TwiSent: A Multi-Stage System for Analyzing Sentiment in Twitter

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Social Media Analysis

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  - Tweets have a poor syntactic and semantic structure
  - Problems like *slangs, ellipses, nonstandard vocabulary etc.*
- Problem is compounded by increasing number of *spams* in Twitter
  - P*romotional* tweets, *bot-generated* tweets, *random links* to websites etc. In fact Twitter contains around 40% tweets as pointless babble

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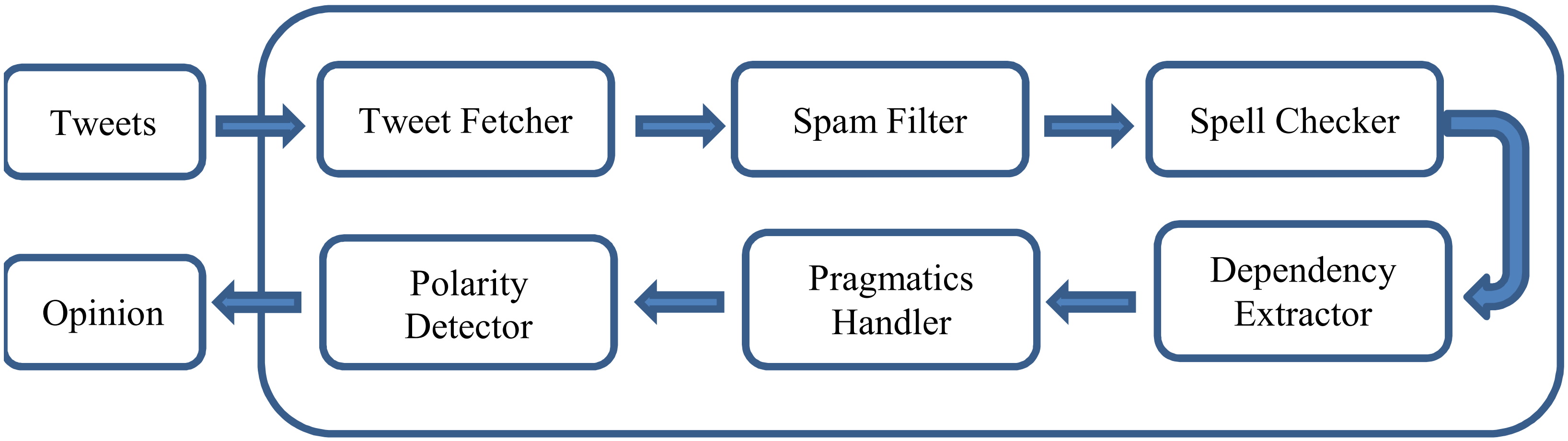
TwiSent: Multi-Stage System Architecture



Spam Categorization and Features

- *Re-tweets*
- *Promotional tweets for some entity*
- *Tweets containing links to some other websites*
- *Tweets in languages other than English*
- *Tweets with incomplete text*
- *Automatically generated tweets by bots*
- *Tweets built primarily for search engines or tweets with excessive off-topic keywords*
- *Multiple tweets offering substantially the same content*

1. *Number of Words per Tweet*	**9.** *Frequency of Foreign Words*
	10. *Validity of First Word*
2. *Average Word Length*	**11.** *Presence / Absence of links*
3. *Frequency of "?" and "!"*	**12.** *Frequency of POS Tags*
	13. *Strength of Character Elongation*
4. *Frequency of Numeral Characters*	**14.** *Frequency of Slang Words*
	15. *Average Positive and Negative Sentiment of Tweets*
5. *Frequency of hashtags*	
6. *Frequency of @users*	
7. *Extent of Capitalization*	
8. *Frequency of the First POS Tag*	

Algorithm for Spam Filter

Input: Build an initial naive bayes classifier NB- C, using the tweet sets *M* (mixed unlabeled set containing spams and non-spams) and *P* (labeled non-spam set)

1: Loop while classifier parameters change

2: for each tweet $t_i \in M$ do

3: Compute $\Pr[c_1 | t_i]$, $\Pr[c_2 | t_i]$ using the current NB //c_1 - non-spam class , c_2 - spam class

4: $\Pr[c_2 | t_i] = 1 - \Pr[c_1 | t_i]$

5: Update $\Pr[f_{i,k} | c_1]$ and $\Pr[c_1]$ given the probabilistically assigned class for all t_i ($\Pr[c_1 | t_i]$). (a new NB-C is being built in the process)

6: end for

7: end loop

$$\Pr[c_j \mid t_i] = \frac{\Pr[c_j] \prod_k \Pr[f_{i,k} | c_j]}{\sum_r \Pr[c_r] \prod_k P(f_{i,k} | c_r)}$$

Categorization of Noisy Text

- Dropping of Vowels - *btfl (beautiful), lvng (loving)*
- Vowel Exchange - *good vs. gud (o,u)*
- Mis-spelt words - *redicule (ridicule), magnificant (magnificent)*
- Text Compression - *shok (shock), terorism (terrorism)*
- Phonetic Transformation - *be8r (better), gud (good), fy9 (fine), gr8 (great)*
- Normalization and Pragmatics - *hapyyyyyy (happy), guuuuud (good)*
- Segmentation with Punctuation - *beautiful, (beautiful)*
- Segmentation with Compound Words - *breathtaking (breath-taking), eyecatching (eye-catching), good-looking (good looking)*
- Hashtags and Segmentation - *#notevenkidding, #worthawatch*
- Combination of all - *#awsummm (awesome), gr88888 (great), amzng,btfl (amazing, beautiful).*

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- Words are marked during normalization, to preserve their pragmatics

  happppyyyyy, normalized to *hapy* and thereafter spell-corrected to *happy,* is marked so as to not lose its pragmatic content

Spell-Checker Algorithm

- **Input:** For string s, let *S* be the set of words in the lexicon starting with the initial letter of *s*.
- /* Module Spell Checker */
- **for** each word *w* ∈ *S* **do**
-   *w'*=vowel_dropped(*w*)
-   *s'*=normalize(*s*)
- */*diff(s,w) gives difference of length between s and w*/*
-   **if** diff(*s'* , *w'*) < offset **then**
-     score[*w*]=min(edit_distance(*s*,*w*),edit_distance(*s*,
-     *w'*), edit_distance(*s'* , *w*))
-   else
-     score[*w*]=max_centinel
-   **end if**
- **end for**

Spell-Checker Algorithm Contd..

- Sort score of each *w* in the Lexicon and retain the top m entries in suggestions(*s*) for the original string *s*
- **for** each *t* in suggestions(*s*) **do**
- $edit_1$=edit_distance(*s'* , *s*)
- */*t.replace(char1,char2) replaces all occurrences of char1 in the string t with char2*/*
- $edit_2$=edit_distance(t.replace(*a* , *e*), *s'*)
- $edit_3$=edit_distance(t.replace(*e* , *a*), *s'*)
- $edit_4$=edit_distance(t.replace(*o* , *u*), *s'*)
- $edit_5$=edit_distance(t.replace(*u* , *o*), *s'*)
- $edit_6$=edit_distance(t.replace(*i* , *e*), *s'*)
- $edit_7$=edit_distance(t.replace(*e*, *i*), *s'*)
- count=overlapping_characters(*t, s'*)
- min_edit=
- min($edit_1$,$edit_2$,$edit_3$,$edit_4$,$edit_5$,$edit_6$,$edit_7$)
- **if** (min_edit ==0 or score[*s'*] == 0) **then**
- adv=-2 */* for exact match assign advantage score */*
- else
- adv=0
- **end if**
- final_score[t]=min_edit+adv+score[*w*]-count;
- **end for**
- return *t* with minimum final_score;

Feature Specific Tweet Analysis

- *I have an **ipod** and it is a <u>great</u> buy but I'm probably the only person that <u>dislikes</u> the iTunes **software**.*
  - *Here the sentiment w.r.t ipod is positive whereas that respect to software is negative*

Opinion Extraction Hypothesis

- *“More closely related words come together to express an opinion about a feature”*

Hypothesis Example

- *"I want to use Samsung which is a great product but am not so sure about using Nokia".*
  - *Here "great" and "product" are related by an adjective modifier relation, "product" and "Samsung" are related by a relative clause modifier relation. Thus "great" and "Samsung" are transitively related.*
  - ***Here "great" and "product" are more related to Samsung than they are to Nokia***
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Relations

- Direct Neighbor Relation
  - Capture **short range dependencies**
  - Any 2 consecutive words (such that none of them is a StopWord) are directly related
  - Consider a sentence *S* and 2 consecutive words $w_i, w_{i+1} \in S$.
  - *If* $w_i, w_{i+1} \notin Stopwords$, then they are directly related.

