Sentiment analysis is a field dedicated to extracting subjective emotions and feelings from text. One common expresses negative or positive feelings. Written reviews are great datasets for doing sentiment analysis becatrain an algorithm.

You'll work with the IMDB dataset: a set of 50,000 highly polarized reviews from the Internet Movie Database. 25,000 reviews for testing, each set consisting of 50% negative and 50% positive reviews.

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from keras.datasets import imdb
```

 \Box

The argument num_words=7500 means you'll only keep the top 7500 most fre- quently occurring words in the allows you to work with vector data of manageable size. The variables train_data and test_data are lists of resequence of words)....list of lists! train_labels and test_labels are lists of 0s and 1s, where 0 stands for negative train_standard in the control of the control of

We will try to convert list of lists into a dataframe. '/content/gdrive/My Drive/Colab Notebooks/IMDB/train/pocontain a sequence (list) of words.

```
vocabulary=7500
```

```
# save np.load
#np_load_old = np.load

# modify the default parameters of np.load
#np.load = lambda *a,**k: np_load_old(*a, allow_pickle=True, **k)

# call load_data with allow_pickle implicitly set to true
#(train_data, train_labels), (test_data, test_labels) = imdb.load_data(num_words=vocab)
# restore np.load for future normal usage
#np.load = np_load_old

np.load.__defaults__=(None, True, True, 'ASCII')
(train_data, train_labels), (test_data, test_labels) = imdb.load_data(num_words=vocabu)
np.load.__defaults_=(None, False, True, 'ASCII')
```

Loads the data as a list of integers

```
print(train_data[0])
```

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the change the A. Taller Cale of the change days a filler of the

it snows that Tokenizing has been done allready

 \Box

```
print(len(train_data[100]))
```

Reviews have already been converted in a sequence of indexed words. One-hot encode the lists to turn them instance, turning the sequence [3, 5] into a 10,000-dimensional vector that would be all 0s except for indices 3

We define a function called vectorize_sequences that takes 2 arguments: review and dimension of vocabular

```
def vectorize_sequences(sequences, dimension=10000):
    results=np.zeros((len(sequences), dimension)) #matrix of 10000 columns and with rows
    for i, sequence in enumerate(sequences):
        results[i, sequence]=1
    return results

X_train=vectorize_sequences(train_data)
X_test=vectorize_sequences(test_data)

print(X_train[0])
print(X_train[0])
print(X_test[0])
```

```
X_train.shape

[] [1, 14, 22, 16, 43, 530, 973, 1622, 1385, 65, 458, 4468, 66, 3941, 4, 173, 3]

X_test.shape

[] 158
```

We currently have a list of lists and will convert to a panda dataframe using the pandas DataFrame construct

```
X_train_df=pd.DataFrame(X_train)
y_train_df=pd.DataFrame(train_labels, columns=['IMDB training labels'])

X_test_df=pd.DataFrame(X_test)
y_test_df=pd.DataFrame(test_labels, columns=['IMDB Testing labels'])

X_train_df.head()
```

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```
[0. 1. 1. ... 0. 0. 0.]
y_train_df['IMDB training labels'].value_counts()
    (25000, 10000)
\Box
Dataset is balanced
we want to merge the training data and labels to make up 1 dataframe
train_df = pd.concat([X_train_df, y_train_df], axis=1) #combined training data and lab
test_df = pd.concat([X_test_df, y_test_df], axis=1) #combined training data and labels
train_df.head()
```

(25000, 10000)

We will use a logistic regression classifier - categorizes data in 2 classes via Sigmoid

from sklearn.linear model import LogisticRegression

```
classifier = LogisticRegression()
classifier.fit(X_train_df, y_train_df)
score = classifier.score(X_test_df, y_test_df)
print("Accuracy:", score)
\Box
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```

Logistics Regression gives us an accuracy of 86%

score=model.score(X_test_df, y_test_df)

print("Accuracy:", score)

```
from sklearn.naive_bayes import MultinomialNB

model=MultinomialNB()

model.fit(X_train_df, y_train_df);
```

```
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Naive Bayes - Multinomial gives us an accuracy of 84%

```
from sklearn.naive_bayes import GaussianNB

model=GaussianNB()

model.fit(X_train_df, y_train_df);
score=model.score(X_test_df, y_test_df)
print("Accuracy:", score)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/logistic.py:432:
    FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/utils/validation.py:724: Data
y = column_or_ld(y, warn=True)
Accuracy: 0.85852
```

Naive Bayes - Gaussian gives us an accuracy of 69% - not a surprise as multinomial assumption is known to Gaussian assumption

Now we will look at Random Forests and Adaboost

```
from sklearn.ensemble import RandomForestClassifier

clf=RandomForestClassifier(n_estimators=100) #n_estimators is the number of tree's in t
```

```
clf.fit(X_train_df,y_train_df)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/utils/validation.py:724: Data
y = column_or_1d(y, warn=True)
Accuracy: 0.8424
```