# **Prediction** in Market Volatility

A case study in predicting market volatility and building short-term trading strategies using data from Reddit's WallStreetBets.

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#### **CONTENT**

- **Project** Approach
- What does the **DATA** tell us?
- Our **PREDICTION** models
- **PERFORMANCE** evaluate
- **CONCLUSION & NEXT STEP**

Helps to make a prediction on stock prices and market volatility.

SCENARIO

The aim of this project is to use data from posts made made on the sub-reddit "Wallstreet-Bets" to make a prediction of given scenario.

Help to predict if specific stocks rose or fell in the given time frame.



#### Covers two datasets:

#### JSON file:

- Contains comment of Reddit's post.
- Performed Sentiment Analysis.

#### Excel file:

Trimmed this huge org.
 provided data as per the
 other similar file hosted on
 Kaggle.

# Predict Market Volatility, why?

How can predicting market volatility add values to business world. Current scenarios' relation between stock market and social media.

Sudden market volatility increment affects the investment so predicting

Market volatility in advance can increase /lead us to profits in

Stock market.

# 80% of investors today use it as their regular Workflow &

Approx. 30% obtain information about the investment market through different

Social Media (it).

Economic Times
Research

## Target Variable

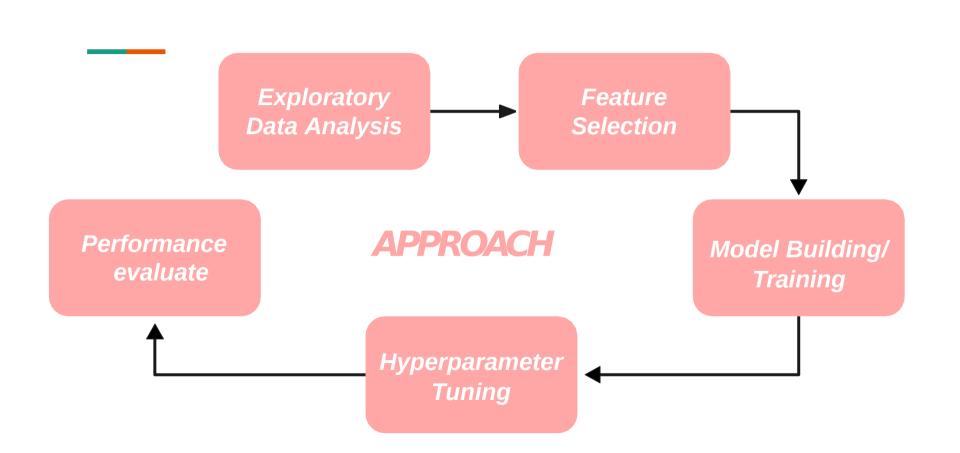
- Created comparing today's close price and yesterday's closing price.
- Check how the **sentiment analysis** of comment made in the day affects the closing price.

Why
Data
Science?

If we Predict the can future profit/ loss, we can AVOID the market volatility and get maximum profit from current stocks.

# **APPROACH**

How data science helps to predict the market volatility, and how we are going to do with it.

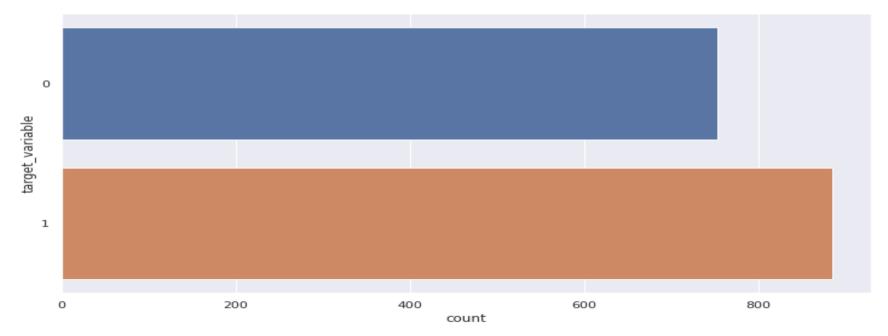


# Data Analysis

What the data told us? Let go for an EDA on the data set.

