# Applied Machine Learning (COMS 4995)
# Final Project Report (Group 19)

## I. Background

The advent of e-commerce is closely intertwined with the end of the era of many brick-and-mortar stores, thanks to its ability to offer exponentially more products and experiences to users without physical limitations. However, a critical issue plaguing this business is delay in deliveries which leads to negative user experience. Companies that do not act to mitigate delivery problems often experience a decline in sales.

We intend to perform a **delivery delay prediction** for an **e-commerce dataset** by comparing different ML models applied to the dataset to determine which best applies to our problem & associated dataset. Such an application can tremendously help a business gain insight into the problems that may cause this delay by looking at trends and potentially mitigate the causes. We begin by exploring our data thoroughly, followed by selecting and applying ML techniques to the problem of predicting sales volume based on a fairly high dimensional dataset that spans multiple years. Finally, we evaluate the performance of our models and select the best among them.

## II. Exploratory Data Analysis

EDA contains several parts:

1. Initial EDA: This part tries to get some basic insights from the data distribution (categorical data and numerical data), find correlations between features and target label (computed in part X), and has an overall insight of target label in time scale.
2. Data Cleaning:
    a. Missing Value: We first drop *review_comment_title*, *review_comment_message, review_answer_timestamp, product_category_name_english* as we do not plan to handle text data in this project. Since there are very few missing values for all attributes (maximum being 3240 for *order_delivered_customer_date*), we'll drop these rows. Dropping such a miniscule number of rows will have negligible effect on the quality of the data or our predictions.
    b. Drop Columns: *customer_unique_id, order_id, customer_id, product_id, seller_id, review_id,* has nothing to do with final prediction so we drop them; *order_estimated_delivery_date, order_delivered_customer_date, review_creation_date, order_approved_at, order_delivered_carrier_date, shipping_limit_date* are also dropped while *order_purchase_timestamp* is kept to denote the date of purchase. The reason is we cannot have this time before the order is delivered which has no sense to include them for prediction.
3. *Data Pr*eprocessing
    a. Target Generation: **is_delayed** (0-1 value) is the target label we want to predict with 1 means the order is delayed. We compute it by comparing *order_estimated_delivery_date* and *order_delivered_customer_date*, if *order_delivered_customer_date* is later then *order_estimated_delivery_date*, then we denote this order as delayed order with is_delayed=1.
    b. Datetime Processing: *order_purchase_timestamp* is split into year, month, day, and daypart (based on hour), and is_holiday (weekend and black friday (2017-11-24))
    c. Compute Distance: Using *geolocation_lat_x, geolocation_lat_y, geolocation_lng_x, geolocation_lng_y*, we can compute the distance between seller and customer using geopy.distance, then all columns mentioned before is dropped.

    d. Compute Volume: *product_length_cm, product_height_cm, product_width_cm* are multiplied to compute the product volume. Then all columns mentioned above is dropped.
4. Encoding
    a. One-hot encoding: *payment_type* (only 4 types)
    b. Target encoding: *order_status, product_category_name, customer_city, customer_state, seller_city, seller_state, daypart*

## III. Model Building & Experiments

Since our dataset is highly imbalanced, we use some sampling methods to process our data. By investigating several sampling methods, our team found that the stratified and the downsampling method give the best performance on our data. Thus, in the following models, we experimented on both sampling methods before fitting the model to the data. For each model, we split the dataset into dev/test data in 80/20 fashion. We used 10-fold cross validation and picked the best model with the highest F-1 scores.

### Baseline Model: Dummy Classifier

For the dummy classifier, we used different strategies, including *most_frequent*, *prior*, *stratified* and *uniform*, to find the model with best performance as our baseline model. As stated above, we have two models for the dummy classifier. The first one is the dummy classifier trained with stratified preprocessing, resulting in the best f-1 score to be 0.1279 by using the *uniform* strategy. And for the other model, we downsampled the training data before feeding it to the dummy classifier. It turns out that the model with *stratified* strategy has the higher f-1 score of 0.1297. Since we have downsampled the data before training, the *stratified* strategy here would have the same meaning as *uniform* strategy. In general, the result indicates that randomly choosing a prediction will get higher f-1 scores performance than using the *most_frequency*/major label. The result also reflects the fact that our dataset is highly imbalanced.

### Logistic Regression

Feeding unscaled data to our logistic regression (LR) model resulted in our model not converging. Further, because of the high imbalance in the labels of our dataset, we had to employ *class_weight = 'balanced'* in our LR model. When we scaled our data using StandardScaler and fed this data to our model, we were able to get an f-1 score of 0.364 with best hyperparameters as *C = 0.1, penalty = 'l2',* and *solver* = '*newton-cg*' (found using GridSearchCV). Area under the AUC curve is found to be 0.86. Downsampling our data did not lead to much difference in the f-1 score or the best hyperparameters - just that the penalty term changed to *'none'*. Area under the curve also remained the same.

### Support Vector Machine (SVM)

In order for the SVM models to converge, we used the scaled/standardized data as the input. Even though SVM can use different types of kernels to separate the data regardless of the linear separability of the data, the training time would be over 8 hours for each model, which isn't feasible. Thus, we used only the linear SVM in our experiments. As recommended in the official documentation, we turn off the *dual* option as the number of data samples is larger than the number of features. By tuning the hyperparameters of loss functions, regularization parameters and penalty types, we achieved the highest f-1 score of 0.1066 on test data with C as 0.5, *squared_hinge* loss and L1 penalty. The corresponding scores of recall and precision are 0.0573 and 0.7519. As for the best model trained with downsampled data, the scores achieved on test data are 0.3676 on f-1 score, 0.739 on recall and 0.2447 on precision. Since the data is highly imbalanced and nonlinearly separable, the performance on the stratified linear SVM model is even poorer than the baseline model. However, when we perform the downsampled methods to the data before

feeding it to the linear SVM model, the performance gets hugely improved and the corresponding f-1 score is much higher than the baseline performance.

**Random Forest**

We have focussed on finding the best values of two important hyperparameters: 'n_estimators' and *'max_depth'* for building our Random Forest (RF) model. We initially began with giving values near the default value of *n_estimators* (100) for GridSearch. However, it soon became clear that our model was performing better on the maximum value of *n_estimators* till we finally found the optimal value to be 300 for *n_estimators* and 27 for *max_depth* after repeatedly performing GridSearch on a wide range of values. Our f-1 score on the model with best hyperparameters is 0.495. Accuracy for this model is very high ≈ 95%, meaning that our RF model clearly overfit. AUC estimates to be 0.9. Using undersampling, our f-1 score worsens to 0.42, changing the best hyperparameters to 250 for *n_estimators* and 23 for *max_depth*.

**XGBoost**

In the XGBoost training process, we tuned several hyperparameters including *learning_rate*, *n_estimators* and *depth* of the model. For the models training with stratified sampling data, we achieved the best model to have the recall of 0.4349, precision of 0.7904 and the f-1 score to be 0.5611 on test data. The best model has the *learning_rate* to be 0.15, *max_depth* to be 10 and *n_estimator* to be 300. As for the model trained with downsampling preprocess, the best model has *learning_rate* of 0.1, *max_depth* of 10 and 300 *n_estimators.* Feeding the test data into the best model, we can get the recall score of 0.82, precision score of 0.2843 and f-1 score of 0.42. By comparing the two models, the model trained with stratified sampling has better performance. And yet, the XGBoost model with stratified sampling method also achieved the highest f-1 score among all models.

**LightGBM**

By training the LightGBM models, which is another type of boosted tree-based model, we aimed to achieve a relevantly "good" performance with less training time. In the LightGBM models, we looked for the best hyperparameters of *num_leaves, max_depth* and *n_estimators.* For the stratified preprocessed model, the best performance of recall of 0.43, precision of 0.78 and f-1 score of 0.55 was achieved by the model with *max_depth* of 20, *n_estimators* of 300 and *num_leaves* of 127. Meanwhile, the downsampled preprocess model with the same *max_depth* and *num_leaves* with 200 *n_estimators* achieved the recall of 0.82, precision of 0.29 and f-1 score of 0.42. Comparing the result from LightGBM models with the XGBoost models, we can find that they achieved similar results with the downsampled sampling method. But for the models trained with stratified sampling method, XGBoost has a much better performance than LightGBM. However, since the training time used by LightGBM is about half of the time used in XGBoost, we can safely change to using the LightGBM model instead of XGBoos model in a huge dataset to avoid the significant training time.

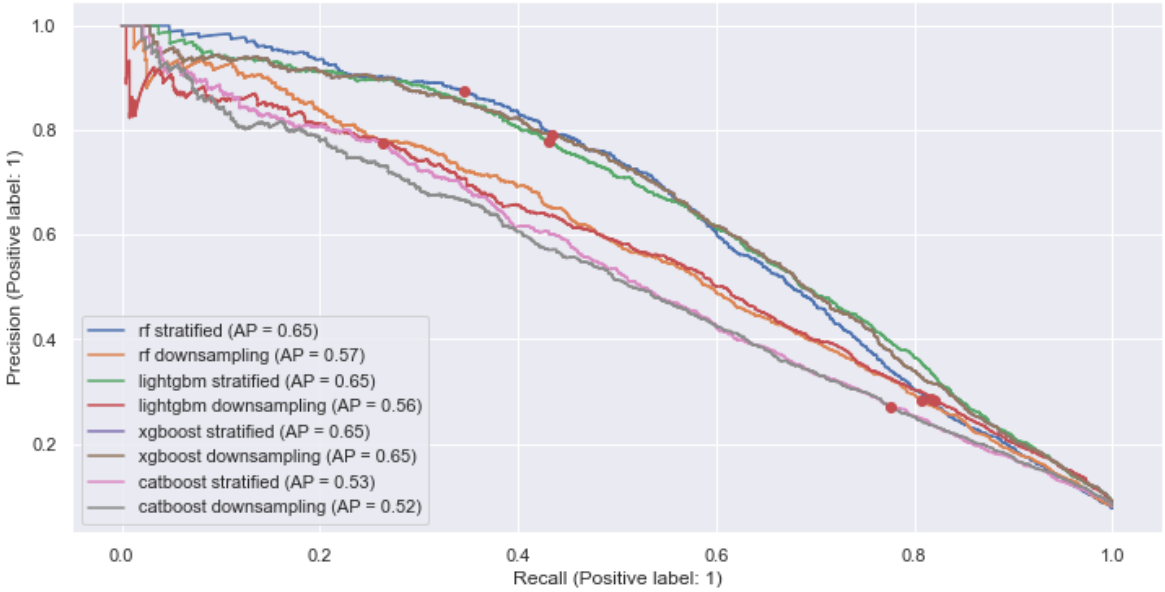
**CatBoost**

In order to train the CatBoost model, we use the encoded dataset. There is no need to use the scaled data because it is a tree based model. The dataset is first split using a stratified split in order to ensure the minority class is properly represented across development and test sets. From there, the *learning_rate*, *n_estimators*, and *max_depth* hyperparameters are tuned using a grid search. The search took approximately one hour and found optimal parameters of *learning_rate*=0.05, *max_depth*=6, and *n_estimators*=100. This tuned model yielded an f1 score of 0.393, precision score of 0.777, recall score of 0.263, and accuracy score of 0.939. The second version of CatBoost was trained on downsampled data. The same hyperparameters of *learning_rate*, *n_estimators*, and *max_depth* were tuned by performing a

grid search on the same range of values. The training took approximately 27 minutes so half as long as the first search on the stratified sampled dataset. The optimal hyperparameters found were *earning_rate*=0.05, *max_depth*=6, and *n_estimators*=100. The tuned model yielded an f1 score of 0.400, precision score of 0.270, recall score of 0.263, and accuracy score of 0.825. Clearly, the model performed significantly better than the dummy model's benchmark and yielded some good results overall.

## IV. Choice of Model

The best model is chosen based on the PR curve. Given *recall=0.8*, lightgbm with stratified sampling achieves better results. The reason why we adopt this strategy is that recall is more important in our prediction as FN (the order is delayed but we predict on-time) is crucial while FP (the order is on-time but we predict delayed) is more acceptable compared with FN.




## V. Conclusion & Future Scope

This project helped us apply the skills and tools we learned during the class. Most important takeaways were:

1. We employed the different data analysis techniques to assess the quality of our data such as checking the distribution, the number of missing values and then worked on improving the quality of our data by eliminating the null values, features that were highly correlated or did not contribute to our label 'is_delayed'.
2. Looking at our use case and the different metrics, we decided which metric suited our use case the best. For all the models, we observe a tremendously high accuracy but we realized that's not the best measure to assess our model. Both precision and recall are equally important for us, so we take its harmonic mean (i.e., the f-1 score) as our metric of comparison.
3. Since our data is highly imbalanced, we used stratified splitting on our data and built different ML models using the best set of hyperparameters for each model found by performing GridSearch.
4. Class imbalance also led to us using Undersampling which means we removed samples from the training dataset that belong to the majority class in order to better balance the class distribution and then evaluated the performance of our models.

In the future, we can extend the scope of this project by training neural networks on our dataset. In addition, we can attempt to get more samples belonging to the class with positive label, if possible.