

智慧金融量化分析

(Artificial Intelligence in Finance and Quantitative Analysis)

金融計量經濟學 (Financial Econometrics)

1101AIFQA07

MBA, IM, NTPU (M6132) (Fall 2021)

Tue 2, 3, 4 (9:10-12:00) (8F40)

戴敏育 副教授

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Institute of Information Management, National Taipei University

<https://web.ntpu.edu.tw/~myday>



課程大綱 (Syllabus)

週次 (Week)	日期 (Date)	內容 (Subject/Topics)
1	2021/09/28	智慧金融量化分析概論 (Introduction to Artificial Intelligence in Finance and Quantitative Analysis)
2	2021/10/05	AI 金融科技: 金融服務創新應用 (AI in FinTech: Financial Services Innovation and Application)
3	2021/10/12	投資心理學與行為財務學 (Investing Psychology and Behavioral Finance)
4	2021/10/19	財務金融事件研究法 (Event Studies in Finance)
5	2021/10/26	智慧金融量化分析個案研究 I (Case Study on AI in Finance and Quantitative Analysis I)
6	2021/11/02	財務金融理論 (Finance Theory)

課程大綱 (Syllabus)

週次 (Week)	日期 (Date)	內容 (Subject/Topics)
7	2021/11/09	數據驅動財務金融 (Data-Driven Finance)
8	2021/11/16	期中報告 (Midterm Project Report)
9	2021/11/23	金融計量經濟學 (Financial Econometrics)
10	2021/11/30	人工智慧優先金融 (AI-First Finance)
11	2021/12/07	智慧金融量化分析產業實務 (Industry Practices of AI in Finance and Quantitative Analysis)
12	2021/12/14	智慧金融量化分析個案研究 II (Case Study on AI in Finance and Quantitative Analysis II)

課程大綱 (Syllabus)

週次 (Week)	日期 (Date)	內容 (Subject/Topics)
13	2021/12/21	財務金融深度學習 (Deep Learning in Finance); 財務金融強化學習 (Reinforcement Learning in Finance)
14	2021/12/28	演算法交易 (Algorithmic Trading); 風險管理 (Risk Management); 交易機器人與基於事件的回測 (Trading Bot and Event-Based Backtesting)
15	2022/01/04	期末報告 I (Final Project Report I)
16	2022/01/11	期末報告 II (Final Project Report II)
17	2022/01/18	學生自主學習 (Self-learning)
18	2022/01/25	學生自主學習 (Self-learning)

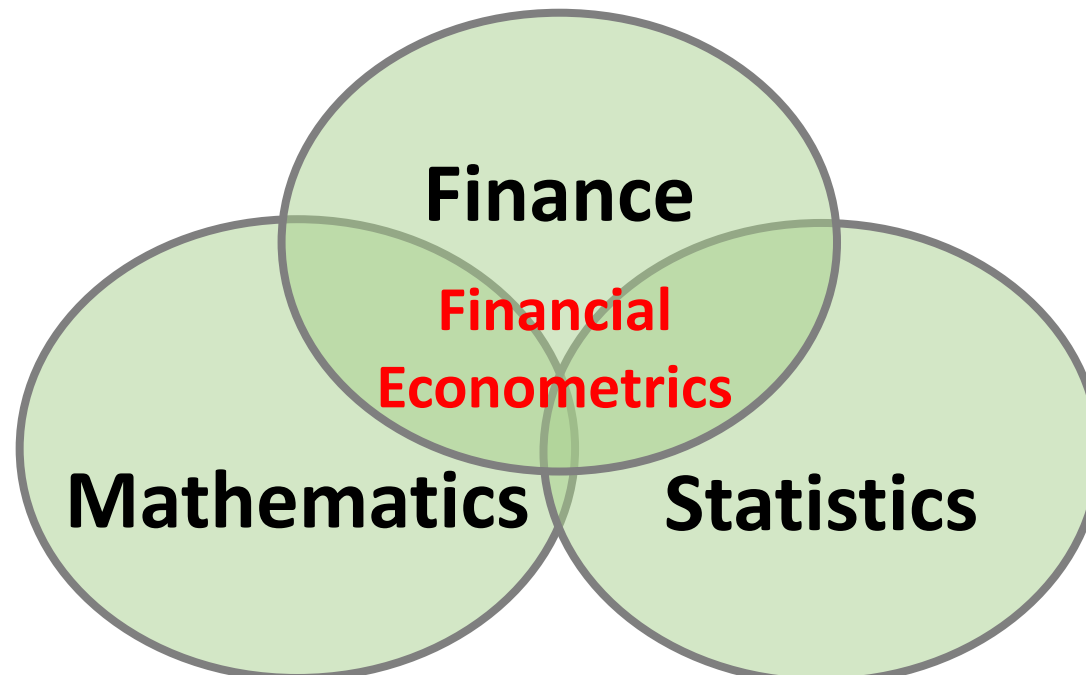
**Financial
Econometrics
and
Machine Learning**

Financial Econometrics and Machine Learning

- **Financial Econometrics**
 - **Financial Theories**
 - **OLS Regression**
- **Machine Learning**
 - **Learning**
 - **Evaluation**
 - **Bias and variance**
 - **Cross-validation**

Financial Econometrics

- The discipline at the intersection of **mathematics, statistics, and finance** that applies such methods to **financial market data** is typically called **financial econometrics**.



Financial Econometrics

(Chris Brooks, 2019)

- **Financial econometrics**
 - the application of **statistical techniques** to problems in **finance**
- Financial econometrics can be useful for testing theories in finance, determining asset prices or returns, testing hypotheses concerning the relationships between variables, examining the effect on financial markets of changes in economic conditions, forecasting future values of financial variables and for financial decision-making.

Financial Econometrics

- **[Financial] econometrics** is the **quantitative application of statistical and mathematical models** using **[financial] data** to develop financial theories or test existing hypotheses in finance and to forecast future trends from historical data.
- It subjects real-world **[financial] data** to statistical trials and then compares and contrasts the results against the **[financial] theory or theories** being tested.

Topics of Financial Econometrics

(Oliver Linton, 2019)

- 1. Econometric**
- 2. Return Predictability and the Efficient Markets Hypothesis**
- 3. Robust Tests and Tests of Nonlinear Predictability of Returns**
- 4. Empirical Market Microstructure**
- 5. Event Study Analysis**
- 6. Portfolio Choice and Testing the Capital Asset Pricing Model**
- 7. Multifactor Pricing Models**

Topics of Financial Econometrics

(Oliver Linton, 2019)

- 8. Present Value Relations**
- 9. Intertemporal Equilibrium Pricing**
- 10. Volatility**
- 11. Continuous Time Processes**
- 12. Yield Curve**
- 13. Risk Management and Tail Estimation**

Applications of Financial Econometrics

(Chris Brooks, 2019)

- 1. Testing whether financial markets are weak-form informationally efficient**
- 2. Testing whether the capital asset pricing model (CAPM) or arbitrage pricing theory (APT) represent superior models for the determination of returns on risky assets**
- 3. Measuring and forecasting the volatility of bond returns**
- 4. Explaining the determinants of bond credit ratings used by the ratings agencies**
- 5. Modelling long-term relationships between prices and exchange rates**

Applications of Financial Econometrics

(Chris Brooks, 2019)

- 6. Determining the optimal hedge ratio for a spot position in oil**
- 7. Testing technical trading rules to determine which makes the most money**
- 8. Testing the hypothesis that earnings or dividend announcements have no effect on stock prices**
- 9. Testing whether spot or futures markets react more rapidly to news**
- 10. Forecasting the correlation between the stock indices of two countries**

Machine Learning and Financial Econometrics

- **ML and DL methods** are able to **discover statistical inefficiencies and even economic inefficiencies** that are not discoverable by **traditional econometric methods**, such as multivariate OLS regression.

Normative Financial Theories

- **Normative financial theories** mostly rely on assumptions and axioms in combination with deduction as the major analytical method to arrive at their central results.
 - **Expected utility theory (EUT)** assumes that agents have the same utility function no matter what state of the world unfolds and that they maximize expected utility under conditions of uncertainty.
 - **Mean-variance portfolio (MVP)** theory describes how investors should invest under conditions of uncertainty assuming that only the expected return and the expected volatility of a portfolio over one period count.

Normative Financial Theories

- The **capital asset pricing model (CAPM)** assumes that only the nondiversifiable market risk explains the expected return and the expected volatility of a stock over one period.
- **Arbitrage pricing theory (APT)** assumes that a number of identifiable risk factors explains the expected return and the expected volatility of a stock over time; admittedly, compared to the other theories, the formulation of APT is rather broad and allows for wide-ranging interpretations.

Financial Econometrics and Regression

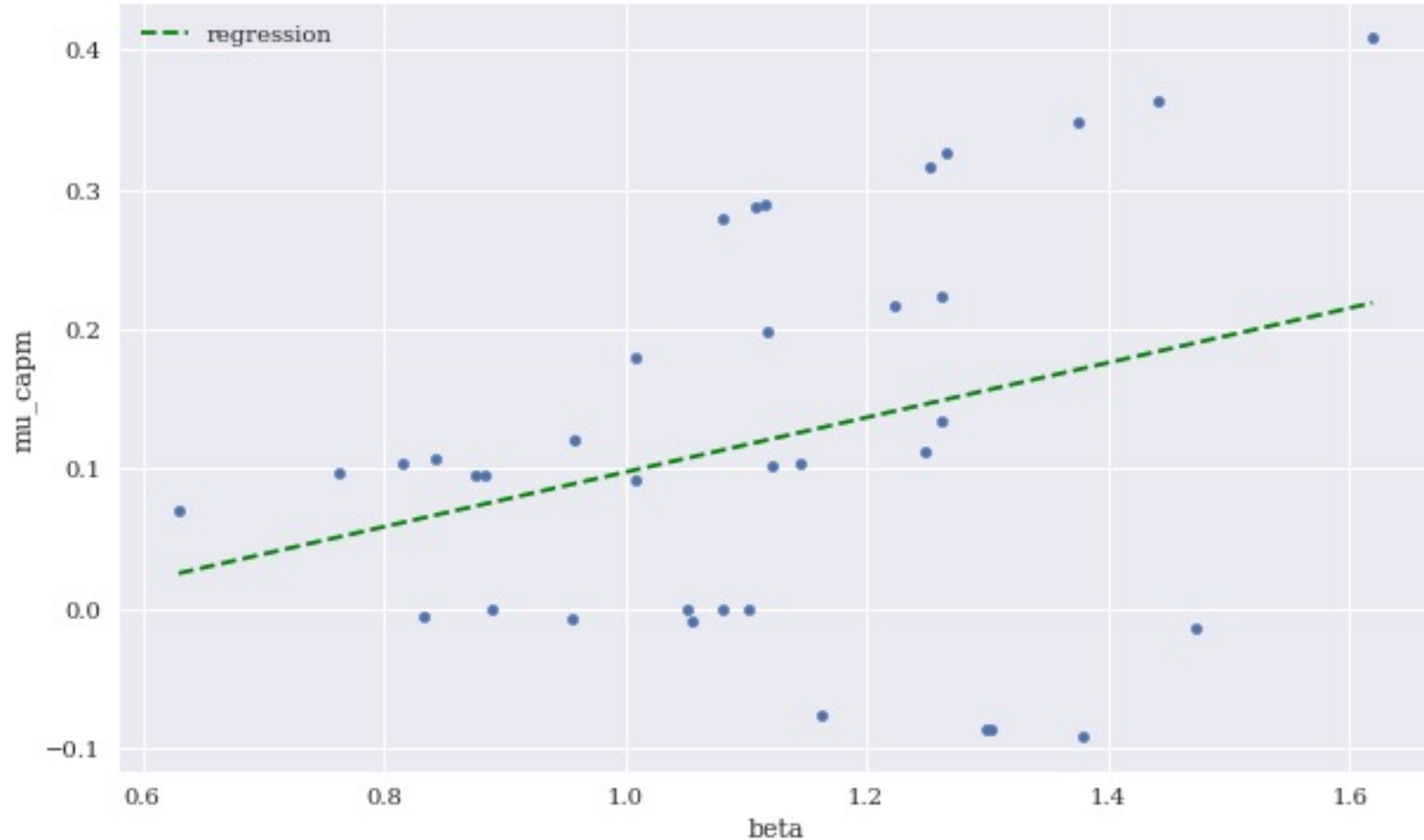
- One of the major tools in **financial econometrics** is **regression**, in both its univariate and multivariate forms
 - $y = \alpha + \beta x$
 - $y = \alpha + \beta_1 x_1 + \beta_2 x_2$
 - $y = \alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3$
- **Regression** is also a central tool in **statistical learning** in general

