labs_alexis_carbillet

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1 Labs Works 1+2 Alexis Carbillet

```
In [1]: #import des librairies
        import numpy as np
        import pandas
        from dateutil.parser import parse
        import datetime
        import pytz
        from nltk.tokenize import TweetTokenizer
        from nltk.corpus import wordnet, stopwords
        import re
        import string
        from nltk.stem import WordNetLemmatizer
        from collections import defaultdict
        from sklearn.decomposition import TruncatedSVD
        from sklearn.cluster import KMeans
        from sklearn.naive_bayes import MultinomialNB
        from sklearn.linear_model import Perceptron, LogisticRegression
        from sklearn.tree import DecisionTreeClassifier
        from sklearn.neighbors import KNeighborsClassifier
        from sklearn.svm import SVC
        from sklearn.metrics import f1_score
        from sklearn.ensemble import RandomForestClassifier
        from sklearn.neural_network import MLPClassifier
        import matplotlib.pyplot as plt
        import random
        from sklearn.decomposition import PCA
        import warnings
```

```
In [2]: warnings.filterwarnings('ignore')
        ## import dataset
        # train
        train = pandas.read_csv('Train.csv')
        # test
        test=pandas.read_csv('Test.csv')
```

The functions below are used for the processing of the tweets.

In [3]:
```python
def to_datetime(datestring):
    time_tuple = parsedate_tz(datestring.strip())
    dt = datetime(*time_tuple[:6])
    return dt - timedelta(seconds=time_tuple[-1])

# text processing
def isSymbol(inputString):
    return bool(re.match(r'[^\w]', inputString))
def hasNumbers(inputString):
    return bool(re.search(r'\d', inputString))

wordnet_lemmatizer = WordNetLemmatizer()

stop = stopwords.words('english')
stop2 = stopwords.words('spanish')
stop3 = stopwords.words('portuguese')
stop4 = stopwords.words('arabic')

def check(word):

    word= word.lower()
    if word in stop:
        return False
    elif word in stop2:
        return False
    elif word in stop3:
        return False
    elif word in stop4:
        return False
    elif hasNumbers(word) or isSymbol(word):
        return False
    else:
        return True


def preprocessing(sen):
    res = []
    for word in sen:
        if check(word):
            res.append(wordnet_lemmatizer.lemmatize(word))
    return res

def in_dict(word):
    if wordnet.synsets(word,lang='eng'):
        return True
    if wordnet.synsets(word,lang='spa'):
        return True
    if wordnet.synsets(word,lang='por'):
```

```
            return True
        if wordnet.synsets(word,lang='jpn'):
            return True
        if wordnet.synsets(word,lang='arb'):
            return True

def replace_elongated_word(word):
    regex = r'(\w*)(\w+)\2(\w*)'
    repl = r'\1\2\3'
    if in_dict(word):
        return word
    new_word = re.sub(regex, repl, word)
    if new_word != word:
        return replace_elongated_word(new_word)
    else:
        return new_word

def detect_elongated_words(row):
    regexrep = r'(\w*)(\w+)(\2)(\w*)'
    words = [''.join(i) for i in re.findall(regexrep, row)]
    for word in words:
        if not in_dict(word):
            row = re.sub(word, replace_elongated_word(word), row)
    return row

def strip_links(text):
    link_regex    = re.compile('((https?):((//)|(\\\\))+([\w\d:#@%/;$()~_?\+-=\\\.&](#
    links         = re.findall(link_regex, text)
    for link in links:
        text = text.replace(link[0], ', ')
    return text

def strip_all_entities(text):
    entity_prefixes = ['@','#']
    for separator in  string.punctuation:
        if separator not in entity_prefixes :
            text = text.replace(separator,' ')
    words = []
    for word in text.split():
        word = word.strip()
        if word:
            if word[0] not in entity_prefixes:
                words.append(word)
    return ' '.join(words)


def getStringBigrams(string):
    if len(string) <= 0: return []
```

```
        if len(string) == 1: return string[0] # Handle strings with only one character = e
        return [string[i]+string[i+1] for i in range(len(string)-1)]

    def getDataBigrams(strings):
        return [getStringBigrams(x) for x in strings]

    def generateDictionary(data):
        '''
        This function identifies unique n-grams in your data.
        '''
        vocab = set()
        for line in data:
            for item in line:
                vocab.add(item)
        dictionary = {}
        i=0
        for item in vocab:
            dictionary[item] = i
            i+=1
        return dictionary

    def doc2Bow(bigramData, dictionary):
        '''
        Take single document in bigram format and return a vector
        '''
        vect = [0]*len(dictionary) # Initialize vector to zero
        for gram in bigramData:
            vect[dictionary[gram]]+=1
        return np.asarray(vect)  # Convert to numpy vector
```

