

# Spam Message Classification

Leo Siu-Yin



#### Spam and Scam Messages

SMS/MMS 水曜日 午前9:47

Your delivery has been stopped at our depot. Trk#: R690382803147 Please resolve the issue here: f94.us/VrVwq The Government has finally approved and have started giving out free \$2,400 Relief Funds to each citizen &Below is how to claim and get yours credit Instantly as I have just did now https://ll.llll.cam

Note: You can only claim and get credited once and it's also limited so get your now Instantly.

- Spam: Messages sent to a large group of recipients without their prior consent.
- Usually advertise for goods/services.
- Scam messages form a high percentage of spam messages.
- Typically trick people into giving away money or personal details by offering an attractive/false deal.
- This year Jan-June: scammed amount increased by >S\$8 million.

#### **Motivation**



#### **Spam Message Classification**:

A step towards building a tool for scam message identification and early scam detection.

#### **Contents**



Dataset



Tools/ Methodology



Model Comparison



Model Evaluation



Conclusion

#### **Dataset**

- Spam Message Collection Dataset from Kaggle.
- 5572 rows of messages.
- All messages are classified into either spam or ham.
- 13.4% spam, 86.6% ham



#### **Tools Used**

















### Methodology

#### **Data Pre-processing**

- 1. Word tokenize
- 2. Convert to lower case
- 3. Remove punctuation except '!'
- 4. Remove stopwords
- Remove words containing digits
- Exploratory Data Analysis

# Model Training Model Comparison

- 1. Train Test Split data
- 2. CountVectorizer
- GridSearchCV across
   10 folds
- 4. Fit data to models
- Comparison of model results

#### **Model Evaluation**

- 1. Result Summary
- 2. Confusion Matrix
- 3. Precision-Recall Curve

#### **Data Pre-processing**

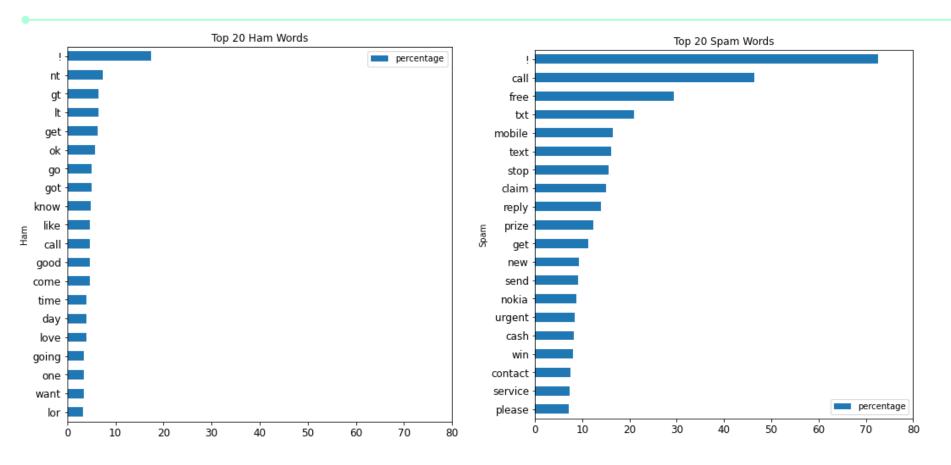
1. After Word Tokenize

['Hello', '!', 'How', "s", 'you', 'and', 'how', 'did', 'saturday', 'go', '?', 'l', 'was', 'just', 'texting', 'to', 'see', 'if', 'you', "'d", 'decided', 'to', 'do', 'anything', 'tomo', '.', 'Not', 'that', 'i', "m", 'trying', 'to', 'invite', 'myself', 'or', 'anything', '!']

- Conversion to lower case
- 3. Punctuation removed except '!'
- 4. Stopwords and words with digits removed

['hello', '!', 'saturday', 'go', 'texting', 'see', 'decided', 'anything', 'tomo', 'trying', 'invite', 'anything', '!']

