### PROJECT BRIEF

Crime in Chicago has been worrisome to the Chicago PD. Reported crimes have been tracked on a daily basis since 2001 and have been provided in the project data file. The Chicago PD would like to drastically reduce the spate of violent crimes reported in the city. Being effective involves knowing crime patterns and where they are likely to occur. It also involves equipping the Police Department appropriately. They have recruited you to conduct full data analytics and uncover insights from the data that can be used to effectively prepare for and respond to crimes. They are interested in gleaning any insights that can help them determine What type of crimes to prepare for, Where these crimes are most likely to occur, What days of the week and periods to expect these crimes

# **Data Exploration**

pd.set\_option('display.max\_columns', None)

13]:	Unname	ed: 0	ID	Case Number	Date	Block	IUCR	Primary Type	Description	Location Description	Arrest	Domestic	Beat	District	Ward	Con
	0	0	6407111	HP485721	07/26/2008 02:30:00 PM	085XX S MUSKEGON AVE	1320	CRIMINAL DAMAGE	TO VEHICLE	STREET	False	False	423	4.0	10.0	
	1	1	11398199	JB372830	07/31/2018 10:57:00 AM	092XX S ELLIS AVE	143C	WEAPONS VIOLATION	UNLAWFUL POSS AMMUNITION	POOL ROOM	True	False	413	4.0	8.0	
	2	2	5488785	HN308568	04/27/2007 10:30:00 AM	062XX N TRIPP AVE	0610	BURGLARY	FORCIBLE ENTRY	RESIDENCE	True	False	1711	17.0	39.0	
	3	3	11389116	JB361368	07/23/2018 08:55:00 AM	0000X N KEELER AVE	0560	ASSAULT	SIMPLE	NURSING HOME/RETIREMENT HOME	False	False	1115	11.0	28.0	
	4	4	12420431	JE297624	07/11/2021 06:40:00 AM	016XX W HARRISON ST	051A	ASSAULT	AGGRAVATED - HANDGUN	PARKING LOT / GARAGE (NON RESIDENTIAL)	False	False	1231	12.0	27.0	
	4															

```
RangeIndex: 2278726 entries, 0 to 2278725
                              Data columns (total 23 columns):
                                 #
                                          Column
                                                                                              Dtype
                                0
                                          Unnamed: 0
                                                                                              int64
                                 1
                                          TD
                                                                                               int64
                                 2
                                          Case Number
                                                                                               object
                                 3
                                                                                              object
                                          Date
                                 4
                                          Block
                                                                                               object
                                 5
                                          IUCR
                                                                                               object
                                 6
                                          Primary Type
                                                                                               object
                                 7
                                          Description
                                                                                              object
                                 8
                                          Location Description
                                                                                              object
                                 9
                                          Arrest
                                                                                               bool
                                 10
                                          Domestic
                                                                                               bool
                                 11
                                          Beat
                                                                                               int64
                                                                                               float64
                                 12
                                          District
                                                                                               float64
                                 13
                                          Ward
                                          Community Area
                                                                                               float64
                                 14
                                          FBI Code
                                                                                               object
                                          X Coordinate
                                                                                               float64
                                 16
                                 17
                                          Y Coordinate
                                                                                               float64
                                                                                               int64
                                 18
                                          Year
                                 19
                                          Updated On
                                                                                               object
                                 20
                                          Latitude
                                                                                               float64
                                 21
                                          Longitude
                                                                                               float64
                                        Location
                                                                                              object
                               dtypes: bool(2), float64(7), int64(4), object(10)
                              memory usage: 369.4+ MB
                      The data comprises of types such as Strings, Integers, Booleans and Floats.
In [15]:
                             #checking the shape of the data
                              crime_data.shape
        Out[15]: (2278726, 23)
In [16]:
                       crime_data.isna().sum()
        Out[16]: Unnamed: 0
                                                                                                   0
                              ID
                               Case Number
                                                                                                   1
                              Date
                                                                                                   0
                              Block
                                                                                                   0
                              IUCR
                                                                                                   0
                              Primary Type
                              Description
                                                                                                   0
                              Location Description
                                                                                            2877
                              Arrest
                                                                                                   a
                              Domestic
                                                                                                   0
                              Beat
                                                                                                   a
                              District
                                                                                                 12
                                                                                        184695
                              Ward
                              Community Area
                                                                                        184267
                              FBI Code
                                                                                                   0
                              X Coordinate
                                                                                          23985
                               Y Coordinate
                                                                                          23985
                              Year
                                                                                                   0
In [17]: ▶ #descritptive statistics of data
                              crime_data.describe()
        Out[17]:
                                                                                                                                                                                           Community
                                                 Unnamed: 0
                                                                                             ID
                                                                                                                     Beat
                                                                                                                                           District
                                                                                                                                                                          Ward
                                                                                                                                                                                                                  X Coordinate Y Coordinate
                                                                                                                                                                                                                                                                                         Year
                                                                                                                                                                                                                                                                                                              Latitude
                                                                                                                                                                                                                                                                                                                                       Long
                                                                                                                                                                                                      Area
                                             2.278726e+06 2.278726e+06 2.278726e+06 2.278714e+06 2.094031e+06
                                                                                                                                                                                                                 2.254741e+06 2.254741e+06 2.278726e+06 2.254741e+06
                                 count
                                                                                                                                                                                      2.094459e+06
                                              1.139362e+06 6.882068e+06 1.186442e+03 1.129072e+01 2.272764e+01
                                                                                                                                                                                     3.752140e+01 1.164569e+06
                                                                                                                                                                                                                                            1.885747e+06 2.009638e+03 4.184209e+01
                                                                                                                                                                                                                                                                                                                                -8.767161
                                     std
                                              6.578117e + 05 \quad 3.419168e + 06 \quad 7.026836e + 02 \quad 6.946692e + 00 \quad 1.383464e + 01 \quad 2.153282e + 01 \quad 1.673955e + 04 \quad 3.209855e + 04 \quad 6.019724e + 00 \quad 1.019724e + 00 \quad 1.01
                                                                                                                                                                                                                                                                                                   8.830434e-02
                                                                                                                                                                                                                                                                                                                                  6.073538
                                              0.000000e+00 6.370000e+02 1.110000e+02 1.000000e+00 1.000000e+00
                                                                                                                                                                                      0.000000e+00 0.000000e+00 0.000000e+00 2.001000e+03 3.661945e+01 -9.168657
                                    min
                                   25%
                                              5.696812e+05 3.716076e+06
                                                                                                   6.210000e+02 6.000000e+00
                                                                                                                                                          1.000000e+01
                                                                                                                                                                                      2.300000e+01
                                                                                                                                                                                                                  1.152948e+06
                                                                                                                                                                                                                                             1.859053e+06 2.004000e+03 4.176866e+01
                                                                                                                                                                                                                                                                                                                               -8.771379
                                                                                                                                                                                     3.200000e+01
                                                                                                   1.034000e+03 1.000000e+01 2.300000e+01
                                                                                                                                                                                                                  1.166060e+06
                                                                                                                                                                                                                                            1.890673e+06 2.009000e+03 4.185578e+01
                                              1.139362e+06 6.885990e+06
```

