



# CYBER HARASSMENT DETECTION

CS 334 FINAL PRESENTATION



by Andrew Chung, James Park





# OVERVIEW



01

## MOTIVATION

Why we chose this topic +  
work done so far



02

## PREPROCESSING

Standardize, binary output,  
tokenization, word-embedding



03

## MODELS + METRICS

Which models we used +  
how they performed

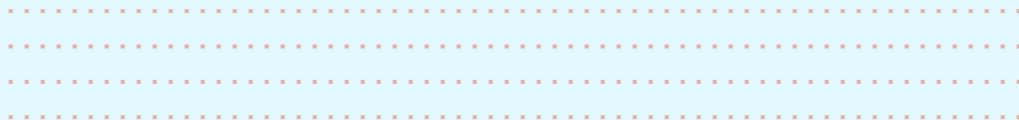


04

## TUNING + FUTURE

KNN and Decision Tree  
Hyperparameters + Improvements  
for future work

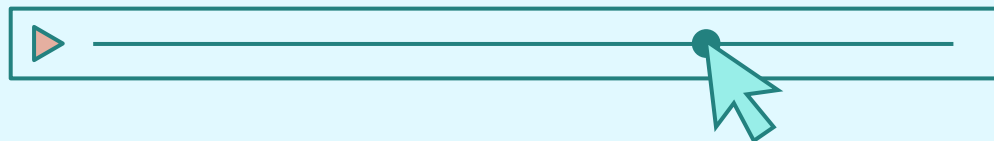




01

# MOTIVATION

Why we chose this topic + work done so far





# STATISTICS



**37%**

## FELT CYBERBULLIED

Middle + High  
schoolers

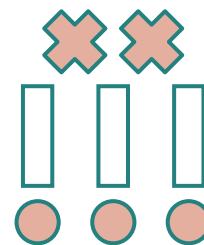
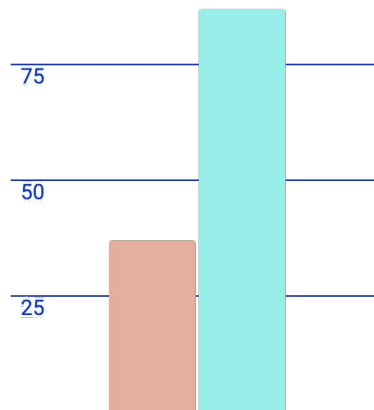


**87%**

## REPORTED CASES

Have observed  
cyberbullying

- Decreased academic performance
- Lack of self esteem
- Suicidal thoughts



# PREVIOUS WORK DONE

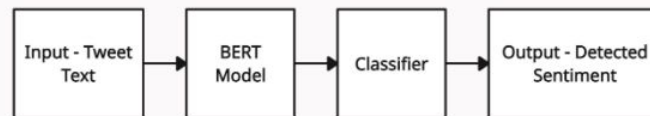
2015

- B. Sri Nandhini and J.I. Sheeba
- FuzZy learning algorithm
- Naïve classifier
- spring.me, myspace.com
- Outdated websites
  - Diction changes over time

2021

- Aditya Desai, Shashank Kalaskar, Omkar Kumbhar, Rashmi Dhumal
- Sentiment analysis
- SVM, Naïve Bayes, BERT
- TF-IDF
- Different approaches
  - Text classification
  - Word-Embedding
  - More transformer models

# PREVIOUS WORK DONE



**Fig.2.** BERT model flow chart based on sentiment analysis

**Table 1.** Comparison of proposed approach with fuzzy classification rule

Dataset	Accuracy		F – Measure		Recall	
	Fuzzy classification rule	Proposed rule	Fuzzy classification rule	Proposed rule	Fuzzy classification rule	Proposed rule
Myspace	.35	.87	.44	.91	.60	.98
Formspring.me	.42	.86	.31	.92	.58	.87

**Table 1.** Accuracy of SVM and Naive Bayes from [3]

Classifier	Accuracy in percentage
Naïve Bayes Classifier	52.70
Support Vector Machine	71.25

**Table 2.** Accuracy of BERT Model

Classifier	Accuracy in percentage
Pre-Trained BERT (testing)	70.89
Pre-Trained BERT (training)	91.90

