Chicago Crime Analysis

This problem deals with crime reporting data from Chicago. Your task is to download data about Crime Reports from the Chicago Open Data Portal and analyze it to better understand what type of crimes get reported in what (type of) neighborhoods.

1. Download reported crime data from the Chicago open data portal for 2017 and 2018.
2. Generate summary statistics for the crime reports data including but not limited to number of crimes of each type, how they change over time, and how they are different by neighborhood. Please use a combination of tables and graphs to present these summary stats.

Import Modules

In [1]:

```
import cenpy as c
import pandas as pd
pd.options.mode.chained_assignment = None
import geopandas as gpd
from shapely.geometry import Point
import seaborn as sns
import matplotlib
import matplotlib.pyplot as plt
import ml_functions as mlf
matplotlib.style.use("ggplot")
%matplotlib inline
```

Data Acquisition

In [2]:

```
# Get Chicago Crime data from 2017 - 2018
crime_df = mlf.get_chicago_crime_data("2017-01-01", "2018-12-31")
```

```
WARNING:root:Requests made without an app_token will be subject to s
trict throttling limits.
```

In [3]:

```
crime_df.head()
```

Out[3]:

	arrest	beat	block	case_number	community_area	date	descriptio
0	True	1034	026XX S CALIFORNIA BLVD	JA529032	30	2017-11-28T21:43:00.000	VIOLEN OFFENDEF ANNUAI REGISTRATIOI
1	True	1221	007XX N SACRAMENTO BLVD	JA545986	23	2017-12-11T19:15:00.000	ARMED HANDGUI
2	False	2222	092XX S RACINE AVE	JB147188	73	2017-10-08T03:00:00.000	NON AGGRAVATEI
3	False	0835	026XX W 79TH ST	JB147595	70	2017-03-28T14:00:00.000	UNLAWFUI ENTR
4	False	0313	060XX S EBERHART AVE	JB147230	42	2017-09-09T20:17:00.000	OVER $50

5 rows × 22 columns

In [4]:

```
crime_df.columns
```

Out[4]:

```
Index(['arrest', 'beat', 'block', 'case_number', 'community_area',
'date',
       'description', 'district', 'domestic', 'fbi_code', 'id', 'iuc
r',
       'latitude', 'location', 'location_description', 'longitude',
       'primary_type', 'updated_on', 'ward', 'x_coordinate', 'y_coor
dinate',
       'year'],
      dtype='object')
```

Data Preprocessing

In [5]:

```
# Drop all rows with NAs in Latitude and Longitude and fix the data type for cer
tain columns

crime_df = mlf.basic_crime_data_processing(crime_df)
```

In [6]:

```
#Create a Geopandas dataframe using Lat. and Lon. from crime_df: crime_gdf
crime_df["coordinates"] = list(zip(crime_df.longitude, crime_df.latitude))
crime_df["coordinates"] = crime_df["coordinates"].apply(Point)
crime_gdf = gpd.GeoDataFrame(crime_df, geometry="coordinates")
crime_gdf = crime_gdf[["date", "year", "community_area", "coordinates", "primary
_type"]]
crime_gdf.crs = {"init":"epsg:4326"}
```

In [7]:

```
crime_gdf.head()
```

Out[7]:

	date	year	community_area	coordinates	primary_type
0	2017-11-28 21:43:00	2017	30	POINT (-87.69463767800001 41.843778126)	OTHER OFFENSE
1	2017-12-11 19:15:00	2017	23	POINT (-87.702169158 41.894475919)	ROBBERY
5	2017-11-23 15:14:00	2017	38	POINT (-87.619098999 41.809342727)	ASSAULT
7	2018-02-04 01:36:00	2018	53	POINT (-87.645661144 41.68073915)	HOMICIDE
8	2018-01-08 06:50:00	2018	77	POINT (-87.659016317 41.99456734)	MOTOR VEHICLE THEFT

Generate summary statistics for the crime reports data including but not limited to number of crimes of each type, how they change over time, and how they are different by neighborhood. Please use a combination of tables and graphs to present these summary stats.

1. The number of crimes of each type:

In [8]:

```
type_cnt_df = crime_gdf.groupby(["primary_type", "year"]).size().to_frame("Coun
t")
type_cnt_df["Total"] = type_cnt_df.groupby(level=0)["Count"].transform("sum")
type_cnt_df = type_cnt_df.sort_values(["Total", "year"], ascending=False)
```

In [9]:

```
type_cnt_df
```

Out[9]:

		Count	Total
primary_type	**year**		
THEFT	**2018**	64025	127611
	2017	63586	127611
BATTERY	**2018**	49718	98855
	2017	49137	98855
CRIMINAL DAMAGE	**2018**	27700	56655
	2017	28955	56655
ASSAULT	**2018**	20341	39592
	2017	19251	39592
DECEPTIVE PRACTICE	**2018**	17862	35630
	2017	17768	35630
OTHER OFFENSE	**2018**	16969	33934
	2017	16965	33934
BURGLARY	**2018**	11687	24633
	2017	12946	24633
NARCOTICS	**2018**	12797	24272
	2017	11475	24272
ROBBERY	**2018**	9679	21548
	2017	11869	21548
MOTOR VEHICLE THEFT	**2018**	9964	21331
	2017	11367	21331
CRIMINAL TRESPASS	**2018**	6881	13680
	2017	6799	13680
WEAPONS VIOLATION	**2018**	5444	10126
	2017	4682	10126
OFFENSE INVOLVING CHILDREN	**2018**	2174	4318
	2017	2144	4318
CRIM SEXUAL ASSAULT	**2018**	1589	3130
	2017	1541	3130
PUBLIC PEACE VIOLATION	**2018**	1362	2858
	2017	1496	2858
...	**...**	...	...
PROSTITUTION	**2018**	717	1451
	2017	734	1451
HOMICIDE	**2018**	586	1262
	2017	676	1262

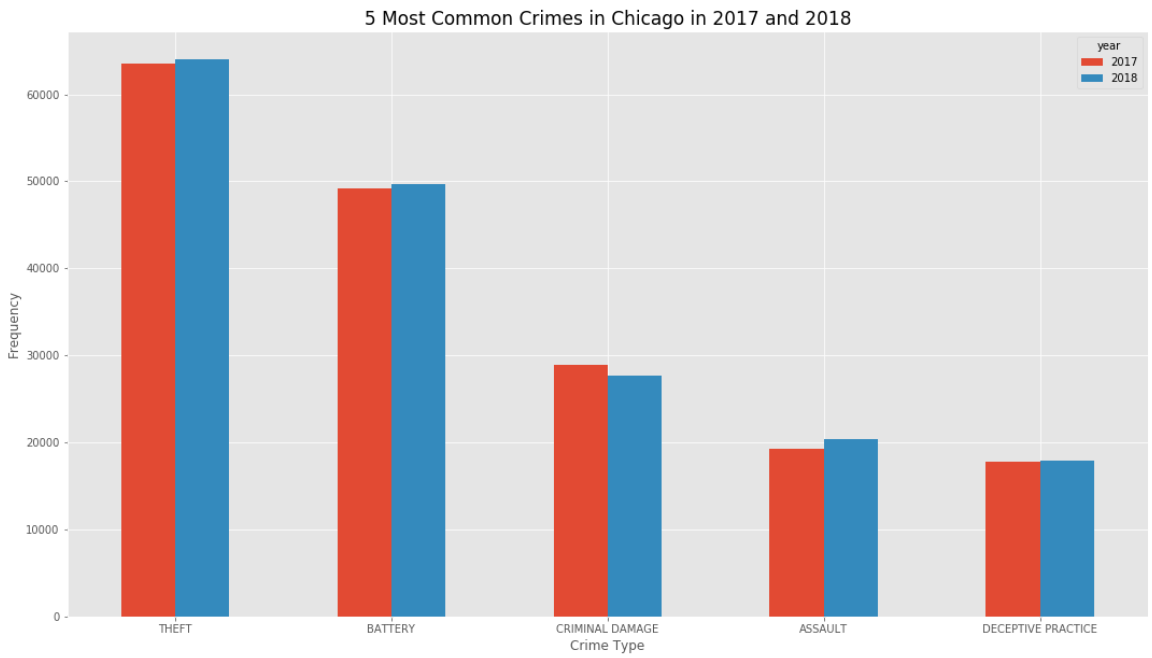
primary_type	year	Count	Total
ARSON	2018	372	816
	2017	444	816
LIQUOR LAW VIOLATION	2018	265	456
	2017	191	456
GAMBLING	2018	201	392
	2017	191	392
STALKING	2018	201	385
	2017	184	385
KIDNAPPING	2018	169	359
	2017	190	359
INTIMIDATION	2018	166	316
	2017	150	316
CONCEALED CARRY LICENSE VIOLATION	2018	148	217
	2017	69	217
OBSCENITY	2018	86	166
	2017	80	166
NON-CRIMINAL	2018	37	74
	2017	37	74
PUBLIC INDECENCY	2018	14	24
	2017	10	24
HUMAN TRAFFICKING	2018	14	22
	2017	8	22
OTHER NARCOTIC VIOLATION	2018	1	12
	2017	11	12
NON-CRIMINAL (SUBJECT SPECIFIED)	2018	3	5
	2017	2	5

