





Fake News Detection



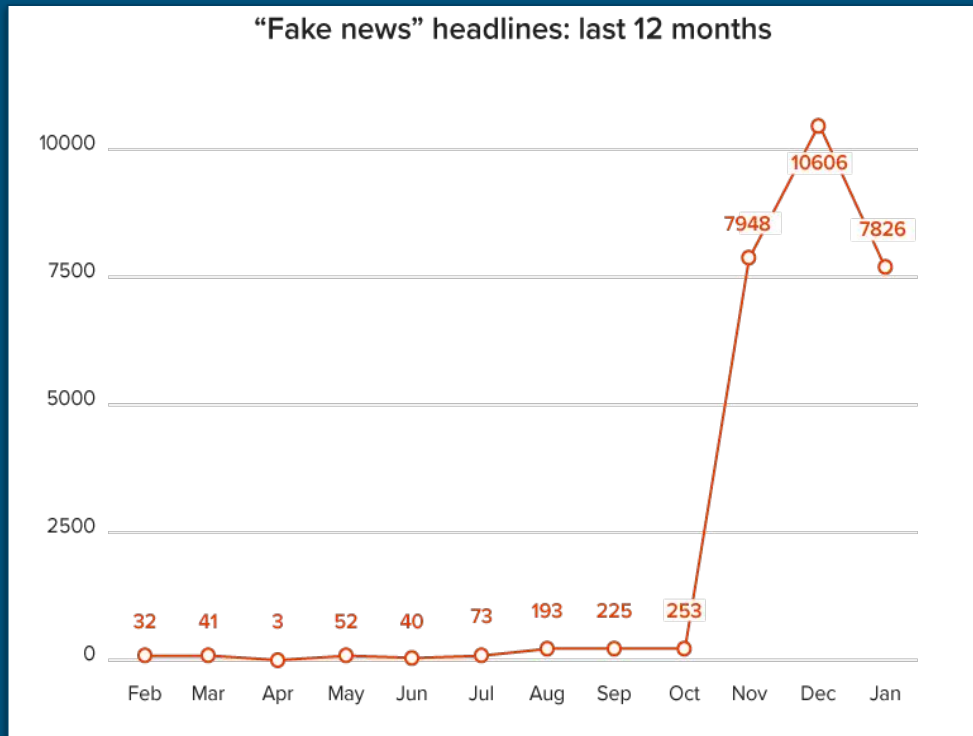
John Curci
Keval Khara
Ashwin Pillai
Ruoxi Qin



[GitHub](#)

Motivation

- ◆ Prevalence of fake news on social media
- ◆ Emerging research area in Natural Language Processing
- ◆ Basic countermeasures inflexible and inefficient
- ◆ Current progress in this area



Problem Statement

- ◆ Develop a machine learning program to identify fake/unreliable news based on content acquired.

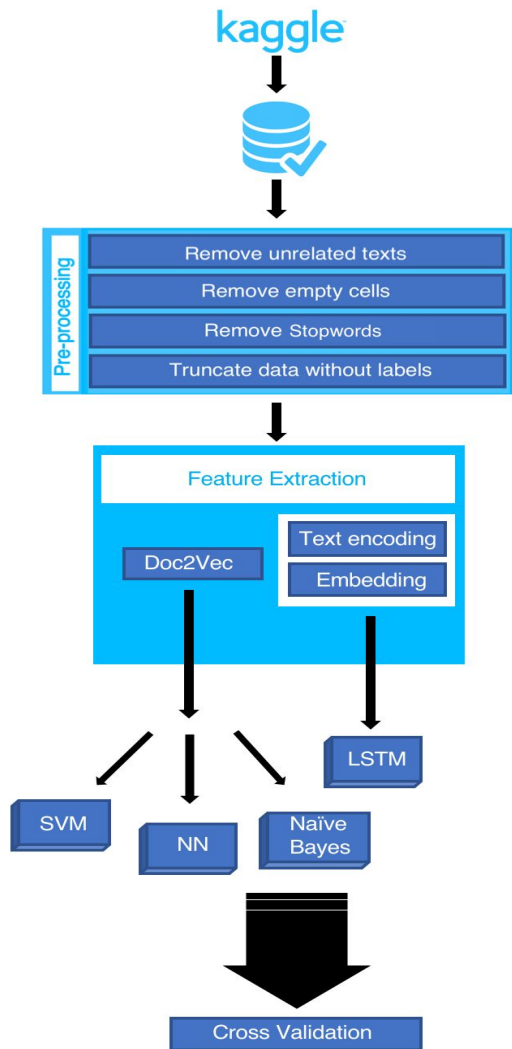


Data

- ◆ Dataset source - Kaggle
- ◆ ID, Title, Author, Text, Label
- ◆ Label 1 - Unreliable
- ◆ Label 0 - Reliable

