RATING PREDICTION USING CUSTOMER REVIEWS

A Comparative Analysis of Various Models and their Generalizability

SUMMARY

INTRODUCTION — Context, dataset and task

MODEL DEVELOPMENT — Data preparation, model training and hyperparameter tuning

MODEL GENERALIZATION — Generalizability of the best model

CONCLUSION — Future direction and improvement

INTRODUCTION

CONTEXT - WHY STUDY

Help to understand customer's like and dislike in order to make better recommendation system

Identify potential issues of the review product (Restaurant, movie and app, etc.)

Measure customer satisfaction

TASK & OBJECTIVE

Task:

- Supervised learning

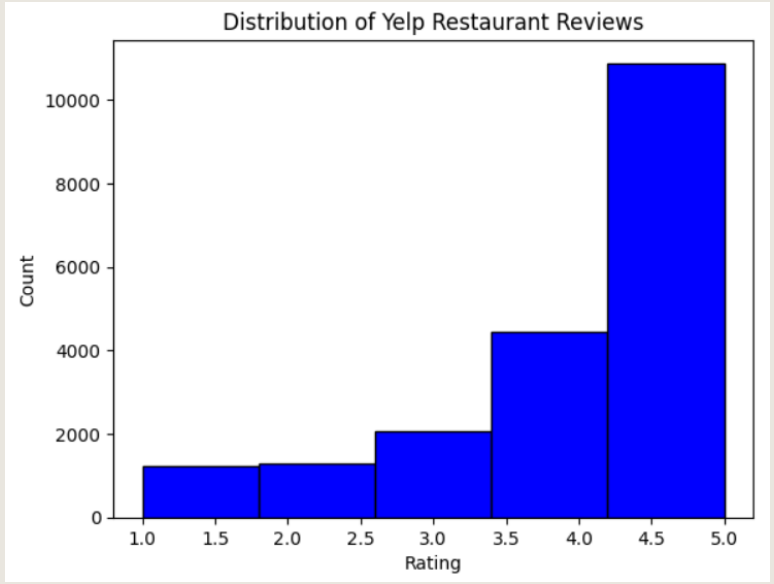
Objective:

- Find the best machine learning model with the lowest MSE on first dataset for prediction rating based on reviews
- Test the best model's generalizability on second dataset

DATASET

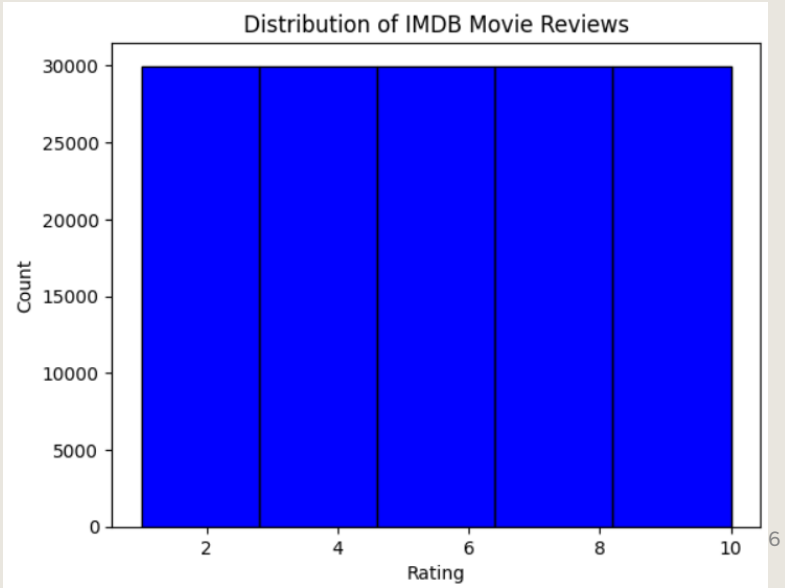
Yelp Restaurant Reviews

- 19 896 Data points
- 1-5 Rating scale, from 1, the lowest rating, to 5, the highest rating
- Dataset for **model training** and **selection**



IMDB Movie Reviews

- 150 000 Data points
- 1-10 Rating scale, from 1, the lowest rating, to 10, the highest rating
- Dataset for **model generalization**

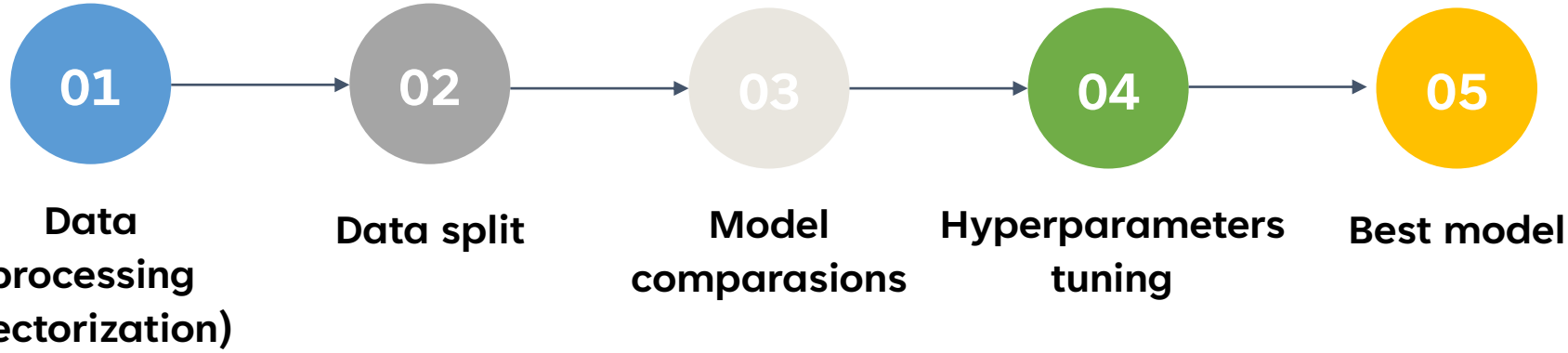


LITERATURE REVIEW

Author(s)	Objectives	Findings	Limitations	Method
Ahmed & Ghabayen., 2020	Improve the accuracy of rating predictions	Prediction framework using deep learning that outperforms existing methods in predicting ratings for online reviews	Depend on the quality and quantity of data used, problem of generalizability	Bidirectional GRU
Sadiq et al., 2021	More accurate prediction of rating to help user's decision making	Use deep learning models to predict the authenticity of numeric ratings and detecting discrepancies between user reviews and numeric ratings	Dataset used is imbalanced in terms of few app categories. Models like LSTM, RNN, GRU, and Bi-LSTM do not perform well on the imbalanced dataset.	CNN, RNN, LSTM, Bidirectional LSTM, GRU

MODEL DEVELOPMENT

PIPELINE


01
02
03
04
05
Data processing (Vectorization)
Data split
Model comparasions
Hyperparameters tuning
Best model

01

DATA PROCESSING

- NLTK:
  - Remove punctuation and stopwords
  - **Tokenize** the text
  - **Lemmatize** the text
  - Join it back into string

Tokenization: separating texts into smaller units, ex: “I like ML” → “I/like/ML”
Lemmatization: grouping different forms of the same word, ex: “drove”, “driving” → “drive”

- TENSORFLOW:
  - Tokenize the text
  - Convert the text to sequences of integers
  - Pad all sequences in order to ensure a fixed length

02

DATA SPLIT

- **Train_test_split** from **sklearn.model_selection**
- **60%** of data points as train dataset
- **40%** of data points as validation dataset

```
# Split the preprocessed data into train and validation sets
y = restaurant["Rating"]
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.4,
random_state=0)
```

03

MODEL COMPARISONS

METHODS USED:

- Average rating (**Baseline**)
- Linear regression
- Bidirectional RNN
- Bidirectional LSTM
- Bidirectional GRU
- CNN

EVALUATION METRIC:

- MSE on validation set

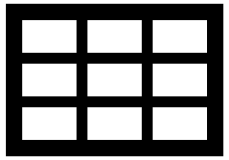
03

MODEL COMPARISONS

AVERAGE RATING (**BASELINE**)

- Predicting the ratings in the validation set with the average ratings from the train set

Train set



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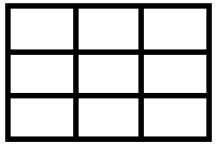
Validation set



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03

MODEL COMPARISONS

LINEAR REGRESSION

- Simple linear regression to predict the ratings
- Train the model on the train set
- Prediction on the validation set

```
# Train a linear regression model on the training set
lr_model = LinearRegression()
lr_model.fit(X_train, y_train)

# Make predictions on the validation set
lr_predictions = lr_model.predict(X_val)

# Calculate the MSE of the linear regression model
lr_mse = mean_squared_error(y_val, lr_predictions)

print("Linear regression MSE:", lr_mse)
```

03

MODEL COMPARISONS

BIDIRECTIONAL RNN

- Combination of two RNNs: one move forward and the other move backward
- Single layer of recurrent neurons
- Use output of the previous step and current input to predict next output
- Good to process sequential data (When the points in the dataset are dependent on the other points in the dataset)

03

MODEL COMPARISONS

BIDIRECTIONAL LSTM

- Special kind of RNN capable of learning long-term dependencies
- Has three gates
  - Input gate
  - Output gate
  - Forget gate
- Train the neural by allowing the input to flow in both directions
- Disadvantage: Short-term memory

03

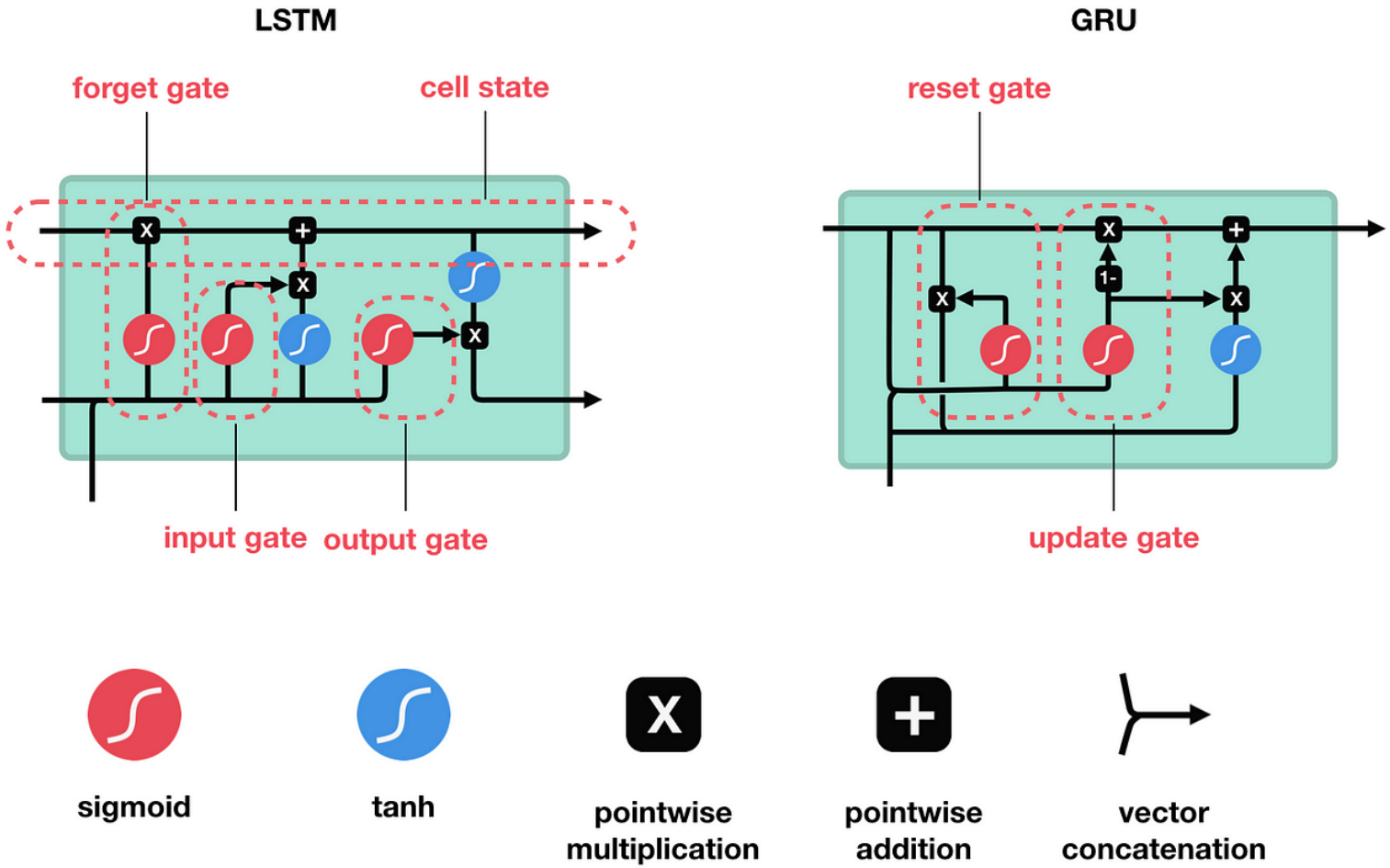
MODEL COMPARISONS

BIDIRECTIONAL GRU

- Variation of the LSTM in term of structure and performance
- Has two gates
  - Update gate
  - Reset gate
- Use of information from previous iteration and next iteration to make predictions about current iteration

03

MODEL COMPARISONS



03

MODEL COMPARISONS

CNN

- Used to perform feature extraction on the data
  - Presence of certain words
  - Order of words
  - Frequency of certain words
- Can handle input sequences of varying lengths

03

PERFORMANCE

	Model	MSE
01	**Average (Baseline)**	1.4340
02	**Linear regression**	1.3549
03	**Bidirectional RNN**	1.0148
04	**Bidirectional LSTM**	0.6064
05	**Bidirectional GRU**	0.6561
06	**CNN**	0.7058

04

HYPERPARAMETERS TUNING

HYPERPARAMETERS TUNED:

- **Embedding dim**: min_value=60, max_value=120, step=20
- **Lstm units**: min_value=32, max_value=96, step=32
- **Dropout rate**: min_value=0.1, max_value=0.5, step=0.1
- **L2 rate**: min_value=0.01, max_value=0.05, step=0.01

PACKAGE USED:

- **RandomSearch** from **KerasTuner**
- Core Code:

```
# Define the hyperparameter search space
tuner = RandomSearch(lstm_model, objective='val_loss',
    max_trials=10, executions_per_trial=3,
    directory='hyperparameter_tuning',
    project_name='yelp_reviews_lstm')
```

04

PERFORMANCE AFTER TUNING

Model	Parameter	Best parameter	MSE
Baseline	NA	NA	1.4436
LSTM	Embedding dim	80	0.5851
	Lstm units	96	
	Dropout rate	0.3	
	L2 rate	0.01	

Model	MSE before tuning
LSTM	0.6064

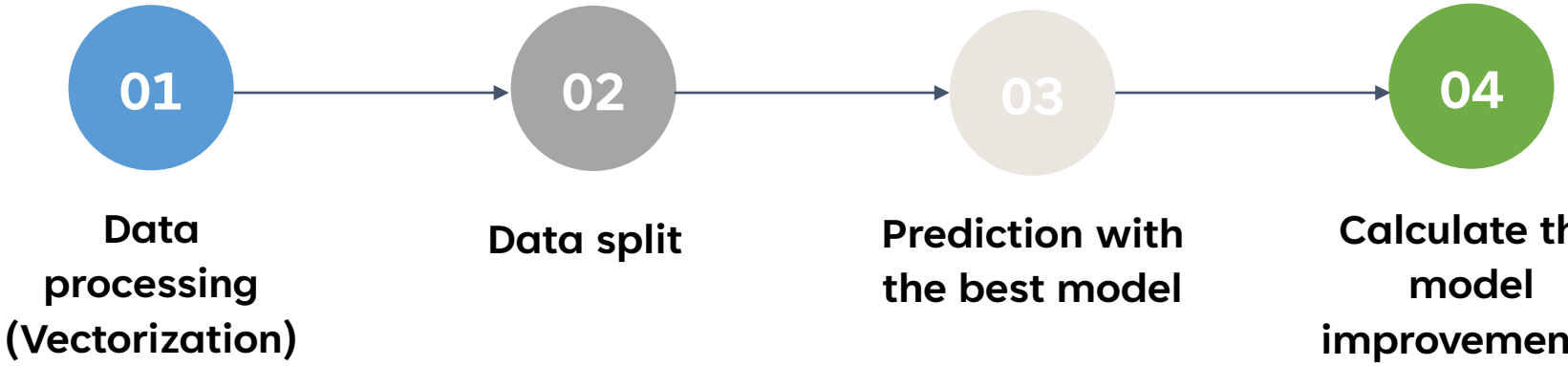
05

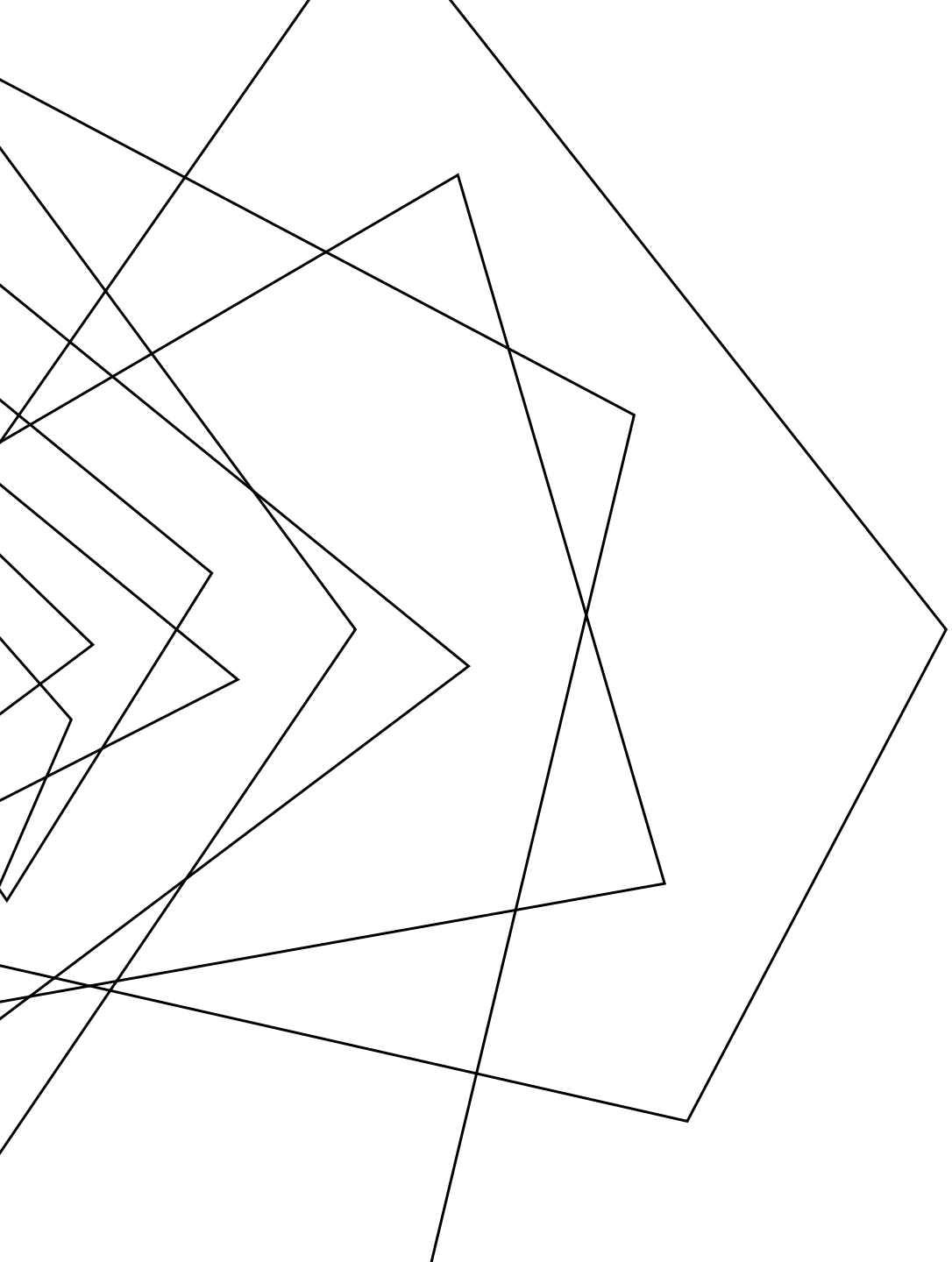
BEST MODEL

- The **LSTM model** shows a superior performance compared to other models in our project.
- **LSTM model** captures well the context and meaning of words in sequential data
- **CNN** and **GRU** models didn’t perform as well as the papers suggest in our project, but they still produced relatively good results than the baseline.