#### Our Target Variable (P/L)

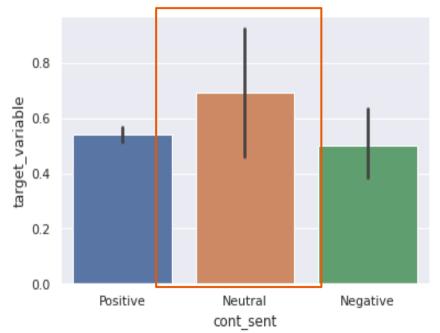
More positive response/profit in datasets.



Neutral > Positive> Negative Responses seems to affect target variable.

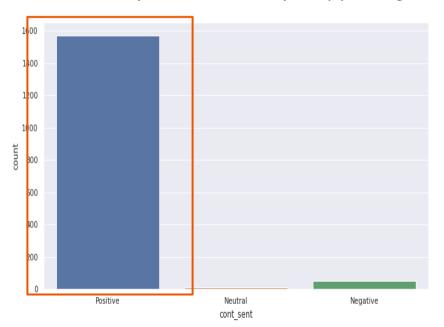


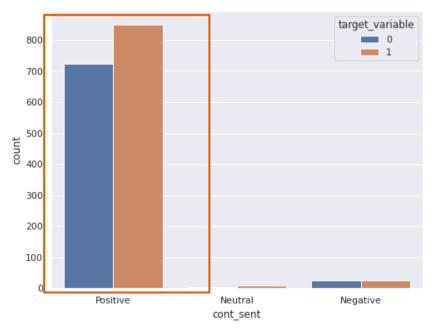
#### Bi-variate Plot (Polarity-Sentiment Analysis)



#### Count Plot (Univariate and Bivariate)

- Univariate Plot (Number of positive responses > Negative > Neutral)
- Positive response influences profit(1) in target variable/Closing Price.





# Relation Among all the Dependent And Independent Variables

Heatmap

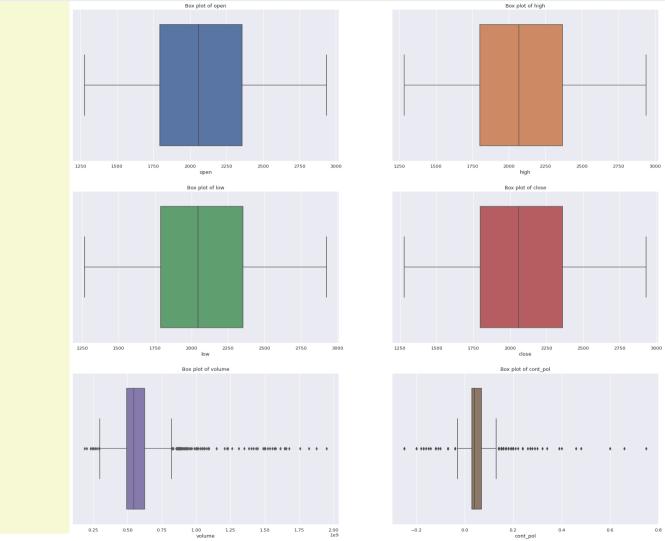
oben	1	1	1	1	-0.0067	-0.46	-0.27	0.96	-0.0019	0.0068	-0.22	-0.13	0.26	-0.015
high					-0.0033		-0.27	0.96	-0.0033	0.0062	-0.22	-0.13	0.26	-0.0045
wol					-0.016		-0.27	0.96	0.00043	0.0078	-0.22	-0.13	0.26	-0.00069
dose	1	1	1	1	-0.011	-0.47	-0.27	0.96	-0.0019	0.0058	-0.22	-0.13	0.26	0.0081
volume	-0.0067	-0.0033	-0.016	-0.011	1	-0.052	-0.054	0.067	-0.089	0.075	-0.018	-0.013	0.022	-0.094
cont_len					-0.052	1	0.19	-0.51	0.051	0.0056	0.033	0.0029	-0.031	-0.013
cont_pol	-0.27	-0.27	-0.27	-0.27	-0.054	0.19	1	-0.31	0.014	-0.013	-0.38	-0.086	0.38	0.0076
date_year	-0.0019	-0.0033	0.96	-0.0019	-0.089	-0.51	0.014	-0.14	-0.14	-0.007	-0.22	-0.12	-0.0054	-0.0048
ay date_month	0.0068	0.0062	0.00043	0.0019	0.075	0.0056	-0.013	-0.007	-0.0071	1	-0.014	0.011	0.0079	-0.021
neg date_day	-0.22	-0.22	-0.22	-0.22	-0.018	0.033	-0.38	-0.22	0.014	-0.014	1	-0.016	-0.89	-0.015
sent neu sent neg	-0.13	-0.13	-0.13	-0.13	-0.013	0.0029	-0.086	-0.12	-0.016	0.011	-0.016	1	-0.44	0.027
sent_pos sent	0.26	0.26	0.26	0.26	0.022	-0.031	0.38	0.26	-0.0054	0.0079	-0.89	-0.44	1	0.00088
target_variable se	-0.015	-0.0045	-0.00069	0.0081	-0.094	-0.013	0.0076	-0.0048	-0.021	-0.045	-0.015	0.027	0.00088	1
target \	oben	high	low	close	olume	nt len	nt_pol	year	month	e_day	nt_neg	nt neu	nt_pos	riable

