Sentiment Analysis & Opinion Mining

:

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CSE634

DATA MINING

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Introduction

What people think?

- Influence of others opinion on our decision-making process.
- Earlier sources of opinions – friends, relatives, customer support etc.
- Todays sources :
  1. Easier to collect opinions from people around the world because of internet.
  2. Review sites – CNET.
  3. Ecommerce sites – Amazon, ebay.
  4. Online opinion sites – Tripadvisor, Yelp.
  5. Social Media – Facebook, Twitter.

References : https://globallogic.com/wp-content/uploads/2014/10/Introduction-to-Sentiment-Analysis.pdf

"People will forget what you said, people will forget what you did, but people will never forget how you made them feel." --- Maya Angelou.

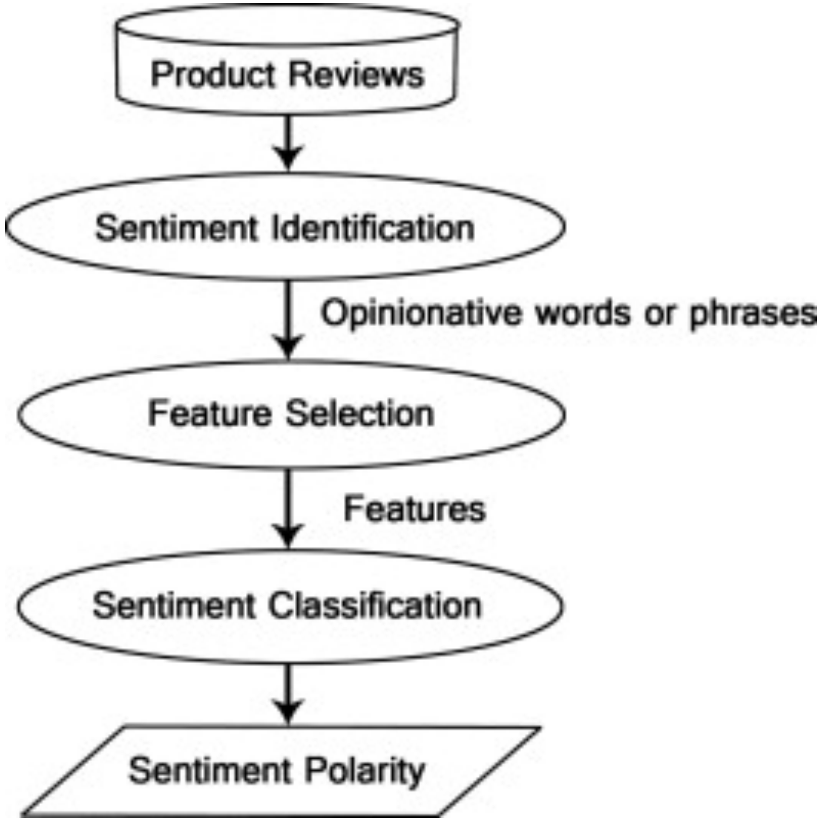
- According to a recent study conducted by Mckinsey, After a positive customer experience, more than 85 percent of customers purchased more. After a negative experience, more than 70 percent purchased less.
- How do the businesses ensure that their customers receive superior service?
- How can they use the feedback from different customers to make their products better?
- How can an organization know whether it's campaign is a success or a failure?
- How can a firm know about the success/failure about it's newly released product?

Reference : https://towardsdatascience.com/five-practical-use-cases-of-customer-sentiment-analysis-for-nps-a3167ac2caaa

The Answer is Sentiment Analysis or in other words Opinion Mining

What is it?

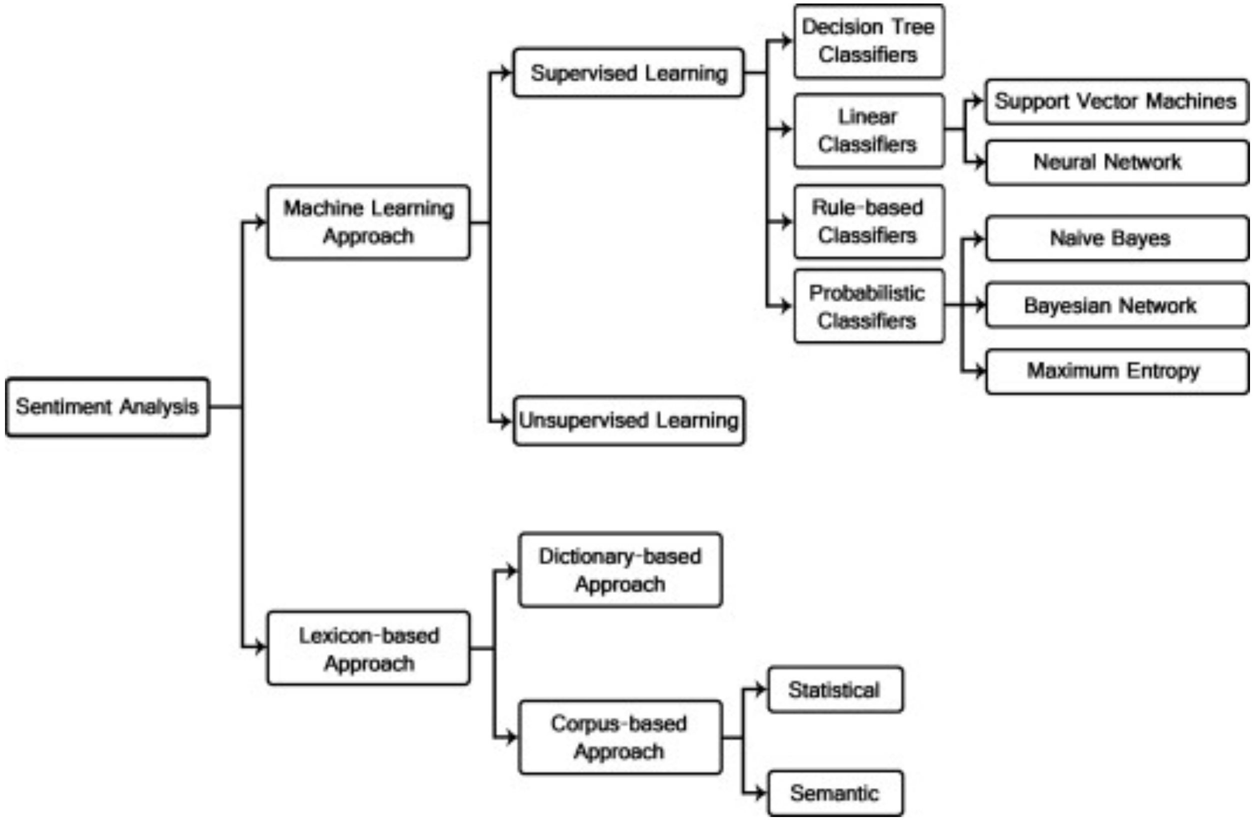
- Sentiment – Feeling or emotion
- Analysis – Survey or study about something
- Sentiment Analysis – Computational Study of people's opinions, attitudes and emotions toward an entity
- The target of Sentiment Analysis/Opinion Mining is to find opinions, identify the sentiments they express, and then classify their polarity according to the adjacent figure.



Reference : https://www.sciencedirect.com/science/article/pii/S2090447914000550

Classification Levels

- A type of Classification Process.
- Three main classification levels
  1. Document level – Ex : “I bought an iPhone a few days ago. It is such a nice phone, although a little large. The touch screen is cool. The voice quality is clear too. I simply love it!”
  2. Sentence level – Ex : “iPhone sales are doing well in this bad economy.”
  3. Aspect level – Ex : “The voice quality of this phone is not good, but the battery life is long”
- Different Classification Techniques



Reference : https://www.sciencedirect.com/science/article/pii/S2090447914000550

Sentiment Classification Techniques

Sentiment classification techniques

Sentiment classification Techniques can be roughly divided into:

1. Machine Learning approach

- ✓ *Supervised*
- ✓ *Unsupervised*

2. Lexicon based approach

- *Dictionary-based approach*
- *Corpus-based approach*

Ref: https://www.sciencedirect.com/science/article/pii/S2090447914000550

Lexicon-based approach

- Many Sentiment Analysis tasks employ ***Opinion words***.
  - *Positive Opinion words* express some desired states. (e.g. *great, fantastic*)
  - *Negative Opinion words* some undesired states. (e.g. *bad, dull*)
- There are also opinion phrases and idioms which together are called ***opinion lexicon***. (e.g. *cost me an arm and a leg*)
- Approaches:
  - ***Dictionary-based approach***
  - ***Corpus-based approach***

Ref: https://www.sciencedirect.com/science/article/pii/S2090447914000550

Dictionary-based approach

Dictionary-based approach

- A small set of opinion words is *collected manually* with known orientations.
- This set is *grown* by searching in the well known corpora(WordNet or thesaurus) for their synonyms and antonyms.
- The newly found words are *added* to the seed list then the next iteration starts.
- The iterative process *stops* when no new words are found.

After the process is completed, *manual inspection* can be carried out to remove or correct errors.

Ref: https://www.sciencedirect.com/science/article/pii/S2090447914000550

Dictionary-based approach

- How is the orientation of an *opinion word* predicted?
  - In general, adjectives share the same orientation as their synonyms and opposite orientations as their antonyms.

```
Procedure OrientationPrediction(adjective_list, seed_list)
begin
  do {
    size1 = # of words in seed_list;
    OrientationSearch(adjective_list, seed_list);
    size2 = # of words in seed_list;
  } while (size1 ≠ size2);
end
```

```
Procedure OrientationSearch(adjective_list, seed_list)
begin
  for each adjective wi in adjective_list
  begin
    if (wi has synonym s in seed_list)
      { wi's orientation= s's orientation;
       add wi with orientation to seed_list; }
    else if (wi has antonym a in seed_list)
      { wi's orientation = opposite orientation of a's
                          orientation;
       add wi with orientation to seed_list; }
  endfor;
end
```

Figure 5: Predicting the semantic orientations of opinion words

Ref: https://www.cs.uic.edu/~liub/publications/kdd04-revSummary.pdf

Dictionary-based approach

- How is the orientation of an *opinion sentence* predicted?
  - In general, we use the dominant orientation of the opinion words in the sentence to determine the orientation of the sentence.

Ref: https://www.cs.uic.edu/~liub/publications/kdd04-revSummary.pdf

```
Procedure SentenceOrietation()
begin
   for each opinion sentence s_i
   begin
      orientation = 0;
      for each opinion word op in s_i
         orientation += wordOrientation(op, s_i);
         /*Positive = 1, Negative = -1, Neutral = 0*/
      if (orientation > 0)  s_i's orientation = Positive;
      else  if (orientation < 0) s_i's orientation = Negative;
            else {
              for each feature f in s_i
                orientation +=
                wordOrientation(f's effective opinion, s_i);
            if (orientation > 0)
               s_i's orientation =  Positive;
            else if (orientation < 0)
                  s_i's orientation = Negative;
               else s_i's orientation = s_i-1's orientation;
           }
   endfor;
end
```

```
Procedure wordOrientation(word, sentence)
begin
   orientation = orientation of word in seed_list;
   If (there is NEGATION_WORD appears closely
        around word in sentence)
      orientation = Opposite(orientation);
end
```

Figure 7: Predicting the orientations of opinion sentences

Dictionary-based approach: Example

The following shows an example summary for the feature "*picture*" of a *digital camera*.

- *Feature*: *picture*
  - *Positive*: 12
    - Overall this is a good camera with a really good picture clarity.
    - The pictures are absolutely amazing - the camera captures the minutest of details.
    - After nearly 800 pictures I have found that this camera takes incredible pictures.

    …
  - *Negative*: 2
    - The pictures come out hazy if your hands shake even for a moment during the entire process of taking a picture.
    - Focusing on a display rack about 20 feet away in a brightly lit room during day time, pictures produced by this camera were blurry and in a shade of orange.

Drawback:

The dictionary based approach has a major disadvantage which is the *inability* to find opinion words with *domain and context specific* orientations.

Ref: https://www.cs.uic.edu/~liub/publications/kdd04-revSummary.pdf

Corpus-based approach

Corpus-based approach

- The Corpus-based approach helps to solve the problem of finding opinion words with ***context specific orientations***.
- Its methods depend on syntactic patterns or patterns that occur together along with a seed list of opinion words to find other opinion words in a large corpus.
- They started with a list of seed opinion adjectives, and used them along with a set of **linguistic constraints** (the constraints are for connectives like AND, OR, BUT, EITHER-OR…) to identify additional adjective opinion words and their orientations.

Ref: https://www.sciencedirect.com/science/article/pii/S2090447914000550

Corpus-based approach

- The conjunction *AND* for example says that conjoined adjectives usually have the *same orientation*(***sentiment consistency***)
- There are also adversative expressions such as *but*, *however* which are indicated as ***opinion changes***.
- In order to determine if two ***conjoined adjectives*** are of the same or different orientations, learning is applied to a large corpus.
- Then, the links between adjectives form a graph and **clustering** is performed on the graph to produce two sets of words: positive and negative.
- Lets discuss how the corpus-based approach is performed using ***Semantic approach,*** an approach which used in many applications to build a lexicon model for the description of verbs, nouns and adjectives to be used in Sentiment Analysis.

Ref: https://www.sciencedirect.com/science/article/pii/S2090447914000550

Semantic approach

- The ***Semantic approach*** gives sentiment values directly and relies on different principles for computing the similarity between words.
- This principle gives similar sentiment values to *semantically close words*.
- We shall discuss an algorithm that, given a topic, automatically finds the people who hold opinions about that topic and the sentiment of each opinion.
- The algorithm contains a module for determining word sentiment and another for combining sentiments within a sentence.
- The algorithm describes an opinion as a quadruple ***[Topic, Holder, Claim, Sentiment]*** in which the Holder believes a Claim about the Topic, and in many cases associates a Sentiment, such as good or bad, with the belief.

Ref: http://www.aclweb.org/anthology/C04-1200

Semantic approach: Algorithm

Given a topic and a set of texts, the system operates in four steps:

1. First it selects sentences that contain both the topic phrase and holder candidates.
2. Next, the holder-based regions of opinion are delimited.
3. Then the sentence sentiment classifier calculates the polarity of all sentiment-bearing words individually.
4. Finally, the system combines them to produce the holder's sentiment for the whole sentence.

Ref: http://www.aclweb.org/anthology/C04-1200

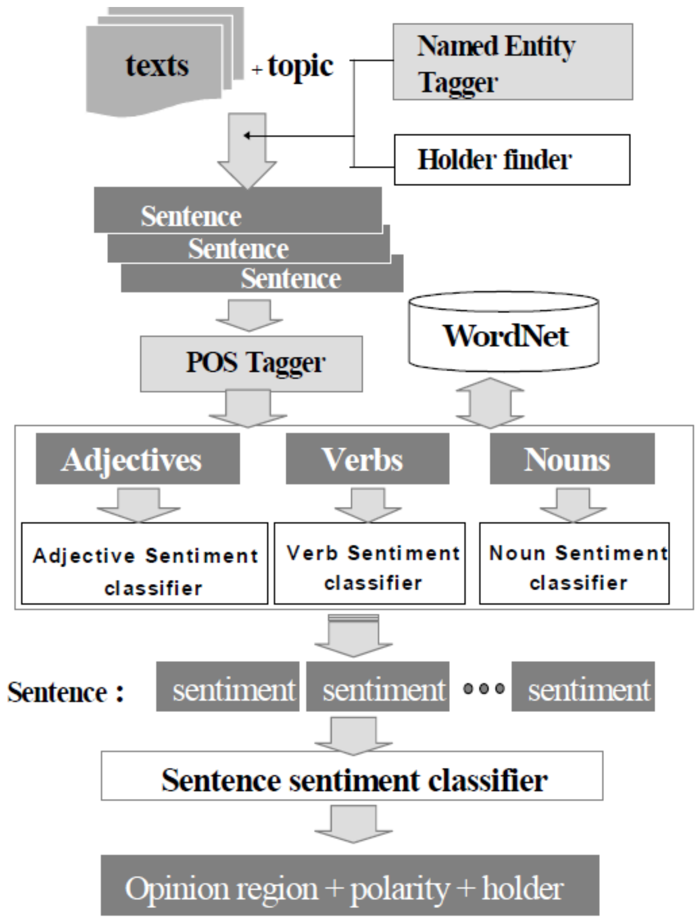


Figure 1: System architecture.

Semantic approach: Algorithm

Word Sentiment Classifier:

- The basic approach is to assemble a small amount of seed words by hand, sorted by polarity into two lists—positive and negative—and then to grow this by adding words obtained from WordNet.
- This model assumes that synonyms of positive words are mostly positive and antonyms mostly negative. e.g., the positive word "good" has synonyms "virtuous, honorable, righteous" and antonyms "evil, disreputable, unrighteous".
- For each seed word, this model extracts from WordNet its expansions and adds them back into the appropriate seed lists.

Ref: http://www.aclweb.org/anthology/C04-1200

Semantic approach: Algorithm

- Some common words such as "great", "strong", "take", and "get" occurred many times in both positive and negative categories.
- This indicated the need to develop a measure of strength of sentiment polarity to determine how strongly a word is positive and also how strongly it is negative.

Model:

- To compute the probability P(w|c) of word w given a sentiment class c, we count the occurrence of w's synonyms in the list of c. The intuition is that the more synonyms occurring in c, the more likely the word belongs.
- We compute both positive and negative sentiment strengths for each word and compare their relative magnitudes as you can see in the table.

Ref: http://www.aclweb.org/anthology/C04-1200

abysmal : NEGATIVE [+ : 0.3811][- : 0.6188]
adequate : POSITIVE [+ : 0.9999][- : 0.0484e-11]
afraid : NEGATIVE [+ : 0.0212e-04][- : 0.9999]
ailing : NEGATIVE [+ : 0.0467e-8][- : 0.9999]
amusing : POSITIVE [+ : 0.9999][- : 0.0593e-07]
answerable : POSITIVE [+ : 0.8655][- : 0.1344]
apprehensible: POSITIVE [+ : 0.9999][- : 0.0227e-07]
averse : NEGATIVE [+ : 0.0454e-05][- : 0.9999]
blame : NEGATIVE [+ : 0.2530][- : 0.7469]

Table 2: Sample output of word sentiment

$$\arg\max_c P(c \mid w) = \arg\max_c P(c)P(w \mid c)$$

$$= \arg\max_c P(c)\frac{\sum_{i=1}^{n} count(syn_i, c)}{count(c)}$$

Semantic approach: Algorithm

Sentence Sentiment Classifier:

- We are interested in the sentiments of the Holder about the Claim. Manual analysis showed that such sentiments can be found most reliably close to the Holder; without either Holder or Topic/Claim nearby as anchor points.
- Near each Holder we then identify a region in which sentiments would be considered; any sentiments outside such a region we take to be of undetermined origin and ignore.

Ref: http://www.aclweb.org/anthology/C04-1200

Semantic approach: Algorithm

Sentiment Region: How large should a region be?

- The algorithm defines the sentiment region in various ways as shown below and experiments proved that with a manually identified topic and holder, the region ***Window4*** (from Holder to sentence end) performs better than other regions.

Window1: full sentence

Window2: words between Holder and Topic

Window3: window2 ± 2 words

Window4: window2 to the end of sentence

Ref: http://www.aclweb.org/anthology/C04-1200

Semantic approach: Algorithm

Classification Models: We have three models to assign a sentiment category to a given sentence.

Model 0: Simply considers the polarities of the sentiments, not the strengths. Here the system assigns the same sentiment to both “the California Supreme Court **agreed** that the state’s new term-limit law was **constitutional**” and “the California Supreme Court **disagreed** that the state’s new term-limit law was **unconstitutional**”.

Model 1: This model computes the harmonic mean (average) of the sentiment strengths in the region:

Model 2: This model computes the geometric mean of the sentiment strengths in the region.

Here **n(c)** is the number of words in the region whose sentiment category is **c**.

✓ If a region contains more and stronger positive than negative words, the sentiment will be positive.

Model 1:

$$P(c \mid s) = \frac{1}{n(c)} \sum_{i=1}^{n} p(c \mid w_i),$$

$$\text{if } \underset{j}{\text{argmax}} \; p(c_j \mid w_i) = c$$

Model 2:

$$P(c \mid s) = 10^{n(c)-1} \times \prod_{i=1}^{n} p(c \mid w_i),$$

$$\textit{if } \underset{j}{\text{argmax}} \; p(c_j \mid w_i) = c$$

Ref: http://www.aclweb.org/anthology/C04-1200

Semantic approach: Examples

a) Public officials throughout California have condemned a **U.S. Senate** vote Thursday to exclude *illegal aliens* from the 1990 census, saying the action will shortchange California in Congress and possibly deprive the state of millions of dollars of federal aid for medical emergency services and other programs for poor people.

- *TOPIC* : illegal alien
- *HOLDER* : U.S. Senate
- *OPINION REGION*: vote/NN Thursday/NNP to/TO exclude/VB illegal/JJ aliens/NNS from/IN the/DT 1990/CD census,/NN
- *SENTIMENT_POLARITY*: **negative**

Ref: http://www.aclweb.org/anthology/C04-1200

Semantic approach: Examples

b) For that reason and others, the Constitutional Convention unanimously rejected *term limits* and the **First Congress** soundly defeated two subsequent term-limit proposals.

- *TOPIC* : term limit
- *HOLDER* : First Congress
- *OPINION REGION*: soundly/RB defeated/VBD two/CD subsequent/JJ term-limit/JJ proposals./NN
- *SENTIMENT_POLARITY*: **negative**

Ref: http://www.aclweb.org/anthology/C04-1200

Applications

Applications

Business and Organizations:

It can be used to give your business valuable insights into how people feel about your product brand or service.

Opinion Search: Interested in other people's opinion when purchasing a product, using a service, tracking political topics

Ads placements: Placing ads in user generated content

Place an ad when one praises a product

Place an ad from a competitor if one criticizes a product

Corporate network: By applying it to your email server, emails could be monitored for their general "tone".

Ex: **Tone Detector** is an Outlook Add-in that determines the "tone" of your email as you type

Reference : https://www.growthaccelerationpartners.com/blog/sentiment-analysis/

What Makes Sentiment Analysis Inaccurate?

What Makes Sentiment Analysis Inaccurate ?

- The first problem is that **some sentences aren't easy to analyze**.
- **Language is complex**. It would be too naive to oversimplify language thinking that its underlying sentiment can always be accurately examined by a machine or an algorithm.
- There are **five** main factors that currently stop us from relying blindly on tools for sentiment analysis:

Context:

A positive or negative sentiment word can have the opposite connotation depending on context.

Ex: "I've **done a great job**".

"My internet provider **does a great job** when it comes to stealing money from me", doing a great job is no longer a positive thing, based on the context ("stealing money from me").

Reference : https://brnrd.me/posts/sentiment-analysis-never-accurate

What Makes Sentiment Analysis Inaccurate ?(Contd.)

Sentiment Ambiguity: A sentence with a positive or negative word doesn't necessarily express any sentiment.

Ex: "*Can you recommend a good tool I could use?*" doesn't express any sentiment,

Likewise, sentences without sentiment words can express sentiment too.

Ex: "*This browser uses a lot of memory*".

Sarcasm: A positive or negative sentiment word can switch sentiment if there is sarcasm in the sentence.

Ex: "Sure, I'm **happy** for my browser to crash right in the middle of my coursework.

We can detect the sarcasm mainly from how the sentence starts with "sure", and the context (we know for a fact that a browser crashing is negative).

Reference : https://brnrd.me/posts/sentiment-analysis-never-accurate

What Makes Sentiment Analysis Inaccurate ?(Contd.)

Comparatives: Social listening tools often misunderstand comparative statements.

Ex: "*Pepsi is much better than Coke*"?

Most social listening tools aren't intelligent enough to "pick sides", leaving them to pick the sentiment based on keywords.

Regional Variations: A word can change sentiment and meaning depending on the language used.

Ex: The word "sick. *That is a sick song!*" vs. "*I'm not feeling well at all, I might be sick*").

For words like '*quite*', '*rather*', '*pretty*': in British English those words take the meaning of "*fairly*", while in American English they take the meaning of "*very*".

Reference : https://brnrd.me/posts/sentiment-analysis-never-accurate

What Makes Sentiment Analysis Inaccurate ?(Contd.)

- The biggest threat to accuracy: **human concordance**
- Even humans don’t agree universally with one another on anything subjective.
- Despite its current flaws, social sentiment has very high potential.
- While it’s easy to treat it as a “soft metric”, it’s very useful when used in context
- Yes you’ve received a positive review, but what does it mean for your brand? What are the underlying opinions behind that specific content?
- **In the right hands, sentiment can be the key to various social analyses, predictions, and ultimately a solid insight into your social performance**

Reference : https://brnrd.me/posts/sentiment-analysis-never-accurate

Research paper

How Do Users Like This Feature? A Fine Grained Sentiment Analysis of App Reviews

Emitza Guzman
Walid Maalej

Published in: Requirements Engineering Conference (RE), 2014 IEEE 22nd International
Date Added to IEEE *Xplore*: 29 September 2014

Reference : https://ieeexplore.ieee.org/document/6912257/

Big Picture

- All major platforms are migrating towards mandating the use of official store for distributing third party applications.
- On an average more than 7000 reviews per day are gathered for popular apps like facebook, instagram on iOS and Android combined.
- User reviews contain mix sentiments for different app features.
- Mining on these reviews to extract such knowledge can play major role in driving the further development and releases and in turn better future for the organization.

Broken on Android

Connectivity Issues

Unsatisfied

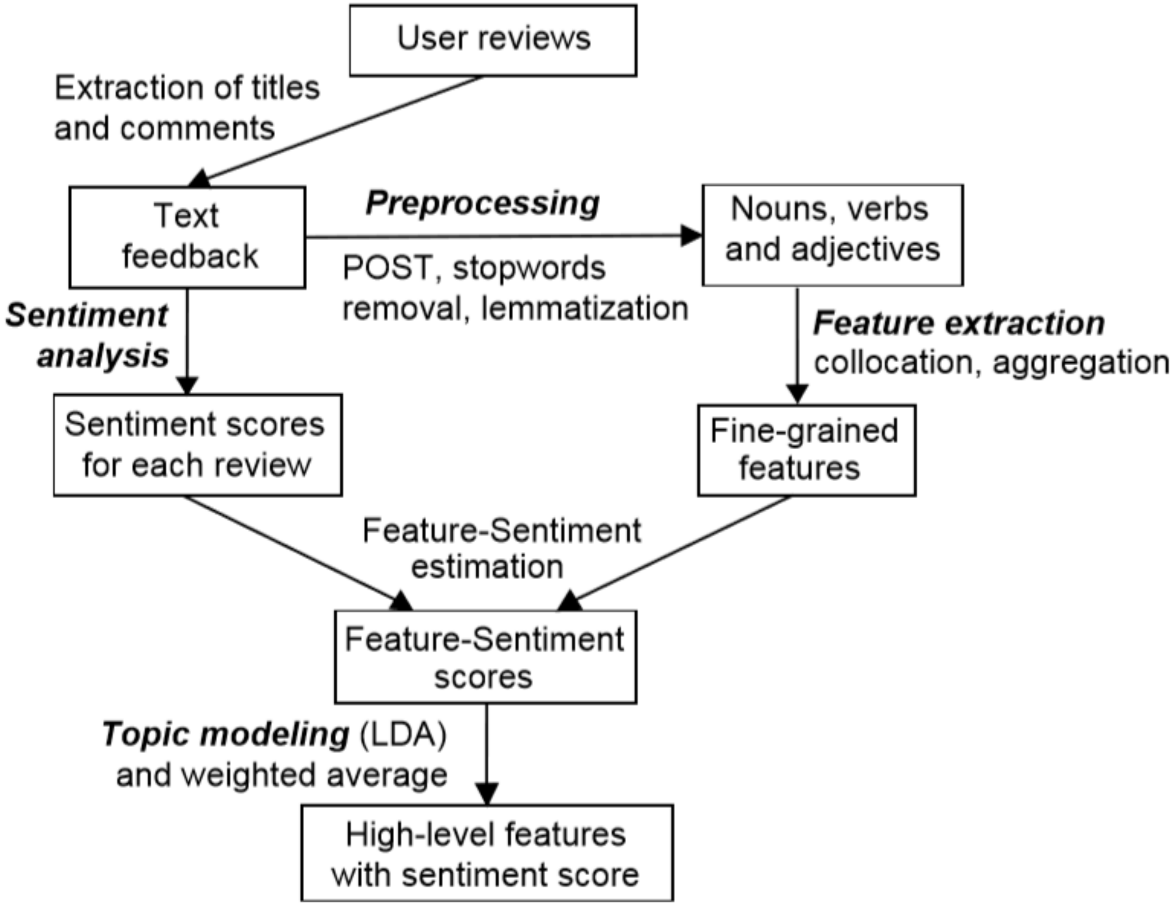
Too Expensive

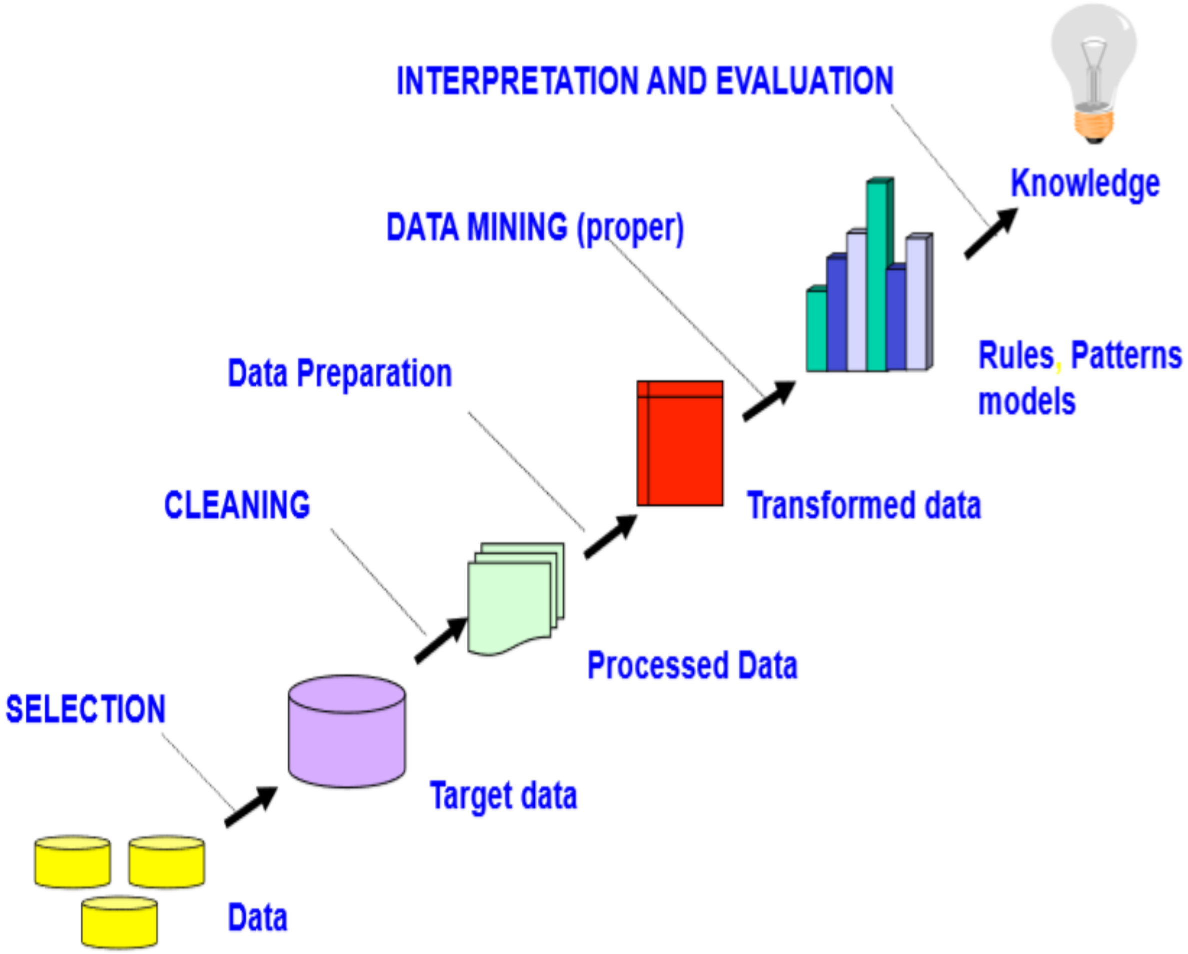
Crashing

Bugs

Reference : https://appbot.co/app-review-sentiment-analysis

Sentimental analysis approach in comparison with KDD





References : http://www3.cs.stonybrook.edu/~cse634/L1ch1introd.pdf; https://ieeexplore.ieee.org/document/6912257/

Evaluation

- The approach was evaluated on 7 popular apps with diverse users with different age groups.(AngryBirds, Dropbox, Evernote, Whatsapp, TripAdvisor, Pinterest, PicsArt).
- The metrics used for evaluation were precision, recall and F-measure.
- Precision up to 91% (59% average) and a recall up to 73% (51% average) was obtained.

References : https://ieeexplore.ieee.org/document/6912257/

Use Case
Uber: A deep dive analysis

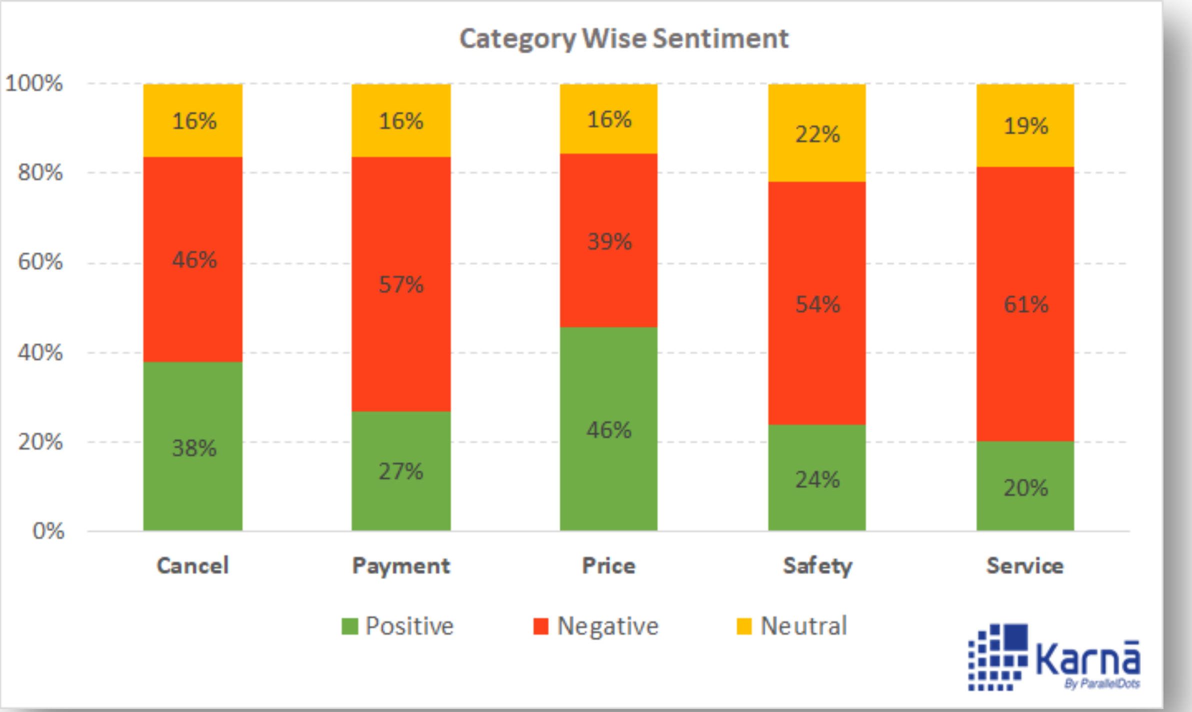
Uber: A deep dive analysis

- A study was done regarding feedbacks for Uber on the online conversations happening on digital media about a few product themes: **Cancel, Payment, Price, Safety and Service**
- For a wide coverage of data sources, data was taken from latest comments on Uber's official Facebook page, Tweets mentioning Uber and latest news articles around Uber.
- Here's a distribution of data points across all the channels:
  - Facebook: **34,173** Comments
  - Twitter: **21,603** Tweets
  - News: **4,245** Articles
- A Sentiment analysis algorithm was run on the pre-defined dataset, as discussed earlier, taking the aforementioned categories in account.

Reference : https://towardsdatascience.com/sentiment-analysis-concept-analysis-and-applications-6c94d6f58c17

Uber: A deep dive analysis (contd.)

- **FACEBOOK:**



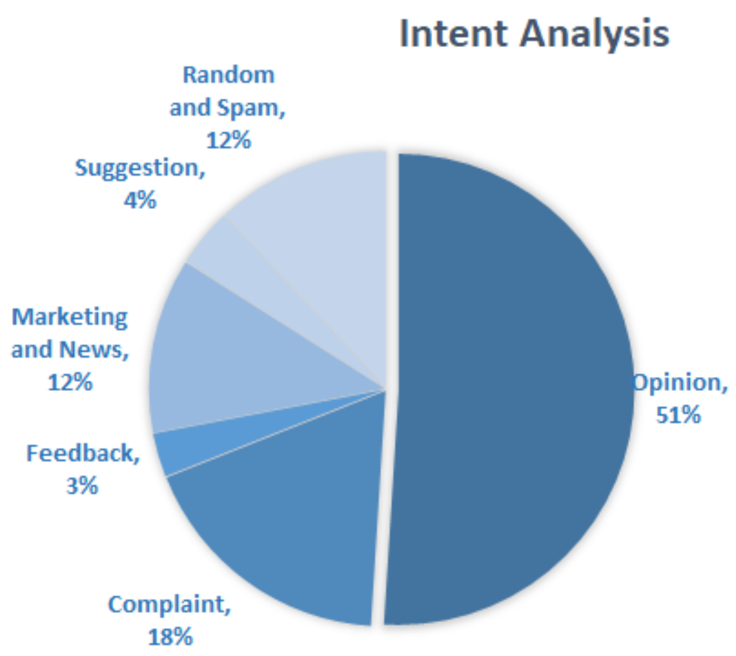
As seen from the analysis, the number of negative comments have outnumbered the positive ones in each category except the **price** for which the numbers are fairly equal.

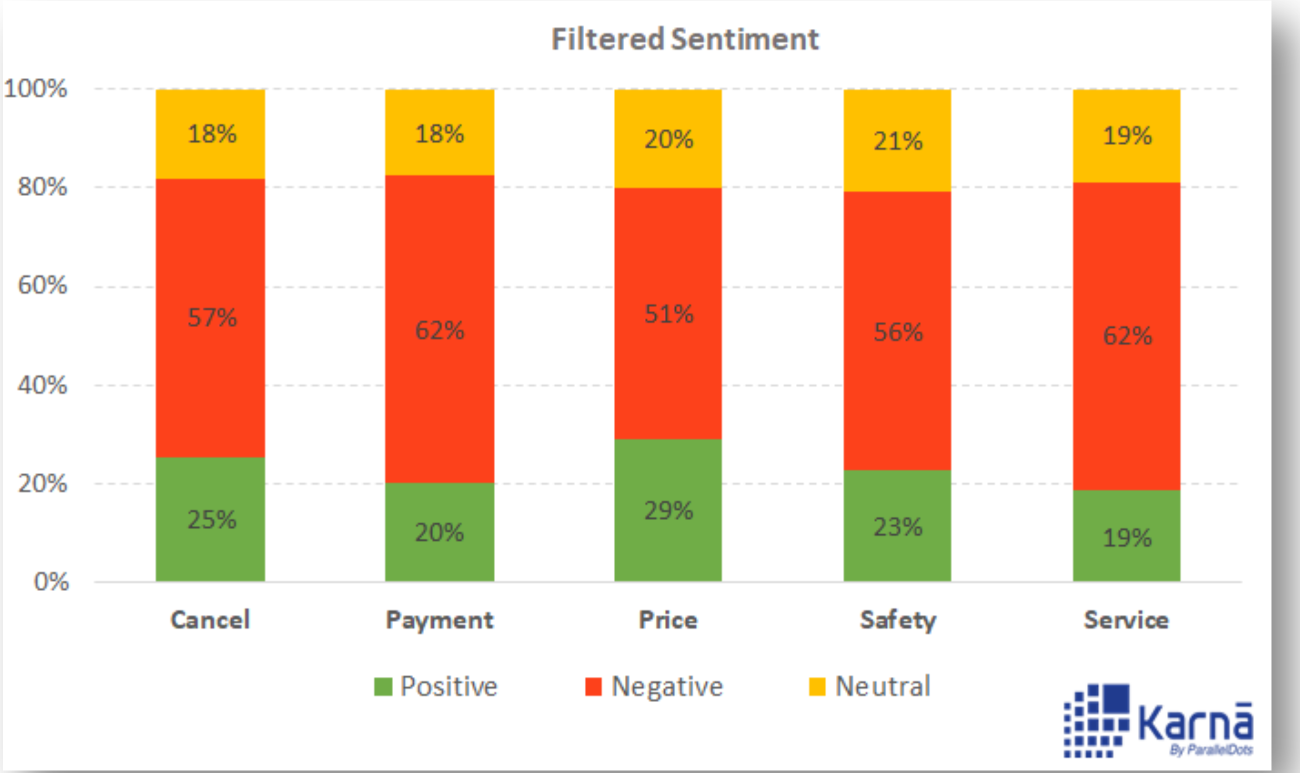
Since the data consists of all the types of input, we need to analyze the intent of each of these comments which will help us analyze only the opinions.

Reference : https://towardsdatascience.com/sentiment-analysis-concept-analysis-and-applications-6c94d6f58c17

Uber: A deep dive analysis (contd.)

- Facebook being a social platform, the comments are crowded *random content, news shares, marketing and promotional content and spam/junk/unrelated content*. Below is a look at the intent analysis on the Facebook comments:

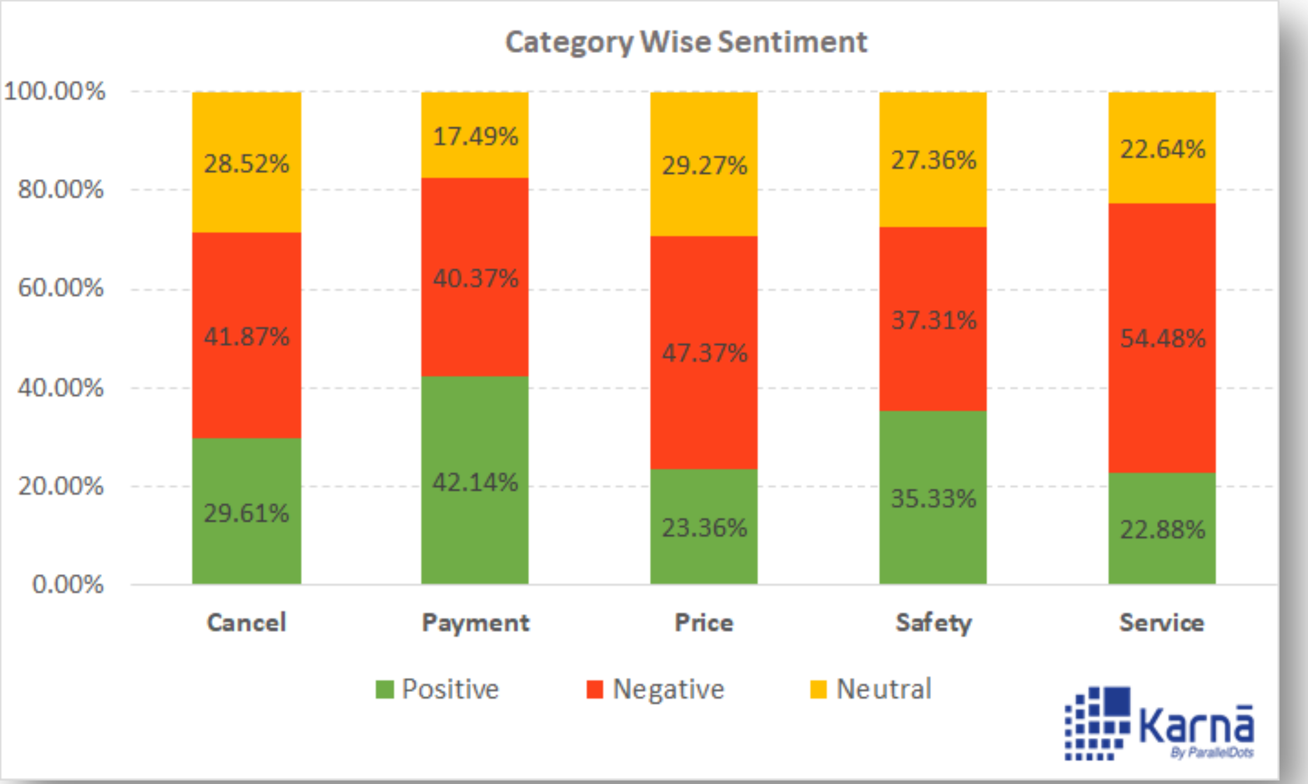


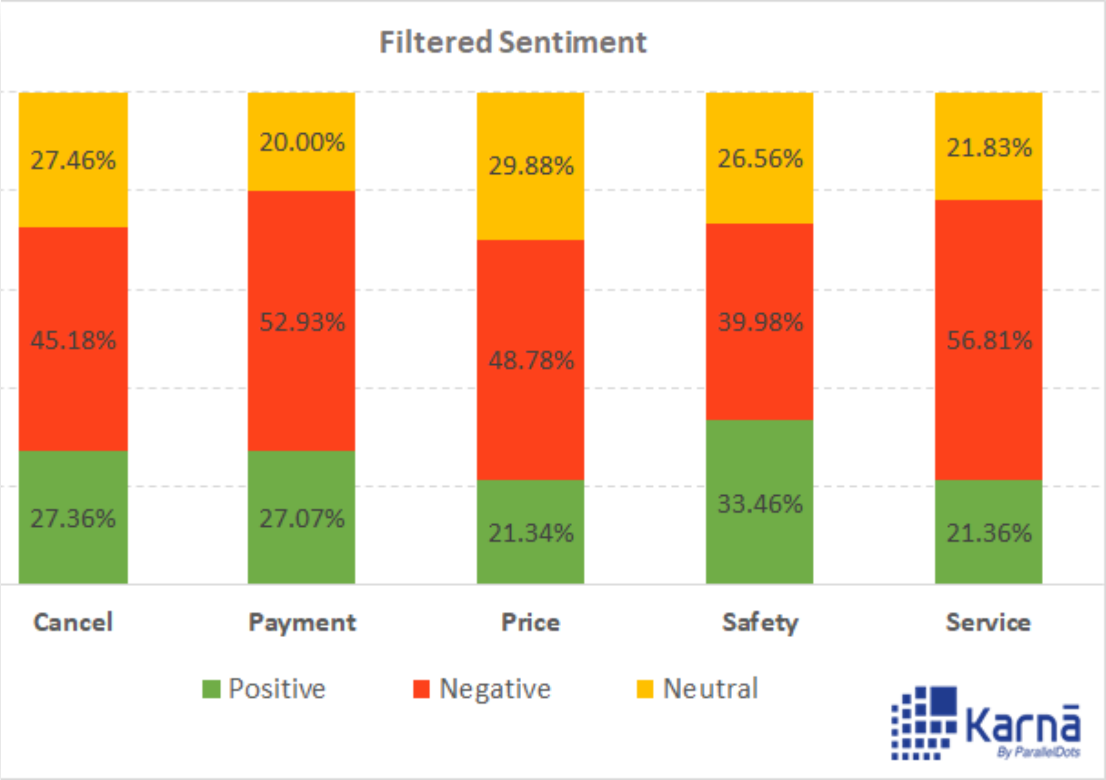


Reference : https://towardsdatascience.com/sentiment-analysis-concept-analysis-and-applications-6c94d6f58c17

Uber: A deep dive analysis (contd.)

- **TWITTER**:





Reference : https://towardsdatascience.com/sentiment-analysis-concept-analysis-and-applications-6c94d6f58c17

Uber: A deep dive analysis (contd.)

TWITTER:

- Such insights are very important for various brands, like Uber, and they can act upon the most critical topics.
- For example, **Service** related Tweets carried the lowest percentage of positive Tweets and highest percentage of Negative ones. Uber can thus analyze such Tweets and act upon them to improve the service quality.
- Alongside, is an example of how is a tweet classified for analysis:

```
…..…….TEXT  ANALYTICS……….
{
  Message "@Uber, the driver (Tony Bridges) was not following
      navigation. I tried to press the SOS Button but the app was
      unresponsive. Utterly irresponsible!!! "
  Intent = "Complaint"
  Emotion = "Angry"
  Sentiment = "Negative"
  Concept = "safety", "mobile application"
  Key Entities = "SOS Button", "Tony Bridges"
  Key Descriptors = "irresponsible" - - - > "app"
}
```

Reference : https://towardsdatascience.com/sentiment-analysis-concept-analysis-and-applications-6c94d6f58c17; https://www.karna.ai/

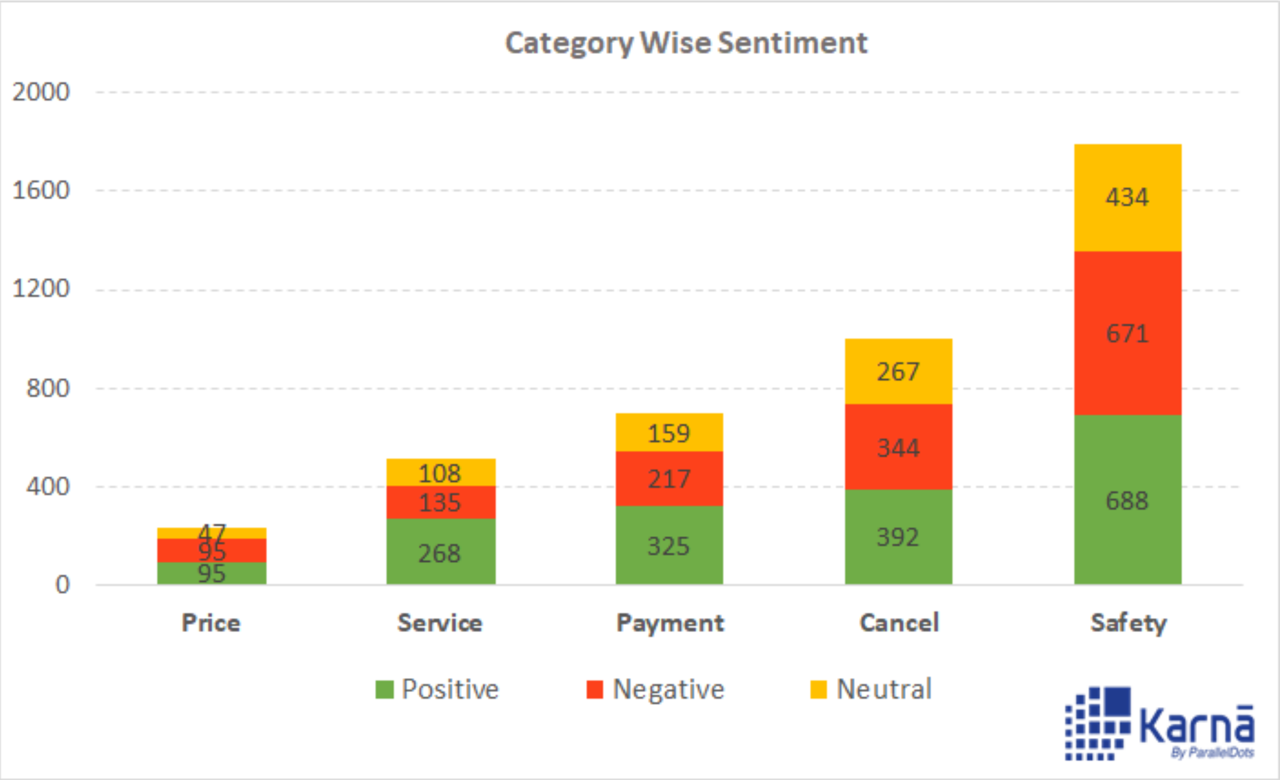
Uber: A deep dive analysis (contd.)

NEWS:

- As we already know, safety has been the most talked about topic in the news. Interestingly, news sentiment is positive overall and individually in each category as well.

CONCLUSION:

- The Uber case study gives a glimpse of the power of Sentiment analysis and also how it can help to improve the services for the company.
- It is better than the overall sentiment and count based metrics of rating.



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- https://www.karna.ai/
- https://www.growthaccelerationpartners.com/blog/sentiment-analysis/
- https://brnrd.me/posts/sentiment-analysis-never-accurate
- https://www.sciencedirect.com/science/article/pii/S2090447914000550
- https://globallogic.com/wp-content/uploads/2014/10/Introduction-to-Sentiment-Analysis.pdf
- https://towardsdatascience.com/five-practical-use-cases-of-customer-sentiment-analysis-for-nps-a3167ac2caaa

Thank you.