64 rows × 2 columns

In [10]:

```
# 5 Most Common Crimes in Chicago

type_cnt_df[:10].Count.unstack().plot.bar(stacked=False, figsize=(18,10), rot=0)
plt.title("5 Most Common Crimes in Chicago in 2017 and 2018", fontsize=17)
plt.xlabel("Crime Type")
plt.ylabel("Frequency")
plt.show()
```



2. How these crimes change over time:

In [11]:

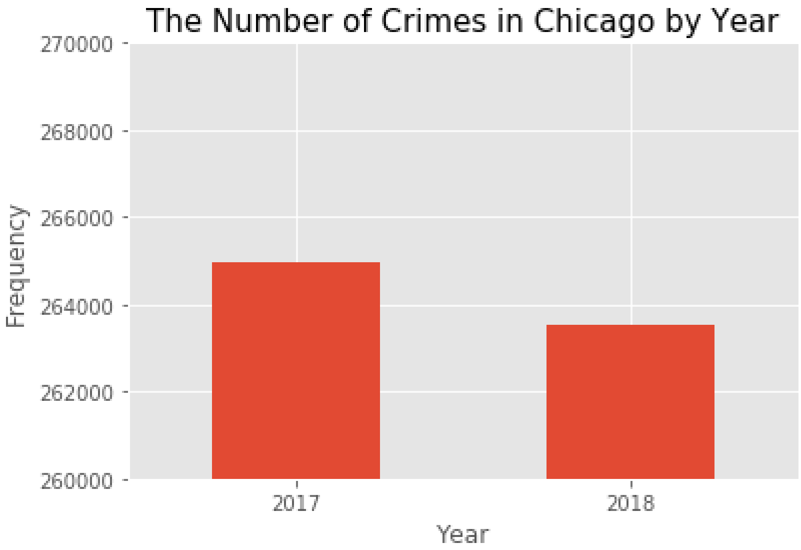
```
year_df = crime_df.groupby(["year"]).size().to_frame("Count")
year_df
```

Out[11]:

year	Count
2017	264980
2018	263538

In [12]:

```
year_df.plot(kind="bar", legend=False, rot=0, ylim=(260000, 270000))
plt.title("The Number of Crimes in Chicago by Year", fontsize=15)
plt.xlabel("Year")
plt.ylabel("Frequency")
plt.show()
```



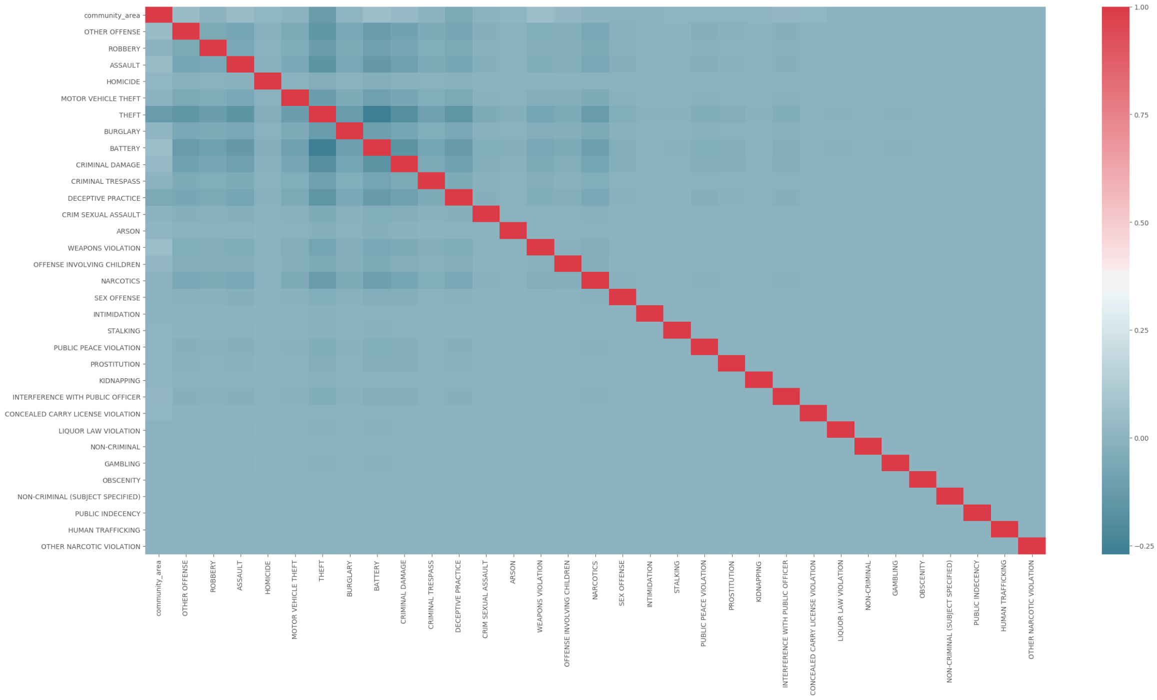
3. How these crimes are different by neighborhood:

In [13]:

```
neighbor_df = pd.concat([crime_df, pd.get_dummies(crime_df["primary_type"])], ax
is=1)
variable_list = ["community_area"] + list(neighbor_df["primary_type"].unique())
```

In [14]:

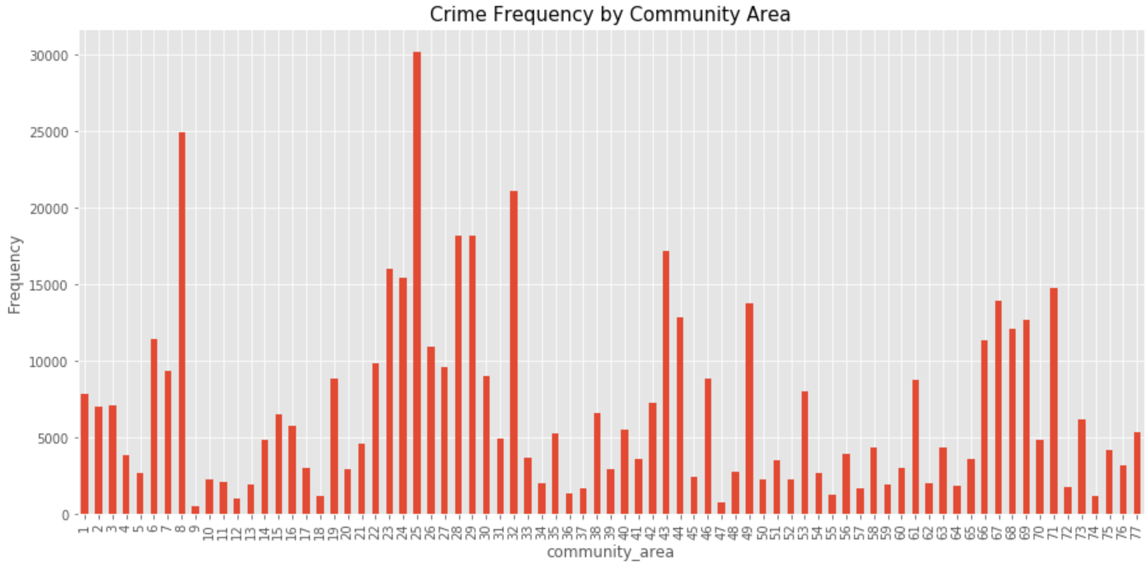
```
# Create a correlation heatmap between different crime types and community area.
corr = neighbor_df[variable_list].corr()
fig = plt.figure(figsize=(30, 15), dpi=100)
sns.heatmap(corr, fmt="g", cmap=sns.diverging_palette(220, 10, as_cmap=True))
plt.show()
```



From this heatmap, it seems like community area is positively correlated with most of crime types.