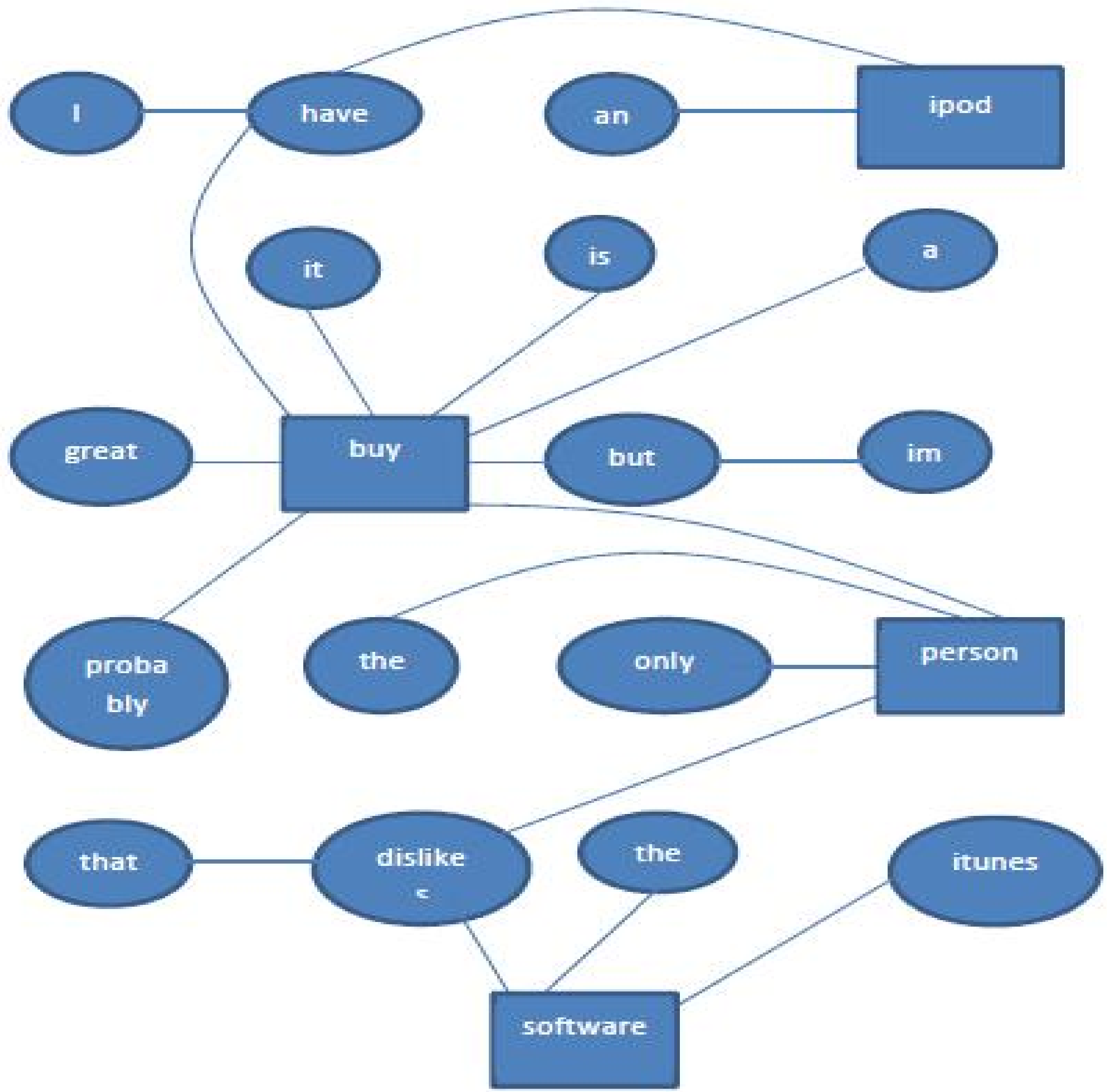
- Dependency Relation
  - Capture **long range dependencies**
  - Let *Dependency_Relation* be the list of **significant relations**.
- Any 2 words w_i and w_j in *S* are directly related, *if* $\exists D_i$ s.t. $D_i(w_i, w_j) \in Dependency\_Relation$

Graph representation

Given a sentence S, let $\boldsymbol{W}$ be the set of all words in the sentence S.

A Graph $G(W, E)$ is constructed such that any $w_i, w_j \in W$ are directly connected by $e_k \in E$, if $\exists R_l$ s.t. $R_l(w_i, w_j) \in R$.

Graph



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Algorithm

i. Initialize n clusters $C_i \ \forall i = 1..n$

ii. Make each $f_i \in F$ the clusterhead of C_i . The target feature f_t is the clusterhead of C_t. Initially, each cluster consists only of the clusterhead.

Algorithm Contd…

iii. Assign each word $w_j \in S$ to cluster C_k

$$s.t.\ \ k = \arg\min_{i \in n} dist(w_j, f_i),$$

Where $dist(w_j, f_i)$ *gives the number of edges, in the shortest path, connecting* w_j *and* f_i *in G.*

Algorithm Contd…

iv. Merge any cluster C_i with C_t *if*,

$$dist(f_i, f_t) < \theta \,,$$

Where θ is some threshold distance.

v. Finally the set of words $w_i \in C_t$ gives the opinion expression regarding the target feature f_t .

