In [1]:
```python
# Initialize Otter
import otter
grader = otter.Notebook("lab4.ipynb")
```

Lab 4: Putting it all together in a mini project

This lab is an optional group lab. You can choose to work alone of in a group of up to four students. You are in charge of how you want to work and who you want to work with. Maybe you really want to go through all the steps of the ML process yourself or maybe you want to practice your collaboration skills, it is up to you! Just remember to indicate who your group members are (if any) when you submit on Gradescope. If you choose to work in a group, you only need to use one of your GitHub repos.

Submission instructions

rubric={mechanics}

You receive marks for submitting your lab correctly, please follow these instructions:

- Follow the general lab instructions.
- Click here to view a description of the rubrics used to grade the questions
- Make at least three commits.
- Push your `.ipynb` file to your GitHub repository for this lab and upload it to Gradescope.
  - Before submitting, make sure you restart the kernel and rerun all cells.
- Also upload a `.pdf` export of the notebook to facilitate grading of manual questions (preferably WebPDF, you can select two files when uploading to gradescope)
- Don't change any variable names that are given to you, don't move cells around, and don't include any code to install packages in the notebook.
- The data you download for this lab **SHOULD NOT BE PUSHED TO YOUR REPOSITORY** (there is also a `.gitignore` in the repo to prevent this).
- Include a clickable link to your GitHub repo for the lab just below this cell
  - It should look something like this https://github.ubc.ca/MDS-2020-21/DSCI_531_labX_yourcwl.

Points: 2

https://github.com/UBC-MDS/dsci573-lab4-auyeung-chan

Introduction

In this lab you will be working on an open-ended mini-project, where you will put all the different things you have learned so far in 571 and 573 together to solve an interesting problem.

A few notes and tips when you work on this mini-project:

Tips

1. Since this mini-project is open-ended there might be some situations where you'll have to use your own judgment and make your own decisions (as you would be doing when you work as a data scientist). Make sure you explain your decisions whenever necessary.
2. **Do not include everything you ever tried in your submission** -- it's fine just to have your final code. That said, your code should be reproducible and well-documented. For example, if you chose your hyperparameters based on some hyperparameter optimization experiment, you should leave in the code for that experiment so that someone else could re-run it and obtain the same hyperparameters, rather than mysteriously just setting the hyperparameters to some (carefully chosen) values in your code.
3. If you realize that you are repeating a lot of code try to organize it in functions. Clear presentation of your code, experiments, and results is the key to be successful in this lab. You may use code from lecture notes or previous lab solutions with appropriate attributions.

Assessment

We don't have some secret target score that you need to achieve to get a good grade. **You'll be assessed on demonstration of mastery of course topics, clear presentation, and the quality of your analysis and results.** For example, if you just have a bunch of code and no text or figures, that's not good. If you instead do a bunch of sane things and you have clearly motivated your choices, but still get lower model performance than your friend, don't sweat it.

A final note

Finally, the style of this "project" question is different from other assignments. It'll be up to you to decide when you're "done" -- in fact, this is one of the hardest parts of real projects. But please don't spend WAY too much time on this... perhaps "several hours" but not "many hours" is a good guideline for a high quality submission. Of course if you're having fun you're welcome to spend as much time as you want! But, if so, try not to do it out of perfectionism or getting the best possible grade. Do it because you're learning and enjoying it. Students from the past cohorts have found such kind of labs useful and fun and we hope you enjoy it as well.

1. Pick your problem and explain the prediction problem

rubric={reasoning}

In this mini project, you will pick one of the following problems:

1. A classification problem of predicting whether a credit card client will default or not. For this problem, you will use Default of Credit Card Clients Dataset. In this data set, there are 30,000 examples and 24 features, and the goal is to estimate whether a person will default (fail to pay) their credit card bills; this column is labeled "default.payment.next.month" in the data. The rest of the columns can be used as features. You may take some ideas and compare your results with the associated research paper, which is available through the UBC library.

OR

2. A regression problem of predicting `reviews_per_month`, as a proxy for the popularity of the listing with New York City Airbnb listings from 2019 dataset. Airbnb could use this sort of model to predict how popular future listings might be before they are posted, perhaps to help guide

hosts create more appealing listings. In reality they might instead use something like vacancy rate or average rating as their target, but we do not have that available here.

Your tasks:

1. Spend some time understanding the problem and what each feature means. Write a few sentences on your initial thoughts on the problem and the dataset.
2. Download the dataset and read it as a pandas dataframe.
3. Carry out any preliminary preprocessing, if needed (e.g., changing feature names, handling of NaN values etc.)

Points: 3

It is a classification problem with tabular data. The data set includes demographic information of each client and their histories of payment of the past 6 months. Success in predicting whether a client will default or not is valuable as it enables banks to assess the risks earlier and impose necessary measures to clients are with high chance of defaulting.

In [2]:
```
import numpy as np
import pandas as pd
from sklearn.model_selection import cross_val_score, cross_validate, train_test_split, G
from sklearn.preprocessing import StandardScaler, FunctionTransformer, OneHotEncoder
from sklearn.pipeline import Pipeline, make_pipeline
from sklearn.compose import make_column_transformer
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC, LinearSVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import LogisticRegression
from sklearn.feature_selection import RFE
from sklearn.metrics import classification_report, confusion_matrix, precision_recall_cu
from joblib import dump, load
from scipy.stats import lognorm, loguniform, randint
import os
import altair as alt
alt.renderers.enable('mimetype')
alt.data_transformers.enable('data_server')

from functions import *
```

In [3]:
```
data_full = pd.read_csv( 'UCI_Credit_Card.csv')
data_full = data_full.rename( columns = { 'PAY_0': 'PAY_1', 'default.payment.next.month'
```

2. Data splitting

rubric={reasoning}

Your tasks:

1. Split the data into train and test portions.

> Make the decision on the `test_size` based on the capacity of your laptop.

Points: 1

In [4]:
```
train_df, test_df = train_test_split( data_full, train_size = 0.2, random_state = 69)
```

3. EDA

rubric={viz,reasoning}

Perform exploratory data analysis on the train set.

Your tasks:

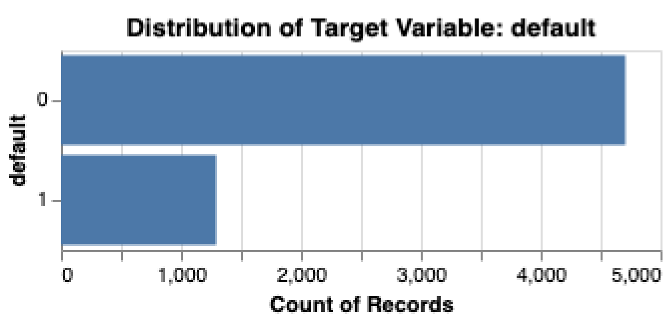
1. Include at least two summary statistics and two visualizations that you find useful, and accompany each one with a sentence explaining it.
2. Summarize your initial observations about the data.
3. Pick appropriate metric/metrics for assessment.

Points: 6

For features related to bill statement amounts and payment amounts, they are highly positively skewed with negative values. It implies that they cannot be simply fixed by logarithmic transformation. For the target variable, there is obvious class imbalance. To balance both the ability to identify defaulting clients and the cost of having false alarms, we will choose f1 score as our main metric for assessment, together with precision and recall for references.

