Option 1 - Data Science/ML

Objectives

1. To gain insights from the dataset to make orgainzed data-driven decisions.
2. Topic Modeling - to extract topics from a large volume of data
3. Design a simple model to predict the number of upVotess based on the time and contents of the title.

Pipeline

1. Data Cleaning : Data cleaning can be performed in many different ways and not limited to the steps followed below. It is an important step that the helps identify relevant instances.
2. Feature Engineering : It helps transform data into features that accuractely reflect the relation to predictive models.
3. Data Visualization : This technique helps draw insights from the dataset. Very useful as it helps articulate the task at hand. (Posts vs Time ; Popular authors ; best time to post news ; word embedding)
4. Text Understanding
5. Topic Modeling : LDA
6. Linear Regression

Importing Libraries and Reading Dataset

```
pip install geotext
```

```
Requirement already satisfied: geotext in /usr/local/lib/python3.7/dist-packages (0.4.0)
```

```
import pandas as pd
import numpy as np
import seaborn as sns
sns.set()
from datetime import datetime, timedelta, date
import matplotlib.pyplot as plt
```

```
%matplotlib inline
import string
from wordcloud import WordCloud
import warnings
warnings.filterwarnings('ignore')
from contextlib import contextmanager
import time
from geotext import GeoText
import re
from collections import Counter
from nltk.corpus import stopwords
import nltk
from nltk.stem import PorterStemmer,WordNetLemmatizer
from wordcloud import WordCloud

# Importing dataset
df=pd.read_csv('/content/drive/MyDrive/Eluvio-DS Challenge/Eluvio_DS_Challenge.csv')
print("Shape of data=>",df.shape)
```

```
Shape of data=> (509236, 8)
```

```
df.info()
df.head(5)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 509236 entries, 0 to 509235
Data columns (total 8 columns):
 #   Column        Non-Null Count   Dtype
---  ------        --------------   -----
 0   time_created  509236 non-null  int64
 1   date_created  509236 non-null  object
 2   up_votes      509236 non-null  int64
 3   down_votes    509236 non-null  int64
 4   title         509236 non-null  object
 5   over_18       509236 non-null  bool
```

1.Data Cleaning

a. Check for missing values

Let’s see if there are any null values present in our dataset.

```
df.isnull().sum()
```

```
time_created    0
date_created    0
up_votes        0
down_votes      0
title           0
over_18         0
author          0
category        0
dtype: int64
```

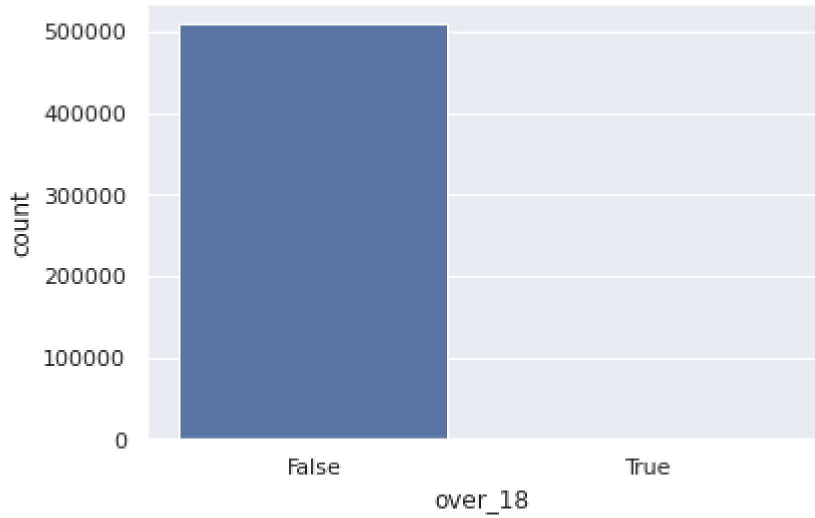
No null values present.

b.Feature Exploration

There are a total of 10 features present in the dataset.

```
sns.countplot(df['over_18'])
print(df['over_18'].value_counts())
```

```
False    508916
True        320
Name: over_18, dtype: int64
```



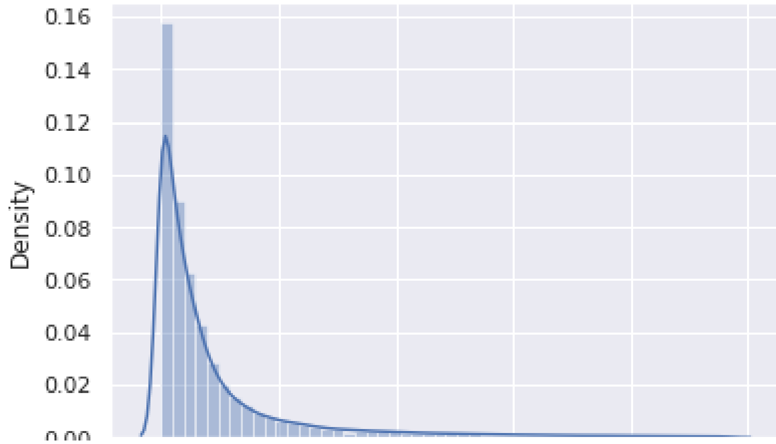

```
print(df['category'].value_counts())
print(df['down_votes'].value_counts())
```

```
worldnews    509236
Name: category, dtype: int64
0    509236
Name: down_votes, dtype: int64
```

--> All down_votes are zero

```
sns.distplot(df[df['up_votes']<=97]['up_votes'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff2341b7750>
```



-->It can be observed that upVotes have zero-inflated distribution and 18% of news have no upvotes.

