

Prova de conceito utilizando o dataset construído pelo grupo

```
1 import pandas as pd
2
3 dados2 = pd.read_csv("Frases TCC.csv", sep=",")
```

```
1 dados = dados2.dropna()
```

```
1 dados
```

	Frase	Indica violência
0	Vou te matar	Sim
1	Eu vou te matar	Sim
2	Eu te mato	Sim
3	Vô te matar	Sim
4	Te mato	Sim
...	...	...
231	Morreu minha planta	Não
232	Mataram as abelhas	Não
233	Matei o pernilongo	Não
234	Morrendo de fome	Não
235	Morto de fome	Não

236 rows × 2 columns

```
1 classificacao = dados["Indica violência"].replace(["Não","Sim"],[0,1])
```

```
1 dados["classificacao"]=classificacao
```

```
1 dados.groupby('classificacao').count()
```

	Frase	Indica violência
classificacao		
0	174	174
1	62	62

```
1 import nltk
2 from nltk import tokenize
3
4 nltk.download('stopwords')
5
6 token_espaco = tokenize.WhitespaceTokenizer()
7
8 token_pontuacao = tokenize.WordPunctTokenizer()

[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
```

```
1 palavras_irrelevantes = nltk.corpus.stopwords.words("portuguese")
2
3 from string import punctuation
4
5 pontuacao = list()
6 for ponto in punctuation:
7     pontuacao.append(ponto)
8
9 pontuacao_stopwords = pontuacao + palavras_irrelevantes
10
11 frase_processada = list()
12 for texto in dados.Frase:
13     nova_frase = list()
14     texto = texto.lower()
15     palavras_texto = token_espaco.tokenize(texto)
16     for palavra in palavras_texto:
17         if '@' not in palavra:
18             if palavra not in pontuacao_stopwords:
19                 nova_frase.append(palavra)
20     frase_processada.append(' '.join(nova_frase))
21
22 dados["tratamento_1"] = frase_processada
```

```
1 dados.head()
```

	Frase	Indica violência	classificacao	tratamento_1
0	Vou te matar	Sim	1	vou matar
1	Eu vou te matar	Sim	1	vou matar
2	Eu te mato	Sim	1	mato
3	Vô te matar	Sim	1	vô matar
4	Te mato	Sim	1	mato

```
1 !pip install unicode
2
3 import unicode
4
5 sem_acentos = [unicode.unidecode(texto) for texto in dados["tratamento_1"]]
```

Collecting unicode  
 Downloading <https://files.pythonhosted.org/packages/d0/42/d9edfed04228bacea2d824904cae367ee9efd05e6cce7ceaaedd0b0ad964/Unidecode-1.1.1-py2.py3-none-any.whl> (238kB)  
 |██| 245kB 6.1MB/s  
Installing collected packages: unicode  
Successfully installed unidecode-1.1.1

```
1 dados["tratamento_2"] = sem_acentos
```

```
1 dados[ 'tratamento_2' ] = sem_acentos
```

```
1 dados.head()
```

	Frase	Indica violência	classificacao	tratamento_1	tratamento_2
0	Vou te matar	Sim	1	vou matar	vou matar
1	Eu vou te matar	Sim	1	vou matar	vou matar
2	Eu te mato	Sim	1	mato	mato
3	Vô te matar	Sim	1	vô matar	vo matar
4	Te mato	Sim	1	mato	mato

```
1 nltk.download('rslp')
```

```
[nltk_data] Downloading package rslp to /root/nltk_data...
[nltk_data]   Unzipping stemmers/rslp.zip.
True
```

```
1 stopwords_sem_acento = [unicode.unidecode(texto) for texto in pontuacao_stopwords]
```

```
1 stemer = nltk.RSLPStemmer()
2
3 frase_processada = list()
4 for tweet in dados["tratamento_2"]:
5     nova_frase = list()
6     palavras_texto = token_pontuacao.tokenize(tweet)
7     for palavra in palavras_texto:
8         if palavra not in stopwords_sem_acento:
9             nova_frase.append(stemer.stem(palavra))
10    frase_processada.append(' '.join(nova_frase))
11
12 dados["tratamento_3"] = frase_processada
```

```
1 dados
```

