Machine Learning

(An Early Draft)[1]

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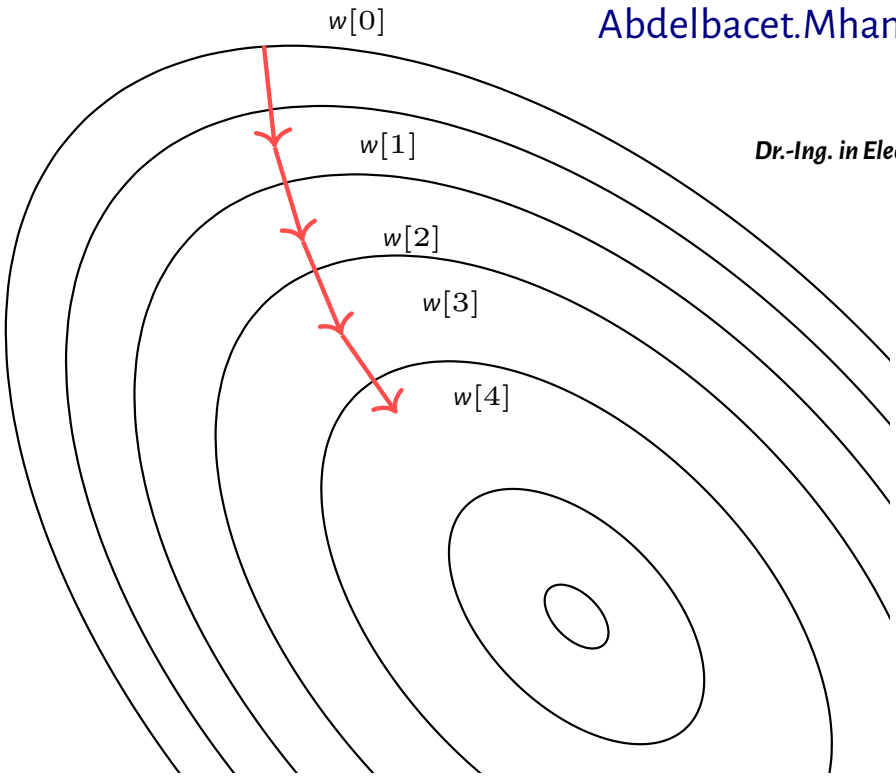
Dr.-Ing. in Electrical Engineering



"Computers are able to see, hear and learn. Welcome to the future."

Dave Waters

"This is nothing. In a few years, that bot will move so fast you'll need a strobe light to see it. Sweet dreams..."

Elon Musk

"Machine intelligence is the last invention that humanity will ever need to make."

Nick Bostrom

[1]Available @ https://github.com/a-mhamdi/isetbz/

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Outline

Next...

Top uses


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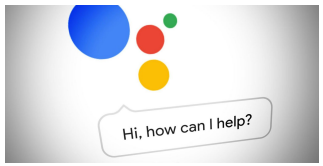
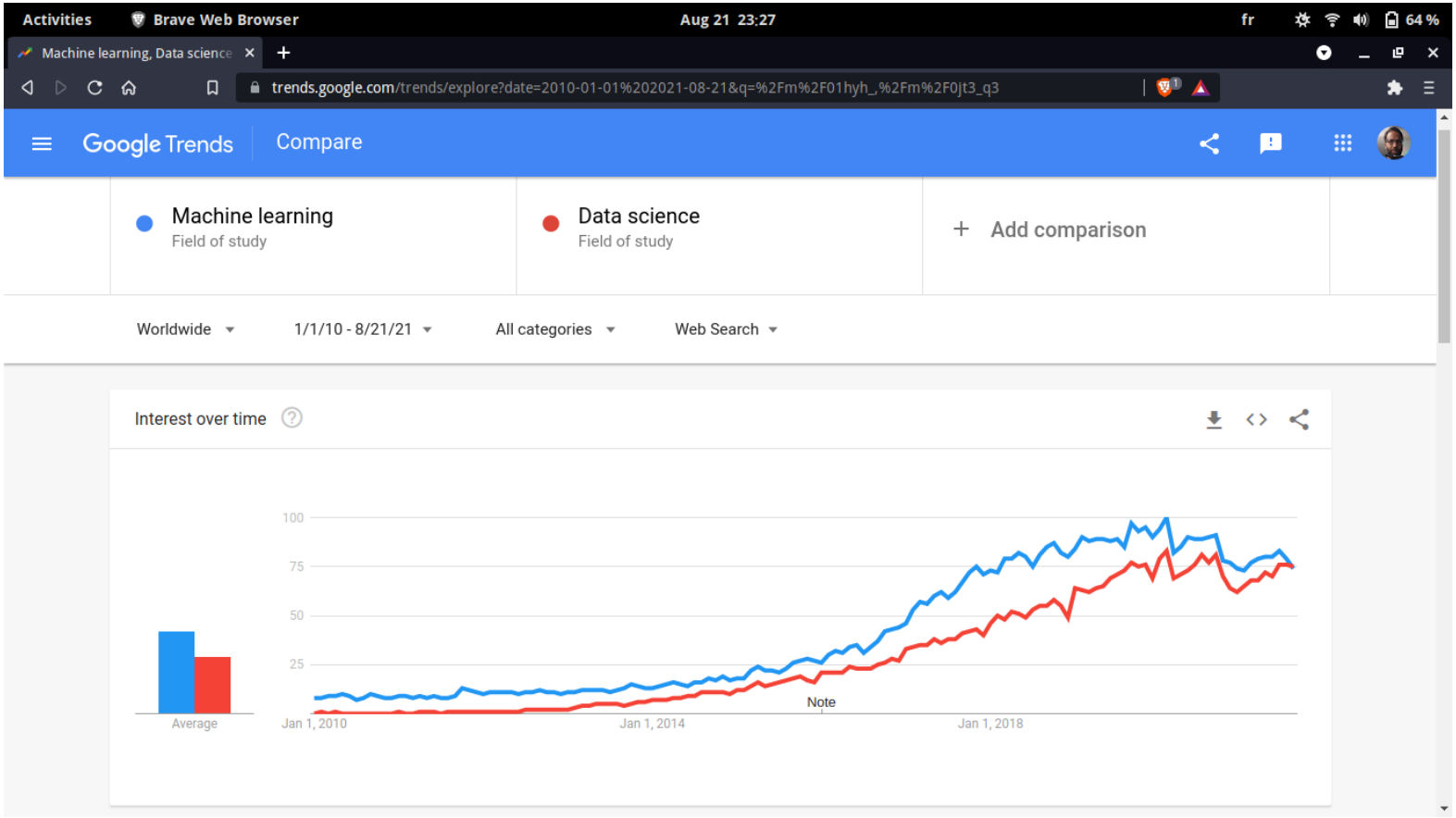

Hi, how can I help?