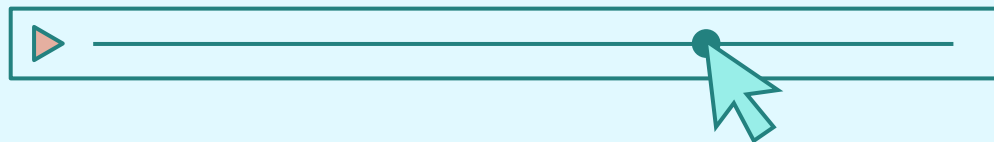
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[https://www.researchgate.net/publication/277568369\\_Online\\_Social\\_Network\\_Bullying\\_Detection\\_Using\\_Intelligence\\_Techniques](https://www.researchgate.net/publication/277568369_Online_Social_Network_Bullying_Detection_Using_Intelligence_Techniques)

02

# PREPROCESSING

Standardize, binary output, tokenization, word-embedding



# DATA:

- From Kaggle
- **Features:** 47000 tweets labelled according to the class of cyberbullying
  - age, ethnicity, gender, religion, other type, not cyberbullying
  - One file divided into two columns:  
**text\_type, cyberbullying\_class**
- **Currently to deal with imbalanced data, we have removed cyberbullying data points to get an even ratio**

kaggle





# PREPROCESSING TASKS



## STANDARDIZE

Remove NAs, stop words, special characters + lowercase



## TOKENIZATION

Split texts into tokens for easier analysis



## BINARY OUTPUT

Change classification from not CB and CB to 0 and 1



## W-EMBEDDING

Train word2vec vectors from training

```
# Text preprocessing function
def preprocess_text(text):
    # Convert text to lowercase
    text = text.lower()

    # Tokenization (split text into words)
    # nltk is a package that allows users to acc
    words = nltk.word_tokenize(text)

    # Remove special characters, numbers, and pu
    words = [re.sub(r'^a-zA-Z', '', word) for word in words]

    # Remove stopwords
    stop_words = set(stopwords.words('english'))
    words = [word for word in words if word not in stop_words]

    return words
```



03

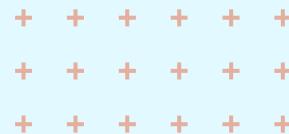
# MODELS + METRICS

Which models we used + how they performed



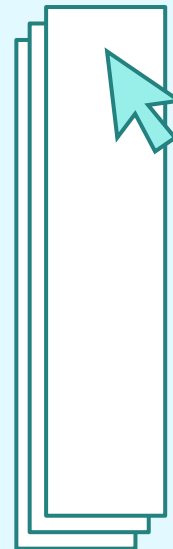


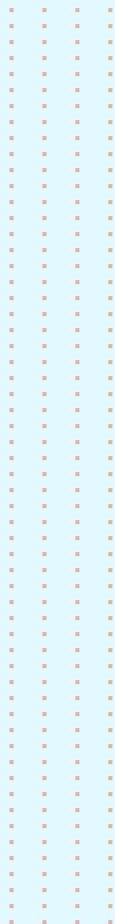
# MODELS:



Our general task was binary classification, and we decided to use the following models:

- KNN
- Decision Tree
- Logistic Regression Model
- BERT-base
- RoBERTa-base
- TWHIN-bert-base





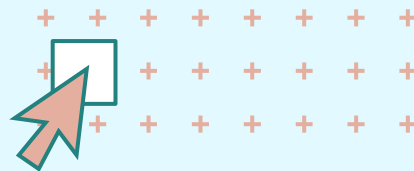
# METRICS:

- F1 scores
  - Allows for comparison between the two binary classifiers(0 and 1)
- AUC-ROC
  - Good for classification models
  - Shows how effectively the model differentiates between the two classes





# CLASSIFICATION REPORT (RAW)



O/1	PRECISION	RECALL	F-1
KNN	.66/.84	.07/.99	.13/.91
DECISION TREE	.68/.88	.33/.97	.44/.92
LOG REGRESSION	.75/.83	.04/1	.08/.91
BERT	.73/.91	.52/.96	.61/.93
ROBERTA	.7/.91	.53/.95	.60/.93
TWHIN-BERT	1/.72	.60/1	.75/.84