# Check the Outliers:

All the variables are outliers free other than:

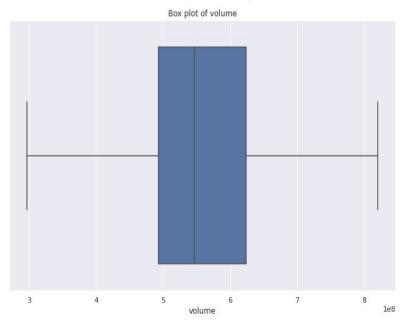
- Volume
- Content Polarity

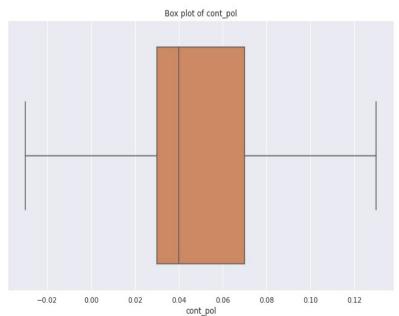
BoxPlot



#### **Box Plot (After):**

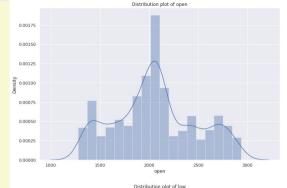
- IQR was performed where the outliers were treated via flooring and capping.
- Volume and Content Polarity columns are now outliers free.

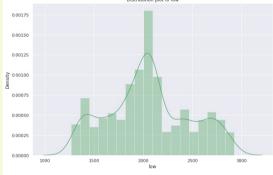


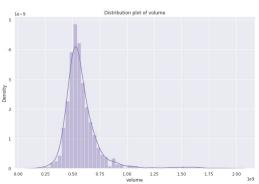


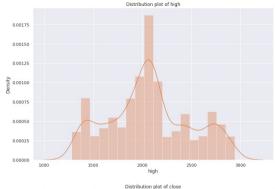
# Data of all the variables are Normally Distributed.

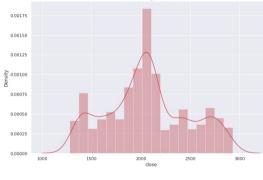
Disribution Plot





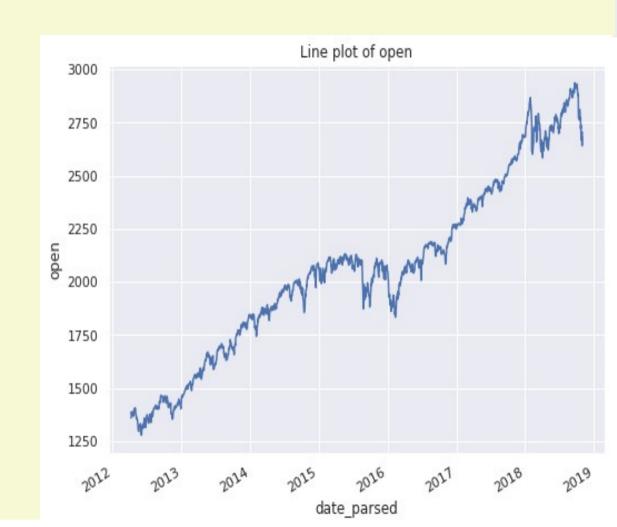






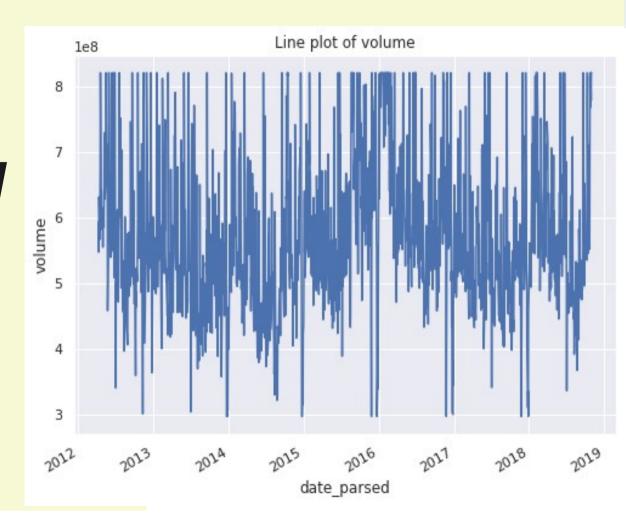
- It seems that all the other variables like: Close, High, Low has similar line plot other than Volume.
- All the variables value seems to increase as per the time.

Line Plot



Volume seems to increase and decrease along with time.

Line Plot



#### **Box Plot (After):**

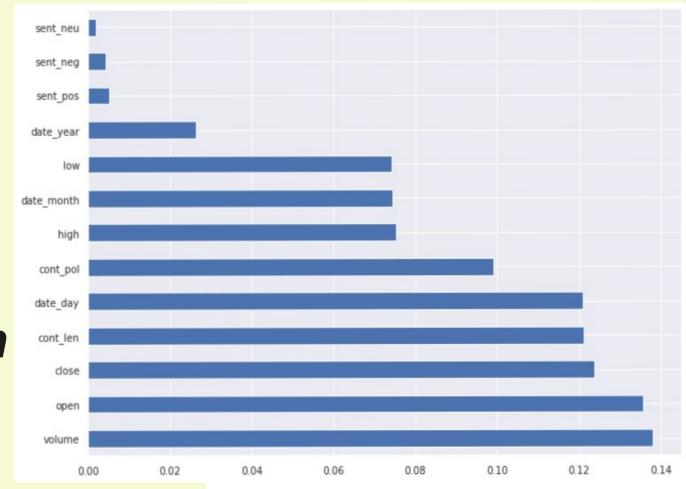
- Seems like closing price and Content Polarity are correlated with one another.
- Closing price increases with year but content polarity seems not to.



## PREDICTION MODEL

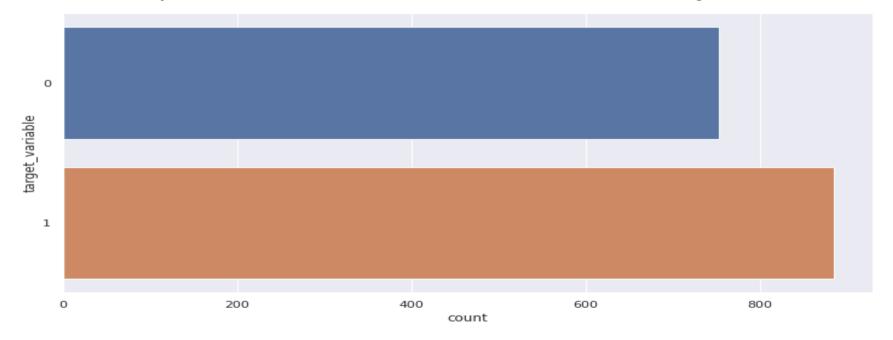
Build a classification model to predict the market volatility.

Most Imp. Features: 1. Volume 2. Open 3. Close 4. Cont len 5. Date



#### TARGET VARIABLE

- Though positive target variable is quite more in comparison to negative target variable we cannot say dataset is imbalanced because data the difference is not so huge.



#### **MODEL Building/Training**

Logistic Regression was selected for a model.

```
!pip install logisticregression
from sklearn.learn_model import LogisticRegression
from sklearn.metrics import classification_report, accuracy_score

log_reg = LogisticRegression
log_reg.fit(x_train, y_train)

y_pred = log_reg.predict(X_test)
print(classification_report(y_test, y_pred))
acc_score = accuracy_score(y_test, y_pred)
acc_score_per = acc_score * 100
print('The accuracy_score is', acc_score, '/', acc_score_per, '%'.)
```

#### MODEL BUILDING - Logistic Regression

- Classification Report and Accuracy score of our model (Before Hyperparameter Tuning)

	precision	recall	f1-score	support	
Θ	0.83	0.43	0.57	161	
1	0.62	0.92	0.74	167	
accuracy			0.68	328	
macro avg	0.73	0.67	0.65	328	
weighted avg	0.73	0.68	0.66	328	

# PERFORMANCE EVALUATION

Hyperparameter Tuning/ Evaluation metrics to increase the accuracy of the model.

**True Negative:** 69 (Predicted Loss as Loss)

False Positive: 92 (Predicted Loss as Profit)

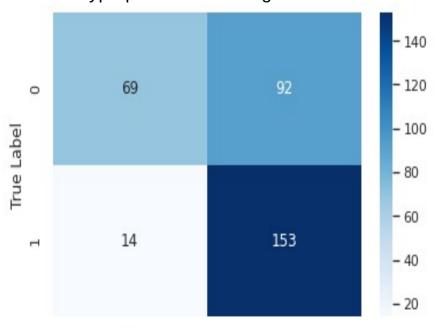
False Negative: 14 (Predicted Profit as Loss)

**True Positive:** 153 (Predicted Profit as Profit)



# **Confusion Matrix**

#### Before Hyperparameter Tuning



Predicted Label

#### **ROC Score**

60.8166400119016626 / 81.66400119016626 %

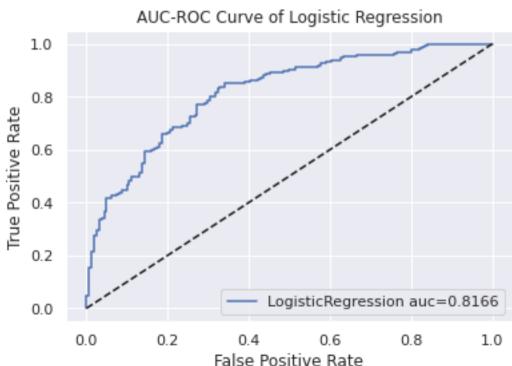
#### Graph

The left corner of model is quite near to top-left corner but not exactly so the roc curve of is average.



### AOC-ROC Curve

#### Before Hyperparameter Tuning



#### Hyperparameter Tuning (GridSearchCV)

```
from sklearn.model_selection import GridSearchCV
penalty=['l1', 'l2', 'elasticnet']
solver=['newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga']
max iter=[100, 200, 300, 350]
random_grid={'penalty':penalty,
             'solver':solver,
             'max_iter':max_iter,
log reg grid search= GridSearchCV(estimator=log reg,
param grid=random grid, cv=20, n jobs=-1, verbose=2)
```

**True Negative:** 148 (Predicted Loss as Loss)

False Positive: 13 (Predicted Loss as Profit)

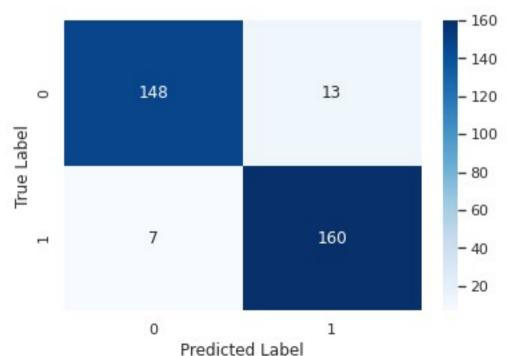
False Negative: 7 (Predicted Profit as Loss)

**True Positive:** 160 (Predicted Profit as Profit)



## **Confusion Matrix**

After Hyperparameter Tuning



#### **ROC Score**

0.98988358686354 / 98.988358686354 %

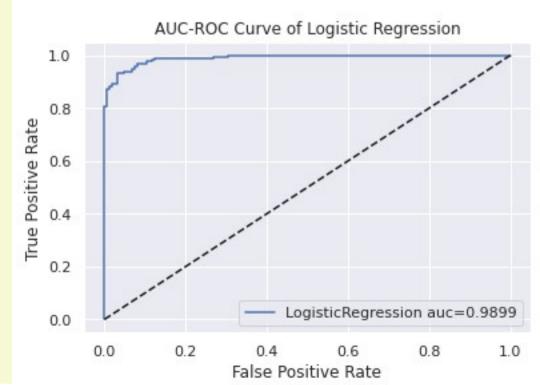
#### Graph

The left corner of model is so close to top-left corner hence model is good.