max 2.278725e+06 1.278199e+07 2.535000e+03 3.100000e+01 5.000000e+01 7.700000e+01 1.205119e+06 1.951622e+06 2.022000e+03 4.202291e+01 -8.752453

5.700000e+01 1.176365e+06 1.909219e+06 2.014000e+03 4.190668e+01

-8.762823

1.709044e+06 9.887568e+06 1.731000e+03 1.700000e+01 3.400000e+01

In [14]: #information about the data
crime\_data.info()

<class 'pandas.core.frame.DataFrame'>

```
df =crime_data.dropna( how='any',subset=['Location Description', 'District', 'Ward', 'Community Area', 'X Coordinate', 'Y Coordin
In [19]:
              #checking to confirm that all missing values have been dropped
               df.isna().sum()
    Out[19]: Unnamed: 0
                                           0
               ID
                                           0
                                           0
               Case Number
               Date
                                           0
               Block
                                           0
               IUCR
                                           0
               Primary Type
                                           0
               Description
                                           0
               Location Description
                                           0
               Arrest
               Domestic
                                           0
               Beat
                                           0
               District
                                           0
               Ward
                                           0
               Community Area
                                           0
               FBI Code
                                           0
               X Coordinate
                                           0
               Y Coordinate
                                           0
                                           0
               Year
               Updated On
                                           0
               Latitude
                                           0
               Longitude
                                           0
               Location
                                           0
               dtype: int64
In [20]: 🔰 #checking for percentage of data left after droping the missing values
               print(round(2070581/2278725 * 100,2), "percentage of the data has been retained.")
               90.87 percentage of the data has been retained.
           After dropping the missing values we are left with 91% of our data which is large enough to carry out the analysis. This was the rationale that guided my thought
           process. I also condsidered the fact that the features with the missing values were not paramount to my analysis.
In [21]:
               df.columns
    Out[21]: Index(['Unnamed: 0', 'ID', 'Case Number', 'Date', 'Block', 'IUCR',
                       'Primary Type', 'Description', 'Location Description', 'Arrest', 'Domestic', 'Beat', 'District', 'Ward', 'Community Area', 'FBI Code', 'X Coordinate', 'Y Coordinate', 'Year', 'Updated On', 'Latitude',
                      'Longitude', 'Location'], dtype='object')
            ▶ #creating a varaible to hold the numerical features
In [22]:
               ds = df[['Beat','District','Ward','Community Area', 'X Coordinate', 'Y Coordinate','Year','Latitude','Longitude']]
In [23]:
           #checking the distribution of the numreical features in the data
               plt.figure(figsize = (20, 10))
               for i in range (len(ds.columns)):
                   plt.subplot(3, 5, i+1)
                    sns.boxplot(x = ds.iloc[:, i])
                   plt.xlabel(ds.columns[i], size = 12)
                                                                     30
                                                                                          30
                    500 1000 1500 2000 2500
                                                             20
                                                                                      20
                                                                                               40
                                                      10
                                                                             ó
                                                                                 10
                                                                                                                             60
                                                                                                                                         0.00 0.25
                                                                                                                                                  0.50 0.75 1.00 1.25
                                                        District
                                                                                                                 Community Area
                           Beat
                                                                                       Ward
                                                                                                                                                 X Coordinate
                                                                                       39
                                                                                               41
                            1.0
                                  1.5
                                             2000
                                                  2005
                                                        2010
                                                            2015
                                                                   2020
                                                                                           40
                                                                                                                    -ġ0
                                                                                                                          -89
                        Y Coordinate
                                                          Year
                                                                                      Latitude
                                                                                                                    Longitude
```

In [18]: ▶ #dropping the missing values from the features

## **Univariate Aanalysis of the Data**

NON-CRIMINAL (SUBJECT SPECIFIED)
Name: Primary Type, dtype: int64

```
In [24]: ▶ #checking for unique types of crime
                df['Primary Type'].unique()
    Out[24]: array(['CRIMINAL DAMAGE', 'WEAPONS VIOLATION', 'BURGLARY', 'ASSAULT',
                         'ROBBERY', 'NARCOTICS', 'MOTOR VEHICLE THEFT', 'BATTERY',
                         'OTHER OFFENSE', 'PROSTITUTION', 'DECEPTIVE PRACTICE', 'THEFT', 'INTIMIDATION', 'INTERFERENCE WITH PUBLIC OFFICER',
                         'CRIMINAL TRESPASS', 'STALKING', 'OFFENSE INVOLVING CHILDREN', 'PUBLIC PEACE VIOLATION', 'CRIM SEXUAL ASSAULT', 'HOMICIDE', 'LIQUOR LAW VIOLATION', 'SEX OFFENSE', 'CRIMINAL SEXUAL ASSAULT', 'KIDNAPPING', 'ARSON', 'GAMBLING',
                         'CONCEALED CARRY LICENSE VIOLATION', 'PUBLIC INDECENCY',
                         'NON - CRIMINAL', 'OTHER NARCOTIC VIOLATION', 'HUMAN TRAFFICKING', 'NON-CRIMINAL', 'OBSCENITY', 'RITUALISM',
                         'NON-CRIMINAL (SUBJECT SPECIFIED)'], dtype=object)
In [25]: ▶ #count of the top ten crimes
                (df['Primary Type'].value_counts().head(10))
    Out[25]: THEFT
                                            436851
                BATTERY
                                            381760
                CRIMINAL DAMAGE
                                            237244
                NARCOTICS
                                            199506
                ASSAULT
                                            135223
                OTHER OFFENSE
                                            128772
                BURGLARY
                                            114981
                MOTOR VEHICLE THEFT
                                             95269
                DECEPTIVE PRACTICE
                                              87658
                ROBBERY
                                              78447
                Name: Primary Type, dtype: int64
In [26]: 

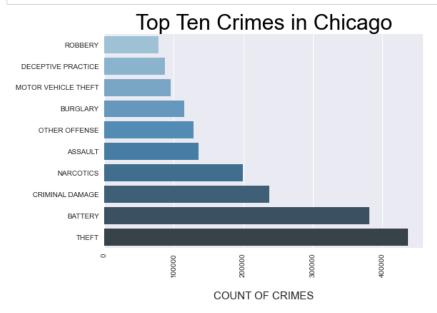
#CRIMES WITH LESS REPORTED CASES
                (df['Primary Type'].value_counts().tail(10))
    Out[26]: STALKING
                CONCEALED CARRY LICENSE VIOLATION
                                                               303
                OBSCENITY
                                                               203
                PUBLIC INDECENCY
                                                                56
                NON-CRIMINAL
                                                                44
                OTHER NARCOTIC VIOLATION
                                                                29
                HUMAN TRAFFICKING
                                                                28
                NON - CRIMINAL
                                                                12
                RITUALISM
```

```
In [27]: # Set the style of the plot first
plt.style.use('seaborn')

# Filter out the Top 10 crimes
top_5_crime = df['Primary Type'].value_counts().sort_values(ascending=False)[:10]

temp = df.groupby('Primary Type', as_index=False).agg({"ID": "count"})
temp = temp.sort_values(by=['ID'], ascending=False).head(10)
temp = temp.sort_values(by='ID', ascending=True)
sns.barplot(x='ID', y='Primary Type', data=temp, palette="Blues_d")

# Work on the aestehtic appeal of the plot
plt.title("Top Ten Crimes in Chicago", fontdict = {'fontsize': 30, 'fontname':'Arial', 'color': '#000000'})
plt.xlabel("'\nCOUNT OF CRIMES", fontdict = {'fontsize': 15})
plt.xticks(rotation=90)
plt.show()
```



76834

76732

76224

74582

FORCIBLE ENTRY

FROM BUILDING

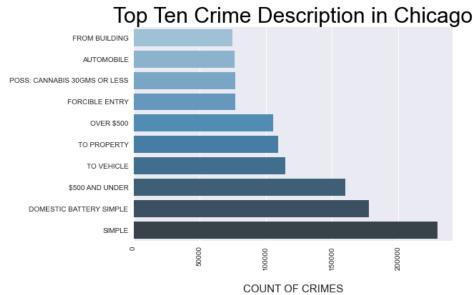
AUTOMOBILE

POSS: CANNABIS 30GMS OR LESS

Name: Description, dtype: int64

This chart shows the top "ten" most common types of crime with "THEFT" and "BATTERY" being he highest with a total case of 436,851 and 381,760 respectively

```
In [28]:
             #checking for unique descrptions of crime
                 df['Description'].unique()
    Out[28]: array(['TO VEHICLE', 'UNLAWFUL POSS AMMUNITION', 'FORCIBLE ENTRY',
                           'SIMPLE', 'AGGRAVATED - HANDGUN', 'STRONGARM - NO WEAPON',
                           'POSS: CANNABIS 30GMS OR LESS', 'AUTOMOBILE',
'MANU/DELIVER: HEROIN (WHITE)', 'DOMESTIC BATTERY SIMPLE',
                           'UNLAWFUL ENTRY', 'OBSCENE TELEPHONE CALLS',
                           'SOLICIT ON PUBLIC WAY', 'COUNTERFEITING DOCUMENT',
                           '$500 AND UNDER', 'POSS: CRACK', 'THEFT/RECOVERY: AUTOMOBILE', 'UNLAWFUL USE HANDGUN', 'FRAUD OR CONFIDENCE GAME',
                           'POCKET-PICKING', 'ILLEGAL USE CASH CARD', 'INTIMIDATION',
                           'TO PROPERTY', 'FROM BUILDING', 'AGGRAVATÉD: OTHER DANG WÉAPON', 'RECKLESS FIREARM DISCHARGE', 'POSS: HEROIN(WHITE)', 'OVER $500',
                           'AGGRAVATED: HANDGUN', 'TELEPHONE THREAT', 'ARMED: HANDGUN',
'OBSTRUCTING JUSTICE', 'TO LAND', 'HOME INVASION',
'AGGRAVATED: KNIFE/CUTTING INSTR', 'FINANCIAL ID THEFT: $300 &UNDER',
                           'HARASSMENT BY TELEPHONE', 'POSS: COCAINE', 'RETAIL THEFT', 'POSS: HEROIN(BRN/TAN)', 'FINANCIAL ID THEFT: OVER $300',
                           'OTHER OFFENSE', 'PRO EMP HANDS NO/MIN INJURY',
                           'OTHER VEHICLE OFFENSE'
                           'AGGRAVATED DOMESTIC BATTERY - OTHER DANGEROUS WEAPON',
In [29]: ▶ #Count of the types of crime descriptions
                 (df['Description'].value_counts().head(10))
    Out[29]: SIMPLE
                                                            229508
                 DOMESTIC BATTERY SIMPLE
                                                            177932
                 $500 AND UNDER
                                                            160216
                 TO VEHICLE
                                                            114783
                 TO PROPERTY
                                                            109282
                 OVER $500
                                                            105688
```

