Деректерді өңдеу мамандарына арналған практикалық статистика (Python)

5-тарау. Жіктеу

Import required Python packages.

In [1]:

```
from pathlib import Path
import pandas as pd
import numpy as np

from sklearn.naive_bayes import MultinomialNB
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.linear_model import LogisticRegression #, LogisticRegressionCV
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix, precision_recall_fscore_support
from sklearn.metrics import roc_curve, accuracy_score, roc_auc_score

import statsmodels.api as sm

from imblearn.over_sampling import SMOTE, ADASYN, BorderlineSMOTE
from pygam import LinearGAM, s, f, l


from dmba import classificationSummary

import seaborn as sns
import matplotlib.pyplot as plt

%matplotlib inline
```

```
no display found. Using non-interactive Agg backend
```

In [2]:

```
try:
    import common
    DATA = common.dataDirectory()
except ImportError:
    DATA = Path().resolve() / 'data'
```

Define paths to data sets. If you don't keep your data in the same directory as the code, adapt the path names.

In [3]:

```
LOAN3000_CSV = DATA / 'loan3000.csv'
LOAN_DATA_CSV = DATA / 'loan_data.csv.gz'
FULL_TRAIN_SET_CSV = DATA / 'full_train_set.csv.gz'
```

Naive Bayes

The Naive Solution

Аңғал Байес

Аңғал шешім

In [4]:

```
loan_data = pd.read_csv(LOAN_DATA_CSV)

# convert to categorical
loan_data.outcome = loan_data.outcome.astype('category')
loan_data.outcome.cat.reorder_categories(['paid off', 'default'])
loan_data.purpose_ = loan_data.purpose_.astype('category')
loan_data.home_ = loan_data.home_.astype('category')
loan_data.emp_len_ = loan_data.emp_len_.astype('category')

predictors = ['purpose_', 'home_', 'emp_len_']
outcome = 'outcome'
X = pd.get_dummies(loan_data[predictors], prefix='', prefix_sep='')
y = loan_data[outcome]

naive_model = MultinomialNB(alpha=0.01, fit_prior=True)
naive_model = MultinomialNB(alpha=1e-10, fit_prior=False)
naive_model.fit(X, y)

new_loan = X.loc[146:146, :]
print('predicted class: ', naive_model.predict(new_loan)[0])

probabilities = pd.DataFrame(naive_model.predict_proba(new_loan),
                             columns=naive_model.classes_)
print('predicted probabilities',)
print(probabilities)
```

```
predicted class:  default
predicted probabilities
    default  paid off
0  0.653699  0.346301
```

Example not in book

Numerical variables are not supported in scikit-learn. The example would need to demonstrate binning a variable and display the probability distribution of the bins.

Кітапта мысал жоқ

Scikit-learn бағдарламасында Сандық айнымалыларға қолдау көрсетілмейді. Мысалда айнымалыны байланыстыруды көрсету және ұяшықтардың ықтималдық үлестірімін көрсету қажет болады.

```
## example not in book

less_naive <- NaiveBayes(outcome ~ borrower_score + payment_inc_ratio +

                         purpose_ + home_ + emp_len_, data = loan_data)

less_naive$table[1:2]
```

```
png(filename=file.path(PSDS_PATH, 'figures', 'psds_naive_bayes.png'),  width = 4, height=3,
units='in', res=300)



stats <- less_naive$table[[1]]

ggplot(data.frame(borrower_score=c(0,1)), aes(borrower_score)) +

 stat_function(fun = dnorm, color='blue', linetype=1,

           arg=list(mean=stats[1, 1], sd=stats[1, 2])) +

 stat_function(fun = dnorm, color='red', linetype=2,

           arg=list(mean=stats[2, 1], sd=stats[2, 2])) +

 labs(y='probability')

dev.off()
```

Discriminant Analysis

A Simple Example

Дискриминантты талдау

Қарапайым мысал

In [5]:

```
loan3000 = pd.read_csv(LOAN3000_CSV)
loan3000.outcome = loan3000.outcome.astype('category')

predictors = ['borrower_score', 'payment_inc_ratio']
outcome = 'outcome'

X = loan3000[predictors]
y = loan3000[outcome]

loan_lda = LinearDiscriminantAnalysis()
loan_lda.fit(X, y)
print(pd.DataFrame(loan_lda.scalings_, index=X.columns))
```

```
                          0
borrower_score     7.175839
payment_inc_ratio -0.099676
```

In [6]:

```
pred = pd.DataFrame(loan_lda.predict_proba(loan3000[predictors]),
                    columns=loan_lda.classes_)
```

