Predators becoming the prey:

using statistical machine learning and computational linguistics to detect sexual predators

By Norbert Eke

Supervisor: Abdallah Mohamed

Outline

1.) **Introduction to the Problem**
2.) Research Questions and Objectives
3.) Introduction to Data Being Used
4.) Algorithm Proposed
5.) Results & Model Selection Explained
6.) Future Works and Conclusion

Background

- **One in five U.S. teenagers** who regularly use the Internet have received an unwanted sexual solicitation via the web. (Crimes Against Children Research Center)

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- "Most **first encounters** between offenders and victims (76%) **happened in online chat rooms**" (Wolak et al., 2004)

- There is a need for better **intelligent systems** that are capable of accurately **detecting sexual predator's dangerous behavior** online

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2. How to **extract semantic details** from conversations, and **detect** conversations containing **malicious intent**?

3. **Which machine learning models can predict** whether or not a conversation contains sexual predatory behavior?

Objective/Mission Statement

Join the powers of computational linguistics with statistical machine learning and **design an approach** that can **detect and classify textual data** as containing sexual predatory or non-predatory behaviour.

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Sexual Predator Identification task

- **Data obtained from PAN**, a community of experts on digital text forensics

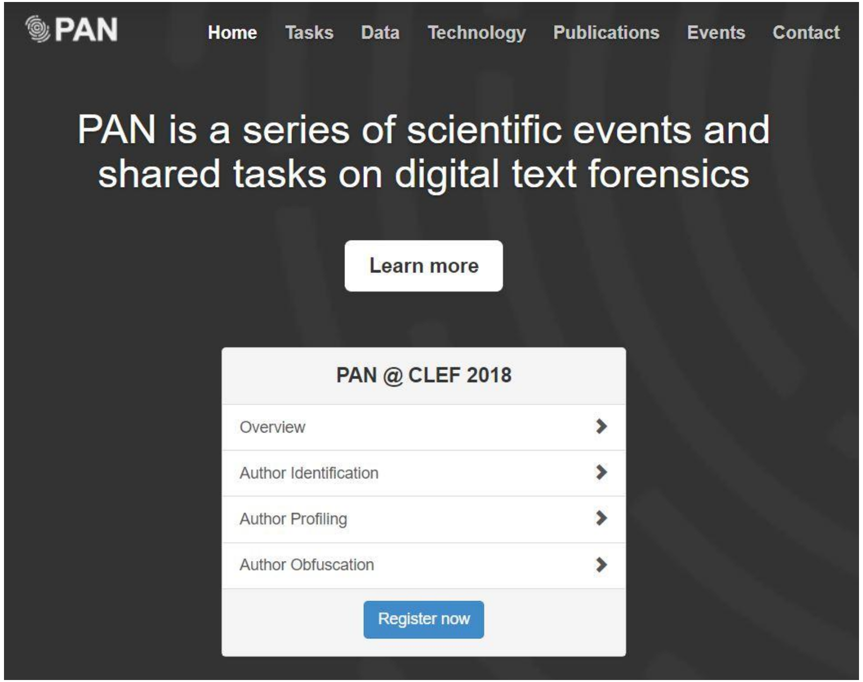

Figure 1: Website for PAN, a community of experts on digital text forensics

Sexual Predator Identification task

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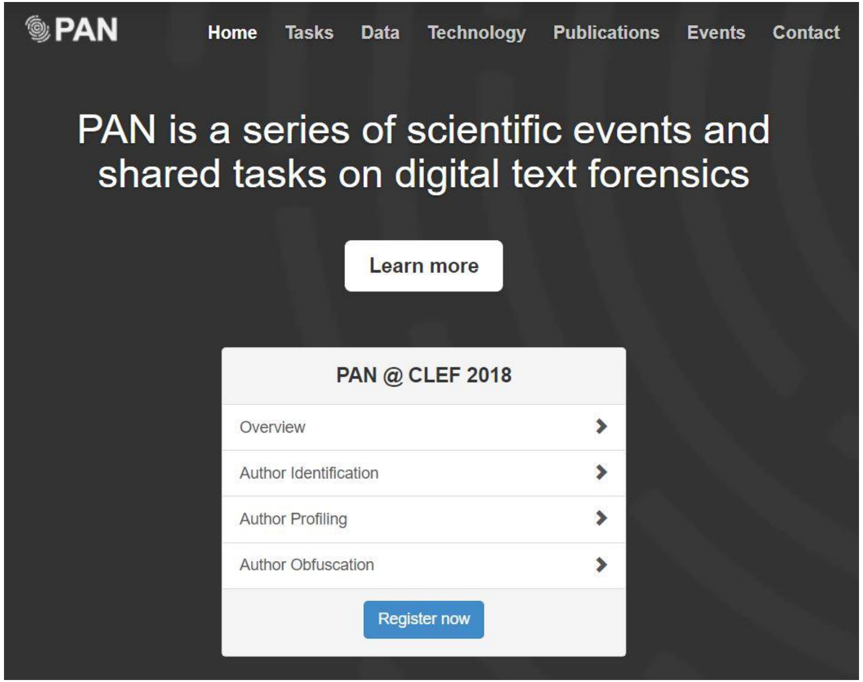
- Contains **thousands of labelled online chat logs**, where minors and adults pretending to be minors are chatting



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Sexual Predator Identification task

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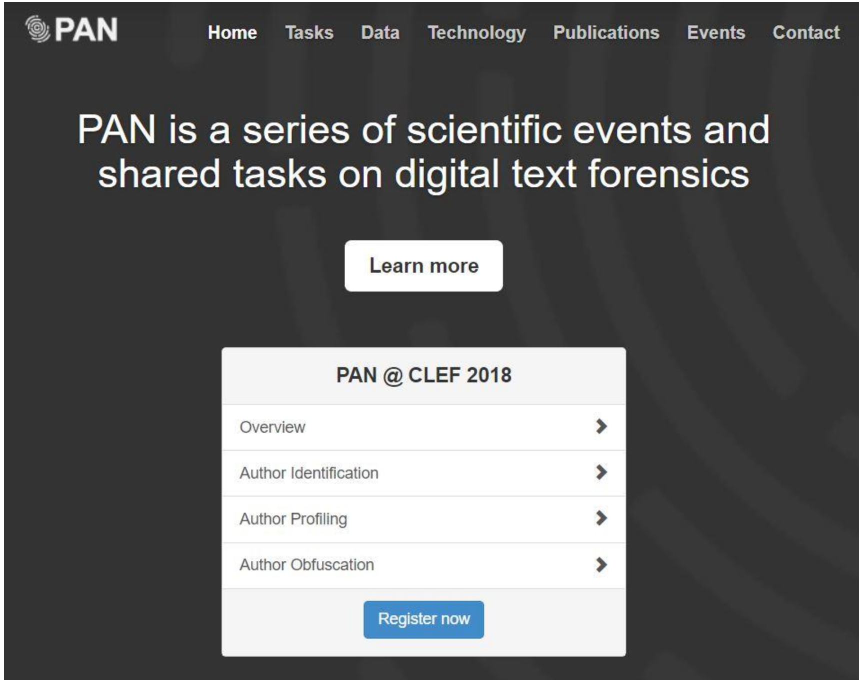
- **Attributes include:** author id, conversation id, message line number, time, message content



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Sexual Predator Identification Data

Online chat-room conversations could contain:

- Misspelled Words
- Slang
- Internet Acronyms
- Inappropriate Language
- Broken Grammar
- Short, Messy and Unstructured Textual Data

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```
...
<conversation id="0042762e26ed295a8576806f5548cad9">
  <message line="3">
    <author>f069dbec9ab3e090972d432db279e3eb</author>
    <time>03:20</time>
    <text>whats up?</text>
  </message>
  <message line="4">
    <author>f069dbec9ab3e090972d432db279e3eb</author>
    <time>03:21</time>
    <text>how u doing?</text>
  </message>
  ...
  <message line="10">
    <author>f069dbec9ab3e090972d432db279e3eb</author>
    <time>04:00</time>
    <text>sse you llater?</text>
  </message>
</conversation>
...
<conversation id="0209b0a30c8eced86863631ada73a530">
  <message line="3">
    <author>0042762e26ed295a8576806f5548cad9</author>
    <time>01:17</time>
    <text>and that i dont touch u</text>
  </message>
</conversation>
```


Figure 2: Sample Raw Conversation data

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Text Cleaning

- **Removal** of:
  - Extra white-spaces
  - HTML tag
  - Hyperlinks
  - Numeric characters
- Autocorrect - **spelling corrector**
- Lowercase conversion (for all words)
- Discarded conversations shorter than 3 words

```
>>> from autocorrect import spell
>>> spell('HTe')
'The'
```

Figure 3: Spelling corrector example

Word2Vec Deep Learning Model

- One of Google's **most famous** deep learning language models

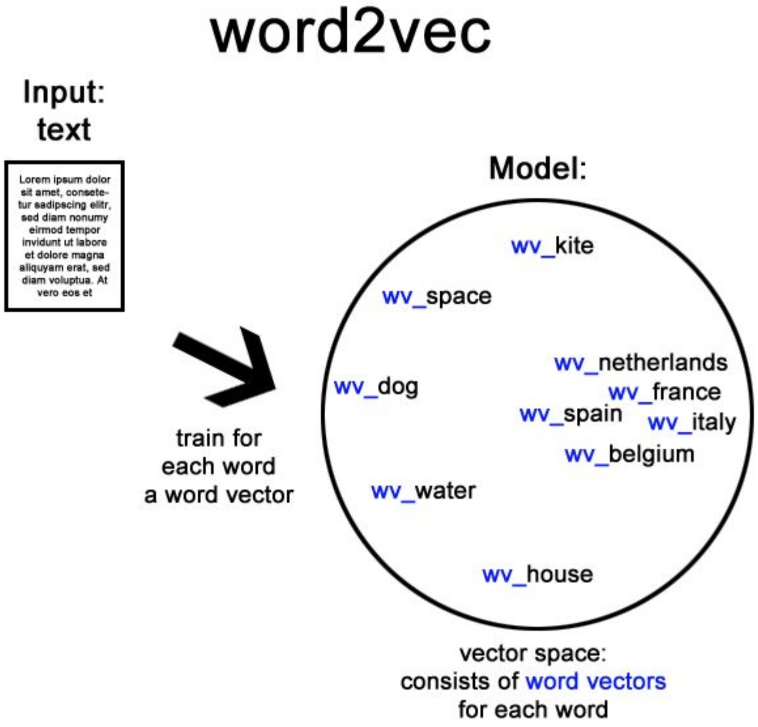

Figure 4: Visual Representation of Word2Vec Model

Word2Vec Deep Learning Model

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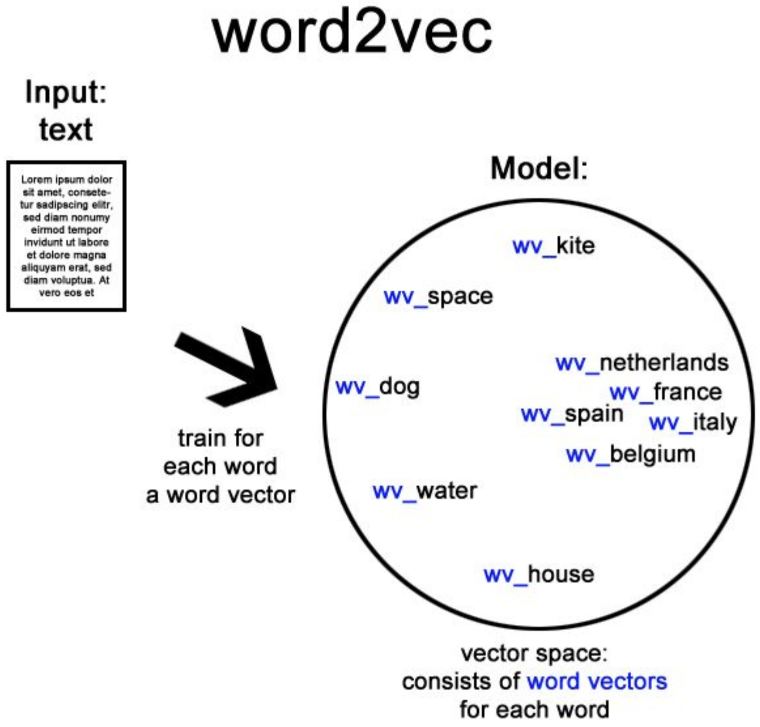
- Model goes through **unsupervised learning** by getting trained on unlabelled textual data



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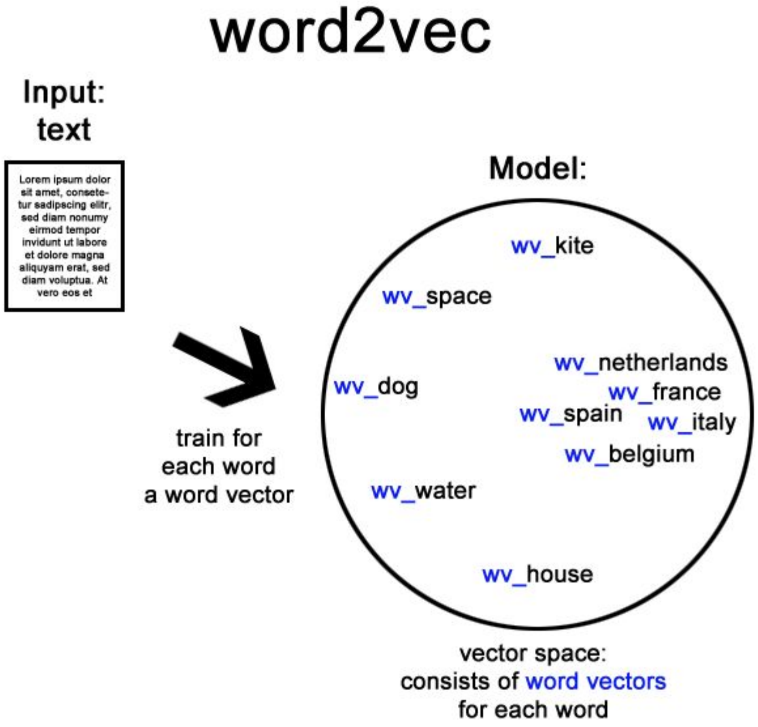
- Model goes through **unsupervised learning** by getting trained on unlabelled textual data
- Word2Vec produces high dimensional vector representations of words (**word vectors**) as output



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Word Vectors

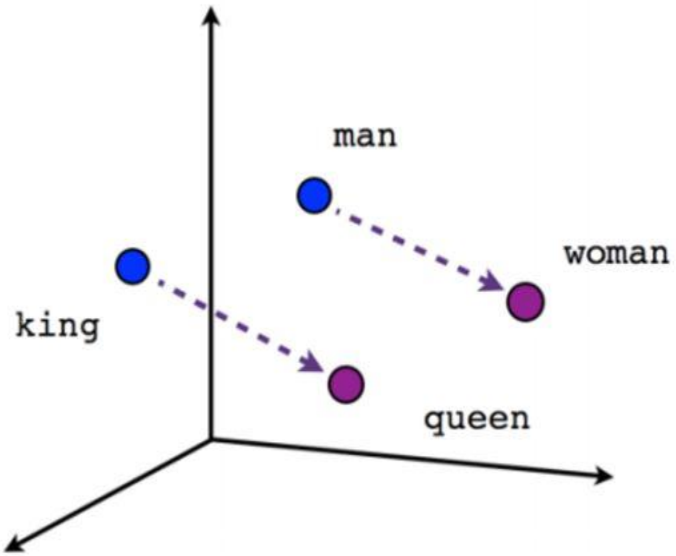
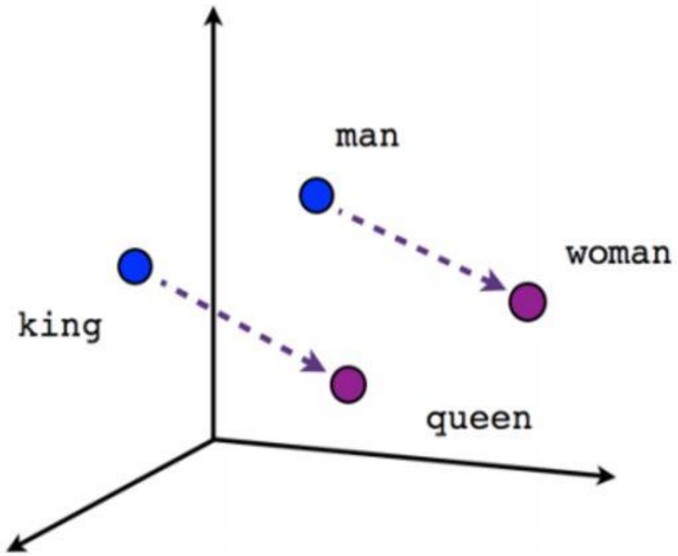


Figure 5: Male - Female Relationship visualized in a low dimensional vector space

- High dimensional **vector representation** of each word

Word Vectors



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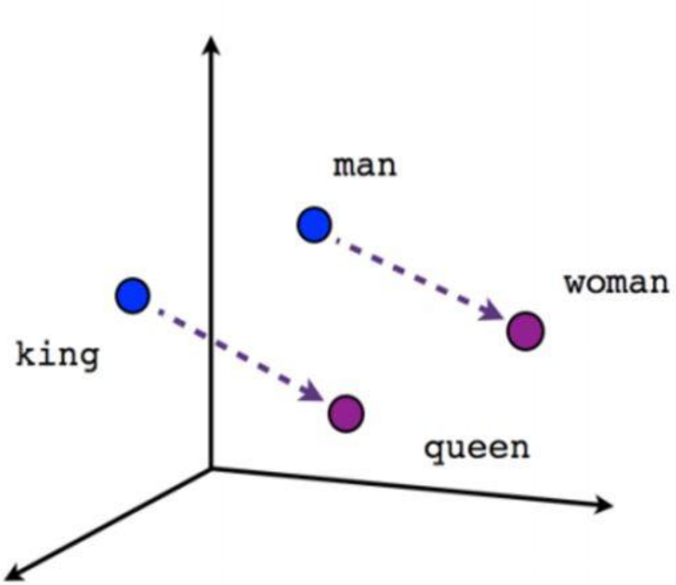
- High dimensional **vector representation** of each word
- Used to **reconstruct linguistic context** of words

Word Vectors



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- High dimensional **vector representation** of each word
- Used to **reconstruct linguistic context** of words
- **Capture semantic similarity** between words

Feature Extraction Process

- A conversation can be represented as a **set n word vectors** (n = number of unique words used in the conversation)

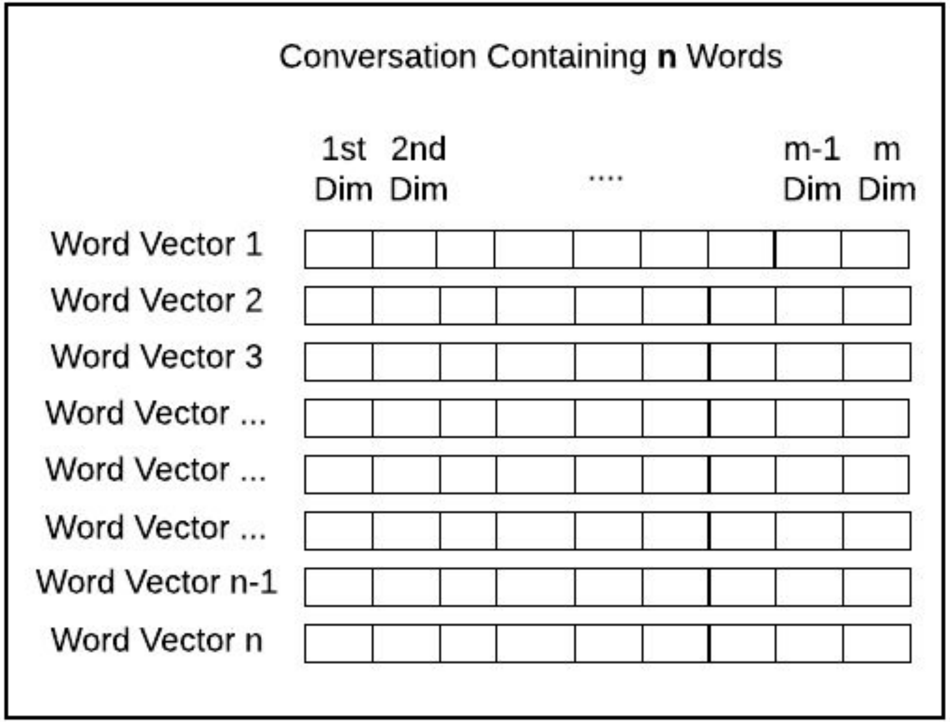

Figure 6: Set of n Word Vectors Representing a Conversation

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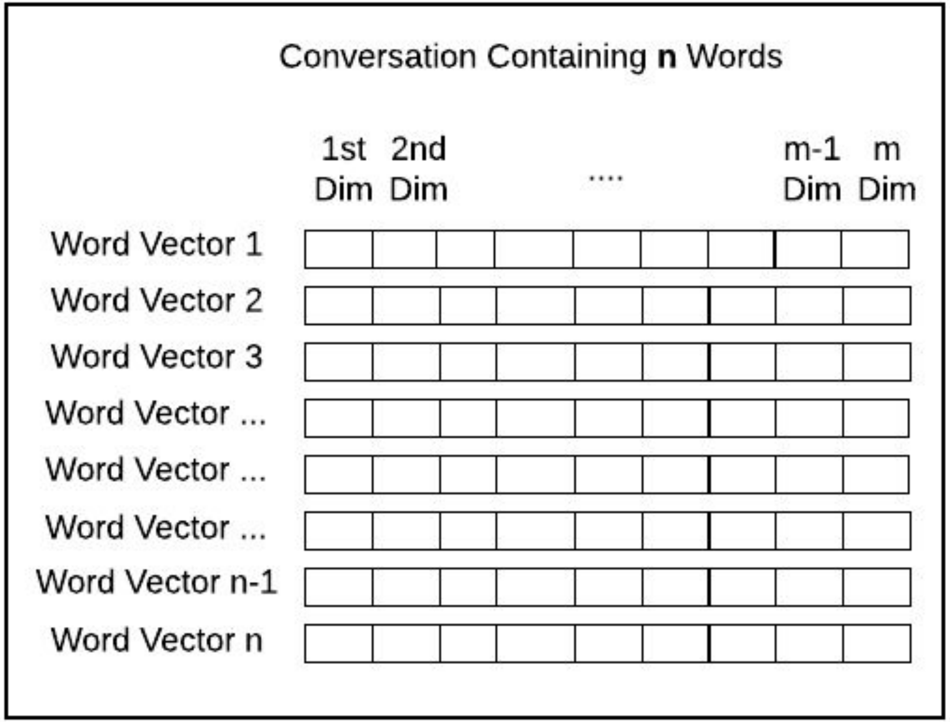
- Need to **extract features** from each conversation's word vectors in order to create **conversation feature vectors**



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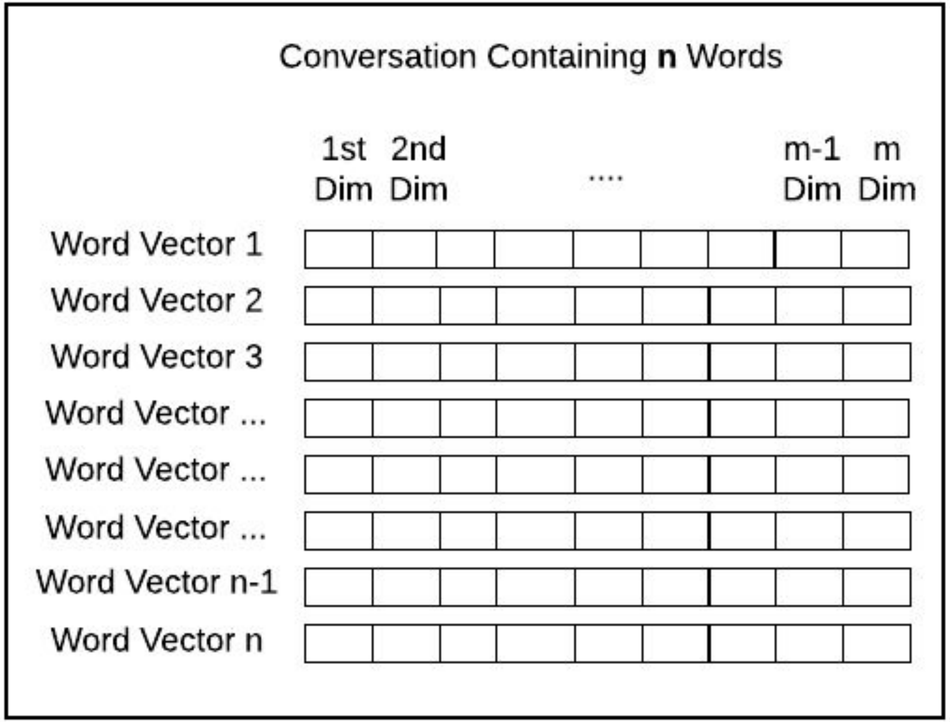
- Used De Boom et. al (2016)'s **Coordinate-wise Word Vector Aggregation** technique as a Feature Extraction Process



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Coordinate-wise Word Vector Aggregation

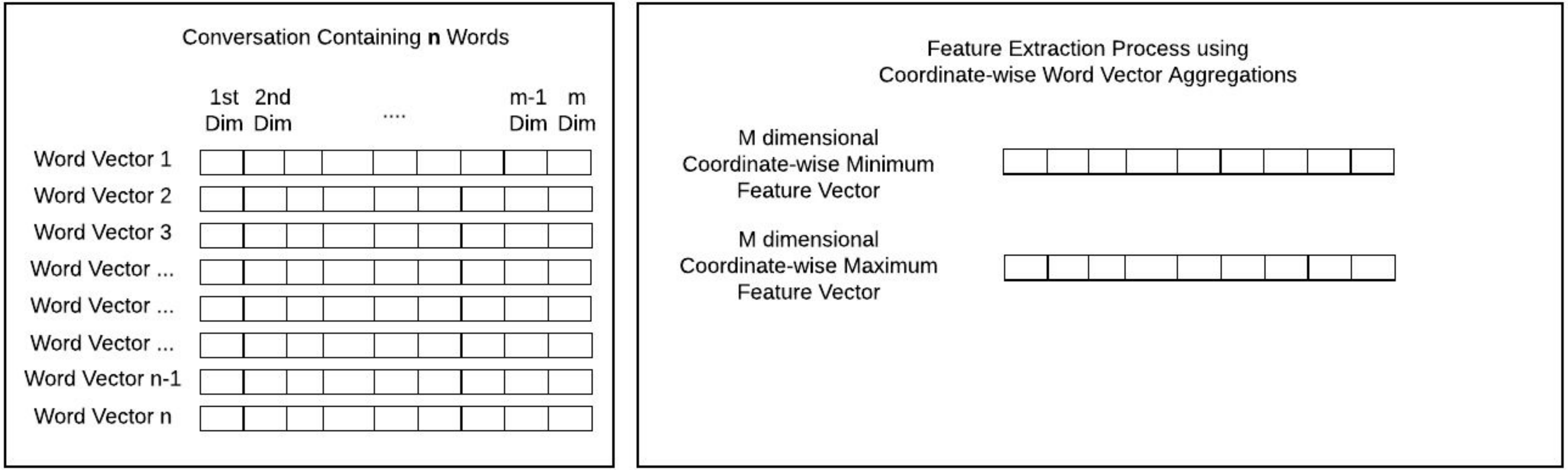

Figure 7: Feature Extraction Process

Coordinate-wise Word Vector Aggregation

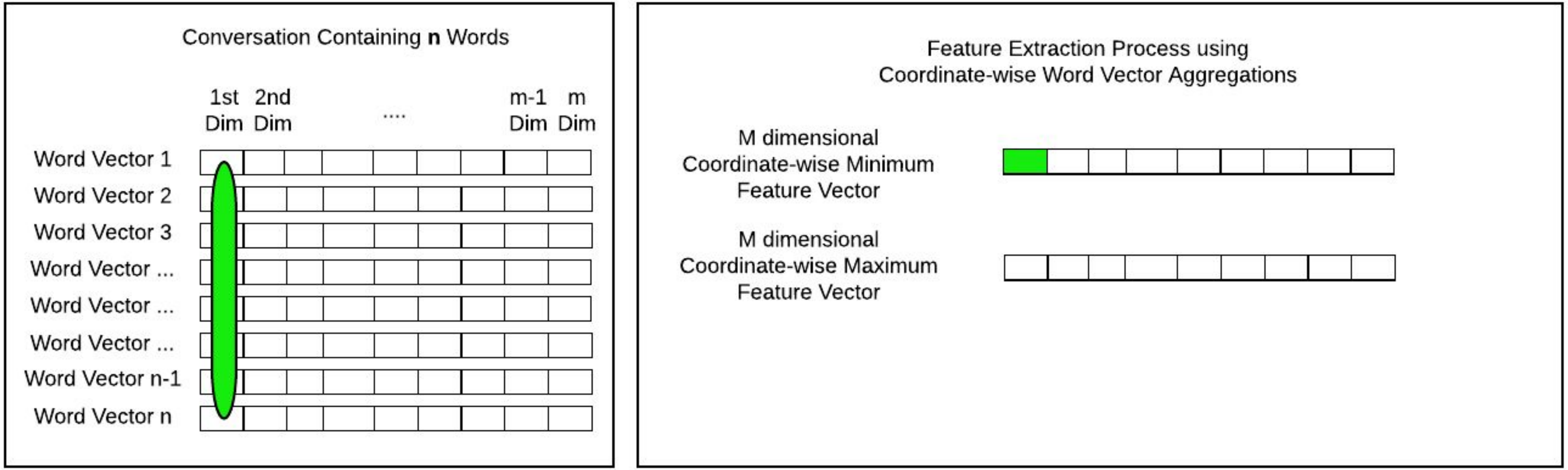

Figure 8: Feature Extraction Process

Coordinate-wise Word Vector Aggregation

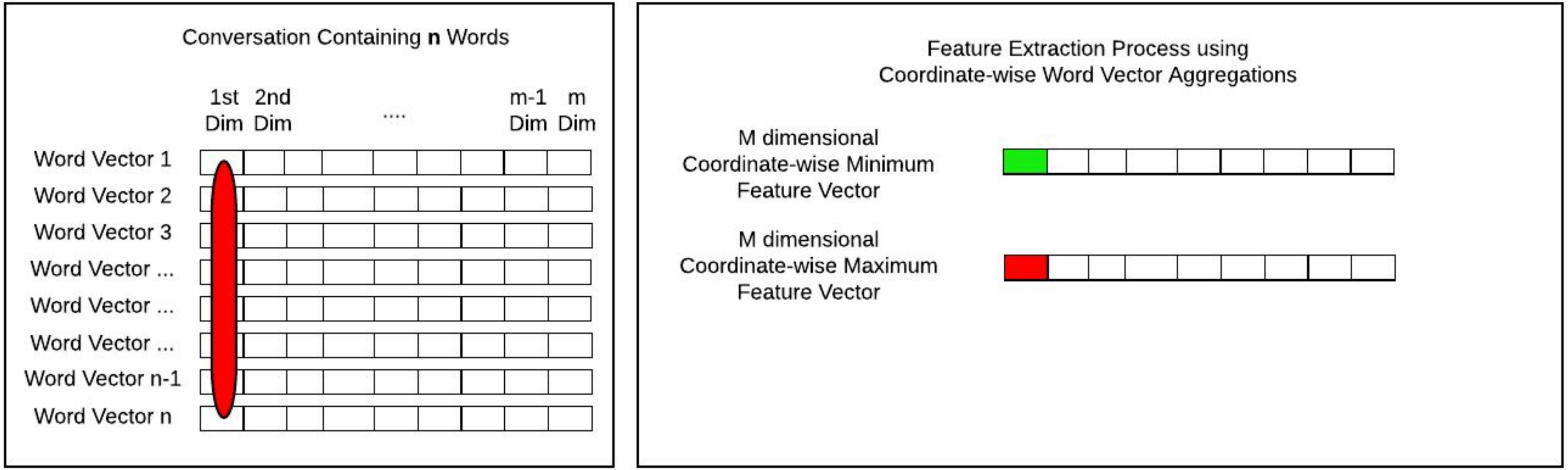

Figure 9: Feature Extraction Process

Coordinate-wise Word Vector Aggregation

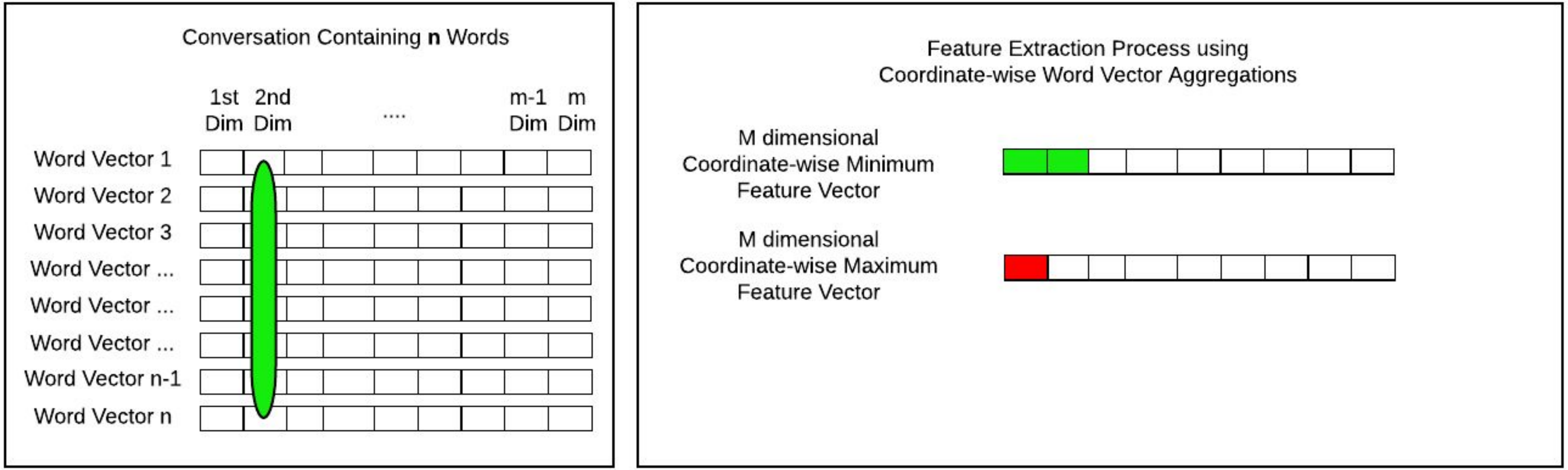

Figure 10: Feature Extraction Process

Coordinate-wise Word Vector Aggregation

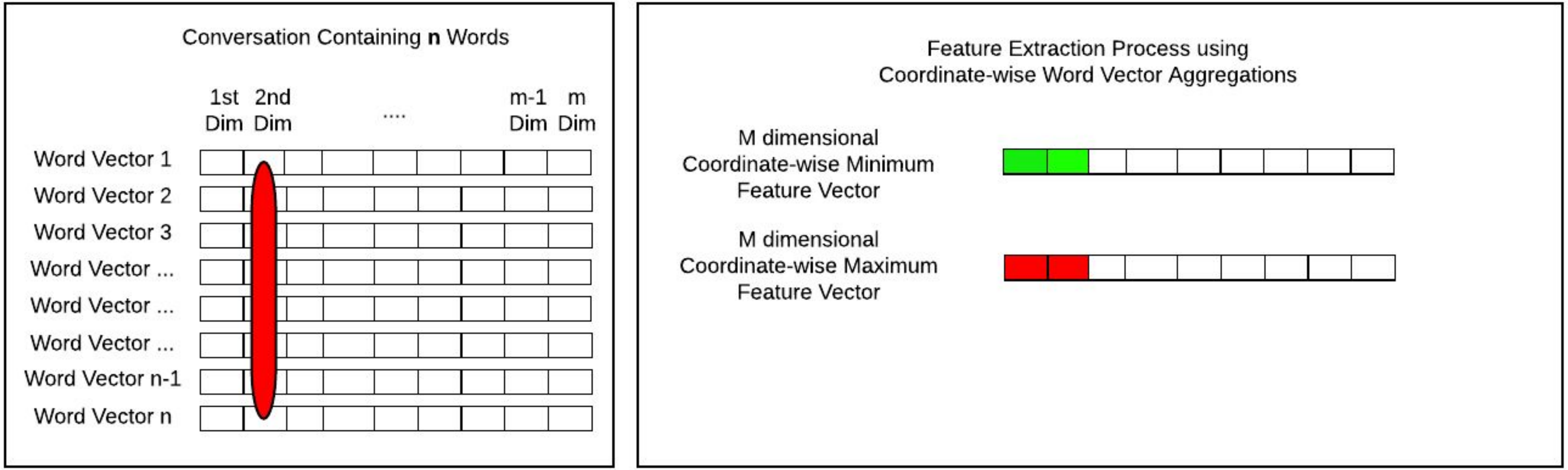

Figure 11: Feature Extraction Process

Coordinate-wise Word Vector Aggregation

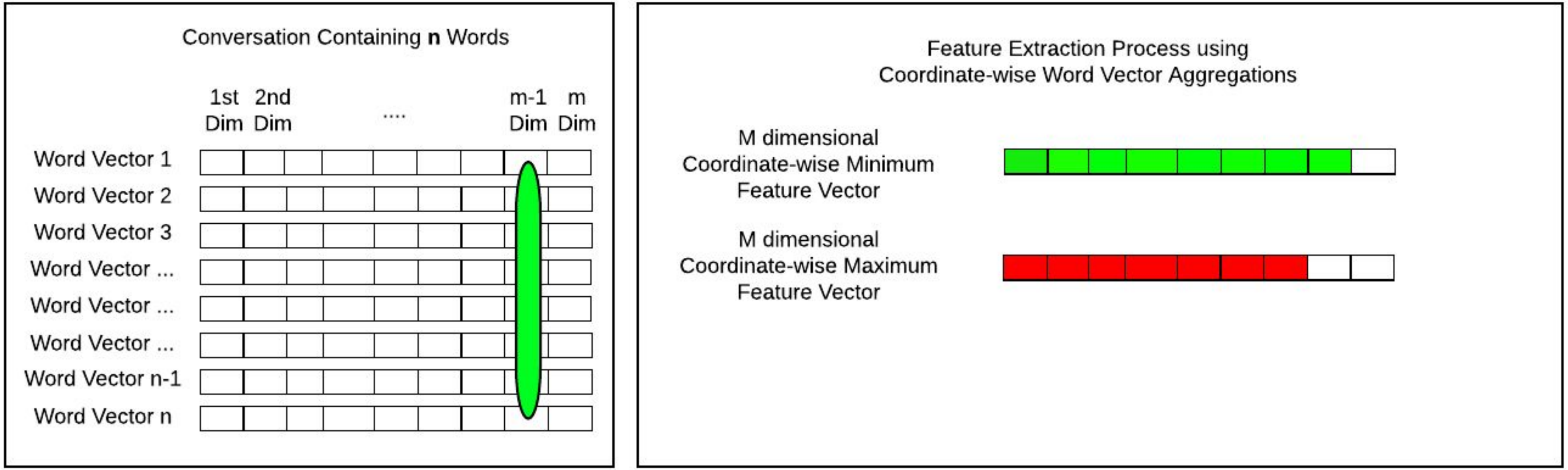

Figure 12: Feature Extraction Process

Coordinate-wise Word Vector Aggregation

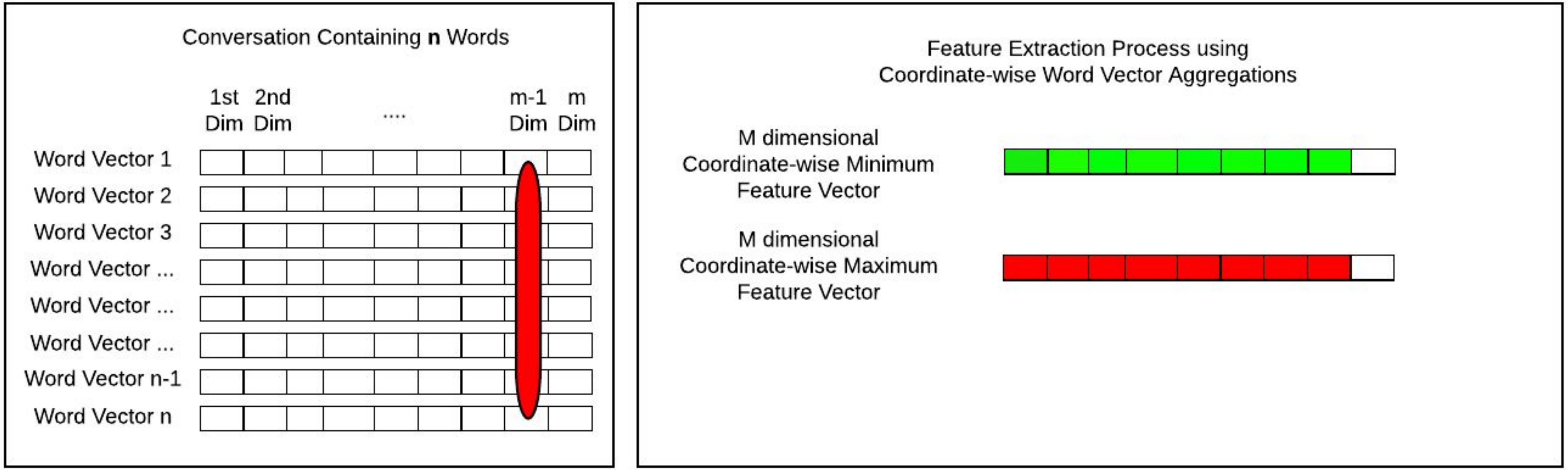

Figure 13: Feature Extraction Process

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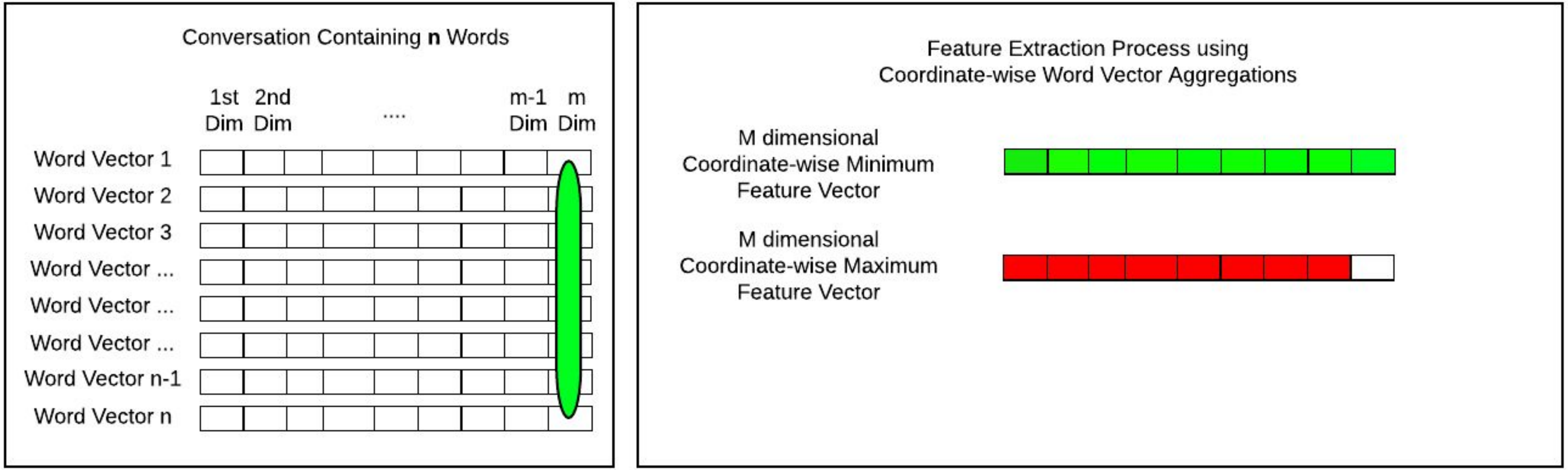

Figure 14: Feature Extraction Process

Coordinate-wise Word Vector Aggregation

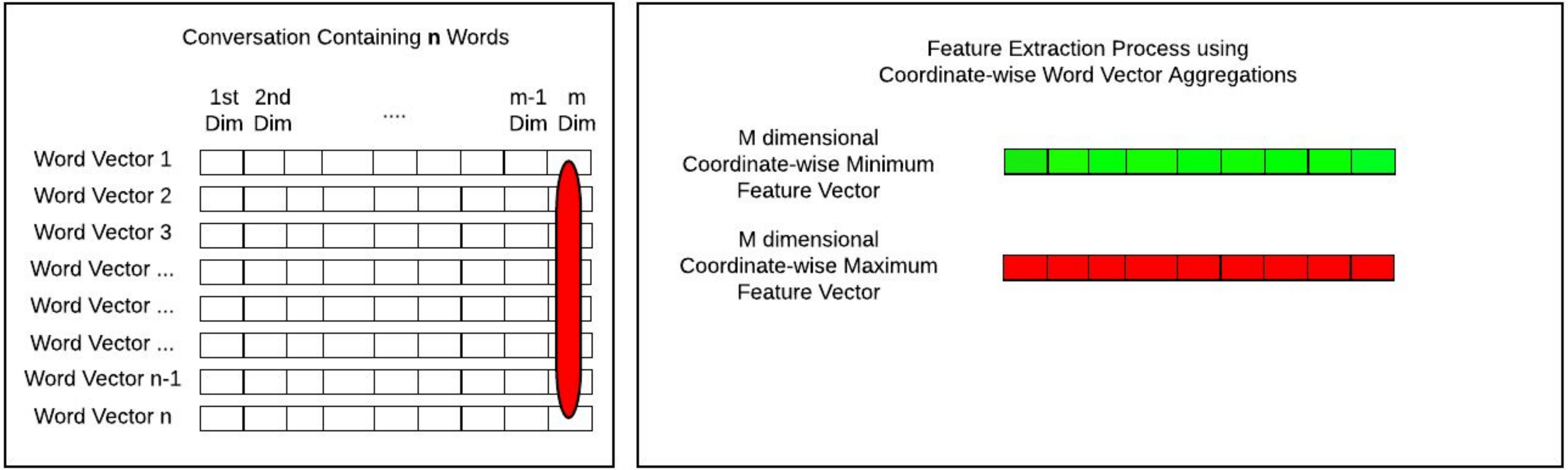

Figure 15: Feature Extraction Process

Conversation MIN-MAX Feature Vector

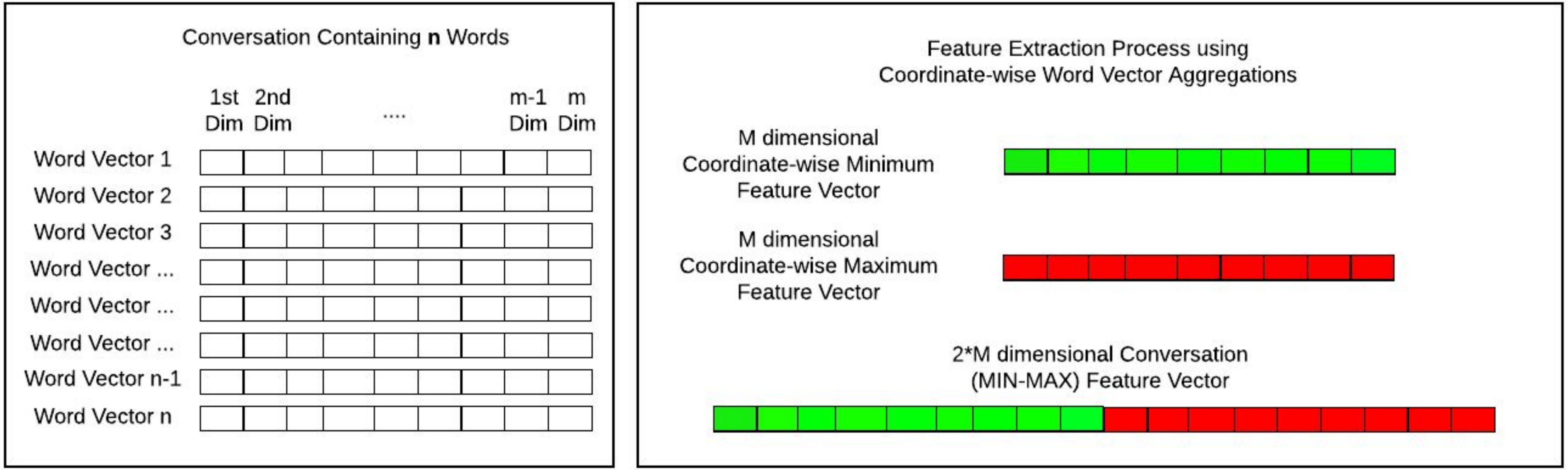

Figure 16: Feature Extraction Process

Sample Conversation Feature Vectors

1	dim1	dim2	dim3	dim4	dim5	dim6	dim7	dim8	dim9	dim10
2	0.326793	0.509899	0.319126	0.294877	0.830449	0.179753	0.158272	0.269415	0.158272	0.187153
3	0.233455	0.149392	0.18206	0.012931	0.281442	0.183503	0.236117	0.23604	0.710034	0.294323
4	0.455681	0.292429	0.268265	0.970831	0.393424	0.364359	0.261243	0.420074	0.255124	0.687304
5	0.435186	0.543371	0.421567	0.431468	0.415848	0.495029	0.476062	0.598359	0.427184	0.707913
6	0.395548	0.324849	0.500006	0.368869	0.741563	0.42329	0.25399	0.420074	0.427184	0.422575
7	0.240186	0.134993	0.123147	0.072401	0.239194	0.105477	0.186437	0.17187	0.308369	0.189388
8	0.137026	0.137568	0.285678	-0.05332	0.534698	0.364102	0.236117	0.089361	0.235917	0.502221
9	0.610423	0.238505	0.765492	0.39827	0.993194	0.112962	0.158272	0.816111	0.220825	0.138676
10	0.557104	0.265102	0.319126	0.212012	0.093506	0.286265	0.274407	0.376721	0.308369	0.435424
11	0.160055	0.413706	0.126338	0.377143	0.475433	0.312591	0.117461	0.562886	0.235337	0.262733
12	0.160055	0.155515	0.421567	0.136305	0.314459	0.210839	0.301609	0.271378	0.090368	0.074593
13	0.395548	0.41569	0.567015	0.487332	0.393424	0.341351	0.371596	0.816111	0.407664	0.327895
14	0.395548	0.335495	0.400459	0.424437	0.415848	0.437937	0.321841	0.547721	0.407664	0.488582
15	0.395548	0.112537	0.18206	0.163788	0.269591	0.247135	0.25399	0.420074	0.133222	0.422575
16	0.105116	0.494306	0.319126	0.316998	0.269591	0.352102	0.25399	0.420074	0.124105	0.422575
17	0.403466	0.335495	0.269617	0.321741	0.281442	0.43677	0.454666	0.816111	0.710034	0.437507
18	0.262715	0.18068	0.212783	-0.03116	0.203668	0.179753	0.113385	0.050921	0.144946	0.163538
19	0.503621	0.494306	0.213058	0.232814	0.393424	0.4216	0.25399	0.420074	0.308369	0.422575
20	0.112298	0.153483	0.18206	0.368869	0.237592	0.312591	0.236117	0.255418	-0.0176	0.294323
21	0.474968	0.317604	0.333141	0.459357	0.284466	0.505133	0.25399	0.420074	0.389327	0.422575

Figure 17: First 10 Dimensions of 20 Sample Conversation Feature Vectors

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2	0.326793	0.509899	0.319126	0.294877	0.830449	0.179753	0.158272	0.269415	0.158272	0.187153
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IN REALITY

My Word Vectors are **400 dimensional**

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18	0.262715	0.18068	0.212783	-0.03116	0.203668	0.179753	0.113385	0.050921	0.144946	0.163538
19	0.503621	0.494306	0.213058	0.232814	0.393424	0.4216	0.25399	0.420074	0.308369	0.422575
20	0.112298	0.153483	0.18206	0.368869	0.237592	0.312591	0.236117	0.255418	-0.0176	0.294323
21	0.474968	0.317604	0.333141	0.459357	0.284466	0.505133	0.25399	0.420074	0.389327	0.422575

Figure 17: First 10 Dimensions of 20 Sample Conversation Feature Vectors

IN REALITY

My Word Vectors are **400 dimensional**

MIN-MAX Feature Vectors are **800 dimensional**

Sample Conversation Feature Vectors

1	dim1	dim2	dim3	dim4	dim5	dim6	dim7	dim8	dim9	dim10
2	0.326793	0.509899	0.319126	0.294877	0.830449	0.179753	0.158272	0.269415	0.158272	0.187153
3	0.233455	0.149392	0.18206	0.012931	0.281442	0.183503	0.236117	0.23604	0.710034	0.294323
4	0.455681	0.292429	0.268265	0.970831	0.393424	0.364359	0.261243	0.420074	0.255124	0.687304
5	0.435186	0.543371	0.421567	0.431468	0.415848	0.495029	0.476062	0.598359	0.427184	0.707913
6	0.395548	0.324849	0.500006	0.368869	0.741563	0.42329	0.25399	0.420074	0.427184	0.422575
7	0.240186	0.134993	0.123147	0.072401	0.239194	0.105477	0.186437	0.17187	0.308369	0.189388
8	0.137026	0.137568	0.285678	-0.05332	0.534698	0.364102	0.236117	0.089361	0.235917	0.502221
9	0.610423	0.238505	0.765492	0.39827	0.993194	0.112962	0.158272	0.816111	0.220825	0.138676
10	0.557104	0.265102	0.319126	0.212012	0.093506	0.286265	0.274407	0.376721	0.308369	0.435424
11	0.160055	0.413706	0.126338	0.377143	0.475433	0.312591	0.117461	0.562886	0.235337	0.262733
12	0.160055	0.155515	0.421567	0.136305	0.314459	0.210839	0.301609	0.271378	0.090368	0.074593
13	0.395548	0.41569	0.567015	0.487332	0.393424	0.341351	0.371596	0.816111	0.407664	0.327895
14	0.395548	0.335495	0.400459	0.424437	0.415848	0.437937	0.321841	0.547721	0.407664	0.488582
15	0.395548	0.112537	0.18206	0.163788	0.269591	0.247135	0.25399	0.420074	0.133222	0.422575
16	0.105116	0.494306	0.319126	0.316998	0.269591	0.352102	0.25399	0.420074	0.124105	0.422575
17	0.403466	0.335495	0.269617	0.321741	0.281442	0.43677	0.454666	0.816111	0.710034	0.437507
18	0.262715	0.18068	0.212783	-0.03116	0.203668	0.179753	0.113385	0.050921	0.144946	0.163538
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My Word Vectors are **400 dimensional**

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For 100.000 conversations ...
DATA = **100.000 x 800 matrix**

Two Stage Classification System

- First stage classification: Train a **Linear Discriminant Analysis Binary Classifier** on conversation feature vectors

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- Obtain 3 groups of conversations with different levels of maliciousness:
  - Group A = conversations most likely do not contain predatory behaviour
  - Group B = conversations possibly could contain predatory behaviour
  - Group C = conversations most likely contain predatory behaviour

Algorithm Highlights

1. **Captures contextual details** by putting an emphasis on insight that lies within the conversation

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1. **Captures contextual details** by putting an emphasis on insight that lies within the conversation

2. Uses a **domain specific feature extraction technique** that **extracts the essential details** from each conversation

3. Creates a highly flexible and customizable **two stage classification system** for detecting and classifying conversations containing sexual predatory behaviour

Outline

1.) Problem Background
2.) Research Questions and Objectives
3.) Introduction to Data Being Used
4.) Algorithm Proposed
5.) Results & Model Selection Explained
6.) Future Works and Conclusion

k-Fold Cross Validation for Results

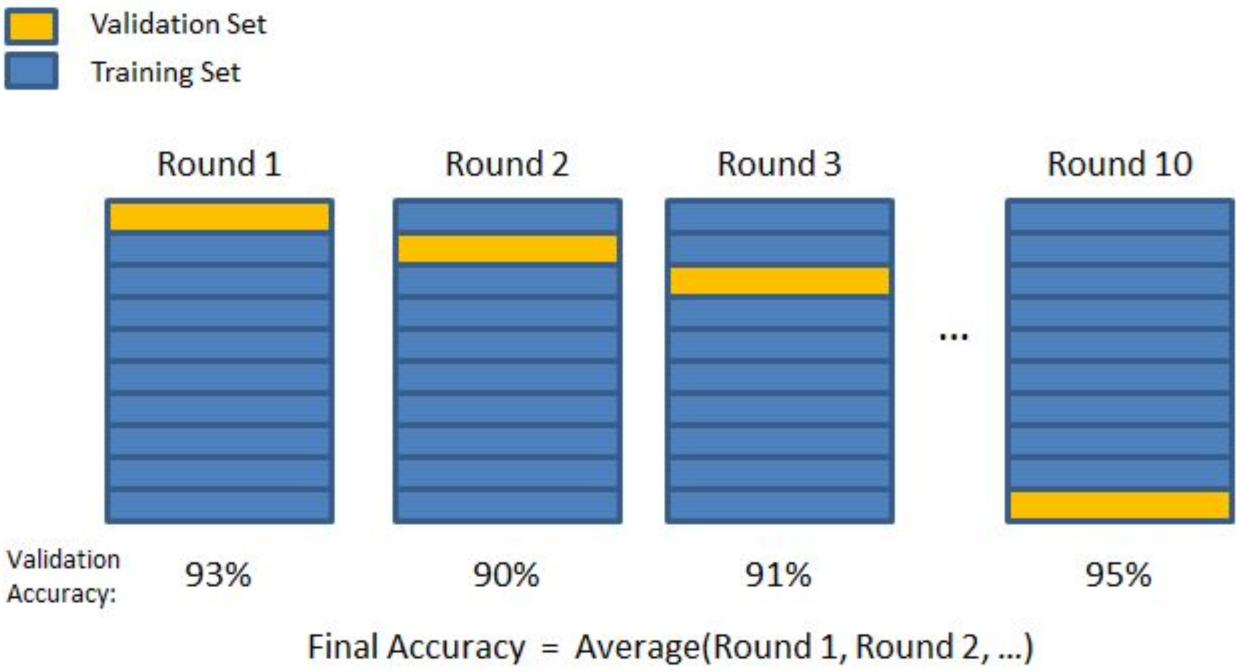

Figure 18: k-fold Cross Validation Visualization

- k = 10 folds
- Dataset contained 155128 conversations
- Took sample of 100000 conversations
- 90000 training set
- 10000 validation set

First Stage Classification

Classification Model	Average Precision	Average Recall	F1 Score
LDA	0.5234	0.9145	0.6658
SVM	0.7686	0.6582	0.7091
Random Forest	0.8241	0.2982	0.4379
LASSO	0.6739	0.6492	0.6613
Gr. Boosting Machine	0.8646	0.3018	0.4474

Table 1: Average Recall and Precision, and Overall F1-Score from the top 5 First Stage Classification Models.

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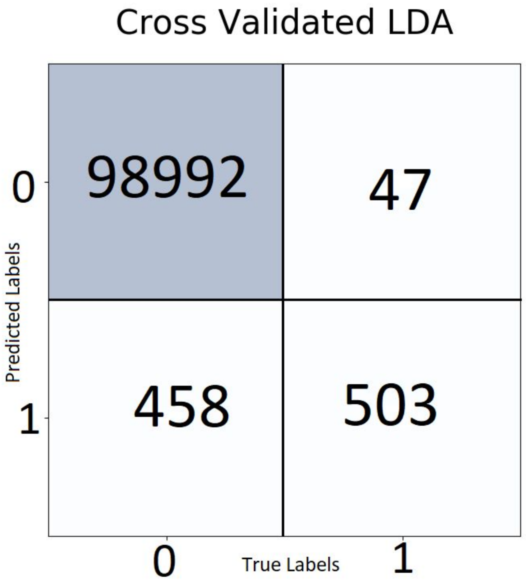

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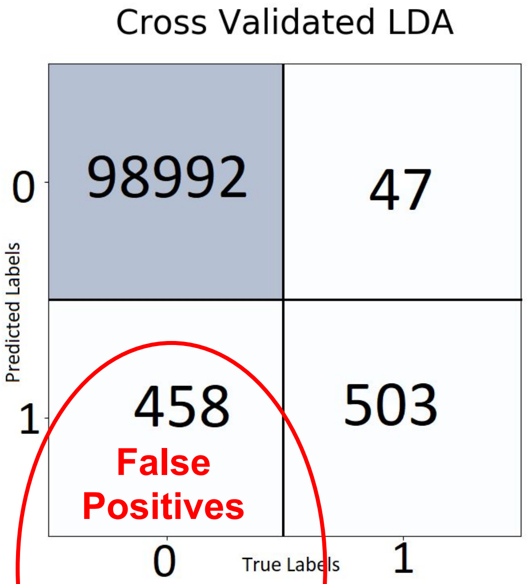

Non-predatory conversations **labelled as Predatory**

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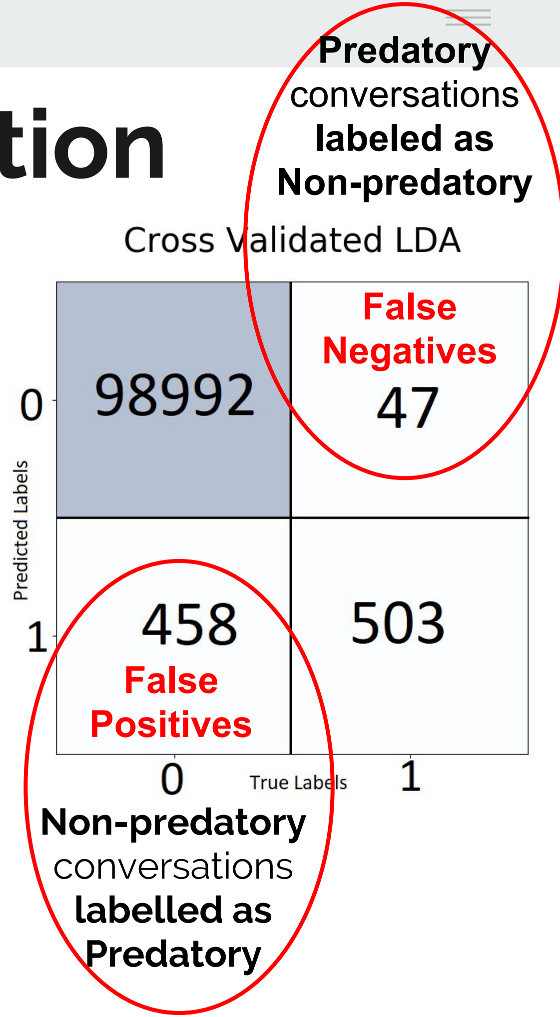

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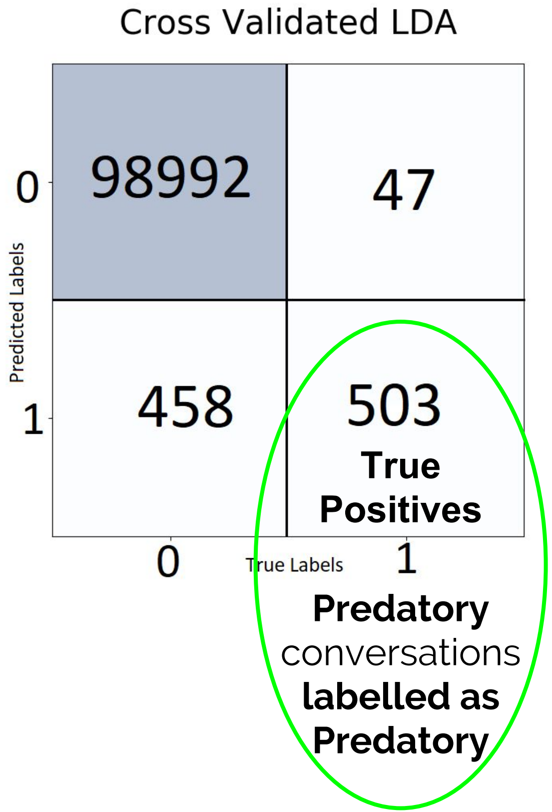

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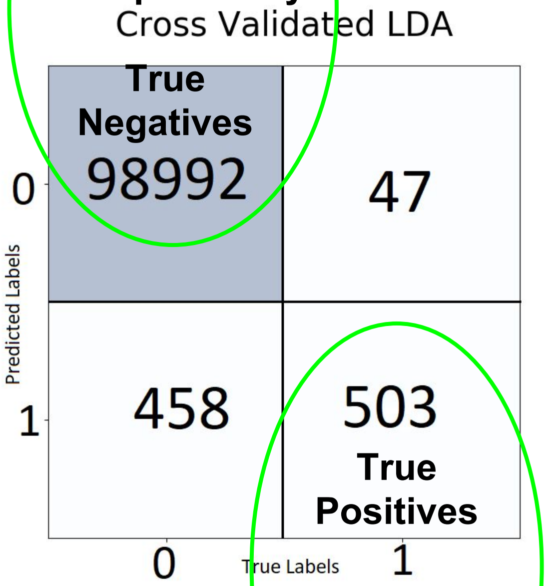
Non-predatory conversations **labeled as Non-predatory**



Predatory conversations **labelled as Predatory**

LDA - Recall

Classification Model	Average Precision	Average Recall	F1 Score
LDA	0.5234	0.9145	0.6658
SVM	0.7686	0.6582	0.7091
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Table 1: Average Recall and Precision, and Overall F1-Score from the top 5 First Stage Classification Models.

Recall = When it's actually predatory, how often does it predict predatory?

Recall = TP / (TP + FN)

= 503 / (503 + 47)

= 0.9145

LDA - Precision

Classification Model	Average Precision	Average Recall	F1 Score
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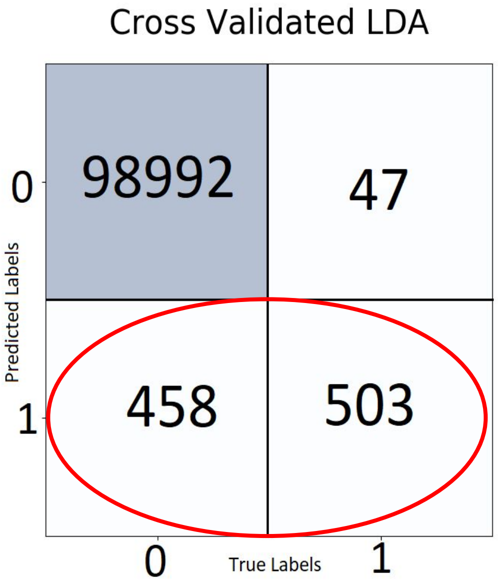
Table 1: Average Recall and Precision, and Overall F1-Score from the top 5 First Stage Classification Models.

Precision = When it predicts Predatory, how often is it correct?



Precision = TP / (TP + FP)

= 503 / (503 + 458)

= 0.5234

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- Main concept behind LDA is **searching for a linear combination of variables** that best separates two (or more) classes

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Discriminant Function:

$$\hat{\delta}_k(x) = x \cdot \frac{\hat{\mu}_k}{\hat{\sigma}^2} - \frac{\hat{\mu}_k^2}{2\hat{\sigma}^2} + \log(\hat{\pi}_k)$$

Where
x is an observation (vector of input variables)
$\hat{\mu}_k$ is the estimated mean of the group k
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$\hat{\mu}_k$ is the estimated mean of the group k
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$\hat{\pi}_k$ is the prior class membership probability of a group k $\Longrightarrow$ In my LDA: $\hat{\pi}_0 = 0.99450,$ $\hat{\pi}_1 = 0.00550.$

The observation X = x gets assigned to the class k for which $\hat{\delta}_k(x)$ is largest.

Second Stage Classification

Classification Model	Average Precision	Average Recall	F1 Score
SVM	0.6928	0.8250	0.7532
Naive Bayes	0.5859	0.9284	0.7185
LASSO	0.7433	0.7714	0.7571
AdaBoost	0.7767	0.8091	0.7926
k-NN	0.6273	0.8966	0.7381

Table 2: Second stage classification process, with cross validated results from the top 5 models, and their average precision, recall measurements, alongside F1-scores.

AdaBoost - Recall

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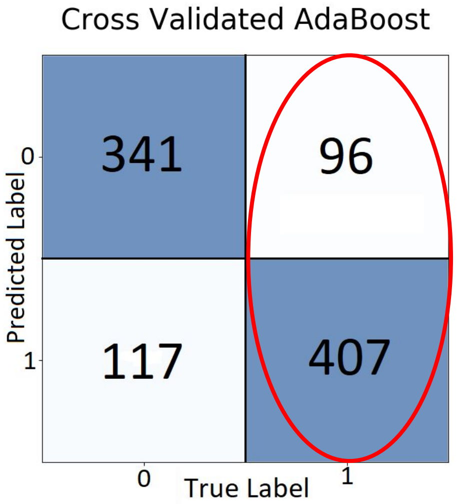
Recall = When it's actually predatory, how often does it predict predatory?



Recall = TP / (TP + FN)

= 407 / (407 + 96)

= 0.8091

AdaBoost - Precision

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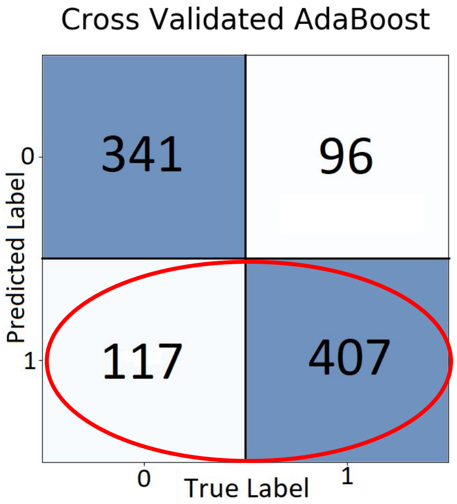
Precision = When it predicts Predatory, how often is it correct?



Precision = TP / (TP + FP)

= 407 / (407 + 117)

= 0.7767

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- AdaBoost (Adaptive Boosting) is an iterative tree based method
- Simple variation on **Bagging algorithm**
- Improves the learning process where the system is not performing well
- Main concept: **Iteratively learns from misclassifications** of previously fitted models

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AdaBoost Pseudo-Algorithm:

N observations, M number of trees (bags)

Initialize observation weights $w_i = 1/N$

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N observations, M number of trees (bags)

Initialize observation weights $w_i = 1/N$
Randomly split data into training and test set
For m = 1 to M:

Fit new model using m trees on training data **(weak classifier)**
Combine and test new model with previously fitted models
Compute error and accuracy for the **combined models**
Update observation weights (correct classifications get less weightage, **misclassifications' weights increase**)
Create new train/test sets randomly* from original data
(*misclassifications have a higher chance of being in the new training set)

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Compute error and accuracy for the **combined models**
Update observation weights (correct classifications get less weightage, **misclassifications' weights increase**)
Create new train/test sets randomly* from original data
(*misclassifications have a higher chance of being in the new training set)

Combine all fitted models based on weight values to create AdaBoost Classifier

Visualization of AdaBoost

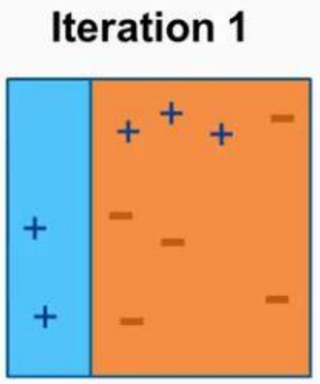

Figure 19: AdaBoost - First Iteration

Visualization of AdaBoost

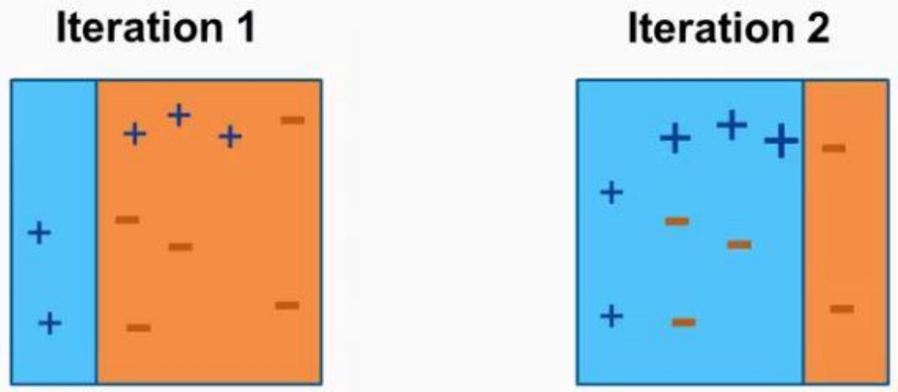

Figure 20: AdaBoost - Second Iteration

Visualization of AdaBoost

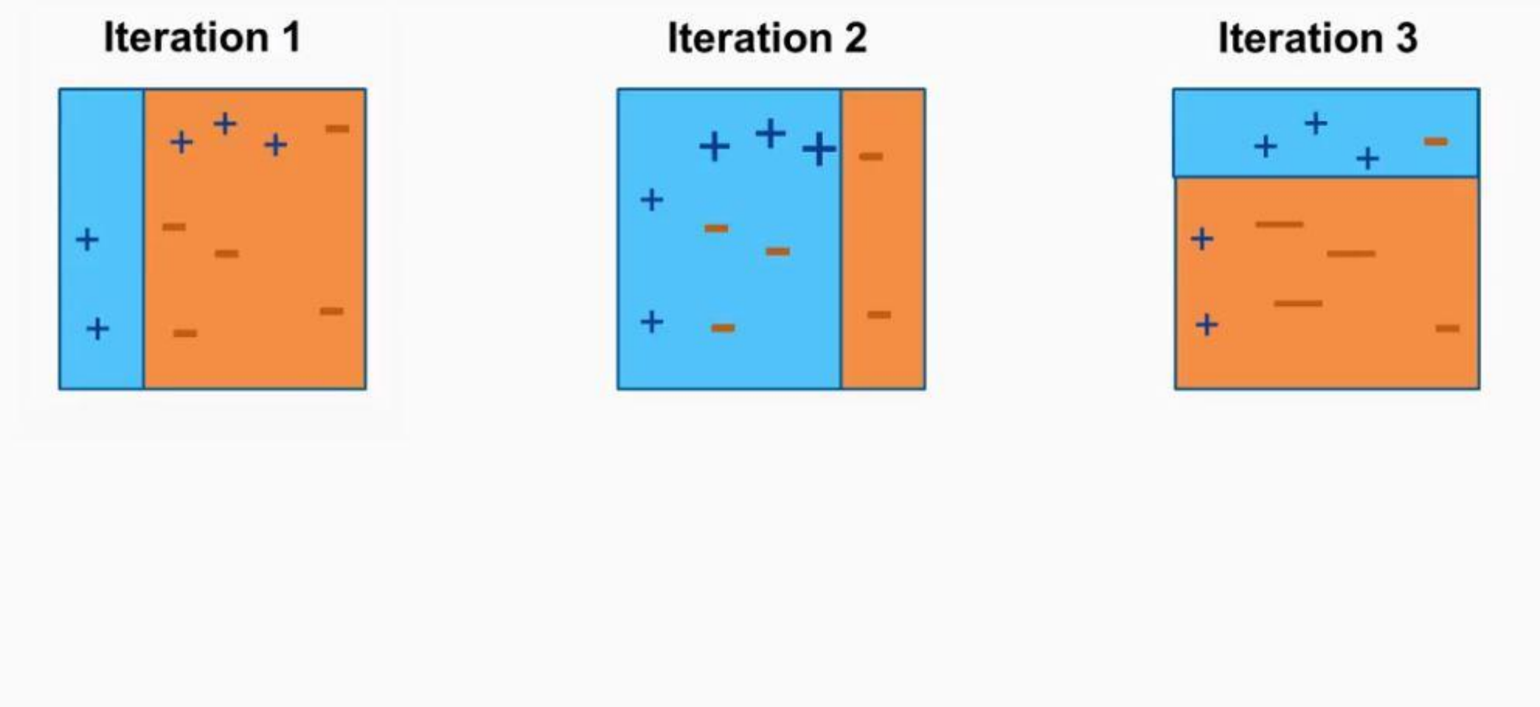

Figure 21: AdaBoost - Third Iteration

Visualization of AdaBoost

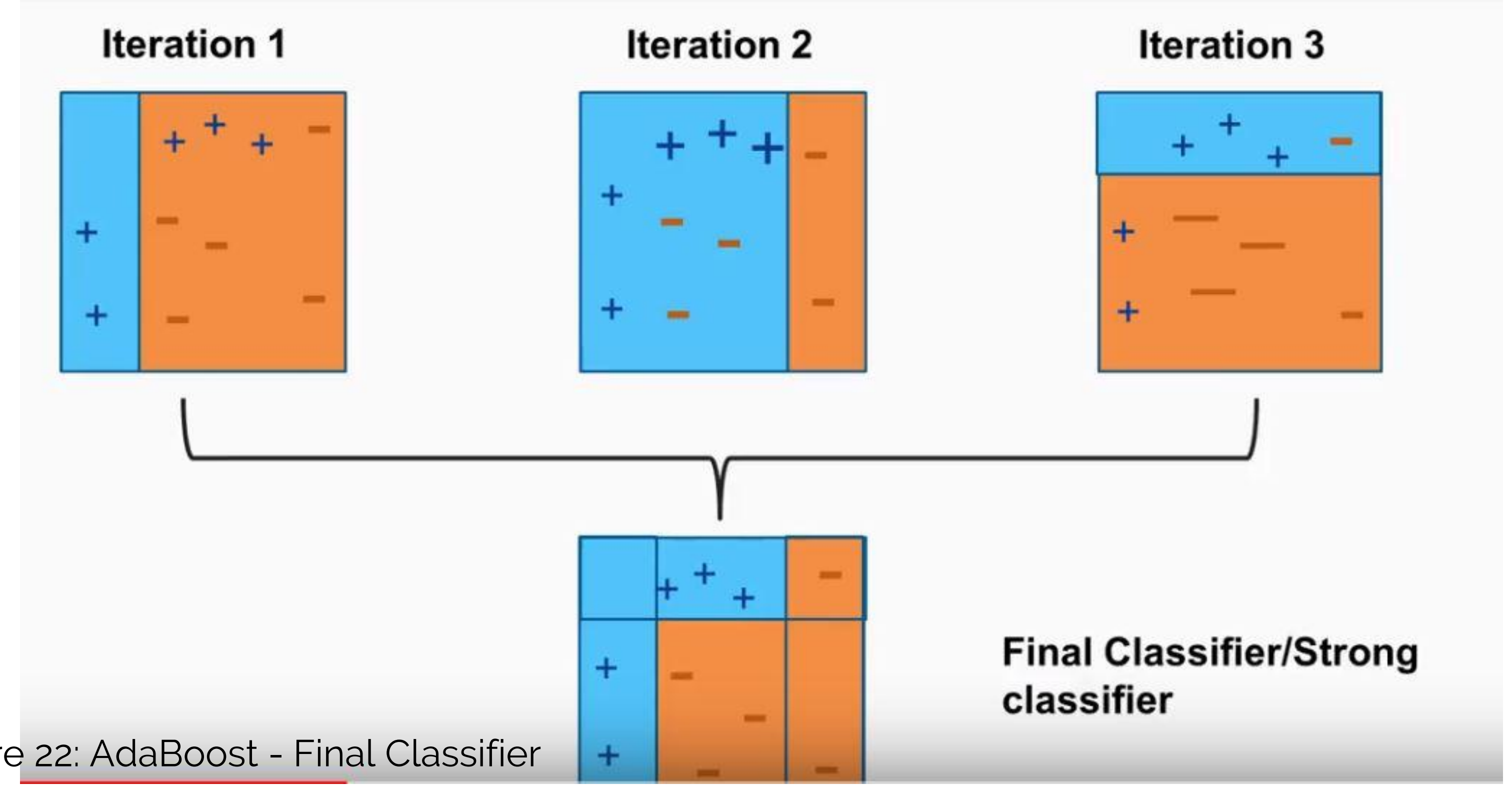

Figure 22: AdaBoost - Final Classifier

Classification System: LDA + AdaBoost

System of Classifiers	Precision	Recall	F1 Score
LDA $\rightarrow$ SVM	0.6928	0.7545	0.7224
LDA $\rightarrow$ Naive Bayes	0.5859	0.8491	0.6934
LDA $\rightarrow$ AdaBoost	0.7767	0.74	0.7579
LDA $\rightarrow$ LASSO	0.7433	0.7055	0.7239
LDA $\rightarrow$ k-NN	0.6273	0.82	0.7108

Table 3: Recall, precision and F1 scores from First Stage classifier combined with each possible second stage classifier.

LDA + AdaBoost Overall Recall

System of Classifiers	Precision	Recall	F1 Score
LDA → SVM	0.6928	0.7545	0.7224
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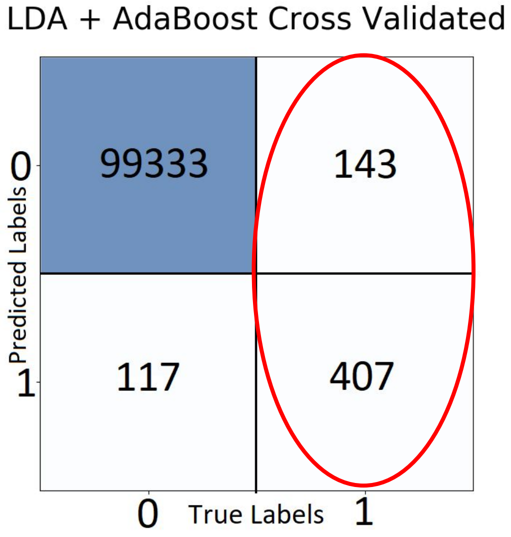

Recall = TP / (TP + FN)

= 407 / (407 + 143)

= 0.74

LDA + AdaBoost Overall Precision

System of Classifiers	Precision	Recall	F1 Score
LDA → SVM	0.6928	0.7545	0.7224
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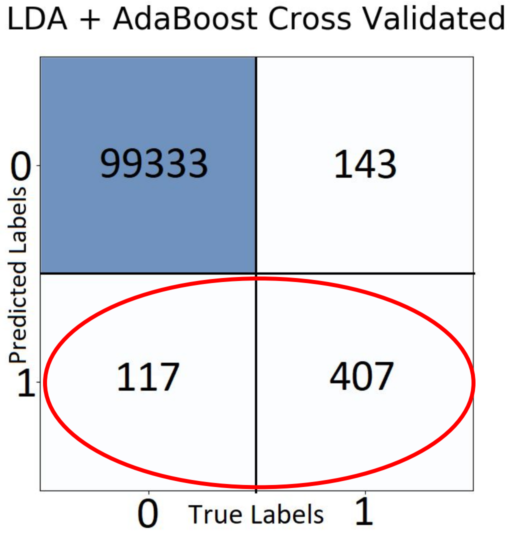

Precision = TP / (TP + FP)

= 407 / (407 + 117)

= 0.7767

LDA + AdaBoost Overall F1 Score

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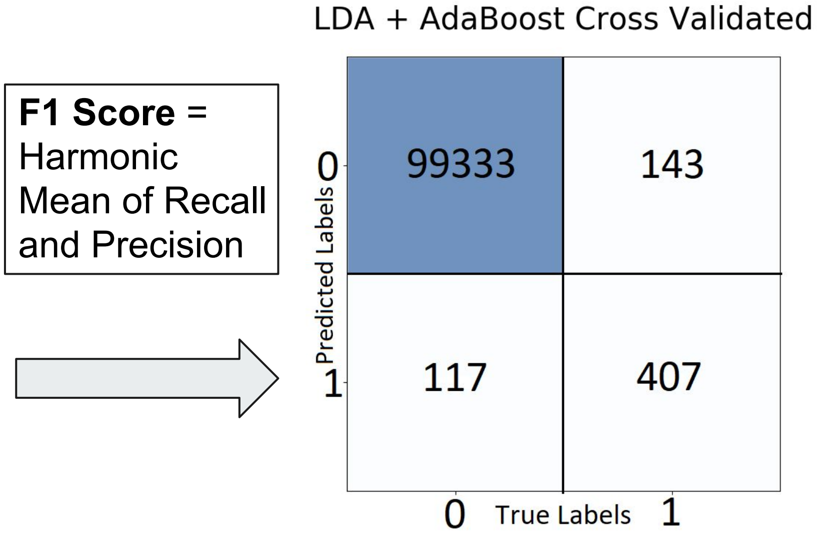
F1 Score = Harmonic Mean of Recall and Precision



F1 Score = 2 * (Recall * Precision) / (Recall + Precision)

= 0.7579

Research Contribution

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2. The **experimentation process of two stage classification** system yielded performance results from 8 different classification models.

Research Significance

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3. Two stage classification system is a **highly flexible** method, therefore future research can be focused on **customizing this approach** to other types of dangerous behavior detection.

Outline

1.) Problem Background
2.) Research Questions and Objectives
3.) Introduction to Data Being Used
4.) Algorithm Proposed
5.) Results & Model Selection Explained
6.) **Future Works and Conclusion**

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3. A **deep learning approach for the classification system** could be considered, by favouring prediction accuracy over model interpretability.

Conclusion

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- Approach could **enhance children's safety in online environments** by detecting malicious behaviour

Acknowledgements

- Supervisor: Dr. Abdallah Mohamed
- Co-Supervisor: Dr. Jeffrey Andrews
- Family and friends, especially Ryan M., Liam W., Ryan K. and Parsa R.

Thank you.

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Appendix

LDA in details

- Z is the linear combination
- Define Score function S(B)

$$Z = \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_d x_d$$

$$S(\beta) = \frac{\beta^T \mu_1 - \beta^T \mu_2}{\beta^T C \beta}$$ Score function

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$$C = \frac{1}{n_1 + n_2}(n_1 C_1 + n_2 C_2)$$ Pooled covariance matrix

Where:

β : Linear model coefficients

C_1, C_2 : Covariance matrices

μ_1, μ_2 : Mean vectors

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$$\beta^T \left(x - \left(\frac{\mu_1 + \mu_2}{2} \right) \right) > \log \frac{p(c_1)}{p(c_2)}$$

Coefficients vector

Data vector

Mean vector

Class probability

A new observation is classified using this equation