Aula 02 - KNN - Exercícios

Exercício 1

Utilizando o dataset breast_cancer_train.csv, desenvolva um modelo KNN (utilizando o sklearn) com o objetivo de prever se o resultado de uma biópsia indica a presença de câncer malígno. Procure fazer com que o seu o modelo não apresente **overfitting** e maximize a acurácia.

Ao final, reporte:

1 - A acurácia, precisão e recall do seu modelo na base utilizada para treino e validação
2 - A acurácia, precisão e recall do seu modelo na base breast_cancer_test.csv
3 - O K escolhido
4 - Qual é a variável mais importante no processo de decisão? Você pode usar uma árvore para responder

In [1]:
```
import pandas as pd
```

In [3]:
```
df_cancer_train = pd.read_csv('breast_cancer_train.csv')
df_cancer_test = pd.read_csv('breast_cancer_test.csv')
```

In [4]:
```
df_cancer_train.head()
```

Out[4]:

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	...	radius_worst	texture_worst	pe
0	857156	B	13.49	22.30	86.91	561.0	0.08752	0.07698	0.047510	0.033840	...	15.15	31.82	
1	844981	M	13.00	21.82	87.50	519.8	0.12730	0.19320	0.185900	0.093530	...	15.49	30.73	
2	88330202	M	17.46	39.28	113.40	920.6	0.09812	0.12980	0.141700	0.088110	...	22.51	44.87	
3	88203002	B	11.22	33.81	70.79	386.8	0.07780	0.03574	0.004967	0.006434	...	12.36	41.78	
4	892189	M	11.76	18.14	75.00	431.1	0.09968	0.05914	0.026850	0.035150	...	13.36	23.39	

5 rows × 32 columns

In [5]:
```
df_cancer_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 455 entries, 0 to 454
Data columns (total 32 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   id                       455 non-null    int64  
 1   diagnosis                455 non-null    object 
 2   radius_mean              455 non-null    float64
 3   texture_mean             455 non-null    float64
 4   perimeter_mean           455 non-null    float64
 5   area_mean                455 non-null    float64
 6   smoothness_mean          455 non-null    float64
 7   compactness_mean         455 non-null    float64
 8   concavity_mean           455 non-null    float64
 9   concave points_mean      455 non-null    float64
 10  symmetry_mean            455 non-null    float64
 11  fractal_dimension_mean   455 non-null    float64
 12  radius_se                455 non-null    float64
 13  texture_se               455 non-null    float64
 14  perimeter_se             455 non-null    float64
 15  area_se                  455 non-null    float64
 16  smoothness_se            455 non-null    float64
 17  compactness_se           455 non-null    float64
 18  concavity_se             455 non-null    float64
 19  concave points_se        455 non-null    float64
 20  symmetry_se              455 non-null    float64
 21  fractal_dimension_se     455 non-null    float64
 22  radius_worst             455 non-null    float64
 23  texture_worst            455 non-null    float64
 24  perimeter_worst          455 non-null    float64
 25  area_worst               455 non-null    float64
 26  smoothness_worst         455 non-null    float64
 27  compactness_worst        455 non-null    float64
 28  concavity_worst          455 non-null    float64
 29  concave points_worst     455 non-null    float64
 30  symmetry_worst           455 non-null    float64
 31  fractal_dimension_worst  455 non-null    float64
dtypes: float64(30), int64(1), object(1)
memory usage: 113.9+ KB
```

In [6]:

```
df_cancer_train['diagnosis'] = df_cancer_train['diagnosis'].map({'M': 1, 'B': 0})

df_cancer_train.head()
```

Out[6]:

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	...	radius_worst	texture_worst	pe
0	857156	0	13.49	22.30	86.91	561.0	0.08752	0.07698	0.047510	0.033840	...	15.15	31.82	
1	844981	1	13.00	21.82	87.50	519.8	0.12730	0.19320	0.185900	0.093530	...	15.49	30.73	
2	88330202	1	17.46	39.28	113.40	920.6	0.09812	0.12980	0.141700	0.088110	...	22.51	44.87	
3	88203002	0	11.22	33.81	70.79	386.8	0.07780	0.03574	0.004967	0.006434	...	12.36	41.78	
4	892189	1	11.76	18.14	75.00	431.1	0.09968	0.05914	0.026850	0.035150	...	13.36	23.39	

