Tencent Mobile App Advertising Conversion Rate Estimate

Background

Computational advertising is one of the most important business models of the Internet, and ad serving is often measured by exposure, clicks, and conversions. Most ad systems are limited by the data reflow of ad performance and can only be optimized by exposure or click as a measure of performance.

Tencent Social Advertising (`http://ads.tencent.com`) leverages the unique capabilities of user identification and conversion tracking data to help advertisers track conversions after an ad is served. The whole process is based on the advertisement conversion data to train the conversion rate prediction model (pCVR, Predicted Conversion Rate), and introduces the pCVR factor in the advertisement ranking to optimize the advertisement serving effect and improve the ROI (return on investment).

Problem Description

This question uses mobile App ads as the research object to predict the probability of App ads being activated after clicking: pCVR=P(conversion=1 | Ad, User, Context). That is, the probability of activation after an ad clicks, given the ad, user, and context.

Dataset Features

ad.csv： creativeID adID camgaignID advertiserID appID appPlatform

app_categories.csv ： appID appCategory

position.csv ： positionID sitesetID positionType

user.csv ： userID age gender education marriageStatus haveBaby hometown residence

train.csv ： label clickTime conversionTime creativeID userID positionID connectionType telecomsOperator

test.csv ： instanceID label clickTime creativeID userID positionID connectionType telecomsOperator

train.csv	
conversionTime	The time users installed or paid for the app after clicking. When label=0, the conversionTime field is an empty string (NaN). If the label is 1, the conversionTime will be provided.
label	Label takes a value of 0 or 1, where 0 means no conversion occurred after clicking, 1 means conversion occurred after clicking
clickTime	User click time, the format is DDHHMM, where DD represents the day after the data set is extracted, HH stands for hour, MM stands for minute
creativeID	The ad content/material directly shown to the user, there can be multiple sets of material under one ad
userID	Uniquely identify a user
positionID	The specific location of the ad exposure, such as the website xxx 's Feeds ad slot.
connectionType	The networking method currently used by mobile devices, including 2G, 3G, 4G, WFI, unknown
telecomsOperato	The operators currently used by mobile devices, including China Mobile, China Unicom, China Telecom, unknown

test.csv	
instanceID	Uniquely identify a test sample
label	value = -1 represents the label occupancy, indicating that it is to be predicted
clickTime	User click time, the format is DDHHMM, where DD represents the day after the data set is extracted, HH stands for hour, MM stands for minute
creativeID	The ad content/material directly shown to the user, there can be multiple sets of material under one ad
userID	Uniquely identify a user
positionID	The specific location of the ad exposure, such as the website xxx 's Feeds ad slot.
connectionType	The networking method currently used by mobile devices, including 2G, 3G, 4G, WFI, unknown
telecomsOperato	The operators currently used by mobile devices, including China Mobile, China Unicom, China Telecom, unknown

position.csv	
positionID	The specific location of the ad exposure, such as the website xxx 's Feeds ad slot.
sitesetID	Sites with multiple ad slots aggregated, such as the website xxx
positionType	For some websites, a manually defined set of specification categories of ad slots, such as the Banner ad slot.

user.csv	
userID	Uniquely identify a user
age	Value range [0, 80], where 0 means unknown
gender	Values include male, female, unknown
education	The current highest level of the user, regardless of the students and graduates, the values include elementary school, junior high school, high school, specialist, undergraduate, master, doctoral, unknown
marriageStatus	The user's current marital status, values include single, engaged, married, unknown.
haveBaby	The status of the baby currently bred by the user, the value includes gestation, baby 0~6 months, baby 6~12 months, baby 1~2 years old, baby 2~3 years old, child rearing but baby age unknown, unknown.
hometown	The birth place of the user, the value is specific to the city-level city, using the secondary code, thousands of digits for the province, and ten single digits for the city. For example, 1806 indicates that the province number is 18, the city number is the number 6 in the province, and the number 0 indicates that it is unknown.
residence	The place where users have lived for a long time in the recent period, the value is specific to the city-level city, and the coding method is the same as that of the hometown.

ad.csv	
advertiserID	Account ID in the social advertising system, corresponding to a specific advertiser
camgaignID	A camgaign is a collection of advertisements, and advertisers can place similar advertisements into the same promotion plan.
adID	A specific ad posted by the advertiser
creativeID	The ad content/material directly shown to the user, there can be multiple sets of material under one ad
appID	A specific app, multiple camgaigns or ads can promote the same app at the same time
appPlatform	The operating system to which the app belongs, the same appID corresponds to only one operating system.

app_categories.csv	
appID	A specific ad posted by the advertiser
appCategory	App category label set by the app developer. The category label has two layers, which are encoded with 3 digits. The hundred digits represent the first category, and the ten digits represent the second category. For example, "210" indicates a The class number is 2, and the secondary class number is 10. If the category is unknown or cannot be obtained, it is marked as 0.

In [13]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
```

In [2]:
```
# data file reading Function
def read_cvs_file(file, logging=False):
    data = pd.read_csv(file)
    if logging:
        print(data.head())
        print("\n data include columns and its unique values as follows: ")

        for i, column in enumerate(data.columns.values):
            print("%2d) %-*s %s" % (i, 20,
                                    column,
                                    data[column].unique()))

        print("\n")
        print(data.describe())
        print("\n")
        print(data.info())
        print("-------------------------------------------------------------------
    return data
```

Step 1： Data Preprocessing

ad info processing

In [3]:
```
# Load ad data - no missing data
ad = read_cvs_file("./data/ad.csv", logging=False)
ad.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6582 entries, 0 to 6581
Data columns (total 6 columns):
creativeID      6582 non-null int64
adID            6582 non-null int64
camgaignID      6582 non-null int64
advertiserID    6582 non-null int64
appID           6582 non-null int64
appPlatform     6582 non-null int64
dtypes: int64(6)
memory usage: 308.6 KB
```

app info processing

In [4]:
```
# Process the app categories data and extract the first level category correspond
def app_categories_process_first_class(category):
    cate = str(category)
    if len(cate) == 1:
        if int(cate) == 0:
            return 0
        else:
            return int(cate)
    else:
        return int(cate[0])

