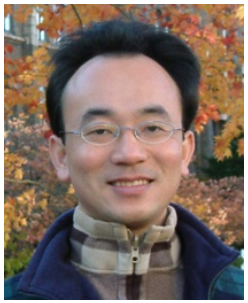
Tamkang University
淡江大學

人工智慧文本分析
(AI for Text Analytics)
人工智慧文本分析課程介紹
(Course Orientation on Artificial Intelligence for Text Analytics)

NTPU
國立臺北大學
National Taipei University

1091AITA01
MBA, IMTKU (M2455) (8418) (Fall 2020)
Thu 3, 4 (10:10-12:00) (B206)



Min-Yuh Day
戴敏育
Associate Professor
副教授
Institute of Information Management, National Taipei University
國立臺北大學 資訊管理研究所
https://web.ntpu.edu.tw/~myday

2020-09-17

人工智慧
文本分析
(Artificial Intelligence for Text Analytics)

淡江大學109學年度第1學期
課程教學計畫表
Fall 2020 (2020.09 - 2021.01)

- 課程名稱：**人工智慧文本分析**
  (Artificial Intelligence for Text Analytics)
- 授課教師：戴敏育 (Min-Yuh Day)
- 開課系級：資管所碩士班 (TLMXM1A)
- 開課資料：選修 單學期 2 學分 (2 Credits, Elective)
- 上課時間：週四 3, 4 (10:10-12:00)
- 上課教室： B206 (淡江大學淡水校園)
  遠距非同步課程

淡江大學

資訊管理學系

資訊創新

管理思維

IMTKU

淡江大學資訊管理系(所)教育目標

Tamkang University 淡江大學

- 致力於資訊科技與經營管理知識之科際整合研究發展，為國家與社會培育兼具資訊技術能力與現代管理知識的中高階人才。

淡江大學資訊管理系(所)核心能力

Tamkang University 淡江大學

- A. 現代管理知識應用。(10%)
- B. 邏輯思考。(10%)
- C. 關鍵分析。(10%)
- **D. 結合資訊技術與管理。(30%)**
- E. 研究與創新。(10%)
- **F. 資料分析與應用。(20%)**
- G. 資通安全管理。
- H. 言辭與文字表達。(10%)

本課程對應校級基本素養之項目與比重

Tamkang University 淡江大學

1. 全球視野 (10%)
2. 資訊運用 (50%)
3. 洞悉未來 (10%)
4. 品德倫理 (10%)
5. 獨立思考 (10%)
7. 團隊合作 (10%)

課程簡介

- 本課程介紹人工智慧文本分析基本概念與研究議題。
- 課程內容包括
  1. 文本分析的基礎：自然語言處理 (NLP)
  2. Python自然語言處理
  3. 處理和理解文本
  4. 文本表達特徵工 程
  5. 文本分類
  6. 文本摘要和主題模型
  7. 文本相似度和分群
  8. 語意分析與命名實體識別 (NER)
  9. 情感分析
  10. 深度學習和通用句子嵌入模型
  11. 問答系統與對話系 統
  12. 文字探勘個案研究

Course Introduction

- This course introduces the fundamental concepts and research issues of artificial intelligence for text analytics.
- Topics include
  1. Foundations of Text Analytics: Natural Language Processing (NLP)
  2. Python for NLP
  3. Processing and Understanding Text
  4. Feature Engineering for Text Representation
  5. Text Classification
  6. Text Summarization and Topic Models
  7. Text Similarity and Clustering
  8. Semantic Analysis and Named Entity Recognition
  9. Sentiment Analysis
  10. The Promise of Deep Learning and Universal Sentence-Embedding Models
  11. Question Answering and Dialogue Systems
  12. Case Study on AI Text Analytics

課程目標
(Objective)

- 瞭解及應用人工智慧文本分析基本概念與研究議題。
  Understand and apply the fundamental concepts and research issues of artificial intelligence for text analytics.

- 進行人工智慧文本分析相關之資訊管理研究。
  Conduct information systems research in the context of artificial intelligence for text analytics.

課程大綱 (Syllabus)

週次 (Week)　日期 (Date)　內容 (Subject/Topics)

1 2020/09/17 人工智慧文本分析課程介紹
(Course Orientation on Artificial Intelligence for Text Analytics)

2 2020/09/24 文本分析的基礎：自然語言處理
(Foundations of Text Analytics: Natural Language Processing; NLP)

3 2020/10/01 中秋節 (Mid-Autumn Festival) 放假一天 (Day off)

4 2020/10/08 Python自然語言處理
(Python for Natural Language Processing)

5 2020/10/15 處理和理解文本
(Processing and Understanding Text)

6 2020/10/22 文本表達特徵工程
(Feature Engineering for Text Representation)

課程大綱 (Syllabus)

週次 (Week)	日期 (Date)	內容 (Subject/Topics)
7	2020/10/29	人工智慧文本分析個案研究 I (Case Study on Artificial Intelligence for Text Analytics I)
8	2020/11/05	文本分類 (Text Classification)
9	2020/11/12	文本摘要和主題模型 (Text Summarization and Topic Models)
10	2020/11/19	期中報告 (Midterm Project Report)
11	2020/11/26	文本相似度和分群 (Text Similarity and Clustering)
12	2020/12/03	語意分析和命名實體識別 (Semantic Analysis and Named Entity Recognition; NER)

課程大綱 (Syllabus)

週次 (Week)	日期 (Date)	內容 (Subject/Topics)
13	2020/12/10	情感分析 (Sentiment Analysis)
14	2020/12/17	人工智慧文本分析個案研究 II (Case Study on Artificial Intelligence for Text Analytics II)
15	2020/12/24	深度學習和通用句子嵌入模型 (Deep Learning and Universal Sentence-Embedding Models)
16	2020/12/31	問答系統與對話系統 (Question Answering and Dialogue Systems)
17	2021/01/07	期末報告 I (Final Project Presentation I)
18	2021/01/14	期末報告 II (Final Project Presentation II)

教學方法與評量方法

- 教學方法

  －講述、討論、
  發表、實作

- 評量方法

  －討論、實作、報告

教材課本

- 教材課本
  - 講義 (Slides)
  - 人工智慧文本分析相關個案與論文 (Cases and Papers related to AI for Text Analytics)

參考書籍 (References)

1. Dipanjan Sarkar (2019),
   Text Analytics with Python: A Practitioner's Guide to Natural Language Processing, Second Edition. APress.
2. Benjamin Bengfort, Rebecca Bilbro, and Tony Ojeda (2018),
   Applied Text Analysis with Python:
   Enabling Language-Aware Data Products with Machine Learning, O'Reilly.
3. Charu C. Aggarwal (2018),
   Machine Learning for Text, Springer.
4. Gabe Ignatow and Rada F. Mihalcea (2017),
   An Introduction to Text Mining: Research Design, Data Collection, and Analysis, SAGE Publications.

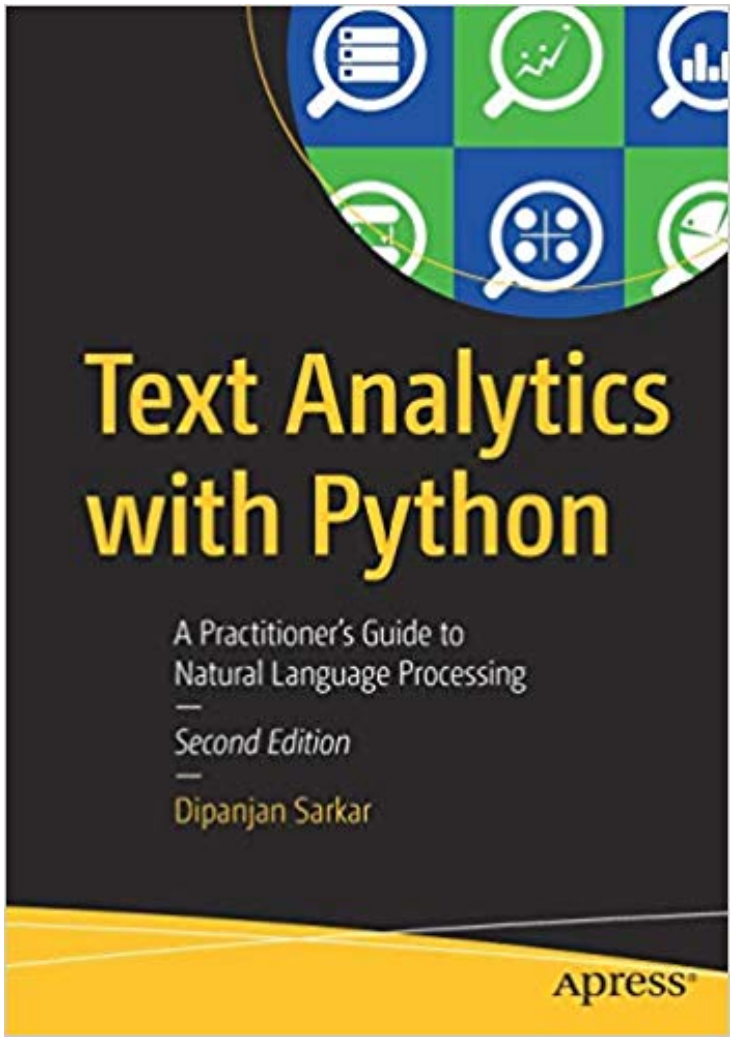
作業與學期成績計算方式

- 作業篇數
  - 3篇
- 學期成績計算方式
  - ☑期中評量：30 %
  - ☑期末評量：30 %
  - ☑其他（課堂參與及報告討論表現）：40 %

Dipanjan Sarkar (2019),

Text Analytics with Python:

A Practitioner's Guide to Natural Language Processing, Second Edition. APress.



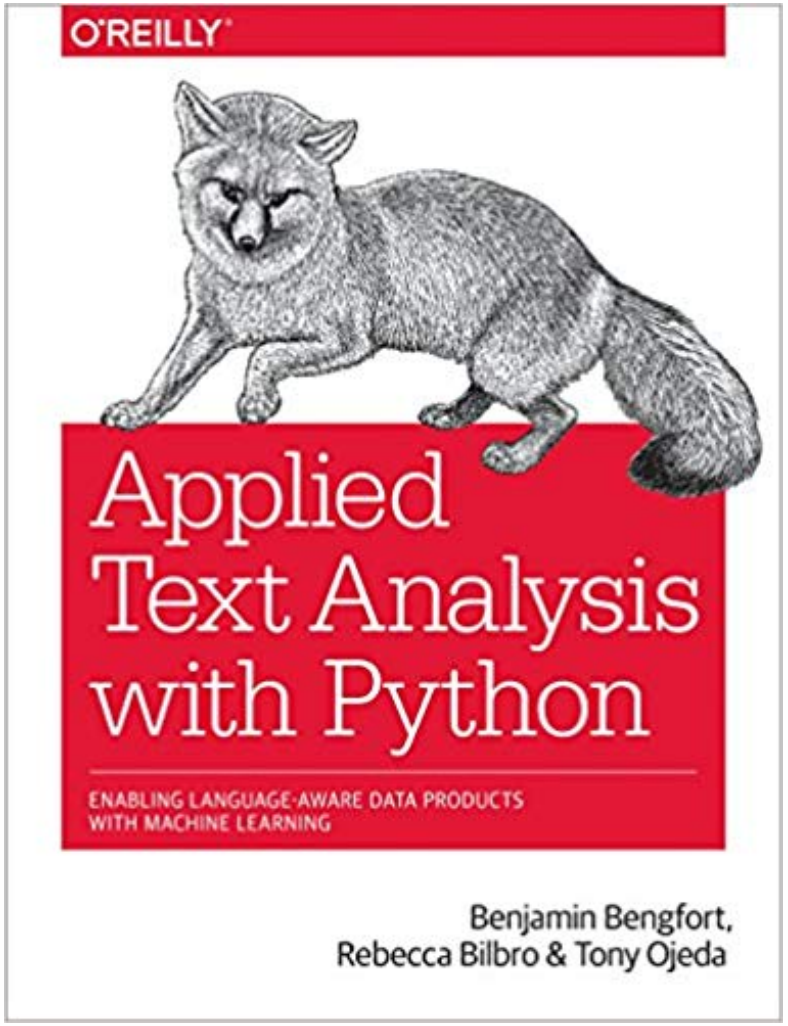
Source: https://www.amazon.com/Text-Analytics-Python-Practitioners-Processing/dp/1484243536

Benjamin Bengfort, Rebecca Bilbro, and Tony Ojeda (2018),

Applied Text Analysis with Python:

Enabling Language-Aware Data Products with Machine Learning,

O'Reilly.

