Desafio:

Precisamos que você crie um repositório no github ou gitlab e inicie um projeto para o problema que vai ser apresentado a seguir. Pode colocar nesse repositório seu código em Python ou um jupyter notebook. É importante que adicione em seu README os passos necessários para que possamos executar e verificar sua implementação. Tendo em mente a base de dados Bias correction of numerical prediction model temperature forecast Data Set (https://archive.ics.uci.edu/ml/datasets/Bias+correction+of+numerical+prediction+model+temperature+forecast) da UCI, queremos que você faça uma análise descritiva dos dados explicando aspectos fundamentais, tais como a distribuição dos dados e correlação entre as variáveis. Fique a vontade para fazer sugestões, alterações e transformações que achar necessárias a fim de facilitar o entendimento do problema.

Além da análise descritiva, queremos que você treine e avalie um modelo de Machine Learning para fazer a estimação da variável Next_Tmax, explicando a qualidade do modelo a partir das métricas de avaliação utilizadas. Como métricas de avaliação, sugerimos como obrigatórias a accuracy, precision e recall. Mas você fica livre de avaliar outras métricas que sejam oportunas de acordo com seu julgamento e necessidade na avaliação do modelo. Queremos que você nos mostre o que fez no código, mas também explique suas decisões e conclusões, pode gerar gráficos ou outras visualizações para auxiliar em sua explicação. Queremos ver também sua linha de raciocínio.

Por fim, queremos ouvir de você o que poderia ser feito de diferente se tivesse mais tempo e mais recursos. Quais outros testes e análises poderiam ser feitas e qual a importância destas.

Não é necessário pensar nesse momento em eficiência ou otimização de código e modelos, mas se considerar oportuno, pode adicionar esse tópico em sua análise. Fique à vontade para determinar o que é relevante.

Nós precisamos receber a sua solução até o dia 13/01/2022. Em caso de algum imprevisto fique à vontade para nos sinalizar, tudo bem?

Em cópia do e-mail está o @Vitor Casadei em caso de possíveis dúvidas em relação ao desafio.

In [1]:
```
import os, sys, glob
```

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as srn
from seaborn import pairplot
```

In [3]:
```
import matplotlib.gridspec as gridspec
from matplotlib.colors import ListedColormap
%matplotlib inline

from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split, GridSearchCV, KFold
from sklearn.linear_model import LogisticRegression, SGDClassifier
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.neighbors import KNeighborsClassifier, NeighborhoodComponentsA
from sklearn.decomposition import PCA
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier, export_graphviz
from sklearn import metrics

import warnings
warnings.filterwarnings("ignore")
```

In [4]:
```
arqs={ n:nome for n,nome in enumerate(glob.glob('*.csv')) }
arqs
```

Out[4]:
```
{0: 'Bias_correction_ucl.csv'}
```

In [5]:
```
df = pd.read_csv(arqs[0], sep=',')
```

In [6]:
```
df.columns
```

Out[6]:
```
Index(['station', 'Date', 'Present_Tmax', 'Present_Tmin', 'LDAPS_RHmin',
       'LDAPS_RHmax', 'LDAPS_Tmax_lapse', 'LDAPS_Tmin_lapse', 'LDAPS_WS',
       'LDAPS_LH', 'LDAPS_CC1', 'LDAPS_CC2', 'LDAPS_CC3', 'LDAPS_CC4',
       'LDAPS_PPT1', 'LDAPS_PPT2', 'LDAPS_PPT3', 'LDAPS_PPT4', 'lat', 'lon
',
       'DEM', 'Slope', 'Solar radiation', 'Next_Tmax', 'Next_Tmin'],
      dtype='object')
```

In [7]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7752 entries, 0 to 7751
Data columns (total 25 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   station           7750 non-null   float64
 1   Date              7750 non-null   object
 2   Present_Tmax      7682 non-null   float64
 3   Present_Tmin      7682 non-null   float64
 4   LDAPS_RHmin       7677 non-null   float64
 5   LDAPS_RHmax       7677 non-null   float64
 6   LDAPS_Tmax_lapse  7677 non-null   float64
 7   LDAPS_Tmin_lapse  7677 non-null   float64
 8   LDAPS_WS          7677 non-null   float64
 9   LDAPS_LH          7677 non-null   float64
 10  LDAPS_CC1         7677 non-null   float64
 11  LDAPS_CC2         7677 non-null   float64
 12  LDAPS_CC3         7677 non-null   float64
 13  LDAPS_CC4         7677 non-null   float64
 14  LDAPS_PPT1        7677 non-null   float64
 15  LDAPS_PPT2        7677 non-null   float64
```

```
 16  LDAPS_PPT3          7677 non-null   float64
 17  LDAPS_PPT4          7677 non-null   float64
 18  lat                 7752 non-null   float64
 19  lon                 7752 non-null   float64
 20  DEM                 7752 non-null   float64
 21  Slope               7752 non-null   float64
 22  Solar radiation     7752 non-null   float64
 23  Next_Tmax           7725 non-null   float64
 24  Next_Tmin           7725 non-null   float64
dtypes: float64(24), object(1)
memory usage: 1.5+ MB
```

In [8]:
```
df = df.loc[~df['Next_Tmax'].isnull()]
```

In [9]:
```
df['Next_Tmax']= df['Next_Tmax'].apply(lambda x: int(round(x)))
```

In [10]:
```
df.describe()
```

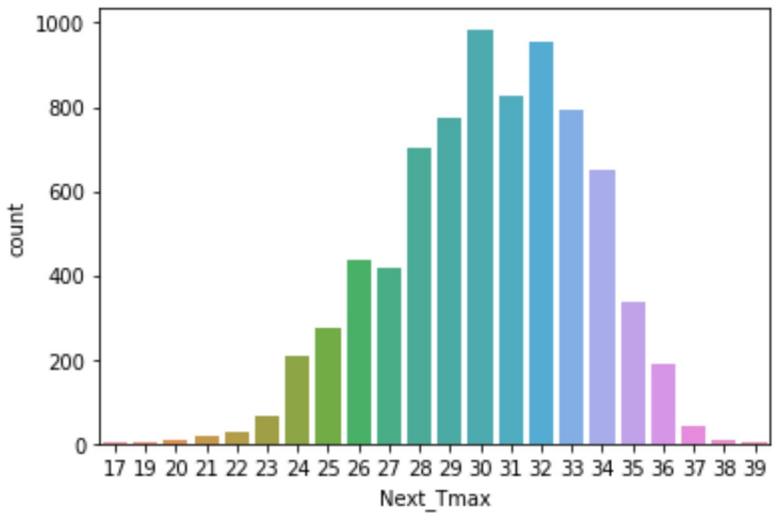
Out[10]:

	station	Present_Tmax	Present_Tmin	LDAPS_RHmin	LDAPS_RHmax	LDAPS_Tmax_laps
count	7723.000000	7665.000000	7665.000000	7650.000000	7650.000000	7650.00000
mean	13.008157	29.769563	23.224631	56.741402	88.369140	29.61625
std	7.214034	2.970766	2.414959	14.654953	7.199065	2.94661
min	1.000000	20.000000	11.300000	19.794666	58.936283	17.62495
25%	7.000000	27.800000	21.700000	45.961137	84.212961	27.67509
50%	13.000000	29.900000	23.400000	55.017689	89.792492	29.70543
75%	19.000000	32.000000	24.900000	67.154766	93.743328	31.71050
max	25.000000	37.600000	29.900000	98.524734	100.000153	38.54225