	Frase	Indica violência	classificacao	tratamento_1	tratamento_2	tratamento_3
0	Vou te matar	Sim	1	vou matar	vou matar	vou mat
1	Eu vou te matar	Sim	1	vou matar	vou matar	vou mat
2	Eu te mato	Sim	1	mato	mato	mat
3	Vô te matar	Sim	1	vô matar	vo matar	vo mat
4	Te mato	Sim	1	mato	mato	mat
...	...	...	...	...	...	...
231	Morreu minha planta	Não	0	morreu planta	morreu planta	morr plant
232	Mataram as abelhas	Não	0	mataram abelhas	mataram abelhas	mat abelh
233	Matei o pernilongo	Não	0	matei pernilongo	matei pernilongo	mat pernilong
234	Morrendo de fome	Não	0	morrendo fome	morrendo fome	morr fom
235	Morto de fome	Não	0	morto fome	morto fome	mort fom

236 rows × 6 columns

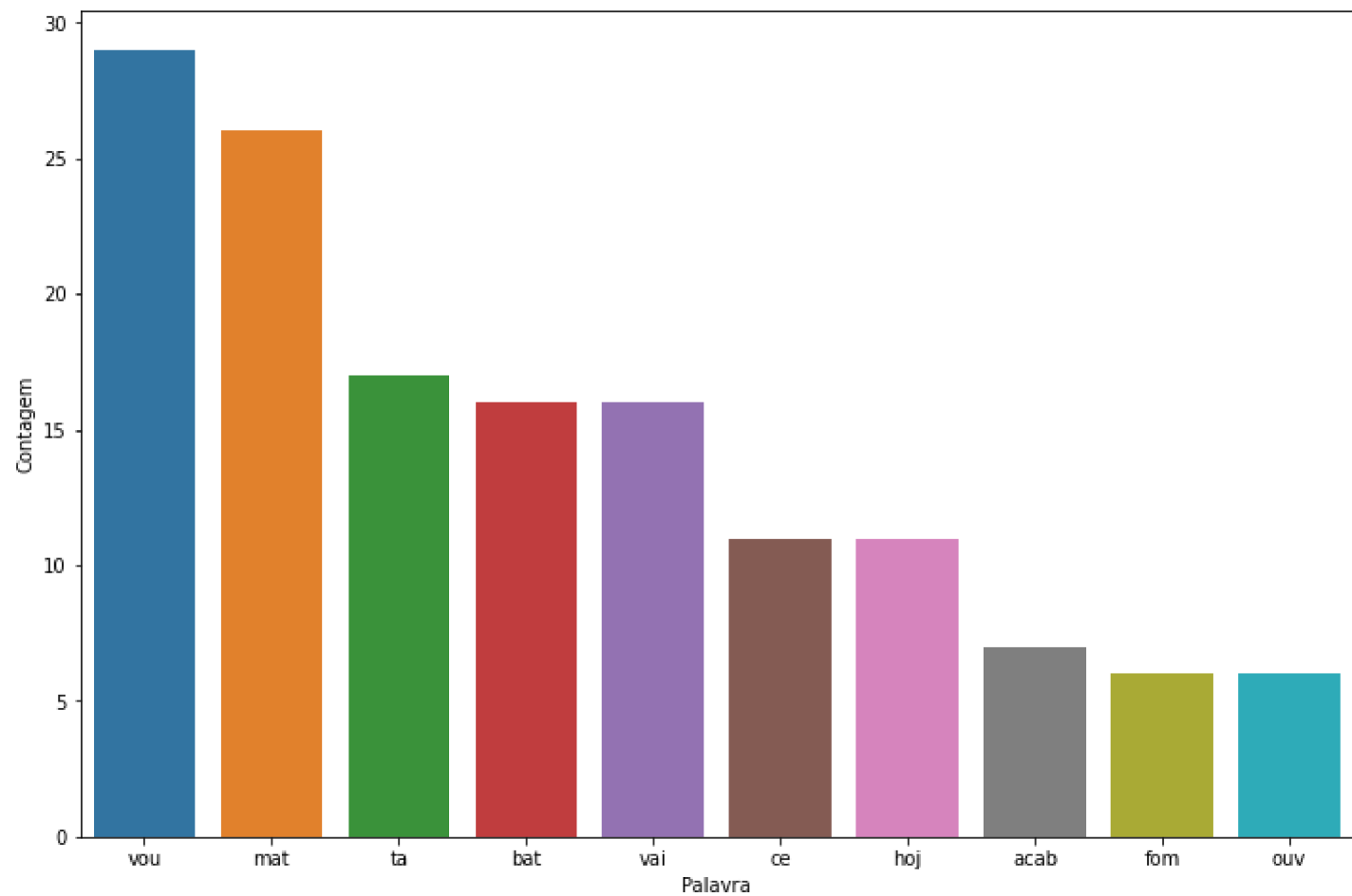
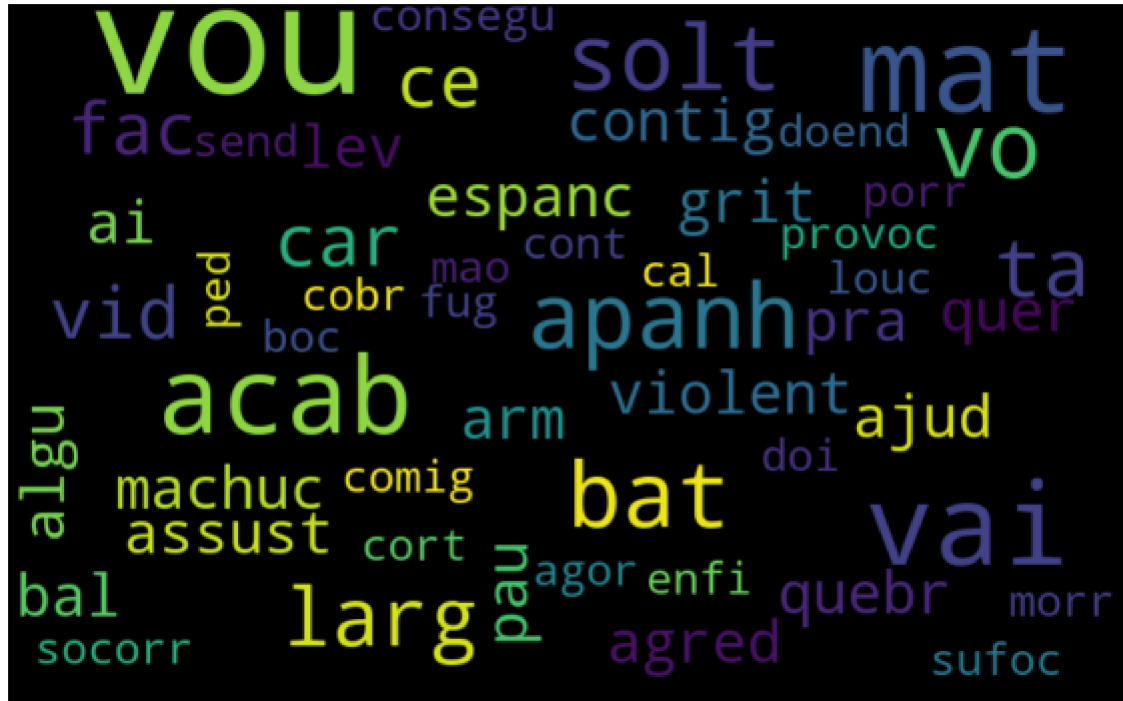
```
1 import matplotlib.pyplot as plt
2 from wordcloud import WordCloud
3 import seaborn as sns

1 def nuvem_palavras_neg(texto, coluna_texto):
2     texto_negativo = texto.query("classificacao == '0'")
3     todas_palavras = ' '.join([texto for texto in texto_negativo[coluna_texto]])
4
5     nuvem_palavras = WordCloud(width=800, height=500, max_font_size=110, collocations=False).generate(todas_palavras)
6
7     plt.figure(figsize=(10,7))
8     plt.imshow(nuvem_palavras, interpolation='bilinear')
9     plt.axis("off")
10    plt.show()
```

```
1 def nuvem_palavras_pos(texto, coluna_texto):
2     texto_positivo = texto.query("classificacao == '1'")
