Estrelas frias do tipo solar x Gigantes vermelhas

April 23, 2022

1 Introdução

Um dos motivos principais para a existência de vida na Terra é a gama de condições favoráveis que o Sol propicia ao nosso planketa. Sendo assim, nota-se que encontrar estrelas do tipo Sol é de extrema importância para a procura de vida fora da Terra.

2 Objetivos

Esse é um projeto inicial que pretende destinguir estrelas frias do tipo solar de gigantes vermelhas usando Machine Learning.

3 Importação das bibliotecas

[16]:
```
import numpy as np # Importando o numpy para trabalhar com matrizes e etc.
import pandas as pd # Importação do pandas para trabalhar com dados.
from pandas_profiling import ProfileReport # Importando o ProfileReport para␣
↪fazer uma análise geral do dataset
"""
Importações para trabalhar com gráficos
"""
import seaborn as sbn
import matplotlib.pyplot as plt
from matplotlib.ticker import AutoMinorLocator
from matplotlib.font_manager import FontProperties
"""
Importações para Machine Learning
"""
"""
train_test_split: Realiza um split nos dados entre treino e teste.
GridSearchCV: Trabalha com ajuste de hiperparâmetros para os algoritmos de ML.
"""
from sklearn.model_selection import train_test_split, GridSearchCV
"""
Ignorar alguns warnings que não afetam o código
"""
import warnings
warnings.filterwarnings("ignore")
```

```python
"""
Importação das métricas de avaliação de um modelo;
"""
from sklearn.metrics import (classification_report, # Report geral
                             accuracy_score, # Acurácia
                             roc_auc_score,
                             roc_curve, # Curva roc
                             confusion_matrix) # Matriz de confusão
"""
MinMaxScaler: Realiza a normalização dos dados
"""
from sklearn.preprocessing import MinMaxScaler
"""
Regressão logística
"""
from sklearn.linear_model import LogisticRegression
"""
Algoritmo dos K vizinhos mais próximos
"""
from sklearn.neighbors import KNeighborsClassifier
"""
Importando do Naive Bayes o algoritmo GaussianNB
"""
from sklearn.naive_bayes import GaussianNB
"""
Algoritmos de aprendizado não supervisionado: KMeans
"""
from sklearn.cluster import KMeans
"""
Importação dos algoritmos ensemble
"""
from sklearn.ensemble import (RandomForestClassifier,
                              ExtraTreesClassifier,
                              AdaBoostClassifier,
                              GradientBoostingClassifier)
"""
SVC: Support vector machine
"""
from sklearn.svm import SVC
"""
Parte das importações para a rede neural
"""
from keras.utils.np_utils import to_categorical
from keras.models import Sequential
from keras.layers import Dense, Dropout
```

4 Chamando os dados

[17]:
```python
"""
Chamando o dataset só com gigantes vermelhas
"""
Gigantes_vermelhas = pd.read_csv("2_parte_RGB_HeB.txt", sep = "|", header =␣
↪None)
Gigantes_vermelhas.columns = ["KIC", "Teff", "e_Teff", "logg", "e_logg", "[Fe/
↪H]",
                  "e_[Fe/H]", "NoCorM", "e_NoCorM", "NoCorR", "e_NoCorR",
                  "RGBcorM", "e_RGBcorM", "RGBcorR", "e_RGBcorR", "ClcorM",
                  "e_ClcorM", "ClcorR", "e_ClcorR", "Phase"]
"""
Mostra na tela a parte superior do DF "Gigantes_vermelhas"
"""
pd.set_option("display.max_columns", len(Gigantes_vermelhas.columns))
Gigantes_vermelhas.head(14)
```

[17]:

	KIC	Teff	e_Teff	logg	e_logg	[Fe/H]	e_[Fe/H]	NoCorM	e_NoCorM	\
0	757137	4751	139	2.383	0.012	-0.08	0.30	1.70	0.14	
1	892010	4834	151	2.161	0.023	0.21	0.30	1.42	0.29	
2	892738	4534	135	1.769	0.022	-0.25	0.30	1.15	0.21	
3	892760	5188	183	2.394	0.011	-0.21	0.30	1.00	0.14	
4	893214	4728	80	2.522	0.008	-0.15	0.15	1.72	0.10	
5	893233	4207	147	1.668	0.012	0.22	0.30	0.86	0.09	
6	1026084	5072	166	2.534	0.013	-0.12	0.30	1.71	0.18	
7	1026180	4718	148	2.471	0.012	-0.02	0.30	1.65	0.17	
8	1026309	4514	80	2.121	0.020	0.25	0.15	2.71	0.42	
9	1026326	5123	162	2.899	0.009	-0.41	0.30	1.32	0.08	
10	1026452	5089	154	2.458	0.010	-0.11	0.30	1.55	0.17	
11	1027110	4190	80	1.699	0.014	-0.27	0.15	1.15	0.13	
12	1027337	4671	80	2.772	0.007	0.29	0.15	1.45	0.08	
13	1027582	5039	155	3.116	0.008	-0.10	0.30	1.42	0.09	

	NoCorR	e_NoCorR	RGBcorM	e_RGBcorM	RGBcorR	e_RGBcorR	ClcorM	\
0	13.91	0.41	1.55	0.13	13.26	0.39	1.72	
1	16.37	1.38	1.36	0.28	16.02	1.34	1.43	
2	23.15	1.62	0.99	0.18	21.49	1.48	1.12	
3	10.51	0.68	1.04	0.15	10.74	0.70	1.00	
4	11.90	0.26	1.54	0.09	11.29	0.24	1.72	
5	22.43	0.95	0.71	0.07	20.46	0.84	0.84	
6	11.69	0.48	1.67	0.17	11.55	0.48	1.75	
7	12.37	0.53	1.50	0.16	11.80	0.50	1.67	
8	23.71	1.35	2.60	0.40	23.22	1.32	2.73	
9	6.77	0.15	1.30	0.08	6.70	0.15	1.36	
10	12.15	0.57	1.53	0.16	12.08	0.57	1.58	
11	25.09	1.09	0.99	0.11	23.27	0.99	1.11	

```
12    8.19      0.16     1.34       0.07     7.89       0.15    1.46
13    5.45      0.12     1.39       0.09     5.41       0.12    1.44

    e_ClcorM  ClcorR  e_ClcorR  Phase
0       0.14   13.97      0.41      1
1       0.30   16.47      1.39      0
2       0.20   22.86      1.60      0
3       0.14   10.52      0.68      2
4       0.10   11.92      0.26      1
5       0.09   22.28      0.94      0
6       0.18   11.83      0.49      2
7       0.17   12.43      0.53      2
8       0.42   23.78      1.35      0
9       0.09    6.85      0.16      1
10      0.17   12.27      0.58      2
11      0.12   24.66      1.07      0
12      0.08    8.23      0.16      1
13      0.09    5.50      0.12      1
```

[18]:

```
"""
Chamando o dataset só com estrelas frias do tipo Sol
"""
Estrelas_do_tipo_Sol = pd.read_csv("age_prediction.txt", sep = "|", header =␣
 ↪None)
Estrelas_do_tipo_Sol.columns = ["Star", "Teff", "e_Teff", "logg",
               "e_logg", "Vt", "e_Vt", "[Fe/H]", "e_[Fe/H]",
               "Mass", "e_Mass", "Age", "e_Age"]
"""
Mostra na tela a parte superior do DF "Estrelas_do_tipo_Sol"
"""
pd.set_option("display.max_columns", len(Estrelas_do_tipo_Sol.columns))
Estrelas_do_tipo_Sol.head(14)
```

[18]:

```
         Star  Teff  e_Teff  logg  e_logg    Vt  e_Vt  [Fe/H]  e_[Fe/H]  \
0    HD 55     4554      88  4.54    0.21  0.06  1.63   -0.67      0.01
1    HD 142    6431     123  4.82    0.11  2.10  0.28    0.05      0.08
2    HD 283    5135      24  4.49    0.07  0.47  0.06   -0.55      0.01
3    HD 361    5888      14  4.54    0.08  1.03  0.03   -0.13      0.01
4    HD 750    5069      32  4.33    0.10  0.66  0.07   -0.30      0.02
5    HD 870    5360      24  4.40    0.08  0.79  0.04   -0.12      0.02
6    HD 967    5595      18  4.59    0.02  0.90  0.05   -0.66      0.01
7    HD 1237   5489      40  4.46    0.11  1.04  0.06    0.06      0.03
8    HD 1320   5699      13  4.55    0.05  0.89  0.02   -0.26      0.01
9    HD 1388   5970      15  4.42    0.05  1.13  0.02    0.00      0.01
10   HD 1461   5740      16  4.36    0.03  0.94  0.02    0.18      0.01
11   HD 1581   5990      15  4.49    0.07  1.24  0.03   -0.18      0.01
12   HD 2025   4851      49  4.49    0.13  0.51  0.18   -0.37      0.02
```

```
13  HD 2071      5729      13  4.49    0.02  0.93  0.02   -0.08      0.01

     Mass  e_Mass     Age  e_Age
0                   4.531  3.824
1   1.230   0.033   1.120  0.904
2   0.717   0.015   5.167  4.107
3   1.029   0.011   0.356  0.283
4   0.752   0.017   4.825  4.118
5   0.859   0.016   1.594  1.591
6   0.764   0.018   7.775  3.945
7   0.924   0.019   1.765  1.696
8   0.912   0.021   2.388  2.005
9   1.061   0.013   3.005  0.802
10  1.050   0.016   1.967  1.153
11  1.026   0.016   2.191  1.052
12  0.706   0.008   4.557  4.047
13  0.987   0.012   0.872  0.591
```

5 Pré-processamento de dados

A nossa classificação vai ser com base em três variáveis preditoras principais: Teff / log(g) / [Fe/H

[19]:
```
Gigantes_vermelhas.drop(["KIC", "NoCorM", "e_NoCorM", "NoCorR", "e_NoCorR",
                   "RGBcorM", "e_RGBcorM", "RGBcorR", "e_RGBcorR", "ClcorM",
                   "e_ClcorM", "ClcorR", "e_ClcorR", "Phase", "e_Teff",␣
 ↪"e_logg", "e_[Fe/H]"], axis = 1, inplace = True)
Estrelas_do_tipo_Sol.drop(["Star", "Vt", "e_Vt",
                          "Mass", "e_Mass", "Age", "e_Age", "e_Teff", "e_logg",␣
 ↪"e_[Fe/H]"], axis = 1, inplace = True)
```

Agora, vamos embaralhar as linhas dos dois Dataframes…

[20]:
```
Gigantes_vermelhas_ = Gigantes_vermelhas.sample(frac=1).reset_index(drop = True)
Estrelas_do_tipo_Sol_ = Estrelas_do_tipo_Sol.sample(frac=1).reset_index(drop =␣
 ↪True)
Gigantes_vermelhas = pd.DataFrame(Gigantes_vermelhas_, columns =␣
 ↪Gigantes_vermelhas.columns)
Estrelas_do_tipo_Sol = pd.DataFrame(Estrelas_do_tipo_Sol_, columns =␣
 ↪Estrelas_do_tipo_Sol.columns)
```

Note que há uma disparidade muito grande entre o número de linhas dos dois Dataframes;

[21]:
```
print(f"Shape_Gigantes_vermelhas = {Gigantes_vermelhas.shape}")
print(f"Shape_Estrelas_do_tipo_Sol = {Estrelas_do_tipo_Sol.shape}")
```

```
Shape_Gigantes_vermelhas = (16094, 3)
Shape_Estrelas_do_tipo_Sol = (451, 3)
```

Vamos pegar apenas 451 linhas do Dataframe das gigantes vermelhas

[22]:
```
Gigantes_vermelhas = Gigantes_vermelhas.loc[0:450]
```

[23]:
```
print(f"Shape_Gigantes_vermelhas = {Gigantes_vermelhas.shape}")
print(f"Shape_Estrelas_do_tipo_Sol = {Estrelas_do_tipo_Sol.shape}")
```

```
Shape_Gigantes_vermelhas = (451, 3)
Shape_Estrelas_do_tipo_Sol = (451, 3)
```

Pronto, agora vamos adicionar a variável target aos Dataframes.

