Tubes AI: Tahap A

Exploratory Data Analysis

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This exploration is done to gain insights on the dataset. It is done on the train set.

In [53]:
```
import pandas as pd
import matplotlib as plt
import math

%matplotlib inline
```

Read Data

In [3]:
```
train = pd.read_csv('../data/tubes2_HeartDisease_train.csv')
train.columns = ['age', 'sex', 'chest_pain_type', 'rest_blood_press
ure', 'serum_cholestrol',
                 'high_fasting_blood_sugar', 'resting_ecg', 'max_he
art_rate', 'exercise_induced_angina',
                 'st_depression', 'peak_exercise_st', 'major_vessel
s_num', 'thal', 'diagnosis']
train_x = train.iloc[:, :13]
train_y = train.iloc[:, 13:]
train.head()
```

Out[3]:

	age	sex	chest_pain_type	rest_blood_pressure	serum_cholestrol	high_fasting_l
0	54	1	4	125	216	0
1	55	1	4	158	217	0
2	54	0	3	135	304	1
3	48	0	3	120	195	0
4	50	1	4	120	0	0

Class Label Distribution

General descriptions:

In [4]:
```
train_y.describe()
```

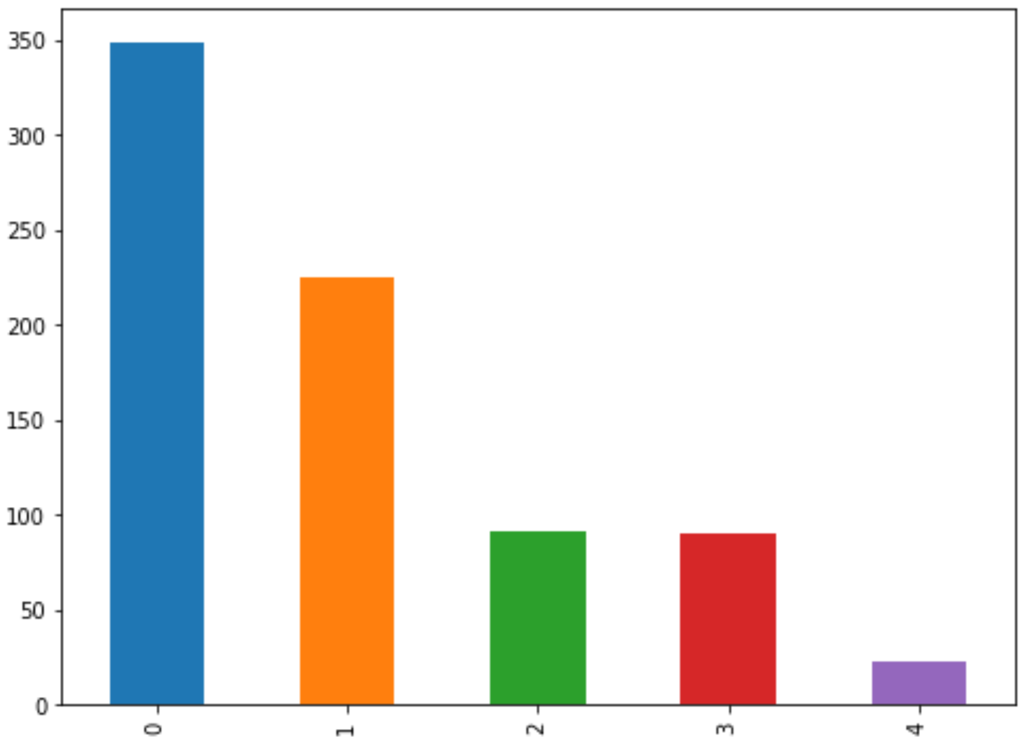
Out[4]:

	diagnosis
count	779.000000
mean	0.989730
std	1.138211
min	0.000000
25%	0.000000
50%	1.000000
75%	2.000000
max	4.000000

Class distribution:

In [5]:
```
train_y['diagnosis'].value_counts().plot(kind='bar', figsize=(8, 6)
)
```

Out[5]: <matplotlib.axes._subplots.AxesSubplot at 0x11867d5c0>



Some Thougts

As we can see, the traning set is imbalanced. Class 0 is significantly overrepresented in the data while class 4 only have less than 30 examples.

Oversampling/undersampling should be done to improve the data's balance.

Features Distribution

A. age

General descriptions:

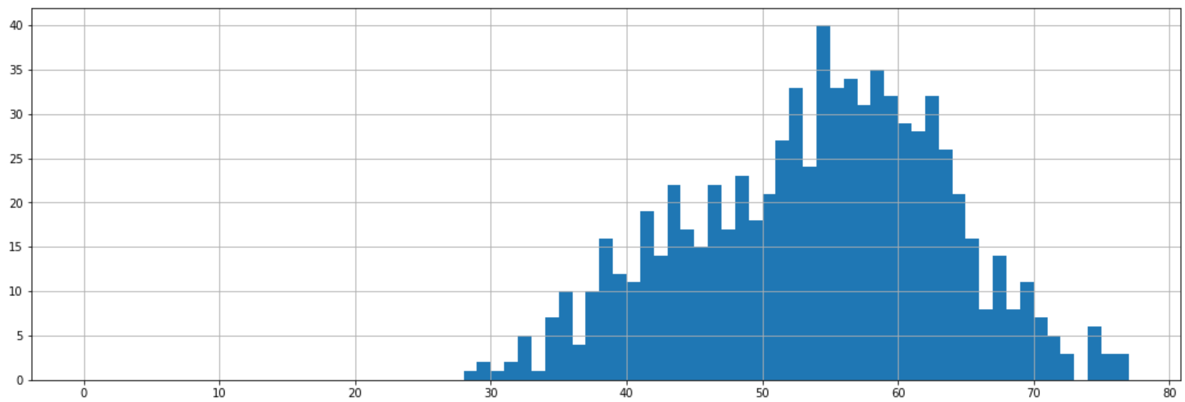
In [6]:
```
age = train_x['age'].astype(int)
age.describe()
```

Out[6]:
```
count    779.000000
mean      53.509628
std        9.505017
min       28.000000
25%       47.000000
50%       54.000000
75%       60.000000
max       77.000000
Name: age, dtype: float64
```

Value distribution:

In [7]:
```
age.hist(bins=age.max(), range=(0, age.max()), figsize=(18, 6))
```

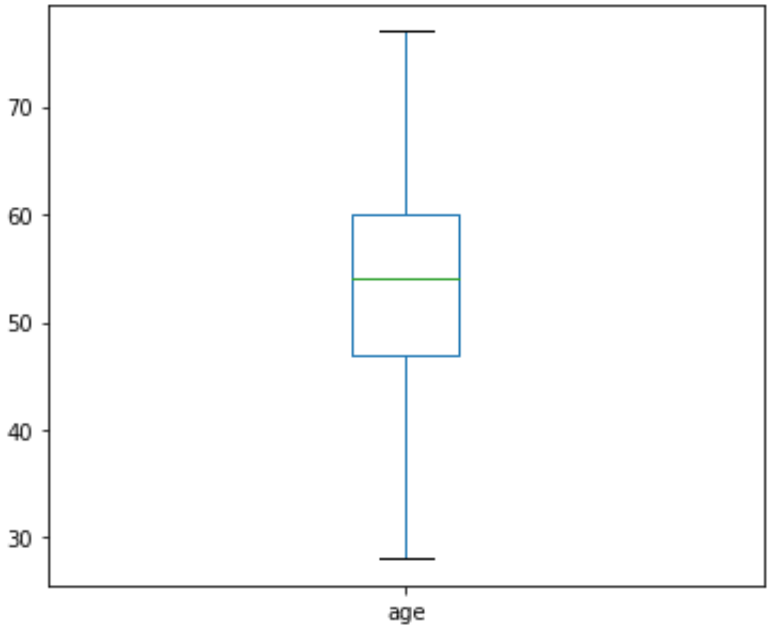
Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0x1186b4400>



Box plot

In [8]:
```
age.plot.box(figsize=(6, 5))
```

Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0x118769da0>



B. sex

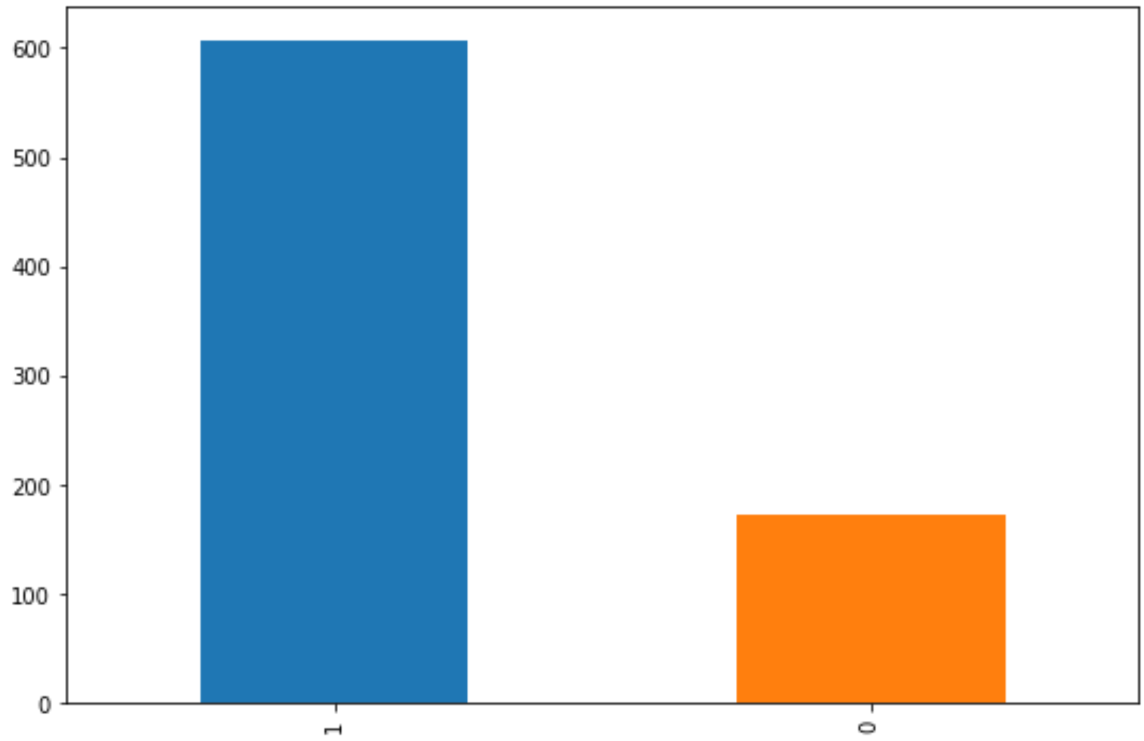
General descriptions:

In [9]:
```
sex = train_x['sex'].astype(int)
sex.describe()
```

Out[9]:
```
count    779.000000
mean       0.779204
std        0.415050
min        0.000000
25%        1.000000
50%        1.000000
75%        1.000000
max        1.000000
Name: sex, dtype: float64
```

