D(St)reams of Anomalies

1. INDUSTRY

Twitter is assigned.

2. DATA SETS

2.1. SOURCE: The dataset is from Github (https://github.com) in this link (https://github.com/numenta/NAB/tree/master/data).

DESCRIPTION: The datasets contains data related to datetime and number of tweets on Apple. The following attributes from the datasets will be used for analysis.

Attribute	Datatype
timestamp	datetime
value	int64

3. IDEAS

3.1. To determine the outliers for number of tweets using IQR and K-Means.

3.2. To determine the outliers using SVM and isolation forest.

4. LOADING THE DATASETS

Load the libraries

In [1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Import the csv files of dataset

In [2]:
```python
tweet_data = pd.read_csv('/Users/madhumithrasubramaniankarthikesh/Downloads/Twitter_volume_AAPL.csv', parse_dates = ['timestamp'], index_col = ['timestamp'])
tweet_data.head()
```

Out[2]:

timestamp	value
2015-02-26 21:42:53	104
2015-02-26 21:47:53	100
2015-02-26 21:52:53	99
2015-02-26 21:57:53	154
2015-02-26 22:02:53	120

5. DATA PREPARATION

5.1 DATA CLEANING AND FEATURE ENGINEERING

Shape of all the data

In [3]:
```python
print("Shape of products: "+str(tweet_data.shape))
```

```
Shape of products: (15902, 1)
```

Information about dataset

In [4]:
```
tweet_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 15902 entries, 2015-02-26 21:42:53 to 2015-04-23 02:4
7:53
Data columns (total 1 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   value   15902 non-null  int64
dtypes: int64(1)
memory usage: 248.5 KB
```

Statistical description of the tweets

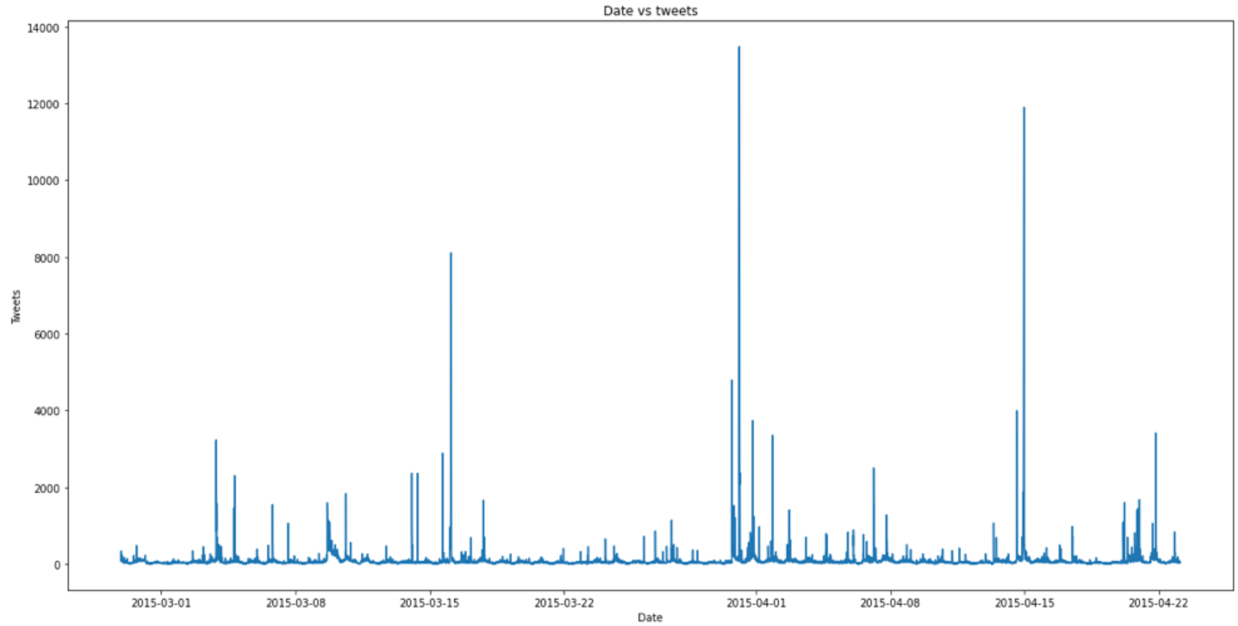
In [5]:
```
tweet_data['value'].describe()
```