5 rows × 32 columns

In [7]:

```
X = df_cancer_train.drop(['id', 'diagnosis'], axis=1)
y = df_cancer_train['diagnosis']

print(X.shape, y.shape)
```

```
(455, 30) (455,)
```

In [8]:

```
# Hold out

from sklearn.model_selection import train_test_split

X_train, X_valid, y_train, y_valid = train_test_split(X,
                                                      y,
                                                      test_size=0.3,
                                                      random_state=12)

print(X_train.shape, y_train.shape)
print(X_valid.shape, y_valid.shape)
```

```
(318, 30) (318,)
(137, 30) (137,)
```

In [9]:

```
from sklearn.neighbors import KNeighborsClassifier
```

In [13]:

```
from sklearn.metrics import accuracy_score, precision_score, recall_score
from matplotlib import pyplot as plt

valores_k = []
taxa_overfit = []

for k in range(1, 30):
    modelo = KNeighborsClassifier(n_neighbors=k)
    modelo.fit(X_train, y_train)

    y_train_pred = modelo.predict(X_train)
```

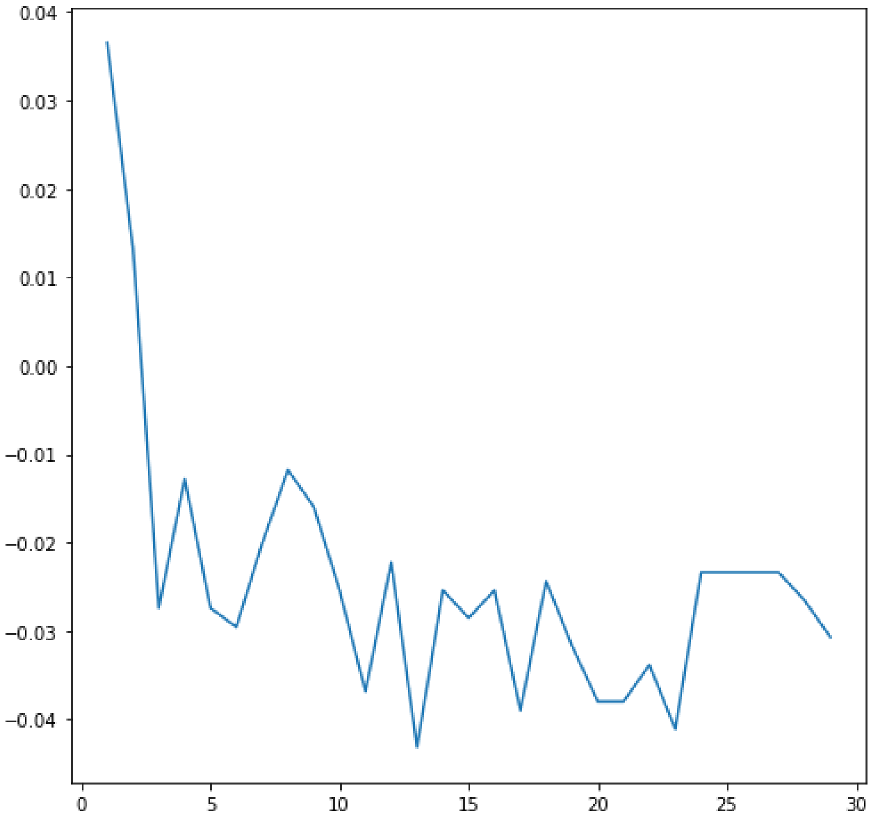
```python
    y_valid_pred = modelo.predict(X_valid)

    acc_train = accuracy_score(y_train, y_train_pred)
    prec_train = precision_score(y_train, y_train_pred)
    rec_train = recall_score(y_train, y_train_pred)

    acc_valid = accuracy_score(y_valid, y_valid_pred)
    prec_valid = precision_score(y_valid, y_valid_pred)
    rec_valid = recall_score(y_valid, y_valid_pred)

    valores_k.append(k)
    taxa_overfit.append(acc_train-acc_valid)

    print('\n##############\n')
    print(f'Treino k={k}:\nAcc: {acc_train:.2f}, Precision: {prec_train:.2f}, Recall: {rec_train:.2f}')
    print(f'Validação k={k}:\nAcc: {acc_valid:.2f}, Precision: {prec_valid:.2f}, Recall: {rec_valid:.2f}')

plt.figure(figsize=(8,8))

plt.plot(valores_k, taxa_overfit)

plt.show()
```

```
##############

Treino k=1:
Acc: 1.00, Precision: 1.00, Recall: 1.00
Validação k=1:
Acc: 0.96, Precision: 0.94, Recall: 0.96

##############

Treino k=2:
Acc: 0.94, Precision: 1.00, Recall: 0.83
Validação k=2:
Acc: 0.93, Precision: 0.97, Recall: 0.81

##############

Treino k=3:
Acc: 0.94, Precision: 0.95, Recall: 0.89
Validação k=3:
Acc: 0.97, Precision: 0.96, Recall: 0.96

##############

Treino k=4:
Acc: 0.94, Precision: 0.97, Recall: 0.87
Validação k=4:
Acc: 0.96, Precision: 0.98, Recall: 0.90

##############

Treino k=5:
Acc: 0.94, Precision: 0.94, Recall: 0.90
Validação k=5:
Acc: 0.97, Precision: 0.98, Recall: 0.94

##############

Treino k=6:
Acc: 0.93, Precision: 0.97, Recall: 0.84
Validação k=6:
Acc: 0.96, Precision: 0.98, Recall: 0.92

##############

Treino k=7:
Acc: 0.94, Precision: 0.94, Recall: 0.90
Validação k=7:
Acc: 0.96, Precision: 0.98, Recall: 0.92

##############

Treino k=8:
```

```
Acc: 0.94, Precision: 0.96, Recall: 0.86