Now the others columns will be processed with those functions:

```
In [4]: def topicProcessing(data):
            for i in range(data.shape[0]):
                dt = data[i]
                if(dt=='twitter'):
                    data[i]=np.int64(1)
                if(dt=='apple'):
                    data[i]=np.int64(2)
                if(dt=='google'):
                    data[i]=np.int64(3)
                if(dt=='microsoft'):
                    data[i]=np.int64(4)

        def sentimentProcessing(data):
            for i in range(data.shape[0]):
                dt = data[i]
                if(dt=='positive'):
```

```
                data[i]=1
            if(dt=='neutral'):
                data[i]=0
            if(dt=='negative'):
                data[i]=-1
            if(dt=='irrelevant'):
                data[i]=-10

    def dateProcessing(train):
        for i in range(train.shape[0]):
            dt = parse(train['TweetDate'][i])
            train['TweetDate'][i]=(dt-datetime.datetime(1970,1,1,tzinfo=pytz.utc)).total_se
        text_merge=""
```

Now there is the machine learning :

```
In [5]: def fit(nb,train,test,y,yt,height,height_f1,type):
            nb.fit(train, y)
            w=nb.score(test, yt)
            z=f1_score(yt, nb.predict(test),average='weighted')
            height.append(w)
            height_f1.append(z)

        def ml(train,test,y,yt,time,subject):
            height=[]
            height_f1=[]
            bars=['bayes','perceptron','MLP','tree','logistic regression','kNN 3 neighbors','kN
            # bayes
            nb = MultinomialNB()
            fit(nb,train,test,y,yt,height,height_f1,'bayes')
            # perceptron
            nb = Perceptron(tol=1e-3, random_state=0)
            fit(nb,train,test,y,yt,height,height_f1,'perceptron')
            # multi-layer perceptron
            nb = MLPClassifier(solver='lbfgs', alpha=1e-5, hidden_layer_sizes=(5, 2), random_st
            fit(nb,train,test,y,yt,height,height_f1,'multi-layer perceptron')
            # tree classifier
            nb = DecisionTreeClassifier(random_state=0)
            fit(nb,train,test,y,yt,height,height_f1,'tree')
            # logistic regression
            nb =LogisticRegression(random_state=0, solver='lbfgs',multi_class='multinomial')
            fit(nb,train,test,y,yt,height,height_f1,'logistic regression')
            # kNN 3
            nb = KNeighborsClassifier(n_neighbors=3)
            fit(nb,train,test,y,yt,height,height_f1,'kNN 3 neighbors')
            # kNN 7
            nb = KNeighborsClassifier(n_neighbors=7)
            fit(nb,train,test,y,yt,height,height_f1,'kNN 7 neighbors')
```

```
    # kNN 15
    nb = KNeighborsClassifier(n_neighbors=15)
    fit(nb,train,test,y,yt,height,height_f1,'kNN 15 neighbors')
    # SVC
    nb = SVC(gamma='auto')
    fit(nb,train,test,y,yt,height,height_f1,'SVC')
    # random forest
    nb = RandomForestClassifier(n_estimators=100, max_depth=2, random_state=0)
    fit(nb,train,test,y,yt,height,height_f1,'random forest')
    y_pos = np.arange(len(bars))
    plt.figure()
    # title1='Mean accuracy for sentiment prediction:'
    # plt.title(title1)
    # plt.bar(y_pos, height)  # Create bars
    # plt.xticks(y_pos, bars, rotation=90) # Create names on the x-axis
    # plt.subplots_adjust(bottom=0.3, top=0.95) # Custom the subplot layout
    # plt.figure()
    title2='F1 score for '+subject+' prediction with time='+time
    plt.title(title2)
    plt.bar(y_pos, height_f1)  # Create bars
    plt.xticks(y_pos, bars, rotation=90) # Create names on the x-axis
    plt.subplots_adjust(bottom=0.3, top=0.95) # Custom the subplot layout
    plt.show()    # Show graphic
    print('the best one for sentiment prediction is ',bars[height_f1.index(max(height_
```

