Twitter Spam Detection based on Deep Learning

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Background

- Authored by Tingmin Wu, Shigang Liu, Jun Zhang and Yang Xiang
    - School of Information Technology, Deakin University, Australia
    - January 2017
    - Cited by 55 future works since

Introduction

- Twitter
  - A social media platform for microblogging
  - Approx each month, 42 million new accounts
- Goal
  - Develop a spam filter based on deep learning
  - Evaluate with other existing techniques
    - ML based
    - URL blacklisting

Introduction

- Compared against Email spam, users are more likely to click on spam links on Twitter instead
  - Twitter: 0.13%
  - Email: 0.0003% to 0.0006%
- On a normal Twitter dataset of 2 million tweets
  - 8% of it is flagged as spam

Introduction

- Previous techniques for spam filtering were
  - Tweet content-based classifier
    - Couldn't generate comparable results
  - Machine learning-based binary classifiers
    - Easily fabricated features, hampering the accuracy
  - Blacklisting filtering is time-consuming

Introduction

- Proposed solution
  - Word2Vec to pre-process tweets
  - Binary detection model to detect spam and non-spam
  - Solve existing problems in other models
    - low speed
    - under-standard accuracy
    - characteristic extraction problem

Literature Review

- Syntax Analysis
  - Analyze tweet on a word level platform
  - Detect shortened URLs
    - Used by spammers to hide malicious URLs
    - Older models cannot handle redirected URLs
  - Extract tweet content, use deep learning to learn syntactic contexts and information
  - Naive Bayes classifier gave more efficient scores

Literature Review

- Feature Analysis
  - Extract tweets using Twitter’s Streaming API
  - Analyze the tweet’s features, like “retweet” and “like” counts.
  - Hashtag extraction
  - Etc...

Literature Review

- Bayesian Model
  - Learning model to detect spammers
- SVM Model
  - Detect both spam and spammers
- Random Forest Model
  - Obtain features from spam profiles
  - Trained by Decorate and LogitBoost algorithms

Literature Review

- Issues with Feature Analysis
  - Spam drift issue
    - Can be solved by fuzzy-based redistribution and asymmetric sampling
  - Feature fabrication in data collection
    - Social graph to expose robust features
    - Understand Twitter profile behaviours

Literature Review

- Blacklist Techniques
  - Blocking malicious websites
  - Time-consuming
  - Manual labelling

Methodology

- Understand and analyse text using a deep neural network with multiple layers
- Word Vector for language analysis
- Text-base Vector for linguistic analysis

Methodology

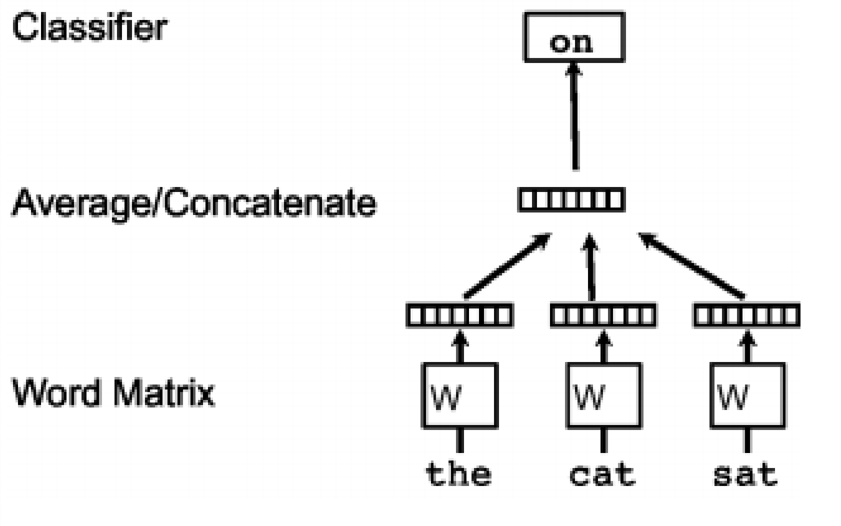
- Apply Word2Vec to map each word into a multidimensional vector
- 2-level neural network using Huffman technique
- Hierarchical softmax
- Improves efficiency in training
    - High-frequency words can be processed fast
- Stochastic gradient descent by backpropagation
- Optimal vectors are extracted for each word by CBOW or Skip-gram

