# Using Kmeans to find safest restaurants to eat

## 0.1 K-Means for Chicago Food Inspections

In [4]:
```
%matplotlib inline

import numpy as np

import matplotlib.pyplot as plt

from mpl_toolkits.mplot3d import Axes3D


import pandas as pd

from sklearn import preprocessing
import sklearn.preprocessing

from sklearn.preprocessing import LabelEncoder from
sklearn.preprocessing import StandardScaler from
sklearn.metrics.pairwise import euclidean_distances

from sklearn.cluster import KMeans
```

In [5]:
```
# Loading drivers dataset
dataset_df = pd.read_csv("c:\\datasets\Chicago_Food_Inspections.csv")
```

In [6]:
```
dataset_df.head(2)
```

Out[6]:
```
Inspection ID DBA Name AKA Name License # \
0 2072076 MODERN WING/TERZO PIANO MODERN WING/TERZO PIANO 1954252.0 1
2072061 PATEL ' S CAFE PATEL ' S CAFE 2036995.0

Facility Type Risk Address City State Zip \ 0 Restaurant Risk 1 (High) 159 E MONROE DR CHICAGO
IL 60604.0 1 Restaurant Risk 1 (High) 2600 W DEVON AVE CHICAGO IL 60659.0

Inspection Date Inspection Type Results \ 0 8/8/2017 Canvass Re-Inspection
Pass 1 8/8/2017 Complaint Re-Inspection Pass
```

1

Violations Latitude Longitude \ 0 18. NO EVIDENCE OF RODENT OR INSECT OUTER OPEN... 41.880740 -87.62270 1 13. NO EVIDENCE OF RODENT OR INSECT INFESTATIO... 41.997755 -87.69483

Location 0 (41.88073951830644, -87.62270010046835) 1 (41.99775478924851, -87.69482972221137)

In [7]: dataset_df.tail(2)

Out[7]: Inspection ID DBA Name AKA Name License # \
26812 1609261 TORTORICE'S PIZZA TORTORICE'S PIZZA 2442943.0 26813 1609260 VANILLE PATTISSERIE VANILLE 2442830.0

Facility Type Risk Address City \ 26812 Restaurant Risk 1 (High) 2101-2103 W IRVIING PARK RD CHICAGO 26813 Restaurant Risk 2 (Medium) 3243 N BROADWAY CHICAGO

State Zip Inspection Date Inspection Type Results Violations \ 26812 IL 60618.0 1/4/2016 License Not Ready NaN 26813 IL 60657.0 1/4/2016 License Not Ready NaN

Latitude Longitude Location 26812 41.954010 -87.681241 (41.95401015404328, -87.68124094099036) 26813 41.941294 -87.644292 (41.94129418083914, -87.64429200618663)

In [8]: dataset_df.dtypes

Out[8]: Inspection ID int64 DBA Name object AKA Name object License # float64 Facility Type object Risk object Address object City object State object Zip float64 Inspection Date object Inspection Type object Results object Violations object Latitude float64 Longitude float64 Location object dtype: object

2

## 0.2 Clean the dirty/messy data

You need to write your python code such that: 1. rows/records/tuples/transactions in the data frame that have missing values for fields/columns will be removed 2. rows/records/tuples/transactions in the data frame that have invalid/abnormal values for fields/columns will be removed 3. Duplicate/redundant values removed and/or replaced Ex- ample 1: CHILDERN'S SERVICE FACILITY CHILDRENS SERVICES FACILITY Example 2: 1023 CHILDERN'S SERVICES FACILITY 1023-CHILDREN'S SERVICES FACILITY

Examples of invalid/dirty/messy data: 1. NaN values in the dataframe (Blank/Empty cells in the CSV file)

2. Every inspection must have an Inspection ID

3. Every inspection must have an Address

In [9]:
```
# The easiest way (though is not the perfect/desired one) to clean your data is to drop the NaN

dataset_df = dataset_df.dropna(axis=0, how='any')
```

In [10]:
```
dataset_df['Zip'] = dataset_df['Zip'].astype(int)
```

In [11]:
```
dataset_df.head(5)
```

Out[11]: Inspection ID DBA Name AKA Name License # \
0 2072076 MODERN WING/TERZO PIANO MODERN WING/TERZO PIANO 1954252.0 1 2072061 PATEL'S CAFE PATEL'S CAFE 2036995.0 2 2072060 KRUNGTHEP THAI CUISINE KRUNGTHEP THAI CUISINE 2340786.0 3 2072037 LAKE SHORE SCHOOLS LAKE SHORE SCHOOLS 2245322.0 4 2072035 THE CATCADE, INC. THE CATCADE 2542576.0

Facility Type Risk Address \ 0 Restaurant Risk 1 (High) 159 E MONROE DR 1 Restaurant Risk 1 (High) 2600 W DEVON AVE 2 Restaurant Risk 1 (High) 3205 N HALSTED ST 3 Daycare Above and Under 2 Years Risk 1 (High) 5611-5621 N CLARK ST 4 Animal Shelter Cafe Permit Risk 3 (Low) 1235 W BELMONT AVE

City State Zip Inspection Date Inspection Type Results \ 0 CHICAGO IL 60604 8/8/2017 Canvass Re-Inspection Pass 1 CHICAGO IL 60659 8/8/2017 Complaint Re-Inspection Pass 2 CHICAGO IL 60657 8/8/2017 Complaint Pass 3 CHICAGO IL 60660 8/8/2017 License Re-Inspection Pass 4 CHICAGO IL 60657 8/8/2017 License Pass

Violations Latitude Longitude \ 0 18. NO EVIDENCE OF RODENT OR INSECT OUTER OPEN... 41.880740 -87.622700 1 13. NO EVIDENCE OF RODENT OR INSECT INFESTATIO... 41.997755 -87.694830 2 34. FLOORS: CONSTRUCTED PER CODE, CLEANED, GOO... 41.940146 -87.649124 3 18. NO EVIDENCE OF RODENT OR

INSECT OUTER OPEN... 41.983864 -87.668689

3
4 41. PREMISES MAINTAINED FREE OF LITTER, UNNECE... 41.939703 -87.660363

| Location | 0 |
|---|---|
| (41.88073951830644, -87.62270010046835) | 1 |
| (41.99775478924851, -87.69482972221137) | 2 |
| (41.940146235765575, -87.64912448509257) | 3 |
| (41.98386367207857, -87.66868894217718) | 4 |
| (41.939702878083544, -87.6603632122827) | |

In [12]:
```
from sklearn.preprocessing import LabelEncoder

list_of_feaatures_to_encode = ['Risk', 'Results'] le =
LabelEncoder()

for i in list_of_feaatures_to_encode:
    enc = le.fit(np.unique(dataset_df[i].values))
    print(enc.classes_) dataset_df[i] =
    le.fit_transform(dataset_df[i])
```

['Risk 1 (High)' 'Risk 2 (Medium)' 'Risk 3 (Low)'] ['Fail'
'No Entry' 'Not Ready' 'Out of Business' 'Pass'
'Pass w/ Conditions']

In [13]:
```
### For the purposes of this example, we store feature data from our
### dataframe `df`, in the `f1`, f2, and `f3` arrays. We combine this into ### a feature matrix `X`
before entering it into the algorithm.

# f1 = dataset_df['Facility Type'].values f0 =
dataset_df['Risk'].values f1 =
dataset_df['Results'].values f2 =
dataset_df['Zip'].values

X=np.matrix(zip(f0,f1, f2)) kmeans =
KMeans(n_clusters=2).fit(X)
```

In [14]:
```
X[:5]
```

Out[14]: matrix([[ 0, 4, 60604], [ 0, 4, 60659], [ 0, 4, 60657], [ 0, 4, 60660], [ 2, 4, 60657]], dtype=int64)

In [15]: kmeans.labels_

Out[15]: array([0, 1, 1, ..., 0, 1, 0])

In [16]: kmeans = KMeans(2, random_state=0).fit_predict(X)



In [17]: kmeans.shape

Out[17]: (20207L,)

In [18]: kmeans

Out[18]: array([1, 0, 0, ..., 1, 0, 1])

In [19]: *# First plot the raw data with no clustering*

```
fig = plt.figure(figsize=(16, 12)) ax =
fig.add_subplot(111, projection='3d')



x_ax = np.array(X[:, 2]).flatten() y_ax =
np.array(X[:, 0]).flatten() z_ax =
np.array(X[:, 1]).flatten()


ax.scatter(x_ax, y_ax, z_ax, marker='o')


ax.set_xlabel('Zip')
ax.set_ylabel('Risk')
ax.set_zlabel('Results')



plt.show()
```

In [20]:
```
# Now plot the data in two clusters of K-Means
# No Scaling on the data yet

fig = plt.figure(figsize=(16, 12)) ax =
fig.add_subplot(111, projection='3d')

kmeans = KMeans(2, random_state=0).fit_predict(X)

x_ax = np.array(X[:, 2]).flatten() y_ax =
np.array(X[:, 0]).flatten() z_ax =
np.array(X[:, 1]).flatten()

ax.scatter(x_ax, y_ax, z_ax, c=kmeans, marker='^')
```

```
ax.set_xlabel('Zip')
ax.set_ylabel('Risk')
```



In [21]:
```
# No scaling on the data yet
# 4 clusters of K-Means

fig = plt.figure(figsize=(16, 12)) ax =
fig.add_subplot(111, projection='3d')
```

```
kmeans = KMeans(4, random_state=0).fit_predict(X)

x_ax = np.array(X[:, 2]).flatten() y_ax =
np.array(X[:, 0]).flatten() z_ax =
np.array(X[:, 1]).flatten()

ax.scatter(x_ax, y_ax, z_ax, c=kmeans, marker='o')
```



```
ax.set_zlabel('Results')

plt.show()
```

In [22]: *# An example to illustrate scaling*

```
XX = np.array([[1,2,100],[4,3,50],[1,1,75],[2,1,95]])

print XX
```

```
[[  1  2  100]  [  4  3
50]  [  1  1  75]  [ 2 1
95]]
```

In [23]: X_scaled = preprocessing.scale(XX)

```
X_scaled
```

8

```
ax.set_xlabel('Zip')
ax.set_ylabel('Risk')
ax.set_zlabel('Results')


plt.show()
```

```
C:\Users\Nathan Wilkins\AppData\Local\Enthought\Canopy\edm\envs\User\lib\site-packages\sklearn\utils\val
  warnings.warn(msg, _DataConversionWarning)
```

Out[23]: array([[-0.81649658, 0.30151134, 1.01600102], [ 1.63299316, 1.50755672, -1.52400152], [-0.81649658, -0.90453403, -0.25400025], [ 0.
, -0.90453403, 0.76200076]])

In [24]: X.shape

Out[24]: (20207L, 3L)

In [25]:
```
# ZIP code Feature is big compared to toher features(Risk and Results)
# We need to Scale the data print
X
```

[[ 0 4 60604] [ 0 4 60659] [
0 4 60657] ..., [ 1 0 60608]
[ 0 4 60638] [ 0 4 60604]]

In [26]:
```
# Scale the data

X_scaled = preprocessing.scale(X)

X_scaled
```

```
C:\Users\Nathan Wilkins\AppData\Local\Enthought\Canopy\edm\envs\User\lib\site-packages\sklearn\utils\val
  warnings.warn(msg, _DataConversionWarning)
```

Out[26]: array([[-0.51859553, 0.38659078, -1.26961213], [-0.51859553,

0.38659078, 1.56102613], [-0.51859553, 0.38659078, 1.45809382], ..., [
1.33811245, -2.05156148, -1.06374753], [-0.51859553, 0.38659078,
0.48023697], [-0.51859553, 0.38659078, -1.26961213]])

In [27]: *# After Scaling the values # 2 clusters using K-Means*

```
fig = plt.figure(figsize=(16, 12))
```

In [28]: # No scaling

```
# 2 Clusters of K-Means

                                         1
                                         0
ax = fig.add_subplot(111, projection='3d')

kmeans = KMeans(2, random_state=0).fit_predict(X_scaled)


x_ax = np.array(X[:, 2]).flatten() y_ax =
np.array(X[:, 0]).flatten() z_ax =
np.array(X[:, 1]).flatten()


ax.scatter(x_ax, y_ax, z_ax, c=kmeans, marker='^')

ax.set_xlabel('Zip')
ax.set_ylabel('Risk')
ax.set_zlabel('Results')


plt.show()


fig = plt.figure(figsize=(16, 12)) ax =
fig.add_subplot(111, projection='3d')

kmeans = KMeans(2, random_state=0).fit_predict(X)


x_ax = np.array(X[:, 2]).flatten() y_ax =
np.array(X[:, 0]).flatten() z_ax =
np.array(X[:, 1]).flatten()


ax.scatter(x_ax, y_ax, z_ax, c=kmeans, marker='^')

ax.set_xlabel('Zip')
ax.set_ylabel('Risk')
ax.set_zlabel('Results')

plt.show()
```

1

1

### 0.3 Requirement #1: Inspect the given dataset and remove any dirty/messy records

In [5]:
```
dataset_df1 = pd.read_csv("c:\\datasets\Chicago_Food_InspectionsA.csv")
df2= pd.read_csv("c:\\datasets\Chicago_Food_InspectionsA.csv")
```

In [6]:
```
dataset_df1.head(2)
```

Out[6]: Inspection ID DBA Name AKA Name License # \
0 2072076 MODERN WING/TERZO PIANO MODERN WING/TERZO PIANO 1954252.0 1 2072061 PATEL ' S CAFE PATEL ' S CAFE 2036995.0

Facility Type Risk Address City State Zip \ 0 Restaurant Risk 1 (High) 159 E MONROE DR CHICAGO IL 60604.0 1 Restaurant Risk 1 (High) 2600 W DEVON AVE CHICAGO IL 60659.0

Inspection Date Inspection Type Results \ 0 8/8/2017 Canvass Re-Inspection Pass 1 8/8/2017 Complaint Re-Inspection Pass

Violations Latitude Longitude \ 0 18. NO EVIDENCE OF RODENT OR INSECT OUTER OPEN... 41.880740 -87.62270 1 13. NO EVIDENCE OF RODENT OR INSECT INFESTATIO... 41.997755 -87.69483

Location 0 (41.88073951830644, -87.62270010046835) 1 (41.99775478924851, -87.69482972221137)

In [7]:
```
dataset_df1.tail(2)
```

Out[7]: Inspection ID DBA Name AKA Name License # \

26812 1609261 TORTORICE'S PIZZA TORTORICE'S PIZZA 2442943.0 26813 1609260 VANILLE PATTISSERIE VANILLE 2442830.0

Facility Type Risk Address City \ 26812 Restaurant Risk 1 (High) 2101-2103 W IRVIING PARK RD CHICAGO 26813 Restaurant Risk 2 (Medium) 3243 N BROADWAY CHICAGO

State Zip Inspection Date Inspection Type Results Violations \ 26812 IL 60618.0 1/4/2016 License Not Ready NaN 26813 IL 60657.0 1/4/2016 License Not Ready NaN

Latitude Longitude Location 26812 41.954010 -87.681241 (41.95401015404328, -87.68124094099036) 26813 41.941294 -87.644292 (41.94129418083914, -87.64429200618663)

In [8]:
```
dataset_df1 = dataset_df1.dropna(axis=0, how='any')
df2=df2.dropna(axis=0, how='any')
```

In [9]:
```
dataset_df1.dtypes
```

1
2

Out[9]: Inspection ID int64 DBA Name object AKA Name object License # float64 Facility Type object Risk object Address object City object State object Zip float64 Inspection Date object Inspection Type object Results object Violations object

Latitude float64 Longitude float64 Location
object dtype: object

### 0.4 Requirement #2: Perform any preprocessing/ scaling needed to the dataset features

In [10]:
```
dataset_df1['Zip'] = dataset_df1['Zip'].astype(int)
```

In [11]:
```
from sklearn.preprocessing import LabelEncoder

list_of_feaatures_to_encode = ['Risk', 'Results'] le =
LabelEncoder()

for i in list_of_feaatures_to_encode:
    enc = le.fit(np.unique(dataset_df1[i].values))
    print(enc.classes_) dataset_df1[i] =
    le.fit_transform(dataset_df1[i])
```

```
['Risk 1 (High)'  'Risk 2 (Medium)'  'Risk 3 (Low)'] ['Fail'
'No Entry'  'Not Ready'  'Out of Business'  'Pass'
 'Pass w/ Conditions']
```

In [12]:
```
f0 = dataset_df1['Risk'].values
f1 = dataset_df1['Results'].values f2 =
dataset_df1['Zip'].values

X=np.matrix(zip(f0,f1, f2))
```

In [13]:
```
X_scaled = preprocessing.scale(X)

X_scaled
```

1
3

```
C:\Users\Nathan Wilkins\AppData\Local\Enthought\Canopy\edm\envs\User\lib\site-packages\sklearn\utils\val
  warnings.warn(msg, _DataConversionWarning)
```

Out[13]:
```
array([[-0.51859553, 0.38659078, -1.26961213], [-0.51859553,
0.38659078, 1.56102613], [-0.51859553, 0.38659078, 1.45809382], ..., [
```

1.33811245, -2.05156148, -1.06374753], [-0.51859553, 0.38659078, 0.48023697], [-0.51859553, 0.38659078, -1.26961213]])

## 0.5 Requirement #3: Use K-MEANS algorithm to cluster the data into two clusters with respect to the following Features: Zip code, Results, Risk

In [14]:
```
kmeans = KMeans(2, random_state=0).fit_predict(X_scaled)
```

## 0.6 Requirement #4: Create a 3D scatter diagram to plot the clusters/results of Requirement #3 for the Zip code, Results, and Risk Features

In [15]:
```
fig = plt.figure(figsize=(16, 12))
ax = fig.add_subplot(111, projection='3d')

kmeans = KMeans(2, random_state=0).fit_predict(X_scaled)


x_ax = np.array(X[:, 2]).flatten() y_ax =
np.array(X[:, 0]).flatten() z_ax =
np.array(X[:, 1]).flatten()


ax.scatter(x_ax, y_ax, z_ax, c=kmeans, marker='^')

ax.set_xlabel('Zip')
ax.set_ylabel('Risk')
ax.set_zlabel('Results')


plt.show()
```

## 0.7 Requirement #5: List the top 5 Zip Codes that got the maximum number of Inspections with High Risk and Failed Result

In [16]:
```
list_of_feaatures_to_encode = ['Risk', 'Results']
le = LabelEncoder()

for i in list_of_feaatures_to_encode:
    enc = le.fit(np.unique(df2[i].values))
    print(enc.classes_) df2[i] =
    le.fit_transform(df2[i])
```

```
['Risk 1 (High)'  'Risk 2 (Medium)'  'Risk 3 (Low)'] ['Fail'
'No Entry'  'Not Ready'  'Out of Business'  'Pass'
 'Pass w/ Conditions']
```

In [19]:
```
Results1=df2[(df2['Results']==0) & (df2['Risk']==1)]
Results1
```

Out[19]: Inspection ID DBA Name \

34 2071895 HAROLD'S CHICKEN SHACK #14 36 2071882 FRESH ZABIHA HALAL SUPER MARKET

1
5

66 2071822 ROSE FOOD MART 92 2015426 SPEEDWAY #8320 139 2071706 DUNKIN DONUTS 146 2071700 BUZZ KILLER ESPRESSO 171 2071648 SWEET FREAKS 177 2071641 BURGER KING 180 2071626 McDONALD'S # 17277 183 2071620 KING'S MARKET 199 2071600 TREE HOUSE ANIMAL FOUNDATION 203 2070020 KATE & JAN, CORP. 206 2071598 WINGSTOP 225 2071558 EDDIE CAFE INC. 231 2071541 TEA LUV LLC/OOOH WEE SWEET TEA 278 2071439 HAROLD'S CHICKEN SHACK #14 333 2071360 STARBUCKS COFFEE #2635 352 2071333 SUPER SAVE 384 1385591 DIVISION FOOD MARKET 385 2071283 JAMBA JUICE 387 2045292 DAMN FINE COFFEE BAR 417 2071226 SURF'S UP SOUTH SHORE 436 2070192 STARBUCKS COFFEE #2635 479 2070132 MAISON MARCEL 492 2070105 POPEYE'S CHICKEN RESTAURANT 549 2070010 DUNKIN DONUTS 567 2069986 SAVE-A-LOT # 858 578 2069960 THE GREAT STEAK & POTATO COMPANY 596 2069926 BURGER KING #6358 627 2069879 MEHRAB SUPER MARKET ... ... ... 25486 1454328 GOGO DOGS, LLC 25502 1631261 HAROLD'S CHICKEN SHACK #14 25544 1631234 ANCIEN 25555 1631219 MCDONALD'S 25582 1385840 IN & OUT FOOD MART 25605 1621365 PALETERIA Y NEVERIA LA FLOR DE MICHOACAN, CORP. 25610 1319438 McDONALD'S 25645 1448177 BURGER KING #11297 25782 1150889 SAM'S FOOD 25808 1950270 7 - ELEVEN 25875 1610135 ENERGYM FITNESS CENTER 25954 1610048 FIVE ONE FOOD MART INC 25992 1454351 MINI HUT INC 26058 1234963 SKYYGREENS 26214 1596272 FLIRTY CUPCAKES 26216 1609805 UNION SUB 1 INC. 26246 1448163 ARTIZONE 26291 1609744 CAPTAIN HOOKS 26446 1609596 LA JEFA

1
6

26488 1632886 PIZZA HUT 317255 26490 2059946 7-ELEVEN #33763B 26523 1609527 KISS DRAGON CO. 26632 1596263 DOMINO'S PIZZA 26655 1609412 STARBUCKS COFFEE #19549 26660 1609407 A LIL SOMTHING HOT 26678 1609402 MARGARITA'S MEAT MARKET 26704 1609375 BEST CHOICE MEATS, INC 26738 1454336 MINI HUT INC 26797 1277430 Fresh Start Mini Mart 26808 1501540 ROYAL DELI

AKA Name License # \ 34 HAROLD'S CHICKEN 2423269.0 36 FRESH ZABIHA HALAL SUPER MARKET 2543495.0 66

ROSE FOOD MART 2543227.0 92 SPEEDWAY #8320 74276.0 139 DUNKIN DONUTS 2536462.0 146 BUZZ KILLER ESPRESSO 2008990.0 171 SWEET FREAKS 2517680.0 177 BURGER KING 2487684.0 180 McDONALD'S (T1 B11) 2487934.0 183 KING'S MARKET 2548877.0 199 PURRFECT ROAST CATFE 2536599.0 203 KATE & JAN HOT DOGS 2384966.0 206 WINGSTOP 2328402.0 225 EDDIE CAFE 2548796.0 231 OOOH WEE SWEET TEA 2548687.0 278 HAROLD'S CHICKEN 2423269.0 333 STARBUCKS COFFEE #2635 1276339.0 352 SUPER SAVE 2368994.0 384 DIVISION FOOD MARKET 2277647.0 385 JAMBA JUICE (T1/B7) 15531.0 387 DAMN FINE 2464692.0 417 SURF'S UP 2463333.0 436 STARBUCKS COFFEE #2635 1276339.0 479 MAISON MARCEL 2523375.0 492 POPEYE'S CHICKEN RESTAURANT 10139.0 549 DUNKIN DONUTS-BASKIN ROBBINS 17349.0 567 SAVE-A-LOT # 858 1272454.0 578 THE GREAT STEAK & POTATO COMPANY 1933456.0 596 BURGER KING 2368795.0 627 MEHRAB SUPER MARKET 2179855.0 ... ... ... 25486 GOGO DOGS, LLC 2326585.0 25502 HAROLD'S CHICKEN 2423269.0 25544 ANICEN 2446389.0 25555 MCDONALD'S 30231.0

1
7

25582 IN & OUT FOOD MART 2231989.0 25605 PALETERIA Y NEVERIA LA FLOR DE MICHOACAN, CORP. 2438045.0 25610 McDONALD'S 1302136.0 25645 BURGER KING 2368804.0 25782 SAM'S FOOD 2120028.0 25808 7 - ELEVEN 63044.0 25875 ENERGYM FITNESS CENTER 2442370.0 25954 51ST QUICK MART & CELLULAR 2256636.0 25992 MINI HUT INC 60836.0 26058 SKYYGREENS 2183566.0 26214 FLIRTY CUPCAKES 2137675.0 26216 UNION SUB 2158449.0 26246 ARTIZONE 2443045.0 26291 CAPTAIN HOOKS/FIREHOUSE STEAK AND LEMONADE 1332616.0 26446 LA JEFA 2423147.0 26488 PIZZA HUT 2432973.0 26490 7-ELEVEN 2368671.0 26523 KISS DRAGON CO. 1488929.0 26632 DOMINO'S PIZZA 2269542.0 26655 STARBUCK'S 2253115.0 26660 A LIL SOMTHING HOT 2428843.0 26678 MARGARITA'S MEAT MARKET 1543381.0 26704 BEST CHOICE MEATS, INC 2411784.0 26738 MINI HUT INC 60836.0 26797 Fresh Start Mini Mart 2183952.0 26808 ROYAL DELI 2115060.0

Facility Type Risk Address City \ 34 Restaurant 1 1208 E 53RD ST CHICAGO 36 Grocery Store 1 2650 W DEVON AVE CHICAGO 66 Grocery Store 1 11300 S WENTWORTH AVE CHICAGO 92 Grocery Store 1 3554 W NORTH AVE CHICAGO 139 Restaurant 1 128 N STATE ST CHICAGO 146 COFFEE SHOP 1 1644 N DAMEN AVE CHICAGO 171 CANDY SHOP 1 9927 S WOOD ST CHICAGO 177 Restaurant 1 748 W DIVERSEY PKWY CHICAGO 180 Restaurant 1 11601 W TOUHY AVE CHICAGO 183 Grocery Store 1 400 E 71st ST CHICAGO 199 Animal Shelter Cafe Permit 1 7225 N WESTERN AVE CHICAGO 203 Mobile Food Preparer 1 324 N LEAVITT ST CHICAGO 206 Restaurant 1 1712 W 119TH ST CHICAGO

225 Restaurant 1 4807 N SPAULDING AVE CHICAGO 231 Restaurant 1 7601 S CICERO AVE CHICAGO 278 Restaurant 1 1208 E 53RD ST CHICAGO 333 Restaurant 1 4753 N BROADWAY CHICAGO 352 GROCERY STORE/GAS STATION 1 6649-6659 S HALSTED ST CHICAGO 384 Grocery Store 1 4201 W DIVISION ST CHICAGO 385 Restaurant 1 11601 W TOUHY AVE CHICAGO



387 Restaurant 1 3317 W ARMITAGE AVE CHICAGO 417 Restaurant 1 2236 E 71ST ST CHICAGO 436 Restaurant 1 4753 N BROADWAY CHICAGO 479 Restaurant 1 3114 N BROADWAY CHICAGO 492 Restaurant 1 616 E 103RD ST CHICAGO 549 Restaurant 1 5000 W IRVING PARK RD CHICAGO 567 Grocery Store 1 2858 E 83RD ST CHICAGO 578 Restaurant 1 7901 S DAMEN AVE CHICAGO 596 Restaurant 1 6400 W IRVING PARK RD CHICAGO 627 Grocery Store 1 2433-35 W DEVON AVE CHICAGO ... ... ... ... ... 25486 Restaurant 1 2858 W CHICAGO AVE CHICAGO 25502 Restaurant 1 1208 E 53RD ST CHICAGO 25544 Restaurant 1 1558 E 53RD ST CHICAGO 25555 Restaurant 1 4946 N MILWAUKEE AVE CHICAGO 25582 Grocery Store 1 401 N LARAMIE AVE CHICAGO 25605 Restaurant 1 4222 W 26TH ST CHICAGO 25610 Restaurant 1 70 E GARFIELD BLVD CHICAGO 25645 Restaurant 1 6900 S HALSTED ST CHICAGO 25782 Grocery Store 1 1822 W 63RD ST CHICAGO 25808 Grocery Store 1 2264 N CLARK ST CHICAGO 25875 Restaurant 1 2150 S CANALPORT AVE CHICAGO 25954 Grocery Store 1 51 E 51st ST CHICAGO 25992 Restaurant 1 6659 W ARCHER AVE CHICAGO 26058 Wholesale 1 1400 W 46TH ST CHICAGO 26214 Restaurant 1 1030 W TAYLOR ST CHICAGO 26216 Restaurant 1 110 E 51ST ST CHICAGO 26246 DISTRIBUTOR 1 1400 W 46TH ST CHICAGO 26291 Restaurant 1 1600 W 13TH ST CHICAGO 26446 Mobile Food Preparer 1 2637 S THROOP ST CHICAGO 26488 Restaurant 1 3045 N PULASKI RD CHICAGO 26490 Grocery Store 1 6200 N SAYRE AVE CHICAGO 26523 Grocery Store 1 2334 S WENTWORTH AVE CHICAGO 26632 Restaurant 1 1234 S CANAL ST CHICAGO 26655 Restaurant 1 633 N ST CLAIR ST CHICAGO 26660 Restaurant 1 1455 W 103RD ST CHICAGO 26678 Grocery Store 1 2709 E 79TH ST CHICAGO 26704 Wholesale 1 9229 S BALTIMORE AVE CHICAGO 26738 Restaurant 1 6659 W ARCHER AVE CHICAGO 26797 Grocery Store 1 854 N KILDARE AVE CHICAGO 26808 Grocery Store 1 2001-2003 S DAMEN AVE CHICAGO

State Zip Inspection Date Inspection Type Results \ 34 IL 60615.0 8/3/2017 Complaint Re-Inspection 0 36 IL 60659.0 8/3/2017 License 0 66 IL 60628.0 8/2/2017 License 0 92 IL 60647.0 8/2/2017 Canvass 0 139 IL 60602.0 8/1/2017 License 0



146 IL 60647.0 8/1/2017 Canvass 0 171 IL 60643.0 7/31/2017 License 0 177 IL 60614.0 7/31/2017 Complaint 0 180 IL 60666.0 7/31/2017 Complaint 0 183 IL 60619.0 7/31/2017

License 0 199 IL 60645.0 7/28/2017 License 0 203 IL 60612.0 7/18/2017 License 0 206 IL 60643.0 7/28/2017 Complaint 0 225 IL 60625.0 7/28/2017 License 0 231 IL 60652.0 7/28/2017 License 0 278 IL 60615.0 7/26/2017 Complaint 0 333 IL 60640.0 7/25/2017 Canvass Re-Inspection 0 352 IL 60621.0 7/25/2017 Canvass 0 384 IL 60651.0 9/8/2014 Short Form Complaint 0 385 IL 60666.0 7/24/2017 Canvass 0 387 IL 60647.0 7/24/2017 Canvass 0 417 IL 60649.0 7/21/2017 Complaint 0 436 IL 60640.0 7/21/2017 Canvass 0 479 IL 60657.0 7/20/2017 License 0 492 IL 60628.0 7/19/2017 Short Form Complaint 0 549 IL 60641.0 7/18/2017 Canvass 0 567 IL 60617.0 7/17/2017 Complaint 0 578 IL 60620.0 7/17/2017 Complaint 0 596 IL 60634.0 7/17/2017 Canvass Re-Inspection 0 627 IL 60659.0 7/14/2017 Canvass 0 ... ... ... ... ... ... 25486 IL 60622.0 11/30/2015 License 0 25502 IL 60615.0 2/3/2016 Complaint 0 25544 IL 60615.0 2/3/2016 License 0 25555 IL 60630.0 2/2/2016 Complaint 0 25582 IL 60644.0 12/24/2014 Canvass 0 25605 IL 60623.0 1/29/2016 License 0 25610 IL 60615.0 3/18/2013 Complaint 0 25645 IL 60621.0 1/28/2016 Complaint 0 25782 IL 60636.0 10/30/2012 Canvass 0 25808 IL 60614.0 8/12/2016 Canvass 0 25875 IL 60608.0 1/25/2016 License 0 25954 IL 60615.0 1/22/2016 Complaint 0 25992 IL 60638.0 1/21/2016 Short Form Complaint 0 26058 IL 60609.0 8/29/2012 License 0 26214 IL 60607.0 1/15/2016 Canvass 0 26216 IL 60615.0 1/15/2016 Complaint 0 26246 IL 60609.0 1/14/2016 License 0 26291 IL 60608.0 1/14/2016 Complaint 0 26446 IL 60608.0 1/12/2016 License 0 26488 IL 60641.0 3/10/2016 License 0 26490 IL 60631.0 6/9/2017 Canvass 0 26523 IL 60616.0 1/8/2016 Canvass 0

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26632 IL 60607.0 1/7/2016 Canvass 0 26655 IL 60611.0 1/7/2016 Canvass 0 26660 IL 60643.0 1/7/2016 License 0 26678 IL 60649.0 1/6/2016 Canvass 0 26704 IL 60617.0 1/6/2016 Complaint 0 26738 IL 60638.0 1/5/2016 Complaint 0 26797 IL 60651.0 10/17/2012 License Re-Inspection 0 26808 IL 60608.0 11/6/2014 Canvass 0

Violations Latitude \ 34 14. PREVIOUS SERIOUS VIOLATION CORRECTED, 7-42... 41.799570 36 11. ADEQUATE NUMBER, CONVENIENT, ACCESSIBLE, D... 41.997719 66 2. FACILITIES TO MAINTAIN PROPER TEMPERATURE -... 41.688846 92 36. LIGHTING: REQUIRED MINIMUM FOOT-CANDLES OF... 41.910108 139 9. WATER SOURCE: SAFE, HOT & COLD UNDER CITY P... 41.883883 146 18. NO EVIDENCE OF RODENT OR INSECT OUTER OPEN... 41.911847 171 16. FOOD PROTECTED DURING STORAGE, PREPARATION... 41.713019 177 29. PREVIOUS MINOR VIOLATION(S) CORRECTED 7-42... 41.932841 180 16. FOOD PROTECTED DURING STORAGE, PREPARATION... 42.008536 183 2. FACILITIES TO MAINTAIN PROPER TEMPERATURE -... 41.765823 199 11. ADEQUATE NUMBER, CONVENIENT, ACCESSIBLE, D... 42.013050 203 9. WATER SOURCE: SAFE, HOT & COLD UNDER CITY P... 41.887434 206 19. OUTSIDE GARBAGE WASTE GREASE AND STORAGE A... 41.677591 225 37. TOILET ROOM DOORS SELF CLOSING: DRESSING R...

41.968692 231 9. WATER SOURCE: SAFE, HOT & COLD UNDER CITY P...
41.754660 278 1. SOURCE SOUND CONDITION, NO SPOILAGE, FOODS ...
41.799570 333 11. ADEQUATE NUMBER, CONVENIENT, ACCESSIBLE, D...
41.968724 352 21. * CERTIFIED FOOD MANAGER ON SITE WHEN POTE...
41.772839 384 3. POTENTIALLY HAZARDOUS FOOD MEETS TEMPERATUR...
41.902479 385 12. HAND WASHING FACILITIES: WITH SOAP AND SAN...
42.008536 387 18. NO EVIDENCE OF RODENT OR INSECT OUTER OPEN...
41.917243 417 1. SOURCE SOUND CONDITION, NO SPOILAGE, FOODS ...
41.766411 436 11. ADEQUATE NUMBER, CONVENIENT, ACCESSIBLE, D...
41.968724 479 38. VENTILATION: ROOMS AND EQUIPMENT VENTED AS...
41.938117 492 35. WALLS, CEILINGS, ATTACHED EQUIPMENT CONSTR...
41.707510 549 6. HANDS WASHED AND CLEANED, GOOD HYGIENIC PRA...
41.953468 567 18. NO EVIDENCE OF RODENT OR INSECT OUTER OPEN...
41.744731 578 22. DISH MACHINES: PROVIDED WITH ACCURATE THER...
41.750189 596 14. PREVIOUS SERIOUS VIOLATION CORRECTED, 7-42... 41.953025 627 38. VENTILATION: ROOMS AND EQUIPMENT VENTED AS... 41.997599 ... ... ... 25486 18. NO EVIDENCE OF RODENT OR INSECT OUTER OPEN... 41.895747 25502 19. OUTSIDE GARBAGE WASTE GREASE AND STORAGE A... 41.799570 25544 38. VENTILATION: ROOMS AND EQUIPMENT VENTED AS... 41.799677 25555 16. FOOD PROTECTED DURING STORAGE, PREPARATION... 41.970678 25582 18. NO EVIDENCE OF RODENT OR INSECT OUTER OPEN... 41.887869 25605 11. ADEQUATE NUMBER, CONVENIENT, ACCESSIBLE, D... 41.844282 25610 33. FOOD AND NON-FOOD CONTACT EQUIPMENT UTENSI... 41.794794

2

1

25645 19. OUTSIDE GARBAGE WASTE GREASE AND STORAGE A... 41.768744
25782 21. * CERTIFIED FOOD MANAGER ON SITE WHEN POTE... 41.779477
25808 34. FLOORS: CONSTRUCTED PER CODE, CLEANED, GOO... 41.923650
25875 2. FACILITIES TO MAINTAIN PROPER TEMPERATURE -... 41.853301
25954 18. NO EVIDENCE OF RODENT OR INSECT OUTER OPEN... 41.801869
25992 18. NO EVIDENCE OF RODENT OR INSECT OUTER OPEN... 41.792094
26058 38. VENTILATION: ROOMS AND EQUIPMENT VENTED AS... 41.810601
26214 32. FOOD AND NON-FOOD CONTACT SURFACES PROPERL... 41.869597
26216 18. NO EVIDENCE OF RODENT OR INSECT OUTER OPEN... 41.802119
26246 11. ADEQUATE NUMBER, CONVENIENT, ACCESSIBLE, D... 41.810601
26291 16. FOOD PROTECTED DURING STORAGE, PREPARATION... 41.865189
26446 10. SEWAGE AND WASTE WATER DISPOSAL, NO BACK S... 41.844671
26488 11. ADEQUATE NUMBER, CONVENIENT, ACCESSIBLE, D... 41.936753
26490 18. NO EVIDENCE OF RODENT OR INSECT OUTER OPEN... 41.994396
26523 18. NO EVIDENCE OF RODENT OR INSECT OUTER OPEN... 41.849954
26632 18. NO EVIDENCE OF RODENT OR INSECT OUTER OPEN... 41.866277

26655 18. NO EVIDENCE OF RODENT OR INSECT OUTER OPEN... 41.893475 26660 24. DISH WASHING FACILITIES: PROPERLY DESIGNED... 41.706621 26678 18. NO EVIDENCE OF RODENT OR INSECT OUTER OPEN... 41.751726 26704 35. WALLS, CEILINGS, ATTACHED EQUIPMENT CONSTR... 41.727396 26738 3. POTENTIALLY HAZARDOUS FOOD MEETS TEMPERATUR... 41.792094 26797 24. DISH WASHING FACILITIES: PROPERLY DESIGNED... 41.896896 26808 34. FLOORS: CONSTRUCTED PER CODE, CLEANED, GOO... 41.854911

Longitude Location 34 -87.596239 (41.799570005698875, -87.5962391078313) 36 -87.696810 (41.99771932496398, -87.69680986396408) 66 -87.627944 (41.688845980258904, -87.62794434817805) 92 -87.716363 (41.91010808224881, -87.71636347779774) 139 -87.628039 (41.883882629163985, -87.6280390685969) 146 -87.677643 (41.911846648306714, -87.67764281908491) 171 -87.667109 (41.71301890051313, -87.66710874351577) 177 -87.648516 (41.9328407126909, -87.64851624582587) 180 -87.914428 (42.008536400868735, -87.91442843927047) 183 -87.615206 (41.765822540753675, -87.61520620272347) 199 -87.690096 (42.01305045298672, -87.69009607266406) 203 -87.681849 (41.88743405025222, -87.68184949426895) 206 -87.664479 (41.6775910650455, -87.66447899825711) 225 -87.710781 (41.96869167173921, -87.71078092200098) 231 -87.741385 (41.75466012439374, -87.74138475860521) 278 -87.596239 (41.799570005698875, -87.5962391078313) 333 -87.659414 (41.96872371055819, -87.65941408749583) 352 -87.644460 (41.772838797055094, -87.64445957890496) 384 -87.731345 (41.902479211319395, -87.73134481666703) 385 -87.914428 (42.008536400868735, -87.91442843927047) 387 -87.711007 (41.917242821418085, -87.71100706313331) 417 -87.569893 (41.76641105932833, -87.56989324244854) 436 -87.659414 (41.96872371055819, -87.65941408749583)

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479 -87.644483 (41.93811706325153, -87.64448281820779) 492 -87.608183 (41.70750956551268, -87.60818281887107) 549 -87.752306 (41.95346817003143, -87.75230593409377) 567 -87.554039 (41.74473083947384, -87.55403913753914) 578 -87.672986 (41.750189342293375, -87.67298583977204) 596 -87.786683 (41.95302475075328, -87.78668323766634) 627 -87.691163

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(41.99759944782518, -87.69116270116571) ... ... ... 25486 -87.699103
(41.89574658400031,     -87.69910280356912)     25502     -87.596239
(41.799570005698875,    -87.5962391078313)      25544     -87.586811
(41.79967733344662,     -87.58681064091066)     25555     -87.763429
(41.9706775856096,      -87.76342894418006)     25582     -87.755193
(41.887869064153996,    -87.75519263581694)     25605     -87.730337
(41.844281925871094,    -87.73033724022376)     25610     -87.622915
(41.79479402426513,     -87.62291510355041)     25645     -87.644651
(41.76874434093266,     -87.64465137816886)     25782     -87.670135
(41.77947732730119,     -87.67013473289414)     25808     -87.639455
(41.923649983244644,    -87.63945496889548)     25875     -87.649930
(41.8533014640748,      -87.649929695282)       25954     -87.623914
(41.80186863276546,     -87.62391427138503)     25992     -87.789068
(41.79209438277045,     -87.78906760858516)     26058     -87.660283
(41.81060129421089,     -87.66028325873228)     26214     -87.652349
(41.86959706650426,     -87.6523490175014)      26216     -87.622115
(41.80211854301136,     -87.62211491496085)     26246     -87.660283
(41.81060129421089,     -87.66028325873228)     26291     -87.666469
(41.865188763426644,    -87.66646924032864)     26446     -87.654962
(41.84467072147077,     -87.6549622241458)      26488     -87.726972
(41.93675319783174,     -87.72697220407252)     26490     -87.802394
(41.99439639473516,     -87.80239443586892)     26523     -87.632094
(41.84995400192252,     -87.63209419559098)     26632     -87.639360
(41.86627726994009,     -87.63936045226205)     26655     -87.622575
(41.89347535770077,     -87.6225746735784)      26660     -87.659603
(41.70662071407754,     -87.65960281980928)     26678     -87.558468
(41.75172636358155,     -87.55846797776616)     26704     -87.548287
(41.727396382754264,    -87.54828692765585)     26738     -87.789068
(41.79209438277045,     -87.78906760858516)     26797     -87.733671
(41.896896075381534,    -87.73367116642495)     26808     -87.675773
(41.85491131910428, -87.67577256587357)

[723 rows x 17 columns]
```

In [32]:
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Results2=Results1['Zip'].value_counts()
Results2.head(5)
```

Out[32]:
```
60608.0    46
60612.0    29    60619.0    29
60623.0 28
```

60647.0 27 Name: Zip,
dtype: int64

## 0.8 Requirement #6: List the top 5 Zip Codes that got the maximum number of Inspections with Low Risk and Pass Result

In [23]:
```
ResultsA=df2[(df2['Results']==4) & (df2['Risk']==2)]
ResultsA
```

Out[23]: Inspection ID DBA Name \

4 2072035 THE CATCADE, INC. 32 2071840 ALBANY LIQUORS AND FOOD 130 2071718 R & R MARATHON 166 2071659 MOON STAR GROCERY 289 2045245 ALDI INC #64 327 2071373 ONE STOP SHOP ONLY 430 2070202 RHODES FOOD MARKET 437 2070196 WALGREENS #12426 444 2070179 FAMILY DOLLAR STORE #6642 451 2070107 MEMO'S CATERING 481 2070126 BRACKET ROOM 501 2070094 AUGUSTA FOOD MARKET INC. 547 2059402 ACE HOTEL CHICAGO 562 1955777 CLARK GROCERY 671 2069802 OPEN OUTCRY BREWING 730 1983233 STOP AND SHOP FOODS, INC. 773 2069685 BESPOKE MEN'S GROOMING 827 2069592 GREAT CENTRAL BREWERY COMPANY 829 2069575 MARATHON FUEL & MINI MART 845 2069535 CITGO 923 2015392 LOCAL GOODS CHICAGO 968 2069406 JJ PEPPERS FOOD STORE 983 2069385 ZEES SUPERMARKET PLUS 1046 1983229 GOOD BLESSINGS DISCOUNT STORE 1052 2069310 KITCHFIX 1064 2069293 CVS/PHARMACY #4061 1077 2069247 RESIDENCE INN 1093 2069258 RESIDENCE INN 1112 2045260 NAVIGATOR TAPROOM 1126 2069241 RESIDENCE INN ... ... ... 25361 1631403 EXPRESS FOOD MARKET 25550 1631227 FAMILY DOLLAR #2465 25573 1621388 DOLLAR TREE #650 25662 1441653 DOLLAR TREE #656 25688 1621265 DOLLAR AND GROCERY LA PEQUENITA 25709 1592082 123 MINI MART 25914 1448170 ALDI INC #92



25927 1610078 TAGA MARATHON 25981 1448164 47TH DOLLAR FOOD & MART 26017 1609992 SOUTH LOOP MART INC. 26038 1609964 EL FARO FOODS 26078 1609926 BONY'S FOOD MARKET, INC. 26355 1609691 Dollar Tree #4143 26382

1435164 STAR FOUR, LTD. 26453 1609585 TBD 26461 1448153 EXPRESSWAY FOODMART INC. 26476 1609571 MARATHON GAS 26517 1442294 CHARLIES CHICAGO 26542 1607285 MARCY'S MART 26611 1467638 EASTSIDE MARATHON INC 26639 1609429 The Victor Bar 26642 1235828 IYANZE 26695 1607269 SEASONS 52 26707 1751415 KIM'S CORNER FOOD 26735 1512560 Walgreens # 07250 26764 1609325 YAAZ MINI MART 26768 1609318 CHICAGO NEWS NOW #1629 26784 1459426 Montefiore 26799 1609275 UPTOWN ARCADE 26807 1609265 CRATER FOOD & LIQUOR

AKA Name License # \ 4 THE CATCADE 2542576.0 32 ALBANY LIQUORS AND FOOD 2535836.0 130 R & R MARATHON 1578493.0 166 MOON STAR GROCERY 2535500.0 289 ALDI INC #64 13976.0 327 ONE STOP SHOP ONLY 2528633.0 430 RHODES FOOD MARKET 2543241.0 437 WALGREENS #12426 1954015.0 444 FAMILY DOLLAR STORE #6642 1678787.0 451 MEMO'S CATERING 2535775.0 481 BRACKET ROOM 2511629.0 501 AUGUSTA FOOD MARKET 2543287.0 547 ACE HOTEL CHICAGO 2501658.0 562 CLARK GROCERY 2535339.0 671 OPEN OUTCRY 2506735.0 730 STOP AND SHOP FOODS, INC. 2542125.0 773 BESPOKE MEN'S GROOMING 2501564.0 827 GREAT CENTRAL BREWERY COMPANY 2496767.0 829 MARATHON FUEL & MINI MART 1741943.0 845 CITGO 2535189.0 923 LOCAL GOODS CHICAGO 2535486.0 968 JJ PEPPERS FOOD STORE 1383441.0 983 ZEES SUPERMARKET PLUS 2534979.0

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1046 GOOD BLESSINGS 2528214.0 1052 KITCHFIX 2535373.0 1064 CVS/PHARMACY #4061 1923099.0 1077 RESIDENCE INN 2534857.0 1093 RESIDENCE INN 2534860.0 1112 NAVIGATOR TAPROOM 2523632.0 1126 RESIDENCE INN 2534856.0 ... ... ... 25361 EXPRESS FOOD MARKET 1648188.0 25550 FAMILY DOLLAR #2465 1047314.0 25573 DOLLAR TREE #650 1958738.0 25662 DOLLAR TREE #656 1873257.0 25688 DOLLAR AND GROCERY LA PEQUENITA 2443403.0 25709 123 MINI MART 2342349.0 25914 ALDI INC #92 13996.0 25927 MARATHON 1379262.0 25981 47TH DOLLAR FOOD &

MART 2442853.0 26017 SOUTH LOOP MART INC. 2443291.0 26038 EL FARO FOODS 2437112.0 26078 BONY'S FOOD MARKET 2432383.0 26355 Dollar Tree 1997939.0 26382 STAR FOUR, LTD. 41784.0 26453 LOGAN SQUARE TAVERN 2397841.0 26461 EXPRESSWAY FOODMART INC. 2433145.0 26476 MARATHON 2129964.0 26517 CHARLIES CHICAGO 35493.0 26542 MARCY'S MART 2433167.0 26611 EASTSIDE MARATHON INC 1275547.0 26639 The Victor Bar 2418860.0 26642 IYANZE 2254173.0 26695 SEASONS 52 2428603.0 26707 KIM'S CORNER FOOD 1741319.0 26735 Walgreens # 07250 1473004.0 26764 YAAZ MINI MART 2442405.0 26768 CHICAGO NEWS NOW 2442532.0 26784 Montefiore School 30041.0 26799 UPTOWN ARCADE 2369312.0 26807 CRATER FOOD & LIQUOR 46477.0

Facility Type Risk Address \ 4 Animal Shelter Cafe Permit 2 1235 W BELMONT AVE 32 Grocery Store 2 3048 W FULLERTON AVE 130 Grocery Store 2 446 E 103RD ST 166 Grocery Store 2 729-733 W 69TH ST 289 Grocery Store 2 1753 N MILWAUKEE AVE 327 Grocery Store 2 249 E 115TH ST 430 Grocery Store 2 525 E MARQUETTE RD 437 Grocery Store 2 315 W CHICAGO AVE

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444 Grocery Store 2 364 E 87TH ST 451 Mobile Food Dispenser 2 1204 W 36TH PL 481 Restaurant 2 1311-1317 S HALSTED ST 501 Grocery Store 2 1000 N HAMLIN AVE 547 Restaurant 2 311-319 N MORGAN ST 562 Grocery Store 2 6660 N CLARK ST 671 Liquor 2 10934-10936 S WESTERN AVE 730 Grocery Store 2 207 E 71ST ST 773 Liquor 2 529 S DEARBORN ST 827 LIQOUR BREWERY TASTING 2 221 N WOOD ST 829 Grocery Store 2 7850 S DR MARTIN LUTHER KING JR DR 845 Grocery Store 2 4603 N PULASKI RD 923 Gift Shop 2 5422 W Devon AVE 968 Grocery Store 2 7101 S KEDZIE AVE 983 Grocery Store 2 7336 S STONY ISLAND AVE 1046 Grocery Store 2 2200 E 73RD ST 1052 Mobile Prepared Food Vendor 2 1731 W GRAND AVE 1064 convenience/drug store 2 520 S STATE ST 1077 Restaurant 2 201 E WALTON ST 1093 Restaurant 2 201 E WALTON ST 1112 TAVERN 2 2211 N MILWAUKEE AVE 1126 Restaurant 2 201 E WALTON ST ... ... ... ... 25361 Grocery Store 2 6914 S WESTERN AVE 25550 Grocery Store 2 811 W 103RD ST 25573 Grocery Store 2 112 W 87TH ST 25662 Grocery Store 2 3016 N ASHLAND AVE 25688 Grocery Store 2 6059 S KILDARE AVE 25709 Grocery Store 2 9101 S COTTAGE GROVE AVE 25914 Grocery Store 2 620 W 63RD ST 25927 Grocery Store 2 7858 S WESTERN AVE 25981 Grocery Store 2 1714 W 47TH ST 26017 Grocery Store 2 1912 S STATE ST 26038 Grocery Store 2 4807 W ARMITAGE AVE 26078 Grocery Store 2 3059 W IRVING PARK RD 26355 Grocery Store 2 2101 E 95th ST BLDG 26382 Grocery Store 2 8201 S EXCHANGE AVE 26453 Liquor 2 2758 W FULLERTON AVE 26461

Grocery Store 2 323 W 47TH ST 26476 Grocery Store 2 332-340 S SACRAMENTO BLVD 26517 TAVERN 2 3726 N BROADWAY 26542 Grocery Store 2 2343 W IRVING PARK RD 26611 Grocery Store 2 834 E 79TH ST 26639 Liquor 2 4011 N Damen AVE 26642 Mobile Food Dispenser 2 4623-4627 N BROADWAY 26695 Restaurant 2 55 E GRAND AVE 26707 Grocery Store 2 1371 W ESTES AVE 26735 Grocery Store 2 2345 W 103RD ST

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26764 Grocery Store 2 1701 N PULASKI RD 26768 Grocery Store 2 222 S RIVERSIDE PLZ 26784 School 2 1310 S Ashland (1600W) 26799 TAVERN 2 4830 N BROADWAY ST 26807 Grocery Store 2 1144 N MILWAUKEE AVE

City State Zip Inspection Date Inspection Type \ 4 CHICAGO IL 60657.0 8/8/2017 License 32 CHICAGO IL 60647.0 8/3/2017 License 130 CHICAGO IL 60628.0 8/1/2017 Complaint Re-Inspection 166 CHICAGO IL 60621.0 7/31/2017 License Re-Inspection 289 CHICAGO IL 60647.0 5/31/2017 Canvass 327 CHICAGO IL 60628.0 7/25/2017 Short Form Complaint 430 CHICAGO IL 60637.0 7/21/2017 License Re-Inspection 437 CHICAGO IL 60654.0 7/21/2017 Complaint Re-Inspection 444 CHICAGO IL 60619.0 7/20/2017 Complaint 451 CHICAGO IL 60609.0 7/19/2017 License Re-Inspection 481 CHICAGO IL 60607.0 7/20/2017 License Re-Inspection 501 CHICAGO IL 60651.0 7/19/2017 License 547 CHICAGO IL 60607.0 6/1/2017 License Re-Inspection 562 CHICAGO IL 60626.0 7/17/2017 License Re-Inspection 671 CHICAGO IL 60643.0 7/13/2017 License Re-Inspection 730 CHICAGO IL 60619.0 7/12/2017 License 773 CHICAGO IL 60605.0 7/11/2017 License Re-Inspection 827 CHICAGO IL 60612.0 7/10/2017 License Re-Inspection 829 CHICAGO IL 60619.0 7/7/2017 Complaint 845 CHICAGO IL 60630.0 7/7/2017 License Re-Inspection 923 CHICAGO IL 60646.0 7/6/2017 License 968 CHICAGO IL 60629.0 7/3/2017 Canvass Re-Inspection 983 CHICAGO IL 60649.0 6/30/2017 License 1046 CHICAGO IL 60649.0 6/30/2017 License Re-Inspection 1052 CHICAGO IL 60622.0 6/30/2017 License 1064 CHICAGO IL 60605.0 6/29/2017 Complaint 1077 CHICAGO IL 60611.0 6/29/2017 License 1093 CHICAGO IL 60611.0 6/29/2017 License 1112 CHICAGO IL 60647.0 6/29/2017 License 1126 CHICAGO IL 60611.0 6/29/2017 License ... ... ... ... ... ... 25361 CHICAGO IL 60636.0 2/5/2016 Complaint 25550 CHICAGO IL 60643.0 2/3/2016 Complaint Re-Inspection 25573 CHICAGO IL 60620.0 1/29/2016 Canvass 25662 CHICAGO IL 60657.0 12/17/2014 Canvass 25688 CHICAGO IL 60629.0 1/28/2016 License Re-Inspection 25709 CHICAGO IL 60619.0 12/23/2015 Canvass Re-Inspection 25914 CHICAGO IL 60621.0 1/22/2016 Complaint 25927 CHICAGO IL 60620.0 1/22/2016 Canvass 25981 CHICAGO IL 60609.0 1/20/2016 License 26017 CHICAGO IL 60616.0 1/21/2016 License

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26038 CHICAGO IL 60639.0 1/21/2016 License 26078 CHICAGO IL 60618.0 1/21/2016 License Re-Inspection 26355 CHICAGO IL 60617.0 1/13/2016 Complaint Re-Inspection

26382 CHICAGO IL 60617.0 4/25/2014 Canvass 26453 CHICAGO IL 60647.0 1/12/2016 License 26461 CHICAGO IL 60609.0 1/11/2016 License 26476 CHICAGO IL 60612.0 1/11/2016 Canvass Re-Inspection 26517 CHICAGO IL 60613.0 1/8/2016 Short Form Complaint 26542 CHICAGO IL 60618.0 1/8/2016 License Re-Inspection 26611 CHICAGO IL 60619.0 1/7/2016 Canvass Re-Inspection 26639 CHICAGO IL 60618.0 1/7/2016 License 26642 CHICAGO IL 60640.0 6/13/2013 License Re-Inspection 26695 CHICAGO IL 60611.0 12/29/2015 License 26707 CHICAGO IL 60626.0 4/5/2016 Complaint 26735 CHICAGO IL 60643.0 12/3/2014 Canvass 26764 CHICAGO IL 60639.0 1/5/2016 License 26768 CHICAGO IL 60606.0 1/5/2016 License 26784 CHICAGO IL 60608.0 5/6/2014 Canvass Re-Inspection 26799 CHICAGO IL 60640.0 1/5/2016 License 26807 CHICAGO IL 60642.0 1/5/2016 Canvass Re-Inspection

Results Violations Latitude \ 4 4 41. PREMISES MAINTAINED FREE OF LITTER, UNNECE... 41.939703 32 4 38. VENTILATION: ROOMS AND EQUIPMENT VENTED AS... 41.924855 130 4 19. OUTSIDE GARBAGE WASTE GREASE AND STORAGE A... 41.707453 166 4 2. FACILITIES TO MAINTAIN PROPER TEMPERATURE -... 41.768754 289 4 40. REFRIGERATION AND METAL STEM THERMOMETERS ... 41.913342 327 4 41. PREMISES MAINTAINED FREE OF LITTER, UNNECE... 41.685285 430 4 18. NO EVIDENCE OF RODENT OR INSECT OUTER OPEN... 41.774740 437 4 2. FACILITIES TO MAINTAIN PROPER TEMPERATURE -... 41.896455 444 4 34. FLOORS: CONSTRUCTED PER CODE, CLEANED, GOO... 41.736603 451 4 18. NO EVIDENCE OF RODENT OR INSECT OUTER OPEN... 41.828094 481 4 22. DISH MACHINES: PROVIDED WITH ACCURATE THER... 41.865020 501 4 36. LIGHTING: REQUIRED MINIMUM FOOT-CANDLES OF... 41.899151 547 4 2. FACILITIES TO MAINTAIN PROPER TEMPERATURE -... 41.887122 562 4 2. FACILITIES TO MAINTAIN PROPER TEMPERATURE -... 42.003443 671 4 18. NO EVIDENCE OF RODENT OR INSECT OUTER OPEN... 41.694578 730 4 34. FLOORS: CONSTRUCTED PER CODE, CLEANED, GOO... 41.765509 773 4 11. ADEQUATE NUMBER, CONVENIENT, ACCESSIBLE, D... 41.875101 827 4 22. DISH MACHINES: PROVIDED WITH ACCURATE THER... 41.885931 829 4 34. FLOORS: CONSTRUCTED PER CODE, CLEANED, GOO... 41.751430 845 4 2. FACILITIES TO MAINTAIN PROPER TEMPERATURE -... 41.964704 923 4 37. TOILET ROOM DOORS SELF CLOSING: DRESSING R... 41.997439 968 4 19. OUTSIDE GARBAGE WASTE GREASE AND STORAGE A... 41.764299 983 4 35. WALLS, CEILINGS, ATTACHED EQUIPMENT CONSTR... 41.761328 1046 4 9. WATER SOURCE: SAFE, HOT & COLD UNDER CITY P... 41.762678 1052 4 30. FOOD IN ORIGINAL CONTAINER, PROPERLY LABEL... 41.890814 1064 4 33. FOOD AND NON-FOOD CONTACT EQUIPMENT UTENSI... 41.875247

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1077 4 34. FLOORS: CONSTRUCTED PER CODE, CLEANED, GOO... 41.899936 1093 4 34. FLOORS: CONSTRUCTED PER CODE, CLEANED, GOO... 41.899936 1112 4 38. VENTILATION: ROOMS AND EQUIPMENT VENTED AS... 41.921076 1126 4 34. FLOORS: CONSTRUCTED PER CODE, CLEANED, GOO... 41.899936 ... ... ... ... 25361 4 35. WALLS,

CEILINGS, ATTACHED EQUIPMENT CONSTR... 41.767845 25550 4 18. NO EVIDENCE OF RODENT OR INSECT OUTER OPEN... 41.706802 25573 4 35. WALLS, CEILINGS, ATTACHED EQUIPMENT CONSTR... 41.736380 25662 4 34. FLOORS: CONSTRUCTED PER CODE, CLEANED, GOO... 41.936595 25688 4 2. FACILITIES TO MAINTAIN PROPER TEMPERATURE -... 41.782309 25709 4 18. NO EVIDENCE OF RODENT OR INSECT OUTER OPEN... 41.729312 25914 4 34. FLOORS: CONSTRUCTED PER CODE, CLEANED, GOO... 41.779920 25927 4 34. FLOORS: CONSTRUCTED PER CODE, CLEANED, GOO... 41.750192 25981 4 36. LIGHTING: REQUIRED MINIMUM FOOT-CANDLES OF... 41.808684 26017 4 33. FOOD AND NON-FOOD CONTACT EQUIPMENT UTENSI... 41.856163 26038 4 32. FOOD AND NON-FOOD CONTACT SURFACES PROPERL... 41.916820 26078 4 18. NO EVIDENCE OF RODENT OR INSECT OUTER OPEN... 41.953826 26355 4 18. NO EVIDENCE OF RODENT OR INSECT OUTER OPEN... 41.722390 26382 4 32. FOOD AND NON-FOOD CONTACT SURFACES PROPERL... 41.746413 26453 4 32. FOOD AND NON-FOOD CONTACT SURFACES PROPERL... 41.924918 26461 4 32. FOOD AND NON-FOOD CONTACT SURFACES PROPERL... 41.808966 26476 4 34. FLOORS: CONSTRUCTED PER CODE, CLEANED, GOO... 41.876353 26517 4 33. FOOD AND NON-FOOD CONTACT EQUIPMENT UTENSI... 41.949969 26542 4 2. FACILITIES TO MAINTAIN PROPER TEMPERATURE -... 41.953914 26611 4 19. OUTSIDE GARBAGE WASTE GREASE AND STORAGE A... 41.751413 26639 4 32. FOOD AND NON-FOOD CONTACT SURFACES PROPERL... 41.954548 26642 4 10. SEWAGE AND WASTE WATER DISPOSAL, NO BACK S... 41.966063 26695 4 35. WALLS, CEILINGS, ATTACHED EQUIPMENT CONSTR... 41.891591 26707 4 33. FOOD AND NON-FOOD CONTACT EQUIPMENT UTENSI... 42.011458 26735 4 34. FLOORS: CONSTRUCTED PER CODE, CLEANED, GOO... 41.706268 26764 4 41. PREMISES MAINTAINED FREE OF LITTER, UNNECE... 41.911777 26768 4 34. FLOORS: CONSTRUCTED PER CODE, CLEANED, GOO... 41.878582 26784 4 18. NO EVIDENCE OF RODENT OR INSECT OUTER OPEN... 41.864720 26799 4 34. FLOORS: CONSTRUCTED PER CODE, CLEANED, GOO... 41.969904 26807 4 29. PREVIOUS MINOR VIOLATION(S) CORRECTED 7-42... 41.902429

Longitude Location 4 -87.660363 (41.939702878083544, -87.6603632122827) 32 -87.704168 (41.92485453942065, -87.7041675433878) 130 -87.611900 (41.707452567818045, -87.61190031411405) 166 -87.642935 (41.7687541393892, -87.64293494450921) 289 -87.681822 (41.91334246823248, -87.68182248081257) 327 -87.616069 (41.6852846288262, -87.61606883053516) 430 -87.612038 (41.77474041266132, -87.61203766276827) 437 -87.636347 (41.89645506344225, -87.63634743378289) 444 -87.615174 (41.73660345424306, -87.61517429063863) 451 -87.655854 (41.82809412610231, -87.65585369468056) 481 -87.646708 (41.865020208177455, -87.64670785662663)

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501 -87.721462 (41.89915058623179, -87.72146228597416) 547 -87.652036 (41.88712191392366, -87.6520357596219) 562 -87.672608 (42.00344265564368, -87.67260765651258) 671 -87.681392 (41.69457792595615, -87.68139221499295) 730 -87.619756 (41.765508831860295, -87.6197557421115) 773 -87.629074 (41.87510142157878, -87.62907407341153) 827 -87.671727 (41.88593098321254, -87.67172706620255) 829 -87.615113 (41.75143029426537, -87.61511273361538) 845 -87.727784 (41.96470447485827, -87.72778380262282) 923 -87.764708 (41.99743919113834, -87.76470781345472) 968 -87.702664 (41.764298991133856, -87.70266397899734) 983 -87.586350 (41.76132792132938, -87.58635037600584) 1046 -87.571243 (41.762677852195615, -87.57124316584647) 1052 -87.670826 (41.89081447511854, -87.67082589997464) 1064 -87.627767 (41.87524726840689, -87.62776718558034) 1077 -87.621802 (41.899936475960715, -87.62180244533546) 1093 -87.621802 (41.899936475960715, -87.62180244533546) 1112 -87.694138 (41.921076157561416, -87.69413785909323) 1126 -87.621802 (41.899936475960715, -87.62180244533546) ... ... ... 25361 -87.683475 (41.76784475060497, -87.68347478773265) 25550 -87.643309 (41.70680241420421, -87.64330932677154) 25573 -87.627509 (41.736380045588184, -87.62750921902564) 25662 -87.668698 (41.936595015315085, -87.66869807574504) 25688 -87.730046 (41.78230921732705, -87.73004617388257) 25709 -87.604500 (41.72931162911995, -87.60449954472107) 25914 -87.640926 (41.77992004734145, -87.64092551074862) 25927 -87.682997 (41.75019172792476, -87.68299672155908) 25981 -87.668096 (41.80868424799463, -87.66809645220071) 26017 -87.627313 (41.856163133092736, -87.62731274858525) 26038 -87.746439 (41.91682044375505, -87.74643855561376) 26078 -87.705512 (41.95382611483376, -87.70551205494066) 26355 -87.572879 (41.72239045369584, -87.57287918538222) 26382 -87.552646 (41.74641257248607, -87.55264648895961) 26453 -87.697354 (41.92491766672106, -87.69735362055471) 26461 -87.634352 (41.8089657832806, -87.63435165125277) 26476 -87.701225 (41.876353229136384, -87.70122482019289) 26517 -87.649021 (41.949969437633726, -87.64902099299884) 26542 -87.687729 (41.953913903217355, -87.68772890356797) 26611 -87.603825 (41.751412847208826, -87.60382478318215) 26639 -87.678619

(41.95454812137176, -87.67861945562349) 26642 -87.657734
(41.96606299325794, -87.65773412452839) 26695 -87.625867
(41.891590741083505, -87.62586713724458) 26707 -87.665572
(42.01145837809315, -87.66557227159977) 26735 -87.680975
(41.70626826171425, -87.68097505861364) 26764 -87.726246
(41.91177704142657, -87.72624572957979) 26768 -87.638579
(41.87858156072147, -87.6385786681057) 26784 -87.666481
(41.86471953736552, -87.66648084397798)

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26799 -87.659842 (41.96990416418005, -87.659841548588) 26807
-87.665254 (41.90242867361201, -87.66525448664798)

[617 rows x 17 columns]

In [31]:
```
ResultsB=ResultsA['Zip'].value_counts()
ResultsB.head(5)
```

Out[31]: 60618.0 33 60632.0 28 60623.0
22 60609.0 22 60629.0 19 Name: Zip,
dtype: int64

## 0.9 Requirement #7: Use K-MEANS algorithm to run TWO experiments to cluster the data into 4 clusters and 10 clusters with respect to the following Features: Zip code, Results, Risk. Comment on the quality of the resulting clusters

In [40]:
```
fig = plt.figure(figsize=(16, 12))
ax = fig.add_subplot(111, projection='3d')

kmeans = KMeans(4, random_state=0).fit_predict(X_scaled)


x_ax = np.array(X[:, 2]).flatten() y_ax =
np.array(X[:, 0]).flatten() z_ax =
np.array(X[:, 1]).flatten()


ax.scatter(x_ax, y_ax, z_ax, c=kmeans, marker='^')

ax.set_xlabel('Zip')
```

```
ax.set_ylabel('Risk')
ax.set_zlabel('Results')


plt.show()
```

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```
In [42]: fig = plt.figure(figsize=(16, 12))
```

```
ax = fig.add_subplot(111, projection='3d')

kmeans = KMeans(10, random_state=0).fit_predict(X_scaled)


x_ax = np.array(X[:, 2]).flatten() y_ax =
np.array(X[:, 0]).flatten() z_ax =
np.array(X[:, 1]).flatten()


ax.scatter(x_ax, y_ax, z_ax, c=kmeans, marker='^')

ax.set_xlabel('Zip')
ax.set_ylabel('Risk')
ax.set_zlabel('Results')


plt.show()
```

### 0.10 Requirement #8: What will be the best value(s) for K to use in the K-MEANS algorithm to cluster the data into K clusters with respect to the following Fea- tures: Results and Risk? Explain your answer for the value of K based on your experimental results.

```
In [ ]: K=2 because we have to use out minds eye to see what makes sense when you look at k=2 you see
            2 logical clusters restaraunts who are in similar zip coded and varying risk but have either fai
```

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