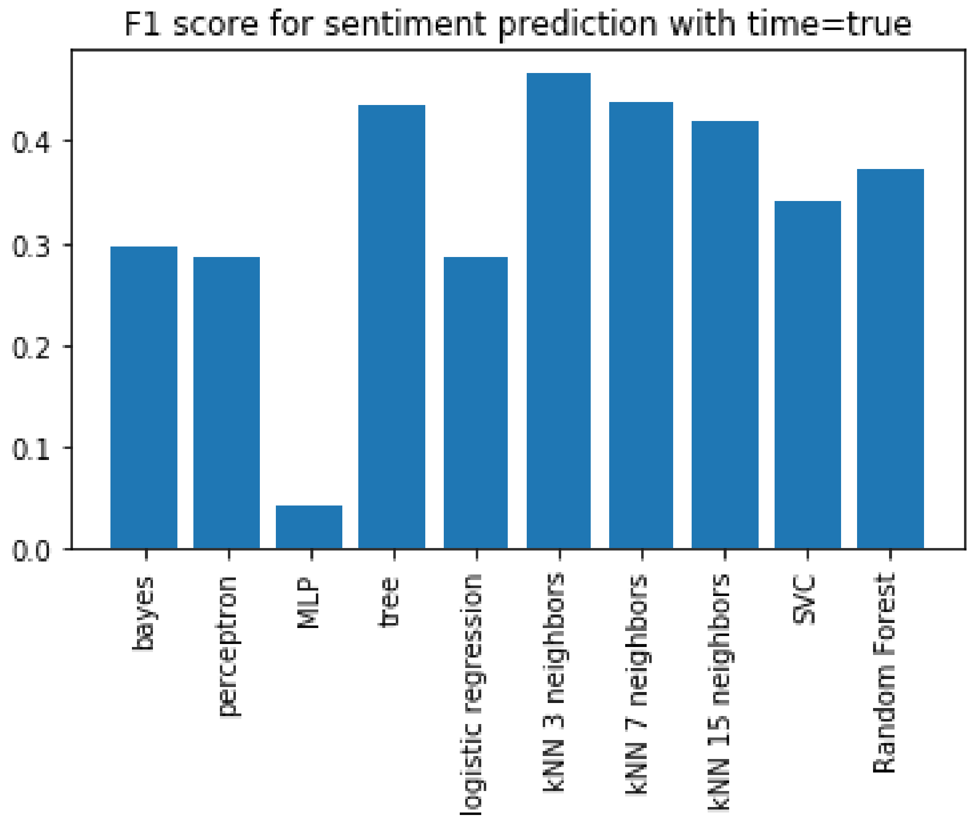
The datasets are processed with this function:

```
In [6]: def processing(train,test,time):
            # labels recuperation
            labels=train['Sentiment']
            train=train.drop(['Sentiment'],axis=1)

            labels_test=test['Sentiment']
            test=test.drop(['Sentiment'],axis=1)

            if(time=='true'):
                # date processing
                dateProcessing(train)
                dateProcessing(test)

            # topic processing
            topicProcessing(train['Topic'])
            topicProcessing(test['Topic'])

            # sentiment processing
            sentimentProcessing(labels)
            sentimentProcessing(labels_test)
```

