In [1]:
```
import credit
```

In [2]:
```
import constant as c
```

In [3]:
```
import utils
```

In [4]:
```
import pandas
```

In [5]:
```
import os
```

In [6]:
```
import numpy
```

# save data from the internet, locally

*unless already done*

In [7]:
```
train_data_file_path, test_data_file_path = credit.saved_tabular_data_file_paths_from_url(
                  data_url=c.data_url,
                  redownload=False,
                  reextract=True,
                  )
                  assert train_data_file_path ==
                  c.train_data_file_path
                  assert test_data_file_path ==
                  c.test_data_file_path
```

```
final files already there
                ../data/
                ├ train.csv
                ├ test.csv
                └ downloaded_data.zip
```

In [8]:
```
import autogluon.tabular
```

# load data as a tabular data set

*same ting as a data frame*

In [9]:
```
train_data = autogluon.tabular.TabularDataset(data=train_data_file_path)
```

## the target is the "aposteriori lack of payment" of the customer

- 0 -> zero delay of payment
- 1 -> difficulties to pay in time

In [11]:
```
train_data.head(2)
```

Out[11]:

| | SK_ID_CURR | TARGET | NAME_CONTRACT_TYPE | CODE_GENDER | FLAG_OWN_CAR | FLAG_OWN_REALTY | CNT_CHILDREN | AMT_INCOME_TOTAL | AMT_CREDIT |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 100002 | 1 | Cash loans | M | N | Y | 0 | 202500.0 | 406597.5 |
| **1** | 100003 | 0 | Cash loans | F | N | N | 0 | 270000.0 | 1293502.5 |

2 rows × 122 columns

# train model and save it locally

*unless already done*

## metric: ROC AUC

it is specify that the AUC will be the valdiation metric
so the credit company can have the freedom to say no or adjust the interest/insurance fee according to the ***payment default likelyhood***

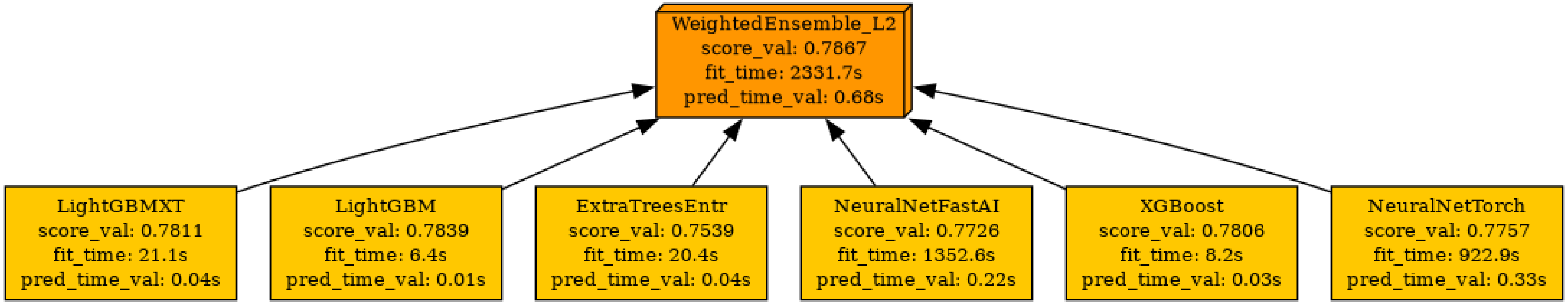
In [13]:
```
if not os.path.exists(c.model_folder_path):
                  print(f"{c.model_folder_path} does not
                    exists")
                  try:
                  predictor = autogluon.tabular.TabularPredictor(
```

```
                  label='TARGET',
                  eval_metric='roc_auc',
                  path = c.model_folder_path,
                  )
                  predictor.fit(
                  train_data=train_data,
                  presets=[
                  'optimize_for_deployment', # will
                    prune not so important sub models
                  'medium_quality' # will speed up training
                  ],
                  time_limit=60*45, #
                    seconds
                  )
                  assert predictor.path == c.model_folder_path
                  print(f"{predictor.predictor_file_name = }")
                  predictor.save()
                  except Exception as error:
                  print(f"somthing went wrong: {error}")
                  print(f"removing the folder: {c.model_folder_path}")
                  utils.delete_everything_inside_folder(c.model_folder_path)
                  utils.delete_empty_folder(c.model_folder_path)
                  assert not os.path.exists(c.model_folder_path)
                  raise(error)
```

In [14]:
```
if os.path.exists(c.model_folder_path):
                  predictor = autogluon.tabular.TabularPredictor.load(c.model_folder_path)
```

