News Analysis for Potential Investment Strategies on Tesla Stock

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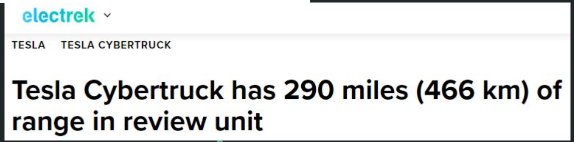
Why This Project?


The New York Times
Tesla Sues Swedish Transport Agency in Dispute Over License Plates
The electric carmaker sued the agency to deliver license plates for its cars, the latest escalation as a labor fight enters its second month.

https://www.nytimes.com/2023/11/28/business/tesla-license-plates-sweden-unions.html


electrek
TESLA TESLA CYBERTRUCK
Tesla Cybertruck has 290 miles (466 km) of range in review unit

https://www.nytimes.com/2023/11/28/business/tesla-license-plates-sweden-unions.html

https://github.com/wangtuguahhh/Sentiment-Analysis-for-Investment-Strategies-on-Tesla-Stock/assets/130683390/dc0161c2-98d2-4d79-b945-afc454476406

LLMs

Data

Free APIs

- NewsAPI
    - limited to past 30 days, data used were from 2023-09-12 to 2023-10-11
    - 1,000 requests per day
    - 345 news articles collected
- MarketStack
    - limited to 1,000 requests per month
    - Stock market closes on weekends and holidays

Method

NLP Task 1: News Classification

A classification tool to tell if a news article was directly related to Tesla or not.

Manually labeled 60% (207 articles) of the news collected.

✨ Flan-T5 model with the following:

- Prompt Engineering / In-Context Learning
- Parameter-Efficient Fine-Tuning (PEFT) with Low-Rank Adaptation (LoRA)

NLP Task 2: News Sentiment Analysis

A sentiment analysis tool to predict if a news article would have positive, negative or neutral impact on Tesla stock.

Manually labeled 60% of the news collected for model performance evaluation.

✨ FinBERT model was used directly since it was developed for financial sentiment analysis based on BERT model.

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News Classification

With Flan-T5

Prompt Engineering

- Zero-shot (didn't work well)
- One-shot
- Few-shot (2, 3, 4, 5 shots)

```
prompt = f"""
Classify if the news is related to Tesla or not.
{context}
Classification output:
"""
```

Zero-shot prompt

```
        Context from news:
        AOC says she's looking to trade in her Tesla for a union-made EV after clash with Elon Musk AOC reiterated on Face the
Nation on Sunday that she wants to trade in her Tesla for a union-made EV.
        Is the context related to Tesla?
        Yes, it is related to Tesla.

    Context from news:
    Mercedes-Benz's $100,000 electric SUV is an awesome Tesla rival – but its blob-like looks aren't for everyone The Mercedes
EQE SUV is an awesome alternative to Tesla's Model X with controversial style.
    Is the context related to Tesla?
```

One-shot prompt

Hallucination Issues

The choice of words in the prompt is more critical than the number of words.

More information in a prompt doesn’t necessarily lead to better outputs.

One-Shot

```
df_one.one_shot_class.value_counts()
```

```
Yes     109
No       96
no        1
Name: one_shot_class, dtype: int64
```

Two-Shot

```
df_one.few_shot_class_2.value_counts()
```

```
No, it is not related to Tesla.    112
Yes                                 73
No                                  14
No, it is not possible to tell       6
```

Three-Shot

```
df_one.few_shot_class_3.value_counts()
```

```
Yes, it is related to Tesla.       90
No                                 75
No, it is not possible to tell     24
Yes                                11
No, it is not related to Tesla.     2
Yes, it is related to Pepsi.        2
```

Four-Shot

```
df_one.few_shot_class_4.value_counts()
```

```
No                                 84
Yes                                61
Yes, it is related to Tesla.       27
No, it is not possible to tell     27
No, it is not related to Tesla.     2
Yes, it is related to Pepsi.        2
```

Five-Shot

```
df_one.few_shot_class_5.value_counts()
```

```
No, it is not possible to tell     73
Yes, it is related to Tesla.       73
No                                 30
No, it is not related to Tesla.    18
Yes                                 5
Yes, it is related to Pepsi.        3
```

Evaluations

One-shot learning provided the best performance on this news classification task with 85% accuracy.