CAPM and APT

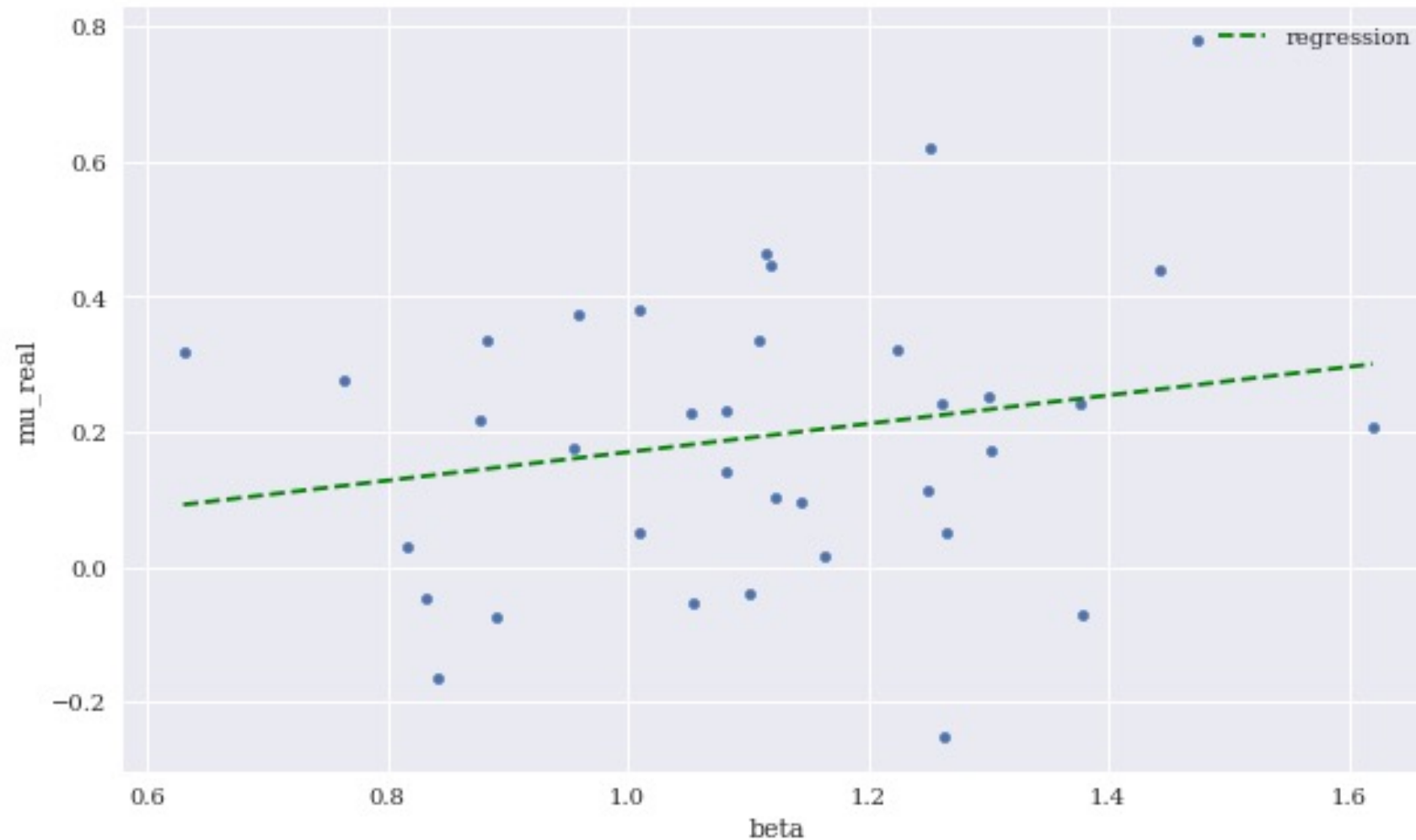
OLS regression

- Both the **CAPM** and the **APT** relate the **output variables** with the relevant **input factors** in **linear** fashion.
- From an econometric point of view, both models are implemented based on linear **ordinary least-squares (OLS) regression**.
- **CAPM**: univariate linear OLS regression
- **APT**: multivariate OLS regression

Expected CAPM return versus beta (including linear regression)



Expected CAPM return versus beta (including linear regression)



Machine Learning

- **Learning**
- **Data: Features, Labels**
- **Success (Loss Function): MSE**
- **Capacity (Model Fit)**
- **Evaluation**
- **Bias and variance**
- **Cross-validation**

Learning

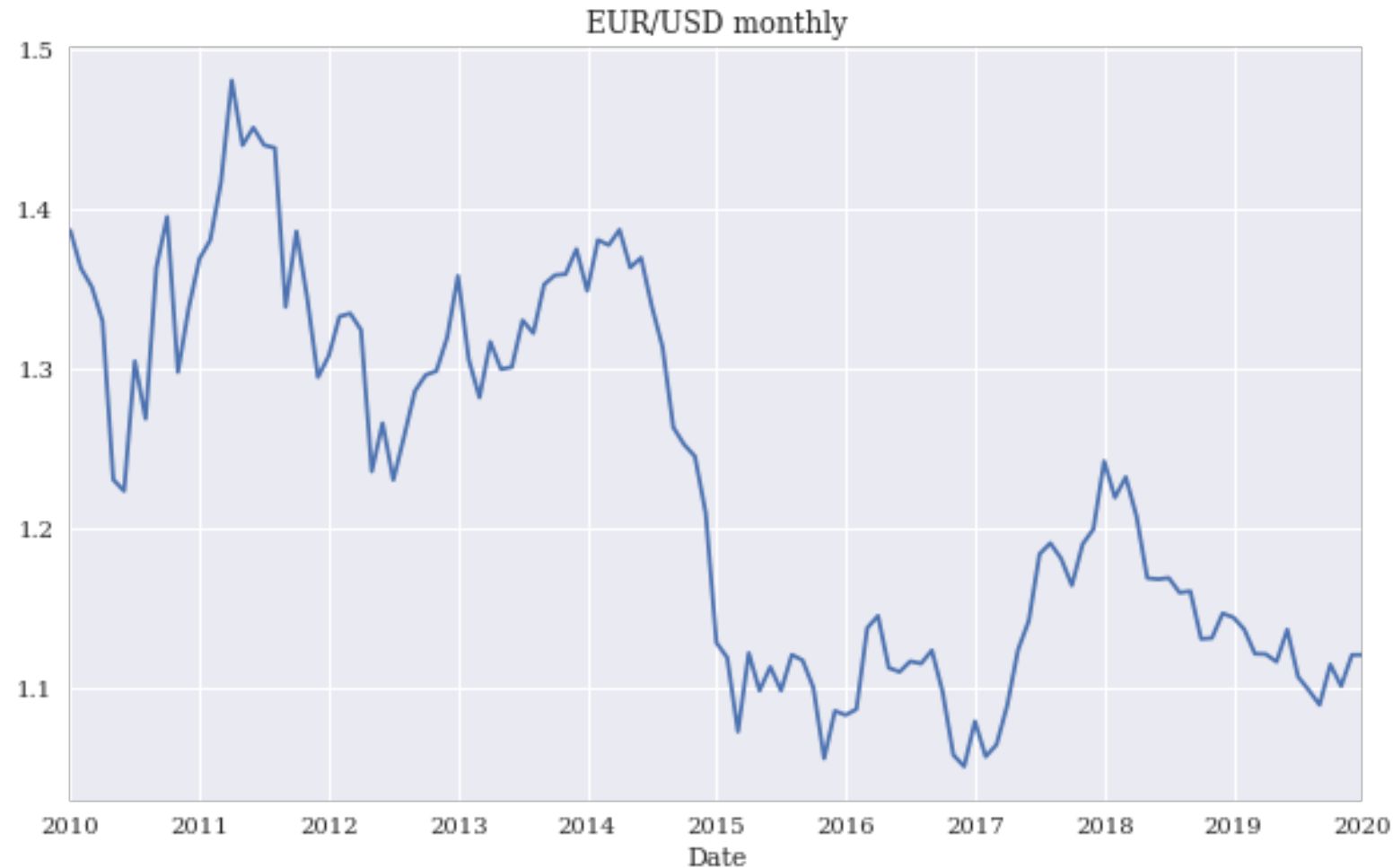
(Mitchell, 1997)

- A computer program is said to **learn** from **experience E** with respect to some class of tasks **T** and **performance measure P**, if its performance at tasks in **T**, as measured by **P**, improves with **experience E**.

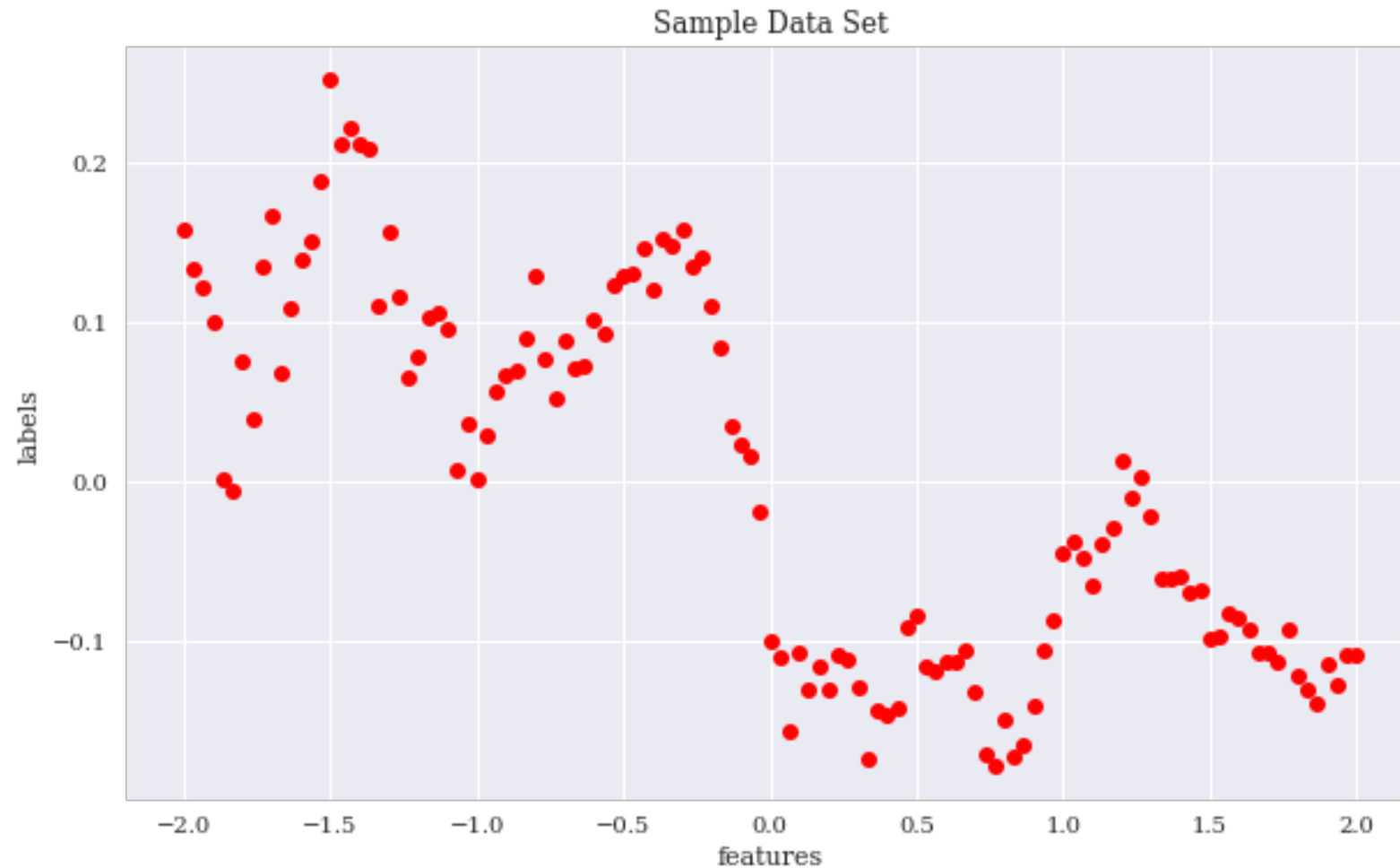
Performance Measure

- **The measure of success for estimation problems**
 - **mean-squared error (MSE)**
- **Classification problems**
 - **accuracy ratio**