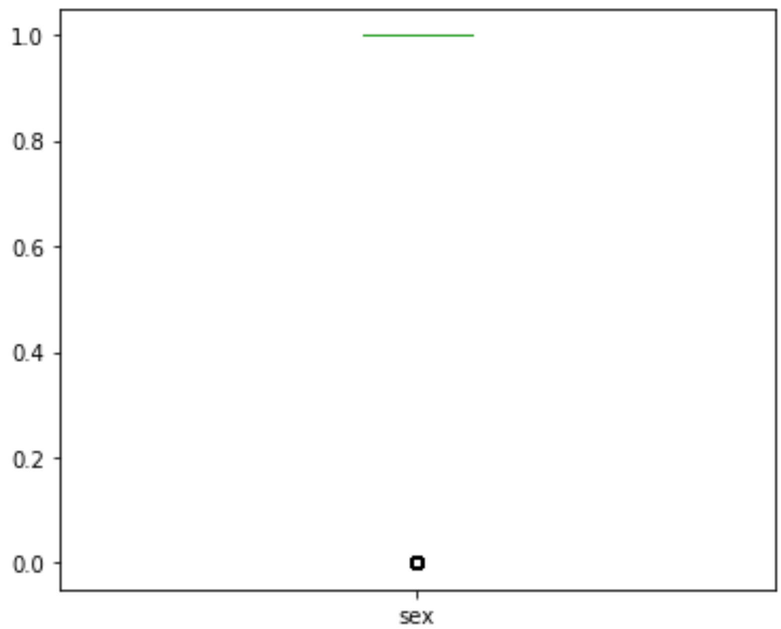
Value distribution:

In [10]:
```
train_x['sex'].value_counts().plot(kind='bar', figsize=(9, 6))
```
Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x11aeb1390>



Box plot

In [11]:
```
sex.plot.box(figsize=(6,5))
```
Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0x11affd5c0>



C. chest_pain_type

General descriptions:

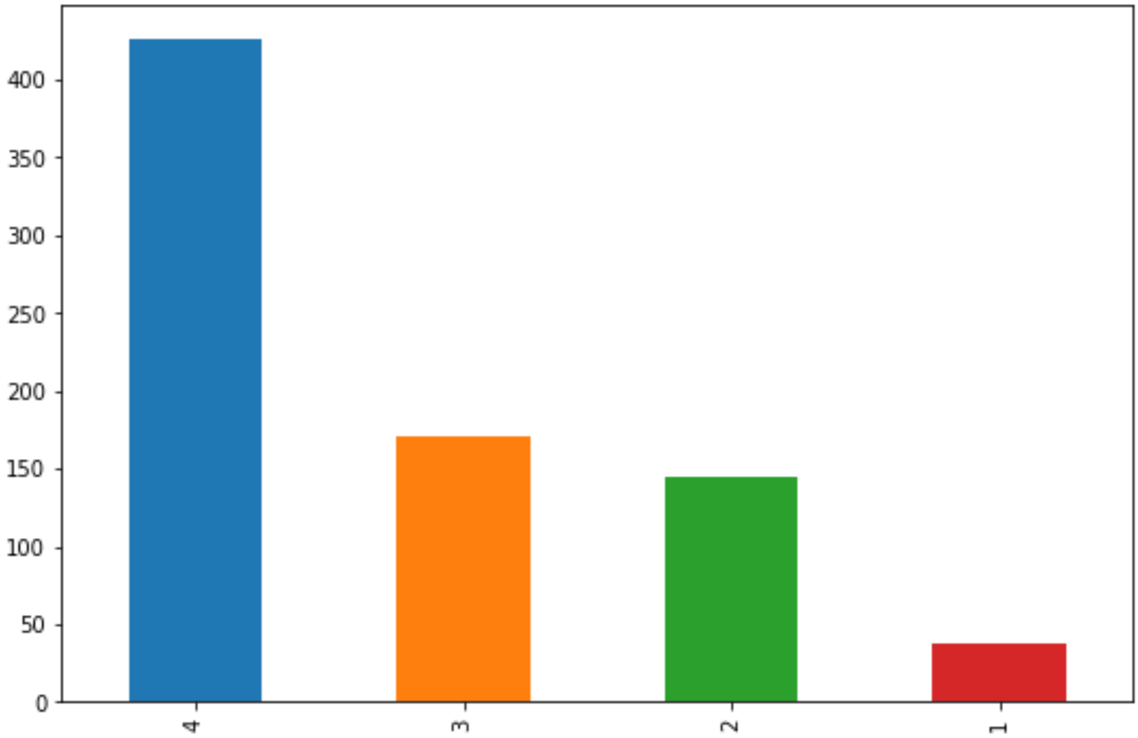
In [12]:
```
chest_pain = train_x['chest_pain_type'].astype(int)
chest_pain.describe()
```

Out[12]:
```
count    779.000000
mean       3.264442
std        0.926284
min        1.000000
25%        3.000000
50%        4.000000
75%        4.000000
max        4.000000
Name: chest_pain_type, dtype: float64
```

Value distribution:

In [13]:
```
train_x['chest_pain_type'].value_counts().plot(kind='bar', figsize=(9, 6))
```

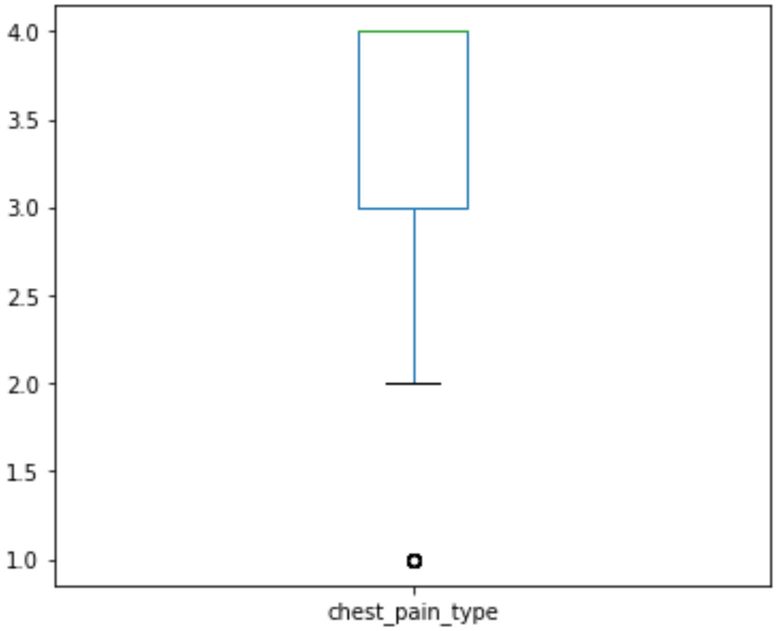
Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x11b12c898>



Box plot

In [14]:
```
chest_pain.plot.box(figsize=(6, 5))
```

Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x11b1f8a90>



D. rest_blood_pressure

Unknown values:

In [15]:
```
print('Num of unknown values:',
      train_x['rest_blood_pressure'][train_x['rest_blood_pressure']
== '?'].count(),
     '/', train_x['rest_blood_pressure'].count())
```

```
Num of unknown values: 47 / 779
```

General descriptions:

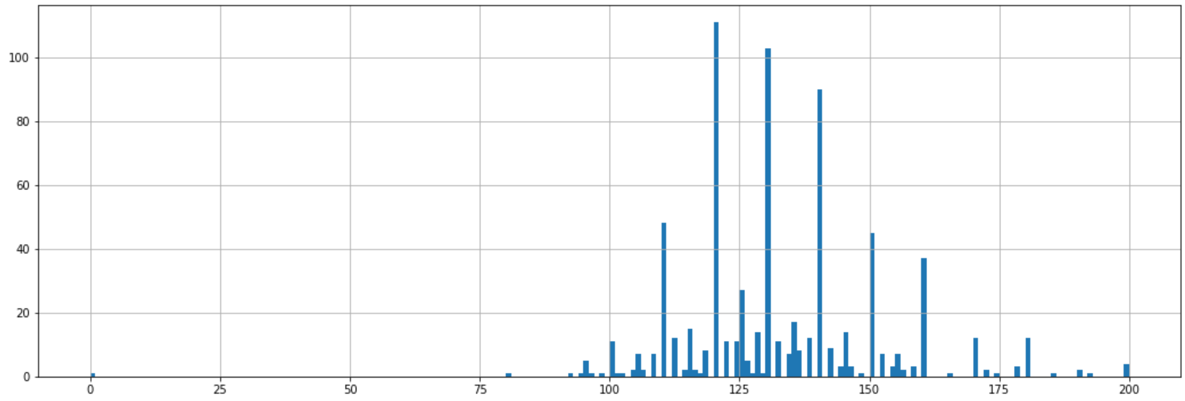
In [16]:
```
rest_blood_pressure = train_x['rest_blood_pressure'][train_x['rest_
blood_pressure'] != '?'].astype(int)
rest_blood_pressure.describe()
```

Out[16]:
```
count    732.000000
mean     132.355191
std       19.133545
min        0.000000
25%      120.000000
50%      130.000000
75%      140.000000
max      200.000000
Name: rest_blood_pressure, dtype: float64
```

Value distribution:

In [17]:
```
rest_blood_pressure.hist(bins=rest_blood_pressure.max(), figsize=(1
8, 6))
```

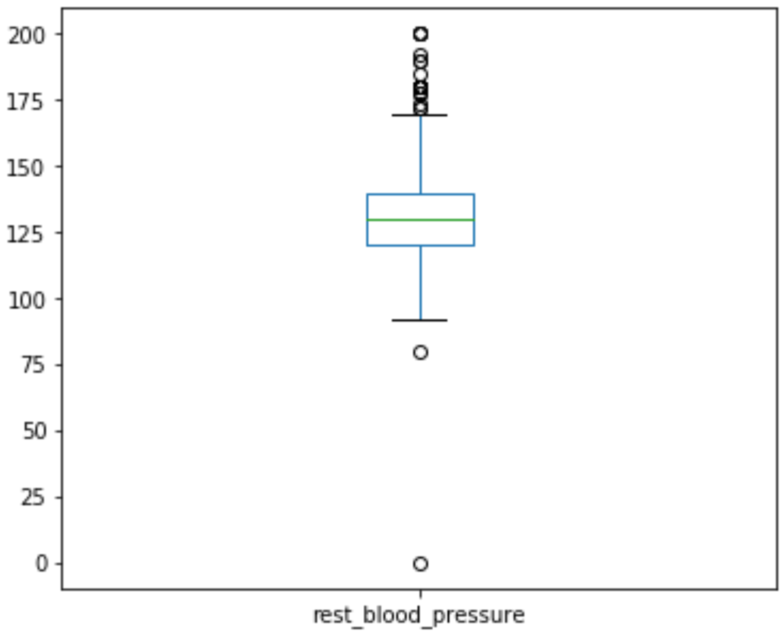
Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x11874b400>



Box plot

In [18]:
```
rest_blood_pressure.plot.box(figsize=(6, 5))
```

Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x11b625eb8>



E. serum_cholestrol

Unknown values:

In [19]:
```
print('Num of unknown values:',
      train_x['serum_cholestrol'][train_x['serum_cholestrol'] == '?
'].count(),
     '/', train_x['serum_cholestrol'].count())
```

```
Num of unknown values: 24 / 779
```

General descriptions:

