Aula 11 - Exercício prático PLN

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1 Considere o seguinte arquivo textual:

20 Newsgroups Dataset

1.1 Escolha 2 tópicos dentre os 20 disponíveis no dataset e faça download dos mesmos.

[ ]:
```
!pip install nltk
```

[1]:
```
import pandas as pd
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import MultinomialNB
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
import nltk
from nltk.corpus import stopwords
nltk.download('stopwords')

import pandas as pd

def read_data(file_path, label):
    with open(file_path, 'r', encoding='utf-8', errors='ignore') as file:
        lines = file.readlines()

    # Criar o DataFrame com cada linha como um documento
    data = pd.DataFrame({'text': lines, 'label': [label] * len(lines)})
    return data



# Concatenar os datasets
data_space = read_data('sci.space.txt', 1)
data_atheism = read_data('alt.atheism.txt', 2)
data = pd.concat([data_space, data_atheism])
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\ealbvit\AppData\Roaming\nltk_data…
[nltk_data]   Package stopwords is already up-to-date!
```

1.2 Gere um Bag of words: Leia o texto e armazene cada palavra em uma posição em um vetor. Faça a contagem da frequência de cada palavra gerando uma matriz termo-frequência. Na última coluna armazene o rótulo do texto ('1' = textos do tópico 1 e '2' = textos do tópico 2)

Story	based	premise	congress	...	work	versions	make	sure	Rótulo
1	2	0	3	...	0	0	0	0	1
0	0	0	0	...	1	5	0	1	2
...	...	...	...	...	...	...	...	...	...

1.3 Remova os stop words (palavras irrelevantes):

Stop Words List

[2]:
```python
# Bag of Words com remoção de stop words
vectorizer = CountVectorizer(stop_words=stopwords.words('english'))
X = vectorizer.fit_transform(data['text'])  # Acessando a coluna de texto pelo␣
 ↪nome
y = data['label']
```

1.4 Escolha dois algoritmos de classificação vistos anteriormente (knn, naive bayes, árvore de decisão, svm, etc) e classifique os textos (separar 70% para treino e 30% para teste). Anexar a saída e % de acerto de cada algoritmo. Pode usar algoritmos de classificação de bibliotecas.

[3]:
```python
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import MultinomialNB
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score

# Verificar a distribuição dos rótulos
print("Distribuição dos rótulos:", y.value_counts())

# Dividir os dados com estratificação
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
 ↪stratify=y)

# Treino e avaliaçao os modelos
nb_classifier = MultinomialNB()
nb_classifier.fit(X_train, y_train)
nb_accuracy = accuracy_score(y_test, nb_classifier.predict(X_test))

# RandomForest com jobs paralelos
```

```python
rf_classifier = RandomForestClassifier(n_jobs=-1, verbose=2)
rf_classifier.fit(X_train, y_train)
rf_accuracy = accuracy_score(y_test, rf_classifier.predict(X_test))

print("Naive Bayes Accuracy:", nb_accuracy)
print("Random Forest Accuracy:", rf_accuracy)
```

```
Distribuição dos rótulos: label
2    120487
1     87114
Name: count, dtype: int64
building tree 1 of 100
building tree 2 of 100
building tree 3 of 100
building tree 4 of 100
building tree 5 of 100
building tree 6 of 100
building tree 7 of 100
building tree 8 of 100
building tree 9 of 100
building tree 10 of 100
building tree 11 of 100
building tree 12 of 100
```

```
[Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 12 concurrent
workers.
```

```
building tree 13 of 100
building tree 14 of 100
building tree 15 of 100
building tree 16 of 100
building tree 17 of 100
building tree 18 of 100
building tree 19 of 100
building tree 20 of 100
building tree 21 of 100
building tree 22 of 100
building tree 23 of 100
building tree 24 of 100
building tree 25 of 100
building tree 26 of 100
building tree 27 of 100
building tree 28 of 100
building tree 29 of 100
building tree 30 of 100
```

```
[Parallel(n_jobs=-1)]: Done  17 tasks      | elapsed:  1.1min
```

```
building tree 31 of 100
building tree 32 of 100
```

```
building tree 33 of 100
building tree 34 of 100
building tree 35 of 100
building tree 36 of 100
building tree 37 of 100
building tree 38 of 100
building tree 39 of 100
building tree 40 of 100
building tree 41 of 100
building tree 42 of 100
building tree 43 of 100
building tree 44 of 100
building tree 45 of 100
building tree 46 of 100
building tree 47 of 100
building tree 48 of 100
building tree 49 of 100
building tree 50 of 100
building tree 51 of 100
building tree 52 of 100
building tree 53 of 100
building tree 54 of 100
building tree 55 of 100
building tree 56 of 100
building tree 57 of 100
building tree 58 of 100
building tree 59 of 100
building tree 60 of 100
building tree 61 of 100
building tree 62 of 100
building tree 63 of 100
building tree 64 of 100
building tree 65 of 100
building tree 66 of 100
building tree 67 of 100
building tree 68 of 100
building tree 69 of 100
building tree 70 of 100
building tree 71 of 100
building tree 72 of 100
building tree 73 of 100
building tree 74 of 100
building tree 75 of 100
building tree 76 of 100
building tree 77 of 100
building tree 78 of 100
building tree 79 of 100
building tree 80 of 100
```

```
building tree 81 of 100
building tree 82 of 100
building tree 83 of 100
building tree 84 of 100
building tree 85 of 100
building tree 86 of 100
building tree 87 of 100
building tree 88 of 100
building tree 89 of 100
building tree 90 of 100
building tree 91 of 100
building tree 92 of 100
building tree 93 of 100
building tree 94 of 100
building tree 95 of 100
building tree 96 of 100
building tree 97 of 100
building tree 98 of 100
building tree 99 of 100
building tree 100 of 100
```

```
[Parallel(n_jobs=-1)]: Done 100 out of 100 | elapsed:  4.8min finished
[Parallel(n_jobs=12)]: Using backend ThreadingBackend with 12 concurrent
workers.
[Parallel(n_jobs=12)]: Done  17 tasks      | elapsed:    1.7s
```

```
Naive Bayes Accuracy: 0.8357123360254332
Random Forest Accuracy: 0.8734445497021563
```