3     todas_palavras = ' '.join([texto for texto in texto_positivo[coluna_texto]])
4
5     nuvem_palavras = WordCloud(width=800, height=500, max_font_size=110, collocations=False).generate(todas_palavras)
6
7     plt.figure(figsize=(10,7))
8     plt.imshow(nuvem_palavras, interpolation='bilinear')
9     plt.axis("off")
10    plt.show()
```

```
1 def pareto(texto, coluna_texto, quantidade):
2     todas_palavras = ' '.join([texto for texto in texto[coluna_texto]])
3
4     token_frase = token_espaco.tokenize(todas_palavras)
5     frequencia = nltk.FreqDist(token_frase)
6     df_frequencia = pd.DataFrame({"Palavra":list(frequencia.keys()),"Frequência":list(frequencia.values())})
7     df_frequencia = df_frequencia.nlargest(quantidade, "Frequência")
8     plt.figure(figsize=(12,8))
9     ax = sns.barplot(data= df_frequencia, x = "Palavra", y = "Frequência")
10    ax.set(ylabel= "Contagem")
11    plt.show()
```

```
1 nuvem_palavras_neg(dados, "tratamento_3")
```



```

1 def trata_frase(frase):
2     frase_tratada = list()
3     nova_frase = list()
4     frase = frase.lower()
5     palavras_texto = token_espaço.tokenize(frase)
6     for palavra in palavras_texto:
7         if '@' not in palavra:
8             if palavra not in pontuacao_stopwords:
9                 nova_frase.append(stemmer.stem(palavra))
10    frase_tratada.append(' '.join(nova_frase))
11    frase_tratada = [unicode.unidecode(frase) for frase in frase_tratada]
12
13    return frase_tratada

