ML Final Project Report - 109550175

0. Github link of my final project :

Github repo : https://github.com/za970120604/NYCU-2022-fall-ML-final-project

Link to logistic regression model weight : https://github.com/za970120604/NYCU-2022-fall-ML-final-project/blob/main/ML%20final%20project/Logistic%20Regression%20model%20weight/logistic.joblib

Link to NN model weight : https://github.com/za970120604/NYCU-2022-fall-ML-final-project/blob/main/ML%20final%20project/Neural%20Network%20model%20weight/NN.h5

1. Brief introduction :

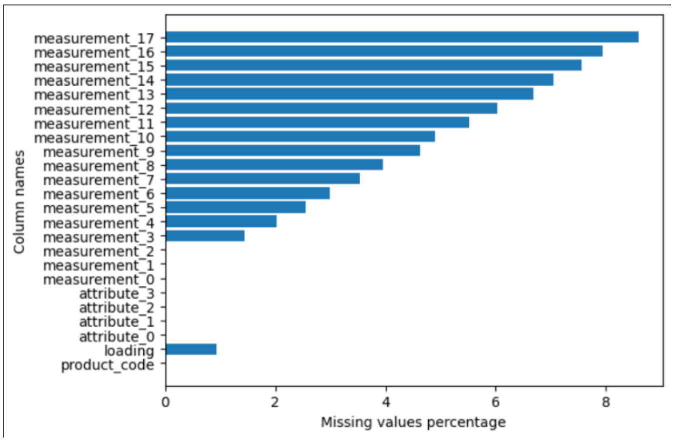
My method is based on simple Logistic-Regression model and some feature engineering method proposed by both other Kaggle competitior and me .

After doing the Grid Search for trying every possible combination of feature engineering and fine tune the model hyperparameter , this model can get a 0.59155 private score.

I also try a model based on Neural-Network and apply the same Grid Search process performed on Logistic-Regression based model , but the performance is not so well , only get a 0.58833 private score.