Length of the title

```
for t, title in enumerate(df[['title']].sample(20, random_state=2019).title):
    print(t, ':', title)
```

```
0 : Iran launches mass production of new surface-to-air missiles
1 : Burkina Faso traders riot over lootings: Merchants set fire to ruling party s headquarters after official

2 : Drought, hail, cold conspire to turn European wine grape harvest in worst in half a century
3 : Pinochet-era death squad members jailed
4 : Peru state energy company reports Amazon oil spill
5 : Miami feds indict 6 on charges of supporting Pakistani Taliban
6 : Ukrainian rebels free four OSCE hostages, four still in captivity
7 : Signs of Changes Taking Hold in Electronics Factories in China

8 : Turnbull, Morrison to speak on tax reform
9 : Panama Papers: Pakistan PM Sharif under fire over offshore accounts
10 : Germany Pushes for Gas Pipeline with Russia
11 : China eyes artificial intelligence for ‘fire-and-forget’ cruise missiles | China is already a global lea
12 : WHO: 7 million premature deaths annually linked to air pollution
13 : Three Turkish soldiers killed as PKK steps up attacks after air strikes — Ynetnews
14 : Daily Beast: Tim Geithner was aware of LIBOR rate fixing in 2007, but chose not to do anything
15 : Iran’s top human rights official censured the hypocritical approach pursued by the self-styled advocates
```

```
16 : Rupert Murdoch Admits Defeat: Now Wants London Times To Appear In Google Search Results
17 : ‘NY Times’ publishes defense of racial segregation in Israel
18 :  Affluenza  teen may delay deportation from Mexico with human rights law
19 : Bundeswehr ammunition gets lost on Berlin-Mali flight
```

--> Note that "length of titles" does not really give much information

Over_18 contents

```
df.over_18.value_counts()
```

```
False    508916
True        320
Name: over_18, dtype: int64
```

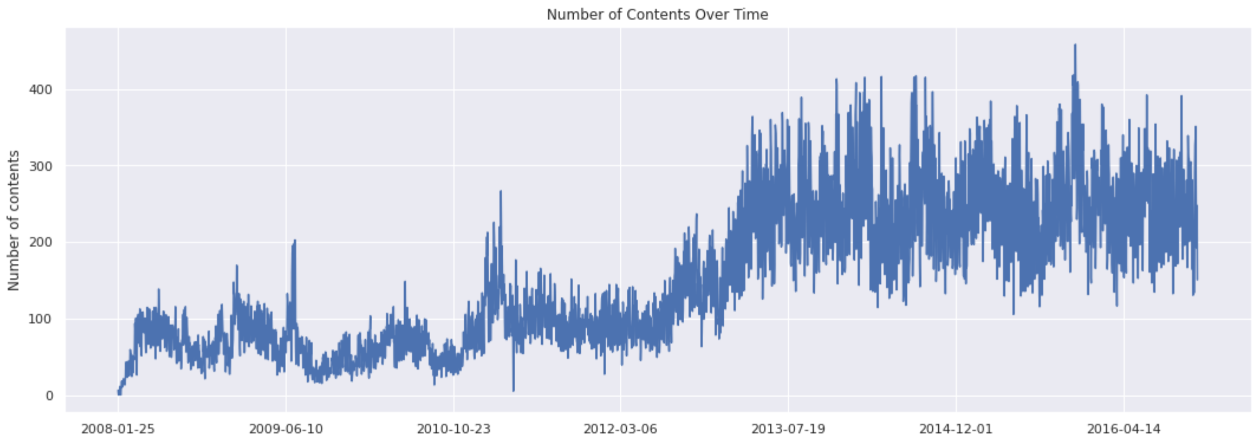
```
for text in df[df.over_18==True].sample(20, random_state=2019).title:
    print(text)
```

```
International Go-Topless Day sees women bare breasts in 50 cities
NSFW: Syrian Internet Restored, Dramatic Footage Emerges [VIDEO]
 Muslim, let s get naked : Ukraine-based activist group Femen Opens First Office Abroad in Paris. For the ope
In pictures: Gaza Massacre (Graphic!  possibly NSFW)
Footage suggests Egypt protesters shot at - NSFW
Tragic story - How the Thai army deals with deserters. Warning - graphic pictures inside.
IDF kills young Palestinian boy. Potentially NSFW.
Tibetan in Delhi Sets Self Alight to Protest Chinese Leader s Visit - NYTimes.com
[NSFL] Australian child molester Peter Scully faces death penalty in Philippines - Scully  filmed his torture
2,500 people killed in Bangladesh by the Govt. on May 6, 2013, however, the World doesn t know about it.
Animal Cruelty in Halal Meat Production in Indonesia supported by Australia (NSFW)
Japanese idol, a member of the girls group AKB48, accused of sexually abusing a child in her  inappropriate
CNN: Videos show glimpse into evidence for Syria intervention
Israeli female soldiers disciplined for racy Facebook photos [NSFW]
Syrian Doctor Describes Treating Chemical Weapons Victims [NSFL] [NPR]
Hundreds of children s bodies piled high after nerve gas attack near Damascus leaves up to 1,300 dead
Japanese woman faces two years in prison for trying to 3D scan her vagina for a special kind of kyak design.
NSFW  A child girl shot in the eye by Syrian security forces.
Tortured puppies covered in hot tar and left for dead in Romanian city
Israeli Rights Group Releases Video of Soldier Executing Wounded Palestinian Suspect
```

--> Contents containing terms like [NSFW, NSFL, NPR] are all classified as over_18

Content vs Time

```
df[['date_created', 'time_created']].groupby('date_created').count().plot(figsize=(18,6), legend=None)
plt.title('Number of Contents Over Time')
plt.ylabel('Number of contents')
plt.xlabel(None)
plt.show()
```



