7. Averaging Model Approach

7.1 Library Imports

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from tqdm import tqdm
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
import xgboost as xgb
from xgboost.sklearn import XGBRegressor
from sklearn.metrics import r2_score
import joblib
import pickle
import warnings
warnings.filterwarnings("ignore")
```

7.2 Data Loading and Preprocessing

In [2]:
```
train = pd.read_csv('train.csv')
print(f"total train datapoints = {len(train)}")
test = pd.read_csv('test.csv')
print(f"total test datapoints = {len(test)}")
```

```
total train datapoints = 4209
total test datapoints = 4209
```

Using LabelEncoder() for encoding categorical features.

In [3]:
```
def preprocess_categorical(data, IDs):
    """
    data : pandas dataframe
    IDs: ID feature
    return: dataframe, labels

    This function takes the dataframe as input,
    encodes the
    categorical features.
    """
    # create empty lists for collecting feature names
    cat_features = []
    Binary_features = []

    # Collect the categorical and binary feature names
    for f in data.columns:
        if data[f].dtype == 'object':
            cat_features.append(f)
        elif data[f].dtype == 'int' and f != 'ID':
            Binary_features.append(f)

    # create categorical feature dataframe
    cat_df = data[cat_features]
    # create binary feature dataframe
    bin_df = data[Binary_features]
    bin_df.insert(0, 'ID', IDs.values)

    # Now encode each categorical feature
    for feature in cat_features:
        encoder = LabelEncoder()
        cat_df[feature] = encoder.fit_transform(cat_df[feature].values)
        filename = f'{feature}encoder.sav'
        joblib.dump(encoder, filename)
    cat_df = pd.DataFrame(cat_df, columns = cat_features)
    cat_df.insert(0, 'ID', IDs.values)
    # Merge binary and categorical dataframes together
    new_data = pd.merge(cat_df, bin_df, on='ID', how='left')
    # return dataframe and labels
    if 'y' in data.columns:
        labels = data['y']
        return new_data, labels
    else:
        return new_data
```

In [4]:
```python
final_train = train.copy()

train_ID = train['ID'].copy()

print(f"{final_train.shape}")
```

```
(4209, 378)
```

In [5]:
```python
final_test = test.copy()

test_ID = test['ID'].copy()

print(f"{final_test.shape}")
```

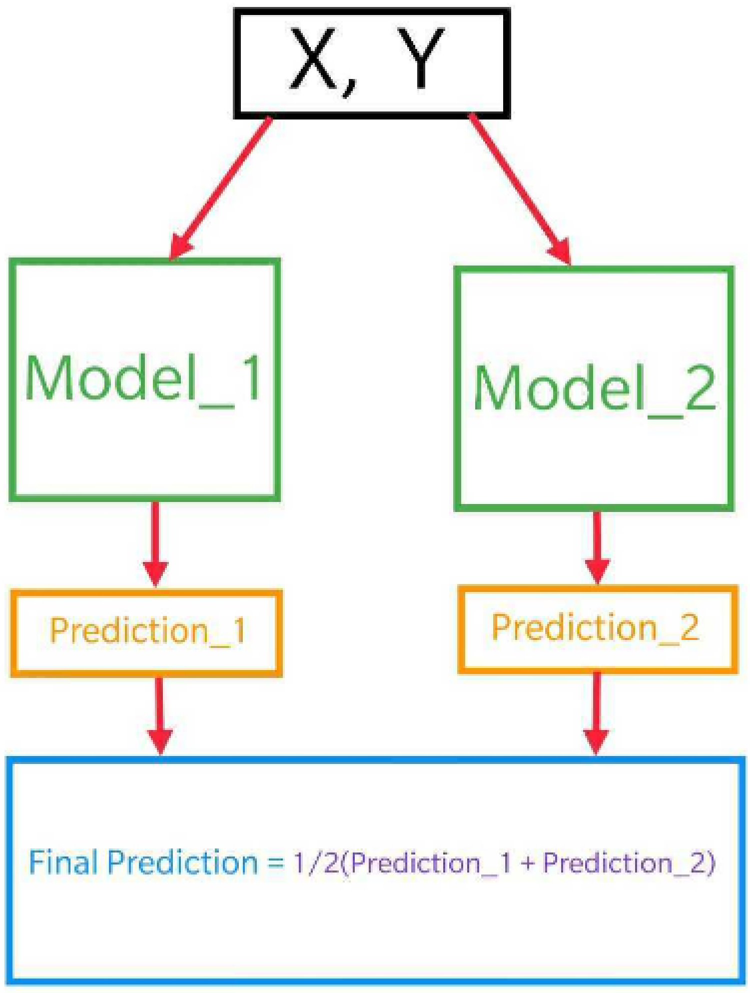
```
(4209, 377)
```

In [6]:
```python
X_train, y_train = preprocess_categorical(final_train, train_ID)
X_test = preprocess_categorical(final_test, test_ID)

print("Train set:")
print(X_train.shape)
print(y_train.shape)
print("Test set:")
print(X_test.shape)
```

```
Train set:
(4209, 377)
(4209,)
Test set:
(4209, 377)
```

7.3 New Averaging Model



- Steps:

1. Create and train model 1 : Xgboost
2. Create and train model 2 : Xgboost
3. Predict values by using trained model 1
4. Predict values by using trained model 2
5. Get average of the values predicted by two models

In [7]:
```python
def averaged_model(X_train,y_train,X_test):
    """
    X_train : train features data
    y_train : train labels
    X_test : test features data
    """

    # get the mean target value
    y_mean = np.mean(y_train)
    # set the seed for reproducing results
    np.random.seed(2)
    # create xgboost model 1 and train it on X_train, y_train
    model_1 = XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=0.7, gamma=3, gpu_id=-1,
             importance_type='gain', interaction_constraints='',
             learning_rate=0.1, max_delta_step=0, max_depth=2,
             min_child_weight=1, monotone_constraints='()',
             n_estimators=100, n_jobs=-1, num_parallel_tree=1, random_state=42,
             reg_alpha=10.0, reg_lambda=1, scale_pos_weight=1, subsample=0.93,
             tree_method='exact', validate_parameters=1, verbosity=None)

    print("Fitting first model...")
    model_1.fit(X_train, y_train)
    # predict target values for train data
    y_tr_pred1 = model_1.predict(X_train)
    # predict target values for test data
    p1 = model_1.predict(X_test)
    # save the model to the disk for future use
    filename = "final_best_model1.pkl"
    model_2 = joblib.dump(model_1, filename)
    print(f'Saved {filename}')
    print("Done.")

    # create parameters list for second xgboost model
    xgb_params = {'eta': 0.0045,
                  'max_depth': 4,
                  'subsample': 0.93,
                  'eval_metric': 'rmse',
                  'base_score': y_mean, # base prediction = mean(target)
                  'colsample_bytree': 0.7,
                  'seed': 2}
    num_boost_rounds = 1250

    # create xgb ready data
    dtrain = xgb.DMatrix(X_train, y_train)
    dtest = xgb.DMatrix(X_test)

    # train xgb model 2
    print("Fitting second model...")
    model_2 = xgb.train(xgb_params, dtrain, num_boost_round=num_boost_rounds)
    # predict target values for train data
    y_tr_pred2 = model_2.predict(dtrain)
    # predict target values for test data
    p2 = model_2.predict(dtest)
    # save the model to the disk for future use
    filename = "final_best_model2.pkl"
    model_2 = joblib.dump(model_2, filename)
    print(f'Saved {filename}')
    print("Done.")

    # average the predictions for train data by both models and calculate the r2_score
    avg_pred = (y_tr_pred1+y_tr_pred2)/2
    print(r2_score(y_train, avg_pred))

    # average the predictions for test data by model 1 and model 2
    final_pred = (p1+p2)/2

    # create pandas series for storing predictions
    pred_test = pd.Series()
    pred_test['y'] = final_pred
    # return the final averaged predictions
    return pred_test['y']
```

In [8]:
```python
final_preds = averaged_model(X_train,y_train,X_test)
```

```
Fitting first model...
Saved final_best_model1.pkl
Done.
Fitting second model...
Saved final_best_model2.pkl
Done.
0.6142291416276575
```

In [9]:
```
submission_Stack = pd.read_csv('sample_submission.csv')
submission_Stack['y'] = final_preds
submission_Stack.to_csv('final-averaged-xgb.csv', index=False)
submission_Stack.head()
```

Out[9]:

	ID	y
0	1	81.276283
1	2	99.784988
2	3	81.343719
3	4	79.509239
4	5	114.750397

Submission and Description	Private Score	Public Score
final-averaged-xgb.csv just now by Harsh Jadhav	0.55179	0.55631

- Train R2 = 0.6142291
- Test Private R2 = 0.55179
- Test Public R2 = 0.55631

8. Model Comparison

In [10]:
```
from prettytable import PrettyTable
# Add Columns
comparison = PrettyTable(["Sr.No.", "Model", "Train", "Kaggle Private", "Kaggle Public"])

# Add rows
comparison.add_row([1,"Knn+Original", "0.58172", "0.43537", "0.4636"])
comparison.add_row([2,"DecisionTree+Original", "0.63128", "0.53732", "0.55129"])
comparison.add_row([3,"DecisionTree+Original+PCA+SVD", "0.61559", "0.53800", "0.55070"])
comparison.add_row([4,"RandomForest+Original", "0.62903", "0.54763", "0.55442"])
comparison.add_row([5,"RandomForest+Original+PCA+SVD", "0.63649", "0.54145", "0.55076"])
comparison.add_row([6,"RandomForest+Original+PCA+SVD\n+GRP+Interactions", "0.65277", "0.54920",
                    "0.54220"])
comparison.add_row([7,"Xgboost+Original+PCA+SVD+GRP\n+Interactions", "0.65518", "0.54682",
                    "0.54759"])
comparison.add_row([8,"Stacked+Original+PCA+SVD+GRP\n+Interactions", "0.65300", "0.55017",
                    "0.55310"])
comparison.add_row([9,"Custom+Original+PCA+SVD+GRP\n+Interactions", "0.279103", "-", "-"])
comparison.add_row([10,"Averaged-xgb+Original","0.614229", "0.55179", "0.55631"])

print(comparison)
```

```
+--------+--------------------------------+----------+----------------+---------------+
| Sr.No. |             Model              |  Train   | Kaggle Private | Kaggle Public |
+--------+--------------------------------+----------+----------------+---------------+
|   1    |          Knn+Original          | 0.58172  |    0.43537     |     0.4636    |
|   2    |     DecisionTree+Original      | 0.63128  |    0.53732     |    0.55129    |
|   3    | DecisionTree+Original+PCA+SVD  | 0.61559  |    0.53800     |    0.55070    |
|   4    |     RandomForest+Original      | 0.62903  |    0.54763     |    0.55442    |
|   5    | RandomForest+Original+PCA+SVD  | 0.63649  |    0.54145     |    0.55076    |
|   6    | RandomForest+Original+PCA+SVD  | 0.65277  |    0.54920     |    0.54220    |
|        |       +GRP+Interactions        |          |                |               |
|   7    |  Xgboost+Original+PCA+SVD+GRP  | 0.65518  |    0.54682     |    0.54759    |
|        |         +Interactions          |          |                |               |
|   8    |  Stacked+Original+PCA+SVD+GRP  | 0.65300  |    0.55017     |    0.55310    |
|        |         +Interactions          |          |                |               |
|   9    |  Custom+Original+PCA+SVD+GRP   | 0.279103 |       -        |       -       |
|        |         +Interactions          |          |                |               |
|   10   |     Averaged-xgb+Original      | 0.614229 |    0.55179     |    0.55631    |
+--------+--------------------------------+----------+----------------+---------------+
```

8. Conclusion

- Averaged model with Original features is performing better than any other models, with score of 0.55179 on private leaderboard and achieves 401th position.

397	▲ 478	Manel Fornos	0.55180	4
398	▼ 231	gh	0.55180	5
399	▼ 186	Akasyanama	0.55180	13
400	▲ 268	ww_ck	0.55180	10
401	▲ 430	JaimeF	0.55179	13
402	▲ 385	Christian Stade-Schuldt	0.55179	1