Clustering

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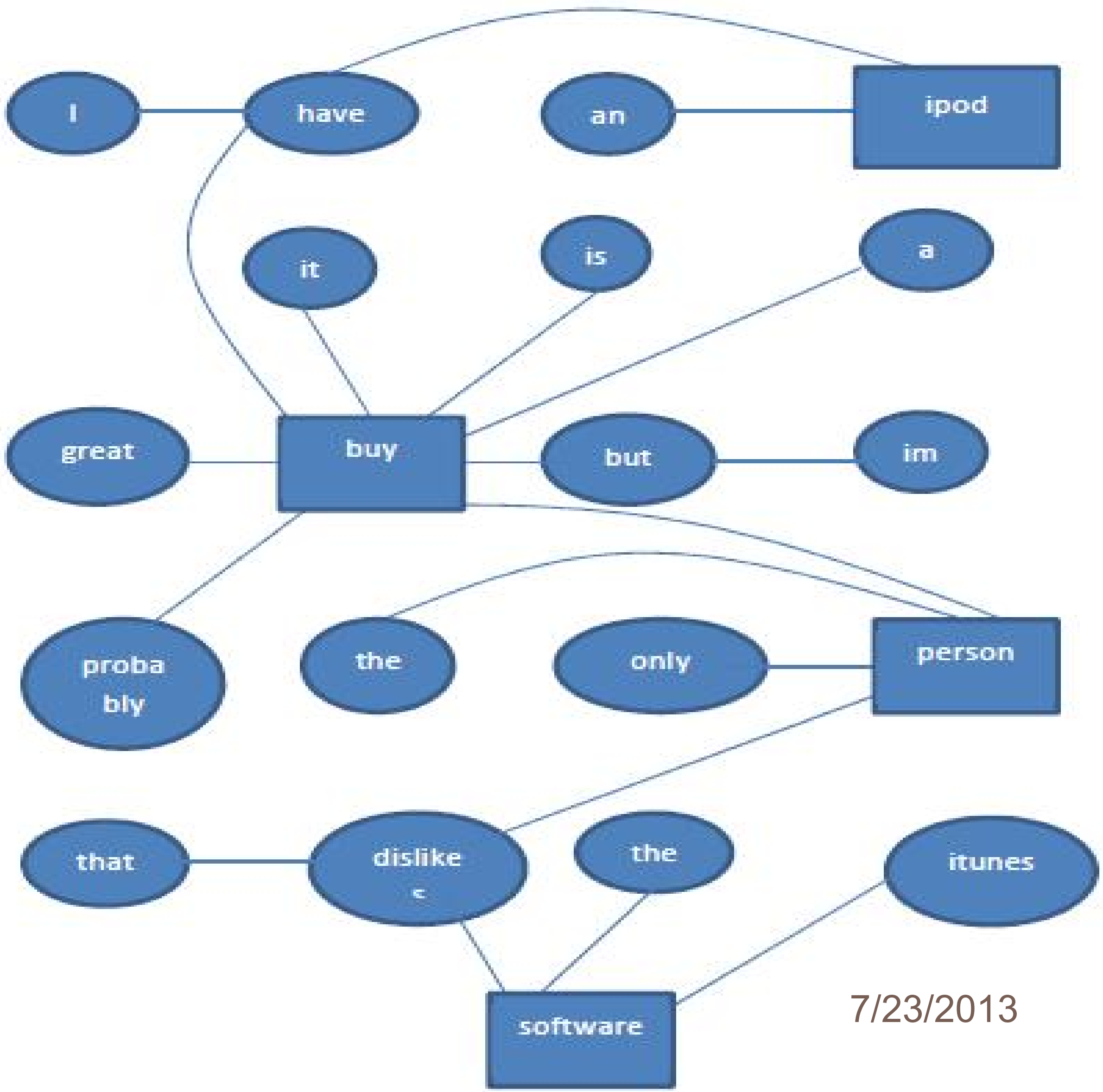