2. Feature Engineering:

```
@contextmanager
def timer(title):
    t0 = time.time()
    yield
    print("{} - done in {:.0f}s".format(title, time.time() - t0))

def places(x):
    count = GeoText(x).countries
    city = GeoText(x).cities
    w = 0
    if not count and not city: return 0
    else:
        w=len(count)+len(city)
        return w

def countries(x):
    count = GeoText(x).countries
    city = GeoText(x).cities
    w = ''
    if not count and not city: return np.nan
    else:
        for country in count:
            w = w+' '+country
        for c in city:
            w = w+' '+c
        return w


def df_feature_engineer(df):
    df['date_created'] = pd.to_datetime(df['date_created'])
    df['day_of_week']=df['date_created'].dt.day_name()
    df['day_of_week_num']=df['date_created'].dt.dayofweek
    df['year'] = df['date_created'].dt.year
    df['month'] = df['date_created'].dt.month
    df['day'] = df['date_created'].dt.day
    df['weekend'] = np.where(df['date_created'].dt.dayofweek>4,1, 0)
    df['years to now'] = (datetime.today() - df['date created']).dt.days/365
```

```
    df['time_created'] = pd.to_datetime(df['time_created'], unit='s')
    df['day_time']=df['time_created'].dt.hour+df['time_created'].dt.minute/60+df['time_created'].dt.second/3600
    df['author_total_posts'] = df['author'].groupby(df['author']).transform('count')
    df = df.drop(columns=['date_created','down_votes','category'])
    df['title_length'] = df['title'].str.split().apply(len)
    df['over_18'] = df['over_18'].map({False:0,True:1})
    df['countries'] = df['title'].apply(lambda x: countries(x))
    df['places'] = df['title'].apply(lambda x: places(x))
    return df
```

```
with timer("New Features and Clean Data"):
    df = df_feature_engineer(df)
```

```
New Features and Clean Data - done in 36s
```

Formatted Data

```
df = df.sort_values(['time_created'], ascending=True)
df.head(1)
```

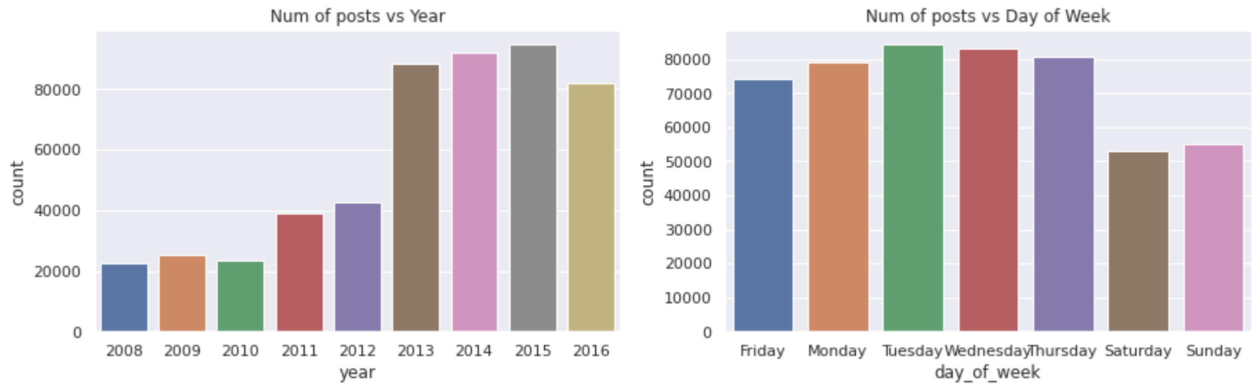
	time_created	up_votes	title	over_18	author	day_of_week	day_of_week_num	year	month	day	weekend	ye
0	2008-01-25 03:34:06	3	Scores killed in Pakistan clashes	0	polar	Friday	4	2008	1	25	0	

3. Data Visualization

1. Countplots: Number of posts vs year and day of the week.

```
f, ax = plt.subplots(1, 2, figsize=(15, 4))
g=sns.countplot(x='day_of_week',data=df,ax=ax[1])
g.set_title('Num of posts vs Day of Week')
g=sns.countplot(x='year',data=df,ax=ax[0])
g.set_title('Num of posts vs Year')
```

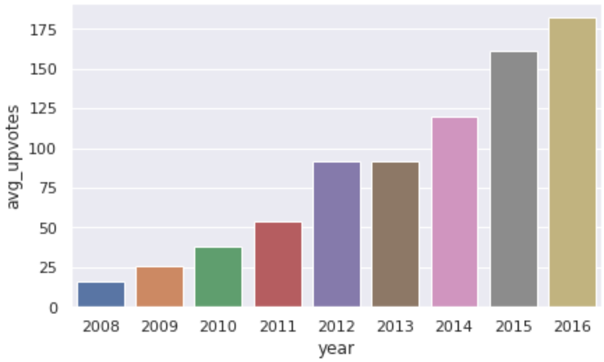
```
Text(0.5, 1.0, 'Num of posts vs Year')
```

