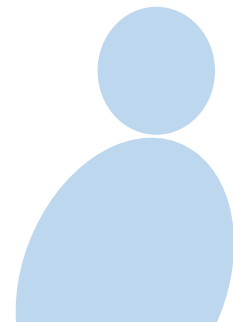


Chapter 2

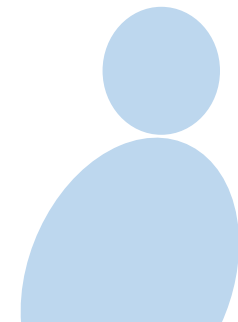
Linear Regression



Linear Regression

- Regression: Algorithm to **predict a** RESPONSE variable y ...
 - based on a set of REGRESSORS or EXPLANATORY VARIABLES

| Year | Sales (Million Euro) | Advertising (Million Euro) |
|------|----------------------------|-------------------------------|
| 1 | 651 | 23 |
| 2 | 762 | 26 |
| 3 | 856 | 30 |
| 4 | 1,063 | 34 |
| 5 | 1,190 | 43 |
| 6 | 1,298 | 48 |
| 7 | 1,421 | 52 |
| 8 | 1,440 | 57 |
| 9 | 1,518 | 58 |



Linear Regression

- Regression: Algorithm to **predict a response** variable y ...

- based on a set of **regressors** or **explanatory variables**

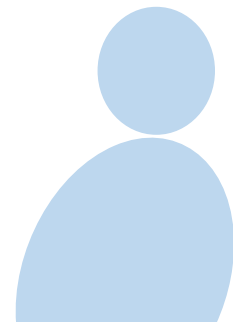
y Response

Regressor x

$x(k)$ — Regressor
 $y(k)$ — Response

k

| Year | Sales (Million Euro) | Advertising (Million Euro) |
|------|----------------------------|-------------------------------|
| 1 | 651 | 23 |
| 2 | 762 | 26 |
| 3 | 856 | 30 |
| 4 | 1,063 | 34 |
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| 9 | 1,518 | 58 |



Linear Regression

- In general the **regressor** \bar{X} can be an n –dimensional vector

- x_1 is the cost of

TV

- x_2 is the cost of

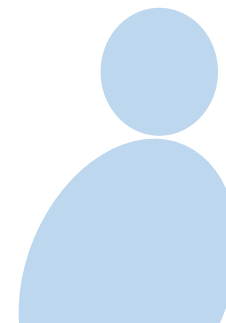
Radio

and so on....

x_3 : Newspaper

multiple regressors.

| | TV | Radio | Newspaper | Sales |
|---|-------|-------|-----------|-------|
| 0 | 230.1 | 37.8 | 69.2 | 22.1 |
| 1 | 44.5 | 39.3 | 45.1 | 10.4 |
| 2 | 17.2 | 45.9 | 69.3 | 9.3 |
| 3 | 151.5 | 41.3 | 58.5 | 18.5 |
| 4 | 180.8 | 10.8 | 58.4 | 12.9 |



Linear Regression

- In general the **regressor** $\bar{\mathbf{x}}$ can be an n –dimensional vector

- x_1 is the cost of **TV advertising**
- x_2 is the cost of **Radio advertising** and so on....

Regression vector

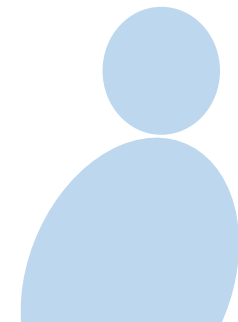
$$\bar{\mathbf{x}} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$$

TV
Radio
Newspaper

| | TV | Radio | Newspaper | Sales |
|---|-------|-------|-----------|-------|
| 0 | 230.1 | 37.8 | 69.2 | 22.1 |
| 1 | 44.5 | 39.3 | 45.1 | 10.4 |
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| 3 | 151.5 | 41.3 | 58.5 | 18.5 |
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k

