# Squeeze Me Baby One More Time

***HOW NOT TO BE A "FOMO" INVESTOR***

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# Fear Of Missing Out

RETAIL INVESTORS GET IN TOO LATE

# Popular Stocks Seem Too Expensive

FAANGS, TESLA, ADOBE ARE EXPENSIVE

- Is there a relatively easy way for retail investors to spot big moves in popular stocks?

- Would this method stand up to testing in linear regression and machine learning models?

- Is there a way for retail investors to take $1000 and profit from big moves?

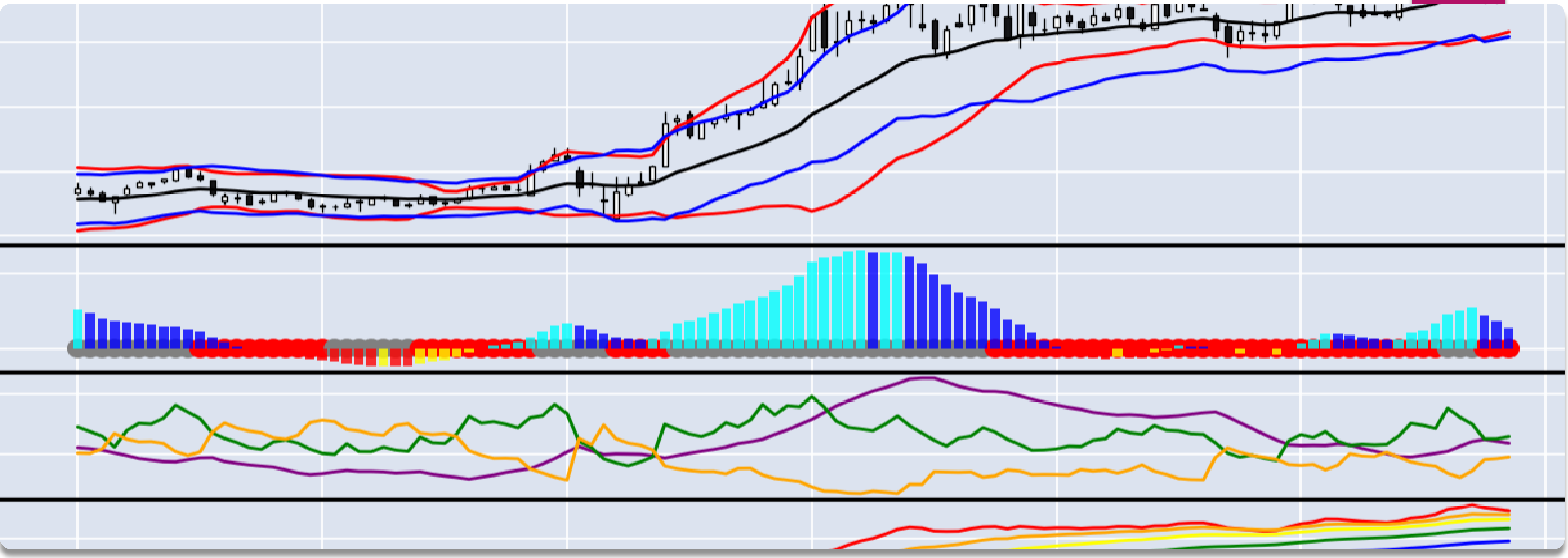
It is not in the thinking that the money is made. It is in the sitting and waiting."

- Jesse Livermore
  Legendary Stock Trader

**TIMING IS A KEY TO SUCCESSFUL STOCK OR COMMODITY TRADING**

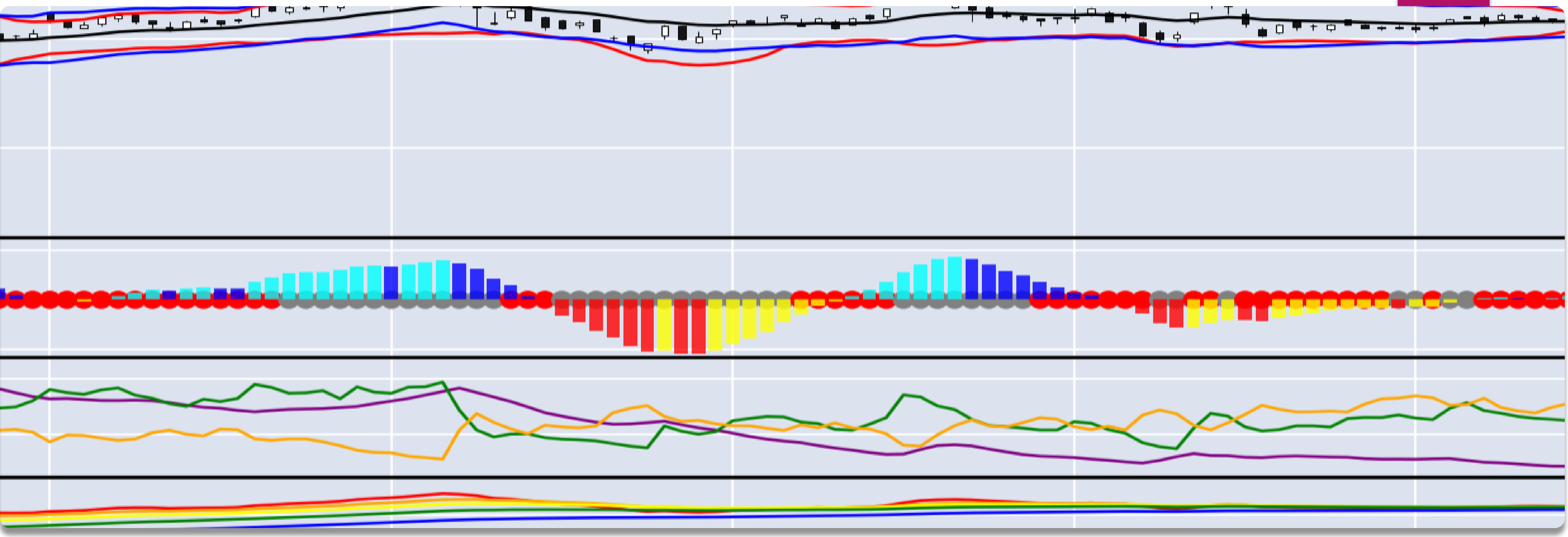
# The TTM Squeeze

**COMBINES BOLLIGER BANDS KELTNER CHANNELS AND  A MOMENTUM HISTOGRAM**

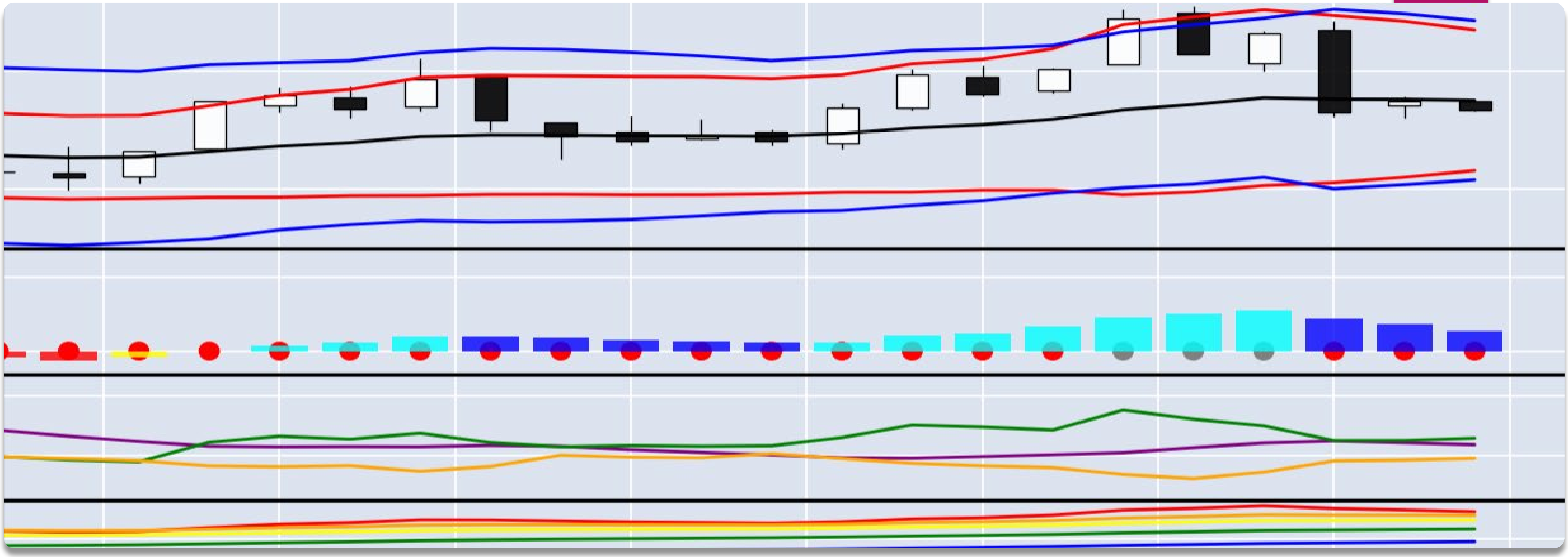


# The Squeeze

Allows you to anticipate a Big Move



Allows you to find entry points and exit points



# You can spot the signal

# We ran the squeeze using three years of Amazon Data

YAHOO FINANCE API

# Then we ran through a Random Forest model

```
[274]: # List the features sorted in descending order by feature importance
       importances = rf_model.feature_importances_
       listed = sorted(zip(rf_model.feature_importances_, X.columns), reverse = True)
       listed

[274]: [(0.7452950056496229, 'pct_change'),
        (0.02686705907491608, 'Close'),
        (0.022922686089089442, 'Volume'),
        (0.02124566719079823, 'Open'),
        (0.015862133611401038, 'lower_KC'),
        (0.015788049538463564, 'atr'),
        (0.013335944608178812, 'value'),
        (0.012601612619136338, 'Low'),
        (0.012430888858084403, 'm_avg_89'),
        (0.012241603101021546, 'adx'),
        (0.012050502141253144, 'm_avg_21'),
        (0.01181998202146395, 'High'),
        (0.011450000394244798, 'lower_BB'),
        (0.011338517811697937, 'upper_KC'),
        (0.011292934392208154, 'm_avg_08'),
        (0.011158715660672822, 'm_avg_34'),
        (0.01112325458204114, 'upper_BB'),
        (0.011047640963740987, 'Moving average'),
        (0.008522829288711592, 'm_avg_55'),
        (0.001604972403252354, 'squeeze_on')]
```