MODEL GENERALIZATION

PIPELINE


01
02
03
04
Data processing (Vectorization)
Data split
Prediction with the best model
Calculate the model improvement %



RESULT ANALYSIS

CALCULATION FORMULA

(Baseline_MSE – LSTM_MSE) / Baseline_MSE * 100%

RESULT COMPARISON

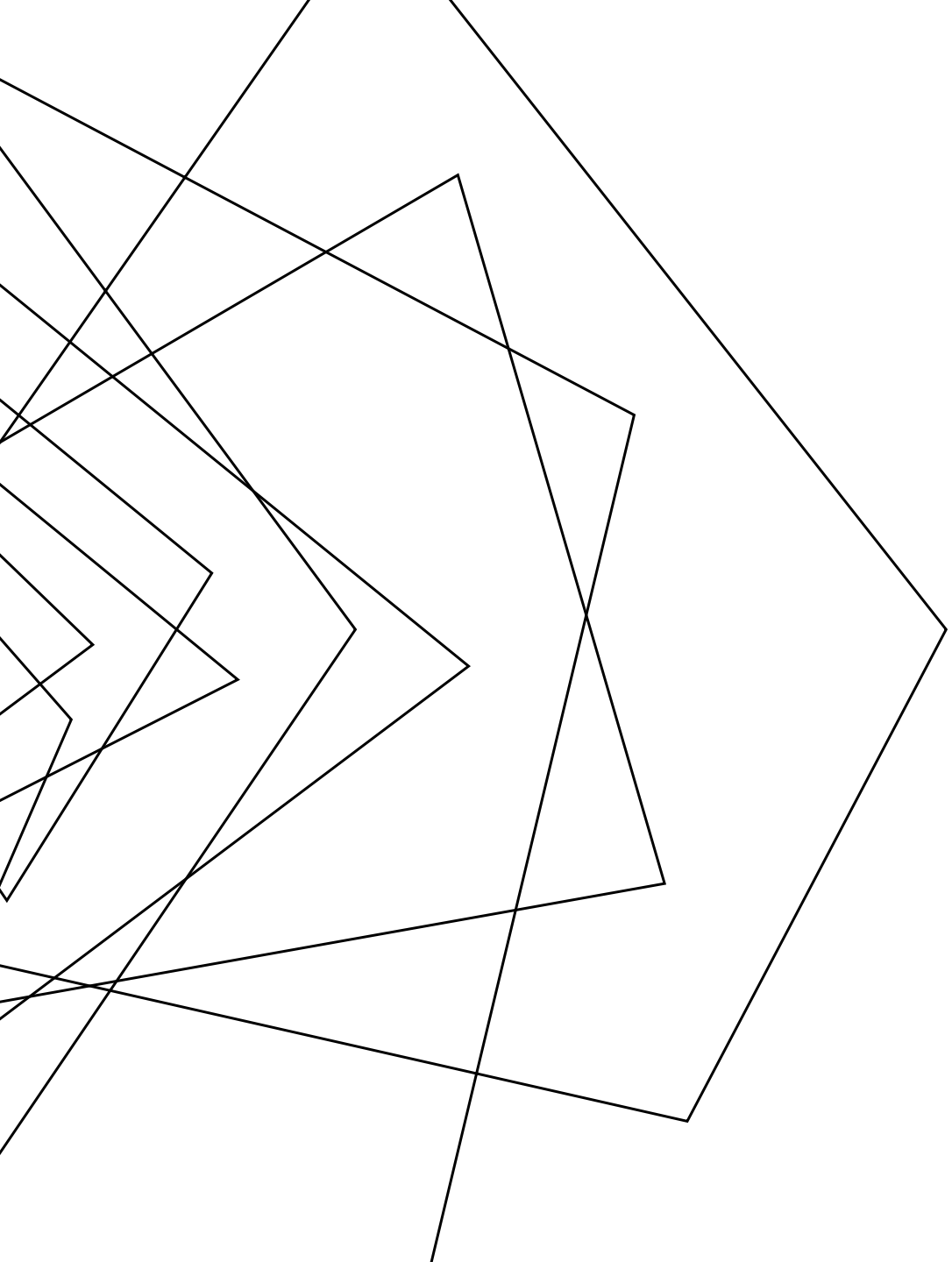
	Baseline	LSTM	Improvement
Restaurant review	1.4334	0.5851	**59.18%**
Movie review	8.2951	4.0056	**51.71%**

CONCLUSION

FUTURE DIRECTION & IMPROVEMENT

- Continue hyperparameter tuning
- Explore different models
- Incorporate sentiment analysis into the rating prediction model by initially dividing the dataset into two separate sets based on positive and negative sentiment. Then, the rating prediction can be performed for both datasets (Qiu et al., 2018 & Ahmed & Ghabayen., 2020)

Author(s)	Objectives	Findings
Qiu et al., 2018	Predictive framework based on sentiment analysis for ratings prediction	Implement sentiment analysis at the aspects-level can improve prediction accuracy



REFERENCE

- Ahmed, B. H., & Ghabayen, A. S. (2020). Review rating prediction framework using Deep Learning. *Journal of Ambient Intelligence and Humanized Computing*, *13*(7), 3423–3432. https://doi.org/10.1007/s12652-020-01807-4

- Qiu, J., Liu, C., Li, Y., & Lin, Z. (2018). Leveraging sentiment analysis at the aspects level to predict ratings of reviews. *Information Sciences*, *451-452*, 295–309. https://doi.org/10.1016/j.ins.2018.04.009

- Sadiq, S., Umer, M., Ullah, S., Mirjalili, S., Rupapara, V., & Nappi, M. (2021). Discrepancy detection between actual user reviews and numeric ratings of Google App Store using Deep learning. *Expert Systems with Applications*, *181*, 115111. https://doi.org/10.1016/j.eswa.2021.115111

- *Understanding LSTM networks*. Understanding LSTM Networks -- colah's blog. (n.d.). Retrieved April 11, 2023, from https://colah.github.io/posts/2015-08-Understanding-LSTMs/?fbclid=IwAR3qLdQD3b1mP4jh4SNQEAE58u-pxTstEqXyjg5w-5TbXK8zWTMu1z5seXc

THANK YOU

Xiao LI

Landry KUBWIMANA

HEC MONTRÉAL

ÉTS Le génie pour l'industrie

ÉCOLE DE TECHNOLOGIE SUPÉRIEURE
Université du Québec

Automatic Fake News Detection

Event: Machine Learning – MATH80629A | MSc. Student: Faramarz Farhangian | April 14th, 2023 (Quebec, CA)

Presented as Final Project, Department of Decision Science, HEC

Agenda

1- Introduction

1.1- Motivations
1.2- Fake news and Related Concepts
1.3- Fake news features
1.4- Fake news perspectives
1.5- Research objectives

2- Comparative study

2.1- Research objectives
2.2- Datasets
2.3- Text Pre-processing
2.4- Text Representation
2.5- Classification Algorithms
2.6- Evaluation Metrics
2.7- Experimental setting

3- Results

3.1- Summary Results
3.2- Complexity

4- Conclusion and Discussion

5- References

6- Question time

Part 1:

Introduction

1. Introduction

1.1. Motivations

- While **fake news is not a new concept**, today's getting more important with the **widespread use of social media**.
- Social media characteristics: **Low cost, Easy access, Rapid circulation**
- These characteristics pave the way for **profiteers** to spread fake news with **political and economic motives.**
- Fake news are problematic and make a real-world consequences like U.S. Presidential election or Nuclear war!
- human ability to distinguish fake news from true news is **poor**

1. Introduction

1.2. Fake news and Related Concepts

Concept	Authenticity	Intention	News?
Deceptive news	Non-factual	Mislead	Yes
False news	Non-factual	Undefined	Yes
Satire news	Non-unified[2]	Entertain	Yes
Disinformation	Non-factual	Mislead	Undefined
Misinformation	Non-factual	Undefined	Undefined
Cherry-picking	Commonly factual	Mislead	Undefined
Clickbait	Undefined	Mislead	Undefined
Rumor	Undefined	Undefined	Undefined

The following concepts are different from fake news based on our definition:

- **Satire news** that has no intent to mislead
- **Rumors** that did not originate from news events
- **misinformation** that is created unintentionally
- **hoaxes** that are only motivated by fun

What Fake news is?

Definition 1.1 (Broad definition of fake news). Fake news is false news.

Definition 1.2 (Narrow definition of fake news) Fake news is a news article that is intentionally and verifiably false.

We **consider the second definition** as the main definition because:

1. It is more ***comprehensive***
2. ***can distinguish fake news from other concepts.***

1. Introduction

1.3. Fake news features

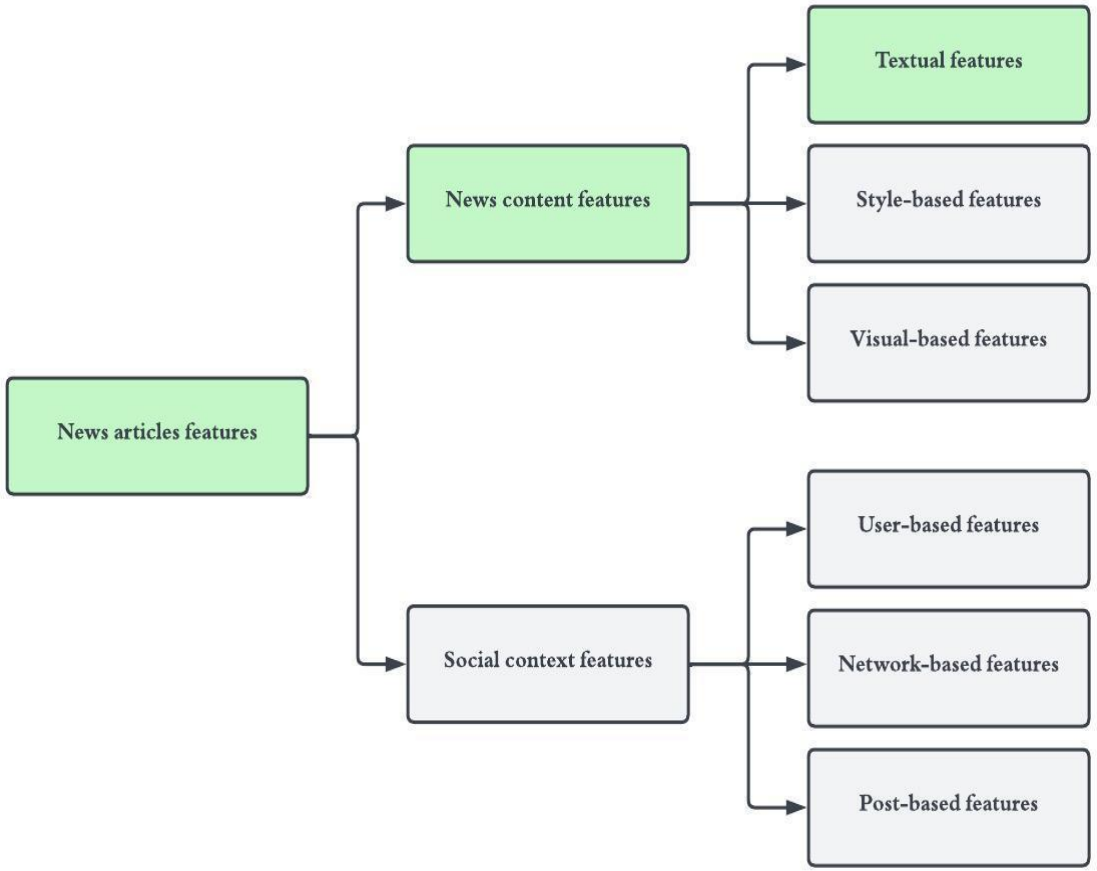
How news content features help?

- News content features describe the meta information related to a piece of news. For example ***headlines, body text, image or videos***.

How social context features help?

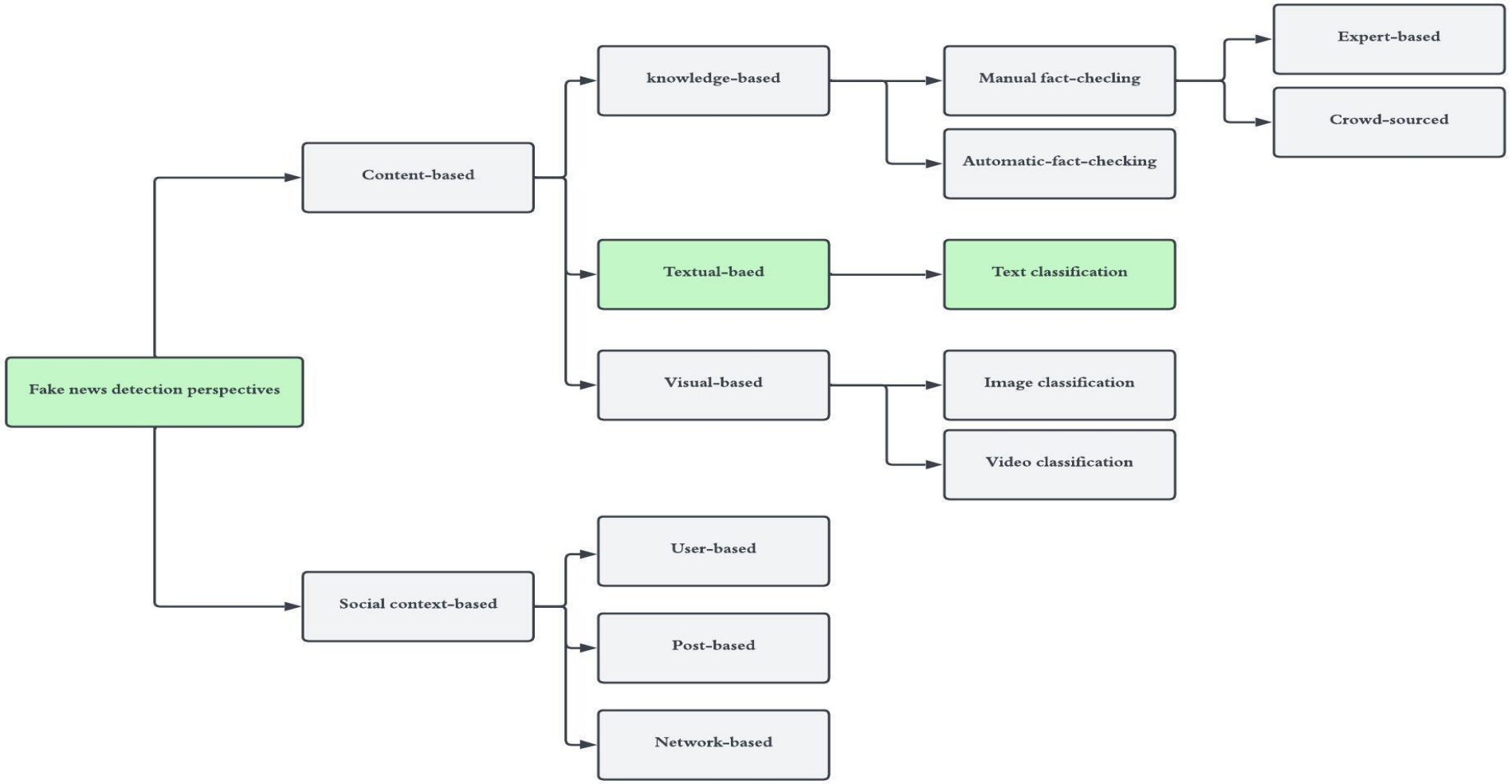
- Social context refers to the entire social environment in which the dissemination of the news operates, **including how the social data is distributed** and **how online users interact with each other**.

- **users, generated posts, other users express their opinions and emotions** through posts/comments, and these users came form different **types of networks** on social media.



1. Introduction

1.4. Fake news perspectives



Part 2:

Comparative Study

2. Comparative Study

2.1. Research objectives

Definition 1.3 *(Fake News Detection) Given the a news article* ***a****, the task of fake news detection is to predict whether the news article a is fake or not.*

$$f(a) = \begin{cases} 0, & \textit{If a is fake} \\ 1, & \textit{Otherwise} \end{cases}$$

- In this study we presents an empirical comparison of state-of-the-art text classifiers and representation techniques using **two benchmark datasets under the same experimental protocol**.
- The study considers fake news detection as a **text classification task** and follows five phases: **Preparing labeling datasets**, **Pre-processing dataset**, **Text representation phase**, **Training classification models**, **Evaluation**.

Research questions

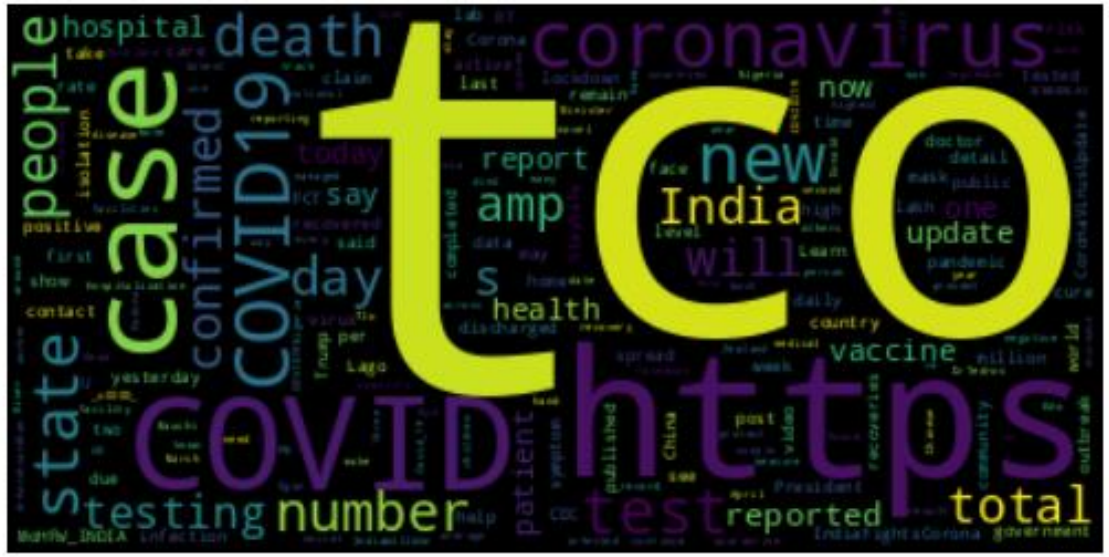
- ***What machine learning models are commonly used for this task?***
- ***What are the various feature extraction methods employed in this task?***
- ***Which models perform best in the same experimental setting?***

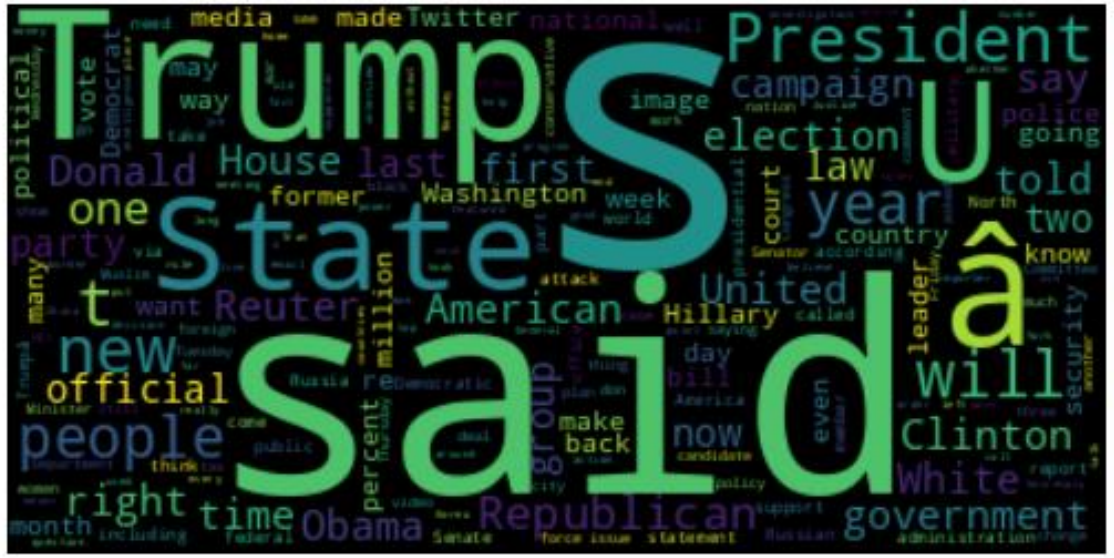
2. Comparative study

2.2. Datasets

This study uses two benchmark datasets from ***various domains to prevent research bias***