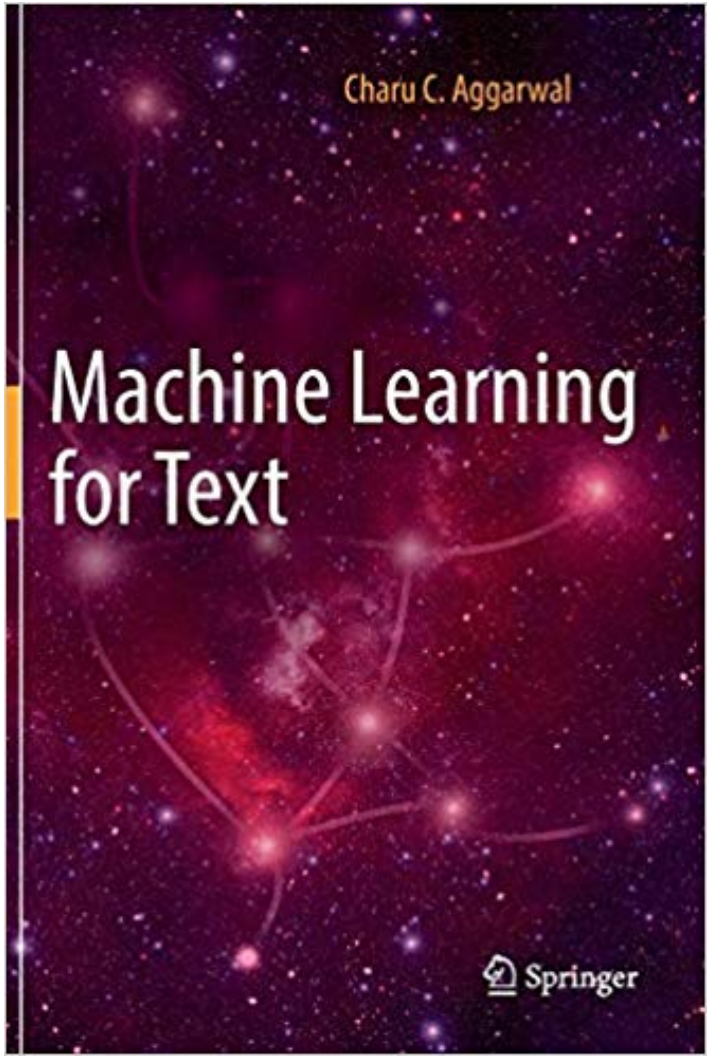


Source: https://www.amazon.com/Applied-Text-Analysis-Python-Language-Aware/dp/1491963042

Charu C. Aggarwal (2018),

Machine Learning for Text,

Springer



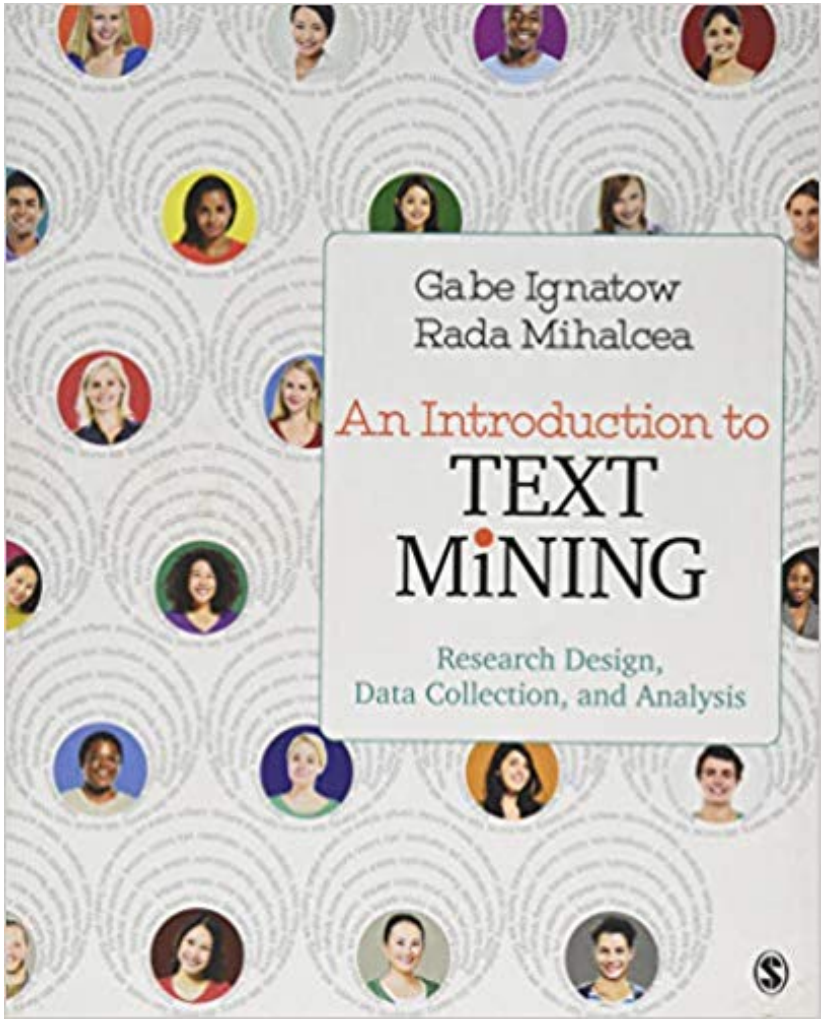
Source: https://www.amazon.com/Machine-Learning-Text-Charu-Aggarwal/dp/3319735306

Gabe Ignatow and Rada F. Mihalcea (2017),

An Introduction to Text Mining:

Research Design, Data Collection, and Analysis,

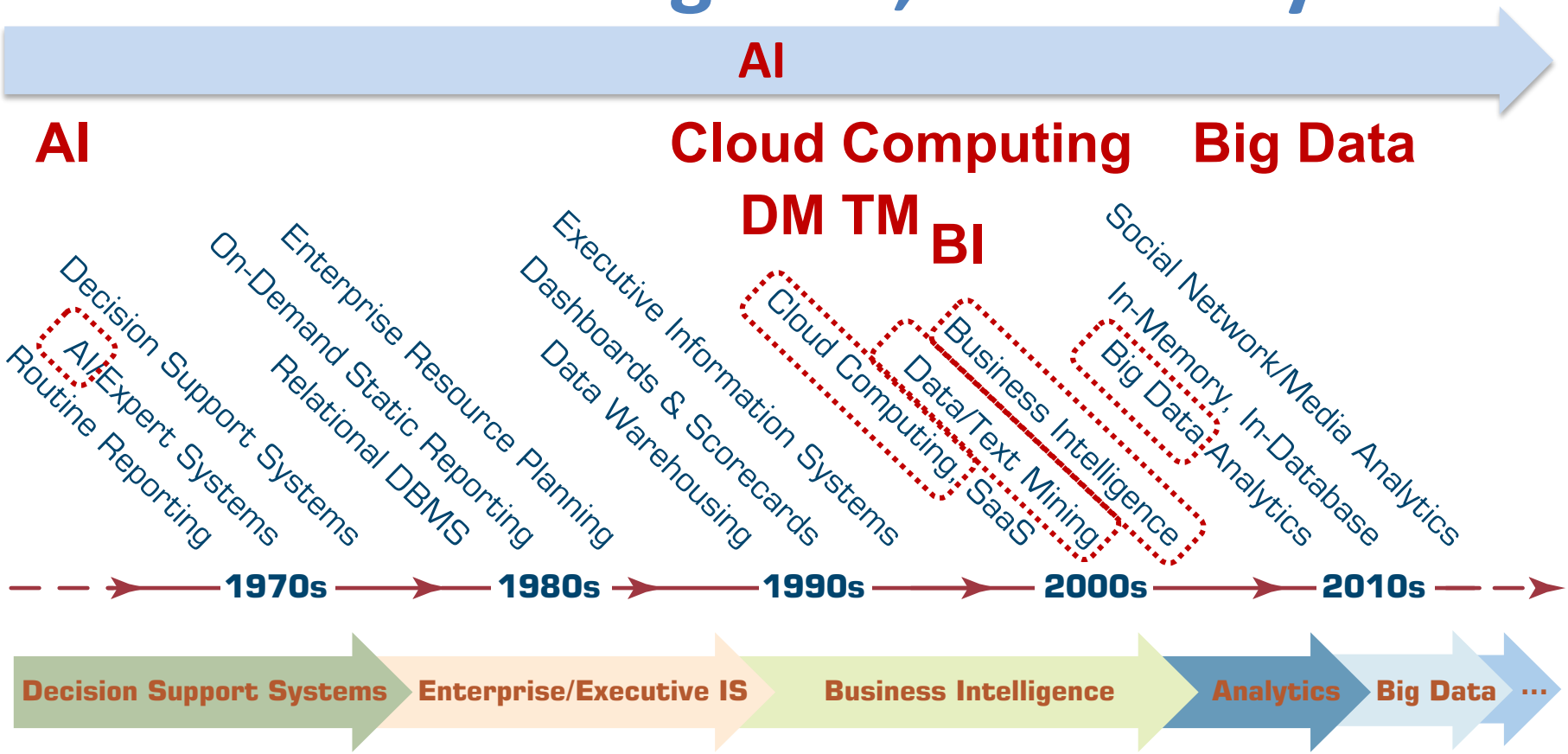
SAGE Publications.



Source: https://www.amazon.com/Introduction-Text-Mining-Research-Collection/dp/1506337007

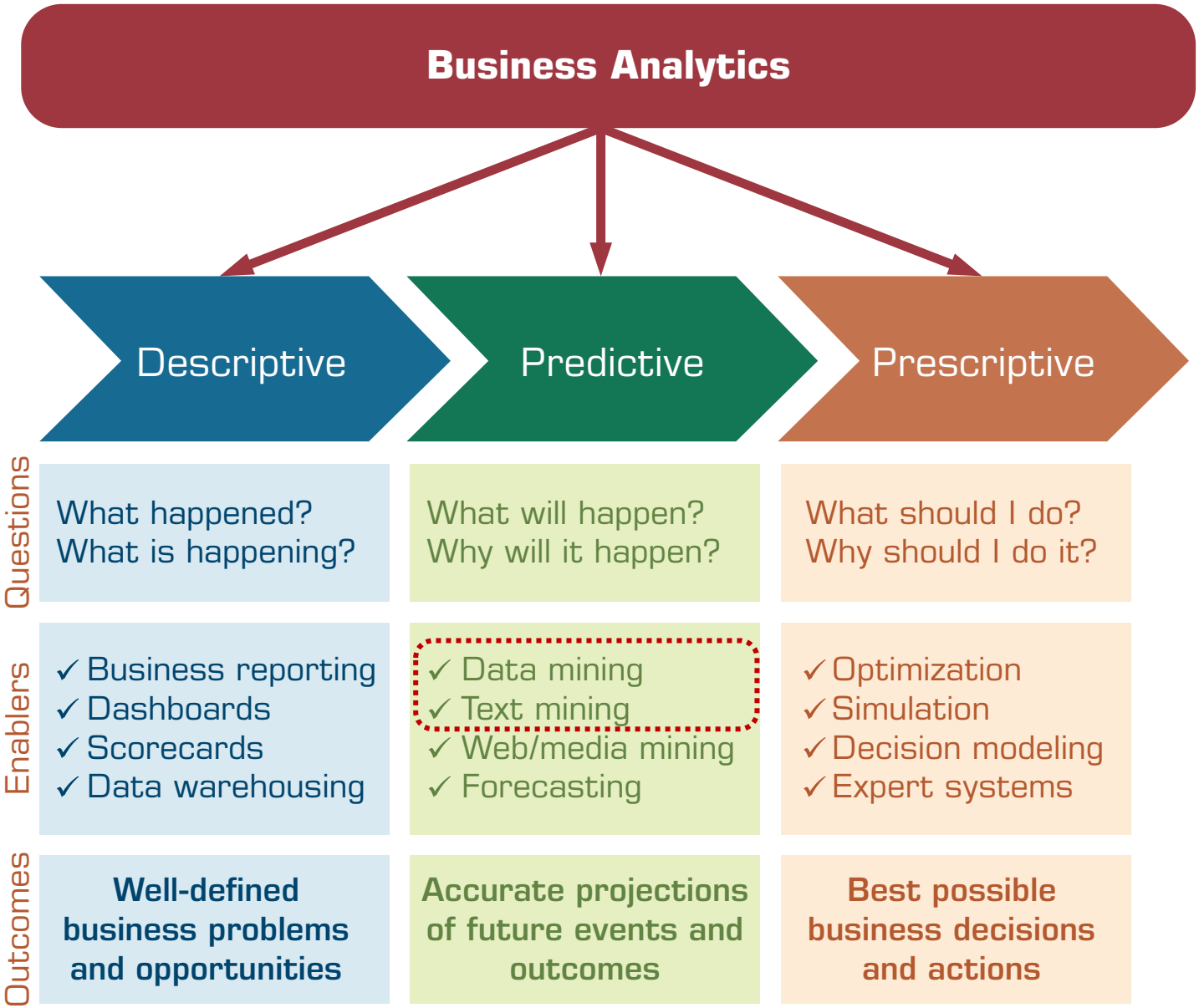
AI, Big Data, Cloud Computing

Evolution of Decision Support, Business Intelligence, and Analytics



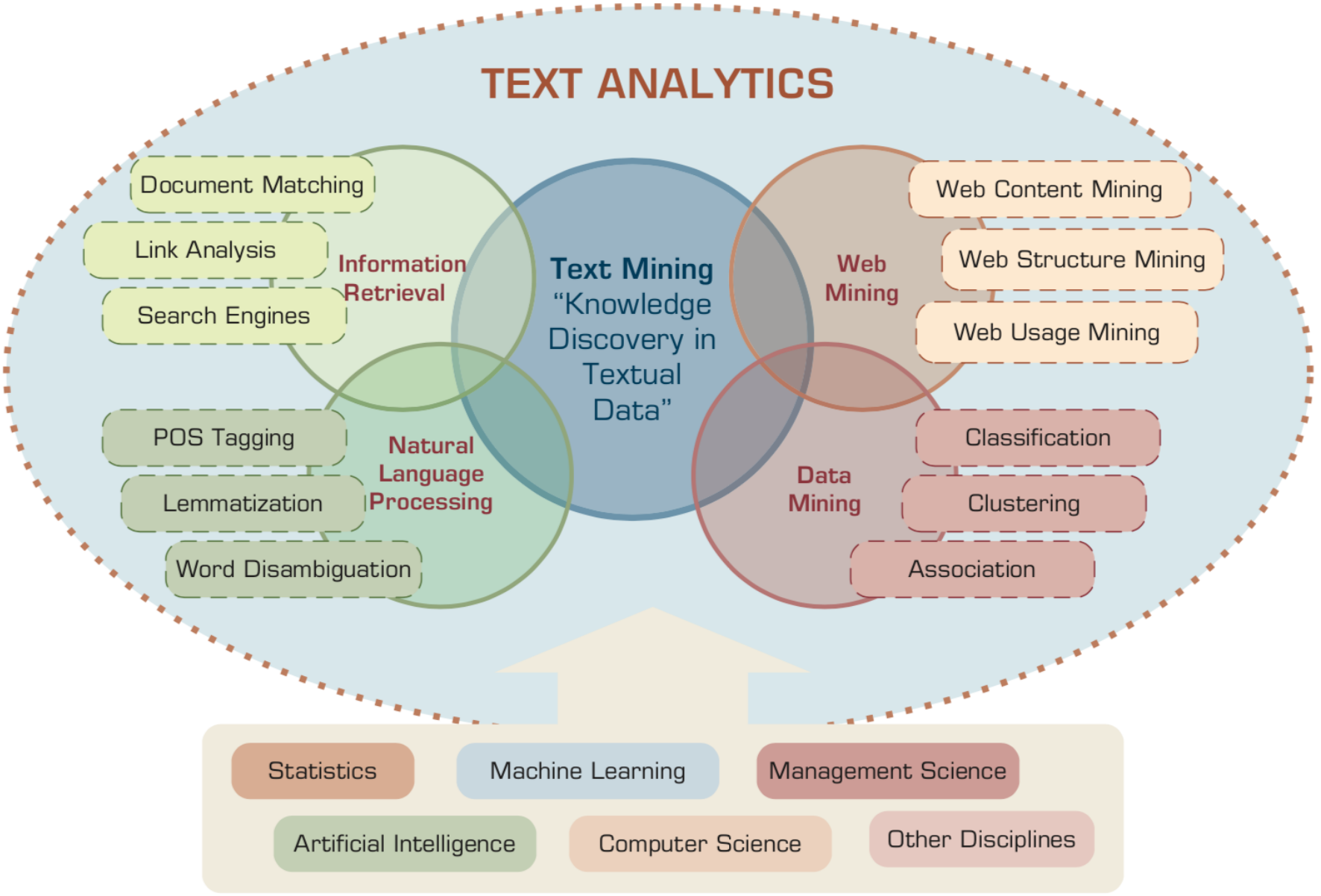
Source: Ramesh Sharda, Dursun Delen, and Efraim Turban (2017),
Business Intelligence, Analytics, and Data Science: A Managerial Perspective, 4th Edition, Pearson