In [5]:
```
alt.Chart( train_df, title = 'Distribution of Target Variable: default').mark_bar().enco
    x = 'count()',
    y = 'default:N'
).properties(
    height = 100,
    width = 300)
```

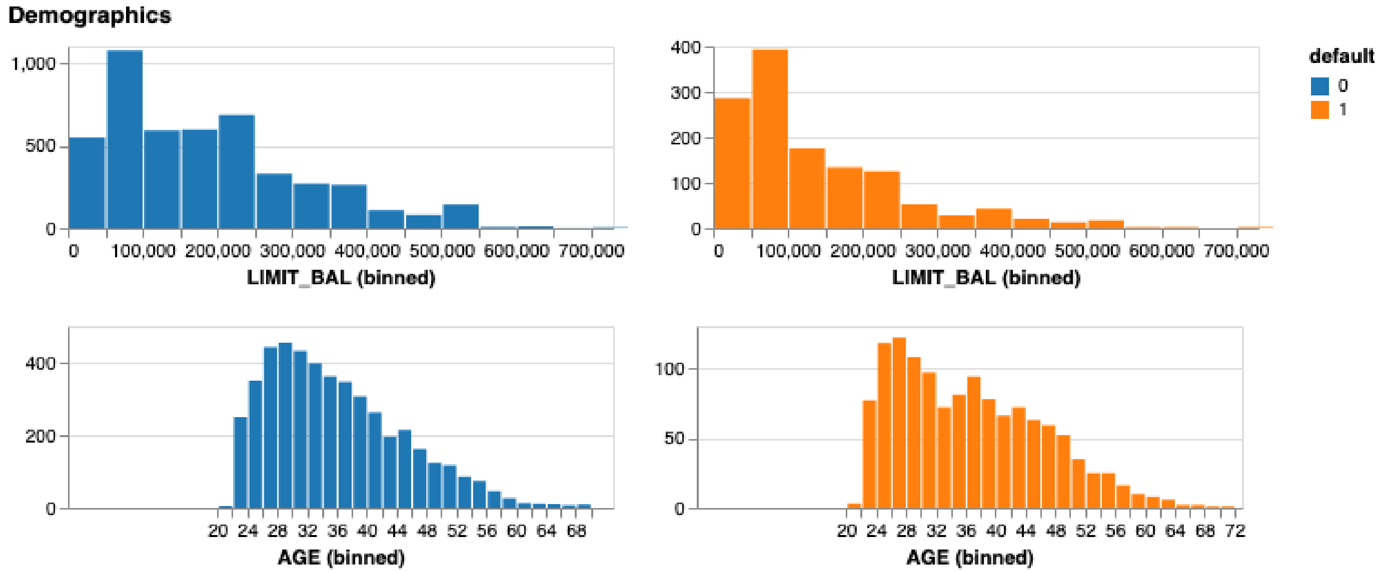
Out[5]:



It can be seen that there is class imbalance in the target variable. More clients do not default.

In [6]:
```
hist( train_df = train_df, feat_list = [ 'LIMIT_BAL', 'AGE'], repeat = True, title = 'De
```

Out[6]:

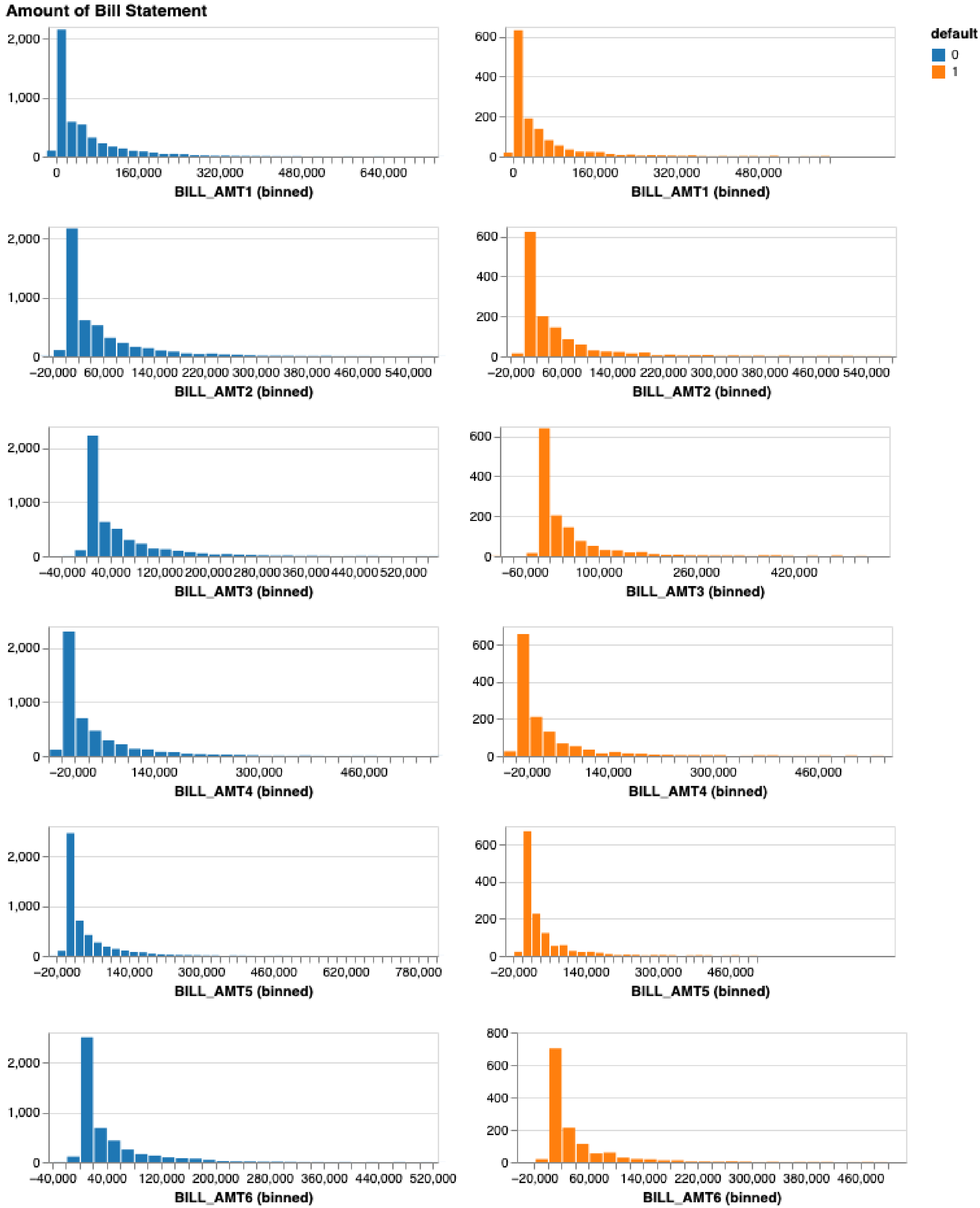


Both amount of credit and age are positively skewed. No visual difference is observed.