Methodology

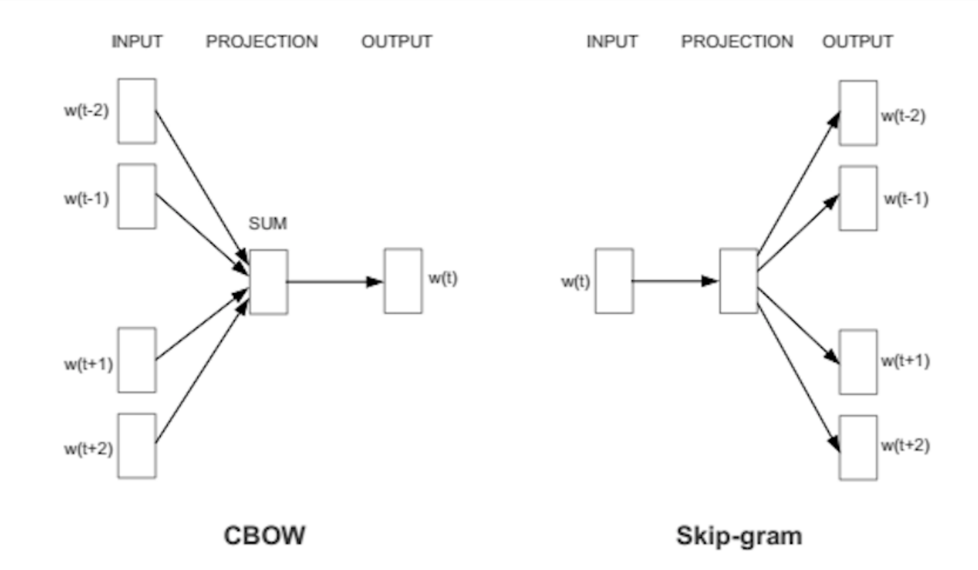
- Doc2Vec training
  - Represent one vector for every tweet using Paragraph Vector modelling
- Word2Vec training
  - Tweet-length with combination of word vectors and unique document vector per record
- Input features for Random Forest or Neural Network
  - Get document representation
  - Form training dataset
  - Form test dataset

Word2Vec

- 2-layer neural net that processes text by "vectorizing" words
- Input is a text corpus and its output is a set of vectors
- Text into a numerical form that deep neural networks can understand.
- Continuous Bag-of-Words model (CBOW) and the Skip-Gram model.