# CLASSIFICATION REPORT (EDITED)



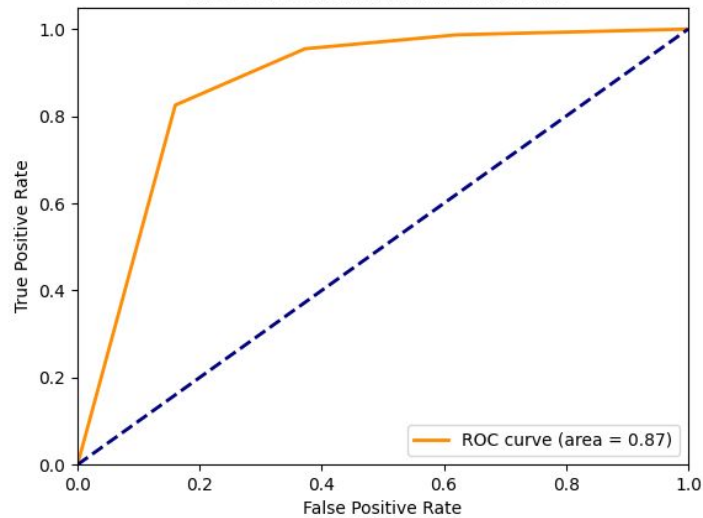
O/1	PRECISION	RECALL	F-1
KNN	.95/.71	.61/.97	.74/.82
DECISION TREE	.81/.89	.9/.97	.85/.84
LOG REGRESSION	.61/.68	.75/.53	.67/.59
BERT	.99/.99	.99/.99	.99/.99
ROBERTA	.99/.99	.99/.99	.99/.99
TWHIN-BERT	.99/.99	.99/.99	.99/.99