# Process the ad categories data and extract the second level category correspond
def app_categories_process_second_class(category):
    cate = str(category)
    if len(cate) < 3:
        return 0
    else:
        return int(cate[1:])
```

In [5]:
```
# Load ad category data
app_categories = read_cvs_file(file="./data/app_categories.csv", logging=False)
app_categories.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 217041 entries, 0 to 217040
Data columns (total 2 columns):
appID          217041 non-null int64
appCategory    217041 non-null int64
dtypes: int64(2)
memory usage: 3.3 MB
```

In [6]:
```
app_categories["app_categories_first_class"] = app_categories["appCategory"].appl
app_categories["app_categories_second_class"] = app_categories["appCategory"].app
app_categories.drop(columns=['appCategory'], axis=1, inplace=True)
app_categories.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 217041 entries, 0 to 217040
Data columns (total 3 columns):
appID                          217041 non-null int64
app_categories_first_class     217041 non-null int64
app_categories_second_class    217041 non-null int64
dtypes: int64(3)
memory usage: 5.0 MB
```

User info processing

In [7]:
```
user = read_cvs_file(file="./data/user.csv", logging=False)
user.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2805118 entries, 0 to 2805117
Data columns (total 8 columns):
userID             int64
age                int64
gender             int64
education          int64
marriageStatus     int64
haveBaby           int64
hometown           int64
residence          int64
dtypes: int64(8)
memory usage: 171.2 MB
```

In [8]:
```
# process province info
def process_province(hometown):
    hometown = str(hometown)
    province = int(hometown[0:2])
    return province

# process city info
def process_city(hometown):
    hometown = str(hometown)
    if len(hometown)>1:
        province = int(hometown[2:])
    else:
        province = 0
    return province
```

In [9]:
```
user['hometown_province'] = user['hometown'].apply(process_province)
user['hometown_city'] = user['hometown'].apply(process_city)
user.drop(columns=['hometown'], axis=1, inplace=True)
```

In [10]:
```
user['residence_province'] = user['residence'].apply(process_province)
user['residence_city'] = user['residence'].apply(process_city)
user.drop(columns=['residence'], axis=1, inplace=True)
```

In [11]:
```
user.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2805118 entries, 0 to 2805117
Data columns (total 10 columns):
userID                int64
age                   int64
gender                int64
education             int64
marriageStatus        int64
haveBaby              int64
hometown_province     int64
hometown_city         int64
residence_province    int64
residence_city        int64
dtypes: int64(10)
memory usage: 214.0 MB
```

Train data processing

In [12]:
```
train_data = read_cvs_file("./data/train.csv", logging=False)
train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3749528 entries, 0 to 3749527
Data columns (total 8 columns):
label                int64
clickTime            int64
conversionTime       float64
creativeID           int64
userID               int64
positionID           int64
connectionType       int64
telecomsOperator     int64
dtypes: float64(1), int64(7)
memory usage: 228.9 MB
```

In [14]:
```
# extract day
def get_time_day(t):
    t = str(t)
    t = int(t[0:2])
    return t

# extract hour
def get_time_hour(t):
    t = str(t)
    t=int(t[2:4])
    return t
```

In [15]:
```
train_data['clickTime_day'] = train_data['clickTime'].apply(get_time_day)
train_data['clickTime_hour'] = train_data['clickTime'].apply(get_time_hour)
train_data.drop(['clickTime'],axis=1,inplace=True)
```

In [16]:
```
#feature- Remove conversionTime because of the strong relationship with label
train_data.drop(['conversionTime'],axis=1,inplace=True)
```

In [17]:
```
train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3749528 entries, 0 to 3749527
Data columns (total 8 columns):
label                int64
creativeID           int64
userID               int64
positionID           int64
connectionType       int64
telecomsOperator     int64
clickTime_day        int64
clickTime_hour       int64
dtypes: int64(8)
memory usage: 228.9 MB
```

position data processing

In [18]:
```
position = read_cvs_file(file='./data/position.csv', logging=False)
position.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7645 entries, 0 to 7644
Data columns (total 3 columns):
positionID      7645 non-null int64
sitesetID       7645 non-null int64
positionType    7645 non-null int64
dtypes: int64(3)
memory usage: 179.3 KB
```

Merge data together

In [19]:
```
# Merge training set and user information by userID
merged_data = pd.merge(train_data, user, on='userID', how="inner")

# Merge training set and ad information by creativeID
merged_data = pd.merge(merged_data, ad, on='creativeID', how="inner")

# Merge training set and app information by appID
merged_data = pd.merge(merged_data, app_categories, on='appID', how="inner")

# Merge training set and ad position information by positionID
merged_data = pd.merge(merged_data, position, on='positionID', how="inner")

merged_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3749528 entries, 0 to 3749527
Data columns (total 26 columns):
label                          int64
creativeID                     int64
userID                         int64
positionID                     int64
connectionType                 int64
telecomsOperator               int64
clickTime_day                  int64
clickTime_hour                 int64
age                            int64
gender                         int64
education                      int64
marriageStatus                 int64
haveBaby                       int64
hometown_province              int64
hometown_city                  int64
residence_province             int64
residence_city                 int64
adID                           int64
camgaignID                     int64
advertiserID                   int64
appID                          int64
appPlatform                    int64
app_categories_first_class     int64
app_categories_second_class    int64
sitesetID                      int64
positionType                   int64
dtypes: int64(26)
memory usage: 772.4 MB
```

In [20]:
```
# int8: -128 to 127 ; int16:-32,768 to +32,767 ; int32:-2147,483,648 to 214748364
merged_data.describe()