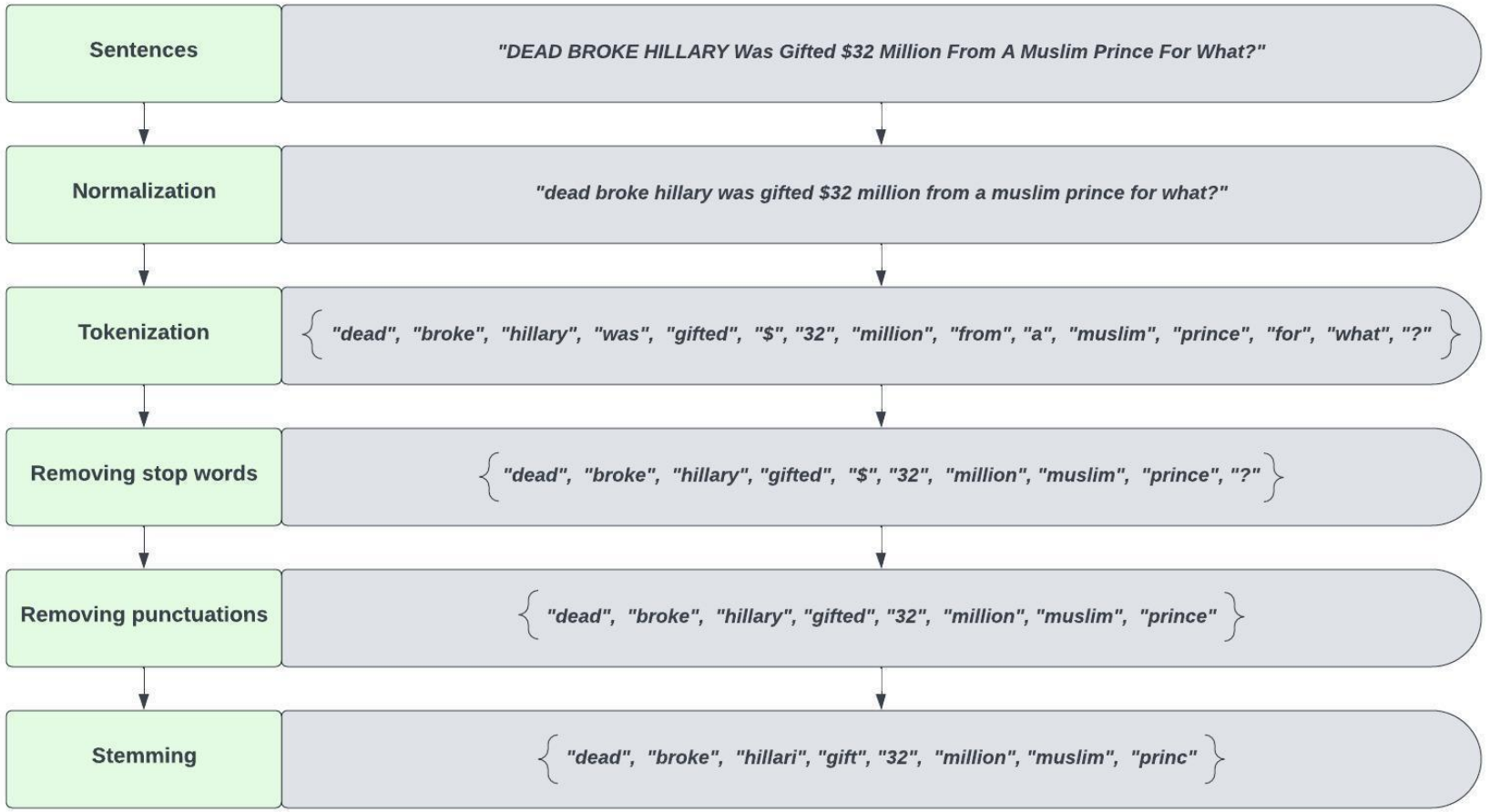
Dataset	Domain	Media	Fact-checking	Size	No. Class	Distribution
ISOT	**Politics & World news**	**Mainstream media**	**Fact-checking websites (expert)**	**44866**	**2**	**(23448,21417)**
COVID	**Covid-19 & Health**	**Twitter**	**Fact-checking websites (expert)**	**10700**	**2**	**(5100,5600)**





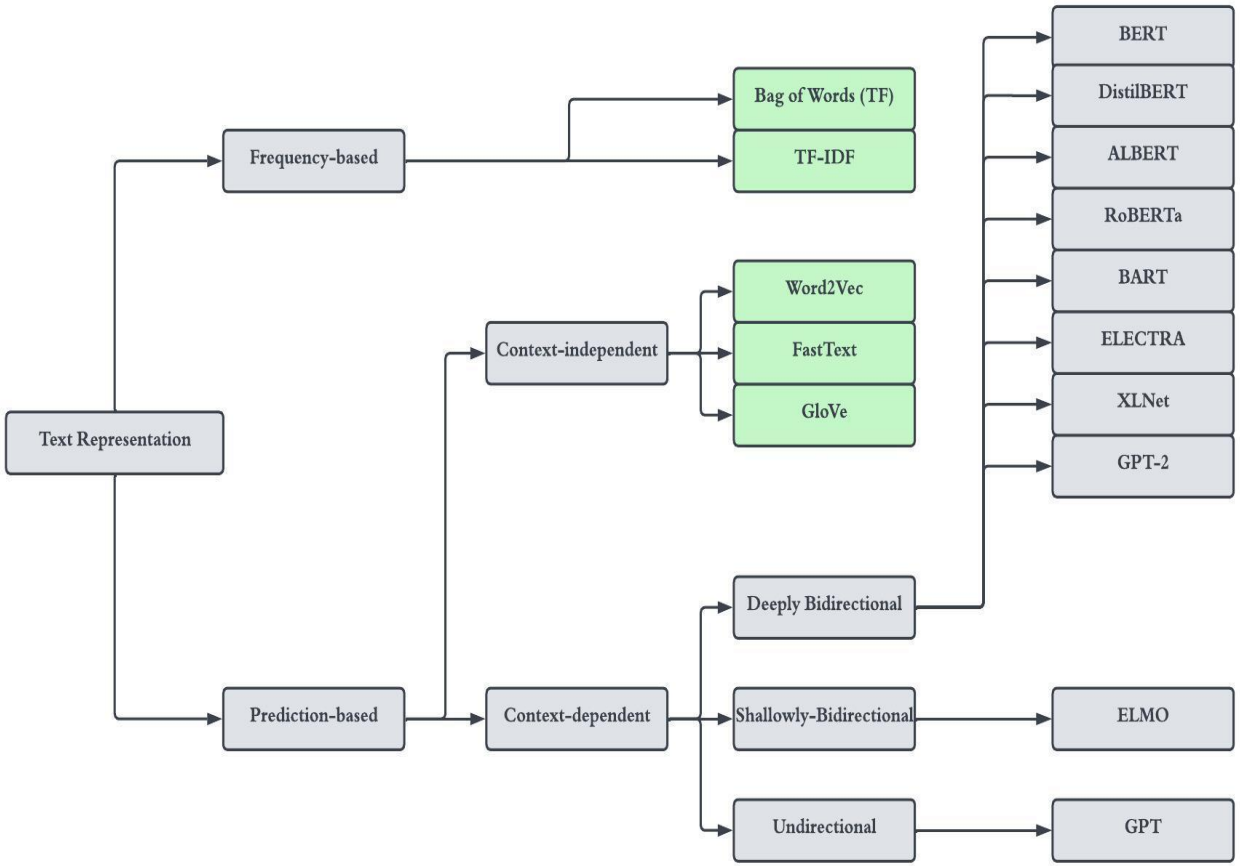
2. Comparative study

2.3. Text Pre-processing



2. Comparative study

2.4. Text Representation



Frequency-based

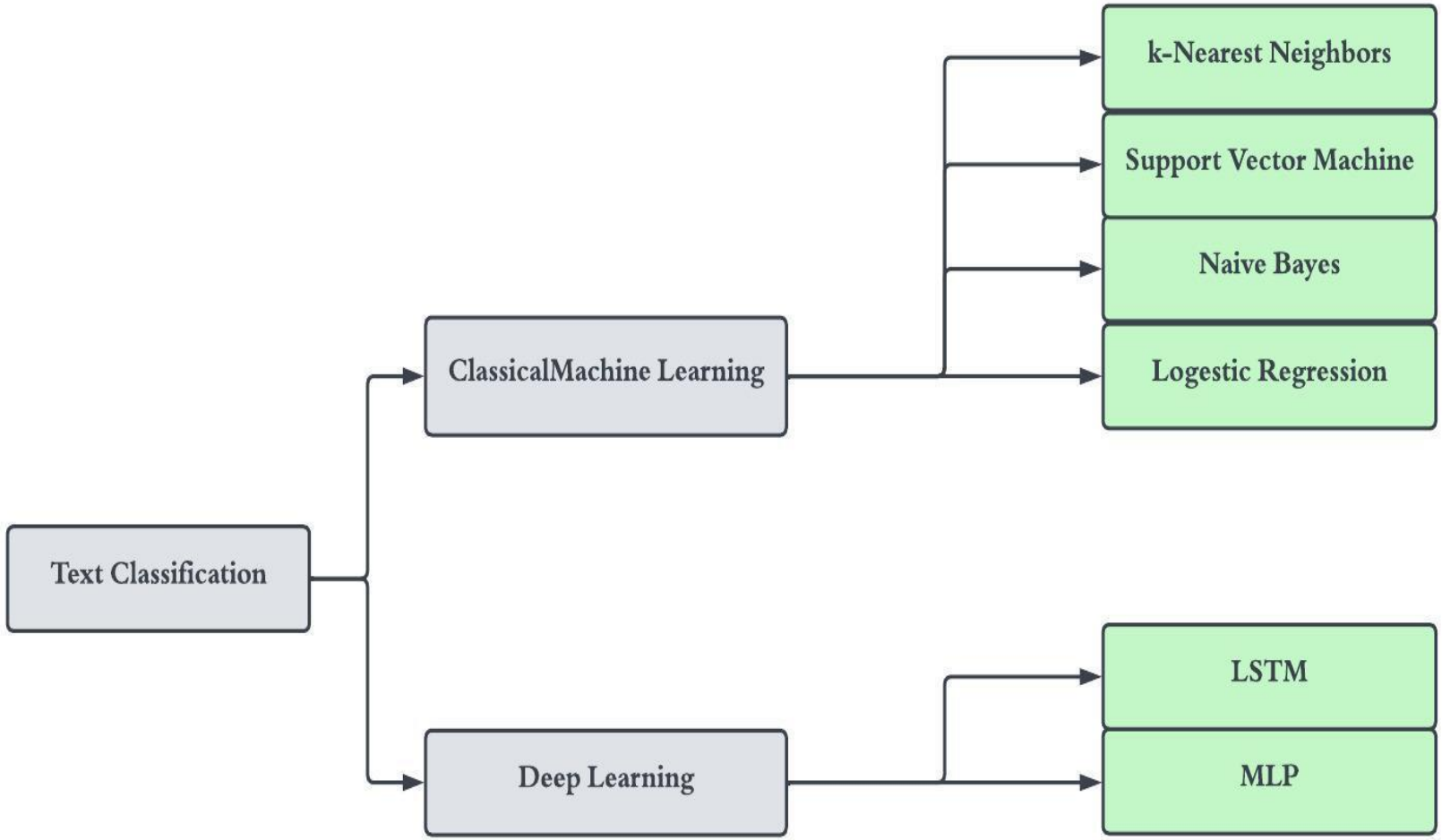
- Focusing on occurrence or co-occurrence of words in a document.
- Very simple and popular
- They do not represent useful information about the meaning and relations between words.
- Bag of Words Or Term Frequency just gives the information about the frequency of words in document and say noting about positions and structure of words also say noting about word importance!
- TF-IDF: scoring and weighting words in order to find the relevant and important words in a document.

Prediction-based

- Create numerical vectors from textual data which has known as word embedding
- Can extract semantic and syntactic features of words.

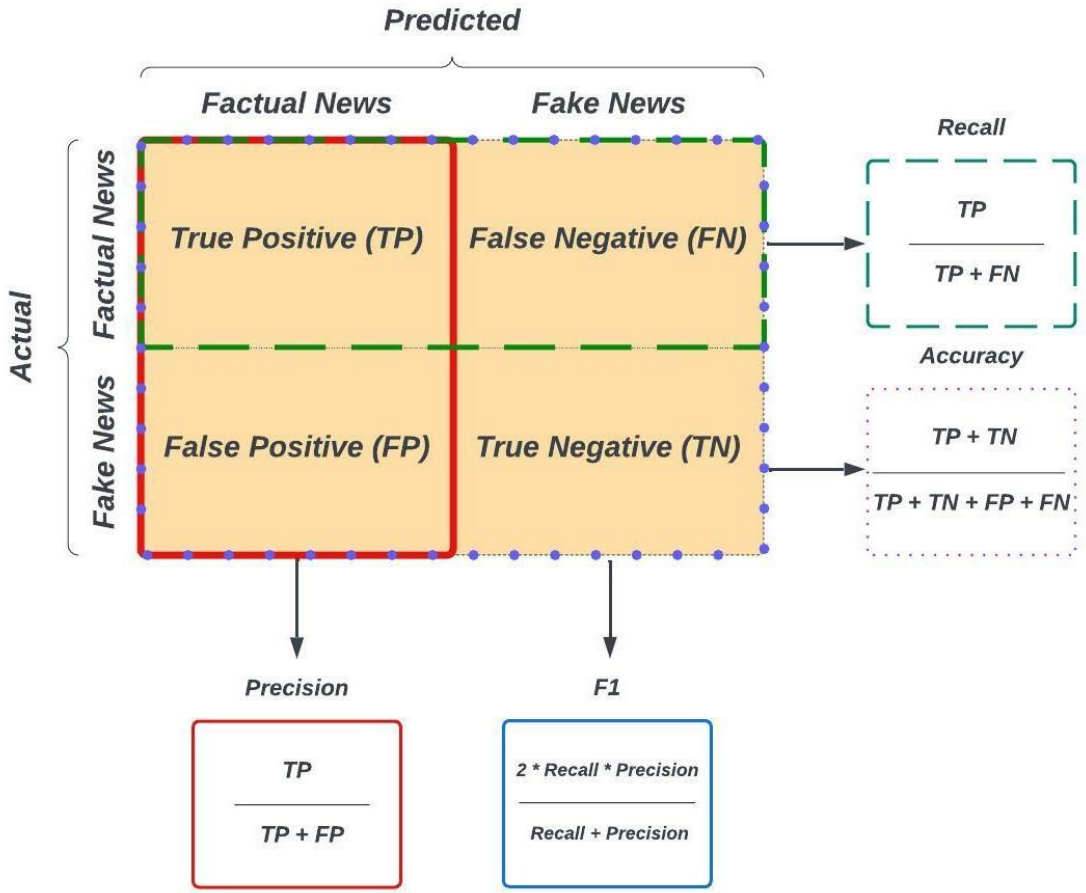
2. Comparative study

2.5. Classification Algorithms



2. Comparative study

2.6. Evaluation Metrics



- **True Positive (TP)** when a news article is predicted as fake news when it is labeled as fake news.
- **True Negative (TN)** when a news article is predicted as real news when it labeled as real news.
- **False Positive (FP)** when a news article predicted as fake news when it labeled as real news.
- **False Negative (FN)** when a news article predicted as real news when it labeled as fake new.

2. Comparative study

2.7. Experimental setting

Text Representation

- In all word embedding methods, we considered the **average of word feature vectors that occurred in each document** in order to represent the feature vector of each document in datasets.
- **Word2Vec** trained over a google news corpus with 300 features retrieved from each sample.
- **GloVe**, trained over a wikigigaword corpus with 300-dimensional feature vectors.
- **Fasttext** trained over the Wikipedia corpus with 300 features per sample.

Classification

- we conducted hyper-parameter tuning using **grid search** techniques to find the optimal hyper-parameter values.
- We used **5-fold cross-validation**.
- We consider **baseline** based on **most frequent strategy**.
- The experiments were conducted on **Colab Pro.**

Method	Hyperparameters
SVM	Kernel:['rbf', 'linear', 'poly', 'sigmoid'] Gamma: [1, 0.1, 0.01, 0.001, 0.0001] C: [0.1, 1, 10, 100, 1000]
LR	solver: ['liblinear'] penalty: ['none', 'l1', 'l2', 'elasticnet'] C: [0.01, 0.1, 1, 10, 100]
KNN	n_neighbors: [1 - 20]
MLP	hidden layer sizes: [(32,), (64,), (128,)] activation: ['relu', 'tanh', 'logistic'] solver: ['adam', 'sgd'] batch size: [16, 32, 64] learning rate: [0.001]
LSTM	Activation function: [sigmoid, ReLU] Batch size: [64, 128, 512] Number of epochs: [5,20,100] Optimizer: [Adam] Learning rate: 0.001 Hidden size: 128 Dropout: 0.2

Part 3:

Results

3. Results

3. Results

In this section, we want to answer the following questions:

(RQ1) What machine learning models are commonly used for this task?

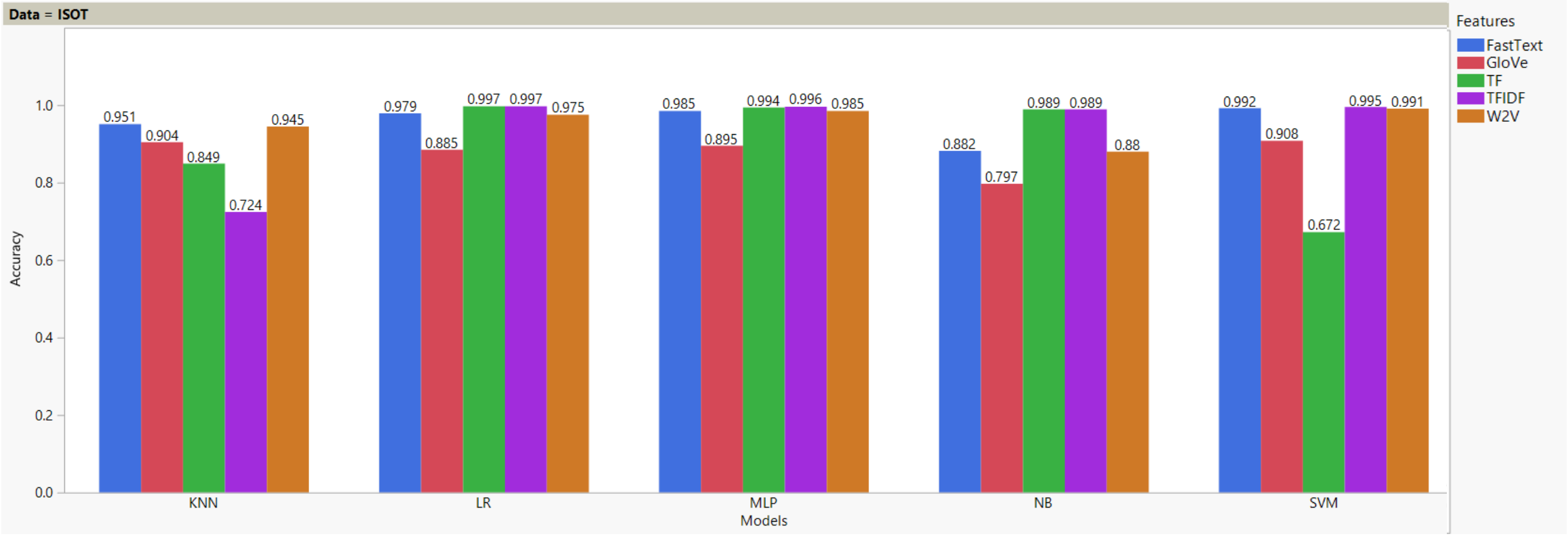
(RQ2) What are the various feature extraction methods employed in this task?

(RQ3) Which models perform best in the same experimental setting?

- We already answer to the **RQ1**, and **RQ2** in **Text representation**, and **Classification algorithms** sections.
- Models has the same level of performance in terms of accuracy, precision, recall, and F1-score, which indicates that it is well balanced in predicting both positive and negative classes. In other words, the model's accuracy is high and it can predict both positive and negative classes with equal efficiency.
- Our baseline performance is 50% because we have balanced data in both dataset.

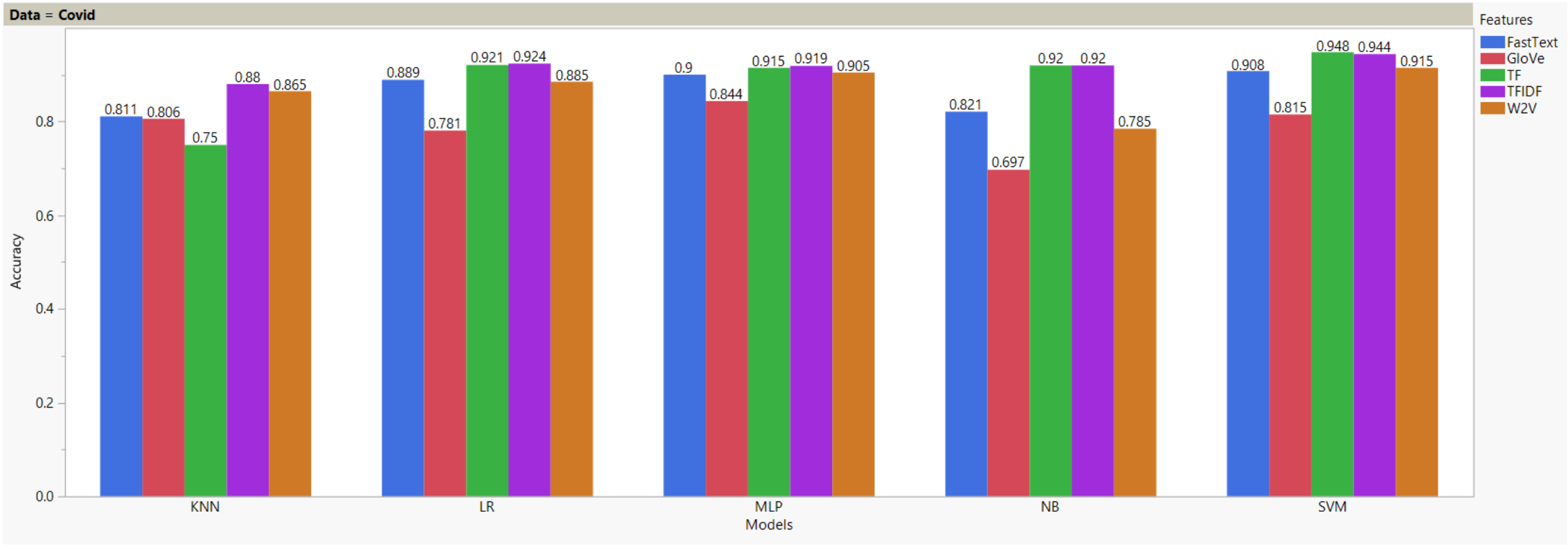
3. Results

3.1. Summary results



3. Results

3.1. Summary results



3. Results

3.2. Complexity

ISOT Dataset										
Models	LR		KNN		NB		SVM		MLP	
Features	Training time	Prediction time	Training time	Prediction time	Training time	Prediction time	Training time	Prediction time	Training time	Prediction time
TF	129.73	0.011	696.17	30.22	1.167	0.074	25061.06	537.18	9026.57	0.192
TFIDF	17.67	0.004	25985.43	3540.55	3.385	0.239	6234.75	185.33	13562.86	0.156
W2V	150.37	0.018	47.2	5.896	2.033	0.098	1736.89	7.065	793.72	0.069
GloVe	170.58	0.003	9.16	1.83	0.464	0.031	899.073	6.65	118.323	0.0225
FastText	1629.17	0.022	37.386	4.169	3.262	0.121	2658.86	5.545	1112.159	0.093

COVID Dataset										
Models	LR		KNN		NB		SVM		MLP	
Features	Training time	Prediction time	Training time	Prediction time	Training time	Prediction time	Training time	Prediction time	Training time	Prediction time
TF	30.79	0.001	6.613	0.774	0.135	0.0046	149.443	1.604	185.243	0.005
TFIDF	0.5	0.0007	27.409	4.178	0.142	0.003	137.517	2.023	206.9	0.004
W2V	109.84	0.029	3.026	1.353	0.55	0.049	649.34	2.232	181.75	0.031
GloVe	4.743	0.001	0.796	0.326	0.125	0.003	72.688	0.6157	68.44	0.004
FastText	125.865	0.002	3.149	0.95	0.8346	0.115	220.23	1.782	390.145	0.0203

Part 4:

Conclusion and Discussion

4. Conclusion and Discussion

- **All of the models outperform the baseline in each metrics.**
- **Frequency-based methods are the best text representation method in this task especially by using classical model.**
- **In ISOT dataset, SVM with frequency-based methods outperformed the others.**
- **In COVID dataset LR with frequency-based methods outperformed the others.**
- **From the word embedding methods, FastText outperformed the others.**
- **Despite the frequency-based methods outperformed but because of the sparse matrix they have more complexity.**
- **In classical machine learning models, KNN, SVM are the most complexity, and LR, and NB is the lowest one.**
- **MLP have more training time but low prediction cost, and FastText, and Word2Vec are more complex than GloVe.**
- **One of the reason that frequency-based methods outperform the word embedding methods is existence of out of vocabulary problem in word embedding methods.**

4. Conclusion and Discussion

- **Multi-modal fake news detection**
- **Fake news detection using Ensemble methods**
- **Fake news detection using weekly supervised methods**
- **Fake news explanation**
- **Fake news detection for different languages like French or Persian**

Part 5:

References

5. References

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“Thank You”

for your attention

Question Time!

MATH60629A
MACHINE LEARNING I: LARGE SCALE DATA ANALYSIS AND DECISION MAKING

FEDERATED LEARNING

SIDDHANT ARORA PHILIPPE BELIVEAU KARAN JOSEPH

PROBLEM STATEMENT

The central research question is to compare the performance of centralized Machine Learning model, Federated Learning model, and Federated Learning with Differential Privacy (DP)

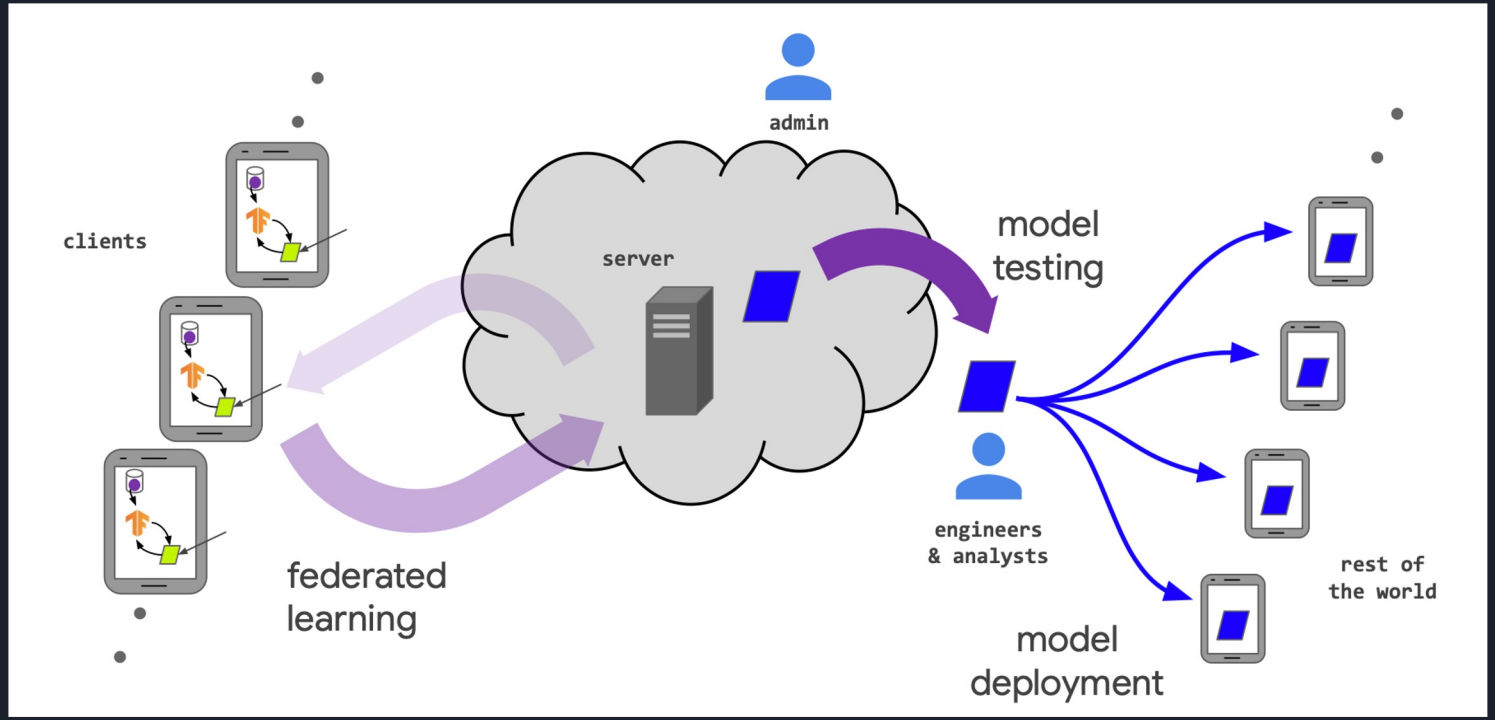
Hypotheses

- Differential privacy could affect the model's performance
- Centralized Machine Learning and Federated Learning models could produce similar accuracy, but federated learning may require more training cycles

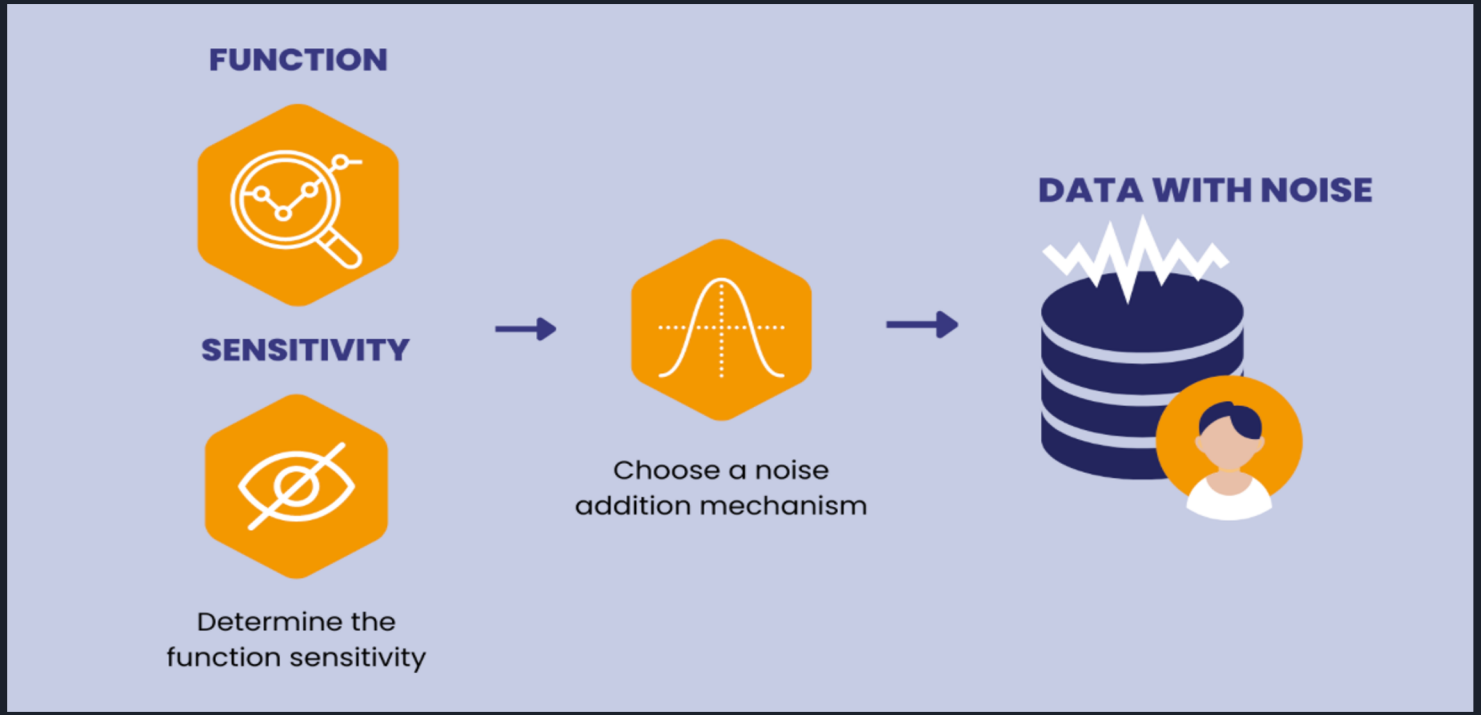
RELATED WORK

- The hospitals' updates are susceptible to information leakage about the patients' data due to model over-fitting to training data (Carlini et al. 2019).
- Differential privacy (DP) (Dwork and Roth 2014) limits an adversary's certainty in inferring a patient's presence in the training dataset.
- Before optimizing the DNN, Gaussian random noise is added to the computed gradients on the patients' data to achieve differentially-private stochastic gradient descent (DPSGD) (Abadi et al. 2016).
- Differential privacy in combination with other techniques such as secure aggregation, homomorphic encryption can establish a better privacy-utility trade-off (Malekzadeh, 2019)

WHAT IS FEDERATED LEARNING?



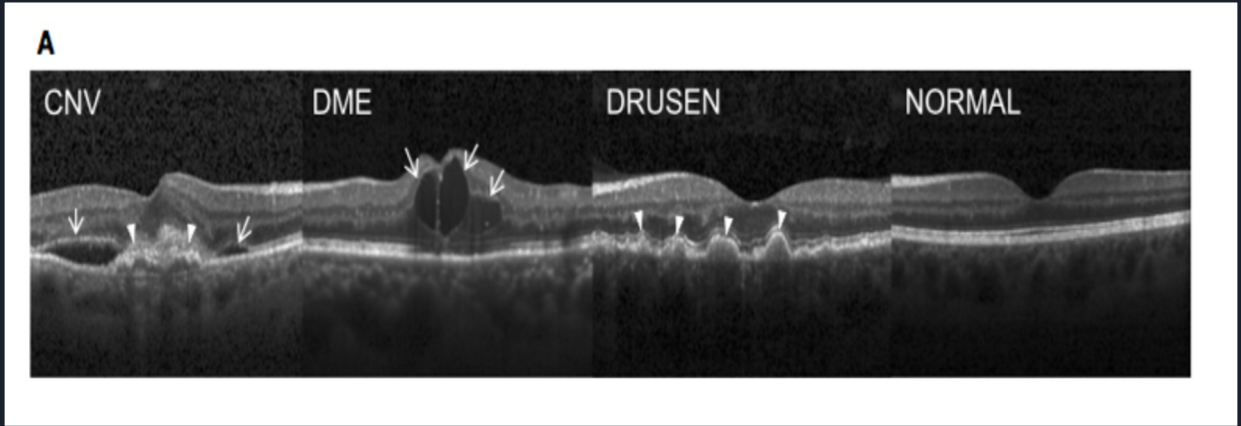
WHAT IS DIFFERENTIAL PRIVACY?



https://www.statice.ai/post/what-is-differential-privacy-definition-mechanisms-examples

ABOUT THE DATASET

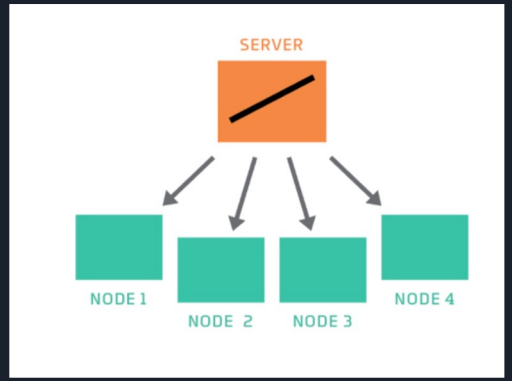
Retinal optical coherence tomography (OCT) is an imaging technique used to capture high-resolution cross sections of the retinas of living patients.

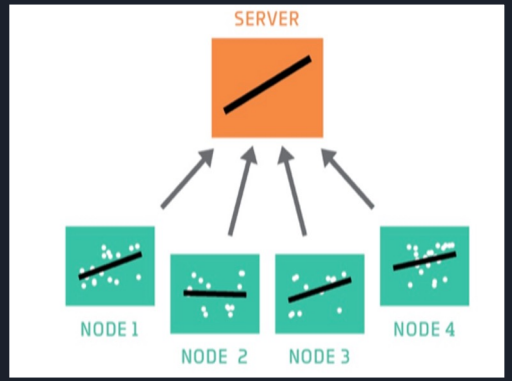


https://www.kaggle.com/datasets/paultimothymooney/kermany2018

ALGORITHM: FEDERATED AVERAGING

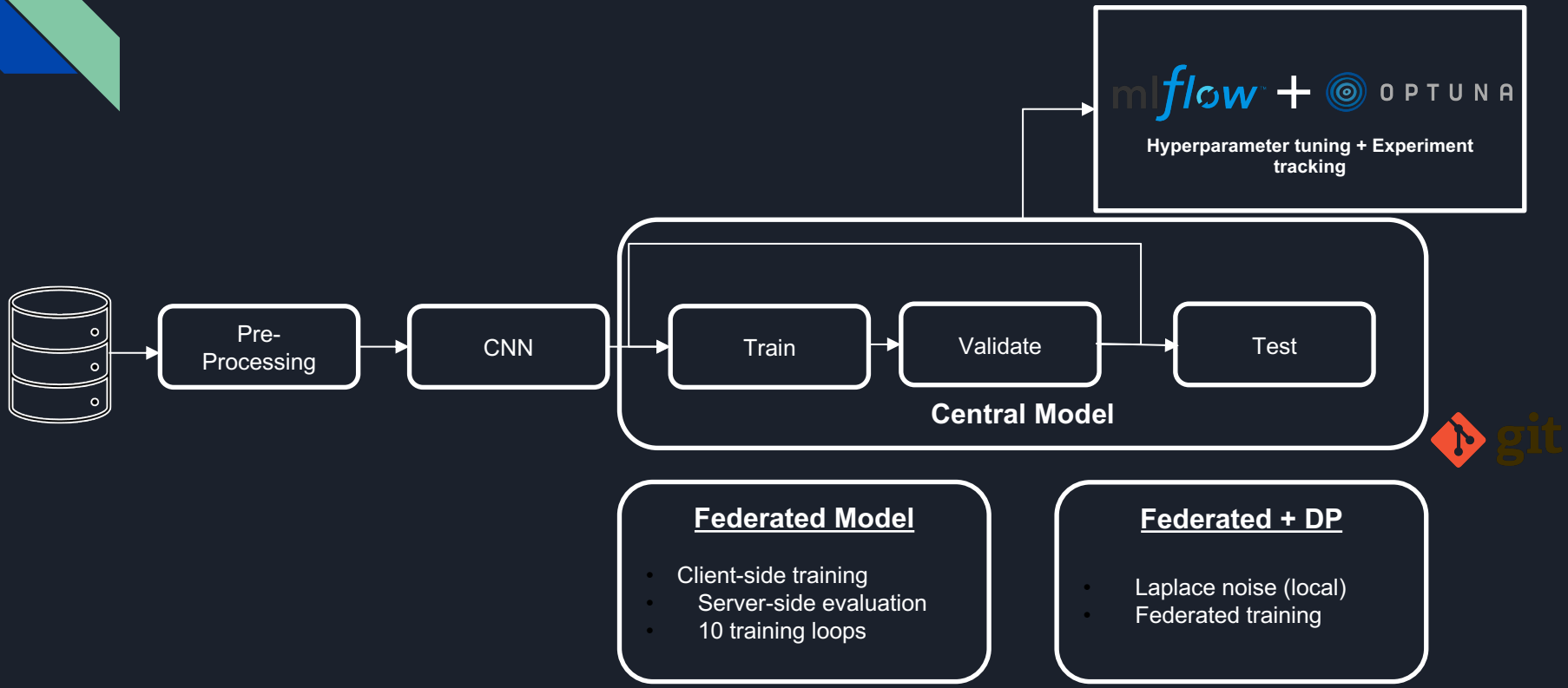
1) The server has on it a machine learning untrained model.
2) Server sends a copy of the model to the nodes/clients.
3) So the nodes acquire or load some training data. Each node has different training data.
4) Then each node incrementally trains the model.
5) Now each node sends a copy of their model back to the server.
6) The server now has four models and it takes the average. And that average model encapsulates information that was present on every node.
7) That was one round of federated learning.
8) And then we repeat, i.e. the newly improved model is sent back to the nodes, and they train some more, and send further improved models back.





https://mike.place/talks/fl/

WORKFLOW


mlflow + OPTUNA
Hyperparameter tuning + Experiment tracking
Pre-Processing
CNN
Train
Validate
Test
Central Model
git
Federated Model
Client-side training
Server-side evaluation
10 training loops
Federated + DP
Laplace noise (local)
Federated training

MODEL STRUCTURE

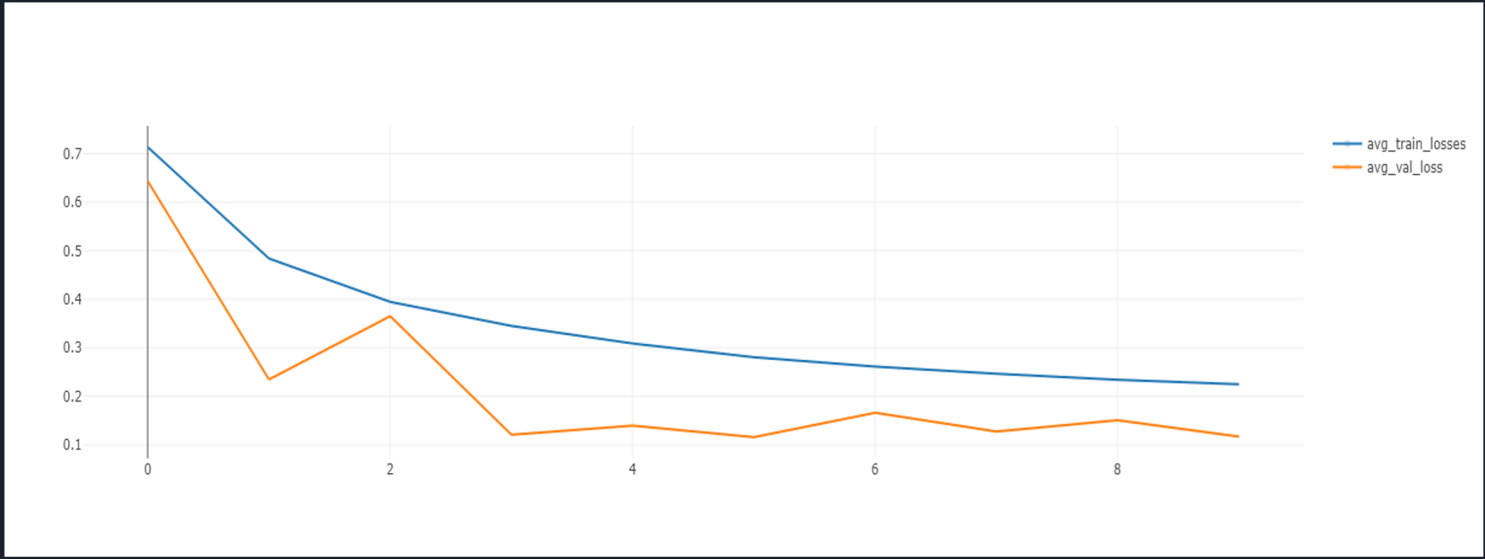
- **Hyperparameter Tuning (Optuna + Mlflow)**
  - Learning Rate = 0.03134
  - Momentum = 0.9
  - Dropout = 0.2
  - Optimizer = Stochastic Gradient Descent (SGD)

```
Retina_Model(
  (conv1): Conv2d(3, 32, kernel_size=(3, 3), stride=(1, 1))
  (conv2): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1))
  (dropout1): Dropout2d(p=0.2, inplace=False)
  (dropout2): Dropout2d(p=0.2, inplace=False)
  (fc1): Linear(in_features=12544, out_features=128, bias=True)
  (fc2): Linear(in_features=128, out_features=4, bias=True)
  (pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1
)
```

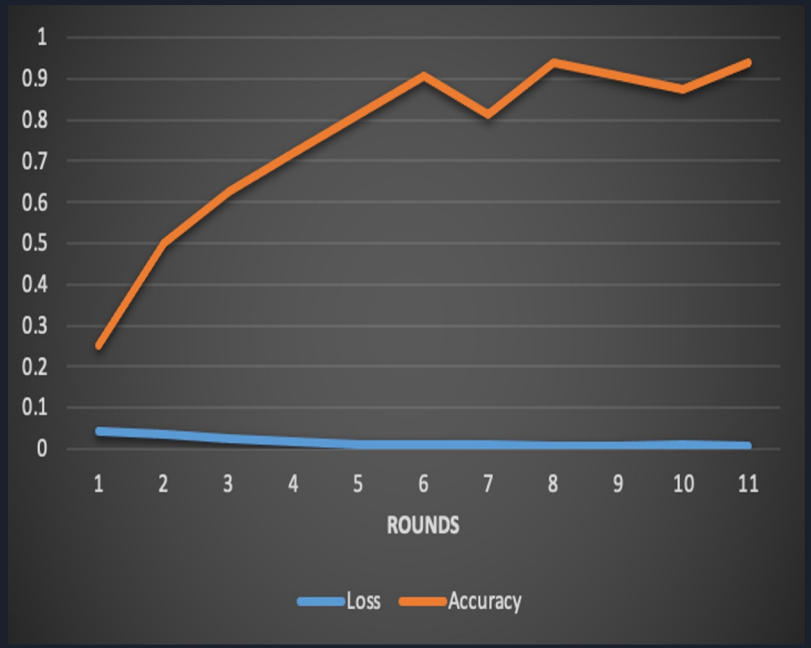
- Loss: Cross Entropy
- Num_Clients: 4 (Number of clients in Federated Learning model)
- Regularization: Dropout and Early Stopping

CENTRALIZED MODEL

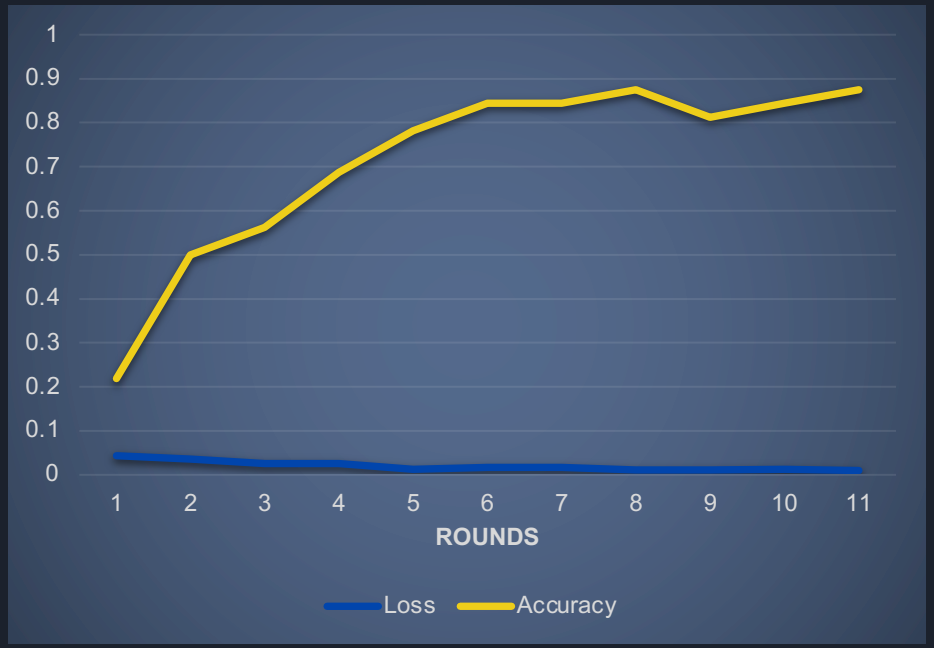
Training and Validation losses



LOSS & ACCURACY ACROSS FEDERATED LEARNING ROUNDS



FEDERATED



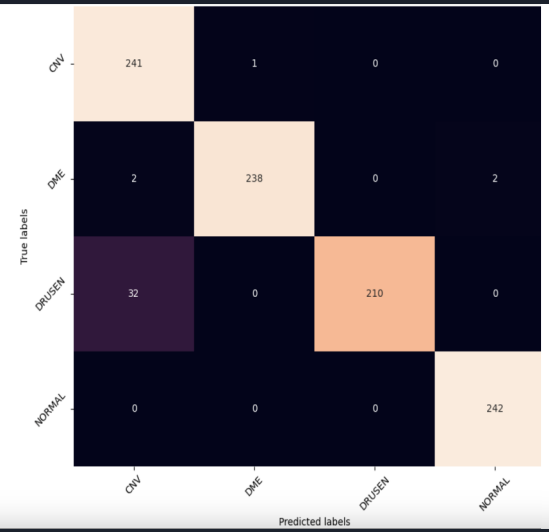
FEDERATED + DIFFERENTIAL PRIVACY

MODEL RESULTS ON THE TEST SET

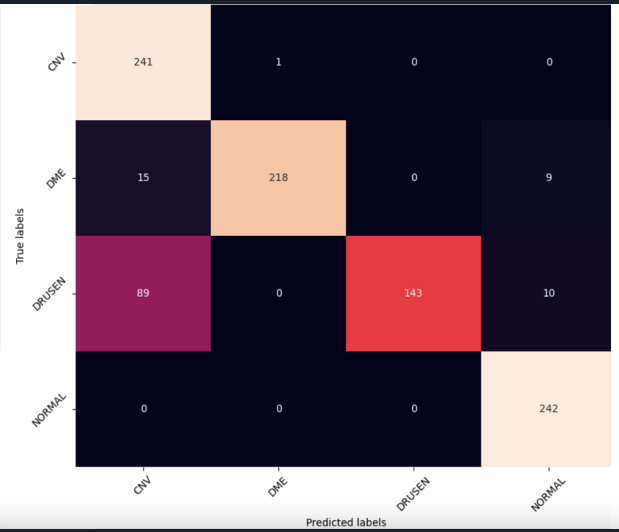
	Centralized		Federated		Federated + Differential Privacy	
	Precision	**Recall**	**Precision**	**Recall**	**Precision**	**Recall**
CNV	0.876	0.996	0.699	0.996	0.824	0.988
DME	0.996	0.983	0.995	0.901	0.982	0.897
DRUSEN	1.000	0.868	1.000	0.591	1.000	0.645
NORMAL	0.992	1.000	0.927	1.000	0.804	1.000
Accuracy	0.962	0.962	0.872	0.872	0.882	0.882
Macro Average	0.966	0.962	0.905	0.872	0.903	0.882
Weighted Average	0.966	0.962	0.905	0.872	0.903	0.882

CONFUSION MATRIX

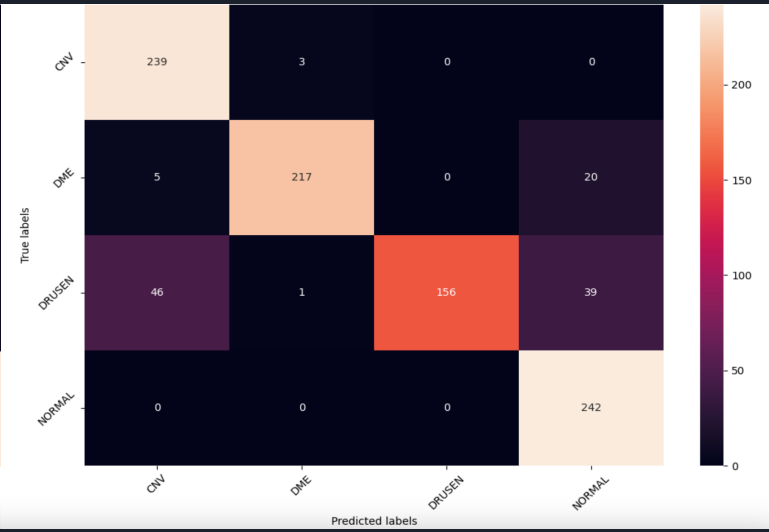
CENTRALIZED



FEDERATED



FEDERATED + DIFFERENTIAL PRIVACY



CONCLUSION

- With differential privacy being introduced, there exists privacy-accuracy tradeoff. As we guarantee more privacy, accuracy goes down and vice-versa. This can be seen from the validation set results:
    - Centralized Machine Learning model: 94%
    - Federated Learning model: 93.5%
    - Federated Learning with Differential Privacy model: 87.5%
- By changing sensitivity and epsilon, the amount of noise to add to the dataset can be adjusted to achieve desired levels of privacy and accuracy.
- Deployment: The Federated learning model can be used to detect eye diseases; training the model on datasets from multiple hospitals can be more accurate compared to a single hospital; integration into mobile apps; cloud-based API integrated with Electronic Health Record (EHR) systems etc.

FUTURE DIRECTION

- Problems with Linear Convergence Rates
  - Low bandwidth channels
  - Limited battery power
  - Client drift
  - Heterogeneity of the system
- Fed-LIN algorithm to facilitate convergence (Mitra, 2021)
- Differential Privacy Stochastic Gradient Descent (DP-SGD)
- Hyperparameter tuning in Federated Learning

Presidental Speeches

TEXT CLASSIFICATION

MARILIE BRETON, MARIA BIANCA GIOADA, SAMIRA YAZDANPOUR

Task

Supervised learning

Create a model that can classify the political parties in **Democratic** or **Republican** based on an American politician’s speech

Overview

1. Data exploration
2. Statistical analysis
3. Text preprocessing
4. Model training
5. Prediction & Results

Dataset

Size : 988 documents

Number of variables: 7

- only using 2 : Party and Summary

Label : binary variable

- democratic and republican

Number of transcripts per party (after cleaning)

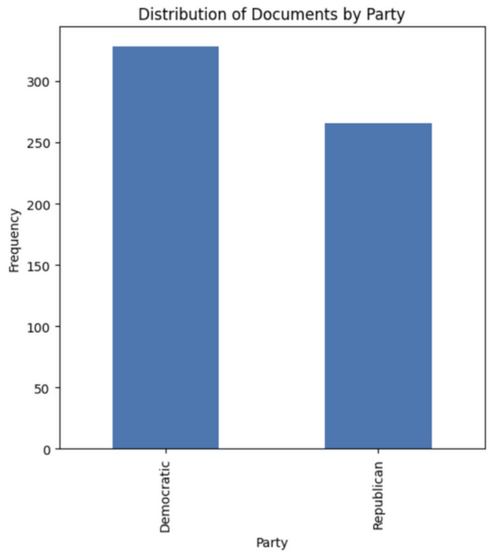
Democratic : 328

Republican : 266

presidential_speeches.csv (22.73 MB)

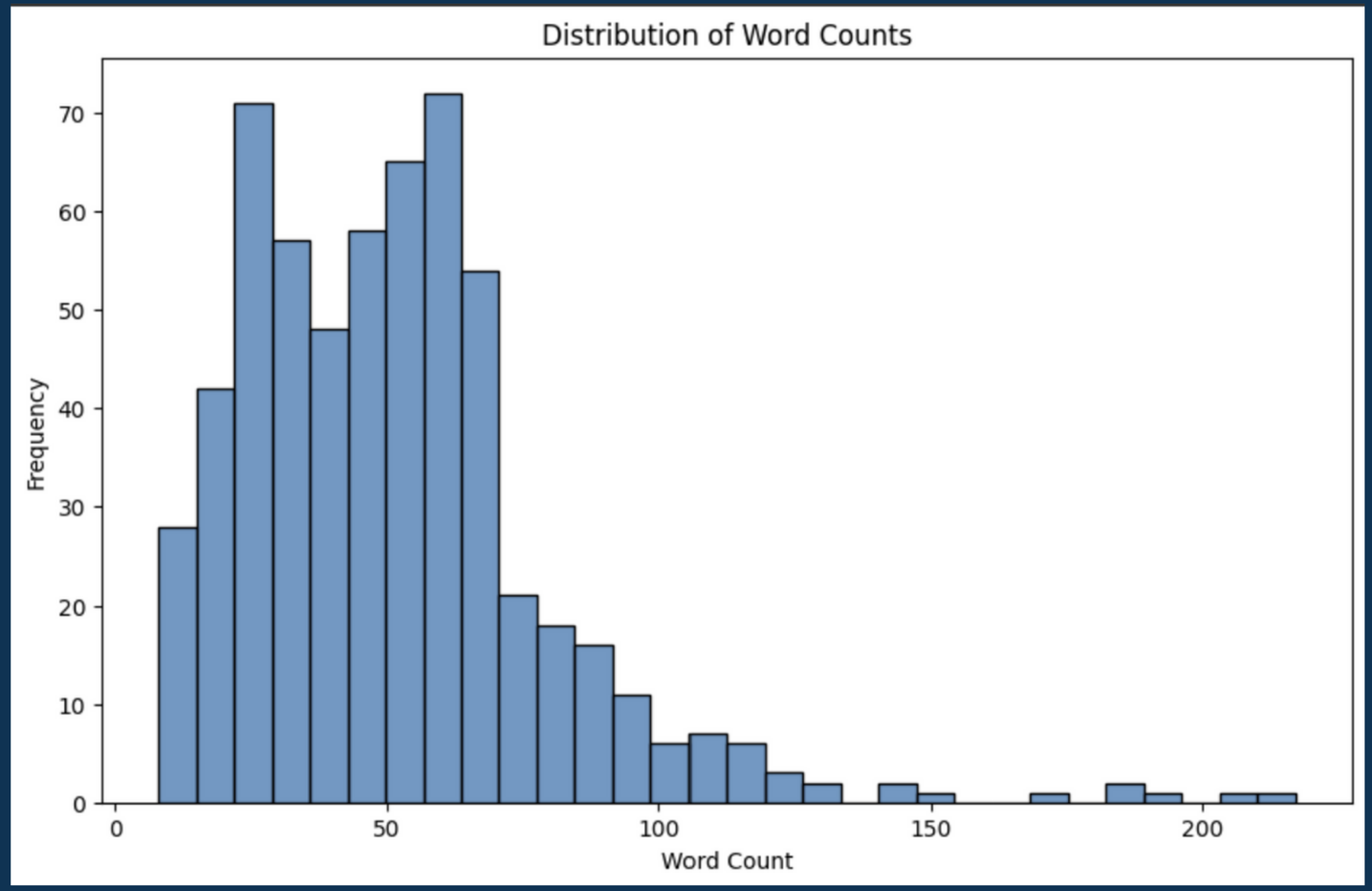
Detail | Compact | Column | 7 of 7 columns

Date	President	Party	Speech Title	Summary	Transcript	URL
1789-04-30	George Washington	Unaffiliated	First Inaugural Address	Washington calls on Congress to avoid local and party partisanship and encourages the adoption of a ...	Fellow Citizens of the Senate and the House of Representatives : Among the vicissitudes incident to l...	https://millercenter.org/the-presidency/presidential-speeches/april-30-1789-first-inaugural-address
1789-10-03	George Washington	Unaffiliated	Thanksgiving Proclamation	At the request of Congress, Washington establishes November 26th as a national holiday of thanks to ...	Whereas it is the duty of all Nations to acknowledge the providence of Almighty God, to obey his wil...	https://millercenter.org/the-presidency/presidential-speeches/october-3-1789-thanksgiving-proclamati...

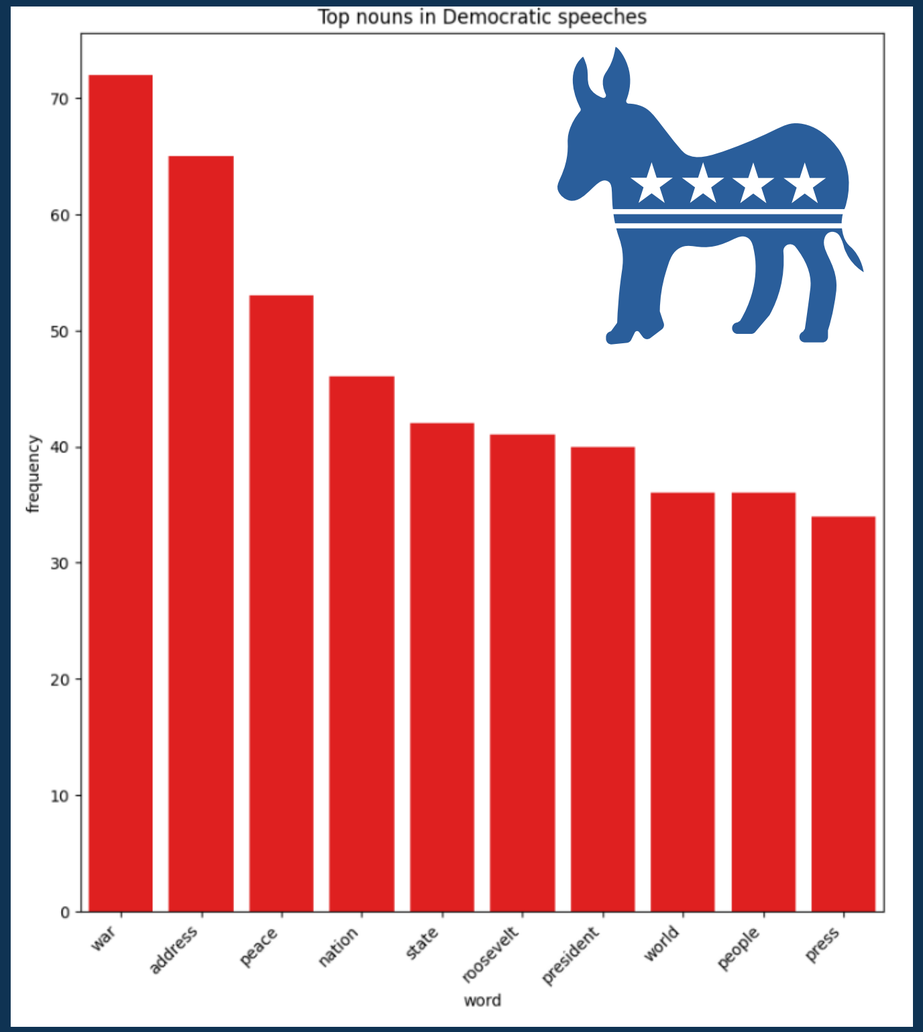


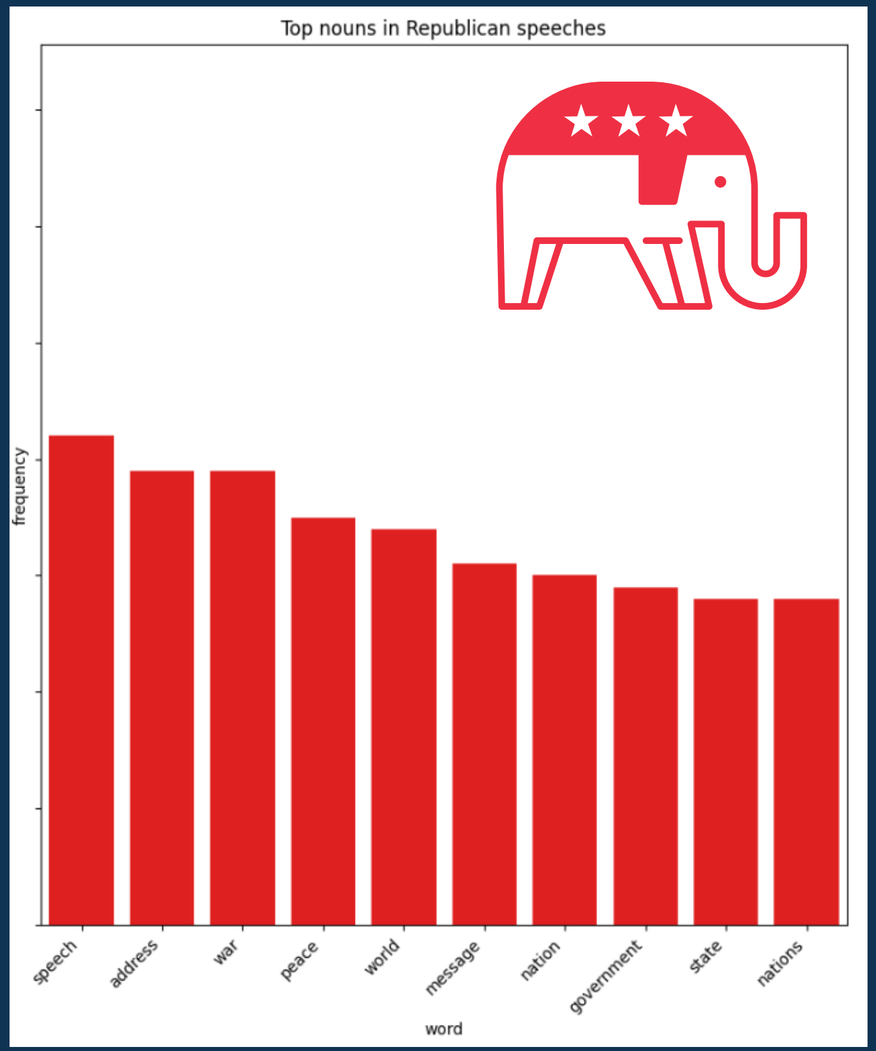
Statistical analysis

```
min         8.000000
25%        30.000000
50%        49.000000
75%        64.000000
max       217.000000
Name: word_count, dtype: float64

Distribution of documents by party:
Democratic    328
Republican    266
Name: Party, dtype: int64

Average word count by party:
Party
Democratic    51.381098
Republican    50.646617
Name: word_count, dtype: float64
```

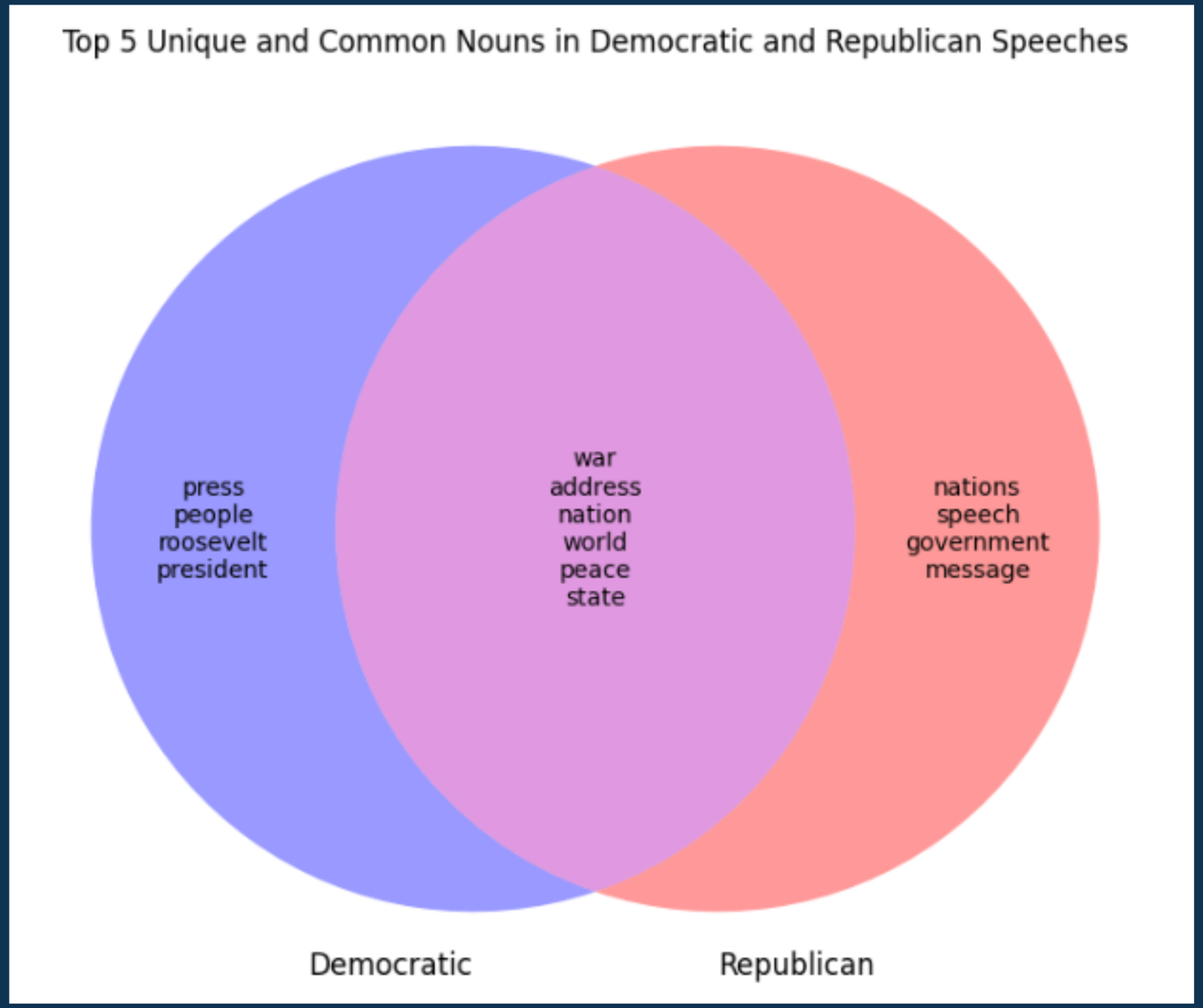


Frequency of words per party





Venn diagram



Approach

1. Text processing using TFIDF
2. Test simple & complex models
3. Compare results with baseline models

Text Processing

1. Remove missing values & special characters
2. Split data in train, test & validation
3. Create a vocabulary & TFIDF matrix
    - matrix dimension : 594 x 4643

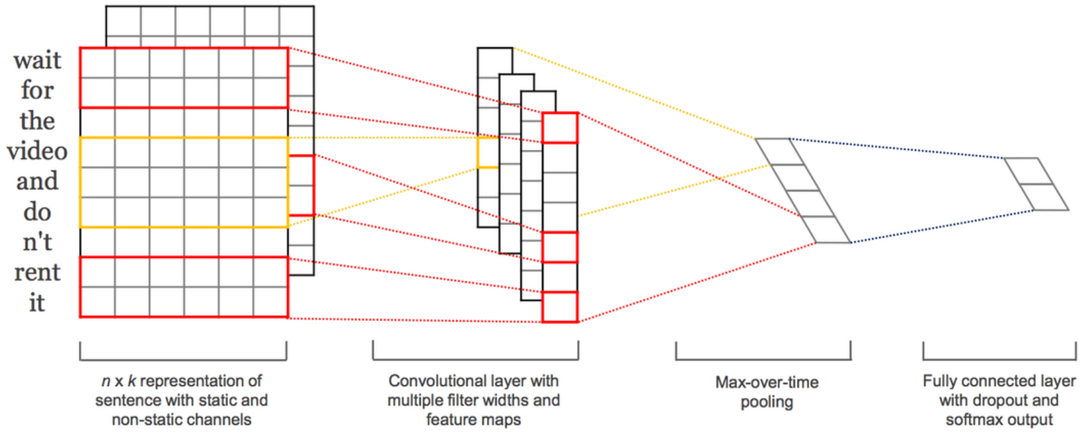
Models trained

Naive Bayes

SVM

Logistic Regression

CNN (4 layers)
convolutional, activation(ReLU), max pooling & fully connected



Pre-trained BERT for Sentiment Analysis

Evaluation setup

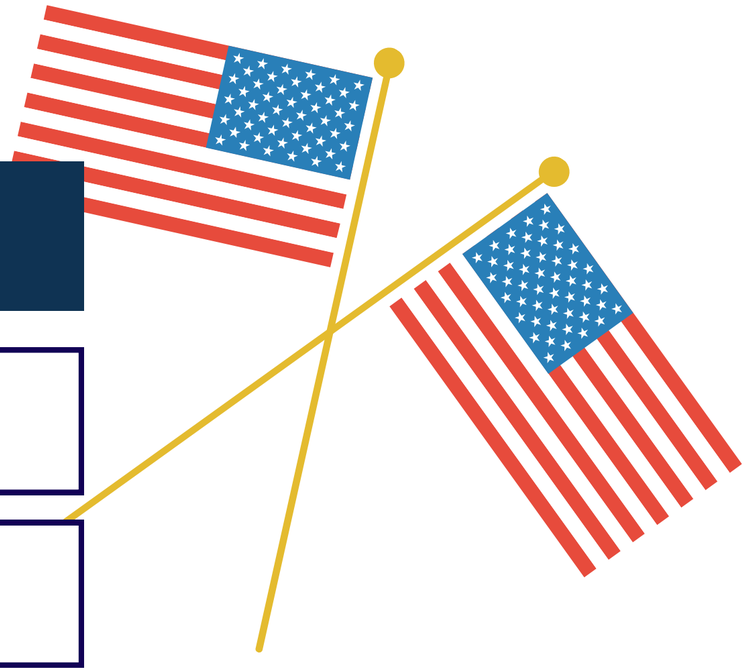
Baseline model: tokenize + model

Data split : 70% train, 15% test and 15% validation

Hyperparameter tunning

- using research grid

Evaluation



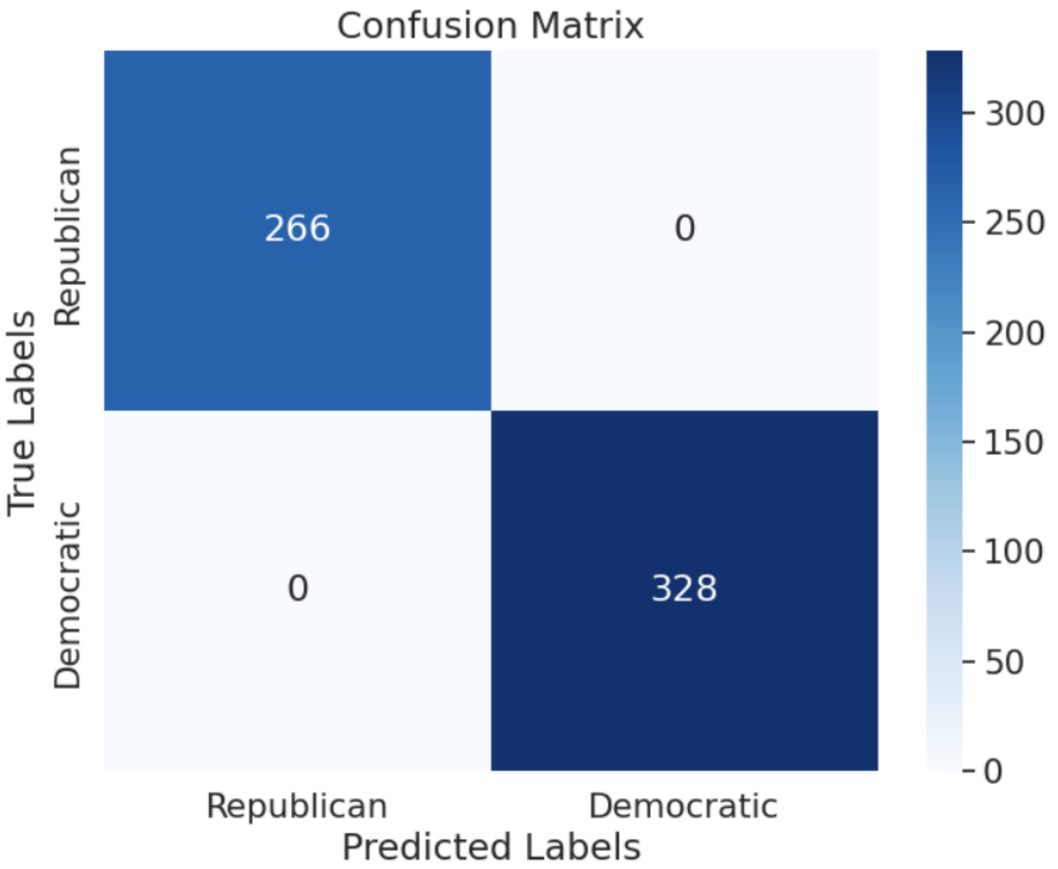
	Accuracy score
SVM	98%
Naive Bayes	95%
Logistic Reg	98%
CNN	100%
Pre-trained BERT for Sentiment Analysis	55%

Chosen model

TFIDF

+

CNN



What's next?

Improvements

- Test with transcript data instead of summary to increase the complexity of the classification task

Extend the work

- Adapt the model to other types of documents that can be classified in 2 categories (e.g. fake news)

Questions?

★ ★ ★

THANK YOU

MARILIE BRETON, MARIA BIANCA GIOADA, SAMIRA YAZDANPOUR

PATRICK CIMON
&
AYMAN BEN MANSOUR

MATH80629A

Is stock return prediction still impossible?

AGENDA

PATRICK CIMON
&
AYMAN BEN MANSOUR
MATH80629A

01 Context and Task

02 Related Works

03 Datasets

04 Approach and Evaluation Setup

05 Results

06 Future Direction

Stock Return Prediction

Context

It is common knowledge amongst portfolio manager that the market shows at least a weak efficicency, which means that past stock prices and their fluctuations do not contain any information about future stock prices.

With recent advances in machine learning is it possible to predict the direction public stock's returns based on its past performance and macroeconomic environment?

Task

Predict next period stock returns' sign (0: negative, 1: positive) with a classification supervised learning algorithm for sequential data:

- Bayesion Structural Time Series

Related Works

- "Deep Learning for Stock Prediction Using Numerical and Textual Information" by Weiwei Shen, Yilin Wang, and Zexi Shen (2019)
- "Predicting Stock Prices with a Feature Fusion LSTM-CNN Model" by Yujun Zhang, Jiahang Li, and Hongyu Liang (2019)
- "A Comparative Study of LSTM and GRU for Stock Price Prediction Using Historical Data" by Ganesh Bonde and Ritesh Kadmawala (2020)
- "Deep Learning for Stock Market Prediction: A Comparative Study of Different Architectures" by Yiding Shen, Yan Yu, and Zhaozheng Yin (2019)
- "Stock Price Prediction using Deep Learning Techniques: A Survey" by Muhammad Asif et al. (2020)
- "Stock Price Prediction Using Attention-based Deep Neural Networks" by I. Kavitha and G. Uma (2020)
- "Stock Price Prediction using Multi-Modal Deep Learning Approach" by Sandeep Kumar et al. (2019)

Key Insights:

- GRUs generally outperform LSTM and CNN.
- The attention head mechanism allows the model to focus on the most relevant features in the input data, potentially leading to better performance compared to models without attention mechanisms.
- Multi-Modal (numerical and textual) approaches show promising results for stock price prediction. The CNNs and LSTM networks, which may result in a more accurate prediction compared to using either method alone.

Dataset

Input Data

- Source : Yahoo Finance
- Train-Val date split: 2000-2017-2021
- Train-Test date split: 2000-2021-2023
- Training Stocks 'MSFT'
    - "D" : 5796 data points
    - "W": 1196 data points
    - "M": 276 data points

Macro-Economics Historical Data

Source: fredapi (Federal Reserve Bank of St-Louis)

- Consumer_Confidence_Index: UMCSENT
- Producer_Price_Index: PPIACO
- Consumer_Price_Index: CPIAUCSL
- Weekly_Claims_For_Unemployment_Insurance: ICSA
- GDP: GDPC1
- Retail_Sales_ex_autos: RSXFS
- Industrial_Production_and_Capacity_Utilization: INDPRO
- Durable_Goods_Orders: DGORDER
- NBER_Recession_marker: USREC

Hyper-parameters

- Phi : ["D", "W", "M"]
- Lamda : Number of lagged return
- Stock
- Date splits

Labels

Binary(Ret. t+1) :

- 0 : Negative return
- 1 : Positive return

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&
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MATH80629A

Approach and Evaluation Setup

Model

Bayesian Structural Time Series

The model consists of three main components:

1. Kalman filter. The technique for time series decomposition.
2. Spike-and-slab method. In this step, the most important regression predictors are selected.
3. Bayesian model averaging. Combining the results and prediction calculation.

Hyper- Param Tunning

- Phi : "W" = Weekly returns
- Lamda : 2-3 lagged returns (weekly)

Date split

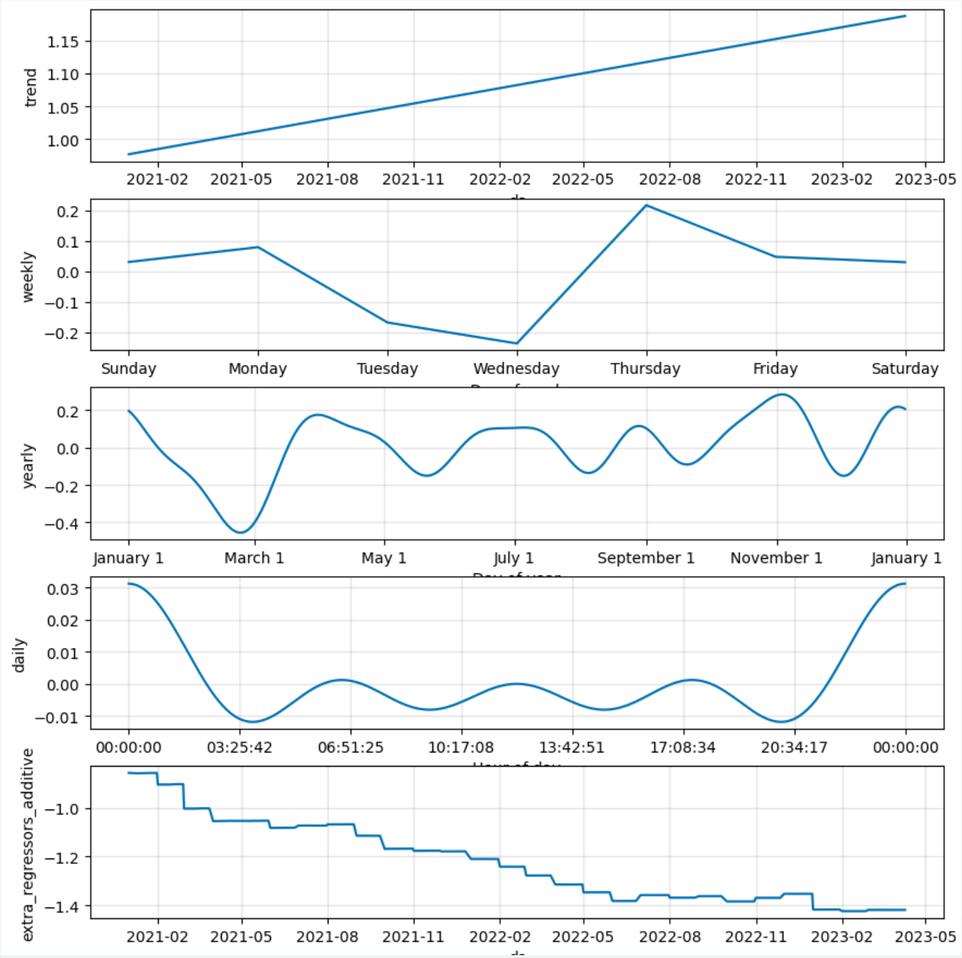
- Train-Val date split: 2000-2017-2021
- Train-Test date split: 2000-2021-2023

Results

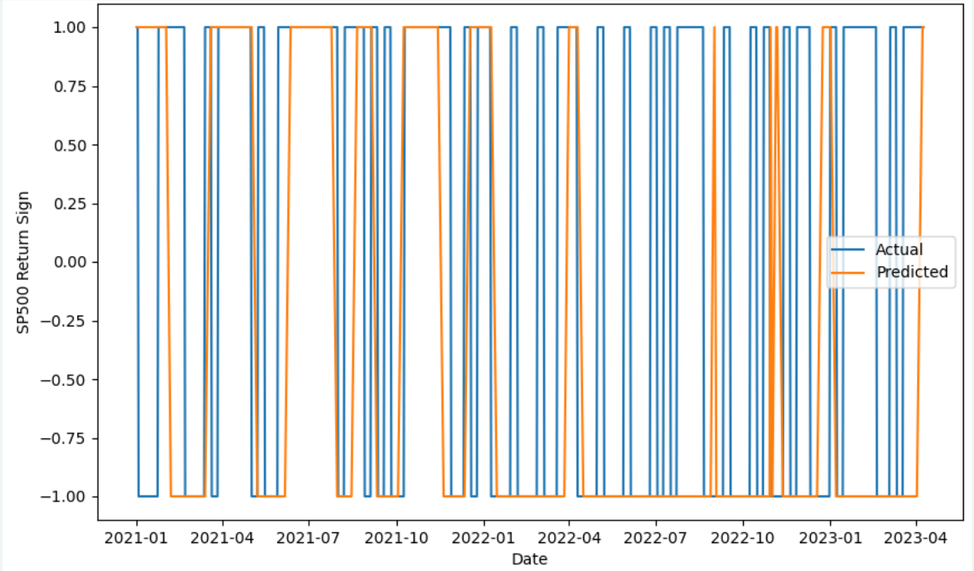
ACCURACY

[51%-61%]

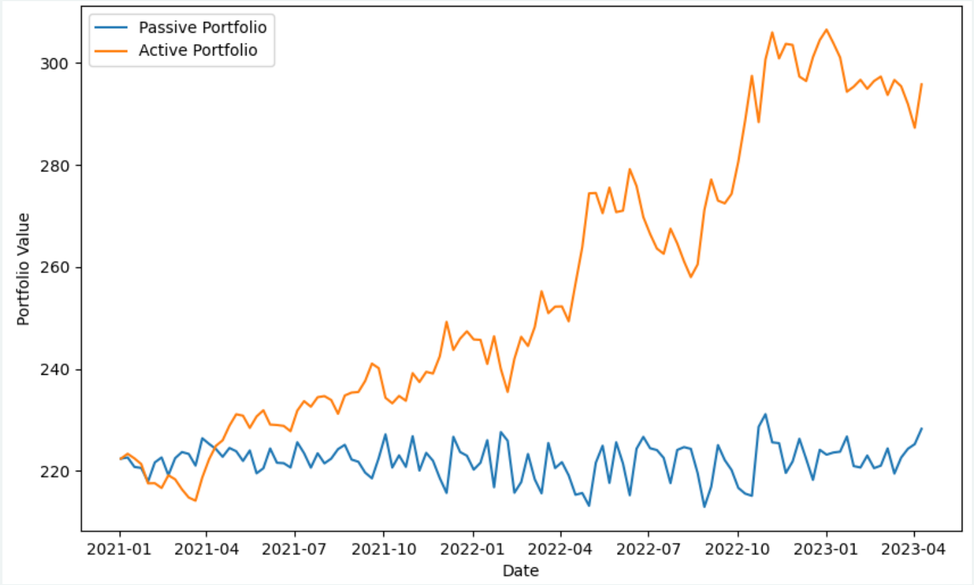
Trends and extra components



MSFT Returns' Sign Predicition



Active vs Passive Portfolio Evolution



Future Direction

- The performance depends a lot on the hyper-parameters (Data split, stocks, frequency, etc.)
- Implementation of portfolio prediction with multiple stocks instead of only one to benefit from the biased coin flip effect
- Data augmentation from multiple similar stocks historical data
- Model additions:
  - A transformer or residual connection and an attention head layer, to focus on the most relevant features in the input data
  - Recurrent neural network layer could be benefical for the longterm dependencies

These changes may help make stock return prediciton possible!

Thank you for listening!
Questions?

PATRICK CIMON
&
AYMAN BEN MANSOUR

MATH80629A

MACHINE LEARNING FOR LARGE SCALE DATA ANALYSIS AND DECISION MAKING

Winter 2023

MOVIE GENRE CLASSIFICATION

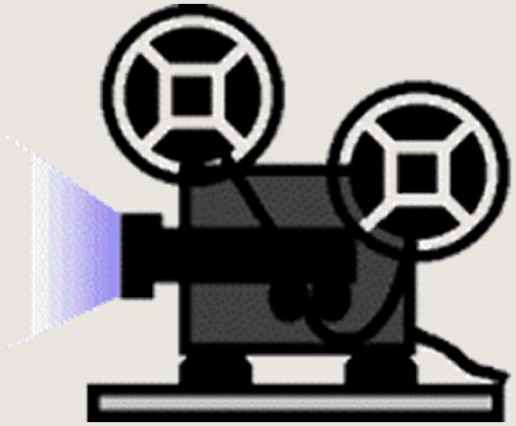
Houri Kechechian
Hadi Mohammadibajgiran
Gelareh Ghaderi

14th April 2023

MOVIE GENRE CLASSIFICATION

AGENDA

- Introduction
- Movie Genre Dataset and task
- Literature review
- Our Approach
- Models of Machine leaning
- Results and Model selection
- Future Direction



INTRODUCTION

Using the description of a movie to classify it into the appropriate genre is one of the interesting tasks in machine learning. It can also help businesses to achieve goals.

Examples:

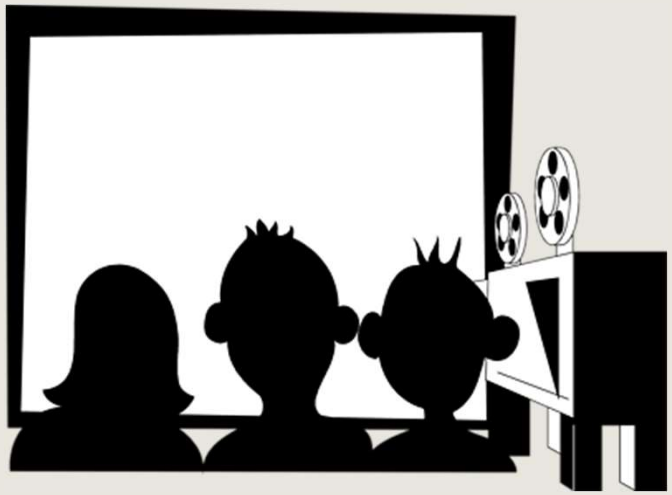
- Revenue generation
- Compliance
- Brand Reputation

TASK

- ❑ Classification (Supervised Learning)

APPLICATIONS

- ❑ Personalization
- ❑ Marketing
- ❑ Trend analysis



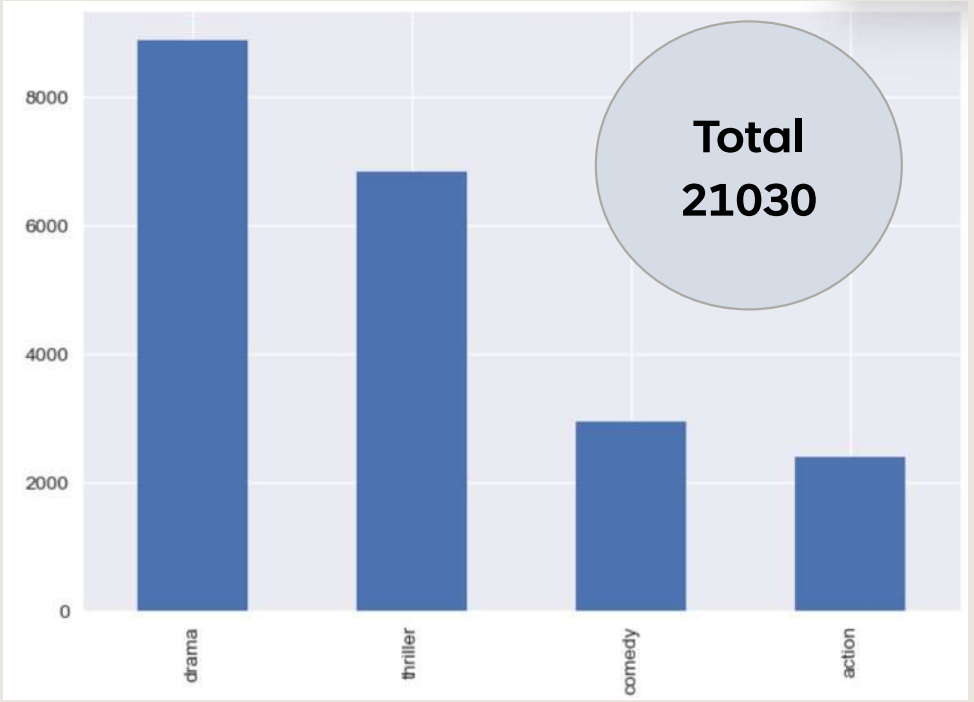
DATA SET

TEXT DATA

- Movie Trailer Script

CLASSES

- Action
- Drama
- Comedy
- Thriller



WORD CLOUD

DRAMA

ACTION

COMEDY

THRILLER

LITERATURE REVIEW

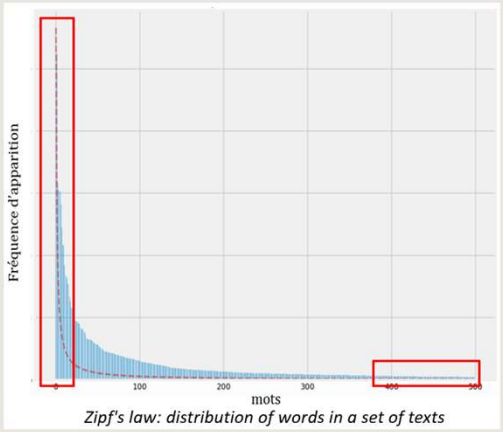
Author(s)	Dates	Methods	Subject
Mert Ertugrul Pinar Karagoz	2018	Applied Bi-directional LSTM, and it performed better than baseline models (LR and Basic RNN)	Movie genre classification from plot summaries of movies
Nikhil Kumar Rajput Bhavya Ahuja Grover	2022	k-nearest neighbor (KNN) algorithm has the best performance	Movie genre classification scheme based on the movie's subtitles
SHERVIN MINAEE, Nal Kalchbrenner	2021	150 deep learning--based models for text classification	Analysis of the performance of different deep learning models on popular benchmarks,

OUR APPROACH ==> WHY

1- Preprocessing data

- Lower Case
- Edit some expressions
- Stop word removal
- Lemmatization
- Embeddings (TF-IDF and Word2vec)

```
text = re.sub(r"n't", " not ", text)
text = re.sub(r"i'm", "i am ", text)
text = re.sub(r"\'re", " are ", text)
text = re.sub(r"\'d", " would ", text)
text = re.sub(r"\'ll", " will ", text)
```



Zipf's law: distribution of words in a set of texts

we use lemmatization for most applications unless we seek to strongly optimize recall.

we have large database and highly contextual and nuanced text

OUR APPROACH ==> WHY

2- Machine learning models

SVM	Data with high-dimensional feature space, and the classes are separable.
KNN	Data is non-linear and the number of classes is small.
Neural Network	Large data with high-dimensional feature space, and the classes are not easily separable
CNN	Large and complex sequential data
RNN	Large and complex sequential data

MACHINE LEARNING MODELS

SVM	KNN	Neural Network	RNN	CNN
TF-IDF C regularaization kernel	TF-IDF n_neighbors weights	TF-IDF activation: relu hidden size max_iter, **Optimizer:** ADAM	**Word Embeddings** **RNN structure:** Embedding Layer Hidden layer (with and without LSTM) Fully Connected Layer **Loss:** Cross entropy **Optimizer:** ADAM	**Word Embeddings** **CNN structure**: Embedding Layer (convolution layer Activation function(ReLu) Max pooling)x2 Fully Connected Layer **Loss:** Cross entropy **Optimizer:** ADAM

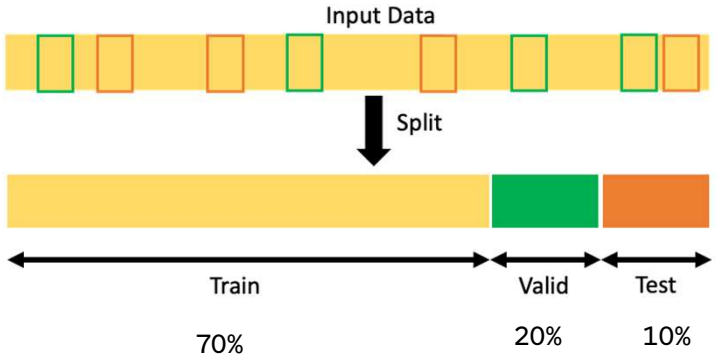
EVALUATION SETUP

Baseline Model:

Random Label Assignment

Splitting the data:

Split the data into Training (70%), Validation (20%) and Test (10 percent) sets.



Hyperparameter Tuning:

Performed hyperparameter tuning on the validation data set and the hyperparameters specific to each model

HYPERPARAMETER TUNING

SVM	Extensive trial and error (C, kernel)
KNN	Extensive trial and error (n_neighbors, weights)
Neural Network	GridSearchCV (hidden_layer_sizes, max_iteration, solver and activation function)
CNN	GridSearchCV (Learning rate, Filters, batch size, number of filters)
RNN	GridSearchCV (learning rate, epoche numbers)

MODEL COMPARISON AND SELECTION

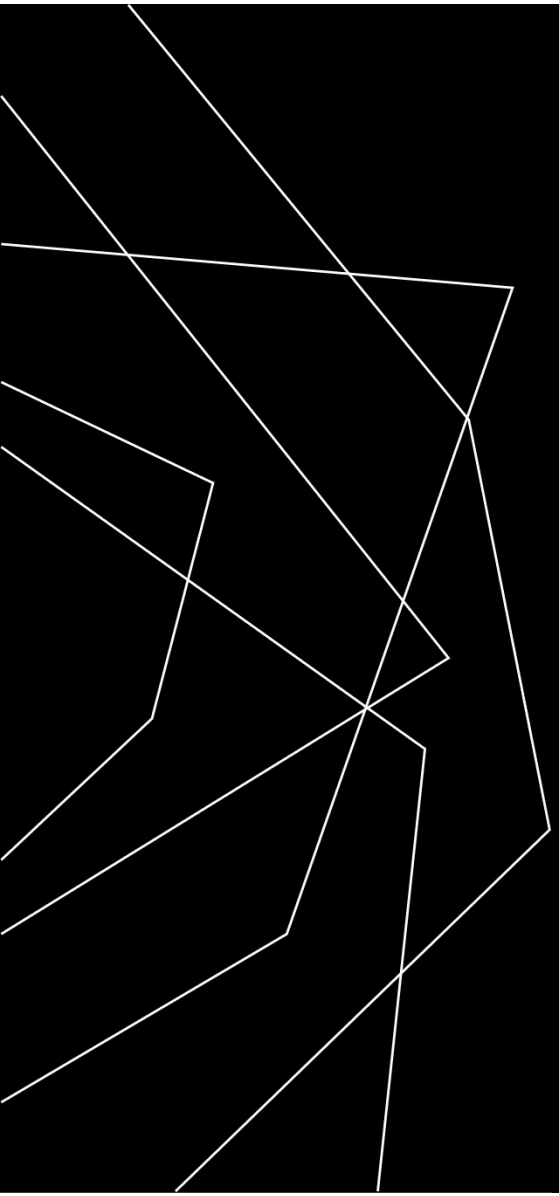
	Baseline	SVM	KNN	Neural Networks	RNN	RNN (LSTM)	CNN
Accuracies	24.8%	72.14%	92.64%	94%	47.65%	86.55%	38.51%

FUTURE DIRECTION

- Using another Word Embedding to improve representation (Glove, BERT)
- Using a larger dataset for better model training
- Using another Tunning models (Dropout, Network architecture,....)
- Test another Models (Naïve base, Random Forest, ...)

REFERENCE

[1] Ertugrul. A, Karagoz. P, 2018, Movie Genre Classification from Plot Summaries Using Bidirectional LSTM, IEEE, Laguna Hills, CA, USA
[2] Rajput N. et al, 2022, A multi-label movie genre classification scheme based on the movie's subtitles, springer, 81, p. 32469–32490.
[3] Minaee S. et al, 2021, Deep Learning--based Text Classification: A Comprehensive Review, ACM Computing Surveys, V (54), No. 62, p. 1–40.
[4] database: NLP(movie genre classification) | Kaggle



THANK YOU!

CUSTOMER CHURN PREDICTION

MATH60629A.W2023

April 14, 2023

Javad Ghasempur Sis - Helen Ma - Jiahua Shang

Agenda

- Introduction
- Dataset
- Models
- Data preprocessing
- Results
- Conclusion & Future direction

What is churn?

"rate at which customers stop doing business with a company or cancel their subscription to a service"

Why is it important?

- Revenue Loss
- Cost of acquisition > Retention cost
- Competitive advantage
- Customer Satistfaction
- Brand reputation

Supervised Learning: Classification Task

Credit Card Customer Dataset

1

Target variable "Attrition_Flag"

10K

observations on customer data

14

numerical variables

5

categorical variables

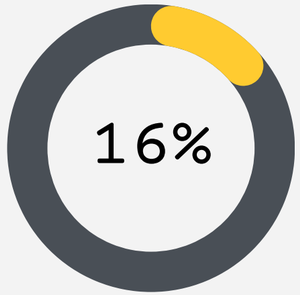
Variable		Description
Target	**Attrition_Flag**	**1 if account is closed, 0 otherwise**
Demographic	Gender Education_Level Marital_Status Income_Category Customer_Age Dependent_Count	2 levels {Male, Female} 7 levels {high school,..., graduate, other} 4 levels {Single, Married, Divorced, Unknown} 7 levels { <40K, 40K-60K, ...80K-120K, >120K} Customer's age (yrs) Number of dependents
Relationship with bank	Months_On_Book Total_Relationship_Count	Period of relationship with bank Total # of products held by the customer
Activity	Months_Inactive_12_Mon Contacts_Count_12_Mon	No. months inactive (last 12 mo) No. contacts (last 12 mo)
Credit card info	Credit_Limit Total_Revolving_Bal Avg_Open_To_Buy Card_category	Credit limit on credit card Total revolving balance on credit card Open to buy credit line 4 levels {Blue, Silver, Gold, Platinum}
Transaction Info	Total_Amt_Chng_Q4_Q1 / Total_Ct_Chng_Q4_Q1 Total_Trans_Amt / Total_Trans_Ct Avg_Utilization_Ratio	Change in transaction amount/count (last 12 mo) Total transaction amount/count (last 12 mo) Average card utilization ratio

Data exploration

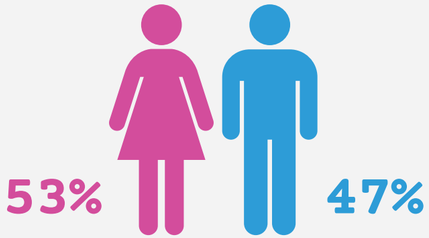
missing values

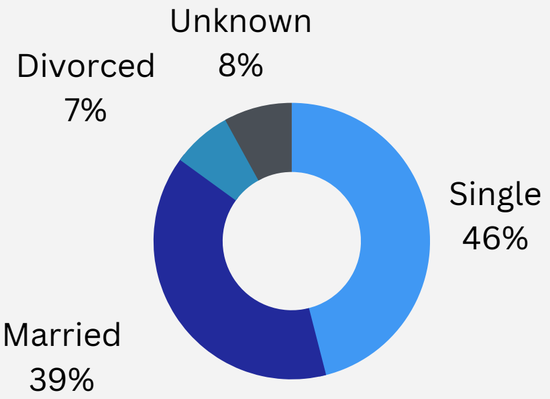
No missing values

Attrited Customer

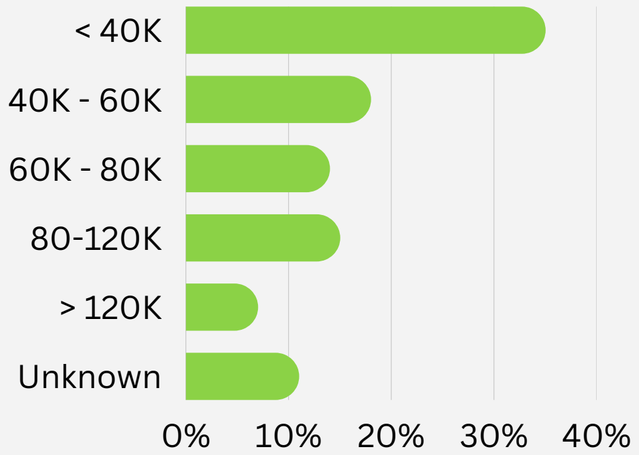


Gender & Marital Status

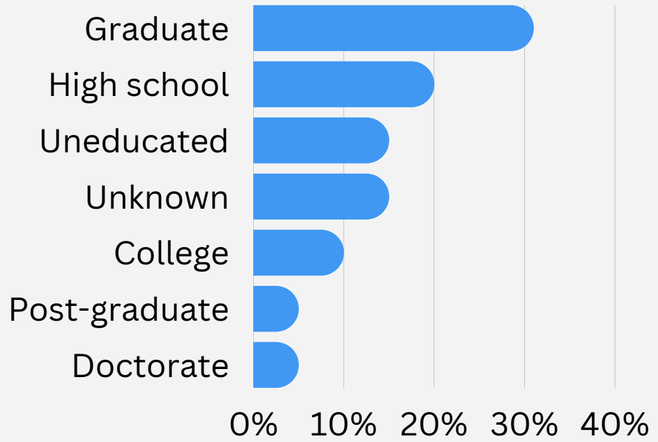




Income Category



Education Level



Credit Card Type

93% Blue

6% Silver

1% Gold and Platinum

Literature Review

Previous research

- "A comparison of machine learning techniques for customer churn prediction," by Vafeiadis et al. (2015)

Churn prediction on a telecommunication Dataset

The authors evaluated the performance of various model:

- Logistic Regression
- Decision Trees
- Random Forests
- Support Vector Machines
- Neural Networks
- Gradient Boosting Machines

★★★ **Best performance** : Gradient Boosting Machines

★★★ **Worst performance** : Neural networks

Model

Baseline

- Majority Classification - predicts the majority class in the set
- Random Classification - randomly assigns labels to test samples.

Linear Classifier

- Assumes Indep. Variables normally distributed - Gaussian Naive Bayes
- Binary classification - Logistic Regression

Model

Advanced Algorithms

- Decision Tree - recursively partitioning the input space into subsets
- Random Forest - combines bagging with feature randomness
  Multiple decision trees
- K-Neighbors classifier - based on the k-nearest neighbors
- Bagging classifier - bootstrap aggregating
- Boosting classifiers
  - Gradient boosting
  - XGBoost
  - Ada-Boost

Model

S.V.C. & Neural Networks

- Support Vector Classifier - finds the best decision boundary that separates the input data into different classes

  Features
  - Non-linear
  - Work well for high dimensional data
  - Computationally expensive

- MLP classifier- an artificial neural network that consists of multiple layers of interconnected nodes.

