Barclays IB Analytics Case Study Submission

Divyansh IIT Kanpur mail: (divyansh21@iitk.ac.in) roll: (210355)

Data Analysis

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
train = pd.read_csv("train.csv")
train.head()
```

```
                                            sentence  \
0  Still short $LNG from $11.70 area...next stop ...
1                                     $PLUG bear raid
2  How Kraft-Heinz Merger Came Together in Speedy...
3     Slump in Weir leads FTSE down from record high
4                $AAPL bounces off support, it seems

                                            snippets target
sentiment_score  \
0  ['Still short $LNG from $11.70 area...next sto...    LNG
-0.543
1                                      ['bear raid']   PLUG
-0.480
2         ['Merger Came Together in Speedy 10 Weeks']  Kraft
0.214
3                           ['down from record high']   Weir
-0.827
4                             ['bounces off support']   AAPL
0.443

                                            aspects    format  label
0   ['Stock/Price Action/Volatility/Short Selling']      post      2
1                 ['Stock/Price Action/Bearish']      post      2
2                          ['Corporate/M&A/M&A']  headline      0
3              ['Market/Volatility/Volatility']  headline      2
4  ['Stock/Price Action/Bullish/Bullish Behaviour']      post      0
```

```
print(train.describe())
print('='*20)
print(train.info())
```

```
       sentiment_score       label
count       961.000000  961.000000
mean          0.142210    0.649324
std           0.408823    0.917891
min          -0.854000    0.000000
25%          -0.260000    0.000000
```

```
50%            0.281000    0.000000
75%            0.461000    2.000000
max            0.975000    2.000000
====================
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 961 entries, 0 to 960
Data columns (total 7 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   sentence         961 non-null    object 
 1   snippets         961 non-null    object 
 2   target           961 non-null    object 
 3   sentiment_score  961 non-null    float64
 4   aspects          961 non-null    object 
 5   format           961 non-null    object 
 6   label            961 non-null    int64  
dtypes: float64(1), int64(1), object(5)
memory usage: 52.7+ KB
None
```

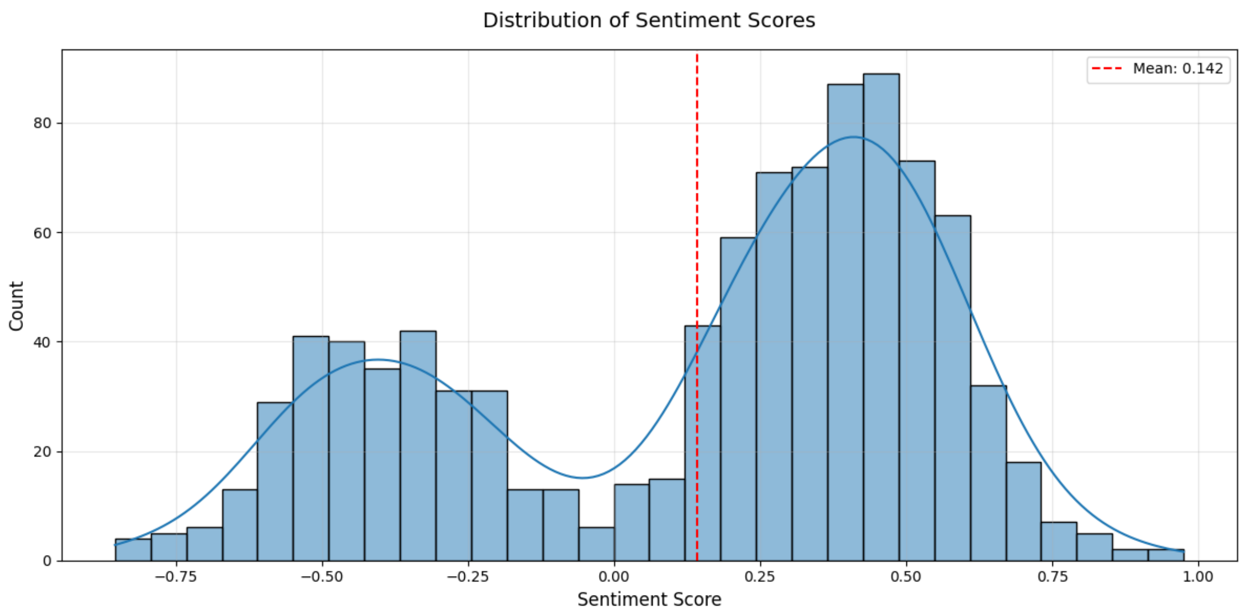
With initial information in hand(above), let's see how the data is distributed and what are the correlations.

Sentiment Distribution

```
plt.figure(figsize=(12, 6))

sns.histplot(data=train, x='sentiment_score', bins=30, kde=True)

plt.axvline(x=train['sentiment_score'].mean(), color='red',
linestyle='--', label=f'Mean: {train["sentiment_score"].mean():.3f}')
# plt.axvline(x=train['sentiment_score'].mean(), linestyle='--',
label=f'Mean: {train["sentiment_score"].mean():.3f}')

plt.title('Distribution of Sentiment Scores', fontsize=14, pad=15)
plt.xlabel('Sentiment Score', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.legend()
plt.grid(True, alpha=0.3)

print("\nSentiment Score Summary Statistics:")
print(train['sentiment_score'].describe())

plt.tight_layout()
plt.show()
```

```
Sentiment Score Summary Statistics:
count    961.000000
mean       0.142210
```