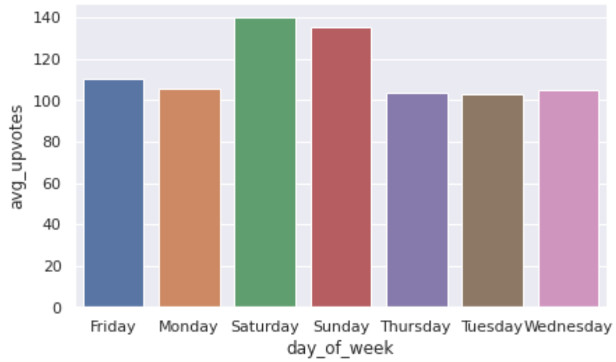


2. Barplots: Average upvotes vs year and day of the week.

```
f, ax = plt.subplots(1, 2, figsize=(15, 4))
plot1 = df.groupby('year').mean()['up_votes'].reset_index(name='avg_upvotes')
sns.barplot(x='year',y='avg_upvotes',data=plot1, ax=ax[0])
plot2 = df.groupby('day_of_week').mean()['up_votes'].reset_index(name='avg_upvotes')
sns.barplot(x='day_of_week',y='avg_upvotes',data=plot2, ax=ax[1])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff224e85b50>
```



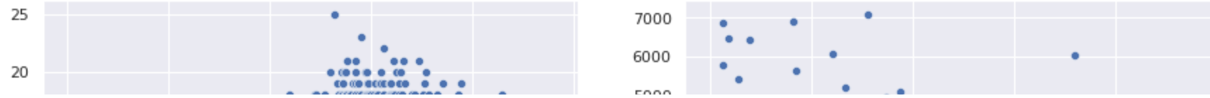


--> From the plots, it can be observed that the number of visitors and posts increase over time. Users tend to be more active.From this, it would quite reasonable to assume that any posts during the weekend receives more upvotes on average.

3. Total upvotes and mean upvotes vs day time.

```
f, ax = plt.subplots(1, 2, figsize=(15, 4))
plot3 = df.groupby('day_time').count()['up_votes'].reset_index(name='count')
sns.scatterplot(x='day_time', y='count', data=plot3, ax=ax[0])
plot4 = df.groupby('day_time').mean()['up_votes'].reset_index(name='avg')
sns.scatterplot(x='day_time', y='avg', data=plot4, ax=ax[1])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff224d45350>
```



--> From the above plot it can be seen that one post in particular received the highest upvotes. Additionally, threre are more posts after 3:00pm.

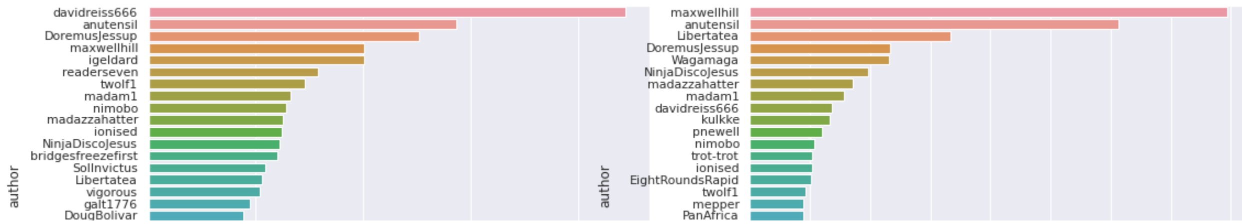

```
#df[df['up_votes'] > 20000] # Comment this line when performing regression
```

4. Top 30 most active authors and top 30 authors with most upvotes.

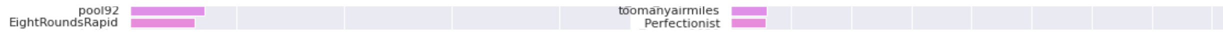
```
f, ax = plt.subplots(1, 2, figsize=(18, 6))
num = 30
sns.countplot(y=df['author'],\
              order = df['author'].value_counts().iloc[:num].index, ax=ax[0])

plot5 = df.groupby('author').sum()['up_votes'].reset_index(name='sum_votes').\
       sort_values(by='sum_votes',ascending=False)
sns.barplot(y='author',x='sum_votes',data=plot5.iloc[:num],ax=ax[1])
```

<matplotlib.axes._subplots.AxesSubplot at 0x7ff224cac710>

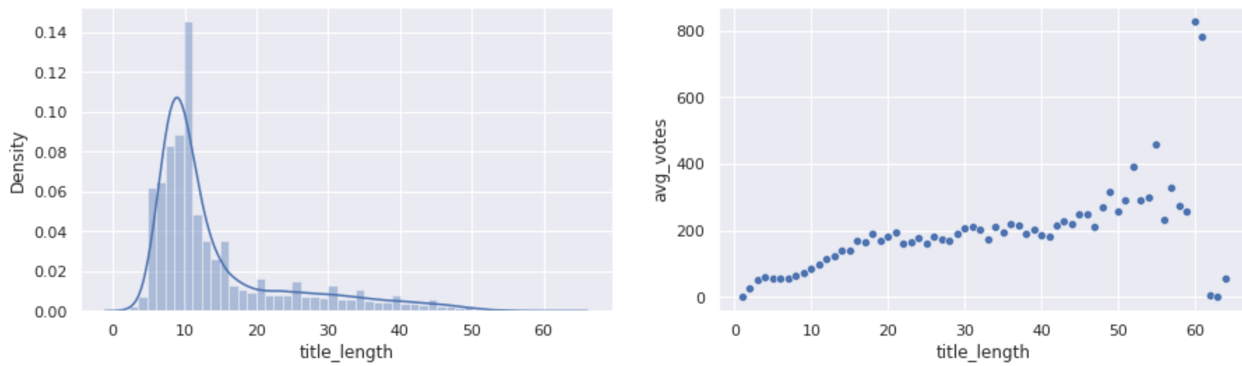


5. Distribution of the length of the news title. Avg votes vs length of news titles.




```
f, ax = plt.subplots(1, 2, figsize=(15, 4))
sns.distplot(df['title_length'],ax=ax[0])
plot6 = df.groupby('title_length').mean()['up_votes'].reset_index(name='avg_votes')
sns.scatterplot(plot6['title_length'],plot6['avg_votes'],ax=ax[1])
```

