Problem Statement

Amazon is an online shopping website that now caters to millions of people everywhere. Over 34,000 consumer reviews for Amazon brand products like Kindle, Fire TV Stick and more are provided. The dataset has attributes like brand, categories, primary categories, reviews.title, reviews.text, and the sentiment. Sentiment is a categorical variable with three levels "Positive", "Negative“, and "Neutral". For a given unseen data, the sentiment needs to be predicted. You are required to predict Sentiment or Satisfaction of a purchase based on multiple features and review text.

In [2]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns



import nltk
from nltk.corpus import stopwords
from nltk.classify import SklearnClassifier

from wordcloud import WordCloud,STOPWORDS
import matplotlib.pyplot as plt
%matplotlib inline
from subprocess import check_output



from sklearn.feature_extraction.text import CountVectorizer
from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences
from keras.models import Sequential
from keras.layers import Dense, Embedding, LSTM, SpatialDropout1D
from sklearn.model_selection import train_test_split
from keras.utils.np_utils import to_categorical
import re
```

```
Using TensorFlow backend.
```

In [3]:

```
train = pd.read_csv("../input/ecommerce/train_data.csv")
test = pd.read_csv("../input/ecommerce/test_data.csv")
```

In [4]:

```
train.head()
```

Out[4]:

	name	brand	categories	primaryCategories	reviews.date	re
0	All-New Fire HD 8 Tablet, 8" HD Display, Wi-Fi...	Amazon	Electronics,iPad & Tablets,All Tablets,Fire Ta...	Electronics	2016-12-26T00:00:00.000Z	Pu on Fr - Pr
1	Amazon - Echo Plus w/ Built-In Hub - Silver	Amazon	Amazon Echo,Smart Home,Networking,Home & Tools...	Electronics,Hardware	2018-01-17T00:00:00.000Z	I p tw A Ec an do
2	Amazon Echo Show Alexa-enabled Bluetooth Speak...	Amazon	Amazon Echo,Virtual Assistant Speakers,Electro...	Electronics,Hardware	2017-12-20T00:00:00.000Z	Ju av A op D a
3	Fire HD 10 Tablet, 10.1 HD Display, Wi-Fi, 16 ...	Amazon	eBook Readers,Fire Tablets,Electronics Feature...	Office Supplies,Electronics	2017-08-04T00:00:00.000Z	ve pr Ex w w ar
4	Brand New Amazon Kindle Fire 16gb 7" Ips Displ...	Amazon	Computers/Tablets & Networking,Tablets & eBook...	Electronics	2017-01-23T00:00:00.000Z	Th 3r pu I'v

In [5]:

```
test.head()
```

Out[5]:

	name	brand	categories	primaryCategories	reviews.date
0	Fire Tablet, 7 Display, Wi-Fi, 16 GB - Include...	Amazon	Fire Tablets,Computers/Tablets & Networking,Ta...	Electronics	2016-05-23T00:00:00.000Z
1	Amazon Echo Show Alexa-enabled Bluetooth Speak...	Amazon	Computers,Amazon Echo,Virtual Assistant Speake...	Electronics,Hardware	2018-01-02T00:00:00.000Z
2	All-New Fire HD 8 Tablet, 8" HD Display, Wi-Fi...	Amazon	Electronics,iPad & Tablets,All Tablets,Fire Ta...	Electronics	2017-01-02T00:00:00.000Z
3	Brand New Amazon Kindle Fire 16gb 7" Ips Displ...	Amazon	Computers/Tablets & Networking,Tablets & eBook...	Electronics	2017-03-25T00:00:00.000Z
4	Amazon Echo Show Alexa-enabled Bluetooth Speak...	Amazon	Computers,Amazon Echo,Virtual Assistant Speake...	Electronics,Hardware	2017-11-15T00:00:00.000Z

In [6]:

```
train.count()
```

Out[6]:

```
name                  4000
brand                 4000
categories            4000
primaryCategories     4000
reviews.date          4000
reviews.text          4000
reviews.title         3990
sentiment             4000
dtype: int64
```

In [7]:

```
#train = train.append(test, ignore_index=True)
test.count()
```

Out[7]:

```
name                  1000
brand                 1000
categories            1000
primaryCategories     1000
reviews.date          1000
reviews.text          1000
reviews.title          997
dtype: int64
```

In [8]:

```
train.duplicated().sum()
```

Out[8]:

```
58
```

There are 58 duplicates, let's drop the duplicate values

In [9]:

```
train = train.drop_duplicates().reset_index(drop=True)
```

In [10]:

```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3942 entries, 0 to 3941
Data columns (total 8 columns):
name                 3942 non-null object
brand                3942 non-null object
categories           3942 non-null object
primaryCategories    3942 non-null object
reviews.date         3942 non-null object
reviews.text         3942 non-null object
reviews.title        3932 non-null object
sentiment            3942 non-null object
dtypes: object(8)
memory usage: 246.5+ KB
```

In [11]:

```
train.dtypes
```

Out[11]:

```
name                 object
brand                object
categories           object
primaryCategories    object
reviews.date         object
reviews.text         object
reviews.title        object
sentiment            object
dtype: object
```

In [12]:

```
train.describe()
```

Out[12]:

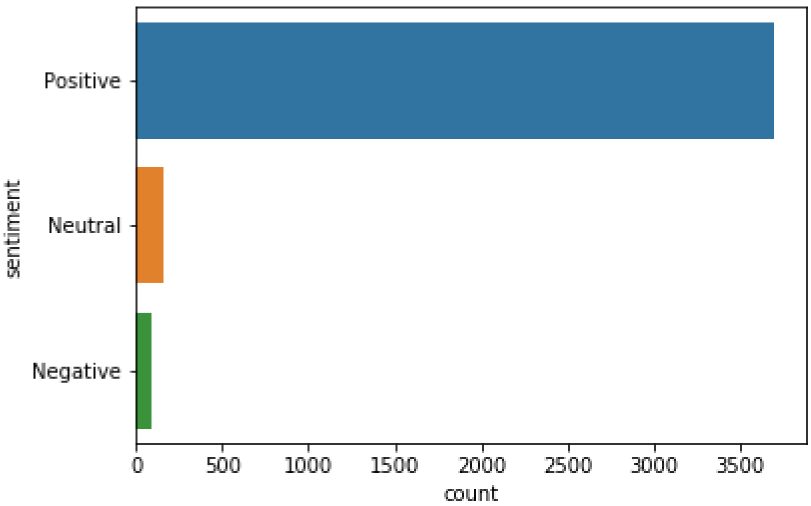
	name	brand	categories	primaryCategories	reviews.date	reviews
count	3942	3942	3942	3942	3942	3942
unique	23	1	23	4	638	3598
top	Amazon Echo Show Alexa-enabled Bluetooth Speak...	Amazon	Electronics,iPad & Tablets,All Tablets,Fire Ta...	Electronics	2017-01-23T00:00:00.000Z	I bough kindle f my 11y grandd
freq	676	3942	628	2562	98	4

Lets Visualize with the class imbalance thing !

Basic EDA of trainig data set

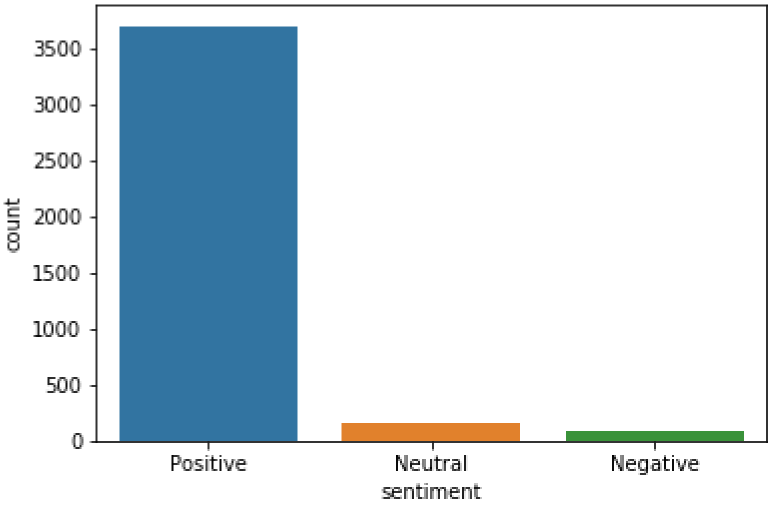
In [13]:

```
sns.countplot(y=train.sentiment);
```



In [14]:

```
sns.countplot( train['sentiment']);
```



Class Imbalance Problem

In [15]:

```
train.sentiment.value_counts()
```

Out[15]:

```
Positive    3694
Neutral      158
Negative      90
Name: sentiment, dtype: int64
```

In [16]:

```
# NA data
train.isnull().sum()
```

Out[16]:

```
name                  0
brand                 0
categories            0
primaryCategories     0
reviews.date          0
reviews.text          0
reviews.title        10
sentiment             0
dtype: int64
```

In [17]:

```
test.isnull().sum()
```

Out[17]:

```
name                 0
brand                0
categories           0
primaryCategories    0
reviews.date         0
reviews.text         0
reviews.title        3
dtype: int64
```

We should rename the column to avoid errors

In [18]:

```
train.columns
```

Out[18]:

```
Index(['name', 'brand', 'categories', 'primaryCategories', 'reviews.
date',
       'reviews.text', 'reviews.title', 'sentiment'],
      dtype='object')
```

In [19]:

```
train.rename(columns = {'reviews.text':'reviews_text', 'reviews.title':'reviews_
title','reviews.date':'reviews_date'}, inplace = True)
```

In [20]:

```
train.columns
```

Out[20]:

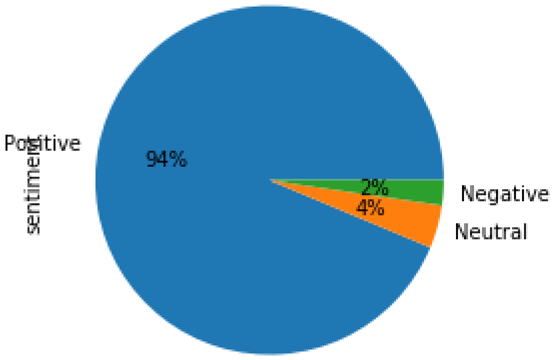
```
Index(['name', 'brand', 'categories', 'primaryCategories', 'reviews_
date',
       'reviews_text', 'reviews_title', 'sentiment'],
      dtype='object')
```

In [21]:

```
train['sentiment'].value_counts().plot(kind='pie', autopct= '%1.0f%%')
```

Out[21]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f720e0aa518>
```



Here I am dropping the Neutral Sentiment as My goal is to work on differentiate the positive and negative

In [22]:

```
train = train[train.sentiment != "Neutral"]
```

Now we are ready for a WordCloud visualization which shows only the most emphatic words of the Positive and Negative sentiment.

In [23]:

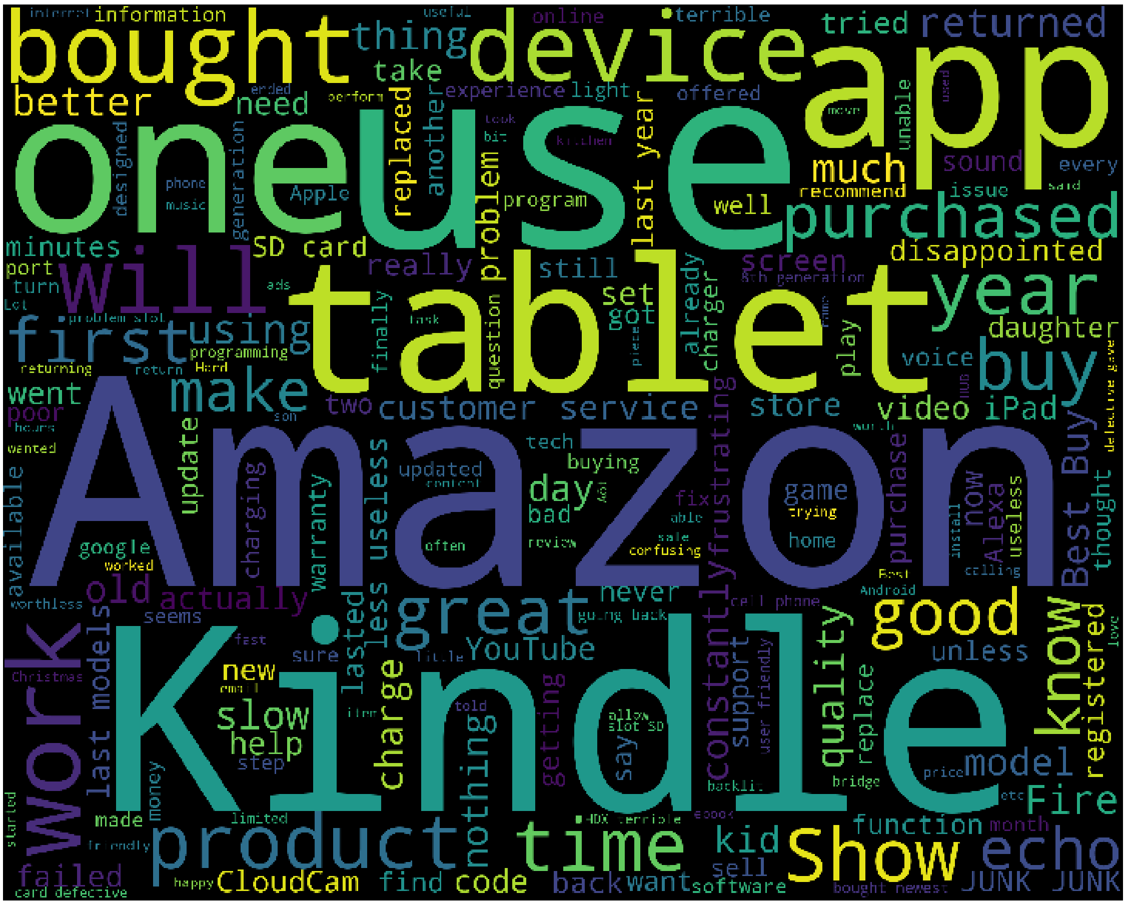
```
train_pos = train[ train['sentiment'] == 'Positive']
train_pos = train_pos['reviews_text']
train_neg = train[ train['sentiment'] == 'Negative']
train_neg = train_neg['reviews_text']

def wordcloud_draw(data, color = 'black'):
    words = ' '.join(data)
    cleaned_word = " ".join([word for word in words.split()
                        if 'http' not in word
                            and not word.startswith('@')
                            and not word.startswith('#')
                            and word != 'RT'
                        ])
    wordcloud = WordCloud(stopwords=STOPWORDS,
                      background_color=color,
                      width=2500,
                      height=2000
                     ).generate(cleaned_word)
    plt.figure(1,figsize=(13, 13))
    plt.imshow(wordcloud)
    plt.axis('off')
    plt.show()

print("Positive words")
wordcloud_draw(train_pos,'white')
print("Negative words")
wordcloud_draw(train_neg)
```

Positive words

Negative words



Data Preprocessing Part

Stopword Removal using NLTK

After the vizualization, we need to remove the hashtags, mentions, links and stopwords from the training set.

Stop Word: Stop Words are words which do not contain important significance to be used in Search Queries. Usually these words are filtered out from search queries because they return vast amount of unnecessary information. (the, for, this etc.)

In [24]:

```
def remove_non_ascii(words):
    """Remove non-ASCII characters from list of tokenized words"""
    new_words = []
    for word in words:
        new_word = unicodedata.normalize('NFKD', word).encode('ascii', 'ignore')
.decode('utf-8', 'ignore')
        new_words.append(new_word)
    return new_words

def to_lowercase(words):
    """Convert all characters to lowercase from list of tokenized words"""
    new_words = []
    for word in words:
        new_word = word.lower()
        new_words.append(new_word)
    return new_words

def remove_punctuation(words):
    """Remove punctuation from list of tokenized words"""
    new_words = []
    for word in words:
        new_word = re.sub(r'[^\w\s]', '', word)
        if new_word != '':
            new_words.append(new_word)
    return new_words

def remove_numbers(words):
    """Remove all interger occurrences in list of tokenized words with textual rep
resentation"""
    new_words = []
    for word in words:
        new_word = re.sub("\d+", "", word)
        if new_word != '':
            new_words.append(new_word)
    return new_words

def remove_stopwords(words):
    """Remove stop words from list of tokenized words"""
    new_words = []
    for word in words:
        if word not in stopwords.words('english'):
            new_words.append(word)
    return new_words
```

```python
def stem_words(words):
    """Stem words in list of tokenized words"""
    stemmer = LancasterStemmer()
    stems = []
    for word in words:
        stem = stemmer.stem(word)
        stems.append(stem)
    return stems

def lemmatize_verbs(words):
    """Lemmatize verbs in list of tokenized words"""
    lemmatizer = WordNetLemmatizer()
    lemmas = []
    for word in words:
        lemma = lemmatizer.lemmatize(word, pos='v')
        lemmas.append(lemma)
    return lemmas

def normalize(words):
    words = remove_non_ascii(words)
    words = to_lowercase(words)
    words = remove_punctuation(words)
    words = remove_numbers(words)
#    words = remove_stopwords(words)
    return words
```

