Report

November 12, 2023

1 Wealthfront Data Science Assignment

1.1 SETUP

You work for a lending company that provides small loans to individual borrowers for 3 or 5 years. The company has collected data on the loans granted in the past few years. Your responsibility is to conduct an analysis of the data and retrieve key data insights as described below. Dataset Description: All the data you need is in the attached CSV file. This table contains the following fields:

- row_id - A unique id for the row
- customer_id - A unique id for the loan borrower
- loan_amount - The amount of the loan requested by the borrower
- funded_amount - The amount of the loan that was actually provided to the borrower
- term - The term of the loan
- interest_rate - The interest rate for the loan
- installment - The monthly payment
- emp_length - Borrower's length of employment at their last job
- home_owner - Borrower's home ownership status
- annual_income - Borrower's annual income
- loan_status - Status of the loan
- purchase - Purpose of the loan
- addr_state - Borrower's state of residence
- dti - Borrower's debt to income ratio
- delinq_2yrs - The frequency of the borrower's credit delinquencies in the last 2 years
- earliest_cr_line - The date the borrower started his/her first credit line (credit card, etc.)
- months_since_last_delinq - The number of months since the borrower was last delinquent on a payment
- open_acc - The number of the borrower's open credit accounts
- revol_bal - The borrower's credit card (i.e. revolving credit line) balance

- total_accounts - The number of the borrower's total credit accounts
- outstanding_principal - Outstanding principal of the loan
- total_payment - Total payment on the loan so far
- total_received_principal - Total principal payments received on the loan so far
- total_received_interest - Total interest payments received on the loan so far

1.2 Tasks:

- Implement one or more models to predict whether a loan will be "good" or "bad"
- Assess the performance of your models, using statistics or charts as necessary
- Discuss the implications of your work and any insights you have uncovered

1.3 Deliverables:

- Report: A summary report of your methodology and findings, including both text and graphs. Maximum 2 pages (excluding figures and tables)
- Code: The code you wrote to conduct the analysis via a public github link (preferred) or plain text files via attachment

2 Supervised Learning

2.1 Introduction

The purpose of this analysis is to use the available data to predict whether a loan will be *good* or *bad*. After removing missing values, column *loan_status* has seven categories, including *Current*, *Fully Paid*, *In Grace Period*, *Late (31-120 days)*, *Late (16-30 days)*, *Charged Off*, and *Default*. Categories *Fully Paid*, *Charged Off*, and *Default* are the only categories where the end result of a loan is determined. Loans from other categories are still in the middle of their lifetime. In order to group loans into two sections of *good* and *bad*, we assume any loan in categories *Late (31-120 days)*, *Late (16-30 days)*, *Charged Off*, and *Default* is bad. Accordingly, we create a binary variable called *loan_failure* which encompasses this information. With this approach %4.23 of the loans in our data is assumed to be *bad*.

Another assumption that we make here is that we assume we want to make predictions on loans at the beginning of the loan course, where no repayment data is available. This assumption would limit the features that we can use in our predictive model. For instance, variables such as *total_pymnt*, *total_rec_prncp* and *total_rec_int* are not accessible when the course of the loan has not started yet.

2.2 Data Preparation

After investigating the data visually, we run a set of data cleaning and feature engineering. For example, we categorize the *mths_since_last_delinq* column and also we create a new feature called *income_to_inst* which is the ratio of annual income to the monthly payment for each customer.

2.3 Feature Selection

We use the Boruta algorithm in the shap-hypetune package to select important features for our task. This algorithm consists of 4 steps:

- Firstly, it adds randomness to the given data set by creating shuffled copies of all features (called shadow features).
- Then, it trains a classifier on the extended data set and applies a feature importance measure to evaluate the importance of each feature where higher means more important
- At every iteration, it checks whether a real feature has a higher importance than the best of its shadow features and constantly removes features that are deemed highly unimportant.
- Finally, the algorithm stops either when all features gets confirmed or rejected or it reaches a specified limit of runs.

Out of 19 features, this algorithm selects 14 of them and we will include them in our model.