Out[5]:
```
count    15902.000000
mean        85.552320
std        321.050721
min          0.000000
25%         29.000000
50%         47.000000
75%         76.000000
max      13479.000000
Name: value, dtype: float64
```

5.2 DATA VISUALIZATION

5.2.1 Days vs tweets

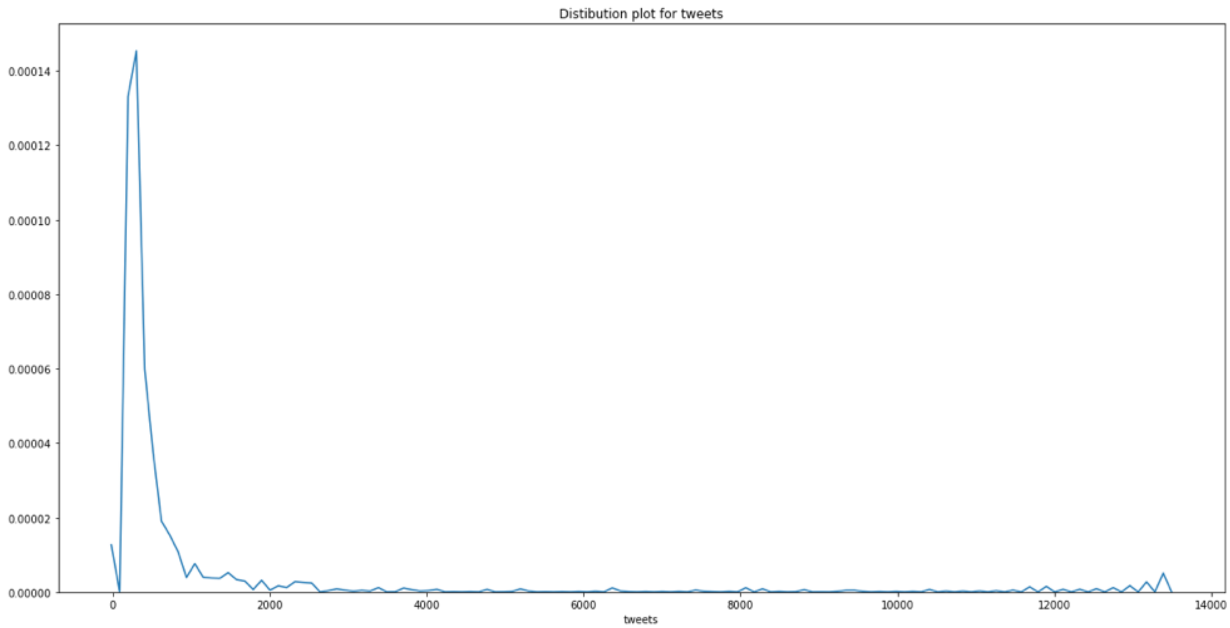
In [6]:
```
plt.figure(figsize=(20,10))
plt.xlabel('Date')
plt.ylabel('Tweets')
plt.title('Date vs tweets')
plt.plot(tweet_data.index,tweet_data['value']);
```



There is no definite pattern observed on number of tweets.Three anomalies are clearly visible with value at 8000, 13000 and 12000.