Validação k=8:
Acc: 0.95, Precision: 0.98, Recall: 0.88

##############

Treino k=9:
Acc: 0.94, Precision: 0.95, Recall: 0.88
Validação k=9:
Acc: 0.96, Precision: 0.98, Recall: 0.90

##############

Treino k=10:
Acc: 0.93, Precision: 0.96, Recall: 0.84
Validação k=10:
Acc: 0.96, Precision: 0.98, Recall: 0.90

##############

Treino k=11:
Acc: 0.93, Precision: 0.95, Recall: 0.86
Validação k=11:
Acc: 0.97, Precision: 0.98, Recall: 0.94

##############

Treino k=12:
Acc: 0.93, Precision: 0.97, Recall: 0.84
Validação k=12:
Acc: 0.96, Precision: 0.98, Recall: 0.90

##############

Treino k=13:
Acc: 0.93, Precision: 0.94, Recall: 0.85
Validação k=13:
Acc: 0.97, Precision: 0.98, Recall: 0.94

##############

Treino k=14:
Acc: 0.93, Precision: 0.97, Recall: 0.83
Validação k=14:
Acc: 0.96, Precision: 0.98, Recall: 0.90

##############

Treino k=15:
Acc: 0.93, Precision: 0.94, Recall: 0.85
Validação k=15:
Acc: 0.96, Precision: 0.98, Recall: 0.90
```

```
##############

Treino k=16:
Acc: 0.93, Precision: 0.97, Recall: 0.83
Validação k=16:
Acc: 0.96, Precision: 0.98, Recall: 0.90

##############

Treino k=17:
Acc: 0.92, Precision: 0.94, Recall: 0.84
Validação k=17:
Acc: 0.96, Precision: 0.98, Recall: 0.92

##############

Treino k=18:
Acc: 0.92, Precision: 0.96, Recall: 0.83
Validação k=18:
Acc: 0.95, Precision: 0.98, Recall: 0.88

##############

Treino k=19:
Acc: 0.92, Precision: 0.95, Recall: 0.83
Validação k=19:
Acc: 0.96, Precision: 0.98, Recall: 0.90

##############

Treino k=20:
Acc: 0.92, Precision: 0.95, Recall: 0.82
Validação k=20:
Acc: 0.96, Precision: 0.98, Recall: 0.90

##############

Treino k=21:
Acc: 0.92, Precision: 0.95, Recall: 0.82
Validação k=21:
Acc: 0.96, Precision: 0.98, Recall: 0.90

##############

Treino k=22:
Acc: 0.92, Precision: 0.96, Recall: 0.80
Validação k=22:
Acc: 0.95, Precision: 0.98, Recall: 0.88

##############
```

```
Treino k=23:
Acc: 0.92, Precision: 0.96, Recall: 0.80
Validação k=23:
Acc: 0.96, Precision: 0.98, Recall: 0.90

##############

Treino k=24:
Acc: 0.92, Precision: 0.97, Recall: 0.80
Validação k=24:
Acc: 0.94, Precision: 0.98, Recall: 0.85

##############

Treino k=25:
Acc: 0.92, Precision: 0.97, Recall: 0.80
Validação k=25:
Acc: 0.94, Precision: 0.98, Recall: 0.85

##############

Treino k=26:
Acc: 0.92, Precision: 0.97, Recall: 0.80
Validação k=26:
Acc: 0.94, Precision: 0.98, Recall: 0.85

##############

Treino k=27:
Acc: 0.92, Precision: 0.97, Recall: 0.80
Validação k=27:
Acc: 0.94, Precision: 0.98, Recall: 0.85

##############

Treino k=28:
Acc: 0.92, Precision: 0.97, Recall: 0.79
Validação k=28:
Acc: 0.94, Precision: 0.98, Recall: 0.85

##############

Treino k=29:
Acc: 0.92, Precision: 0.97, Recall: 0.80
Validação k=29:
Acc: 0.95, Precision: 0.98, Recall: 0.88
```