```
std         0.408823
min        -0.854000
25%        -0.260000
50%         0.281000
75%         0.461000
max         0.975000
Name: sentiment_score, dtype: float64
```



Sentiment_score analysis

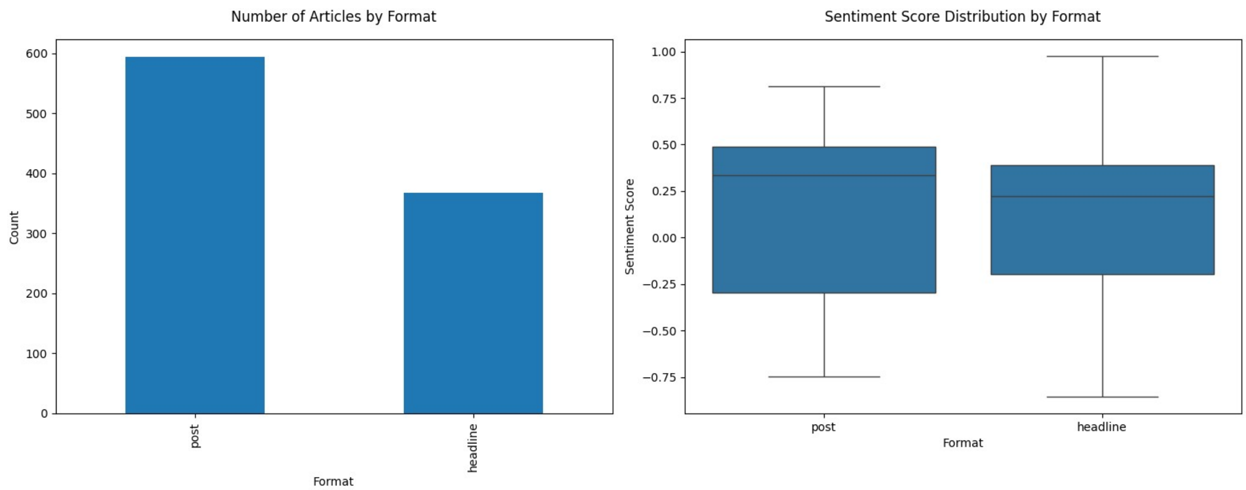
- The sentiment scores have normal distribution in both negative and positive domain individually
- Neutral sentiments are fairly less in number

Formats Analysis

```
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(15, 6))

format_counts = train['format'].value_counts()
format_counts.plot(kind='bar', ax=ax1)
ax1.set_title('Number of Articles by Format', fontsize=12, pad=15)
ax1.set_xlabel('Format')
ax1.set_ylabel('Count')

sns.boxplot(data=train, x='format', y='sentiment_score', ax=ax2)
ax2.set_title('Sentiment Score Distribution by Format', fontsize=12,
pad=15)
ax2.set_xlabel('Format')
ax2.set_ylabel('Sentiment Score')

print("\nFormat-wise Sentiment Analysis:")
```

```
format_stats = train.groupby('format')['sentiment_score'].agg([
    'count', 'mean', 'std', 'min', 'max'
]).round(3)
print(format_stats)

plt.tight_layout()
plt.show()
```

```
Format-wise Sentiment Analysis:
          count   mean    std    min    max
format
headline    367  0.114  0.393 -0.854  0.975
post        594  0.160  0.418 -0.745  0.814
```

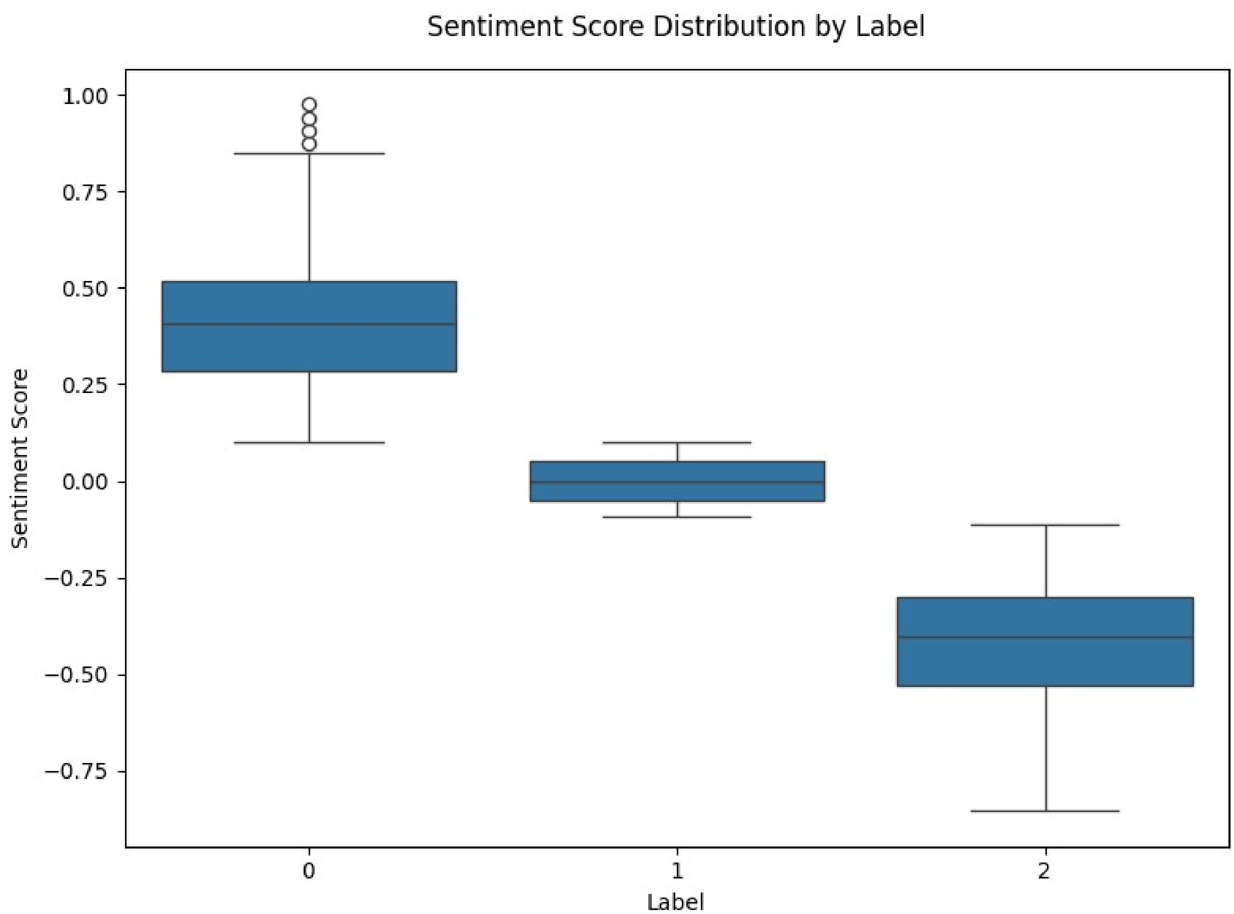


Note : As we can see that the type of article doesn't really affect the sentiment of the post.

Labels Analysis