In [15]:

```
crime_df.groupby(["community_area"]).size().plot(kind="bar", figsize=(15, 7))
plt.title("Crime Frequency by Community Area", fontsize=15)
plt.xlabel("community_area")
plt.ylabel("Frequency")
plt.show()
```



Although there is no obvious pattern, some community areas definitely have more crimes than others, which supports the observation made from the heatmap.

Data Augmentation and APIs

All of the crime data you just analyzed have a block address and lat/long fields. The task now is to augment that data with American Community Survey data. For each crime report, use one of the census APIs to get some additional data (at least 3-4 useful variables) about the block or zipcode where the crime report came from. This could include information about demographics of the block or zipcode (race, income, family size, etc.).

Based on this augmented data, provide some descriptive statistics to describe:

1. What types of blocks have reports of “Battery”?
2. What types of blocks get “Homicide”?
3. Does that change over time in the data you collected?
4. What is the difference in blocks that get “Deceptive Practice” vs “Sex Offense”?

Using Cenpy, I will get access to ACS 5-Year Dataset.

In [16]:

```
# 5-Year ACS Dataset for 2017
dataset = "ACSDT5Y2017"
c.explorer.explain(dataset)
```

Out[16]:

```
{'ACS 5-Year Detailed Tables': 'The American Community Survey (ACS)
is an ongoing survey that provides data every year -- giving communi
ties the current information they need to plan investments and servi
ces. The ACS covers a broad range of topics about social, economic,
demographic, and housing characteristics of the U.S. population.  Su
mmary files include the following geographies: nation, all states (i
ncluding DC and Puerto Rico), all metropolitan areas, all congressio
nal districts (114th congress), all counties, all places, and all tr
acts and block groups.  Summary files contain the most detailed cros
s-tabulations, many of which are published down to block groups. The
data are population and housing counts. There are over 64,000 variab
les in this dataset.'}
```

In [17]:

```
# Connect to the dataset
conn = c.base.Connection("ACSDT5Y2017")
conn
```

Out[17]:

```
Connection to ACS 5-Year Detailed Tables (ID: https://api.census.go
v/data/id/ACSDT5Y2017)
```

We will be augmenting the crime dataset with block group-level data with:

1. Median Household Income (B19013_001E)
2. Educational Attainment (B23006_001E, B23006_023E)
3. Race, specifically race other than White (B02001_001E, B02001_002E)
4. Citizenship (B05001_001E, B05001_006E)

In [18]:

```
# Querying for Dataset

variables = ["B19013_001E", "B02001_001E", "B02001_002E", "B05001_001E", "B05001_006E", "B23006_001E", "B23006_023E", "GEO_ID"]
geo_unit = "tract:*"
geo_filter = {"state": "17", "county": "031"}

acs_df = conn.query(variables, geo_unit=geo_unit, geo_filter=geo_filter)
acs_df.rename(columns={"B19013_001E":"Income", "B02001_001E":"Total_race", "B02001_002E": "White_alone", "B05001_001E": "Total_citizen", "B05001_006E": "Not_citizen", "B23006_001E": "Total_edu", "B23006_023E": "Bach_above"}, inplace=True)

# Drop median income below 0 and fix the data type

acs_df["Income"] = acs_df["Income"].astype(int)
acs_df["Total_race"] = acs_df["Total_race"].astype(int)
acs_df["White_alone"] = acs_df["White_alone"].astype(int)
acs_df["Total_citizen"] = acs_df["Total_citizen"].astype(int)
acs_df["Not_citizen"] = acs_df["Not_citizen"].astype(int)
acs_df["Total_edu"] = acs_df["Total_edu"].astype(int)
acs_df["Bach_above"] = acs_df["Bach_above"].astype(int)
acs_df = acs_df[acs_df.Income > 0]
```

In [19]:

```
acs_df.head()
```

Out[19]:

	Income	Total_race	White_alone	Total_citizen	Not_citizen	Total_edu	Bach_above	
0	84863	5541	5032	5541	126	3002	1059	1400
1	57045	1600	1094	1600	144	965	147	1400
2	44063	6464	2842	6464	2169	3122	91	1400
3	24972	2307	1255	2307	738	1084	40	1400
4	35016	3298	2012	3298	1132	1647	87	1400

Feature Engineering

In [20]:

```
# Create features using the dataset
acs_df["Race_other"] = (acs_df["Total_race"] - acs_df["White_alone"])/acs_df["Total_race"]
acs_df["Citizen"] = (acs_df["Total_citizen"] - acs_df["Not_citizen"])/acs_df["Total_citizen"]
acs_df["Low_edu"] = (acs_df["Total_edu"] - acs_df["Bach_above"])/acs_df["Total_edu"]

acs_df.head()
```

Out[20]:

	Income	Total_race	White_alone	Total_citizen	Not_citizen	Total_edu	Bach_above	
0	84863	5541	5032	5541	126	3002	1059	1400000(
1	57045	1600	1094	1600	144	965	147	1400000(
2	44063	6464	2842	6464	2169	3122	91	1400000(
3	24972	2307	1255	2307	738	1084	40	1400000(
4	35016	3298	2012	3298	1132	1647	87	1400000(

Since the Chicago Crime Dataset is based on blocks whereas the ACS dataset is based on block group, I need to spatial merge two datasets using the available spatial information.

In [21]:

```
conn.set_mapservice("tigerWMS_ACS2017")
acs_geodata = conn.mapservice.query(layer=8, where='STATE = 17')
acs_geodata = acs_geodata[["TRACT", "geometry"]]
acs_geodata.rename(columns={"TRACT": "tract"}, inplace=True)
```

In [22]:

```
acs_geodata.head()
```

Out[22]:

	tract	geometry
0	002000	POLYGON ((-9904428.386399999 4847994.095700003...
1	807700	POLYGON ((-9770208.138699999 5164415.615199998...
2	807900	POLYGON ((-9769643.860200001 5161260.4639, -97...
3	809000	POLYGON ((-9765776.843699999 5169287.108499996...
4	870100	POLYGON ((-10106515.007 4983976.344999999, -10...

In [23]:

```
# Merge acs_df and acs_geodata
merged_acs_df = pd.merge(acs_df, acs_geodata, on=["tract"])
```

However, because the spatial data for this merged dataset is in a different format as the Chicago Crime Dataset, I must first convert it before I can spatial join two datasets.

