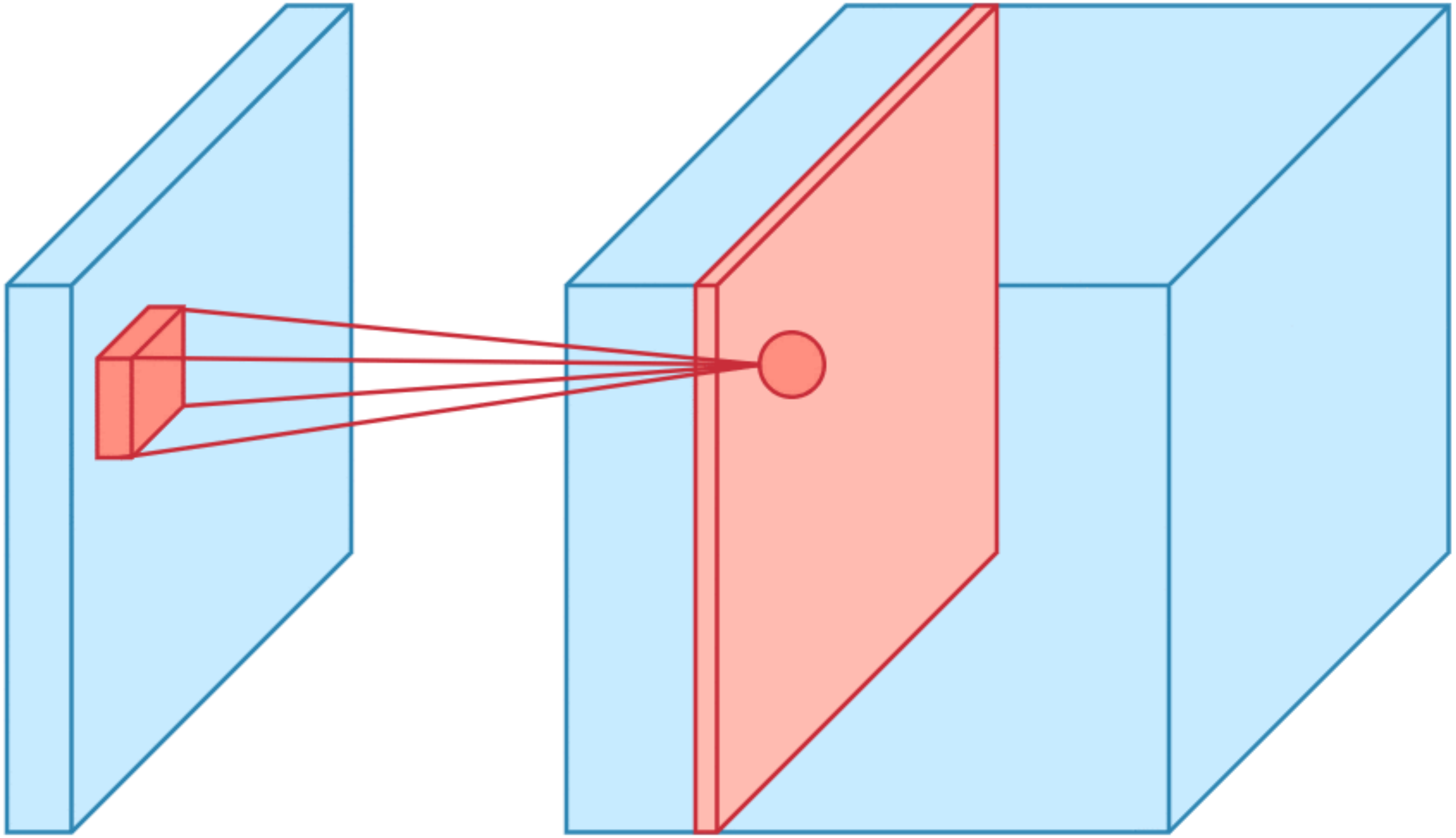
10 different filters 10 feature maps of size 32x32x1



final output of the convolution layer:
a volume of size 32x32x10

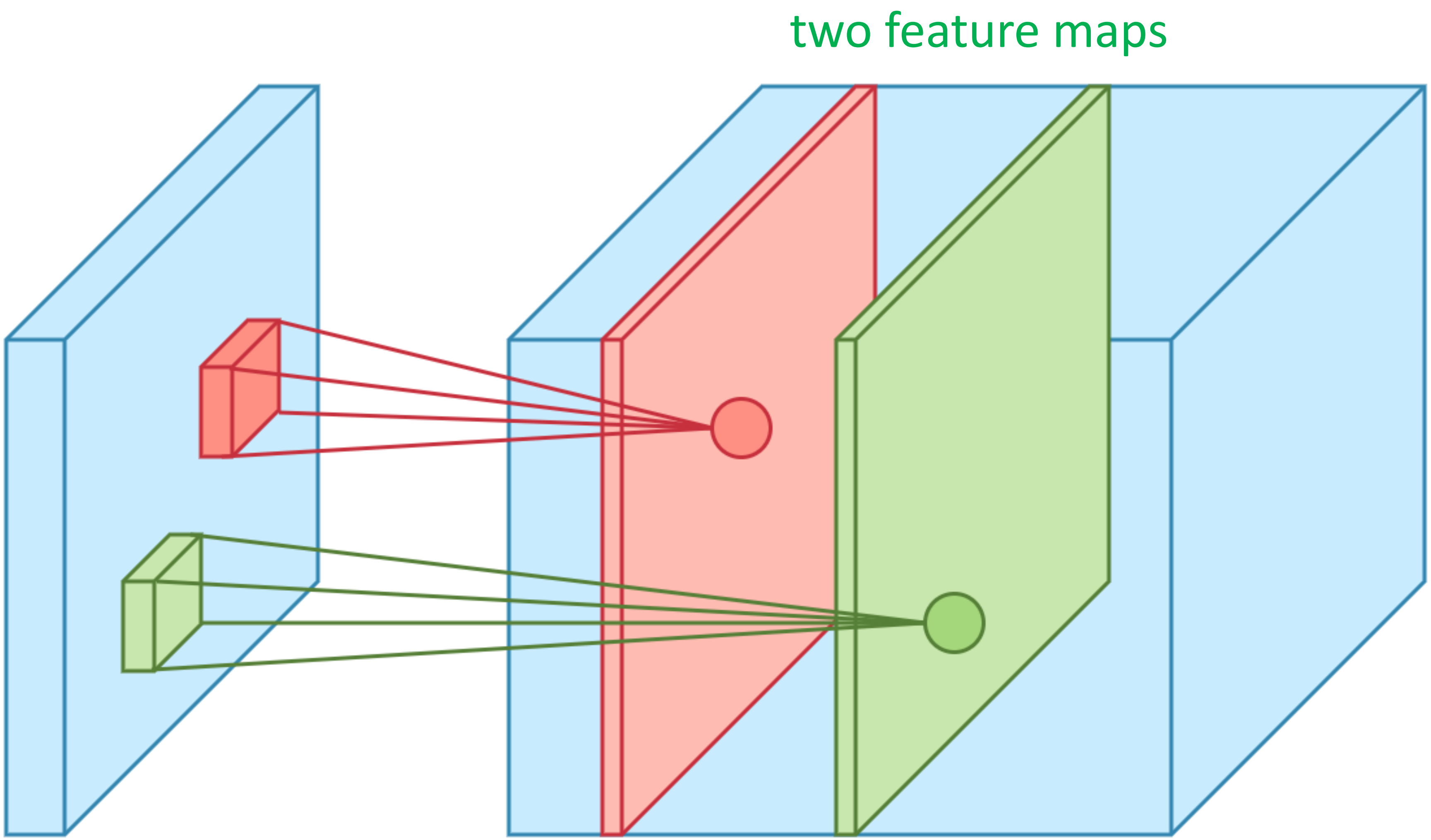
Source: Arden Dertat (2017), Applied Deep Learning - Part 4: Convolutional Neural Networks,
https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

CNN Convolution Layer
Sliding operation at 4 locations



Source: Arden Dertat (2017), Applied Deep Learning - Part 4: Convolutional Neural Networks,
https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

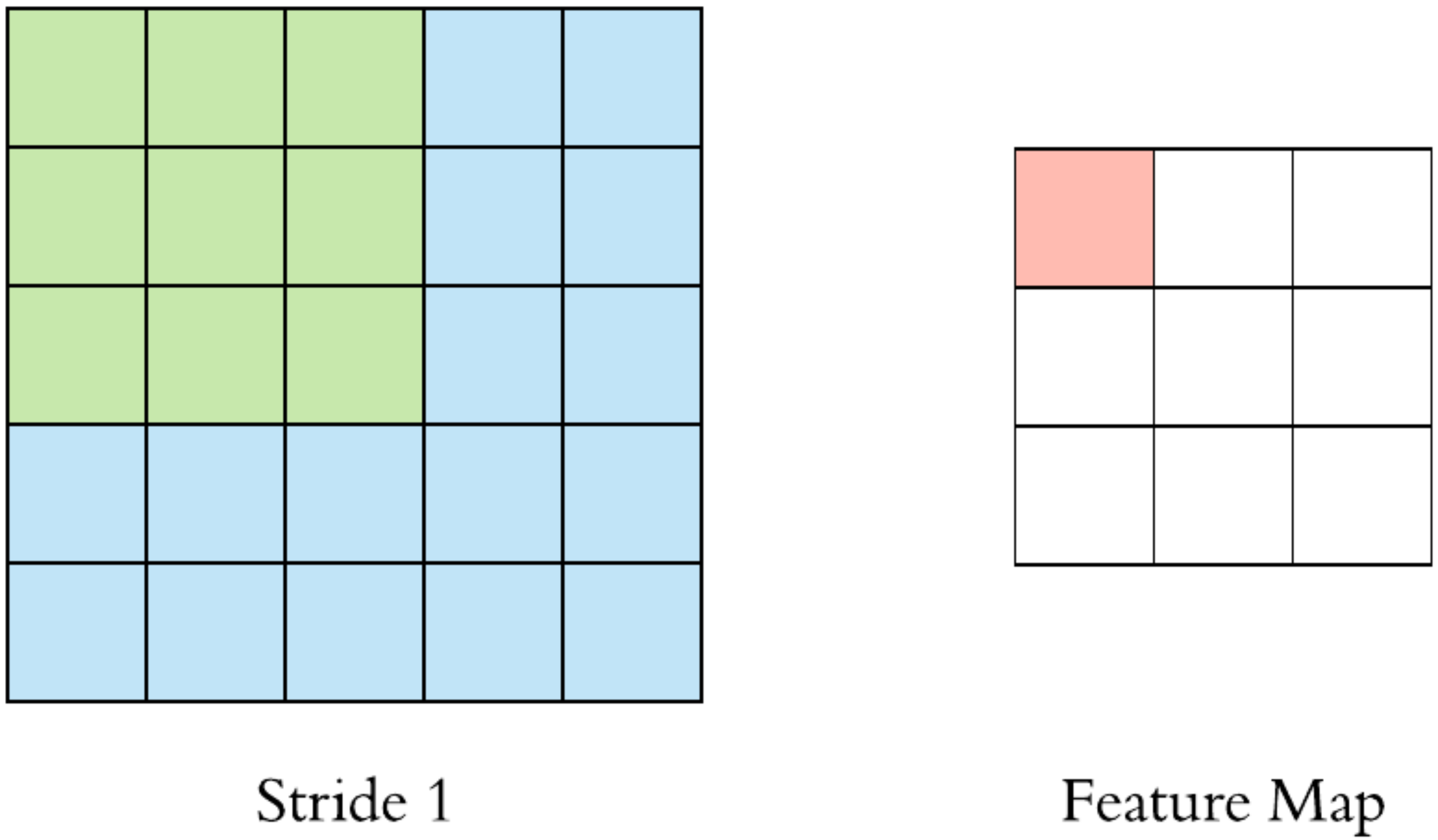
CNN Convolution Layer



Source: Arden Dertat (2017), Applied Deep Learning - Part 4: Convolutional Neural Networks,
https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

CNN Convolution Layer

Stride specifies how much
we move the convolution filter at each step



Source: Arden Dertat (2017), Applied Deep Learning - Part 4: Convolutional Neural Networks, https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

CNN Convolution Layer

Stride specifies how much
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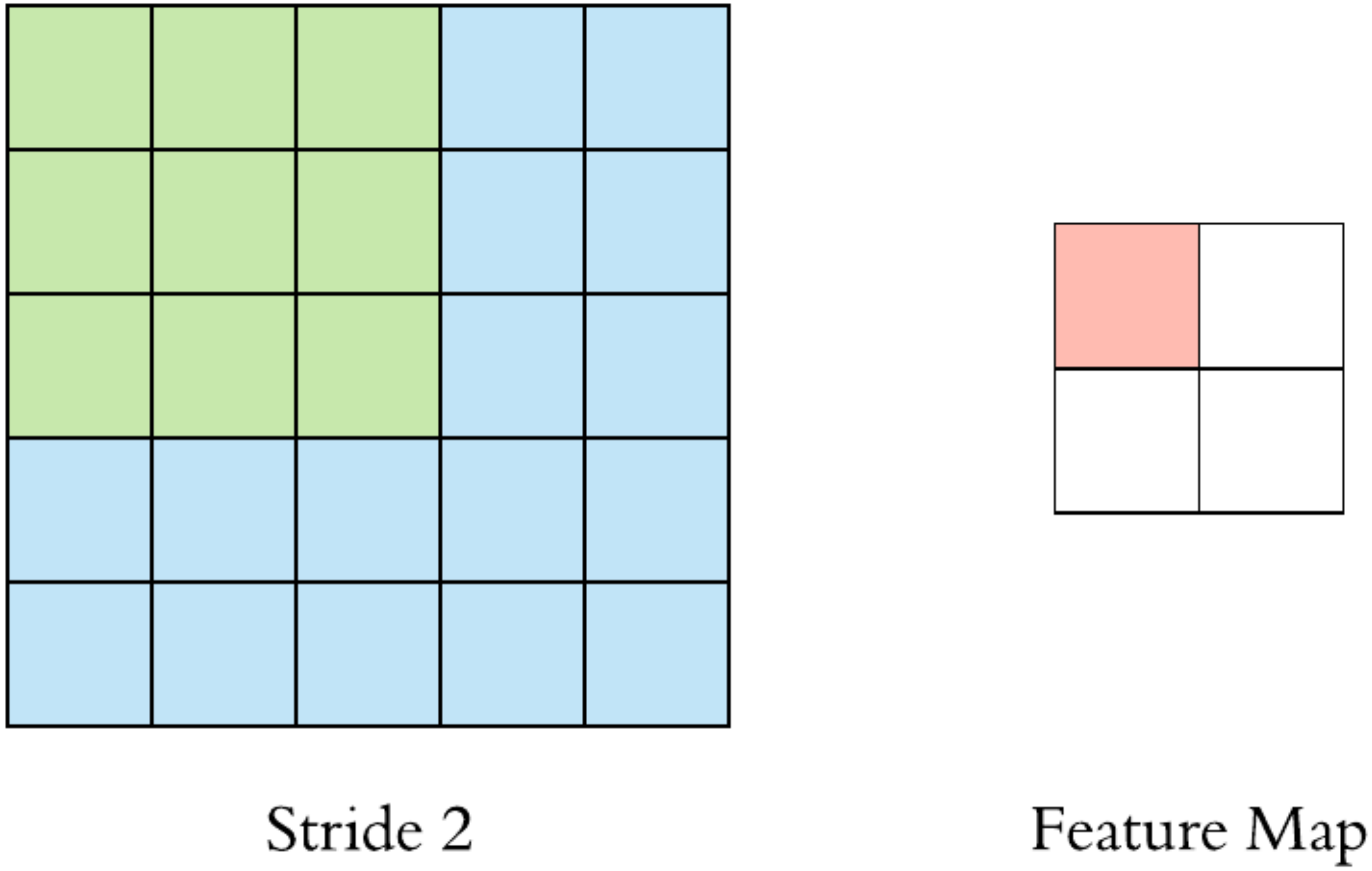
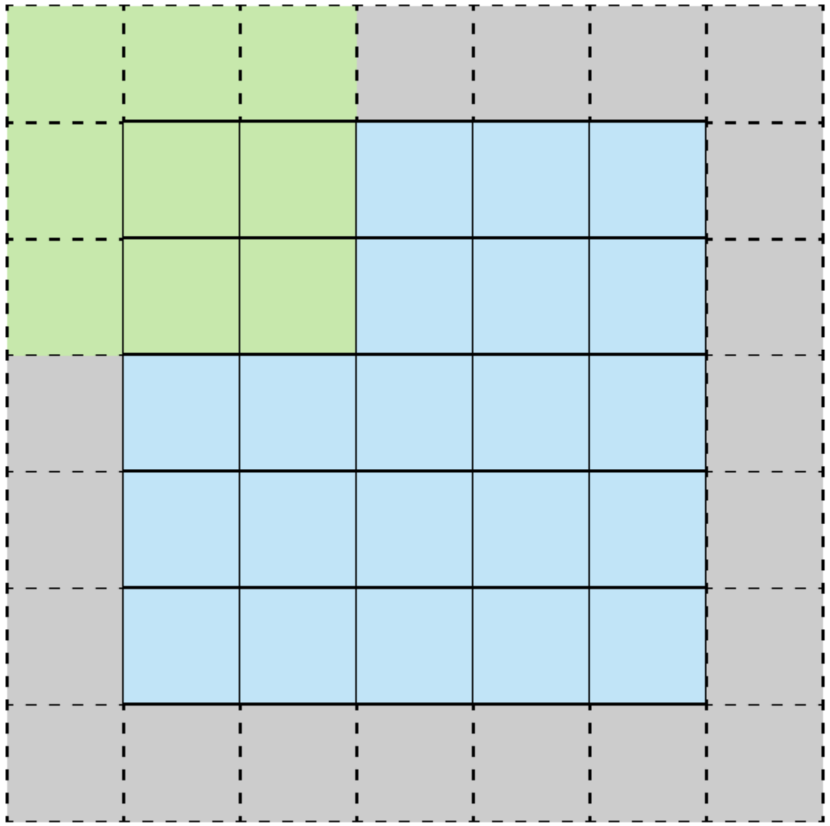


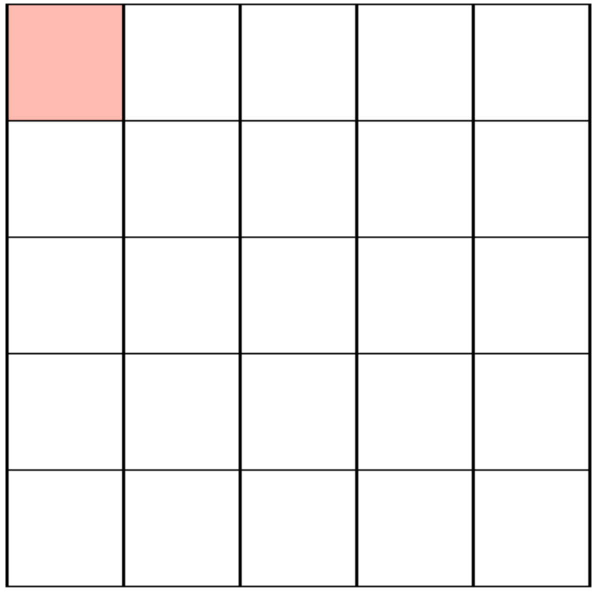
Source: Arden Dertat (2017), Applied Deep Learning - Part 4: Convolutional Neural Networks,
https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

CNN Convolution Layer

Stride 1 with **Padding**



Stride 1 with Padding

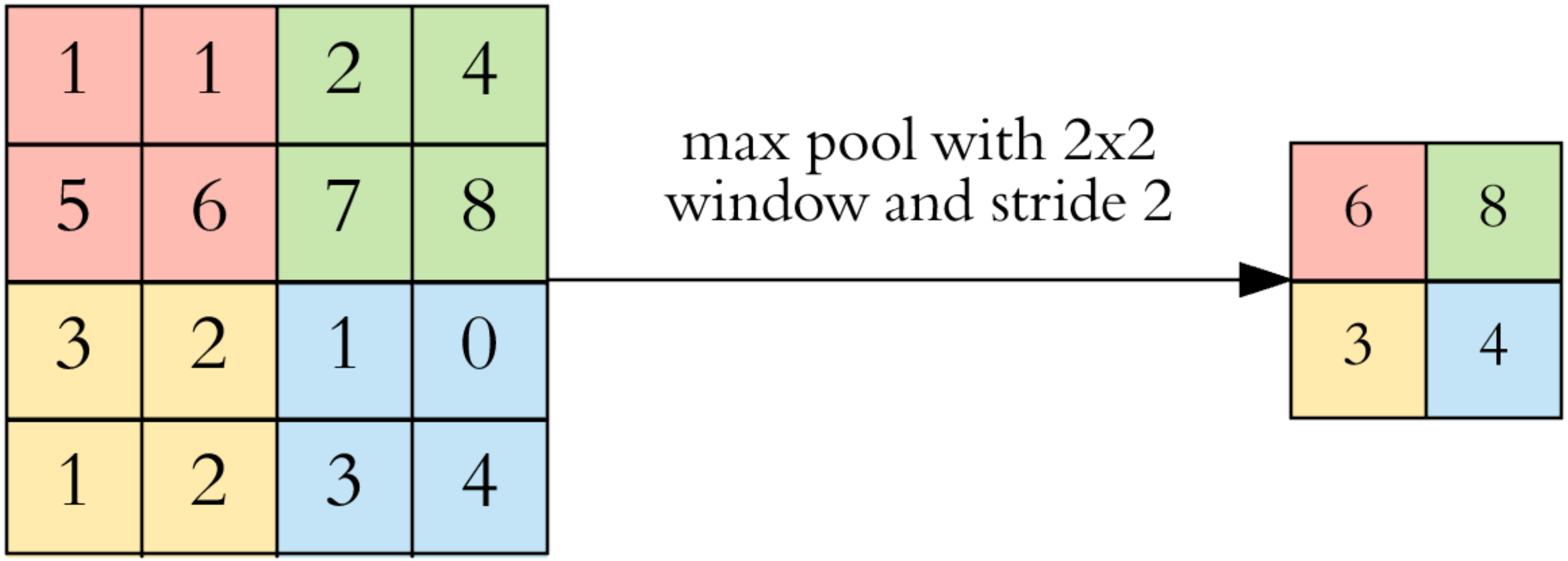


Feature Map

Source: Arden Dertat (2017), Applied Deep Learning - Part 4: Convolutional Neural Networks,
https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

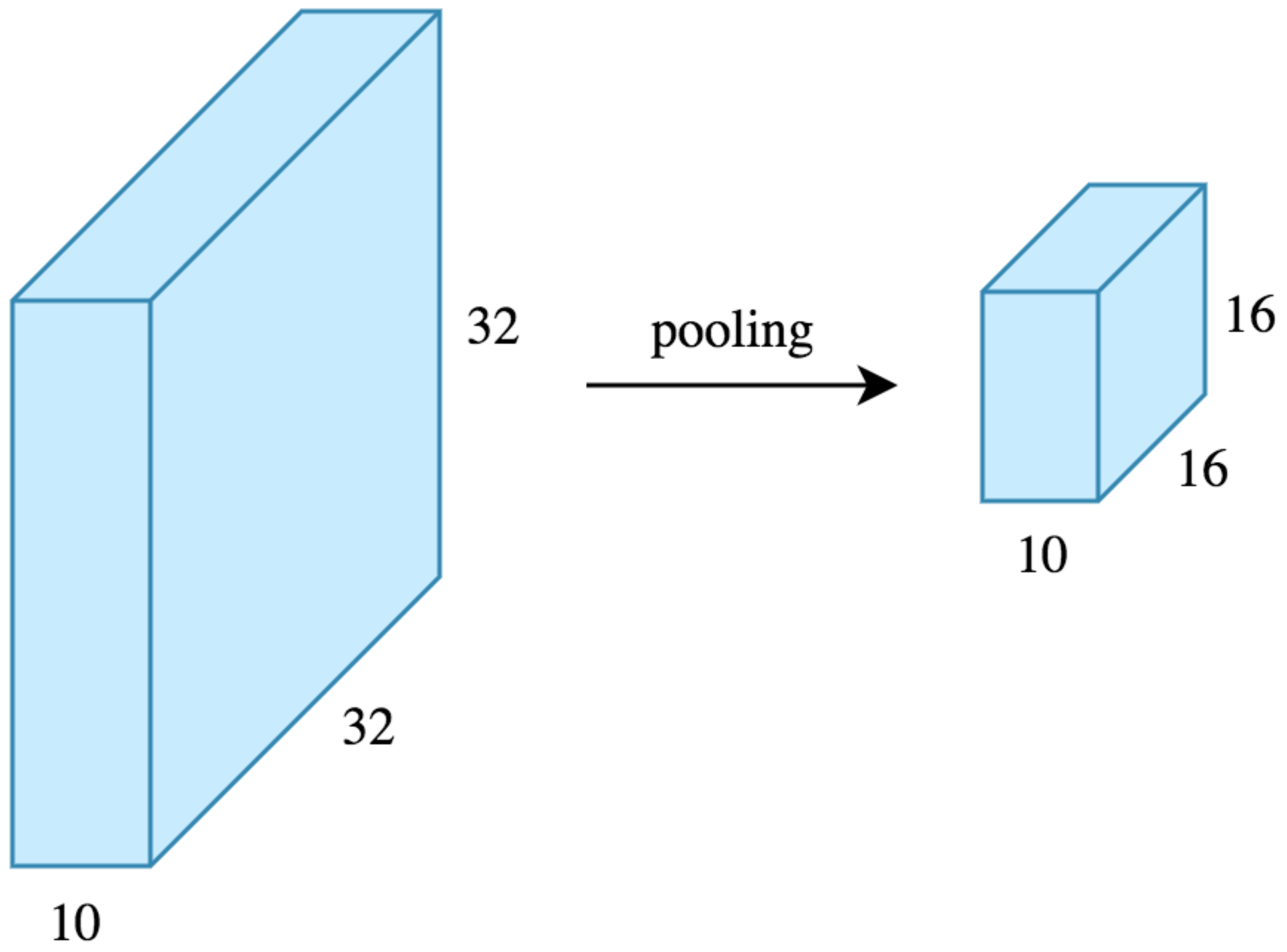
CNN Pooling Layer

Max Pooling



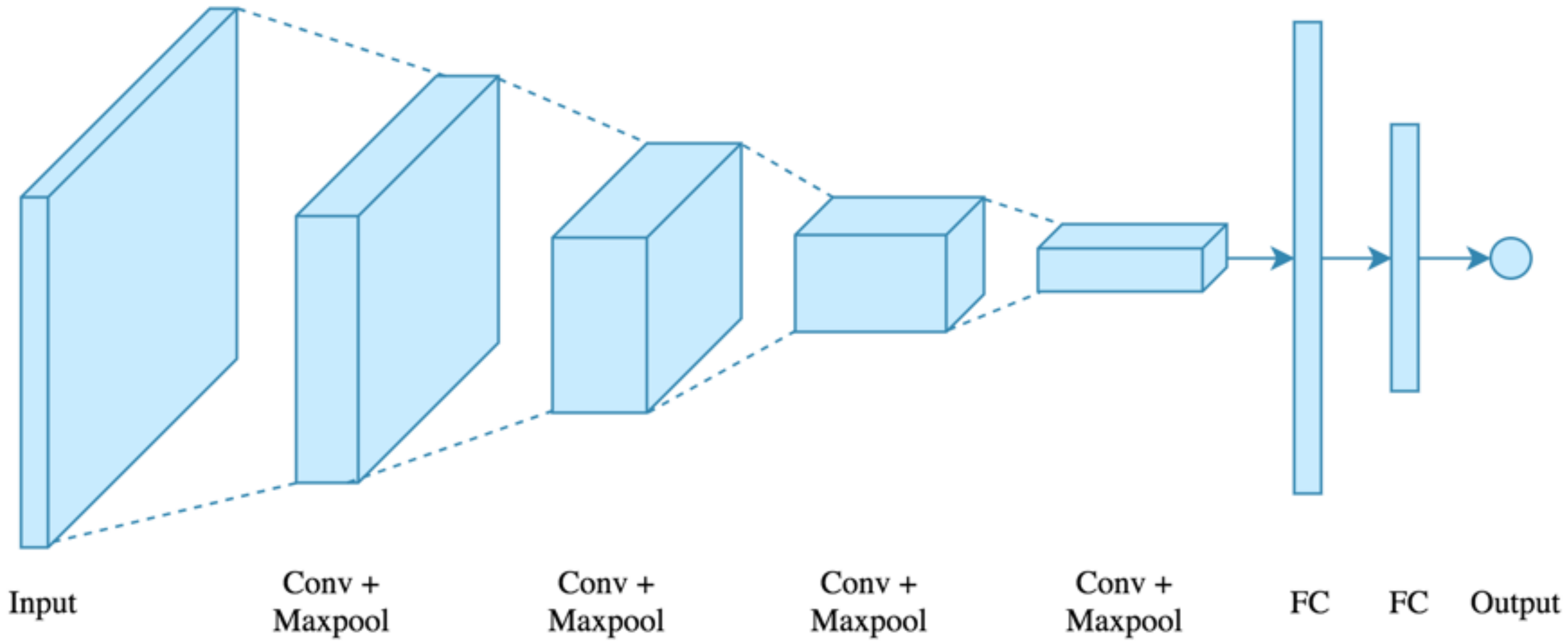
Source: Arden Dertat (2017), Applied Deep Learning - Part 4: Convolutional Neural Networks,
https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

CNN Pooling Layer



Source: Arden Dertat (2017), Applied Deep Learning - Part 4: Convolutional Neural Networks, https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

CNN Architecture
4 convolution + pooling layers, followed by 2 fully connected layers



Source: Arden Dertat (2017), Applied Deep Learning - Part 4: Convolutional Neural Networks,
https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

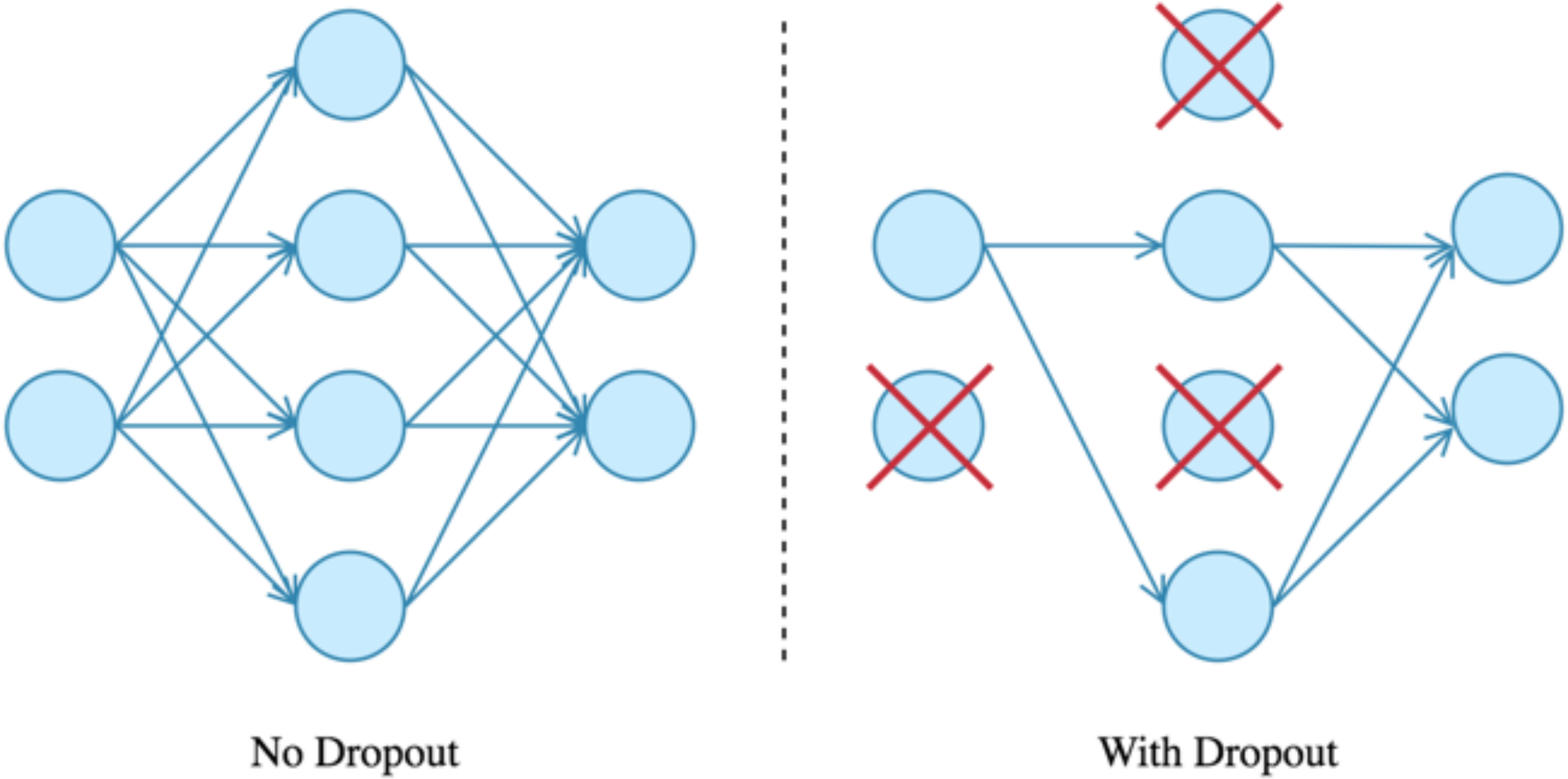
CNN Architecture
4 convolution + pooling layers, followed by 2 fully connected layers

https://gist.github.com/ardendertat/0fc5515057c47e7386fe04e9334504e3

```
model = Sequential()
model.add(Conv2D(32, (3, 3), activation='relu', padding='same', name='conv_1',
                 input_shape=(150, 150, 3)))
model.add(MaxPooling2D((2, 2), name='maxpool_1'))
model.add(Conv2D(64, (3, 3), activation='relu', padding='same', name='conv_2'))
model.add(MaxPooling2D((2, 2), name='maxpool_2'))
model.add(Conv2D(128, (3, 3), activation='relu', padding='same', name='conv_3'))
model.add(MaxPooling2D((2, 2), name='maxpool_3'))
model.add(Conv2D(128, (3, 3), activation='relu', padding='same', name='conv_4'))
model.add(MaxPooling2D((2, 2), name='maxpool_4'))
model.add(Flatten())
model.add(Dropout(0.5))
model.add(Dense(512, activation='relu', name='dense_1'))
model.add(Dense(128, activation='relu', name='dense_2'))
model.add(Dense(1, activation='sigmoid', name='output'))
```

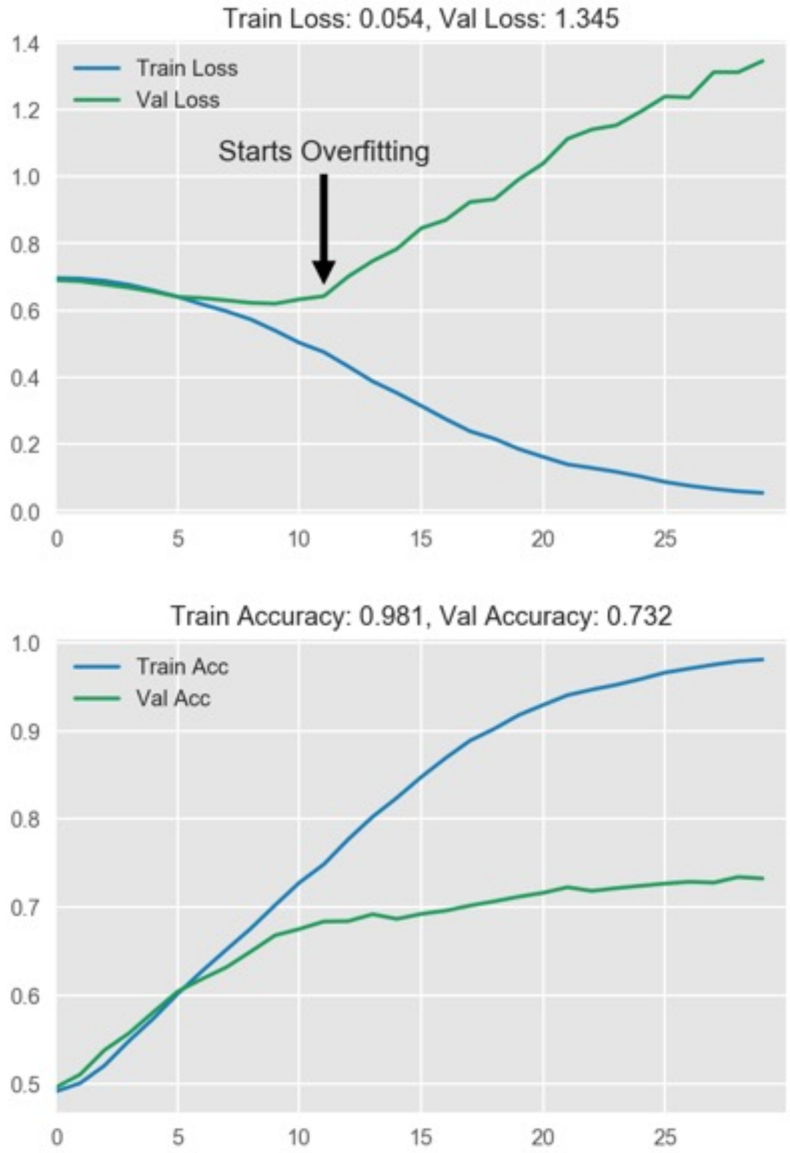
Source: Arden Dertat (2017), Applied Deep Learning - Part 4: Convolutional Neural Networks,
https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

Dropout



Source: Arden Dertat (2017), Applied Deep Learning - Part 4: Convolutional Neural Networks,
https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

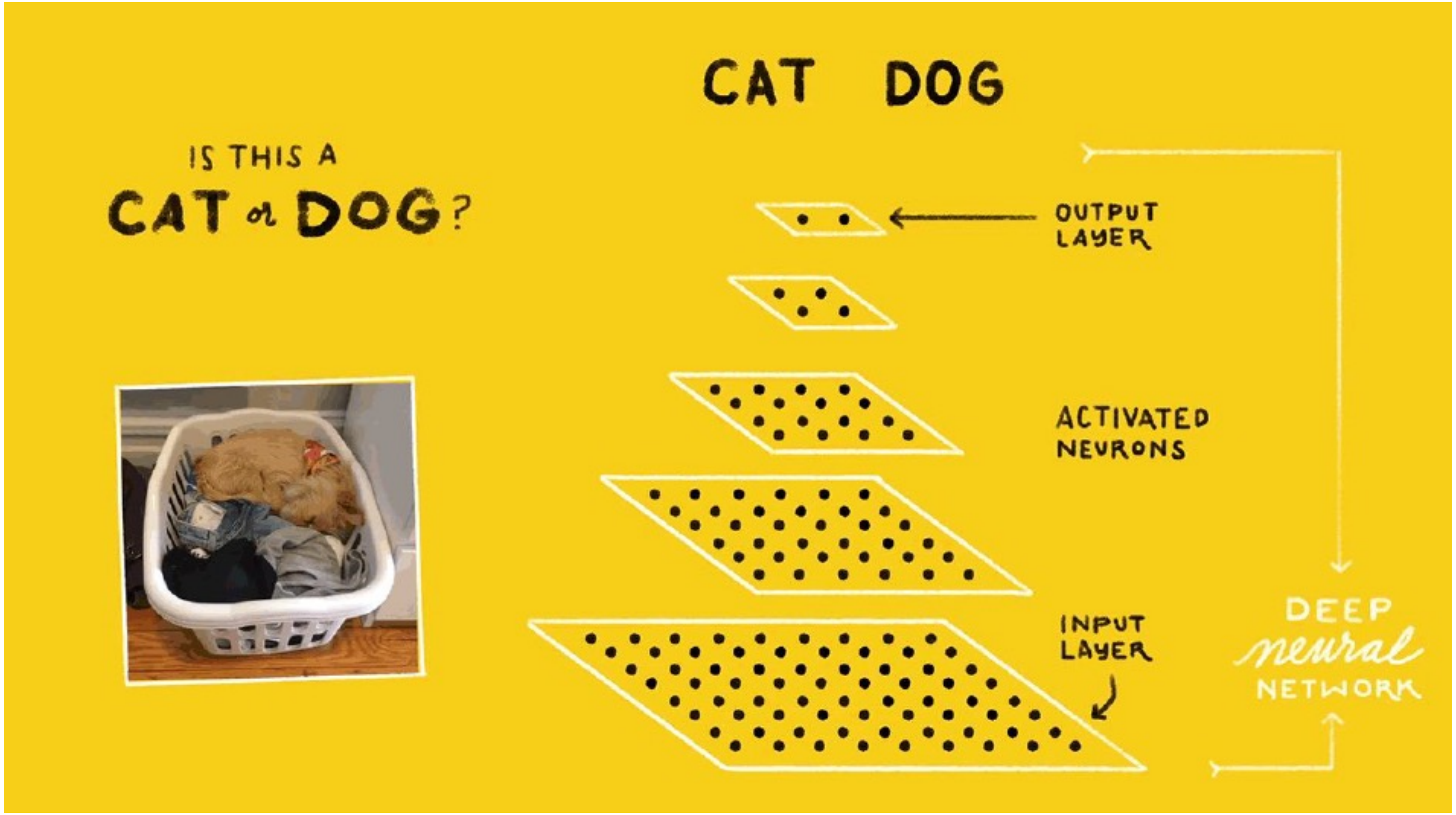
Model Performance



Source: Arden Dertat (2017), Applied Deep Learning - Part 4: Convolutional Neural Networks, https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

Visual Recognition

Image Classification

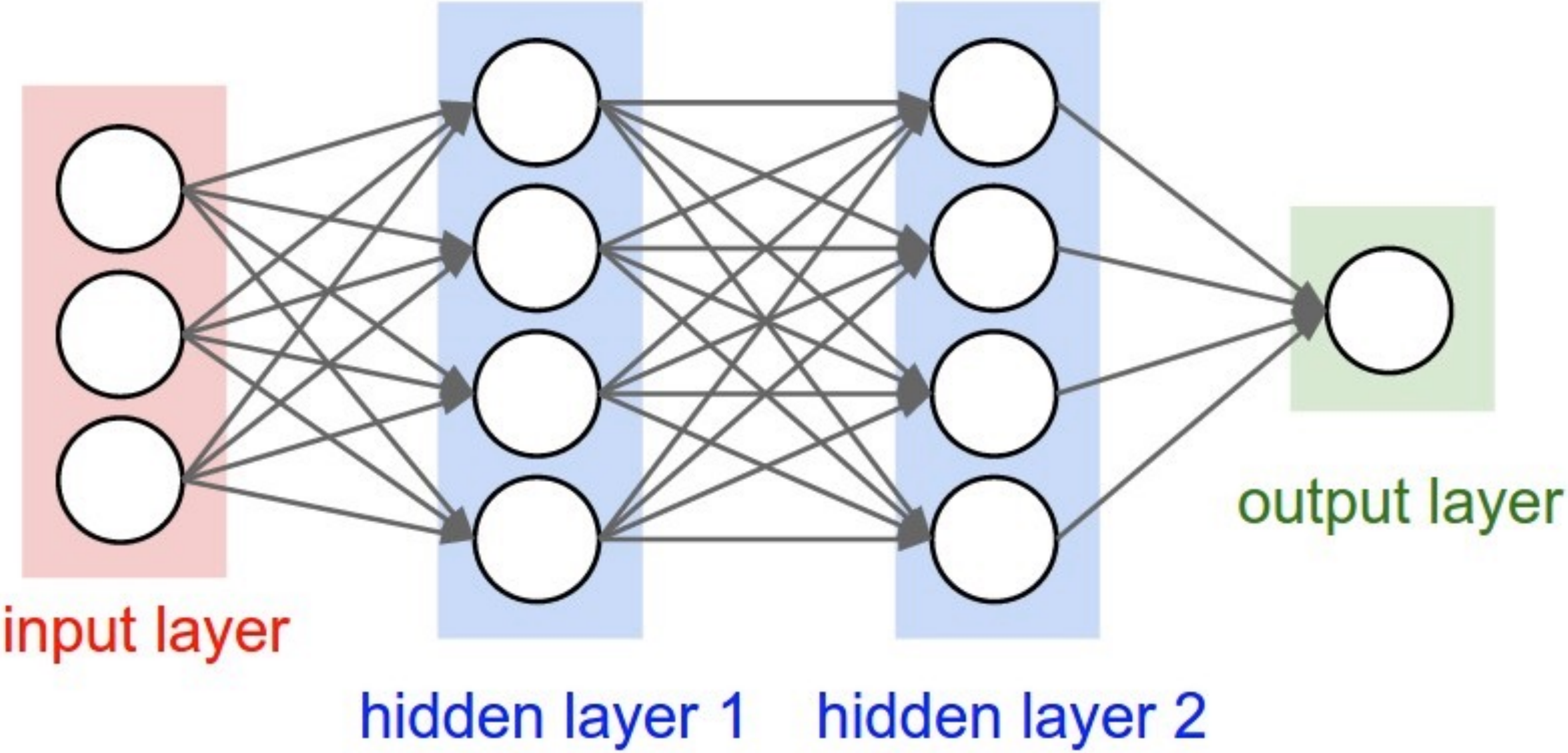


Source: Jeff Dean (2016), Large-Scale Deep Learning For Building Intelligent Computer Systems, WSDM 2016

Convolutional Neural Networks (CNNs / ConvNets)

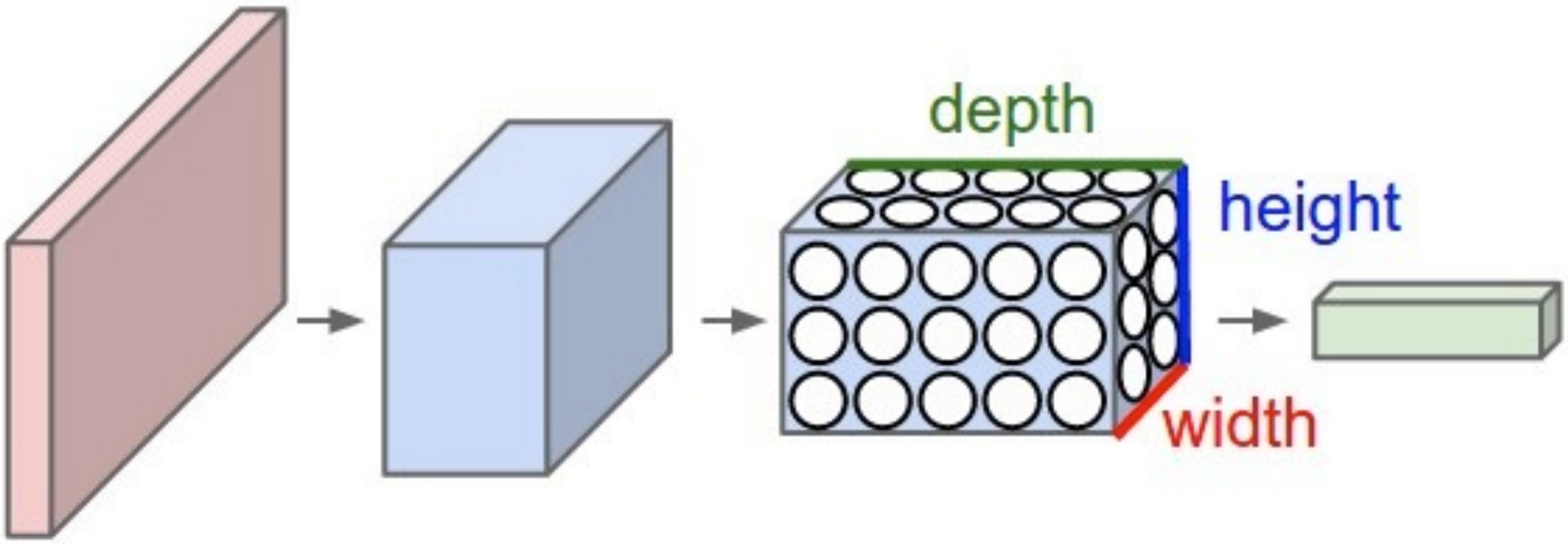
http://cs231n.github.io/convolutional-networks/

A regular 3-layer Neural Network



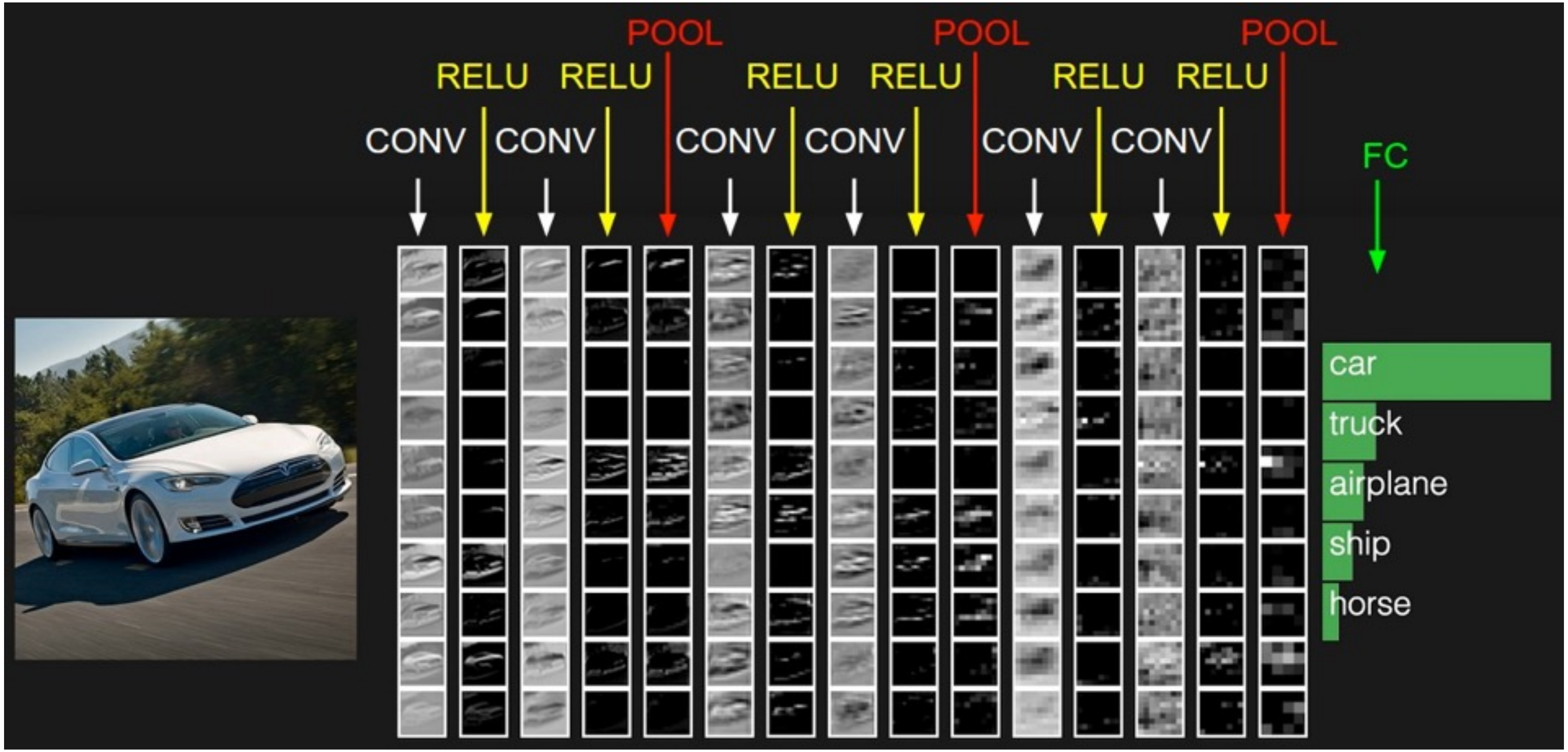
http://cs231n.github.io/convolutional-networks/

A ConvNet arranges its neurons in three dimensions (width, height, depth)



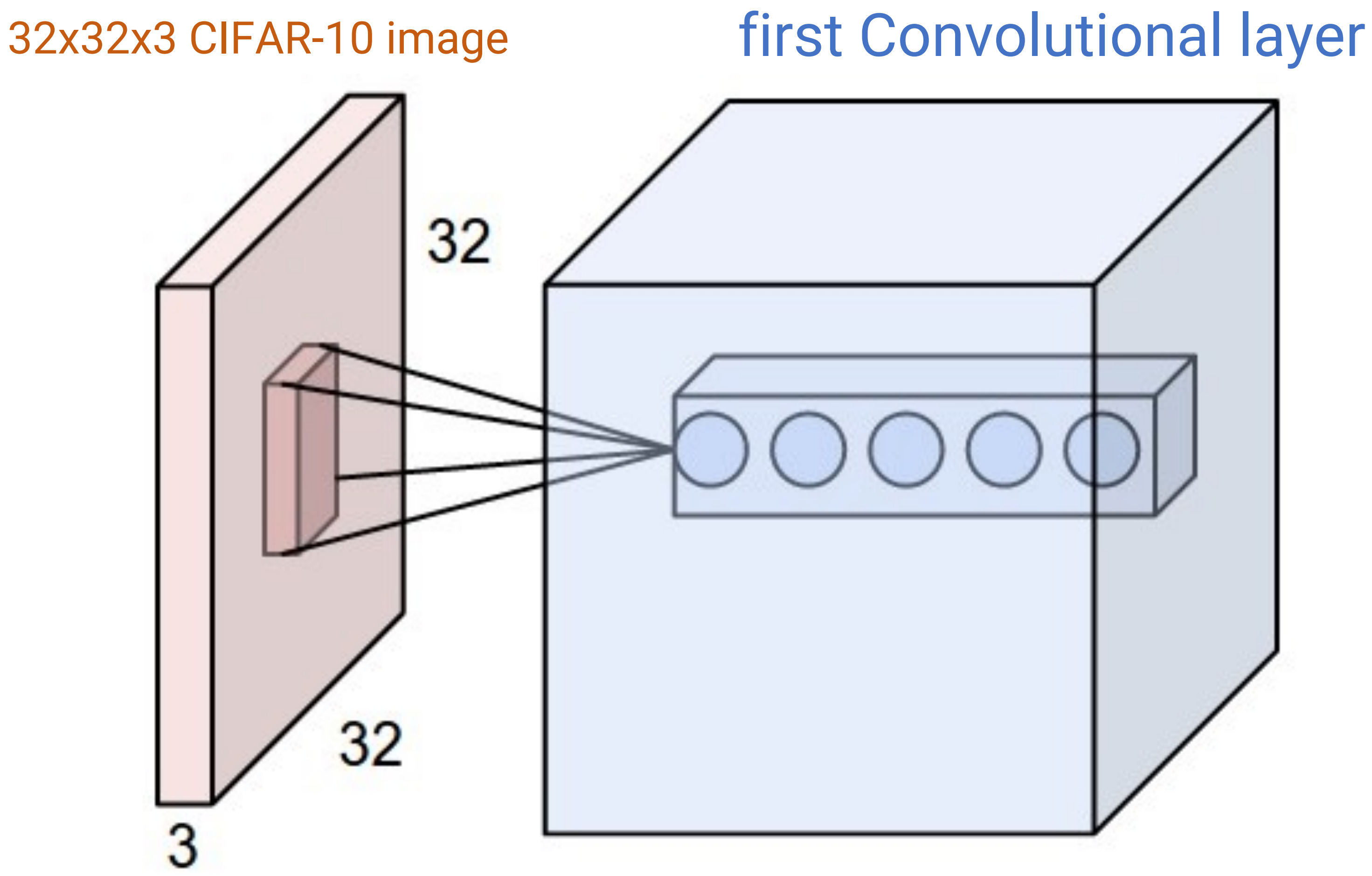
http://cs231n.github.io/convolutional-networks/

The activations of an example ConvNet architecture.