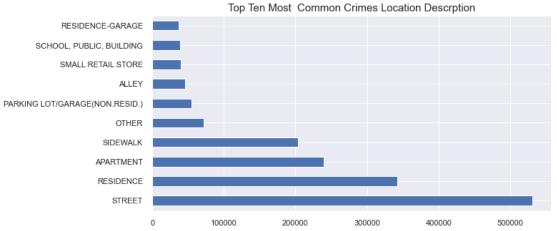


simple accounted for the highest type of crime description with a total of 229,508

Name: Location Description, dtype: int64

```
In [31]: ▶ #count of top crime location description
             (df['Location Description'].value_counts().head(10))
   Out[31]: STREET
                                               530430
             RESIDENCE
                                               342699
             APARTMENT
                                               239322
             SIDEWALK
                                               203853
             OTHER
                                                72077
             PARKING LOT/GARAGE(NON.RESID.)
                                                54754
             ALLEY
                                                46316
             SMALL RETAIL STORE
                                                39603
             SCHOOL, PUBLIC, BUILDING
                                                39152
             RESIDENCE-GARAGE
                                                36433
             Name: Location Description, dtype: int64
In [32]: ▶ #count of least crime location description
             (df['Location Description'].value_counts().tail(10))
   Out[32]: CLEANERS/LAUNDROMAT
             VEHICLE-COMMERCIAL - ENTERTAINMENT/PARTY BUS
                                                             1
             SCHOOL YARD
                                                             1
             CHA STAIRWELL
                                                             1
             CHA PLAY LOT
                                                             1
             VEHICLE-COMMERCIAL - TROLLEY BUS
                                                             1
             GOVERNMENT BUILDING
             CTA SUBWAY STATION
                                                             1
             EXPRESSWAY EMBANKMENT
                                                             1
             SEWER
```





Street had the highest amount of crime incidences with a total of 530,430 of all reported location descriptions, which accounted for 26% of the reported crime locations descriptions in Chicago.

```
In [34]:
          ▶ #count of blocks with most crime cases in chicago
             (df['Block'].value_counts().head(15))
   Out[34]: 100XX W OHARE ST
                                                    4090
             001XX N STATE ST
                                                    4006
             076XX S CICERO AVE
                                                    2998
             008XX N MICHIGAN AVE
                                                    2785
             0000X N STATE ST
                                                    2412
             0000X W TERMINAL ST
                                                    1780
             064XX S DR MARTIN LUTHER KING JR DR
                                                    1680
             063XX S DR MARTIN LUTHER KING JR DR
                                                    1635
             023XX S STATE ST
                                                    1358
             001XX W 87TH ST
                                                    1341
             012XX S WABASH AVE
                                                    1297
             006XX N MICHIGAN AVE
                                                    1260
             008XX N STATE ST
                                                    1251
             057XX S CICERO AVE
                                                    1216
             009XX W BELMONT AVE
                                                    1175
             Name: Block, dtype: int64
         #count of blocks with least crime cases in chicago
In [35]:
             (df['Block'].value_counts().tail(10))
   Out[35]: 007XX W 46TH PL
             003XX N Halsted St
                                       1
             124XX S INDIANA AVE
                                       1
             007XX E 124TH ST
                                       1
             006XX N Clark St
                                       1
             004XX W ONTARIO ST ER
                                       1
             009XX W VERNON PARK PL
                                       1
```

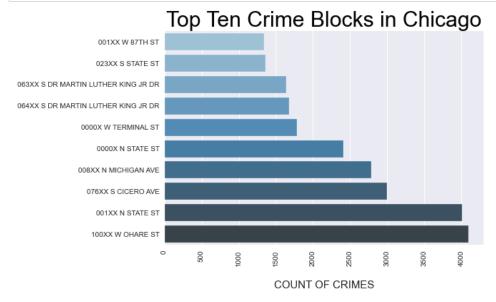
041XX N Sheridan Rd 023XX S CARPENTER ST

Name: Block, dtype: int64

010XX E 111th St

1

1

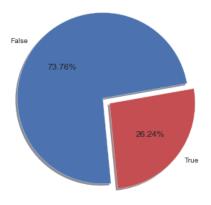


This chart shows the top ten blocks in chicago with the highest rate of crime, we can see that 100xx W OHARE ST had the highest rate of crime with a total case of 4,090, closely followed by 100xx N STATE ST with a total case of 4006. It can also be seen that, the North, South and the West were the top location amongst the top ten blocks with the highest rate of crimes.

Name: Arrest, dtype: int64

<Figure size 1080x360 with 0 Axes>

# Crimes Leading To Arrest or Not

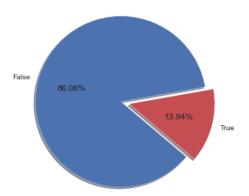


This pie chart shows that 73% of the crimes cases did not lead to an arrest whilst 26% led to an arrest. It will be intresting to futher understand why a high rate of crime does not translate to high rate of arrest, rather there seems to be a very low rate of arrest.

```
In [39]:  ▶ #count of domestic cases
             df['Domestic'].value_counts()
   Out[39]: False
                      1781975
                       288606
             True
             Name: Domestic, dtype: int64
In [40]: ▶ #pie chart showing the percetange of Domestic cases or not.
             plt.figure(figsize = (15, 5))
             color = ['b', 'r']
label = ('False', 'True')
             sizes = df['Domestic'].value_counts()
             explode = (0.1,0)
             fig1, ax1 = plt.subplots()
             ax1.pie (sizes, explode = explode, labels = label, colors = color, autopct='%2.2f%%', shadow = True, startangle=10)
             ax1=('equal')
             plt.title('Crimes Reported as Domestic case or not', fontdict = {'fontsize': 30, 'fontname':'Arial', 'color': '#000000'})
             plt.show()
```

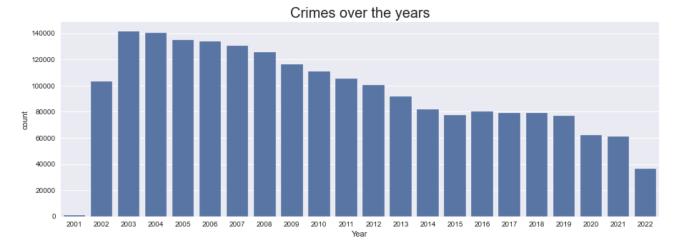
<Figure size 1080x360 with 0 Axes>

# Crimes Reported as Domestic case or not



```
Out[41]: 2003
                   141488
                   140152
            2004
            2005
                   134629
            2006
                   133955
            2007
                   130308
            2008
                   125713
            2009
                   116308
            2010
                   110900
           2011
                   105436
            2002
                   103271
            2012
                   100524
            2013
                    91534
           2014
                    82094
            2016
                    80235
            2017
                    79317
                    79265
           2018
            2015
                    77264
            2019
                    77205
            2020
                    62277
           2021
                    60855
            2022
                    36671
            2001
                    1180
           Name: Year, dtype: int64
```

```
In [42]: #distribution of crime over the years chart
    plt.figure(figsize = (15, 5))
    sns.countplot(data = df, x='Year', color = 'b')
    plt.title('Crimes over the years', fontsize = 20)
    plt.show()
```



From the chart 2003 and 2004 had the highest cases of crimes with a total of 141,488 and 140,152 respectively There was a consistent reduction in the rate of crime as years began to increase from 2003. The lowest rate of crime was reported in the year 2001 with a total case of 1180. From 2001 which had the lowest rate of crime and 2003 which had the highest, there was 118% increase in the rate of crime.

```
In [43]: ▶ #splitting the date feature to get more insights
             dfSub = df
             tCol = dfSub.Date
             List = [(datetime.ctime(parse(x[0:-3])),x[-2:]) for x in tCol]
             dayList = []
             monthList = []
             periodList = []
             for row in List:
                 day = row[0][0:4]
                 month = row[0][4:7]
                 if row[1]=='AM':
                     period = 'Morning'
                 elif row[1] =='PM' and int(row[0][11:13])<4:</pre>
                     period = 'Afternoon'
                 elif row[1] =='PM' and int(row[0][11:13])<6:</pre>
                     period = 'Evening'
                 elif row[1] =='PM' and int(row[0][11:13])>6:
                     period = 'Night'
                 else:
                     period = 'Unknown'
                 dayList.append(day)
                 monthList.append(month)
                 periodList.append(period)
             print(len(dayList), len(monthList), len(periodList))
             dfSub['month'] = monthList
             dfSub['week'] = dayList
             dfSub['day']= periodList
             dfSub.head()
             2070581 2070581 2070581
             C:\Users\HP\AppData\Local\Temp\ipykernel_12692\1485210365.py:29: SettingWithCopyWarning:
             A value is trying to be set on a copy of a slice from a DataFrame.
             Try using .loc[row_indexer,col_indexer] = value instead
             See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-ver
             sus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
               dfSub['month'] = monthList
             C:\Users\HP\AppData\Local\Temp\ipykernel_12692\1485210365.py:30: SettingWithCopyWarning:
             A value is trying to be set on a copy of a slice from a DataFrame.
             Try using .loc[row_indexer,col_indexer] = value instead
             See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-ver
             sus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
               dfSub['week'] = dayList
             C:\Users\HP\AppData\Local\Temp\ipykernel_12692\1485210365.py:31: SettingWithCopyWarning:
             A value is trying to be set on a copy of a slice from a DataFrame.
             Try using .loc[row_indexer,col_indexer] = value instead
             See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-ver
```

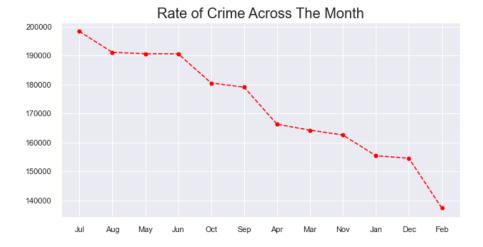
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user\_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user\_guide/indexing.html#returning-a-view-versus-a-copy)

dfSub['day']= periodList

Out[43]

]:	Unna	amed: 0	ID	Case Number	Date	Block	IUCR	Primary Type	Description	Location Description	Arrest	Domestic	Beat	District	Ward	Con
-	0	0	6407111	HP485721	07/26/2008 02:30:00 PM	085XX S MUSKEGON AVE	1320	CRIMINAL DAMAGE	TO VEHICLE	STREET	False	False	423	4.0	10.0	
	1	1	11398199	JB372830	07/31/2018 10:57:00 AM	092XX S ELLIS AVE	143C	WEAPONS VIOLATION	UNLAWFUL POSS AMMUNITION	POOL ROOM	True	False	413	4.0	8.0	
	2	2	5488785	HN308568	04/27/2007 10:30:00 AM	062XX N TRIPP AVE	0610	BURGLARY	FORCIBLE ENTRY	RESIDENCE	True	False	1711	17.0	39.0	
	3	3	11389116	JB361368	07/23/2018 08:55:00 AM	0000X N KEELER AVE	0560	ASSAULT	SIMPLE	NURSING HOME/RETIREMENT HOME	False	False	1115	11.0	28.0	
	4	4	12420431	JE297624	07/11/2021 06:40:00 AM	016XX W HARRISON ST	051A	ASSAULT	AGGRAVATED - HANDGUN	PARKING LOT / GARAGE (NON RESIDENTIAL)	False	False	1231	12.0	27.0	
4																•

```
Out[44]: Jul
                    198320
                    191098
             Aug
             May
                    190591
                    190568
             Jun
                    180506
             0ct
             Sep
                    179078
             Apr
                    166273
             Mar
                    164240
                    162565
             Nov
             Jan
                    155411
                    154559
             Dec
             Feb
                    137372
             Name: month, dtype: int64
In [45]: ▶ #rate of crime during across the month
             sns.set(style="darkgrid")
             plt.figure(figsize = (10, 5))
             plt.title('Rate of Crime Across The Month', fontsize = 20)
             plt.plot(df['month'].value_counts(), color = 'red',linestyle='--', marker='o')
             plt.show()
```



July had the highest rate of crime with a total case of 198,320 whilst Feburary had the lowest with 137,372 cases. We can safely make the assertion that the summer tends to have the highest rate of crime cases as it can be seen in the months of Jun, Jul, Aug,Sep, which accounted for 37% of the crimes. It is also quite obvious that the rate of crime during the warmer periods are usually at its peak compared to the cool season.