## admire the complexity of the model

In [15]:
```
predictor.plot_ensemble_model(filename=c.models_graph_file_name)
                  utils.show_image_from_path(c.models_graph_file_path)
```




# perform prediction on test data set for submission

In [16]:

```
test_data = autogluon.tabular.TabularDataset(data=test_data_file_path)
                    test_data.head(2)
```

Out[16]:

| | SK_ID_CURR | NAME_CONTRACT_TYPE | CODE_GENDER | FLAG_OWN_CAR | FLAG_OWN_REALTY | CNT_CHILDREN | AMT_INCOME_TOTAL | AMT_CREDIT | AMT_ANI |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 100001 | Cash loans | F | N | Y | 0 | 135000.0 | 568800.0 | 20 |
| **1** | 100005 | Cash loans | M | N | Y | 0 | 99000.0 | 222768.0 | 17 |

2 rows × 121 columns

In [17]:

```
test_data.head(4)
```

Out[17]:

| | SK_ID_CURR | NAME_CONTRACT_TYPE | CODE_GENDER | FLAG_OWN_CAR | FLAG_OWN_REALTY | CNT_CHILDREN | AMT_INCOME_TOTAL | AMT_CREDIT | AMT_ANI |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 100001 | Cash loans | F | N | Y | 0 | 135000.0 | 568800.0 | 20 |
| **1** | 100005 | Cash loans | M | N | Y | 0 | 99000.0 | 222768.0 | 17 |
| **2** | 100013 | Cash loans | M | Y | Y | 0 | 202500.0 | 663264.0 | 6 |
| **3** | 100028 | Cash loans | F | N | Y | 2 | 315000.0 | 1575000.0 | 4 |

4 rows × 121 columns

In [40]:
```
test_prediction_result = predictor.predict(test_data)
                test_prediction_result.head(2)
```

Out[40]:
```
0 0
                1 0
                Name: TARGET, dtype: int64
```

In [39]:
```
test_probability_prediction_result =
                predictor.predict_proba(test_data)
                test_probability_prediction_result.head(2)
```

Out[39]:

| | 0 | 1 |
|---|---|---|
| **0** | 0.957126 | 0.042874 |
| **1** | 0.850687 | 0.149313 |

## result submission

- first column is the client ID
- second column is the client's ***payment default likelihood***

In [20]:
```
submission_data = pandas.concat(
                objs=[
                test_data['SK_ID_CURR'], # client id
                test_probability_prediction_result[1],# probability client will not pay in
                  time
                ],
                axis=1
                ).rename(
                columns={
                'SK_ID_CURR': 'SK_ID_CURR',
                1: 'TARGET'
                },
                )
                print(f"we
                  output in a column the probability fo a a client (SK_ID_CURR) to be a good payer
                  (target)")
                submission_data.head()
```

```
we output in a column the probability fo a a client (SK_ID_CURR) to be a good payer (target)
```

Out[20]:

| | SK_ID_CURR | TARGET |
|---|---|---|
| **0** | 100001 | 0.042874 |
| **1** | 100005 | 0.149313 |
| **2** | 100013 | 0.024527 |
| **3** | 100028 | 0.040429 |
| **4** | 100038 | 0.160621 |

In [21]:

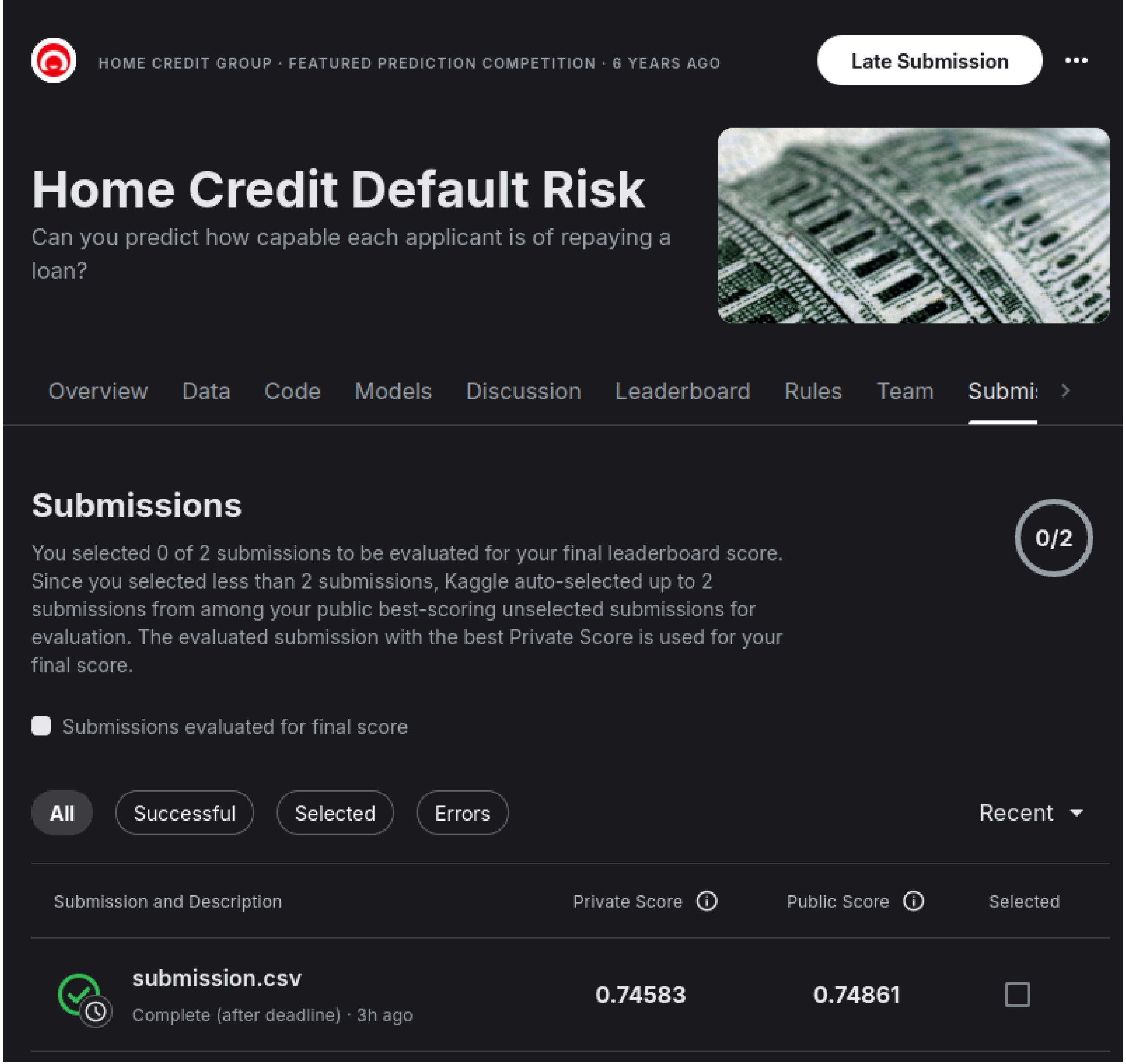
```
credit.saved_data_frame_path_from_data_frame(
                  data_frame=submission_data,
                  data_folder_path=c.results_folder_path,
                  # data_frame_file_name='submission.csv',
                  data_frame_file_name=c.submission_file_name,
                  save_index=False,
                  )
```

Out[21]: '../results/submission.csv'