  Features
  - Can capture complexity of data
  - Computationally expensive

Performance Metrics

Potential performance metrics

- Accuracy = (TP+TN) / (TP+TN+FP+FN)
- Recall (Sensitivity) = TP / (TP+FN)
- Specificity = TN / (TN+FP)
- Precision = TP / (TP+FP)
- F-Score = 2 (Precision x Recall) / (Precision + Recall)

Objective: Maximize correct predictions of customer who will churn

		ACTUAL	
		Positive (Churn =1)	Negative (Churn = 0)
PREDICTED	Positive (Churn =1)	True Positive	False Positive
	Negative (Churn = 0)	False Negative	True Negative

the cost of FN could be significant as failing to predict a churn event may result in the loss of a customer

Performance Metrics

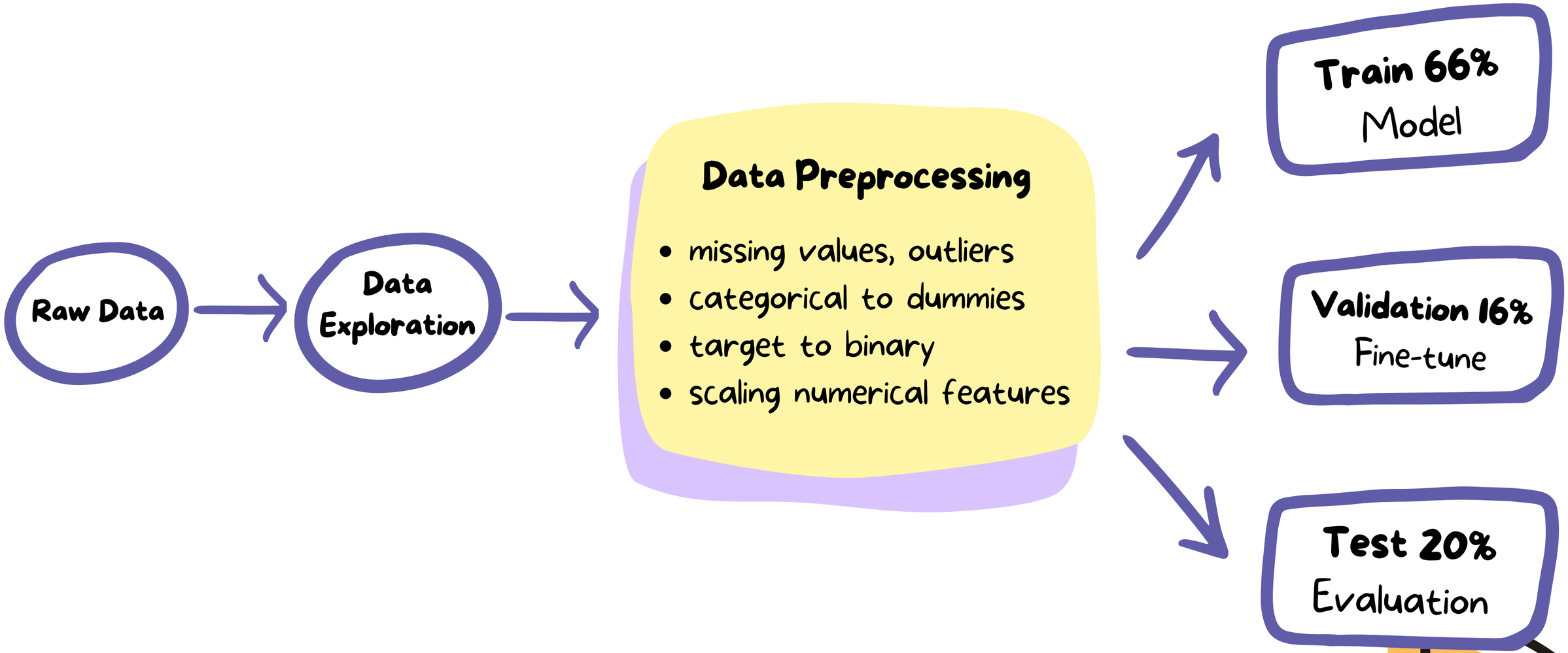
Recall (Sensitivity) = TP / (TP+FN)

In the case of predicting customer churn, we consider that it is more important to focus on **correctly identifying churn cases**.

By using **recall,** the model will be optimized to correctly identify the churn events, even if it comes at the expense of accuracy.

		ACTUAL	
		Positive (Churn =1)	Negative (Churn = 0)
PREDICTED	Positive (Churn =1)	True Positive	False Positive
	Negative (Churn = 0)	False Negative	True Negative

Data Preprocessing



Hyperparameter Tuning

- Grid-search Method -
  - Specify range of values
  - Search over all possible combinations
- Performance Comparision -
  - Evaluate on validation sets
  - Best performance hyperparameter selected
- Alogorithms
  - GridSearchCV
  - RandomizedSearchCV

Results of models

#	classifier	Recall	Accuracy	Precision	F1	CV_score
1	Decision Tree	91.13%	89.59%	62.08%	73.85%	93.62%
2	Gradient Boosting	89.91%	97.04%	91.59%	90.74%	99.10%
3	XGBoost	88.07%	96.54%	90.28%	89.16%	99.29%
4	Random Forest	85.63%	95.36%	85.63%	85.63%	98.54%
5	Bagging	85.02%	96.25%	91.15%	87.97%	97.94%
6	AdaBoost	82.57%	95.36%	87.95%	85.17%	98.68%
7	MLP	74.01%	91.46%	73.33%	73.67%	94.13%
8	Support Vector Classification	69.72%	91.91%	77.82%	73.55%	94.47%
9	Logistic Regression	55.05%	89.93%	75.95%	63.83%	92.38%
10	Gaussian Naive Bayes	53.82%	86.77%	60.07%	56.77%	85.63%
11	K-Neighbors	31.80%	87.12%	73.24%	44.35%	80.82%
12	Baseline_Random	16.62%	51.33%	50.15%	24.96%	NA
13	Baseline_Majority	0.00%	83.86%	0.00%	0.00%	NA

Results on another dataset

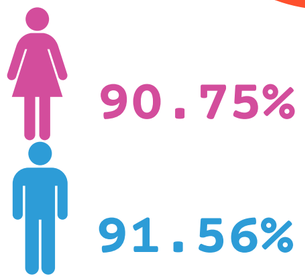
Classifie	recall (test)	f1-score (test)	cv_score (train)	accuracy (test)	precision (test)
Decision Tree	77.1%	74.4%	84.9%	92.4%	71.8%
Gradient Boosting	75.0%	80.9%	90.5%	94.9%	87.8%
Bagging	72.9%	71.1%	84.0%	91.5%	69.3%
Random Forest	70.8%	74.7%	89.5%	93.1%	79.1%
XGBoost	70.8%	79.1%	89.7%	94.6%	89.5%
Gaussian Naive Bayes	67.7%	31.6%	56.6%	57.9%	20.6%
MLP	53.1%	54.3%	79.7%	87.1%	55.4%
Support Vector Classification	46.9%	52.0%	82.3%	87.6%	58.4%
AdaBoost	41.7%	50.6%	77.9%	88.3%	64.5%
Logistic Regression	27.1%	36.4%	78.4%	86.4%	55.3%
Baseline_Random	12.8%	20.0%		48.3%	44.8%
K-Neighbors	6.3%	11.3%	63.5%	85.9%	60.0%
Baseline_Majority	0.0%	0.0%		85.6%	0.0%

Fairness

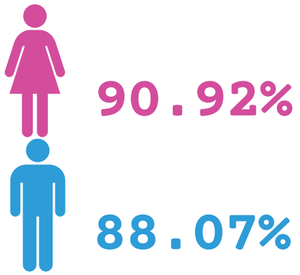
Equal opportunity difference (EOD) score of 0.0356
There's a diference of 3.56% in TPR between two gender group

Evaluation of Final Model

Recall by Gender
Diff : 0.81%



Accuracy by Gender
Diff: 2.85%

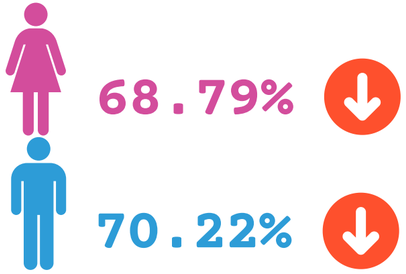


Evaluation of Final Model + Fairness Algorithm (Post-processing approach)

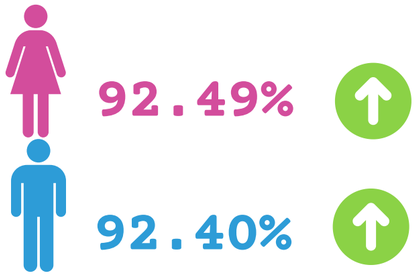
Demographic Parity (ensure that the % of positive outcomes is the same accross groups)

- Suggested threshold by algorithm = 0.80

Recall by Gender
Diff: 1.43%



Accuracy by Gender
Diff: 0.09%



Conclusion Future Direction

Dataset 1 : Decision Tree
91.1% Recall
89.9% Accuracy

Dataset 2 : Decision Tree
77.1% Recall
92.4% Accuracy

Business context :

- interpretability, implementation
- Future Direction: fairness marketing

Thank you

Prediction of airline ratings using text reviews from passengers

Ilya Cardoso
Leonardo Aguilar

Task and Dataset

- **Supervised learning:** prediction of a target (transformation of flight rating) based on passangers reviews (text data) and the airline name.

- **Classification task:** the model will be trained on a labeled dataset of reviews, where each review is labeled as **"good“ (3), “fair”(2) and "poor“(1),** based on the overall rating given by the reviewer.

- Data webscrapped from https://www.airlinequality.com/ - independent customer forum not affiliated to any particular airline

- Data is inputed directly by travelers based on an online form, including the rating (label) for the travel.

Task and Dataset

Dataset: 15,800 data points consisting of passanger reviews for 14 airlines.

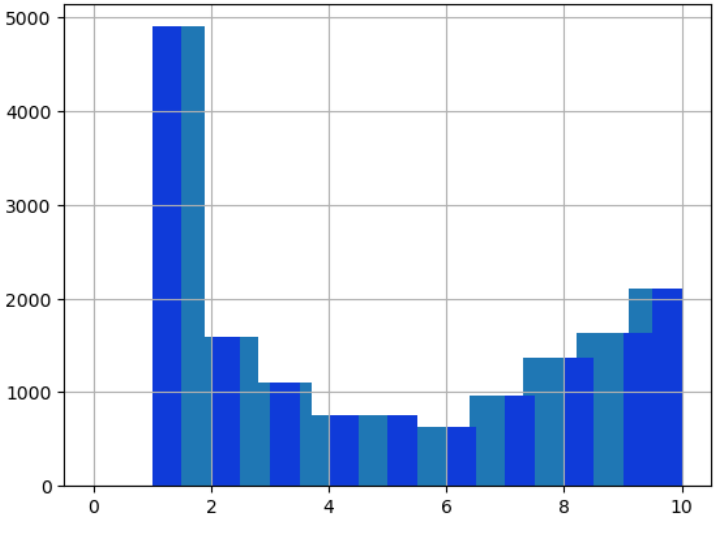
Label: named “class” in the dataset. Corresponds to the 3 classes the ratings are grouped into.

Sample data point:

Class	Review	Airline
1	Flew from Amman to London on Nov. 14 2022. Not sure what type of aircraft it was. My Ticket was economy plus. The flight is 5h35m. We received exactly 250ml of water and about 10 potato chips. The seats did not recline and there was no entertainment system. Any other food or drink had to be purchased. So we couldn't even get a warm cup of coffee or teas. It is the third time I have flown with BA recently and was unhappy each time but did not write a review. Will honestly never fly them again if I can help it.	American Airlines

Task and Dataset

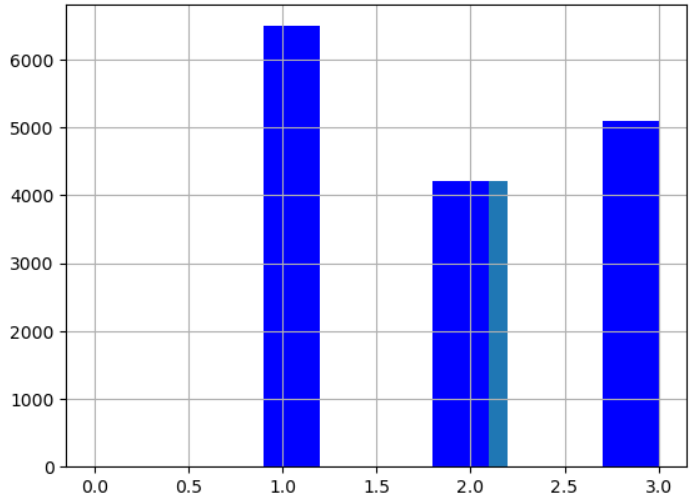
Distribution of the label (ratings) with original scale from 1 to 10



Highly unbalanced distribution

```
1     4904
10    2101
9     1631
2     1587
8     1371
3     1108
7      963
5      759
4      751
6      625
Name: Ratings
```

Distribution of the label (Class) grouped into 3 classes: poor(1), fair(2), Good(3)




```
1    6491
3    5103
2    4206
Name: Class
```

Literature review

- Eibe Frank and Mark Hall. *A Simple Approach to Ordinal Classification*. Department of Computer Science University of Waikato Hamilton, New Zealand.

- http://seekinginference.com/applied_nlp/distilbert.html#distilbert-hyperband-and-asha-hyperparameter-search-with-optuna

- Takuya Akiba, Shotaro Sano, Toshihiko Yanase, Takeru Ohta, and Masanori Koyama. 2019. Optuna: A Next-generation Hyperparameter Optimization Framework

- Different tutorials on NLP, Scikit learn documentation on machine learning algorithms

Your Approach

1. **NLP Processing:**
   - TF-IDF (linear and ensemble models)
   - RNN: Processing for usage of Distilbert
2. **Ordinal Classification:** output variable has a ordinal characteristic (poor<fair<Good)
3. **Dimensionality:**
   - Feature selection
   - Hyperparameter tunning strategy
4. Try **different machine learning models to evaluate and compare** their performance on text data.
   - Logistic regression
   - Naives Bayes
   - Ensemble Methods (random forest, stochastic gradient boosting)
   - Neuronal network: fine tuning of DistilBert model

Approaches:
Linear and Ensemble Models

Approach: NLP Techniques – TF-IDF

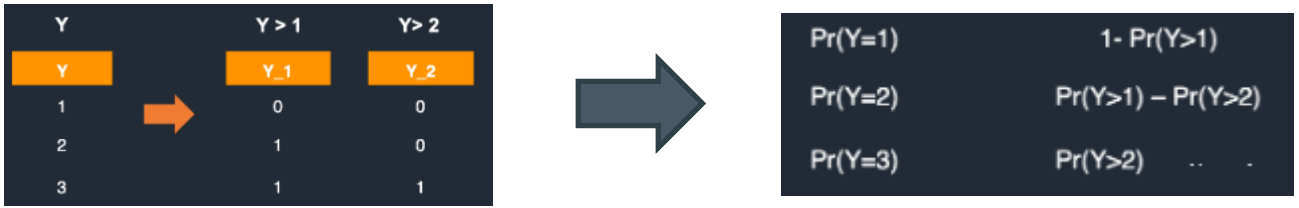
Applied in logistic, NB and ensemble models.

- Punctuation, characters removal
- Tokenization
- Stop words removal
- Lemmatization
- Convert to numerical format (TF-IDF representation).

```
Dimensions of features array: (15800, 29591)
Dimensions of label series: (15800,)
```

Approach: Ordinal Classification

- **Label** (passanger rating) has an **ordinal characteristic** (poor<fair<good)
- No Python libraries that allow ordinal classification for all algorithms. **Solution**: Eibe Franck and Mark Hall. *A simple approach to Ordinal Classification.*
- Convert k-class regression problem into a k-1 binary classification problem:



- Define a customized ordinal classifier on top to BaseEstimator. Custom scoring in parameter tunning that penalizes missclasification using quadratic weight for the distance between label classes.

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Approach: Dimensionality

1. **Feature selection (computational contraints):** select best 2,000 out of 29,591 initial features in TF-IDF array.

2. **Strategy for hyperparameter tunning:**
    a. Experiment using a grid search with discrete values based on previous experience
    b. Identify best hyperparameters
    c. Define a space search with continuous ranges for parameters and run bayesian optimization

Evaluation Setup

- Baseline model - Majority class classification

  Majority class: 1

  Baseline accuracy (majority class classification): 41.08%

- Hyperparameter tunning using cross-validation. (random state used in training)
- Split train and test set (80% and 20%) - used the same train and test set in all models. Estimate results based on test set predictions.

Hyperparameter Tunning

3-step approach:

1. Train model using default hyperparameter values.
2. Identify optimal hyperparameters
3. Perform hyperparameter tunning using a grid search with a range continuous values (bayesian optimization with Optuna library)

Logistic:

NB

Hyperparameter Tuning

- Logistic: Alpha, max_iter, penalty
- NB: alpha, fit_prior
- Boosting: colsample_bytree': lambda_l2’, learning_rate’, max_depth': n_estimators': 500, num_leaves

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Results: base models (no tunning)

Metric/Model	Logistic Regression (SGDClassifier)	Naïve Bayes	Random Forest	Gradient Boosting
Accuracy	76.77%	69.68%	75.69%	77.05%
Sensitivity	68.45%	60.04%	60.23%	70.29%
Specificity	85.82%	83.41%	90.40%	85.52%
ROC AUC class 1	0.9387	0.9123	0.9366	0.9348
ROC AUC class 2	0.8125	0.7442	0.7904	0.8061
ROC AUC class 3	0.9516	0.8979	0.9455	0.9534

Results: hyperparameter tunning – grid search

Metric/Model	Logistic Regression	Naïve Bayes	Random Forest	Gradient Boosting
Accuracy	76.99%	70.12%	75.76%	78.70%
Sensitivity	66.16%	62.43%	58.82%	74.47%
Specificity	88.69%	83.60%	90.68%	86.08%
ROC AUC class 1	0.9360	0.9131	0.9383	0.9410
ROC AUC class 2	0.8050	0.7386	0.8152	0.8299
ROC AUC class 3	0.9555	0.8951	0.9452	0.9591

Results: hyperparameter tunning – bayesian optimization

Metric/Model	Logistic Regression	Naïve Bayes	Random Forest	Gradient Boosting
Accuracy	76.99%	70.09%	N/A	78.86%
Sensitivity	64.18%	62.35%	N/A	75.03%
Specificity	89.11%	83.60%	N/A	86.51%
ROC AUC class 1	0.9403	0.9131	N/A	0.9436
ROC AUC class 2	0.8140	0.7384	N/A	0.8334
ROC AUC class 3	0.9552	0.8951	N/A	0.9593

Models performance on the validation set

Approaches:
Deep Learning Model

Transform the input data

- Get the pretrain tokenizer
  - It give use the possiblity to transform the words in sentence (a review) in some index if the word is part of the vocabulary
  - The vocabulary contain 28996 words
    - Word : issued = 3010

```
list(tokenizer.vocab.keys())[3010]
```

```
'issued'
```

- Get the needed format from the reviews
  - Tensors
    - Inputs_ids : Sentences (reviews) with all the word index
      - Each sentence can contain 512
    - Attention_mask : For each sentences with value of 1 for a word contain in the vocabulary of the tokenizer

Get pretain model

- DistilBert model for classification is use
  - It’s smaller version of full Bert model
    - It’s faster and required less resources than full Bert model
    - It can reach up to 97% of the performance obtain by the full Bert
  - The name of the DistilBert for classification is
    - `DistilBertForSequenceClassification`
- Put the model on the device used for training , validation and testing
  - We get the architecture of the model
  - We get the pretrain weights
  - We get the pretrain hyper-parameters

Fine tuning

- Combine the transform data and the pretrain model by :
  - Splitting the input data in those proportions :
    - 80% for training
    - 10% for validation
    - 10% for testing
  - training and validating the model to :
    - Adjust the weight with our dataset to fit our task

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Hyperparameter tunning

- Search true some hype-parameter by minimizing a loss function
  - Optuna was used and it permit to try some value for the hyper-parameter to optimize
    - Dropout
    - Weight-decay
    - Learning-rate

Taking care of ordinality

- We applied all the steps mentions before on two models
- We combine the models to get the final result

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Future Direction

- Use state of the art techniques in NLP to improve results.
- Use techniques to balance the dataset (of keeping the original scale of data).
- Use Interpretable AI to understand features contribution to results.
- Leverage on parallel computing technologies to improve Hyperparameter optimization process.
- For the neural network model:
  - We can improve the performance If we have more resource and time by:
  - Enlarge our dataset
    - Train the full Bert model
  - We can extend our work by changing our problem and try to predict other features like the airline
    - Then we can provide more insight to the airlines