Gigante vermelha = 0

Estrela do tipo Sol = 1

[24]:
```
target = []
for i in range(0, 451):
    target.append(0)
target = pd.DataFrame(target, columns = ["target"])
Gigantes_vermelhas = pd.concat([Gigantes_vermelhas, target], axis = 1)
Gigantes_vermelhas.head()
```

[24]:

	Teff	logg	[Fe/H]	target
0	4981	3.083	0.19	0
1	4885	2.420	-0.20	0
2	4997	2.888	0.07	0
3	4784	2.953	0.25	0
4	4743	2.837	0.31	0

[25]:
```
target = []
for i in range(0, 451):
    target.append(1)
target = pd.DataFrame(target, columns = ["target"])
Estrelas_do_tipo_Sol = pd.concat([Estrelas_do_tipo_Sol, target], axis = 1)
Estrelas_do_tipo_Sol.head()
```

[25]:

	Teff	logg	[Fe/H]	target
0	5848	4.43	0.19	1
1	6037	4.49	-0.07	1
2	5591	4.45	-0.25	1
3	5700	4.22	0.23	1
4	5584	4.40	0.08	1

Hora de concatenar os dois Dataframes…

[26]:
```
Concatenado_GV_SSOL = pd.concat([Gigantes_vermelhas, Estrelas_do_tipo_Sol],␣
↪axis = 0)
Concatenado_GV_SSOL = Concatenado_GV_SSOL.sample(frac = 1).reset_index(drop =␣
↪True)
Concatenado_GV_SSOL = pd.DataFrame(Concatenado_GV_SSOL, columns =␣
↪Estrelas_do_tipo_Sol.columns)
```

```python
Concatenado_GV_SSOL.head(30)
```

[26]:

	Teff	logg	[Fe/H]	target
0	4958	2.438	-0.41	0
1	4868	2.317	-1.03	0
2	4875	4.390	-0.28	1
3	4839	4.450	-0.32	1
4	6004	4.520	0.00	1
5	4967	1.894	-1.60	0
6	4786	2.878	-0.03	0
7	5896	4.510	-0.04	1
8	5800	4.410	-0.47	1
9	4988	3.127	0.23	0
10	5145	2.422	-0.27	0
11	5292	4.210	0.25	1
12	4917	2.604	-0.43	0
13	4738	2.367	0.08	0
14	5244	2.397	-0.49	0
15	4811	2.823	-0.21	0
16	5781	4.370	-0.01	1
17	4294	1.912	0.01	0
18	6061	4.610	-0.19	1
19	4915	3.140	-0.22	0
20	5834	4.280	-0.16	1
21	4683	2.663	0.05	0
22	5757	4.390	-0.22	1
23	4531	2.250	-0.01	0
24	5967	4.480	0.05	1
25	4721	2.514	-0.12	0
26	5204	2.897	0.11	0
27	4956	4.410	-0.43	1
28	4896	2.512	-0.16	0
29	4858	2.430	-0.31	0

6 Dtypes

[27]:
```python
Concatenado_GV_SSOL.dtypes
```

[27]:
```
Teff        int64
logg      float64
[Fe/H]    float64
target      int64
dtype: object
```

7 Análise dos dados

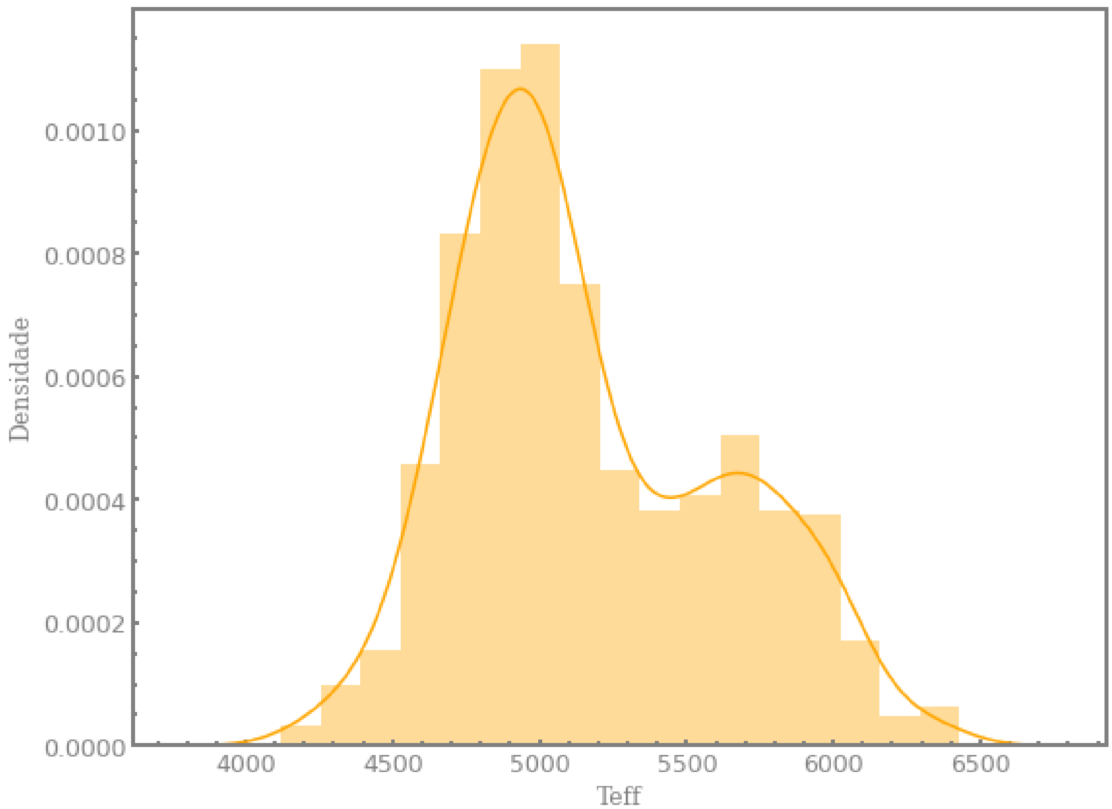
[28]:
```
ProfileReport(Concatenado_GV_SSOL)
```

```
Summarize dataset:   0%|          | 0/18 [00:00<?, ?it/s]

Generate report structure:   0%|          | 0/1 [00:00<?, ?it/s]

Render HTML:   0%|          | 0/1 [00:00<?, ?it/s]

<IPython.core.display.HTML object>
```

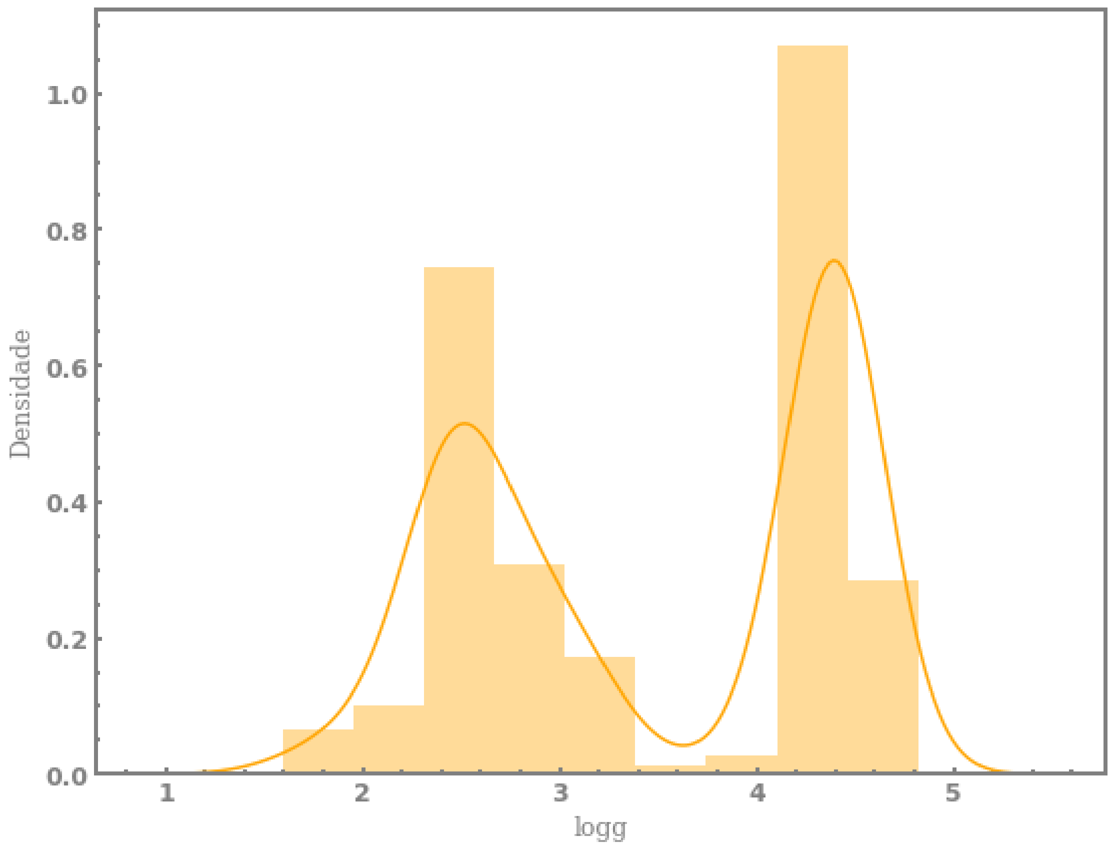
[28]:

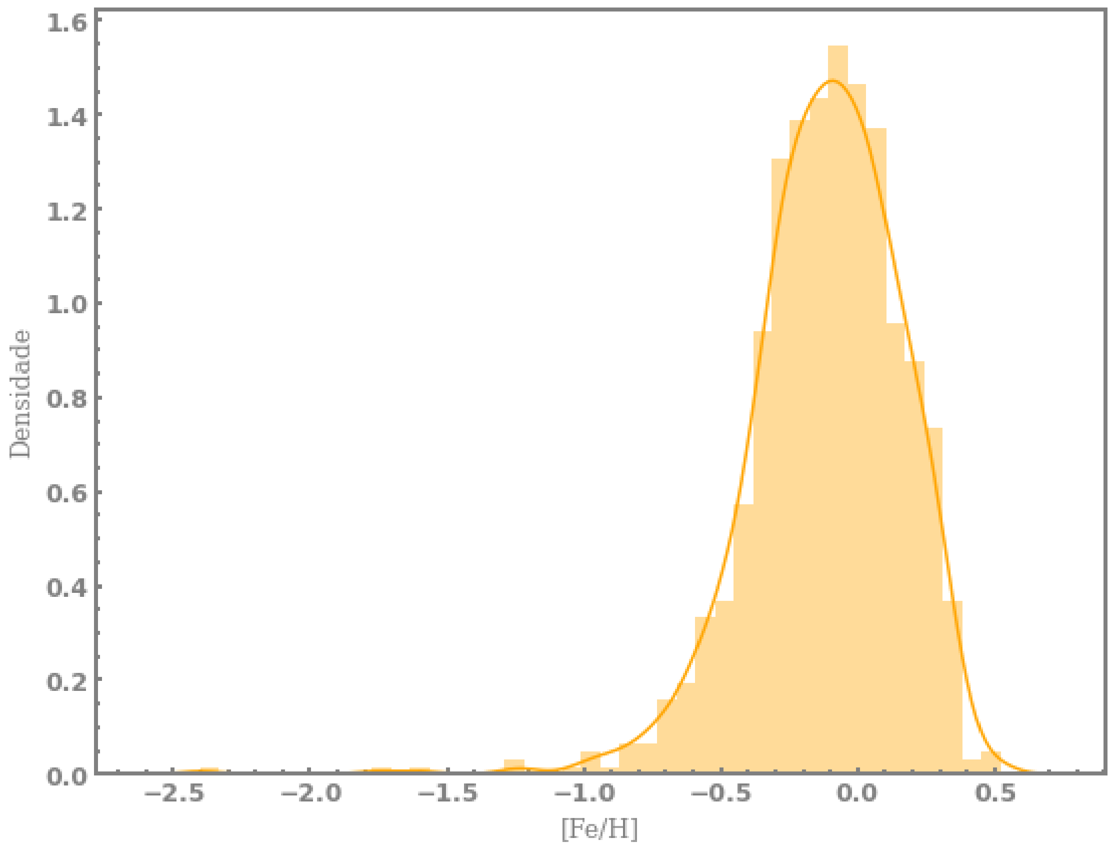
[29]:
```
"""
Criação da primeira fonte de texto
"""
Font1 = {"family":"serif", # Family da fonte
         "weight":"normal", # Peso da fonte
         "color": "gray", # cor da fornte
         "size": 12.4} # size da fonte
"""
Plotando histogramas para cada variável característica
"""
for i in Concatenado_GV_SSOL.drop(["target"], axis = 1).columns:
    """
    Alocando a figura
    """
    fig, ax = plt.subplots(figsize = (9, 7))
    """
    Plot do gráfico
    """
    sbn.distplot(Concatenado_GV_SSOL.drop(["target"], axis = 1)[i], color =␣
 ↪"orange")
    plt.grid(False)
    """
    Redefinição da grossura dos eixos e da cor dos mesmos
    """
    for axis in ["left", "right", "top", "bottom"]:
        ax.spines[axis].set_linewidth(2)
        ax.spines[axis].set_color("gray")
    """
    Trabalha com os ticks do gráfico
    """
    ax.xaxis.set_minor_locator(AutoMinorLocator())
    ax.yaxis.set_minor_locator(AutoMinorLocator())
    ax.tick_params(axis = "both", direction = "in", labelcolor = "gray",␣
 ↪labelsize = 12.4)
    ax.tick_params(which = "minor", direction = "in", width = 2, color = "gray")
```

```
    ax.tick_params(which = "major", direction = "in", color = "gray", length=3.
↪4, width = 2)
    """
    Labels
    """
    ax.set_ylabel("Densidade", fontdict = Font1)
    ax.set_xlabel(f"{i}", fontdict = Font1)
    """
    Tudo em negrito
    """
    plt.rcParams["font.weight"] = "bold"
    plt.rcParams["axes.labelweight"] = "bold"
    """
    Fundo branco
    """
    fig.patch.set_facecolor("white")
    Cor_fundo = plt.gca()
    Cor_fundo.set_facecolor("white")
    Cor_fundo.patch.set_alpha(1)
    fig.patch.set_facecolor("white")
    """
    Mostrar gráfico
    """
    plt.show()
```



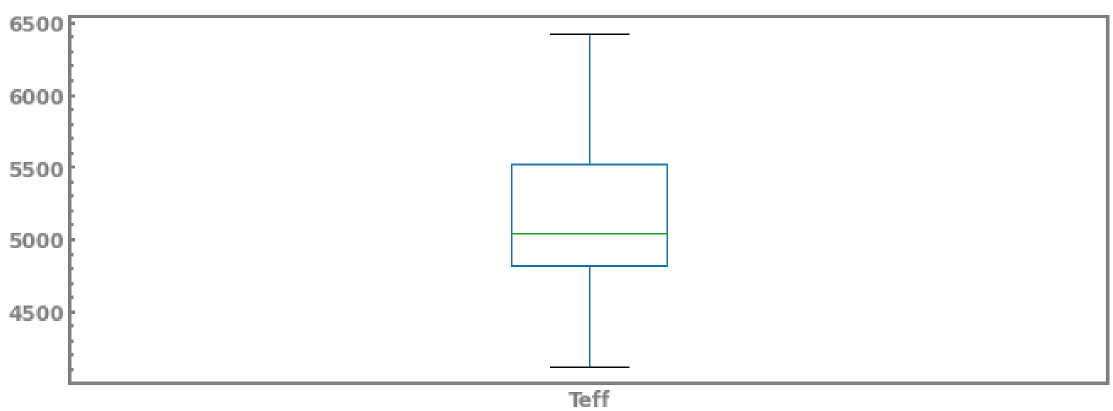
0.0010
0.0008
0.0006
0.0004
0.0002
0.0000
Densidade
4000
4500
5000
5500
6000
6500
Teff

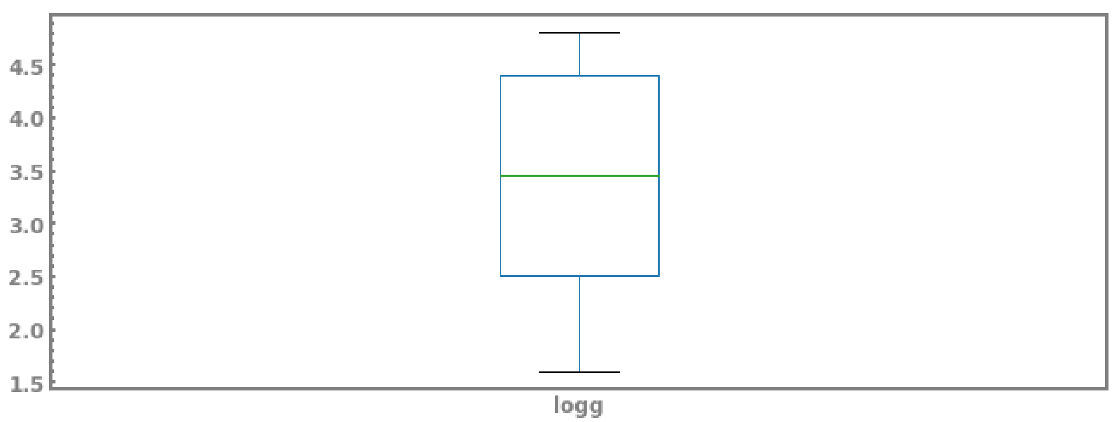

Densidade
logg
1.0
0.8
0.6
0.4
0.2
0.0
1
2
3
4
5

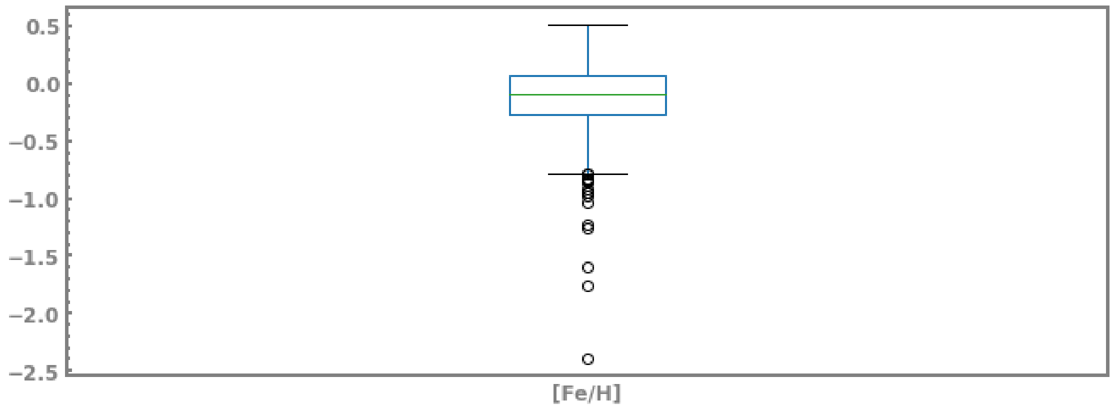


[30]:
```
"""
Plot dos histogramas para cada variável
"""
for i in Concatenado_GV_SSOL.drop(["target"], axis = 1).columns:
    """
    Alocando a figura
    """
    fig, ax = plt.subplots(figsize=(11,4))
    """
    Plot do gráfico
    """
    Concatenado_GV_SSOL.drop(["target"], axis = 1).boxplot(column = i, grid =␣
 ↪False, fontsize=12)
    fig.patch.set_facecolor("white")
    for axis in ["left", "right", "top", "bottom"]:
        ax.spines[axis].set_linewidth(2)
        ax.spines[axis].set_color("gray")
    ax.xaxis.set_minor_locator(AutoMinorLocator())
    ax.yaxis.set_minor_locator(AutoMinorLocator())
```

```python
    ax.tick_params(axis = "both", direction = "in", labelcolor = "gray", labelsize = 12, bottom = False)
    ax.tick_params(which = "minor", direction = "in", width = 2, color = "gray", bottom = False)
    ax.tick_params(which = "major", direction = "in", color = "gray", length=3.4, width = 2, bottom = False)
    """
    Tudo em negrito
    """
    plt.rcParams["font.weight"] = "bold"
    plt.rcParams["axes.labelweight"] = "bold"
    """
    Fundo branco
    """
    fig.patch.set_facecolor("white")
    Cor_fundo = plt.gca()
    Cor_fundo.set_facecolor("white")
    Cor_fundo.patch.set_alpha(1)
    fig.patch.set_facecolor("white")
    plt.show()
```

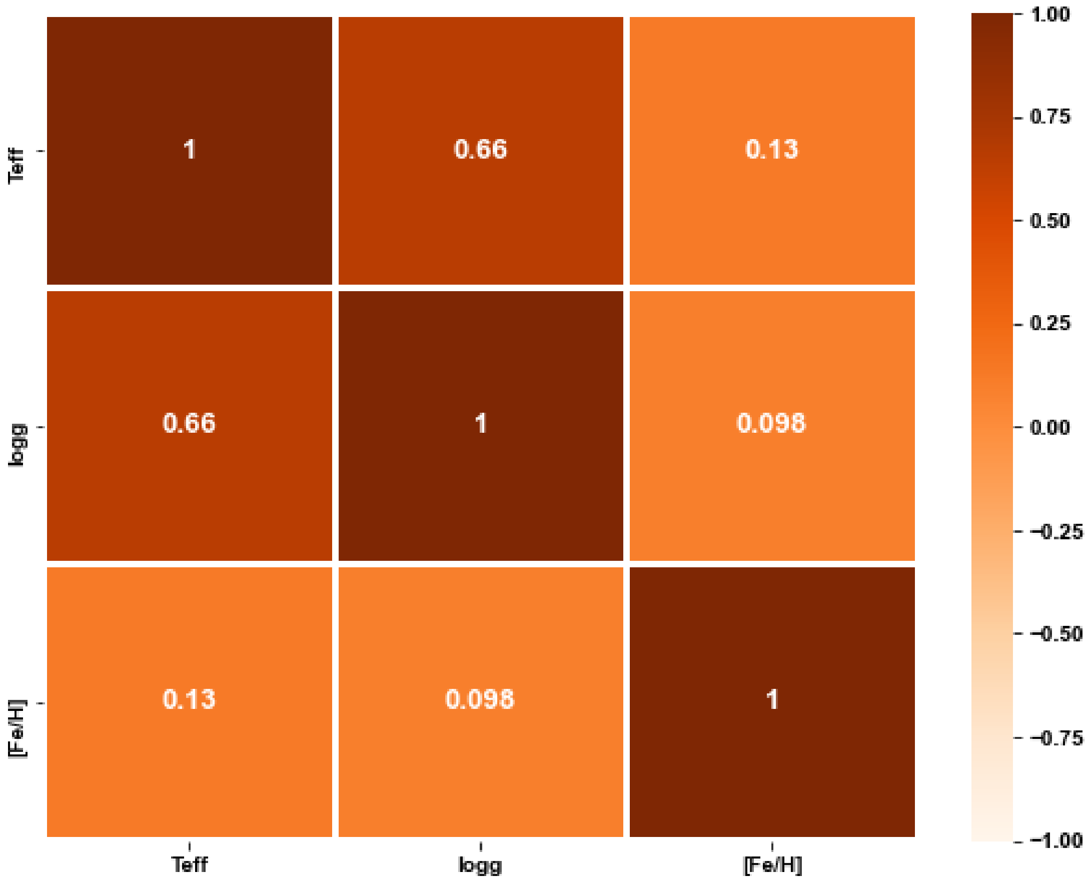






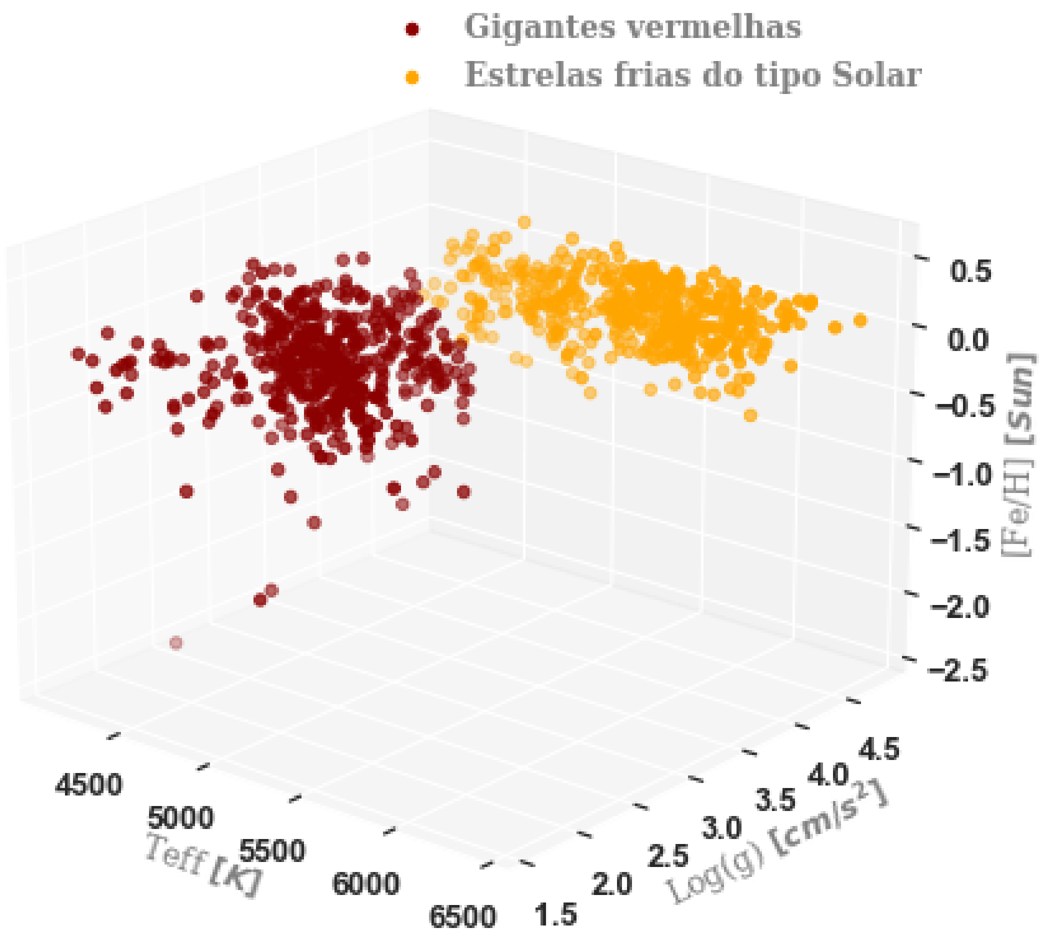
[31]:
```
ax, fig = plt.subplots(figsize = (9, 7))
"""
Matriz de correlação entre as variáveis mostrada na forma de um mapa de calor
"""
sbn.heatmap(Concatenado_GV_SSOL.drop(["target"], axis = 1).corr(), # Matriz de␣
 ↪correlação
            annot = True, # Anotar p = True
            vmin = -1, # p min
            vmax = 1, # p max
            cmap = "Oranges", # Colormap
            linewidths = 2, # width da linha de controno entre as células do␣
 ↪mapa de calor
            linecolor = "white", # cor de tais linhas
            annot_kws = {"size": 13.2}) # size dos números no heatmap
"""
Mudando o size da fonte dos labels
"""
sbn.set(font_scale=1.15)
"""
Tudo em negrito
"""
plt.rcParams["font.weight"] = "bold"
plt.rcParams["axes.labelweight"] = "bold"
"""


"""
fig.patch.set_facecolor("white")
"""
Mostrar gráfico
"""
```

```
plt.show()
```