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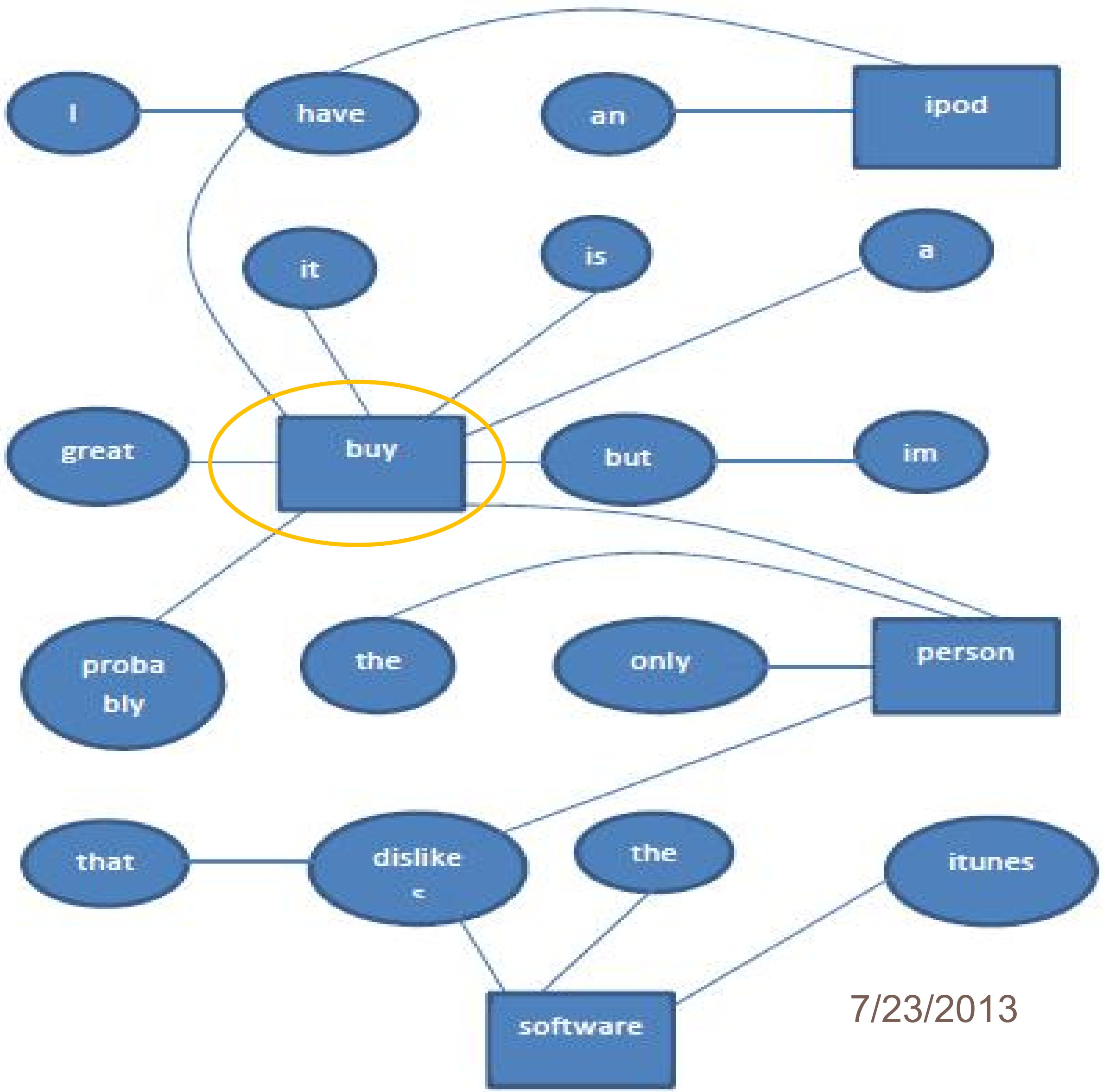
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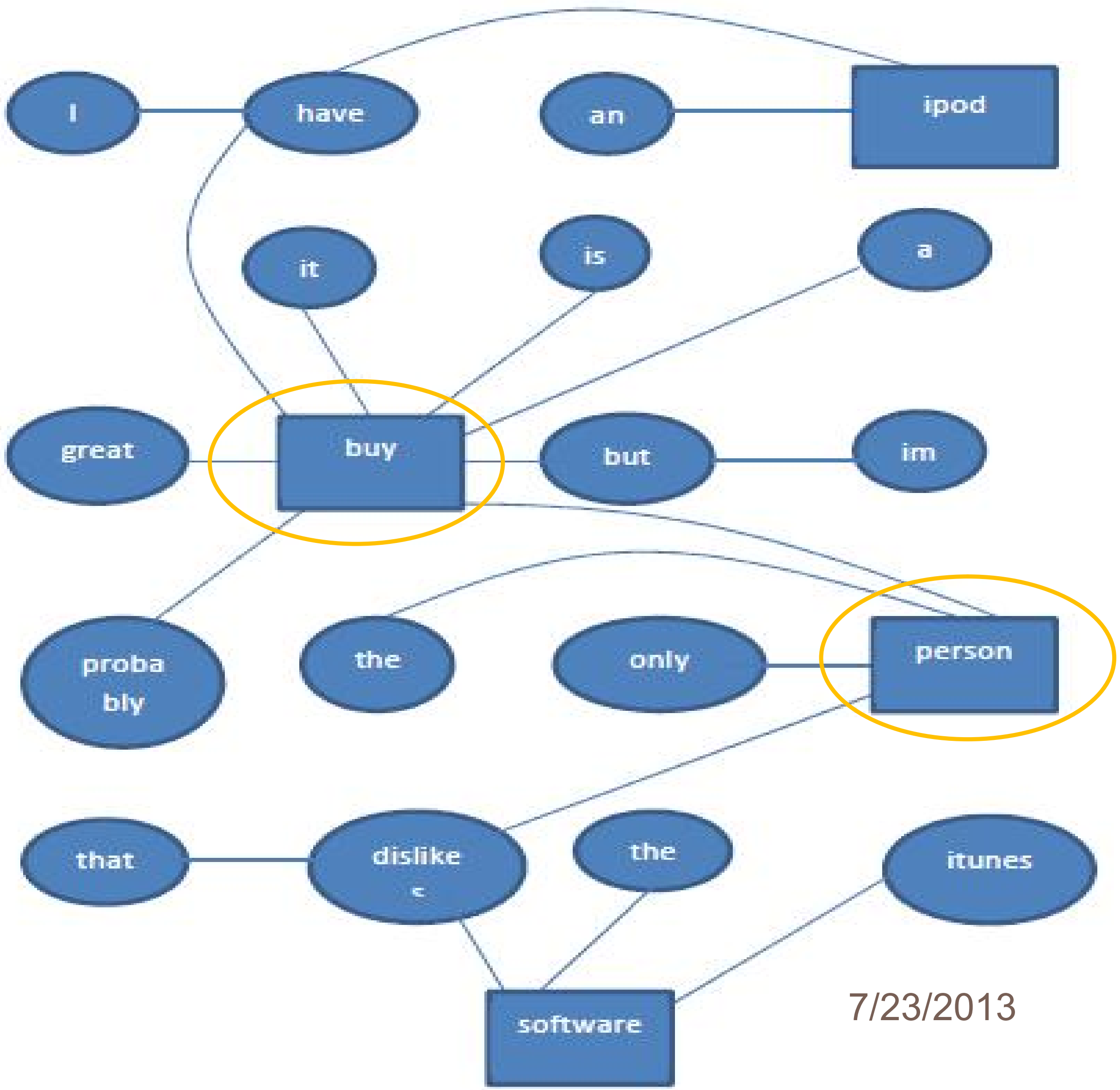
