mini_project_1_team_2

October 14, 2020

1 Mini Project 1: Logistic Regression Classifier

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1.2 1. Import external libraries and load external file into data frame

[1]:
```
import sys
sys.path.append('/content/drive/My Drive/Colab Notebooks/Mini Project 1 ECSE␣
↪551 Team 2')
```

IMPORTANT: when any change is made to external py libraries, Factory Reset of Runtime is required!

[2]:
```
from google.colab import drive
drive.mount('/content/drive', force_remount= True)
```

```
Mounted at /content/drive
```

[3]:
```
from logistic_regression_models import LogisticRegression_gradient_descent,␣
↪LogisticRegression_maximum_likelihood
from feature_engineering import re_sample, logarithm_transformer,␣
↪standard_scaler, quadratic_feature_tester
from model_evaluation import Acc_eval, cross_val, model_test
```

[4]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import time
import os
import warnings
from sklearn.utils import shuffle
from scipy import special

warnings.filterwarnings('ignore'),
np.set_printoptions(precision=2)

force_re_run = False
```

[5]:

```
# paths for different files to be used in this notebook. change them if you␣
↪download them in a different computer!

hepatitis_file_path =  'https://raw.githubusercontent.com/rgmartin/ECSE551/main/
↪hepatitis.csv'
bankrupcy_file_path = 'https://raw.githubusercontent.com/rgmartin/ECSE551/main/
↪bankrupcy.csv'

result_file_path =  '/content/drive/My Drive/Colab Notebooks/Mini Project 1␣
↪ECSE 551 Team 2/result.csv'
accuracies_M1H_path = '/content/drive/My Drive/Colab Notebooks/Mini Project 1␣
↪ECSE 551 Team 2/aux_matrix/accuracies_M1H.csv'
times_M1H_path = '/content/drive/My Drive/Colab Notebooks/Mini Project 1 ECSE␣
↪551 Team 2/aux_matrix/times_M1H.csv'
accuracies_M1H_image_path = '/content/drive/My Drive/Colab Notebooks/Mini␣
↪Project 1 ECSE 551 Team 2/images_for_report/accuracies_M1H_image.png'
times_M1H_image_path = '/content/drive/My Drive/Colab Notebooks/Mini Project 1␣
↪ECSE 551 Team 2/images_for_report/times_M1H_image.png'

accuracies_M2H_path = '/content/drive/My Drive/Colab Notebooks/Mini Project 1␣
↪ECSE 551 Team 2/aux_matrix/accuracies_M2H.csv'
times_M2H_path = '/content/drive/My Drive/Colab Notebooks/Mini Project 1 ECSE␣
↪551 Team 2/aux_matrix/times_M2H.csv'
accuracies_M2H_image_path = '/content/drive/My Drive/Colab Notebooks/Mini␣
↪Project 1 ECSE 551 Team 2/images_for_report/accuracies_M2H_image.png'
times_M2H_image_path = '/content/drive/My Drive/Colab Notebooks/Mini Project 1␣
↪ECSE 551 Team 2/images_for_report/times_M2H_image.png'

accuracies_M1B_path = '/content/drive/My Drive/Colab Notebooks/Mini Project 1␣
↪ECSE 551 Team 2/aux_matrix/accuracies_M1B.csv'
times_M1B_path = '/content/drive/My Drive/Colab Notebooks/Mini Project 1 ECSE␣
↪551 Team 2/aux_matrix/times_M1B.csv'
accuracies_M1B_image_path = '/content/drive/My Drive/Colab Notebooks/Mini␣
↪Project 1 ECSE 551 Team 2/images_for_report/accuracies_M1B_image.png'
times_M1B_image_path = '/content/drive/My Drive/Colab Notebooks/Mini Project 1␣
↪ECSE 551 Team 2/images_for_report/times_M1B_image.png'

accuracies_M2B_path = '/content/drive/My Drive/Colab Notebooks/Mini Project 1␣
↪ECSE 551 Team 2/aux_matrix/accuracies_M2B.csv'
times_M2B_path = '/content/drive/My Drive/Colab Notebooks/Mini Project 1 ECSE␣
↪551 Team 2/aux_matrix/times_M2B.csv'
accuracies_M2B_image_path = '/content/drive/My Drive/Colab Notebooks/Mini␣
↪Project 1 ECSE 551 Team 2/images_for_report/accuracies_M2B_image.png'
times_M2B_image_path = '/content/drive/My Drive/Colab Notebooks/Mini Project 1␣
↪ECSE 551 Team 2/images_for_report/times_M2B_image.png'
```

1.3 2. Accuracy and running time

1.3.1 2.1 Hepatitis

[6]:
```
df_data = pd.read_csv(hepatitis_file_path)
```

[7]:
```
rel_tol_sample = 5 # samples of rel_tol to be tested
learn_rate_sample = 30 # samples of learn_rate to be tested

min_learn_rate =  0.001
max_learn_rate = 1
exp_step = np.log10(max_learn_rate/min_learn_rate) / (learn_rate_sample-1)

rel_tol_range = (1/10**(np.arange(1,1+rel_tol_sample)))
learn_rate_range = min_learn_rate * (10 **(exp_step * np.
 ↪arange(0,learn_rate_sample)))
```

2.1.1 Gradient descent (M1-H)

[8]:
```
external_file_is_present = os.path.isfile(accuracies_M1H_path)
```

[9]:
```
if force_re_run or not external_file_is_present:
  best = 0

  accuracies_gd = np.zeros((rel_tol_sample, learn_rate_sample)) # accuracy␣
 ↪matrix
  time_cost_gd = np.zeros((rel_tol_sample, 1)) #time cost per train/validate␣
 ↪matrix