2. The first-step , a quick look into the dataset :

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26570 entries, 0 to 26569
Data columns (total 24 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   product_code    26570 non-null  object
 1   loading         26320 non-null  float64
 2   attribute_0     26570 non-null  object
 3   attribute_1     26570 non-null  object
 4   attribute_2     26570 non-null  int64
 5   attribute_3     26570 non-null  int64
 6   measurement_0   26570 non-null  int64
 7   measurement_1   26570 non-null  int64
 8   measurement_2   26570 non-null  int64
 9   measurement_3   26189 non-null  float64
 10  measurement_4   26032 non-null  float64
 11  measurement_5   25894 non-null  float64
 12  measurement_6   25774 non-null  float64
 13  measurement_7   25633 non-null  float64
 14  measurement_8   25522 non-null  float64
 15  measurement_9   25343 non-null  float64
 16  measurement_10  25270 non-null  float64
 17  measurement_11  25102 non-null  float64
 18  measurement_12  24969 non-null  float64
 19  measurement_13  24796 non-null  float64
...
 23  measurement_17  24286 non-null  float64
dtypes: float64(16), int64(5), object(3)
```



The above 2 figure shows the attribute of this dataset(after dropping out “id” and “failure” columns) : the left one tells us that there are some “categorical” columns whose “Dtype” are labeled as “object” ; the right one tells us that there are quite a lot missing value in these columns , which means that a reasonable way to fill in these NaN blocks can help model perform well , and fortunately all categorical columns have no missing values , which saves our life.

3. A closer look into this dataset and derive some feature enginnering ideas :

feature		fail		miss		failure rate	z	p-value
loading	:	44	/	250	=	0.176	-1.41	0.157
measurement_3	:	61	/	381	=	0.160	-2.50	0.012
measurement_4	:	128	/	538	=	0.238	1.43	0.151
measurement_5	:	172	/	676	=	0.254	2.66	0.008
measurement_6	:	171	/	796	=	0.215	0.15	0.879
measurement_7	:	197	/	937	=	0.210	-0.18	0.860
measurement_8	:	218	/	1048	=	0.208	-0.36	0.716
measurement_9	:	283	/	1227	=	0.231	1.54	0.123
measurement_10	:	277	/	1300	=	0.213	0.04	0.967
measurement_11	:	311	/	1468	=	0.212	-0.07	0.944
measurement_12	:	356	/	1601	=	0.222	0.95	0.340
measurement_13	:	373	/	1774	=	0.210	-0.24	0.809
measurement_14	:	413	/	1874	=	0.220	0.82	0.411
measurement_15	:	430	/	2009	=	0.214	0.16	0.876
measurement_16	:	436	/	2110	=	0.207	-0.67	0.502
measurement_17	:	499	/	2284	=	0.218	0.69	0.493

A missing feature might be the indicator of failure . As shown in above :
When measurement_3 is missing, failure rate is 0.160 (much lower than average).
When measurement_5 is missing, failure rate is 0.254 (much higher than average).
Not only considering the failure rate , these 2 columns have abs(z) > 2.5 ; p-value < 2 % . It is sufficient to tell us that :
P(failure rates | missing measurement_3) and
P(failure rates | missing measurement_5)
have a huge deviation when comparing to average failure rates , so we can consider adding 2 columns in the code :

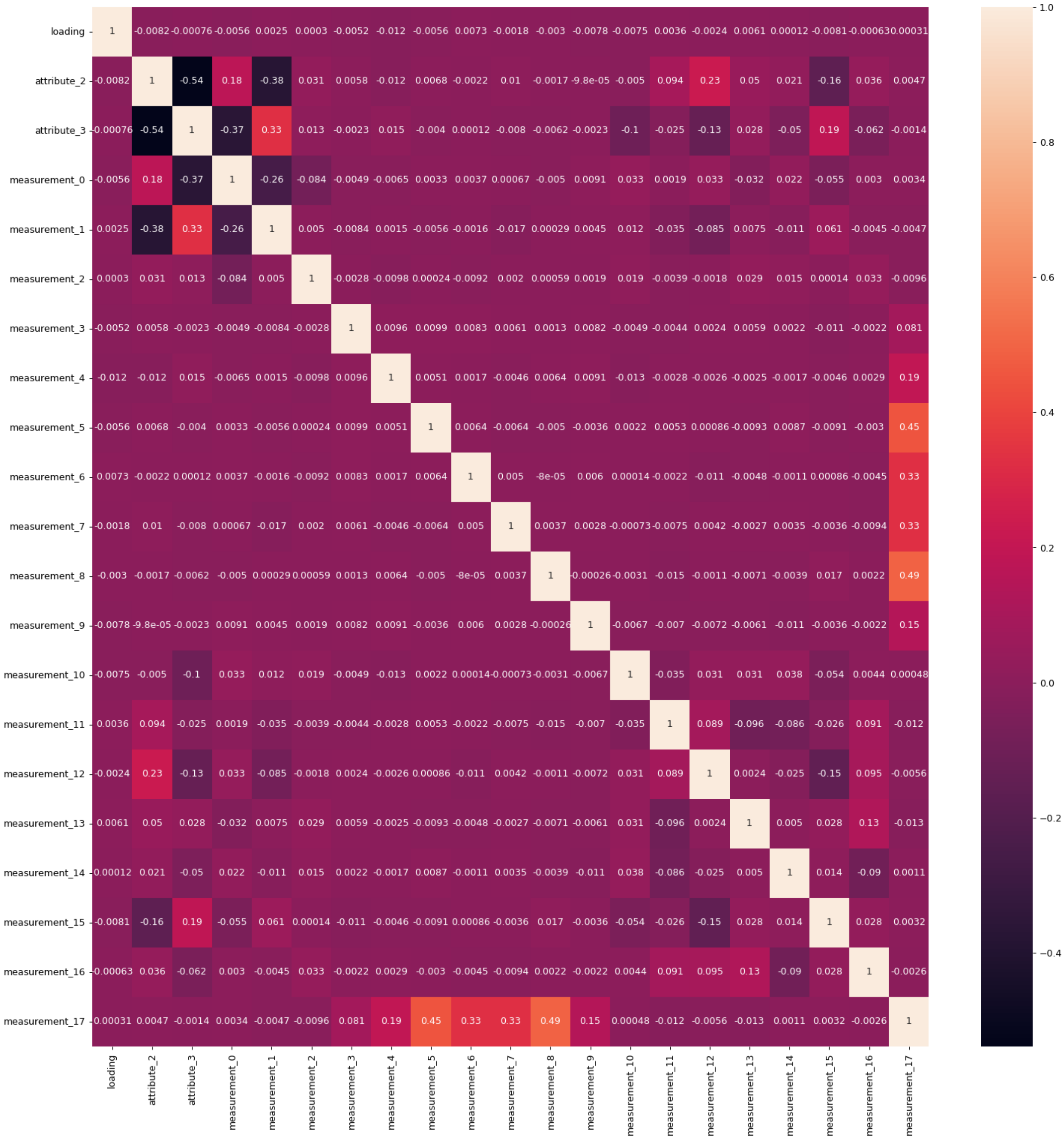
```
train_df['m_3_missing'] = train_df.measurement_3.isna()

train_df['m_5_missing'] = train_df.measurement_5.isna()
```

cited : https://www.kaggle.com/code/ambrosm/tpsaug22-eda-which-makes-sense/notebook

