

Aspect Based Sentiment Analysis using LSTM & BERT

Module - 1 (Aspect Based Sentiment Analysis):

Tasks: To train classifiers to detect aspects and their sentiments from a review sentence.

Dataset used:

The dataset consist of two xml files:

1. Train xml

It consists of text which is the review of the user's aspects about the restaurant along with their respective sentiment (polarity) i.e. Positive, Negative or Neutral.

2. Test xml

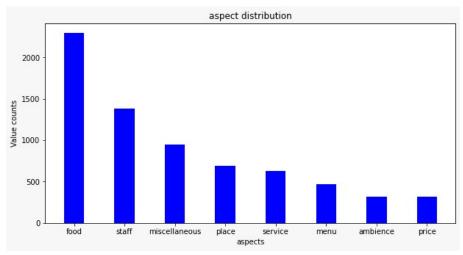
The test data consists of sentences which have text as the user's review of the restaurant.

Data Preprocessing:

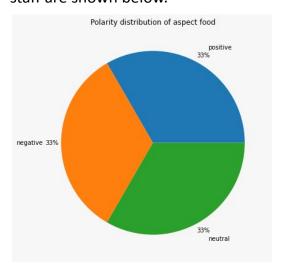
- 1. Converted XML to CSV file.
- 2. Added id to each of the text.
- 3. In our original train data we had two aspects for each review so have created a dataframe where for each aspect category we have assigned the same text for a given review.

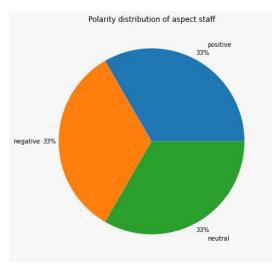
	id	text	aspect_category	polarity
0	0	It might be the best sit down food I've had in	food	positive
1	1	It might be the best sit down food I've had in	place	neutral
2	2	Hostess was extremely accommodating when we ar	staff	positive
3	3	Hostess was extremely accommodating when we ar	miscellaneous	neutral

4. In our train data we have 8 aspect categories: food, staff, miscellaneous, place, service, menu, ambience & price.



5. Checked the polarity distribution within each aspect category. We found that there is no polarity imbalance within the aspects. Polarity distribution for the aspect category "food" & staff are shown below.





6. Performed Label Encoding on Polarity i.e.(Positive: 0, Negative: 1 & Neutral: 2)

	id	text	aspect_category	polarity	polarity_new
0	0	It might be the best sit down food I've had in	food	positive	0
1	1	It might be the best sit down food I've had in	place	neutral	2
2	2	Hostess was extremely accommodating when we ar	staff	positive	0
3	3	Hostess was extremely accommodating when we ar	miscellaneous	neutral	2
4	4	We were a couple of minutes late for our reser	miscellaneous	neutral	2

7. Reformatted the train data based on aspect category.

For each aspect we have splitted the given train data into train and validation set in the ratio 60:40

Model 1: BERT based model for Aspect Based Sentiment Analysis

Link of Google Colab Code File:

https://colab.research.google.com/drive/1c wai1HKhLrGuUV5E4rXH3Ex2xVwlzRml

Report all the hyperparameters used to train the model, epochs, learning rate, hidden representation size etc.

- 1. Imported the pre-trained BERT model and added
 - 1.1. Dropout layer with probability 0.3
 - 1.2. One extra linear layer with input features as 768 and output features as 3 (since we have three sentiment classes in our data, i.e. positive, negative & neutral). We have used the *'bert-base-uncased'* architecture of BERT for our analysis.

```
(pooler): BertPooler(
    (dense): Linear(in_features=768, out_features=768, bias=True)
    (activation): Tanh()
)
)
(drop): Dropout(p=0.3, inplace=False)
  (out): Linear(in_features=768, out_features=3, bias=True)
)
```

- 2. We have used BertTokeniser to tokenize our input train & validation data to the model.
- 3. Trained the Bert Model on train data with following hyperparameters:

```
TRAIN_MAX_LEN = 140
VALID_MAX_LEN = 140
TRAIN_BATCH_SIZE = 16
VALID_BATCH_SIZE = 16
EPOCHS = 10
BERT_MODEL = 'bert-base-uncased'
LEARNING_RATE = 3e-5
```

Loss Function used	Optimizer used
CrossEntropy Loss	Adam Optimizer

If review text length is too big then we will clip it to 140 characters. The Batch size used to train the model was taken as 16 with 10 epochs and learning rate of 3e-5.

4. For each of the aspect categories, we have trained our model for 10 epochs and stored the one with best accuracy as the bin file. As a result we have 8 best models for each of the aspect categories which are used later for aspect detection on the test data.

5. Observation: Report the training-validation loss/accuracy plots.

5.1. Aspect Category: "food"

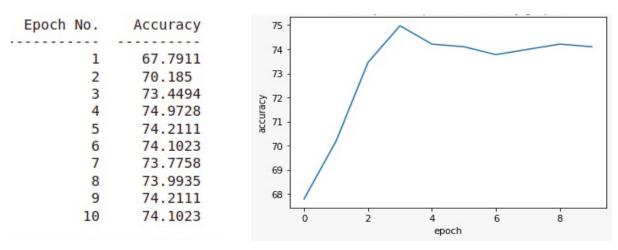


Fig: 5.1.1 Fig: 5.1.2

Here Fig: 5.1.1 shows the accuracy of the model at each epoch and Fig: 5.1.2 shows the Accuracy plot for the aspect category "food". Here we can see that the **4th model has the best Accuracy i.e. 74.9728**% which we have saved as a bin file for further aspect detection on test data.

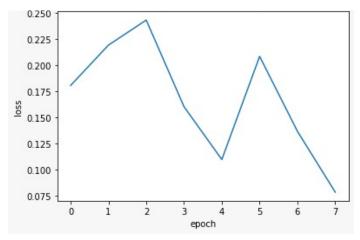
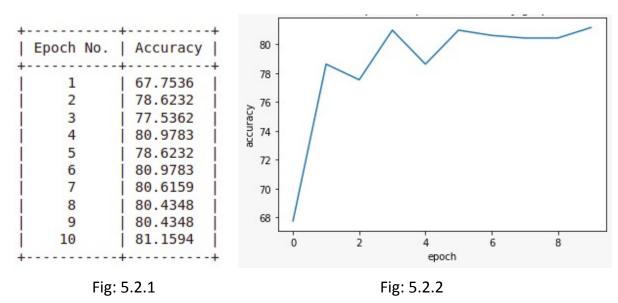


Fig: 5.1.3

Fig 5.1.3 shows the Loss Plot for the selected model 4, which is our best model for the aspect category "food".

5.2. Aspect Category: "staff"



Here Fig: 5.2.1 shows the accuracy of the model at each epoch and Fig: 5.2.2 shows the Accuracy plot for the aspect category "staff". Here we can see that the **10th model has the** best Accuracy i.e. 81.1594% which we have saved as a bin file for further aspect detection on test data.

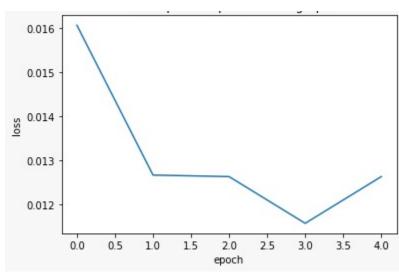


Fig 5.2.3 shows the Loss Plot for the selected model 10, which is our best model for the aspect category "staff".

Fig: 5.2.3

5.3. Aspect Category: "place"

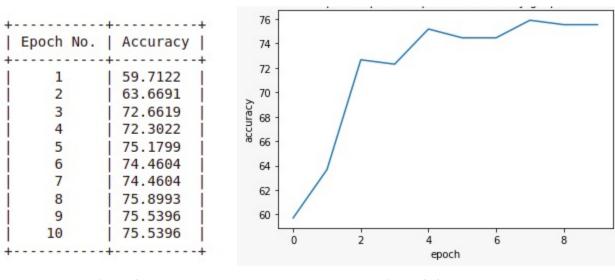


Fig: 5.3.1 Fig: 5.3.2

Here Fig: 5.3.1 shows the accuracy of the model at each epoch and Fig: 5.3.2 shows the Accuracy plot for the aspect category "place". Here we can see that the **8th model has the best Accuracy i.e. 75.8993%** which we have saved as a bin file for further aspect detection on test data.

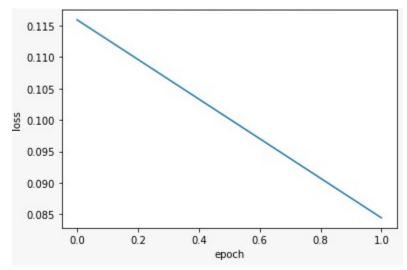
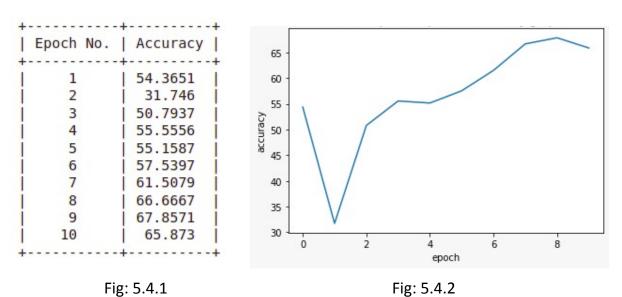


Fig: 5.3.3

Fig 5.3.3 shows the Loss Plot for the selected model 8, which is our best model for the aspect category "place".

5.4. Aspect Category: "service"



Here Fig: 5.4.1 shows the accuracy of the model at each epoch and Fig: 5.4.2 shows the Accuracy plot for the aspect category "service". Here we can see that the **9th model has the best Accuracy i.e. 67.8571%** which we have saved as a bin file for further aspect detection on test data.

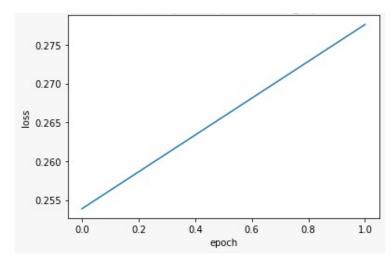


Fig: 5.4.3

Fig 5.4.3 shows the Loss Plot for the selected model 9, which is our best model for the aspect category *"service"*.

5.5. Best Model Accuracy and Loss Plot for aspect category: price, miscellaneous, menu, ambience.

Aspect category	Best Model Accuracy	Accuracy Plot of all the models	Loss Plot of best model
price	55.468%	55 - 54 - 53 - 52 - 52 - 55 - 50 - 49 - 6 8 epoch	0115 - 0110 - 0105 - 0100 - 0105 - 0100 - 0105 - 0100 - 0105 - 0100 - 0105 - 0100 - 0105 - 0100 - 0105 - 0100 - 0105 - 0100 - 01
miscellaneous	68.073%	68 - 67 - 66 - 765	0110 - 0108 - 0106 - 0104 - 0102 - 050 075 100 125 150 175 200 epoch
menu	74.468%	70 - 60 - 60 - 60 - 60 - 60 - 60 - 60 - 6	0016 - 0015 - 0014 - 0013 - 0012 - 00 0 0 5 10 15 20 25 30 35 40 epoch
ambience	55.038%	ambience epoch 8 epoch vs accuracy graph 55 50 40 35 0 2 4 6 8 epoch	0 250 0 225 0 200 0 175 0 150 0 125 0 100 0 075 0 1 2 3 4 5 6 7

6. Inference:

We used the best model obtained in the previous steps for aspect detection of each review in the test data. The output file for aspect and their polarity detection on test data has been enclosed in the attached file.

negative	price	positive	food	Overall, it is a nice place and if you don't m
negative	food	neutral	staff	We waited 15 minutes for a menu, another 20 fo
negative	menu	neutral	staff	the dishes are a little too recherche and too
negative	miscellaneous	negative	price	The pricing isn't quite clear and look out for
negative	food	positive	menu	the menu looked great, but the food was the bi
negative	ambience	neutral	staff	My boyfriend and I went one Friday night to fi
positive	staff	positive	food	The Pink Pony's brunch is among the very best
positive	miscellaneous	positive	food	The environment is a touch loud (although the

Fig: 6.1 : Aspect Based Sentiment Analysis output on test data

Here if we see any review for instance,

"Overall, it is a nice place and if you don't mind possible attitude and the not-so-cheap prices, it is a great place to meet for coffee or drinks (they have a nice selection of that too!"

The aspects detected in this review are "food" and its sentiment (polarity) is "positive" and another aspect detected is "price" having a "negative' sentiment.

By analyzing the test data, we observed that most of the text reviews have correctly detected the aspect categories along with their polarity.

Also we have selected the best two aspects based on their normalized aspect score for each of the test review data.

Model 2: LSTM based model for Aspect Based Sentiment Analysis

Link of Google Colab Code File:

https://colab.research.google.com/drive/10 I4S1RfYiIO0K wBt adiXSL5m-eYw

1. Report all the hyperparameters used to train the model, epochs, learning rate, hidden representation size etc.

1. LSTM Model: Created a LSTM based model with following layers as shown in the figure below.

Model: "sequential_1"

Layer (type)	Output Shape	Param #
embedding_1 (Embedding)	(None, 67, 256)	1280000
dropout_1 (Dropout)	(None, 67, 256)	0
lstm_2 (LSTM)	(None, 67, 256)	525312
lstm_3 (LSTM)	(None, 256)	525312
dense_1 (Dense)	(None, 3)	771

Total params: 2,331,395 Trainable params: 2,331,395 Non-trainable params: 0

2. Data Preprocessing: Converted all the text data into lower case and removed all the special characters if present.

- 3. Tokenized the data.
- 4. Train-Validation Split (80:20)
- 5. Trained the LSTM model on train data with following hyperparameters:

Number of Epochs	Batch Size	Loss Function	Optimizer
5	32	Categorical CrossEntropy Loss	Adam

6. For each of the aspect categories, we have trained our model for 5 epochs and stored the one with best accuracy as the bin file. As a result we have 8 best models for each of the aspect categories which are used later for aspect detection on the test data.

7. Observation: Report the training-validation loss/accuracy plots.

7.1. Aspect Category: "food"

Train Accuracy	Train Loss	Validation Accuracy	Validation Loss
94.12%	0.1701	63.04%	1.1806

7.2. Aspect Category: "staff"

Train Accuracy	Train Loss	Validation Accuracy	Validation Loss
94.02%	0.1837	71.73%	1.2216

7.3. Aspect Category: "place"

Train Accuracy	Train Loss	Validation Accuracy	Validation Loss
85.74%	0.3203	66.91%	0.8979

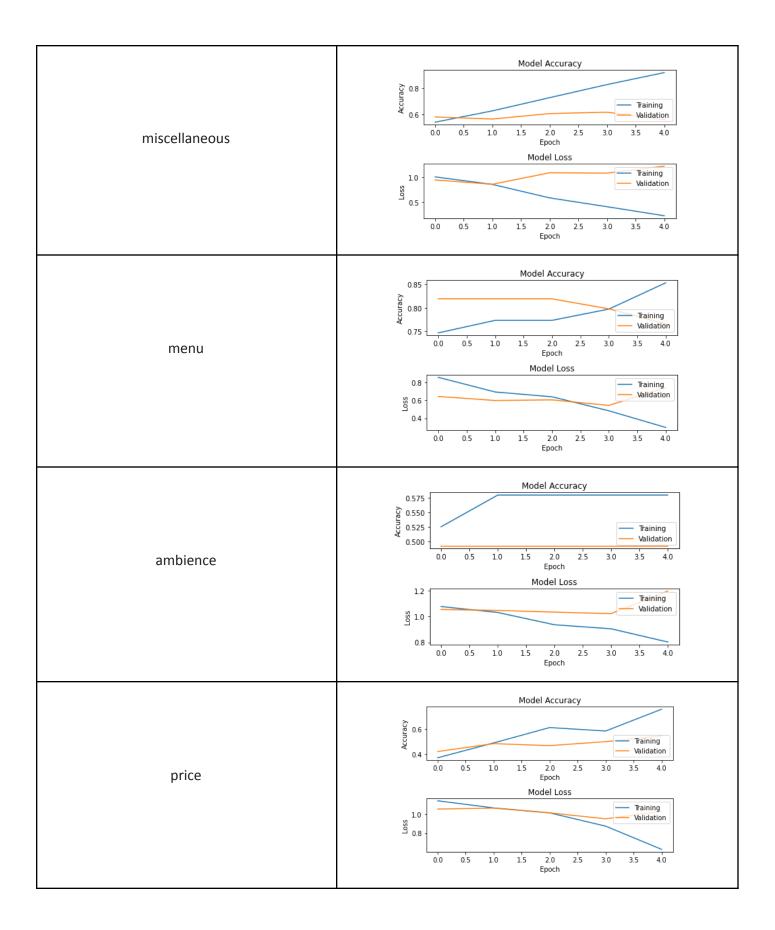
7.4. Aspect Category: "service"

Train Accuracy	Train Loss	Validation Accuracy	Validation Loss
89.68%	0.3106	55.56%	1.4150

7.5. Best Model Accuracy and Loss Plot for aspect category: price, miscellaneous, menu, ambience.

Aspect Category	Train Accuracy	Train Loss	Validation Accuracy	Validation Loss
miscellaneous	92.07%	0.2235	55.79%	1.2278
menu	85.33%	0.2974	76.60%	0.7384
ambience	57.98%	0.8030	49.23%	1.1976
price	75.69%	0.6298	54.69%	1.0299

Aspect Category	Accuracy & Loss Plot		
food	Model Accuracy 0.9 0.9 0.0 0.0 0.0 0.0 0.0 0.		
staff	Model Accuracy 109 0.8 0.7 0.0 0.5 10 15 20 25 30 35 4.0 Epoch Model Loss Training Validation Validation Validation Validation Validation Validation Epoch From Model Loss Training Validation Validation Epoch Epoch		
place	Model Accuracy 0.8 0.7 0.6 0.0 0.5 10 15 2.0 2.5 3.0 3.5 4.0 Walidation Model Loss Training Validation Validation		
service	Model Accuracy 0.8 0.0 0.0 0.5 10 15 20 25 30 35 4.0 Faining Walidation 0.5 0.0 0.5 10 15 20 25 30 35 4.0 Epoch Model Loss Faining Walidation Epoch Epoch Faining Walidation		



8. Inference

We used the best model obtained in the previous steps for aspect detection of each review in the test data. The output file for aspect and their polarity detection on test data has been enclosed in the attached file.

For each of the test reviews we have selected the aspect and their sentiment with a score greater than 0.7.

Compare results of accuracy from the two models – overall as well as aspect level, resource requirements (quality of results after a fixed amount of training) [i.e., both quantitative and qualitative results, varying epochs/data/hyperparameters etc. report the one you have varied]

Model	Batch Size	Epoch	Loss	Optimizer
BERT	16	10	CrossEntropy	Adam
LSTM	32	5	Categorical CrossEntropy	Adam

Aspect Category	Model Accuracy		
	BERT	LSTM	
food	74.9728%	63.04%	
staff	81.1594%	71.73%	
place	75.8993%	66.91%	
service	67.8571%	55.56%	
miscellaneous	68.073%	55.79%	
menu	74.468%	76.60%	
ambience	55.038%	49.23%	
price	55.468%	54.69%	

We observed that the quality of aspect based sentiment analysis in the BERT model was better than that of the LSTM.