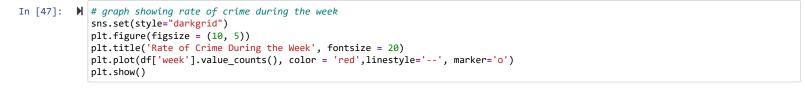
Thu 294212 Mon 292254 Sun 282364

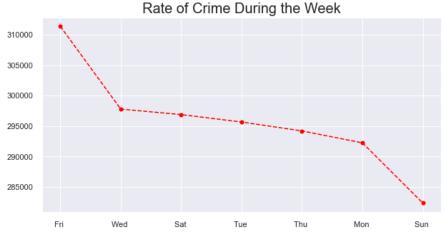
Name: week, dtype: int64

▶ #count of crime during each month

df['month'].value\_counts()

In [44]:



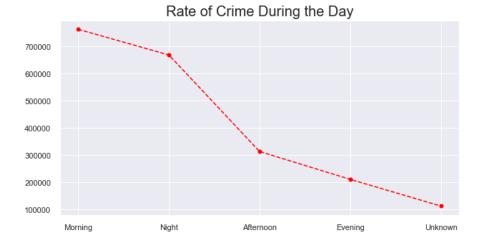


Friday had the highest amount of crime cases with 311,383, this day accounted for 15% of the crimes.

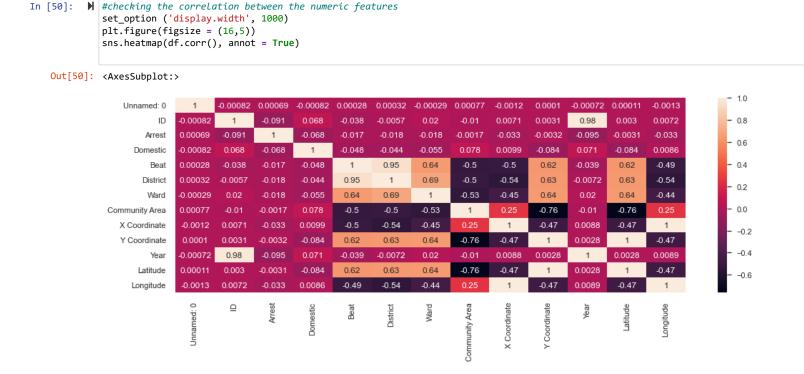
▶ #count of crimes during the day

In [48]:

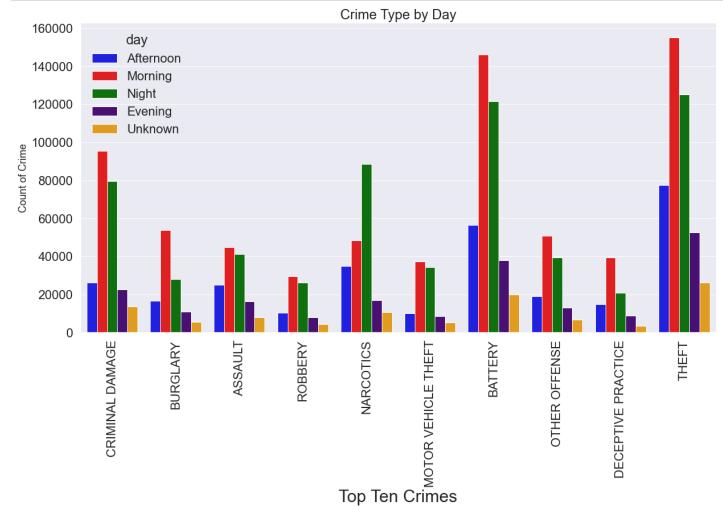
```
df['day'].value_counts()
   Out[48]: Morning
                          763321
            Night
                          668835
            Afternoon
                          313855
             Evening
                          211358
             Unknown
                          113212
            Name: day, dtype: int64
In [49]:
         #graph showing the rate of crime during the day.
             sns.set(style="darkgrid")
            plt.figure(figsize = (10, 5))
            plt.title('Rate of Crime During the Day', fontsize = 20)
            plt.plot(df['day'].value_counts(), color = 'red',linestyle='--', marker='o')
            plt.show()
```



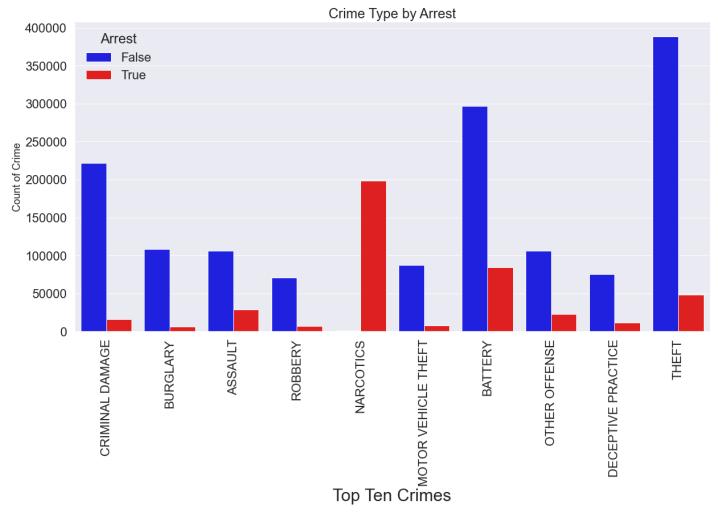
The chart shows that majority of the crimes tend to happen in the morning with a total case of 763,321 closely followed by night with a total case of 668,835. This collectively resulted in 69% crime rate during this period