5.2.2 Distribution plot of the tweets

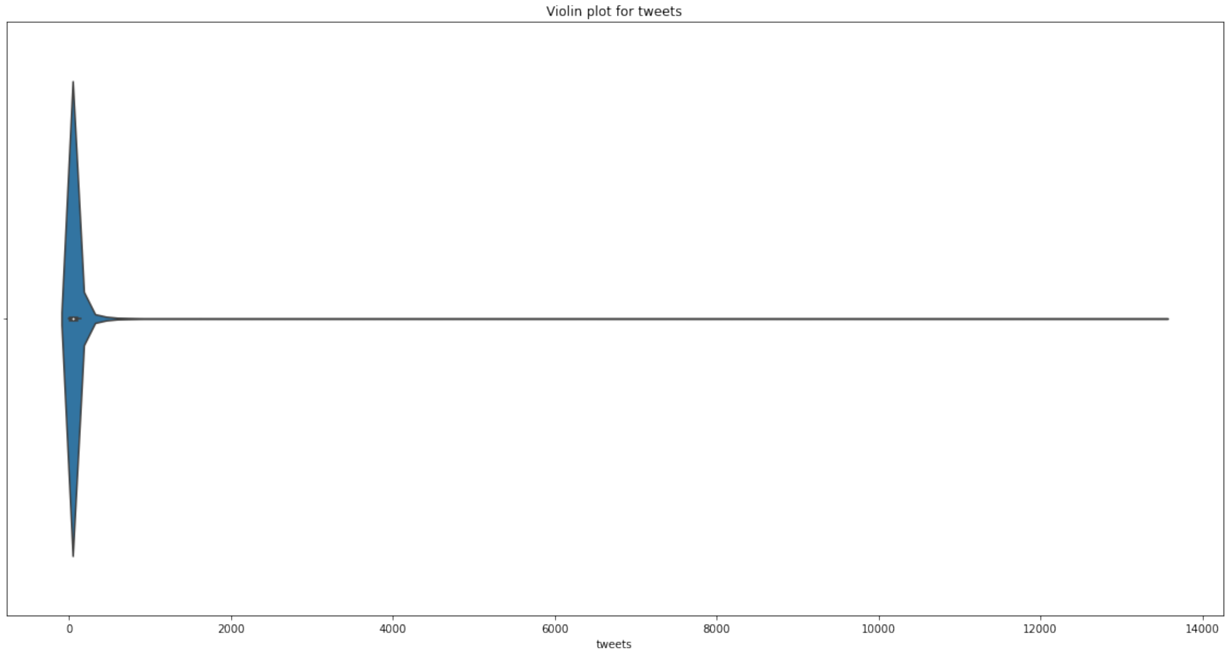
In [7]:
```
import seaborn as sns
plt.figure(figsize=[20,10])
sns.distplot(tweet_data['value'], hist=False)
plt.title('Distibution plot for tweets')
plt.xlabel('tweets')
plt.show()
```



The number of tweets above 2000 can be considered as outliers.

5.2.3 Violin plot for tweets

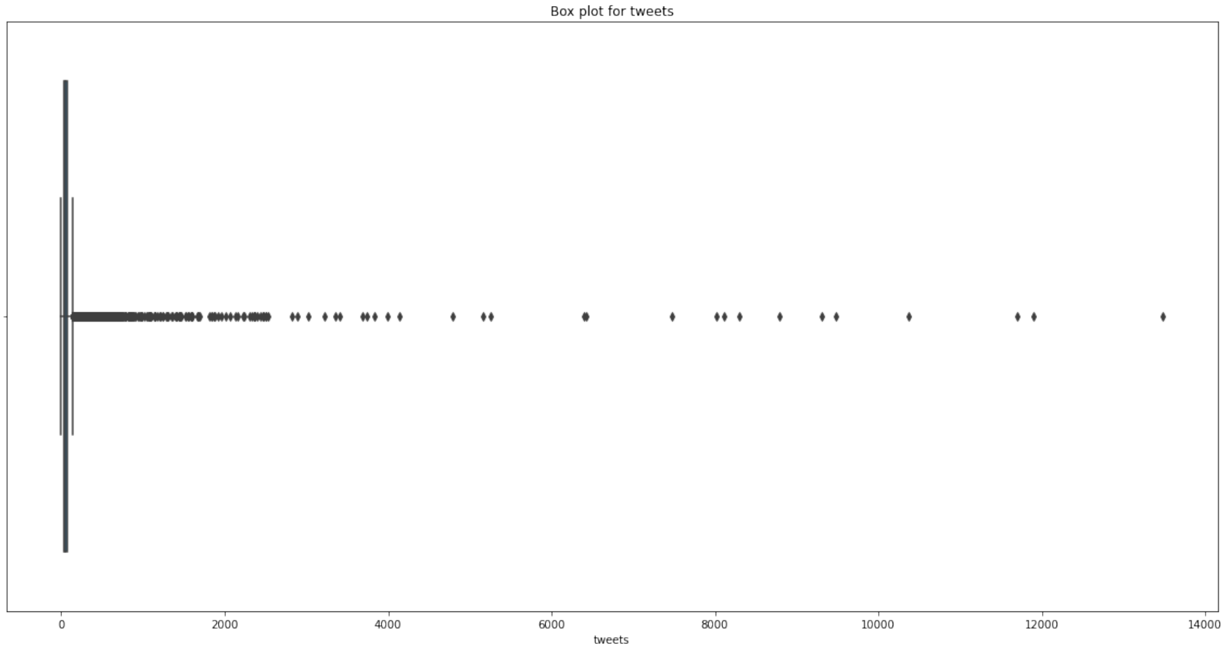
In [8]:
```
plt.figure(figsize=[20,10])
sns.violinplot(x=tweet_data['value'])
plt.title('Violin plot for tweets')
plt.xlabel('tweets')
plt.show()
```



