```
#Questão 01
```

Considerando-se a base de dados de breast-cancer.csv disponível no CANVAS, pede-se:

```
##01.)
```

Implemente a Árvore de decisão, Naive Bayes e Random Forest, em Python. Faça uma comparação destes três algoritmos utilizando as métricas, recall, precision e F1-Score, para cada uma das classes (câncer recorrente/Não recorrente). Discuta os resultados obtidos e veja se o desbalanceamento da base está prejudicando o treinamento

```
# Sistema
import sys
# Data processing
import numpy as np
import pandas as pd
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import OneHotEncoder
# Data visualization
import pickle
import seaborn as sns
import plotly.express as px
import matplotlib.pyplot as plt
# Model and performance
from sklearn import tree
from sklearn.naive bayes import GaussianNB
from sklearn.compose import ColumnTransformer
from sklearn.tree import DecisionTreeClassifier
from sklearn.model selection import GridSearchCV
from yellowbrick.classifier import ConfusionMatrix
from sklearn.ensemble import RandomForestClassifier
from sklearn.model selection import train test split
from sklearn.metrics import accuracy score, confusion matrix,
classification_report
# Oversampling and under sampling
from imblearn.under sampling import TomekLinks
from imblearn.over sampling import SMOTE
Abrindo agruivo do csv
base = pd.read csv('/content/sample data/breast-cancer.csv', ',')
base
<ipython-input-3-64dladlddd9e>:1: FutureWarning: In a future version
of pandas all arguments of read csv except for the argument
'filepath_or_buffer' will be keyword-only.
  base = pd.read csv('/content/sample data/breast-cancer.csv', ',')
```

```
40-49
                          15-19
                                      0-2
                                                             3 right
              premeno
                                                ves
left up
     50-59
1
                 ge40
                          15 - 19
                                      0-2
                                                 no
                                                             1
                                                                right
central
                                      0 - 2
                                                             2
                                                                 left
     50-59
                 ge40
                          35 - 39
                                                 no
left_low
                                      0-2
     40-49
                          35-39
                                                             3
                                                                right
              premeno
                                                yes
left low
     40-49
              premeno
                          30-34
                                      3-5
                                                             2
                                                                 left
                                                yes
right up
. .
                                       . . .
                                                           . . .
                                                                   . . .
                  . . .
                             . . .
                                                . . .
    50-59
                                                             2
281
                 ge40
                          30 - 34
                                      6-8
                                                yes
                                                                 left
left low
282
    50-59
              premeno
                          25-29
                                      3-5
                                                             2
                                                                 left
                                                yes
left low
283
    30-39
             premeno
                          30-34
                                      6-8
                                                             2
                                                                right
                                                yes
right_up
                          15 - 19
                                      0-2
                                                             2
                                                                right
284 50-59
              premeno
                                                 no
left low
                          40 - 44
                                      0-2
                                                             3
                                                                 left
285
    50-59
                 ge40
                                                 no
right up
    irradiat
                               Class
0
                  recurrence-events
          no
1
              no-recurrence-events
          no
2
          no
                  recurrence-events
3
         yes
               no-recurrence-events
4
          no
                  recurrence-events
          . . .
281
          no
               no-recurrence-events
282
         yes
               no-recurrence-events
283
               no-recurrence-events
          no
284
          no
               no-recurrence-events
285
          no
               no-recurrence-events
[286 rows x 10 columns]
Contando quantidade de instâncias
np.unique(base['Class'], return counts=True), sns.countplot(x =
base['Class']);
np.unique(base['age'], return counts=True), sns.countplot(x =
base['age'])
np.unique(base['menopause'], return counts=True), sns.countplot(x =
base['menopause'])
np.unique(base['tumorsize'], return counts=True), sns.countplot(x =
base['tumorsize'])
```

```
np.unique(base['invnodes'], return counts=True), sns.countplot(x =
base['invnodes'])
np.unique(base['degmalig'], return counts=True), sns.countplot(x =
base['degmalig'])
Tratamento de dados ausentes (imputação de dados)
base.replace('?', np.nan, inplace = True)
base.isnull().sum()
              0
age
menopause
              0
tumorsize
              0
invnodes
              0
nodecaps
              8
degmalig
              0
breast
              0
              1
breastquad
irradiat
              0
Class
              0
dtype: int64
base['nodecaps'].fillna(base['nodecaps'].mode()[0], inplace=True)
base['breastquad'].fillna(base['breastquad'].mode()[0], inplace=True)
base.isnull().sum()
              0
age
menopause
              0
tumorsize
              0
invnodes
              0
nodecaps
              0
              0
degmalig
breast
              0
breastquad
              0
irradiat
              0
Class
              0
dtype: int64
Separando os atributos de entrada e de classe
X prev = base.iloc[:, 0:9].values
X_prev_label = base.iloc[:, 0:9]
X prev label
       age menopause tumorsize invnodes nodecaps degmalig breast
breastquad \
     40-49
             premeno
                          15 - 19
                                      0-2
                                                            3 right
                                               yes
left up
     50-59
                                      0-2
                 ge40
                          15 - 19
                                                no
                                                               right
central
     50-59
                 ge40
                          35-39
                                      0-2
                                                            2
                                                                left
                                                no
```