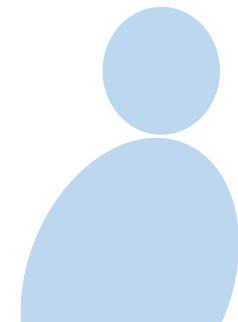
$y(k)$
 $x_1(k)$
 $x_2(k)$
 $x_3(k)$



Linear Regression

- In general the **regressor** $\bar{\mathbf{X}}$ can be an n —dimensional vector
 - x_1 is the cost of **TV advertising**
 - x_2 is the cost of **Radio advertising** and so on....

| | TV | Radio | Newspaper | Sales |
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| 3 | 151.5 | 41.3 | 58.5 | 18.5 |
| 4 | 180.8 | 10.8 | 58.4 | 12.9 |



Regression: Other Examples

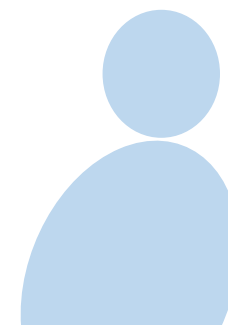
- Example 1

Microsoft

- $y(k)$ = Price of **particular stock** at time k

Facebook
Amazon
Google

- $x_1(k), x_2(k), \dots, x_N(k)$: Prices of **related stocks** at time k



Linear Regression Model

$$y(k) = h_0 + h_1 x_1(k) + h_2 x_2(k) + \dots + h_n x_n(k) + \epsilon(k)$$

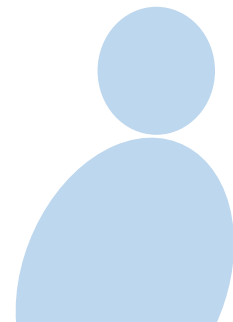
Bias

Regression
coefficients

Bias

Model
Error

Regressors



Linear Regression Model

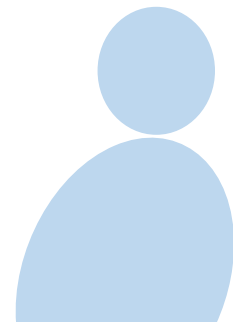
$$y(k) = h_0 + h_1 x_1(k) + h_2 x_2(k) + \dots + h_n x_n(k) + \epsilon(k)$$

$$= \begin{bmatrix} 1 & x_1(k) & x_2(k) & \dots & x_n(k) \end{bmatrix} \begin{bmatrix} h_0 \\ h_1 \\ \vdots \\ h_n \end{bmatrix} + \epsilon(k)$$

$\underbrace{\hspace{10em}}_{\tilde{x}^T(k)} \quad \underbrace{\hspace{2em}}_{\tilde{h}}$

+ $\epsilon(k)$ Model Error

$$= \tilde{x}^T(k) \cdot \tilde{h} + \epsilon(k)$$



Linear Regression Model

$$y(k)$$

$$= h_0 + h_1 x_1(k) + \cdots + h_n x_n(k) + \epsilon(k)$$

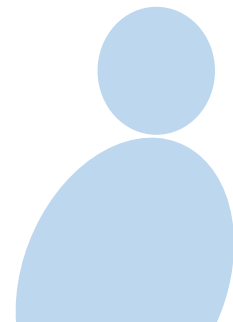
$$= \underbrace{\begin{bmatrix} 1 & x_1(k) & x_2(k) & \dots & x_n(k) \end{bmatrix}}_{\bar{\mathbf{x}}^T(k)} \underbrace{\begin{bmatrix} h_0 \\ h_1 \\ \vdots \\ h_n \end{bmatrix}}_{\bar{\mathbf{h}}} + \underbrace{\epsilon(k)}_{\text{Model Error}}$$

Regression
vector

Regressors

Regression
coefficient vector

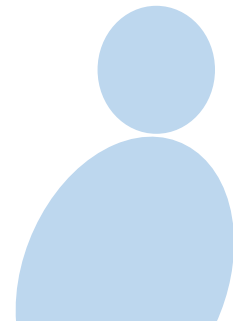
$$y(k) = \bar{\mathbf{x}}^T(k) \bar{\mathbf{h}} + \epsilon(k)$$