In [24]:

```
merged_acs_gdf = gpd.GeoDataFrame(merged_acs_df, geometry="geometry")
merged_acs_gdf.crs = {"init":"epsg:3395"}
merged_acs_gdf = merged_acs_gdf.to_crs({"init":"epsg:4326"})
```

In [25]:

```
# Spatial join Chicago Crime Dataset and ACS Dataset
crime_bg_df = gpd.sjoin(crime_gdf, merged_acs_gdf, op="within")
crime_bg_df = crime_bg_df.reset_index()
crime_bg_df = crime_bg_df[["date", "primary_type", "tract", "year", "Income", "R
ace_other", "Citizen", "Low_edu"]]
crime_bg_df = crime_bg_df.dropna()
crime_bg_df["Income"] = crime_bg_df["Income"].astype(int)
crime_bg_df["year"] = crime_bg_df["year"].astype(int)
crime_bg_df["tract"] = crime_bg_df["tract"].astype(int)
crime_bg_df["Race_other"] = crime_bg_df["Race_other"].astype(float)
crime_bg_df["Citizen"] = crime_bg_df["Citizen"].astype(float)
crime_bg_df["Low_edu"] = crime_bg_df["Low_edu"].astype(float)
```

In [26]:

```
crime_bg_df.head()
```

Out[26]:

	date	primary_type	tract	year	Income	Race_other	Citizen	Low_edu
0	2017-11-28 21:43:00	OTHER OFFENSE	823400	2017	47287	0.562338	0.922649	0.838395
1	2018-01-08 09:36:00	DECEPTIVE PRACTICE	823400	2018	47287	0.562338	0.922649	0.838395
2	2018-01-12 22:13:00	OTHER OFFENSE	823400	2018	47287	0.562338	0.922649	0.838395
3	2018-01-15 17:10:00	OTHER OFFENSE	823400	2018	47287	0.562338	0.922649	0.838395
4	2018-01-17 07:09:00	BATTERY	823400	2018	47287	0.562338	0.922649	0.838395

1. What types of blocks have reports of “Battery”?

2. What types of blocks get “Homicide”?

In [27]:

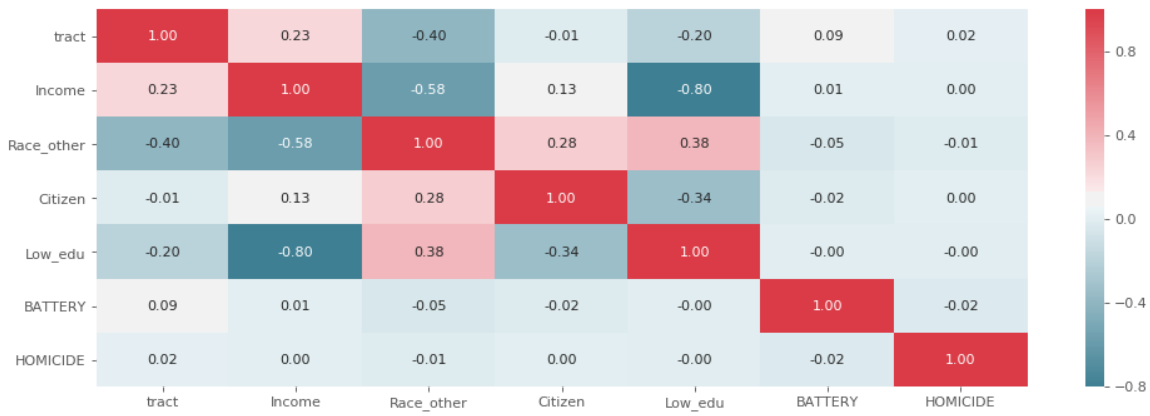
```
crime_bg_df.describe()
```

Out[27]:

	tract	year	Income	Race_other	Citizen	Low
count	523831.000000	523831.000000	523831.000000	523831.000000	523831.000000	523831.00
mean	764296.968616	2017.498636	50772.686408	0.597623	0.950486	0.76
std	105382.827386	0.499999	19816.264746	0.310104	0.062312	0.12
min	490600.000000	2017.000000	12660.000000	0.005914	0.609947	0.13
25%	730201.000000	2017.000000	36307.000000	0.319461	0.930352	0.70
50%	823302.000000	2017.000000	48391.000000	0.583236	0.972450	0.80
75%	827901.000000	2018.000000	61736.000000	0.907900	0.990907	0.85
max	842800.000000	2018.000000	202727.000000	1.000000	1.000000	0.98

In [28]:

```
## Create a correlation heatmap of various demographic features and "Battery"/"H
omicide"
corr_crime_df = pd.concat([crime_bg_df, pd.get_dummies(crime_bg_df["primary_typ
e"])], axis=1)
corr2 = corr_crime_df[["tract", "Income", "Race_other", "Citizen", "Low_edu", "B
ATTERY", "HOMICIDE"]].corr()
fig = plt.figure(figsize=(15, 5), dpi=80)
sns.heatmap(corr2, annot=True, fmt=".2f", cmap=sns.diverging_palette(220, 10, as
_cmap=True))
plt.show()
```

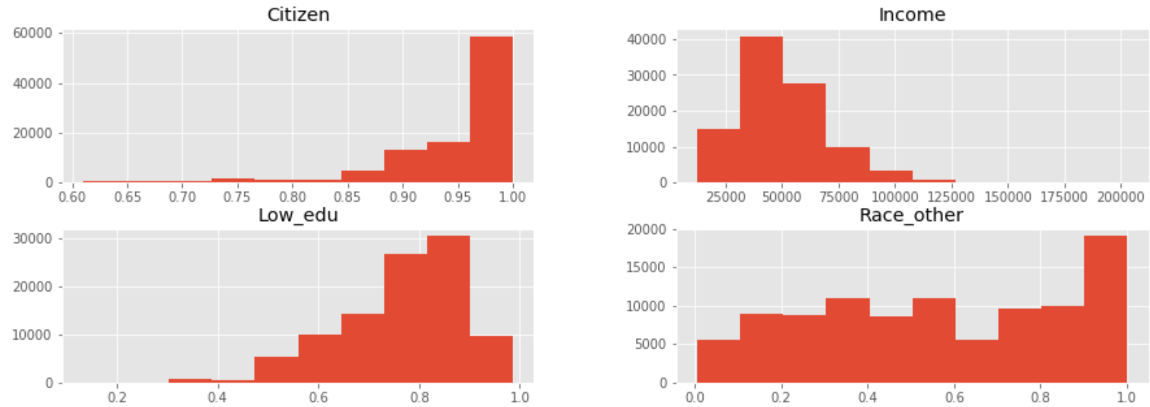


The correlation heatmap does not seem to add anything to our understanding of "Battery" and "Homicide."

Histograms of "Battery" for all demographical features:

In [29]:

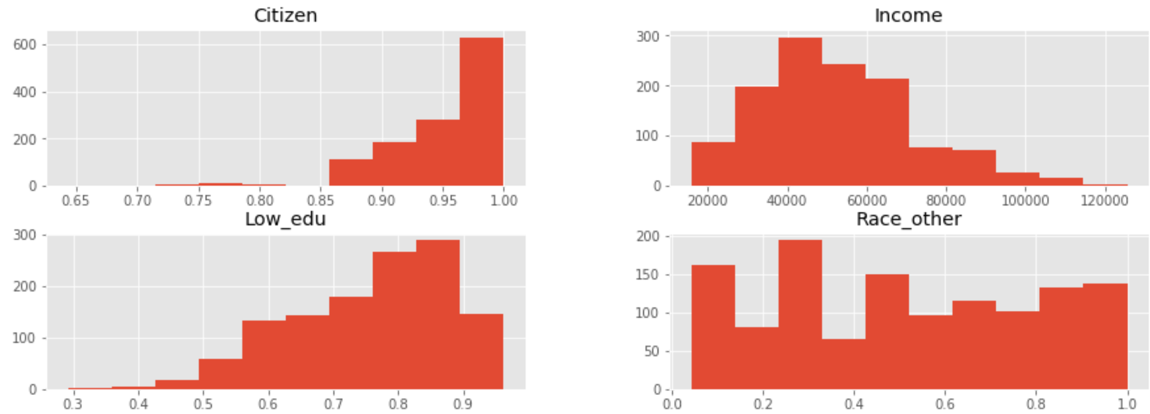
```
demo_feature_list = ["Citizen", "Income", "Race_other", "Low_edu"]
mlf.get_hist_for_features(crime_bg_df, "primary_type", "BATTERY", demo_feature_l
ist)
```



Similarly, here are histograms of "Homicide" for all demographical features:

In [30]:

```
mlf.get_hist_for_features(crime_bg_df, "primary_type", "HOMICIDE", demo_feature_
list)
```



It seems like tracts with:

1. higher proportion of US citizens,
2. low median income,
3. higher proportion of people with low education (without Bachelor's degree)

have higher incidents of both batteries and homicides.

As to the proportion of races other than White, however, the relationship is not so clear from the plot.

3. Does that change over time in the data you collected?

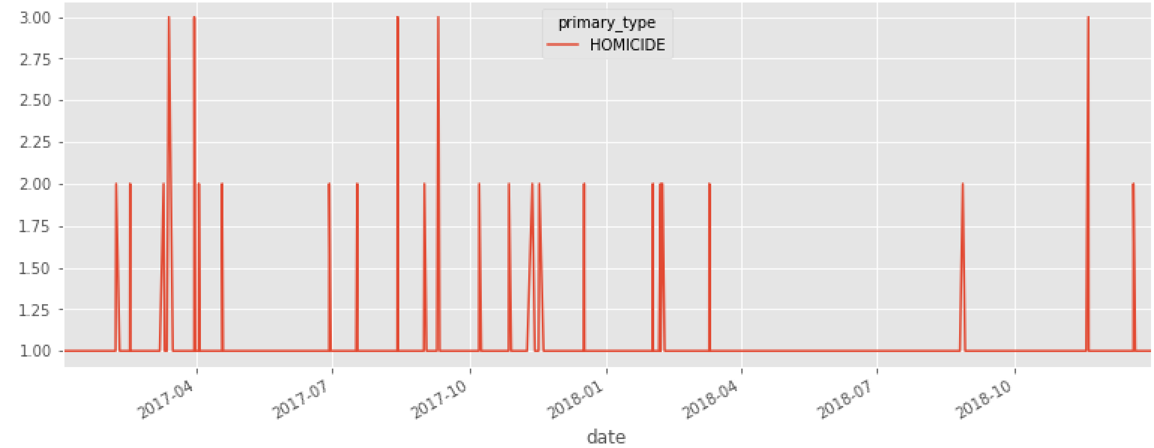
In [31]:

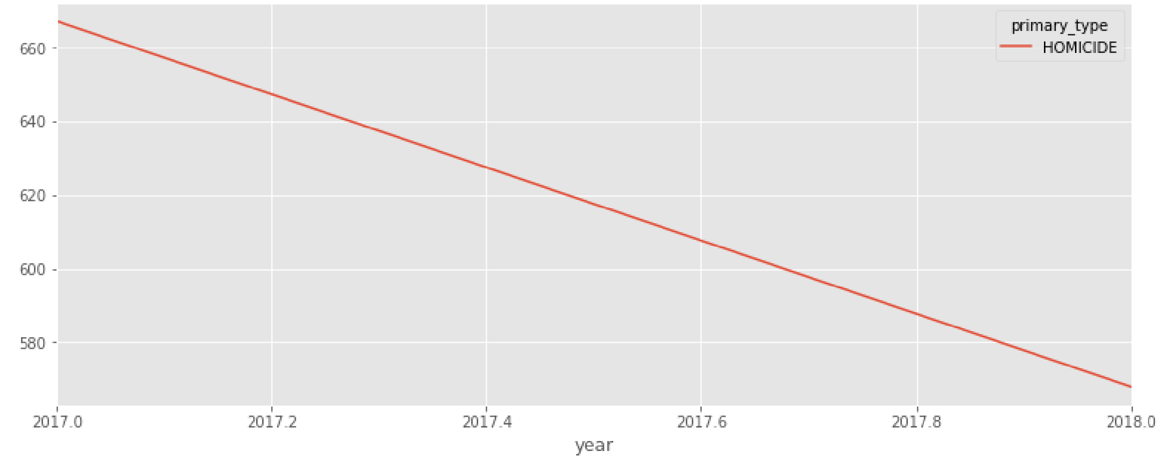
```
# create weekday column
crime_bg_df['weekday'] = crime_bg_df['date'].dt.dayofweek
```

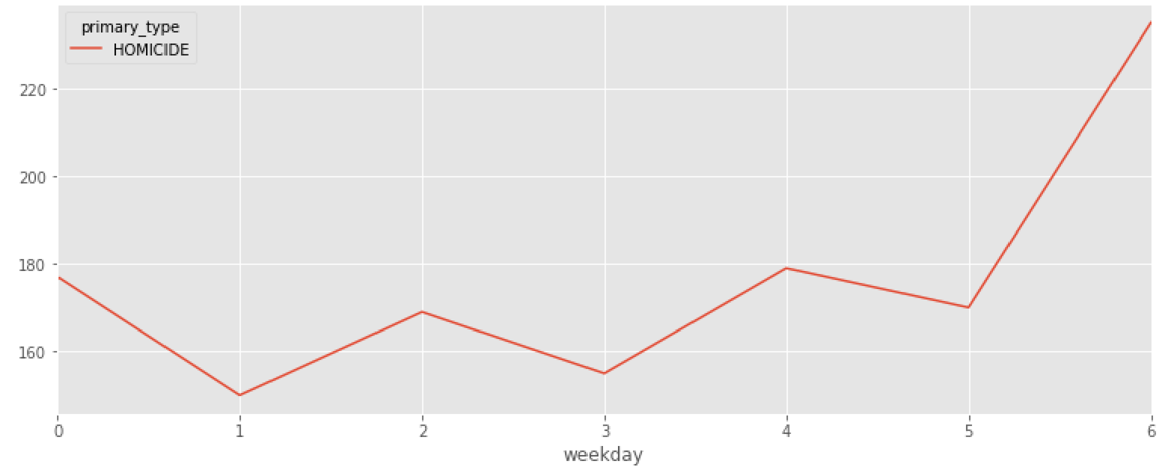
Here are some plots showing change over time (by *year* and *date*) for "Battery" and "Homicide."

In [32]:

```
# Get plots to show change over time
mlf.get_plots_by_time(crime_bg_df, "HOMICIDE")
```

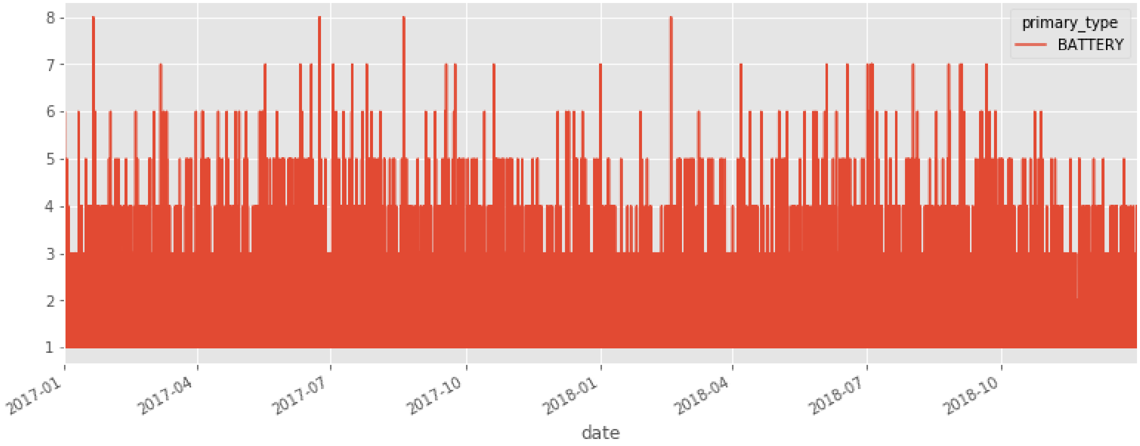


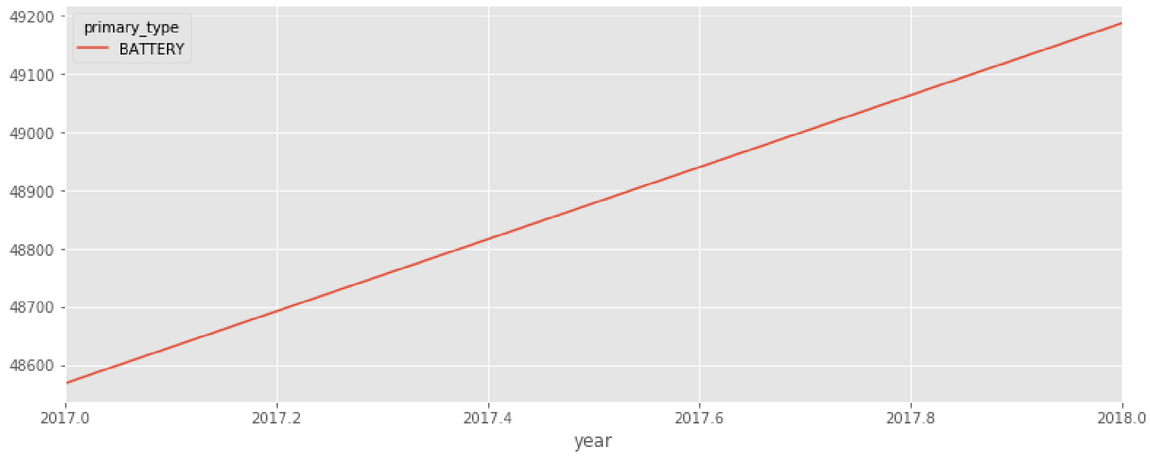


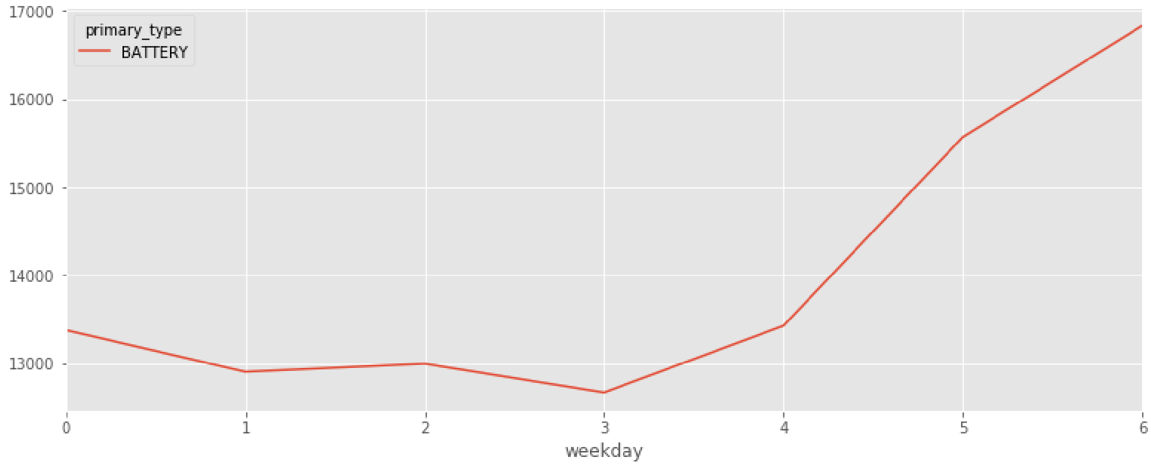


In [33]:

```
mlf.get_plots_by_time(crime_bg_df, "BATTERY")
```







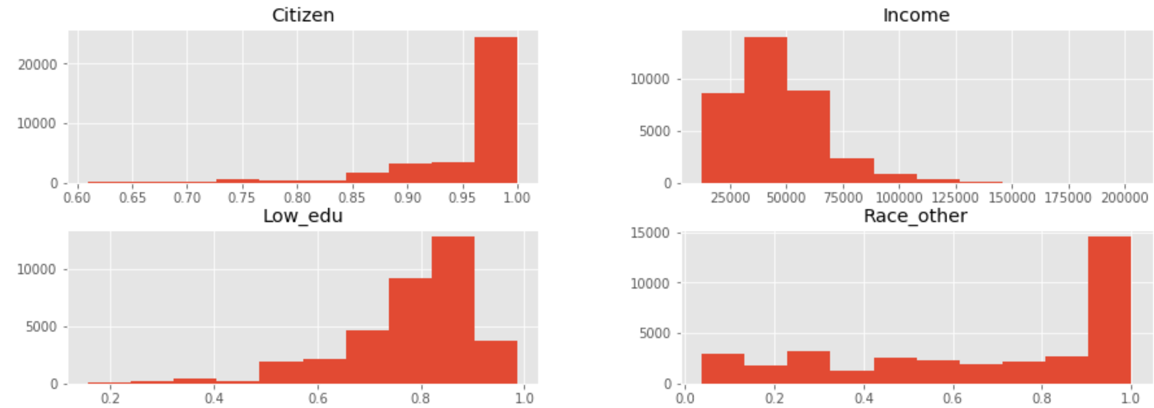
Considering the fact that batteries are more "common" crime than homicides, it makes sense to see more "spikes" for "Battery." From the data we have, it seems like "Battery" increased over the year while "Homicide" decreased.

Looking these two crimes as a weekly cycle, we see that these crimes occur more on weekends than weekdays.

4. What is the difference in blocks that get “Deceptive Practice” vs “Sex Offense”?

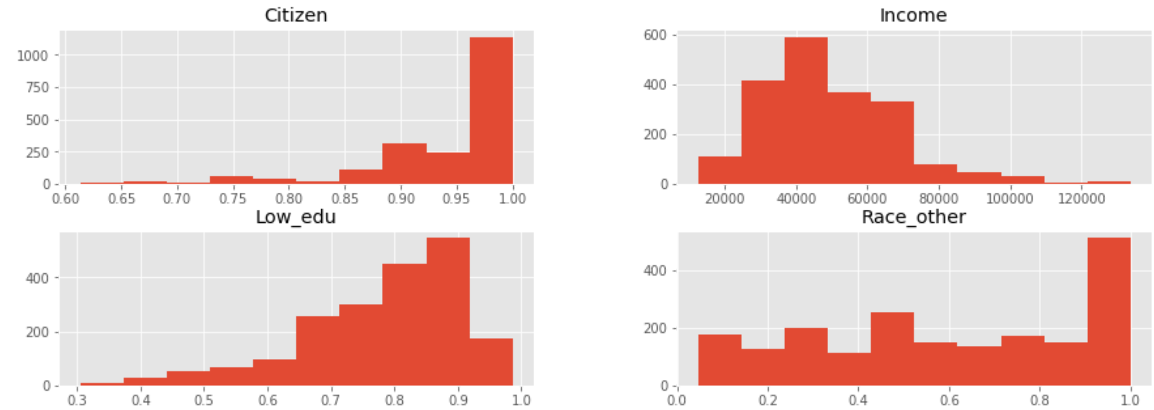
In [34]:

```
# DECEPTIVE PRACTICE
mlf.get_hist_for_features(crime_bg_df, "primary_type", "DECEPTIVE PRACTICE", dem
o_feature_list)
```



In [35]:

```
# SEX OFFENSE
mlf.get_hist_for_features(crime_bg_df, "primary_type", "SEX OFFENSE", demo_featu
re_list)
```



For both **deceptive practice** and **sex offense**, we see similar patterns as we have previously seen with **battery** and **homicide**.

There are more **deceptive practices** and **sex offenses** in tracts with:

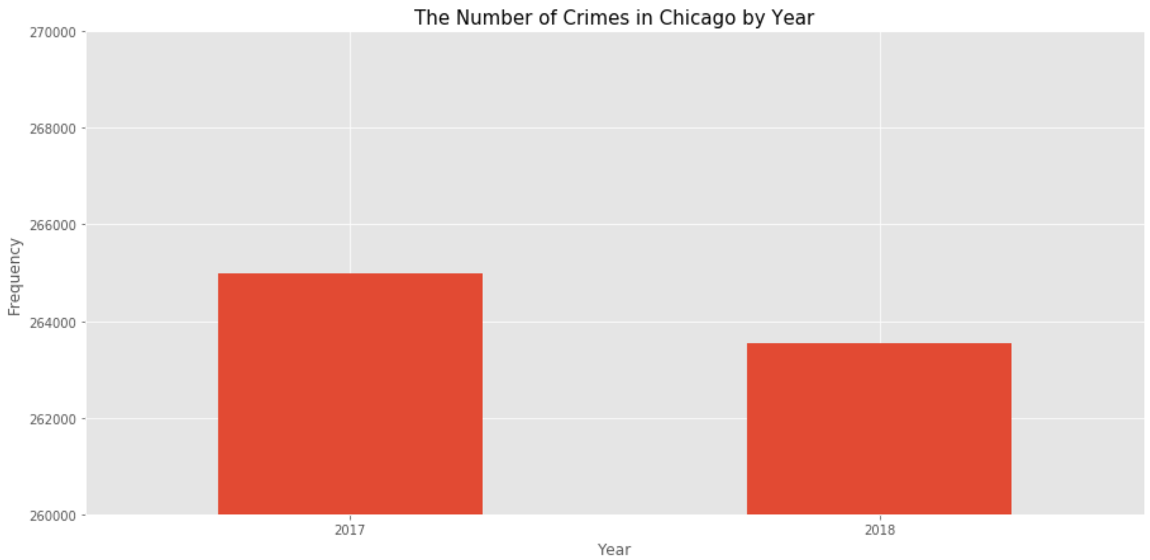
1. Higher proportion of US citizens,
2. Lower median income,
3. Lower educational attainment,
4. Higher proportion of races other than White.

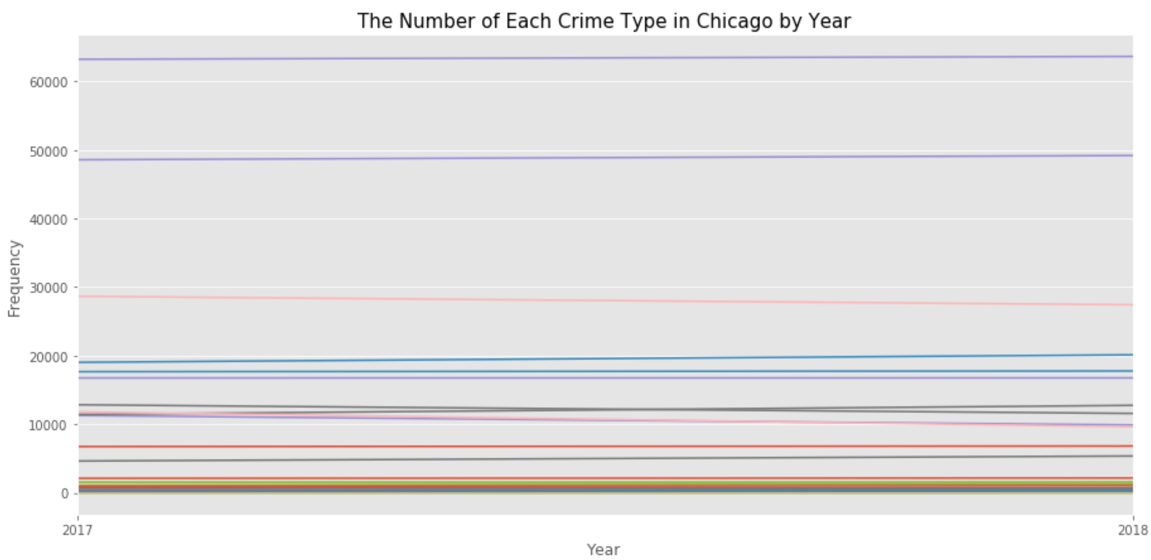
Analysis and Communication

1. Describe how crime has changed in Chicago from 2017 to 2018?

In [36]:

```
year_df.plot(kind="bar", legend=False, rot=0, ylim=(260000, 270000), figsize=(15
,7))
plt.title("The Number of Crimes in Chicago by Year", fontsize=15)
plt.xlabel("Year")
plt.ylabel("Frequency")
crime_bg_df.groupby(['year', 'primary_type']).size().unstack().plot(figsize=(15,
7), legend=False, xticks=range(2017, 2019))
plt.title("The Number of Each Crime Type in Chicago by Year", fontsize=15)
plt.xlabel("Year")
plt.ylabel("Frequency")
plt.show()
```





Although the overall number of crimes in Chicago decreased, there does not seem to be any radical change for each crime type.

2. One of the alderman candidates from recent elections has some crime statistics on his website: ***[https://www.ringer4results.com/node/8 (https://www.ringer4results.com/node/8)](https://www.ringer4results.com/node/8)***

First, we will only look at crimes reported between June 26th and July 26th of 2017 and 2018.

In [37]:

```
# Get Chicago Crime data from June 26th, 2017/2018 to July 26th, 2017/2018
crime_17_df = mlf.get_chicago_crime_data("2017-06-26", "2017-07-26")
crime_18_df = mlf.get_chicago_crime_data("2018-06-26", "2018-07-26")
```

```
WARNING:root:Requests made without an app_token will be subject to s
trict throttling limits.
WARNING:root:Requests made without an app_token will be subject to s
trict throttling limits.
```

In [38]:

```
# Basic crime data preprocessing

crime_17_df = mlf.basic_crime_data_processing(crime_17_df)
crime_18_df = mlf.basic_crime_data_processing(crime_18_df)
```

In [39]:

```
# Filter for the 43rd Ward
ward_43_17_df = crime_17_df[crime_17_df["ward"] == 43]
ward_43_18_df = crime_18_df[crime_18_df["ward"] == 43]
```

In [40]:

```
var_of_int = ["ROBBERY", "BATTERY", "BURGLARY", "MOTOR VEHICLE THEFT"]

ward_43_17_df = ward_43_17_df.loc[ward_43_17_df["primary_type"].isin(var_of_int
)]
ward_43_18_df = ward_43_18_df.loc[ward_43_18_df["primary_type"].isin(var_of_int
)]
```

In [41]:

```
ward_43_17 = ward_43_17_df["primary_type"].value_counts()
ward_43_17
```

Out[41]:

```
BATTERY                41
ROBBERY                17
BURGLARY               16
MOTOR VEHICLE THEFT     6
Name: primary_type, dtype: int64
```

In [42]:

```
ward_43_18 = ward_43_18_df["primary_type"].value_counts()
ward_43_18
```

Out[42]:

```
BATTERY                37
BURGLARY               14
ROBBERY                11
MOTOR VEHICLE THEFT    10
Name: primary_type, dtype: int64
```

As we can see, with the exception of motor vehicle theft, other three mentioned crimes have decreased over the same time-frame.

In fact, if we look at the percentage:

In [43]:

```
for var in var_of_int:
    print("{} in 2018: {}% of that in 2017".format(var, str(round((ward_43_18[va
r] / ward_43_17[var])*100, 2))))
```

```
ROBBERY in 2018: 64.71% of that in 2017
BATTERY in 2018: 90.24% of that in 2017
BURGLARY in 2018: 87.5% of that in 2017
MOTOR VEHICLE THEFT in 2018: 166.67% of that in 2017
```

Based on the data we have, we cannot accept the statistics of this alderman candidate.

Furthermore, even if the numbers are correct, the conclusions may be misleading given the low number of crimes in his ward since a slight increase in the number of crimes will show a huge increase in percentages.

3. As you know, there will be a new mayor in Chicago very soon. Based on these summary statistics, provide 5 key findings to the new mayor's office about crime in Chicago and what they should focus on in order to deal with crime in Chicago.

4. What are some of the key caveats of your recommendations and limitations of the analysis that you just did?

In [44]:

```
crime_17 = crime_17_df["primary_type"].value_counts()
crime_18 = crime_18_df["primary_type"].value_counts()
crime_17_set = set(crime_17_df["primary_type"].unique())
crime_18_set = set(crime_18_df["primary_type"].unique())
crime_set = crime_17_set.intersection(crime_18_set)

for crime in crime_set:
    print("{} in 2018: {}% of that in 2017".format(crime, str(round((crime_18[cr
ime] / crime_17[crime])*100, 2))))
```

```
BATTERY in 2018: 106.61% of that in 2017
SEX OFFENSE in 2018: 85.57% of that in 2017
STALKING in 2018: 121.05% of that in 2017
HOMICIDE in 2018: 70.73% of that in 2017
CONCEALED CARRY LICENSE VIOLATION in 2018: 260.0% of that in 2017
MOTOR VEHICLE THEFT in 2018: 83.67% of that in 2017
ASSAULT in 2018: 107.75% of that in 2017
BURGLARY in 2018: 94.73% of that in 2017
KIDNAPPING in 2018: 57.14% of that in 2017
CRIMINAL TRESPASS in 2018: 92.68% of that in 2017
PROSTITUTION in 2018: 60.87% of that in 2017
NARCOTICS in 2018: 112.12% of that in 2017
PUBLIC PEACE VIOLATION in 2018: 84.14% of that in 2017
OFFENSE INVOLVING CHILDREN in 2018: 113.38% of that in 2017
CRIMINAL DAMAGE in 2018: 100.19% of that in 2017
THEFT in 2018: 102.68% of that in 2017
INTERFERENCE WITH PUBLIC OFFICER in 2018: 116.07% of that in 2017
GAMBLING in 2018: 252.94% of that in 2017
INTIMIDATION in 2018: 133.33% of that in 2017
ROBBERY in 2018: 89.84% of that in 2017
WEAPONS VIOLATION in 2018: 106.29% of that in 2017
ARSON in 2018: 108.82% of that in 2017
CRIM SEXUAL ASSAULT in 2018: 114.93% of that in 2017
DECEPTIVE PRACTICE in 2018: 107.78% of that in 2017
OBSCENITY in 2018: 100.0% of that in 2017
NON-CRIMINAL in 2018: 133.33% of that in 2017
OTHER OFFENSE in 2018: 102.59% of that in 2017
LIQUOR LAW VIOLATION in 2018: 136.0% of that in 2017
```

Based on these summary statistics and the data exploration, several suggestions can be made:

1. Considering the fact that the overall number of crimes decreased over the year, they should maintain the current efforts to fight crimes in the city.
2. However, theft being one of the highest crimes committed in Chicago, they should look for ways to lower the number of thefts.
3. To further decrease the number of crimes, they should focus more of their efforts in fighting crimes on Fridays and Weekends,
4. They can focus on coming up with specific measures for few specific crime types such as gambling and concealed carry license violation, which increased most radically over the year.
5. Consistent with the existing literature on socioeconomic status and crimes, neighborhoods with low education and low income are still vulnerable to crimes. In the short term, more police patrols on these neighborhoods could lower the number of crimes. However, as a long-term strategy, they should think about a way to increase education and income in those neighborhoods.

Some of the key caveats and limitations of the analysis are:

1. Because we did not run any statisical tests on the data, we cannot be sure whether the difference we see between 2017 and 2018 is statiscally and economically meaningful. It is very much possible that nothing really changed despite the slight decrease in number of crimes.
2. Furthermore, for the convenience of the analysis, we excluded all data entries with empty latitude or longitude information. If there are some patterns in the missing data, this analysis would not be able to catch such patterns.

Question 3

Assume you are running the 911 call center for Chicago. You get a call from someone at 2111 S Michigan Ave

1. Of the types of crimes you have data for, which crime type is the most likely given the call came from 2111 S Michigan Ave? What are the probabilities for each type of request?

A call from 2111 S Michigan Ave will be recorded as "021XX S MICHIGAN AVE" for "block" in our dataset.

Therefore, we should look at the data where "block" == "021XX S MICHIGAN AVE".

In [45]:

```
ma_crime_df = crime_df[crime_df["block"] == "021XX S MICHIGAN AVE"]
ma_crime_list = list(ma_crime_df["primary_type"].unique())
total_crime = ma_crime_df["primary_type"].count()
ma_crime = ma_crime_df["primary_type"].value_counts()
```

Battery is most likely given the call came from 2111 S Michigan Avenue. Below are the probabilities for each type of crimes reported in 21XX S Michigan Avenue.

In [46]:

```
for crime in ma_crime_list:
    print("{}: {}".format(crime, str(round(ma_crime[crime] / total_crime, 2))))
```

```
DECEPTIVE PRACTICE: 0.1
ROBBERY: 0.03
BATTERY: 0.27
ASSAULT: 0.1
THEFT: 0.1
OTHER OFFENSE: 0.2
BURGLARY: 0.02
CRIMINAL DAMAGE: 0.1
CRIMINAL TRESPASS: 0.02
PUBLIC PEACE VIOLATION: 0.02
MOTOR VEHICLE THEFT: 0.03
```

2. Let's now assume that a call comes in about Theft. Which is more likely – that the call came from Garfield Park or Uptown? How much more or less likely is it to be from Garfield Park vs Uptown?

Because both **Garfield Park** and **Uptown** are Neighborhood-level labels, we will download the neighborhood spatial data from the Chicago Data Portal that we can spatial join to our crime dataset.

In [47]:

```
neighbor_url = "https://data.cityofchicago.org/api/geospatial/bbvz-uum9?method=e
xport&format=GeoJSON"

neighbor_gdf = mlf.get_gdf_from_geojson(neighbor_url)
neighbor_gdf = neighbor_gdf[["pri_neigh", "geometry"]]
neighbor_gdf = neighbor_gdf.rename(columns={"pri_neigh": "neighborhood"})
neighbor_gdf.crs = {"init":"epsg:4326"}
```

In [48]:

```
neighbor_gdf.head()
```

Out[48]:

	neighborhood	geometry
0	Grand Boulevard	(POLYGON ((-87.60670812560372 41.8168137713739...
1	Printers Row	(POLYGON ((-87.62760697485348 41.8743709778537...
2	United Center	(POLYGON ((-87.66706868914602 41.8888518776954...
3	Sheffield & DePaul	(POLYGON ((-87.65833494805533 41.9216614422918...
4	Humboldt Park	(POLYGON ((-87.74059567509266 41.8878231689323...

In [49]:

```
crime_neighbor_df = gpd.sjoin(crime_gdf, neighbor_gdf, op="within")
```

In [50]:

```
# Simple Data Preprocessing
crime_neighbor_df = crime_neighbor_df.reset_index()[["date", "primary_type", "ne
ighborhood"]]
total_theft = crime_neighbor_df[crime_neighbor_df["primary_type"] == "THEFT"].sh
ape[0]
gp_theft = crime_neighbor_df[(crime_neighbor_df["neighborhood"] == "Garfield Par
k") & (crime_neighbor_df["primary_type"] == "THEFT")].shape[0]
up_theft = crime_neighbor_df[(crime_neighbor_df["neighborhood"] == "Uptown") & (
crime_neighbor_df["primary_type"] == "THEFT")].shape[0]
```

In [51]:

```
print("Given that a call came in about theft:")
for number, neighborhood in [(gp_theft, "Garfield Park"), (up_theft, "Uptown")]:
    print("The likelihood that the call came from {} is {}".format(neighborhood,
str(round(number / total_theft, 5))))
```

```
Given that a call came in about theft:
The likelihood that the call came from Garfield Park is 0.01962
The likelihood that the call came from Uptown is 0.01539
```

Therefore, it is more likely that the call came from Garfield Park than from Uptown by approximately 0.004.