## RANDOM FOREST SHOWED US WHICH FEATURES ARE MOST IMPORTANT TO TEST

# Our results were

```
cm
```

```
[272]: array([[65,  1],
              [ 0, 73]], dtype=int64)
```

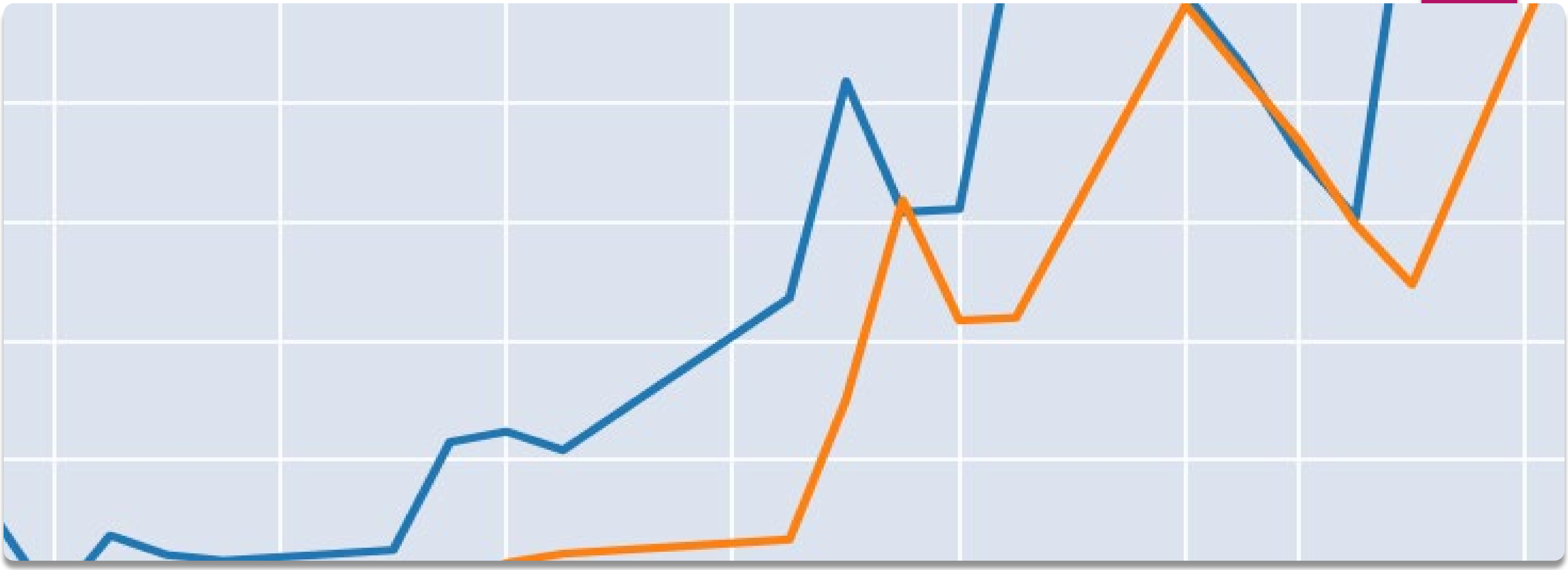
```
[273]: # Print the imbalanced classification report
       print(classification_report_imbalanced(y_test, predictions))
```

```
                   pre       rec       spe        f1       geo       iba       sup

          0       1.00      0.98      1.00      0.99      0.99      0.98        66
          1       0.99      1.00      0.98      0.99      0.99      0.99        73

avg / total       0.99      0.99      0.99      0.99      0.99      0.98       139
```

```
[274]: # List the features sorted in descending order by feature importance
       importances = rf_model.feature_importances_
       listed = sorted(zip(rf_model.feature_importances_, X.columns), reverse = True)
       listed
```

# And tested it with a Linear Regression Model

STOCK DATA IS TIME SERIES DATA WHICH TENDS TO WORK WELL WITH LINEAR REGRESSION



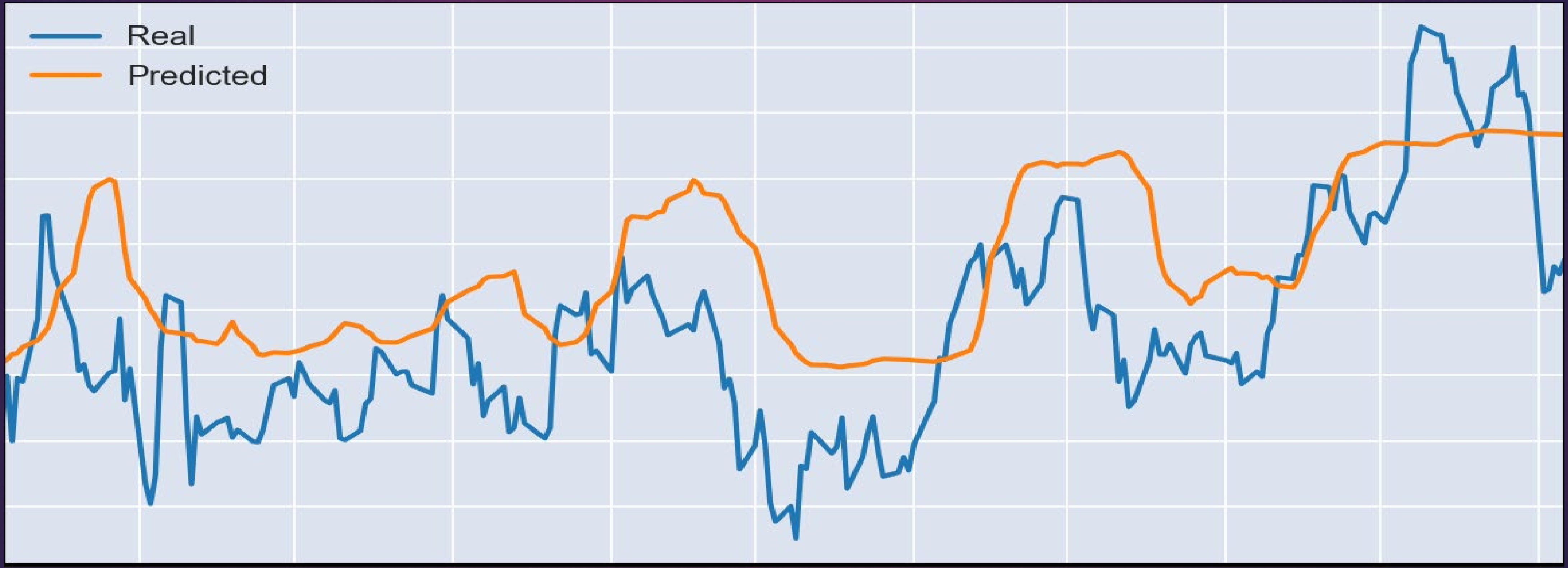
A  fairly close correlation between the Actual Prices and Predicted Prices

