Sentiment Analysis for Stock Price Prediction in Python

How we can predict stock price movements using Twitter

James Briggs Dec 4, 2020 · 9 min read ★

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Do the markets reflect rational behavior or human irrationality? Mass psychology's effects may not be the only factor driving the markets, but it's unquestionably significant [1].

This fascinating quality is something that we can measure and use to predict market movement with surprising accuracy levels.

With the real-time information available to us on massive social media platforms like Twitter, we have all the data we could ever need to create these predictions.

But then comes the question, how can our computer understand what this unstructured text data means?

That is where sentiment analysis comes in. Sentiment analysis is a particularly interesting branch of Natural Language Processing (NLP), which is used to rate the language used in a body of text.

Through sentiment analysis, we can take thousands of tweets about a company and judge whether they are generally positive or negative (the sentiment) in real-time! We will cover:

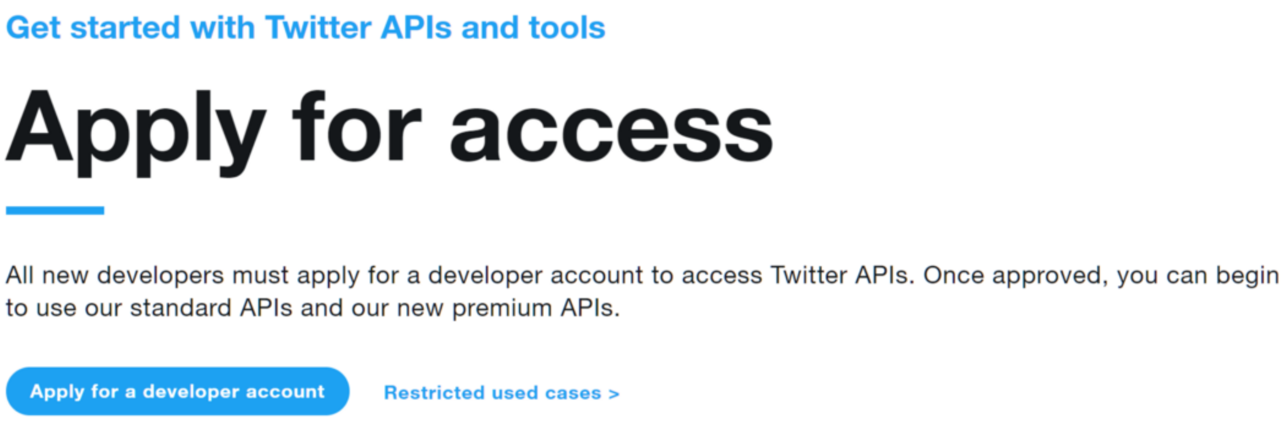
```
> Getting Twitter Developer Access
  - API Setup

> Twitter API
  - Searching for Tweets
  - Improving our Request

> Building Our Dataset

> Sentiment Analysis
  - Flair
  - Analyzing Tesla Tweets
```

If you're here for sentiment analysis in Flair — I cover it more succinctly in this video:

