Introduction to Machine Learning

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Final Project – Report

1. Environment Details

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import csv
import math

from sklearn.linear_model import LogisticRegression, LinearRegression
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.impute import SimpleImputer, KNNImputer
from sklearn.pipeline import make_pipeline
from sklearn.metrics import roc_auc_score, accuracy_score
from sklearn.model_selection import cross_validate, StratifiedKFold

from feature_engine.encoding import WoEEncoder

from colorama import Fore, Back, Style

from joblib import dump
from joblib import load
```

```python
from google.colab import drive
drive.mount('/content/drive')
```

```
[ ] # Requirements #
    # !pip install -r requirements.txt
    # or
    !pip install numpy pandas matplotlib scikit-learn joblib feature_engine colorama
```

Below are all the libraries needed to run the code, you can install the libraries by pip install libraries or simply install the requirements.txt.

2. Implementation Details

a. Train.ipynb

```python
[ ] def impute_null_values(df, features, pcodes):

        # Impute null values in a dataframe using a KNNImputer model #

        # Create KNNImputer model with 15 neighbors
        model = KNNImputer(n_neighbors=15)
        # model = KNNImputer(n_neighbors=3)
        # model = KNNImputer(n_neighbors=5)

        for pcode in pcodes:
            # Get rows of data where product_code is equal to the current value of `pcode`
            mask = df['product_code'] == pcode
            feature_subset = df.loc[mask, features]

            # Calculate the number of null values in the feature subset before imputation
            null_before = feature_subset.isnull().sum().sum()

            # Use the KNN model to impute null values in the feature subset
            imputed = model.fit_transform(feature_subset)

            # Calculate the number of null values in the imputed feature subset
            null_after = pd.isnull(imputed).sum().sum()

            # Calculate the number of null values that were imputed
            null_imputed = null_before - null_after

            # Print a message indicating how many null values were imputed for the current product code
            print(f"Imputing Product Code {pcode}:.... \n -> {null_imputed} null values imputed")

            # Replace the feature subset in the original data with the imputed version
            df.loc[mask, features] = imputed

        return df
```

```python
[ ] train = impute_null_values(train, features, train['product_code'].unique())
    # train.query("m3_missing != 0 and m5_missing != 0").head()
```

```python
# Initialize the Train Path #
# myPATH = "tabular-playground-series-aug-2022"
myPATH = '/content/drive/MyDrive/ML-Final-Project/tabular-playground-series-aug-2022'
train = pd.read_csv(f'{myPATH}/train.csv')

# For Feature Selection #
train2 = pd.DataFrame.copy(train)
if 'failure' in train2:
    target = train2.pop('failure')

print(f'train {train.shape}')
train.head()
```

train (26570, 26)

	id	product_code	loading	attribute_0	attribute_1	attribute_2	attribute_3	measurem
0	0	A	80.10	material_7	material_8	9	5	
1	1	A	84.89	material_7	material_8	9	5	
2	2	A	82.43	material_7	material_8	9	5	
3	3	A	101.07	material_7	material_8	9	5	
4	4	A	188.06	material_7	material_8	9	5	

5 rows × 26 columns

```python
def scale_function(X, cols):
    scaler = StandardScaler()
    #scaler = MinMaxScaler()

    X_scaled = scaler.fit_transform(X[cols])
    X_scaled = pd.DataFrame(X_scaled, columns=cols, index=X.index)
    X_scaled = pd.concat([X.drop(cols, axis=1), X_scaled], axis=1)

    assert len(X) == len(X_scaled)

    return X_scaled
```

As there are null values present in both the training and test datasets, so we need to perform imputation (replacing null values) on the data. One method is to use *KNNImputer* from *sklearn.impute* module. By using the *impute_null_values* function we can impute all the null values and assign it by KNNImputer. After testing with different imputer module and the parameter of nearest neighbor, *KNNImputer* with *n_neighbor* = 15 has the highest accuracy for the model.

As we need to perform feature selection later, scaling the data is an important preprocessing step. Scaling the data ensures that all features are on a similar scale, thus making it easier to compare the importance of different feature. The scale_function will be used when training the model.

i. Training without Feature Selection

```python
def train_model(select_feature, X, y):
    # Initialize lists to store feature importances
    importance_list = []

