Aspect based emotion analysis

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Aspect based emotion analysis

- Aspect based emotion analysis aims to extract various aspects of reviews and determine the corresponding emotion for each aspect category. The term ‘aspect’ refers to an attribute or a component of the product
- Instead of classifying the overall emotion of a review into anger, sadness, happiness, surprise and joy aspect-based analysis allows us to associate specific emotion to different aspects of a product and such a analysis provides greater insight to the emotions expressed in the written reviews.
- **Dataset** : SemEval (2014 and 2016) dataset(Restaurant)

Problem

- No aspect based emotion tagged dataset available
- Verification of results?
- Dataset:
    - SemEval 14 and 16 of Restaurant reviews
    - Aspect labelled as Positive, Negative or Neutral in the dataset.
    - Aspects can be multiple words also.
    - Not each sentence may have a aspect present.

Solution

- Dataset is tagged using sentiments <Positive , Negative ,Neutral > for each aspect Identified in the sentence.
- We used the backmapping approach to evaluate the solution.
- Emotions Identified for each aspect were classified as Positive , Negative and Neutral.
- Then above mapping was used to evaluate the result.

Pipeline

- **Data Pre-processing**
  - We have done preprocessing for all the reviews in the dataset by removing unwanted characters,links etc.
  - Example : Not only was the food outstanding, but the little 'perks' were great.
  - After preprocessing :not only was the food outstanding but the little perks were great
- **Aspect Terms Extraction**
  - Each token of review is marked with B,I,O encoding scheme.where B, I and O denote the beginning,inside and outside entities of aspect terms
  - We have used a CRF(Conditional Random Field) to classify the aspect terms
  - The classifier is trained with the following set of features: a)word information,b)Part-of-Speech (PoS) tag information c)previous chunk label information,d)Prefixes and suffixes information
  - We were able to achieve an accuracy of 80%
- Output : ['O', 'O', 'O', 'O', 'B-A', 'O', 'O', 'O', 'O', 'B-A', 'O' 'O']
- Aspects : ['food', 'perks']

Pipeline

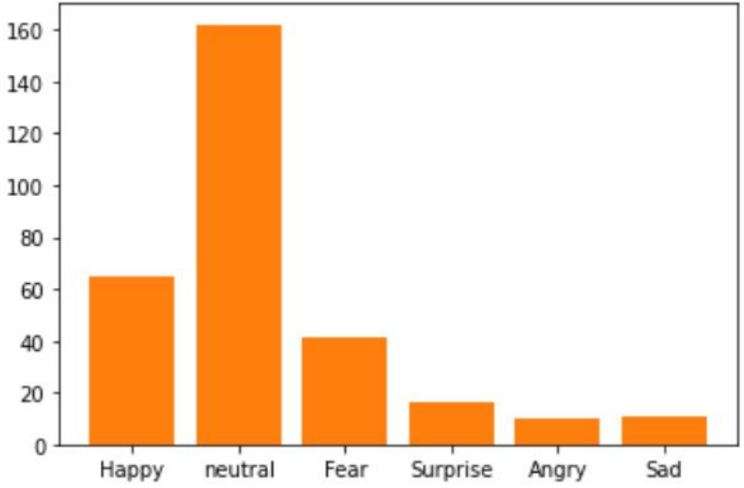
- **Dependency word extractor from aspects**
  - Extracted emotion related words using stanford nlp stanza dependency parser
- **Emotion Tagger based on the words extracted**
  - Tagging all the aspects with a particular emotion based on the dependent words extracted
  - 4 different types of emotion tagging methods
    - NRC Lexicon
    - text2emotion library
    - Tf-idf SVM based
    - Logistic Regression
- **Mapping the aspect emotion to positive or negative polarity**
  - Trust, surprise, happy, joy - positive
  - Fear, anger, disgust, sadness - negative

Results

- NRC Lexicon
  - Precision = 0.697
  - Recall = 0.497
  - f1-score = 0.580
- SVM
  - Precision = 0.620
  - Recall = 0.442
  - f1-score = 0.516
- Text2emotion
  - Precision = 0.643
  - Recall = 0.458
  - f1-score = 0.535
- Logistic Regression
  - Precision = 0.674
  - Recall = 0.480
  - f1-score = 0.561

Analysis

- Aspect extraction module is efficient in detecting aspects correctly most often with an accuracy of 80% as stated before
- The emotion tagger module for all 4 different methods are detecting ‘neutral’ most frequently which is not actually the case
- This is attributed to the dependency words that were extracted were only part of sentences/words which are not well defining or explaining that aspect
- Dependency words extractor part -Bottleneck
    - Improving or changing methodology
    - Using other DL/attention based methods can be looked into



Future Scope

- The dependency word extractor can be modified using Deep learning based methods such as attention framework to take into consideration all the context present around the aspects
- Combining with the current sentiment analysis techniques to have a better classification of emotion
- Aspect based Emotion tagged dataset can be useful for various paradigms of emotion and sentiment analysis

Assignment 3: Constituency parsing

Tools Used:

- **Benepar parser** for generating constituency parse tree

Input: Sentence string

Output: **CP tree object**

Example:

Input String:

Vinken will join the board as a nonexecutive director

Output: tree object in the below form

```
(S
  (NP (NNP Vinken))
  (VP
    (MD will)
    (VP
      (VB join)
      (NP (DT the) (NN board))
      (PP (IN as) (NP (DT a) (JJ nonexecutive)
(NN director))))))
```

Assignment 3: CP to DP

Paper Reference:

- Johansson, Richard, and Pierre Nugues. "Extended constituent-to-dependency conversion for English." (2007).

Methodology: (from lecture slides - Speech and Language Processing, Jurafksy & Martin, Ch-15, 2019)

1. Mark the head child of each node in a phrase structure, using the appropriate head rules.
2. In the dependency structure, make the head of each non-head child depend on the head of the head-child.

Assignment 3: CP to DP (Output examples)

INPUT: ***Vinken will join the board as a nonexecutive director***

OUTPUT: Actual code output

Head == Label ==> **modifier**

- join == nsubj ==> Vinken
- join == aux ==> will
- join == dobj ==> board
- join == prep ==> as
- board == det ==> the
- as == pobj ==> director
- director == det ==> a
- director == amod ==> nonexecutive

Actual output f**or verification** using spacy dependency parsing