  for row in np.arange(0,rel_tol_sample):
      print('Running', end='')
      start_time = time.time()
      for col in np.arange(0, learn_rate_sample):
          X, y = re_sample(df_data, 'ClassLabel', 42)
          print('.', end='', flush=True)
          # create model
          clf  =␣
 ↪LogisticRegression_gradient_descent(learning_rate=learn_rate_range[col],␣
 ↪max_iter=100000, rel_tol = rel_tol_range[row],  print_time=False)
          # K-fold train and validation
          accuracies_gd[row, col] = cross_val(clf,X,y,10)
          # save best result so far
          if (best < accuracies_gd[row, col]):
              best = accuracies_gd[row, col]
              learn_rate_save = learn_rate_range[col]
              rel_tol_save = rel_tol_range[row]
      time_cost_gd[row, 0] = (time.time() - start_time)/learn_rate_sample
```

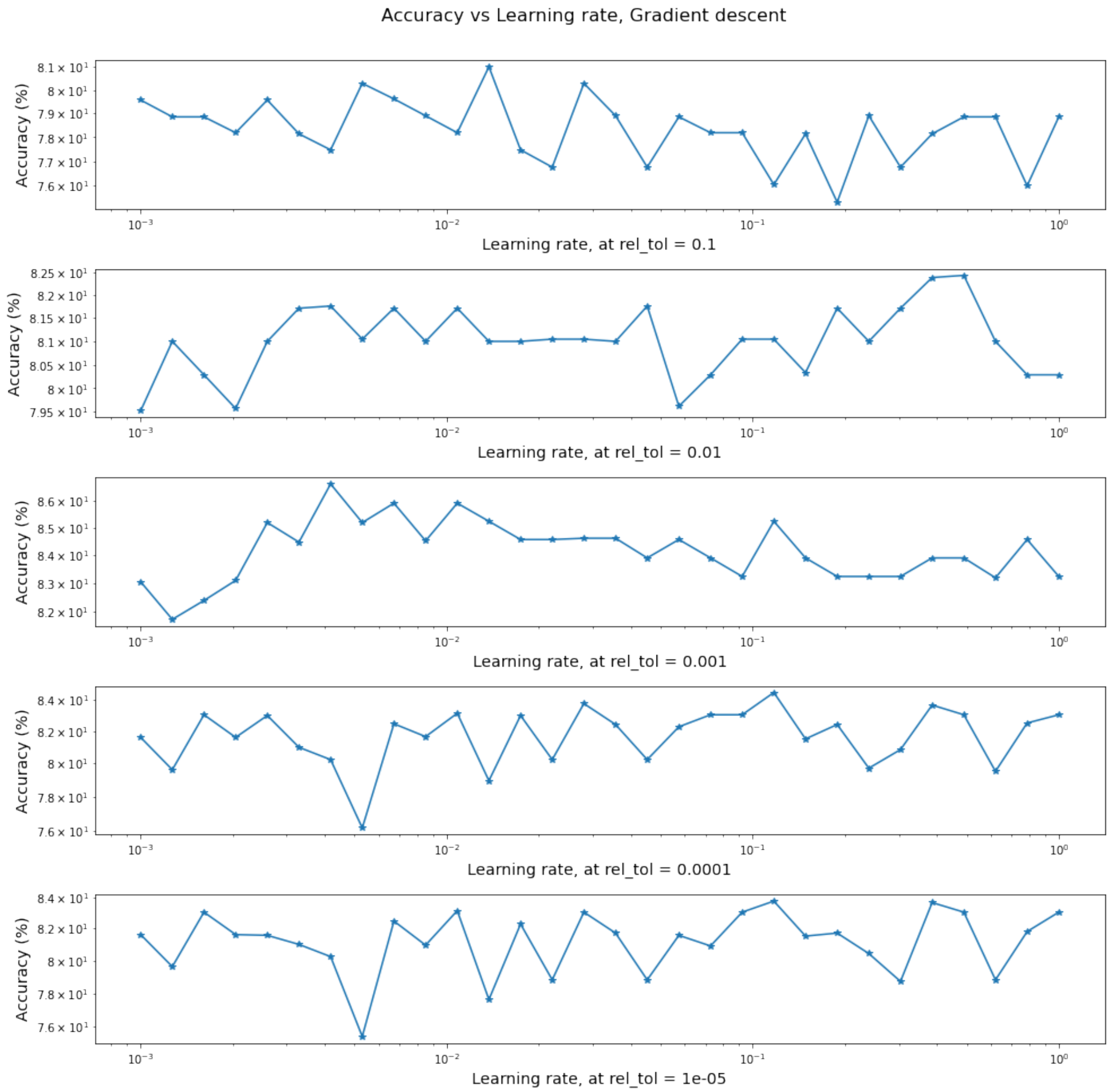
```
    print("\nTrain and test time: %.2f seconds in total, average %.2f per␣
↪rate"
          % (time.time() - start_time, time_cost_gd[row, 0]))
```

[10]:
```
if force_re_run or not external_file_is_present:
  np.savetxt(accuracies_M1H_path, accuracies_gd,delimiter=',')
  np.savetxt(times_M1H_path, time_cost_gd,delimiter=',')
  f = open(result_file_path, "w")
  f.write('M1H, best accuracy is ' + str(best) + ', at lr = ' +␣
↪str(learn_rate_save) + ', rt = ' + str(rel_tol_save) + '\n')
  f.close()
else:
  accuracies_gd = np.genfromtxt(accuracies_M1H_path,delimiter=',')
  time_cost_gd = np.genfromtxt(times_M1H_path,delimiter=',')
```

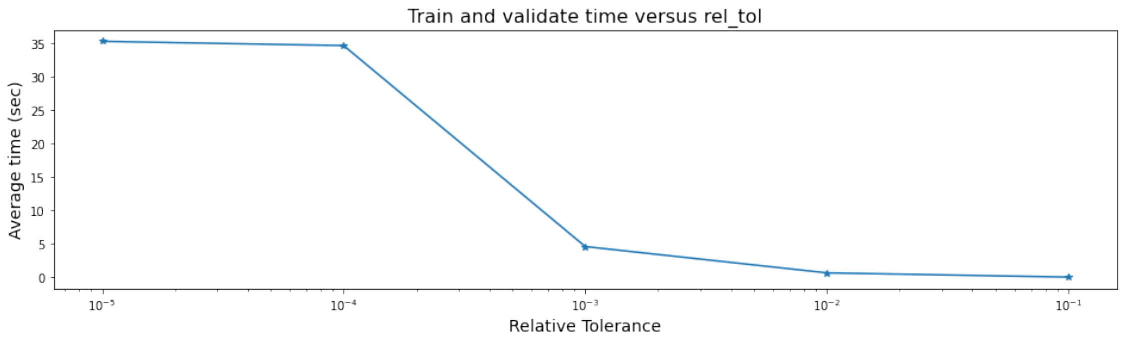
[11]:
```
plt.rcParams.update({'font.size': 10})
```

2.1.2 Plot of Gradient descent

[12]:
```
plt.figure(figsize=(16, 16))
for row in np.arange(0,rel_tol_sample):
    plt.subplot(rel_tol_sample, 1, row+1)
    plt.plot(learn_rate_range, accuracies_gd[row, :],'*-')
    plt.xscale('log')
    plt.yscale('log')
    plt.ylabel('Accuracy (%)', fontsize = 14)
    plt.xlabel('Learning rate, at rel_tol = ' + str(rel_tol_range[row]),␣
↪fontsize = 14)
plt.subplots_adjust(hspace=0.4)
plt.suptitle('Accuracy vs Learning rate, Gradient descent', fontsize=16, y = 0.
↪92)
plt.savefig(accuracies_M1H_image_path)
```



[13]:
```
plt.figure(figsize=(16,4))
plt.plot(rel_tol_range, time_cost_gd,'*-')
plt.ylabel('Average time (sec)', fontsize = 14)
plt.xscale('log')
plt.xlabel('Relative Tolerance', fontsize = 14)
plt.title('Train and validate time versus rel_tol', fontsize=16)
plt.savefig(times_M1H_image_path)
```



2.1.3 Maximum likelihood (M2-H)

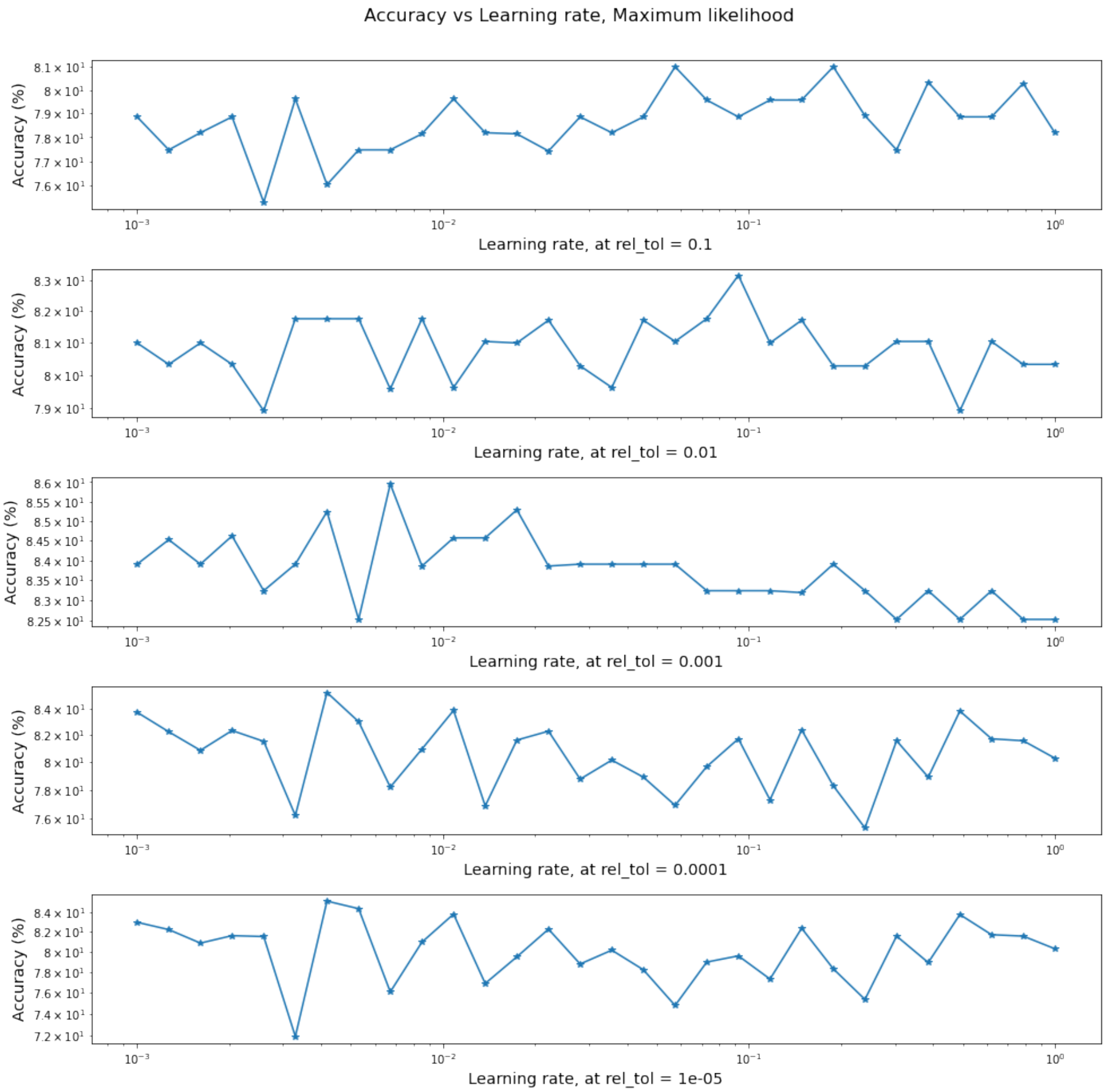
[14]:
```
external_file_is_present = os.path.isfile(accuracies_M2H_path)
```

[15]:
```
if force_re_run or not external_file_is_present:
  best = 0