In [7]:

```
hist( train_df = train_df, feat_list = [ 'BILL_AMT1', 'BILL_AMT2', 'BILL_AMT3', 'BILL_AM
     repeat = True, title = 'Amount of Bill Statement', n_bins = 50)
```

Out[7]:

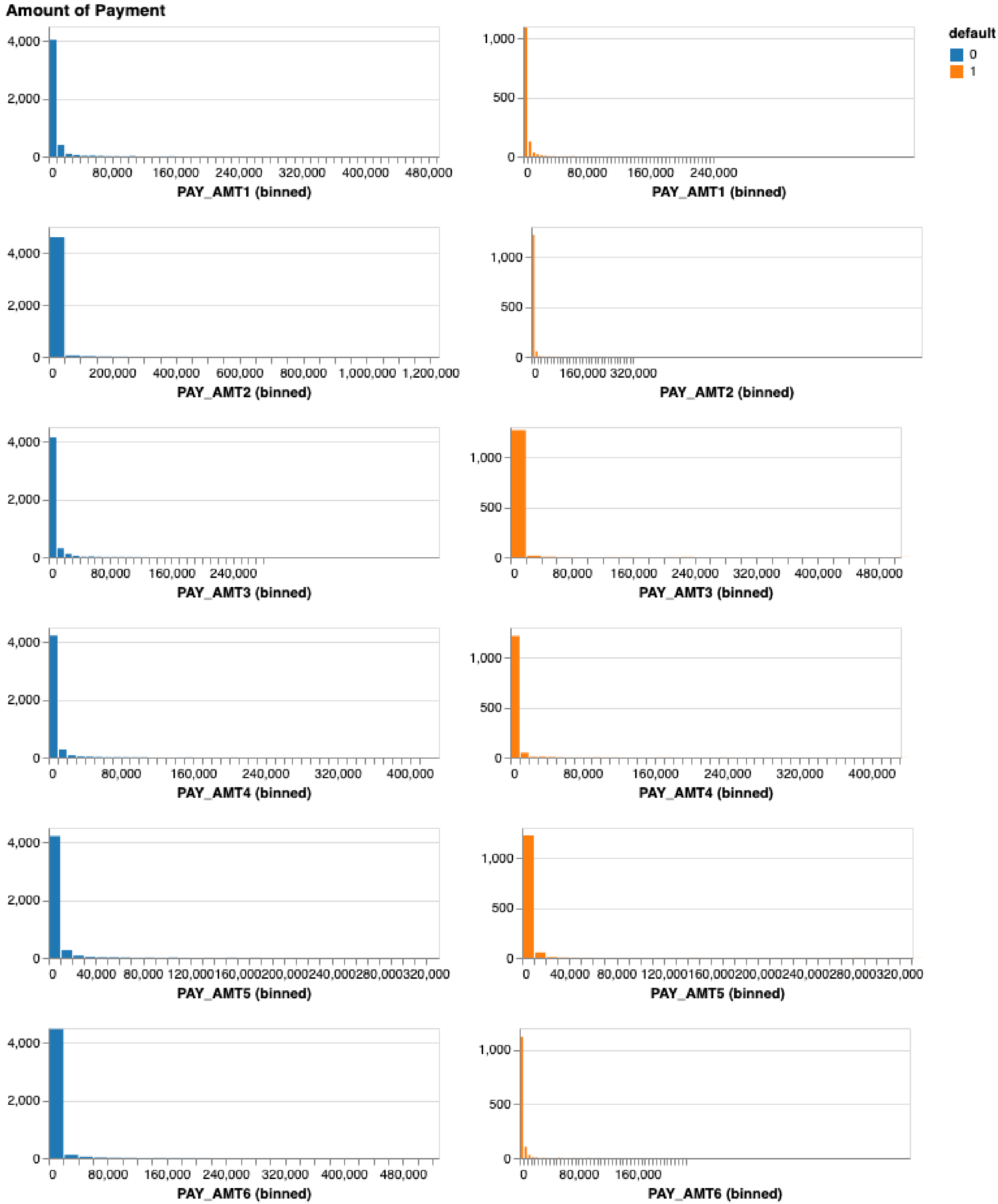


All amounts of bill statements are positively skewed. No visual difference is observed.

In [8]:

```
hist( train_df = train_df, feat_list = [ 'PAY_AMT1', 'PAY_AMT2', 'PAY_AMT3', 'PAY_AMT4',
     repeat = True, title = 'Amount of Payment', n_bins = 50)
```

Out [8]:

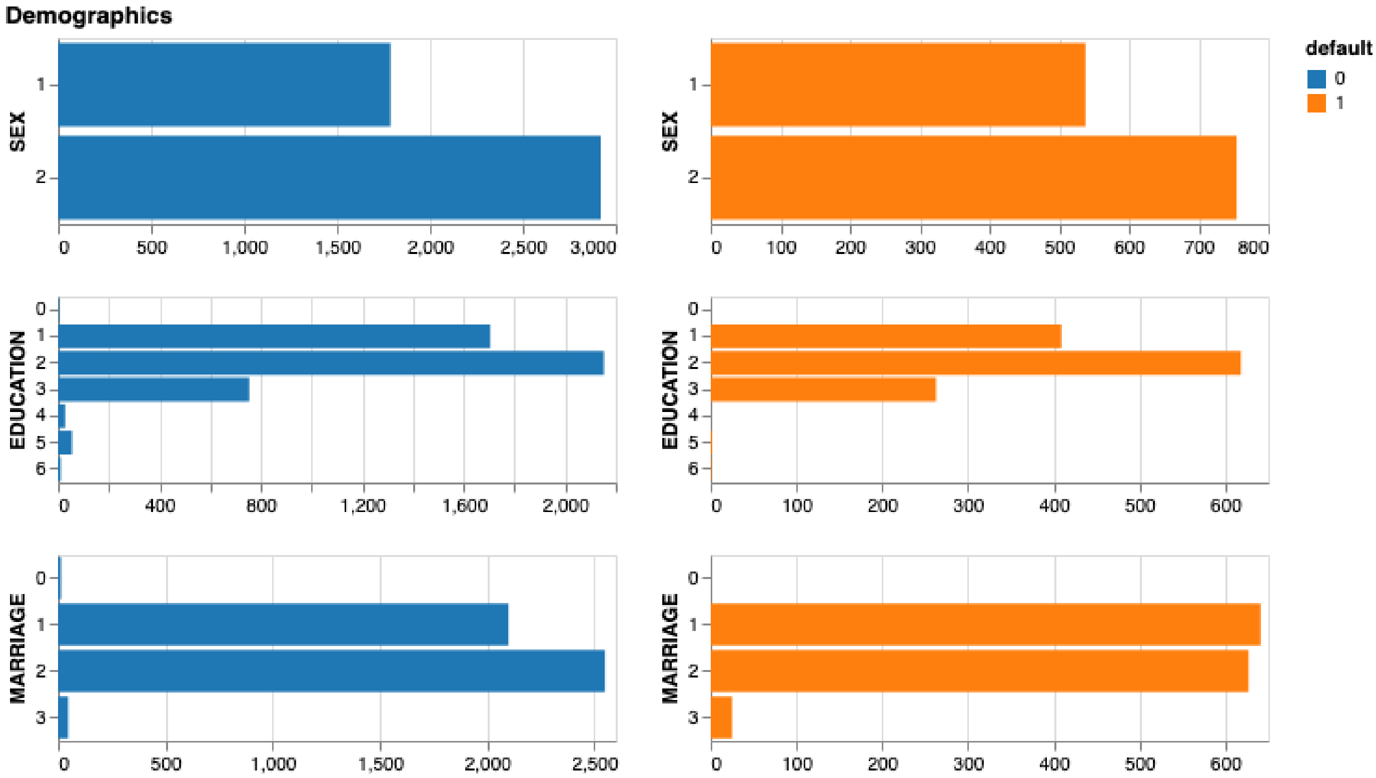


Amounts of payments are heavily positively skewed. No visual difference is observed.

In [9]:

```
bar( train_df = train_df, feat_list = [ ('SEX', [ 1, 2]), ('EDUCATION', [ 0, 1, 2, 3, 4,
                                        ( 'MARRIAGE', [ 0, 1, 2, 3])],
    repeat = True, title = 'Demographics')
```

Out[9]:

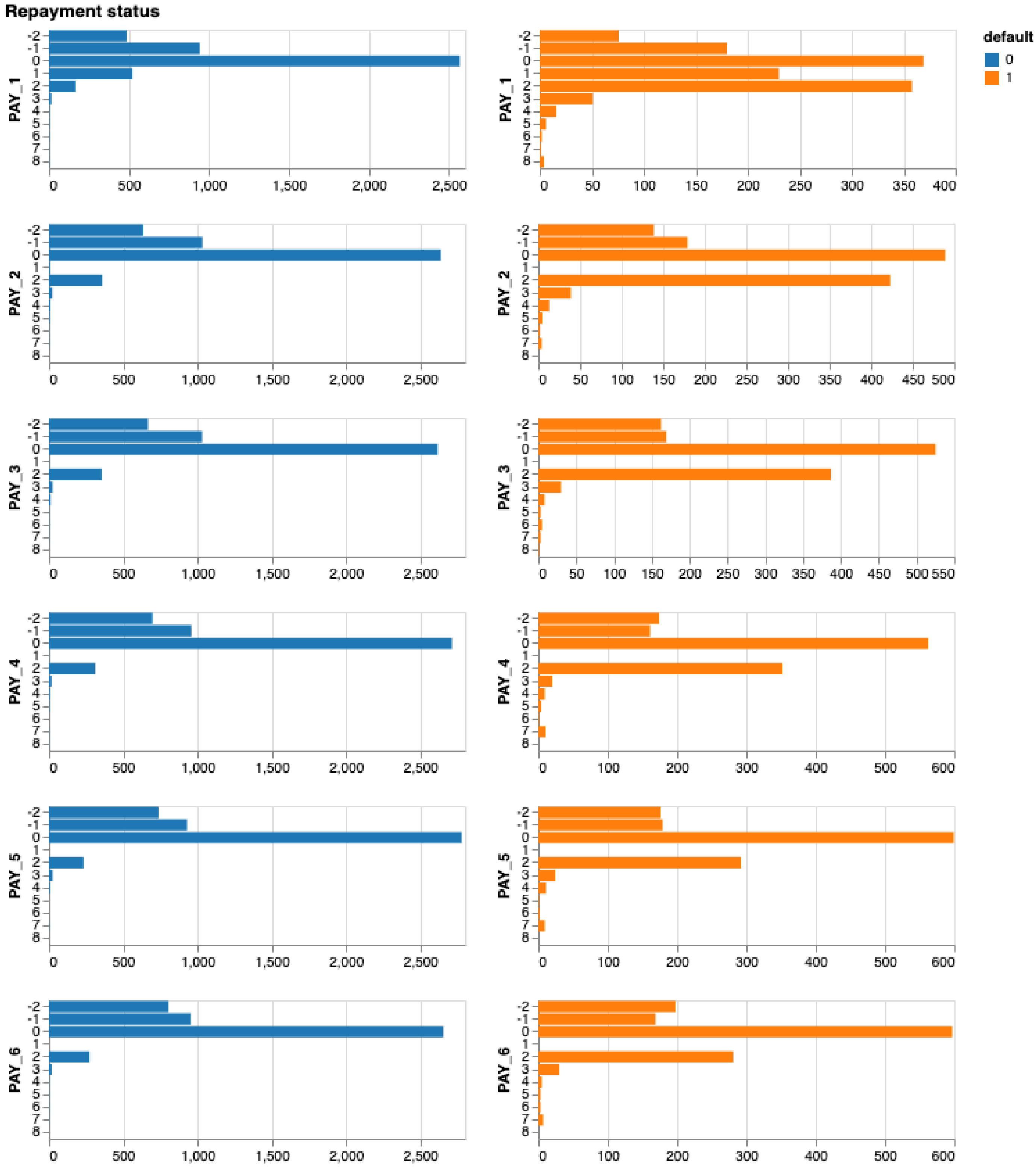


There are some missing values, undocumented. More data cleaning should be done. No visual difference is observed.

In [10]:

```
bar( train_df = train_df, feat_list = [ ('PAY_1', list( range( -2, 9))),
                                        ('PAY_2', list( range( -2, 9))),
                                        ('PAY_3', list( range( -2, 9))),
                                        ('PAY_4', list( range( -2, 9))),
                                        ('PAY_5', list( range( -2, 9))),
                                        ('PAY_6', list( range( -2, 9)))],
     repeat = True, title = 'Repayment status')
```

Out[10]:



There are some missing values, undocumented. More data cleaning should be done. No visual difference is observed.

4. Feature engineering (Challenging)

rubric={reasoning}

Your tasks:

1. Carry out feature engineering. In other words, extract new features relevant for the problem and work with your new feature set in the following exercises. You may have to go back and forth

between feature engineering and preprocessing.

Points: 0.5

...

5. Preprocessing and transformations

rubric={accuracy,reasoning}

Your tasks:

1. Identify different feature types and the transformations you would apply on each feature type.
2. Define a column transformer, if necessary.

Points: 4

In [11]:
```
train_df.describe()
```

Out[11]:

	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_1
count	6000.000000	6000.000000	6000.00000	6000.000000	6000.000000	6000.000000	6000.000000
mean	15080.959500	166932.666667	1.61250	1.861500	1.550833	35.417500	-0.006333
std	8616.929849	129111.214658	0.48722	0.798806	0.524845	9.245635	1.154057
min	12.000000	10000.000000	1.00000	0.000000	0.000000	21.000000	-2.000000
25%	7532.500000	50000.000000	1.00000	1.000000	1.000000	28.000000	-1.000000
50%	15101.000000	140000.000000	2.00000	2.000000	2.000000	34.000000	0.000000
75%	22458.000000	240000.000000	2.00000	2.000000	2.000000	41.000000	0.000000
max	29988.000000	730000.000000	2.00000	6.000000	3.000000	72.000000	8.000000

8 rows × 25 columns

In [12]:
```
from sklearn.preprocessing import PowerTransformer

cols_std = [ 'AGE'] # Numeric
cols_pow_std = [ 'LIMIT_BAL', 'PAY_AMT1', 'PAY_AMT2', 'PAY_AMT3', 'PAY_AMT4', 'PAY_AMT5'
                 'BILL_AMT1', 'BILL_AMT2', 'BILL_AMT3', 'BILL_AMT5', 'BILL_AMT5', 'BILL_A
               ] # Numeric and highly skewed
cols_cat = [ 'SEX', 'EDUCATION', 'MARRIAGE', 'PAY_1', 'PAY_2', 'PAY_3', 'PAY_4', 'PAY_5'
cols_drop = [ 'ID']


pipe_pow_std = make_pipeline(
    PowerTransformer(), StandardScaler())

column_transformer = make_column_transformer(
    ( StandardScaler(), cols_std),
    ( pipe_pow_std, cols_pow_std),
    ( OneHotEncoder(handle_unknown = 'ignore', sparse = False), cols_cat),
    ( 'drop', cols_drop)
)
```