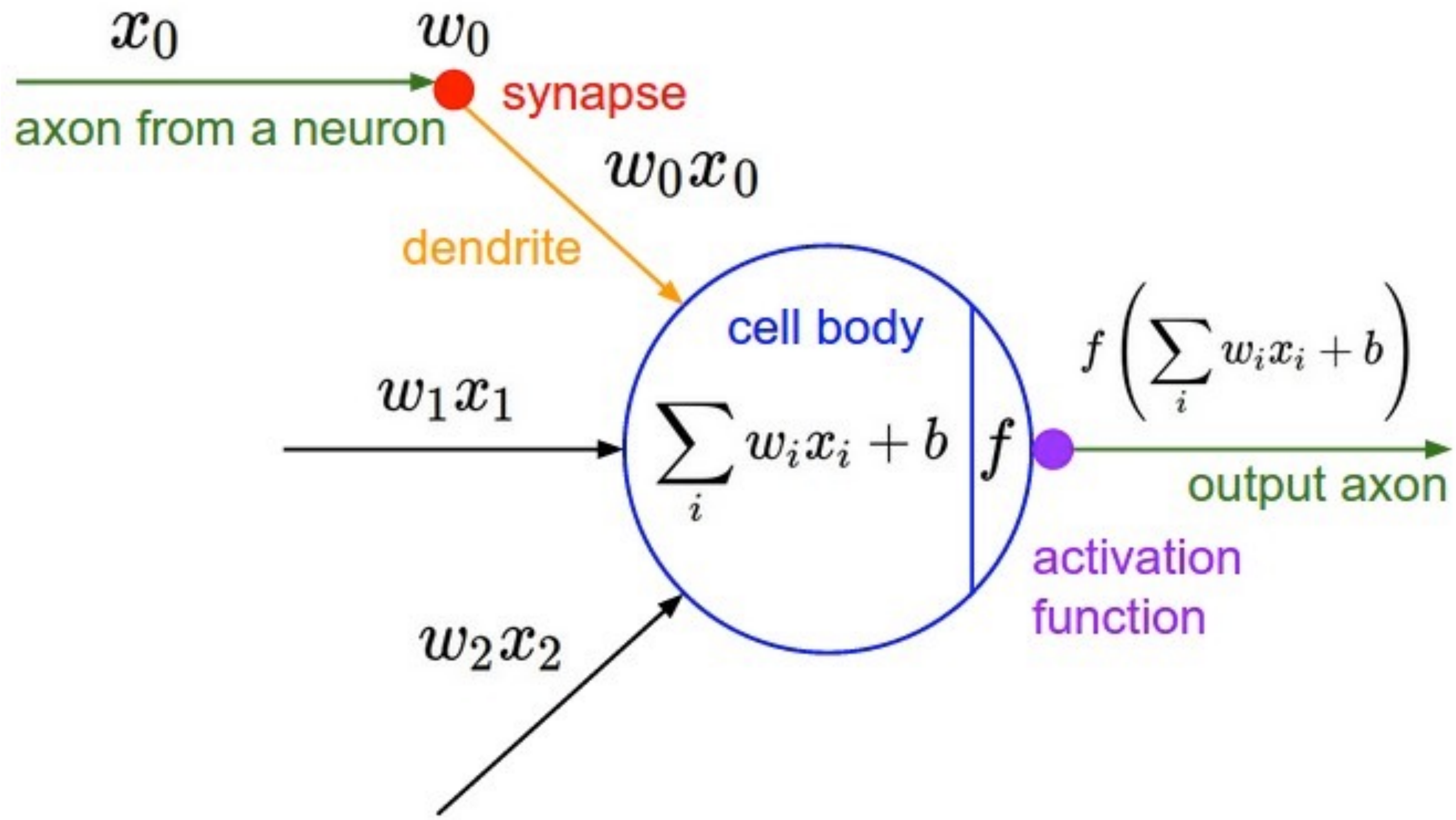
http://cs231n.github.io/convolutional-networks/

ConvNets



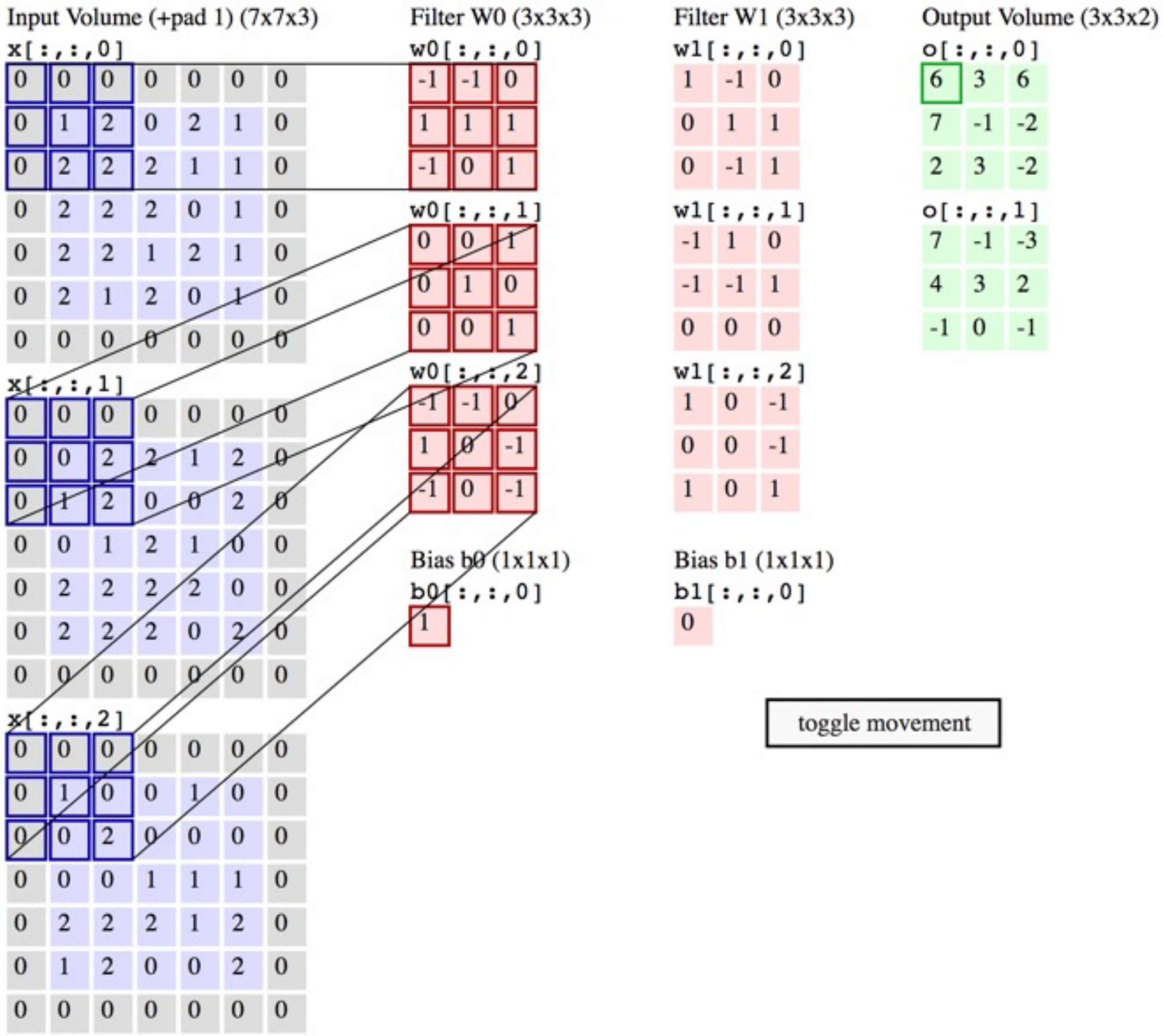
http://cs231n.github.io/convolutional-networks/

ConvNets



http://cs231n.github.io/convolutional-networks/

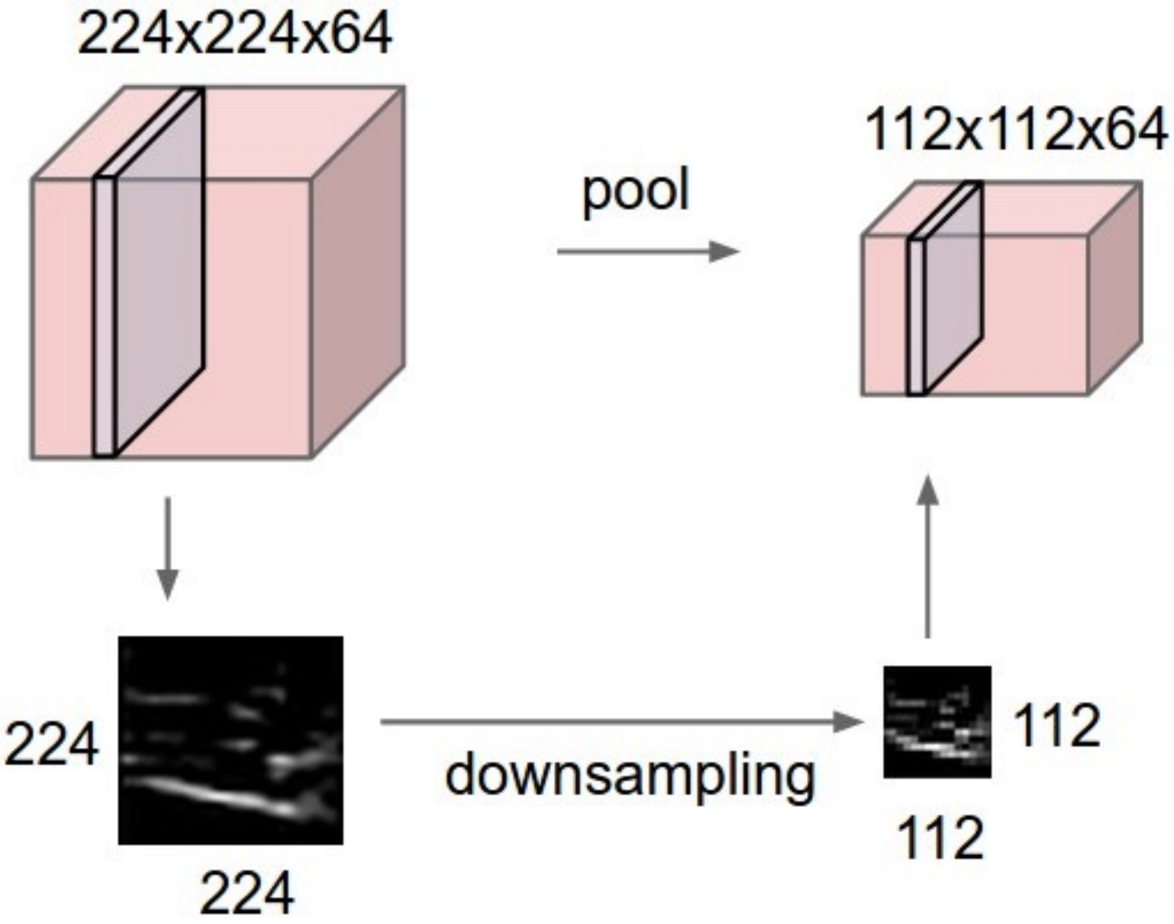
Convolution Demo



http://cs231n.github.io/convolutional-networks/

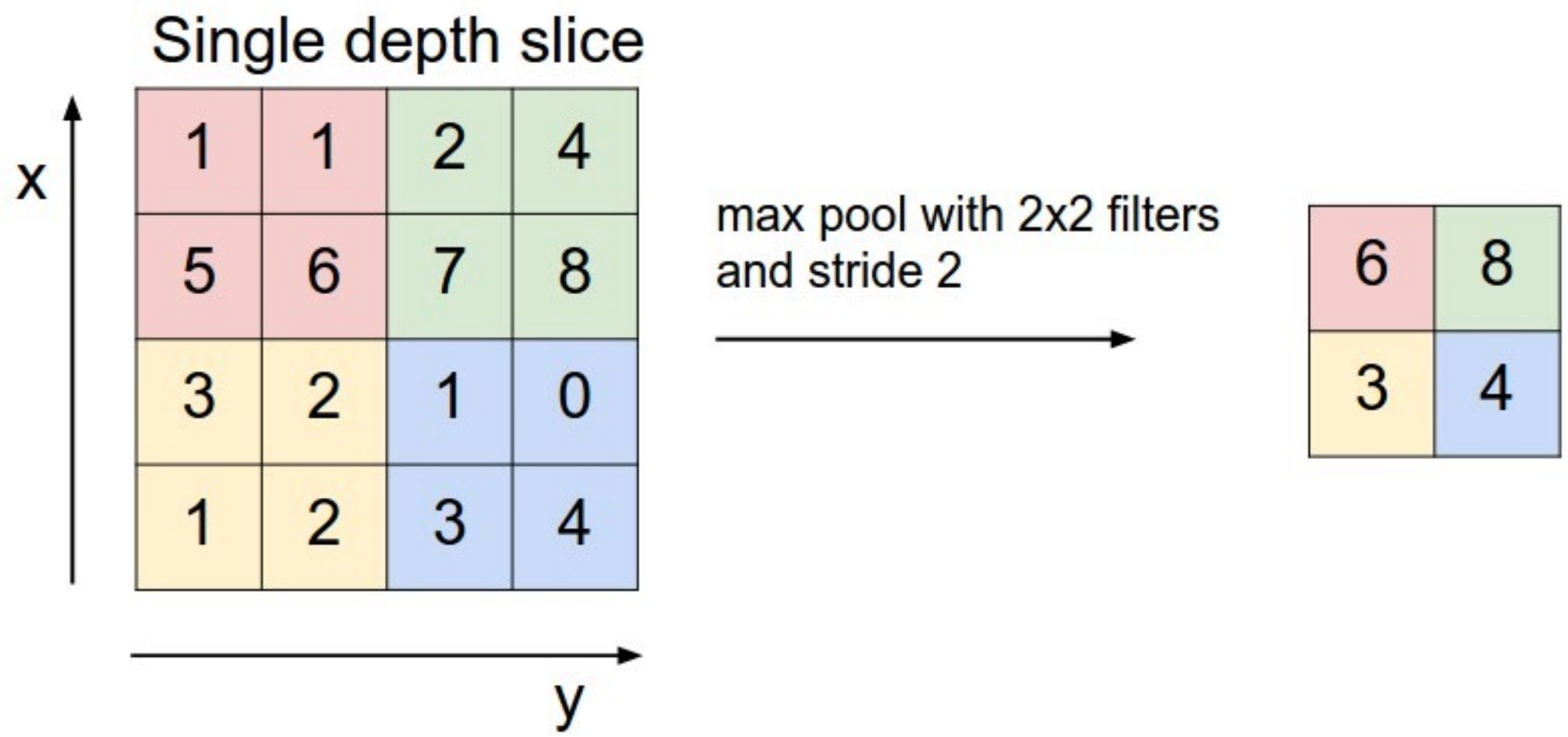
ConvNets

input volume of size [224x224x64]
is pooled with **filter** size 2, **stride** 2
into output volume of size [112x112x64]



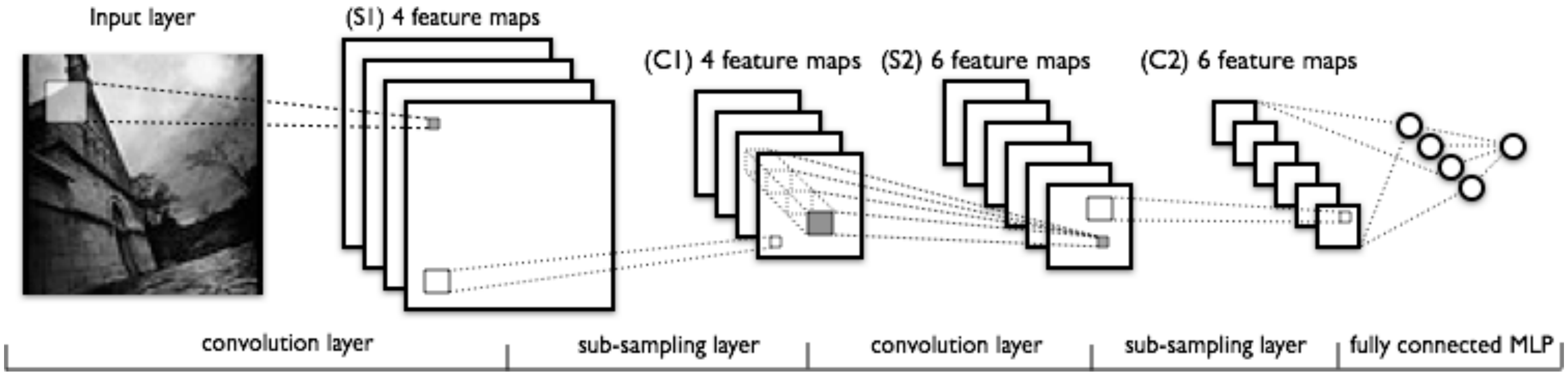
http://cs231n.github.io/convolutional-networks/

ConvNets
max pooling



http://cs231n.github.io/convolutional-networks/

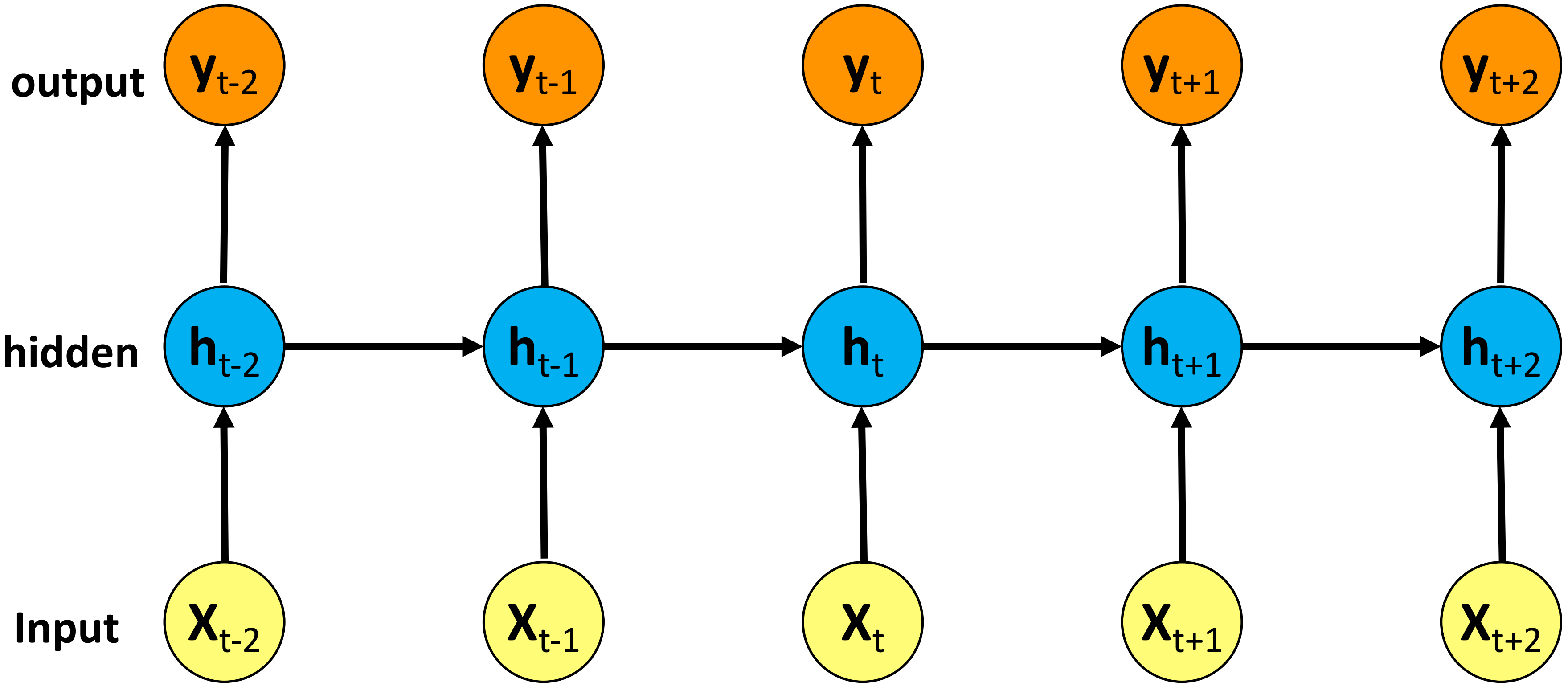
Convolutional Neural Networks (CNN) (LeNet)



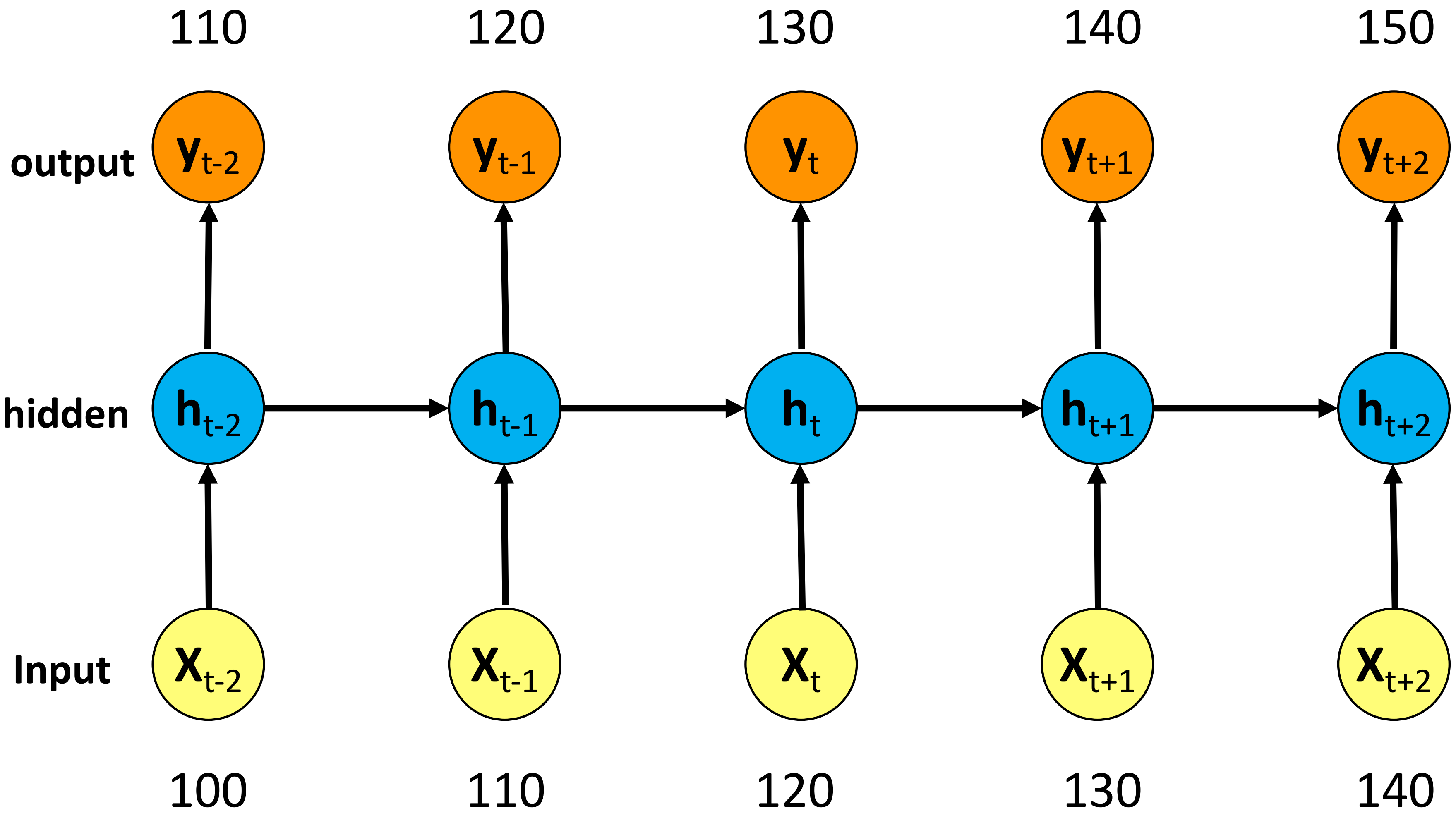
Source: http://deeplearning.net/tutorial/lenet.html

Recurrent
Neural Networks
(RNN)

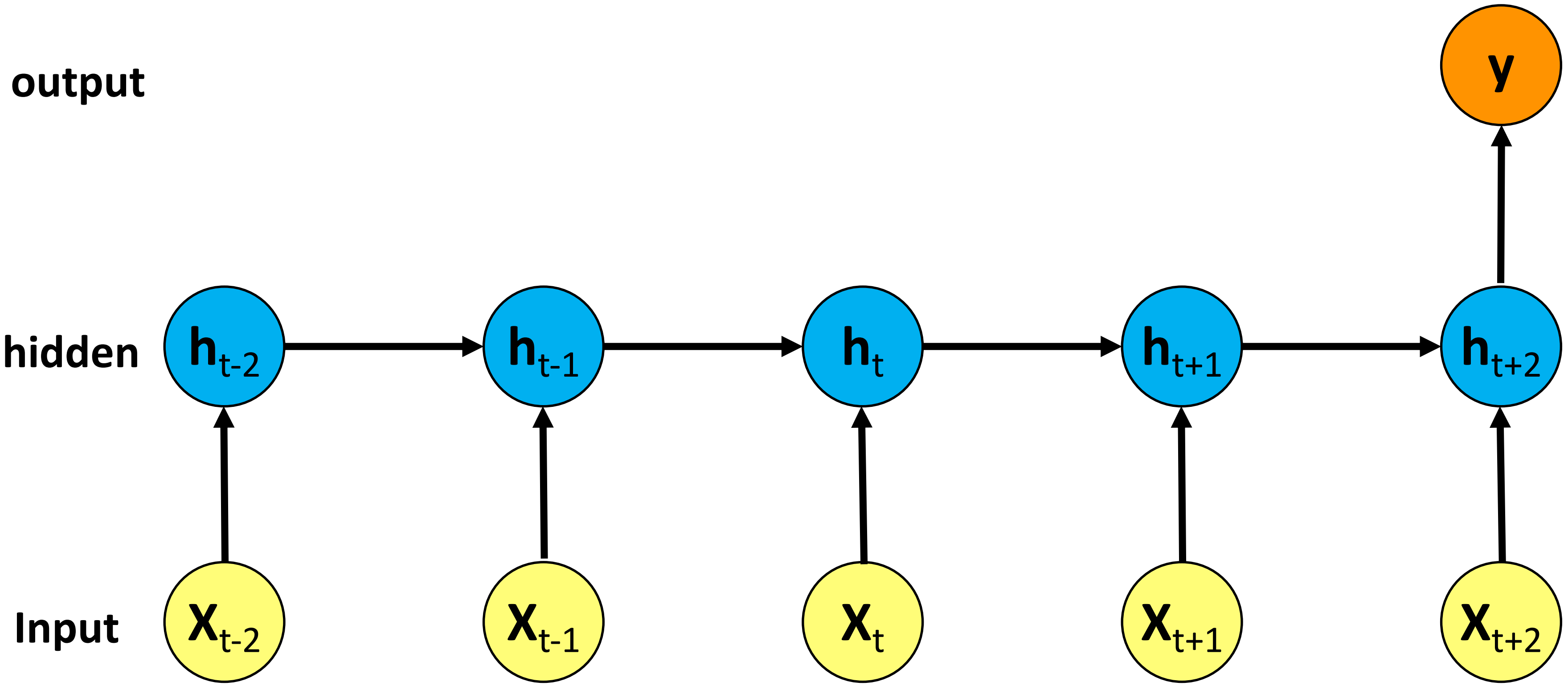
Recurrent Neural Networks (RNN)



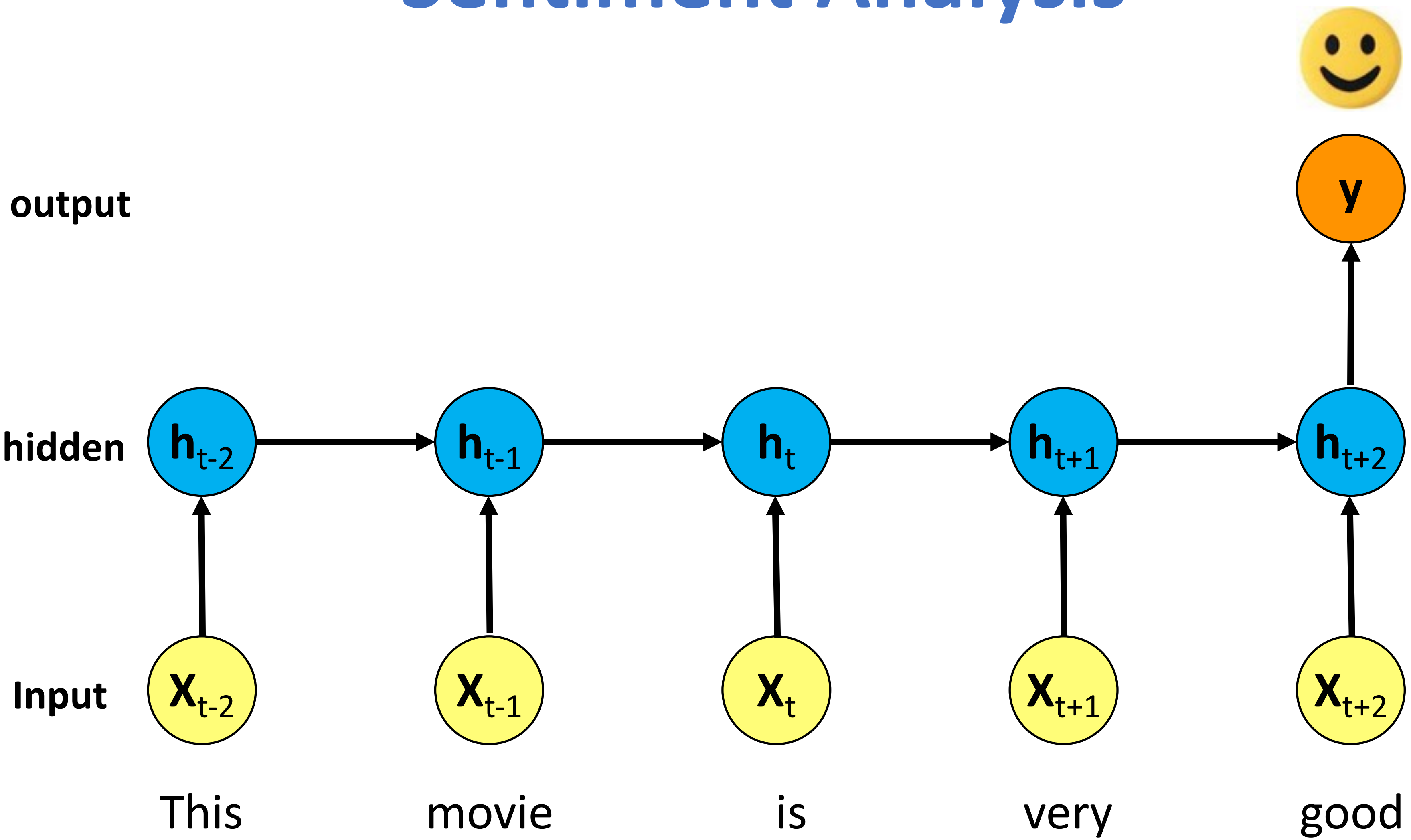
Recurrent Neural Networks (RNN)
Time Series Forecasting



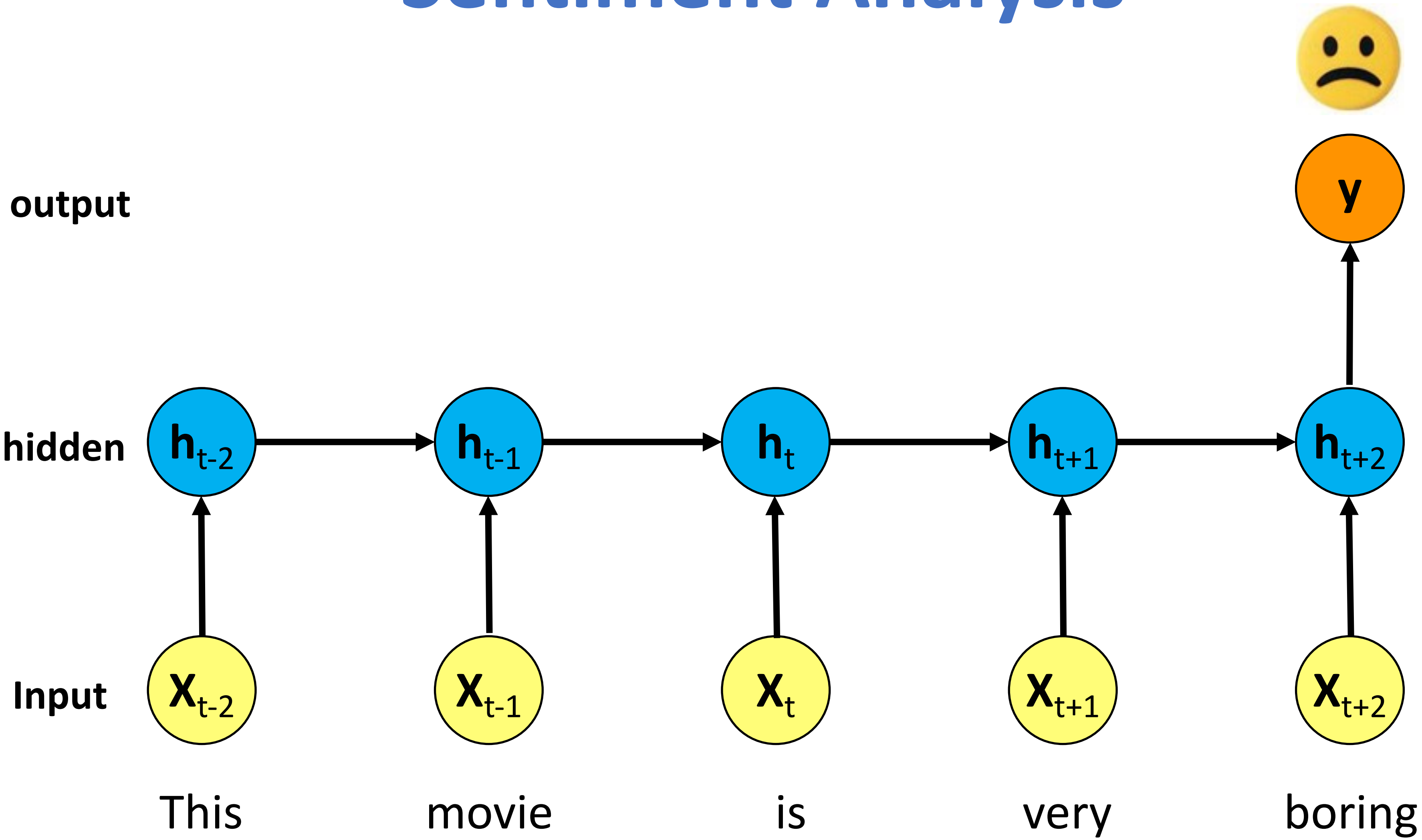
Recurrent Neural Networks (RNN)



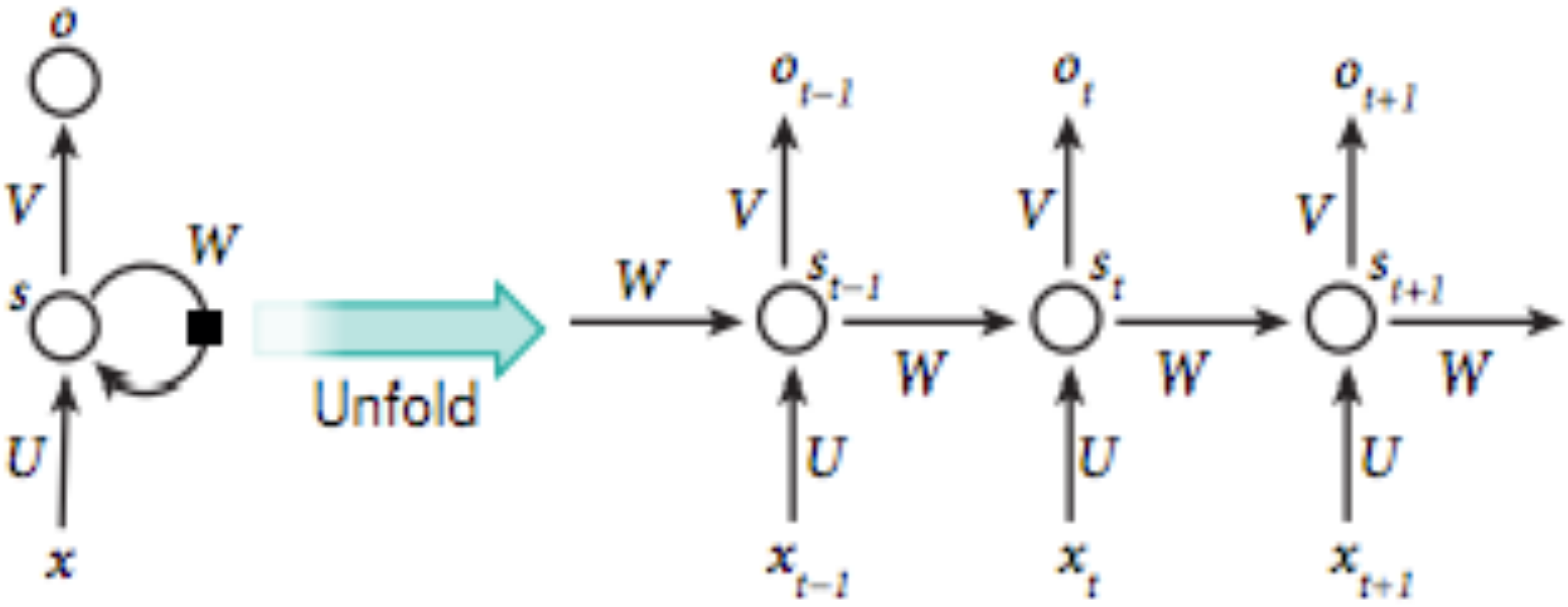
Recurrent Neural Networks (RNN)
Sentiment Analysis



Recurrent Neural Networks (RNN)
Sentiment Analysis

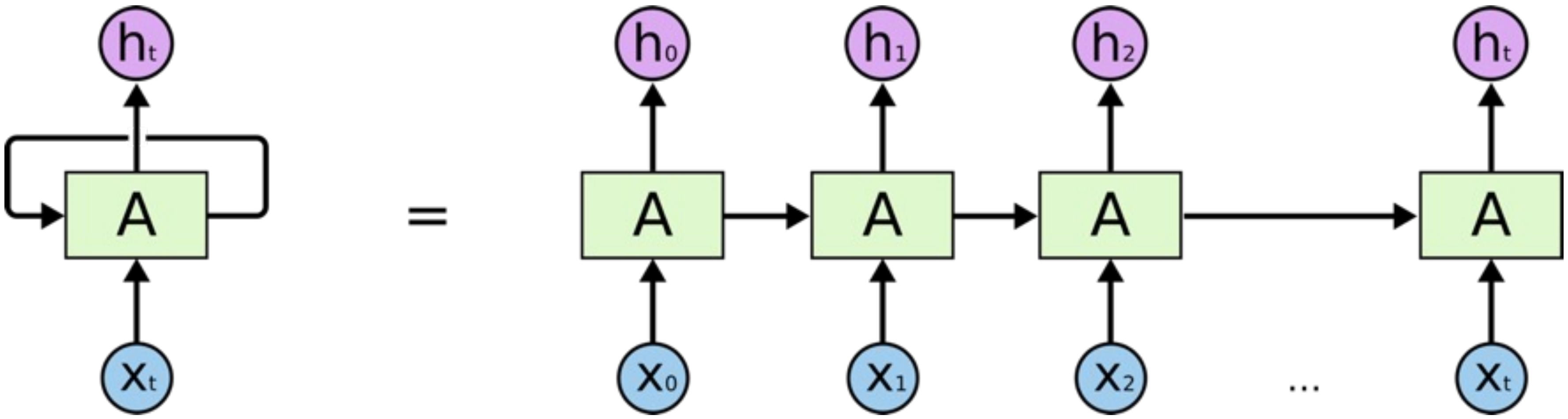


Recurrent Neural Network (RNN)



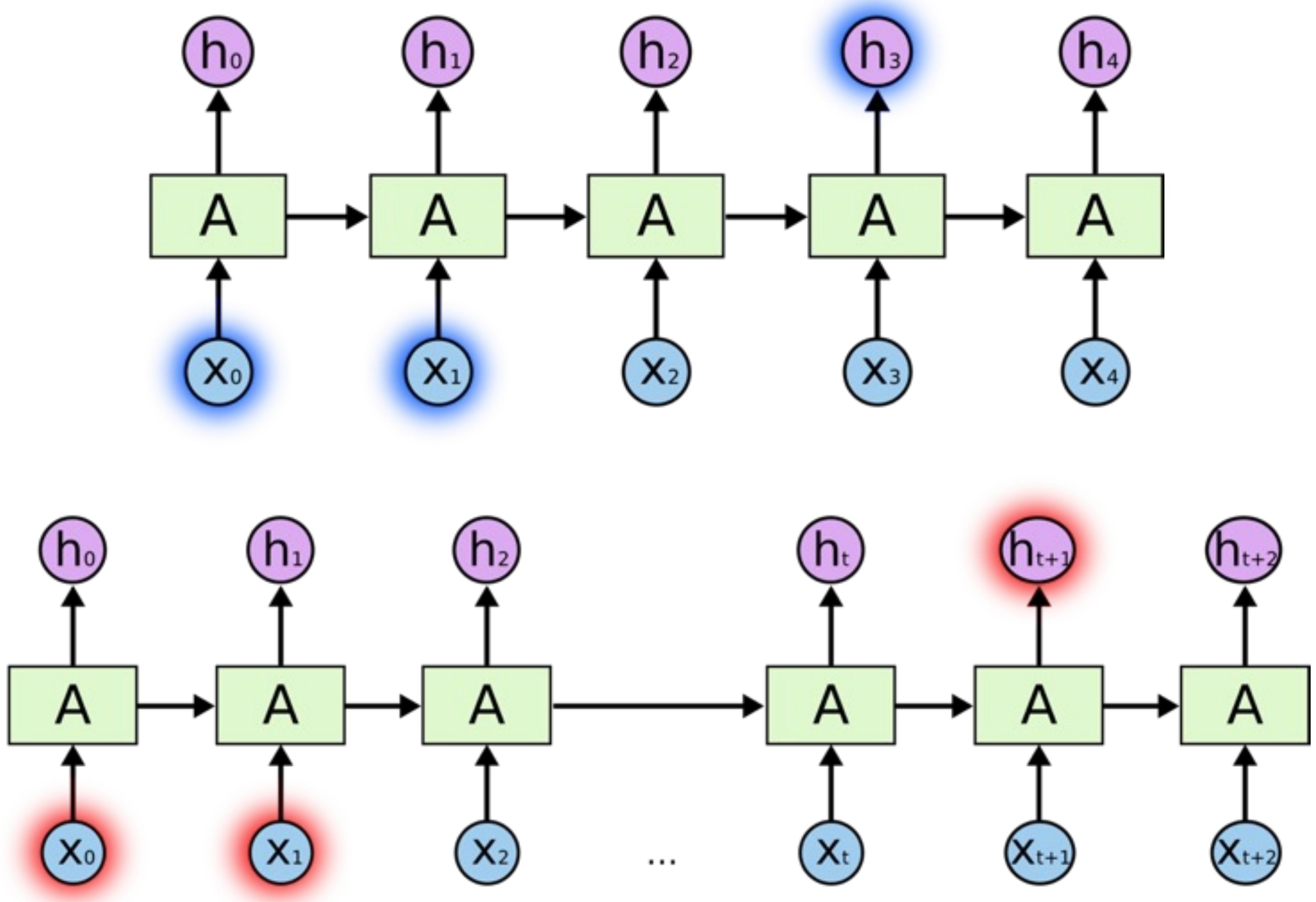
Source: LeCun, Yann, Yoshua Bengio, and Geoffrey Hinton. "Deep learning." Nature 521, no. 7553 (2015): 436-444.

RNN



Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

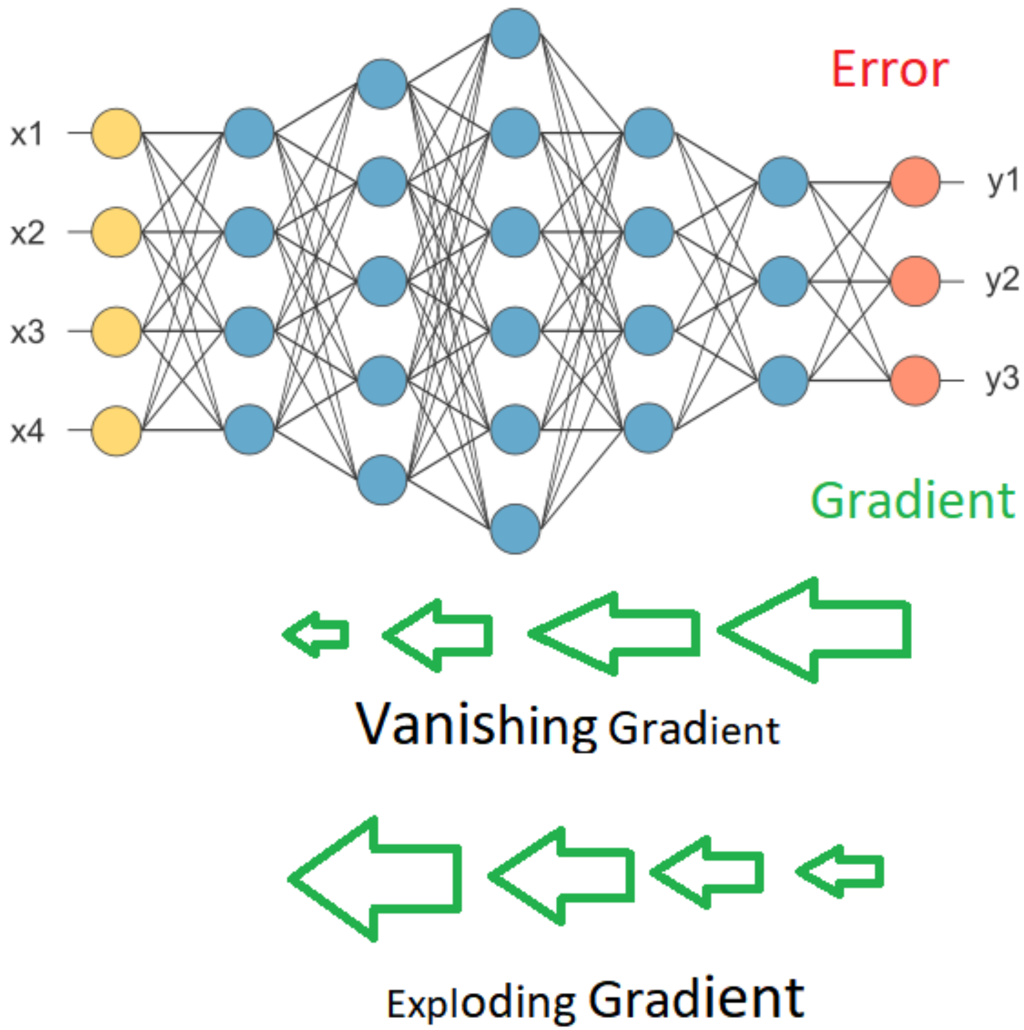
RNN long-term dependencies



I grew up in France… I speak fluent French.

