data_description

June 7, 2019

[5]:
```
import warnings
from os import path

import pandas as pd
import numpy as np
import statsmodels.api as sm
from patsy import dmatrices
from sklearn import metrics, model_selection
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.exceptions import ConvergenceWarning
from scipy.stats import variation
import matplotlib.pyplot as plt

warnings.filterwarnings(action='ignore', category=ConvergenceWarning)

# %matplotlib inline
```

1 General Data Description

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1.0.1 Dataset

A simulated data set containing information on four hundred customers. The aim here is to predict which customers will default on their credit card debt. Credit data set records balance (average credit card debt for a number of individuals) as well as several quantitative predictors: age, cards (number of credit cards), education (years of education), income (in thousands of dollars), limit (credit limit), and rating (credit rating).

> taken from "An Introduction to Statistical Learning, with applications in R" (Springer, 2013) with permission from the authors: G. James, D. Witten, T. Hastie and R. Tibshirani

`Income`: Annual income in $1,000's

`Limit`: Credit limit
`Rating`: Credit rating
`Cards`: Number of credit cards
`Age`: Age in years
`Education`: Number of years of education
`Gender`: A factor with levels `Male` and `Female`
`Student`: A factor with levels `No` and `Yes` indicating whether the individual was a student
`Married`: A factor with levels `No` and `Yes` indicating whether the individual was married
`Ethnicity`: A factor with levels `African American`, `Asian`, and `Caucasian` indicating the individual's ethnicity
`Balance`: Average monthly credit card balance in $

[6]:
```
source_dir = '../data'
source_file = 'credit.csv'

def read_csv(source):
    return pd.read_csv(path.join(source_dir, source), low_memory=False)

data = read_csv(source_file)
print(f"shape: {data.shape}")
data.head()
```

```
shape: (400, 12)
```

[6]:
```
   Unnamed: 0   Income  Limit  Rating  Cards  Age  Education  Gender Student  \
0           1   14.891   3606     283      2   34         11    Male      No
1           2  106.025   6645     483      3   82         15  Female     Yes
2           3  104.593   7075     514      4   71         11    Male      No
3           4  148.924   9504     681      3   36         11  Female      No
4           5   55.882   4897     357      2   68         16    Male      No

  Married  Ethnicity  Balance
0     Yes  Caucasian      333
1     Yes      Asian      903
2      No      Asian      580
3      No      Asian      964
4     Yes  Caucasian      331
```

1.0.2 Prepare data

Drop null and column 'Unnamed: 0' that is the index column from dataset

[7]:
```
data.dropna(inplace=True)
data.drop(columns=['Unnamed: 0'], inplace=True)
print(f"shape: {data.shape}")
data.head()
```

```
shape: (400, 11)
```

[7]:
```
      Income  Limit  Rating  Cards  Age  Education  Gender Student Married  \
0   14.891   3606     283      2   34         11    Male      No     Yes
1  106.025   6645     483      3   82         15  Female     Yes     Yes
2  104.593   7075     514      4   71         11    Male      No      No
3  148.924   9504     681      3   36         11  Female      No      No
4   55.882   4897     357      2   68         16    Male      No     Yes

   Ethnicity  Balance
0  Caucasian      333
1      Asian      903
2      Asian      580
3      Asian      964
4  Caucasian      331
```

There were no rows with empty data.

Check column types

[8]:
```
data.dtypes
```

[8]:
```
Income        float64
Limit           int64
Rating          int64
Cards           int64
Age             int64
Education       int64
Gender         object
Student        object
Married        object
Ethnicity      object
Balance         int64
dtype: object
```

Rename all columns to lowercase and set categorical columns to 'category':

[9]:
```
data.rename(columns={n: n.lower() for n in data.columns}, inplace=True)
categorical_columns = [
    'gender',
        'student',
        'married',
    'ethnicity'
]
for name in categorical_columns:
        data[name] = data[name].astype('category')
print(data.dtypes)
data.head()
```

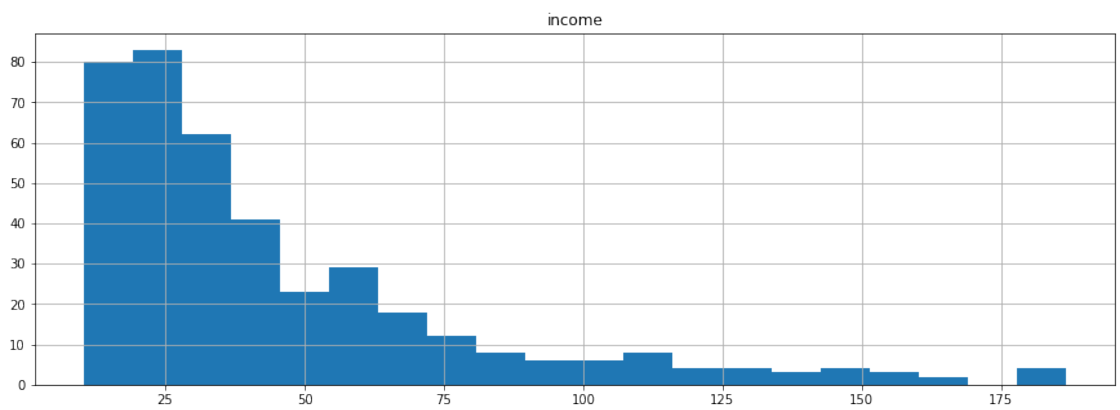
```
income        float64
limit           int64
rating          int64
```

```
cards            int64
age              int64
education        int64
gender        category
student       category
married       category
ethnicity     category
balance          int64
dtype: object
```

[9]:
```
    income  limit  rating  cards  age  education  gender student married  \
0   14.891   3606     283      2   34         11    Male      No     Yes
1  106.025   6645     483      3   82         15  Female     Yes     Yes
2  104.593   7075     514      4   71         11    Male      No      No
3  148.924   9504     681      3   36         11  Female      No      No
4   55.882   4897     357      2   68         16    Male      No     Yes

   ethnicity  balance
0  Caucasian      333
1      Asian      903
2      Asian      580
3      Asian      964
4  Caucasian      331
```