left_low 3 40-49 left_low 4 40-49 right_up	premeno premeno	35-39 30-34	0-2 3-5	yes yes	3	right left
 281 50-59 left low	ge40	30-34	6-8	yes	2	left
282 50-59 left low	premeno	25-29	3-5	yes	2	left
283 30-39 right up	premeno	30-34	6-8	yes	2	right
284 50-59 left low	premeno	15-19	0-2	no	2	right
285 50-59 right_up	ge40	40 - 44	0-2	no	3	left

irradiat 0 no 1 no 2 no 3 yes 4 no 281 no 282 yes 283 no 284 no 285 no

[286 rows x 9 columns]

y_classe = base.iloc[:, 9].values
y_classe

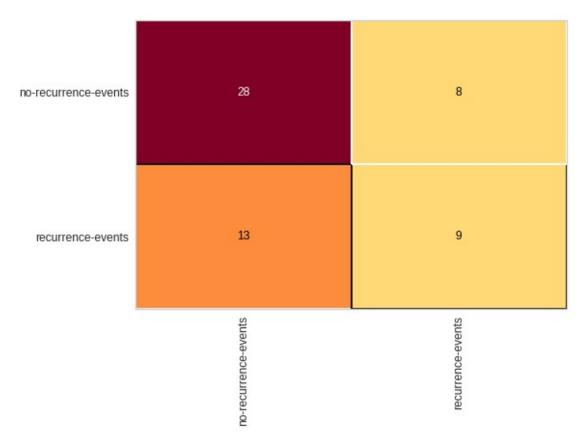
Tratamento de dados categóricos label_encoder = LabelEncoder()