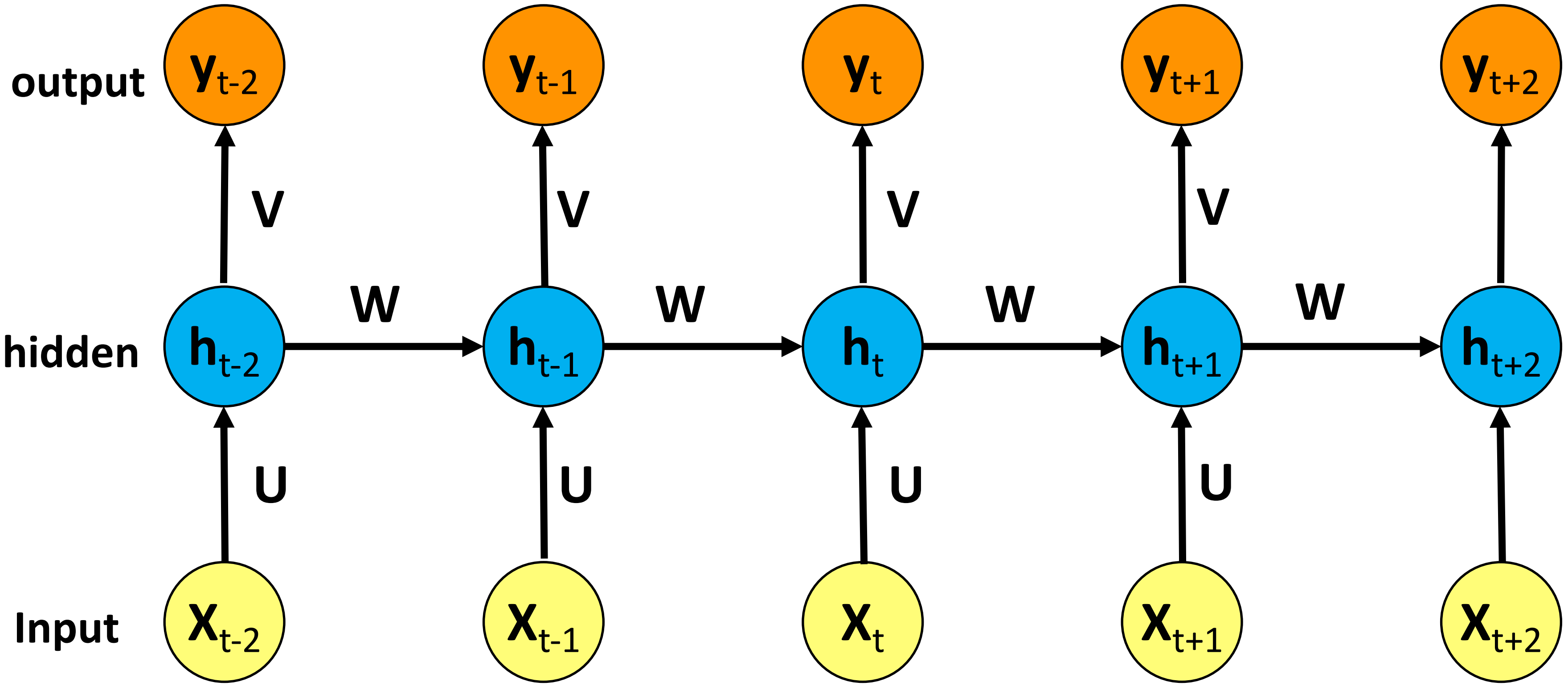
Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Vanishing Gradient
Exploding Gradient

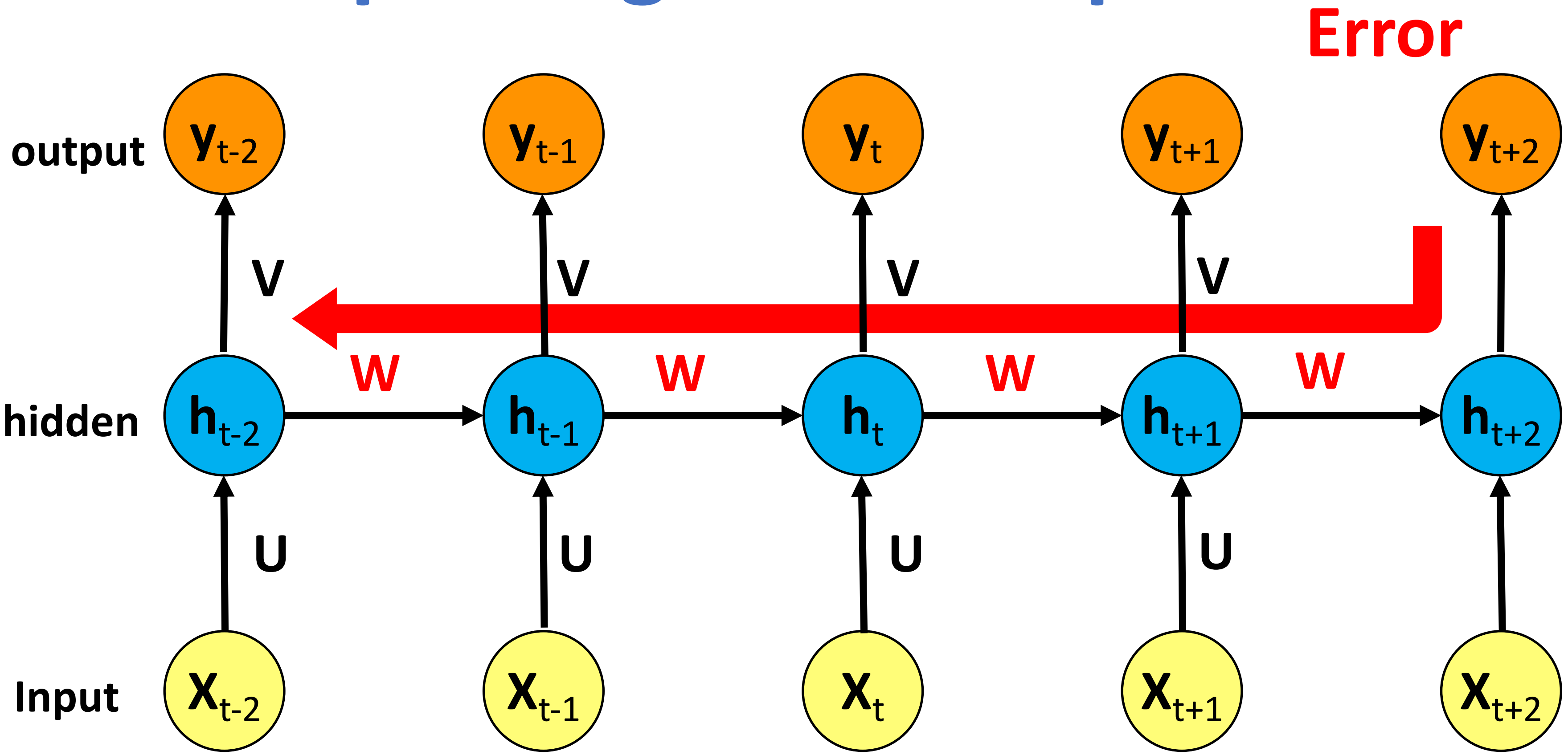


Source: https://medium.com/deep-math-machine-learning-ai/chapter-10-1-deepnlp-lstm-long-short-term-memory-networks-with-math-21477f8e4235

Recurrent Neural Networks (RNN)



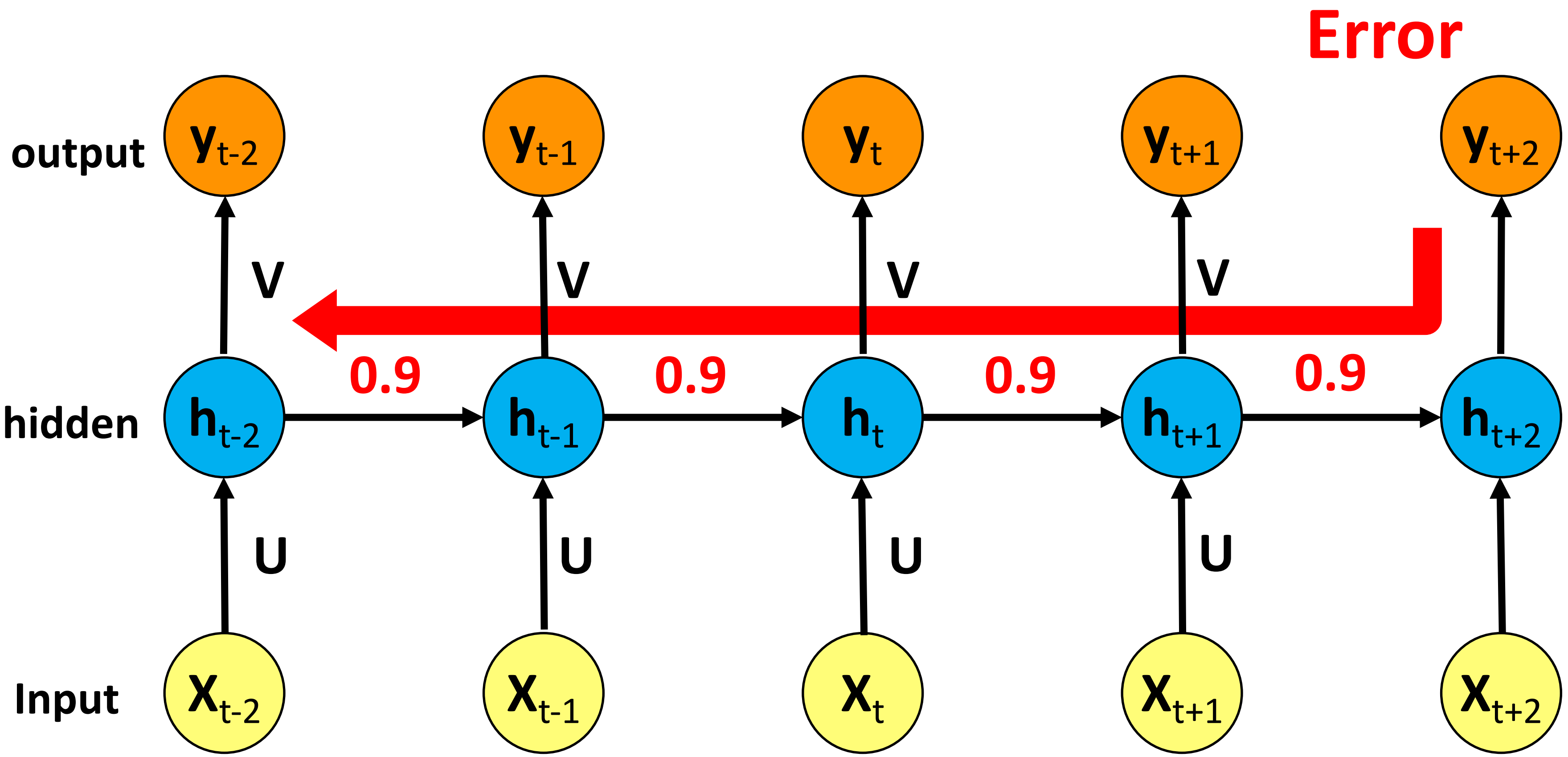
RNN
Vanishing Gradient problem
Exploding Gradient problem



if $|W| < 1$ (Vanishing)
if $|W| > 1$ (Exploding)

Source: https://medium.com/deep-math-machine-learning-ai/chapter-10-1-deepnlp-lstm-long-short-term-memory-networks-with-math-21477f8e4235

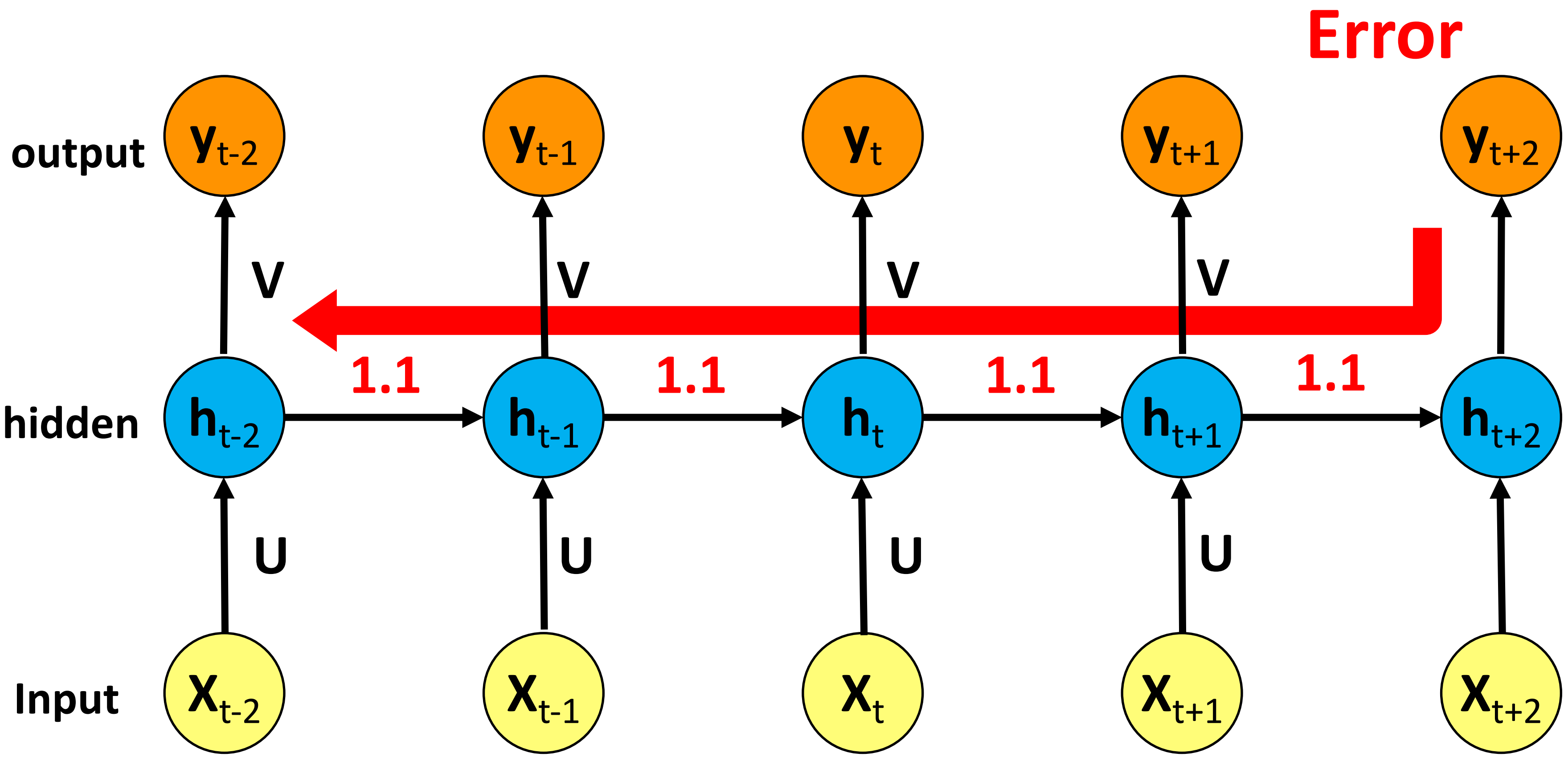
RNN
Vanishing Gradient problem



W = 0.9 < 1 (Vanishing)

Source: https://medium.com/deep-math-machine-learning-ai/chapter-10-1-deepnlp-lstm-long-short-term-memory-networks-with-math-21477f8e4235

RNN
Exploding Gradient problem



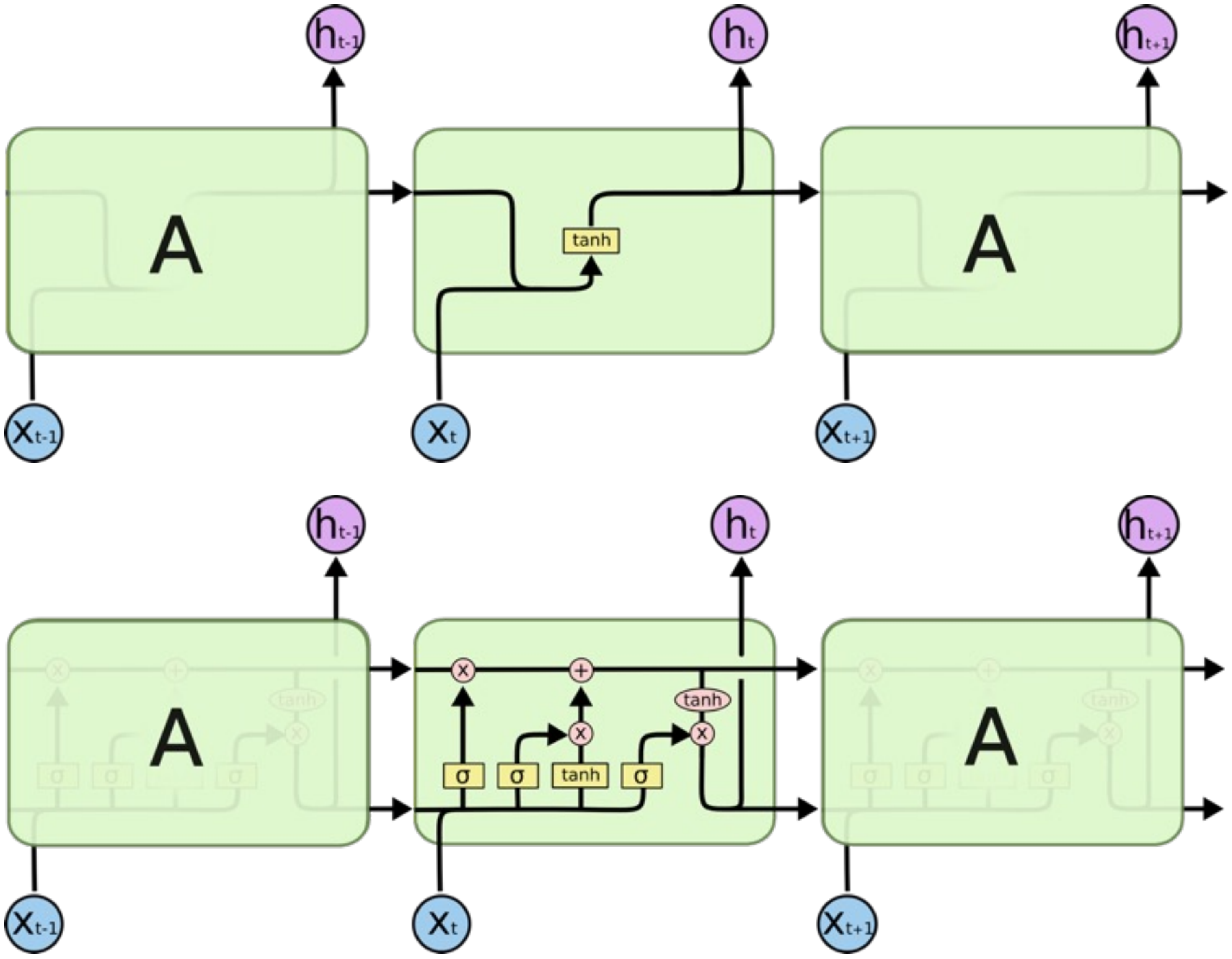
W = 1.1 > 1 (Exploding)

Source: https://medium.com/deep-math-machine-learning-ai/chapter-10-1-deepnlp-lstm-long-short-term-memory-networks-with-math-21477f8e4235

RNN LSTM

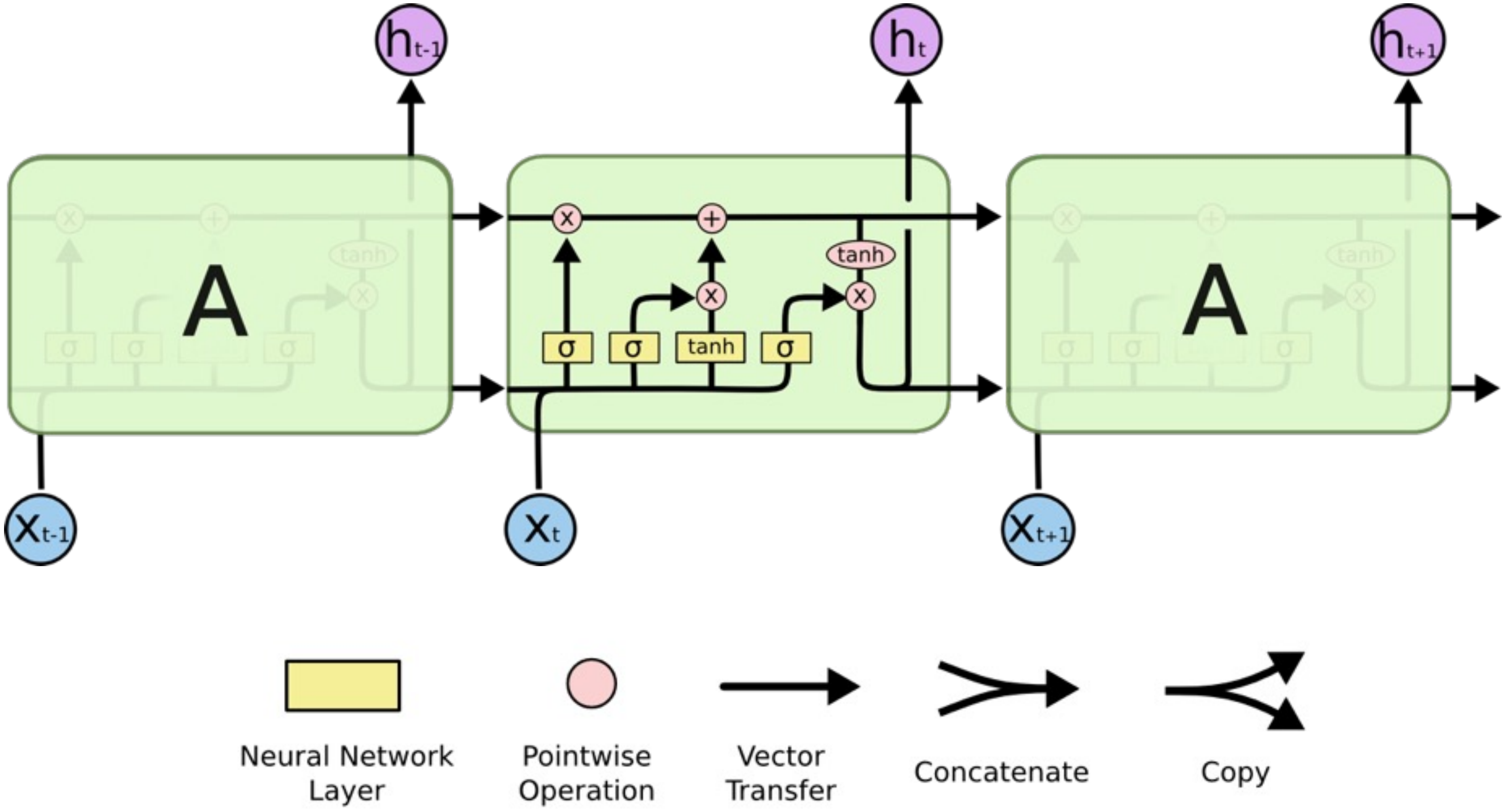
RNN

LSTM



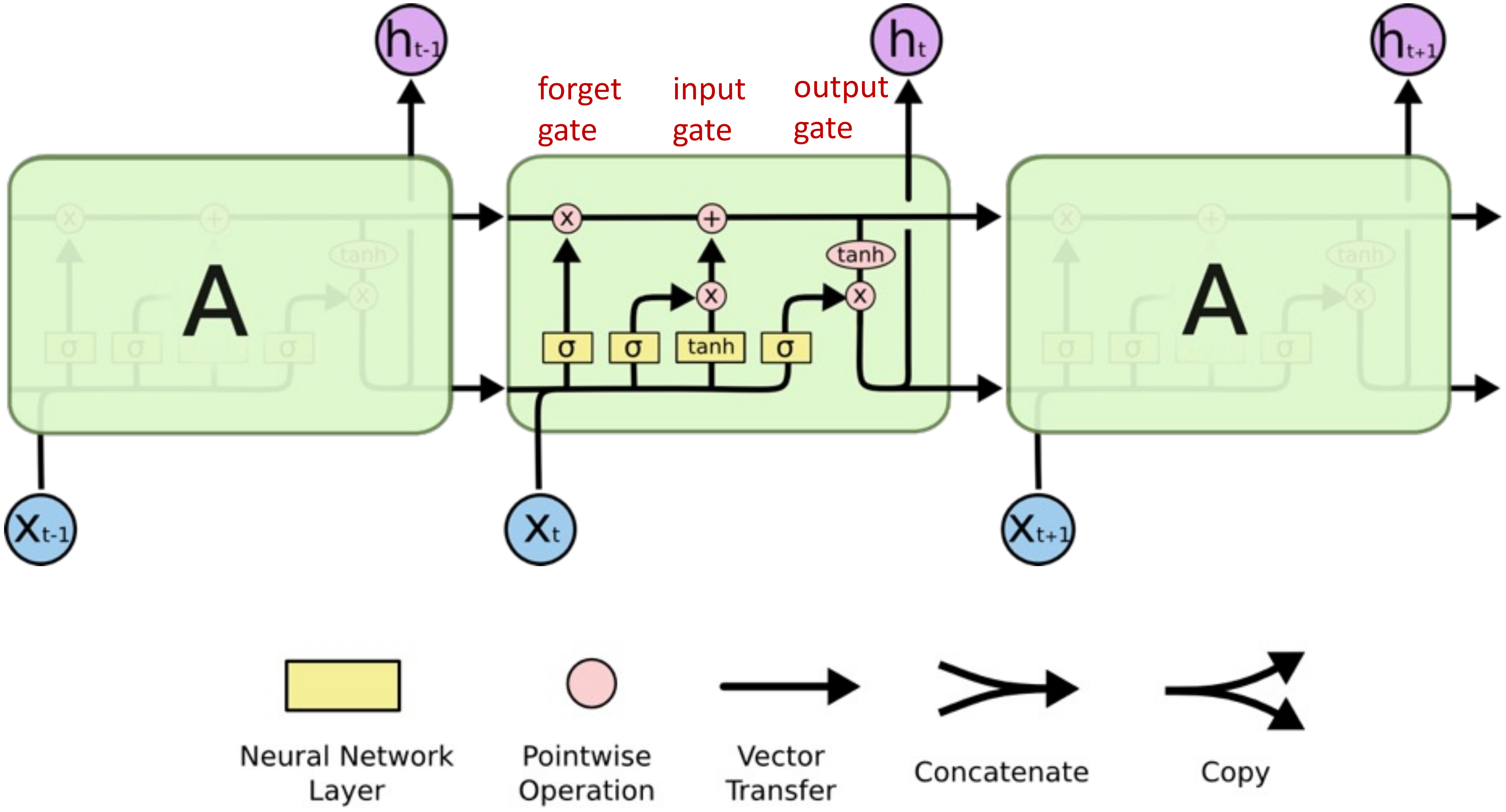
Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Long Short Term Memory (LSTM)



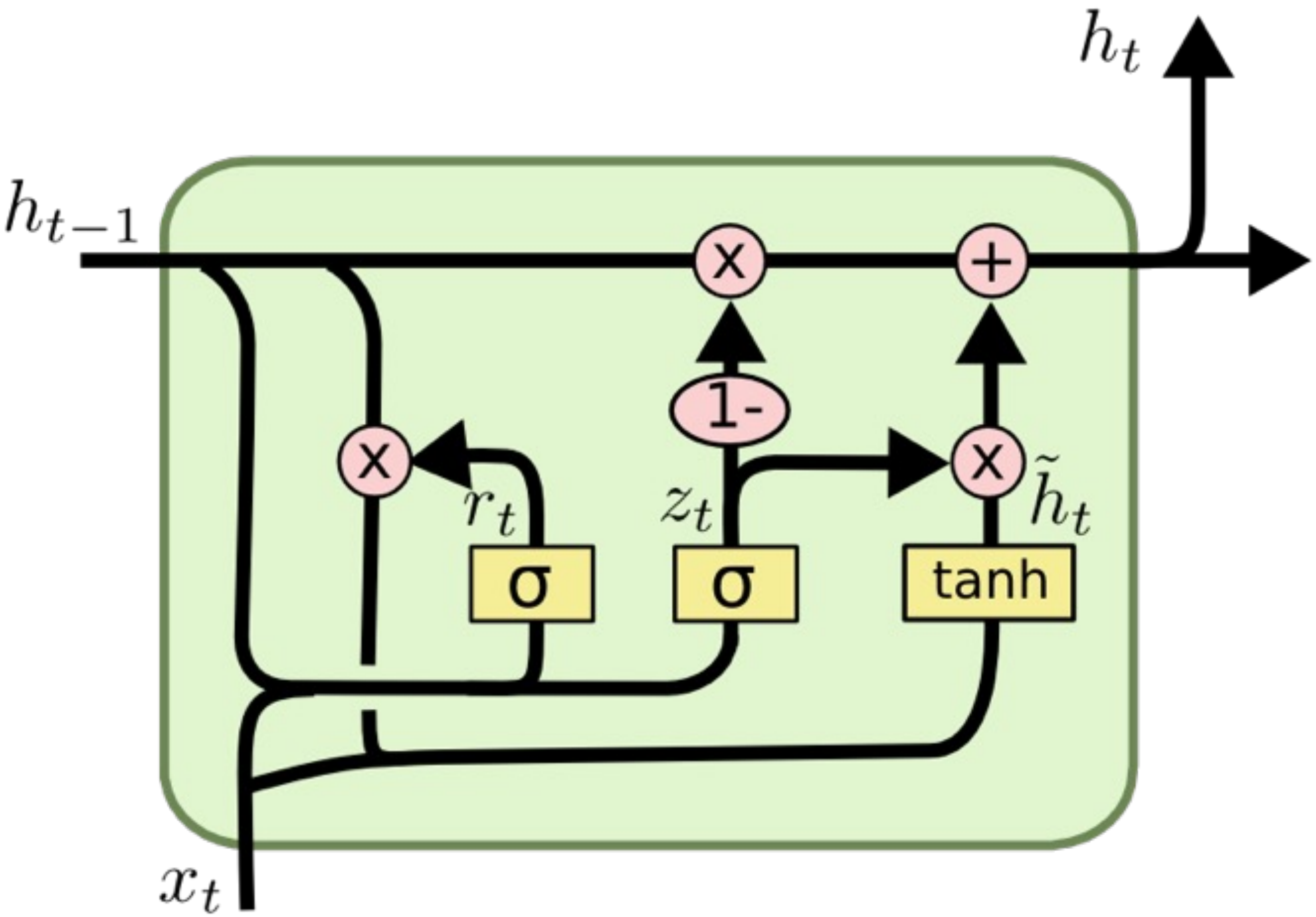
Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Long Short Term Memory (LSTM)



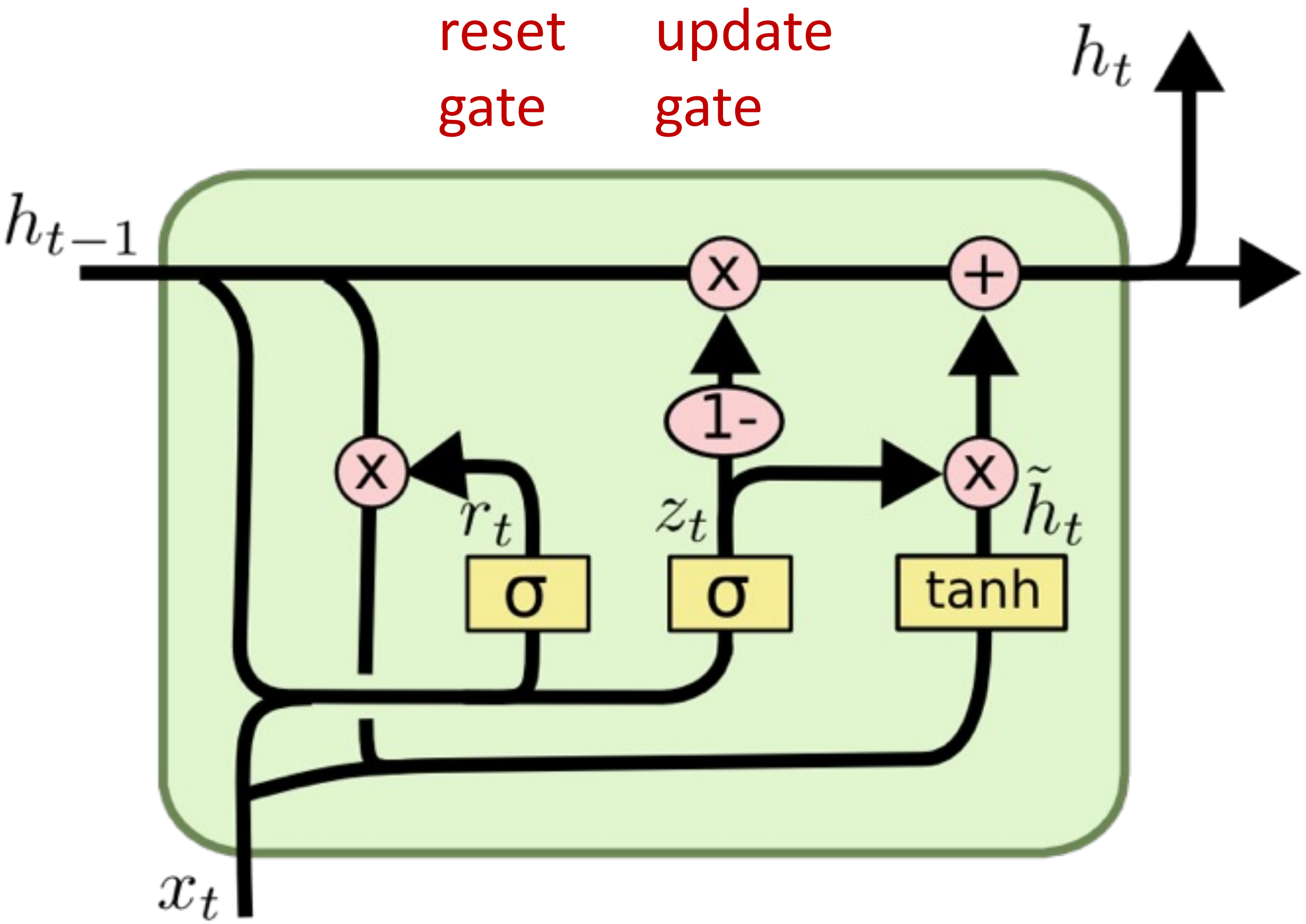
Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Gated Recurrent Unit (GRU)



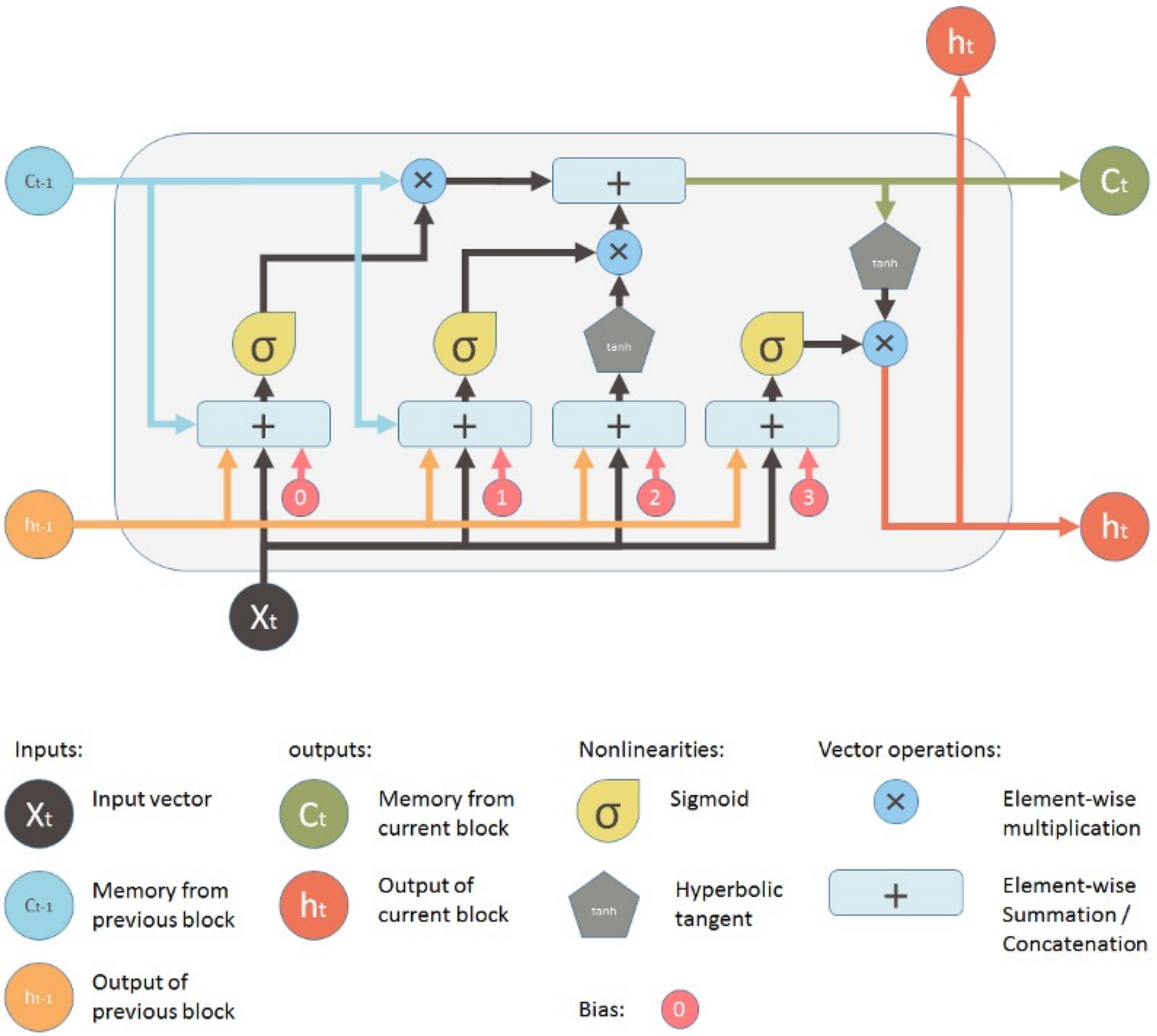
Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Gated Recurrent Unit (GRU)



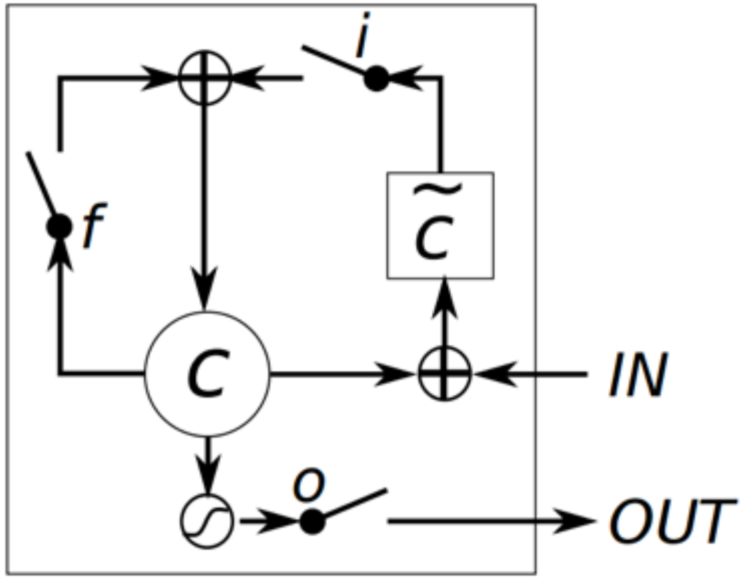
Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

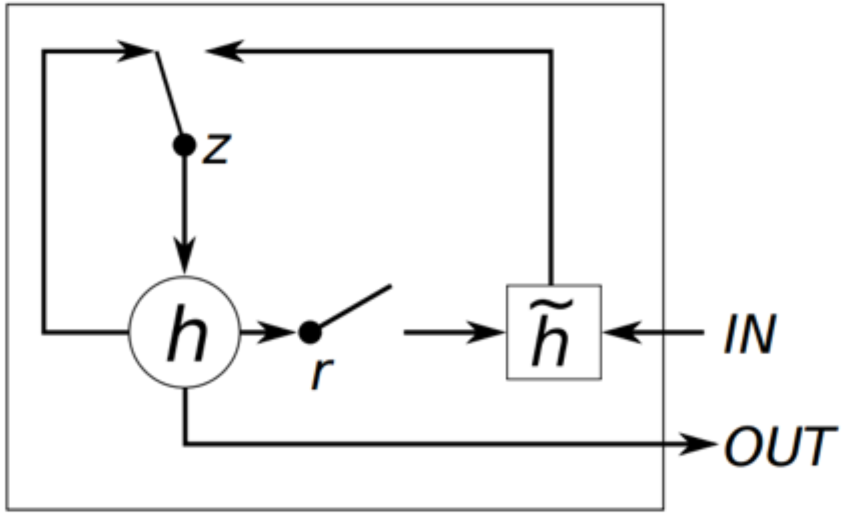
LSTM



Source: Shi Yan (2016), Understanding LSTM and its diagrams, https://medium.com/mlreview/understanding-lstm-and-its-diagrams-37e2f46f1714

LSTM vs GRU





LSTM

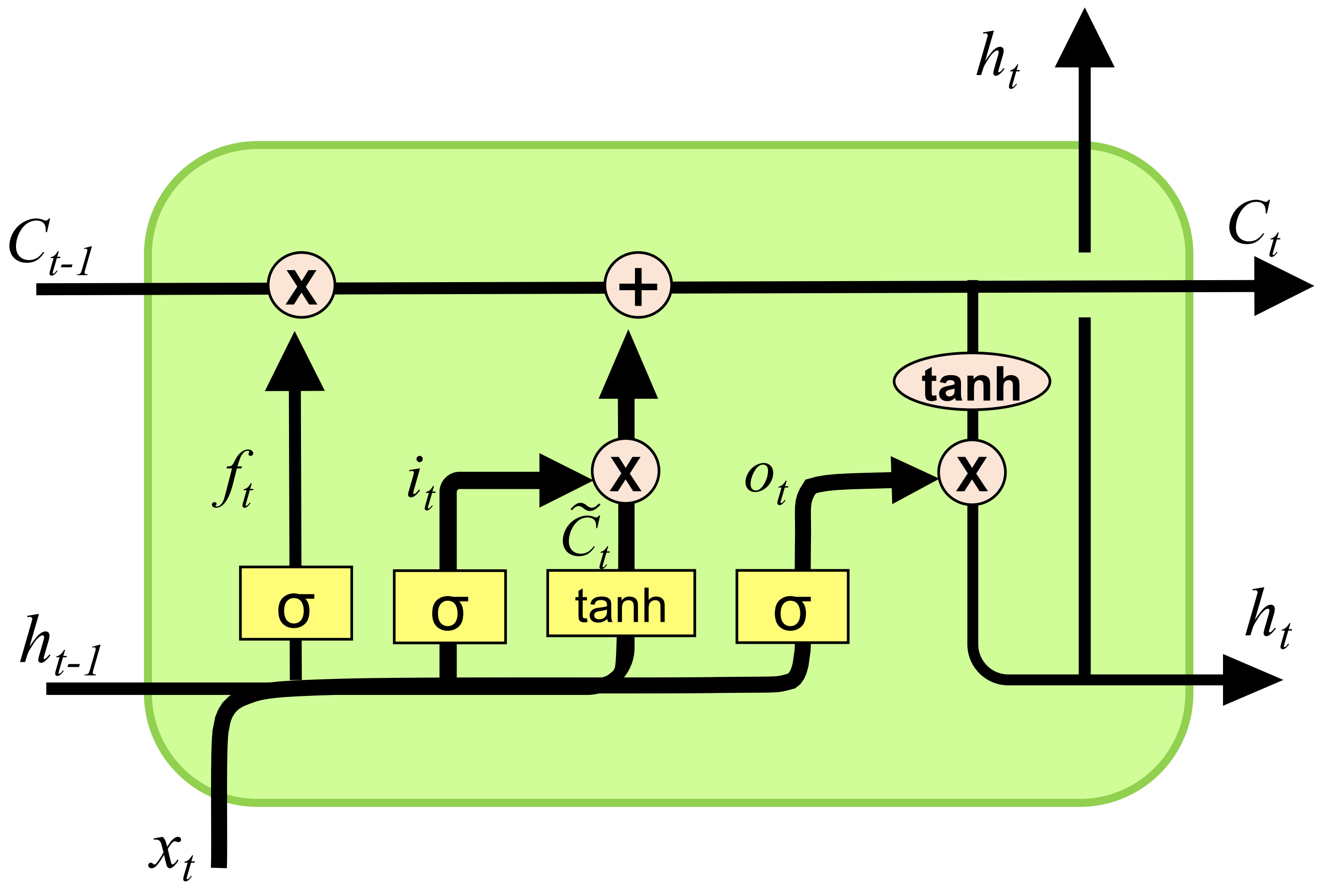
i, f and o are the input, forget and output gates, respectively.
c and c˜ denote the memory cell and the new memory cell content.

GRU

r and z are the reset and update gates, and h and h˜ are the activation and the candidate activation.

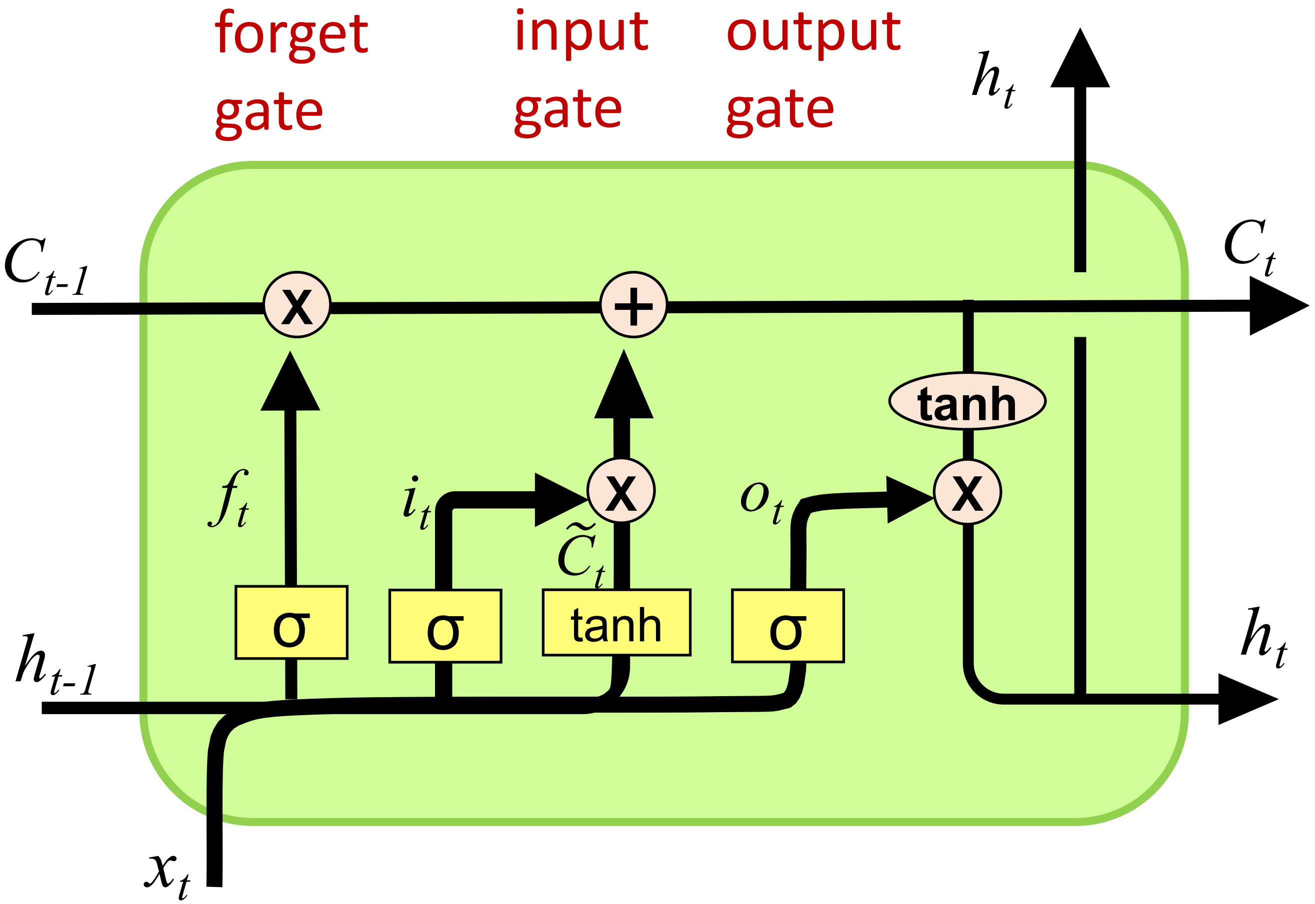
Source: Chung, Junyoung, Caglar Gulcehre, KyungHyun Cho, and Yoshua Bengio. "Empirical evaluation of gated recurrent neural networks on sequence modeling." *arXiv preprint arXiv:1412.3555* (2014).

Long Short Term Memory (LSTM)



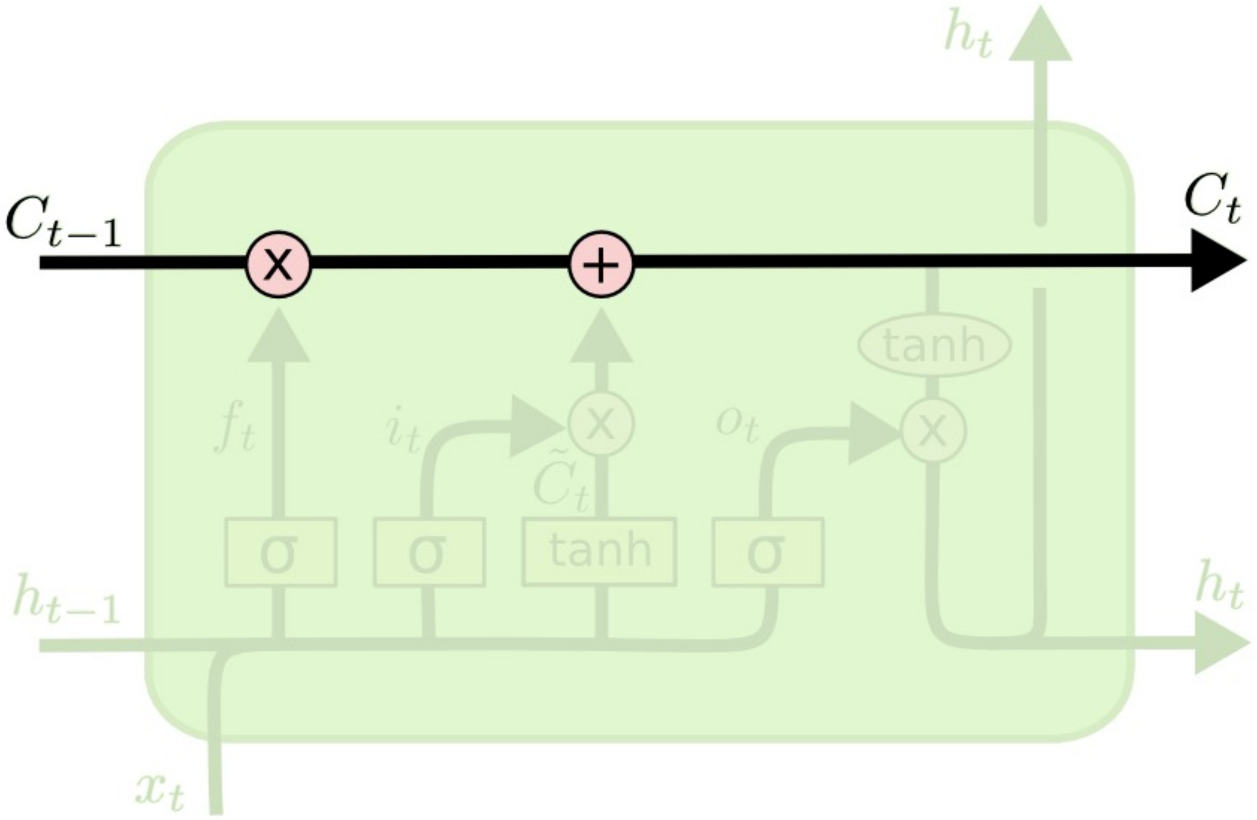
Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Long Short Term Memory (LSTM)



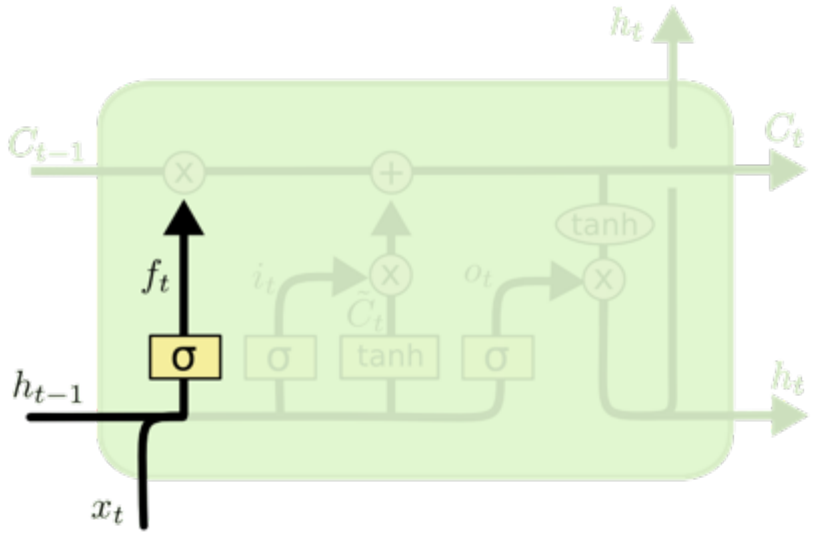
Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

LSTM
Memory state (C)



Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

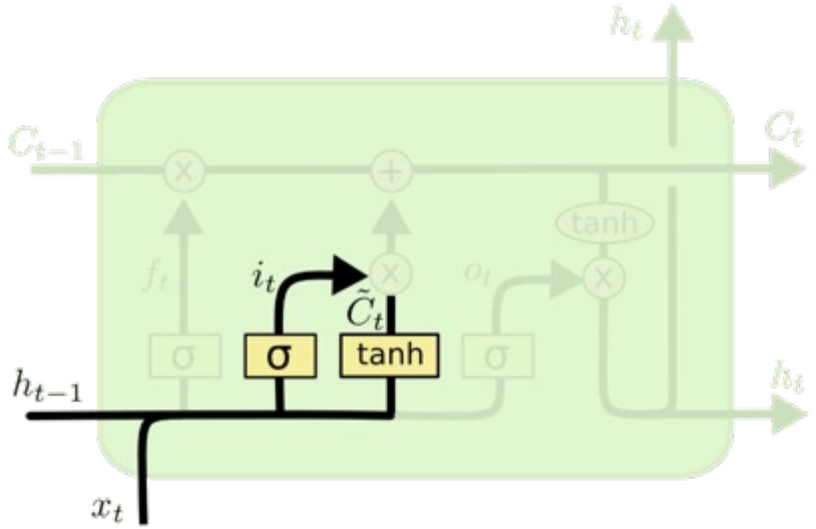
LSTM
forget gate (f)



$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \ + \ b_f\right)$$

Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

LSTM
input gate (i)

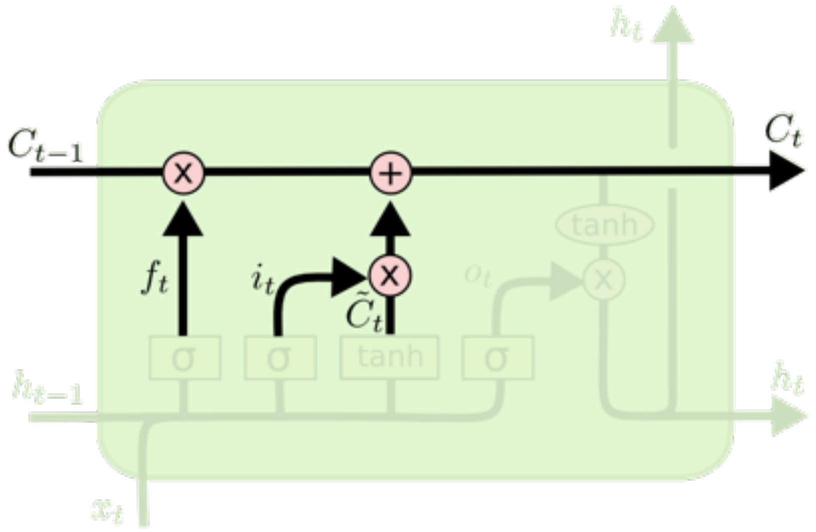


$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \; + \; b_i\right)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \; + \; b_C)$$

Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

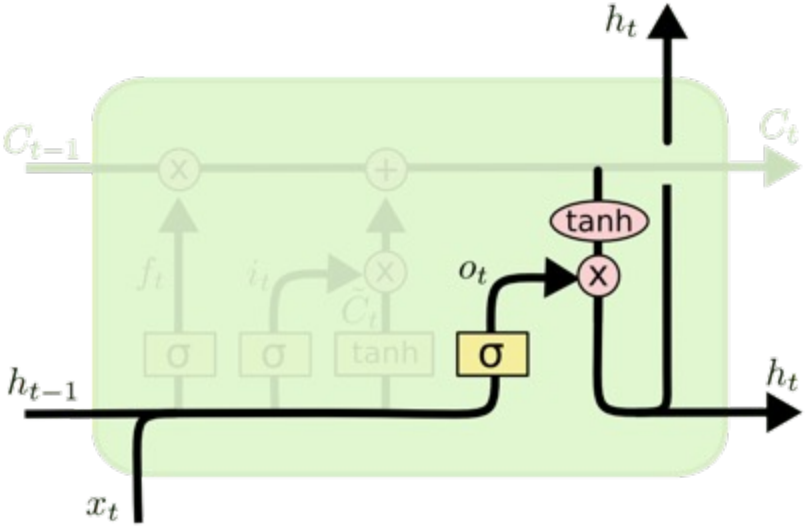
LSTM
Memory state (C)



$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

LSTM
output gate (o)