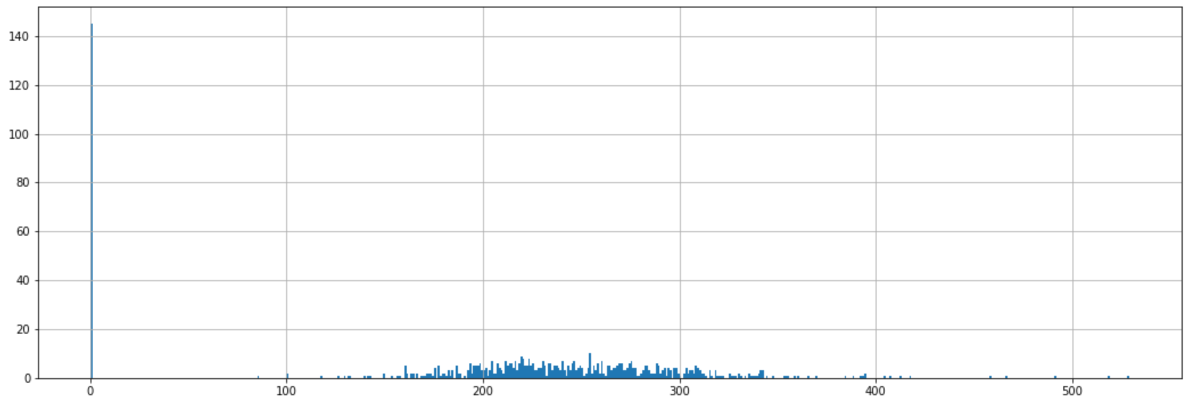
In [20]:
```
serum_cholestrol = train_x['serum_cholestrol'][train_x['serum_chole
strol'] != '?'].astype(int)
serum_cholestrol.describe()
```

Out[20]:
```
count    755.000000
mean     200.309934
std      109.938501
min        0.000000
25%      177.000000
50%      225.000000
75%      270.000000
max      529.000000
Name: serum_cholestrol, dtype: float64
```

Value distribution:

In [21]:
```
serum_cholestrol.hist(bins=serum_cholestrol.max(), figsize=(18, 6))
```

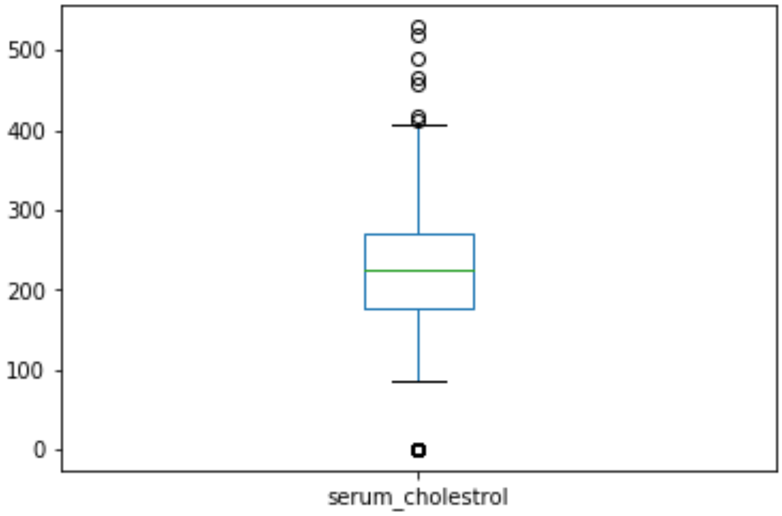
Out[21]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x11b726ac8>
```



Box plot

In [22]:
```
serum_cholestrol.plot.box()
```

Out[22]: <matplotlib.axes._subplots.AxesSubplot at 0x11bcc7080>



F. high_fasting_blood_sugar

Unknown values:

In [29]:
```
print('Num of unknown values:',
      train_x['rest_blood_pressure'][train_x['rest_blood_pressure']
== '?'].count(),
     '/', train_x['rest_blood_pressure'].count())
```

```
Num of unknown values: 47 / 779
```

General descriptions:

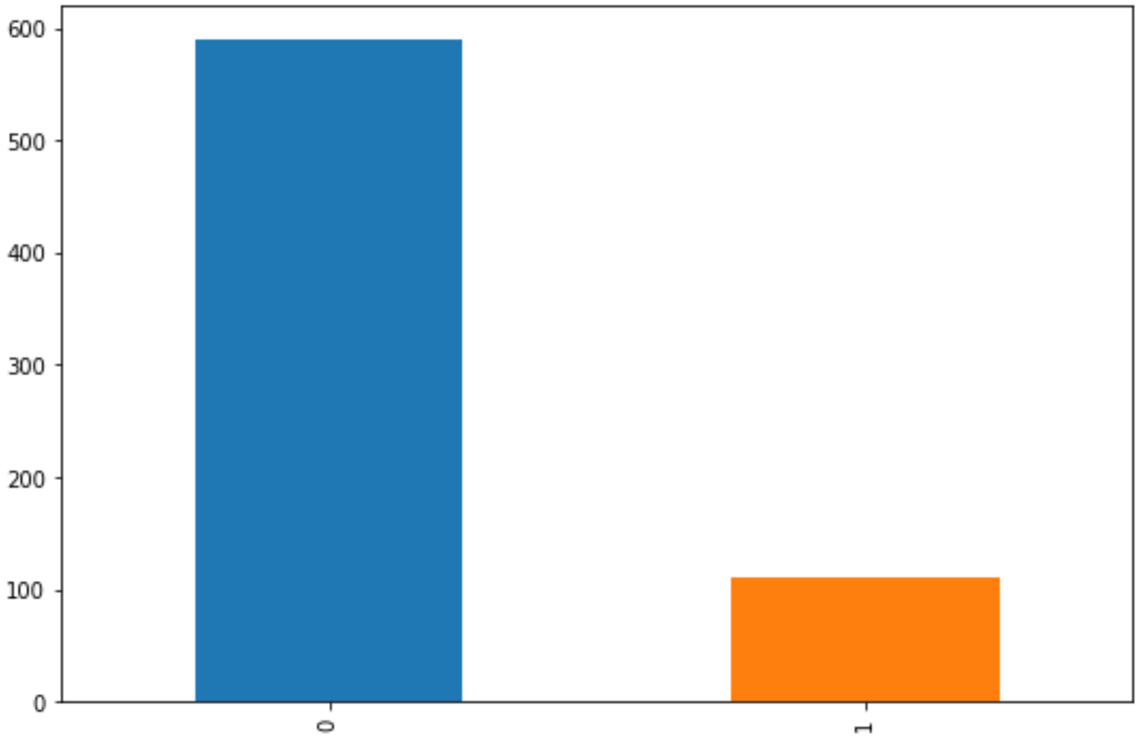
In [38]:
```
high_fasting_blood_sugar = train_x['serum_cholestrol'][train_x['ser
um_cholestrol'] != '?'].astype(int)
high_fasting_blood_sugar.describe()
```

Out[38]:
```
count    755.000000
mean     200.309934
std      109.938501
min        0.000000
25%      177.000000
50%      225.000000
75%      270.000000
max      529.000000
Name: serum_cholestrol, dtype: float64
```

Value distribution:

In [35]:
```
high_fasting_blood_sugar.value_counts().plot(kind='bar', figsize=(9
, 6))
```

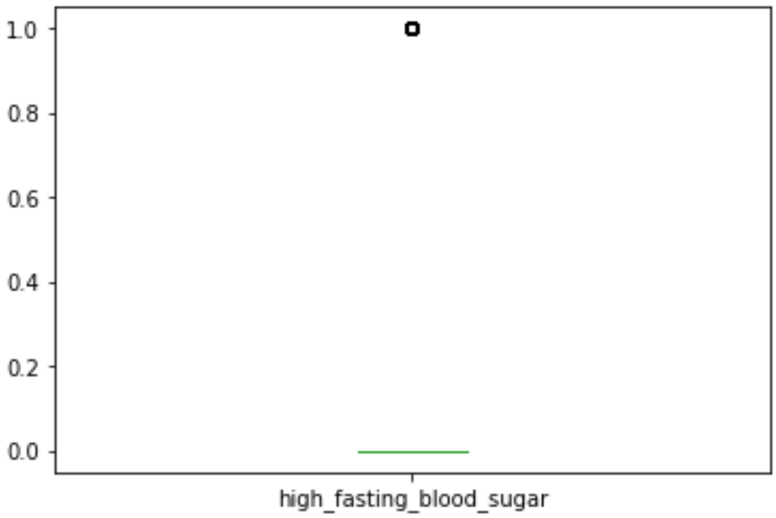
Out[35]: <matplotlib.axes._subplots.AxesSubplot at 0x11e634b00>



Box plot

In [36]:
```
high_fasting_blood_sugar.plot.box()
```

Out[36]: <matplotlib.axes._subplots.AxesSubplot at 0x11e7c8d68>



G. resting_ecg

Unknown values:

```
In [37]: print('Num of unknown values:',
               train_x['resting_ecg'][train_x['resting_ecg'] == '?'].count()
         ,
               '/', train_x['resting_ecg'].count())
```

```
Num of unknown values: 1 / 778
```

General descriptions:

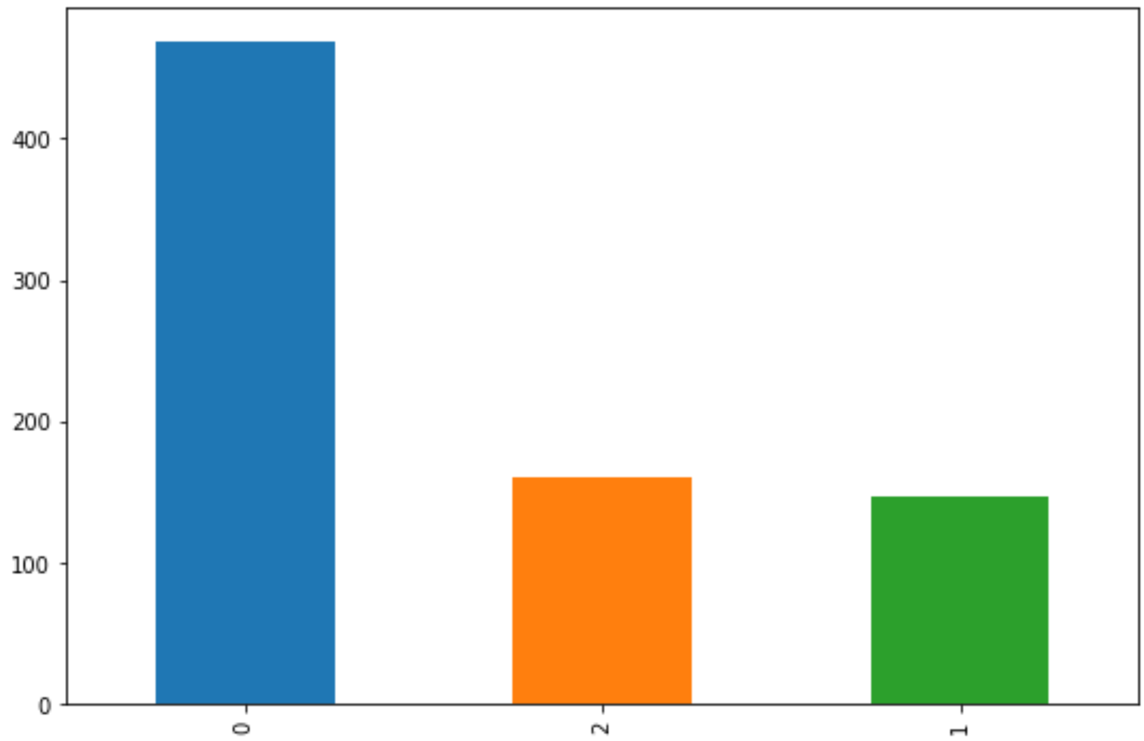
```
In [58]: train_x = train_x.dropna(subset=['resting_ecg'])
         resting_ecg = train_x['resting_ecg'].astype(int)
         resting_ecg.describe()
```