```

```
1 resultados = pd.DataFrame(columns=['Classificador',
2                                     'Acurácia',
3                                     'Precisão [0]',
4                                     'Precisão [1]',
5                                     'Recall [0]',
6                                     'Recall [1]',
7                                     'Fscore [0]',
8                                     'Fscore [1]',
9                                     'Support [0]',
10                                    'Support [1]',
11                                    ])
```

```

1 from sklearn.feature_extraction.text import TfidfVectorizer
2
3 from sklearn.linear_model import LogisticRegression
4
5 from sklearn.model_selection import train_test_split
6
7 from sklearn.metrics import accuracy_score, f1_score, precision_score, recall_score
8
9 from sklearn.metrics import precision_recall_fscore_support as score
10
11 tfidf1 = TfidfVectorizer(lowercase=False, ngram_range=(1,2))
12
13 tfidf2 = tfidf1.fit_transform(dados["tratamento_3"])
14 treino, teste, classe_treino, classe_teste = train_test_split(tfidf2, dados["classificacao"], random_state=42)
15 classificador = LogisticRegression(random_state=0, solver='lbfgs', class_weight='balanced')
16 classificador.fit(treino, classe_treino)
17 acuracia = classificador.score(teste, classe_teste)
18
19 precision, recall, fscore, support = score(classificador.predict(teste[:]), classe_teste)
20
21 resultados = resultados.append({
22     'Classificador': 'LogisticRegression',
23     'Acurácia': acuracia,