  accuracies_ml = np.zeros((rel_tol_sample, learn_rate_sample)) # accuracy␣
↪matrix
  time_cost_ml = np.zeros((rel_tol_sample, 1)) #time cost per train/validate␣
↪matrix

  for row in np.arange(0,rel_tol_sample):
      print('Running', end='')
      start_time = time.time()
      for col in np.arange(0, learn_rate_sample):
          X, y = re_sample(df_data, 'ClassLabel', 43)
          print('.', end='', flush=True)
          # create model
          clf  =␣
↪LogisticRegression_maximum_likelihood(learning_rate=learn_rate_range[col],␣
↪max_iter=100000, rel_tol = rel_tol_range[row],  print_time=False)
          # K-fold train and validation
          accuracies_ml[row, col] = cross_val(clf,X,y,10)
          # save best result so far
          if (best < accuracies_ml[row, col]):
              best = accuracies_ml[row, col]
              learn_rate_save = learn_rate_range[col]
              rel_tol_save = rel_tol_range[row]
      time_cost_ml[row, 0] = (time.time() - start_time)/learn_rate_sample
      print("\nTrain and test time: %.2f seconds in total, average %.2f per␣
↪rate"
           % (time.time() - start_time, time_cost_ml[row, 0]))
```

[16]:
```
if force_re_run or not external_file_is_present:
  np.savetxt(accuracies_M2H_path, accuracies_ml,delimiter=',')
  np.savetxt(times_M2H_path, time_cost_ml,delimiter=',')
  f = open(result_file_path, "a")
  f.write('M1H, best accuracy is ' + str(best) + ', at lr = ' +␣
↪str(learn_rate_save) + ', rt = ' + str(rel_tol_save) + '\n')
  f.close()
else:
  accuracies_ml = np.genfromtxt(accuracies_M2H_path,delimiter=',')
  time_cost_ml = np.genfromtxt(times_M2H_path,delimiter=',')
```

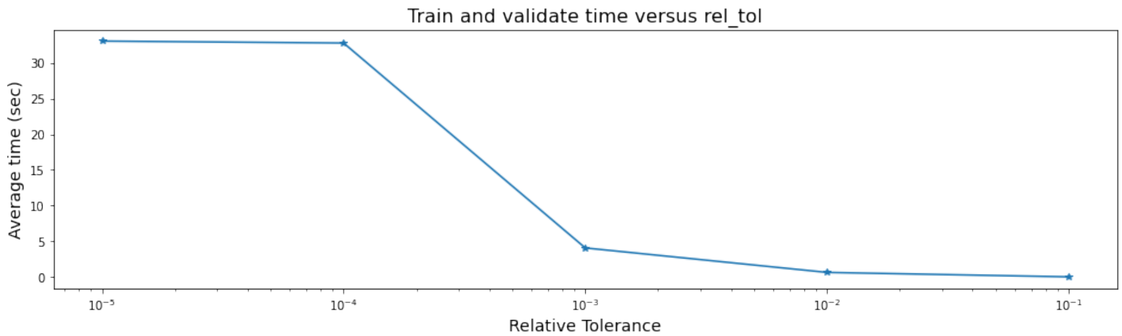
2.1.4 Plot of Maximum likelihood

[17]:
```
plt.figure(figsize=(16, 16))
for row in np.arange(0,rel_tol_sample):
    plt.subplot(rel_tol_sample, 1, row+1)
    plt.plot(learn_rate_range, accuracies_ml[row, :],'*-')
    plt.xscale('log')
    plt.yscale('log')
    plt.ylabel('Accuracy (%)', fontsize = 14)
    plt.xlabel('Learning rate, at rel_tol = ' + str(rel_tol_range[row]),␣
↪fontsize = 14)
plt.subplots_adjust(hspace=0.4)
plt.suptitle('Accuracy vs Learning rate, Maximum likelihood', fontsize=16, y =␣
↪0.92)
plt.savefig(accuracies_M2H_image_path)
```



[18]:

```
plt.figure(figsize=(16,4))
plt.plot(rel_tol_range, time_cost_ml,'*-')
plt.ylabel('Average time (sec)', fontsize = 14)
plt.xscale('log')
plt.xlabel('Relative Tolerance', fontsize = 14)
plt.title('Train and validate time versus rel_tol', fontsize=16)
plt.savefig(times_M2H_image_path)
```



1.3.2 2.2 Bankrupcy

[19]:
```
df_data = pd.read_csv(bankrupcy_file_path)
```

[20]:
```
rel_tol_sample = 5 # samples of rel_tol to be tested
learn_rate_sample = 30 # samples of learn_rate to be tested

min_learn_rate =  0.001
max_learn_rate = 1
exp_step = np.log10(max_learn_rate/min_learn_rate) / (learn_rate_sample-1)

rel_tol_range = (1/10**(np.arange(1,1+rel_tol_sample)))
learn_rate_range = min_learn_rate * (10 **(exp_step * np.
 ↪arange(0,learn_rate_sample)))
```

2.2.1 Gradient descent M1-B

[21]:
```
external_file_is_present = os.path.isfile(accuracies_M1B_path)
```

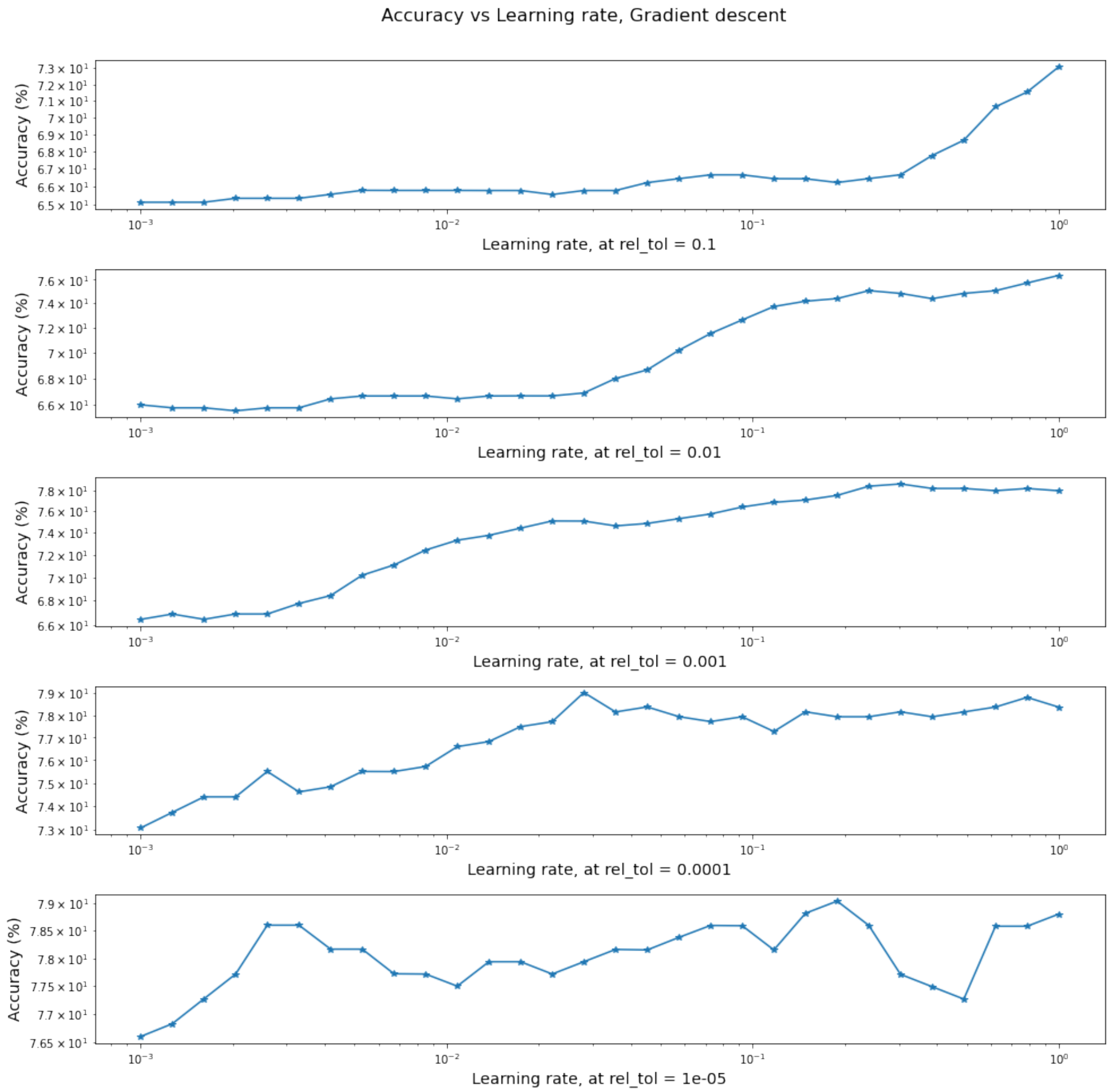
[22]:
```
if force_re_run or not external_file_is_present:
  best = 0
  accuracies_gd = np.zeros((rel_tol_sample, learn_rate_sample)) # accuracy␣
 ↪matrix
  time_cost_gd = np.zeros((rel_tol_sample, 1)) #time cost per train/validate␣
 ↪matrix