6. Baseline model

rubric={accuracy}

Your tasks:

1. Train a baseline model for your task and report its performance.

Points: 2

In [13]:
```
from sklearn.dummy import DummyClassifier

X_train, y_train = train_df.drop( 'default', axis = 1), train_df[ 'default']
X_test, y_test = test_df.drop( 'default', axis = 1), test_df[ 'default']

dummy = DummyClassifier()
pipe_dummy = make_pipeline(
    column_transformer, dummy)

result_dict = {}

cv_scoring_metrics = [ 'accuracy', 'precision', 'recall', 'f1']
result = cross_validate( pipe_dummy, X_train, y_train, cv = 5, scoring = cv_scoring_metr
```

```
/opt/miniconda3/envs/573/lib/python3.10/site-packages/sklearn/metrics/_classification.py:1334: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 due to no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/opt/miniconda3/envs/573/lib/python3.10/site-packages/sklearn/metrics/_classification.py:1334: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 due to no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/opt/miniconda3/envs/573/lib/python3.10/site-packages/sklearn/metrics/_classification.py:1334: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 due to no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/opt/miniconda3/envs/573/lib/python3.10/site-packages/sklearn/metrics/_classification.py:1334: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 due to no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/opt/miniconda3/envs/573/lib/python3.10/site-packages/sklearn/metrics/_classification.py:1334: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 due to no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/opt/miniconda3/envs/573/lib/python3.10/site-packages/sklearn/metrics/_classification.py:1334: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 due to no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/opt/miniconda3/envs/573/lib/python3.10/site-packages/sklearn/metrics/_classification.py:1334: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 due to no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/opt/miniconda3/envs/573/lib/python3.10/site-packages/sklearn/metrics/_classification.py:1334: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 due to no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/opt/miniconda3/envs/573/lib/python3.10/site-packages/sklearn/metrics/_classification.py:1334: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 due to no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/opt/miniconda3/envs/573/lib/python3.10/site-packages/sklearn/metrics/_classification.py:1334: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 due to no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

In [14]:
```
result_dict[ 'dummy'] = pd.DataFrame( result).agg( [ 'mean', 'std']).T
result_dict[ 'dummy']
```

Out[14]:

	mean	std
fit_time	0.044197	0.001608
score_time	0.005001	0.000669
test_accuracy	0.784500	0.000456
train_accuracy	0.784500	0.000114
test_precision	0.000000	0.000000
train_precision	0.000000	0.000000
test_recall	0.000000	0.000000
train_recall	0.000000	0.000000
test_f1	0.000000	0.000000
train_f1	0.000000	0.000000

7. Linear models

rubric={accuracy,reasoning}

Your tasks:

1. Try a linear model as a first real attempt.
2. Carry out hyperparameter tuning to explore different values for the regularization hyperparameter.
3. Report cross-validation scores along with standard deviation.
4. Summarize your results.

Points: 8

As the discrepancies between train and validation scores are small, we reason that the model is not overfitting. The logistic regression model achives a cross-validation precision of 0.46, a recall of 0.64, and an f1 score of 0.54.

In [15]:
```
param_grid = {
    "logisticregression__C": loguniform(1e-3, 1e3)}

pipe_lr = make_pipeline(column_transformer, LogisticRegression(max_iter = 2000, class_we

random_search = RandomizedSearchCV(
    pipe_lr,
    param_grid,
    scoring = 'f1',
    n_iter=50,
    n_jobs=-1,
    random_state=69,
    return_train_score=True,
)
```

In [16]:
```
random_search.fit(X_train, y_train)
print("Best hyperparameter values: ", random_search.best_params_)
# print("Best score: %0.3f" % (random_search.best_score_))
```

```
Best hyperparameter values:  {'logisticregression__C': 1.2004186825129166}
```

In [17]:
```
best_c = random_search.best_params_['logisticregression__C']
pipe_lr_opt = make_pipeline(column_transformer, LogisticRegression(max_iter = 2000, clas
```

In [18]:
```
result = cross_validate( pipe_lr_opt, X_train, y_train, cv = 5, scoring = cv_scoring_met
```

In [19]:
```
result_dict[ 'lr'] = pd.DataFrame( result).agg( [ 'mean', 'std']).T
result_dict['lr']
```

Out[19]:

	mean	std
fit_time	0.149669	0.009815
score_time	0.004903	0.000124
test_accuracy	0.763333	0.020867
train_accuracy	0.764500	0.005070
test_precision	0.465090	0.034327
train_precision	0.466792	0.008084
test_recall	0.641130	0.037803
train_recall	0.650810	0.009510
test_f1	0.538927	0.035049
train_f1	0.543621	0.007546

8. Different models

rubric={accuracy,reasoning}

Your tasks:

1. Try out three other models aside from the linear model.
2. Summarize your results in terms of overfitting/underfitting and fit and score times. Can you beat the performance of the linear model?

Points: 10

From the cross-validation results, it is seen that all classifers are seriously overfitting as the discrepancy between the train and validation score is large, for precision, recall and f1. They all perform worse compared to the linear model.

In [20]:
```
column_transformer.fit( X_train)
print( f'There are {len( cols_std + cols_pow_std)} numeric columns')
print( f'There are {len( column_transformer.named_transformers_[ "onehotencoder"].get_fe
```

```
There are 14 numeric columns
There are 74 categorical columns
```

In [21]:
```
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier, HistGra


pipe_rfc = make_pipeline( column_transformer, RandomForestClassifier( n_estimators = 500
pipe_gbc = make_pipeline( column_transformer, GradientBoostingClassifier( n_estimators =
pipe_hgbc = make_pipeline( column_transformer, HistGradientBoostingClassifier( categoric
```

In [22]:
```
cv_rfc = pd.DataFrame( cross_validate( pipe_rfc, X_train, y_train, cv = 5, scoring = cv_
                      ).agg( [ 'mean', 'std']).T
cv_gbc = pd.DataFrame( cross_validate( pipe_gbc, X_train, y_train, cv = 5, scoring = cv_
                      ).agg( [ 'mean', 'std']).T
cv_hgbc = pd.DataFrame( cross_validate( pipe_hgbc, X_train, y_train, cv = 5, scoring = c
                       ).agg( [ 'mean', 'std']).T
```

In [23]:
```python
result_dict[ 'RFC'] = cv_rfc
result_dict[ 'GBC'] = cv_gbc
result_dict[ 'HGBC'] = cv_hgbc