# **Exploratory Data Analysis**



# **Exploratory Data Analysis: Topic Modeling**

Topic #0 (Ham):

nt ok like got go come good get know time love day going home sorry lor still see want da

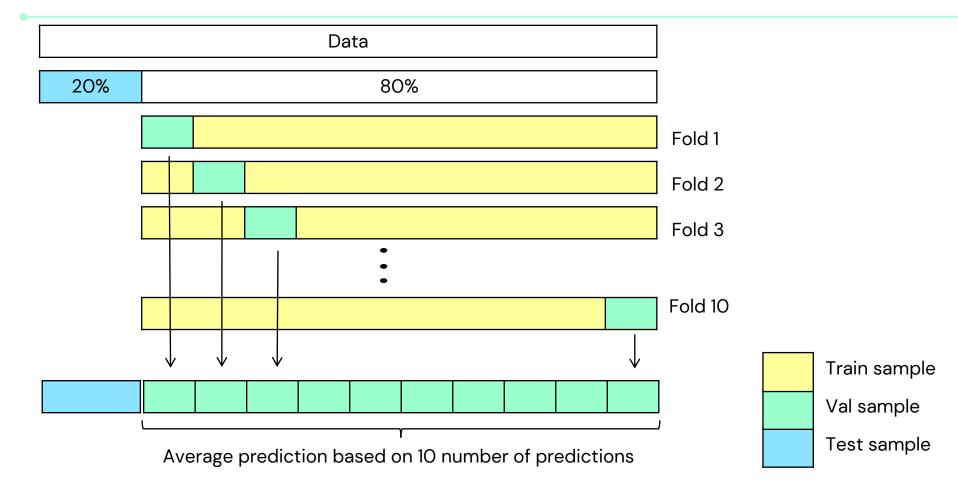
Topic #1 (Spam):

call gt lt free txt text get mobile stop reply new claim send please number prize week message phone win

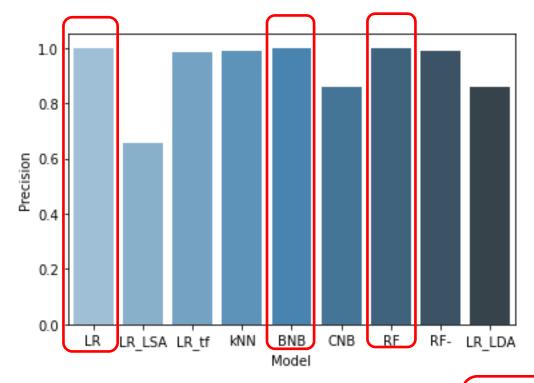
#### **Models Used**

Logistic Complement K- Nearest Random Bernoulli Regression **Neighbours Naïve Bayes Forest** Naïve Bayes **CountVectoriser** CountVectoriser CountVectoriser CountVectoriser CountVectoriser **Tfidf Vectoriser** CountVectoriser with LSA CountVectoriser with LDA

#### **GridSearchCV**

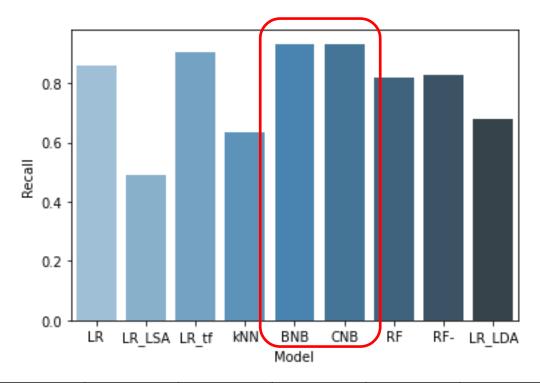


# **Modeling Results and Comparison: Precision**



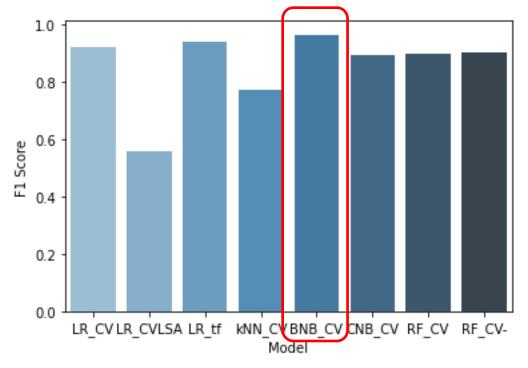
Model	LR	LR_LSA	LR_tf	kNN	BNB	CNB	RF	RF-	LR_LDA
Precision	1	0.66	0.98	0.99	1	0.86	1	0.99	0.86