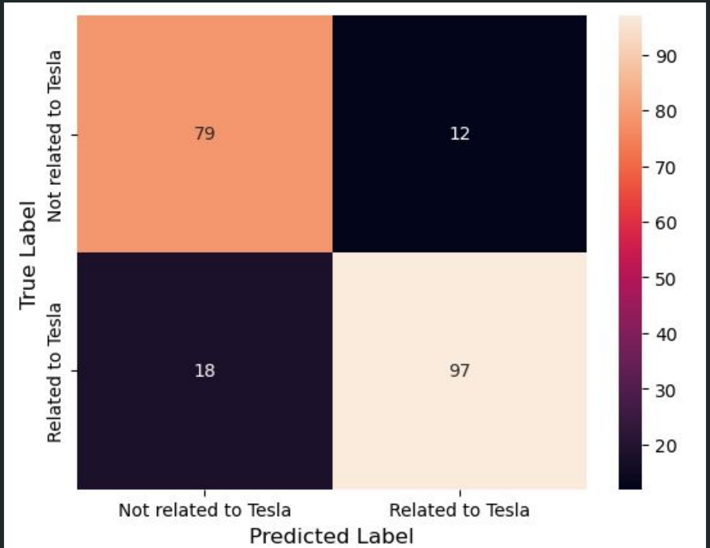
One-Shot

	precision	recall	f1-score	support
no	0.81	0.87	0.84	91
yes	0.89	0.84	0.87	115
accuracy			0.85	206
macro avg	0.85	0.86	0.85	206
weighted avg	0.86	0.85	0.85	206

Four-Shot

	precision	recall	f1-score	support
no	0.75	0.94	0.84	90
yes	0.94	0.75	0.84	113
accuracy			0.84	203
macro avg	0.85	0.85	0.84	203
weighted avg	0.86	0.84	0.84	203

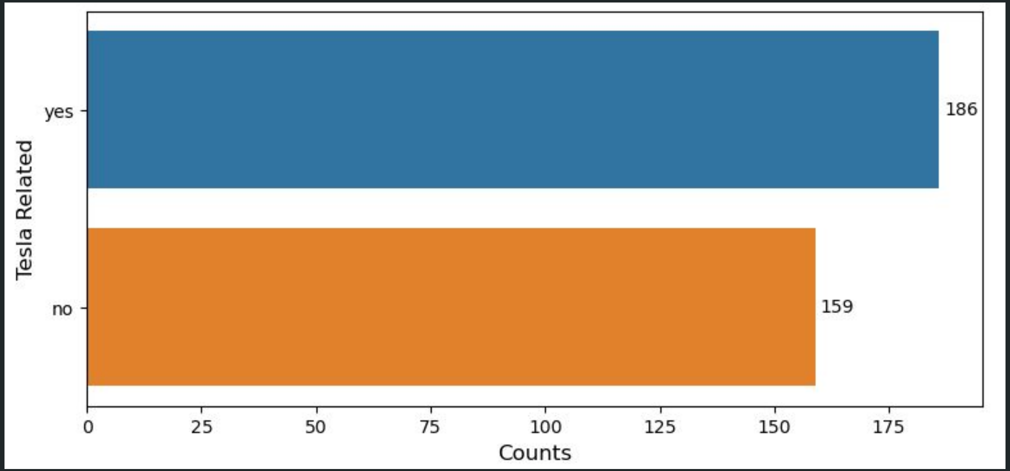
One-Shot



Distribution

News related to Tesla and news not related to Tesla were evenly distributed in the collected data.