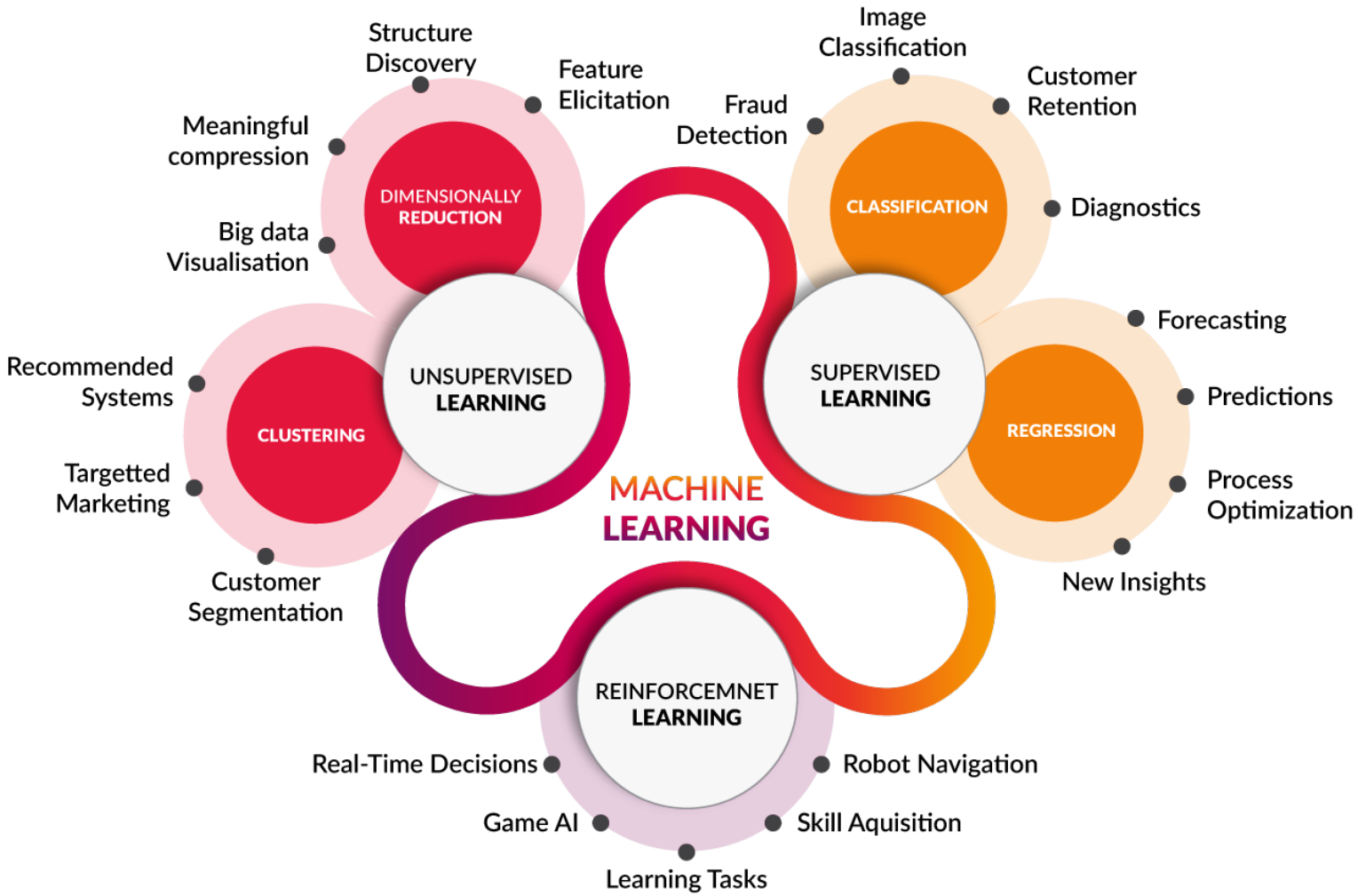

amazon
alexa


Hi, I'm Cortana.

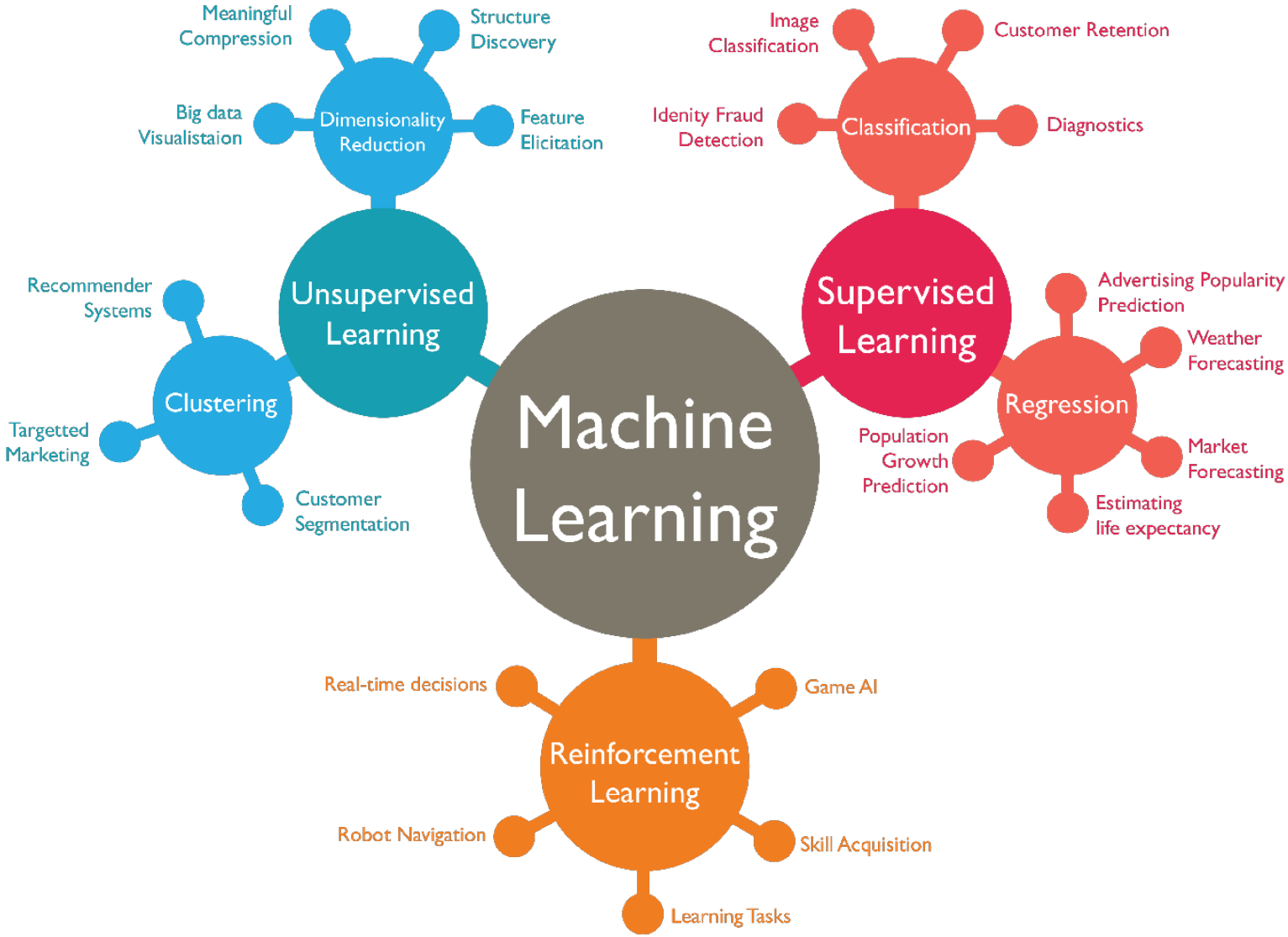


"Numbers represent search interest relative to the highest point on the chart for the given region and time.

