Estimation, Detection and Analysis II

02 - Advanced Classification
neural networks
Support Vector Machines
nearest neighbor

neural networks

1. Install the keras package

2. Define libraries to import

```
from numpy import loadtxt
from keras.models import Sequential
from keras.layers import Dense
from keras.utils.vis_utils import plot_model
```

3. Read the pima-indians-diabetes.data.csv file found in Moodle and divide it into independent (X) and dependent (Y) variables

```
dataset = loadtxt( 'file_path/pima-indians-diabetes.data.csv', delimiter=',')
X = dataset [:, 0:8]
y = dataset [:, 8]
```

4. Define the model:

```
model = Sequential( )
model.add(Dense(12, input_dim=8, activation='relu'))
model.add(Dense(8, activation='relu'))
model.add(Dense(1, activation='sigmoid'))
```

5. compile the model

```
model.compile (loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
```

6. Fit the model

```
model.fit(X, y, epochs=150, batch_size=10)
```

7. Evaluate the model:

```
_, accuracy = model.evaluate(X, y)
print( 'Accuracy: %.2f' % (accuracy * 100))
```

8. Calculate predictions, round (to give 0 or 1) and view

```
predictions = model.predict(X)
rounded = [round(x[0]) for x in predictions]
print(predictions)
```

9. View the template (text)

```
print( model.summary ())
```

10. View the model (plot 'model_plot.png' saved in the project)

```
11. plot_model(model, to_file='model_plot.png', show_shapes=True, show_layer_names=True)
```

12. Run again a few times. What happens to accuracy? Why?

13. Changing model parameters to check the effect in terms of accuracy

Support Vector Machines

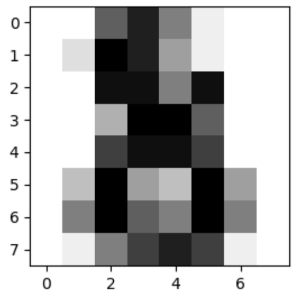
1. Define libraries to import

```
from sklearn import model_selection
from sklearn.model _selection import GridSearchCV
from sklearn.svm import SVC
from sklearn.metrics import classification_report
from sklearn import datasets
```

2. Load the dataset digits

```
digits = datasets.load _digits()
```

This dataset [1]aims to identify handwritten numbers, each digit is represented by an image, for example:



3. In order to use this dataset, it is necessary to "flatten" it. At the same time, it separates into *features* (X) and target (y):

```
n_samples = len( digits.images )
X = digits.images .reshape((n_samples, -1))
y = digits.target
```

4. Since SVMs require several parameters, we will use a grid search to choose the best combination of parameters for this particular dataset. For this, we need to separate the dataset (features and target) into training (80% of the data) and test (20%):

```
X_train, X_test, y_train, y_test = model_selection.train _test_split (X, y,
test_size=0.2, train_size=0.8)
```

5. Next, we define the parameters we want to *tune* and the metrics to use in the process:

```
tuned_parameters = [{'kernel': ['rbf'], 'gamma': [1e-3, 1e-4],
'C': [1, 10, 100, 1000]},
{'kernel': ['linear'], 'C': [1, 10, 100, 1000]}]

scores = ['precision', 'recall']
```

6. Finally, we run the *grid search* with *cross validation* :

```
for score in scores:
print("# Tuning hyper-parameters for %s" % score)
print()

clf = GridSearchCV(
SVC(), tuned_parameters, scoring='%s_macro' % score
)
clf.fit(X_train, y_train)

    print( "Best parameters set found on development set:")
print()
print(clf.best_params_)
```

[1] http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.25.6299&rep=rep1&type=pdf

```
print()
print("Grid scores on development set:")
print()
means = clf.cv_results_['mean_test_score']
stds = clf.cv_results_['std_test_score']
for mean, std, params in zip(means, stds, clf.cv_results_['params']):
        print( "%0.3f (+/-%0.03f) for %r"
% (mean, std*2, params))
print()

print("Detailed classification report:")
print()
print("The model is trained on the full development set.")
    print( "The scores are computed on the full evaluation set.")
print()
y_true, y_pred = y_test, clf.predict(X_test)
    print( classification_report(y_true, y_pred))
    print( )
```