X_prev_label

age	menopause	tumorsize	invnodes	nodecaps	degmalig	breast
breastquad 0 40-49	\ premeno	15-19	0-2	ves	3	right
left_up	•		0 2	, 03	3	J
1 50-59	ge40	15-19	0-2	no	1	right
central	a a 10	25 20	0.2		2	1 . 4 +
2 50-59	ge40	35-39	0-2	no	Z	left
left_low					_	
3 40-49	premeno	35-39	0-2	yes	3	right
left low						

```
40-49
                          30-34
                                     3-5
                                                           2
                                                               left
4
             premeno
                                               ves
right up
. .
                            . . .
                                      . . .
                                               . . .
                                                         . . .
                  . . .
. . .
281 50-59
                                                               left
                ge40
                          30-34
                                     6-8
                                                           2
                                               yes
left_low
282 50-59
             premeno
                          25-29
                                     3-5
                                                           2
                                                               left
                                               yes
left_low
283 30-39
             premeno
                          30-34
                                     6-8
                                                           2
                                                              right
                                               yes
right up
284 50-59
             premeno
                          15-19
                                     0-2
                                                           2
                                                              right
                                                no
left_low
285 50-59
                                                               left
                          40 - 44
                                     0-2
                                                           3
                ge40
                                                no
right up
    irradiat
0
          no
1
          no
2
          no
3
         yes
4
          no
         . . .
. .
281
          no
282
         yes
283
          no
284
          no
285
          no
[286 rows x 9 columns]
label encoder age = LabelEncoder()
label encoder menopause = LabelEncoder()
label encoder tumorsize = LabelEncoder()
label encoder invnodes = LabelEncoder()
label encoder nodecaps = LabelEncoder()
label encoder breast = LabelEncoder()
label_encoder_irradiat = LabelEncoder()
X prev[:,0] = label encoder age.fit transform(X prev[:,0])
X prev[:,1] = label encoder menopause.fit transform(X prev[:,1])
X prev[:,2] = label encoder tumorsize.fit transform(X prev[:,2])
X prev[:,3] = label encoder invnodes.fit transform(X prev[:,3])
X prev[:,4] = label encoder nodecaps.fit transform(X prev[:,4])
X prev[:,6] = label encoder breast.fit transform(X prev[:,6])
X prev[:,8] = label encoder irradiat.fit transform(X prev[:,8])
np.set printoptions(threshold=sys.maxsize)
X prev
```

```
Binarizar atributos não ordinais
onehotencoder base = ColumnTransformer(transformers=[('OneHot',
OneHotEncoder(), [7])], remainder='passthrough')
X_prev= onehotencoder_base.fit_transform(X_prev)
X prev
Método de amostragem Holdout
X_treino, X_teste, y_treino, y_teste = train_test_split(X_prev,
y classe, test size = 0.20, random state = 0)
y classe.shape
(286,)
X treino.shape
(228, 13)
X teste.shape
(58, 13)
Treinamento do modelo
Árvore de Decisão
AD X treino = X_treino
AD_y_treino = y_treino
AD X teste = X teste
AD_y_teste = y_teste
AD modelo = DecisionTreeClassifier(criterion='gini')
AD_modelo.fit(AD_X_treino, AD_y_treino)
DecisionTreeClassifier()
AD previsoes = AD modelo.predict(AD X teste)
accuracy score(AD y teste, AD previsoes)
0.6379310344827587
confusion_matrix(AD_y_teste, AD_previsoes)
array([[28,
             8],
       [13, 9]])
AD cm = ConfusionMatrix(AD modelo)
AD cm.fit(AD X treino, AD y treino)
AD_cm.score(AD_X_teste, AD_y_teste)
0.6379310344827587
```



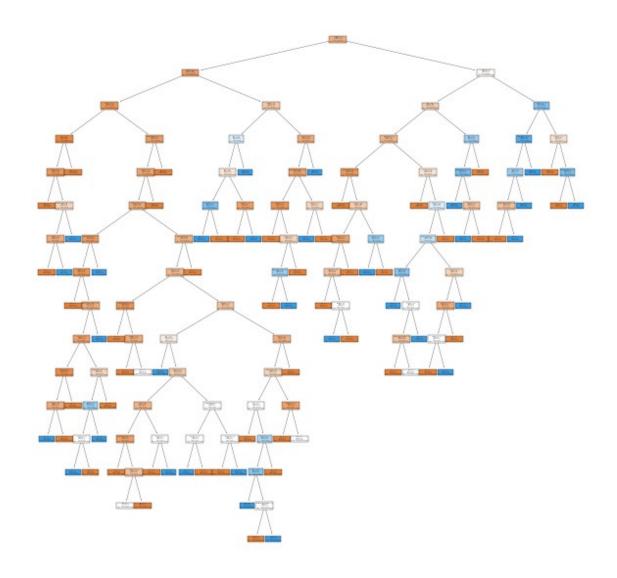
print(classification_report(AD_y_teste, AD_previsoes))

	precision	recall	f1-score	support
no-recurrence-events recurrence-events	0.68 0.53	0.78 0.41	0.73 0.46	36 22
accuracy macro avg weighted avg	0.61 0.62	0.59 0.64	0.64 0.59 0.63	58 58 58

```
AD_previsores = ['breastquadleftup', 'breastquadcentral',
'breastquadhleftlow', 'breastquadhrightup', 'breastquadhrightdown',
'age', 'menopause', 'tumorsize', 'invnodes', 'nodecaps', 'degmalig',
'breast', 'irradiat']
```

figura, eixos = plt.subplots(nrows=1, ncols=1, figsize=(10,10))

tree.plot_tree(AD_modelo, feature_names=AD_previsores, class_names =
AD_modelo.classes_, filled=True);