• • •

Getting Twitter Developer Access

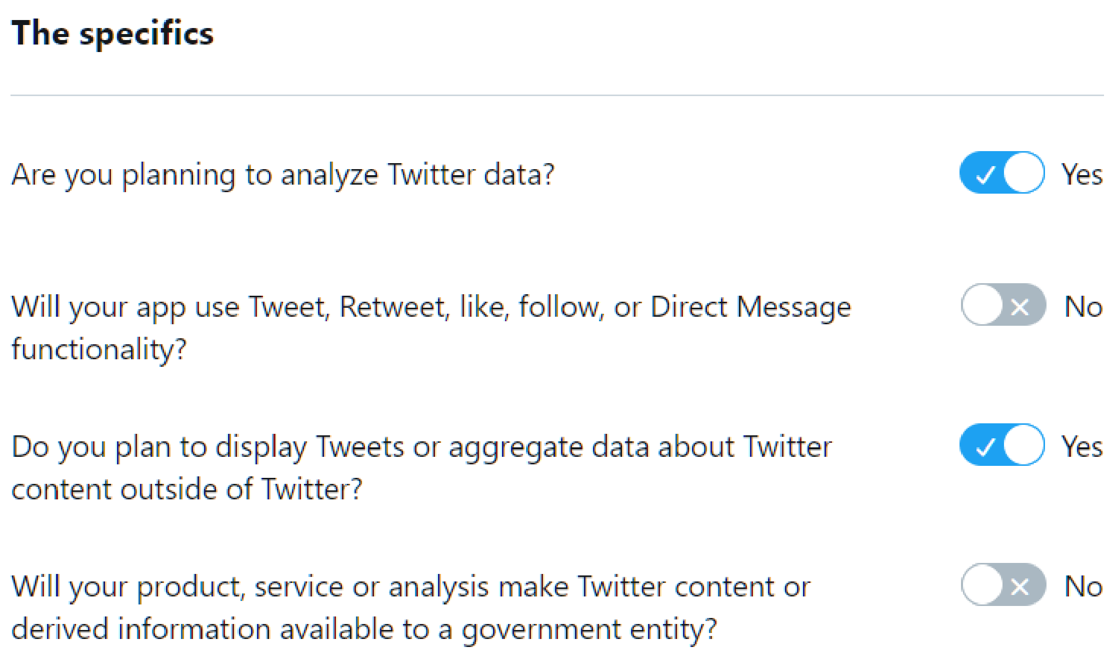
The very first thing we need to apply for Twitter developer access. We can do this by heading over to dev.twitter.com and clicking the Apply button (top-right corner).



Get started with Twitter APIs and tools

Apply for access

All new developers must apply for a developer account to access Twitter APIs. Once approved, you can begin to use our standard APIs and our new premium APIs.



The specifics

Are you planning to analyze Twitter data? ✓ Yes

Will your app use Tweet, Retweet, like, follow, or Direct Message functionality? ✕ No

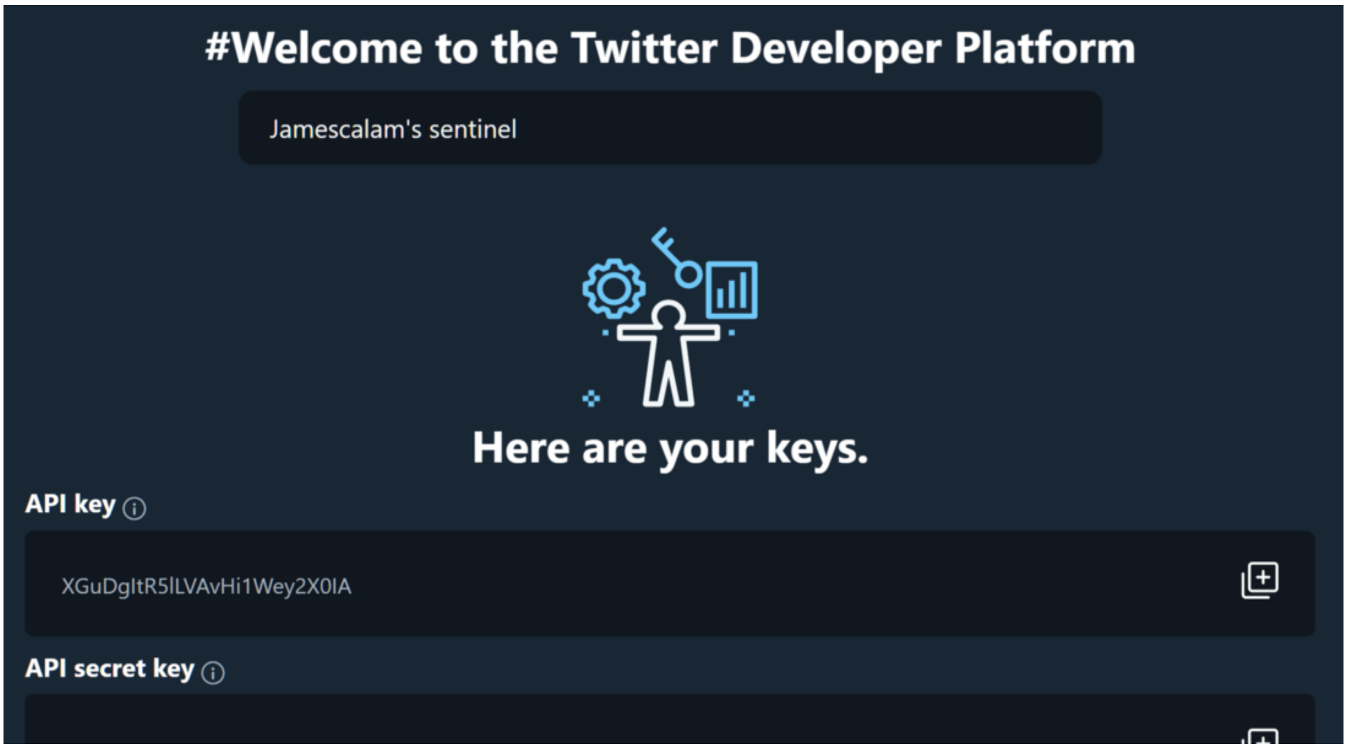
Do you plan to display Tweets or aggregate data about Twitter content outside of Twitter? ✓ Yes

