Day 104: NLP Papers Summary – SentiHood: Targeted Aspect Based Sentiment Analysis Dataset For Urban Neighbourhoods

By Ryan 13th April 2020 No Comments

Objective and Contribution

This paper introduces the task of targeted aspect-based sentiment analysis (TABSA). This work extends aspect-based sentiment analysis that assumes only a single entity per document and targeted sentiment analysis that assumes only a single sentiment towards a target entity. The contributions are as follow:

1. Introduce the task of targeted aspect-based sentiment analysis (TABSA)

2. Introduce the SentiHood dataset, which it's base don text taken from question answering platform of Yahoo!
3. Develop few strong baseline models using logistic regression and LSTM for future benchmarking

The limitation of aspect-based sentiment analysis (ABSA) and targeted sentiment analysis

Sentiment analysis (overall sentiment) –> ABSA and targeted sentiment analysis –> Targeted ABSA.

ABSA involves extracting sentiment towards different aspects of an entity in the same unit of text. The dataset used for ABSA mostly assume that only one entity is discussed in one review snippet but the opinion on multiple aspects can be expressed. Targeted sentiment analysis perform sentiment analysis towards a certain target entity mentions in given sentences. This task assumes only a single sentiment for each entity and dataset so far only contains a single target entity per unit of text.

TABSA vs ABSA

I think the best way to illustrate the difference in the two tasks is through an example.

AN EXAMPLE FROM THE ABSA DATASET:

"The design of the space is good but the service is horrid!"

ABSA task is to identify a positive sentiment towards ambiance aspect and a negative sentiment towards the service aspect. However, it is assumed that both these opinions are expressed about the same restaurant.

A SYNTHETIC EXAMPLE OF TABSA DATASET:

"The design of the space is great in McDonalds but the service is horrid, on the other hand, the staff in KFC are very friendly and the food is always delicious."

In this example, there are two target entities: McDonalds and KFC. Current ABSA task can only recognise that positive and negative opinions are expressed towards the service aspect, but it cannot identify the target entity for each of these opinions. TABSA aims to extract target entities and its respective aspects and relevant sentiments.

SentiHood Dataset

Sentence	Labels
The cheap parts of London are **Edmonton** and **Tottenham** and they are all poor, crime ridden and crowded with immigrants	(Edmonton,price,Positive) (Tottenham,price,Positive) (Edmonton,safety,Negative) (Tottenham,safety,Negative)
Hampstead area, more expensive but a better quality of living than in **Tufnell Park**	(Hampstead,price,Negative) (Hampstead,live,Positive)

Table 1: Examples of input sentences and output labels in the system.

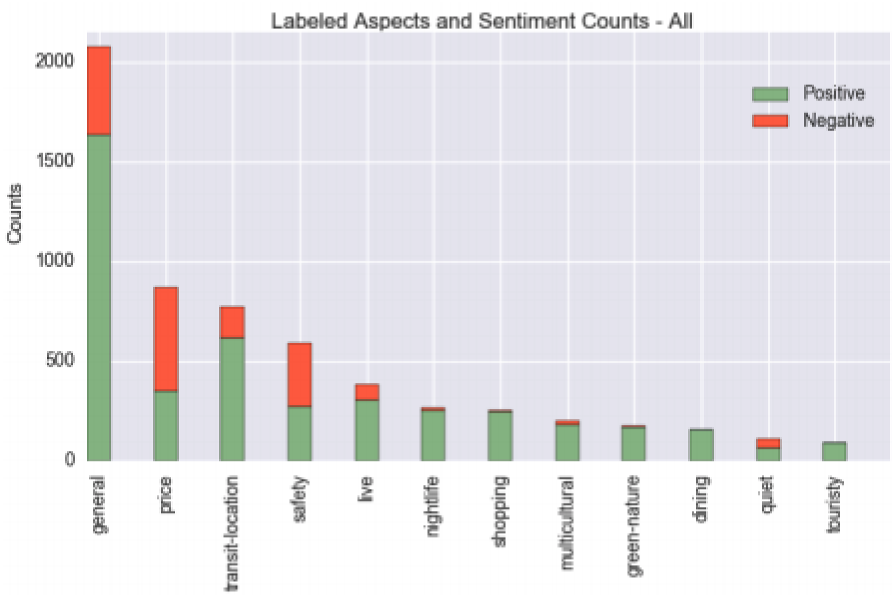
- Contains annotated sentences containing one or two location entity mentions
- It has 5215 sentences
  - 3862 sentences with a single location entity
  - 1353 sentences with two location entities
- Below is a figure of the different aspects within the dataset and the number of sentences belonging to each aspect. The dataset only has positive or negative sentiment
  - 

Figure 1: Number of annotated aspects and their sentiments.

- Location entity names are masked by location1 and location2
- The dataset also include polarity class “None” where a sentence does not contain an opinion for the aspect a of location l.

The TABSA task is essentially given a sentence, provide a list of tuples (l, a, p) where p he polarity for the aspect a of entity l.

Experiments

Selected the four most frequent aspects from dataset: “price”, “safety”, “transit-location”, and “general”. Results are broken down to single location sentences, two locations sentences, and overall test set. The idea is that results on single location sentences will showcase the model’s ability to perform correct sentiment analysis and the results on two locations sentences will show the model’s ability to detect the relevant sentiment of an aspect and recognise the target entity of the opinion.

BASELINE MODELS

- Different variation of logistic regression with linguistic features
- LSTM with final and location output state

EVALUATION

- F1 score – aspect detection
- Accuracy – sentiment classification
- AUC (Area under the ROC curve) – both aspect and sentiment detection

Results

- The best performing model is logistic regression with location masking and POS information. The underperforming of LSTM might be due to lack of training data.
- The consistent outperformance of logistic regression over LSTM highlights the advantage of features engineering when the volume of data is low.

Conclusion and Future Work

- Ways to improve baselines can involve using parse trees for identifying context of each location
- Data augmentation can be used to make models more robust to variations in the data

Source: https://www.aclweb.org/anthology/C16-1146.pdf

Ryan

Data Scientist

Previous Post

Day 103: NLP Papers Summary - Utilizing BERT for Aspect-Based Sentiment Analysis

Next Post

Day 105: NLP Papers Summary - Aspect Level Sentiment Classification with

Sentiment Analysis via Constructing Auxiliary Sentence

Attention-over-Attention Neural Networks

Data Science Natural Language Processing NLP Papers Summary

Day 365: NLP Papers Summary – A Survey on Knowledge Graph Embedding

Ryan
30th December 2020

Data Science Implementation Natural Language Processing

Day 364: Ryan's PhD Journey – OpenKE-PyTorch Library Analysis + code snippets for 11 KE models

Ryan
29th December 2020

Data Science Ryan's PhD Journey

Day 363: Ryan's PhD Journey – Literature Review – Knowledge Acquisition – 1st Passes XIV

Ryan
28th December 2020