# AUROC CURVE



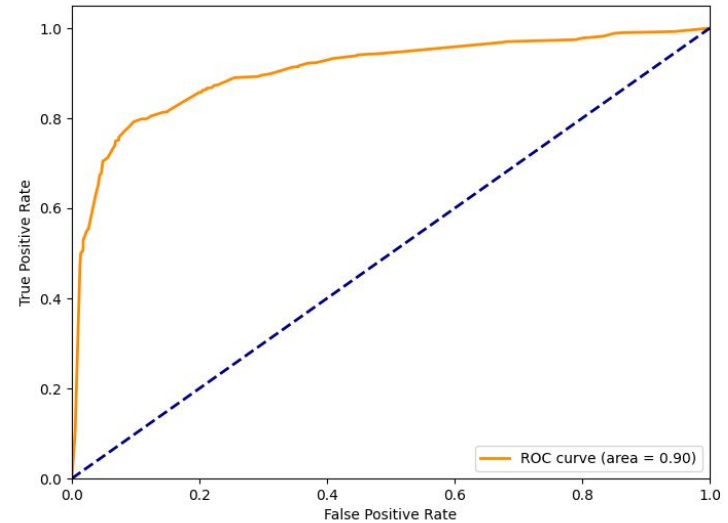
## KNN

ROC Curve for KNN with Best K-value



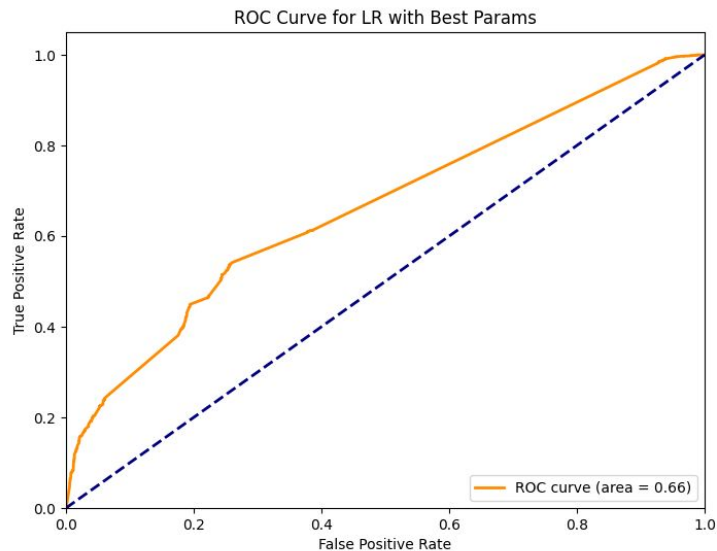
## DECISION TREE

ROC Curve for DT with Best Params

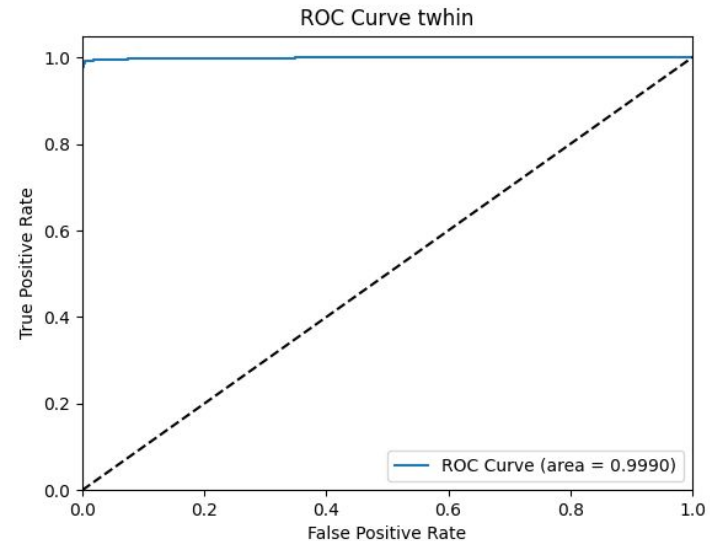


# AUROC CURVE

## LOGISTIC REGRESSION



## TWHIN



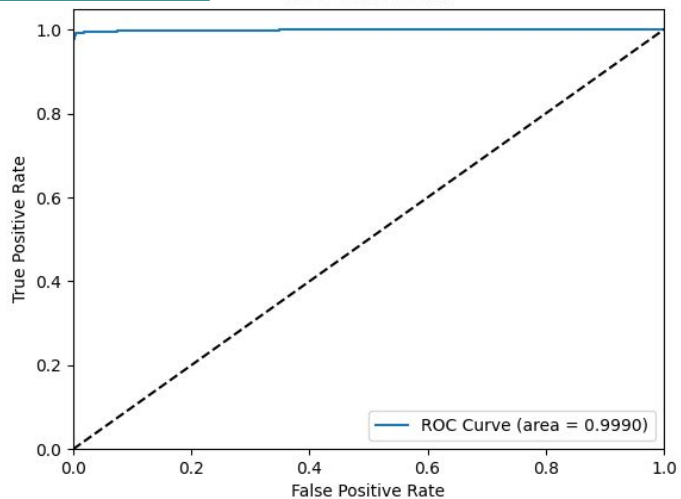