Will your product, service or analysis make Twitter content or derived information available to a government entity? ✕ No

On the ‘How will you use the Twitter API or Twitter data?’ page, select yes or no, as shown above. I have put a few example answers here — these are only valid for this specific use-case, so please adjust them to your own needs where relevant.

We submit our answers and complete the final agreement and verification steps. Once complete, we should find ourselves at the app registration screen.

App Setup



#Welcome to the Twitter Developer Platform

Jamescalam's sentinel

Here are your keys.

API key

XGuDgltR5lLVAvHi1Wey2X0IA

API secret key

First, we give our app a name. It has to be unique, so be creative. We will receive our API keys; this is the only time we will see them, so keep them somewhere safe (and secret)!

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Twitter API

Now we have our API set up; we can begin pulling tweet data. We will focus on Tesla for this article.

Searching for Tweets

We will be using the `requests` library to interact with the Twitter API. We can search for the most recent tweets given a query through the `/tweets/search/recent` endpoint.

Together with the Twitter API address, this gives us:

```
https://api.twitter.com/1.1/tweets/search/recent
```

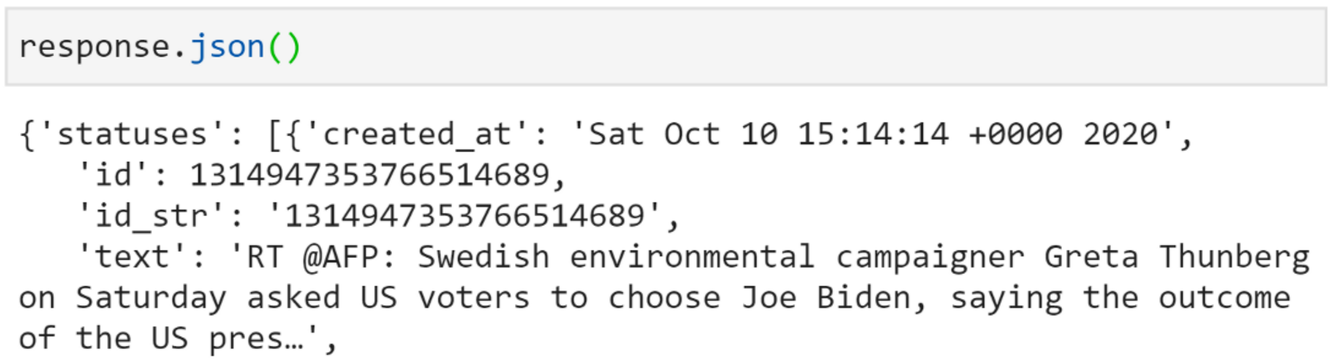
We need two more parts before sending our request, (1) authorization and (2) a search query.

The bearer token given to us earlier is used for authorization — which we pass through the `authorization` key in our request header.

Finally, we can specify our search query by adding `?q=<SEARCH QUERY>` to our API address. Putting these all together in a search for Telsa will give us:

```
requests.get(
    'https://api.twitter.com/1.1/search/tweets.json?q=tesla',
    headers={
        'authorization': 'Bearer '+BEARER_TOKEN
})
```

Our request will not return exactly what we want. If we take a look at the very first entry of our returned request we will see very quickly that we are not returning the full length of tweets — and that they may not even be relevant:



```
response.json()
```

```
{'statuses': [{'created_at': 'Sat Oct 10 15:14:14 +0000 2020',
   'id': 1314947353766514689,
   'id_str': '1314947353766514689',
   'text': 'RT @AFP: Swedish environmental campaigner Greta Thunberg
on Saturday asked US voters to choose Joe Biden, saying the outcome
of the US pres…',
```

