1. Introduction

This competition focuses on creating a machine-learning model to distinguish Bot users from genuine users based on a given dataset of Twitter accounts. Bot Twitter accounts are hard to distinguish simply based on observation as they are able to mimic genuine accounts with similar usernames, descriptions and Twitter following. These Bot accounts could commit ad fraud which would lead to wasted marketing budgets, inaccurate performance metrics for marketers, fake engagement and fraudulent clicks.

The high-level approach is to be able to classify whether the account is a Bot account through a Machine Learning pipeline with high confidence. My key strategies include iteratively testing different model architectures, data processing and feature engineering to achieve the best Area Under the Receiver Operating Characteristic (AUC ROC) score. Some highlight strategies include feature engineering by fine-tuning a Large Language Model to provide probabilities of whether the account is a Bot account based on the categorical features, as well as using an ensemble architecture. The dataset given consists of 19 features with a mixture of categorical and numerical features (see Appendix A for table).

2. Methodology

2.1 Data preprocessing and feature engineering

Data Preprocessing

Exploratory Data Analysis (EDA) reveals that most of the numerical features suffer from extreme skewness. To address this, a log transformation was applied onto the numerical features and appended to the dataframe (see Appendix B for graph).

Ultimately, I settled on an ensemble approach using **XGBoost, CatBoost and LightGBM**. The process of reaching this architecture will be explained in the later parts, but indicated here first as the preceding data preprocessing steps are specific to ensure the compatibility with the model.

XGBoost and LightGBM require all features to be in numerical form, so further processing of categorical features was required. Firstly, boolean features (see Appendix A for table) were converted to corresponding binary features. Secondly, *'lang'*, *'location'* features had to be OneHotEncoded (OHE). Missing values were replaced with an "unknown" category. EDA shows high cardinality of both features, with 'lang' having 48 unique features and 'location' having 8884 unique features. Further analysis shows that 99.15% and 45.64% of all rows are captured in the top 30 categories of *'lang'* and *'location'* respectively (see Appendix C for table). Hence a threshold of 30 categories were chosen. I acknowledge the lack of representation of categories for the 'location' feature and will address this with feature engineering. Other encoding methods were explored such as LabelEncoding and TargetEncoding, but produced poorer results. Next, the feature names undergo sanitisation, such as replacing special character, spaces, consecutive underscores and leading/trailing whitespaces with underscores for compatibility with LightGBM. Finally, the processed features are dropped from the dataframes. *'created_at', 'profile_image_url' 'profile_background_image_url'* is dropped as *'account_age_days', 'default_profile'* and *'default_profile_image'* captures those information. *'screen_name'* and *'id'* were dropped to reduce noise.

CatBoost can directly process categorical features, so a separate dataframe was created that does not go through binary encoding and OHE. *‘created_at’, ‘profile_image_url’, ‘profile_background_image_url’, ‘screen_name’* and *‘id’* were dropped from the dataframe for the aforementioned reasons.

To take advantage of built-in missing data handling and XGBoost, CatBoost and LightGBM, the missing values from the dataset were not dealt with. Furthermore, since all three models are tree-based models, they are naturally robust to outliers, so no outlier handling was considered. Scaling is not applied on the numerical features for the same reason.

Feature Engineering

EDA on the training data shows that more Bot accounts do not have descriptions compared to genuine accounts (see Appendix D for graph). To capture this behavior, a binary feature to indicate whether that account has a description as well as a feature that indicates the length of the description were added to capture this behavior.

Domain specific features were added, including but not limited to: Network (log value of friend count multiplied by log value of follower count) and average favourites per tweets (log value of favourite count divided by log value of statuses count). These features help capture meaningful patterns in user behavior and engagement that generic features might miss, enabling the model to better distinguish between different user types or predict target outcomes with improved accuracy.

The dataset was also enriched with 2 features that were the outputs of fine-tuned LLMs. This idea came from the intuition that LLMs can be leveraged to understand the semantic meaning of *‘description’*. *‘bot_prob_from_desc’* is a feature produced by fine-tuning DistilBERT from HuggingFace on the ‘description’ feature using 5-fold cross-validation. Each fold contains a new binary classification model (by adding a classification head to the model) that generates Bot probability predictions on the validation and test set, with final test predictions averaged across all 5 folds to create an ensemble Bot probability score. The idea for this feature came from the concern that the *‘lang’* and *‘location’* features were not represented enough from OHE. *‘bot_desc_from_cat’* is the same implementation of the previous feature, except a json object containing *‘description’, ‘lang’, ‘location’* and *‘screen_name’* (in this order) was passed to the LLM for training. These 2 fine-tuned model features were separately generated and appended to the dataset in the feature engineering step. These features helped improve AUC ROC scores significantly.

2.2 Model Development and Validation

The final models selected were XGBoost, CatBoost and LightGBM. A soft voting ensemble architecture was implemented. Since the data was already split into train and test, the train dataset was further split into test and validation data in an 80-20 split **during the iterative testing phase**. This data is passed to the three models for training. The final ensemble prediction will be calculated by averaging the probabilities from each model before producing a final binary prediction. During the averaging calculations, more weight (XGBoost: CatBoost: LightGBM = 2:1:1) was given to the XGBoost model as it produced the best AUC scores. In the final run of the pipeline, the models were given the full training dataset (instead of only 80% of the train dataset after train and validation split). **This version of the pipeline is the version in the notebook that was submitted.**

Hyperparameter tuning in the form of GridSearch was conducted on XGBoost and CatBoost models with each model having their own parameter grid. Both grids are uniform with a cardinality of 2 to balance between performance and training speed and were executed with a 5-fold cross validation that was sampled using StratifiedKFold to maintain class proportions. Additionally, hyperparameter tuning when fine tuning the LLMs was also conducted. This involved manually tuning the training epochs, warmup steps and learning rate. Different models from HuggingFace were also tested, including a RoBERTa-base model made for sentiment analysis trained on tweets. Eventually, DistilBERT produced the best AUC results when integrated with the main pipeline despite taking shorter to fine-tune.

To ensure models are not overfitted, *'reg_alpha'* and *'reg_lambda'* parameters were included in the Gridsearch for XGBoost and *'l2_leaf_reg'* for CatBoost. Furthermore, AUC scores between train and validation datasets were closely monitored to ensure that excessive divergence was not present. In addition, a good indicator that the model is not overfitted is to monitor submissions AUC scores, as this informs us how well the model is performing on an unseen test dataset.

Efforts to address class imbalance included synthetic oversampling using SMOTE and ADASYN as well as class weighting with *scale_pos_weight,* all of which surprisingly produced poorer results. An explanation for this could be that the interpolation of features by these methods added noise to the data by creating samples that do not reflect real bot behaviour. Furthermore, the gradient boosting tree-based models used in the stack are robust to imbalance and optimise imbalance-agnostic metrics like logloss.

My evaluation approach involved using MLFlow to track AUC, accuracy, precision, recall and F1 scores for each training run and comparing them. The changes for each run was documented and the code executed was saved as an artifact for reference.

2.3 Model Exploration and Final Strategy

Single model architectures were explored, such as Linear Regression and Neural Networks, but through iterative testing of model types, the final model choice was narrowed down to tree-based models. Further testing with ensemble architectures produced better results, so ensemble architectures were adopted.

Firstly, different combinations of models were tested. With the goal to increase generalisability of the final model, diverse models were initially selected, with an ensemble of Logistic Regression, Random Forest and XGBoost being selected. Upon producing disappointing AUC results, I pivoted to using an ensemble of three tree-based models, namely XGBoost, CatBoost and LightGBM. XGBoost consistently produced good results alone, so it was retained. Given the high cardinality of the categorical features, CatBoost was selected next for its ability to handle categorical variables natively without encoding. Finally, LightGBM was chosen for its computational efficiency and leaf-wise tree growth, which provides a complementary learning approach to XGBoost's level-wise splitting. This stack performed much better and was selected as the final stack. Stacking ensemble architecture with various meta models were tested, but produced poorer results than the ensemble architecture.

3. Results and Discussion

The final test AUC score of (see Appendix E for table) shows a 0.01774 (1.91%) improvement over baseline (0.92773) and 0.0127 (1.90%) improvement over my first submission (0.93277) (see Appendix F for graph). Some strengths of my model include the rich feature engineering brought about by leveraging LLMs to extract semantic meaning from the categorical features. The strong AUC score indicates that this model can detect bots accurately and the small gap between validation and test set (0.00883) shows that the model is reasonably general. As for limitations, the categorical feature encoding could be handled in a more sophisticated way. The Recall score indicates that this model is missing about 21% of actual bots, and can be seen to be biased towards Precision. This means the model is more focused on producing fewer false alarms (banning genuine users) than catching all bots. This model behavior can be traced to the classification threshold being 0.5. Depending on the trade off between the cost incurred when bots are allowed to slip through and frustration from users getting falsely banned, the Recall-Precision balance can be adjusted.

4. Conclusion and Reflection

My main takeaways from this project is to start simple and be creative when building ML pipelines. Something that worked well for me was starting with a clean and robust base pipeline as it will serve as a boilerplate to build and iterate on. I also learnt to not be constrained by best practices and to just try alternative methodologies as every dataset is different and requires different processing. Sometimes I would get caught up and would stubbornly proceed in one direction, which slowed me down. For example, I initially decided not to use OHE to encode the categorical features, which led me to stick with other encoding methods. This unknowingly produced inferior results, and it was not until I took a step back to reevaluate my assumptions and methods that I found that OHE actually produced better results. Through building this pipeline, I have come to realise the cat-and-mouse nature of AI driven fraud. While we are feature engineering to detect bots, it is very likely that these bots are also studying what features we are looking out for in order to evade them. In this sense, fraud detection is less about building the perfect model to catch all bots, but rather to maintain pressure on the bots themselves to continually adapt.

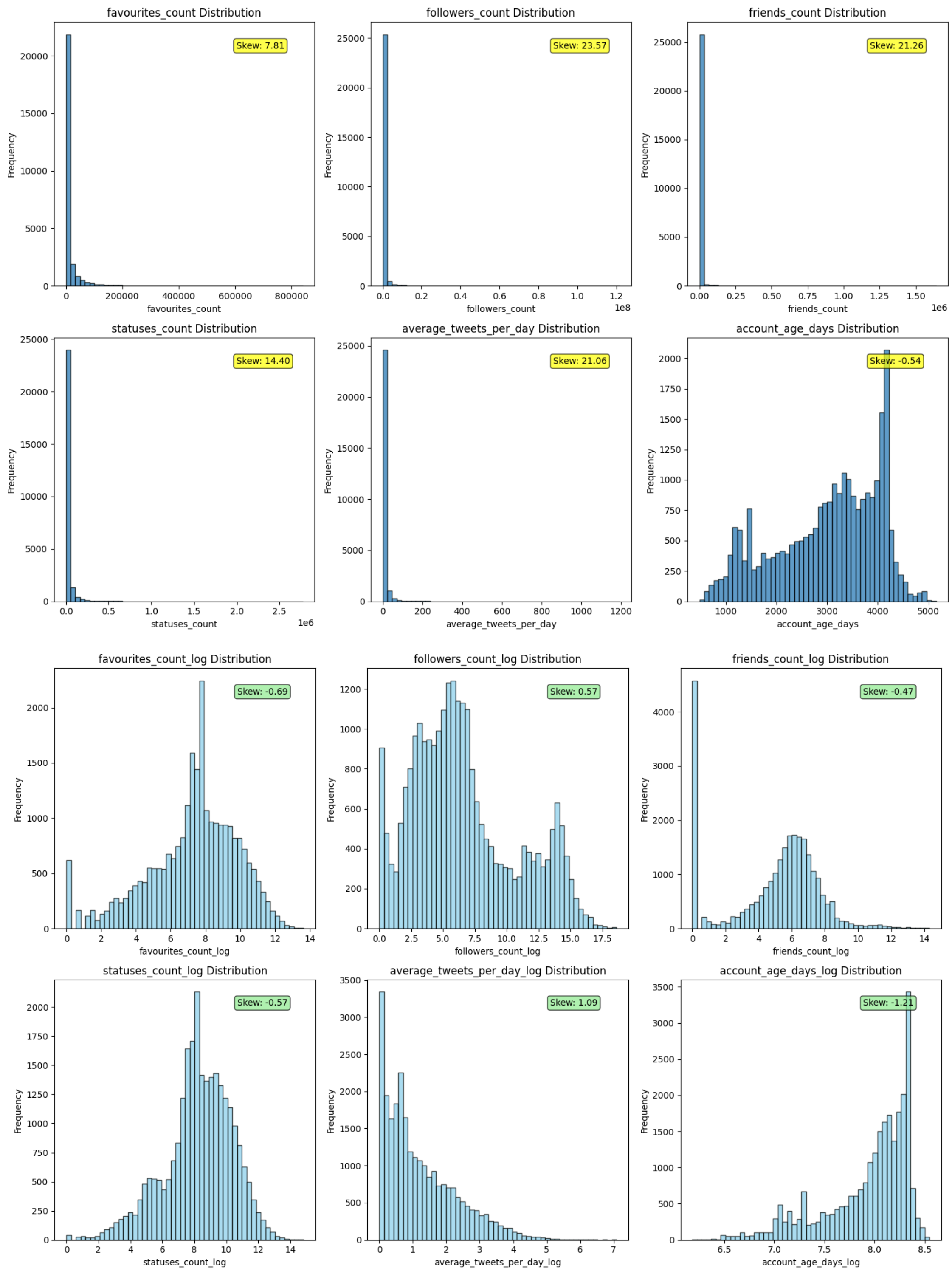
5. Appendix

Appendix A
Features of the dataset

Feature name	Description	Datatype
created_at	The date and time when the Twitter account was created.	numerical (datetime)
default_profile	Indicates whether the user has a default profile settings	categorical (boolean)
default_profile_image	Indicates whether the user has a default profile image.	categorical (boolean)
description	The user's profile description or bio.	categorical (string)
favourites_count	The number of tweets the user has liked.	numerical (integer)
followers_count	The number of followers the user has.	numerical (integer)
friends_count	The number of accounts the user is following.	numerical (integer)
geo_enabled	Indicates whether the user has enabled location services.	categorical (boolean)
id	The unique identifier for the Twitter account.	numerical (integer)
lang (object)	The language preference set for the account.	categorical (string)
location (object)	The location information provided by the user.	categorical (string)
profile_background_image_url	URL of the user's profile background image.	categorical (string)
profile_image_url	URL of the user's profile image.	categorical (string)
screen_name	The user's Twitter handle or username.	categorical (string)
statuses_count	The total number of tweets posted by the user.	numerical (integer)
verified	Indicates whether the account is verified by Twitter.	categorical (boolean)
average_tweets_per_day	The average number of tweets posted per day.	numerical (integer)
account_age_days	The age of the account in days.	numerical (integer)
target	The classification label indicating whether the account is a bot or not. 1 means it is a bot.	numerical (integer)

Appendix B

Dark blue histogram shows before log-transformation and light blue shows after



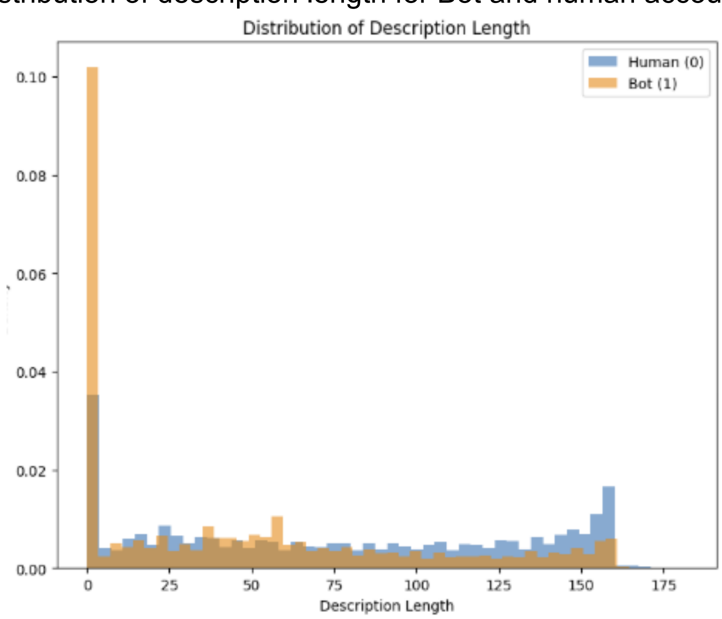
Appendix C

Percentage rows covered by top N categories for 'lang' and 'location'

	Feature	
	lang	location
Categories Covered	% of Rows captured	% of Rows captured
5	85.27	38.73
10	91.31	40.85
15	94.40	42.37
20	96.61	43.62
25	98.26	44.70
30	99.15	45.64
35	99.62	46.42
40	99.86	47.13
48	100.00	48.15

Appendix D

Distribution of description length for Bot and human accounts



Appendix E
Evaluation metrics of final model

Metric	Train dataset score	Validation dataset score	Test (Kaggle) dataset score
AUC	0.9789	0.9528	0.94547
Accuracy	0.9287	0.8932	-
Precision	0.9348	0.8800	-
Recall	0.8464	0.7888	-
F1	0.8884	0.8319	-

Appendix F
Model improvement over attempts