```
Out[58]: count    777.000000
         mean       0.603604
         std        0.809026
         min        0.000000
         25%        0.000000
         50%        0.000000
         75%        1.000000
         max        2.000000
         Name: resting_ecg, dtype: float64
```

Value distribution:

```
In [59]: resting_ecg.value_counts().plot(kind='bar', figsize=(9, 6))
```

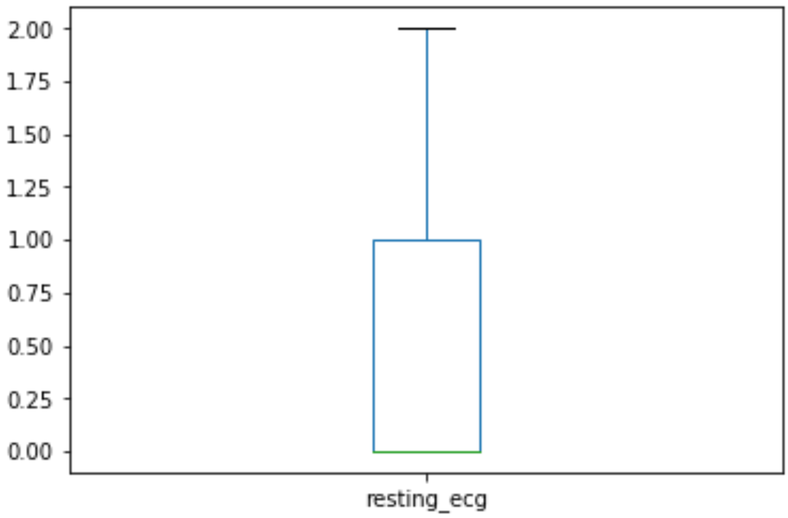
```
Out[59]: <matplotlib.axes._subplots.AxesSubplot at 0x11f2d2048>
```



Box plot

In [60]:
```
resting_ecg.plot.box()
```

Out[60]: <matplotlib.axes._subplots.AxesSubplot at 0x11f36a6a0>



H. max_heart_rate

Unknown values:

In [61]:
```
print('Num of unknown values:',
      train_x['max_heart_rate'][train_x['max_heart_rate'] == '?'].count(),
     '/', train_x['max_heart_rate'].count())
```

```
Num of unknown values: 44 / 777
```

General descriptions:

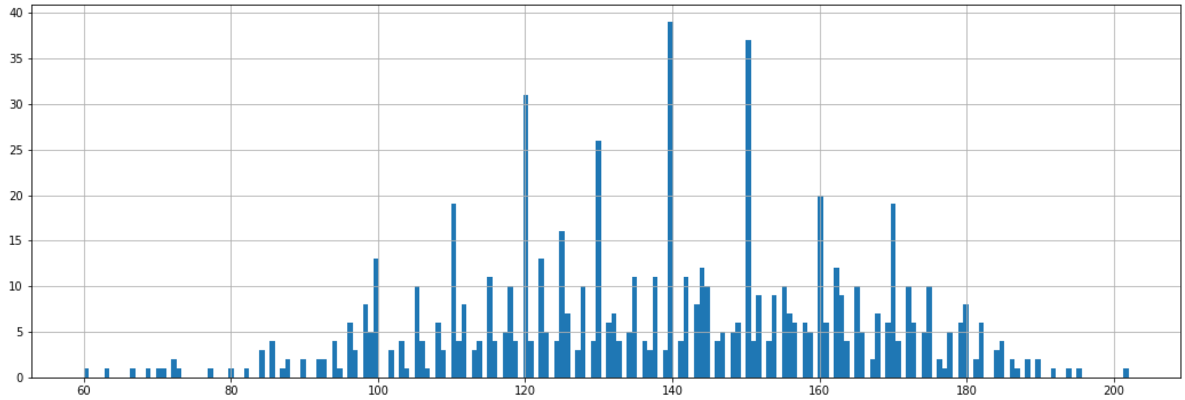
In [65]:
```
max_heart_rate = train_x['max_heart_rate'][train_x['max_heart_rate'] != '?'].astype(int)
max_heart_rate.describe()
```

Out[65]:
```
count    733.000000
mean     138.330150
std       26.116074
min       60.000000
25%      120.000000
50%      140.000000
75%      159.000000
max      202.000000
Name: max_heart_rate, dtype: float64
```

Value distribution:

In [67]:
```
max_heart_rate.hist(bins=max_heart_rate.max(), figsize=(18, 6))
```

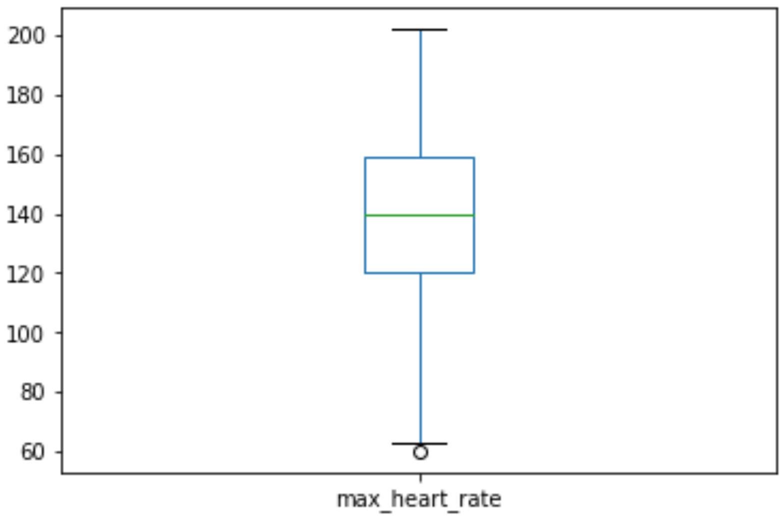
Out[67]: <matplotlib.axes._subplots.AxesSubplot at 0x11f4ad470>



Box plot

In [68]:
```
max_heart_rate.plot.box()
```

Out[68]: <matplotlib.axes._subplots.AxesSubplot at 0x11f6c3438>



I. exercise_induced_angina

Unknown values:

In [69]:
```
print('Num of unknown values:',
      train_x['exercise_induced_angina'][train_x['exercise_induced_
angina'] == '?'].count(),
     '/', train_x['exercise_induced_angina'].count())
```

Num of unknown values: 44 / 777

General descriptions:

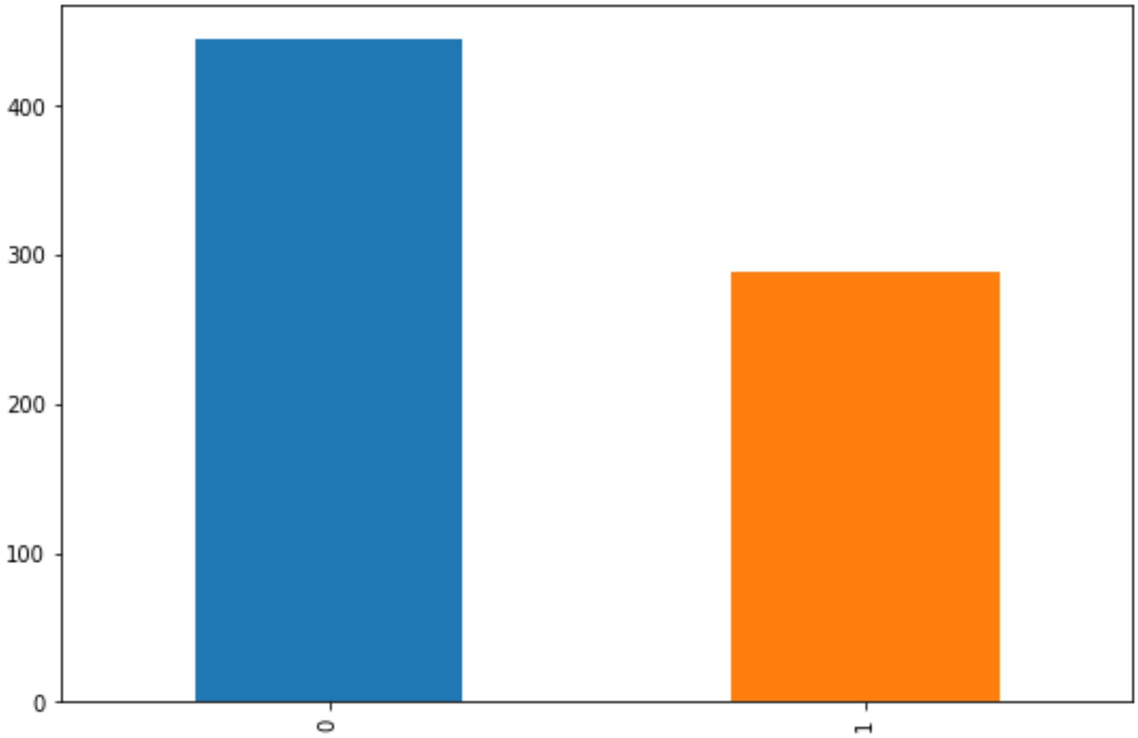
In [70]:
```
exercise_induced_angina = train_x['exercise_induced_angina'][train_
x['exercise_induced_angina'] != '?'].astype(int)
exercise_induced_angina.describe()
```

Out[70]:
```
count    733.000000
mean       0.392906
std        0.488730
min        0.000000
25%        0.000000
50%        0.000000
75%        1.000000
max        1.000000
Name: exercise_induced_angina, dtype: float64
```

Value distribution:

In [71]:
```
exercise_induced_angina.value_counts().plot(kind='bar', figsize=(9,
6))
```

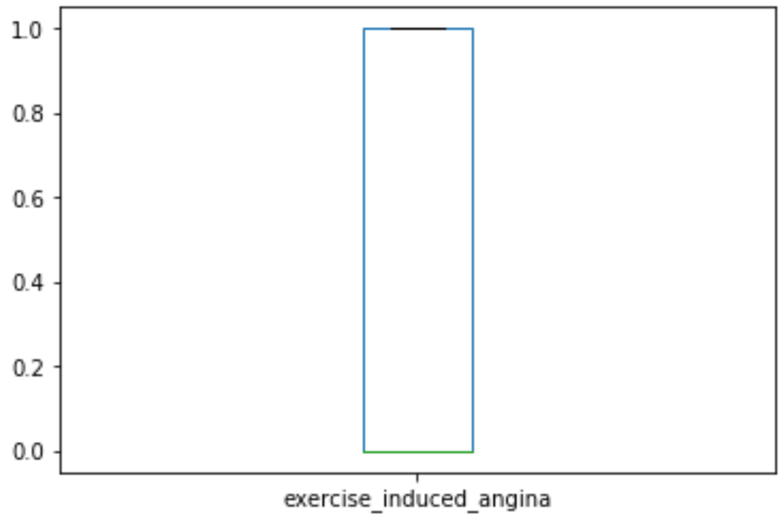
Out[71]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x11f7ad3c8>
```



Box plot

In [72]:
```
exercise_induced_angina.plot.box()
```

Out[72]: <matplotlib.axes._subplots.AxesSubplot at 0x11f9cb240>



J. st_depression

Unknown values:

In [73]:
```
print('Num of unknown values:',
      train_x['st_depression'][train_x['st_depression'] == '?'].cou
nt(),
     '/', train_x['st_depression'].count())
```

```
Num of unknown values: 49 / 777
```

General descriptions:

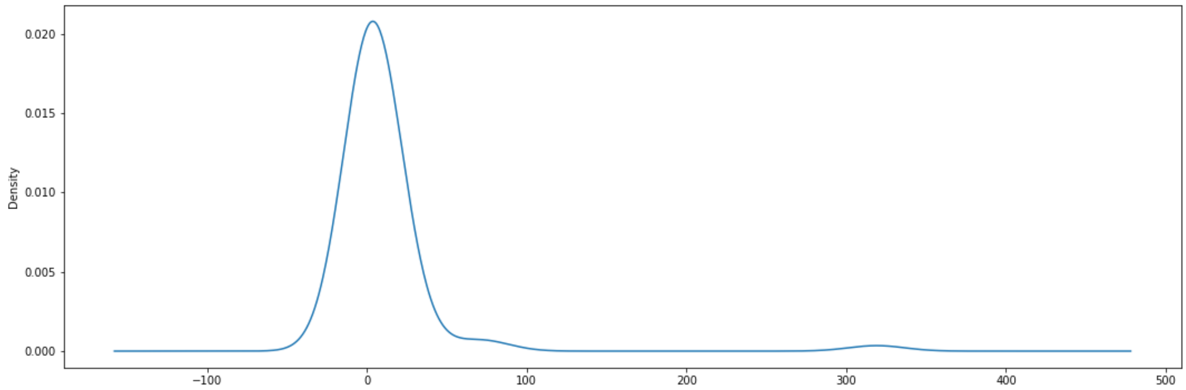
In [75]:
```
st_depression = train_x['st_depression'][train_x['st_depression'] !
= '?'].astype(float)
st_depression.describe()
```

Out[75]:
```
count    728.000000
mean       3.947940
std        7.796939
min       -2.600000
25%        0.000000
50%        1.000000
75%        3.000000
max       62.000000
Name: st_depression, dtype: float64
```

Value distribution:

```
In [79]: st_depression.value_counts().plot(kind='density', figsize=(18, 6))
```

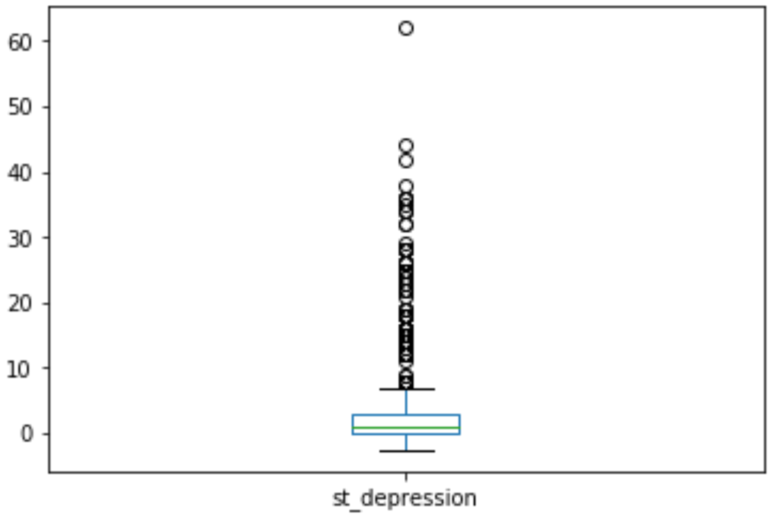
Out[79]: <matplotlib.axes._subplots.AxesSubplot at 0x11feacd30>



Box plot

```
In [80]: st_depression.plot.box()
```

Out[80]: <matplotlib.axes._subplots.AxesSubplot at 0x11ffd4c88>



K. peak_exercise_st

Unknown values:

```
In [81]: print('Num of unknown values:',
               train_x['peak_exercise_st'][train_x['peak_exercise_st'] == '?
         '].count(),
               '/', train_x['peak_exercise_st'].count())
```

```
Num of unknown values: 261 / 777
```

General descriptions:

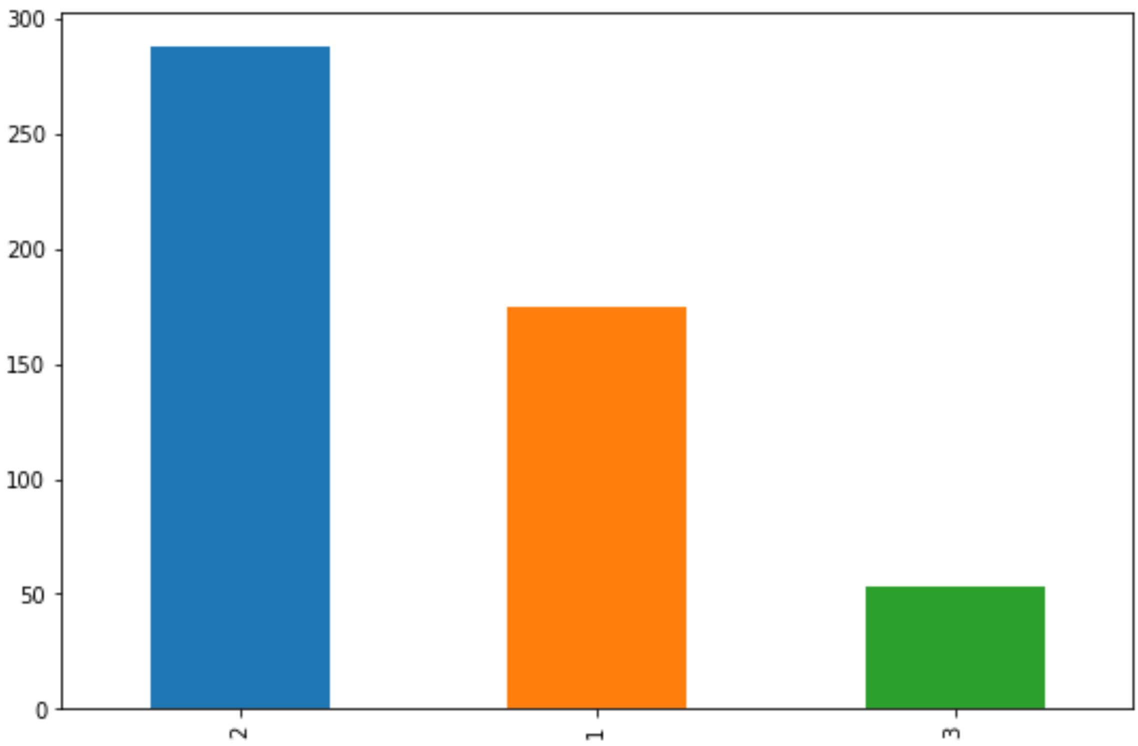
In [87]:
```
peak_exercise_st = train_x['peak_exercise_st'][train_x['peak_exerci
se_st'] != '?'].astype(int)
peak_exercise_st.describe()
```

Out[87]:
```
count    516.000000
mean       1.763566
std        0.621859
min        1.000000
25%        1.000000
50%        2.000000
75%        2.000000
max        3.000000
Name: peak_exercise_st, dtype: float64
```

Value distribution:

In [88]:
```
peak_exercise_st.value_counts().plot(kind='bar', figsize=(9, 6))
```

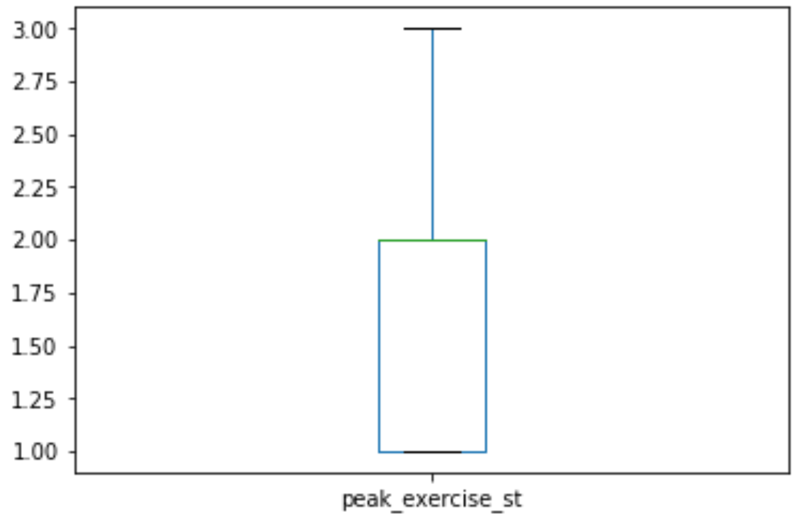
Out[88]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1201a6f60>
```



Box plot

In [89]:
```
peak_exercise_st.plot.box()
```

Out[89]: <matplotlib.axes._subplots.AxesSubplot at 0x120246eb8>



L. major_vessels_num

Unknown values:

In [90]:
```
print('Num of unknown values:',
      train_x['major_vessels_num'][train_x['major_vessels_num'] ==
'?'].count(),
     '/', train_x['major_vessels_num'].count())
```