# result from kaggle submission

In [22]:

```
utils.show_image_from_path(c.submission_result_file_path)
```



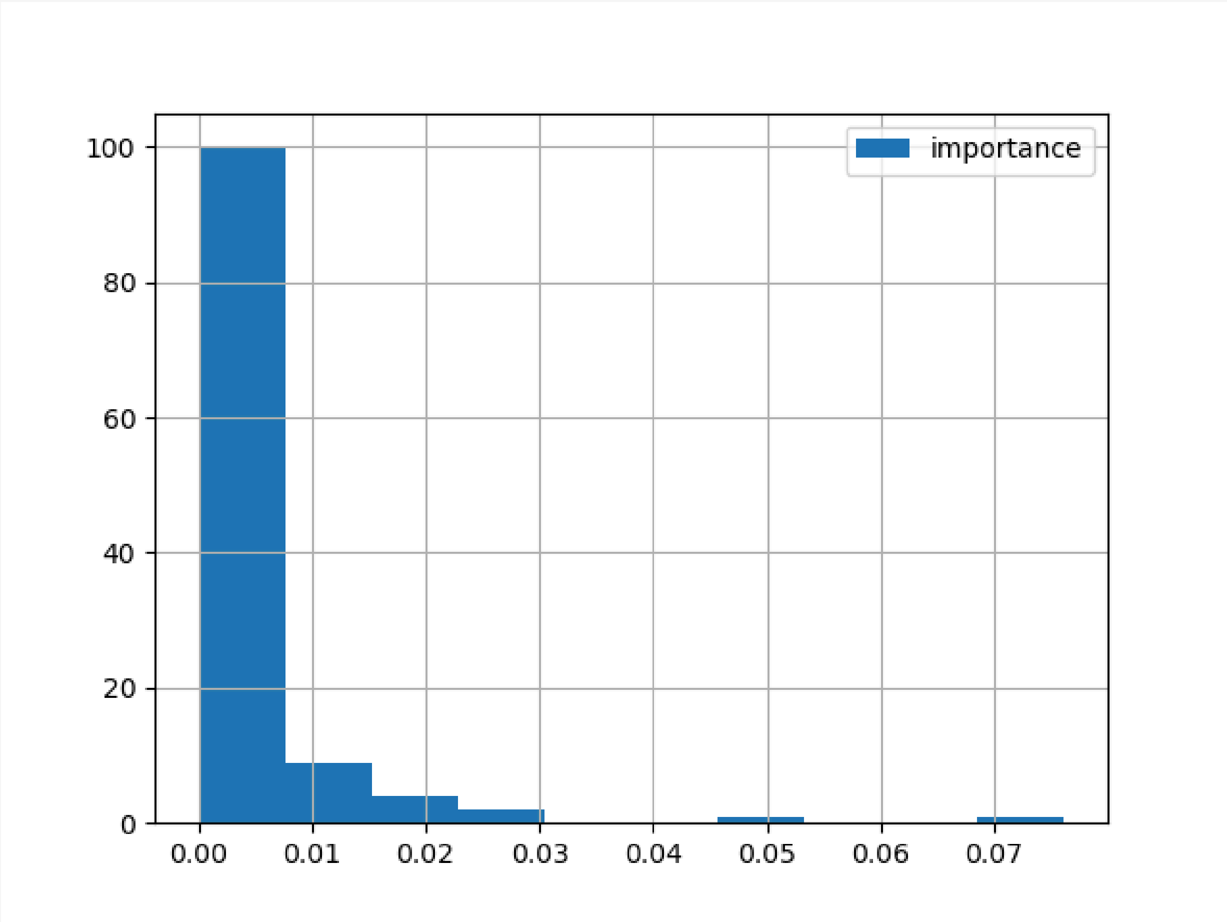

## feature importance analysis

which feature (value) weighted the most into the prediciton output

In [24]:
```
if not os.path.exists(c.feature_importances_tab_file_path):
                  feature_importances = predictor.feature_importance(
                  data=train_data,
                  subsample_size=1000,
                  time_limit=60*20,
                  )
                  assert c.feature_importances_tab_file_path == credit.saved_data_frame_path_from_data_frame(
                  data_frame=feature_importances,
                  data_folder_path=c.dashboard_folder_path,
                  data_frame_file_name=c.feature_importances_tab_file_name,
                  save_index=True,
                  )
                  feature_importances = pandas.read_csv(
                  filepath_or_buffer=c.feature_importances_tab_file_path,
                  index_col=0,
                  )
                  feature_importances.head(20)
```

Out[24]:

In [25]:




In [26]:

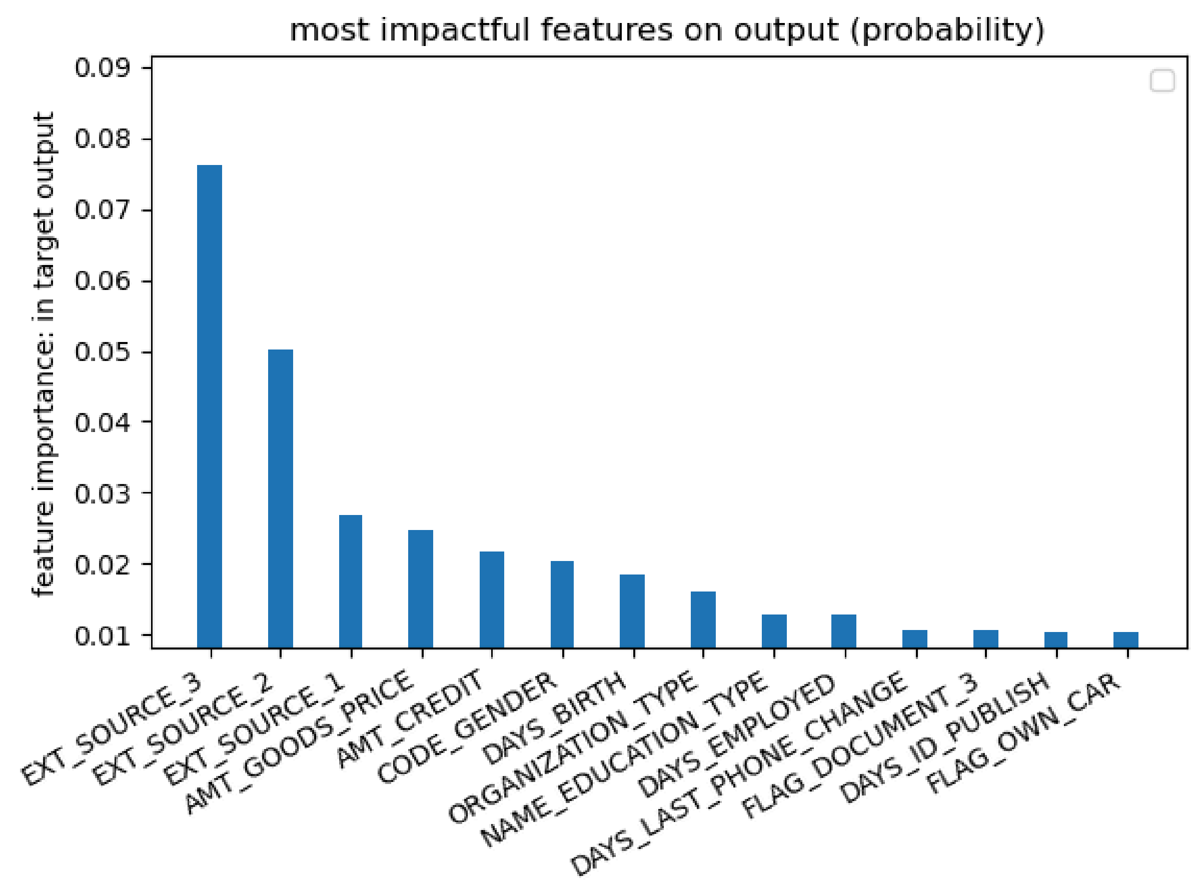
```
most_important_features = feature_importances[
                             feature_importances['importance'] > 0.01
                             ]
                             most_important_feature_names = most_important_features.index.values
```