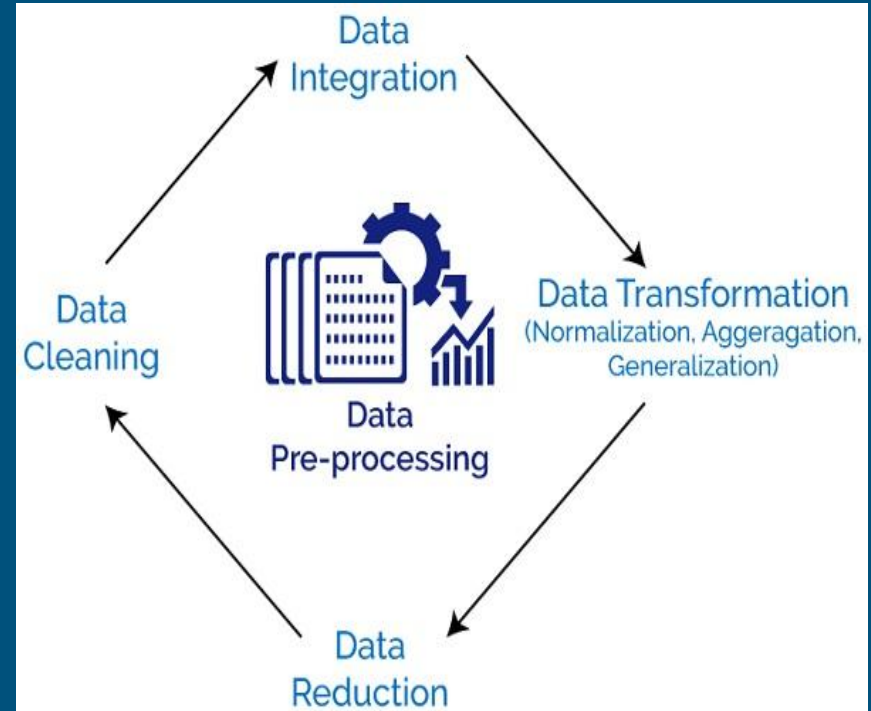
| id | title | author | text | label | |
|-----------------|-------------------|---------------------|--------------------|----------------|----|
| 0 | House Der | Darrell Luc | House | 1 | |
| 1 | FLYNN: Hi | Daniel J. F | Ever get th | 0 | |
| 2 | Why the T | Consortiur | Why the | 1 | |
| 3 | 15 Civilian | Jessica Pul | Videos 15 | 1 | |
| 4 | Iranian wo | Howard Po | Print | 1 | |
| 5 | Jackie Ma | Daniel Nus | In these tr | 0 | |
| 6 | Life: Life C | nan | Ever | 1 | |
| 7 | Benoît H | Alissa J. Ru | PARIS "â€" | 0 | |
| 8 | Excerpts F | nan | Donald J. T | 0 | |
| 9 | A Back-Ch | Megan Tw | A week be | 0 | |
| 10 | Obamaâ€™ | Aaron Klei | Organizing | 0 | |
| 11 | BBC Come | Chris Tom | The BBC p | 0 | |
| 12 | Russian Re | Amando F | The | 1 | |
| 13 | US Official | Jason Ditz | Clinton | 1 | |
| 14 | Re: Yes, Th | AnotherAr | Yes, | | |
| BART SIMPSONSON | | | | | |
| Hey | itâ€™s jus | channels | and programs | fellating them | da |
| Itâ€™s not | I imagine | oil compa | difficult to know | who to trust | o |
| In any soc | most people | do nothing. | Itâ€™s up to the | minority to | |
| If I read the | article correctly | the government | is targeting | conserv | |
| The DNC is | stupid and | but these j@ck@sses | ramp it up to 11.) | Ta | |
| I almost p | which wa | especially | 1 | | |