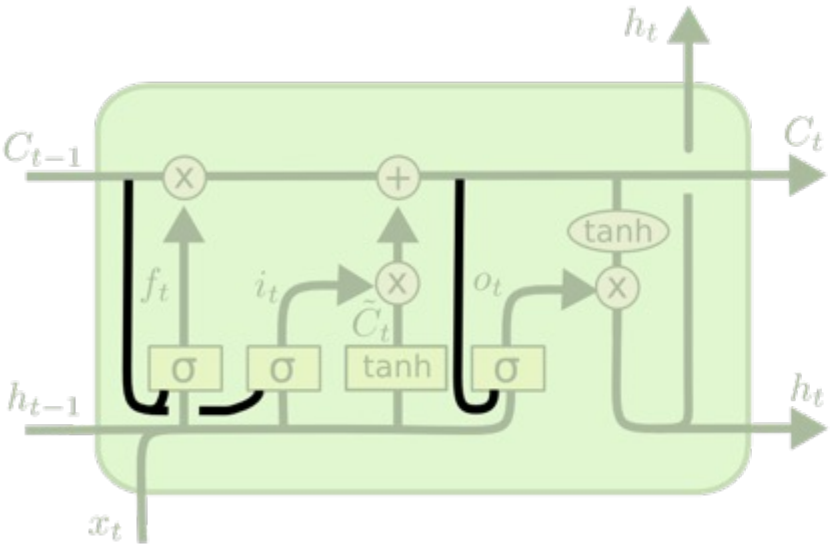


$$o_t = \sigma\left(W_o\ [h_{t-1}, x_t]\ +\ b_o\right)$$

$$h_t = o_t * \tanh\left(C_t\right)$$

Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

LSTM
forget (f), input (i), output (o) gates

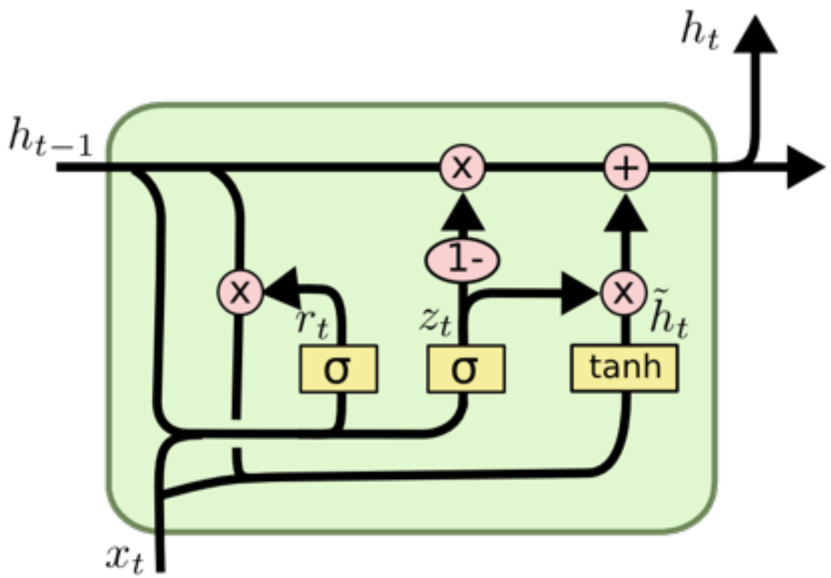


$$f_t = \sigma\left(W_f \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] \ + \ b_f\right)$$
$$i_t = \sigma\left(W_i \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] \ + \ b_i\right)$$
$$o_t = \sigma\left(W_o \cdot [\boldsymbol{C_t}, h_{t-1}, x_t] \ + \ b_o\right)$$

Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Gated Recurrent Unit (GRU)

update (z), reset (r) gates



$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

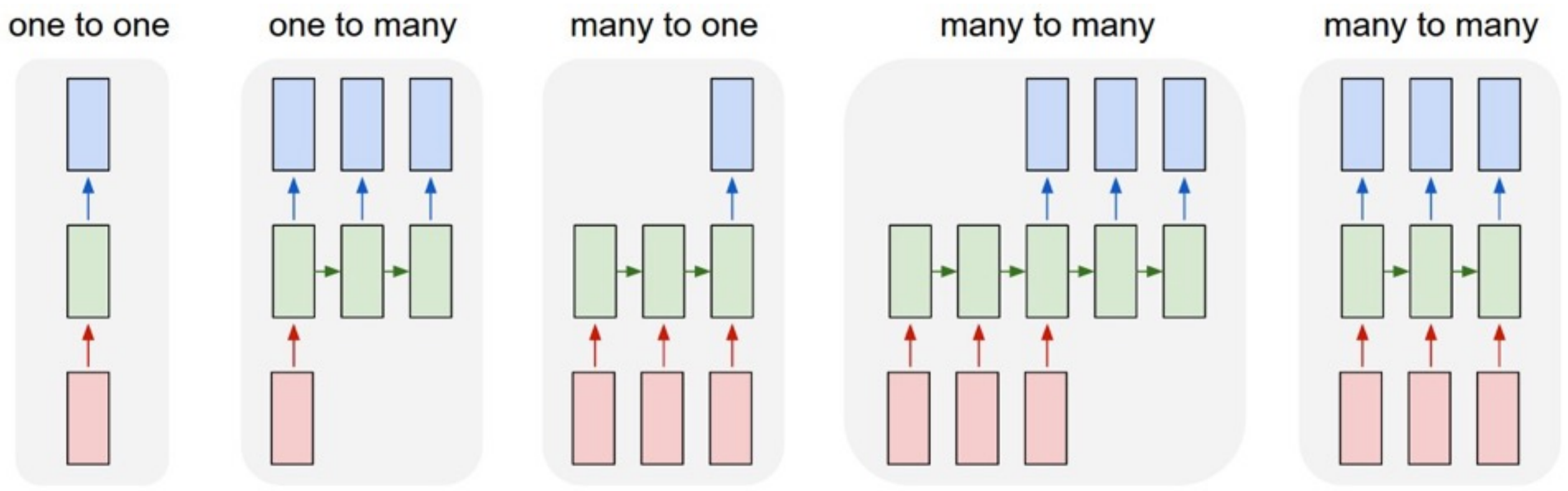
$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

LSTM Recurrent Neural Network



Traditional Neural Network

Music Generation

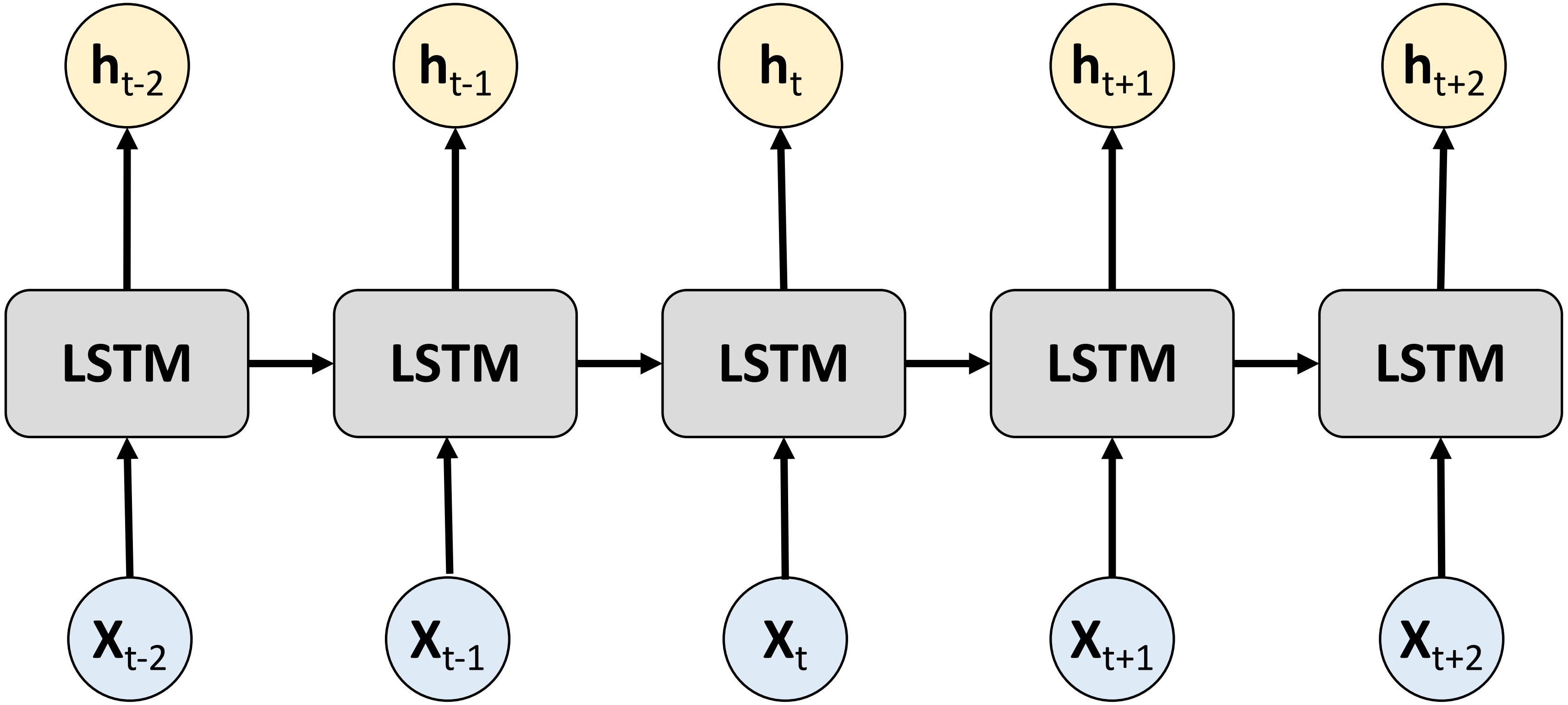
Sentiment Classification

Name Entity Recognition

Machine Translation

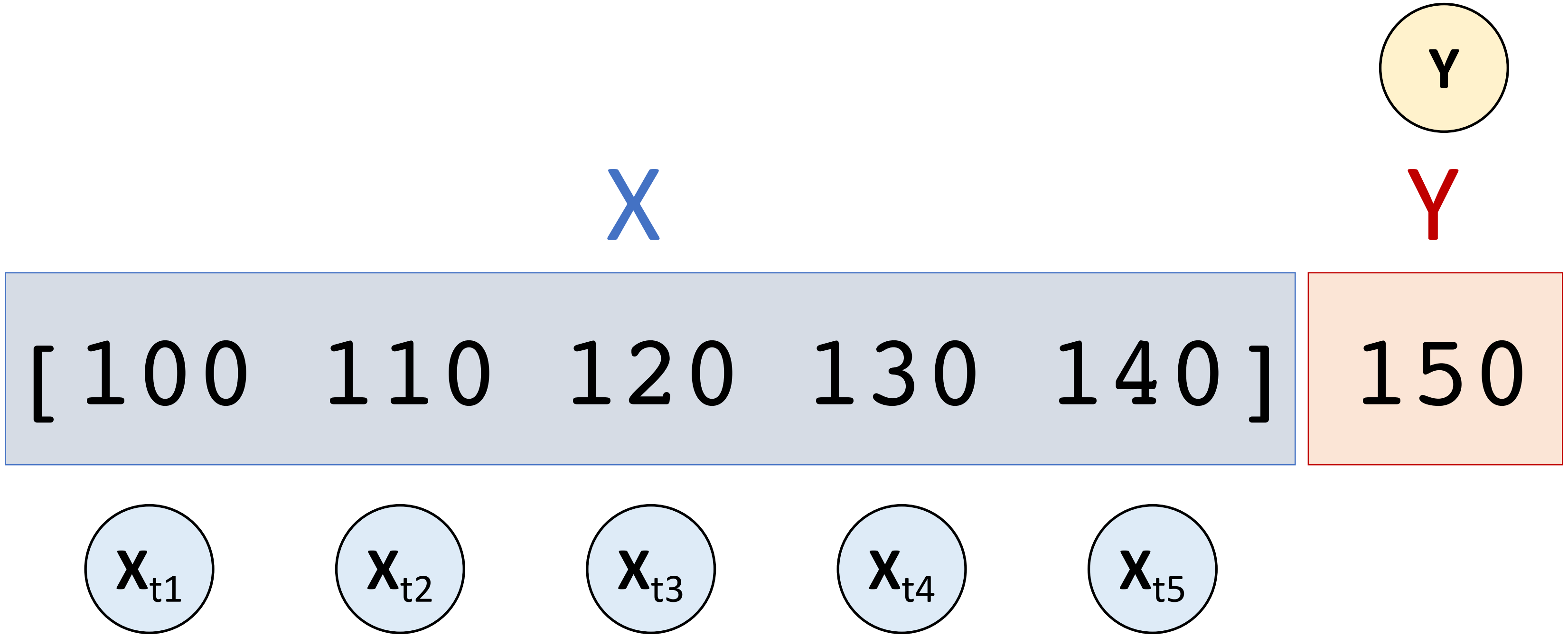
Source: https://github.com/Vict0rSch/deep_learning/tree/master/keras/recurrent

Long Short Term Memory (LSTM) for Time Series Forecasting

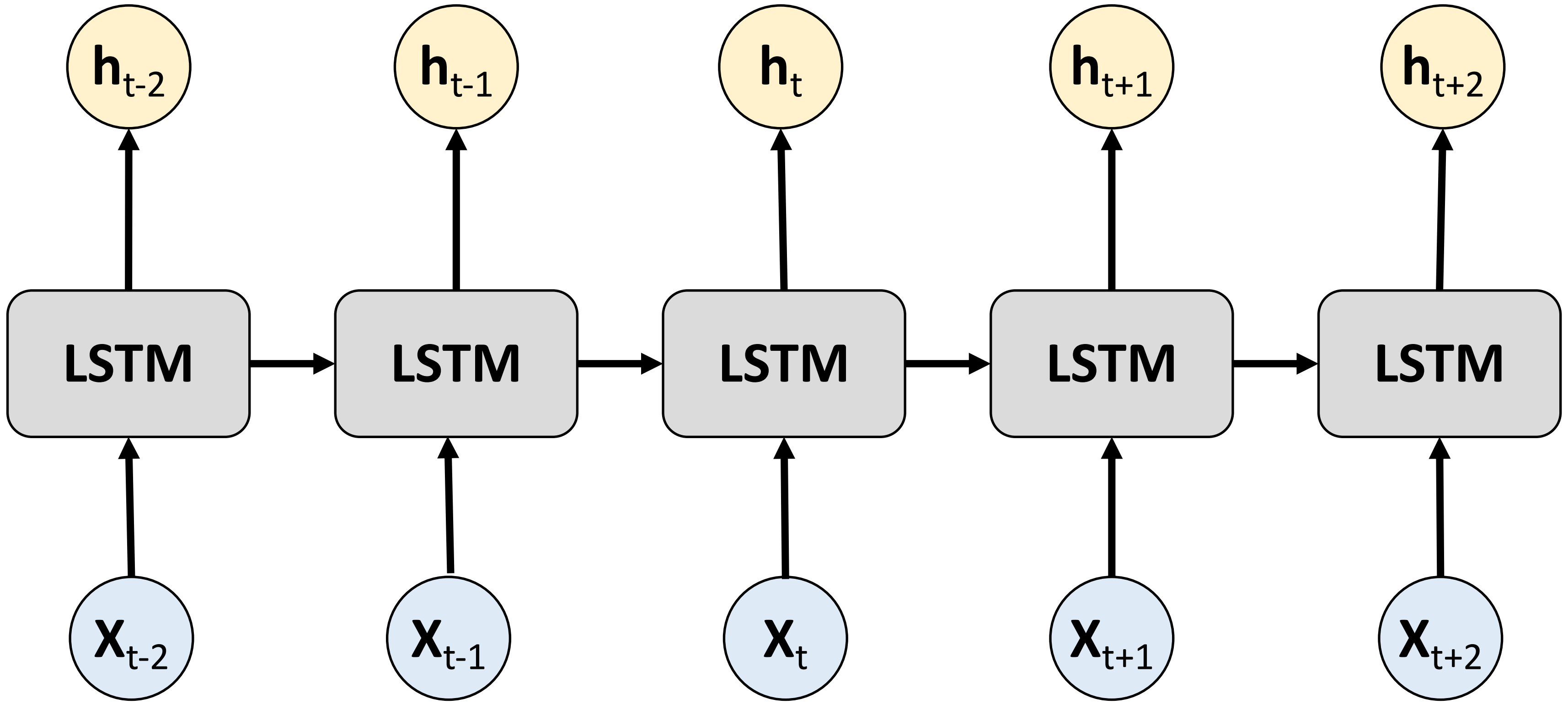


Time Series Data

[100, 110, 120, 130, 140, 150]



Long Short Term Memory (LSTM) for Time Series Forecasting

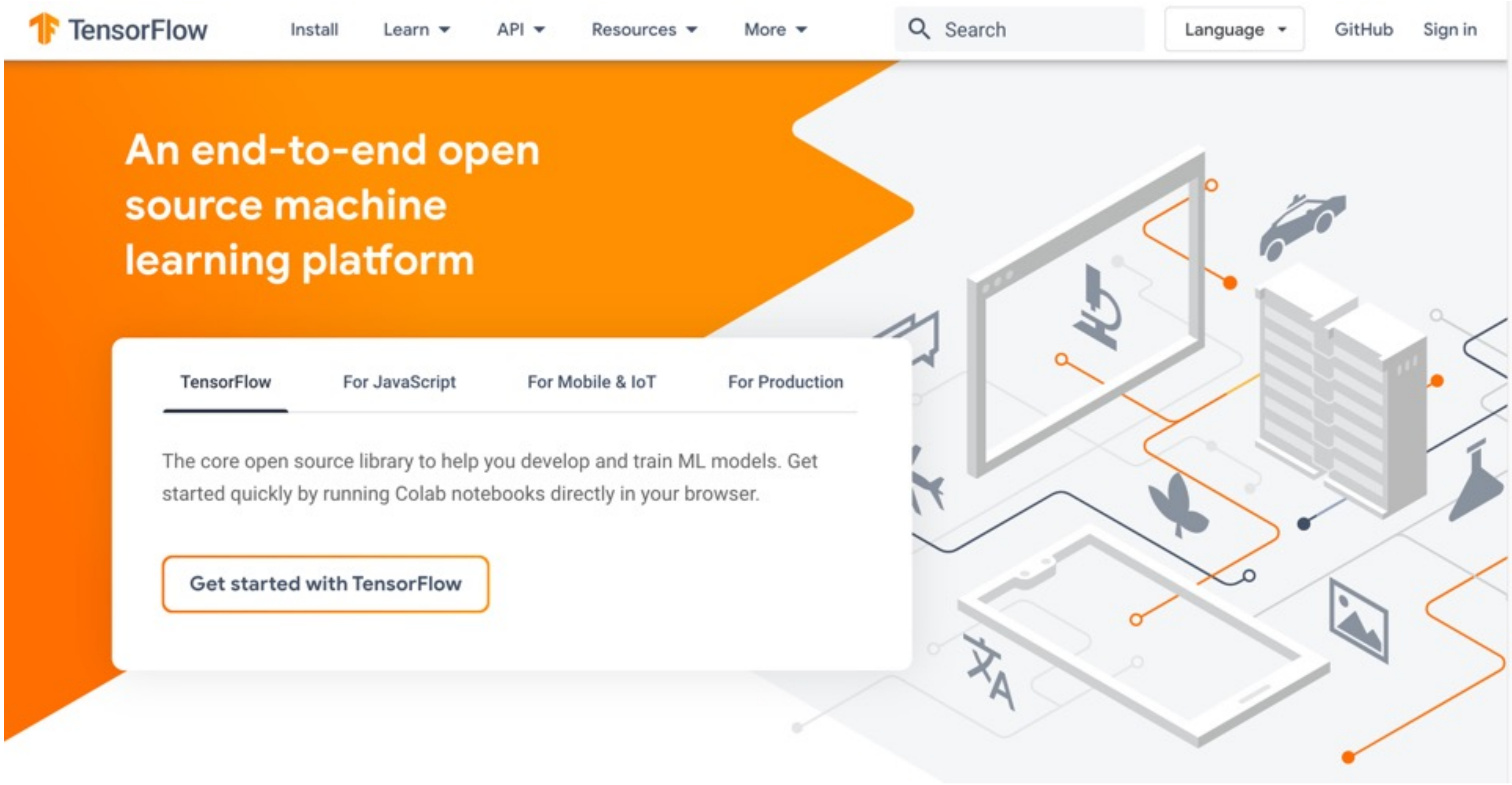


Time Series Data

`[10, 20, 30, 40, 50, 60, 70, 80, 90]`

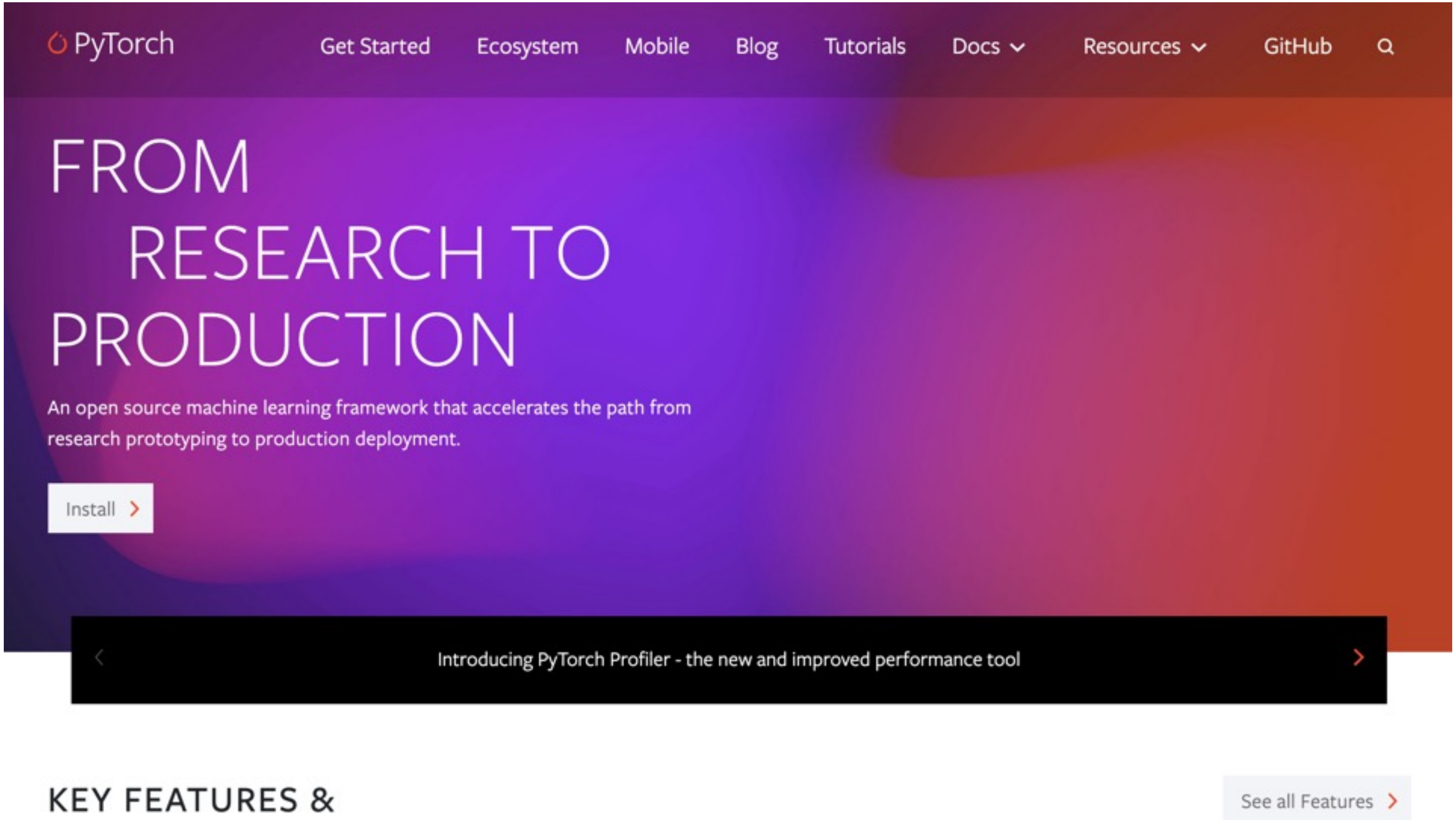
X	Y
[10 20 30]	40
[20 30 40]	50
[30 40 50]	60
[40 50 60]	70
[50 60 70]	80
[60 70 80]	90

TensorFlow



https://www.tensorflow.org/

PyTorch



https://pytorch.org/

TensorFlow

- An end-to-end open source
  machine learning platform.
- The core open source library to help you develop and train ML models.
- Get started quickly by running
  Colab notebooks directly in your browser.

https://www.tensorflow.org/

TensorFlow

Why TensorFlow 2.0

Why TensorFlow

TensorFlow is an end-to-end open source platform for machine learning. It has a comprehensive, flexible ecosystem of tools, libraries and community resources that lets researchers push the state-of-the-art in ML and developers easily build and deploy ML powered applications.

About →

Easy model building

Build and train ML models easily using intuitive high-level APIs like Keras with eager execution, which makes for immediate model iteration and easy debugging.

Robust ML production anywhere

Easily train and deploy models in the cloud, on-prem, in the browser, or on-device no matter what language you use.

Powerful experimentation for research

A simple and flexible architecture to take new ideas from concept to code, to state-of-the-art models, and to publication faster.

TensorFlow

TensorFlow 2.0 vs. 1.X

```
# TensorFlow 2.0
outputs = f(input)

# TensorFlow 1.X
outputs = session.run(f(placeholder), feed_dict={placeholder: input})
```

Source: https://www.tensorflow.org/guide/effective_tf2

TensorFlow 2.0

TensorFlow

```
import tensorflow as tf
mnist = tf.keras.datasets.mnist

(x_train, y_train),(x_test, y_test) = mnist.load_data()
x_train, x_test = x_train / 255.0, x_test / 255.0

model = tf.keras.models.Sequential([
  tf.keras.layers.Flatten(input_shape=(28, 28)),
  tf.keras.layers.Dense(128, activation='relu'),
  tf.keras.layers.Dropout(0.2),
  tf.keras.layers.Dense(10, activation='softmax')
])

model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

model.fit(x_train, y_train, epochs=5)
model.evaluate(x_test, y_test)
```

https://www.tensorflow.org/overview/

TensorFlow

TensorFlow 2 Quick Start

beginner.ipynb

File Edit View Insert Runtime Tools Help Last edited on October 2 by lamberta

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TensorFlow 2 quickstart for beginners

View on TensorFlow.org Run in Google Colab View source on GitHub Download notebook

This short introduction uses Keras to:

1. Build a neural network that classifies images.
2. Train this neural network.
3. And, finally, evaluate the accuracy of the model.

This is a Google Colaboratory notebook file. Python programs are run directly in the browser—a great way to learn and use TensorFlow. To follow this tutorial, run the notebook in Google Colab by clicking the button at the top of this page.

1. In Colab, connect to a Python runtime: At the top-right of the menu bar, select *CONNECT*.
2. Run all the notebook code cells: Select *Runtime* > *Run all*.

Download and install the TensorFlow 2 package. Import TensorFlow into your program:

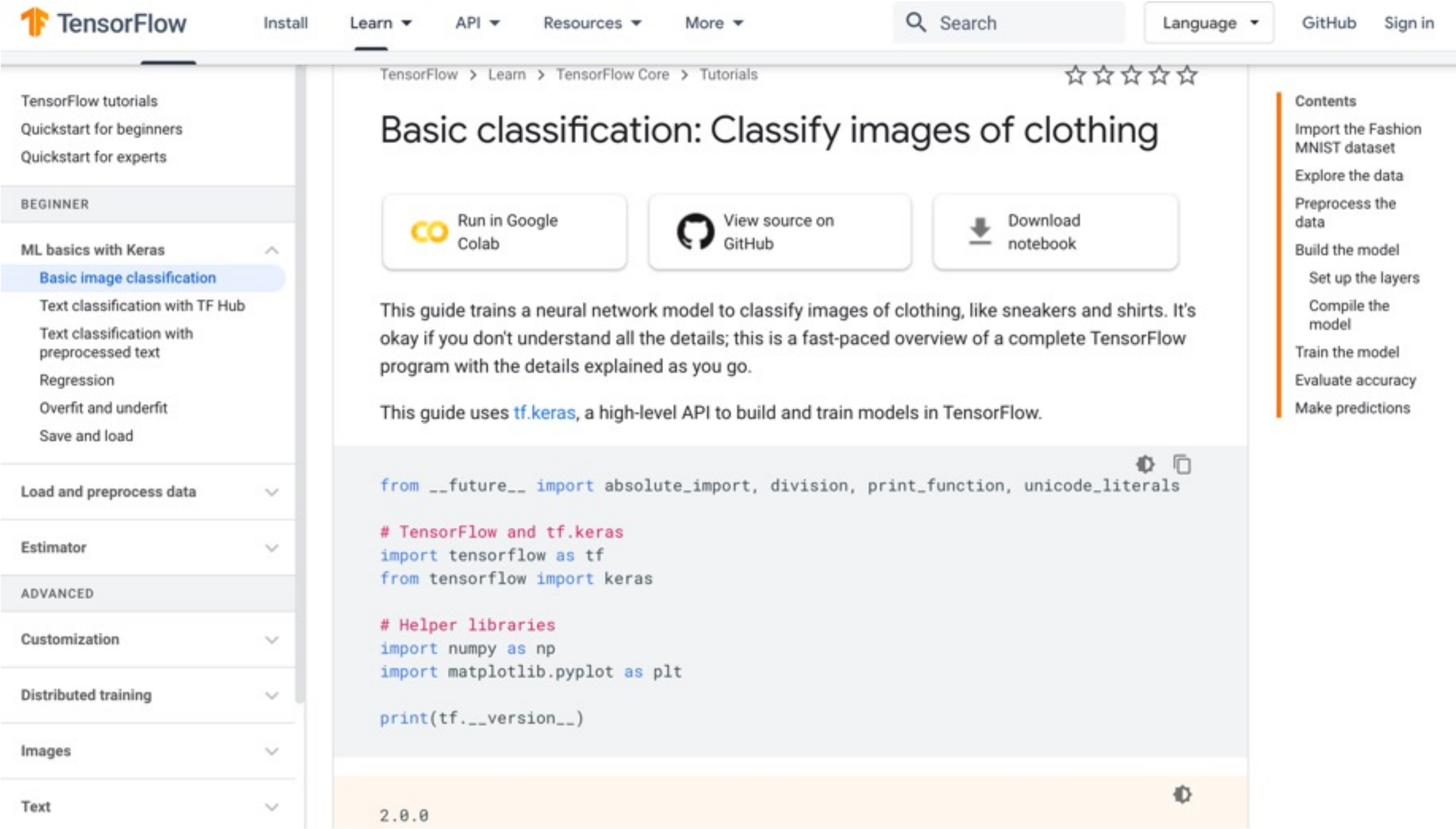
```
from __future__ import absolute_import, division, print_function, unicode_literals

# Install TensorFlow
try:
  # %tensorflow_version only exists in Colab.
  %tensorflow_version 2.x
except Exception:
  pass
```

https://colab.research.google.com/github/tensorflow/docs/blob/master/site/en/tutorials/quickstart/beginner.ipynb

TensorFlow

TensorFlow Image Classification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TensorFlow tutorials
Quickstart for beginners
Quickstart for experts

BEGINNER

ML basics with Keras
Basic image classification
Text classification with TF Hub
Text classification with preprocessed text
Regression
Overfit and underfit
Save and load

Load and preprocess data

Estimator

ADVANCED

Customization

Distributed training

Images

Text

Basic classification: Classify images of clothing

Run in Google Colab | View source on GitHub | Download notebook

This guide trains a neural network model to classify images of clothing, like sneakers and shirts. It's okay if you don't understand all the details; this is a fast-paced overview of a complete TensorFlow program with the details explained as you go.

This guide uses tf.keras, a high-level API to build and train models in TensorFlow.

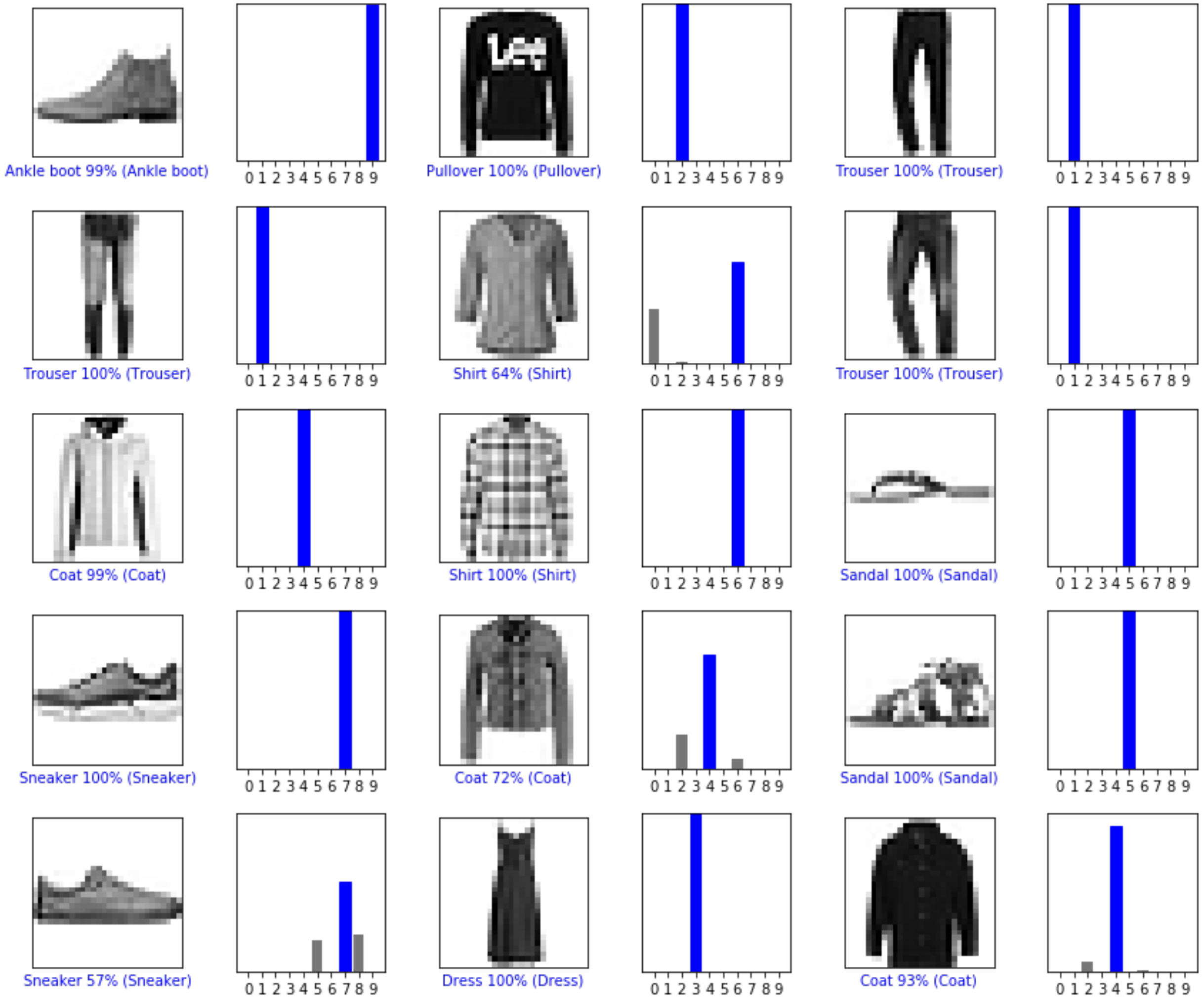
```
from __future__ import absolute_import, division, print_function, unicode_literals

# TensorFlow and tf.keras
import tensorflow as tf
from tensorflow import keras

# Helper libraries
import numpy as np
import matplotlib.pyplot as plt

print(tf.__version__)
```

```
2.0.0
```

Contents
Import the Fashion MNIST dataset
Explore the data
Preprocess the data
Build the model
Set up the layers
Compile the model
Train the model
Evaluate accuracy
Make predictions

https://www.tensorflow.org/tutorials/keras/classification

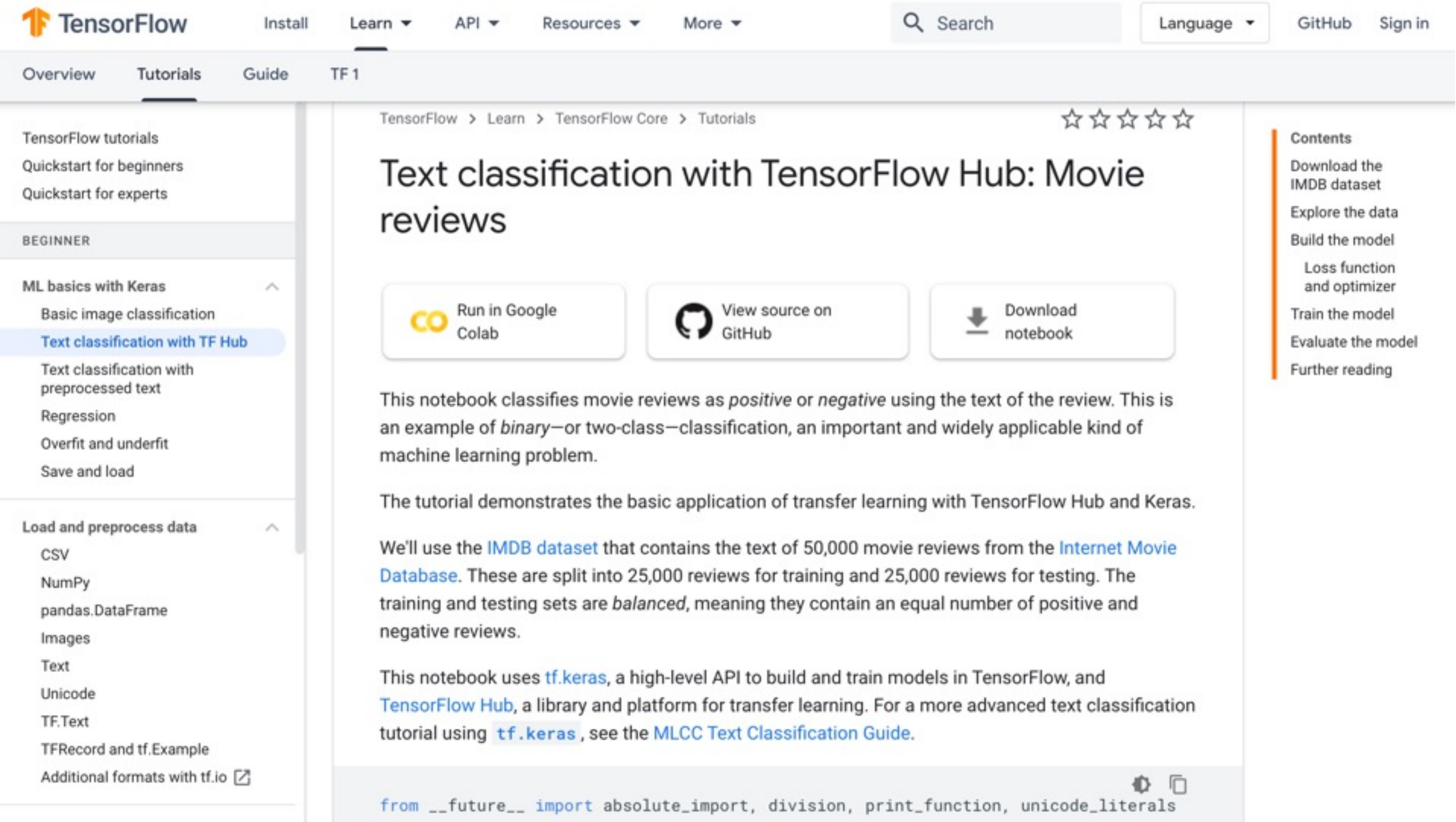
Image Classification
Fashion MNIST dataset



https://www.tensorflow.org/tutorials/keras/classification

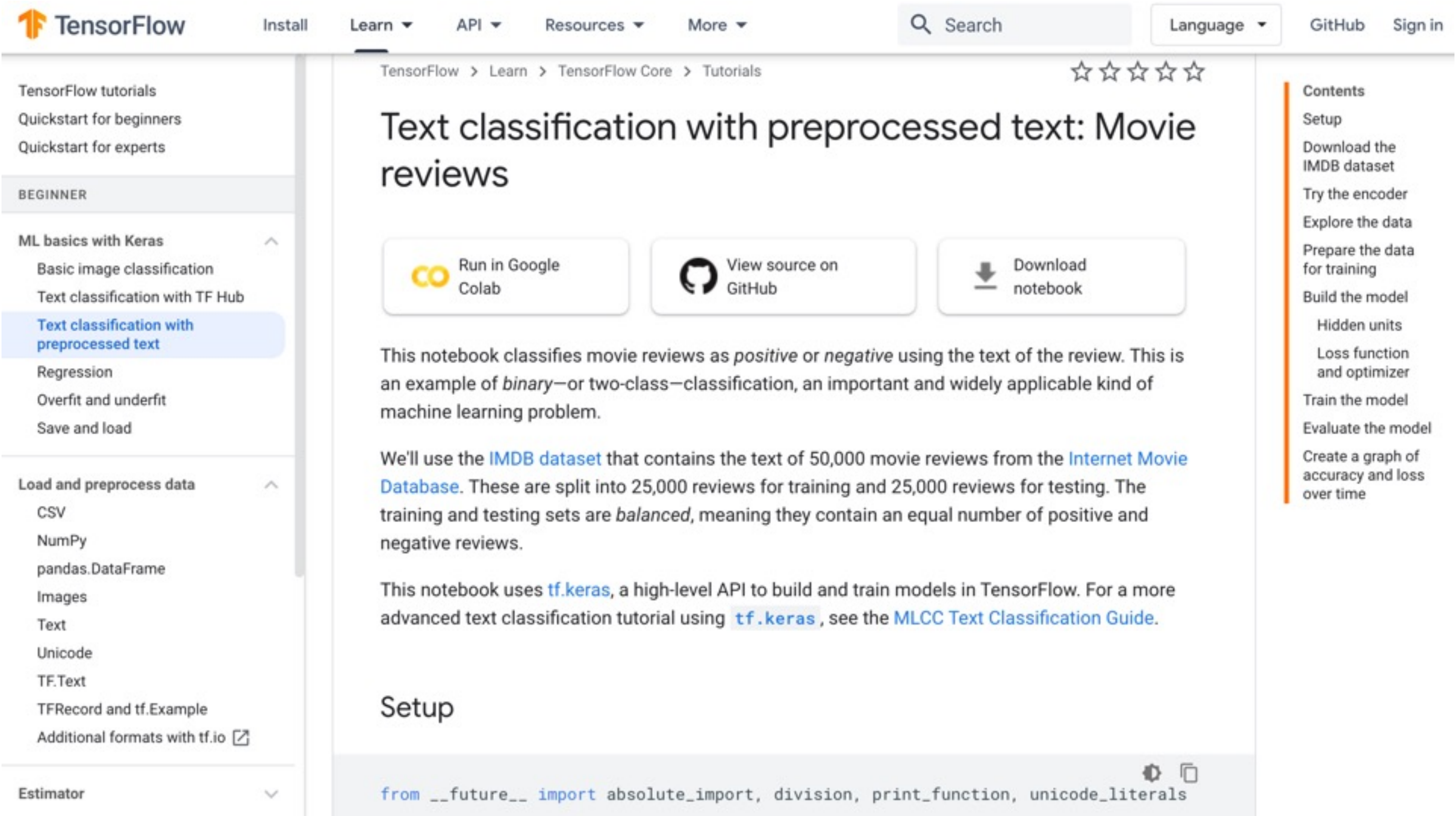
TensorFlow

Text Classification with TF Hub



https://www.tensorflow.org/tutorials/keras/text_classification_with_hub

Text Classification with Pre Text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CSV
NumPy
pandas.DataFrame
Images
Text
Unicode
TF.Text
TFRecord and tf.Example
Additional formats with tf.io
Estimator

Text classification with preprocessed text: Movie reviews

Run in Google Colab | View source on GitHub | Download notebook

This notebook classifies movie reviews as *positive* or *negative* using the text of the review. This is an example of *binary*—or two-class—classification, an important and widely applicable kind of machine learning problem.

We'll use the IMDB dataset that contains the text of 50,000 movie reviews from the Internet Movie Database. These are split into 25,000 reviews for training and 25,000 reviews for testing. The training and testing sets are *balanced*, meaning they contain an equal number of positive and negative reviews.

This notebook uses tf.keras, a high-level API to build and train models in TensorFlow. For a more advanced text classification tutorial using `tf.keras`, see the MLCC Text Classification Guide.

Setup

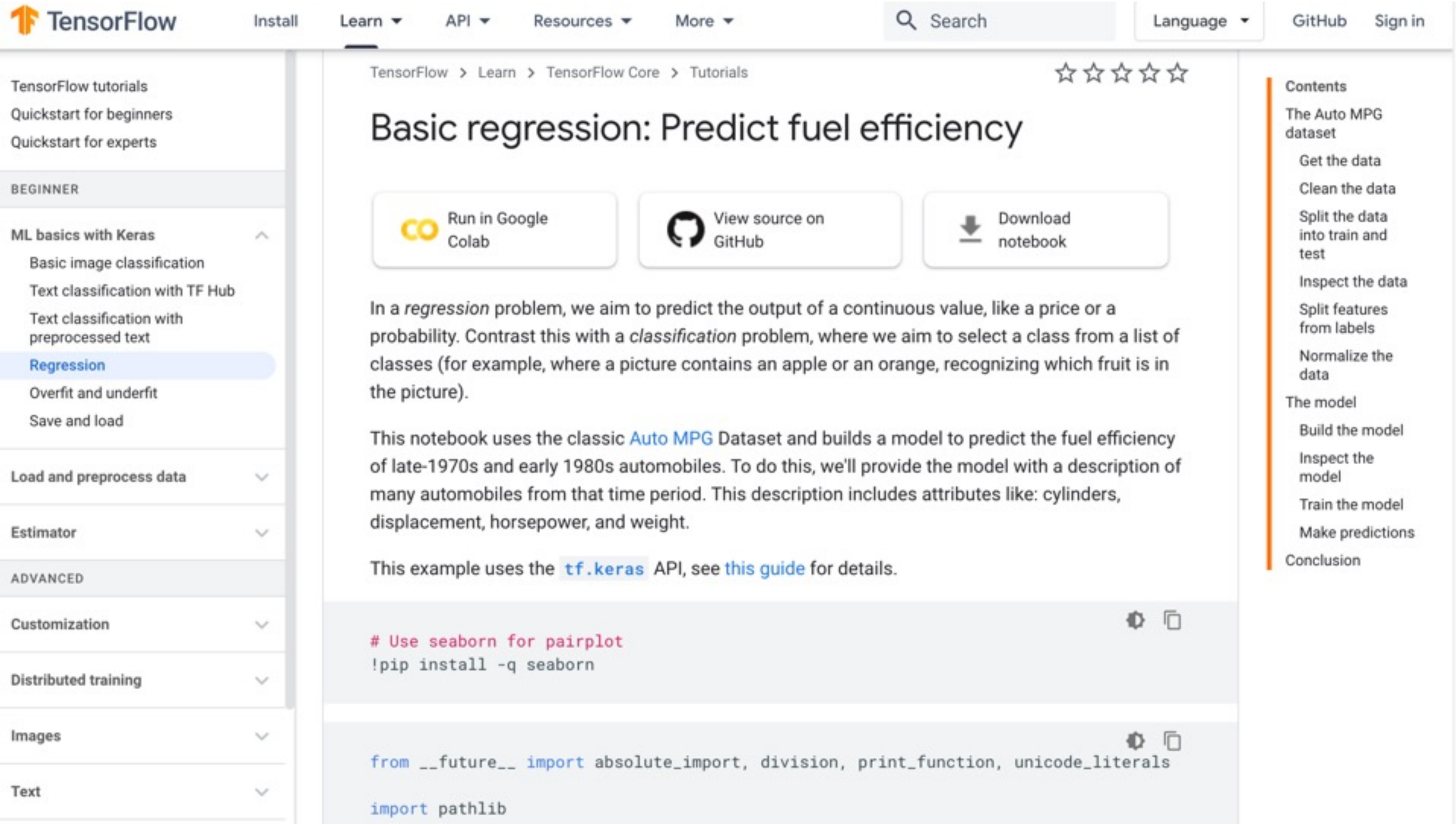
```
from __future__ import absolute_import, division, print_function, unicode_literals
```

Contents
Setup
Download the IMDB dataset
Try the encoder
Explore the data
Prepare the data for training
Build the model
Hidden units
Loss function and optimizer
Train the model
Evaluate the model
Create a graph of accuracy and loss over time

https://www.tensorflow.org/tutorials/keras/text_classification

TensorFlow

Regression



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Images
Text

TensorFlow > Learn > TensorFlow Core > Tutorials

Basic regression: Predict fuel efficiency

Run in Google Colab | View source on GitHub | Download notebook

In a *regression* problem, we aim to predict the output of a continuous value, like a price or a probability. Contrast this with a *classification* problem, where we aim to select a class from a list of classes (for example, where a picture contains an apple or an orange, recognizing which fruit is in the picture).

This notebook uses the classic Auto MPG Dataset and builds a model to predict the fuel efficiency of late-1970s and early 1980s automobiles. To do this, we'll provide the model with a description of many automobiles from that time period. This description includes attributes like: cylinders, displacement, horsepower, and weight.

