Frequent pattern and association rule mining

Dataset

- [Oakland Crime Statistics 2011 to 2016 (https://www.kaggle.com/cityofoakland/oakland-crime-statistics-2011-to-2016)](https://www.kaggle.com/cityofoakland/oakland-crime-statistics-2011-to-2016)

这个数据集由2011年至2016年的奥克兰犯罪统计数据组成。

Data analysis requirements

1. Data pre-process

In [1]:
```
import os
import time
import json
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from progressbar import *
from mpl_toolkits.mplot3d import Axes3D

# timekeeping
timekeeping = time.time()

# load csv file
data2011 = pd.read_csv('../Oakland-Crime-Statistics-2011-to-2016/re
cords-for-2011.csv')
data2012 = pd.read_csv('../Oakland-Crime-Statistics-2011-to-2016/re
cords-for-2012.csv')
data2013 = pd.read_csv('../Oakland-Crime-Statistics-2011-to-2016/re
cords-for-2013.csv')
data2014 = pd.read_csv('../Oakland-Crime-Statistics-2011-to-2016/re
cords-for-2014.csv')
data2015 = pd.read_csv('../Oakland-Crime-Statistics-2011-to-2016/re
cords-for-2015.csv')
data2016 = pd.read_csv('../Oakland-Crime-Statistics-2011-to-2016/re
cords-for-2016.csv')

# descriptors of the raw datase
print('2011:')
data2011.info()
print('2012:')
data2012.info()
print('2013:')
data2013.info()
print('2014:')
data2014.info()
print('2015:')
data2015.info()
print('2016:')
data2016.info()
```

```
2011:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 180016 entries, 0 to 180015
Data columns (total 10 columns):
 #   Column                      Non-Null Count   Dtype
---  ------                      --------------   -----
 0   Agency                      180015 non-null  object
 1   Create Time                 180015 non-null  object
 2   Location                    180016 non-null  object
 3   Area Id                     179112 non-null  float64
 4   Beat                        179496 non-null  object
 5   Priority                    180015 non-null  float64
```

```
 6   Incident Type Id           180015 non-null  object
 7   Incident Type Description  180015 non-null  object
 8   Event Number               180015 non-null  object
 9   Closed Time                180009 non-null  object
dtypes: float64(2), object(8)
memory usage: 13.7+ MB
2012:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 187431 entries, 0 to 187430
Data columns (total 11 columns):
 #   Column                     Non-Null Count   Dtype
---  ------                     --------------   -----
 0   Agency                     187430 non-null  object
 1   Create Time                187430 non-null  object
 2   Area Id                    186016 non-null  float64
 3   Beat                       186447 non-null  object
 4   Priority                   187430 non-null  float64
 5   Incident Type Id           187430 non-null  object
 6   Incident Type Description  187430 non-null  object
 7   Event Number               187430 non-null  object
 8   Closed Time                187412 non-null  object
 9   Location 1                 187361 non-null  object
 10  Zip Codes                  175 non-null     float64
dtypes: float64(3), object(8)
memory usage: 15.7+ MB
2013:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 188052 entries, 0 to 188051
Data columns (total 10 columns):
 #   Column                     Non-Null Count   Dtype
---  ------                     --------------   -----
 0   Agency                     188051 non-null  object
 1   Create Time                188051 non-null  object
 2   Location                   188052 non-null  object
 3   Area Id                    185794 non-null  float64
 4   Beat                       186874 non-null  object
 5   Priority                   188051 non-null  float64
 6   Incident Type Id           188051 non-null  object
 7   Incident Type Description  188047 non-null  object
 8   Event Number               188051 non-null  object
 9   Closed Time                188050 non-null  object
dtypes: float64(2), object(8)
memory usage: 14.3+ MB
2014:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 187480 entries, 0 to 187479
Data columns (total 11 columns):
 #   Column                     Non-Null Count   Dtype
---  ------                     --------------   -----
 0   Agency                     187480 non-null  object
 1   Create Time                187480 non-null  object
 2   Area Id                    9693 non-null    float64
 3   Beat                       186263 non-null  object
```

```
 4   Priority                    187480 non-null  int64  
 5   Incident Type Id            187480 non-null  object 
 6   Incident Type Description  187339 non-null  object 
 7   Event Number                187480 non-null  object 
 8   Closed Time                 187480 non-null  object 
 9   Location 1                  187438 non-null  object 
 10  Zip Codes                   177 non-null     float64
dtypes: float64(2), int64(1), object(8)
memory usage: 15.7+ MB
2015:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 192581 entries, 0 to 192580
Data columns (total 10 columns):
 #   Column                      Non-Null Count   Dtype 
---  ------                      --------------   ----- 
 0   Agency                      192581 non-null  object
 1   Create Time                 192581 non-null  object
 2   Location                    192581 non-null  object
 3   Area Id                     192581 non-null  object
 4   Beat                        191256 non-null  object
 5   Priority                    192581 non-null  int64 
 6   Incident Type Id            192581 non-null  object
 7   Incident Type Description  192338 non-null  object
 8   Event Number                192581 non-null  object
 9   Closed Time                 192581 non-null  object
dtypes: int64(1), object(9)
memory usage: 14.7+ MB
2016:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 110828 entries, 0 to 110827
Data columns (total 10 columns):
 #   Column                      Non-Null Count   Dtype  
---  ------                      --------------   -----  
 0   Agency                      110827 non-null  object 
 1   Create Time                 110827 non-null  object 
 2   Location                    110828 non-null  object 
 3   Area Id                     110827 non-null  object 
 4   Beat                        110247 non-null  object 
 5   Priority                    110827 non-null  float64
 6   Incident Type Id            110827 non-null  object 
 7   Incident Type Description  110827 non-null  object 
 8   Event Number                110827 non-null  object 
 9   Closed Time                 110827 non-null  object 
dtypes: float64(1), object(9)
memory usage: 8.5+ MB
```

这6年的数据集中共包括10个共同的属性： `Agency` 、 `Create Time` 、 `Location`（`Location 1` and `Location`）、 `Area Id` 、 `Beat` 、 `Priority` 、 `Incident Type Id` 、 `Incident Type Description` 、 `Event Number` 、 `Closed Time`

另外，只有2012和2014年的数据中包括了 `Zip Codes` 属性，且缺失值非常多，所以在频繁模式与关联规则挖掘过程中去掉该属性，然后把2012和2014年的数据中属性字段 `Location 1` 改为统一的字段 `Location` 。这里2013年的字段 `Location` 多出来一个空格，也需要将该字段统一

In [2]:
```
# delete 'Zip Codes attribute
data2012 = data2012.drop('Zip Codes', 1)
data2014 = data2014.drop('Zip Codes', 1)

# rename 'Location 1' with 'Location'
data2012.rename(columns={'Location 1': 'Location'}, inplace = True)
data2013.rename(columns={'Location ': 'Location'}, inplace=True)
data2014.rename(columns={'Location 1': 'Location'}, inplace=True)
```

In [3]:
```
data2011_frequency = {key: data2011[key].value_counts() for key in
data2011.columns}
print(data2011_frequency)
```

```
{'Agency': OP    180015
Name: Agency, dtype: int64, 'Create Time': 2011-06-02T00:00:00.000
4
2011-03-27T00:22:41.000    3
2011-09-21T14:05:59.000    3
2011-05-03T19:30:24.000    2
2011-09-10T13:09:26.000    2
                          ..
2011-09-14T00:00:00.000    1
2011-06-26T00:29:05.000    1
2011-02-26T22:50:25.000    1
2011-04-02T05:04:20.000    1
2011-06-06T10:07:44.000    1
Name: Create Time, Length: 179451, dtype: int64, 'Location':  INTE
RNATIONAL BLVD        3866
 MACARTHUR BLVD            3129
 AV&INTERNATIONAL BLVD     3067
 BROADWAY                  2132
 FOOTHILL BLVD             1791
                           ...
14TH WILLOW ST                1
GRAND EARHART RD              1
MACARTHUR AV&D ST             1
REDWOOD PIEDMONT AV           1
EDES ALICE ST                 1
Name: Location, Length: 32505, dtype: int64, 'Area Id': 1.0    791
52
2.0    67261
3.0    32699
Name: Area Id, dtype: int64, 'Beat': 04X     7410
08X     6885
26Y     5478
30Y     5295
06X     5119
```

```
23X     5051
30X     4956
19X     4955
34X     4673
29X     4483
20X     4287
27Y     4159
07X     4134
31Y     4082
25X     4022
35X     3880
33X     3849
03X     3819
32X     3711
27X     3703
09X     3630
21Y     3435
32Y     3125
22X     3061
26X     2978
02Y     2970
10X     2967
14X     2733
03Y     2726
22Y     2664
12Y     2651
05X     2633
02X     2614
31X     2603
21X     2593
17Y     2582
24Y     2575
13Z     2546
15X     2509
24X     2459
12X     2422
10Y     2383
01X     2210
28X     2191
17X     2133
11X     2087
13Y     2017
35Y     1956
31Z     1870
18Y     1778
16Y     1561
14Y     1492
25Y     1482
13X     1122
18X     1063
16X      994
05Y      710
PDT2      20
```

```
Name: Beat, dtype: int64, 'Priority': 2.0    143314
1.0     36699
0.0         2
Name: Priority, dtype: int64, 'Incident Type Id': 933R      17348
911H      12817
SECCK     11393
415       10752
10851      7180
          ...
10801         1
FLOOD         1
963           1
MTHLAB        1
148           1
Name: Incident Type Id, Length: 263, dtype: int64, 'Incident Type
Description': ALARM-RINGER            17348
911 HANG-UP             12817
SECURITY CHECK          11393
STOLEN VEHICLE           7180
415 UNKNOWN              6624
                        ...
INJURE TELEPHONE/POW        1
LOCKOUT                     1
ASSAULT ON A POLICE         1
PLAYING BALL IN STRE        1
OBSTRUCTING JUSTICE-        1
Name: Incident Type Description, Length: 265, dtype: int64, 'Event
Number': LOP110216000538    1
LOP111003000732    1
LOP111031000539    1
LOP110531000847    1
LOP110804001120    1
                  ..
LOP110302000970    1
LOP111116000689    1
LOP111007000035    1
LOP110127000940    1
LOP110228000936    1
Name: Event Number, Length: 180015, dtype: int64, 'Closed Time': 2
011-08-01T19:50:11.000    2
2011-12-28T18:22:52.000    2
2011-02-21T18:03:57.000    2
2011-10-13T15:48:36.000    2
2011-06-08T09:52:38.000    2
                          ..
2011-06-21T15:28:04.000    1
2011-07-31T00:06:02.000    1
2011-03-10T14:33:34.000    1
2011-05-02T18:44:54.000    1
2011-11-08T23:21:31.000    1
Name: Closed Time, Length: 179506, dtype: int64}
```

根据2011年的各项属性的频数，选取共同属性中的部分属性来进行分析，选取的属性为： Agency 、 Location 、 Area Id 、 Beat 、 Priority 、 Incident Type Id 、 Incident Type Description 、 Event Number

In [4]:
```
attribute_seleted = ['Agency', 'Location', 'Area Id', 'Beat', 'Priority', 'Incident Type Id', 'Incident Type Description', 'Event Number']

data2011_seleted = data2011[['Agency', 'Location', 'Area Id', 'Beat', 'Priority', 'Incident Type Id', 'Incident Type Description', 'Event Number']]
data2012_seleted = data2012[['Agency', 'Location', 'Area Id', 'Beat', 'Priority', 'Incident Type Id', 'Incident Type Description', 'Event Number']]
data2013_seleted = data2013[['Agency', 'Location', 'Area Id', 'Beat', 'Priority', 'Incident Type Id', 'Incident Type Description', 'Event Number']]
data2014_seleted = data2014[['Agency', 'Location', 'Area Id', 'Beat', 'Priority', 'Incident Type Id', 'Incident Type Description', 'Event Number']]
data2015_seleted = data2015[['Agency', 'Location', 'Area Id', 'Beat', 'Priority', 'Incident Type Id', 'Incident Type Description', 'Event Number']]
data2016_seleted = data2016[['Agency', 'Location', 'Area Id', 'Beat', 'Priority', 'Incident Type Id', 'Incident Type Description', 'Event Number']]
```

为了方便挖掘更全面的关联规则，把6年以来的所有数据合并起来

In [5]:
```
# data = pd.concat([data2011_seleted,
#                   data2012_seleted,
#                   data2013_seleted,
#                   data2014_seleted,
#                   data2015_seleted,
#                   data2016_seleted], axis=0)
data = pd.concat([data2011_seleted])
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 180016 entries, 0 to 180015
Data columns (total 8 columns):
 #   Column                     Non-Null Count   Dtype  
---  ------                     --------------   -----  
 0   Agency                     180015 non-null  object 
 1   Location                   180016 non-null  object 
 2   Area Id                    179112 non-null  float64
 3   Beat                       179496 non-null  object 
 4   Priority                   180015 non-null  float64
 5   Incident Type Id           180015 non-null  object 
 6   Incident Type Description  180015 non-null  object 
 7   Event Number               180015 non-null  object 
dtypes: float64(2), object(6)
memory usage: 11.0+ MB
```

针对该数据集进行分析之后，针对缺失的数值，决定采用 将缺失部分剔除

In [6]:
```
data_clean = data.dropna()
data_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 178777 entries, 0 to 180014
Data columns (total 8 columns):
 #   Column                     Non-Null Count   Dtype  
---  ------                     --------------   -----  
 0   Agency                     178777 non-null  object 
 1   Location                   178777 non-null  object 
 2   Area Id                    178777 non-null  float64
 3   Beat                       178777 non-null  object 
 4   Priority                   178777 non-null  float64
 5   Incident Type Id           178777 non-null  object 
 6   Incident Type Description  178777 non-null  object 
 7   Event Number               178777 non-null  object 
dtypes: float64(2), object(6)
memory usage: 12.3+ MB
```

至此，完成了对数据集进行处理，转换成适合进行关联规则挖掘的形式

2. Find frequent patterns

定义全局的支持度和置信度的阈值

In [7]:
```
min_sup = 0.1
min_conf = 0.5
```

In [8]:
```
# Convert DataFrame to a dictionary store
data_dict = []
for line in data_clean.values.tolist():
    data_set = []
    for i, value in enumerate(line):
        if not value:
            data_set.append((attribute_seleted[i], 'NA'))
        else:
            data_set.append((attribute_seleted[i], value))
    data_dict.append(data_set)
```

In [9]:
```
# Generate a number of cell candidate item sets
def C1_generation(dataset):
    C1 = []
    progress = ProgressBar()
    for data in progress(dataset):
        for item in data:
            if [item] not in C1:
                C1.append([item])
    return [frozenset(item) for item in C1]

# Filter item sets with support below the threshold
def Ck_low_support_filtering(dataset, Ck):
    Ck_count = dict()
    for data in dataset:
        for cand in Ck:
            if cand.issubset(data):
                if cand not in Ck_count:
                    Ck_count[cand] = 1
                else:
                    Ck_count[cand] += 1

    num_items = float(len(dataset))
    return_list = []
    sup_rata = dict()

    # Filter infrequent itemsets
    for key in Ck_count:
        support  = Ck_count[key] / num_items
        if support >= min_sup:
            return_list.insert(0, key)
```

```
        sup_rata[key] = support
    return return_list, sup_rata

# check whether the sub set is frequent item
def apriori_gen(Fk, k):
    return_list = []
    len_Fk = len(Fk)

    for i in range(len_Fk):
        for j in range(i+1, len_Fk):
            # When the k-2nd item is the same, combine the two sets
            F1 = list(Fk[i])[:k-2]
            F2 = list(Fk[j])[:k-2]
            F1.sort()
            F2.sort()
            if F1 == F2:
                return_list.append(Fk[i] | Fk[j])
    return return_list


# apriori algorithm
def apriori(dataset):
        C1 = C1_generation(dataset)  # Generate a number of cell ca
ndidate item sets
        dataset = [set(data) for data in dataset]
        F1, sup_rata = Ck_low_support_filtering(dataset, C1)
        F = [F1]
        k = 2
        while len(F[k-2]) > 0:
            # When the candidate item element is greater than 2, th
e subitem set is checked frequently when merging
            Ck = apriori_gen(F[k-2], k)

            # Filter item sets with support below the threshold
            Fk, support_k = Ck_low_support_filtering(dataset, Ck)
            sup_rata.update(support_k)
            F.append(Fk)
            k += 1
        return F, sup_rata
```

In [10]:
```
# Get frequent sets
freq_set, sup_rata = apriori(data_dict)
sup_rata_out = sorted(sup_rata.items(), key=lambda d: d[1], reverse
=True)
print("sup_rata ", sup_rata)
```

```
100% |############################################################
############|
IOPub data rate exceeded.
The notebook server will temporarily stop sending output
to the client in order to avoid crashing it.
To change this limit, set the config variable
`--NotebookApp.iopub_data_rate_limit`.

Current values:
NotebookApp.iopub_data_rate_limit=1000000.0 (bytes/sec)
NotebookApp.rate_limit_window=3.0 (secs)
```

3. Derive the association rules and calculate their support and confidence

In [11]:
```
# evaluation rule
def cal_conf(freq_set, H, sup_rata, strong_rules_list):
    prunedH = []
    for reasoned_item in H:
        sup = sup_rata[freq_set]
        conf = sup / sup_rata[freq_set - reasoned_item]
        lift = conf / sup_rata[reasoned_item]
        jaccard = sup / (sup_rata[freq_set - reasoned_item] + sup_r
ata[reasoned_item] - sup)
        if conf >= min_conf:
            strong_rules_list.append((freq_set - reasoned_item, rea
soned_item, sup, conf, lift, jaccard))
            prunedH.append(reasoned_item)
    return prunedH

def rules_from_reasoned_item(freq_set, H, sup_rata, strong_rules_li
st):
    """
    H -> the list of elements that appear at the right of the rule
    """
    m = len(H[0])
    if len(freq_set) > (m+1):
        Hmp1 = apriori_gen(H, m+1)
        Hmp1 = cal_conf(freq_set, Hmp1, sup_rata, strong_rules_list
)
        if len(Hmp1) > 1:
            rules_from_reasoned_item(freq_set, Hmp1, sup_rata, stro
ng_rules_list)
```

基于Apriori算法，首先从一个频繁项集开始，接着创建一个规则列表，其中规则右部只包含一个元素，然后对这些规则进行测试。接下来合并所有的剩余规则列表来创建一个新的规则列表，其中规则右部包含两个元素。这种方法称作分级法。

In [12]:
```
# Generate strong association rules
def generate_rules(F, sup_rata):
    """
    :param F: frequent sets
    :param sup_rata: asupport for frequent sets
    :return: list of strong association rules
    """
    strong_rules_list = []
    for i in range(1, len(F)):
        for freq_set in F[i]:
            H1 = [frozenset([item]) for item in freq_set]
            # Here, only get a collection with two or more elements
            if i > 1:
                rules_from_reasoned_item(freq_set, H1, sup_rata, st
rong_rules_list)
            else:
                cal_conf(freq_set, H1, sup_rata, strong_rules_list)
    return strong_rules_list
```

In [13]:
```
# get strong association rules
strong_rules_list = generate_rules(freq_set, sup_rata)
strong_rules_list = sorted(strong_rules_list, key=lambda x: x[3], r
everse=True)
print("strong_rules_list ", strong_rules_list)
```

```
strong_rules_list  [(frozenset({('Area Id', 3.0)}), frozenset({('A
gency', 'OP')}), 0.18262975662417424, 1.0, 1.0, 0.1826297566241742
4), (frozenset({('Area Id', 2.0)}), frozenset({('Agency', 'OP')}),
0.3756187876516554, 1.0, 1.0, 0.3756187876516554), (frozenset({('P
riority', 2.0)}), frozenset({('Agency', 'OP')}), 0.795253304395979
3, 1.0, 1.0, 0.7952533043959793), (frozenset({('Area Id', 1.0)}),
frozenset({('Agency', 'OP')}), 0.44175145572417035, 1.0, 1.0, 0.44
175145572417035), (frozenset({('Priority', 1.0)}), frozenset({('Ag
ency', 'OP')}), 0.2047355084826348, 1.0, 1.0, 0.2047355084826348),
(frozenset({('Area Id', 1.0)}), frozenset({('Priority', 2.0)}), 0.
35613082219748626, 0.8061791706236151, 1.0137388504609035, 0.40429
260858521715), (frozenset({('Area Id', 1.0)}), frozenset({('Priori
ty', 2.0), ('Agency', 'OP')}), 0.35613082219748626, 0.806179170623
6151, 1.0137388504609035, 0.40429260858521715), (frozenset({('Agen
cy', 'OP')}), frozenset({('Priority', 2.0)}), 0.7952533043959793,
0.7952533043959793, 1.0, 0.7952533043959793), (frozenset({('Area I
d', 2.0)}), frozenset({('Priority', 2.0)}), 0.2960951352802654, 0.
7882862759113654, 0.9912392335296165, 0.3384807212737388), (frozen
set({('Area Id', 2.0)}), frozenset({('Priority', 2.0), ('Agency',
'OP')}), 0.2960951352802654, 0.7882862759113654, 0.991239233529616
5, 0.3384807212737388), (frozenset({('Area Id', 3.0)}), frozenset(
{('Priority', 2.0)}), 0.14302734691822774, 0.7831546707503829, 0.9
847864402716494, 0.1713198394672134), (frozenset({('Area Id', 3.0)
}), frozenset({('Priority', 2.0), ('Agency', 'OP')}), 0.1430273469
1822774, 0.7831546707503829, 0.9847864402716494, 0.171319839467213
4)]
```

In [15]:
```
# Save the frequent patterns
out_path = './results'
freq_set_file = open(os.path.join(out_path, 'frequent_pattern.json'
), 'w')
for (key, value) in sup_rata_out:
    result_dict = {'set': None, 'sup': None}
    set_result = list(key)
    sup_result = value
    if sup_result < min_sup:
        continue
    result_dict['set'] = set_result
    result_dict['sup'] = sup_result
    json_str = json.dumps(result_dict, ensure_ascii=False)
    freq_set_file.write(json_str + '\n')
freq_set_file.close()

# Save the strong association rules
rules_file = open(os.path.join(out_path, 'association_rule.json'),
'w')
for result in strong_rules_list:
    result_dict = {'X_set': None, 'Y_set': None, 'sup': None, 'conf
': None, 'lift': None, 'jaccard': None}
    X_set, Y_set, sup, conf, lift, jaccard = result
    result_dict['X_set'] = list(X_set)
    result_dict['Y_set'] = list(Y_set)
    result_dict['sup'] = sup
    result_dict['conf'] = conf
    result_dict['lift'] = lift
    result_dict['jaccard'] = jaccard

    json_str = json.dumps(result_dict, ensure_ascii=False)
    rules_file.write(json_str + '\n')
rules_file.close()
```

4. Evaluation rule

除了支持度(Sup)和置信度(Conf)两项度量规则之外， 还是实现了Lift和Jaccard，计算公式如下：

$$Sup(X) = \frac{count(X)}{count(data)}$$

$$Conf(X \rightarrow Y) = \frac{Sup(X \cup Y)}{Sup(X)}$$

$$Lift(X \rightarrow Y) = \frac{Sup(X \cup Y)}{Sup(X) \times Sup(Y)}$$

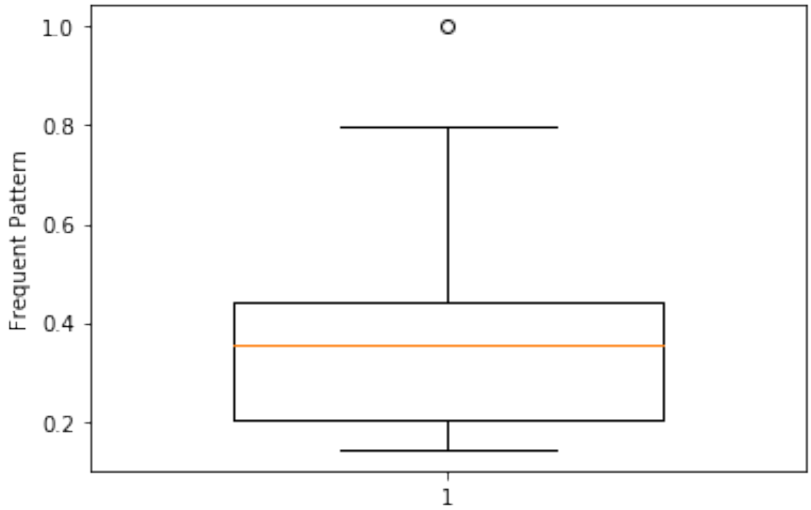
$$Jaccard(X \rightarrow Y) = \frac{Sup(X \cup Y)}{Sup(X) + Sup(Y) - Sup(X \cup Y)}$$

In [16]:
```
# evaluation rule
def cal_conf(freq_set, H, sup_rata, strong_rules_list):
    prunedH = []
    for reasoned_item in H:
        sup = sup_rata[freq_set]
        conf = sup / sup_rata[freq_set - reasoned_item]
        lift = conf / sup_rata[reasoned_item]
        jaccard = sup / (sup_rata[freq_set - reasoned_item] + sup_r
ata[reasoned_item] - sup)
        if conf >= min_conf:
            strong_rules_list.append((freq_set - reasoned_item, rea
soned_item, sup, conf, lift, jaccard))
            prunedH.append(reasoned_item)
    return prunedH
```

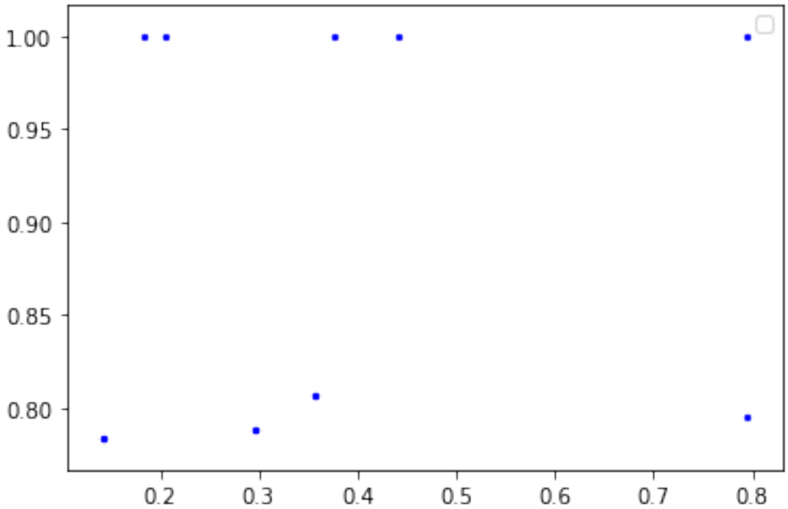
5. Visualizatoin

In [17]:
```
def visualization():
    with open('./results/frequent_pattern.json') as f:
        freq = [json.loads(each) for each in f.readlines()]

    with open('./results/association_rule.json') as f:
        rules = [json.loads(each) for each in f.readlines()]

    freq_sup = [each['sup'] for each in freq]
    plt.boxplot(freq_sup,
                sym='o',
                vert=True,
                widths=0.6,
                meanline=True)
    plt.ylabel('Frequent Pattern')
    plt.show()

    rules_sup = [each['sup'] for each in rules]
    rules_conf = [each['conf'] for each in rules]


    plt.scatter(rules_sup, rules_conf, s=20, c='b', marker='.')
    plt.xlabel = 'Support'
    plt.ylabel = 'Confidence'
    plt.legend(loc='best')
    plt.show()
```

In [18]:
```
visualization()
```




```
No handles with labels found to put in legend.
```



In [19]:
```
m, s = divmod(time.time()-timekeeping, 60)
h, m = divmod(m, 60)
print ('run time: %02d:%02d:%02d' % (h, m, s))
```

```
run time: 01:16:30
```

6. Analysis

由于时间关系，本次实验未采用所有数据，仅使用2011年的数据共用时 `1:16:30` ，挖掘中得到的频繁模式与关联规则会分别保存在 `./results/frequent_pattern.json` 和 `./results/association_rule.json` 中

In [20]:
```
with open('./results/frequent_pattern.json') as f:
    freq = [json.loads(each) for each in f.readlines()]

with open('./results/association_rule.json') as f:
    rules = [json.loads(each) for each in f.readlines()]

print('frequent_pattern.json')
print(freq)

print('association_rule.json')
print(rules)
```

frequent_pattern.json

[{'set': [['Agency', 'OP']], 'sup': 1.0}, {'set': [['Priority', 2.0]], 'sup': 0.7952533043959793}, {'set': [['Priority', 2.0], ['Agency', 'OP']], 'sup': 0.7952533043959793}, {'set': [['Area Id', 1.0]], 'sup': 0.44175145572417035}, {'set': [['Agency', 'OP'], ['Area Id', 1.0]], 'sup': 0.44175145572417035}, {'set': [['Area Id', 2.0]], 'sup': 0.3756187876516554}, {'set': [['Agency', 'OP'], ['Area Id', 2.0]], 'sup': 0.3756187876516554}, {'set': [['Priority', 2.0], ['Area Id', 1.0]], 'sup': 0.35613082219748626}, {'set': [['Priority', 2.0], ['Agency', 'OP'], ['Area Id', 1.0]], 'sup': 0.35613082219748626}, {'set': [['Priority', 2.0], ['Area Id', 2.0]], 'sup': 0.2960951352802654}, {'set': [['Priority', 2.0], ['Agency', 'OP'], ['Area Id', 2.0]], 'sup': 0.2960951352802654}, {'set': [['Priority', 1.0]], 'sup': 0.2047355084826348}, {'set': [['Priority', 1.0], ['Agency', 'OP']], 'sup': 0.2047355084826348}, {'set': [['Area Id', 3.0]], 'sup': 0.18262975662417424}, {'set': [['Area Id', 3.0], ['Agency', 'OP']], 'sup': 0.18262975662417424}, {'set': [['Priority', 2.0], ['Area Id', 3.0]], 'sup': 0.14302734691822774}, {'set': [['Priority', 2.0], ['Area Id', 3.0], ['Agency', 'OP']], 'sup': 0.14302734691822774}]

association_rule.json

[{'X_set': [['Area Id', 3.0]], 'Y_set': [['Agency', 'OP']], 'sup': 0.18262975662417424, 'conf': 1.0, 'lift': 1.0, 'jaccard': 0.18262975662417424}, {'X_set': [['Area Id', 2.0]], 'Y_set': [['Agency', 'OP']], 'sup': 0.3756187876516554, 'conf': 1.0, 'lift': 1.0, 'jaccard': 0.3756187876516554}, {'X_set': [['Priority', 2.0]], 'Y_set': [['Agency', 'OP']], 'sup': 0.7952533043959793, 'conf': 1.0, 'lift': 1.0, 'jaccard': 0.7952533043959793}, {'X_set': [['Area Id', 1.0]], 'Y_set': [['Agency', 'OP']], 'sup': 0.44175145572417035, 'conf': 1.0, 'lift': 1.0, 'jaccard': 0.44175145572417035}, {'X_set': [['Priority', 1.0]], 'Y_set': [['Agency', 'OP']], 'sup': 0.2047355084826348, 'conf': 1.0, 'lift': 1.0, 'jaccard': 0.2047355084826348}, {'X_set': [['Area Id', 1.0]], 'Y_set': [['Priority', 2.0]], 'sup': 0.35613082219748626, 'conf': 0.8061791706236151, 'lift': 1.0137388504609035, 'jaccard': 0.40429260858521715}, {'X_set': [['Area Id', 1.0]], 'Y_set': [['Priority', 2.0], ['Agency', 'OP']], 'sup': 0.35613082219748626, 'conf': 0.8061791706236151, 'lift': 1.0137388504609035, 'jaccard': 0.40429260858521715}, {'X_set': [['Agency', 'OP']], 'Y_set': [['Priority', 2.0]], 'sup': 0.7952533043959793, 'conf': 0.7952533043959793, 'lift': 1.0, 'jaccard': 0.7952533043959793}, {'X_set': [['Area Id', 2.0]], 'Y_set': [['Priority', 2.0]], 'sup': 0.2960951352802654, 'conf': 0.7882862759113654, 'lift': 0.9912392335296165, 'jaccard': 0.3384807212737388}, {'X_set': [['Area Id', 2.0]], 'Y_set': [['Priority', 2.0], ['Agency', 'OP']], 'sup': 0.2960951352802654, 'conf': 0.7882862759113654, 'lift': 0.9912392335296165, 'jaccard': 0.3384807212737388}, {'X_set': [['Area Id', 3.0]], 'Y_set': [['Priority', 2.0]], 'sup': 0.14302734691822774, 'conf': 0.7831546707503829, 'lift': 0.9847864402716494, 'jaccard': 0.1713198394672134}, {'X_set': [['Area Id', 3.0]], 'Y_set': [['Priority', 2.0], ['Agency', 'OP']], 'sup': 0.14302734691822774, 'conf': 0.7831546707503829, 'lift': 0.9847864402716494, 'jaccard': 0.1713198394672134}]

根据频繁模式可知：

- 频繁一项集：
  - `Agency=OP` 的支持度是1，体现不出什么有价值的信息，故忽略;
  - `Priority=2.0` 的支持度为0.795,也就是说该地区的犯罪等级大多是 `2`；
  - `Area Id=1.0` 时支持度为0.442，说明在该地区的犯罪事实出现最多， `Area Id=2.0` 的支持度为0.375，比 `Area Id=1.0` 稍微低一些，这说明了该地区的犯罪记录为第二多。
- 频繁二项集（除去包含 `Agency=OP` 的项）：
  - `Priority=2.0 & Area Id=1.0` 的支持度最高，为0.356，说明该地区的犯罪等级大多数为 `2`

根据关联规则可知（除去 `Agency==OP` ）：

- `Area Id=2.0 → Priority=2.0` 的支持度(sup)=0.296，置信度(conf)=0.788，lift=0.991，jaccard=0.338，这说明犯罪的严重性与所在地有着较强联系。