2.4 Hyper-parameter Tuning:

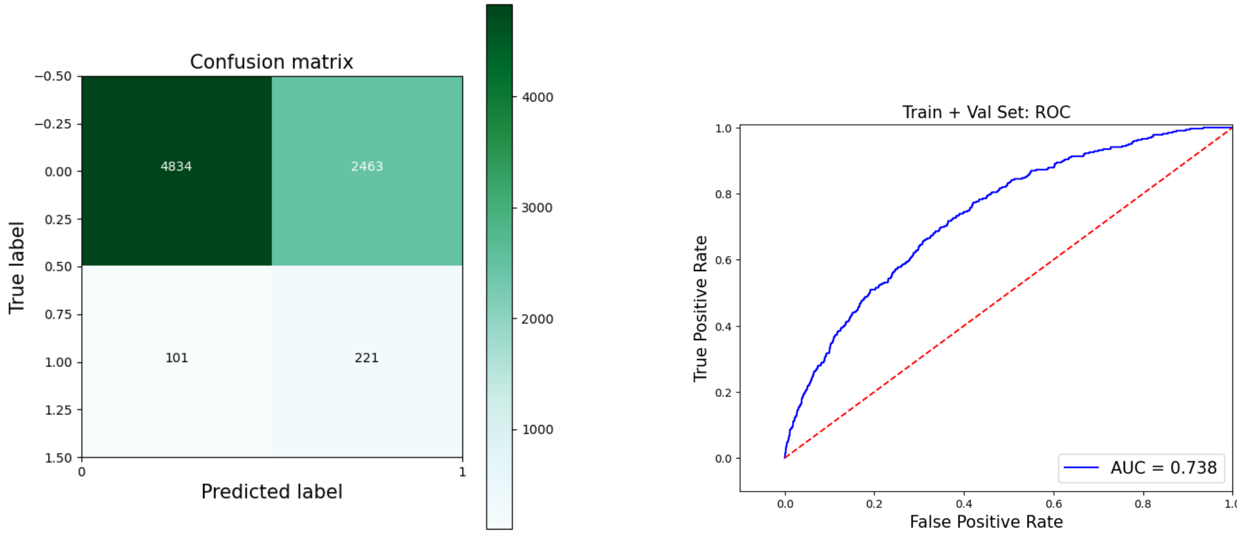
We decided to use a GBM model using the lighgbm package to build our predictive model. In order to find the best set of hyper-parameters, we use the Bayesian optimization available in the optuna package, while optimizing our search over a higher F1 score, assuming that predicting both classes correctly is important. We also take into account the unbalanced nature of the data.

2.5 Model Evaluation:

In order to assess the model's performance, we look at various metrics including AUC, accuracy, precision, recall, and F1 score on our test data.

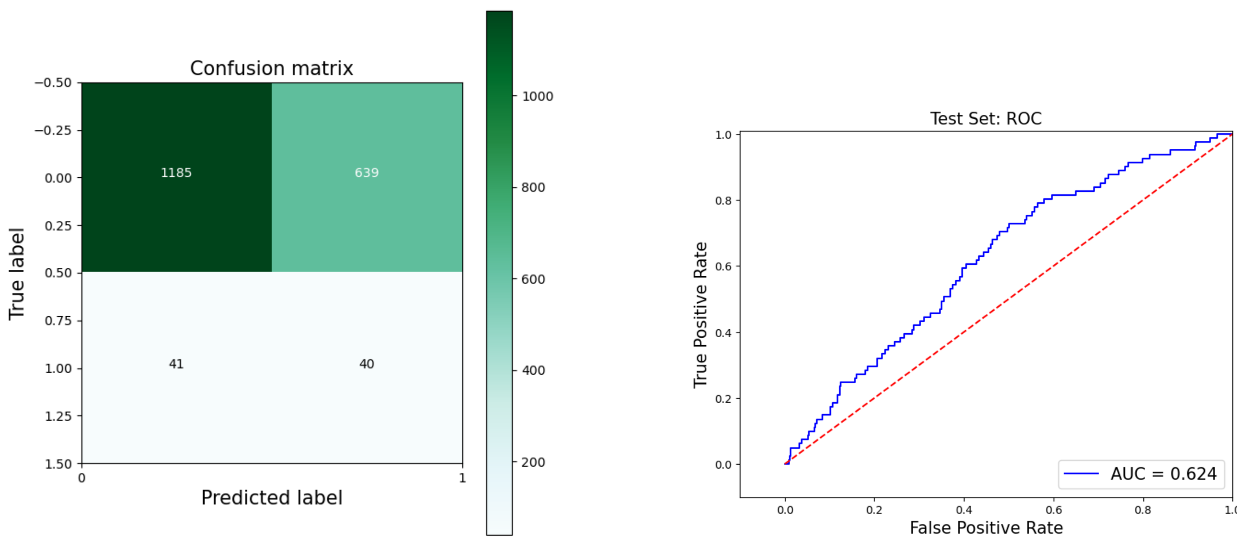
[29]:
```
perf_analysis(model = gbm_model, data = train_val_df, features =␣
↪features_impo_bor, y_var = y_var, which_data = 'Train + Val Set')
```

```
************** Performance: Train + Val Set ****************
Accuracy: 0.66, Precision: 0.08, Recall: 0.69, F1: 0.15
```




```
[30]: perf_analysis(model = gbm_model, data = test_df, features = features_impo_bor,␣
      ↪y_var = y_var, which_data = 'Test Set')
```

```
************** Performance: Test Set ***************
Accuracy: 0.64, Precision: 0.06, Recall: 0.49, F1: 0.11
```