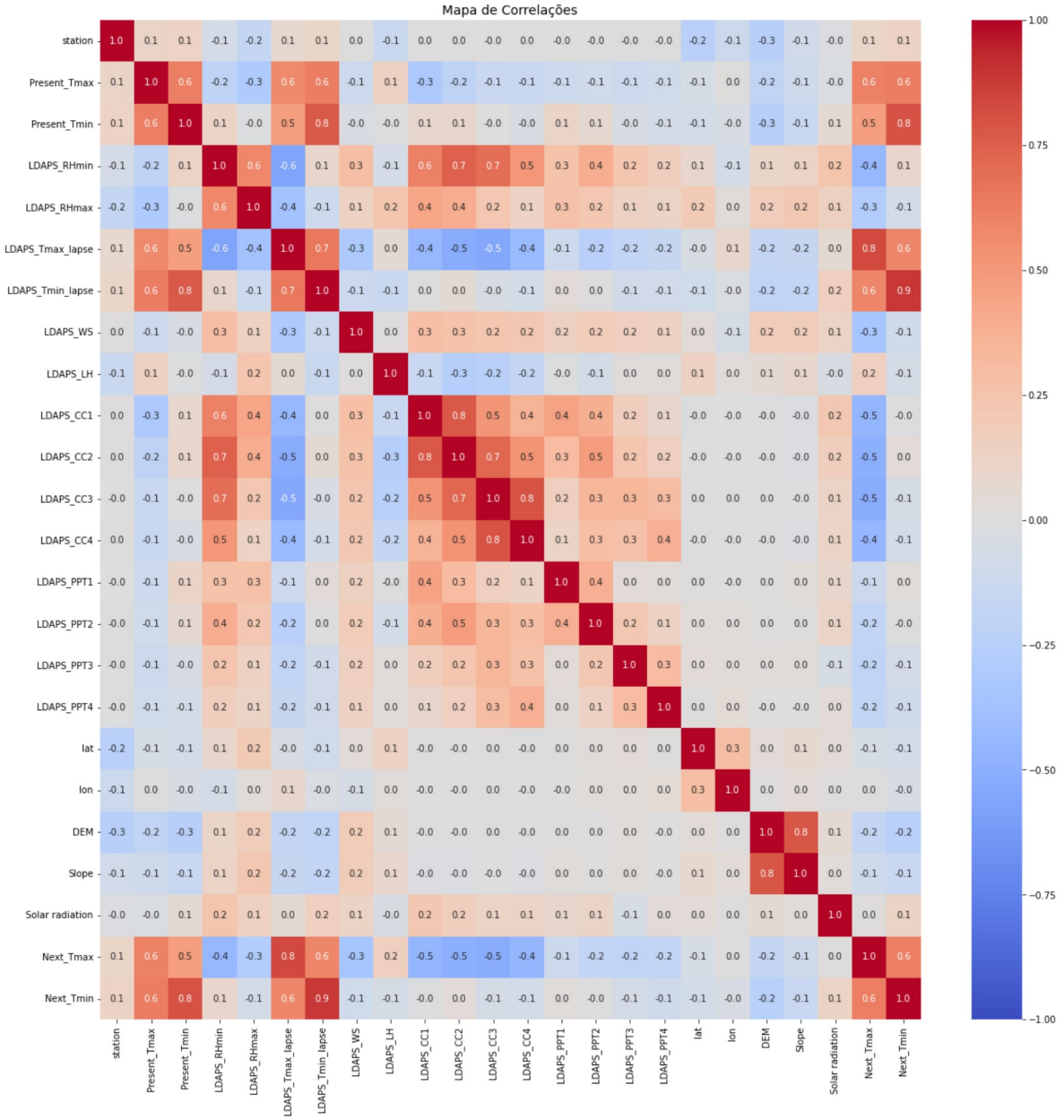
8 rows × 24 columns

In [11]:
```
srn.countplot(df['Next_Tmax'])
```

Out[11]:
```
<AxesSubplot:xlabel='Next_Tmax', ylabel='count'>
```



In [12]:
```
f, ax = plt.subplots(figsize = (20,20))
srn.heatmap(df.corr(), annot=True, fmt='.1f',
            ax=ax, cmap='coolwarm', vmin=-1, vmax=1)
plt.xticks(rotation=90)
plt.yticks(rotation=0)
plt.title('Mapa de Correlações', size=14);
```



In [13]:
```
flt = np.abs(df.corr()['Next_Tmax']) > .59
```

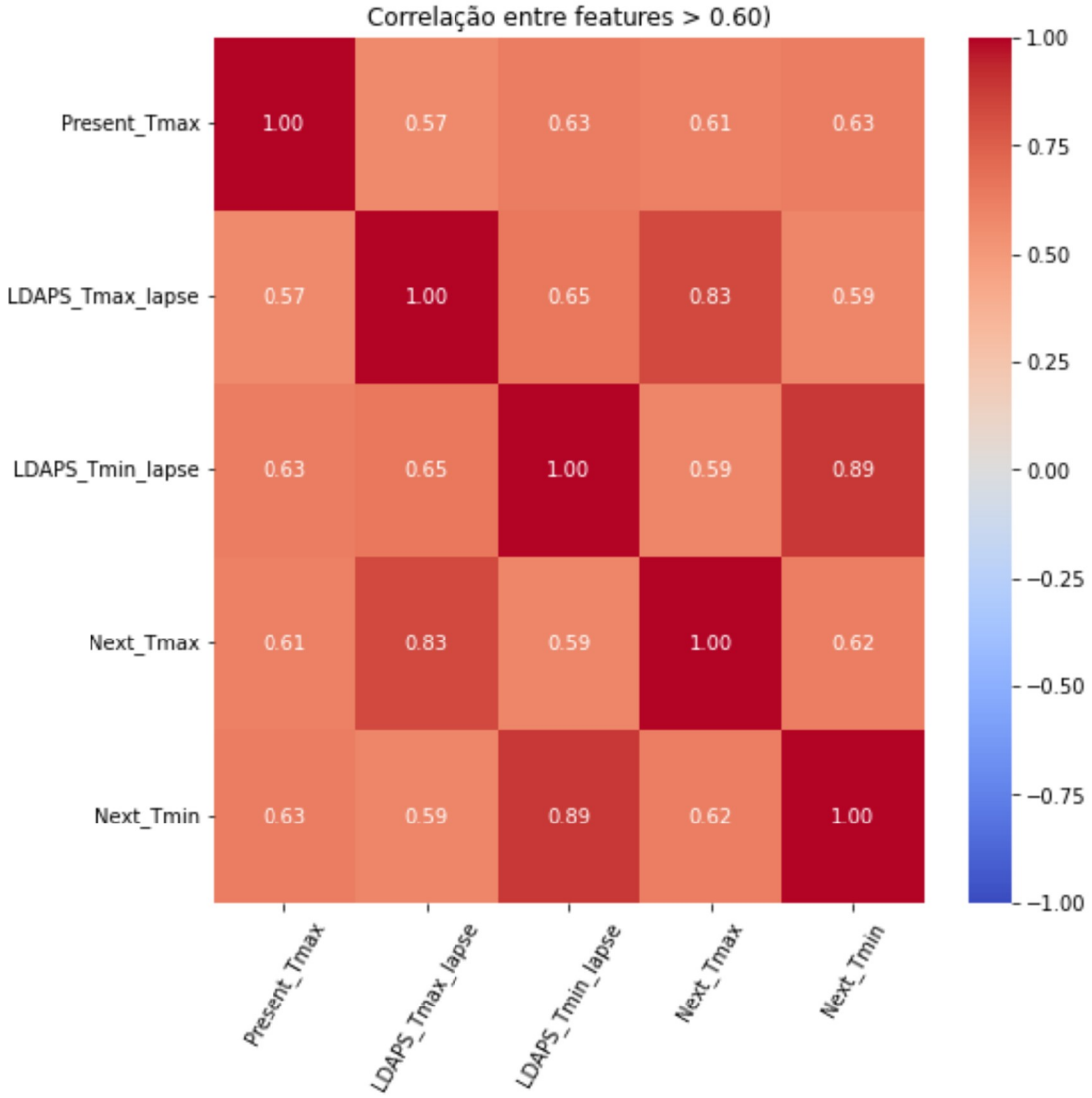
In [14]:
```
flt
```

Out[14]:
```
station              False
Present_Tmax          True
Present_Tmin         False
LDAPS_RHmin          False
LDAPS_RHmax          False
LDAPS_Tmax_lapse      True
LDAPS_Tmin_lapse      True
LDAPS_WS             False
LDAPS_LH             False
```

```
LDAPS_CC1           False
LDAPS_CC2           False
LDAPS_CC3           False
LDAPS_CC4           False
LDAPS_PPT1          False
LDAPS_PPT2          False
LDAPS_PPT3          False
LDAPS_PPT4          False
lat                 False
lon                 False
DEM                 False
Slope               False
Solar radiation     False
Next_Tmax            True
Next_Tmin            True
Name: Next Tmax, dtype: bool
```

In [15]:
```
corr_feat = df.corr().columns[flt].tolist()
```

In [16]:
```
f, ax = plt.subplots(figsize = (8,8))
srn.heatmap(df[corr_feat].corr(), annot=True, fmt='.2f',
            ax=ax, cmap='coolwarm',vmin=-1,vmax=1)
plt.xticks(rotation=60)
plt.yticks(rotation=0)
plt.title('Correlação entre features > 0.60)');
```



In [17]:
```
df= df.loc[~df['Present_Tmax'].isnull()]
```

In [18]:
```
df= df.loc[~df['LDAPS_Tmax_lapse'].isnull()]
```

In [19]:
```
df= df.loc[~df['LDAPS_Tmin_lapse'].isnull()]
```

In [20]:
```
df= df.loc[~df['Next_Tmin'].isnull()]
```

In [21]:
```
df.corr()
```

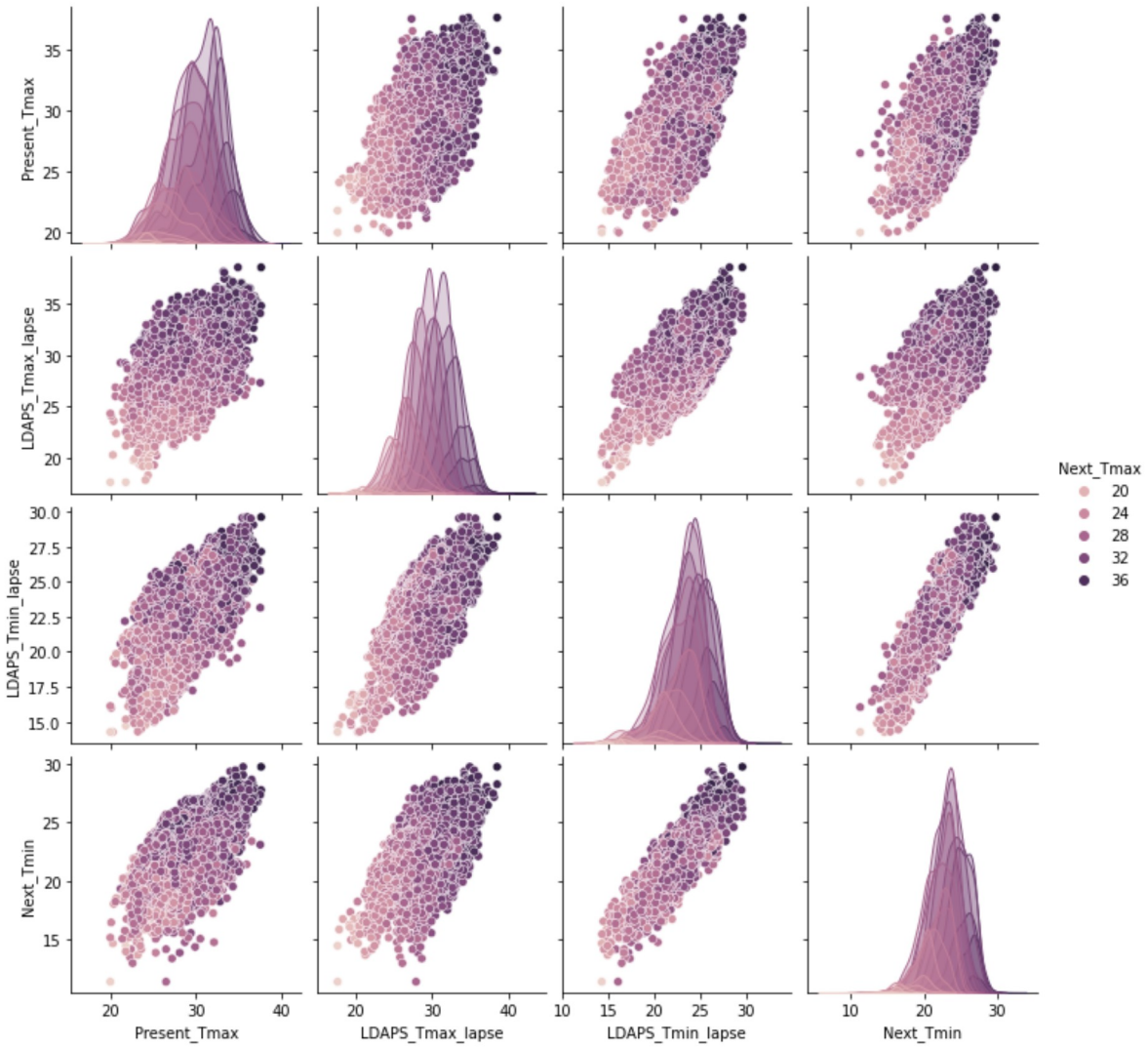
Out[21]:

	station	Present_Tmax	Present_Tmin	LDAPS_RHmin	LDAPS_RHmax	LDAPS
station	1.000000	0.113301	0.133282	-0.067846	-0.169351	
Present_Tmax	0.113301	1.000000	0.616291	-0.206529	-0.303867	
Present_Tmin	0.133282	0.616291	1.000000	0.124516	-0.015260	
LDAPS_RHmin	-0.067846	-0.206529	0.124516	1.000000	0.579035	
LDAPS_RHmax	-0.169351	-0.303867	-0.015260	0.579035	1.000000	
LDAPS_Tmax_lapse	0.069856	0.574947	0.469881	-0.565579	-0.373342	
LDAPS_Tmin_lapse	0.105277	0.629656	0.772811	0.087319	-0.115966	
LDAPS_WS	0.005822	-0.122206	-0.034831	0.291387	0.133150	
LDAPS_LH	-0.132129	0.136401	-0.009656	-0.069574	0.240453	
LDAPS_CC1	0.006539	-0.314411	0.085882	0.613281	0.436418	
LDAPS_CC2	0.003526	-0.215191	0.091572	0.745043	0.391177	
LDAPS_CC3	-0.000161	-0.144658	-0.002900	0.688440	0.225570	
LDAPS_CC4	0.005005	-0.141384	-0.044822	0.514552	0.128209	
LDAPS_PPT1	-0.001954	-0.109440	0.114859	0.260943	0.267867	
LDAPS_PPT2	-0.007635	-0.099354	0.070025	0.390090	0.227823	
LDAPS_PPT3	-0.013865	-0.120804	-0.046608	0.239580	0.133673	
LDAPS_PPT4	-0.011085	-0.100955	-0.064180	0.170301	0.119518	
lat	-0.239118	-0.052594	-0.079332	0.086238	0.195849	
lon	-0.118845	0.009215	-0.043030	-0.076101	0.027026	
DEM	-0.256706	-0.187753	-0.251791	0.101876	0.177314	
Slope	-0.091721	-0.105532	-0.146422	0.123620	0.220092	
Solar radiation	-0.021194	-0.020531	0.061699	0.243164	0.147950	
Next_Tmax	0.105516	0.609670	0.463490	-0.442685	-0.286979	
Next_Tmin	0.128184	0.622100	0.797795	0.095574	-0.073069	

24 rows × 24 columns

In [22]:
```
srn.pairplot(df[corr_feat], "Next_Tmax")
```

Out[22]:
```
<seaborn.axisgrid.PairGrid at 0x1837f633b80>
```

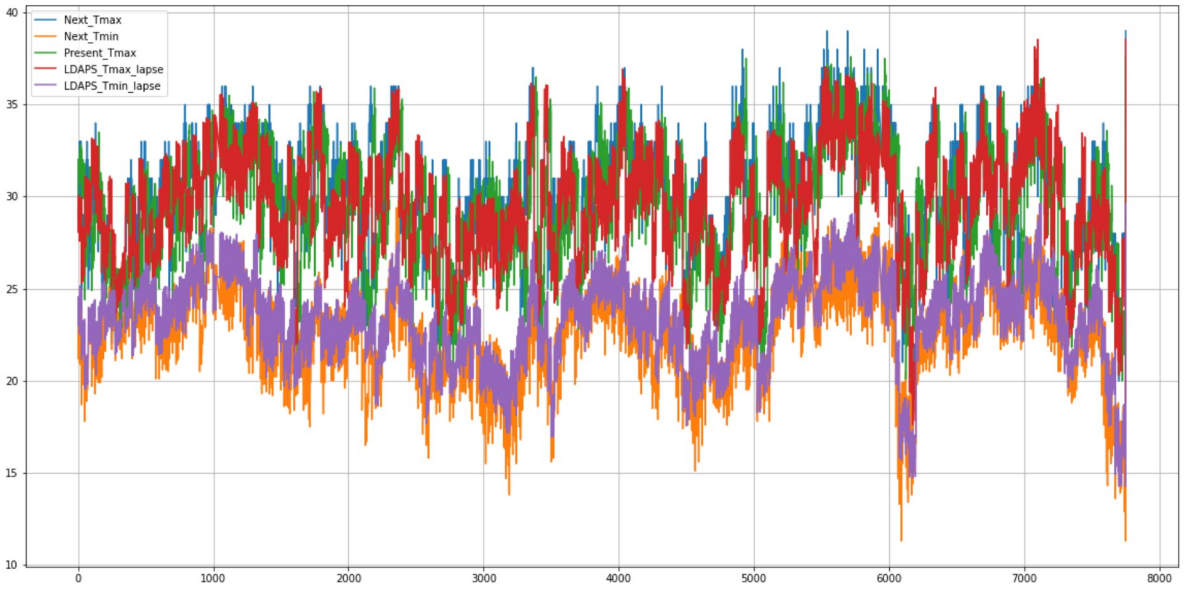


In [ ]:
```
```

In [23]:
```
def classification_and_fit_model(model, data, predictors, outcome):
    model.fit(data[predictors], data[outcome])
    predictions = model.predict(data[predictors])
    accuracy =metrics.accuracy_score(predictions, data[outcome])
    print('Accuracy : %s' % '{0:.3%}'.format(accuracy))
    kf = KFold(n_splits=5)
    error = []
    for train, test in kf.split(data):
        train_predictors = data[predictors].iloc[train,:]
        train_target = data[outcome].iloc[train]
        model.fit(train_predictors, train_target)
        error.append(model.score(data[predictors].iloc[test,:],
                                 data[outcome].iloc[test]))
        print('Cross-Validation Score : %s' % '{0:.3%}'.format(np.mean(erro
    model.fit(data[predictors],data[outcome])
```

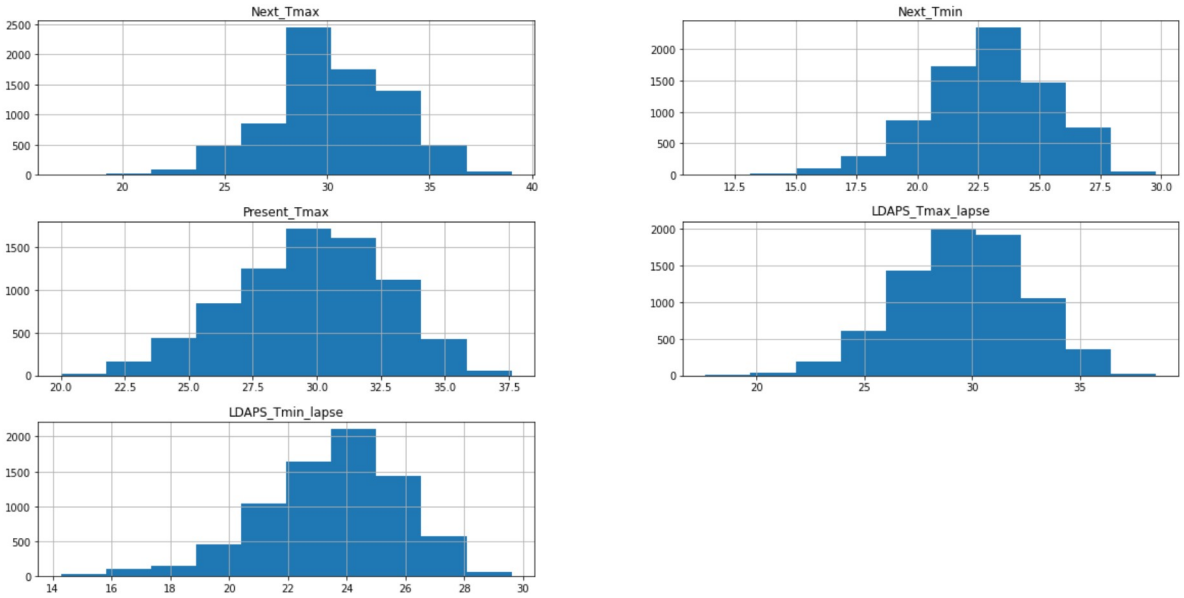
In [24]:
```
df[['Next_Tmax', 'Next_Tmin', 'Present_Tmax', 'LDAPS_Tmax_lapse', 'LDAPS_Tm
```

Out[24]:
```
<AxesSubplot:>
```



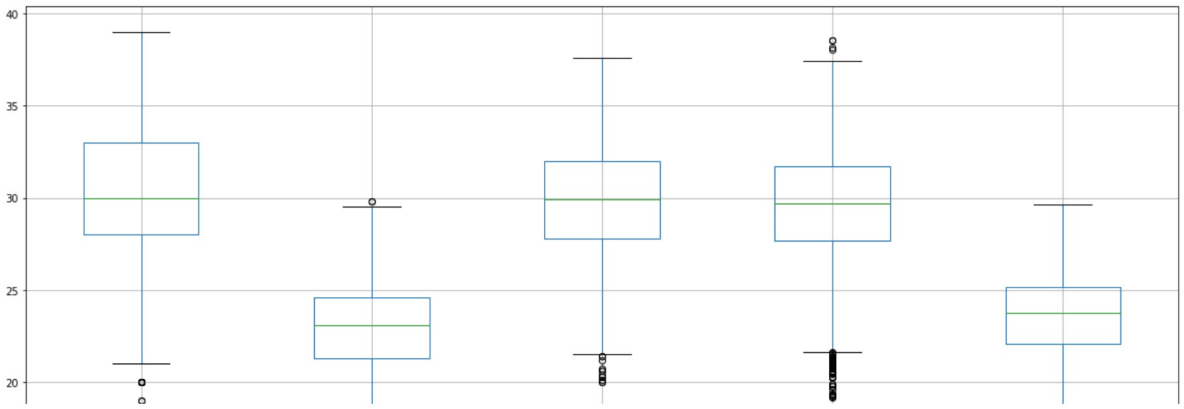
In [25]:
```
df[['Next_Tmax', 'Next_Tmin', 'Present_Tmax', 'LDAPS_Tmax_lapse', 'LDAPS_Tm
```

Out[25]:
```
array([[<AxesSubplot:title={'center':'Next_Tmax'}>,
        <AxesSubplot:title={'center':'Next_Tmin'}>],
       [<AxesSubplot:title={'center':'Present_Tmax'}>,
        <AxesSubplot:title={'center':'LDAPS_Tmax_lapse'}>],
       [<AxesSubplot:title={'center':'LDAPS_Tmin_lapse'}>,
        <AxesSubplot:>]], dtype=object)
```



In [26]:
```
df[['Next_Tmax', 'Next_Tmin', 'Present_Tmax', 'LDAPS_Tmax_lapse', 'LDAPS_Tm
```

Out[26]:
```
<AxesSubplot:>
```



In [27]:
```
predictor = ['Present_Tmax', 'LDAPS_Tmax_lapse', 'LDAPS_Tmin_lapse']
```

In [28]:
```
outcome = 'Next_Tmax'
```

In [29]:
```
arModelos = []
dctModelo = {'Algoritimo':'', 'Modelo':False}
```

In [30]:
```
X_train, X_test, y_train, y_test = train_test_split(df[predictor], df[outcc
```

Modelo Linear : Ridge

In [31]:
```
from sklearn.linear_model import RidgeClassifier
```

In [32]:
```
model = RidgeClassifier()
```

In [33]:
```
dctModelo['Algoritimo'] = 'Modelo Linear: Ridge'
dctModelo['Modelo']     = model
arModelos.append(dctModelo.copy())
```

Gradiente Descendente Estocástico

In [34]:
```
model = SGDClassifier()
```

In [35]:
```
dctModelo['Algoritimo'] = 'Gradiente Descendente Estocástico'
dctModelo['Modelo']     = model
arModelos.append(dctModelo.copy())
```

Árvore de Decisão

In [36]:
```
model = DecisionTreeClassifier()
```

In [37]:
```
dctModelo['Algoritimo'] = 'Árvore de Decisão'
dctModelo['Modelo']     = model
arModelos.append(dctModelo.copy())
```

In [ ]:
```

```

Florestas Aleatórias

In [38]:
```
model = RandomForestClassifier(n_estimators=100, min_samples_split=25, max_
```

In [39]:
```
dctModelo['Algoritimo'] = 'Florestas Aleatórias'
dctModelo['Modelo']     = model
arModelos.append(dctModelo.copy())
```

In [ ]:
```

```

Classificador Multi Layer Perceptron para Rede Neural

In [40]:
```
from sklearn.neural_network import MLPClassifier
```

In [41]:
```
model = MLPClassifier()
```

In [42]:
```
dctModelo['Algoritimo'] = 'Multi Layer Perceptron'
dctModelo['Modelo']     = model
arModelos.append(dctModelo.copy())
```

Máquinas de Vetores de Suporte

In [43]:
```
from sklearn.svm import LinearSVC
```

In [44]:
```
model = LinearSVC()
```

In [45]:
```
dctModelo['Algoritimo'] = 'Máquinas de Vetores de Suporte'
dctModelo['Modelo']     = model
arModelos.append(dctModelo.copy())
```

In [ ]:
```

```

K Vizinhos mais Próximos

In [46]:
```
from sklearn.neighbors import KNeighborsClassifier
```

In [47]:
```
model = KNeighborsClassifier()
```

In [48]:
```
dctModelo['Algoritimo'] = 'K Vizinhos mais Próximos'
dctModelo['Modelo']     = model
arModelos.append(dctModelo.copy())
```

In [ ]:
```

```

Bayesian

In [49]:
```
from sklearn.naive_bayes import GaussianNB
```

In [50]:
```
model = GaussianNB()
```

In [51]:
```
dctModelo['Algoritimo'] = 'Método Bayesiano'
dctModelo['Modelo']     = model
arModelos.append(dctModelo.copy())
```

In [52]:
```
arModelos
```

Out[52]:
```
[{'Algoritimo': 'Modelo Linear: Ridge', 'Modelo': RidgeClassifier()},
 {'Algoritimo': 'Gradiente Descendente Estocástico',
  'Modelo': SGDClassifier()},
 {'Algoritimo': 'Árvore de Decisão', 'Modelo': DecisionTreeClassifier()},
 {'Algoritimo': 'Florestas Aleatórias',
  'Modelo': RandomForestClassifier(max_depth=7, max_features=3, min_samples
_split=25)},
 {'Algoritimo': 'Multi Layer Perceptron', 'Modelo': MLPClassifier()},
 {'Algoritimo': 'Máquinas de Vetores de Suporte', 'Modelo': LinearSVC()},
 {'Algoritimo': 'K Vizinhos mais Próximos', 'Modelo': KNeighborsClassifier
()},
 {'Algoritimo': 'Método Bayesiano', 'Modelo': GaussianNB()}]
```

Benchmark

Validação Cruzada

In [53]:
```
for i in arModelos:
    print(i['Algoritimo'])
    classification_and_fit_model(i['Modelo'], df, predictor, outcome)
    print('=' * 50)
```

```
Modelo Linear: Ridge
Accuracy : 22.556%
Cross-Validation Score : 22.069%
```

```
Cross-Validation Score : 19.499%
Cross-Validation Score : 19.960%
Cross-Validation Score : 18.561%
Cross-Validation Score : 18.551%
------------------------------------------------
Gradiente Descendente Estocástico
Accuracy : 11.752%
Cross-Validation Score : 16.140%
Cross-Validation Score : 16.074%
Cross-Validation Score : 16.535%
Cross-Validation Score : 15.942%
Cross-Validation Score : 14.862%
================================================
Árvore de Decisão
Accuracy : 100.000%
Cross-Validation Score : 19.565%
Cross-Validation Score : 17.754%
Cross-Validation Score : 17.501%
Cross-Validation Score : 17.984%
Cross-Validation Score : 17.866%
------------------------------------------------
Florestas Aleatórias
Accuracy : 37.787%
Cross-Validation Score : 26.614%
Cross-Validation Score : 26.021%
Cross-Validation Score : 25.758%
Cross-Validation Score : 25.807%
Cross-Validation Score : 25.323%
================================================
Multi Layer Perceptron
Accuracy : 25.652%
Cross-Validation Score : 27.075%
Cross-Validation Score : 24.506%
Cross-Validation Score : 24.572%
Cross-Validation Score : 22.036%
Cross-Validation Score : 22.200%
------------------------------------------------
Máquinas de Vetores de Suporte
Accuracy : 15.441%
Cross-Validation Score : 18.511%
Cross-Validation Score : 15.152%
Cross-Validation Score : 15.371%
Cross-Validation Score : 13.373%
Cross-Validation Score : 13.307%
================================================
K Vizinhos mais Próximos
Accuracy : 49.196%
Cross-Validation Score : 20.487%
Cross-Validation Score : 20.059%
Cross-Validation Score : 19.433%
Cross-Validation Score : 19.598%
Cross-Validation Score : 19.078%
------------------------------------------------
Método Bayesiano
Accuracy : 26.719%
Cross-Validation Score : 22.793%
Cross-Validation Score : 23.419%
Cross-Validation Score : 24.133%
Cross-Validation Score : 24.835%
Cross-Validation Score : 24.229%
------------------------------------------------
```

Acurácia do Modelo em dados de teste

In [54]:
```
for i in arModelos:
    print(i['Algoritimo'])
    i['Modelo'].fit(X_train, y_train)
    predictions = i['Modelo'].predict(X_test)
    accuracy = metrics.accuracy_score(predictions, y_test)
    print('Acurácia : %s' % '{0:.3%}'.format(accuracy))
    #print(metrics.classification_report(y_test, i['Modelo'].predict(X_test
    print('=' * 50)
```

```
Modelo Linear: Ridge
Acurácia : 22.617%
==================================================
Gradiente Descendente Estocástico
Acurácia : 12.297%
==================================================
Árvore de Decisão
Acurácia : 23.628%
==================================================
Florestas Aleatórias
Acurácia : 29.161%
==================================================
Multi Layer Perceptron
Acurácia : 24.286%
==================================================
Máquinas de Vetores de Suporte
Acurácia : 0.044%
==================================================
K Vizinhos mais Próximos
Acurácia : 23.671%
==================================================
Método Bayesiano
Acurácia : 26.702%
==================================================
```

Métricas de avaliação: Precisão, Revocação e Especificidade

In [55]:
```
for i in arModelos:
    print(i['Algoritimo'])
    print(metrics.classification_report(y_test, i['Modelo'].predict(X_test)
    print('=' * 50)
```

```
Modelo Linear: Ridge
              precision    recall  f1-score   support

          17       0.00      0.00      0.00         1
          19       0.00      0.00      0.00         1
          20       0.00      0.00      0.00         1
          21       0.00      0.00      0.00         7
          22       0.00      0.00      0.00         5
          23       0.00      0.00      0.00        18
          24       0.00      0.00      0.00        73
          25       0.00      0.00      0.00        83
          26       0.21      0.25      0.23       126
          27       0.00      0.00      0.00       126
          28       0.17      0.35      0.23       196
          29       0.00      0.00      0.00       248
          30       0.24      0.54      0.34       295
          31       0.00      0.00      0.00       231
```

32	0.25	0.54	0.34	283
33	0.22	0.40	0.29	238
34	0.21	0.05	0.08	205
35	0.00	0.00	0.00	93
36	0.00	0.00	0.00	36
37	0.00	0.00	0.00	9
38	0.00	0.00	0.00	1
39	0.00	0.00	0.00	1
accuracy			0.23	2277
macro avg	0.06	0.10	0.07	2277
weighted avg	0.13	0.23	0.16	2277

Gradiente Descendente Estocástico

	precision	recall	f1-score	support
17	0.00	0.00	0.00	1
19	0.00	0.00	0.00	1
20	0.00	0.00	0.00	1
21	0.00	0.00	0.00	7
22	0.00	0.00	0.00	5
23	0.00	0.00	0.00	18
24	0.00	0.00	0.00	73
25	0.00	0.00	0.00	83
26	0.00	0.00	0.00	126
27	0.00	0.00	0.00	126
28	0.10	1.00	0.18	196
29	0.00	0.00	0.00	248
30	0.00	0.00	0.00	295
31	0.00	0.00	0.00	231
32	0.00	0.00	0.00	283
33	0.00	0.00	0.00	238
34	0.35	0.41	0.38	205
35	0.00	0.00	0.00	93
36	0.00	0.00	0.00	36
37	0.00	0.00	0.00	9
38	0.00	0.00	0.00	1
39	0.00	0.00	0.00	1
accuracy			0.12	2277
macro avg	0.02	0.06	0.03	2277
weighted avg	0.04	0.12	0.05	2277

==========

Árvore de Decisão

	precision	recall	f1-score	support
17	1.00	1.00	1.00	1
19	0.00	0.00	0.00	1
20	0.00	0.00	0.00	1
21	0.29	0.29	0.29	7
22	0.11	0.20	0.14	5
23	0.12	0.11	0.12	18
24	0.41	0.36	0.38	73
25	0.30	0.27	0.28	83
26	0.23	0.25	0.24	126
27	0.16	0.18	0.17	126
28	0.22	0.24	0.23	196
29	0.24	0.23	0.23	248
30	0.23	0.22	0.23	295
31	0.17	0.19	0.18	231
32	0.26	0.25	0.25	283

```
              33       0.26      0.27      0.26       238
              34       0.31      0.26      0.29       205
              35       0.17      0.17      0.17        93
              36       0.20      0.31      0.24        36
              37       0.25      0.22      0.24         9
              38       0.00      0.00      0.00         1
              39       0.00      0.00      0.00         1

        accuracy                           0.24      2277
       macro avg       0.22      0.23      0.22      2277
    weighted avg       0.24      0.24      0.24      2277

================================================
Florestas Aleatórias
                  precision    recall  f1-score   support

              17       0.00      0.00      0.00         1
              19       0.00      0.00      0.00         1
              20       0.00      0.00      0.00         1
              21       0.36      0.57      0.44         7
              22       0.00      0.00      0.00         5
              23       0.00      0.00      0.00        18
              24       0.37      0.52      0.43        73
              25       0.47      0.23      0.31        83
              26       0.29      0.33      0.31       126
              27       0.23      0.02      0.04       126
              28       0.25      0.36      0.30       196
              29       0.28      0.21      0.24       248
              30       0.26      0.37      0.30       295
              31       0.18      0.16      0.17       231
              32       0.32      0.44      0.37       283
              33       0.33      0.26      0.29       238
              34       0.37      0.36      0.36       205
              35       0.29      0.16      0.21        93
              36       0.29      0.44      0.35        36
              37       0.00      0.00      0.00         9
              38       0.00      0.00      0.00         1
              39       0.00      0.00      0.00         1

        accuracy                           0.29      2277
       macro avg       0.20      0.20      0.19      2277
    weighted avg       0.29      0.29      0.28      2277

------------------------------------------------
Multi Layer Perceptron
                  precision    recall  f1-score   support

              17       0.00      0.00      0.00         1
              19       0.00      0.00      0.00         1
              20       0.00      0.00      0.00         1
              21       0.00      0.00      0.00         7
              22       0.00      0.00      0.00         5
              23       0.00      0.00      0.00        18
              24       0.34      0.32      0.33        73
              25       0.22      0.02      0.04        83
              26       0.28      0.17      0.21       126
              27       0.15      0.43      0.23       126
              28       0.26      0.03      0.05       196
              29       0.17      0.01      0.02       248
              30       0.21      0.83      0.34       295
              31       0.00      0.00      0.00       231
              32       0.25      0.03      0.06       283
              33       0.31      0.24      0.27       238
```

34	0.37	0.52	0.43	205
35	0.32	0.28	0.30	93
36	0.00	0.00	0.00	36
37	0.00	0.00	0.00	9
38	0.00	0.00	0.00	1
39	0.00	0.00	0.00	1
accuracy			0.24	2277
macro avg	0.13	0.13	0.10	2277
weighted avg	0.22	0.24	0.17	2277

Máquinas de Vetores de Suporte

	precision	recall	f1-score	support
17	0.00	1.00	0.00	1
19	0.00	0.00	0.00	1
20	0.00	0.00	0.00	1
21	0.00	0.00	0.00	7
22	0.00	0.00	0.00	5
23	0.00	0.00	0.00	18
24	0.00	0.00	0.00	73
25	0.00	0.00	0.00	83
26	0.00	0.00	0.00	126
27	0.00	0.00	0.00	126
28	0.00	0.00	0.00	196
29	0.00	0.00	0.00	248
30	0.00	0.00	0.00	295
31	0.00	0.00	0.00	231
32	0.00	0.00	0.00	283
33	0.00	0.00	0.00	238
34	0.00	0.00	0.00	205
35	0.00	0.00	0.00	93
36	0.00	0.00	0.00	36
37	0.00	0.00	0.00	9
38	0.00	0.00	0.00	1
39	0.00	0.00	0.00	1
accuracy			0.00	2277
macro avg	0.00	0.05	0.00	2277
weighted avg	0.00	0.00	0.00	2277

==========

K Vizinhos mais Próximos

	precision	recall	f1-score	support
17	0.00	0.00	0.00	1
19	0.00	0.00	0.00	1
20	0.25	1.00	0.40	1
21	0.75	0.43	0.55	7
22	0.17	0.20	0.18	5
23	0.27	0.22	0.24	18
24	0.34	0.33	0.34	73
25	0.23	0.33	0.27	83
26	0.18	0.25	0.21	126
27	0.21	0.25	0.23	126
28	0.19	0.21	0.20	196
29	0.18	0.18	0.18	248
30	0.26	0.27	0.27	295
31	0.18	0.17	0.17	231
32	0.26	0.25	0.26	283
33	0.30	0.23	0.26	238
34	0.30	0.25	0.27	205

```
           35       0.27      0.22      0.24        93
           36       0.34      0.33      0.34        36
           37       0.00      0.00      0.00         9
           38       0.00      0.00      0.00         1
           39       0.00      0.00      0.00         1

    accuracy                           0.24      2277
   macro avg       0.21      0.23      0.21      2277
weighted avg       0.24      0.24      0.24      2277

================================================
Método Bayesiano
              precision    recall  f1-score   support

           17       0.00      0.00      0.00         1
           19       0.00      0.00      0.00         1
           20       0.17      1.00      0.29         1
           21       0.50      0.43      0.46         7
           22       0.00      0.00      0.00         5
           23       0.00      0.00      0.00        18
           24       0.25      0.38      0.31        73
           25       0.24      0.14      0.18        83
           26       0.27      0.29      0.28       126
           27       0.00      0.00      0.00       126
           28       0.22      0.32      0.26       196
           29       0.29      0.18      0.22       248
           30       0.26      0.36      0.30       295
           31       0.22      0.13      0.16       231
           32       0.29      0.41      0.34       283
           33       0.29      0.27      0.28       238
           34       0.38      0.36      0.37       205
           35       0.19      0.14      0.16        93
           36       0.24      0.44      0.31        36
           37       0.27      0.33      0.30         9
           38       0.00      0.00      0.00         1
           39       0.00      0.00      0.00         1

    accuracy                           0.27      2277
   macro avg       0.18      0.24      0.19      2277
weighted avg       0.25      0.27      0.25      2277
```

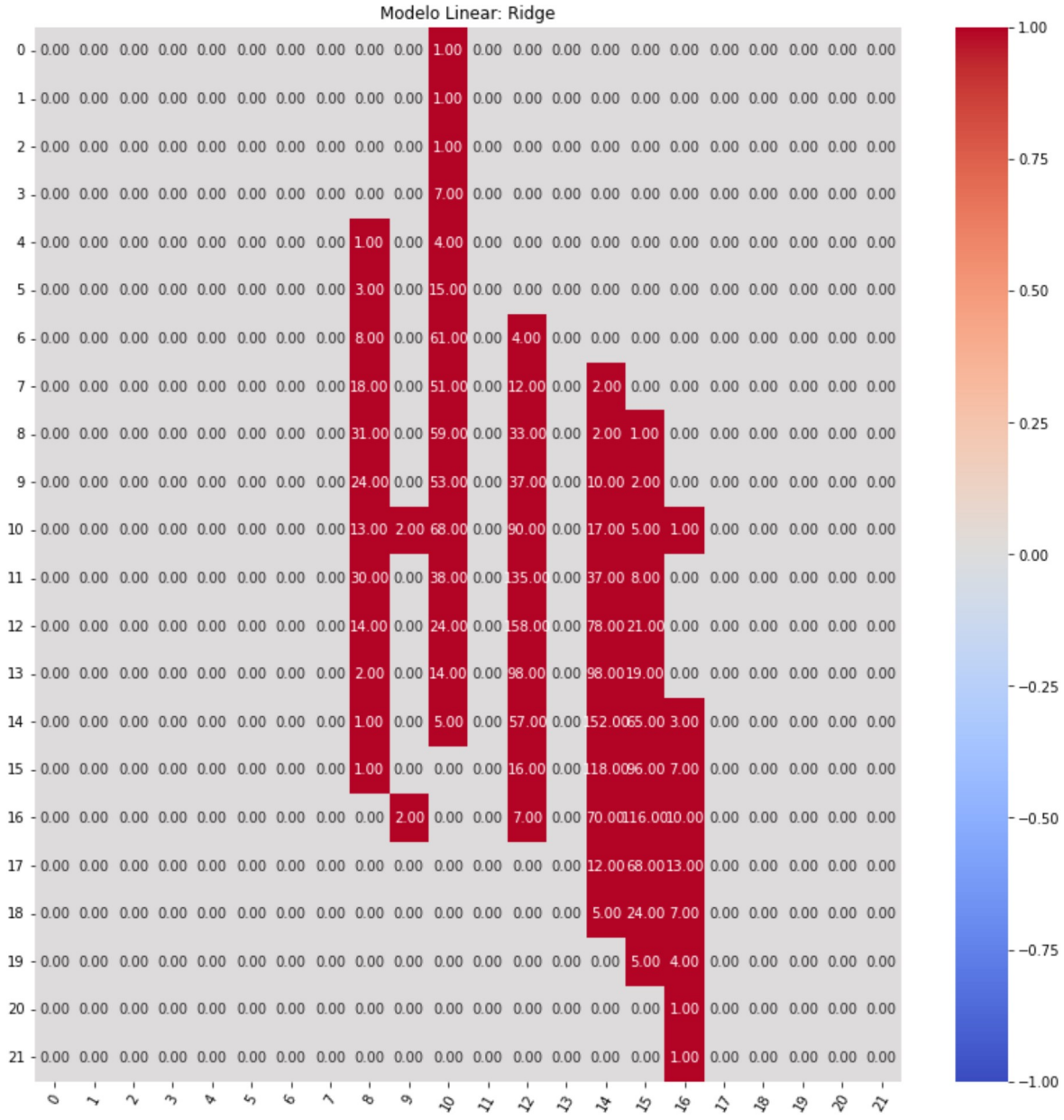
In [ ]:

In [ ]:

Matriz de Confusão

In [56]:

```
for i in arModelos:
    matrix_pred = metrics.confusion_matrix(y_test, i['Modelo'].predict(X_te
    f, ax = plt.subplots(figsize = (14,14))
    srn.heatmap(matrix_pred, annot=True, fmt='.2f',
                ax=ax, cmap='coolwarm',vmin=-1,vmax=1)
    plt.xticks(rotation=60)
    plt.yticks(rotation=0)
    plt.title(i['Algoritimo']);
```


Modelo Linear: Ridge
0 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 1.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
1 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 1.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
2 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 1.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
3 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 7.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
4 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 1.00 0.00 4.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
5 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 3.00 0.00 15.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
6 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 8.00 0.00 61.00 0.00 4.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
7 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 18.00 0.00 51.00 0.00 12.00 0.00 2.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
8 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 31.00 0.00 59.00 0.00 33.00 0.00 2.00 1.00 0.00 0.00 0.00 0.00 0.00 0.00
9 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 24.00 0.00 53.00 0.00 37.00 0.00 10.00 2.00 0.00 0.00 0.00 0.00 0.00 0.00
10 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 13.00 2.00 68.00 0.00 90.00 0.00 17.00 5.00 1.00 0.00 0.00 0.00 0.00 0.00
11 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 30.00 0.00 38.00 0.00 135.00 0.00 37.00 8.00 0.00 0.00 0.00 0.00 0.00 0.00
12 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 14.00 0.00 24.00 0.00 158.00 0.00 78.00 21.00 0.00 0.00 0.00 0.00 0.00 0.00
13 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 2.00 0.00 14.00 0.00 98.00 0.00 98.00 19.00 0.00 0.00 0.00 0.00 0.00 0.00
14 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 1.00 0.00 5.00 0.00 57.00 0.00 152.00 65.00 3.00 0.00 0.00 0.00 0.00 0.00
15 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 1.00 0.00 0.00 0.00 16.00 0.00 118.00 96.00 7.00 0.00 0.00 0.00 0.00 0.00
16 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 2.00 0.00 0.00 7.00 0.00 70.00 116.00 10.00 0.00 0.00 0.00 0.00 0.00
17 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 12.00 68.00 13.00 0.00 0.00 0.00 0.00 0.00
18 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 5.00 24.00 7.00 0.00 0.00 0.00 0.00 0.00
19 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 5.00 4.00 0.00 0.00 0.00 0.00 0.00
20 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 1.00 0.00 0.00 0.00 0.00 0.00
21 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 1.00 0.00 0.00 0.00 0.00 0.00
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21
1.00
0.75
0.50
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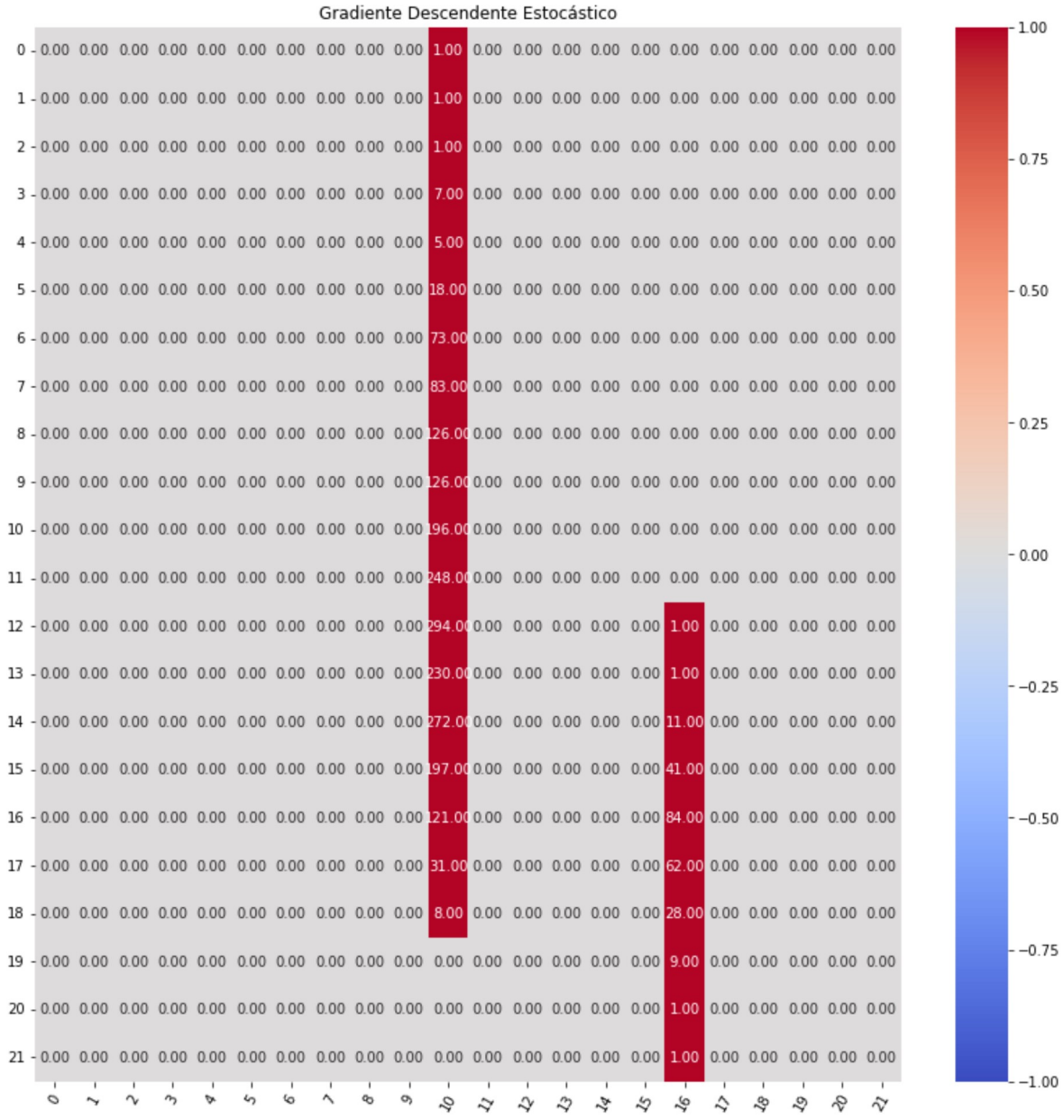
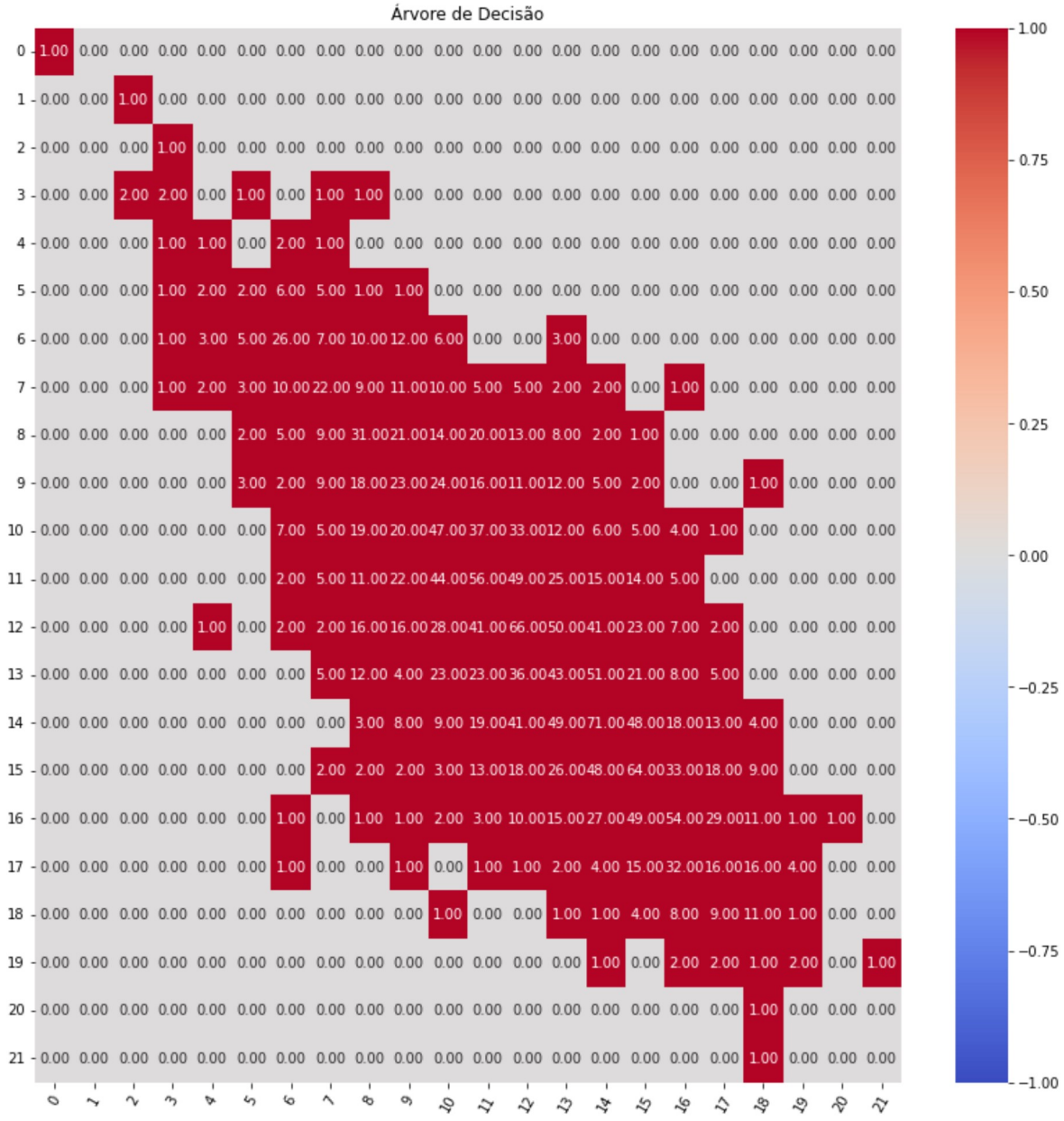
0.00
−0.25
−0.50
−0.75
−1.00


Gradiente Descendente Estocástico
0 - 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 1.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
1 - 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 1.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
2 - 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 1.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
3 - 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 7.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
4 - 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 5.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
5 - 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 18.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
6 - 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 73.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
7 - 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 83.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
8 - 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 126.0 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
9 - 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 126.0 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
10 - 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 196.0 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
11 - 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 248.0 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
12 - 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 294.0 0.00 0.00 0.00 0.00 0.00 1.00 0.00 0.00 0.00 0.00 0.00
13 - 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 230.0 0.00 0.00 0.00 0.00 0.00 1.00 0.00 0.00 0.00 0.00 0.00
14 - 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 272.0 0.00 0.00 0.00 0.00 0.00 11.00 0.00 0.00 0.00 0.00 0.00
15 - 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 197.0 0.00 0.00 0.00 0.00 0.00 41.00 0.00 0.00 0.00 0.00 0.00
16 - 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 121.0 0.00 0.00 0.00 0.00 0.00 84.00 0.00 0.00 0.00 0.00 0.00
17 - 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 31.00 0.00 0.00 0.00 0.00 0.00 62.00 0.00 0.00 0.00 0.00 0.00
18 - 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 8.00 0.00 0.00 0.00 0.00 0.00 28.00 0.00 0.00 0.00 0.00 0.00
19 - 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 9.00 0.00 0.00 0.00 0.00 0.00
20 - 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 1.00 0.00 0.00 0.00 0.00 0.00
21 - 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 1.00 0.00 0.00 0.00 0.00 0.00
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00


Árvore de Decisão
0 1.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
1 0.00 0.00 1.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
2 0.00 0.00 0.00 1.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
3 0.00 0.00 2.00 2.00 0.00 1.00 0.00 1.00 1.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
4 0.00 0.00 0.00 1.00 1.00 0.00 2.00 1.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
5 0.00 0.00 0.00 1.00 2.00 2.00 6.00 5.00 1.00 1.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
6 0.00 0.00 0.00 1.00 3.00 5.00 26.00 7.00 10.00 12.00 6.00 0.00 0.00 3.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
7 0.00 0.00 0.00 1.00 2.00 3.00 10.00 22.00 9.00 11.00 10.00 5.00 5.00 2.00 2.00 0.00 1.00 0.00 0.00 0.00 0.00 0.00
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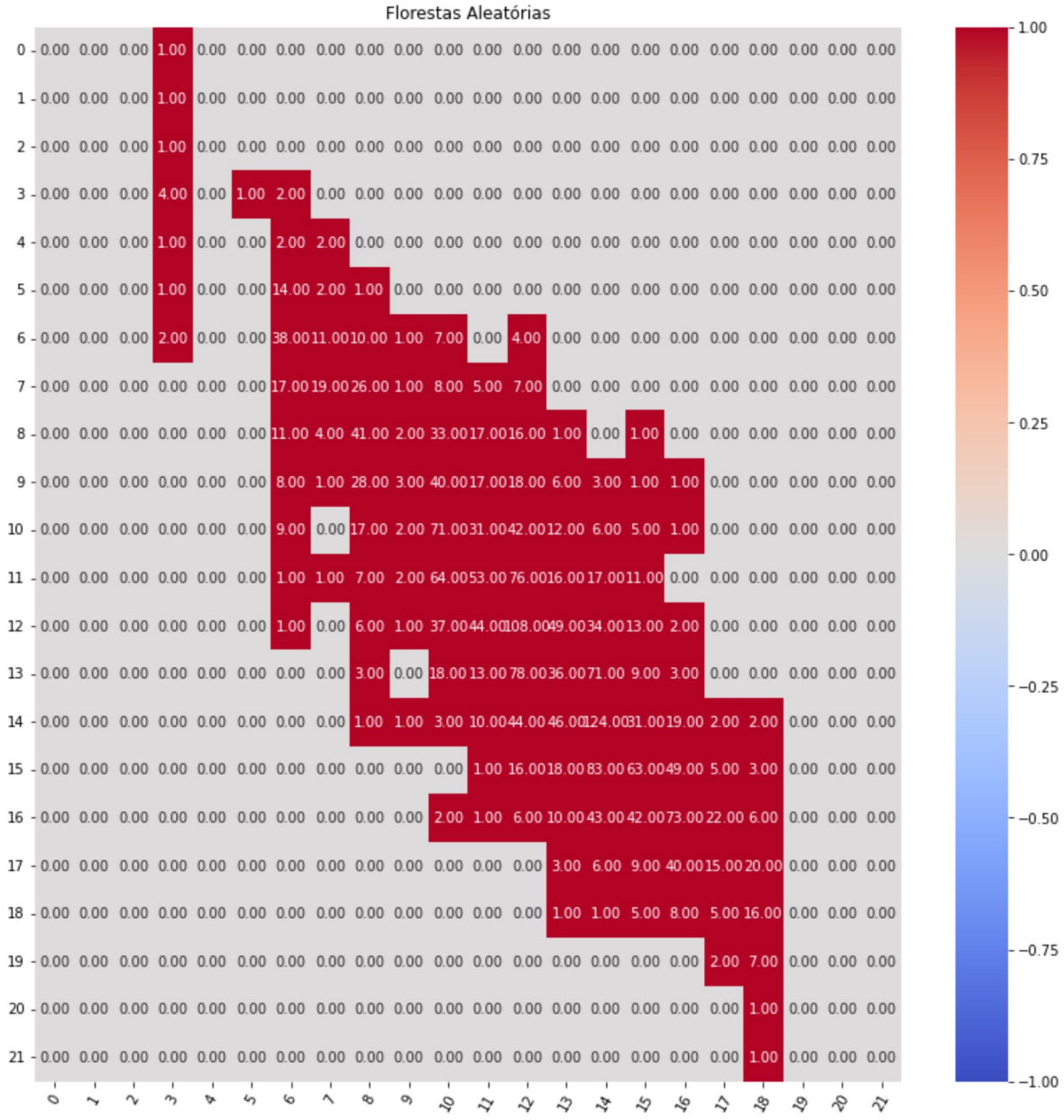
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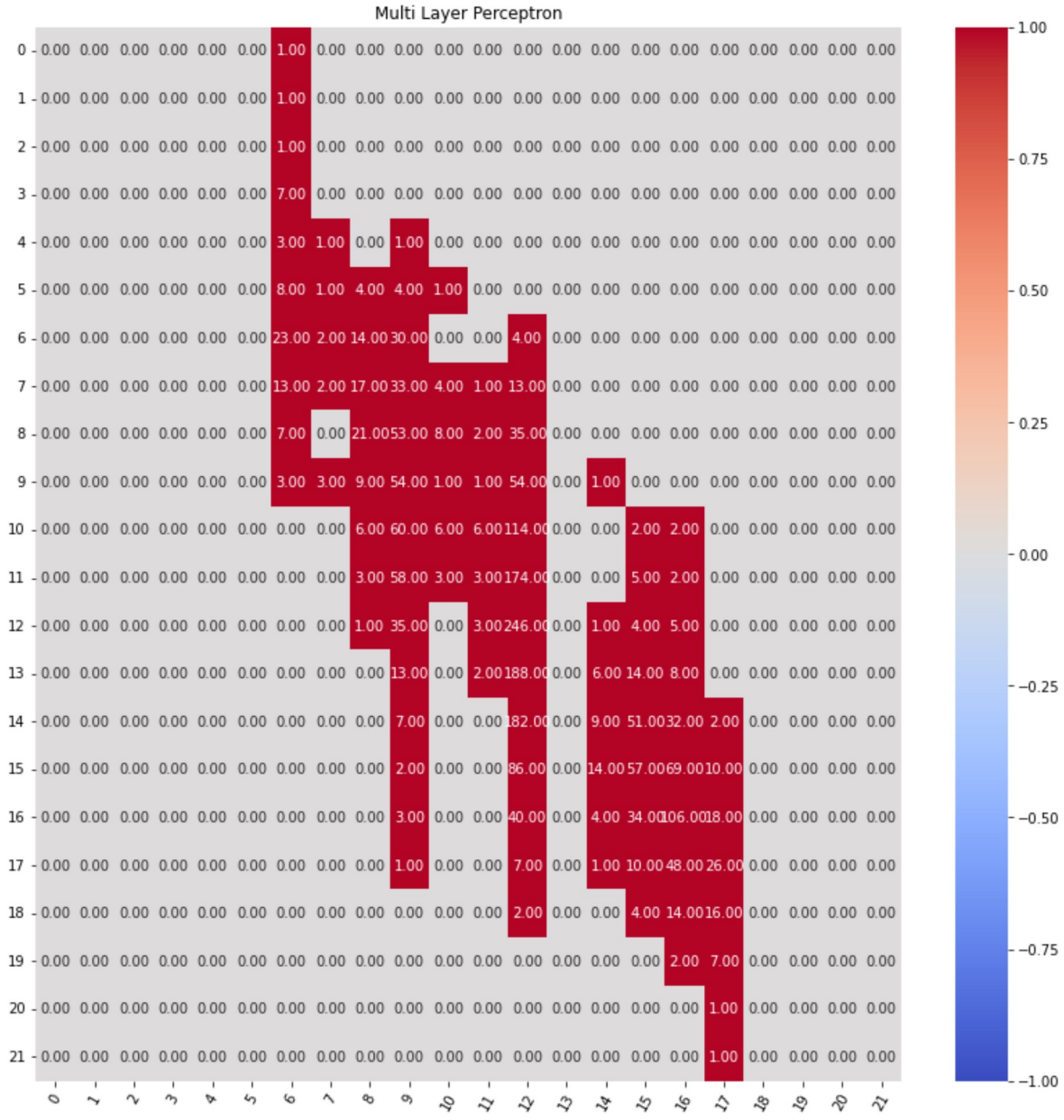
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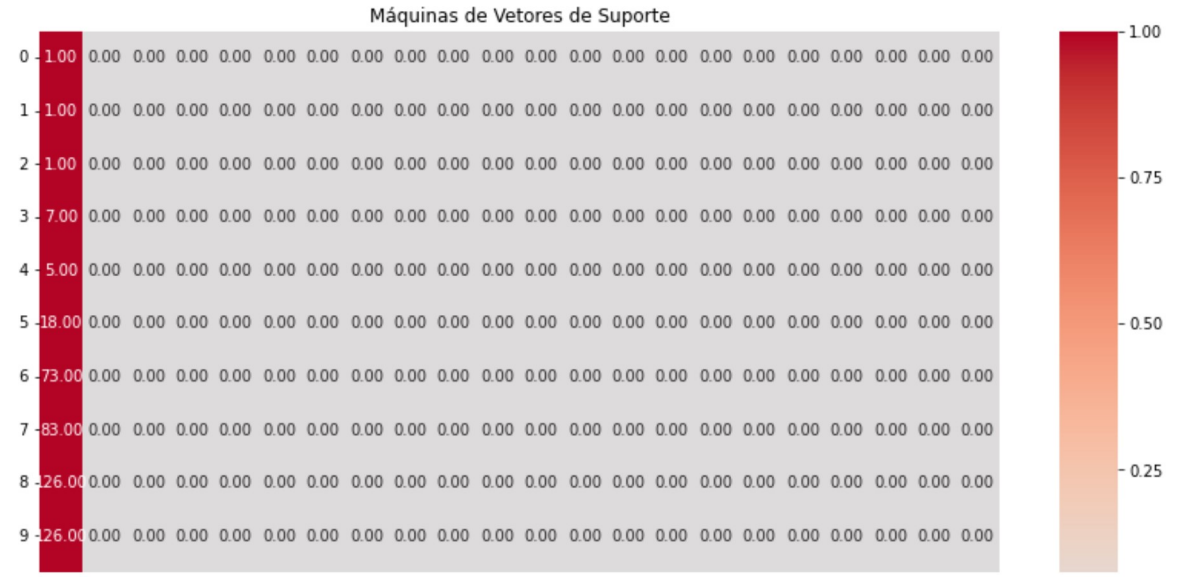
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Considerações

- A variável Next_Tmax apresenta uma distribuição simétrica
- As variáveis 'Present_Tmax', 'LDAPS_Tmax_lapse', 'LDAPS_Tmin_lapse' apresentam uma correlação com a variável Next_Tmax maior ou igual a 60%, estando assim aptas para utilização na criação de um modelo preditivo
- Apesar destas features apresentarem alguns outliers, elas seguem uma mesma tendência, o que me leva a crer que os outliers não devem atrapalhar, a princípio, a construção do modelo preditivo
- Entres os algoritimos testados as Florestas Aleatórias a princípio apresentaram a melhor acurácia, porém não foi feito nenhum ajuste nos dados nem quanto a parametrização do modelo.
- Um próximo passo seria ajustar os hyperparâmetros para o modelo e se necessário uma nova análise nos dados o que poderia gera por exemplo criação de novas features a partir das existentes com o objetivo de aperfeiçoar o modelo final.
- Neste exemplo foi utilizado como métrica de avaliação a precisão, revocação e especificidade. Existem outras métricas como curva ROC, AUC, Lift que poderão ser utilizadas para análise do modelo.
- A variável Next_Tmax foi convertida de contínua para discreta para poder ser utilizada na predição
- Na continuidade deste teste, vale a pena investir nos algoritimos KNN e DecisionTree e Florestas Aleatórias, considerando a validação cruzada as métricas utilizadas e a matriz de confusão.

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