Fortunately, we can easily fix the tweet truncation by adding another parameter `tweet_mode=extended` to our request. Which will look like:

```
/search/tweets.json?q=tesla&tweet_mode=extended
```

As we add more and more parameters, the API address string can quickly get overcrowded and messy. To avoid this, we can move them into a dictionary — which we then feed to the `params` argument of our get request.

```
params = {'q': 'tesla'
          'tweet_mode': 'extended'}

requests.get(
    'https://api.twitter.com/1.1/search/tweets.json',
    params=params,
    headers={'authorization': 'Bearer '+BEARER_TOKEN}
})
```

We can improve our request further. First, we can tell Twitter which language tweets to return (otherwise we get everything) with `lang=en` for English. Adding `count=100` increases the maximum number of tweets to return to 100.

```
        'tweet_mode': 'extended',
        'lang': 'en',
        'count': '100'
    }
```

. . .

Building Our Dataset

Once we have our API request setup, we can begin running it to populate our dataset.

```
def get_data(tweet):
    data = {
        'id': tweet['id_str'],
        'created_at': tweet['created_at'],
        'text': tweet['full_text']
    }
    return data
```

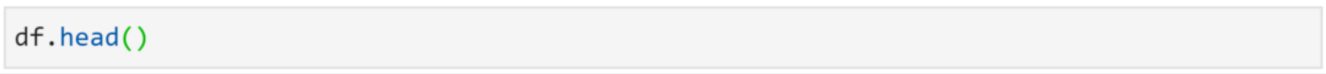
Each tweet returned by the API contains just three fields that we want to keep. Those are the tweet ID `'id_str'`, creation date `'created_at'`, and untruncated text `'full_text'`. We extract these in a function called `get_data`.

Our response is not just one tweet — it contains many. So we need to iterate through each of these and extract the information we need.

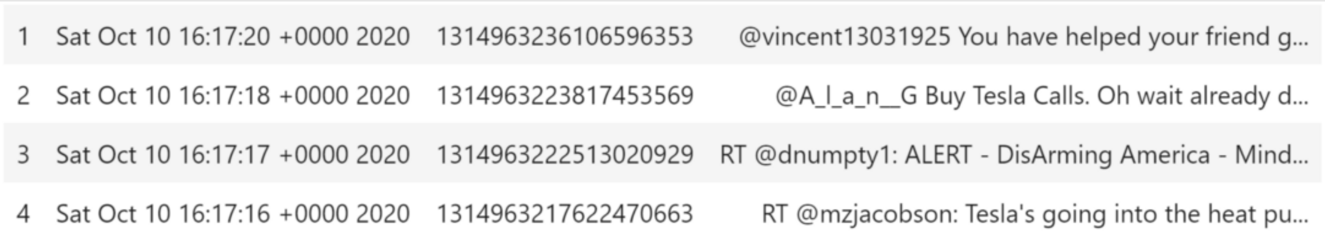
```
df = pd.DataFrame()

for tweet in response.json()['statuses']:
    row = get_data(tweet)
    df = df.append(row, ignore_index=True)
```

We first transform the API response into a Python dictionary using `.json()` — we then access the list of tweets through `['statuses']`. We then extract tweet data with `get_data` and append to our dataframe `df`. Giving us:



```
df.head()
```



1	Sat Oct 10 16:17:20 +0000 2020	1314963236106596353	@vincent13031925 You have helped your friend g...
2	Sat Oct 10 16:17:18 +0000 2020	1314963223817453569	@A_l_a_n__G Buy Tesla Calls. Oh wait already d...
3	Sat Oct 10 16:17:17 +0000 2020	1314963222513020929	RT @dnumpty1: ALERT - DisArming America - Mind...
4	Sat Oct 10 16:17:16 +0000 2020	1314963217622470663	RT @mzjacobson: Tesla's going into the heat pu...

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Sentiment Analysis

We will be using a pre-trained sentiment analysis model from the `flair` library. As far as pre-trained models go, this is one of the most powerful.

This model splits the text into character-level tokens and uses the DistilBERT model to make predictions.

The advantage of working at the character-level (as opposed to word-level) is that words that the network has never seen before can still be assigned a sentiment.