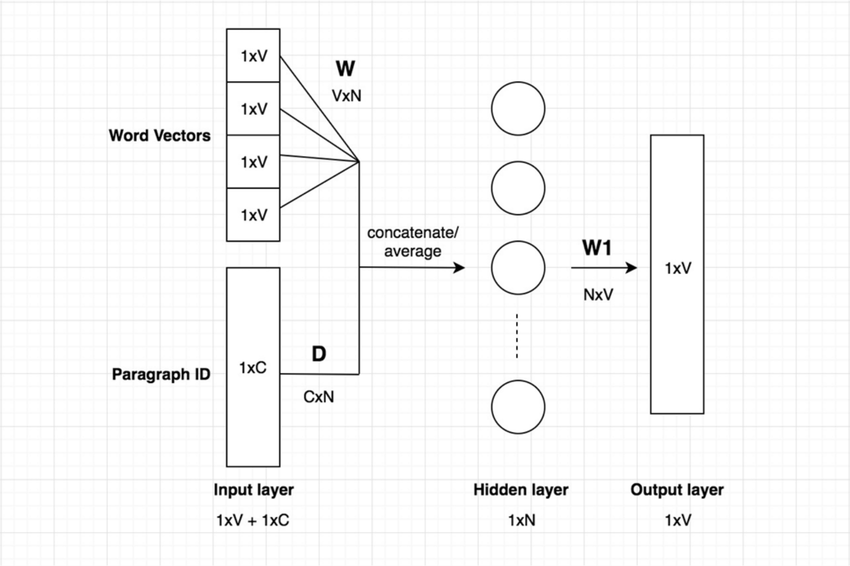
Word2Vec



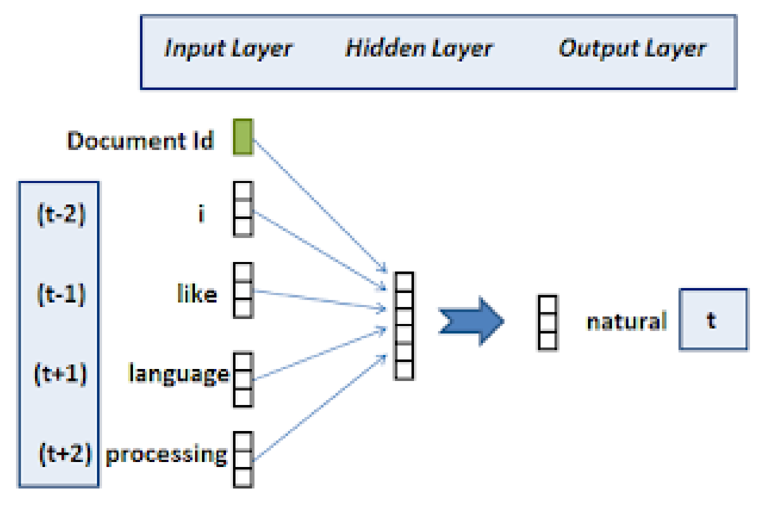
INPUT
PROJECTION
OUTPUT
w(t-2)
w(t-1)
SUM
w(t)
w(t+1)
w(t+2)
CBOW
INPUT
PROJECTION
OUTPUT
w(t)
w(t-2)
w(t-1)
w(t+1)
w(t+2)
Skip-gram

Doc2Vec

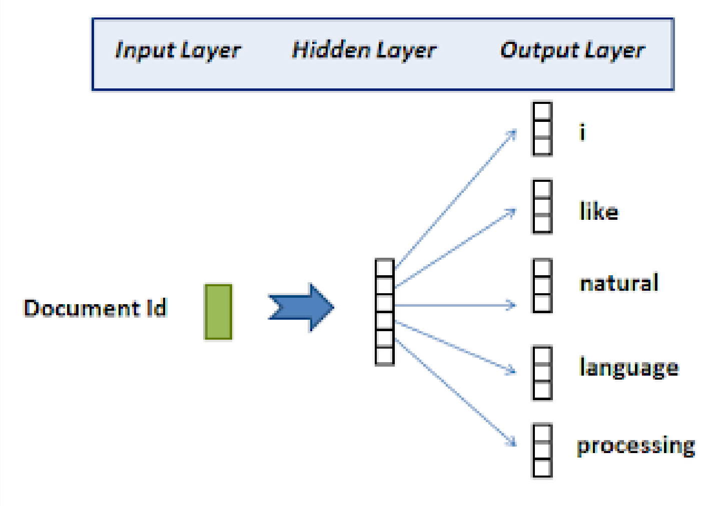
- Doc2vec is an NLP tool
- Represent documents as a vector and is a generalizing of the word2vec method.