# userID
```

Out[20]:

	label	creativeID	userID	positionID	connectionType	telecomsOperator
count	3.749528e+06	3.749528e+06	3.749528e+06	3.749528e+06	3.749528e+06	3.749528e+06
mean	2.487300e-02	3.261575e+03	1.405349e+06	3.702799e+03	1.222590e+00	1.605879e+00
std	1.557380e-01	1.829643e+03	8.088094e+05	1.923724e+03	5.744428e-01	8.491127e-01
min	0.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	0.000000e+00	0.000000e+00
25%	0.000000e+00	1.540000e+03	7.058698e+05	2.579000e+03	1.000000e+00	1.000000e+00
50%	0.000000e+00	3.465000e+03	1.407062e+06	3.322000e+03	1.000000e+00	1.000000e+00
75%	0.000000e+00	4.565000e+03	2.105989e+06	4.896000e+03	1.000000e+00	2.000000e+00
max	1.000000e+00	6.582000e+03	2.805118e+06	7.645000e+03	4.000000e+00	3.000000e+00

8 rows × 26 columns

In [21]:
```
userId_S = pd.DataFrame(merged_data['userID'], dtype='int32')
camgaignID_S = pd.DataFrame(merged_data['camgaignID'], dtype='int16')
adID_S = pd.DataFrame(merged_data['adID'], dtype='int16')
positionID_S = pd.DataFrame(merged_data['positionID'], dtype='int16')
creativeID_S = pd.DataFrame(merged_data['creativeID'], dtype='int16')
```

In [22]:
```
merged_data_compress = pd.DataFrame(merged_data, dtype='int8')
merged_data_compress['userID'] = userId_S
merged_data_compress['camgaignID'] = camgaignID_S
merged_data_compress['adID'] = adID_S
merged_data_compress['positionID'] = positionID_S
merged_data_compress['creativeID'] = creativeID_S
```

In [23]:
```
merged_data_compress.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3749528 entries, 0 to 3749527
Data columns (total 26 columns):
label                          int8
creativeID                     int16
userID                         int32
positionID                     int16
connectionType                 int8
telecomsOperator               int8
clickTime_day                  int8
clickTime_hour                 int8
age                            int8
gender                         int8
education                      int8
marriageStatus                 int8
haveBaby                       int8
hometown_province              int8
hometown_city                  int8
residence_province             int8
residence_city                 int8
adID                           int16
camgaignID                     int16
advertiserID                   int8
appID                          int8
appPlatform                    int8
app_categories_first_class     int8
app_categories_second_class    int8
sitesetID                      int8
positionType                   int8
dtypes: int16(4), int32(1), int8(21)
memory usage: 146.6 MB
```

In [24]:
```
print(merged_data['userID'].unique().shape)
print(merged_data['creativeID'].unique().shape)
print(merged_data['appID'].unique().shape)
print(merged_data['positionID'].unique().shape)
print(merged_data['camgaignID'].unique().shape)
print(merged_data['advertiserID'].unique().shape)
```

```
(2595627,)
(6315,)
(50,)
(7219,)
(677,)
(89,)
```

In [ ]:
```
# train_user_ad_app_pos.drop(axis=1, columns=['creativeID', 'userID', 'appID', 'p
```

In [ ]:
```
merged_data_compress.columns
```

Step 2: Feature Enginnering

Separate data and labels

In [26]:
```
# feature part
X = merged_data_compress.iloc[:,1:]
```

In [27]:
```
# label part
y = merged_data_compress.loc[:,['label']] # columns Series
```

Random forest modeling && feature importance ranking

In [28]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [29]:
```
forest = RandomForestClassifier(n_estimators=100,
                                random_state=0,
                                n_jobs=-1)
```

In [31]:
```
forest.fit(X.values, y.values.ravel())
```

Out[31]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=100, n_jobs=-1,
            oob_score=False, random_state=0, verbose=0, warm_start=False)
```

In [32]:
```
feat_labels = X.columns
feat_labels
```

Out[32]:
```
Index(['creativeID', 'userID', 'positionID', 'connectionType',
       'telecomsOperator', 'clickTime_day', 'clickTime_hour', 'age', 'gender',
       'education', 'marriageStatus', 'haveBaby', 'hometown_province',
       'hometown_city', 'residence_province', 'residence_city', 'adID',
       'camgaignID', 'advertiserID', 'appID', 'appPlatform',
       'app_categories_first_class', 'app_categories_second_class',
       'sitesetID', 'positionType'],
      dtype='object')
```

In [33]:
```
importances = forest.feature_importances_
importances
```

Out[33]:
```
array([0.02557551, 0.17113458, 0.06481588, 0.00436067, 0.03453989,
       0.076338  , 0.09405691, 0.0875135 , 0.01321131, 0.05031221,
       0.03113971, 0.01879074, 0.06247256, 0.05239632, 0.0843336 ,
       0.06762492, 0.01733232, 0.01335282, 0.00610102, 0.00581847,
       0.0008678 , 0.00270089, 0.00731277, 0.00282943, 0.00506817])
```

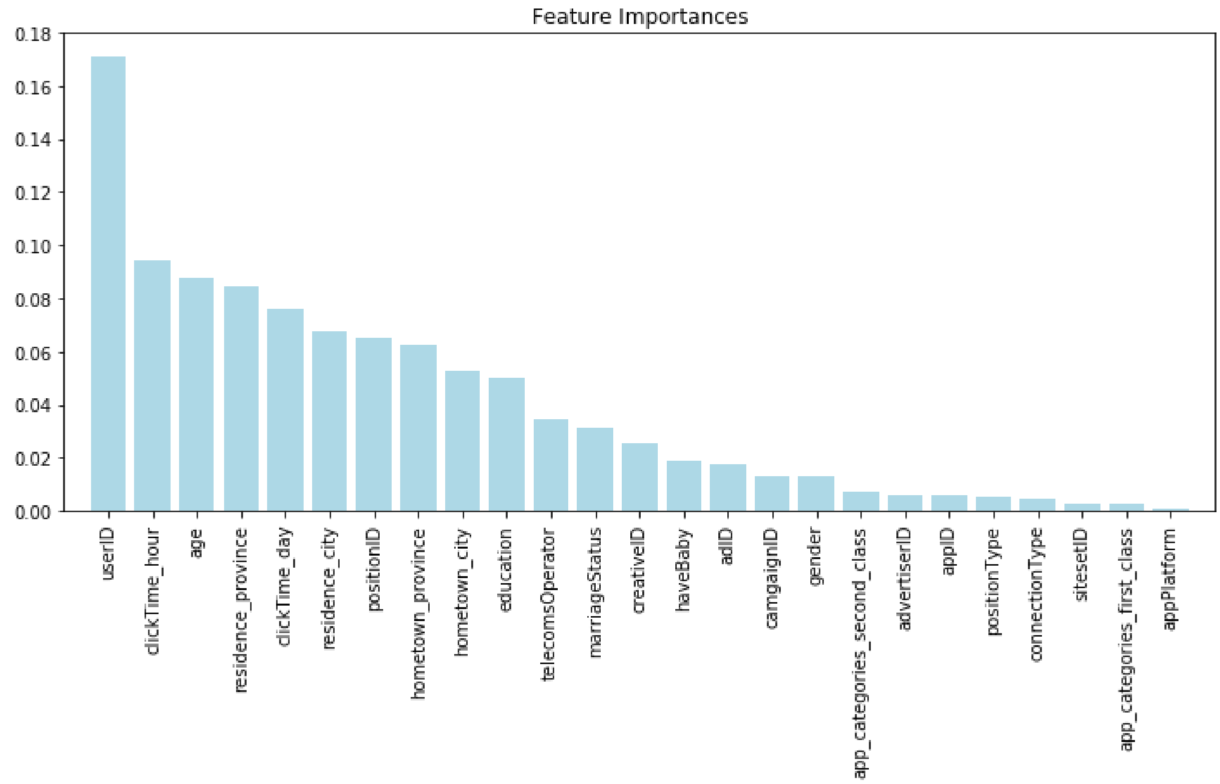
In [34]:
```
indices = np.argsort(importances)[::-1]
indices
```

Out[34]:
```
array([ 1,  6,  7, 14,  5, 15,  2, 12, 13,  9,  4, 10,  0, 11, 16, 17,  8,
       22, 18, 19, 24,  3, 23, 21, 20], dtype=int64)
```

In [36]:
```
for f in range(X.values.shape[1]):
    print("%2d) %-*s %f" % (f+1, 30,
                            feat_labels[indices[f]],
                            importances[indices[f]]))
```

```
 1) userID                         0.171135
 2) clickTime_hour                 0.094057
 3) age                            0.087514
 4) residence_province             0.084334
 5) clickTime_day                  0.076338
 6) residence_city                 0.067625
 7) positionID                     0.064816
 8) hometown_province              0.062473
 9) hometown_city                  0.052396
10) education                      0.050312
11) telecomsOperator               0.034540
12) marriageStatus                 0.031140
13) creativeID                     0.025576
14) haveBaby                       0.018791
15) adID                           0.017332
16) camgaignID                     0.013353
17) gender                         0.013211
18) app_categories_second_class    0.007313
19) advertiserID                   0.006101
20) appID                          0.005818
21) positionType                   0.005068
22) connectionType                 0.004361
23) sitesetID                      0.002829
24) app_categories_first_class     0.002701
25) appPlatform                    0.000868
```

In [38]:
```
plt.figure(figsize=(10, 6.5)) # 1000 * 650
plt.title('Feature Importances')
plt.bar(range(X.values.shape[1]),
        importances[indices],
        color='lightblue',
        align='center')

plt.xticks(range(X.values.shape[1]),
           feat_labels[indices], rotation=90)

plt.xlim([-1, X.values.shape[1]])
plt.tight_layout()
#plt.savefig('./random_forest.png', dpi=300)
plt.show()
```



Performing one-hot encoding on nominal features

Batch processing features function

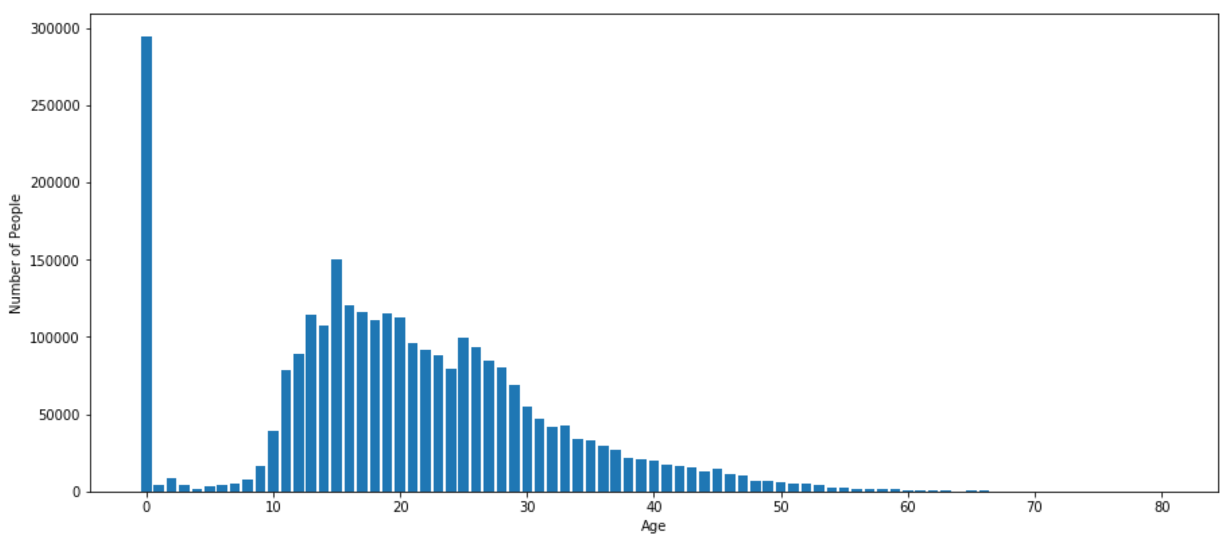
In [28]:
```
# Batch processing attribute requireing one-hot encoding  (accepting binning)
def batch_get_dummies(df, f_list, bins=None):
    dummies_f = None
    for f in f_list:
        if(bins and (f in bins)):
            dummies_f = pd.get_dummies(pd.cut(df[f], bins[f], right=False), prefi
        else:
            dummies_f = pd.get_dummies(df[f], prefix=f, dtype='int8')

        df = pd.concat([df,dummies_f],axis=1)
        df.drop([f],axis=1, inplace=True)

    return df
```

Analyze the age distribution

In [40]:
```
age_distribution = user.age.value_counts(sort=False)
```

In [41]:
```
import matplotlib.pyplot as plt
%matplotlib inline
```

In [42]:
```
plt.figure(figsize=(15, 6.5)) # 1500 * 650
plt.bar(age_distribution.index, age_distribution.values)
plt.xlabel("Age")
plt.ylabel("Number of People")
plt.show()
```



One-hot encoding processing

In [1]:
```
age_bins = [0,1,10,20,30,40,50,60,70,90]
hour_bins = [0,7,9,12,14,18,25] # use 25 for including 24
```

In [30]:
```
feature_list = ['age','gender', 'marriageStatus', 'hometown_province', 'hometown_
                'residence_city', 'app_categories_second_class','app_categories_f
                'connectionType','sitesetID', 'positionType']

bins = {'age' : age_bins, 'clickTime_hour' : hour_bins}
```

In [31]:
```
X_dummies = batch_get_dummies(X, bins=bins, f_list=feature_list)
X_dummies.head()
```

Out[31]:

	creativeID	userID	positionID	clickTime_day	clickTime_hour	education	haveBaby	adID	cam
0	3089	2798058	293	17	0	1	1	1321	
1	3089	1683269	293	18	0	0	0	1321	
2	3089	240899	293	19	10	1	0	1321	
3	2230	2177495	293	18	23	1	1	2841	
4	2230	417301	293	20	1	0	1	2841	

5 rows × 175 columns

In [46]:
```
X_dummies.columns
```

Out[46]:
```
Index(['creativeID', 'userID', 'positionID', 'clickTime_day', 'clickTime_hour',
       'education', 'haveBaby', 'adID', 'camgaignID', 'advertiserID',
       ...
       'connectionType_4', 'sitesetID_0', 'sitesetID_1', 'sitesetID_2',
       'positionType_0', 'positionType_1', 'positionType_2', 'positionType_3',
       'positionType_4', 'positionType_5'],
      dtype='object', length=175)
```

The original data set is too large, which leads to memory overflow and showing MemoryError when processing; Therefore, I will conduct stratified sampling and reduce the quantity on the original data set according to the category proportion of the original data set

In [32]:
```
from sklearn.model_selection import train_test_split
```

In [33]:
```
X_Sampled, X_unused, y_Sampled, y_unused = train_test_split(X_dummies, y,
                                                            test_size=0.4,
                                                            random_state=0,
                                                            stratify=y)
```

In [34]:
```
X_Sampled.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2249716 entries, 758268 to 1357484
Columns: 175 entries, creativeID to positionType_5
dtypes: int16(4), int32(1), int8(170)
memory usage: 407.6 MB
```

Partitioning a dataset into separate training and test sets(holdout method)

In [50]:
```
# stratify ensures that both training and test datasets have the same class propo
X_train, X_test, y_train, y_test = train_test_split(X_Sampled, y_Sampled,
                                                    test_size=0.4,
                                                    random_state=0,
                                                    stratify=y_Sampled)
```

In [51]:
```
X_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1349829 entries, 1763393 to 1711162
Columns: 175 entries, creativeID to positionType_5
dtypes: int16(4), int32(1), int8(170)
memory usage: 244.6 MB
```

In [52]:
```
X_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 899887 entries, 3672702 to 3522917
Columns: 175 entries, creativeID to positionType_5
dtypes: int16(4), int32(1), int8(170)
memory usage: 163.1 MB
```

Step 3： Model Building

Streamlining workflows with pipelines

In [56]:
```
from sklearn.pipeline import make_pipeline
from sklearn.linear_model import LogisticRegression
```

In [57]:
```
pipe_lr = make_pipeline(LogisticRegression(random_state=1, penalty='l2'))
```

K-fold cross-validation

First aspect

In [58]:
```
from sklearn.model_selection import StratifiedKFold
```

In [59]:
```
X_train_np = X_train.values
y_train_np = y_train.values.ravel()

kfold = StratifiedKFold(n_splits=10, random_state=1).split(X_train_np, y_train_np

scores = []
for k, (train, test) in enumerate(kfold):
    pipe_lr.fit(X_train_np[train], y_train_np[train])
    score = pipe_lr.score(X_train_np[test], y_train_np[test])
    scores.append(score)
    print('Fold: %2d, Class dist.: %s, Acc: %.3f' % (k+1,
          np.bincount(y_train_np[train]), score))

print('\nCV accuracy: %.3f +/- %.3f' % (np.mean(scores), np.std(scores)))
```

```
Fold:  1, Class dist.: [1184629   30216], Acc: 0.975
Fold:  2, Class dist.: [1184629   30216], Acc: 0.975
Fold:  3, Class dist.: [1184629   30216], Acc: 0.975
Fold:  4, Class dist.: [1184629   30216], Acc: 0.975
Fold:  5, Class dist.: [1184629   30217], Acc: 0.975
Fold:  6, Class dist.: [1184630   30217], Acc: 0.975
Fold:  7, Class dist.: [1184630   30217], Acc: 0.975
Fold:  8, Class dist.: [1184630   30217], Acc: 0.975
Fold:  9, Class dist.: [1184630   30217], Acc: 0.975
Fold: 10, Class dist.: [1184630   30217], Acc: 0.975

CV accuracy: 0.975 +/- 0.000
```

Second aspect

In [60]:
```
from sklearn.model_selection import cross_val_score
```

In [61]:
```
scores = cross_val_score(estimator=pipe_lr,
                         X=X_train_np,
                         y=y_train_np,
                         cv=5,
                         n_jobs=1)
print('CV accuracy scores: %s' % scores)
print('CV accuracy: %.3f +/- %.3f' % (np.mean(scores), np.std(scores)))
```

```
CV accuracy scores: [0.9751265  0.9751265  0.9751265  0.9751265  0.97513011]
CV accuracy: 0.975 +/- 0.000
```

test X_test to get accuracy score

In [62]:
```
y_model_lr = pipe_lr.predict(X_test.values)
from sklearn.metrics import accuracy_score
accuracy_score(y_test.values, y_model_lr)
```