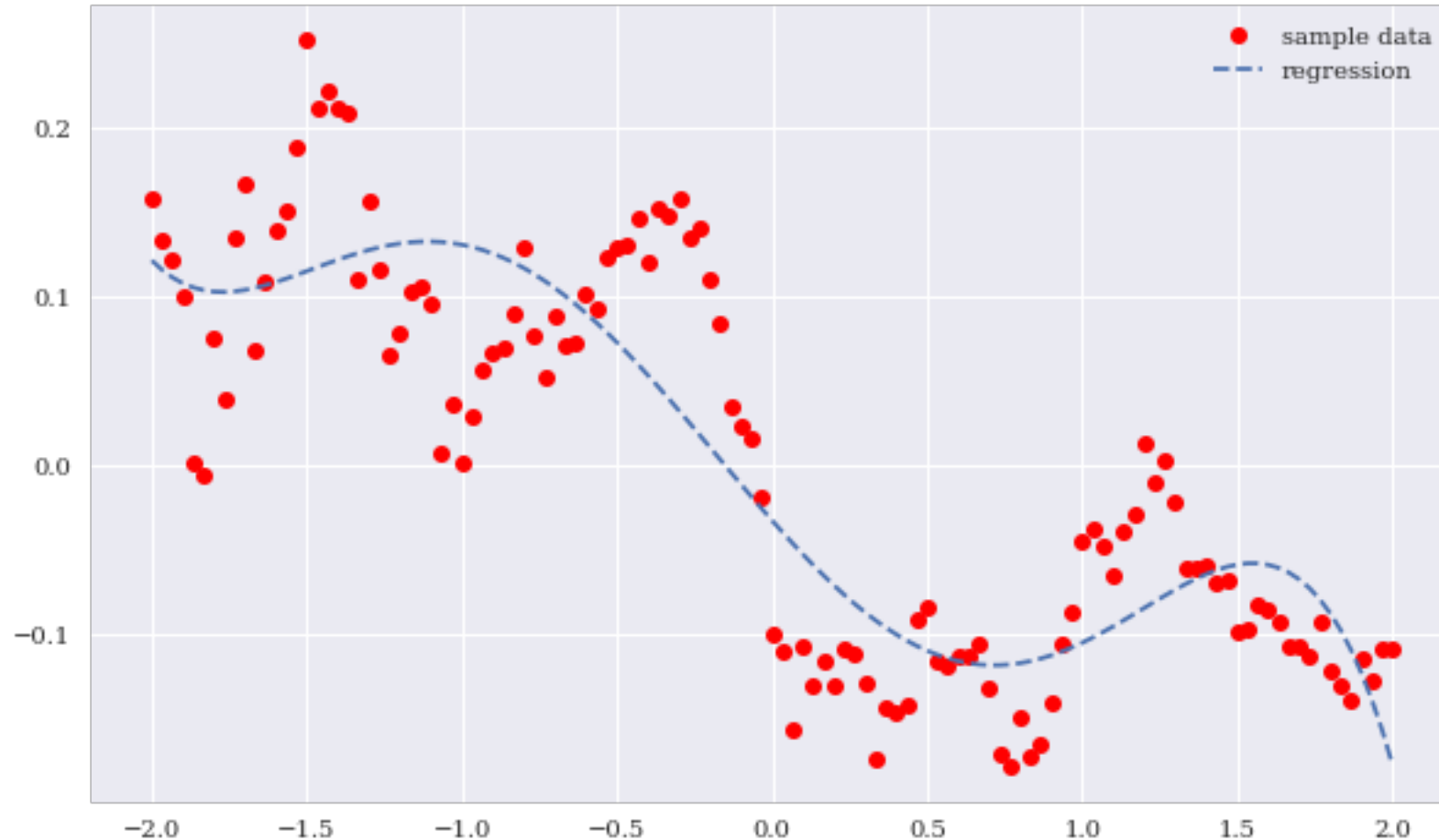
EUR/USD exchange rate as time series (monthly)



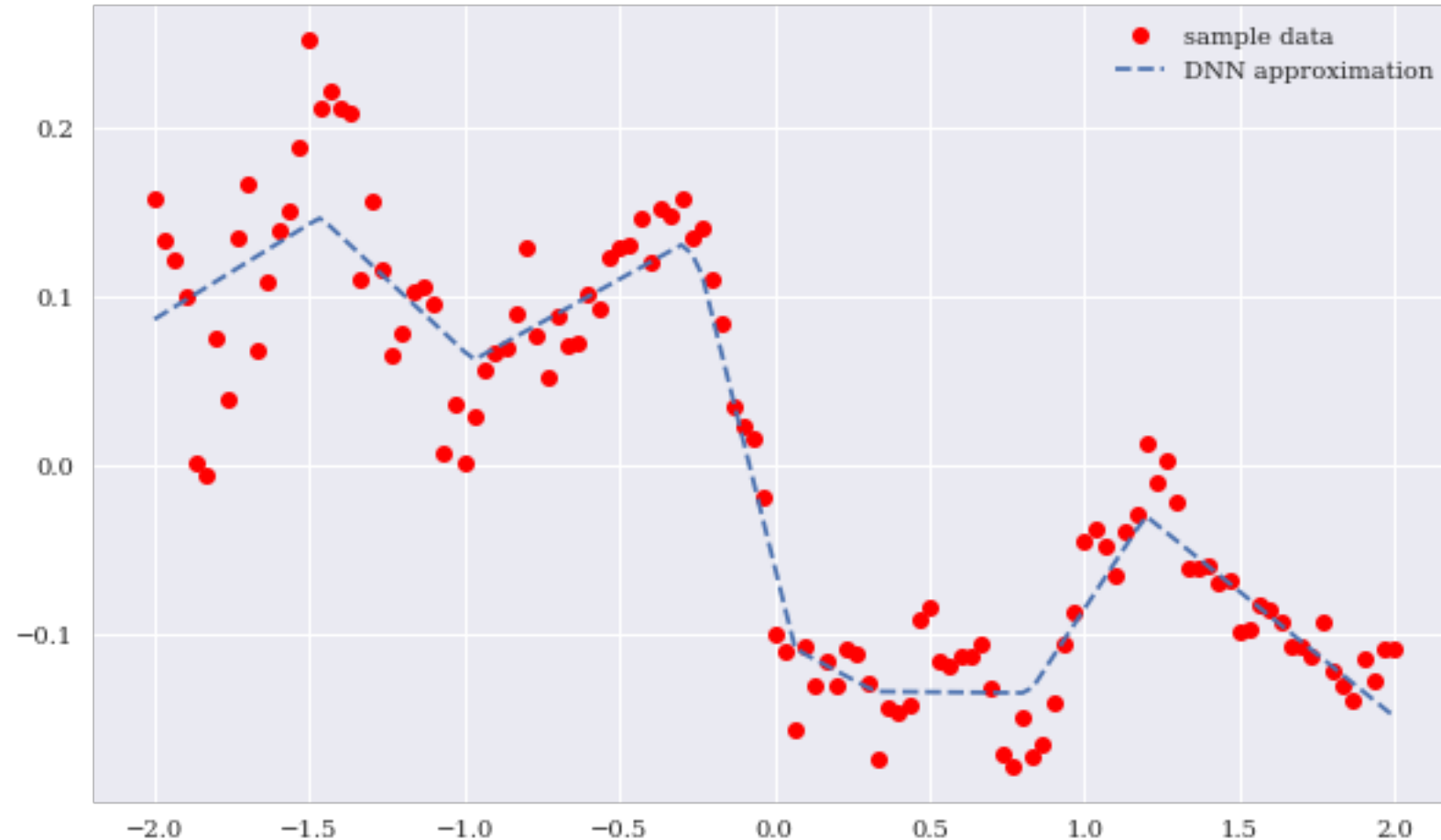
Sample data set



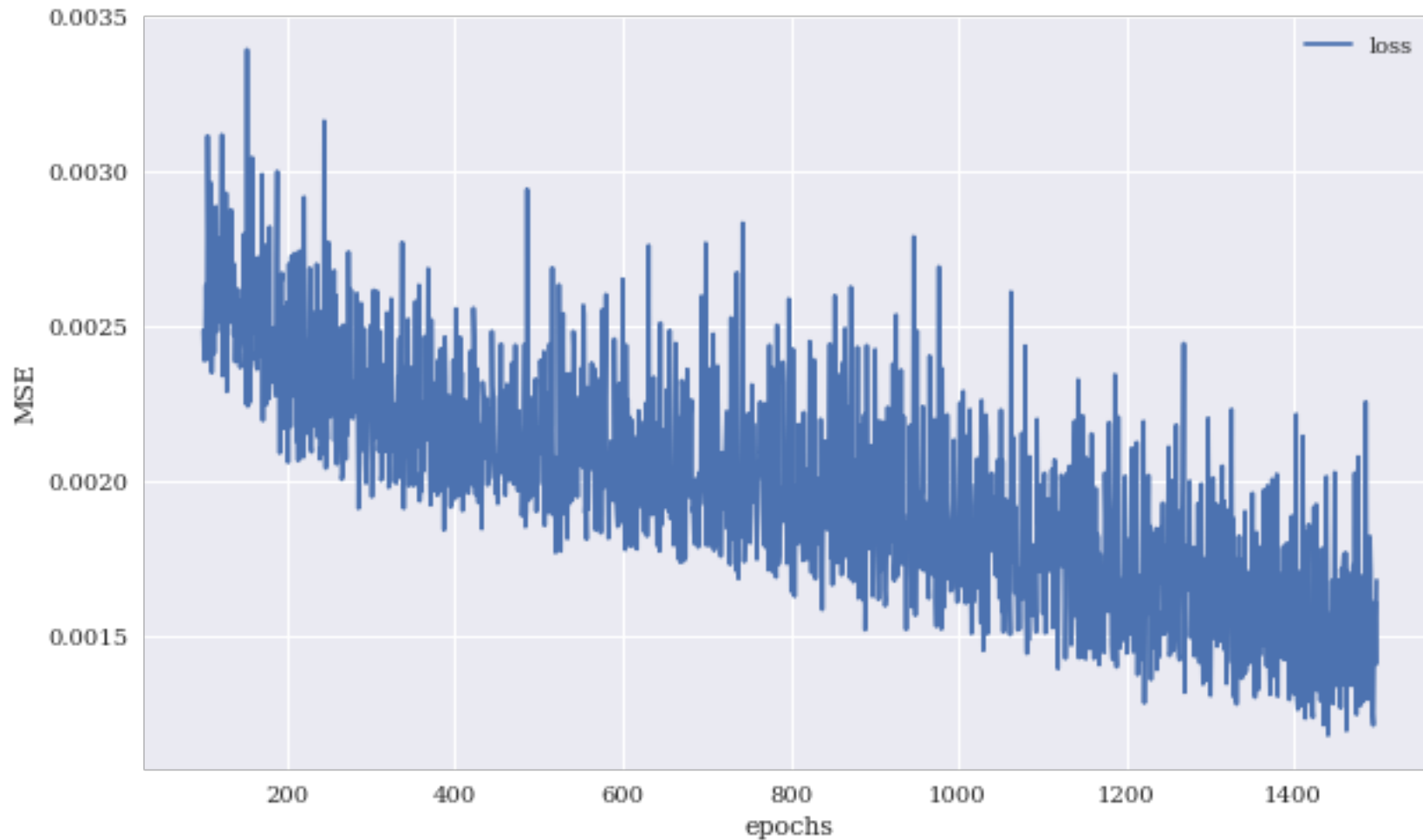
Sample data and cubic regression line



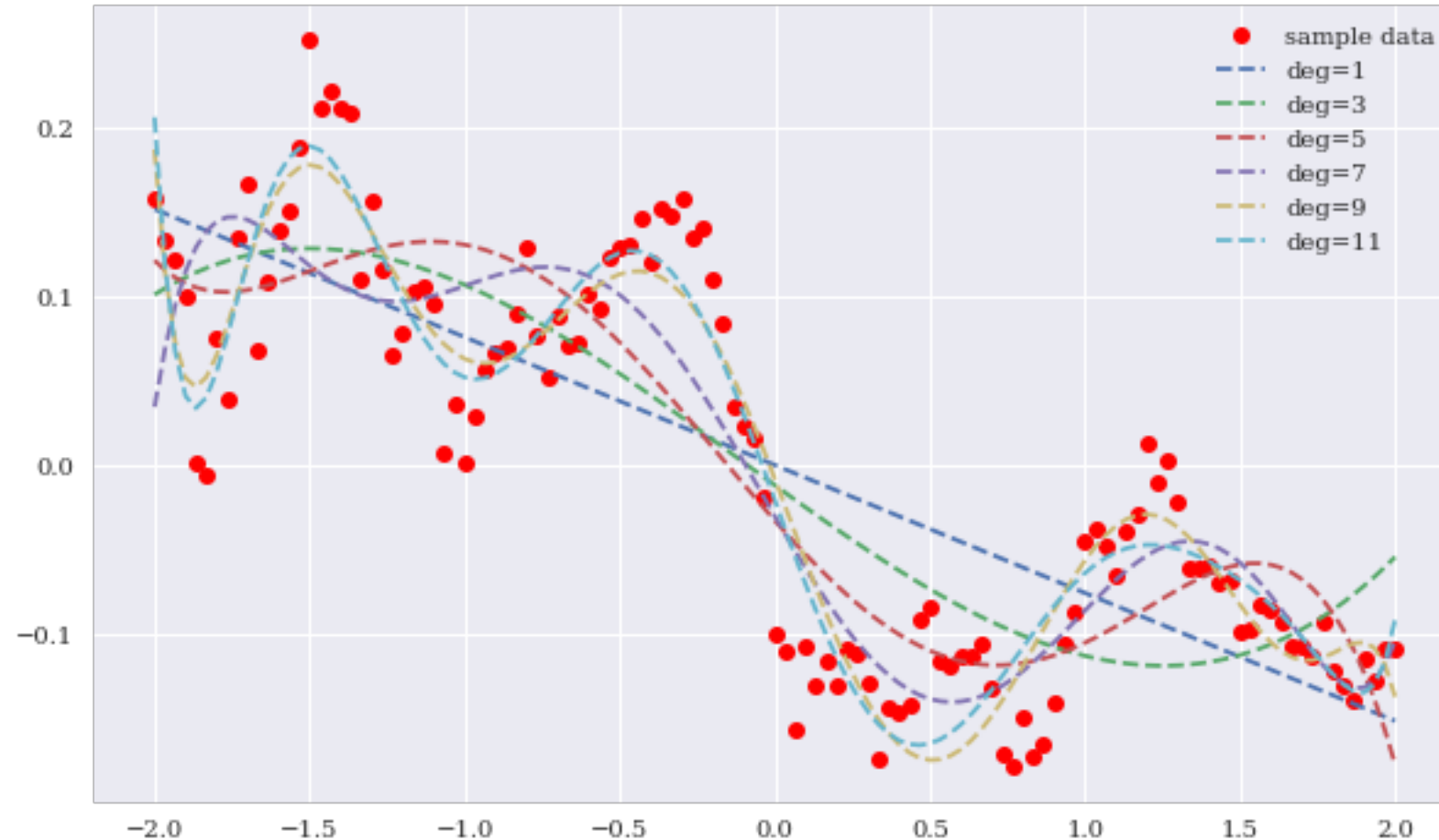
Sample data and neural network approximation



MSE values against number of training epochs



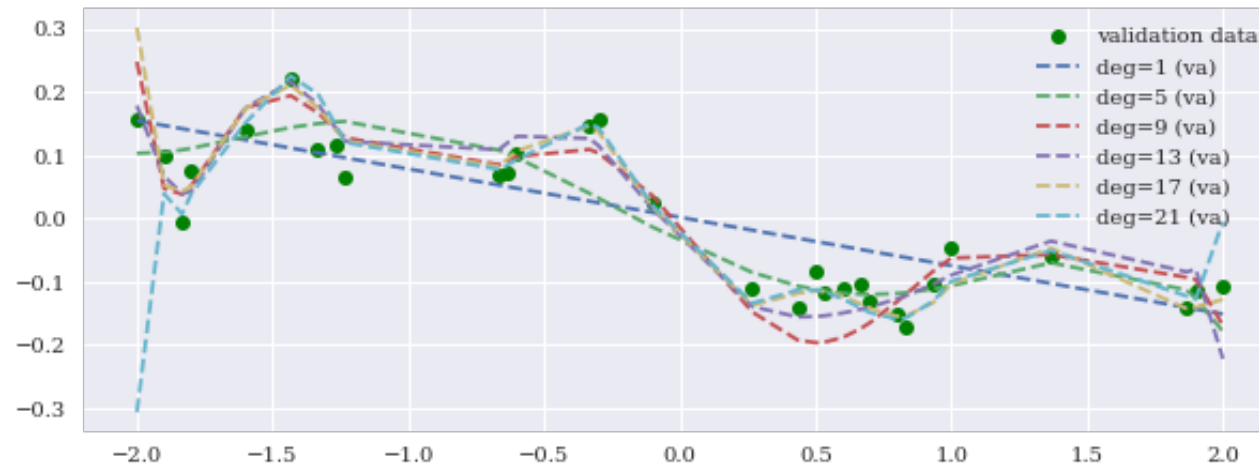
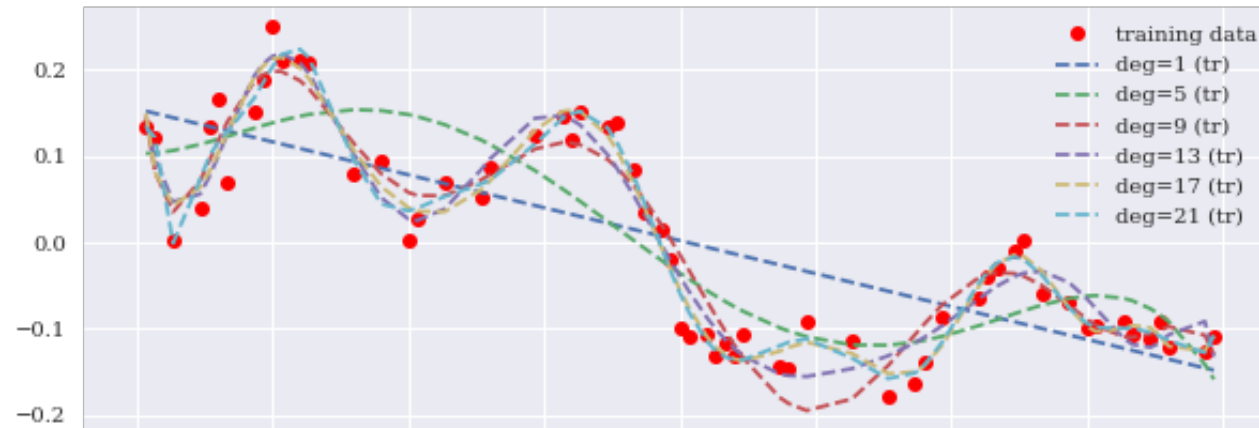
Regression lines for different highest degrees



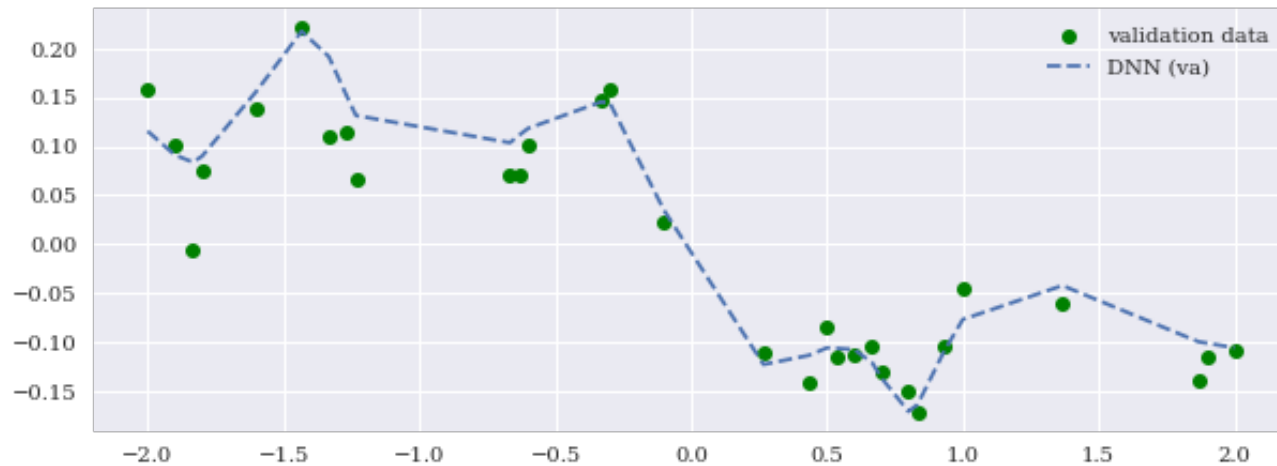
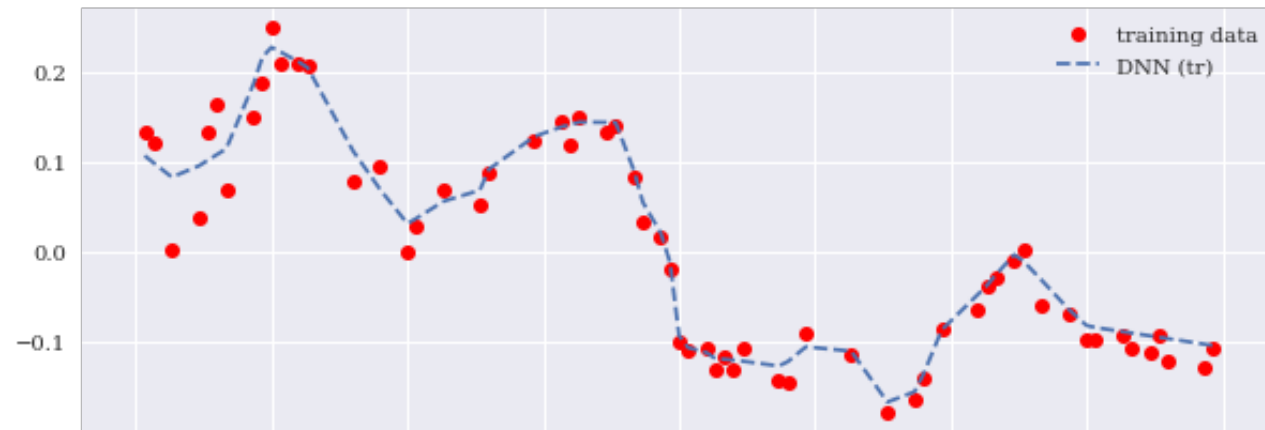
Sample data and DNN approximation (higher capacity)



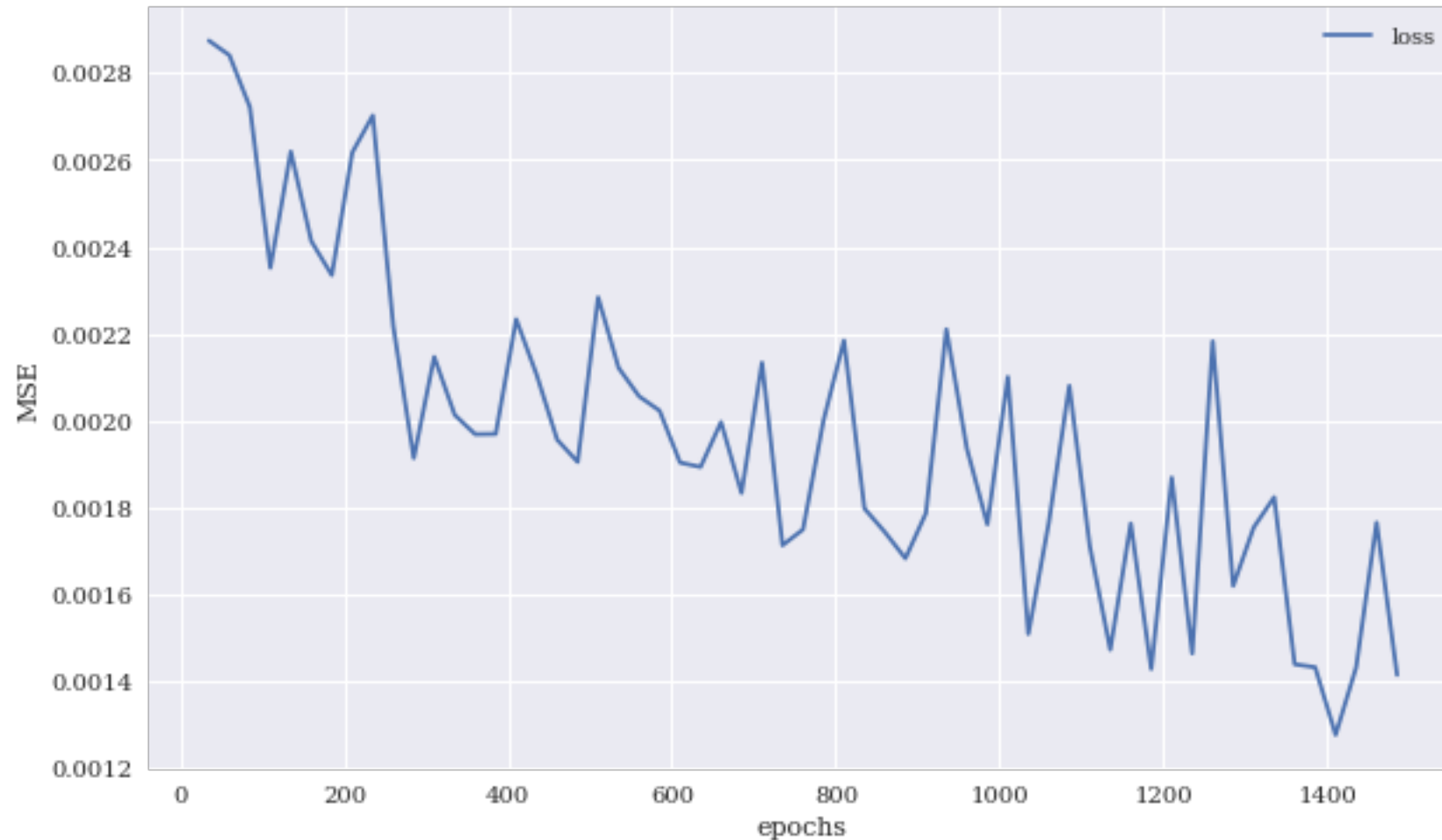
Training and validation data including regression fits



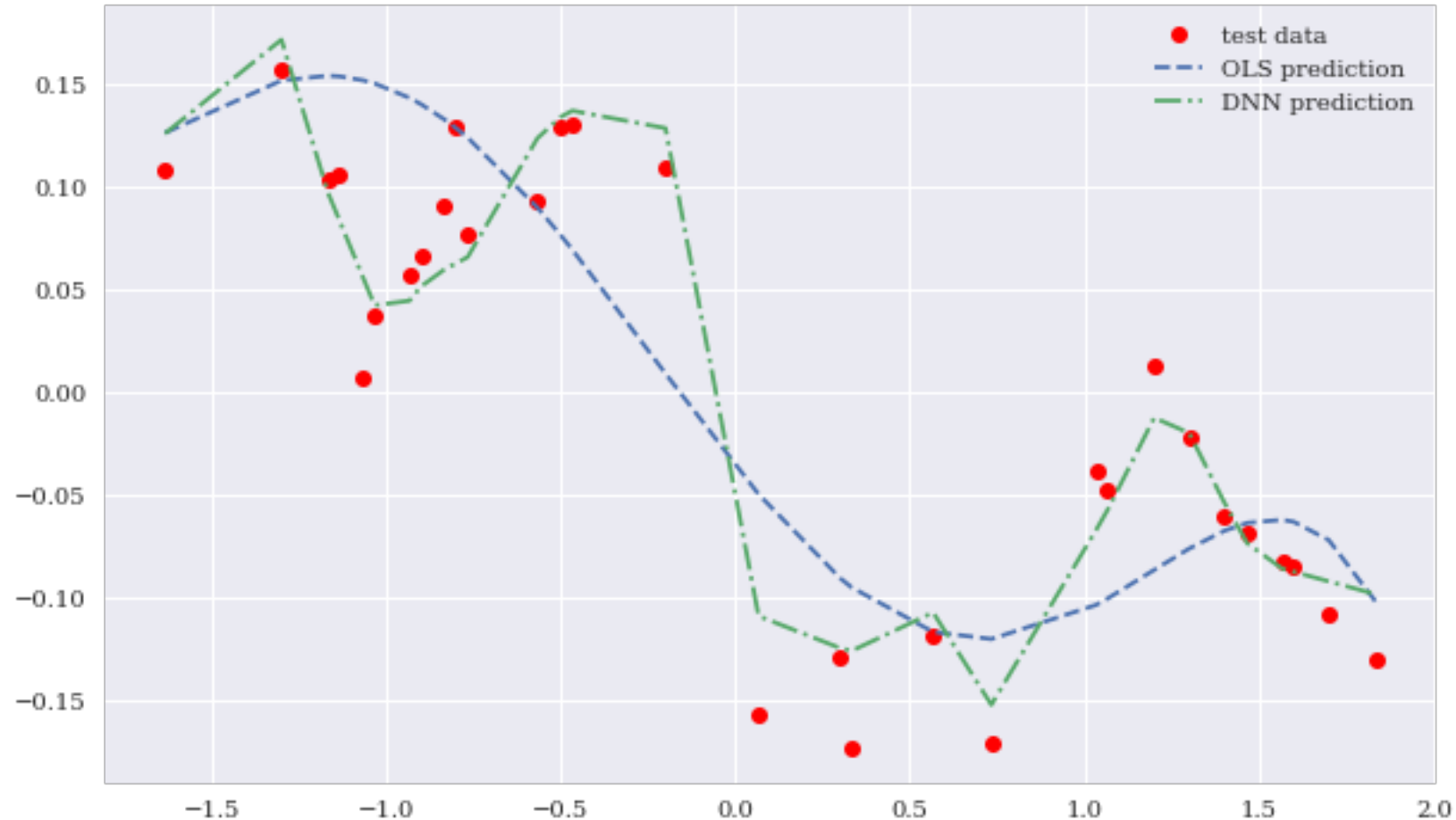
Training and validation data including DNN predictions



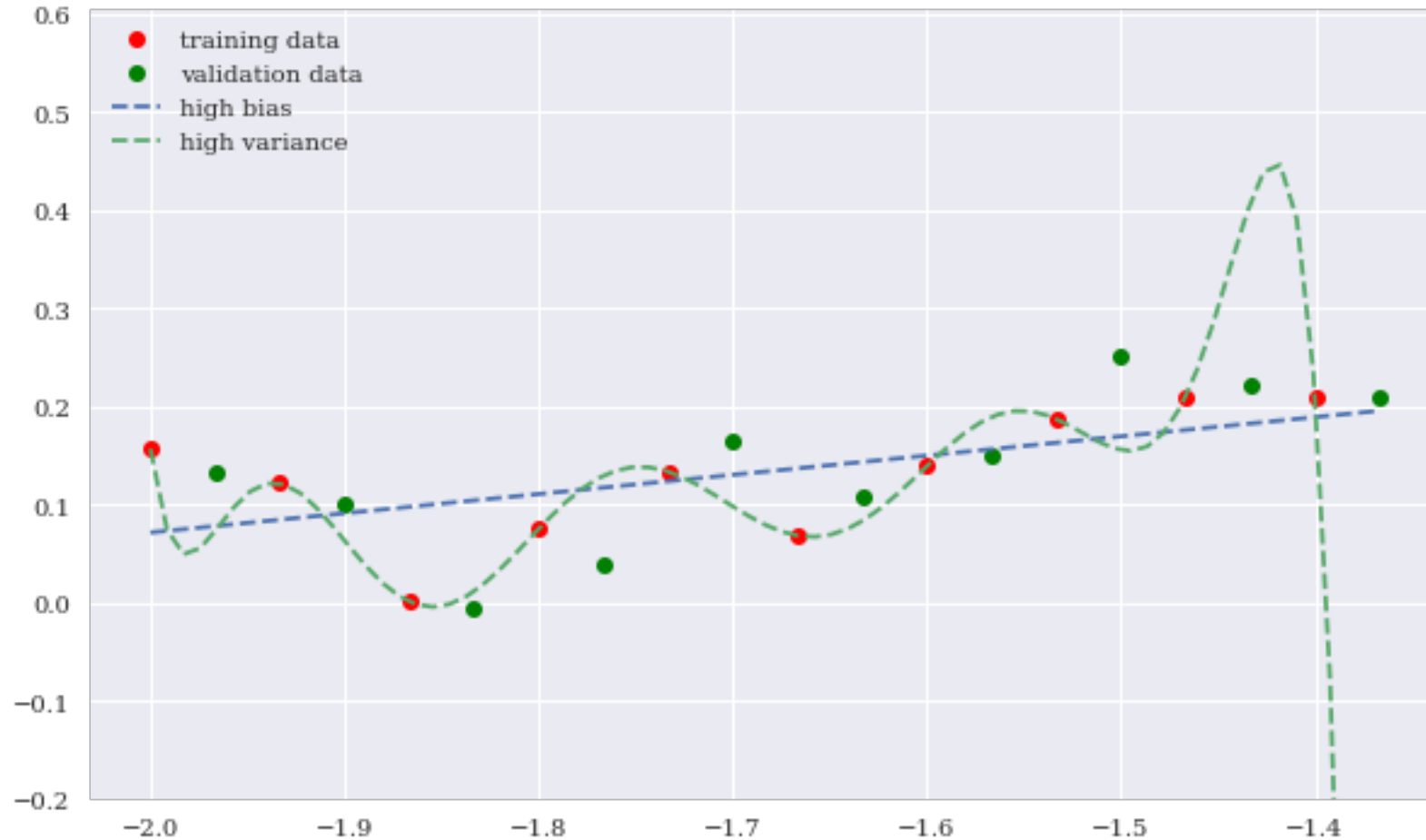
MSE values for DNN model on the training and validation data sets



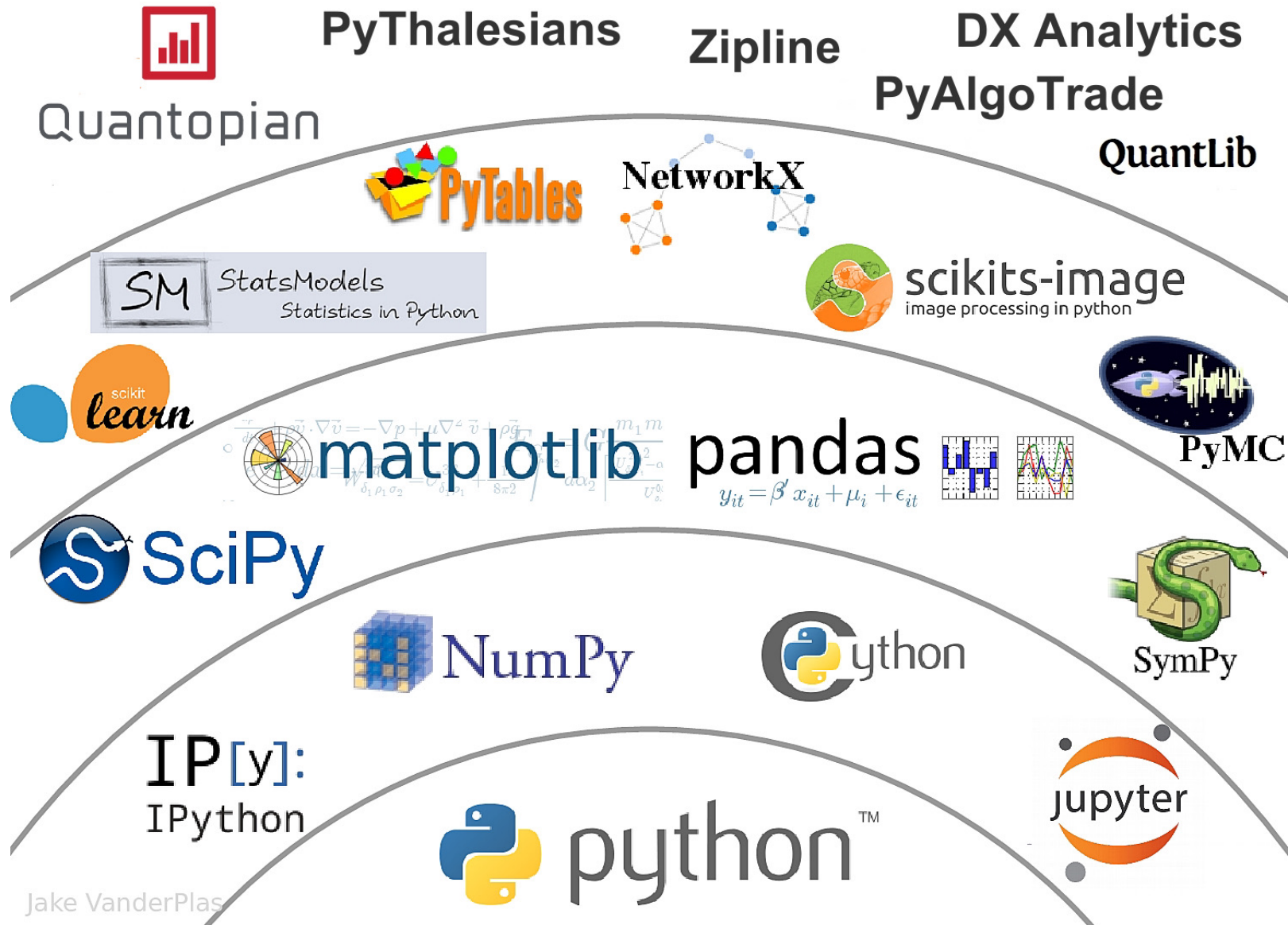
Test data and predictions from OLS regression and the DNN model



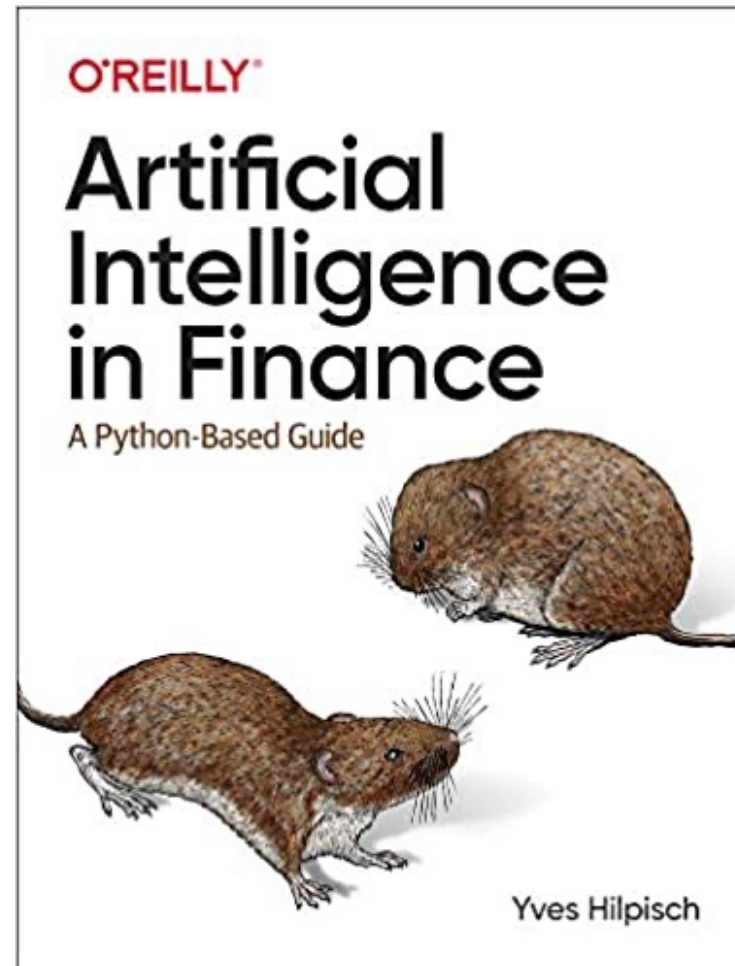
High bias and high variance OLS regression fits



The Quant Finance PyData Stack



Yves Hilpisch (2020),
Artificial Intelligence in Finance:
A Python-Based Guide,
O'Reilly



Yves Hilpisch (2020), **Artificial Intelligence in Finance: A Python-Based Guide**, O'Reilly

yhilpisch / aiif Public <https://github.com/yhilpisch/aiif> Notifications Star 98 Fork 77

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yves Code updates for TF 2.3. e334251 on Dec 8, 2020 4 commits


code	Code updates for TF 2.3.	11 months ago
.gitignore	Code updates for TF 2.3.	11 months ago
LICENSE.txt	Code updates.	11 months ago
README.md	Code updates.	11 months ago

☰ README.md

Artificial Intelligence in Finance

About this Repository

This repository provides Python code and Jupyter Notebooks accompanying the **Artificial Intelligence in Finance** book published by [O'Reilly](#).



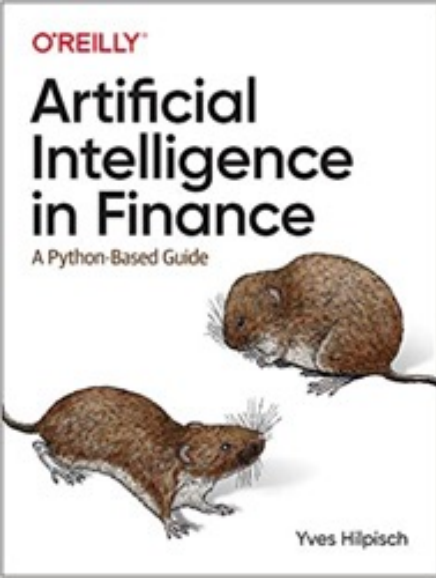
About
Jupyter Notebooks and code for the book **Artificial Intelligence in Finance** (O'Reilly) by Yves Hilpisch.
home.tpq.io/books/aiif
[Readme](#)
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Releases
No releases published

Packages
No packages published

Languages

- Jupyter Notebook 97.4%
- Python 2.6%



Yves Hilpisch (2020), **Artificial Intelligence in Finance: A Python-Based Guide**, O'Reilly

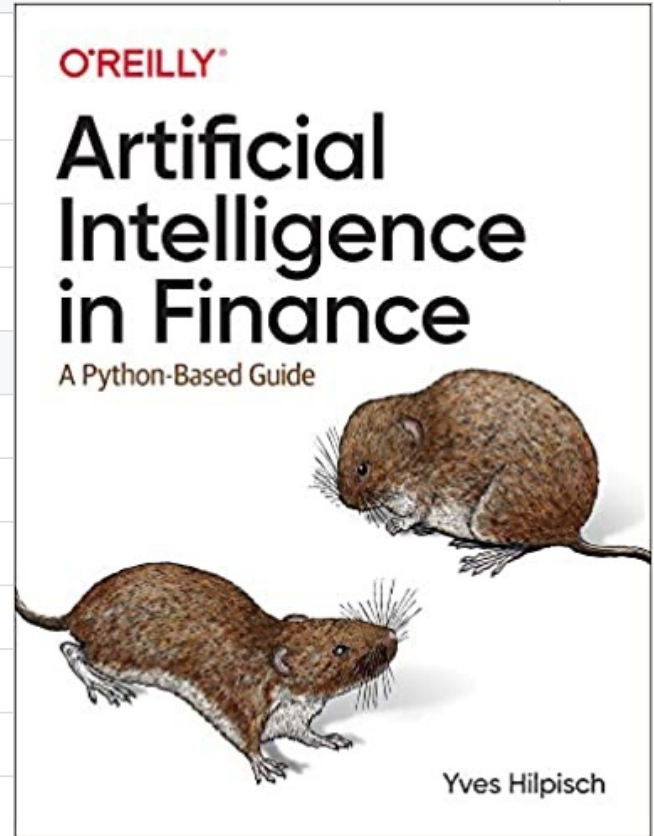
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yves Code updates for TF 2.3. e334251 on Dec 8, 2020 History

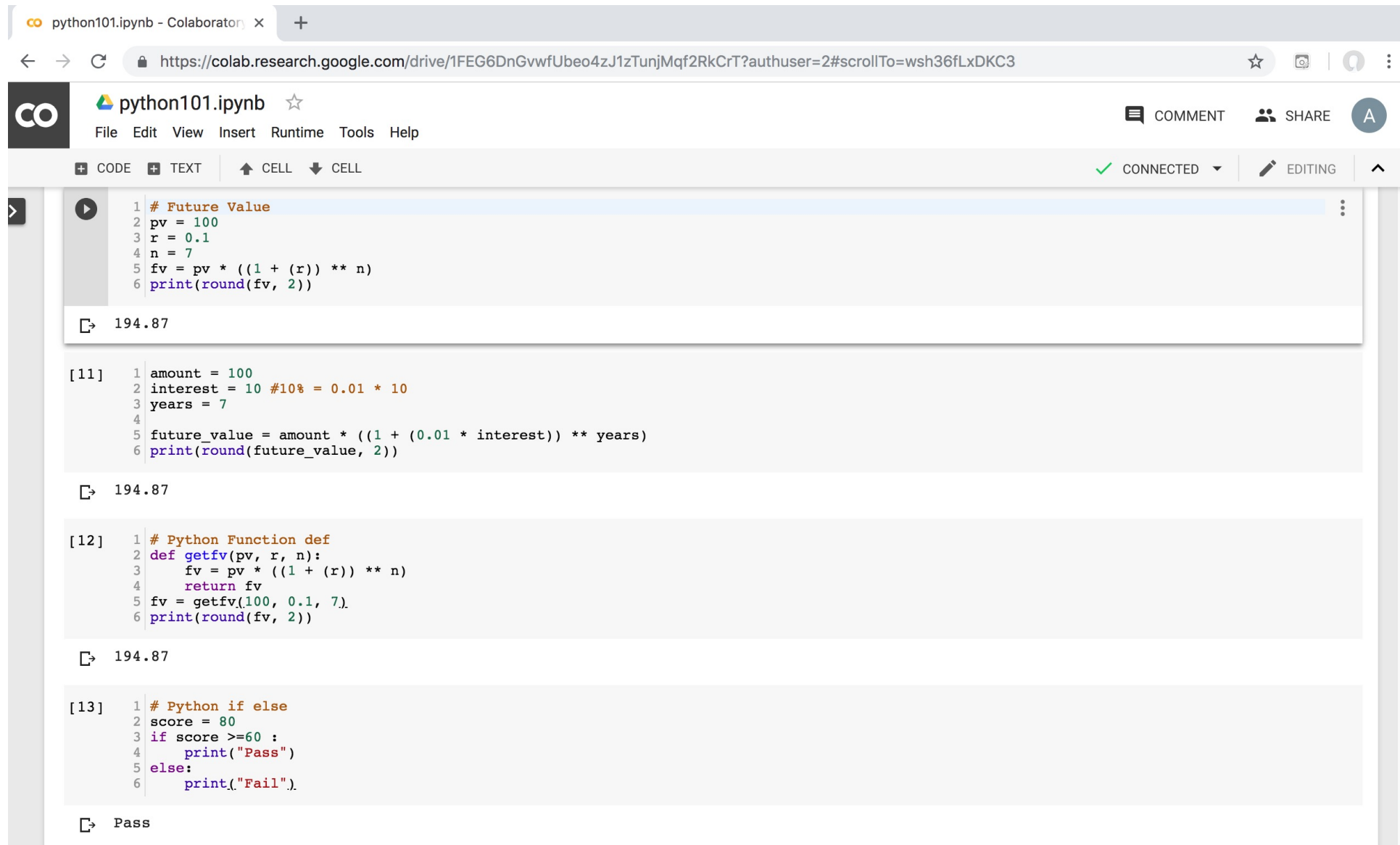
..	
oanda	Code updates for TF 2.3.
01_artificial_intelligence.ipynb	Code updates for TF 2.3.
02_superintelligence.ipynb	Code updates for TF 2.3.
03_normative_finance.ipynb	Code updates for TF 2.3.
04_data_driven_finance_a.ipynb	Initial commit.
04_data_driven_finance_b.ipynb	Initial commit.
05_machine_learning.ipynb	Code updates for TF 2.3.
06_ai_first_finance.ipynb	Code updates for TF 2.3.
07_dense_networks.ipynb	Code updates for TF 2.3.
08_recurrent_networks.ipynb	Code updates for TF 2.3.
09_reinforcement_learning_a.ipynb	Code updates.
09_reinforcement_learning_b.ipynb	Code updates for TF 2.3.



Source: <https://github.com/yhilpisch/aiif/tree/main/code>

Python in Google Colab (Python101)

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



The screenshot shows a Google Colab notebook titled "python101.ipynb". The interface includes a top navigation bar with "File", "Edit", "View", "Insert", "Runtime", "Tools", and "Help" menus. On the right, there are "COMMENT", "SHARE", and a user profile icon. Below the navigation bar, there are tabs for "CODE", "TEXT", "CELL", and "CELL", along with a "CONNECTED" status indicator and an "EDITING" mode button.

The notebook contains four code cells, each followed by its output:

- Cell 1:** A code cell with the following Python code:

```
1 # Future Value
2 pv = 100
3 r = 0.1
4 n = 7
5 fv = pv * ((1 + (r)) ** n)
6 print(round(fv, 2))
```

The output is "194.87".
- Cell 2:** A code cell with the following Python code:

```
[11] 1 amount = 100
2 interest = 10 #10% = 0.01 * 10
3 years = 7
4
5 future_value = amount * ((1 + (0.01 * interest)) ** years)
6 print(round(future_value, 2))
```

The output is "194.87".
- Cell 3:** A code cell with the following Python code:

```
[12] 1 # Python Function def
2 def getfv(pv, r, n):
3     fv = pv * ((1 + (r)) ** n)
4     return fv
5 fv = getfv(100, 0.1, 7)
6 print(round(fv, 2))
```

The output is "194.87".
- Cell 4:** A code cell with the following Python code:

```
[13] 1 # Python if else
2 score = 80
3 if score >=60 :
4     print("Pass")
5 else:
6     print("Fail").
```

The output is "Pass".

<https://tinyurl.com/aintpupython101>

Python in Google Colab (Python101)

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

The screenshot shows a Google Colab notebook titled "python101.ipynb". The interface includes a top navigation bar with "File", "Edit", "View", "Insert", "Runtime", "Tools", and "Help" menus, along with "Comment", "Share", and "Settings" icons. A "Table of contents" sidebar on the left lists various topics, with "Uncertainty and Risk" selected. The main content area displays a table of contents with expandable sections: "AI in Finance", "Normative Finance and Financial Theories", and "Uncertainty and Risk". Below the table of contents, a code cell is visible, containing Python code that uses NumPy to define variables for stock and bond prices and returns.

python101.ipynb ☆

File Edit View Insert Runtime Tools Help [All changes saved](#)

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Table of contents

- AI in Finance
 - Normative Finance and Financial Theories
 - Uncertainty and Risk**
 - Expected Utility Theory (EUT)
 - Mean-Variance Portfolio Theory (MVPT)
 - Capital Asset Pricing Model (CAPM)
 - Arbitrage Pricing Theory (APT)
 - Deep Learning for Financial Time Series Forecasting
 - Portfolio Optimization and Algorithmic Trading
 - Investment Portfolio Optimisation with Python
 - Efficient Frontier Portfolio Optimisation in Python
 - Investment Portfolio Optimization

▼ AI in Finance

- Source: Yves Hilpisch (2020), Artificial Intelligence in Finance: A Python-Based Guide, O'Reilly Media.
- Github: <https://github.com/yhilpisch/aiif/>

▼ Normative Finance and Financial Theories

▼ Uncertainty and Risk

```
1 import numpy as np
2
3 #The prices of the stock and bond today.
4 S0 = 10
5 B0 = 10
6 print('S0', S0)
7 print('B0', B0)
8
9 #The uncertain payoff of the stock and bond tomorrow.
10 S1 = np.array((20, 5))
11 B1 = np.array((11, 11))
12 print('S1', S1)
13 print('B1', B1)
14
15 #The market price vector
16 M0 = np.array((S0, B0))
```

<https://tinyurl.com/aintpupython101>

Python in Google Colab (Python101)



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 - Linear Relationships
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- Portfolio Optimization and Algorithmic Trading
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 - Efficient Frontier Portfolio Optimisation in Python
 - Investment Portfolio Optimization

▼ Data Driven Finance

▼ Financial Econometrics and Regression

```
[18] 1 import numpy as np
      2
      3 def f(x):
      4     return 2 + 1 / 2 * x
      5
      6 x = np.arange(-4, 5)
      7 x
```

```
array([-4, -3, -2, -1,  0,  1,  2,  3,  4])
```

```
1 y = f(x)
2 y
```

```
array([ 0.00,  0.50,  1.00,  1.50,  2.00,  2.50,  3.00,  3.50,  4.00])
```

```
1 print('x', x)
2
3 print('y', y)
4
5 beta = np.cov(x, y, ddof=0)[0, 1] / x.var()
6 print('beta', beta)
```

Python in Google Colab (Python101)

CO python101.ipynb ☆

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Machine Learning

Data

```
1 import numpy as np
2 import pandas as pd
3 from pylab import plt, mpl
4 np.random.seed(100)
5 plt.style.use('seaborn')
6 mpl.rcParams['savefig.dpi'] = 300
7 mpl.rcParams['font.family'] = 'serif'
8
9 url = 'http://hilpisch.com/aiif_eikon_eod_data.csv'
10
11 raw = pd.read_csv(url, index_col=0, parse_dates=True)['EUR=']
12 raw.head()
```

Date	
2010-01-01	1.4323
2010-01-04	1.4411
2010-01-05	1.4368
2010-01-06	1.4412
2010-01-07	1.4318

Name: EUR=, dtype: float64

```
[2] 1 raw.tail()
```

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- Financial Econometrics and Machine Learning
 - Machine Learning**
 - Data
 - Success
 - Capacity
 - Evaluation
 - Bias & Variance
 - Cross-Validation

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 - Cross-Validation

+ Code + Text

RAM Disk

Editing

Success

```
1 def MSE(l, p):  
2     return np.mean([(1 - p) ** 2])
```

```
[9] 1 reg = np.polyfit(f, l, deg=5)  
2     reg
```

```
array([-0.01910626, -0.0147182 ,  0.10990388,  0.06007211, -0.20833598,  
       -0.03275423])
```

```
[10] 1 p = np.polyval(reg, f)  
2     p
```

```
array([[ 0.12088427,  0.11526131,  0.11080193,  0.10739461,  0.10493286,  
         0.10331514,  0.10244475,  0.10222973,  0.10258281,  0.10342126,  
         0.10466683,  0.10624564,  0.1080881 ,  0.1101288 ,  0.11230643,  
         0.11456366,  0.11684709,  0.11910711,  0.12129784,  0.123377 ,  
         0.12530587,  0.12704913,  0.12857481,  0.1298542 ,  0.1308617 ,  
         0.1315748 ,  0.13197395,  0.13204243,  0.13176634,  0.13113443,  
         0.13013803,  0.12877097,  0.12702948,  0.12491207,  0.12241947,  
         0.11955452,  0.11632208,  0.11272891,  0.10878364,  0.1044966 ,  
         0.09987977,  0.09494668,  0.0897123 ,  0.08419296,  0.07840627,  
         0.07237098,  0.06610693,  0.05963494,  0.05297671,  0.04615473,  
         0.03919218,  0.03211286,  0.02494106,  0.01770149,  0.01041918,  
         0.00311939, -0.00417251, -0.0114311 , -0.01863101, -0.02574704,  
        -0.03275423, -0.03962796, -0.04634406, -0.05287887, -0.05920936,  
        -0.06531322, -0.07116897, -0.07675602, -0.08205478, -0.08704677,  
        -0.09171147, -0.09600254, -0.10001567, -0.10320002, -0.10604674])
```

Python in Google Colab (Python101)

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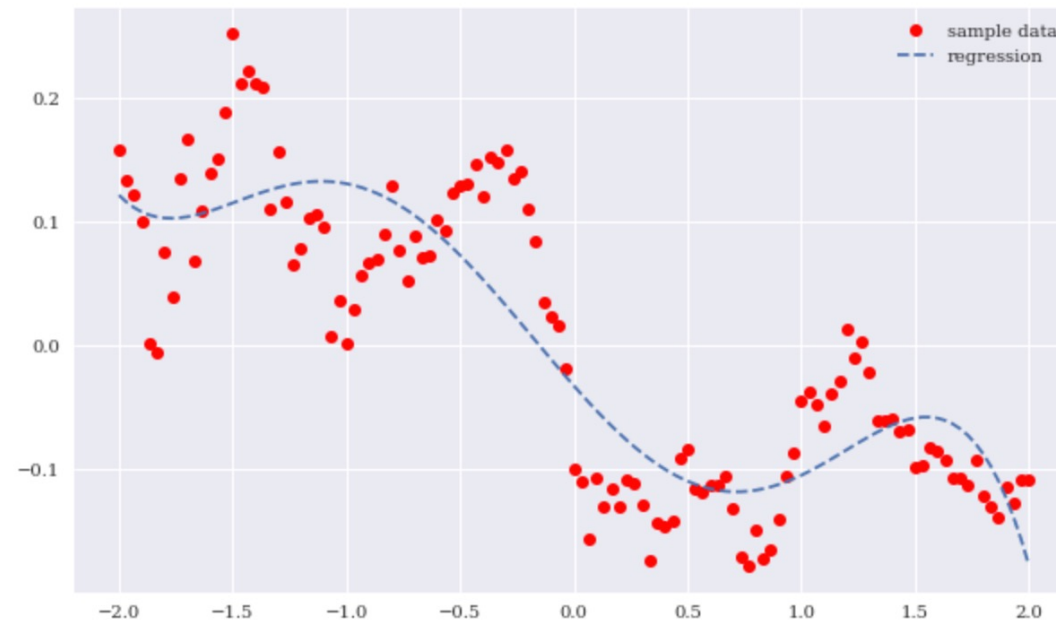
+ Code + Text

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```
[11] 1 MSE(l, p)
0.003416642295737103
```

```
1 plt.figure(figsize=(10, 6))
2 plt.plot(f, l, 'ro', label='sample data')
3 plt.plot(f, p, '--', label='regression')
4 plt.legend()
```

<matplotlib.legend.Legend at 0x7f66a41d5750>



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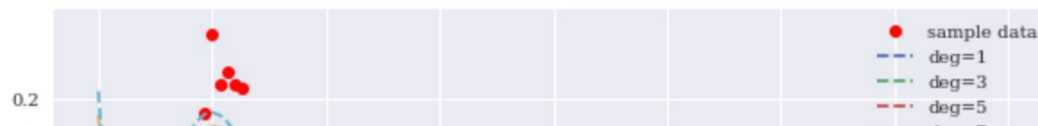
Capacity

```
[21] 1 reg = {}  
      2 for d in range(1, 12, 2):  
      3     reg[d] = np.polyfit(f, l, deg=d)  
      4     p = np.polyval(reg[d], f)  
      5     mse = MSE(l, p)  
      6     print(f'{d:2d} | MSE={mse}')  
      7  
      8  
      9  
     10  
     11
```

```
1 | MSE=0.005322474034260403  
3 | MSE=0.004353110724143185  
5 | MSE=0.003416642295737103  
7 | MSE=0.002738950177235401  
9 | MSE=0.0014119616263308346  
11 | MSE=0.0012651237868752398
```

```
1 plt.figure(figsize=(10, 6))  
2 plt.plot(f, l, 'ro', label='sample data')  
3 for d in reg:  
4     p = np.polyval(reg[d], f)  
5     plt.plot(f, p, '--', label=f'deg={d}')  
6 plt.legend()
```

<matplotlib.legend.Legend at 0x7f6630300310>



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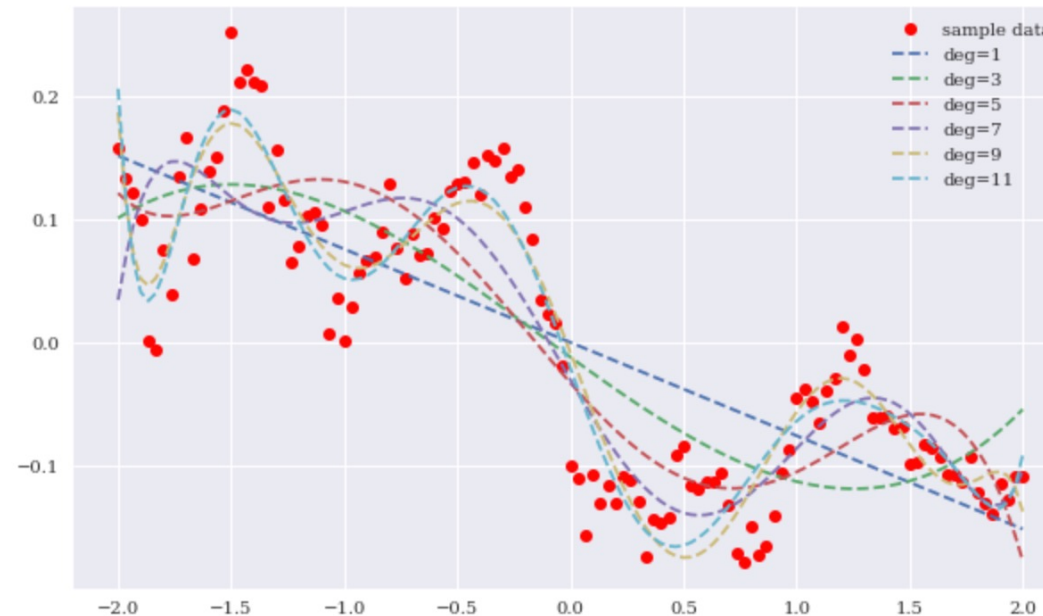
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```
9 | MSE=0.0014119616263308346
11 | MSE=0.0012651237868752398
```

```
1 plt.figure(figsize=(10, 6))
2 plt.plot(f, l, 'ro', label='sample data')
3 for d in reg:
4     p = np.polyval(reg[d], f)
5     plt.plot(f, p, '--', label=f'deg={d}')
6 plt.legend()
```

<matplotlib.legend.Legend at 0x7f6630300310>



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```
def create_dnn_model(hl=1, hu=256):  
    ''' Function to create Keras DNN model.  
    Parameters  
    =====  
    hl: int  
    number of hidden layers  
    hu: int  
    number of hidden units (per layer)  
    '''  
    model = Sequential()  
    for _ in range(hl):  
        model.add(Dense(hu, activation='relu', input_dim=1))  
    model.add(Dense(1, activation='linear'))  
    model.compile(loss='mse', optimizer='rmsprop')  
    return model  
  
model = create_dnn_model(3)  
  
model.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
dense_2 (Dense)	(None, 256)	512
dense_3 (Dense)	(None, 256)	65792
dense_4 (Dense)	(None, 256)	65792
dense_5 (Dense)	(None, 1)	257

=====
Total params: 132,353
Trainable params: 132,353
Non-trainable params: 0

Python in Google Colab (Python101)



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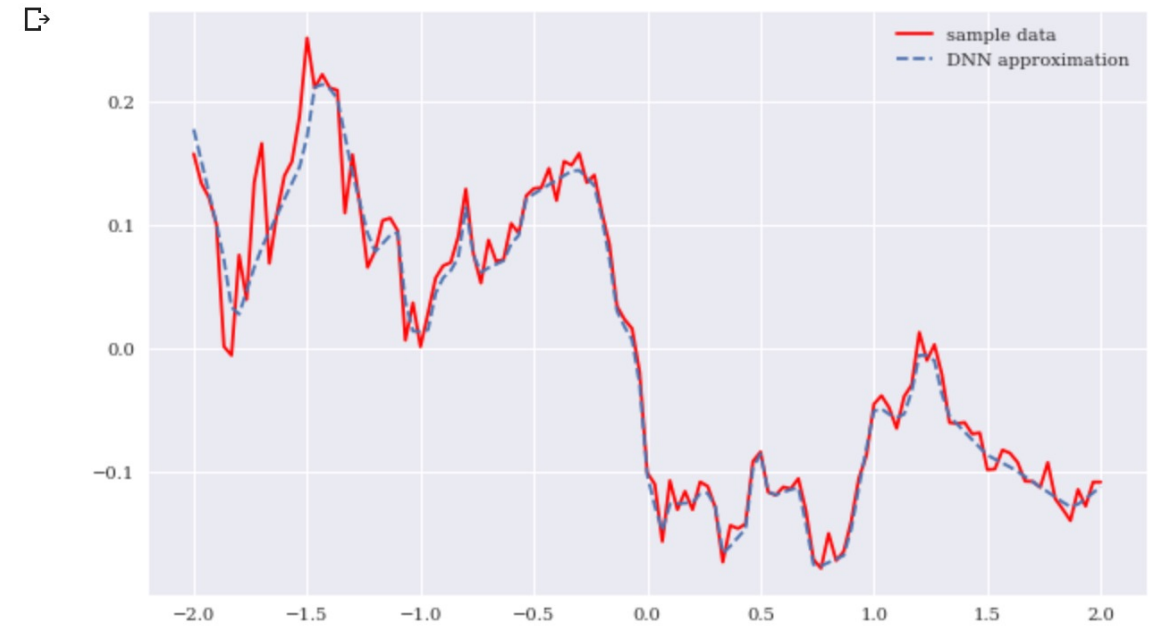
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```
+ Code + Text  
xelas.callbacks.history at 0x716830199610  
0s  
1 p = model.predict(f).flatten()  
2  
3 MSE(l, p)  
4  
5 plt.figure(figsize=(10, 6))  
6 plt.plot(f, l, 'r', label='sample data')  
7 plt.plot(f, p, '--', label='DNN approximation')  
8 plt.legend();
```



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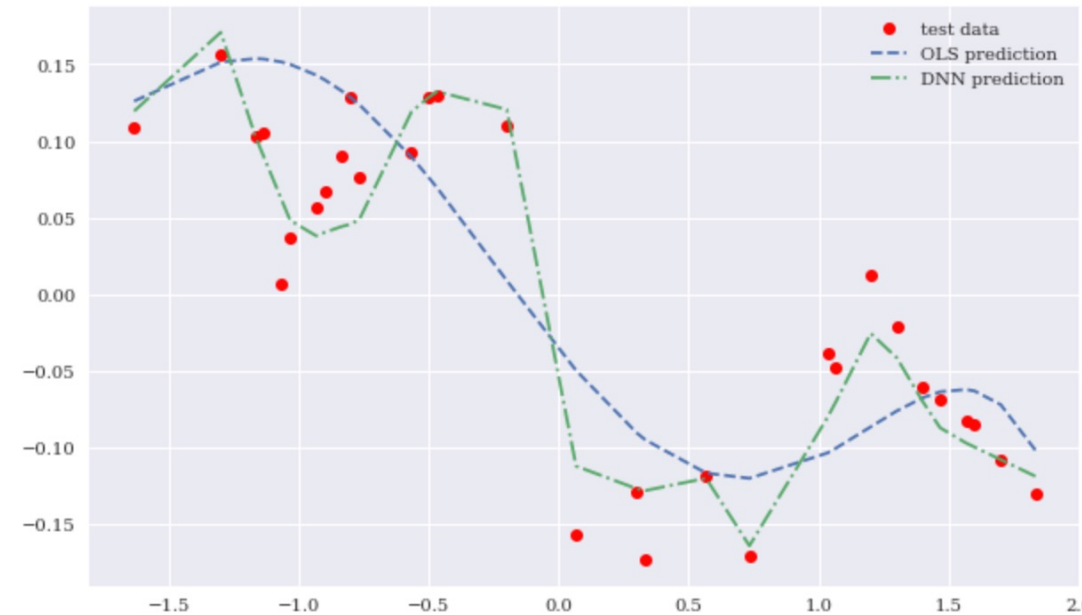
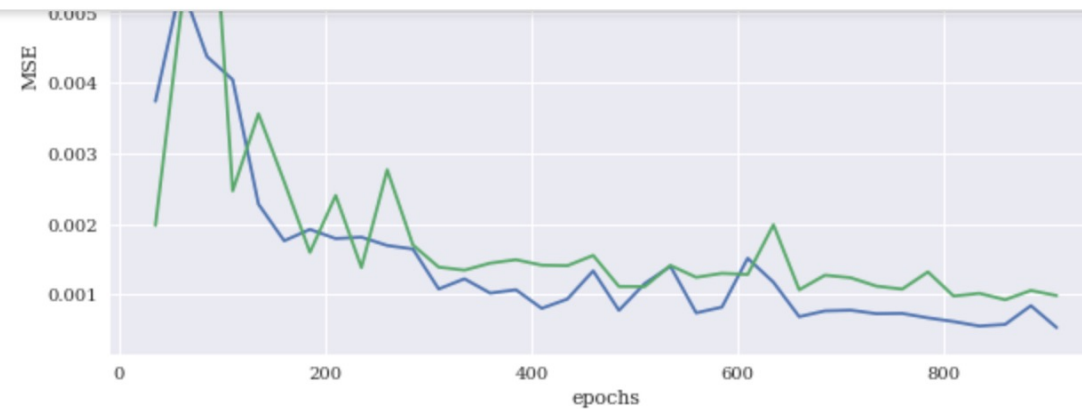
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Summary

- **Financial Econometrics**
 - **Financial Theories**
 - **OLS Regression**
- **Machine Learning**
 - **Learning**
 - **Evaluation**
 - **Bias and variance**
 - **Cross-validation**

References

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- Chris Brooks (2019), Introductory Econometrics for Finance, 4th Edition, Cambridge University Press
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