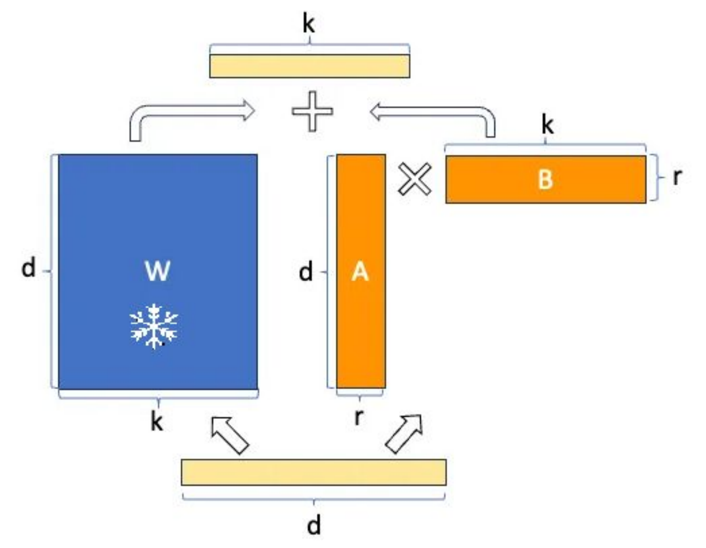
Classification labels from Flan-T5 with one-shot learning.



PEFT with LoRA

LoRA technique was implemented for Flan-T5 to tune the pre-trained model to perform the news classification task.

Data with manual labels were used for tuning.



PEFT with LoRA: Data Pre-processing

Zero-shot prompt was used to clarify the classification task for tuning.

```
# convert text to a prompt for classification task
def create_prompt(news):
  return f"""
  Classify if the following news paragraph is directly related to Tesla or not.\n\n
      {news}\n\n
  Is the news directly related to Tesla?
  """
```

torch.utils.data.Dataset was used to create a Pytorch dataset class to store the embeddings of the data and true labels for tuning.

PEFT with LoRA: Training

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```
# create LoRA training configuration
lora_config = LoraConfig(
    r = 32,  # rank
    target_modules = ["q", "v"],
    lora_alpha = 32,
    lora_dropout = 0.05,
    bias = 'none',
    task_type = TaskType.SEQ_2_SEQ_LM  # for Flan-T5
)
```

```
# add LoRA adapter to the original LLM
peft_model = get_peft_model(original_model, lora_config)
print(print_number_of_trainable_model_parameters(peft_model))
```

```
Trainable model paramters: 3538944
All model paramters: 251116800
Percentage of trainables: 1.41 %
```

LoRA significantly reduced the number of trainable parameters.

```
# define training arguments
out_dir = f'./peft-tesla-classification-training-{str(int(time.time()))}'

peft_training_args = TrainingArguments(
    output_dir = out_dir,
    evaluation_strategy = 'epoch',
    logging_strategy = 'epoch',
    learning_rate = 1e-4,
    num_train_epochs = 20,
    save_strategy = "epoch",
    load_best_model_at_end = True,
    metric_for_best_model = 'eval_loss',
    greater_is_better = False,
    per_device_train_batch_size = 1,
    per_device_eval_batch_size = 1
)
```

```
# define trainer
peft_trainer = Trainer(
    model = peft_model,
    args = peft_training_args,
    train_dataset = traindata,
    eval_dataset = valdata
)
```

```
# start training
peft_trainer.train()
```

[2880/2880 14:21, Epoch 20/20]

Epoch	Training Loss	Validation Loss
1	30.759100	4.750241
2	4.414000	1.810738
3	1.583900	0.268391
4	0.470500	0.105635
5	0.236800	0.061598
6	0.154500	0.044009
7	0.116400	0.035154
8	0.091400	0.027932
9	0.077900	0.026098
10	0.068900	0.023801
11	0.061100	0.021528
12	0.056600	0.020919
13	0.052700	0.019945
14	0.050600	0.019461
15	0.048000	0.018610
16	0.046900	0.018168
17	0.045100	0.018195
18	0.044300	0.017663
19	0.042800	0.017523
20	0.042200	0.017329

PEFT with LoRA: Evaluation

With the best adapter found through LoRA, the tuned Flan-T5 model didn't provide reasonable outputs for this news classification task.

Manual Labels

```
df_train['manual_baseline'].value_counts()

Yes, it is directly related to Tesla.       82
No, it is not directly related to Tesla     62
Name: manual_baseline, dtype: int64
```

```
df_val['manual_baseline'].value_counts()

Yes, it is directly related to Tesla.       17
No, it is not directly related to Tesla     15
Name: manual_baseline, dtype: int64
```

```
df_test['manual_baseline'].value_counts()

Yes, it is directly related to Tesla.       17
No, it is not directly related to Tesla     14
Name: manual_baseline, dtype: int64
```

```
df_train['peft_1127ml_output'].value_counts()

Yes, it is directly related to Tesla.      143
No, it is not directly related to Tesla      1
Name: peft_1127ml_output, dtype: int64
```

```
df_val['peft_1127ml_output'].value_counts()

Yes, it is directly related to Tesla.       31
No, it is not directly related to Tesla      1
Name: peft_1127ml_output, dtype: int64
```

```
df_test['peft_1127ml_output'].value_counts()

Yes, it is directly related to Tesla.    31
Name: peft_1127ml_output, dtype: int64
```

Model Predictions

Sentiment Analysis

With FinBERT

FinBERT for sentiment analysis:

transformers library was used to create a sentiment analysis pipeline using FinBERT model.

```
model_name = "ProsusAI/finbert"

tokenizer = AutoTokenizer.from_pretrained(model_name)
model = AutoModelForSequenceClassification.from_pretrained(model_name)

# create a pipeline for sentiment analysis
sent_ana = pipeline(task = 'sentiment-analysis', model = model, tokenizer = tokenizer)
```

FinBERT model has two outputs, one sentiment label and a confidence score of the label.

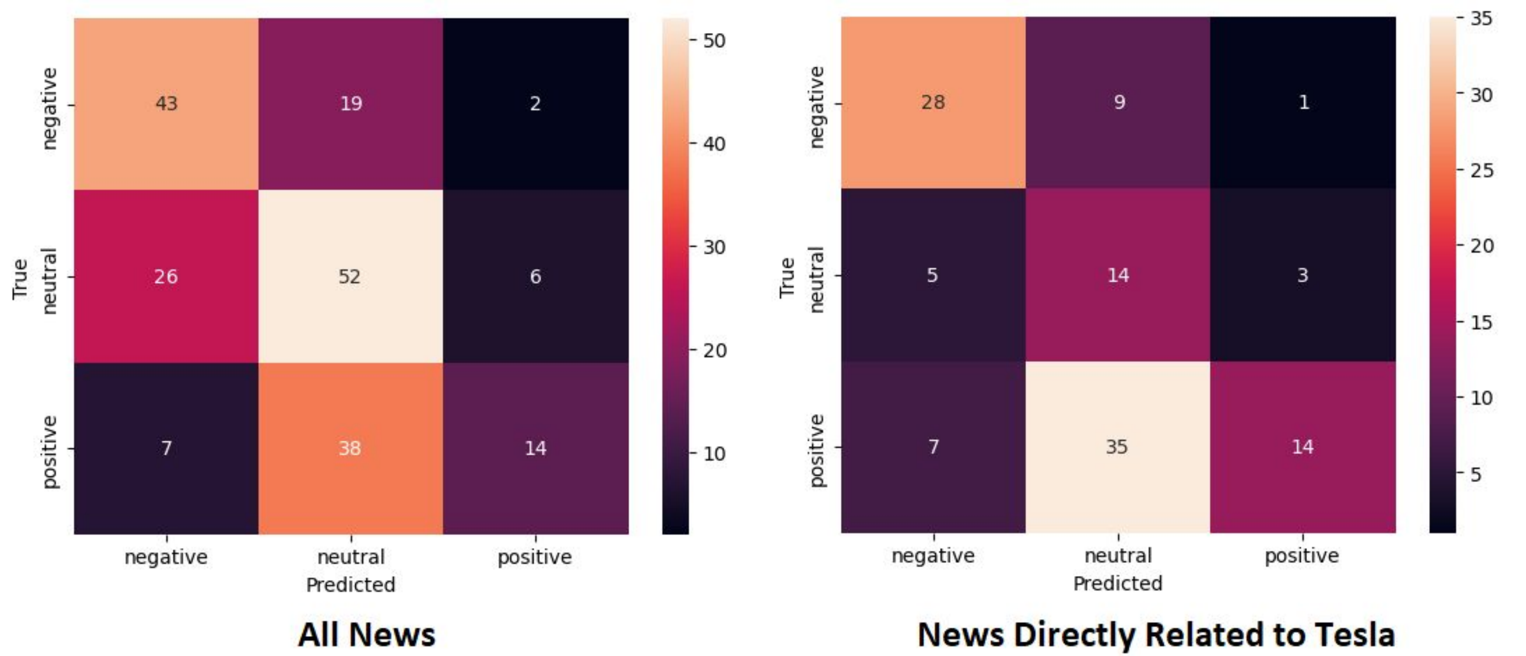
```
# test 1
text = 'Tesla just launched its first self-driving car!'