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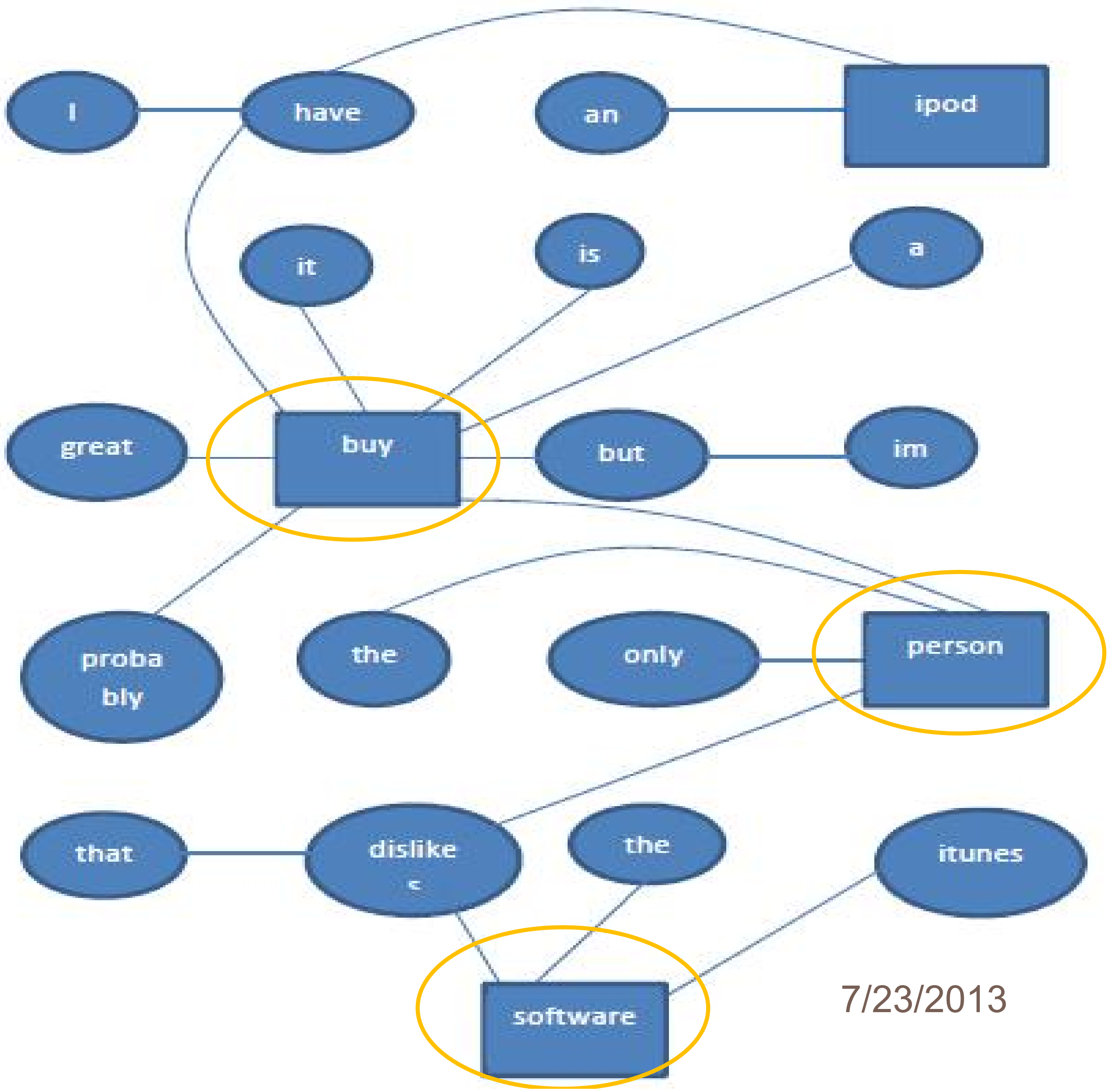
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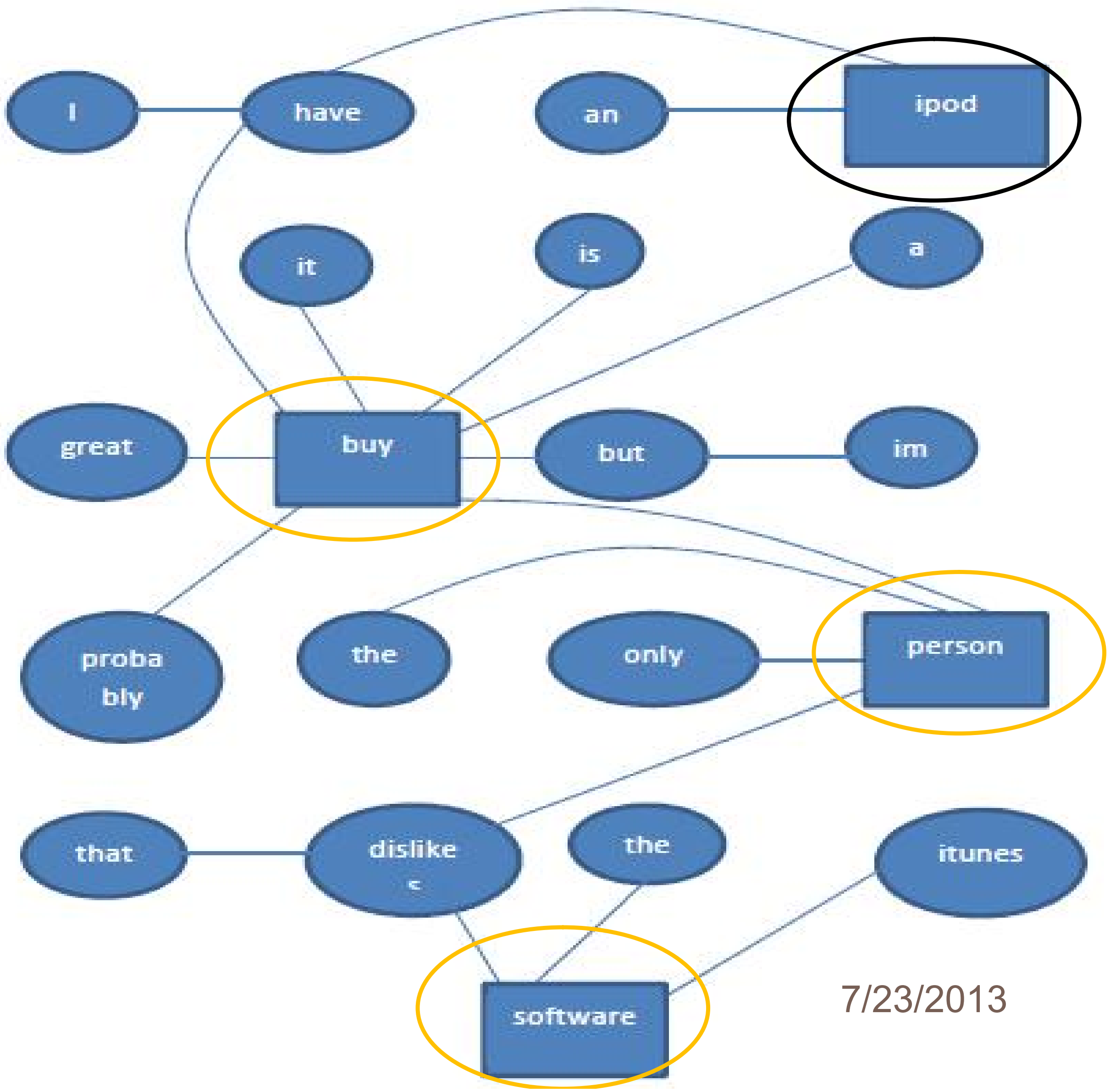