<matplotlib.axes._subplots.AxesSubplot at 0x7ff223feb2d0>

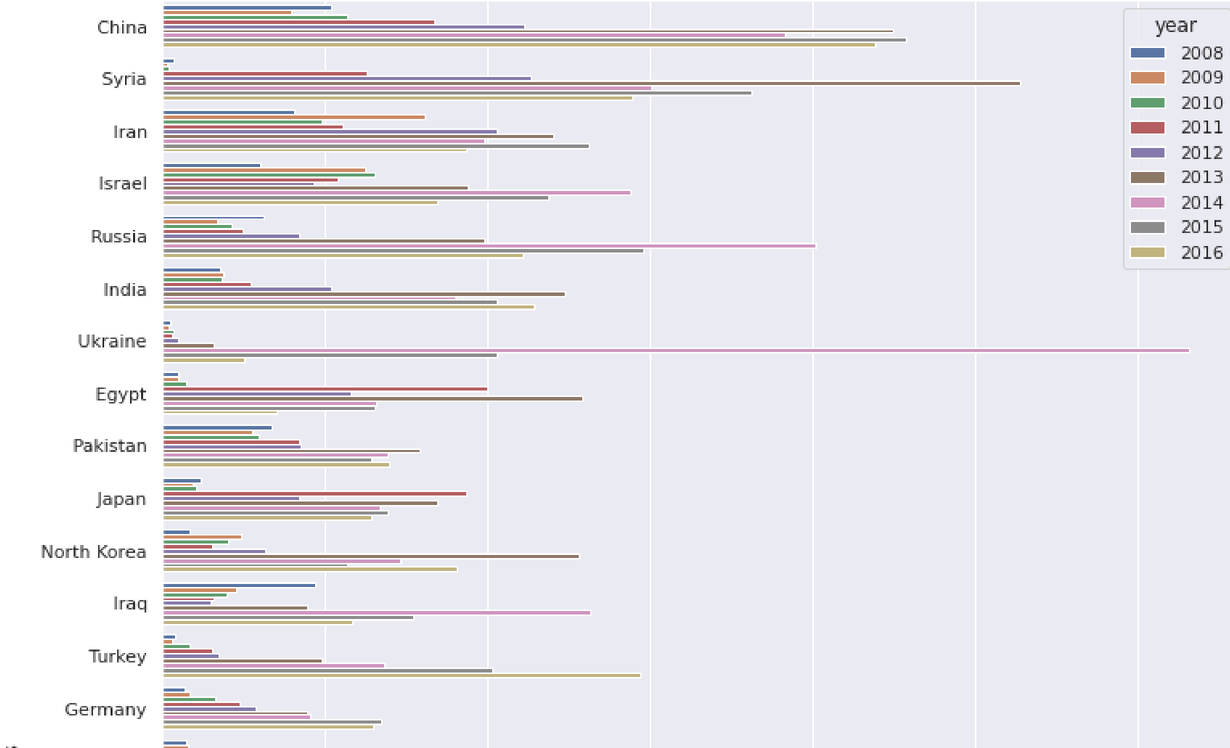


--> We can see that when the length of the words is around 12, there is a peak in the number of upvotes but gradually decreases with the increase in word length and almost reaches zero after 55.

6. Top 30 countries in the news with different years.

```
fig = plt.figure(figsize=(12,18))
sns.countplot(y=df['countries'],\
              order = df['countries'].value_counts().iloc[:30].index, hue=df['year'])
```

<matplotlib.axes._subplots.AxesSubplot at 0x7ff2241bec10>



--> Not enough can be inferred from the this plot. We can see that the countries mentioned differ year by year. For example, we can see that there count for Ukraine increased in 2014 due to [Ukraine's Revolution]

---

4. Text Understanding


```
import nltk
nltk.download('stopwords')
nltk.download('punkt')
nltk.download('wordnet')
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
True
```

a. Word cleaning and lemmatization

```
text = df['title']

lemma=WordNetLemmatizer()
stopwords_en = stopwords.words('english')


def text_process(text):
    text = re.sub(r"\'s", " ", text)
    text = re.sub(r",", " ", text)
    text = re.sub(r"\.", "", text)
    text = re.sub(r"U-turn", "Uturn", text)
    text = re.sub(r"New York Times", "NewYorkTimes", text)
    text = re.sub(r"\^", " ^ ", text)
    text = re.sub(r"U of", "University of", text)
    text = re.sub(r"N Korea", "NorthKorea", text)
    text = re.sub(r"'", " ", text)
    text = re.sub(r"(\d+)(k)", r"\g<1>000", text)
    text = re.sub(r"U S", "US", text)
    text = re.sub(r"U S ", "US", text)
    text = re.sub(r"U N", "UN", text)
    text = re.sub(r"U N ", "UN", text)
    text = re.sub(r"@\S+", "", text)

    word=nltk.word_tokenize(text.lower())
    new_word=[w for w in word if w not in stopwords_en and w.isalpha()]
    new_word=[lemma.lemmatize(w, "v") for w in new_word]
    return new_word
```

```
print('='*50)
print(text[381])
print('='*50)
print(text_process(text[381]))
```

```
==================================================
 Iran Defiant Ahead of U.N. Nuclear Watchdog Report
==================================================
['iran', 'defiant', 'ahead', 'un', 'nuclear', 'watchdog', 'report']
```

