ASPECT-BASED OPINION MINING OF PRODUCT REVIEWS IN MICROBLOGS USING MOST RELEVANT FREQUENT CLUSTERS OF TERMS

by

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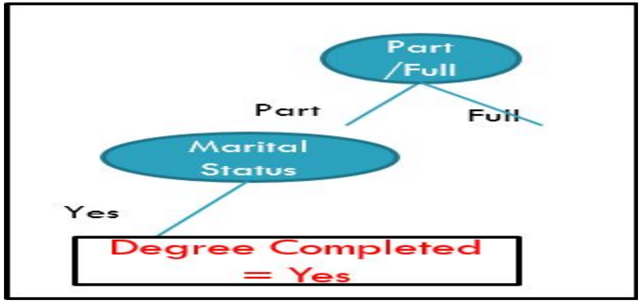
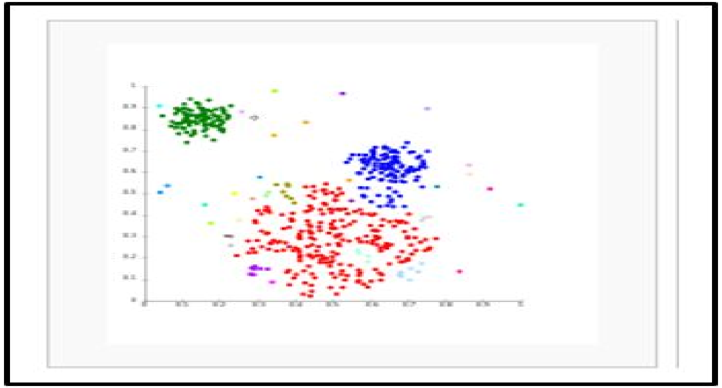
Data Mining

Classification



Clustering



Id	Marital Status	Part/Full	Family Income	Degree Completed
1	Yes	Part	80K	No
2	Yes	Part	40K	Yes
3	No	Part	70K	No
4	No	Full	80	Yes
5	No	Full	30	Yes
6	Yes	Full	80K	No
7	Yes	Part	65K	Yes

Association & Seq. Pat. Mining

Marital Status="Yes" => Degree Completed = "No"

Confidence = 50%

Support = 29%

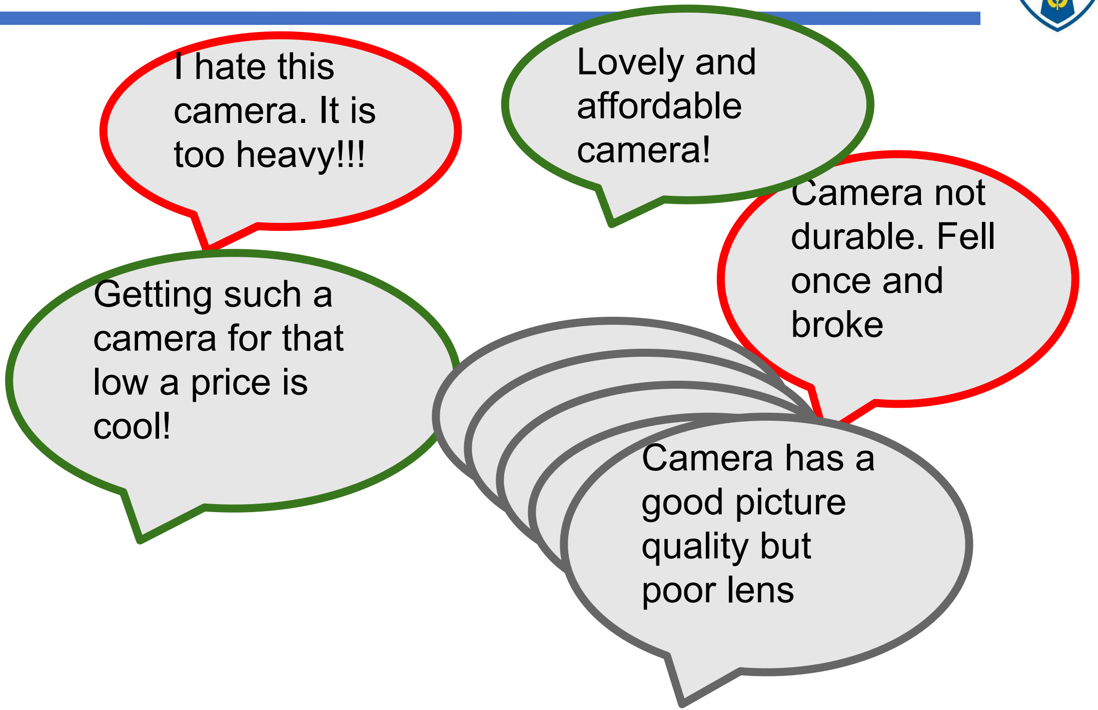
1 Introduction (Opinion Mining)

Producers want consumers' feedback on products.

- What parts they like?
- What features they hate?

The parts and features of a product are the ***aspect*** of the product.

What the consumers' think about the product is the ***opinion*** of that product.