Doc2Vec



Distributed Memory Model



Distributed Bag of Words Model

Methodology

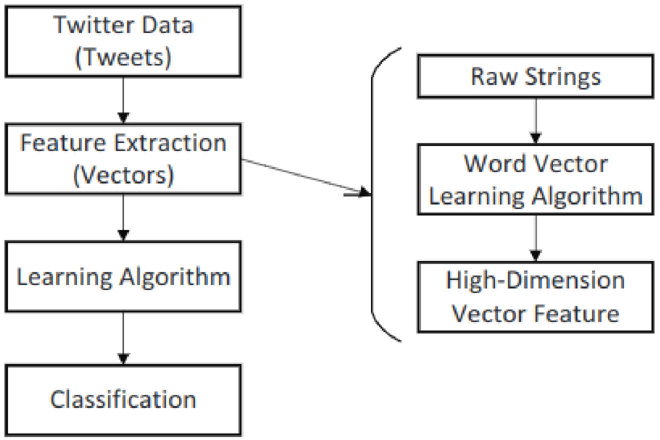


Figure 2: New Twitter classification workflow based on deep learning

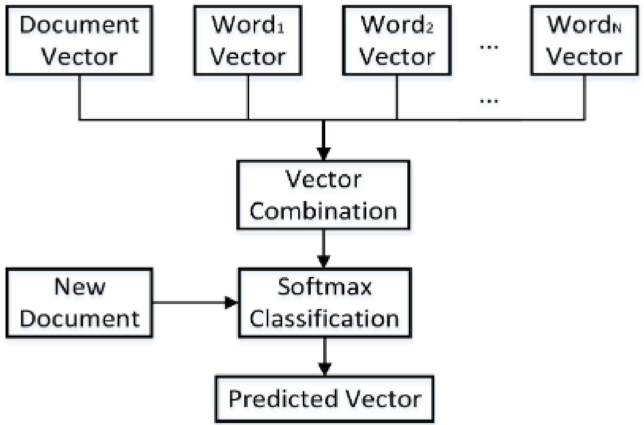


Figure 3: The procedure of learning document vector, where N represents the number of the words in a document.

Methodology

$$\vec{D} = \{d_1, d_2, \ldots, d_M\},$$

where M is the dimension amount of the document vector, d is the value for each level of it.

$$\vec{t} = (\vec{D}, label),$$

where t represents the concatenate vector, and label is the tweet flag of spam or non-spam.

$$T = (\vec{t_1}, \vec{t_2}, \ldots, \vec{t_N}),$$

$$\vec{L} = (l_1, l_2, \ldots, l_n) = C(\vec{D_1}, \vec{D_2}, \ldots, \vec{D_n}),$$

where n is the tweets number of testing data.

Evaluation

- Gathered data for 10-days
  - contains 1,376,206 spam tweets and 673,836 non-spam messages
- 4 sub-datasets
  - Dataset 1 and 3: 1:1 spam to non-spam
  - Dataset 2 and 4: 1:19 spam to non-spam

Table 2: Sample Datasets

Dataset No	Dataset Type	Spam : Non-spam
1	Continuous	5k : 5k
2	Continuous	5k : 95k
3	Random	5k : 5k
4	Random	5k : 95k

Evaluation

- Basic Setup (Java)
  - KNIME Analytics Platform
  - Windows 10, I7 CPU, 12GB RAM
- First Layer: Doc2Vec with 2% learning rate and size of 200
- Second Layer: Rotating traditional machine learning models
- Looped 100 times, Calculate mean of each performance metric
- 60-40 train test split

Evaluation

- Recall, Precision, F-Measure and Accuracy metric for each classifier
- Confusion Matrix
  - TP: number of spam tweets classified correctly
  - FP: number of non-spam tweets classified wrongly
  - TN: number of non-spam tweets classified correctly
  - FN: number of spam tweets classified wrongly

Table 3: Confusion Matrix

	Predicted	
	Spam	Non-spam
Spam	TP	FP
Non-spam	FN	TN

Evaluation

- Text-based using Deep Learning
  - Random Forest
    - process the word representation trained by WordVector Technique
  - Neural Network
    - MLP with input extracted by WordVector
  - Decision Tree
    - Greedy splitting method for tree building

Evaluation

- Traditional Text-based (Vertical Comparison)
  - Palladian
    - Ngrams text classifier
  - Naive Bayes
    - Detect words distribution in documents
  - Naive Bayes (Frequencies)
    - Term frequency

Evaluation

- Feature-based Supported by Machine Learning (Horizontal Comparison)
    - Naive Bayes
        - 2-layered, label of spam/non-spam and the other for set of features
    - Random Forest
    - Decision Tree
        - C4.5, traditional machine learning

Evaluation

- Deep Learning vs Syntax-based
  - MLP performs better in Recall, F-measure and Accuracy
  - 25% higher precision
  - Outperforms the rest
- Deep Learning vs Feature-based
  - F-Measure is 30% higher than Random Forest
  - 9 times higher than Naive Bayes

Evaluation - Deep Learning

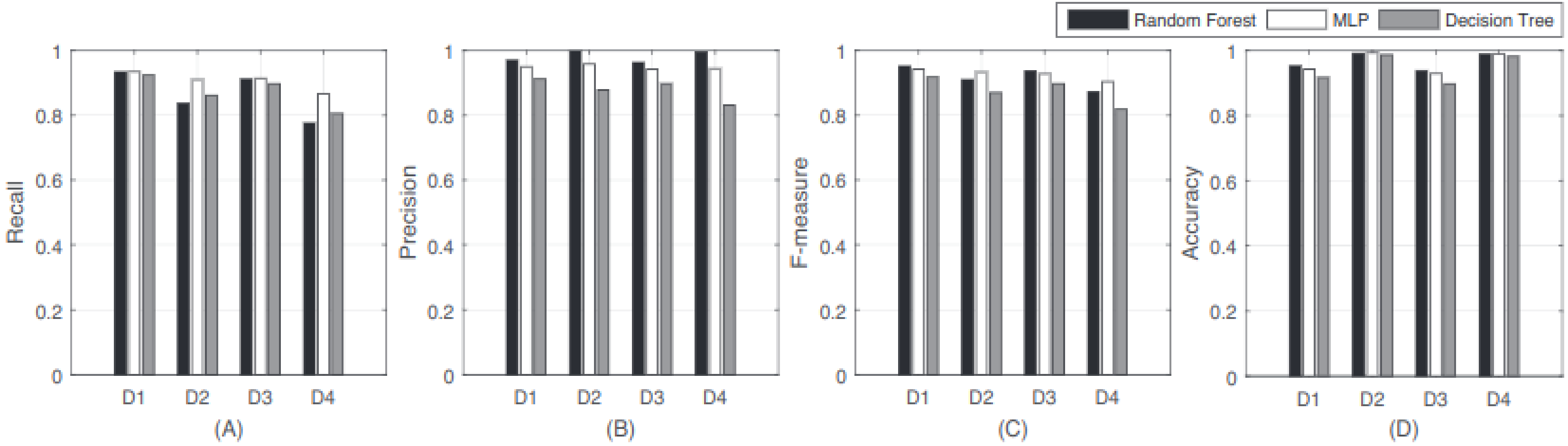


Figure 4: Performance Value of our detection method based on deep learning based on 4 sampled datasets. (A) Recall; (B) Precision; (C) F-measure; (D) Accuracy

Evaluation - Traditional Text (VC)

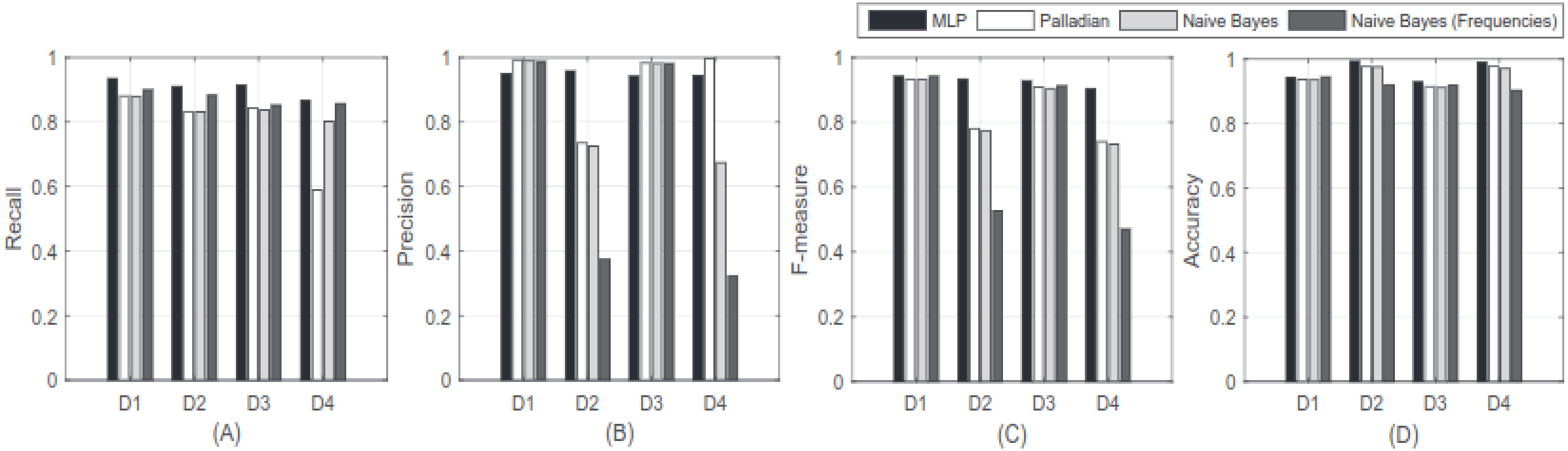


Figure 5: Vertical Comparison of performance values between our technique and traditional text-based detection approaches based on 4 sampled datasets. (A) Recall; (B) Precision; (C) F-measure; (D) Accuracy

Evaluation - Feature SVM (HC)

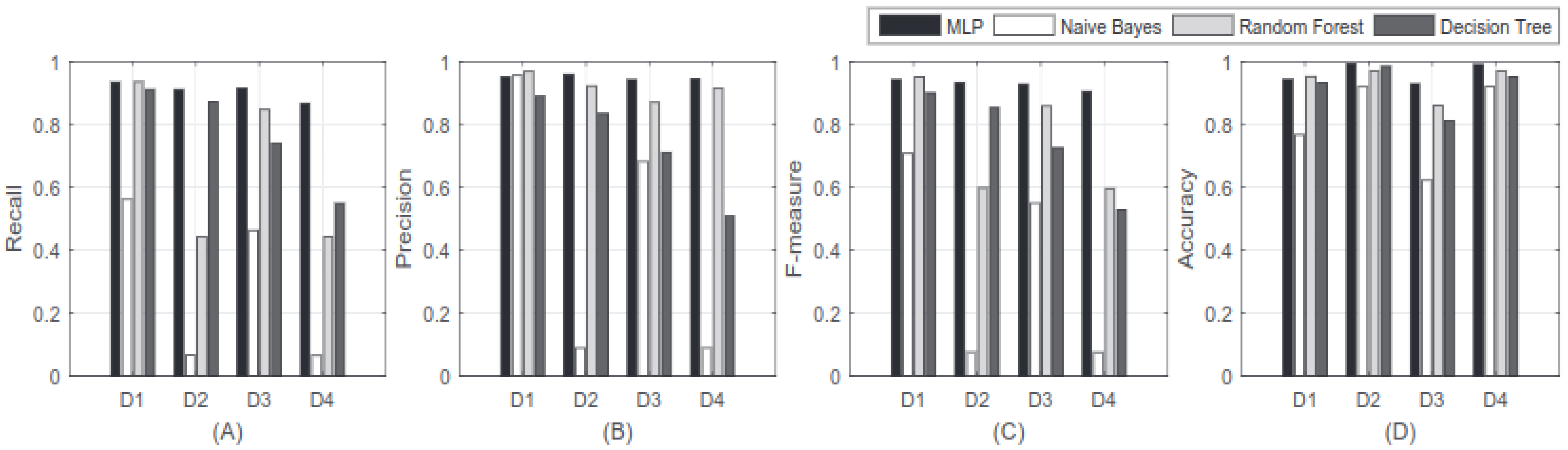


Figure 6: Horizontal Comparison of performance values between our technique and feature-based methods based on 4 sampled datasets. (A) Recall; (B) Precision; (C) F-measure; (D) Accuracy

Discussion

- Spam Ratio
  - Performance stays the same
  - Achieves better recall of 2.45%
  - F-measure of Naive Bayes
    - 60% in 1:1 dataset
    - 12% in 1:19 dataset

Table 4: Impact of the Spam Ratio by Dataset 1 and 2 using MLP

Unit: %	Recall	Precision	F-measure	Accuracy
Dataset 1	93.48	95.04	94.25	94.30
Dataset 2	91.03	95.84	93.37	99.35

Discussion

- Dataset Dissection
    - Performance is stable
    - Continuous dataset performs better than random dataset

Table 5: Impact on Sample Dataset Discretisation of Dataset 1 and 3 using MLP

Unit: %	Recall	Precision	F-measure	Accuracy
Dataset 1	93.48	95.04	94.25	94.30
Dataset 3	91.48	94.23	92.83	92.94

Conclusion

- Explored issues around spam detection on Twitter data
- Proposed a new classification method using DL
- Utilized WordVector techniques for pre-processing
- Computation with high-multidimensional vectors

Conclusion - Future Works

- Explore theoretical studies on the deep learning framework
- Compare against other classifiers outside from the ones mentioned
- Collect more real data from other social media platforms (Facebook)
- Study the feedback of works that cited this paper

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The End