SENTIMENT - ANALYSIS

If you’re learning Python and would like to develop a machine learning model then a library that you want to seriously consider is scikit-learn. Scikit-learn (also known as sklearn) is a machine learning library used in Python that provides many unsupervised and supervised learning algorithms.

In this simple guide, we’re going to create a machine learning model that will predict whether a movie review is positive or negative. This is known as binary text classification and will help us explore the scikit-learn library while building a basic machine learning model from scratch. These are the topics we’re going to learn in this project

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The Dataset and The Problem to Solve

In this guide, we'll use an IMDB dataset of 50k movie reviews available on Kaggle. The dataset contains 2 columns (review and sentiment) that will help us identify whether a review is positive or negative.

Problem formulation: Our goal is to find which machine learning model is best suited to predict sentiment (output) given a movie review (input).

Preparing The Data

Reading the dataset

After you download the dataset, make sure the file is in the same place where your Python script is located. Then, we'll read the file using the Pandas library.

```
import pandas as pddf_review = pd.read_csv('IMDB Dataset.csv')
df_review
```

Note: If you don't have some of the libraries used in this guide, you can easily install a library with pip on your terminal or command prompt (e.g.,`pip install scikit-learn)`

The dataset looks like the picture below.

	review	sentiment
0	One of the other reviewers has mentioned that ...	positive
1	A wonderful little production. The...	positive
2	I thought this was a wonderful way to spend ti...	positive
3	Basically there's a family where a little boy ...	negative
4	Petter Mattei's "Love in the Time of Money" is...	positive
...	...	...
49995	I thought this movie did a down right good job...	positive
49996	Bad plot, bad dialogue, bad acting, idiotic di...	negative
49997	I am a Catholic taught in parochial elementary...	negative
49998	I'm going to have to disagree with the previou...	negative
49999	No one expects the Star Trek movies to be high...	negative

Image by Tonmoy

This dataset contains 50000 rows; however, **to train our model faster in the following steps, we're going to take a smaller sample of 10000 rows. This small sample will contain 9000 positive and 1000 negative reviews to make the data imbalanced** (so I can teach you undersampling and oversampling techniques in the next step)

We're going to create this small sample with the following code. The name of this imbalanced dataset will be`df_review_imb`

```
df_positive =
df_review[df_review['sentiment']=='positive'][:9000]
df_negative =
df_review[df_review['sentiment']=='negative'][:1000]df_review_im
b = pd.concat([df_positive, df_negative])
```

Dealing with Imbalanced Classes

In most cases, you'll have a large amount of data for one class, and much fewer observations for other classes. This is known as imbalanced data because the number of observations per class is not equally distributed.

Let's take a look at how our `df_review_imb` dataset is distributed.

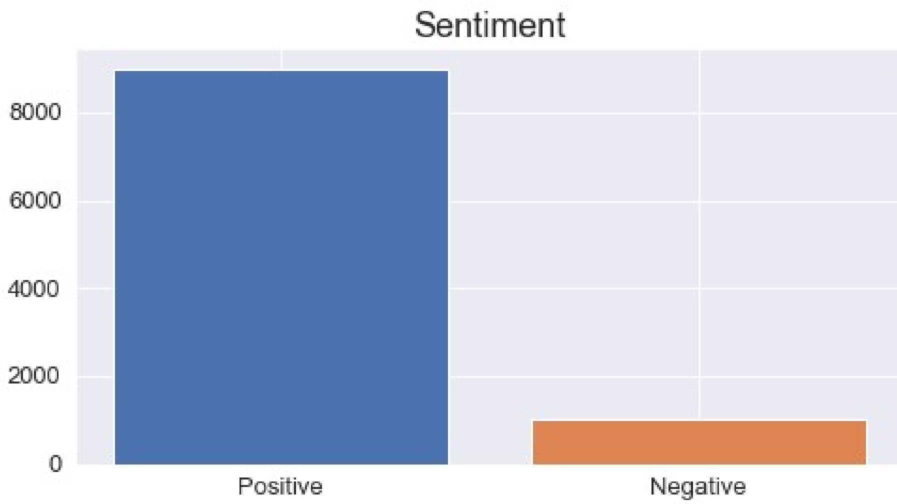


Image by author

As we can see there are more positive than negative reviews in `df_review_imb` so we have imbalanced data.

