Multi-Label Classification

In [36]:

```
import os
import pandas as pd
from pandas.plotting import autocorrelation_plot
import numpy as np
import matplotlib.pyplot as plt
from mpl_toolkits import mplot3d
%matplotlib inline

from sklearn.model_selection import train_test_split
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import MinMaxScaler

from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input
from tensorflow.keras.layers import Dense
from tensorflow.keras.models import Sequential
from tensorflow.keras.utils import plot_model
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint
from sklearn.metrics import accuracy_score
```

In [6]:

```
df = pd.read_csv('C:\Repos\DS-3FeaturesClassification\df_data.csv')
df['_target'] = df['target']
df = pd.get_dummies(df,columns=['target'],prefix = ['target'])

x = np.dstack( (
                np.array(df['x1']),
                np.array(df['x2']),
                np.array(df['x3'])
                )
            )

y = np.dstack( (
                np.array(df['target_low']),
                np.array(df['target_med']),
                np.array(df['target_high'])
               )
            )
```

In [9]:

```
print(x.shape)
print(y.shape)
```

```
(1, 10000, 3)
(1, 10000, 3)
```

In [10]:

```
x = x[0,:,:]
y = y[0,:,:]
```

In [11]:

```
df
```

Out[11]:

	x1	x2	x3	_target	target_high	target_low	target_med

	x1	x2	x3	_target	target_high	target_low	target_med
0	2.71	10.86	-36.45	med	0	0	1
1	9.88	5.76	-54.63	med	0	0	1
2	82.87	1.73	0.83	med	0	0	1
3	12.99	10.40	-59.60	med	0	0	1
4	60.10	8.84	-45.87	med	0	0	1
...	...	...	...	...	...	...	...
9995	65.03	13.47	-28.30	high	1	0	0
9996	62.24	7.42	-50.47	high	1	0	0
9997	45.37	3.68	-33.13	high	1	0	0
9998	-1.97	6.07	-28.04	high	1	0	0
9999	49.80	12.34	6.84	high	1	0	0

10000 rows × 7 columns

DATA EXPLORATORY ANALYSIS

as we can see in the graphs below, the population of "low" class, marked with red points, is predominant over the other classes, taking 60% of the data set.

In [18]:

```
df_low = df.loc[df['_target'] == 'low']

df_med = df.loc[df['_target'] == 'med']

df_high = df.loc[df['_target'] == 'high']
```

In [19]:

```
ax = plt.axes(projection='3d')

x_low = df_low['x1']
y_low = df_low['x2']
z_low = df_low['x3']
ax.scatter3D(x_low, y_low, z_low, c=z_low, cmap='Reds');

x_med = df_med['x1']
y_med = df_med['x2']
z_med = df_med['x3']
ax.scatter3D(x_med, y_med, z_med, c=z_med, cmap='Blues');

x_high = df_high['x1']
y_high = df_high['x2']
z_high = df_high['x3']
ax.scatter3D(x_high, y_high, z_high, c=z_high, cmap='Greens');
```

In [21]:

```
ax = plt.axes(projection='3d')
x_low = df_low['x1']
y_low = df_low['x2']
z_low = df_low['x3']
ax.scatter3D(x_low, y_low, z_low, c=z_low, cmap='Reds');
```

In [22]:

```
ax = plt.axes(projection='3d')
x_med = df_med['x1']
```

```
y_med = df_med['x2']
z_med = df_med['x3']
ax.scatter3D(x_med, y_med, z_med, c=z_med, cmap='Blues');
```

In [23]:

```
ax = plt.axes(projection='3d')
x_high = df_high['x1']
y_high = df_high['x2']
z_high = df_high['x3']
ax.scatter3D(x_high, y_high, z_high, c=z_high, cmap='Greens');
```

In [24]:

```
df['target_low'].value_counts(normalize=True)
```

Out[24]:

```
1    0.6
0    0.4
Name: target_low, dtype: float64
```

In [25]:

```
df['target_med'].value_counts(normalize=True)
```

Out[25]:

```
0    0.9
1    0.1
Name: target_med, dtype: float64
```

In [26]:

```
df['target_low'].value_counts(normalize=True)
```

Out[26]:

```
1    0.6
0    0.4
Name: target_low, dtype: float64
```

In [28]:

```
arr_dict = {0:"low", 1:"med", 2:"high"}
def arr2class(_arr):
    return arr_dict[np.argmax(_arr)]
```

The first approach to be taken will be with artificial neural networks, for this the data will be divided into training and test sets

In [29]:

```
x_train, x_test, y_train, y_test = train_test_split(x, y)
true_arr = []
for arr in y_test:
    true_arr.append(arr2class(arr))

df_pred = pd.DataFrame()
df_pred['true'] = true_arr
```

