In [130]:
```
import pandas as pd
import matplotlib.pyplot as plt
import plotly.express as px
import seaborn as sns
import datetime
import pyLDAvis
import pyLDAvis.gensim_models as gensimvis
import warnings
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from wordcloud import WordCloud
from sklearn.utils import shuffle

warnings.filterwarnings("ignore")
```

In [2]:
```
df = pd.read_csv('Eluvio_DS_Challenge.csv')
df.head()
```

Out[2]:

	time_created	date_created	up_votes	down_votes	title	over_18	author	category
0	1201232046	2008-01-25	3	0	Scores killed in Pakistan clashes	False	polar	worldnews
1	1201232075	2008-01-25	2	0	Japan resumes refuelling mission	False	polar	worldnews
2	1201232523	2008-01-25	3	0	US presses Egypt on Gaza border	False	polar	worldnews
3	1201233290	2008-01-25	1	0	Jump-start economy: Give health care to all	False	fadi420	worldnews
4	1201274720	2008-01-25	4	0	Council of Europe bashes EU&UN terror blacklist	False	mhermans	worldnews

Checking for missing values

In [3]:
```
df.isna().sum()
```

Out[3]:
```
time_created    0
date_created    0
up_votes        0
down_votes      0
title           0
over_18         0
author          0
category        0
dtype: int64
```

Checking various categories to see if there is variability in columns that can be explored for information

In [4]:
```
df['category'].value_counts()
```

Out[4]:
```
worldnews    509236
Name: category, dtype: int64
```

In [5]:
```
df['down_votes'].value_counts()
```

Out[5]:
```
0    509236
Name: down_votes, dtype: int64
```

The columns, 'down_votes' and 'category' have only one type of entry hence carry no information. (all texts have 0 down_vote and all categories are worldnews) and are dropped

In [6]:
```
usage_info = df.drop(columns=['title','time_created','category','down_votes'])
usage_info.head()
```

Out[6]:

	date_created	up_votes	over_18	author
0	2008-01-25	3	False	polar
1	2008-01-25	2	False	polar
2	2008-01-25	3	False	polar
3	2008-01-25	1	False	fadi420
4	2008-01-25	4	False	mhermans

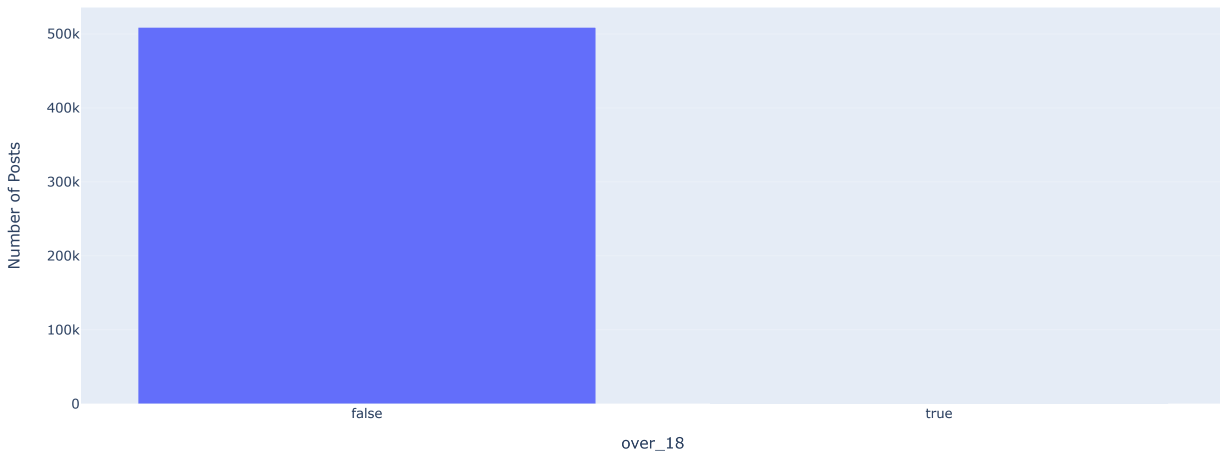
Checking counting the number of posts for each category in the over_18 category.

In [7]:
```
up_votes_df = usage_info.groupby('over_18',as_index=False).count()[['over_18','up_votes']].rename(columns={'up_votes':'Number of Posts'})
up_votes_df
```

Out[7]:

	over_18	Number of Posts
0	False	508916
1	True	320

In [182]:
```
px.bar(up_votes_df, x='over_18',y='Number of Posts', height=500, width=1200)
```



Reformatting the Date Created column so analysis can be made on the new posted on monthly basis

In [9]:
```
usage_info['Month Posted'] = pd.to_datetime(usage_info['date_created']).dt.month
usage_info['date_created'] = pd.to_datetime(usage_info['date_created']).dt.strftime('%Y-%m')
usage_info.head()
```

Out[9]:

	date_created	up_votes	over_18	author	Month Posted
0	2008-01	3	False	polar	1
1	2008-01	2	False	polar	1
2	2008-01	3	False	polar	1
3	2008-01	1	False	fadi420	1
4	2008-01	4	False	mhermans	1