In [27]:

```
# feature_importances['importance'].plot(kind='bar')
                             credit.plot_stuff_with_bars(
                             labels=most_important_features.index.values,
                             data=most_important_features['importance'],
                             label=None,
                             y_axis_label='feature
                               importance: in target output',
                             chart_title='most impactful
                               features on output (probability)',
                             folder_path=c.dashboard_folder_path,
                             file_name='most_important_features.png',
```

```
)
```

```
/home/wam/kood/credit-scoring/notebooks/credit.py:556: UserWarning: No artists with labels
                        found to put in legend. Note that artists whose label start with an underscore are ignored when
                        legend() is called with no argument.
                        axis.legend()
```




In [28]:
```
bad_payers = train_data[
                        train_data['TARGET'] == 1
                        ]
                        good_payers = train_data[
                        train_data['TARGET'] == 0
                        ]
```

# feature importance at the client scale

## determine "normal profile"

- of a good payer customer
- of a bad payer customer

define a function that take a population and return a customer data where each column value is the median of its represnting population

In [29]:
```
def normal_feature_values(data):
                          new_data_frame = pandas.DataFrame(columns=data.columns).reindex(range(1))
                          for column in data.columns:
                          values = data[column].values
                          if numpy.issubdtype(values.dtype, numpy.number):
                          values = values[~numpy.isnan(values)]
                          populations, edges = numpy.histogram(values)
                          max_bin_middle_value = edges[numpy.argmax(populations)]+edges[numpy.argmax(populations+1)]/2
                          new_data_frame[column]=max_bin_middle_value

                          if not numpy.issubdtype(values.dtype, numpy.number):
                          try:
                          uniques, counts = numpy.unique(values, return_counts=True)
                          except:
                          values = numpy.array( [str(value) for value in values] )
                          uniques, counts = numpy.unique(values, return_counts=True)

                          most_frequent_index = numpy.argmax(counts)
                          most_frequent_value = uniques[most_frequent_index]
                          new_data_frame[column]=most_frequent_value

                          return new_data_frame
```

In [30]:
```
normal_dude = normal_feature_values(train_data)
                          normal_dude[most_important_feature_names]
```

Out[30]:

| | EXT_SOURCE_3 | EXT_SOURCE_2 | EXT_SOURCE_1 | AMT_GOODS_PRICE | AMT_CREDIT | CODE_GENDER | DAYS_BIRTH | ORGANIZATION_TYPE | NAMI |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 0.941047 | 0.89775 | 0.732946 | 60750.0 | 67500.0 | F | -21877.5 | Business Entity Type 3 | S |

In [31]:
```
normal_good_payer_dude = normal_feature_values(good_payers)
                          normal_good_payer_dude[most_important_feature_names]
```

Out[31]:

| | EXT_SOURCE_3 | EXT_SOURCE_2 | EXT_SOURCE_1 | AMT_GOODS_PRICE | AMT_CREDIT | CODE_GENDER | DAYS_BIRTH | ORGANIZATION_TYPE | NAMI |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 0.938912 | 0.89775 | 0.732946 | 60750.0 | 67500.0 | F | -21877.5 | Business Entity Type 3 | |

In [32]:

```
normal_bad_payer_dude = normal_feature_values(bad_payers)
                          normal_bad_payer_dude[most_important_feature_names]
```

Out[32]:

| | EXT_SOURCE_3 | EXT_SOURCE_2 | EXT_SOURCE_1 | AMT_GOODS_PRICE | AMT_CREDIT | CODE_GENDER | DAYS_BIRTH | ORGANIZATION_TYPE | NAMI |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 0.403758 | 0.852465 | 0.296448 | 67500.0 | 664902.0 | F | -16764.0 | Business Entity Type 3 | |

In [33]:

```
predictor.predict_proba(bad_payers[0:1])[1]
```

Out[33]:

```
0 0.520779
                        Name: 1, dtype: float64
```

## profile individual customer

compare client with the archetype of the other population to highlight detrimental/favorable criteria

In [34]:

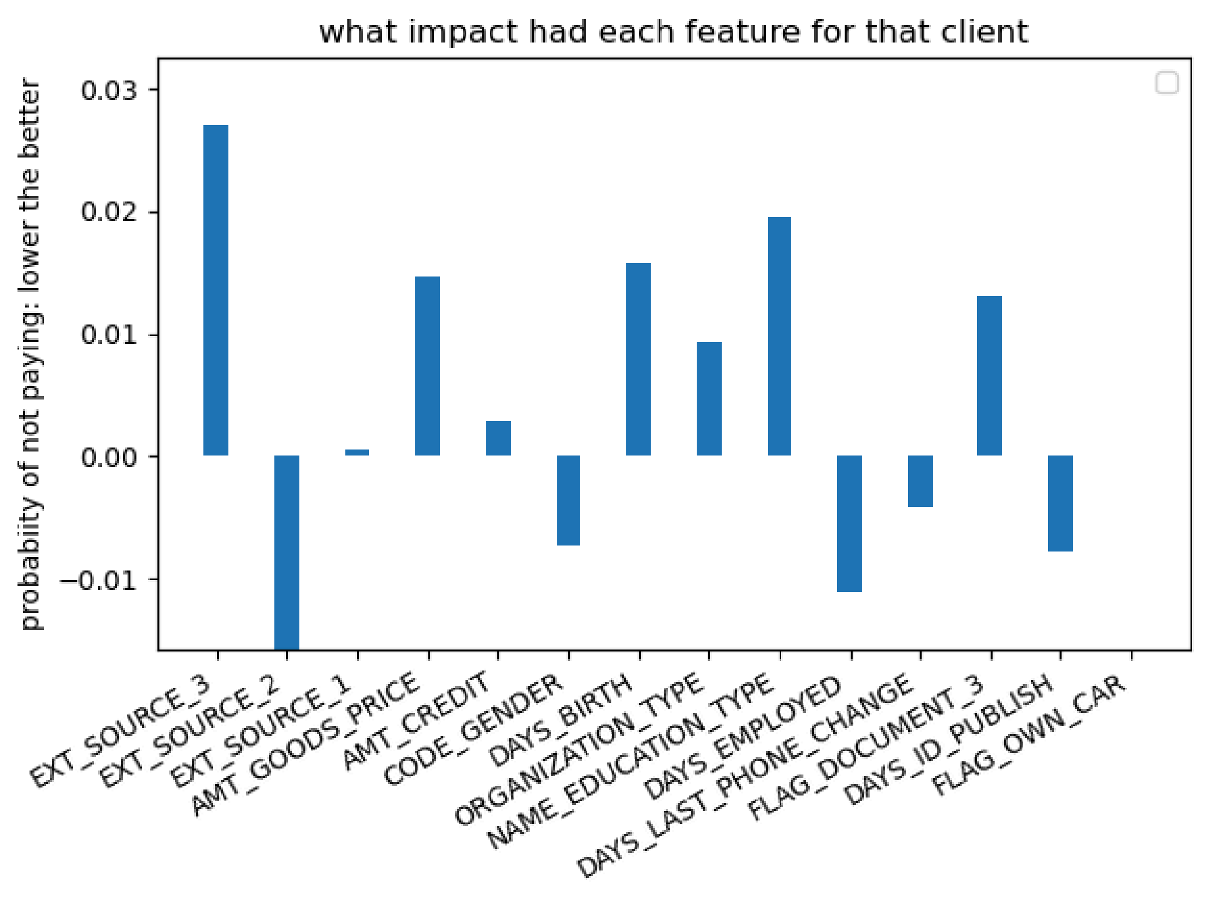
```
def what_feature_is_impactful(srcutinee, referencee, predict_proba, only_those_columns=None):
                          mutant_srcutinee = srcutinee.copy()
                          columns = pandas.DataFrame(columns=srcutinee.columns) if only_those_columns is
                          None else only_those_columns
                          scrutinee_proba = predict_proba(srcutinee)
                          how_impactful_it_was = []
                          for column in columns:
                          old_value = mutant_srcutinee[column].iloc[0]
                          referee_value = referencee[column].iloc[0]
                          mutant_srcutinee[column] = referencee[column]*-100
                          new_proba = predict_proba(mutant_srcutinee)
                          how_impactful_it_was.append((scrutinee_proba - new_proba).values[0])
                          mutant_srcutinee= srcutinee.copy()
                          return how_impactful_it_was, only_those_columns
```

In [35]:

```
impacts, impactul_columns = what_feature_is_impactful(
                          srcutinee=bad_payers[3:4],
                          referencee=normal_good_payer_dude,
```

```python
                predict_proba=lambda
                row:predictor.predict_proba(row)[1] ,
                only_those_columns=most_important_feature_names
                )
                credit.plot_stuff_with_bars(
                labels=impactul_columns,
                data=impacts,
                label=None,
                y_axis_label='probabiity of not
                  paying: lower the better',
                chart_title='what impact had
                  each feature for that client',
                folder_path=c.client_output_folder_path,
                file_name='bad_client.png',
                )
```

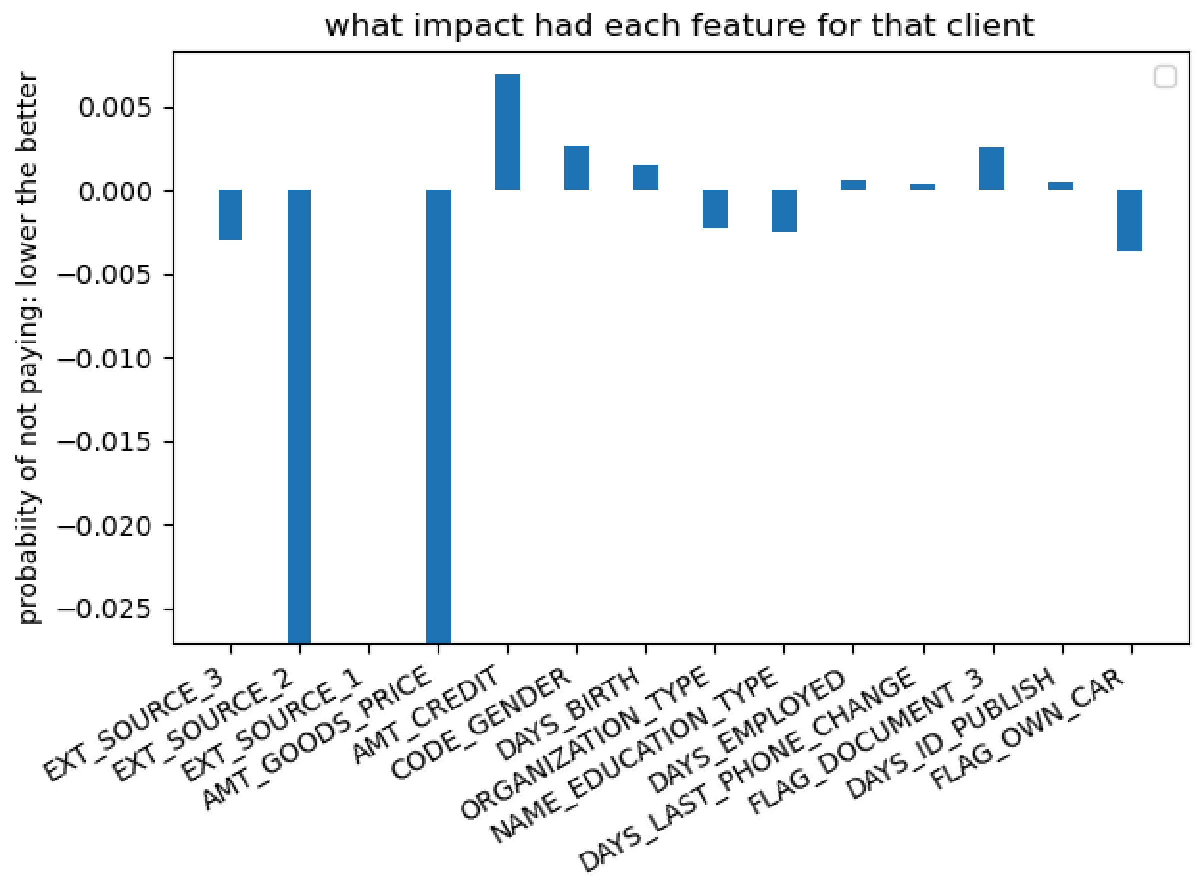
```
WARNING: Int features without null values at train time contain null values at inference
                        time! Imputing nulls to 0. To avoid this, pass the features as floats during fit!
                        WARNING: Int features with nulls: ['DAYS_BIRTH']
                        WARNING: Int features without null values at train time contain null values at inference time!
                        Imputing nulls to 0. To avoid this, pass the features as floats during fit!
                        WARNING: Int features with nulls: ['DAYS_EMPLOYED']
                        WARNING: Int features without null values at train time contain null values at inference time!
                        Imputing nulls to 0. To avoid this, pass the features as floats during fit!
                        WARNING: Int features with nulls: ['DAYS_ID_PUBLISH']
                        /home/wam/kood/credit-scoring/notebooks/credit.py:556: UserWarning: No artists with labels found
                        to put in legend. Note that artists whose label start with an underscore are ignored when
                        legend() is called with no argument.
                        axis.legend()
```




In [42]:

```
impacts, impactul_columns = what_feature_is_impactful(
                          srcutinee=good_payers[6:7],
                          referencee=normal_good_payer_dude,
                          predict_proba=lambda
                          row:predictor.predict_proba(row)[1] ,
                          only_those_columns=most_important_feature_names
                          )
                          credit.plot_stuff_with_bars(
                          labels=impactul_columns,
                          data=impacts,
                          label=None,
                          y_axis_label='probabiity of not
                            paying: lower the better',
                          chart_title='what impact had
                            each feature for that client',
                          folder_path=c.client_output_folder_path,
                          file_name='good_client.png',
                          )
```

```
WARNING: Int features without null values at train time contain null values at inference
                    time! Imputing nulls to 0. To avoid this, pass the features as floats during fit!
                    WARNING: Int features with nulls: ['DAYS_BIRTH']
                    WARNING: Int features without null values at train time contain null values at inference time!
                    Imputing nulls to 0. To avoid this, pass the features as floats during fit!
                    WARNING: Int features with nulls: ['DAYS_EMPLOYED']
                    WARNING: Int features without null values at train time contain null values at inference time!
                    Imputing nulls to 0. To avoid this, pass the features as floats during fit!
                    WARNING: Int features with nulls: ['DAYS_ID_PUBLISH']
                    /home/wam/kood/credit-scoring/notebooks/credit.py:556: UserWarning: No artists with labels found
                    to put in legend. Note that artists whose label start with an underscore are ignored when
                    legend() is called with no argument.
                    axis.legend()
```




a client from the test data set

In [41]:
```
impacts, impactul_columns = what_feature_is_impactful(
                                srcutinee=test_data[3:4],
```

```
                    referencee=normal_bad_payer_dude,
                    predict_proba=lambda
                    row:predictor.predict_proba(row)[1] ,
                    only_those_columns=most_important_feature_names
                    )
                    credit.plot_stuff_with_bars(
                    labels=impactul_columns,
                    data=impacts,
                    label=None,
                    y_axis_label='probabiity of not
                      paying: lower the better',
                    chart_title='what impact had
                      each feature for that client',
                    folder_path=c.client_output_folder_path,
                    file_name='test_client.png',
                    )
```

```
WARNING: Int features without null values at train time contain null values at inference
                        time! Imputing nulls to 0. To avoid this, pass the features as floats during fit!
                        WARNING: Int features with nulls: ['DAYS_BIRTH']
                        WARNING: Int features without null values at train time contain null values at inference time!
                        Imputing nulls to 0. To avoid this, pass the features as floats during fit!
                        WARNING: Int features with nulls: ['DAYS_EMPLOYED']
                        WARNING: Int features without null values at train time contain null values at inference time!
                        Imputing nulls to 0. To avoid this, pass the features as floats during fit!
                        WARNING: Int features with nulls: ['DAYS_ID_PUBLISH']
                        /home/wam/kood/credit-scoring/notebooks/credit.py:556: UserWarning: No artists with labels found
                        to put in legend. Note that artists whose label start with an underscore are ignored when
                        legend() is called with no argument.
                        axis.legend()
```

what impact had each feature for that client
probabiity of not paying: lower the better
0.010
0.005
0.000
−0.005
−0.010
−0.015
EXT_SOURCE_3
EXT_SOURCE_2
EXT_SOURCE_1
AMT_GOODS_PRICE
AMT_CREDIT
CODE_GENDER
DAYS_BIRTH
ORGANIZATION_TYPE
NAME_EDUCATION_TYPE
DAYS_EMPLOYED
DAYS_LAST_PHONE_CHANGE
FLAG_DOCUMENT_3
DAYS_ID_PUBLISH
FLAG_OWN_CAR


In [ ]: