Pizza

November 30, 2019

[1]:
```
import pandas as pd
import statsmodels.api as sm
import statsmodels.formula.api as smf
import numpy as np
from sklearn.metrics import confusion_matrix, classification_report
import warnings
warnings.filterwarnings('ignore')
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime
import plotly.express as px
```

0.1 data reading

[2]:
```
data_2017_18 = pd.read_csv("./data/
↪Datafiniti_Pizza_Restaurants_and_the_Pizza_They_Sell_May19.csv")
```

[3]:
```
data_2017_18.head()
```

[3]:
```
                     id             dateAdded           dateUpdated  \
0  AVz3Y-7h3D1zeR_xDAqm  2017-06-30T05:05:40Z  2019-05-01T15:43:09Z
1  AVweGPFF_7pvs4fzAAzQ  2016-04-02T04:02:49Z  2019-05-01T15:27:50Z
2  AVwdRGa9_7pvs4fz4E3K  2016-03-03T18:39:49Z  2019-05-01T12:52:25Z
3  AVwdX4psIN2L1WUfvJB1  2016-03-29T05:08:59Z  2019-05-01T12:52:20Z
4  AVwdaeTtkufWRAb55pSH  2016-03-31T02:34:04Z  2019-05-01T12:50:45Z

             address                                         categories  \
0   4203 E Kiehl Ave  Pizza,Restaurant,American restaurants,Pizza Pl...
1  25 E Camelback Rd                      Pizza,Pizza Place,Restaurants
2    3703 Paxton Ave                 Restaurant,Pizza Place,Restaurants
3    30495 John R Rd       Pizza,Carry-out food,Pizza Place,Restaurants
4   3600 Eastern Ave  Pizza,American restaurants,Pizza Place,Pizza e...

            primaryCategories             city country  \
0  Accommodation & Food Services         Sherwood      US
1  Accommodation & Food Services          Phoenix      US
2  Accommodation & Food Services       Cincinnati      US
```

```
3  Accommodation & Food Services  Madison Heights      US
4  Accommodation & Food Services        Baltimore      US

                                         keys   latitude  ...  \
0     us/ar/sherwood/4203ekiehlave/-1051391616  34.832300  ...
1       us/az/phoenix/25ecamelbackrd/-727422936  33.509266  ...
2    us/oh/cincinnati/3703paxtonave/-619797122  39.144883  ...
3  us/mi/madisonheights/30495johnrrd/-874863116  42.516669  ...
4   us/md/baltimore/3600easternave/-1270965359  39.286630  ...

  menus.currency                                   menus.dateSeen  \
0            USD  2018-05-01T04:25:37.197Z,2018-04-16T04:36:02.3...
1            USD  2018-03-03T02:38:06.381Z,2018-01-18T20:18:10.0...
2            USD  2018-04-10T07:58:34.585Z,2018-04-21T05:43:21.4...
3            USD          2016-10-20T21:50:02Z,2016-03-29T05:08:59Z
4            USD                               2016-03-31T02:34:04Z

                                 menus.description    menus.name  \
0                                              NaN  Cheese Pizza
1                                              NaN  Pizza Cookie
2  a saucelessampcomma double cheese pizza with a...  Pizza Blanca
3                                              NaN   Small Pizza
4                                              NaN     Pizza Sub

                name postalCode priceRangeCurrency priceRangeMin  \
0   Shotgun Dans Pizza      72120                USD             0
1     Sauce Pizza Wine      85012                USD             0
2        Mios Pizzeria      45209                USD             0
3  Hungry Howies Pizza      48071                USD            25
4     Spartan Pizzeria      21224                USD             0

  priceRangeMax province
0            25       AR
1            25       AZ
2            25       OH
3            40       MI
4            25       MD

[5 rows x 24 columns]
```

[4]:
```
data_2017_18.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 24 columns):
id                     10000 non-null object
dateAdded              10000 non-null object
dateUpdated            10000 non-null object
```

```
address                 10000 non-null object
categories              10000 non-null object
primaryCategories       10000 non-null object
city                    10000 non-null object
country                 10000 non-null object
keys                    10000 non-null object
latitude                10000 non-null float64
longitude               10000 non-null float64
menuPageURL             1679 non-null object
menus.amountMax         10000 non-null float64
menus.amountMin         10000 non-null float64
menus.currency          10000 non-null object
menus.dateSeen          10000 non-null object
menus.description       3718 non-null object
menus.name              10000 non-null object
name                    10000 non-null object
postalCode              9996 non-null object
priceRangeCurrency      10000 non-null object
priceRangeMin           10000 non-null int64
priceRangeMax           10000 non-null int64
province                10000 non-null object
dtypes: float64(4), int64(2), object(18)
memory usage: 1.8+ MB
```

[5]:
```
data_2017_18.shape
```

[5]:
```
(10000, 24)
```

1 checking duplicate ids

[6]:
```
dup_data_2017_18 = data_2017_18.drop_duplicates('id')
```

[7]:
```
data_2017_18.loc[data_2017_18['id']=='AVwc7s1wIN2L1WUfqehD']
```

[7]:
```
                      id             dateAdded           dateUpdated  \
14  AVwc7s1wIN2L1WUfqehD  2015-10-21T17:51:11Z  2019-05-01T12:42:05Z
15  AVwc7s1wIN2L1WUfqehD  2015-10-21T17:51:11Z  2019-05-01T12:42:05Z
16  AVwc7s1wIN2L1WUfqehD  2015-10-21T17:51:11Z  2019-05-01T12:42:05Z

              address                       categories  \
14  146 N Glendora Ave  Pizza,Restaurant,Pizza Place
15  146 N Glendora Ave  Pizza,Restaurant,Pizza Place
16  146 N Glendora Ave  Pizza,Restaurant,Pizza Place

               primaryCategories      city country  \
14  Accommodation & Food Services  Glendora      US
15  Accommodation & Food Services  Glendora      US
16  Accommodation & Food Services  Glendora      US
```

```
                                      keys   latitude  ...  \
14  us/ca/glendora/146nglendoraave/-1511428239  34.137502  ...
15  us/ca/glendora/146nglendoraave/-1511428239  34.137502  ...
16  us/ca/glendora/146nglendoraave/-1511428239  34.137502  ...

   menus.currency                                    menus.dateSeen  \
14            USD  2018-02-18T15:21:05.726Z,2018-02-27T05:14:30.5...
15            USD                          2018-05-11T22:26:10.666Z
16            USD                          2018-05-11T22:26:10.666Z

                              menus.description         menus.name  \
14                                          NaN  Three Cheese Pizza
15   Topped with mozzarellaampcomma feta and ricotta  Three Cheese Pizza
16  Includes 1 toppingampcomma additional toppings...     Pizza Sandwich

           name postalCode priceRangeCurrency priceRangeMin priceRangeMax  \
14  Domenicos Jr      91741                USD             0            25
15  Domenicos Jr      91741                USD             0            25
16  Domenicos Jr      91741                USD             0            25

   province
14       CA
15       CA
16       CA

[3 rows x 24 columns]
```

1.1 here the data contains the duplicate ids but every id can be seen as a order and if you order more than 1 item from menu, then this id will be present that many times.

2 checking missing values in dataset

[8]:
```
print("Number of absent data : \n{}".format(data_2017_18.isnull().sum()))
```

```
Number of absent data :
id                        0
dateAdded                 0
dateUpdated               0
address                   0
categories                0
primaryCategories         0
city                      0
country                   0
keys                      0
```

```
latitude                 0
longitude                0
menuPageURL           8321
menus.amountMax          0
menus.amountMin          0
menus.currency           0
menus.dateSeen           0
menus.description     6282
menus.name               0
name                     0
postalCode               4
priceRangeCurrency       0
priceRangeMin            0
priceRangeMax            0
province                 0
dtype: int64
```

[9]:
```
data_2017_18 = data_2017_18.drop(['menuPageURL'],axis=1)
```

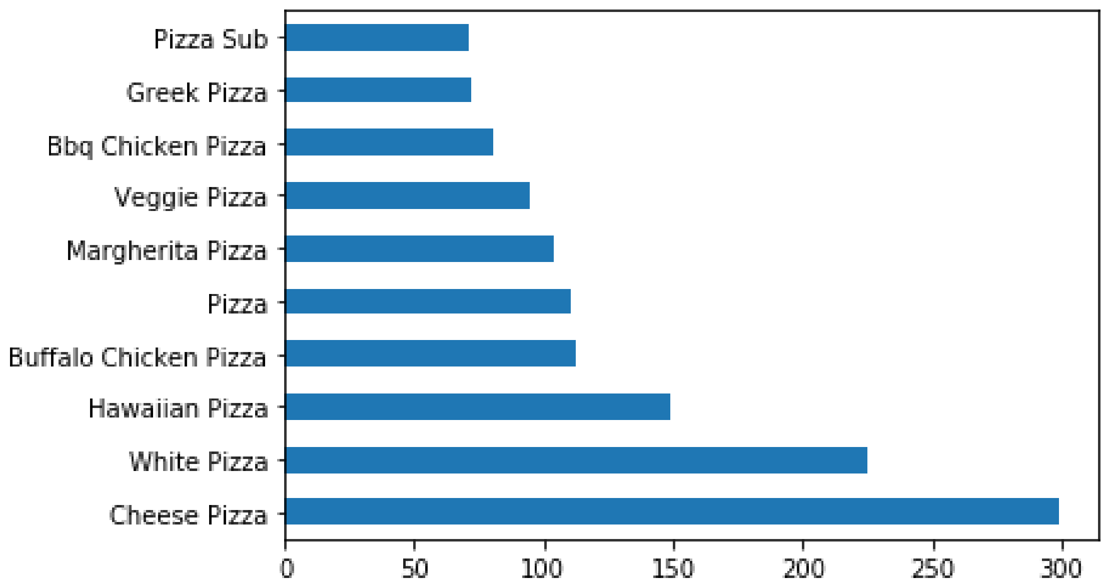
2.1 Which are the top 10 pizzas ?

[10]:
```
pizza_menu = data_2017_18['menus.name'].value_counts()
print(pizza_menu[:15])
```

```
Cheese Pizza              299
White Pizza               225
Hawaiian Pizza            149
Buffalo Chicken Pizza     112
Pizza                     111
Margherita Pizza          104
Veggie Pizza               95
Bbq Chicken Pizza          81
Greek Pizza                72
Pizza Sub                  71
Pizza Burger               70
Taco Pizza                 68
Sicilian Pizza             66
Pizza Steak                55
Pizza Bread                54
Name: menus.name, dtype: int64
```

[11]:
```
pizza_menu[:10].plot(kind='barh')
```

[11]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f3a1d228358>
```



[12]:
```
diffPizza = data_2017_18['menus.name'].value_counts()
print("Different pizzas : {}".format(diffPizza.count()))
```

```
Different pizzas : 4749
```

2.2 Which are the top 10 cities with the most pizza restaurant ?

[13]:
```
pizza_city = data_2017_18['city'].value_counts()
```

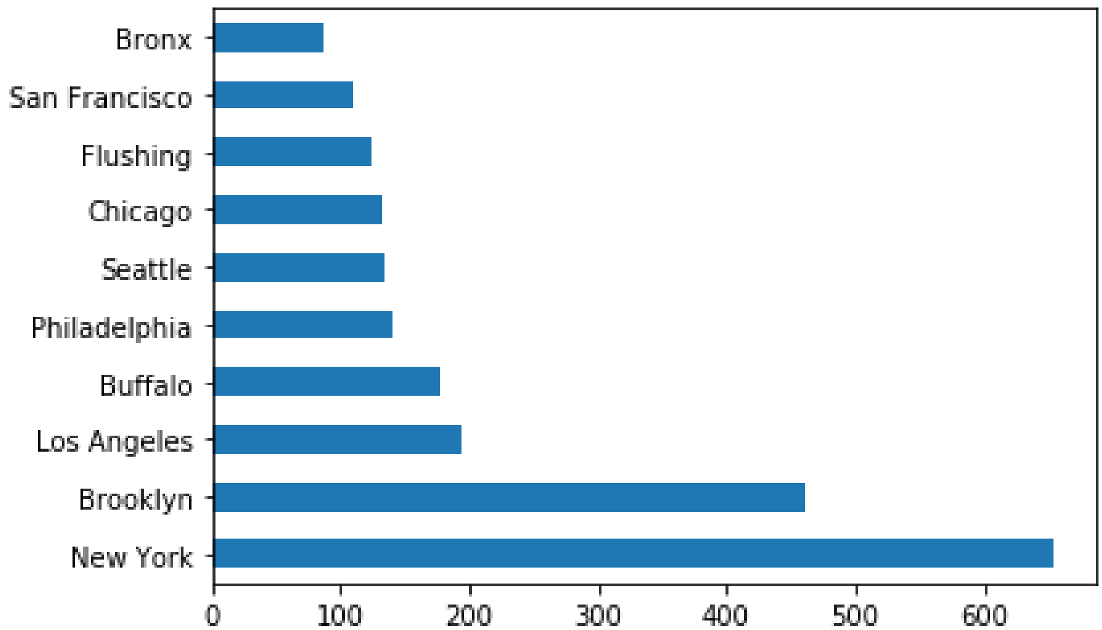
[14]:
```
city_top_4 = pizza_city[:4].keys()
```

[15]:
```
print(pizza_city[:15])
```

```
New York         655
Brooklyn         460
Los Angeles      193
Buffalo          178
Philadelphia     140
Seattle          135
Chicago          133
Flushing         124
San Francisco    110
Bronx             88
Springfield       85
Charlotte         84
Pittsburgh        74
Mesa              73
Austin            66
Name: city, dtype: int64
```

[16]:
```
pizza_city[:10].plot(kind='barh')
```

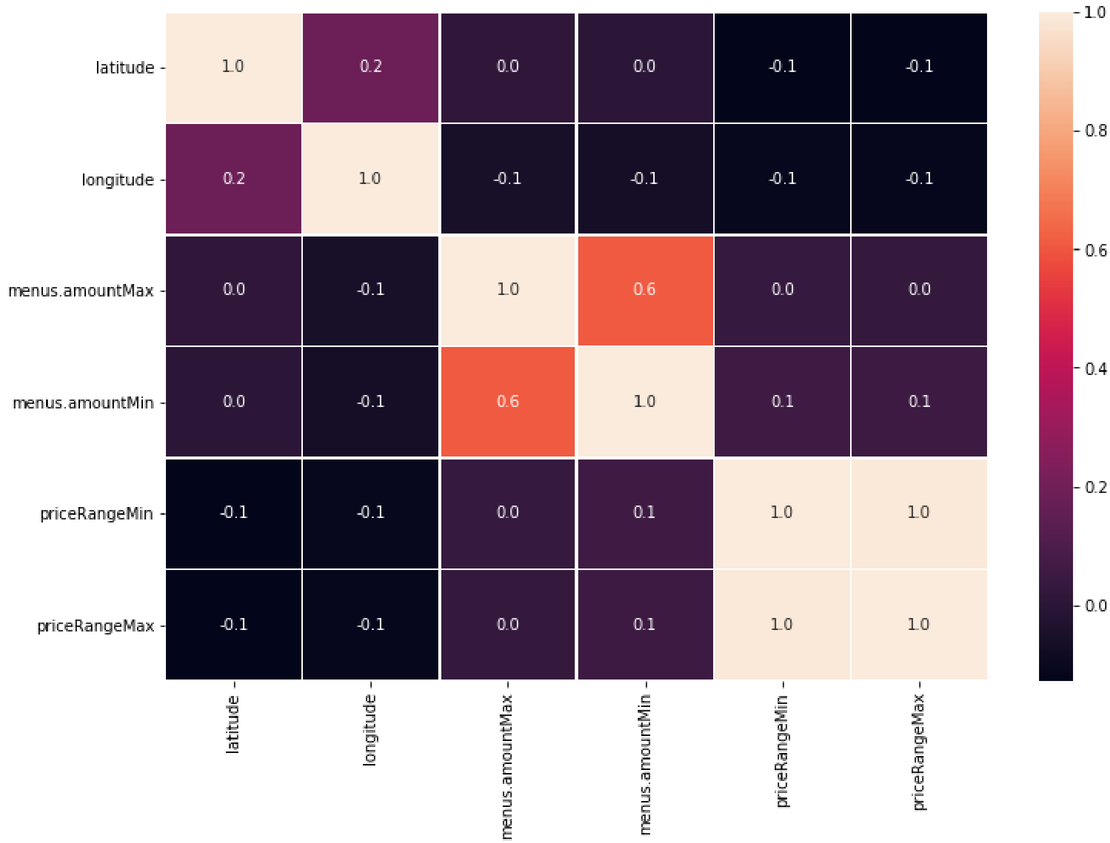
[16]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3a176c7a90>



2.3 heatmap for the data

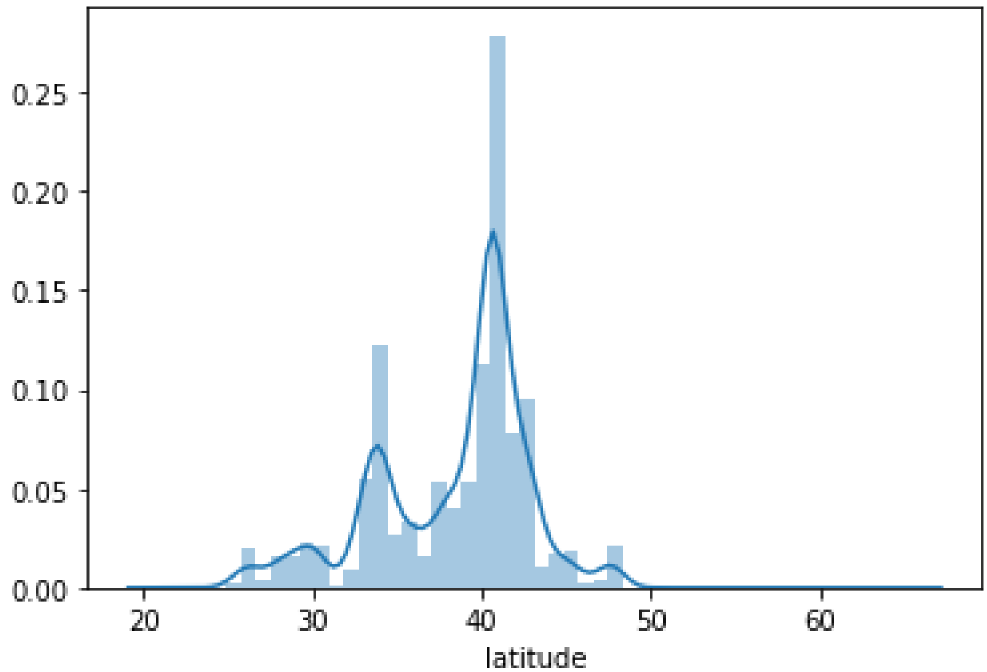
[17]:
```
f,ax = plt.subplots(figsize=(12, 8))
sns.heatmap(data_2017_18.corr(), annot=True, linewidths=.5, fmt= '.1f',ax=ax)
```

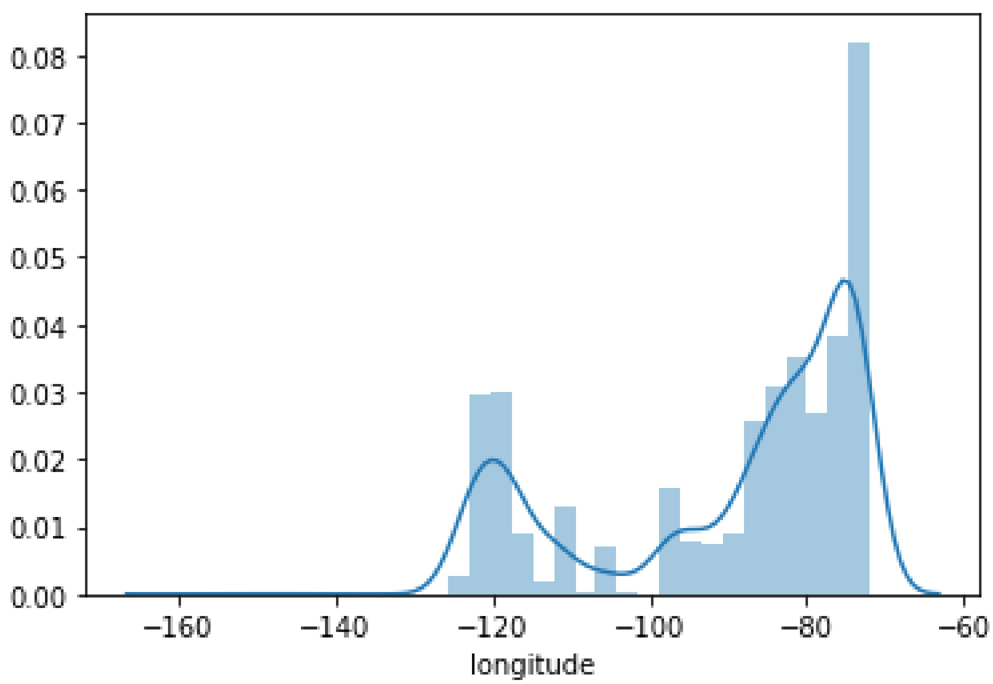
[17]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3a176401d0>

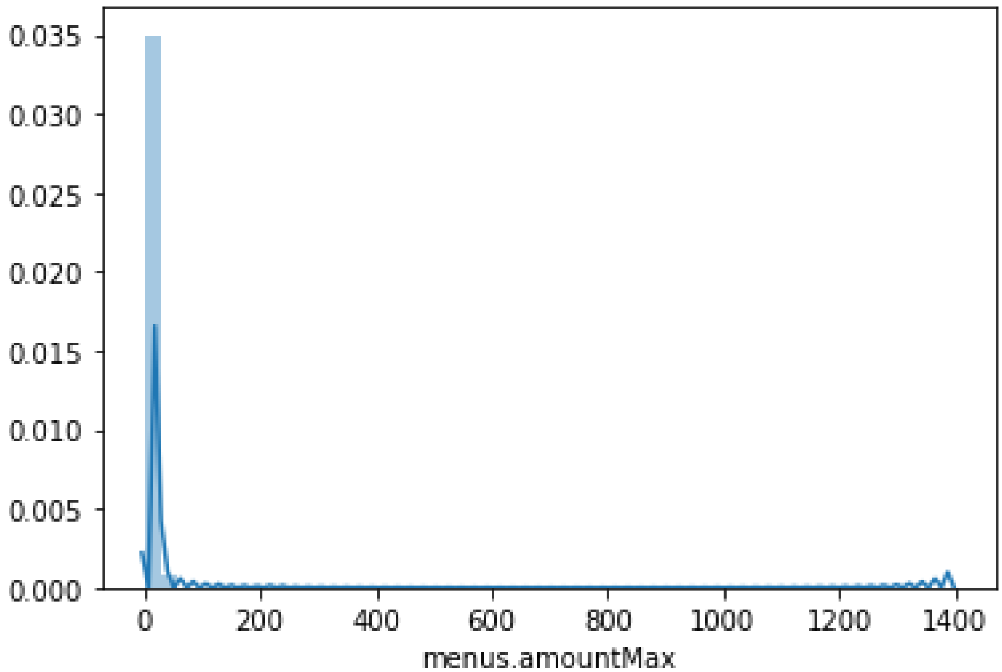


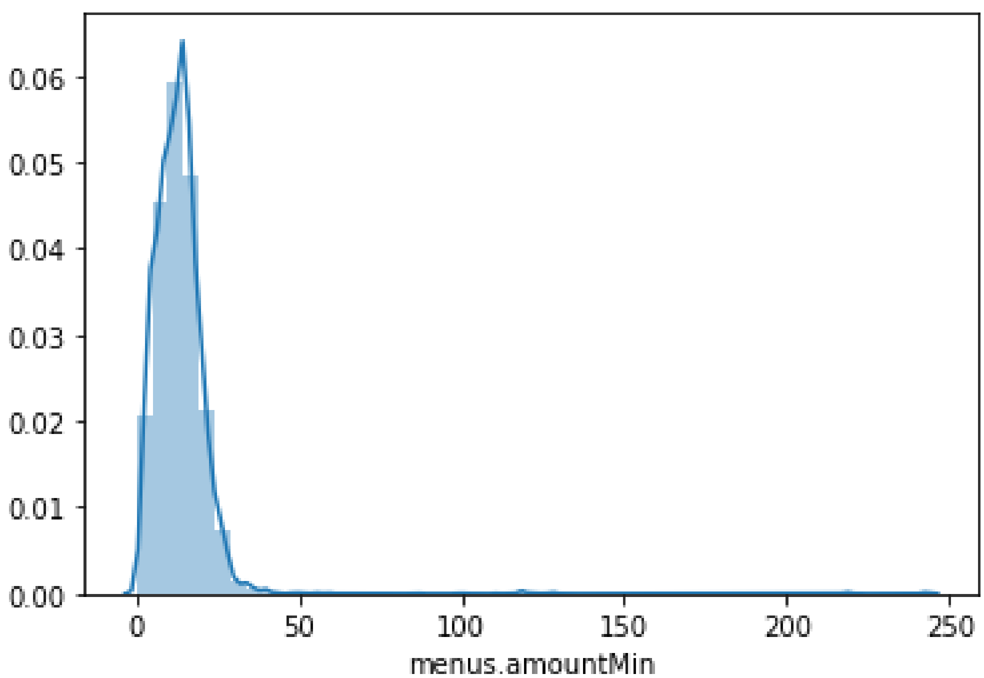
3 Distribution plots for the data

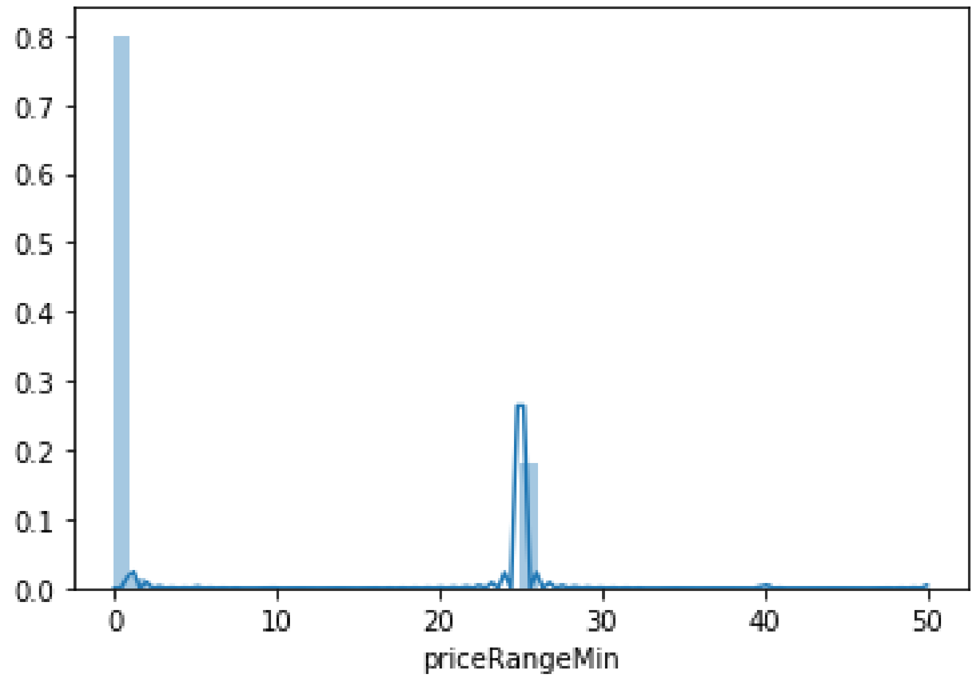
[18]:
```
for i in data_2017_18.keys():
    try:
        sns.distplot(data_2017_18[i])
        plt.show()
    except:
        pass
```

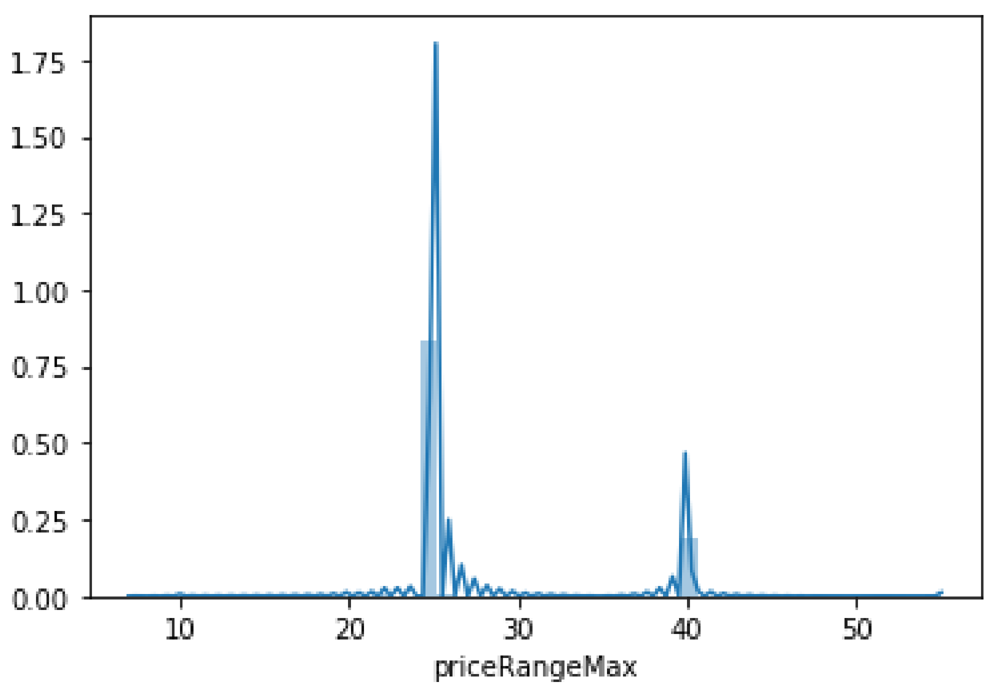

0.25
0.20
0.15
0.10
0.05
0.00
20
30
40
50
60
latitude

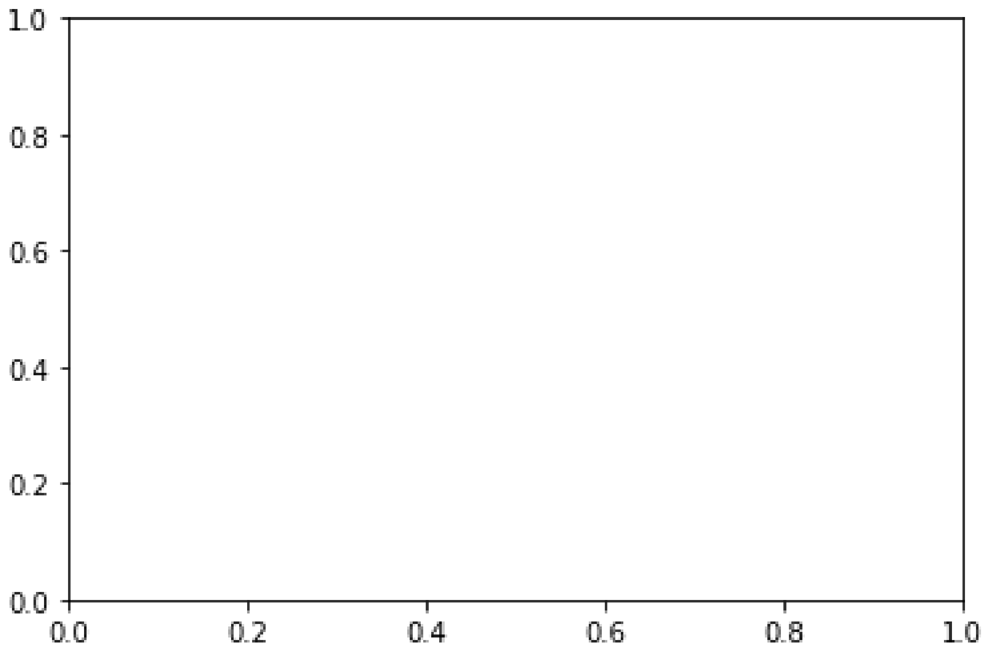

0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0.00
−160
−140
−120
−100
−80
−60
longitude


0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
0
200
400
600
800
1000
1200
1400
menus.amountMax


0.06
0.05
0.04
0.03
0.02
0.01
0.00
0
50
100
150
200
250
menus.amountMin


0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
0
10
20
30
40
50
priceRangeMin

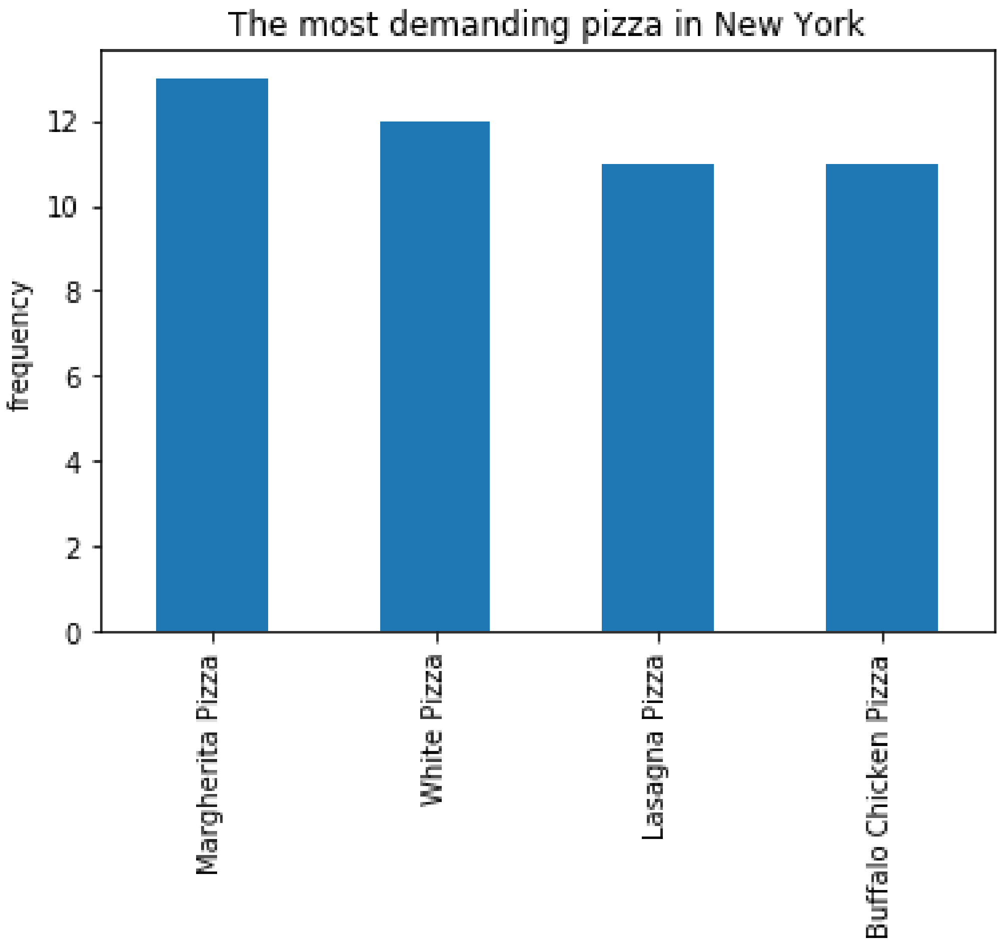

1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
10
20
30
40
50
priceRangeMax

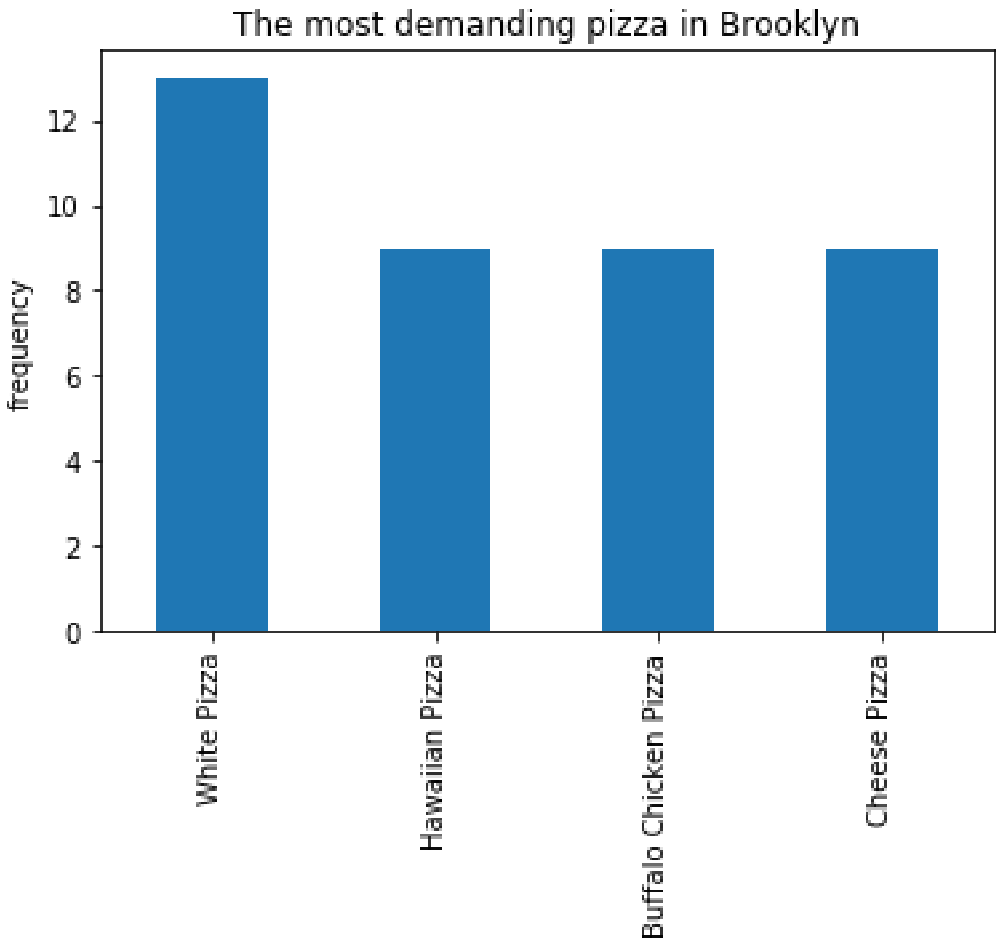


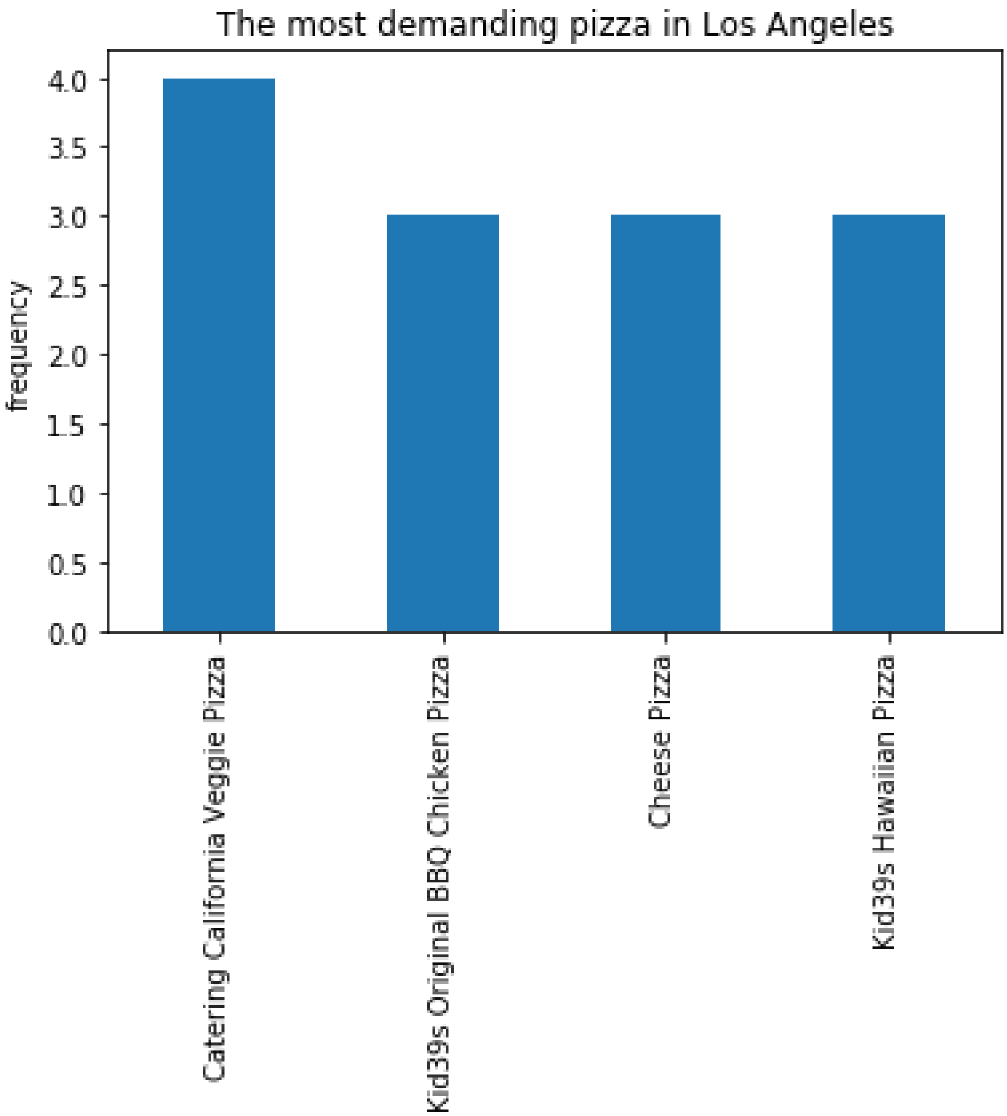
3.1 Which are the most demanding pizza in top 4 cities ?

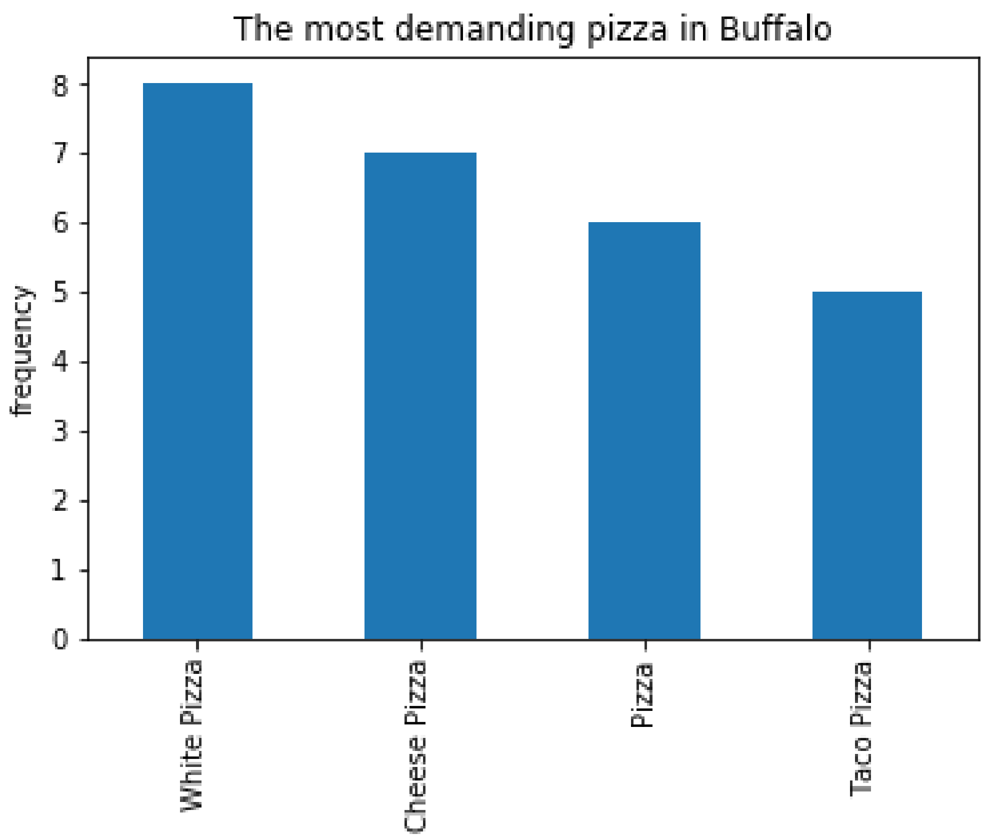
[19]:
```
def citywise_pizza_subplot(pizza,i,j):
    ax_arr[i,j].bar(pizza[:4],1)
    ax_arr[i,j].plot()
    ax_arr[i,j].set_title(' plot',fontsize=20)
    ax_arr[i,j].set_ylabel("hee",fontsize=20)
    ax_arr[i,j].set_xlabel('freq',fontsize=15)
    ax_arr[i,j].legend(loc = 'lower right', prop={'size': 16})
```

[20]:
```
for city in city_top_4:
    df_city_top_4 = data_2017_18.loc[data_2017_18['city']==city]
    city_top_pizza = df_city_top_4['menus.name'].value_counts()
    city_top_pizza[:4].plot.bar()
    plt.title("The most demanding pizza in "+str(city))
    plt.ylabel("frequency")
    plt.show()
```


The most demanding pizza in New York
frequency
12
10
8
6
4
2
0
Margherita Pizza
White Pizza
Lasagna Pizza
Buffalo Chicken Pizza


The most demanding pizza in Brooklyn
frequency
0
2
4
6
8
10
12
White Pizza
Hawaiian Pizza
Buffalo Chicken Pizza
Cheese Pizza


The most demanding pizza in Los Angeles
frequency
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Catering California Veggie Pizza
Kid39s Original BBQ Chicken Pizza
Cheese Pizza
Kid39s Hawaiian Pizza



3.2 timeSeries on maxamount and minamount

[21]:
```
date_objects_added = [datetime.strptime(date,'%Y-%m-%dT%H:%M:%SZ').date() for␣
 ↪date in data_2017_18["dateAdded"]]
```

[22]:
```
timeSeries_max_amount= px.
 ↪line(data_2017_18,date_objects_added,data_2017_18['menus.amountMax'])
timeSeries_min_amount= px.
 ↪line(data_2017_18,date_objects_added,data_2017_18['menus.amountMin'])
```

[23]:
```
timeSeries_max_amount.show()
timeSeries_min_amount.show()
```

3.3 Which are the cheapest and the most expensive pizza and its pizza restaurant?

[24]:
```
most_expensive = data_2017_18[['name','menus.name','menus.
 ↪amountMax']][data_2017_18['menus.amountMax']==data_2017_18['menus.
 ↪amountMax'].max()]
print(most_expensive)
```

```
      name  menus.name  menus.amountMax
9337  Rocco's  Taco Pizza           1395.0
```

3.4 second most expensive pizzas

[25]:
```
data_second_exp = data_2017_18[data_2017_18['menus.amountMax'] != 1395.0]
```

[26]:
```
second_most_expensive = data_second_exp[['name','menus.name','menus.
 ↪amountMax']][data_second_exp['menus.amountMax']==data_second_exp['menus.
 ↪amountMax'].max()]
print(second_most_expensive)
```

```
                          name                                 menus.name  \
3270  California Pizza Kitchen    Vegetarian Large Pizza Catering Package
3285  California Pizza Kitchen   Adventurous Large Pizza Catering Package
3287  California Pizza Kitchen  CPK Classics Large Pizza Catering Package
4774  California Pizza Kitchen    Vegetarian Large Pizza Catering Package
4775  California Pizza Kitchen   Adventurous Large Pizza Catering Package

      menus.amountMax
3270            243.0
3285            243.0
3287            243.0
4774            243.0
4775            243.0
```

We can infer that most expensive pizza i.e "Taco Pizza" is offered by "Rocco's" for 1395.0.

[27]:
```
data_2017_18[['name','menus.name','menus.amountMin']][data_2017_18['menus.
 ↪amountMin']==data_2017_18['menus.amountMin'][data_2017_18['menus.amountMin'].
 ↪gt(0)].min()]
```

[27]:
```
                                   name              menus.name  \
804                  Fratellis Pizzeria       Pizza By the Slice
2777                          DiAngelos             6" Pizza Sub
2778                          DiAngelos        French Bread Pizza
7827  Stacia's Gourmet Pizza and Pasta  Garlic Herb Pizza Crust

      menus.amountMin
804              0.25
2777             0.25
2778             0.25
7827             0.25
```

we can infer that cheapest pizza are offered by 3 restaurant, namely Fratellis Pizzeria,DiAngelos and Stacia's Gourmet Pizza and Pasta

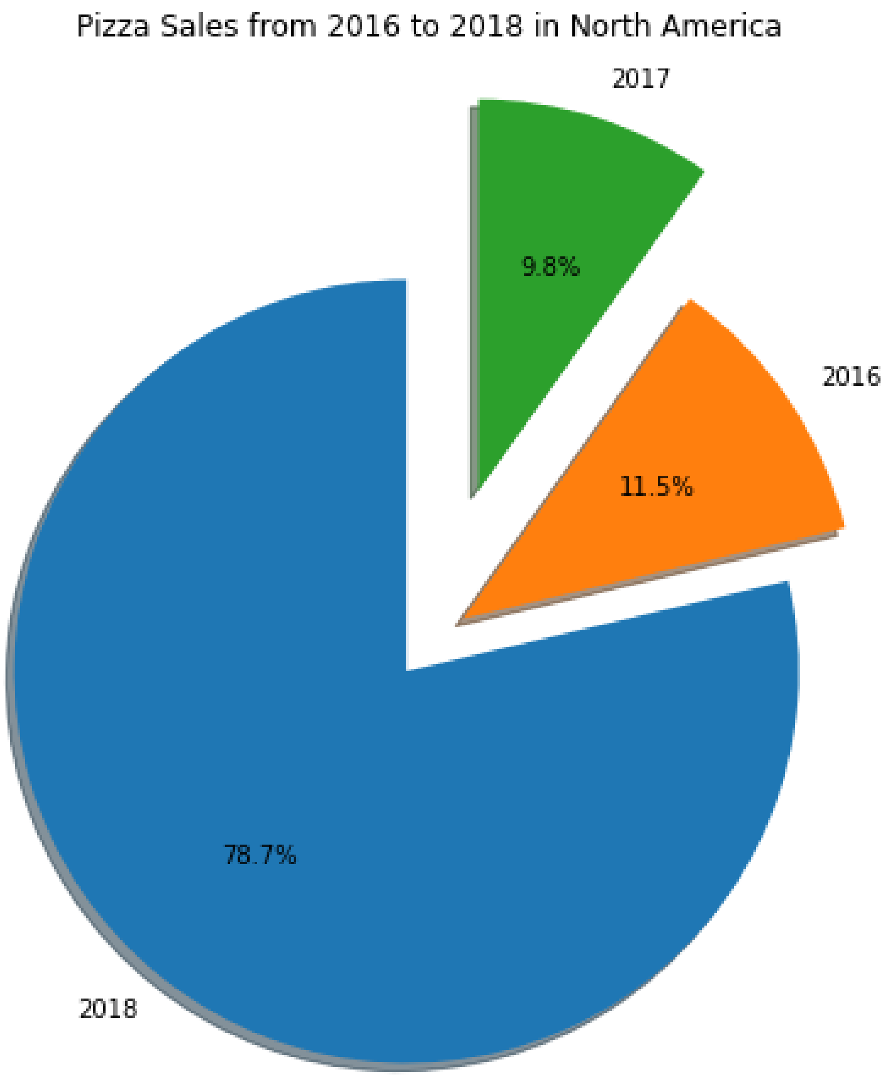
4 sales from 2016 to 2018

[28]:
```
bypass=data_2017_18["menus.name"]==data_2017_18["menus.name"].value_counts().
 ↪nlargest(1).index[0]
data=data_2017_18[bypass]
data['menus.dateSeen']= data['menus.dateSeen'].str[0:10]
data['menus.dateSeen']= pd.to_datetime(data['menus.dateSeen'])
years= pd.DatetimeIndex(data['menus.dateSeen']).year.value_counts().index
data_annual=pd.DatetimeIndex(data['menus.dateSeen']).year.value_counts().values
```

[29]:
```
fig, ax = plt.subplots(figsize=(8, 8))

data = data_annual[:3]
ingredients = years[:3]

explode = (0.1, 0.1, 0.4)
ax.pie(data,
       explode=explode,
       labels=ingredients,
       autopct='%1.1f%%',
       shadow=True,
       startangle=90)
ax.axis('equal')
ax.set_title("Pizza Sales from 2016 to 2018 in North America")
plt.show()
```



[30]:
```
import plotly.express as px
import pandas as pd
df1 = pd.DataFrame(dict(years=ingredients, sales=[233, 40,  25]))
df2 = pd.DataFrame(dict(market=data))
fig = px.bar(df1, x=df1.years, y=df2.market, color=df1.sales)
fig.show()
```

5 Apriori Algorithm for Association Rule Mining

5.0.1 The association rule algorithm used to find out if customer orders one type of pizza, then he will order which other pizza with it, using the support and confidence level as thresholds.

[31]:
```python
from apyori import apriori
```

[32]:
```python
apriori_data =[]
unique_ids = list(set(data_2017_18['id']))
```

[33]:
```python
for ids in unique_ids:
    ls=[]
    tmpdf = data_2017_18.loc[data_2017_18['id']==ids]
    ls=list(set(tmpdf['menus.name']))
    apriori_data.append(ls)
```

support = 7/2285 (assuming ordering 7 pizza a week)

[34]:
```python
association_rules = apriori(apriori_data, min_support=0.0030, min_confidence=0.
↪2, min_lift=3, min_length=2)
association_results = list(association_rules)
```

[35]:
```python
print(len(association_results))
```

```
56
```

[36]:
```python
print(association_results[6])
```

```
RelationRecord(items=frozenset({'BBQ Chicken Pizza', 'Buffalo Chicken Pizza'}),
support=0.004814004376367615,
ordered_statistics=[OrderedStatistic(items_base=frozenset({'BBQ Chicken
Pizza'}), items_add=frozenset({'Buffalo Chicken Pizza'}),
confidence=0.2391304347826087, lift=5.57564330079858)])
```

The confidence level for the rule is 0.239 which shows that out of all the orders that contain BBQ Chicken Pizza, 23.9% of the orders also contain Buffalo Chicken Pizza.

The lift of 5.57 tells us that BBQ Chicken Pizza is 5.57 times more likely to be ordered by the customers who order Buffalo Chicken Pizza.

6 Printing all association results

[37]:
```python
for item in association_results:
    pair = item[0]
    items = [x for x in pair]
    if 'Add' in str(items[0]) or 'Add' in str(items[1]):
        pass
    else:
```

```python
        print("Rule: " + items[0] + " -> " + items[1])
        print("Support: " + str(item[1]))
        print("Confidence: " + str(item[2][0][2]))
        print("Lift: " + str(item[2][0][3]))
        print("=====================================")
```

```
Rule: Medium Pizza Offers -> Any Large Pizza
Support: 0.00787746170678337
Confidence: 0.5
Lift: 39.39655172413793
=====================================
Rule: BBQ Chicken Pizza -> Buffalo Chicken Pizza
Support: 0.004814004376367615
Confidence: 0.2391304347826087
Lift: 5.57564330079858
=====================================
Rule: BBQ Chicken Pizza -> Hawaiian Pizza
Support: 0.004814004376367615
Confidence: 0.2391304347826087
Lift: 4.203177257525083
=====================================
Rule: White Pizza -> BBQ Chicken Pizza
Support: 0.005689277899343545
Confidence: 0.2826086956521739
Lift: 3.4532666821669373
=====================================
Rule: Lasagna Pizza -> Baked Ziti Pizza
Support: 0.00350109409190372
Confidence: 0.2962962962962963
Lift: 15.387205387205386
=====================================
Rule: Baked Ziti Pizza -> Salad Pizza
Support: 0.003063457330415755
Confidence: 0.25925925925925924
Lift: 20.427841634738186
=====================================
Rule: White Pizza -> Baked Ziti Pizza
Support: 0.004814004376367615
Confidence: 0.40740740740740744
Lift: 4.978213507625273
=====================================
Rule: Hawaiian Pizza -> Bbq Chicken Pizza
Support: 0.007439824945295405
Confidence: 0.24285714285714285
Lift: 4.268681318681319
=====================================
Rule: Big Murphy39s Stuffed Pizza Baking Required -> ChicagoStyle Stuffed Pizza
```

```
Baking Required
Support: 0.003063457330415755
Confidence: 0.6363636363636364
Lift: 161.56565656565655
=====================================
Rule: Hawaiian Pizza Baking Required -> Big Murphy39s Stuffed Pizza Baking
Required
Support: 0.00350109409190372
Confidence: 0.7272727272727273
Lift: 118.7012987012987
=====================================
Rule: Buffalo Chicken Pizza -> Blt Pizza
Support: 0.003063457330415755
Confidence: 0.5
Lift: 11.658163265306122
=====================================
Rule: Chicken Parmigiana Pizza -> Buffalo Chicken Pizza
Support: 0.003938730853391685
Confidence: 0.4285714285714286
Lift: 9.992711370262391
=====================================
Rule: Hawaiian Pizza -> Buffalo Chicken Pizza
Support: 0.01050328227571116
Confidence: 0.24489795918367346
Lift: 4.3045525902668755
=====================================
Rule: Lasagna Pizza -> Buffalo Chicken Pizza
Support: 0.004814004376367615
Confidence: 0.25
Lift: 5.829081632653061
=====================================
Rule: White Pizza -> Buffalo Chicken Pizza
Support: 0.011378555798687089
Confidence: 0.26530612244897955
Lift: 3.241842191422023
=====================================
Rule: Hawaiian Pizza Baking Required -> ChicagoStyle Stuffed Pizza Baking
Required
Support: 0.003063457330415755
Confidence: 0.7777777777777778
Lift: 126.94444444444444
=====================================
Rule: Chicken Parmigiana Pizza -> Hawaiian Pizza
Support: 0.00350109409190372
Confidence: 0.380952380952381
Lift: 6.695970695970696
=====================================
Rule: Chicken Parmigiana Pizza -> Margherita Pizza
```

```
Support: 0.003063457330415755
Confidence: 0.33333333333333337
Lift: 8.36996336996337
======================================
Rule: Chicken Parmigiana Pizza -> White Pizza
Support: 0.00350109409190372
Confidence: 0.380952380952381
Lift: 4.654952890247008
======================================
Rule: White Pizza -> Chicken Pizza
Support: 0.00525164113785558
Confidence: 0.5
Lift: 6.109625668449198
======================================
Rule: Hawaiian Pizza Baking Required -> Cowboy Pizza Baking Required
Support: 0.00350109409190372
Confidence: 0.7272727272727273
Lift: 118.7012987012987
======================================
Rule: Pepperoni Pizza Baking Required -> Cowboy Pizza Baking Required
Support: 0.003063457330415755
Confidence: 0.6363636363636364
Lift: 121.17424242424242
======================================
Rule: Hawaiian Pizza Baking Required -> Create Your Own Family Size Pizza Baking
Required
Support: 0.00350109409190372
Confidence: 1.0
Lift: 163.21428571428572
======================================
Rule: Deluxe Pizza -> Hawaiian Pizza
Support: 0.003063457330415755
Confidence: 0.3888888888888889
Lift: 6.835470085470085
======================================
Rule: Deluxe Pizza -> Veggie Pizza
Support: 0.003063457330415755
Confidence: 0.3888888888888889
Lift: 11.10763888888889
======================================
Rule: Greek Pizza -> Hawaiian Pizza
Support: 0.00612691466083151
Confidence: 0.22580645161290325
Lift: 3.968982630272953
======================================
Rule: Greek Pizza -> Mexican Pizza
Support: 0.00350109409190372
Confidence: 0.33333333333333337
```

```
Lift: 12.284946236559142
=====================================
Rule: Lasagna Pizza -> Hawaiian Pizza
Support: 0.005689277899343545
Confidence: 0.2954545454545454
Lift: 5.1931818181818175
=====================================
Rule: Mexican Pizza -> Hawaiian Pizza
Support: 0.003063457330415755
Confidence: 0.2916666666666667
Lift: 5.126602564102564
=====================================
Rule: Pepperoni Pizza -> Hawaiian Pizza
Support: 0.00437636761487965
Confidence: 0.2631578947368421
Lift: 4.625506072874494
=====================================
Rule: Salad Pizza -> Hawaiian Pizza
Support: 0.003938730853391685
Confidence: 0.3103448275862069
Lift: 5.454907161803714
=====================================
Rule: Veggie Pizza -> Hawaiian Pizza
Support: 0.010065645514223195
Confidence: 0.28750000000000003
Lift: 5.053365384615385
=====================================
Rule: Pepperoni Pizza Baking Required -> Hawaiian Pizza Baking Required
Support: 0.00350109409190372
Confidence: 0.5714285714285714
Lift: 108.80952380952381
=====================================
Rule: HotNReady Large Pizza -> Supreme Pizza
Support: 0.00437636761487965
Confidence: 0.5555555555555555
Lift: 34.309309309309306
=====================================
Rule: Lasagna Pizza -> Salad Pizza
Support: 0.00525164113785558
Confidence: 0.2727272727272727
Lift: 21.489028213166144
=====================================
Rule: White Pizza -> Lasagna Pizza
Support: 0.00612691466083151
Confidence: 0.3181818181818182
Lift: 3.8879436071949436
=====================================
Rule: Veggie Pizza -> Meat Lovers Pizza
```

```
Support: 0.003063457330415755
Confidence: 0.23333333333333334
Lift: 6.664583333333334
=====================================
Rule: White Pizza -> Meat Lovers Pizza
Support: 0.00350109409190372
Confidence: 0.26666666666666666
Lift: 3.2584670231729054
=====================================
Rule: Medium Gourmet Vegetarian Gluten Free Crust Pizza Baking Required ->
Medium Papa39s Favorite Gluten Free Crust Pizza Baking Required
Support: 0.003063457330415755
Confidence: 0.6363636363636364
Lift: 207.72727272727272
=====================================
Rule: Pepperoni Pizza Baking Required -> Medium Gourmet Vegetarian Gluten Free
Crust Pizza Baking Required
Support: 0.00437636761487965
Confidence: 0.9090909090909091
Lift: 173.10606060606057
=====================================
Rule: Pizza Burger -> Pizza Fries
Support: 0.005689277899343545
Confidence: 0.30952380952380953
Lift: 10.880952380952381
=====================================
Rule: Pizza Burger -> Pizza Steak
Support: 0.00700218818380744
Confidence: 0.24615384615384617
Lift: 10.81656804733728
=====================================
Rule: Pizza By the Slice -> Pizza By The Slice
Support: 0.004814004376367615
Confidence: 0.42307692307692313
Lift: 31.184863523573206
=====================================
Rule: Pizza Fries -> Pizza Steak
Support: 0.00700218818380744
Confidence: 0.380952380952381
Lift: 16.73992673992674
=====================================
Rule: White Pizza -> Salad Pizza
Support: 0.00437636761487965
Confidence: 0.3448275862068965
Lift: 4.2135349437580665
=====================================
Rule: White Pizza -> Spinach Pizza
Support: 0.00350109409190372
```

```
Confidence: 0.3076923076923077
Lift: 3.7597696421225835
=====================================
Rule: Vegetable Pizza -> White Pizza
Support: 0.00437636761487965
Confidence: 0.37037037037037035
Lift: 4.5256486432957015
=====================================
Rule: Medium Pizza Offers -> Any Large Pizza
Support: 0.00437636761487965
Confidence: 0.43478260869565216
Lift: 55.19323671497584
=====================================
Rule: White Pizza -> Hawaiian Pizza
Support: 0.003063457330415755
Confidence: 0.2916666666666667
Lift: 3.5639483065953654
=====================================
Rule: White Pizza -> Veggie Pizza
Support: 0.003063457330415755
Confidence: 0.30434782608695654
Lift: 3.718902580795164
=====================================
```