Prediction with Machine Learning for Economists

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Tasks for Assignment 3

I discuss my idea and steps before the codes

Design the target (fast growth), then build models to predict fast growth of firms.

In [116]:

```
import pandas as pd
import numpy as np
from plotnine import *
import patsy
from sklearn.model_selection import train_test_split, KFold, GridSearchCV
from sklearn.linear_model import LogisticRegressionCV
import sklearn.metrics as metrics
from sklearn.metrics import confusion_matrix, roc_curve, mean_squared_error, roc_auc
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from py_helper_functions import *

import warnings
warnings.filterwarnings('ignore')
```

Import data

In [117]:

```
data = pd.read_csv('cs_bisnode_panel.csv')
```

We need to drop attributes that have a lot of missing values even though they may help the results.

In [118]:

```
# drop variables with many NAs
data = data.drop(columns = ['COGS', 'finished_prod', 'net_dom_sales', 'net_exp_sales
data = data.query('year != 2016')  # because third as many companies in 2016 as in e
```

Label engineering

Take the company's id and year as a Cartesian product, and use np.nan to replace missing values.

In [119]:

```
# Combine year(2005-2015) and comp_id, This will increase the number of entries in t
# because not every company will have complete data from year 2005 to 2015 before th
data = data.set_index(['year','comp_id']).unstack(fill_value='toReplace').stack().re
# So only way I counld define it as Nan
data = data.replace('toReplace', np.nan)
```

Create a new attribute status_alive, that is, whether the company is alive or not, which will help build the target later

In [120]:

```
# generate status_alive; if sales larger than zero and not-NA, then firm is alive
data['status_alive'] = ((False == data['sales'].isna()) & data['sales'] > 0).astype(
```

If the current company survives and current sales are 1.2 times the company's sales two years ago, then we think the company has grown rapidly. And fast_growth is the target.

In [121]:

```
# target(fast growth): if there are sales in this year and also sales two years befo
# and the current sales is 120% of two years before
# Status_in_two_year: data.groupby('comp_id')['status_alive'].shift(2)
# Sales_two_year_120%: ((data['sales'] / data.groupby('comp_id')['sales'].shift(2))
data['sales_120_percent'] = ((data['sales'] / data.groupby('comp_id')['sales'].shift

data['fast_growth'] = ((data['status_alive'] == 1) &
                       (data.groupby('comp_id')['status_alive'].shift(2) == 1) &
                       (data['sales_120_percent'] == 1)).astype(int)
```

In [122]:

```
data = data.query('year <= 2013')
```

process the sales and add related features

In [123]:

```
# sales missing many values
# sales process
data['sales']=np.where(data['sales'] < 0, 1, data['sales'])  # if sales < 0 output 1
```

In [124]:

```
data = data.assign(
    # sales < 0 => 0  Nan => Nan
    ln_sales = np.where(data['sales'] > 0 , np.log(data['sales'] + 1e-10), (np.where
    sales_mil=data['sales']/1000000,
    sales_mil_log = np.where(data['sales'] > 0, np.log((data['sales']/1000000) + 1e-
)
```

In [125]:

```
# replace w 0 for new firms + add dummy to capture it
data['age'] = np.where(data['year'] - data['founded_year'] < 0, 0, data['year'] - da

# new company or not
data['new'] = np.where(((data['age'] <= 1) | (data['balsheet_notfullyear']==1)), 1 ,
data['new']=np.where(data['new'].isna(), 1, data['new'] )
```

Sample design

We choose the sample that the company survived in 2013

In [126]:

```
# look at cross section
data=data.query('year==2013 & status_alive == 1')
# look at firms below 10m euro revenues and above 1000 euros
data=data.query('sales_mil <= 10 & sales_mil >= 0.001')  # 1000eur - 10000000eur
```

In [127]:

```
data.fast_growth.describe()
```

Out[127]:

```
count    21464.000000
mean         0.302320
std          0.459274
min          0.000000
25%          0.000000
50%          0.000000
75%          1.000000
max          1.000000
Name: fast_growth, dtype: float64
```

Feature engineering

We have done some additional feature engineering based on existing features

In [128]:

```
# change some industry category codes
data['ind2_cat'] = data['ind2'].copy()
data['ind2_cat'] = np.where(data['ind2']>56, 60, data['ind2_cat'])
data['ind2_cat'] = np.where(data['ind2']<26, 20, data['ind2_cat'])
data['ind2_cat'] = np.where((data['ind2']<55) & (data['ind2']>35), 40, data['ind2_ca
data['ind2_cat'] = np.where(data['ind2']==31, 30, data['ind2_cat'])
data['ind2_cat'] = np.where(data['ind2'].isna(), 99, data['ind2_cat'])
```

In [129]:

```
# Firm characteristics
data['age2'] = data['age'] ** 2
data['foreign_management'] = np.where(data['foreign'] >= 0.5, 1, np.where(data['fore
data['gender_m'] = data['gender'].astype("category")
data['m_region_loc'] = data['region_m'].astype("category")
```

In [130]:

```
# look at more financial variables, create ratios
# assets can't be negative. Change them to 0 and add a flag.
data['flag_asset_problem'] = np.where(((data['intang_assets'] < 0) | (data['curr_ass
data['flag_asset_problem'] = np.where(((data['intang_assets'].isna()) | (data['curr_
```

In [131]:

```
data['intang_assets'] = np.where(data['intang_assets'] < 0, 0, data['intang_assets']
data['curr_assets'] = np.where(data['curr_assets'] < 0, 0, data['curr_assets'])
data['fixed_assets'] = np.where(data['fixed_assets'] < 0, 0, data['fixed_assets'])
```

In [132]:

```
# generate total assets
data['total_assets_bs'] = data['intang_assets'] + data['curr_assets'] + data['fixed_
```

In [133]:

```
pl_names = ['extra_exp','extra_inc',  'extra_profit_loss', 'inc_bef_tax' ,'inventori
              'material_exp', 'profit_loss_year', 'personnel_exp']
bs_names = ['intang_assets', 'curr_liab', 'fixed_assets', 'liq_assets', 'curr_assets
              'share_eq', 'subscribed_cap', 'tang_assets' ]
```

In [134]:

```
# divide all pl_names elements by sales and create new column for it
data[[col + '_pl' for col in pl_names]] = data[pl_names].div(data['sales'], axis='ir
```

In [135]:

```
# divide all bs_names elements by total_assets_bs and create new column for it
data[[col +'_bs' for col in bs_names]] =  data[bs_names].div(data['total_assets_bs']
# get Nan values where total_assets_bs is NaN
for col in bs_names:
    data[[col +'_bs']] = np.where(data['total_assets_bs'].isna(), np.nan, data[col +
```

In [136]:

```
# creating flags, and winsorizing tails

# Variables that represent accounting items that cannot be negative (e.g. materials)
zero = ['extra_exp_pl', 'extra_inc_pl', 'inventories_pl', 'material_exp_pl', 'person
         'curr_liab_bs', 'fixed_assets_bs', 'liq_assets_bs', 'curr_assets_bs', 'su
         'intang_assets_bs']

data[[col +'_flag_high' for col in zero]] = np.where(data[zero].isna(), np.nan, (dat
# make change, ratio should not greater than 1
data[[col for col in zero]] = np.where(data[zero].isna(), np.nan, np.where(data[zerc

data[[col +'_flag_error' for col in zero]] = np.where(data[zero].isna(), np.nan, (da
# make change, ratio should not smaller than 0
data[[col for col in zero]] = np.where(data[zero].isna(), np.nan, np.where(data[zerc
```

In [137]:

```
# for vars that could be any, but are mostly between -1 and 1
anyof = ['extra_profit_loss_pl', 'inc_bef_tax_pl', 'profit_loss_year_pl', 'share_eq_

data[[col +'_flag_low' for col in anyof]] = np.where(data[anyof].isna(), np.nan, (da
# make change, value smaller than -1 change to be -1
data[[col for col in anyof]] = np.where(data[anyof].isna(), np.nan, np.where((data[a

data[[col +'_flag_high' for col in anyof]] = np.where(data[anyof].isna(), np.nan, (d
# make change, value greater than 1 change to be 1
data[[col for col in anyof]] = np.where(data[anyof].isna(), np.nan, np.where((data[a

data[[col +'_flag_zero' for col in anyof]] = np.where(data[anyof].isna(), np.nan, (d
# make change, the value of _quad will between 0 and 1.
data[[col +'_quad' for col in anyof]] = np.where(data[anyof].isna(), np.nan, data[ar
```