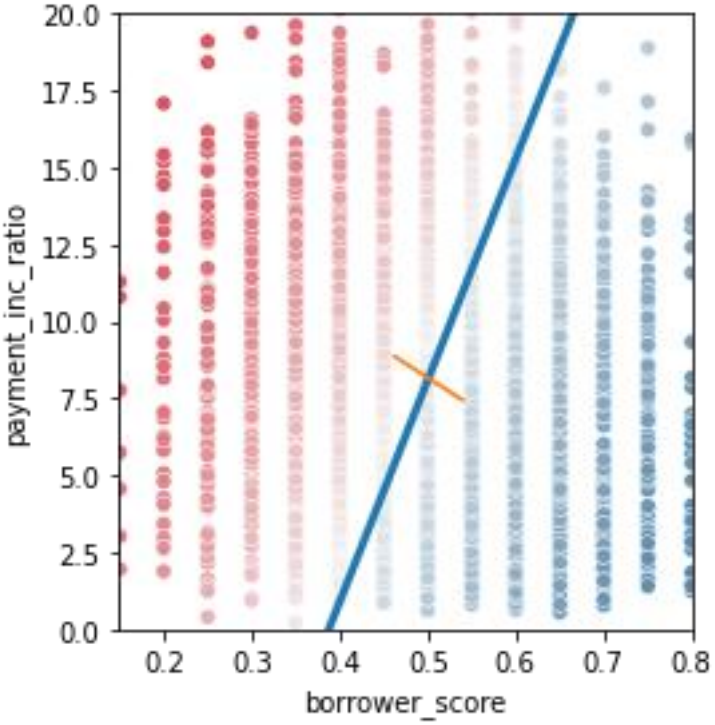
```
print(pred.head())
```

```
    default  paid off
0  0.553544  0.446456
1  0.558953  0.441047
2  0.272696  0.727304
3  0.506254  0.493746
4  0.609952  0.390048
```

Figure 5.1

In [7]:

```
# Use scalings and center of means to determine decision boundary
center = np.mean(loan_lda.means_, axis=0)
slope = - loan_lda.scalings_[0] / loan_lda.scalings_[1]
intercept = center[1] - center[0] * slope

# payment_inc_ratio for borrower_score of 0 and 20
x_0 = (0 - intercept) / slope
x_20 = (20 - intercept) / slope

lda_df = pd.concat([loan3000, pred['default']], axis=1)
lda_df.head()

fig, ax = plt.subplots(figsize=(4, 4))
g = sns.scatterplot(x='borrower_score', y='payment_inc_ratio',
                    hue='default', data=lda_df,
                    palette=sns.diverging_palette(240, 10, n=9,
as_cmap=True),
                    ax=ax, legend=False)

ax.set_ylim(0, 20)
ax.set_xlim(0.15, 0.8)
ax.plot((x_0, x_20), (0, 20), linewidth=3)
ax.plot(*loan_lda.means_.transpose())

plt.tight_layout()
plt.show()
```



Logistic regression

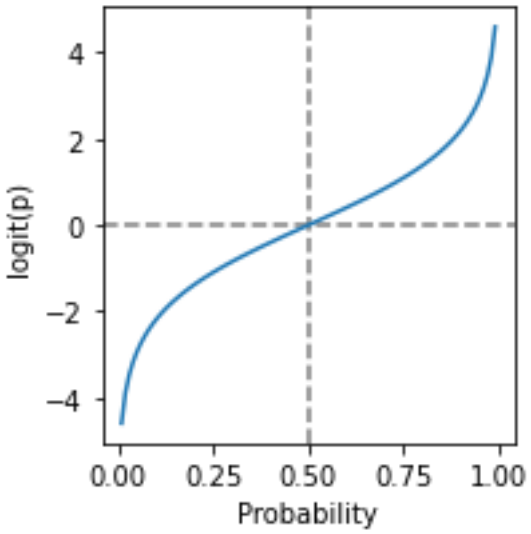
Logistic Response Function and Logit

Логистикалық регрессия

Логистикалық жауап беру функциясы және Логит

In [8]:

```
p = np.arange(0.01, 1, 0.01)
df = pd.DataFrame({
    'p': p,
    'logit': np.log(p / (1 - p)),
    'odds': p / (1 - p),
})

fig, ax = plt.subplots(figsize=(3, 3))
ax.axhline(0, color='grey', linestyle='--')
ax.axvline(0.5, color='grey', linestyle='--')
ax.plot(df['p'], df['logit'])
ax.set_xlabel('Probability')
ax.set_ylabel('logit(p)')

plt.tight_layout()
plt.show()
```



Logistic Regression and the GLM

The package *scikit-learn* has a specialised class for LogisticRegression. *Statsmodels* has a more general method based on generalized linear model (GLM).

Логистикалық регрессия және GLM

Scikit-learn пакетінде логистикалық регрессияға арналған арнайы сынып бар. Statsmodels жалпыланған сызықтық модельге (GLM) негізделген жалпы әдіске ие.

In [9]:

```
predictors = ['payment_inc_ratio', 'purpose_', 'home_', 'emp_len_',
              'borrower_score']
outcome = 'outcome'
X = pd.get_dummies(loan_data[predictors], prefix='', prefix_sep='',
                   drop_first=True)
y = loan_data[outcome] # .cat.categories

logit_reg = LogisticRegression(penalty='l2', C=1e42, solver='liblinear')
logit_reg.fit(X, y)

print('intercept ', logit_reg.intercept_[0])
print('classes', logit_reg.classes_)
pd.DataFrame({'coeff': logit_reg.coef_[0]},
             index=X.columns)
```

```
intercept  -1.6380882883923482
classes ['default' 'paid off']
```

Out[9]:

	coeff
payment_inc_ratio	-0.079728

	coeff
borrower_score	4.611037
debt_consolidation	-0.249342
home_improvement	-0.407614
major_purchase	-0.229376
medical	-0.510087
other	-0.620534
small_business	-1.215662
OWN	-0.048453
RENT	-0.157355
> 1 Year	0.357463

Note that the intercept and coefficients are reversed compared to the R model.