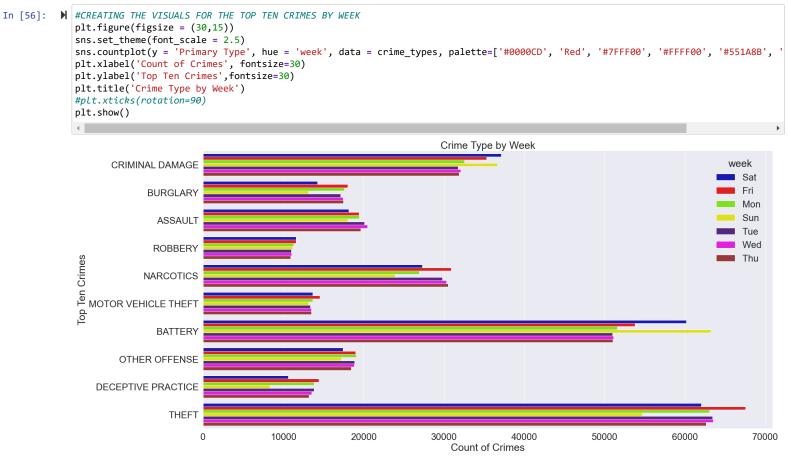
## **BIVARIATE ANALYSIS**



The chart shows that the top ten crimes tend to take place in the morning and at night. It also shows that there is also a very high tendency for THEFT to take place in the afternoon and also BATTERY

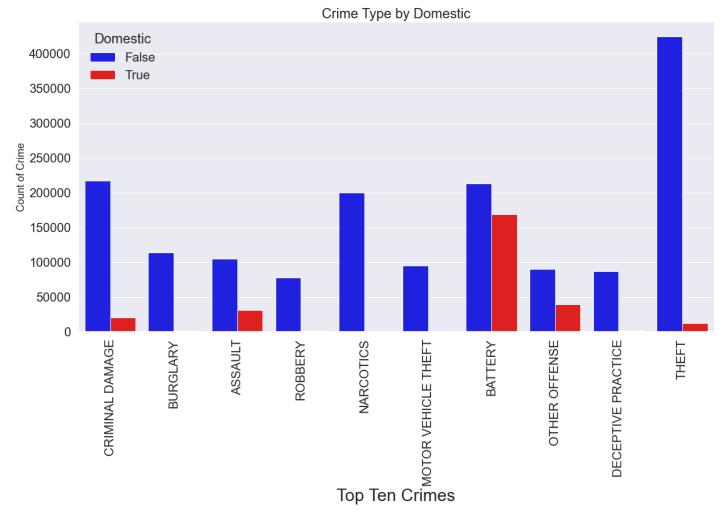


The chart shows that the ratio to arrest based on the top ten crimes is quite low. Amongst the Top ten cases Narcotics was the crime with the highest rate of arrest



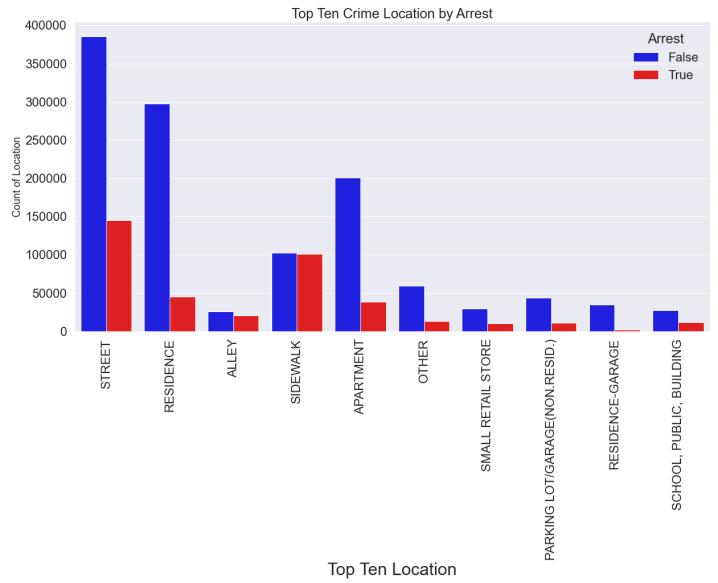
From the chart, the week does not have a significant impact on the type of crime, there seems to be almost equal occurence of crime based on the week. For the two most frequesnt crimes in chicago which are Battery and Theft, there seems to be more cases of Battery on sundays and saturday (weekends), For Theft there is a high frequency of it occruing on Friday.

```
In [57]:  #CREATING THE VISUALS FOR THE TOP TEN CRIMES BY DOMESTIC RELATED
    plt.figure(figsize = (20,10))
    sns.set_theme(font_scale = 2)
    sns.countplot(x = 'Primary Type', hue = 'Domestic', data = crime_types, palette=['Blue', 'Red'])
    plt.xlabel('Top Ten Crimes', fontsize=30)
    plt.ylabel('Count of Crime', fontsize=18)
    plt.title('Crime Type by Domestic')
    plt.xticks(rotation=90)
    plt.show()
```

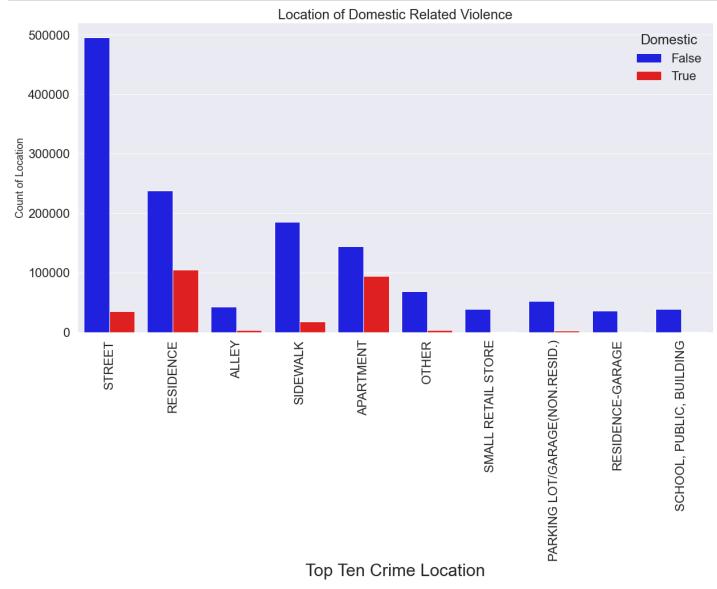


Most of the crimes were not Domestic, Battery was the crime that had the most Domestic cases. Somce of the crimes such as Criminal Damage, Assault, Theft and Other Offenses had a few cases that were Domestic