1.0.3 Income groups

[10]:
```python
_ = data.hist(column='income', bins=20, figsize=(15,5))
```



Frequency of income. The vast majority of customers find in bins with smaller income.
Add `Income Group` column with categories:

- `The Poor`: income up to $18,000
- `Working Class`: income above \$18,000 up to $60,000

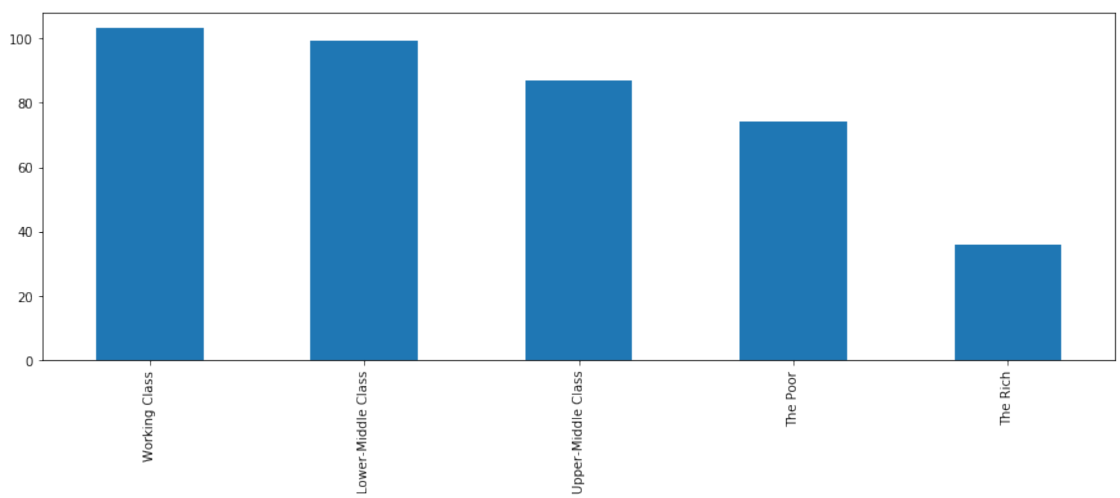
- `Middle Class`: income above \$60,000 up to $100,000
- `The Rich`: income above $100,000

[11]:
```python
income_groups = {
         'The Poor': 0, # - 18
        'Working Class': 18, # - 50
        'Lower-Middle Class': 30, # - 100
        'Upper-Middle Class': 50, # - 100
        'The Rich': 100, # - ...
}
data['income_group'] = pd.cut(data['income'], list(income_groups.values()) +␣
 ↪[data['income'].max()], right=False, labels=income_groups.keys())
data.head()
```

[11]:
```
    income  limit  rating  cards  age  education  gender student married  \
0   14.891   3606     283      2   34         11    Male      No     Yes
1  106.025   6645     483      3   82         15  Female     Yes     Yes
2  104.593   7075     514      4   71         11    Male      No      No
3  148.924   9504     681      3   36         11  Female      No      No
4   55.882   4897     357      2   68         16    Male      No     Yes

   ethnicity  balance        income_group
0  Caucasian      333            The Poor
1      Asian      903            The Rich
2      Asian      580            The Rich
3      Asian      964            The Rich
4  Caucasian      331  Upper-Middle Class
```

Rows per `Income Group`

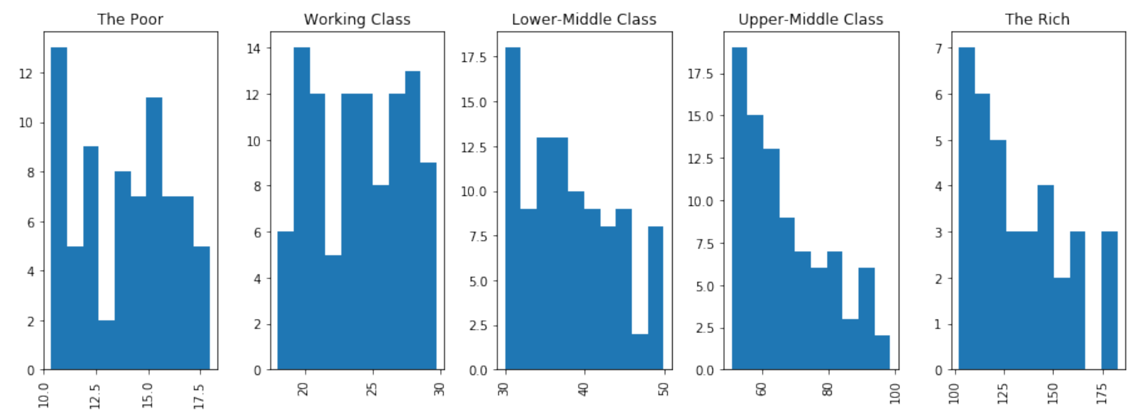
[12]:
```python
_ = data['income_group'].value_counts().plot(kind='bar', figsize=(15,5))
```



Number of customers in every income group. The number of customers in the working class and lower-middle class is similar. The two extreme groups (the poor and the reach) have the less representatives.

Income histogram by `Income Group`

[13]:
```python
_ = data.hist(column='income', by='income_group', layout=(1, 5), figsize=(15,5))
```



It can be seen that the majority of customers of the upper-middle class has income closer to the lower range.

Balance boxplot by `Income Group`

[14]:
```python
_ = data.boxplot(column='balance', by='income_group', figsize=(15,5))
```

First quartile for first three groups balance is around \$0, but the third quartile rises with the group. Also none of the customers from the Rich group has avarege balance equal to \$0 and half of these customers have balance beetwen ~700-1400.

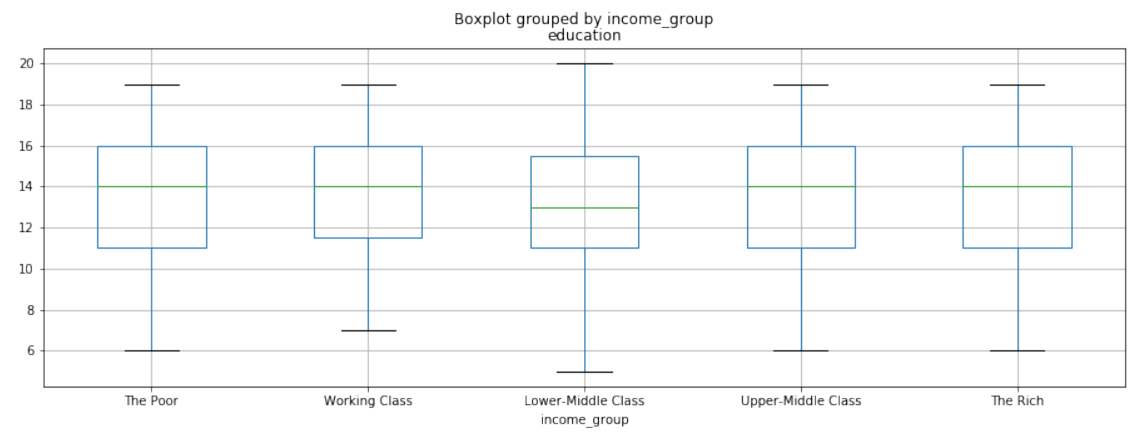
Age boxplot by `Income Group`

[15]:
```python
_ = data.boxplot(column='age', by='income_group', figsize=(15,5))
```

The Rich group consists of rather older clients. First three group are quite similar, but interesting fact is that the median of age is lower in Lower-Middle Class than in Working Class or the Poor.

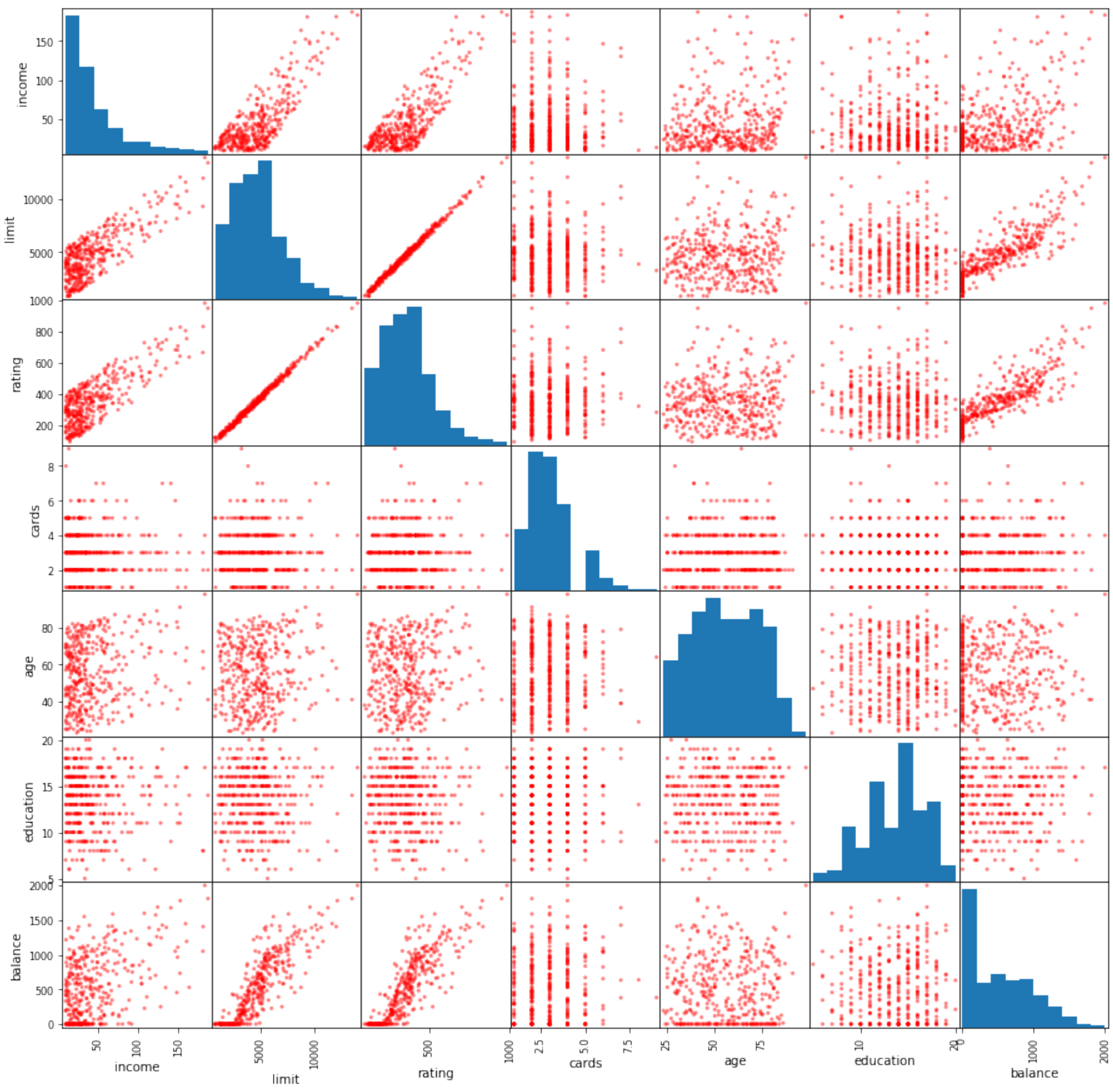
`Education` boxplot by `Income Group`

[16]:
```
_ = data.boxplot(column='education', by='income_group', figsize=(15,5))
```



Education years for all groups have similar distribution for all groups. The lower-middle class has the widest range and also median is one year lower than for other groups.