PROBLEM: Too many opinions about different parts of the product for the producer to manually process.

1.1 Aspect-based Opinion Mining (ABOM)

- Aspect-based Opinion Mining aims at mining the aspects of a product and the opinions expressed on each of the aspects of the product.

Post Collection

“When I first opened the package, iPhone looked free of scuffs, scratches etc. There were minor scratches on the screen that were hard to see from far away. The charger took forever to charge up before it could boot up. Later on I realized there was a pinkish rectangular hue in the center of the screen”

↓

Obtaining Candidate Aspects

Package, iphone, scuffs, minor, scratches, screen, charger, charge, boot, hue

↓

Candidate Aspect Pruning

screen, charger

↓

Aspect Opinion Detection

Screen: Negative
Charger: Negative

1.2 Microblogs

Microblogs are frequent, short posts made on web blogs e.g Twitter.

Features:

- **Large volume** of posts (6,000 posts/ sec)
- **Unconventional writing**. E.g., “*btw, my b8ry died on me iphone while hooked on some vidz*”
- **Noisy Texts**. E.g. “*My new "Alibaba"-branded China-made iPhone cord is possibly the coolest thing you'll see this week. Greeeennnnnnn. ðŸ’š http://t.co/vH6LHMok12*”

1.2 Microblogs

- **Justification for ABOM in Microblogs:**
  - Microblogs provide a large volume and steady flow of opinions.
  - Consumers are more frequently turning to social media such as microblogs to conduct independent searches before making purchasing decisions (Volmer and Precourt, 2008).
  - 68% of consumers trust what other consumers post online about a product (Nielsen, 2013).
  - There is a strong correlation (0.70) between opinions about a product on Twitter and consumers' confidence about that product (European Central Bank, 2014).
  - Twitter is expected to receive a revenue of $2.27 billion for mobile advertising in 2015 (Twitter, 2015)

1.3 Motivation

Existing Systems	Research Goal	Technique to Obtain Relevant Aspects	Limitations
Entity Identifier (Spina et. al 2011)	To obtain words from Microblogs that are relevant to the product.	Term Frequency-Inverse Document Frequency (TF-IDF). Based on the frequency of occurrence of a word in posts about a product and posts about a different product.	Accuracy easily affected by spam posts.
Twitter Aspect Classifier (Lek and Poo, 2013)	To obtain opinion polarity of microblog posts about a product based on the opinion polarity of the aspects in the post.	Pointwise Mutual information (PMI). Based on the number of google search results of a word and a product to determine relevancy	Google searches vary by geographic locations and by user
Twitter Summarization Framework (Li and Li, 2013).	To extract the aspects of brands and give a summary of opinions expressed.	Topic Tendency Score (TTS). An extension of TF-IDF by also using the frequency of a word occurring in some certain phrases.	Accuracy easily affected by spam posts.

1.4 Thesis Problem

Given a collection of microblog posts, *C* about a product, *P:*

Can we mine the aspects of that product in such a way that the "noise" in microblog posts does not affect the accuracy of the system? Noise includes:

a. **Spam** - Posts that are repeated multiple times by a robot
b. **Advertisements** - Posts that aim to sell and do not express an opinion on the product. E.g. "*iphone chargers available here for sale. http://asdsahobvvw.com*".
c. **Buzz Posts** - Posts are frequently repeated due to a popular event or happening. E.g., "*obama call with an iphone", "obama uses an iphone", "obama caught with iphone"*.
d. **Competitor's Products** - Posts that mention competitor's products along with the product. E.g., "*samsung upgrades Android on galaxy in light of iPhone release*"

1.5 Thesis Contributions

1. An algorithm called **Microblog Aspect Miner (MAM)** which takes in raw and unprocessed microblog posts about a product as the input and outputs the relevant aspects of the products and their opinion polarity. It does this by:
   i. Classifying microblog posts as objective and subjective posts before mining aspects.
   ii. Clustering the most frequent nouns using KMeans to remove the noisy candidate aspects and get the true aspects of the product.
2. A **Subjectivity Module** for calculating the subjectivity score of a post by using the positive and negative scores of words from SentiWordNet (Esuli and Sebastiani 2006).
3. A microblog specific **language model** which generates a vector representation for words in microblog posts based on the co-occurrence of words and contexts of words using the word2vec algorithm (Mikolov et al. 2013).

2. 0 Related Work

Similarity Functions

- Similarity of words is often measured using the cosine distance (Manning et al., 2008) which is the ratio of the dot product of the vectors and the product of their magnitude.

$$\text{Sim }(A,B) = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}}$$

Dog = [0.8, 0.9, 0.8, 0.7, 0.8]

Cat = [0.9, 0.7, 0.7, 0.9, 0.9]

Chair = [0.1, 0.2, 0.3, 0.1, 0.1]

Similarity Matrix

	Dog	Cat	Chair
Dog	1	0.98	0.91
Cat	0.98	1	084
Chair	0.91	0.84	1

2.0 Related Works (cont)

Vector Representation of Words

Definition:

The vocabulary, *V* of a collection of posts are all the words used in the post, *X*. For example, if "I like the University", "Data mining rules", "I hate the library" are 3 posts and they make up a collection, the vocabulary of the collection is given by:

$V = X_1 \cup X_2 \cup X_3 =$ {I, like, the, University Data, mining, rules, hate, library}

Standard Representation of Words:

- Words are represented in a $\mathbb{R}^{|V \times X|}$ matrix.
- Matrix can grow very large as *X* increases - *curse of dimensionality*. What happens if we have 400,000 posts?
- Does not capture semantic relationships between words. For example, *university* ([100]) is more similar to *like* ([100]) than to *library* ([001]). This should not be so.