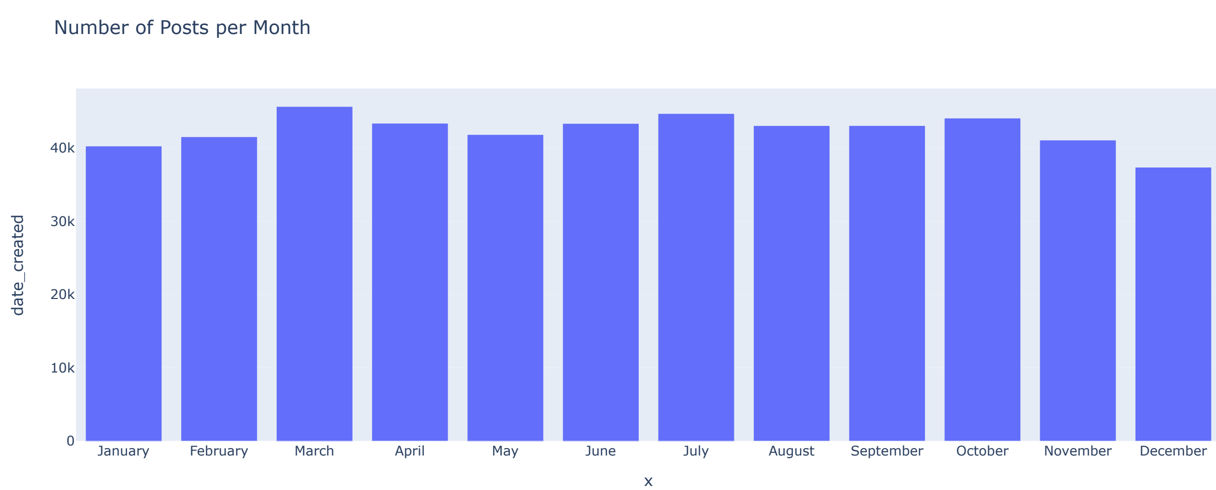
Checking the total number of posts made in each month

In [10]:
```
monthly_df = usage_info.groupby('Month Posted', as_index=False).count()
monthly_df.head()
```

Out[10]:

	Month Posted	date_created	up_votes	over_18	author
0	1	40258	40258	40258	40258
1	2	41518	41518	41518	41518
2	3	45651	45651	45651	45651
3	4	43363	43363	43363	43363
4	5	41826	41826	41826	41826

In [180]:
```
months = ['January', 'February', 'March', 'April', 'May', 'June', 'July', 'August', 'September', 'October', 'November', 'December']
px.bar(monthly_df,x=months, y='date_created', title='Number of Posts per Month', height=500, width=1200)
```



Grouping the number number of posts to check the trend of posts in terms of numbers over the years

In [12]:
```
trend_df = usage_info.groupby('date_created',as_index=False).count()
trend_df.head()
```

Out[12]:

	date_created	up_votes	over_18	author	Month Posted
0	2008-01	18	18	18	18
1	2008-02	622	622	622	622
2	2008-03	1922	1922	1922	1922
3	2008-04	2649	2649	2649	2649
4	2008-05	2786	2786	2786	2786

Plotting the trend of the number of posts made over the years which shows a growing number of posts.

In [ ]:
```
px.line(trend_df, x='date_created',y='up_votes', title='Trend of Number of Posts Over The Years',
        labels={'up_votes': 'Number of User Activity', 'date_created': 'Date'},height=500, width=1200)
```

Extracting only the text data for analysis

In [111]:
```
text_data = df['title']
```

WORKING WITH THE TEXT DATA

In [16]:
```
import gensim
from gensim.utils import simple_preprocess
from gensim.parsing.preprocessing import STOPWORDS
from nltk.stem import WordNetLemmatizer, SnowballStemmer
from nltk.stem.porter import *
import numpy as np
# np.random.seed(2018)
import nltk
from nltk.stem.porter import PorterStemmer
from nltk.stem import WordNetLemmatizer
nltk.download('wordnet')
```

```
[nltk_data] Downloading package wordnet to
[nltk_data]     C:\Users\tetteh\AppData\Roaming\nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
```

Out[16]:
```
True
```

In [17]:
```
text_data.head() #= text_data.map(lambda x:re.sub('[,\.!?:;-]','',x))
```

Out[17]:
```
0                   Scores killed in Pakistan clashes
1                    Japan resumes refuelling mission
2                     US presses Egypt on Gaza border
3        Jump-start economy: Give health care to all
4    Council of Europe bashes EU&UN terror blacklist
Name: title, dtype: object
```

Preprocessing the text

In [18]:
```
def lemmatize_stemming(text):
    #stemming and lemmatizing
    return PorterStemmer().stem(WordNetLemmatizer().lemmatize(text, pos='v'))

def preprocess(text):
    result = []
    #looping through the different words in a given row
    if gensim.utils.simple_preprocess(text):
        for token in gensim.utils.simple_preprocess(text):
            # taking out stopwords and all words longer than 2 letters then applying stemming and lemmatization
            if token not in gensim.parsing.preprocessing.STOPWORDS and len(token) >= 3:
                result.append(lemmatize_stemming(token))
    return result
```

In [19]:
```
processed_text = text_data.apply(preprocess)
processed_text
```

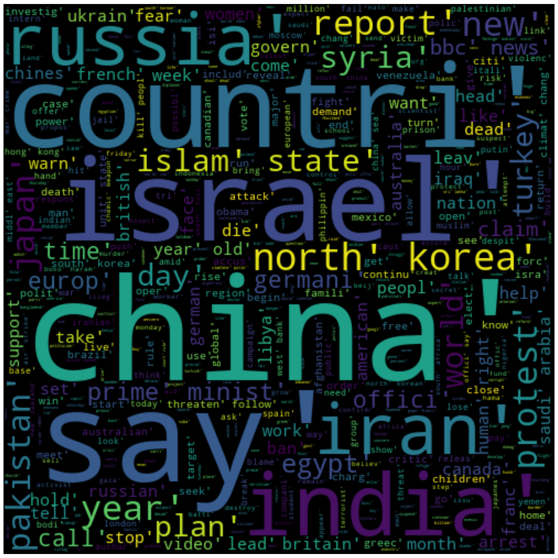
Out[19]:
```
0                             [score, kill, pakistan, clash]
1                            [japan, resum, refuel, mission]
2                               [press, egypt, gaza, border]
3                       [jump, start, economi, health, care]
4                  [council, europ, bash, terror, blacklist]
                                ...
509231    [heil, trump, donald, trump, alt, right, white...
509232                    [peopl, specul, madelein, mccann]
509233           [professor, receiv, arab, research, award]
509234    [nigel, farag, attack, respons, trump, ambassa...
509235    [palestinian, wield, knife, shoot, dead, west,...
Name: title, Length: 509236, dtype: object
```

In [20]:
```
word_cloud = str(list(processed_text))
```

Visualizing the most frequent words used in the news

In [21]:
```
WordCloud(max_words=500, width=500, height=500).generate(word_cloud).to_image()
```