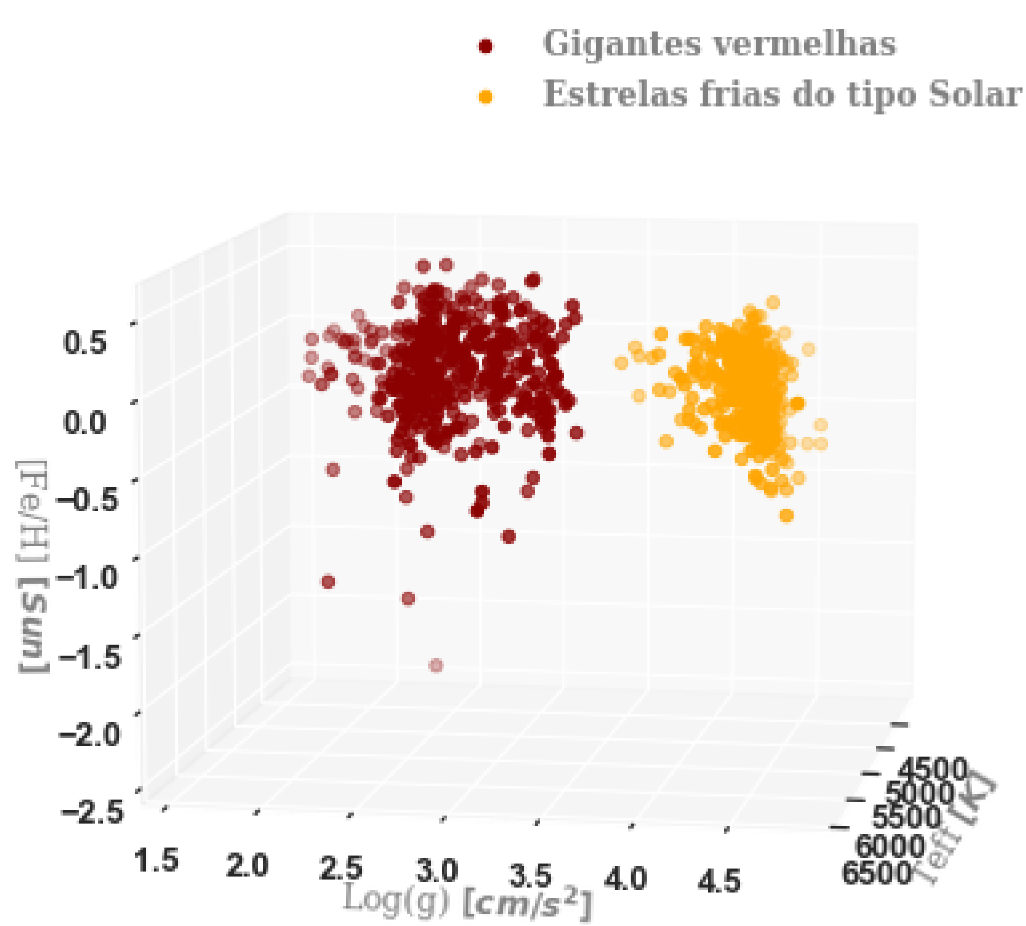
[32]:
```
"""
Criação da 2º fonte
"""
Font2 = FontProperties(family = "serif",
                      weight = "bold",
                      style = "normal",
                      size = 12)
fig = plt.figure(figsize = (7, 10)) # Alocar a figura
ax = fig.add_subplot(projection = "3d") # plot 3d
ax.scatter(Concatenado_GV_SSOL[Concatenado_GV_SSOL["target"] == 0]["Teff"],
           Concatenado_GV_SSOL[Concatenado_GV_SSOL["target"] == 0]["logg"],
           Concatenado_GV_SSOL[Concatenado_GV_SSOL["target"] == 0]["[Fe/H]"], c␣
 ↪= "darkred", label = "Gigantes vermelhas")
ax.scatter(Concatenado_GV_SSOL[Concatenado_GV_SSOL["target"] == 1]["Teff"],
           Concatenado_GV_SSOL[Concatenado_GV_SSOL["target"] == 1]["logg"],
```

```
            Concatenado_GV_SSOL[Concatenado_GV_SSOL["target"] == 1]["[Fe/H]"], c␣
 ↪= "orange", label = "Estrelas frias do tipo Solar")
ax.view_init(20, -50) # Ângulo de visão
"""
Labels
"""
ax.set_xlabel("Teff $[K]$", fontdict = Font1)
ax.set_ylabel("Log(g) $[cm/s^{2}]$", fontdict = Font1)
ax.set_zlabel("[Fe/H] $[Sun]$", fontdict = Font1)
"""
Fundo branco
"""
fig.patch.set_facecolor("white")
Cor_fundo = plt.gca()
Cor_fundo.set_facecolor("white")
Cor_fundo.patch.set_alpha(1)
"""
Legenda
"""
plt.legend(frameon = False, prop = Font2, labelcolor = "gray")
"""
Mostrar o gráfico
"""
plt.show()
```



[33]:
```
Font2 = FontProperties(family = "serif",
                       weight = "bold",
                       style = "normal",
                       size = 12)
fig = plt.figure(figsize = (7, 10))
ax = fig.add_subplot(projection = "3d")
ax.scatter(Concatenado_GV_SSOL[Concatenado_GV_SSOL["target"] == 0]["Teff"],
           Concatenado_GV_SSOL[Concatenado_GV_SSOL["target"] == 0]["logg"],
           Concatenado_GV_SSOL[Concatenado_GV_SSOL["target"] == 0]["[Fe/H]"], c␣
 ↪= "darkred", label = "Gigantes vermelhas")
ax.scatter(Concatenado_GV_SSOL[Concatenado_GV_SSOL["target"] == 1]["Teff"],
           Concatenado_GV_SSOL[Concatenado_GV_SSOL["target"] == 1]["logg"],
           Concatenado_GV_SSOL[Concatenado_GV_SSOL["target"] == 1]["[Fe/H]"], c␣
 ↪= "orange", label = "Estrelas frias do tipo Solar")
ax.view_init(9, 10)
```

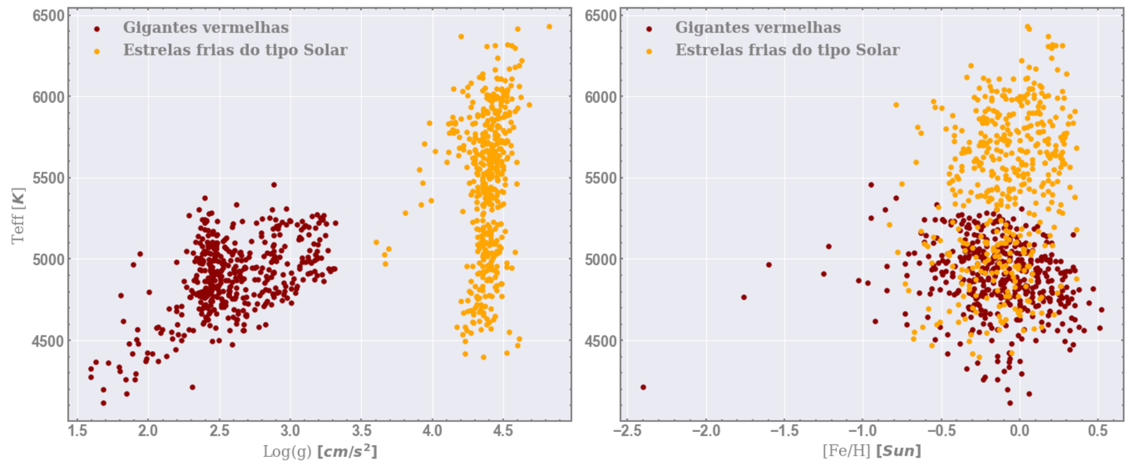
```
ax.set_xlabel("Teff $[K]$", fontdict = Font1)
ax.set_ylabel("Log(g) $[cm/s^{2}]$", fontdict = Font1)
ax.set_zlabel("[Fe/H] $[Sun]$", fontdict = Font1)
fig.patch.set_facecolor("white")
Cor_fundo = plt.gca()
Cor_fundo.set_facecolor("white")
Cor_fundo.patch.set_alpha(1)
plt.legend(frameon = False, prop = Font2, labelcolor = "gray")
plt.show()
```



Na visualização 3d percebe-se a formação de aglomerados bem definidos de dados.

```
[34]: """
Criação das 3º e 4º fontes
```

```python
"""
Font3 = {"family":"serif", "weight":"normal", "color": "gray", "size": 18}
Font4 = FontProperties(family = "serif",
                       weight = "bold",
                       style = "normal",
                       size = 18)
fig, axs = plt.subplots(nrows = 1, # 1 linha
                        ncols = 2, # 2 colunas
                        figsize = (19, 8)) # tamanho da figura
axs[0].scatter(Concatenado_GV_SSOL[Concatenado_GV_SSOL["target"] == 0]["logg"],␣
 ↪Concatenado_GV_SSOL[Concatenado_GV_SSOL["target"] == 0]["Teff"], s = 30, c =␣
 ↪"darkred", label = "Gigantes vermelhas")
axs[0].scatter(Concatenado_GV_SSOL[Concatenado_GV_SSOL["target"] == 1]["logg"],␣
 ↪Concatenado_GV_SSOL[Concatenado_GV_SSOL["target"] == 1]["Teff"], s = 30, c =␣
 ↪"orange", label = "Estrelas frias do tipo Solar")
axs[1].scatter(Concatenado_GV_SSOL[Concatenado_GV_SSOL["target"] == 0]["[Fe/
 ↪H]"], Concatenado_GV_SSOL[Concatenado_GV_SSOL["target"] == 0]["Teff"], s =␣
 ↪30, c = "darkred", label = "Gigantes vermelhas")
axs[1].scatter(Concatenado_GV_SSOL[Concatenado_GV_SSOL["target"] == 1]["[Fe/
 ↪H]"], Concatenado_GV_SSOL[Concatenado_GV_SSOL["target"] == 1]["Teff"], s =␣
 ↪30, c = "orange", label = "Estrelas frias do tipo Solar")
axs[0].set_xlabel("Log(g) $[cm/s^{2}]$", fontdict = Font3)
axs[1].set_xlabel("[Fe/H] $[Sun]$", fontdict = Font3)
axs[0].set_ylabel("Teff [$K$]", fontdict = Font3)
for i in range(0, 2):
    for axis in ["left", "right", "top", "bottom"]:
        axs[i].spines[axis].set_linewidth(2)
        axs[i].spines[axis].set_color("gray")
    axs[i].xaxis.set_minor_locator(AutoMinorLocator())
    axs[i].yaxis.set_minor_locator(AutoMinorLocator())
    axs[i].tick_params(axis = "both", direction = "in", labelcolor = "gray",␣
 ↪labelsize = 18, top = True, right = True, left = True, bottom = True)
    axs[i].tick_params(which='minor', direction = "in", length=2, color='gray',␣
 ↪width = 2, top = True, right = True, left = True, bottom = True)
    axs[i].tick_params(which='major', direction = "in", color='gray', length=3.
 ↪4, width = 2, top = True, right = True, left = True, bottom = True)
fig.tight_layout()
axs[0].legend(frameon = False, prop = Font4, labelcolor = "gray")
axs[1].legend(frameon = False, prop = Font4, labelcolor = "gray")
plt.show()
```



8 Split dos dados

[35]:
```
"""
x: DF com apenas variáveis preditoras
"""
x = Concatenado_GV_SSOL.drop(["target"], axis = 1)
Norm = MinMaxScaler(feature_range = (0, 1))
"""
Normalizar x
"""
x_norm = Norm.fit_transform(x)
x_norm = pd.DataFrame(x_norm, columns = x.columns)
"""
y: Série com a variável target
"""
y = Concatenado_GV_SSOL["target"]
"""
y_neural_network: y para a rede neural
"""
y_neural_network = to_categorical(y)
"""
Splits dos dados
"""
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.3,␣
 ↪random_state = 101)
x_train_norm, x_test_norm, y_train_norm, y_test_norm = train_test_split(x_norm,␣
 ↪y, test_size = 0.3, random_state = 101)
```

```
x_train_norm_neural_network, x_test_norm_neural_network,␣
↪y_train_norm_neural_network, y_test_norm_neural_network =␣
↪train_test_split(x_norm, y_neural_network, test_size = 0.3, random_state =␣
↪101)
x_train_neural_network, x_test_neural_network, y_train_neural_network,␣
↪y_test_neural_network = train_test_split(x, y_neural_network, test_size = 0.
↪3, random_state = 101)
```

9 Modelos de Machine Learning

10 Regressão logística

[87]:
```
"""
Ajuste de hiperparâmetros para a regressão logística
"""
Logistic_regression = LogisticRegression()
penalty = ["l1", "l2", "elasticnet"]
C = np.array([0.0007, 0.001, 0.005, 0.009, 0.01])
param_grid = {"C": C, "penalty": penalty}
Grid_Logistic_regression = GridSearchCV(estimator = Logistic_regression,␣
↪param_grid = param_grid, cv = 5, n_jobs=-1)
Grid_Logistic_regression.fit(x_train, y_train)
print(f"Penalty = {Grid_Logistic_regression.best_estimator_.penalty} // C =␣
↪{Grid_Logistic_regression.best_estimator_.C}")
```

```
Penalty = l2 // C = 0.005
```

[88]:
```
"""
Processo de treinamento
"""
Logistic_regression = LogisticRegression(penalty = "l2", C = 0.005)
Logistic_regression.fit(x_train, y_train)
```

[88]:
```
LogisticRegression(C=0.005)
```

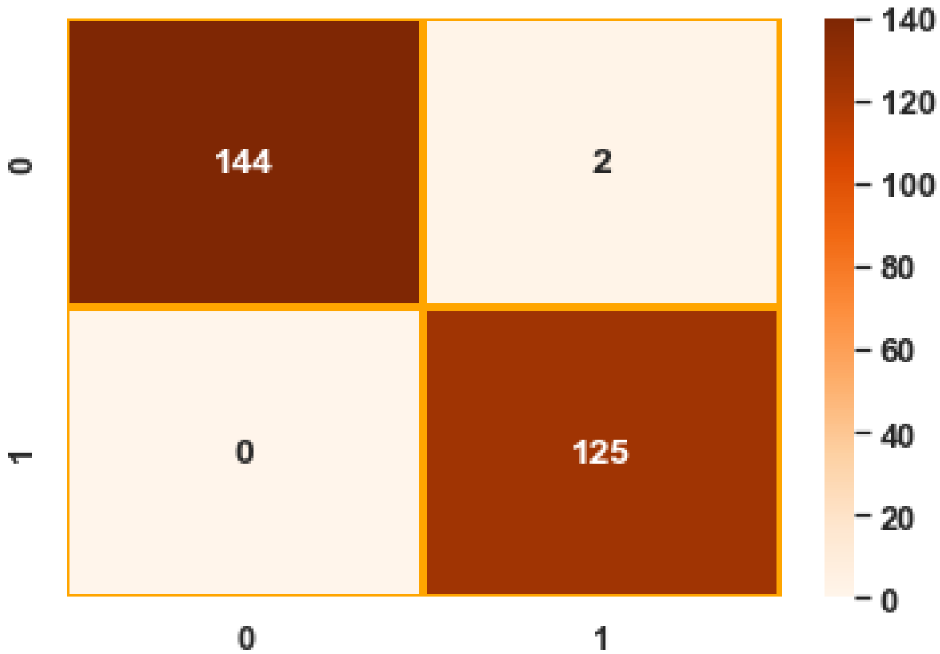
[89]:
```
"""
Processo de predição
"""
y_pred_Logistic_regression = Logistic_regression.predict(x_test)
"""
Report geral
"""
print(classification_report(y_test, y_pred_Logistic_regression))
```

```
              precision    recall  f1-score   support

           0       1.00      0.99      0.99       146
```

```
           1       0.98      1.00      0.99       125

    accuracy                           0.99       271
   macro avg       0.99      0.99      0.99       271
weighted avg       0.99      0.99      0.99       271
```

[90]:

```
"""
Mapa de calor para a matriz de confusão
"""
Matrix_Logistic_regression = confusion_matrix(y_test,␣
 ↪y_pred_Logistic_regression)
sbn.heatmap(Matrix_Logistic_regression,
            annot = True,
            vmin = 0,
            vmax = 140,
            cmap = "Oranges",
            fmt = "g",
            linewidths=2,
            linecolor="orange")
plt.show()
```



[91]:

```
"""
Predições de probabilidades para construção da curva roc
"""
```

```
y_pred_proba_Logistic_regression = Logistic_regression.predict_proba(x_test)
y_pred_proba_Logistic_regression = y_pred_proba_Logistic_regression[:, 1]
print(f"roc_auc_score_Logistic_regression = {roc_auc_score(y_test,␣
↪y_pred_proba_Logistic_regression)}")
```

```
roc_auc_score_Logistic_regression = 1.0
```

11 KNN

[92]:
```
KNN = KNeighborsClassifier()
n_neighbors = np.array([20, 10, 9, 8, 7, 6, 5, 4, 3])
p = np.array([1, 2, 3, 4, 5, 6, 7])
metric = ["euclidean", "manhattan", "minkowski", "chebyshev"]
param_grid = {"n_neighbors": n_neighbors, "p": p, "metric": metric}
Grid_KNN = GridSearchCV(estimator = KNN, param_grid = param_grid, cv = 5,␣
↪n_jobs=-1)
Grid_KNN.fit(x_train_norm, y_train_norm)
print(f"n neighbors = {Grid_KNN.best_estimator_.n_neighbors} // p = {Grid_KNN.
↪best_estimator_.p} // metric = {Grid_KNN.best_estimator_.metric}")
```

```
n neighbors = 20 // p = 1 // metric = euclidean
```

[93]:
```
KNN = KNeighborsClassifier(n_neighbors = 20, p = 1, metric = "euclidean")
KNN.fit(x_train_norm, y_train_norm)
```

[93]:
```
KNeighborsClassifier(metric='euclidean', n_neighbors=20, p=1)
```

[94]:
```
y_pred_KNN = KNN.predict(x_test_norm)
print(accuracy_score(y_test_norm, y_pred_KNN))
```

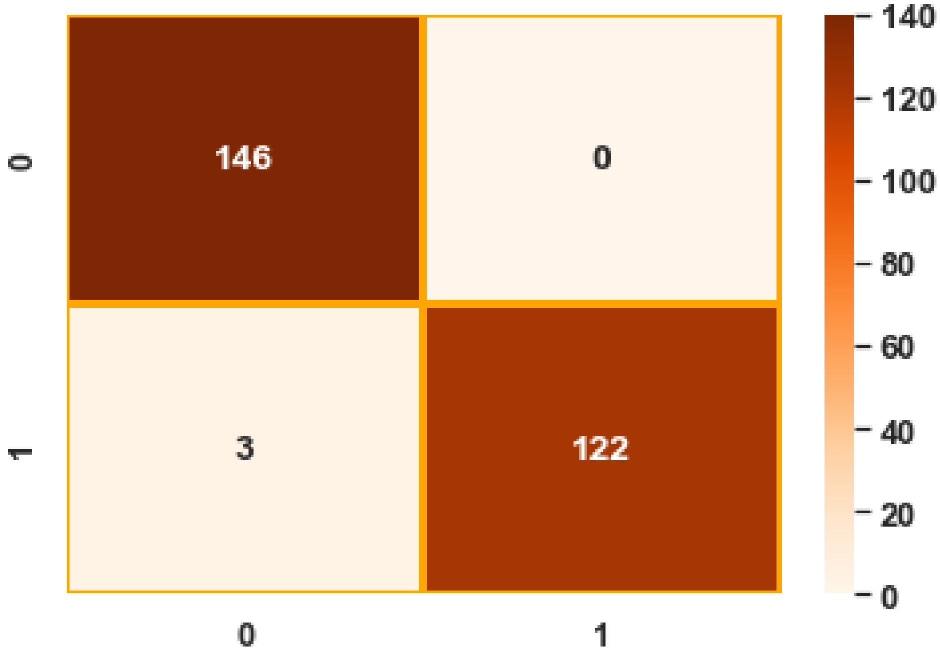
```
0.988929889298893
```

[95]:
```
print(classification_report(y_test_norm, y_pred_KNN))
```

```
              precision    recall  f1-score   support

           0       0.98      1.00      0.99       146
           1       1.00      0.98      0.99       125

    accuracy                           0.99       271
   macro avg       0.99      0.99      0.99       271
weighted avg       0.99      0.99      0.99       271
```

[96]:
```
Matrix_KNN = confusion_matrix(y_test_norm, y_pred_KNN)
sbn.heatmap(Matrix_KNN,
            annot = True,
            vmin = 0,
            vmax = 140,
```

```
            cmap = "Oranges",
            fmt = "g",
            linewidths=2,
            linecolor="orange")
plt.show()
```



[97]:

```
y_pred_proba_KNN = KNN.predict_proba(x_test_norm)
y_pred_proba_KNN = y_pred_proba_KNN[:, 1]
print(f"roc_auc_score_KNN = {roc_auc_score(y_test_norm, y_pred_proba_KNN)}")
```

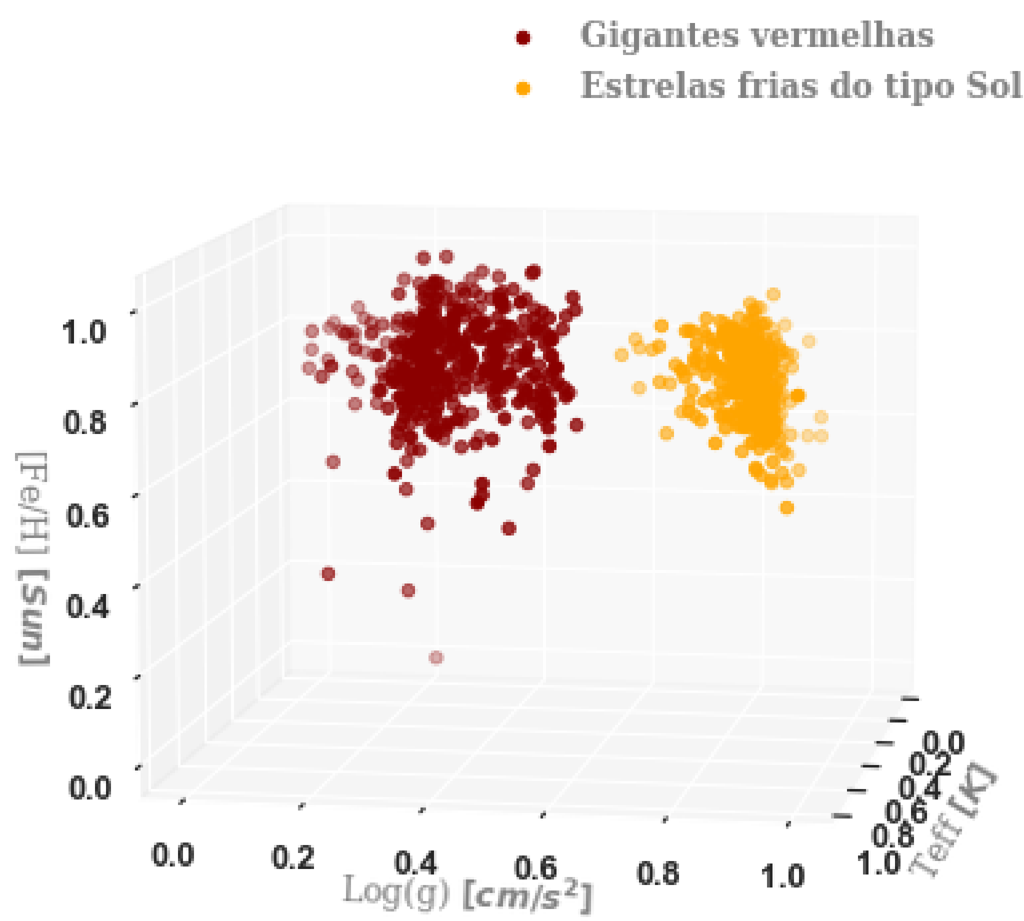
```
roc_auc_score_KNN = 1.0
```

12 KMeans

[98]:

```
K = pd.concat([x_norm, y], axis = 1)
Font2 = FontProperties(family = "serif",
                       weight = "bold",
                       style = "normal",
                       size = 12)
fig = plt.figure(figsize = (7, 10))
ax = fig.add_subplot(projection = "3d")
ax.scatter(K[K["target"] == 0]["Teff"],
           K[K["target"] == 0]["logg"],
           K[K["target"] == 0]["[Fe/H]"], c = "darkred", label = "Gigantes␣
 ↪vermelhas")
```

```
ax.scatter(K[K["target"] == 1]["Teff"],
           K[K["target"] == 1]["logg"],
           K[K["target"] == 1]["[Fe/H]"], c = "orange", label = "Estrelas frias␣
 ↪do tipo Sol")
ax.view_init(9, 10)
ax.set_xlabel("Teff $[K]$", fontdict = Font1)
ax.set_ylabel("Log(g) $[cm/s^{2}]$", fontdict = Font1)
ax.set_zlabel("[Fe/H] $[Sun]$", fontdict = Font1)
fig.patch.set_facecolor("white")
Cor_fundo = plt.gca()
Cor_fundo.set_facecolor("white")
Cor_fundo.patch.set_alpha(1)
plt.legend(frameon = False, prop = Font2, labelcolor = "gray")
plt.show()
```



[99]:
```
K_Means = KMeans(n_clusters=2, init = "k-means++", max_iter = 999, n_init = 10)
K_Means.fit(x_norm)
```

[99]:
```
KMeans(max_iter=999, n_clusters=2)
```

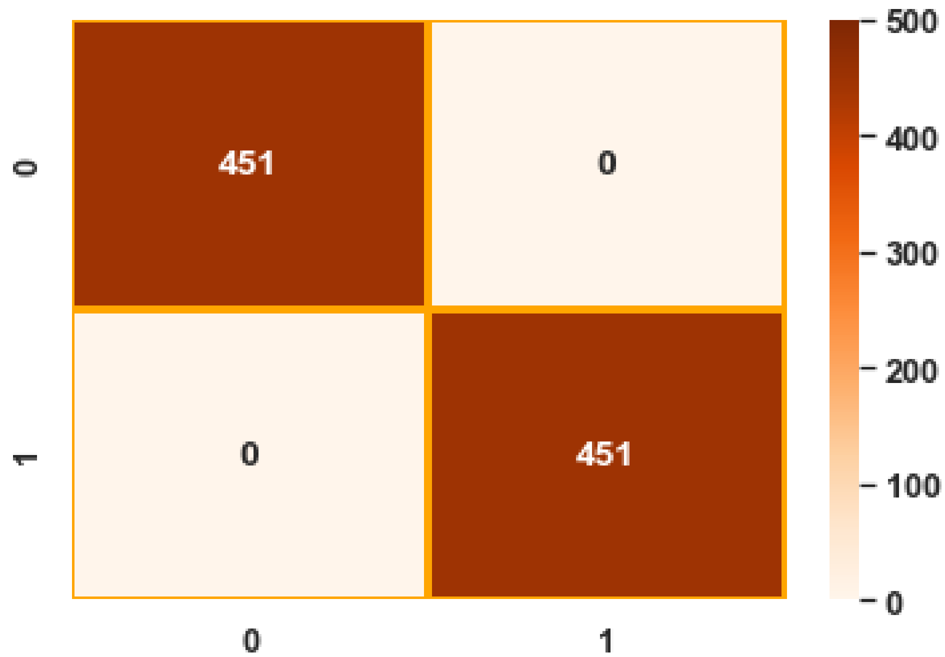
[100]:
```
y_predict_KMeans = K_Means.predict(x_norm)
y_predict_KMeans = pd.DataFrame(y_predict_KMeans)
#y_predict_KMeans = y_predict_KMeans.replace({0:1, 1:0})
print(accuracy_score(y, y_predict_KMeans))
```

```
1.0
```

[101]:
```
print(classification_report(y, y_predict_KMeans))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       451
           1       1.00      1.00      1.00       451

    accuracy                           1.00       902
   macro avg       1.00      1.00      1.00       902
weighted avg       1.00      1.00      1.00       902
```

[102]:
```
Matrix_KMeans = confusion_matrix(y, y_predict_KMeans)
sbn.heatmap(Matrix_KMeans,
            annot = True,
            vmin = 0,
            vmax = 500,
            cmap = "Oranges",
            fmt = "g",
            linewidths=2,
            linecolor="orange")
plt.show()
```



13 Naive Bayes

[103]:
```
NB = GaussianNB()
NB.fit(x_train, y_train)
```

[103]:
```
GaussianNB()
```

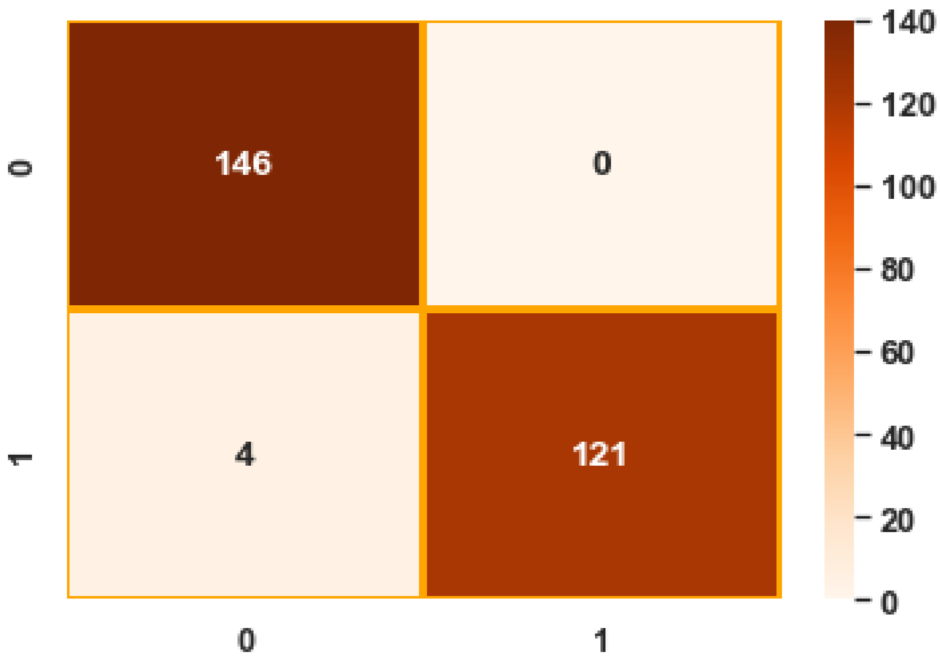
[104]:
```
y_pred_NB = NB.predict(x_test)
print(accuracy_score(y_test, y_pred_NB))
```

```
0.985239852398524
```

[105]:
```
print(classification_report(y_test, y_pred_NB))
```

```
              precision    recall  f1-score   support

           0       0.97      1.00      0.99       146
           1       1.00      0.97      0.98       125

    accuracy                           0.99       271
   macro avg       0.99      0.98      0.99       271
weighted avg       0.99      0.99      0.99       271
```

[106]:
```
Matrix_NB = confusion_matrix(y_test, y_pred_NB)
sbn.heatmap(Matrix_NB,
            annot = True,
            vmin = 0,
            vmax = 140,
            cmap = "Oranges",
            fmt = "g",
            linewidths=2,
            linecolor="orange")
plt.show()
```



14 Random Forest

[107]:
```
%%time
Random_Forest = RandomForestClassifier()
max_depth = np.array([1, 2, 3, 4, 5, 6, 7])
min_samples_split = np.array([2, 3, 4, 5])
min_samples_leaf = np.array([2, 3, 4, 5])
param_grid = {"max_depth": max_depth, "min_samples_split": min_samples_split,␣
 ↪"min_samples_leaf": min_samples_leaf}
Grid_Random_Forest = GridSearchCV(estimator = Random_Forest, param_grid =␣
 ↪param_grid, cv = 5, n_jobs = -1)
Grid_Random_Forest.fit(x_train, y_train)
```

```
print(f"max_depth = {Grid_Random_Forest.best_estimator_.max_depth} //␣
↪min_samples_split = {Grid_Random_Forest.best_estimator_.min_samples_split} //
↪ min_samples_leaf = {Grid_Random_Forest.best_estimator_.min_samples_leaf}")
```

```
max_depth = 1 // min_samples_split = 3 // min_samples_leaf = 2
Wall time: 24.4 s
```

[108]:
```
Random_Forest = RandomForestClassifier(max_depth = 1, min_samples_split = 3,␣
↪min_samples_leaf = 2)
Random_Forest.fit(x_train, y_train)
```

[108]:
```
RandomForestClassifier(max_depth=1, min_samples_leaf=2, min_samples_split=3)
```

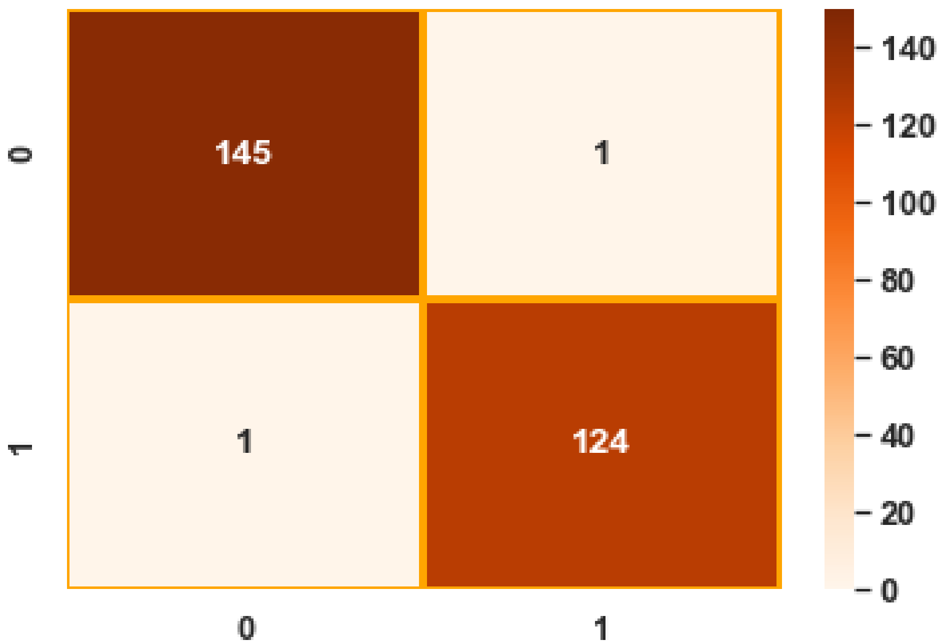
[109]:
```
y_pred_Random_Forest = Random_Forest.predict(x_test)
print(accuracy_score(y_test, y_pred_Random_Forest))
```

```
0.992619926199262
```

[110]:
```
print(classification_report(y_test, y_pred_Random_Forest))
```

```
              precision    recall  f1-score   support

           0       0.99      0.99      0.99       146
           1       0.99      0.99      0.99       125

    accuracy                           0.99       271
   macro avg       0.99      0.99      0.99       271
weighted avg       0.99      0.99      0.99       271
```

[111]:
```
Matrix_Random_Forest = confusion_matrix(y_test, y_pred_Random_Forest)
sbn.heatmap(Matrix_Random_Forest,
            annot = True,
            vmax = 150,
            vmin = 0,
            fmt = "g",
            cmap = "Oranges",
            linewidths = 2,
            linecolor = "orange")
plt.show()
```



15 Extra Trees

[112]:
```
%%time
Extra_trees_classifier = ExtraTreesClassifier()
max_depth = np.array([1, 2, 3, 4, 5, 6])
min_samples_split = np.array([2, 3, 4, 5, 6, 7, 8, 9])
min_samples_leaf = np.array([2, 3, 4, 5])
param_grid = {"max_depth": max_depth, "min_samples_split": min_samples_split,␣
↪"min_samples_leaf": min_samples_leaf}
Grid_Extra_trees_classifier = GridSearchCV(estimator = Extra_trees_classifier,␣
↪param_grid = param_grid, cv = 5, n_jobs = -1)
Grid_Extra_trees_classifier.fit(x_train, y_train)
print(f"max_depth = {Grid_Extra_trees_classifier.best_estimator_.max_depth} //␣
↪min_samples_split = {Grid_Extra_trees_classifier.best_estimator_.
↪min_samples_split} // min_samples_leaf = {Grid_Extra_trees_classifier.
↪best_estimator_.min_samples_leaf}")
```

```
max_depth = 1 // min_samples_split = 2 // min_samples_leaf = 2
Wall time: 44.9 s
```

[113]:
```
Extra_trees_classifier = ExtraTreesClassifier(max_depth = 1, min_samples_split␣
↪= 2, min_samples_leaf = 2)
Extra_trees_classifier.fit(x_train, y_train)
```

[113]:
```
ExtraTreesClassifier(max_depth=1, min_samples_leaf=2)
```

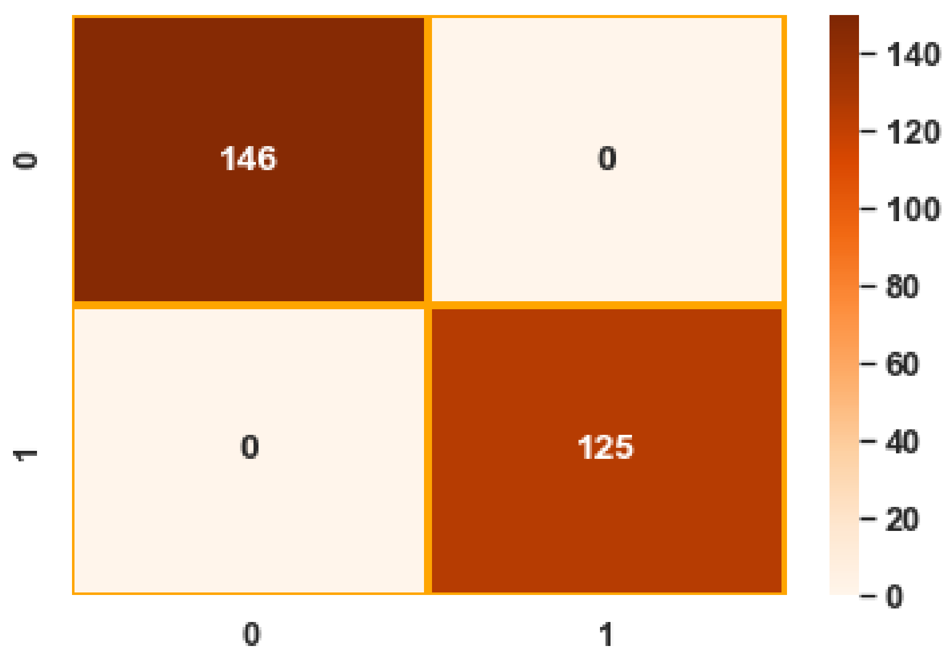
[114]:
```
y_pred_Extra_Trees = Extra_trees_classifier.predict(x_test)
print(accuracy_score(y_test, y_pred_Extra_Trees))
```

```
1.0
```

[115]:
```
print(classification_report(y_test, y_pred_Extra_Trees))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       146
           1       1.00      1.00      1.00       125

    accuracy                           1.00       271
   macro avg       1.00      1.00      1.00       271
weighted avg       1.00      1.00      1.00       271
```

[116]:
```
Matrix_Extra_trees_classifier = confusion_matrix(y_test, y_pred_Extra_Trees)
sbn.heatmap(Matrix_Extra_trees_classifier,
            annot = True,
            vmax = 150,
            vmin = 0,
            fmt = "g",
            cmap = "Oranges",
            linewidths = 2,
            linecolor = "orange")
plt.show()
```



16 AdaBoost

[117]:
```
Adaboost = AdaBoostClassifier(n_estimators=500)
learning_rate = np.array([0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8])
param_grid = {"learning_rate": learning_rate}
Grid_Adaboost = GridSearchCV(estimator = Adaboost, param_grid = param_grid, cv␣
↪= 5, n_jobs = -1)
Grid_Adaboost.fit(x_train, y_train)
print(f"learning_rate = {Grid_Adaboost.best_estimator_.learning_rate}")
```

```
learning_rate = 0.1
```

[118]:
```
Adaboost = AdaBoostClassifier(n_estimators=500, learning_rate = 0.1)
Adaboost.fit(x_train, y_train)
```

[118]:
```
AdaBoostClassifier(learning_rate=0.1, n_estimators=500)
```

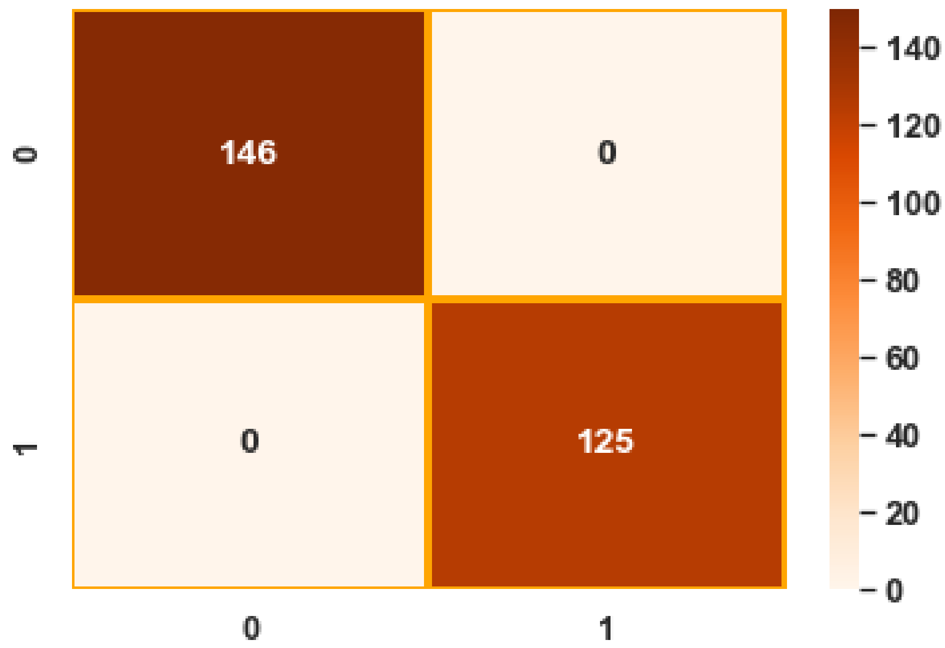
[119]:
```
y_pred_Adaboost = Adaboost.predict(x_test)
print(accuracy_score(y_test, y_pred_Adaboost))
```

```
1.0
```

[120]:
```
print(classification_report(y_test, y_pred_Adaboost))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       146
           1       1.00      1.00      1.00       125

    accuracy                           1.00       271
   macro avg       1.00      1.00      1.00       271
weighted avg       1.00      1.00      1.00       271
```

[121]:
```
Matrix_Adaboost = confusion_matrix(y_test, y_pred_Adaboost)
sbn.heatmap(Matrix_Adaboost,
            annot = True,
            vmax = 150,
            vmin = 0,
            fmt = "g",
            cmap = "Oranges",
            linewidths = 2,
            linecolor = "orange")
plt.show()
```



17 Gradient boosting

[122]:
```
GradientBoosting = GradientBoostingClassifier(n_estimators=200)
learning_rate = np.array([0.1, 0.2, 0.3, 0.4])
min_samples_split = np.array([2, 3, 4, 5])
min_samples_leaf = np.array([2 , 3 ,4 ,5])
max_depth = np.array([2 , 3 ,4 ,5])
param_grid_GradientBoosting = {"learning_rate": learning_rate,␣
↪"min_samples_split": min_samples_split,
                              "min_samples_leaf": min_samples_leaf, "max_depth"␣
↪: max_depth}
Grid_GradientBoosting = GridSearchCV(estimator = GradientBoosting, param_grid =␣
↪param_grid_GradientBoosting, cv = 5, n_jobs=-1)
Grid_GradientBoosting.fit(x_train, y_train)
print(f"GradientBoosting: learning_rate  = {Grid_GradientBoosting.
↪best_estimator_.learning_rate} // min_samples_split = {Grid_GradientBoosting.
↪best_estimator_.min_samples_split} // min_samples_leaf =␣
↪{Grid_GradientBoosting.best_estimator_.min_samples_leaf}")
```

```
GradientBoosting: learning_rate  = 0.1 // min_samples_split = 2 //
min_samples_leaf = 2
```

[123]:
```
GradientBoosting = GradientBoostingClassifier(n_estimators=200, learning_rate ␣
↪= 0.1, min_samples_split = 2, min_samples_leaf = 2)
```

```
GradientBoosting.fit(x_train, y_train)
```

[123]: GradientBoostingClassifier(min_samples_leaf=2, n_estimators=200)

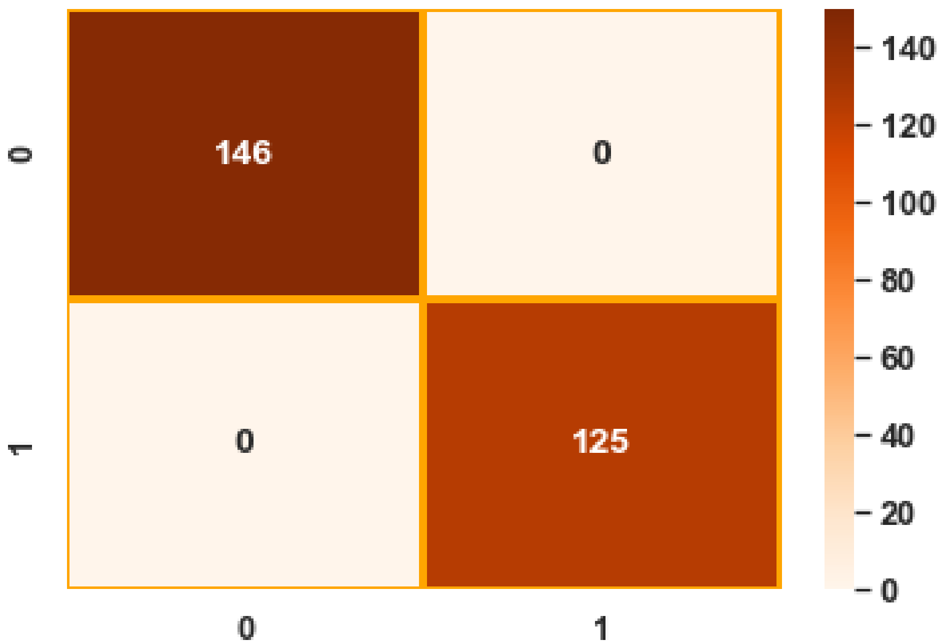
[124]:
```
y_pred_GradientBoosting = GradientBoosting.predict(x_test)
print(accuracy_score(y_test, y_pred_GradientBoosting))
```

1.0

[125]:
```
print(classification_report(y_test, y_pred_GradientBoosting))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       146
           1       1.00      1.00      1.00       125

    accuracy                           1.00       271
   macro avg       1.00      1.00      1.00       271
weighted avg       1.00      1.00      1.00       271
```

[126]:
```
Matrix_GradientBoosting = confusion_matrix(y_test, y_pred_GradientBoosting)
sbn.heatmap(Matrix_GradientBoosting,
            annot = True,
            vmax = 150,
            vmin = 0,
            fmt = "g",
            cmap = "Oranges",
            linewidths = 2,
            linecolor = "orange")
plt.show()
```



18 SVM

[127]:
```
from sklearn.model_selection import KFold
from sklearn.svm import SVC
svc = SVC()
C = np.array([0.0001, 0.0006, 0.001, 0.005])
kernel = ["linear", "poly", "rbf", "sigmoid"]
degree = np.array([1, 2, 3, 4, 5, 6, 7, 8])
param_grid = {"C":C, "kernel": kernel, "degree": degree}
kfold = KFold(n_splits = 3, shuffle = True)
Grid_SVM = GridSearchCV(estimator = svc, param_grid = param_grid, cv = kfold,␣
↪n_jobs=-1)
Grid_SVM.fit(x_train_norm, y_train_norm)
print(f"C = {Grid_SVM.best_estimator_.C} // kernel = {Grid_SVM.best_estimator_.
↪kernel} // degree = {Grid_SVM.best_estimator_.degree}")
```

```
C = 0.0006 // kernel = poly // degree = 2
```

[128]:
```
svc = SVC(C = 0.0006, kernel = "poly", degree = 2)
svc.fit(x_train_norm, y_train_norm)
```

[128]:
```
SVC(C=0.0006, degree=2, kernel='poly')
```

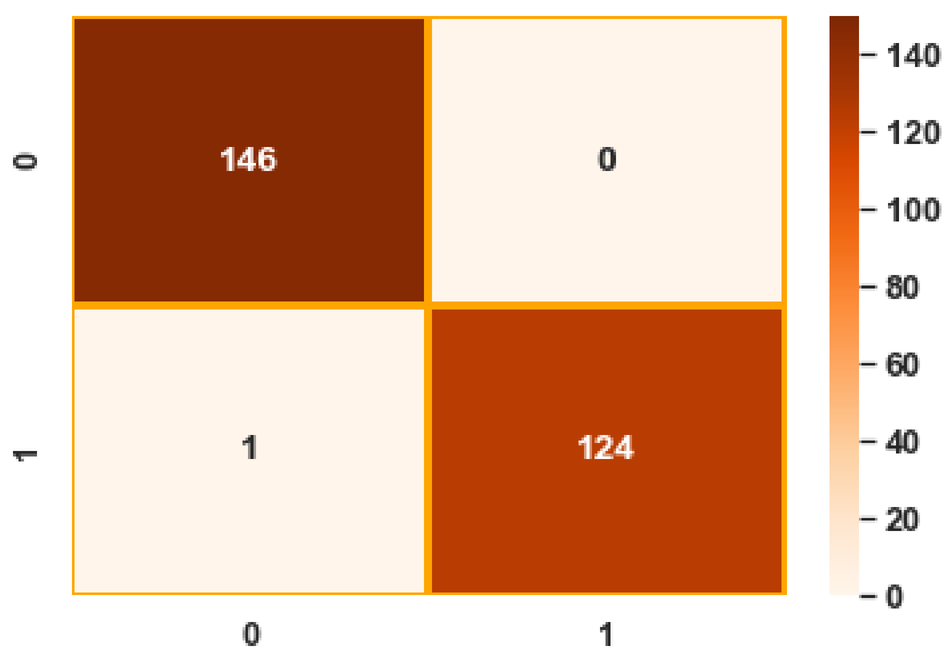
[129]:
```
y_pred_SVC = svc.predict(x_test_norm)
print(accuracy_score(y_test_norm, y_pred_SVC))
```

```
0.996309963099631
```

[130]:
```
print(classification_report(y_test_norm, y_pred_SVC))
```

```
              precision    recall  f1-score   support

           0       0.99      1.00      1.00       146
           1       1.00      0.99      1.00       125

    accuracy                           1.00       271
   macro avg       1.00      1.00      1.00       271
weighted avg       1.00      1.00      1.00       271
```

[131]:
```
Matrix_svm = confusion_matrix(y_test_norm, y_pred_SVC)
sbn.heatmap(Matrix_svm,
            annot = True,
            vmax = 150,
            vmin = 0,
            fmt = "g",
            cmap = "Oranges",
            linewidths = 2,
            linecolor = "orange")
plt.show()
```



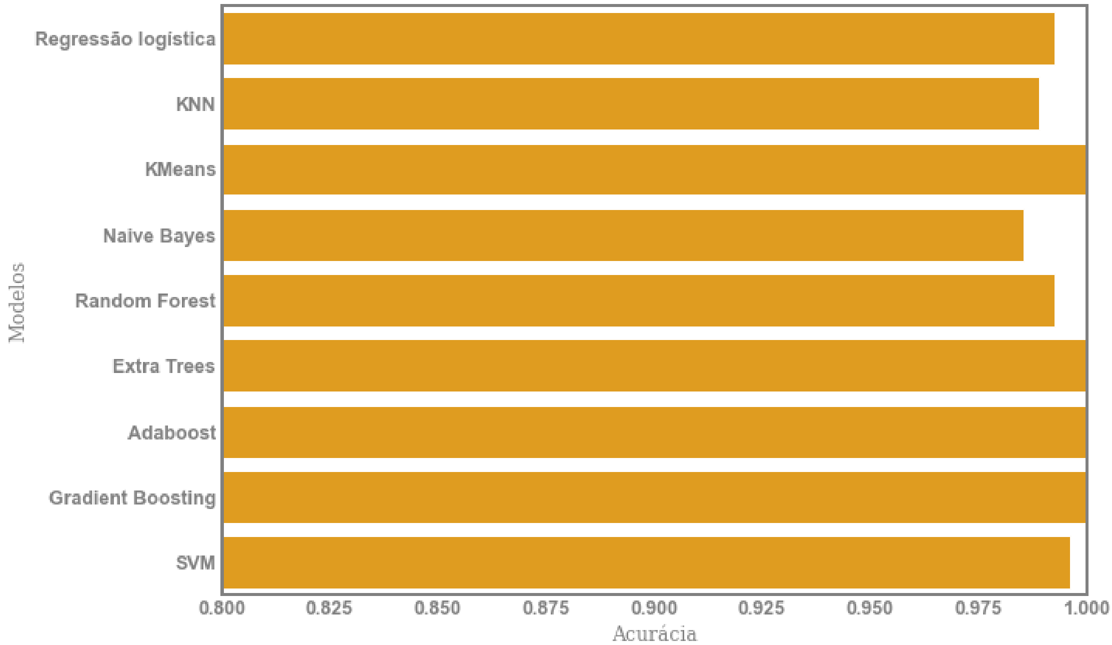
Análise geral

```
[132]: Lista_de_modelos = ["Regressão logística", "KNN", "KMeans",
                        "Naive Bayes", "Random Forest", "Extra Trees",
                        "Adaboost", "Gradient Boosting", "SVM"]
       Lista_de_acuracias = [accuracy_score(y_test, y_pred_Logistic_regression),
                            accuracy_score(y_test_norm, y_pred_KNN),
                            accuracy_score(y, y_predict_KMeans),
                            accuracy_score(y_test, y_pred_NB),
                            accuracy_score(y_test, y_pred_Random_Forest),
                            accuracy_score(y_test, y_pred_Extra_Trees),
                            accuracy_score(y_test, y_pred_Adaboost),
                            accuracy_score(y_test, y_pred_GradientBoosting),
                            accuracy_score(y_test_norm, y_pred_SVC)]
       Lista_de_modelos = pd.DataFrame(Lista_de_modelos, columns = ["Modelos"])
       Lista_de_acuracias = pd.DataFrame(Lista_de_acuracias, columns = ["acc"])
       acc_model = pd.concat([Lista_de_modelos, Lista_de_acuracias], axis = 1)
       acc_model
```

```
[132]:                Modelos      acc
       0  Regressão logística  0.99262
       1                  KNN  0.98893
       2               KMeans  1.00000
       3          Naive Bayes  0.98524
       4        Random Forest  0.99262
       5          Extra Trees  1.00000
       6             Adaboost  1.00000
       7    Gradient Boosting  1.00000
       8                  SVM  0.99631
```

```
[133]: font5 = {"family": "serif", "weight": "normal", "color": "gray", "size": 12.4}
       fig, ax = plt.subplots(figsize = (10, 7))
       sbn.barplot(x = "acc", y = "Modelos", data = acc_model, color = "orange")
       plt.xlabel("Acurácia",fontdict = font5)
       plt.ylabel("Modelos", fontdict = font5)
       for axis in ["left", "right", "top", "bottom"]:
           ax.spines[axis].set_linewidth(2)
           ax.spines[axis].set_color("gray")
       ax.xaxis.set_minor_locator(AutoMinorLocator())
       ax.yaxis.set_minor_locator(AutoMinorLocator())
       ax.tick_params(axis = "both", direction = "in", labelcolor = "gray", labelsize␣
        ↪= 12.4)
       ax.tick_params(which = "minor", direction = "in", width = 2, color = "gray",␣
        ↪left = False)
       ax.tick_params(which = "major", direction = "in", color = "gray", length=3.4,␣
        ↪width = 2)
       fig.patch.set_facecolor("white")
       Cor_fundo = plt.gca()
       Cor_fundo.set_facecolor("white")
```

```
Cor_fundo.patch.set_alpha(1)
plt.xlim(0.8, 1)
plt.show()
```



19 Redes neurais

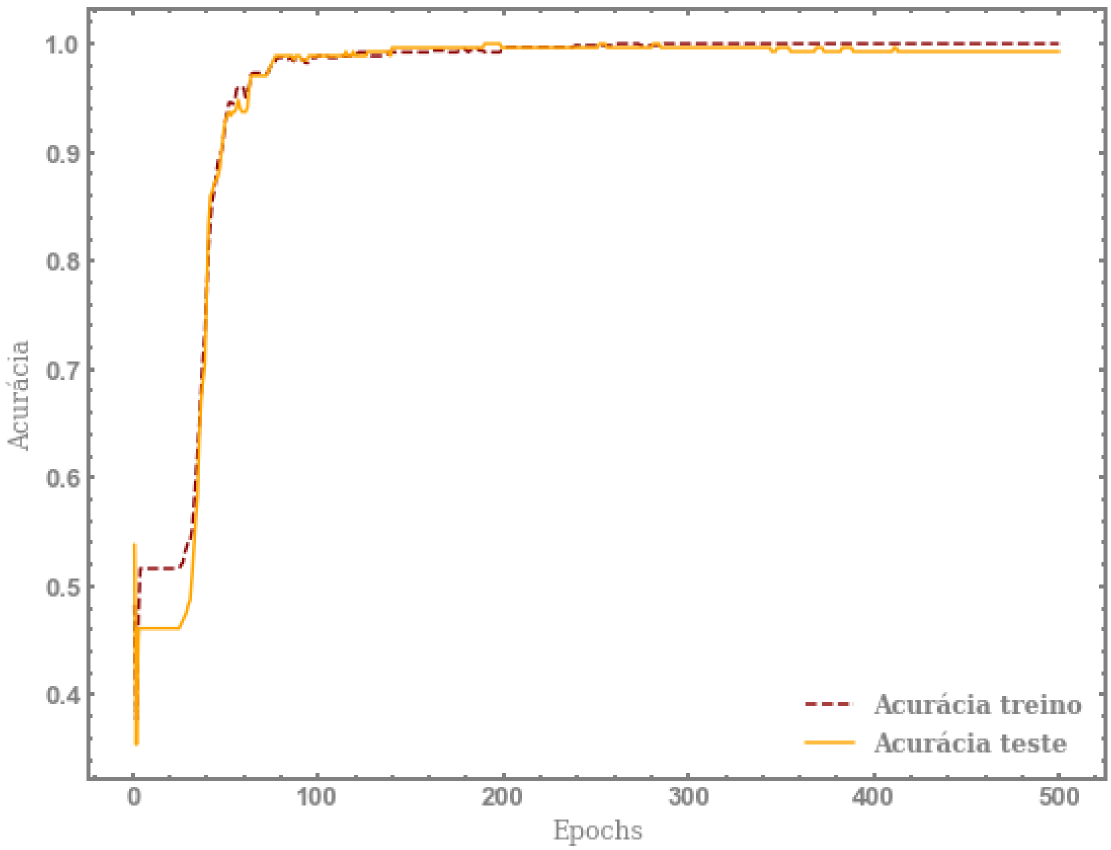
[134]:
```
"""
Montagem da rede
"""
Modelo = Sequential()
Modelo.add(Dense(4, input_dim = 3, kernel_initializer = "normal", activation =␣
 ↪"relu"))
Modelo.add(Dense(2, kernel_initializer = "normal", activation = "softmax"))
```

[135]:
```
from keras.optimizers import Adam
optimizer = Adam() # Optimizador Adam()
Modelo.compile(loss = "categorical_crossentropy", optimizer = optimizer,␣
 ↪metrics = ["acc"])
History = Modelo.fit(x_train_norm_neural_network, y_train_norm_neural_network,␣
 ↪epochs = 500, batch_size = 200, validation_data=(x_test_norm_neural_network,␣
 ↪y_test_norm_neural_network), verbose = 0)
```

[136]:
```
acc_test = History.history["val_acc"]
max(acc_test)
```

[136]: 1.0

[138]:
```
"""
Gráfico de comparação entre acurácia de treino e teste
"""
acc_train = History.history["acc"]
epochs = range(1, len(acc_train) + 1)
fig, ax = plt.subplots(figsize = (9, 7))
ax.plot(epochs, acc_train, "--g", color = "darkred", label = "Acurácia treino")
ax.plot(epochs, acc_test, "-b", color = "orange", label = "Acurácia teste")
for axis in ["left", "right", "top", "bottom"]:
        ax.spines[axis].set_linewidth(2)
        ax.spines[axis].set_color("gray")
ax.xaxis.set_minor_locator(AutoMinorLocator())
ax.yaxis.set_minor_locator(AutoMinorLocator())
ax.tick_params(axis = "both", direction = "in", labelcolor = "gray", labelsize␣
 ↪= 13, top = True, right = True, left = True, bottom = True)
ax.tick_params(which='minor', direction = "in", length=2, color='gray', width =␣
 ↪2, top = True, right = True, left = True, bottom = True)
ax.tick_params(which='major', direction = "in", color='gray', length=3.4, width␣
 ↪= 2, top = True, right = True, left = True, bottom = True)
ax.legend(frameon = False, prop = Font2, labelcolor = "gray")
ax.set_xlabel("Epochs", fontdict = Font1)
ax.set_ylabel("Acurácia", fontdict = Font1)
fig.patch.set_facecolor("white")
Cor_fundo = plt.gca()
Cor_fundo.set_facecolor("white")
Cor_fundo.patch.set_alpha(1)
plt.show()
```


1.0
0.9
0.8
0.7
0.6
0.5
0.4
Acurácia
0
100
200
300
400
500
Epochs
Acurácia treino
Acurácia teste