Group 62

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In [ ]:

```
import numpy as np
import matplotlib.pyplot as plt
import sklearn.linear_model as lm
%matplotlib inline
```

Task 1

In [ ]:

```
#transcribed from hemnet, prices in million SEK, living-area in m^2

villa_prices = np.array([7, 4.895, 5.85, 4.9, 10.3, 6.7, 6.8, 6.12, 5.35, 7.7, 7.25,
                4.05, 1.9, 6.55, 6.33, 6.08, 7.85, 7.8, 4.9, 7.3, 6.9, 3.4, 7.1, 4.5
living_area = np.array([138, 160, 144, 84, 219, 140, 164, 187, 120, 150, 194, 120, 9
                152, 108, 80, 228, 140, 120, 262, 210, 146, 230, 240, 65, 188, 122,

# list(zip(villa_prices, living_area))
```

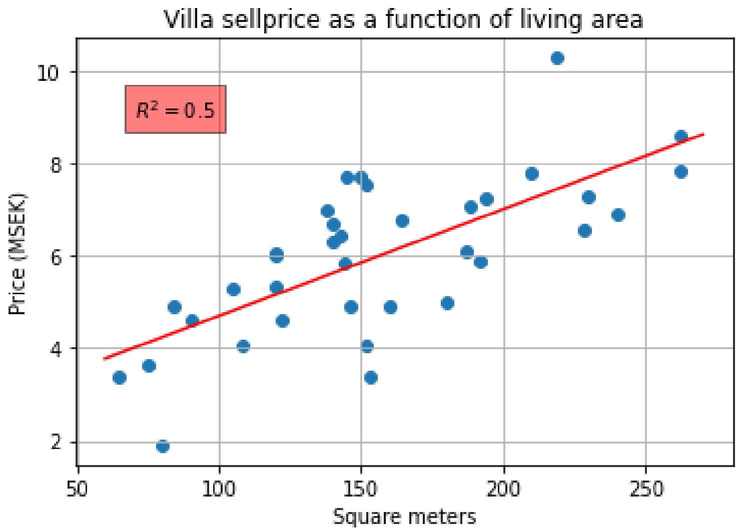
In [ ]:

```
#regression

linReg = lm.LinearRegression()

linReg.fit(living_area.reshape(-1,1), villa_prices)

r2 = linReg.score(living_area.reshape(-1,1), villa_prices)
coef = linReg.coef_[0]
intercept = linReg.intercept_

print("Slope = ", coef)
print("Intercept = ", intercept)
```

```
Slope =  0.023132744168234725
Intercept =  2.3907936306816584
```

In [ ]:

```
#Regression plot

plt.title('Villa sellprice as a function of living area')
plt.grid(True)
plt.text(70, 9, r"$R^2 = $" + str(np.round(r2, 2)), bbox = {'facecolor': 'red', 'alp
plt.xlabel('Square meters')
plt.ylabel('Price (MSEK)')
plt.scatter(living_area, villa_prices)
plt.plot([60, 270], [coef*60 + intercept, coef*270 + intercept], 'r-')
plt.show()
plt.close()
```



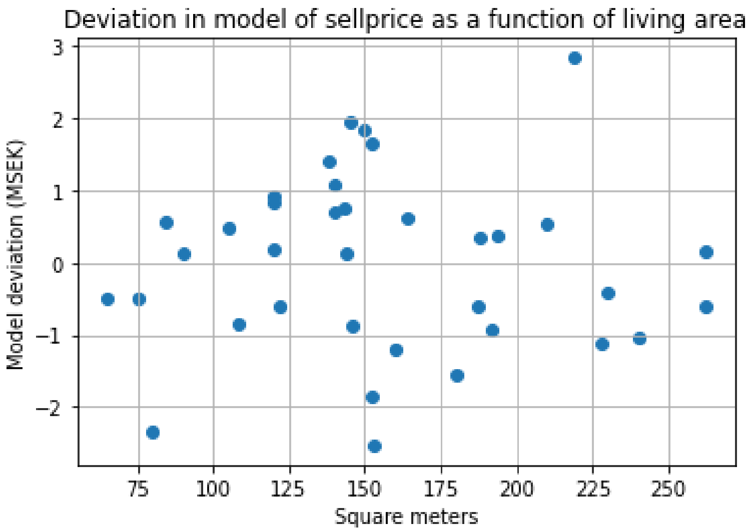
In [ ]:

```
#Prediction

def predicted_price(sqMetres):
    return np.round(coef*sqMetres + intercept, 2)

print("Cost of 100sqm villa in Landvetter: ", predicted_price(100), "million SEK")
print("Cost of 150sqm villa in Landvetter: ", predicted_price(150), "million SEK")
print("Cost of 200sqm villa in Landvetter: ", predicted_price(200), "million SEK")
```

```
Cost of 100sqm villa in Landvetter:  4.7 million SEK
Cost of 150sqm villa in Landvetter:  5.86 million SEK
Cost of 200sqm villa in Landvetter:  7.02 million SEK
```

In [ ]:

```
residual_price = villa_prices - predicted_price(living_area)

plt.title('Deviation in model of sellprice as a function of living area')
plt.grid(True)
plt.xlabel('Square meters')
plt.ylabel('Model deviation (MSEK)')
plt.scatter(living_area, residual_price)
plt.show()
plt.close()


print("Sum of residuals:", np.round(sum(residual_price), 4))
print("Mean of residuals:", np.round(np.mean(residual_price), 4))
print("Variance of residuals:", np.round(np.var(residual_price), 4))
print("SD of residuals:", np.round(np.std(residual_price), 4))
```




```
Sum of residuals: -0.003
Mean of residuals: -0.0001
Variance of residuals: 1.4128
SD of residuals: 1.1886
```

Seemingly randomly distributed around zero. Indicates good fit with linear regression. However the variance is big, which indicates that more factors should be included for more precise estimates.

Task 2

In [ ]:

```
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn import metrics

import seaborn as sns
```

In [ ]:

```
iris = load_iris()

print(iris.DESCR)#150 flowers with 4 attributes each
```

```
.. _iris_dataset:

Iris plants dataset
--------------------

**Data Set Characteristics:**

    :Number of Instances: 150 (50 in each of three classes)
    :Number of Attributes: 4 numeric, predictive attributes and the class
    :Attribute Information:
        - sepal length in cm
        - sepal width in cm
        - petal length in cm
        - petal width in cm
        - class:
                - Iris-Setosa
                - Iris-Versicolour
                - Iris-Virginica

    :Summary Statistics:

    ============== ==== ==== ======= ===== ====================
                    Min  Max   Mean    SD   Class Correlation
    ============== ==== ==== ======= ===== ====================
    sepal length:   4.3  7.9   5.84   0.83    0.7826
    sepal width:    2.0  4.4   3.05   0.43   -0.4194
    petal length:   1.0  6.9   3.76   1.76    0.9490  (high!)
    petal width:    0.1  2.5   1.20   0.76    0.9565  (high!)
    ============== ==== ==== ======= ===== ====================

    :Missing Attribute Values: None
    :Class Distribution: 33.3% for each of 3 classes.
    :Creator: R.A. Fisher
    :Donor: Michael Marshall (MARSHALL%PLU@io.arc.nasa.gov)
    :Date: July, 1988

The famous Iris database, first used by Sir R.A. Fisher. The dataset is taken
from Fisher's paper. Note that it's the same as in R, but not as in the UCI
Machine Learning Repository, which has two wrong data points.

This is perhaps the best known database to be found in the
pattern recognition literature.  Fisher's paper is a classic in the field and
is referenced frequently to this day.  (See Duda & Hart, for example.)  The
data set contains 3 classes of 50 instances each, where each class refers to a
type of iris plant.  One class is linearly separable from the other 2; the
latter are NOT linearly separable from each other.

.. topic:: References

   - Fisher, R.A. "The use of multiple measurements in taxonomic problems"
     Annual Eugenics, 7, Part II, 179-188 (1936); also in "Contributions to
     Mathematical Statistics" (John Wiley, NY, 1950).
   - Duda, R.O., & Hart, P.E. (1973) Pattern Classification and Scene Analysis.
     (Q327.D83) John Wiley & Sons.  ISBN 0-471-22361-1.  See page 218.
   - Dasarathy, B.V. (1980) "Nosing Around the Neighborhood: A New System
     Structure and Classification Rule for Recognition in Partially Exposed
     Environments".  IEEE Transactions on Pattern Analysis and Machine
     Intelligence, Vol. PAMI-2, No. 1, 67-71.
   - Gates, G.W. (1972) "The Reduced Nearest Neighbor Rule".  IEEE Transactions
     on Information Theory, May 1972, 431-433.
   - See also: 1988 MLC Proceedings, 54-64.  Cheeseman et al"s AUTOCLASS II
     conceptual clustering system finds 3 classes in the data.
   - Many, many more ...
```