Linear Regression

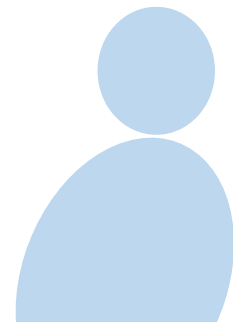
- This is termed Linear Regression
- h_0, h_1, \dots, h_n are termed the **Regression coefficients**

We have to
learn the Regression
coefficient vector h



Linear Regression

- This is termed ***Linear Regression***
- h_0, h_1, \dots, h_n are termed the **Regression coefficients**



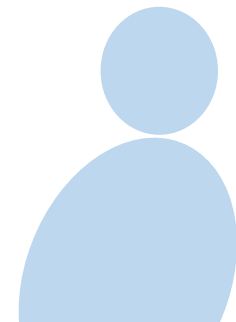
Training Data

- The **regression coefficients** can be computed as follows

- Consider the availability of Training Pairs $(y(k), \bar{x}(k))$

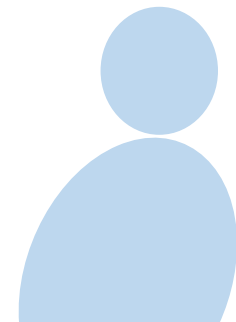
- for $k = 1, 2, \dots, M$

$$\begin{array}{l} y(1), \bar{x}(1) \\ y(2), \bar{x}(2) \\ \vdots \\ y(M), \bar{x}(M) \end{array}$$



Training Data

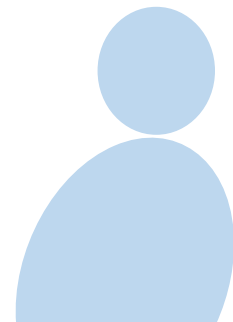
- The **regression coefficients** can be computed as follows
- Consider the availability of **training pairs** $(y(k), \bar{\mathbf{x}}(k))$
 - for $k = 1, 2, \dots, M$



Model Computation

- The **training set** can be expressed as

$$\underbrace{\begin{bmatrix} y(1) \\ y(2) \\ \vdots \\ y(M) \end{bmatrix}} = \begin{bmatrix} \bar{x}^T(1) \\ \bar{x}^T(2) \\ \vdots \\ \bar{x}^T(M) \end{bmatrix} \bar{h} + \begin{bmatrix} \epsilon(1) \\ \epsilon(2) \\ \vdots \\ \epsilon(M) \end{bmatrix}$$



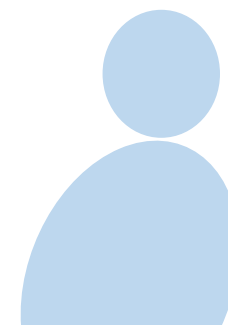
Model Computation

- The **training set** can be expressed as

Regression
Learning
Model.

$$\underbrace{\begin{bmatrix} y(1) \\ y(2) \\ \vdots \\ y(M) \end{bmatrix}}_{\substack{\bar{\mathbf{y}} \\ M \times 1}} = \underbrace{\begin{bmatrix} \bar{\mathbf{x}}^T(1) \\ \bar{\mathbf{x}}^T(2) \\ \vdots \\ \bar{\mathbf{x}}^T(M) \end{bmatrix}}_{\substack{\bar{\mathbf{X}} \\ M \times (n+1)}} \bar{\mathbf{h}} + \underbrace{\begin{bmatrix} \epsilon(1) \\ \epsilon(2) \\ \vdots \\ \epsilon(M) \end{bmatrix}}_{\substack{\bar{\epsilon} \\ M \times 1}}$$