[17]:
```
_ = pd.plotting.scatter_matrix(data, color="red", figsize=(15, 15))
```



Correlation observations: - strong positive correlation between rating and limit. - some positive correlation beetween limit and income, rating and income, limit and balance, rating and balance.

1.0.4 Analyze data to prepare model

[18]:
```
data.describe()
```

[18]:
```
           income        limit       rating       cards         age  \
count  400.000000   400.000000   400.000000  400.000000  400.000000
mean    45.218885  4735.600000   354.940000    2.957500   55.667500
std     35.244273  2308.198848   154.724143    1.371275   17.249807
min     10.354000   855.000000    93.000000    1.000000   23.000000
25%     21.007250  3088.000000   247.250000    2.000000   41.750000
50%     33.115500  4622.500000   344.000000    3.000000   56.000000
75%     57.470750  5872.750000   437.250000    4.000000   70.000000
```

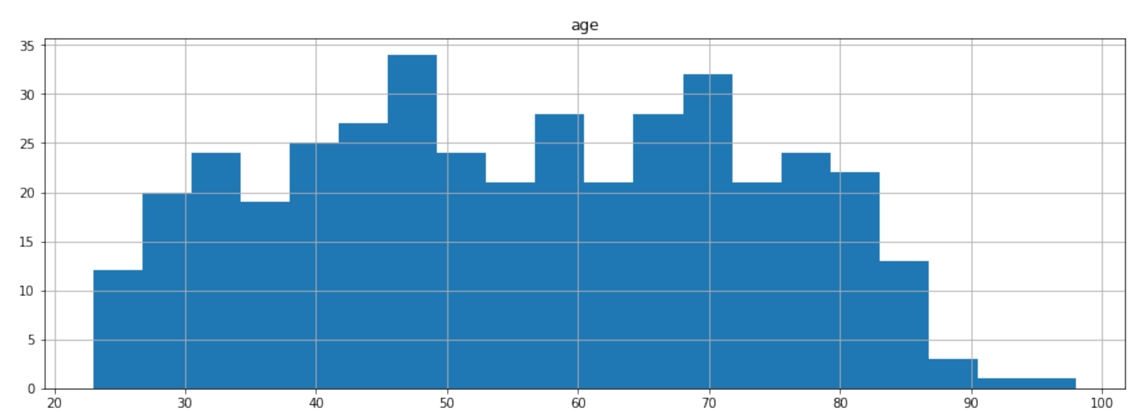
```
max    186.634000  13913.000000  982.000000    9.000000   98.000000

        education      balance
count  400.000000   400.000000
mean    13.450000   520.015000
std      3.125207   459.758877
min      5.000000     0.000000
25%     11.000000    68.750000
50%     14.000000   459.500000
75%     16.000000   863.000000
max     20.000000  1999.000000
```

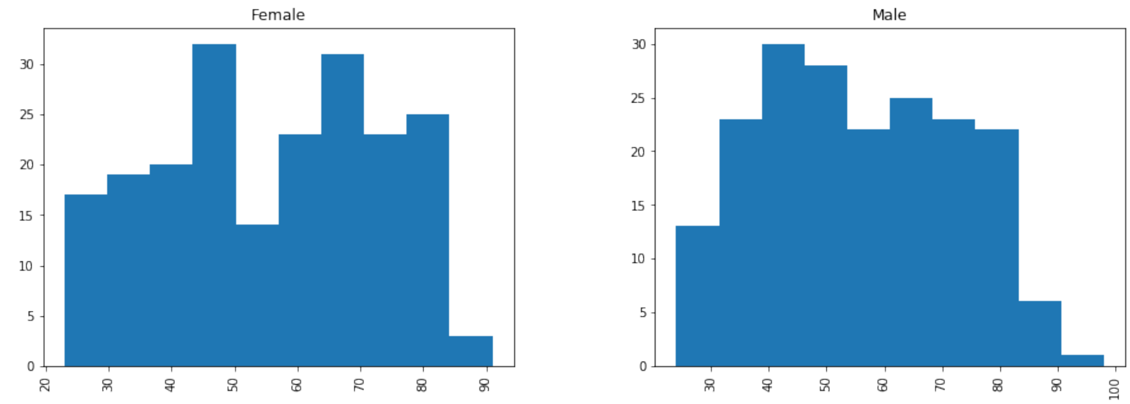
[19]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 400 entries, 0 to 399
Data columns (total 12 columns):
income          400 non-null float64
limit           400 non-null int64
rating          400 non-null int64
cards           400 non-null int64
age             400 non-null int64
education       400 non-null int64
gender          400 non-null category
student         400 non-null category
married         400 non-null category
ethnicity       400 non-null category
balance         400 non-null int64
income_group    399 non-null category
dtypes: category(5), float64(1), int64(6)
memory usage: 27.5 KB
```

Age histograms: all and by gender.

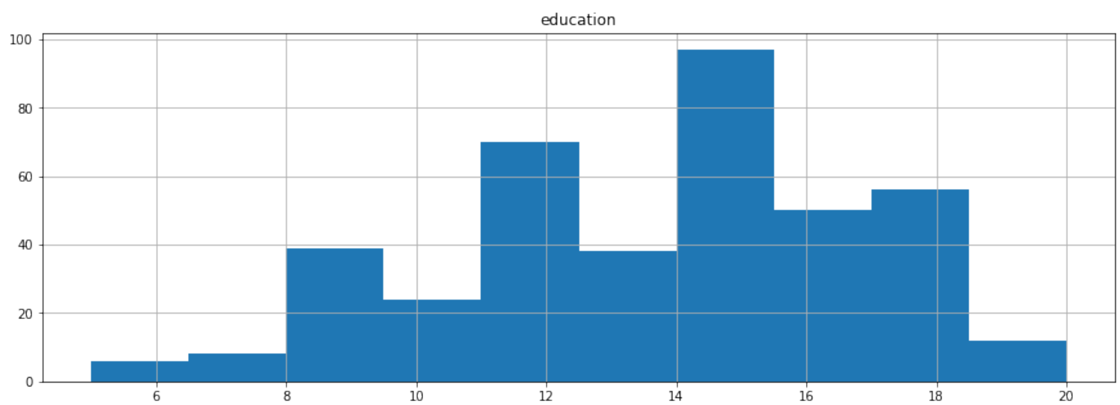
[20]:
```
_ = data.hist(column='age', bins=20, figsize=(15,5))
_ = data.hist(column='age', bins=10, by='gender', layout=(1,2), figsize=(15,5))
```

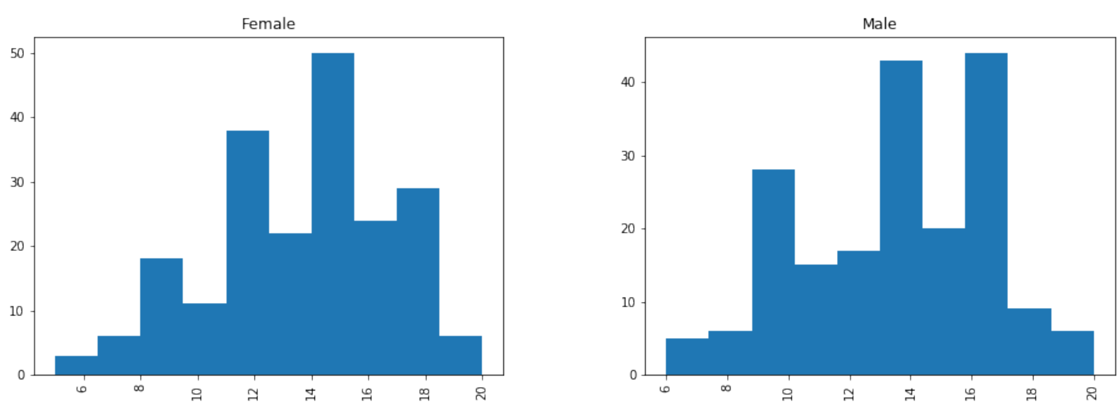


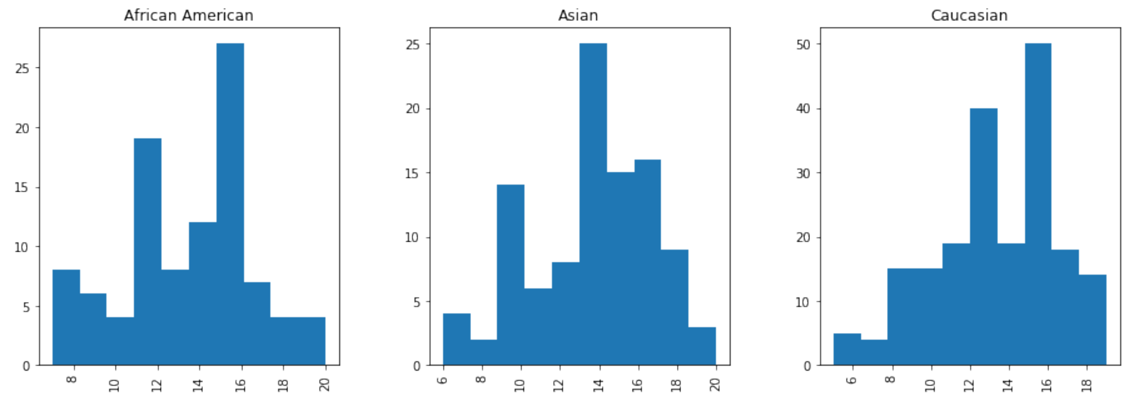


Frequency of age is rather evenly distributed
Education histograms: all, by gender and by ethencity.

[21]:
```
_ = data.hist(column='education', figsize=(15,5))
_ = data.hist(column='education', by='gender', layout=(1,2), figsize=(15,5))
_ = data.hist(column='education', by='ethnicity', layout=(1,3), figsize=(15,5))
```

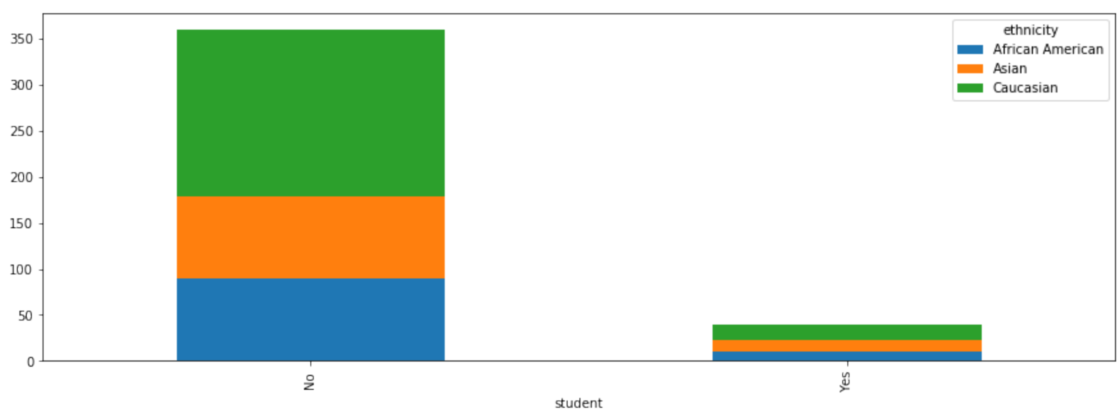


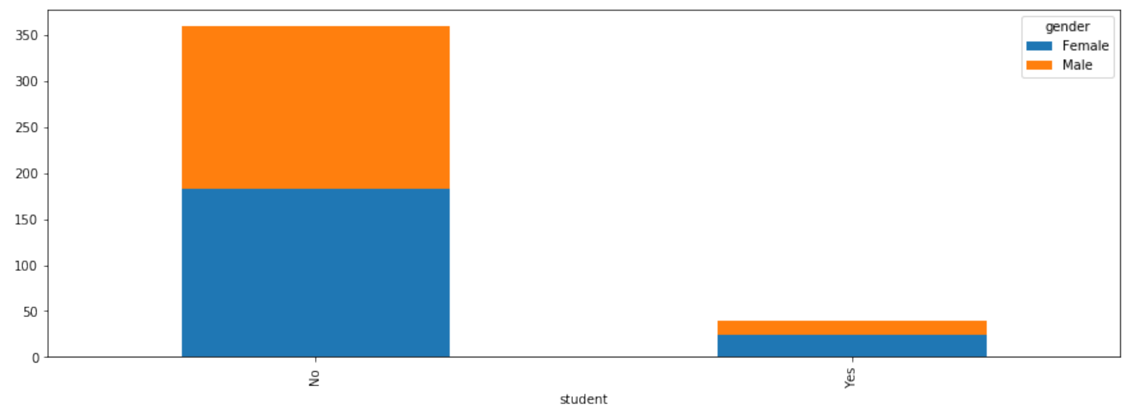


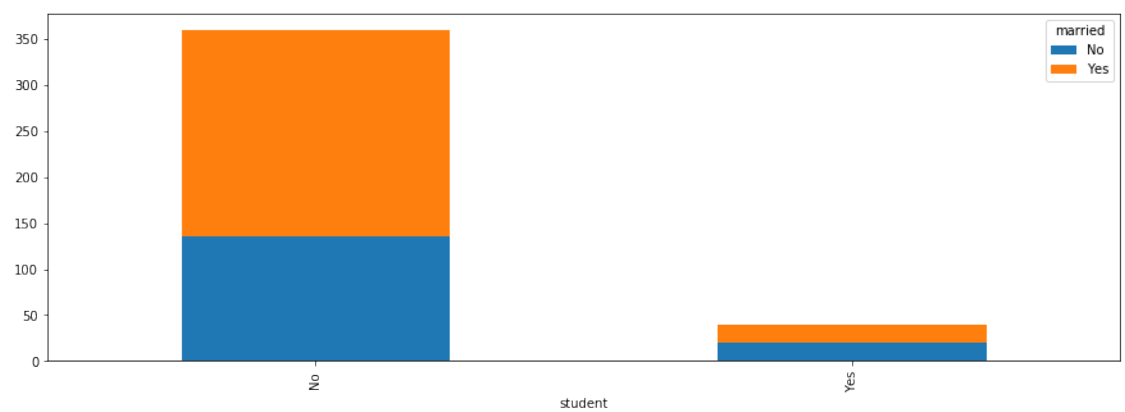


Ethenicity, gender and married status grouped by student status.

[22]:
```
_ = data.groupby('student')['ethnicity'].value_counts().unstack(1).
↪plot(kind='bar', stacked=True, figsize=(15,5))
_ = data.groupby('student')['gender'].value_counts().unstack(1).
↪plot(kind='bar', stacked=True, figsize=(15,5))
_ = data.groupby('student')['married'].value_counts().unstack(1).
↪plot(kind='bar', stacked=True, figsize=(15,5))
```



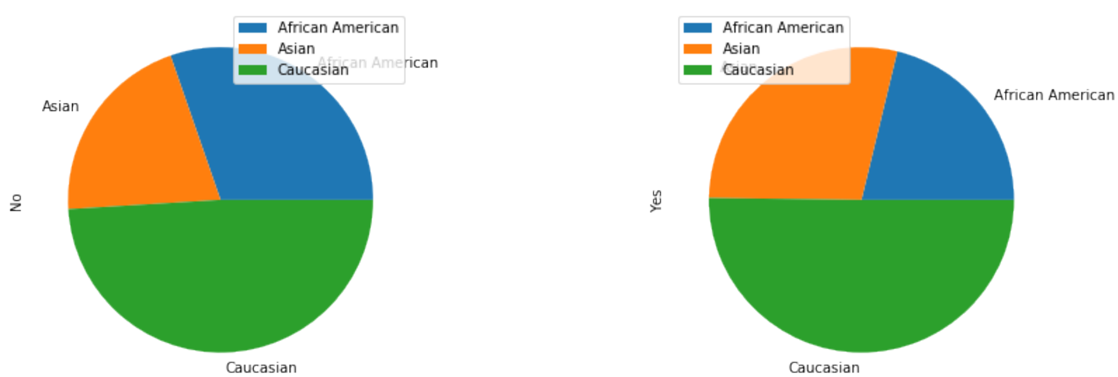


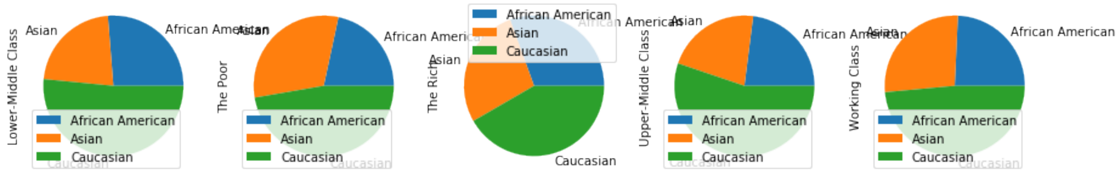


Around half of the students in the sample are Caucasian. Female/Male proporion are almost equal. Most of the students are married.

Pie plots with proportions of ethnicity dependent on marriage status and income group.

[23]:
```
_ = data.groupby('ethnicity')['married'].value_counts().unstack(1).plot(kind='pie', subplots=True, figsize=(15,5))
_ = data.groupby('ethnicity')['income_group'].value_counts().unstack(1).plot(kind='pie', subplots=True, figsize=(15,10))
```

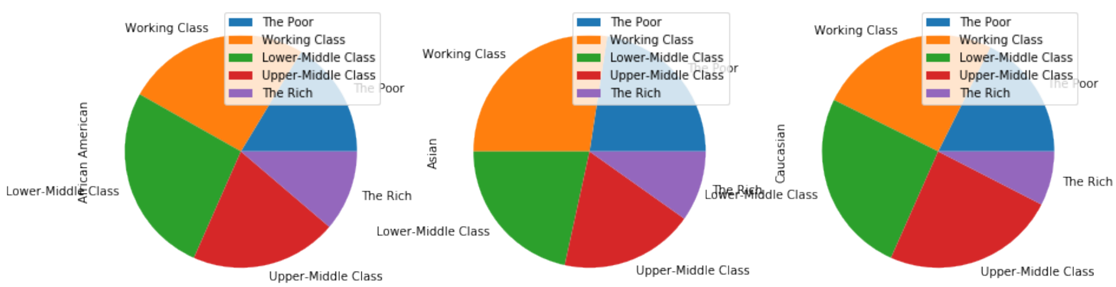


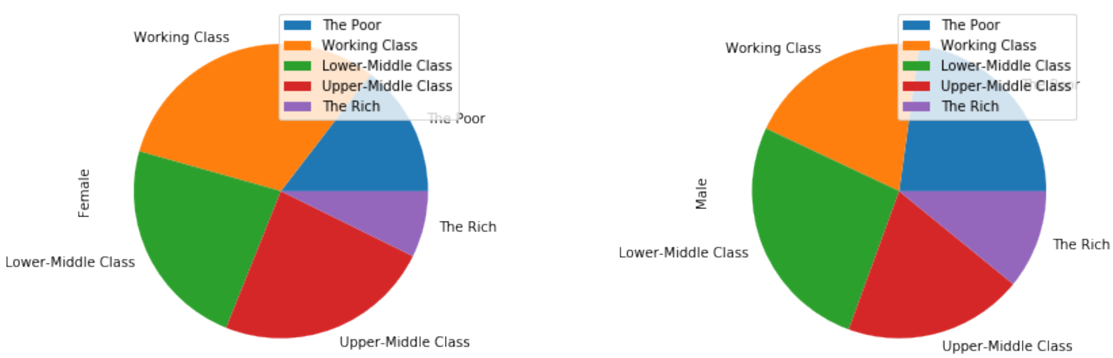


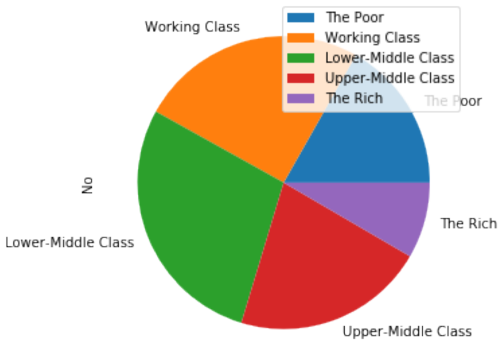
Caucasian marriage status is similar but proportionally more Asians in the sample are married than African American.
The most evenly distributed by ethenicity income group is the Rich. Asians occupy the largest percentage in the Poor group.

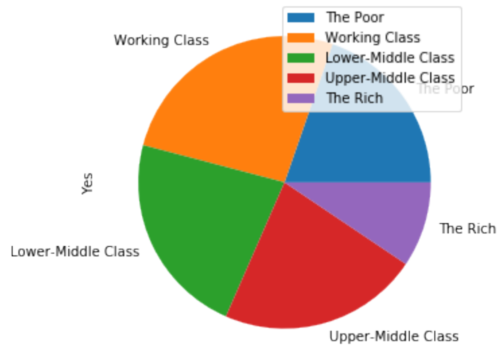
Pie plots with proportions of income group dependent on ethinicity, gender and marriage status.

[24]:
```
_ = data.groupby('income_group')['ethnicity'].value_counts().unstack(1).
↪plot(kind='pie', subplots=True, figsize=(15,5))
_ = data.groupby('income_group')['gender'].value_counts().unstack(1).
↪plot(kind='pie', subplots=True, figsize=(15,5))
_ = data.groupby('income_group')['married'].value_counts().unstack(1).
↪plot(kind='pie', subplots=True, figsize=(15,5))
```



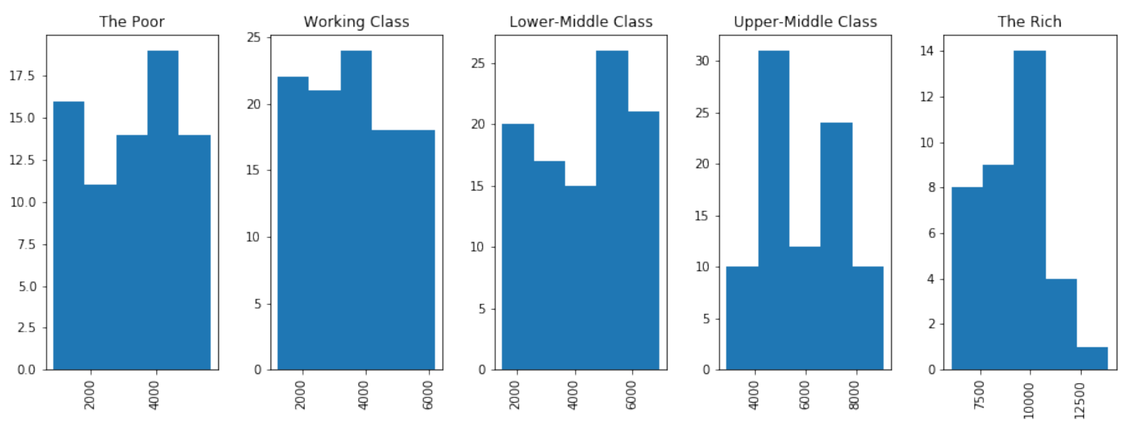


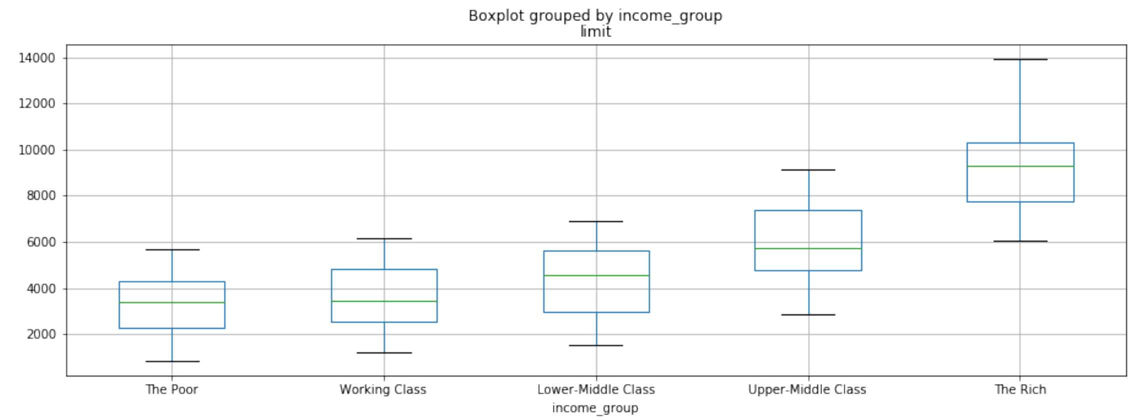


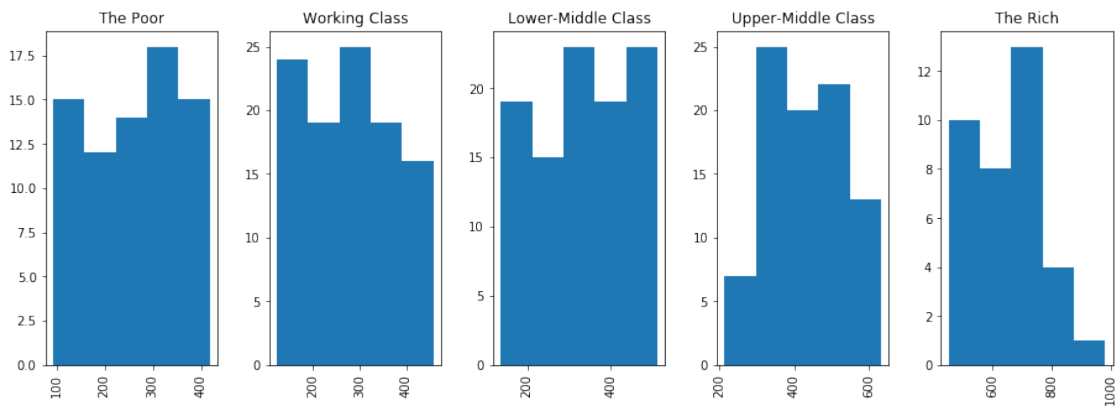


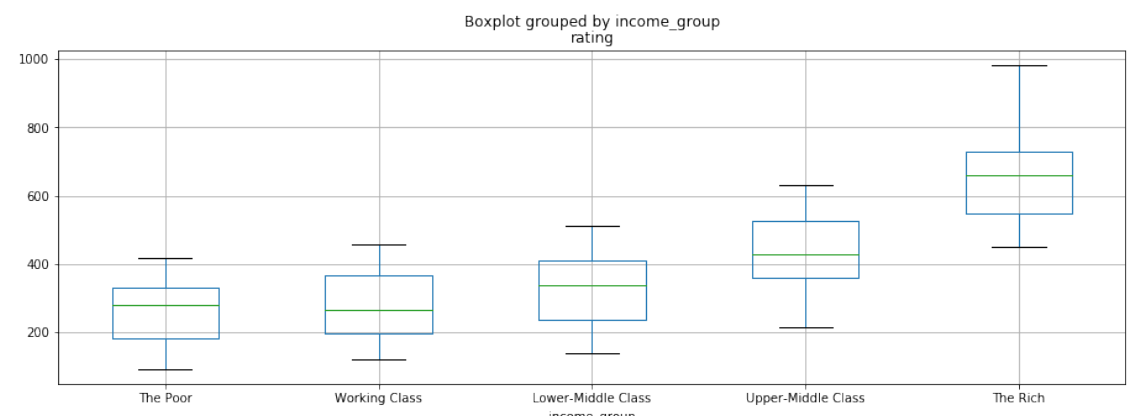
For African American and Caucasian share between lower-middle class and working class is similar. Asians have largest percentage of working class. The Rich group income occupy the largest percentage in African American distribution.
Between Female and Male can notice that the Poor group occupy more share in Male plot and working class is greater in Female.
Marriage statuses are similarly distribiuted. A little bit more customers in marriage are in upper-middle class and not married customers have bigger share in lower-middle class.

[27]:
```
for col in ["limit", "rating"]:
        _ = data.hist(column=col, by="income_group", bins=5, layout=(1,5),␣
 ↪figsize=(15,5))
        _ = data.boxplot(column=col, by="income_group", figsize=(15,5))
```









Limit and rating attributes have very similar box plots. It is visible that the Rich group has much higher values for these two attributes than the rest of the groups. Also Upper-Middle Class stand outs a little bit more from first three groups.

Coefficient of variation (determine how much the group is differentiated from certain attributes):

[ ]:
```
columns = ["income", "limit", "rating", "cards", "age", "education", "balance"]
values = [variation(data[x]) for x in columns]
plt.scatter(columns, values)
```

Customers are the most diverse in terms of balance and income, and the least in terms of years of education.