```
plt.figure(figsize=(8, 6))

sns.boxplot(data=train, x='label', y='sentiment_score')
plt.title('Sentiment Score Distribution by Label', fontsize=12,
pad=15)
plt.xlabel('Label')
plt.ylabel('Sentiment Score')

print("\nLabel-wise Sentiment Analysis:")
label_stats = train.groupby('label')['sentiment_score'].agg([
    'count', 'mean', 'std'
]).round(3)
print(label_stats)

plt.tight_layout()
plt.show()
```

```
Label-wise Sentiment Analysis:
        count   mean    std
label
0         632  0.409  0.162
1          34 -0.001  0.060
2         295 -0.413  0.156
```



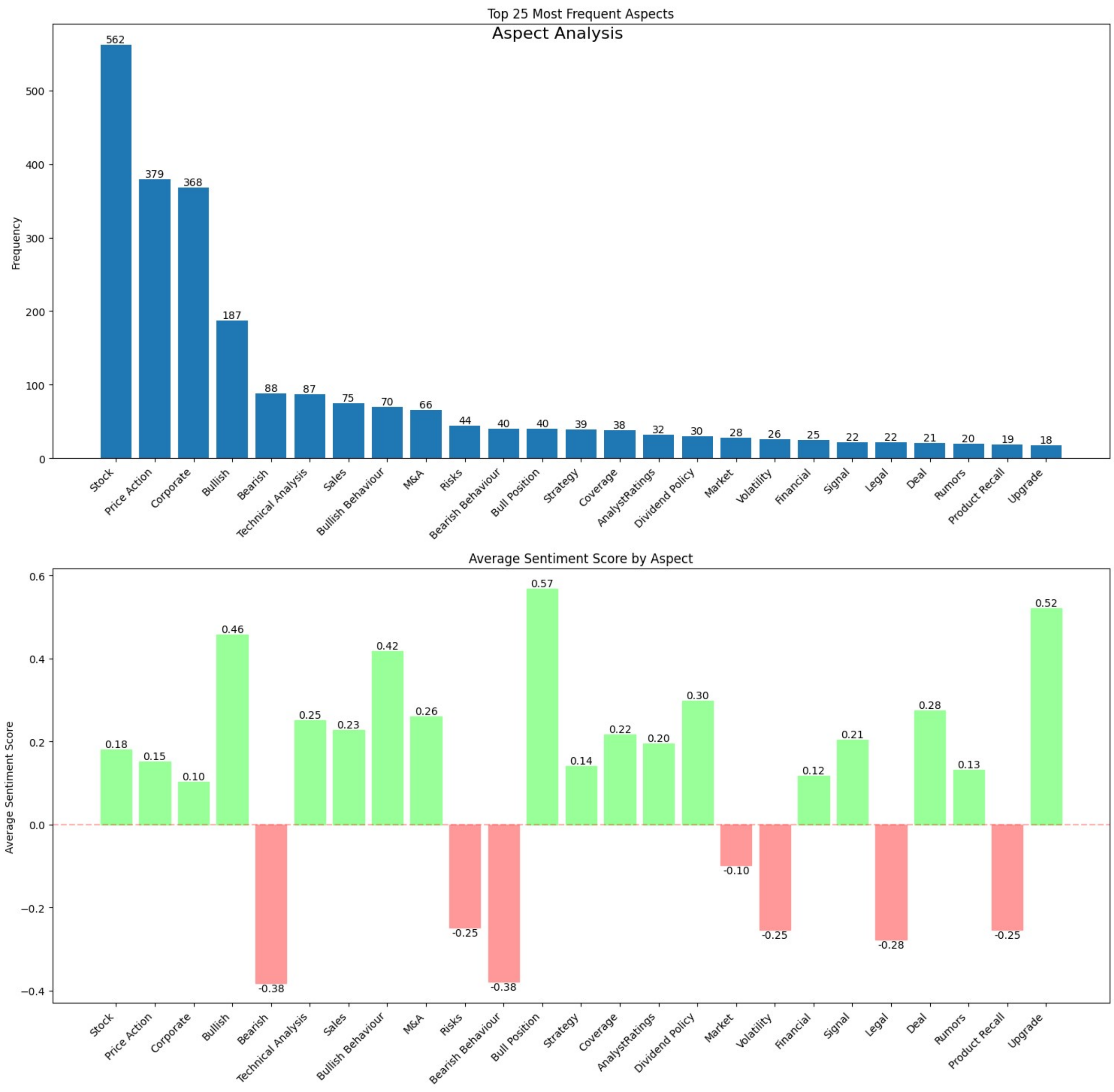
Note The lable must not be the part of the training data otherwise it will make the sentiment score prediction too trivial since there is a very sharp correlation between them

Aspects analysis

```
aspect_list = []
aspect_sentiments = {}

for i in range(len(train)):
    aspects = train.iloc[i]['aspects'][2:-2].split('/')
    aspects = np.unique(aspects).tolist()
    sentiment = train.iloc[i]['sentiment_score']

    for aspect in aspects:
```

```
        aspect_list.append(aspect)
        if aspect not in aspect_sentiments:
            aspect_sentiments[aspect] = []
        aspect_sentiments[aspect].append(sentiment)

aspect_counts = pd.Series(aspect_list).value_counts()
aspect_mean_sentiment = {aspect: np.mean(sentiments)
                        for aspect, sentiments in
aspect_sentiments.items()}

top_20_aspects = aspect_counts.head(25)
# top_20_aspects = aspect_counts.head(20)
top_20_sentiments = {aspect: aspect_mean_sentiment[aspect]
                    for aspect in top_20_aspects.index}
# top_20_sentiments = {aspect: aspect_mean_sentiment[aspect]
#                     for aspect in top_25_aspects.index}

fig, (ax1, ax2) = plt.subplots(2, 1, figsize=(15, 15))
fig.suptitle('Aspect Analysis', fontsize=16, y=0.95)

bars = ax1.bar(range(len(top_20_aspects)), top_20_aspects.values)
ax1.set_xticks(range(len(top_20_aspects)))
# bars = ax1.bar(range(len(aspects)), aspects.values)
# ax1.set_xticks(range(len(aspects)))

ax1.set_xticklabels(top_20_aspects.index, rotation=45, ha='right')
ax1.set_title('Top 25 Most Frequent Aspects')
ax1.set_ylabel('Frequency')

for bar in bars:
    height = bar.get_height()
    ax1.text(bar.get_x() + bar.get_width()/2., height,
             f'{int(height)}',
             ha='center', va='bottom')

sentiment_values = list(top_20_sentiments.values())
bars = ax2.bar(range(len(top_20_sentiments)), sentiment_values)
ax2.set_xticks(range(len(top_20_sentiments)))
ax2.set_xticklabels(top_20_sentiments.keys(), rotation=45, ha='right')
# ax2.set_xticklabels(top_20_sentiments.keys(), rotation=45,
ha='right')
ax2.set_title('Average Sentiment Score by Aspect')
ax2.set_ylabel('Average Sentiment Score')
ax2.axhline(y=0, color='r', linestyle='--', alpha=0.3)

for i, bar in enumerate(bars):
    if sentiment_values[i] < 0:
        bar.set_color('#ff9999')
    else:
        bar.set_color('#99ff99')
```

```
    height = bar.get_height()
    ax2.text(bar.get_x() + bar.get_width()/2., height,
            f'{height:.2f}',
            ha='center', va='bottom' if height > 0 else 'top')

plt.tight_layout()
plt.show()
```



Note: Apart from what is very evident from the above plot, the key takeaway for further task will be that sentiment score predictiona and aspect classification are not completely independent task we can try to benefit from on another

Preprocessing Data

Here, we will vectorize the data using a bert (finetuned for financial settings) and also prepare a dataloader to training task

```python
import torch
from torch.utils.data import Dataset, DataLoader
from torch.optim import AdamW
from transformers import AutoTokenizer, AutoModel
import ast
from sklearn.preprocessing import MultiLabelBinarizer
import re
```

```
/home/divyansh/Documents/Barclays_submission/barclay/lib/python3.12/
site-packages/tqdm/auto.py:21: TqdmWarning: IProgress not found.
Please update jupyter and ipywidgets. See
https://ipywidgets.readthedocs.io/en/stable/user_install.html
  from .autonotebook import tqdm as notebook_tqdm
```

```python
# clean sentences for clean tokenization and less noise
def clean(text):
    text = str(text)
    text = re.sub(r'http\S+|www\S+', '', text)
    text = text.replace('$', '')
    text = text.replace('#', '')
    text = re.sub(r'\s+', ' ', text)

    text = text.strip()
    return text

# Preprocess data to extract features and also prepare the Dataset
loader
class FinancialAspectDataset(Dataset):
    def __init__(self, csv_file, tokenizer_name='ProsusAI/finbert',
max_length=128):
        self.df = pd.read_csv(csv_file)

        self.tokenizer = AutoTokenizer.from_pretrained(tokenizer_name)
        self.max_length = max_length

        with open("unique_aspects", 'r') as file:
            aspects_list = [line.strip() for line in file]

        self.aspects = aspects_list #unique aspects

        self.mlb = MultiLabelBinarizer()
        self.aspect_labels = self.mlb.fit_transform(self.aspects)
        self.aspect_classes = self.mlb.classes_
        self.num_aspects = len(self.aspect_classes)
```

```
    def __len__(self):
        return len(self.df)

    def process_aspects(self, aspects):
        aspect_names = np.unique(aspects[2:-2].split('/')).tolist()
        true_mask = [self.aspects.index(a) for a in aspect_names if a
!= '']
        aspect_ids = [0]*len(self.aspects)
        for m in true_mask:
            aspect_ids[m] = 1
        return aspect_ids

    def __getitem__(self, idx):
        row = self.df.iloc[idx]

        sentence = str(row['sentence'])
        snippet = ast.literal_eval(row['snippets'])[0]
        # print("snippet: ", snippet)
        target = str(row['target'])
        # print("target: ", target)

        sentence_encoding = self.tokenizer(
            clean(sentence),
            padding='max_length',
            truncation=True,
            max_length=self.max_length,
            return_tensors='pt'
        )
        snippet_encoding = self.tokenizer(
            clean(snippet),
            padding='max_length',
            truncation=True,
            max_length=self.max_length,
            return_tensors='pt'
        )
        target_encoding = self.tokenizer(
            clean(target),
            padding='max_length',
            truncation=True,
            max_length=32,  # intentionally kam rakha hai
            return_tensors='pt'
        )

        aspect_label_ids = self.process_aspects(row['aspects'])
        return {
            'sentence_ids': sentence_encoding['input_ids'].squeeze(0),
            'sentence_mask':
sentence_encoding['attention_mask'].squeeze(0),
            'snippet_ids': snippet_encoding['input_ids'].squeeze(0),
            'snippet_mask':
```

```
snippet_encoding['attention_mask'].squeeze(0),
            'target_ids': target_encoding['input_ids'].squeeze(0),
            'target_mask':
target_encoding['attention_mask'].squeeze(0),
            'aspect_label_ids': (torch.tensor(aspect_label_ids,
dtype=float)).squeeze(0),
            'sentiment_score':
torch.FloatTensor([float(row['sentiment_score'])])
        }

# Create data loaders
seed = 42
csv_file = "train.csv"
batch_size = 8
torch.manual_seed(seed)
dataset = FinancialAspectDataset(csv_file)
train_loader = DataLoader(
    dataset,
    batch_size=batch_size,
    shuffle=True
)

for batch in train_loader:
    print(batch.keys())
    break
```

```
dict_keys(['sentence_ids', 'sentence_mask', 'snippet_ids',
'snippet_mask', 'target_ids', 'target_mask', 'aspect_label_ids',
'sentiment_score'])
```

ML Modelling

Main thing to notice here is that, for any `sentence` or `snippet`, the `target` governs the aspect and sentiment_score. So, from the sentences we would need retrieve what is being talked about the target. We will do this by attention mechanism with `target` as the querry

```
# Modelling target based attention
class TargetAttention(torch.nn.Module):
    def __init__(self, hidden_dim):
        super().__init__()
        # 8 -> 2 or 4
        self.attention = torch.nn.MultiheadAttention(
            embed_dim=hidden_dim,
            num_heads=2,
            dropout=0.1
        )

        self.hidden_dim = 768
        # self.dim_reducer = torch.nn.Linear(-1, self.hidden_dim)
```

```
    def forward(self, sentence_encoding, snippet_encoding,
target_encoding):
        # sentence_reduced = self.dim_reducer(sentence_encoding)
        # snippet_reduced = self.dim_reducer(snippet_encoding)
        # target_reduced = self.dim_reducer(target_encoding)

        attn_output, attn_weights = self.attention(
            query   =   target_encoding,
            key     =   sentence_encoding,
            value   =   snippet_encoding
        )

        return attn_output, attn_weights

# Modelling the final model
# have both sentiment score and aspect classification

class AspectDetectionModel(torch.nn.Module):
    def __init__(self, num_aspects):
        super().__init__()
        self.finbert = AutoModel.from_pretrained('ProsusAI/finbert')

        for param in self.finbert.parameters():
            param.requires_grad = False

        for param in self.finbert.encoder.layer[-2:].parameters():
            param.requires_grad = True

        self.target_attention = TargetAttention(hidden_dim=768)

        self.aspect_classifier = torch.nn.Sequential(
            torch.nn.Linear(768, 128),
            torch.nn.ReLU(),
            torch.nn.Dropout(0.2),
            torch.nn.Linear(128, num_aspects),
        )
        self.sentiment_regressor = torch.nn.Sequential(
            torch.nn.Linear(768, 128),
            torch.nn.ReLU(),
            torch.nn.Dropout(0.2),
            torch.nn.Linear(128, 1),
            torch.nn.Tanh()
        )

    def forward(self, sentence_ids, sentence_mask,
                              snippet_ids, snippet_mask,
                              target_ids, target_mask):
        sentence_encoding = self.finbert(sentence_ids, sentence_mask)
[0]  # [batch_size, seq_len, 768]
```

```
        sentence_encoding = sentence_encoding[:, 0, :] # B, H
        # print("sent_encoding: ",sentence_encoding.shape)
        snippet_encoding = self.finbert(snippet_ids, snippet_mask)[0]
        snippet_encoding = snippet_encoding[:, 0, :]
        # print("snippet_encoding: ",snippet_encoding.shape)
        target_encoding = self.finbert(target_ids, target_mask)[0]
        target_encoding = target_encoding[:,0,:]
        # print("target_encoding: ",target_encoding.shape)

        target_aware_output, _ = self.target_attention(
            sentence_encoding=sentence_encoding,
            snippet_encoding=snippet_encoding,
            target_encoding=target_encoding
        )

        # print("attn_output: ",target_aware_output.shape)

        aspect_logits = self.aspect_classifier(target_aware_output)
        sentiment_score = 
self.sentiment_regressor(target_aware_output)
        # print("output_logits: ",aspect_logits.shape)
        # print(aspect_logits[0])
        return aspect_logits, sentiment_score
```

Note : Key thing to note here is that I am training for both aspect task and sentiment score prediction task simultaneously so that they can get benefit from each other's loss

```
device = torch.device("cuda:0" if torch.cuda.is_available() else 
"cpu")
print(device)

ASPECT_LIST = 119
num_epochs = 3

model = AspectDetectionModel(num_aspects=ASPECT_LIST).to(device)
criterion = torch.nn.BCEWithLogitsLoss()
sentiment_criterion = torch.nn.MSELoss()

optimizer = AdamW([
    {'params': model.finbert.parameters(), 'lr': 2e-5},
    {'params': model.target_attention.parameters(), 'lr': 1e-4},
    {'params': model.aspect_classifier.parameters(), 'lr': 1e-3},
    {'params': model.sentiment_regressor.parameters(), 'lr': 1e-3}
])

print(model)

cuda:0
AspectDetectionModel(
  (finbert): BertModel(
```

```
    (embeddings): BertEmbeddings(
      (word_embeddings): Embedding(30522, 768, padding_idx=0)
      (position_embeddings): Embedding(512, 768)
      (token_type_embeddings): Embedding(2, 768)
      (LayerNorm): LayerNorm((768,), eps=1e-12,
elementwise_affine=True)
      (dropout): Dropout(p=0.1, inplace=False)
    )
    (encoder): BertEncoder(
      (layer): ModuleList(
        (0-11): 12 x BertLayer(
          (attention): BertAttention(
            (self): BertSdpaSelfAttention(
              (query): Linear(in_features=768, out_features=768,
bias=True)
              (key): Linear(in_features=768, out_features=768,
bias=True)
              (value): Linear(in_features=768, out_features=768,
bias=True)
              (dropout): Dropout(p=0.1, inplace=False)
            )
            (output): BertSelfOutput(
              (dense): Linear(in_features=768, out_features=768,
bias=True)
              (LayerNorm): LayerNorm((768,), eps=1e-12,
elementwise_affine=True)
              (dropout): Dropout(p=0.1, inplace=False)
            )
          )
          (intermediate): BertIntermediate(
            (dense): Linear(in_features=768, out_features=3072,
bias=True)
            (intermediate_act_fn): GELUActivation()
          )
          (output): BertOutput(
            (dense): Linear(in_features=3072, out_features=768,
bias=True)
            (LayerNorm): LayerNorm((768,), eps=1e-12,
elementwise_affine=True)
            (dropout): Dropout(p=0.1, inplace=False)
          )
        )
      )
    )
    (pooler): BertPooler(
      (dense): Linear(in_features=768, out_features=768, bias=True)
      (activation): Tanh()
    )
  )
```

```
  (target_attention): TargetAttention(
    (attention): MultiheadAttention(
      (out_proj): NonDynamicallyQuantizableLinear(in_features=768, 
out_features=768, bias=True)
    )
  )
  (aspect_classifier): Sequential(
    (0): Linear(in_features=768, out_features=128, bias=True)
    (1): ReLU()
    (2): Dropout(p=0.2, inplace=False)
    (3): Linear(in_features=128, out_features=119, bias=True)
  )
  (sentiment_regressor): Sequential(
    (0): Linear(in_features=768, out_features=128, bias=True)
    (1): ReLU()
    (2): Dropout(p=0.2, inplace=False)
    (3): Linear(in_features=128, out_features=1, bias=True)
    (4): Tanh()
  )
)
```

Remarks

- I have taken BCE with logits loss for taining for aspect classifications since it is a multi-lable classification task
- I have MSE loss for training for sentiment score since it will help us to converge nicely

Training code

```
# Training loop
aspect_loss_hist = []
sentiment_loss_hist = []
tot_loss_hist = []
for epoch in range(num_epochs):
    model.train()
    epoch_loss = 0
    cnt = 0
    for batch in train_loader:
        cnt += 1
        sentence_ids = batch['sentence_ids'].to(device)
        sentence_mask = batch['sentence_mask'].to(device)
        snippet_ids = batch['snippet_ids'].to(device)
        snippet_mask = batch['snippet_mask'].to(device)
        target_ids = batch['target_ids'].to(device)
        target_mask = batch['target_mask'].to(device)

        aspect_labels = batch['aspect_label_ids'].to(device)  # Binary 
matrix [batch_size, num_aspects]
        true_sentiment_scores = batch['sentiment_score'].to(device)
```

```
        # print("true: ", aspect_labels.shape)

        # print("forward pass: ")
        aspect_logits, pred_sentiment_score = model(sentence_ids,
sentence_mask,
                                  snippet_ids, snippet_mask,
                                  target_ids, target_mask)

        # print("pred: ", aspect_logits.shape)

        aspect_loss = criterion(aspect_logits, aspect_labels)
        sentiment_loss =
sentiment_criterion(pred_sentiment_score.squeeze(),
true_sentiment_scores.squeeze())

        loss = aspect_loss + sentiment_loss

        aspect_loss_hist.append(aspect_loss.cpu())
        sentiment_loss_hist.append(sentiment_loss.cpu())
        tot_loss_hist.append(loss.cpu())

        if cnt%20==0:
            print(f"{int(cnt)}/{(epoch+1)}:")
            print("\t loss:           ", loss.item())
            print("\t aspect_loss:    ", aspect_loss.item())
            print("\t sentiment_loss: ", sentiment_loss.item())
        epoch_loss += loss

        optimizer.zero_grad()
        loss.backward()

        torch.nn.utils.clip_grad_norm_(model.parameters(),
max_norm=1.0)

        optimizer.step()

    print("\n----------------------------")
    print(f"epoch_loss @{epoch+1}: ", (epoch_loss/cnt).item())
    print("----------------------------\n")
```

```
20/1:
	 loss:            0.22312268990428508
	 aspect_loss:     0.07568399983794749
	 sentiment_loss:  0.14743869006633759
40/1:
	 loss:            0.18400817801941094
	 aspect_loss:     0.07950721373546775
	 sentiment_loss:  0.10450096428394318
60/1:
	 loss:            0.20157609199870283
```

```
       aspect_loss:     0.09958910261977369
       sentiment_loss:  0.10198698937892914
80/1:
       loss:            0.238621167008992
       aspect_loss:     0.07556530005228118
       sentiment_loss:  0.16305586695671082
100/1:
       loss:            0.2157115586759413
       aspect_loss:     0.06234645328539259
       sentiment_loss:  0.1533651053905487
120/1:
       loss:            0.2043880509376964
       aspect_loss:     0.0656071888447246
       sentiment_loss:  0.1387808620929718

----------------------------
epoch_loss @1:  0.2374676589029084
----------------------------

20/2:
       loss:            0.22366478924929095
       aspect_loss:     0.08252172057806444
       sentiment_loss:  0.1411430686712265
40/2:
       loss:            0.22960695565654698
       aspect_loss:     0.08407306612445777
       sentiment_loss:  0.14553388953208923
60/2:
       loss:            0.2324608774276591
       aspect_loss:     0.06595473600348004
       sentiment_loss:  0.16650614142417908
80/2:
       loss:            0.2058108243621698
       aspect_loss:     0.09099126788748413
       sentiment_loss:  0.11481955647468567
100/2:
       loss:            0.2062686459482217
       aspect_loss:     0.06451030833130122
       sentiment_loss:  0.14175833761692047
120/2:
       loss:            0.23545260688274347
       aspect_loss:     0.08916388412921869
       sentiment_loss:  0.14628872275352478

----------------------------
epoch_loss @2:  0.23999978897119834
----------------------------

20/3:
       loss:            0.29498068566488866
```

```
        aspect_loss:     0.08237056012320168
        sentiment_loss:  0.212610125541687
40/3:
        loss:            0.2681108398222122
        aspect_loss:     0.06626723537675473
        sentiment_loss:  0.20184360444545746
60/3:
        loss:            0.2791772207260883
        aspect_loss:     0.07921150531776312
        sentiment_loss:  0.1999657154083252
80/3:
        loss:            0.24841993511654437
        aspect_loss:     0.0719596988055855
        sentiment_loss:  0.17646023631095886
100/3:
        loss:            0.2669205499672088
        aspect_loss:     0.08182571659318538
        sentiment_loss:  0.18509483337402344
120/3:
        loss:            0.23924344700189823
        aspect_loss:     0.06825140040727848
        sentiment_loss:  0.17099204659461975

----------------------------
epoch_loss @3:  0.2371134593134463
----------------------------
```

```
from sklearn.metrics import precision_recall_fscore_support,
mean_squared_error

def flat(arr):
    a = []
    for i in range(len(arr)):
        # print(i)
        if arr[i].shape == torch.Size([]):
            a.append(arr[i].item())
            break
        for j in range(len(arr[i])):
            a.append(arr[i][j].item())

    return a


def metric_eval(data_loader):
    model.eval()
    total_aspect_loss = 0
    total_sentiment_loss = 0
    val_steps = 0
```

```
    all_aspect_predictions = []
    all_true_aspects = []
    all_sentiment_predictions = []
    all_true_sentiments = []

    with torch.no_grad():
        for batch in data_loader:
            sentence_ids = batch['sentence_ids'].to(device)
            sentence_mask = batch['sentence_mask'].to(device)
            snippet_ids = batch['snippet_ids'].to(device)
            snippet_mask = batch['snippet_mask'].to(device)
            target_ids = batch['target_ids'].to(device)
            target_mask = batch['target_mask'].to(device)

            aspect_labels = batch['aspect_label_ids'].to(device)
            sentiment_scores = batch['sentiment_score'].to(device)

            aspect_logits, pred_sentiment = model(sentence_ids,
sentence_mask,
                                                  snippet_ids,
snippet_mask,
                                                  target_ids,
target_mask)

            aspect_loss = criterion(aspect_logits, aspect_labels)
            sentiment_loss =
sentiment_criterion(pred_sentiment.squeeze(),
sentiment_scores.squeeze())

            total_aspect_loss += aspect_loss.item()
            total_sentiment_loss += sentiment_loss.item()
            val_steps += 1

            aspect_predictions = torch.sigmoid(aspect_logits) > 0.2


            aspect_predictions = aspect_predictions.cpu().numpy()
            true_aspects = aspect_labels.cpu().numpy()
            sentiment_predictions = pred_sentiment.squeeze().cpu()
            true_sentiments = sentiment_scores.squeeze().cpu()

            all_aspect_predictions.append(aspect_predictions)
            all_true_aspects.append(true_aspects)
            all_sentiment_predictions.append(sentiment_predictions)
            all_true_sentiments.append(true_sentiments)

    all_aspect_predictions = np.vstack(all_aspect_predictions)
    all_true_aspects = np.vstack(all_true_aspects)
    # all_sentiment_predictions = np.vstack(all_sentiment_predictions)
    # all_true_sentiments = np.vstack(all_true_sentiments)
```

```
    all_sentiment_predictions = flat(all_sentiment_predictions)
    all_true_sentiments = flat(all_true_sentiments)
    # Calculate metrics
    precision_micro, recall_micro, f1_micro, _ =
precision_recall_fscore_support(
        all_true_aspects, all_aspect_predictions, average='micro'
    )

    sentiment_mse = mean_squared_error(all_true_sentiments,
all_sentiment_predictions)
    avg_aspect_loss = total_aspect_loss / val_steps
    avg_sentiment_loss = total_sentiment_loss / val_steps

    print(f"Aspect Loss: {avg_aspect_loss:.4f}")
    print(f"Sentiment MSE Loss: {avg_sentiment_loss:.4f}")

    print("\nAspect Classification Metrics (Micro-averaged):")
    print(f"Precision: {precision_micro:.4f}")
    print(f"Recall: {recall_micro:.4f}")
    print(f"F1-score: {f1_micro:.4f}")

    print("\nSentiment Regression Metrics:")
    print(f"MSE: {sentiment_mse:.4f}")
    print('-'*60)

print("Eval Metric on Training Data")
print('-'*60)
metric_eval(train_loader)
```

```
Eval Metric on Training Data
------------------------------------------------------------

Validation Results:
Aspect Loss: 0.0680
Sentiment MSE Loss: 0.1557

Aspect Classification Metrics (Micro-averaged):
Precision: 0.4584
Recall: 0.5059
F1-score: 0.4810

Sentiment Regression Metrics:
MSE: 0.1544
------------------------------------------------------------
```

```
val_data = FinancialAspectDataset("validation.csv")
val_loader = DataLoader(
    val_data,
    batch_size=batch_size,
    shuffle=True
```

```
)
print("Eval Metric on Validation Data")
print('-'*60)

model.eval()
total_aspect_loss = 0
total_sentiment_loss = 0
val_steps = 0

all_aspect_predictions = []
all_true_aspects = []
all_sentiment_predictions = []
all_true_sentiments = []

with torch.no_grad():
    for batch in val_loader:
        sentence_ids = batch['sentence_ids'].to(device)
        sentence_mask = batch['sentence_mask'].to(device)
        snippet_ids = batch['snippet_ids'].to(device)
        snippet_mask = batch['snippet_mask'].to(device)
        target_ids = batch['target_ids'].to(device)
        target_mask = batch['target_mask'].to(device)

        aspect_labels = batch['aspect_label_ids'].to(device)
        sentiment_scores = batch['sentiment_score'].to(device)

        aspect_logits, pred_sentiment = model(sentence_ids,
sentence_mask,
                                            snippet_ids, snippet_mask,
                                            target_ids, target_mask)

        aspect_loss = criterion(aspect_logits, aspect_labels)
        sentiment_loss = sentiment_criterion(pred_sentiment.squeeze(),
sentiment_scores.squeeze())

        total_aspect_loss += aspect_loss.item()
        total_sentiment_loss += sentiment_loss.item()
        val_steps += 1

        aspect_predictions = torch.sigmoid(aspect_logits) > 0.2


        aspect_predictions = aspect_predictions.cpu().numpy()
        true_aspects = aspect_labels.cpu().numpy()
        sentiment_predictions = pred_sentiment.squeeze().cpu()
        true_sentiments = sentiment_scores.squeeze().cpu()

        all_aspect_predictions.append(aspect_predictions)
        all_true_aspects.append(true_aspects)
        all_sentiment_predictions.append(sentiment_predictions)
```

```
        all_true_sentiments.append(true_sentiments)

all_aspect_predictions = np.vstack(all_aspect_predictions)
all_true_aspects = np.vstack(all_true_aspects)
# all_sentiment_predictions = np.vstack(all_sentiment_predictions)
# all_true_sentiments = np.vstack(all_true_sentiments)

all_sentiment_predictions = flat(all_sentiment_predictions)
all_true_sentiments = flat(all_true_sentiments)
# Calculate metrics
precision_micro, recall_micro, f1_micro, _ =
precision_recall_fscore_support(
    all_true_aspects, all_aspect_predictions, average='micro'
)

sentiment_mse = mean_squared_error(all_true_sentiments,
all_sentiment_predictions)
avg_aspect_loss = total_aspect_loss / val_steps
avg_sentiment_loss = total_sentiment_loss / val_steps

print(f"Aspect Loss: {avg_aspect_loss:.4f}")
print(f"Sentiment MSE Loss: {avg_sentiment_loss:.4f}")

print("\nAspect Classification Metrics (Micro-averaged):")
print(f"Precision: {precision_micro:.4f}")
print(f"Recall: {recall_micro:.4f}")
print(f"F1-score: {f1_micro:.4f}")

print("\nSentiment Regression Metrics:")
print(f"MSE: {sentiment_mse:.4f}")
# print('-'*60)
```

```
Eval Metric on Validation Data
------------------------------------------------------------
Aspect Loss: 0.0716
Sentiment MSE Loss: 0.1169

Aspect Classification Metrics (Micro-averaged):
Precision: 0.4582
Recall: 0.4275
F1-score: 0.4423

Sentiment Regression Metrics:
MSE: 0.1175
```