After applying tokenization and normalization

```
def word_freq(s):
    txt = s.str.lower().str.cat(sep=' ')
    words = text_process(txt)
    words_dist = nltk.FreqDist(w for w in words)
    return words_dist

for year in range(2008, 2017):
    words_dist=word_freq(df[df['year']==year]['title'])
    res=[]
    for w, count in words_dist.most_common(10): res.append(w)
    print(year, res)
```

```
2008 ['us', 'say', 'kill', 'china', 'war', 'world', 'attack', 'iraq', 'iran', 'new']
2009 ['us', 'israel', 'iran', 'say', 'gaza', 'kill', 'world', 'war', 'new', 'israeli']
2010 ['us', 'israel', 'say', 'kill', 'world', 'china', 'new', 'iran', 'war', 'attack']
2011 ['say', 'kill', 'us', 'protest', 'libya', 'egypt', 'new', 'china', 'government', 'force']
2012 ['say', 'kill', 'us', 'china', 'syria', 'iran', 'new', 'news', 'police', 'attack']
2013 ['say', 'us', 'syria', 'kill', 'china', 'new', 'attack', 'world', 'police', 'korea']
2014 ['say', 'us', 'ukraine', 'russia', 'kill', 'new', 'china', 'state', 'attack', 'russian']
2015 ['say', 'us', 'kill', 'china', 'attack', 'new', 'russia', 'state', 'isis', 'syria']
2016 ['say', 'us', 'china', 'kill', 'attack', 'new', 'syria', 'russia', 'state', 'police']
```

```
words_dist=word_freq(df['title'])
len(words_dist)
#words_dist
```

```
72208
```

```
wordcloud = WordCloud(width=1600, height=800,background_color='white').generate_from_frequencies(words_dist)
fig = plt.figure(figsize=(15,5), facecolor='c')
plt.imshow(wordcloud)
plt.axis('off')
plt.tight_layout()
plt.show()
words_dist['bbc']
```


```
5729
```

Word2Vec Embedding

```
import gensim
filename = '/content/drive/MyDrive/Eluvio-DS Challenge/GoogleNews-vectors-negative300.bin.gz'
model = gensim.models.KeyedVectors.load_word2vec_format(filename, binary=True)
```

```
def Word2Vec(model, titles_list):
    big_title_string = ' '.join(titles_list)
    words = text_process(big_title_string)
    vectorList = [model[word] for word in words if word in model.vocab]
    wordsFiltered = [word for word in words if word in model.vocab]
    wrd2vec_dict = dict(zip(wordsFiltered, vectorList))
    dic = pd.DataFrame.from_dict(wrd2vec_dict, orient='index')
    print('Shape of dictionary',dic.shape)
    return dic


titles_list = [title for title in text]
dic = Word2Vec(model, titles_list)
```

```
Shape of dictionary (38301, 300)
```

t-Distributed Stochastic Neighbor Embedding (t-SNE)- It is non-linear dimensionality reduction technqiue that is particularly helpful for high-dimensinoal datasets. It can be used in image processing, speech processing, genomic data and Natural Language Processing.

```
pip install adjustText
```

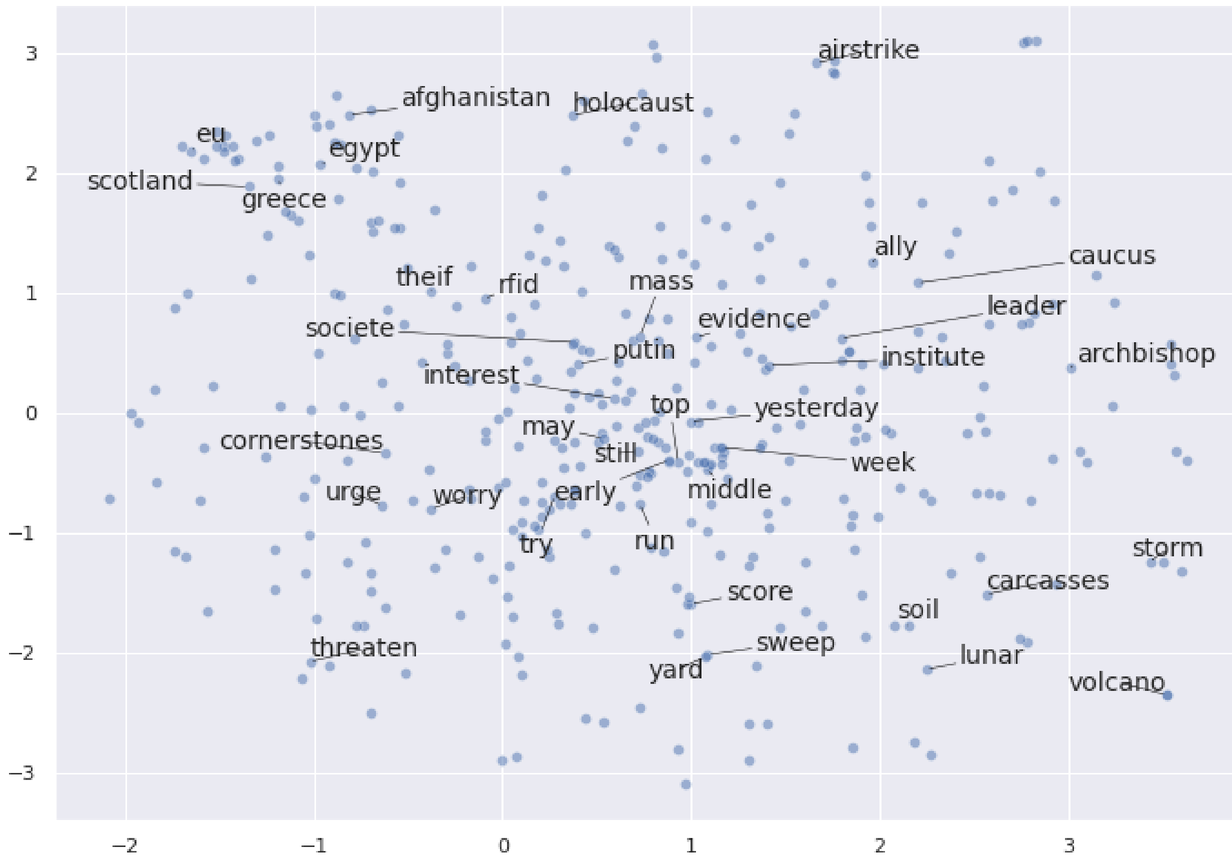
```
Requirement already satisfied: adjustText in /usr/local/lib/python3.7/dist-packages (0.7.3)
Requirement already satisfied: numpy in /usr/local/lib/python3.7/dist-packages (from adjustText) (1.19.5)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.7/dist-packages (from adjustText) (3.2.2)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/dist-packages (from matplotlib->adjus
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.7/dist-packages (from matplotli
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.7/dist-packages (from matplotlib->
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr/local/lib/python3.7/dist-pack
Requirement already satisfied: six in /usr/local/lib/python3.7/dist-packages (from cycler>=0.10->matplotlib->
```

```
from sklearn.manifold import TSNE
from adjustText import adjust_text
tsne = TSNE(n_components = 2, init = 'random', random_state = 10, perplexity = 100)
tsne_df = tsne.fit_transform(dic[0:400])

fig, ax = plt.subplots(figsize = (11.7, 8.27))
sns.scatterplot(tsne_df[:, 0], tsne_df[:, 1], alpha = 0.5)
texts = []
```

```
words_to_plot = list(np.arange(0, 400, 10))
for word in words_to_plot: texts.append(plt.text(tsne_df[word, 0], tsne_df[word, 1], dic.index[word], fontsize = 1
adjust_text(texts, force_points = 0.4, force_text = 0.4, expand_points = (2,1), expand_text = (1,2), arrowprops =
```

```
424
```



Doc2Vec

To reduce the training process of a traditional Doc2Vec embedding teechnique,the average embedding of each word in title text is considered.

```
class Doc2Vec:
    def __init__(self, model, corpus):
        self.word2vec_model = model
        self.corpus = corpus

    def document_vector(self, doc):
        doc = [word for word in doc if word in self.word2vec_model.vocab]
        return np.mean(self.word2vec_model[doc], axis=0)

    def filter_docs(self, texts, condition_on_doc):
        number_of_docs = len(self.corpus)
        texts = [text for (text, doc) in zip(texts, self.corpus)
                 if condition_on_doc(doc)]
        corpus = [doc for doc in self.corpus if condition_on_doc(doc)]
        print("{} documents removed".format(number_of_docs - len(corpus)))
        return (corpus, texts)

    def vector_representation(self, doc): return not all(word not in self.word2vec_model.vocab for word in doc)
```

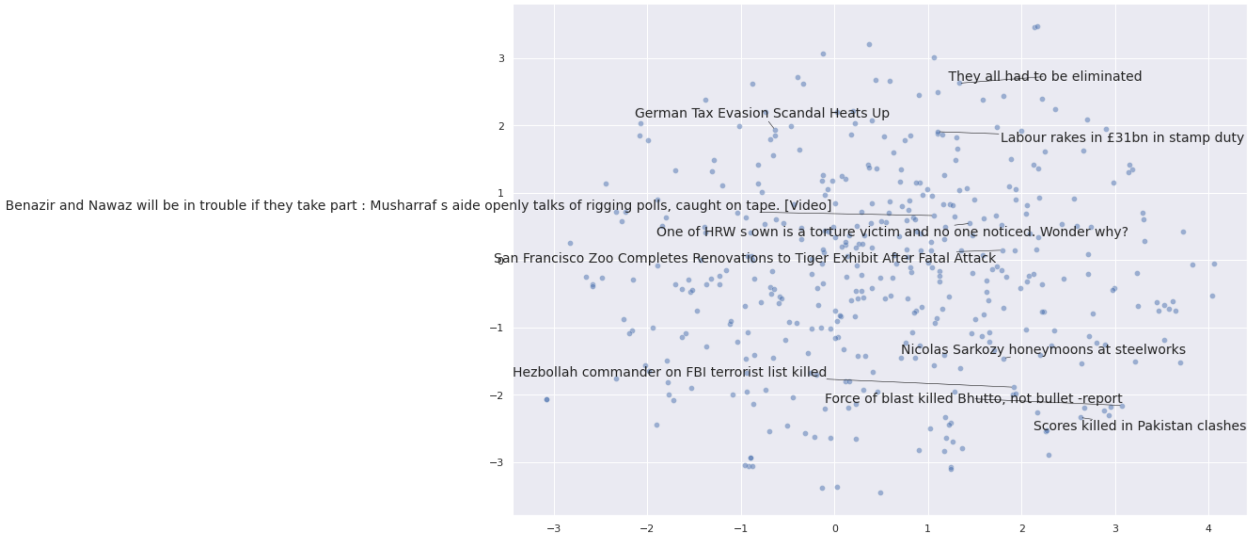
```
corpus = df['title'].map(text_process)
temp = Doc2Vec(model, corpus)
corpus, titles_left = temp.filter_docs(titles_list, lambda doc: temp.vector_representation(doc))
# Initialize an array for the size of the corpus
x = []
for doc in corpus:
    x.append(temp.document_vector(doc))
docvec = np.array(x)
```

```
171 documents removed
```

```
# Initialize t-SNE
tsne = TSNE(n_components = 2, init = 'random', random_state = 10, perplexity = 100)
tsne_df = tsne.fit_transform(docvec[:400])
fig, ax = plt.subplots(figsize = (14, 10))
sns.scatterplot(tsne_df[:, 0], tsne_df[:, 1], alpha = 0.5)
```

```
texts = []
titles_to_plot = list(np.arange(0, 400, 40))
for title in titles_to_plot: texts.append(plt.text(tsne_df[title, 0], tsne_df[title, 1], titles_list[title], fonts
adjust_text(texts, force_points = 0.4, force_text = 0.4,expand_points = (2,1), expand_text = (1,2), arrowprops = d
```

```
87
```