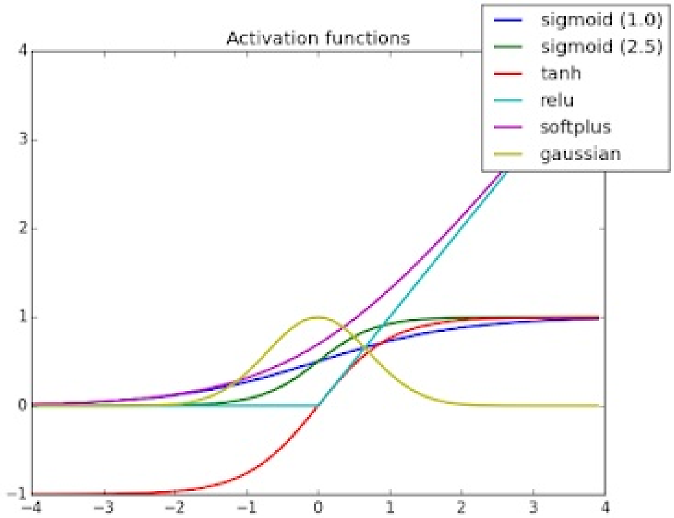
Activation and optimizer function.

Activation function

As we convert the negative values into individual scales from 0 to 1 for each feature x1, x2, x3 we can better use the activation functions compatible with those values, in this case ReLu is suitable for selecting features since its derivative produces a function step that will disable or activate features for each label.

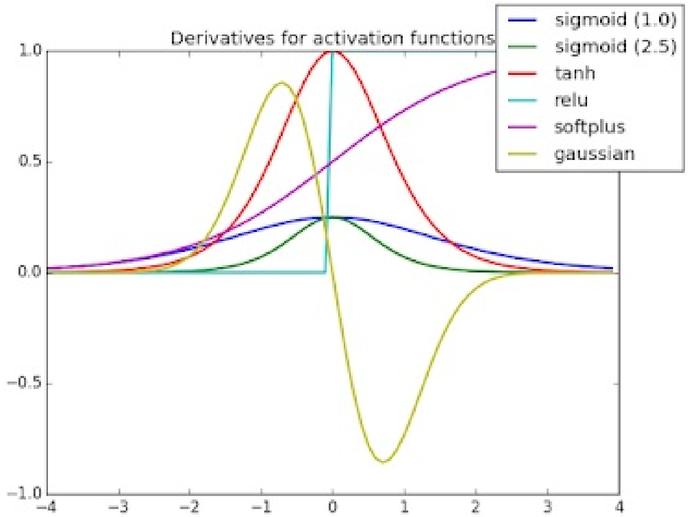
Activation functions image

[



]

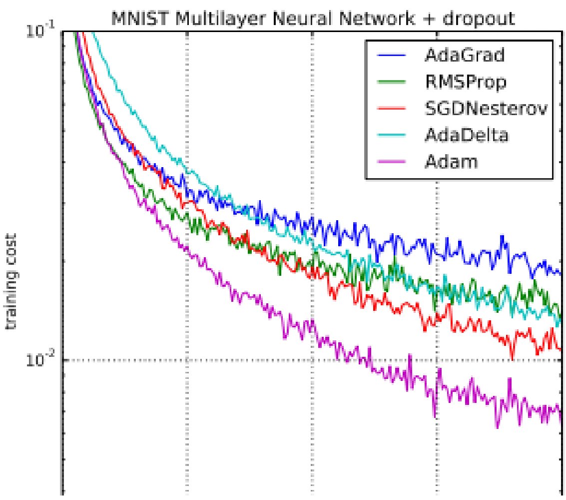
[

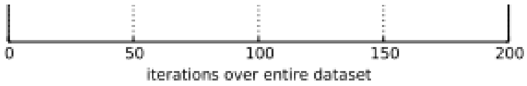


]

Optimizer for the backpropagation training will be chosen Adam, which in comparison to other gradient readjustment optimizers, is the one that converges faster!

[





]

Source: Machine Learning Mastery https://machinelearningmastery.com/adam-optimization-algorithm-for-deep-learning/

Building models.