pd.concat( result_dict, axis = 1)
```

Out[23]:

	dummy		lr		RFC		GBC		
	mean	std	mean	std	mean	std	mean	std	me
fit_time	0.044197	0.001608	0.149669	0.009815	0.716720	0.029364	6.947910	0.106138	1.2361
score_time	0.005001	0.000669	0.004903	0.000124	0.071632	0.004279	0.009976	0.000272	0.0145
test_accuracy	0.784500	0.000456	0.763333	0.020867	0.816833	0.011732	0.812667	0.011747	0.8180
train_accuracy	0.784500	0.000114	0.764500	0.005070	0.999708	0.000186	0.894917	0.002782	0.9220
test_precision	0.000000	0.000000	0.465090	0.034327	0.657611	0.066173	0.617430	0.055354	0.6403
train_precision	0.000000	0.000000	0.466792	0.008084	0.998649	0.000863	0.903279	0.009390	0.9632
test_recall	0.000000	0.000000	0.641130	0.037803	0.319395	0.020609	0.349568	0.020446	0.3588
train_recall	0.000000	0.000000	0.650810	0.009510	1.000000	0.000000	0.573860	0.011344	0.6635
test_f1	0.000000	0.000000	0.538927	0.035049	0.429236	0.027486	0.445932	0.027314	0.4594
train_f1	0.000000	0.000000	0.543621	0.007546	0.999324	0.000432	0.701779	0.009394	0.7856

9. Feature selection (Challenging)

rubric={reasoning}

Your tasks:

Make some attempts to select relevant features. You may try `RFECV`, forward selection or L1 regularization for this. Do the results improve with feature selection? Summarize your results. If you see improvements in the results, keep feature selection in your pipeline. If not, you may abandon it in the next exercises unless you think there are other benefits with using less features.

Points: 0.5

Type your answer here, replacing this text.

...

10. Hyperparameter optimization

rubric={accuracy,reasoning}

Your tasks:

Make some attempts to optimize hyperparameters for the models you've tried and summarize your results. In at least one case you should be optimizing multiple hyperparameters for a single model. You may use `sklearn`'s methods for hyperparameter optimization or fancier Bayesian optimization methods.

- GridSearchCV
- RandomizedSearchCV
- scikit-optimize

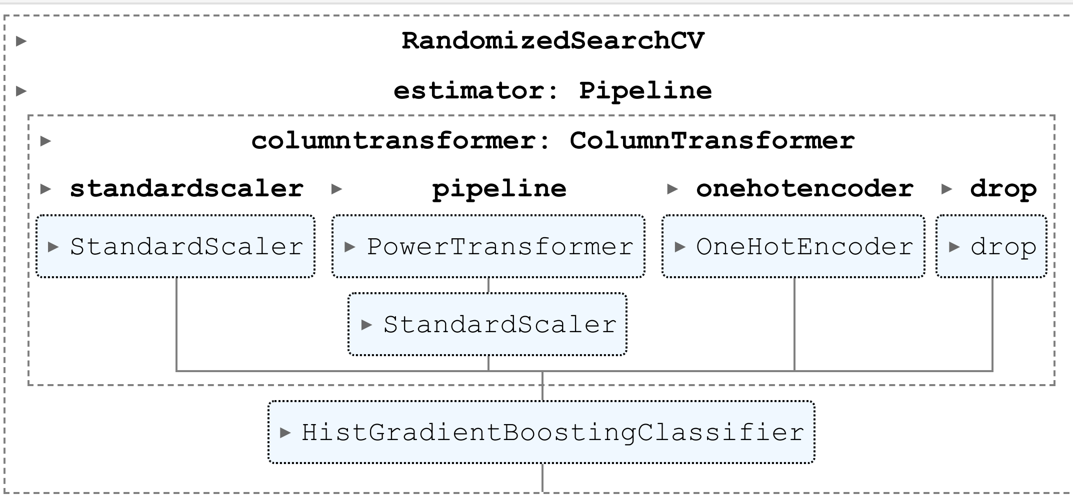
Points: 6

Overfitting is even more serious after hyperparameter optimization. Logistic regression is still the best model.

In [24]:
```
param_dist_rfc = {
    'randomforestclassifier__max_depth': [ 10*x for x in range( 1, 11)],
    'randomforestclassifier__max_features': [ 'sqrt', 'log2'],
    'randomforestclassifier__criterion': [ 'gini', 'entropy', 'log_loss'],
    'randomforestclassifier__bootstrap': [ True, False]
}

param_dist_gbc = {
    'gradientboostingclassifier__max_depth': [ 10*x for x in range( 1, 11)],
    'gradientboostingclassifier__max_features': [ 'sqrt', 'log2'],
    'gradientboostingclassifier__criterion': [ 'friedman_mse', 'squared_error']
}

param_dist_hgbc = {
    'histgradientboostingclassifier__max_depth': [ 10*x for x in range( 1, 11)],
    'histgradientboostingclassifier__learning_rate': np.linspace( 0.1, 1, 10)
}

search_rfc = RandomizedSearchCV(
    pipe_rfc, param_dist_rfc, n_iter = 15, cv = 3, scoring = 'f1', n_jobs=-1, return_tra
)

search_gbc = RandomizedSearchCV(
    pipe_gbc, param_dist_gbc, n_iter = 15, cv = 3, scoring = 'f1', n_jobs=-1, return_tra
)

search_hgbc = RandomizedSearchCV(
    pipe_hgbc, param_dist_hgbc, n_iter = 15, cv = 3, scoring = 'f1', n_jobs=-1, return_t
)
```

In [25]:
```
search_rfc.fit( X_train, y_train)
search_gbc.fit( X_train, y_train)
search_hgbc.fit( X_train, y_train)
```

Out[25]:



In [26]:
```
best_params_rfc = search_rfc.best_params_
best_params_gbc = search_gbc.best_params_
best_params_hgbc = search_hgbc.best_params_
```

In [27]:
```
best_params_rfc, best_params_gbc, best_params_hgbc
```

Out[27]:
```
({'randomforestclassifier__max_features': 'sqrt',
  'randomforestclassifier__max_depth': 10,
  'randomforestclassifier__criterion': 'log_loss',
  'randomforestclassifier__bootstrap': False},
 {'gradientboostingclassifier__max_features': 'sqrt',
  'gradientboostingclassifier__max_depth': 80,
  'gradientboostingclassifier__criterion': 'squared_error'},
 {'histgradientboostingclassifier__max_depth': 40,
  'histgradientboostingclassifier__learning_rate': 0.2})
```

In [28]:
```
pipe_rfc_opt = make_pipeline( column_transformer, RandomForestClassifier(
    n_estimators = 500, class_weight = 'balanced',
    max_features = best_params_rfc[ 'randomforestclassifier__max_features'],
    max_depth = best_params_rfc[ 'randomforestclassifier__max_depth'],
    criterion = best_params_rfc[ 'randomforestclassifier__criterion'],
    bootstrap =  best_params_rfc[ 'randomforestclassifier__bootstrap'],
    n_jobs = -1, random_state = 69))

pipe_gbc_opt = make_pipeline( column_transformer, GradientBoostingClassifier(
    max_features = best_params_gbc[ 'gradientboostingclassifier__max_features'],
    max_depth = best_params_gbc[ 'gradientboostingclassifier__max_depth'],
    criterion = best_params_gbc[ 'gradientboostingclassifier__criterion'],
    n_estimators = 500, random_state = 69))

pipe_hgbc_opt = make_pipeline( column_transformer, HistGradientBoostingClassifier(
    max_depth = best_params_hgbc[ 'histgradientboostingclassifier__max_depth'],
    learning_rate = best_params_hgbc[ 'histgradientboostingclassifier__learning_rate'],
    categorical_features = [ range( 14, 68)], random_state = 69))