In [10]:

```
print(loan_data['purpose_'].cat.categories)
print(loan_data['home_'].cat.categories)
print(loan_data['emp_len_'].cat.categories)
```

```
Index(['credit_card', 'debt_consolidation', 'home_improvement',
       'major_purchase', 'medical', 'other', 'small_business'],
      dtype='object')
Index(['MORTGAGE', 'OWN', 'RENT'], dtype='object')
Index([' < 1 Year', ' > 1 Year'], dtype='object')
```

Not in book : If you have a feature or outcome variable that is ordinal, use the scikit-learn OrdinalEncoder to replace the categories (here, 'paid off' and 'default') with numbers. In the below code, we replace 'paid off' with 0 and 'default' with 1. This reverses the order of the predicted classes and as a consequence, the coefficients will be reversed.

In [11]:

```
from sklearn.preprocessing import OrdinalEncoder
enc = OrdinalEncoder(categories=[['paid off', 'default']])
y_enc = enc.fit_transform(loan_data[[outcome]]).ravel()

logit_reg_enc = LogisticRegression(penalty="l2", C=1e42, solver='liblinear')
logit_reg_enc.fit(X, y_enc)

print('intercept ', logit_reg_enc.intercept_[0])
print('classes', logit_reg_enc.classes_)
pd.DataFrame({'coeff': logit_reg_enc.coef_[0]},
             index=X.columns)
```

```
intercept  1.6378909416318836
classes [0. 1.]
```

Out[11]:

	coeff
payment_inc_ratio	0.079739
borrower_score	-4.612183
debt_consolidation	0.249414
home_improvement	0.407734
major_purchase	0.229710
medical	0.510744
other	0.620800
small_business	1.214936
OWN	0.048211
RENT	0.157288
> 1 Year	-0.356794

Predicted Values from Logistic Regression

Логистикалық регрессиядан болжамды мәндер

In [12]:

```
pred = pd.DataFrame(logit_reg.predict_log_proba(X),
                    columns=logit_reg.classes_)
print(pred.describe())
```

```
            default      paid off
count  45342.000000  45342.000000
mean      -0.757850     -0.760423
std        0.378032      0.390419
min       -2.768873     -3.538865
25%       -0.985728     -0.977164
50%       -0.697366     -0.688946
75%       -0.472209     -0.467076
max       -0.029476     -0.064787
```

In [13]:

```
pred = pd.DataFrame(logit_reg.predict_proba(X),
```

```
                    columns=logit_reg.classes_)
print(pred.describe())
```

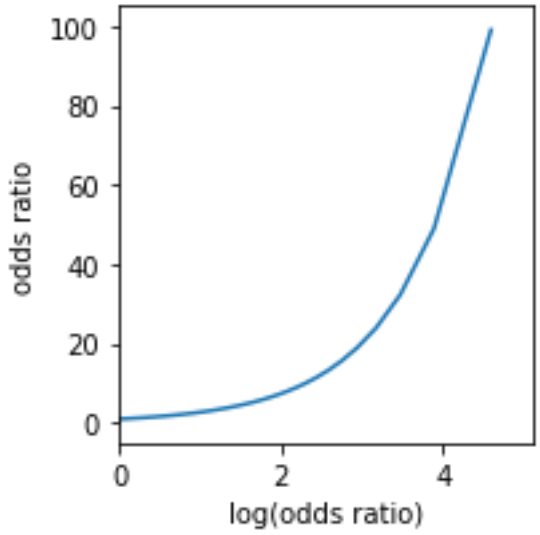
```
            default      paid off
count  45342.000000  45342.000000
mean       0.500001      0.499999
std        0.167336      0.167336
min        0.062733      0.029046
25%        0.373167      0.376377
50%        0.497895      0.502105
75%        0.623623      0.626833
max        0.970954      0.937267
```

Interpreting the Coefficients and Odds Ratios

Коэффициенттер мен коэффициенттерді түсіндіру

In [14]:

```
fig, ax = plt.subplots(figsize=(3, 3))
ax.plot(df['logit'], df['odds'])
ax.set_xlabel('log(odds ratio)')
ax.set_ylabel('odds ratio')
ax.set_xlim(0, 5.1)
ax.set_ylim(-5, 105)

plt.tight_layout()
plt.show()
```



Assessing the Model

For comparison, here the GLM model using *statsmodels*. This method requires that the outcome is mapped to numbers.

Модельді бағалау

Салыстыру үшін біз statsmodels көмегімен GLM моделін ұсынамыз. Бұл әдіс нәтижені сандармен салыстыруды талап етеді.

In [15]:

```
# use GLM (general linear model) with the binomial family to
```

```
# fit a logistic regression
y_numbers = [1 if yi == 'default' else 0 for yi in y]
logit_reg_sm = sm.GLM(y_numbers, X.assign(const=1),
                      family=sm.families.Binomial())
logit_result = logit_reg_sm.fit()
print(logit_result.summary())
```

```
                 Generalized Linear Model Regression Results
==============================================================================
=
Dep. Variable:                      y   No. Observations:                4534
2
Model:                            GLM   Df Residuals:                    4533
0
Model Family:                Binomial   Df Model:                          1
1
Link Function:                  Logit   Scale:                         1.000
0
Method:                          IRLS   Log-Likelihood:                -28757
.
Date:                Tue, 26 Apr 2022   Deviance:                       57515
.
Time:                        19:56:17   Pearson chi2:                 4.54e+0
4
No. Iterations:                     4   Pseudo R-squ. (CS):             0.111
2
Covariance Type:            nonrobust
==============================================================================
=========
                         coef    std err          z      P>|z|      [0.025
0.975]
------------------------------------------------------------------------------
---------
payment_inc_ratio      0.0797      0.002     32.058      0.000       0.075
0.085
borrower_score        -4.6126      0.084    -55.203      0.000      -4.776
-4.449
debt_consolidation     0.2494      0.028      9.030      0.000       0.195
0.303
home_improvement       0.4077      0.047      8.747      0.000       0.316
0.499
major_purchase         0.2296      0.054      4.277      0.000       0.124
0.335
medical                0.5105      0.087      5.882      0.000       0.340
0.681
other                  0.6207      0.039     15.738      0.000       0.543
0.698
small_business         1.2153      0.063     19.192      0.000       1.091
1.339
OWN                    0.0483      0.038      1.271      0.204      -0.026
0.123
RENT                   0.1573      0.021      7.420      0.000       0.116
0.199
 > 1 Year             -0.3567      0.053     -6.779      0.000      -0.460
-0.254
const                  1.6381      0.074     22.224      0.000       1.494
1.783
==============================================================================
=========
```