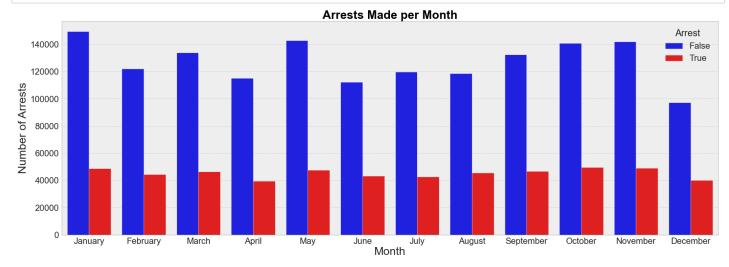
In [61]: | #CREATING THE VISUALS FOR THE TOP TEN CRIME LOCATIONS BY ARREST
 plt.figure(figsize = (20,10))
 sns.set\_theme(font\_scale = 2)
 sns.countplot(x = 'Location Description', hue = 'Arrest', data = crime\_location, palette=['Blue', 'Red'])
 plt.xlabel('Top Ten Location', fontsize=30)
 plt.ylabel('Count of Location', fontsize=18)
 plt.title('Top Ten Crime Location by Arrest')
 plt.xticks(rotation=90)
 plt.show()



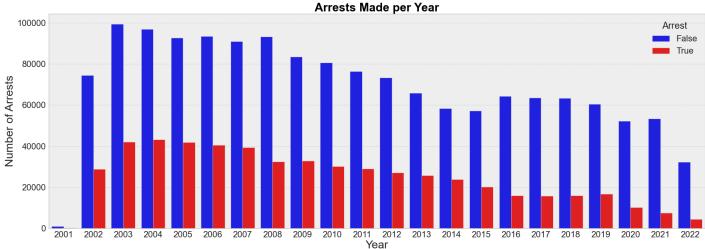
This chart clearly shows that most arrest tend to happen on the street which also correlate with the fact that the street had the highest rate of reported crime cases. The Sidewalk was also the second highest location in terms of arrest. Arrests were also recorded in places such as Resisdence, Alley and Apartment. This further buttresses the point that these places are hotspots for crime



Residence and Apartment were the two Locations where domestic related violence tend to occur the most

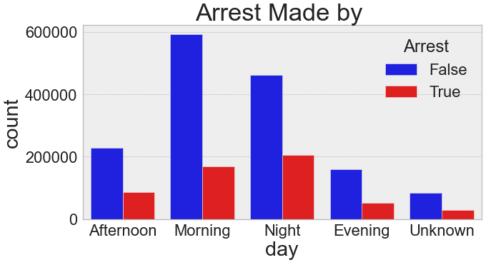


From the chart we can see that arrest were made accros each month with no month outrightly outperfroming any in terms of arrest.



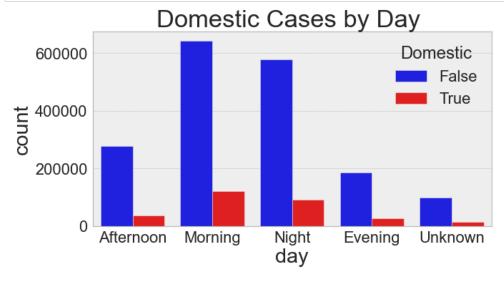
2003, 2004, 2005, 2006, 2007, were the years where the most arrest were made. From our analysis of the rate of crime by year we know that as the year increased the rate of crime began to reducce This also has an effect on the rate of arrest, as the year increase the rate of arrest reduced.





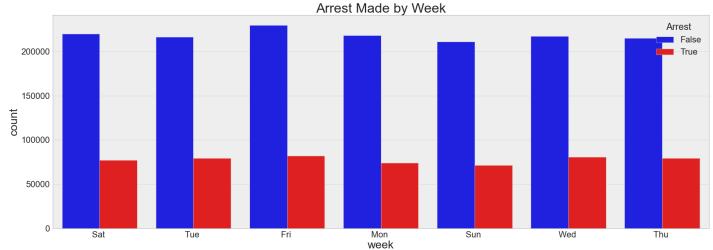
From the chart we can see that we tend to have more arrest in the Morning and at Night, this definitely correlate with the fact that these are the periods when most crimes tend to take place.

```
In [66]: M #domestic violence made during the day
plt.figure(figsize = (10,5))
sns.countplot(x = 'day', hue = 'Domestic', data = df, palette=['Blue', 'Red'])
plt.title('Domestic Cases by Day ')
plt.show()
```



There are more cases of Domestic violence in the Moring and there were also cases at Night





In terms of arrest during the week, there were no significant difference as there were arrest made with almost equal rate across each day of the week

SUMMARY OF FINDINGS I started out by carrying out a univariate analysis to tease out important concepts from each individual feature from the data set, then I went ahead to carry out a bivariate analysis that is, getting insight by pairing key features together. Based on that I was able come up with the following findings.

\*We now know the Top ten crimes in chicago \*The top ten crime Locations \*The top types crime description \*The blocks where these crimes tend to occur \*The day, week, month and year patterns of these crimes \*The percentage of crime based on deomestic violence. \*Arrest made based on top ten crimes \*Arrest Made based on Location \*Arrest made during the day, week, month and year \*Domestic violence based on location \*Domestic related violence based on top ten crimes Domestic violence during the day.

#### Conclusion

Based on the analysis carried out, it was discovered that 75% of the crimes committed did not lead to an arrest, I can safely make the recommendation that, if more arrest can be made, it can further help reduced the spate of violent crimes in the state of Chicago. There is also a clear understanding of the most frequent types of crimes and the fact that these crimes tend to happen in the North, West and South streets in Chicago, we can deploy a robust network that can look into checkmating the activities that goes on around these places. Most crimes tend to happen in the summer and fall season as well as in the morning and at night, I can further recommend that patrols can increase during these periods.

In [ ]:	M	
In [ ]:	M	
In [ ]:	M	