In [ ]:

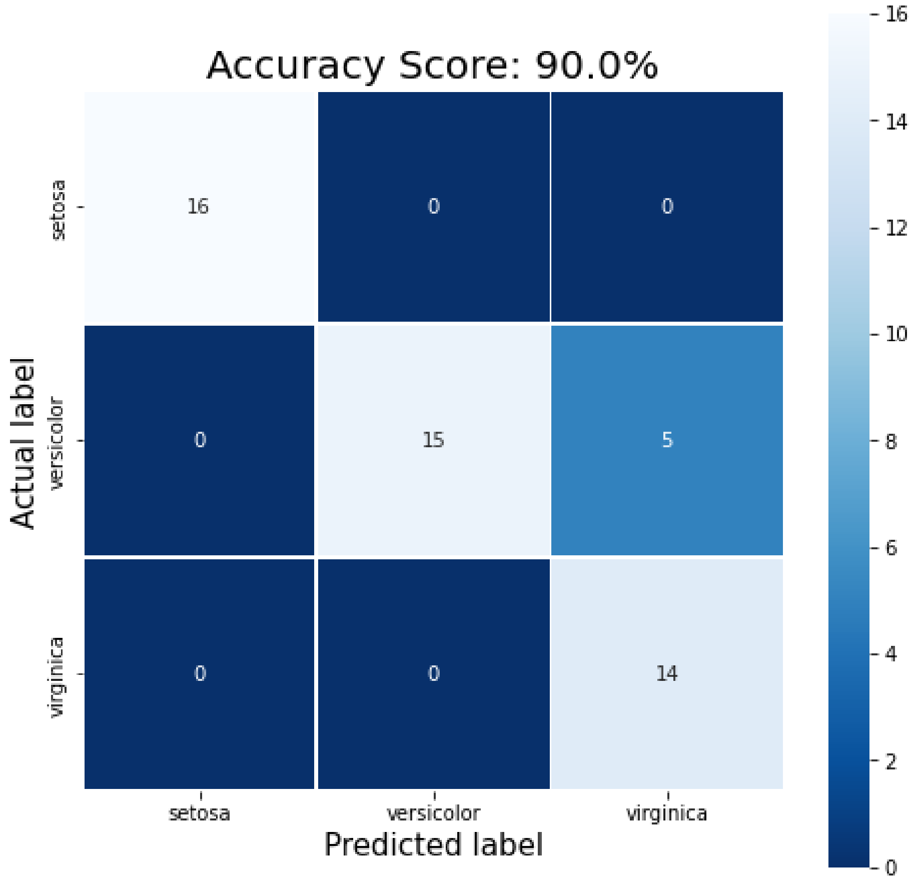
```
training_data, test_data, training_labels, test_labels = train_test_split(iris.data,
```

```
logReg = LogisticRegression(multi_class='ovr', solver='liblinear')
logReg.fit(training_data, training_labels)

predictions = logReg.predict(test_data)

score = logReg.score(test_data, test_labels)
print("The model predicted the test data with", score*100, "% accuracy")
```

```
The model predicted the test data with 90.0 % accuracy
```