Use splines

In [16]:

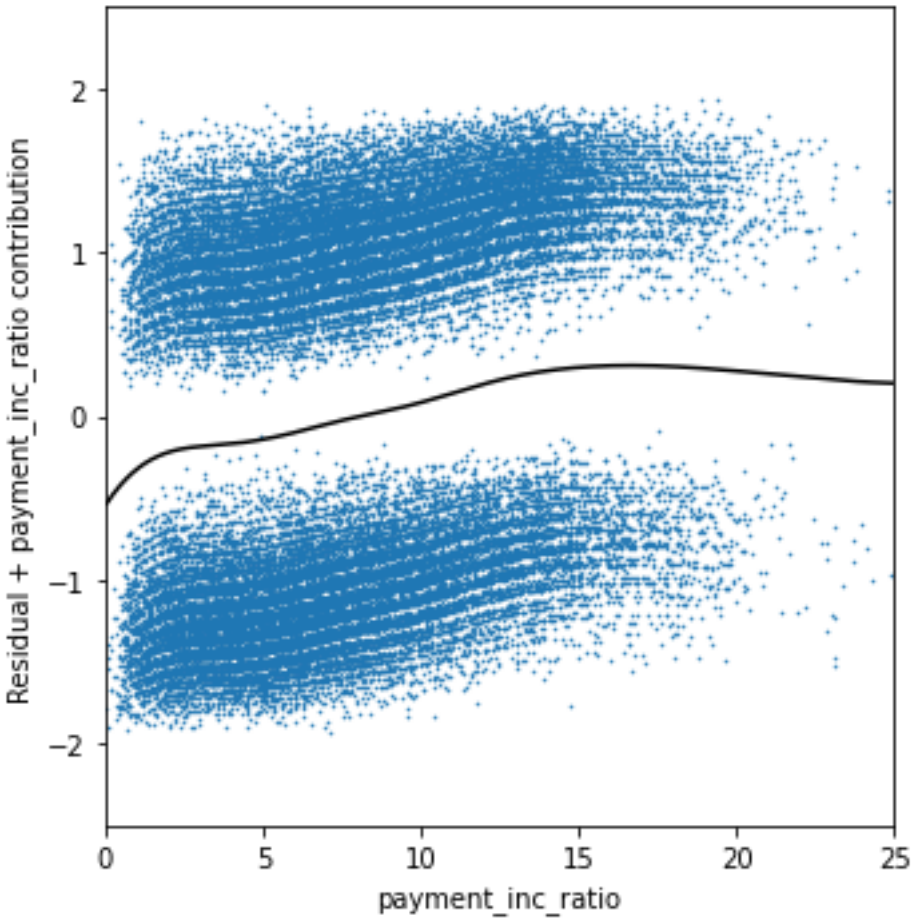
```
import statsmodels.formula.api as smf
formula = ('outcome ~ bs(payment_inc_ratio, df=8) + purpose_ + ' +
           'home_ + emp_len_ + bs(borrower_score, df=3)')
model = smf.glm(formula=formula, data=loan_data,
family=sm.families.Binomial())
results = model.fit()
print(results.summary())
```

```
                             Generalized Linear Model Regression Results
==============================================================================
========================
Dep. Variable:     ['outcome[default]', 'outcome[paid off]']   No. Observatio
ns:                45342
Model:                                                 GLM   Df Residuals:
45321
Model Family:                                     Binomial   Df Model:
20
Link Function:                                       Logit   Scale:
1.0000
Method:                                               IRLS   Log-Likelihood
:                -28731.
Date:                                   Tue, 26 Apr 2022   Deviance:
57462.
Time:                                           19:56:17   Pearson chi2:
4.54e+04
No. Iterations:                                        6   Pseudo R-squ.
(CS):             0.1122
Covariance Type:                               nonrobust
==============================================================================
======================
                                   coef    std err          z      P>|z|
[0.025      0.975]
------------------------------------------------------------------------------
---------------------
Intercept                          1.5756      0.331      4.765      0.000
0.928       2.224
purpose_[T.debt_consolidation]     0.2486      0.028      8.998      0.000
0.194       0.303
purpose_[T.home_improvement]       0.4097      0.047      8.757      0.000
0.318       0.501
purpose_[T.major_purchase]         0.2382      0.054      4.416      0.000
0.132       0.344
purpose_[T.medical]                0.5206      0.087      5.980      0.000
0.350       0.691
purpose_[T.other]                  0.6284      0.040     15.781      0.000
0.550       0.706
purpose_[T.small_business]         1.2250      0.063     19.305      0.000
1.101       1.349
home_[T.OWN]                       0.0498      0.038      1.309      0.191
-0.025       0.124
home_[T.RENT]                      0.1577      0.021      7.431      0.000
0.116       0.199
emp_len_[T. > 1 Year]             -0.3526      0.053     -6.699      0.000
-0.456      -0.249
bs(payment_inc_ratio, df=8)[0]     0.7042      0.342      2.060      0.039
0.034       1.374
bs(payment_inc_ratio, df=8)[1]     0.6621      0.198      3.351      0.001
0.275       1.049
```

```
bs(payment_inc_ratio, df=8)[2]     0.8118      0.245      3.309      0.001
0.331       1.293
bs(payment_inc_ratio, df=8)[3]     1.0377      0.223      4.644      0.000
0.600       1.476
bs(payment_inc_ratio, df=8)[4]     1.1901      0.233      5.112      0.000
0.734       1.646
bs(payment_inc_ratio, df=8)[5]     2.8404      0.316      8.980      0.000
2.220       3.460
bs(payment_inc_ratio, df=8)[6]    -1.3427      1.229     -1.092      0.275
-3.752       1.067
bs(payment_inc_ratio, df=8)[7]     7.1094      6.393      1.112      0.266
-5.420      19.639
bs(borrower_score, df=3)[0]       -2.9011      0.533     -5.448      0.000
-3.945      -1.857
bs(borrower_score, df=3)[1]       -2.6056      0.196    -13.284      0.000
-2.990      -2.221
bs(borrower_score, df=3)[2]       -5.7421      0.508    -11.313      0.000
-6.737      -4.747
==============================================================================
=====================
```

In [17]:

```
from statsmodels.genmod.generalized_linear_model import GLMResults
def partialResidualPlot(model, df, outcome, feature, fig, ax):
    y_actual = [0 if s == 'default' else 1 for s in df[outcome]]
    y_pred = model.predict(df)
    org_params = model.params.copy()
    zero_params = model.params.copy()
    # set model parametes of other features to 0
    for i, name in enumerate(zero_params.index):
        if feature in name:
            continue
        zero_params[i] = 0.0
    model.initialize(model.model, zero_params)
    feature_prediction = model.predict(df)
    ypartial = -np.log(1/feature_prediction - 1)
    ypartial = ypartial - np.mean(ypartial)
    model.initialize(model.model, org_params)
    results = pd.DataFrame({
        'feature': df[feature],
        'residual': -2 * (y_actual - y_pred),
        'ypartial': ypartial/ 2,
    })
    results = results.sort_values(by=['feature'])

    ax.scatter(results.feature, results.residual, marker=".", s=72./fig.dpi)
    ax.plot(results.feature, results.ypartial, color='black')
    ax.set_xlabel(feature)
    ax.set_ylabel(f'Residual + {feature} contribution')
    return ax

fig, ax = plt.subplots(figsize=(5, 5))
partialResidualPlot(results, loan_data, 'outcome', 'payment_inc_ratio', fig,
ax)
ax.set_xlim(0, 25)
ax.set_ylim(-2.5, 2.5)


plt.tight_layout()
plt.show()
```



Жіктеу модельдерін бағалау

Шатасу матрицасы

In [18]:

```
# Confusion matrix
pred = logit_reg.predict(X)
pred_y = logit_reg.predict(X) == 'default'
true_y = y == 'default'
true_pos = true_y & pred_y
true_neg = ~true_y & ~pred_y
false_pos = ~true_y & pred_y
false_neg = true_y & ~pred_y

conf_mat = pd.DataFrame([[np.sum(true_pos), np.sum(false_neg)],
[np.sum(false_pos), np.sum(true_neg)]],
                        index=['Y = default', 'Y = paid off'],
                        columns=['Yhat = default', 'Yhat = paid off'])
print(conf_mat)
```

```
              Yhat = default  Yhat = paid off
Y = default            14336             8335
Y = paid off            8148            14523
```

In [19]:

```
print(confusion_matrix(y, logit_reg.predict(X)))
```

```
[[14336  8335]
 [ 8148 14523]]
```

The package *dmba* contains the function classificationSummary that prints confusion matrix and accuracy for a classification model.

In [20]:

```
classificationSummary(y, logit_reg.predict(X),
                      class_names=logit_reg.classes_)
```

```
Confusion Matrix (Accuracy 0.6365)

         Prediction
  Actual  default paid off
 default    14336     8335
paid off     8148    14523
```

Precision, Recall, and Specificity

The *scikit-learn* function precision_recall_fscore_support returns precision, recall, fbeta_score and support.

In [21]:

```
conf_mat = confusion_matrix(y, logit_reg.predict(X))
print('Precision', conf_mat[0, 0] / sum(conf_mat[:, 0]))
print('Recall', conf_mat[0, 0] / sum(conf_mat[0, :]))
print('Specificity', conf_mat[1, 1] / sum(conf_mat[1, :]))
```

```
Precision 0.6376089663760897
Recall 0.6323496978518812
Specificity 0.6405981209474659
```

In [22]:

```
precision_recall_fscore_support(y, logit_reg.predict(X),
                                labels=['default', 'paid off'])
```

Out[22]:

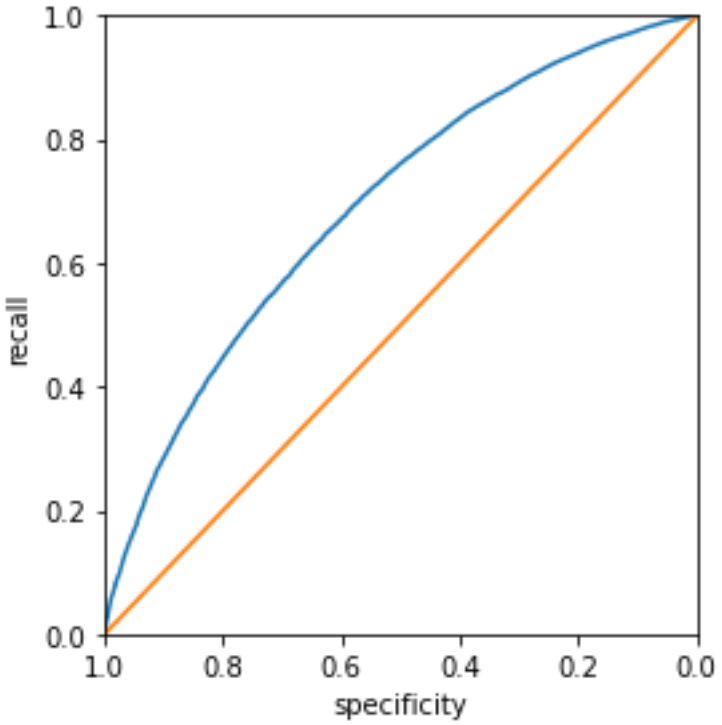
```
(array([0.63760897, 0.63535742]),
 array([0.6323497 , 0.64059812]),
 array([0.63496844, 0.63796701]),
 array([22671, 22671]))
```

ROC Curve

The function roc_curve in *Scikit-learn* calculates all the information that is required for plotting a ROC curve.

In [23]:

```
fpr, tpr, thresholds = roc_curve(y, logit_reg.predict_proba(X)[:, 0],
                                 pos_label='default')
roc_df = pd.DataFrame({'recall': tpr, 'specificity': 1 - fpr})

ax = roc_df.plot(x='specificity', y='recall', figsize=(4, 4), legend=False)
ax.set_ylim(0, 1)
ax.set_xlim(1, 0)
ax.plot((1, 0), (0, 1))
ax.set_xlabel('specificity')
ax.set_ylabel('recall')


plt.tight_layout()
plt.show()
```



AUC

Accuracy can easily be calculated using the *scikit-learn* function accuracy_score.

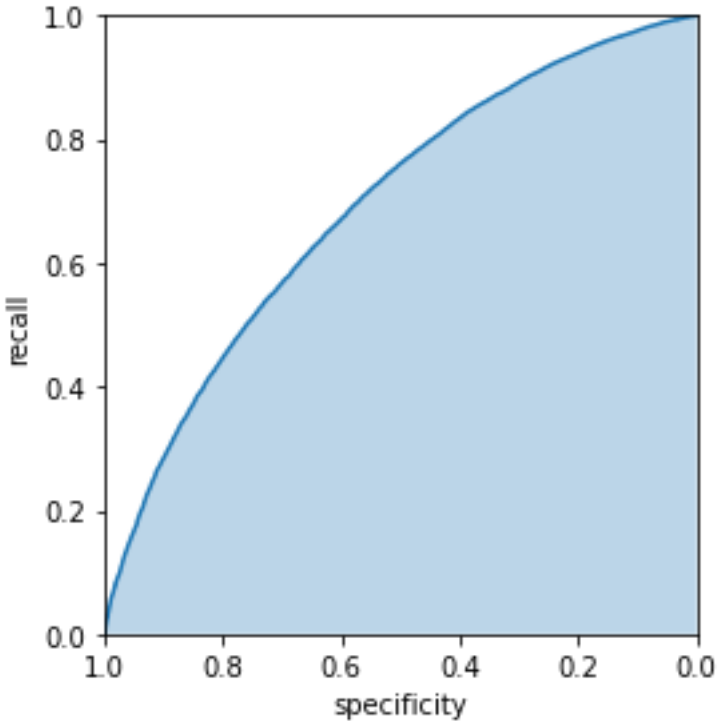
In [24]:

```
print(np.sum(roc_df.recall[:-1] * np.diff(1 - roc_df.specificity)))
print(roc_auc_score([1 if yi == 'default' else 0 for yi in y],
logit_reg.predict_proba(X)[:, 0]))
```

```
0.691710795288669
0.6917108731135808
```

In [25]:

```
fpr, tpr, thresholds = roc_curve(y, logit_reg.predict_proba(X)[:,0],
                                 pos_label='default')
roc_df = pd.DataFrame({'recall': tpr, 'specificity': 1 - fpr})

ax = roc_df.plot(x='specificity', y='recall', figsize=(4, 4), legend=False)
ax.set_ylim(0, 1)
ax.set_xlim(1, 0)
# ax.plot((1, 0), (0, 1))
ax.set_xlabel('specificity')
ax.set_ylabel('recall')
ax.fill_between(roc_df.specificity, 0, roc_df.recall, alpha=0.3)


plt.tight_layout()
plt.show()
```



Strategies for Imbalanced Data

Undersampling

The results differ from the R version, however are equivalent to results obtained using the R code. Model based results are of similar magnitude.