    # Initialize variables to store average AUC and accuracy scores
    avg_auc = 0
    avg_acc = 0

    # Initialize variables to store OOF AUC and accuracy scores
    oof_auc = 0
    oof_acc = 0

    # Initialize empty arrays to store OOF predictions
    oof_preds_proba = np.zeros(len(X))
    oof_preds = np.zeros(len(X))

    # Define stratified k-fold cross-validation object with 5 splits
    kf = StratifiedKFold(n_splits=5, shuffle=True, random_state=0)

    # Loop through the k-fold splits
    for fold_idx, (train_idx, val_idx) in enumerate(kf.split(X, y)):

        # Split data into training and validation sets
        X_train, X_val = X.iloc[train_idx], X.iloc[val_idx]
        y_train, y_val = y.iloc[train_idx], y.iloc[val_idx]

        # Scale data using the scale_data() function
        X_train_scaled = scale_function(X_train, select_feature)
        X_val_scaled = scale_function(X_val, select_feature)

        # Testing HyperParameters -------------------------------------------------------------
        # Fit logistic regression model on training data
        # model = LogisticRegression(max_iter=1000, C=0.0001, penalty='l2', solver='newton-cg')
        # model = LogisticRegression(C=0.1, penalty='l2', solver='newton-cg', random_state = 0)
        model = LogisticRegression(penalty='l1', C=0.01, solver='liblinear', random_state=1)
        model.fit(X_train_scaled[select_feature], y_train)

        # Make predictions on validation data
        val_preds_proba = model.predict_proba(X_val_scaled[select_feature])[:, 1]
        val_preds = model.predict(X_val_scaled[select_feature])

        # Compute and accumulate AUC and accuracy scores for validation set
        score = roc_auc_score(y_val, val_preds_proba)
        avg_auc += roc_auc_score(y_val, val_preds_proba) / 5
        avg_acc += accuracy_score(y_val, val_preds) / 5

        # Store OOF predictions
        oof_preds_proba[val_idx] = val_preds_proba
        oof_preds[val_idx] = val_preds

        # Append feature importances to lists
        importance_list.append(model.coef_.ravel())

        # Print current fold number
        print(f"Fold {fold_idx}: ROC-AUC = {score:.5f}")

    # Print average AUC and accuracy scores
    print(f"{Fore.GREEN}{Style.BRIGHT}Average auc = {round(avg_auc, 5)}")

    # Compute and print OOF AUC and accuracy scores
    oof_auc = roc_auc_score(y, oof_preds_proba)
    oof_acc = accuracy_score(y, oof_preds)
    print(f"{Fore.BLUE}{Style.BRIGHT}OOF auc = {round(oof_auc, 5)}")

    # Create dataframe of feature importances
    importance_df = pd.DataFrame(np.array(importance_list).T, index=X[select_feature].columns)
    importance_df['mean'] = importance_df.mean(axis=1).abs()
    importance_df['feature'] = X[select_feature].columns
    importance_df = importance_df.sort_values('mean', ascending=False).reset_index().head(10)

    # Plot top 20 features as horizontal bar chart
    plt.figure(figsize=(14,4))
    plt.barh(importance_df.index, importance_df['mean'], color='lightgreen')
    plt.gca().invert_yaxis()
    plt.yticks(ticks=importance_df.index, labels=importance_df['feature'])
    plt.title('Logistic Regression Feature Importances')
    plt.show()

    # Return model
    return model
```

2.1 Training without Feature Selection

```python
# Initial Training without any Feature Selection
X = train.drop(['failure'], axis=1)
y = train['failure'].astype(int)

print(features)
model1 = train_model(features, X, y)
```

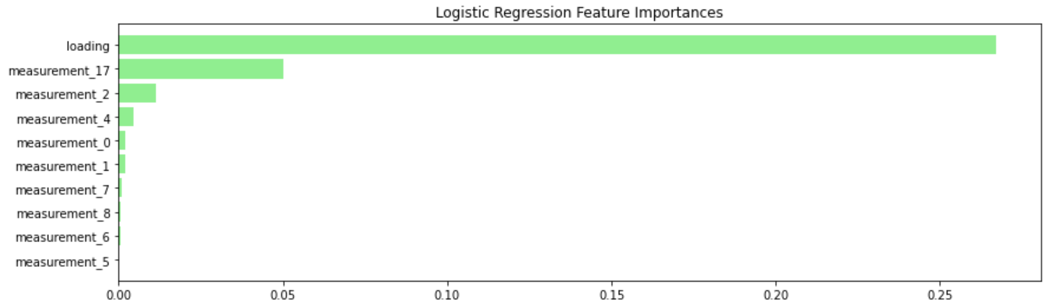
```
['loading', 'measurement_0', 'measurement_1', 'measurement_2', 'measurement_3', 'measurement_4',
Fold 0: ROC-AUC = 0.60100
Fold 1: ROC-AUC = 0.59172
Fold 2: ROC-AUC = 0.58052
Fold 3: ROC-AUC = 0.59276
Fold 4: ROC-AUC = 0.58383
Average auc = 0.58997
OOF auc = 0.58989
```

This *train_model* function is designed to train a logistic regression model on a provided dataset using k-fold cross-validation. The script first splits the data into training and validation sets using a stratified k-fold cross-validation object with 5 splits. This ensures that each fold contains roughly the same proportions of the different classes in the dataset.

It applies feature scaling to the data by using a *scale_function* which scales the data according to the feature selected. A logistic regression model is then fit to the training data with the selected features. After several trials and error with the hyperparameter of the Logistic Regression model, using the *'liblinear'* solver and L1 regularization with a *regularization strength* of 0.01, *random_state*=1 obtained the best result.

Predictions are then made on the validation data, and the area under the receiver operating characteristic (ROC) curve (AUC) and accuracy scores are calculated and accumulated over the 5 folds. The average AUC and accuracy scores are then printed at the end of the script. Additionally, it also stores out-of-fold predictions, which are used to compute out-of-fold AUC and accuracy scores.

Furthermore, the *train_model* function also appends feature importances to lists and creates a dataframe of feature importances sorted by the mean importance of the feature, it prints the top 10 feature importances.



ii. Training with Feature Selection

Now, to improve the model accuracy, we implement Feature Engineering.

2.2 Training with Feature Selection

```
[19] train2['m3_missing'] = train2['measurement_3'].isnull().astype(np.int8)
     train2['m5_missing'] = train2['measurement_5'].isnull().astype(np.int8)

     X_train2 = impute_null_values(train2, features, train2['product_code'].unique())

     Imputing Product Code A:....
      -> 3849 null values imputed
     Imputing Product Code B:....
      -> 3975 null values imputed
     Imputing Product Code C:....
      -> 4344 null values imputed
     Imputing Product Code D:....
      -> 3973 null values imputed
     Imputing Product Code E:....
      -> 4132 null values imputed
```

```
[21] # Encoding for attribute_0 using WoEEncoder #
     woe_encoder = WoEEncoder(variables=['attribute_0'])
     woe_encoder.fit(X_train2, target)

     X_train2 = woe_encoder.transform(X_train2)
     # X_test2 = woe_encoder.transform(X_test2)
```

```
print(X_train2.columns)
model2 = train_model(optimized_features, X_train2, target)

Index(['id', 'product_code', 'loading', 'attribute_0', 'attribute_1',
       'attribute_2', 'attribute_3', 'measurement_0', 'measurement_1',
       'measurement_2', 'measurement_3', 'measurement_4', 'measurement_5',
       'measurement_6', 'measurement_7', 'measurement_8', 'measurement_9',
       'measurement_10', 'measurement_11', 'measurement_12', 'measurement_13',
       'measurement_14', 'measurement_15', 'measurement_16', 'measurement_17',
       'm3_missing', 'm5_missing', 'measurement(3*5)', 'missing(3*5)', 'area'],
      dtype='object')
Fold 0: ROC-AUC = 0.60033
Fold 1: ROC-AUC = 0.59179
Fold 2: ROC-AUC = 0.58138
Fold 3: ROC-AUC = 0.59186
Fold 4: ROC-AUC = 0.58482
Average auc = 0.59003
OOF auc = 0.58998
```

```
# Important Feature Engineering #
X_train2['measurement(3*5)'] = X_train2['measurement_3'] * X_train2['measurement_5']
X_train2['missing(3*5)'] = X_train2['m5_missing'] * X_train2['m3_missing']
X_train2['area'] = X_train2['attribute_2'] * X_train2['attribute_3']

X_train2[['area', 'm3_missing', 'm5_missing', 'missing(3*5)', 'measurement_3', 'measurement_5', 'measurement(3*5)']].query("m3_missing != 0 and m5_missing != 0").head()
```

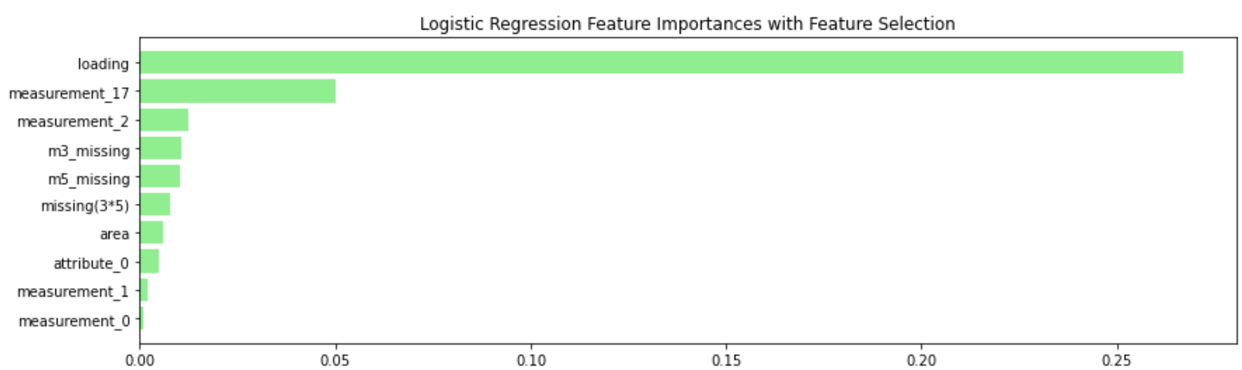
```
[23] optimized_features = [
         'loading',
         'attribute_0',
         'area',
         'measurement_17',
         'measurement_0',
         'measurement_1',
         'measurement_2',
         'm3_missing',
         'm5_missing',
         'measurement(3*5)',
         'missing(3*5)'
     ]
```

The above code utilizes feature engineering to select a subset of the available features for training the logistic regression model. The selected features are listed in the optimized_features list and include various measurements, attributes, and calculated values. The process of selecting these features likely involved analyzing the feature importance of the model trained with all available features, as well as researching and implementing additional features based on analysis of feature correlations and discussion on Kaggle. Breakdown of the features:

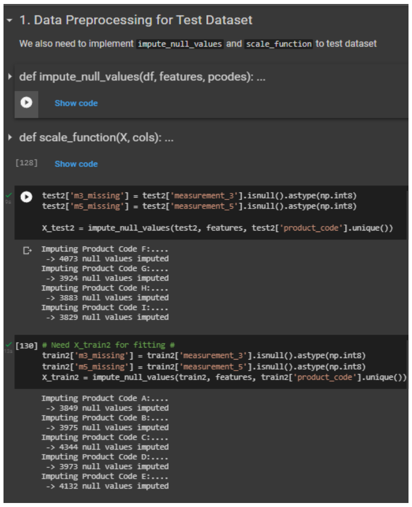
1. Analyzing the feature importance from training the model will all features, we pick the top features loading, measurement 0 - 2 (integer distribution), and measurement 17(float distribution) among the other features.

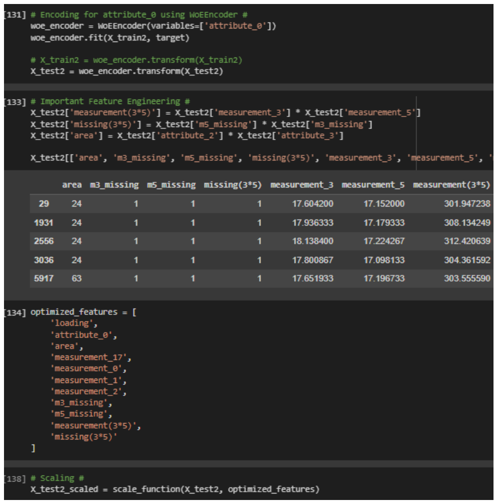
2. Researching a lot of kaggle discussions about feature correlations and EDA analysis, we create the features:
   - *attribute_0*
   - *area*
   - *m3_missing*
   - *m5_missing*
   - *measurement(3*5)*
   - *missing(3*5)*

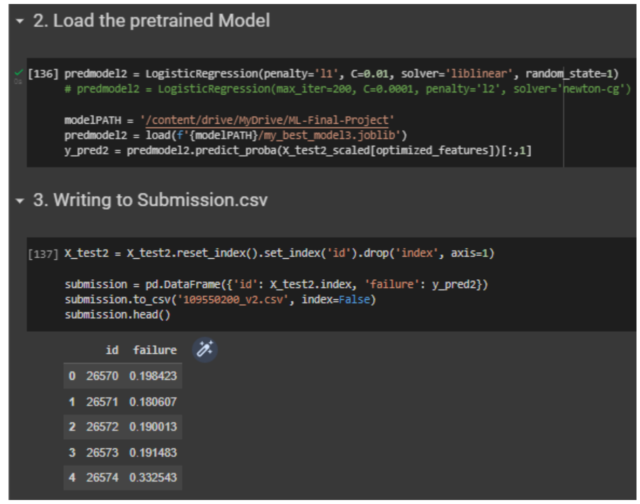
   a) *attribute_0* contains string value that represent categorical features that should be one-hot-encoded
   b) *area* is obtained by multiplying attribute_2 and attribute_3 with the assumption that these data might represent the dimensions (width * length)
   c) *m3_missing* and *m5_missing* is based on this discussion https://www.kaggle.com/competitions/tabular-playground-series-aug-2022/discussion/342319
   d) *measurement(3*5)* and *missing(3*5)* is based on this discussion https://www.kaggle.com/competitions/tabular-playground-series-aug-2022/discussion/343368



b. Inference.ipynb





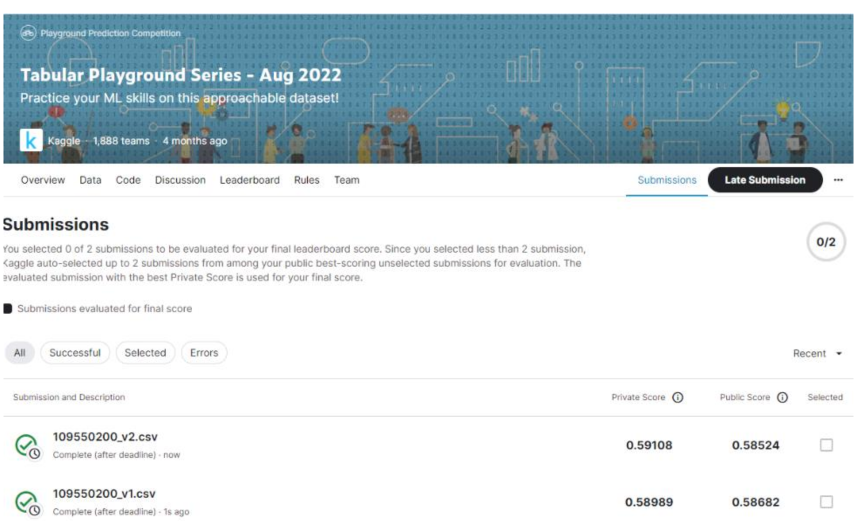


In order to use the trained model to make predictions, the test dataset must first be preprocessed to ensure that it is in the same format as the training data. This includes imputing any null values, selecting the same features as those used in the training data, and scaling the data using the selected features.

Then, load the pre-trained model from a file, which has been trained and saved from the previous process, in this case *my_best_model3.joblib*. Use the loaded model to predict the test data, it will output the predicted classes or probabilities of the test dataset. Finally writing the prediction to the submission.csv

3. Final Result

Github Link : https://github.com/NicoA07/MachineLearning-FinalProject
Model Weight Link: https://github.com/NicoA07/MachineLearning-FinalProject/blob/main/my_best_model3.joblib



Reference:

https://www.kaggle.com/competitions/tabular-playground-series-aug-2022/discussion/349299
https://www.kaggle.com/competitions/tabular-playground-series-aug-2022/discussion/343960
https://www.kaggle.com/competitions/tabular-playground-series-aug-2022/discussion/349541
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