In [ ]:

```
conf_matrix  = metrics.confusion_matrix(test_labels, predictions)

def plot_confusion_matrix(conf_matrix, plot = True, save = False, filename = None):
    plt.figure(figsize=(8,8)) #size in inches
    sns.heatmap(conf_matrix, annot=True, linewidths=.5, square = True, cmap = 'Blues
    plt.ylabel('Actual label', size=15)
    plt.xlabel('Predicted label', size=15)
    plt.title('Accuracy Score: {fscore:.{precision}f}%'.format(fscore = score*100, p
    if save:
        plt.savefig(filename)
    if plot:
        plt.show()
    plt.close()

plot_confusion_matrix(conf_matrix, save = False, filename = 'LogReg_confusion_matrix
```



Task 3 and 4

In [ ]:

```
from sklearn.neighbors import KNeighborsClassifier

#k nearest neighbors and plot export
```

```python
weigths = ['uniform', 'distance']
for i in range(2):
    print(weigths[i])
    for n_neighbors in range(1, 10):
        k_neig = KNeighborsClassifier(weights = weigths[i], n_neighbors=n_neighbors)
        k_neig.fit(training_data, training_labels)
        score = k_neig.score(test_data, test_labels)
        print(n_neighbors, ":", score)

        predictions = k_neig.predict(test_data)
        conf_matrix  = metrics.confusion_matrix(test_labels, predictions)
        plot_confusion_matrix(conf_matrix, save = True, plot = False, filename = 'kr



print("Too large k, k = 100")
k_neig = KNeighborsClassifier(weights = 'uniform', n_neighbors=100)
k_neig.fit(training_data, training_labels)
score = k_neig.score(test_data, test_labels)
print("uniform :", score)


predictions = k_neig.predict(test_data)
conf_matrix  = metrics.confusion_matrix(test_labels, predictions)
plot_confusion_matrix(conf_matrix, save = True, plot = False, filename = 'knn_100_ur


k_neig = KNeighborsClassifier(weights = 'distance', n_neighbors=100)
k_neig.fit(training_data, training_labels)
score = k_neig.score(test_data, test_labels)
print("distance :", score)


predictions = k_neig.predict(test_data)
conf_matrix  = metrics.confusion_matrix(test_labels, predictions)
plot_confusion_matrix(conf_matrix, save = True, plot = False, filename = 'knn_100_di
```

```
uniform
1 : 0.96
2 : 0.94
3 : 0.96
4 : 0.96
5 : 0.94
6 : 0.96
7 : 0.92
8 : 0.96
9 : 0.96
distance
1 : 0.96
2 : 0.96
3 : 0.96
4 : 0.96
5 : 0.96
6 : 0.96
7 : 0.96
8 : 0.96
9 : 0.96
Too large k, k = 100
uniform : 0.28
distance : 0.94
```

When k-grows, more datapoints will be considered when predicting the value of a new datapoint. Too large K might lead to datapoints far away influencing the result and underfitting. Too low k and the model might be overfitted.

In [ ]:

```
#plotting

%matplotlib widget

from mpl_toolkits import mplot3d #plot 3 of 4 attributes

fig = plt.figure(figsize=(10,10))
ax = plt.axes(projection='3d')


zipped_data = list(zip(training_data, training_labels))
zipped_data.sort(key = lambda arr: arr[1])

colors = {0: 'ro', 1: 'bo', 2:'go'}

for elem in zipped_data:
    ax.plot(elem[0][1], elem[0][2], elem[0][3], colors[elem[1]])

ax.set_xlabel('sepal width in cm')
ax.set_ylabel('petal length in cm')
ax.set_zlabel('petal width in cm')
ax.view_init(10, 30)

plt.show()
```

Figure