Out[62]:
```
0.9751268770412285
```

Step 4： Model Evaluation

Diagnosing bias and variance problems with learning curves

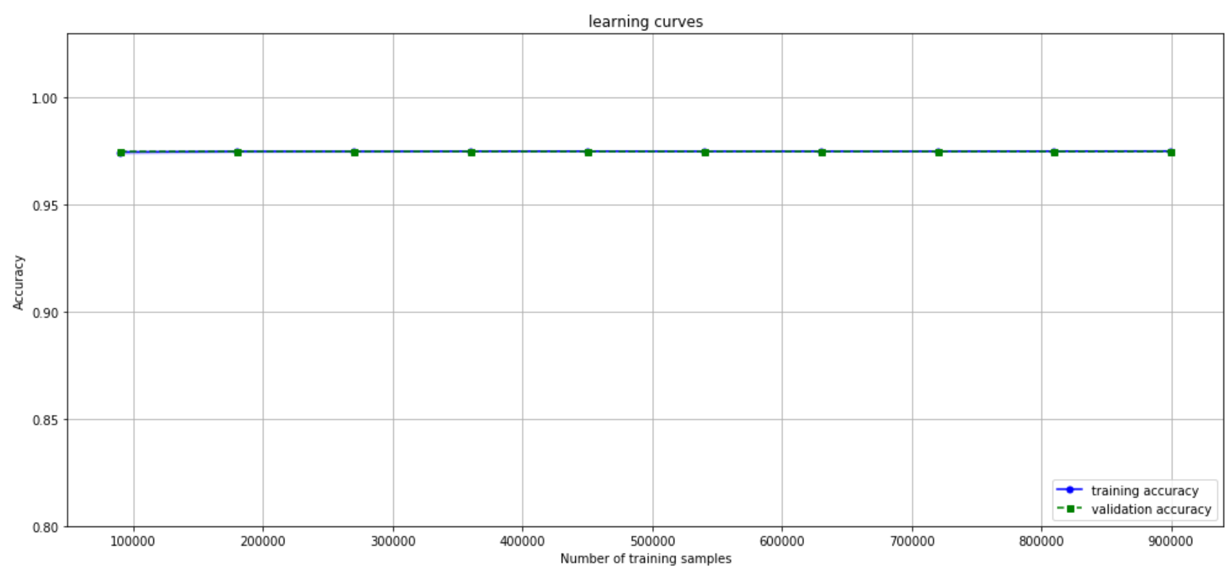
detect whether the model suffers from high variance or high bias, and whether the collection of more data could help address this problem

In [63]:
```
from sklearn.model_selection import learning_curve
```

In [72]:
```
# use 10 evenly spaced, relative intervals for the training set sizes
train_sizes, train_scores, test_scores = learning_curve(estimator=pipe_lr,
                                                        X=X_train_np,
                                                        y=y_train_np,
                                                        train_sizes=np.linspace(0.
                                                        cv=3,
                                                        n_jobs=1)
```

In [73]:
```
train_mean = np.mean(train_scores, axis=1)
train_std = np.std(train_scores, axis=1)
test_mean = np.mean(test_scores, axis=1)
test_std = np.std(test_scores, axis=1)
```

In [74]:
```
plt.figure(figsize=(14, 6.5)) # 1400 * 650
plt.plot(train_sizes, train_mean,
         color='blue', marker='o',
         markersize=5, label='training accuracy')

plt.fill_between(train_sizes,
                 train_mean + train_std,
                 train_mean - train_std,
                 alpha=0.15, color='blue')

plt.plot(train_sizes, test_mean,
         color='green', linestyle='--',
         marker='s', markersize=5,
         label='validation accuracy')

plt.fill_between(train_sizes,
                 test_mean + test_std,
                 test_mean - test_std,
                 alpha=0.15, color='green')

plt.grid()
plt.title('learning curves')
plt.xlabel('Number of training samples')
plt.ylabel('Accuracy')
plt.legend(loc='lower right')
plt.ylim([0.8, 1.03])
plt.tight_layout()
#plt.savefig('images/06_05.png', dpi=300)
plt.show()
```



Addressing over- or underfitting with validation curves

Validation curves are a useful tool for improving the performance of a model by addressing issues such as overfitting or underfitting. Validation curves are related to learning curves, but instead of plotting the training and test accuracies as functions of the sample size, we vary the values of the model parameters.

In [75]:
```
from sklearn.model_selection import validation_curve
```

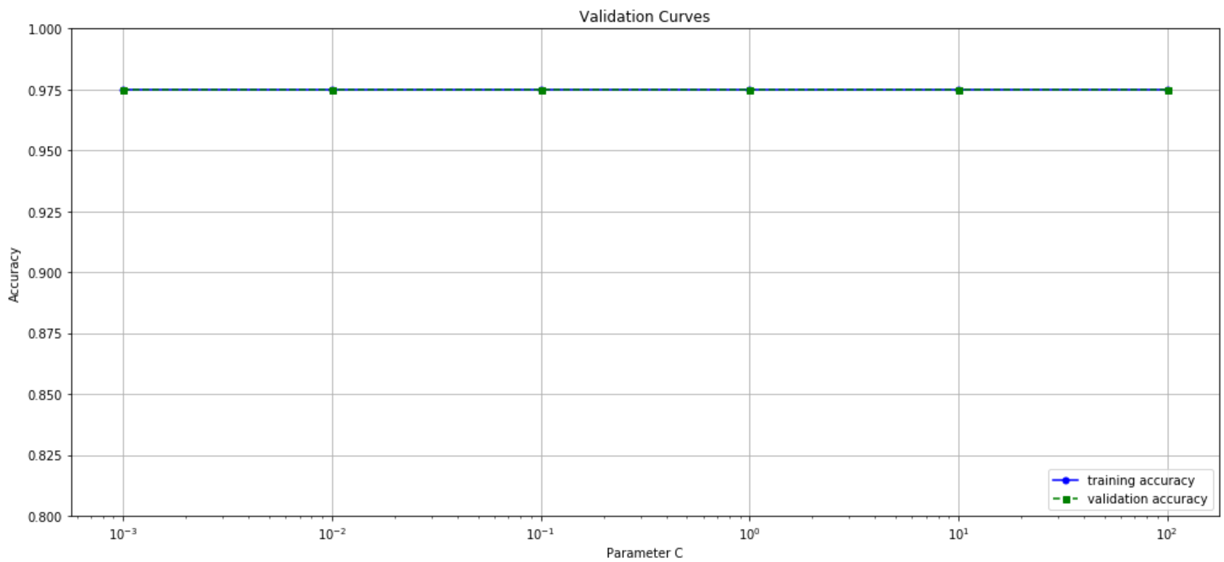
In [76]:
```
lr_C_param_range = [0.001, 0.01, 0.1, 1.0, 10.0, 100.0]
```

In [78]:
```
train_scores, test_scores = validation_curve(
                estimator=pipe_lr,
                X=X_train_np,
                y=y_train_np,
                param_name='logisticregression__C',
                param_range=lr_C_param_range,
                cv=3)
```

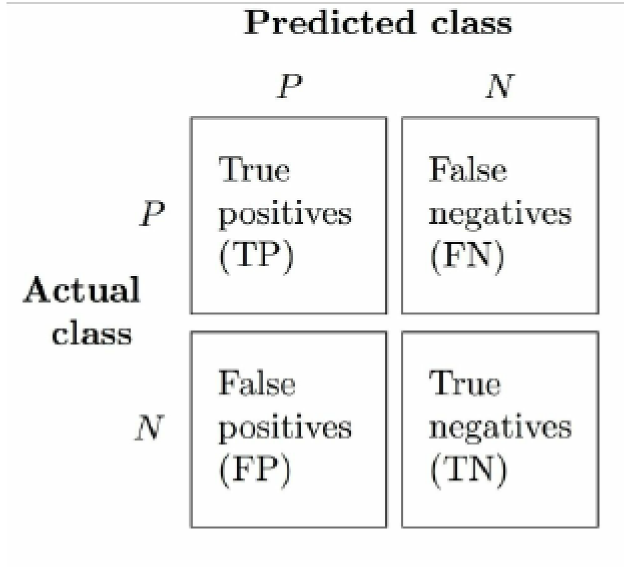
In [80]:
```
train_mean = np.mean(train_scores, axis=1)
train_std = np.std(train_scores, axis=1)
test_mean = np.mean(test_scores, axis=1)
test_std = np.std(test_scores, axis=1)
```

In [82]:

```
plt.figure(figsize=(14, 6.5)) # 1400 * 650
plt.plot(lr_C_param_range, train_mean,
         color='blue', marker='o',
         markersize=5, label='training accuracy')

plt.fill_between(lr_C_param_range, train_mean + train_std,
                 train_mean - train_std, alpha=0.15,
                 color='blue')

plt.plot(lr_C_param_range, test_mean,
         color='green', linestyle='--',
         marker='s', markersize=5,
         label='validation accuracy')

plt.fill_between(lr_C_param_range,
                 test_mean + test_std,
                 test_mean - test_std,
                 alpha=0.15, color='green')

plt.grid()
plt.title('Validation Curves')
plt.xscale('log')
plt.legend(loc='lower right')
plt.xlabel('Parameter C')
plt.ylabel('Accuracy')
plt.ylim([0.8, 1.0])
plt.tight_layout()
# plt.savefig('images/06_06.png', dpi=300)
plt.show()
```



Confusion Matrix

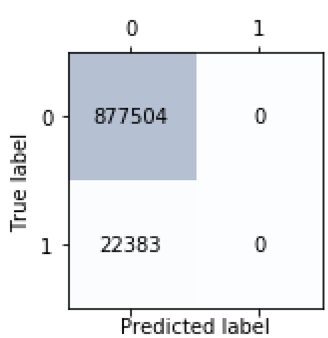


In [88]:
```
y_test_np = y_test.values.ravel()
```

In [79]:
```
from sklearn.metrics import confusion_matrix
```

In [83]:
```
y_pred_lr = pipe_lr.predict(X_test.values)
confmat = confusion_matrix(y_true=y_test_np, y_pred=y_pred_lr)
```

In [84]:
```
fig, ax = plt.subplots(figsize=(2.5, 2.5))
ax.matshow(confmat, cmap=plt.cm.Blues, alpha=0.3)

for i in range(confmat.shape[0]):
    for j in range(confmat.shape[1]):
        ax.text(x=j, y=i, s=confmat[i, j], va='center', ha='center')

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

plt.tight_layout()
#plt.savefig('images/06_09.png', dpi=300)
plt.show()
```



In [85]:
```
from sklearn.metrics import precision_score, recall_score, f1_score
```

In [89]:
```
print('Precision: %.3f' % precision_score(y_true=y_test_np, y_pred=y_pred_lr))
print('Recall: %.3f' % recall_score(y_true=y_test_np, y_pred=y_pred_lr))
print('F1 Score: %.3f' % f1_score(y_true=y_test_np, y_pred=y_pred_lr))
```

```
C:\Users\Public\Anaconda3\lib\site-packages\sklearn\metrics\classification.py:1
135: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 due
to no predicted samples.
  'precision', 'predicted', average, warn_for)

Precision: 0.000
Recall: 0.000
F1 Score: 0.000

C:\Users\Public\Anaconda3\lib\site-packages\sklearn\metrics\classification.py:1
135: UndefinedMetricWarning: F-score is ill-defined and being set to 0.0 due to
no predicted samples.
  'precision', 'predicted', average, warn_for)
```

Class imbalance data

In [90]:
```
positive_num = y_Sampled[y_Sampled['label']==1].values.shape[0]
negative_num = y_Sampled[y_Sampled['label']==0].values.shape[0]

negative_num/float(positive_num)
```

Out[90]:
```
39.20437121361045
```

training a model on such a dataset that achieves approximately 97.5 percent test accuracy would mean our model hasn't learned anything useful from the features provided in this dataset

the upsampling of the minority class by drawing new samples from the dataset with replacement

In [35]:
```
from sklearn.utils import resample
```

In [36]:
```
y_Sampled_np = y_Sampled.values.ravel()
X_Sampled_np = X_Sampled.values
```