DistilBERT is a distilled version of the powerful BERT transformer model — which in-short means — it is a 'small' model (only *66 million* parameters) AND is still super powerful [2].

Flair

To use the flair model, we first need to import the library with `pip install flair`. Once installed, we import and initialize the model like so:

```
import flair
sentiment_model = flair.models.TextClassifier.load('en-sentiment')
```

If you have issues installing Flair, it is likely due to your PyTorch/Tensorflow installations. For PyTorch, go here to get the correct installation command — and for Tensorflow type `pip install tensorflow` *(add* `-U` *at the end to upgrade).*

All we need to do now is tokenize our text by passing it through `flair.data.Sentence(<TEXT HERE>)` and calling the `.predict` method on our model.

```
sentence = flair.data.Sentence(TEXT)
sentiment_model.predict(sentence)
```

By calling the `predict` method we add the sentiment rating to the data stored in `sentence`. We can see how it works by predicting the sentiment for a simple phrase:

```
sentence = flair.data.Sentence('hello world')
```

```
sentence
```

```
Sentence: "hello world"   [− Tokens: 2]
```

```
sentiment_model.predict(sentence)
```

```
sentence
```

```
Sentence: "hello world"   [− Tokens: 2  − Sentence-Labels: {'label': [POSITIVE (0.9759)]}]
```

And let's try something negative:

```
sentence = flair.data.Sentence('you suck')
sentiment_model.predict(sentence)
sentence
```

```
Sentence: "you suck"   [− Tokens: 2  − Sentence-Labels: {'label': [NEGATIVE (0.9948)]}]
```

It works on our two easy test cases, but we don't know about actual tweets — which involve special characters and more complex language.

Analyzing Tesla Tweets

Most of our tweets are very messy. Cleaning text data is fundamental, although we will just do the bare minimum in this example.

```
whitespace = re.compile(r"\s+")
web_address = re.compile(r"(?i)http(s):\/\/[a-z0-9.~_\-\/]+")
tesla = re.compile(r"(?i)@Tesla(?=\b)")
user = re.compile(r"(?i)@[a-z0-9_]+")

# we then use the sub method to replace anything matching
tweet = whitespace.sub(' ', tweet)
tweet = web_address.sub('', tweet)
```

Using regular expressions (RegEx) through the `re` module, we can quickly identify excessive whitespace, web addresses, and Twitter users. If these expressions look like hieroglyphs to you — I covered all of these methods in a RegEx article here.

Now we have our clean(ish) tweet — we can tokenize it by converting it into a sentence object, and then predict the sentiment:

```
sentence = flair.data.Sentence(tweet)
sentiment_model.predict(sentence)
```

Finally, we extract our predictions and add them to our `tweets` dataframe. We can access the label object (the prediction) by typing `sentence.labels[0]`. With this, we call `score` to get our confidence/probability score, and `value` for the *POSITIVE/NEGATIVE* prediction:

```
probability = sentence.labels[0].score  # numerical value 0-1
sentiment = sentence.labels[0].value  # 'POSITIVE' or 'NEGATIVE'
```

We can append the `probability` and `sentiment` to lists which we then merge with our `tweets` dataframe. Putting all of these parts together will give us:

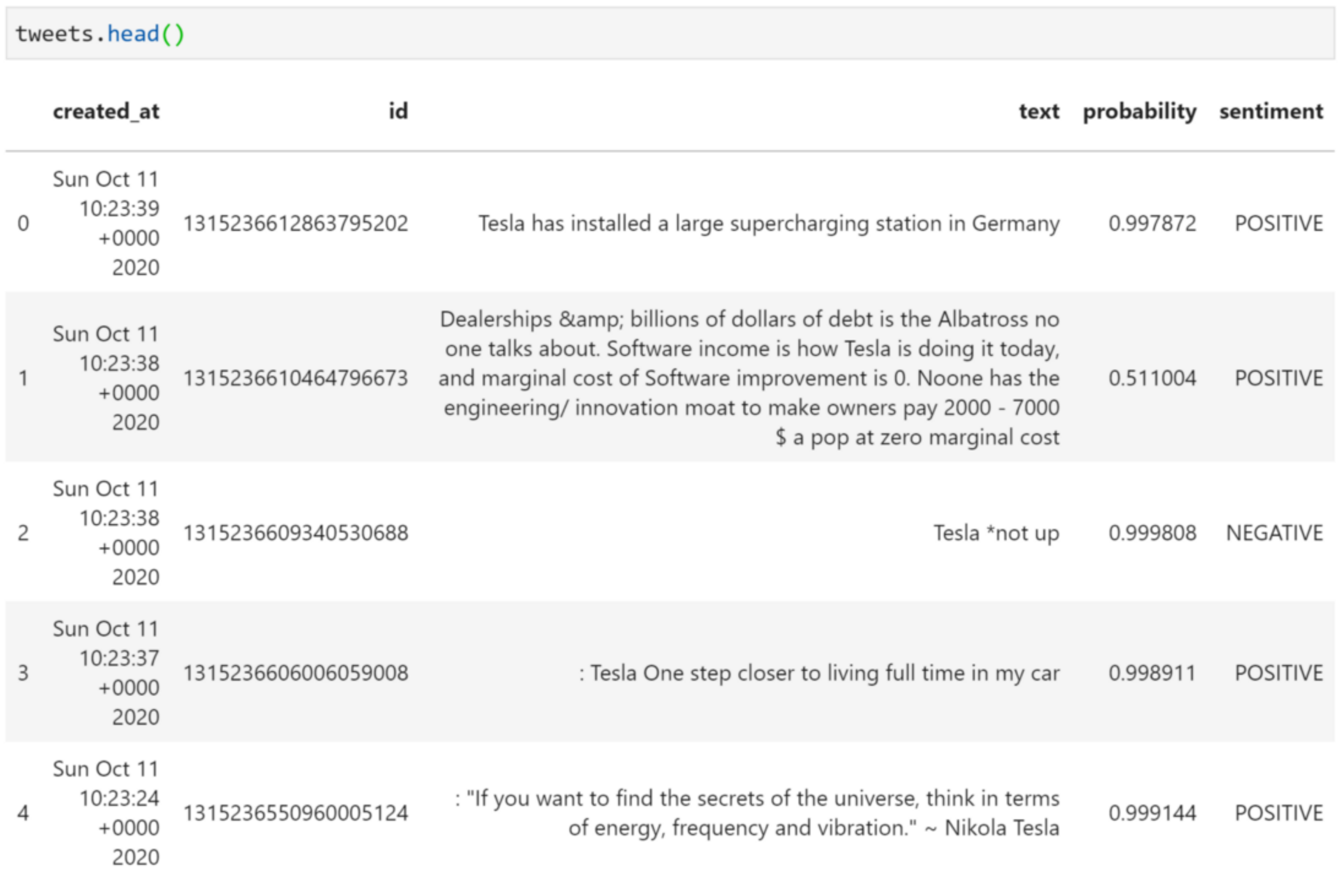
```
# we will append probability and sentiment preds later
probs = []
sentiments = []

# use regex expressions (in clean function) to clean tweets
tweets['text'] = tweets['text'].apply(clean)

for tweet in tweets['text'].to_list():
    # make prediction
    sentence = flair.data.Sentence(tweet)
    sentiment_model.predict(sentence)
    # extract sentiment prediction
    probs.append(sentence.labels[0].score)  # numerical score 0-1
    sentiments.append(sentence.labels[0].value)  # 'POSITIVE' or 'NEGATIVE'
```

```
tweets['probability'] = probs
tweets['sentiment'] = sentiments
```

sentiment_prediction.py hosted with ♡ by GitHub view raw



```
tweets.head()
```

	created_at	id	text	probability	sentiment
0	Sun Oct 11 10:23:39 +0000 2020	1315236612863795202	Tesla has installed a large supercharging station in Germany	0.997872	POSITIVE
1	Sun Oct 11 10:23:38 +0000 2020	1315236610464796673	Dealerships &amp; billions of dollars of debt is the Albatross no one talks about. Software income is how Tesla is doing it today, and marginal cost of Software improvement is 0. Noone has the engineering/ innovation moat to make owners pay 2000 - 7000 $ a pop at zero marginal cost	0.511004	POSITIVE
2	Sun Oct 11 10:23:38 +0000 2020	1315236609340530688	Tesla *not up	0.999808	NEGATIVE
3	Sun Oct 11 10:23:37 +0000 2020	1315236606006059008	: Tesla One step closer to living full time in my car	0.998911	POSITIVE
4	Sun Oct 11 10:23:24 +0000 2020	1315236550960005124	: "If you want to find the secrets of the universe, think in terms of energy, frequency and vibration." ~ Nikola Tesla	0.999144	POSITIVE

A quick look at the head of our dataframe shows some pretty impressive results. The second tweet is assigned a positive sentiment, but with a low level of confidence (0.51) — as a human, I'm also not sure whether this is a positive or negative tweet either.

Tweet number three, *"Tesla *not up"*, demonstrates how effective using character-level embeddings can be.

With word embeddings, it is improbable that our model would recognize '*not' as matching the word 'not'. Our character-level model doesn't trip up and accurately classifies the tweet as negative.

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Historical Performance

By plotting Tesla tweets' sentiment alongside Tesla's historical stock price performance, we can assess our approach's potential viability.

TSLA Tweets

First, we need more data. Twitter offers the past seven days of data on their free API tier, so we will go back in 60-minute windows and extract ~100 tweets from within each of these windows.

To do this, we need to use v2 of the Twitter API — which is slightly different — but practically the same in functionality as v1. The full code, including API setup, is included below.

We tell the API our from-to datetime using the `start_time` and `end_time` parameters respectively, both require a datetime string in the format *YYYY-MM-DDTHH:mm:ssZ*.

```python
from datetime import datetime, timedelta
import requests
import pandas as pd

# read bearer token for authentication
with open('bearer_token.txt') as fp:
    BEARER_TOKEN = fp.read()

# setup the API request
endpoint = 'https://api.twitter.com/2/tweets/search/recent'
headers = {'authorization': f'Bearer {BEARER_TOKEN}'}
params = {
    'query': '(tesla OR tsla OR elon musk) (lang:en)',
    'max_results': '100',
    'tweet.fields': 'created_at,lang'
}

dtformat = '%Y-%m-%dT%H:%M:%SZ'  # the date format string required by twitter

# we use this function to subtract 60 mins from our datetime string
def time_travel(now, mins):
    now = datetime.strptime(now, dtformat)
    back_in_time = now - timedelta(minutes=mins)
    return back_in_time.strftime(dtformat)

now = datetime.now()  # get the current datetime, this is our starting point
```

```python
df = pd.DataFrame()  # initialize dataframe to store tweets

df = pd.DataFrame()  # initialize dataframe to store tweets
while True:
    if datetime.strptime(now, dtformat) < last_week:
        # if we have reached 7 days ago, break the loop
        break
    pre60 = time_travel(now, 60)  # get 60 minutes before 'now'
    # assign from and to datetime parameters for the API
    params['start_time'] = pre60
    params['end_time'] = now
    response = requests.get(endpoint,
                            params=params,
                            headers=headers)  # send the request
    now = pre60  # move the window 60 minutes earlier
    # iteratively append our tweet data to our dataframe
    for tweet in response.json()['data']:
        row = get_data(tweet)  # we defined this function earlier
        df = df.append(row, ignore_index=True)
```

We write a function for subtracting 60 minutes from our datetime string — and integrate it into a loop that will run until we reach seven days into the past.

Inside this loop, we send our request for tweets within the 60-minute window — and then extract the information we want and append to our dataframe.

The result is a dataframe containing ~17K tweets containing the word 'tesla' from the past seven days.

```python
df.head()
```

	created_at	id	lang	text
0	2020-10-11T15:46:19.000Z	1315317815268847618	und	https://t.co/h2ho91Jlft
1	2020-10-11T15:46:17.000Z	1315317808142708737	tr	@sanbel25 Tesla\n#CanYaman\n#ÖzgeGürel\n#BayYa...
2	2020-10-11T15:46:11.000Z	1315317784222609408	en	RT @maxH6294: @CannaFrom RETWEET\n\n #THRIV...
3	2020-10-11T15:46:11.000Z	1315317783874465792	fi	@miikaaulio @Olkurola @pvesterbacka @VentureBe...
4	2020-10-11T15:46:10.000Z	1315317780590153728	es	Protector eléctrico general, marca: TESLA; par...

~12K tweets.

TSLA Ticker

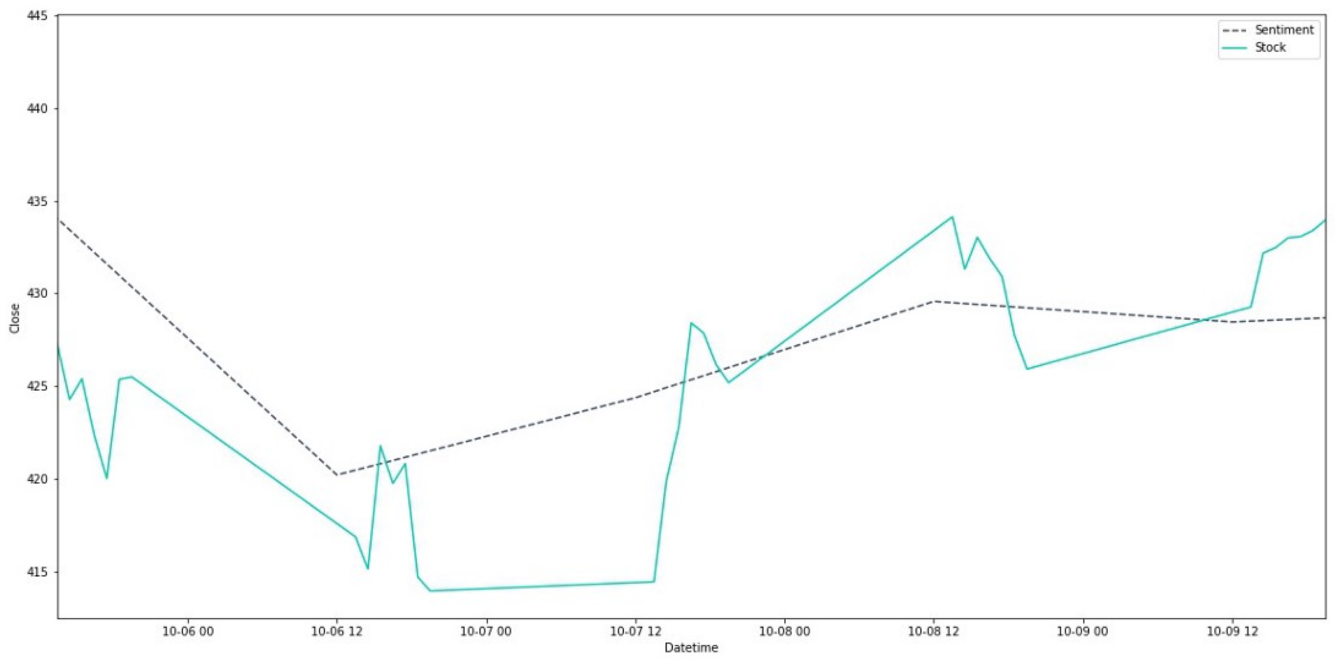
Next up, we need to extract our stock data from Yahoo Finance using the `yfinance` library — `pip install yfinance` if needed.

```
tsla = yf.Ticker("TSLA")

tsla_stock = tsla.history(
    start=(data['created_at'].min()).strftime('%Y-%m-%d'),
    end=data['created_at'].max().strftime('%Y-%m-%d'),
    interval='60m'
).reset_index()
```

We initialize a `Ticker` object for TSLA, then use the `history` method to extract stock data between the `min` and `max` dates contained in our tweets data, with an `interval` of sixty minutes.

With a few transformations, we can overlay the average daily sentiment of our Tesla tweets above the stock price for Monday-Friday:



TSLA stock prices Monday-Friday. The sentiment (originally scored from -1 to +1 has been multiplied to accentuate +ve or -ve sentiment, and centered on the average stock price value for the week.

an initial positive outcome to investigate further.

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That's all for this introductory guide to sentiment analysis for stock prediction in Python. We've covered the basics of:

- The Twitter API
- Sentiment analysis with Flair
- Yahoo Finance
- Comparing our tweet sentiments against real stock data

There's plenty more to learn to implement an effective predictive model based on sentiment, but it's a great start.

I hope you enjoyed the article! I also cover more programming/data science over on YouTube here. If you have any questions or ideas, let me know via Twitter or in the comment below.

Thanks for reading!

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References

[1] Psychology influences markets (2013), California Institute of Technology

[2] V. Sanh, Smaller, faster, cheaper, lighter: Introducing DistilBERT, a distilled version of BERT (2019), Medium

[3] V. Sanh, DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter (2019), NeurIPS

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