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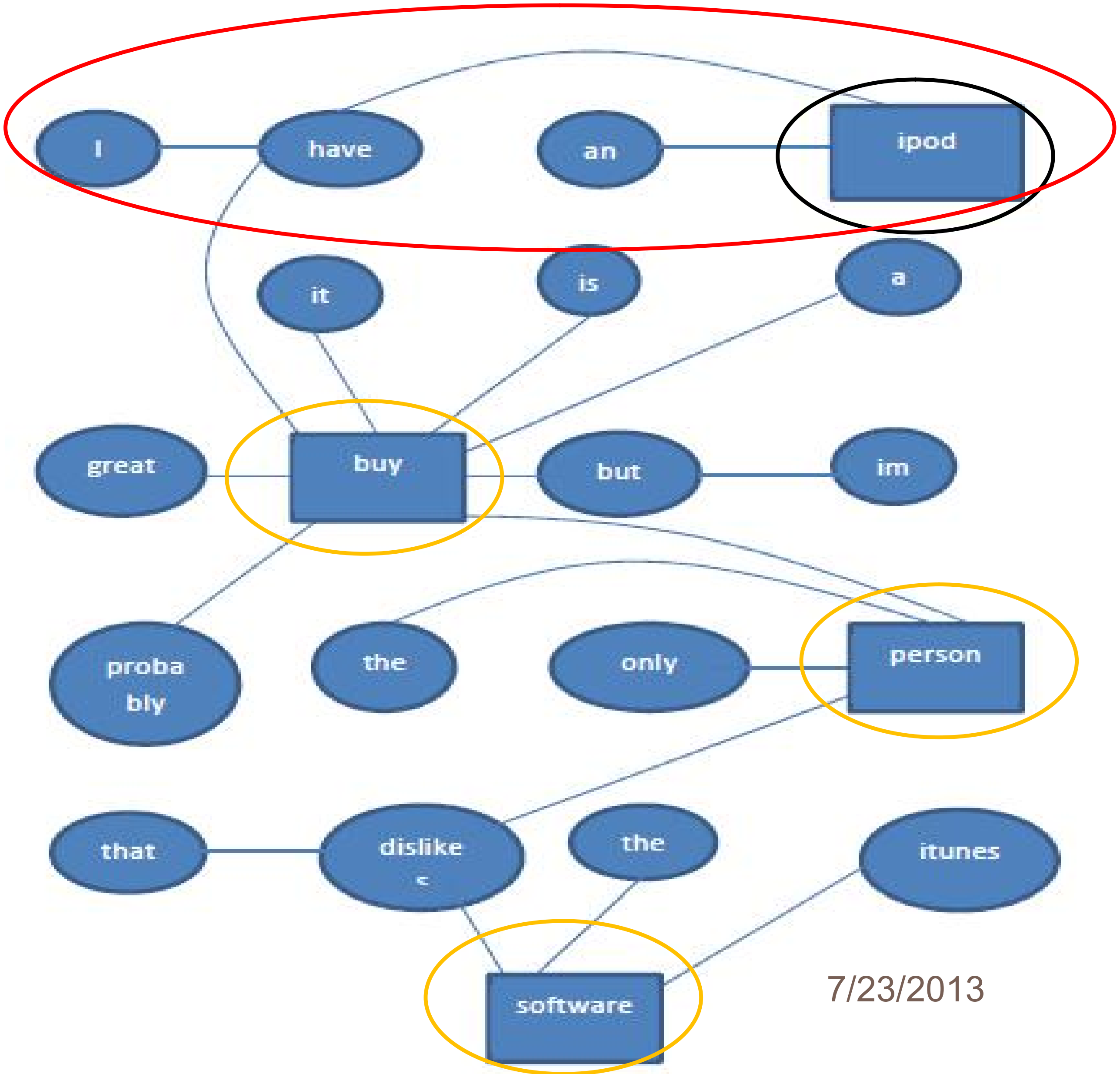
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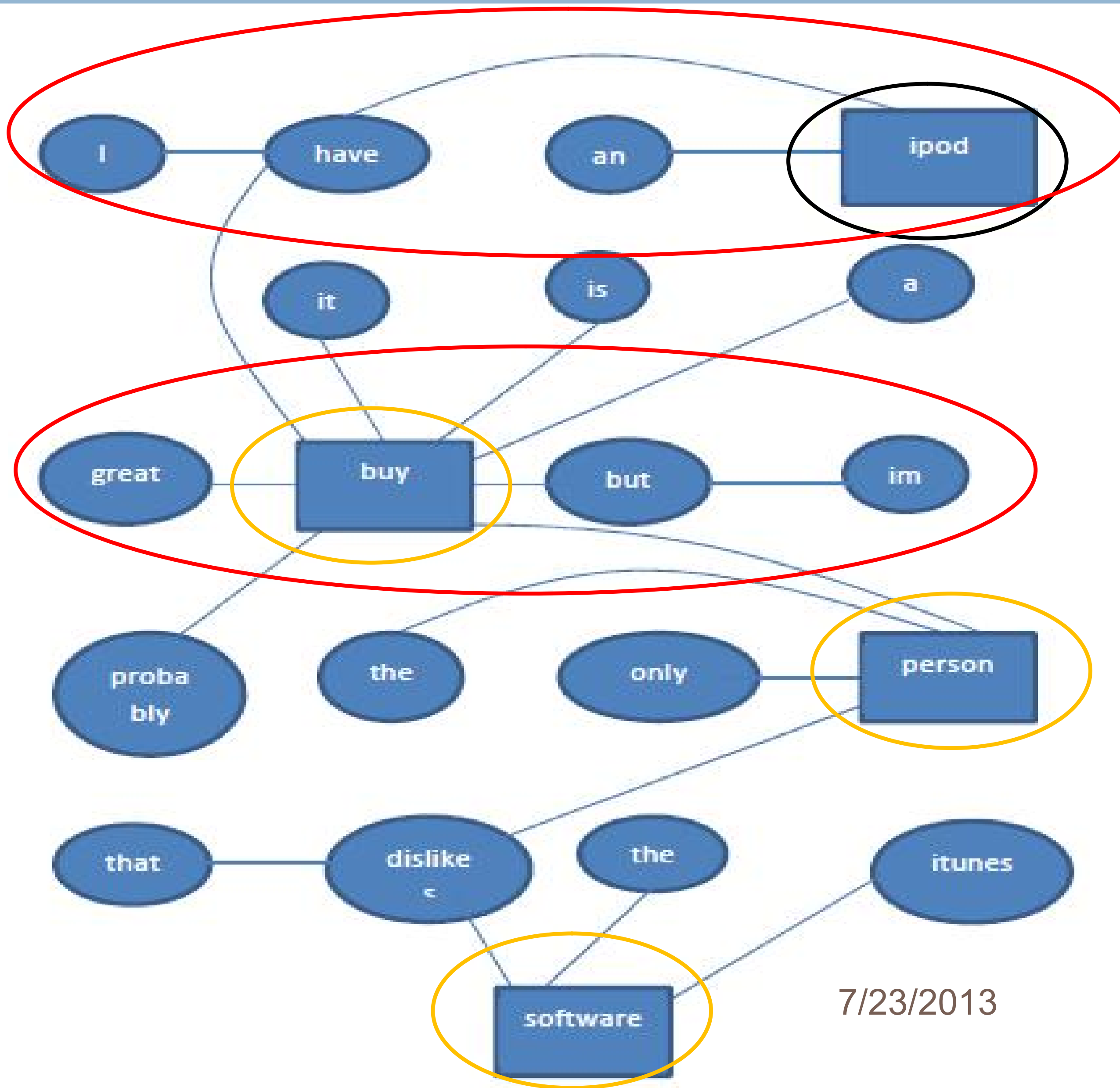
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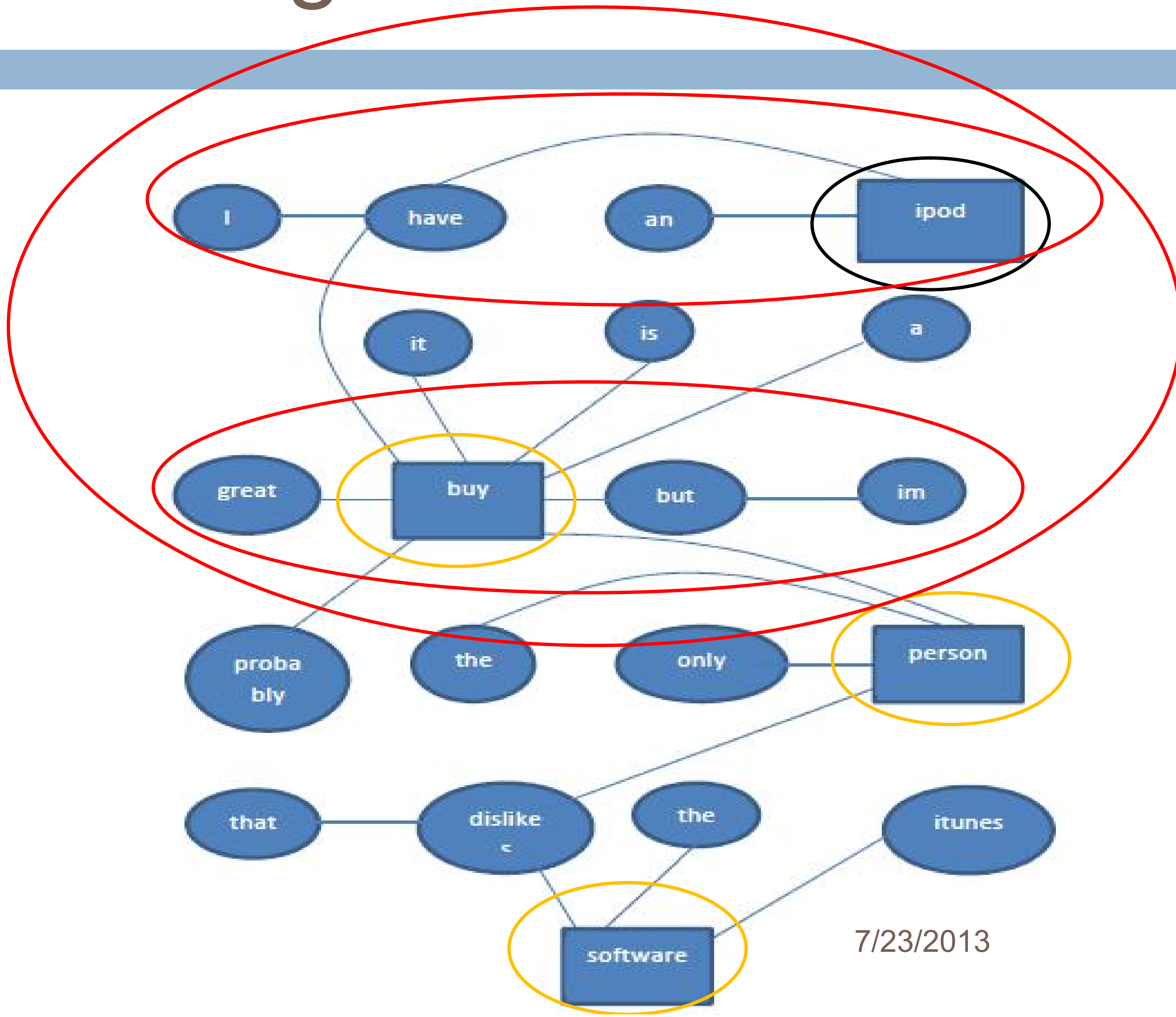
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- *Use of Hashtags* - *#overrated, #worthawatch.* More weightage is given by repeating them thrice
- *Use of Emoticons* - ☺ *(happy)*, ☹ *(sad)*
- *Use of Capitalization* - where words are written in capital letters to express intensity of user sentiments
  - *Full Caps* - Example: *I HATED that movie.* More weightage is given by repeating them thrice
  - *Partial Caps*- Example: *She is a Loving mom*. More weightage is given by repeating them twice

Spam Filter Evaluation

2-Class Classification

Tweets	Total Tweets	Correctly Classified	Misclassified	Precision (%)	Recall (%)
All	7007	3815	3192	54.45	55.24
Only spam	**1993**	**1838**	**155**	**92.22**	**92.22**
Only non-spam	5014	2259	2755	45.05	-

4-Class Classification

Tweets	Total Tweets	Correctly Classified	Misclassified	Precision (%)	Recall (%)
All	7007	5010	1997	**71.50**	**54.29**
Only spam	1993	1604	389	80.48	80.48
Only non-spam	5014	4227	787	84.30	-

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Lexicon-based
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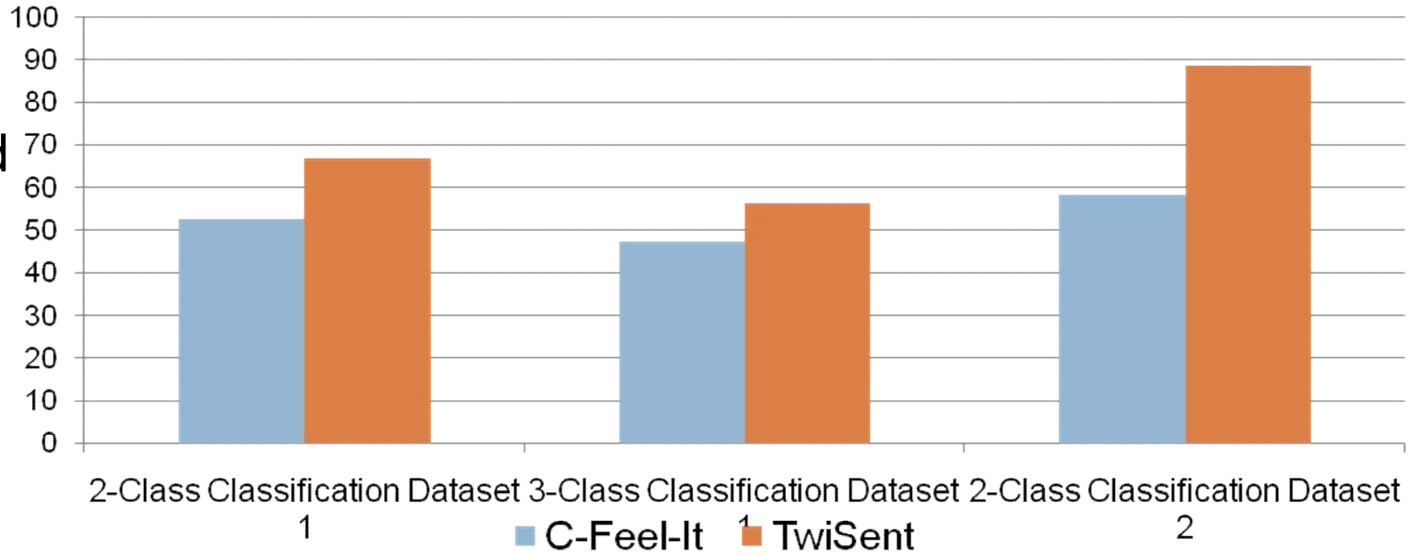

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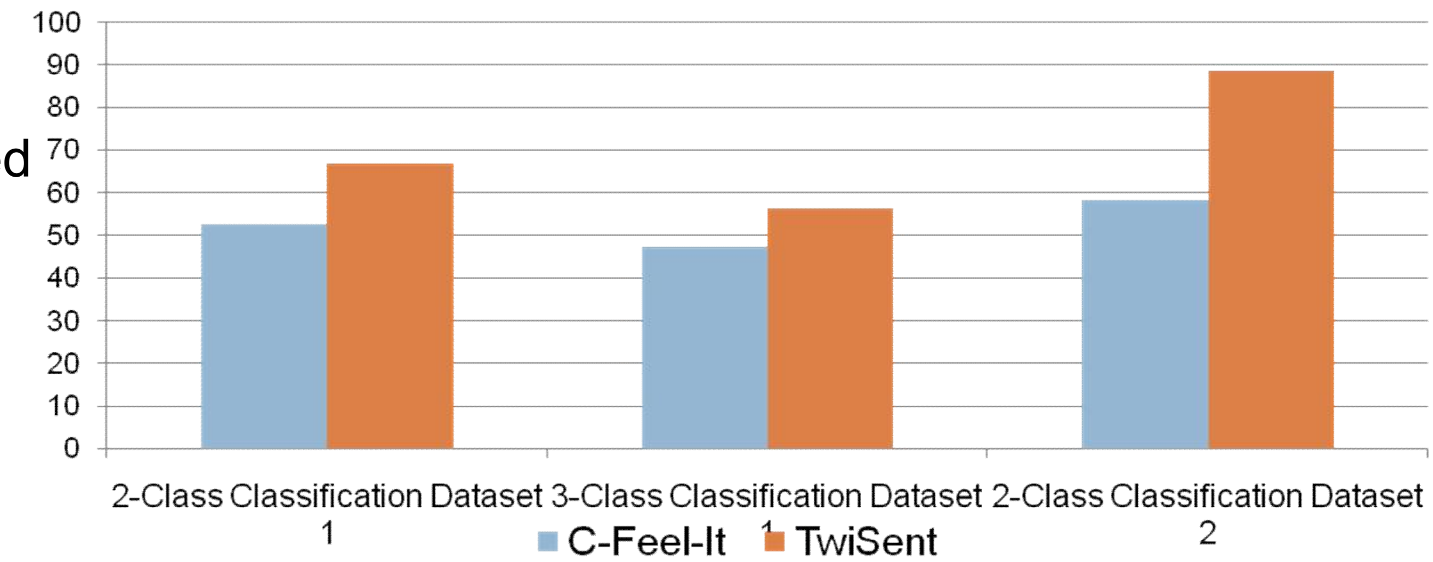

Supervised Classification

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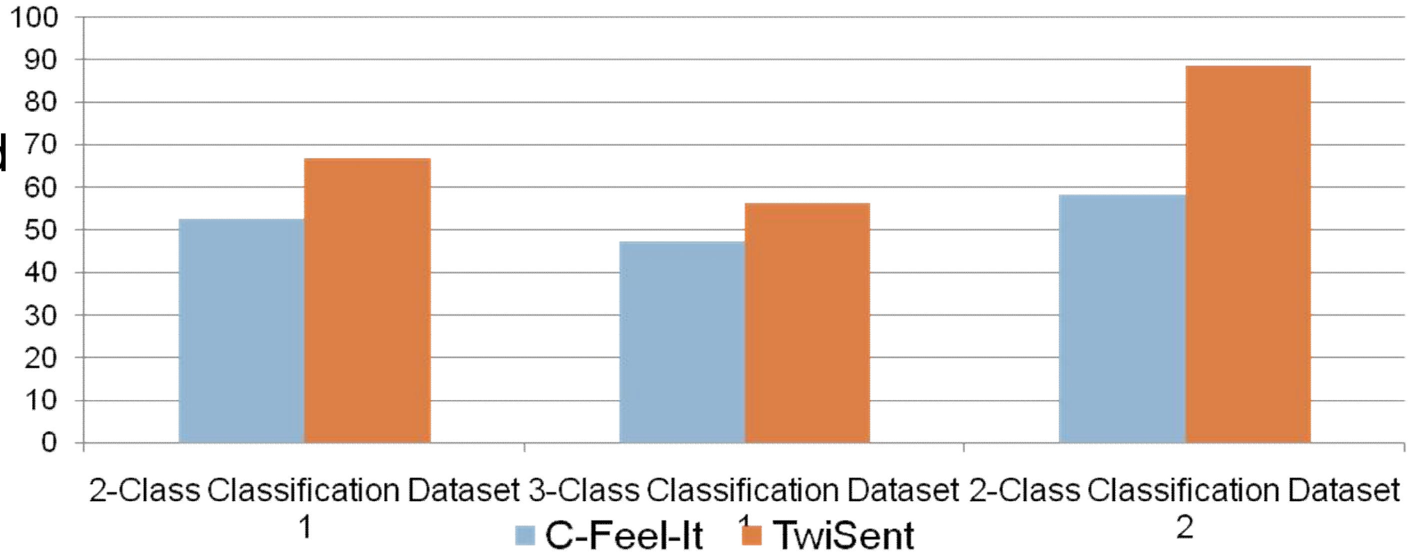

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System	2-class Accuracy	Precision/Recall
C-Feel-It	50.8	53.16/72.96
TwiSent	**68.19**	**64.92/69.37**