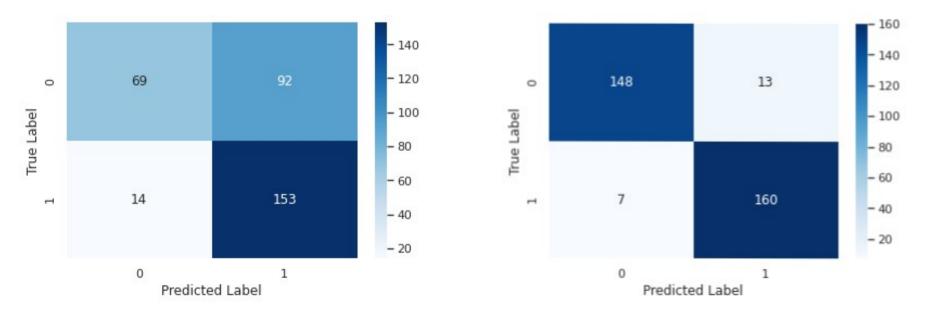
#### AOC-ROC Curve

After Hyperparameter Tuning



#### **MODELS PERFORMANCES**

- Classification Report and Accuracy score of our model ( After Hyperparameter Tuning)
- Increment in True Positive/ False Positive as expected...



#### MODEL BUILDING - Logistic Regression

- Classification Report and Accuracy score of our model ( After Hyperparameter Tuning)

	precision	recall	f1-score	support	
0	0.95	0.92	0.94	161	
1	0.92	0.96	0.94	167	
accuracy			0.94	328	
macro avg	0.94	0.94	0.94	328	
weighted avg	0.94	0.94	0.94	328	

# Model Deployment

Flask along with HTML/CSS was used to deploy in local server. Later deployed using Heroku.

# MODEL DEPLOYMENT

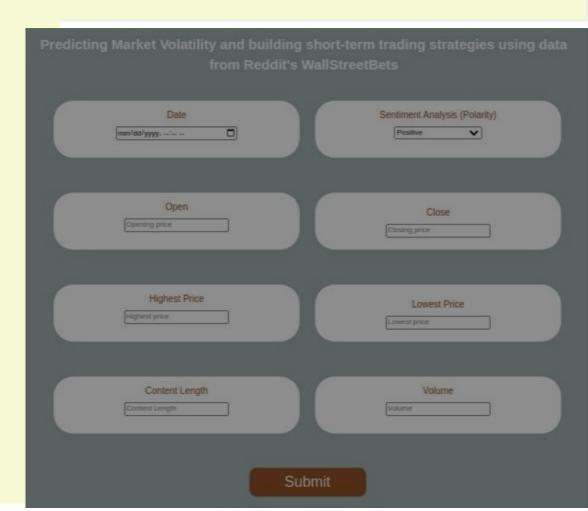
#### **Tools:**

Flask, HTML, CSS, Heroku

#### Input

Date, Sentiment Analysis, Open, Close, Higher Price, Lower Price, Content Length, Close





# MODEL DEPLOYMENT

#### Tools:

Flask, HTML, CSS, Heroku

#### Output

Gives the predicted output from the trained model in the form of Profit/Loss.



#### **Result:**



# CONCLUSION

#### **MODEL CONCLUSION:**

**CONDITIONS** which have the following characteristics,

- Having HIGH opening price itself;
- High Volume;
- Positive Sentiment Analysis;
- Lengthy/Informative Detailed comments;

are likely to lead us to Profit.

#### WHAT CAN WE DO

#### General

- 1. Publish more **Positive Contents**;
- 2. Promote more **detailed and informative** contents
- 3. Reduce/Remove the **negative contents** from Social Media asap if found.

# LIMITATION & NEXT STEP

#### HOW TO IMPROVE

#### 1. Only applied Logistic Regression:

Apply and compare other tuned performance.

#### 2. Used only Reddit's API:

Collect API from as much as resources possible.

# END