Naive Bayes

```
NB_X_treino = X_treino
NB_y_treino = y_treino

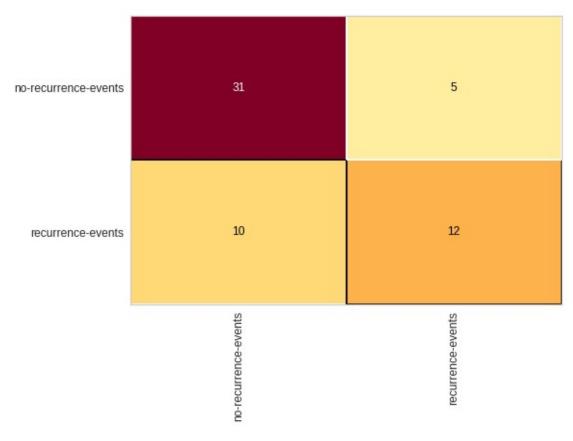
NB_X_teste = X_teste
NB_y_teste = y_teste

NB_modelo = GaussianNB()
NB_modelo.fit(X_treino, y_treino)

NB_previsoes = NB_modelo.predict(NB_X_teste)
accuracy_score(NB_y_teste, NB_previsoes)
0.7413793103448276
confusion_matrix(NB_y_teste, NB_previsoes)
```

NB_cm = ConfusionMatrix(NB_modelo)
NB_cm.fit(NB_X_treino, NB_y_treino)
NB_cm.score(NB_X_teste, NB_y_teste)

0.7413793103448276



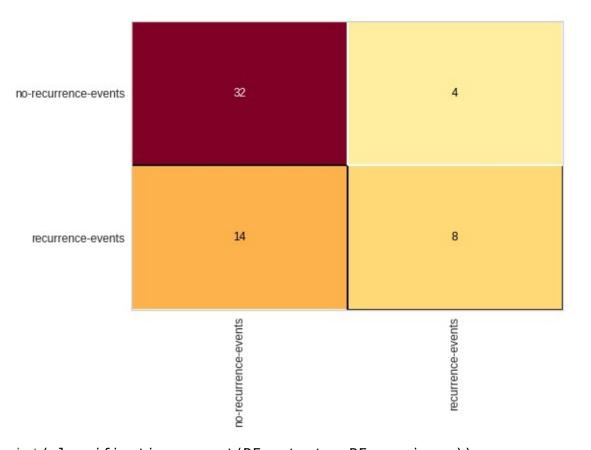
print(classification_report(NB_y_teste, NB_previsoes))

	precision	recall	f1-score	support
no-recurrence-events recurrence-events	0.76 0.71	0.86 0.55	0.81 0.62	36 22
accuracy macro avg weighted avg	0.73 0.74	0.70 0.74	0.74 0.71 0.73	58 58 58

Random Forest

RF_X_treino = X_treino RF_y_treino = y_treino

0.6896551724137931

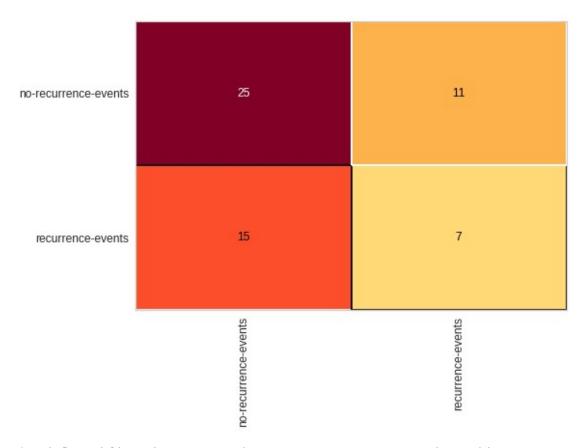


print(classification_report(RF_y_teste, RF_previsoes))