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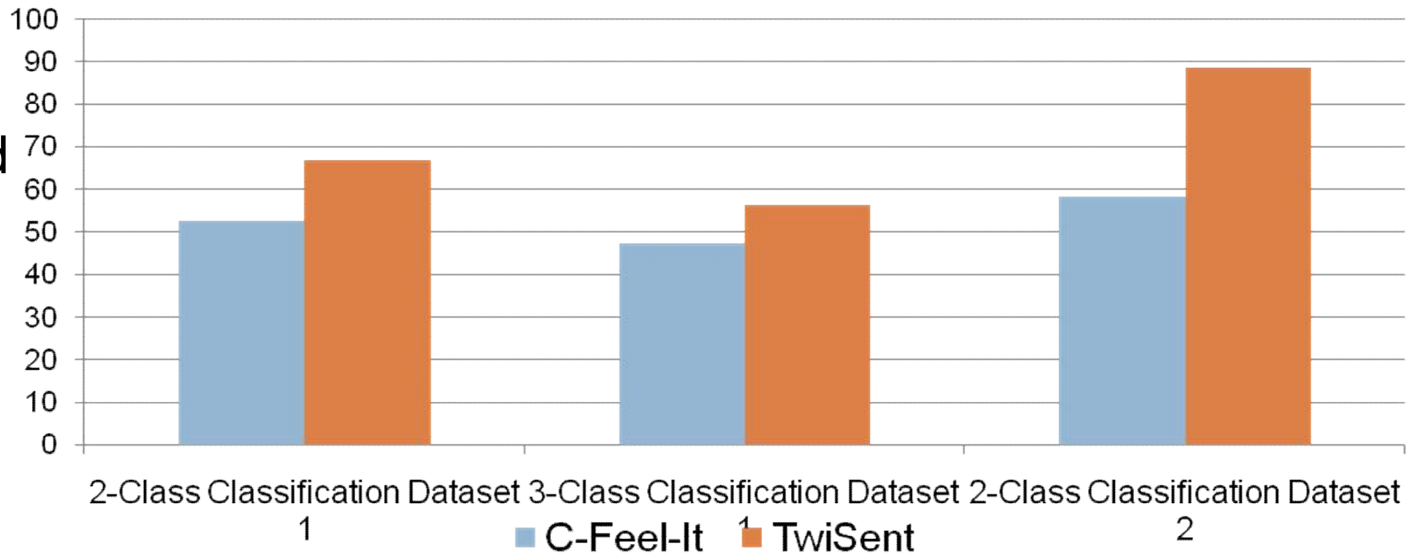

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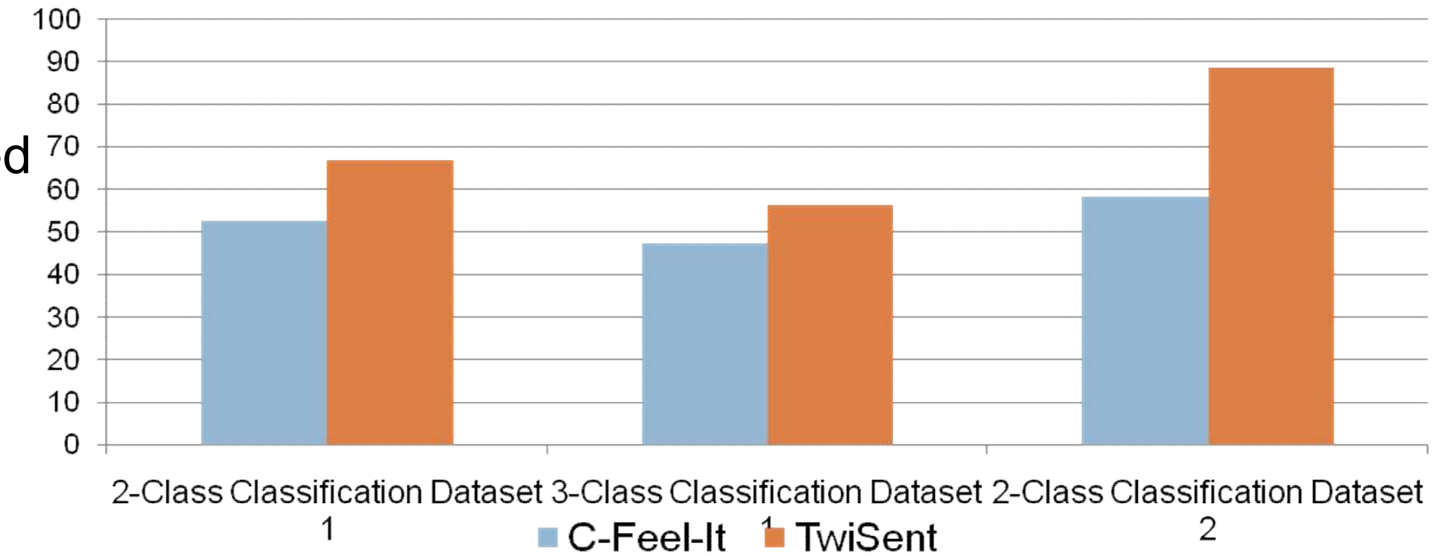
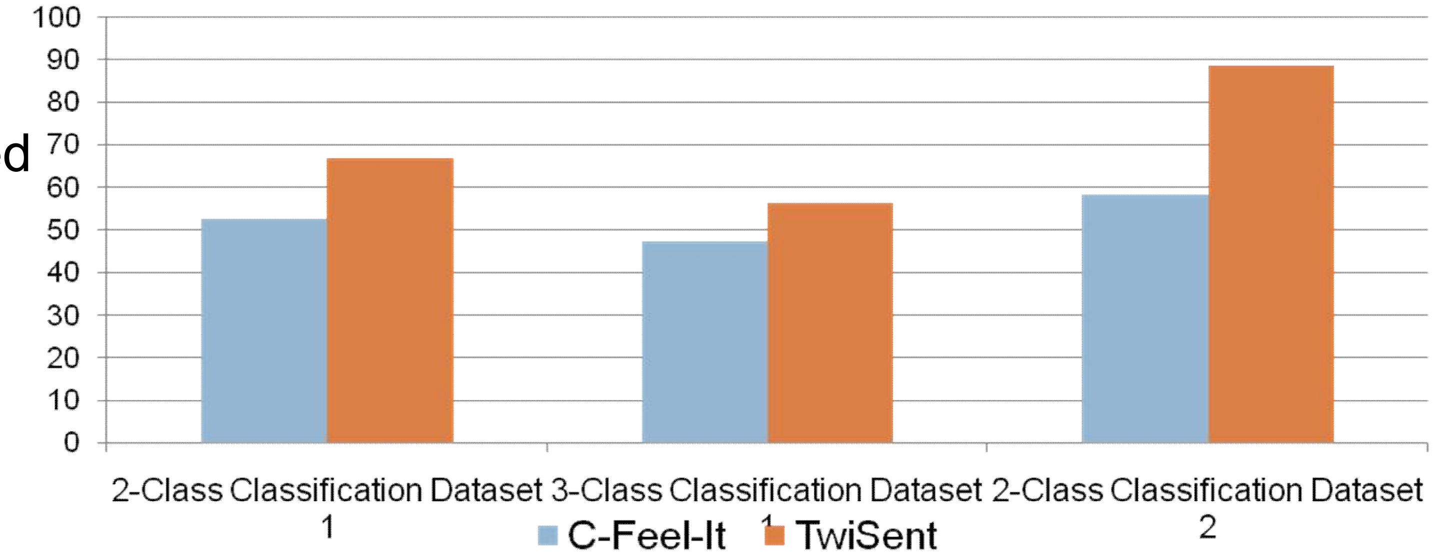


Ablation Test

System	2-class Accuracy	Precision/Recall
C-Feel-It	50.8	53.16/72.96
TwiSent	**68.19**	**64.92/69.37**

TwiSent Evaluation

Lexicon-based Classification



Ablation Test

Module Removed	Accuracy	Statistical Significance Confidence (%)
Entity-Specificity	65.14	95
Spell-Checker	64.2	99
Pragmatics Handler	63.51	99
Complete System	**66.69**	**-**