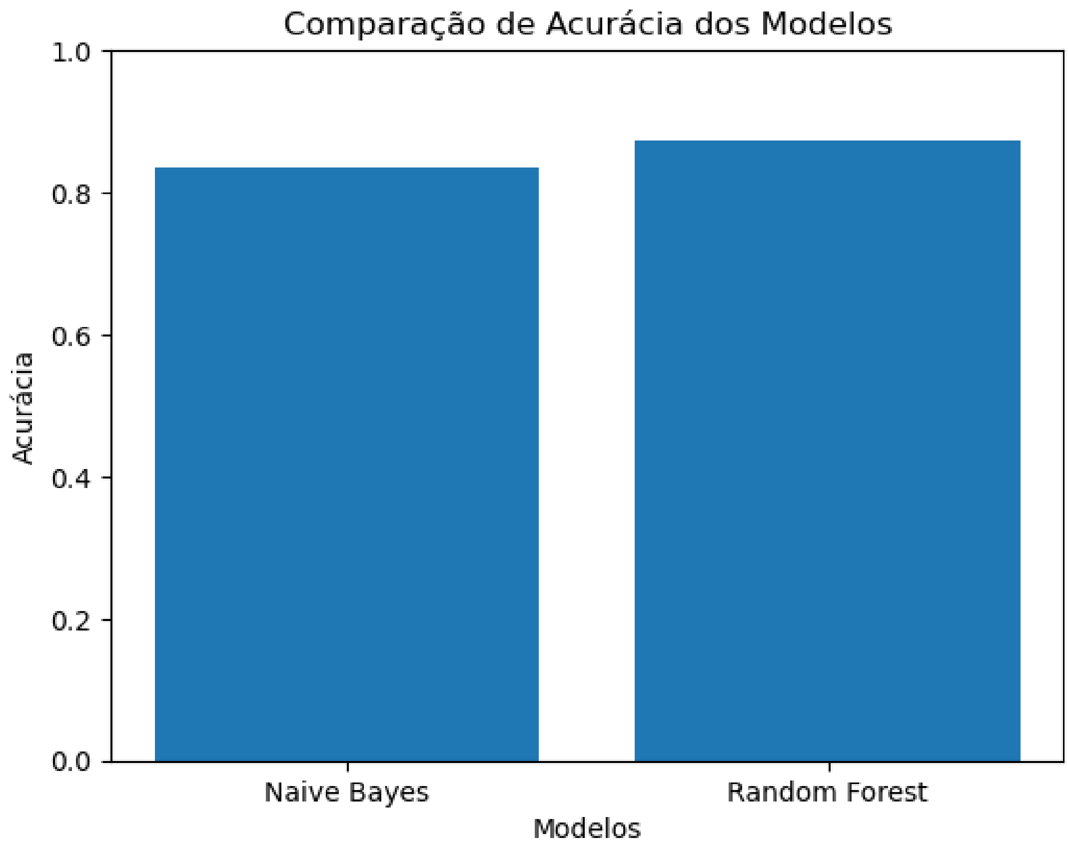
```
[Parallel(n_jobs=12)]: Done 100 out of 100 | elapsed:    8.7s finished
```

[4]:

```python
import matplotlib.pyplot as plt

accuracies = {'Naive Bayes': nb_accuracy, 'Random Forest': rf_accuracy}

plt.bar(accuracies.keys(), accuracies.values())
plt.xlabel('Modelos')
plt.ylabel('Acurácia')
plt.title('Comparação de Acurácia dos Modelos')
plt.ylim(0, 1)  # Acurácia varia entre 0 e 1
plt.show()
```



[8]:

```
# Obtenha as probabilidades das palavras para cada classe
class_probabilities = nb_classifier.feature_log_prob_

# Obtenha os nomes das características (palavras)
feature_names = vectorizer.get_feature_names_out()

# Exiba as top N palavras para cada classe
N = 50
for i, class_probability in enumerate(class_probabilities):
    print(f"Top {N} words for class {i+1}:")
    # Ordenar as probabilidades e pegar os top N índices
    top_indices = class_probability.argsort()[-N:]
    for j in top_indices:
        print(f"{feature_names[j]}: {np.exp(class_probability[j])}")  #␣
↪Converter log probabilidade de volta para probabilidade
    print("\n")
```

```
Top 50 words for class 1:
toronto: 0.0012948442958701266
well: 0.001316365253696224
```

two: 0.0013378862115223204
years: 0.0013450598641310183
long: 0.001384514953478862
use: 0.0013881017797832114
program: 0.0013916886060875609
high: 0.0013952754323919095
sky: 0.0014239700428267056
access: 0.001441904174348452
see: 0.0014562514795658493
spacecraft: 0.0014813592636962957
satellite: 0.0014921197426093432
pat: 0.0014921197426093432
know: 0.0015997245317398252
solar: 0.0015997245317398252
data: 0.0016068981843485233
people: 0.0016535269263050656
may: 0.001707329320870307
us: 0.001718089799783354
much: 0.0017539580628268489
new: 0.0017826526732616437
think: 0.0018041736310877396
mission: 0.0018830838097834257
system: 0.001929712551739968
get: 0.0019942754252182567
first: 0.002008622730435654
time: 0.0020265568619574023
henry: 0.0020588382986965466
could: 0.0021234011721748343
shuttle: 0.0021341616510878836
moon: 0.002141335303696582
orbit: 0.0022274191350009 67
gov: 0.0022668742243488107
launch: 0.0023959999713053 87
also: 0.002417520929131484
earth: 0.002661425117827242
like: 0.003088257448044818
article: 0.003210209542392698
com: 0.003479221515218902
one: 0.0035150897782623945
writes: 0.004031592766088706
nasa: 0.004512227490871522
document_id: 0.004989275389349992
newsgroup: 0.0051506825730457135
would: 0.00518296400978486
subject: 0.005340784367176233
sci: 0.00587163466021994
edu: 0.008457736425655848
space: 0.01410698785500613

```
Top 50 words for class 2:
bible: 0.0016176899150118047
islam: 0.0016771638089460635
true: 0.0016771638089460635
right: 0.0016801375036427763
things: 0.0016860848930362008
livesey: 0.0016950059771263406
christian: 0.0017217692293967567
also: 0.0017425850922737453
system: 0.0017455587869704596
argument: 0.0017693483445441627
may: 0.00180800637560143
point: 0.0018139537649948557
good: 0.0018704539642324007
something: 0.0019091119952896673
make: 0.0019239804687732323
moral: 0.0019358752475600823
jesus: 0.001941822636953509
must: 0.001965612194527211
morality: 0.0020012965308877665
us: 0.002039954561945033
said: 0.0021321390975431328
evidence: 0.0021856656020839645
could: 0.0021856656020839645
well: 0.00219161299147739
way: 0.002206481464960955
time: 0.0022808238323787765
even: 0.0023224555581327576
see: 0.002355166199796599
keith: 0.002471140292968402
religion: 0.002631719806590896
many: 0.0026674041429514505
believe: 0.0027982467096068168
atheists: 0.0028309573512706582
like: 0.0028487995194509358
know: 0.0029499051391391733
document_id: 0.0032859326398677288
say: 0.0036338549193831375
newsgroup: 0.003678460339833828
think: 0.0038895926633004444
alt: 0.004296988836750109
article: 0.0043891733723482075
com: 0.004823332798068289
people: 0.005248571139698228
would: 0.005251544834394941
subject: 0.005611361892697199
```

```
writes: 0.005635151450270904
atheism: 0.006191232358556209
one: 0.00646778596535051
god: 0.006497522912317637
edu: 0.010134351526397493
```