  for row in np.arange(0,rel_tol_sample):
      print('Running', end='')
      start_time = time.time()
      for col in np.arange(0, learn_rate_sample):
          X, y = re_sample(df_data, 'ClassLabel', 44)
          print('.', end='', flush=True)
          # create model
```

```
        clf  =␣
↪LogisticRegression_gradient_descent(learning_rate=learn_rate_range[col],␣
↪max_iter=100000, rel_tol = rel_tol_range[row],  print_time=False)
        # K-fold train and validation
        accuracies_gd[row, col] = cross_val(clf,X,y,10)
        # save best result so far
        if (best < accuracies_gd[row, col]):
            best = accuracies_gd[row, col]
            learn_rate_save = learn_rate_range[col]
            rel_tol_save = rel_tol_range[row]
    time_cost_gd[row, 0] = (time.time() - start_time)/learn_rate_sample
    print("\nTrain and test time: %.2f seconds in total, average %.2f per␣
↪rate"
          % (time.time() - start_time, time_cost_gd[row, 0]))
```

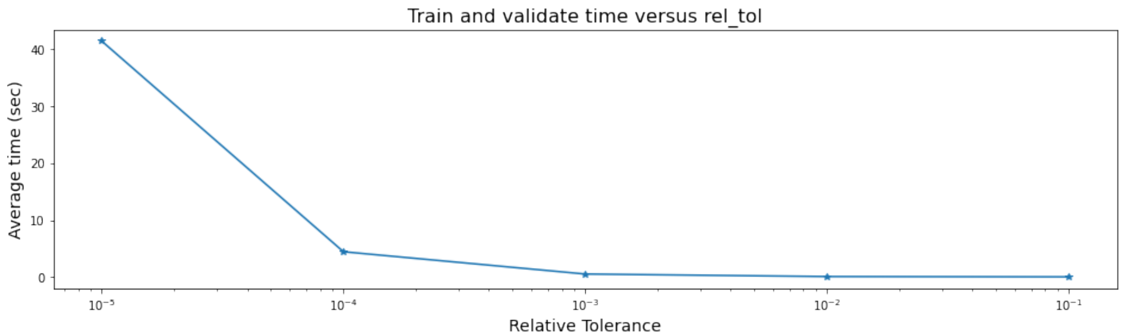
```
[23]: if force_re_run or not external_file_is_present:
        np.savetxt(accuracies_M1B_path, accuracies_gd,delimiter=',')
        np.savetxt(times_M1B_path, time_cost_gd,delimiter=',')
        f = open(result_file_path, "a")
        f.write('M1H, best accuracy is ' + str(best) + ', at lr = ' +␣
      ↪str(learn_rate_save) + ', rt = ' + str(rel_tol_save) + '\n')
        f.close()
      else:
        accuracies_gd = np.genfromtxt(accuracies_M1B_path,delimiter=',')
        time_cost_gd = np.genfromtxt(times_M1B_path,delimiter=',')
```

2.2.2 Plot of Gradient descent

```
[24]: plt.figure(figsize=(16, 16))
      for row in np.arange(0,rel_tol_sample):
          plt.subplot(rel_tol_sample, 1, row+1)
          plt.plot(learn_rate_range, accuracies_gd[row, :],'*-')
          plt.xscale('log')
          plt.yscale('log')
          plt.ylabel('Accuracy (%)', fontsize = 14)
          plt.xlabel('Learning rate, at rel_tol = ' + str(rel_tol_range[row]),␣
      ↪fontsize = 14)
      plt.subplots_adjust(hspace=0.4)
      plt.suptitle('Accuracy vs Learning rate, Gradient descent', fontsize=16, y = 0.
      ↪92)
      plt.savefig(accuracies_M1B_image_path)
```



[25]:
```
plt.figure(figsize=(16,4))
plt.plot(rel_tol_range, time_cost_gd,'*-')
plt.ylabel('Average time (sec)', fontsize = 14)
plt.xscale('log')
plt.xlabel('Relative Tolerance', fontsize = 14)
plt.title('Train and validate time versus rel_tol', fontsize=16)
plt.savefig(times_M1B_image_path)
```



2.2.3. Maximum likelihood M2-B

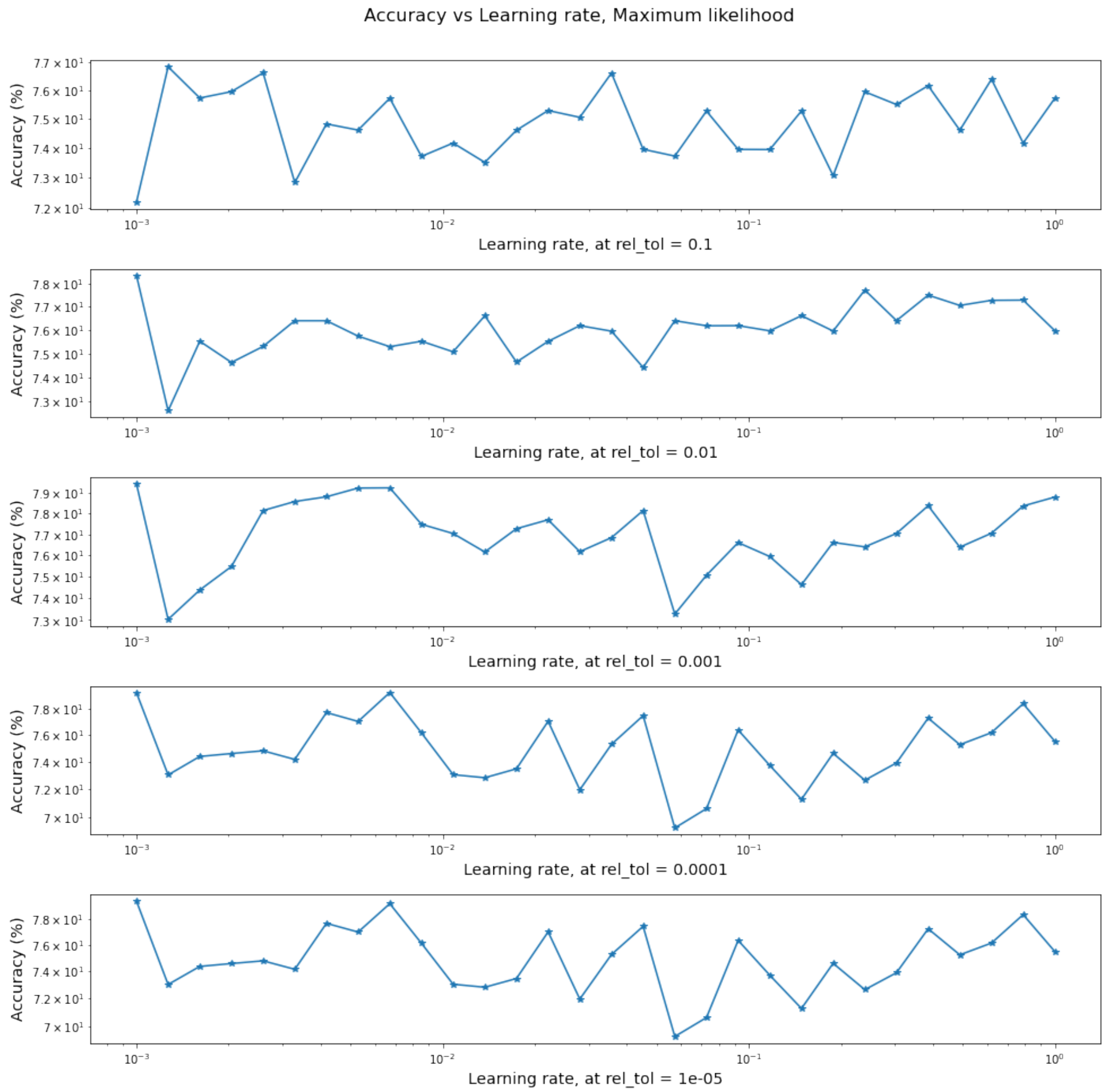
[26]:
```
external_file_is_present = os.path.isfile(accuracies_M2B_path)
```

[27]:
```
if force_re_run or not external_file_is_present:
  best = 0
  rel_tol_range = (1/10**(np.arange(1,1+rel_tol_sample)))
  learn_rate_range = np.linspace(0.01, 0.51, learn_rate_sample)
  accuracies_ml = np.zeros((rel_tol_sample, learn_rate_sample)) # accuracy␣
↪matrix
  time_cost_ml = np.zeros((rel_tol_sample, 1)) #time cost per train/validate␣
↪matrix