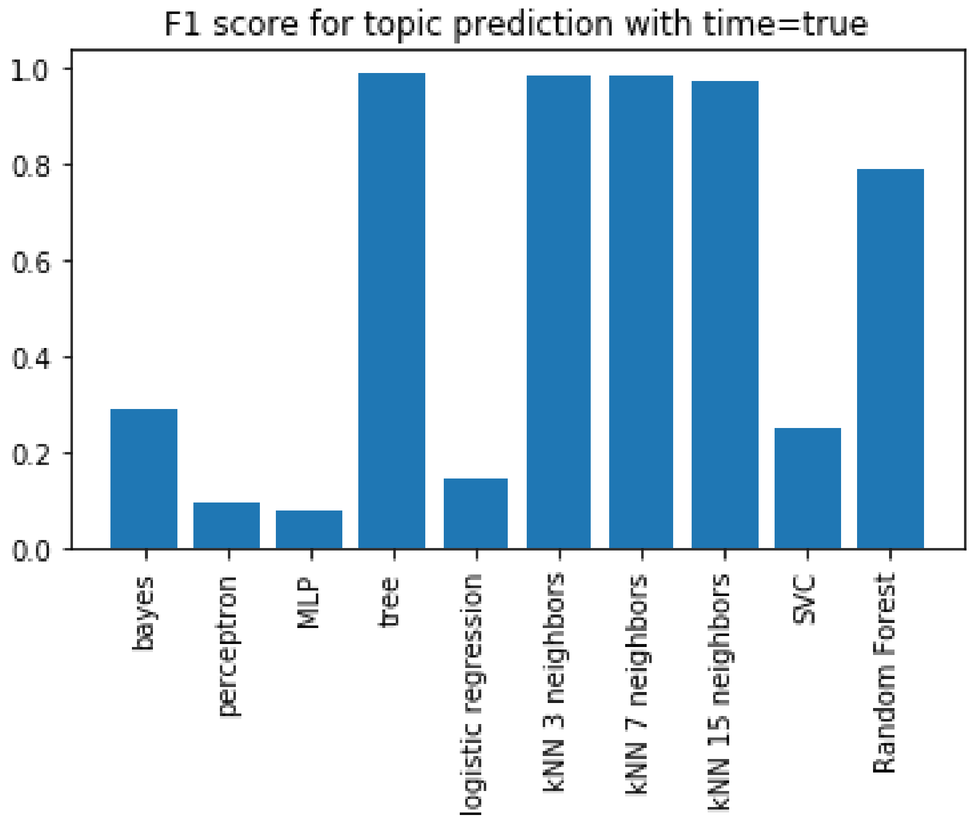
```
# text processing
l=[]
x=labels.shape[0]
for i in range(x):
    l.append([])
    a=train['TweetText'][i]
    b=a.encode('ascii','ignore')
    b=b.decode('utf8')
    b=b.lower()
    b=strip_all_entities(strip_links(b))
    puk=TweetTokenizer()
    cleaneded=puk.tokenize(b) # put clean when corrected
    cc=preprocessing(cleaneded)
    for item in cc:
        if len(item)>2: # we don't want to have useless words
            l[i].append(detect_elongated_words(item))
    tempo=' '.join(l[i])
    if len(tempo)>3:
        train['TweetText'][i]=tempo

    else: # message useless are deleted
        train['TweetText'][i]=''
        # delete the nul label and its features
        del labels[i]
        train=train.drop(i,axis=0)

l=[]
x=labels_test.shape[0]
for i in range(x):
    l.append([])
    a=test['TweetText'][i]
    b=a.encode('ascii','ignore')
    b=b.decode('utf8')
    b=b.lower()
    b=strip_all_entities(strip_links(b))
    puk=TweetTokenizer()
    cleaneded=puk.tokenize(b) # put clean when corrected
    cc=preprocessing(cleaneded)
    for item in cc:
        if len(item)>2: # we don't want to have useless words
            l[i].append(detect_elongated_words(item))
    tempo=' '.join(l[i])
    if len(tempo)>3:
        test['TweetText'][i]=tempo

    else: # message useless are deleted
        test['TweetText'][i]=''
        # delete the nul label and its features
```

```
                del labels_test[i]
                test=test.drop(i,axis=0)

        ## feature extraction
        # train
        nGramData = getDataBigrams(train['TweetText'])
        dictionary = generateDictionary(nGramData)
        data = [doc2Bow(nGramData[i], dictionary) for i in range(len(nGramData))]
        svd = TruncatedSVD(n_components=100)
        X_reduced = svd.fit_transform(data)
        # test
        nGramData = getDataBigrams(test['TweetText'])
        dictionary = generateDictionary(nGramData)
        data = [doc2Bow(nGramData[i], dictionary) for i in range(len(nGramData))]
        svd = TruncatedSVD(n_components=100)
        X_reduced2 = svd.fit_transform(data)

        ## classification sentiment
        # naive bayes
        train['TweetText'] = X_reduced
        test['TweetText'] = X_reduced2
        y=pandas.DataFrame.transpose(pandas.DataFrame([labels])).values.ravel()
        yt=pandas.DataFrame.transpose(pandas.DataFrame([labels_test])).values.ravel()
        ml(train,test,y,yt,time,'sentiment')

        ## classification topic
        y2=pandas.DataFrame.transpose(pandas.DataFrame(train['Topic'])).values.ravel()
        yt2=pandas.DataFrame.transpose(pandas.DataFrame(test['Topic'])).values.ravel()
        y2=y2.astype('int')
        yt2=yt2.astype('int')
        train2=train.drop(['Topic'],axis=1)
        test2=test.drop(['Topic'],axis=1)
        ml(train2,test2,y2,yt2,time,'topic')
```