To resample our data we use the `imblearn` library. You can either undersample positive reviews or oversample negative reviews (you need to choose based on the data you're working with). In this case, we'll use the `RandomUnderSampler`

First, we create a new instance of `RandomUnderSampler (rus)`, we add `random_state=0` just to control the randomization of the algorithm. Then we resample the imbalanced dataset `df_review_imb` by fitting `rus` with `rus.fit_resample(x, y)` where "x" contains the data which have to be sampled and "y" corresponds to labels for each sample in "x".

After this, `x` and `y` are balanced and we'll store it in a new dataset named `df_review_bal.` We can compare the imbalanced and balanced dataset with the following code.

```
IN [0]: print(df_review_imb.value_counts('sentiment'))
        print(df_review_bal.value_counts('sentiment'))OUT
[0]:positive    9000
        negative    1000

        negative    1000
        positive    1000
```

As we can see, now our dataset is equally distributed.

Note 1: If you get the following error when using the `RandomUnderSampler`

IndexError: only integers, slices (`:`), ellipsis (`...`), numpy.newaxis (`None`) and integer or boolean arrays are valid indices

You can use an alternative to `RandomUnderSampler`. Try the code below:

The `df_review_bal` dataframe should have now 1000 positive and negative reviews as shown above.

Note 2: Usually before splitting data into train and test sets, we should clean the data. In this example, the data is already cleaned;

however, real-world data is dirty, so whenever you need to clean data check the guide below to learn the best practices of data cleaning in Python.

Splitting data into train and test set

Before we work with our data, we need to split it into a train and test set. The `train` dataset will be used to fit the model, while the `test` dataset will be used to provide an unbiased evaluation of a final model fit on the training dataset.

We'll use sklearn's `train_test_split` to do the job. In this case, we set 33% to the test data.

```
from sklearn.model_selection import train_test_splittrain, test
= train_test_split(df_review_bal, test_size=0.33,
random_state=42)
```

Now we can set the independent and dependent variables within our train and test set.

```
train_x, train_y = train['review'], train['sentiment']
test_x, test_y = test['review'], test['sentiment']
```

Let's see what each of them mean:

- **train_x:** Independent variables (review) that will be used to train the model. Since we specified `test_size = 0.33`, 67% of observations from the data will be used to fit the model.
- **train_y:** Dependent variables (sentiment) or target label that need to be predicted by this model.

- **test_x:** The remaining `33%` of independent variables that will be used to make predictions to test the accuracy of the model.
- **test_y:** Category labels that will be used to test the accuracy between actual and predicted categories.

Text Representation (Bag of Words)

Classifiers and learning algorithms expect numerical feature vectors rather than raw text documents. This is why we need to turn our movie review text into numerical vectors. There are many text representation techniques such as one-hot encoding, bag of words, and wor2vec.

For this simple, we'll use bag of words (BOW) since we care about the frequency of the words in text reviews; however, the order of words is irrelevant. Two common ways to represent bag of words are CountVectorizer and Term Frequency, Inverse Document Frequency (TF-IDF). Before we choose any of them, I'll give you an easy-to-understand demonstration of how they work.

CountVectorizer

The CountVectorizer gives us the frequency of occurrence of words in a document. Let's consider the following sentences.

```
review = [“I love writing code in Python. I love Python code”,
          “I hate writing code in Java. I hate Java code”]
```

The representation with CountVectorizer will look like this,

	code	hate	java	love	python	writing
review1	2	0	0	2	2	1
review2	2	2	2	0	0	1

Image by author

As you can see the numbers inside the matrix represent the number of times each word was mentioned in each review. Words like “love,” “hate,” and “code” have the same frequency (2) in this example.

Term Frequency, Inverse Document Frequency (TF-IDF)

The TF-IDF computes “weights” that represents how important a word is to a document in a collection of documents (aka corpus). The TF-IDF value increases proportionally to the number of times a word appears in the document and is offset by the number of documents in the corpus that contain the word.

The representation with TF-IDF will look like the picture below for the same text we used before.

	code	hate	java	love	python	writing
review1	0.438501	0.000000	0.000000	0.616298	0.616298	0.21925
review2	0.438501	0.616298	0.616298	0.000000	0.000000	0.21925

Image by author

Unlike, the previous example the word “code” doesn’t have the same weight as the words “love” or “hate.” This happens because “code” appears in both reviews; therefore, its weight decreased.

Turning our text data into numerical vectors

In our original dataset, we want to identify unique/representative words for positive reviews and negative reviews, so we'll choose the TF-IDF. To turn text data into numerical vectors with TF-IDF, we write the following code.

```
from sklearn.feature_extraction.text import TfidfVectorizertfidf
= TfidfVectorizer(stop_words='english')
train_x_vector = tfidf.fit_transform(train_x)
train_x_vectorOut[0]: <1340x20625 sparse matrix of type '<class
'numpy.float64'>'
      with 118834 stored elements in Compressed Sparse Row
format>
```

In the code above, we create a new instance of `TfidfVectorizer(tfidf)`, we removed English stopwords and then fit (finds the internal parameters of a model) and transform (applies the parameters to the data) the train_x (text reviews)

The `train_x_vector` we just created is a sparse matrix with a shape of 1340 reviews and 20625 words (whole vocabulary used in the reviews). You can display this matrix like the pictures I used in the examples above with the following code

```
pd.DataFrame.sparse.from_spmatrix(train_x_vector,
                                  index=train_x.index,

columns=tfidf.get_feature_names())
```

However, keep in mind that you'll find lots of '0' since its a sparse matrix with 1340x20625 elements where only 118834 elements are different from "0"

Finally, let's also transform the `test_x_vector`, so we can test the accuracy of the model later (we don't need to fit `tfidf` again since we already did it with the training data.)

```
test_x_vector = tfidf.transform(test_x)
```

Note: We could better prepare the text data in order to develop better models by using tokenization and removing extra words we consider irrelevant apart from the stopword list CountVectorizer and Tfidf have by default. Check the article below for more information about tokenization with Python.

Model Selection

Now that we have numerical data, we can experiment with different machine learning models and evaluate their accuracy.

Supervised vs Unsupervised learning

Machine learning algorithms are divided between supervised learning and unsupervised learning. In the first, models are trained using labeled data, while in the second patterns are inferred from the unlabeled input data.

In our example, our input (review) and output (sentiment) are clearly identified, so we can say we have labeled input and output data; therefore, we're dealing with supervised learning. Two common types of supervised learning algorithms are Regression and Classification.

- **Regression**: They're used to predict **continuous values** such as price, salary, age, etc
- **Classification**: They're used to predict **discrete values** such as male/female, spam/not spam, positive/negative, etc.

That said, it's now evident that we should use classification algorithms. We will benchmark the following four classification models.

Note: I'm going to leave the theory behind each model for you to research. I'm going to focus on the code and how we choose the best model based on the scores.

Support Vector Machines (SVM)

To fit an SVM model, we need to introduce the input (text reviews as numerical vectors) and output (sentiment)

```
from sklearn.svm import SVCsvc = SVC(kernel='linear')
svc.fit(train_x_vector, train_y)
```

After fitting `svc` we can predict whether a review is positive or negative with the `.predict()` method.

```
print(svc.predict(tfidf.transform(['A good movie'])))
print(svc.predict(tfidf.transform(['An excellent movie'])))
print(svc.predict(tfidf.transform(['I did not like this movie at
all'])))
```

If you run the code above, you'll obtain that the first and second reviews are positive, while the third is negative.

Decision Tree

To fit a decision tree model, we need to introduce the input (text reviews as numerical vectors) and output (sentiment)

```
from sklearn.tree import DecisionTreeClassifierdec_tree =
DecisionTreeClassifier()
dec_tree.fit(train_x_vector, train_y)
```

Naive Bayes

To fit a Naive Bayes model, we need to introduce the input (text reviews as numerical vectors) and output (sentiment)

```
from sklearn.naive_bayes import GaussianNBgnb = GaussianNB()
gnb.fit(train_x_vector.toarray(), train_y)
```

Logistic Regression

To fit a Logistic Regression model, we need to introduce the input (text reviews as numerical vectors) and output (sentiment)

```
from sklearn.linear_model import LogisticRegressionlog_reg =
LogisticRegression()
log_reg.fit(train_x_vector, train_y)
```

Model Evaluation

In this section, we'll see traditional metrics used to evaluate our models.

Mean Accuracy

To obtain the mean accuracy of each model, just use the `.score` method with the test samples and true labels as shown below.

```
# svc.score('Test samples', 'True
labels')svc.score(test_x_vector, test_y)
dec_tree.score(test_x_vector, test_y)
gnb.score(test_x_vector.toarray(), test_y)
log_reg.score(test_x_vector, test_y)
```

After printing each of them, we obtain the mean accuracy.

SVM: 0.84
Decision tree: 0.64
Naive Bayes: 0.63
Logistic Regression: 0.83

SVM and Logistic Regression perform better than the other two classifiers, with SVM having a slight advantage (84% of accuracy). **To show how the other metrics work, we'll focus only on SVM.**

F1 Score

F1 Score is the weighted average of Precision and Recall. Accuracy is used when the True Positives and True negatives are more important while F1-score is used when the False Negatives and False Positives are crucial. Also, F1 takes into account how the data is distributed, so it's useful when you have data with imbalance classes.

F1 score is calculated with the following formula.

```
F1 Score = 2*(Recall * Precision) / (Recall + Precision)F1 score
reaches its best value at 1 and worst score at 0.
```

To obtain the F1 score, we need the true labels and predicted labels

```
f1_score(y_true, y_pred)
from sklearn.metrics import f1_scoref1_score(test_y,
svc.predict(test_x_vector),
         labels=['positive', 'negative'],
         average=None)
```

The scores obtained for positive labels is 0.84, while negative labels is 0.83.

Classification report

We can also build a text report showing the main classification metrics that include those calculated before. To obtain the classification report, we need the true labels and predicted labels

```
classification_report(y_true, y_pred)
from sklearn.metrics import
classification_reportprint(classification_report(test_y,
                            svc.predict(test_x_vector),
                            labels=['positive', 'negative']))
```

After printing, we obtain the following report.

```
              precision    recall  f1-score   support

    positive       0.83      0.87      0.85       335
    negative       0.85      0.82      0.83       325

    accuracy                           0.84       660
   macro avg       0.84      0.84      0.84       660
weighted avg       0.84      0.84      0.84       660
```

As we can see, the accuracy and f1-score are the same as those previously calculated.

Confusion Matrix

A confusion matrix) is a table that allows visualization of the performance of an algorithm. This table typically has two rows and two columns that report the number of false positives, false negatives, true positives, and true negatives (check the graph in this link in case you don't understand these terms)

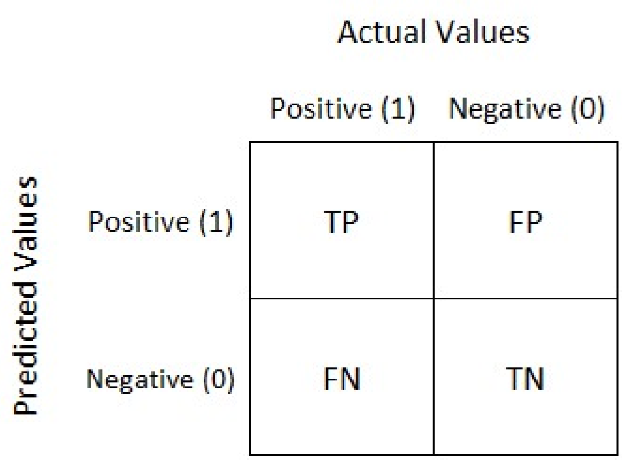
To obtain the confusion matrix, we need the true labels and predicted labels.

```
from sklearn.metrics import confusion_matrixconf_mat =
confusion_matrix(test_y,
                            svc.predict(test_x_vector),
                            labels=['positive', 'negative'])
```

After running the code below, we'll obtain the following array as output.

```
array([[290,  45],
       [ 60, 265]])
```

To understand what that means check this picture below.



As you can see, each element of the array represents one of the four squares in the confusion matrix (e.g., our model detected 290 true positives)

Tuning the Model

Finally, it’s time to maximize our model’s performance.

GridSearchCV

This is technique consists of an exhaustive search on specified parameters in order to obtain the optimum values of hyperparameters. To do so, we write the following code.

```
from sklearn.model_selection import GridSearchCV#set the
parameters
parameters = {‘C’: [1,4,8,16,32] ,’kernel’:[‘linear’, ‘rbf’]}
svc = SVC()
svc_grid = GridSearchCV(svc,parameters, cv=5)

svc_grid.fit(train_x_vector, train_y)
```

As you can see the code it’s not so different from the one we wrote to fit the SVM model; however, now we specified some parameters to obtain the optimum model.

After fitting the model, we obtain the best score, parameters, and estimators with the following code.

```
IN [0]: print(svc_grid.best_params_)
        print(svc_grid.best_estimator_)OUT [0]: {'C': 1,
'kernel': 'linear'}
         SVC(C=1, kernel='linear')
```

That’s it! Now you’re ready to create your own machine learning model using sklearn! All the code written in this guide can be found on my [GitHub]