We can initially model the neural network with 9 neurons at the input, inferring that each 1 of the 3 outputs is a specific combination of 3 features x1, x2, x3 of the input. The output will be 3 neurons because we will have a binary classification of 3 labels high (1.0.0), low (0.1.0), med (0.0.1)

In [103]:

```
current_model = 'mlp1'
mlp1 = Sequential()
mlp1.add(Dense(9, input_dim=3, kernel_initializer='he_uniform', activation='tanh')) #tan
h para admitir entrada de valores negativos
mlp1.add(Dense(3, activation='relu')) # saida com função degrau
mlp1.compile(loss='binary_crossentropy', optimizer='adam')
mlp1.save_weights(current_model + "_wheigts_initial.h5")

history1 = mlp1.fit(x_train, y_train, verbose=0, epochs=9)
results1 = mlp1.predict(x_test)

test_arr = []
for arr in results1:
    test_arr.append(arr2class(arr))
df_pred['mlp1_predicted_class'] = test_arr
df_pred['mlp1_score'] = np.where(df_pred["true"] == df_pred["mlp1_predicted_class"], Tru
e, False)
df_pred['mlp1_score'].describe()
```

Out[103]:

```
count      2500
unique        2
top        True
freq       1457
Name: mlp1_score, dtype: object
```

NEW SPLIT OF THE SET IN (TRAINING / VALIDATION) AND TEST, SCALA OF VALUES FOR 0/1 AND RELU FUNCTION IN ENTRY

In [43]:

```
def plot_history(history, start_epoch=0):
    start_epoch = 10
    plt.figure(figsize=(10,4))
    plt.title('História Treino')
    plt.plot(history.history['loss'][start_epoch:], label='Train Loss')
    plt.plot(history.history['val_loss'][start_epoch:], label='Validation Loss')
    plt.legend()
```

In [30]:

```
x_train_2, x_val, y_train_2, y_val = train_test_split(x_train, y_train)
```

In [38]:

```
x_train_2_scaler = MinMaxScaler([0,1]).fit(x_train_2.reshape(-1,1))
x_val_scaler = MinMaxScaler([0,1]).fit(x_val.reshape(-1,1))
```

In [39]:

```
x_train_2_scaled = x_train_2_scaler.transform(x_train_2)
x_val_scaled = x_val_scaler.transform(x_val)
```

In [45]:

```
current_model = 'mlp2'
mlp2 = Sequential()
mlp2.add(Dense(9, input_dim=3, kernel_initializer='he_uniform', activation='relu')) #tan
h para admitir entrada de valores negativos
mlp2.add(Dense(3, activation='relu')) # saida com função degrau
mlp2.compile(loss='binary_crossentropy', optimizer='adam')
mlp2.save_weights(current_model + "_wheigts_initial.h5")
```

In [47]:

```
print(x_train_2_scaled.shape, y_train_2.shape)

# train
n_epochs = 100
# parada antecipada
es = EarlyStopping(monitor = 'val_loss', mode = 'min', verbose = 1,
                   patience = 30, restore_best_weights=True)

history2 = mlp2.fit(
            x_train_2_scaled,
            y_train_2,
            epochs = n_epochs,
            verbose = 1,
            validation_data = (x_val_scaled , y_val),
            callbacks=[es])

plot_history(history2)
mlp2.save('mlp2_trained')
```

```
(5625, 3) (5625, 3)
Restoring model weights from the end of the best epoch.
Epoch 00064: early stopping
INFO:tensorflow:Assets written to: mlp2_trained\assets
```

To use the new MLP2 model we will have to scale the array x_test

In [54]:

```
x_test_scaler = MinMaxScaler([0,1]).fit(x_test.reshape(-1,1))
x_test_scaled = x_test_scaler.transform(x_test)
x_test_scaled
```

Out[54]:

```
array([[0.86046365, 0.43117933, 0.40250142],
       [0.59042385, 0.41450319, 0.15577032],
       [0.48405028, 0.45006633, 0.33074348],
       ...,
       [0.82900638, 0.42473628, 0.27856737],
       [0.40900764, 0.43395869, 0.35203083],
       [0.94289685, 0.48550313, 0.34975681]])
```

In [56]:

```
results_mlp2 = mlp1.predict(x_test_scaled)
results_mlp2
```

Out[56]:

```
array([[0.36375463, 0.22891437, 0.67513865],
       [0.2526784 , 0.19955194, 0.53333384],
       [0.03021828, 0.23778287, 0.475385  ],
       ...,
```

```
        [0.4076537 , 0.21288669, 0.6645062 ],
        [0.        , 0.23413564, 0.42250285],
        [0.44352633, 0.24689716, 0.7541945 ]], dtype=float32)
```

In [57]:

```
test_arr = []
for arr in results_mlp2:
    test_arr.append(arr2class(arr))
df_pred['mlp2_predicted_class'] = test_arr
df_pred['mlp2_score'] = np.where(df_pred["true"] == df_pred["mlp2_predicted_class"], True, False)
df_pred['mlp2_score'].describe()
```

Out[57]:

```
count      2500
unique        2
top       False
freq       1774
Name: mlp2_score, dtype: object
```