The number of tweets greater than 1000 are outliers.

5.2.4 Box plot for tweets

In [9]:
```
plt.figure(figsize=[20,10])
sns.boxplot(x=tweet_data['value'])
plt.title('Box plot for tweets')
plt.xlabel('tweets')
plt.show()
```



The number of tweets greater than 500 can even be considered as outliers.

5.2.5 Seasonal Decomposition

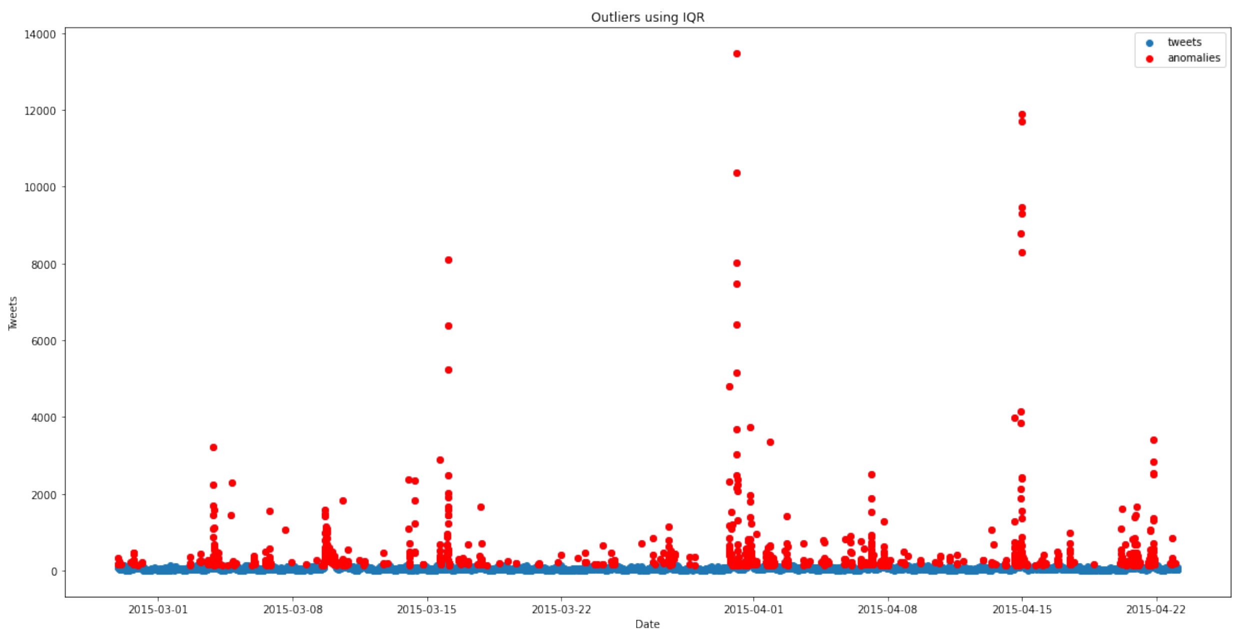
In [10]:
```python
from statsmodels.tsa.seasonal import seasonal_decompose
result = seasonal_decompose(tweet_data['value'], model='additive',peri
od=365)
fig = plt.figure()
fig = result.plot()
fig.set_size_inches(15, 12)
```

```
<Figure size 432x288 with 0 Axes>
```