	precision	recall	f1-score	support		
no-recurrence-events recurrence-events	0.70 0.67	0.89 0.36		36 22		
accuracy macro avg weighted avg	0.68 0.68	0.63 0.69		58 58 58		
<pre>Treinamento com balancea balanceamento_under = X_under, y_under = ba y_treino)</pre>	TomekLinks(sampling_	strategy='a	auto')		
X_under.shape, y_unde	er.shape					
((213, 13), (213,))						
np.unique(y_treino, r	eturn_counts	=True)				
<pre>(array(['no-recurrence-events', 'recurrence-events'], dtype=object), array([165, 63]))</pre>						
np.unique(y_under, re	eturn_counts=	True)				
<pre>(array(['no-recurrenc array([150, 63]))</pre>	<pre>(array(['no-recurrence-events', 'recurrence-events'], dtype=object), array([150, 63]))</pre>					
Árvore de Decisão AD2_X_under = X_under AD2_y_under = y_under						
AD2_X_teste = X_teste AD2_y_teste = y_teste						
AD2_modelo = Decision AD2_modelo.fit(AD2_X_			ion='gini')			
DecisionTreeClassifie	er()					
AD2_previsoes = AD2_modelo.predict(AD2_X_teste)						
accuracy_score(AD2_y_teste, AD2_previsoes)						
0.5517241379310345						
<pre>confusion_matrix(AD2_</pre>	y_teste, AD2	_previsoe	s)			
array([[25, 11], [15, 7]])						

```
AD2_cm = ConfusionMatrix(AD2_modelo)
AD2_cm.fit(AD2_X_under, AD2_y_under)
AD2_cm.score(AD2_X_teste, AD2_y_teste)
```

0.5517241379310345



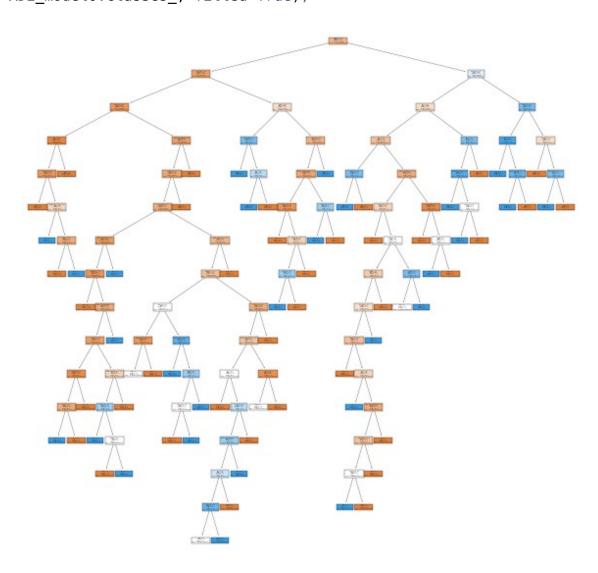
print(classification_report(AD2_y_teste, AD2_previsoes))

	precision	recall	f1-score	support
no-recurrence-events recurrence-events	0.62 0.39	0.69 0.32	0.66 0.35	36 22
accuracy macro avg weighted avg	0.51 0.54	0.51 0.55	0.55 0.50 0.54	58 58 58

```
AD2_previsores = ['breastquadleftup', 'breastquadcentral',
'breastquadhleftlow', 'breastquadhrightup', 'breastquadhrightdown',
'age', 'menopause', 'tumorsize', 'invnodes', 'nodecaps', 'degmalig',
'breast', 'irradiat']
```

figura, eixos = plt.subplots(nrows=1, ncols=1, figsize=(10,10))

tree.plot_tree(AD2_modelo, feature_names=AD2_previsores, class_names =
AD2_modelo.classes_, filled=True);