In [26]:

```
full_train_set = pd.read_csv(FULL_TRAIN_SET_CSV)
print(full_train_set.shape)
```

```
(119987, 19)
```

In [27]:

```
print('percentage of loans in default: ',
print(      100 * np.mean(full_train_set.outcome == 'default')))
```

```
18.894546909248504
percentage of loans in default:  None
```

In [28]:

```
predictors = ['payment_inc_ratio', 'purpose_', 'home_', 'emp_len_',
              'dti', 'revol_bal', 'revol_util']
outcome = 'outcome'
X = pd.get_dummies(full_train_set[predictors], prefix='', prefix_sep='',
                   drop_first=True)
y = full_train_set[outcome]

full_model = LogisticRegression(penalty='l2', C=1e42, solver='liblinear')
full_model.fit(X, y)
print('percentage of loans predicted to default: ',
print(      100 * np.mean(full_model.predict(X) == 'default')))
```

```
0.9759390600648404
percentage of loans predicted to default:  None
```

In [29]:

```
(np.mean(full_train_set.outcome == 'default') /
 np.mean(full_model.predict(X) == 'default'))
```

Out[29]:

```
19.360375747224595
```

Oversampling and Up/Down Weighting

In [30]:

```
default_wt = 1 / np.mean(full_train_set.outcome == 'default')
wt = [default_wt if outcome == 'default' else 1 for outcome in
full_train_set.outcome]

full_model = LogisticRegression(penalty="l2", C=1e42, solver='liblinear')
full_model.fit(X, y, wt)
print('percentage of loans predicted to default (weighting): ',
print(      100 * np.mean(full_model.predict(X) == 'default')))
```

```
61.79836148916132
percentage of loans predicted to default (weighting):  None
```

Data Generation

The package *imbalanced-learn* provides an implementation of the *SMOTE* and similar algorithms.

In [31]:

```
X_resampled, y_resampled = SMOTE().fit_resample(X, y)
print('percentage of loans in default (SMOTE resampled): ',
      100 * np.mean(y_resampled == 'default'))

full_model = LogisticRegression(penalty="l2", C=1e42, solver='liblinear')
full_model.fit(X_resampled, y_resampled)
print('percentage of loans predicted to default (SMOTE): ',
      100 * np.mean(full_model.predict(X) == 'default'))


X_resampled, y_resampled = ADASYN().fit_resample(X, y)
print('percentage of loans in default (ADASYN resampled): ',
      100 * np.mean(y_resampled == 'default'))

full_model = LogisticRegression(penalty="l2", C=1e42, solver='liblinear')
full_model.fit(X_resampled, y_resampled)
print('percentage of loans predicted to default (ADASYN): ',
print(      100 * np.mean(full_model.predict(X) == 'default')))
```

```
percentage of loans in default (SMOTE resampled):  50.0
percentage of loans predicted to default (SMOTE):  29.503196179586123
percentage of loans in default (ADASYN resampled):  48.56040383751355
27.735504679673635
percentage of loans predicted to default (ADASYN):  None
```

Exploring the Predictions

In [32]:

```
loan3000 = pd.read_csv(LOAN3000_CSV)

predictors = ['borrower_score', 'payment_inc_ratio']
outcome = 'outcome'
```

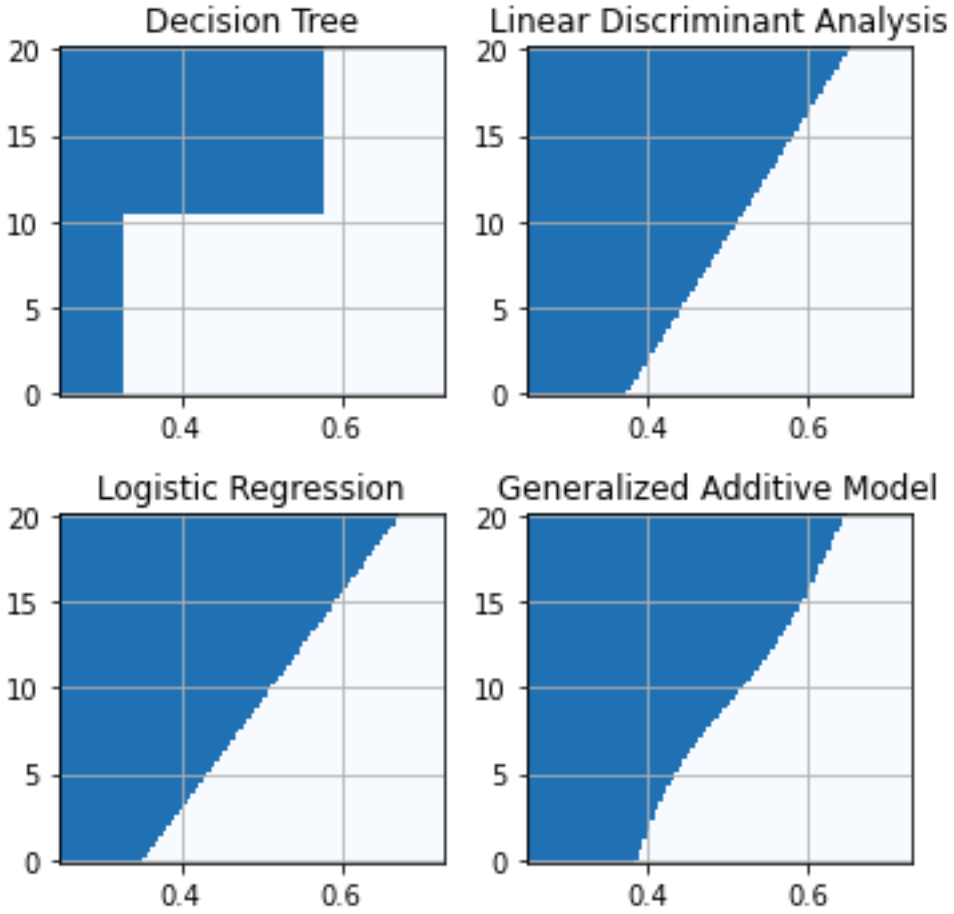
```
X = loan3000[predictors]
y = loan3000[outcome]

loan_tree = DecisionTreeClassifier(random_state=1, criterion='entropy',
                                   min_impurity_decrease=0.003)
loan_tree.fit(X, y)

loan_lda = LinearDiscriminantAnalysis()
loan_lda.fit(X, y)

logit_reg = LogisticRegression(penalty="l2", solver='liblinear')
logit_reg.fit(X, y)


## model
gam = LinearGAM(s(0) + s(1))
print(gam.gridsearch(X.values, [1 if yi == 'default' else 0 for yi in y]))
```

```
100% (11 of 11) |########################| Elapsed Time: 0:00:00 Time:  0:00:
00
LinearGAM(callbacks=[Deviance(), Diffs()], fit_intercept=True,
   max_iter=100, scale=None, terms=s(0) + s(1) + intercept,
   tol=0.0001, verbose=False)
```

In [33]:

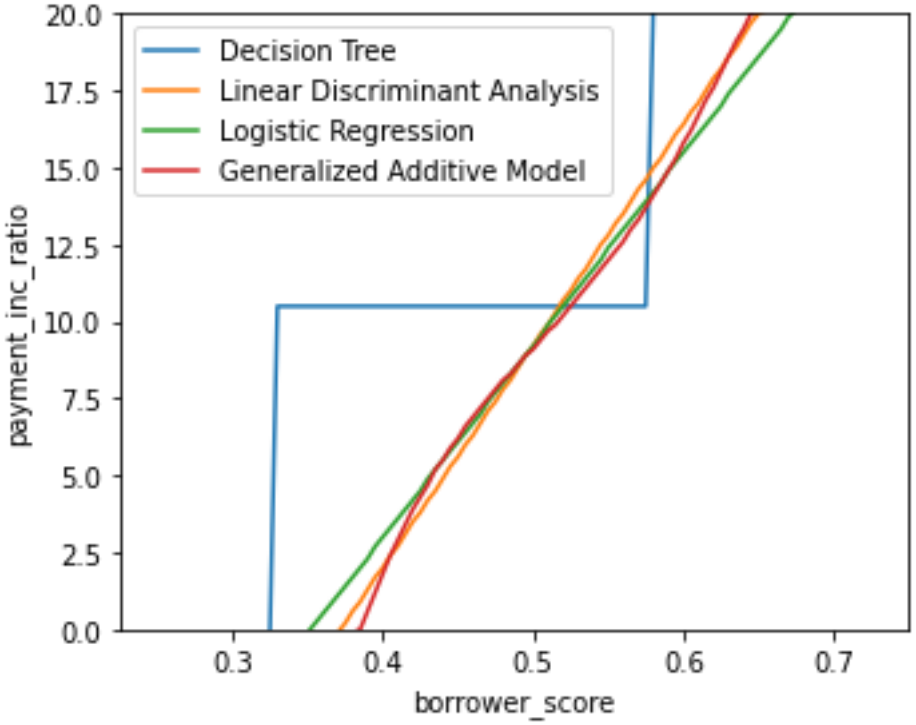
```
models = {
    'Decision Tree': loan_tree,
    'Linear Discriminant Analysis': loan_lda,
    'Logistic Regression': logit_reg,
    'Generalized Additive Model': gam,
}

fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(5, 5))

xvalues = np.arange(0.25, 0.73, 0.005)
yvalues = np.arange(-0.1, 20.1, 0.1)
xx, yy = np.meshgrid(xvalues, yvalues)
X = pd.DataFrame({
    'borrower_score': xx.ravel(),
    'payment_inc_ratio': yy.ravel(),
})

boundary = {}

for n, (title, model) in enumerate(models.items()):
    ax = axes[n // 2, n % 2]
    predict = model.predict(X)
    if 'Generalized' in title:
        Z = np.array([1 if z > 0.5 else 0 for z in predict])
    else:

        Z = np.array([1 if z == 'default' else 0 for z in predict])
    Z = Z.reshape(xx.shape)
    boundary[title] = yvalues[np.argmax(Z > 0, axis=0)]
    boundary[title][Z[-1,:] == 0] = yvalues[-1]

    c = ax.pcolormesh(xx, yy, Z, cmap='Blues', vmin=0.1, vmax=1.3,
shading='auto')
    ax.set_title(title)
    ax.grid(True)
```

```
plt.tight_layout()
plt.show()
```



In [34]:

```
boundary['borrower_score'] = xvalues
boundaries = pd.DataFrame(boundary)

fig, ax = plt.subplots(figsize=(5, 4))
boundaries.plot(x='borrower_score', ax=ax)
ax.set_ylabel('payment_inc_ratio')
ax.set_ylim(0, 20)


plt.tight_layout()
plt.show()
```


Decision Tree
Linear Discriminant Analysis
Logistic Regression
Generalized Additive Model
payment_inc_ratio
borrower_score
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
0.3
0.4
0.5
0.6
0.7