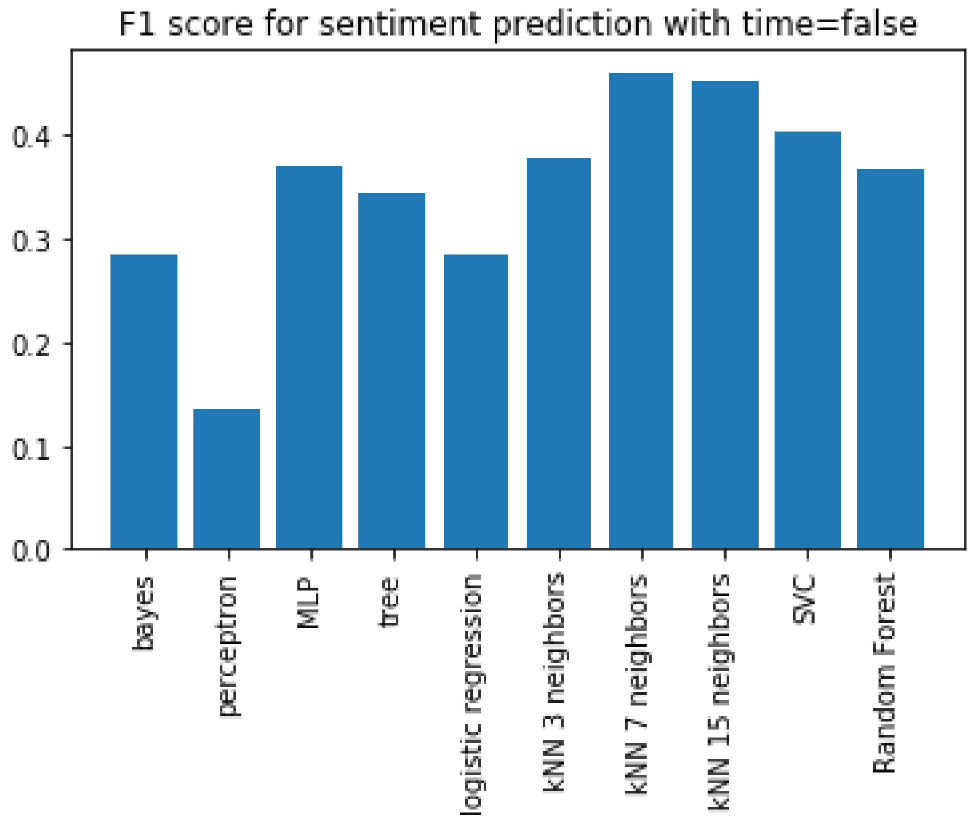
```
In [7]: processing(train, test, 'true')
        # without the time
        test=test.drop(['TweetDate'],axis=1)
        train=train.drop(['TweetDate'],axis=1)
        processing(train, test, 'false')
```