# We ran the squeeze through a Long Short-Term Memory (LSTM) Machine Learning Model

USING THESE PARAMETERS:

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm (LSTM)                  (None, 10, 5)             140
_________________________________________________________________
dropout (Dropout)            (None, 10, 5)             0
_________________________________________________________________
lstm_1 (LSTM)                (None, 10, 5)             220
_________________________________________________________________
dropout_1 (Dropout)          (None, 10, 5)             0
_________________________________________________________________
lstm_2 (LSTM)                (None, 5)                 220
_________________________________________________________________
dropout_2 (Dropout)          (None, 5)                 0
_________________________________________________________________
dense (Dense)                (None, 1)                 6
=================================================================
Total params: 586
Trainable params: 586
Non-trainable params: 0
_________________________________________________________________
```

# We got the following results:



# But Amazon trades at over $3000 a share, how can a retail investor trade Amazon?

# Instead of buying the stock buy and sell options.

AN OPTION CAN CONTROL 100 SHARES OF A STOCK AT A FRACTION OF THE PRICE OF THE ACTUAL STOCK SHARES. THE PRICE OF THE OPTIONS WILL VARY BASED UPON THE LENGTH OF THE OPTION PURCHASED.

# We created an algorithmic trading model to predict results

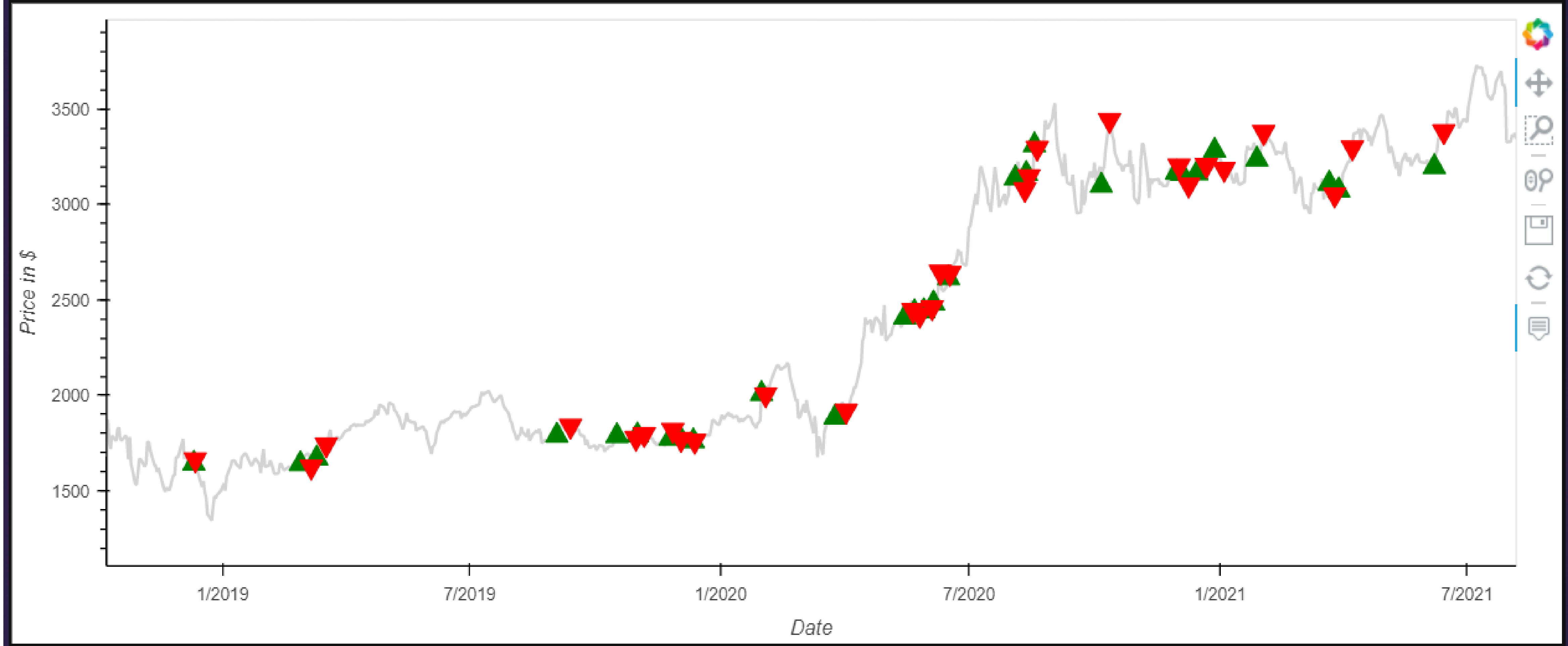
WHAT WOULD HAVE HAPPENED IF A RETAIL INVESTOR HAD FOLLOWED THIS MODEL STARTING OUT WITH $ 1000 AT THE BEGINNING OF 2021

# The formula for the trading strategy is:

WE CALCULATED IN AND OUT POINTS BASED ON THE SQUEEZE MODEL, DESIGNED TO ENTER AT THE START OF AN UPWARD SQUEEZE AND OUT AT A RISE OF 2 X AVERAGE TRUE RANGE (ATR).

IT WOULD WORK FOR A DOWNWARD SQUEEZE, BUT MOST RETAIL INVESTORS ARE NOT COMFORTABLE WITH SHORT SELLING, SO WE KEPT IT SIMPLE.

# Our results:



3500
3000
2500
2000
1500
Price in $
1/2019
7/2019
1/2020
7/2020
1/2021
7/2021
Date

# Conclusions

- IS THERE A RELATIVELY EASY WAY FOR RETAIL INVESTORS TO SPOT BIG MOVES IN POPULAR STOCKS?

- WOULD THIS METHOD STAND UP TO TESTING IN LINEAR REGRESSION AND MACHINE LEARNING MODELS?

- IS THERE A WAY FOR RETAIL INVESTORS TO TAKE $1000 AND PROFIT FROM A BIG MOVE?

# Is there A relatively easy way for retail investors to spot big moves in popular stocks?

**ANSWER:**

**YES, THE TTM SQUEEZE MODEL CAN HELP RETAIL INVESTORS ANTICIPATE A BIG MOVE**

# Would this method stand up to testing in linear regression and machine learning models?

**ANSWER:**

**YES, THE TTM SQUEEZE HELD UP REASONABLY WELL WHEN RUN THROUGH, RANDOM FOREST, EASY ENSEMBLE,  LINEAR REGRESSION, AND LSTM MODELS**

# Is there a way for retail investors to take $1000 and profit from a big move?

ANSWER:

WE WERE ABLE TO SPOT AN OPPORTUNITY WHERE A WELL-TIMED OPTIONS TRADE OF AMAZON , USING THE SQUEEZE STRATEGY, WOULD HAVE TURNED $ 1000 INTO $ 30,000.

THAT WAS FOR A SINGLE TRADE IN JUNE-JULY OF 2021.

The two- week time constraint did not allow us a finish writing some code that could be helpful.

The proposed code would calculate what the return on an initial $ 1000 would be for an investor executing the squeeze/options strategy over the course of 2021, so far.

That may be for a subsequent project.