In [138]:

```
# dropping flags with no variation
flag_columns = [col for col in data.columns if 'flag' in col]
data = data.drop(data[flag_columns].std()[(data[flag_columns].std() == 0)].index, ax
```

In [139]:

```
# CEO age
data['ceo_age'] = data['year'] - data['birth_year']
data = data.assign(
    flag_low_ceo_age = (data['ceo_age'] < 25).astype(int),
    flag_high_ceo_age = (data['ceo_age'] > 75).astype(int),
    flag_miss_ceo_age = (data['ceo_age'].isna()).astype(int)
)

data['ceo_age'] = np.where(data['ceo_age'] < 25, 25, data['ceo_age'])
data['ceo_age'] = np.where(data['ceo_age'] > 75, 75, data['ceo_age'])
data['ceo_age'] = np.where(data['ceo_age'].isna(), data['ceo_age'].mean(), data['cec
data['ceo_young'] = (data['ceo_age'] < 40).astype(int)
```

In [140]:

```
# number emp, very noisy measure
data['labor_avg_mod'] = np.where(data['labor_avg'].isna(), data['labor_avg'].mean(),
data['flag_miss_labor_avg'] = (data['labor_avg'].isna()).astype(int)
```

In [141]:

```
data = data.drop(['labor_avg'], axis=1)
```

In [142]:

```
# create category type variables
data['urban_m'] = data['urban_m'].astype("category")
data['ind2_cat'] = data['ind2_cat'].astype("category")
data['fast_growth_f'] = data['fast_growth'].astype("category")
data['fast_growth_f'] = data['fast_growth_f'].cat.rename_categories(['no_fast_growth
```

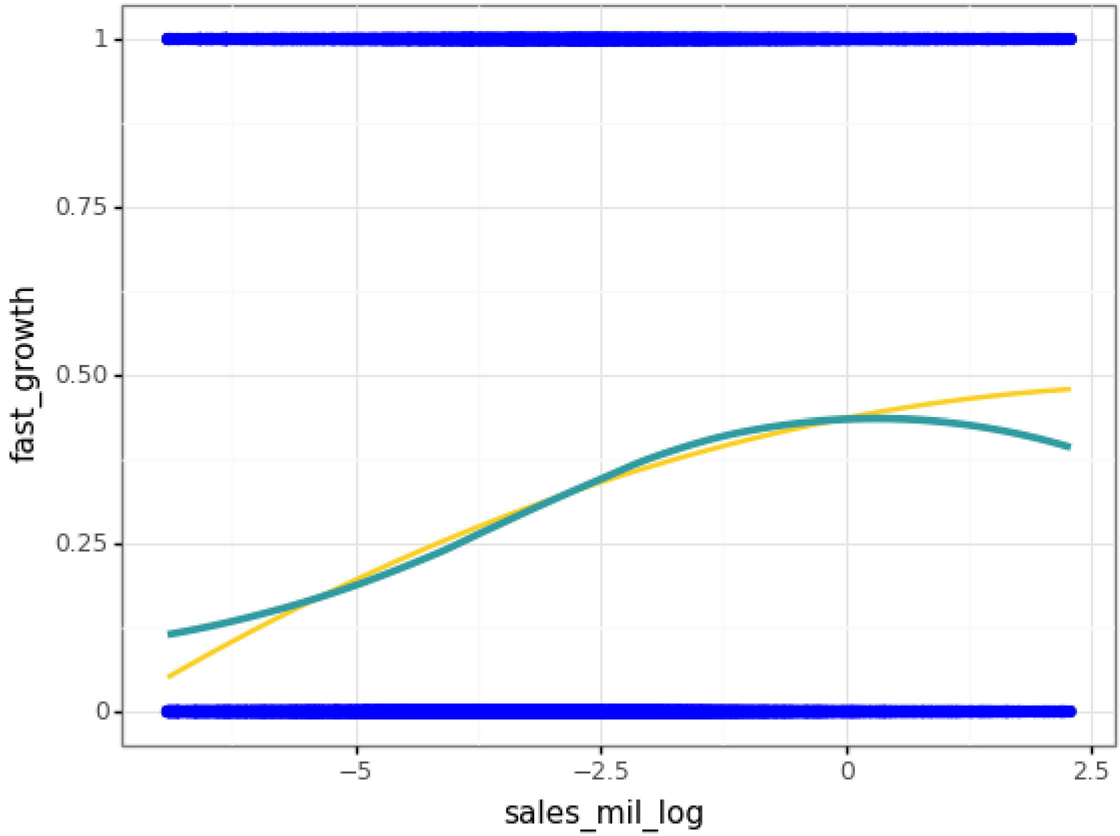
In [143]:

```
data['sales_mil_log_sq'] = data['sales_mil_log']**2
```

Draw the fitting graph between sales_mil_log and target fast_growth

In [144]:

```
# The bigger the sale, the lower the probability that the company will not exit afte
ggplot(data, aes(x = 'sales_mil_log', y = 'fast_growth')) + geom_point(
    color = 'blue') + geom_smooth(
    method='lm', formula='y ~ x + I(x**2)',  color=color[3], se = False) + geom_smoo
    method = 'loess', color=color[4], se = False, size=1.5, span=0.9) + labs(
    x='sales_mil_log', y='fast_growth'
) + theme_bw()
```



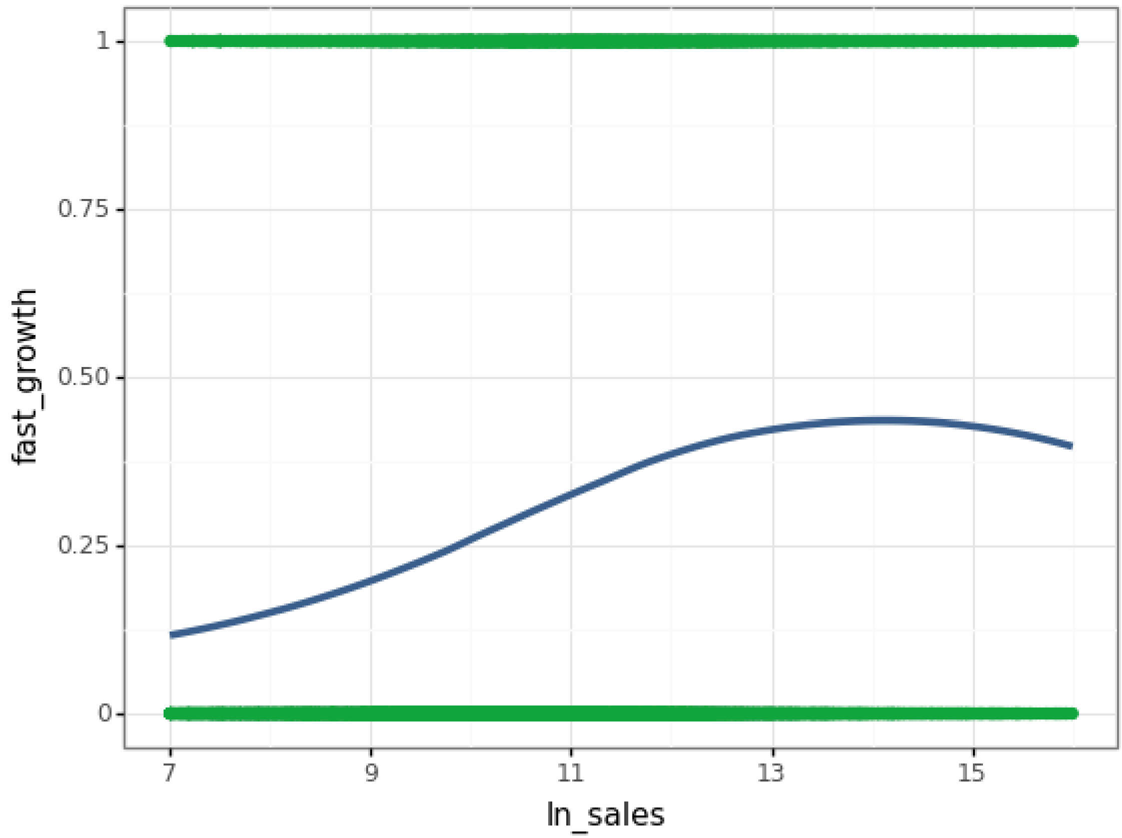
Out[144]:

<ggplot: (8786252442041)>

Draw the fitting graph between ln_sales and target fast_growth

In [145]:

```
# Within a certain range, the greater the increase in sales,
# the lower the probability of the company exiting after two years
ggplot(data, aes(x = 'ln_sales', y = 'fast_growth')) + geom_point(
    color=color[1]) + geom_smooth(
    method = 'loess', color=color[0], se = False, size=1.5, span=0.9) + labs(
    x='ln_sales', y='fast_growth') + scale_x_continuous(
    limits=(7, 16), breaks = seq(7, 20, by = 2)
) + theme_bw()
```



Out[145]:

```
<ggplot: (8786166972609)>
```

In [146]:

```
# no more imputation, drop obs if key vars missing
data = data.dropna(subset = ['liq_assets_bs', 'foreign', 'ind'])
```

In [147]:

```
# drop missing
data = data.dropna(subset = ['age', 'foreign', 'material_exp_pl', 'm_region_loc'])
```

In [148]:

```
# drop unused factor levels
for col in data.select_dtypes(include=['category']).columns:
    data[col] = data[col].cat.remove_unused_categories()
```

In [149]:

```
data.to_csv('bisnode_firms_clean.csv',index=False)
```

Predicting fast growing firms

Logit, Random Forest and GBM are used for prediction

In [150]:

```
data = pd.read_csv('bisnode_firms_clean.csv')
```

Define helper functions

In [151]:

```
def regression_results(y_true, y_pred):
    # Regression metrics
    explained_variance=metrics.explained_variance_score(y_true, y_pred)
    mean_absolute_error=metrics.mean_absolute_error(y_true, y_pred)
    mse=metrics.mean_squared_error(y_true, y_pred)
    median_absolute_error=metrics.median_absolute_error(y_true, y_pred)
    r2=metrics.r2_score(y_true, y_pred)

    print('explained_variance: ', round(explained_variance,4))
    print('r2: ', round(r2,4))
    print('MAE: ', round(mean_absolute_error,4))
    print('MSE: ', round(mse,4))
    print('RMSE: ', round(np.sqrt(mse),4))

def coef_matrix(X, model):

    coef_matrix = pd.concat([pd.DataFrame(X.columns),pd.DataFrame(np.transpose(model
    coef_matrix.columns = ['variable', 'coefficient']
    coef_matrix = coef_matrix.append({'variable': 'Intercept', 'coefficient': np.ass
    return(coef_matrix)

def cv_summary(lambdas, C_values, model):
    d = {'lambdas': lambdas, 'C_values': C_values, 'mean_cv_score': model.scores_[1]
    return(pd.DataFrame(data=d))

def create_roc_plot(y_true, y_pred):
    fpr, tpr, thresholds = roc_curve(y_true, y_pred)
    all_coords = pd.DataFrame({
        'fpr': fpr,
        'tpr': tpr,
        'thresholds': thresholds
    })

    plot = ggplot(all_coords, aes(x = 'fpr', y = 'tpr')) \
        + geom_line(color=color[0], size = 0.7) \
        + geom_area(position = 'identity', fill = 'mediumaquamarine', alpha = 0.3) \
        + xlab("False Positive Rate (1-Specifity)") \
        + ylab("True Positive Rate (Sensitivity)") \
        + geom_abline(intercept = 0, slope = 1,  linetype = "dotted", color = "black
        + scale_y_continuous(limits = (0, 1), breaks = seq(0, 1, .1), expand = (0, 0
        + scale_x_continuous(limits = (0, 1), breaks = seq(0, 1, .1), expand = (0.01
        + theme_bw()
    return(plot)

def sigmoid_array(x):
    return(1 / (1 + np.exp(-x)))

def generate_fold_prediction(model, X, fold, param_index):
    fold_coef = model.coefs_paths_[1][fold,param_index,:]
    return(sigmoid_array(np.dot(X, np.transpose(fold_coef)[:-1]) +  np.transpose(fol

def create_loss_plot(all_coords, optimal_threshold, curr_exp_loss):
    all_coords_copy = all_coords.copy()
    all_coords_copy['loss'] = (all_coords_copy.false_pos*FP + all_coords_copy.false_

    t = optimal_threshold
    l = curr_exp_loss

    plot = ggplot(all_coords_copy, aes(x = 'thresholds', y = 'loss')) + \
```

```
        geom_line(color=color[0], size=0.7) + \
        scale_x_continuous(breaks = seq(0, 1.1, by = 0.1)) + \
        coord_cartesian(xlim=(0,1))+ \
        geom_vline(xintercept = t , color = color[0] ) + \
        annotate(geom = "text", x = t - 0.01, y= max(all_coords_copy.loss) - 0.4,
                 label="best threshold: " + str(round(t,2)),
                 colour=color[1], angle=90, size = 7) +\
        annotate(geom = "text", x = t + 0.06, y= l,\
                 label= str(round(l, 2)), size = 7) +\
        theme_bw()
    return(plot)


def create_roc_plot_with_optimal(all_coords, optimal_threshold):
    all_coords_copy = all_coords.copy()
    all_coords_copy['sp'] = all_coords_copy.true_neg/all_coords_copy.neg
    all_coords_copy['se'] = all_coords_copy.true_pos/all_coords_copy.pos

    best_coords = all_coords_copy[all_coords_copy.thresholds == optimal_threshold]
    sp = best_coords.sp.values[0]
    se = best_coords.se.values[0]

    plot = ggplot(all_coords_copy, aes(x = 'sp', y = 'se')) +\
        geom_line(color=color[0], size=0.7) +\
        scale_y_continuous(breaks = seq(0, 1.1, by = 0.1)) +\
        scale_x_reverse(breaks = seq(0, 1.1, by = 0.1)) +\
        geom_point(data = pd.DataFrame({'sp': [sp], 'se': [se]})) +\
        annotate(geom = "text", x = sp, y = se + 0.03,
                 label = str(round(sp, 2)) + ', ' + str(round(se, 2)), size = 7) +\
        theme_bw()
    return(plot)
```

Define variable sets

In [152]:

```
rawvars = ["curr_assets", "curr_liab", "extra_exp", "extra_inc", "extra_profit_loss"
              "inc_bef_tax", "intang_assets", "inventories", "liq_assets", "material
              "profit_loss_year", "sales", "share_eq", "subscribed_cap"]
qualityvars = ["balsheet_flag", "balsheet_length", "balsheet_notfullyear"]
engvar = ["total_assets_bs", "fixed_assets_bs", "liq_assets_bs", "curr_assets_bs",
            "share_eq_bs", "subscribed_cap_bs", "intang_assets_bs", "extra_exp_pl",
            "extra_inc_pl", "extra_profit_loss_pl", "inc_bef_tax_pl", "inventories_p
            "material_exp_pl", "profit_loss_year_pl", "personnel_exp_pl"]
engvar2 = ["extra_profit_loss_pl_quad", "inc_bef_tax_pl_quad",
             "profit_loss_year_pl_quad", "share_eq_bs_quad"]
engvar3=[]
for col in data.columns:
    if col.endswith('flag_low') or col.endswith('flag_high') or col.endswith('flag_e
        engvar3.append(col)

d1 = []
hr = ["female", "ceo_age", "flag_high_ceo_age", "flag_low_ceo_age",
        "flag_miss_ceo_age", "ceo_count", "labor_avg_mod",
        "flag_miss_labor_avg", "foreign_management"]
```

In [153]:

```
#Creat dummy columns from category variables and drop first level
ind2_catmat = patsy.dmatrix("0 + C(ind2_cat)",data, return_type="dataframe")
ind2_catmat = ind2_catmat.drop(['C(ind2_cat)[26.0]'], axis=1)

m_region_locmat = patsy.dmatrix("0 + C(m_region_loc)",data, return_type="dataframe")
m_region_locmat = m_region_locmat.drop(['C(m_region_loc)[Central]'], axis=1)

urban_mmat = patsy.dmatrix("0 + C(urban_m)",data, return_type="dataframe")
urban_mmat = urban_mmat.drop(['C(urban_m)[1.0]'], axis=1)
```