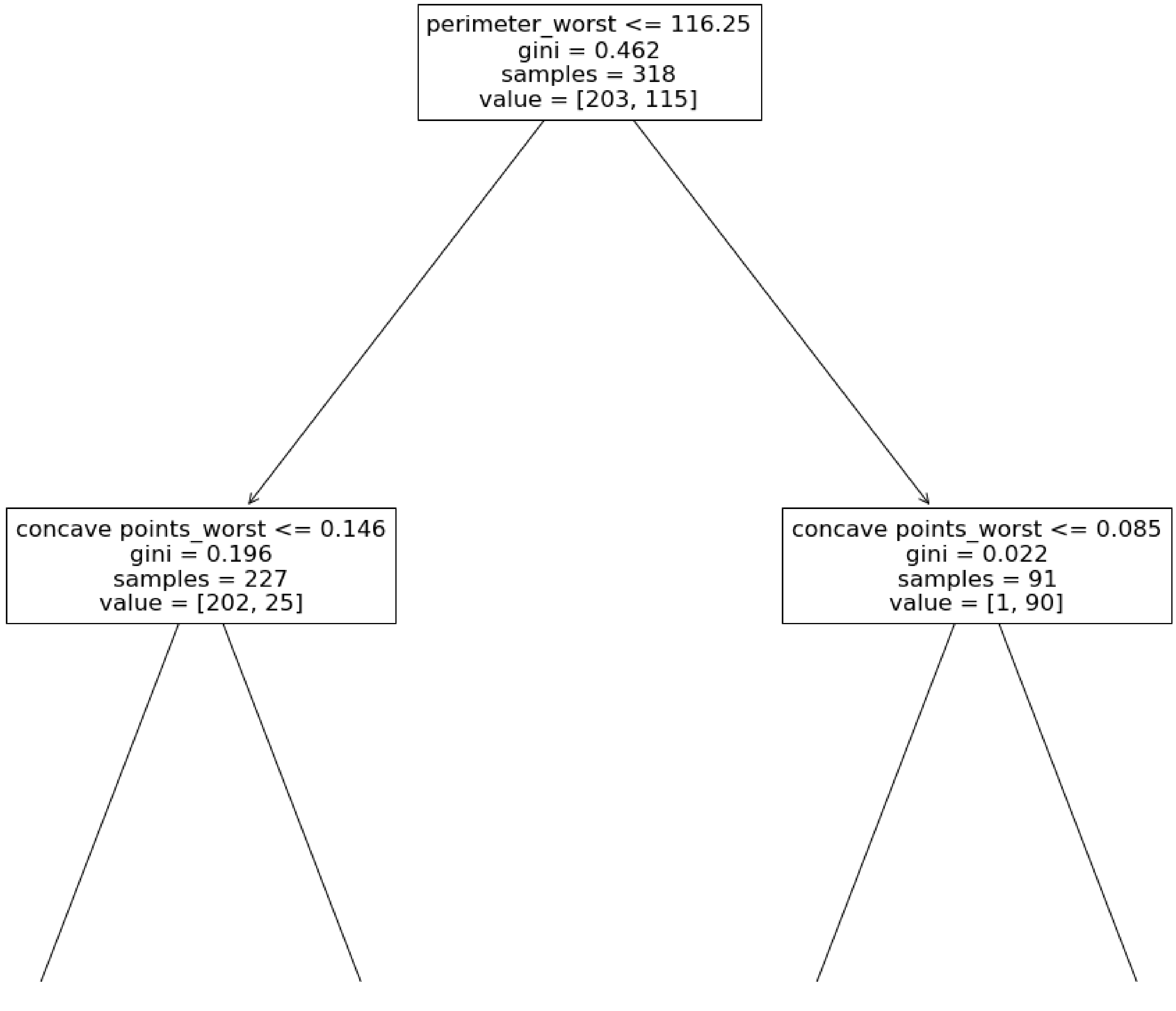


In [18]:
```
modelo = KNeighborsClassifier(n_neighbors=12)

modelo.fit(X_train, y_train)

y_train_pred = modelo.predict(X_train)

y_valid_pred = modelo.predict(X_valid)
```

In [19]:
```
acc_train = accuracy_score(y_train, y_train_pred)
prec_train = precision_score(y_train, y_train_pred)
rec_train = recall_score(y_train, y_train_pred)

acc_valid = accuracy_score(y_valid, y_valid_pred)
prec_valid = precision_score(y_valid, y_valid_pred)
rec_valid = recall_score(y_valid, y_valid_pred)

print(f'Treino:\nAcc: {ac12c_train:.2f}, Precision: {prec_train:.2f}, Recall: {rec_train:.2f}')
print(f'Validação:\nAcc: {acc_valid:.2f}, Precision: {prec_valid:.2f}, Recall: {rec_valid:.2f}')
```

```
Treino:
Acc: 0.93, Precision: 0.97, Recall: 0.84
Validação:
Acc: 0.96, Precision: 0.98, Recall: 0.90
```

In [20]:
```
from sklearn.tree import DecisionTreeClassifier, plot_tree

arvore_auxiliar = DecisionTreeClassifier(max_depth=2)

arvore_auxiliar.fit(X_train, y_train)

plt.figure(figsize=(20, 20))
plot_tree(arvore_auxiliar, feature_names=X_train.columns)
plt.show()
```


perimeter_worst <= 116.25
gini = 0.462
samples = 318
value = [203, 115]
concave points_worst <= 0.146
gini = 0.196
samples = 227
value = [202, 25]
concave points_worst <= 0.085
gini = 0.022
samples = 91
value = [1, 90]

Resultados

1 - A acurácia, precisão e recall do seu modelo na base utilizada para treino e validação

In [21]:
```
print(f'Treino:\nAcc: {acc_train:.2f}, Precision: {prec_train:.2f}, Recall: {rec_train:.2f}')
print(f'Validação:\nAcc: {acc_valid:.2f}, Precision: {prec_valid:.2f}, Recall: {rec_valid:.2f}')
```

```
Treino:
Acc: 0.93, Precision: 0.97, Recall: 0.84
Validação:
Acc: 0.96, Precision: 0.98, Recall: 0.90
```

2 - A acurácia, precisão e recall do seu modelo na base breast_cancer_test.csv

In [22]:
```
df_cancer_test['diagnosis'] = df_cancer_test['diagnosis'].map({'M': 1, 'B': 0})

df_cancer_test.head()
```

Out[22]:

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	...	radius_worst	texture_worst	pe
0	84348301	1	11.42	20.38	77.58	386.1	0.14250	0.28390	0.24140	0.10520	...	14.91	26.50	
1	84358402	1	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.19800	0.10430	...	22.54	16.67	
2	843786	1	12.45	15.70	82.57	477.1	0.12780	0.17000	0.15780	0.08089	...	15.47	23.75	
3	846226	1	19.17	24.80	132.40	1123.0	0.09740	0.24580	0.20650	0.11180	...	20.96	29.94	
4	855133	1	14.99	25.20	95.54	698.8	0.09387	0.05131	0.02398	0.02899	...	14.99	25.20	

5 rows × 32 columns

In [23]:
```
df_cancer_test['predict'] = modelo.predict(df_cancer_test[X_train.columns])
```

In [25]:
```
acc_test = accuracy_score(df_cancer_test['diagnosis'], df_cancer_test['predict'])
prec_test = precision_score(df_cancer_test['diagnosis'], df_cancer_test['predict'])
rec_test = recall_score(df_cancer_test['diagnosis'], df_cancer_test['predict'])

print(f'Teste:\nAcc: {acc_test:.2f}, Precision: {prec_test:.2f}, Recall: {rec_test:.2f}')
```

```
Teste:
Acc: 0.89, Precision: 0.95, Recall: 0.78
```

3 - O K escolhido

Foi escolhido k=12.

4 - Qual é a variável mais importante no processo de decisão? Você pode usar uma árvore para responder

Baseado na árvore, a variável mais importante é a perimeter_worst.

Exercício 2

Utilizando o dataset movies_data.csv, desenvolva um modelo que, dada a escolha de um filme, apresente uma sugestão com os 3 filmes mais parecidos.

Dica: adapte a classe KNN_Custom, vista na aula, para resolver esse problema.

In [26]:
```
df_movies = pd.read_csv('movies_data.csv')

df_movies.head()
```

Out[26]:

	Movie Name	IMDB Rating	Biography	Drama	Thriller	Comedy	Crime	Mystery	History	Label
0	The Imitation Game	8.0	1	1	1	0	0	0	0	0
1	Ex Machina	7.7	0	1	0	0	0	1	0	0
2	A Beautiful Mind	8.2	1	1	0	0	0	0	0	0
3	Good Will Hunting	8.3	0	1	0	0	0	0	0	0
4	Forrest Gump	8.8	0	1	0	0	0	0	0	0

In [89]:
```
import numpy as np
from scipy import stats

# Definição da nossa classe

class KNN_Custom:
```

```python
    def __init__(self, k, data):
        # Inicializando nosso modelo

        self._k = k + 1
        self._data = data.copy()

    def predict(self, movie, features):

        # Garantimos que estamos tratando uma array do numpy
        X = self._data.loc[self._data['Movie Name'] == movie, features].to_numpy().reshape(-1)

        # Criamos nossa tabela de distâncias
        self._dist_table = pd.DataFrame(columns=['sample_index', 'distance'])

        # Iteramos sobre todos os pontos
        for i in range(len(self._data)):
            # Selecionamos o ponto atual
            ponto_atual = self._data[features].iloc[i].to_numpy()

            # Calculamos a distância
            dist = np.linalg.norm(X-ponto_atual)

            # Adicionamos o valos à tabela
            self._dist_table = self._dist_table.append({'sample_index': i, 'distance': dist}, ignore_index=True)


        # Ordenamos a tabela pela distância
        self._dist_table = self._dist_table.sort_values('distance')

        # Selecionamos os índices com as K menores distâncias
        self._vetor_indices = self._dist_table.sort_values('distance')['sample_index'].to_numpy()[1:self._k]

        # Retornamos a moda das categorias selecionadas
        return self._data.loc[self._vetor_indices, 'Movie Name']

    def __repr__(self):
        return f'KNN implementado manualmente! K={self._k}'
```

In [90]:

```python
modelo = KNN_Custom(k=3, data=df_movies)
```

In [91]:

```python
features = df_movies.drop('Movie Name', axis=1).columns.to_list()
features
```

Out[91]:
```
['IMDB Rating',
 'Biography',
 'Drama',
 'Thriller',
 'Comedy',
 'Crime',
 'Mystery',
 'History',
 'Label']
```

In [94]:
```
movie = 'Forrest Gump'

modelo.predict(movie, features)
```

Out[94]:
```
12.0         Interstellar
3.0      Good Will Hunting
15.0            Inception
Name: Movie Name, dtype: object
```

In [ ]: