A Modern Approach To Feature-based Customer Opinion Mining

By Norbert Eke

My Journey Into Customer Review Information Retrieval

...

How to get from customer reviews to ***insight*** ?

Outline

1.) Introduction
2.) Deep Learning for Text Understanding
3.) Feature-based Opinion Mining
4.) Conclusion

Why should I care about customer reviews ?

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- **51%** of consumers use the Internet even before making a purchase **in shops** (Verdict Research, May 2009) *

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  - Only 12% are prepared to read more than 10 reviews (all from Shrestha, 2016)
- Need a way to interpret the content of the reviews, without reading them all

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- Interpret and categorize the opinions of customers in an automated way

Customer reviews

- Title of review
- Name of reviewer
- Date of reviewing
- Rate given
- Raw, unstructured text

2/10

"one big bad experience"

John Belanger (Canada) 15th May 2017

✅ **Verified Review** | Booked a vacation to Las Vegas with Westjet Vacations, Ottawa to Toronto to Vegas out bound and the reverse on the way home. Flight from Ottawa to Toronto was delayed one hour, a bad start but we were going to have to wait three hours for connection in Toronto, so not to bad. Flight from Toronto to Vegas was one hour late initially. Finally boarded one hour late, taxied to runway and stopped. Eventually we were told that there was a proble with the long range weather radar and we advto return to the terminal and deplane and change aircraft. Eventually we reboarded and took off three hours late. So instead of arriving at 10:30 pm we arrived at 1:30 am. Five days later on the return home we were about one hour late departing Vegas, this then caused us to miss our connecting flight to Ottawa. We were told before we deplaned that everyone connecting to Ottawa were already booked onto the next flight out of Toronto at 9 am. We now had to pick up our luggage which was supposed to be booked through to Ottawa. When we picked up our luggage one piece was now torn and had a broken wheel. When we went to the Westjet desk to get new boarding passes for the flight we were informed that we would now be on a flight departing Toronto at 12:00 pm instead of at 9 am, a four hour delay from our original flight time. We are now waiting in Toronto for our new flight to Ottawa, hopefully it will e on time but I am not very optimistic that this will happen. This was our first time flying Westjet and it will definitely be our last. Nothing but one big bad experience.

Customer reviews

Review text = experience or opinion

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Someone’s experience or opinion

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Word2Vec

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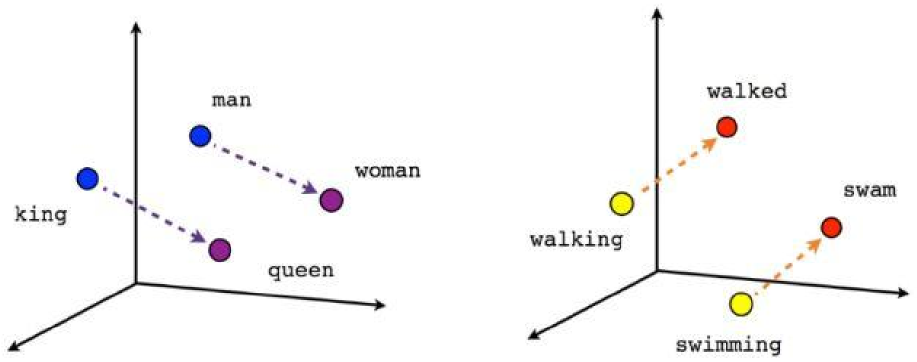
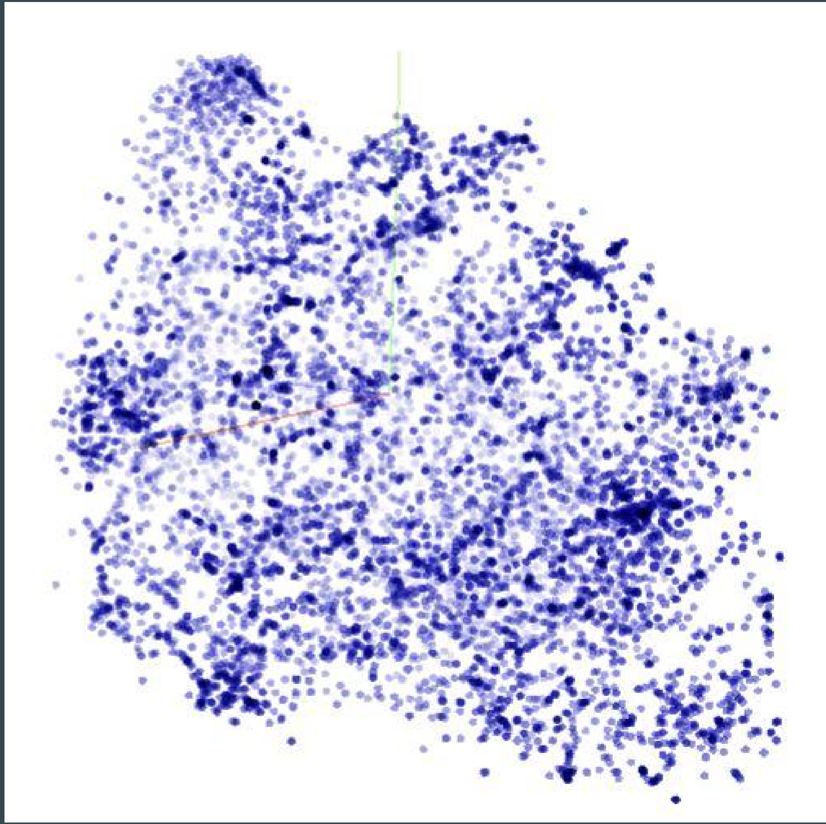


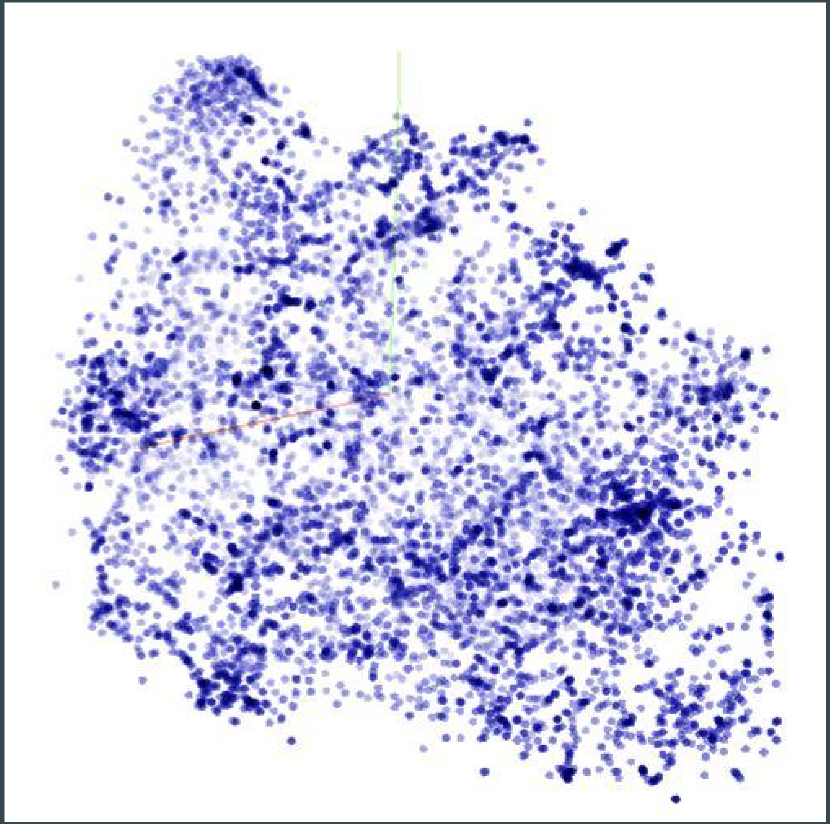
- Computes continuous distributed representation of words
- Creates high dimensional vector representation (word embedding) of each word
- Reconstructs linguistic contexts of words
- Captures the semantic similarity between words

Word Vector Space



- Typically several hundred dimensions

Word Vector Space



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- Each unique word is assigned a corresponding vector in the space

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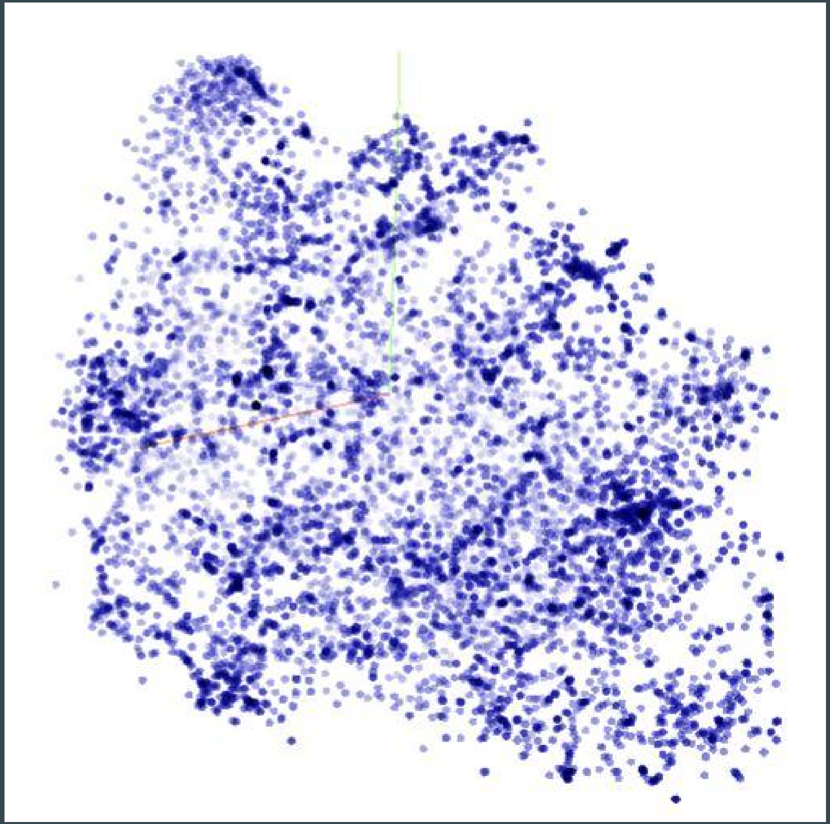
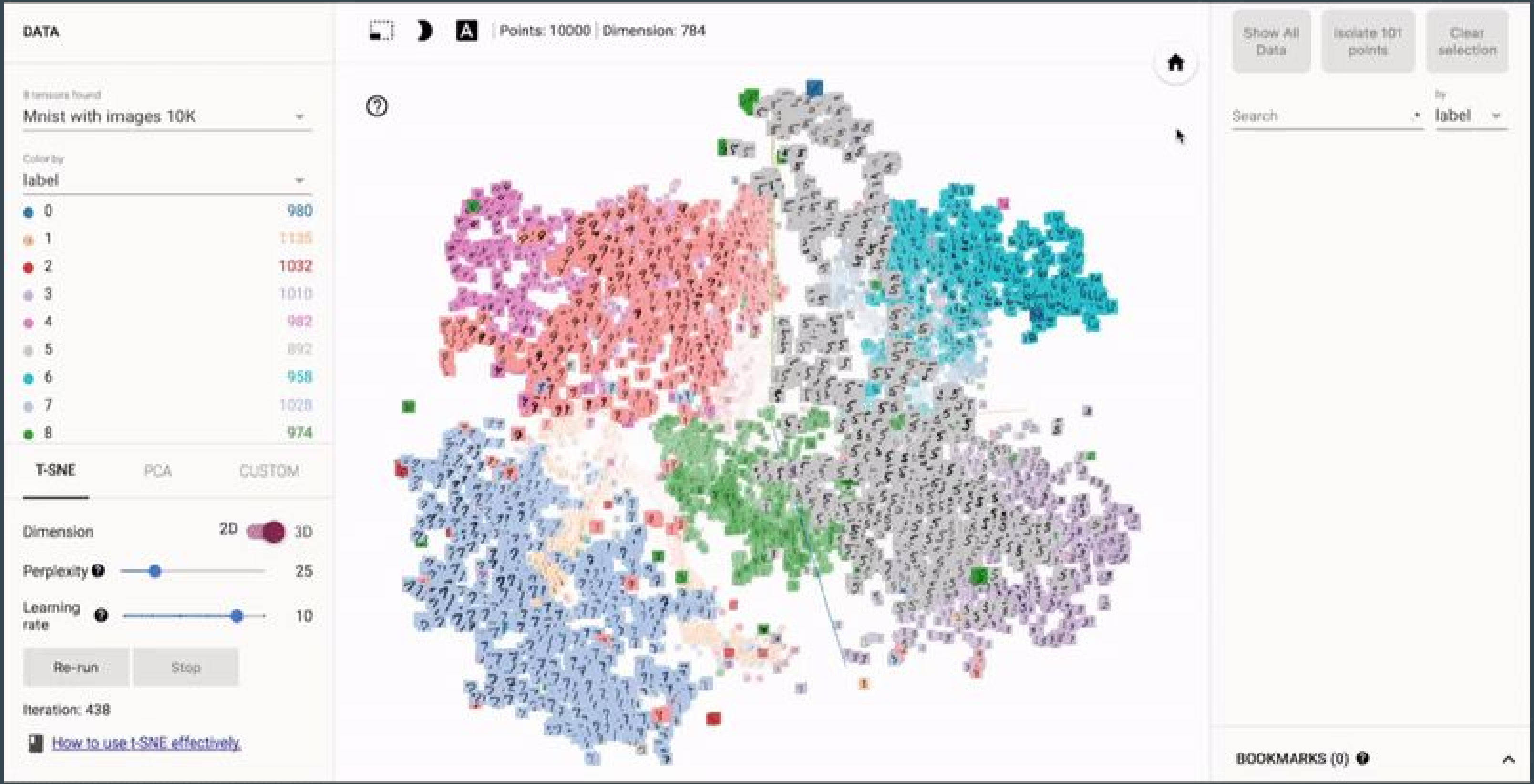


- Typically several hundred dimensions
- Each unique word is assigned a corresponding vector in the space
- Words that share common contexts are located in close proximity to one another

Word Vector Space



Linguistic Regularities in Word Vector Space

Expression	*Nearest token*
Paris - France + Italy	Rome
bigger - big + cold	colder
sushi - Japan + Germany	bratwurst
Cu - copper + gold	Au
Windows - Microsoft + Google	Android
Montreal Canadiens - Montreal + Toronto	Toronto Maple Leafs

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Opinion Mining

- Opinion is a subjective belief, and is the result of emotion or interpretation of facts (https://en.wikipedia.org/wiki/Opinion)

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- Opinion mining is the detection of patterns among opinions (Moghaddam & Ester, 2012)
- Thriving research area (Liu 2012)
  - NLP, ML, data and text mining

Features & Feature based Opinion Mining (FBOM)

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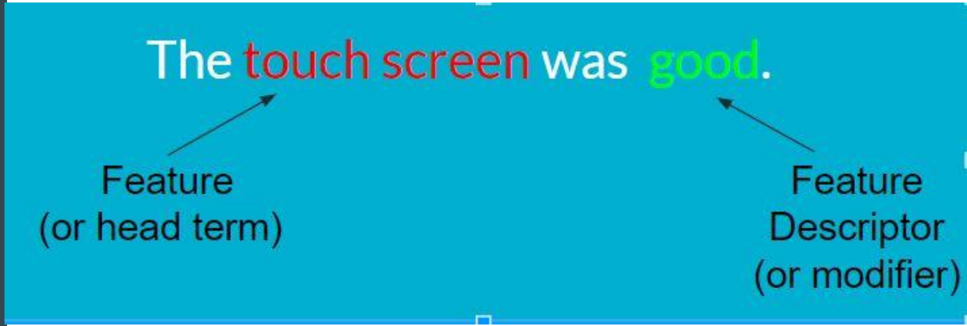
- Feature: characteristic or aspect of product
- Feature based Opinion Mining: opinions patterns about every feature of the product, classified into positive/negative opinions
- FBOM was solved using NLP and text mining, but not Word Vector Spaces

Feature based Opinion Mining sample output

Digital_camera_1:
Feature: **picture quality**
Positive: 253
<individual review sentences>
Negative: 6
<individual review sentences>
Feature: **size**
Positive: 134
<individual review sentences>
Negative: 10
<individual review sentences>

Opinion Phrases



- Opinion Phrase: <head term, modifier>

E.g. <LCD, blurry>, <screen,inaccurate>, <display, poor>

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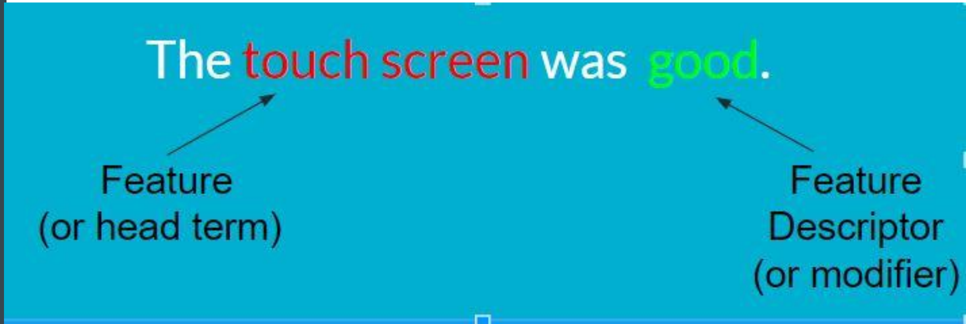