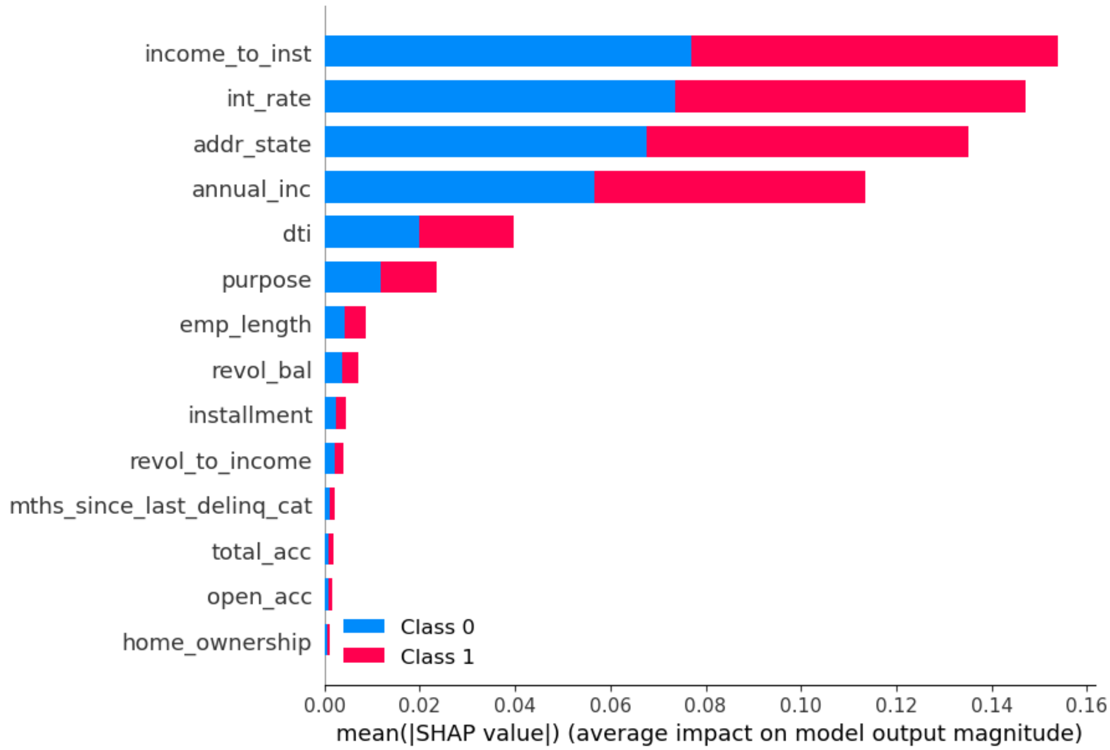


2.6 Interpretations

In order to understand the associations between our independent features and the target variable, we look at the SHAP plots and values. The plot below shows that the ratio of income to installments, interest rate, and state of residence are predictive of failure likelihood.