5.3 ANOMALY DETECTION

5.3.1 Interquartile Range

In [11]:
```
Q3=76;
Q1=29;
IQR = Q3 - Q1;
lower_range = Q1 - (1.5 * IQR)
upper_range = Q3 + (1.5 * IQR)
t=tweet_data;
t['outlier']=1;
t.loc[(t.value < lower_range) | (t.value > upper_range), 'outlier'] =
-1;
t_=t[t["outlier"] == -1]
plt.figure(figsize=[20,10])
plt.scatter(t.index, t['value'],label='tweets')
plt.scatter(t_.index, t_.value, color='r', label='anomalies')
plt.legend()
plt.title('Outliers using IQR')
plt.xlabel('Date')
plt.ylabel('Tweets')
plt.show()
```



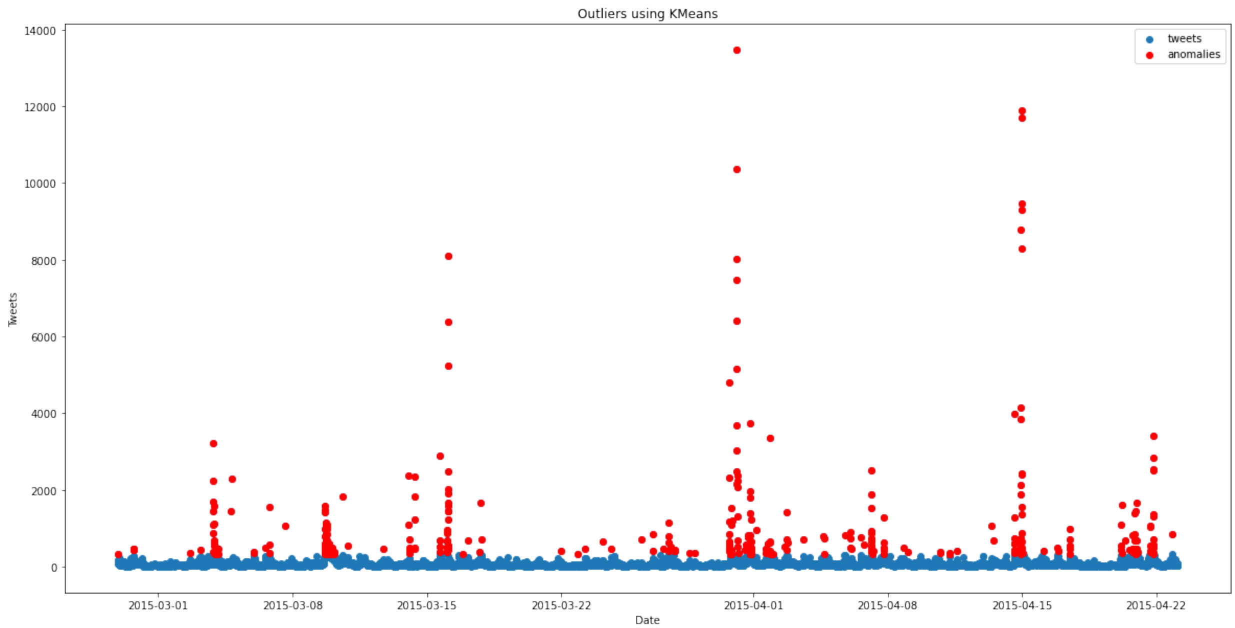
The IQR finds only the anomalies in high values.