In [37]:
```
X_upsampled, y_upsampled = resample(X_Sampled_np[y_Sampled_np == 1],
                                    y_Sampled_np[y_Sampled_np == 1],
                                    replace=True,
                                    n_samples=X_Sampled_np[y_Sampled_np == 0].sha
                                    random_state=123)
```

In [38]:
```
X_bal = np.vstack((X_Sampled_np[y_Sampled_np == 0], X_upsampled))
y_bal = np.hstack((y_Sampled_np[y_Sampled_np == 0], y_upsampled))
```

In [100]:
```
positive_num = y_bal[y_bal == 1].shape[0]
negative_num = y_bal[y_bal == 0].shape[0]

negative_num/float(positive_num)
```

Out[100]:
```
1.0
```

In [39]:
```
X_bal.shape
```

Out[39]:
```
(4387518, 175)
```

Step5：Model optimization

Repeated Data Processing

In [41]:
```
X_bal_pd = pd.DataFrame(X_bal)
y_bal_pd = pd.DataFrame(y_bal)
bal_pd = pd.concat([X_bal_pd, y_bal_pd], axis=1)
```

In [42]:
```
bal_pd.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4387518 entries, 0 to 4387517
Columns: 176 entries, 0 to 0
dtypes: int32(175), int8(1)
memory usage: 2.9 GB
```

In [45]:
```
bal_sampled = bal_pd.sample(frac=0.1)
```

In [46]:
```
bal_sampled.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 438752 entries, 2162470 to 468981
Columns: 176 entries, 0 to 0
dtypes: int32(175), int8(1)
memory usage: 296.7 MB
```

In [51]:
```
# feature part
X_bal = bal_sampled.iloc[:,1:].values
# label part
y_bal = bal_sampled.iloc[:,-1].values.ravel() # columns Series
```

In [54]:
```
positive_num = y_bal[y_bal == 1].shape[0]
negative_num = y_bal[y_bal == 0].shape[0]

negative_num/float(positive_num)
```

Out[54]:
```
0.9980964091354145
```

In [55]:
```
X_train, X_test, y_train, y_test = train_test_split(X_bal, y_bal,
                                                    test_size=0.4,
                                                    random_state=0,
                                                    stratify=y_bal)
```

Repeated Model Building and Training

In [61]:
```
from sklearn.pipeline import make_pipeline
from sklearn.linear_model import LogisticRegression

pipe_lr_new = make_pipeline(LogisticRegression(random_state=1, penalty='l2'))
```

In [62]:
```
from sklearn.model_selection import cross_val_score
scores = cross_val_score(estimator=pipe_lr_new,
                         X=X_train,
                         y=y_train,
                         cv=5,
                         n_jobs=1)
print('CV accuracy scores: %s' % scores)
print('CV accuracy: %.3f +/- %.3f' % (np.mean(scores), np.std(scores)))
```

```
CV accuracy scores: [1. 1. 1. 1. 1.]
CV accuracy: 1.000 +/- 0.000
```

In [64]:
```
rf = RandomForestClassifier(n_estimators=100, max_features=0.6)

scores = cross_val_score(estimator=rf,
                         X=X_train,
                         y=y_train,
                         cv=5,
                         n_jobs=1)
print('CV accuracy scores: %s' % scores)
print('CV accuracy: %.3f +/- %.3f' % (np.mean(scores), np.std(scores)))
```

```
CV accuracy scores: [0.9326315  0.9326315  0.9323128  0.9324512  0.9326315]
CV accuracy:0.932 +/-0.000
```

Fine-tuning machine learning models via grid search

In [65]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestClassifier

param_grid = {
              #'n_estimators': [100],
              'n_estimators': [10, 100, 500, 1000],
              'max_features':[0.6, 0.7, 0.8, 0.9]
             }

rf = RandomForestClassifier()
rfc = GridSearchCV(rf, param_grid, scoring = 'neg_log_loss', cv=3, n_jobs=2)
rfc.fit(X_train, y_train)

print(rfc.best_score_)
print(rfc.best_params_)
```

Step 6： Prediction from New data

use test data provided to test Classifiers

In [74]:
```
test_data = read_cvs_file("./data/test.csv", logging=False)
#test_data.info()

test_data['clickTime_day'] = test_data['clickTime'].apply(get_time_day)
test_data['clickTime_hour'] = test_data['clickTime'].apply(get_time_hour)
test_data.drop(['clickTime'],axis=1,inplace=True)

test_data_clean = test_data.iloc[:,2:]
test_data_clean.head()

# Merge training set and user information by userID
merged_data = pd.merge(test_data_clean, user, on='userID', how="inner")

# Merge training set and ad information by creativeID
merged_data = pd.merge(merged_data, ad, on='creativeID', how="inner")

# Merge training set and app information by appID
merged_data = pd.merge(merged_data, app_categories, on='appID', how="inner")

# Merge training set and ad position information by positionID
merged_data = pd.merge(merged_data, position, on='positionID', how="inner")

# merged_data.info()
```

In [73]:
```
# feature part
X = merged_data.iloc[:,1:]

X_test_dummies = batch_get_dummies(X, bins=bins, f_list=feature_list)

x_test_np = np.array(X_test_dummies,dtype='int32')

x_test_np.shape
```

Out[73]: (338489, 172)

In [ ]:
```
result_predict_prob = []
result_predict=[]
clfs = [rf, pipe_lr_new]
scale = len(clfs)

for i in range(scale):
    result_indiv = clfs[i].predict(x_test_np)
    result_indiv_proba = clfs[i].predict_proba(x_test_np)[:,1]
    result_predict.append(result_indiv)
    result_predict_prob.append(result_indiv_proba)


result_predict_prob = np.reshape(result_predict_prob,[-1,scale])
result_predict = np.reshape(result_predict,[-1,scale])

result_predict_prob = np.mean(result_predict_prob,axis=1)
result_predict = max_count(result_predict)


result_predict_prob = np.array(result_predict_prob).reshape([-1,1])


test_data['prob'] = result_predict_prob
test_data = test_data.loc[:,['instanceID','prob']]
test_data.to_csv('predict.csv',index=False)

print("prediction done!")
```