In [154]:

```
# Define X1
basevars = data[["sales_mil_log", "sales_mil_log_sq"]]
X1 = pd.concat([basevars, ind2_catmat], axis=1)
# Define X2
X2additional_vars = data[["fixed_assets_bs", "share_eq_bs","curr_liab_bs", "curr_lia
                          "curr_liab_bs_flag_error",  "age", "foreign_management"]]
X2 = pd.concat([X1, X2additional_vars], axis=1)
# Define X3
firm = pd.concat([data[["age", "age2", "new"]], ind2_catmat, m_region_locmat, urban_
X3 = pd.concat([data[["sales_mil_log", "sales_mil_log_sq"] + engvar + d1], firm], ax
# Define X4
X4 = pd.concat([data[["sales_mil_log", "sales_mil_log_sq"] + engvar + d1 \
                                        + engvar2 + engvar3 + hr + qualityvars], firm], axi
```

In [155]:

```
# Define X5
#Creat matrix for interactions1 variables
int1mat = patsy.dmatrix("0 + C(ind2_cat):age + C(ind2_cat):age2 + \
                + C(ind2_cat):sales_mil_log + C(ind2_cat):ceo_age + C(ind2_cat):fore
                + C(ind2_cat):female + C(ind2_cat):C(urban_m) + C(ind2_cat):labor_av
#Drop first level to get k-1 dummies out of k categorical levels
for col in int1mat.columns:
    if col.startswith('C(ind2_cat)[26.0]') or col.endswith('C(urban_m)[1.0]'):
        int1mat = int1mat.drop([col], axis=1)

#Creat matrix for interactions2 variables
int2mat = patsy.dmatrix("0 + sales_mil_log:age + sales_mil_log:female + sales_mil_lo
                + sales_mil_log:foreign_management", data, return_type="dataframe")
X5 = pd.concat([X4, int1mat, int2mat], axis=1)
```

In order to achieve a fair comparison, the same number of features as the logit model is used for the other two models

In [156]:

```
# Define rfvars for RF (no interactions, no modified features)
rfvars = X5.copy()
```

In [157]:

```
# Define rfvars for RF (no interactions, no modified features)
gbmvars = X5.copy()
```

In [158]:

```
y = data['fast_growth']
```

Separate train and holdout data

In [159]:

```
index_train, index_holdout= train_test_split(
    data.index.values, train_size=round(0.8*len(data.index)), random_state=42)

y_train = y.iloc[index_train]
y_holdout = y.iloc[index_holdout]
```

PART I - PREDICT PROBABILITIES

In [160]:

```
# specify cross-validation method
k = KFold(n_splits=5, shuffle=True, random_state=42)
```

Train logit models

In [161]:

```
# no regularisation needed so setting the paremeter to very high value
C_value_logit=[1e20]
```

In [162]:

```
# Train Logit Models -----------------------------------------------
logit_model_vars = [X1.iloc[index_train], X2.iloc[index_train], X3.iloc[index_train]

logit_models = dict()
CV_RMSE_folds = dict()

for i in range(len(logit_model_vars)):
    LRCV_brier = LogisticRegressionCV(Cs=C_value_logit, cv=k, refit=True, scoring='r
                         solver="newton-cg", tol=1e-7, random_state=42)
    logit_models['X'+str(i+1)] = LRCV_brier.fit(logit_model_vars[i], y_train)
    # Calculate RMSE on test for each fold
    CV_RMSE_folds['X'+str(i+1)] = np.sqrt(-1*(logit_models['X'+str(i+1)].scores_[1])
```

PART I

No loss fn

In [163]:

```
# Calculate AUC for each folds --------------------------------
CV_AUC_folds = dict()

#refit logit models with AUC so we have AUC values for the same cv split
for i in range(len(logit_model_vars)):
    LRCV_auc = LogisticRegressionCV(Cs=C_value_logit, cv=k, refit=True, scoring='roc
                            solver="newton-cg", tol=1e-7, random_state=42)
    LRCV_auc_fit = LRCV_auc.fit(logit_model_vars[i], y_train)
    # Calculate AUC on test for each fold
    CV_AUC_folds['X'+str(i+1)] = LRCV_auc_fit.scores_[1][:,0].tolist()
```

In [164]:

```
# For each model: average RMSE and average AUC for models --------------------------
CV_RMSE = dict()
CV_AUC = dict()
nvars = dict()

for key in logit_models:
    CV_RMSE[key] = np.mean(CV_RMSE_folds[key])
    CV_AUC[key] = np.mean(CV_AUC_folds[key])

for key in logit_models:
    nvars[key] = logit_models[key].n_features_in_
```

In [165]:

```
# We have 5 logit models. For each we have a 5-CV RMSE and AUC.
# We pick our preferred model based on that. --------------------------------------
logit_summary1 = np.transpose(pd.DataFrame.from_dict([nvars,CV_RMSE,CV_AUC], orient=
logit_summary1.columns = ['Number of predictors', 'CV RMSE', 'CV AUC']
```

In [166]:

```
logit_summary1
```

Out[166]:

	Number of predictors	CV RMSE	CV AUC
X1	9.0	0.454952	0.617490
X2	16.0	0.454116	0.625344
X3	31.0	0.428237	0.737948
X4	74.0	0.428712	0.736242
X5	141.0	0.426765	0.741170

In [167]:

```
# Take best model and estimate RMSE on holdout  -------------------------------------

best_model = logit_models['X5']
best_model_X_holdout = X5.iloc[index_holdout]

logit_predicted_probabilities_holdout = best_model.predict_proba(best_model_X_holdou
best_rmse_holdout = np.sqrt(metrics.mean_squared_error(y_holdout, logit_predicted_pr
round(best_rmse_holdout, 3)
```

Out[167]:

```
0.422
```

In [168]:

```
# discrete ROC (with thresholds in steps) on holdout --------------------------------
thresholds = seq(0.05, 0.8, by = 0.01)
cm = dict()
true_positive_rates = []
false_positive_rates = []
holdout_prediction = []
for thr in thresholds:
    holdout_prediction = np.where(logit_predicted_probabilities_holdout < thr, 0, 1)
    cm_thr = confusion_matrix(y_holdout, holdout_prediction, labels=[0,1])
    cm[thr] = cm_thr
    tn, fp, fn, tp = cm_thr.ravel()
    true_positive_rates.append(tp/(tp+fn))
    false_positive_rates.append(fp/(fp+tn))
```

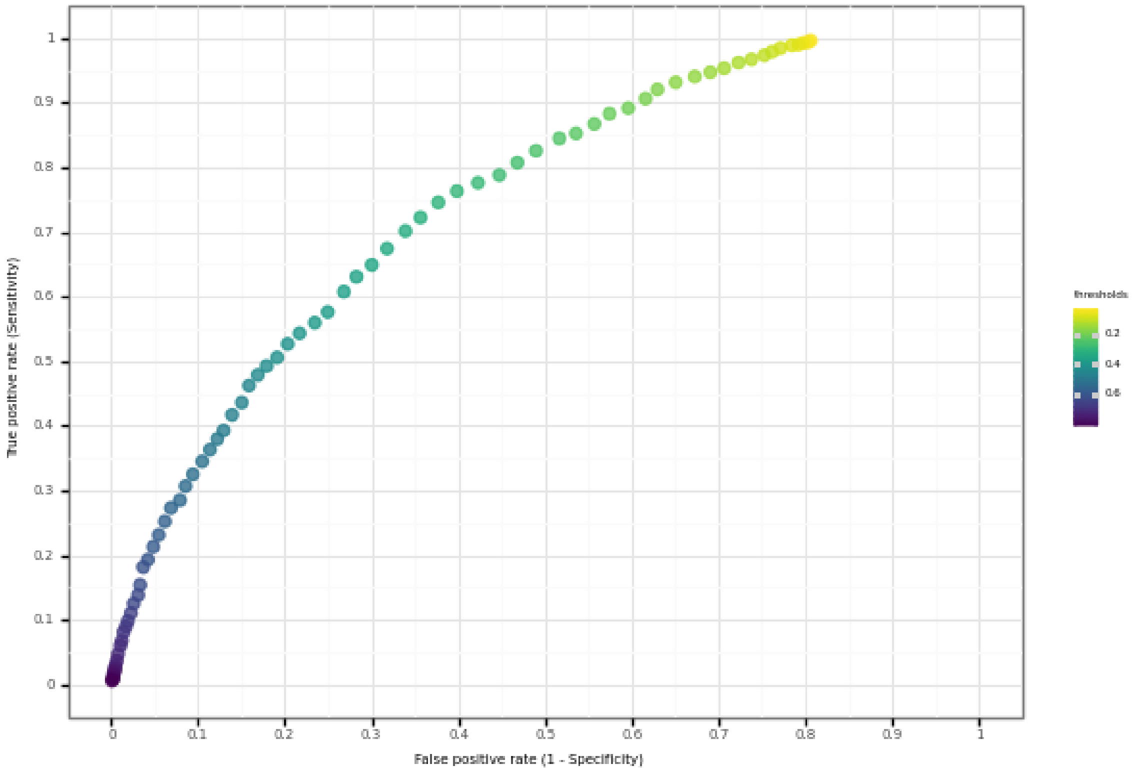
In [169]:

```
tpr_fpr_for_thresholds = pd.DataFrame(
    {'thresholds': thresholds,
     'true_positive_rates': true_positive_rates,
     'false_positive_rates': false_positive_rates})
```

ROC graph with different thresholds

In [170]:

```
ggplot(tpr_fpr_for_thresholds, aes(x = 'false_positive_rates', y = 'true_positive_ra
        + labs(x = "False positive rate (1 - Specificity)", y = "True positive rate 
        + geom_point(size=2, alpha=0.8) + scale_color_continuous(trans = 'reverse')\
        + scale_x_continuous(limits=(0,1), breaks = seq(0, 1.01, by = 0.1))\
        + scale_y_continuous(limits=(0,1), breaks = seq(0, 1.01, by = 0.1))\
        + theme_bw()\
        +theme(legend_position="right",
            axis_text=element_text(size=5),
            axis_title=element_text(size=5),
            legend_text = element_text(size = 4),
            legend_title = element_text(size = 4),
            legend_key_size=6)
```

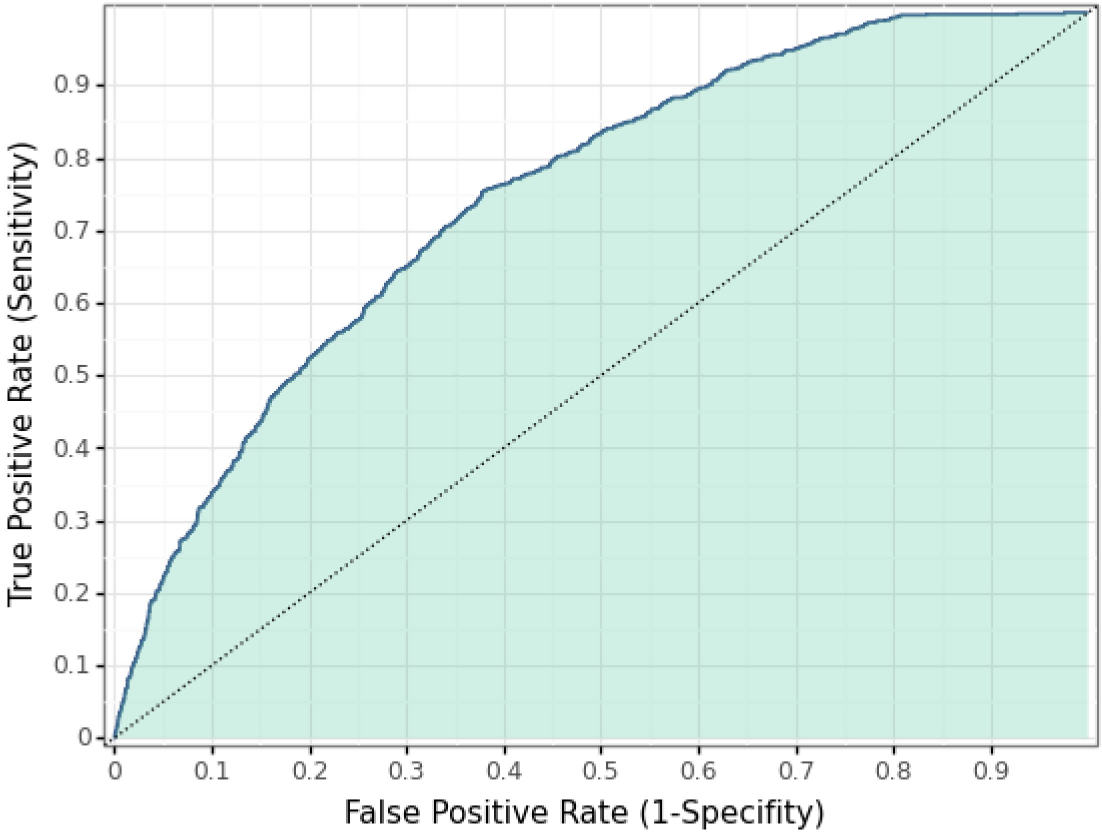


Out[170]:

```
<ggplot: (8786280184185)>
```

In [171]:

```
create_roc_plot(y_holdout, logit_predicted_probabilities_holdout)
```



Out[171]:

```
<ggplot: (8786281839761)>
```

In [172]:

```
# Confusion table with different tresholds -----------------------------------------

# fast_growth: the threshold 0.5 is used to convert probabilities to binary classes
logit_class_prediction = best_model.predict(best_model_X_holdout)

values, counts = np.unique(logit_class_prediction.tolist(), return_counts=True)
print(values[0],' (no fast_growth): ',counts[0])
print(values[1],' (fast_growth): ',counts[1])
```

```
0  (no fast_growth):  3060
1  (fast_growth):  717
```

In [173]:

```
# confusion matrix: summarize different type of errors and successfully predicted ca
# positive = "yes": explicitly specify the positive case
cm_object1 = confusion_matrix(y_holdout, logit_class_prediction, labels=[0,1])
cm1 = pd.DataFrame(cm_object1,
    index=['Actul no fast_growth', 'Actual fast_growth'],
    columns=['Predicted no fast_growth', 'Predicted fast_growth'])
cm1
```

Out[173]:

	Predicted no fast_growth	Predicted fast_growth
Actul no fast_growth	2327	299
Actual fast_growth	733	418

In the binary classification, the conventional approach is to output the category when the model predicts that the probability of a category is greater than or equal to 0.5. Otherwise, it is another category. The result of confusion matrix is same as before

In [174]:

```
# we can apply different thresholds

# 0.5 same as before
holdout_prediction = np.where(logit_predicted_probabilities_holdout < 0.5, 0, 1)
cm_object1b = confusion_matrix(y_holdout, holdout_prediction, labels=[0,1])
cm1b = pd.DataFrame(cm_object1b,
    index=['Actul no fast_growth', 'Actual fast_growth'],
    columns=['Predicted no fast_growth', 'Predicted fast_growth'])
cm1b
```

Out[174]:

	Predicted no fast_growth	Predicted fast_growth
Actul no fast_growth	2327	299
Actual fast_growth	733	418

In [175]:

```
# a sensible choice: mean of predicted probabilities
mean_predicted_fast_growth_prob = np.mean(logit_predicted_probabilities_holdout)
round(mean_predicted_fast_growth_prob, 3)
```

Out[175]:

```
0.31
```

Try another approach, when the category is judged to be greater than a certain threshold (not 0.5), it is the category.

In [176]:

```
holdout_prediction = np.where(logit_predicted_probabilities_holdout < mean_predictec
cm_object2 = confusion_matrix(y_holdout, holdout_prediction, labels=[0,1])
cm2 = pd.DataFrame(cm_object2,
    index=['Actul no fast_growth', 'Actual fast_growth'],
    columns=['Predicted no fast_growth', 'Predicted fast_growth'])
cm2
```

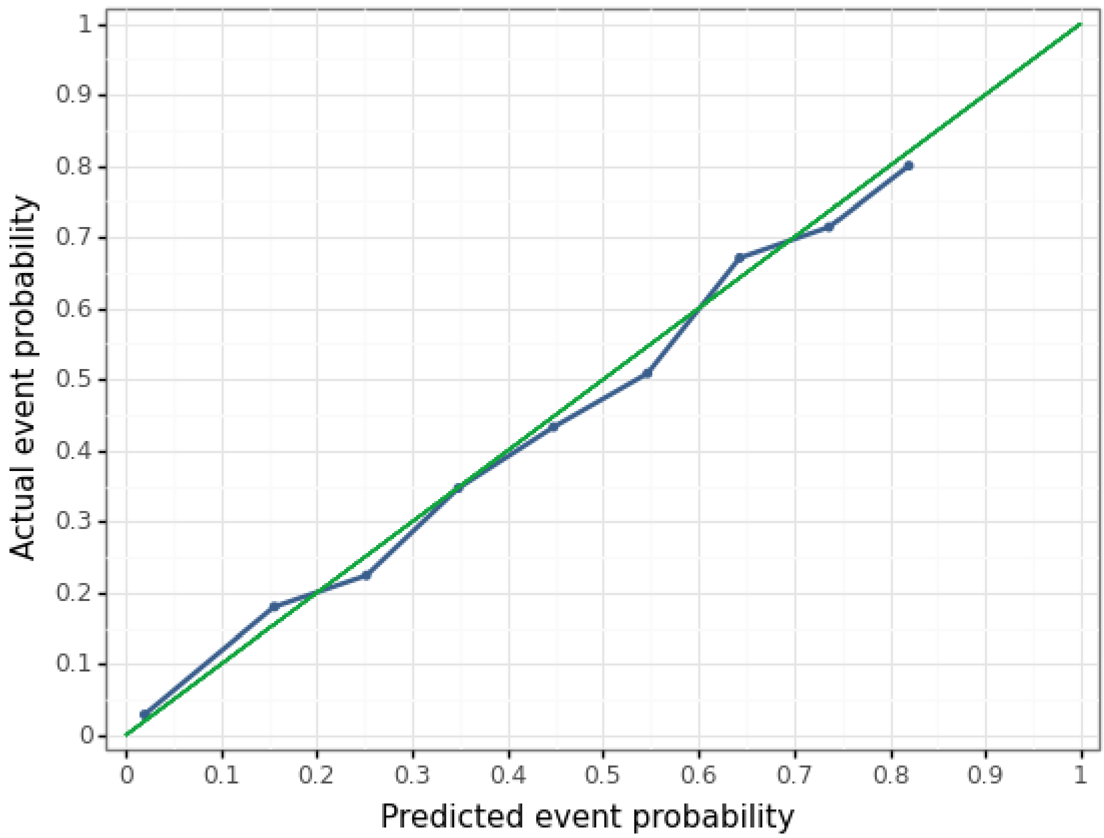
Out[176]:

	Predicted no fast_growth	Predicted fast_growth
Actul no fast_growth	1637	989
Actual fast_growth	293	858

In [177]:

```
# Calibration curve ----------------------------------------------------------
# how well do estimated vs actual event probabilities relate to each other?

holdout = pd.concat([best_model_X_holdout, y_holdout], axis=1)
holdout["best_logit_no_loss_pred"] = logit_predicted_probabilities_holdout
create_calibration_plot(holdout, file_name = "ch17-figure-1-logit-m4-calibration",\
                        prob_var='best_logit_no_loss_pred', actual_var='fast_growth'
                        y_lab="Actual event probability", n_bins=10, breaks=None)
```



Out[177]:

```
<ggplot: (8786229182425)>
```

PART II.

We have a loss function

PREDICTION WITH LOGIT

In this experiment, the number of negative cases is more than the number of positive cases, so the penalty factor for judging a positive class as a negative class is greater than the cost of misjudging a negative class as a positive class.

In [178]:

```
# Introduce loss function
# relative cost of of a false negative classification (as compared with a false posi
FP = 1
FN = 5
cost = FN/FP
# the prevalence, or the proportion of cases in the population (n.cases/(n.controls+
prevelance = y_train.sum()/len(y_train)
```

We have the loss function, and then find the best judgment threshold for the model to achieve the smallest judgment error.

In [179]:

```
# Draw ROC Curve and find optimal threshold with loss function ---------------------
# The optimal cut-off is the threshold that maximizes the distance to the identity (

best_thresholds_cv = dict()
expected_loss_cv = dict()
fold5_threshold = dict()
fold5_expected_loss = dict()
fold5_all_coords = dict()

for i, model_name in enumerate(logit_models):
    best_thresholds = []
    expected_loss =[]
    if model_name != 'LASSO':
        X = logit_model_vars[i]
        c_index = 0
    else:
        X = normalized_logitvars
        c_index = best_lambda_i
    fold = 0
    for train_index, test_index in k.split(X):
        X_fold = X.iloc[test_index,:]
        y_fold = y_train.iloc[test_index]
        pred_fold = generate_fold_prediction(logit_models[model_name], X_fold, fold,
        false_pos_rate, true_pos_rate, thresholds = roc_curve(y_fold, pred_fold)
        optimal_threshold = sorted(list(zip(
            np.abs(true_pos_rate + (1 - prevelance)/(cost * prevelance)*(1-false_pos
                                    thresholds)), key=lambda i: i[0], reverse=Tru
        best_thresholds.append(optimal_threshold)
        threshold_prediction = np.where(pred_fold < optimal_threshold, 0, 1)
        tn, fp, fn, tp = confusion_matrix(y_fold, threshold_prediction, labels=[0,1]
        curr_exp_loss = (fp*FP + fn*FN)/len(y_fold)
        expected_loss.append(curr_exp_loss)
        fold = fold+1

    best_thresholds_cv[model_name] = np.mean(best_thresholds)
    expected_loss_cv[model_name] = np.mean(expected_loss)

    # for fold #5
    fold5_threshold[model_name] = optimal_threshold
    fold5_expected_loss[model_name] = curr_exp_loss

    all_coords = pd.DataFrame({
        'false_pos': false_pos_rate*sum(y_fold == 0),
        'true_pos': true_pos_rate*sum(y_fold == 1),
        'false_neg': sum(y_fold == 1) - true_pos_rate*sum(y_fold == 1),
        'true_neg': sum(y_fold == 0) - false_pos_rate*sum(y_fold == 0),
        'pos': sum(y_fold == 1),
        'neg': sum(y_fold == 0),
        'n': len(y_fold),
        'thresholds': thresholds
    })

    fold5_all_coords[model_name] = all_coords
```

In [180]:

```
logit_summary2 = pd.DataFrame(best_thresholds_cv.items(),columns=['Model', 'Avg of c
logit_summary2['Threshold for Fold5'] = fold5_threshold.values()
logit_summary2['Avg expected loss'] = expected_loss_cv.values()
logit_summary2['Expected loss for Fold5'] = fold5_expected_loss.values()
```

In [181]:

```
logit_summary2
```

Out[181]:

	Model	Avg of optimal thresholds	Threshold for Fold5	Avg expected loss	Expected loss for Fold5
0	X1	0.177295	0.190212	0.665829	0.671963
1	X2	0.151930	0.149542	0.673971	0.689176
2	X3	0.143063	0.140801	0.544619	0.541543
3	X4	0.148817	0.159312	0.547863	0.547170
4	X5	0.159429	0.165606	0.541970	0.537239

In [182]:

```
# Pick best model based on average expected loss ----------------------------------
#X5
best_logit_optimal_treshold = best_thresholds_cv["X5"]

# Get expected loss on holdout
holdout_treshold = np.where(logit_predicted_probabilities_holdout < best_logit_optin
tn, fp, fn, tp = confusion_matrix(y_holdout, holdout_treshold, labels=[0,1]).ravel()
expected_loss_holdout = (fp*FP + fn*FN)/len(y_holdout)
round(expected_loss_holdout, 3)
```

Out[182]:

0.56

In [183]:

```
cm_object3 = confusion_matrix(y_holdout, holdout_treshold, labels=[0,1])
cm3 = pd.DataFrame(cm_object3,
    index=['Actul no fast_growth', 'Actual fast_growth'],
    columns=['Predicted no fast_growth', 'Predicted fast_growth'])
cm3
```

Out[183]:

	Predicted no fast_growth	Predicted fast_growth
Actul no fast_growth	812	1814
Actual fast_growth	60	1091

PREDICTION WITH RANDOM FOREST

In [184]:

```
rfvars_train = rfvars.iloc[index_train]
rfvars_holdout = rfvars.iloc[index_holdout]
```

Probability forest

In [185]:

```
grid = {'max_features': [5, 6, 7],
        'criterion':['gini'],
        'min_samples_split': [11, 16]} #1 more than in R because here condition for
```

In [186]:

```
prob_forest = RandomForestClassifier(random_state=42, n_estimators=500, oob_score=Tr
prob_forest_grid = GridSearchCV(prob_forest, grid, cv=k, refit='accuracy',
                                scoring = ['accuracy', 'roc_auc', 'neg_brier_score']
```

