Sentiment Analysis using Word-Graphs

SUPER

Social sensors for secUrity assessments and Proactive EmeRgencies management

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SUPER Project

Co-funded by the European Commission's 7th Framework Programme

SUPER is a joint effort of social media and emergency management experts towards introducing a holistic, integrated and privacy-friendly approach to the use of social media in emergencies and security incidents.

Hurricane Sandy 2012 Oct 27 – Nov 1: 20M + Tweets

Picture from: www.theworld4realz.com

Social Sensors

- Event - SubEvent Detection
- Topic Community Tracking
- Sentiment Analysis
- Behaviour Abalysis
- Rumour Spreading Identification – Credibility
- Intelligent Fusion and Reasoning

Improve-Modify

Probabilistic Method Component

Deep Learning Component

Word Graph Representation Component

N

Sentiment Analysis 1/2

What is our principal challenge?

To detect Sentiment Polarities of published textual posts in SN!

Sentiments:

+ Positive

- Negative

= Neutral

Sentiment Analysis 2/2

How?

SA Problem → Text Classification Problem

What is our Contribution?

- **Different Reprsentation Model (No BoW)**
- **Similarity Measures**

Valuable information:

Neighborhood of the Words

Sequence of words

Example:

+

The Movie is not boring
I do like it

-

I do not like the Movie
It is boring

Same Set of Words Different Sentiments

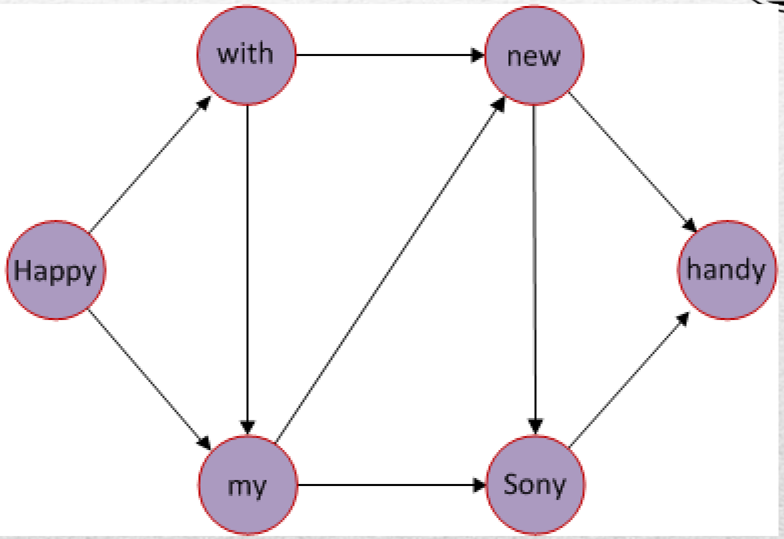
A good solution is the Word Graphs!

Directed & Unweighted Graph

- Nodes → Words
- Edges → join neighbor Words
- Vicinity → Frame N
- Direction → Sequence of words in the original text