Out[21]:



In [22]:
```
dictionary = gensim.corpora.Dictionary(processed_text)
```

In [ ]:
```
# count = 0
# for k, v in dictionary.iteritems():
#     print(k, v)
#     count += 1
#     if count > 10:
#         break
```

In [35]:
```
dictionary.filter_extremes(no_below=2, no_above=0.5, keep_n=1000000)
```

In [36]:
```
## Creating a bag of words
bo_words = [dictionary.doc2bow(doc) for doc in processed_text]
```

In [37]:
```
len(bo_words)
```

Out[37]:
```
509236
```

In [38]:
```
#Selecting a row to see what is in the bag for that row
for i in range(len(bo_words[1])):
    print("Word number {} (\"{}\") appears {} times.".format(bo_words[1][i][0],
                                                    dictionary[bo_words[1][i][0]],
bo_words[1][i][1]))
```

```
Word number 4 ("japan") appears 1 times.
Word number 5 ("mission") appears 1 times.
Word number 6 ("refuel") appears 1 times.
Word number 7 ("resum") appears 1 times.
```

Building the LDA model to create topic clusters

In [45]:
```
lda_model = gensim.models.LdaMulticore(bo_words, num_topics=3, id2word=dictionary, passes=10, workers=3)
```

In [46]:
```
LDAvis_prepared = gensimvis.prepare(lda_model, bo_words, dictionary)
```

In [47]:
```
# pyLDAvis.save_html(LDAvis_prepared, 'ldavis_vis_'+ str(3) +'.html')
LDAvis_prepared.topic_info
```

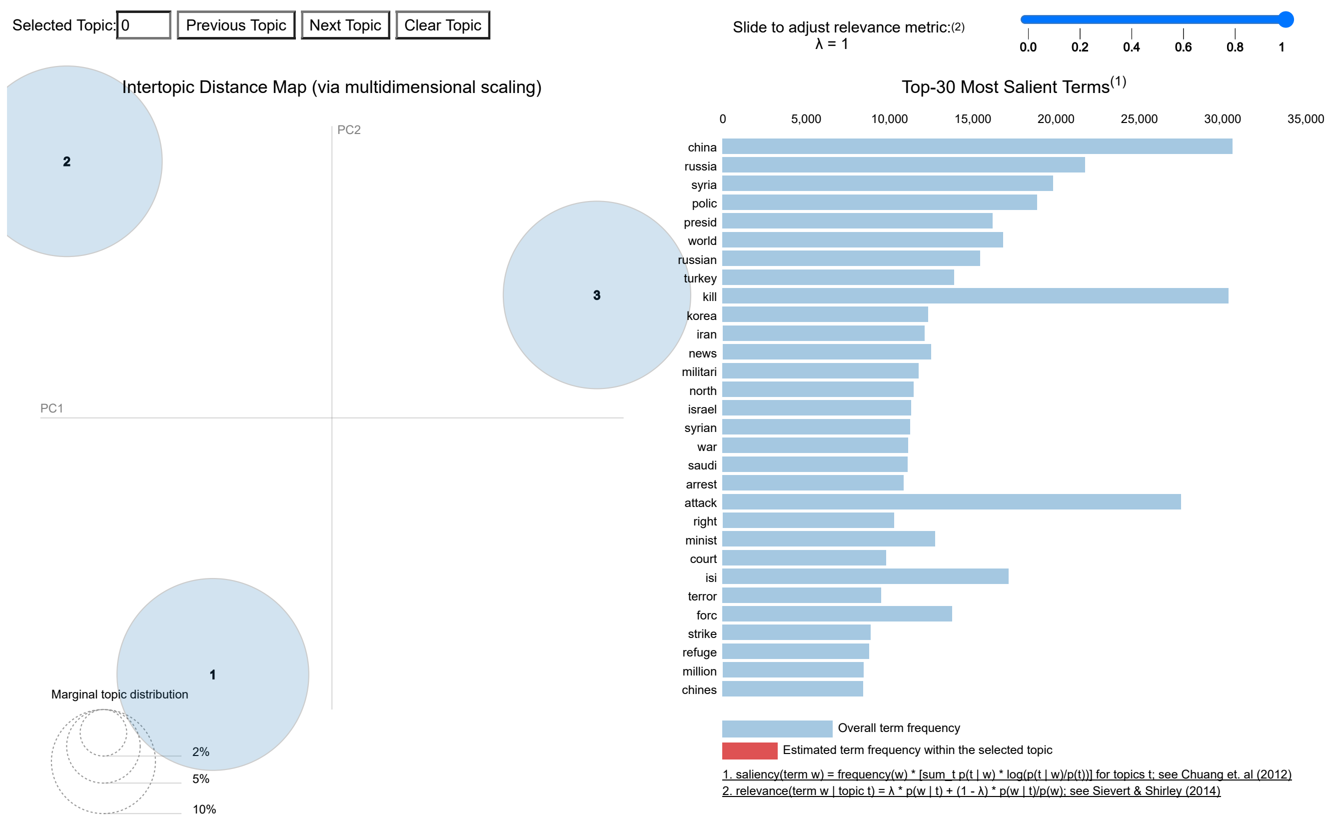
Out[47]:

	Term	Freq	Total	Category	logprob	loglift
271	china	30617.000000	30617.000000	Default	30.0000	30.0000
233	russia	21754.000000	21754.000000	Default	29.0000	29.0000
3209	syria	19839.000000	19839.000000	Default	28.0000	28.0000
908	polic	18873.000000	18873.000000	Default	27.0000	27.0000
978	presid	16202.000000	16202.000000	Default	26.0000	26.0000
...	...	...	...	...	...	...
116	leader	9226.239593	11703.818205	Topic3	-5.1058	0.8870
206	attack	13161.177685	27530.759554	Topic3	-4.7505	0.3868
1498	islam	8362.916705	12118.681600	Topic3	-5.2040	0.7539
1420	south	7892.194947	13765.840290	Topic3	-5.2619	0.5685
532	offici	6886.012136	12071.775448	Topic3	-5.3983	0.5635

170 rows × 6 columns

In [48]:
```
pyLDAvis.display(LDAvis_prepared)
```

Out[48]:



Topic 0 tokens

Topic 0 seems to be centred around international trade relations, finance, and climate change

In [49]:
```
np.array(LDAvis_prepared.token_table[LDAvis_prepared.token_table['Topic']==1].sort_values('Freq', ascending=False)['Term']).T
```

Out[49]:
```
array(['china', 'japan', 'world', 'record', 'brazil', 'water', 'climat',
       'chines', 'trade', 'largest', 'billion', 'million', 'chang',
       'scientist', 'cut', 'oil', 'rise', 'global', 'drug', 'market',
       'compani', 'food', 'greec', 'tax', 'energi', 'studi', 'island',
       'africa', 'research', 'fund', 'sea', 'olymp', 'caus', 'brexit',
       'mexico', 'bank', 'power', 'india', 'europ', 'time', 'new',
       'countri', 'year', 'nation', 'warn', 'plan', 'south', 'peopl',
       'ban', 'report', 'govern', 'death', 'say', 'offici', 'german',
       'british', 'state', 'minist', 'children', 'pari', 'french',
       'refuge'], dtype=object)
```

Topic 1 tokens

Topic 1 seems to be centered around human right and civil unrests.

In [50]:
```
np.array(LDAvis_prepared.token_table[LDAvis_prepared.token_table['Topic']==2].sort_values('Freq', ascending=False)['Term']).T
```

Out[50]:
```
array(['court', 'right', 'women', 'bbc', 'polic', 'school', 'charg',
       'saudi', 'video', 'muslim', 'law', 'arrest', 'man', 'old', 'crash',
       'terror', 'murder', 'sentenc', 'jail', 'abus', 'suspect',
       'investig', 'woman', 'alleg', 'famili', 'prison', 'arabia',
       'crime', 'sex', 'journalist', 'plane', 'pari', 'news', 'children',
       'british', 'german', 'french', 'anti', 'death', 'protest', 'ban',
       'attack', 'year', 'peopl', 'report', 'govern', 'kill', 'islam',
       'india', 'offici', 'time', 'say', 'leader', 'isi', 'nation', 'new',
       'bomb', 'state', 'forc', 'plan', 'countri', 'mexico', 'refuge',
       'brexit', 'minist', 'caus', 'warn', 'olymp', 'chines', 'war',
       'world'], dtype=object)
```

Topic 2 tokens

Topic 2 seems to be centered around terrorism and news about international war

In [52]:
```
np.array(LDAvis_prepared.token_table[LDAvis_prepared.token_table['Topic']==3].sort_values('Freq', ascending=False)['Term']).T
```

Out[52]:
```
array(['russia', 'ukrain', 'syria', 'strike', 'border', 'presid',
       'turkey', 'syrian', 'korea', 'north', 'militari', 'iraq', 'israel',
       'peac', 'isra', 'yemen', 'russian', 'obama', 'iran', 'missil',
       'putin', 'troop', 'war', 'palestinian', 'talk', 'rebel', 'elect',
       'armi', 'milit', 'iraqi', 'refuge', 'minist', 'forc', 'bomb',
       'isi', 'leader', 'state', 'islam', 'kill', 'south', 'offici',
       'say', 'warn', 'attack', 'plan', 'govern', 'report', 'countri',
       'nation', 'europ', 'protest', 'anti', 'power', 'french', 'new',
       'peopl', 'bank', 'time', 'news', 'sea', 'crime', 'brexit', 'ban',
       'saudi', 'year'], dtype=object)
```

Classifying the topics of each news title

In [53]:
```
def topic_pred(bow):
    (topic0,topic0_prob),(topic1,topic1_prob),(topic2,topic2_prob)=lda_model.get_document_topics(bow,minimum_probability=0)

    return np.argmax([topic0_prob,topic1_prob,topic2_prob])
```

In [54]:
```
bow_df = pd.DataFrame({'Bag_Of_Words': bo_words})
```

In [55]:
```
bow_df['Topic'] = bow_df['Bag_Of_Words'].apply(topic_pred)
```

In [56]:
```
usage_info['Topic_Num'] = bow_df['Topic']
usage_info.head()
```

Out[56]:

	date_created	up_votes	over_18	author	Month Posted	Topic_Num
0	2008-01	3	False	polar	1	2
1	2008-01	2	False	polar	1	0
2	2008-01	3	False	polar	1	2
3	2008-01	1	False	fadi420	1	0
4	2008-01	4	False	mhermans	1	1

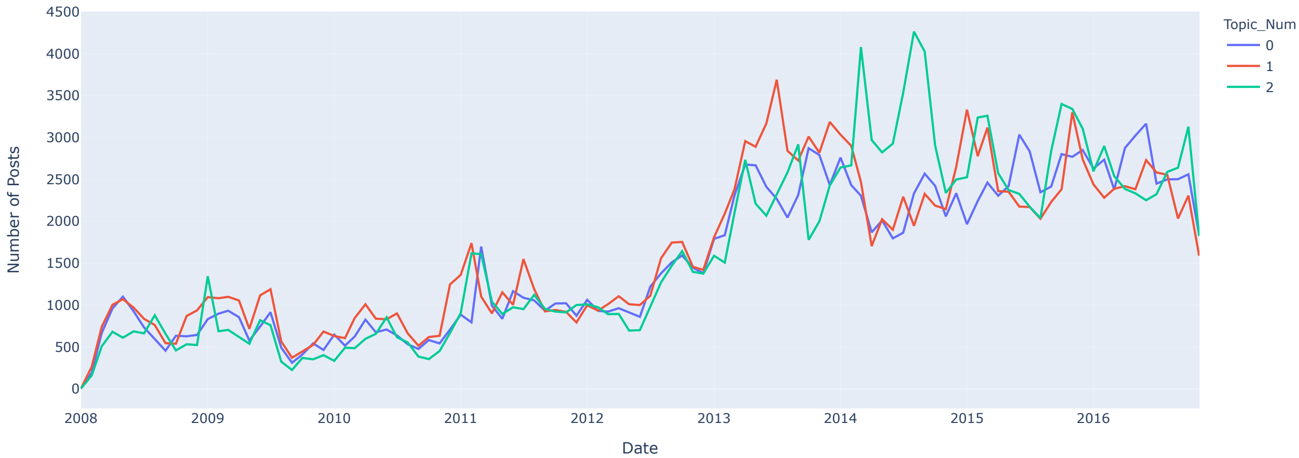
In [57]:
```
num_posts_trend = usage_info.groupby(['date_created','Topic_Num'],as_index=False).count()[['date_created','Topic_Num','up_votes']]
num_posts_trend = num_posts_trend.rename(columns = {'up_votes':'Num_posts'})
num_posts_trend.head()
```