In [25]:

```python
# First step - tokenizing phrases
train['reviews_text'] = train['reviews_text'].apply(nltk.word_tokenize)

# Second step - passing through prep functions
#train['reviews_text'] = train['reviews_text'].apply(normalize)
train['reviews_text'].head()
```

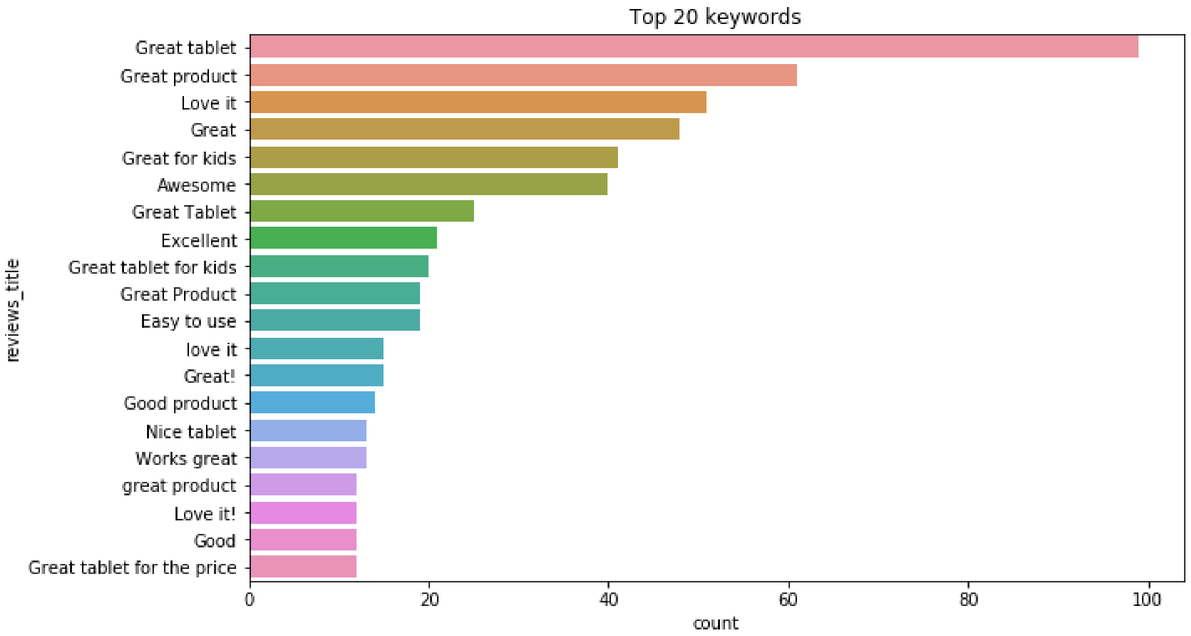
Out[25]:

```
0    [Purchased, on, Black, FridayPros, -, Great, P...
1    [I, purchased, two, Amazon, in, Echo, Plus, an...
3    [very, good, product, ., Exactly, what, I, wan...
4    [This, is, the, 3rd, one, I, 've, purchased, ....
5    [This, is, a, great, product, ., Light, weight...
Name: reviews_text, dtype: object
```

Let's visualize the most common keywords

In [26]:

```
# Most common keywords
plt.figure(figsize=(10,6))
sns.countplot(y=train.reviews_title, order = train.reviews_title.value_counts().
iloc[:20].index)
plt.title('Top 20 keywords')
plt.show()
# train.keyword.value_counts().head(10)
```



In [ ]:

```

```