Workflow



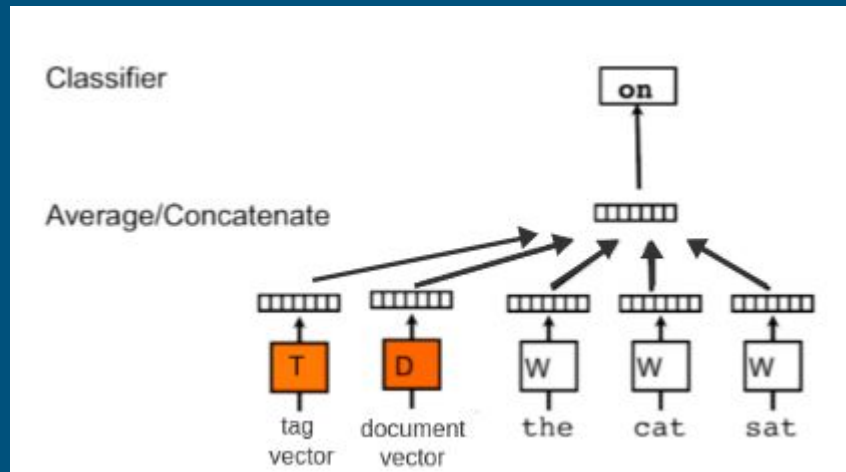
Data Preprocessing

- Perform various text cleaning steps (remove all non-alphanumeric characters, delete stopwords, delete missing rows, etc.)
- For Doc2Vec, convert to LabeledSentences(), comma separated word format



Doc2Vec Model

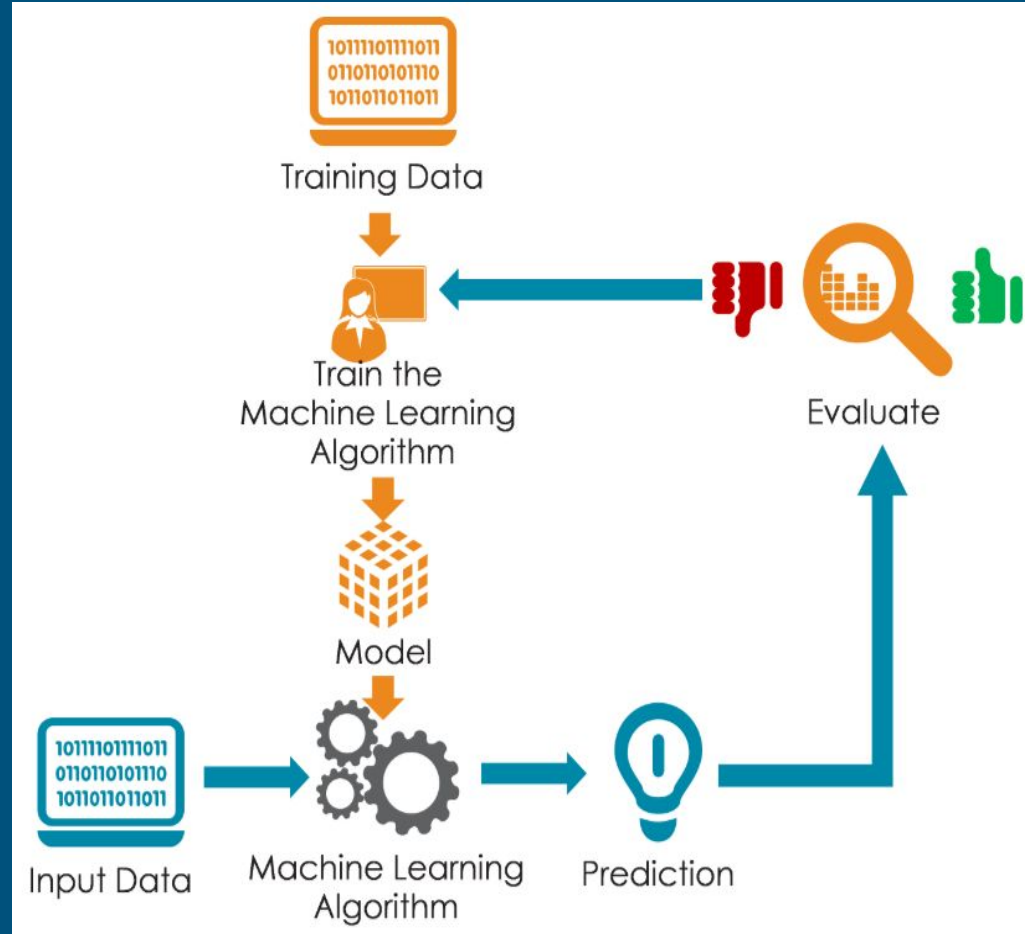
- ◆ Based on Word2Vec model
- ◆ Preserves word order information
- ◆ Extracts Word2Vec features and adds an additional “document vector” with information about the entire document



Training a Model

◆ Models used-

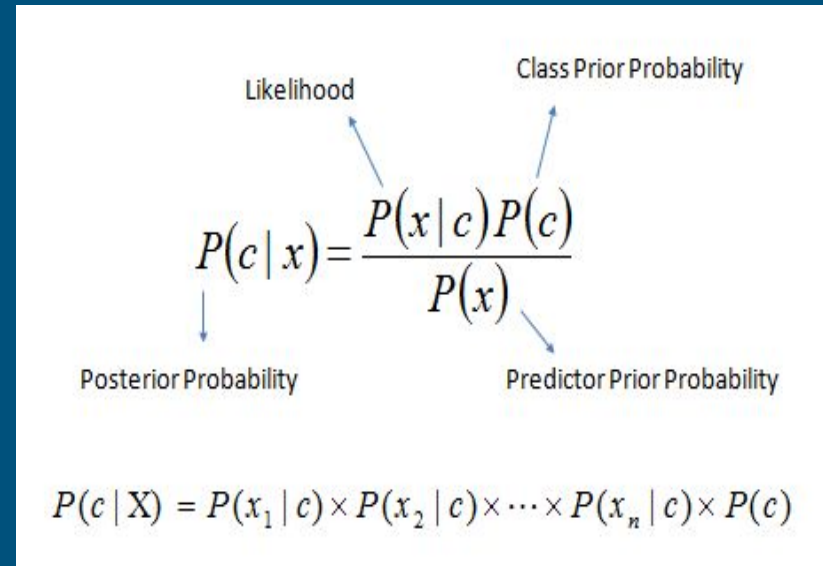
- Naive Bayes
- Support Vector Machine (SVM)
- Neural Network
- Long Short-Term Memory (LSTM)



Naive Bayes

◆ Classification technique based on Bayes' theorem with an assumption of independence among predictors

1. Convert data set into a frequency table
2. Create likelihood table by finding probabilities
3. Use Naive Bayesian equation to calculate posterior probability for each class



The diagram shows the Naive Bayes equation with labels for its components:

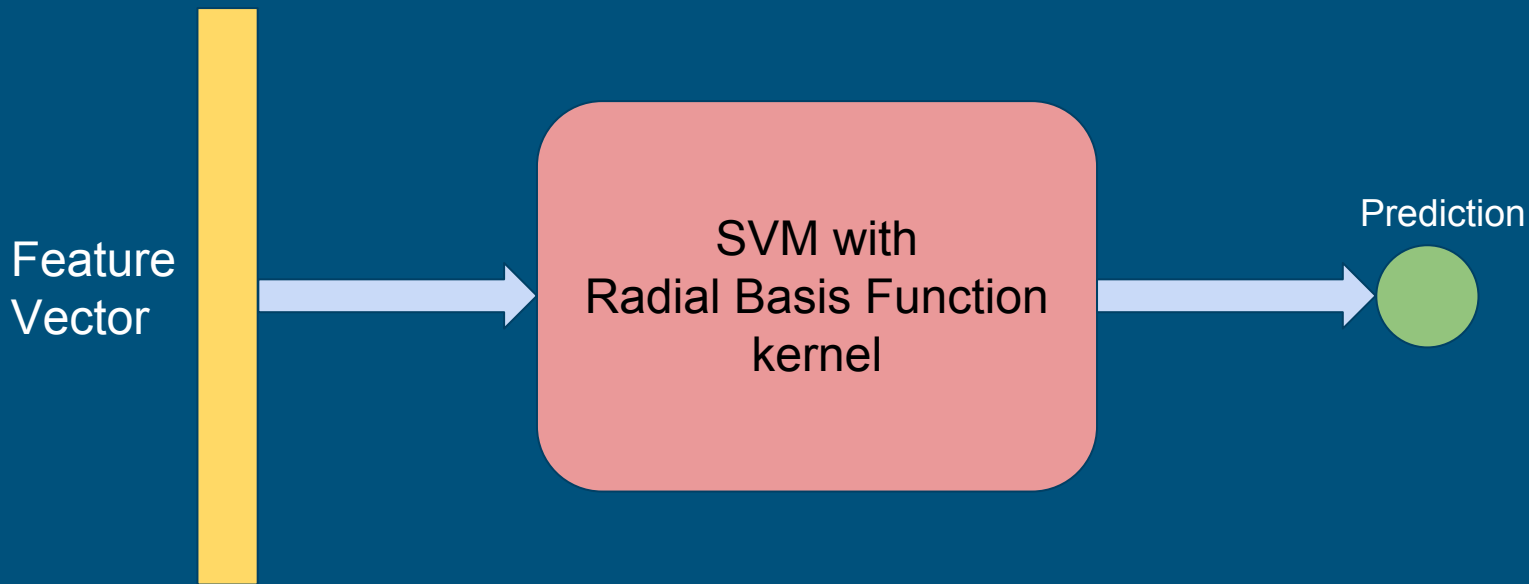
$$P(c|x) = \frac{P(x|c)P(c)}{P(x)}$$

Labels and arrows:

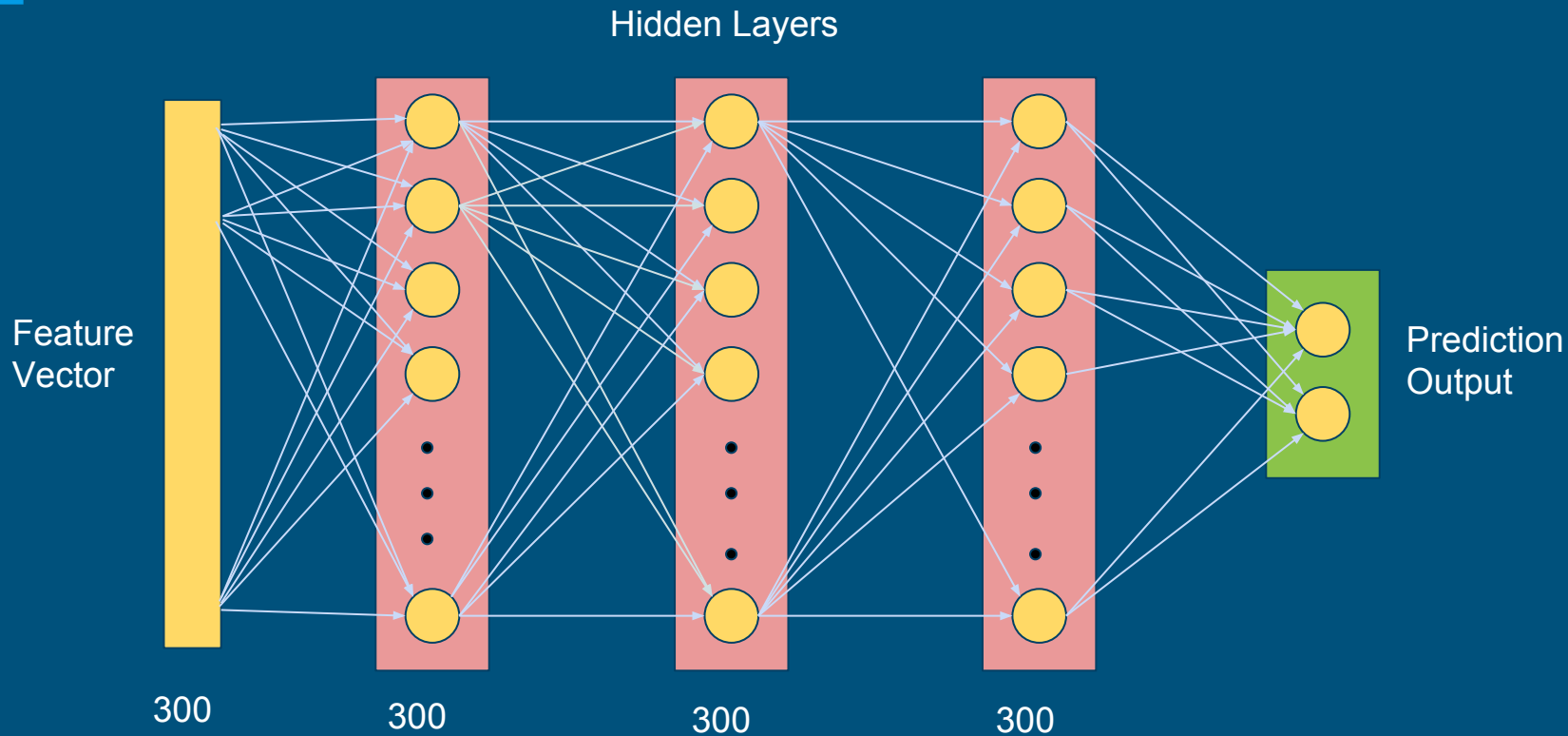
- Likelihood** points to $P(x|c)$
- Class Prior Probability** points to $P(c)$
- Posterior Probability** points to $P(c|x)$
- Predictor Prior Probability** points to $P(x)$

$$P(c|X) = P(x_1|c) \times P(x_2|c) \times \dots \times P(x_n|c) \times P(c)$$

Support Vector Machine (SVM)



Neural Network



Neural Network

TensorFlow

Hidden Layer Structure
(300, 300)
(300, 300, 300)

Learning rate:
0.001

Training Steps:
20000

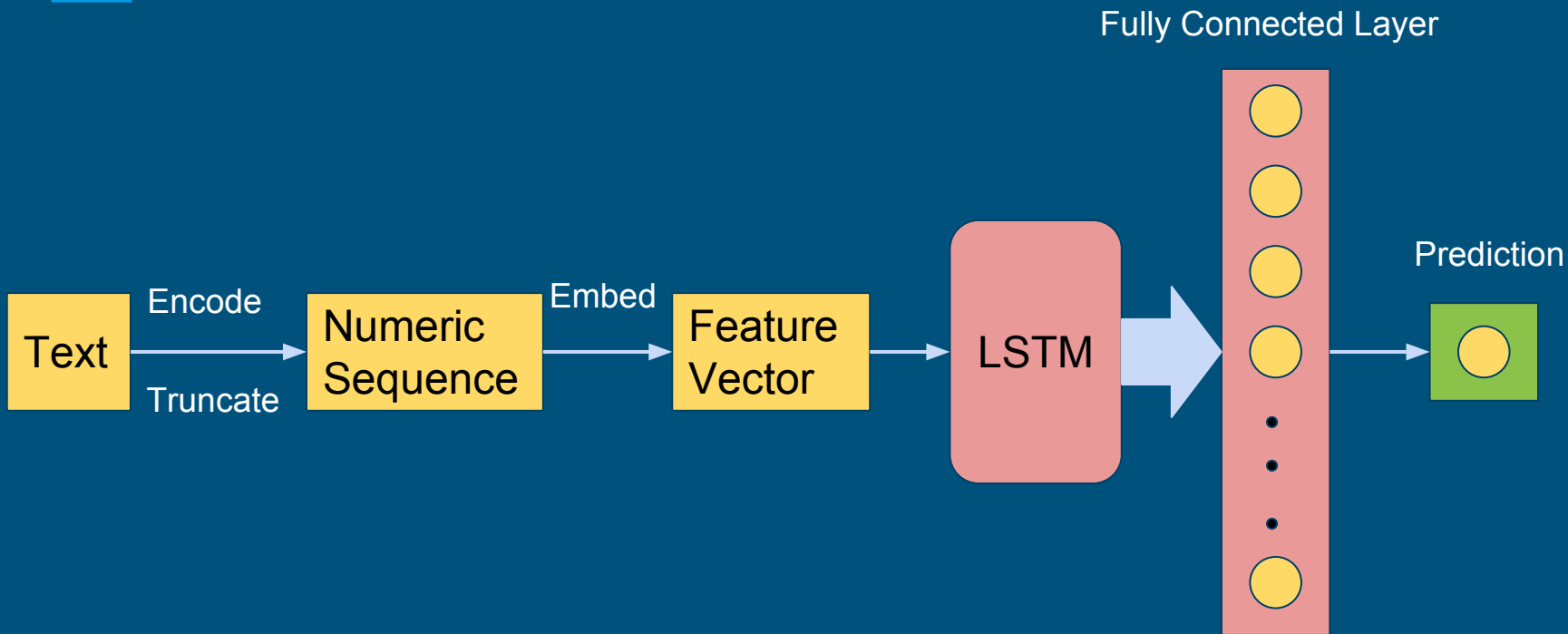
Keras

Hidden Layer Structure
(256, 256, 80)

Learning rate:
0.01

Training Steps:
10000

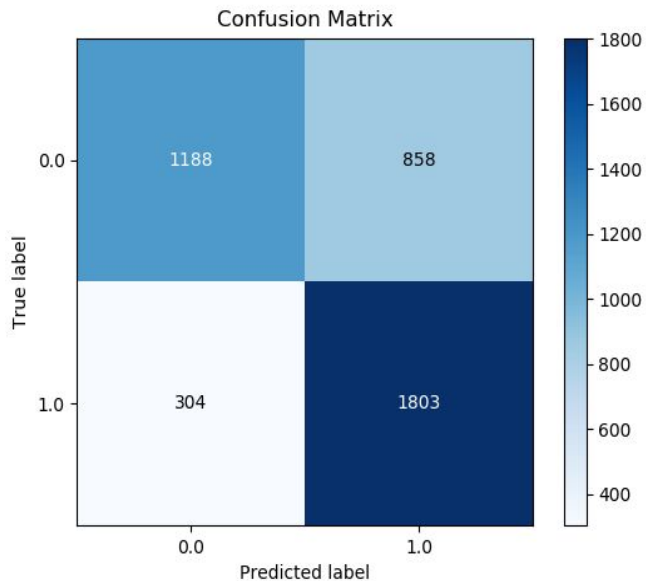
LSTM



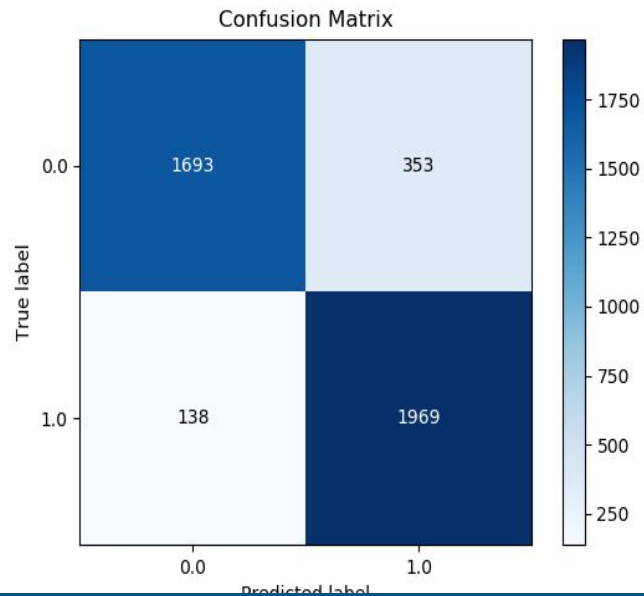
Comparison of Models

| Model | Accuracy |
|---------------------------------|----------|
| Naive Bayes | 72.94% |
| SVM | 88.42% |
| Neural Network using TensorFlow | 81.42% |
| Neural Network using Keras | 92.62% |
| LSTM | 94.53% |

Confusion Matrices

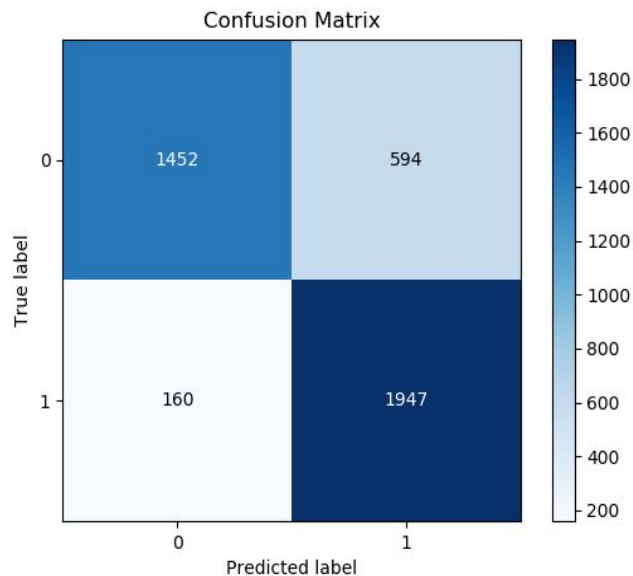


Naive Bayes

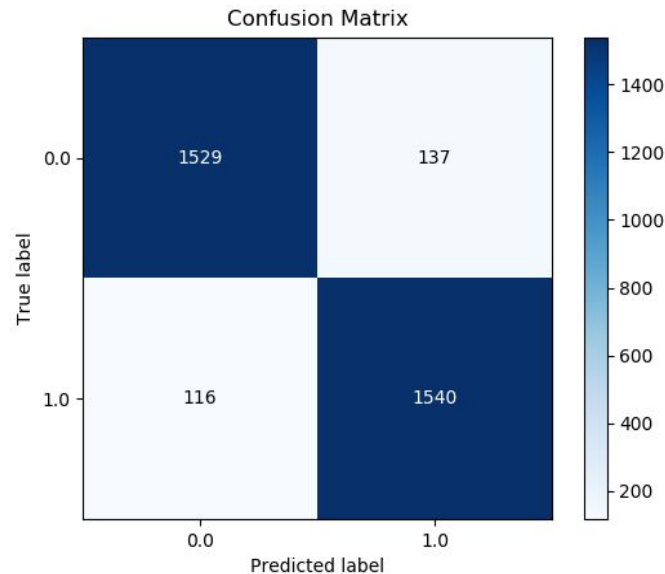


SVM

Confusion Matrices

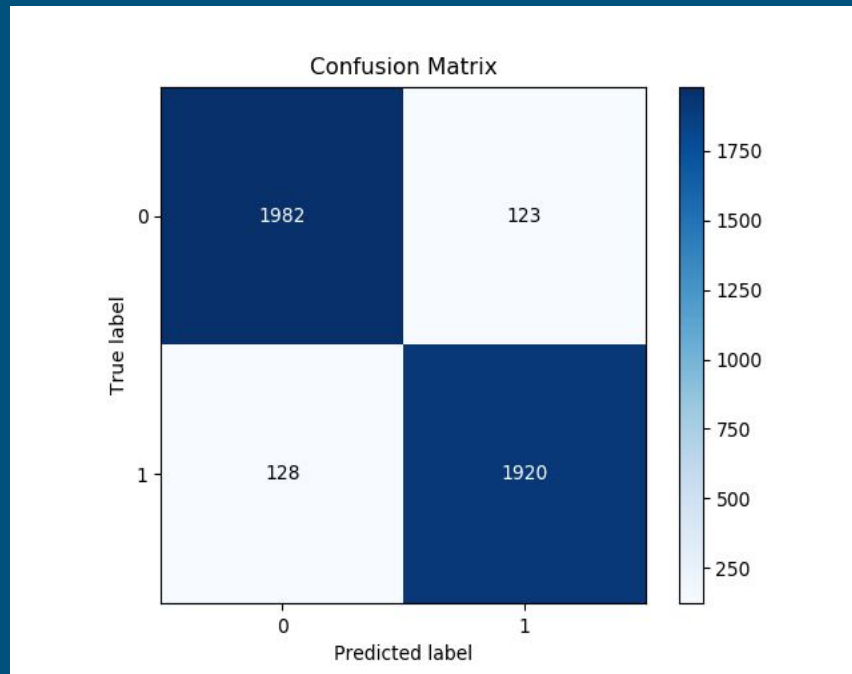


Neural Network using TensorFlow



Neural Network using Keras

Confusion Matrices



LSTM

Challenges Faced

- ◆ Lack of clean data to directly work with might have slowed down our progress
- ◆ The loss to value of information in a real scenario for news is very high
- ◆ Content based classification is just a part of the whole picture
- ◆ Distinguish between click-bait and actual fake news



Future Work

- ◆ Assemble the classifiers to achieve better performance - Adam Boost
- ◆ Check the sources of the news
- ◆ Search the news on the web to check the content of the news



Data's all, folks!
Thank You!

Thanks to Prof. Sang ("Peter") Chin, Kieran Wang, Gavin Brown
and Ken Zhou for their guidance!

References

- ◆ [Fake News Detection: A Data Mining Perspective](#)
- ◆ [Fake News Identification - Stanford CS 229](#)
- ◆ [BS Detector](#)
- ◆ [Datasets from Kaggle](#)