Three Types of Analytics



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

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

Text Analytics

- **Text Analytics =**
  Information Retrieval +
  Information Extraction +
  Data Mining +
  Web Mining
- **Text Analytics =**
  Information Retrieval +
  Text Mining

Text mining

- Text Data Mining
- Knowledge Discovery in Textual Databases

Application Areas of Text Mining

- Information extraction
- Topic tracking
- Summarization
- Categorization
- Clustering
- Concept linking
- Question answering

Natural Language Processing (NLP)

- Natural language processing (NLP) is an important component of text mining and is a subfield of artificial intelligence and computational linguistics.

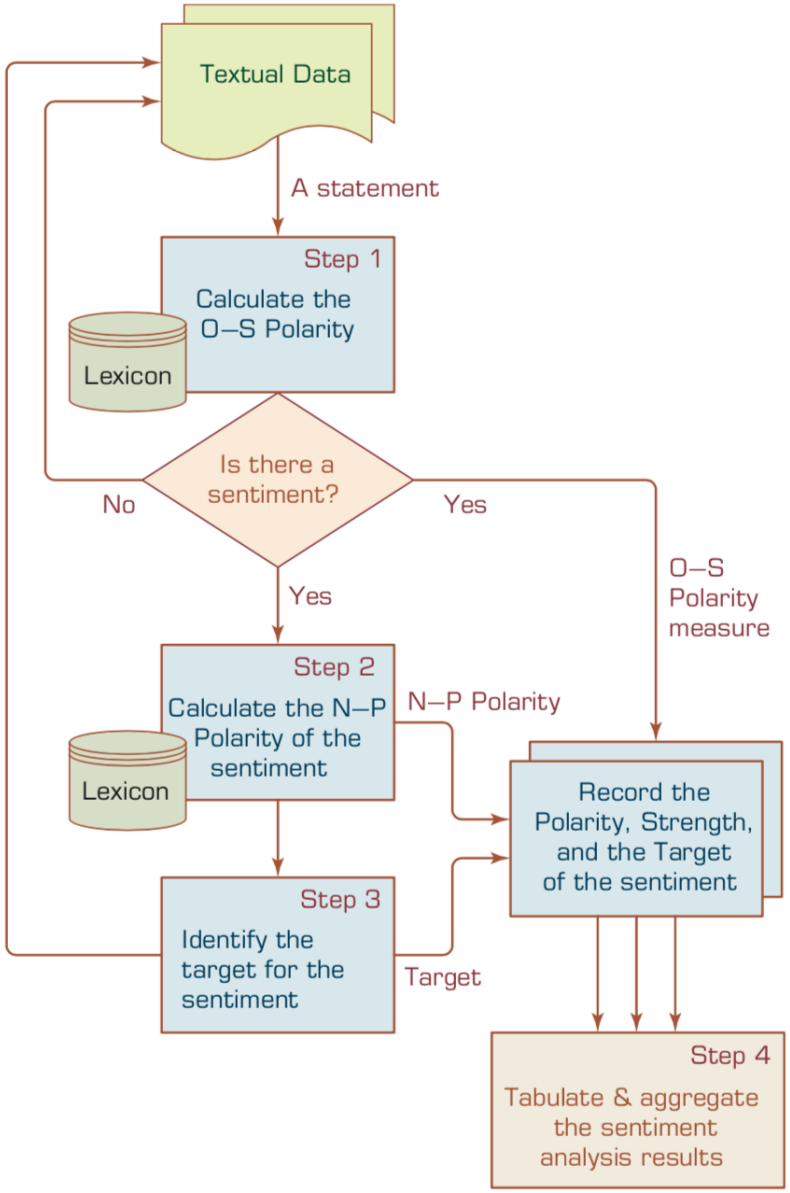
Natural Language Processing (NLP)

- Part-of-speech tagging
- Text segmentation
- Word sense disambiguation
- Syntactic ambiguity
- Imperfect or irregular input
- Speech acts

NLP Tasks

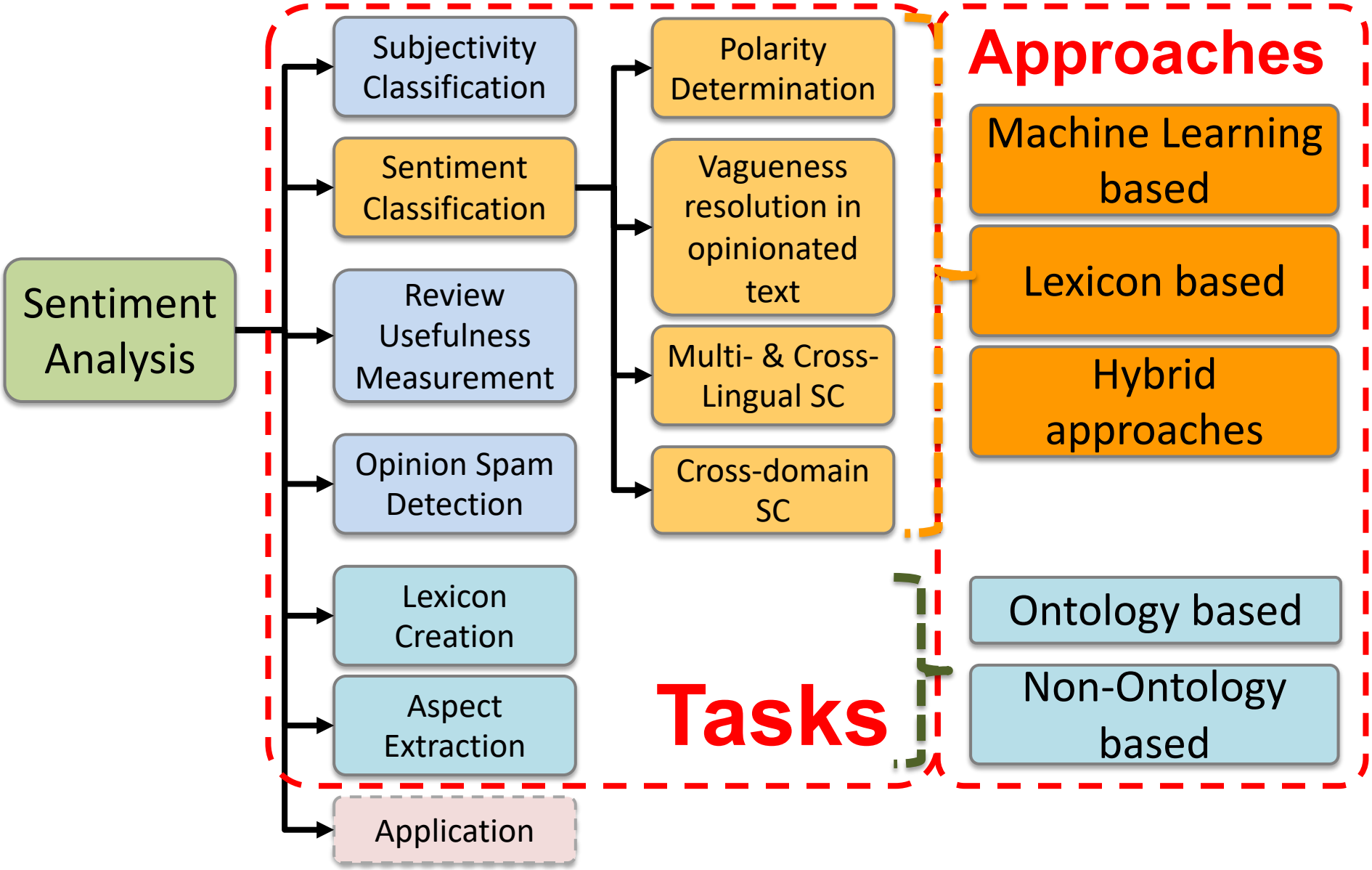
- Question answering
- Automatic summarization
- Natural language generation
- Natural language understanding
- Machine translation
- Foreign language reading
- Foreign language writing.
- Speech recognition
- Text-to-speech
- Text proofing
- Optical character recognition

A Multistep Process to Sentiment Analysis



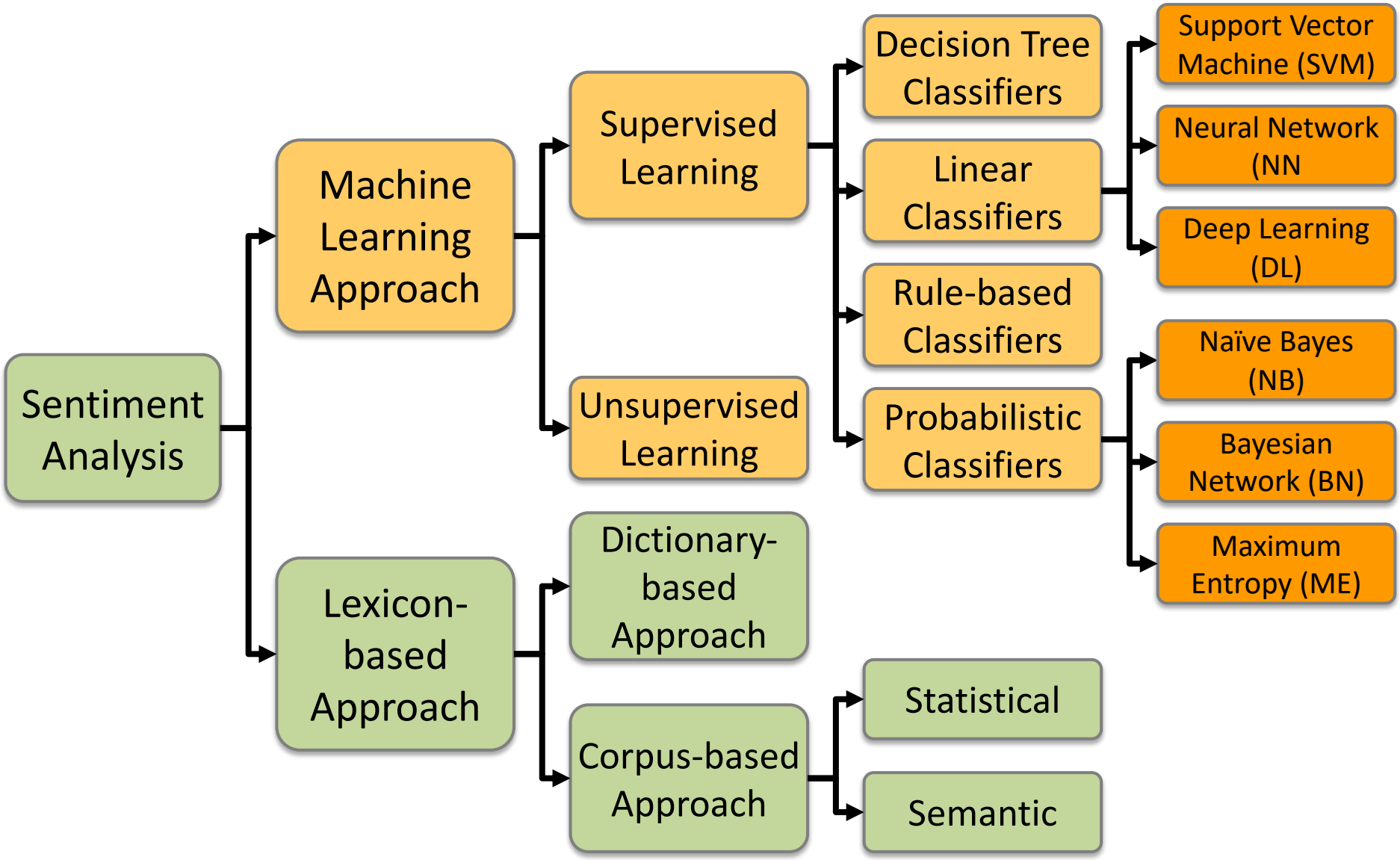
Source: Ramesh Sharda, Dursun Delen, and Efraim Turban (2017), Business Intelligence, Analytics, and Data Science: A Managerial Perspective, 4th Edition, Pearson

Sentiment Analysis



Source: Kumar Ravi and Vadlamani Ravi (2015), "A survey on opinion mining and sentiment analysis: tasks, approaches and applications." Knowledge-Based Systems, 89, pp.14-46.

