Using Machine Learning Models

数据科学 –
机器学习模型入门

房贷放款评估
使用Logistical Regression

Nov 2020
Microsoft Reactor | Ryan Chung

```
led by player to
.load_image("kg.png")
(self):
ialize Dog object and create Text o
g, self).__init__(image = Dog.image
                  x = games.mouse.x
                  bottom = games.sc
re = games.Text(value = 0, size =
                top = 5, right =
reen.add(self.score)
games.Text(value = 0, size =
           top = 5, left =
```

Microsoft

Ryan Chung

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Founder / MobileDev.TW

@ryanchung403 on WeChat
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Microsoft

Reactor

developer.microsoft.com/reactor/

@MSFTReactor on Twitter

房贷放款评估

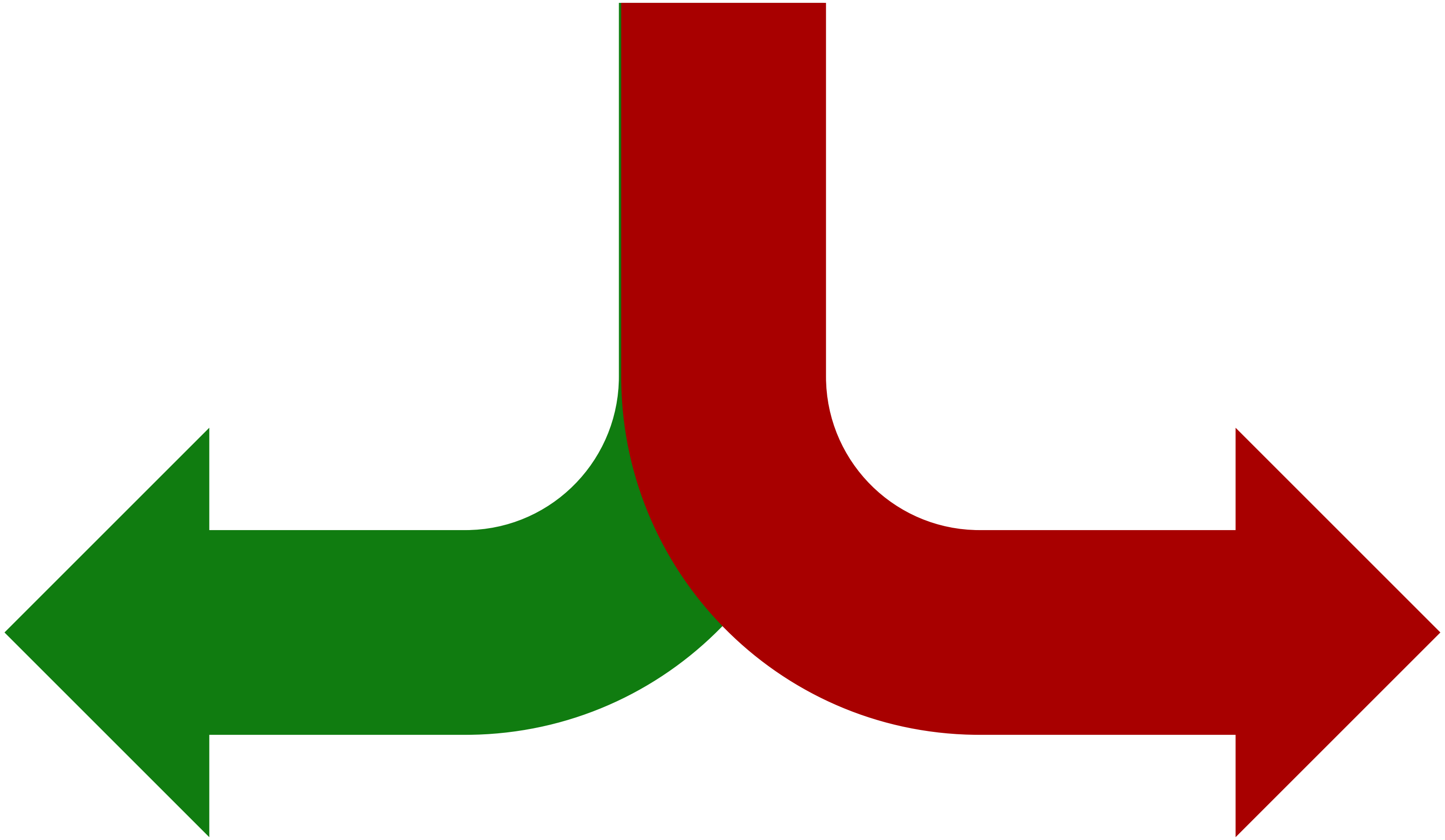
- 评估客户是否符合贷款标准
  - 性别
  - 婚姻状况
  - 教育程度
  - 收入
  - 借贷金额
  - 信用纪录

数据说明

变数名称	说明	变数名称	说明
Loan_ID	唯一识别ID	**CoapplicantIncome**	共同申请人收入
Gender	性别(Male/Female)	**LoanAmount**	借贷金额(美金千元)
Married	是否已婚 (Y/N)	**Loan_Amount_Term**	借贷时间(月)
Dependents	家属人数	**Credit_History**	信用纪录(1/0)
Education	教育程度 (Graduate/ Under Graduate)	**Property_Area**	房产位置 Urban/ Semi Urban/ Rural
Self_Employed	是否为自雇者 (Y/N)	**Loan_Status**	是否核准借贷 (Y/N)
ApplicantIncome	申请者本人收入		

目标

- 建立机器学习模型，决定是否要核准贷款
  - Yes
  - No



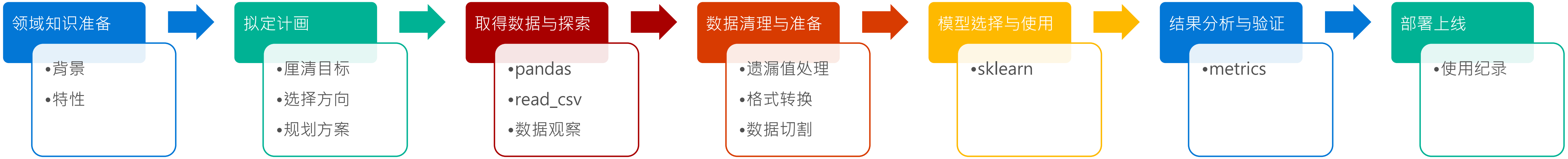
数据科学家的职业道德

- 只搜集必要的、分析需要的数据
- 界定与去除机敏性数据
- 判断错误的备援方案准备

性别与婚姻状态

- 属于个人隐私数据，可考虑去除

数据科学处理流程



领域知识准备
- 背景
- 特性

拟定计画
- 厘清目标
- 选择方向
- 规划方案

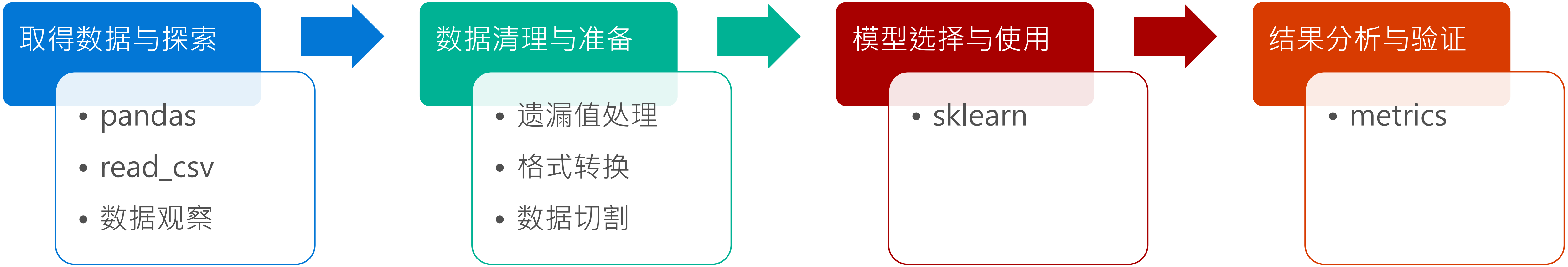
取得数据与探索
- pandas
- read_csv
- 数据观察

数据清理与准备
- 遗漏值处理
- 格式转换
- 数据切割

模型选择与使用
- sklearn

结果分析与验证
- metrics

部署上线
- 使用纪录



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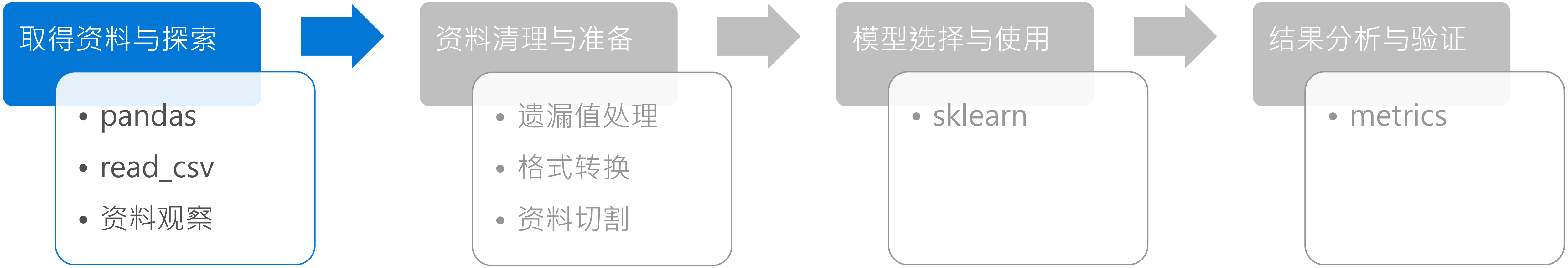

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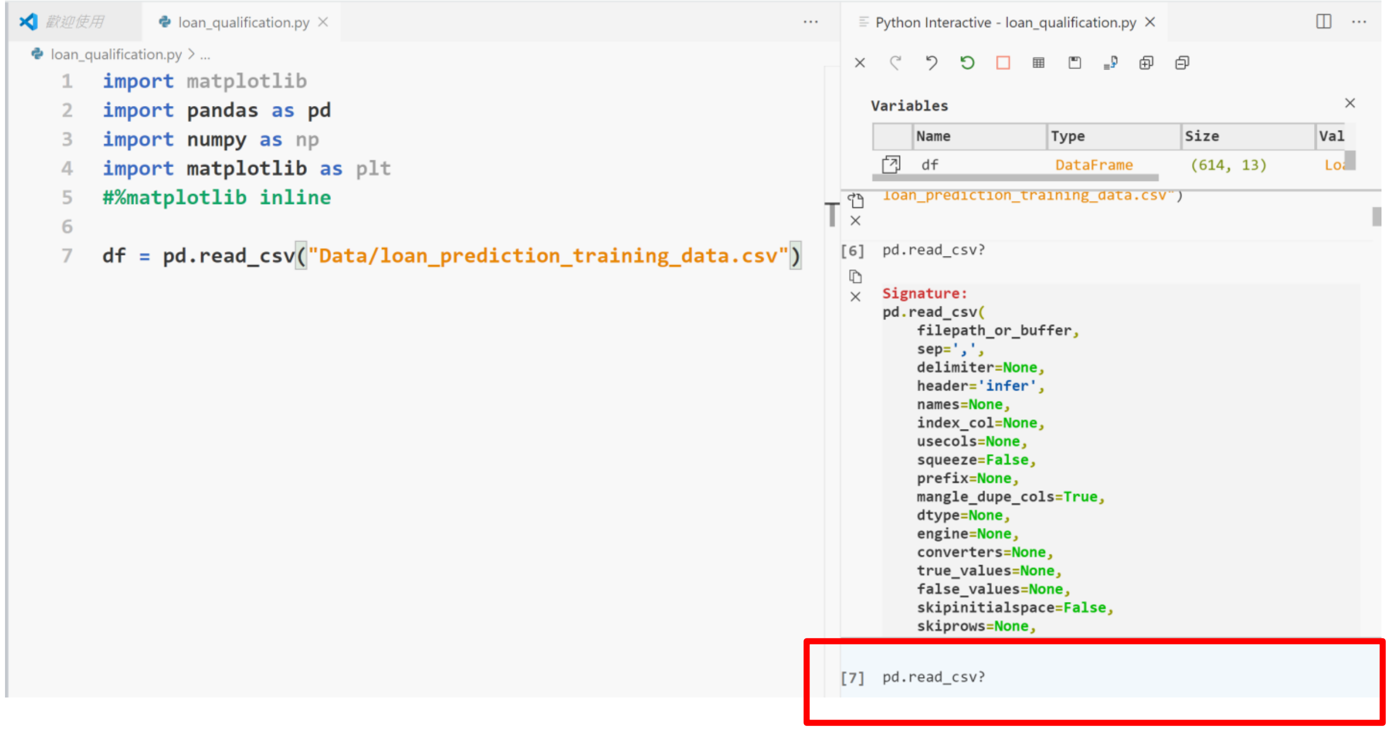
```
import matplotlib
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
#%matplotlib inline

df = pd.read_csv("Data/loan_prediction_training_data.csv")
```

查阅方法说明

- 在VS Code中，可在右下方区块输入方法名称，最后加上问号，即可获得说明
- 例如：pd.read_csv?


歡迎使用
loan_qualification.py
loan_qualification.py > ...
Python Interactive - loan_qualification.py

```
import matplotlib
import pandas as pd
import numpy as np
import matplotlib as plt
#%matplotlib inline

df = pd.read_csv("Data/loan_prediction_training_data.csv")
```

Variables

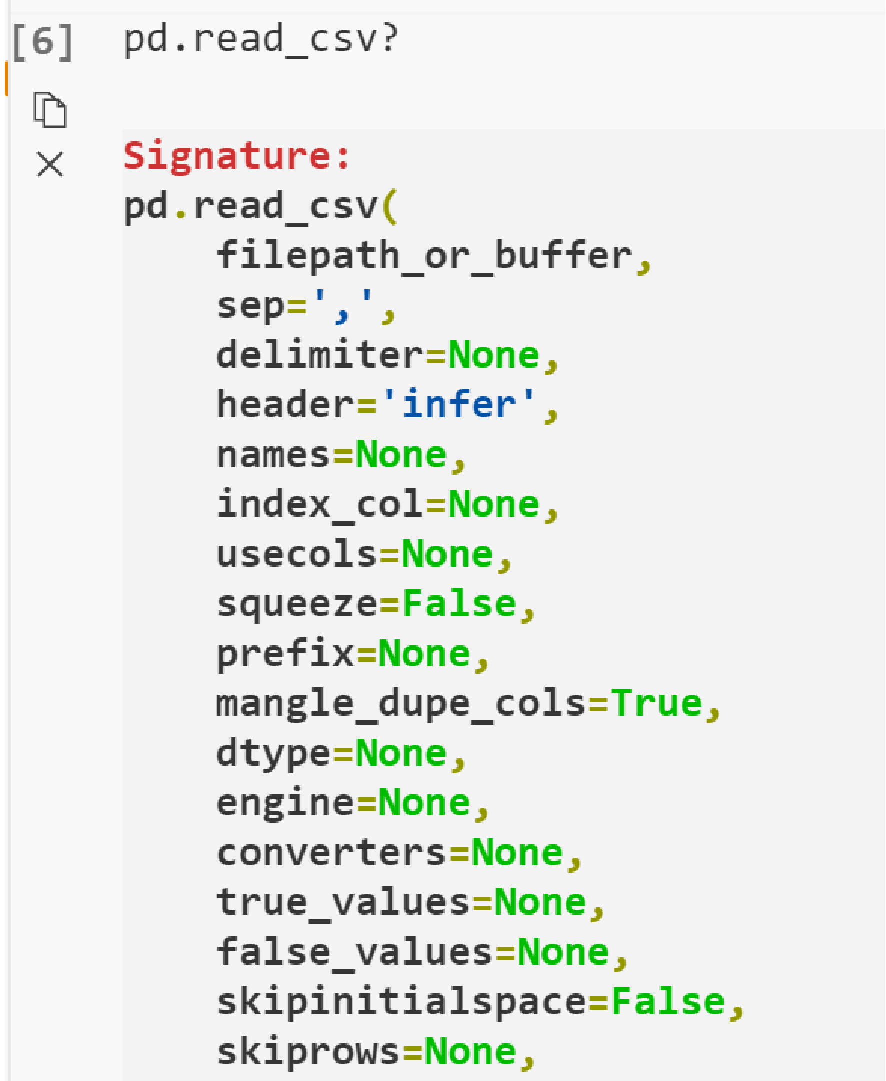
Name	Type	Size	Val
df	DataFrame	(614, 13)	Lo

```
loan_prediction_training_data.csv")

[6]  pd.read_csv?

Signature:
pd.read_csv(
    filepath_or_buffer,
    sep=',',
    delimiter=None,
    header='infer',
    names=None,
    index_col=None,
    usecols=None,
    squeeze=False,
    prefix=None,
    mangle_dupe_cols=True,
    dtype=None,
    engine=None,
    converters=None,
    true_values=None,
    false_values=None,
    skipinitialspace=False,
    skiprows=None,

[7]  pd.read_csv?
```



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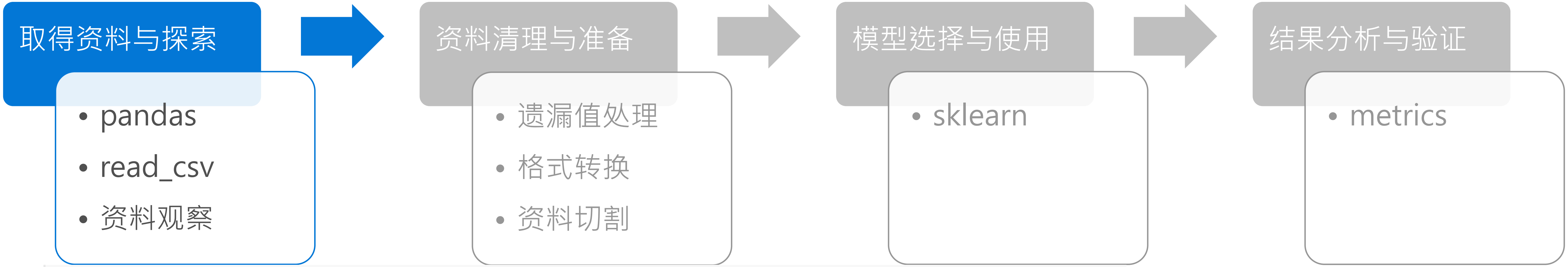
```

继续探索数据 df.describe()



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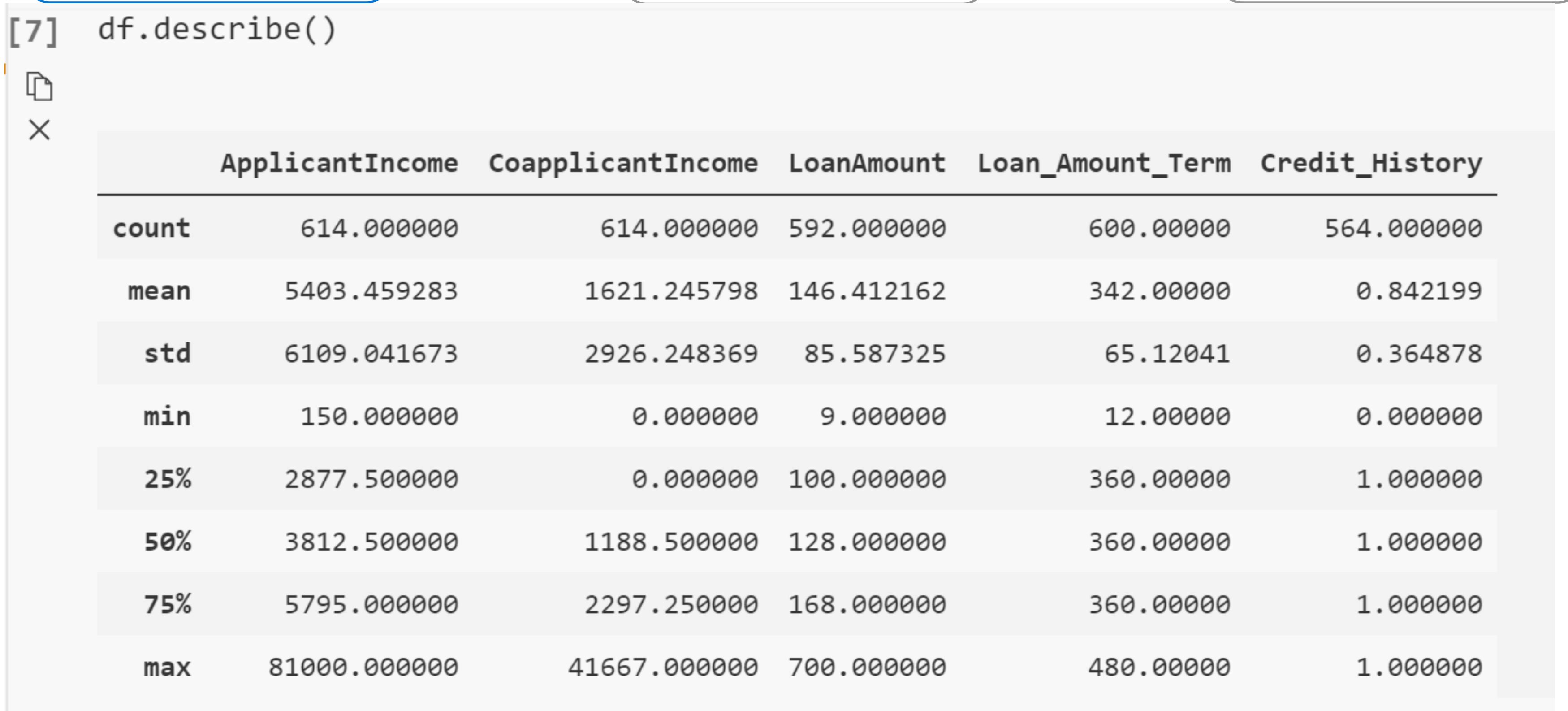
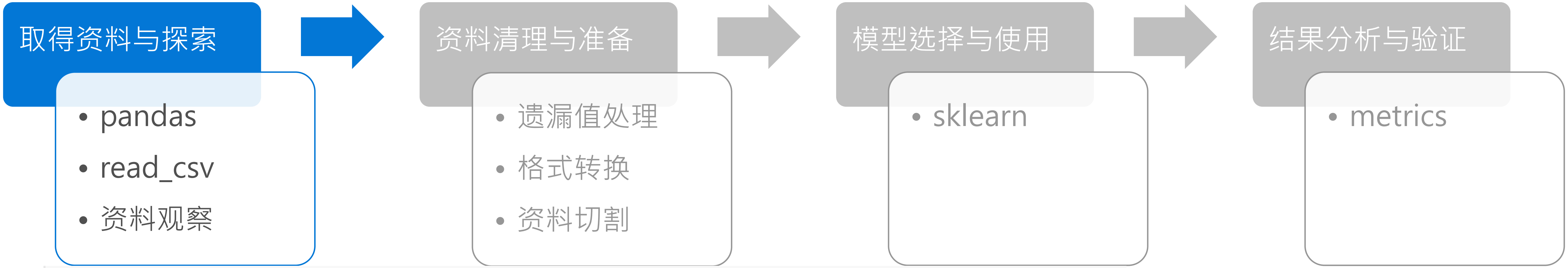


```
[7] df.describe()
```

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	614.000000	614.000000	592.000000	600.00000	564.000000
mean	5403.459283	1621.245798	146.412162	342.00000	0.842199
std	6109.041673	2926.248369	85.587325	65.12041	0.364878
min	150.000000	0.000000	9.000000	12.00000	0.000000
25%	2877.500000	0.000000	100.000000	360.00000	1.000000
50%	3812.500000	1188.500000	128.000000	360.00000	1.000000
75%	5795.000000	2297.250000	168.000000	360.00000	1.000000
max	81000.000000	41667.000000	700.000000	480.00000	1.000000

Q.从这里可得知哪几项有缺失值?

继续探索数据 df.describe()



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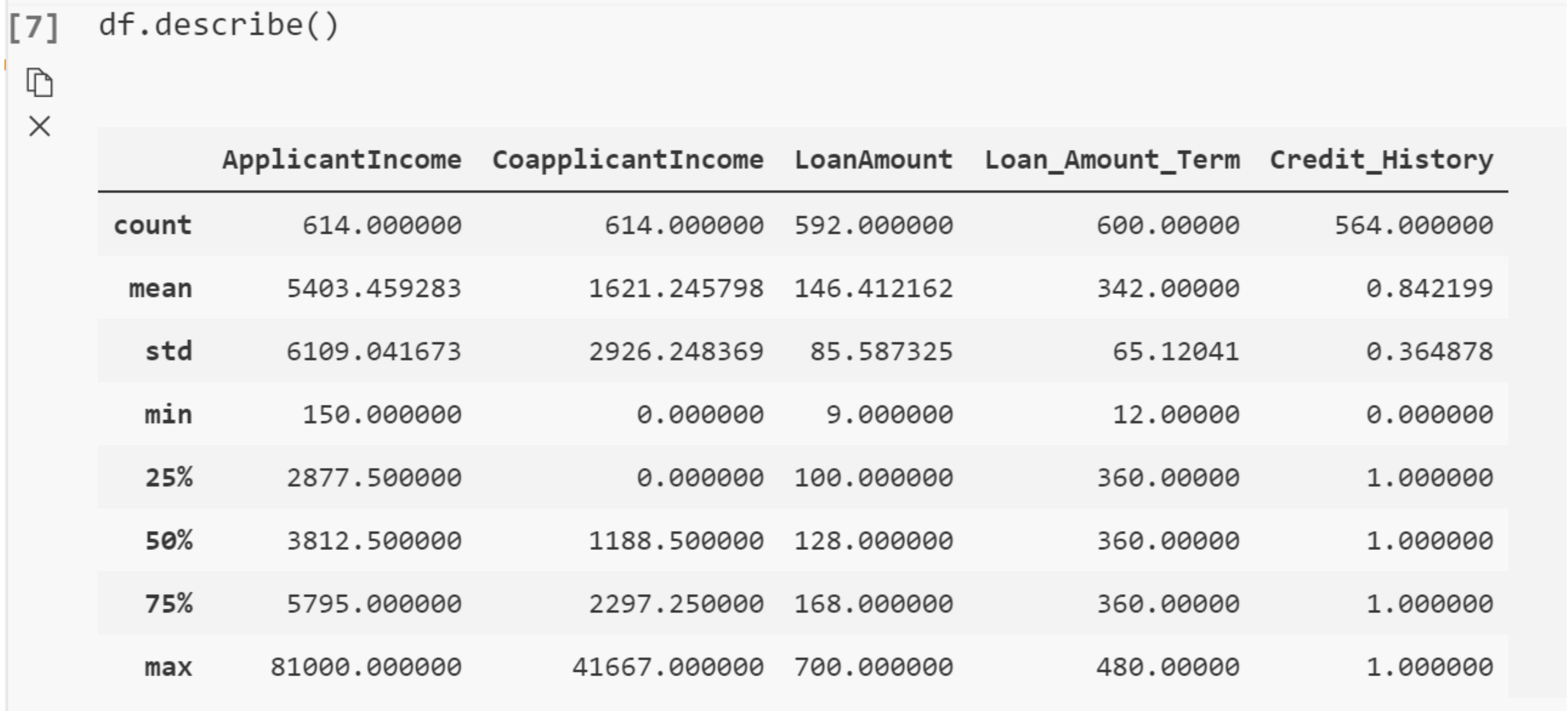

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[7] df.describe()
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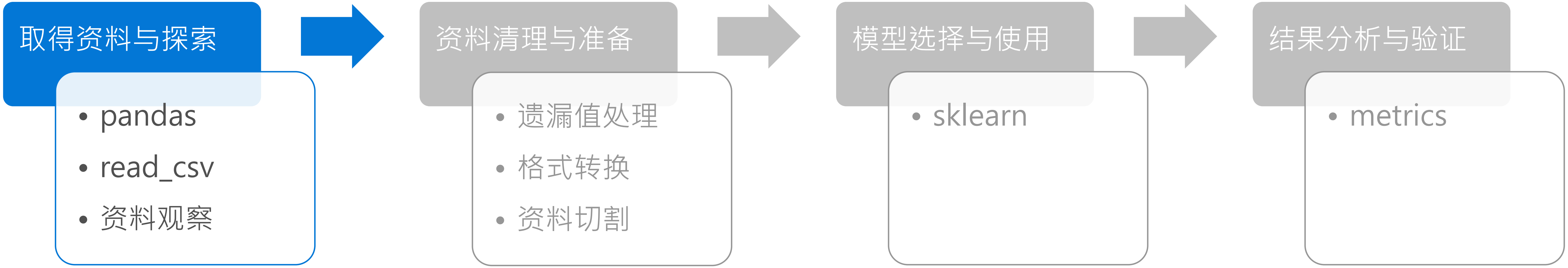
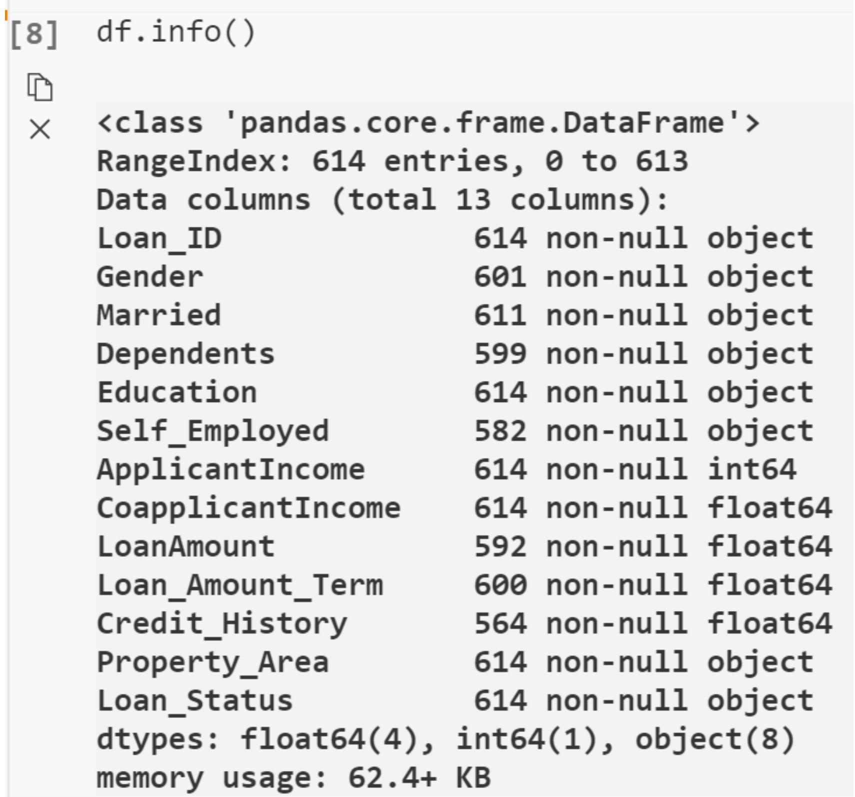
max	81000.000000	41667.000000	700.000000	480.00000	1.000000

Q. Credit_History 为1的有几笔?

继续探索数据 df.info()



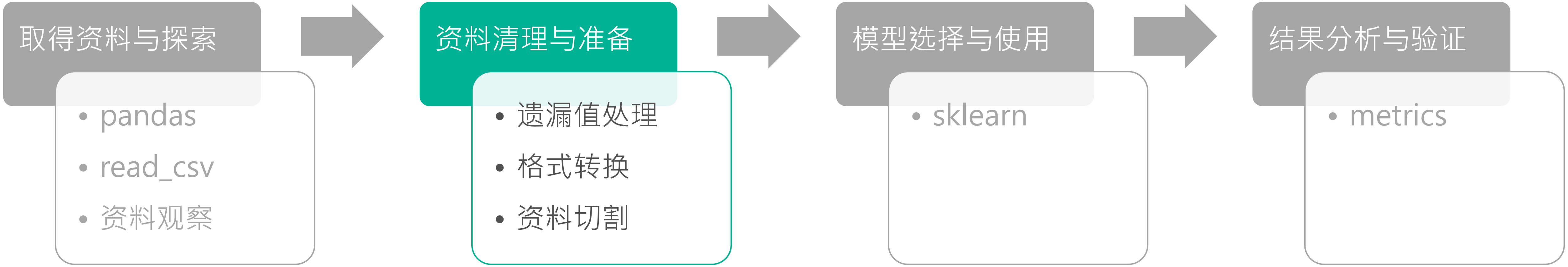


```
[8]  df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 13 columns):
Loan_ID              614 non-null object
Gender               601 non-null object
Married              611 non-null object
Dependents           599 non-null object
Education            614 non-null object
Self_Employed        582 non-null object
ApplicantIncome      614 non-null int64
CoapplicantIncome    614 non-null float64
LoanAmount           592 non-null float64
Loan_Amount_Term     600 non-null float64
Credit_History       564 non-null float64
Property_Area        614 non-null object
Loan_Status          614 non-null object
dtypes: float64(4), int64(1), object(8)
memory usage: 62.4+ KB
```

共有614笔资料

去除性别、婚姻数据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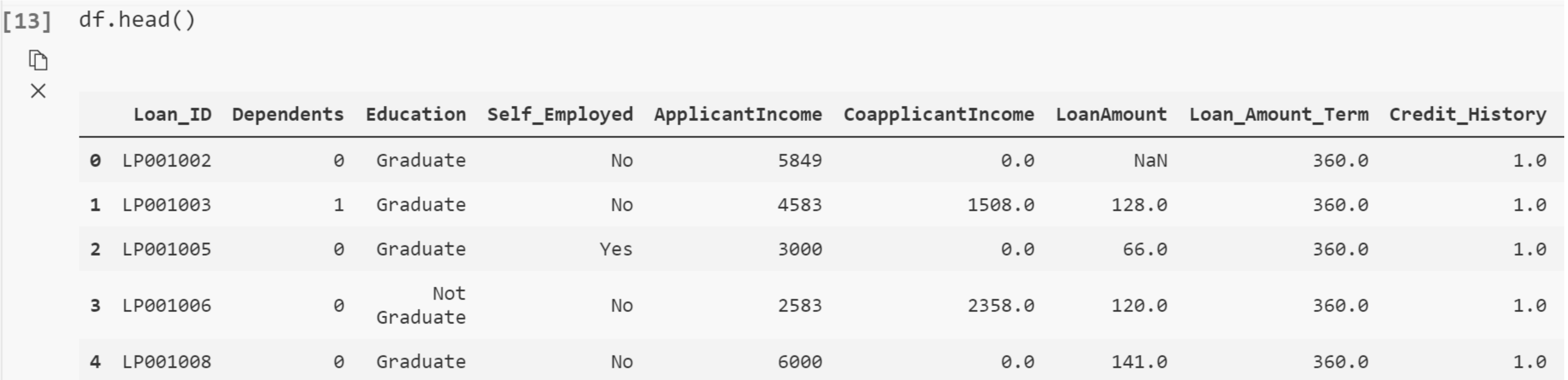
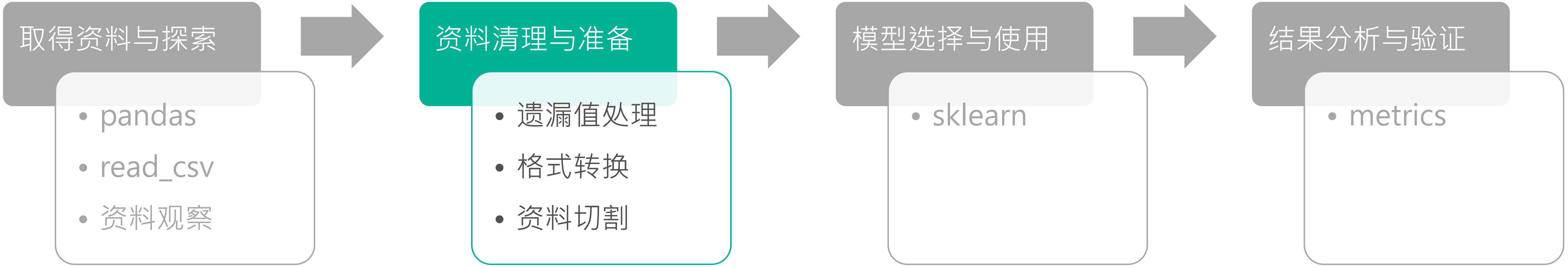
```
#剔除Gender, Married栏位与资料
df_no_G_M = df.drop(columns=['Gender','Married'])
#存成csv档
df_no_G_M.to_csv('loan_prediction_training_data_no_G_M.csv')
```


```
[13] df.head()
```

	Loan_ID	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
0	LP001002	0	Graduate	No	5849	0.0	NaN	360.0	1.0
1	LP001003	1	Graduate	No	4583	1508.0	128.0	360.0	1.0
2	LP001005	0	Graduate	Yes	3000	0.0	66.0	360.0	1.0
3	LP001006	0	Not Graduate	No	2583	2358.0	120.0	360.0	1.0
4	LP001008	0	Graduate	No	6000	0.0	141.0	360.0	1.0

调阅数据



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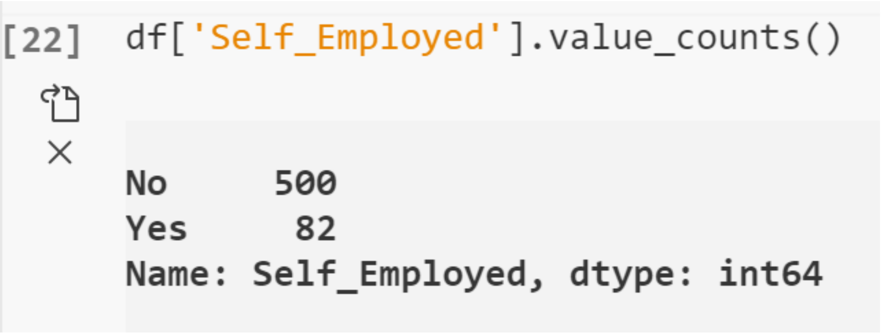
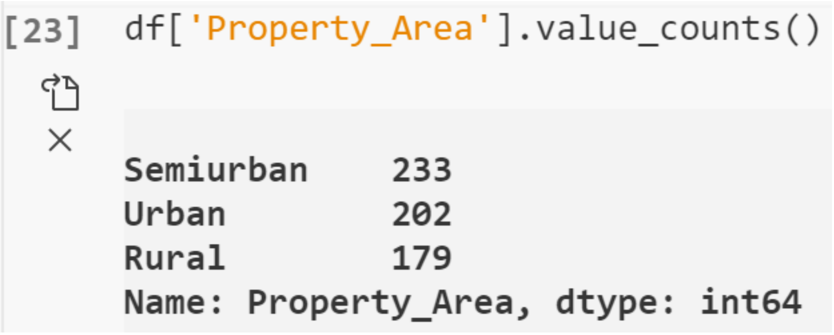
```
df['Self_Employed'].value_counts()
df['Property_Area'].value_counts()
df['Education'].value_counts()
```



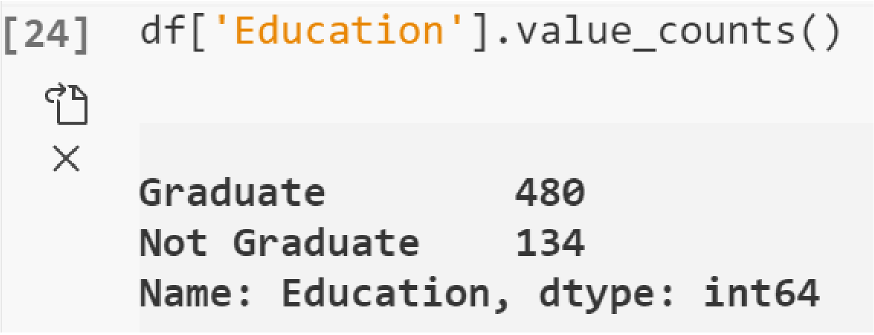
```
[22]  df['Self_Employed'].value_counts()

No      500
Yes      82
Name: Self_Employed, dtype: int64
```



```
[23]  df['Property_Area'].value_counts()

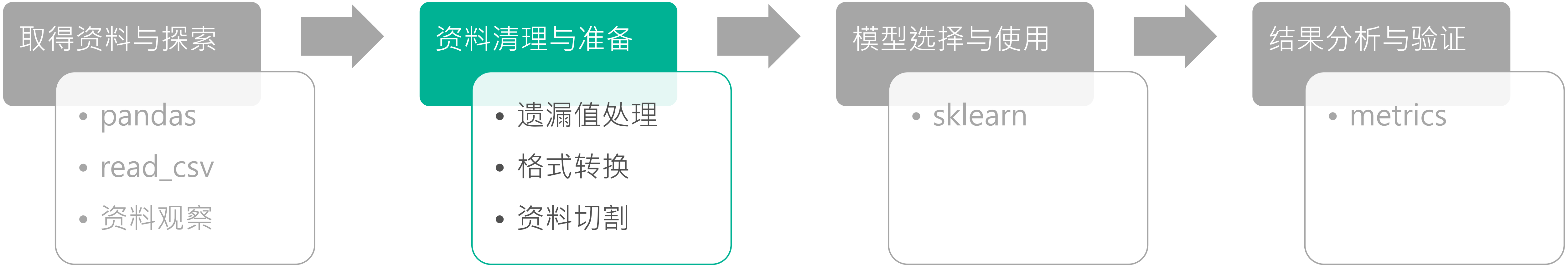
Semiurban    233
Urban        202
Rural        179
Name: Property_Area, dtype: int64
```



```
[24]  df['Education'].value_counts()

Graduate        480
Not Graduate    134
Name: Education, dtype: int64
```

调阅数据- 收入分布情形



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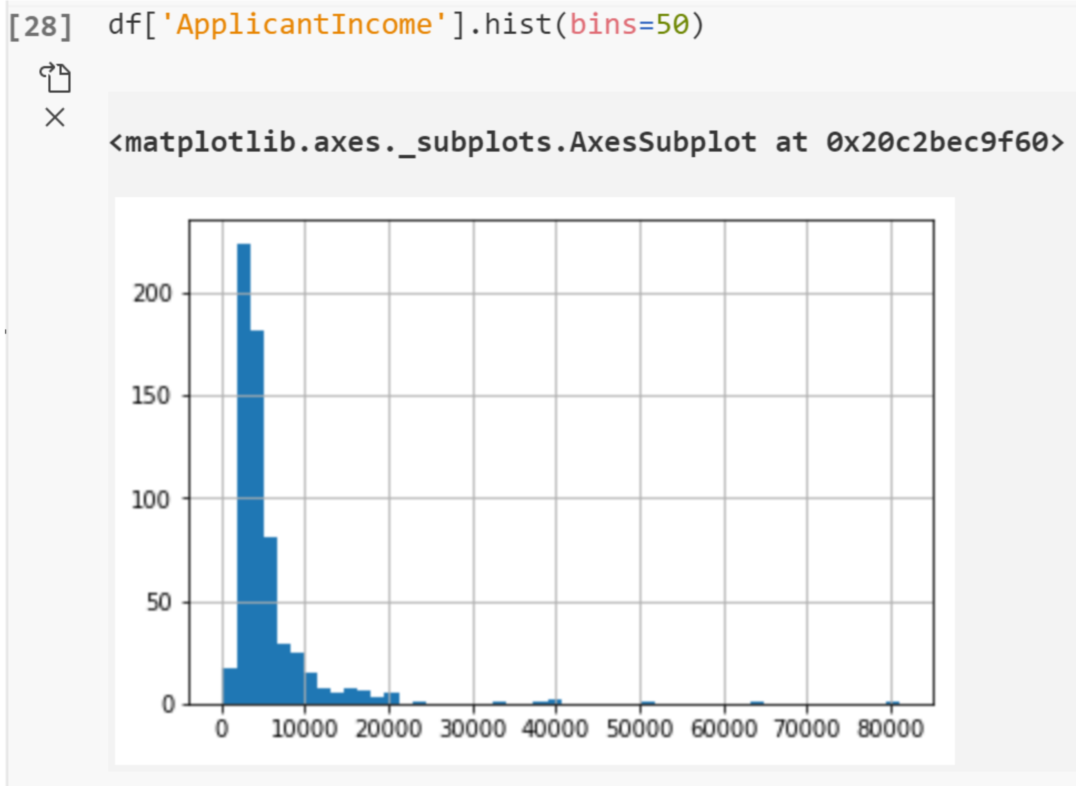
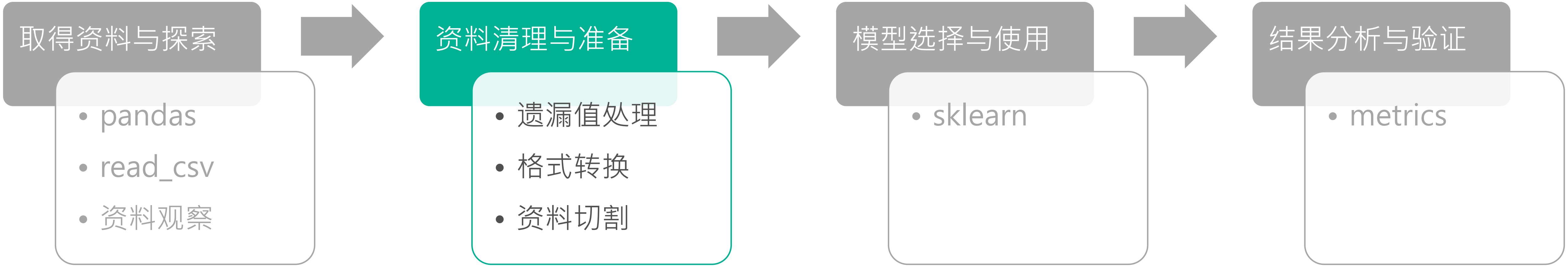
```
df['ApplicantIncome'].hist(bins=50)
```



```
[28]  df['ApplicantIncome'].hist(bins=50)

<matplotlib.axes._subplots.AxesSubplot at 0x20c2bec9f60>
```

调阅数据- 收入分布情形 – 换一种图试试



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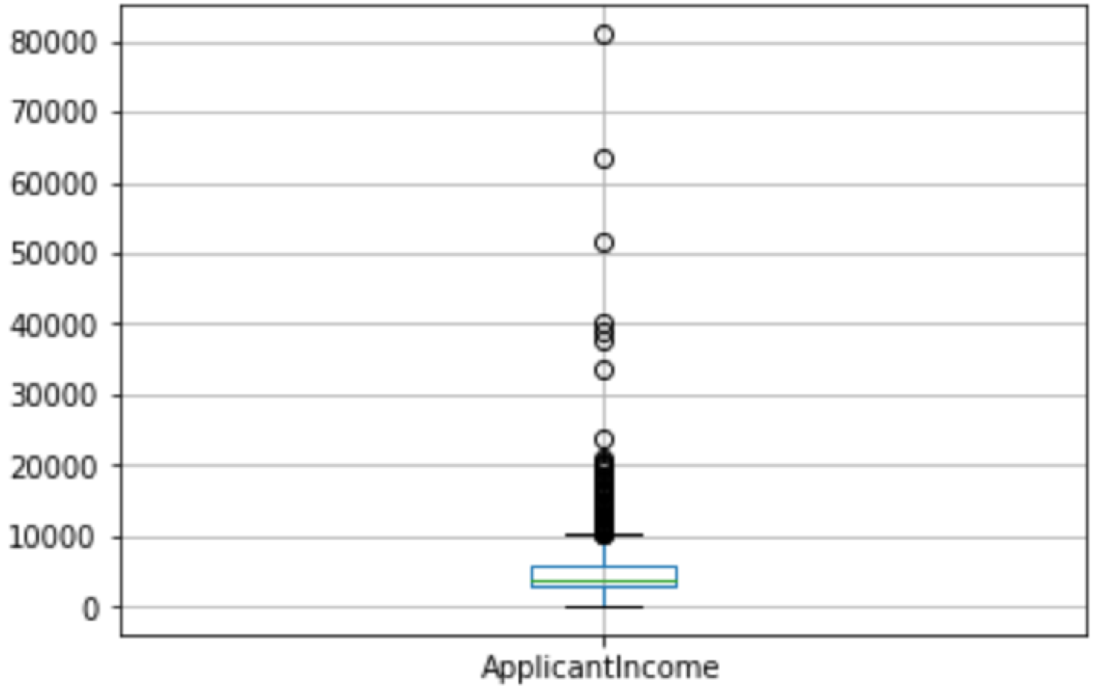
```
df.boxplot(column='ApplicantIncome')
```

Q. 看来有蛮多收入特别高的人
跟教育程度有没有关联性呢?



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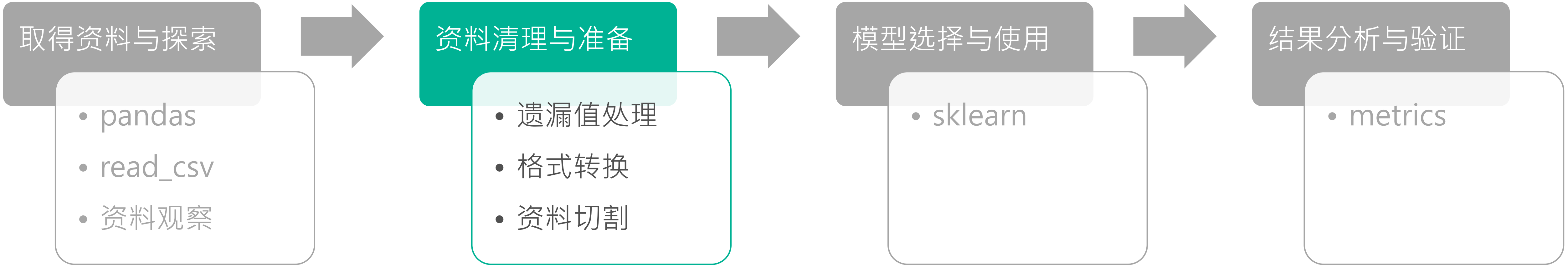

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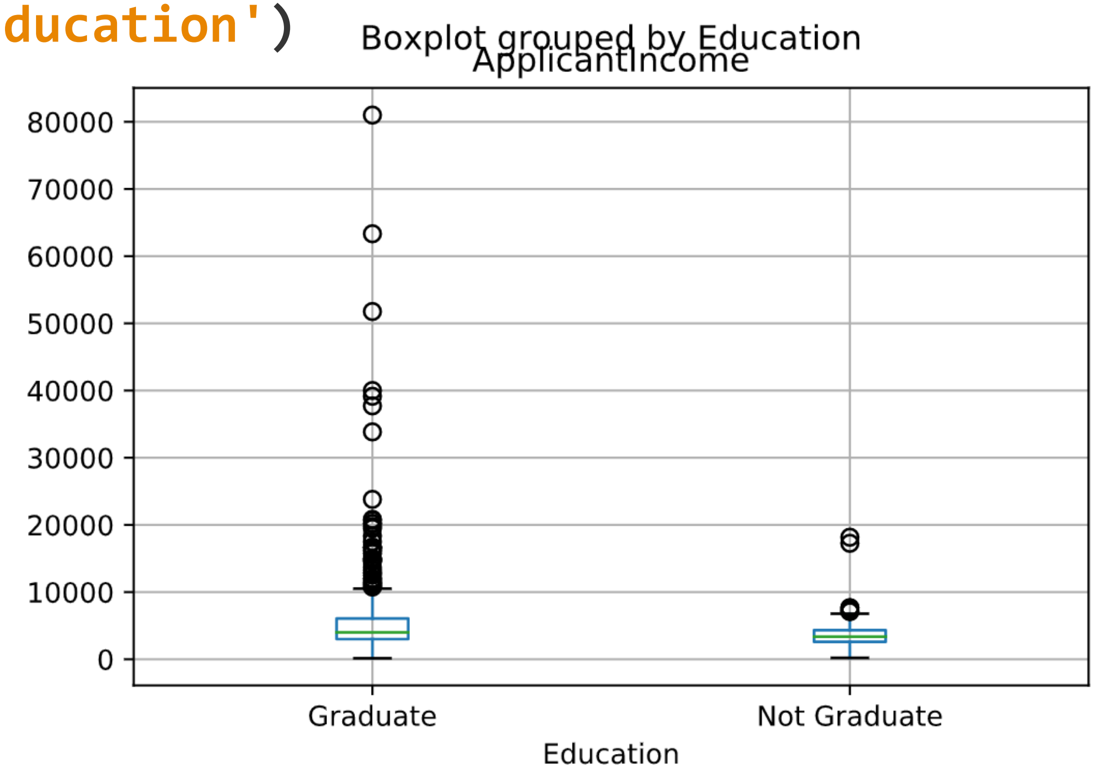
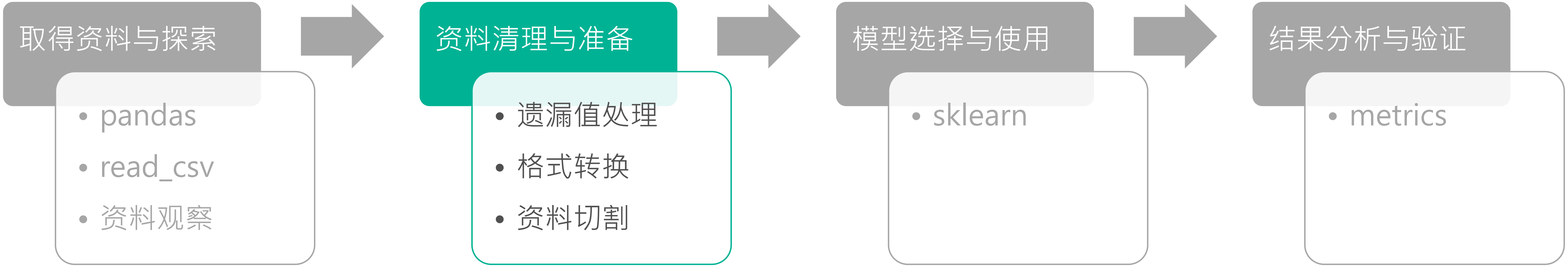
```
df.boxplot(column='ApplicantIncome', by = 'Education')
```

Q. 看来有蛮多收入特别高的人
跟教育程度有没有关联性呢?

几乎都在有毕业的那一边!



调阅数据– 借贷金额分布情形



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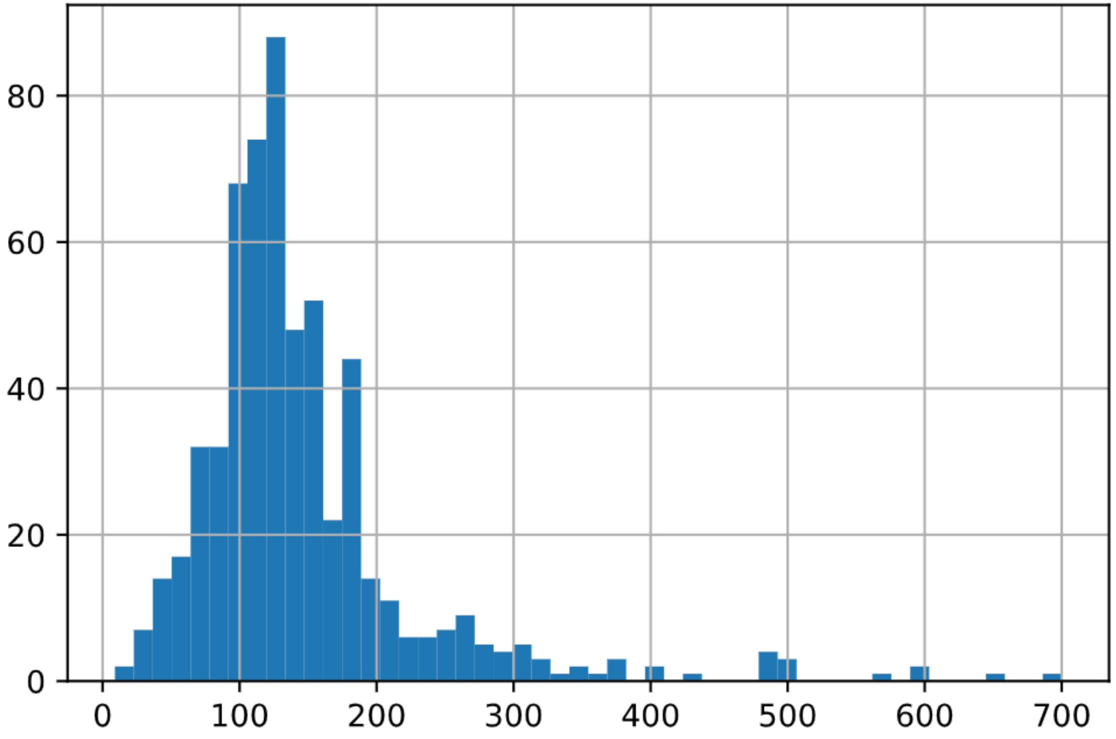
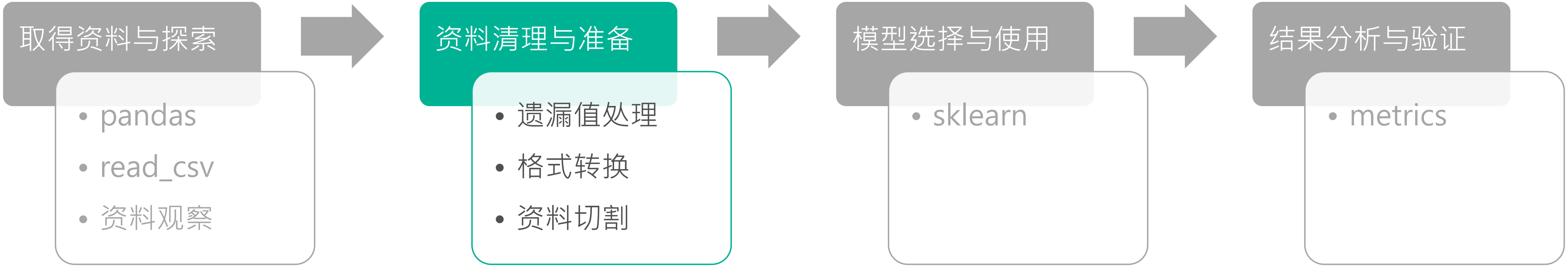
```
df['LoanAmount'].hist(bins=50)
```



(美金千元)

调阅数据-借贷金额分布情形 – 换一种图



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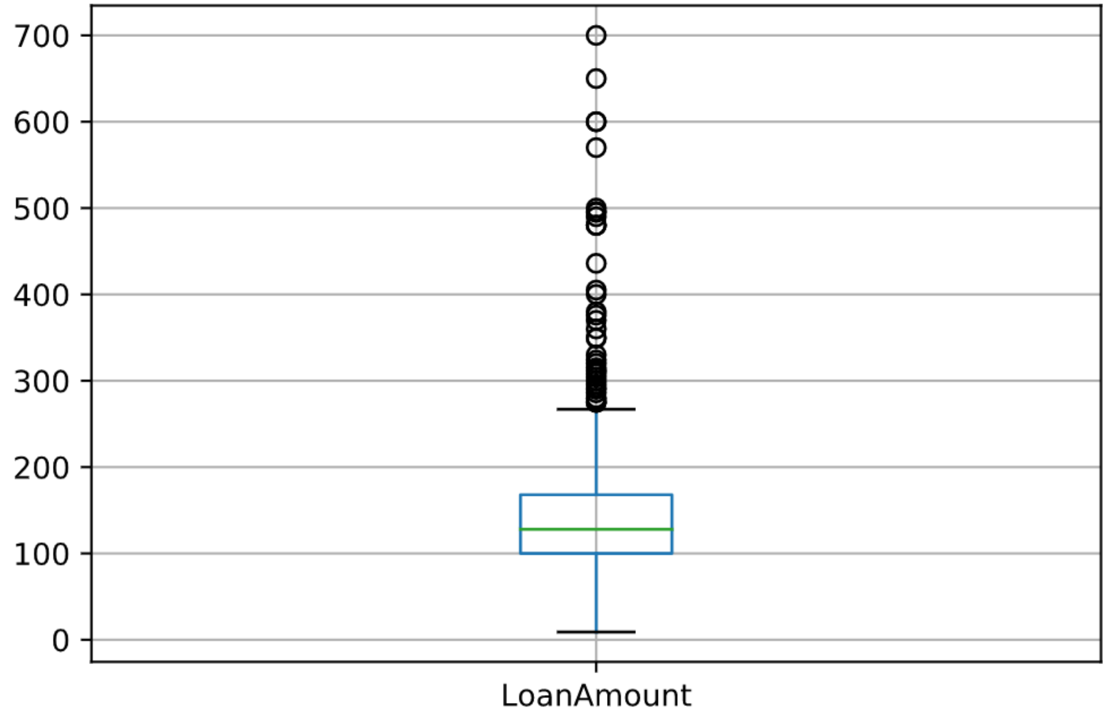
```
df.boxplot(column='LoanAmount')
```

Q. 也有蛮多借贷金额特别高的人
跟教育程度有没有关联性呢?



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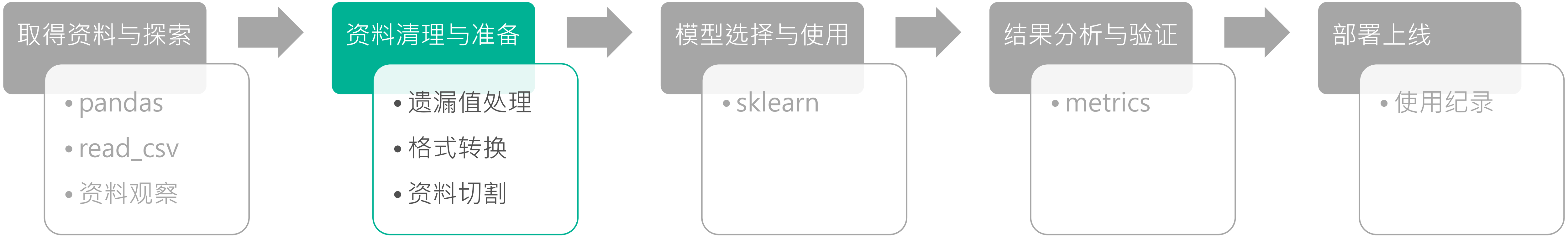

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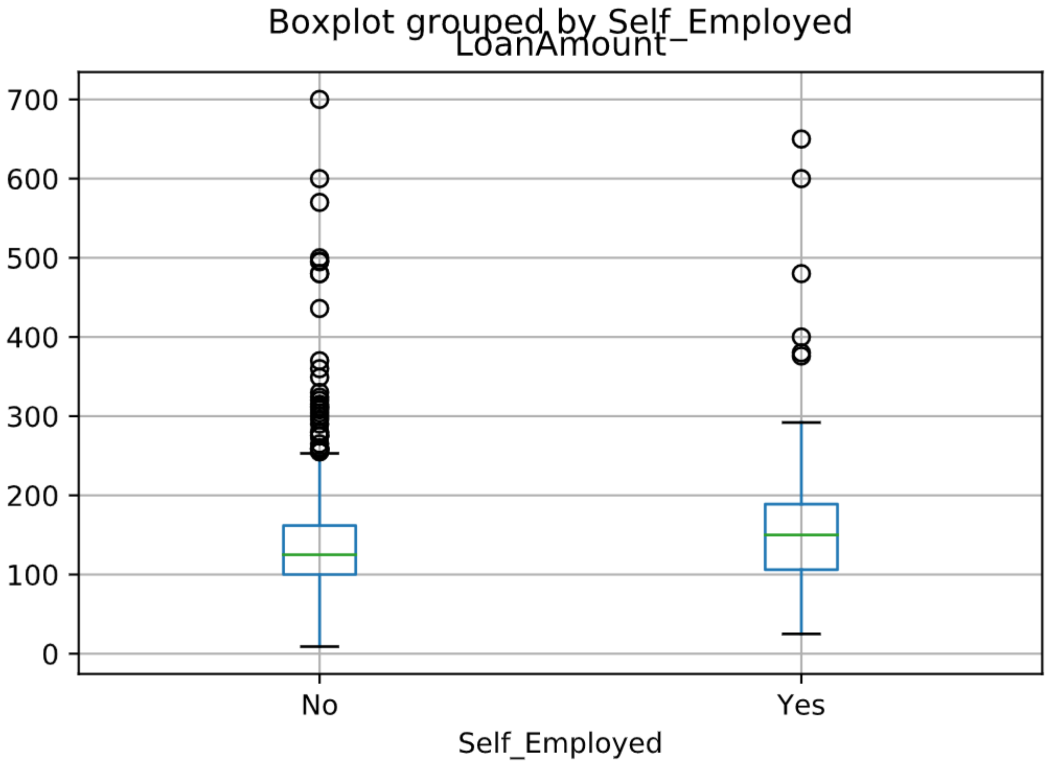
练习

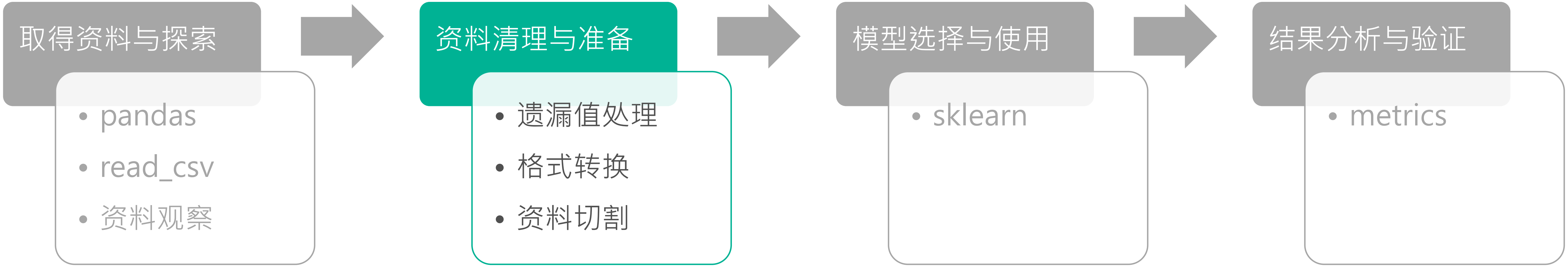
借贷金额高低与是否为自营商的关联

收入高低与是否为自营商的关联

…



调阅数据– 信用纪录 VS. 借贷状态



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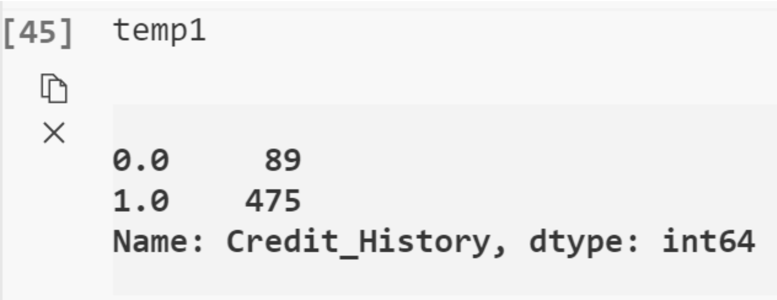
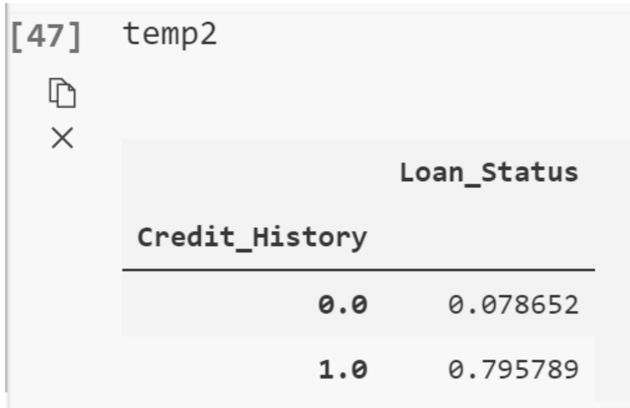
```
temp1 = df['Credit_History'].value_counts(ascending=True)

temp2 = df.pivot_table(values='Loan_Status', index=['Cre
dit_History'],aggfunc=lambda x: x.map({'Y':1,'N':0}).mea
n())
```



```
[45]  temp1

0.0     89
1.0    475
Name: Credit_History, dtype: int64
```

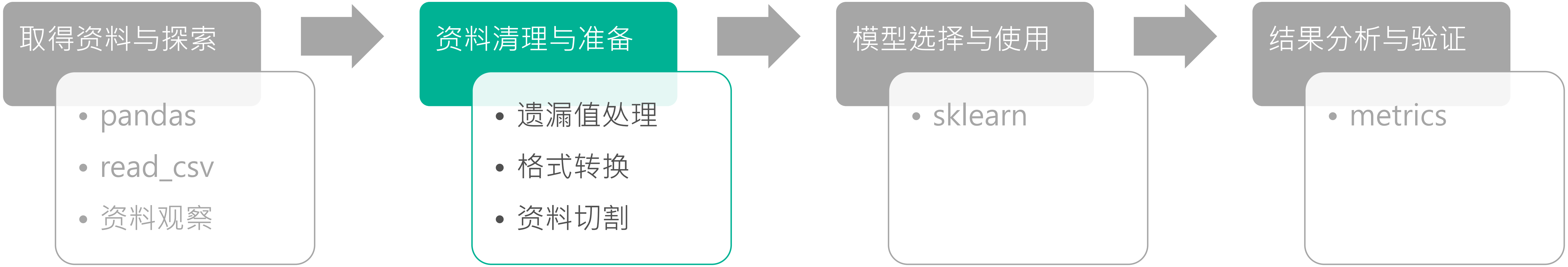


```
[47]  temp2

                Loan_Status
Credit_History
           0.0     0.078652
           1.0     0.795789
```

有信用纪录的借贷成功比例高很多！

调阅数据– 信用纪录 VS. 借贷状态(视觉化)



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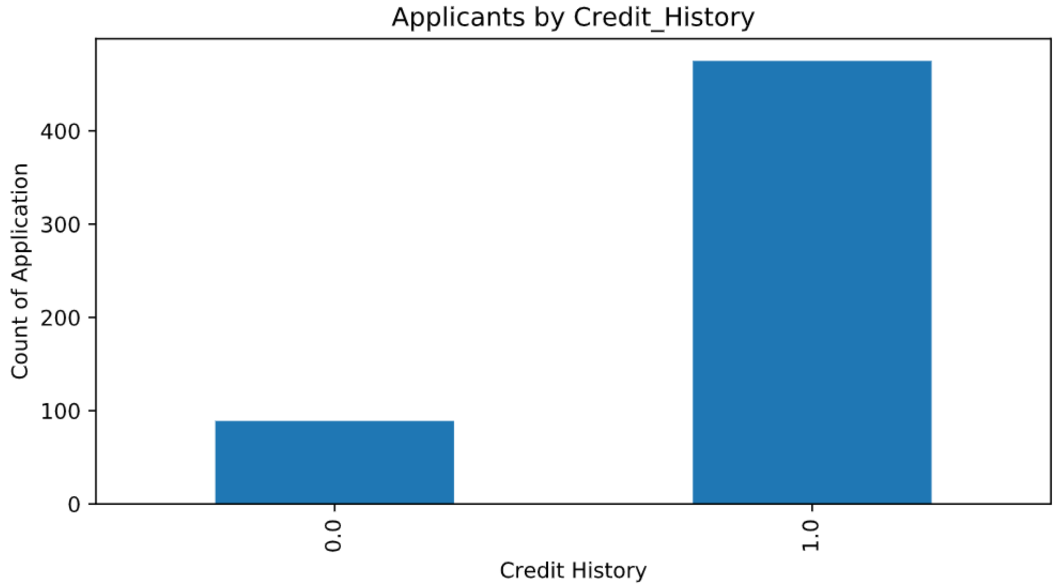
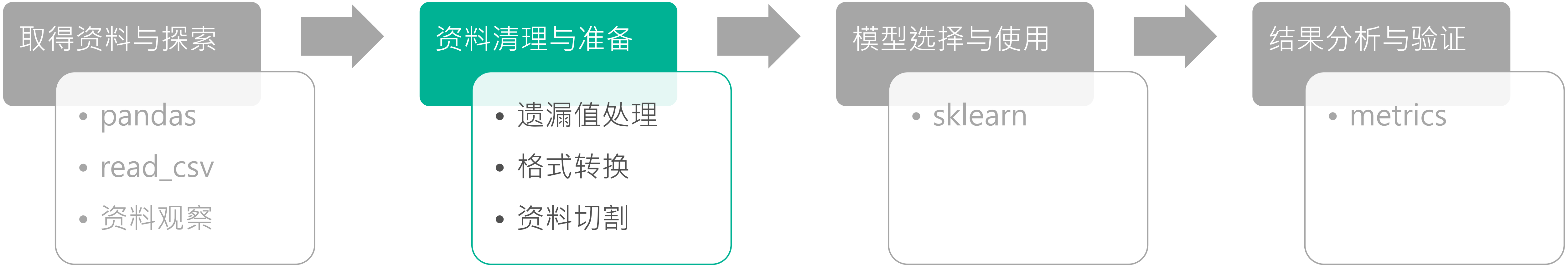
```
fig = plt.figure(figsize=(8,4))
ax1 = fig.add_subplot(111)
ax1.set_xlabel('Credit History')
ax1.set_ylabel('Count of Application')
ax1.set_title('Applicants by Credit_History')
temp1.plot(kind = 'bar')
```



调阅数据– 信用纪录 VS. 借贷状态(视觉化)



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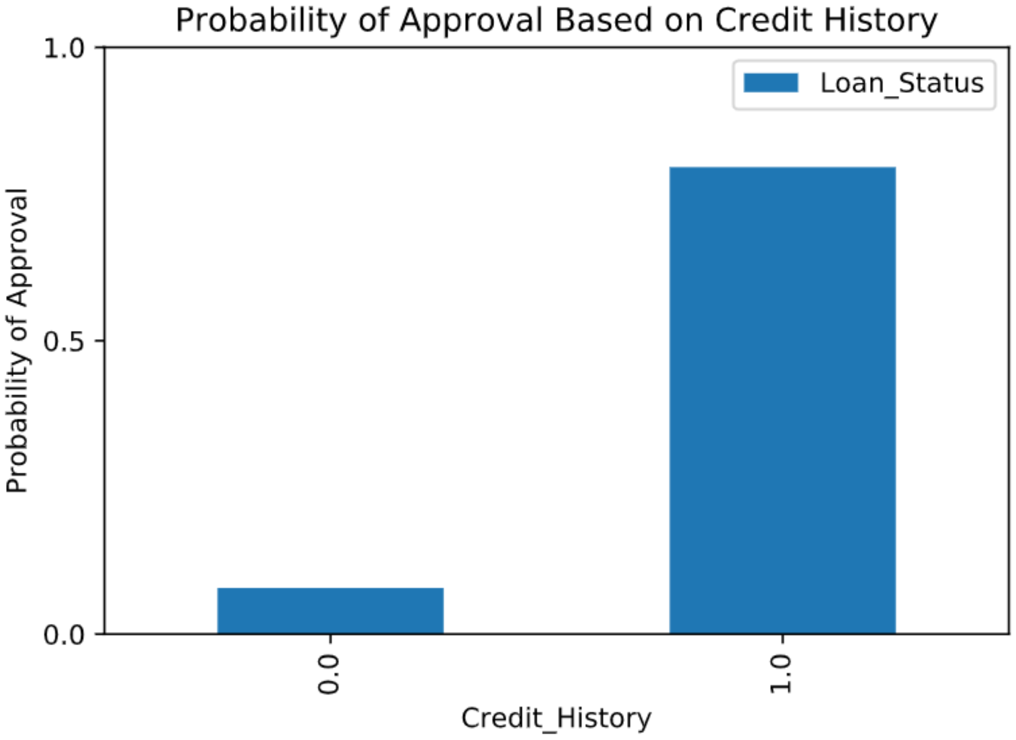
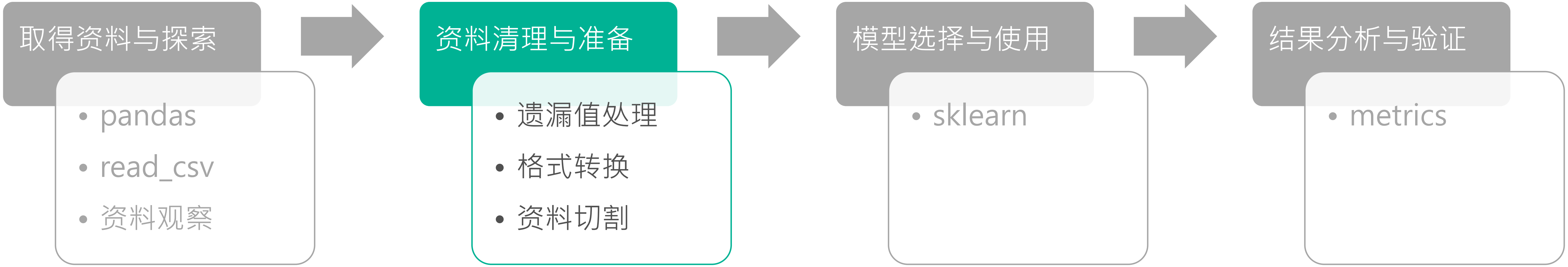
```
temp2.plot(kind = 'bar',yticks=[0,0.5,1]
,ylabel='Probability of Approval',title=
'Probability of Approval Based on Credit
 History')
```



调阅数据– 房产位置 VS. 借贷状态



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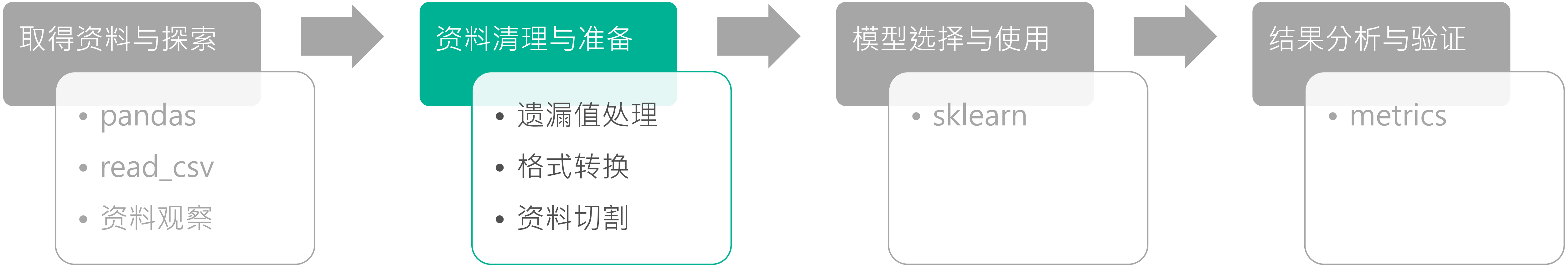
请用相同方式

观察房产位置与借贷状态是否有关连性

调阅数据– 自雇者 VS. 借贷状态



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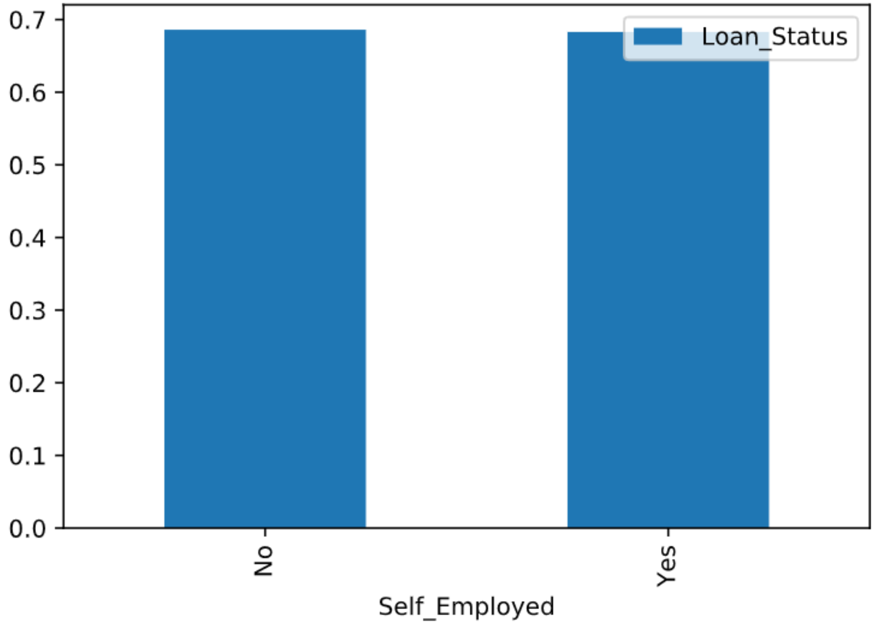
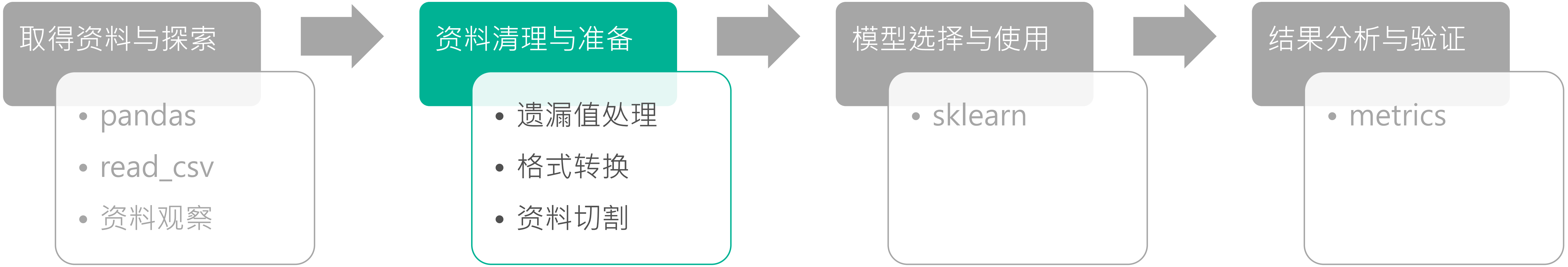
练习

请用相同方式

观察自雇者与借贷状态是否有关连性



调阅数据– 信用纪录 VS. 借贷状态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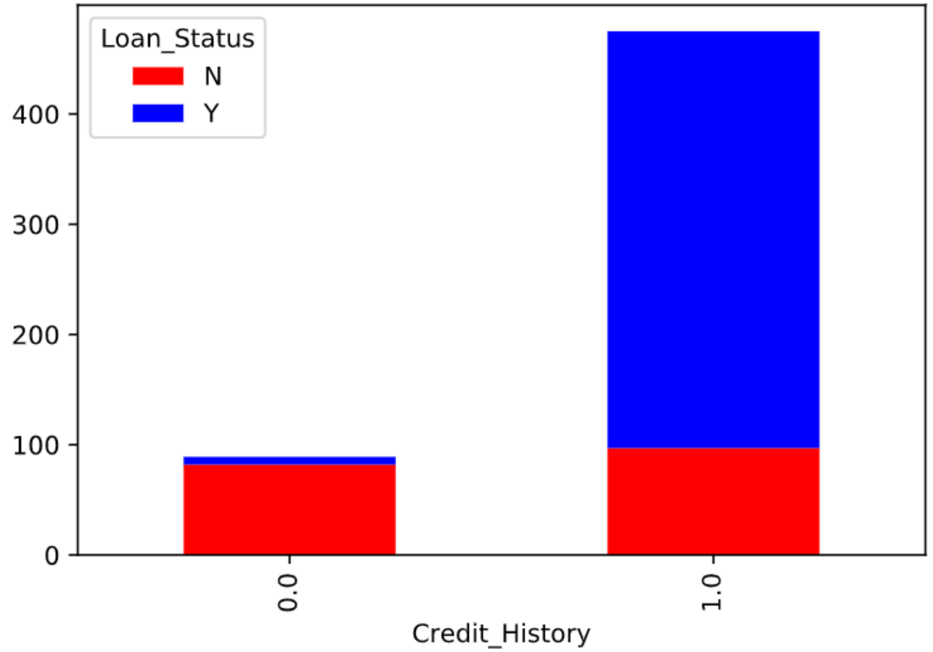
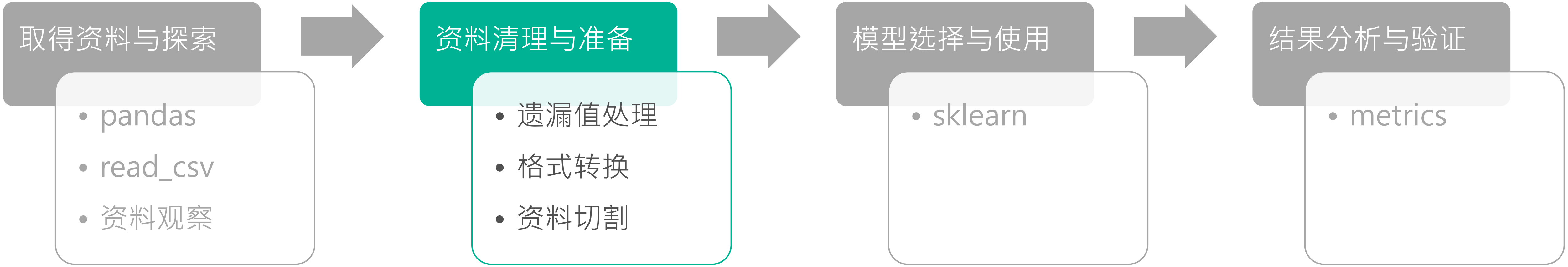
换一种呈现方式！