5.3.2 KMeans to find anomalies

In [12]:

```
import random
import numpy as np
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.datasets.samples_generator import make_blobs
%matplotlib inline
from sklearn.preprocessing import OneHotEncoder

t=tweet_data.reset_index()
# print(t)
del t['timestamp']

kmeans = KMeans(n_clusters = 1)
kmeans.fit(t)
center = kmeans.cluster_centers_
t['distance']=np.sqrt((t['value'] - center[0][0])**2)
t['time']=tweet_data.index
t_ = t.sort_values(by=['distance'],ascending=False)

#considering above one std as anomaly
print("Number of values greater than one standard deviation",len(t_.lo
c[t_['value'] > 321]))

plt.figure(figsize=[20,10])
plt.scatter(t.time, t['value'],label='tweets')
plt.scatter(t_[:410].time, t_[:410].value, color='r',label='anomalies'
)
plt.legend()
plt.title('Outliers using KMeans')
plt.xlabel('Date')
plt.ylabel('Tweets')
plt.show()
```

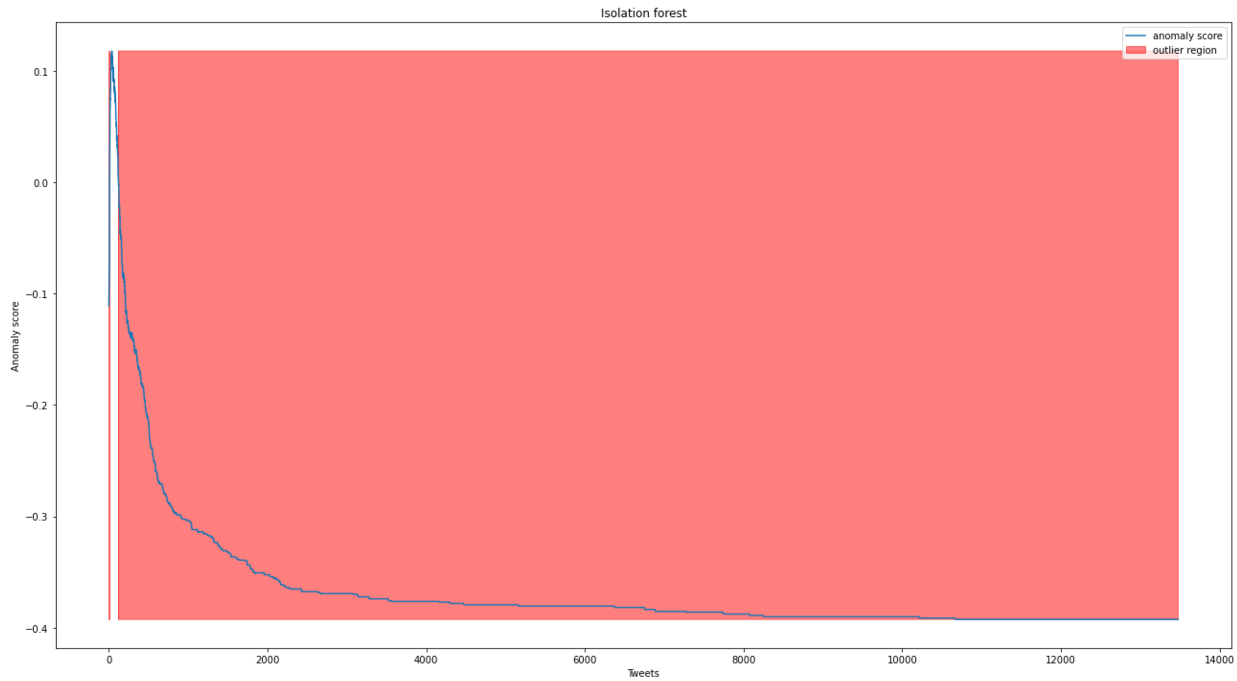
```
/Users/madhumithrasubramaniankarthikesh/anaconda3/lib/python3.8/site
-packages/sklearn/utils/deprecation.py:143: FutureWarning: The sklea
rn.datasets.samples_generator module is  deprecated in version 0.22
and will be removed in version 0.24. The corresponding classes / fun
ctions should instead be imported from sklearn.datasets. Anything th
at cannot be imported from sklearn.datasets is now part of the priva
te API.
  warnings.warn(message, FutureWarning)

Number of values greater than one standard deviation 410
```