  for row in np.arange(0,rel_tol_sample):
      print('Running', end='')
      start_time = time.time()
      for col in np.arange(0, learn_rate_sample):
          X, y = re_sample(df_data, 'ClassLabel', 45)
          print('.', end='', flush=True)
          # create model
          clf  =␣
↪LogisticRegression_maximum_likelihood(learning_rate=learn_rate_range[col],␣
↪max_iter=100000, rel_tol = rel_tol_range[row],  print_time=False)
          # K-fold train and validation
          accuracies_ml[row, col] = cross_val(clf,X,y,10)
          # save best result so far
          if (best < accuracies_ml[row, col]):
              best = accuracies_ml[row, col]
              learn_rate_save = learn_rate_range[col]
              rel_tol_save = rel_tol_range[row]
      time_cost_ml[row, 0] = (time.time() - start_time)/learn_rate_sample
      print("\nTrain and test time: %.2f seconds in total, average %.2f per␣
↪rate"
            % (time.time() - start_time, time_cost_ml[row, 0]))
```

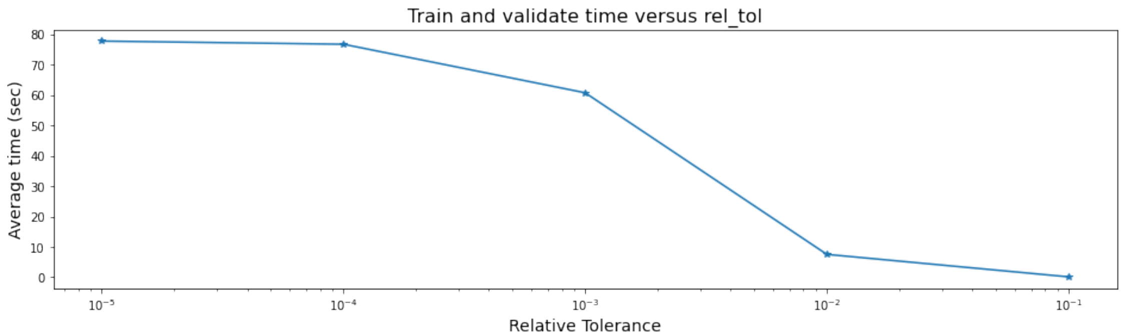
[28]:
```
if force_re_run or not external_file_is_present:
  np.savetxt(accuracies_M2B_path, accuracies_ml,delimiter=',')
  np.savetxt(times_M2B_path, time_cost_ml,delimiter=',')
  f = open(result_file_path, "a")
  f.write('M2B, best accuracy is ' + str(best) + ', at lr = ' +␣
↪str(learn_rate_save) + ', rt = ' + str(rel_tol_save) + '\n')
  f.close()
else:
  accuracies_ml = np.genfromtxt(accuracies_M2B_path,delimiter=',')
  time_cost_ml = np.genfromtxt(times_M2B_path,delimiter=',')
```

2.2.4 Plot of Maximum likelihood

[29]:
```
plt.figure(figsize=(16, 16))
for row in np.arange(0,rel_tol_sample):
    plt.subplot(rel_tol_sample, 1, row+1)
    plt.plot(learn_rate_range, accuracies_ml[row, :],'*-')
    plt.xscale('log')
    plt.yscale('log')
    plt.ylabel('Accuracy (%)', fontsize = 14)
    plt.xlabel('Learning rate, at rel_tol = ' + str(rel_tol_range[row]),␣
↪fontsize = 14)
plt.subplots_adjust(hspace=0.4)
plt.suptitle('Accuracy vs Learning rate, Maximum likelihood', fontsize=16, y =␣
↪0.92)
plt.savefig(accuracies_M2B_image_path)
```



[30]:
```
plt.figure(figsize=(16,4))
plt.plot(rel_tol_range, time_cost_ml,'*-')
plt.ylabel('Average time (sec)', fontsize = 14)
plt.xscale('log')
plt.xlabel('Relative Tolerance', fontsize = 14)
plt.title('Train and validate time versus rel_tol', fontsize=16)
plt.savefig(times_M2B_image_path)
```



1.4 3. Model optimization

[31]:
```
no_of_models = 4
acc_original = np.zeros((no_of_models,))
acc_normalized = np.zeros((no_of_models,))
acc_standardized =  np.zeros((no_of_models,))
acc_norm_std =  np.zeros((no_of_models,))
acc_squared =  np.zeros((no_of_models,))
```

Hepatitis modelling - gradient descent

1. Data adquisition

[32]:
```
df_data = pd.read_csv(hepatitis_file_path)

features = [feature for feature in df_data if feature not in ['ClassLabel']]
continuous_features = [ feature for feature in df_data if len(df_data[feature].
 ↪unique()) > 25]
discrete_features = [ feature for feature in df_data if len(df_data[feature].
 ↪unique()) < 25]
discrete_features = discrete_features[:-1]
model_index = 0
```

2. Feature engineering

[33]:
```
clf  = LogisticRegression_gradient_descent(learning_rate=0.1, max_iter=100000,␣
 ↪rel_tol=0.01,  print_time=False)
```

Let's first try with the original data

[34]:
```
X,y =re_sample(df_data)
```

[35]:
```
acc_original[model_index] = cross_val(clf,X,y,10)
print('Accuracy with original data = ', acc_original[model_index])
```

```
Accuracy with original data =  81.0
```

Now let's try normalize the data

```
[36]: log_transformed_df = logarithm_transformer(df_data)
```

```
[37]: X2, y2 = re_sample(log_transformed_df)
```

```
[38]: acc_normalized[model_index] = cross_val(clf,X2,y2,10)
      print('Accuracy with normalized data = ', acc_normalized[model_index])
```

```
Accuracy with normalized data =  80.28571428571429
```

Let's instead standarize the data

```
[39]: standard_df = standard_scaler(df_data)
```

```
[40]: X3,y3 =re_sample(standard_df)
```

```
[41]: acc_standardized[model_index] = cross_val(clf,X3,y3,10)
      print('Accuracy with standarized data = ', acc_standardized[model_index])
```

```
Accuracy with standarized data =  86.57142857142858
```

Finally, let's try the combination of logarithmization and standarization

```
[42]: standard_log_df = standard_scaler(logarithm_transformer(df_data))
```

```
[43]: X4,y4 = re_sample(standard_log_df)
```

```
[44]: acc_norm_std[model_index] = cross_val(clf,X4,y4,10)
      print('Accuracy with standarized and log data = ', acc_norm_std[model_index])
```

```
Accuracy with standarized and log data =  86.61904761904762
```

Just another test, let's try incorporating squared features by turn and train the model with the resulting data

```
[45]: feature_to_square = ''
      for feature in features:
        quadratic_feature_df =  quadratic_feature_tester(standard_log_df,[feature])
        X5,y5 = re_sample(quadtratic_feature_df)
        acc5 = cross_val(clf, X5, y5, 10)
        if acc5>acc_squared[model_index]:
          acc_squared[model_index] = acc5
          feature_to_square = feature
        print('Accuracy with feature {} square  = {}'.format(feature, acc5))
      print('Maximum accuracy: {:f}, which corresponds to squaring \'{}\' '.
       ↪format(acc_squared[model_index],feature_to_square))
```

```
Accuracy with feature age square  = 87.28571428571429
Accuracy with feature sex square  = 87.28571428571429
Accuracy with feature steroid square  = 86.57142857142858
Accuracy with feature antivirals square  = 86.61904761904762
Accuracy with feature fatigue square  = 86.61904761904762
Accuracy with feature malaise square  = 86.61904761904762
Accuracy with feature anorexia square  = 86.61904761904762
Accuracy with feature liver_big square  = 87.28571428571429
Accuracy with feature liver_firm square  = 86.57142857142858
Accuracy with feature spleen_palable square  = 86.57142857142858
Accuracy with feature spiders square  = 84.52380952380952
Accuracy with feature ascites square  = 87.23809523809523
Accuracy with feature varices square  = 85.85714285714286
Accuracy with feature bilirubin square  = 85.0952380952381
Accuracy with feature alk_phosphate square  = 87.28571428571429
Accuracy with feature sgot square  = 86.61904761904762
Accuracy with feature albumin square  = 86.61904761904762
Accuracy with feature protime square  = 84.52380952380952
Accuracy with feature histology square  = 86.61904761904762
Maximum accuracy: 87.285714, which corresponds to squaring 'age'
```

Hepatitis modelling - maximum likelihood

1. Data adquisition

[46]:
```
df_data = pd.read_csv(hepatitis_file_path)

features = [feature for feature in df_data if feature not in ['ClassLabel']]
continuous_features = [ feature for feature in df_data if len(df_data[feature].
 ↪unique()) > 25]
discrete_features = [ feature for feature in df_data if len(df_data[feature].
 ↪unique()) < 25]
discrete_features = discrete_features[:-1]
model_index = 1
```

2. Feature engineering

[47]:
```
clf  = LogisticRegression_maximum_likelihood(learning_rate=0.1,␣
 ↪max_iter=100000, rel_tol=0.01,  print_time=False)
```

Let's first try with the original data

[48]:
```
X,y =re_sample(df_data)
```

[49]:
```
acc_original[model_index] = cross_val(clf,X,y,10)
print('Accuracy with original data = ', acc_original[model_index])
```

```
Accuracy with original data =  80.33333333333334
```

Now let's try normalize the data

[50]:
```
log_transformed_df = logarithm_transformer(df_data)
```

[51]:
```
X2, y2 = re_sample(log_transformed_df)
```

[52]:
```
acc_normalized[model_index] = cross_val(clf,X2,y2,10)
print('Accuracy with normalized data = ', acc_normalized[model_index])
```

```
Accuracy with normalized data =  83.0952380952381
```

Let's instead standarize the data

[53]:
```
standard_df = standard_scaler(df_data)
```

[54]:
```
X3,y3 =re_sample(standard_df)
```

[55]:
```
acc_standardized[model_index] = cross_val(clf,X3,y3,10)
print('Accuracy with standarized data = ', acc_standardized[model_index])
```

```
Accuracy with standarized data =  82.38095238095238
```

Finally, let's try the combination of logarithmization and standarization

[56]:
```
standard_log_df = standard_scaler(logarithm_transformer(df_data))
```

[57]:
```
X4,y4 = re_sample(standard_log_df)
```

[58]:
```
acc_norm_std[model_index] = cross_val(clf,X4,y4,10)
print('Accuracy with standarized and log data = ', acc_norm_std[model_index])
```

```
Accuracy with standarized and log data =  83.0952380952381
```

We conclude that taking logs and then applying standarization is the best feature engineering to apply!!!

Just another test, let's try incorporating squared features by turn and train the model with the resulting data

[59]:
```
feature_to_square = ''
for feature in features:
  quadtratic_feature_df =  quadratic_feature_tester(standard_log_df,[feature])
  X5,y5 = re_sample(quadtratic_feature_df)
  acc5 = cross_val(clf, X5, y5, 10)
  if acc5>acc_squared[model_index]:
    acc_squared[model_index] = acc5
    feature_to_square = feature
  print('Accuracy with feature {} squared  = {}'.format(feature, acc5))
print('Maximum accuracy: {:f}, which corresponds to squaring \'{}\' '.
 ↪format(acc_squared[model_index],feature_to_square))
```

```
Accuracy with feature age squared  = 83.0952380952381
Accuracy with feature sex squared  = 81.66666666666667
Accuracy with feature steroid squared  = 83.14285714285715
Accuracy with feature antivirals squared  = 83.19047619047619
Accuracy with feature fatigue squared  = 83.80952380952381
Accuracy with feature malaise squared  = 83.0952380952381
Accuracy with feature anorexia squared  = 82.47619047619048
Accuracy with feature liver_big squared  = 82.42857142857144
Accuracy with feature liver_firm squared  = 82.42857142857144
Accuracy with feature spleen_palable squared  = 83.80952380952381
Accuracy with feature spiders squared  = 81.66666666666667
Accuracy with feature ascites squared  = 83.0952380952381
Accuracy with feature varices squared  = 83.14285714285715
Accuracy with feature bilirubin squared  = 82.38095238095238
Accuracy with feature alk_phosphate squared  = 81.0952380952381
Accuracy with feature sgot squared  = 83.0952380952381
Accuracy with feature albumin squared  = 80.38095238095238
Accuracy with feature protime squared  = 83.80952380952381
Accuracy with feature histology squared  = 83.85714285714286
Maximum accuracy: 83.857143, which corresponds to squaring 'histology'
```

Bankruptcy modelling - gradient descent

1. Data adquisition

[60]:
```
df_data = pd.read_csv(bankrupcy_file_path)

features = [feature for feature in df_data if feature not in ['ClassLabel']]
continuous_features = [ feature for feature in df_data if len(df_data[feature].
↪unique()) > 25]
discrete_features = [ feature for feature in df_data if len(df_data[feature].
↪unique()) < 25]
discrete_features = discrete_features[:-1]
model_index = 2
```

2. Feature engineering

[61]:
```
clf  = LogisticRegression_gradient_descent(learning_rate=0.1, max_iter=100000,␣
↪rel_tol=0.01,  print_time=False)
```

Let's first try with the original data

[62]:
```
X,y =re_sample(df_data)
```

[63]:
```
acc_original[model_index] = cross_val(clf,X,y,10)
print('Accuracy with original data = ', acc_original[model_index])
```

```
Accuracy with original data =  72.85507246376811
```

Now let's try normalize the data

[64]:
```
log_transformed_df = logarithm_transformer(df_data)
```

[65]:
```
X2, y2 = re_sample(log_transformed_df)
```

[66]:
```
acc_normalized[model_index] = cross_val(clf,X2,y2,10)
print('Accuracy with normalized data = ', acc_normalized[model_index])
```

```
Accuracy with normalized data =  44.811594202898554
```

Let's instead standarize the data

[67]:
```
standard_df = standard_scaler(df_data)
```

[68]:
```
X3,y3 =re_sample(standard_df)
```

[69]:
```
acc_standardized[model_index] = cross_val(clf,X3,y3,10)
print('Accuracy with standarized data = ', acc_standardized[model_index])
```

```
Accuracy with standarized data =  73.97584541062801
```

Finally, let's try the combination of logarithmization and standarization

[70]:
```
standard_log_df = standard_scaler(logarithm_transformer(df_data))
```

[71]:
```
X4,y4 = re_sample(standard_df)
```

[72]:
```
acc_norm_std[model_index] = cross_val(clf,X4,y4,10)
print('Accuracy with standarized and log data = ', acc_norm_std[model_index])
```

```
Accuracy with standarized and log data =  73.97584541062801
```

Just another test, let's try incorporating squared features by turn and train the model with the resulting data

[73]:
```
feature_to_square = ''
for feature in features:
  quadratic_feature_df =  quadratic_feature_tester(standard_df,[feature])
  X5,y5 = re_sample(quadtratic_feature_df)
  acc5 = cross_val(clf, X5, y5, 10)
  if acc5>acc_squared[model_index]:
    acc_squared[model_index] = acc5
    feature_to_square = feature
  print('Accuracy with feature {} square  = {}'.format(feature, acc5))
print('Maximum accuracy: {:f}, which corresponds to squaring \'{}\' '.
 ↪format(acc_squared[model_index],feature_to_square))
```

```
Accuracy with feature attribute1 square  = 73.7536231884058
Accuracy with feature attribute2 square  = 73.97584541062801
```