# AUROC CURVE



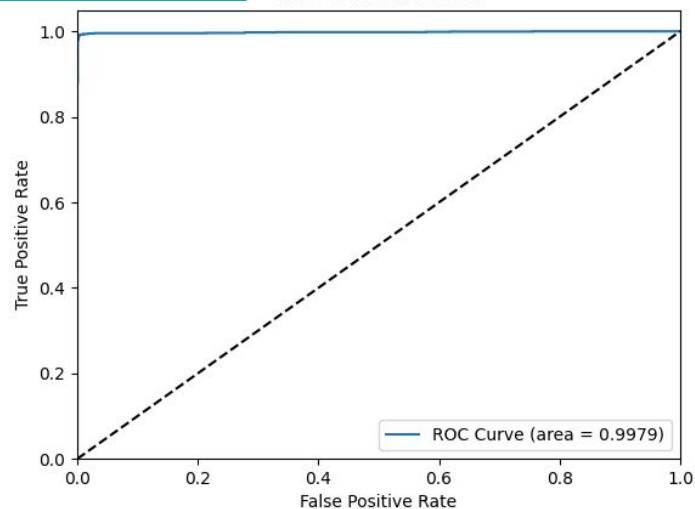
**BERT**

ROC Curve BERT



**RoBERTa**

ROC Curve RoBERTa

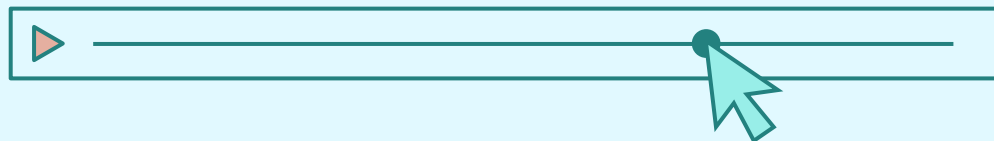


04

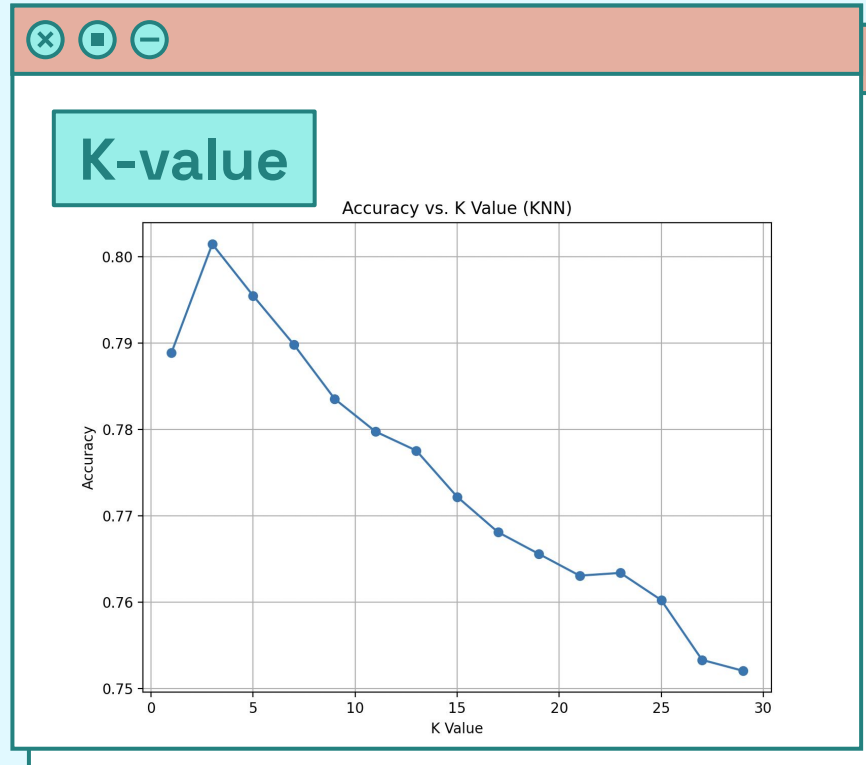
# TUNING + FUTURE

KNN and Decision Tree Hyperparameters + Improvements for future work