7. The output will be:

```
# Tuning hyper-parameters for precision

Best parameters set found on development set:

{'C': 1, 'gamma': 0.001, 'kernel': 'rbf'}

Grid scores on development set:

0.987 (+/-0.008) for {'C': 1, 'gamma': 0.001, 'kernel': 'rbf'}
0.967 (+/-0.015) for {'C': 1, 'gamma': 0.0001, 'kernel': 'rbf'}
0.985 (+/-0.011) for {'C': 10, 'gamma': 0.001, 'kernel': 'rbf'}
0.984 (+/-0.010) for {'C': 10, 'gamma': 0.0001, 'kernel': 'rbf'}
0.985 (+/-0.011) for {'C': 100, 'gamma': 0.001, 'kernel': 'rbf'}
0.983 (+/-0.011) for {'C': 100, 'gamma': 0.0001, 'kernel': 'rbf'}
0.985 (+/-0.011) for {'C': 1000, 'gamma': 0.001, 'kernel': 'rbf'}
0.983 (+/-0.011) for {'C': 1000, 'gamma': 0.0001, 'kernel': 'rbf'}
0.973 (+/-0.019) for {'C': 1, 'kernel': 'linear'}
0.973 (+/-0.019) for {'C': 10, 'kernel': 'linear'}
0.973 (+/-0.019) for {'C': 100, 'kernel': 'linear'}
0.973 (+/-0.019) for {'C': 1000, 'kernel': 'linear'}

Detailed classification report:

The model is trained on the full development set.
The scores are computed on the full evaluation set.

precision recall f1-score support

0 1.00 1.00 1.00 34
1 1.00 1.00 1.00 45
2 1.00 1.00 1.00 37
3 1.00 1.00 1.00 37
4 1.00 1.00 1.00 32
5 1.00 1.00 1.00 39
6 1.00 1.00 1.00 43
7 1.00 1.00 1.00 30
8 1.00 1.00 1.00 33
9 1.00 1.00 1.00 30

accuracy 1.00 360
macro avg 1.00 1.00 1.00 360
weighted avg 1.00 1.00 1.00 360


# Tuning hyper-parameters for recall

Best parameters set found on development set:

{'C': 1, 'gamma': 0.001, 'kernel': 'rbf'}
```

```
Grid scores on development set:

0.987 (+/-0.008) for {'C': 1, 'gamma': 0.001, 'kernel': 'rbf'}
0.965 (+/-0.016) for {'C': 1, 'gamma': 0.0001, 'kernel': 'rbf'}
0.984 (+/-0.011) for {'C': 10, 'gamma': 0.001, 'kernel': 'rbf'}
0.984 (+/-0.010) for {'C': 10, 'gamma': 0.0001, 'kernel': 'rbf'}
0.984 (+/-0.011) for {'C': 100, 'gamma': 0.001, 'kernel': 'rbf'}
0.983 (+/-0.012) for {'C': 100, 'gamma': 0.0001, 'kernel': 'rbf'}
0.984 (+/-0.011) for {'C': 1000, 'gamma': 0.001, 'kernel': 'rbf'}
0.983 (+/-0.012) for {'C': 1000, 'gamma': 0.0001, 'kernel': 'rbf'}
0.973 (+/-0.019) for {'C': 1, 'kernel': 'linear'}
0.973 (+/-0.019) for {'C': 10, 'kernel': 'linear'}
0.973 (+/-0.019) for {'C': 100, 'kernel': 'linear'}
0.973 (+/-0.019) for {'C': 1000, 'kernel': 'linear'}

Detailed classification report:

The model is trained on the full development set.
The scores are computed on the full evaluation set.

precision recall f1-score support

0 1.00 1.00 1.00 34
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7 1.00 1.00 1.00 30
8 1.00 1.00 1.00 33
9 1.00 1.00 1.00 30

accuracy 1.00 360
macro avg 1.00 1.00 1.00 360
weighted avg 1.00 1.00 1.00 360
```

More examples of using SVM: https://towardsdatascience.com/the-complete-guide-to-support-vector-machine-svm-f1a820d8af0b

K Nearest Neighbors

1. Define libraries to import

```
import pandas as pd
from sklearn.model _selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
import matplotlib.pyplot as plt
import seaborn as sns
```

2. load the dataset

```
df = pd.read _csv('file_path/titanic_train.csv', sep=";")
```

3. Define the independent (X) and dependent (y) variables

```
X = df.drop ('Survived', axis=1)
y = df.Survived
```

4. Split X and y into training and testing

```
X_train, X_test, y_train, y_test = train_test_split(X,y, random_state=42)
```

5. Define which columns should be considered numeric and categorical

```
numerical = ['Age', "SibSp", "Parch", 'Fare']
```

```
categorical = ["Pclass", "Sex"]
```

6. define scaling

```
#defining train and test index variables for casting the scaled numerical values in a dataframe
X_train_index = X_train.index
X_test_index = X_test.index

#instantiating OneHotEncoder and defining the train and test features to be encoded
ohe = OneHotEncoder()
X_train_ohe = X_train[categorical]
X_test_ohe = X_test[categorical]

#fitting the encoder to the train set and transforming both the train and test set
X_train_encoded = ohe.fit_transform(X_train_ohe)
X_test_encoded = ohe.transform(X_test_ohe)

#instantiating StandardScaler and defining continuous variables to be scaled
ss = StandardScaler()
X_train_cont = X_train[numerical ].astype (float)
X_test_cont = X_test[numerical ].astype (float)

#scaling the continuous features and casting results as dataframes
X_train_scaled = pd.DataFrame (ss.fit_transform(X_train_cont), columns=X_train_cont.columns, index=X_train_index)
X_test_scaled = pd.DataFrame (ss.transform(X_test_cont), columns=X_test_cont.columns, index=X_test_index)

#defining the columns for the train and test splits
train_columns = ohe.get_feature_names(input_features=X_train_ ohe.columns )
test_columns = ohe.get_feature_names(input_features=X_test_ ohe.columns )

#casting the encoded X_train and X_test as dataframes
X_train_processed = pd.DataFrame (X_train_encoded.todense(), columns=train_columns, index=X_train_index)
X_test_processed = pd.DataFrame (X_test_encoded.todense(), columns=test_columns, index=X_test_index)

#combining the encoded and scaled dataframes for a preprocessed
#X_train and X_test
X_train = pd.concat([X_train_scaled, X_train_processed], axis=1)
X_test = pd.concat([X_test_scaled, X_test_processed], axis=1)
```

7. Define a function for evaluation

```
def evaluation( k,d,type,y, y_hat):
precision = round( precision_score(y, y_hat)*100,1)
recall = round( recall_score(y, y_hat)*100,1)
accuracy = round( accuracy_score(y, y_hat)*100,1)
f1 = round( f1_score(y, y_hat)*100,1)
return [ k,d ,type,recall,accuracy,precision,f1]
```

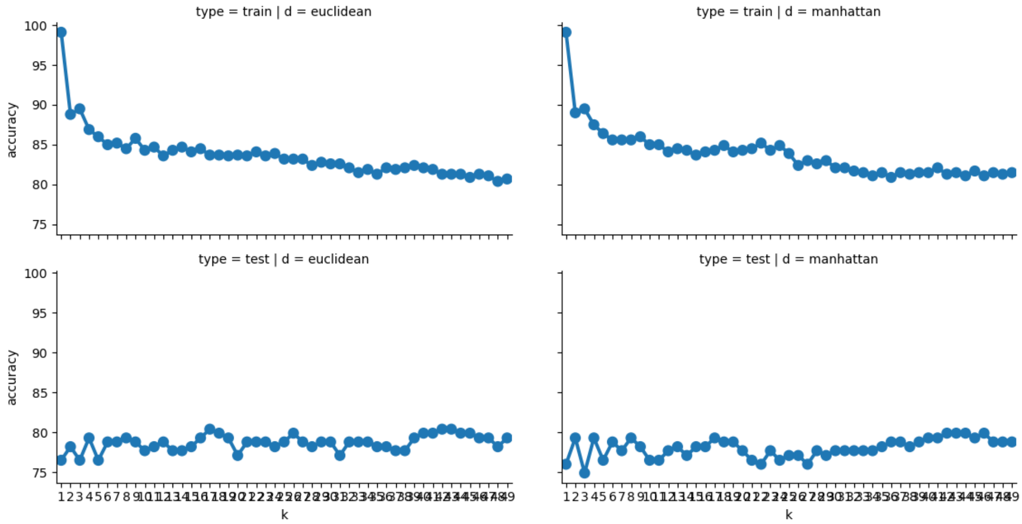
8. Instantiate and run Knn with all k ϵ [1.50] and using Euclidean and Manhattan distances

```
possible_ks = range(1, 50)
possible_distances = ['euclidean', 'manhattan']
results = []
for d in possible_distances:
for k in possible_ks:
knn = KNeighborsClassifier( n_neighbors=k, metric=d)
        knn.fit( X_train, y_train)
y_hat_train = knn.predict (X_train)
y_hat_test = knn.predict (X_test)
        results.append (evaluation(k,d,"train",y_train, y_hat_train))
results.append(evaluation(k, d, "test", y_test, y_hat_test))
```