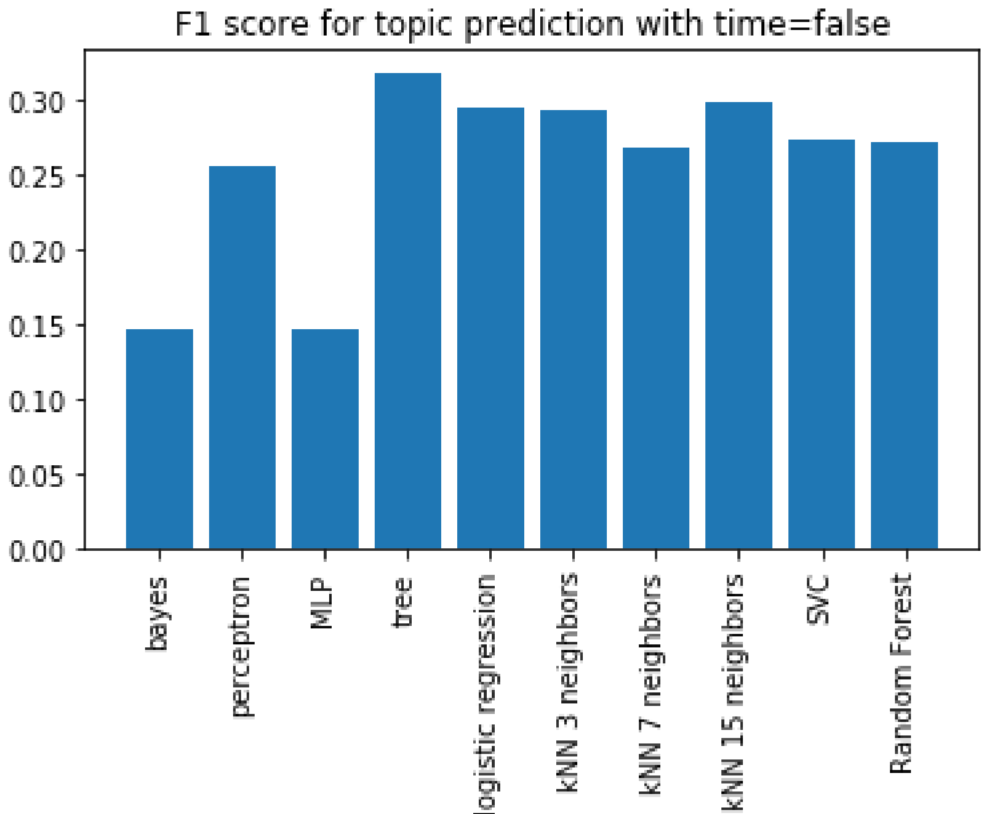

```
the best one for sentiment prediction is  kNN 3 neighbors  with a F1 score of  0.46591783782044
```




```
the best one for sentiment prediction is  tree  with a F1 score of  0.9900990099009901
```




```
the best one for sentiment prediction is  kNN 7 neighbors  with a F1 score of  0.4595586901935
```




```
the best one for sentiment prediction is  tree  with a F1 score of  0.3173798098399649
```

To conclude, 10 differents classifiers have been used. According to the results obtained during the test step. The best classifier for the sentiment prediction is the kNN 3 neighbors with a F1 score of 0.4659178378204406 with the time column in input and it is the kNN 7 neighbors with a F1 score of 0.45955869019351836 without the time column in input.

About the topic prediction, with the time column, the best classifier is the tree with a F1 score of 0.9900990099009901 and without the time column, the best classifier is still the tree but with a F1 score of 0.3173798098399649

The time column is very important for the topic prediction. In fact, most tweets about the same topic have been collected in short amount of time. This explains the important influence of this column on the topic prediction.