```
Accuracy with feature attribute3 square  = 73.54106280193237
Accuracy with feature attribute4 square  = 73.09178743961353
Accuracy with feature attribute5 square  = 75.29951690821255
Accuracy with feature attribute6 square  = 74.19806763285024
Accuracy with feature attribute7 square  = 73.7536231884058
Accuracy with feature attribute8 square  = 74.63768115942028
Accuracy with feature attribute9 square  = 73.97101449275362
Accuracy with feature attribute10 square  = 73.97584541062801
Accuracy with feature attribute11 square  = 74.19323671497584
Accuracy with feature attribute12 square  = 73.97584541062801
Accuracy with feature attribute13 square  = 73.74879227053141
Accuracy with feature attribute14 square  = 73.7536231884058
Accuracy with feature attribute15 square  = 74.19323671497582
Accuracy with feature attribute16 square  = 74.85507246376814
Accuracy with feature attribute17 square  = 74.63768115942028
Accuracy with feature attribute18 square  = 73.7536231884058
Accuracy with feature attribute19 square  = 73.74879227053141
Accuracy with feature attribute20 square  = 73.74879227053141
Accuracy with feature attribute21 square  = 73.97584541062801
Accuracy with feature attribute22 square  = 73.97101449275362
Accuracy with feature attribute23 square  = 73.74879227053141
Accuracy with feature attribute24 square  = 73.97584541062801
Accuracy with feature attribute25 square  = 74.19323671497584
Accuracy with feature attribute26 square  = 74.85024154589374
Accuracy with feature attribute27 square  = 73.53140096618357
Accuracy with feature attribute28 square  = 73.97101449275362
Accuracy with feature attribute29 square  = 73.52657004830918
Accuracy with feature attribute30 square  = 73.74879227053141
Accuracy with feature attribute31 square  = 73.74879227053141
Accuracy with feature attribute32 square  = 73.53140096618357
Accuracy with feature attribute33 square  = 74.41545893719805
Accuracy with feature attribute34 square  = 74.42028985507247
Accuracy with feature attribute35 square  = 73.53623188405797
Accuracy with feature attribute36 square  = 73.74879227053141
Accuracy with feature attribute37 square  = 73.53623188405797
Accuracy with feature attribute38 square  = 73.53623188405797
Accuracy with feature attribute39 square  = 73.74879227053141
Accuracy with feature attribute40 square  = 73.97584541062801
Accuracy with feature attribute41 square  = 73.97101449275361
Accuracy with feature attribute42 square  = 73.74879227053141
Accuracy with feature attribute43 square  = 73.74879227053141
Accuracy with feature attribute44 square  = 73.74879227053141
Accuracy with feature attribute45 square  = 73.97584541062801
Accuracy with feature attribute46 square  = 73.97101449275362
Accuracy with feature attribute47 square  = 74.18840579710145
Accuracy with feature attribute48 square  = 73.96618357487924
Accuracy with feature attribute49 square  = 73.74879227053141
Accuracy with feature attribute50 square  = 73.97584541062801
```

```
Accuracy with feature attribute51 square  = 73.7584541062802
Accuracy with feature attribute52 square  = 73.30917874396135
Accuracy with feature attribute53 square  = 73.7487922705314
Accuracy with feature attribute54 square  = 73.97101449275362
Accuracy with feature attribute55 square  = 74.19806763285024
Accuracy with feature attribute56 square  = 73.53140096618357
Accuracy with feature attribute57 square  = 75.06763285024155
Accuracy with feature attribute58 square  = 73.74879227053141
Accuracy with feature attribute59 square  = 74.19323671497584
Accuracy with feature attribute60 square  = 73.7536231884058
Accuracy with feature attribute61 square  = 74.19806763285024
Accuracy with feature attribute62 square  = 73.74879227053141
Accuracy with feature attribute63 square  = 73.97584541062801
Accuracy with feature attribute64 square  = 73.7487922705314
Maximum accuracy: 75.299517, which corresponds to squaring 'attribute5'
```

Bankruptcy modelling - maximum likelihood

1. Data adquisition

[74]:
```
df_data = pd.read_csv(bankrupcy_file_path)

features = [feature for feature in df_data if feature not in ['ClassLabel']]
continuous_features = [ feature for feature in df_data if len(df_data[feature].
 ↪unique()) > 25]
discrete_features = [ feature for feature in df_data if len(df_data[feature].
 ↪unique()) < 25]
discrete_features = discrete_features[:-1]
model_index = 3
```

2. Feature engineering

[75]:
```
clf  = LogisticRegression_maximum_likelihood(learning_rate=0.1,␣
 ↪max_iter=100000, rel_tol=0.01,  print_time=False)
```

Let's first try with the original data

[76]:
```
X,y =re_sample(df_data)
```

[77]:
```
acc_original[model_index] = cross_val(clf,X,y,10)
print('Accuracy with original data = ', acc_original[model_index])
```

```
Accuracy with original data =  75.5024154589372
```

Now let's try normalize the data

[78]:
```
log_transformed_df = logarithm_transformer(df_data)
```

[79]:
```
X2, y2 = re_sample(log_transformed_df)
```

[80]:
```
acc_normalized[model_index] = cross_val(clf,X2,y2,10)
print('Accuracy with normalized data = ', acc_normalized[model_index])
```

```
Accuracy with normalized data =  44.811594202898554
```

Let's instead standarize the data

[81]:
```
standard_df = standard_scaler(df_data)
```

[82]:
```
X3,y3 =re_sample(standard_df)
```

[83]:
```
acc_standardized[model_index] = cross_val(clf,X3,y3,10)
print('Accuracy with standarized data = ', acc_standardized[model_index])
```

```
Accuracy with standarized data =  78.34782608695652
```

Finally, let's try the combination of logarithmization and standarization

[84]:
```
standard_log_df = standard_scaler(logarithm_transformer(df_data))
```

[85]:
```
X4,y4 = re_sample(standard_df)
```

[86]:
```
acc_norm_std[model_index] = cross_val(clf,X4,y4,10)
print('Accuracy with standarized and log data = ', acc_norm_std[model_index])
```

```
Accuracy with standarized and log data =  78.34782608695652
```

We conclude that taking logs and then applying standarization is the best feature engineering to apply!!!

Squaring features

[87]:
```
feature_to_square = ''
for feature in features:
  quadtratic_feature_df =  quadratic_feature_tester(standard_df,[feature])
  X5,y5 = re_sample(quadtratic_feature_df)
  acc5 = cross_val(clf, X5, y5, 10)
  if acc5>acc_squared[model_index]:
    acc_squared[model_index] = acc5
    feature_to_square = feature
  print('Accuracy with feature {} square  = {}'.format(feature, acc5))
print('Maximum accuracy: {:f}, which corresponds to squaring \'{}\' '.
 ↪format(acc_squared[model_index],feature_to_square))
```

```
Accuracy with feature attribute1 square  = 78.34782608695653
Accuracy with feature attribute2 square  = 76.80193236714976
Accuracy with feature attribute3 square  = 74.3671497584541
Accuracy with feature attribute4 square  = 78.1159420289855
Accuracy with feature attribute5 square  = 78.3671497584541
Accuracy with feature attribute6 square  = 77.47826086956522
```

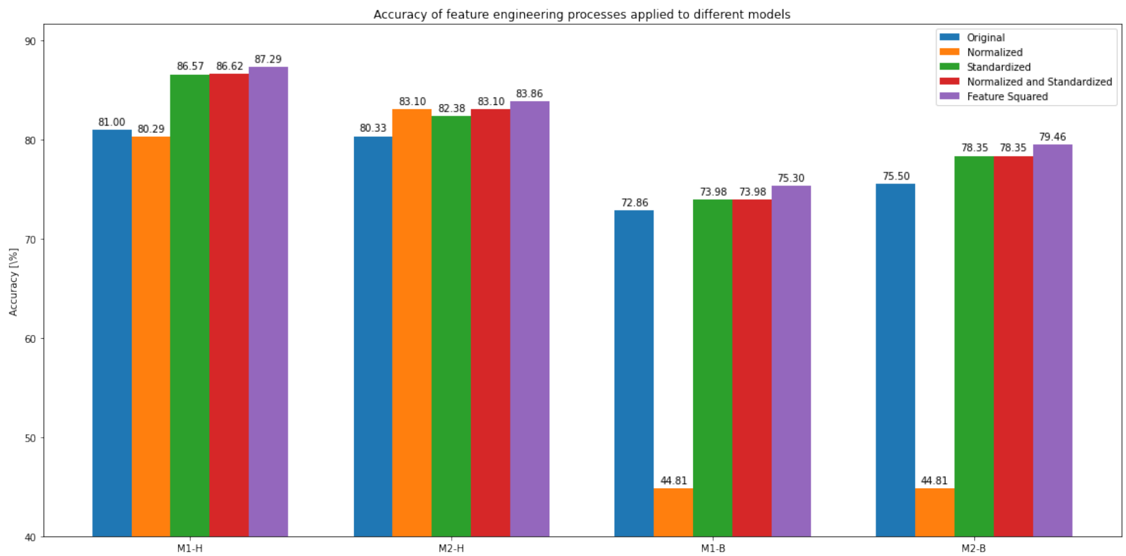
```
Accuracy with feature attribute7 square  = 77.90338164251207
Accuracy with feature attribute8 square  = 77.48309178743962
Accuracy with feature attribute9 square  = 78.36231884057972
Accuracy with feature attribute10 square  = 77.25603864734299
Accuracy with feature attribute11 square  = 77.02898550724638
Accuracy with feature attribute12 square  = 75.27536231884059
Accuracy with feature attribute13 square  = 77.03864734299518
Accuracy with feature attribute14 square  = 77.90821256038647
Accuracy with feature attribute15 square  = 76.82608695652172
Accuracy with feature attribute16 square  = 78.3719806763285
Accuracy with feature attribute17 square  = 78.58937198067633
Accuracy with feature attribute18 square  = 76.79710144927535
Accuracy with feature attribute19 square  = 76.59420289855072
Accuracy with feature attribute20 square  = 77.68599033816426
Accuracy with feature attribute21 square  = 77.2512077294686
Accuracy with feature attribute22 square  = 76.37198067632849
Accuracy with feature attribute23 square  = 78.34299516908212
Accuracy with feature attribute24 square  = 77.02898550724639
Accuracy with feature attribute25 square  = 78.55555555555556
Accuracy with feature attribute26 square  = 76.15942028985506
Accuracy with feature attribute27 square  = 78.56521739130434
Accuracy with feature attribute28 square  = 79.02415458937197
Accuracy with feature attribute29 square  = 77.70531400966185
Accuracy with feature attribute30 square  = 77.68599033816426
Accuracy with feature attribute31 square  = 77.46376811594202
Accuracy with feature attribute32 square  = 79.46376811594203
Accuracy with feature attribute33 square  = 76.14492753623188
Accuracy with feature attribute34 square  = 78.57971014492753
Accuracy with feature attribute35 square  = 77.91787439613526
Accuracy with feature attribute36 square  = 78.57487922705315
Accuracy with feature attribute37 square  = 78.14009661835749
Accuracy with feature attribute38 square  = 75.70048309178745
Accuracy with feature attribute39 square  = 77.69082125603865
Accuracy with feature attribute40 square  = 76.79710144927536
Accuracy with feature attribute41 square  = 79.01449275362319
Accuracy with feature attribute42 square  = 78.14009661835749
Accuracy with feature attribute43 square  = 78.1256038647343
Accuracy with feature attribute44 square  = 77.70048309178743
Accuracy with feature attribute45 square  = 75.4830917874396
Accuracy with feature attribute46 square  = 77.91787439613526
Accuracy with feature attribute47 square  = 77.47826086956522
Accuracy with feature attribute48 square  = 78.14975845410629
Accuracy with feature attribute49 square  = 79.04347826086958
Accuracy with feature attribute50 square  = 76.36714975845412
Accuracy with feature attribute51 square  = 77.01932367149759
Accuracy with feature attribute52 square  = 77.48309178743962
Accuracy with feature attribute53 square  = 77.47826086956522
Accuracy with feature attribute54 square  = 79.02415458937199
```

```
Accuracy with feature attribute55 square  = 78.59420289855072
Accuracy with feature attribute56 square  = 78.57004830917874
Accuracy with feature attribute57 square  = 79.02415458937199
Accuracy with feature attribute58 square  = 77.46859903381643
Accuracy with feature attribute59 square  = 77.92753623188405
Accuracy with feature attribute60 square  = 77.90821256038647
Accuracy with feature attribute61 square  = 75.47826086956522
Accuracy with feature attribute62 square  = 77.90821256038647
Accuracy with feature attribute63 square  = 77.47342995169082
Accuracy with feature attribute64 square  = 79.01449275362317
Maximum accuracy: 79.463768, which corresponds to squaring 'attribute32'
```

1.4.1 4. Accuracy visualization

[88]:
```python
labels = ['M1-H','M2-H','M1-B','M2-B']

x = np.arange(len(labels))
width = 0.15

f,a = plt.subplots(figsize = (16,8))

rects1 = a.bar(x-4*  width/2, acc_original,    width,label='Original')
rects2 = a.bar(x -2*width/2, acc_normalized,  width,label='Normalized')
rects3 = a.bar(x, acc_standardized,width,label='Standardized')
rects4 = a.bar(x+2*width/2, acc_norm_std,    width,label='Normalized and␣
↪Standardized')
rects5 = a.bar(x+4*width/2, acc_squared,     width,label='Feature Squared')

# Add some text for labels, title and custom x-axis tick labels, etc.
a.set_ylabel('Accuracy [\%]')
a.set_title('Accuracy of feature engineering processes applied to different␣
↪models')
a.set_xticks(x)
a.set_ylim(bottom=40)
a.set_xticklabels(labels)
a.legend( loc='best')

def autolabel(rects):
    """Attach a text label above each bar in *rects*, displaying its height."""
    for rect in rects:
        height = rect.get_height()
        a.annotate('{:.2f}'.format(height),
                    xy=(rect.get_x() + rect.get_width() / 2, height),
                    xytext=(0, 3),  # 3 points vertical offset
                    textcoords="offset points",
                    ha='center', va='bottom')
autolabel(rects1)
```

```
autolabel(rects2)
autolabel(rects3)
autolabel(rects4)
autolabel(rects5)

f.tight_layout()

plt.show()
```



1.5 4. Proposed Model

1.5.1 Hepatitis Dataset

[89]:
```
# training data
df_data = pd.read_csv(hepatitis_file_path)
standard_log_df = standard_scaler(logarithm_transformer(df_data))
```

[90]:
```
# testing data (TBD)
df_data_test = pd.read_csv(hepatitis_file_path)
standard_log_df_test = standard_scaler(logarithm_transformer(df_data_test))
```

[91]:
```
X_val, y_val = re_sample(standard_log_df, 'ClassLabel', 42)
X, y = re_sample(standard_log_df_test, 'ClassLabel', 42)
```

[92]:
```
accuracies_gd = np.genfromtxt(accuracies_M1H_path,delimiter=',')
time_cost_gd = np.genfromtxt(times_M1H_path,delimiter=',')
```

[93]:
```
m1h_max = np.unravel_index(np.argmax(accuracies_gd), accuracies_gd.shape)
learning_rate_m1h = m1h_max[1]
rel_tol_m1h = m1h_max[0]

# create model
clf  =␣
↪LogisticRegression_gradient_descent(learning_rate=learn_rate_range[learning_rate_m1h],␣
↪max_iter=100000, rel_tol = rel_tol_range[rel_tol_m1h],  print_time=False)

# final result
print(model_test(clf, X_val, y_val, X, y))

# accuracies = cross_val(clf,X,y,10)
# print(accuracies)
```

85.2112676056338

1.5.2 Bankruptcy Dataset

[94]:
```
# training data
df_data = pd.read_csv(bankrupcy_file_path)
standard_log_df = standard_scaler(logarithm_transformer(df_data))
```

[95]:
```
# testing data (TBD)
df_data_test = pd.read_csv(bankrupcy_file_path)
standard_log_df_test = standard_scaler(logarithm_transformer(df_data_test))
```

[96]:
```
X_val, y_val = re_sample(df_data, 'ClassLabel', 45)
X, y = re_sample(df_data_test, 'ClassLabel', 45)
```

[97]:
```
accuracies_ml = np.genfromtxt(accuracies_M2B_path,delimiter=',')
time_cost_ml = np.genfromtxt(times_M2B_path,delimiter=',')
```

[98]:
```
m2b_max = np.unravel_index(np.argmax(accuracies_ml), accuracies_ml.shape)
learning_rate_m2b = m2b_max[1]
rel_tol_m2b = m2b_max[0]

# create model
clf  =␣
↪LogisticRegression_maximum_likelihood(learning_rate=learn_rate_range[learning_rate_m2b],␣
↪max_iter=100000, rel_tol = rel_tol_range[rel_tol_m2b],  print_time=False)

# final result
print(model_test(clf, X_val, y_val, X, y))

# accuracies = cross_val(clf,X,y,10)
# print(accuracies)
```

```
81.23620309050773
```

[98]:

```

```