M Responses
M Regression Vectors.
M errors.
M x 1



Least Squares

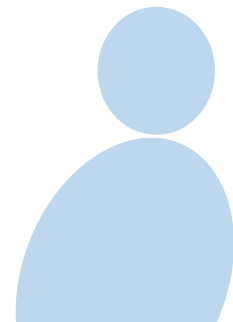
$$\bar{y} = X\bar{h} + \bar{\epsilon}$$

Least Squares

$$\bar{\epsilon} = \bar{y} - X\bar{h}$$

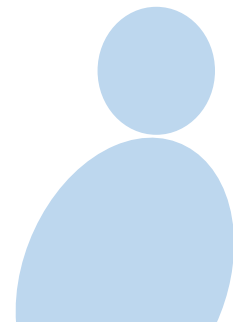
min Error
min $\|\bar{\epsilon}\|_2^2$

$$\min \| \bar{y} - X\bar{h} \|^2$$



Least Squares

$$\min \left\| \underbrace{\bar{\mathbf{y}} - \mathbf{X} \bar{\mathbf{h}}}_{\bar{\boldsymbol{\epsilon}}} \right\|^2$$

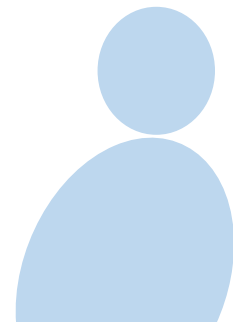


Model Computation

- The **regression coefficients** are given as

$$\bar{h} = (X^T X)^{-1} X^T \bar{y}$$

Regression Vector



Model Computation

- The **regression coefficients** are given as

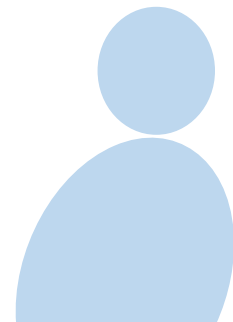
$$\bar{\mathbf{h}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \bar{\mathbf{y}}$$

\mathbf{X} : Tall matrix
 \Rightarrow NOT square.

Regression coeff vector

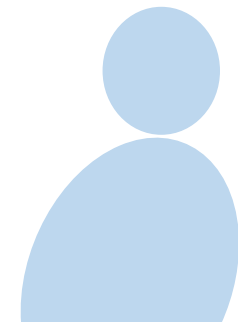
$(\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T$: Pseudoinverse

$$(\mathbf{X}^T \mathbf{X})^{-1} (\mathbf{X}^T \mathbf{X}) = \mathbf{I}$$



The Boston Housing Dataset

- The **Boston Housing Dataset** is a derived from information collected by the U.S. Census Service *USA.*
 - Concerning housing in the area of Boston MA.
-



- The following describes the dataset columns:

- **CRIM** - per capita crime rate by town
- **ZN** - proportion of residential land zoned for lots over 25,000 sq.ft.
- **INDUS** - proportion of non-retail business acres per town.
- **CHAS** - Charles River dummy variable (1 if tract bounds river; 0 otherwise)
- **NOX** - nitric oxides concentration (parts per 10 million)
- **RM** - average number of rooms per dwelling
- **AGE** - proportion of owner-occupied units built prior to 1940
- **DIS** - weighted distances to five Boston employment centres
- **RAD** - index of accessibility to radial highways
- **TAX** - full-value property-tax rate per \$10,000
- **PTRATIO** - pupil-teacher ratio by town
- **MEDV** - Median value of owner-occupied homes in \$1000's

CrimeRate

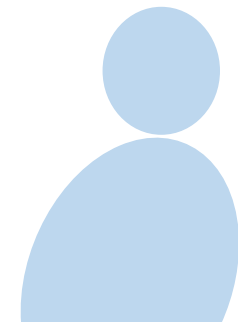
Pollution

Number of rooms

Response

Regressors:

11 Regressors:



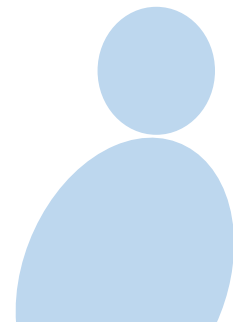
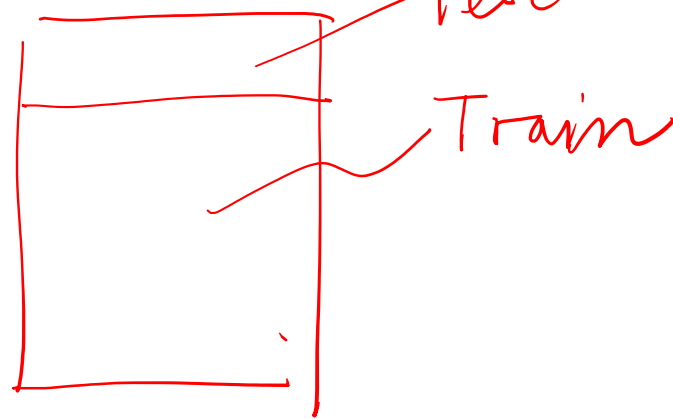
```
1 import numpy as np
2 from sklearn.linear_model import LinearRegression
3 from sklearn.model_selection import train_test_split
4 from sklearn.metrics import mean_squared_error
5 from sklearn.metrics import r2_score
6 import pandas as pd
7
```

SciKit.learn

Linear Regression

import numpy

Data Handling



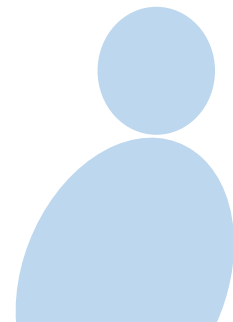
```
7  
8 BosData = pd.read_csv('BostonHousing.csv')  
9 X = BosData.iloc[:,0:11]  
10 y = BosData.iloc[:, 13] # MEDV: Median value of owner-occupied homes in $1000s  
11
```