result = sent_ana(text)
result
```

```
[{'label': 'neutral', 'score': 0.8160327672958374}]
```

FinBERT for sentiment analysis: Evaluation

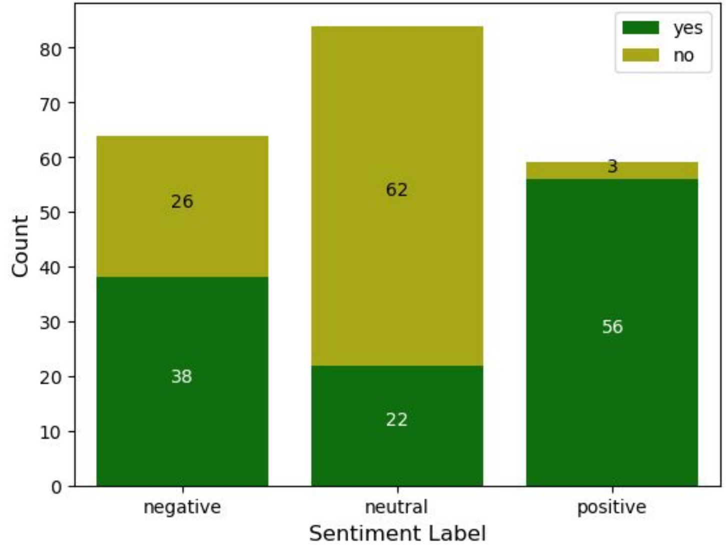
FinBERT tended to label positive news as neutral ones.



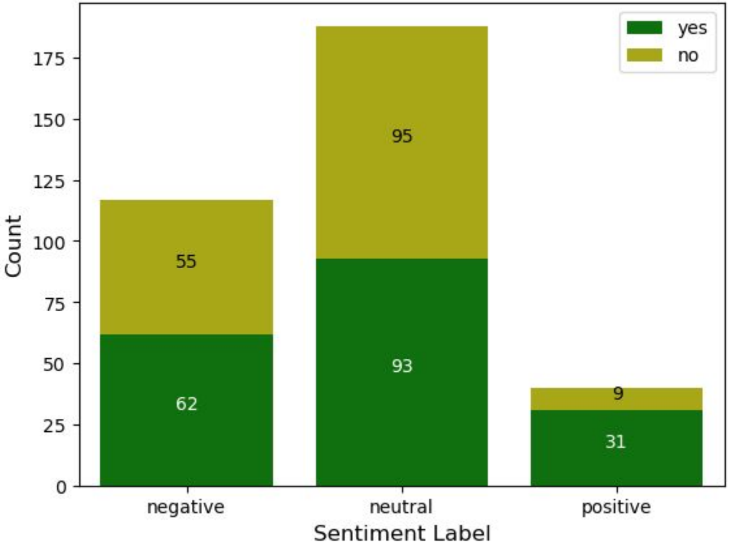
FinBERT for sentiment analysis: Evaluation

The majority of the news were neutral ones.

Manual labels involved human intelligence on potential impact of neutral context.



Manual Labels



FinBERT Predictions from Description

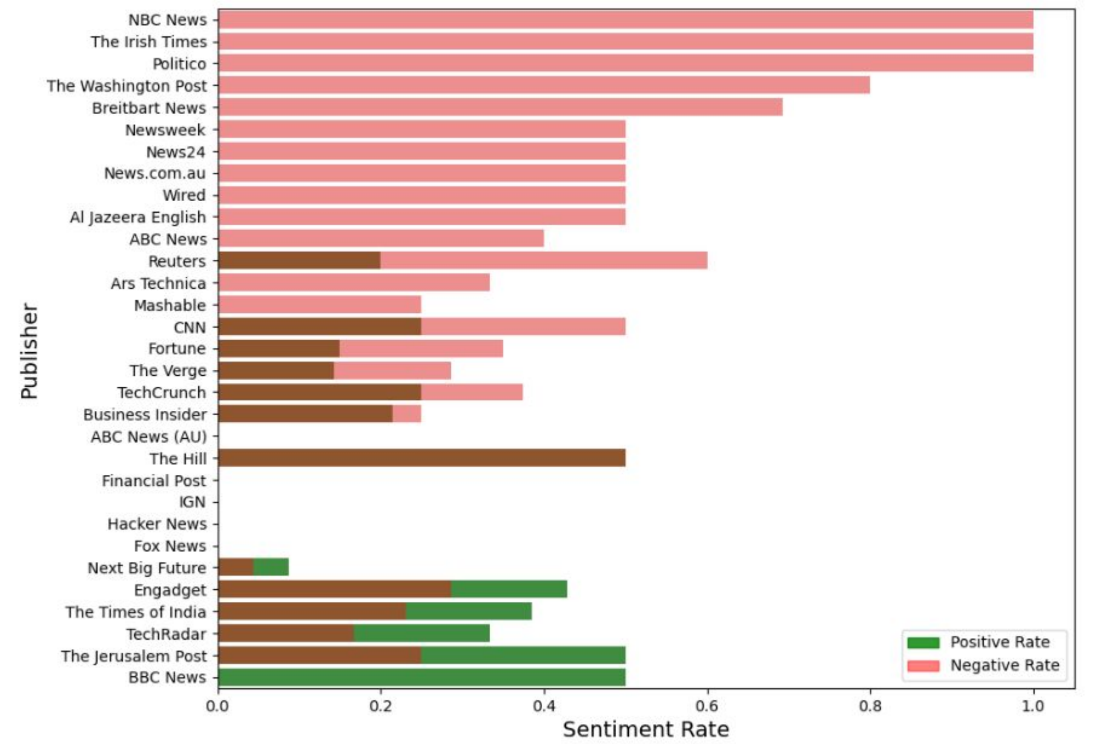
Sentiment of Publishers

Based on FinBERT predictions.

The majority of publishers were more on the neutral side.