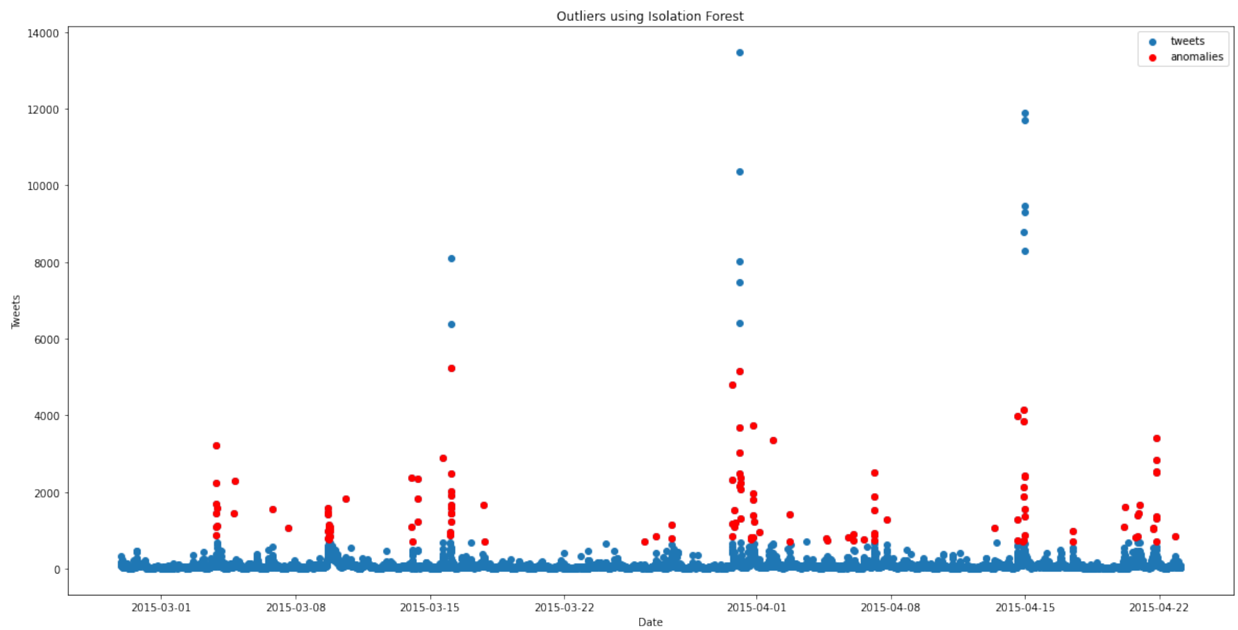


The K-Means also finds only the anomalies in high values when considering one standard deviation

5.3.3 Isolation forest to detect anomalies

In [13]:
```
from sklearn.ensemble import IsolationForest
plt.figure(figsize=(22, 12), facecolor='w', edgecolor='k')


isolation_forest = IsolationForest()
isolation_forest.fit(tweet_data['value'].values.reshape(-1,1))

xx = np.linspace(tweet_data['value'].min(), tweet_data['value'].max(),
len(tweet_data)).reshape(-1,1)
anomaly_score = isolation_forest.decision_function(xx)
outlier = isolation_forest.predict(xx)
plt.plot(xx, anomaly_score, label='anomaly score')
plt.fill_between(xx.T[0], np.min(anomaly_score), np.max(anomaly_score)
,
                 where=outlier==-1, color='r',
                 alpha=.5, label='outlier region')
plt.legend()
plt.title('Isolation forest');
plt.xlabel('Tweets');
plt.ylabel('Anomaly score');

t=tweet_data;
t=t.sort_values(by='value', ascending=False)
t['outlier']=outlier;

t_=t[t["outlier"] == 1]
plt.figure(figsize=[20,10])
plt.scatter(t.index, t['value'],label='tweets')
plt.scatter(t_.index, t_.value, color='r',label='anomalies')
plt.legend()
plt.title('Outliers using Isolation Forest')
plt.xlabel('Date')
plt.ylabel('Tweets')
plt.show()


anomaly=t.loc[t['outlier']==1]
outliers_counter = len(t[t['value'] > anomaly.value.min()])
print("Number of outliers as estimated :",outliers_counter)
print("Accuracy percentage:", 100*list(t['outlier']).count(1)/(outlier
s_counter))
```