```

```
23         'Recall [0]': recall[0],
24         'Precisão [0]': precision[0],
25         'Precisão [1]': precision[1],
26         'Recall [0]': recall[0],
27         'Recall [1]': recall[1],
28         'Fscore [0]': fscore[0],
29         'Fscore [1]': fscore[1],
30         'Support [0]': support[0],
31         'Support [1]': support[1]
32     }, ignore_index=True)
33
34     print('accuracy: {}'.format(acuracia))
35     print('precision: {}'.format(precision))
36     print('recall: {}'.format(recall))
37     print('fscore: {}'.format(fscore))
38     print('support: {}'.format(support))
39
40     accuracy: 0.8305084745762712
41     precision: [0.91304348 0.53846154]
42     recall: [0.875      0.63636364]
43     fscore: [0.89361702 0.58333333]
44     support: [48 11]
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```
2
3 from sklearn.linear_model import PassiveAggressiveClassifier
4
5 from sklearn.model_selection import train_test_split
6
7 from sklearn.metrics import accuracy_score, f1_score, precision_score, recall_score
8
9 from sklearn.metrics import precision_recall_fscore_support as score
10
11 tfidf1 = TfidfVectorizer(lowercase=False,ngram_range=(1,2))
12
13 tfidf2 = tfidf1.fit_transform(dados["tratamento_3"])
14 treino, teste, classe_treino, classe_teste = train_test_split(tfidf2, dados["classificacao"], random_state=42)
15 classificador = PassiveAggressiveClassifier(max_iter=1000, random_state=0, tol=1e-3)
16 classificador.fit(treino, classe_treino)
17 acuracia = classificador.score(teste, classe_teste)
18
19 precision, recall, fscore, support = score(classificador.predict(teste[:]), classe_teste)
20
21 resultados = resultados.append({
22     'Classificador': 'PassiveAggressiveClassifier',
23     'Acurácia': acuracia,
24     'Precisão [0]': precision[0],
25     'Precisão [1]': precision[1],
26     'Recall [0]': recall[0],
27     'Recall [1]': recall[1],
28     'Fscore [0]': fscore[0],
29     'Fscore [1]': fscore[1],
30     'Support [0]': support[0],
31     'Support [1]': support[1]
32 }, ignore_index=True)
33
34 print('accuracy: {}'.format(acuracia))
35 print('precision: {}'.format(precision))
36 print('recall: {}'.format(recall))
37 print('fscore: {}'.format(fscore))
38 print('support: {}'.format(support))
39
40 accuracy: 0.8135593220338984
41 precision: [0.84782609 0.69230769]
42 recall: [0.90697674 0.5625      ]
43 fscore: [0.87640449 0.62068966]
44 support: [43 16]
```

```
1 from sklearn.feature_extraction.text import TfidfVectorizer
2
3 from sklearn.neural_network import MLPClassifier
4
5 from sklearn.model_selection import train_test_split
6
7 from sklearn.metrics import accuracy_score, f1_score, precision_score, recall_score
8
9 from sklearn.metrics import precision_recall_fscore_support as score
10
11 tfidf1 = TfidfVectorizer(lowercase=False,ngram_range=(1,2))
12
13 tfidf2 = tfidf1.fit_transform(dados["tratamento_3"])
14 treino, teste, classe_treino, classe_teste = train_test_split(tfidf2, dados["classificacao"], random_state=42)
15 classificador = MLPClassifier(alpha=1, max_iter=1000, solver='lbfgs', random_state=0)
16 classificador.fit(treino, classe_treino)
17 acuracia = classificador.score(teste, classe_teste)
18
19 precision, recall, fscore, support = score(classificador.predict(teste[:]), classe_teste)
20
21 resultados = resultados.append({
22     'Classificador': 'MLPClassifier',
23     'Acurácia': acuracia,
24     'Precisão [0]': precision[0],
25     'Precisão [1]': precision[1],
26     'Recall [0]': recall[0],
27     'Recall [1]': recall[1],
28     'Fscore [0]': fscore[0],
29     'Fscore [1]': fscore[1],
30     'Support [0]': support[0],
31     'Support [1]': support[1]
32 }, ignore_index=True)
33
34 print('accuracy: {}'.format(acuracia))
35 print('precision: {}'.format(precision))
36 print('recall: {}'.format(recall))
37 print('fscore: {}'.format(fscore))
38 print('support: {}'.format(support))
39
40 accuracy: 0.847457627118644
41 precision: [0.97826087 0.38461538]
42 recall: [0.8490566  0.83333333]
43 fscore: [0.90909091 0.52631579]
44 support: [53  6]
```

```
1 from sklearn.feature_extraction.text import TfidfVectorizer
2
3 from sklearn.neighbors import KNeighborsClassifier
4
5 from sklearn.model_selection import train_test_split
6
7 from sklearn.metrics import accuracy_score, f1_score, precision_score, recall_score
8
9 from sklearn.metrics import precision_recall_fscore_support as score
10
11 tfidf1 = TfidfVectorizer(lowercase=False,ngram_range=(1,2))
12
13 tfidf2 = tfidf1.fit_transform(dados["tratamento_3"])
14 treino, teste, classe_treino, classe_teste = train_test_split(tfidf2, dados["classificacao"], random_state=42)
15 classificador = KNeighborsClassifier(19)
16 classificador.fit(treino, classe_treino)
17 acuracia = classificador.score(teste, classe_teste)
18
19 precision, recall, fscore, support = score(classificador.predict(teste[:]), classe_teste)
20
21 resultados = resultados.append({
22     'Classificador': 'KNeighborsClassifier',
23     'Acurácia': acuracia,
24     'Precisão [0]': precision[0],
25     'Precisão [1]': precision[1],
26     'Recall [0]': recall[0],
27     'Recall [1]': recall[1],
28     'Fscore [0]': fscore[0],
29     'Fscore [1]': fscore[1],
30     'Support [0]': support[0],
31     'Support [1]': support[1]
32 }, ignore_index=True)
33
34 print('accuracy: {}'.format(acuracia))
35 print('precision: {}'.format(precision))
36 print('recall: {}'.format(recall))
37 print('fscore: {}'.format(fscore))
38 print('support: {}'.format(support))
39
40 accuracy: 0.847457627118644
41 precision: [0.97826087 0.38461538]
42 recall: [0.8490566  0.83333333]
43 fscore: [0.90909091 0.52631579]
44 support: [53  6]
```