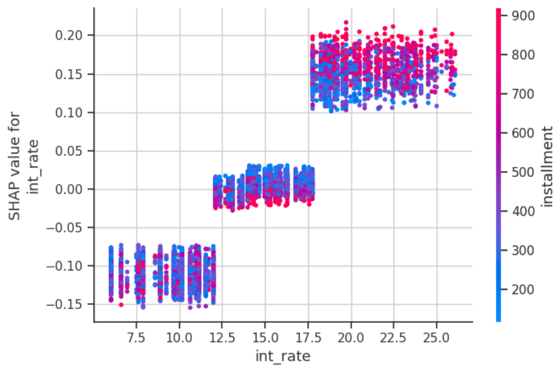
```
[32]: explainer = shap.TreeExplainer(gbm_model)
      shap_values = explainer.shap_values(train_val_df[features_impo_bor])
```

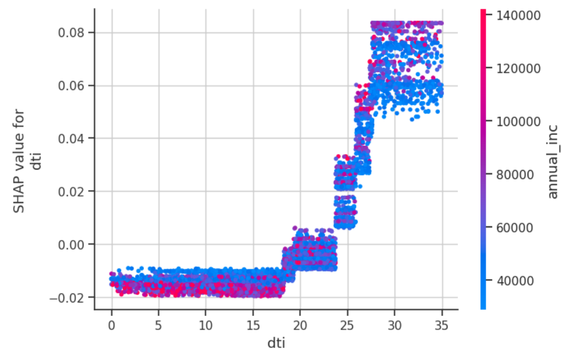
```
shap.summary_plot(shap_values, train_val_df[features_impo_bor], feature_names =
    features_impo_bor, max_display = 14)
```

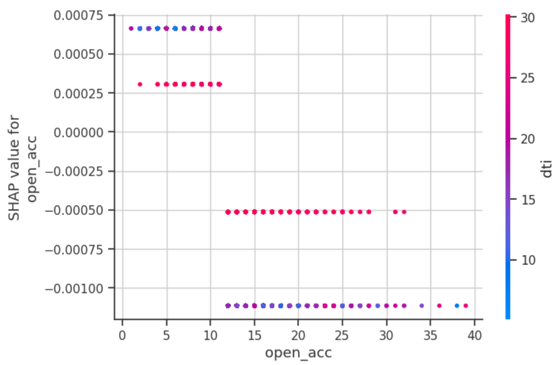


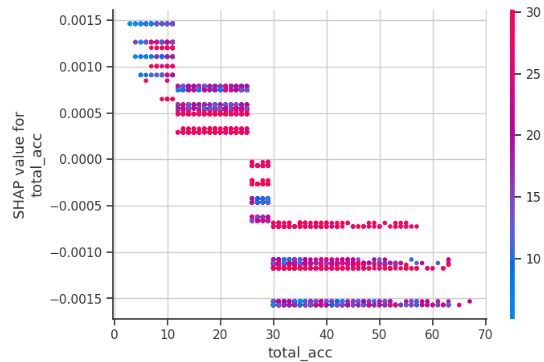
To take a closer look, we can investigate each variable individually. Below, you can see that interest rate and debt-to-income ratio have a positive relation with loan failure likelihood. On the other hand, the number of open accounts and the number of total accounts both have an inverse association with failure likelihood. Moreover, customers on mortgages are less likely to fail compared to renters.

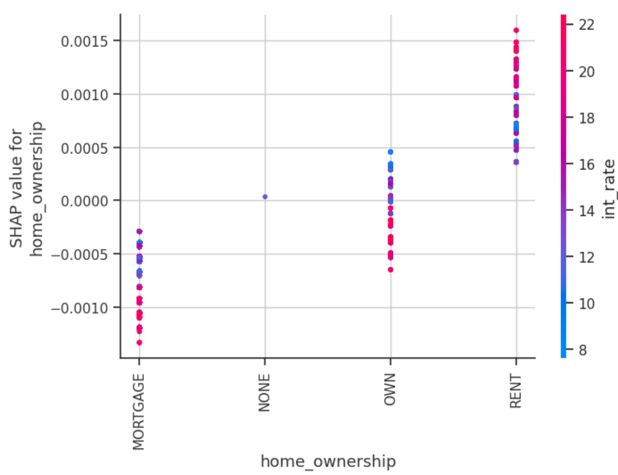
[136]:
```
top_inds = np.argsort(-np.sum(np.abs(shap_values[1]), 0))

for i in range(len(top_inds)):
    shap.dependence_plot(features_impo_bor[i], shap_values[1],
    train_val_df[features_impo_bor])
```











3 Unsupervised Learning

While we approached this problem from a supervised learning angle, a major limitation of our analysis is that the target variable is not fully realized. In particular, current loans can turn *bad* in the future. Considering this, we hypothesize that loans fall into two clusters based on their initial characteristics: a cluster of loans that fail at some point, and a cluster of loans that will not fail.