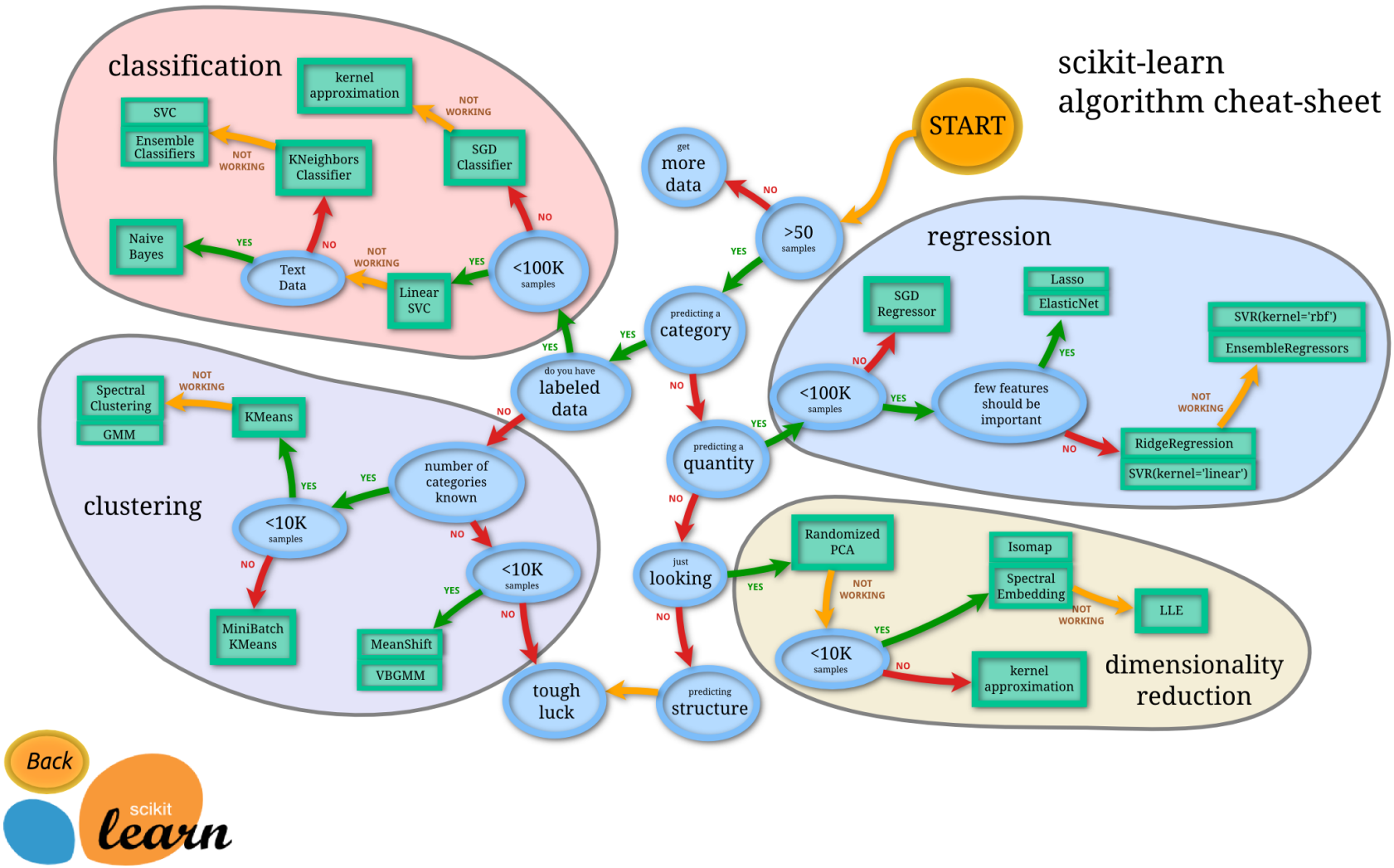
- A value of 100 is the peak popularity for the term;
- A value of 50 means that the term is half as popular;
- A score of 0 means there was not enough data for this term."



https://www.cognub.com/index.php/cognitive-platform/

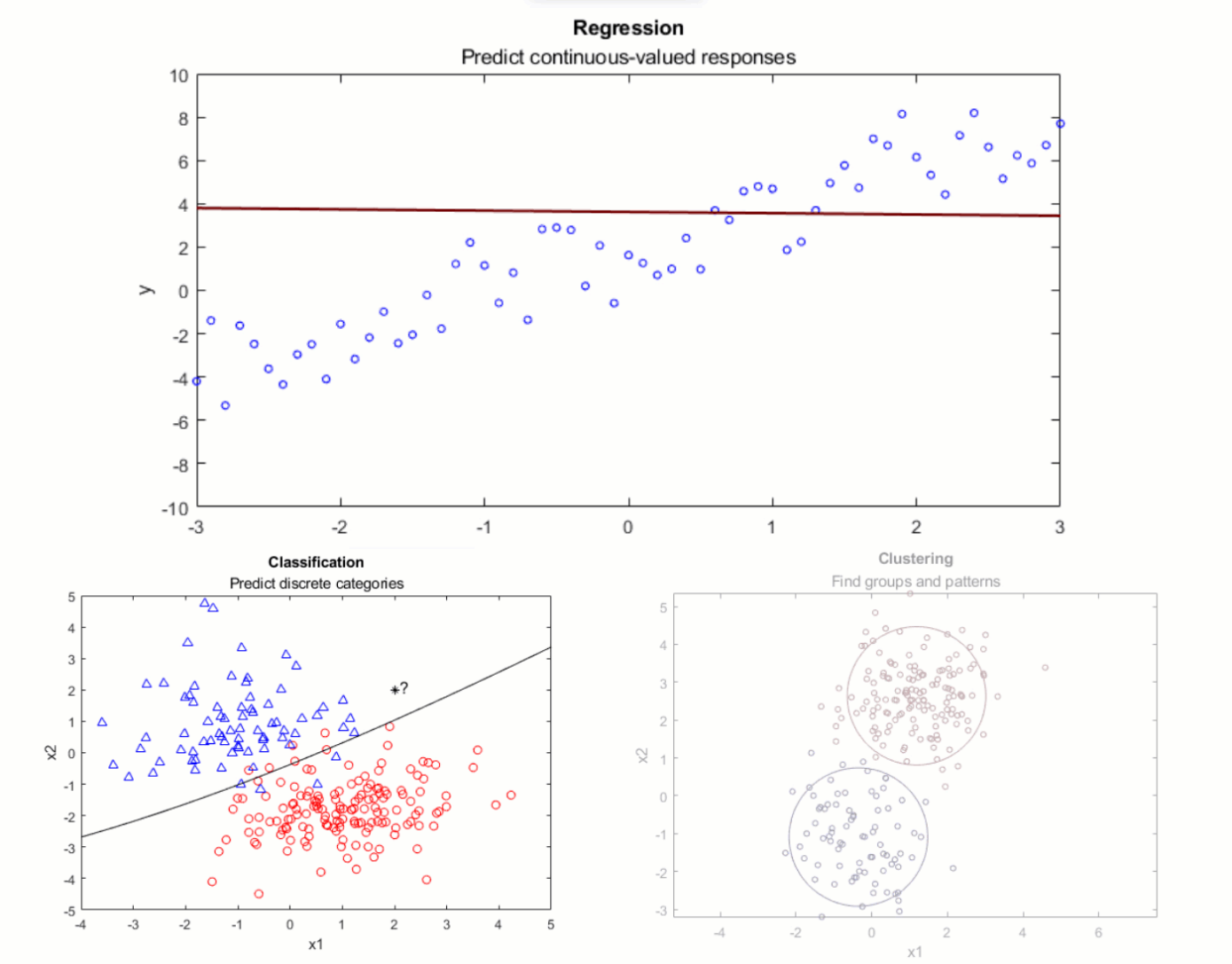


https://vitalflux.com/great-mind-maps-for-learning-machine-learning/



https://scikit-learn.org/stable/tutorial/machine_learning_map/index.html

Regression | Classification | Clustering



https://github.com/MathWorks-Teaching-Resources/Machine-Learning-for-Regression

Machine Learning Definition

Arthur Samuel (1959)

Machine Learning: Field of study that gives computers the ability to learn without being explicitly programmed.

Tom Mitchell (1998)

Well-posed Learning Problem: A computer is said to learn from experience $\mathcal{E}$ with respect to some task $\mathcal{T}$ and some performance measure $\mathcal{P}$, if its performance on $\mathcal{T}$, as measured by $\mathcal{P}$, improves with experience $\mathcal{E}$.

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Task #1

Suppose your email program watches which emails you do or do not mark as spam, and based on that learns how to better filter spam. What is the task $\mathcal{T}$ in this setting?

1. Classifying emails as spam or not spam;
2. Watching you label emails as spam or not spam;
3. The number (or fraction) of emails correctly classified as spam/not spam;
4. None of the above-this not a machine learning problem.

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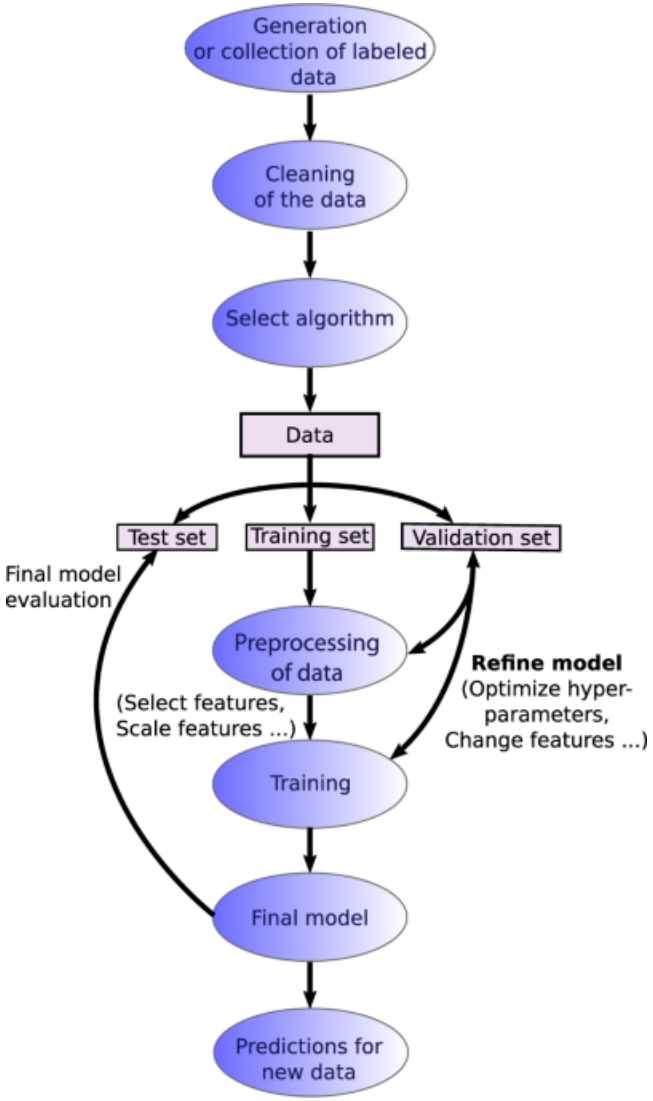
Next...

Overall Methodology

[Sch+19]



Data Preprocessing Template (1/7)

Importing the libraries

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

Importing the dataset

[2]:
```
df = pd.read_csv('datasets/Data.csv')
df.head()
```

[2]:

	Country	Age	Salary	Purchased
0	France	44.0	72000.0	No
1	Spain	27.0	48000.0	Yes
2	Germany	30.0	54000.0	No
3	Spain	38.0	61000.0	No
4	Germany	40.0	NaN	Yes

Extracting independant and dependant variables

[3]:
```
X = df.iloc[:, :-1].values
y = df.iloc[:, -1].values
```

Data Preprocessing Template (2/7)

[4]:
```
print(X) # Features
```

```
[['France' 44.0 72000.0]
 ['Spain' 27.0 48000.0]
 ['Germany' 30.0 54000.0]
 ['Spain' 38.0 61000.0]
 ['Germany' 40.0 nan]
 ['France' 35.0 58000.0]
 ['Spain' nan 52000.0]
 ['France' 48.0 79000.0]
 ['Germany' 50.0 83000.0]
 ['France' 37.0 67000.0]]
```

[5]:
```
print(y) # Target
```

```
['No' 'Yes' 'No' 'No' 'Yes' 'Yes' 'No' 'Yes' 'No' 'Yes']
```

Data Preprocessing Template (3/7)

Imputation transformer for completing missing values

https://scikit-learn.org/stable/modules/generated/sklearn.impute.SimpleImputer.html

[6]:
```
from sklearn.impute import SimpleImputer
```

[7]:
```
imputer = SimpleImputer(missing_values=np.nan, strategy='mean')
imputer.fit(X[:, 1:3])
X[:, 1:3] = imputer.transform(X[:, 1:3])
```

[8]:
```
print(X)
```

```
[['France' 44.0 72000.0]
 ['Spain' 27.0 48000.0]
 ['Germany' 30.0 54000.0]
 ['Spain' 38.0 61000.0]
 ['Germany' 40.0 63777.77777777778]
 ['France' 35.0 58000.0]
 ['Spain' 38.77777777777778 52000.0]
 ['France' 48.0 79000.0]
 ['Germany' 50.0 83000.0]
 ['France' 37.0 67000.0]]
```

Data Preprocessing Template (4/7)

How to encode categorical data?

Case of Independent Variable

[9]:
```
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
```

[10]:
```
ct = ColumnTransformer(transformers=[('encoder', OneHotEncoder(),␣
↪[0])], remainder='passthrough')
X = np.array(ct.fit_transform(X))
```

[11]:
```
print(X)
```

```
[[1.0 0.0 0.0 44.0 72000.0]
 [0.0 0.0 1.0 27.0 48000.0]
 [0.0 1.0 0.0 30.0 54000.0]
 [0.0 0.0 1.0 38.0 61000.0]
 [0.0 1.0 0.0 40.0 63777.77777777778]
 [1.0 0.0 0.0 35.0 58000.0]
 [0.0 0.0 1.0 38.77777777777778 52000.0]
 [1.0 0.0 0.0 48.0 79000.0]
 [0.0 1.0 0.0 50.0 83000.0]
 [1.0 0.0 0.0 37.0 67000.0]]
```

Data Preprocessing Template (5/7)

Case of Dependent Variable

[12]:
```
from sklearn.preprocessing import LabelEncoder
```

[13]:
```
le = LabelEncoder()
y = le.fit_transform(y)
```

[14]:
```
print(y)
```

```
[0 1 0 0 1 1 0 1 0 1]
```

Splitting the dataset into Training set and Test set

[15]:
```
from sklearn.model_selection import train_test_split
```

https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.train_test_split.html

[16]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.
↪2, random_state=1)
```

[17]:
```
print(X_train)
```

Data Preprocessing Template (6/7)

```
[[0.0 0.0 1.0 38.77777777777778 52000.0]
 [0.0 1.0 0.0 40.0 63777.77777777778]
 [1.0 0.0 0.0 44.0 72000.0]
 [0.0 0.0 1.0 38.0 61000.0]
 [0.0 0.0 1.0 27.0 48000.0]
 [1.0 0.0 0.0 48.0 79000.0]
 [0.0 1.0 0.0 50.0 83000.0]
 [1.0 0.0 0.0 35.0 58000.0]]
```

[18]:
```
print(X_test)
```

```
[[0.0 1.0 0.0 30.0 54000.0]
 [1.0 0.0 0.0 37.0 67000.0]]
```

[19]:
```
print(y_train)
```

```
[0 1 0 0 1 1 0 1]
```

[20]:
```
print(y_test)
```

```
[0 1]
```

Data Preprocessing Template (7/7)

Scaling of features

[21]:
```
from sklearn.preprocessing import StandardScaler
```

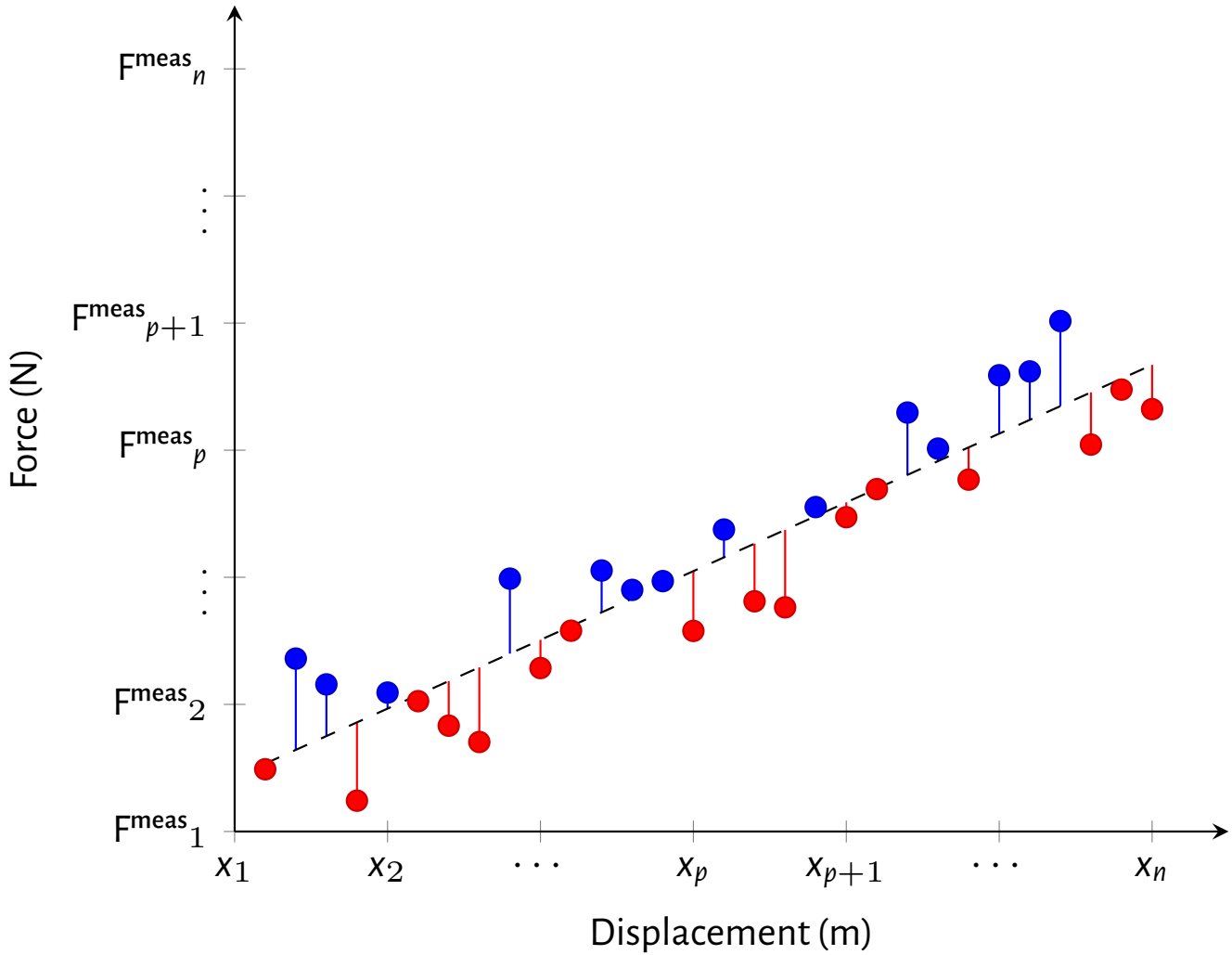
[22]:
```
sc = StandardScaler()
X_train[:, 3:] = sc.fit_transform(X_train[:, 3:])
X_test[:, 3:] = sc.transform(X_test[:, 3:])
```

[23]:
```
print(X_train)
```

```
[[0.0 0.0 1.0 -0.19159184384578545 -1.0781259408412425]
 [0.0 1.0 0.0 -0.014117293757057777 -0.07013167641635372]
 [1.0 0.0 0.0 0.566708506533324 0.633562432710455]
 [0.0 0.0 1.0 -0.30453019390224867 -0.3078661727429786 7]
 [0.0 0.0 1.0 -1.9018011447007988 -1.420463615551582]
 [1.0 0.0 0.0 1.1475343068237058 1.232653363453549]
 [0.0 1.0 0.0 1.4379472069688968 1.5749910381638885]
 [1.0 0.0 0.0 -0.7401495441200351 -0.5646194287757332]]
```

[24]:
```
print(X_test)
```

```
[[0.0 1.0 0.0 -1.4661817944830124 -0.9069571034860727]
 [1.0 0.0 0.0 -0.44973664397484414 0.2056403393225306]]
```


Force (N)
F^{meas}_n
F^{meas}_{p+1}
F^{meas}_p
F^{meas}_2
F^{meas}_1
x_1
x_2
x_p
x_{p+1}
x_n
Displacement (m)

Consider the example of a spring. Our main goal is to determine the stiffness k of this spring, given some experimental data. The mathematical model *(Hooke's law)*:

$$F = kx \tag{1}$$

Restoring force is proportional to displacement.

Table: Measurements of couple $(x_i, \mathrm{F}^{\mathrm{meas}}{}_i)$

x_i	x_1	$\cdots$	x_p	$\cdots$	x_n
$\mathrm{F}^{\mathrm{meas}}{}_i$	$\mathrm{F}^{\mathrm{meas}}{}_1$	$\cdots$	$\mathrm{F}^{\mathrm{meas}}{}_p$	$\cdots$	$\mathrm{F}^{\mathrm{meas}}{}_n$

$$\begin{aligned} \mathrm{F}^{\mathrm{meas}}{}_i &= \mathrm{F}_i + \varepsilon_i \\ &= kx_i + \varepsilon_i, \end{aligned} \tag{2}$$

where F_i denotes the unknown real value of the force applied to the spring. In order to estimate the stiffness value k, we can consider the quadratic criterion:

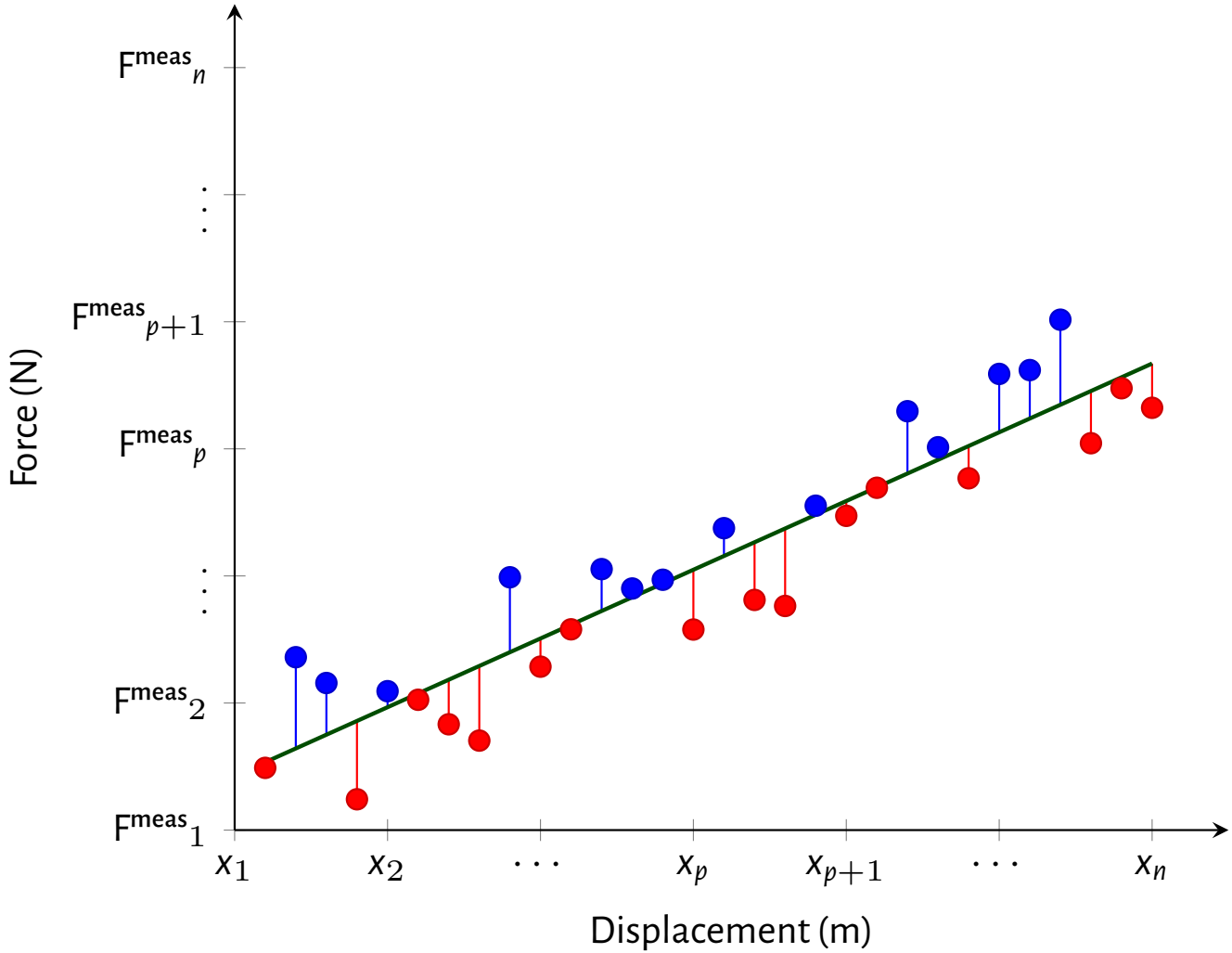
$$\begin{aligned} \mathcal{J} &= \sum_{i=1}^{n} \varepsilon_i^2 \\ &= \sum_{i=1}^{n} \left(\mathrm{F}^{\mathrm{meas}}{}_i - kx_i\right)^2 \end{aligned}$$

$$\frac{\partial \mathcal{J}}{\partial k} = 0 \tag{3}$$

$$2\sum_{i=1}^{n}\left(\mathrm{F}^{\mathrm{meas}}{}_i - kx_i\right)\sum_{i=1}^{n}\frac{\partial\left(\mathrm{F}^{\mathrm{meas}}{}_i - kx_i\right)}{\partial k} = 0$$

$$\sum_{i=1}^{n}\left(\mathrm{F}^{\mathrm{meas}}{}_i - kx_i\right)\sum_{i=1}^{n}x_i = 0$$

$$\sum_{i=1}^{n}\mathrm{F}^{\mathrm{meas}}{}_i\, x_i = k\sum_{i=1}^{n}x_i^2 \iff \boxed{\hat{k} = \frac{\sum_{i=1}^{n}\mathrm{F}^{\mathrm{meas}}{}_i\, x_i}{\sum_{i=1}^{n}x_i^2}}$$


Force (N)
F^{meas}_n
F^{meas}_{p+1}
F^{meas}_p
F^{meas}_2
F^{meas}_1
x_1
x_2
x_p
x_{p+1}
x_n
Displacement (m)

Simple Linear Regression (1/6)

Importing the libraries

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

Importing the dataset

[2]:
```
df = pd.read_csv('datasets/Salary_Data.csv')
df.head()
```

[2]:

	YearsExperience	Salary
0	1.1	39343.0
1	1.3	46205.0
2	1.5	37731.0
3	2.0	43525.0
4	2.2	39891.0

[3]:
```
X = df.iloc[:, :-1].values
y = df.iloc[:, -1].values
```

Splitting the dataset into the Training set and Test set

Simple Linear Regression (2/6)

[4]:
```
from sklearn.model_selection import train_test_split
```

[5]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=1/
↪3, random_state=0)
```

Training the Simple Linear Regression model on the Training set

[6]:
```
from sklearn.linear_model import LinearRegression
```

[7]:
```
regressor = LinearRegression()
regressor.fit(X_train, y_train)
```

[7]:
```
LinearRegression()
```

Predicting the Test set results

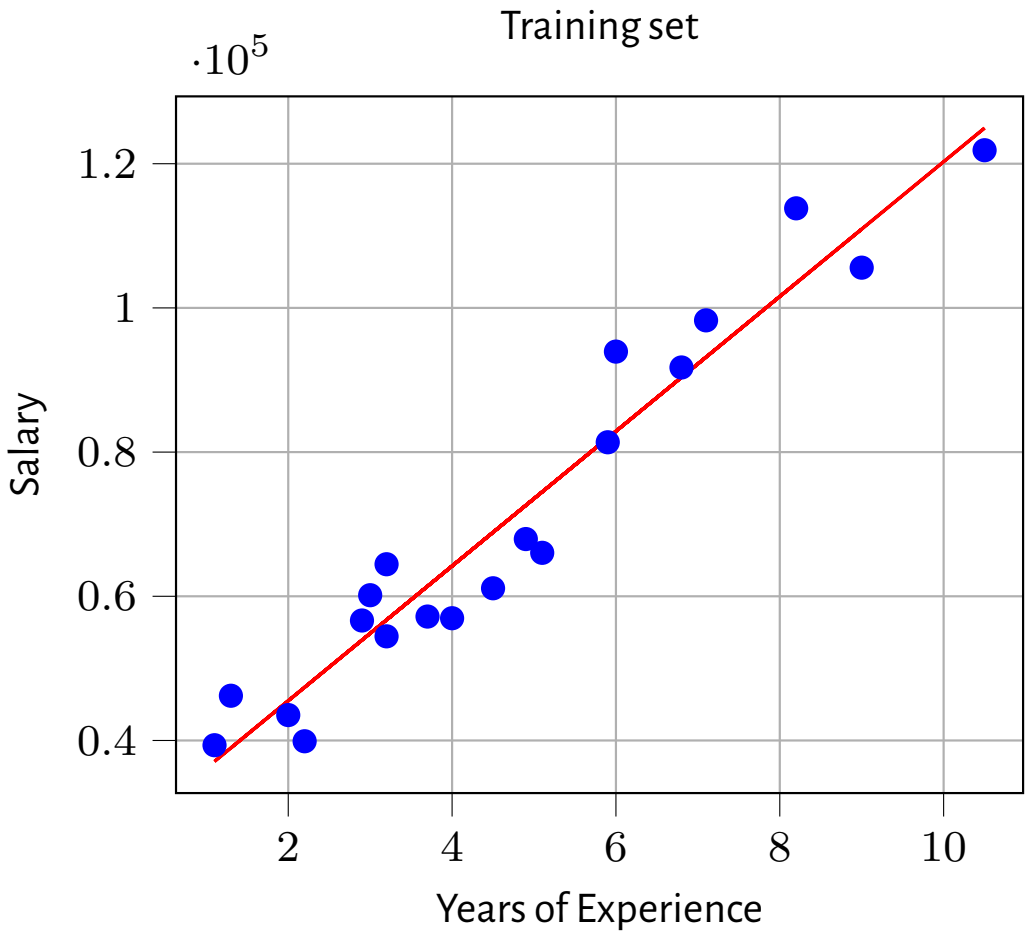
[8]:
```
y_pred = regressor.predict(X_test)
```

Visualising the Training set results

Simple Linear Regression (3/6)

[9]:
```
plt.scatter(X_train, y_train, color='blue')
plt.plot(X_train, regressor.predict(X_train), color='red')
plt.title('Training set')
plt.xlabel('Years of Experience')
plt.ylabel('Salary')
plt.grid()
```

Simple Linear Regression (4/6)

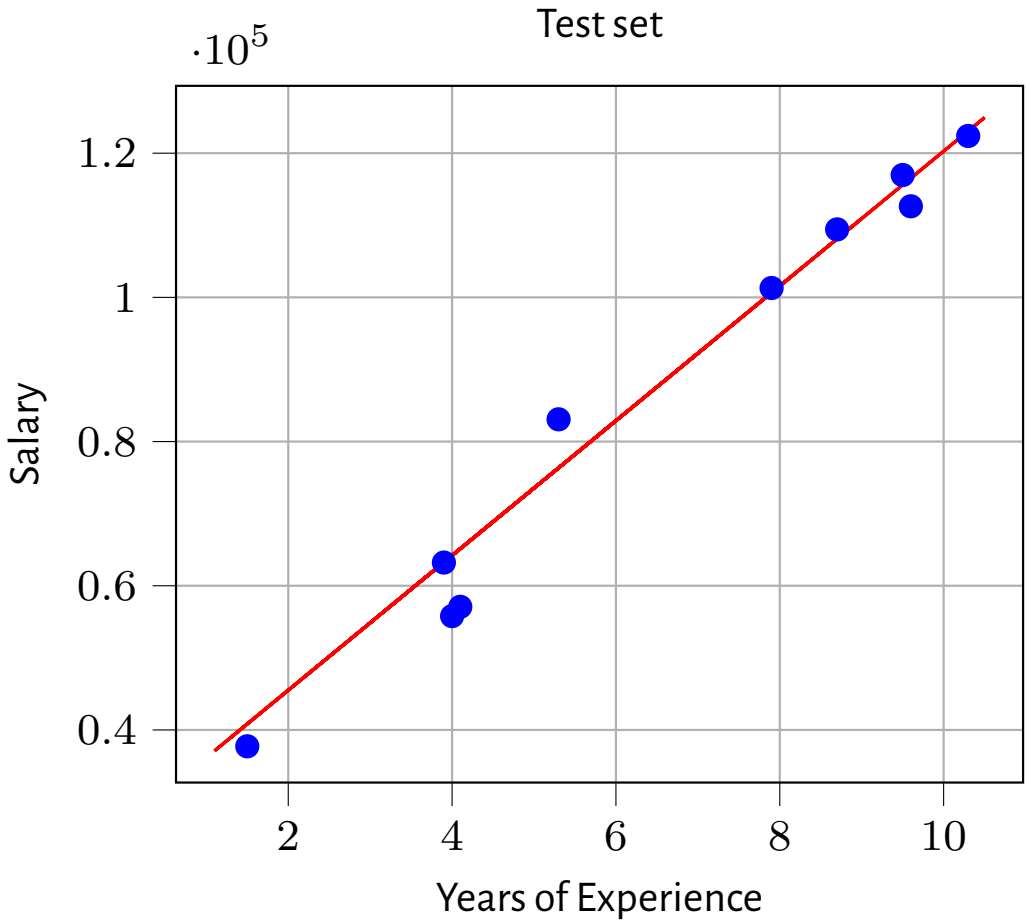


Simple Linear Regression (5/6)

Visualising the Test set results

[10]:
```
plt.scatter(X_test, y_test, color='blue')
plt.plot(X_train, regressor.predict(X_train), color='red')
plt.title('Test set')
plt.xlabel('Years of Experience')
plt.ylabel('Salary')
plt.grid()
```

Simple Linear Regression (6/6)



This example consists on determining the unknown couple $(y_0,\ v_0)$ of a mobile solid. We assume that the trajectory is linear. The mathematical model that relates the position y to time t is given by this equation:

$$y = y_0 + vt \tag{4}$$

Table: Measurements of position y

t_i	t_1	$\cdots$	t_p	$\cdots$	t_n
$y^{meas}{}_i$	$y^{meas}{}_1$	$\cdots$	$y^{meas}{}_p$	$\cdots$	$y^{meas}{}_n$

$$\begin{aligned} y^{meas}{}_i &= y_i + \varepsilon_i \\ &= y_0 + vt_i + \varepsilon_i, \end{aligned} \tag{5}$$

where y_i denotes the unknown real value of the position y at time point t_i.
In order to estimate the values taken by the couple $\begin{bmatrix} y_0, & v \end{bmatrix}^T$, we consider the quadratic criterion again, as follows:

$$\begin{aligned} \mathcal{J} &= \sum_{i=1}^{n} \varepsilon_i^2 \\ &= \varepsilon^T \times \varepsilon \end{aligned}$$

The vector ε is set by $\varepsilon_i, \ \forall i \geq 1$:

$$\varepsilon = \begin{bmatrix} \varepsilon_1 & \cdots & \varepsilon_n \end{bmatrix}^T$$

$$\frac{\partial \mathcal{J}}{\partial \begin{bmatrix} y_0 \\ \\ v \end{bmatrix}} = 0 \tag{6}$$

Multiple Linear Regression (1/8)

Importing the libraries

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

Importing the dataset

[2]:
```
df = pd.read_csv('datasets/50_Startups.csv')
df.head()
```

[2]:

	R&D Spend	Administration	Marketing Spend	State	Profit
0	165349.20	136897.80	471784.10	New York	192261.83
1	162597.70	151377.59	443898.53	California	191792.06
2	153441.51	101145.55	407934.54	Florida	191050.39
3	144372.41	118671.85	383199.62	New York	182901.99
4	142107.34	91391.77	366168.42	Florida	166187.94

[3]:
```
X = df.iloc[:, :-1].values
y = df.iloc[:, -1].values
```

[4]:
```
print(X)
```

Multiple Linear Regression (2/8)

```
[[165349.2 136897.8 471784.1 'New York']
 [162597.7 151377.59 443898.53 'California']
 [153441.51 101145.55 407934.54 'Florida']
 [144372.41 118671.85 383199.62 'New York']
 [142107.34 91391.77 366168.42 'Florida']
 [131876.9 99814.71 362861.36 'New York']
 [134615.46 147198.87 127716.82 'California']
 [130298.13 145530.06 323876.68 'Florida']
 [120542.52 148718.95 311613.29 'New York']
 [123334.88 108679.17 304981.62 'California']
 [101913.08 110594.11 229160.95 'Florida']
 [100671.96 91790.61 249744.55 'California']
 [93863.75 127320.38 249839.44 'Florida']
 [91992.39 135495.07 252664.93 'California']
 [119943.24 156547.42 256512.92 'Florida']
 [114523.61 122616.84 261776.23 'New York']
 [78013.11 121597.55 264346.06 'California']
 [94657.16 145077.58 282574.31 'New York']
 [91749.16 114175.79 294919.57 'Florida']
 [86419.7 153514.11 0.0 'New York']
 [76253.86 113867.3 298664.47 'California']
 [78389.47 153773.43 299737.29 'New York']
 [73994.56 122782.75 303319.26 'Florida']
```

Multiple Linear Regression (3/8)

```
[67532.53 105751.03 304768.73 'Florida']
[77044.01 99281.34 140574.81 'New York']
[64664.71 139553.16 137962.62 'California']
[75328.87 144135.98 134050.07 'Florida']
[72107.6 127864.55 353183.81 'New York']
[66051.52 182645.56 118148.2 'Florida']
[65605.48 153032.06 107138.38 'New York']
[61994.48 115641.28 91131.24 'Florida']
[61136.38 152701.92 88218.23 'New York']
[63408.86 129219.61 46085.25 'California']
[55493.95 103057.49 214634.81 'Florida']
[46426.07 157693.92 210797.67 'California']
[46014.02 85047.44 205517.64 'New York']
[28663.76 127056.21 201126.82 'Florida']
[44069.95 51283.14 197029.42 'California']
[20229.59 65947.93 185265.1 'New York']
[38558.51 82982.09 174999.3 'California']
[28754.33 118546.05 172795.67 'California']
[27892.92 84710.77 164470.71 'Florida']
[23640.93 96189.63 148001.11 'California']
[15505.73 127382.3 35534.17 'New York']
[22177.74 154806.14 28334.72 'California']
[1000.23 124153.04 1903.93 'New York']
```

Multiple Linear Regression (4/8)

```
[1315.46 115816.21 297114.46 'Florida']
[0.0 135426.92 0.0 'California']
[542.05 51743.15 0.0 'New York']
[0.0 116983.8 45173.06 'California']]
```

Encoding categorical data

[5]:
```
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
```

[6]:
```
ct = ColumnTransformer(transformers=[('encoder', OneHotEncoder(),␣
↪[3])], remainder='passthrough')
X = np.array(ct.fit_transform(X))
```

[7]:
```
print(X)
```

Multiple Linear Regression (5/8)

```
[[0.0 0.0 1.0 165349.2 136897.8 471784.1]
 [1.0 0.0 0.0 162597.7 151377.59 443898.53]
 [0.0 1.0 0.0 153441.51 101145.55 407934.54]
 [0.0 0.0 1.0 144372.41 118671.85 383199.62]
 [0.0 1.0 0.0 142107.34 91391.77 366168.42]
 [0.0 0.0 1.0 131876.9 99814.71 362861.36]
 [1.0 0.0 0.0 134615.46 147198.87 127716.82]
 [0.0 1.0 0.0 130298.13 145530.06 323876.68]
 [0.0 0.0 1.0 120542.52 148718.95 311613.29]
 [1.0 0.0 0.0 123334.88 108679.17 304981.62]
 [0.0 1.0 0.0 101913.08 110594.11 229160.95]
 [1.0 0.0 0.0 100671.96 91790.61 249744.55]
 [0.0 1.0 0.0 93863.75 127320.38 249839.44]
 [1.0 0.0 0.0 91992.39 135495.07 252664.93]
 [0.0 1.0 0.0 119943.24 156547.42 256512.92]
 [0.0 0.0 1.0 114523.61 122616.84 261776.23]
 [1.0 0.0 0.0 78013.11 121597.55 264346.06]
 [0.0 0.0 1.0 94657.16 145077.58 282574.31]
 [0.0 1.0 0.0 91749.16 114175.79 294919.57]
 [0.0 0.0 1.0 86419.7 153514.11 0.0]
 [1.0 0.0 0.0 76253.86 113867.3 298664.47]
 [0.0 0.0 1.0 78389.47 153773.43 299737.29]
 [0.0 1.0 0.0 73994.56 122782.75 303319.26]
```

Multiple Linear Regression (6/8)

```
[0.0 1.0 0.0 67532.53 105751.03 304768.73]
[0.0 0.0 1.0 77044.01 99281.34 140574.81]
[1.0 0.0 0.0 64664.71 139553.16 137962.62]
[0.0 1.0 0.0 75328.87 144135.98 134050.07]
[0.0 0.0 1.0 72107.6 127864.55 353183.81]
[0.0 1.0 0.0 66051.52 182645.56 118148.2]
[0.0 0.0 1.0 65605.48 153032.06 107138.38]
[0.0 1.0 0.0 61994.48 115641.28 91131.24]
[0.0 0.0 1.0 61136.38 152701.92 88218.23]
[1.0 0.0 0.0 63408.86 129219.61 46085.25]
[0.0 1.0 0.0 55493.95 103057.49 214634.81]
[1.0 0.0 0.0 46426.07 157693.92 210797.67]
[0.0 0.0 1.0 46014.02 85047.44 205517.64]
[0.0 1.0 0.0 28663.76 127056.21 201126.82]
[1.0 0.0 0.0 44069.95 51283.14 197029.42]
[0.0 0.0 1.0 20229.59 65947.93 185265.1]
[1.0 0.0 0.0 38558.51 82982.09 174999.3]
[1.0 0.0 0.0 28754.33 118546.05 172795.67]
[0.0 1.0 0.0 27892.92 84710.77 164470.71]
[1.0 0.0 0.0 23640.93 96189.63 148001.11]
[0.0 0.0 1.0 15505.73 127382.3 35534.17]
[1.0 0.0 0.0 22177.74 154806.14 28334.72]
[0.0 0.0 1.0 1000.23 124153.04 1903.93]
```

Multiple Linear Regression (7/8)

```
[0.0 1.0 0.0 1315.46 115816.21 297114.46]
[1.0 0.0 0.0 0.0 135426.92 0.0]
[0.0 0.0 1.0 542.05 51743.15 0.0]
[1.0 0.0 0.0 0.0 116983.8 45173.06]]
```

Splitting the dataset into the Training set and Test set

[8]:
```
from sklearn.model_selection import train_test_split
```

[9]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.
↪2, random_state=0)
```

Training the Multiple Linear Regression model on the Training set

[10]:
```
from sklearn.linear_model import LinearRegression
```

[11]:
```
regressor = LinearRegression()
regressor.fit(X_train, y_train)
```

[11]:
```
LinearRegression()
```

Predicting the Test set results

Multiple Linear Regression (8/8)

[12]:
```
y_pred = regressor.predict(X_test)
np.set_printoptions(precision=2)
print(np.concatenate((y_pred.reshape(len(y_pred),1), y_test.
↪reshape(len(y_test),1)),1))
```

```
[[103015.2  103282.38]
 [132582.28 144259.4 ]
 [132447.74 146121.95]
 [ 71976.1   77798.83]
 [178537.48 191050.39]
 [116161.24 105008.31]
 [ 67851.69  81229.06]
 [ 98791.73  97483.56]
 [113969.44 110352.25]
 [167921.07 166187.94]]
```

Next...

Next...

Further Reading

I. El Naqa and M. J. Murphy. "What Is Machine Learning?" In: *Machine Learning in Radiation Oncology: Theory and Applications*. Ed. by I. El Naqa, R. Li, and M. J. Murphy. Cham: Springer International Publishing, 2015, pp. 3–11. DOI: 10.1007/978-3-319-18305-3_1.

J. Schmidt et al. "Recent advances and applications of machine learning in solid-state materials science". In: *npj Computational Materials* 5.1 (Aug. 2019). DOI: 10.1038/s41524-019-0221-0 (cit. on p. 15).