On the more positive side were mostly tech publishers.

There were some popular publishers more on the negative side.



Correlation with Stock Movements

Data Pre-processing

Calculate daily positive, negative, neutral news and corresponding rates based on FinBERT predictions on news directly related to Tesla.

Merge with Tesla stock price data.

- Close - Open = Inday Move
- Close Today - Close Yesterday = Yesterday Move

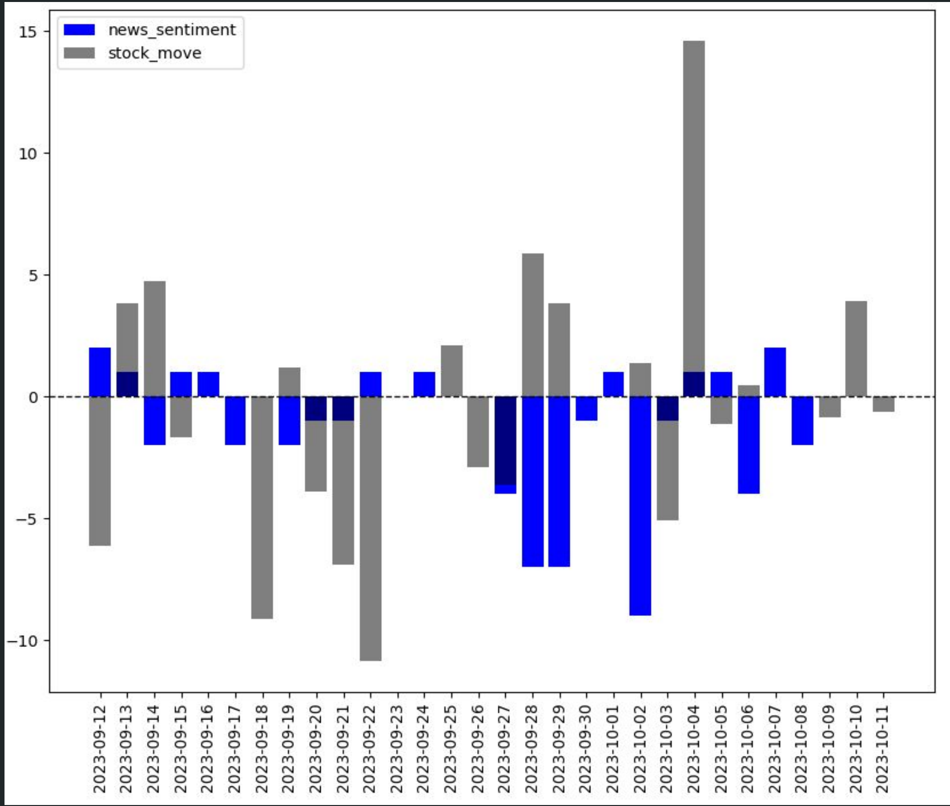
	date	positive_num	negative_num	nuetral_num	positive_rate	negative_rate	neutral_rate	open	close	inday_move	yesterday_move
0	2023-09-12	3	2	16	0.142857	0.095238	0.761905	270.76	267.48	-3.28	-6.10
1	2023-09-13	2	5	21	0.071429	0.178571	0.750000	270.07	271.30	1.23	3.82

Correlation Plots

If the two bars shared the same polarity, then the stock movements correlated with the news sentiments.

news sentiments = positive news - negative news

stock_move = yesterday move

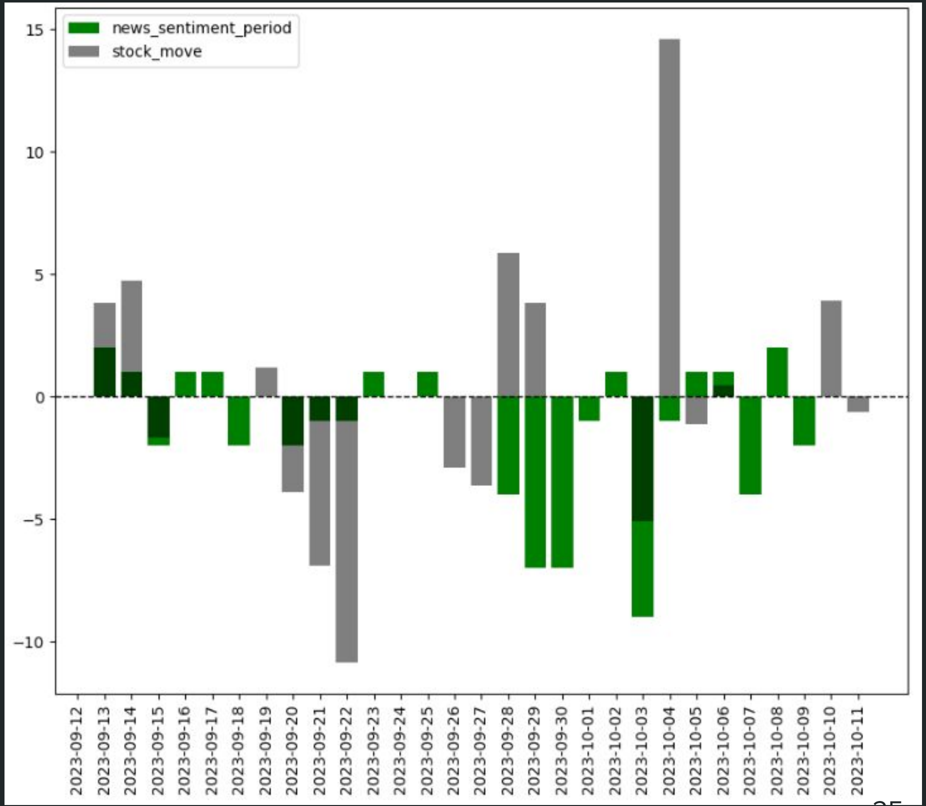


Correlation Plots

The news sentiment was shifted by 1 day to check if the stock move was correlated with the news happened yesterday.

news sentiments_period = [positive news - negative news] of yesterday

The match was slightly better, but only for a few days.

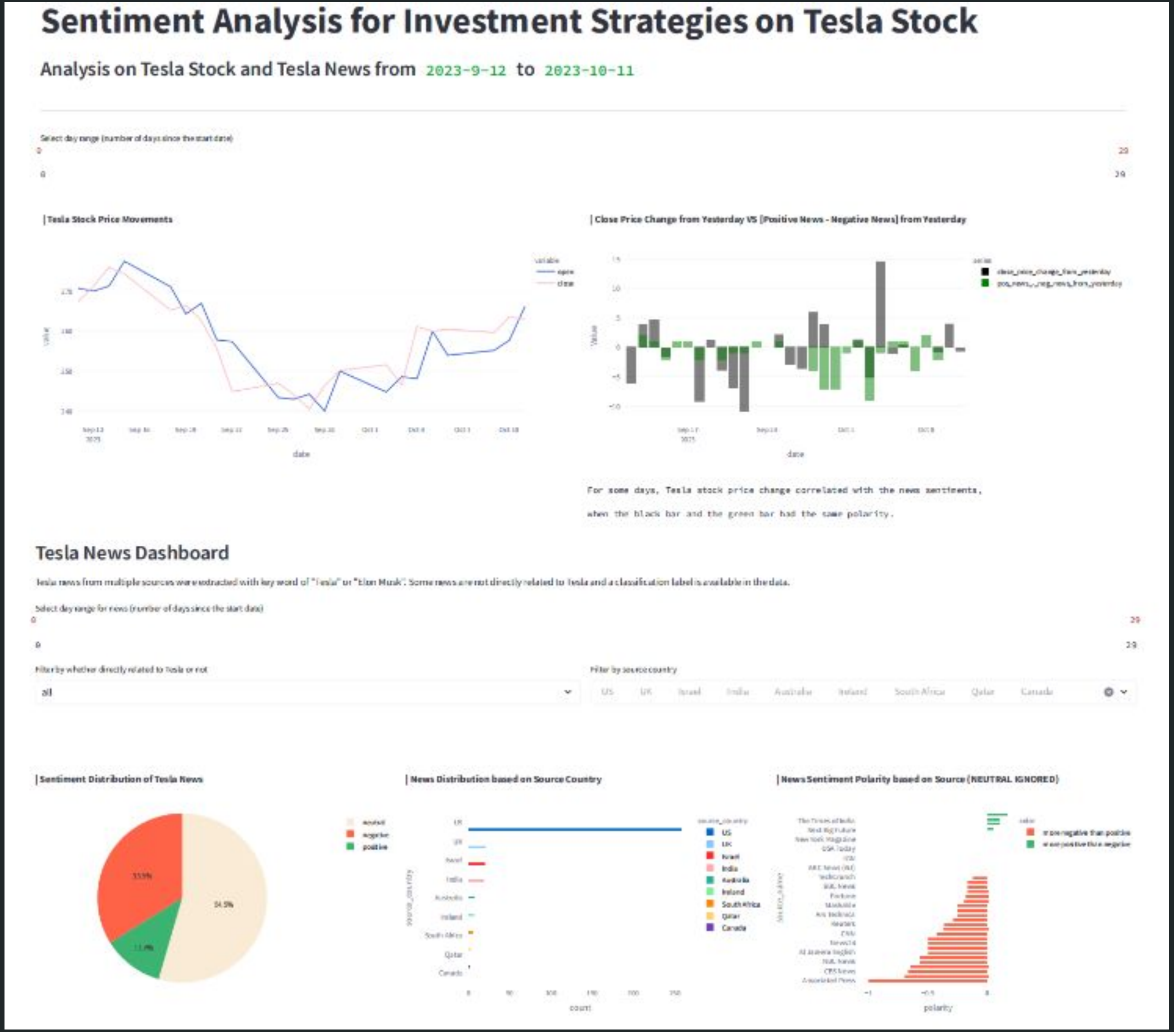


Deploy to Streamlit

Streamlit Sharing

[Dashboard]

[Deployment Code]



Takeaways

- Prompt engineering works better than fine-tuning when data is limited.
- Hallucination issues can happen when including more examples in the prompt.
- PEFT with LoRA significantly reduces the cost of fine-tuning a LLM.
- The majority of news related to Tesla were neutral ones.
- Tech publishers were more on the positive side when reporting on Tesla.
- No clear correlation was found between news sentiments and Tesla stock price movements.

Next Steps

- Collect more data for LLM tuning
- Other LLMs such as Llama-2 and GPT4 for the NLP tasks
- Incorporate other factors to better predict the stock price movements

Acknowledgement

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