Pandas

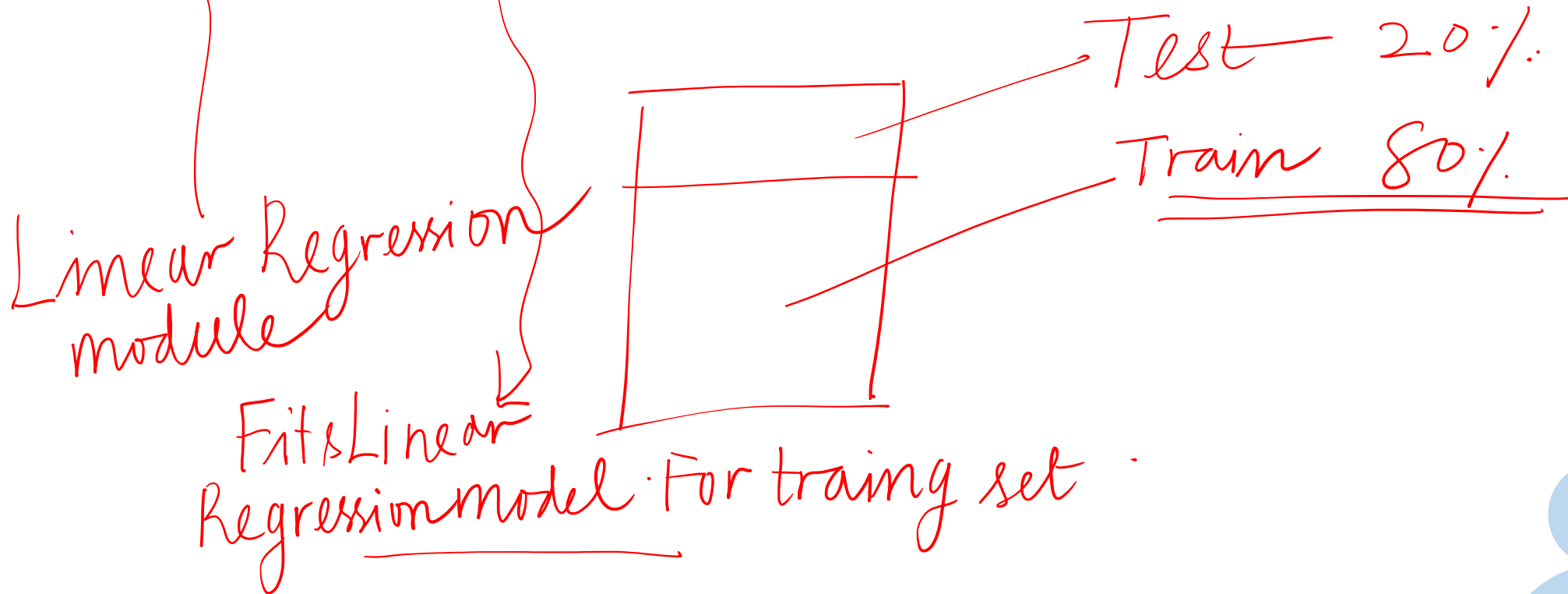
Read CSV file
Boston housing data

11 Regressors
in each Regression vector

→ Response
Median home price




```
11
12 X_train, X_test, y_train, y_test = \
13     train_test_split(X, y, test_size = 0.2, random_state=5)
14 reg = LinearRegression()
15 reg.fit(X_train, y_train)
16
```



```

17 y_train_predict = reg.predict(X_train)
18 rmse = np.sqrt(mean_squared_error(y_train, y_train_predict));
19 r2 = r2_score(y_train, y_train_predict)
20

```

R2 score

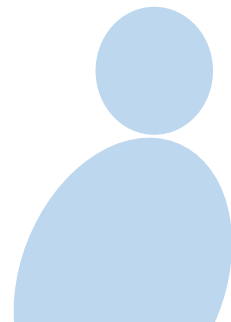
Using model learnt
Predict Response for
Training set

→ Root MSE
Root mean square
error

$$RMSE = \sqrt{\frac{1}{N} \sum_{k=1}^N (y(k) - \hat{y}(k))^2}$$

MSE

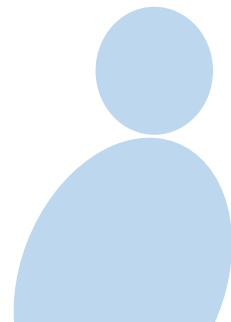
mean squared error
Between training response
& prediction from model.



```
20  
21 print('Train RMSE =', rmse)  
22 print('Train R2 score =', r2)  
23 print("\n")  
24
```

RMSE

R2 score



```
24
25 y_test_predict = reg.predict(X_test)
26 rmse = (np.sqrt(mean_squared_error(y_test, y_test_predict)))
27 r2 = r2_score(y_test, y_test_predict)
28 print('Test RMSE =', rmse)
29 print('Test R2 score =', r2)
30
```

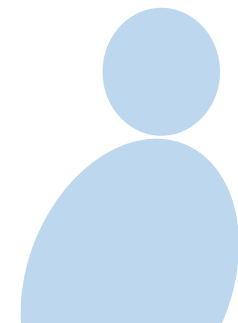
Run prediction for Test set

Print RMSE for test set

Print R2 score for test set

compute RMSE for test

compute R2 score for test



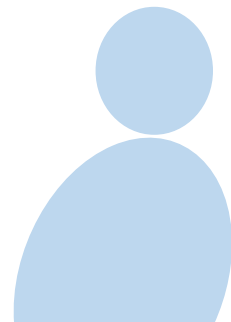
```
Train RMSE = 5.511467677842388  
Train R2 score = 0.6463832866583819
```

```
Test RMSE = 4.287105260205546  
Test R2 score = 0.7652527354155101
```

```
In [9]:
```

Test
Set

Training set



Instructors may use this white area (14.5 cm / 25.4 cm) for the text.
Three options provided below for the font size.

Font: Avenir (Book), Size: 32, Colour: Dark Grey

Font: Avenir (Book), Size: 28, Colour: Dark Grey

Font: Avenir (Book), Size: 24, Colour: Dark Grey

Do not use the space below.