9. Graphically visualize the results in terms of accuracy (training and testing)

```
results = pd.DataFrame (results,
columns=["k","d","type","recall","accuracy","precision","f1"])
g = sns.FacetGrid (results, col="d", row="type")
g.map(sns.pointplot, "k", "accuracy")
plt.show ()
```

The result should be:



10. What is ok that allows better performance? We can confirm:

```
res_test = results[(results['type ']= ="test")]
print(res_test.loc[[res_test["accuracy" ].idxmax ()]])
```

Result:

```
kd type recall accuracy precision f1
33 17 euclidean test 70.8 80.4 78.5 74.5
```

11. We can now create the “best” model to later apply to test data. In a new file, we repeat the process, but this time setting ok to 17 and the Euclidean distance. We can then compute predictions for each of the examples in the test set.

```
import pandas as pd
from sklearn.preprocessing import StandardScaler, OneHotEncoder

from sklearn.neighbors import KNeighborsClassifier

df_train = pd.read_csv('file_path/titanic_train.csv', sep=";")
df_train = df_train[['Survived', 'Pclass', 'Age', 'SibSp', 'Parch', 'Fare', 'Sex']]

X_train = df_ train.drop ('Survived', axis=1)
y_train = df_train.Survived

df_test = pd.read_csv('C:/Users/Catarina/Dropbox/Aulas/UPT/2020_2021/2_semestre/EDA2/02-
ClassificacaoAvancada/titanic_test.csv', sep=";")
df_test = df_test[['Pclass', 'Age', 'SibSp', 'Parch', 'Fare', 'Sex']]

X_test = df_test

#importing scaler and encoder

#defining numerical and categorical features in dataframe
numerical = ['Age', "SibSp", "Parch", 'Fare']
categorical = ["Pclass", "Sex"]

#defining train and test index variables for casting the scaled
#numerical values in a dataframe
X_train_index = X_train.index
```

```
X_test_index = X_ test.index

#instantiating OneHotEncoder and defining the train and test
#features to be encoded
ohe = OneHotEncoder()
X_train_ohe = X_train[categorical]
X_test_ohe = X_test[categorical]

#fitting the encoder to the train set and transforming both
#the train and test set
X_train_encoded = ohe.fit_transform(X_train_ohe)
X_test_encoded = ohe.transform(X_test_ohe)

#instantiating StandardScaler and defining continuous variables
#to be scaled
ss = StandardScaler()
X_train_cont = X_train[numerical ].astype (float)
X_test_cont = X_test[numerical ].astype (float)

#scaling the continuous features and casting results as dataframes
X_train_scaled = pd.DataFrame (ss.fit_transform(X_train_cont),
columns=X_train_cont.columns,
index=X_train_index)
X_test_scaled = pd.DataFrame(ss.transform(X_test_cont), columns=X_test_cont.columns,
index=X_test_index)

#defining the columns for the train and test splits
train_columns = ohe.get_feature_names(input_features=X_train_ ohe.columns )
test_columns = ohe.get_feature_names(input_features=X_test_ ohe.columns )

#casting the encoded X_train and X_test as dataframes
X_train_processed = pd.DataFrame(X_train_encoded.todense(), columns=train_columns,
index=X_train_index)
X_test_processed = pd.DataFrame(X_test_encoded.todense(), columns=test_columns,
index=X_test_index)

#combining the encoded and scaled dataframes for a preprocessed
#X_train and X_test
X_train = pd.concat([X_train_scaled, X_train_processed], axis=1)
X_test = pd.concat ([X_test_scaled, X_test_processed], axis=1)

# instantiating and fitting K Neighbors Classifier
knn = KNeighborsClassifier( n_neighbors=17, metric='euclidean')
knn.fit( X_train, y_train)
# predictions =
print(knn.predict(X_test))
```

Result:

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