Sentiment Classification Techniques



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.

Example of Opinion: review segment on iPhone

"I bought an iPhone a few days ago.

It was such a nice phone.

The touch screen was really cool.

The voice quality was clear too.

However, my mother was mad with me as I did not tell her before I bought it.

She also thought the phone was too expensive, and wanted me to return it to the shop. … "

Source: Bing Liu (2011) , "Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data," Springer, 2nd Edition,

Example of Opinion: review segment on iPhone

"(1) I bought an iPhone a few days ago.

(2) It was such a **nice** phone.

(3) The touch screen was really **cool**.

+Positive Opinion

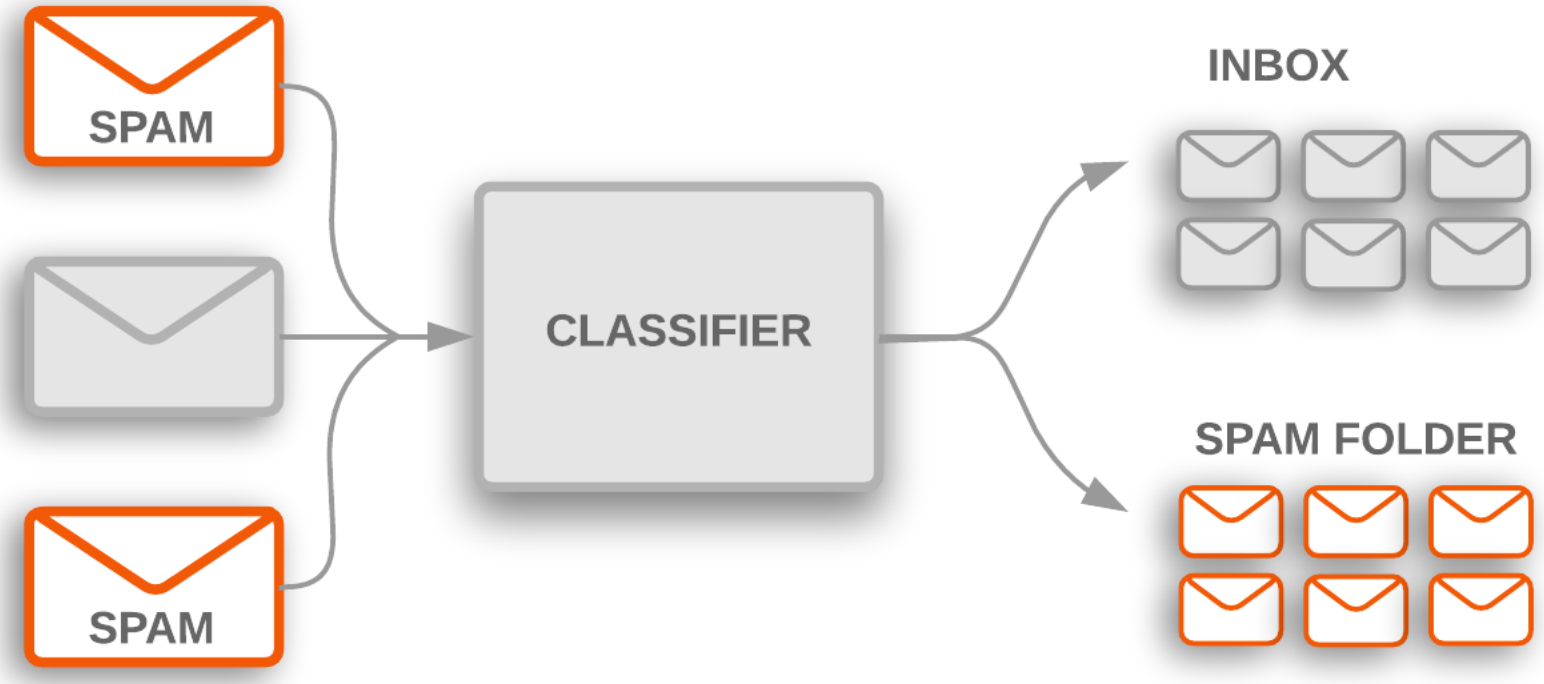
(4) The voice quality was **clear** too.

(5) However, my mother was mad with me as I did not tell her before I bought it.

(6) She also thought the phone was too **expensive**, and wanted me to return it to the shop. … "

-Negative Opinion

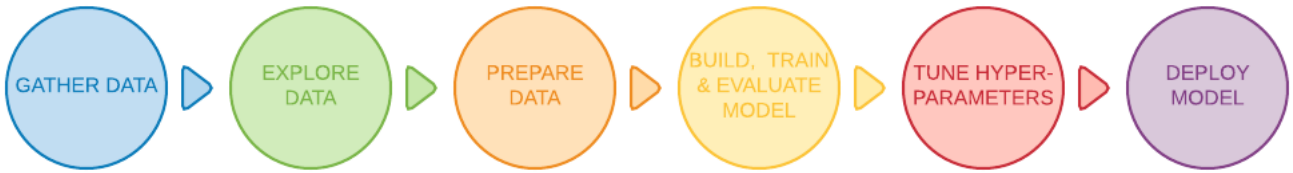
Text Classification



Source: https://developers.google.com/machine-learning/guides/text-classification/

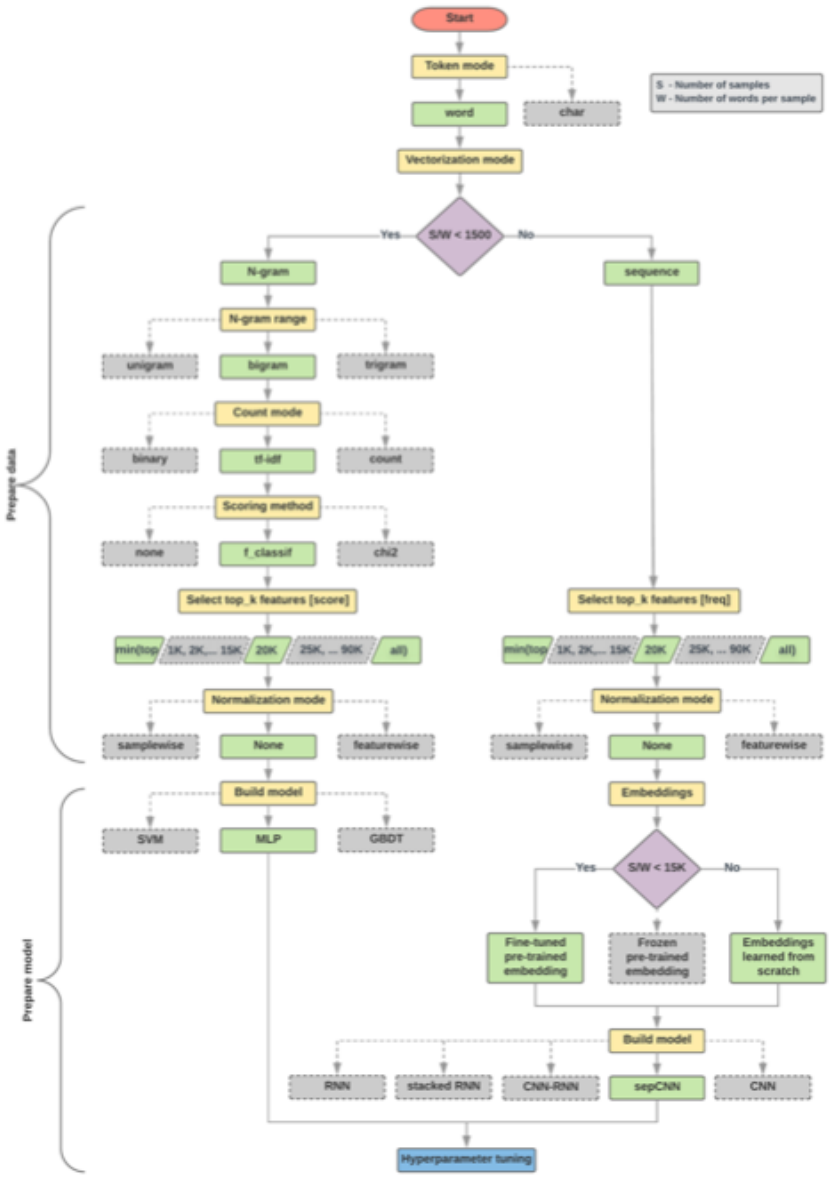
Text Classification Workflow

- Step 1: Gather Data
- Step 2: Explore Your Data
- Step 2.5: Choose a Model*
- Step 3: Prepare Your Data
- Step 4: Build, Train, and Evaluate Your Model
- Step 5: Tune Hyperparameters
- Step 6: Deploy Your Model



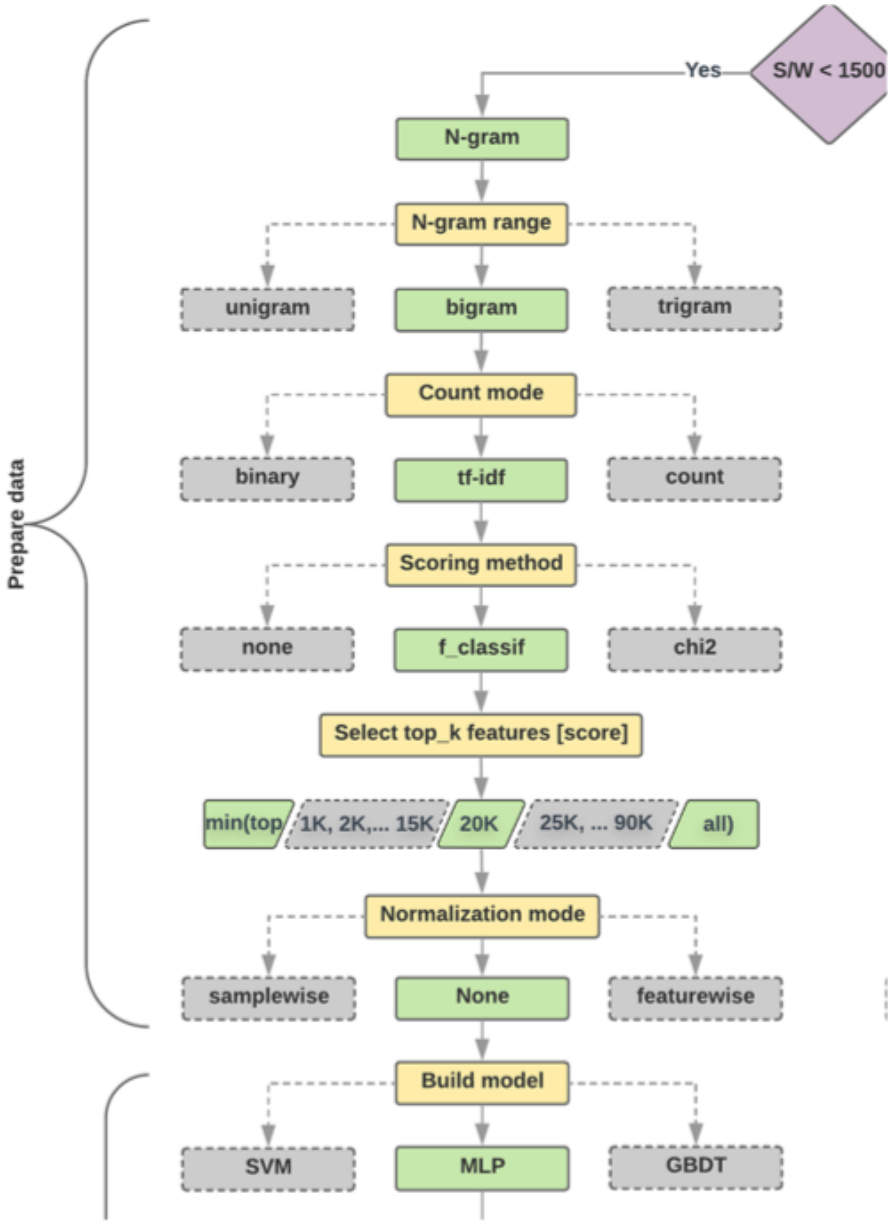
Source: https://developers.google.com/machine-learning/guides/text-classification/

Text Classification Flowchart



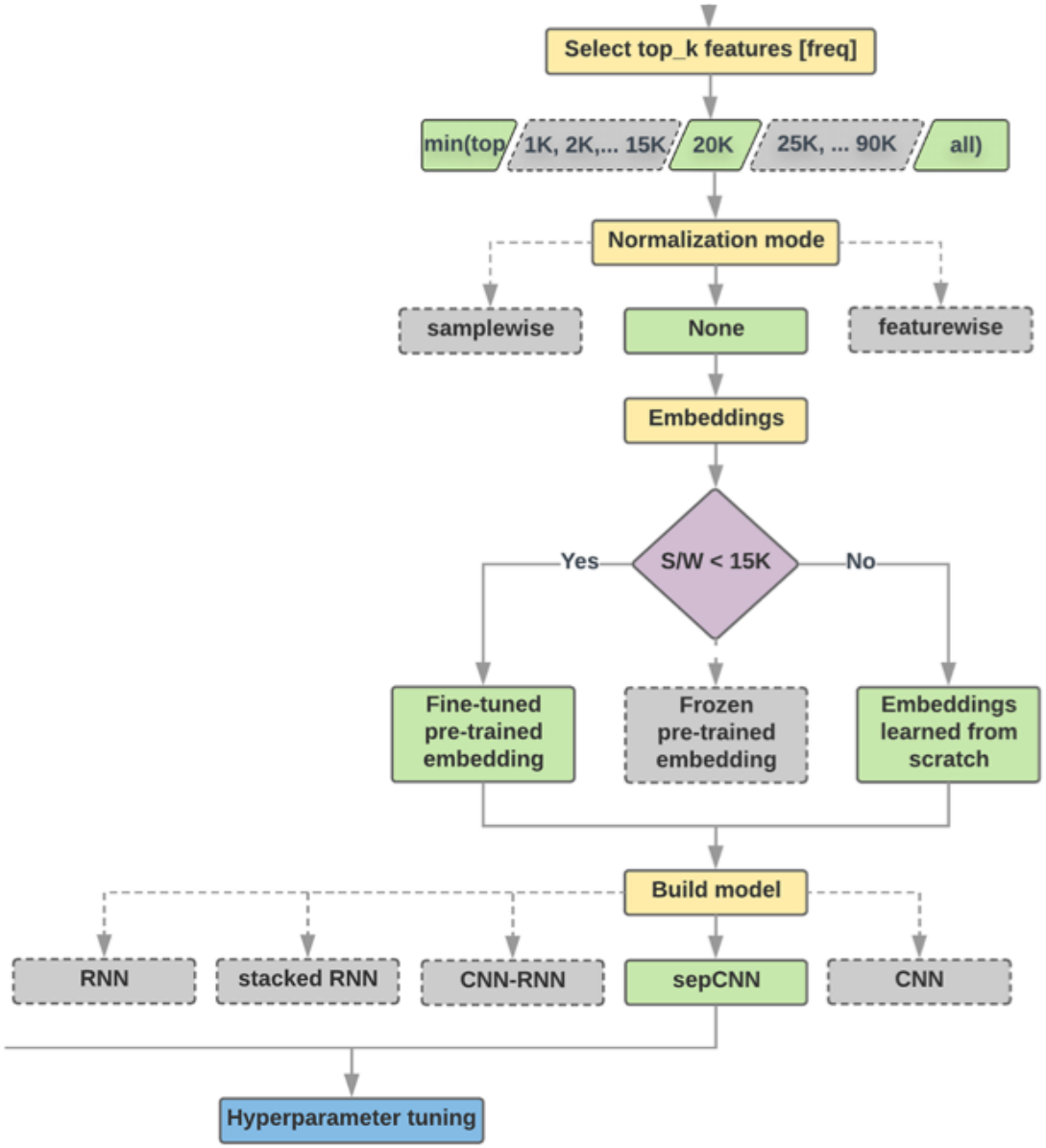
Source: https://developers.google.com/machine-learning/guides/text-classification/step-2-5

Text Classification S/W<1500: N-gram



Source: https://developers.google.com/machine-learning/guides/text-classification/step-2-5

Text Classification S/W>=1500: Sequence

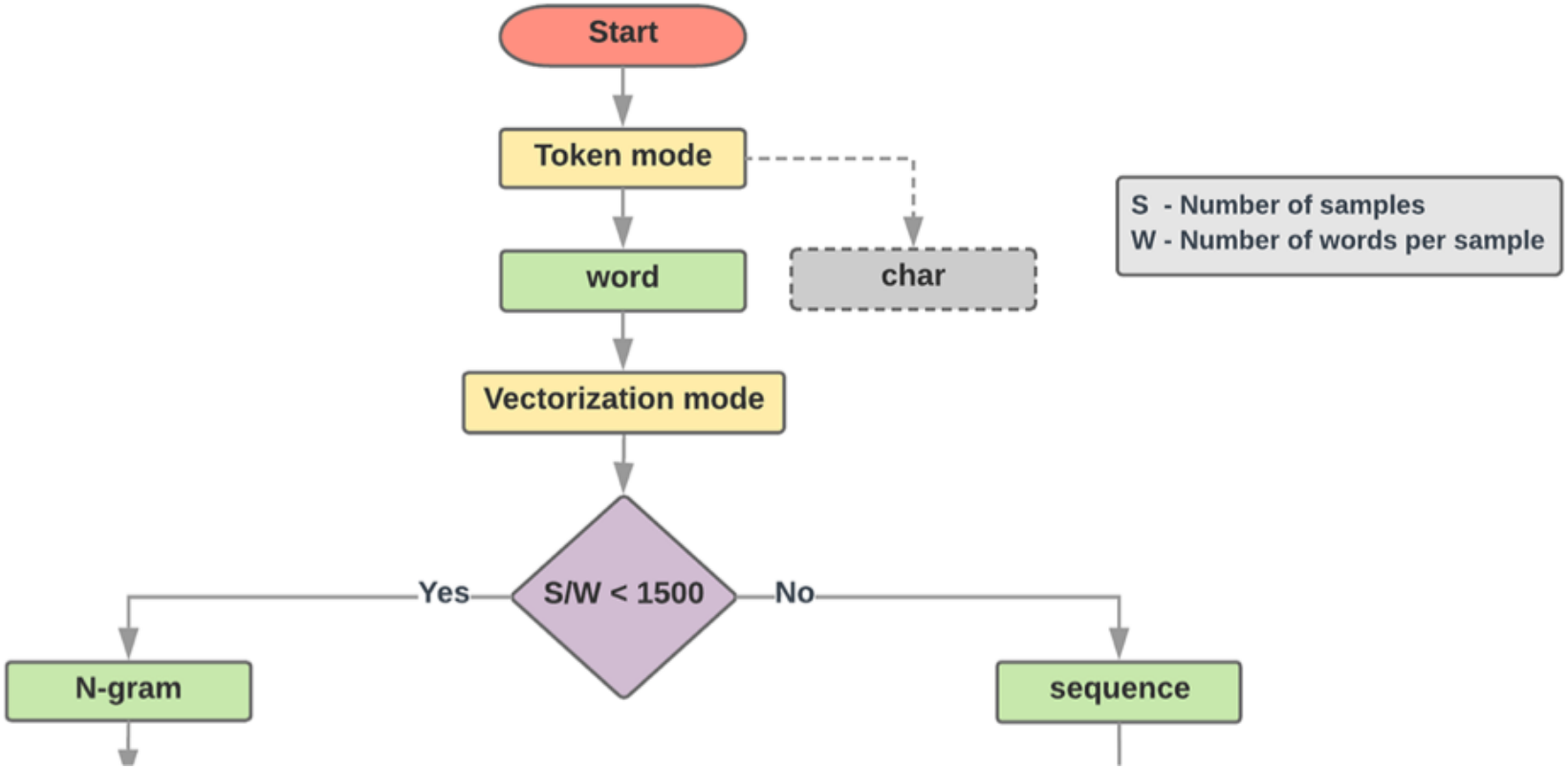


Source: https://developers.google.com/machine-learning/guides/text-classification/step-2-5

Step 2.5: Choose a Model

Samples/Words < 1500

150,000/100 = 1500



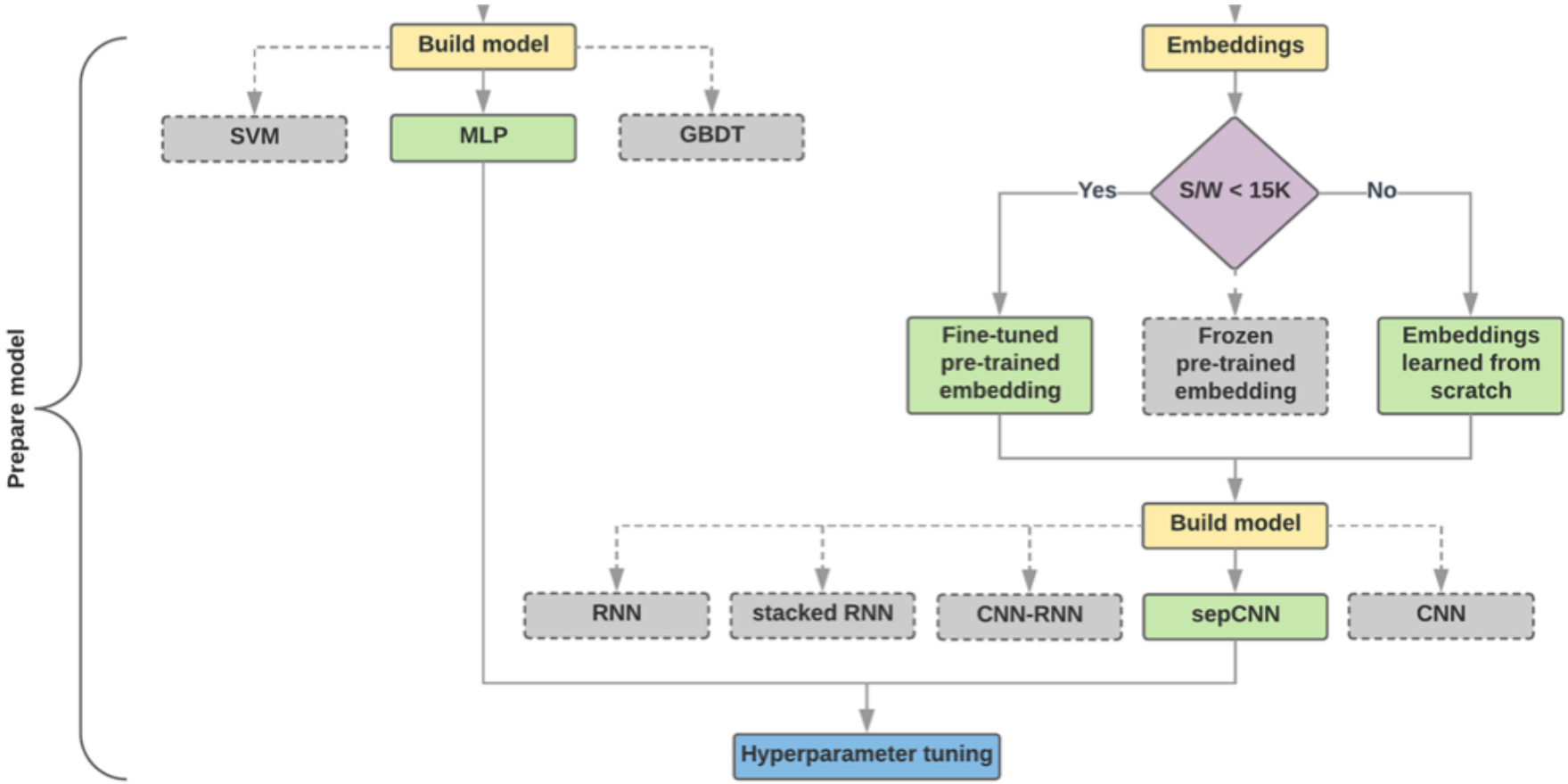
IMDb review dataset,
the samples/words-per-sample ratio is ~ 144

Source: https://developers.google.com/machine-learning/guides/text-classification/step-2-5

Step 2.5: Choose a Model

Samples/Words < 15,000

1,500,000/100 = 15,000



Source: https://developers.google.com/machine-learning/guides/text-classification/step-2-5

Step 3: Prepare Your Data

```
Texts:
T1: 'The mouse ran up the clock'
T2: 'The mouse ran down'

Token Index:
{'the': 1, 'mouse': 2, 'ran': 3, 'up': 4, 'clock': 5, 'down': 6,}.
   NOTE: 'the' occurs most frequently,
         so the index value of 1 is assigned to it.
         Some libraries reserve index 0 for unknown tokens,
         as is the case here.

Sequence of token indexes:
T1: 'The mouse ran up the clock' =
      [1,  2,   3, 4,  1,  5]
T1: 'The mouse ran down' =
      [1,   2,   3,  6]
```

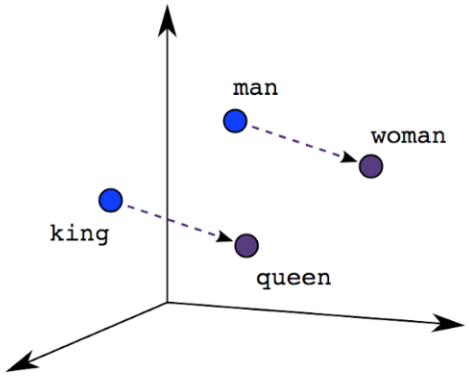
Source: https://developers.google.com/machine-learning/guides/text-classification/step-3

One-hot encoding

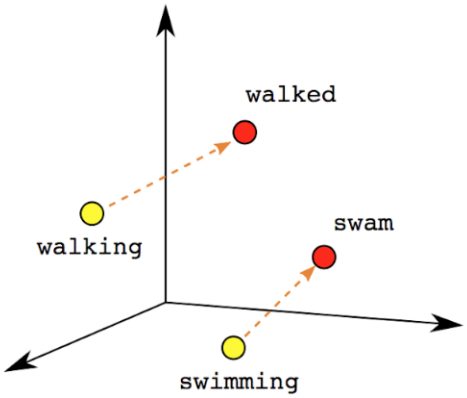
```
                'The mouse ran up the clock' =

The      1   [ [0, 1, 0, 0, 0, 0, 0],
mouse    2     [0, 0, 1, 0, 0, 0, 0],
ran      3     [0, 0, 0, 1, 0, 0, 0],
up       4     [0, 0, 0, 0, 1, 0, 0],
the      1     [0, 1, 0, 0, 0, 0, 0],
clock    5     [0, 0, 0, 0, 0, 1, 0] ]

                [0, 1, 2, 3, 4, 5, 6]
```

Source: https://developers.google.com/machine-learning/guides/text-classification/step-3

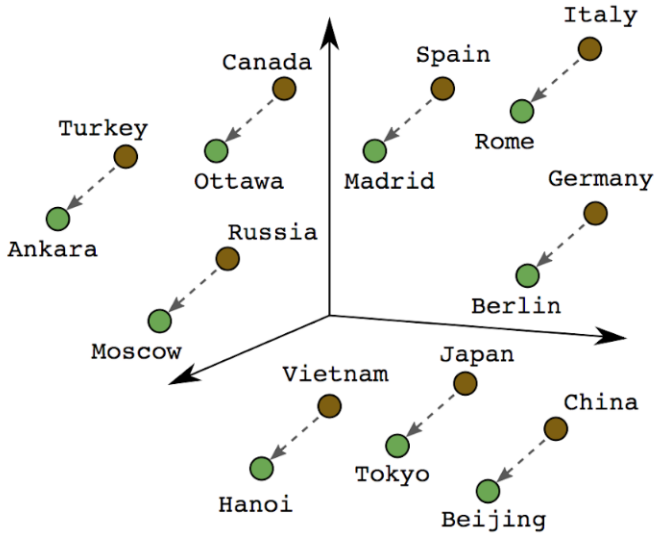
Word embeddings



Male-Female



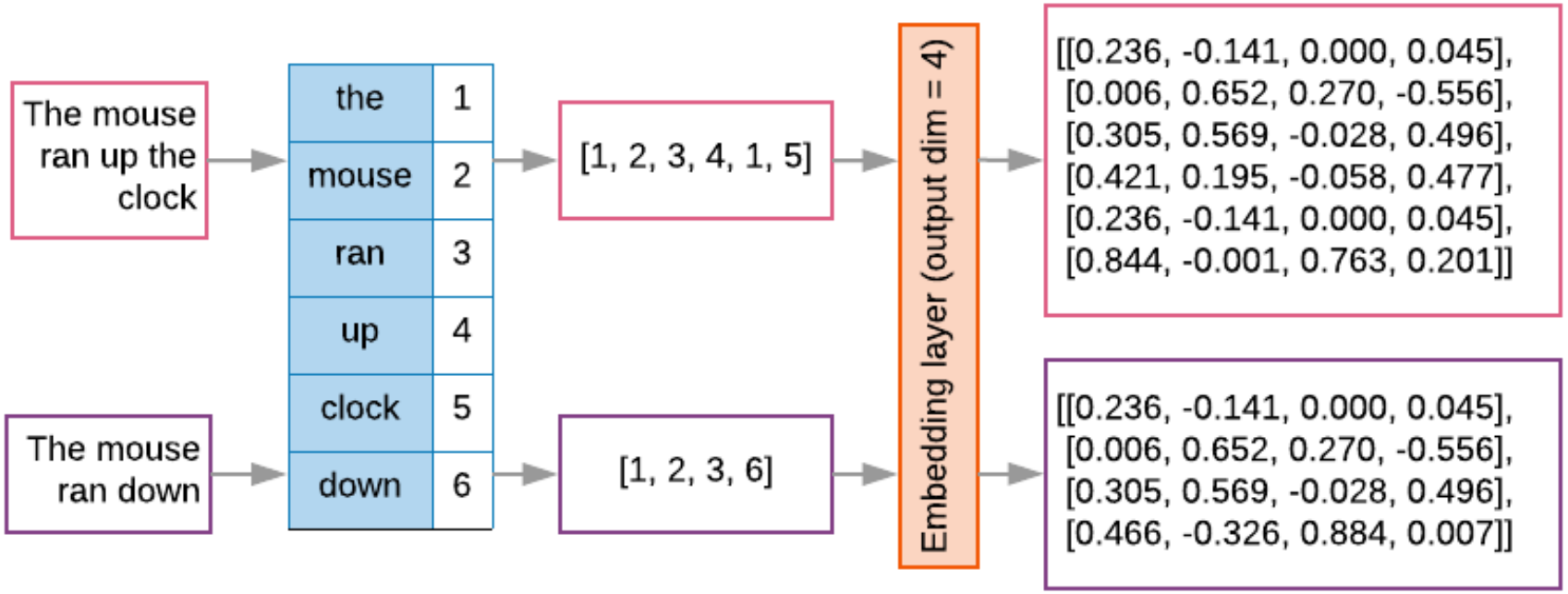
Verb Tense



Country-Capital

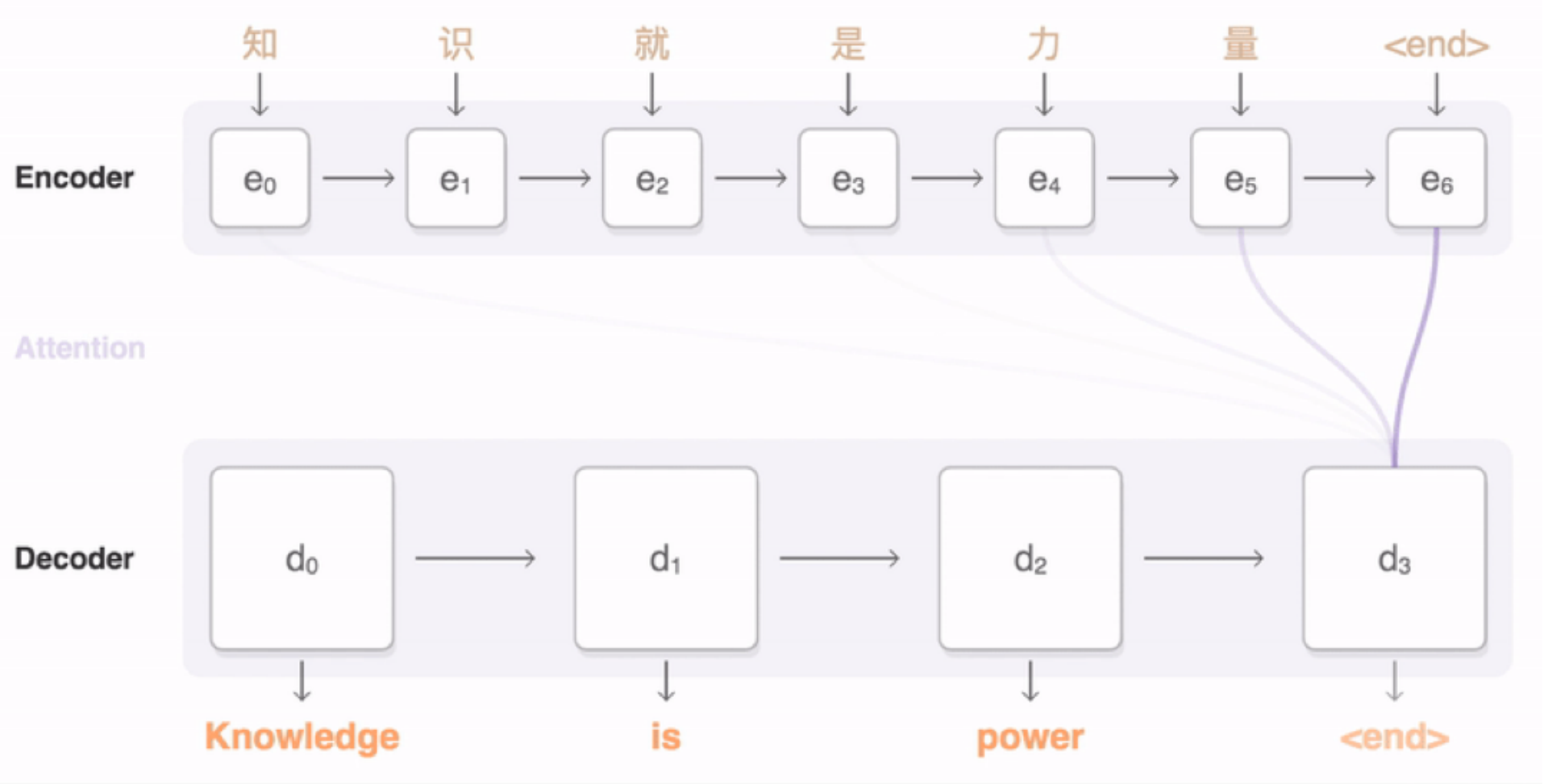
Source: https://developers.google.com/machine-learning/guides/text-classification/step-3

Word embeddings



Source: https://developers.google.com/machine-learning/guides/text-classification/step-3

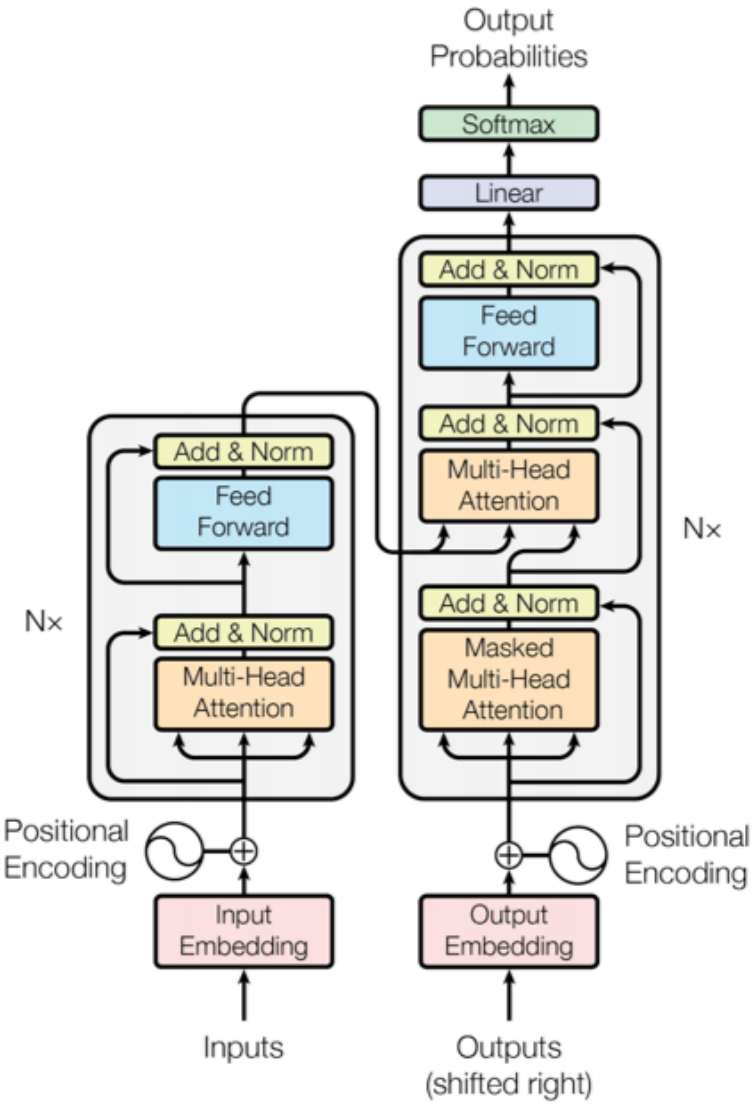
Sequence to Sequence (Seq2Seq)



Source: https://google.github.io/seq2seq/

Transformer (Attention is All You Need)

(Vaswani et al., 2017)

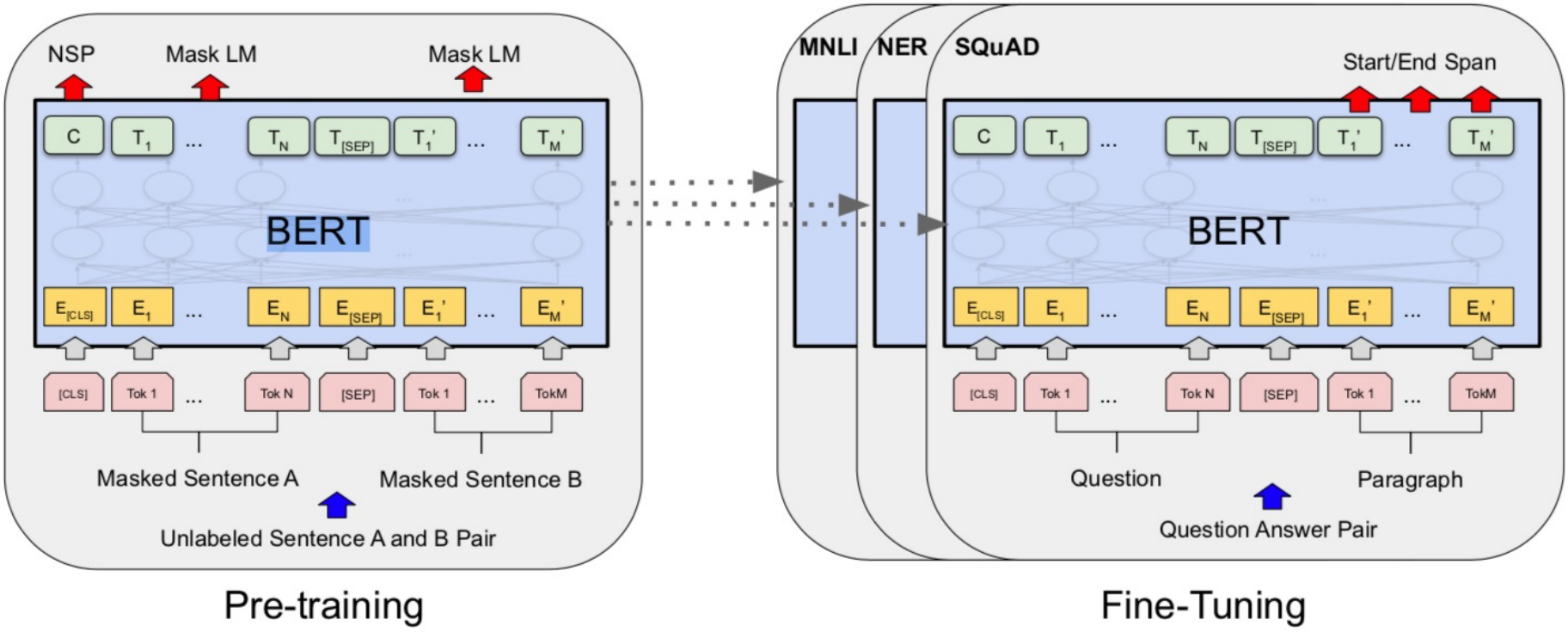


Source: Vaswani, Ashish, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Łukasz Kaiser, and Illia Polosukhin. "Attention is all you need." In *Advances in neural information processing systems*, pp. 5998-6008. 2017.

BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

BERT (Bidirectional Encoder Representations from Transformers)

Overall pre-training and fine-tuning procedures for BERT

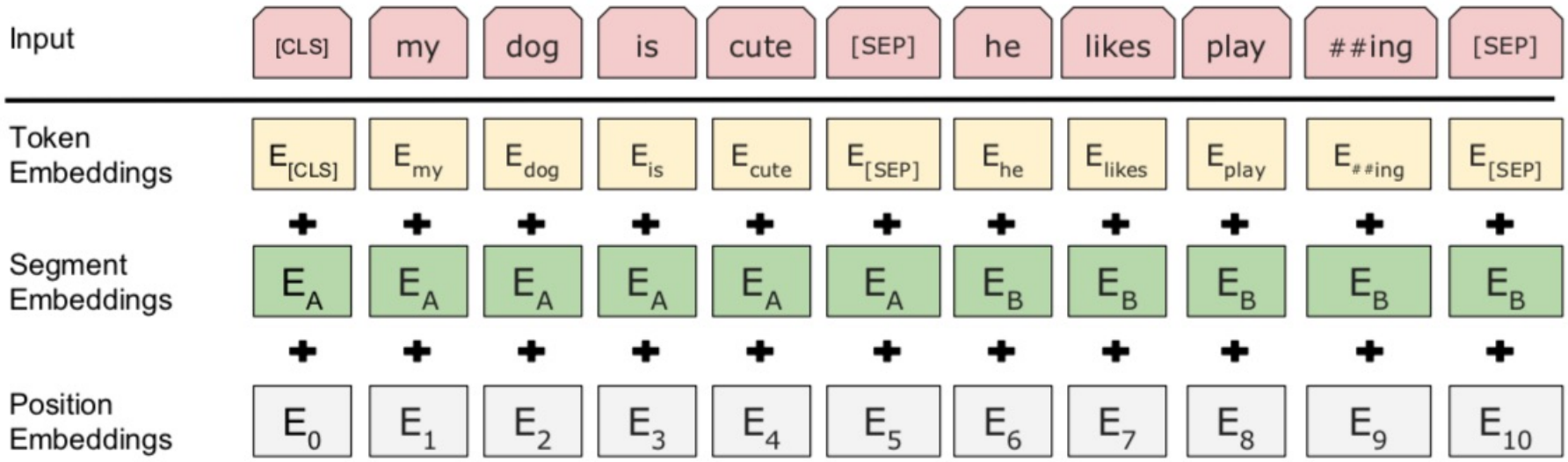


Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018).
"Bert: Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805.

BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

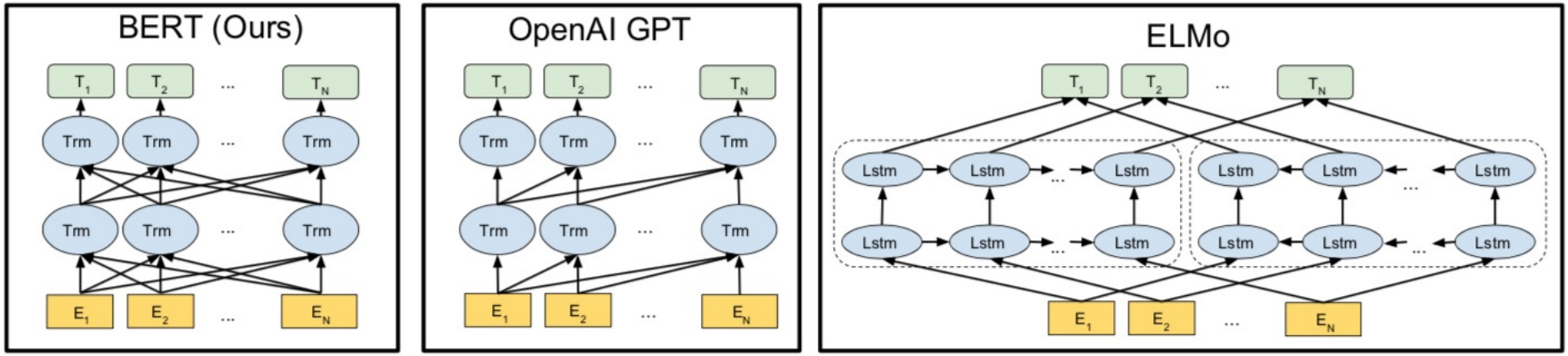
BERT (Bidirectional Encoder Representations from Transformers)

BERT input representation



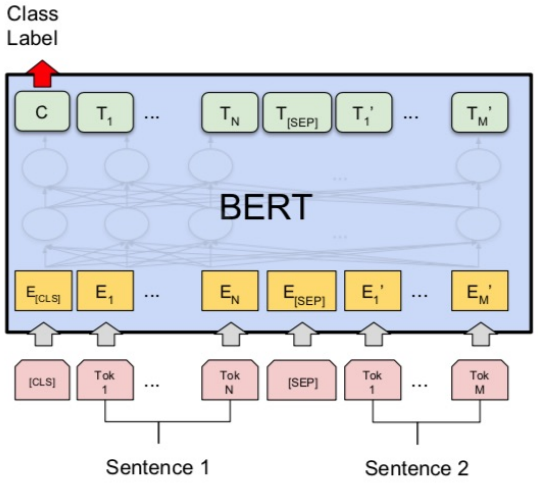
Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018).
"Bert: Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805.

BERT, OpenAI GPT, ELMo

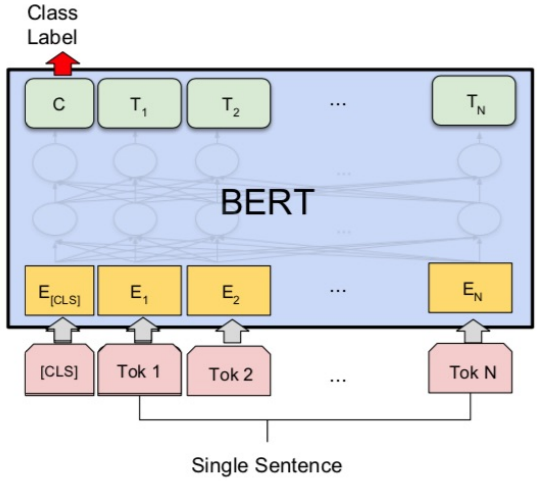


Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018).
"Bert: Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805.

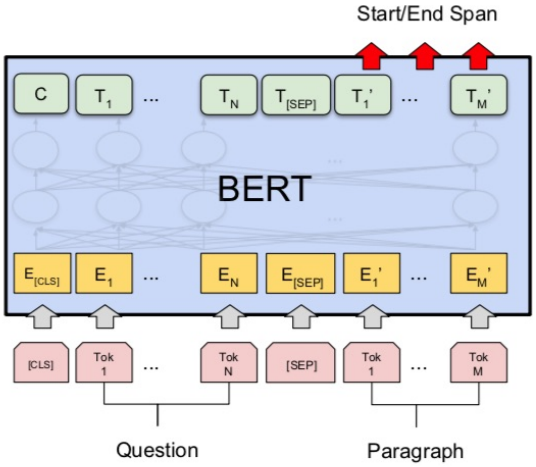
Fine-tuning BERT on Different Tasks



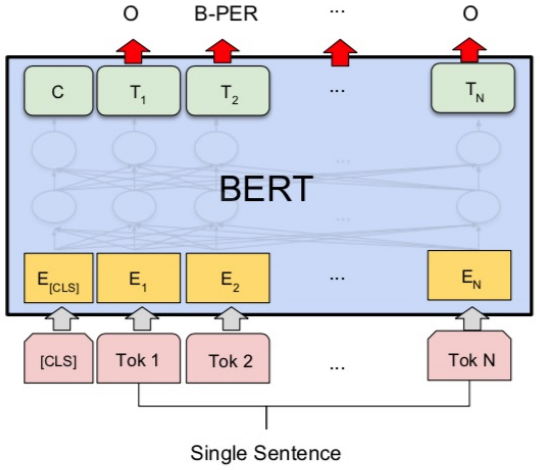
(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG



(b) Single Sentence Classification Tasks: SST-2, CoLA



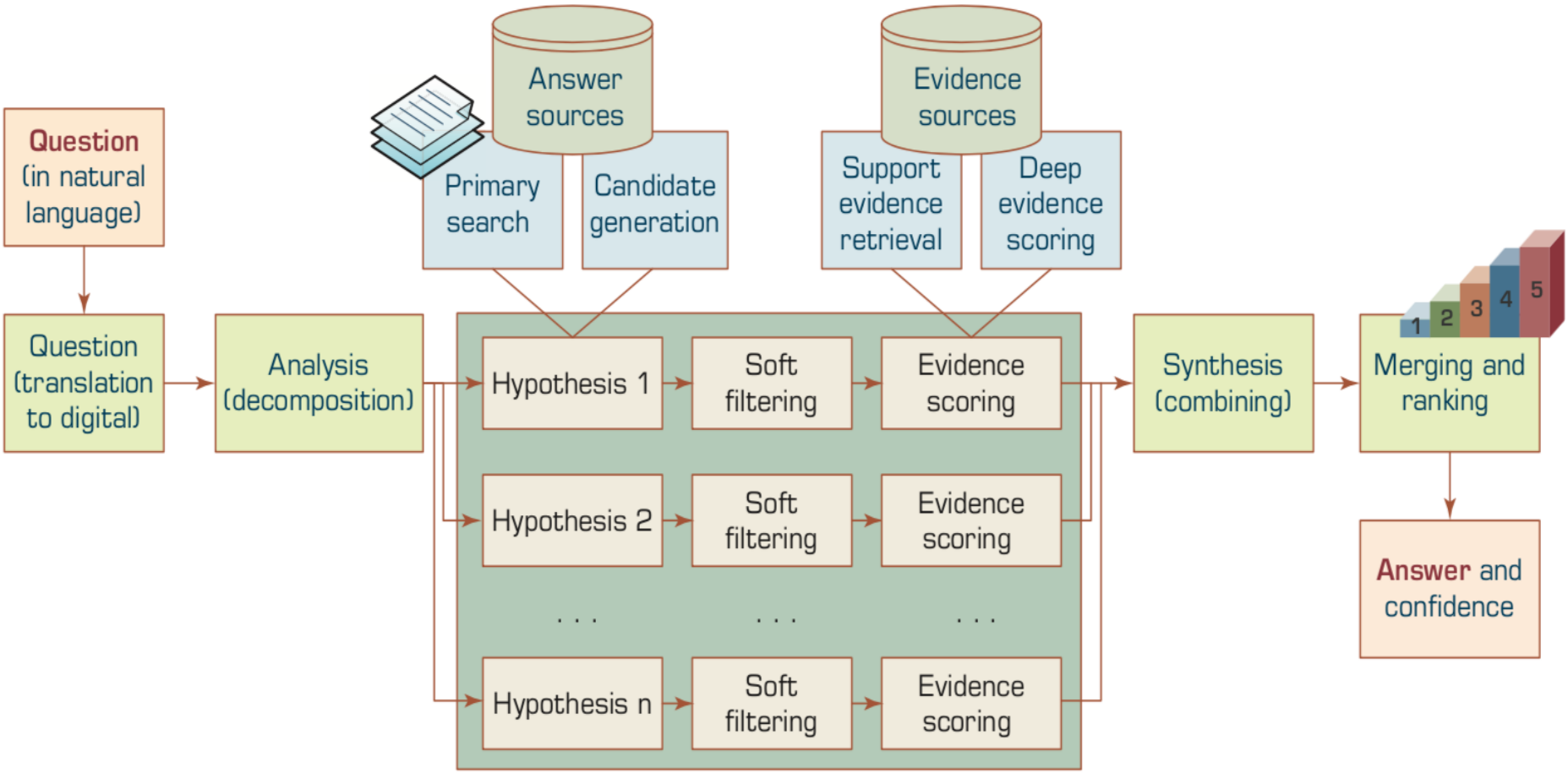
(c) Question Answering Tasks: SQuAD v1.1



(d) Single Sentence Tagging Tasks: CoNLL-2003 NER

Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018). "Bert: Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805.

A High-Level Depiction of DeepQA Architecture

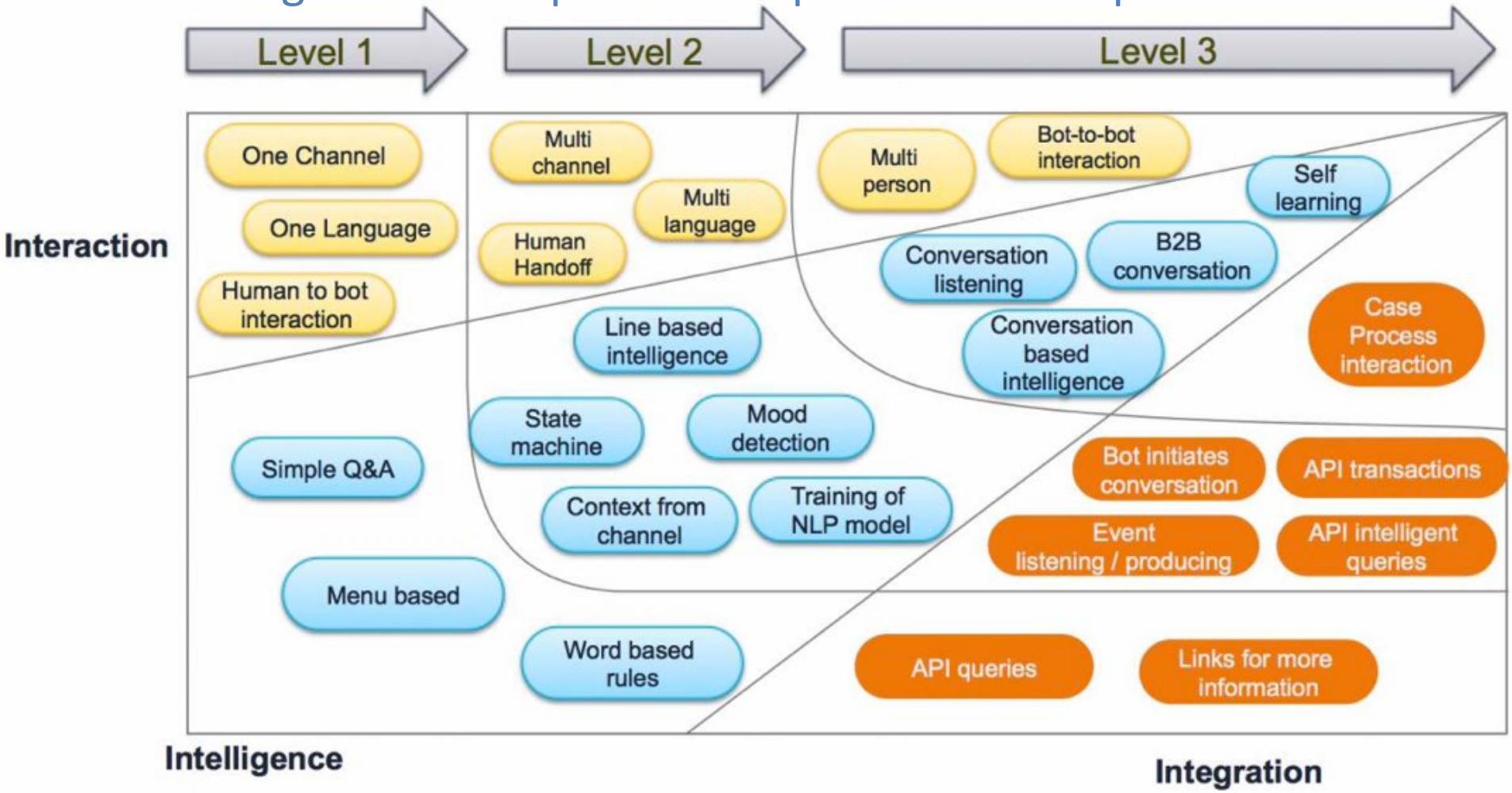


Source: Ramesh Sharda, Dursun Delen, and Efraim Turban (2017), Business Intelligence, Analytics, and Data Science: A Managerial Perspective, 4th Edition, Pearson

Chatbots

Bot Maturity Model

Customers want to have simpler means to interact with businesses and get faster response to a question or complaint.