## Modeling Results and Comparison: Recall



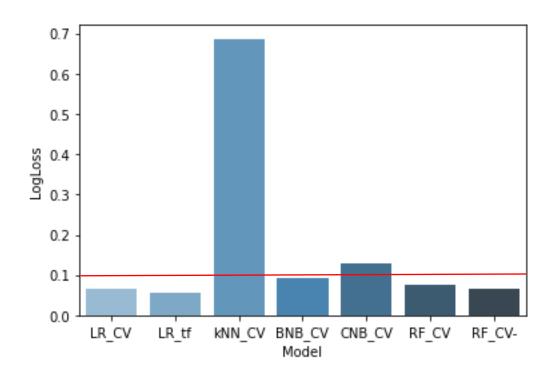
Model	LR	LR_LSA	LR_tf	kNN	BNB	CNB	RF	RF-	LR_LDA
Recall	0.86	0.49	0.90	0.63	0.93	0.93	0.82	0.83	0.68

# Modeling Results and Comparison: F1 Score



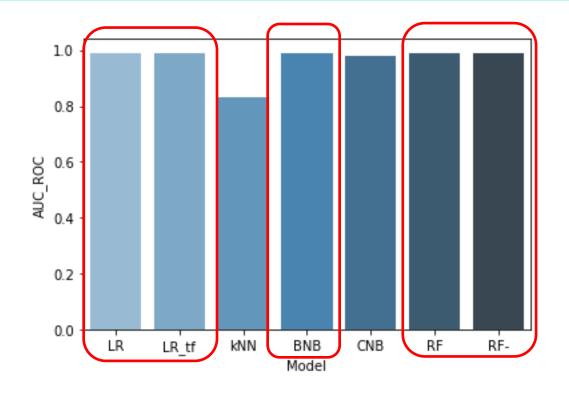
Model	LR	LR_LSA	LR_tf	kNN	BNB	CNB	RF	RF-	LR_LDA
F1 Score	0.92	0.56	0.94	0.77	0.97	0.90	0.90	0.90	0.76

# Modeling Results and Comparison: Log Loss



Model	LR	LR_tf	kNN	BNB	CNB	RF	RF-
LogLoss	0.07	0.06	0.69	0.09	0.13	0.07	0.07

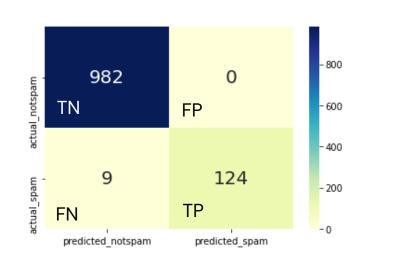
# Modeling Results and Comparison: AUC ROC

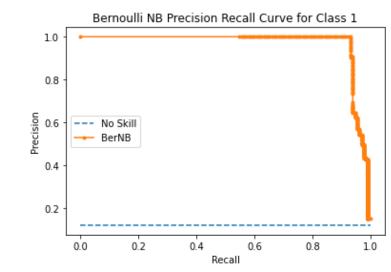


Model	LR	LR_tf	kNN	BNB	CNB	RF	RF_CV-
AUC_ROC	0.99	0.99	0.83	0.99	0.98	0.99	0.99

# **Result Summary**

Model	LR	LR_LSA	LR_tf	kNN	BNB	CNB	RF	RF-	LR_LDA
Precision	1	0.66	0.98	0.99	1	0.86	1	0.99	0.86
Recall	0.86	0.49	0.90	0.63	0.93	0.93	0.82	0.83	0.68
F1 Score	0.92	0.56	0.94	0.77	0.97	0.90	0.90	0.90	0.76
LogLoss	0.07	N.A.	0.06	0.69	0.09	0.13	0.07	0.07	N.A.
AUC ROC	0.99	N.A.	0.99	0.83	0.99	0.98	0.99	0.99	N.A.





#### Conclusion

- A more customised pre-processing step is important for precision.
- Logistic Regression and Naive Bayes models have performed better than other models.
- A model with 100% precision has been built.

#### **Future Work**

- 1. Investigate performance of models based on Tfidf vectoriser.
- 2. Use word embeddings trained with neural-network for classification.

# **THANKS!**

Do you have any questions? syleo22@gmail.com https://github.com/syleo22/SiuYin\_Projects https://www.linkedin.com/in/syleo/







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