5. Topic Modeling

Topic Modeling(Statistical Modeling) is used to help understand the abstract topics that occur in datasets. **Latent Dirichlet Allocation (LDA)** is one such technique which helps classify text content in a document to a particular topic. The process involves building a topic for a document model, words for topic model which is designed as Dirichlet distributions.

```
sample = text.sample(frac=0.1)
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
cv = CountVectorizer(analyzer = text_process)
text_matrix = cv.fit_transform(sample)
```

```
def get_top_n_words(n, keys, document_term_matrix, count_vectorizer):
    top_word_indices = []
    for topic in range(n_topics):
        temp_vector_sum = 0
        for i in range(len(keys)):
            if keys[i] == topic:
                temp_vector_sum += document_term_matrix[i]
        temp_vector_sum = temp_vector_sum.toarray()
        top_n_word_indices = np.flip(np.argsort(temp_vector_sum)[0][-n:],0)
        top_word_indices.append(top_n_word_indices)
    top_words = []
    for topic in top_word_indices:
        topic_words = []
        for index in topic:
            temp_word_vector = np.zeros((1,document_term_matrix.shape[1]))
            temp_word_vector[:,index] = 1
            the_word = count_vectorizer.inverse_transform(temp_word_vector)[0][0]
            topic_words.append(the_word.encode('ascii').decode('utf-8'))
        top_words.append(" ".join(topic_words))
    return top_words
```

```
from sklearn.decomposition import LatentDirichletAllocation
n_topics = 8
lda_model = LatentDirichletAllocation(n_components=n_topics, learning_method='online',
                                          random_state=0, verbose=0)
lda_topic_matrix = lda_model.fit_transform(text_matrix)
lda_keys = lda_topic_matrix.argmax(axis=1).tolist()
count_pairs = Counter(lda_keys).items()
categlda_categoriesories = [pair[0] for pair in count_pairs]
lda_counts = [pair[1] for pair in count_pairs]
top_n_words_lda = get_top_n_words(10, lda_keys, text_matrix, cv)

for i in range(len(top_n_words_lda)):
    print("Topic {}: ".format(i+1), top_n_words_lda[i])
```

```
Topic 1:  korea north china government say ban german us germany south
Topic 2:  china us minister saudi say arabia prime sea uk south
Topic 3:  say kill us attack state syria force china president report
Topic 4:  world news say iran india nuclear bbc china bank global
Topic 5:  police protest say arrest court kill call charge right case
Topic 6:  russia say syria us new ukraine eu military gaza strike
Topic 7:  kill people un die years say turkey chinese bomb show
Topic 8:  us say israel new find attack war russia get world
```

6.Regression

We can use Linear Regression to predict the number of upVotes based on titles.

```
df_concat = df[df['up_votes']<20000]
```

```
df_concat = df_concat[['title', 'over_18', 'day_of_week_num','year', 'month', 'day', \
      'weekend', 'years_to_now','day_time','author_total_posts','title_length','places','up_votes']]
```

```
vectors = pd.DataFrame(docvec)
vectors['title'] = titles_left
main = pd.concat((vectors, df_concat), axis=1)
```

```
main.dropna(axis=0, inplace=True)
main.head(1)
```

	0	1	2	3	4	5	6	7	8	9	10	11
0	-0.045776	0.086182	0.162781	0.033356	-0.012695	0.103027	0.002197	-0.133911	-0.05481	0.18335	-0.049713	-0.270142

1 rows × 314 columns

```
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
def model_diagnostics(model, pr=True):
    y_predicted = model.predict(X_val)
    r2 = r2_score(y_val, y_predicted)
    mse = mean_squared_error(y_val, y_predicted)
    mae = mean_absolute_error(y_val, y_predicted)
    if pr:
        print(f"R-Sq: {r2:.4}")
        print(f"RMSE: {np.sqrt(mse)}")
        print(f"MAE: {mae}")
```

```
from sklearn.model_selection import train_test_split
X=main.drop(columns=['up_votes','title'])
y=main['up_votes']
X_train, X_val, y_train, y_val = train_test_split(X, y,test_size=0.1,random_state=101)
```

```
reg = LinearRegression().fit(X_train, y_train)
model_diagnostics(reg)
```

```
R-Sq: 0.01724
RMSE: 554.8813009641437
MAE: 189.97354044082957
```

Conclusions

Many conclusions can be drawn from this NLP analyis. Distribution of News vs Time: It can be observed that users access news articles online evidenced with the increase in the number of upVotes. It can also be oberved that there were a lot of terror attacks that happened between 2008 to 2016 which was deduced from Bag-of-Words model.The Linear Regression did not perform that well. Future work can involve Tree-based ensemble classifier.

Future Work

1. We can perform sentiment analysis on the title to test accurate content of the news and also maybe to certain extent could help determine it's influence on the number of upvotes.
2. LSTM model can be used for regression analysis as it defintitely provides faster processing time and performance.