In [187]:

```
prob_forest_fit = prob_forest_grid.fit(rfvars_train, y_train)
```

In [188]:

```
#create CV summary table
cv_accuracy = np.zeros([6])
for i in range(5):
    cv_accuracy = cv_accuracy + prob_forest_fit.cv_results_['split' + str(i) + '_tes
cv_accuracy = cv_accuracy/5

cv_auc = np.zeros([6])
for i in range(5):
    cv_auc = cv_auc + prob_forest_fit.cv_results_['split' + str(i) + '_test_roc_auc'
cv_auc = cv_auc/5

cv_rmse = np.zeros([6])
for i in range(5):
    cv_rmse = cv_rmse +np.sqrt(-1*(prob_forest_fit.cv_results_['split' + str(i) + '_
cv_rmse = cv_rmse/5

prob_forest_cv_results = pd.DataFrame({
    'max_features': prob_forest_fit.cv_results_['param_max_features'],
    'min_samples_split': prob_forest_fit.cv_results_['param_min_samples_split'],
    'cv_accuracy': cv_accuracy,
    'cv_auc': cv_auc,
    'cv_rmse': cv_rmse
})
```

In [189]:

```
prob_forest_cv_results
```

Out[189]:

	max_features	min_samples_split	cv_accuracy	cv_auc	cv_rmse
0	5	11	0.725208	0.755991	0.422332
1	5	16	0.723818	0.756269	0.422448
2	6	11	0.726135	0.756153	0.422120
3	6	16	0.726267	0.757813	0.421671
4	7	11	0.728121	0.757566	0.421493
5	7	16	0.728849	0.757669	0.421505

In [190]:

```
#obtain optimal parameter values
best_mtry = prob_forest_fit.best_params_['max_features']
best_min_node_size = prob_forest_fit.best_params_['min_samples_split']
```

In [191]:

```
# Get average (ie over the folds) RMSE and AUC ------------------------------------
prob_forest_best_results = prob_forest_cv_results[(prob_forest_cv_results.max_featur
                          (prob_forest_cv_results.min_samples_split == best_min_node_siz
prob_forest_best_results_index = prob_forest_best_results.index.values[0]

CV_RMSE['rf_p'] = prob_forest_best_results.cv_rmse.values[0]
CV_AUC['rf_p'] = prob_forest_best_results.cv_auc.values[0]
```

In [192]:

```
# Get fold level RMSE and AUC ------------------------------------

CV_RMSE_folds_rf_p = list()
for i in range(5):
    rmse = np.sqrt(-1*(prob_forest_fit.cv_results_['split' + str(i) + '_test_neg_bri
    CV_RMSE_folds_rf_p.append(rmse)
CV_RMSE_folds['rf_p'] = CV_RMSE_folds_rf_p

CV_AUC_folds_rf_p = list()
for i in range(5):
    rmse = prob_forest_fit.cv_results_['split' + str(i) + '_test_roc_auc'][prob_fore
    CV_AUC_folds_rf_p.append(rmse)
CV_AUC_folds['rf_p'] = CV_AUC_folds_rf_p
```

In [193]:

```
# Now use loss function and search for best thresholds and expected loss over folds
best_thresholds = list()
expected_loss = list()

fold = 0
for train_index, test_index in k.split(rfvars_train):
    X_fold = rfvars_train.iloc[test_index,:]
    y_fold = y_train.iloc[test_index]

    X_fold_train = rfvars_train.iloc[train_index,:]
    y_fold_train = y_train.iloc[train_index]

    prob_forest_best = RandomForestClassifier(random_state=42, n_estimators=500, oob
                        criterion = 'gini', max_features = best_mtry, min_samples_split
    prob_forest_best_fold = prob_forest_best.fit(X_fold_train, y_fold_train)
    pred_fold = prob_forest_best_fold.predict_proba(X_fold)[:,1]

    false_pos_rate, true_pos_rate, threshold = roc_curve(y_fold, pred_fold)
    best_threshold = sorted(list(zip(np.abs(true_pos_rate + (1 - prevelance)/(cost *
                                threshold)), key=lambda x: x[0], reverse=True
    best_thresholds.append(best_threshold)
    threshold_prediction = np.where(pred_fold < best_threshold, 0, 1)
    tn, fp, fn, tp = confusion_matrix(y_fold, threshold_prediction, labels=[0,1]).ra
    curr_exp_loss = (fp*FP + fn*FN)/len(y_fold)
    expected_loss.append(curr_exp_loss)

fold5_threshold_rf = best_threshold
fold5_expected_loss_rf = curr_exp_loss

all_coords_rf = pd.DataFrame({
    'false_pos': false_pos_rate*sum(y_fold == 0),
    'true_pos': true_pos_rate*sum(y_fold == 1),
    'false_neg': sum(y_fold == 1) - true_pos_rate*sum(y_fold == 1),
    'true_neg': sum(y_fold == 0) - false_pos_rate*sum(y_fold == 0),
    'pos': sum(y_fold == 1),
    'neg': sum(y_fold == 0),
    'n': len(y_fold),
    'thresholds': threshold
})
```

In [194]:

```
fold5_threshold_rf = best_threshold
fold5_expected_loss_rf = curr_exp_loss

all_coords_rf = pd.DataFrame({
    'false_pos': false_pos_rate*sum(y_fold == 0),
    'true_pos': true_pos_rate*sum(y_fold == 1),
    'false_neg': sum(y_fold == 1) - true_pos_rate*sum(y_fold == 1),
    'true_neg': sum(y_fold == 0) - false_pos_rate*sum(y_fold == 0),
    'pos': sum(y_fold == 1),
    'neg': sum(y_fold == 0),
    'n': len(y_fold),
    'thresholds': threshold
})
```

In [195]:

```
expected_loss_cv['rf_p'] = np.mean(expected_loss)
best_thresholds_cv['rf_p'] = np.mean(best_thresholds)
```

In [196]:

```
# Take model to holdout and estimate RMSE, AUC and expected loss -------------------
prob_forest_fit_best = prob_forest_fit.best_estimator_
rf_predicted_probabilities_holdout = prob_forest_fit_best.predict_proba(rfvars_holdc
rmse_rf = np.sqrt(mean_squared_error(y_holdout, rf_predicted_probabilities_holdout))
round(rmse_rf, 3)
```

Out[196]:

0.416

In [197]:

```
# ROC AUC  on holdout
auc_rf = roc_auc_score(y_holdout, rf_predicted_probabilities_holdout)
round(auc_rf, 3)
```

Out[197]:

0.765

In [198]:

```
# Get expected loss on holdout
holdout_treshold = np.where(rf_predicted_probabilities_holdout < best_thresholds_cv[
tn, fp, fn, tp = confusion_matrix(y_holdout, holdout_treshold, labels=[0,1]).ravel()
expected_loss_holdout = (fp*FP + fn*FN)/len(y_holdout)
round(expected_loss_holdout, 3)
```

Out[198]:

0.562

In [199]:

```
cm_object3 = confusion_matrix(y_holdout, holdout_treshold, labels=[0,1])
cm3 = pd.DataFrame(cm_object3,
    index=['Actul no fast_growth', 'Actual fast_growth'],
    columns=['Predicted no fast_growth', 'Predicted fast_growth'])
cm3
```

Out[199]:

	Predicted no fast_growth	Predicted fast_growth
Actul no fast_growth	975	1651
Actual fast_growth	94	1057

PREDICTION WITH GBM

In [200]:

```
gbmvars_train = gbmvars.iloc[index_train]
gbmvars_holdout = gbmvars.iloc[index_holdout]
```

In [201]:

```
grid = {
    "loss":["deviance"],
    "learning_rate": [0.1, 0.15, 0.18],
    "max_depth":[3, 5],
    "criterion": ["friedman_mse"],
    "n_estimators":[50]
    }
```

In [202]:

```
prob_gbm = GradientBoostingClassifier(random_state=42, n_estimators=500)
prob_gbm_grid = GridSearchCV(prob_gbm, grid, cv=k, refit='accuracy',
                                scoring = ['accuracy', 'roc_auc', 'neg_brier_score']
```