To find these clusters, we use the k-prototypes algorithm which cal cluster mixed data, including both numerical and categorical.

3.1 Data Preparation

We split our data into train and test and normalize our numeric features.

[60]:
```
for i in cat_vars:
    df[i] = df[i].astype(str)



train_df, test_df = train_test_split(
    df, test_size=0.2, random_state=2023, stratify = df[y_var]
)

train_df = train_df.reset_index(drop = True)
test_df = test_df.reset_index(drop = True)

scaler = preprocessing.MinMaxScaler()
train_df[cont_vars] = scaler.fit_transform(train_df[cont_vars])
test_df[cont_vars] = scaler.transform(test_df[cont_vars])
```

3.2 Clustering

We assume there are two clusters in our data. Using the k-prototypes algorithm, we find the clusters on the train set and determine the cluster that each loan belongs to. Cluster 0 contains %38.4 of the data and the remaining belongs to cluster 1. The average failure rate (with the same definition as in the previous section) in cluster 0 is %4.4, while this number for cluster 1 is %4. Even though the difference is small, we can say that we found two clusters where one of them is more likely to fail compared to the other one (a quick hypothesis testing can determine the significance of the difference in the proportions). We call them bad and good clusters.

[95]:
```
kproto = KPrototypes(n_clusters=2, init='Cao', random_state = 2023)
clusters = kproto.fit_predict(train_df.loc[:, train_df.columns != y_var],␣
↪categorical=[0, 1, 2, 3, 4, 5])
labels = pd.DataFrame(clusters)
train_df = pd.concat((train_df,labels),axis=1)
train_df = train_df.rename({0:'labels'},axis=1)
```

[96]:
```
train_df['labels'].value_counts(normalize = True, dropna = False)
```

[96]:
```
labels
1    0.61596
0    0.38404
Name: proportion, dtype: float64
```

[97]:
```
agg_df = train_df.groupby(['labels'])[['loan_failure']].mean().reset_index()
agg_df
```

[97]:

	labels	loan_failure
0	0	0.044429
1	1	0.040912

Finding the cluster assignments in the test set, we see a similar distribution and differences in terms of failure rate.

[98]:
```
clusters = kproto.predict(test_df.loc[:, test_df.columns != y_var],␣
↪categorical=[0, 1, 2, 3, 4, 5])
labels = pd.DataFrame(clusters)
test_df = pd.concat((test_df,labels),axis=1)
test_df = test_df.rename({0:'labels'},axis=1)
```

[99]:
```
test_df['labels'].value_counts(normalize = True, dropna = False)
```

[99]:
```
labels
1    0.629921
0    0.370079
Name: proportion, dtype: float64
```

[100]:
```
agg_df = test_df.groupby(['labels'])[['loan_failure']].mean().reset_index()
agg_df
```

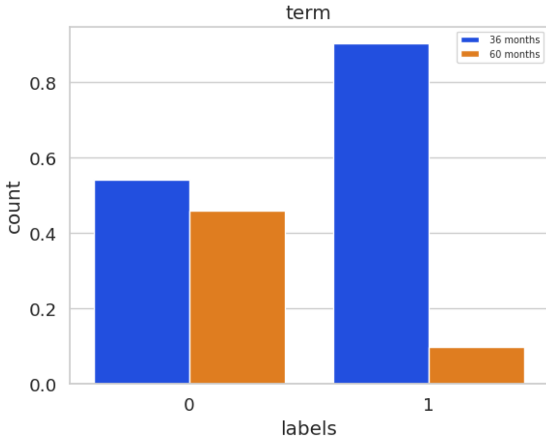
[100]:

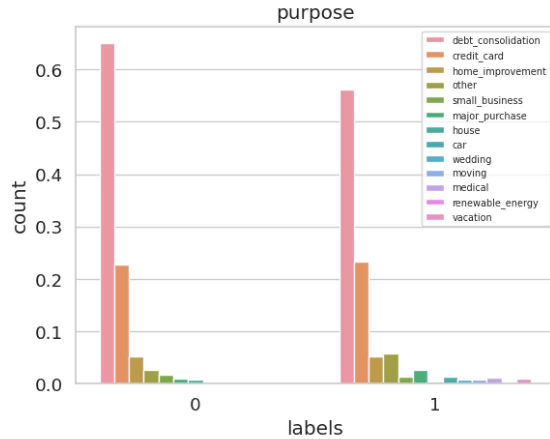
	labels	loan_failure
0	0	0.046809
1	1	0.040000

3.3 Interpretation

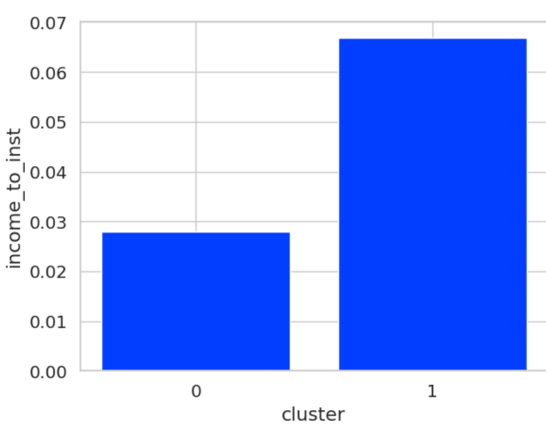
Let's look at some of the differences between these two clusters. The cluster is more populated with short-term loans compared to the bad cluster. Moreover, loans for debt consolidation purposes are more likely to fail. Looking at some of the numeric features, loans in the bad cluster tend to have lower income-to-installment ratios and higher interest rates.

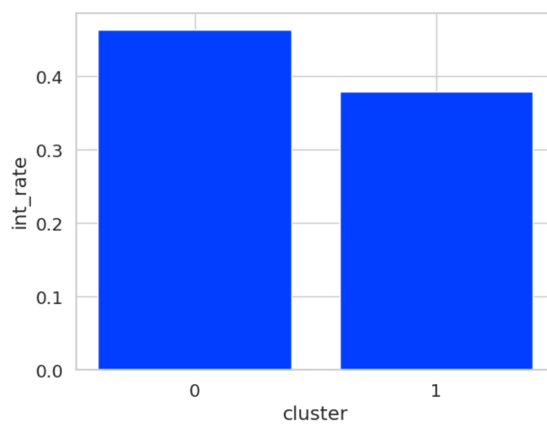
[180]:
```
for i in ['term',
          'purpose',
         ]:
    agg_df = pd.DataFrame(train_df.groupby(['labels'])[[i]].value_counts().
↪reset_index())
    agg_df['count'] = agg_df['count']/agg_df.groupby('labels')['count'].
↪transform('sum')
    plt.figure()
    sns.barplot(data=agg_df, x='labels', y='count', hue=i)
    plt.legend(fontsize=7, title_fontsize='40')
    plt.title(i)
    plt.show()
```





[148]:
```python
for i in ['income_to_inst', 'int_rate']:
    agg_df = pd.DataFrame(train_df.groupby(['labels'])[[i]].mean().reset_index())
    plt.bar(agg_df['labels'], agg_df[i])
    plt.xlabel('cluster')
    plt.ylabel(i)
    plt.xticks([0,1])
    plt.show()
```





3.4 Conclusion

From our supervised analysis, we learned that the ratio of income to installments, interest rate, and state of residence are predictive of failure likelihood, where interest rate and debt-to-income ratio have a positive relation with loan failure likelihood. On the other hand, the number of open accounts and the number of total accounts both have an inverse association with failure likelihood. Moreover, customers on mortgages are less likely to fail compared to renters.

Moreover, from our unsupervised analysis, we understood that the good cluster is more populated with short-term loans compared to the bad cluster. Moreover, loans for debt consolidation purposes are more likely to fail. Looking at some of the numeric features, loans in the bad cluster tend to have lower income-to-installment ratios and higher interest rates.

These findings can have direct implications for the marketing efforts of the loaning company. By targeting the customer segments with lower failure likelihood, the company can ensure that the loans can be fully paid and not defaulted. Moreover, one can revisit the loan approval process with these findings in order to minimize the approval of loans which are more likely to fail.