Out[57]:

	date_created	Topic_Num	Num_posts
0	2008-01	0	6
1	2008-01	1	5
2	2008-01	2	7
3	2008-02	0	194
4	2008-02	1	266

Vissualizing the trend in number of posts over the time period

In [63]:
```
px.line(num_posts_trend, x='date_created', y='Num_posts', color = 'Topic_Num', labels={'Num_posts':'Number of Posts', 'date_created':'Date'}
        ,height=500, width=1200)
```



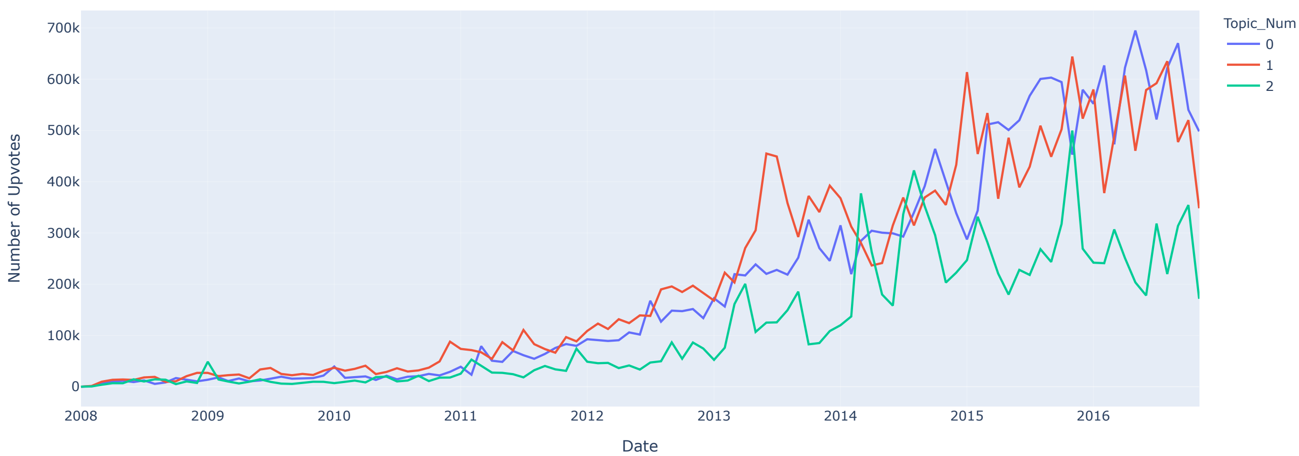
In [60]:
```
num_upvotes_trend = usage_info.groupby(['date_created','Topic_Num'],as_index=False).sum()[['date_created','Topic_Num','up_votes']]
num_upvotes_trend = num_upvotes_trend.rename(columns={'up_votes':'Num_Upvotes'})
num_upvotes_trend.head()
```

Out[60]:

	date_created	Topic_Num	Num_Upvotes
0	2008-01	0	8
1	2008-01	1	29
2	2008-01	2	33
3	2008-02	0	904
4	2008-02	1	1531

The number of upvotes over time

In [62]:
```
px.line(num_upvotes_trend, x='date_created', y='Num_Upvotes', color = 'Topic_Num', labels={'Num_Upvotes':'Number of Upvotes', 'date_created':'Date'},
        height=500, width=1200)
```



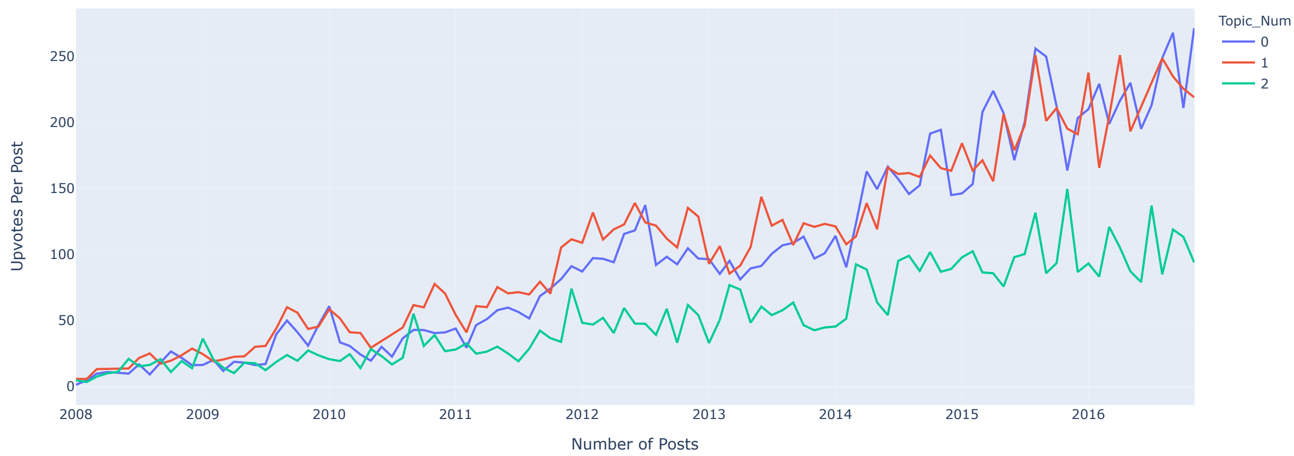
In [64]:
```
upvotes_per_post = num_upvotes_trend.merge(num_posts_trend, how='left', on = ['date_created','Topic_Num'])
upvotes_per_post['Upvotes_Per_Post'] = upvotes_per_post['Num_Upvotes']/upvotes_per_post['Num_posts']
upvotes_per_post.head()
```