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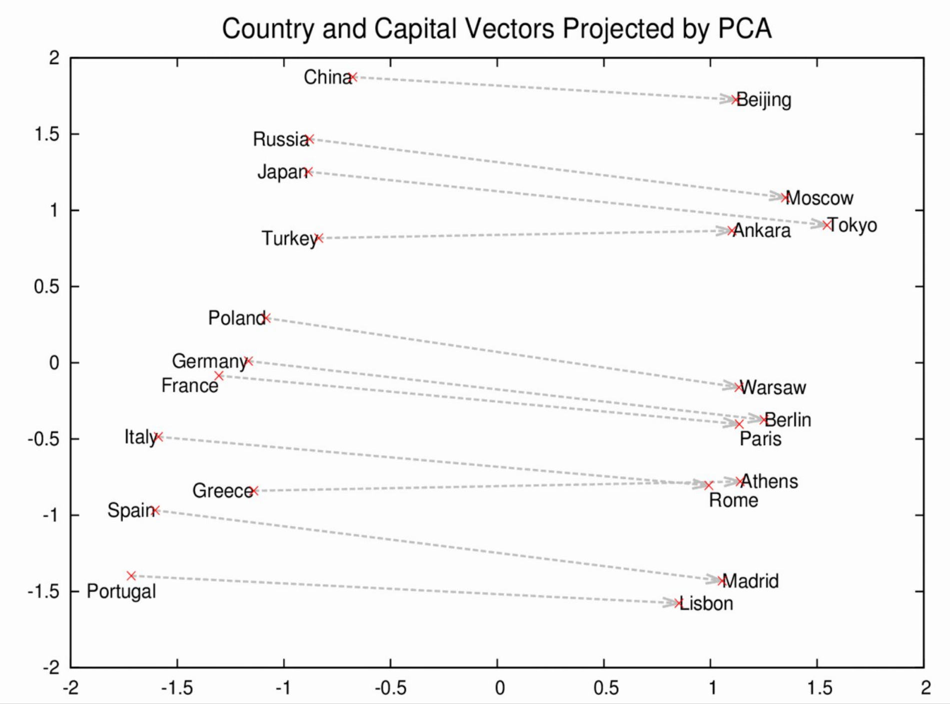
- Main goal is to design a technique that identifies these opinion phrases

What Google did and what we are trying to do



Google found Country - Capital relations

We are trying to find Feature - Descriptor relations

What are our results so far?

Early results from the vector space

- Dimensionality reduction to reduce 300D to 197 D

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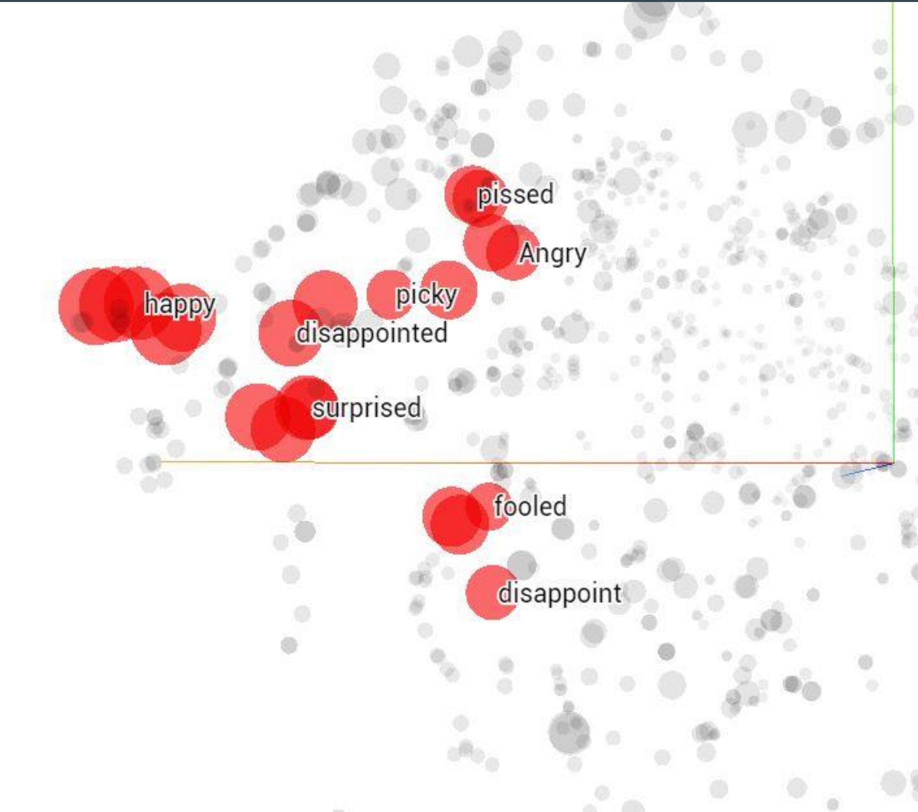
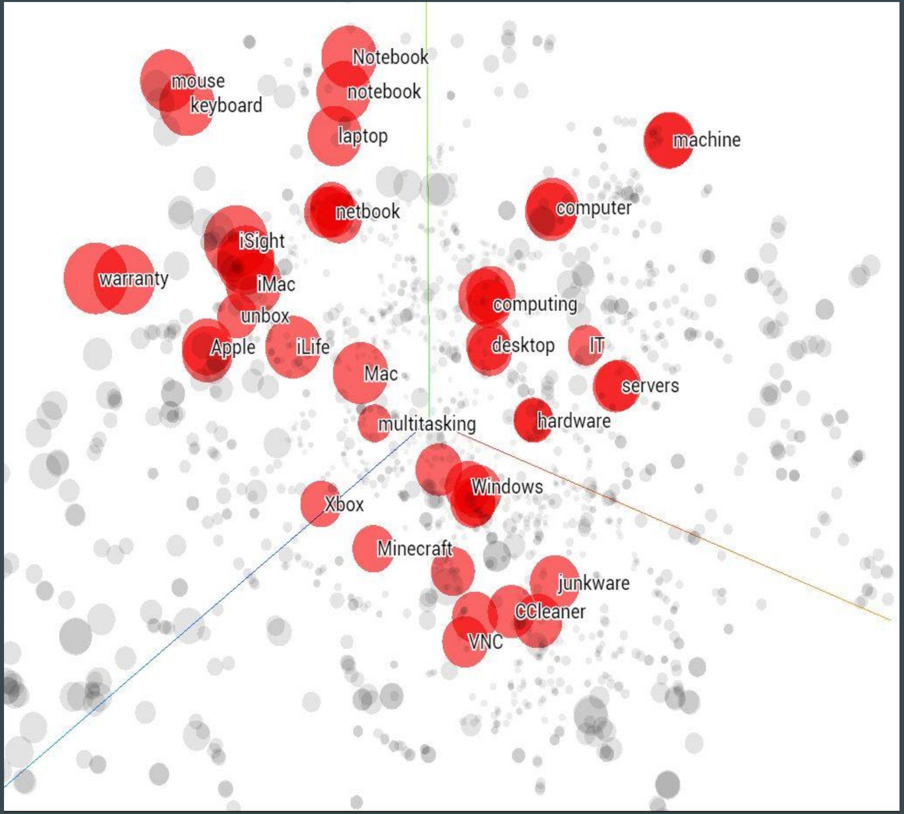
- t-SNE to reduce dimensions and visualize local neighbourhoods
- Model based Clustering to obtain feature and feature descriptor clusters
- Currently trying to link the words from 2 clusters to find relation vectors

t-SNE 3d visualization of the vector space

'Emotion' words



Tech words



Clustering of words in 197 D

Feature words Cluster

Descriptor words Cluster

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- Separated feature and feature descriptor words clusters
- Possible to link feature and feature descriptor words in the high dim. space to find relation vectors
- Possible to project high dim. Relation vector to 2D

What are the Plans for Future Work?

Current and Future Work

- Supervised Feature - feature descriptor linkage

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- Feature - Feature Descriptor Relation Vector projection into 2D

Current and Future Work

- Supervised Feature - feature descriptor linkage
- Feature - Feature Descriptor Relation Vector projection into 2D
- Train classifier to classify positive/negative opinion phrases

References

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Questions?

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