MLP2 scored worse than MLP1

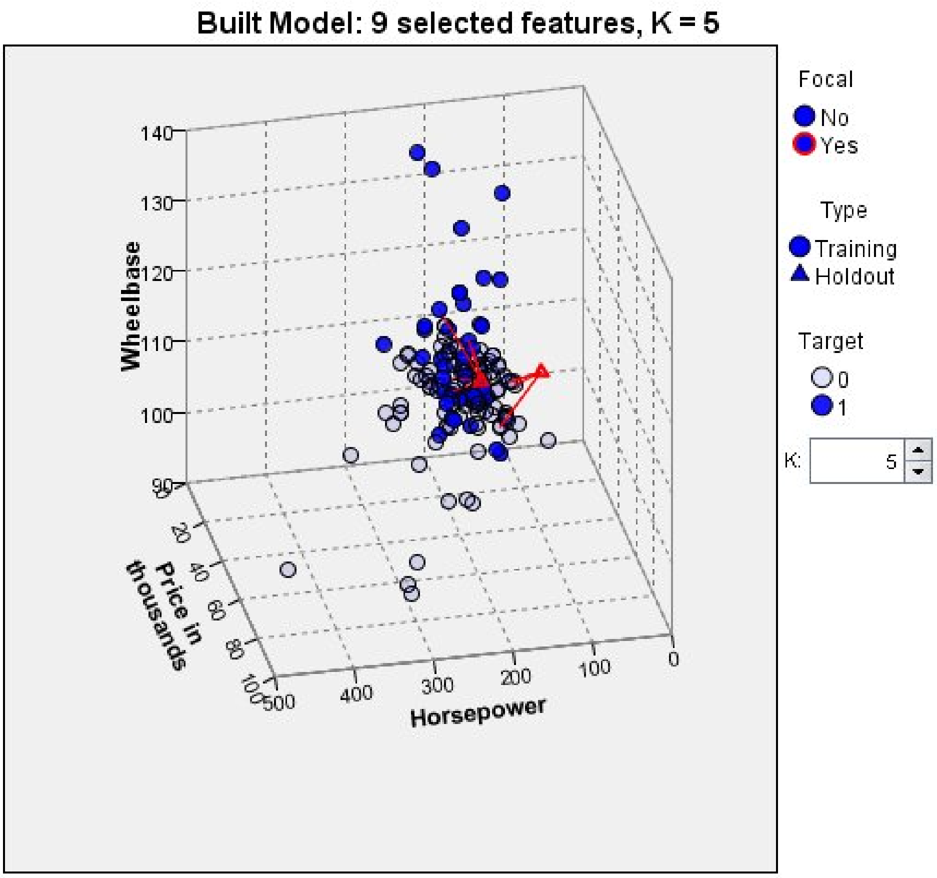
KNN

For this problem we can use the popular KNN algorithm (K - Nearest Neighbors), as it is a supervised training algorithm (and this problem has the supervised value y = "target" for each training entry)

And the training entries have quantitative values that can be interpreted as Euclidean distances in the space between the features up to the supervised value.

In the example below, features x1, x2, x3 could be interpreted as Wheelbase, price in thousands and horsepower.

[



]

Source: IBM Knowledge Center, Nearest Neighbors Analysis, Using Nearest Neighbor Analysis to Assess New

Vehicle Offerings link:
https://www.ibm.com/support/knowledgecenter/bs/SSLVMB_24.0.0/components/knn/knn_carsales_check-type_modelviewer_feature-space.html

In [91]:

```
knn_clf=KNeighborsClassifier()
knn_clf.fit(x_train,y_train)
results2 = knn_clf.predict(x_test)

test_arr = []
for arr in results2:
    test_arr.append(arr2class(arr))
df_pred['knn_predicted_class'] = test_arr
df_pred['knn_score'] = np.where(df_pred["true"] == df_pred["knn_predicted_class"], True,
False)
df_pred['knn_score'].describe()
```

Out[91]:

```
count     2500
unique       2
top       True
freq      1379
Name: knn_score, dtype: object
```

Comparing

In [109]:

```
print("\n\n     MLP \n\n", df_pred['mlp1_score'].value_counts(normalize=True))
print("\n\n     KNN \n\n", df_pred['knn_score'].value_counts(normalize=True))
```

```
     MLP

 True     0.5828
False    0.4172
Name: mlp1_score, dtype: float64


     KNN

 True     0.5516
False    0.4484
Name: knn_score, dtype: float64
```

BEST NEURAL NETWORK HIT 58.28% AND KNN 55.16%

Among the chosen methods KNN and Deep Learning with perceptron networks had very close results and converging to a quick memorization of learning for the population + present of labels, "low" that contemplate 60% of the total data set.