```
attribute_2
6    10455
5     5765
8     5250
9     5100
Name: attribute_2, dtype: int64
attribute_3
8    11015
9     5343
6     5112
5     5100
Name: attribute_3, dtype: int64
product_code
C    5765
E    5343
B    5250
D    5112
A    5100
Name: product_code, dtype: int64
attribute_0
material_7    21320
material_5     5250
Name: attribute_0, dtype: int64
attribute_1
material_8    10865
material_5    10362
material_6     5343
Name: attribute_1, dtype: int64
```

Another feature engineering idea is that : although the dataset only gives us 3 categorical columns : product_code , attribute_0 and attribute_1 , but we can observed that attribute_2 and attribute_3 only have 4 unique values , so we can see both of them as categorical columns for the future imputation procedure.



Last but not least , after we printing out the correlations among different features using heatmap , we can see that attribute_2 and attribute_3 have higher negative correlation with other columns , so we can try to eliminate them to avoid the well known issue in machine learning data preprocessing : “problem of collinearity”

4. Different model

```python
def data_preprocessing(new_df , numerical_col , categorical_col):
    nn = []
    cc = []
    for f in new_df.columns:
        if f in numerical_col:
            nn.append(f)
        else:
            cc.append(f)
    # print(nn)
    # print(cc)
    numerical_pipe = Pipeline([
        ('impute', SimpleImputer()),
        ('scale', MinMaxScaler()),
    ])
    categorical_pipe = Pipeline([
        ('encode', OrdinalEncoder())
    ])
    preprocessor = ColumnTransformer([
        ('numeric', numerical_pipe, nn),
        ('categorical', categorical_pipe, cc),
    ])
    return preprocessor
```

Before trying different model , we need to impute the missing value in the dataset and scale them in order to make every block in the dataset contribute the same. In this project I use SimpleImputer() and MinMaxScaler() for numerical columns , and OrdinalEncoder() for categorical columns(Note that I mentioned that we can try to see attribute_2 and attribute_3 as categorical column , and they also don’t have missing value just as the original categorical column product_code , attribute_0 and attribute_1 , so we don’t need imputer in the categorical pipeline).

```python
def feature_engineering(df , num_col , cat_col , try_add_m3m5_missing , try_self_defined_columns , try_drop_attr2 , try_drop_attr3):
    df_modified = df.copy()
    if try_add_m3m5_missing == True:
        df_modified['m_3_missing'] = df_modified.measurement_3.isna()
        df_modified['m_5_missing'] = df_modified.measurement_5.isna()
        cat_col = cat_col + ["m_3_missing" , "m_5_missing"]
    if try_drop_attr2 == True :
        df_modified = df_modified.drop(["attribute_2"] , axis = 1)
        num_col = list(set(num_col) - set(["attribute_2"]))
    if try_drop_attr3 == True :
        df_modified = df_modified.drop(["attribute_3"] , axis = 1)
        num_col = list(set(num_col) - set(["attribute_3"]))
    if try_self_defined_columns == True and try_drop_attr2 == False and try_drop_attr3 == False:
        cat_col = cat_col + ["attribute_2" , "attribute_3"]
        num_col = list(set(num_col) - set(["attribute_2" , "attribute_3"]))

    return df_modified , num_col , cat_col
```

And the above code is for feature engineering ,
“try_add_m3m5_missing” is whether to add 2 additional columns (m_3_missng and m_5_missing)to the original dataframe.
“try_self_defined_columns” is whether to see attribute_2 and attribute_3 as categorical columns.
“try_drop_attrX” is whether to drop attribute_X in the original dataset for training.
I’ll run a big 2*4 for loop for feature engineering Grid Search and submit all these result to Kaggle and pick the best private scored one for every model.

Method 1 : Logistic-Regression based

```python
import joblib
y = label_df.values
for try_add_m3m5_missing in [True , False]:
    for try_self_defined_columns in [True , False]:
        for try_drop_attr2 in [True , False]:
            for try_drop_attr3 in [True , False]:
                # Train
                new_train_df , num_col , cat_col = feature_engineering(train_df , numerical_columns ,
                categorical_columns , try_add_m3m5_missing , try_self_defined_columns , try_drop_attr2 , try_drop_attr3)
                # print(num_col)
                # print(cat_col)
                preprocessor = data_preprocessing(new_train_df , num_col , cat_col)
                preprocessed_new_train = preprocessor.fit_transform(new_train_df)
                # print(np.argwhere(np.isnan(preprocessed_new_train)))
                model = LogisticRegression(**{'penalty': 'l1', 'tol': 0.031674753150821515, 'C': 0.1,
                'fit_intercept': True, 'solver': 'saga', 'max_iter': 2200})
                model.fit(preprocessed_new_train , y)
                joblib.dump(model , "logistic.joblib")
```

The above hyper parameter for model itself is the fine tuned one , and the best feature engineering parameter is “all True”

Submission and Description	Private Score	Public Score	Selected
109550175.csv Complete (after deadline) · now	0.59155	0.5844	

Method 2 : NN based

```python
y = label_df.values
for try_add_m3m5_missing in [True , False]:
    for try_self_defined_columns in [True , False]:
        for try_drop_attr2 in [True , False]:
            for try_drop_attr3 in [True , False]:
                # Train
                new_train_df , num_col , cat_col = feature_engineering(train_df , numerical_columns ,
                categorical_columns , try_add_m3m5_missing , try_self_defined_columns , try_drop_attr2 , try_drop_attr3)
                preprocessor = data_preprocessing(new_train_df , num_col , cat_col)
                preprocessed_new_train = preprocessor.fit_transform(new_train_df)
                # print(np.argwhere(np.isnan(preprocessed_new_train)))
                model = keras.Sequential([
                    layers.Dense(32, input_shape=[preprocessed_new_train.shape[1]] , activation='swish'),
                    layers.Dropout(0.2),
                    layers.Dense(32, activation='swish'),
                    layers.Dropout(0.2),
                    layers.Dense(1, activation='sigmoid'),
                ])
                model.compile(
                    optimizer = tf.keras.optimizers.Adam(),
                    loss='binary_crossentropy',
                    metrics=[keras.metrics.AUC(name = 'auc')],
                )
                early_stopping = keras.callbacks.EarlyStopping(
                    patience=5,
                    min_delta=0.001,
                    restore_best_weights=True,
                )
                model.fit(
                    preprocessed_new_train, y,
                    batch_size = 128 ,
                    epochs=200,
                    callbacks=[early_stopping],
                    verbose = 0
                )
                model.save('NN_model.h5')
```

The above hyper parameter for model itself is the fine tuned one , and the best feature engineering parameter is “all True , without try_self_defined_columns”

Submission and Description	Private Score	Public Score	Selected
109550175_tryNN.csv Complete (after deadline) · now	0.58833	0.5829	

After tons of times of trial and error , I figure out that the more complicated NN structure won’t lead to higher private score , 2 or 3 layers is enough .

5. Abalation studies regarding feature engineering

Submission and Description	Private Score	Public Score	Selected
check.csv Complete (after deadline) · now	0.5888	0.58331	☐
check.csv Complete (after deadline) · 1m ago	0.59062	0.58342	☐
check.csv Complete (after deadline) · 2m ago	0.5897	0.58353	☐
check.csv Complete (after deadline) · 2m ago	0.59004	0.58372	☐
check.csv Complete (after deadline) · 3m ago	0.58989	0.58317	☐
check.csv Complete (after deadline) · 4m ago	0.59008	0.58347	☐

Below is 6 submissions without feature engineering(in the Grid Search for loop all 4 parameters set to False), which has an average of 0.589855 . So it shows that the feature engineering proposed above indeed does some improvement .

6. Summary :

This seemingly complicated dataset can be solved by a simple logistic regression with a not bad answer surprisingly , and as refer to my previous experience the more complicated neural network architecture doesn't yield better result , with 2 or 3 levels is good enough. And I think the most valuable part of this project is that I figure out some reasonable feature engineering that actually help my score , and also my patient about spending such a long time on adjusting the hyperparameter. After finishing this project , I feel a great sense of accomplishment because this is the first Kaggle project I do it from scratch with a complete data preprocessing , feature engineering , model selection and fine tuning stages. This experience significantly enhace my enthusiasm to doing ML-related job.