Naive Bayes

```
NB2_X_under = X_under
NB2_y_under = y_under

NB2_X_teste = X_teste
NB2_y_teste = y_teste

NB2_modelo = GaussianNB()
NB2_modelo.fit(NB2_X_under, NB2_y_under)

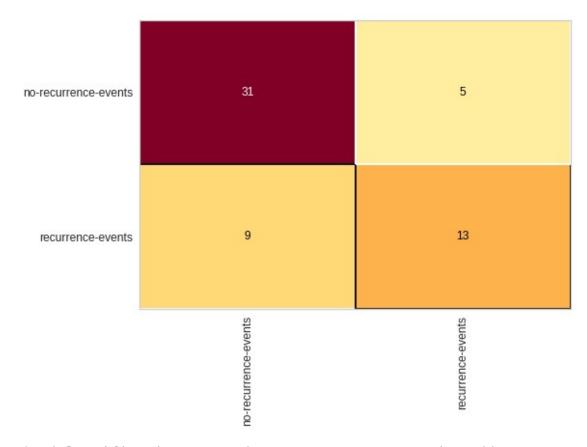
NB2_previsoes = NB2_modelo.predict(NB2_X_teste)
accuracy_score(NB2_y_teste,NB2_previsoes)
0.7586206896551724
```

confusion_matrix(NB2_y_teste, NB2_previsoes)

array([[31, 5], [9, 13]])

NB2_cm = ConfusionMatrix(NB2_modelo)
NB2_cm.fit(NB2_X_under, NB2_y_under)
NB2_cm.score(NB2_X_teste, NB2_y_teste)

0.7586206896551724



print(classification_report(NB2_y_teste, NB2_previsoes))

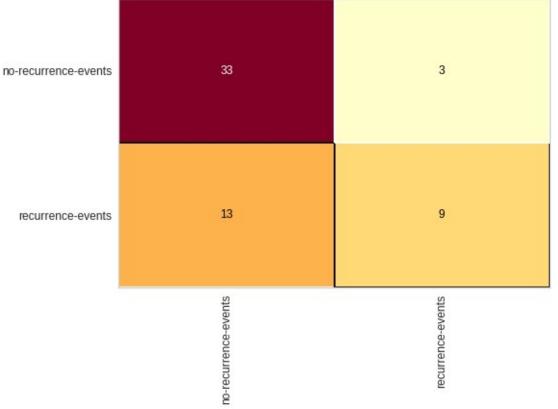
	precision	recall	f1-score	support
no-recurrence-events recurrence-events	0.78 0.72	0.86 0.59	0.82 0.65	36 22
accuracy macro avg weighted avg	0.75 0.75	0.73 0.76	0.76 0.73 0.75	58 58 58

Random Forest

RF2_X_under = X_under RF2_y_under = y_under

```
RF2_X_{teste} = X_{teste}
RF2_y_teste = y_teste
RF2 modelo = RandomForestClassifier(n estimators=100, max features=6,
criterion='gini', random_state = 0)
RF2_modelo.fit(RF2_X_under, RF2_y_under)
RF2_previsoes = RF2_modelo.predict(RF2_X_teste)
accuracy_score(RF2_y_teste, RF2_previsoes)
0.7241379310344828
confusion_matrix(RF2_y_teste, RF2_previsoes)
array([[33,
             3],
       [13,
             9]])
RF2_cm = ConfusionMatrix(RF2_modelo)
RF2_cm.fit(RF2_X_under, RF2_y_under)
RF2_cm.score(RF2_X_teste, RF2_y_teste)
0.7241379310344828
```

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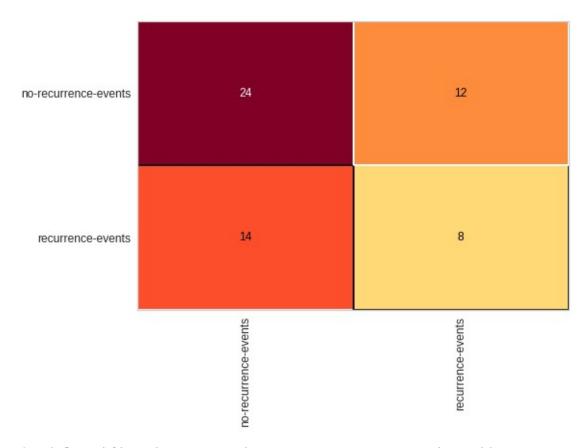
print(classification_report(RF2_y_teste, RF2_previsoes))

	precision	recall	f1-score	support
no-recurrence-events recurrence-events	0.72 0.75	0.92 0.41	0.80 0.53	36 22
accuracy macro avg weighted avg	0.73 0.73	0.66 0.72	0.72 0.67 0.70	58 58 58

```
Treinamento com balanceamento de dados usando o método oversampling
# Randomly over sample the minority class
balanceamento over = SMOTE(sampling strategy = 'auto')
X over, y over = balanceamento over.fit resample(X treino, y treino)
X over.shape, y over.shape
((330, 13), (330,))
np.unique(y treino, return counts=True)
(array(['no-recurrence-events', 'recurrence-events'], dtype=object),
array([165, 63]))
np.unique(y over, return counts=True)
(array(['no-recurrence-events', 'recurrence-events'], dtype=object),
array([165, 165]))
Árvore de Decisão
AD3 X over = X over
AD3 y over = y over
AD3 X teste = X teste
AD3_y_teste = y_teste
AD3 modelo = DecisionTreeClassifier(criterion = 'gini')
AD3 modelo.fit(AD3 X over, AD3 y over)
DecisionTreeClassifier()
AD3 previsoes = AD3 modelo.predict(AD3 X teste)
accuracy_score(AD3_y_teste, AD3_previsoes)
0.5517241379310345
confusion_matrix(AD3_y_teste, AD3_previsoes)
array([[24, 12],
       [14, 8]])
```

```
AD3_cm = ConfusionMatrix(AD3_modelo)
AD3_cm.fit(AD3_X_over, AD3_y_over)
AD3_cm.score(AD3_X_teste, AD3_y_teste)
```

0.5517241379310345



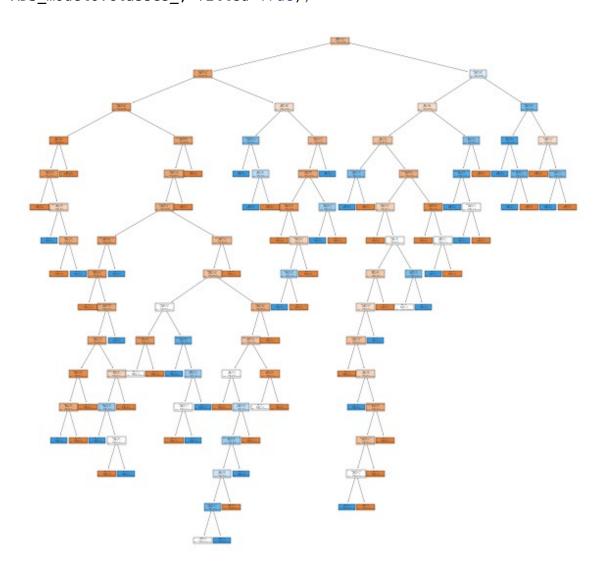
print(classification_report(AD3_y_teste, AD3_previsoes))

	precision	recall	f1-score	support
no-recurrence-events recurrence-events	0.63 0.40	0.67 0.36	0.65 0.38	36 22
accuracy macro avg weighted avg	0.52 0.54	0.52 0.55	0.55 0.51 0.55	58 58 58

```
AD3_previsores = ['breastquadleftup', 'breastquadcentral',
'breastquadhleftlow', 'breastquadhrightup', 'breastquadhrightdown',
'age', 'menopause', 'tumorsize', 'invnodes', 'nodecaps', 'degmalig',
'breast', 'irradiat']
```

figura, eixos = plt.subplots(nrows=1, ncols=1, figsize=(10,10))

tree.plot_tree(AD2_modelo, feature_names=AD3_previsores, class_names =
AD3_modelo.classes_, filled=True);



Naive Bayes

```
NB3_X_over = X_over
NB3_y_over = y_over

NB3_X_teste = X_teste
NB3_y_teste = y_teste

NB3_modelo = GaussianNB()
NB3_modelo.fit(NB3_X_over, NB3_y_over)

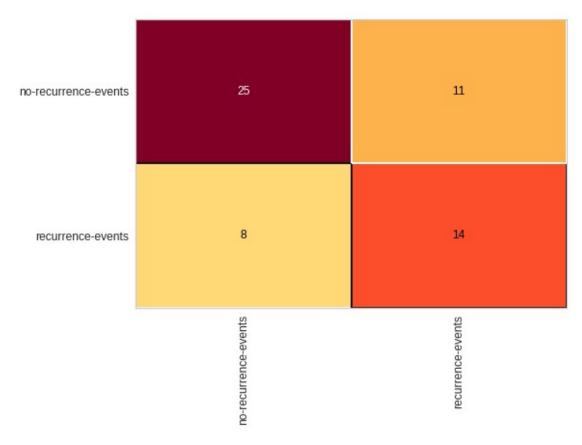
NB3_previsoes = NB3_modelo.predict(NB3_X_teste)
accuracy_score(NB3_y_teste,NB3_previsoes)
0.6724137931034483
```

 ${\tt confusion_matrix(NB3_y_teste, NB3_previsoes)}$

array([[25, 11], [8, 14]])

NB3_cm = ConfusionMatrix(NB3_modelo)
NB3_cm.fit(NB3_X_over, NB3_y_over)
NB3_cm.score(NB3_X_teste, NB3_y_teste)

0.6724137931034483



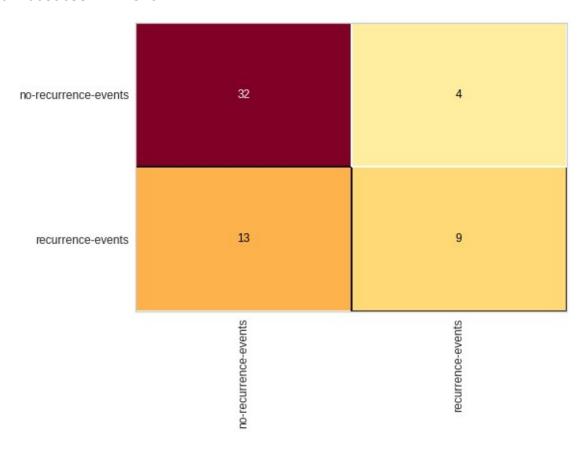
print(classification_report(NB3_y_teste, NB3_previsoes))

	precision	recall	f1-score	support
no-recurrence-events recurrence-events	0.76 0.56	0.69 0.64	0.72 0.60	36 22
accuracy macro avg weighted avg	0.66 0.68	0.67 0.67	0.67 0.66 0.68	58 58 58

Random Forest

RF3_X_over = X_over RF3_y_over = y_over

```
RF3_X_{teste} = X_{teste}
RF3_y_teste = y_teste
RF3 modelo = RandomForestClassifier(n estimators=100, max features=6,
criterion='gini', random_state = 0)
RF3_modelo.fit(RF3_X_over, RF3_y_over)
RF3_previsoes = RF3_modelo.predict(RF3_X_teste)
accuracy_score(RF3_y_teste, RF3_previsoes)
0.7068965517241379
confusion_matrix(RF2_y_teste, RF2_previsoes)
array([[33,
             3],
       [13,
             9]])
RF3_cm = ConfusionMatrix(RF3_modelo)
RF3_cm.fit(RF3_X_over, RF3_y_over)
RF3_cm.score(RF3_X_teste, RF3_y_teste)
0.7068965517241379
```



print(classification_report(RF3_y_teste, RF3_previsoes))

	precision	recall	f1-score	support
no-recurrence-events recurrence-events	0.71 0.69	0.89 0.41	0.79 0.51	36 22
accuracy macro avg weighted avg	0.70 0.70	0.65 0.71	0.71 0.65 0.69	58 58 58