```
temp5 = pd.crosstab(df['Credit_History'],df
['Loan_Status'])
temp5.plot(kind='bar', stacked=True, color=
['red','blue'],grid=False)
```



调阅数据– 信用纪录/性别 VS. 借贷状态



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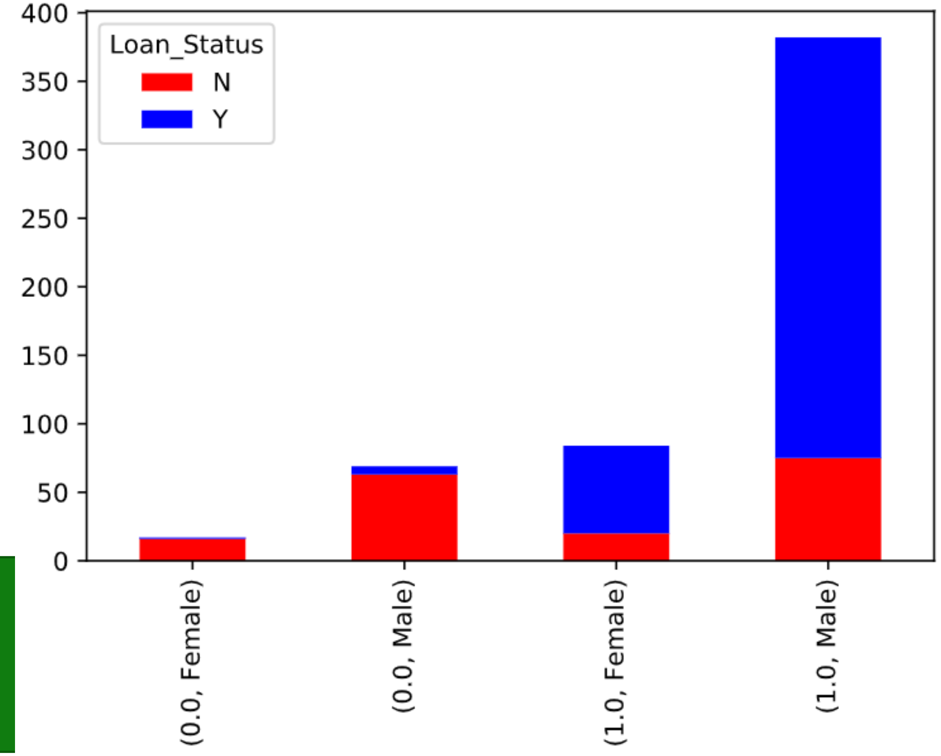
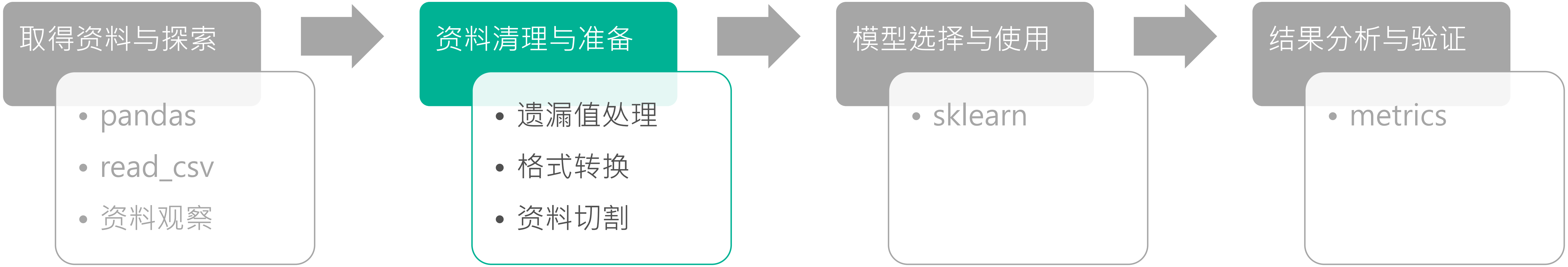
```
temp6 = pd.crosstab([df['Credit_History']]
,df['Gender']],df['Loan_Status'])
temp6.plot(kind='bar',stacked=True, color
=['red','blue'])
```



男性&有信用纪录的，借贷核准机会最大！
注意：有使用到性别栏位，前面若有删除需重新载入数据

调阅数据– 遗漏值综览



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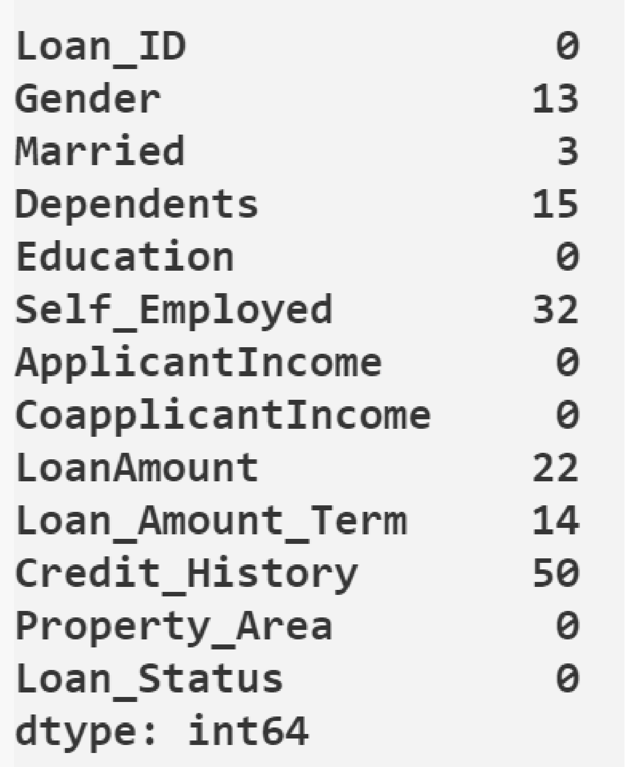
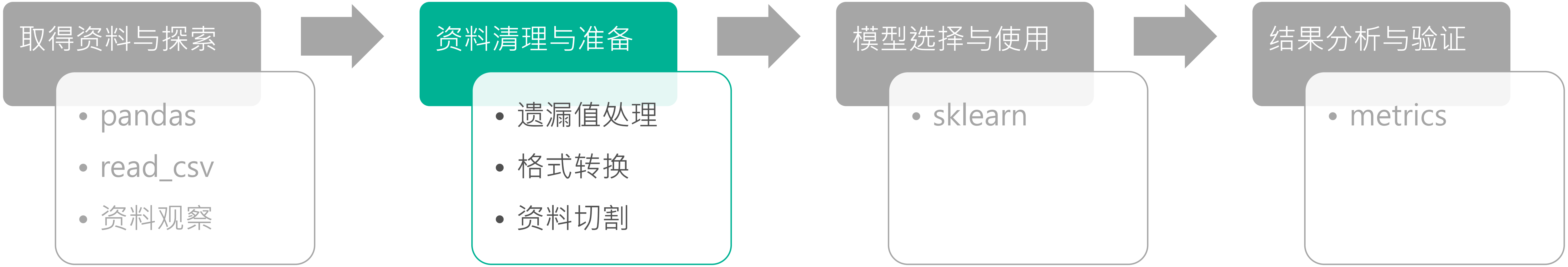
```
df.apply(lambda x: sum(x.isnull()),axis=0)
```



```
Loan_ID               0
Gender               13
Married               3
Dependents           15
Education             0
Self_Employed        32
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           22
Loan_Amount_Term     14
Credit_History       50
Property_Area         0
Loan_Status           0
dtype: int64
```

遗漏值最多的是：信用纪录、是否为自雇者、借贷金额

处理借贷金额的遗漏值I – 使用平均值



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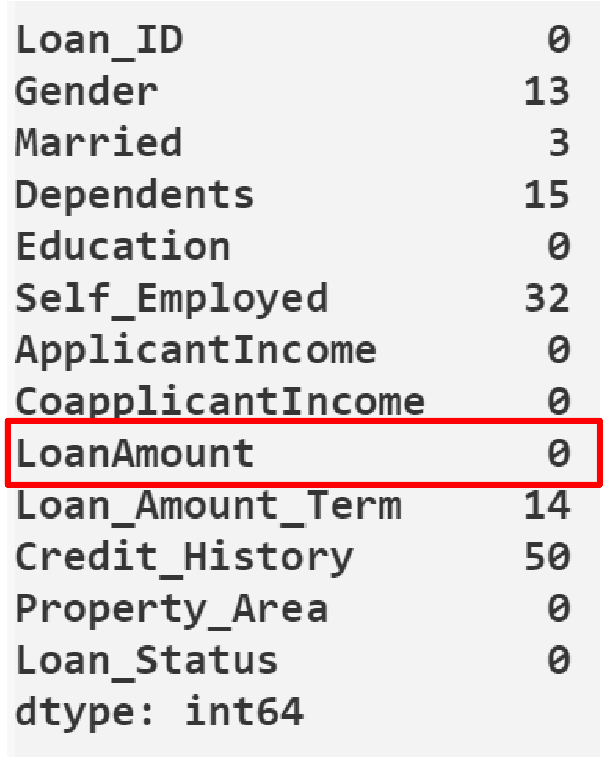
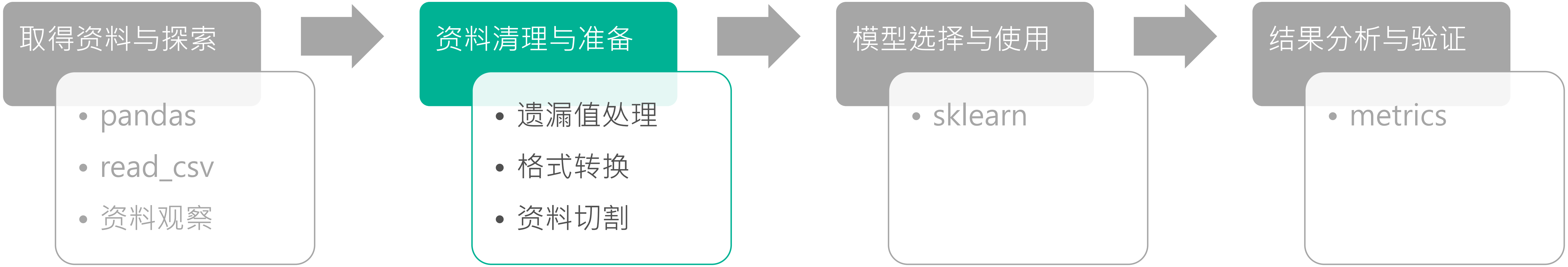
```
df['LoanAmount'].fillna(df['LoanAmount'].mean(),
inplace=True)
df.apply(lambda x: sum(x.isnull()),axis=0)
```



```
Loan_ID               0
Gender               13
Married               3
Dependents           15
Education             0
Self_Employed        32
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount            0
Loan_Amount_Term     14
Credit_History       50
Property_Area         0
Loan_Status           0
dtype: int64
```

填补完成后，再次查阅遗漏值

处理借贷金额的遗漏值 – 查看填补值



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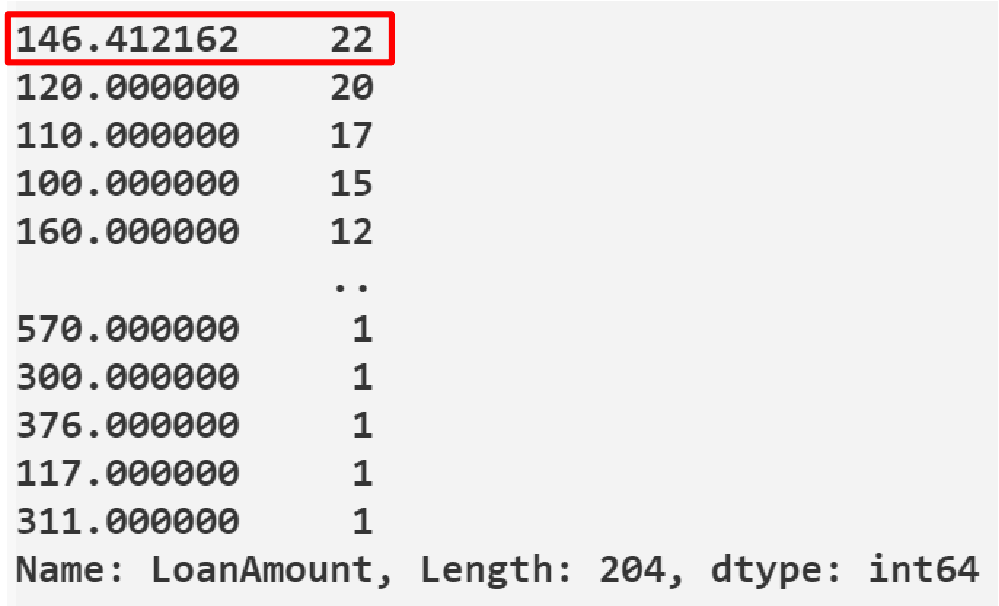
```
df['LoanAmount'].fillna(df['LoanAmount'].mean(),
inplace=True)
df.apply(lambda x: sum(x.isnull()),axis=0)

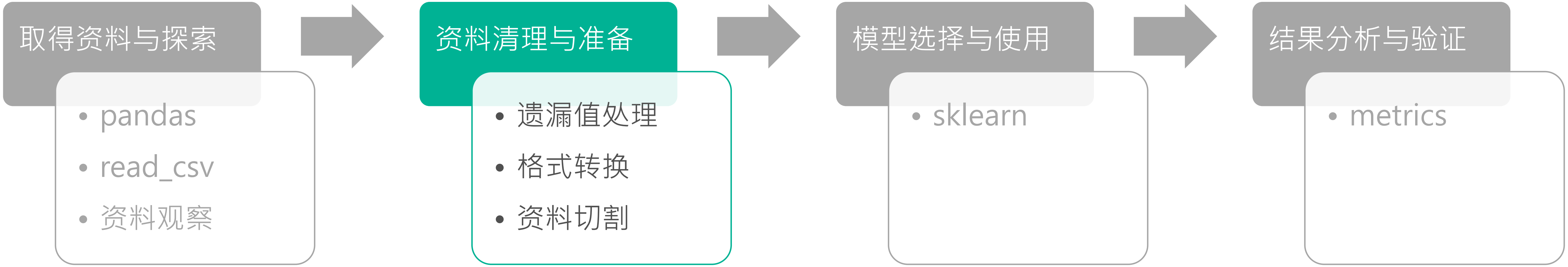
df['LoanAmount'].value_counts()
```



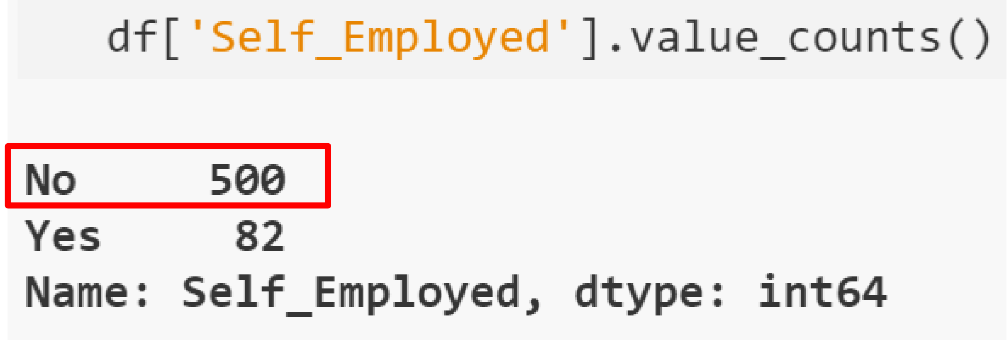
```
146.412162    22
120.000000    20
110.000000    17
100.000000    15
160.000000    12
              ..
570.000000     1
300.000000     1
376.000000     1
117.000000     1
311.000000     1
Name: LoanAmount, Length: 204, dtype: int64
```

填补完成后，再次查阅遗漏值

处理是否为自雇者的遗漏值 – 使用多数

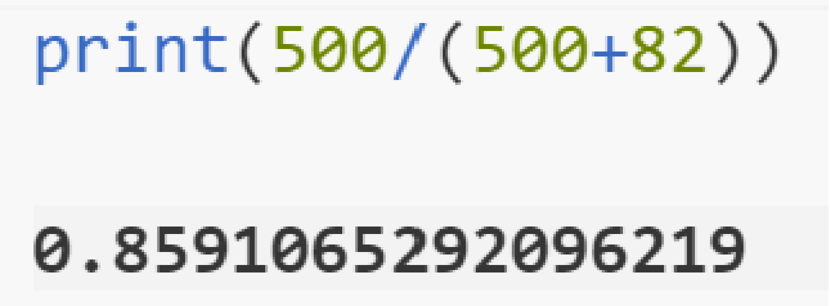


```
df['Self_Employed'].value_counts()
print(500/(500+82))
```



```
df['Self_Employed'].value_counts()

No        500
Yes        82
Name: Self_Employed, dtype: int64
```

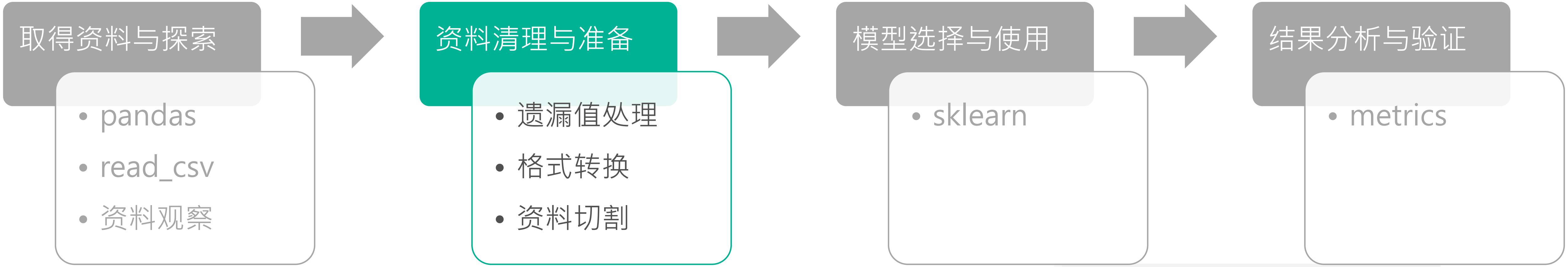


```
print(500/(500+82))

0.8591065292096219
```

非自雇者的比例为85.9 %

处理是否为自雇者的遗漏值 – 使用多数



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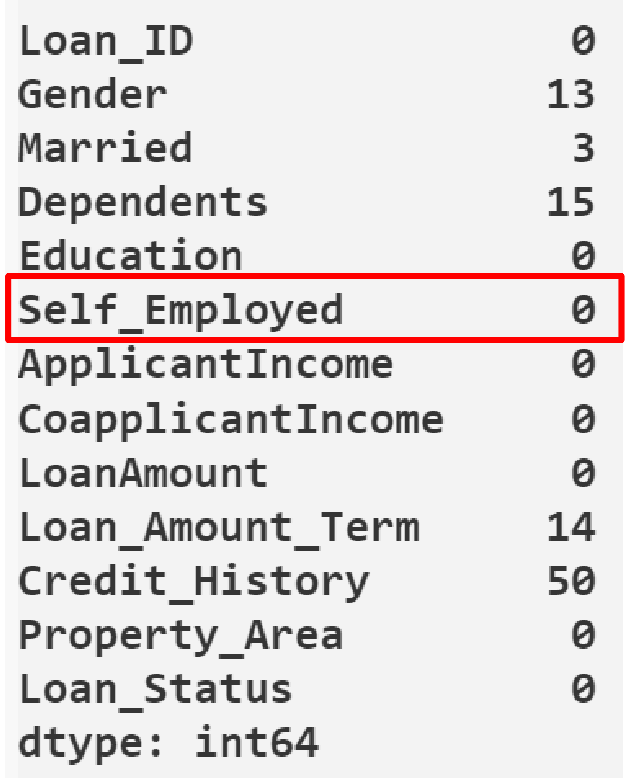
```
df['Self_Employed'].value_counts()
print(500/(500+82))

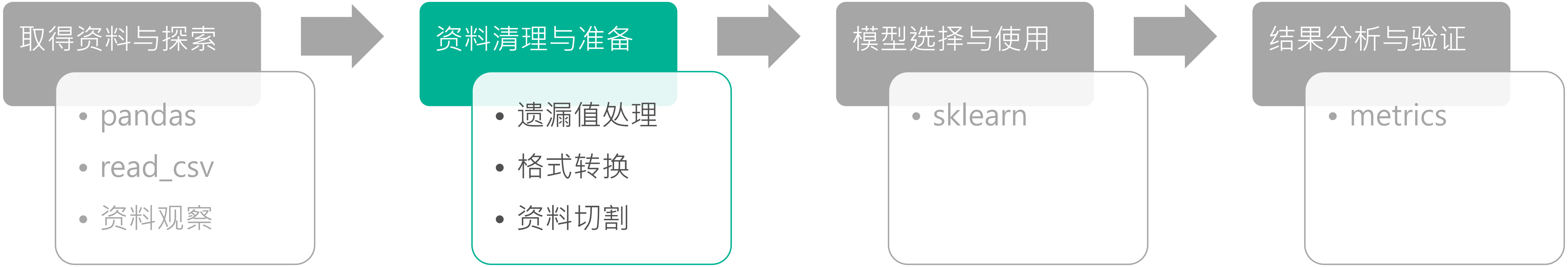
df['Self_Employed'].fillna("No", inplace=True)
```



```
Loan_ID               0
Gender               13
Married               3
Dependents           15
Education             0
Self_Employed         0
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount            0
Loan_Amount_Term     14
Credit_History       50
Property_Area         0
Loan_Status           0
dtype: int64
```

所以使用No来填补是否为自雇者的遗漏值

处理借贷金额的遗漏值II – 取得个别情况的中位数



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```
table =
df.pivot_table(values='LoanAmount',index='Self_Employed',columns='Education',aggfunc
=np.median)
def fage(x):
    return table.loc[x['Self_Employed'],x['Education']]

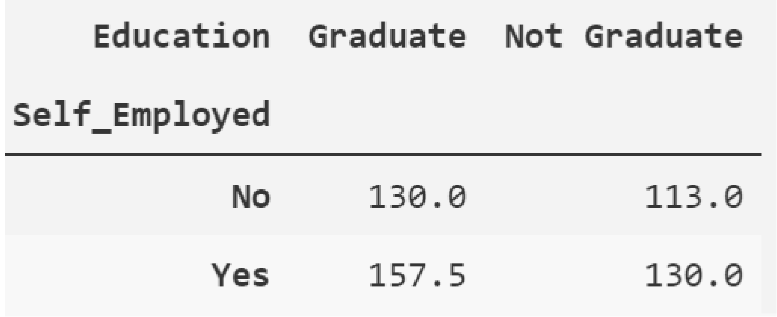
df['LoanAmount'].fillna(df.apply(fage, axis=1),inplace=True)
```

依是否毕业、是否为自雇者分成四类，算出个别中位数

使用该中位数来填补

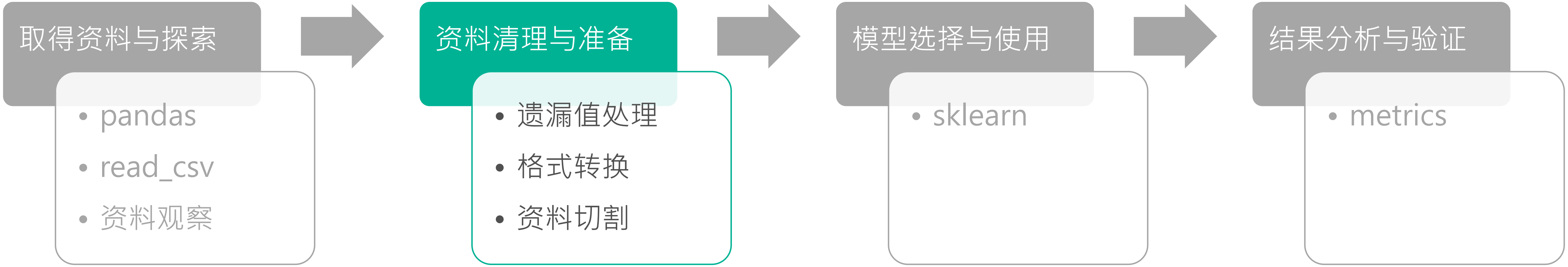
注意：需先确认要用到的Self_Employed、Education已无遗漏值

注意二：实作时记得先将方法一(用平均值填补借贷金额遗漏值)还原



```
    Education  Graduate  Not Graduate
Self_Employed
           No     130.0         113.0
          Yes     157.5         130.0
```

借贷金额的观察 – 取对数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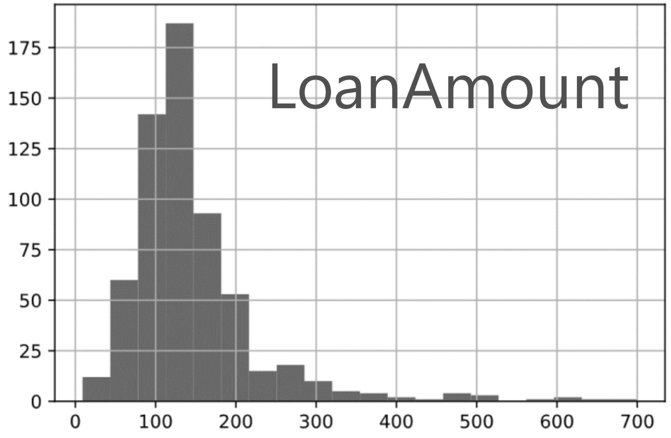
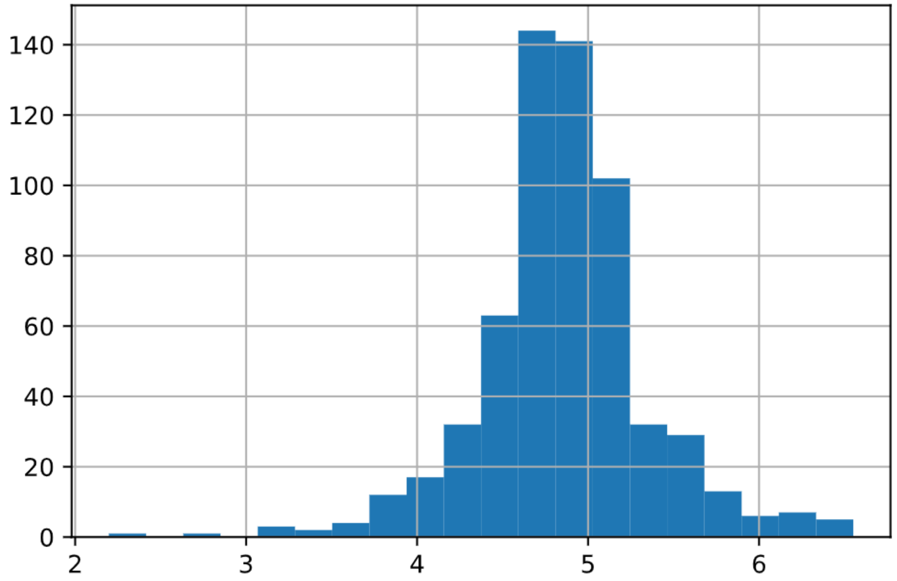
```
df['LoanAmount_log'] = np.log(df['LoanAmount'])
df['LoanAmount_log'].hist(bins=20)
```

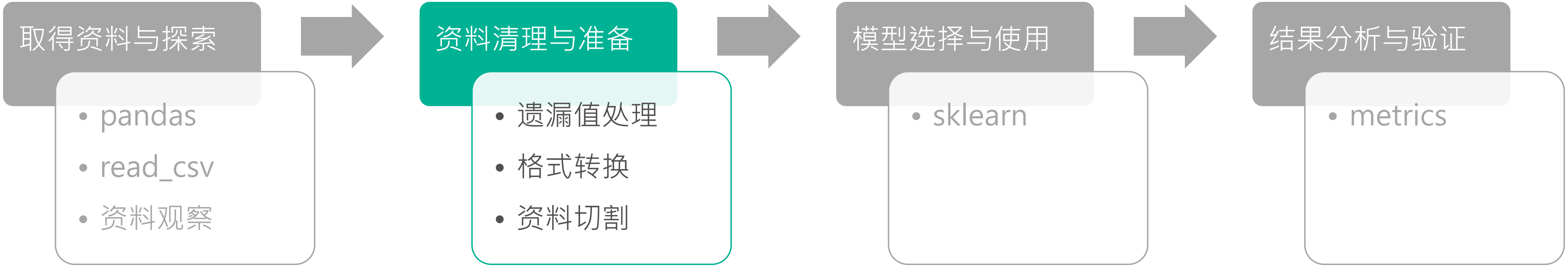




LoanAmount_log

透过对数的转换来处理异常值，而非删除

申请者本人收入 + 共同申请者收入



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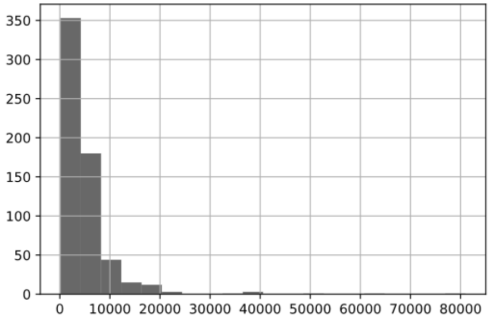
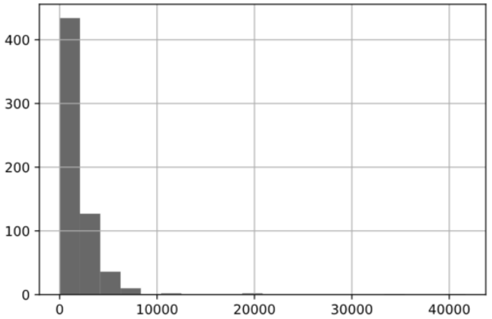
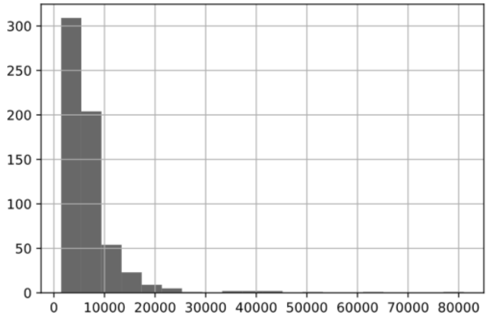
```
df['TotalIncome'] = df['ApplicantIncome']+df['CoapplicantIncome']
df['TotalIncome_log'] = np.log(df['TotalIncome'])
df['TotalIncome_log'].hist(bins=20)
```



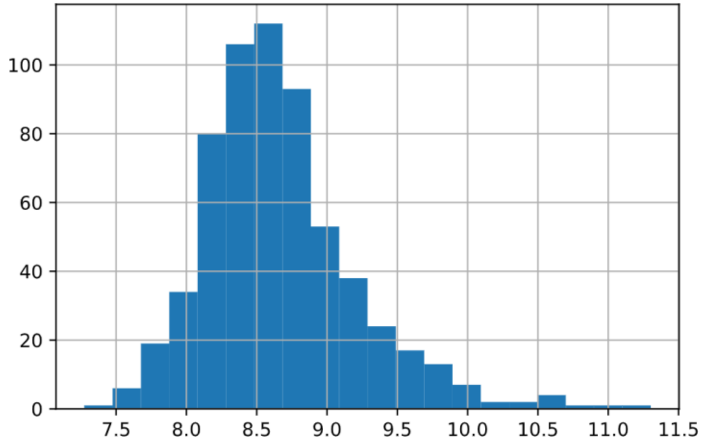
ApplicantIncome



CoapplicantIncome



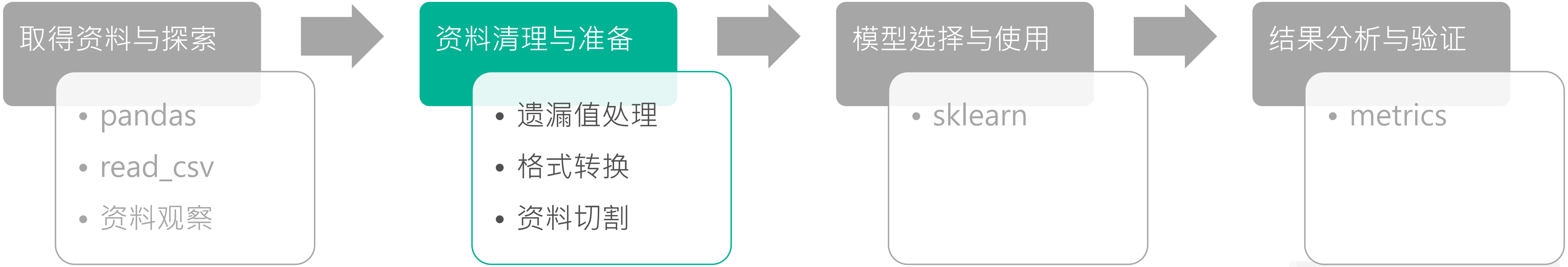
TotalIncome



TotalIncome_log

透过对数的转换来处理异常值，而非删除

遗漏值填补：剩下的都用最高频率值填补



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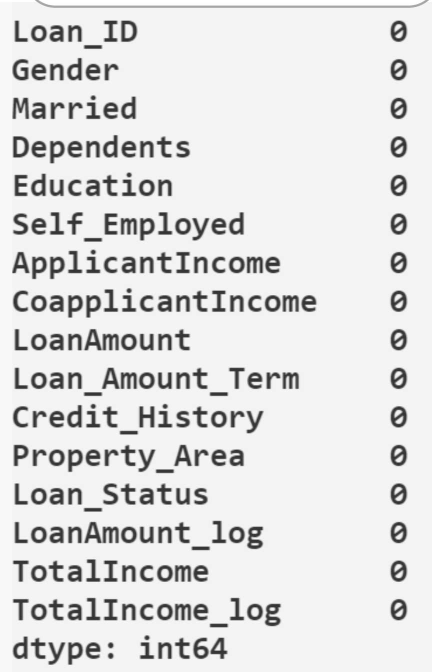
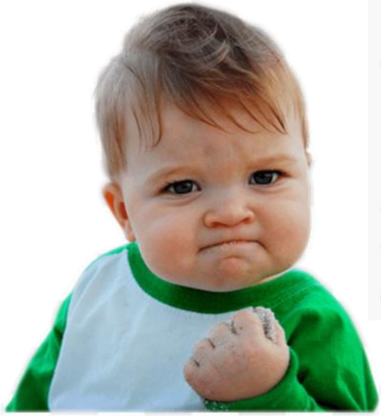
```
df['Gender'].fillna(df['Gender'].mode()[0],inplace=True)
df['Married'].fillna(df['Married'].mode()[0],inplace=True)
df['Dependents'].fillna(df['Dependents'].mode()[0],inplace=True)
df['Loan_Amount_Term'].fillna(df['Loan_Amount_Term'].mode()[0],inplace=True)
df['Credit_History'].fillna(df['Credit_History'].mode()[0],inplace=True)

df.apply(lambda x: sum(x.isnull()),axis=0)
```

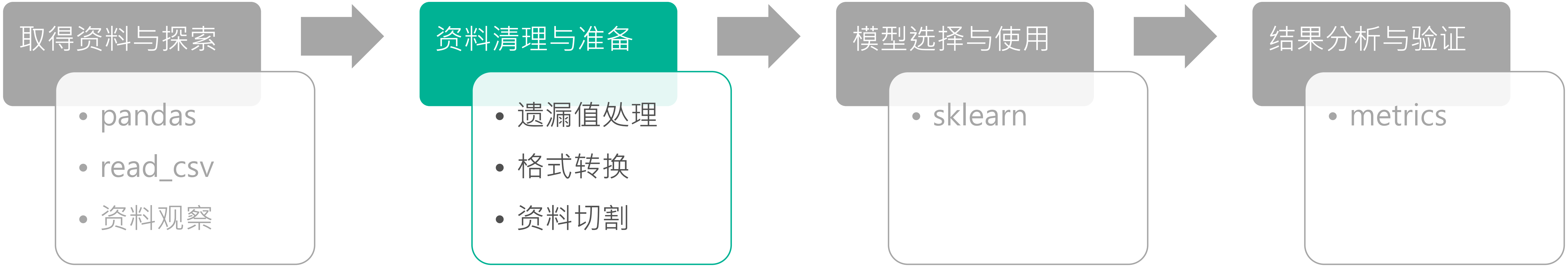


```
Loan_ID              0
Gender               0
Married              0
Dependents           0
Education            0
Self_Employed        0
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           0
Loan_Amount_Term     0
Credit_History       0
Property_Area        0
Loan_Status          0
LoanAmount_log       0
TotalIncome          0
TotalIncome_log      0
dtype: int64
```



一个集合的mode就是最常出现的值，可能回传多个所以取第0个

将非数值转换为数值



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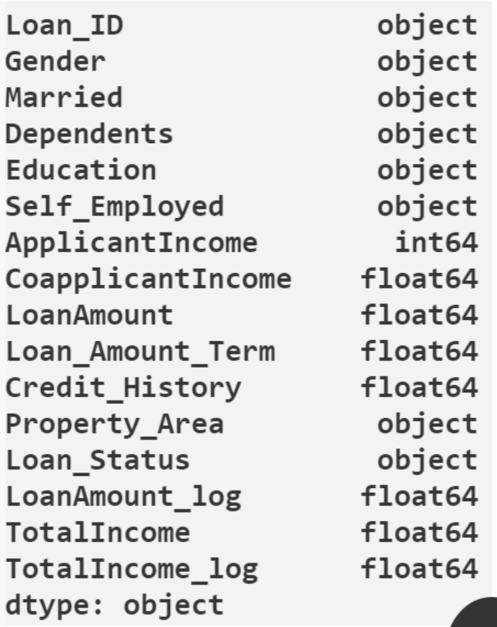
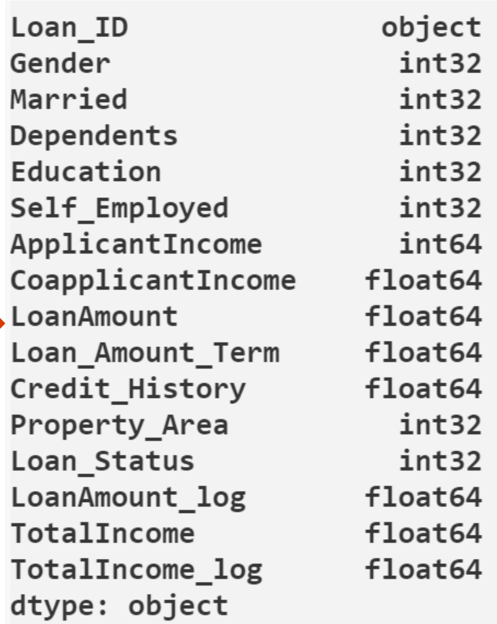
```
df.dtypes
from sklearn.preprocessing import LabelEncoder

var_mod = ['Gender','Married','Dependents','Education',
'Self_Employed','Property_Area','Loan_Status']
le = LabelEncoder()
for i in var_mod:
    df[i] = le.fit_transform(df[i])
df.dtypes
```



```
Loan_ID               object
Gender                object
Married               object
Dependents            object
Education             object
Self_Employed         object
ApplicantIncome        int64
CoapplicantIncome    float64
LoanAmount           float64
Loan_Amount_Term     float64
Credit_History       float64
Property_Area         object
Loan_Status           object
LoanAmount_log       float64
TotalIncome          float64
TotalIncome_log      float64
dtype: object
```

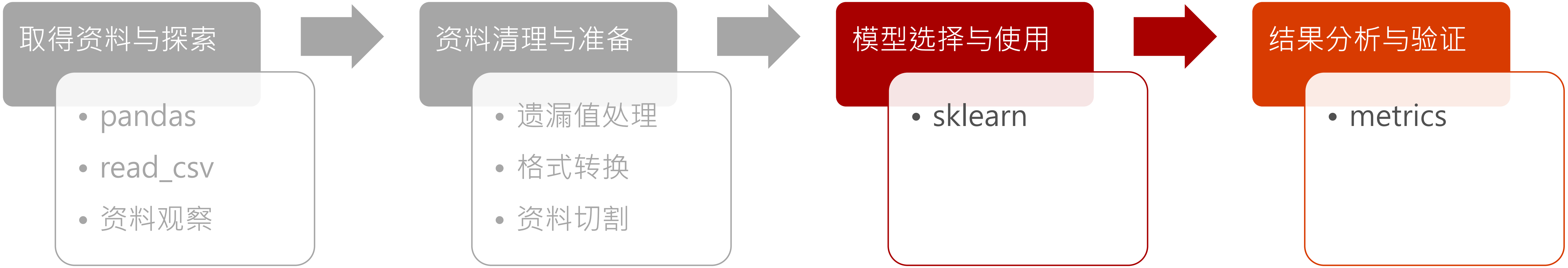


```
Loan_ID               object
Gender                 int32
Married                int32
Dependents             int32
Education              int32
Self_Employed          int32
ApplicantIncome        int64
CoapplicantIncome    float64
LoanAmount           float64
Loan_Amount_Term     float64
Credit_History       float64
Property_Area          int32
Loan_Status            int32
LoanAmount_log       float64
TotalIncome          float64
TotalIncome_log      float64
dtype: object
```

fit_transform()：回传处理好的数值

pngmart.com

使用LogisticRegression

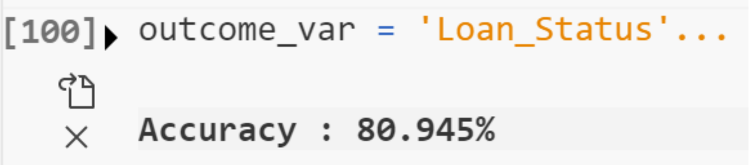


先只用信用纪录来进行训练

```
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn import metrics

def loan_model(model, data, predictors, outcome):
    model.fit(data[predictors],data[outcome])
    predictions = model.predict(data[predictors])
    accuracy = metrics.accuracy_score(predictions, data[outcome])
    print("Accuracy : %s" % "{0:.3%}".format(accuracy))
    model.fit(data[predictors],data[outcome])

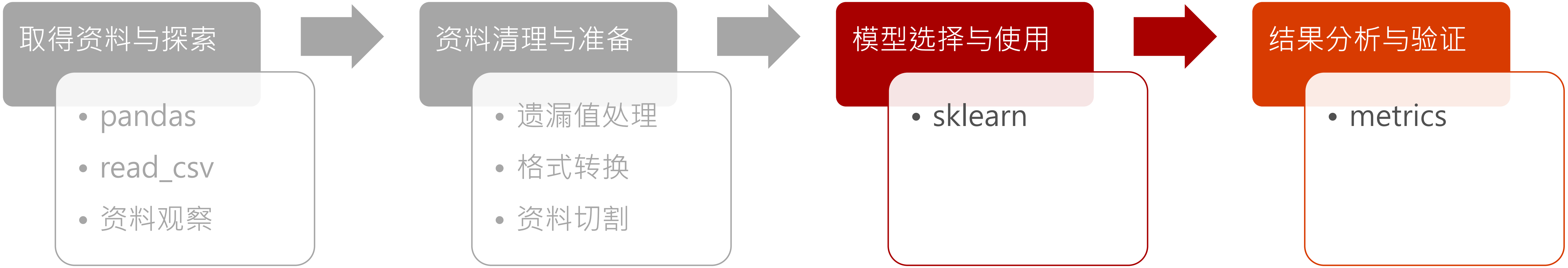
outcome_var = 'Loan_Status'
model = LogisticRegression()
predictor_var = ['Credit_History']
loan_model(model,df,predictor_var,outcome_var)
```



```
[100] outcome_var = 'Loan_Status'...

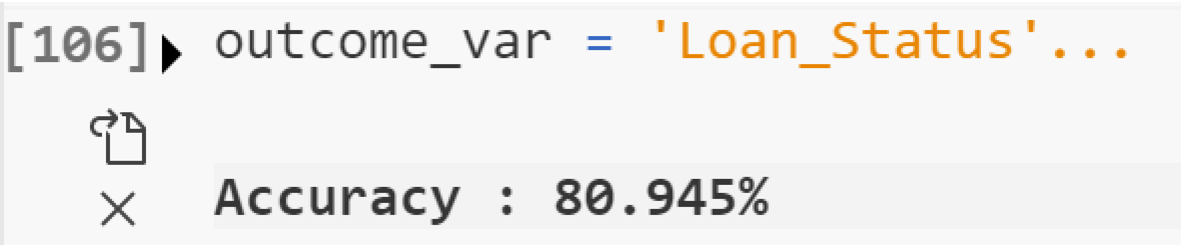
Accuracy : 80.945%
```

使用DecisionTree试试



```
from sklearn.tree import DecisionTreeClassifier, export_graphviz
outcome_var = 'Loan_Status'
model2 = DecisionTreeClassifier()
predictor_var2 = ['Credit_History']
loan_model(model2, df, predictor_var2, outcome_var)
```

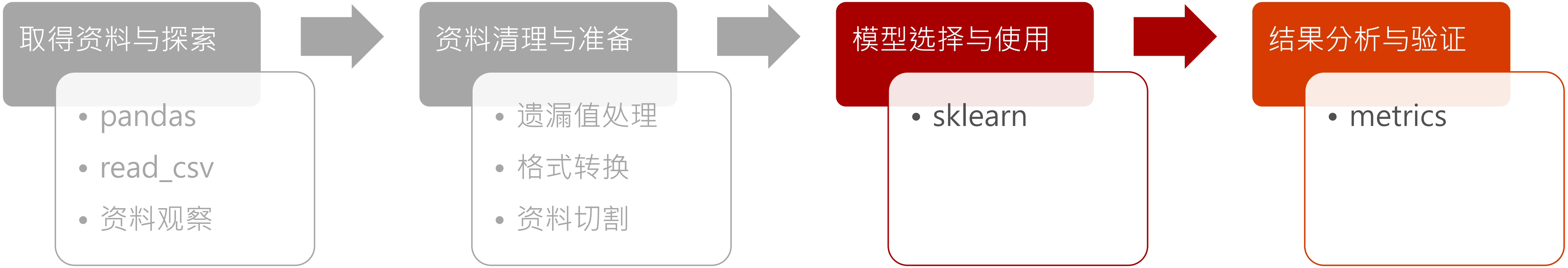
结果相同



```
[106] outcome_var = 'Loan_Status'...

Accuracy : 80.945%
```

多加几个预测参数试试



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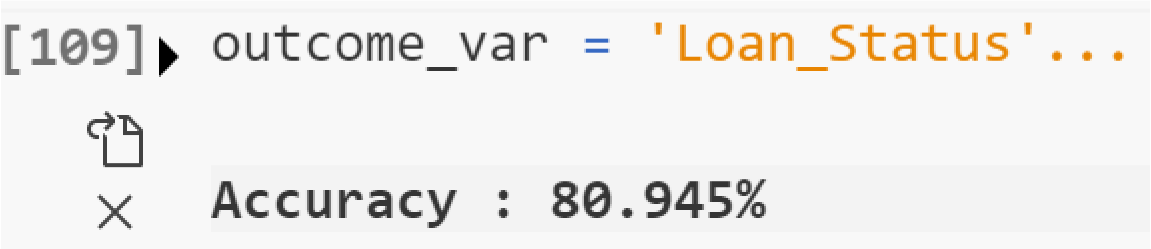
```
outcome_var = 'Loan_Status'
model = LogisticRegression()
predictor_var = ['Credit_History','Gender','Married','Education']
loan_model(model,df,predictor_var,outcome_var)
```

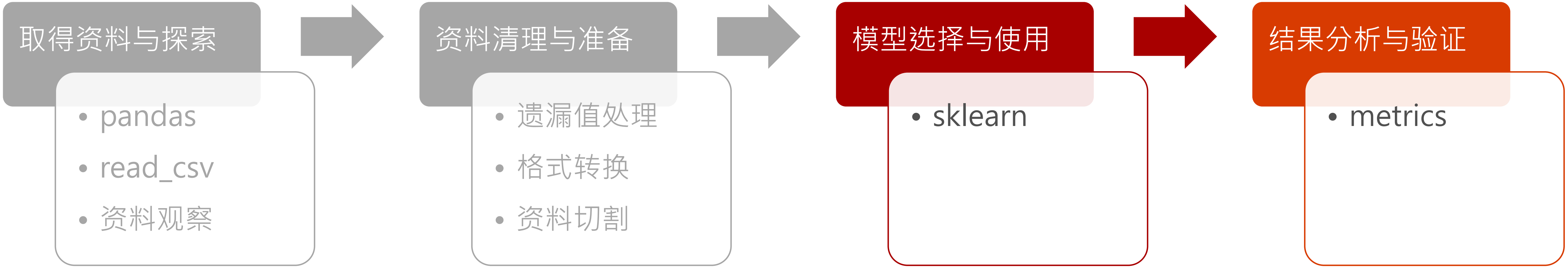
结果相同



```
[109] outcome_var = 'Loan_Status'...

Accuracy : 80.945%
```

再换一个模型



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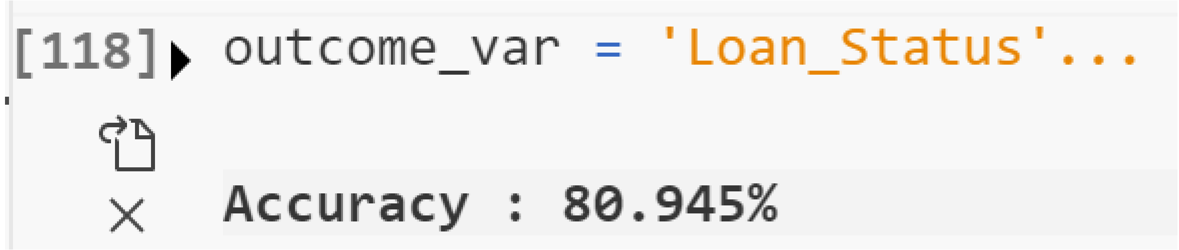
```
outcome_var = 'Loan_Status'
model3 = RandomForestClassifier(n_estimators=10)
predictor_var3 = ['Credit_History','Gender','Married','Education']
loan_model(model3,df,predictor_var3,outcome_var)
```

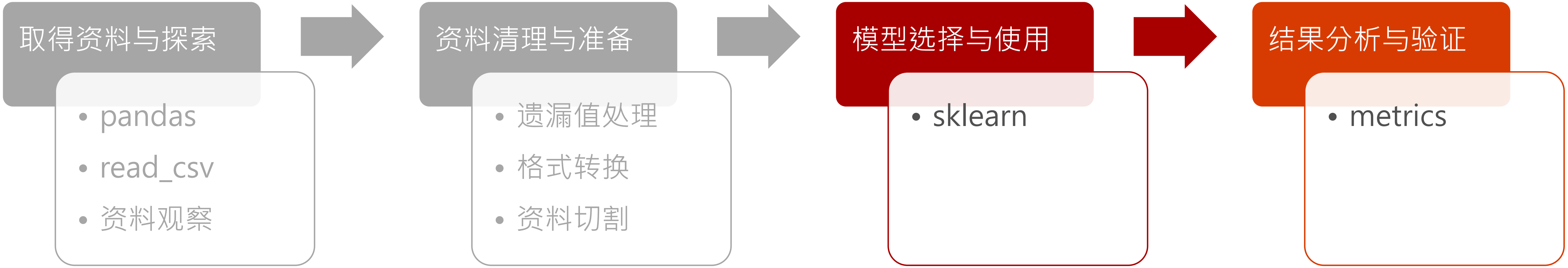
结果相同



```
[118] outcome_var = 'Loan_Status'...

      Accuracy : 80.945%
```

再多加几个参数，包含调整过的参数



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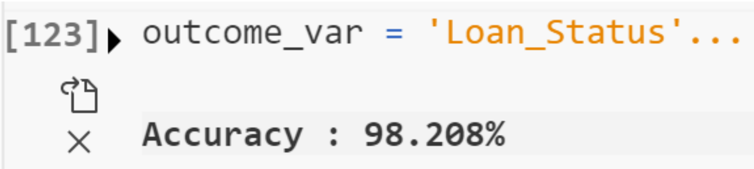
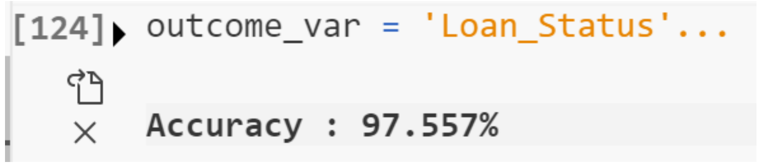
```
outcome_var = 'Loan_Status'
model2 = DecisionTreeClassifier()
predictor_var2 = ['Gender','Married','Dependents',
'Education','Self_Employed','Credit_History','Property_Area','LoanAmount_log']
loan_model(model2, df, predictor_var2, outcome_var)
```



```
[123] outcome_var = 'Loan_Status'...

Accuracy : 98.208%
```

```
outcome_var = 'Loan_Status'
model3 = RandomForestClassifier(n_estimators=10)
predictor_var3 = ['Gender','Married','Dependents',
'Education','Self_Employed','Credit_History','Property_Area','LoanAmount_log']
loan_model(model3,df,predictor_var3,outcome_var)
```

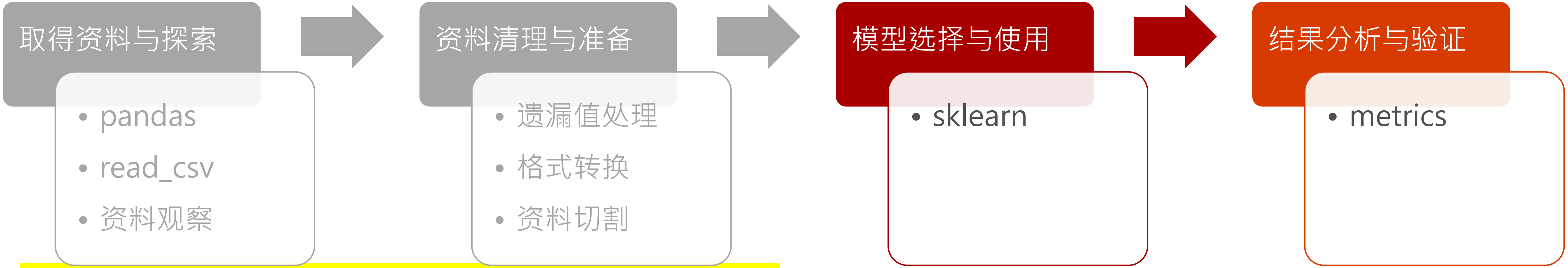


```
[124] outcome_var = 'Loan_Status'...

Accuracy : 97.557%
```

终于有了较佳的成果!

将数据分成测试与训练



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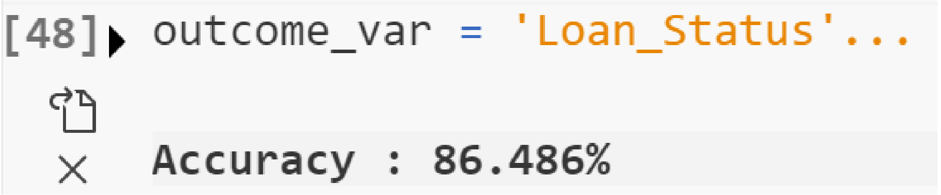
```
from sklearn.model_selection import train_test_split
def loan_modelv2(model, data, predictors, outcome, t_size, rs_number):
    X = data[predictors]
    y = data[outcome]
    X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=t_size,random_state=rs_number)
    model.fit(X_train[predictors],y_train)
    predictions = model.predict(X_test)
    accuracy = metrics.accuracy_score(predictions, y_test)
    print("Accuracy : %s" % "{0:.3%}".format(accuracy))
    model.fit(X_train[predictors],y_train)

outcome_var = 'Loan_Status'
model = LogisticRegression()
predictor_var = ['Gender', 'Education','Self_Employed','Credit_History','Property_Area','LoanAmount_log']
loan_modelv2(model,df,predictor_var,outcome_var,0.3,8)
```



```
[48] outcome_var = 'Loan_Status'...

Accuracy : 86.486%
```

虽然低一些，但比较贴近真实状况

小结

- 成熟的模型未必一定能带来最佳成效，数据的筛选与转换有时才是胜出的关键!
- 多了解各种模型的特性与使用时机，多多实验，累积经验
- 特征工程(Feature Engineering)影响力高，让数据更适合当前的模型!

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感谢聆听

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