2120192797-亓志强-基于人口普查数据的收入预测模型构建及比较分析

数据来自UCI的(Adult Data Set)[https://archive.ics.uci.edu/ml/datasets/adult]数据集，该数据集包括三个文件，`adult.names`为数据集的说明文件，包括数据来源以及各指标的名称和说明。(https://archive.ics.uci.edu/ml/datasets/adult%5D%E6%95%B0%E6%8D%AE%E9%9B%86%EF%BC%8C%E8%AF%A5%E6%adult.data 和 adult.test 分别为已分割好的训练集和测试集，本文将这两个数据集进行合并，在处理的过程中重新划分样本的训练集和测试集。

In [1]:
```
# 控制页面大小
from IPython.core.display import display, HTML
# display(HTML("<style>.container { width:100% !important; }</style>"))  # 宽度100%
# display(HTML("<style>.container {}</style>"))  # 恢复正常
```

1 导入数据包

In [2]:
```
## 导入相关数据包
# 数据处理
import time, datetime, math, random
from io import StringIO
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split

# 可视化
import matplotlib.pyplot as plt  # 绘图
import missingno  # 缺失值可视化
import seaborn as sns  # 绘图库
from pandas.plotting import scatter_matrix #绘制散布矩阵图
# from mpl_toolkits.mplot3d import Axes3D #绘制三维图

# 分类模型
# import sklearn.ensemble as ske # 包含了一套分类算法
from sklearn import datasets, model_selection, tree, preprocessing, metrics, linear_model
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import LinearRegression, LogisticRegression, Ridge, Lasso, SGDClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import VotingClassifier
from sklearn.svm import SVC
# from sklearn.svm import LinearSVC

# 自动调参器 - 随机探索
import scipy.stats as st
from scipy.stats import randint as sp_randint # 随机变量
# from sklearn.model_selection import GridSearchCV # 自动调参工具（网格搜索）
from sklearn.model_selection import RandomizedSearchCV # 自动调参工具（随机采样）

# 计算模型评价指标
from sklearn.metrics import precision_recall_fscore_support, roc_curve, auc
from sklearn.metrics import precision_recall_curve
from sklearn.metrics import average_precision_score, f1_score, precision_score, recall_score

# 控制提示信息
import warnings
warnings.filterwarnings('ignore')

# 便于在notebook中显示图形并可省略plt.show()，简化代码
%matplotlib inline

```

2 导入数据集

In [3]:
```
## 载入原始样本的训练集和测试集
# 本题目数据不含标题行，缺失值在文件中用? 表示，测试集首行非数据需剔除
headers = ['age', 'workclass', 'final-weight',
           'education', 'education-num',
           'marital-status', 'occupation',
           'relationship', 'race', 'sex',
           'capital-gain', 'capital-loss',
           'hours-per-week', 'country',
           'income-level']  # 定义数据表头即参数名
# headers = ['年龄', '工作类型', '权重',
#            '受教育程度', '受教育时长',
#            '婚姻情况', '职业',
#            '家庭角色', '种族', '性别',
#            '资本收益', '资本支出',
#            '周工作小时数', '国籍',
#            '收入等级']
adult_data = pd.read_csv('dataset/adult.data',
                         header=None,
                         names=headers,
                         sep=',\s',
                         na_values=["?"],
                         engine='python')  # 导入数据集给出的训练集
adult_test = pd.read_csv('dataset/adult.test',
                         header=None,
                         names=headers,
                         sep=',\s',
                         na_values=["?"],
                         engine='python',
                         skiprows=1)  # 导入数据集给出的测试集
```

In [4]:
```
## 合并两个数据集
dataset = adult_data.append(adult_test)
# 由于导入时分别为两数据集添加了索引，故对合并后的DataFrame重新创建索引并覆盖原索引
dataset.reset_index(inplace=True, drop=True)
```

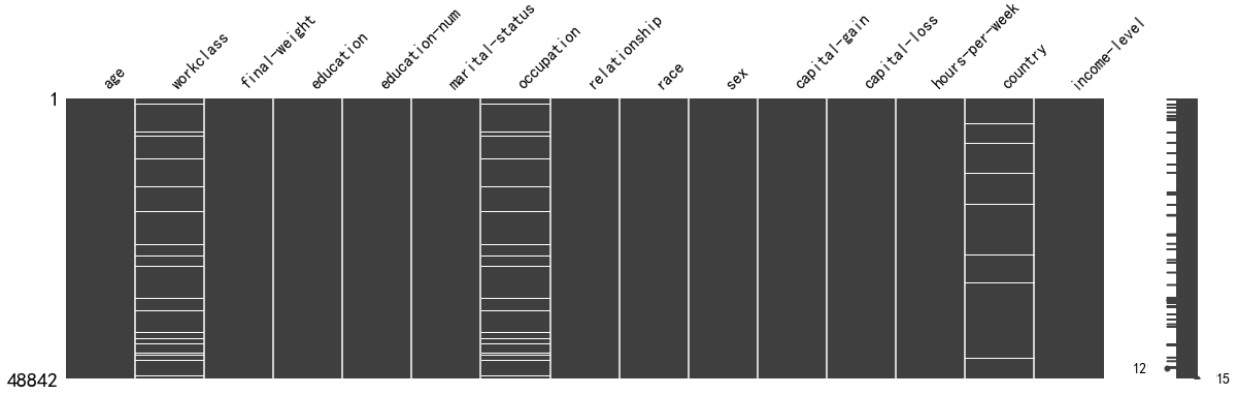
3 数据预处理

3.1 处理缺失值

3.1.1 查看数据缺失分布情况

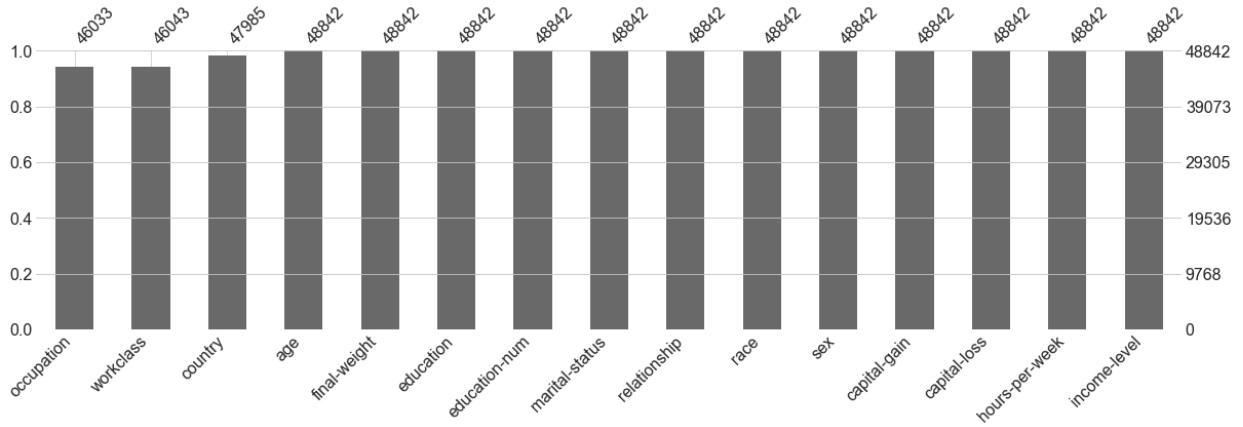
In [5]:
```
# 查看缺失值分布情况
missingno.matrix(dataset, figsize = (20,5))
```

Out[5]: <matplotlib.axes._subplots.AxesSubplot at 0x148dfc7cf60>



In [6]:
```
# 创建缺失值统计条形图并按缺失数量升序排列
plt.style.use('seaborn-whitegrid')
missingno.bar(dataset, sort='ascending', figsize = (20,5))
```

Out[6]: <matplotlib.axes._subplots.AxesSubplot at 0x148dff14128>



In [7]:
```
dataset.describe(include='all')
```

Out[7]:

	age	workclass	final-weight	education	education-num	marital-status	occupation	relationship	race	sex	
count	48842.000000	46043	4.884200e+04	48842	48842.000000	48842	46033	48842	48842	48842	4
unique	NaN	8	NaN	16	NaN	7	14	6	5	2	
top	NaN	Private	NaN	HS-grad	NaN	Married-civ-spouse	Prof-specialty	Husband	White	Male	
freq	NaN	33906	NaN	15784	NaN	22379	6172	19716	41762	32650	
mean	38.643585	NaN	1.896641e+05	NaN	10.078089	NaN	NaN	NaN	NaN	NaN	
std	13.710510	NaN	1.056040e+05	NaN	2.570973	NaN	NaN	NaN	NaN	NaN	
min	17.000000	NaN	1.228500e+04	NaN	1.000000	NaN	NaN	NaN	NaN	NaN	
25%	28.000000	NaN	1.175505e+05	NaN	9.000000	NaN	NaN	NaN	NaN	NaN	
50%	37.000000	NaN	1.781445e+05	NaN	10.000000	NaN	NaN	NaN	NaN	NaN	
75%	48.000000	NaN	2.376420e+05	NaN	12.000000	NaN	NaN	NaN	NaN	NaN	
max	90.000000	NaN	1.490400e+06	NaN	16.000000	NaN	NaN	NaN	NaN	NaN	9

数据集共包含48842个样本，其中occupation、workclass、country三个指标存在缺失值。

3.1.2 处理缺失样本

In [8]:
```
dataset.dropna(axis=0, how='any', inplace=True)
dataset.describe(include='all')
```

Out[8]:

	age	workclass	final-weight	education	education-num	marital-status	occupation	relationship	race	sex	
count	45222.000000	45222	4.522200e+04	45222	45222.000000	45222	45222	45222	45222	45222	4
unique	NaN	7	NaN	16	NaN	7	14	6	5	2	
top	NaN	Private	NaN	HS-grad	NaN	Married-civ-spouse	Craft-repair	Husband	White	Male	
freq	NaN	33307	NaN	14783	NaN	21055	6020	18666	38903	30527	
mean	38.547941	NaN	1.897347e+05	NaN	10.118460	NaN	NaN	NaN	NaN	NaN	
std	13.217870	NaN	1.056392e+05	NaN	2.552881	NaN	NaN	NaN	NaN	NaN	
min	17.000000	NaN	1.349200e+04	NaN	1.000000	NaN	NaN	NaN	NaN	NaN	
25%	28.000000	NaN	1.173882e+05	NaN	9.000000	NaN	NaN	NaN	NaN	NaN	
50%	37.000000	NaN	1.783160e+05	NaN	10.000000	NaN	NaN	NaN	NaN	NaN	
75%	47.000000	NaN	2.379260e+05	NaN	13.000000	NaN	NaN	NaN	NaN	NaN	
max	90.000000	NaN	1.490400e+06	NaN	16.000000	NaN	NaN	NaN	NaN	NaN	9

由于本题目数据量较为充足，含有缺失值的样本也较少，故采取直接删除含缺失值样本的方式对缺失值进行处理。 处理后共删除48842-45222=3620个样本，剩余45222个有效样本

3.2 处理数据异常

In [9]:
```
# 处理年收入指标
# 由于年收入指标存在四种值，‘>50K’，‘>50K.’，‘<=50K’，‘<=50K.’，故本题中将‘>50K’和‘>50K.’，‘<=50K’和‘<=
dataset.loc[dataset['income-level'] == '>50K.', 'income-level'] = '>50K'
dataset.loc[dataset['income-level'] == '<=50K.', 'income-level'] = '<=50K'

# 删除无用的final-weight指标
dataset = dataset.drop(['final-weight'],axis=1)
```

3.3 对数据整体进行描述

In [10]:
```
# 预览数据
dataset.head(5) # 前5行
# dataset.tail(5) # 后5行
```

Out[10]:

	age	workclass	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week	count
0	39	State-gov	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	Unite Stat
1	50	Self-emp-not-inc	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	Unite Stat
2	38	Private	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	Unite Stat
3	53	Private	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	Unite Stat
4	28	Private	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	Cul

In [11]:

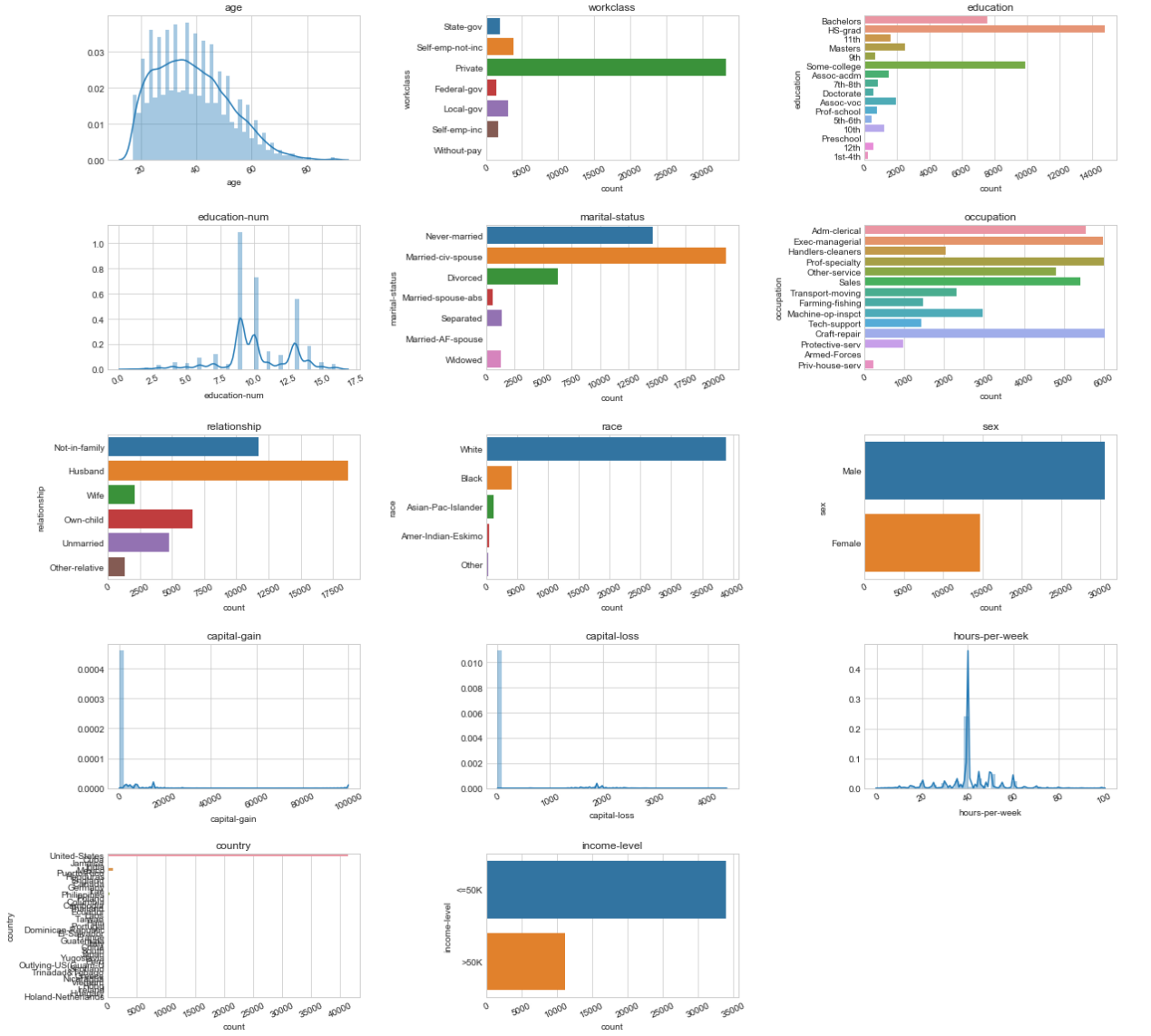
```
# 对数值变量进行描述
dataset.describe(include='all')
```