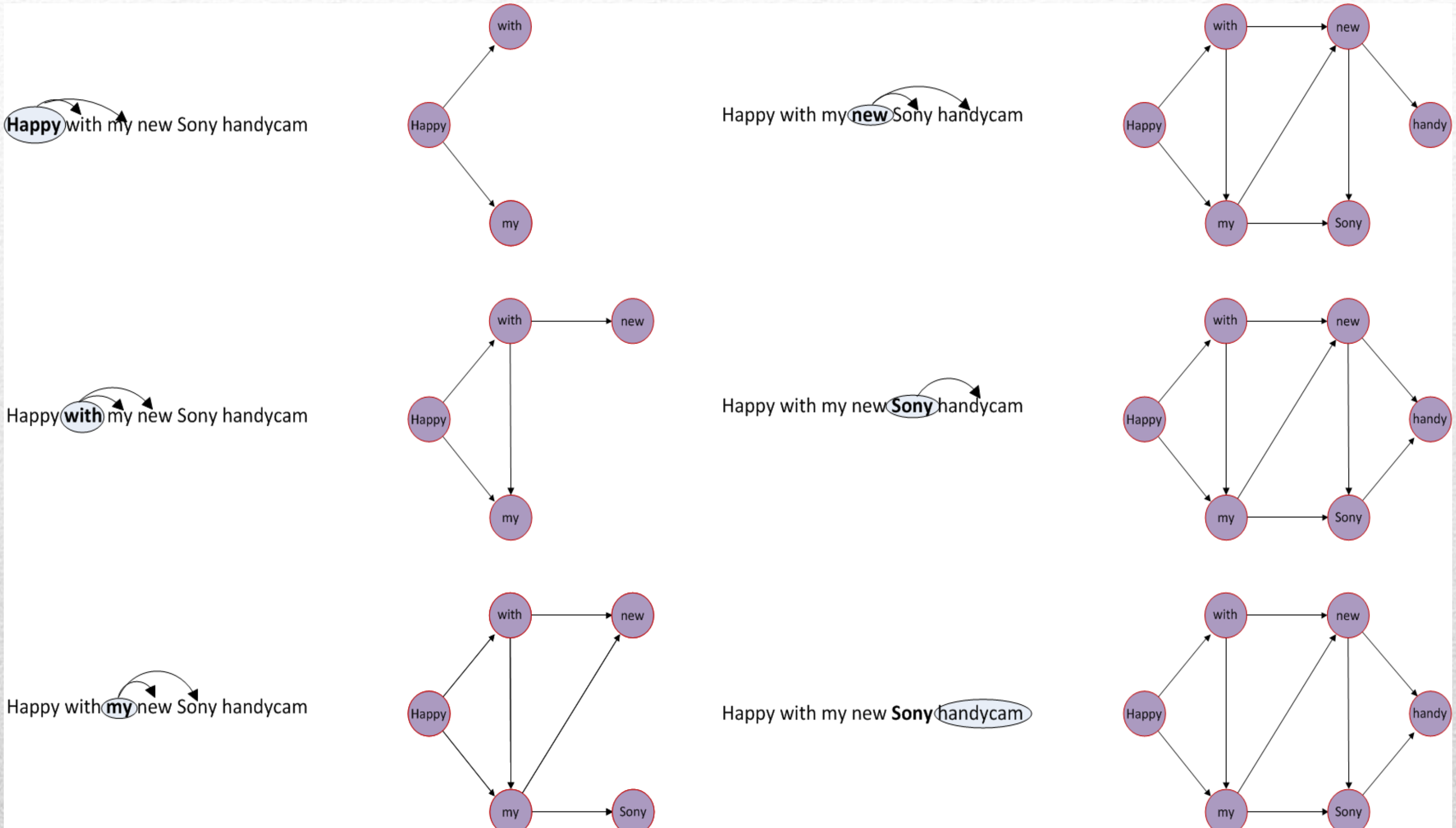
Word Graph Representation

Happy with my new Sony handycam



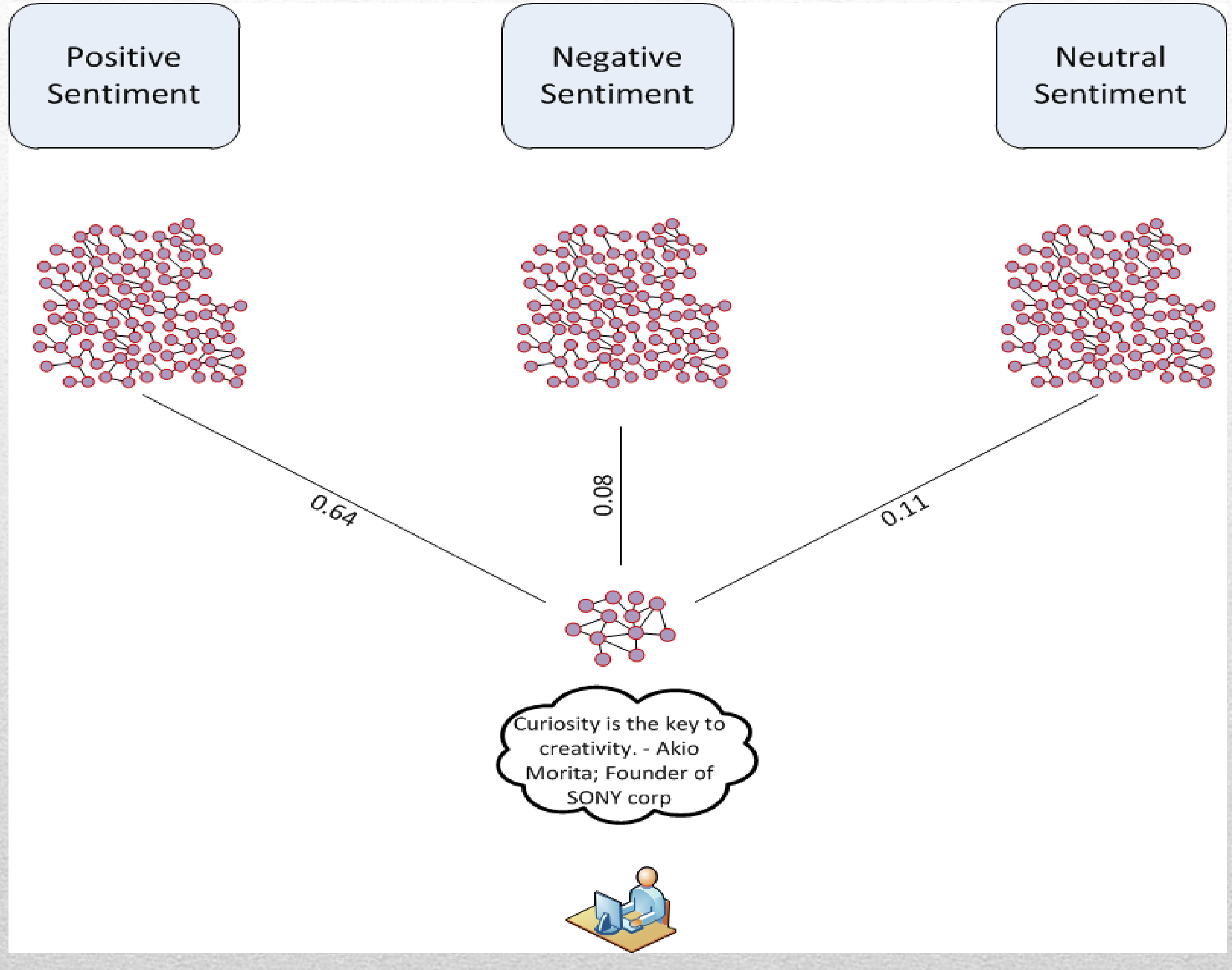
N=2

Graph Construction

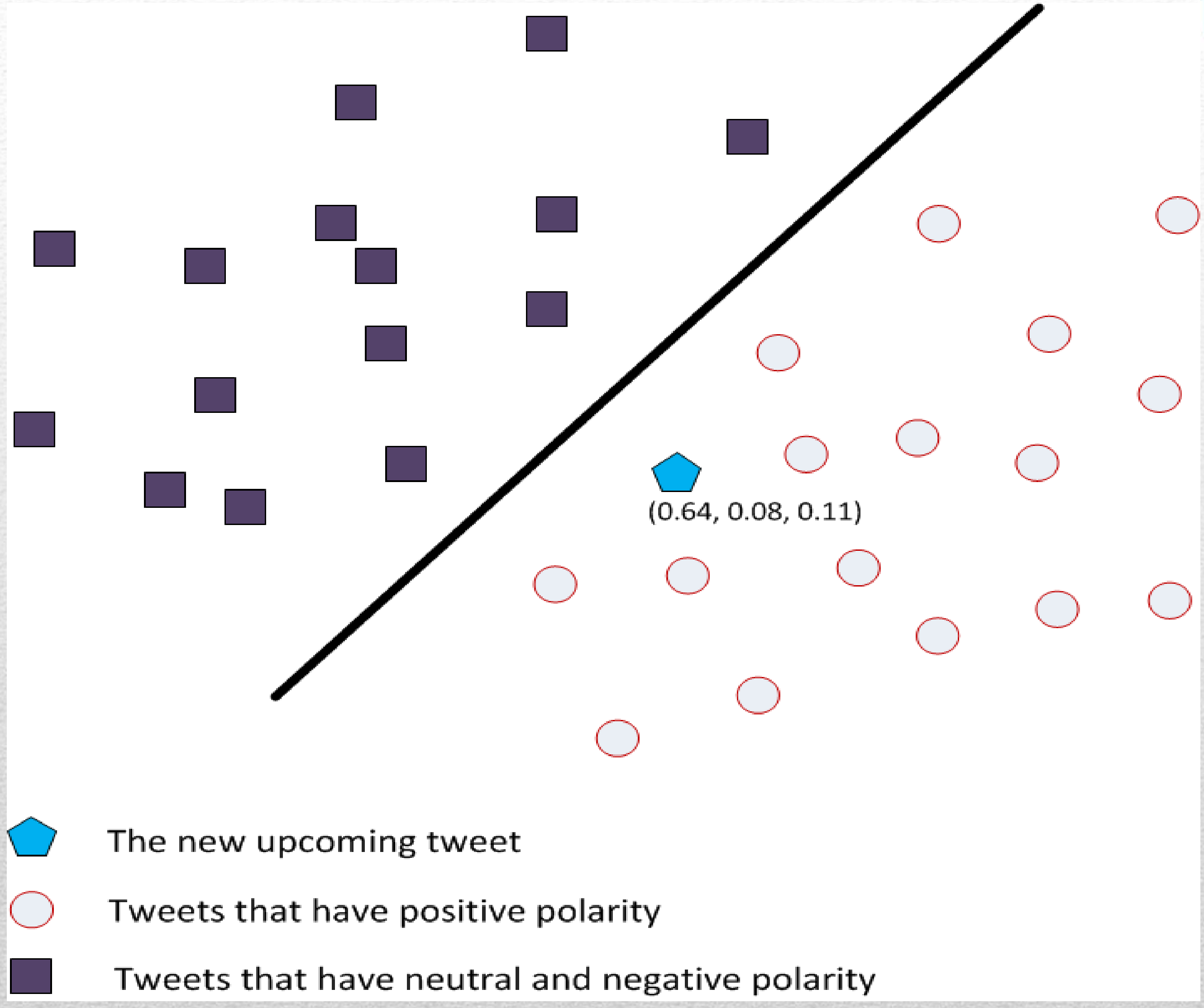


N=2

Word Graph Representation

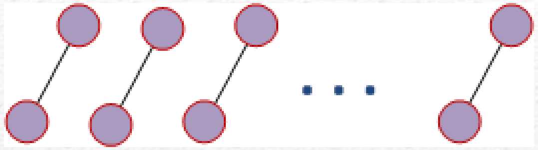


Classification



Graph Similarity Metrics:

- **Containment Similarity**



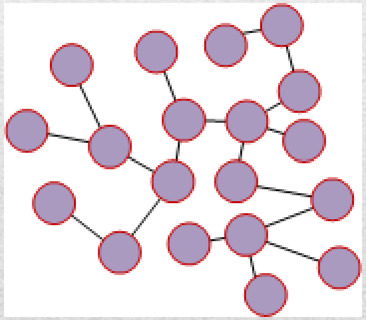
  # Common Edges # Max Edges Normalization

- **Maximum Common SubGraph**

  # Nodes

  # Undirected Edges

  # Directed Edges



ORGANIZATION LOGO

SUPER

Feature Selection techniques:

- Nodes
- Edges

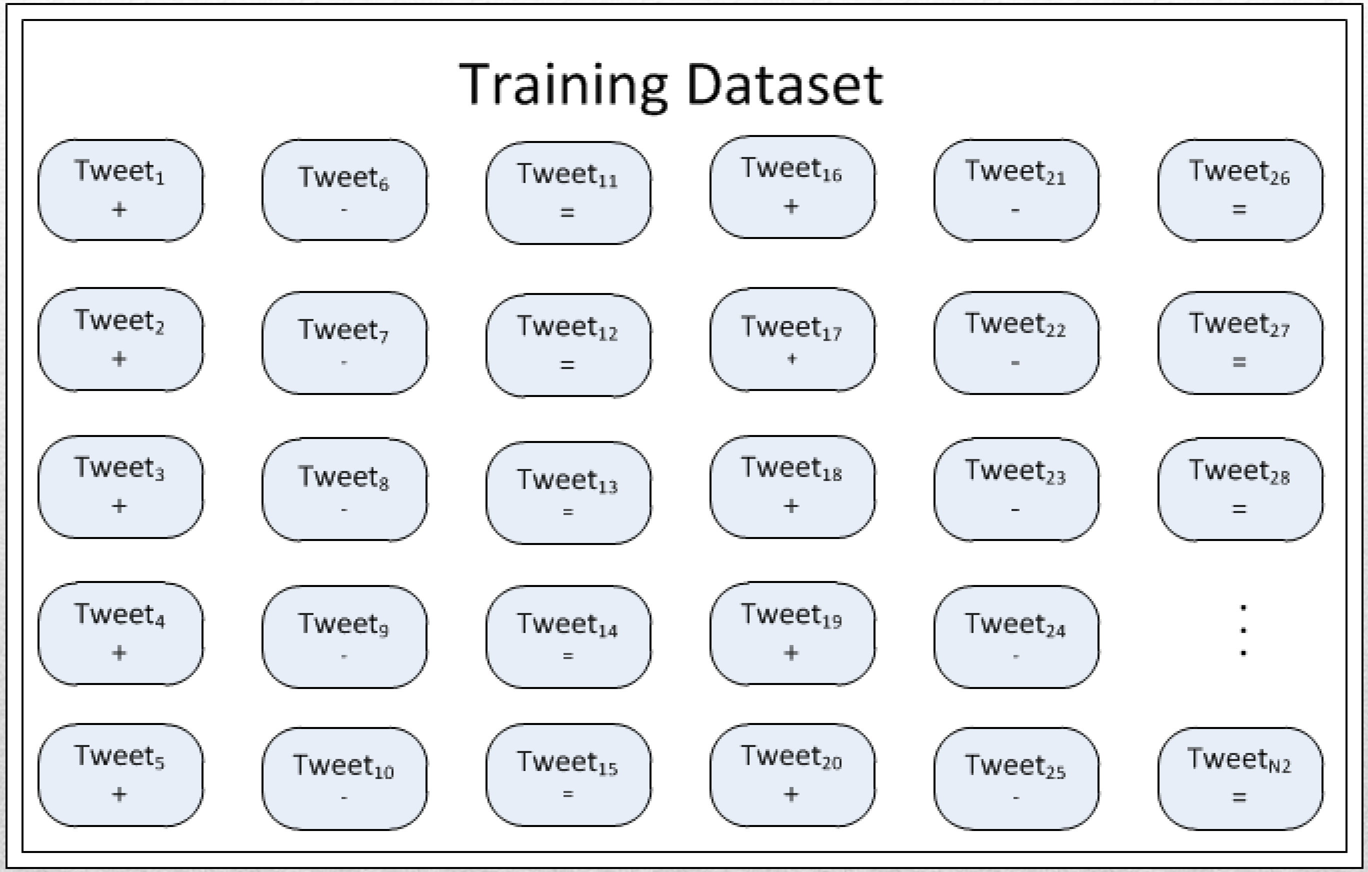
Benefits:

- Improve the Accuracy
- Decrease the Dimensionality & Computation

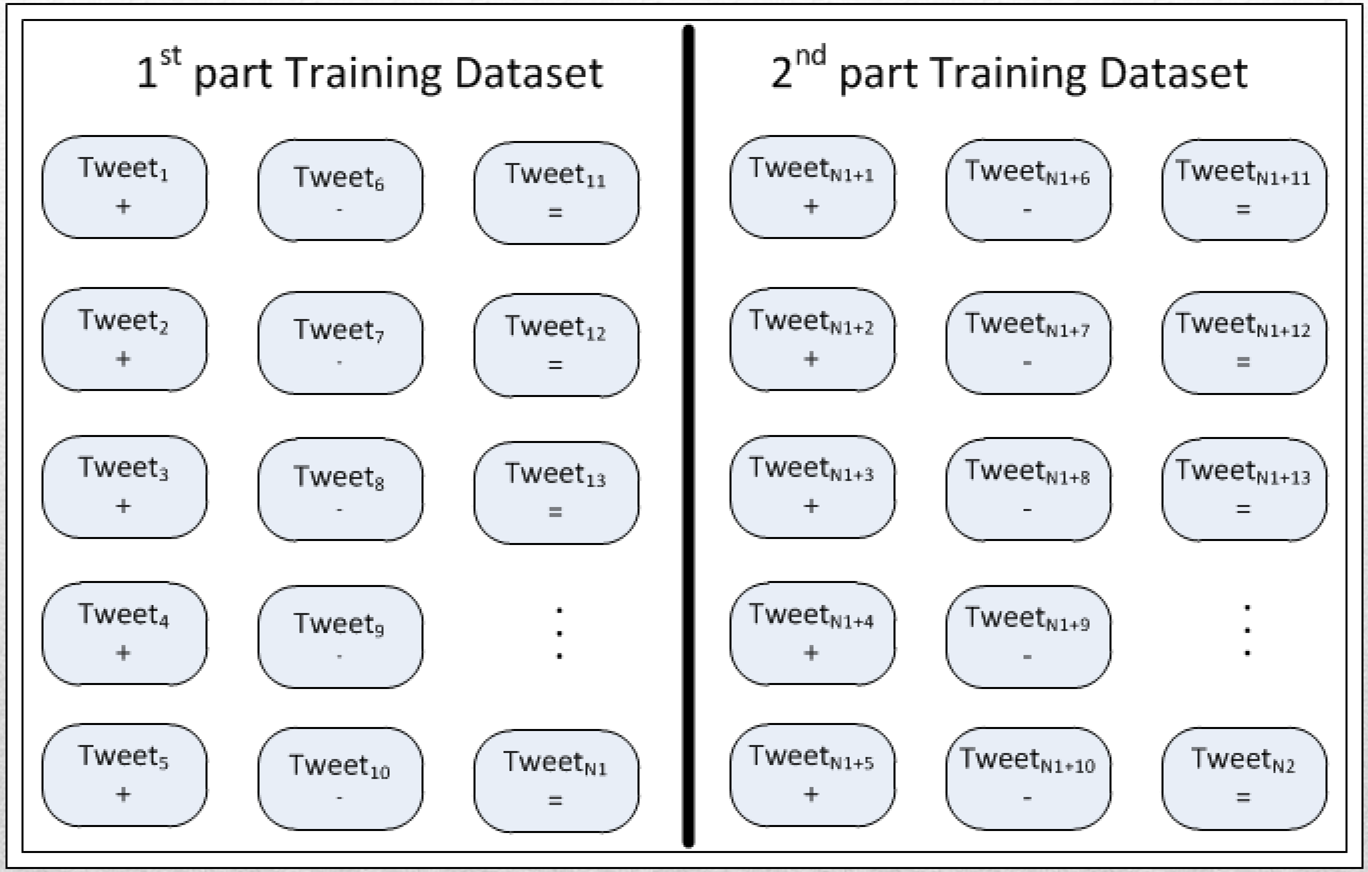
Mutual Information:

The Appropriateness and the Contribution of each Edge for the Accurate Sentiment Prediction + - =

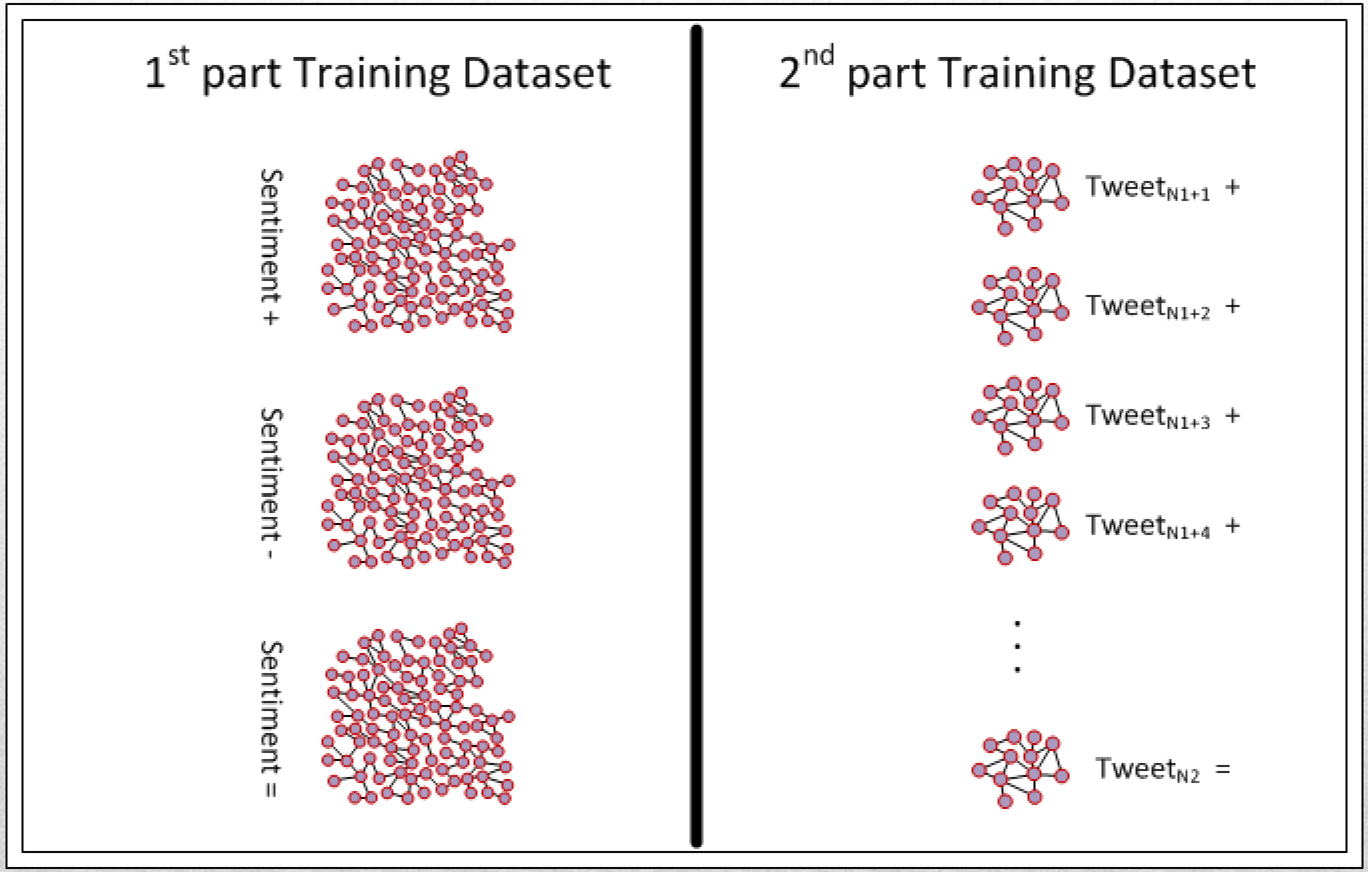
Stage 1/7


Training Dataset
Tweet$_1$ +
Tweet$_2$ +
Tweet$_3$ +
Tweet$_4$ +
Tweet$_5$ +
Tweet$_6$ -
Tweet$_7$ -
Tweet$_8$ -
Tweet$_9$ -
Tweet$_{10}$ -
Tweet$_{11}$ =
Tweet$_{12}$ =
Tweet$_{13}$ =
Tweet$_{14}$ =
Tweet$_{15}$ =
Tweet$_{16}$ +
Tweet$_{17}$ +
Tweet$_{18}$ +
Tweet$_{19}$ +
Tweet$_{20}$ +
Tweet$_{21}$ -
Tweet$_{22}$ -
Tweet$_{23}$ -
Tweet$_{24}$ -
Tweet$_{25}$ -
Tweet$_{26}$ =
Tweet$_{27}$ =
Tweet$_{28}$ =
⋮
Tweet$_{N2}$ =