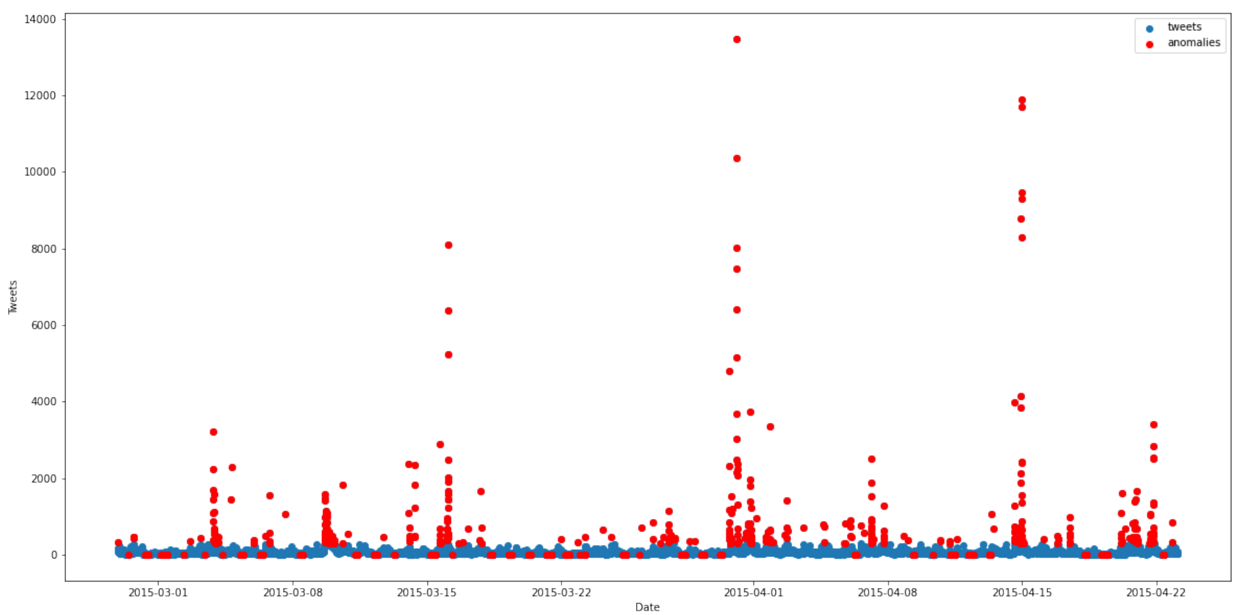



```
Number of outliers as estimated : 144
Accuracy percentage: 90.97222222222223
```

5.3.4 One Class SVM

In [14]:

```
from sklearn.svm import OneClassSVM
svm = OneClassSVM(kernel='rbf', gamma='scale', nu=0.05).fit(tweet_data
['value'].values.reshape(-1,1))
pred = svm.predict(tweet_data['value'].values.reshape(-1,1))
anom_index = np.where(pred==-1)
t=tweet_data.reset_index()
values = list([t.iloc[index] for index in anom_index])
values[0].value
plt.figure(figsize=[20,10])
plt.scatter(tweet_data.index, tweet_data['value'],label='tweets')
plt.scatter(values[0].timestamp, values[0]['value'], color='r',label='
anomalies')
plt.xlabel('Date')
plt.ylabel('Tweets')
plt.legend()
plt.show()
if svm.fit_status_==0:
    print("Correctly fitted");
    print("Raw scores :",svm.score_samples(tweet_data['value'].values.
reshape(-1,1)))
else:
    print("Not correctly fitted");
```




```
Correctly fitted
Raw scores : [430.83715219 430.40821058 430.29220265 ... 419.3682906
7 411.398351
 415.99948652]
```