In [203]:

```
prob_gbm_fit = prob_gbm_grid.fit(gbmvars_train, y_train)
```

In [204]:

```
#create CV summary table
cv_accuracy = np.zeros([6])
for i in range(5):
    cv_accuracy = cv_accuracy + prob_gbm_fit.cv_results_['split' + str(i) + '_test_a
cv_accuracy = cv_accuracy/5

cv_auc = np.zeros([6])
for i in range(5):
    cv_auc = cv_auc + prob_gbm_fit.cv_results_['split' + str(i) + '_test_roc_auc']
cv_auc = cv_auc/5

cv_rmse = np.zeros([6])
for i in range(5):
    cv_rmse = cv_rmse +np.sqrt(-1*(prob_gbm_fit.cv_results_['split' + str(i) + '_tes
cv_rmse = cv_rmse/5

prob_gbm_cv_results = pd.DataFrame({
    'learning_rate': prob_gbm_fit.cv_results_['param_learning_rate'],
    'max_depth': prob_gbm_fit.cv_results_['param_max_depth'],
    'cv_accuracy': cv_accuracy,
    'cv_auc': cv_auc,
    'cv_rmse': cv_rmse
})
```

In [205]:

```
prob_gbm_cv_results
```

Out[205]:

	learning_rate	max_depth	cv_accuracy	cv_auc	cv_rmse
0	0.1	3	0.722627	0.756058	0.422432
1	0.1	5	0.726334	0.757378	0.421342
2	0.15	3	0.725407	0.757251	0.421672
3	0.15	5	0.726400	0.755794	0.421926
4	0.18	3	0.724613	0.756476	0.421727
5	0.18	5	0.721037	0.754299	0.422881

In [206]:

```
# obtain optimal parameter values
best_mtry = prob_gbm_fit.best_params_['learning_rate']
best_min_node_size = prob_gbm_fit.best_params_['max_depth']
```

In [207]:

```
# Get average (ie over the folds) RMSE and AUC ------------------------------------
prob_gbm_best_results = prob_gbm_cv_results[(prob_gbm_cv_results.learning_rate == be
                      (prob_gbm_cv_results.max_depth == best_min_node_size)]
prob_gbm_best_results_index = prob_gbm_best_results.index.values[0]

CV_RMSE['gbm_p'] = prob_gbm_best_results.cv_rmse.values[0]
CV_AUC['gbm_p'] = prob_gbm_best_results.cv_auc.values[0]
```

In [208]:

```
# Get fold level RMSE and AUC ------------------------------------

CV_RMSE_folds_rf_p = list()
for i in range(5):
    rmse = np.sqrt(-1*(prob_gbm_fit.cv_results_['split' + str(i) + '_test_neg_brier_
    CV_RMSE_folds_rf_p.append(rmse)
CV_RMSE_folds['rf_p'] = CV_RMSE_folds_rf_p

CV_AUC_folds_rf_p = list()
for i in range(5):
    rmse = prob_gbm_fit.cv_results_['split' + str(i) + '_test_roc_auc'][prob_gbm_bes
    CV_AUC_folds_rf_p.append(rmse)
CV_AUC_folds['rf_p'] = CV_AUC_folds_rf_p
```

In [209]:

```
# Now use loss function and search for best thresholds and expected loss over folds
best_thresholds = list()
expected_loss = list()

fold = 0
for train_index, test_index in k.split(gbmvars_train):
    X_fold = gbmvars_train.iloc[test_index, :]
    y_fold = y_train.iloc[test_index]

    X_fold_train = gbmvars_train.iloc[train_index, :]
    y_fold_train = y_train.iloc[train_index]

    prob_gbm_best = GradientBoostingClassifier(random_state=42, n_estimators=50, cri
                                                learning_rate=best_mtry, max_depth
    prob_gbm_best_fold = prob_gbm_best.fit(X_fold_train, y_fold_train)
    pred_fold = prob_gbm_best_fold.predict_proba(X_fold)[:, 1]

    false_pos_rate, true_pos_rate, threshold = roc_curve(y_fold, pred_fold)
    best_threshold = \
    sorted(list(zip(np.abs(true_pos_rate + (1 - prevelance) / (cost * prevelance) *
                    threshold)), key=lambda x: x[0], reverse=True)[0][1]
    best_thresholds.append(best_threshold)
    threshold_prediction = np.where(pred_fold < best_threshold, 0, 1)
    tn, fp, fn, tp = confusion_matrix(y_fold, threshold_prediction, labels=[0, 1]).r
    curr_exp_loss = (fp * FP + fn * FN) / len(y_fold)
    expected_loss.append(curr_exp_loss)

fold5_threshold_gbm = best_threshold
fold5_expected_loss_gbm = curr_exp_loss

all_coords_gbm = pd.DataFrame({
    'false_pos': false_pos_rate * sum(y_fold == 0),
    'true_pos': true_pos_rate * sum(y_fold == 1),
    'false_neg': sum(y_fold == 1) - true_pos_rate * sum(y_fold == 1),
    'true_neg': sum(y_fold == 0) - false_pos_rate * sum(y_fold == 0),
    'pos': sum(y_fold == 1),
    'neg': sum(y_fold == 0),
    'n': len(y_fold),
    'thresholds': threshold
})
```

In [210]:

```
fold5_threshold_gbm = best_threshold
fold5_expected_loss_gbm = curr_exp_loss

all_coords_gbm = pd.DataFrame({
    'false_pos': false_pos_rate*sum(y_fold == 0),
    'true_pos': true_pos_rate*sum(y_fold == 1),
    'false_neg': sum(y_fold == 1) - true_pos_rate*sum(y_fold == 1),
    'true_neg': sum(y_fold == 0) - false_pos_rate*sum(y_fold == 0),
    'pos': sum(y_fold == 1),
    'neg': sum(y_fold == 0),
    'n': len(y_fold),
    'thresholds': threshold
})
```

In [211]:

```
expected_loss_cv['gbm_p'] = np.mean(expected_loss)
best_thresholds_cv['gbm_p'] = np.mean(best_thresholds)
```

In [212]:

```
# Take model to holdout and estimate RMSE, AUC and expected loss -------------------
prob_gbm_fit_best = prob_gbm_fit.best_estimator_
gbm_predicted_probabilities_holdout = prob_gbm_fit_best.predict_proba(gbmvars_holdou
rmse_gbm = np.sqrt(mean_squared_error(y_holdout, gbm_predicted_probabilities_holdout
round(rmse_gbm, 3)
```

Out[212]:

0.416

In [213]:

```
# ROC AUC on holdout
auc_gbm = roc_auc_score(y_holdout, gbm_predicted_probabilities_holdout)
round(auc_gbm, 3)
```

Out[213]:

0.764

In [214]:

```
# Get expected loss on holdout
holdout_treshold = np.where(gbm_predicted_probabilities_holdout < best_thresholds_cv
tn, fp, fn, tp = confusion_matrix(y_holdout, holdout_treshold, labels=[0,1]).ravel()
expected_loss_holdout = (fp*FP + fn*FN)/len(y_holdout)
round(expected_loss_holdout, 3)
```

Out[214]:

0.547

In [215]:

```
cm_object3 = confusion_matrix(y_holdout, holdout_treshold, labels=[0,1])
cm3 = pd.DataFrame(cm_object3,
    index=['Actul no fast_growth', 'Actual fast_growth'],
    columns=['Predicted no fast_growth', 'Predicted fast_growth'])
cm3
```

Out[215]:

	Predicted no fast_growth	Predicted fast_growth
Actul no fast_growth	781	1845
Actual fast_growth	44	1107

Final results

In [216]:

```
nvars['rf_p'] = len(rfvars.columns)
nvars['gbm_p'] = len(gbmvars.columns)
```

In [217]:

```
summary_results = pd.DataFrame({"Model": list(nvars.keys()),
                              "Number of predictors": list(nvars.values()),
                              "CV RMSE": list(CV_RMSE.values()),
                              "CV AUC": list(CV_AUC.values()),
                              "CV threshold": list(best_thresholds_cv.values()),
                              "CV expected Loss": list(expected_loss_cv.values())
                               })
```

In [218]:

```
summary_results
```

Out[218]:

	Model	Number of predictors	CV RMSE	CV AUC	CV threshold	CV expected Loss
0	X1	9	0.454952	0.617490	0.177295	0.665829
1	X2	16	0.454116	0.625344	0.151930	0.673971
2	X3	31	0.428237	0.737948	0.143063	0.544619
3	X4	74	0.428712	0.736242	0.148817	0.547863
4	X5	141	0.426765	0.741170	0.159429	0.541970
5	rf_p	141	0.421505	0.757669	0.216233	0.536542
6	gbm_p	141	0.421926	0.755794	0.145089	0.534027

From the final results, random forest performed best in RMSE and AUC, followed by GBM.

In [ ]:

```
```