

Objective

The aim is to classifying emotions present in the text documents by applying various NLP techniques such as Tokenization, Lemmatization, POS tagging and many more.

Problem Statement

To understand and classify polarity of sentences within text documents at sentence-level analysis using Natural Language Processing.



Positive

Brilliant Work! Good Job!

Neutral

Job is Doable. Plan sounds Okay.





Negative

Cake tastes Bitter.
I hate walking.

What is Sentiment Analysis?

Sentiment Analysis (emotion Al) is a sub-field of NLP that tries to identify & extract opinions within a given text across blogs, reviews, social media, forums, news etc. It's a Natural Language Processing algorithm that gives you a general idea about the positive, neutral, and negative sentiment of texts.

Architecture

Data pre-processing Tokenization of data Removal of words **lemmatization**

Data collection

Feature Extraction Polarity detection Calculation of results and model evaluation

Related Work and Novelty

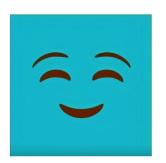
- □ There has been a steady undercurrent of interest for quite a while. For example, determining whether a review is positive or negative.^[1]
- A number of researchers have explored learning words and phrases with prior positive or negative polarity. [2]
- Another work^[3] where the researchers classify the contextual polarity of sentiment expressions and use manually developed patterns to classify polarity.

In contrast, we begin with a lexicon of words with established prior polarities and identify the contextual polarity of phrases and sentences in which instances of those words appear in the corpus. In addition to this, our system assign one sentiment per sentence as well as it assigns contextual polarity to individual expressions because usually sentences often contain more than one sentiment expression.

Data pre-processing

- 1. **Tokenization of data**: In this process, after the data is retrieved from the dataset. The data which is taken is in the form of sentences and phrases. Now, these sentences and phrases are tokenized into words, so that it is easily understandable.
- 2. **Removal of stop words**: Stop words are the words that the search engine has programmed to ignore when both indexing and retrieving of entries. Articles are the best examples of stop words.
- 3. **Stemming and Lemmatization**: Stemming and lemmatization is the process of converting the words into their root words so that they can be analyzed as a single item.
- 4. **P-O-S tagging**: Parts-of-Speech tagging is optional in sentiment polarity detection. It helps us to classify the words into a verb, adverb, adjective, noun etc. These words are then mapped to sentiment dictionary.

Sentiment Analysis



Happy



Surprised



Sad



Proud



Angry



In Love



Disappointed



Scared

```
if 1 == "joy":
        int_y_val.append(0)
    if 1 == "sadness":
        int_y_val.append(1)
    if 1 == "anger":
        int_y_val.append(2)
    if 1 == "fear":
        int_y_val.append(3)
    if 1 == "love":
        int_y_val.append(4)
    if 1 == "surprise":
        int_y_val.append(5)
int y train, int y test, int y val = np.array(int y train), np.array(int y test), np.array(int y val)
from sklearn import preprocessing
from keras.utils import np_utils
le = preprocessing.LabelEncoder()
le.fit(int y train)
encoded v train = le.transform(int v train)
encoded_y_test = le.transform(int_y_test)
encoded v val = le.transform(int v val)
encoded y train = np utils.to categorical(encoded y train)
encoded y test = np utils.to categorical(encoded y test)
encoded y val = np utils.to categorical(encoded y val)
print(encoded_y_train)
print(int_y_train[:10])
```

for 1 in v val:

Data Preparation

```
from tensorflow.python.keras.preprocessing.sequence import pad sequences
from nltk.corpus import stopwords
stopwords = stopwords.words('english')
stopwords[:5]
['i', 'me', 'my', 'myself', 'we']
x train cl = []
x test cl = []
x \text{ val cl} = []
# Deleting stopwords
for text in x train:
    text = text.split()
    text = [word for word in text if word not in stopwords]
    text = " ".join(text)
    x train cl.append(text)
for text in x test:
    text = text.split()
    text = [word for word in text if word not in stopwords]
    text = " ".join(text)
    x test cl.append(text)
```

from tensorflow.python.keras.preprocessing.text import Tokenizer

import nltk

nltk.download('stopwords')

Tokenization

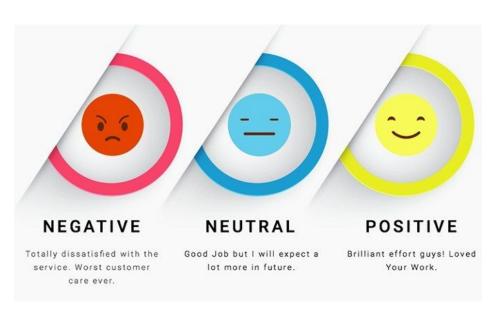
```
from tensorflow.python.keras.models import Sequential
from tensorflow.python.keras.layers import Dense, CuDNNGRU, Embedding, Bidirectional
model = Sequential()
model.add(Embedding(input_dim=2000
                   ,output_dim=100
                   ,input length=20))
model.add(Bidirectional(CuDNNGRU(units=16,return_sequences=True)))
model.add(Bidirectional(CuDNNGRU(units=8)))
model.add(Dense(6,activation="softmax"))
model.compile(loss="categorical_crossentropy",optimizer="rmsprop",metrics=["accuracy"])
model.summary()
```

Model: "sequential"

Layer (type)	Output	Shape	Param #
embedding (Embedding)	(None,	20, 100)	200000
bidirectional (Bidirectional	(None,	20, 32)	11328
bidirectional_1 (Bidirection	(None,	16)	2016
dense (Dense)	(None,	6)	102
Total params: 213,446 Trainable params: 213,446 Non-trainable params: 0			

Model and Prediction

Applications



- Social Media Monitoring
- Customer Support and feedback
- Brand monitoring and reputation management
- Product analysis
- Market and competitor research

Conclusion

Thus, polarity detection on the text document is performed and different emotions are observed and classified into positive, negative and neutral by using NLTK.

References

- Riloff and J. Wiebe. 2003. Learning extraction patterns for subjective expressions. In EMNLP-2003.
- Takamura, Hiroya & Inui, Takashi &
 Okumura, Manabu. (2005). Extracting
 emotional polarity of words using spin model.
- 3. J. Yi, T. Nasukawa, R. Bunescu and W. Niblack, "Sentiment analyzer: extracting sentiments about a given topic using natural language processing techniques," *Third IEEE International Conference on Data Mining*, Melbourne, FL, USA, 2003, pp. 427-434, doi: 10.1109/ICDM.2003.1250949.

Thank You

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