V	X_1	X_2	X_3
i	1	1	0
like	1	0	0
the	1	1	0
university	1	0	0
data	0	1	0
mining	0	1	0
rules	0	1	0
hate	0	0	1
library	0	0	1

2.0 Related Works (cont.)

Distributed Word Representation (Word Embeddings).

- Each word in the vocabulary is represented by a vector in such a way that semantically similar words have similar vectors.
- The length of the vector is fixed (usually between 100-500) and the values of the vectors are obtained in such a way that words that have similar contexts have similar vector values.

Get a collection of documents → Train words so that words with similar contexts have similar vector values → Cat = (-0.25, 0.31, 0.22, -0.15, …..)
Dog = (-0.35, 0.29, 0.20, -0.20, ….)
Chair= (0.87, -0.90, 0.80, -0.82,….)

source: twitter, wikipedia etc.

Using word2vec algorithm (Mikolov et al. 2013)

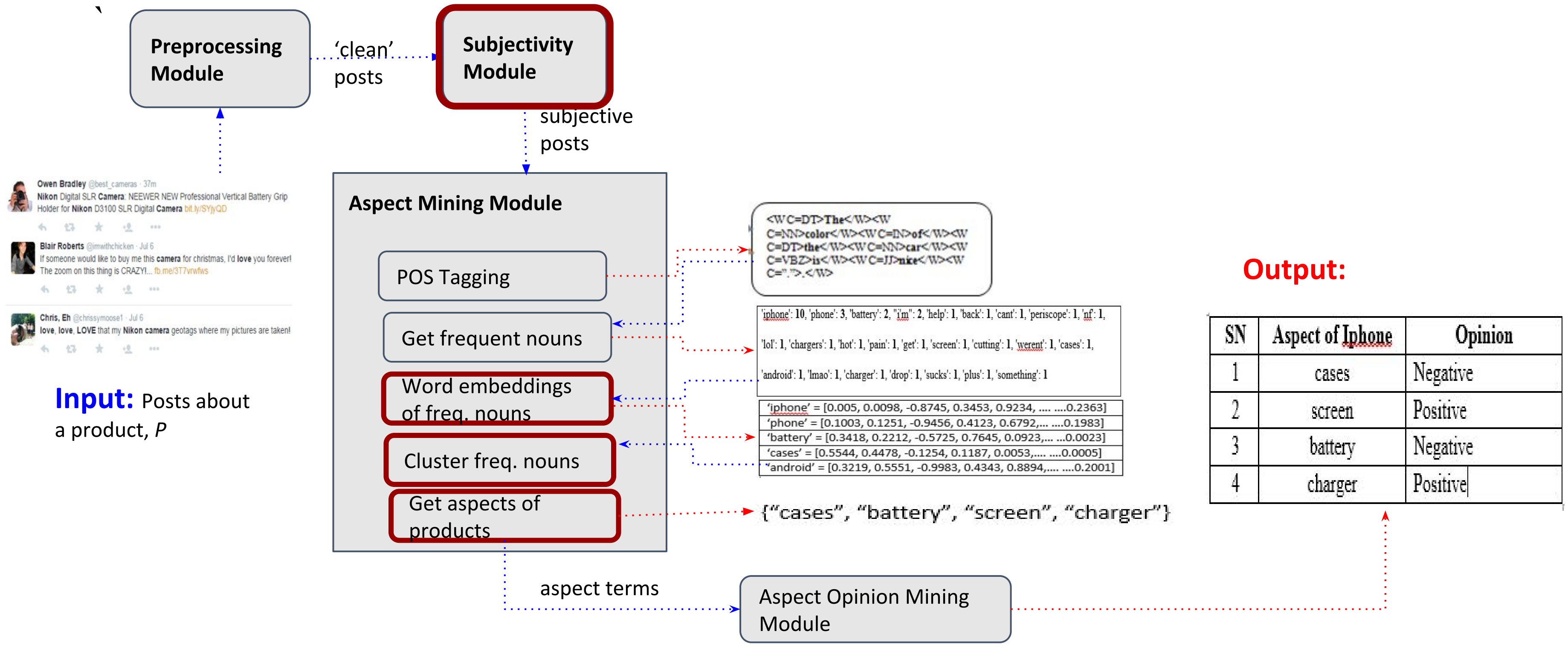
This is the language model which has a word embedding for every word in the vocabulary

3.0 Proposed Solution

We propose Microblog Aspect Miner (MAM). Given a collection of Microblog posts, *C*, about a product, *P*, MAM takes the following major steps:

1. Classifies of the microblog posts into subjective and objective posts using a proposed subjectivity score calculated based on the opinion scores of words from SentiWordNet (Esuli and Sebastiani, 2006).
2. Represents the frequent nouns in the subjective posts as vectors so that nouns similar to the products have a similar vector value using word2vec (Mikolov, 2013).
3. Uses K-Means clustering algorithm to the generated vectors of the frequent nouns to obtain a cluster of aspects relevant to the product.
4. The elements of the relevant aspect cluster are ranked to obtain the most relevant aspects using a proposed aspect-product similarity threshold, which is based on Cosine Similarities

Solution Framework



3.1 Preprocessing Module

AIM: To "clean up" the microblog posts

STEP 1

Obtain a collection of posts about a product from Twitter API (twitter.com/search-home).

STEP 2

Remove all URLs, RTs, any word that starts with a '@' and any word that does not start with an English letter or a digit. This is done using the regular expression:

"(@[A-Za-z0-9]+)|([^0-9A-Za-z'#%-?,\" \t])|(\w+:\/\/\S+)|(RT)"

STEP 3 : Processed tweets sent to subjectivity module

	Original Tweet	Kept for Processing	Preprocessed Tweet
P1	Amazon Prime Video Introduces Offline Viewing for iPhone and iPad http://t.co/BttbFRyfTX Mitchel Broussard	No	-
P2	iPhone 6 are a pain for phone cases ðŸ˜, I mean why make a phone so thin & not bring out good phone cases.	Yes	iPhone 6 are a pain for phone cases, I mean why make a phone so thin; not bring out good phone cases.
P3	RT @SohailThoughts: TOP 5 Reasons to Buy iPhone 6.	No	-
P4	@rowanaelin both bc i have a friend who downloads books using her iphone	Yes	both bc i have a friend who downloads books using her iphone
P5	Lol i like videos and u taking me wth an iPhone.im happy because the pictures are superb SMH #CliveNaidoo vs #MetroCop	Yes	Lol i like videos and u taking me wth an iPhone.im happy because the pictures are superb SMH CliveNaidoo vs MetroCop

3.2 Subjectivity Module

AIM: To obtain only the subjective posts about the product consequently eliminating spam posts and advertisements which make up the noise in microblog posts.

Definition: A subjective post is a post that expresses an opinion. An objective post is a post that does not express an opinion. E.g.,

Subjective Posts	Objective Posts
I love the University of Windsor	University of Windsor is a school in Canada
I hate the iphone's charger	Buy your iPhone chargers here!
I like the new Prime Minister of Canada	Canada has a new Prime Minister

3.2 Subjectivity Module (cont.)

We propose a formula for calculating the subjectivity score, *S* of a post, *P* by taking the average of sentiment score of each word.

$$S_p = \frac{\sum_{i=1}^{n} s_{wi}}{n}$$

S_{wi} = pos_score + neg_score

S_p - subjectivity score of post P.

w - a word in P

n - number of words in P

SentiWordNet (Esuli and Sebastiani, 2006) is used to get the value of *w*. SentiWordNet is a lexicon that gives a positive, negative and objective (neutral) score to each word. Scores are between 1 and 0.

E.g, "*I love pictures*"

1. Get the positive and negative score of each word in each post from SentiWordNet.
   I (0.0, 0.0), love(0.625, 0.0), pictures (0.0,0.0)
2. Use the scores to calculate the S_p
   ((0.0 + 0.0) + (0.625 + 0.0) + (0.0 + 0.0))/3 = 0.208
3. If S_p is greater than 0.04, the post is subjective. Else, the post is objective.

Why a threshold of 0.04?

3.2 Subjectivity Module (cont.)

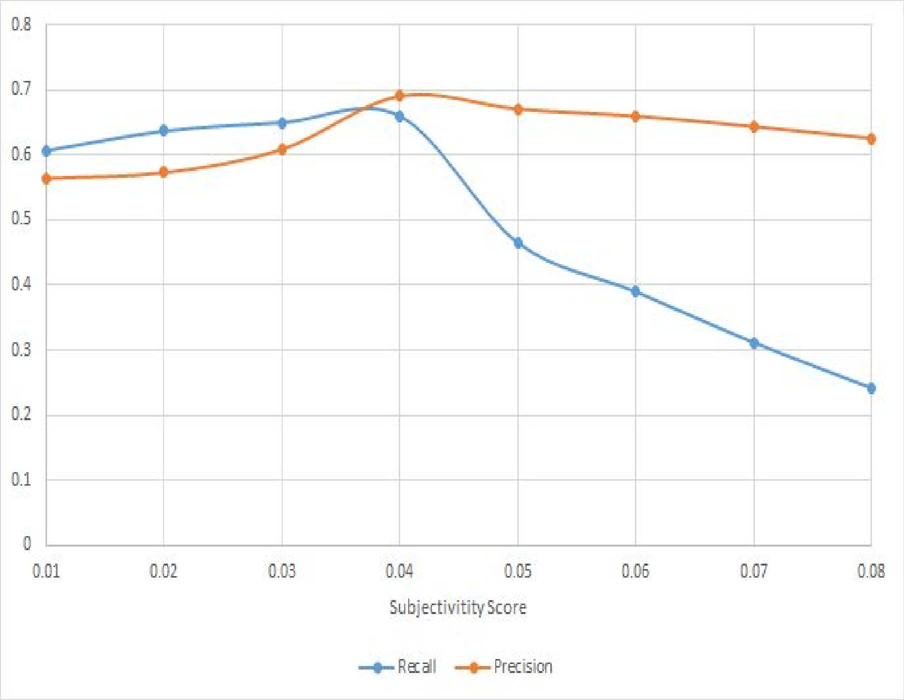
DATASET (Sentiment 140)

- 321 total tweets
- 178 subjective
- 143 objective

$$Precision = \frac{\#\ of\ predicted\ subjective\ posts\ that\ are\ subjective\ posts}{total\ predicted\ subjective\ posts}$$

$$Recall = \frac{\#\ of\ predicted\ subjective\ posts\ that\ are\ subjective\ posts}{total\ number\ of\ actual\ subjective\ posts\ in\ the\ dataset}$$

0.04 gave the best precision and recall



3.3 Aspect Mining Module (cont.)

The following steps are taken in the Aspect Mining Module:

STEP 1

Get the subjective posts from the subjectivity module.

STEP 2

POS tag the subjective posts using NLTK_PosTagger (NLTK, 2015) to assign parts of speech to each word in the posts.

STEP 3

Get the frequent nouns in the subjective posts using association rule mining. These are the candidate aspects

STEP 4

Obtain the vector representations (word embeddings) of the frequent nouns from the vocabulary of the language model that was trained with the word2vec algorithm (Mikolov 2013).

i cant conect my iphone 6 with the android moto 360. Help me please.
iPhone 6 are a pain for phone cases I mean why make a phone so thin & ; not bring out
Definitely need to get this iPhone screen fixed
lol was talking about the iPhone 6s on his periscope

[**('i', 'NN')**, ('cant', 'VBP'), **('connect', 'NN')**, ('my', 'PRP$'), **('iphone', 'NN')**, ('6', 'CD'), ('with', 'IN'), ('the', 'DT'), ('android', 'JJ'), **('moto', 'NN')**, ('360', 'CD'), ('.', '.'), ('Help', 'VB'), ('me', 'PRP'), ('please', 'VB')]

'iphone': **10**, 'phone': **3**, 'battery': **2**, "i'm": **2**, 'help': **1**, 'back': **1**, 'cant': **1**, 'periscope': **1**, 'nf': **1**,

'lol': **1**, 'chargers': **1**, 'hot': **1**, 'pain': **1**, 'get': **1**, 'screen': **1**, 'cutting': **1**, 'werent': **1**, 'cases': **1**,

'android': **1**, 'lmao': **1**, 'charger': **1**, 'drop': **1**, 'sucks': **1**, 'plus': **1**, 'something': **1**

'iphone' = [0.005, 0.0098, -0.8745, 0.3453, 0.9234, ...0.2363]
'phone' = [0.1003, 0.1251, -0.9456, 0.4123, 0.6792,... ....0.1983]
'battery' = [0.3418, 0.2212, -0.5725, 0.7645, 0.0923,... ...0.0023]
'cases' = [0.5544, 0.4478, -0.1254, 0.1187, 0.0053,.... ....0.0005]
'android' = [0.3219, 0.5551, -0.9983, 0.4343, 0.8894,.... ....0.2001]

3.3 Aspect Mining Module (cont.)

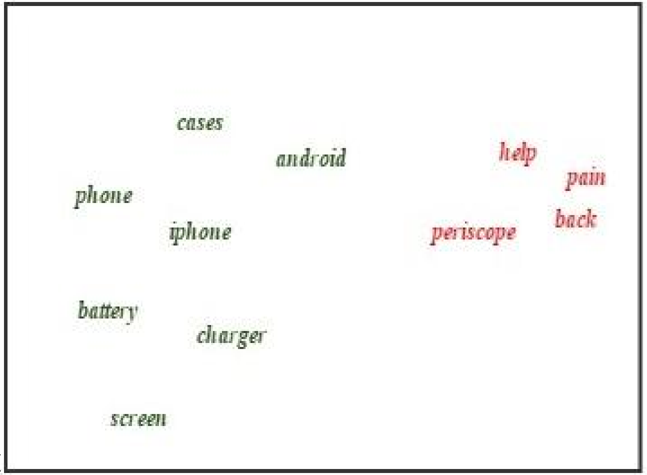
STEP 5

Cluster the vectors of the candidate aspects using KMeans with k=2:

I. Assign one of the centers (C_1) to be the vector representation of the product and the other center is randomly assigned (C_2).
II. Assign words to the nearest center
III. Recompute the center of C_2
IV. Repeat steps II and III until the C_2 remains constant.

STEP 6

Discard words in cluster of C_2 (noisy aspects) and keep the words in cluster of C_1



STEP 7

Words in C_1 that have a similarity of less than 0.7 with the product are considered aspects of the product.

The aspects are ranked in descending order to get relevancy.

1st:Screen; 2nd:Cases; 3rd:Charger

x	Sim(iphone, *x*)
iphone	1.0000
cases	0.5672
android	0.7785
phone	0.7158
battery	0.4642
screen	0.5685
charger	0.5584

3.4 Aspect Opinion Mining Module

AIM: To get the polarity of the aspects discovered by the Aspect Mining Module

STEP 1

Obtain the list of aspects from the Aspect Mining Module

STEP 2

Check the subjective posts for were the aspect terms were used

STEP 3

Get the nearest modifier to the aspect term in the posts

STEP 4

Use SentiWordNet (Esuli and Sebastiani, 2006) to determine the polarity of the modifier of the aspect

STEP 5

The polarity of the modifier is assigned as the polarity of the opinion on the aspect.

4.0 Results and Experiments

Datasets

- 500,000 tweets on 4 different products and brands (iphone, starbucks, xbox and sony)
- Downloaded from the Twitter Search API (twitter.com/search-home)

Systems Implemented

MAM - as proposed in this thesis

PMI - Lek and Poo, 2013

FN - Spina et. al, 2011 (Baseline)

- The top 20 aspects of each of the products was obtained for each system
- 3 human judges rate how relevant the aspects are to the products on a scale of 0-3 with 3 being relevant and 0 being not relevant
- The judges scores were validated using the Cohen's and Fleiss' Kappa (Fleiss, Cohen and Everitt 1969)

4.1 Kappa Scores

$\kappa = \frac{Po-Pc}{1-Pc}$ (Fleiss, Cohen and Everitt 1969)

$P_c = \sum_{j=1}^{k} p_j^2$ (Fleiss, Cohen and Everitt 1969)

$P_j = \frac{1}{Nn} \sum_{i=1}^{N} n_{ij}$ (Fleiss, Cohen and Everitt 1969)

$P_o = \frac{1}{Nn(n-1)} \left(\sum_{i=1}^{N} \sum_{j=1}^{k} n_{ij}^2 - n \right)$

k - # of ratings that can be given
N - # of aspects scored
n - number of judges
n_{ij} - # of judges who assigned the i-th aspect to the j-th category

	J1	J2	J3
case	3	3	3
gold	0	1	1
screen	3	3	3

	0	*1*	*2*	*3*	P_i
case	0	0	0	3	1
gold	1	2	0	0	0.33
screen	0	0	0	3	1
TOTAL	**1**	**2**	**0**	**6**	**2.33**
P_j	0.11	0.22	0	0.67	

$P_i(\text{case}) = (0^2+0^2+0^2+3^2-3)/(3 * 2) = 1$

$P_o = 2.33/3.00 = 0.766$
$P_c = 0.11^2 + 0.22^2 + 0^2 + 0.67^2 = 0.5904$

$\kappa = (0.766 - 0.5904) / (1 - 0.5904) = 0.4287$

4.1 Kappa Scores (cont.)

Kappa scores to measure judges' agreement for each product

Dataset	Kappa Score
Iphone	0.6073
Starbucks	0.6517
Sony	0.6107
Xbox	0.6271

A kappa score of 0.6 is enough to validate the judges scoring (Spina et. al, 2011; Das and Kanan, 2013)

Kappa interpretation (Sim and Wright, 2005)

κ	
< 0	Poor Agreement
0.01 – 0.20	Slight agreement
0.21 – 0.40	Fair agreement
0.41 – 0.60	Moderate agreement
0.61 – 0.80	Substantial agreement
0.81 – 1.00	Almost perfect agreement

4.2 Evaluation Metrics

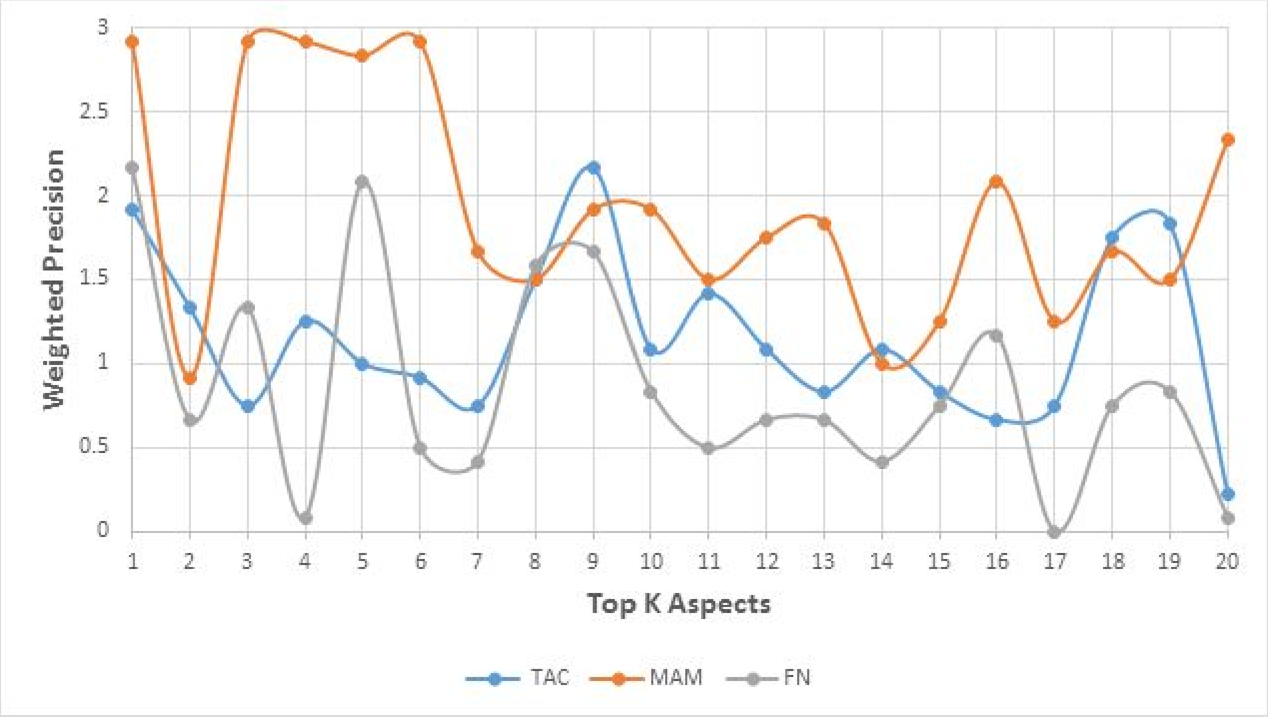
Accuracy– This measures amount of relevant aspects that were among the top 20 aspects. The relevant aspects are those aspects given a score of 3 by the judges.

Weighted Precision (Sakai 2007) – This measures the relevancy of the aspect to the product based on the scoring of the judges. Let *R(a)* be the average rating given by the judges for each aspect, *a*, the weighted precision is given as:

Weighted Precision = $\frac{\sum_{1}^{K} R(a)}{K}$ (Sakai 2007)

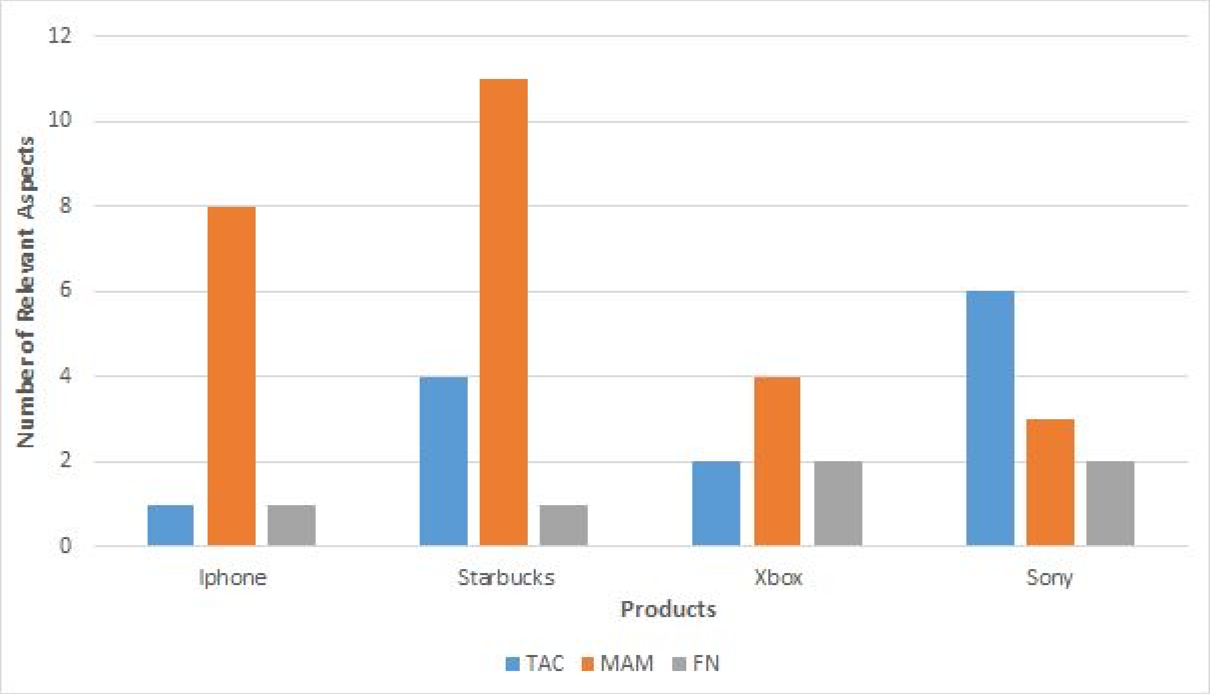
Where K = 20.

4.3 Weighted Precision



	Average Weighted Precision
MAM	1.929
TAC	1.157
FN	0.868

4.4 Accuracy



Relevant Aspects are aspects that were given a score of 3 by all judges.

5.0 Conclusion & Future Work

- An algorithm, MAM, is proposed to address the problem of noise in microblogs and accurately discover aspects of products from microblogs.
- Performs more accurately than TAC and TF-IDF based systems.
- A proposed method for classifying microblog posts into subjective and objective posts.

Future Work:

- Aggregating all social media platforms like blogs, news, bulletin boards and not just microblogs to perform ABOM.
- Consideration of multi-word aspects. E.g hard disk.
- Considering Microblog posts that are in languages other than English

6.0 References

Bengio, Y., Ducharme, R., Vincent, P., & Janvin, C. (2003). A neural probabilistic language model. The Journal of Machine Learning Research, 3, 1137-1155.

Diao, Q., Qiu, M., Wu, C. Y., Smola, A. J., Jiang, J., & Wang, C. (2014, August). Jointly modeling aspects, ratings and sentiments for movie recommendation (jmars). In *Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining* (pp. 193-202). ACM.

Esuli, A., & Sebastiani, F. (2006, May). Sentiwordnet: A publicly available lexical resource for opinion mining. In *Proceedings of LREC* (Vol. 6, pp. 417-422).

Europaeu. (2015). Europaeu. Retrieved 26 November, 2015, from https://www.ecb.europa.eu/pub/pdf/scpsps/ecbsp5.en.pdf

Fellbaum, C. (1998). *WordNet*. Blackwell Publishing Ltd.

Feldman, Ronen. 2013. “Techniques and Applications for Sentiment Analysis.” Communications of the ACM 56 (4): 82–89.

Fleiss, J. L., Cohen, J., & Everitt, B. S. (1969). Large sample standard errors of kappa and weighted kappa. *Psychological Bulletin*, *72*(5), 323.

Hu, M., & Liu, B. (2004, August). Mining and summarizing customer reviews. In Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining (pp. 168-177). ACM.

Jin, W., Ho, H. H., & Srihari, R. K. (2009, June). OpinionMiner: a novel machine learning system for web opinion mining and extraction. In Proceedings of the 15th ACM SIGKDD international conference on Knowledge discovery and data mining (pp. 1195-1204). ACM.

Lek, H. H., & Poo, D. C. (2013, November). Aspect-based Twitter sentiment classification. In Tools with Artificial Intelligence (ICTAI), 2013 IEEE 25th International Conference on (pp. 366-373). IEEE.

6.0 References

Li, Y. M., & Li, T. Y. (2013). Deriving market intelligence from microblogs. Decision Support Systems, 55(1), 206-217.

Manning, C. D., Raghavan, P., & Schütze, H. (2008). Introduction to information retrieval (Vol. 1, p. 496). Cambridge: Cambridge university press.

Mikolov, T., Chen, K., Corrado, G., & Dean, J. (2013). Efficient estimation of word representations in vector space. arXiv preprint arXiv: 1301.3781.

Moghaddam, S., & Ester, M. (2010, October). Opinion digger: an unsupervised opinion miner from unstructured product reviews. In Proceedings of the 19th ACM international conference on Information and knowledge management (pp. 1825-1828). ACM.

Nielsencom. (2015). Nielsencom. Retrieved 26 November, 2015, from http://www.nielsen.com/us/en/insights/news/2013/under-the-influence-consumer-trust-in-advertising.html

Owoputi, O., O'Connor, B., Dyer, C., Gimpel, K., & Schneider, N. (2012). Part-of-speech tagging for Twitter: Word clusters and other advances. School of Computer Science, Carnegie Mellon University, Tech. Rep.

Pennington, J., Socher, R., & Manning, C. D. (2014). Glove: Global vectors for word representation. Proceedings of the Empiricial Methods in Natural Language Processing (EMNLP 2014), 12, 1532-1543.

6.0 References

Sakai, T. (2007, July). Alternatives to bpref. In *Proceedings of the 30th annual international ACM SIGIR conference on Research and development in information retrieval* (pp. 71-78). ACM.

Santorini, B. (1990). Part-of-speech tagging guidelines for the Penn Treebank Project (3rd revision).

Smith, A. E., & Humphreys, M. S. (2006). Evaluation of unsupervised semantic mapping of natural language with Leximancer concept mapping. Behavior Research Methods, 38(2), 262-279.

Suresh, V., Roohi, S., & Eirinaki, M. (2014, October). Aspect-based opinion mining and recommendationsystem for restaurant reviews. In *Proceedings of the 8th ACM Conference on Recommender systems* (pp. 361-362). ACM.

Toutanova, K., & Manning, C. D. (2000, October). Enriching the knowledge sources used in a maximum entropy part-of-speech tagger. In Proceedings of the 2000 Joint SIGDAT conference on Empirical methods in natural language processing and very large corpora: held in conjunction with the 38th Annual Meeting of the Association for Computational Linguistics-Volume 13 (pp. 63-70). Association for Computational Linguistics.

Twitterinccom. (2015). Twitter About. Retrieved 26 November, 2015, from https://investor.twitterinc.com/releasedetail.cfm?ReleaseID=909177

Vollmer, C., & Precourt, G. (2008). Always on: Advertising, marketing, and media in an era of consumer control. McGraw Hill Professional.

Wittgenstein, L. (1953). Philosophical Investigations Oxford. Eng.: Blackwell.

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