Out[11]:

	age	workclass	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	
count	45222.000000	45222	45222	45222.000000	45222	45222	45222	45222	45222	45222.000000	4
unique	NaN	7	16	NaN	7	14	6	5	2	NaN	
top	NaN	Private	HS-grad	NaN	Married-civ-spouse	Craft-repair	Husband	White	Male	NaN	
freq	NaN	33307	14783	NaN	21055	6020	18666	38903	30527	NaN	
mean	38.547941	NaN	NaN	10.118460	NaN	NaN	NaN	NaN	NaN	1101.430344	
std	13.217870	NaN	NaN	2.552881	NaN	NaN	NaN	NaN	NaN	7506.430084	
min	17.000000	NaN	NaN	1.000000	NaN	NaN	NaN	NaN	NaN	0.000000	
25%	28.000000	NaN	NaN	9.000000	NaN	NaN	NaN	NaN	NaN	0.000000	
50%	37.000000	NaN	NaN	10.000000	NaN	NaN	NaN	NaN	NaN	0.000000	
75%	47.000000	NaN	NaN	13.000000	NaN	NaN	NaN	NaN	NaN	0.000000	
max	90.000000	NaN	NaN	16.000000	NaN	NaN	NaN	NaN	NaN	99999.000000	

In [12]:

```
# 绘制每个变量的分布状况
def plot_distribution(dataset, cols, width, height, hspace, wspace):
    plt.style.use('seaborn-whitegrid')
    fig = plt.figure(figsize=(width,height))
    fig.subplots_adjust(left=None, bottom=None, right=None, top=None, wspace=wspace, hspace=hspace
    rows = math.ceil(float(dataset.shape[1]) / cols)
    for i, column in enumerate(dataset.columns):
        ax = fig.add_subplot(rows, cols, i + 1)
        ax.set_title(column)
        if dataset.dtypes[column] == np.object:
            g = sns.countplot(y=column, data=dataset)
            substrings = [s.get_text()[:18] for s in g.get_yticklabels()]
            g.set(yticklabels=substrings)
            plt.xticks(rotation=25)
        else:
            g = sns.distplot(dataset[column])
            plt.xticks(rotation=25)

plot_distribution(dataset, cols=3, width=20, height=20, hspace=0.45, wspace=0.5)
```



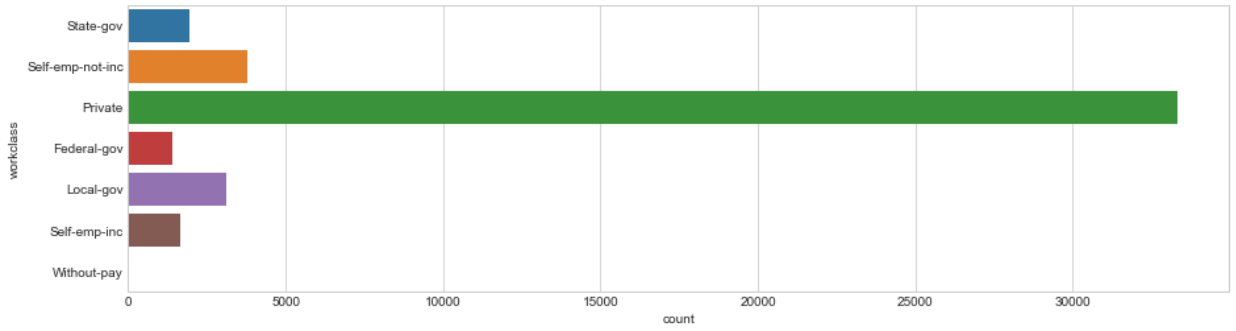
3.4 对各个离散型指标进行分析

本文所用的数据涉及多个分类变量，下面将对这些变量进行检查和处理

3.4.1 工作类型

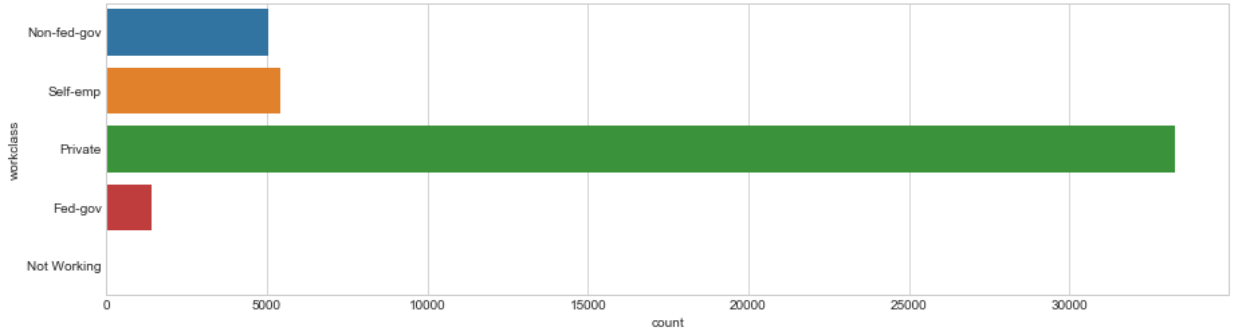
本文数据集共有8种数据类型：私人（Private）、自由职业非公司（Self-emp-not-inc）、自由职业公司（Self-emp-inc）、联邦政府（Federal-gov）、地方政府（Local-gov）、州政府（State-gov）、无薪（Without-pay）、无工作经验（Never-worked）；

In [13]:
```
# 工作类型
# 私营工作在样本中占比较大，不工作和无收入工作样本数量极小
plt.style.use('seaborn-whitegrid')
plt.figure(figsize=(15,4))
sns.countplot(y="workclass", data=dataset);
```



In [14]:
```
# 根据上述数据分布情况和实际考虑，将上述8种类型的工作类型分为5类：
dataset.loc[dataset['workclass'] == 'Without-pay', 'workclass'] = 'Not Working'
dataset.loc[dataset['workclass'] == 'Never-worked', 'workclass'] = 'Not Working'
dataset.loc[dataset['workclass'] == 'Federal-gov', 'workclass'] = 'Fed-gov'
dataset.loc[dataset['workclass'] == 'State-gov', 'workclass'] = 'Non-fed-gov'
dataset.loc[dataset['workclass'] == 'Local-gov', 'workclass'] = 'Non-fed-gov'
dataset.loc[dataset['workclass'] == 'Self-emp-not-inc', 'workclass'] = 'Self-emp'
dataset.loc[dataset['workclass'] == 'Self-emp-inc', 'workclass'] = 'Self-emp'
dataset.loc[dataset['workclass'] == 'Private', 'workclass'] = 'Private'
```

In [15]:
```
plt.style.use('seaborn-whitegrid')
fig = plt.figure(figsize=(15,4))
sns.countplot(y="workclass", data=dataset);
```



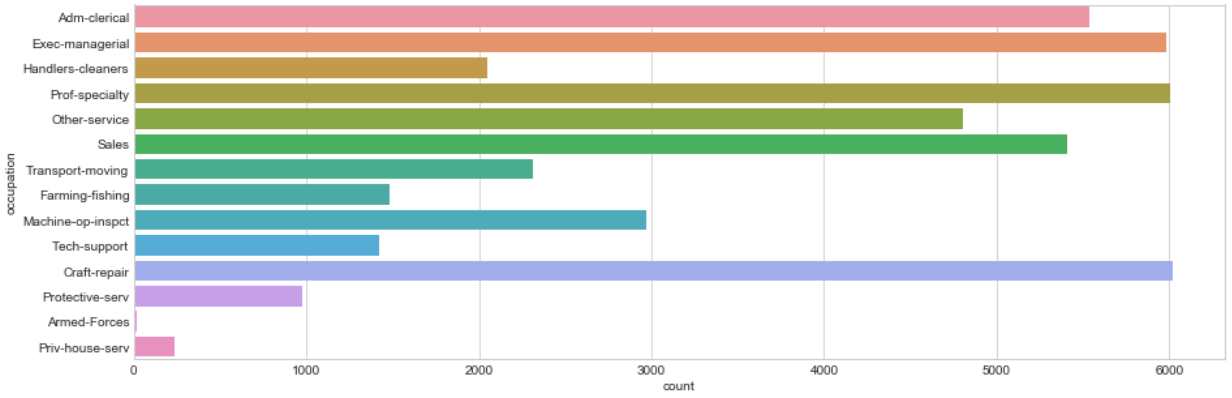
3.4.2 职业

本数据集中职业共有14种类型如下：

Tech-support（技术支持），Craft-repair（手工艺维修），Other-service（其他职业），Sales（销售），Exec-managerial（执行主管），Prof-specialty（专业技术），Handlers-cleaners（劳工保洁），Machine-op-inspct（机械操作），Adm-clerical（管理文书），Farming-fishing（农业捕捞），Transport-moving（运输），Priv-house-serv（家政服务），Protective-serv（保安），Armed-Forces（军人）

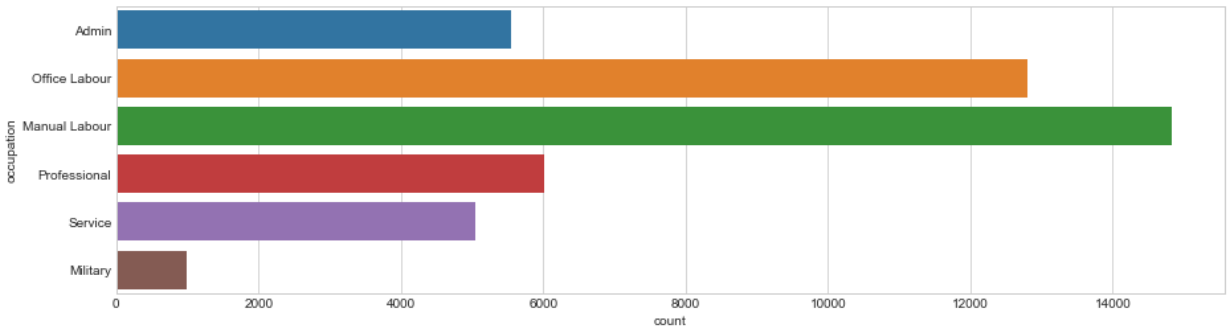
为便于后续分析，将其合并为

In [16]:
```
## 职业
plt.style.use('seaborn-whitegrid')
plt.figure(figsize=(15,5))
sns.countplot(y="occupation", data=dataset);
```



In [17]:
```
# 职业共存在14类，按职业类型进行归纳并划分为
#
dataset.loc[dataset['occupation'] == 'Adm-clerical', 'occupation'] = 'Admin'  # 行政文员
dataset.loc[dataset['occupation'] == 'Armed-Forces', 'occupation'] = 'Military'  # 军队
dataset.loc[dataset['occupation'] == 'Protective-serv', 'occupation'] = 'Military'  # 军队
dataset.loc[dataset['occupation'] == 'Craft-repair', 'occupation'] = 'Manual Labour'  # 体力劳动者
dataset.loc[dataset['occupation'] == 'Transport-moving', 'occupation'] = 'Manual Labour'  # 体力劳
dataset.loc[dataset['occupation'] == 'Farming-fishing', 'occupation'] = 'Manual Labour'  # 体力劳动
dataset.loc[dataset['occupation'] == 'Handlers-cleaners', 'occupation'] = 'Manual Labour'  # 体力劳
dataset.loc[dataset['occupation'] == 'Machine-op-inspct', 'occupation'] = 'Manual Labour'  # 体力劳
dataset.loc[dataset['occupation'] == 'Exec-managerial', 'occupation'] = 'Office Labour'  # 文书工作
dataset.loc[dataset['occupation'] == 'Sales', 'occupation'] = 'Office Labour'  # 文书工作
dataset.loc[dataset['occupation'] == 'Tech-support', 'occupation'] = 'Office Labour'  # 文书工作
dataset.loc[dataset['occupation'] == 'Other-service', 'occupation'] = 'Service'  # 服务人员
dataset.loc[dataset['occupation'] == 'Priv-house-serv', 'occupation'] = 'Service'  # 服务人员
dataset.loc[dataset['occupation'] == 'Prof-specialty', 'occupation'] = 'Professional'  # 技术人员
```

In [18]:
```
plt.style.use('seaborn-whitegrid')
fig = plt.figure(figsize=(15,4))
sns.countplot(y="occupation", data=dataset);
```

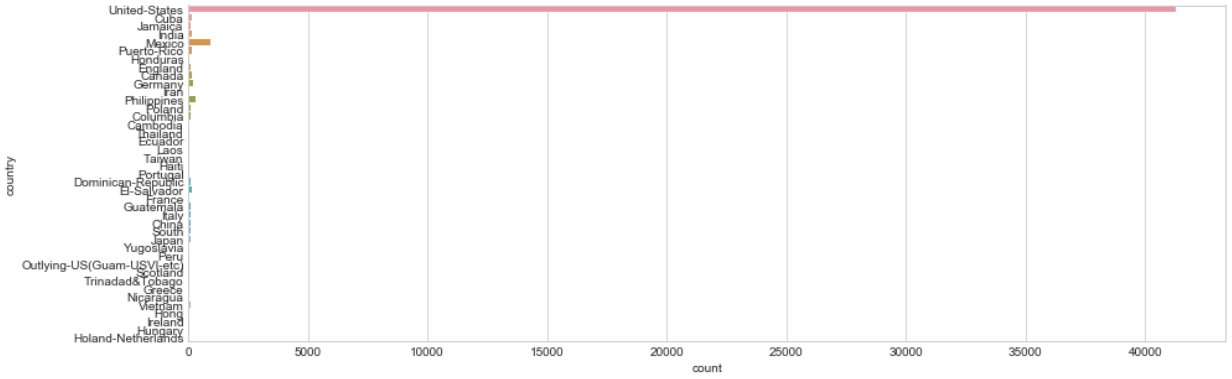


3.4.3 国籍

数据说明里共列出41个国家和地区，除美国外大部分国家和地区的样本都很少，故在此按照地域对这些国家和地区进行合并

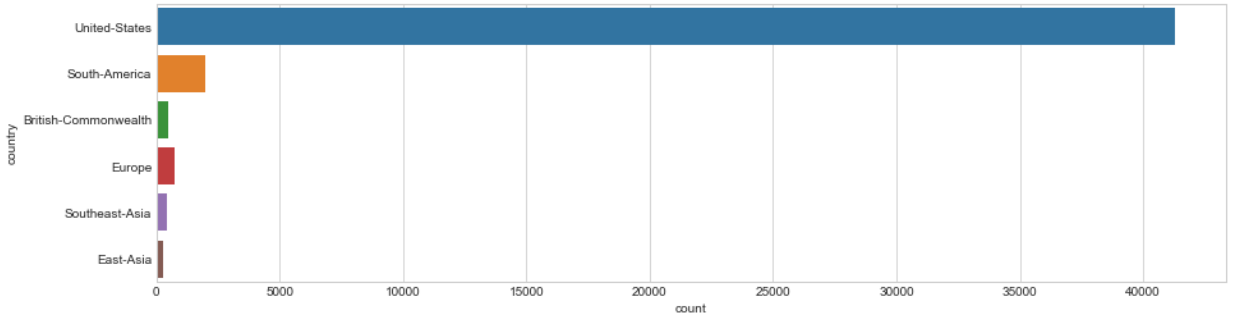
United-States, Cambodia, England, Puerto-Rico, Canada, Germany, Outlying-US(Guam-USVI-etc), India, Japan, Greece, South, China, Cuba, Iran, Honduras, Philippines, Italy, Poland, Jamaica, Vietnam, Mexico, Portugal, Ireland, France, Dominican-Republic, Laos, Ecuador, Taiwan, Haiti, Columbia, Hungary, Guatemala, Nicaragua, Scotland, Thailand, Yugoslavia, El-Salvador, Trinadad&Tobago, Peru, Hong, Holand-Netherlands.

In [19]:
```
plt.style.use('seaborn-whitegrid')
plt.figure(figsize=(15,5))
sns.countplot(y="country", data=dataset);
```



In [20]:
```
dataset.loc[dataset['country'] == 'China'                    , 'country'] = 'East-Asia'
dataset.loc[dataset['country'] == 'Hong'                     , 'country'] = 'East-Asia'
dataset.loc[dataset['country'] == 'Taiwan'                   , 'country'] = 'East-Asia'
dataset.loc[dataset['country'] == 'Japan'                    , 'country'] = 'East-Asia'

dataset.loc[dataset['country'] == 'Thailand'                 , 'country'] = 'Southeast-Asia'
dataset.loc[dataset['country'] == 'Vietnam'                  , 'country'] = 'Southeast-Asia'
dataset.loc[dataset['country'] == 'Laos'                     , 'country'] = 'Southeast-Asia'
dataset.loc[dataset['country'] == 'Philippines'              , 'country'] = 'Southeast-Asia'
dataset.loc[dataset['country'] == 'Cambodia'                 , 'country'] = 'Southeast-Asia'

dataset.loc[dataset['country'] == 'Columbia'                 , 'country'] = 'South-America'
dataset.loc[dataset['country'] == 'Cuba'                     , 'country'] = 'South-America'
dataset.loc[dataset['country'] == 'Dominican-Republic'       , 'country'] = 'South-America'
dataset.loc[dataset['country'] == 'Ecuador'                  , 'country'] = 'South-America'
dataset.loc[dataset['country'] == 'Guatemala'                , 'country'] = 'South-America'
dataset.loc[dataset['country'] == 'El-Salvador'              , 'country'] = 'South-America'
dataset.loc[dataset['country'] == 'Haiti'                    , 'country'] = 'South-America'
dataset.loc[dataset['country'] == 'Honduras'                 , 'country'] = 'South-America'
dataset.loc[dataset['country'] == 'Mexico'                   , 'country'] = 'South-America'
dataset.loc[dataset['country'] == 'Nicaragua'                , 'country'] = 'South-America'
dataset.loc[dataset['country'] == 'Outlying-US(Guam-USVI-etc)' , 'country'] = 'South-America'
dataset.loc[dataset['country'] == 'Peru'                     , 'country'] = 'South-America'
dataset.loc[dataset['country'] == 'Jamaica'                  , 'country'] = 'South-America'
dataset.loc[dataset['country'] == 'Puerto-Rico'              , 'country'] = 'South-America'
dataset.loc[dataset['country'] == 'Trinadad&Tobago'          , 'country'] = 'South-America'

dataset.loc[dataset['country'] == 'Canada'                   , 'country'] = 'British-Commonweal
dataset.loc[dataset['country'] == 'England'                  , 'country'] = 'British-Commonweal
dataset.loc[dataset['country'] == 'India'                    , 'country'] = 'British-Commonweal
dataset.loc[dataset['country'] == 'Ireland'                  , 'country'] = 'British-Commonweal
dataset.loc[dataset['country'] == 'Scotland'                 , 'country'] = 'British-Commonweal

dataset.loc[dataset['country'] == 'France'                   , 'country'] = 'Europe'
dataset.loc[dataset['country'] == 'Germany'                  , 'country'] = 'Europe'
dataset.loc[dataset['country'] == 'Italy'                    , 'country'] = 'Europe'
dataset.loc[dataset['country'] == 'Holand-Netherlands'       , 'country'] = 'Europe'
dataset.loc[dataset['country'] == 'Greece'                   , 'country'] = 'Europe'
dataset.loc[dataset['country'] == 'Hungary'                  , 'country'] = 'Europe'
dataset.loc[dataset['country'] == 'Iran'                     , 'country'] = 'Europe'
dataset.loc[dataset['country'] == 'Yugoslavia'               , 'country'] = 'Europe'
dataset.loc[dataset['country'] == 'Poland'                   , 'country'] = 'Europe'
dataset.loc[dataset['country'] == 'Portugal'                 , 'country'] = 'Europe'
dataset.loc[dataset['country'] == 'South'                    , 'country'] = 'Europe'

dataset.loc[dataset['country'] == 'United-States'            , 'country'] = 'United-States'
```

In [21]:
```
plt.style.use('seaborn-whitegrid')
fig = plt.figure(figsize=(15,4))
sns.countplot(y="country", data=dataset);
```

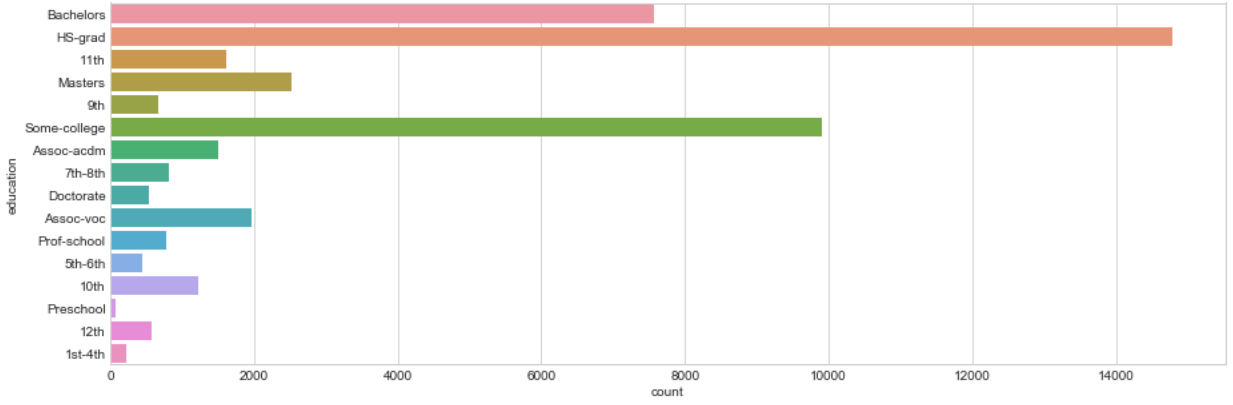


3.4.4 受教育程度

受教育程度共有16个类别，在此按照等级进行合并以简化分析

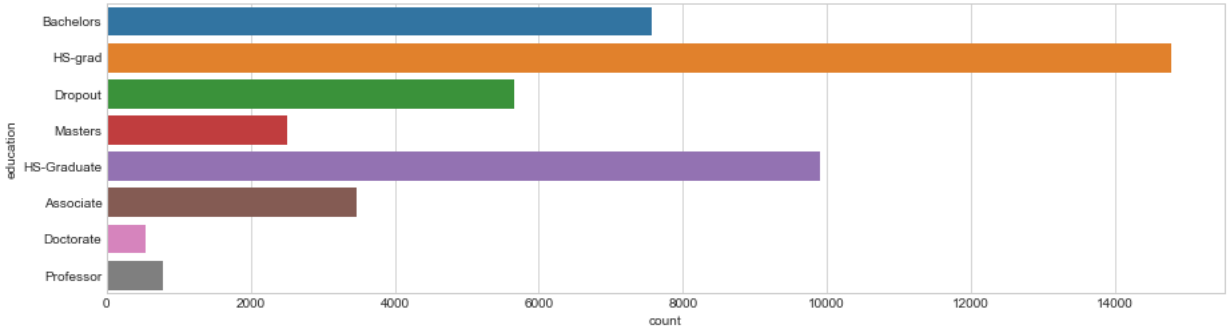
Bachelors（学士），Some-college（大学未毕业），11th（高二），HS-grad（高中毕业）,Prof-school（职业学校），Assoc-acdm（大学专科），Assoc-voc（准职业学位），9th（初三）,7th-8th（初中一、二年级），12th（高三），Masters（硕士），1st-4th（小学1-4年级），10th（高一），Doctorate（博士），5th-6th（小学5、6年级），Preschool（幼儿园）.

In [22]:
```
plt.style.use('seaborn-whitegrid')
plt.figure(figsize=(15,5))
sns.countplot(y="education", data=dataset);
```



In [23]:
```
dataset.loc[dataset['education'] == 'Preschool'    , 'education'] = 'Dropout'  # 退学
dataset.loc[dataset['education'] == '1st-4th'      , 'education'] = 'Dropout'  # 退学
dataset.loc[dataset['education'] == '5th-6th'      , 'education'] = 'Dropout'  # 退学
dataset.loc[dataset['education'] == '7th-8th'      , 'education'] = 'Dropout'  # 退学
dataset.loc[dataset['education'] == '9th'          , 'education'] = 'Dropout'  # 退学
dataset.loc[dataset['education'] == '10th'         , 'education'] = 'Dropout'  # 退学
dataset.loc[dataset['education'] == '11th'         , 'education'] = 'Dropout'  # 退学
dataset.loc[dataset['education'] == '12th'         , 'education'] = 'Dropout'  # 退学
dataset.loc[dataset['education'] == 'Assoc-acdm'   , 'education'] = 'Associate'  # 专科
dataset.loc[dataset['education'] == 'Assoc-voc'    , 'education'] = 'Associate'  # 专科
dataset.loc[dataset['education'] == 'HS-Grad'      , 'education'] = 'HS-Graduate'  # 高中
dataset.loc[dataset['education'] == 'Some-college' , 'education'] = 'HS-Graduate'  # 高中
dataset.loc[dataset['education'] == 'Prof-school'  , 'education'] = 'Professor'  # 职业
dataset.loc[dataset['education'] == 'Bachelors'    , 'education'] = 'Bachelors'  # 学士
dataset.loc[dataset['education'] == 'Masters'      , 'education'] = 'Masters'  # 硕士
dataset.loc[dataset['education'] == 'Doctorate'    , 'education'] = 'Doctorate'  # 博士

```

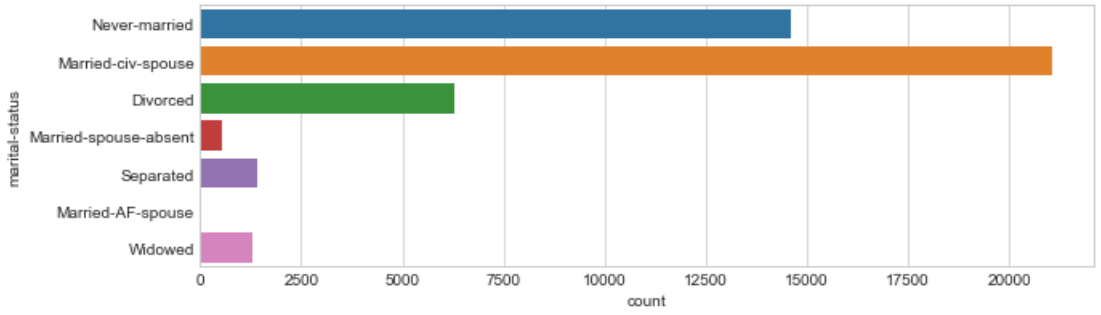
In [24]:
```
plt.style.use('seaborn-whitegrid')
fig = plt.figure(figsize=(15,4))
sns.countplot(y="education", data=dataset);
```



3.4.5 婚姻状态

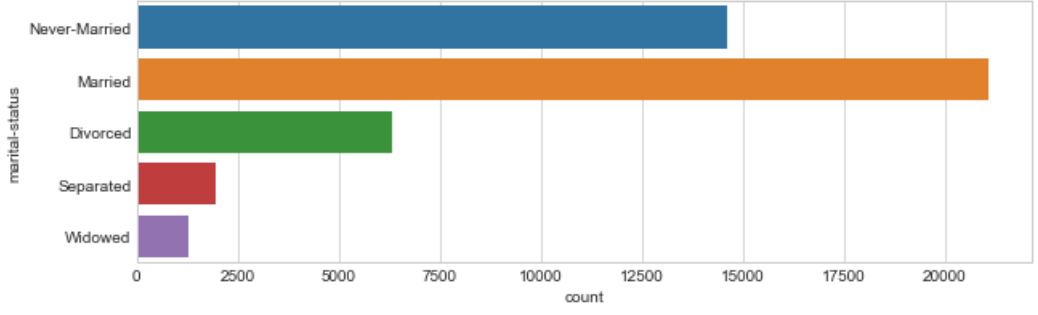
数据说明里共列出7种婚姻状态Married-civ-spouse（已婚平民配偶），Divorced（离婚），Never-married（未婚），Separated（分居），Widowed（丧偶），Married-spouse-absent（已婚配偶异地），arried-AF-spouse（已婚军属）

In [25]:
```
plt.style.use('seaborn-whitegrid')
plt.figure(figsize=(10,3))
sns.countplot(y="marital-status", data=dataset);
```



In [26]:
```
dataset.loc[dataset['marital-status'] == 'Never-married'        , 'marital-status'] = 'Never-Marri
dataset.loc[dataset['marital-status'] == 'Divorced'             , 'marital-status'] = 'Divorced'
dataset.loc[dataset['marital-status'] == 'Widowed'              , 'marital-status'] = 'Widowed'  #
dataset.loc[dataset['marital-status'] == 'Married-spouse-absent', 'marital-status'] = 'Separated'
dataset.loc[dataset['marital-status'] == 'Separated'            , 'marital-status'] = 'Separated'
dataset.loc[dataset['marital-status'] == 'Married-AF-spouse'    , 'marital-status'] = 'Married'  #
dataset.loc[dataset['marital-status'] == 'Married-civ-spouse'   , 'marital-status'] = 'Married'  #
```

In [27]:
```
plt.style.use('seaborn-whitegrid')
fig = plt.figure(figsize=(10,3))
sns.countplot(y="marital-status", data=dataset);
```



3.4.6 查看各指标分布情况

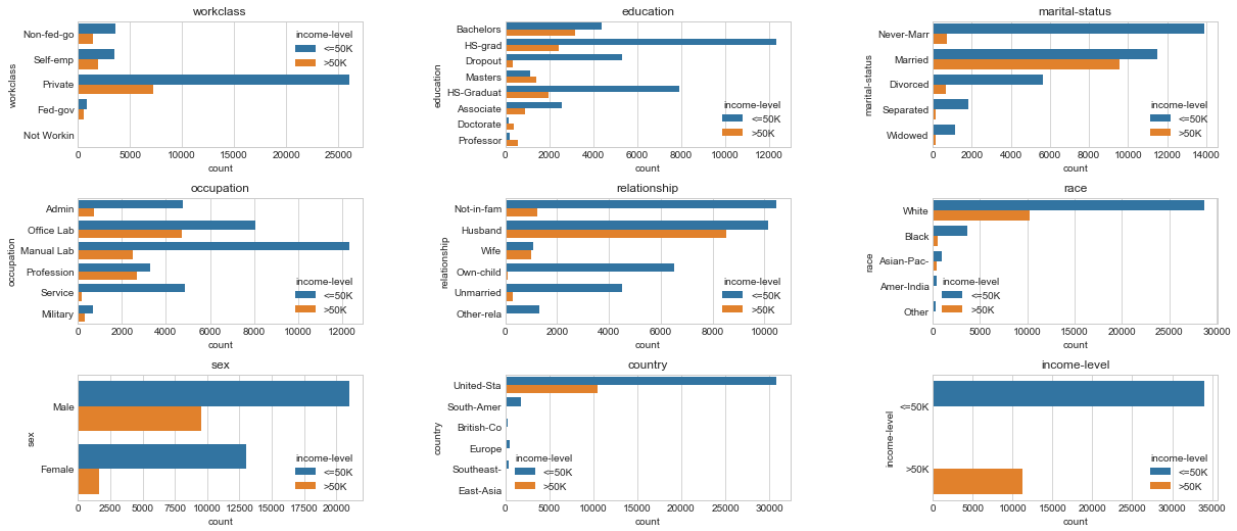
In [28]:

```
# def plot_distribution(dataset, cols, width, height, hspace, wspace):
#     plt.style.use('seaborn-whitegrid')
#     fig = plt.figure(figsize=(width,height))
#     fig.subplots_adjust(left=None, bottom=None, right=None, top=None, wspace=wspace, hspace=hspa
#     rows = math.ceil(float(dataset.shape[1]) / cols)
#     for i, column in enumerate(dataset.columns):
#         ax = fig.add_subplot(rows, cols, i + 1)
#         ax.set_title(column)
#         if dataset.dtypes[column] == np.object:
#             g = sns.countplot(y=column, data=dataset)
#             substrings = [s.get_text()[:18] for s in g.get_yticklabels()]
#             g.set(yticklabels=substrings)
#             plt.xticks(rotation=25)
#         else:
#             g = sns.distplot(dataset[column])
#             plt.xticks(rotation=25)
# 由于plot_distribution()函数在上文中已定义，故在此直接调用
plot_distribution(dataset, cols=3, width=20, height=20, hspace=0.45, wspace=0.5)
```

4 探索变量间的相关关系

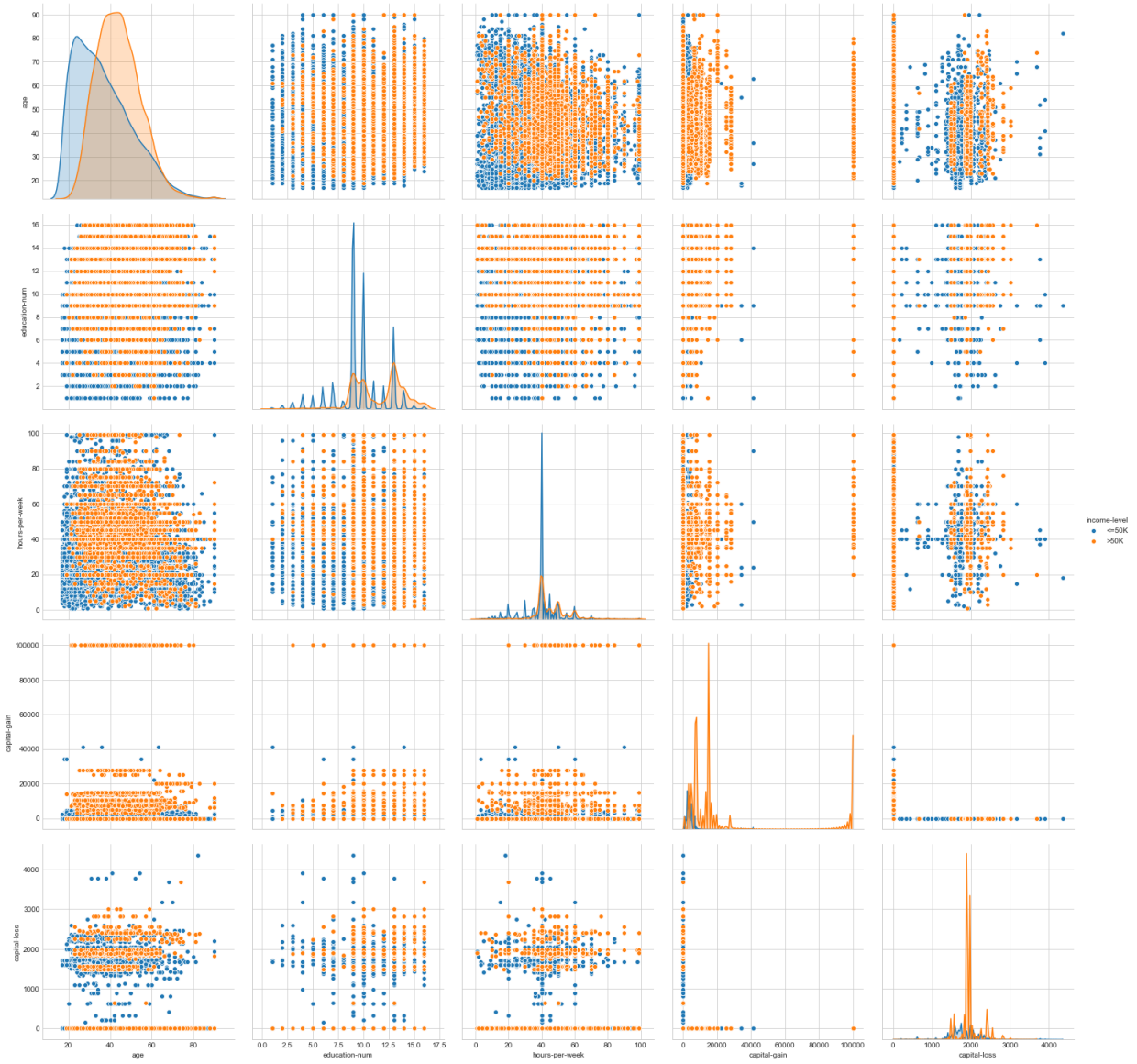
In [29]:

```python
# 探索各分类变量对收入指标的影响
# 暂时不用这张表了
def plot_bivariate_bar(dataset, hue, cols=5, width=20, height=15, hspace=0.2, wspace=0.5):
    plt.style.use('seaborn-whitegrid')
    fig = plt.figure(figsize=(width,height))
    fig.subplots_adjust(left=None, bottom=None, right=None, top=None, wspace=wspace, hspace=hspace
    rows = math.ceil(float(dataset.shape[1]) / cols)
    i = 1
    for column in dataset.columns:
        if dataset.dtypes[column] == np.object:
            ax = fig.add_subplot(rows, cols, i)
            i = i + 1
            ax.set_title(column)
            g = sns.countplot(y=column, hue=hue, data=dataset)
            substrings = [s.get_text()[:10] for s in g.get_yticklabels()]
            g.set(yticklabels=substrings)

plot_bivariate_bar(dataset, hue='income-level', cols=3, width=20, height=15, hspace=0.4, wspace=0.
```



In [30]:

```
# 探索各连续型变量对收入指标的影响
# 暂时不用这张表
sns.pairplot(dataset[['age','education-num','hours-per-week','income-level','capital-gain','capita
             hue="income-level",
             diag_kind="kde",
             size=4);
```

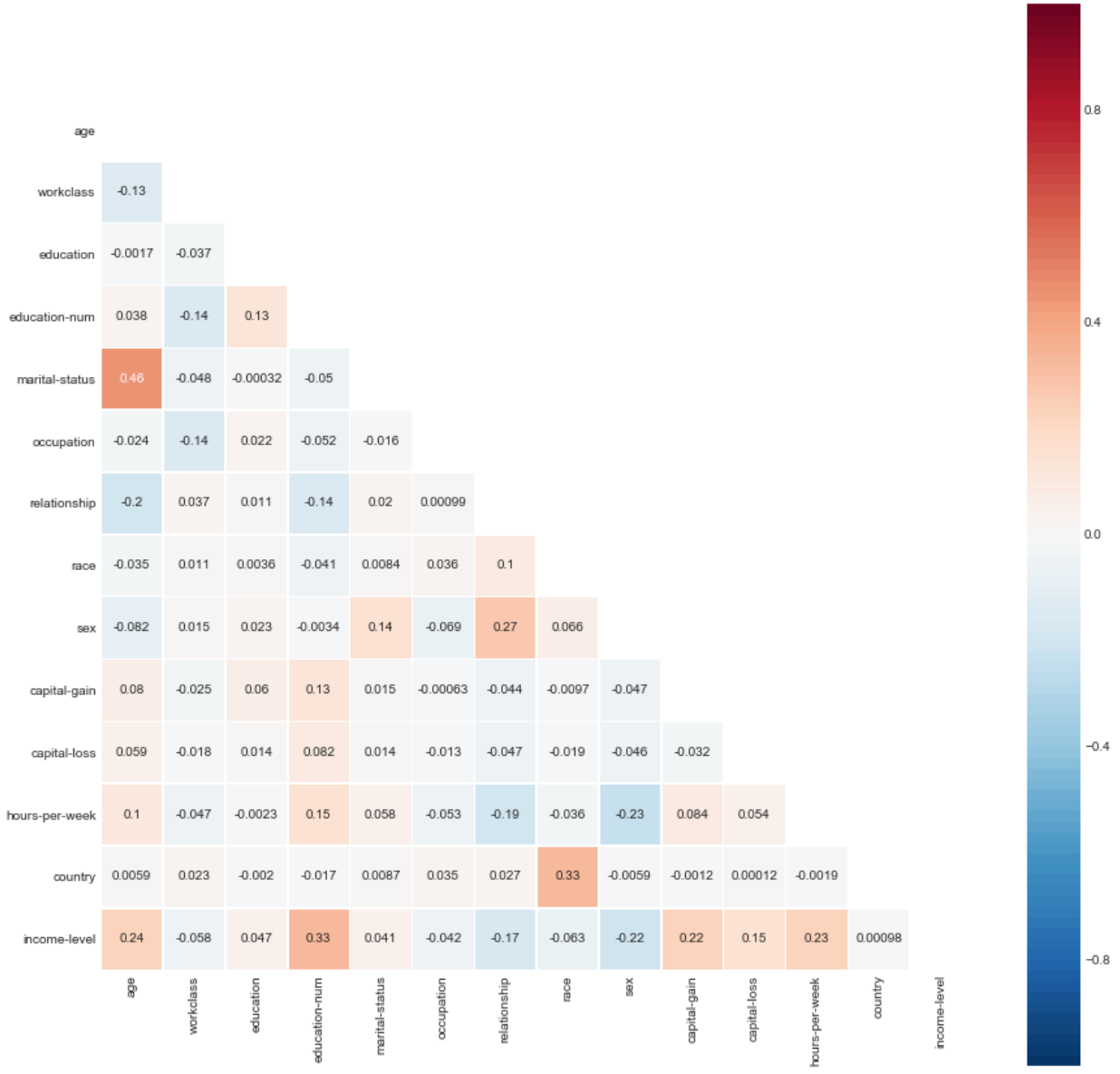


In [31]:

```
## 复制数据集，并将其中的离散字符串变量转化为数值型，以便进行相关分析
dataset_num = dataset.copy() # 复制数据集

dataset_num['workclass'] = dataset_num['workclass'].factorize()[0]
dataset_num['education'] = dataset_num['education'].factorize()[0]
dataset_num['marital-status'] = dataset_num['marital-status'].factorize()[0]
dataset_num['occupation'] = dataset_num['occupation'].factorize()[0]
dataset_num['relationship'] = dataset_num['relationship'].factorize()[0]
dataset_num['race'] = dataset_num['race'].factorize()[0]
dataset_num['sex'] = dataset_num['sex'].factorize()[0]
dataset_num['country'] = dataset_num['country'].factorize()[0]
dataset_num['income-level'] = dataset_num['income-level'].factorize()[0]

```

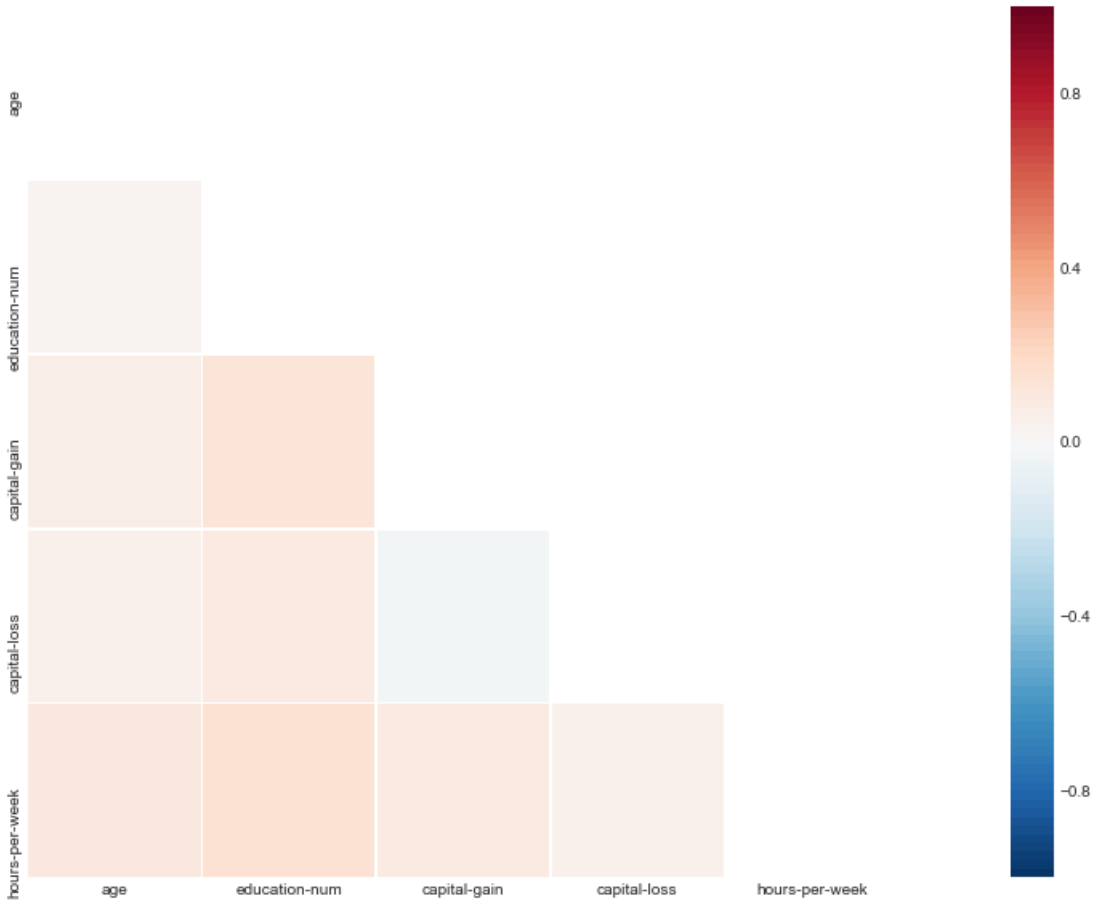
In [32]:

```
# 绘制相关性图谱，检查变量间的相关性
plt.style.use('seaborn-whitegrid')
fig = plt.figure(figsize=(15, 15))

mask = np.zeros_like(dataset_num.corr(), dtype=np.bool)
mask[np.triu_indices_from(mask)] = True
sns.heatmap(dataset_num.corr(), vmin=-1, vmax=1, square=True,
            cmap=sns.color_palette("RdBu_r", 100),
            mask=mask, annot=True, linewidths=.5);
```



通过相关分析可见，各变量间不存在较为明显的共线性，暂不对变量进行筛选

In [33]:
```
plt.style.use('seaborn-whitegrid')
fig = plt.figure(figsize=(25,10))
mask = np.zeros_like(dataset.corr(), dtype=np.bool)
mask[np.triu_indices_from(mask)] = True
sns.heatmap(dataset.corr(),
            vmin=-1, vmax=1,
            square=True,
            cmap=sns.color_palette("RdBu_r", 100),
            mask=mask,
            linewidths=.5);
```



5 切分数据集

In [34]:
```
# 切分自变量和因变量
y_data=dataset_num['income-level']  # 取收入水平income-level列
x_data=dataset_num.drop(['income-level'],axis=1)  # 排除收入水平income-level列，剩下的列作为x_data
```

In [35]:
```
# 切分训练集和测试集
x_train,x_test,y_train,y_test = train_test_split(
    x_data,
    y_data,
    test_size=0.2,
    random_state=1,
    stratify=y_data)

```

5.1 设置一个随机数种子

In [36]:
```
# random.seed(1)
```

6 构建分类器

6.1 构建分类器训练测试的通用函数

In [37]:
```
# 存取变量 - 便于模型跑死后中断重新载入已训练好的数据集，节约调试时间
import dill

# 存储 - 存储当前工作区变量
dill.dump_session('variables.pkl')
```

In [38]:
```
import dill
# 读取 - 读取当前工作区变量
dill.load_session('variables.pkl')
```

In [39]:
```
# 构建函数用于计算TPR(True Positive Rate)和FPR(False Positive Rate)并绘制ROC曲线
def plot_roc_curve(y_test, preds):
    fpr, tpr, threshold = metrics.roc_curve(y_test, preds)
    roc_auc = metrics.auc(fpr, tpr)
    plt.title('ROC')
    plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
    plt.legend(loc = 'lower right')
    plt.plot([0, 1], [0, 1],'r--')
    plt.xlim([-0.01, 1.01])
    plt.ylim([-0.01, 1.01])
    plt.ylabel('TPR')
    plt.xlabel('FPR')
    plt.show()
```

In [40]:
```
# 构造一个模型套用的样板，自动调用训练集对传入的模型进行训练，使用验证集对模型进行检验，并输出相关指标
def fit_ml_algo(algo, X_train, y_train, X_test, cv):
    model = algo.fit(X_train, y_train)
    test_pred = model.predict(X_test)
    try:
        probs = model.predict_proba(X_test)[:,1]
    except Exception as e:
        probs = "Unavailable"
        print('Warning: Probs unavaliable.')
        print('Reason: ', e)


    acc = round(model.score(X_test, y_test) * 100, 2)
    # CV
    train_pred = model_selection.cross_val_predict(algo,
                                                   X_train,
                                                   y_train,
                                                   cv=cv,
                                                   n_jobs = -1)
    acc_cv = round(metrics.accuracy_score(y_train, train_pred) * 100, 2)
    return train_pred, test_pred, acc, acc_cv, probs
```

In [41]:
```
# 汇报候选模型参数
def report(results, n_top=5):
    for i in range(1, n_top + 1):
        candidates = np.flatnonzero(results['rank_test_score'] == i)
        for candidate in candidates:
            print("Model with rank: {0}".format(i))
            print("Mean validation score: {0:.3f} (std: {1:.3f})".format(
                  results['mean_test_score'][candidate],
                  results['std_test_score'][candidate]))
            print("Parameters: {0}\n".format(results['params'][candidate]))
```

In [42]:

```
# 构建绘制P-R曲线方法
def plot_pr_curve(y_test, probs):
    precision, recall, _ = precision_recall_curve(y_test, probs)
    plt.step(recall, precision, color='b', alpha=0.2,
             where='post')
    plt.fill_between(recall, precision, step='post', alpha=0.2,
                     color='b')
    plt.xlabel('Recall')
    plt.ylabel('Precision')
    plt.ylim([0.0, 1.05])
    plt.xlim([0.0, 1.0])
    plt.title('2-class Precision-Recall curve: AP={0:0.2f}'.format(
              average_precision_score(y_test, probs)))
```

6.2 Logistic Regression

In [43]:

```
# Logistic回归

# 设置超参数并构建随机搜索器
n_iter_search = 10  # 训练10次，数值越大，获得的参数精度越大，但是搜索时间越长
param_dist = {'penalty': ['l2', 'l1'],
                          'class_weight': [None, 'balanced'],
                          'C': np.logspace(-20, 20, 10000),
                          'intercept_scaling': np.logspace(-20, 20, 10000)}
random_search = RandomizedSearchCV(LogisticRegression(),   # 使用的分类器
                                   n_jobs=-1, # 使用所有的CPU进行训练，默认为1，使用1个CPU
                                   param_distributions=param_dist,
                                   n_iter=n_iter_search) # 训练次数
start = time.time()
random_search.fit(x_train, y_train)
print("RandomizedSearchCV took %.2f seconds for %d candidates"
      " parameter settings." % ((time.time() - start), n_iter_search))
report(random_search.cv_results_)
```

```
RandomizedSearchCV took 78.67 seconds for 10 candidates parameter settings.
Model with rank: 1
Mean validation score: 0.789 (std: 0.003)
Parameters: {'penalty': 'l2', 'intercept_scaling': 4.2861089500154226e-20, 'class_weight': None, 'C': 0.118551
5920962379}

Model with rank: 2
Mean validation score: 0.789 (std: 0.003)
Parameters: {'penalty': 'l2', 'intercept_scaling': 0.0022373553845475773, 'class_weight': None, 'C': 155424382
9725976.5}

Model with rank: 3
Mean validation score: 0.762 (std: 0.004)
Parameters: {'penalty': 'l1', 'intercept_scaling': 0.03748498882741727, 'class_weight': 'balanced', 'C': 98061
6394868363.1}

Model with rank: 4
Mean validation score: 0.752 (std: 0.000)
Parameters: {'penalty': 'l1', 'intercept_scaling': 51.30633790483969, 'class_weight': None, 'C': 1.21564979406
20604e-12}

Model with rank: 4
Mean validation score: 0.752 (std: 0.000)
Parameters: {'penalty': 'l1', 'intercept_scaling': 5.859718966860556e+18, 'class_weight': None, 'C': 1.1389526
00585518e-15}
```

In [44]:
```
# 调用随机搜索器得到的参数最优的Logistic回归模型进行训练,
start_time = time.time()
train_pred_log, test_pred_log, acc_log, acc_cv_log, probs_log = fit_ml_algo(
#                                                                 LogisticRegression(n_jobs = -1)
                                                                random_search.best_estimator_,
                                                                x_train,
                                                                y_train,
                                                                x_test,
                                                                10)
log_time = (time.time() - start_time)
print("Accuracy: %s" % acc_log)
print("Accuracy CV 10-Fold: %s" % acc_cv_log)
print("Running Time: %s s" % datetime.timedelta(seconds=log_time).seconds)
```

```
Accuracy: 79.1
Accuracy CV 10-Fold: 78.89
Running Time: 3 s
```

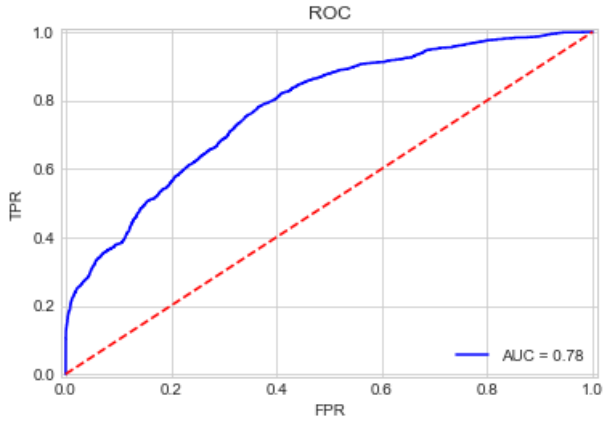
In [45]:
```
# 其中列表左边的一列为分类的标签名，右边support列为每个标签的出现次数. avg / total行为各列的均值 (support
# precision recall f1-score三列分别为各个类别的精确度/召回率及 F1 F1值.
# 训练集样本表现
print(metrics.classification_report(y_train, train_pred_log))
```

```
              precision    recall  f1-score   support

           0       0.81      0.94      0.87     27211
           1       0.65      0.32      0.43      8966

    accuracy                           0.79     36177
   macro avg       0.73      0.63      0.65     36177
weighted avg       0.77      0.79      0.76     36177
```

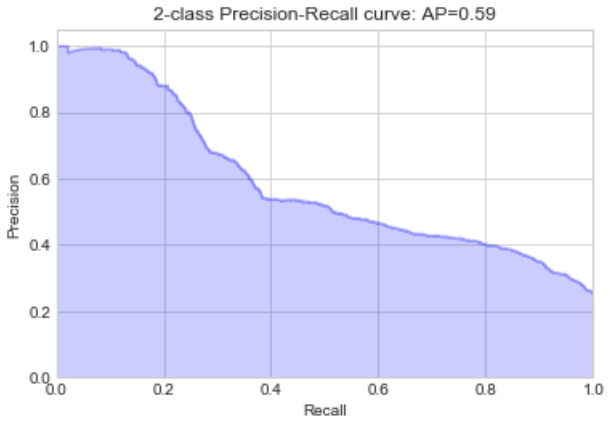
In [46]:
```
# 测试集样本表现
print(metrics.classification_report(y_test, test_pred_log))
```

```
              precision    recall  f1-score   support

           0       0.81      0.95      0.87      6803
           1       0.66      0.32      0.43      2242

    accuracy                           0.79      9045
   macro avg       0.74      0.63      0.65      9045
weighted avg       0.77      0.79      0.76      9045
```

In [47]:
```
# 绘制ROC
plot_roc_curve(y_test, probs_log)
```



In [48]:
```
# 绘制P-R曲线
plot_pr_curve(y_test, probs_log)
```



6.3 KNN

In [49]:
```
# k-Nearest Neighbors
start_time = time.time()
train_pred_knn, test_pred_knn, acc_knn, acc_cv_knn, probs_knn\
= fit_ml_algo(KNeighborsClassifier(n_neighbors = 3,
                                   n_jobs = -1),
                                   x_train,
                                   y_train,
                                   x_test,
                                   10)
knn_time = (time.time() - start_time)
print("Accuracy: %s" % acc_knn)
print("Accuracy CV 10-Fold: %s" % acc_cv_knn)
print("Running Time: %s s" % datetime.timedelta(seconds=knn_time).seconds)
```

```
Accuracy: 82.74
Accuracy CV 10-Fold: 82.64
Running Time: 36 s
```

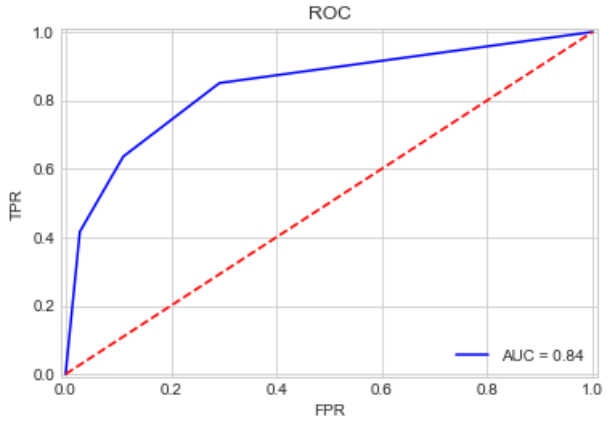
In [50]:
```
# 训练集样本表现
print(metrics.classification_report(y_train, train_pred_knn))
```

```
              precision    recall  f1-score   support

           0       0.88      0.89      0.89     27211
           1       0.66      0.63      0.64      8966

    accuracy                           0.83     36177
   macro avg       0.77      0.76      0.76     36177
weighted avg       0.82      0.83      0.83     36177
```

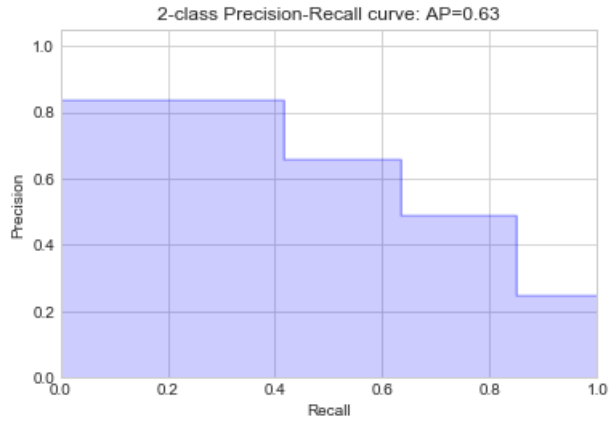
In [51]:
```
# 测试集样本表现
print(metrics.classification_report(y_test, test_pred_knn))
```

```
              precision    recall  f1-score   support

           0       0.88      0.89      0.89      6803
           1       0.66      0.64      0.65      2242

    accuracy                           0.83      9045
   macro avg       0.77      0.76      0.77      9045
weighted avg       0.83      0.83      0.83      9045
```

In [52]:
```
# 绘制ROC
plot_roc_curve(y_test, probs_knn)
```



In [53]:
```
# 绘制P-R曲线
plot_pr_curve(y_test, probs_knn)
```



6.4 Gaussian Naive Bayes

In [54]:
```
# Gaussian Naive Bayes
start_time = time.time()
train_pred_gaussian, test_pred_gaussian, acc_gaussian, acc_cv_gaussian, probs_gau\
= fit_ml_algo(GaussianNB(),
              x_train,
              y_train,
              x_test,
              10)
gaussian_time = (time.time() - start_time)
print("Accuracy: %s" % acc_gaussian)
print("Accuracy CV 10-Fold: %s" % acc_cv_gaussian)
print("Running Time: %s s" % datetime.timedelta(seconds=gaussian_time).seconds)
```

```
Accuracy: 80.19
Accuracy CV 10-Fold: 79.88
Running Time: 0 s
```

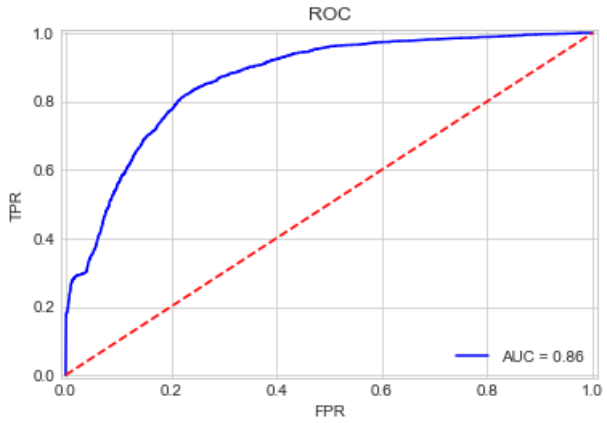
In [55]:
```
# 训练集样本表现
print(metrics.classification_report(y_train, train_pred_gaussian))
```

	precision	recall	f1-score	support
0	0.81	0.95	0.88	27211
1	0.69	0.35	0.46	8966
accuracy			0.80	36177
macro avg	0.75	0.65	0.67	36177
weighted avg	0.78	0.80	0.77	36177

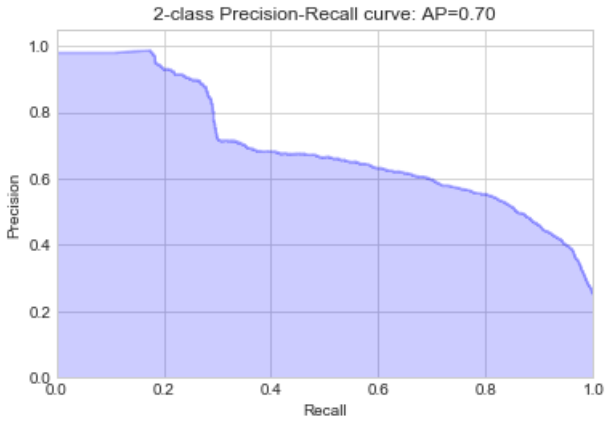
In [56]:
```
# 测试集样本表现
print(metrics.classification_report(y_test, test_pred_gaussian))
```

	precision	recall	f1-score	support
0	0.82	0.95	0.88	6803
1	0.70	0.35	0.47	2242
accuracy			0.80	9045
macro avg	0.76	0.65	0.67	9045
weighted avg	0.79	0.80	0.78	9045

In [57]:
```
# 绘制ROC
plot_roc_curve(y_test, probs_gau)
```



In [58]:
```
# 绘制P-R曲线
plot_pr_curve(y_test, probs_gau)
```



6.5 Linear SVC

In [59]:
```
# Linear SVC
start_time = time.time()
# kernel = ‘linear’, ‘poly’, ‘rbf’, ‘sigmoid’, ‘precomputed’
svc_clf = SVC(probability=True, max_iter=1000, kernel='linear')
train_pred_svc, test_pred_svc, acc_linear_svc, acc_cv_linear_svc, probs_svc\
= fit_ml_algo(svc_clf,
              x_train,
              y_train,
              x_test,
              10)
linear_svc_time = (time.time() - start_time)
print("Accuracy: %s" % acc_linear_svc)
print("Accuracy CV 10-Fold: %s" % acc_cv_linear_svc)
print("Running Time: %s s" % datetime.timedelta(seconds=linear_svc_time).seconds)
```

```
Accuracy: 53.29
Accuracy CV 10-Fold: 35.68
Running Time: 62 s
```

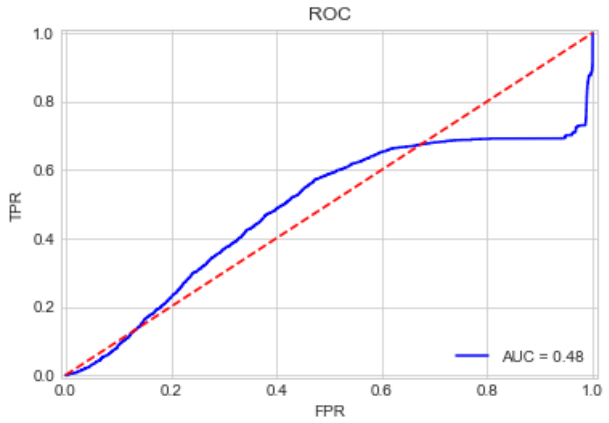
In [60]:
```
# 训练集样本表现
print(metrics.classification_report(y_train, train_pred_svc))
```

```
              precision    recall  f1-score   support

           0       0.68      0.28      0.39     27211
           1       0.21      0.59      0.31      8966

    accuracy                           0.36     36177
   macro avg       0.44      0.44      0.35     36177
weighted avg       0.56      0.36      0.37     36177
```

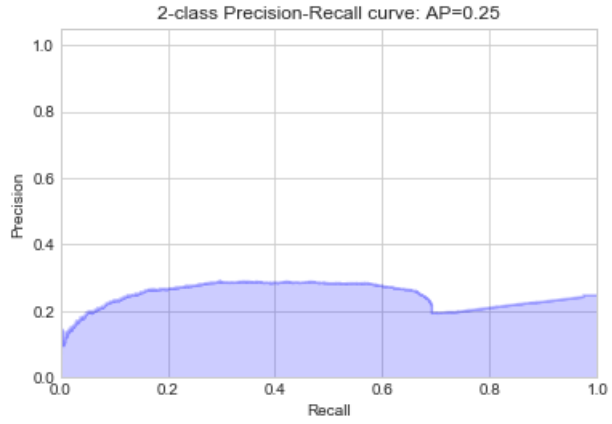
In [61]:
```
# 测试集样本表现
print(metrics.classification_report(y_test, test_pred_svc))
```

	precision	recall	f1-score	support
0	0.79	0.52	0.63	6803
1	0.28	0.58	0.38	2242
accuracy			0.53	9045
macro avg	0.54	0.55	0.50	9045
weighted avg	0.66	0.53	0.56	9045

In [62]:
```
# 绘制ROC
plot_roc_curve(y_test, probs_svc)
```



In [63]:
```
# 绘制P-R曲线
plot_pr_curve(y_test, probs_svc)
```



6.6 Stochastic Gradient Descent

In [64]:
```
# Stochastic Gradient Descent 随机梯度下降
start_time = time.time()
train_pred_sgd, test_pred_sgd, acc_sgd, acc_cv_sgd, probs_sgd\
= fit_ml_algo(
                SGDClassifier(n_jobs = -1, loss='log'),
                x_train,
                y_train,
                x_test,
                10)
sgd_time = (time.time() - start_time)
print("Accuracy: %s" % acc_sgd)
print("Accuracy CV 10-Fold: %s" % acc_cv_sgd)
print("Running Time: %s s" % datetime.timedelta(seconds=sgd_time).seconds)
```

```
Accuracy: 77.06
Accuracy CV 10-Fold: 76.66
Running Time: 2 s
```

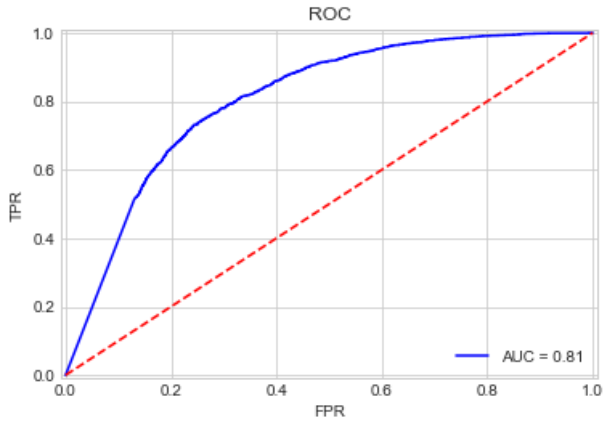
In [65]:
```
# 训练集样本表现
print(metrics.classification_report(y_train, train_pred_sgd))
```

```
              precision    recall  f1-score   support

           0       0.83      0.87      0.85     27211
           1       0.53      0.46      0.49      8966

    accuracy                           0.77     36177
   macro avg       0.68      0.66      0.67     36177
weighted avg       0.76      0.77      0.76     36177
```

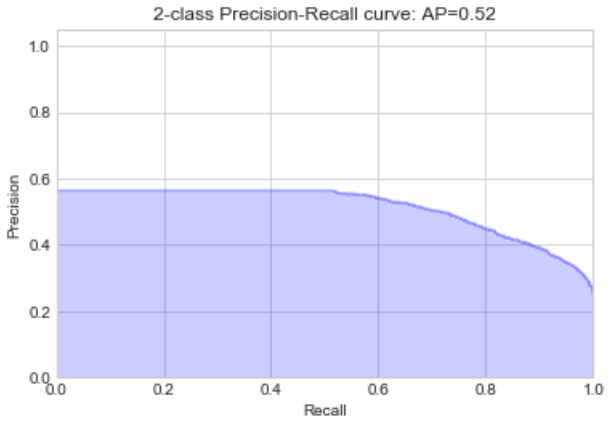
In [66]:
```
# 测试集样本表现
print(metrics.classification_report(y_test, test_pred_sgd))
```

```
              precision    recall  f1-score   support

           0       0.87      0.82      0.84      6803
           1       0.53      0.62      0.57      2242

    accuracy                           0.77      9045
   macro avg       0.70      0.72      0.71      9045
weighted avg       0.78      0.77      0.78      9045
```

In [67]:
```
# 绘制ROC
plot_roc_curve(y_test, probs_sgd)
```



In [68]:
```
# 绘制P-R曲线
plot_pr_curve(y_test, probs_sgd)
```



6.7 Decision Tree Classifier

In [69]:
```
# Decision Tree Classifier
start_time = time.time()
train_pred_dt, test_pred_dt, acc_dt, acc_cv_dt, probs_dt\
= fit_ml_algo(DecisionTreeClassifier(),
              x_train,
              y_train,
              x_test,
              10)
dt_time = (time.time() - start_time)
print("Accuracy: %s" % acc_dt)
print("Accuracy CV 10-Fold: %s" % acc_cv_dt)
print("Running Time: %s s" % datetime.timedelta(seconds=dt_time).seconds)
```

```
Accuracy: 82.1
Accuracy CV 10-Fold: 81.68
Running Time: 1 s
```

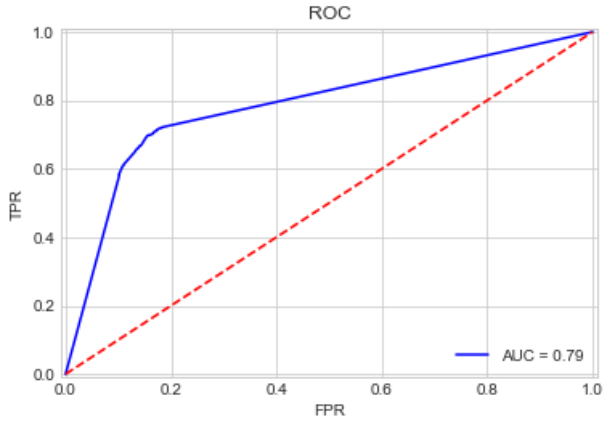
In [70]:
```
# 训练集样本表现
print(metrics.classification_report(y_train, train_pred_dt))
```

```
              precision    recall  f1-score   support

           0       0.87      0.89      0.88     27211
           1       0.64      0.60      0.62      8966

    accuracy                           0.82     36177
   macro avg       0.75      0.75      0.75     36177
weighted avg       0.81      0.82      0.82     36177
```

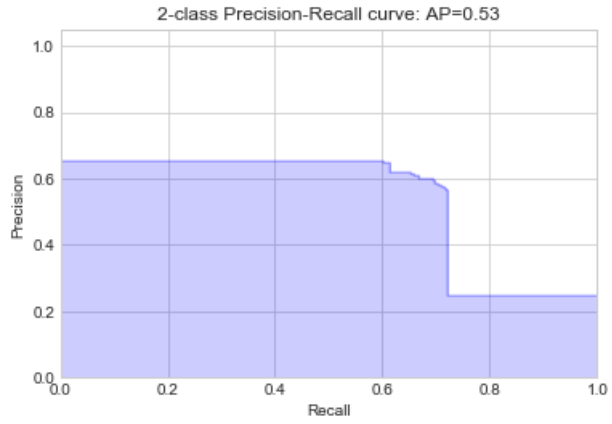
In [71]:
```
# 测试集样本表现
print(metrics.classification_report(y_test, test_pred_dt))
```

```
              precision    recall  f1-score   support

           0       0.87      0.89      0.88      6803
           1       0.65      0.61      0.63      2242

    accuracy                           0.82      9045
   macro avg       0.76      0.75      0.76      9045
weighted avg       0.82      0.82      0.82      9045
```

In [72]:
```
# 绘制ROC
plot_roc_curve(y_test, probs_dt)
```



In [73]:
```
# 绘制P-R曲线
plot_pr_curve(y_test, probs_dt)
```



6.8 Random Forest Classifier

In [74]:

```
# Random Forest Classifier - Random Search for Hyperparameters

# Utility function to report best scores
# def report(results, n_top=5):
#     for i in range(1, n_top + 1):
#         candidates = np.flatnonzero(results['rank_test_score'] == i)
#         for candidate in candidates:
#             print("Model with rank: {0}".format(i))
#             print("Mean validation score: {0:.3f} (std: {1:.3f})".format(
#                   results['mean_test_score'][candidate],
#                   results['std_test_score'][candidate]))
#             print("Parameters: {0}\n".format(results['params'][candidate]))

# 从中调参的超参数集合
param_dist = {"max_depth": [10, None],
              "max_features": sp_randint(1, 11),
              "min_samples_split": sp_randint(2, 20),
              "min_samples_leaf": sp_randint(1, 11),
              "bootstrap": [True, False],
              "criterion": ["gini", "entropy"]}

# Run Randomized Search
n_iter_search = 10
random_search = RandomizedSearchCV(
                                   RandomForestClassifier(n_estimators=10),
                                   n_jobs = -1,
                                   param_distributions=param_dist,
                                   n_iter=n_iter_search)

start = time.time()
random_search.fit(x_train, y_train)
print("RandomizedSearchCV took %.2f seconds for %d candidates"
      " parameter settings." % ((time.time() - start), n_iter_search))
report(random_search.cv_results_)
```

```
RandomizedSearchCV took 5.81 seconds for 10 candidates parameter settings.
Model with rank: 1
Mean validation score: 0.857 (std: 0.001)
Parameters: {'bootstrap': False, 'criterion': 'gini', 'max_depth': 10, 'max_features': 8, 'min_samples_leaf': 4, 'min_samples_split': 3}

Model with rank: 2
Mean validation score: 0.856 (std: 0.002)
Parameters: {'bootstrap': False, 'criterion': 'gini', 'max_depth': None, 'max_features': 4, 'min_samples_leaf': 6, 'min_samples_split': 12}

Model with rank: 3
Mean validation score: 0.856 (std: 0.001)
Parameters: {'bootstrap': True, 'criterion': 'entropy', 'max_depth': 10, 'max_features': 9, 'min_samples_leaf': 9, 'min_samples_split': 18}

Model with rank: 4
Mean validation score: 0.855 (std: 0.000)
Parameters: {'bootstrap': True, 'criterion': 'entropy', 'max_depth': 10, 'max_features': 9, 'min_samples_leaf': 4, 'min_samples_split': 2}

Model with rank: 5
Mean validation score: 0.855 (std: 0.000)
Parameters: {'bootstrap': True, 'criterion': 'entropy', 'max_depth': None, 'max_features': 2, 'min_samples_leaf': 8, 'min_samples_split': 11}
```

In [75]:
```
# rfc = RandomForestClassifier(n_estimators=10,
#                              min_samples_leaf=2,
#                              min_samples_split=17,
#                              criterion='gini',
#                              max_features=8)
# Random Forest Classifier
# 使用随机搜索器算得的最优超参数模型进行计算
start_time = time.time()
rfc = random_search.best_estimator_
train_pred_rf, test_pred_rf, acc_rf, acc_cv_rf, probs_rf = fit_ml_algo(
                                                           rfc,
                                                           x_train,
                                                           y_train,
                                                           x_test,
                                                           10)
rf_time = (time.time() - start_time)
print("Accuracy: %s" % acc_rf)
print("Accuracy CV 10-Fold: %s" % acc_cv_rf)
print("Running Time: %s s" % datetime.timedelta(seconds=rf_time).seconds)
```

```
Accuracy: 86.2
Accuracy CV 10-Fold: 85.74
Running Time: 3 s
```

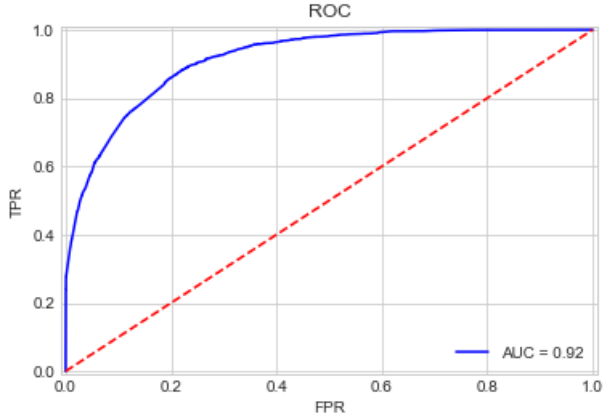
In [76]:
```
# 测试集样本表现
print(metrics.classification_report(y_train, train_pred_rf))
```

```
              precision    recall  f1-score   support

           0       0.88      0.94      0.91     27211
           1       0.77      0.60      0.68      8966

    accuracy                           0.86     36177
   macro avg       0.83      0.77      0.79     36177
weighted avg       0.85      0.86      0.85     36177
```

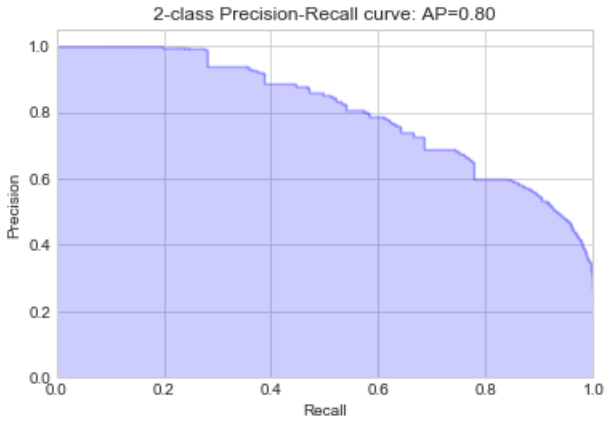
In [77]:
```
# 训练集样本表现
print(metrics.classification_report(y_test, test_pred_rf))
```

```
              precision    recall  f1-score   support

           0       0.88      0.95      0.91      6803
           1       0.79      0.61      0.69      2242

    accuracy                           0.86      9045
   macro avg       0.83      0.78      0.80      9045
weighted avg       0.86      0.86      0.86      9045
```

In [78]:
```
# 绘制ROC
plot_roc_curve(y_test, probs_rf)
```



In [79]:
```
# 绘制P-R曲线
plot_pr_curve(y_test, probs_rf)
```



6.9 Gradient Boosting Trees

In [80]:
```
# Gradient Boosting Trees 梯度提升决策树
start_time = time.time()
train_pred_gbt, test_pred_gbt, acc_gbt, acc_cv_gbt, probs_gbt\
= fit_ml_algo(GradientBoostingClassifier(),
              x_train,
              y_train,
              x_test,
              10)
gbt_time = (time.time() - start_time)
print("Accuracy: %s" % acc_gbt)
print("Accuracy CV 10-Fold: %s" % acc_cv_gbt)
print("Running Time: %s s" % datetime.timedelta(seconds=gbt_time).seconds)
```

```
Accuracy: 86.19
Accuracy CV 10-Fold: 85.97
Running Time: 19 s
```

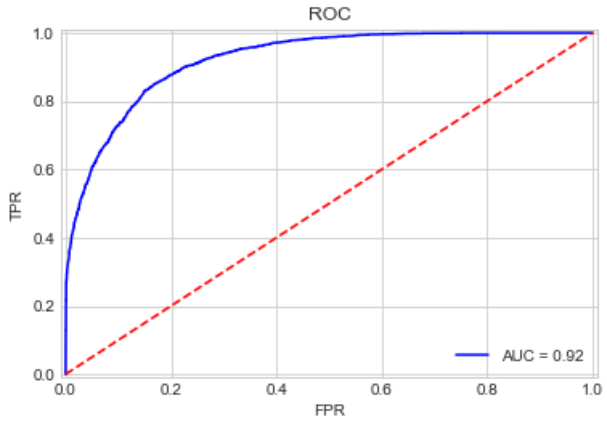
In [81]:
```
# 训练集样本表现
print(metrics.classification_report(y_train, train_pred_gbt))
```

```
              precision    recall  f1-score   support

           0       0.88      0.95      0.91     27211
           1       0.79      0.59      0.68      8966

    accuracy                           0.86     36177
   macro avg       0.83      0.77      0.79     36177
weighted avg       0.85      0.86      0.85     36177
```

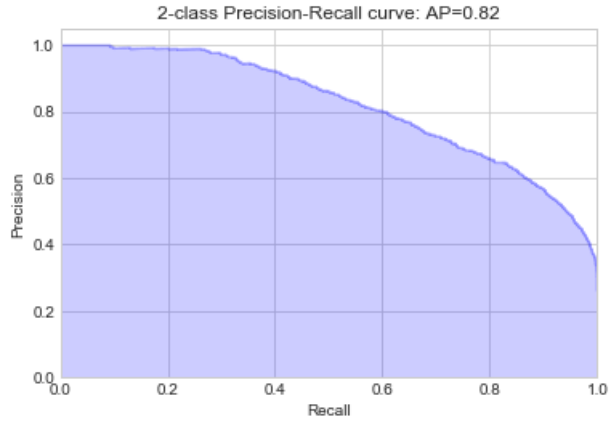
In [82]:
```
# 测试集样本表现
print(metrics.classification_report(y_test, test_pred_gbt))
```

```
              precision    recall  f1-score   support

           0       0.87      0.95      0.91      6803
           1       0.81      0.58      0.68      2242

    accuracy                           0.86      9045
   macro avg       0.84      0.77      0.79      9045
weighted avg       0.86      0.86      0.85      9045
```

In [83]:
```
# 绘制ROC
plot_roc_curve(y_test, probs_gbt)
```



In [84]:
```
# 绘制P-R曲线
plot_pr_curve(y_test, probs_gbt)
```



6.10 AdaBoost

In [85]:
```
# AdaBoost Classifier
start_time = time.time()
train_pred_adb, test_pred_adb, acc_adb, acc_cv_adb, probs_adb\
= fit_ml_algo(AdaBoostClassifier(),
              x_train,
              y_train,
              x_test,
              10)
adb_time = (time.time() - start_time)
print("Accuracy: %s" % acc_adb)
print("Accuracy CV 10-Fold: %s" % acc_cv_adb)
print("Running Time: %s s" % datetime.timedelta(seconds=adb_time).seconds)
```

```
Accuracy: 85.86
Accuracy CV 10-Fold: 85.41
Running Time: 7 s
```

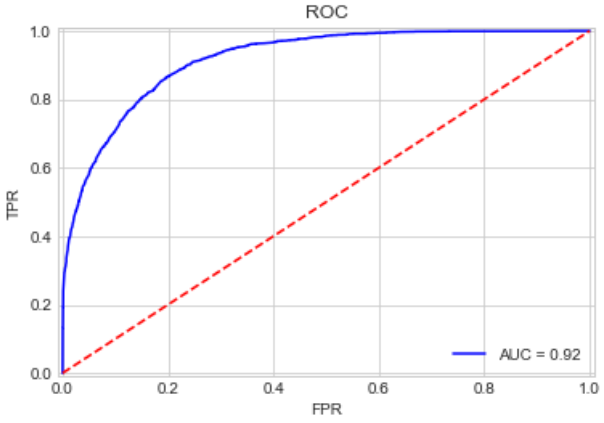
In [86]:
```
# 训练集样本表现
print(metrics.classification_report(y_train, train_pred_adb))
```

```
              precision    recall  f1-score   support

           0       0.88      0.94      0.91     27211
           1       0.76      0.61      0.67      8966

    accuracy                           0.85     36177
   macro avg       0.82      0.77      0.79     36177
weighted avg       0.85      0.85      0.85     36177
```

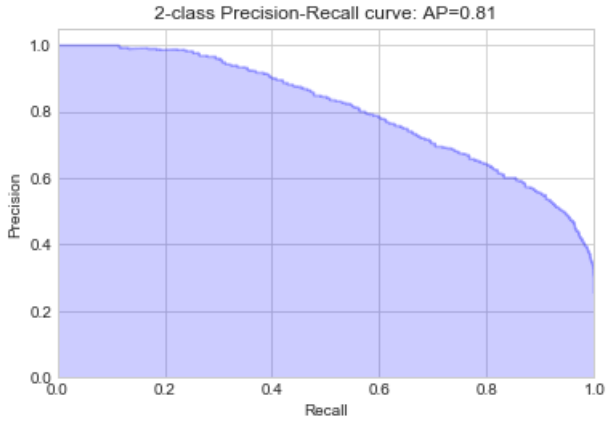
In [87]:
```
# 测试集样本表现
print(metrics.classification_report(y_test, test_pred_adb))
```

```
              precision    recall  f1-score   support

           0       0.88      0.94      0.91      6803
           1       0.77      0.62      0.68      2242

    accuracy                           0.86      9045
   macro avg       0.82      0.78      0.80      9045
weighted avg       0.85      0.86      0.85      9045
```

In [88]:
```
# 绘制ROC
plot_roc_curve(y_test, probs_adb)
```



In [89]:
```
# 绘制P-R曲线
plot_pr_curve(y_test, probs_adb)
```



6.11 VotingClassifier

In [90]:
```
# Voting Classifier
start_time = time.time()
voting_clf = VotingClassifier(estimators=[
    ('log_clf', LogisticRegression()),
    ('gnb_clf', GaussianNB()),
    ('rf_clf', RandomForestClassifier(n_estimators=10)),
    ('gb_clf', GradientBoostingClassifier()),
    ('dt_clf', DecisionTreeClassifier(random_state=666))],
                             voting='soft', n_jobs = -1)
train_pred_vot, test_pred_vot, acc_vot, acc_cv_vot, probs_vot\
= fit_ml_algo(voting_clf,
              x_train,
              y_train,
              x_test,
              10)
vot_time = (time.time() - start_time)
print("Accuracy: %s" % acc_vot)
print("Accuracy CV 10-Fold: %s" % acc_cv_vot)
print("Running Time: %s s" % datetime.timedelta(seconds=vot_time).seconds)
```

```
Accuracy: 84.94
Accuracy CV 10-Fold: 84.75
Running Time: 24 s
```

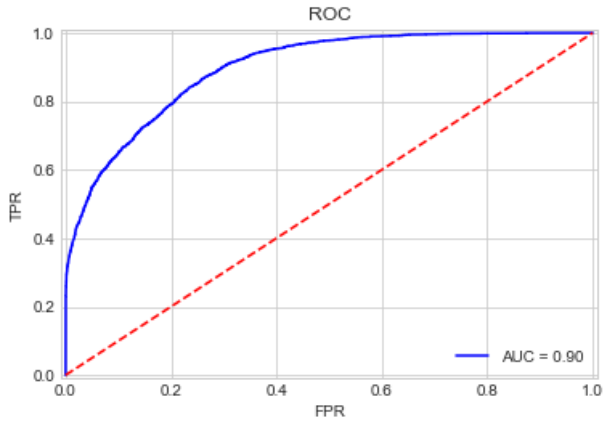
In [91]:
```
# 训练集样本表现
print(metrics.classification_report(y_train, train_pred_vot))
```

```
              precision    recall  f1-score   support

           0       0.86      0.95      0.90     27211
           1       0.78      0.53      0.63      8966

    accuracy                           0.85     36177
   macro avg       0.82      0.74      0.77     36177
weighted avg       0.84      0.85      0.84     36177
```

In [92]:
```
# 测试集样本表现
print(metrics.classification_report(y_test, test_pred_vot))
```

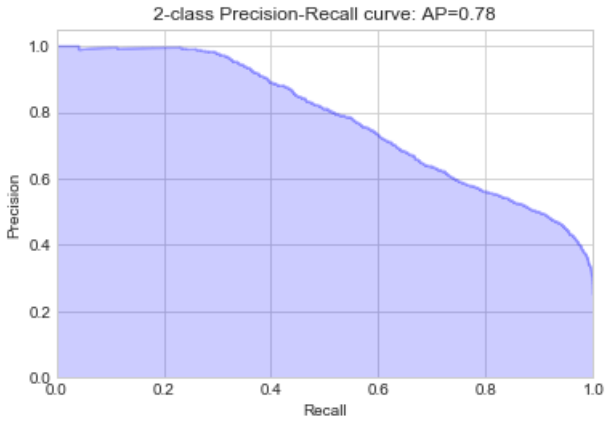
```
              precision    recall  f1-score   support

           0       0.86      0.95      0.90      6803
           1       0.79      0.54      0.64      2242

    accuracy                           0.85      9045
   macro avg       0.82      0.74      0.77      9045
weighted avg       0.84      0.85      0.84      9045
```

In [93]:
```
# 绘制ROC
plot_roc_curve(y_test, probs_vot)
```



In [94]:

```
# 绘制P-R曲线
plot_pr_curve(y_test, probs_vot)
```



7 结果排序

In [95]:

```
models = pd.DataFrame({
    'Model': ['KNN', 'Logistic Regression',
              'Random Forest', 'Naive Bayes',
              'Stochastic Gradient Decent', 'Linear SVC',
              'Decision Tree', 'Gradient Boosting Trees',
              'AdaBoost', 'Voting'],
    'Acc': [
        acc_knn, acc_log, acc_rf,
        acc_gaussian, acc_sgd,
        acc_linear_svc, acc_dt,
        acc_gbt, acc_adb, acc_vot
    ],
    'Acc_cv': [
        acc_cv_knn, acc_cv_log,
        acc_cv_rf, acc_cv_gaussian,
        acc_cv_sgd, acc_cv_linear_svc,
        acc_cv_dt, acc_cv_gbt,
        acc_cv_adb, acc_cv_vot
    ],
    'precision': [
        round(precision_score(y_test,test_pred_knn), 3),
        round(precision_score(y_test,test_pred_log), 3),
        round(precision_score(y_test,test_pred_rf), 3),
        round(precision_score(y_test,test_pred_gaussian), 3),
        round(precision_score(y_test,test_pred_sgd), 3),
        round(precision_score(y_test,test_pred_svc), 3),
        round(precision_score(y_test,test_pred_dt), 3),
        round(precision_score(y_test,test_pred_gbt), 3),
        round(precision_score(y_test,test_pred_adb), 3),
        round(precision_score(y_test,test_pred_vot), 3),
    ],
    'recall': [
        round(recall_score(y_test,test_pred_knn), 3),
        round(recall_score(y_test,test_pred_log), 3),
        round(recall_score(y_test,test_pred_rf), 3),
        round(recall_score(y_test,test_pred_gaussian), 3),
        round(recall_score(y_test,test_pred_sgd), 3),
        round(recall_score(y_test,test_pred_svc), 3),
        round(recall_score(y_test,test_pred_dt), 3),
        round(recall_score(y_test,test_pred_gbt), 3),
        round(recall_score(y_test,test_pred_adb), 3),
        round(recall_score(y_test,test_pred_vot), 3),
    ],
    'F1': [
        round(f1_score(y_test,test_pred_knn,average='binary'), 3),
        round(f1_score(y_test,test_pred_log,average='binary'), 3),
        round(f1_score(y_test,test_pred_rf,average='binary'), 3),
        round(f1_score(y_test,test_pred_gaussian,average='binary'), 3),
        round(f1_score(y_test,test_pred_sgd,average='binary'), 3),
        round(f1_score(y_test,test_pred_svc,average='binary'), 3),
        round(f1_score(y_test,test_pred_dt,average='binary'), 3),
        round(f1_score(y_test,test_pred_gbt,average='binary'), 3),
        round(f1_score(y_test,test_pred_adb,average='binary'), 3),
        round(f1_score(y_test,test_pred_vot,average='binary'), 3),
    ],
})
models.sort_values(by='Acc', ascending=False)
```

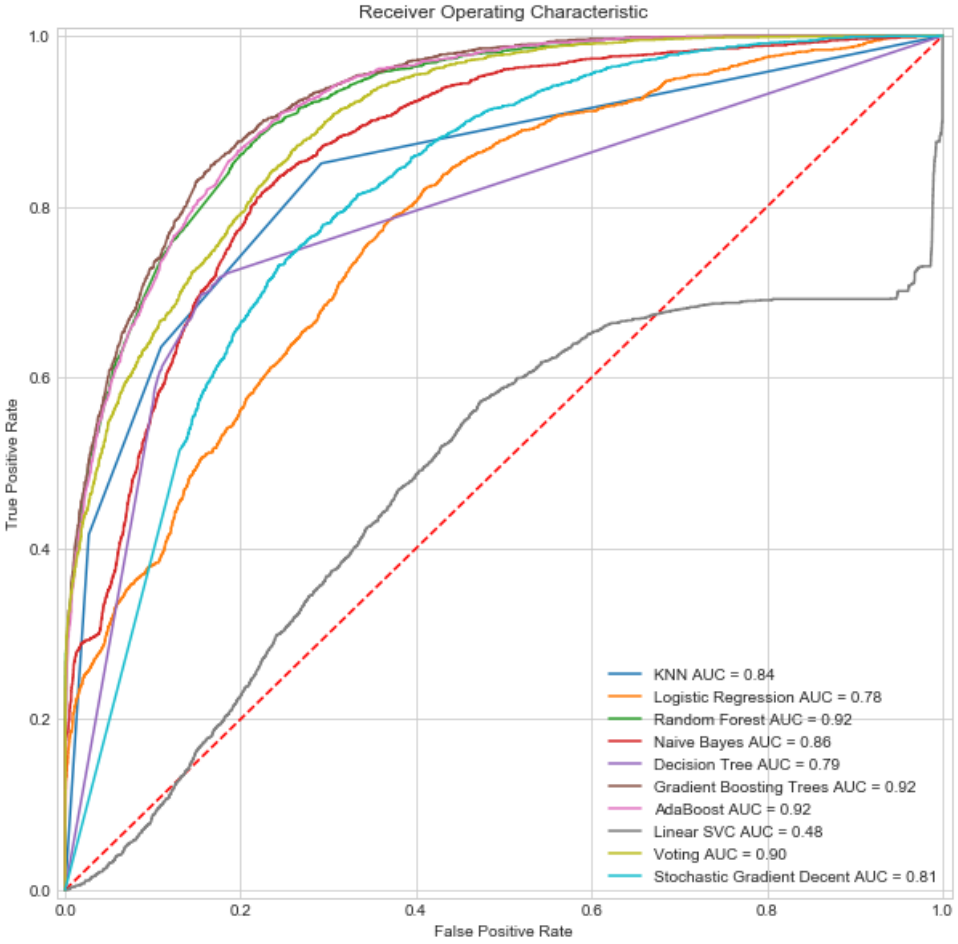
Out[95]:

	Model	Acc	Acc_cv	precision	recall	F1
2	Random Forest	86.20	85.74	0.786	0.609	0.686
7	Gradient Boosting Trees	86.19	85.97	0.808	0.581	0.676
8	AdaBoost	85.86	85.41	0.766	0.618	0.684
9	Voting	84.94	84.75	0.788	0.537	0.639
0	KNN	82.74	82.64	0.657	0.636	0.646
6	Decision Tree	82.10	81.68	0.647	0.612	0.629
3	Naive Bayes	80.19	79.88	0.702	0.349	0.466
1	Logistic Regression	79.10	78.89	0.665	0.317	0.429
4	Stochastic Gradient Decent	77.06	76.66	0.532	0.622	0.573

	Model	Acc	Acc_cv	precision	recall	F1
5	Linear SVC	53.29	35.68	0.283	0.576	0.379

In [96]:

```
plt.style.use('seaborn-whitegrid')
fig = plt.figure(figsize=(10,10))
models = [
    'KNN',
    'Logistic Regression',
    'Random Forest',
    'Naive Bayes',
    'Decision Tree',
    'Gradient Boosting Trees',
    'AdaBoost',
    'Linear SVC',
    'Voting',
    'Stochastic Gradient Decent'
]
probs = [
    probs_knn,
    probs_log,
    probs_rf,
    probs_gau,
    probs_dt,
    probs_gbt,
    probs_adb,
    probs_svc,
    probs_vot,
    probs_sgd
]
colormap = plt.cm.tab10 #nipy_spectral, Set1, Paired, tab10, gist_ncar
colors = [colormap(i) for i in np.linspace(0, 1,len(models))]
plt.title('Receiver Operating Characteristic')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([-0.01, 1.01])
plt.ylim([-0.01, 1.01])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
def plot_roc_curves(y_test, prob, model):
    fpr, tpr, threshold = metrics.roc_curve(y_test, prob)
    roc_auc = metrics.auc(fpr, tpr)
    label = model + ' AUC = %0.2f' % roc_auc
    plt.plot(fpr, tpr, 'b', label=label, color=colors[i])
    plt.legend(loc = 'lower right')
for i, model in list(enumerate(models)):
    plot_roc_curves(y_test, probs[i], models[i])
```


Receiver Operating Characteristic
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
KNN AUC = 0.84
Logistic Regression AUC = 0.78
Random Forest AUC = 0.92
Naive Bayes AUC = 0.86
Decision Tree AUC = 0.79
Gradient Boosting Trees AUC = 0.92
AdaBoost AUC = 0.92
Linear SVC AUC = 0.48
Voting AUC = 0.90
Stochastic Gradient Decent AUC = 0.81

In [97]:

```
# 构建绘制P-R曲线方法
fig = plt.figure(figsize=(10,10))
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.ylim([0.0, 1.05])
plt.xlim([0.0, 1.0])
plt.title('2-class Precision-Recall Curve')
colormap = plt.cm.tab10 #nipy_spectral, Set1, Paired, gist_ncar
colors = [colormap(i) for i in np.linspace(0, 1,len(models))]
def plot_pr_curve_overall(y_test, probs, model):
    precision, recall, _ = precision_recall_curve(y_test, probs)
    label = (model + ' AP={0:0.2f}'.format(average_precision_score(y_test, probs)))
    plt.step(recall, precision, color=colors[i],
             where='post', label=label)
#     plt.fill_between(recall, precision, step='post', alpha=0.2, color=colors[i])
    plt.legend(bbox_to_anchor=(1.05, 0), loc=3, borderaxespad=0)
for i, model in list(enumerate(models)):
    plot_pr_curve_overall(y_test, probs[i], models[i])
```