Out[64]:

	date_created	Topic_Num	Num_Upvotes	Num_posts	Upvotes_Per_Post
0	2008-01	0	8	6	1.333333
1	2008-01	1	29	5	5.800000
2	2008-01	2	33	7	4.714286
3	2008-02	0	904	194	4.659794
4	2008-02	1	1531	266	5.755639

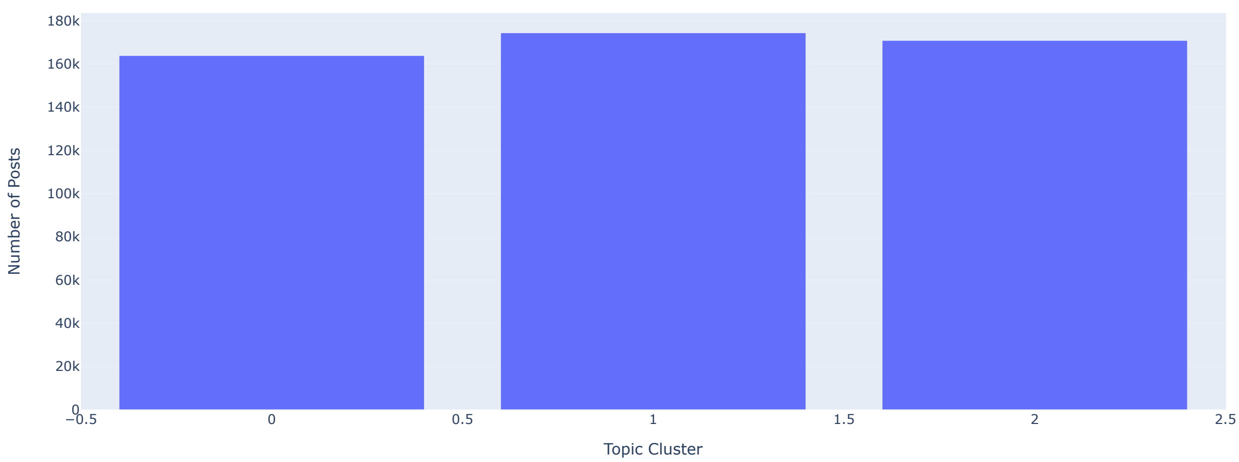
Number of upvotes per post over the year (to view the average reaction to the different types of new over time)

In [65]:
```
px.line(upvotes_per_post, x='date_created', y='Upvotes_Per_Post', color='Topic_Num',
        labels={'Upvotes_Per_Post': 'Upvotes Per Post', 'date_created':'Number of Posts'}, height=500, width=1200)
```



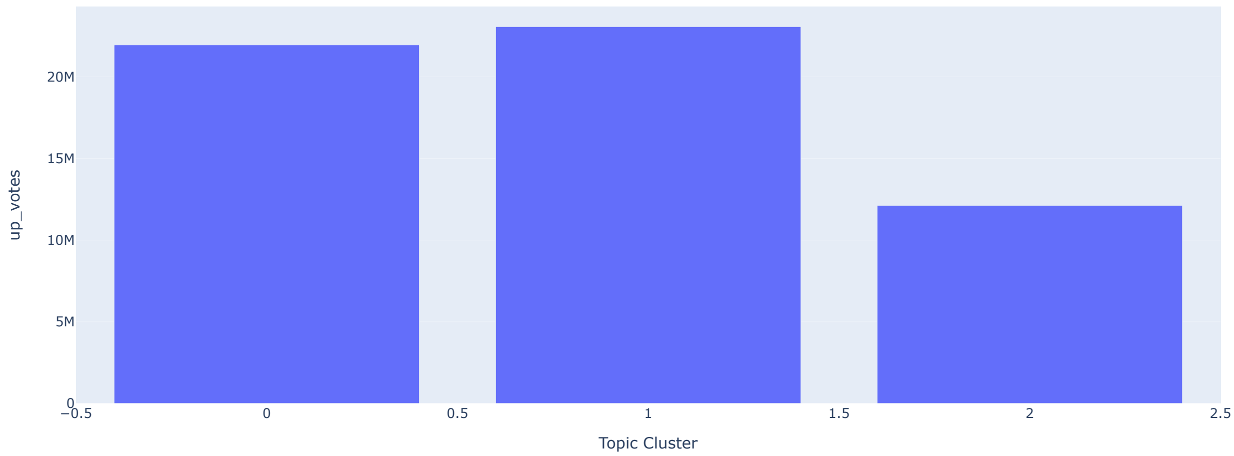
Total number of news posts per topic cluster

In [67]:
```
px.bar(usage_info.groupby('Topic_Num',as_index=False).count(),
       x='Topic_Num', y='over_18', labels={'Topic_Num': 'Topic Cluster', 'over_18':'Number of Posts'}, height=500, width=1200)
```



Total Number of upvotes per news topic cluster

In [68]:
```
px.bar(usage_info.groupby('Topic_Num',as_index=False).sum(), x='Topic_Num', y='up_votes',
       labels={'Topic_Num': 'Topic Cluster', 'over_18':'Number of Upvotes'}, height=500, width=1200)
```



Function to categorize the titles into two classes, i.e High upvote posts and Low upvote posts for each title.

The box plot is used to create the categories with the outliers above the upper fence implying they tend to have very

high reactions while the others are classified as normal/low reaction

In [76]:
```
# px.box(usage_info, x='up_votes', title='Boxplot of Upvotes on Each Post', height=500, width=1200)
```

In [71]:
```
# the upper fence of 38 is used as the boundary
def upvote_cat(votes):
    if votes>38:
        return "high"
    return "low"
```

In [72]:
```
# Transforming the text to vectors
X = TfidfVectorizer(min_df=0.002,stop_words=gensim.parsing.preprocessing.STOPWORDS, tokenizer=preprocess).fit_transform(text_data)
```

In [73]:
```
print(X[10])
```

```
  (0, 591)	0.6040354187846927
  (0, 863)	0.48253982776834614
  (0, 482)	0.5024486683556599
  (0, 569)	0.387094126974977
```

In [113]:
```
text_data = pd.DataFrame(text_data)
```

In [114]:
```
usage_info['Categorical Upvote'] = usage_info['up_votes'].apply(upvote_cat)
```

In [115]:
```
text_data['Categorical Upvote'] = usage_info['Categorical Upvote']
```

Creating a balanced dataset by downsampling the Categorical Upvote Low class

In [132]:
```
balanced_data = shuffle(pd.concat([text_data[text_data['Categorical Upvote']=='low'].sample(80000),
                                   text_data[text_data['Categorical Upvote']=='high']])).reset_index()
balanced_data['Categorical Upvote'].value_counts()
```

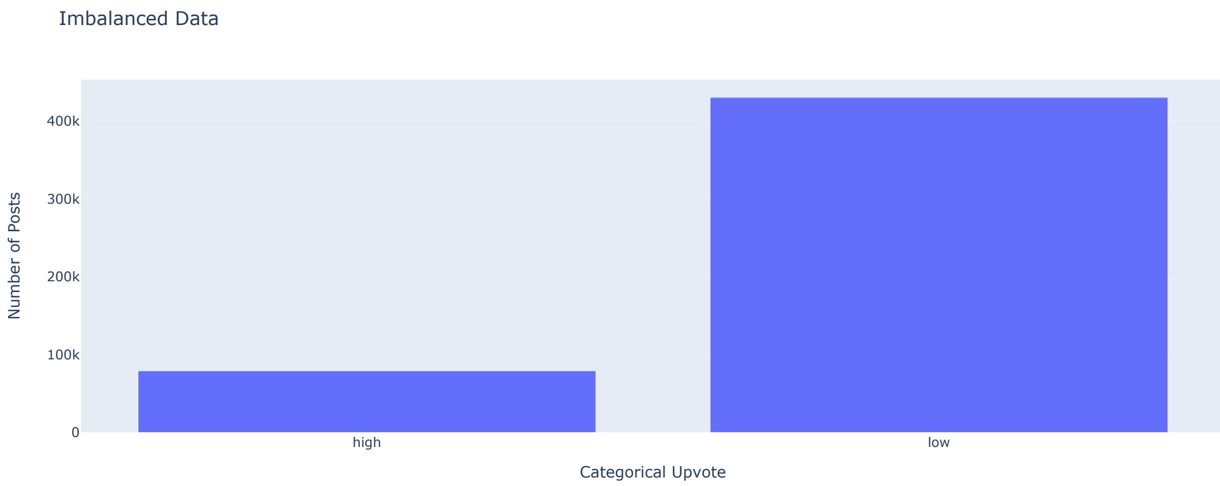
Out[132]:
```
low     80000
high    79068
Name: Categorical Upvote, dtype: int64
```

Creating a dummy variable using the two classes and picking the 'High' class meaning 0 means 'Low' and 1 means 'High'

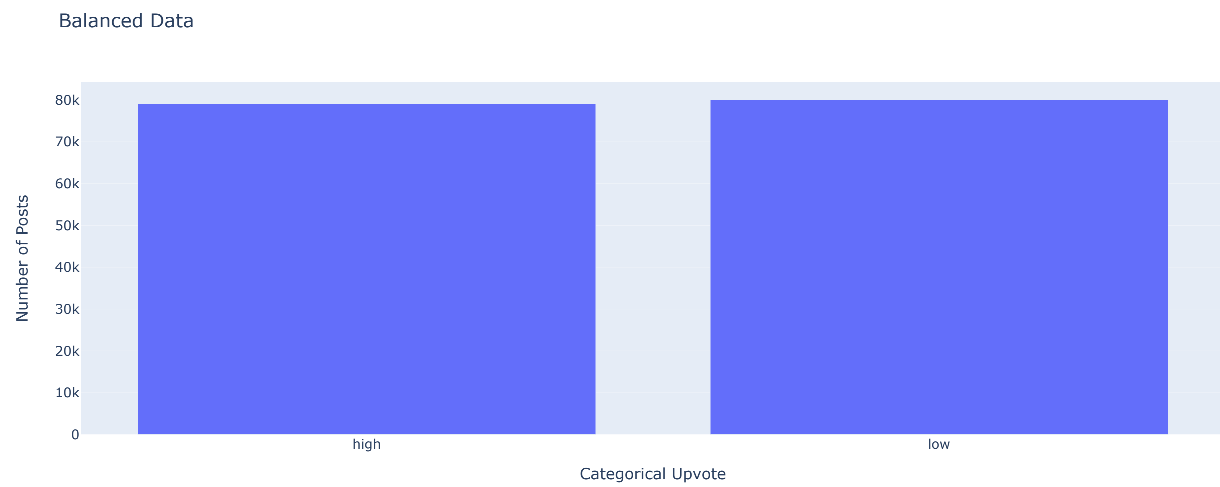
In [133]:
```
balanced_X = balanced_data['title']
balanced_y = pd.get_dummies(balanced_data['Categorical Upvote'])['high']
```

In [134]:
```
X_balanced = TfidfVectorizer(min_df=0.001,stop_words=gensim.parsing.preprocessing.STOPWORDS, tokenizer=preprocess).fit_transform(balanced_X)
```

In [135]:
```
px.bar(usage_info.groupby('Categorical Upvote', as_index=False).count(),
       x='Categorical Upvote', y='date_created',opacity=1, labels={'date_created':'Number of Posts'}, height=500, width=1200, title='Imbalanced Data')
```



In [136]:
```
px.bar(balanced_data.groupby('Categorical Upvote', as_index=False).count(),
       x='Categorical Upvote', y='index',opacity=1, labels={'index':'Number of Posts'}, height=500, width=1200, title='Balanced Data')
```



In [143]:
```
y = pd.get_dummies(usage_info['Categorical Upvote'])
y_used = y['high']
y_used.head()
```

Out[143]:
```
0    0
1    0
2    0
3    0
4    0
Name: high, dtype: uint8
```

Splitting the data into train and test set

In [144]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y_used, random_state = 42, test_size = 0.25)
```

In [146]:
```
X_train_balanced, X_test_balanced, y_train_balanced, y_test_balanced = train_test_split(X_balanced,balanced_y, random_state = 42, test_size = 0.25)
```

Building a Random Forest Classifier

In [148]:
```
## Building a random forest classifier
from sklearn.ensemble import RandomForestClassifier
rdcf = RandomForestClassifier()
rdcf.fit(X_train,y_train)
rdcf.score(X_test,y_test)
```

Out[148]:
```
0.8376548397992286
```

In [150]:
```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
print(classification_report(y_test,rdcf.predict(X_test)))
```

```
              precision    recall  f1-score   support

           0       0.85      0.99      0.91    107628
           1       0.23      0.02      0.04     19681

    accuracy                           0.84    127309
   macro avg       0.54      0.50      0.48    127309
weighted avg       0.75      0.84      0.78    127309
```

In [149]:
```
# fitting and testing on the balanced dataset
rdcf_bal = RandomForestClassifier()
rdcf_bal.fit(X_train_balanced,y_train_balanced)
rdcf_bal.score(X_test_balanced,y_test_balanced)
```

Out[149]: 0.6121658661704429

In [157]:
```
print(classification_report(y_test_balanced,rdcf_bal.predict(X_test_balanced)))
```

```
              precision    recall  f1-score   support

           0       0.62      0.60      0.61     20001
           1       0.61      0.62      0.61     19766

    accuracy                           0.61     39767
   macro avg       0.61      0.61      0.61     39767
weighted avg       0.61      0.61      0.61     39767
```

Building and training Logistic Regression Model

In [154]:
```
#inbalanced classification
from sklearn.linear_model import LogisticRegression
log = LogisticRegression()
log.fit(X_train,y_train)
log.score(X_test,y_test)
```

Out[154]: 0.8456354224760229

In [153]:
```
print(classification_report(y_test,log.predict(X_test)))
```

```
              precision    recall  f1-score   support

           0       0.85      1.00      0.92    107628
           1       0.53      0.01      0.02     19681

    accuracy                           0.85    127309
   macro avg       0.69      0.50      0.47    127309
weighted avg       0.80      0.85      0.78    127309
```

In [155]:
```
log_bal = LogisticRegression()
log_bal.fit(X_train_balanced,y_train_balanced)
log_bal.score(X_train_balanced,y_train_balanced)
```

Out[155]: 0.6449401094710019

In [156]:
```
print(classification_report(y_test_balanced,log_bal.predict(X_test_balanced)))
```

```
              precision    recall  f1-score   support

           0       0.63      0.64      0.64     20001
           1       0.63      0.62      0.62     19766

    accuracy                           0.63     39767
   macro avg       0.63      0.63      0.63     39767
weighted avg       0.63      0.63      0.63     39767
```

Building and training a Gradient Boosting Classifier

In [159]:
```
from sklearn.ensemble import GradientBoostingClassifier
gboost = GradientBoostingClassifier()
gboost.fit(X_train,y_train)
gboost.score(X_test,y_test)
```

Out[159]: 0.8455097440086718

In [160]:
```
print(classification_report(y_test,gboost.predict(X_test)))
```

```
              precision    recall  f1-score   support

           0       0.85      1.00      0.92    107628
           1       0.67      0.00      0.00     19681

    accuracy                           0.85    127309
   macro avg       0.76      0.50      0.46    127309
weighted avg       0.82      0.85      0.78    127309
```

In [161]:
```
gboost_bal = GradientBoostingClassifier()
gboost_bal.fit(X_train_balanced,y_train_balanced)
gboost_bal.score(X_test_balanced,y_test_balanced)
```

Out[161]: 0.5940604018407222

In [162]:
```
print(classification_report(y_test_balanced,gboost_bal.predict(X_test_balanced)))
```

```
              precision    recall  f1-score   support

           0       0.57      0.75      0.65     20001
           1       0.63      0.44      0.52     19766

    accuracy                           0.59     39767
   macro avg       0.60      0.59      0.58     39767
weighted avg       0.60      0.59      0.58     39767
```

KNN

In [176]:
```
k_neigh = KNeighborsClassifier(n_neighbors=5)
k_neigh.fit(X_train,y_train)
train_acc = k_neigh.score(X_train,y_train)
test_acc = k_neigh.score(X_test,y_test)
print(f'Training accuracy is: {train_acc}')
print(f'Testing accuracy is: {test_acc}')
```

```
Training accuracy is: 0.8546371427000448
Testing accuracy is: 0.8355183058542601
```

In [178]:
```
print(classification_report(y_test,k_neigh.predict(X_test)))
```

```
              precision    recall  f1-score   support

           0       0.85      0.98      0.91    107628
           1       0.25      0.03      0.06     19681

    accuracy                           0.84    127309
   macro avg       0.55      0.51      0.48    127309
weighted avg       0.75      0.84      0.78    127309
```

In [177]:
```
k_neigh_bal = KNeighborsClassifier(n_neighbors=5)
k_neigh_bal.fit(X_train_balanced,y_train_balanced)
train_acc_bal = k_neigh_bal.score(X_train_balanced,y_train_balanced)
test_acc_bal = k_neigh_bal.score(X_test_balanced,y_test_balanced)
print(f'Training accuracy is: {train_acc_bal}')
print(f'Testing accuracy is: {test_acc_bal}')
```

```
Training accuracy is: 0.6487707563222438
Testing accuracy is: 0.5218397163477255
```

In [179]:
```
print(classification_report(y_test_balanced,k_neigh_bal.predict(X_test_balanced)))
```

```
              precision    recall  f1-score   support

           0       0.52      0.80      0.63     20001
           1       0.54      0.24      0.33     19766

    accuracy                           0.52     39767
   macro avg       0.53      0.52      0.48     39767
weighted avg       0.53      0.52      0.48     39767
```

In [ ]: