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	[illegible]	[illegible]	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

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)]
```

Escalando dados para deep learning

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
```

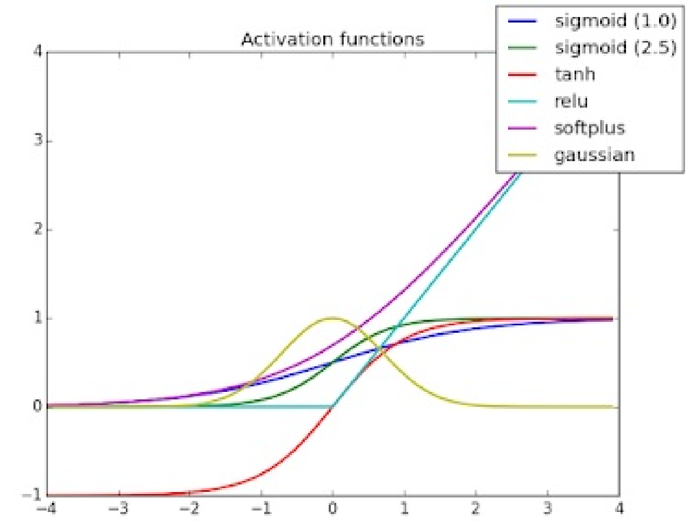
Função de ativação e otimizador.

Função de ativação

Como convertemos os valores negativos em escalas individuais de 0 a 1 para cada feature x1,x2,x3 podemos utilizar melhor as funções de ativação compatíveis com tais valores, no caso a ReLu é apropriada para o seleção de features visto que sua derivada produz uma função degrau que irá desativar ou ativar features para cada label.

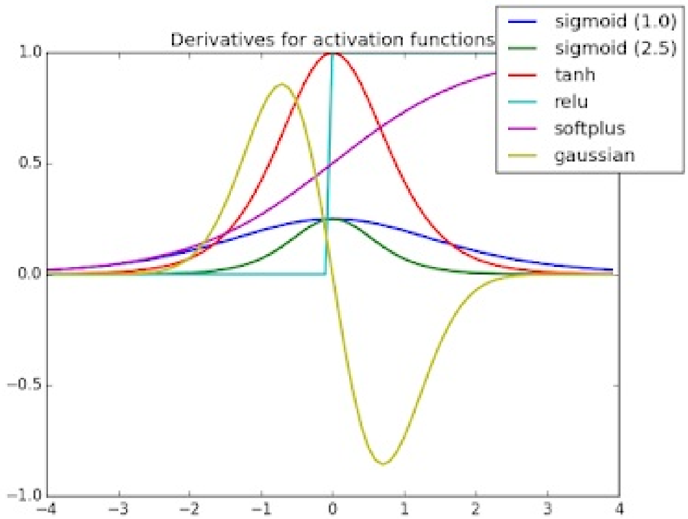
Funções de ativação:

[



]

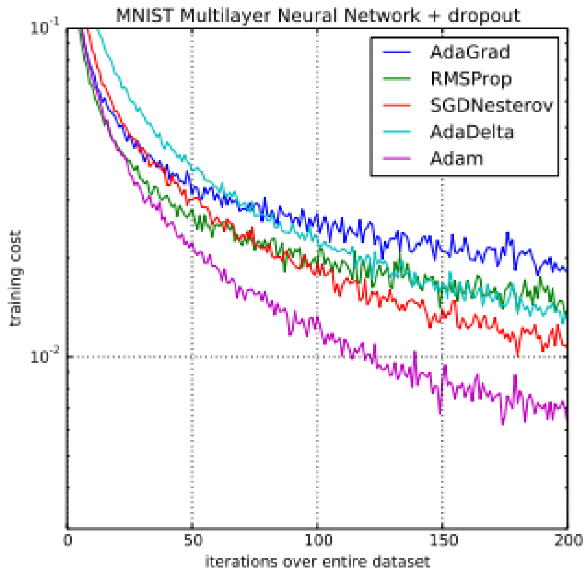
[



]

Otimizador para o treino backpropagation será escolhido Adam, que em comparação a outros otimizadores de reajuste de gradiente, é o que converge mais rápido!

[



]

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

Modelagem da rede.

Podemos modelar inicialmente a rede neural com 9 neuronios na entrada, inferindo que cada 1 das 3 saídas é uma combinação específica de 3 features x1,x2,x3 da entrada. A saída será de 3 neuronios pois teremos uma classificação binária de 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
```

NOVO SPLIT DO CONJUNTO EM (TREINO / VALIDAÇÃO) E TESTE, SCALA DOS VALORES PARA 0/1 E FUNÇÃO RELU NA ENTRADA

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
```

Para utilizar a MLP2 teremos que escalar o vetor 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 se saiu pior do que MLP1

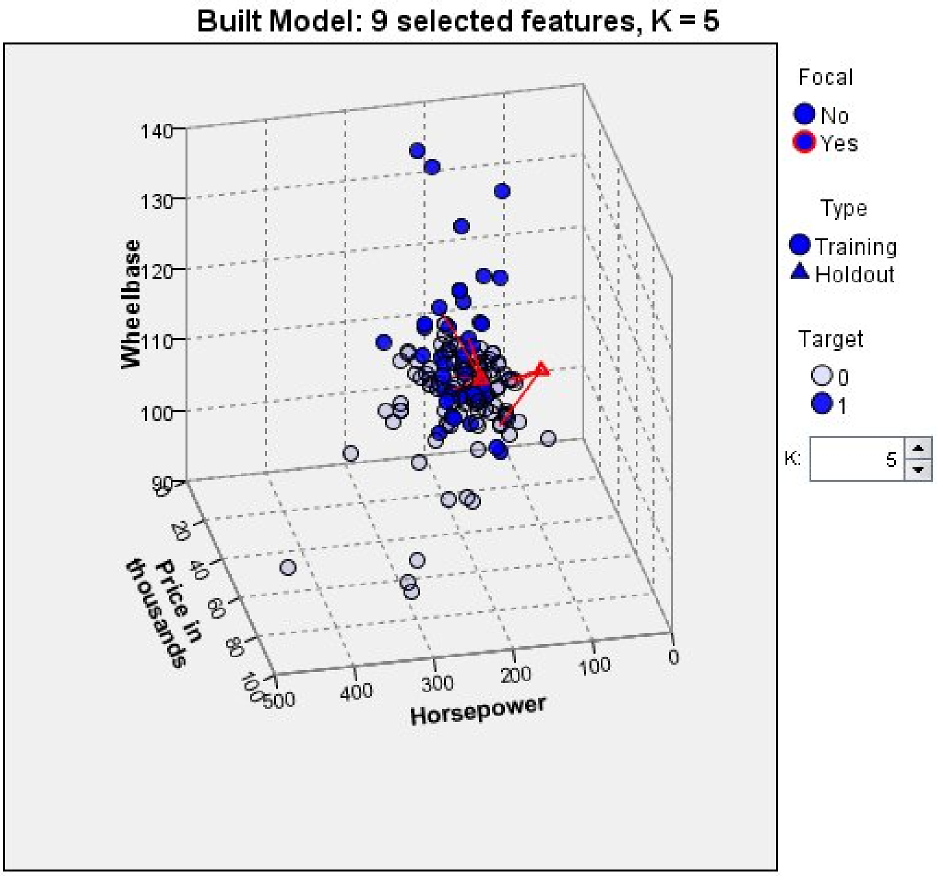
KNN

Para este problema podemos utilizar o algoritmo popular KNN(K — Nearest Neighbors), pois é um algoritmo de treino supervisionado (e este problema temos o valor supervisionado y = "target" para cada entrada de treinamento)

E as entradas de treino possuem valores quantitativos que podem ser interpretados como distancias euclidianas no espaço entre as features até o valor supervisionado.

No exemplo abaixo, as features x1,x2,x3 poderiam ser intepretadas como Wheelbase, price in thousands e horsepower.

[



]

Fonte: 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
```

COMPARANDO

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
```

MELHOR REDE NEURAL ACERTOU 58,28% E KNN 55,16%

Entre os métodos escolhidos KNN e Deep Learning com redes perceptron tiveram resultados muitos próximos e convergindo à uma rápida memorização de aprendizado para a população + presente de labels, "low" que contemplam 60% do conjunto total de dados.