Stage 2/7

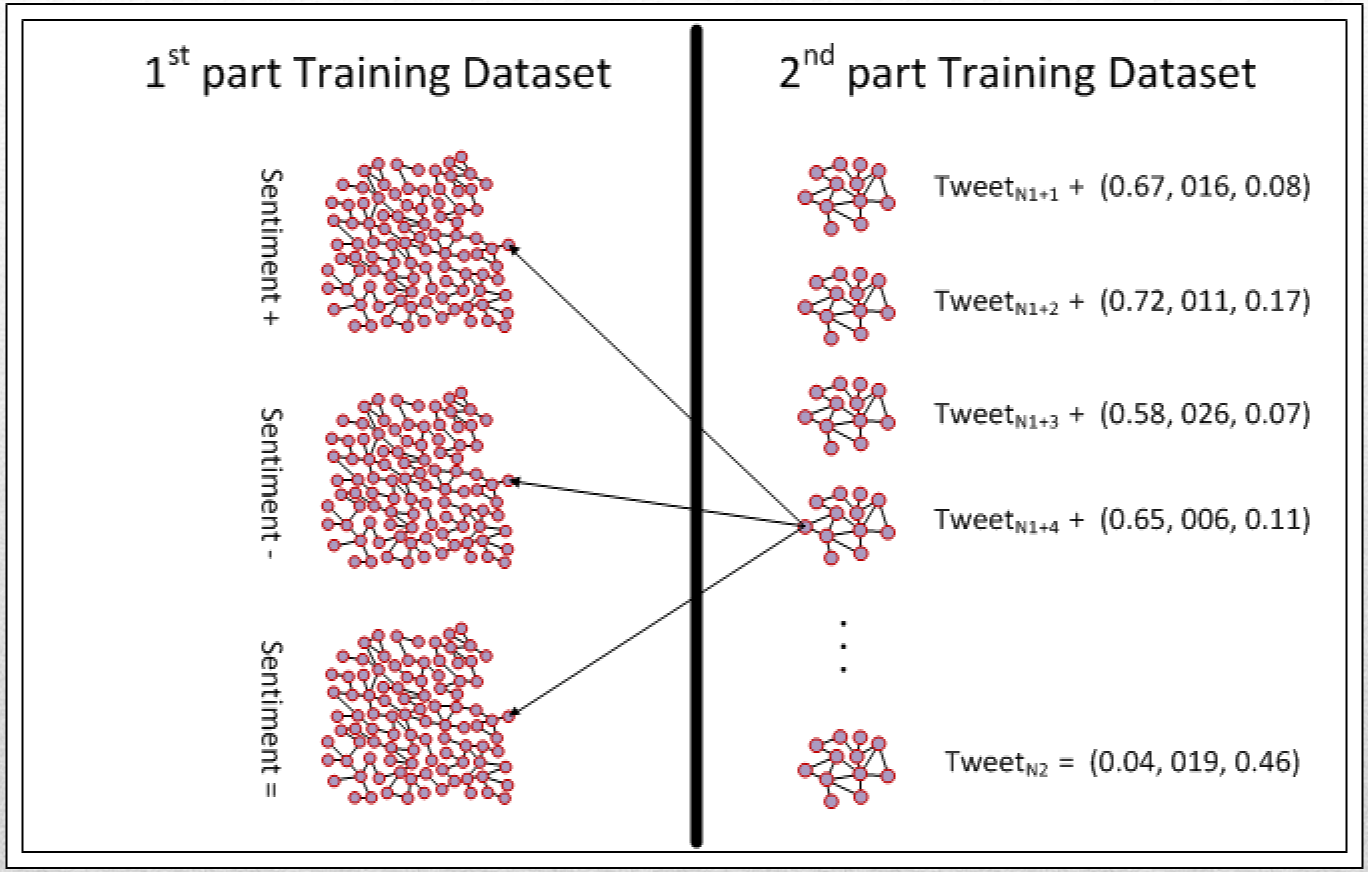

1st part Training Dataset
2nd part Training Dataset
Tweet1 +
Tweet6 -
Tweet11 =
Tweet2 +
Tweet7 -
Tweet12 =
Tweet3 +
Tweet8 -
Tweet13 =
Tweet4 +
Tweet9 -
Tweet5 +
Tweet10 -
TweetN1 =
TweetN1+1 +
TweetN1+6 -
TweetN1+11 =
TweetN1+2 +
TweetN1+7 -
TweetN1+12 =
TweetN1+3 +
TweetN1+8 -
TweetN1+13 =
TweetN1+4 +
TweetN1+9 -
TweetN1+5 +
TweetN1+10 -
TweetN2 =

Stage 3/7



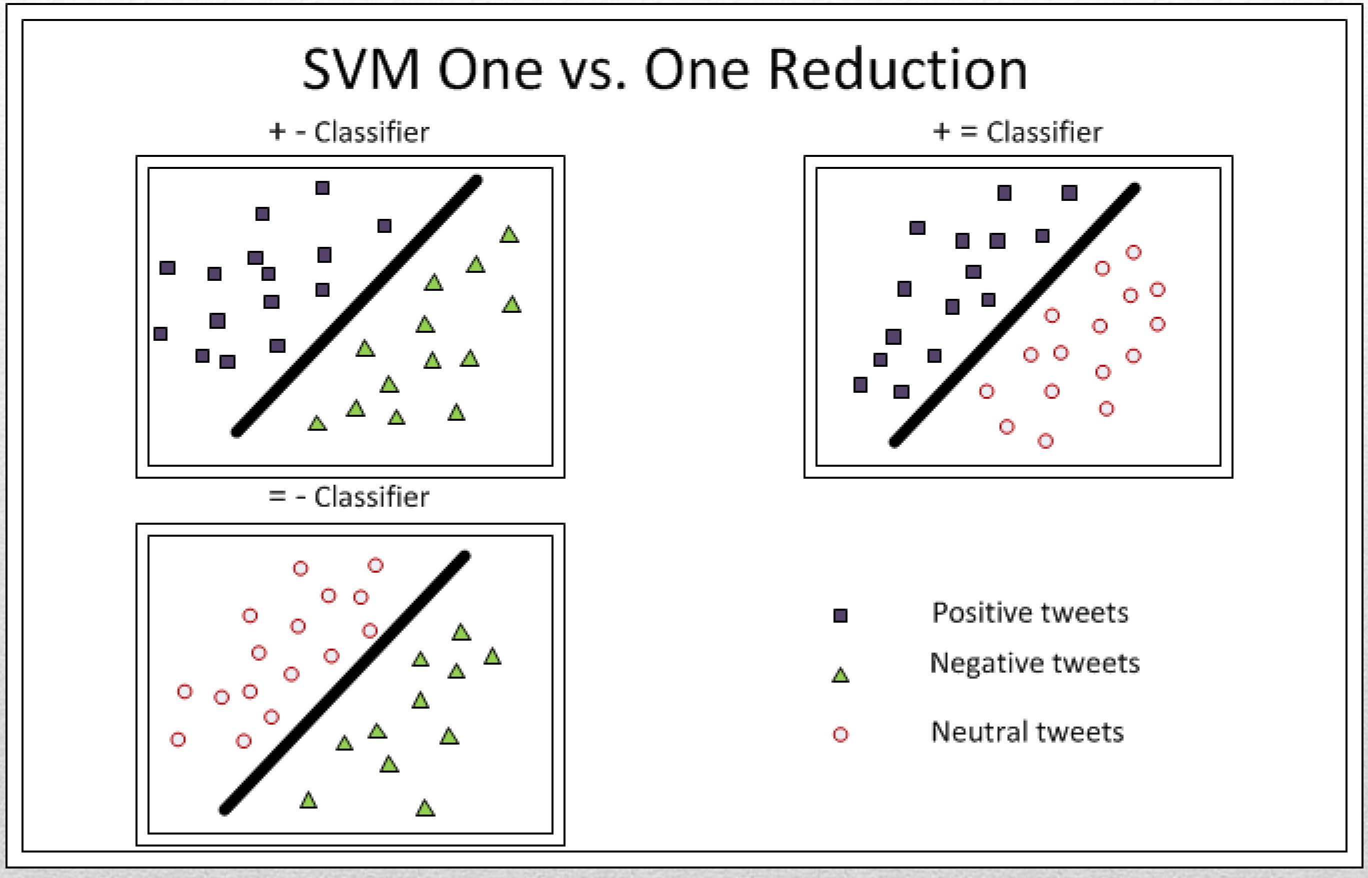
1st part Training Dataset
Sentiment +
Sentiment -
Sentiment =
2nd part Training Dataset
Tweet N1+1 +
Tweet N1+2 +
Tweet N1+3 +
Tweet N1+4 +
Tweet N2 =

Stage 4/7

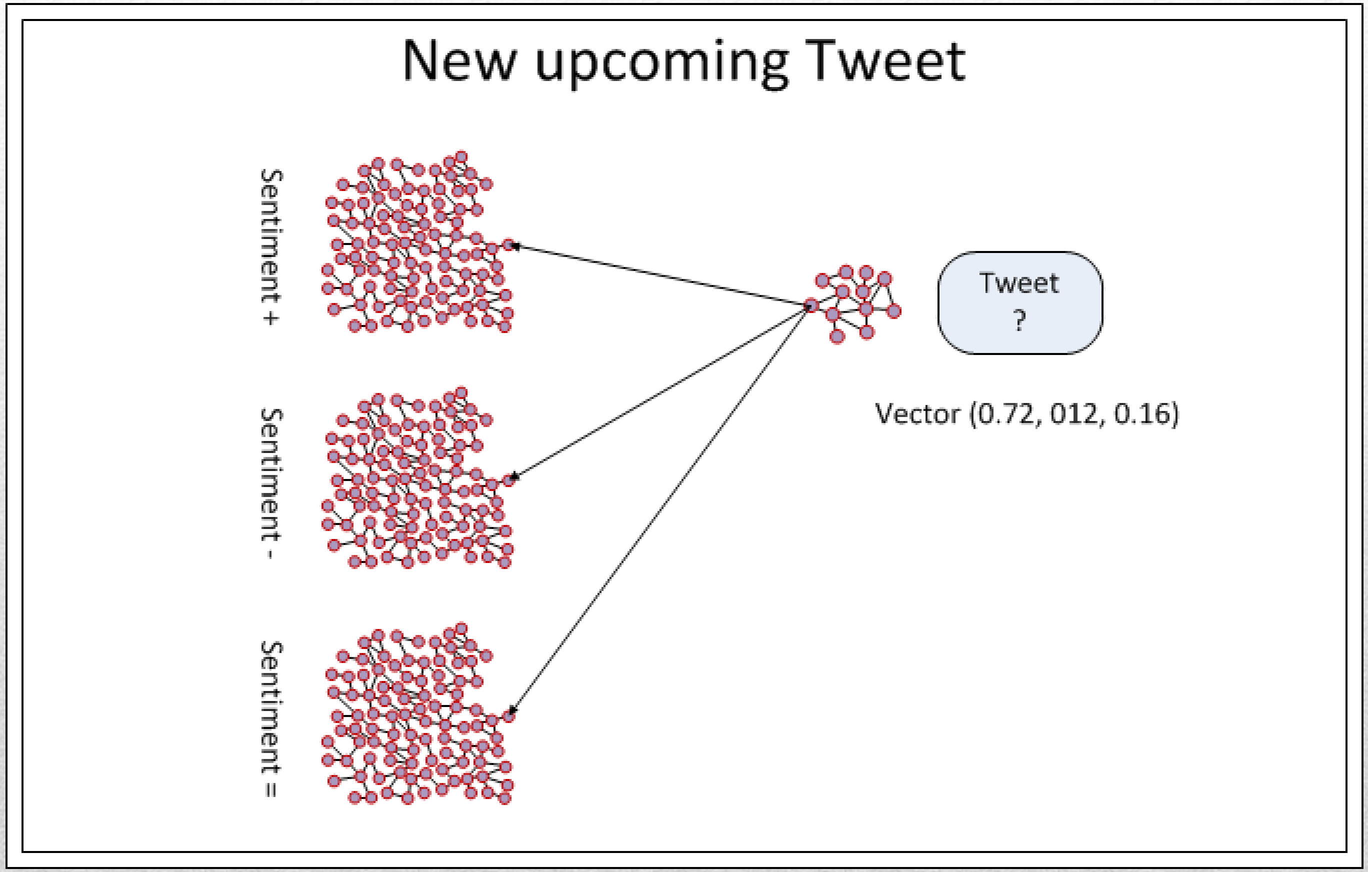


1st part Training Dataset
2nd part Training Dataset
Sentiment +
Sentiment -
Sentiment =
TweetN1+1 + (0.67, 016, 0.08)
TweetN1+2 + (0.72, 011, 0.17)
TweetN1+3 + (0.58, 026, 0.07)
TweetN1+4 + (0.65, 006, 0.11)
TweetN2 = (0.04, 019, 0.46)

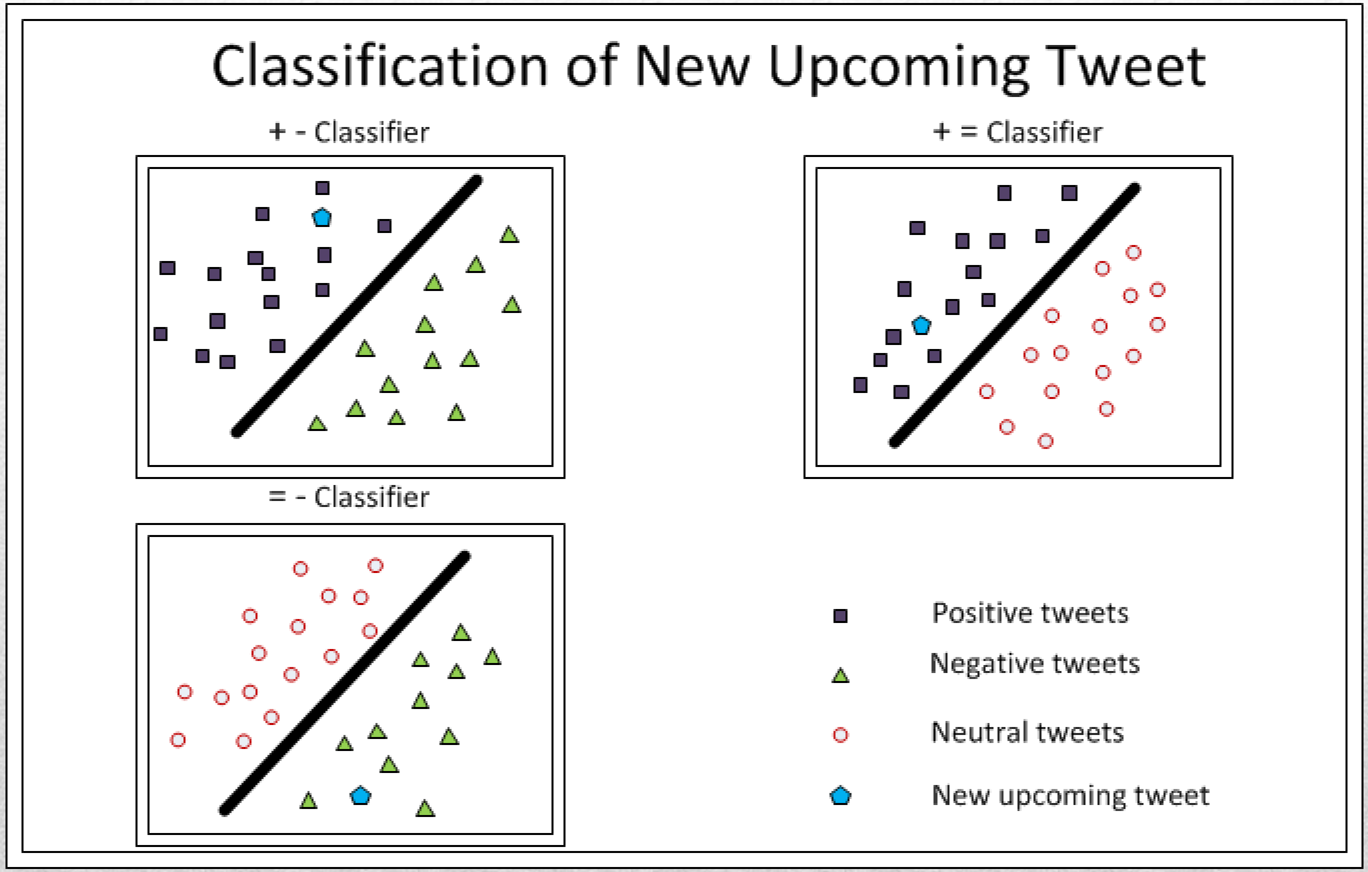
Stage 5/7


SVM One vs. One Reduction
+ - Classifier
+ = Classifier
= - Classifier
Positive tweets
Negative tweets
Neutral tweets

Stage 6/7


New upcoming Tweet
Sentiment +
Sentiment -
Sentiment =
Tweet
?
Vector (0.72, 012, 0.16)

Stage 7/7


Classification of New Upcoming Tweet
+ - Classifier
+ = Classifier
= - Classifier
Positive tweets
Negative tweets
Neutral tweets
New upcoming tweet

Evaluation

Public available Dataset from the research Language-Independent Twitter Sentiment Analysis of Sascha, Hufenhaus and Albayark

The dataset is manually annotated by workers on Amazon's Mehanical Turk

10594 tweets

+ 2334

- 1486

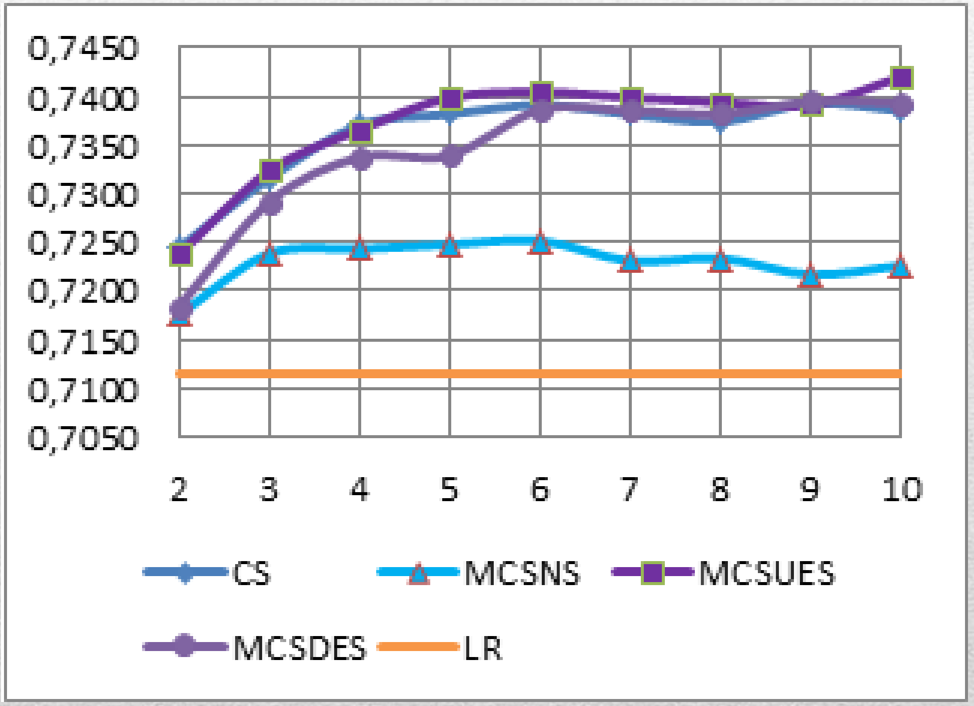
= 6774

SA Accuracy with SOA Methods

Method	4Gram	4Gram Graphs
Bayesian Network	0.6788	0.6791
C4.5	0.6828	0.6896
SVM	0.6777	0.6847
Logistic Regression	0.6822	**0.7115**
Simple Logistic Regression	0.6816	0.7109
Multi-Layer Perceptron	0.6788	0.7069
Best-First Tree	0.6790	0.6840
Functional Tree	0.6822	0.7079

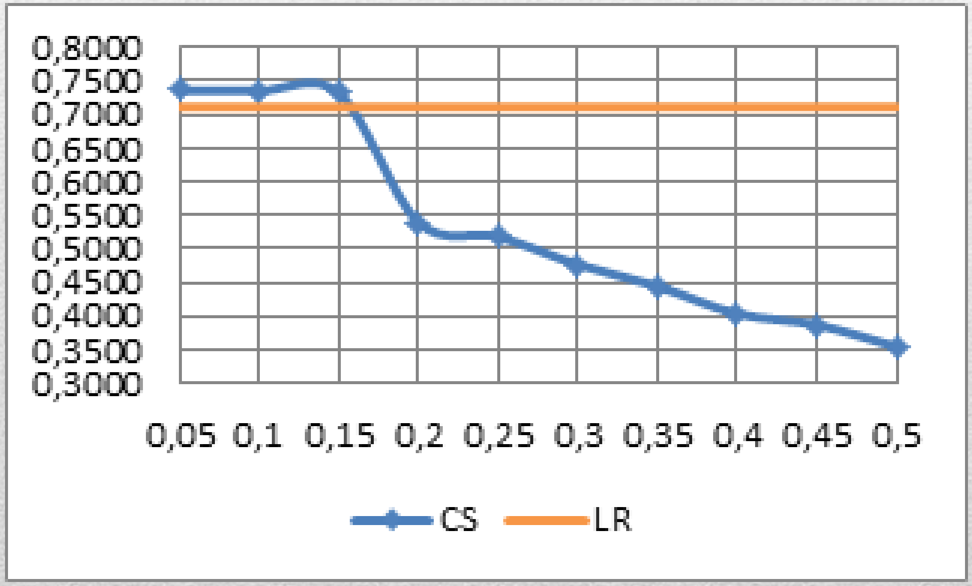
10-Fold Cross Validation
Various size of N (2 - 10) Frame Window
Various Graph Similarity Metrics

No Graph Filering
SVM Classifier



10-Fold Cross Validation
Four-Words Frame size
Mutual Information on Edges as Feature Selection technique
MCS Graph similarity techniques in combination with MI deteriorates the Accuracy of the method

Contanimen Similarity
SVM Classifier



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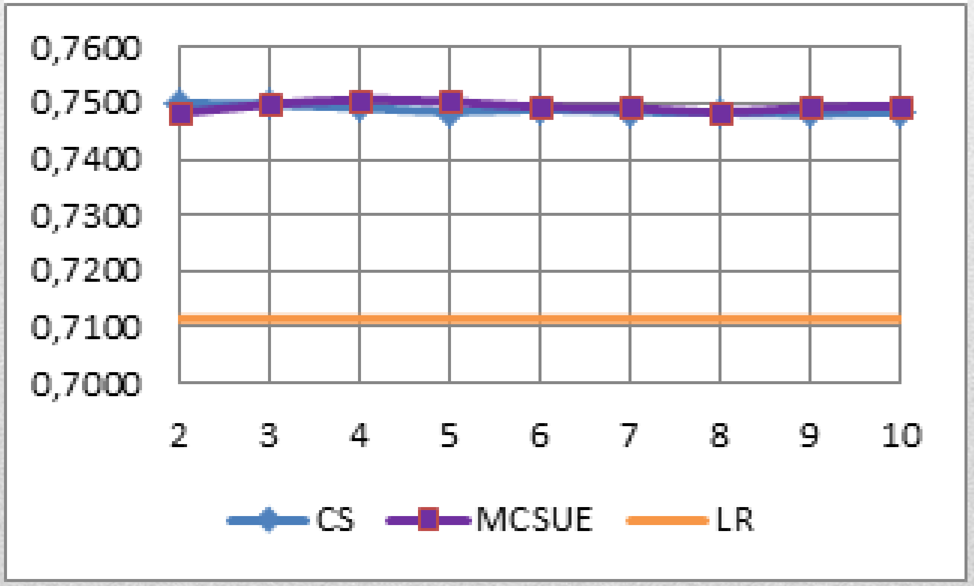
10-Fold Cross Validation
Various size of N (2 – 10) Frame Window
Containment Similarity
MCSUE Similarity

Gaussian Bayes classifier
No Graph filtering



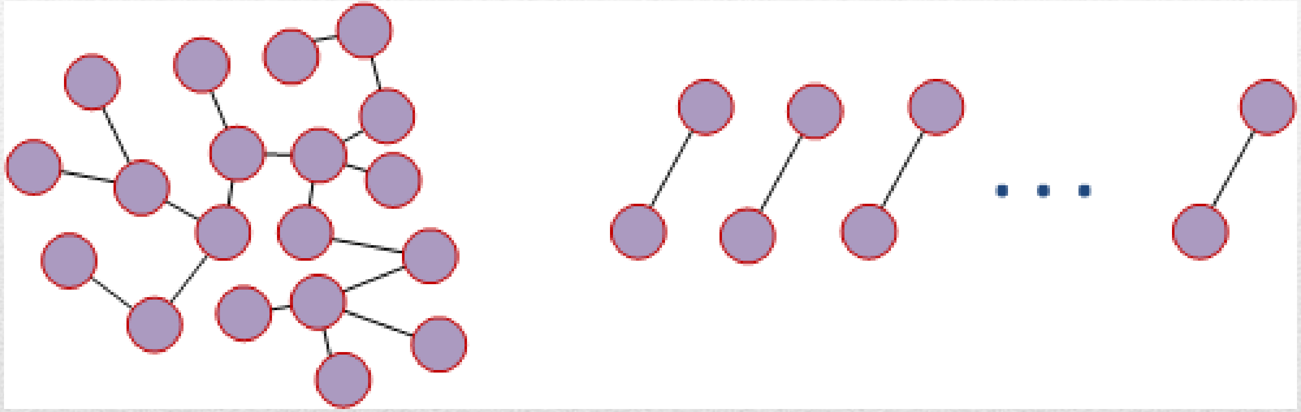
Conclusions 1/3

WGSA:

- Vicinity & sequence of the words-terms.
- Writing characteristics & Partial Matching.
- Polysemy
- Evolution of the Annotated Dataset
- The discard of the edges with low MI has as a result to separate the MCS that captures the sentiment.

Conclusions 2/3

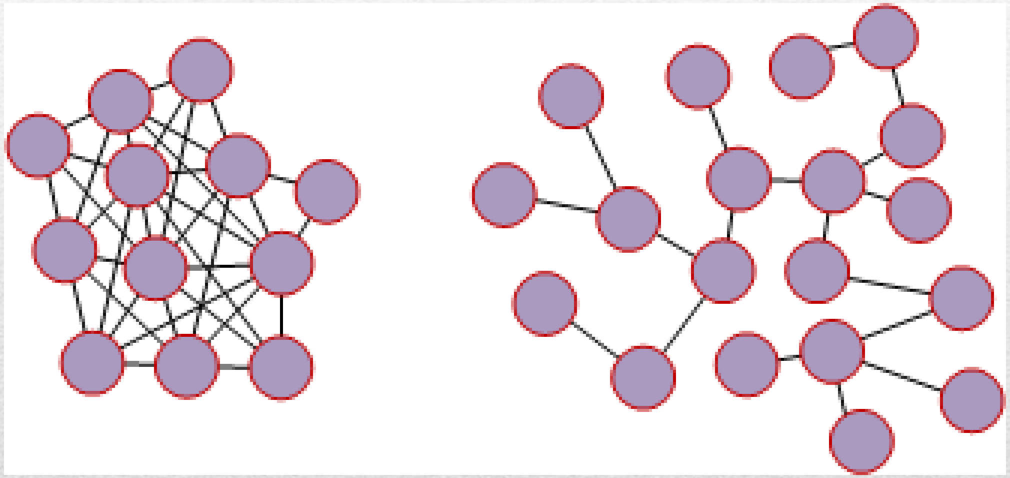
MCS>CS



A correlation among a few common words is more important than the existance of many common word pairs.

Conclusions 3/3

MCSUES>MCSNS



The Dense Correlation among few words is more important than the sparse correlation between many words.

Future work

- Weighted Graphs
- Graph Similarity metrics
- Targeted Sentiment Analysis
- More Sentiments
- Different Training Dataset to Testing Dataset

Thank you for your attention!