Source: https://www.capgemini.com/2017/04/how-can-chatbots-meet-expectations-introducing-the-bot-maturity/

Dialogue on Airline Travel Information System (ATIS)

The ATIS (Airline Travel Information System) Dataset

https://www.kaggle.com/siddhadev/atis-dataset-from-ms-cntk

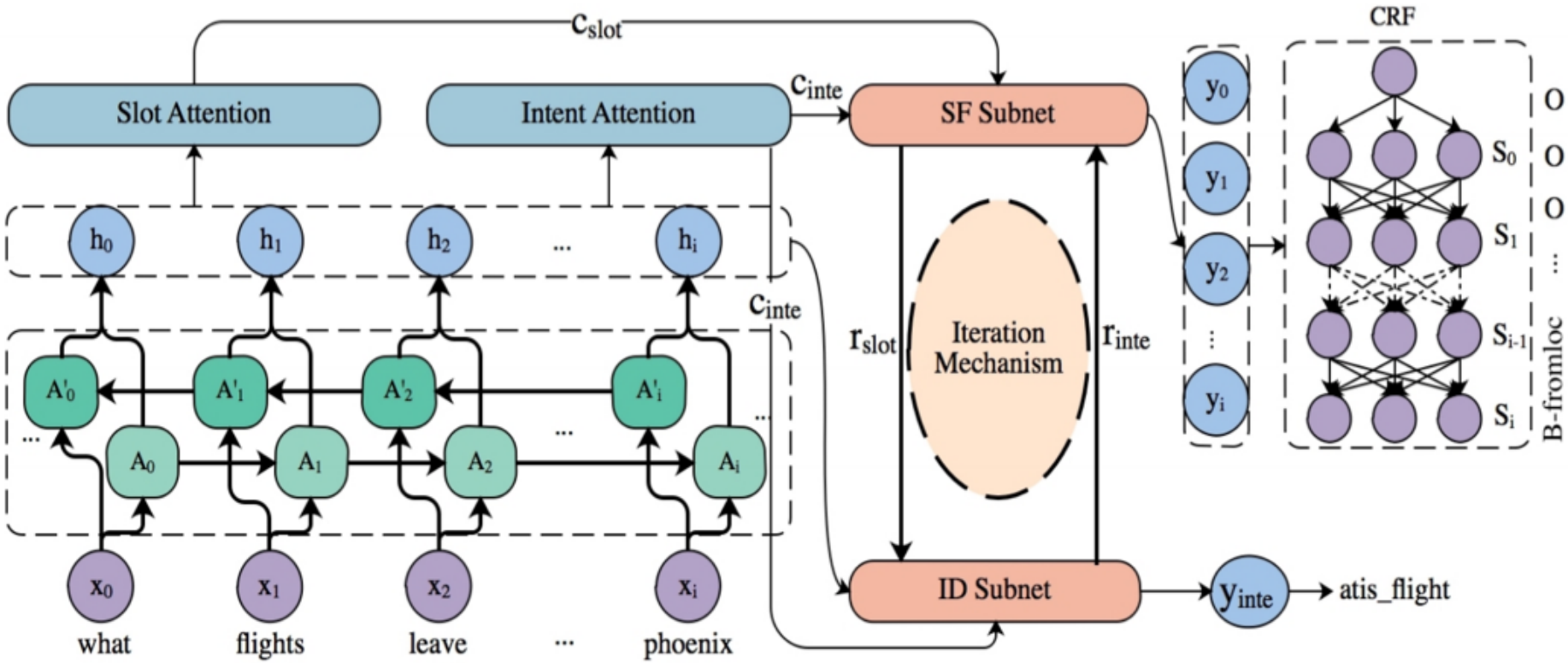
Sentence	what	flights	leave	from	phoenix
Slots	O	O	O	O	B-fromloc
Intent	atis_flight				

Training samples: 4978
Testing samples: 893
Vocab size: 943
Slot count: 129
Intent count: 26

Source: Haihong, E., Peiqing Niu, Zhongfu Chen, and Meina Song. "A novel bi-directional interrelated model for joint intent detection and slot filling." In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pp. 5467-5471. 2019.

SF-ID Network (E et al., 2019)
Slot Filling (SF)
Intent Detection (ID)

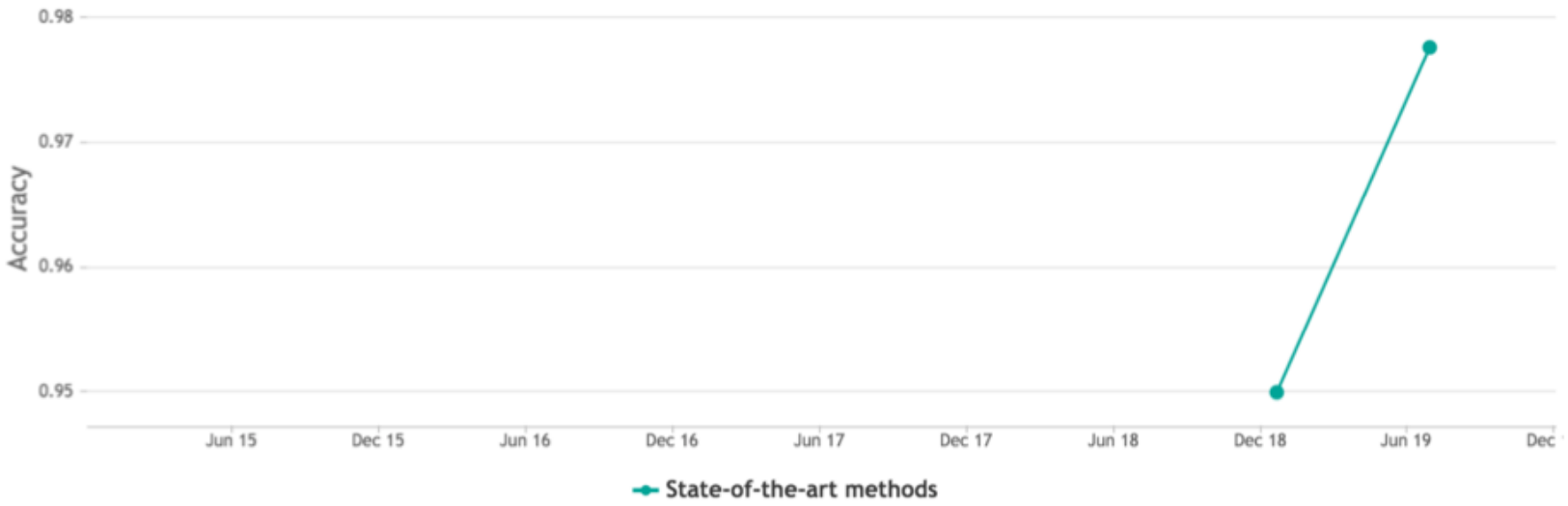
A Novel Bi-directional Interrelated Model for Joint Intent Detection and Slot Filling



Source: Haihong, E., Peiqing Niu, Zhongfu Chen, and Meina Song. "A novel bi-directional interrelated model for joint intent detection and slot filling." In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pp. 5467-5471. 2019.

Intent Detection on ATIS State-of-the-art

Intent Detection on ATIS



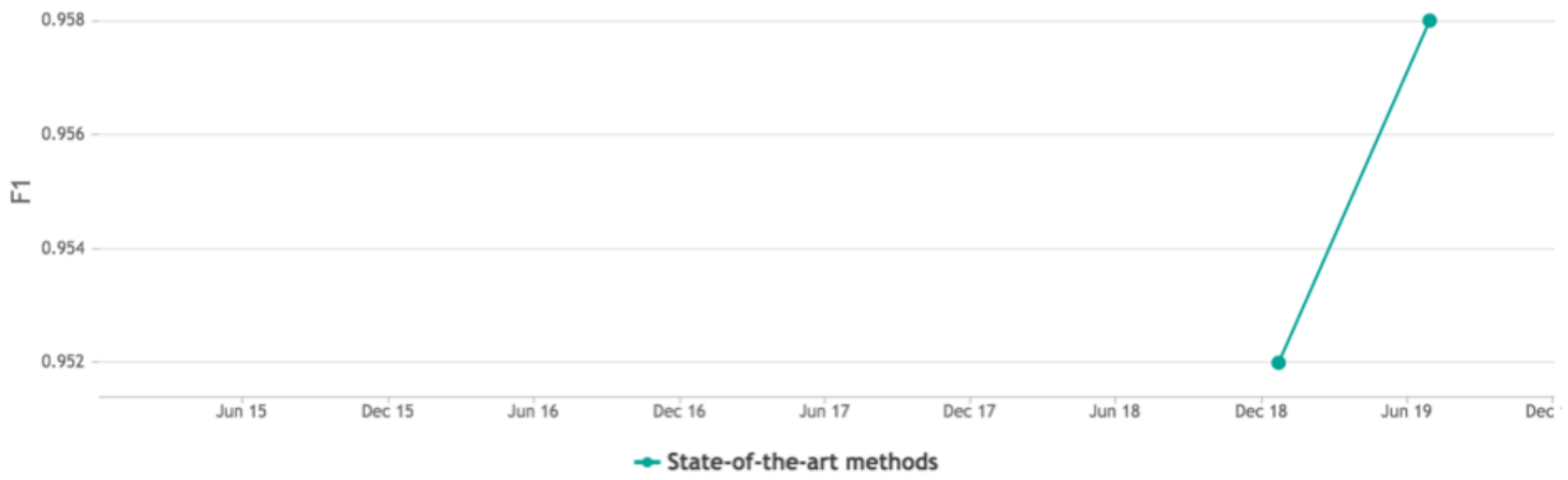
Edit

RANK	METHOD	ACCURACY	PAPER TITLE	YEAR	PAPER	CODE
1	**SF-ID**	0.9776	A Novel Bi-directional Interrelated Model for Joint Intent Detection and Slot Filling	2019		
2	**Capsule-NLU**	0.950	Joint Slot Filling and Intent Detection via Capsule Neural Networks	2018		

Source: https://paperswithcode.com/sota/intent-detection-on-atis

Slot Filling on ATIS State-of-the-art

Slot Filling on ATIS



Edit

RANK	METHOD	F1	PAPER TITLE	YEAR	PAPER	CODE
1	SF-ID	0.958	A Novel Bi-directional Interrelated Model for Joint Intent Detection and Slot Filling	2019		
2	Capsule-NLU	0.952	Joint Slot Filling and Intent Detection via Capsule Neural Networks	2018		

Source: https://paperswithcode.com/sota/slot-filling-on-atis

Restaurants Dialogue Datasets

- MIT Restaurant Corpus
  - https://groups.csail.mit.edu/sls/downloads/restaurant/
- CamRest676
  (Cambridge restaurant dialogue domain dataset)
  - https://www.repository.cam.ac.uk/handle/1810/260970
- DSTC2 (Dialog State Tracking Challenge 2 & 3)
  - http://camdial.org/~mh521/dstc/

任務型對話系統

The Evaluation of Chinese Human-Computer Dialogue Technology, SMP2019-ECDT

- 自然語言理解
  Natural Language Understanding (NLU)
- 對話管理
  Dialog Management (DM)
- 自然語言生成
  Natural Language Generation (NLG)

Source: http://conference.cipsc.org.cn/smp2019/evaluation.html
https://github.com/OnionWang/SMP2019-ECDT-NLU

Course Introduction

- This course introduces the fundamental concepts and research issues of artificial intelligence for text analytics.
- Topics include
  1. Foundations of Text Analytics: Natural Language Processing (NLP)
  2. Python for NLP
  3. Processing and Understanding Text
  4. Feature Engineering for Text Representation
  5. Text Classification
  6. Text Summarization and Topic Models
  7. Text Similarity and Clustering
  8. Semantic Analysis and Named Entity Recognition
  9. Sentiment Analysis
  10. The Promise of Deep Learning and Universal Sentence-Embedding Models
  11. Question Answering and Dialogue Systems
  12. Case Study on AI Text Analytics

人工智慧文本分析
(AI for Text Analytics)
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