导入包、模块

```
# 基础
import os
import zipfile
import numpy as np
import pandas as pd
# 画图
import seaborn as sns
import matplotlib.pyplot as plt
from matplotlib import font_manager as fm
from matplotlib import cm
% matplotlib inline
plt.style.use('ggplot')
# 中文图输出
from pylab import mpl
mpl.rcParams['font.sans-serif'] = ['STZhongsong'] # 指定默认字体: 解决plot不能显
mpl.rcParams['axes.unicode_minus'] = False
                                                  #解决保存图像是负号'-'显示为方
块的问题
# 数据集归一化
from sklearn import datasets
from sklearn import preprocessing
#切割训练数据和样本数据
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import StratifiedKFold,cross_val_score
# 模型
from sklearn.neighbors import KNeighborsClassifier
from sklearn.neural_network import MLPClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
# from sklearn.metrics import mean_squared_error
from sklearn.metrics import *
# 导出决策树
import graphviz
import pydotplus
from sklearn.tree import export_graphviz
from sklearn.externals.six import StringIO
```

```
C:\ProgramData\Anaconda3\lib\site-
packages\sklearn\ensemble\weight_boosting.py:29: DeprecationWarning:
numpy.core.umath_tests is an internal NumPy module and should not be imported.
It will be removed in a future NumPy release.
from numpy.core.umath_tests import inner1d
```

```
# 定义一个路径引用的函数

def file_path(dir_path,dir_name):
    con_path =
"D:\\onedrive\\02_work\\01_ScienceResearch\\01_undergraduate_thesis\\01_data\\"
    path = os.path.join(con_path,dir_path,dir_name)
    return path
```

导入原始数据

对2010-2016年经济指标文件解压

读入数据

```
# 去掉各个变量的标签
pd.read_csv(file_path("01_rawdata","ACS_10_5YR_DP02_with_ann.csv"))
[1:].to_csv(file_path("02_output","ACS_10_5YR_DP02_with_ann.csv"),encoding="utf-
pd.read_csv(file_path("01_rawdata","ACS_11_5YR_DP02_with_ann.csv"))
[1:].to_csv(file_path("02_output","ACS_11_5YR_DP02_with_ann.csv"),encoding="utf-
pd.read_csv(file_path("01_rawdata","ACS_12_5YR_DP02_with_ann.csv"))
[1:].to_csv(file_path("02_output","ACS_12_5YR_DP02_with_ann.csv"),encoding="utf-
8-sig")
pd.read_csv(file_path("01_rawdata","ACS_13_5YR_DP02_with_ann.csv"))
[1:].to_csv(file_path("02_output","ACS_13_5YR_DP02_with_ann.csv"),encoding="utf-
8-sig")
pd.read_csv(file_path("01_rawdata","ACS_14_5YR_DP02_with_ann.csv"))
[1:].to_csv(file_path("02_output","ACS_14_5YR_DP02_with_ann.csv"),encoding="utf-
8-sig")
pd.read_csv(file_path("01_rawdata","ACS_15_5YR_DP02_with_ann.csv"))
[1:].to_csv(file_path("02_output","ACS_15_5YR_DP02_with_ann.csv"),encoding="utf-
pd.read_csv(file_path("01_rawdata","ACS_16_5YR_DP02_with_ann.csv"))
[1:].to_csv(file_path("02_output","ACS_16_5YR_DP02_with_ann.csv"),encoding="utf-
# 读入2010-2016年经济指标数据
ACS_{10_5YR_DP02_with_ann} =
pd.read_csv(file_path("02_output","ACS_10_5YR_DP02_with_ann.csv"),na_values=["
(X)","*****","***","-","+","N"])
ACS_{11_5YR_DP02_with_ann} =
pd.read_csv(file_path("02_output","ACS_11_5YR_DP02_with_ann.csv"),na_values=["
(X)","*****","***","-","+","N"])
```

```
ACS_{12_5YR_DP02_with_ann} =
pd.read_csv(file_path("02_output","ACS_12_5YR_DP02_with_ann.csv"),na_values=["
(X)","*****","***","**","-","+","N"])
ACS_13_5YR_DP02_with_ann =
pd.read_csv(file_path("02_output","ACS_13_5YR_DP02_with_ann.csv"),na_values=["
(X)","*****","***","-","+","N"])
ACS_14_5YR_DP02_with_ann =
pd.read_csv(file_path("02_output","ACS_14_5YR_DP02_with_ann.csv"),na_values=["
(X)","*****","***","-","+","N"])
ACS_15_5YR_DP02_with_ann =
pd.read_csv(file_path("02_output","ACS_15_5YR_DP02_with_ann.csv"),na_values=["
(X)","*****","***","-","+","N"])
ACS_16_5YR_DP02_with_ann =
pd.read_csv(file_path("02_output","ACS_16_5YR_DP02_with_ann.csv"),na_values=["
(X)","*****","***","-","+","N"])
# # 读入各个地区阿片类使用量数据
MCM_NFLIS_Data=pd.read_excel(file_path("01_rawdata","MCM_NFLIS_Data.xlsx"),sheet
_ne=1)
# # 读入药物具体分类数据
MCM_NFLIS_Medication=pd.read_csv(file_path("01_rawdata","class_medication.csv"))
# 读入变量标签数据
ACS_10_5YR_DP02_metadata =
pd.read_csv(file_path("01_rawdata","ACS_10_5YR_DP02_metadata.csv"),header=None)
ACS_11_5YR_DP02_metadata =
pd.read_csv(file_path("01_rawdata","ACS_11_5YR_DP02_metadata.csv"),header=None)
ACS_12_5YR_DP02_metadata =
pd.read_csv(file_path("01_rawdata","ACS_12_5YR_DP02_metadata.csv"),header=None)
ACS_13_5YR_DP02_metadata =
pd.read_csv(file_path("01_rawdata","ACS_13_5YR_DP02_metadata.csv"),header=None)
ACS_14_5YR_DP02_metadata =
pd.read_csv(file_path("01_rawdata","ACS_14_5YR_DP02_metadata.csv"),header=None)
ACS_15_5YR_DP02_metadata =
pd.read_csv(file_path("01_rawdata","ACS_15_5YR_DP02_metadata.csv"),header=None)
ACS_16_5YR_DP02_metadata =
pd.read_csv(file_path("01_rawdata","ACS_16_5YR_DP02_metadata.csv"),header=None)
```

数据处理

整理ACS_ALL_5YR_DP02数据

```
## 处理无效数据
# 2010
# 删除类型异常的变量 (NaN、(x))
typedata = ACS_10_5YR_DP02_with_ann.dtypes.reset_index()
nonnormal_var = typedata.loc[typedata.ix[:,1] == "object"]["index"][2:].tolist()
ACS_10_5YR_DP02_DropNorm = ACS_10_5YR_DP02_with_ann.drop(nonnormal_var,axis=1)
# 删除全为空的变量 (列)
ACS_10_5YR_DP02_DropColumn=ACS_10_5YR_DP02_DropNorm.dropna(axis=1,how="all")
# 用列均值填补缺失数据
for column in
list(ACS_10_5YR_DP02_DropColumn.columns[ACS_10_5YR_DP02_DropColumn.isnull().sum()
) > 0]):
    mean_val = ACS_10_5YR_DP02_DropColumn[column].mean()
    ACS_10_5YR_DP02_DropColumn[column].fillna(mean_val, inplace=True)
# 2011
```

```
# 删除类型异常的变量(NaN、(x))
typedata = ACS_11_5YR_DP02_with_ann.dtypes.reset_index()
nonnormal_var = typedata.loc[typedata.ix[:,1] == "object"]["index"][2:].tolist()
ACS_11_5YR_DP02_DropNorm = ACS_11_5YR_DP02_with_ann.drop(nonnormal_var,axis=1)
# 删除全为空的变量(列)
ACS_11_5YR_DP02_DropColumn=ACS_11_5YR_DP02_DropNorm.dropna(axis=1,how="all")
# 用列均值填补缺失数据
for column in
list(ACS_11_5YR_DP02_DropColumn.columns[ACS_11_5YR_DP02_DropColumn.isnull().sum(
) > 0]):
   mean_val = ACS_11_5YR_DP02_DropColumn[column].mean()
   ACS_11_5YR_DP02_DropColumn[column].fillna(mean_val, inplace=True)
# 2012
# 删除类型异常的变量(NaN、(x))
typedata = ACS_12_5YR_DP02_with_ann.dtypes.reset_index()
nonnormal_var = typedata.loc[typedata.ix[:,1] == "object"]["index"][2:].tolist()
ACS_12_5YR_DP02_DropNorm = ACS_12_5YR_DP02_with_ann.drop(nonnormal_var,axis=1)
# 删除全为空的变量(列)
ACS_12_5YR_DP02_DropColumn=ACS_12_5YR_DP02_DropNorm.dropna(axis=1,how="all")
# 用列均值填补缺失数据
for column in
list(ACS_12_5YR_DP02_DropColumn.columns[ACS_12_5YR_DP02_DropColumn.isnull().sum(
) > 0]):
   mean_val = ACS_12_5YR_DP02_DropColumn[column].mean()
   ACS_12_5YR_DP02_DropColumn[column].fillna(mean_val, inplace=True)
# 2013
# 删除类型异常的变量(NaN、(x))
typedata = ACS_13_5YR_DP02_with_ann.dtypes.reset_index()
nonnormal_var = typedata.loc[typedata.ix[:,1] == "object"]["index"][2:].tolist()
ACS_13_5YR_DP02_DropNorm = ACS_13_5YR_DP02_with_ann.drop(nonnormal_var,axis=1)
# 删除全为空的变量(列)
ACS_13_5YR_DP02_DropColumn=ACS_13_5YR_DP02_DropNorm.dropna(axis=1,how="all")
# 用列均值填补缺失数据
for column in
list(ACS_13_5YR_DP02_DropColumn.columns[ACS_13_5YR_DP02_DropColumn.isnull().sum(
) > 0]):
   mean_val = ACS_13_5YR_DP02_DropColumn[column].mean()
   ACS_13_5YR_DP02_DropColumn[column].fillna(mean_val, inplace=True)
# 2013
# 删除类型异常的变量(NaN、(x))
typedata = ACS_14_5YR_DP02_with_ann.dtypes.reset_index()
nonnormal_var = typedata.loc[typedata.ix[:,1] == "object"]["index"][2:].tolist()
ACS_14_5YR_DP02_DropNorm = ACS_14_5YR_DP02_with_ann.drop(nonnormal_var,axis=1)
# 删除全为空的变量(列)
ACS_14_5YR_DP02_DropColumn=ACS_14_5YR_DP02_DropNorm.dropna(axis=1, how="all")
# 用列均值填补缺失数据
for column in
list(ACS_14_5YR_DP02_DropColumn.columns[ACS_14_5YR_DP02_DropColumn.isnull().sum(
) > 0]):
   mean_val = ACS_14_5YR_DP02_DropColumn[column].mean()
   ACS_14_5YR_DP02_DropColumn[column].fillna(mean_val, inplace=True)
# 2015
# 删除类型异常的变量(NaN、(x))
typedata = ACS_15_5YR_DP02_with_ann.dtypes.reset_index()
```

```
nonnormal_var = typedata.loc[typedata.ix[:,1] == "object"]["index"][2:].tolist()
ACS_15_5YR_DP02_DropNorm = ACS_15_5YR_DP02_with_ann.drop(nonnormal_var,axis=1)
# 删除全为空的变量(列)
ACS_15_5YR_DP02_DropColumn=ACS_15_5YR_DP02_DropNorm.dropna(axis=1, how="all")
# 用列均值填补缺失数据
for column in
list(ACS_15_5YR_DP02_DropColumn.columns[ACS_15_5YR_DP02_DropColumn.isnull().sum(
) > 0]):
    mean_val = ACS_15_5YR_DP02_DropColumn[column].mean()
    ACS_15_5YR_DP02_DropColumn[column].fillna(mean_val, inplace=True)
# 2016
# 删除类型异常的变量(NaN、(x))
typedata = ACS_16_5YR_DP02_with_ann.dtypes.reset_index()
nonnormal_var = typedata.loc[typedata.ix[:,1] == "object"]["index"][2:].tolist()
ACS_16_5YR_DP02_DropNorm = ACS_16_5YR_DP02_with_ann.drop(nonnormal_var,axis=1)
# 删除全为空的变量(列)
ACS_16_5YR_DP02_DropColumn=ACS_16_5YR_DP02_DropNorm.dropna(axis=1, how="all")
# 用列均值填补缺失数据
for column in
list(ACS_16_5YR_DP02_DropColumn.columns[ACS_16_5YR_DP02_DropColumn.isnull().sum(
) > 0]):
    mean_val = ACS_16_5YR_DP02_DropColumn[column].mean()
    ACS_16_5YR_DP02_DropColumn[column].fillna(mean_val, inplace=True)
# 纵向合并2010-2016年的数据到一个数据框中、# 删除第一行数据(变量标签)
ACS_ALL_5YR_DP02=pd.concat([ACS_10_5YR_DP02_DropColumn,
                          ACS_11_5YR_DP02_DropColumn,
                          ACS_12_5YR_DP02_DropColumn,
                          ACS_13_5YR_DP02_DropColumn,
                          ACS_14_5YR_DP02_DropColumn,
                          ACS_15_5YR_DP02_DropColumn,
                          ACS_16_5YR_DP02_DropColumn], axis=0, join="outer", keys=
[2010,2011,2012,2013,2014,2015,2016]).reset_index().convert_objects(convert_nume
ric=True)
# 用列均值填补缺失数据(合并各年份数据之后)
for column in list(ACS_ALL_5YR_DP02.columns[ACS_ALL_5YR_DP02.isnull().sum() >
0]):
    mean_val = ACS_ALL_5YR_DP02[column].mean()
    ACS_ALL_5YR_DP02[column].fillna(mean_val, inplace=True)
# 删除无效的变量(索引,中间产生变量、地理位置),重命名年份变量
ACS_ALL_5YR_DP02_clear = ACS_ALL_5YR_DP02.ix[:,:-2].drop(["GE0.display-
label","level_1","GEO.id"],axis=1).rename(columns={"level_0":"YYYYY"})
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:5:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
C:\ProgramData\Anaconda3\lib\site-packages\pandas\core\generic.py:5434:
SettingWithCopyWarning:
```

A value is trying to be set on a copy of a slice from a DataFrame

```
See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
  self._update_inplace(new_data)
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:17:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:29:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:41:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:53:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:65:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:77:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
```

```
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:93:
FutureWarning: Sorting because non-concatenation axis is not aligned. A future
version
of pandas will change to not sort by default.
To accept the future behavior, pass 'sort=False'.
To retain the current behavior and silence the warning, pass 'sort=True'.
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:93:
FutureWarning: convert_objects is deprecated. To re-infer data dtypes for
object columns, use DataFrame.infer_objects()
For all other conversions use the data-type specific converters pd.to_datetime,
pd.to_timedelta and pd.to_numeric.
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:99:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
```

整理MCM NFLIS Data数据

```
# 对阿片类药物使用情况数据键值重命名
MCM_NFLIS_Data_Rename=MCM_NFLIS_Data.rename(columns={"FIPS_Combined":"GEO.id2"})
# 删除2017相关数据
MCM_NFLIS_Data_Drop17=MCM_NFLIS_Data_Rename.loc[MCM_NFLIS_Data_Rename["YYYY"] !=
2017]
# 匹配药物分类数据
MCM_NFLIS_Class=pd.merge(MCM_NFLIS_Data_Drop17, MCM_NFLIS_Medication, how="left", o
n=["SubstanceName","YYYY"])
# 删除一些无效变量
MCM_NFLIS_Class_Clear_Drop=MCM_NFLIS_Class.drop(["FIPS_State","FIPS_County","Sub
stanceName","code"],axis=1)
# 按照中文名药物分类求和
MCM_NFLIS_Class_Clear =
MCM_NFLIS_Class_Clear_Drop.groupby(["YYYY","GEO.id2","State","COUNTY","Substance
class",
                                                      "SubstanceName_c"])
["DrugReports"].sum().reset_index()
```

整理ACS_All_5YR_DP02_metadata数据

匹配阿片类药物使用情况

```
# 合并阿片类使用情况与相关经济指标
NFLIS_and_ACS_ALL=pd.merge(ACS_ALL_5YR_DP02_Clear,MCM_NFLIS_Class_Clear,how="rig
ht",on=["YYYY","GEO.id2"])
```

按照三类药物数据透视

```
# 分类计数
NFLIS_and_ACS_ALL_ClassSum =
NFLIS_and_ACS_ALL.groupby(["GEO.id2", "State", "COUNTY",
"SubstanceClass","YYYY"])["DrugReports"].sum().reset_index()
# 数据诱视表
NFLIS_and_ACS_ALL_Pivot = pd.pivot_table(data=NFLIS_and_ACS_ALL_ClassSum,
["GEO.id2", "State", "SubstanceClass", "COUNTY"],
                                        columns=["YYYY"], values=
["DrugReports"])
# 缺失值填补、转置
NFLIS_and_ACS_ALL_Clear =
NFLIS_and_ACS_ALL_Pivot[2:].fillna(0).stack().reset_index()
# 合并
NFLIS_and_ACS_ALL_Out = pd.merge(NFLIS_and_ACS_ALL_Clear,
                                ACS_ALL_5YR_DP02_Clear,
                                on=["GEO.id2","YYYY"],how="left")
# 根据药物量分层
NFLIS_and_ACS_ALL_Out["DrugReportsclass"] =
np.where(NFLIS_and_ACS_ALL_Out["DrugReports"] >= 5000,"7、5000人以上",
np.where(NFLIS_and_ACS_ALL_Out["DrugReports"] >= 1000,"6、1000-4999人",
np.where(NFLIS_and_ACS_ALL_Out["DrugReports"] >= 500,"5、500-999人",
np.where(NFLIS_and_ACS_ALL_Out["DrugReports"] >= 100,"4、100-499人",
 np.where(NFLIS_and_ACS_ALL_Out["DrugReports"] >= 10,"3、10-99人",
np.where(NFLIS_and_ACS_ALL_Out["DrugReports"] >= 1,"2、1-9人","1、0人")))))
```

图1: 所有类阿片类药物构成饼图

整理数据为直接可用

饼图

```
# 设置画布和子图
Figure1, axes = plt.subplots(figsize=(20,15),ncols=2)
Figure1_ax1,Figure1_ax2 = axes.ravel()
# 设置参数:颜色盘-colormap;间隙-与labels——对应,数值越大离中心区越远
explode = [x * 0.00325 for x in range(len(NFLIS_Figure1_Data))]
colors=cm.rainbow(np.arange(len(Figure1_sizes))/len(Figure1_sizes))
# 画饼图: 类别太多取消标签labels; 每个类别离中心的距离;
patches, texts =
Figure1_ax1.pie(Figure1_sizes, labels=None, shadow=False, explode=explode, startangl
e=0,colors=colors)
# 子图: ax1-饼图、ax2-图例
Figure1_ax1.axis('equal')
Figure1_ax2.axis('off')
Figure1_ax2.legend(patches,Figure1_labels,loc="center left",fontsize="xx-large")
# 调整大小、读取图片
plt.tight_layout()
Figure1 = plt.gcf()
```



图2: 所有类阿片类药物数量条图

整理数据为直接可用

```
# 提取画图数据"YYYY","SubstanceName","DrugReports","State"; 排序;
NFLIS_Figure2_Data = MCM_NFLIS_Class_Clear.groupby(["SubstanceName_c"])
["DrugReports"].sum().reset_index().sort_values(by="DrugReports",ascending=True)
```

条图

```
# 设置画布
```

```
plt.figure(figsize=(16,10))
# 设置参数: 颜色盘-colormap
color=cm.rainbow(np.arange(len(NFLIS_Figure2_Data))/len(NFLIS_Figure2_Data))
# 从高到低排列,改变y轴刻度的排列顺序
plt.yticks(np.arange(len(NFLIS_Figure2_Data['SubstanceName_c'])),
NFLIS_Figure2_Data['SubstanceName_c'])
# 水平条图
plt.barh(np.arange(len(NFLIS_Figure2_Data['SubstanceName_c'])),
NFLIS_Figure2_Data['DrugReports'], color=color)
# 坐标轴标签
plt.ylabel("阿片类药物名")
plt.xlabel("报告量")
# 格式整理导出
plt.tight_layout()
Figure2 = plt.gcf()
```



图3: 五个州阿片类药物数量热力图

整理数据为直接可用

```
# 提取画图数据"YYYY","SubstanceName","DrugReports","State"
NFLIS_Figure3_Clear1 =
MCM_NFLIS_Class_Clear.groupby(["State","YYYY","SubstanceName_c"])
["DrugReports"].sum().reset_index()
# 提取各个州的数据
NFLIS_Figure3_KY = NFLIS_Figure3_Clear1.loc[(NFLIS_Figure3_Clear1["State"] ==
"KY")]
NFLIS_Figure3_OH = NFLIS_Figure3_Clear1.loc[(NFLIS_Figure3_Clear1["State"] ==
"он")]
NFLIS_Figure3_PA = NFLIS_Figure3_Clear1.loc[(NFLIS_Figure3_Clear1["State"] ==
"PA")]
NFLIS_Figure3_VA = NFLIS_Figure3_Clear1.loc[(NFLIS_Figure3_Clear1["State"] ==
"VA")]
NFLIS_Figure3_WV = NFLIS_Figure3_Clear1.loc[(NFLIS_Figure3_Clear1["State"] ==
"WV")]
# 匹配每种药物 (解决某年可能没有某种药)
NFLIS_Figure3_KY_merge = pd.merge(NFLIS_Figure3_KY,MCM_NFLIS_Medication,how =
"right", on = ["YYYY", "SubstanceName_c"])
NFLIS_Figure3_OH_merge = pd.merge(NFLIS_Figure3_OH,MCM_NFLIS_Medication,how =
"right", on = ["YYYY", "SubstanceName_c"])
NFLIS_Figure3_PA_merge = pd.merge(NFLIS_Figure3_PA,MCM_NFLIS_Medication,how =
"right", on = ["YYYY", "SubstanceName_c"])
NFLIS_Figure3_VA_merge = pd.merge(NFLIS_Figure3_VA,MCM_NFLIS_Medication,how =
"right", on = ["YYYY", "SubstanceName_c"])
NFLIS_Figure3_WV_merge = pd.merge(NFLIS_Figure3_WV,MCM_NFLIS_Medication,how =
"right", on = ["YYYY", "SubstanceName_c"])
# 将数据转置为dataframe矩阵
NFLIS_Figure3_pivot_KY = NFLIS_Figure3_KY_merge.pivot_table(index =
"SubstanceName_c", columns = "YYYY", values = "DrugReports")
NFLIS_Figure3_pivot_OH = NFLIS_Figure3_OH_merge.pivot_table(index =
"SubstanceName_c",columns = "YYYY",values = "DrugReports")
NFLIS_Figure3_pivot_PA = NFLIS_Figure3_PA_merge.pivot_table(index =
"SubstanceName_c",columns = "YYYY",values = "DrugReports")
NFLIS_Figure3_pivot_VA = NFLIS_Figure3_VA_merge.pivot_table(index =
"SubstanceName_c",columns = "YYYY",values = "DrugReports")
```

```
NFLIS_Figure3_pivot_WV = NFLIS_Figure3_WV_merge.pivot_table(index =
"SubstanceName_c",columns = "YYYY",values = "DrugReports")
```

热力图

```
# 设置画布大小
f, (Figure3_ax1, Figure3_ax2, Figure3_ax3, Figure3_ax4, Figure3_ax5) =
plt.subplots(ncols=5, figsize=(30,10))
# 设置连续调色板cubehelix_palette,as_camp传入matplotlib
cmap=sns.cubehelix_palette(start=1,rot=3,gamma=0.8,as_cmap=True)
# KY州
sns.heatmap(NFLIS_Figure3_pivot_KY,cmap=cmap,linewidths=0.05,ax=Figure3_ax1,cbar
=False)
Figure3_ax1.set_title("肯塔基州",fontsize=30)
Figure3_ax1.set_xlabel('')
Figure3_ax1.set_ylabel('阿片类药物名',fontsize=35)
sns.heatmap(NFLIS_Figure3_pivot_OH,cmap=cmap,linewidths=0.05,ax=Figure3_ax2,cbar
Figure3_ax2.set_title("俄亥俄州",fontsize=30)
Figure3_ax2.set_xlabel('')
Figure3_ax2.set_ylabel(' ')
Figure3_ax2.set_yticklabels([])
sns.heatmap(NFLIS_Figure3_pivot_PA,cmap=cmap,linewidths=0.05,ax=Figure3_ax3,cbar
=False)
Figure3_ax3.set_title("宾夕法尼亚州",fontsize=30)
Figure3_ax3.set_xlabel('年份',fontsize=35)
Figure3_ax3.set_ylabel('')
Figure3_ax3.set_yticklabels([])
# VA州
sns.heatmap(NFLIS_Figure3_pivot_VA,cmap=cmap,linewidths=0.05,ax=Figure3_ax4,cbar
=False)
Figure3_ax4.set_title("弗吉尼亚州",fontsize=30)
Figure3_ax4.set_xlabel('')
Figure3_ax4.set_ylabel('')
Figure3_ax4.set_yticklabels([])
# WV州
sns.heatmap(NFLIS_Figure3_pivot_WV,cmap=cmap,linewidths=0.05,ax=Figure3_ax5,cbar
Figure3_ax5.set_title("西弗吉尼亚州",fontsize=30)
Figure3_ax5.set_xlabel('')
Figure3_ax5.set_ylabel('')
Figure3_ax5.set_yticklabels([])
plt.tight_layout()
Figure3 = plt.gcf()
```



图4: 五个州三类阿片药物量折线图

整理数据为直接可用

五个州的总量情况分组

```
NFLIS_Fugure3_Clear1 = MCM_NFLIS_Class_Clear.groupby(["YYYY", "SubstanceClass"])
["DrugReports"].sum().reset_index()
NFLIS_Fugure3_Class1_all =
NFLIS_Fugure3_Clear1.loc[(NFLIS_Fugure3_Clear1["SubstanceClass"] == "半合成阿片类
药物")]
NFLIS_Fugure3_Class2_all =
NFLIS_Fugure3_Clear1.loc[(NFLIS_Fugure3_Clear1["SubstanceClass"] == "合成阿片类药
物")]
NFLIS_Fugure3_Class3_all =
NFLIS_Fugure3_Clear1.loc[(NFLIS_Fugure3_Clear1["SubstanceClass"] == "非合成阿片类
# 五个州的分别情况分组
NFLIS_Fugure3_Class =
MCM_NFLIS_Class_Clear.groupby(["YYYY","State","SubstanceClass"])
["DrugReports"].sum().reset_index()
NFLIS_Fugure3_Class1 =
NFLIS_Fugure3_Class.loc[(NFLIS_Fugure3_Class["SubstanceClass"] == "半合成阿片类药
物")]
NFLIS_Fugure3_Class2 =
NFLIS_Fugure3_Class.loc[(NFLIS_Fugure3_Class["SubstanceClass"] == "合成阿片类药
NFLIS_Fugure3_Class3 =
NFLIS_Fugure3_Class.loc[(NFLIS_Fugure3_Class["SubstanceClass"] == "非合成阿片类药
物")]
# 对每个州进行汇合
NFLIS_Figure2_Data_Class1 =
NFLIS_Fugure3_Class1.pivot_table(index="YYYY",columns="State",values="DrugReport
s").reset_index()
NFLIS_Figure2_Data_Class2 =
NFLIS_Fugure3_Class2.pivot_table(index="YYYY",columns="State",values="DrugReport
s").reset_index()
NFLIS_Figure2_Data_Class3 =
NFLIS_Fugure3_Class3.pivot_table(index="YYYY",columns="State",values="DrugReport
s").reset_index()
```

折线图

```
# 创建画布、6个子图
plt.figure(figsize=(15,10))
f4 = plt.figure(figsize=(20,15))
Figure_ax1 = f4.add_subplot(2, 3, 1)
Figure\_ax2 = f4.add\_subplot(2, 3, 2)
Figure_ax3 = f4.add_subplot(2, 3, 3)
Figure_ax4 = f4.add_subplot(2, 3, 4)
Figure\_ax5 = f4.add\_subplot(2, 3, 5)
Figure_ax6 = f4.add_subplot(2, 3, 6)
# KY州不同类型药物的折线图
Figure_ax1.plot(NFLIS_Figure2_Data_Class1["YYYY"],NFLIS_Figure2_Data_Class1["KY"
],label="半合成阿片类药物",linewidth=2)
Figure_ax1.plot(NFLIS_Figure2_Data_Class2["YYYY"],NFLIS_Figure2_Data_Class2["KY"
],label="合成阿片类药物",linewidth=2)
Figure_ax1.plot(NFLIS_Figure2_Data_Class3["YYYY"], NFLIS_Figure2_Data_Class3["KY"
],label="非合成阿片类药物",linewidth=2)
Figure_ax1.set_title("肯塔基州")
Figure_ax1.legend(loc=2)
Figure_ax1.grid(axis='x')
```

```
#设置数字标签
for a,b in
zip(NFLIS_Figure2_Data_Class1["YYYY"],NFLIS_Figure2_Data_Class1["KY"]):
    Figure_ax1.text(a, b+0.001, '%s' % b, ha='center', va= 'bottom', fontsize=11)
for a,b in
zip(NFLIS_Figure2_Data_Class2["YYYY"],NFLIS_Figure2_Data_Class2["KY"]):
    Figure_ax1.text(a, b+0.001, '%s' % b, ha='center', va= 'bottom', fontsize=11)
zip(NFLIS_Figure2_Data_Class3["YYYY"],NFLIS_Figure2_Data_Class3["KY"]):
    Figure_ax1.text(a, b+0.001, '%s' % b, ha='center', va= 'bottom', fontsize=11)
# OH州不同类型药物的折线图
Figure_ax2.plot(NFLIS_Figure2_Data_Class1["YYYY"],NFLIS_Figure2_Data_Class1["OH"
],label="半合成阿片类药物",linewidth=2)
Figure_ax2.plot(NFLIS_Figure2_Data_Class2["YYYY"], NFLIS_Figure2_Data_Class2["OH"
],label="合成阿片类药物",linewidth=2)
Figure_ax2.plot(NFLIS_Figure2_Data_Class3["YYYY"],NFLIS_Figure2_Data_Class3["OH"
],label="非合成阿片类药物",linewidth=2)
Figure_ax2.set_title("俄亥俄州")
Figure_ax2.legend(loc=2)
Figure_ax2.grid(axis='x')
#设置数字标签**
for a,b in
zip(NFLIS_Figure2_Data_Class1["YYYY"],NFLIS_Figure2_Data_Class1["OH"]):
    Figure_ax2.text(a, b+0.001, '%s' % b, ha='center', va= 'bottom', fontsize=11)
zip(NFLIS_Figure2_Data_Class2["YYYY"],NFLIS_Figure2_Data_Class2["OH"]):
    Figure_ax2.text(a, b+0.001, '%s' % b, ha='center', va= 'bottom', fontsize=11)
for a,b in
zip(NFLIS_Figure2_Data_Class3["YYYY"], NFLIS_Figure2_Data_Class3["OH"]):
    Figure_ax2.text(a, b+0.001, '%s' % b, ha='center', va= 'bottom', fontsize=11)
# PA州不同类型药物的折线图
Figure_ax3.plot(NFLIS_Figure2_Data_Class1["YYYY"],NFLIS_Figure2_Data_Class1["PA"
],label="半合成阿片类药物",linewidth=2)
Figure_ax3.plot(NFLIS_Figure2_Data_Class2["YYYY"],NFLIS_Figure2_Data_Class2["PA"
],label="合成阿片类药物",linewidth=2)
Figure_ax3.plot(NFLIS_Figure2_Data_Class3["YYYY"],NFLIS_Figure2_Data_Class3["PA"
], label="非合成阿片类药物", linewidth=2)
Figure_ax3.set_title("宾夕法尼亚州")
Figure_ax3.legend(loc=2)
Figure_ax3.grid(axis='x')
#设置数字标签**
for a,b in
zip(NFLIS_Figure2_Data_Class1["YYYY"],NFLIS_Figure2_Data_Class1["PA"]):
    Figure_ax3.text(a, b+0.001, '%s' % b, ha='center', va= 'bottom', fontsize=11)
for a,b in
zip(NFLIS_Figure2_Data_Class2["YYYY"],NFLIS_Figure2_Data_Class2["PA"]):
    Figure_ax3.text(a, b+0.001, '%s' % b, ha='center', va= 'bottom', fontsize=11)
for a,b in
zip(NFLIS_Figure2_Data_Class3["YYYY"],NFLIS_Figure2_Data_Class3["PA"]):
    Figure_ax3.text(a, b+0.001, '%s' % b, ha='center', va= 'bottom', fontsize=11)
# VA州不同类型药物的折线图
Figure_ax4.plot(NFLIS_Figure2_Data_Class1["YYYY"], NFLIS_Figure2_Data_Class1["VA"
],label="半合成阿片类药物",linewidth=2)
Figure_ax4.plot(NFLIS_Figure2_Data_Class2["YYYY"], NFLIS_Figure2_Data_Class2["VA"
],label="合成阿片类药物",linewidth=2)
```

```
Figure_ax4.plot(NFLIS_Figure2_Data_Class3["YYYY"], NFLIS_Figure2_Data_Class3["VA"
],label="非合成阿片类药物",linewidth=2)
Figure_ax4.set_title("弗吉尼亚州")
Figure_ax4.grid(axis="x")
Figure_ax4.legend(loc=2)
for a,b in
zip(NFLIS_Figure2_Data_Class1["YYYY"],NFLIS_Figure2_Data_Class1["VA"]):
    Figure_ax4.text(a, b+0.001, '%s' % b, ha='center', va= 'bottom', fontsize=11)
for a,b in
zip(NFLIS_Figure2_Data_Class2["YYYY"], NFLIS_Figure2_Data_Class2["VA"]):
    Figure_ax4.text(a, b+0.001, '%s' % b, ha='center', va= 'bottom', fontsize=11)
for a,b in
zip(NFLIS_Figure2_Data_Class3["YYYY"], NFLIS_Figure2_Data_Class3["VA"]):
    Figure_ax4.text(a, b+0.001, '%s' % b, ha='center', va= 'bottom', fontsize=11)
# WV州不同类型药物的折线图
Figure_ax5.plot(NFLIS_Figure2_Data_Class1["YYYY"],NFLIS_Figure2_Data_Class1["WV"
],label="半合成阿片类药物",linewidth=2)
Figure_ax5.plot(NFLIS_Figure2_Data_Class2["YYYY"],NFLIS_Figure2_Data_Class2["WV"
],label="合成阿片类药物",linewidth=2)
Figure_ax5.plot(NFLIS_Figure2_Data_Class3["YYYY"],NFLIS_Figure2_Data_Class3["WV"
], label="非合成阿片类药物", linewidth=2)
Figure_ax5.set_title("西弗吉尼亚州")
Figure_ax5.legend(loc=2)
Figure_ax5.grid(axis='x')
#设置数字标签**
for a,b in
zip(NFLIS_Figure2_Data_Class1["YYYY"],NFLIS_Figure2_Data_Class1["WV"]):
    Figure_ax5.text(a, b+0.001, '%s' % b, ha='center', va= 'bottom', fontsize=11)
for a,b in
zip(NFLIS_Figure2_Data_Class2["YYYY"],NFLIS_Figure2_Data_Class2["WV"]):
    Figure_ax5.text(a, b+0.001, '%s' % b, ha='center', va= 'bottom', fontsize=11)
for a,b in
zip(NFLIS_Figure2_Data_Class3["YYYY"],NFLIS_Figure2_Data_Class3["WV"]):
    Figure_ax5.text(a, b+0.001, '%s' % b, ha='center', va= 'bottom', fontsize=11)
# 5个州总的不同类型药物的折线图
Figure_ax6.plot(NFLIS_Fugure3_Class1_all["YYYY"],NFLIS_Fugure3_Class1_all["DrugR
eports"], label="半合成阿片类药物", linewidth=2)
Figure_ax6.plot(NFLIS_Fugure3_Class2_all["YYYY"],NFLIS_Fugure3_Class2_all["DrugR
eports"], label="合成阿片类药物", linewidth=2)
Figure_ax6.plot(NFLIS_Fugure3_Class3_all["YYYY"], NFLIS_Fugure3_Class3_all["DrugR
eports"], label="非合成阿片类药物", linewidth=2)
Figure_ax6.set_title("总量")
Figure_ax6.legend(loc=2)
Figure_ax6.grid(axis='x')
for a,b in
zip(NFLIS_Fugure3_Class1_all["YYYY"], NFLIS_Fugure3_Class1_all["DrugReports"]):
    Figure_ax6.text(a, b+0.001, '%s' % b, ha='center', va= 'bottom',fontsize=11)
for a,b in
zip(NFLIS_Fugure3_Class2_all["YYYY"], NFLIS_Fugure3_Class2_all["DrugReports"]):
    Figure_ax6.text(a, b+0.001, '%s' % b, ha='center', va= 'bottom', fontsize=11)
for a,b in
zip(NFLIS_Fugure3_Class3_all["YYYY"], NFLIS_Fugure3_Class3_all["DrugReports"]):
    Figure_ax6.text(a, b+0.001, '%s' % b, ha='center', va= 'bottom', fontsize=11)
plt.tight_layout()
Figure4 = plt.gcf()
```



变量选择

相关系数计算

计算各个年份相关系数

```
# 计算2010年相关系数
df_corr_2010 =
NFLIS_and_ACS_ALL_Out.loc[(NFLIS_and_ACS_ALL_Out["YYYY"]==2010)].corr().reset_in
df_corr_ext_2010 = df_corr_2010.loc[(df_corr_2010["index"].str.contains("HC"))]
df_corr_ext_2010_part =
df_corr_ext_2010[["index","DrugReports"]].rename(columns={"DrugReports":"2010年相
关系数","index":"变量名"})
# 计算2011年相关系数
df_corr_2011 =
NFLIS_and_ACS_ALL_Out.loc[(NFLIS_and_ACS_ALL_Out["YYYY"]==2011)].corr().reset_in
dex()
df_corr_ext_2011 = df_corr_2011.loc[(df_corr_2011["index"].str.contains("HC"))]
df_corr_ext_2011_part =
df_corr_ext_2011[["index","DrugReports"]].rename(columns={"DrugReports":"2011年相
关系数","index":"变量名"})
# 计算2012年相关系数
df_{corr_2012} =
NFLIS_and_ACS_ALL_Out.loc[(NFLIS_and_ACS_ALL_Out["YYYY"]==2012)].corr().reset_in
dex()
df_corr_ext_2012 = df_corr_2012.loc[(df_corr_2012["index"].str.contains("HC"))]
df_corr_ext_2012_part =
df_corr_ext_2012[["index","DrugReports"]].rename(columns={"DrugReports":"2012年相
关系数","index":"变量名"})
# 计算2013年相关系数
df_corr_2013 =
NFLIS_and_ACS_ALL_Out.loc[(NFLIS_and_ACS_ALL_Out["YYYY"]==2013)].corr().reset_in
dex()
df_corr_ext_2013 = df_corr_2013.loc[(df_corr_2013["index"].str.contains("HC"))]
df_corr_ext_2013_part =
df_corr_ext_2013[["index","DrugReports"]].rename(columns={"DrugReports":"2013年相
关系数","index":"变量名"})
# 计算2014年相关系数
df_corr_2014 =
NFLIS_and_ACS_ALL_Out.loc[(NFLIS_and_ACS_ALL_Out["YYYY"]==2014)].corr().reset_in
dex()
df_corr_ext_2014 = df_corr_2014.loc[(df_corr_2014["index"].str.contains("HC"))]
df_corr_ext_2014_part =
df_corr_ext_2014[["index","DrugReports"]].rename(columns={"DrugReports":"2014年相
关系数","index":"变量名"})
# 计算2015年相关系数
df_corr_2015 =
NFLIS_and_ACS_ALL_Out.loc[(NFLIS_and_ACS_ALL_Out["YYYY"]==2015)].corr().reset_in
dex()
```

```
df_corr_ext_2015 = df_corr_2015.loc[(df_corr_2015["index"].str.contains("HC"))]
df_corr_ext_2015_part =
df_corr_ext_2015[["index","DrugReports"]].rename(columns={"DrugReports":"2015年相
关系数","index":"变量名"})
# 计算2016年相关系数
df_corr_2016 =
NFLIS_and_ACS_ALL_Out.loc[(NFLIS_and_ACS_ALL_Out["YYYY"]==2016)].corr().reset_in
df_corr_ext_2016 = df_corr_2016.loc[(df_corr_2016["index"].str.contains("HC"))]
df_corr_ext_2016_part =
df_corr_ext_2016[["index","DrugReports"]].rename(columns={"DrugReports":"2016年相
关系数","index":"变量名"})
# 计算全部数据的相关系数
df_corr_all = NFLIS_and_ACS_ALL_Out.corr().reset_index()
df_corr_ext_all = df_corr_all.loc[(df_corr_all["index"].str.contains("HC"))]
df_corr_ext_all_part = df_corr_ext_all[["index", "DrugReports"]].rename(columns=
{"DrugReports":"合计相关系数","index":"变量名"})
```

合并各个年份的相关系数

```
# 合并各个年份的相关系数
df_corr_merge_10_11 =
pd.merge(df_corr_ext_2010_part,df_corr_ext_2011_part,on="变量名",how="outer")
df_corr_merge_11_12 = pd.merge(df_corr_merge_10_11,df_corr_ext_2012_part,on="变量
名",how="outer")
df_corr_merge_12_13 = pd.merge(df_corr_merge_11_12,df_corr_ext_2013_part,on="变量
名",how="outer")
df_corr_merge_13_14 = pd.merge(df_corr_merge_12_13,df_corr_ext_2014_part,on="变量
名",how="outer")
df_corr_merge_14_15 = pd.merge(df_corr_merge_13_14,df_corr_ext_2015_part,on="变量
名",how="outer")
df_corr_merge_15_16 = pd.merge(df_corr_merge_14_15,df_corr_ext_2016_part,on="变量
名",how="outer")
df_corr_merge_all = pd.merge(df_corr_merge_15_16,df_corr_ext_all_part,on="变量
名",how="outer")
# 计算平均数
df_corr_merge_all["均值"] = df_corr_merge_all[["2010年相关系数","2011年相关系
数","2012年相关系数",
                                            "2013年相关系数","2014年相关系
数","2015年相关系数","2016年相关系数"]].mean(axis=1)
# 排序: 倒序
All_Corr = df_corr_merge_all.sort_values(by=["均值"],ascending=False).round(4)
```

选择相关系数大于0.5的变量

```
NFLIS_and_ACS_ALL_Out.ix[:,list(NFLIS_and_ACS_ALL_Out[connames])+list(All_Corr_C ondi["变量名"])].dropna()

C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:14:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing

See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-deprecated
```

统计推断

connames.append(conval)

归一化

```
data=NFLIS_and_ACS_All_Corr_Condi.ix[:,list(All_Corr_Condi["变量名"])]
NFLIS_and_ACS_All_Condi_Normal_CH = (data - data.mean())/data.std()
# 合并
NFLIS_and_ACS_All_Condi_Normal = pd.concat([NFLIS_and_ACS_All_Corr_Condi.ix[:,list(NFLIS_and_ACS_All_Corr_Condi[connames])],
NFLIS_and_ACS_All_Condi_Normal_CH],axis=1)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:1:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
  """Entry point for launching an IPython kernel.
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:4:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
  after removing the cwd from sys.path.
```

训练集与测试集

```
Complex =
NFLIS_and_ACS_All_Condi_Normal.ix[NFLIS_and_ACS_All_Condi_Normal["SubstanceClass
"] == "合成阿片类药物"]
Non\_Complex =
NFLIS_and_ACS_All_Condi_Normal.ix[NFLIS_and_ACS_All_Condi_Normal["SubstanceClass
"] == "非合成阿片类药物"]
Semi_Complex =
NFLIS_and_ACS_All_Condi_Normal.ix[NFLIS_and_ACS_All_Condi_Normal["SubstanceClass
"] == "半合成阿片类药物"]
Complex_x_train,Complex_x_test,Complex_y_train,Complex_y_test =
train_test_split(Complex.ix[:,list(All_Corr_Condi["变量名"])],
Complex.ix[:,"DrugReportsclass"],
test_size=0.3,
random_state=1234 )
Non_Complex_x_train, Non_Complex_x_test, Non_Complex_y_train, Non_Complex_y_test =
train_test_split(Non_Complex.ix[:,list(All_Corr_Condi["变量名"])],
               Non_Complex.ix[:,"DrugReportsclass"],
               test_size=0.3,
                random_state=1234 )
Semi_Complex_x_train,Semi_Complex_x_test,Semi_Complex_y_train,Semi_Complex_y_tes
t = train_test_split(Semi_Complex.ix[:,list(All_Corr_Condi["变量名"])],
                    Semi_Complex.ix[:,"DrugReportsclass"],
                    test_size=0.3,
                    random_state=1234 )
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:1:
```

```
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
  """Entry point for launching an IPython kernel.
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:2:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
```

```
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:3:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
  This is separate from the ipykernel package so we can avoid doing imports
until
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:5:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
  \mathbf{n} \mathbf{n} \mathbf{n}
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:6:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:9:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
  if __name__ == '__main__':
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:10:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
  # Remove the CWD from sys.path while we load stuff.
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:13:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
```

```
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-deprecated
    del sys.path[0]
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:14:
DeprecationWarning:
    ix is deprecated. Please use
    .loc for label based indexing or
    .iloc for positional indexing

See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-deprecated
```

KNN

```
Complex_KNN = KNeighborsClassifier()
Complex_KNN.fit(Complex_x_train,Complex_y_train)
Complex_KNN_Y_Predict = Complex_KNN.predict(Complex_x_test)
Complex_KNN_train_score = Complex_KNN.score(Complex_x_train, Complex_y_train)
Complex_KNN_test_score = Complex_KNN.score(Complex_x_test, Complex_y_test)
Non_Complex_KNN = KNeighborsClassifier()
Non_Complex_KNN.fit(Non_Complex_x_train,Non_Complex_y_train)
Non_Complex_KNN_Y_Predict = Non_Complex_KNN.predict(Non_Complex_x_test)
Non_Complex_KNN_train_score = Non_Complex_KNN.score(Non_Complex_x_train,
Non_Complex_y_train)
Non_Complex_KNN_test_score = Complex_KNN.score(Non_Complex_x_test,
Non_Complex_y_test)
Semi_Complex_KNN = KNeighborsClassifier()
Semi_Complex_KNN.fit(Semi_Complex_x_train,Semi_Complex_y_train)
Semi_Complex_KNN_Y_Predict = Semi_Complex_KNN.predict(Semi_Complex_x_test)
Semi_Complex_KNN_train_score = Semi_Complex_KNN.score(Semi_Complex_x_train,
Semi_Complex_y_train)
Semi_Complex_KNN_test_score = Semi_Complex_KNN.score(Semi_Complex_x_test,
Semi_Complex_y_test)
```

决策树

```
# 决策树
Complex_Decision = DecisionTreeClassifier()
Complex_Decision.fit(Complex_x_train,Complex_y_train)
Complex_Decision_Y_Predict = Complex_Decision.predict(Complex_x_test)
Complex_Decision_train_score = Complex_Decision.score(Complex_x_train,
Complex_y_train)
Complex_Decision_test_score = Complex_Decision.score(Complex_x_test,
Complex_y_test)
Non_Complex_Decision = DecisionTreeClassifier()
Non_Complex_Decision.fit(Non_Complex_x_train,Non_Complex_y_train)
Non_Complex_Decision_Y_Predict =
Non_Complex_Decision.predict(Non_Complex_x_test)
Non_Complex_Decision_train_score =
Non_Complex_Decision.score(Non_Complex_x_train, Non_Complex_y_train)
Non_Complex_Decision_test_score = Complex_Decision.score(Non_Complex_x_test,
Non_Complex_y_test)
Semi_Complex_Decision = DecisionTreeClassifier()
```

```
Semi_Complex_Decision.fit(Semi_Complex_x_train,Semi_Complex_y_train)
Semi_Complex_Decision.yr_Predict =
Semi_Complex_Decision.predict(Semi_Complex_x_test)
Semi_Complex_Decision_train_score =
Semi_Complex_Decision.score(Semi_Complex_x_train, Semi_Complex_y_train)
Semi_Complex_Decision_test_score =
Semi_Complex_Decision.score(Semi_Complex_x_test, Semi_Complex_y_test)
```

随机森林

```
# 随机森林
Complex_RFC = RandomForestClassifier()
Complex_RFC.fit(Complex_x_train,Complex_y_train)
Complex_RFC_Y_Predict = Complex_RFC.predict(Complex_x_test)
Complex_RFC_train_score = Complex_RFC.score(Complex_x_train, Complex_y_train)
Complex_RFC_test_score = Complex_RFC.score(Complex_x_test, Complex_y_test)
Non_Complex_RFC = RandomForestClassifier()
Non_Complex_RFC.fit(Non_Complex_x_train,Non_Complex_y_train)
Non_Complex_RFC_Y_Predict = Non_Complex_RFC.predict(Non_Complex_x_test)
Non_Complex_RFC_train_score = Non_Complex_RFC.score(Non_Complex_x_train,
Non_Complex_y_train)
Non_Complex_RFC_test_score = Complex_RFC.score(Non_Complex_x_test,
Non_Complex_y_test)
Semi_Complex_RFC = RandomForestClassifier()
Semi_Complex_RFC.fit(Semi_Complex_x_train,Semi_Complex_y_train)
Semi_Complex_RFC_Y_Predict = Semi_Complex_RFC.predict(Semi_Complex_x_test)
Semi_Complex_RFC_train_score = Semi_Complex_RFC.score(Semi_Complex_x_train,
Semi_Complex_y_train)
Semi_Complex_RFC_test_score = Semi_Complex_RFC.score(Semi_Complex_x_test,
Semi_Complex_y_test)
```

支持向量机

```
# SVM
Complex_SVM = SVC()
Complex_SVM.fit(Complex_x_train,Complex_y_train)
Complex_SVM_Y_Predict = Complex_SVM.predict(Complex_x_test)
Complex_SVM_train_score = Complex_SVM.score(Complex_x_train, Complex_y_train)
Complex_SVM_test_score = Complex_SVM.score(Complex_x_test, Complex_y_test)
Non\_Complex\_SVM = SVC()
Non_Complex_SVM.fit(Non_Complex_x_train,Non_Complex_y_train)
Non_Complex_SVM_Y_Predict = Non_Complex_SVM.predict(Non_Complex_x_test)
Non_Complex_SVM_train_score = Non_Complex_SVM.score(Non_Complex_x_train,
Non_Complex_y_train)
Non_Complex_SVM_test_score = Complex_SVM.score(Non_Complex_x_test,
Non_Complex_y_test)
Semi\_Complex\_SVM = SVC()
Semi_Complex_SVM.fit(Semi_Complex_x_train,Semi_Complex_y_train)
Semi_Complex_SVM_Y_Predict = Semi_Complex_SVM.predict(Semi_Complex_x_test)
Semi_Complex_SVM_train_score = Semi_Complex_SVM.score(Semi_Complex_x_train,
Semi_Complex_y_train)
Semi_Complex_SVM_test_score = Semi_Complex_SVM.score(Semi_Complex_x_test,
Semi_Complex_y_test)
```

神经网络

```
# 神经网络
Complex_MLP = MLPClassifier(solver='lbfgs', alpha=1e-5,hidden_layer_sizes=(5,
5), random_state=1)
Complex_MLP.fit(Complex_x_train,Complex_y_train)
Complex_MLP_Y_Predict = Complex_MLP.predict(Complex_x_test)
Complex_MLP_train_score = Complex_MLP.score(Complex_x_train, Complex_y_train)
Complex_MLP_test_score = Complex_MLP.score(Complex_x_test, Complex_y_test)
Non_Complex_MLP = MLPClassifier(solver='lbfgs', alpha=1e-5,hidden_layer_sizes=
(5, 5), random_state=1)
Non_Complex_MLP.fit(Non_Complex_x_train,Non_Complex_y_train)
Non_Complex_MLP_Y_Predict = Non_Complex_MLP.predict(Non_Complex_x_test)
Non_Complex_MLP_train_score = Non_Complex_MLP.score(Non_Complex_x_train,
Non_Complex_y_train)
Non_Complex_MLP_test_score = Complex_MLP.score(Non_Complex_x_test,
Non_Complex_y_test)
Semi_Complex_MLP = MLPClassifier(solver='lbfgs', alpha=1e-5,hidden_layer_sizes=
(5, 5), random_state=1)
Semi_Complex_MLP.fit(Semi_Complex_x_train,Semi_Complex_y_train)
Semi_Complex_MLP_Y_Predict = Semi_Complex_MLP.predict(Semi_Complex_x_test)
Semi_Complex_MLP_train_score = Semi_Complex_MLP.score(Semi_Complex_x_train,
Semi_Complex_y_train)
Semi_Complex_MLP_test_score = Semi_Complex_MLP.score(Semi_Complex_x_test,
Semi_Complex_y_test)
```

线性回归

```
# 线性回归
Complex_LR = LogisticRegression()
Complex_LR.fit(Complex_x_train,Complex_y_train)
Complex_LR_Y_Predict = Complex_LR.predict(Complex_x_test)
Complex_LR_train_score = Complex_LR.score(Complex_x_train, Complex_y_train)
Complex_LR_test_score = Complex_LR.score(Complex_x_test, Complex_y_test)
Non_Complex_LR = LogisticRegression()
Non_Complex_LR.fit(Non_Complex_x_train,Non_Complex_y_train)
Non_Complex_LR_Y_Predict = Non_Complex_LR.predict(Non_Complex_x_test)
Non_Complex_LR_train_score = Non_Complex_LR.score(Non_Complex_x_train,
Non_Complex_y_train)
Non_Complex_LR_test_score = Complex_LR.score(Non_Complex_x_test,
Non_Complex_y_test)
Semi_Complex_LR = LogisticRegression()
Semi_Complex_LR.fit(Semi_Complex_x_train,Semi_Complex_y_train)
Semi_Complex_LR_Y_Predict = Semi_Complex_LR.predict(Semi_Complex_x_test)
Semi_Complex_LR_train_score = Semi_Complex_LR.score(Semi_Complex_x_train,
Semi_Complex_y_train)
Semi_Complex_LR_test_score = Semi_Complex_LR.score(Semi_Complex_x_test,
Semi_Complex_y_test)
```

模型评估

特征重要性

特征重要性计算

```
Non_Complex_Imp = 100.0*(Non_Complex_RFC.feature_importances_/
                            max(Non_Complex_RFC.feature_importances_))
Non_Complex_Importance =
pd.DataFrame(np.array([Non_Complex_x_test.columns,Non_Complex_Imp]).T,
                                      columns=["Var","非合成类重要度"])
Non_Complex_Importance["非合成类重要度"].astype("float")
Non_Complex_Importance_Sort= Non_Complex_Importance.sort_values(by="非合成类重要
度",ascending=False)
# 合成类
Complex_Imp = 100.0*(Complex_RFC.feature_importances_/
                            max(Complex_RFC.feature_importances_))
Complex_Importance =
\verb|pd.DataFrame(np.array([Complex\_x\_test.columns,Complex\_Imp]).T|,\\
                                 columns=["Var","合成类重要度"])
Complex_Importance["合成类重要度"].astype("float")
Complex_Importance_Sort= Complex_Importance.sort_values(by="合成类重要
度",ascending=False)
# 半合成类
Semi_Complex_Imp = 100.0*(Semi_Complex_RFC.feature_importances_/
                            max(Semi_Complex_RFC.feature_importances_))
Semi_Complex_Importance =
\verb|pd.DataFrame(np.array([Semi\_Complex\_x\_test.columns,Semi\_Complex\_Imp]).T|,\\
                                          columns=["Var","半合成类重要度"])
Semi_Complex_Importance["半合成类重要度"].astype("float")
Semi_Complex_Importance_Sort= Semi_Complex_Importance.sort_values(by="半合成类重要
度",ascending=False)
```

变量名匹配

KFold验证

非合成类

```
scoring='accuracy',
                            cv=strKFold)
Non_Complex_RFC_Kfold = cross_val_score(Non_Complex_RFC,
                            Non_Complex.ix[:,list(All_Corr_Condi["变量名"])],
                            Non_Complex.ix[:,"DrugReportsclass"],
                            scoring='accuracy',
                            cv=strKFold)
Non_Complex_SVM_Kfold = cross_val_score(Non_Complex_SVM,
                            Non_Complex.ix[:,list(All_Corr_Condi["变量名"])],
                            Non_Complex.ix[:,"DrugReportsclass"],
                            scoring='accuracy',
                            cv=strKFold)
Non_Complex_MLP_Kfold = cross_val_score(Non_Complex_MLP,
                            Non_Complex.ix[:,list(All_Corr_Condi["变量名"])],
                            Non_Complex.ix[:,"DrugReportsclass"],
                            scoring='accuracy',
                            cv=strKFold)
Non_Complex_LR_Kfold = cross_val_score(Non_Complex_LR,
                            Non_Complex.ix[:,list(All_Corr_Condi["变量名"])],
                            Non_Complex.ix[:,"DrugReportsclass"],
                            scoring='accuracy',
                            cv=strKFold)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:3:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
  This is separate from the ipykernel package so we can avoid doing imports
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:4:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
  after removing the cwd from sys.path.
C:\ProgramData\Anaconda3\lib\site-
packages\sklearn\model_selection\_split.py:605: Warning: The least populated
class in y has only 8 members, which is too few. The minimum number of members
in any class cannot be less than n_splits=10.
  % (min_groups, self.n_splits)), Warning)
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:8:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
```

```
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:9:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
  if __name__ == '__main__':
C:\ProgramData\Anaconda3\lib\site-
packages\sklearn\model_selection\_split.py:605: Warning: The least populated
class in y has only 8 members, which is too few. The minimum number of members
in any class cannot be less than n_splits=10.
  % (min_groups, self.n_splits)), Warning)
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:13:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
  del sys.path[0]
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:14:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
C:\ProgramData\Anaconda3\lib\site-
packages\sklearn\model_selection\_split.py:605: Warning: The least populated
class in y has only 8 members, which is too few. The minimum number of members
in any class cannot be less than n_splits=10.
  % (min_groups, self.n_splits)), Warning)
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:18:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:19:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
```

```
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
C:\ProgramData\Anaconda3\lib\site-
packages\sklearn\model_selection\_split.py:605: Warning: The least populated
class in y has only 8 members, which is too few. The minimum number of members
in any class cannot be less than n_splits=10.
  % (min_groups, self.n_splits)), Warning)
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:23:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:24:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
C:\ProgramData\Anaconda3\lib\site-
packages\sklearn\model_selection\_split.py:605: Warning: The least populated
class in y has only 8 members, which is too few. The minimum number of members
in any class cannot be less than n_splits=10.
  % (min_groups, self.n_splits)), Warning)
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:28:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:29:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
C:\ProgramData\Anaconda3\lib\site-
packages\sklearn\model_selection\_split.py:605: Warning: The least populated
class in y has only 8 members, which is too few. The minimum number of members
in any class cannot be less than n_splits=10.
  % (min_groups, self.n_splits)), Warning)
```

合成类

```
strKFold = StratifiedKFold(n_splits=10,shuffle=False,random_state=1234)
Complex_KNN_Kfold = cross_val_score(Complex_KNN,
                            Complex.ix[:,list(All_Corr_Condi["变量名"])],
                            Complex.ix[:,"DrugReportsclass"],
                            scoring='accuracy',
                            cv=strKFold)
Complex_Decision_Kfold = cross_val_score(Complex_Decision,
                            Complex.ix[:,list(All_Corr_Condi["变量名"])],
                            Complex.ix[:,"DrugReportsclass"],
                            scoring='accuracy',
                            cv=strKFold)
Complex_RFC_Kfold = cross_val_score(Complex_RFC,
                            Complex.ix[:,list(All_Corr_Condi["变量名"])],
                            Complex.ix[:,"DrugReportsclass"],
                            scoring='accuracy',
                            cv=strKFold)
Complex_SVM_Kfold = cross_val_score(Complex_SVM,
                            Complex.ix[:,list(All_Corr_Condi["变量名"])],
                            Complex.ix[:,"DrugReportsclass"],
                            scoring='accuracy',
                            cv=strKFold)
Complex_MLP_Kfold = cross_val_score(Complex_MLP,
                            Complex.ix[:,list(All_Corr_Condi["变量名"])],
                            Complex.ix[:,"DrugReportsclass"],
                            scoring='accuracy',
                            cv=strKFold)
Complex_LR_Kfold = cross_val_score(Complex_LR,
                            Complex.ix[:,list(All_Corr_Condi["变量名"])],
                            Complex.ix[:,"DrugReportsclass"],
                            scoring='accuracy',
                            cv=strKFold)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:3:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
  This is separate from the ipykernel package so we can avoid doing imports
until
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:4:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
  after removing the cwd from sys.path.
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:8:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
```

```
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:9:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
  if __name__ == '__main__':
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:13:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
  del sys.path[0]
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:14:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:18:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:19:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:23:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
```

```
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:24:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:28:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:29:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
```

半合成类

```
strKFold = StratifiedKFold(n_splits=10,shuffle=False,random_state=1234)
Semi_Complex_KNN_Kfold = cross_val_score(Semi_Complex_KNN,
                            Semi_Complex.ix[:,list(All_Corr_Condi["变量名"])],
                            Semi_Complex.ix[:,"DrugReportsclass"],
                            scoring='accuracy',
                            cv=strKFold)
Semi_Complex_Decision_Kfold = cross_val_score(Semi_Complex_Decision,
                            Semi_Complex.ix[:,list(All_Corr_Condi["变量名"])],
                            Semi_Complex.ix[:,"DrugReportsclass"],
                            scoring='accuracy',
                            cv=strKFold)
Semi_Complex_RFC_Kfold = cross_val_score(Semi_Complex_RFC,
                            Semi_Complex.ix[:,list(All_Corr_Condi["变量名"])],
                            Semi_Complex.ix[:,"DrugReportsclass"],
                            scoring='accuracy',
                            cv=strKFold)
Semi_Complex_SVM_Kfold = cross_val_score(Semi_Complex_SVM,
                            Semi_Complex.ix[:,list(All_Corr_Condi["变量名"])],
                            Semi_Complex.ix[:,"DrugReportsclass"],
                            scoring='accuracy',
                            cv=strKFold)
Semi_Complex_MLP_Kfold = cross_val_score(Semi_Complex_MLP,
```

```
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:3:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
  This is separate from the ipykernel package so we can avoid doing imports
until
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:4:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
  after removing the cwd from sys.path.
C:\ProgramData\Anaconda3\lib\site-
packages\sklearn\model_selection\_split.py:605: Warning: The least populated
class in y has only 2 members, which is too few. The minimum number of members
in any class cannot be less than n_splits=10.
  % (min_groups, self.n_splits)), Warning)
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:8:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:9:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
  if __name__ == '__main__':
```

```
C:\ProgramData\Anaconda3\lib\site-
packages\sklearn\model_selection\_split.py:605: Warning: The least populated
class in y has only 2 members, which is too few. The minimum number of members
in any class cannot be less than n_splits=10.
  % (min_groups, self.n_splits)), Warning)
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:13:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
  del sys.path[0]
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:14:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
C:\ProgramData\Anaconda3\lib\site-
packages\sklearn\model_selection\_split.py:605: Warning: The least populated
class in y has only 2 members, which is too few. The minimum number of members
in any class cannot be less than n_splits=10.
  % (min_groups, self.n_splits)), Warning)
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:18:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:19:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
C:\ProgramData\Anaconda3\lib\site-
packages\sklearn\model_selection\_split.py:605: Warning: The least populated
class in y has only 2 members, which is too few. The minimum number of members
in any class cannot be less than n_splits=10.
  % (min_groups, self.n_splits)), Warning)
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:23:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
```

```
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:24:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
C:\ProgramData\Anaconda3\lib\site-
packages\sklearn\model_selection\_split.py:605: Warning: The least populated
class in y has only 2 members, which is too few. The minimum number of members
in any class cannot be less than n_splits=10.
  % (min_groups, self.n_splits)), Warning)
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:28:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:29:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
C:\ProgramData\Anaconda3\lib\site-
packages\sklearn\model_selection\_split.py:605: Warning: The least populated
class in y has only 2 members, which is too few. The minimum number of members
in any class cannot be less than n_splits=10.
  % (min_groups, self.n_splits)), Warning)
```

Kfold结果值

非合成类

```
Non_Complex_Kfold_Outdata = pd.DataFrame(np.array([Non_Complex_KNN_Kfold, Non_Complex_Decision_Kfold, Non_Complex_RFC_Kfold, Non_Complex_SVM_Kfold, Non_Complex_SVM_Kfold, Non_Complex_MLP_Kfold, Non_Complex_MLP_Kfold,

Non_Complex_LR_Kfold]).T.round(3),

columns=["KNN","决策树","随机森林","支持向量机","神经网络","线性回归"])

Non_Complex_Kfold_Box = Non_Complex_Kfold_Outdata.stack().reset_index()

Non_Complex_Kfold_Box = Non_Complex_Kfold_Box.rename(columns={"level_1":"各类机器学习算法","0":"Kfold值"})
```

合成类

半合成类

```
Semi_Complex_Kfold_Outdata = pd.DataFrame(np.array([Semi_Complex_KNN_Kfold, Semi_Complex_Decision_Kfold, Semi_Complex_RFC_Kfold, Semi_Complex_SVM_Kfold, Semi_Complex_SVM_Kfold, Semi_Complex_MLP_Kfold,

Semi_Complex_LR_Kfold]).T.round(3),

Columns=["KNN","决策树","随机森林","支持向量机","神经网络","线性回归"])

Semi_Complex_Kfold_Box = Semi_Complex_Kfold_Outdata.stack().reset_index()

Semi_Complex_Kfold_Box = Semi_Complex_Kfold_Box.rename(columns={"level_1":"各类机器学习算法","0":"Kfold值"})
```

Kfold箱式图

```
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:3:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
  This is separate from the ipykernel package so we can avoid doing imports
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:8:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:13:
DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing
See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-
deprecated
  del sys.path[0]
```



导出结果

数据清洗结果

```
# 整理后的ACS_ALL
ACS_ALL_5YR_DP02.to_csv(file_path("02_output","ACS_ALL_5YR_DP02.csv"),encoding="
utf-8-sig")
# 整理后的MCM_NFLIS
```

```
MCM_NFLIS_Class_Clear.to_csv(file_path("02_output","MCM_NFLIS_Class_Clear.csv"),
encoding="utf-8-sig")
# 整理后的ACS_All_5YR_DP02_metadata
ACS_All_5YR_DP02_metadata_Dup.to_csv(file_path("02_output","ACS_All_5YR_DP02_met
adata_Dup.csv"),encoding="utf-8-sig")
# 按照三类药物数据合并
NFLIS_and_ACS_ALL_Out.to_csv(file_path("02_output","NFLIS_and_ACS_ALL_Out.csv"),
encoding="utf-8-sig")
# 相关系数大于0.5的变量
All_Corr_Condi.to_csv(file_path("02_output","All_Corr_Condi.csv"),encoding="utf-
8-sig")
# 相关系数大于0.5的变量的社会经济数据表
NFLIS_and_ACS_All_Corr_Condi.to_csv(file_path("02_output","NFLIS_and_ACS_All_Cor
r_Condi.csv"),encoding="utf-8-sig")
# 归一化后相关系数大于0.5的变量的社会经济数据表
NFLIS_and_ACS_All_Condi_Normal.to_csv(file_path("02_output","NFLIS_and_ACS_All_C
ondi_Normal.csv"), encoding="utf-8-sig")
```

统计描述结果

```
NFLIS_Figure2_Data_Class1.to_csv(file_path("02_output","NFLIS_Figure2_Data_Class
1.csv"),encoding="utf-8-sig")
NFLIS_Figure2_Data_Class2.to_csv(file_path("02_output","NFLIS_Figure2_Data_Class
2.csv"),encoding="utf-8-sig")
NFLIS_Figure2_Data_Class3.to_csv(file_path("02_output","NFLIS_Figure2_Data_Class
3.csv"),encoding="utf-8-sig")

Figure1.savefig(file_path("02_output","Figure1_Pie.jpg"),dpi=500)
Figure2.savefig(file_path("02_output","Figure2_Bar.jpg"),dpi=500)
Figure3.savefig(file_path("02_output","Figure3_HeatMap.jpg"),dpi=500)
Figure4.savefig(file_path("02_output","Figure4_Plot.jpg"),dpi=500)
```

模型评估结果

```
# Kfold箱式图
All_Box.savefig(file_path("02_output","All_Box.jpg"),dpi=500)
# 三类药物特征重要度
All_Importance_Rename.to_csv(file_path("02_output","All_Importance_Rename.csv"),encoding="utf-8-sig")
# K折验证
Complex_Kfold_Outdata.to_csv(file_path("02_output","Complex_Kfold_Outdata.csv"),encoding="utf-8-sig")
Semi_Complex_Kfold_Outdata.to_csv(file_path("02_output","Semi_Complex_Kfold_Outdata.csv"),encoding="utf-8-sig")
Non_Complex_Kfold_Outdata.to_csv(file_path("02_output","Non_Complex_Kfold_Outdata.csv"),encoding="utf-8-sig")
```

模型的混淆矩阵

```
print('KNN合成类混淆矩阵为: ', confusion_matrix(Complex_y_test,
Complex_KNN_Y_Predict), sep='\n')
```

```
print('KNN半合成类混淆矩阵为: ', confusion_matrix(Semi_Complex_y_test,
Semi_Complex_KNN_Y_Predict), sep='\n')
print('KNN非合成类混淆矩阵为: ', confusion_matrix(Non_Complex_y_test,
Non_Complex_KNN_Y_Predict), sep='\n')
print('Decision合成类混淆矩阵为: ', confusion_matrix(Complex_y_test,
Complex_Decision_Y_Predict(), sep='\n')
print('Decision半合成类混淆矩阵为: ', confusion_matrix(Semi_Complex_y_test,
Semi_Complex_Decision_Y_Predict), sep='\n')
print('Decision非合成类混淆矩阵为: ', confusion_matrix(Non_Complex_y_test,
Non_Complex_Decision_Y_Predict), sep='\n')
print('RFC合成类混淆矩阵为:', confusion_matrix(Complex_y_test,
Complex_RFC_Y_Predict), sep='\n')
print('RFC半合成类混淆矩阵为: ', confusion_matrix(Semi_Complex_y_test,
Semi_Complex_RFC_Y_Predict(), sep='\n')
print('RFC非合成类混淆矩阵为:', confusion_matrix(Non_Complex_y_test,
Non_Complex_RFC_Y_Predict), sep='\n')
print('SVM合成类混淆矩阵为: ', confusion_matrix(Complex_y_test,
Complex_SVM_Y_Predict), sep='\n')
print('SVM半合成类混淆矩阵为: ', confusion_matrix(Semi_Complex_y_test,
Semi_Complex_SVM_Y_Predict), sep='\n')
print('SVM非合成类混淆矩阵为:', confusion_matrix(Non_Complex_y_test,
Non_Complex_SVM_Y_Predict), sep='\n')
print('MLP合成类混淆矩阵为:', confusion_matrix(Complex_y_test,
Complex_MLP_Y_Predict), sep='\n')
print('MLP半合成类混淆矩阵为: ', confusion_matrix(Semi_Complex_y_test,
Semi_Complex_MLP_Y_Predict(), sep='\n')
print('MLP非合成类混淆矩阵为: ', confusion_matrix(Non_Complex_y_test,
Non_Complex_MLP_Y_Predict), sep='\n')
print('LR合成类混淆矩阵为: ', confusion_matrix(Complex_y_test,
Complex_LR_Y_Predict(), sep='\n')
print('LR半合成类混淆矩阵为: ', confusion_matrix(Semi_Complex_y_test,
Semi_Complex_LR_Y_Predict), sep='\n')
print('LR非合成类混淆矩阵为: ', confusion_matrix(Non_Complex_y_test,
Non_Complex_LR_Y_Predict), sep='\n')
```

```
KNN合成类混淆矩阵为:
[[ 31 51 15 4 0 0]
[ 44 150 103 4 0 0]
[ 12 84 354 24 0 0]
[ 0 5 40 37 0 0]
[ 0 0 0 1 1 0 ]
[ 0 0 0 1 0 0]]
KNN半合成类混淆矩阵为:
[[ 22 38 13 1 0 0]
[ 23 127 91 4 0 0]
[ 9 71 331 39 0 0]
[ 1 5 55 91 4
               07
[ 0 0 1 14 5 0 ]
[ 0 0 0
          4 3
               911
KNN非合成类混淆矩阵为:
[[132 149 6 0]
```

```
[112 376 19
           0]
[ 7 54 40
           0]
Γ 0 0 2
           011
Decision合成类混淆矩阵为:
[[ 40 46 13
           2 0
                 0]
[ 49 140 106
           6 0
                 0]
[ 24 99 311 40 0
                 0]
[ 3 3 31 42
              3
                 0]
0 0 0
           0 2
                 0]
0 0 0
           0
             1
                 0]]
Decision半合成类混淆矩阵为:
[[ 20 34 18
          2 0
                 0]
[ 29 128 84
           4 0
                 0]
[ 14 93 299 43 1 0]
[ 5 5 44 97 5
                 0]
[ 0 0 2
          7 11
                0]
0 0 0
          1 2 13]]
Decision非合成类混淆矩阵为:
[[138 131 18
           0]
[150 301 56
           0]
[ 13 37 49
           2]
[ 0 0 0
           2]]
RFC合成类混淆矩阵为:
[[ 35 43 23
          0 0 0]
[ 32 180 88
           1 0 0]
[ 5 95 367
           7 0 0]
[ 0 3 38 39 2 0]
0 0 0
           0 2 0]
[ 0 0 0
           0 1 0]]
RFC半合成类混淆矩阵为:
[[ 23 38 10
                0]
          3 0
[ 24 139 80
          2
              0 0]
[ 7 85 328 30 0 0]
[ 1 3 55 93 4
                0]
[ 0 0
        0
           14
             4
                 2]
[ 0 0 1
          1 2 12]]
RFC非合成类混淆矩阵为:
[[157 126 4
           0]
[132 366 9
           0]
[ 4 55 42
           0]
Γ 0 0 0
           211
SVM合成类混淆矩阵为:
[[ 0 73 27 1 0
                0]
[ 0 178 123
           0 0 0]
[ 0 80 388
          6 0
                 0]
Γ 0 2 60 20 0
                07
[ 0 0
       0
           1
              1
                0]
[ 0 0 0
           1
              0
                 0]]
SVM半合成类混淆矩阵为:
[[ 0 57 14
           3 0 0]
[ 0 150 92
                 07
           3
              0
[ 0 77 339
           34
              0
                 0]
[ 0 1 74
                0]
           80
             1
[ 0 0 1 17
                 1]
              1
0 0 0
          4
              1 11]]
SVM非合成类混淆矩阵为:
[[ 65 222 0 0]
[ 31 476 0 0]
```

```
[ 0 70 31 0]
[ 0 0 1
          1]]
MLP合成类混淆矩阵为:
[[ 22 52 23 4 0 0]
[ 22 160 115  4  0  0]
[ 2 71 379 22 0 0]
[ 0 1 43 38 0 0]
  0
     0 0 2 0 0]
[ 0 0
        0 1 0 0]]
MLP半合成类混淆矩阵为:
[[ 0 56 16 2 0 0]
[ 1 143 98 3 0 0]
  4 81 319 45 0 1]
[ 1 1 59 95 0 0]
1
     0
       0 15 0
               4]
[ 0 0 0 6 0 10]]
MLP非合成类混淆矩阵为:
[[131 156 0 0]
[ 84 419 4
          0]
[ 3 64 34
           0]
[ 0 0 0 2]]
LR合成类混淆矩阵为:
[[ 0 65 35 1 0 0]
[ 1 173 126 1 0 0]
  0 68 398 8 0 0]
[ 0 1 57 24 0 0]
  0 0 0
          0 2 0]
[ 0 0 0 1 0 0]]
LR半合成类混淆矩阵为:
[[ 0 46 26 2 0 0]
[ 0 90 153 2 0 0]
  0 32 389 29 0 0]
  0 1 87 67 1 0]
[ 0 0 1 18 0 1 ]
0 0
       0
          4 0 12]]
LR非合成类混淆矩阵为:
[[104 181 2 0]
[ 48 453 6 0]
[ 2 62 37 0]
0 0 0
          2]]
```

模型的评估报告

```
print("最近邻法合成阿片类: ")
print(classification_report(Complex_KNN_Y_Predict,Complex_y_test))
print("最近邻法非合成阿片类: ")
print(classification_report(Non_Complex_KNN_Y_Predict,Non_Complex_y_test))
print("最近邻法半合成阿片类: ")
print(classification_report(Semi_Complex_KNN_Y_Predict,Semi_Complex_y_test))

print("决策树合成阿片类: ")
print(classification_report(Complex_Decision_Y_Predict,Complex_y_test))
print("决策树非合成阿片类: ")
print(classification_report(Non_Complex_Decision_Y_Predict,Non_Complex_y_test))
print("决策树半合成阿片类: ")
print(classification_report(Semi_Complex_Decision_Y_Predict,Semi_Complex_y_test))
)
```

```
print("随机森林合成阿片类:")
print(classification_report(Complex_RFC_Y_Predict,Complex_y_test))
print("随机森林非合成阿片类:")
print(classification_report(Non_Complex_RFC_Y_Predict,Non_Complex_y_test))
print("随机森林半合成阿片类:")
print(classification_report(Semi_Complex_RFC_Y_Predict,Semi_Complex_y_test))
print("支持向量机合成阿片类:")
print(classification_report(Complex_SVM_Y_Predict,Complex_y_test))
print("支持向量机非合成阿片类:")
print(classification_report(Non_Complex_SVM_Y_Predict,Non_Complex_y_test))
print("支持向量机半合成阿片类:")
print(classification_report(Semi_Complex_SVM_Y_Predict,Semi_Complex_y_test))
print("神经网络合成阿片类:")
print(classification_report(Complex_MLP_Y_Predict,Complex_y_test))
print("神经网络非合成阿片类:")
print(classification_report(Non_Complex_MLP_Y_Predict,Non_Complex_y_test))
print("神经网络半合成阿片类:")
print(classification_report(Semi_Complex_MLP_Y_Predict,Semi_Complex_y_test))
print("线性回归合成阿片类:")
print(classification_report(Complex_LR_Y_Predict,Complex_y_test))
print("线性回归非合成阿片类:")
print(classification_report(Non_Complex_LR_Y_Predict,Non_Complex_y_test))
print("线性回归半合成阿片类:")
print(classification_report(Semi_Complex_LR_Y_Predict,Semi_Complex_y_test))
```

最近邻法合成阿片	类:			
	precision	recall	f1-score	support
1、0人	0.31	0.36	0.33	87
2、1-9人		0.50		290
	0.75	0.69		
	0.75			71
	0.50	1.00		1
6、1000-4999人		0.00		0
avg / total	0.61	0.60	0.60	961
最近邻法非合成阿	〕片类:			
	precision	recall f	1-score	support
1、0人	0.46	0.53	0.49	251
2、1-9人	0.74	0.65	0.69	579
3、10-99人	0.40	0.60	0.48	67
4、100-499人	0.00	0.00	0.00	0
avg / total	0.64	0.61	0.62	897
最近邻法半合成阿	〕 「片类 :			
	precision	recall	f1-score	support
1、0人	0.30	0.40	0.34	55
2、1-9人	0.52	0.53	0.52	241

3、10-99人	0.74	0.67	0.70	491
4、100-499人	0.58	0.59	0.59	153
5、500-999人	0.25			12
6、1000-4999人	0.56	1.00	0.72	9
avg / total	0.62	0.61	0.61	961
决策树合成阿片类:				
pre	ecision	recall f	1-score	support
1、0人	0.40			116
2、1-9人	0.47	0.49	0.48	288
3、10-99人	0.66	0.67	0.67	461
4、100-499人	0.51	0.47	0.49	90
5、500-999人	1.00	0.33	0.50	6
6、1000-4999人	0.00	0.00	0.00	0
avg / total	0.56	0.56	0.55	961
决策树非合成阿片类:				
pred	cision	recall f1	-score	support
1、0人				
2、1-9人			0.62	
	0.49		0.44	123
4、100-499人	1.00	0.50	0.67	4
avg / total	0.54	0.55	0.54	897
决策树半合成阿片类:			-	
	ecision	recall f	1-score	support
pre				
pre 1、0人	0.27	0.29	0.28	68
pre 1、0人 2、1-9人	0.27 0.52	0.29	0.28	68 260
pre 1、0人 2、1-9人 3、10-99人	0.27 0.52 0.66	0.29 0.49 0.67	0.28 0.51 0.67	68 260 447
り pre 1、0人 2、1-9人 3、10-99人 4、100-499人	0.27 0.52 0.66 0.62	0.29 0.49 0.67 0.63	0.28 0.51 0.67 0.63	68 260 447 154
1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人	0.27 0.52 0.66 0.62 0.55	0.29 0.49 0.67 0.63 0.58	0.28 0.51 0.67 0.63 0.56	68 260 447
り pre 1、0人 2、1-9人 3、10-99人 4、100-499人	0.27 0.52 0.66 0.62 0.55	0.29 0.49 0.67 0.63 0.58	0.28 0.51 0.67 0.63 0.56	68 260 447 154
1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人 6、1000-4999人	0.27 0.52 0.66 0.62 0.55 0.81	0.29 0.49 0.67 0.63 0.58 1.00	0.28 0.51 0.67 0.63 0.56 0.90	68 260 447 154 19
1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人	0.27 0.52 0.66 0.62 0.55 0.81	0.29 0.49 0.67 0.63 0.58 1.00	0.28 0.51 0.67 0.63 0.56 0.90	68 260 447 154 19
1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人 6、1000-4999人 avg / total	0.27 0.52 0.66 0.62 0.55 0.81	0.29 0.49 0.67 0.63 0.58 1.00	0.28 0.51 0.67 0.63 0.56 0.90	68 260 447 154 19
1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人 6、1000-4999人 avg / total 随机森林合成阿片类:	0.27 0.52 0.66 0.62 0.55 0.81	0.29 0.49 0.67 0.63 0.58 1.00	0.28 0.51 0.67 0.63 0.56 0.90	68 260 447 154 19 13
1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人 6、1000-4999人 avg / total 随机森林合成阿片类:	0.27 0.52 0.66 0.62 0.55 0.81	0.29 0.49 0.67 0.63 0.58 1.00	0.28 0.51 0.67 0.63 0.56 0.90	68 260 447 154 19 13
1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人 6、1000-4999人 avg / total 随机森林合成阿片类: pre	0.27 0.52 0.66 0.62 0.55 0.81 0.59	0.29 0.49 0.67 0.63 0.58 1.00 0.59	0.28 0.51 0.67 0.63 0.56 0.90 0.59	68 260 447 154 19 13 961
1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人 6、1000-4999人 avg / total 随机森林合成阿片类:	0.27 0.52 0.66 0.62 0.55 0.81	0.29 0.49 0.67 0.63 0.58 1.00 0.59	0.28 0.51 0.67 0.63 0.56 0.90 0.59	68 260 447 154 19 13 961
1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人 6、1000-4999人 avg / total 随机森林合成阿片类: pre	0.27 0.52 0.66 0.62 0.55 0.81 0.59	0.29 0.49 0.67 0.63 0.58 1.00 0.59	0.28 0.51 0.67 0.63 0.56 0.90 0.59	68 260 447 154 19 13 961 support
1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人 6、1000-4999人 avg / total 随机森林合成阿片类: pre	0.27 0.52 0.66 0.62 0.55 0.81 0.59	0.29 0.49 0.67 0.63 0.58 1.00 0.59	0.28 0.51 0.67 0.63 0.56 0.90 0.59	68 260 447 154 19 13 961 support
1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人 6、1000-4999人 avg / total 随机森林合成阿片类: pre 1、0人 2、1-9人	0.27 0.52 0.66 0.62 0.55 0.81 0.59 ecision 0.35 0.60 0.77	0.29 0.49 0.67 0.63 0.58 1.00 0.59	0.28 0.51 0.67 0.63 0.56 0.90 0.59	68 260 447 154 19 13 961 support 72 321 516
1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人 6、1000-4999人 avg / total 随机森林合成阿片类: pre 1、0人 2、1-9人 3、10-99人	0.27 0.52 0.66 0.62 0.55 0.81 0.59 ecision 0.35 0.60 0.77	0.29 0.49 0.67 0.63 0.58 1.00 0.59	0.28 0.51 0.67 0.63 0.56 0.90 0.59	68 260 447 154 19 13 961 support 72 321 516 47
1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人 6、1000-4999人 avg / total 随机森林合成阿片类: pre 1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人	0.27 0.52 0.66 0.62 0.55 0.81 0.59 ecision 0.35 0.60 0.77 0.48	0.29 0.49 0.67 0.63 0.58 1.00 0.59 recall f	0.28 0.51 0.67 0.63 0.56 0.90 0.59	68 260 447 154 19 13 961 support 72 321 516 47
1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人 6、1000-4999人 avg / total 随机森林合成阿片类: pre 1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人	0.27 0.52 0.66 0.62 0.55 0.81 0.59 ecision 0.35 0.60 0.77 0.48 1.00	0.29 0.49 0.67 0.63 0.58 1.00 0.59 recall f	0.28 0.51 0.67 0.63 0.56 0.90 0.59 61-score 0.40 0.58 0.74 0.60 0.57	68 260 447 154 19 13 961 support 72 321 516 47 5
1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人 6、1000-4999人 avg / total 随机森林合成阿片类: pre 1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人 6、1000-4999人	0.27 0.52 0.66 0.62 0.55 0.81 0.59 ecision 0.35 0.60 0.77 0.48 1.00 0.00	0.29 0.49 0.67 0.63 0.58 1.00 0.59 recall f	0.28 0.51 0.67 0.63 0.56 0.90 0.59 E1-score 0.40 0.58 0.74 0.60 0.57 0.00	68 260 447 154 19 13 961 support 72 321 516 47 5
1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人 6、1000-4999人 avg / total 随机森林合成阿片类: pre 1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人	0.27 0.52 0.66 0.62 0.55 0.81 0.59 ecision 0.35 0.60 0.77 0.48 1.00 0.00	0.29 0.49 0.67 0.63 0.58 1.00 0.59 recall f	0.28 0.51 0.67 0.63 0.56 0.90 0.59 E1-score 0.40 0.58 0.74 0.60 0.57 0.00	68 260 447 154 19 13 961 support 72 321 516 47 5
1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人 6、1000-4999人 avg / total 随机森林合成阿片类: pre 1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人 6、1000-4999人	0.27 0.52 0.66 0.62 0.55 0.81 0.59 ecision 0.35 0.60 0.77 0.48 1.00 0.00	0.29 0.49 0.67 0.63 0.58 1.00 0.59 recall f	0.28 0.51 0.67 0.63 0.56 0.90 0.59 E1-score 0.40 0.58 0.74 0.60 0.57 0.00	68 260 447 154 19 13 961 support 72 321 516 47 5
1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人 6、1000-4999人 avg / total 随机森林合成阿片类: pre 1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人 6、1000-4999人 avg / total 随机森林非合成阿片类	0.27 0.52 0.66 0.62 0.55 0.81 0.59 ecision 0.35 0.60 0.77 0.48 1.00 0.00 0.67	0.29 0.49 0.67 0.63 0.58 1.00 0.59 recall f	0.28 0.51 0.67 0.63 0.56 0.90 0.59 E1-score 0.40 0.58 0.74 0.60 0.57 0.00 0.65	68 260 447 154 19 13 961 support 72 321 516 47 5 0
1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人 6、1000-4999人 avg / total 随机森林合成阿片类: pre 1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人 6、1000-4999人 avg / total 随机森林非合成阿片类	0.27 0.52 0.66 0.62 0.55 0.81 0.59 ecision 0.35 0.60 0.77 0.48 1.00 0.00 0.67	0.29 0.49 0.67 0.63 0.58 1.00 0.59 recall f	0.28 0.51 0.67 0.63 0.56 0.90 0.59 E1-score 0.40 0.58 0.74 0.60 0.57 0.00 0.65	68 260 447 154 19 13 961 support 72 321 516 47 5 0
1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人 6、1000-4999人 avg / total 随机森林合成阿片类: pre 1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人 6、1000-4999人 avg / total 随机森林非合成阿片类	0.27 0.52 0.66 0.62 0.55 0.81 0.59 ecision 0.35 0.60 0.77 0.48 1.00 0.00 0.67 :	0.29 0.49 0.67 0.63 0.58 1.00 0.59 recall f	0.28 0.51 0.67 0.63 0.56 0.90 0.59 61-score 0.40 0.58 0.74 0.60 0.57 0.00 0.65	68 260 447 154 19 13 961 support 72 321 516 47 5 0
1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人 6、1000-4999人 avg / total 随机森林合成阿片类: pre 1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人 6、1000-4999人 avg / total 随机森林非合成阿片类	0.27 0.52 0.66 0.62 0.55 0.81 0.59 ecision 0.35 0.60 0.77 0.48 1.00 0.00 0.67 :	0.29 0.49 0.67 0.63 0.58 1.00 0.59 recall f 0.49 0.56 0.71 0.83 0.40 0.00 0.65	0.28 0.51 0.67 0.63 0.56 0.90 0.59 61-score 0.40 0.58 0.74 0.60 0.57 0.00 0.65	68 260 447 154 19 13 961 support 72 321 516 47 5 0 961 support 293

3、10-99人	0.42	0.76	0.54	55
4、100-499人	1.00	1.00	1.00	2
avg / total	0.65	0.63	0.64	897
随机森林半合成阿	片类:			
	precision	recall	f1-score	support
1、0人	0.31	0.42	0.36	55
2、1-9人	0.57	0.52	0.55	265
3、10-99人	0.73	0.69	0.71	474
4、100-499人	0.60	0.65	0.62	143
	0.20			10
6、1000-4999人				
avg / total	0.64	0.62	0.63	961
9 / 20241	3.01	0.02	0.03	301
支持向量机合成阿	片类:			
~141.4 ± 0.0 □ bVbd	precision	recall	f1-score	support
	p. 001310II	· ccaii	. 1 30016	Sapport
1 0 4	0.00	0.00	0.00	0
	0.59			
3、10-99人				
4、100-499人				
	0.50			
6、1000-4999人	0.00	0.00	0.00	0
/ +-+-1	0.72	0 61	0.00	0.01
avo / total	0.72	0.61	0.66	961
u.g / cocu.				
_	际 上米			
支持向量机非合成		recall f	-score	sunnor+
支持向量机非合成	阿片类: precision	recall f	-1-score	support
支持向量机非合成	precision			
支持向量机非合成 1、0人	precision 0.23	0.68	0.34	96
支持向量机非合成 1、0人 2、1-9人	0.23 0.94	0.68 0.62	0.34 0.75	96 768
支持向量机非合成 1、0人 2、1-9人 3、10-99人	0.23 0.94 0.31	0.68 0.62 0.97	0.34 0.75 0.47	96 768 32
支持向量机非合成 1、0人 2、1-9人	0.23 0.94 0.31	0.68 0.62	0.34 0.75	96 768
支持向量机非合成 1、0人 2、1-9人 3、10-99人 4、100-499人	0.23 0.94 0.31 0.50	0.68 0.62 0.97 1.00	0.34 0.75 0.47 0.67	96 768 32 1
支持向量机非合成 1、0人 2、1-9人 3、10-99人	0.23 0.94 0.31 0.50	0.68 0.62 0.97	0.34 0.75 0.47 0.67	96 768 32
支持向量机非合成 1、0人 2、1-9人 3、10-99人 4、100-499人 avg / total	0.23 0.94 0.31 0.50	0.68 0.62 0.97 1.00	0.34 0.75 0.47 0.67	96 768 32 1
支持向量机非合成 1、0人 2、1-9人 3、10-99人 4、100-499人	0.23 0.94 0.31 0.50 0.84	0.68 0.62 0.97 1.00	0.34 0.75 0.47 0.67	96 768 32 1
支持向量机非合成 1、0人 2、1-9人 3、10-99人 4、100-499人 avg / total	0.23 0.94 0.31 0.50	0.68 0.62 0.97 1.00	0.34 0.75 0.47 0.67	96 768 32 1
支持向量机非合成 1、0人 2、1-9人 3、10-99人 4、100-499人 avg / total 支持向量机半合成	0.23 0.94 0.31 0.50 0.84 阿片类: precision	0.68 0.62 0.97 1.00 0.64	0.34 0.75 0.47 0.67 0.69	96 768 32 1 897
支持向量机非合成 1、0人 2、1-9人 3、10-99人 4、100-499人 avg / total 支持向量机半合成 1、0人	0.23 0.94 0.31 0.50 0.84 阿片类: precision	0.68 0.62 0.97 1.00 0.64	0.34 0.75 0.47 0.67 0.69 f1-score	96 768 32 1 897 support
支持向量机非合成 1、0人 2、1-9人 3、10-99人 4、100-499人 avg / total 支持向量机半合成 1、0人 2、1-9人	0.23 0.94 0.31 0.50 0.84 阿片类: precision 0.00 0.61	0.68 0.62 0.97 1.00 0.64 recall	0.34 0.75 0.47 0.67 0.69 f1-score 0.00 0.57	96 768 32 1 897 support
支持向量机非合成 1、0人 2、1-9人 3、10-99人 4、100-499人 avg / total 支持向量机半合成 1、0人 2、1-9人 3、10-99人	0.23 0.94 0.31 0.50 0.84 阿片类: precision 0.00 0.61 0.75	0.68 0.62 0.97 1.00 0.64 recall 0.00 0.53 0.65	0.34 0.75 0.47 0.67 0.69 f1-score 0.00 0.57 0.70	96 768 32 1 897 support 0 285 520
支持向量机非合成 1、0人 2、1-9人 3、10-99人 4、100-499人 avg / total 支持向量机半合成 1、0人 2、1-9人 3、10-99人 4、100-499人	0.23 0.94 0.31 0.50 0.84 阿片类: precision 0.00 0.61 0.75 0.51	0.68 0.62 0.97 1.00 0.64 recall 0.00 0.53 0.65 0.57	0.34 0.75 0.47 0.67 0.69 f1-score 0.00 0.57 0.70 0.54	96 768 32 1 897 support 0 285 520 141
支持向量机非合成 1、0人 2、1-9人 3、10-99人 4、100-499人 avg / total 支持向量机半合成 1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人	0.23 0.94 0.31 0.50 0.84 阿片类: precision 0.00 0.61 0.75 0.51	0.68 0.62 0.97 1.00 0.64 recall 0.00 0.53 0.65 0.57 0.33	0.34 0.75 0.47 0.67 0.69 f1-score 0.00 0.57 0.70 0.54 0.09	96 768 32 1 897 support 0 285 520 141 3
支持向量机非合成 1、0人 2、1-9人 3、10-99人 4、100-499人 avg / total 支持向量机半合成 1、0人 2、1-9人 3、10-99人 4、100-499人	0.23 0.94 0.31 0.50 0.84 阿片类: precision 0.00 0.61 0.75 0.51	0.68 0.62 0.97 1.00 0.64 recall 0.00 0.53 0.65 0.57	0.34 0.75 0.47 0.67 0.69 f1-score 0.00 0.57 0.70 0.54 0.09	96 768 32 1 897 support 0 285 520 141
支持向量机非合成 1、0人 2、1-9人 3、10-99人 4、100-499人 avg / total 支持向量机半合成 1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人 6、1000-4999人	0.23 0.94 0.31 0.50 0.84 阿片类: precision 0.00 0.61 0.75 0.51 0.05	0.68 0.62 0.97 1.00 0.64 recall 0.00 0.53 0.65 0.57 0.33 0.92	0.34 0.75 0.47 0.67 0.69 f1-score 0.00 0.57 0.70 0.54 0.09 0.79	96 768 32 1 897 support 0 285 520 141 3 12
支持向量机非合成 1、0人 2、1-9人 3、10-99人 4、100-499人 avg / total 支持向量机半合成 1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人	0.23 0.94 0.31 0.50 0.84 阿片类: precision 0.00 0.61 0.75 0.51 0.05	0.68 0.62 0.97 1.00 0.64 recall 0.00 0.53 0.65 0.57 0.33 0.92	0.34 0.75 0.47 0.67 0.69 f1-score 0.00 0.57 0.70 0.54 0.09 0.79	96 768 32 1 897 support 0 285 520 141 3
支持向量机非合成 1、0人 2、1-9人 3、10-99人 4、100-499人 avg / total 支持向量机半合成 1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人 6、1000-4999人 avg / total	0.23 0.94 0.31 0.50 0.84 阿片类: precision 0.00 0.61 0.75 0.51 0.05 0.69	0.68 0.62 0.97 1.00 0.64 recall 0.00 0.53 0.65 0.57 0.33 0.92	0.34 0.75 0.47 0.67 0.69 f1-score 0.00 0.57 0.70 0.54 0.09 0.79	96 768 32 1 897 support 0 285 520 141 3 12
支持向量机非合成 1、0人 2、1-9人 3、10-99人 4、100-499人 avg / total 支持向量机半合成 1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人 6、1000-4999人	0.23 0.94 0.31 0.50 0.84 阿片类: precision 0.00 0.61 0.75 0.51 0.05 0.69	0.68 0.62 0.97 1.00 0.64 recall 0.00 0.53 0.65 0.57 0.33 0.92	0.34 0.75 0.47 0.67 0.69 f1-score 0.00 0.57 0.70 0.54 0.09 0.79	96 768 32 1 897 support 0 285 520 141 3 12
支持向量机非合成 1、0人 2、1-9人 3、10-99人 4、100-499人 avg / total 支持向量机半合成 1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人 6、1000-4999人 avg / total	0.23 0.94 0.31 0.50 0.84 阿片类: precision 0.00 0.61 0.75 0.51 0.05 0.69	0.68 0.62 0.97 1.00 0.64 recall 0.00 0.53 0.65 0.57 0.33 0.92	0.34 0.75 0.47 0.67 0.69 f1-score 0.00 0.57 0.70 0.54 0.09 0.79	96 768 32 1 897 support 0 285 520 141 3 12
支持向量机非合成 1、0人 2、1-9人 3、10-99人 4、100-499人 avg / total 支持向量机半合成 1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人 6、1000-4999人 avg / total 神经网络合成阿片	0.23 0.94 0.31 0.50 0.84 阿片类: precision 0.00 0.61 0.75 0.51 0.05 0.69	0.68 0.62 0.97 1.00 0.64 recall 0.00 0.53 0.65 0.57 0.33 0.92	0.34 0.75 0.47 0.67 0.69 f1-score 0.00 0.57 0.70 0.54 0.09 0.79	96 768 32 1 897 support 0 285 520 141 3 12 961
支持向量机非合成 1、0人 2、1-9人 3、10-99人 4、100-499人 avg / total 支持向量机半合成 1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人 6、1000-4999人 avg / total 神经网络合成阿片 1、0人	0.23 0.94 0.31 0.50 0.84 阿片类: precision 0.00 0.61 0.75 0.51 0.05 0.69	0.68 0.62 0.97 1.00 0.64 recall 0.00 0.53 0.65 0.57 0.33 0.92 0.60	0.34 0.75 0.47 0.67 0.69 f1-score 0.00 0.57 0.70 0.54 0.09 0.79 0.64 f1-score	96 768 32 1 897 support 0 285 520 141 3 12 961 support 46
支持向量机非合成 1、0人 2、1-9人 3、10-99人 4、100-499人 avg / total 支持向量机半合成 1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人 6、1000-4999人 avg / total 神经网络合成阿片 1、0人 2、1-9人	0.23 0.94 0.31 0.50 0.84 阿片类: precision 0.00 0.61 0.75 0.51 0.05 0.69 0.67 类: precision	0.68 0.62 0.97 1.00 0.64 recall 0.00 0.53 0.65 0.57 0.33 0.92 0.60	0.34 0.75 0.47 0.67 0.69 f1-score 0.00 0.57 0.70 0.54 0.09 0.79 0.64 f1-score	96 768 32 1 897 support 0 285 520 141 3 12 961 support 46
支持向量机非合成 1、0人 2、1-9人 3、10-99人 4、100-499人 avg / total 支持向量机半合成 1、0人 2、1-9人 3、10-99人 4、100-499人 5、500-999人 6、1000-4999人 avg / total 神经网络合成阿片 1、0人	0.23 0.94 0.31 0.50 0.84 阿片类: precision 0.00 0.61 0.75 0.51 0.05 0.69 0.67 类: precision	0.68 0.62 0.97 1.00 0.64 recall 0.00 0.53 0.65 0.57 0.33 0.92 0.60	0.34 0.75 0.47 0.67 0.69 f1-score 0.00 0.57 0.70 0.54 0.09 0.79 0.64 f1-score	96 768 32 1 897 support 0 285 520 141 3 12 961 support 46

F F00 000 l				
5、500-999人	0.00	0.00	0.00	0
6、1000-4999人	0.00	0.00	0.00	0
avg / total	0.67	0.62	0.64	961
神经网络非合成阿	∫片类 :			
	precision	recall f	1-score	support
	p. 55.5.5.			
1、0人	0.46	0.60	0.52	218
2、1-9人		0.66	0.73	639
3、10-99人		0.89	0.73	38
4、100-499人	1.00	1.00	1.00	2
4、100-499人	1.00	1.00	1.00	۷
/	0.70	0.65	0.67	007
avg / total	0.72	0.65	0.67	897
	r II NA			
神经网络半合成阿				
	precision	recall ·	f1-score	support
1、0人		0.00		7
2、1-9人	0.58	0.51	0.54	281
3、10-99人	0.71	0.65	0.68	492
4、100-499人	0.61	0.57	0.59	166
5、500-999人	0.00	0.00	0.00	0
6、1000-4999人	0.62	0.67	0.65	15
avg / total	0.65	0.59	0.62	961
<i>J</i> ,				
线性回归合成阿片	一类:			
2 III /4 II /4 I / 1/ 1	precision	recall ·	f1-score	support
	precision	Γετατί	11 30010	зиррот с
1、0人	0.00	0.00	0.00	1
2、1-9人		0.56	0.57	307
3、10-99人		0.65	0.73	616
4、100-499人		0.69	0.41	35
5、500-999人		1.00	1.00	2
6、1000-4999人	0.00	0.00	0.00	0
avg / total	0.73	0.62	0.67	961
线性回归非合成阿	〕片类:			
	precision	recall f	1-score	support
				154
1、0人	0.36	0.68	0.47	T)-
1、0人 2、1-9人		0.68 0.65	0.47 0.75	
2、1-9人	0.89	0.65	0.75	696
2、1-9人 3、10-99人	0.89 0.37	0.65 0.82	0.75 0.51	696 45
2、1-9人	0.89 0.37	0.65	0.75	696
2、1-9人 3、10-99人 4、100-499人	0.89 0.37 1.00	0.65 0.82 1.00	0.75 0.51 1.00	696 45 2
2、1-9人 3、10-99人	0.89 0.37 1.00	0.65 0.82 1.00	0.75 0.51 1.00	696 45 2
2、1-9人 3、10-99人 4、100-499人 avg / total	0.89 0.37 1.00	0.65 0.82 1.00	0.75 0.51 1.00	696 45 2
2、1-9人 3、10-99人 4、100-499人	0.89 0.37 1.00 0.78	0.65 0.82 1.00 0.66	0.75 0.51 1.00 0.69	696 45 2 897
2、1-9人 3、10-99人 4、100-499人 avg / total	0.89 0.37 1.00	0.65 0.82 1.00 0.66	0.75 0.51 1.00 0.69	696 45 2 897
2、1-9人 3、10-99人 4、100-499人 avg / total 线性回归半合成阿	0.89 0.37 1.00 0.78 J片类: precision	0.65 0.82 1.00 0.66	0.75 0.51 1.00 0.69	696 45 2 897 support
2、1-9人 3、10-99人 4、100-499人 avg / total 线性回归半合成阿 1、0人	0.89 0.37 1.00 0.78 J片类: precision 0.00	0.65 0.82 1.00 0.66	0.75 0.51 1.00 0.69 f1-score	696 45 2 897 support
2、1-9人 3、10-99人 4、100-499人 avg / total 线性回归半合成阿	0.89 0.37 1.00 0.78 J片类: precision 0.00	0.65 0.82 1.00 0.66	0.75 0.51 1.00 0.69 f1-score	696 45 2 897 support
2、1-9人 3、10-99人 4、100-499人 avg / total 线性回归半合成阿 1、0人	0.89 0.37 1.00 0.78 J片类: precision 0.00 0.37	0.65 0.82 1.00 0.66	0.75 0.51 1.00 0.69 f1-score 0.00 0.43	696 45 2 897 support
2、1-9人 3、10-99人 4、100-499人 avg / total 线性回归半合成阿 1、0人 2、1-9人	0.89 0.37 1.00 0.78 J片类: precision 0.00 0.37 0.86	0.65 0.82 1.00 0.66 recall -	0.75 0.51 1.00 0.69 f1-score 0.00 0.43 0.70	696 45 2 897 support 0 169
2、1-9人 3、10-99人 4、100-499人 avg / total 线性回归半合成阿 1、0人 2、1-9人 3、10-99人	0.89 0.37 1.00 0.78 J片类: precision 0.00 0.37 0.86 0.43	0.65 0.82 1.00 0.66 recall -	0.75 0.51 1.00 0.69 f1-score 0.00 0.43 0.70 0.48	696 45 2 897 support 0 169 656
2、1-9人 3、10-99人 4、100-499人 avg / total 线性回归半合成阿 1、0人 2、1-9人 3、10-99人 4、100-499人	0.89 0.37 1.00 0.78 J片类: precision 0.00 0.37 0.86 0.43 0.00	0.65 0.82 1.00 0.66 recall 0.00 0.53 0.59 0.55	0.75 0.51 1.00 0.69 f1-score 0.00 0.43 0.70 0.48	696 45 2 897 support 0 169 656 122

0.72

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packages\sklearn\metrics\classification.py:1137: UndefinedMetricWarning: Recall
and F-score are ill-defined and being set to 0.0 in labels with no true samples.
  'recall', 'true', average, warn_for)
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C:\ProgramData\Anaconda3\lib\site-
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and F-score are ill-defined and being set to 0.0 in labels with no true samples.
  'recall', 'true', average, warn_for)
```