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26         recall [0] : recall[0],
27         'Recall [1]': recall[1],
28         'Fscore [0]': fscore[0],
29         'Fscore [1]': fscore[1],
30         'Support [0]': support[0],
31         'Support [1]': support[1]
32     }, ignore_index=True)
33
34     print('accuracy: {}'.format(acuracia))
35     print('precision: {}'.format(precision))
36     print('recall: {}'.format(recall))
37     print('fscore: {}'.format(fscore))
38     print('support: {}'.format(support))
39
40     accuracy: 0.8135593220338984
41     precision: [0.95652174 0.30769231]
42     recall: [0.83018868 0.66666667]
43     fscore: [0.88888889 0.42105263]
44     support: [53  6]
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```
3 from sklearn.tree import DecisionTreeClassifier
4
5 from sklearn.model_selection import train_test_split
6
7 from sklearn.metrics import accuracy_score, f1_score, precision_score, recall_score
8
9 from sklearn.metrics import precision_recall_fscore_support as score
10
11 tfidf1 = TfidfVectorizer(lowercase=False,ngram_range=(1,2))
12
13 tfidf2 = tfidf1.fit_transform(dados["tratamento_3"])
14 treino, teste, classe_treino, classe_teste = train_test_split(tfidf2, dados["classificacao"], random_state=42)
15 classificador = DecisionTreeClassifier(random_state=0)
16 classificador.fit(treino, classe_treino)
17 acuracia = classificador.score(teste, classe_teste)
18
19 precision, recall, fscore, support = score(classificador.predict(teste[:]), classe_teste)
20
21 resultados = resultados.append({
22     'Classificador': 'DecisionTreeClassifier',
23     'Acurácia': acuracia,
24     'Precisão [0]': precision[0],
25     'Precisão [1]': precision[1],
26     'Recall [0]': recall[0],
27     'Recall [1]': recall[1],
28     'Fscore [0]': fscore[0],
29     'Fscore [1]': fscore[1],
30     'Support [0]': support[0],
31     'Support [1]': support[1]
32 }, ignore_index=True)
33
34 print('accuracy: {}'.format(acuracia))
35 print('precision: {}'.format(precision))
36 print('recall: {}'.format(recall))
37 print('fscore: {}'.format(fscore))
38 print('support: {}'.format(support))
39
40 accuracy: 0.847457627118644
41 precision: [0.93478261 0.53846154]
42 recall: [0.87755102 0.7      ]
43 fscore: [0.90526316 0.60869565]
44 support: [49 10]
```

```
1 from sklearn.feature_extraction.text import TfidfVectorizer
2
3 from sklearn.ensemble import RandomForestClassifier
4
5 from sklearn.model_selection import train_test_split
6
7 from sklearn.metrics import accuracy_score, f1_score, precision_score, recall_score
8
9 from sklearn.metrics import precision_recall_fscore_support as score
10
11 tfidf1 = TfidfVectorizer(lowercase=False,ngram_range=(1,2))
12
13 tfidf2 = tfidf1.fit_transform(dados["tratamento_3"])
14 treino, teste, classe_treino, classe_teste = train_test_split(tfidf2, dados["classificacao"], random_state=42)
15 classificador = RandomForestClassifier(n_estimators=25, random_state=0)
16 classificador.fit(treino, classe_treino)
17 acuracia = classificador.score(teste, classe_teste)
18
19 precision, recall, fscore, support = score(classificador.predict(teste[:]), classe_teste)
20
21 resultados = resultados.append({
22     'Classificador': 'RandomForestClassifier',
23     'Acurácia': acuracia,
24     'Precisão [0]': precision[0],
25     'Precisão [1]': precision[1],
26     'Recall [0]': recall[0],
27     'Recall [1]': recall[1],
28     'Fscore [0]': fscore[0],
29     'Fscore [1]': fscore[1],
30     'Support [0]': support[0],
31     'Support [1]': support[1]
32 }, ignore_index=True)
33
34 print('accuracy: {}'.format(acuracia))
35 print('precision: {}'.format(precision))
36 print('recall: {}'.format(recall))
37 print('fscore: {}'.format(fscore))
38 print('support: {}'.format(support))
39
40 accuracy: 0.8305084745762712
41 precision: [0.97826087 0.30769231]
42 recall: [0.83333333 0.8      ]
43 fscore: [0.9      0.44444444]
44 support: [54  5]
```

```
1 from sklearn.feature_extraction.text import TfidfVectorizer
2
3 from sklearn.ensemble import AdaBoostClassifier
4
5 from sklearn.model_selection import train_test_split
6
7 from sklearn.metrics import accuracy_score, f1_score, precision_score, recall_score
8
9 from sklearn.metrics import precision_recall_fscore_support as score
10
11 tfidf1 = TfidfVectorizer(lowercase=False,ngram_range=(1,2))
12
13 tfidf2 = tfidf1.fit_transform(dados["tratamento_3"])
14 treino, teste, classe_treino, classe_teste = train_test_split(tfidf2, dados["classificacao"], random_state=42)
15 classificador = AdaBoostClassifier(n_estimators=20, random_state=0)
16 classificador.fit(treino, classe_treino)
17 acuracia = classificador.score(teste, classe_teste)
18
19 precision, recall, fscore, support = score(classificador.predict(teste[:]), classe_teste)
20
21 resultados = resultados.append({
22     'Classificador': 'AdaBoostClassifier',
23     'Acurácia': acuracia,
24     'Precisão [0]': precision[0],
25     'Precisão [1]': precision[1],
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26         'Recall [0]': recall[0],
27         'Recall [1]': recall[1],
28         'Fscore [0]': fscore[0],
29         'Fscore [1]': fscore[1],
30         'Support [0]': support[0],
31         'Support [1]': support[1]
32     }, ignore_index=True)
33
34     print('accuracy: {}'.format(acuracia))
35     print('precision: {}'.format(precision))
36     print('recall: {}'.format(recall))
37     print('fscore: {}'.format(fscore))
38     print('support: {}'.format(support))
39
40     accuracy: 0.8305084745762712
41     precision: [0.93478261 0.46153846]
42     recall: [0.86         0.66666667]
43     fscore: [0.89583333 0.54545455]
44     support: [50  9]
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	Classificador	Acurácia	Precisão [0]	Precisão [1]	Recall [0]	Recall [1]	Fscore [0]	Fscore [1]	Support [0]	Support [1]
0	LogisticRegression	0.830508	0.913043	0.538462	0.875000	0.636364	0.893617	0.583333	48	11
1	SGDClassifier	0.915254	0.978261	0.692308	0.918367	0.900000	0.947368	0.782609	49	10
2	Perceptron	0.762712	0.760870	0.769231	0.921053	0.476190	0.833333	0.588235	38	21
3	PassiveAggressiveClassifier	0.813559	0.847826	0.692308	0.906977	0.562500	0.876404	0.620690	43	16
4	MLPClassifier	0.847458	0.978261	0.384615	0.849057	0.833333	0.909091	0.526316	53	6
5	KNeighborsClassifier	0.813559	0.956522	0.307692	0.830189	0.666667	0.888889	0.421053	53	6
6	SVC	0.847458	1.000000	0.307692	0.836364	1.000000	0.910891	0.470588	55	4
7	GaussianProcessClassifier	0.864407	1.000000	0.384615	0.851852	1.000000	0.920000	0.555556	54	5
8	DecisionTreeClassifier	0.847458	0.934783	0.538462	0.877551	0.700000	0.905263	0.608696	49	10
9	RandomForestClassifier	0.830508	0.978261	0.307692	0.833333	0.800000	0.900000	0.444444	54	5
10	AdaBoostClassifier	0.830508	0.934783	0.461538	0.860000	0.666667	0.895833	0.545455	50	9
11	GaussianNB	0.627119	0.586957	0.769231	0.900000	0.344828	0.710526	0.476190	30	29
12	QuadraticDiscriminantAnalysis	0.372881	0.282609	0.692308	0.764706	0.214286	0.412698	0.327273	17	42

```
1 resultados.to_excel("classificadores.xlsx")
```

```
1 import pickle
2 pickle.dump(classificador, open('modelo.sav', 'wb'))
3 pickle.dump(tfidf1, open("vectorizer.pickle", "wb"))
```

```
1
```