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+ + + + + +



# KNN (EDITED)

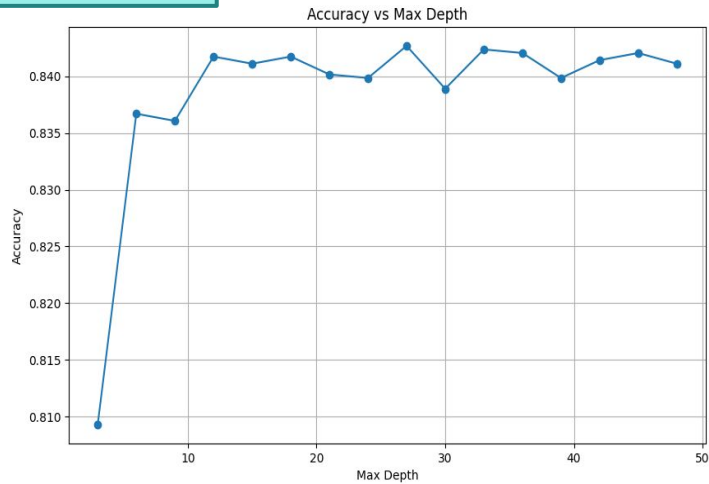


# DECISION TREE (EDITED)



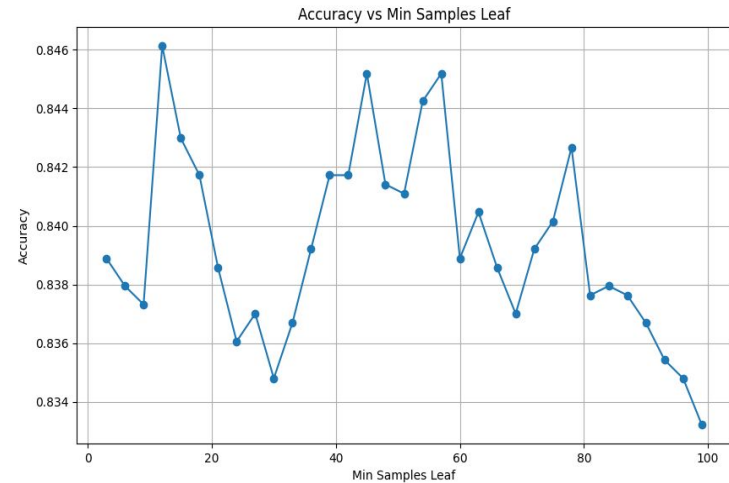
Depth

Min Leaf = 12

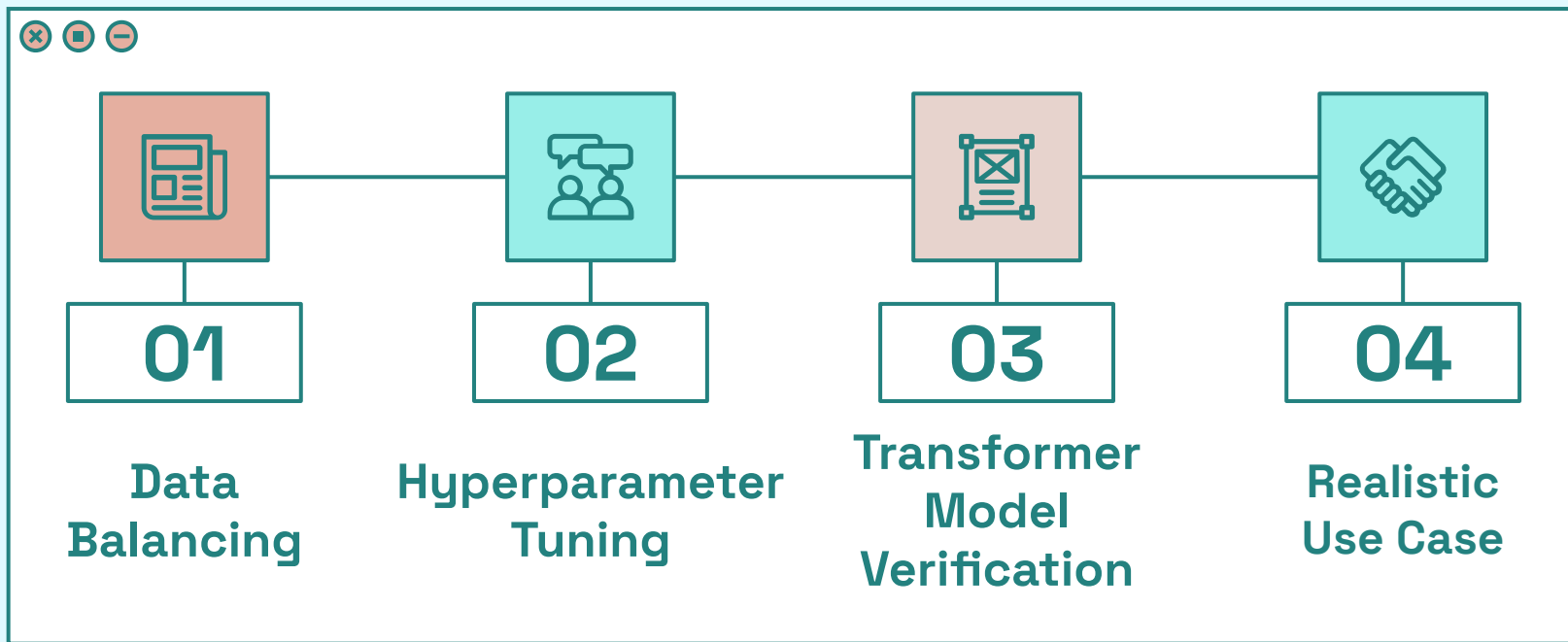


Min Leaf

Max Depth = 27



# FUTURE WORK





THANK  
YOU!

