Introduction

This notebook was prepared to analyze the public dataset "Airplane Crashes and Fatalities Since 1908", hosted by Open Data by Socrata, and available for download from this URL: https://www.kaggle.com/saurograndi/airplane-crashes-since-1908 (https://www.kaggle.com/saurograndi/airplane-crashes-since-1908).

It explores some hypothesis regarding flight safety in today's perspective and proceeds on building an ML model on a given topic (which depends on further understanding of the dataset).

0. Data Exploration

In [1]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import random
from collections import Counter

%matplotlib inline
```

In [2]:

```
pd.set_option('display.max_rows', 200)
```

In [3]:

```
sns.set(style="whitegrid")
sns.set_color_codes("pastel")
```

In [4]:

```
# util function
def na_stats(df):
    """
    Displays the number of not null values per column.
    """
    total_len = len(df)
    date_notnull = len(df[df.date.notnull()])
    time_notnull = len(df[df.time.notnull()])
    loc_notnull = len(df[df.location.notnull()])
    oper_notnull = len(df[df.operator.notnull()])
    route_notnull = len(df[df.route.notnull()])
    type_notnull = len(df[df.type.notnull()])
    aboard_notnull = len(df[df.aboard.notnull()])
    fatal_notnull = len(df[df.fatalities.notnull()])
    ground_notnull = len(df[df.ground.notnull()])
    summ_notnull = len(df[df.summary.notnull()])

    print('total_len: ',total_len)
    print('date_notnull: ',date_notnull)
    print('time_notnull: ',time_notnull)
    print('loc_notnull: ',loc_notnull)
    print('oper_notnull: ',oper_notnull)
    print('route_notnull: ',route_notnull)
    print('type_notnull: ',type_notnull)
    print('aboard_notnull: ',aboard_notnull)
    print('fatal_notnull: ',fatal_notnull)
    print('ground_notnull: ',ground_notnull)
    print('summ_notnull: ',summ_notnull)

def plot_max_month(df):
    crashes_per_year = Counter(df['year'])
    years = list(crashes_per_year.keys())

    months_covered = []
    for i in years:
        months_covered.append(max(df[df.year == i].month))

    grid = plt.figure(figsize=(14, 10))
    grid = sns.barplot( x=years, y=months_covered, color='b')
    grid.set(ylabel="Month", xlabel="Year", title="Max Month In Dataset")
    grid.set_xticklabels(grid.get_xticklabels(),rotation=70, fontsize=10)
    plt.show()

def plot_crash(df):
    """
    Plot number of aircraft crashes
    """
    crashes_per_year = Counter(df['year'])
    years = list(crashes_per_year.keys())
    crashes_year = list(crashes_per_year.values())

    print('Total number of crashes: ',len(df))
    print('Min year: ',min(years))
    print('Max year: ',max(years))

    grid = plt.figure(figsize=(14, 10))
    grid = sns.barplot( x=years, y=crashes_year, color='g')
    grid.set(ylabel="Crash", xlabel="Year", title="Plane crashes per year")
    grid.set_xticklabels(grid.get_xticklabels(),rotation=70, fontsize=10)
```

```
    plt.show()

def plot_fatal(df, begin=1908, end=2009):
    """
    Plot number of passenger fatalities on aircrafts.
    """
    df_tmp = df[['year','fatalities']].copy()
    plt.figure(figsize=(20, 6))
    plt.plot(df_tmp.groupby('year').sum())
    plt.title(f'Fatalities per year ({begin}-{end})')
    plt.xlabel('Year')
    plt.ylabel('Fatalities')
    plt.xlim([begin, end])

def plot_passenger(df):
    """
    Plots number of passengers on airplanes from 1970 to 2009
    """
    plt.figure(figsize=(14, 10))
    plt.plot(df)
    plt.xticks(rotation=70)
    plt.show()

def process_worldbank():
    """
    Download and preprocess worldbank data
    """
    # download data
    df = pd.read_csv('worldbank/API_IS.AIR.PSGR_DS2_en_csv_v2_673046.csv', skipr
ows=4)

    # cleaning data, and aggregating it so that we have count of passengers for
 each year from 1970 to 2009.
    df = df.drop(['Country Name', 'Country Code', 'Indicator Name','Indicator Co
de'], axis=1)
    df = pd.DataFrame({'passengers':df.sum(axis=0)})
    df = df[df.passengers > 0]
    df = df[:40] # limit data up to 2009
    return df
```

In [5]:

```
data = pd.read_csv('Airplane_Crashes_and_Fatalities_Since_1908.csv')
```

In [6]:

```
data.head()
```

Out[6]:

	Date	Time	Location	Operator	Flight #	Route	Type	Registration	cn/
0	09/17/1908	17:18	Fort Myer, Virginia	Military - U.S. Army	NaN	Demonstration	Wright Flyer III	NaN	
1	07/12/1912	06:30	AtlantiCity, New Jersey	Military - U.S. Navy	NaN	Test flight	Dirigible	NaN	Na
2	08/06/1913	NaN	Victoria, British Columbia, Canada	Private	-	NaN	Curtiss seaplane	NaN	Na
3	09/09/1913	18:30	Over the North Sea	Military - German Navy	NaN	NaN	Zeppelin L-1 (airship)	NaN	Na
4	10/17/1913	10:30	Near Johannisthal, Germany	Military - German Navy	NaN	NaN	Zeppelin L-2 (airship)	NaN	Na

Most of the fields from the dataset are pretty self-explanatory, however some like `Ground` and `cn/ln` are rather vague.

From data.world (https://data.world/data-society/airplane-crashes/discuss/mqytenrq#wzyiq7ck (https://data.world/data-society/airplane-crashes/discuss/mqytenrq#wzyiq7ck)), we learn that `Ground` stands for the amount of death on the ground, while `cn/ln` is the manufacturer's serial number.

In [7]:

```
# renaming the column for simplicity
new_col_name = ['date','time','location','operator','flight_num','route','type',
'registration','cn_ln','aboard','fatalities','ground','summary']
data.columns = new_col_name
```

In [8]:

```
data.head()
```

Out[8]:

	date	time	location	operator	flight_num	route	type	registration
0	09/17/1908	17:18	Fort Myer, Virginia	Military - U.S. Army	NaN	Demonstration	Wright Flyer III	NaN
1	07/12/1912	06:30	AtlantiCity, New Jersey	Military - U.S. Navy	NaN	Test flight	Dirigible	NaN
2	08/06/1913	NaN	Victoria, British Columbia, Canada	Private	-	NaN	Curtiss seaplane	NaN
3	09/09/1913	18:30	Over the North Sea	Military - German Navy	NaN	NaN	Zeppelin L-1 (airship)	NaN
4	10/17/1913	10:30	Near Johannisthal, Germany	Military - German Navy	NaN	NaN	Zeppelin L-2 (airship)	NaN

The many fields provided in the dataset gives us a few lense that we can use to understand the data.

Fields suchs as `flight_num` , `cn_ln` and `registration` however - wouldn't give us that much information. Hence we'll proceed to remove them from our analysis.

In [9]:

```
data = data.drop(['flight_num', 'registration', 'cn_ln'], axis=1)
```

We now look at the completeness of the dataset, to understand whether the fields that we have are reliable or not for us to make assumptions with.

In [10]:

```
na_stats(data)
```

```
total_len:  5268
date_notnull:  5268
time_notnull:  3049
loc_notnull:  5248
oper_notnull:  5250
route_notnull:  3562
type_notnull:  5241
aboard_notnull:  5246
fatal_notnull:  5256
ground_notnull:  5246
summ_notnull:  4878
```

Looks like all the columns are usable.

Next we look at introducting some new features from existing fields. Some of the obvious ones are:

1. Year
2. Month
3. Day

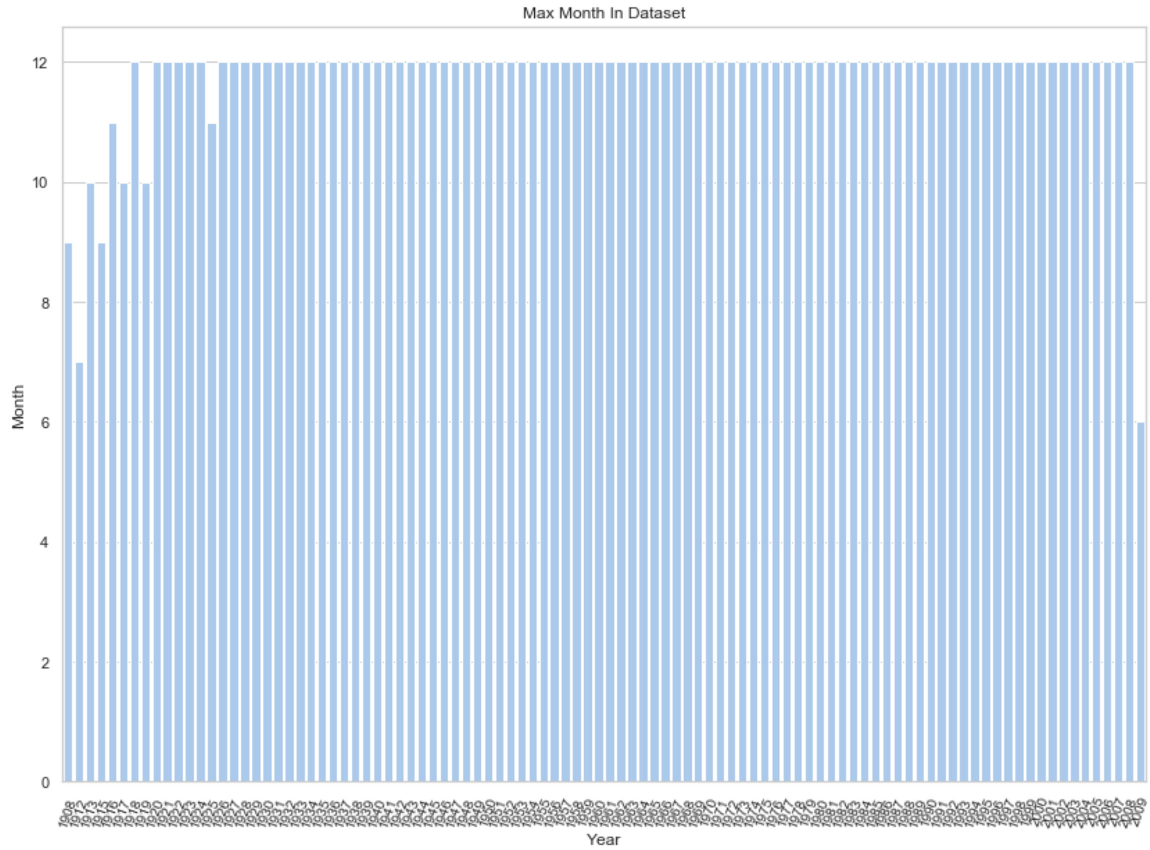
In [11]:

```
data['date'] = pd.to_datetime(data['date'])
data['year'] = data['date'].map(lambda x: x.year)
data['month'] = data['date'].map(lambda x: x.month)
data['day'] = data['date'].map(lambda x: x.day)
```

Should we include 2009?

In [12]:

```
plot_max_month(data)
```



The above shows that in most years crashes happen up to December, but 2009 has only up to June. This imply that the dataset itself was last updated for data up to June 2009, hence we should disregard the year 2009 when making our analysis.

In [13]:

```
data = data[data.date < '2009']
max(data.date)
```

Out[13]:

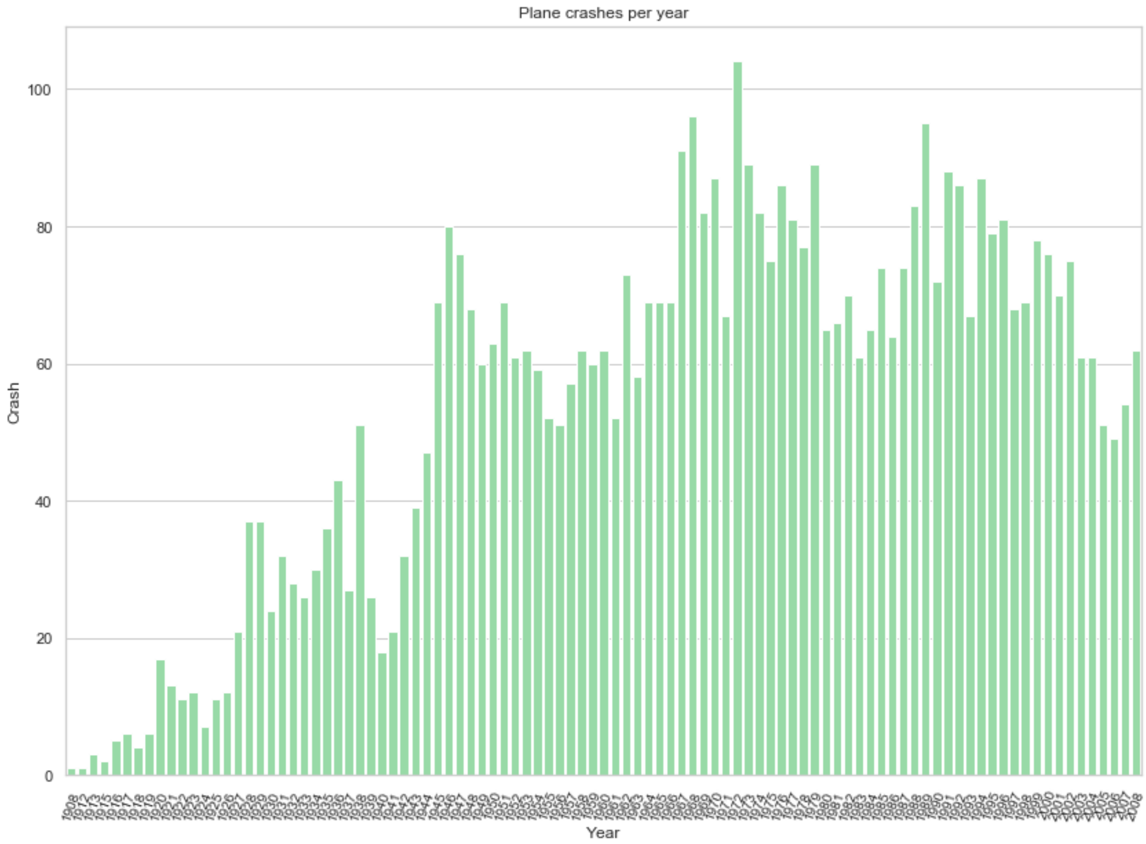
```
Timestamp('2008-12-15 00:00:00')
```

Commercial VS Military

In [14]:

```
plot_crash(data)
```

```
Total number of crashes:  5244
Min year:  1908
Max year:  2008
```



Looking at the above diagram, it would appear that airline crashes have peaked at around 1970, and slowly decrease up to 2009.

Circling back to our original question, is is safer to board a flight nowadays? Assuming that we are talking about civilians, it is reasonable then to exclude data points that belongs to military activities and private flights. Let's look deeper into the distribution of flight types in our data.

In [15]:

```
# unique operators
len(data.operator.unique())
```

Out[15]:

```
2461
```

In [16]:

```
data['operator'] = data.operator.astype('str')
```

In [17]:

```
# define flight type
data['flight_type'] = 'unknown'
data.loc[(data['operator'].str.contains('Military')),'flight_type'] = 'military'
data.loc[(data['operator'] == 'Private'),'flight_type'] = 'others'
data.loc[(data['operator'] == 'US Aerial Mail Service'), 'flight_type'] = 'other
s'
```

In [18]:

```
# check for other types of flight types randomly.
vals = data[(data['operator'].str.contains('Air')) & (data.flight_type == 'unkno
wn')].operator
random_values = random.sample(set(vals), 200)
random_values[:5] # we look at 200 random entries
```

Out[18]:

```
['Alaska International Air',
 'Avtex Air Services',
 'Orient Airways',
 'Air Martinique',
 'Baikal Air']
```

Seems that there are essentially just 2 types of flight in the dataset, `military` and `commercial`. We have also added an `others` category to contain flights from private aircraft and the US Mail.

Let's assign all the `unknown` flight types to `commercial`.

In [19]:

```
data.loc[data['flight_type'] == 'unknown','flight_type'] = 'commercial'
data_comm = data[data.flight_type == 'commercial']
data_comm.head()
```

Out[19]:

	date	time	location	operator	route	type	aboard	fatalities	ground	summary
24	1919-10-02	NaN	Newcastle, England	Aircraft Transport and Travel	NaN	De Havilland DH-4	1.0	1.0	0.0	NaN
26	1919-10-20	NaN	English Channel	Aircraft Transport and Travel	NaN	De Havilland DH-4	NaN	NaN	NaN	NaN
34	1920-08-16	NaN	Bedford, England	By Air	NaN	Armstrong-Whitworth F-K-8	1.0	1.0	0.0	NaN
39	1920-10-02	NaN	Off Port Vendres, France	Latecoere Airlines	NaN	Salmson 2-A-2	2.0	2.0	0.0	NaN
40	1920-10-05	NaN	Valencia, Spain	Latecoere Airlines	NaN	Breguet 14	2.0	2.0	0.0	Crashed while landing

Now that we've cleaned our data, let's proceed with the analysis

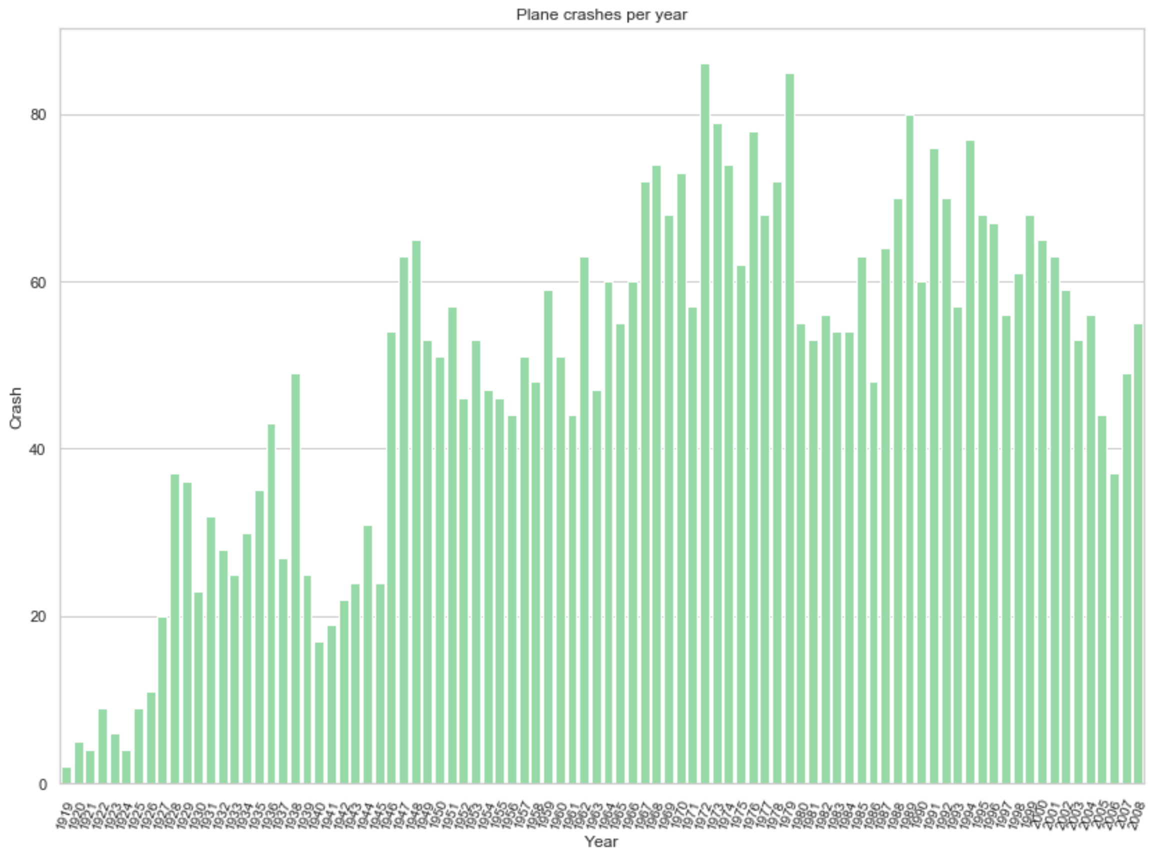
1. Analysis

TASK: Justify whether it is safer to take the aircraft nowadays. Support your decision with data.

In [20]:

```
plot_crash(data_comm)
```

```
Total number of crashes:  4400
Min year:  1919
Max year:  2008
```

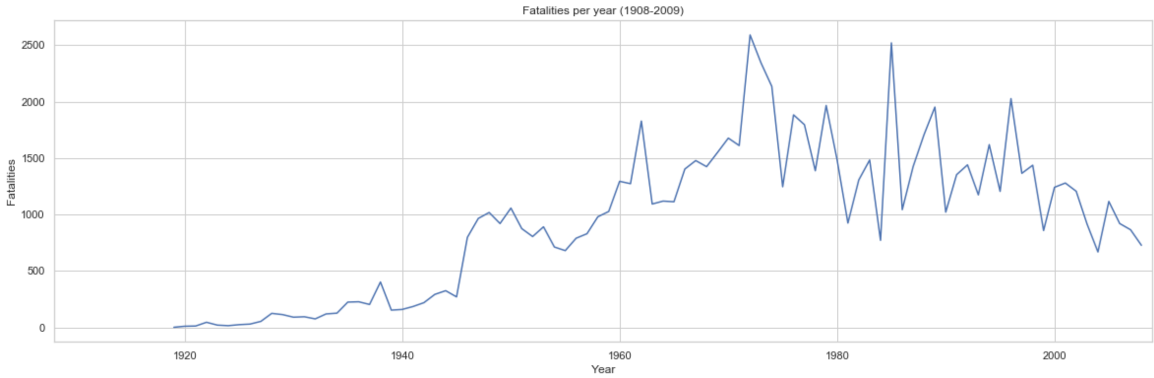


It would seem that it is indeed true that there are now lesser crashes since 1970s.

Let's now look at the fatalities over the year.

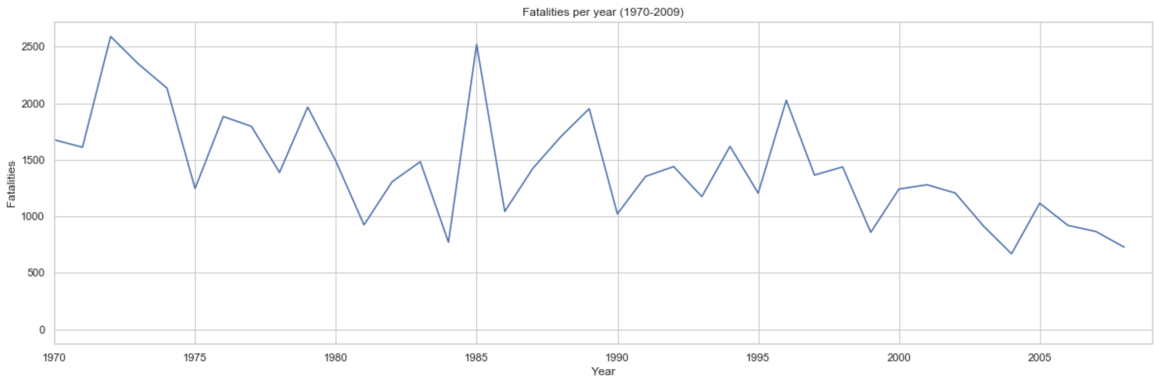
In [21]:

```
# fatalities for all period
plot_fatal(data_comm)
```



In [22]:

```
# fatalities from 1970
plot_fatal(data_comm,1970,2009)
```



Based on the above plots; we see a decline in passengers death over the years since 1970 to 2009.

As a comparison, let us also download an extra dataset from the Worldbank, to look at the total number of passengers carried over the same period.

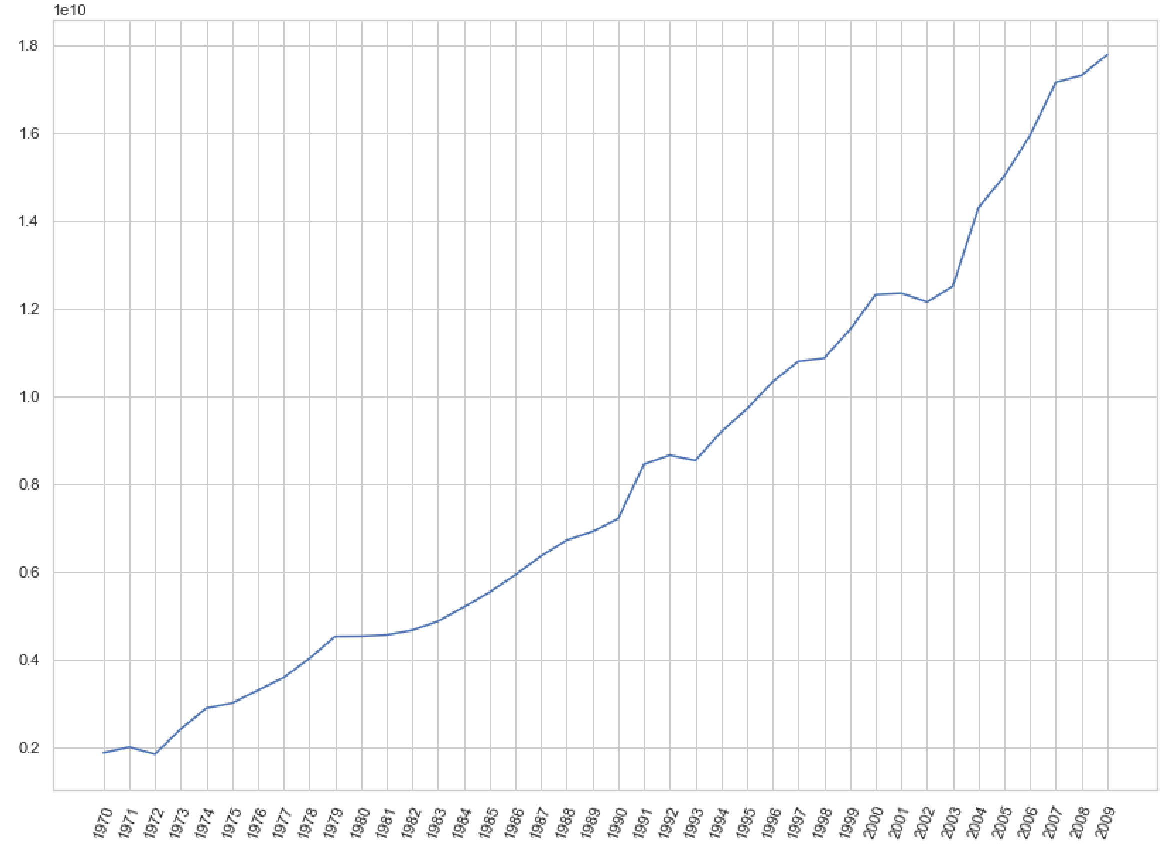
URL: [https://data.worldbank.org/indicator/IS.AIR.PSGR?end=2008&start=1970&view=chart (https://data.worldbank.org/indicator/IS.AIR.PSGR?end=2008&start=1970&view=chart)](https://data.worldbank.org/indicator/IS.AIR.PSGR?end=2008&start=1970&view=chart)

In [23]:

```
wb_data = process_worldbank()
```

In [24]:

```
plot_passenger(wb_data)
```



The above demonstrates a steep increase in aircraft passengers from 0.2 billion in 1970 to about 1.8 billion in 2009.

Let's check for correlation between the two sets of numbers.

In [25]:

```
# prepare data for correlation analysis
## prepare fatalities
df_tmp = data_comm[['year','fatalities']].copy()
df_tmp = df_tmp.groupby('year', as_index=False).sum()
df_tmp['year'] = df_tmp.year.astype('str')

## prepare passengers
wb_tmp = wb_data.copy()
wb_tmp['year'] = wb_tmp.index.astype('str')
wb_tmp.reset_index(inplace=True)
wb_tmp = wb_tmp.drop(['index'],axis=1)

## merge
df = pd.merge(wb_tmp, df_tmp, how='left', on='year')
df = df[['year','passengers','fatalities']]

# get correlation
df['passengers'].corr(df['fatalities'])
```

Out[25]:

```
-0.6070368400462807
```

What this means is that the 2 features are somewhat negatively correlated.

It means that as the number of passenger keep on increasing, we'll see that the number of fatalities will keep decreasing, but not by the same proportion.

Conclusion

We started this analysis by looking at the trend of airplane crashes overtime since 1908. We conclude that the rate has been steadily decreasing since 1970.

Then we looked at the number of fatalities that occured in those crashes. We note that the number has been steadily declining as well since 1970.

We then looked at the amount of passengers that has been travelling over the years since 1970, to see whether there is a correlation between the number of passengers travelling and the number of fatalities recorded. We discovered that there is a negative correlation between the 2 records, which meant that as the number of passengers keep on increasing, we expect to see a decrease in the number of fatalities.

Based on the facts above, we conclude that it is indeed safer to take the aircraft nowadays.

2. Machine Learning

TASK: Apply machine learning technique to predict any interesting topic of this.

Introduction

For this task I've decided to take a look at the causes of the flight crashes.

Methodology

Instead of analyzing the text manually using a text lexicon (ie. counting frequency of keywords such as `engine failure`, `weather` or `show down`), we'll be using doc2vec to vectorize the text and use K-means to cluster the vectors according to their topic similarity.

To assess the accuracy of the model, we're going to visually inspect each cluster (this is an unsupervised training after all) that was trained on the training set. Further tweaks will need to be made based on the results.

Following an acceptable model, we'll proceed to further test the model using the test dataset, to see how the each cluster classification holds up against the new unseen data.

In [26]:

```
import nltk, math
import re
import os
import gensim

from sklearn.model_selection import train_test_split
from gensim.models import Doc2Vec
from nltk.cluster.kmeans import KMeansClusterer
from nltk.corpus import stopwords
from sklearn.manifold import TSNE

NEW_STOP_WORDS = ['crashed','aircraft','plane','flight']
NUM_CLUSTERS=6 # since we don't know the optimal number of K, let's first set th
is to 6.
MODEL_FN = 'airplane-crash-doc2vec.model'

stop_words = stopwords.words('english')
stop_words.extend(NEW_STOP_WORDS)
stop_words = set(stop_words)
```

In [27]:

```
# utils
def read_corpus(fname, tokens_only=False):
    for i, line in enumerate(fname):
        tokens = gensim.utils.simple_preprocess(line)
        tokens = [w for w in tokens if not w in stop_words]
        if tokens_only:
            yield tokens
        else:
            # For training data, add tags
            yield gensim.models.doc2vec.TaggedDocument(tokens, [i])

def preprocess_document(text):
    return ''.join([x if x.isalnum() or x.isspace() else " " for x in text ]).sp
lit()

def get_titles_by_cluster(id):
    list = []
    for x in range(0, len(assigned_clusters)):
        if (assigned_clusters[x] == id):
            list.append(used_lines[x])
    return list

def get_topics(titles):
    from collections import Counter
    words = [preprocess_document(x) for x in titles]
    words = [word for sublist in words for word in sublist]
    filtered_words = [word for word in words if word not in stop_words]
    count = Counter(filtered_words)
    print(count.most_common()[:5])


def cluster_to_topics(id):
    get_topics(get_titles_by_cluster(id))

def plotScatter(keyword, df_dx, tsne_df):
    fig = plt.figure(figsize=(10,15))
    ax = fig.add_subplot(1, 1, 1)

    pos_found_x = []
    pos_found_y = []
    found_names = []

    pos_rest_x = []
    pos_rest_y = []

    for term_id, pos in tsne_df.iterrows():
        term_name = df_dx[df_dx.index == term_id]['summary'].values[0].lower()

        if keyword in term_name:
            pos_found_x.append(pos['x'])
            pos_found_y.append(pos['y'])
        else:
            pos_rest_x.append(pos['x'])
            pos_rest_y.append(pos['y'])

    ax.scatter(pos_rest_x, pos_rest_y, c='blue')
    ax.scatter(pos_found_x, pos_found_y, c='red')

def infer_vector(data):
```

```
    print("Inferring vectors")
    vectors = []
    duplicate_dict = {}
    used_lines = []
    for i, t in enumerate(data):
        t = t.lower()
        if t not in duplicate_dict:
            duplicate_dict[t] = True
            used_lines.append(t)
            vectors.append(model.infer_vector(preprocess_document(t)))

    print("Done")
    return vectors, duplicate_dict, used_lines
```

In [28]:

```
# create train and test file.
data_comm = data_comm[data_comm.summary.notnull()]
summary = data_comm.summary

# split 30% as test set and use the rest as train
train, test = train_test_split(summary, shuffle=False, random_state=42, test_siz
e=0.30)

print(train.shape)
print(test.shape)
```

```
(2865,)
(1229,)
```

In [29]:

```
train_corpus = list(read_corpus(train))
test_corpus = list(read_corpus(test, tokens_only=True))
```

Training the model

We make use of gensim library to train the model using `doc2vec`

In [30]:

```
# define model
model = gensim.models.doc2vec.Doc2Vec(vector_size=50, min_count=10, epochs=40)

# build vocab
model.build_vocab(train_corpus)

# train the model
model.train(train_corpus, total_examples=model.corpus_count, epochs=model.epochs
)

# save model
model.save(MODEL_FN)
```

Load model and apply K-Means

In [31]:

```
model = Doc2Vec.load(MODEL_FN)
```

In [32]:

```
vectors, duplicate_dict, used_lines = infer_vector(train)
```

```
Inferring vectors
Done
```

In [55]:

```
# apply K-means
kclusterer = KMeansClusterer(NUM_CLUSTERS, distance=nltk.cluster.util.cosine_dis
tance, repeats=25)
assigned_clusters = kclusterer.cluster(vectors, assign_clusters=True)
```

In [56]:

```
train_cluster = pd.DataFrame({'summary':used_lines, 'cluster':assigned_clusters
})
```

In [57]:

```
cluster_no = 0
print('Cluster size: ',len(train_cluster[train_cluster.cluster == cluster_no]))
cluster_to_topics(cluster_no)
```

```
Cluster size:  428
[('mountain', 199), ('pilot', 157), ('weather', 119), ('route', 10
7), ('altitude', 104)]
```

In [58]:

```
cluster_no = 1
print('Cluster size: ',len(train_cluster[train_cluster.cluster == cluster_no]))
cluster_to_topics(cluster_no)
```

```
Cluster size:  254
[('engine', 218), ('fuel', 142), ('failure', 104), ('landing', 88),
('engines', 75)]
```

In [59]:

```
cluster_no = 2
print('Cluster size: ',len(train_cluster[train_cluster.cluster == cluster_no]))
cluster_to_topics(cluster_no)
```

```
Cluster size:  378
[('approach', 303), ('runway', 259), ('landing', 163), ('pilot', 13
7), ('crew', 111)]
```

In [60]:

```
cluster_no = 3
print('Cluster size: ',len(train_cluster[train_cluster.cluster == cluster_no]))
cluster_to_topics(cluster_no)
```

```
Cluster size:  1193
[('engine', 188), ('failure', 174), ('pilot', 162), ('cargo', 145),
('takeoff', 140)]
```

In [61]:

```
cluster_no = 4
print('Cluster size: ',len(train_cluster[train_cluster.cluster == cluster_no]))
cluster_to_topics(cluster_no)
```

```
Cluster size:  259
[('fire', 92), ('landing', 54), ('crew', 53), ('pilot', 51), ('en',
45)]
```

In [62]:

```
cluster_no = 5
print('Cluster size: ',len(train_cluster[train_cluster.cluster == cluster_no]))
cluster_to_topics(cluster_no)
```

```
Cluster size:  212
[('pilot', 96), ('runway', 82), ('takeoff', 75), ('crew', 68), ('con
trol', 58)]
```

The above excerpts highlights a few topics for the clusters:

1. Cluster 0 : Mountain
2. Cluster 1 : Engine failure
3. Cluster 2 : Crash at runway (landing/approaching)
4. Cluster 3 : Engine failure
5. Cluster 4 : Fire
6. Cluster 5 : Crash at runway (takeoff)

Many of topic seem to overlap each other. Let's look at the cluster visually.

In [45]:

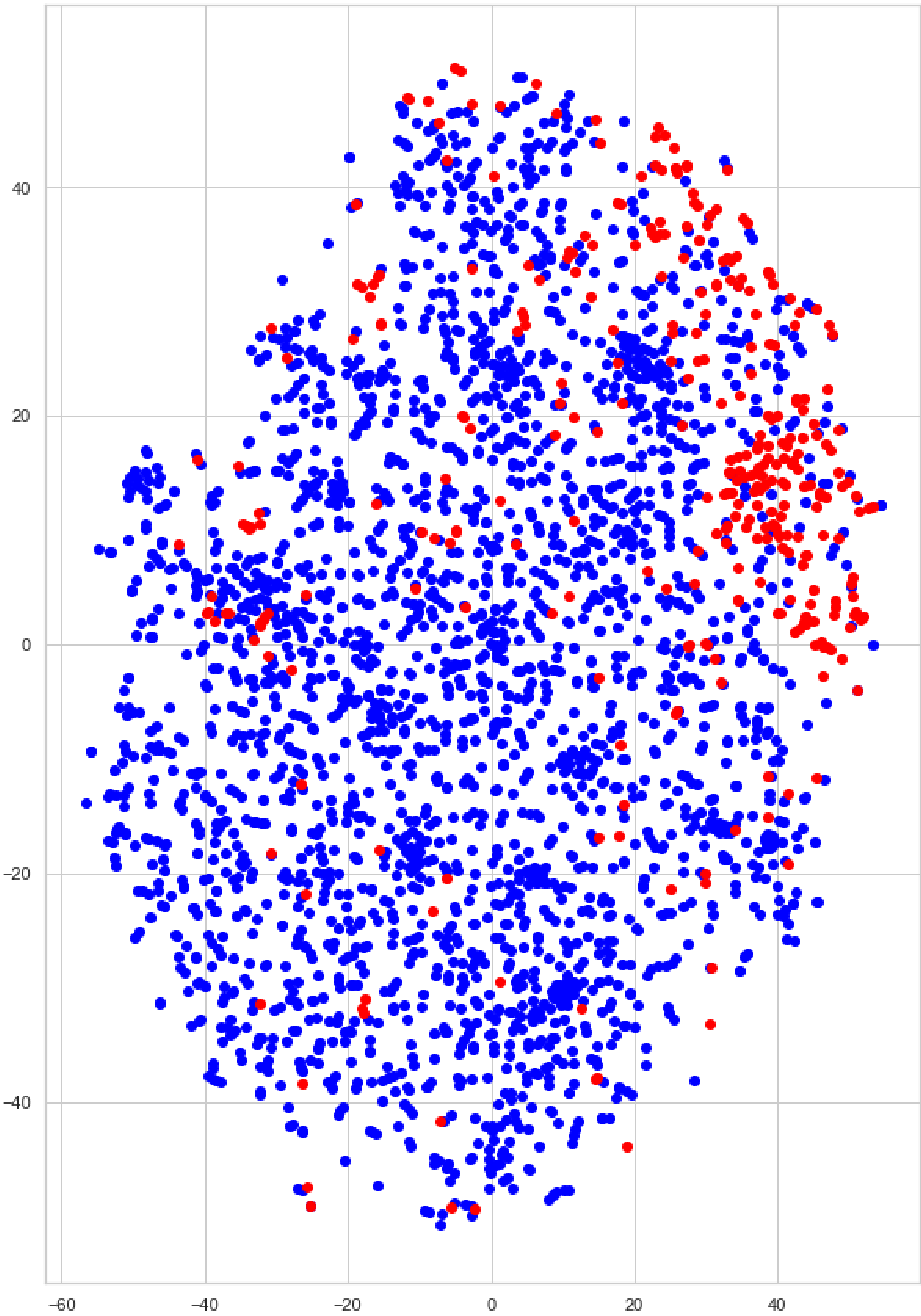
```
doc_tags=list(range(len(train_corpus)))
X = model[doc_tags]

tsne = TSNE(n_components=2)
X_tsne = tsne.fit_transform(X)
df = pd.DataFrame(X_tsne, index=doc_tags, columns=['x', 'y'])
```

In [46]:

```
df_summary = pd.DataFrame(train).reset_index()[['summary']]
```

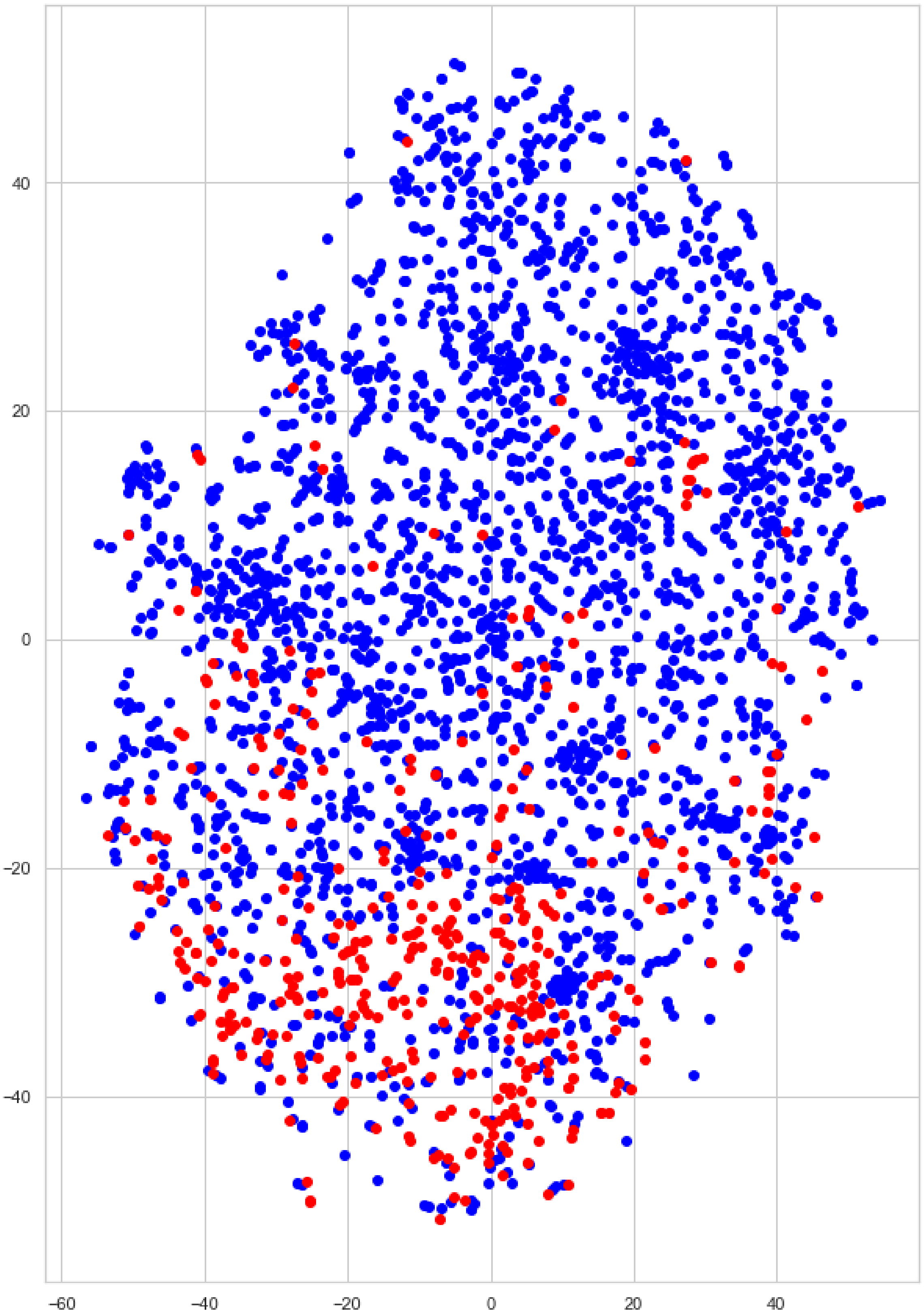
In [47]:

```
plotScatter(keyword='weather',df_dx= df_summary, tsne_df=df)
```



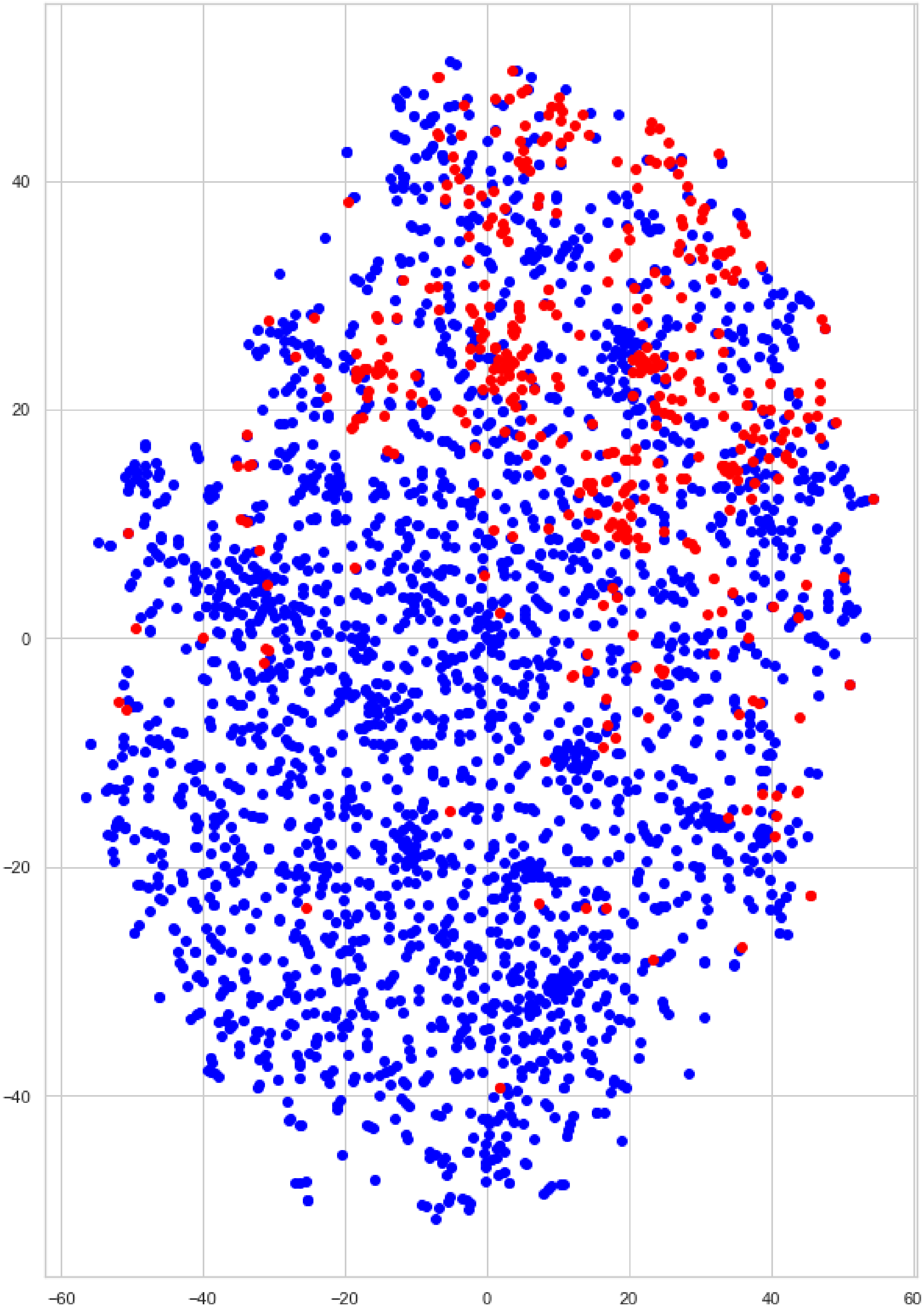
In [48]:

```
plotScatter(keyword='engine',df_dx= df_summary, tsne_df=df)
```



In [49]:

```
plotScatter(keyword='mountain',df_dx= df_summary, tsne_df=df)
```



Based on the above result, we see that our clusters aren't that good.

1. Use more stopwords to clean the clusters
2. Use less clusters (or combine existing ones)
3. Retrain the model using better hyperparameters.

Applying model to test dataset

(to be done)

In [ ]:

```

```