cv_rfc_opt = pd.DataFrame( cross_validate( pipe_rfc_opt, X_train, y_train, cv = 5, scori
                     ).agg( [ 'mean', 'std']).T
cv_gbc_opt = pd.DataFrame( cross_validate( pipe_gbc_opt, X_train, y_train, cv = 5, scori
                     ).agg( [ 'mean', 'std']).T
cv_hgbc_opt = pd.DataFrame( cross_validate( pipe_hgbc_opt, X_train, y_train, cv = 5, sco
                      ).agg( [ 'mean', 'std']).T
```

In [29]:
```
result_dict[ 'RFC_opt'] = cv_rfc_opt
result_dict[ 'GBC_opt'] = cv_gbc_opt
result_dict[ 'HGBC_opt'] = cv_hgbc_opt

pd.concat( result_dict, axis = 1)
```

Out[29]:

	dummy		lr		RFC		GBC		
	mean	std	mean	std	mean	std	mean	std	me
fit_time	0.044197	0.001608	0.149669	0.009815	0.716720	0.029364	6.947910	0.106138	1.2361
score_time	0.005001	0.000669	0.004903	0.000124	0.071632	0.004279	0.009976	0.000272	0.0145
test_accuracy	0.784500	0.000456	0.763333	0.020867	0.816833	0.011732	0.812667	0.011747	0.8180
train_accuracy	0.784500	0.000114	0.764500	0.005070	0.999708	0.000186	0.894917	0.002782	0.9220
test_precision	0.000000	0.000000	0.465090	0.034327	0.657611	0.066173	0.617430	0.055354	0.6403
train_precision	0.000000	0.000000	0.466792	0.008084	0.998649	0.000863	0.903279	0.009390	0.9632
test_recall	0.000000	0.000000	0.641130	0.037803	0.319395	0.020609	0.349568	0.020446	0.3588
train_recall	0.000000	0.000000	0.650810	0.009510	1.000000	0.000000	0.573860	0.011344	0.6635
test_f1	0.000000	0.000000	0.538927	0.035049	0.429236	0.027486	0.445932	0.027314	0.4594
train_f1	0.000000	0.000000	0.543621	0.007546	0.999324	0.000432	0.701779	0.009394	0.7856

In [30]:
```python
result_dict_opt = {
    'LogReg': pd.DataFrame( result).agg( [ 'mean', 'std']).T,
    'RFC_opt': cv_rfc_opt,
    'GBC_opt': cv_gbc_opt,
    'HGBC_opt': cv_hgbc_opt}
pd.concat( result_dict_opt, axis = 1)
```

Out[30]:

	LogReg		RFC_opt		GBC_opt		HGBC_opt	
	mean	std	mean	std	mean	std	mean	std
fit_time	0.149669	0.009815	0.946233	0.024279	4.871022	0.642162	1.195025	0.017132
score_time	0.004903	0.000124	0.067204	0.004426	0.035244	0.005248	0.013585	0.000599
test_accuracy	0.763333	0.020867	0.789000	0.013142	0.811667	0.012091	0.811500	0.017484
train_accuracy	0.764500	0.005070	0.884625	0.004829	0.999708	0.000186	0.976250	0.002398
test_precision	0.465090	0.034327	0.510131	0.028812	0.615322	0.056826	0.606329	0.074996
train_precision	0.466792	0.008084	0.707318	0.012180	1.000000	0.000000	0.996334	0.000581
test_recall	0.641130	0.037803	0.544455	0.025137	0.343375	0.017936	0.367325	0.034875
train_recall	0.650810	0.009510	0.792922	0.010710	0.998647	0.000865	0.893080	0.011174
test_f1	0.538927	0.035049	0.526659	0.026359	0.440293	0.025974	0.456710	0.043761
train_f1	0.543621	0.007546	0.747630	0.009535	0.999323	0.000433	0.941856	0.006199

11. Interpretation and feature importances

rubric={accuracy,reasoning}

Your tasks:

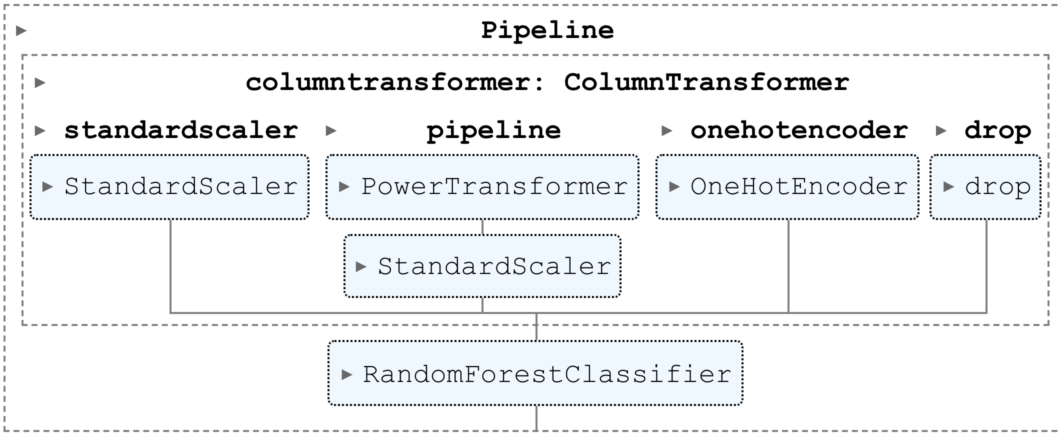
1. Use the methods we saw in class (e.g., `eli5`, `shap`) (or any other methods of your choice) to examine the most important features of one of the non-linear models.
2. Summarize your observations.

Points: 8

From the graph above, we can see that `PAY_1_2` and `PAY_2_2` has the highest weight in the random forest classifier.

In [31]:
```
pipe_rfc_opt.fit(X_train, y_train)
```

Out[31]:



In [32]:
```
column_names = (cols_std + cols_pow_std + column_transformer.named_transformers_["onehot
```

In [33]:
```
import eli5

eli5.explain_weights(pipe_rfc_opt.named_steps["randomforestclassifier"], feature_names=c
```

Out[33]:

Weight	Feature
0.1035 ± 0.1657	PAY_1_2
0.0610 ± 0.1453	PAY_2_2
0.0498 ± 0.0490	PAY_AMT1
0.0481 ± 0.0441	LIMIT_BAL
0.0463 ± 0.0935	PAY_1_0
0.0407 ± 0.1211	PAY_3_2
0.0406 ± 0.0373	PAY_AMT2
0.0393 ± 0.0396	PAY_AMT3
0.0374 ± 0.0321	BILL_AMT1
0.0368 ± 0.1032	PAY_4_2
0.0351 ± 0.0286	BILL_AMT2
0.0347 ± 0.0340	PAY_AMT6
0.0327 ± 0.0299	PAY_AMT5
0.0322 ± 0.0300	BILL_AMT3
0.0319 ± 0.0265	BILL_AMT5
0.0315 ± 0.0292	BILL_AMT5
0.0315 ± 0.0305	PAY_AMT4
0.0314 ± 0.0278	BILL_AMT6
0.0303 ± 0.0892	PAY_5_2
0.0270 ± 0.0183	AGE
… 68 more …	

12. Results on the test set

rubric={accuracy,reasoning}

Your tasks:

1. Try your best performing model on the test data and report test scores.
2. Do the test scores agree with the validation scores from before? To what extent do you trust your results? Do you think you've had issues with optimization bias?
3. Take one or two test predictions and explain them with SHAP force plots.

Points: 6

The test scores are consistent with the cross-validation scores. It implies that the model is with good generalizability.

In [34]:
```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
pipe_lr_opt.fit( X_train, y_train)
y_hat = pipe_lr_opt.predict( X_test)
print( f'Test accuracy is { accuracy_score( y_test, y_hat):.2f}.')
print( f'Test precision is { precision_score( y_test, y_hat):.2f}.')
print( f'Test recall is { recall_score( y_test, y_hat):.2f}.')
print( f'Test f1 score is { f1_score( y_test, y_hat):.2f}.')
```

```
Test accuracy is 0.76.
Test precision is 0.46.
Test recall is 0.61.
Test f1 score is 0.53.
```

In [35]:
```
X_train_enc = pd.DataFrame(
    data=column_transformer.transform(X_train),
    columns=column_names,
    index=X_train.index,
)
```

In [36]:
```
X_test_enc = pd.DataFrame(
    data = column_transformer.transform(X_test),
    columns = column_names,
    index = X_test.index
)
```

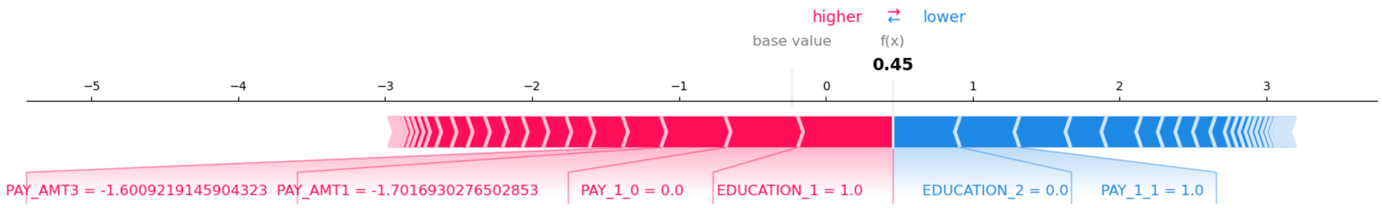
In [37]:
```
import shap

lr_explainer = shap.LinearExplainer(pipe_lr_opt.named_steps["logisticregression"], X_tra
shap_values = lr_explainer.shap_values(X_test_enc)
```

```
/opt/miniconda3/envs/573/lib/python3.10/site-packages/tqdm/auto.py:22: TqdmWarning: IPro
gress not found. Please update jupyter and ipywidgets. See https://ipywidgets.readthedoc
s.io/en/stable/user_install.html
  from .autonotebook import tqdm as notebook_tqdm
```

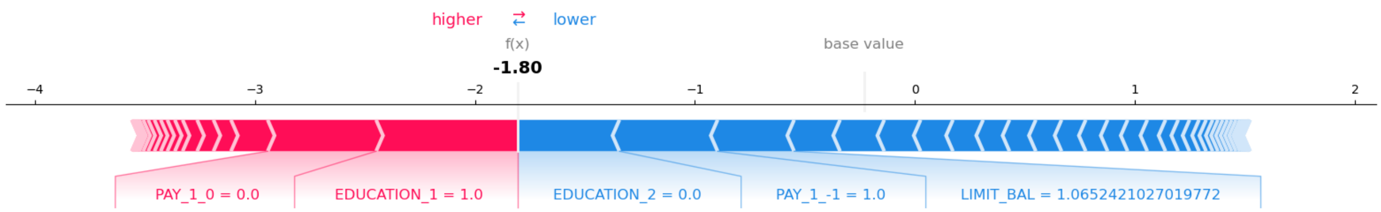
In [38]:
```
shap_values.shape
```

Out[38]:
```
(24000, 88)
```

In [39]:
```
shap.force_plot(
    lr_explainer.expected_value,
    shap_values[1,:],
    X_test_enc.iloc[1,:],
    matplotlib=True
)
```



In [40]:
```
shap.force_plot(
    lr_explainer.expected_value,
    shap_values[2,:],
    X_test_enc.iloc[2,:],
    matplotlib=True
)
```



13. Summary of results

rubric={reasoning}

Imagine that you want to present the summary of these results to your boss and co-workers.

Your tasks:

1. Create a table summarizing important results.
2. Write concluding remarks.
3. Discuss other ideas that you did not try but could potentially improve the performance/interpretability .
4. Report your final test score along with the metric you used at the top of this notebook.

Points: 8

In conclusion, the logistic regression model is the best model to be employed. It has good prediction performane and interpretability. The model achieves a test f1 score of 0.53, a test precision of 0.46, and a test recall of 0.61. It suggests the model can identify around 61% of all defaulting clients, while having 54% as false alarms.

What we have not done includes tuning the threshold for the decision boundary and evaluating whether the predicted probability output can be realiably used in risk assessment.

In [41]:
```
cv_train_scores = result_dict_opt[ 'LogReg'].loc[
    [ 'train_accuracy', 'train_precision', 'train_recall', 'train_f1'], 'mean'
    ].reset_index( drop = True)
```

```
cv_test_scores = result_dict_opt[ 'LogReg'].loc[
    [ 'test_accuracy', 'test_precision', 'test_recall', 'test_f1'], 'mean'
    ].reset_index( drop = True)
```

In [42]:
```
pd.DataFrame({
    'Scores': [ 'accuracy', 'precision', 'recall', 'f1'], 'CV - Train': cv_train_scores,
    'Test': [ accuracy_score( y_test, y_hat), precision_score( y_test, y_hat), recall_sc
}).set_index( 'Scores')
```

Out[42]:

Scores	CV - Train	Validation	Test
accuracy	0.764500	0.763333	0.756708
precision	0.466792	0.465090	0.464682
recall	0.650810	0.641130	0.610706
f1	0.543621	0.538927	0.527780

14. Creating a data analysis pipeline (Challenging)

rubric={reasoning}

Your tasks:

- In 522 you learned how build a reproducible data analysis pipeline. Convert this notebook into scripts and create a reproducible data analysis pipeline with appropriate documentation. Submit your project folder in addition to this notebook on GitHub and briefly comment on your organization in the text box below.

Points: 2

Type your answer here, replacing this text.

15. Your takeaway from the course (Challenging)

rubric={reasoning}

Your tasks:

What is your biggest takeaway from this course?

Points: 0.25

Data science and machine learning is not blindly plugging models to the data. Most effort should be put on feature engineering and interpretability.

Restart, run all and export a PDF before submitting

Before submitting, don't forget to run all cells in your notebook to make sure there are no errors and so that the TAs can see your plots on Gradescope. You can do this by clicking the ▶▶ button or going to `Kernel -> Restart Kernel and Run All Cells...` in the menu. This is not only important for MDS, but a good habit you should get into before ever committing a notebook to GitHub, so that your collaborators can run it from top to bottom without issues.

After running all the cells, export a PDF of the notebook (preferably the WebPDF export) and upload this PDF together with the ipynb file to Gradescope (you can select two files when uploading to Gradescope)

Help us improve the labs

The MDS program is continually looking to improve our courses, including lab questions and content. The following optional questions will not affect your grade in any way nor will they be used for anything other than program improvement:

1. Approximately how many hours did you spend working or thinking about this assignment (including lab time)?

Ans: 5. Hyperparameter tuning takes a lot of time.

2. Do you have any feedback on the lab you be willing to share? For example, any part or question that you particularly liked or disliked?

Ans:

In [ ]:
```

```