This example uses the `tf.keras` API, see this guide for details.

```
# Use seaborn for pairplot
!pip install -q seaborn
```

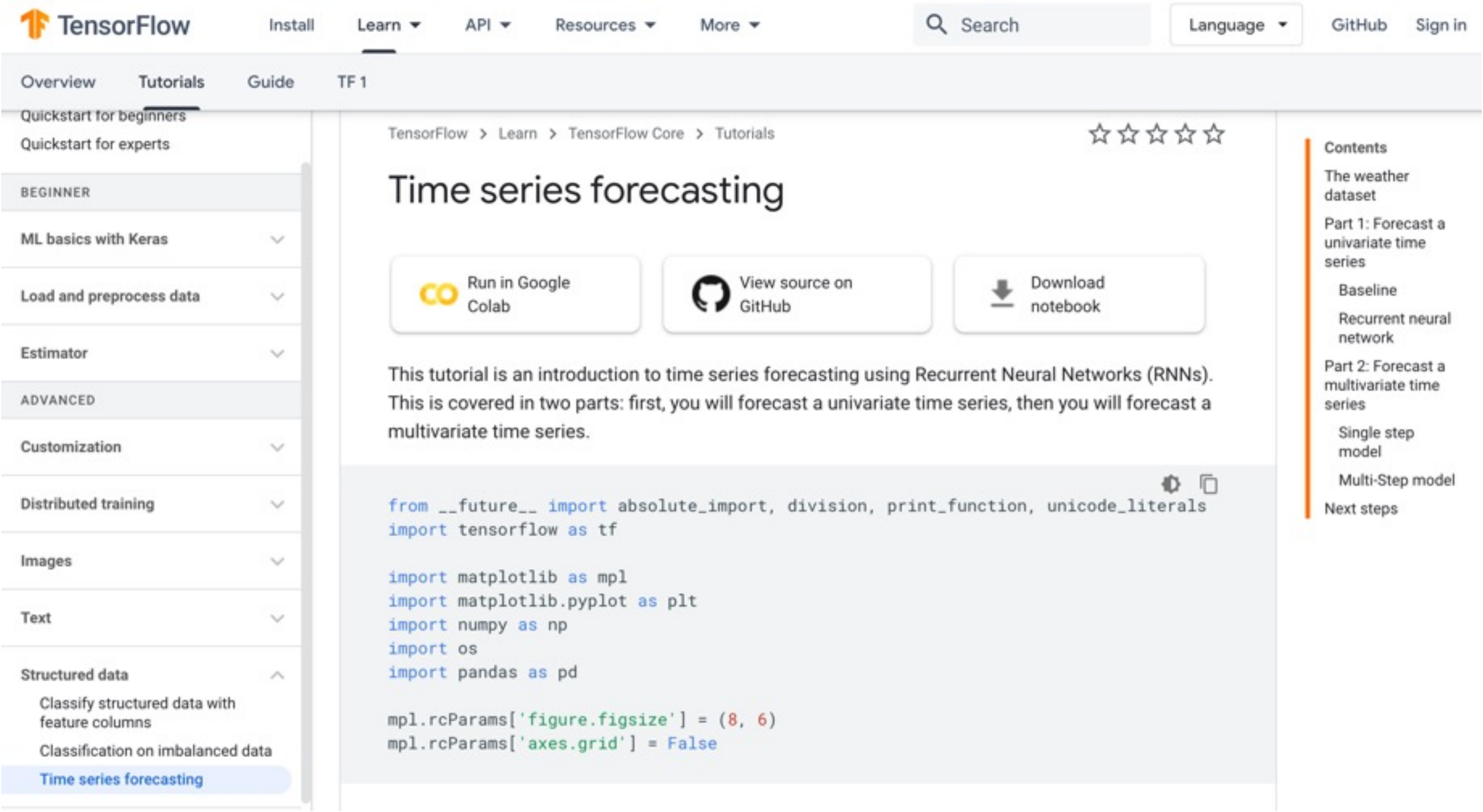
```
from __future__ import absolute_import, division, print_function, unicode_literals

import pathlib
```

Contents
The Auto MPG dataset
Get the data
Clean the data
Split the data into train and test
Inspect the data
Split features from labels
Normalize the data
The model
Build the model
Inspect the model
Train the model
Make predictions
Conclusion

https://www.tensorflow.org/tutorials/keras/regression

TensorFlow 2.0
Time Series Forecasting

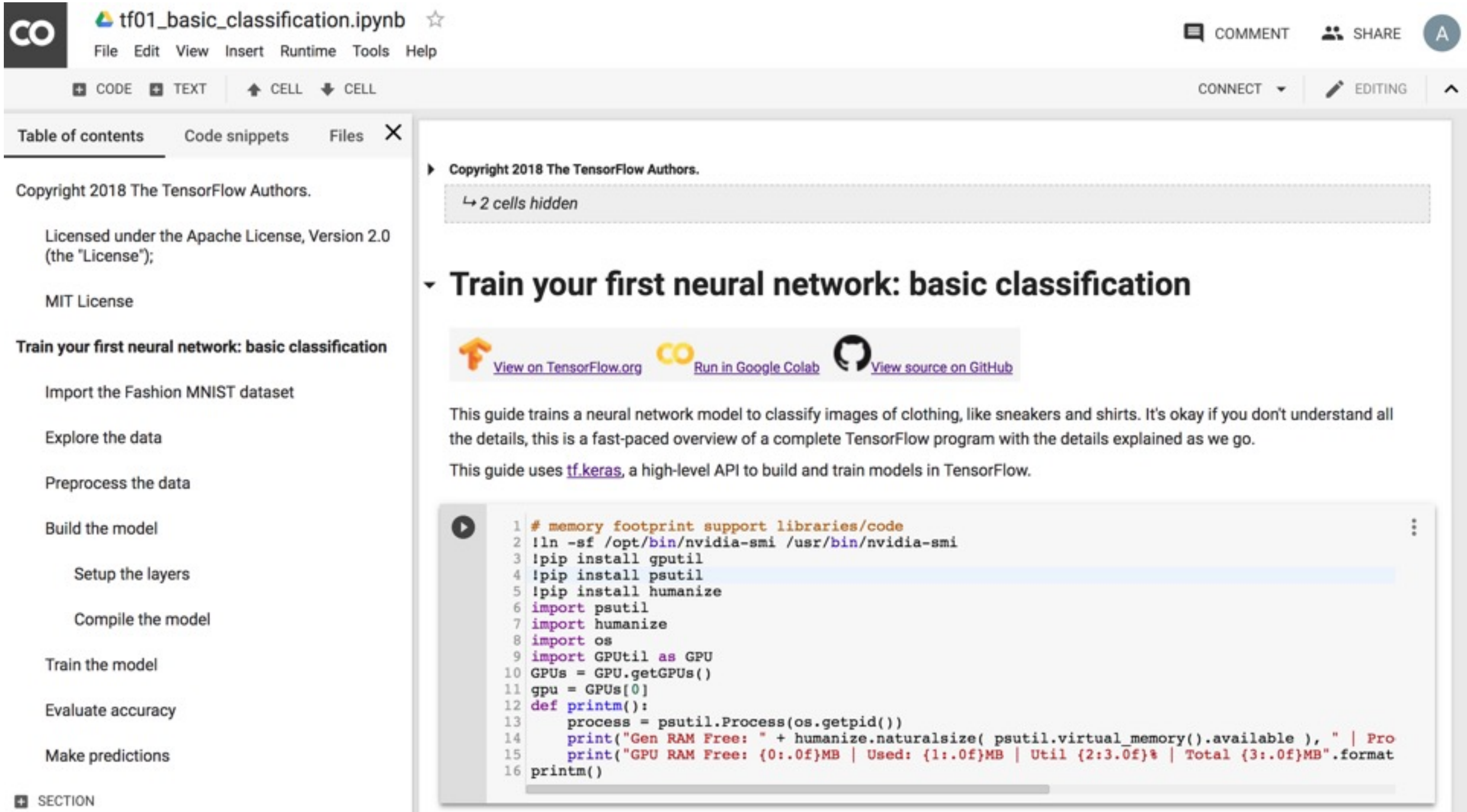


https://www.tensorflow.org/tutorials/structured_data/time_series

Basic Classification

Fashion MNIST Image Classification

https://colab.research.google.com/drive/19PJOJi1vn1kjcutlzNHjRSLbeVl4kd5z

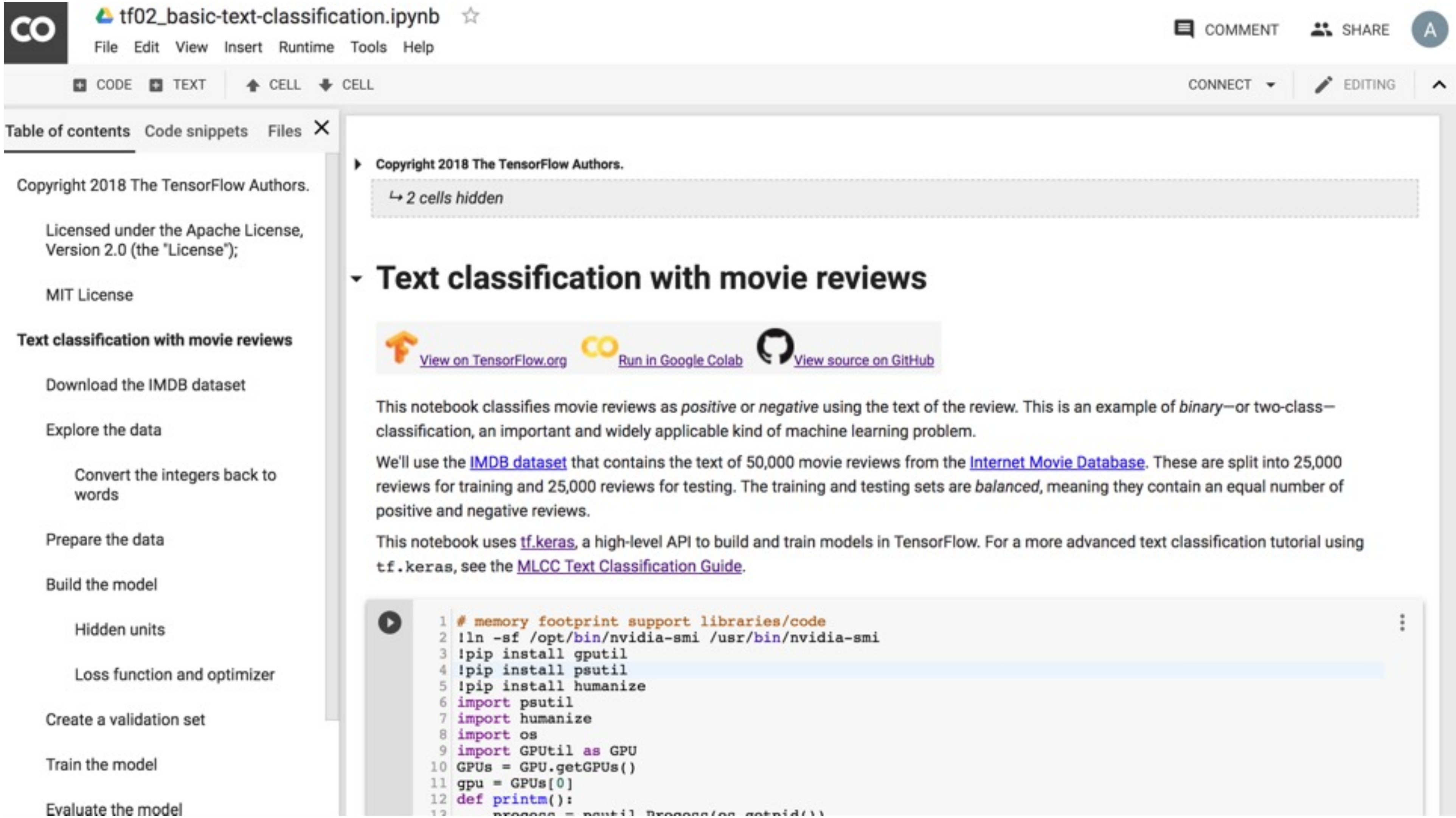


Source: https://colab.research.google.com/github/tensorflow/docs/blob/master/site/en/tutorials/keras/basic_classification.ipynb

Text Classification

IMDB Movie Reviews

https://colab.research.google.com/drive/1x16h1GhHsLIrLYtPCvCHaoO1W-i_gror

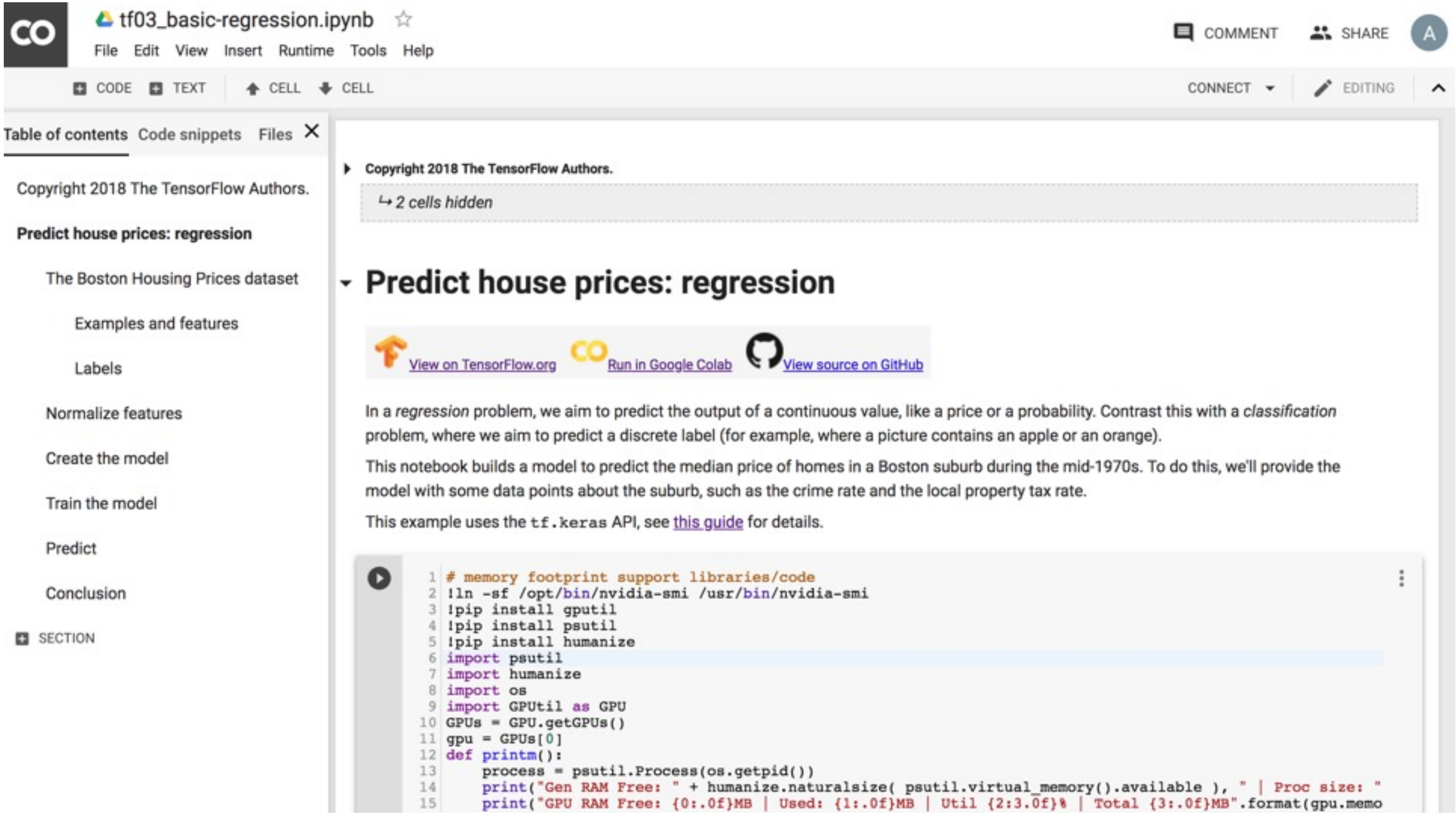


Source: https://colab.research.google.com/github/tensorflow/docs/blob/master/site/en/tutorials/keras/basic_text_classification.ipynb

Basic Regression

Predict House Prices

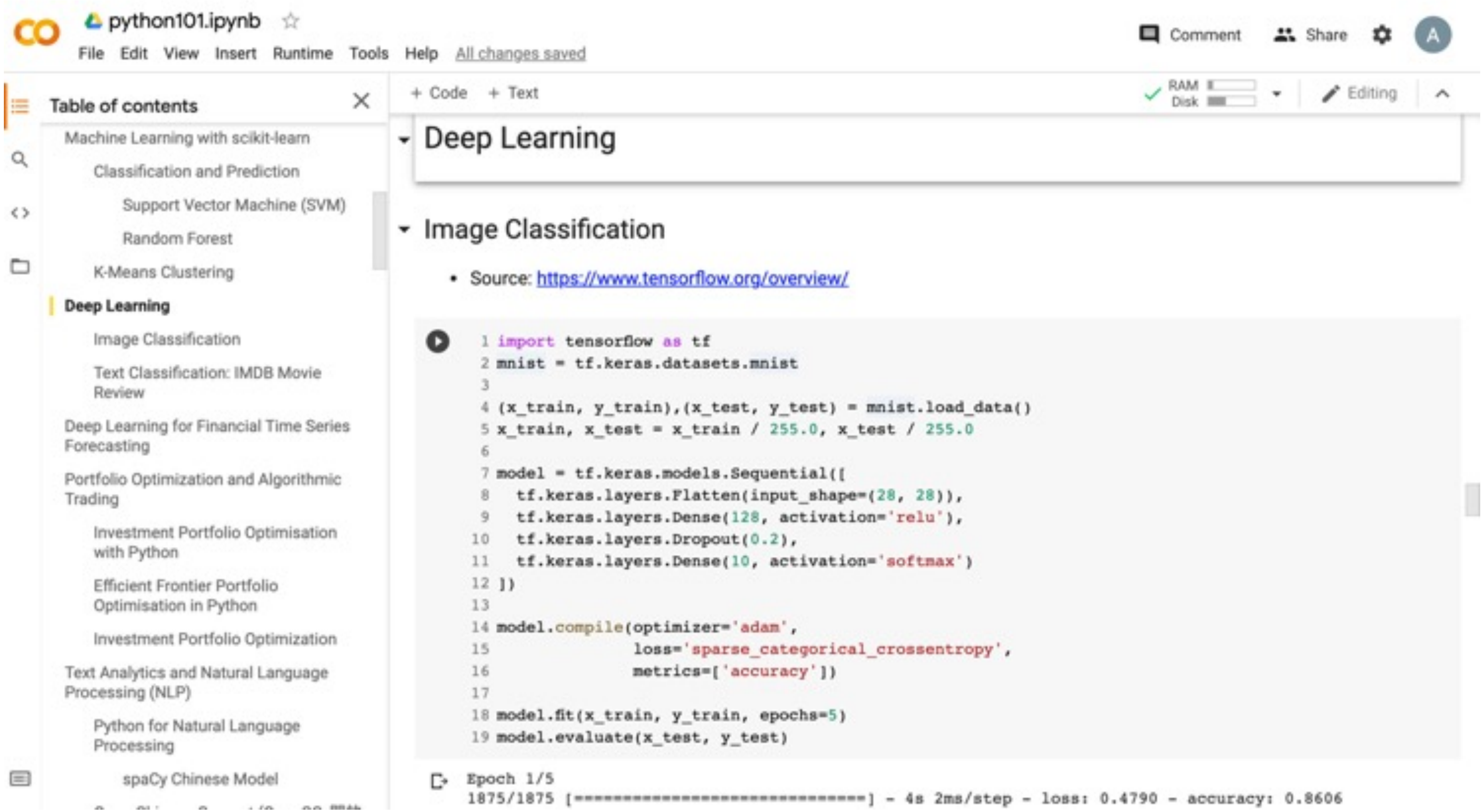
https://colab.research.google.com/drive/1v4c8ZHTnRtgd2_25K_AURjR6SCVBRdlj



Source: https://colab.research.google.com/github/tensorflow/docs/blob/master/site/en/tutorials/keras/basic_regression.ipynb

Python in Google Colab (Python101)

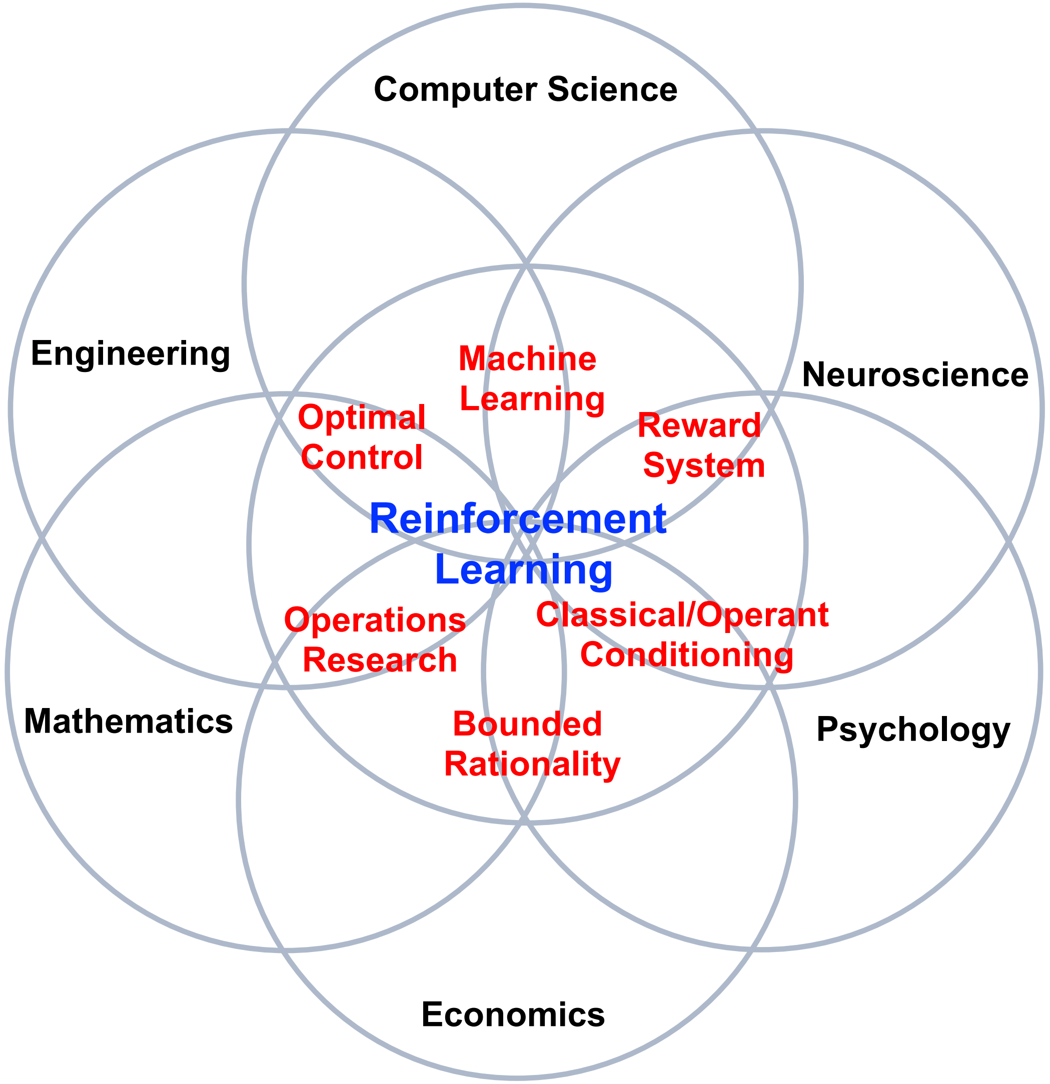
https://colab.research.google.com/drive/1FEG6DnGvwfUbeo4zJ1zTunjMqf2RkCrT



https://tinyurl.com/aintpupython101

Reinforcement Learning

Reinforcement Learning (RL)

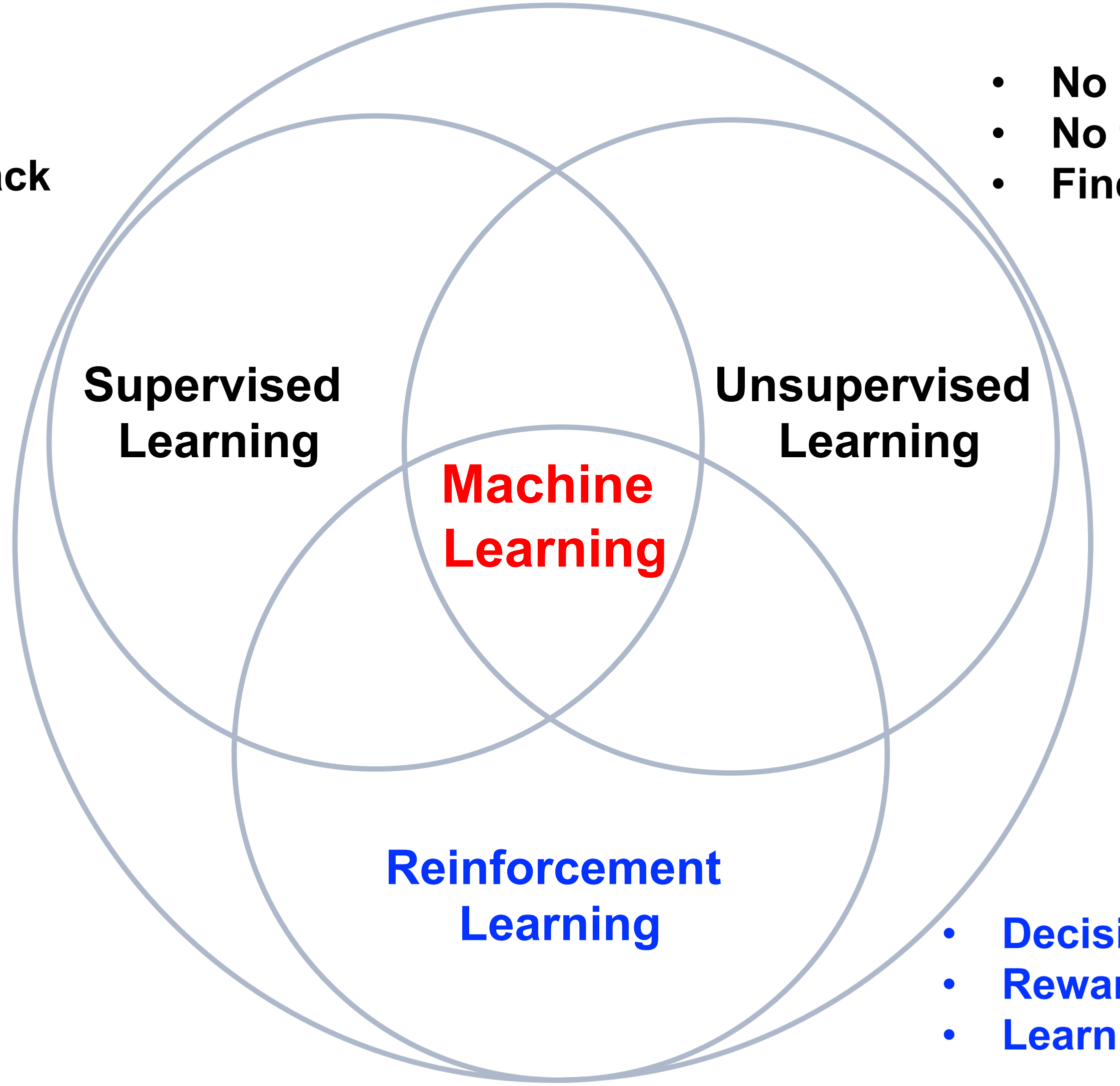


Source: David Silver (2015), Introduction to reinforcement learning, https://www.youtube.com/playlist?list=PLqYmG7hTraZDM-OYHWgPebj2MfCFzFObQ

Branches of Machine Learning (ML)
Reinforcement Learning (RL)

- Labeled data
- Direct feedback
- Predict

- No Labels
- No feedback
- Find hidden structure



- Decision process
- Reward system
- Learn series of actions

Source: David Silver (2015), Introduction to reinforcement learning, https://www.youtube.com/playlist?list=PLqYmG7hTraZDM-OYHWgPebj2MfCFzFObQ

David Silver (2015), Introduction to reinforcement learning

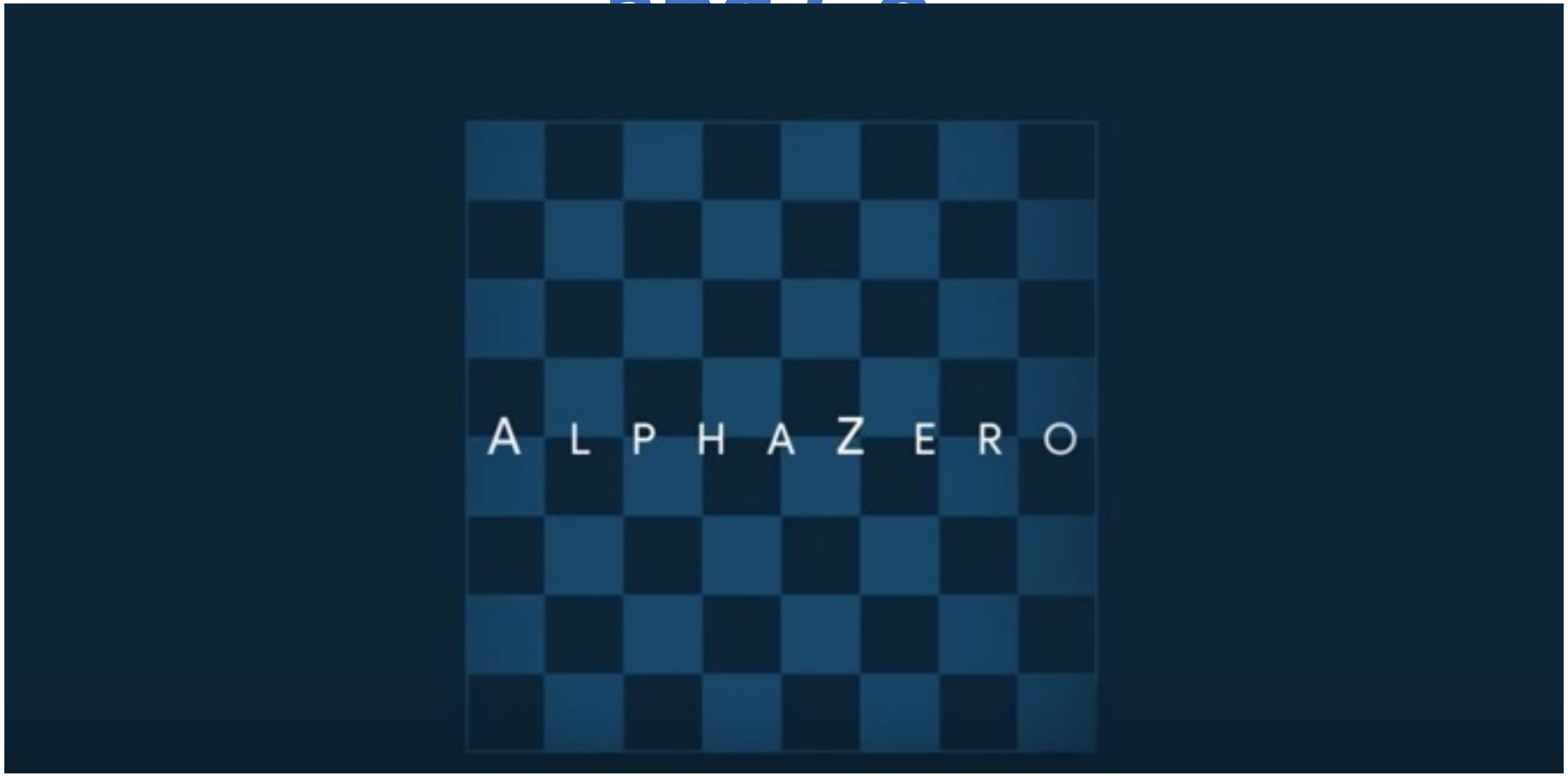
- Elementary Reinforcement Learning
  - 1: Introduction to Reinforcement Learning
  - 2: Markov Decision Processes
  - 3: Planning by Dynamic Programming
  - 4: Model-Free Prediction
  - 5: Model-Free Control
- Reinforcement Learning in Practice
  - 6: Value Function Approximation
  - 7: Policy Gradient Methods
  - 8: Integrating Learning and Planning
  - 9: Exploration and Exploitation
  - 10: Case Study: RL in Classic Games

Source: David Silver (2015), Introduction to reinforcement learning, https://www.youtube.com/playlist?list=PLqYmG7hTraZDM-OYHWgPebj2MfCFzFObQ

Reinforcement Learning
AlphaZero (AZ) and AlphaGo Zero (AZ0)

- AlphaZero (Silver et al., 2018)
  - A general reinforcement learning algorithm that masters chess, shogi, and Go through self-play. (Science)
- AlphaGo Zero (Silver et al., 2017)
  - Mastering the game of Go without human knowledge (Nature)

AlphaZero: Shedding new light on the grand games of chess, shogi and Go

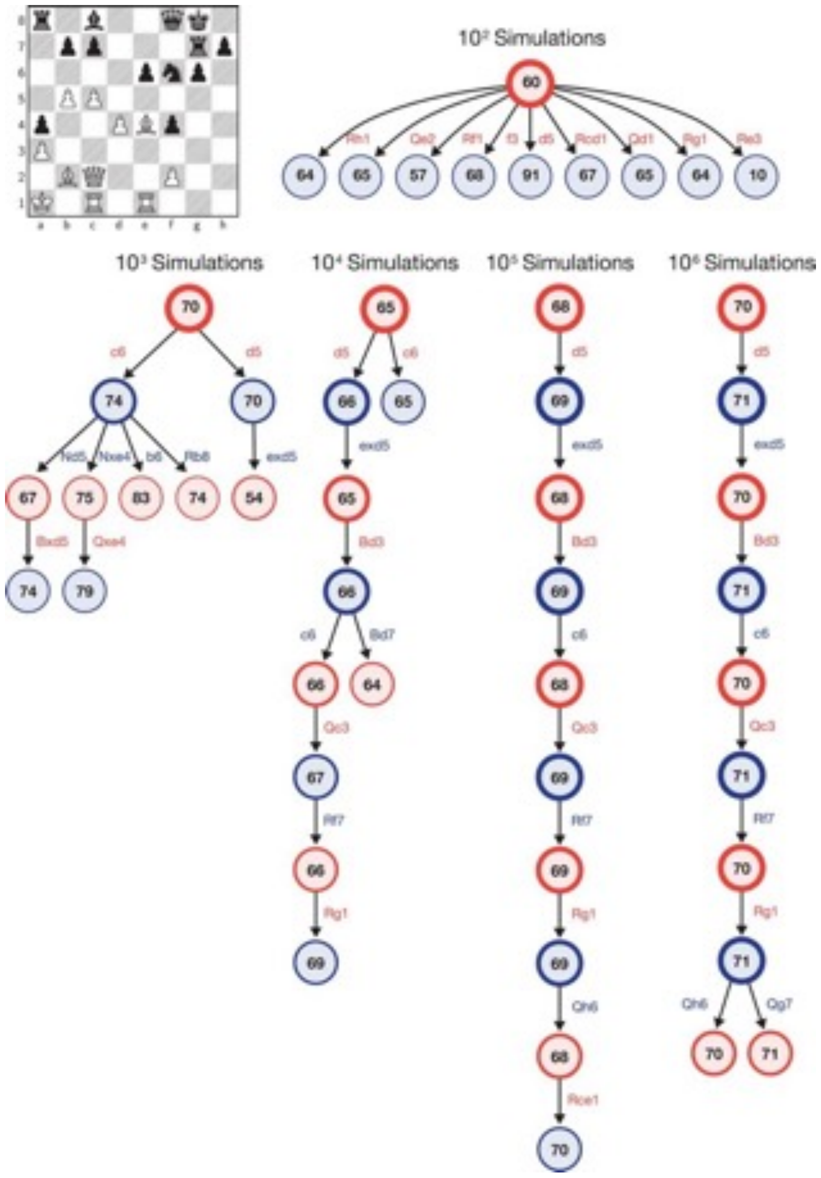


https://www.youtube.com/watch?v=7L2sUGcOgh0

AlphaZero
A general reinforcement learning algorithm that masters chess, shogi, and Go through self-play

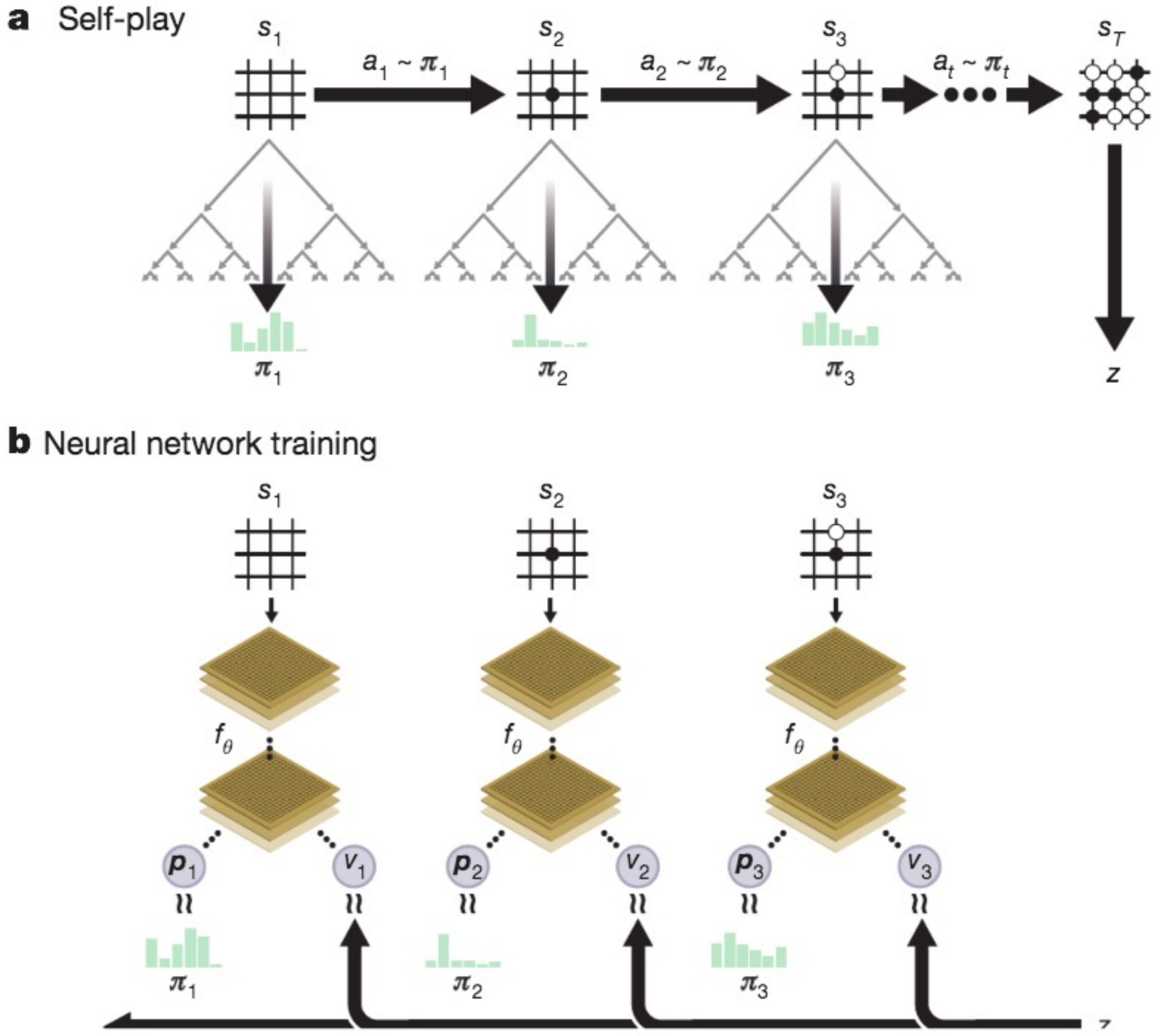
Source: David Silver et al. (2018), "A general reinforcement learning algorithm that masters chess, shogi, and Go through self-play." Science 362, no. 6419 (2018): 1140-1144.

AlphaZero's search procedure



Source: David Silver et al. (2018), "A general reinforcement learning algorithm that masters chess, shogi, and Go through self-play." Science 362, no. 6419 (2018): 1140-1144.

Self-play reinforcement learning in AlphaGo Zero

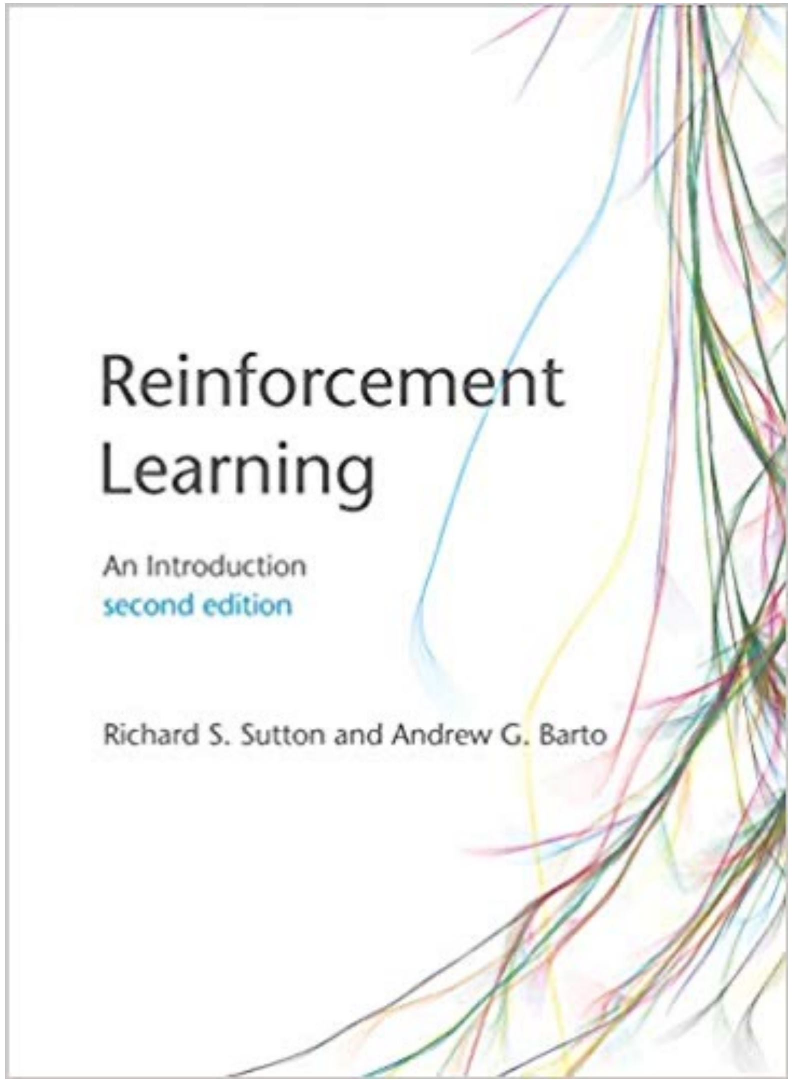


Source: David Silver et al. (2017), "Mastering the game of Go without human knowledge." Nature 550 (2017): 354–359.

Richard S. Sutton & Andrew G. Barto (2018),

Reinforcement Learning: An Introduction,

2nd Edition, A Bradford Book



Source: Richard S. Sutton & Andrew G. Barto (2018), Reinforcement Learning: An Introduction, 2nd Edition, A Bradford Book.
https://www.amazon.com/Reinforcement-Learning-Introduction-Adaptive-Computation/dp/0262039249

Reinforcement learning

- Reinforcement learning is
  learning what to do
  —how to map situations to actions
  —so as to maximize a numerical reward signal.

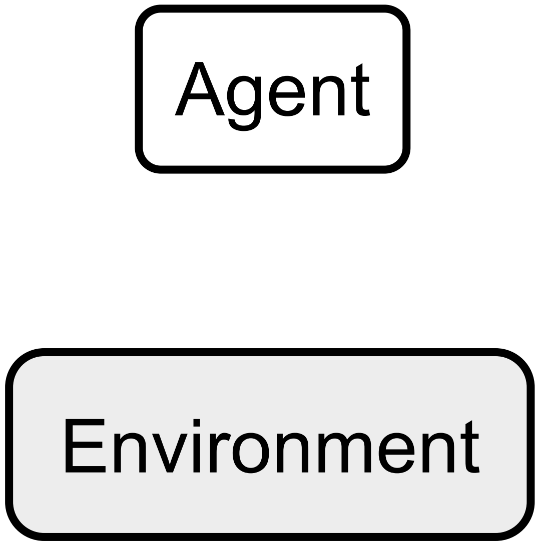
Source: Richard S. Sutton & Andrew G. Barto (2018), Reinforcement Learning: An Introduction, 2nd Edition, A Bradford Book.

Two most important distinguishing features of reinforcement learning

- **trial-and-error search**
- **delayed reward**

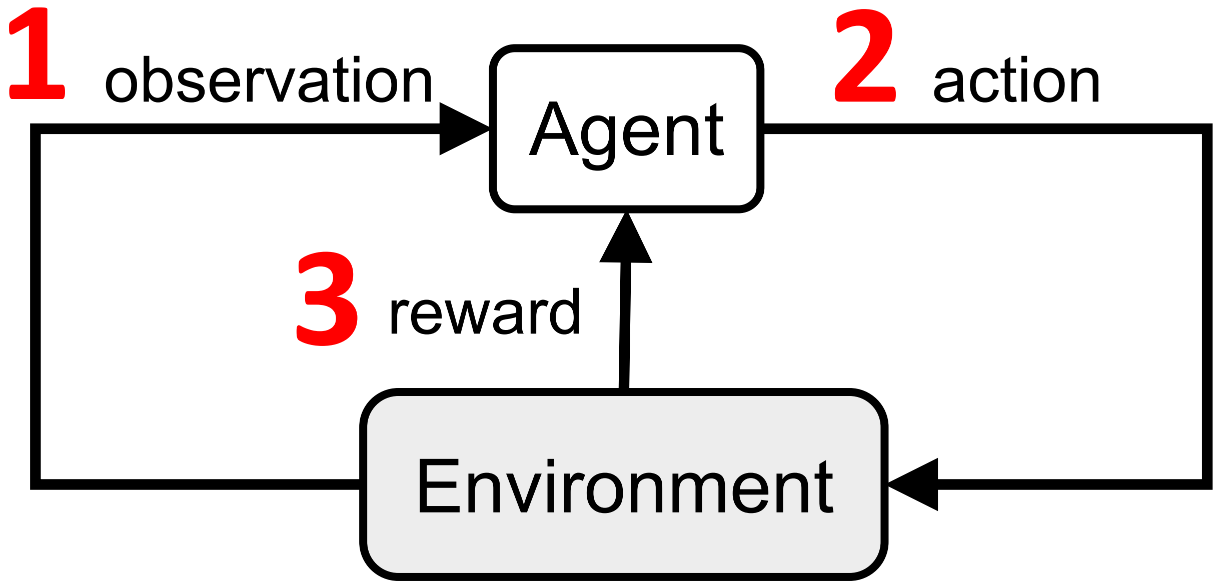
Source: Richard S. Sutton & Andrew G. Barto (2018), Reinforcement Learning: An Introduction, 2nd Edition, A Bradford Book.

Reinforcement Learning (DL)



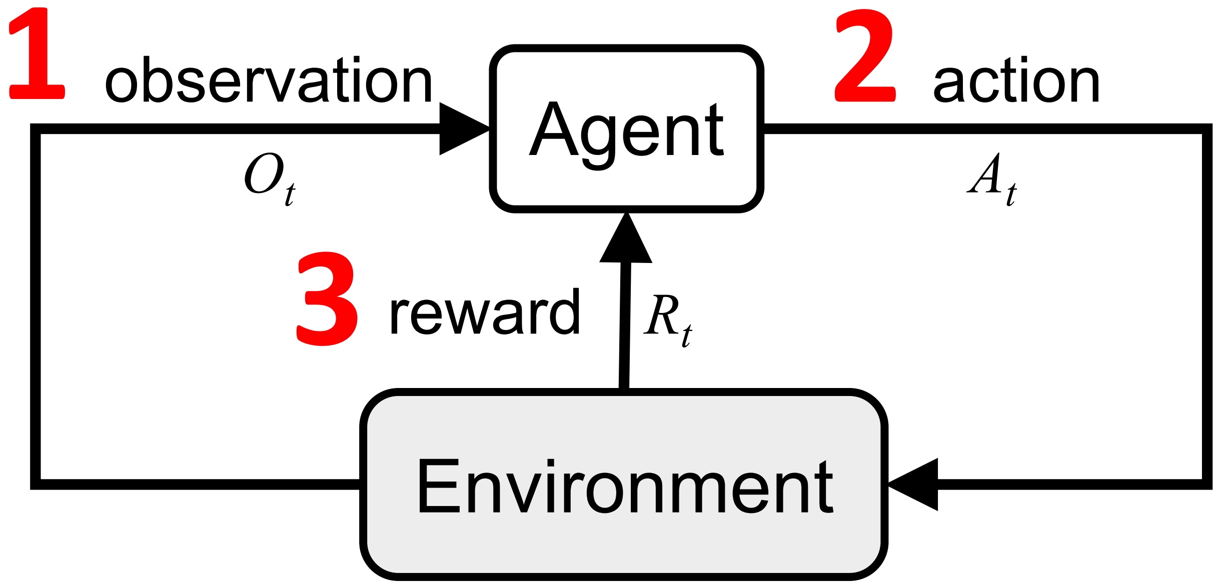
Source: Richard S. Sutton & Andrew G. Barto (2018), Reinforcement Learning: An Introduction, 2nd Edition, A Bradford Book.

Reinforcement Learning (DL)



Source: Richard S. Sutton & Andrew G. Barto (2018), Reinforcement Learning: An Introduction, 2nd Edition, A Bradford Book.

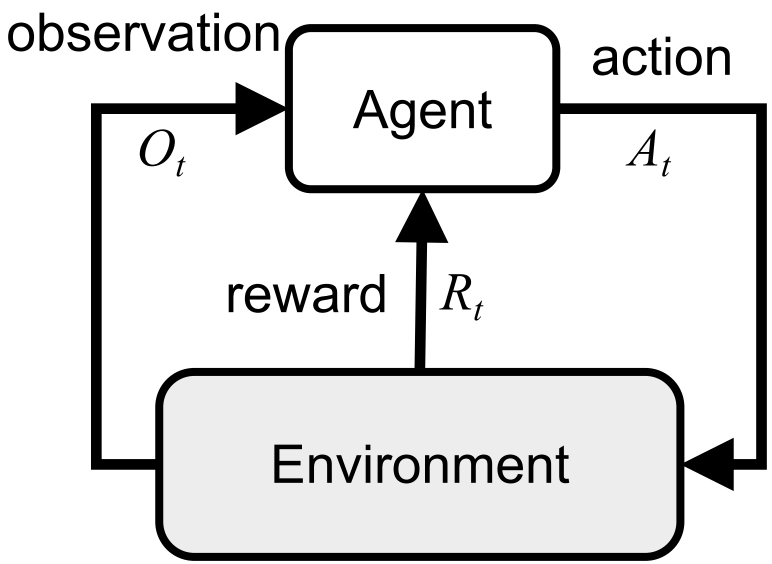
Reinforcement Learning (DL)



Source: Richard S. Sutton & Andrew G. Barto (2018), Reinforcement Learning: An Introduction, 2nd Edition, A Bradford Book.

Agent and Environment

- **At each step *t* the agent:**
  - **Executes action A_t**
  - **Receives observation O_t**
  - **Receives scalar reward R_t**
- **The environment:**
  - **Receives action A_t**
  - **Emits observation O_{t+1}**
  - **Emits scalar reward R_{t+1}**
- **t increments at env. step**



Source: David Silver (2015), Introduction to reinforcement learning, https://www.youtube.com/playlist?list=PLqYmG7hTraZDM-OYHWgPebj2MfCFzFObQ

History and State

- The history is the sequence of observations, actions, rewards

$$H_t = O_1, A_1, R_1, \ldots, A_{t-1}, O_t, R_t$$

- i.e. all observable variables up to time t
- i.e. the sensorimotor stream of a robot or embodied agent
- What happens next depends on the history:
  - The agent selects actions
  - The environment selects observations/rewards
- State is the information used to determine what happens next
- Formally, state is a function of the history:

$$S_t = f(H_t)$$

Source: David Silver (2015), Introduction to reinforcement learning, https://www.youtube.com/playlist?list=PLqYmG7hTraZDM-OYHWgPebj2MfCFzFObQ

Information State

- An information state (a.k.a. Markov state) contains all useful information from the history.
- Definition

  A state S_t is Markov if and only if

  $$P[S_{t+1} \mid S_t] = P[S_{t+1} \mid S_1,\ldots,S_t]$$

- "The future is independent of the past given the present"

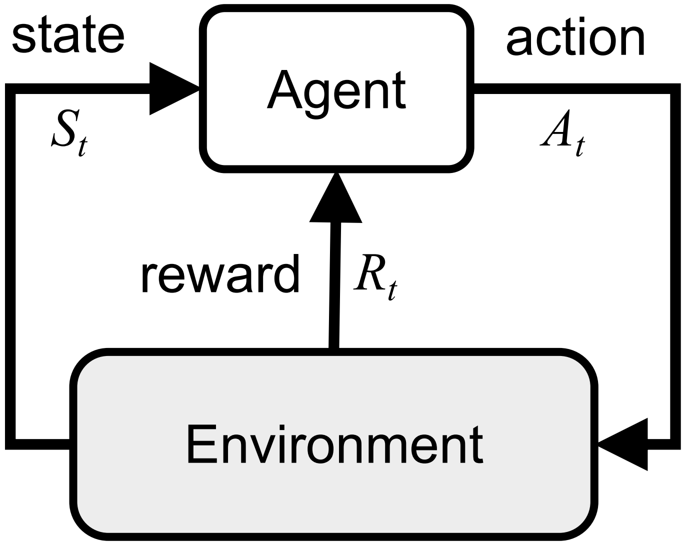
  $$H_{1:t} \rightarrow S_t \rightarrow H_{t+1:\infty}$$

- Once the state is known, the history may be thrown away i.e. The state is a sufficient statistic of the future
- The environment state S_t^e is Markov
- The history H_t is Markov

Source: David Silver (2015), Introduction to reinforcement learning, https://www.youtube.com/playlist?list=PLqYmG7hTraZDM-OYHWgPebj2MfCFzFObQ

Fully Observable Environments

- **Full observability**:
  - agent directly observes environment state
  - Agent state = environment state = information state
  - Formally, this is a Markov decision process (MDP)



Source: David Silver (2015), Introduction to reinforcement learning, https://www.youtube.com/playlist?list=PLqYmG7hTraZDM-OYHWgPebj2MfCFzFObQ

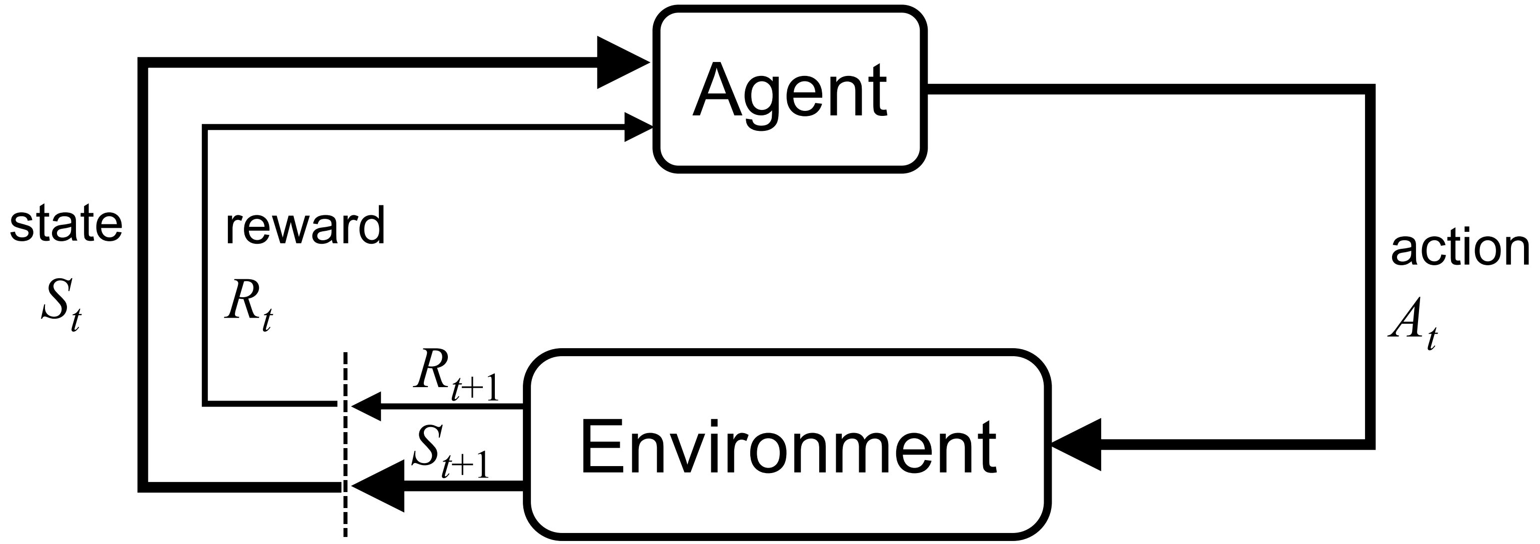
Partially Observable Environments

- **Partial observability**: agent **indirectly** observes environment
  - A robot with camera vision isn't told its absolute location
  - A trading agent only observes current prices
  - A poker playing agent only observes public cards
- Now agent state ≠ environment state
- Formally this is a **partially observable Markov decision process (POMDP)**
- Agent must construct its own state representation S^a_t, e.g.
  - Complete history: $S^a_t = H_t$
  - **Beliefs** of environment state: $S^a_t = (P[S^e_t = s_1],...,P[S^e_t = s_n])$
  - Recurrent neural network: $S^a_t = \sigma(S^a_{t-1} W_s + O_t W_o)$

Source: David Silver (2015), Introduction to reinforcement learning, https://www.youtube.com/playlist?list=PLqYmG7hTraZDM-OYHWgPebj2MfCFzFObQ

Reinforcement Learning (DL)

The Agent-Environment Interaction in a Markov Decision Process (MDP)



Source: Richard S. Sutton & Andrew G. Barto (2018), Reinforcement Learning: An Introduction, 2nd Edition, A Bradford Book.

Characteristics of Reinforcement Learning

- No supervisor, only a **reward** signal
- Feedback is **delayed**, not instantaneous
- **Time** really matters (**sequential**, non i.i.d data)
- Agent's **actions** affect the subsequent data it receives

Source: David Silver (2015), Introduction to reinforcement learning, https://www.youtube.com/playlist?list=PLqYmG7hTraZDM-OYHWgPebj2MfCFzFObQ

Examples of Reinforcement Learning

- **Make a humanoid robot walk**
- **Play may different Atari games better than humans**
- **Manage an investment portfolio**

Source: David Silver (2015), Introduction to reinforcement learning, https://www.youtube.com/playlist?list=PLqYmG7hTraZDM-OYHWgPebj2MfCFzFObQ

Examples of Rewards

- Make a humanoid robot walk
  - +ve reward for forward motion
  - -ve reward for falling over
- Play may different Atari games better than humans
  - +/-ve reward for increasing/decreasing score
- Manage an investment portfolio
  - +ve reward for each $ in bank

Source: David Silver (2015), Introduction to reinforcement learning, https://www.youtube.com/playlist?list=PLqYmG7hTraZDM-OYHWgPebj2MfCFzFObQ

Sequential Decision Making

- Goal: select actions to maximize total future reward
- Actions may have long term consequence
- Reward may be delayed
- It may be better to sacrifice immediate reward to gain more long-term reward
- Examples:
  - A financial investment (may take months to mature)
  - Blocking opponent moves (might help winning chances many moves from now)

Source: David Silver (2015), Introduction to reinforcement learning, https://www.youtube.com/playlist?list=PLqYmG7hTraZDM-OYHWgPebj2MfCFzFObQ

Elements of Reinforcement Learning

- Agent
- Environment
- Policy
- Reward signal
- Value function
- Model

Source: Richard S. Sutton & Andrew G. Barto (2018), Reinforcement Learning: An Introduction, 2nd Edition, A Bradford Book.