```
Num of unknown values: 512 / 777
```

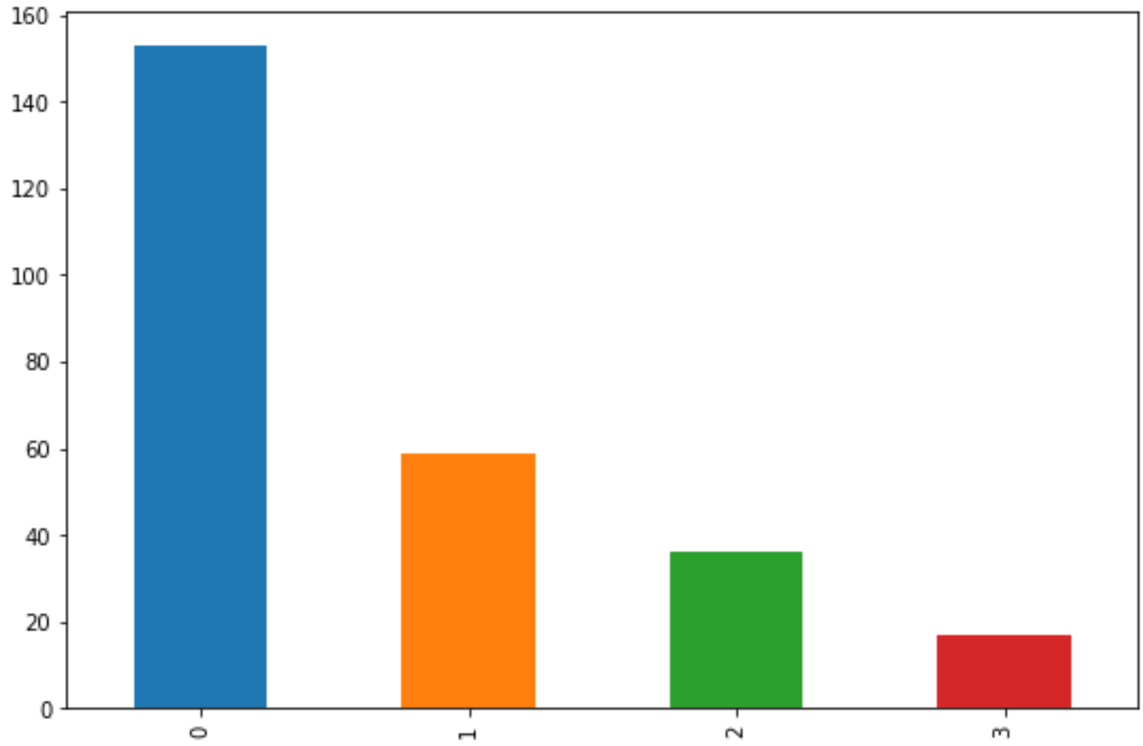
General descriptions:

In [93]:
```
major_vessels_num = train_x['major_vessels_num'][train_x['major_ves
sels_num'] != '?'].astype(int)
major_vessels_num.describe()
```

Out[93]:
```
count    265.000000
mean       0.686792
std        0.935422
min        0.000000
25%        0.000000
50%        0.000000
75%        1.000000
max        3.000000
Name: major_vessels_num, dtype: float64
```

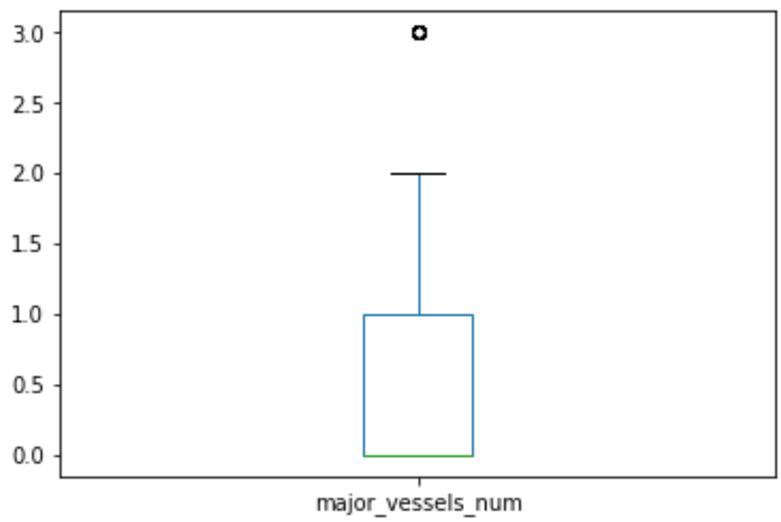
Value distribution:

In [94]:
```
major_vessels_num.value_counts().plot(kind='bar', figsize=(9, 6))
```
Out[94]: <matplotlib.axes._subplots.AxesSubplot at 0x12038a550>



Box plot

In [95]:
```
major_vessels_num.plot.box()
```
Out[95]: <matplotlib.axes._subplots.AxesSubplot at 0x120256898>



M. thal

Unknown values:

In [96]:
```
print('Num of unknown values:',
      train_x['thal'][train_x['thal'] == '?'].count(),
     '/', train_x['thal'].count())
```

```
Num of unknown values: 406 / 777
```

General descriptions:

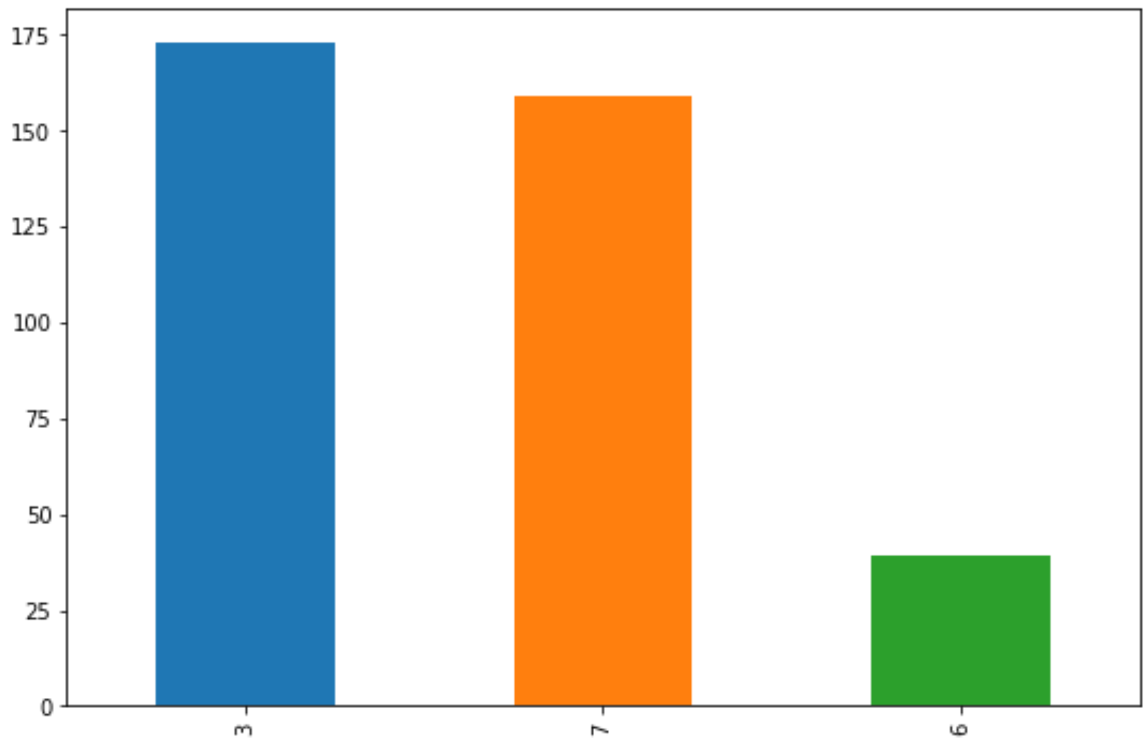
In [101]:
```
thal = train_x['thal'][train_x['thal'] != '?'].astype(int)
thal.describe()
```

Out[101]:
```
count    371.000000
mean       5.029650
std        1.921904
min        3.000000
25%        3.000000
50%        6.000000
75%        7.000000
max        7.000000
Name: thal, dtype: float64
```

Value distribution:

In [102]:
```
thal.value_counts().plot(kind='bar', figsize=(9, 6))
```

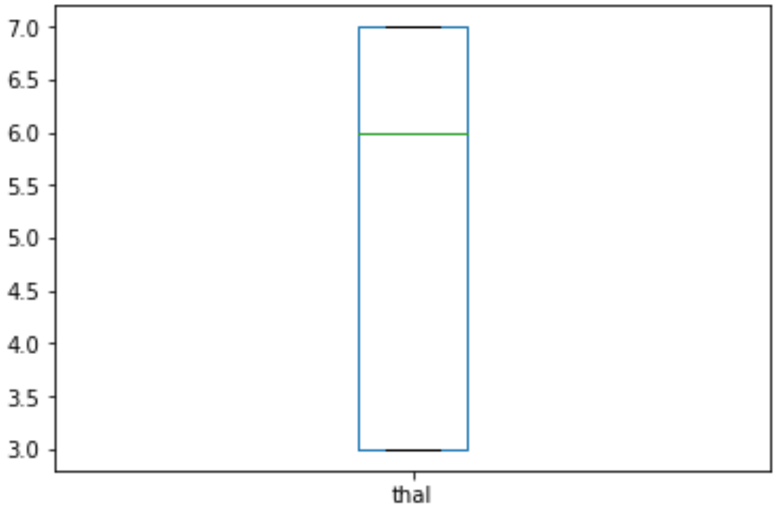
Out[102]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x120562b70>
```



Box plot

In [103]:
```
thal.plot.box()
```

Out[103]: <matplotlib.axes._subplots.AxesSubplot at 0x120267048>



End of Section

Heart Disease Model

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In [219]:
```
import pandas as pd
import numpy as np
```

Data Preparation & Preprocessing

Training data for health disease is read using Pandas' `read_csv()` method, and is preprocessed as such to be ready to fit into the learning model.

Load data

Training data are read and the data are split between features and labels. The resulting data read are 13 columns as attributes and 1 column as label. A total of 779 rows are read.

In [307]:
```
train = pd.read_csv('../data/tubes2_HeartDisease_train.csv')
train.columns = ['age', 'sex', 'chest_pain_type', 'rest_blood_press
ure', 'serum_cholestrol',
                 'high_fasting_blood_sugar', 'resting_ecg', 'max_he
art_rate', 'exercise_induced_angina',
                 'st_depression', 'peak_exercise_st', 'major_vessel
s_num', 'thal', 'diagnosis']
train_x = train.iloc[:, :13]
train_y = train.iloc[:, 13:]

train_x.head()
```

Out[307]:

	age	sex	chest_pain_type	rest_blood_pressure	serum_cholestrol	high_fasting_l
0	54	1	4	125	216	0
1	55	1	4	158	217	0
2	54	0	3	135	304	1
3	48	0	3	120	195	0
4	50	1	4	120	0	0

Preprocessing

Handle missing values

Some data contain unknown value in some of their attributes, therefore needed to be processed.

The string '?' that represents the unknown value is replaced with NaN to make data uniformly numeric, and all data are cast into float to process NaN as well (NaN is represented as float in Numpy).

In [308]:
```
train_x = train_x.replace('?', np.nan).astype(float)
```

For now, mean of each attributes is used to input value to the unknown-valued data for the free-discrete attributes, and mode of each attributes is used for the ranged discrete attributes.

In [309]:
```
categorical_attributes = ["sex", "chest_pain_type", "high_fasting_b
lood_sugar", "resting_ecg", "exercise_induced_angina", "peak_exerci
se_st", "major_vessels_num", "thal"]
series_attributes = ["age", "rest_blood_pressure", "serum_cholestro
l", "max_heart_rate", "st_depression"]

train_x[categorical_attributes] = train_x[categorical_attributes].f
illna(train_x.mode().iloc[0])
train_x[series_attributes] = train_x[series_attributes].fillna(trai
n_x.mean())
train_x[categorical_attributes] = train_x[categorical_attributes].a
stype('category')

train_x_original = train_x.copy()
train_y_original = train_y.copy()

train_x.head()
```

Out[309]:

	age	sex	chest_pain_type	rest_blood_pressure	serum_cholestrol	high_fasting_
0	54.0	1.0	4.0	125.0	216.0	0.0
1	55.0	1.0	4.0	158.0	217.0	0.0
2	54.0	0.0	3.0	135.0	304.0	1.0
3	48.0	0.0	3.0	120.0	195.0	0.0
4	50.0	1.0	4.0	120.0	0.0	0.0

Drop columns with lots of missing values

Feature columns with a high number of missing values are dropped to ease the model's learning.