Elements of Reinforcement Learning

- **Policy**
  - **Agent's behavior**
  - **It is a map from state to action**
- **Reward signal**
  - **The goal of a reinforcement learning problem**
- **Value function**
  - **How good is each state and/or action**
  - **A prediction of future reward**
- **Model**
  - **Agent's representation of the environment**

Source: Richard S. Sutton & Andrew G. Barto (2018), Reinforcement Learning: An Introduction, 2nd Edition, A Bradford Book.

Major Components of an RL Agent

1. **Policy**: agent's behaviour function
2. **Value** function: how good is each state and/or action
3. **Model**: agent's representation of the environment

Source: David Silver (2015), Introduction to reinforcement learning, https://www.youtube.com/playlist?list=PLqYmG7hTraZDM-OYHWgPebj2MfCFzFObQ

Policy

- **A policy is the agent's behaviour**
- **It is a map from state to action, e.g.**
  - **Deterministic policy:** $a = \pi(s)$
  - **Stochastic policy:** $\pi(a|s) = P[A_t = a|S_t = s]$

Source: David Silver (2015), Introduction to reinforcement learning, https://www.youtube.com/playlist?list=PLqYmG7hTraZDM-OYHWgPebj2MfCFzFObQ

Value Function

- **Value function** is a prediction of future reward
- **Used to evaluate the goodness/badness of states**
- **And therefore to select between actions, e.g.**

$$v_\pi(s) = E_\pi [R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \ldots | S_t = s]$$

Model

- A **model** predicts what the environment will do next
- $\boldsymbol{P}$ **predicts the next state**
- $\boldsymbol{R}$ **predicts the next (immediate) reward, e.g.**

$$P^a_{ss'} = P[S_{t+1} = s' \mid S_{t+1} = s, A_t = a]$$

$$R^a_s = E[R_{t+1} \mid S_t = s, A_t = a]$$

Source: David Silver (2015), Introduction to reinforcement learning, https://www.youtube.com/playlist?list=PLqYmG7hTraZDM-OYHWgPebj2MfCFzFObQ

Reinforcement Learning

- **Value Based**
  - No Policy (Implicit)
  - **Value Function**
- **Policy Based**
  - **Policy**
  - No Value Function
- **Actor Critic**
  - **Policy**
  - **Value Function**

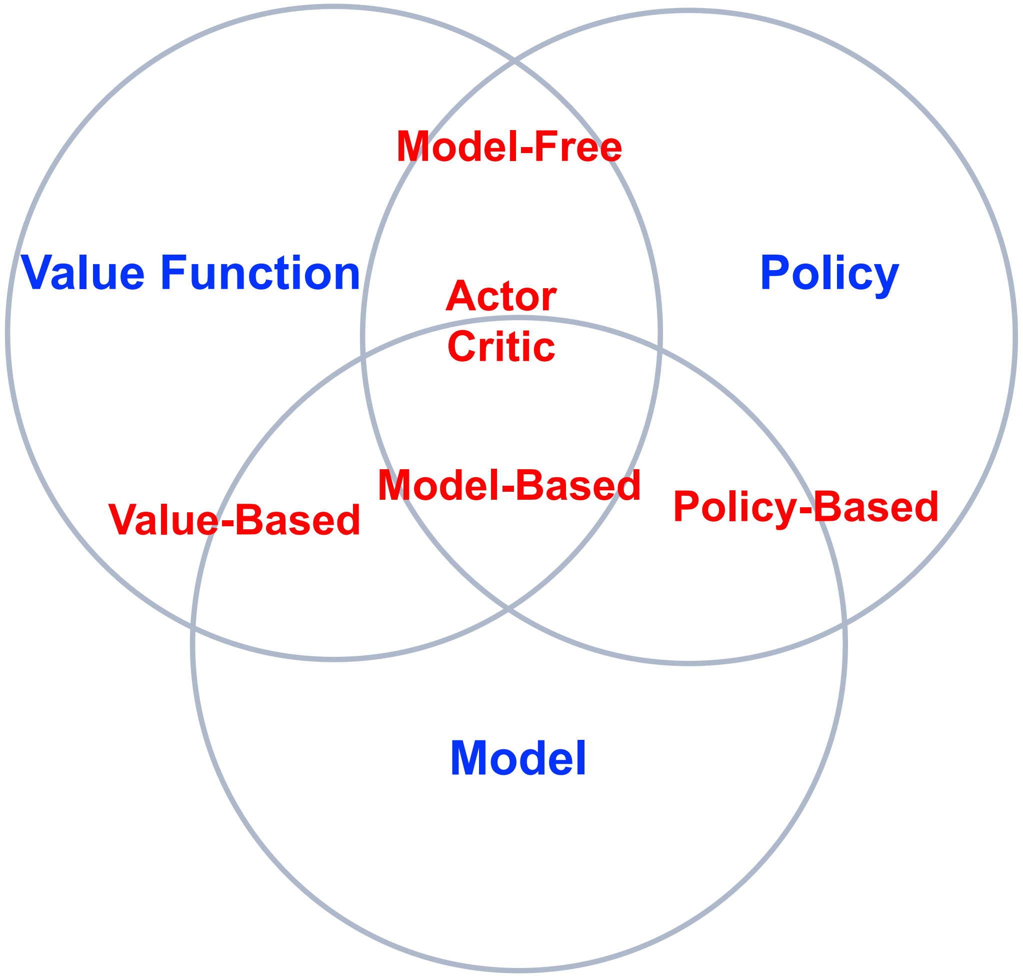
Source: David Silver (2015), Introduction to reinforcement learning, https://www.youtube.com/playlist?list=PLqYmG7hTraZDM-OYHWgPebj2MfCFzFObQ

Reinforcement Learning

- **Model Free**
  - **Policy and/or Value Function**
  - No Model
- **Model Based**
  - **Policy and/or Value Function**
  - **Model**

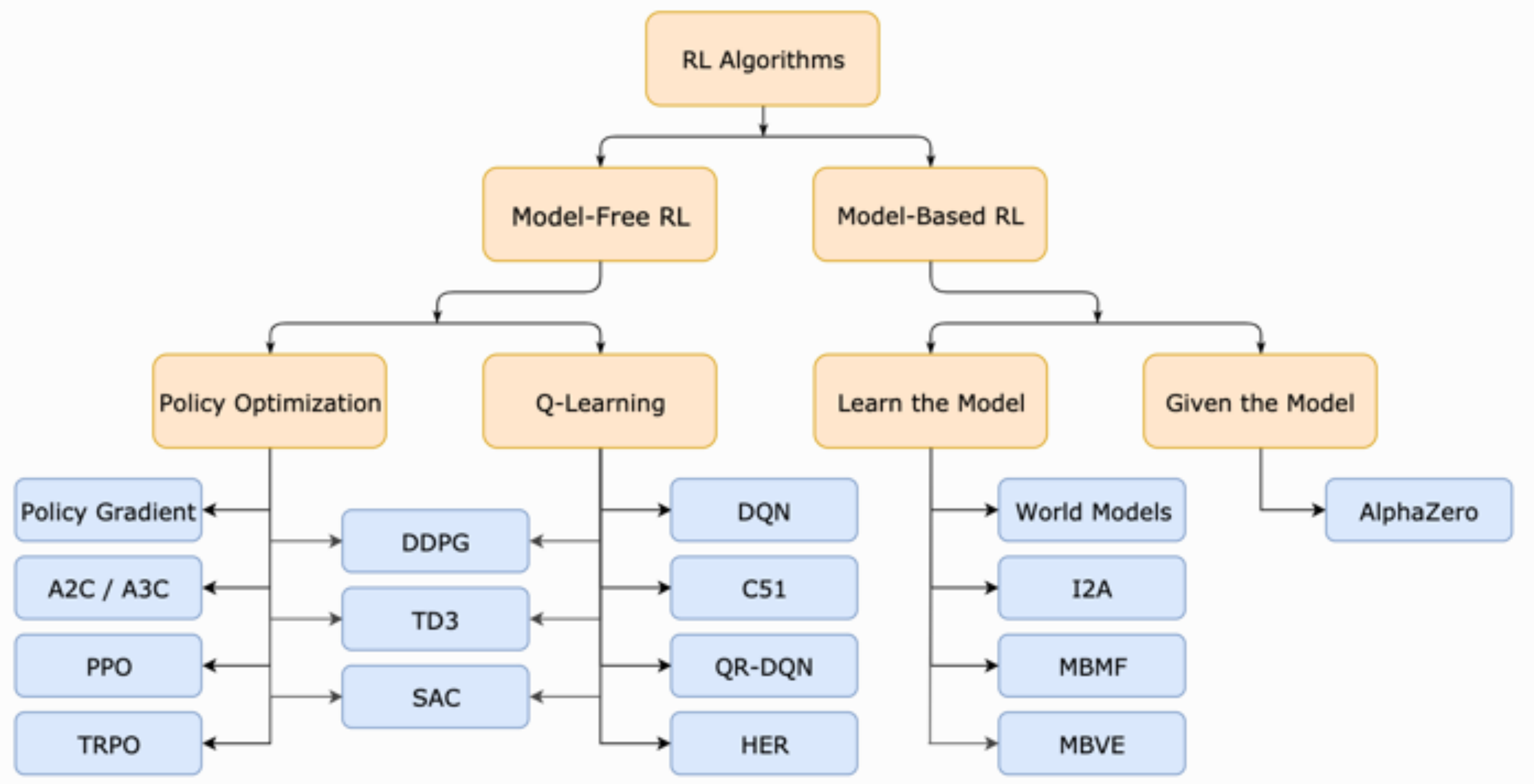
Source: David Silver (2015), Introduction to reinforcement learning, https://www.youtube.com/playlist?list=PLqYmG7hTraZDM-OYHWgPebj2MfCFzFObQ

Reinforcement Learning (RL) Taxonomy



Source: David Silver (2015), Introduction to reinforcement learning, https://www.youtube.com/playlist?list=PLqYmG7hTraZDM-OYHWgPebj2MfCFzFObQ

Reinforcement Learning (RL)
A Taxonomy of RL Algorithms



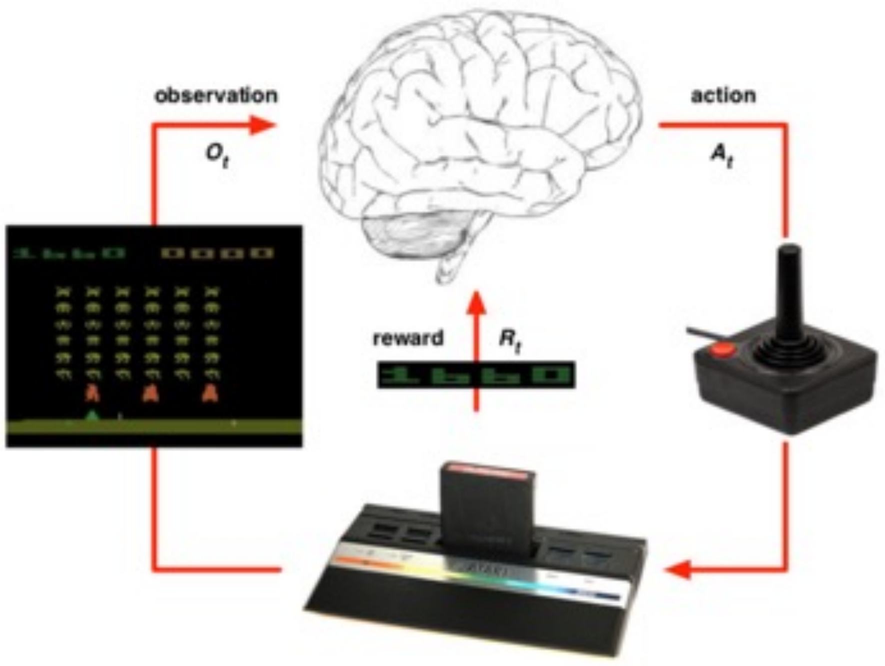
Source: https://spinningup.openai.com/en/latest/spinningup/rl_intro2.html

Learning and Planning

- **Two fundamental problems in sequential decision making**
  - **Reinforcement Learning**
    - The environment is initially unknown
    - The agent interacts with environment
    - The agent improves its policy
  - **Planning**
    - A model of the environment is known
    - The agent performs computations with its model (without any external interaction)
    - The agent improves its policy
    - a.k.a deliberation, reasoning, introspection, pondering, thought, search

Source: David Silver (2015), Introduction to reinforcement learning, https://www.youtube.com/playlist?list=PLqYmG7hTraZDM-OYHWgPebj2MfCFzFObQ

Atari Example: Reinforcement Learning

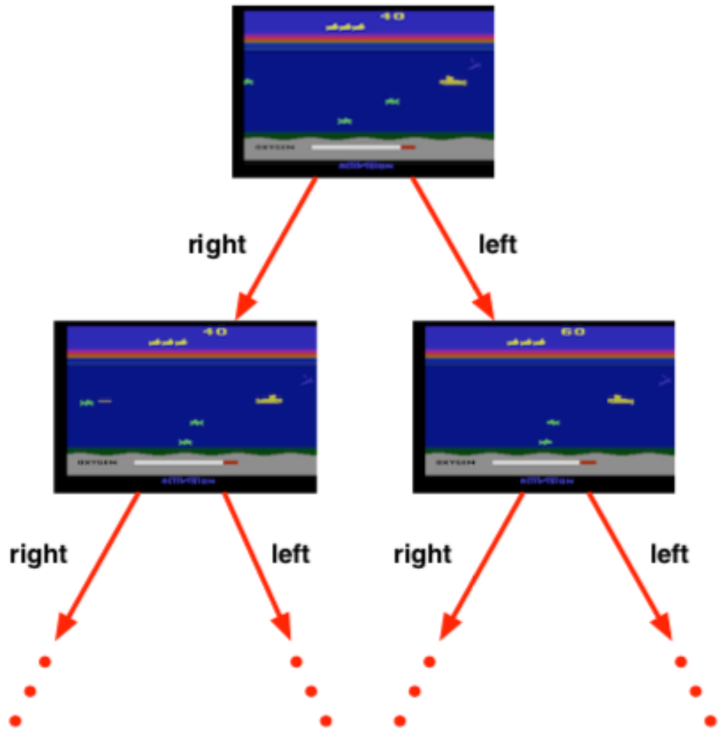


- **Rules of the game are unknown**
- **Learn directly from interactive game-play**
- **Pick actions on joystick, see pixels and scores**

Source: David Silver (2015), Introduction to reinforcement learning, https://www.youtube.com/playlist?list=PLqYmG7hTraZDM-OYHWgPebj2MfCFzFObQ

Atari Example: Planning

- Rules of the game are known
- Can query emulator
  - perfect model inside agent's brain
- If I take action a from state s:
  - what would the next state be?
  - what would the score be?
- Plan ahead to find optimal policy
  - e.g. tree search



Source: David Silver (2015), Introduction to reinforcement learning, https://www.youtube.com/playlist?list=PLqYmG7hTraZDM-OYHWgPebj2MfCFzFObQ

Exploration and Exploitation

- Reinforcement learning is like trial-and-error learning
- The agent should discover a good policy
- From its experiences of the environment
- Without losing too much reward along the way
- Exploration finds more information about the environment
- Exploitation exploits known information to maximise reward
- It is usually important to explore as well as exploit

Source: David Silver (2015), Introduction to reinforcement learning, https://www.youtube.com/playlist?list=PLqYmG7hTraZDM-OYHWgPebj2MfCFzFObQ

Exploration and Exploitation Examples

- Restaurant Selection
  - Exploitation: Go to your favorite restaurant
  - Exploration: Try a new restaurant
- Online Banner Advertisements
  - Exploitation: Show the most successful advert
  - Exploration: Show a different advert

Source: David Silver (2015), Introduction to reinforcement learning, https://www.youtube.com/playlist?list=PLqYmG7hTraZDM-OYHWgPebj2MfCFzFObQ

Exploration and Exploitation Examples

- Oil Drilling
  - Exploitation: Drill at the best known location
  - Exploration: Drill at a new location
- Game Playing
  - Exploitation: Play the move you believe is best
  - Exploration: Play an experimental move

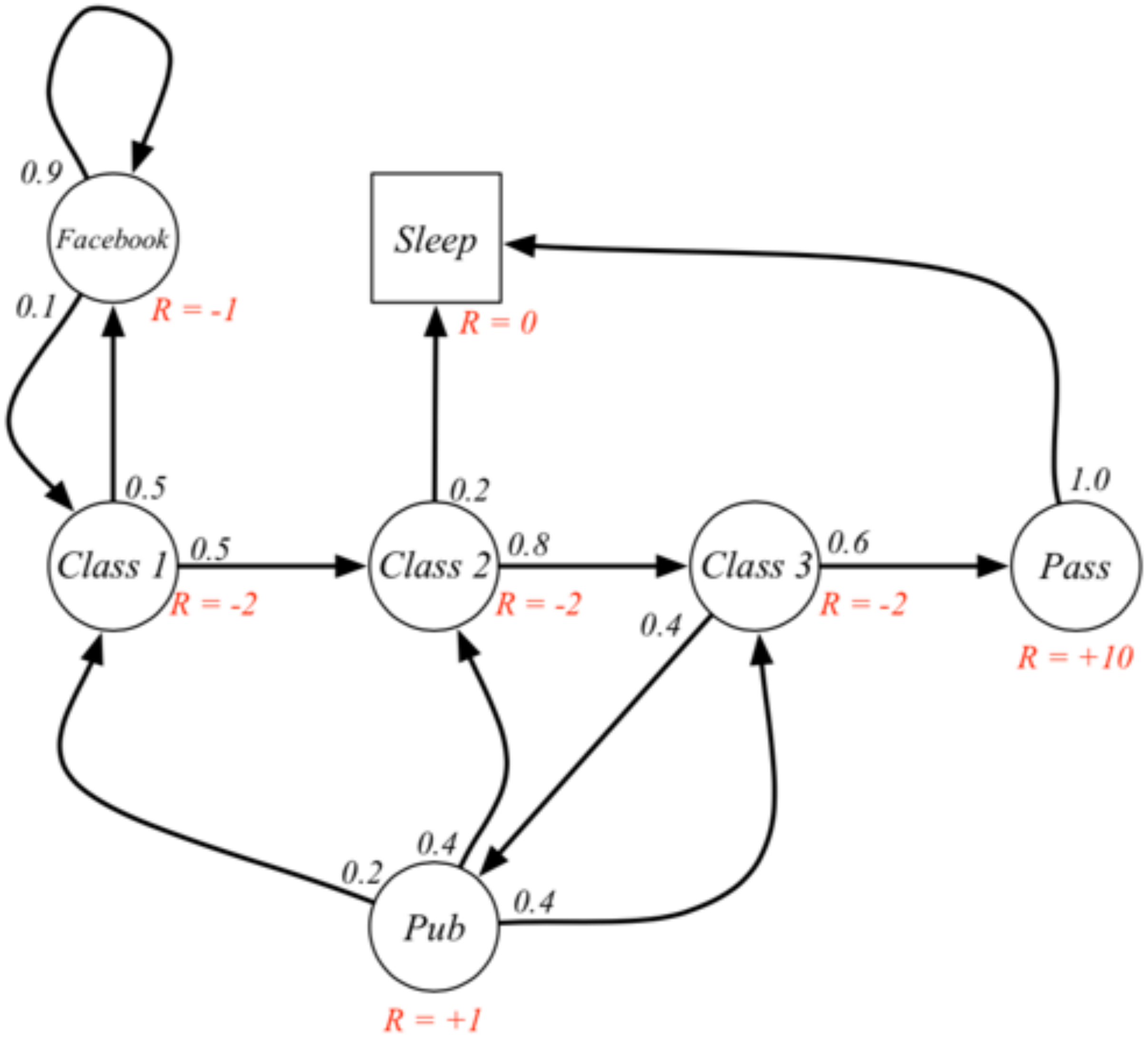
Source: David Silver (2015), Introduction to reinforcement learning, https://www.youtube.com/playlist?list=PLqYmG7hTraZDM-OYHWgPebj2MfCFzFObQ

Prediction and Control

- Prediction: evaluate the future
  - Given a policy
- Control: optimize the future
  - Find the best policy

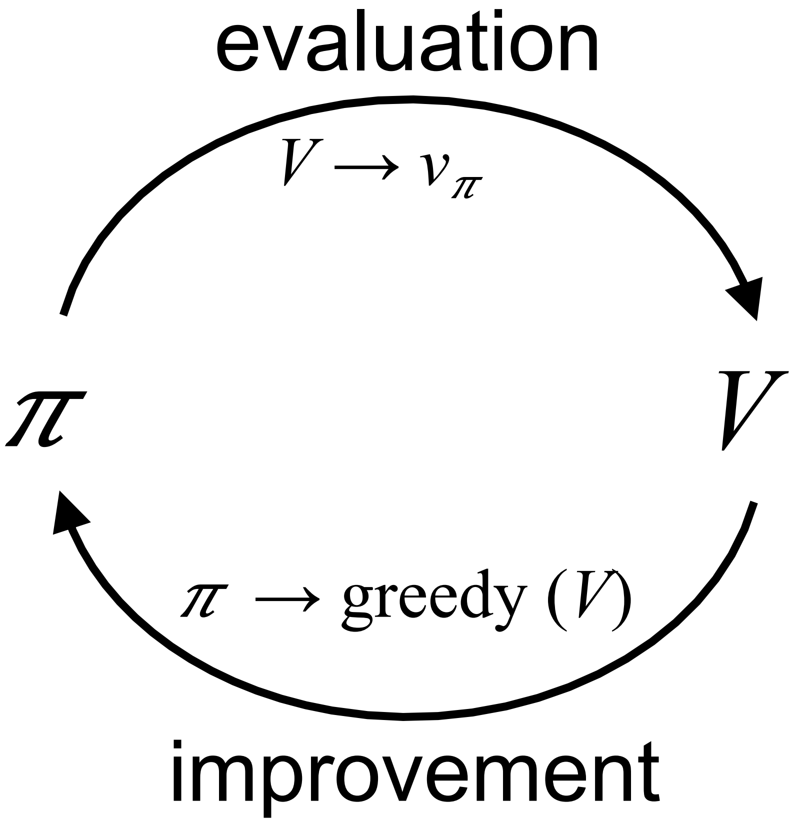
Source: David Silver (2015), Introduction to reinforcement learning, https://www.youtube.com/playlist?list=PLqYmG7hTraZDM-OYHWgPebj2MfCFzFObQ

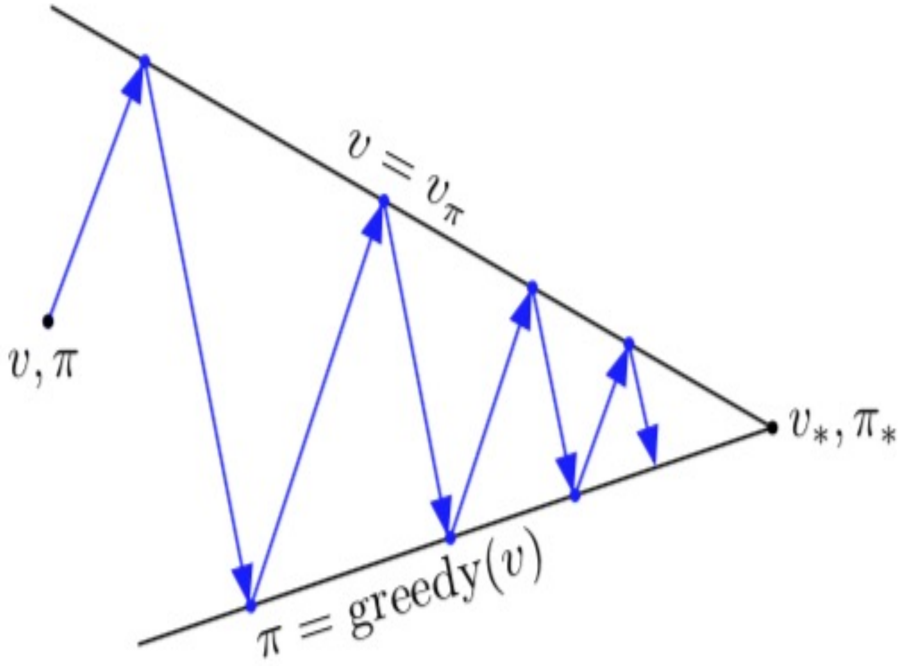
Markov Decision Processes (MDP)
Example: Student MDP



Source: David Silver (2015), Introduction to reinforcement learning, https://www.youtube.com/playlist?list=PLqYmG7hTraZDM-OYHWgPebj2MfCFzFObQ

Generalized Policy Iteration (GPI)



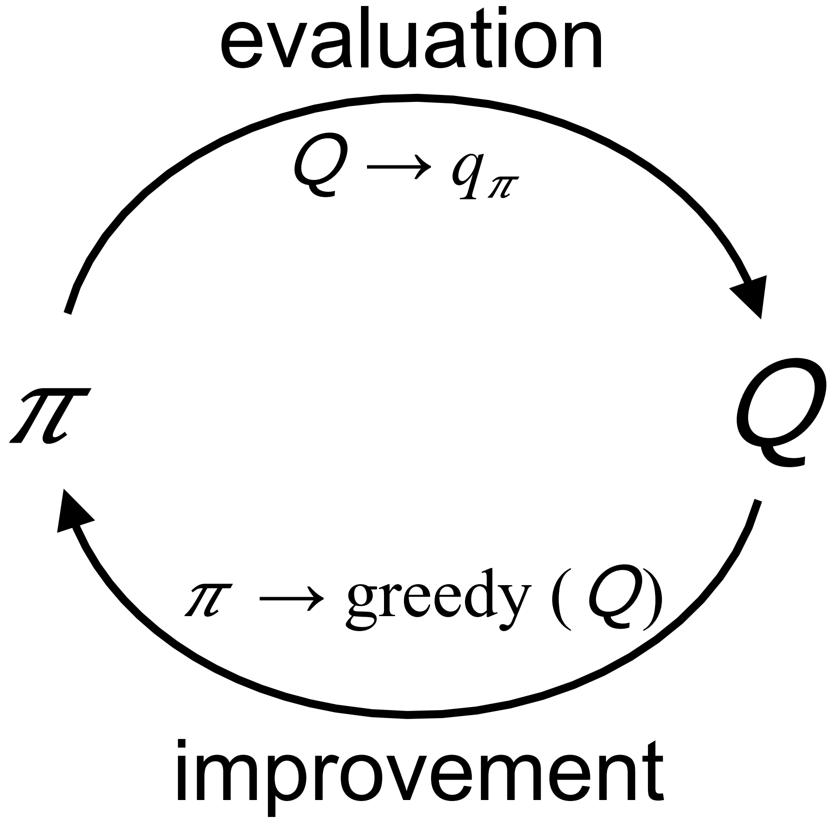


$$\pi_* \rightleftarrows v_*$$

Source: Richard S. Sutton & Andrew G. Barto (2018), Reinforcement Learning: An Introduction, 2nd Edition, A Bradford Book.

Generalized Policy Iteration (GPI)

Any iteration of **policy evaluation** and **policy improvement**, independent of their granularity.



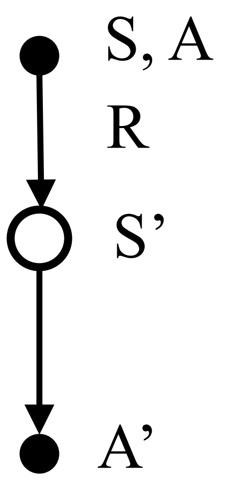
Source: Richard S. Sutton & Andrew G. Barto (2018), Reinforcement Learning: An Introduction, 2nd Edition, A Bradford Book.

Temporal-Difference (TD) Learning

- **Sarsa: On-policy TD Control**
- **Q-learning: Off-policy TD Control**

SARSA (state-action-reward-state-action) On-policy TD Control

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha[R_{t+1} + \gamma \; Q(S_{t+1}, A_{t+1}) - Q(S_t, A_t)]$$

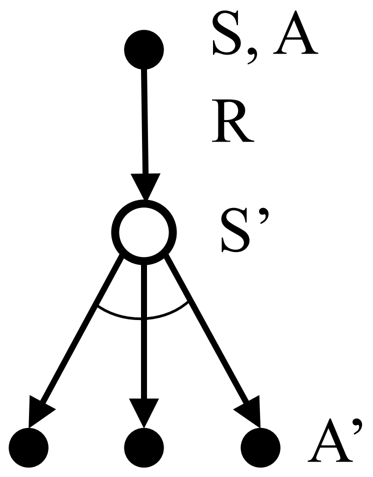


SARSA

Q-learning (Watkins, 1989)

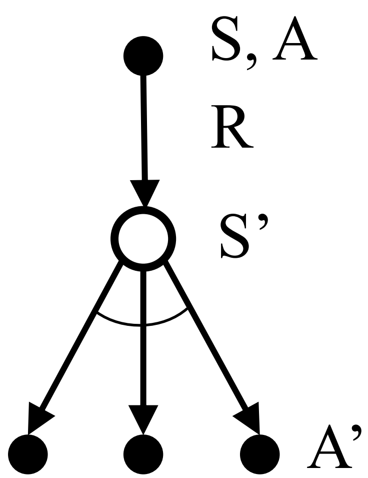
Off-policy TD Control

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha[R_{t+1} + \gamma \max Q(S_{t+1}, a) - Q(S_t, A_t)]$$

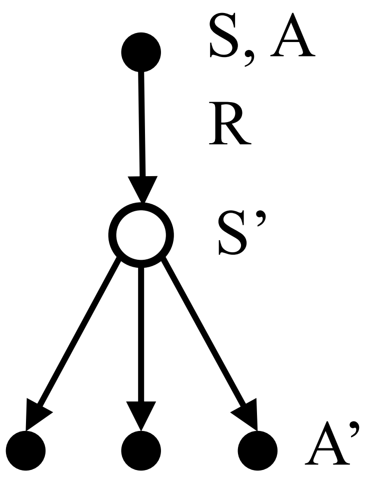


Q-learning

Q-learning and Expected SARSA



Q-learning



Expected SARSA

Q-learning and Double Q-learning

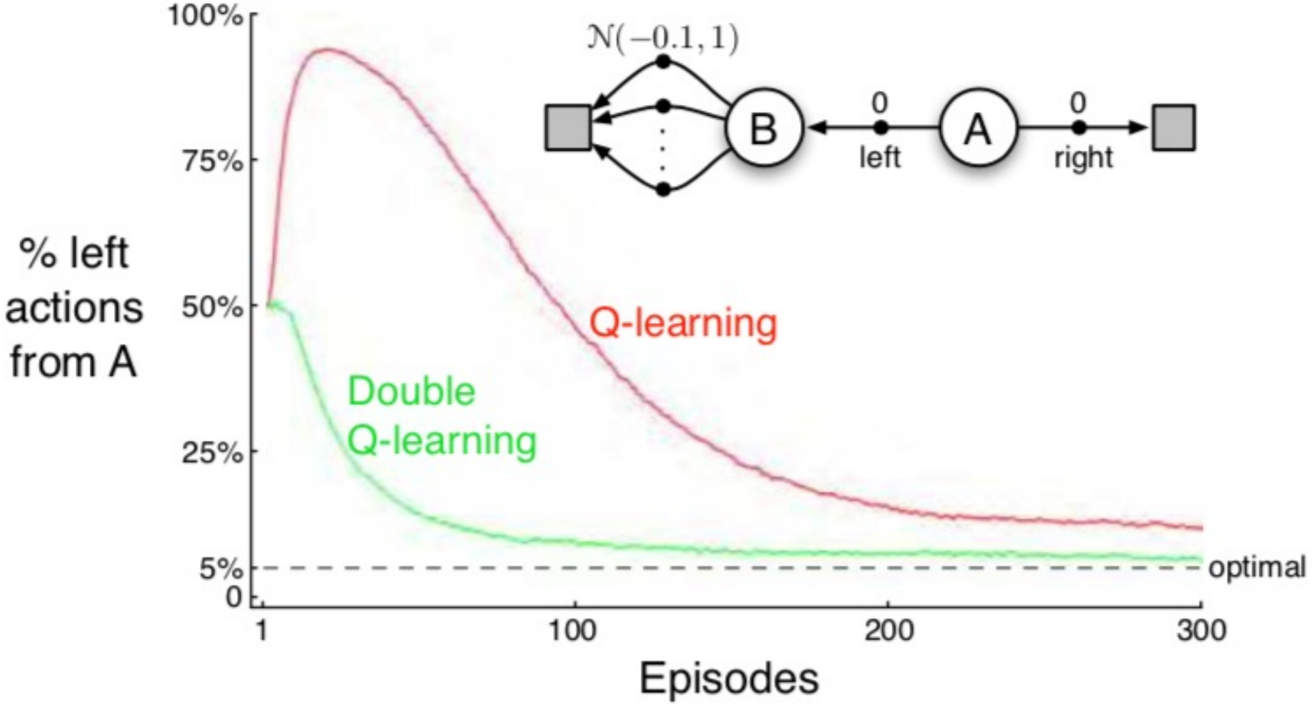


Figure 6.5: Comparison of Q-learning and Double Q-learning on a simple episodic MDP (shown inset). Q-learning initially learns to take the left action much more often than the right action, and always takes it significantly more often than the 5% minimum probability enforced by ε-greedy action selection with $\varepsilon = 0.1$. In contrast, Double Q-learning is essentially unaffected by maximization bias. These data are averaged over 10,000 runs. The initial action-value estimates were zero. Any ties in ε-greedy action selection were broken randomly.

Source: Richard S. Sutton & Andrew G. Barto (2018), Reinforcement Learning: An Introduction, 2nd Edition, A Bradford Book.

n-step methods for sate-action value

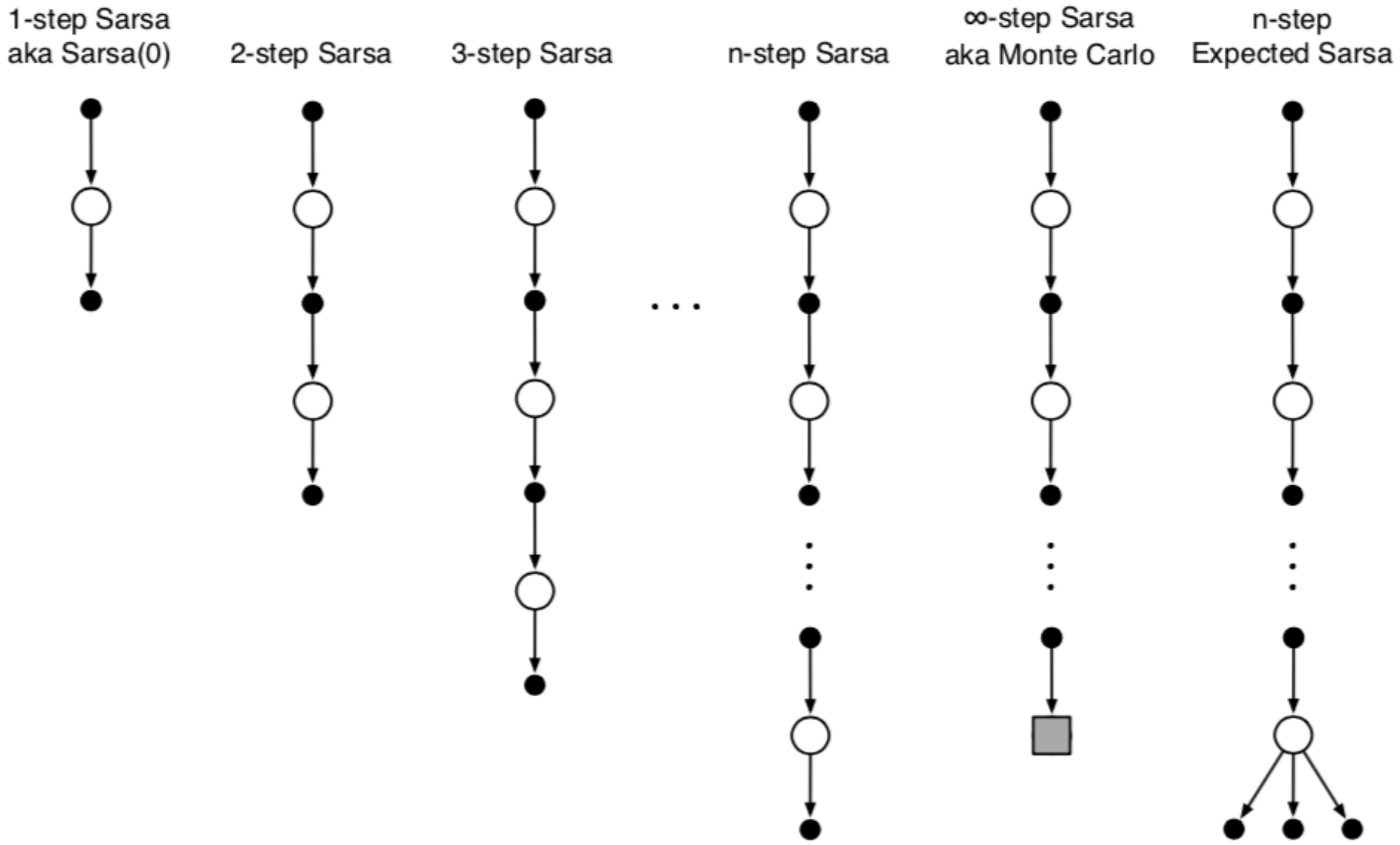
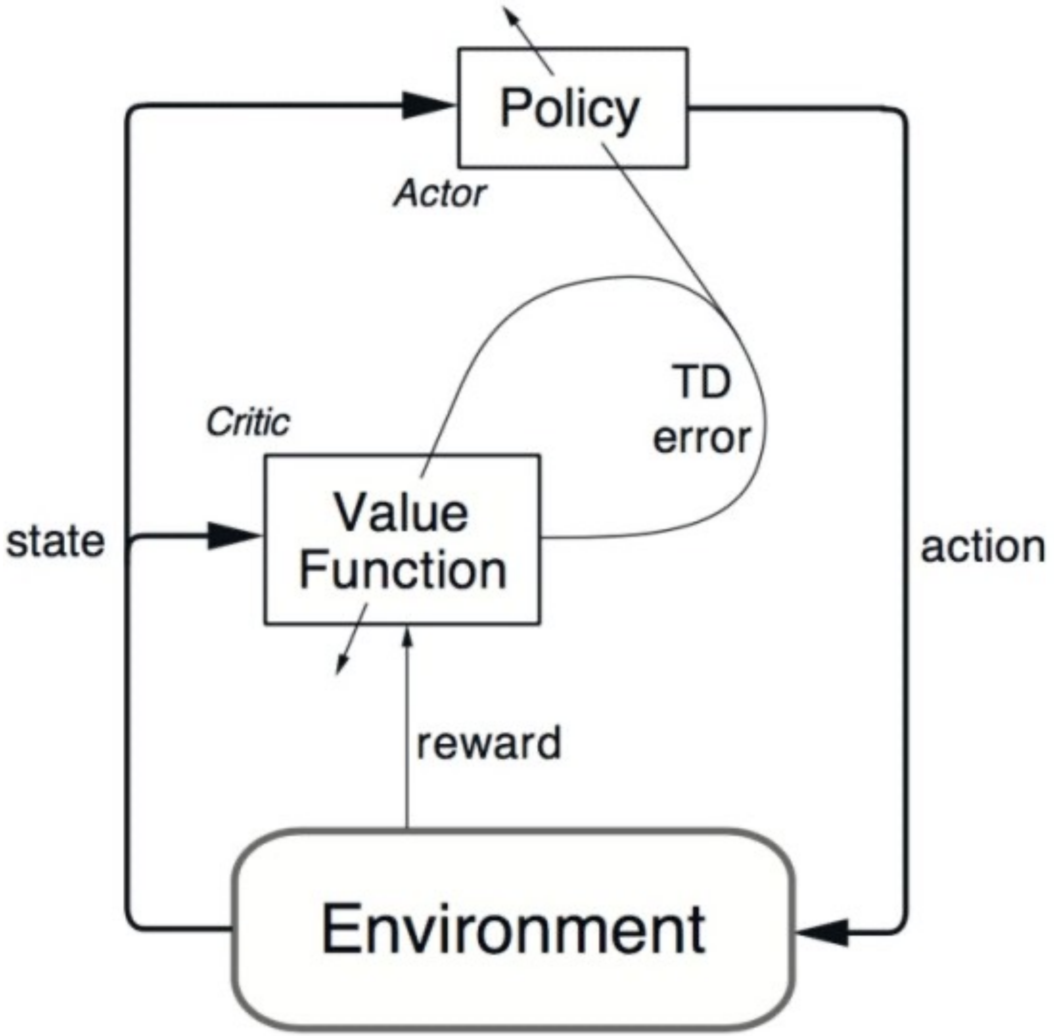


Figure 7.3: The backup diagrams for the spectrum of n-step methods for state–action values. They range from the one-step update of Sarsa(0) to the up-until-termination update of the Monte Carlo method. In between are the n-step updates, based on n steps of real rewards and the estimated value of the nth next state–action pair, all appropriately discounted. On the far right is the backup diagram for n-step Expected Sarsa.

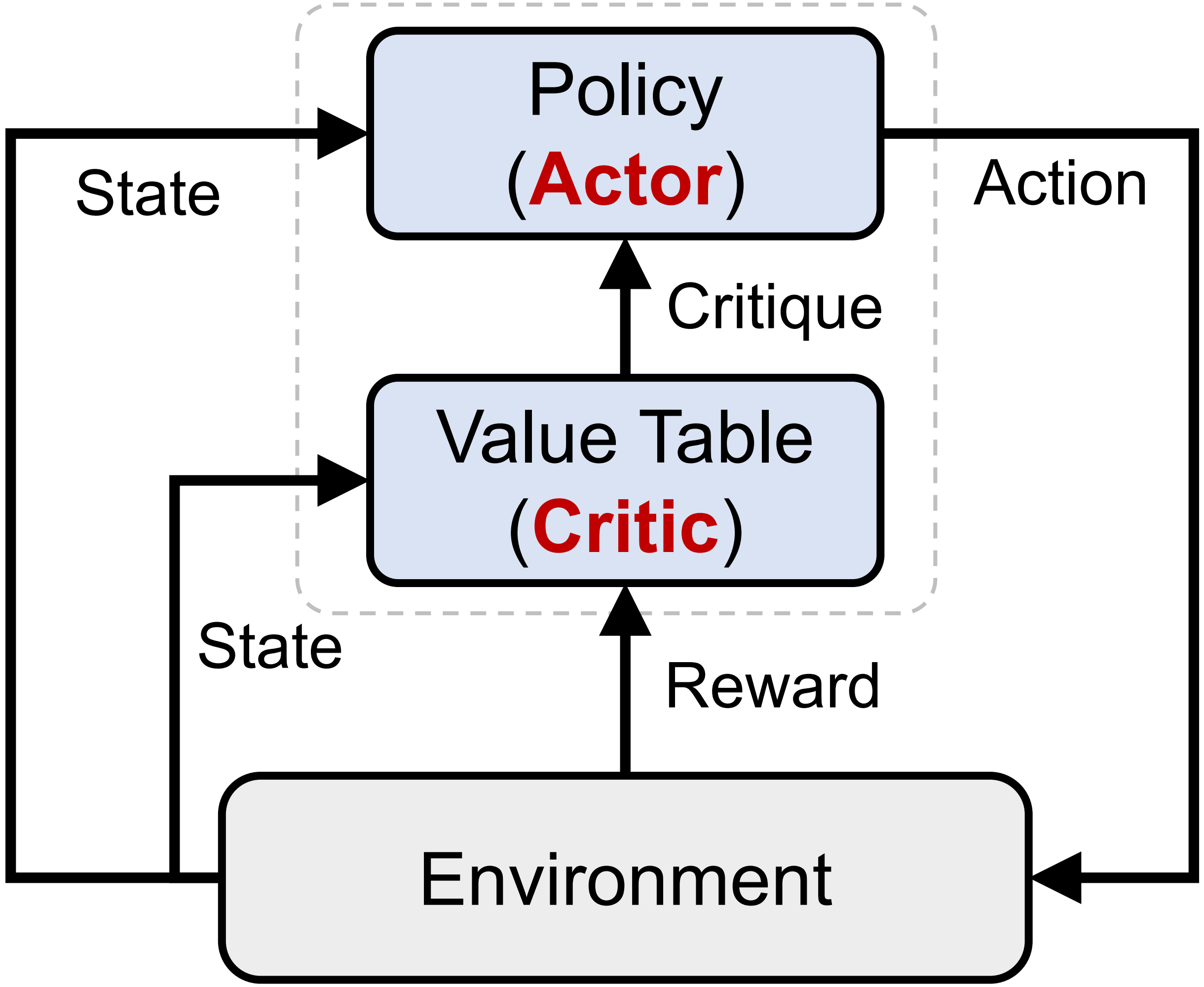
Source: Richard S. Sutton & Andrew G. Barto (2018), Reinforcement Learning: An Introduction, 2nd Edition, A Bradford Book.

Reinforcement Learning
Actor-Critic (AC) Architecture



Source: https://www.kdnuggets.com/2018/03/5-things-reinforcement-learning.html

Reinforcement Learning
Actor-Critic (AC) Learning Methods



Reinforcement Learning Methods

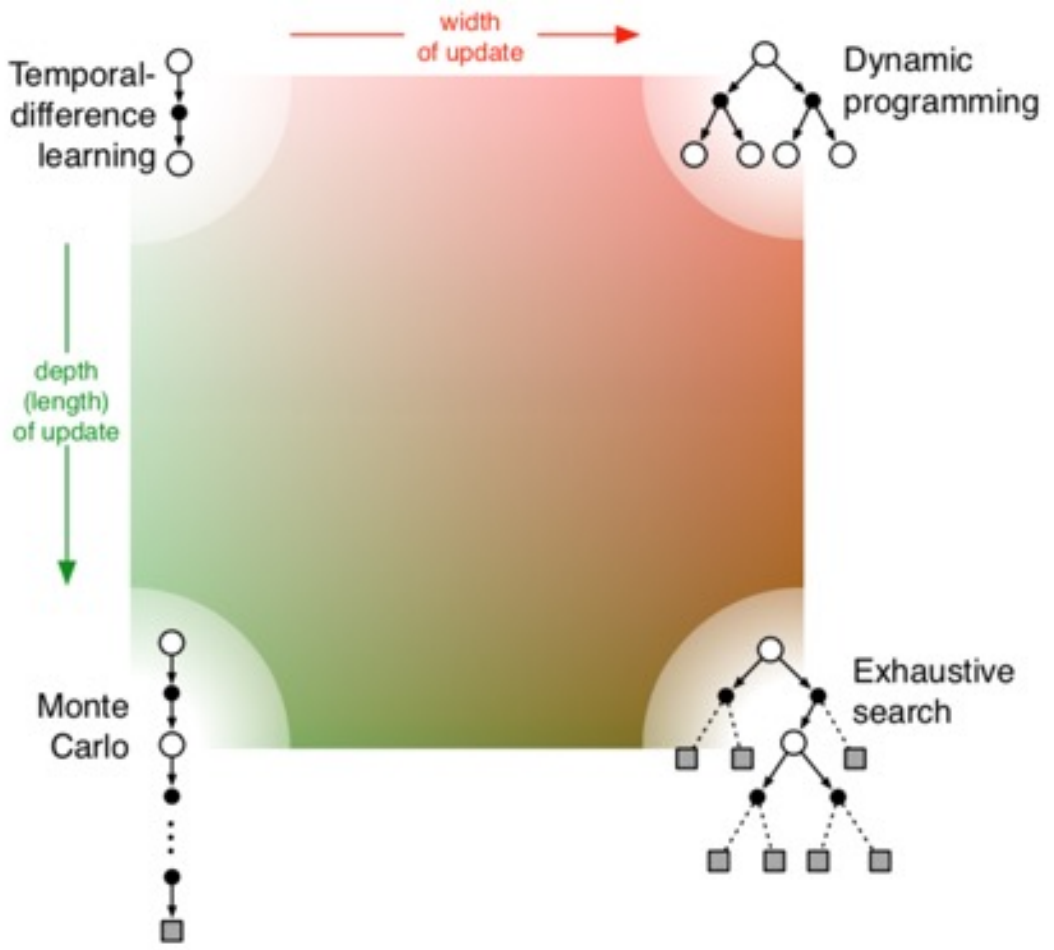


Figure 8.11: A slice through the space of reinforcement learning methods, highlighting the two of the most important dimensions explored in Part I of this book: the depth and width of the updates.

Source: Richard S. Sutton & Andrew G. Barto (2018), Reinforcement Learning: An Introduction, 2nd Edition, A Bradford Book.

Monte Carlo Tree Search (MCTS)

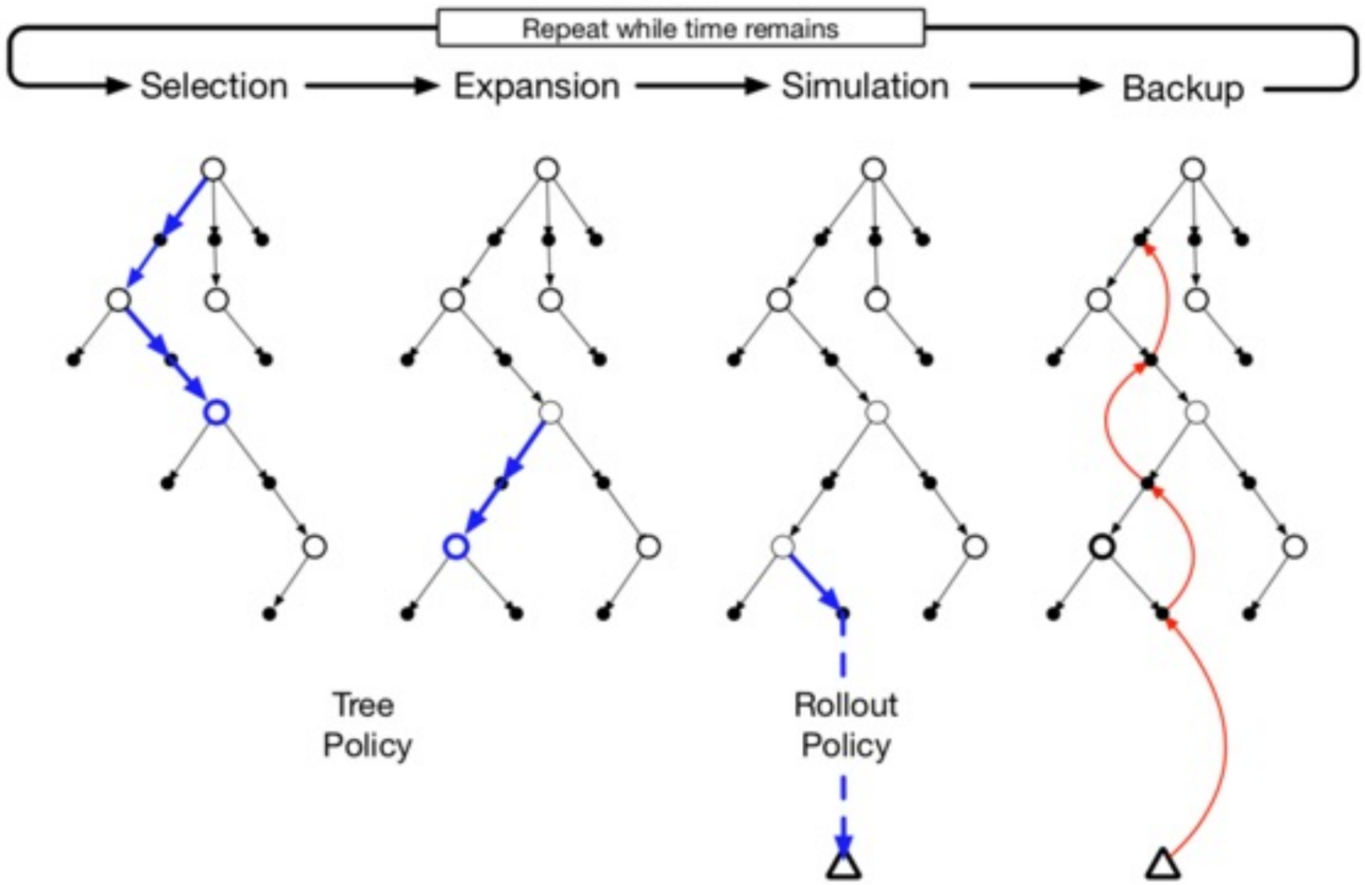
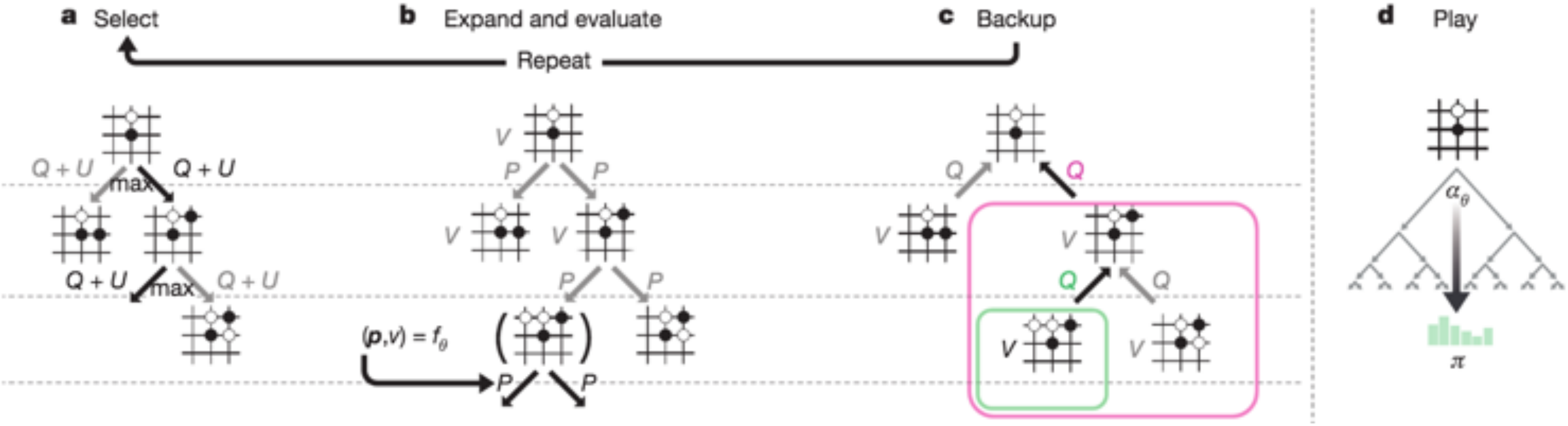


Figure 8.10: Monte Carlo Tree Search. When the environment changes to a new state, MCTS executes as many iterations as possible before an action needs to be selected, incrementally building a tree whose root node represents the current state. Each iteration consists of the four operations **Selection**, **Expansion** (though possibly skipped on some iterations), **Simulation**, and **Backup**, as explained in the text and illustrated by the bold arrows in the trees. Adapted from Chaslot, Bakkes, Szita, and Spronck (2008).

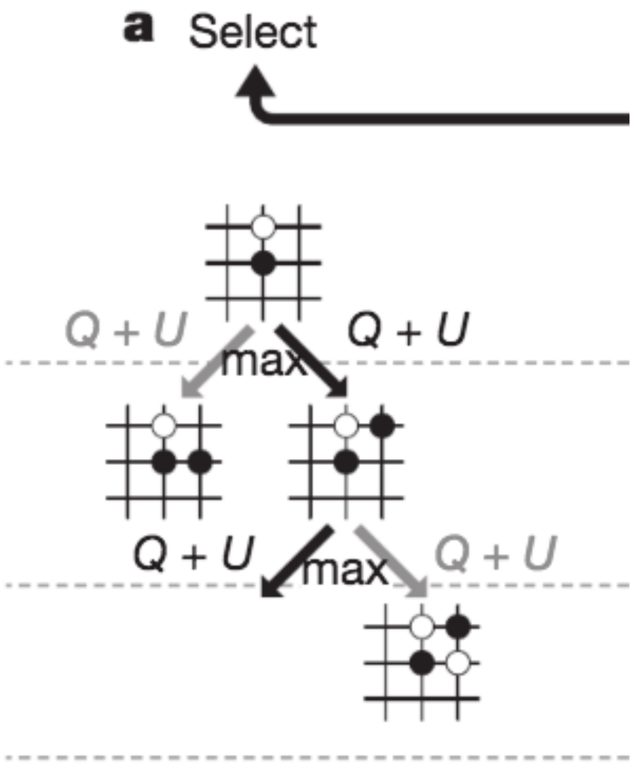
Source: Richard S. Sutton & Andrew G. Barto (2018), Reinforcement Learning: An Introduction, 2nd Edition, A Bradford Book.

Monte Carlo Tree Search (MCTS)
MCTS in AlphaGo Zero



Source: David Silver et al. (2017), "Mastering the game of Go without human knowledge." Nature 550 (2017): 354–359.

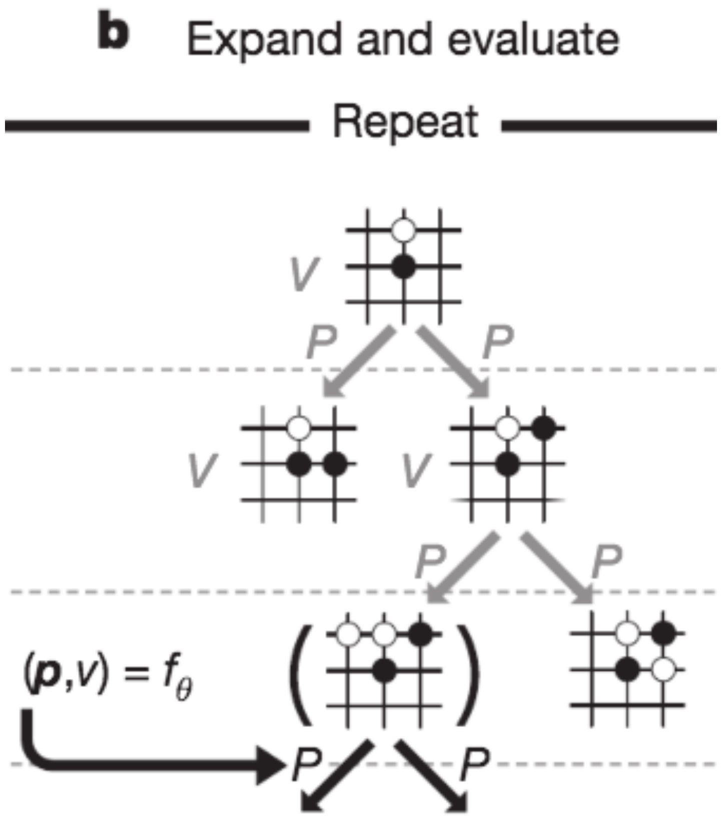
MCTS in AlphaGo Zero



a: Each simulation traverses the tree by selecting the edge with maximum action value Q, plus an upper confidence bound U that depends on a stored prior probability P and visit count N for that edge (which is incremented once traversed).

Source: David Silver et al. (2017), "Mastering the game of Go without human knowledge." Nature 550 (2017): 354–359.

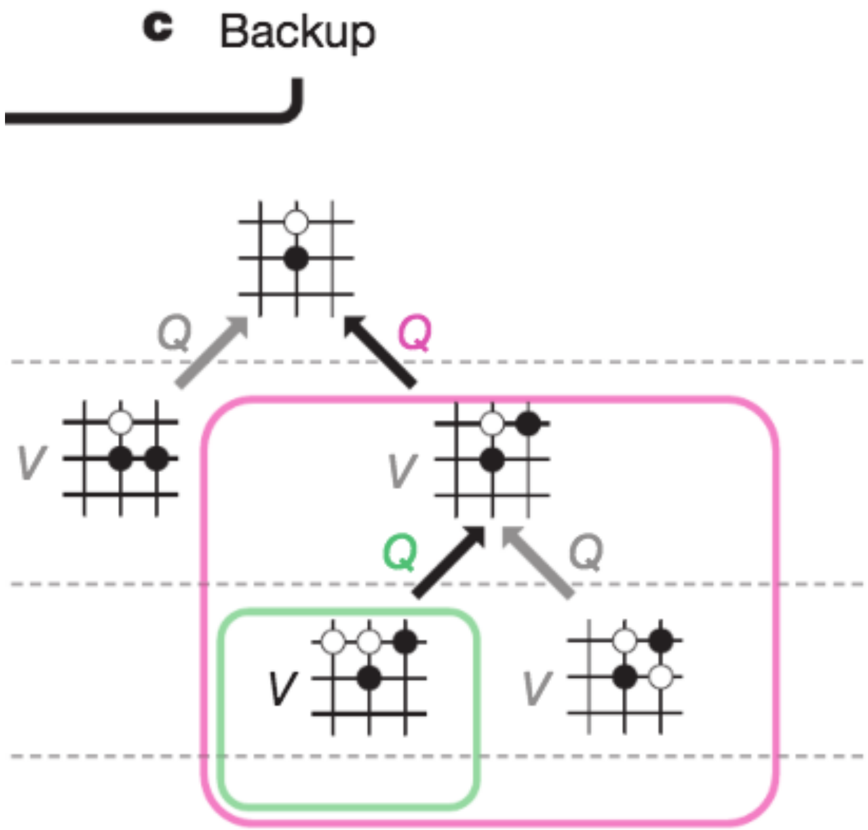
MCTS in AlphaGo Zero



b: The leaf node is expanded and the associated position s is evaluated by the neural network $(P(s, \cdot), V(s)) = f_\theta(s)$; the vector of P values are stored in the outgoing edges from s.

Source: David Silver et al. (2017), "Mastering the game of Go without human knowledge." Nature 550 (2017): 354–359.

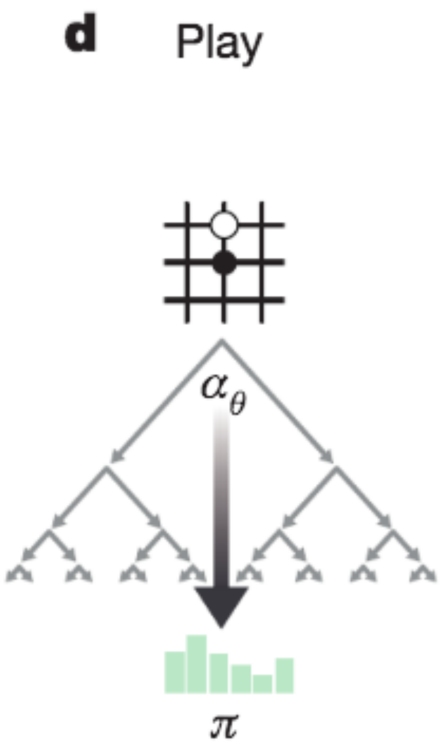
MCTS in AlphaGo Zero



c: Action value Q is updated to track the mean of all evaluations V in the subtree below that action

Source: David Silver et al. (2017), "Mastering the game of Go without human knowledge." Nature 550 (2017): 354–359.

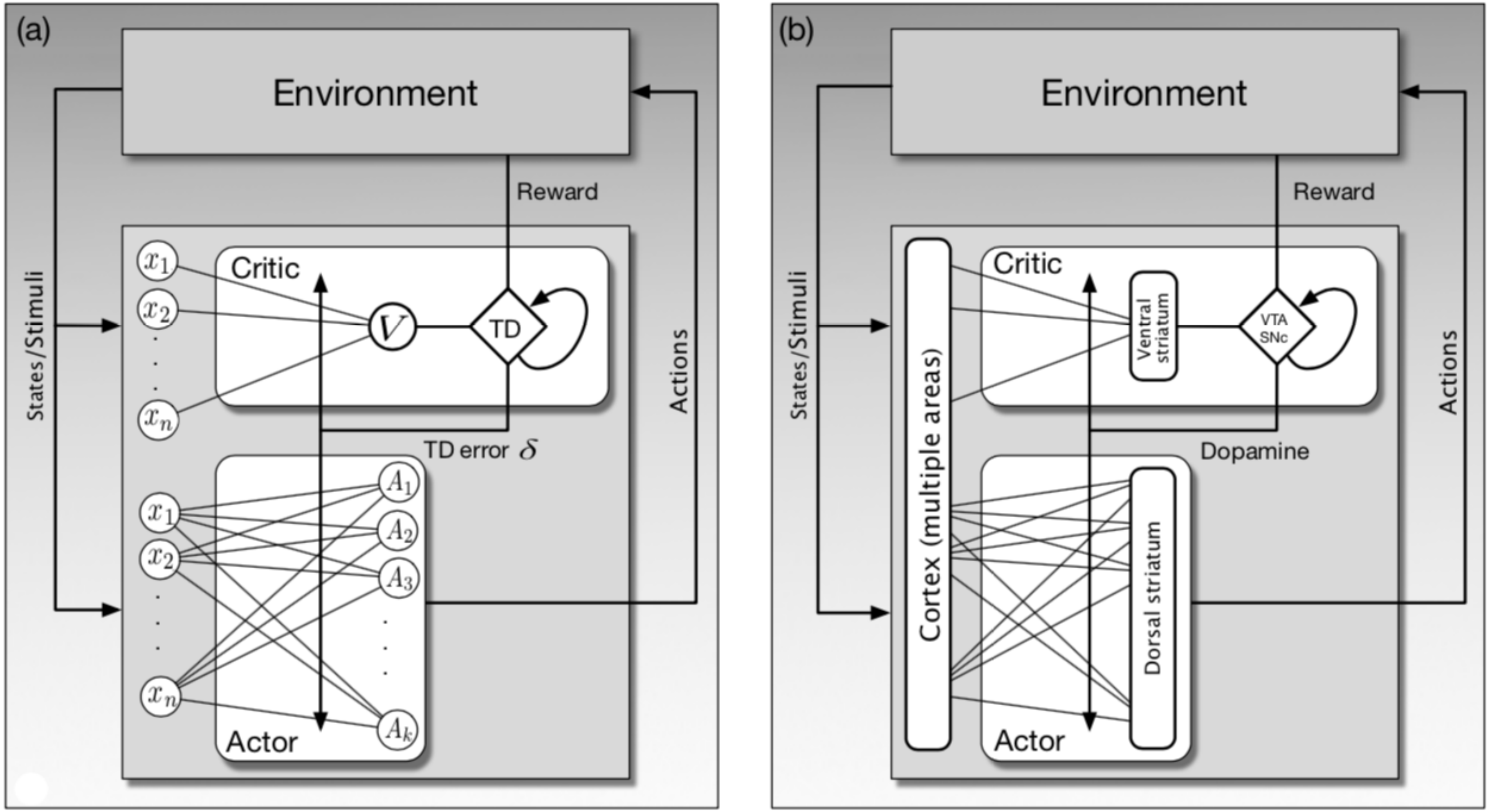
MCTS in AlphaGo Zero



d: Once the search is complete, search probabilities π are returned, proportional to $N^{1/\tau}$, where N is the visit count of each move from the root state and τ is a parameter controlling temperature.

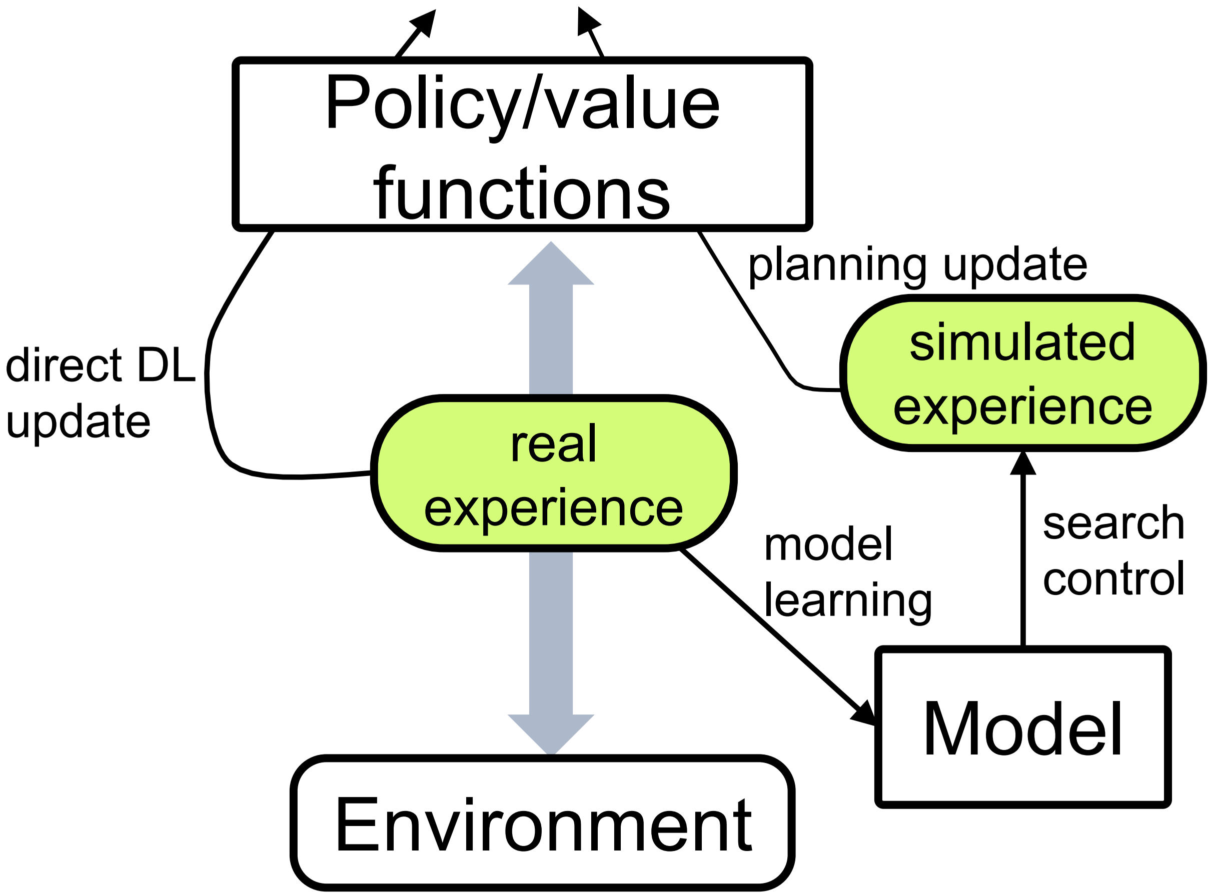
Source: David Silver et al. (2017), "Mastering the game of Go without human knowledge." Nature 550 (2017): 354–359.

Reinforcement Learning
Actor Critic ANN



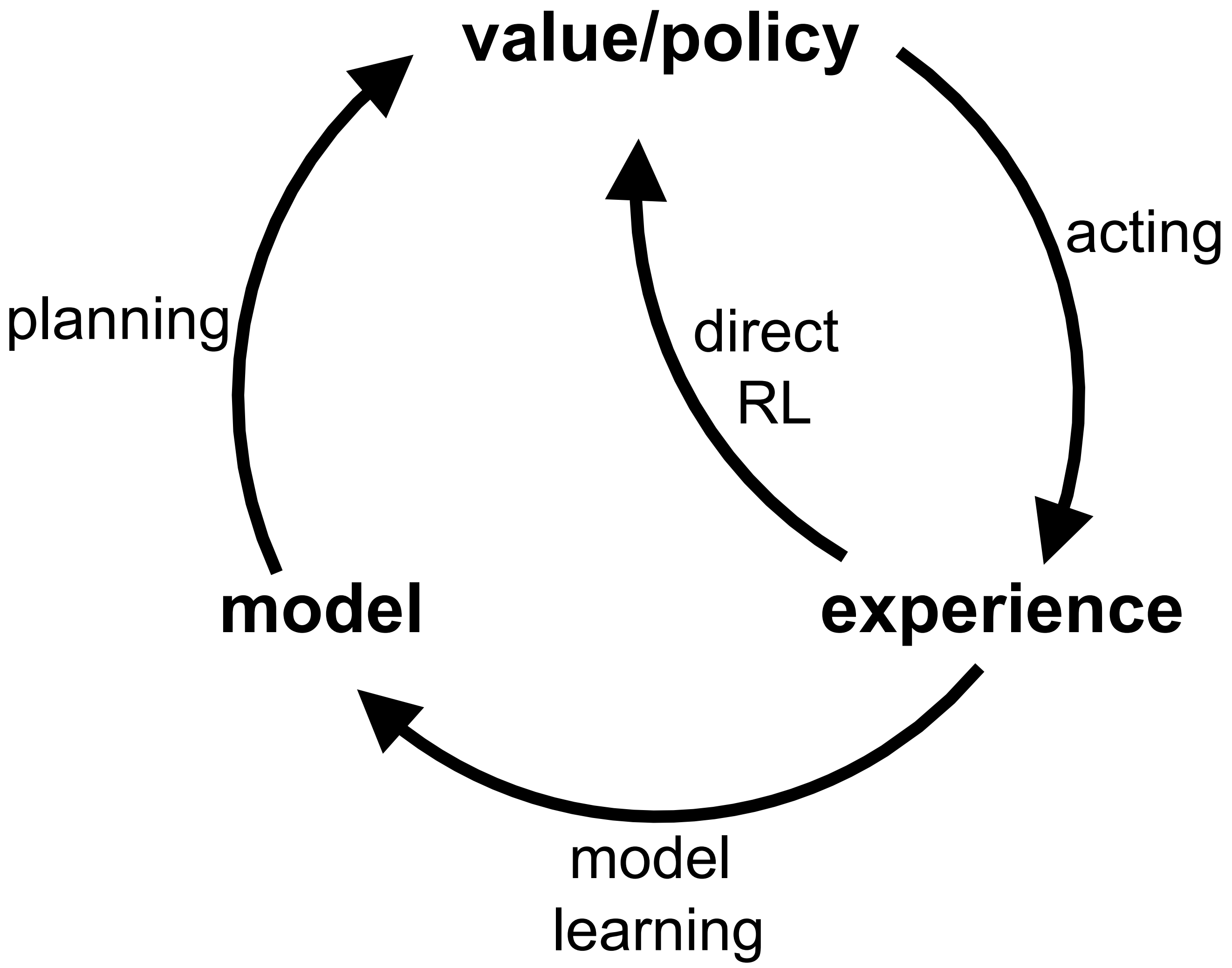
Source: Richard S. Sutton & Andrew G. Barto (2018), Reinforcement Learning: An Introduction, 2nd Edition, A Bradford Book.

Reinforcement Learning
General Dyna Architecture



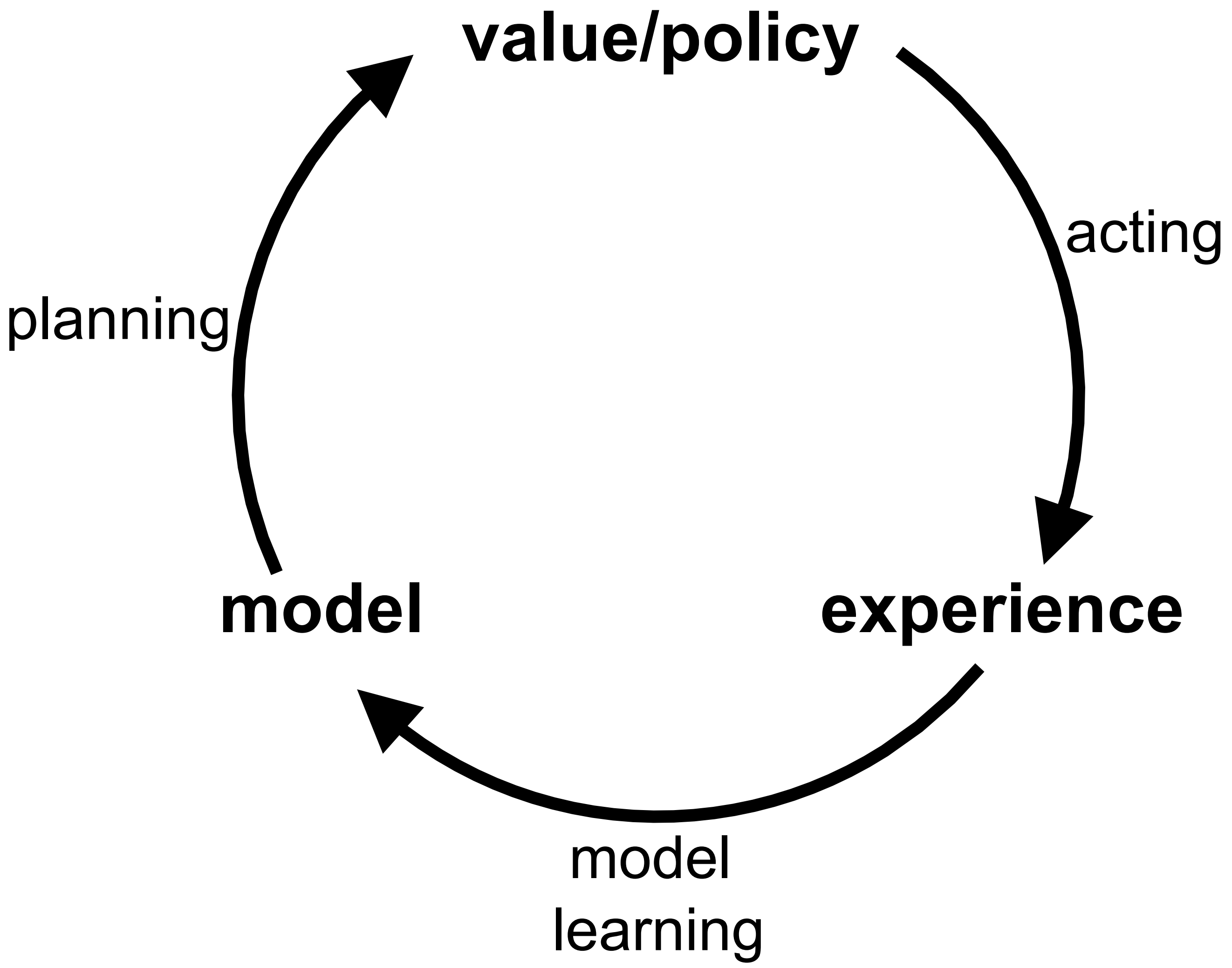
Source: Richard S. Sutton & Andrew G. Barto (2018), Reinforcement Learning: An Introduction, 2nd Edition, A Bradford Book.

Dyna:
Integrated Planning, Acting, and Learning



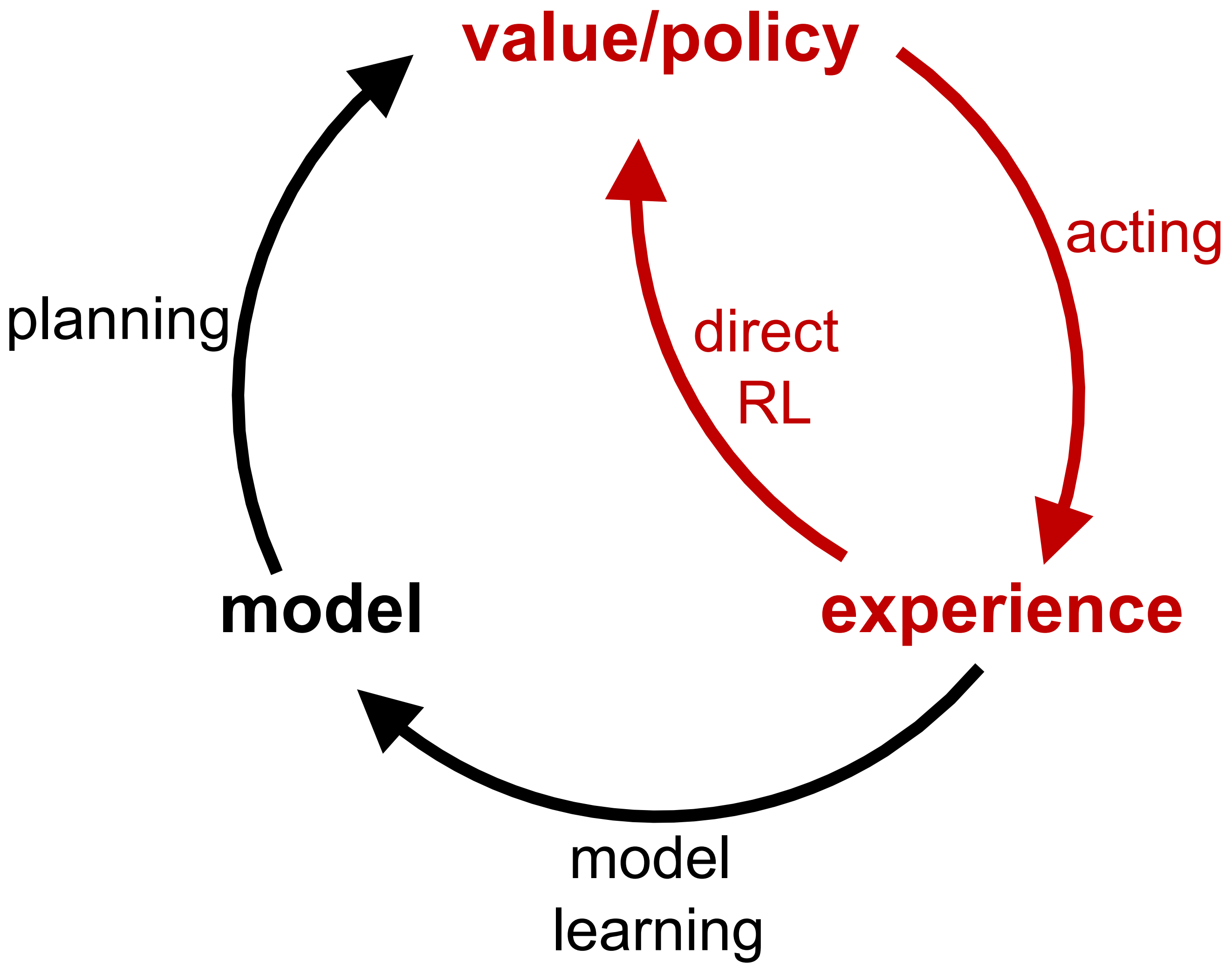
Source: Richard S. Sutton & Andrew G. Barto (2018), Reinforcement Learning: An Introduction, 2nd Edition, A Bradford Book.

Model-Based RL



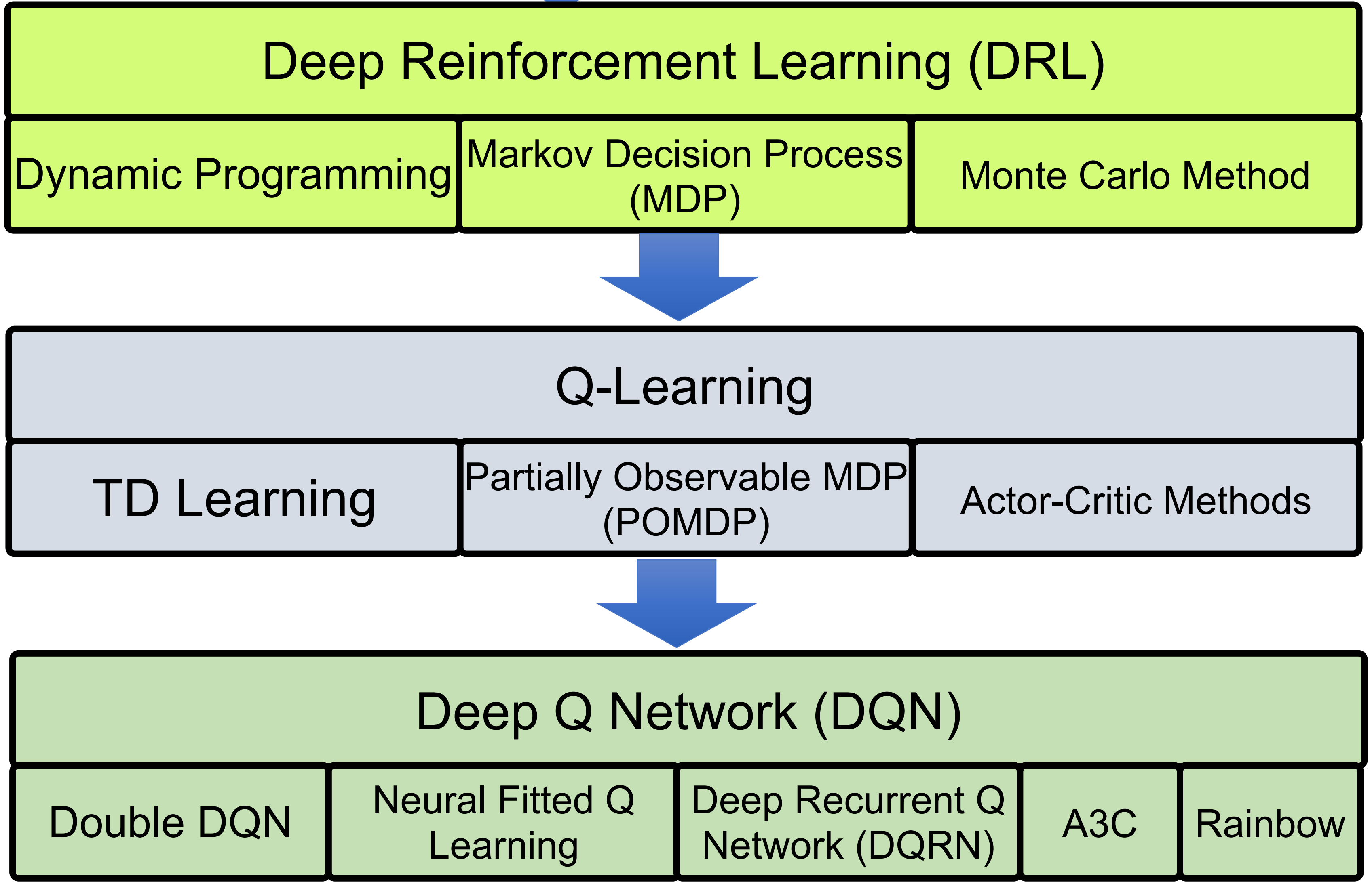
Source: Richard S. Sutton & Andrew G. Barto (2018), Reinforcement Learning: An Introduction, 2nd Edition, A Bradford Book.

Model-Free RL
(DQN, A3C)



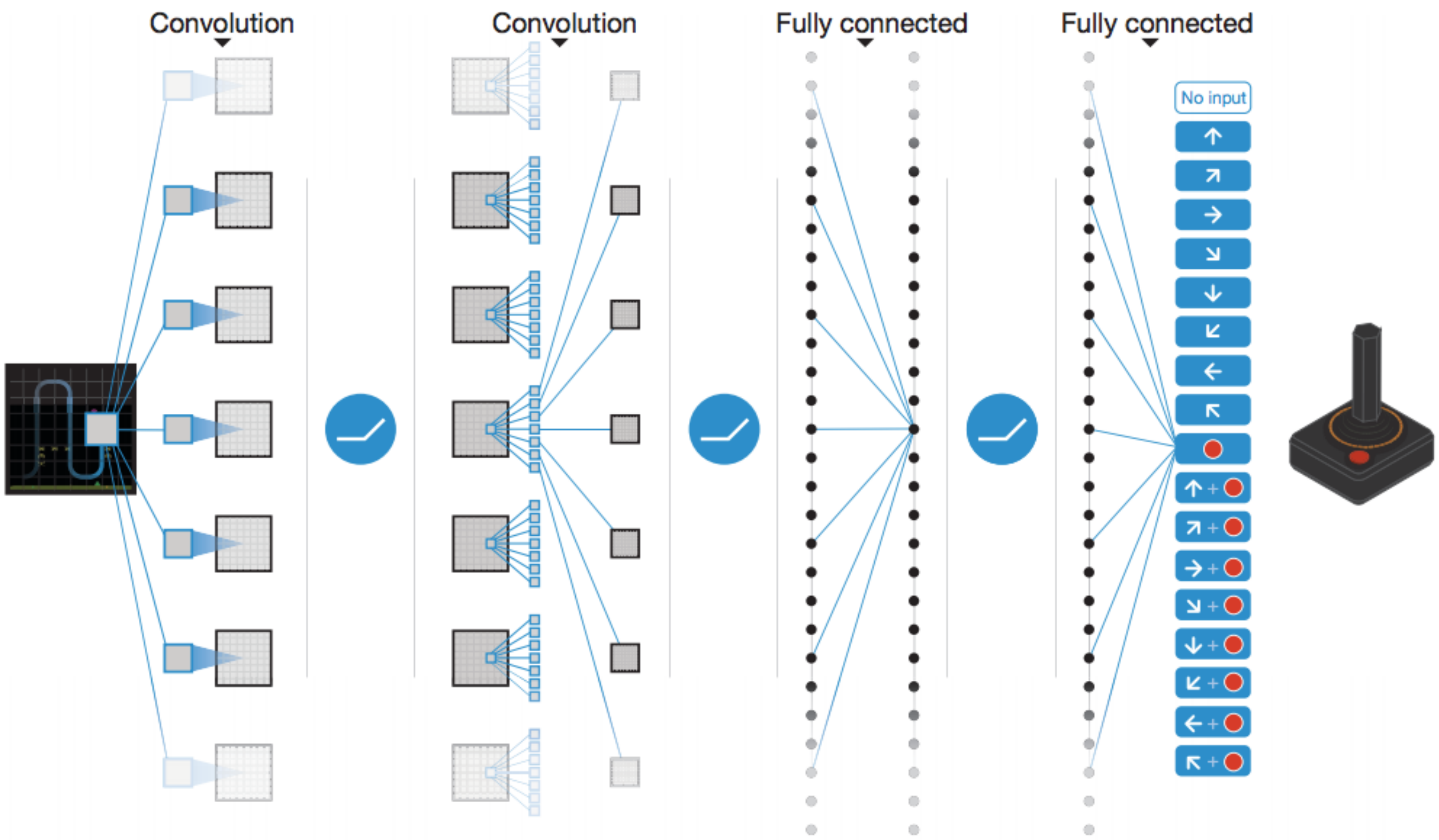
Source: Richard S. Sutton & Andrew G. Barto (2018), Reinforcement Learning: An Introduction, 2nd Edition, A Bradford Book.

Reinforcement Learning Algorithms



Source: https://amitray.com/deep-learning-past-present-and-future-a-review/

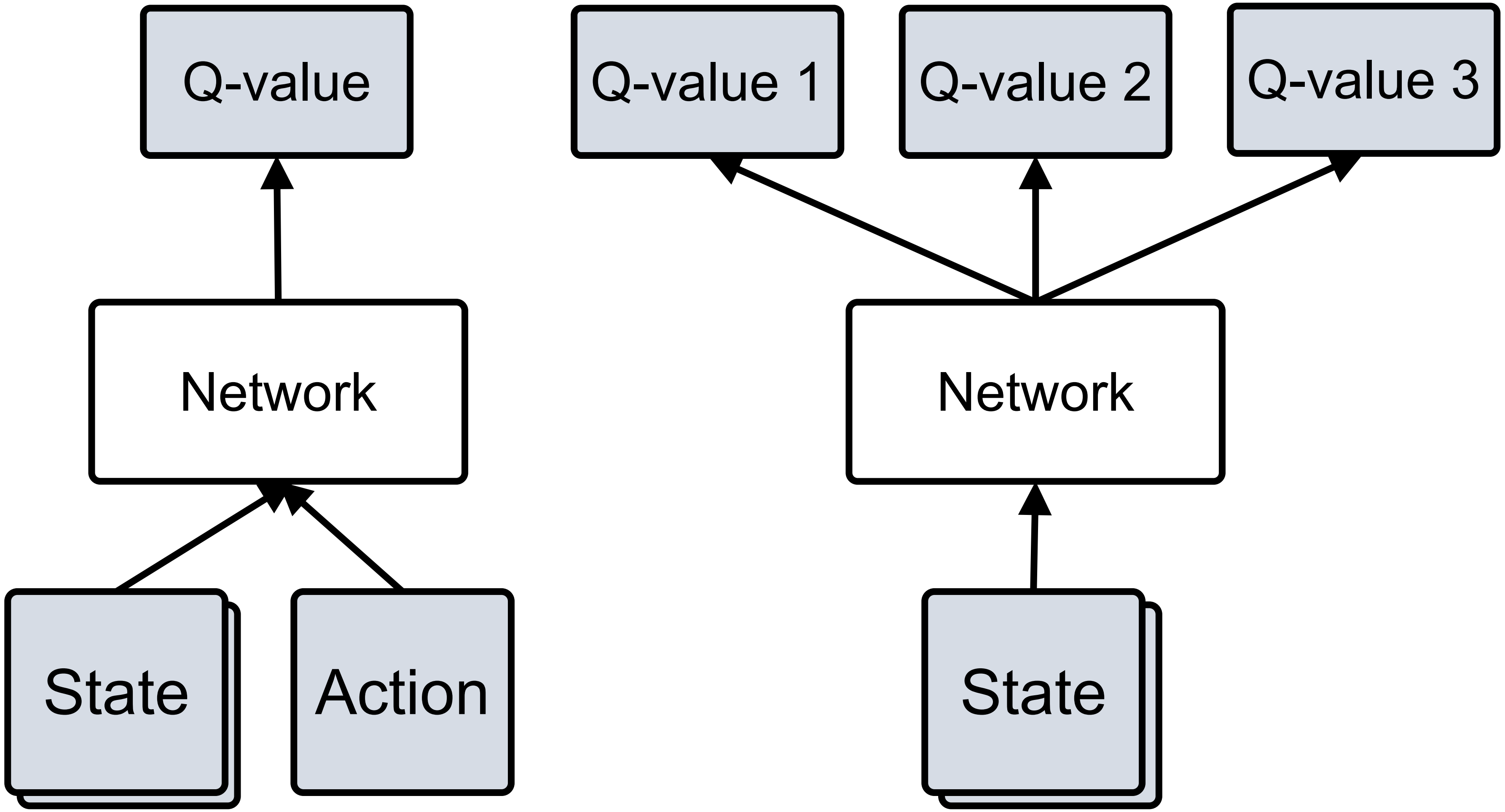
Human-level control through deep reinforcement learning (DQN)



Schematic illustration of the convolutional neural network

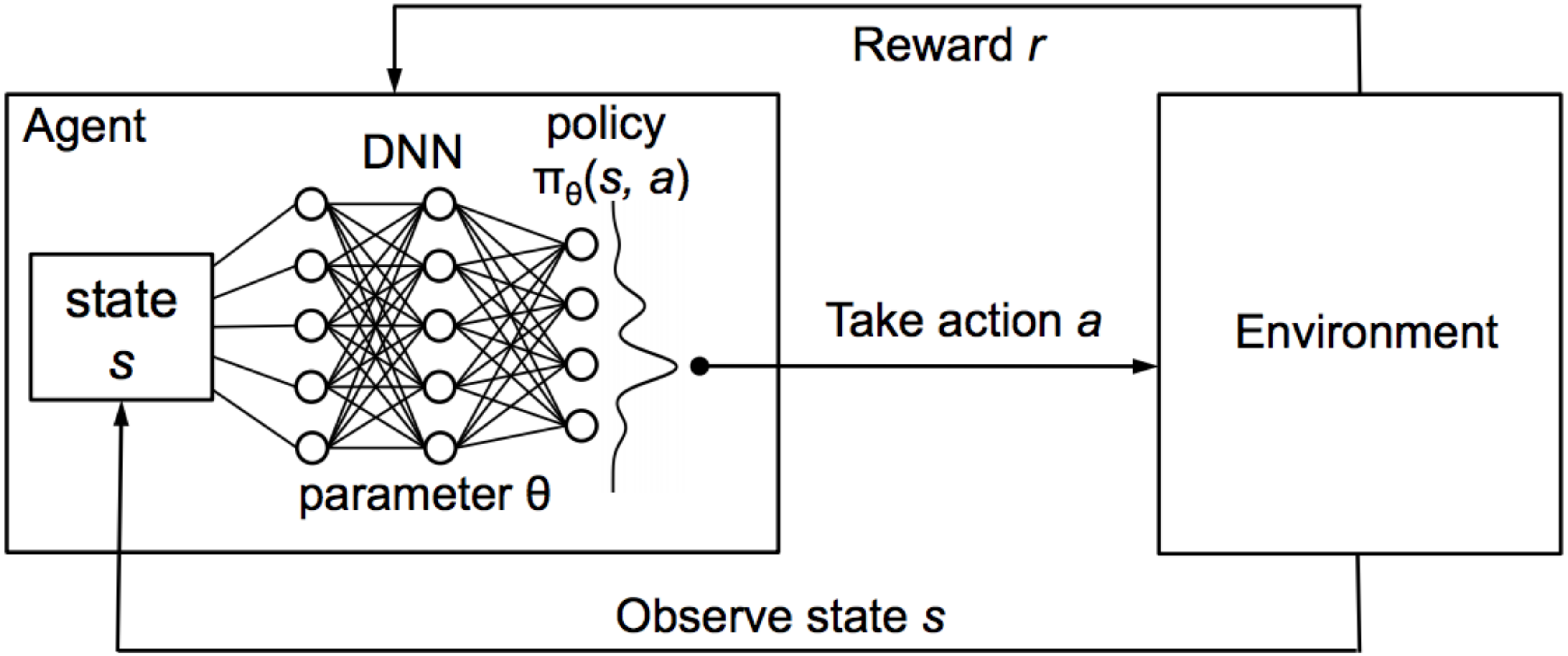
Source: Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Andrei A. Rusu, Joel Veness, Marc G. Bellemare, Alex Graves et al. "Human-level control through deep reinforcement learning." Nature 518, no. 7540 (2015): 529.

Deep Q-Network (DQN)



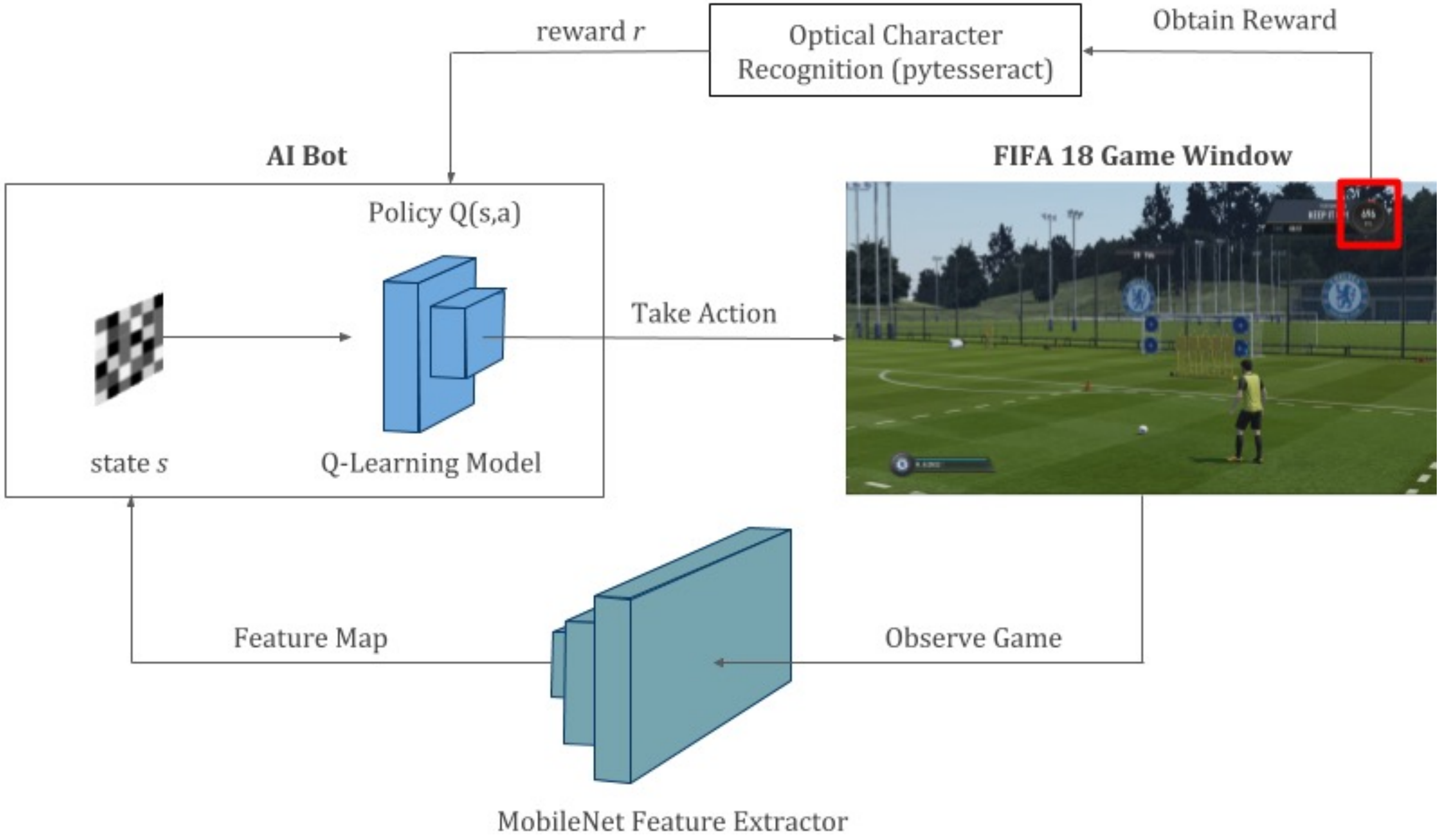
Source: https://neuro.cs.ut.ee/demystifying-deep-reinforcement-learning/

Reinforcement Learning with policy represented via DNN



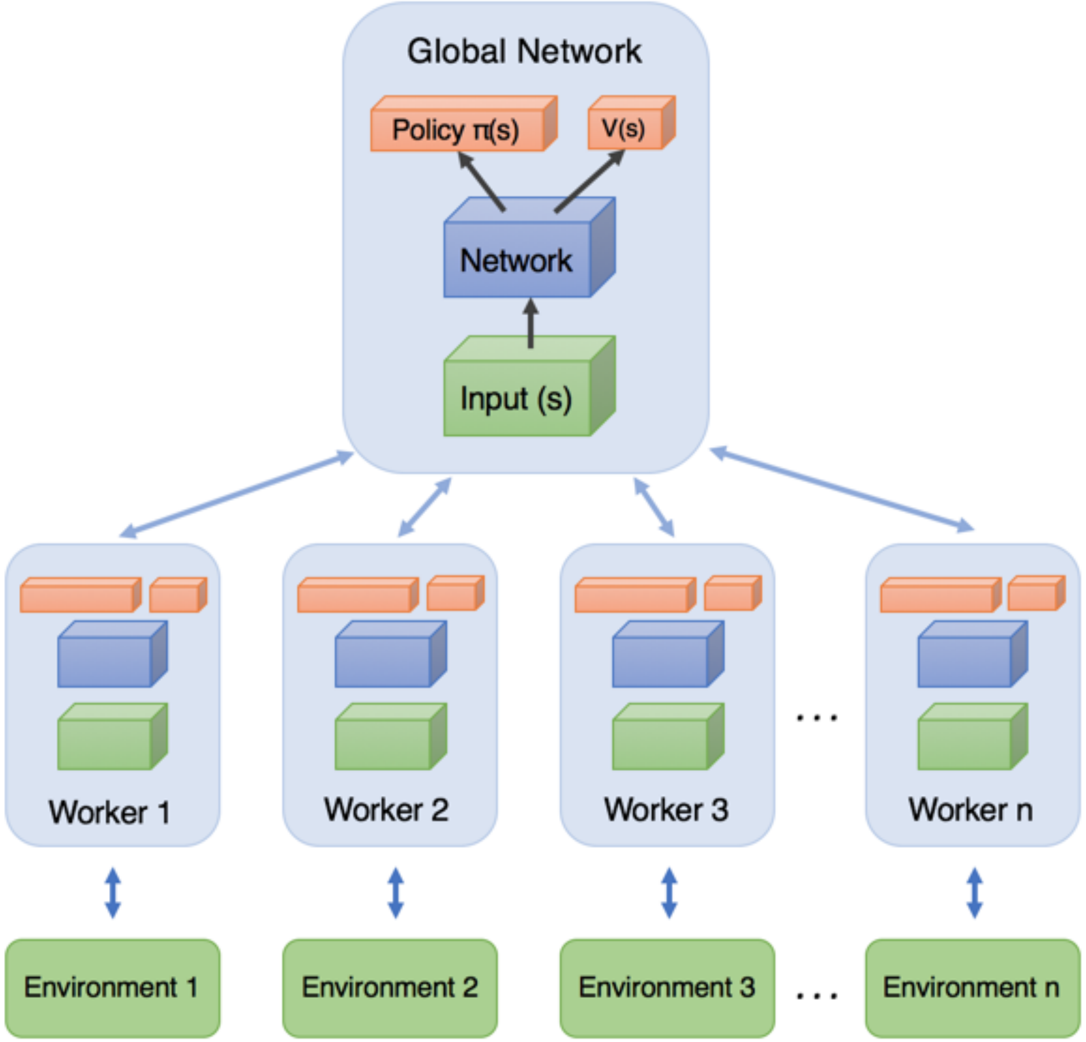
Source: Hongzi Mao, Mohammad Alizadeh, Ishai Menache, and Srikanth Kandula. (2016) "Resource management with deep reinforcement learning." In Proceedings of the 15th ACM Workshop on Hot Topics in Networks, pp. 50-56. ACM, 2016.

Reinforcement Learning
Deep Q-Learning in FIFA 18



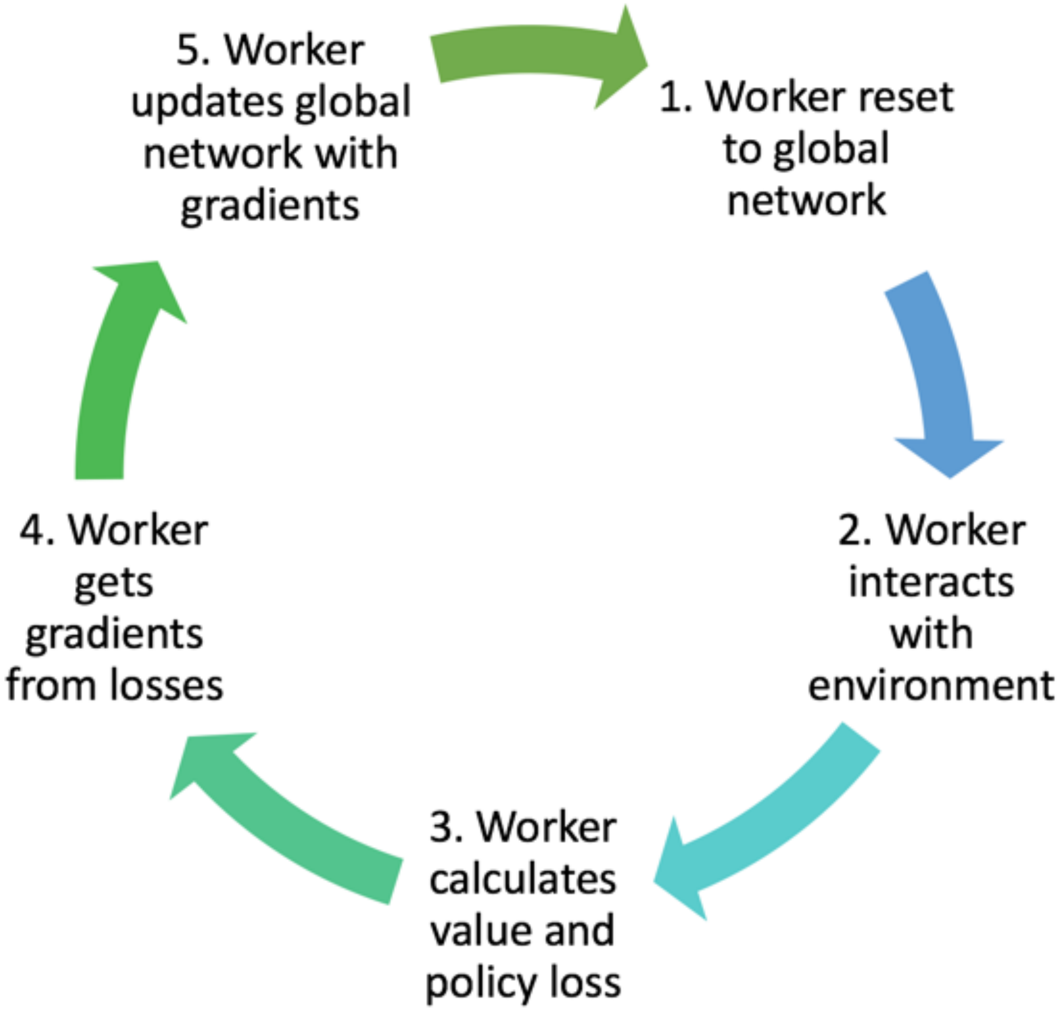
Source: https://towardsdatascience.com/using-deep-q-learning-in-fifa-18-to-perfect-the-art-of-free-kicks-f2e4e979ee66

Asynchronous Advantage Actor-Critic (A3C)



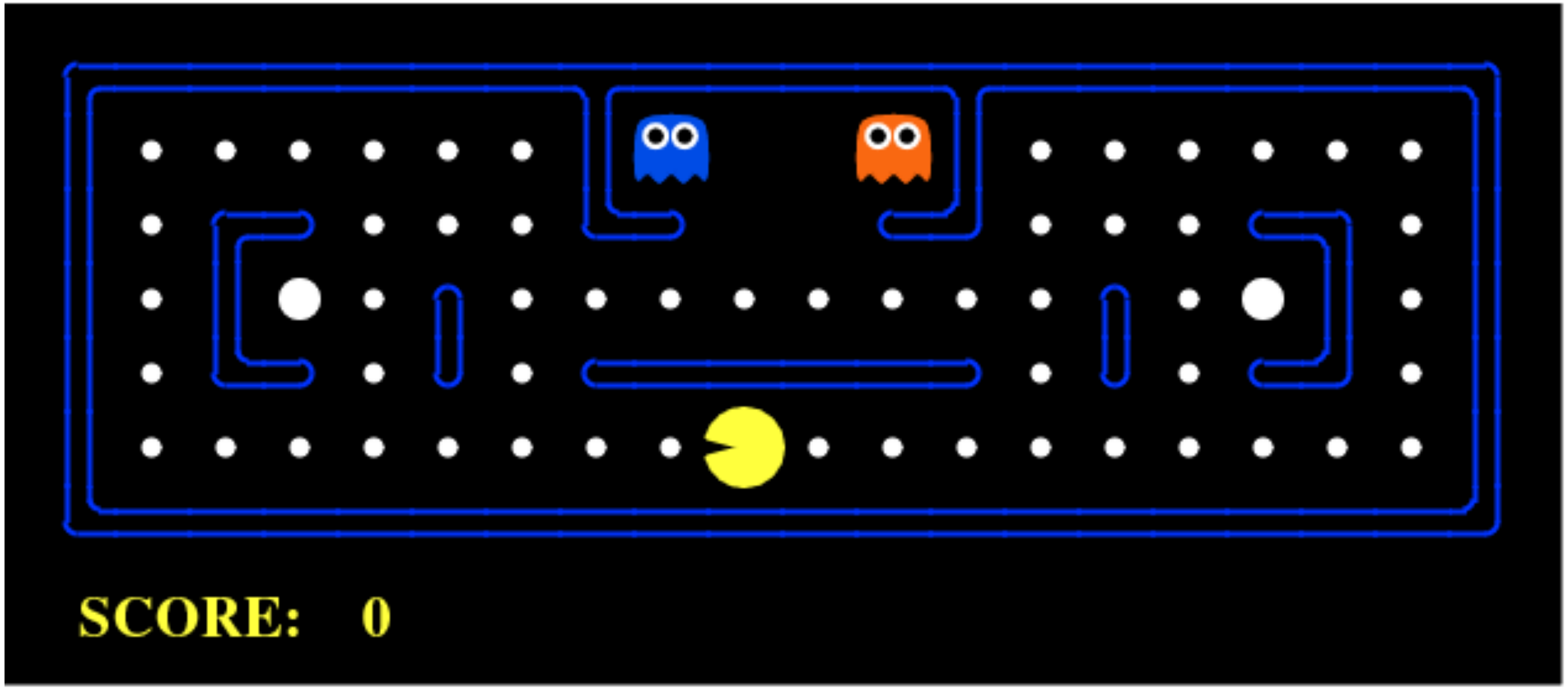
Source: https://medium.com/emergent-future/simple-reinforcement-learning-with-tensorflow-part-8-asynchronous-actor-critic-agents-a3c-c88f72a5e9f2

Training workflow of each worker agent in A3C



Source: https://medium.com/emergent-future/simple-reinforcement-learning-with-tensorflow-part-8-asynchronous-actor-critic-agents-a3c-c88f72a5e9f2

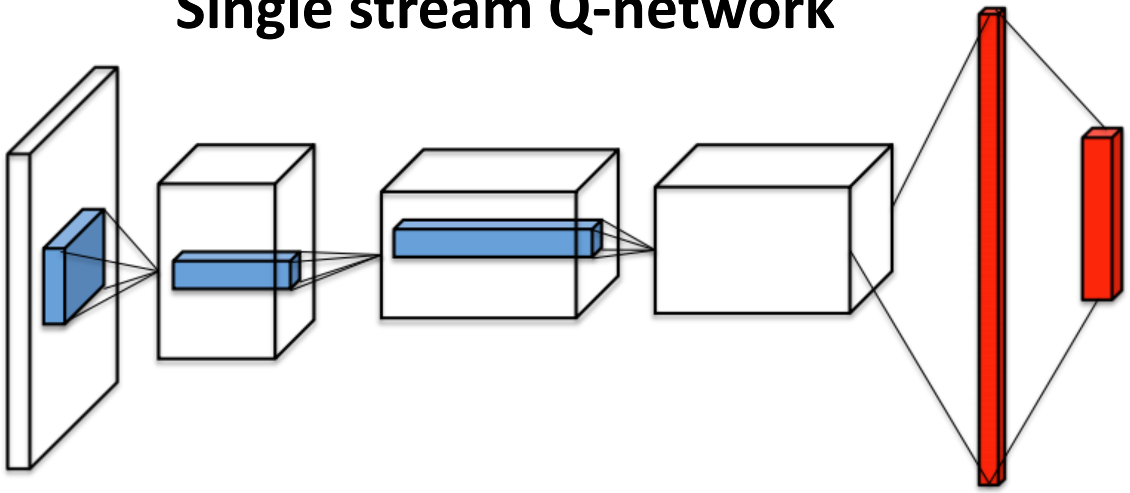
Reinforcement Learning Example: PCMAN



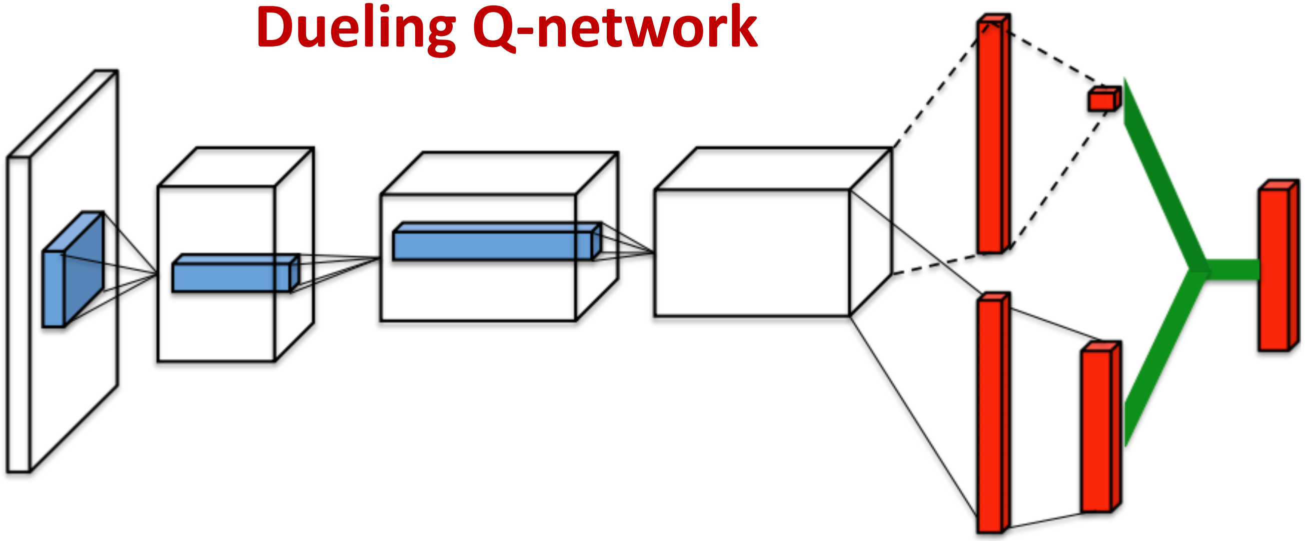
Source: https://www.kdnuggets.com/2018/03/5-things-reinforcement-learning.html

Dueling Network Architectures for Deep Reinforcement Learning

Single stream Q-network

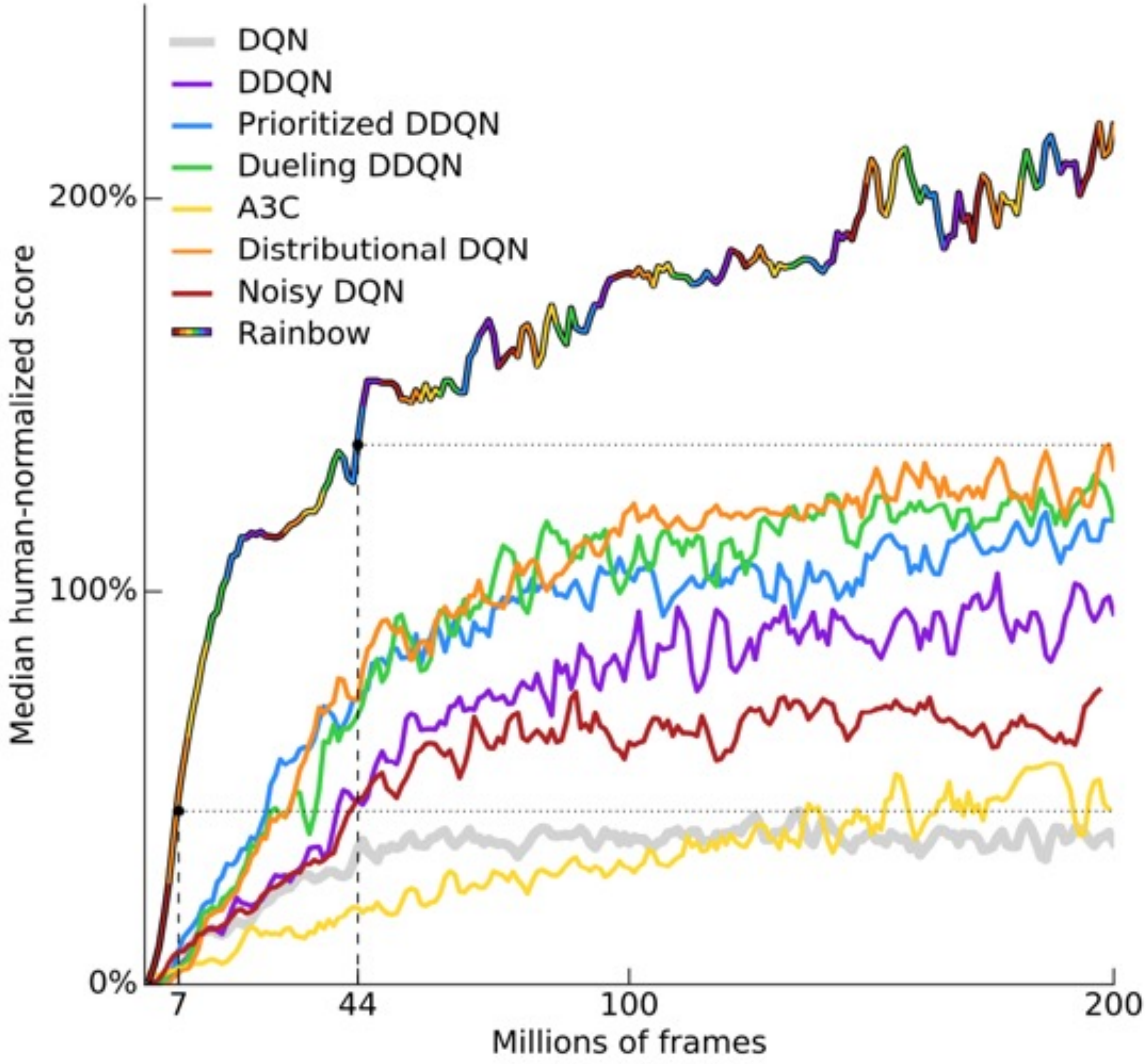


Dueling Q-network



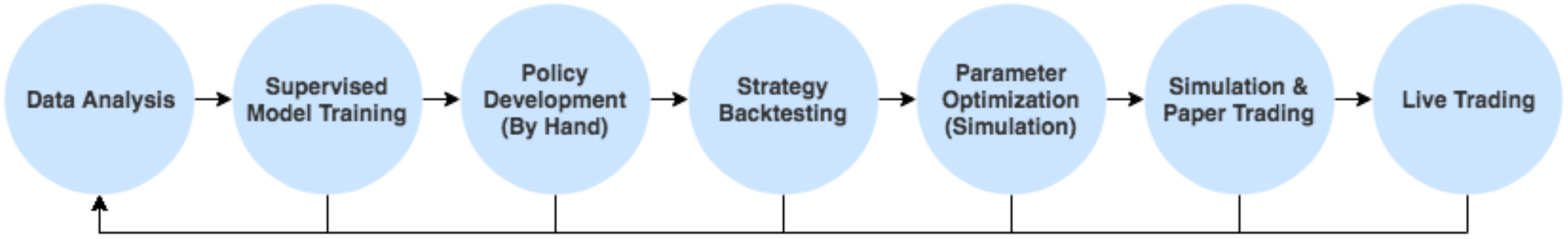
Source: Ziyu Wang et al. (2015). "Dueling network architectures for deep reinforcement learning." arXiv preprint arXiv:1511.06581 (2015)

Rainbow: Combining improvements in deep reinforcement learning



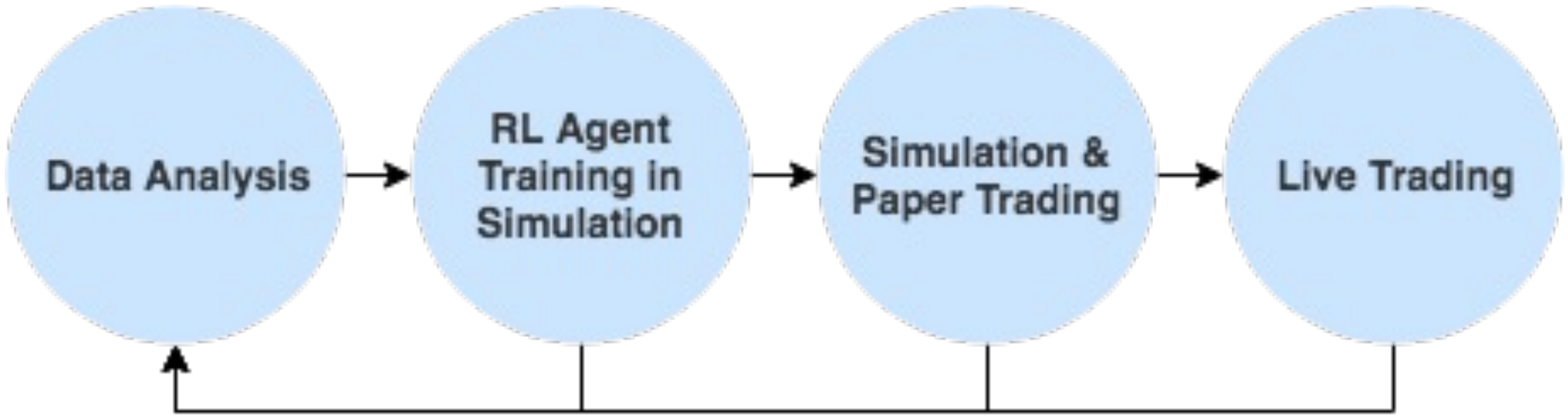
Source: Matteo Hessel, Joseph Modayil, Hado Van Hasselt, Tom Schaul, Georg Ostrovski, Will Dabney, Dan Horgan, Bilal Piot, Mohammad Azar, and David Silver (2017). "Rainbow: Combining improvements in deep reinforcement learning." arXiv preprint arXiv:1710.02298 (2017).

A Typical Strategy Development Workflow



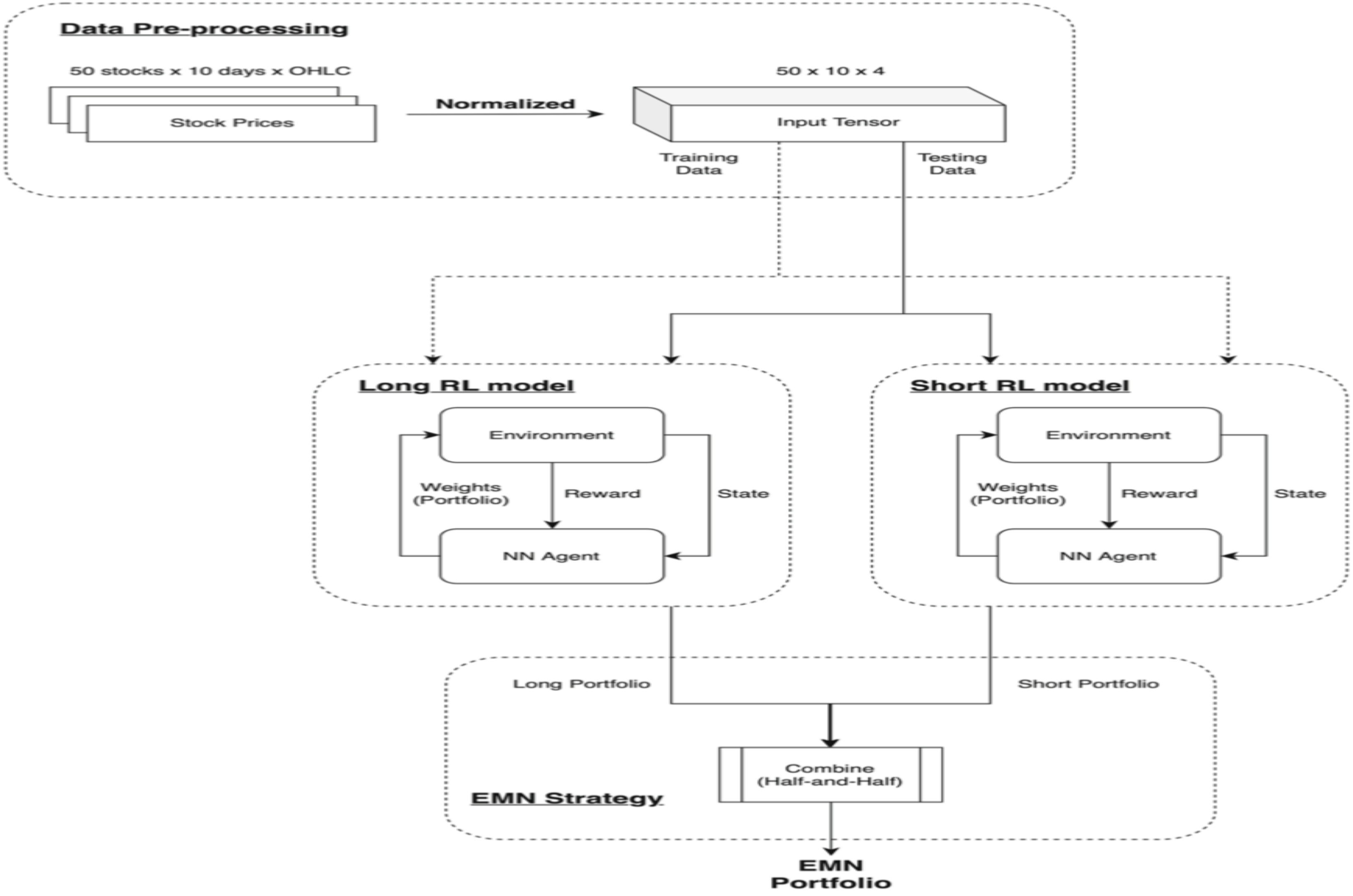
Source: http://www.wildml.com/2018/02/introduction-to-learning-to-trade-with-reinforcement-learning/

Reinforcement Learning (RL) in Trading Strategies



Source: http://www.wildml.com/2018/02/introduction-to-learning-to-trade-with-reinforcement-learning/

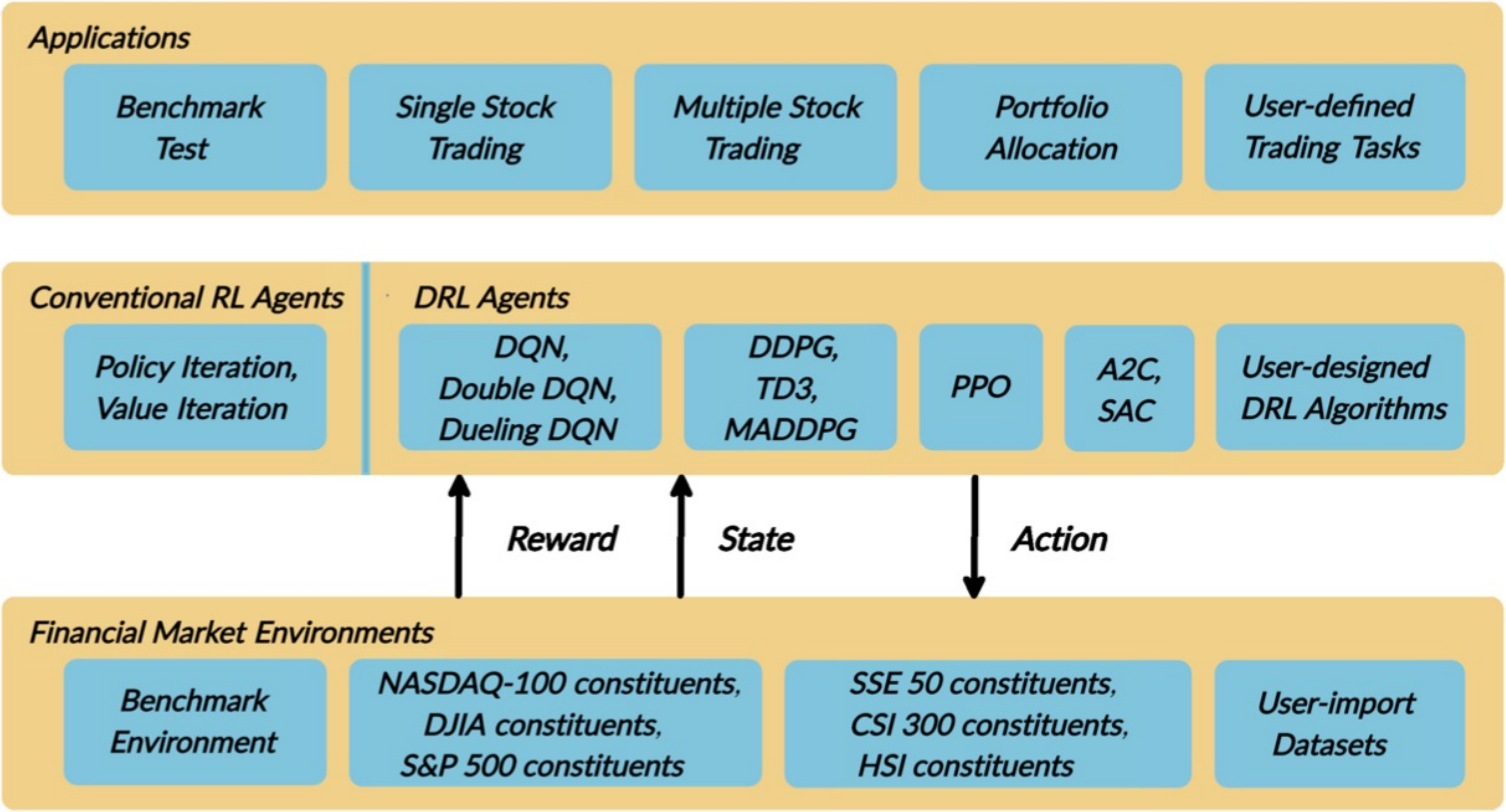
Portfolio management system in equity market neutral using reinforcement learning
(Wu et al., 2021)



Source: Mu-En Wu, Jia-Hao Syu, Jerry Chun-Wei Lin, and Jan-Ming Ho. "Portfolio management system in equity market neutral using reinforcement learning." Applied Intelligence (2021): 1-13.

FinRL:

A Deep Reinforcement Learning Library for Automated Stock Trading in Quantitative Finance



Source: Xiao-Yang Liu, Hongyang Yang, Qian Chen, Runjia Zhang, Liuqing Yang, Bowen Xiao, and Christina Dan Wang (2020). "FinRL: A Deep Reinforcement Learning Library for Automated Stock Trading in Quantitative Finance." arXiv preprint arXiv:2011.09607 (2020).

FinRL

Deep Reinforcement Learning Algorithms

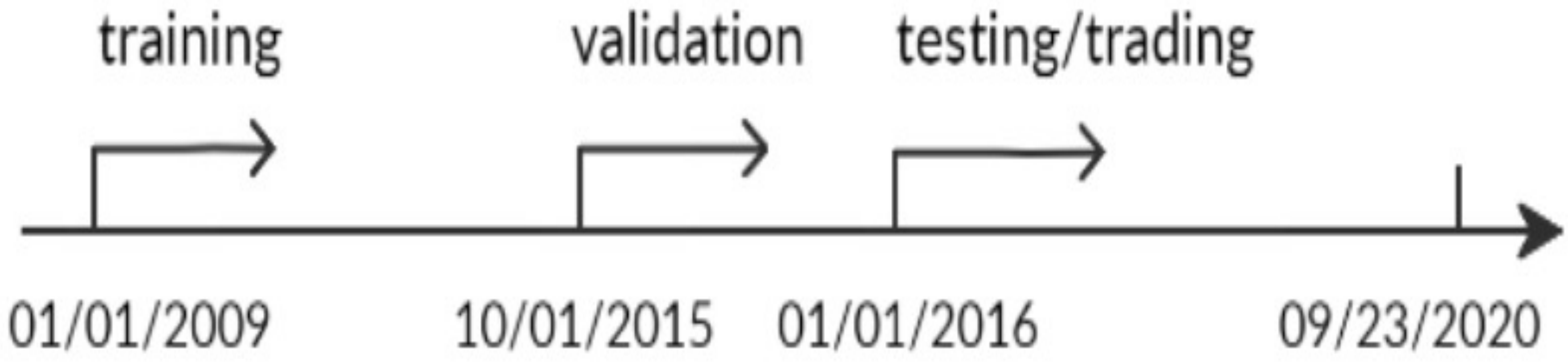
Algorithms	Input	Output	Type	State-action spaces support	Finance use cases support	Features and Improvements	Advantages
DQN	States	Q-value	Value based	Discrete only	Single stock trading	Target network, experience replay	Simple and easy to use
Double DQN	States	Q-value	Value based	Discrete only	Single stock trading	Use two identical neural network models to learn	Reduce overestimations
Dueling DQN	States	Q-value	Value based	Discrete only	Single stock trading	Add a specialized dueling Q head	Better differentiate actions, improves the learning
DDPG	State action pair	Q-value	Actor-critic based	Continuous only	Multiple stock trading, portfolio allocation	Being deep Q-learning for continuous action spaces	Better at handling high-dimensional continuous action spaces
A2C	State action pair	Q-value	Actor-critic based	Discrete and continuous	All use cases	Advantage function, parallel gradients updating	Stable, cost-effective, faster and works better with large batch sizes
PPO	State action pair	Q-value	Actor-critic based	Discrete and continuous	All use cases	Clipped surrogate objective function	Improve stability, less variance, simply to implement
SAC	State action pair	Q-value	Actor-critic based	Continuous only	Multiple stock trading, portfolio allocation	Entropy regularization, exploration-exploitation trade-off	Improve stability
TD3	State action pair	Q-value	Actor-critic based	Continuous only	Multiple stock trading, portfolio allocation	Clipped double Q-Learning, delayed policy update, target policy smoothing.	Improve DDPG performance
MADDPG	State action pair	Q-value	Actor-critic based	Continuous only	Multiple stock trading, portfolio allocation	Handle multi-agent RL problem	Improve stability and performance

Source: Xiao-Yang Liu, Hongyang Yang, Qian Chen, Runjia Zhang, Liuqing Yang, Bowen Xiao, and Christina Dan Wang (2020). "FinRL: A Deep Reinforcement Learning Library for Automated Stock Trading in Quantitative Finance." arXiv preprint arXiv:2011.09607 (2020).

FinRL:

A Deep Reinforcement Learning Library for Automated Stock Trading in Quantitative Finance

Evaluation of Trading Performance Training-Validation-Testing Flow



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Reinforcement Learning (RL)
FinRL
Performance of single stock trading
using Proximal policy optimization (PPO) in the FinRL library

Source: Xiao-Yang Liu, Hongyang Yang, Qian Chen, Runjia Zhang, Liuqing Yang, Bowen Xiao, and Christina Dan Wang (2020). "FinRL: A Deep Reinforcement Learning Library for Automated Stock Trading in Quantitative Finance." arXiv preprint arXiv:2011.09607 (2020).

Reinforcement Learning (RL)
FinRL

Performance of multiple stock trading and portfolio allocation using the FinRL library

Source: Xiao-Yang Liu, Hongyang Yang, Qian Chen, Runjia Zhang, Liuqing Yang, Bowen Xiao, and Christina Dan Wang (2020). "FinRL: A Deep Reinforcement Learning Library for Automated Stock Trading in Quantitative Finance." arXiv preprint arXiv:2011.09607 (2020).

Reinforcement Learning (RL) FinRL

Performance of single stock trading using Proximal policy optimization (PPO) in the FinRL library

2019/01/01-2020/09/23	SPY	QQQ	GOOGL	AMZN	AAPL	MSFT	S&P 500
Initial value	100,000	100,000	100,000	100,000	100,000	100,000	100,000
Final value	127,044	163,647	174,825	192,031	173,063	172,797	133,402
Annualized return	14.89%	32.33%	37.40%	44.94%	36.88%	36.49%	17.81%
Annualized Std	9.63%	27.51%	33.41%	29.62%	25.84%	33.41%	27.00%
Sharpe ratio	1.49	1.16	1.12	1.40	1.35	1.10	0.74
Max drawdown	20.93%	28.26%	27.76%	21.13%	22.47%	28.11%	33.92%

Source: Xiao-Yang Liu, Hongyang Yang, Qian Chen, Runjia Zhang, Liuqing Yang, Bowen Xiao, and Christina Dan Wang (2020). "FinRL: A Deep Reinforcement Learning Library for Automated Stock Trading in Quantitative Finance." arXiv preprint arXiv:2011.09607 (2020).

Reinforcement Learning (RL)
FinRL
Performance of multiple stock trading and portfolio allocation
over the DJIA constituents stocks using the FinRL library

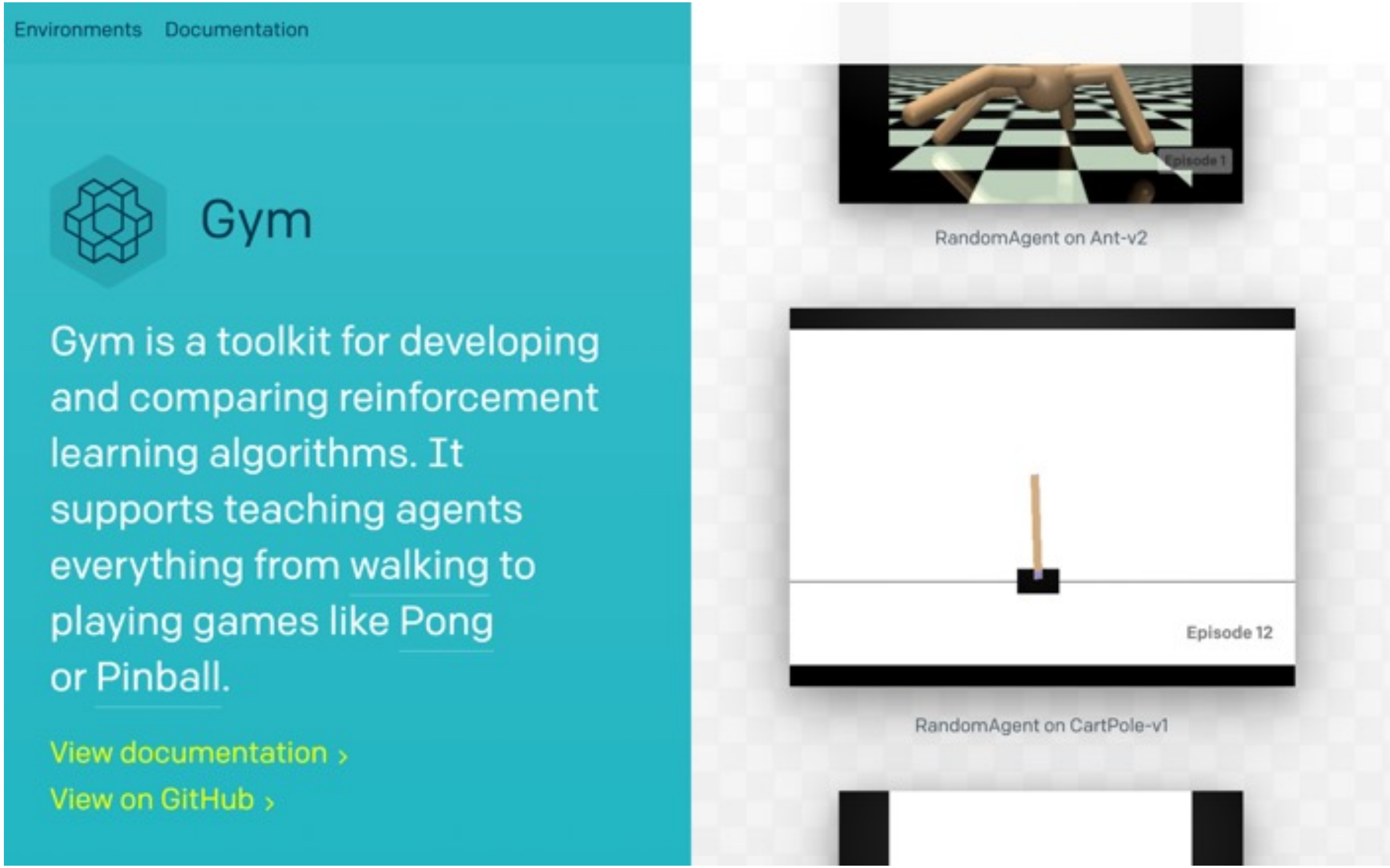
2019/01/01-2020/09/23	TD3	DDPG	Min-Var.	DJIA
Initial value	1,000,000	1,000,000	1,000,000	1,000,000
Final value	1,403,337; 1,381,120	1,396,607; 1,281,120	1,171,120	1,185,260
Annualized return	21.40%; 17.61%	20.34%; 15.81%	8.38%	10.61%
Annualized Std	14.60%; 17.01%	15.89%; 16.60%	26.21%	28.63%
Sharpe ratio	1.38; 1.03	1.28; 0.98	0.44	0.48
Max drawdown	11.52% 12.78%	13.72%; 13.68%	34.34%	37.01%

Source: Xiao-Yang Liu, Hongyang Yang, Qian Chen, Runjia Zhang, Liuqing Yang, Bowen Xiao, and Christina Dan Wang (2020). "FinRL: A Deep Reinforcement Learning Library for Automated Stock Trading in Quantitative Finance." arXiv preprint arXiv:2011.09607 (2020).

Deep Reinforcement Learning Library

- **OpenAI Gym**
- **Google Dopamine**
- **RLlib**
- **Horizon**
- **FinRL**

Open AI Gym



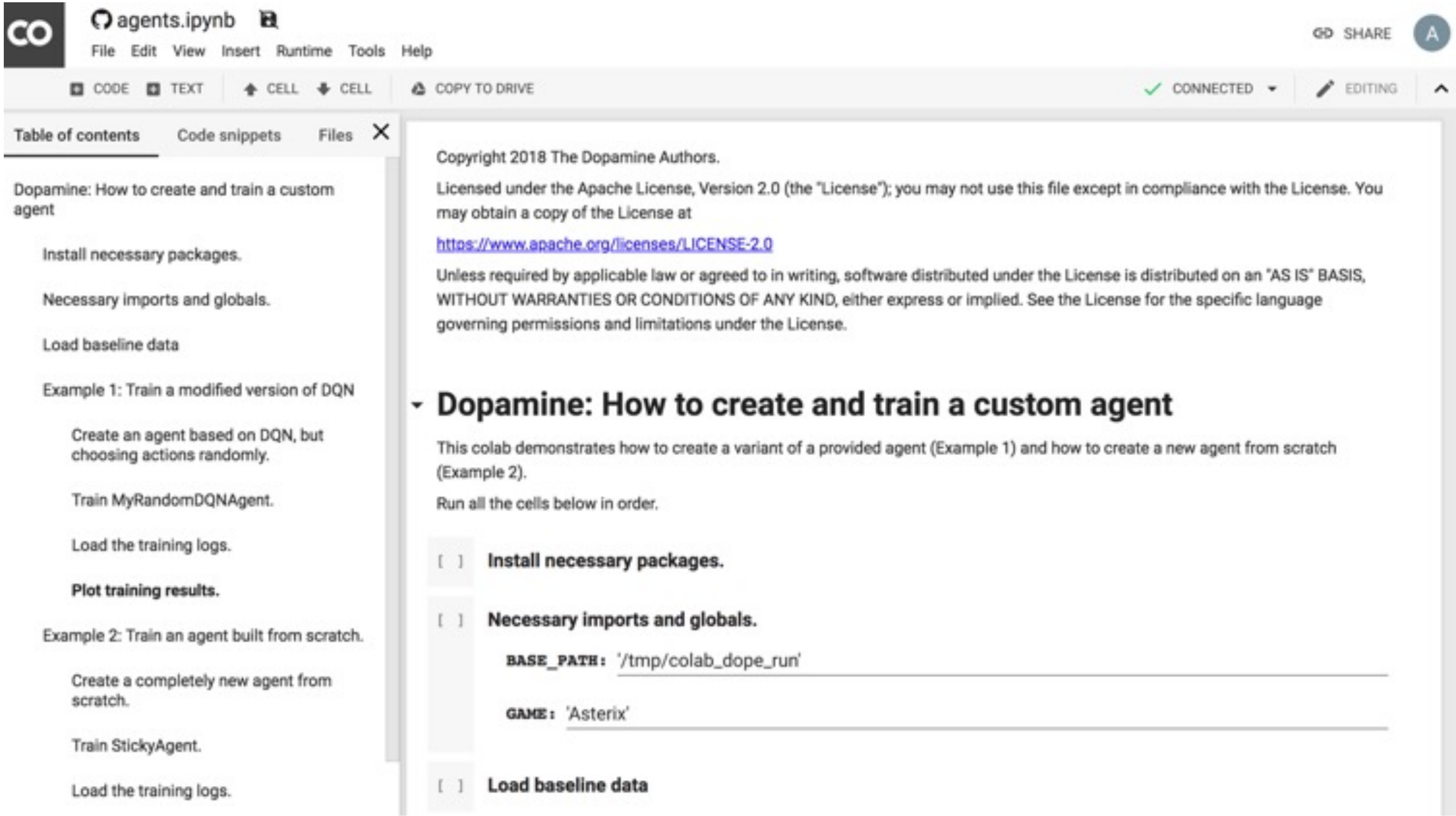
https://gym.openai.com/

Google Dopamine

Dopamine is a research framework for fast prototyping of reinforcement learning algorithms.

https://github.com/google/dopamine

Deep Reinforcement Learning
Dopamine Colab Examples
DQN Rainbow



https://colab.research.google.com/github/google/dopamine/blob/master/dopamine/colab/agents.ipynb

RLlib:
Scalable Reinforcement Learning

Examples
Tune API Reference
Contributing to Tune

RLLIB

RLlib: Scalable Reinforcement Learning
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RLlib Training APIs
RLlib Environments
RLlib Models, Preprocessors, and Action Distributions
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RLlib Offline Datasets
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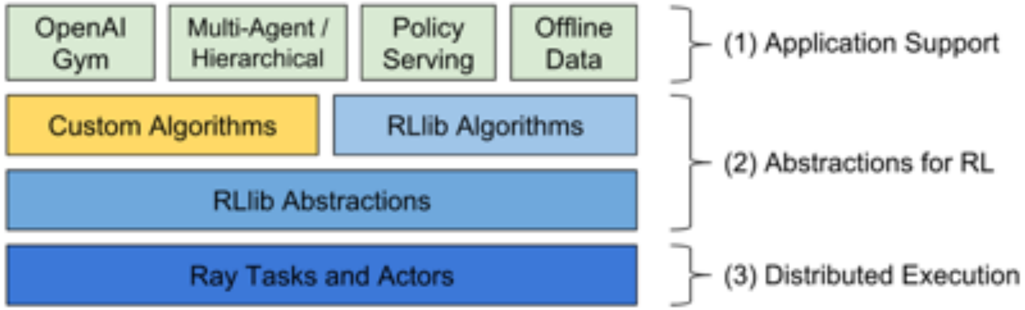
Contributing to RLlib

RAY SGD

RaySGD: Distributed Training

RLlib: Scalable Reinforcement Learning

RLlib is an open-source library for reinforcement learning that offers both high scalability and a unified API for a variety of applications. RLlib natively supports TensorFlow, TensorFlow Eager, and PyTorch, but most of its internals are framework agnostic.



To get started, take a look over the custom env example and the API documentation. If you're looking to develop custom algorithms with RLlib, also check out concepts and custom algorithms.

RLlib in 60 seconds

The following is a whirlwind overview of RLlib. For a more in-depth guide, see also the full table of contents and RLlib blog posts. You may also want to skim the list of built-in algorithms. Look out for the and icons to see which algorithms are available for each framework.

Contents

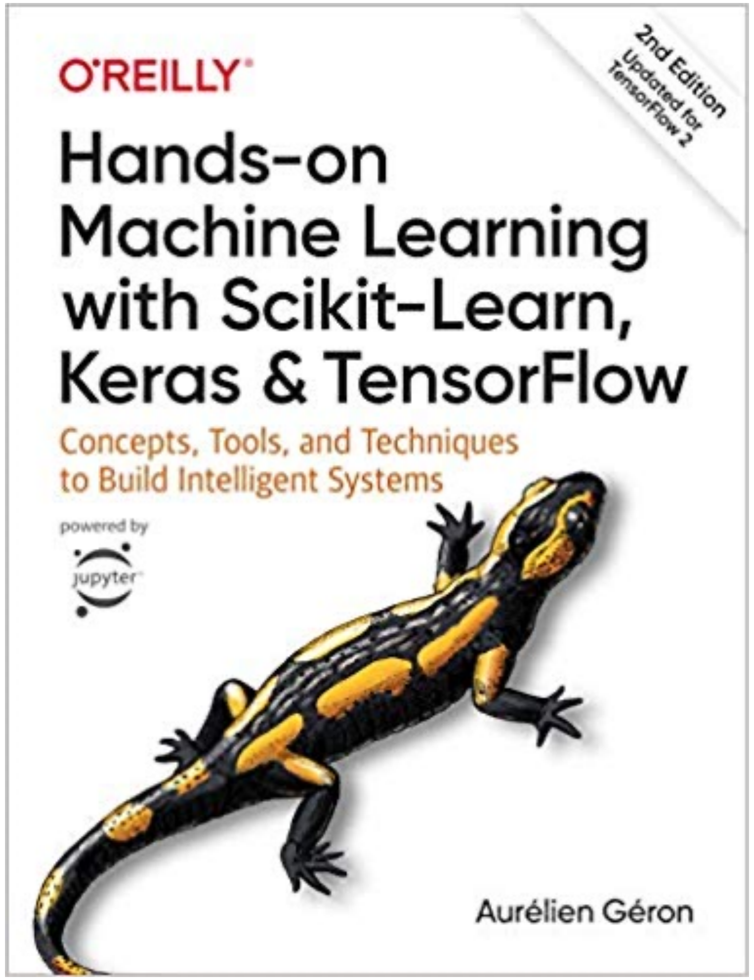
v: master

https://docs.ray.io/en/master/rllib.html

Aurélien Géron (2019),

Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems, 2nd Edition

O'Reilly Media, 2019



https://github.com/ageron/handson-ml2

Source: https://www.amazon.com/Hands-Machine-Learning-Scikit-Learn-TensorFlow/dp/1492032646/

Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow

Notebooks

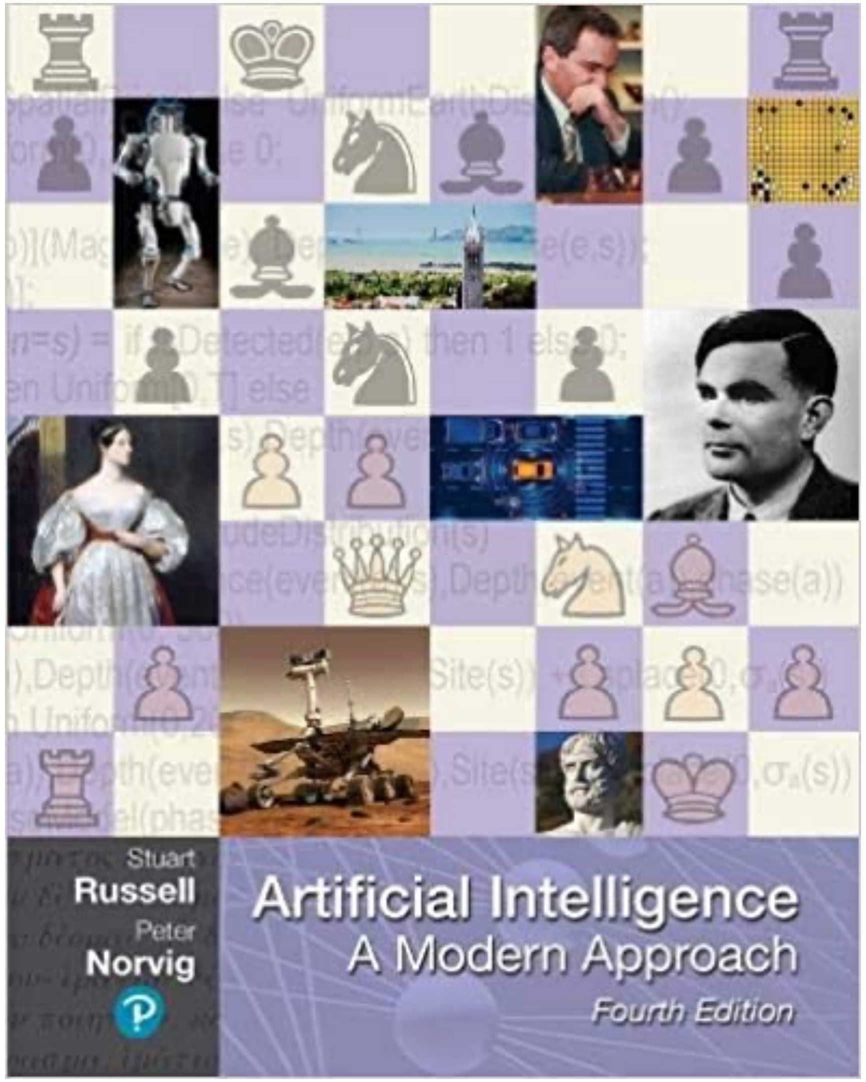
1. The Machine Learning landscape
2. End-to-end Machine Learning project
3. Classification
4. Training Models
5. Support Vector Machines
6. Decision Trees
7. Ensemble Learning and Random Forests
8. Dimensionality Reduction
9. Unsupervised Learning Techniques
10. Artificial Neural Nets with Keras
11. Training Deep Neural Networks
12. Custom Models and Training with TensorFlow
13. Loading and Preprocessing Data
14. Deep Computer Vision Using Convolutional Neural Networks
15. Processing Sequences Using RNNs and CNNs
16. Natural Language Processing with RNNs and Attention
17. Representation Learning Using Autoencoders
18. Reinforcement Learning
19. Training and Deploying TensorFlow Models at Scale

https://github.com/ageron/handson-ml2

Stuart Russell and Peter Norvig (2020),

Artificial Intelligence: A Modern Approach,

4th Edition, Pearson



Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson

https://www.amazon.com/Artificial-Intelligence-A-Modern-Approach/dp/0134610997/

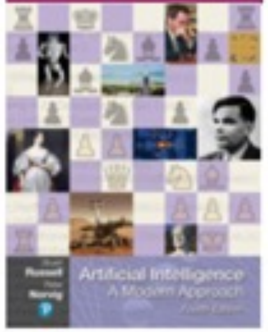
Artificial Intelligence: A Modern Approach (AIMA)

- **Artificial Intelligence: A Modern Approach (AIMA)**
  - http://aima.cs.berkeley.edu/
- **AIMA Python**
  - http://aima.cs.berkeley.edu/python/readme.html
  - https://github.com/aimacode/aima-python
- **Learning**
  - http://aima.cs.berkeley.edu/python/learning.html

Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson

Artificial Intelligence: A Modern Approach (AIMA)

- ⌂ US Edition
- ⌂ Global Edition
- Acknowledgements
- Code
- Courses
- Editions
- Errata
- Exercises
- Figures
- Instructors Page
- Pseudocode
- Reviews



Artificial Intelligence: A Modern Approach, 4th US ed.

by Stuart Russell and Peter Norvig

The authoritative, most-used AI textbook, adopted by over 1500 schools.

Table of Contents for the US Edition (or see the Global Edition)

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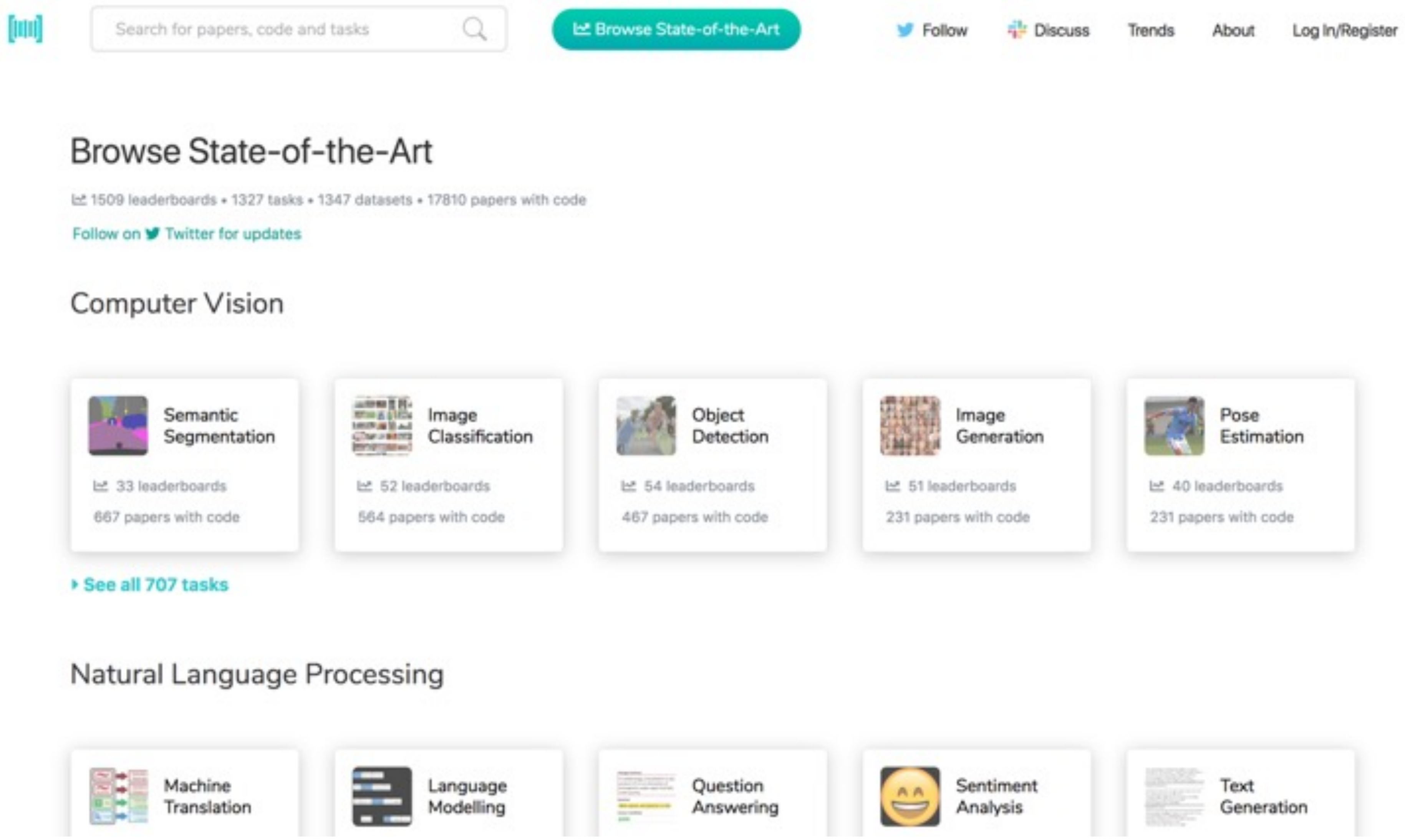
Figures (pdf)
Code (website); Pseudocode (pdf)
Covers: US, Global

http://aima.cs.berkeley.edu/

Papers with Code
State-of-the-Art (SOTA)



https://paperswithcode.com/sota

Summary

- **Deep Learning**
  - **Neural Networks (NN)**
  - **Convolutional Neural Networks (CNN)**
  - **Recurrent Neural Networks (RNN)**
- **Reinforcement Learning (RL)**
  - **Markov Decision Processes (MDP)**
- **Deep Reinforcement Learning (DRL) Algorithms**
  - **SARSA**
  - **Q-Learning**
  - **DQN**
  - **A3C**
  - **Rainbow**

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- Omer Berat Sezer, Mehmet Ugur Gudelek, and Ahmet Murat Ozbayoglu (2020), "Financial time series forecasting with deep learning: A systematic literature review: 2005–2019." Applied Soft Computing 90 (2020): 106181.
- Deep Learning Basics: Neural Networks Demystified, https://www.youtube.com/playlist?list=PLiaHhY2iBX9hdHaRr6b7XevZtgZRa1PoU
- Deep Learning SIMPLIFIED, https://www.youtube.com/playlist?list=PLjJh1vlSEYgvGod9wWiydumYl8hOXixNu
- 3Blue1Brown (2017), But what *is* a Neural Network? | Chapter 1, deep learning, https://www.youtube.com/watch?v=aircAruvnKk
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