In [310]:
```
train_x = train_x.drop('thal', 1)
train_x = train_x.drop('major_vessels_num', 1)

train_x.head()
```

Out[310]:

	age	sex	chest_pain_type	rest_blood_pressure	serum_cholestrol	high_fasting_
0	54.0	1.0	4.0	125.0	216.0	0.0
1	55.0	1.0	4.0	158.0	217.0	0.0
2	54.0	0.0	3.0	135.0	304.0	1.0
3	48.0	0.0	3.0	120.0	195.0	0.0
4	50.0	1.0	4.0	120.0	0.0	0.0

Use One-Hot Encoding for Categorical Data

In [311]:
```
train_x = pd.get_dummies(train_x, prefix=[
    "sex", "chest_pain_type", "high_fasting_blood_sugar", "resting_
ecg",
    "exercise_induced_angina", "peak_exercise_st"])

train_x.head()
```

Out[311]:

	age	rest_blood_pressure	serum_cholestrol	max_heart_rate	st_depression	sex
0	54.0	125.0	216.0	140.0	0.0	0
1	55.0	158.0	217.0	110.0	2.5	0
2	54.0	135.0	304.0	170.0	0.0	1
3	48.0	120.0	195.0	125.0	0.0	1
4	50.0	120.0	0.0	156.0	0.0	0

5 rows × 21 columns

Oversampling Procedure

Artificially increase the number of minority data by duplicating rows to get a more balanced dataset.

In [312]:
```
def oversample_label(train_x, train_y):
    diag_2 = train_y['diagnosis'] == 2
    train_x_diag_2 = train_x[diag_2]
    train_y_diag_2 = train_y[diag_2]
    train_x_oversampled = train_x.append([train_x_diag_2] * 2, igno
re_index=True)
    train_y_oversampled = train_y.append([train_y_diag_2] * 2, igno
re_index=True)

    diag_3 = train_y['diagnosis'] == 3
    train_x_diag_3 = train_x[diag_3]
    train_y_diag_3 = train_y[diag_3]
    train_x_oversampled = train_x_oversampled.append([train_x_diag_
3] * 2, ignore_index=True)
    train_y_oversampled = train_y_oversampled.append([train_y_diag_
3] * 2, ignore_index=True)

    diag_4 = train_y['diagnosis'] == 4
    train_x_diag_4 = train_x[diag_4]
    train_y_diag_4 = train_y[diag_4]
    train_x_oversampled = train_x.append([train_x_diag_4] * 3, igno
re_index=True)
    train_y_oversampled = train_y.append([train_y_diag_4] * 3, igno
re_index=True)

    assert(train_x_oversampled.count()[0] == train_y_oversampled.co
unt()[0])

    train_x_preprocessed = train_x_oversampled.copy()
    train_y_preprocessed = train_y_oversampled.copy()
    return train_x_preprocessed, train_y_preprocessed
```

Training Model

Here the training data is fitted into a model which will represent the hypothesis model of the learning method used. As the data is labelled discretely, classification models are suitable for the data. For this testing, we will use Native Bayesian, kNN (k-Nearest Neighbor), DTL (Decision Tree Learning), and MLP (Multi-layered Perceptron).

In [313]:
```
import itertools
import warnings
import matplotlib.pyplot as plt

from sklearn.naive_bayes import GaussianNB
from sklearn import tree
from sklearn.neighbors import KNeighborsClassifier
from sklearn.neural_network import MLPClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, accuracy_score, preci
sion_score, recall_score, f1_score
from sklearn.base import clone
from sklearn.model_selection import KFold

warnings.filterwarnings('ignore')
```

Helpers

In [314]:
```
def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shap
e[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.ylabel('True label')
    plt.xlabel('Predicted label')
    plt.tight_layout()
```

Training Procedure

For training data and measuring the model prediction performance, we use **N-Fold Cross Validation** testing schema, with each iteration splitting the data as testing data and training data, fitting the model with the training data and checking the prediction with the testing data

In [315]:
```
def prepare_and_execute_train_data(model, X, y, n_split=100):
    kf = KFold(n_splits = n_split)

    curr_model = clone(model)

    curr_fold = 1
    accuracy_scores = []
    precision_scores = []
    recall_scores = []
    f1_scores = []
    total_confusion_matrix = None

    for train_index, test_index in kf.split(X, y):
        X_train, y_train = oversample_label(X.ix[train_index], y.ix
[train_index])
        X_test, y_test = X.ix[test_index], y.ix[test_index]
        X_train = np.array(X_train)
        X_test = np.array(X_test)
        y_train = np.array(y_train)
        y_test = np.array(y_test)

        curr_model.fit(X_train, y_train)

        curr_prediction = curr_model.predict(X_test)

        curr_accuracy = accuracy_score(y_test, curr_prediction)
        curr_precision = precision_score(y_test, curr_prediction, a
verage='macro')
        curr_recall = recall_score(y_test, curr_prediction, average
='macro')
        curr_f1 = f1_score(y_test, curr_prediction, average='macro'
)

        if total_confusion_matrix is not None:
            total_confusion_matrix += confusion_matrix(y_test, curr
_prediction)
        else:
            total_confusion_matrix = confusion_matrix(y_test, curr_
prediction)

        accuracy_scores.append(curr_accuracy)
        precision_scores.append(curr_precision)
        recall_scores.append(curr_recall)
        f1_scores.append(curr_f1)

        curr_fold += 1

    print('\nMean Prediction Peformance: ')
```

```
    print('Mean Accuracy:       ', np.mean(accuracy_scores))
    print('Mean Precision:      ', np.mean(precision_scores))
    print('Mean Recall:         ', np.mean(recall_scores))
    print('Mean F1:             ', np.mean(f1_scores))

    plt.figure()
    plot_confusion_matrix(total_confusion_matrix, classes=[0, 1, 2, 
3, 4], normalize=True,
            title='Normalized confusion matrix')
    return curr_model
```

Native Bayesian

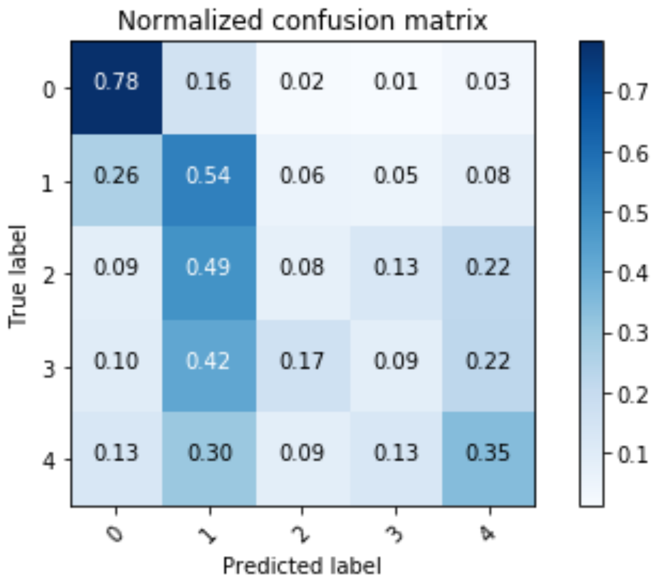
Here the Gaussian Native Bayesian Classifier is used to fit the learning model.

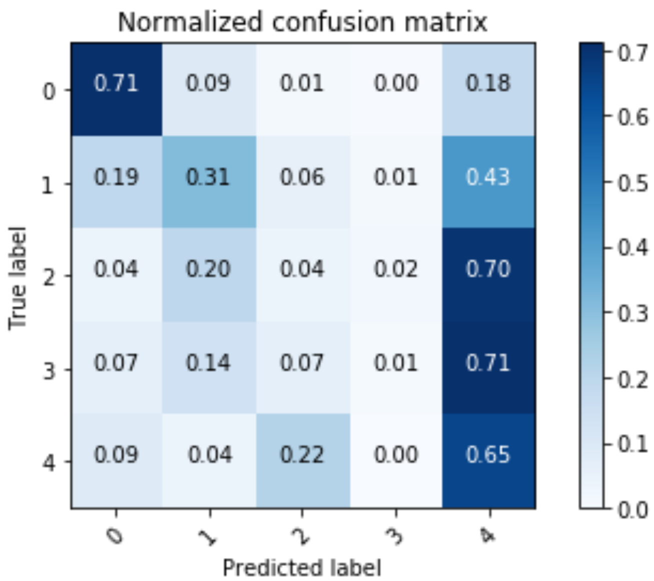
In [323]:
```
nb_og = GaussianNB()
nb_og = prepare_and_execute_train_data(nb_og, train_x_original, tra
in_y_original, 5)

nb = GaussianNB()
nb = prepare_and_execute_train_data(nb, train_x, train_y, 5)
```

```
Mean Prediction Peformance:
Mean Accuracy:      0.5366335814722911
Mean Precision:     0.35507868009810767
Mean Recall:        0.36871720004696673
Mean F1:            0.33129703960922996

Mean Prediction Peformance:
Mean Accuracy:      0.4338709677419355
Mean Precision:     0.31151482553765575
Mean Recall:        0.33554542258407355
Mean F1:            0.25603209099787627
```



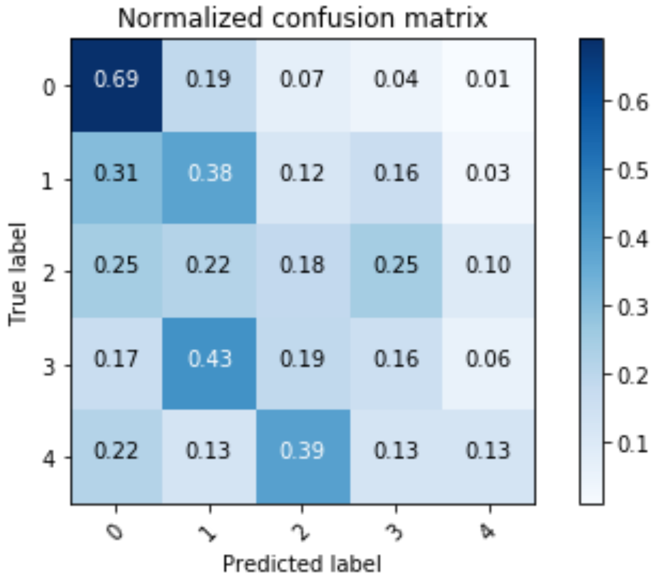


Decision Tree Learning

The Decision Tree Classifier model is used to fit the learning model.

```
In [317]: dtc = tree.DecisionTreeClassifier()
          dtc = prepare_and_execute_train_data(dtc, train_x, train_y, 5)
```

```
Mean Prediction Peformance:
Mean Accuracy:      0.4634408602150538
Mean Precision:     0.30666843624435663
Mean Recall:        0.30574925707824663
Mean F1:            0.30216613902768075
```

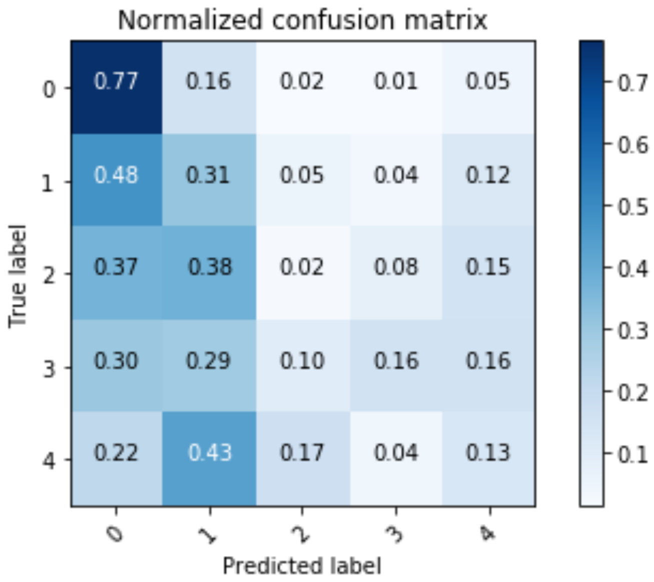


k-Nearest Neighbor

The KNN Classifier is used to fit the learning model

In [318]:
```
knn = KNeighborsClassifier()
knn = prepare_and_execute_train_data(knn, train_x, train_y, 5)
```

```
Mean Prediction Peformance:
Mean Accuracy:      0.45695616211745244
Mean Precision:     0.3108984284162483
Mean Recall:        0.274708587821595
Mean F1:            0.26602445693619653
```



Multi-layered Perceptron

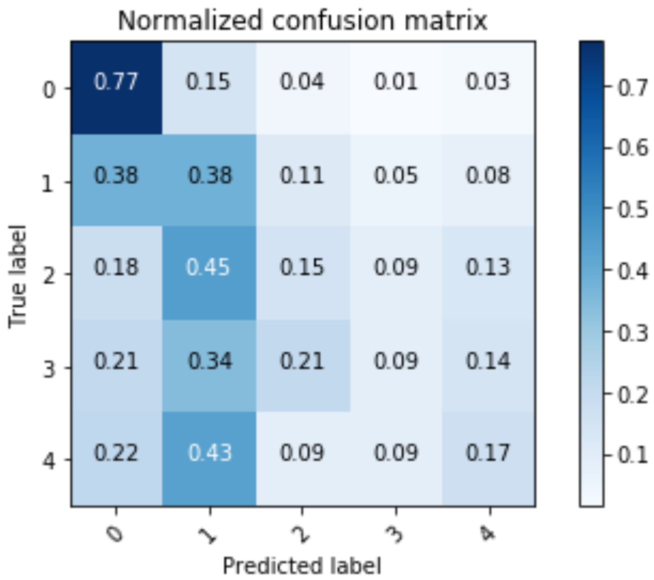
Here the MLP Classifier is used to fit the learning model.

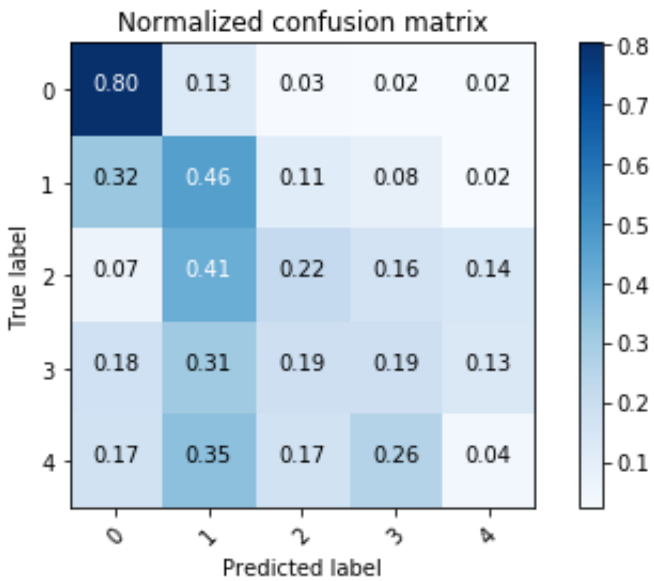
In [325]:
```
mlp_og = MLPClassifier(max_iter=1000)
mlp_og = prepare_and_execute_train_data(mlp_og, train_x_original, t
rain_y_original, 5)

mlp = MLPClassifier(solver='lbfgs', alpha=1e-5, max_iter=2000,
                    hidden_layer_sizes=(200, 80))
mlp = prepare_and_execute_train_data(mlp, train_x, train_y, 5)
```

```
Mean Prediction Peformance:
Mean Accuracy:       0.4890984284532672
Mean Precision:      0.3268094442144511
Mean Recall:         0.32326644352471534
Mean F1:             0.29412371739634147

Mean Prediction Peformance:
Mean Accuracy:       0.5416956162117452
Mean Precision:      0.3599965558231598
Mean Recall:         0.3467324186195325
Mean F1:             0.3448365454401615
```





Model Finalization and Export

The model with the best prediction performance is chosen and exported as a Sklearn model for use in predicting (classifying) test data.

In [326]:
```
from sklearn.externals import joblib
```

Choose the best-scored model

The model with the best prediction performance is finalized and ready to be exported here.

In [327]:
```
chosen_model = mlp
chosen_model
```

Out[327]:
```
MLPClassifier(activation='relu', alpha=1e-05, batch_size='auto', b
eta_1=0.9,
       beta_2=0.999, early_stopping=False, epsilon=1e-08,
       hidden_layer_sizes=(200, 80), learning_rate='constant',
       learning_rate_init=0.001, max_iter=1000, momentum=0.9,
       nesterovs_momentum=True, power_t=0.5, random_state=None,
       shuffle=True, solver='lbfgs', tol=0.0001, validation_fracti
on=0.1,
       verbose=False, warm_start=False)
```

Export model to external file

Here the finalized model is dumped into an external file using sklearn's joblib method. The exported model will be saved and can be used to predict the test data.

In [328]:
```
joblib.dump(chosen_model, '../models/heart_disease.joblib', compres
s=1)
```

Out[328]:
```
['../models/heart_disease.joblib']
```

End of Section

Model Import and Prediction

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In this section, the exported model will be imported and used to predict test data

```
In [61]: import pandas as pd
         import numpy as np
         import matplotlib.pyplot as plt
         from sklearn.externals import joblib
```

Model Import & Data Preparation

Model Import

Here the external file which holds the exported model from the training section is imported and assigned to a variable

```
In [53]: imported_model = joblib.load('../models/heart_disease.joblib')
         imported_model
```

```
Out[53]: MLPClassifier(activation='relu', alpha=1e-05, batch_size='auto', b
         eta_1=0.9,
                beta_2=0.999, early_stopping=False, epsilon=1e-08,
                hidden_layer_sizes=(200, 80), learning_rate='constant',
                learning_rate_init=0.001, max_iter=1000, momentum=0.9,
                nesterovs_momentum=True, power_t=0.5, random_state=None,
                shuffle=True, solver='lbfgs', tol=0.0001, validation_fracti
         on=0.1,
                verbose=False, warm_start=False)
```

Load Test Data

Test data are loaded here

In [46]:
```
test = pd.read_csv('../data/tubes2_HeartDisease_test.csv')
test.columns = ['age', 'sex', 'chest_pain_type', 'rest_blood_pressu
re', 'serum_cholestrol',
                  'high_fasting_blood_sugar', 'resting_ecg', 'max_he
art_rate', 'exercise_induced_angina',
                  'st_depression', 'peak_exercise_st', 'major_vessel
s_num', 'thal']

test.head()
```

Out[46]:

	age	sex	chest_pain_type	rest_blood_pressure	serum_cholestrol	high_fasting_l
0	60	1	2	160	267	1
1	61	1	4	148	203	0
2	54	1	4	130	242	0
3	48	1	4	120	260	0
4	57	0	1	130	308	0

Preprocessing

Handle missing values

Some data contain unknown value in some of their attributes, therefore needed to be processed.

The string '?' that represents the unknown value is replaced with NaN to make data uniformly numeric, and all data are cast into float to process NaN as well (NaN is represented as float in Numpy).

In [47]:
```
test = test.replace('?', np.nan).astype(float)
```

For now, mean of each attributes is used to input value to the unknown-valued data for the free-discrete attributes, and mode of each attributes is used for the ranged discrete attributes.

In [48]:
```
categorical_attributes = ["sex", "chest_pain_type", "high_fasting_b
lood_sugar", "resting_ecg", "exercise_induced_angina", "peak_exerci
se_st", "major_vessels_num", "thal"]
series_attributes = ["age", "rest_blood_pressure", "serum_cholestro
l", "max_heart_rate", "st_depression"]

test[categorical_attributes] = test[categorical_attributes].fillna(
test.mode().iloc[0])
test[series_attributes] = test[series_attributes].fillna(test.mean(
))
test[categorical_attributes] = test[categorical_attributes].astype(
'category')

test.head()
```

Out[48]:

	age	sex	chest_pain_type	rest_blood_pressure	serum_cholestrol	high_fasting_
0	60.0	1.0	2.0	160.0	267.0	1.0
1	61.0	1.0	4.0	148.0	203.0	0.0
2	54.0	1.0	4.0	130.0	242.0	0.0
3	48.0	1.0	4.0	120.0	260.0	0.0
4	57.0	0.0	1.0	130.0	308.0	0.0

Rearrange Columns

Columns are rearranged with one-hot encoding to make it equivalent with the preprocessed train data

In [49]:
```
test = test.drop('thal', 1)
test = test.drop('major_vessels_num', 1)

test = pd.get_dummies(test, prefix=[
    "sex", "chest_pain_type", "high_fasting_blood_sugar", "resting_
ecg",
    "exercise_induced_angina", "peak_exercise_st"])


test.head()
```

Out[49]:

	age	rest_blood_pressure	serum_cholestrol	max_heart_rate	st_depression	sex
0	60.0	160.0	267.0	157.0	0.5	0
1	61.0	148.0	203.0	161.0	0.0	0
2	54.0	130.0	242.0	91.0	1.0	0
3	48.0	120.0	260.0	115.0	2.0	0
4	57.0	130.0	308.0	98.0	1.0	1

5 rows × 21 columns

Test Data Prediction

Here the test data will be labeled using model prediction fitted from the training data

In [50]:
```
from sklearn.naive_bayes import GaussianNB
from sklearn import tree
from sklearn.neighbors import KNeighborsClassifier
from sklearn.neural_network import MLPClassifier
```

Predicting Test Data

In [54]:
```
test = np.array(test)
predicted_test = imported_model.predict(test)
predicted_test
```

Out[54]:
```
array([0, 0, 1, 1, 0, 0, 2, 2, 0, 1, 2, 1, 0, 0, 0, 4, 3, 0, 0, 1,
0, 2,
       0, 1, 3, 0, 1, 3, 4, 1, 0, 3, 2, 0, 1, 0, 0, 0, 0, 0, 1, 0,
0, 1,
       1, 1, 1, 4, 1, 1, 1, 1, 4, 2, 0, 1, 1, 1, 1, 0, 0, 0, 3, 3,
0, 0,
       1, 0, 0, 0, 1, 0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 2, 1, 3, 0, 3,
1, 0,
       0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 3, 0, 0, 0, 1, 0, 0, 1,
1, 4,
       1, 3, 0, 0, 0, 2, 0, 3, 0, 1, 2, 1, 0, 1, 0, 0, 0, 3, 3, 1,
0, 1,
       3, 2, 3, 3, 0, 0, 0, 0, 0])
```

Visualizing Predicted Data

In [64]:
```
x, y = np.unique(predicted_test, return_counts=True)
plt.bar(x, y)
```

Out[64]:
```
<Container object of 5 artists>
```