DSC530_FINAL_PROJECT_RAHMANZAI

March 4, 2022

[178]:
```
from __future__ import print_function, division



import thinkplot
import random
import numpy as np
import pandas as pd
import scipy.stats as stats
import matplotlib.pyplot as plt
%matplotlib inline


from statsmodels.formula.api import ols
from scipy import stats
import statsmodels.api as sm
```

[2]:
```
#Dataset#1:  CVE® is a list of publicly disclosed cybersecurity vulnerabilities.
 ↪obtained from mitre.org.
# Data generated in 2022-01-21.  Data is from Jan 1999 to Jan 2022.
allitems = pd.read_csv("allitems.csv")
allitems.head()
#WE just needed the first column data. I will be extracting the year from this␣
 ↪column as will be my dependent variable as CVE
# listed is identified by year.
```

[2]:

	Description
0	CVE-1999-0001
1	CVE-1999-0002
2	CVE-1999-0003
3	CVE-1999-0004
4	CVE-1999-0005

[3]:
```
type(allitems)
# shows the data is in a dataframe
```

[3]: pandas.core.frame.DataFrame

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 226679 entries, 0 to 226678
Data columns (total 1 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   Description  226679 non-null  object
dtypes: object(1)
memory usage: 1.7+ MB
```

[5]:
```
allitems['Year']=allitems['Description'].str.split('-').str[1]
allitems.head()
allitems.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 226679 entries, 0 to 226678
Data columns (total 2 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   Description  226679 non-null  object
 1   Year         226679 non-null  object
dtypes: object(2)
memory usage: 3.5+ MB
```

[6]:
```
allitems['Vulnerabilities']=allitems['Description']
allitems.head()
```

[6]:

	Description	Year	Vulnerabilities
0	CVE-1999-0001	1999	CVE-1999-0001
1	CVE-1999-0002	1999	CVE-1999-0002
2	CVE-1999-0003	1999	CVE-1999-0003
3	CVE-1999-0004	1999	CVE-1999-0004
4	CVE-1999-0005	1999	CVE-1999-0005

[7]:
```
Y=allitems['Year']
Y.min()
```

[7]: '1999'

[8]:
```
Y.max()
```

[8]: '2022'

[223]:
```
allitems.describe(include='all')
```

[223]:

	Description	Year	Vulnerabilities
count	226679	226679	226679
unique	226679	24	226679

```
top     CVE-1999-0001    2020   CVE-1999-0001
freq                1   31086               1
```

[9]:
```
## Dataset2:  Read the cyber-operations-incidents.csv containing the CVS of␣
↪cyber incidents from 2005 to 2020, as reported by the
##Council of Foreign Relations
```

[10]:
```
cyberops_df = pd.read_csv("cyber-operations-incidents.csv")
cyberops_df.head()

cyberops_df.tail(10)
```

[10]:
```
                                                 Title       Date  \
471              Compromise of the Pentagon's NIPRNet  8/17/2006
472              Compromise at U.S. Naval War College  12/4/2006
473                                        Titan Rain  8/25/2005
474                                            Trisis        NaN
475                                          APT-C-23        NaN
476  Compromises of government embassies, telecommu…        NaN
477                                           Kimusky        NaN
478                                         Leafminer        NaN
479                                          Allanite        NaN
480  Targeting of sporting and anti-doping organiza…        NaN

                                         Affiliations  \
471                                               NaN
472                                               NaN
473  Believed to be partially the work of PLA Unit …
474                 Also known as Triton and Xenotime
475           Also known as AridViper and Desert Falcon.
476             Believed to be the work of MuddyWater.
477             Also known as Thallium and Smoke Screen
478                                               NaN
479  Believed to be responsible for the targeting o…
480                                            APT 28

                                          Description Response  \
471  Threat actors accessed unclassified informatio…      NaN
472  This undefined cyber incident at the U.S. Nava…      NaN
473  Titan Rain was a string of cyber operations th…      NaN
474  This threat actor targets the Triconex safety …      NaN
475  Previously targeted Israeli soldiers by preten…      NaN
476  A group has attacked 131 victims in thirty org…      NaN
477  This threat actor targeted foreign ministries …      NaN
478  This threat actor targets government organizat…      NaN
479  This threat actor targets business and industr…      NaN
480  Just prior to news reports suggesting that the…      NaN
```

```
                                                Victims  \
471                         U.S. Department of Defense
472                                  Naval War College
473  U.S. Department of State, U.S. Department of D…
474                                       Saudi Arabia
475                             Israel Defense Forces
476  Russian Federation, Pakistan, Saudi Arabia, Tu…
477  France, Slovakia, Stanford University, U.S. Th…
478  Egypt, Israel, Saudi Arabia, United Arab Emira…
479                      United States, United Kingdom
480  Sixteen national and international sporting an…

                        Sponsor       Type                    Category  \
471                       China  Espionage                    Military
472                       China  Espionage                    Military
473                       China  Espionage        Military, Government
474                         NaN   Sabotage              Private sector
475         Palestine, State of        NaN                         NaN
476  Iran (Islamic Republic of)  Espionage  Government, Private sector
477                         NaN        NaN  Government, Private sector
478  Iran (Islamic Republic of)        NaN  Private sector, Government
479          Russian Federation  Espionage              Private sector
480          Russian Federation  Espionage   Civil society, Government

                                              Sources_1  \
471  http://www.csmonitor.com/2007/0914/p01s01-woap…
472  http://fcw.com/articles/2006/12/04/china-is-su…
473  http://www.washingtonpost.com/wp-dyn/content/a…
474  https://www.fireeye.com/blog/threat-research/2…
475  https://www.bleepingcomputer.com/news/security…
476  https://www.symantec.com/blogs/threat-intellig…
477  https://blog.prevailion.com/2019/09/autumn-ape…
478  https://www.symantec.com/blogs/threat-intellig…
479      https://dragos.com/blog/20180510Allanite.html
480  https://blogs.microsoft.com/on-the-issues/2019…

                                              Sources_2  \
471  http://gcn.com/articles/2006/08/17/red-storm-r…
472  http://www.nbcnews.com/id/16057306/ns/technolo…
473  http://content.time.com/time/magazine/article/…
474  https://www.fireeye.com/blog/threat-research/2…
475  https://research.checkpoint.com/2020/hamas-and…
476  https://www.cyberscoop.com/middle-east-group-g…
477                                              NaN
478                                              NaN
479      https://www.us-cert.gov/ncas/alerts/TA17-293A
```

```
480  https://www.zdnet.com/article/microsoft-russia…

                                                Sources_3
471                                                   NaN
472                                                   NaN
473  http://www.theguardian.com/technology/2007/sep…
474       https://dragos.com/blog/trisis/TRISIS-01.pdf
475  https://malpedia.caad.fkie.fraunhofer.de/actor…
476                                                   NaN
477                                                   NaN
478                                                   NaN
479                                                   NaN
480  https://www.wired.com/story/fancy-bear-antidop…
```

[11]:
```
cyberops_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 481 entries, 0 to 480
Data columns (total 12 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Title         481 non-null    object
 1   Date          474 non-null    object
 2   Affiliations  347 non-null    object
 3   Description   481 non-null    object
 4   Response      86 non-null     object
 5   Victims       453 non-null    object
 6   Sponsor       439 non-null    object
 7   Type          447 non-null    object
 8   Category      458 non-null    object
 9   Sources_1     475 non-null    object
 10  Sources_2     355 non-null    object
 11  Sources_3     168 non-null    object
dtypes: object(12)
memory usage: 45.2+ KB
```

[12]:
```
cyberops_df['Year']=cyberops_df['Date'].str.split('/').str[2]
cyberops_df['Year']
cyberops_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 481 entries, 0 to 480
Data columns (total 13 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Title         481 non-null    object
 1   Date          474 non-null    object
 2   Affiliations  347 non-null    object
```

```
 3   Description   481 non-null    object
 4   Response      86 non-null     object
 5   Victims       453 non-null    object
 6   Sponsor       439 non-null    object
 7   Type          447 non-null    object
 8   Category      458 non-null    object
 9   Sources_1     475 non-null    object
 10  Sources_2     355 non-null    object
 11  Sources_3     168 non-null    object
 12  Year          474 non-null    object
dtypes: object(13)
memory usage: 49.0+ KB
```

[13]:
```
df2 = cyberops_df[["Year", "Category", "Type","Description","Title",␣
↪"Affiliations", "Victims", "Sponsor" ]]

df2.tail(10)
```

[13]:
```
     Year                     Category       Type  \
471  2006                     Military  Espionage
472  2006                     Military  Espionage
473  2005         Military, Government  Espionage
474   NaN               Private sector   Sabotage
475   NaN                          NaN        NaN
476   NaN  Government, Private sector  Espionage
477   NaN  Government, Private sector        NaN
478   NaN  Private sector, Government        NaN
479   NaN               Private sector  Espionage
480   NaN   Civil society, Government  Espionage

                                           Description  \
471  Threat actors accessed unclassified informatio…
472  This undefined cyber incident at the U.S. Nava…
473  Titan Rain was a string of cyber operations th…
474  This threat actor targets the Triconex safety …
475  Previously targeted Israeli soldiers by preten…
476  A group has attacked 131 victims in thirty org…
477  This threat actor targeted foreign ministries …
478  This threat actor targets government organizat…
479  This threat actor targets business and industr…
480  Just prior to news reports suggesting that the…

                                                 Title  \
471               Compromise of the Pentagon's NIPRNet
472               Compromise at U.S. Naval War College
473                                         Titan Rain
474                                             Trisis
```

```
475                                         APT-C-23
476  Compromises of government embassies, telecommu…
477                                          Kimusky
478                                        Leafminer
479                                         Allanite
480  Targeting of sporting and anti-doping organiza…

                                    Affiliations  \
471                                              NaN
472                                              NaN
473  Believed to be partially the work of PLA Unit …
474                 Also known as Triton and Xenotime
475          Also known as AridViper and Desert Falcon.
476              Believed to be the work of MuddyWater.
477           Also known as Thallium and Smoke Screen
478                                              NaN
479  Believed to be responsible for the targeting o…
480                                           APT 28

                                         Victims  \
471                      U.S. Department of Defense
472                               Naval War College
473  U.S. Department of State, U.S. Department of D…
474                                    Saudi Arabia
475                          Israel Defense Forces
476  Russian Federation, Pakistan, Saudi Arabia, Tu…
477  France, Slovakia, Stanford University, U.S. Th…
478  Egypt, Israel, Saudi Arabia, United Arab Emira…
479                  United States, United Kingdom
480  Sixteen national and international sporting an…

                      Sponsor
471                     China
472                     China
473                     China
474                       NaN
475        Palestine, State of
476  Iran (Islamic Republic of)
477                       NaN
478  Iran (Islamic Republic of)
479         Russian Federation
480         Russian Federation
```

[14]:
```
cyberopsfinal_df = df2.copy() # Create duplicate of data
cyberopsfinal_df.dropna(subset = ['Year'], inplace = True)
cyberopsfinal_df.tail()
#I removed the Nan or blank Year rows by using the dropna command
```

```
#as above.  The number of records reduced from 481 to 474.
#Below shows 473 as first index row is 0 but total records are 474.
cyberopsfinal_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 474 entries, 0 to 473
Data columns (total 8 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Year          474 non-null    object
 1   Category      452 non-null    object
 2   Type          443 non-null    object
 3   Description   474 non-null    object
 4   Title         474 non-null    object
 5   Affiliations  341 non-null    object
 6   Victims       446 non-null    object
 7   Sponsor       434 non-null    object
dtypes: object(8)
memory usage: 33.3+ KB
```

[15]:
```
Type_category=cyberopsfinal_df.groupby(['Type']).count()
Type_category
#As seen below, espionage has the highest frequency than any other type in␣
 ↪aggregate.
```

[15]:
```
                    Year  Category  Description  Title  Affiliations  Victims  \
Type
Data destruction      14        14           14     14            11       13
Defacement             5         5            5      5             3        5
Denial of service     18        18           18     18             6       18
Doxing                 6         6            6      6             6        6
Espionage            371       361          371    371           270      353
Financial Theft        7         7            7      7             7        7
Sabotage              22        22           22     22            17       22

                   Sponsor
Type
Data destruction        12
Defacement               5
Denial of service       18
Doxing                   6
Espionage              338
Financial Theft          7
Sabotage                21
```

[225]:
```
cyberopsfinal_df.describe(include='all')
```

[225]:
```
         Year        Category       Type  \
count     474             452        443
unique     16              24          7
top      2020  Private sector  Espionage
freq       88             126        371

                                              Description  \
count                                                 474
unique                                                472
top     Gamaredon, a Russian-speaking APT, targeted Uk…
freq                                                    3

                                         Title  \
count                                      474
unique                                     470
top     Targeting of Ukrainian government entities
freq                                         4

                                 Affiliations        Victims Sponsor
count                                     341            446     434
unique                                    257            381      39
top     Believed to be the work of APT 28  United States   China
freq                                       15             21     167
```

[16]:
```python
### Dataset3:  Read the Security Incidents file.  This dataset looks at the␣
↪data security incidents which have been reported to the Information
## Commissioners Office (ICO).


Secincident_df = pd.read_csv("Security Incident totals.csv")
Secincident_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 140 entries, 0 to 139
Data columns (total 31 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   Index                           140 non-null    int64
 1   Quarter                         140 non-null    object
 2   Financial Year                  140 non-null    object
 3   Quarter Start                   140 non-null    object
 4   Quarter End                     140 non-null    object
 5   Cyber Security Incident?        140 non-null    object
 6   Incident Type                   140 non-null    object
 7   Central Government              87 non-null     float64
 8   Charitable and voluntary        106 non-null    float64
 9   Education and childcare         123 non-null    float64
 10  Finance, insurance and credit   115 non-null    float64
```

```
 11   General business                 116 non-null    float64
 12   Health                           115 non-null    float64
 13   Justice                          72 non-null     float64
 14   Land or property services        98 non-null     float64
 15   Legal                            100 non-null    float64
 16   Local government                 100 non-null    float64
 17   Marketing                        34 non-null     float64
 18   Media                            43 non-null     float64
 19   Membership association           71 non-null     float64
 20   Online Technology and Telecoms   87 non-null     float64
 21   Political                        23 non-null     float64
 22   Regulators                       27 non-null     float64
 23   Religious                        46 non-null     float64
 24   Retail and manufacture           116 non-null    float64
 25   Social care                      81 non-null     float64
 26   Transport and leisure            98 non-null     float64
 27   Unassigned                       1 non-null      float64
 28   Utilities                        61 non-null     float64
 29   Sum of complaint categories      140 non-null    int64
 30   Total Complaints                 140 non-null    int64
dtypes: float64(22), int64(3), object(6)
memory usage: 34.0+ KB
```

[17]:
```
#Next, I also extract the year from the Quarter End field as Year is my␣
↪Dependent variable indicating
#also the occurance of a vulnerability.
Secincident_df['Year']=Secincident_df['Quarter End'].str.split('/').str[2]
Secincident_df.head()
Secincident_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 140 entries, 0 to 139
Data columns (total 32 columns):
 #    Column                           Non-Null Count  Dtype
---   ------                           --------------  -----
 0    Index                            140 non-null    int64
 1    Quarter                          140 non-null    object
 2    Financial Year                   140 non-null    object
 3    Quarter Start                    140 non-null    object
 4    Quarter End                      140 non-null    object
 5    Cyber Security Incident?         140 non-null    object
 6    Incident Type                    140 non-null    object
 7    Central Government               87 non-null     float64
 8    Charitable and voluntary         106 non-null    float64
 9    Education and childcare          123 non-null    float64
 10   Finance, insurance and credit    115 non-null    float64
 11   General business                 116 non-null    float64
 12   Health                           115 non-null    float64
```

```
 13  Justice                          72 non-null     float64
 14  Land or property services        98 non-null     float64
 15  Legal                            100 non-null    float64
 16  Local government                 100 non-null    float64
 17  Marketing                        34 non-null     float64
 18  Media                            43 non-null     float64
 19  Membership association           71 non-null     float64
 20  Online Technology and Telecoms   87 non-null     float64
 21  Political                        23 non-null     float64
 22  Regulators                       27 non-null     float64
 23  Religious                        46 non-null     float64
 24  Retail and manufacture           116 non-null    float64
 25  Social care                      81 non-null     float64
 26  Transport and leisure            98 non-null     float64
 27  Unassigned                       1 non-null      float64
 28  Utilities                        61 non-null     float64
 29  Sum of complaint categories      140 non-null    int64
 30  Total Complaints                 140 non-null    int64
 31  Year                             140 non-null    object
dtypes: float64(22), int64(3), object(7)
memory usage: 35.1+ KB
```

[18]:
```
Secincident_df['Year'].min()
```

[18]:
```
'2019'
```

[19]:
```
Secincident_df['Year'].max()
```

[19]:
```
'2020'
```

[20]:
```
Secincident_df.groupby(['Cyber Security Incident?']).count()
```

[20]:
```
                          Index  Quarter  Financial Year  Quarter Start  \
Cyber Security Incident?
N                            90       90              90             90
Y                            50       50              50             50

                          Quarter End  Incident Type  Central Government  \
Cyber Security Incident?
N                                  90             90                  66
Y                                  50             50                  21

                          Charitable and voluntary  Education and childcare  \
Cyber Security Incident?
N                                               67                       77
Y                                               39                       46

                          Finance, insurance and credit  …  Regulators  \
```

```
Cyber Security Incident?                                           …
N                                                             73  …          22
Y                                                             42  …           5

                           Religious  Retail and manufacture  Social care  \
Cyber Security Incident?
N                                 30                      70           60
Y                                 16                      46           21

                           Transport and leisure  Unassigned  Utilities  \
Cyber Security Incident?
N                                             63           0         43
Y                                             35           1         18

                           Sum of complaint categories  Total Complaints  Year
Cyber Security Incident?
N                                                   90                90    90
Y                                                   50                50    50

[2 rows x 31 columns]
```

[21]:

```python
##Analyzing the file as shown above, found out that not every record is a␣
↪breach.
# We will filter only those records where cyber incidents happened

df2 = Secincident_df[(Secincident_df['Cyber Security Incident?'] == 'Y')]
Secincidentfinal_df = df2[["Year","Cyber Security Incident?", "Incident Type"]]

Secincidentfinal_df.head()

Secincidentfinal_df.info()

Secincidentfinal_df["Year"].min()

Secincidentfinal_df["Year"].max()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 50 entries, 0 to 139
Data columns (total 3 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Year                      50 non-null     object
 1   Cyber Security Incident?  50 non-null     object
 2   Incident Type             50 non-null     object
dtypes: object(3)
memory usage: 1.6+ KB
```

[21]: '2020'

[22]:
```
Secincidentfinal_df.head()
```

[22]:
```
   Year Cyber Security Incident?                   Incident Type
0  2019                        Y               Unauthorised access
1  2019                        Y                       Brute Force
2  2019                        Y  Hardware/software misconfiguration
3  2019                        Y                           Malware
4  2019                        Y              Other cyber incident
```

[226]:
```
Secincidentfinal_df.describe(include='all')
```

[226]:
```
        Year Cyber Security Incident?        Incident Type
count     50                       50                   50
unique     2                        1                    8
top     2020                        Y  Unauthorised access
freq      29                       50                    7
```

[228]:
```
#Dataset#4:  Read the PRC Data Breach Chronology.csv" file.  It contains the␣
 ↪Security incidents in the US
#collected by a non-profit. 9015 records.  Oldest date of incident January 2005␣
 ↪and the latest October 2019.
#No data in 2020.  These are all incidents in the US.

PRCBreach_df = pd.read_csv("PRC Data Breach Chronology.csv")
PRCBreach_df.head()
```

[228]:
```
  Date Made Public                                          Company  \
0         3/3/2006                                     PayDay OK LLC
1         1/4/2012  SF Fire Credit Union, Pacifica-Coastside Credi…
2        2/18/2012                   BDO USA, Rubio's Restaurants, Inc.
3        2/22/2012                          DHI Mortgage Company, Ltd.
4        3/12/2012                          Impairment Resources, LLC

            City       State Type of breach Type of organization  \
0            NaN  New Jersey           HACK                  BSF
1  San Francisco  California           PORT                  BSF
2      San Diego  California           PORT                  BSR
3         Austin       Texas           HACK                  BSF
4      San Diego  California           PORT                  MED

  Total Records                            Description of incident  \
0            88  The company's website was breached sometime ar…
1             0  The December 29, 2011 theft of a laptop from a…
2             0  BDO was contracted by Rubio's to perform finan…
3             0  On February 10, 2012, DHI Mortgage became awar…
4        14,000  An office burglary on New Year's Eve 2011 resu…
```

```
           Information Source          Source URL  Year of Breach  \
0  California Attorney General  https://oag.ca.gov/            2006
1  California Attorney General                  NaN            2012
2  California Attorney General                  NaN            2012
3  California Attorney General                  NaN            2012
4  California Attorney General                  NaN            2012

    Latitude   Longitude  Unnamed: 13  Unnamed: 14 Unnamed: 15
0  40.058324  -74.405661          NaN          NaN         NaN
1  37.774930 -122.419416          NaN          NaN         NaN
2  32.715329 -117.157255          NaN          NaN         NaN
3  30.267153  -97.743061          NaN          NaN         NaN
4  32.715329 -117.157255          NaN          NaN         NaN
```

[229]:
```
PRCBreach_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9015 entries, 0 to 9014
Data columns (total 16 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   Date Made Public         9015 non-null   object
 1   Company                  9015 non-null   object
 2   City                     5690 non-null   object
 3   State                    8436 non-null   object
 4   Type of breach           8926 non-null   object
 5   Type of organization     9015 non-null   object
 6   Total Records            9009 non-null   object
 7   Description of incident  9012 non-null   object
 8   Information Source       8962 non-null   object
 9   Source URL               3607 non-null   object
 10  Year of Breach           9015 non-null   int64
 11  Latitude                 6541 non-null   float64
 12  Longitude                6541 non-null   float64
 13  Unnamed: 13              0 non-null      float64
 14  Unnamed: 14              0 non-null      float64
 15  Unnamed: 15              1 non-null      object
dtypes: float64(4), int64(1), object(11)
memory usage: 1.1+ MB
```

[230]:
```
PRCBreach_df['Year of Breach'].max()
```

[230]: 2019

[231]:
```
PRCBreach_df['Year of Breach'].min()
```

[231]: 2005

[232]:
```
##Analyzing the file as shown above, found out that not every record is a cyber␣
↪breach.  We will filter only those records
#where cyberincidents happened.  THere are total 2533 records as opposed to␣
↪9015 in the original dataset.
df_PRC= PRCBreach_df[(PRCBreach_df['Type of breach'] == 'HACK')]
PRCBreach_final_df = df_PRC[["Year of Breach","Type of breach"]]

PRCBreach_final_df.head()
PRCBreach_final_df.info()

PRCBreach_final_df["Year of Breach"].min()
PRCBreach_final_df["Year of Breach"].max()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2533 entries, 0 to 8962
Data columns (total 2 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Year of Breach  2533 non-null   int64
 1   Type of breach  2533 non-null   object
dtypes: int64(1), object(1)
memory usage: 59.4+ KB
```

[232]: 2019

[233]:
```
PRCBreach_final_df.head()
```

[233]:

	Year of Breach	Type of breach
0	2006	HACK
3	2012	HACK
8	2012	HACK
15	2012	HACK
16	2012	HACK

HISTOGRAMS/PLOTS Of VARIABLES

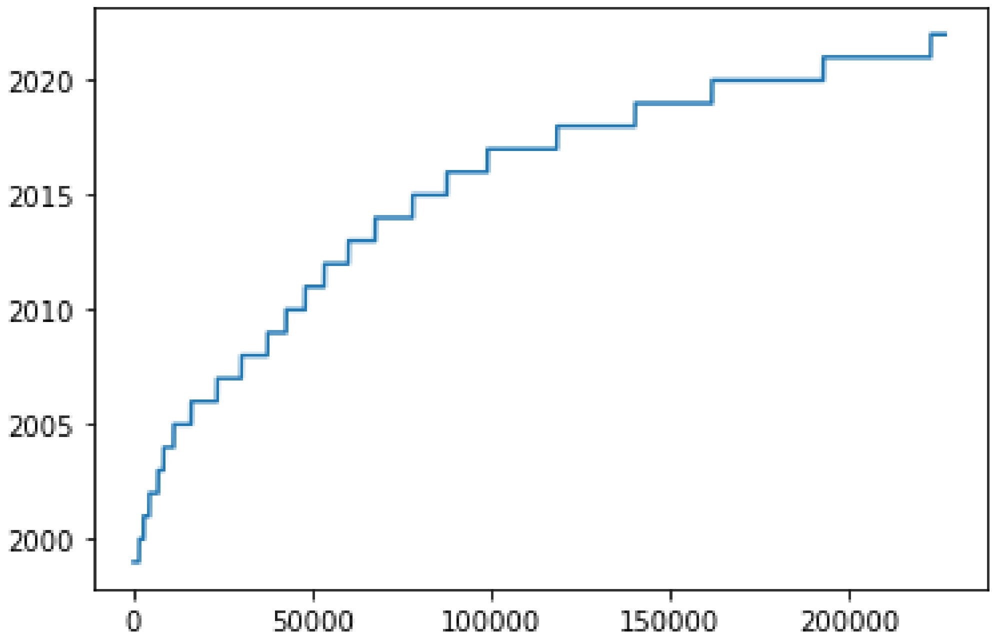
[235]:
```
PRCBreach_final_df.describe(include='all')
```

[235]:

	Year of Breach	Type of breach
count	2533.000000	2533
unique	NaN	1
top	NaN	HACK
freq	NaN	2533
mean	2013.680221	NaN
std	3.330823	NaN
min	2005.000000	NaN
25%	2012.000000	NaN
50%	2014.000000	NaN

```
75%        2016.000000              NaN
max        2019.000000              NaN
```

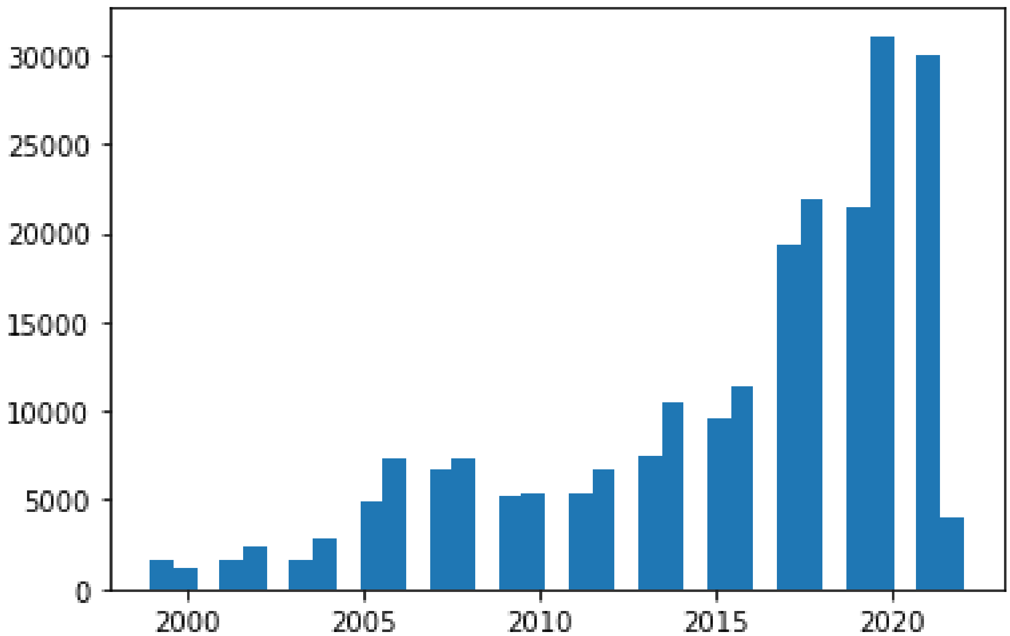
[29]:
```
#Dataset1:  NAME (CVEs vs. Year)




dfallitems=Y.astype(float)
#where Y was calculated above as Y=allitems['Year']. Year was extracted from
 ↪the description field of the vulnerability.
# The plot shows that the number of vulnerabilities are increasing by year.

dfallitems.plot()
plt.show()
```



[30]:
```
#Another way of showing it via Histogram.
plt.hist(dfallitems, bins=35, label = 'Data')
```

[30]:
```
(array([ 1579.,  1243.,     0.,  1573.,  2436.,     0.,  1600.,  2779.,
            0.,  4899.,  7254.,     0.,  6763.,  7321.,     0.,  5160.,
         5340.,     0.,  5336.,  6723.,     0.,  7493., 10453.,     0.,
         9573., 11322.,     0., 19395., 21859.,     0., 21460., 31086.,
            0., 30002.,  4030.]),
 array([1999.        , 1999.65714286, 2000.31428571, 2000.97142857,
```

```
        2001.62857143, 2002.28571429, 2002.94285714, 2003.6       ,
        2004.25714286, 2004.91428571, 2005.57142857, 2006.22857143,
        2006.88571429, 2007.54285714, 2008.2       , 2008.85714286,
        2009.51428571, 2010.17142857, 2010.82857143, 2011.48571429,
        2012.14285714, 2012.8       , 2013.45714286, 2014.11428571,
        2014.77142857, 2015.42857143, 2016.08571429, 2016.74285714,
        2017.4       , 2018.05714286, 2018.71428571, 2019.37142857,
        2020.02857143, 2020.68571429, 2021.34285714, 2022.        ]),
 <BarContainer object of 35 artists>)
```

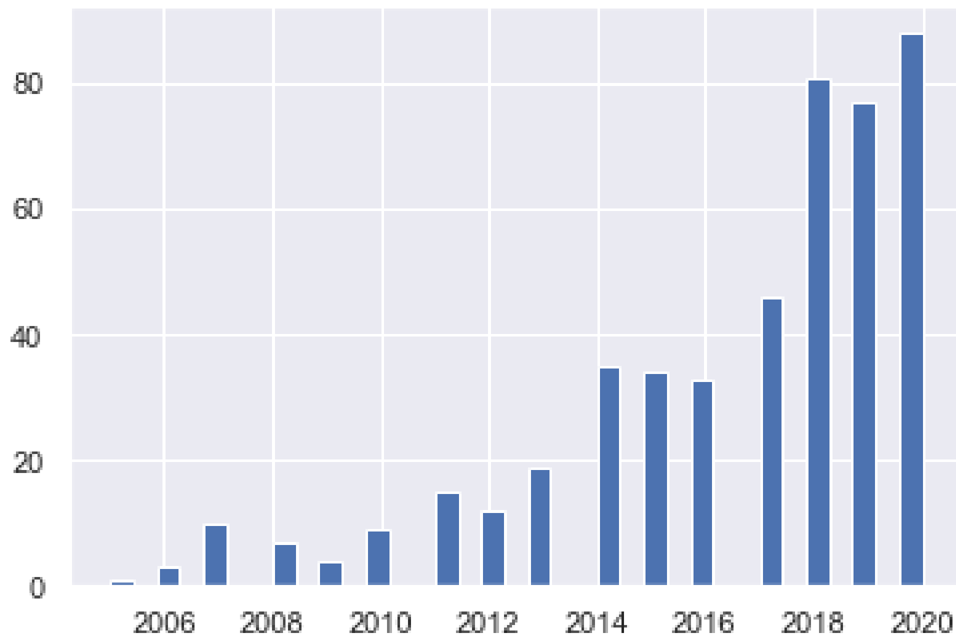


[31]:
```
#Dataset2 - cyber-operations-incidents.csv containing the CVS of cyber␣
 ↪incidents from 2005 to 2020 (Incidents (Name) vs.
#Year (I computed this variable from the date field))

#As seen above I had to create the Year field and extracting it from the Date␣
 ↪field so I can compare with the no. on
#incidents
```

[190]:
```
X=cyberopsfinal_df['Year']
dfcyberopsfinal_df=X.astype(float)
plt.hist(dfcyberopsfinal_df, bins=35, label = 'Data')
```

[190]:
```
(array([ 1.,  0.,  3.,  0., 10.,  0.,  0.,  7.,  0.,  4.,  0.,  9.,  0.,
         0., 15.,  0., 12.,  0., 19.,  0.,  0., 35.,  0., 34.,  0., 33.,
         0.,  0., 46.,  0., 81.,  0., 77.,  0., 88.]),
```

```
array([2005.        , 2005.42857143, 2005.85714286, 2006.28571429,
       2006.71428571, 2007.14285714, 2007.57142857, 2008.        ,
       2008.42857143, 2008.85714286, 2009.28571429, 2009.71428571,
       2010.14285714, 2010.57142857, 2011.        , 2011.42857143,
       2011.85714286, 2012.28571429, 2012.71428571, 2013.14285714,
       2013.57142857, 2014.        , 2014.42857143, 2014.85714286,
       2015.28571429, 2015.71428571, 2016.14285714, 2016.57142857,
       2017.        , 2017.42857143, 2017.85714286, 2018.28571429,
       2018.71428571, 2019.14285714, 2019.57142857, 2020.        ]),
<BarContainer object of 35 artists>)
```



[33]:
```
#  In this dataset, we also had a type of incident field.  We wanted to see
↪which type of incident was more pronounced in our data

#Make another histogram by Type
```

[34]:
```
Type_category=cyberopsfinal_df.groupby(['Type']).count()
Type_category
```

[34]:

Type	Year	Category	Description	Title	Affiliations	Victims	\
Data destruction	14	14	14	14	11	13	
Defacement	5	5	5	5	3	5	
Denial of service	18	18	18	18	6	18	
Doxing	6	6	6	6	6	6	

```
Espionage           371       361          371    371         270     353
Financial Theft       7         7            7      7           7       7
Sabotage             22        22           22     22          17      22

                  Sponsor
Type
Data destruction       12
Defacement              5
Denial of service      18
Doxing                  6
Espionage             338
Financial Theft         7
Sabotage               21
```

[35]:
```
df4=cyberopsfinal_df.groupby(['Type']).size().reset_index(name='Count')
df4.head()
# reset_index() converts the above series back to dataframe. name='Count'␣
↪changes 0 label for count column to "Count"
```

[35]:

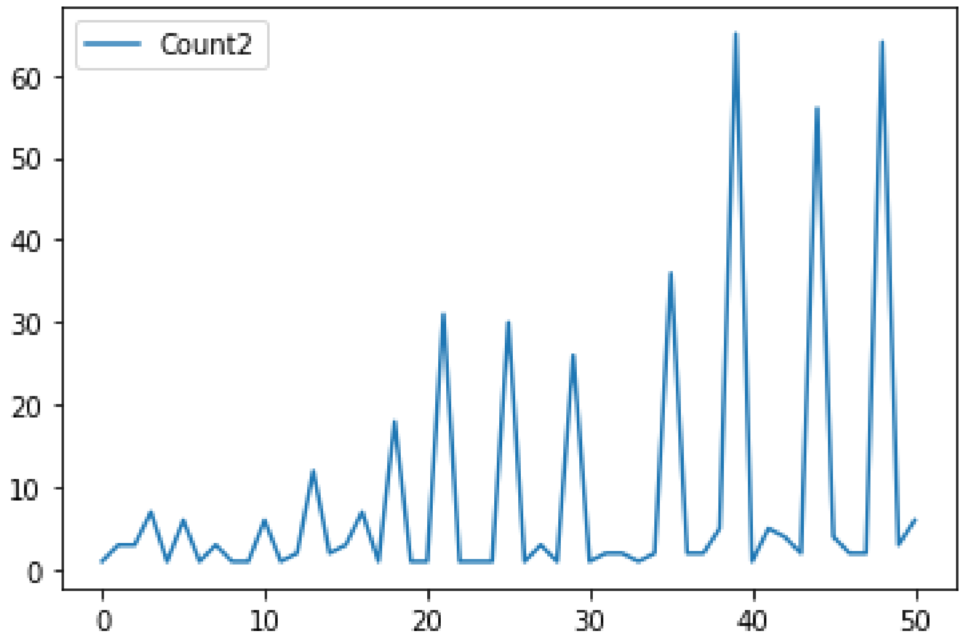
	Type	Count
0	Data destruction	14
1	Defacement	5
2	Denial of service	18
3	Doxing	6
4	Espionage	371

[36]:
```
df5=cyberopsfinal_df.groupby(['Year', 'Type']).size().reset_index(name="Count2")
df5.head()
```

[36]:

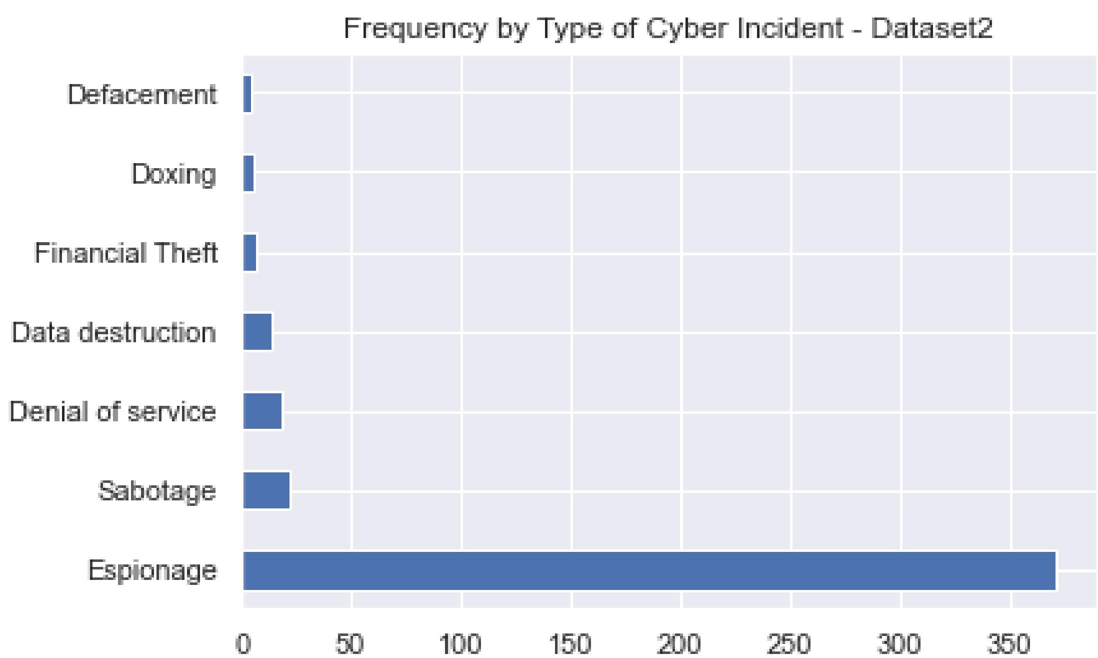
	Year	Type	Count2
0	2005	Espionage	1
1	2006	Espionage	3
2	2007	Denial of service	3
3	2007	Espionage	7
4	2008	Denial of service	1

[37]:
```
df5.plot()
plt.show()
```



[188]:
```
cyberopsfinal_df["Type"].value_counts().plot(kind='barh', title="Frequency by␣
↪Type of Cyber Incident - Dataset2")
# As you can see Espionage has the most occurances.
```

[188]: <AxesSubplot:title={'center':'Frequency by Type of Cyber Incident - Dataset2'}>



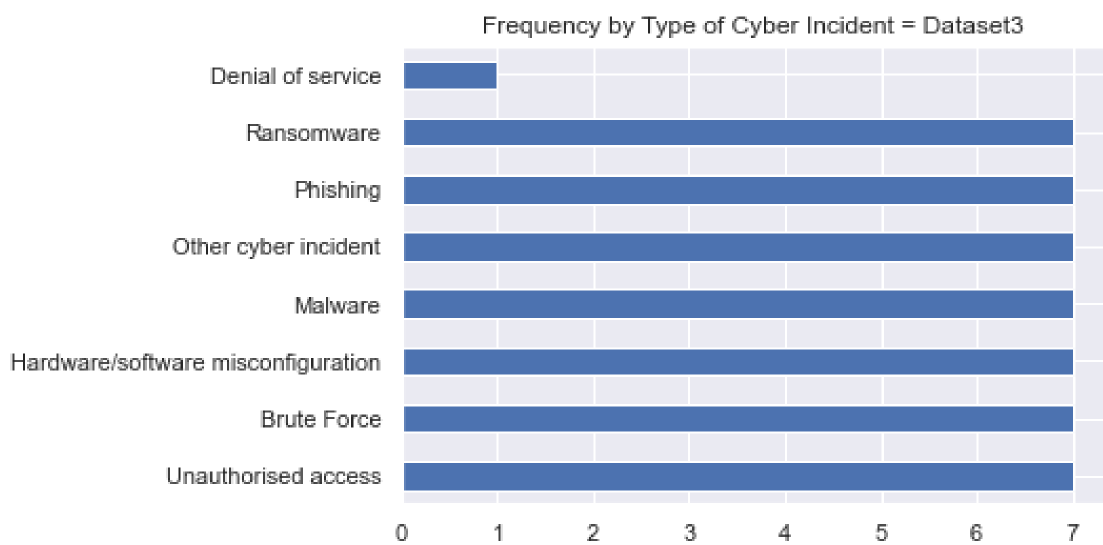
[39]:
```
# Dataset3: Read the Security Incidents file.  This dataset looks at the data␣
↪security incidents which have been
#reported to the Information Commissioners Office (ICO).
```

[40]:
```
Secincidentfinal_df['Incident Type'].value_counts()
```

[40]:
```
Unauthorised access                  7
Brute Force                          7
Hardware/software misconfiguration   7
Malware                              7
Other cyber incident                 7
Phishing                             7
Ransomware                           7
Denial of service                    1
Name: Incident Type, dtype: int64
```

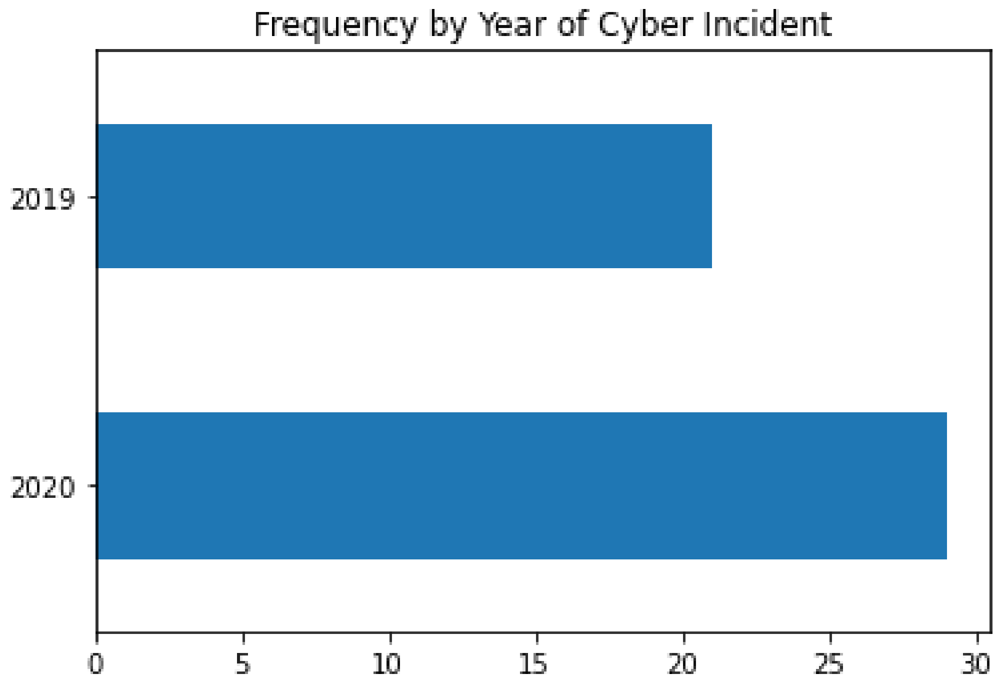
[187]:
```
Secincidentfinal_df['Incident Type'].value_counts().plot(kind='barh',␣
↪title="Frequency by Type of Cyber Incident = Dataset3")
```

[187]:
```
<AxesSubplot:title={'center':'Frequency by Type of Cyber Incident = Dataset3'}>
```



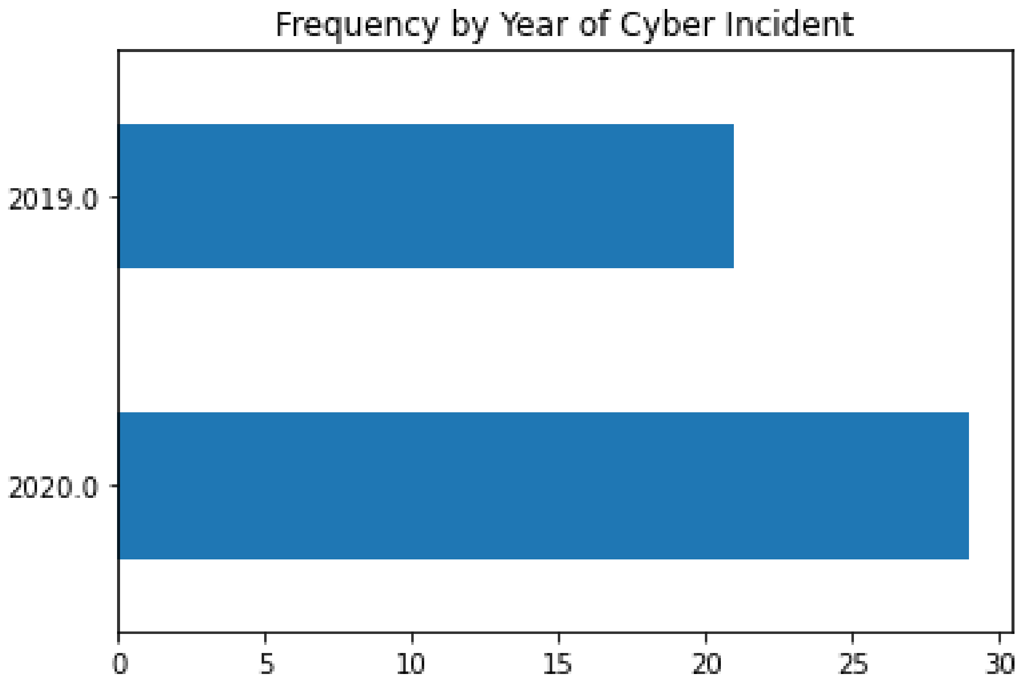
[42]:
```
Secincidentfinal_df['Year'].value_counts().plot(kind='barh', title="Frequency␣
↪by Year of Cyber Incident")

#SHows that there were more incidents in 2020 compared to 2021.
```

[42]:
```
<AxesSubplot:title={'center':'Frequency by Year of Cyber Incident'}>
```



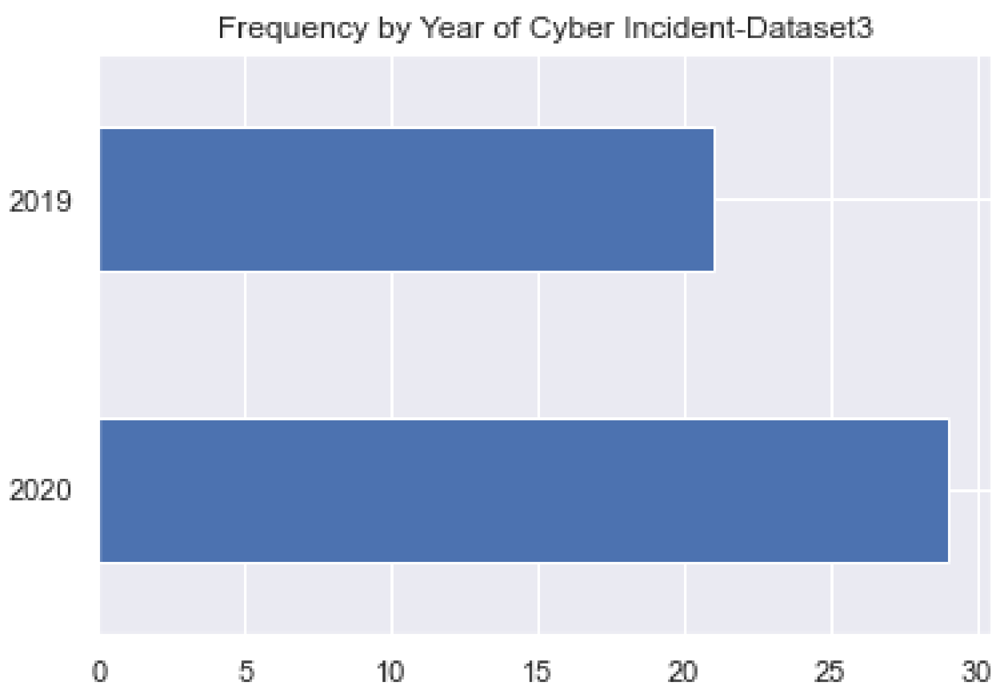
[43]:
```
dfsecincidents=Secincidentfinal_df['Year'].astype(float)
dfsecincidents.value_counts().plot(kind='barh', title="Frequency by Year of␣
↪Cyber Incident")
#redid the graph with Year as a float.  Same results
```

[43]:
```
<AxesSubplot:title={'center':'Frequency by Year of Cyber Incident'}>
```




```
[186]: Secincidentfinal_df['Year'].value_counts().plot(kind='barh', title="Frequency␣
        ↪by Year of Cyber Incident-Dataset3")
```

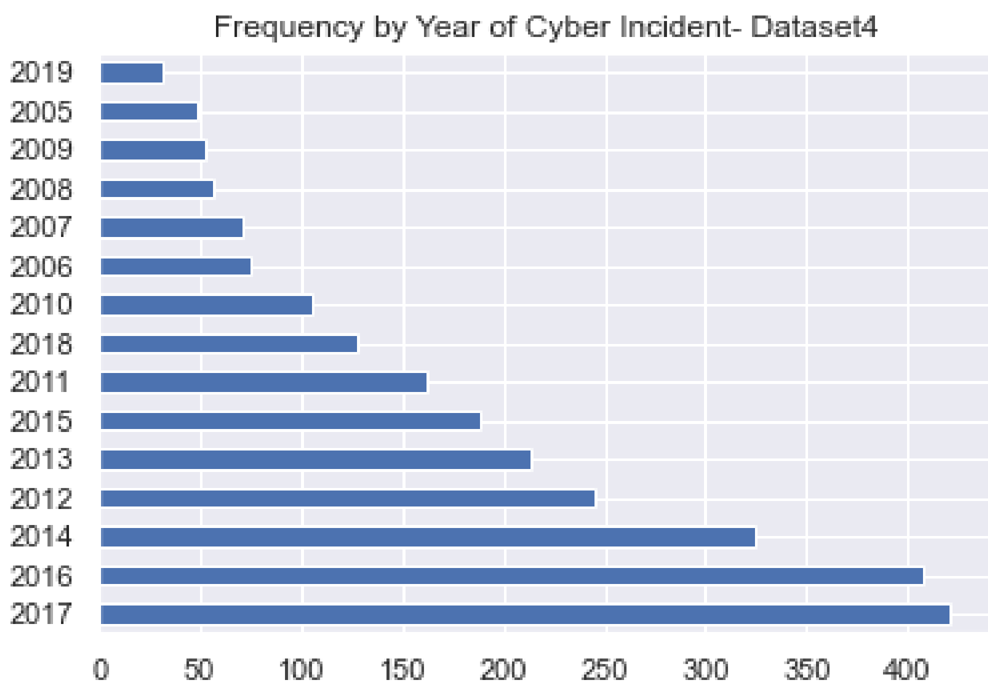
```
[186]: <AxesSubplot:title={'center':'Frequency by Year of Cyber Incident-Dataset3'}>
```



[45]:
```
# Dataset4: Read the PRC Data Breach Chronology.csv" file.  It contains the␣
↪Security incidents in the US
#collected by a non-profit. 9015 records.  Oldest date of incident January 2005␣
↪and the latest October 2019.
#No data in 2020.  These are all incidents in the US.
```

[185]:
```
PRCBreach_final_df['Year of Breach'].value_counts().plot(kind='barh',␣
↪title="Frequency by Year of Cyber Incident- Dataset4")

#This dataset shows that the highest hacking incidents happened in 2014 and␣
↪2015.  2019 was the lowest.  No data provided in 2020.
#  Feel this dataset may not have accurate or complete information.  We may not␣
↪use this dataset in our analysis.
```

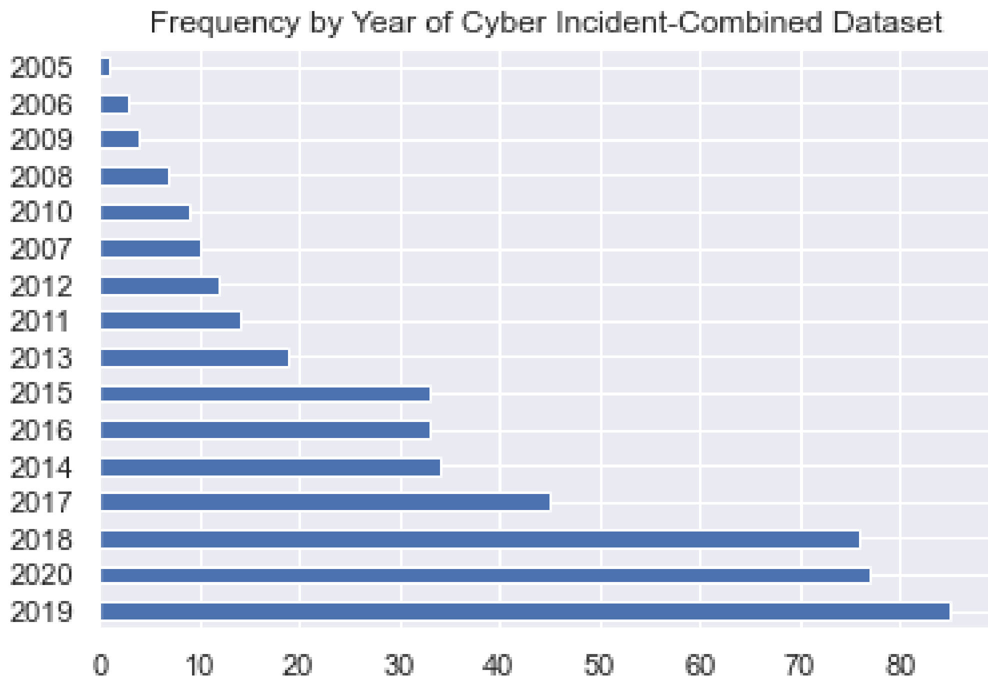
[185]: <AxesSubplot:title={'center':'Frequency by Year of Cyber Incident- Dataset4'}>



[184]:
```
#Combined Dataset:  Histogram of the combined dataset of the two incidents␣
↪datasets (Cyber Operations and Security Incidents)

big_df ['Year'].value_counts().plot(kind='barh', title="Frequency by Year of␣
↪Cyber Incident-Combined Dataset")
```

```
#See code below how big_df was created by merging two datasets (Dataset2 -
↪CyberOps and Dataset3 = SecIncidents above)
```

[184]: `<AxesSubplot:title={'center':'Frequency by Year of Cyber Incident-Combined Dataset'}>`



[ ]:

[47]:
```
#PMF:  Dataset2 on field Type
#Type_category=cyberopsfinal_df.groupby(['Type']).count()
#Type_category
```

[58]:
```
cyberopsfinal_df.head()
```

[58]:
```
   Year                  Category              Type  \
0  2020                Government         Espionage
1  2020                Government         Espionage
2  2020            Private sector  Data destruction
3  2020                  Military         Espionage
4  2020  Government, Private sector         Espionage

                                         Description  \
0  The suspected Russian hackers conducted a week…
```

```
1  The suspected North Korean threat actor Konni …
2  Responsible for attacking infrastructure that …
3  The Hamas-associated threat actor APT-C-23 tar…
4  Iranian hackers attacked high-end networking e…

                                              Title Affiliations  \
0                  Attack on Austrian foreign ministry        Turla
1  Spear-phishing campaign against unnamed U.S. g…  Konni Group
2                      Australian Signals Directorate          NaN
3                      Catfishing of Israeli soldiers     APT-C-23
4  Targeting of U.S. companies and government age…   Fox Kitten

                                    Victims  \
0                 Austrian Foreign Ministry
1          Employees of the U.S. government
2                                       NaN
3     Israeli Defense Forces (IDF) soldiers
4  U.S. government agencies, U.S. companies

                                   Sponsor
0                       Russian Federation
1  Korea (Democratic People's Republic of)
2                                Australia
3                     Palestine, State of
4               Iran (Islamic Republic of)
```

[48]:
```python
df_1 = cyberopsfinal_df["Type"].value_counts()
df_1
```

[48]:
```
Espionage           371
Sabotage             22
Denial of service    18
Data destruction     14
Financial Theft       7
Doxing                6
Defacement            5
Name: Type, dtype: int64
```

[49]:
```python
sum1 = len(cyberopsfinal_df["Type"].value_counts())
sum1
```

[49]: 7

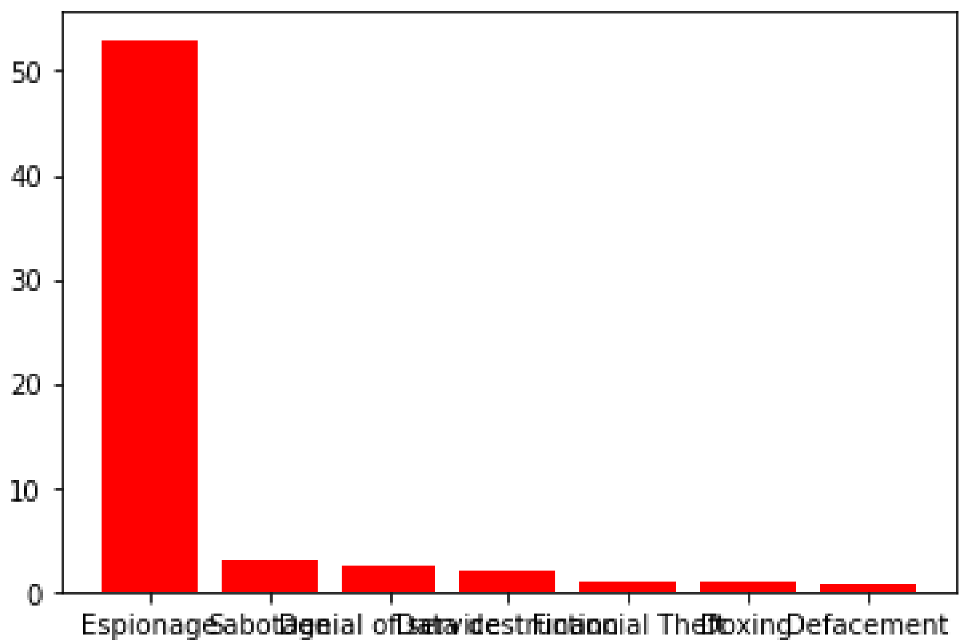
[50]:
```python
df_2=pd.DataFrame(df_1)
```

[51]:
```python
df_2["item"]=df_2.index
```

```
[52]: df_2['probability']=df_2['Type']/sum1
df_2
```

```
[52]:                     Type              item  probability
      Espionage            371         Espionage    53.000000
      Sabotage              22          Sabotage     3.142857
      Denial of service     18 Denial of service     2.571429
      Data destruction      14  Data destruction     2.000000
      Financial Theft        7   Financial Theft     1.000000
      Doxing                 6            Doxing     0.857143
      Defacement             5        Defacement     0.714286
```

```
[53]: plt.bar(df_2['item'], df_2['probability'], color='r')
plt.show()
```

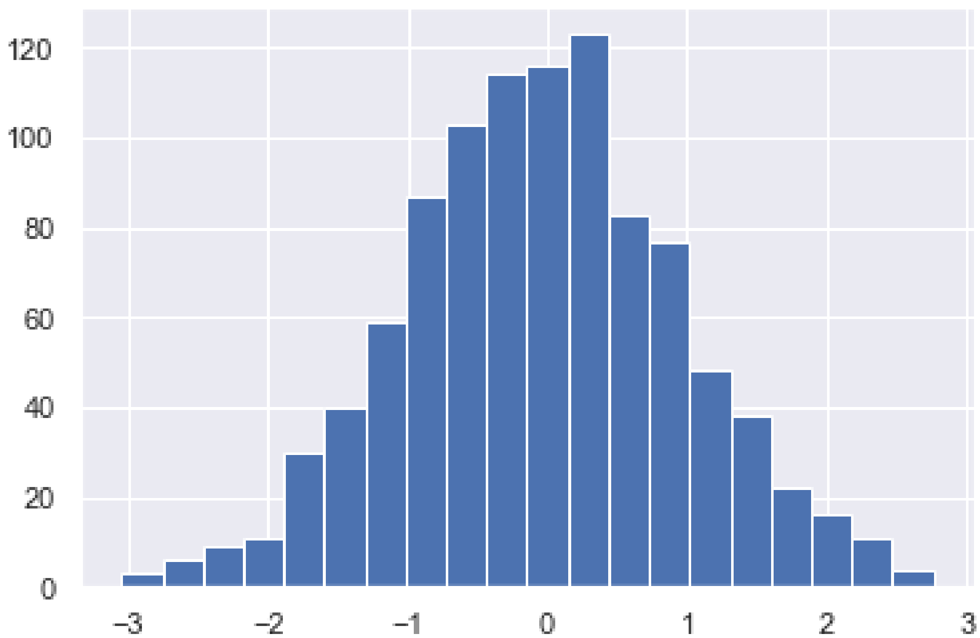



```
[54]: #CDF:  Dataset2 on field Type
import seaborn as sns
sns.set()
```

```
[55]: #first create normal distribution and generate random values
np.random.seed(0)
X_rand = np.random.normal(loc=0, scale=1.0, size=1000)
```

```
[56]: #Now visualize the above
plt.hist(X_rand, bins=20)
```

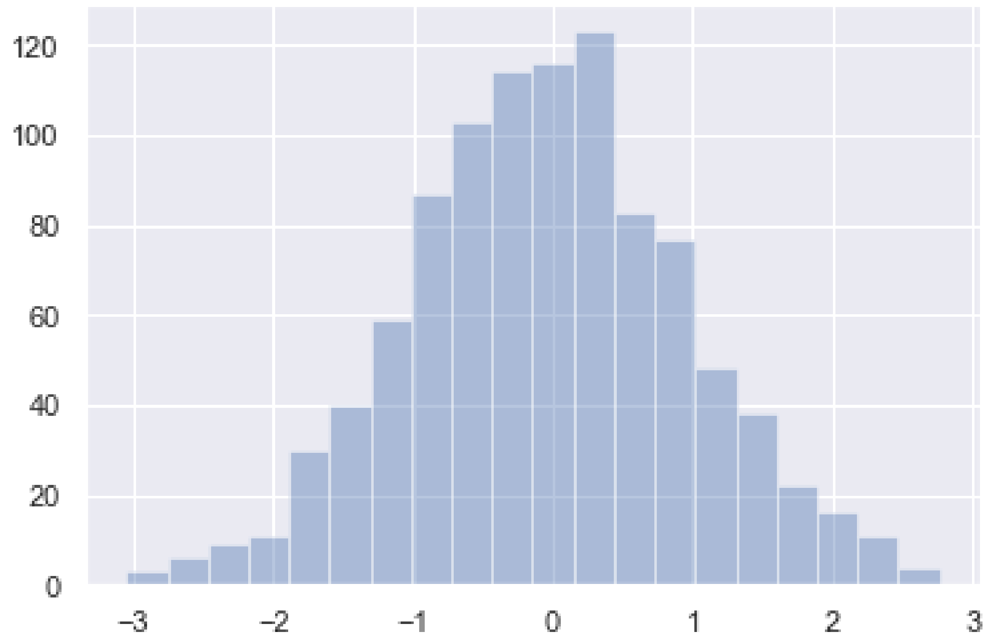
[56]:
```
(array([  3.,   6.,   9.,  11.,  30.,  40.,  59.,  87., 103., 114., 116.,
        123.,  83.,  77.,  48.,  38.,  22.,  16.,  11.,   4.]),
 array([-3.04614305, -2.75586815, -2.46559324, -2.17531833, -1.88504342,
        -1.59476851, -1.3044936 , -1.0142187 , -0.72394379, -0.43366888,
        -0.14339397,  0.14688094,  0.43715585,  0.72743075,  1.01770566,
         1.30798057,  1.59825548,  1.88853039,  2.1788053 ,  2.46908021,
         2.75935511]),
 <BarContainer object of 20 artists>)
```



[57]:
```
#Or
sns.distplot(X_rand, bins=20, kde=False)
```

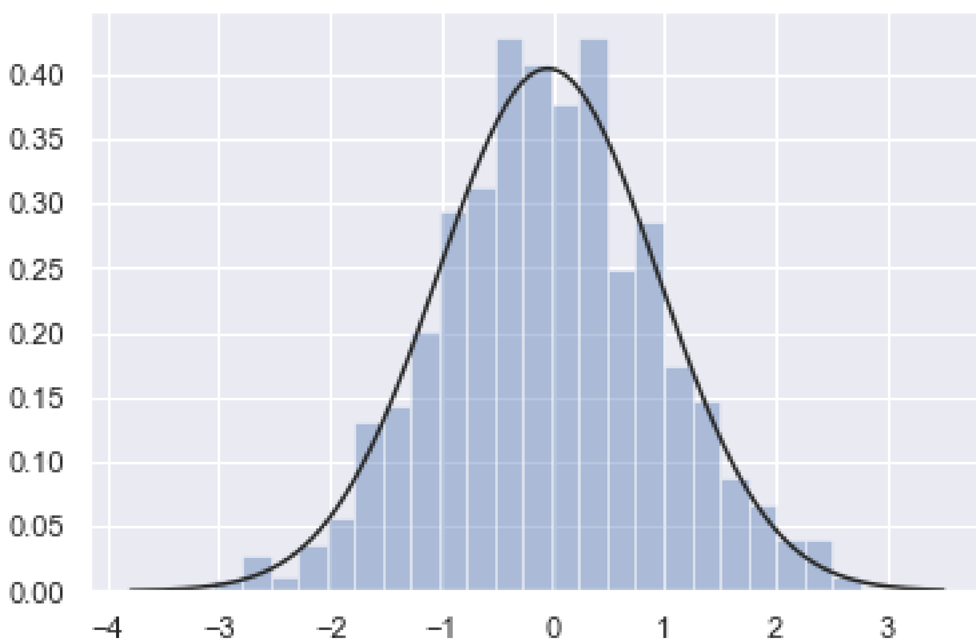
```
C:\Users\saima\anaconda3\envs\srahmanzaiDSC530\lib\site-
packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a
deprecated function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar flexibility)
or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

[57]: <AxesSubplot:>



[58]:
```
sns.distplot(X_rand, fit=stats.norm, kde=False)
```

[58]: <AxesSubplot:>



[59]:
```
#Distribution fitting
```

[60]:
```
loc, scale=stats.norm.fit(X_rand)
loc, scale
```

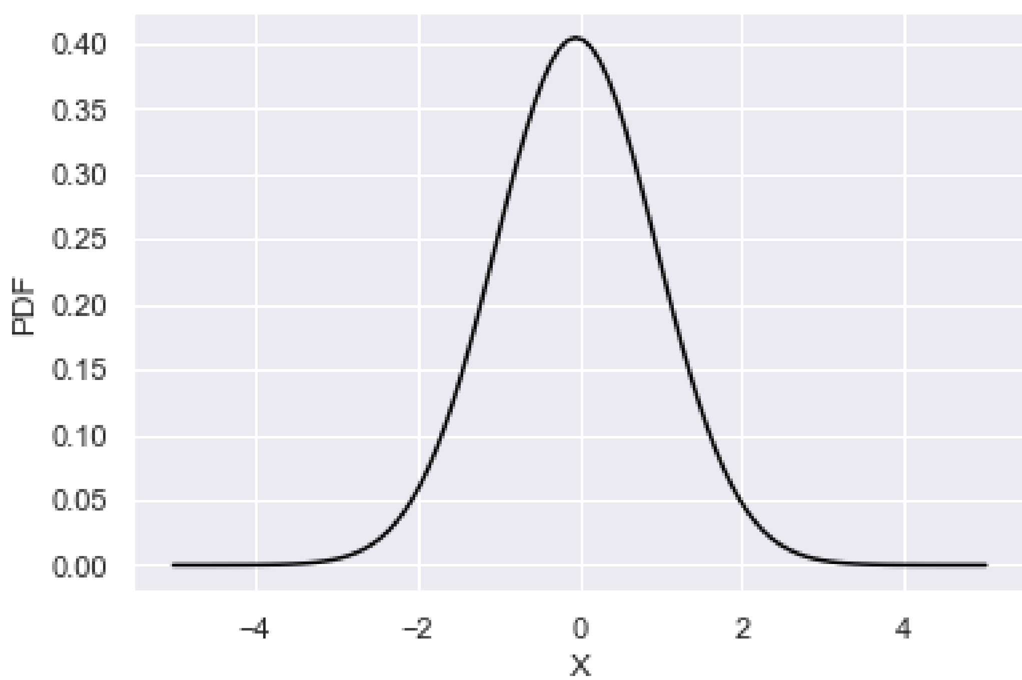
[60]: (-0.045256707490195384, 0.9870331586690257)

[61]:
```
#Calculate PDF
#linear space value of x

x=np.linspace(start=-5, stop=5, num=100)
```

[62]:
```
#pdf
pdf=stats.norm.pdf(x, loc=loc, scale=scale)
```

[63]:
```
#plot
plt.plot(x,pdf,color='black')
plt.xlabel('X')
plt.ylabel('PDF')
```

[63]: Text(0, 0.5, 'PDF')



[64]:
```
#CDF

#cdf=stats.norm.cdf(x, loc=loc, scale=scale)
```

```
#cdf = stats.norm.cdf(df_1, loc=loc, scale=scale)

#cdf1=stats.norm.cdf(df_1, loc=loc, scale=scale)
#cdf1
```

[65]:
```
mu=df_1.mean()
mu
#where df_1 is cyberopsfinal_df["Type"].value_counts()
```

[65]: 63.285714285714285

[66]:
```
sigma=df_1.std()
sigma
```

[66]: 135.84269614240617

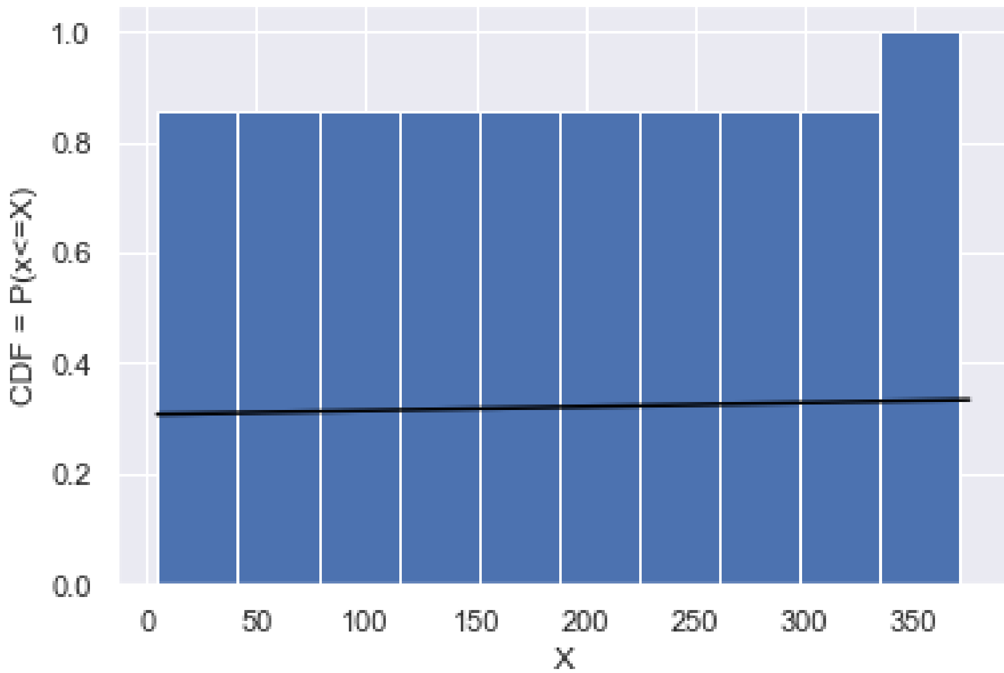
[67]:
```
cdf=stats.norm.cdf(x, loc=mu, scale=sigma)
```

[68]:
```
x=np.linspace(start=5, stop=375, num=100)
```

[69]:
```
df_1 = cyberopsfinal_df["Type"].value_counts()
df_1
```

[69]:
```
Espionage           371
Sabotage             22
Denial of service    18
Data destruction     14
Financial Theft       7
Doxing                6
Defacement            5
Name: Type, dtype: int64
```

[70]:
```
#plot
plt.hist(df_1, density=True, cumulative= True)
plt.plot(x,cdf,color='black')

plt.xlabel('X')
plt.ylabel('CDF = P(x<=X)')
plt.show()
```



[71]:
```
#For Analytics Distribution, I will create a pareto chart of variable Type in␣
↪the dataframe cyberopsfinal_df
```

[72]:
```
df_1 = cyberopsfinal_df["Type"].value_counts()
```

[85]:
```
df_2=pd.DataFrame(df_1)
```

[73]:
```
df_2["item"]=df_2.index
```

[74]:
```
df_3=df_2.sort_values(by='Type', ascending=False)
df_3
```

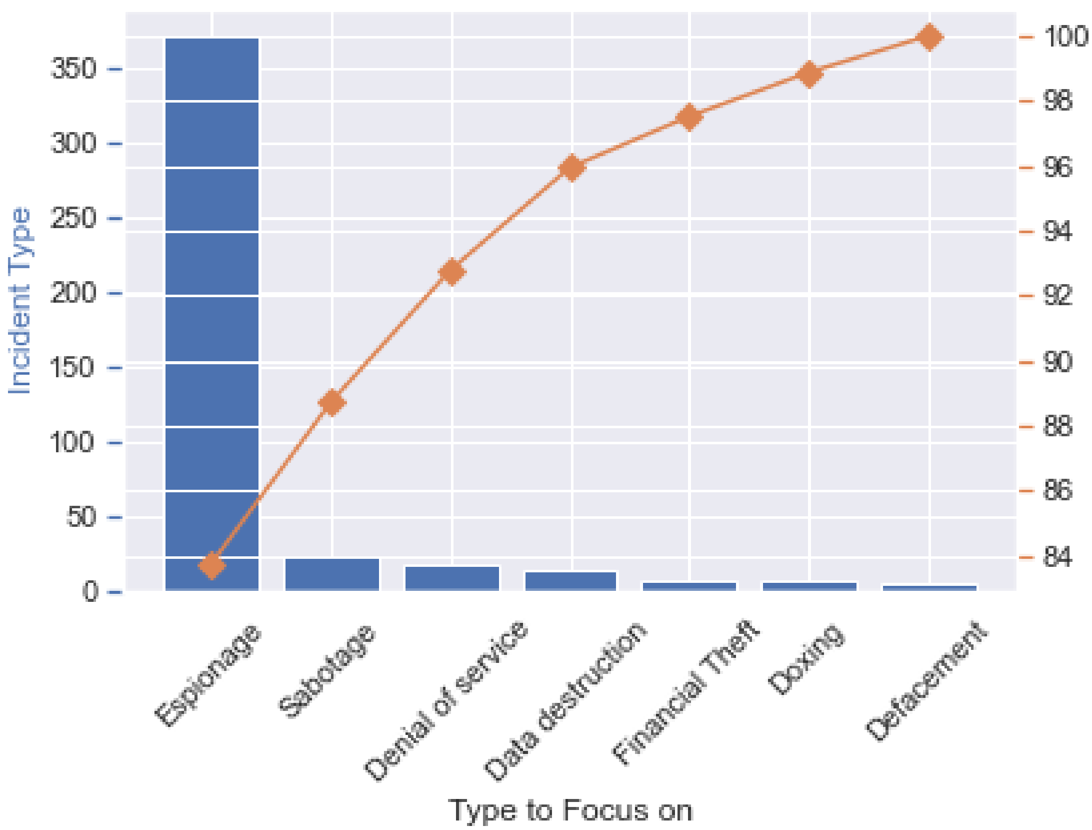
[74]:

	Type	item	probability
Espionage	371	Espionage	53.000000
Sabotage	22	Sabotage	3.142857
Denial of service	18	Denial of service	2.571429
Data destruction	14	Data destruction	2.000000
Financial Theft	7	Financial Theft	1.000000
Doxing	6	Doxing	0.857143
Defacement	5	Defacement	0.714286

[75]:
```
df_3["cumpercentage"]=df_3["Type"].cumsum()/df_3["Type"].sum()*100
```

[76]:
```python
fig, ax1=plt.subplots()
ax1.bar(df_3.item, df_3["Type"], color="C0")
ax1.set_ylabel("Incident Type", color="C0")
ax1.tick_params(axis="y", color="C0")
ax1.set_xlabel("Type to Focus on")
ax1.set_xticklabels(df_3["item"], rotation=45)
ax2=ax1.twinx()
ax2.plot(df_3.item, df_3["cumpercentage"], color="C1", marker="D", ms=7)
#ax2.yaxis.set_major_formatter(formatter)
ax2.tick_params(axis="y", color="C1")
plt.show()
```

```
C:\Users\saima\AppData\Local\Temp/ipykernel_21752/542301559.py:6: UserWarning:
FixedFormatter should only be used together with FixedLocator
  ax1.set_xticklabels(df_3["item"], rotation=45)
```



[77]:
```python
#Based on the above Paretto Distribution, Espionage Type is significant and
#need to be addressed to tackle this Cyber Incident Type
```

[78]:
```
# Merging two incident files together and then analyzing the results (Cyber Ops␣
↪and Sec_Incident files)>  I extracted
# two fields from each file Year and Type.  I also renamed the Type names to␣
↪make sure they are the same before merging.
```

[116]:
```
df3_cyberops = cyberopsfinal_df[["Year", "Type"]]


df3_cyberops.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 474 entries, 0 to 473
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   Year    474 non-null    object
 1   Type    443 non-null    object
dtypes: object(2)
memory usage: 11.1+ KB
```

[81]:
```
df4_Secincident = Secincidentfinal_df[["Year", "Incident Type"]]
df4_Secincident.rename( columns={"Incident Type":"Type" } ,inplace=True)
df4_Secincident.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 50 entries, 0 to 139
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   Year    50 non-null     object
 1   Type    50 non-null     object
dtypes: object(2)
memory usage: 1.2+ KB
```

```
C:\Users\saima\anaconda3\envs\srahmanzaiDSC530\lib\site-
packages\pandas\core\frame.py:5039: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  return super().rename(
```

[82]:
```
big_df = pd.concat([df3_cyberops, df4_Secincident], ignore_index=True)
big_df.info()
big_df
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 524 entries, 0 to 523
Data columns (total 2 columns):
```

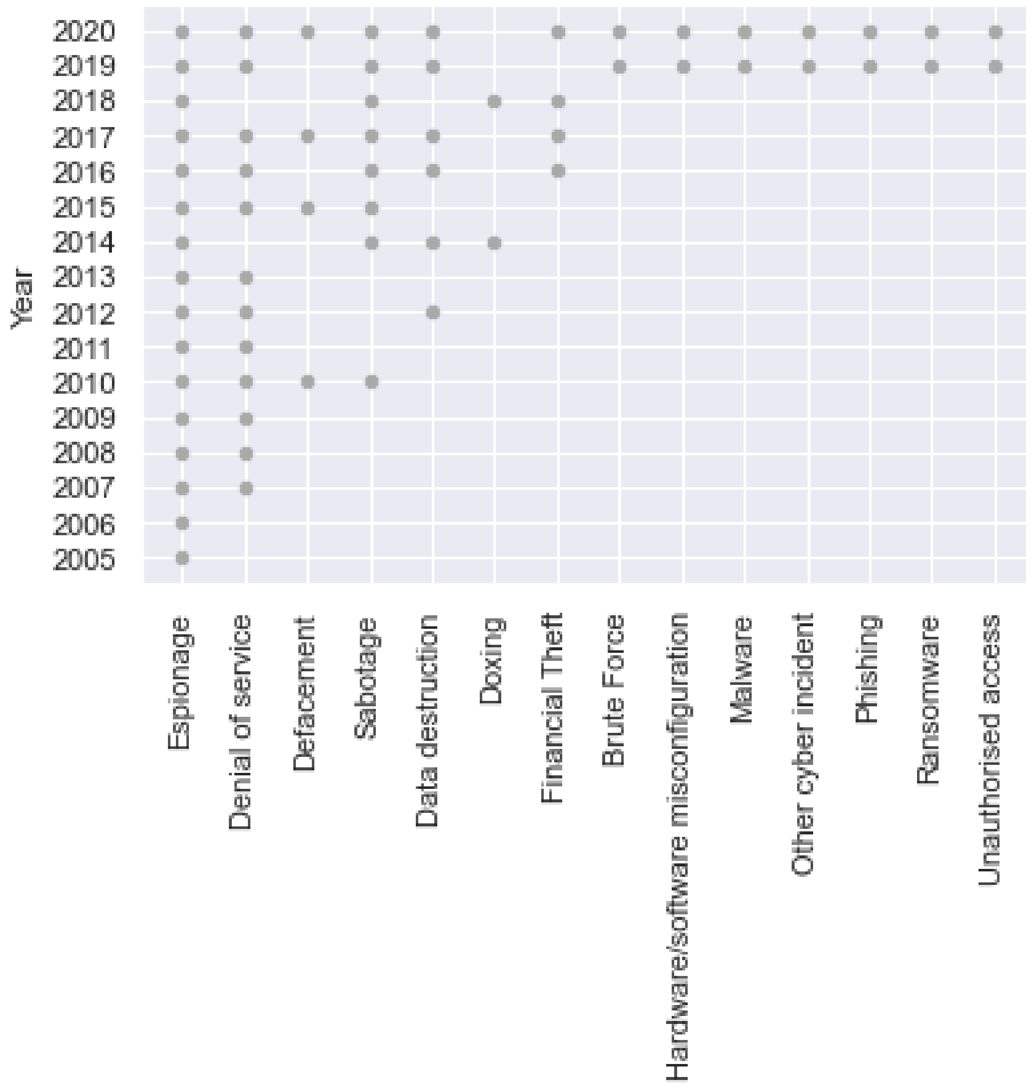
```
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   Year    524 non-null    object
 1   Type    493 non-null    object
dtypes: object(2)
memory usage: 8.3+ KB
```

[82]:

```
     Year                  Type
0    2020             Espionage
1    2020             Espionage
2    2020      Data destruction
3    2020             Espionage
4    2020             Espionage
..    …                    …
519  2020               Malware
520  2020  Other cyber incident
521  2020              Phishing
522  2020            Ransomware
523  2020   Unauthorised access

[524 rows x 2 columns]
```

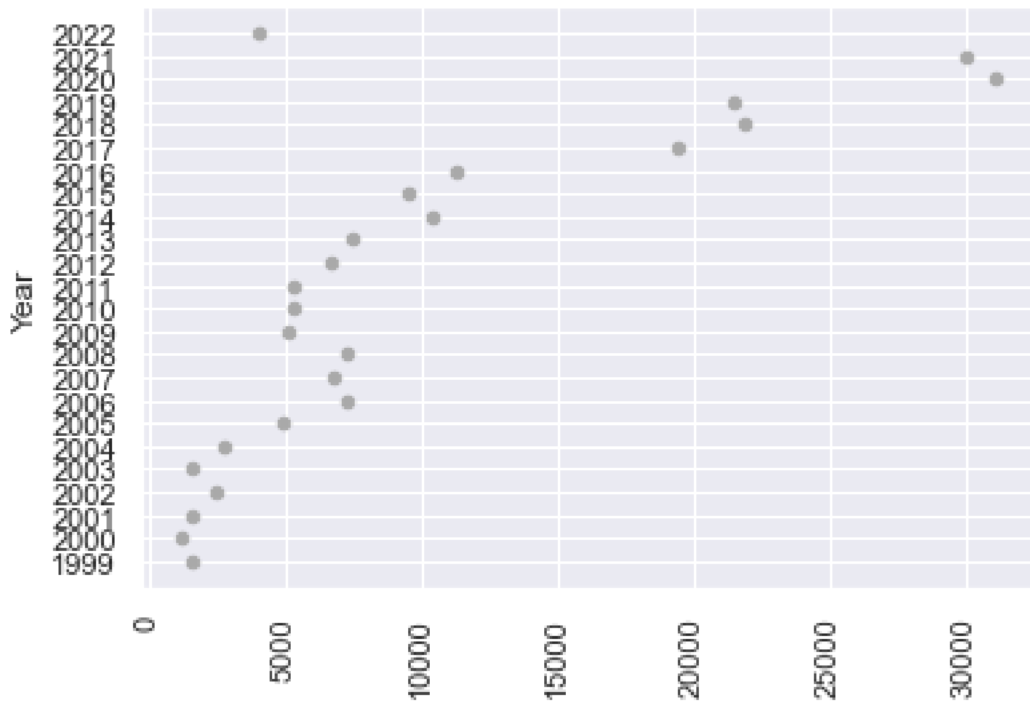
[83]:

```
# Create scatterplot of the combined dataset and focus on the two variables␣
 ↪Year and Type of incident

import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
from pandas import Series, DataFrame

from pylab import rcParams
from pandas.plotting import scatter_matrix



df5=big_df.groupby(['Year', 'Type']).size().reset_index(name="Count2")
df5.head()

df5.plot(kind='scatter', x='Type', y='Year', c='darkgrey')
plt.xticks(rotation=90)
plt.xlabel("")
plt.show()
#The scatterchart below shows a strong positive linear relationship between␣
 ↪variables Year and Type of incidents.  As Years pass, the incidents increase.
 ↪ Espionage having the most
#frequency or use almost every year.
```

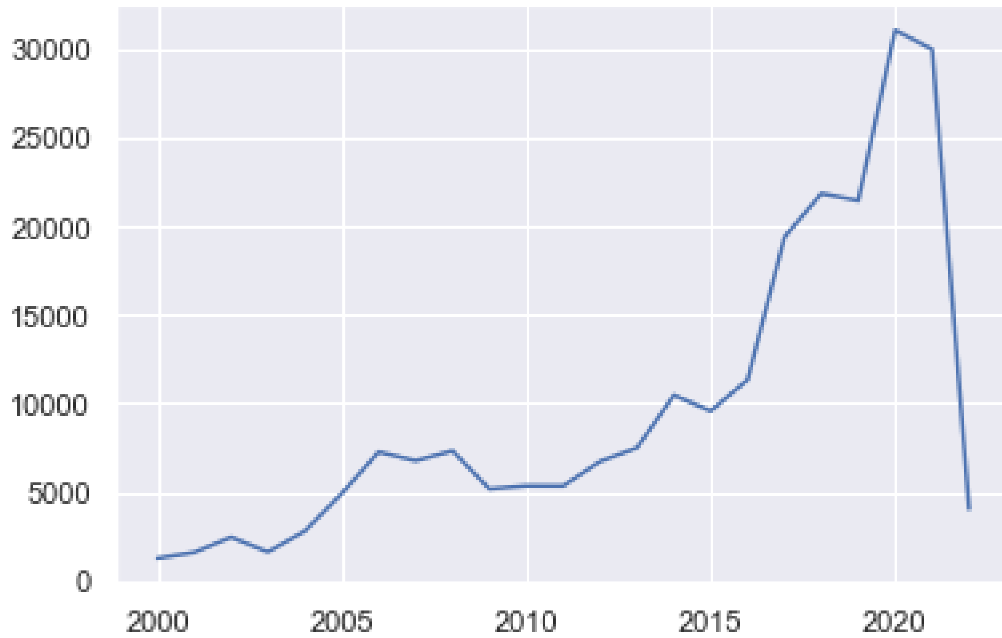


[84]:
```
#We had one dataset that showed vulnerabilities.  One of my hypothesis that␣
↪vulnerabilities increase with as years grow.  I
#drew a scatter plot diagram between the year and the number of vulnerabilities.
↪  The scatter plot shows a strong positive linear
#relationship as shown below.

import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
from pandas import Series, DataFrame

from pylab import rcParams
from pandas.plotting import scatter_matrix
```

```
df6=allitems.groupby(['Year']).size().reset_index(name="Count2")
df6.head()
df6.tail()


df6.plot(kind='scatter', x='Count2', y='Year', c='darkgrey')
plt.xticks(rotation=90)
plt.xlabel("")
plt.show()
```



[98]:
```
#Hypothesis Testing:Onthe Vulnerabilities Dataset:

FirstSample = df6[1:30]['Year_int']
SecondSample = df6[1:30]['Count2']
pyplot.plot(FirstSample, SecondSample)
pyplot.show()
```




```
[99]: #Hypothesis testing using Pearson Correlation between the Year and Type count␣
      ↪variables for the vulnerabiltiy dataset
      from scipy.stats import pearsonr
      stat, p = pearsonr(FirstSample, SecondSample)
      print('stat=%3f, p=%5f' % (stat, p))

      if p > 0.05:
          print('Independent Samples')
      else:
          print('Dependent Samples')
```

```
stat=0.760836, p=0.000025
Dependent Samples
```

```
[ ]: #Covariance, Pearson's correlation,
     #We calculated the Covariance, Pearson's correlation on the vulnerability␣
     ↪dataset first showing Security incidents by
     #time over the years.
```

```
[174]: #Correlation on Vulnerability dataset

       df6.head()
       df6['Year_int'] = df6['Year'].astype('int')
       df6.info()
       df6.corr()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 24 entries, 0 to 23
Data columns (total 3 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Year      24 non-null     object
 1   Count2    24 non-null     int64
 2   Year_int  24 non-null     int32
dtypes: int32(1), int64(1), object(1)
memory usage: 608.0+ bytes
```

[174]:

	Count2	Year_int
Count2	1.000000	0.766761
Year_int	0.766761	1.000000

[175]:

```
# Covariance for the Vulnerabiliies dataset
df6.cov()
#Covariance is a part of statistics and it is the measure of the
#relationship between two random variables or random problems.
```

[175]:

	Count2	Year_int
Count2	7.691212e+07	47549.108696
Year_int	4.754911e+04	50.000000

[ ]:

```
#The Pearson correlation coefficient, often referred to as Pearson’s r, is a␣
↪measure of linear correlation between two
#variables. This means that the Pearson correlation coefficient measures a␣
↪normalized measurement of covariance
#(i.e., a value between -1 and 1 that shows how much variables vary together).
```

[179]:

```
##### Regression Analysis for variables in the vulnerability dataset.

df6.head()
```

[179]:

	Year	Count2	Year_int
0	1999	1579	1999
1	2000	1243	2000
2	2001	1573	2001
3	2002	2436	2002
4	2003	1600	2003

[180]:

```
reg2=ols("Year_int ~ Count2", df6).fit()
reg2.summary()
```

[180]:

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
```

```
Dep. Variable:               Year_int   R-squared:                       0.588
Model:                            OLS   Adj. R-squared:                  0.569
Method:                 Least Squares   F-statistic:                     31.39
Date:                Fri, 04 Mar 2022   Prob (F-statistic):           1.24e-05
Time:                        01:07:23   Log-Likelihood:                -69.850
No. Observations:                  24   AIC:                             143.7
Df Residuals:                      22   BIC:                             146.1
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept   2004.6609      1.408   1423.295      0.000    2001.740    2007.582
Count2         0.0006      0.000      5.602      0.000       0.000       0.001
==============================================================================
Omnibus:                       14.103   Durbin-Watson:                   0.746
Prob(Omnibus):                  0.001   Jarque-Bera (JB):               14.692
Skew:                           1.331   Prob(JB):                     0.000645
Kurtosis:                       5.757   Cond. No.                     1.90e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 1.9e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

[ ]:

```

```

[100]:

```
#Hypothesis testing using Pearson Correlation on the combined datset by Year␣
↪and Count of how many incidents by Year.
#In order to do that, first I had to prep the file make some numeric␣
↪conversions as Hypothesis works on numeric fields as
#shown below.
```

[ ]:

```
#testing df5 again using encoding to change categoricl variables to numeric so␣
↪I can
#run statistic commands, remove N/As etc.
```

[160]:

```
big_df = pd.concat([df3_cyberops, df4_Secincident], ignore_index=True)
big_df['Year_int'] = big_df['Year'].astype('int')
big_df.info()
big_df.isnull().sum()
big_df.dropna(inplace=True)
big_df.isnull().sum()
```

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

```
RangeIndex: 524 entries, 0 to 523
Data columns (total 3 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Year      524 non-null    object
 1   Type      493 non-null    object
 2   Year_int  524 non-null    int32
dtypes: int32(1), object(2)
memory usage: 10.4+ KB
```

[160]:
```
Year        0
Type        0
Year_int    0
dtype: int64
```

[161]:
```
big_df.Type.unique()
```

[161]:
```
array(['Espionage', 'Data destruction', 'Financial Theft', 'Sabotage',
       'Defacement', 'Denial of service', 'Doxing', 'Unauthorised access',
       'Brute Force', 'Hardware/software misconfiguration', 'Malware',
       'Other cyber incident', 'Phishing', 'Ransomware'], dtype=object)
```

[162]:
```
#!pip install scikit-learn
from sklearn.preprocessing import LabelEncoder
le= LabelEncoder()
df=le.fit_transform(big_df['Type'])
df
series=pd.Series((df), name="Type_Num")
series
```

[162]:
```
0       5
1       5
2       1
3       5
4       5
       ..
488     8
489     9
490    10
491    11
492    13
Name: Type_Num, Length: 493, dtype: int32
```

[163]:
```
big_df=pd.concat([big_df, series], axis=1)

big_df
```

```
[163]:      Year                  Type  Year_int  Type_Num
       0    2020             Espionage    2020.0       5.0
       1    2020             Espionage    2020.0       5.0
       2    2020      Data destruction    2020.0       1.0
       3    2020             Espionage    2020.0       5.0
       4    2020             Espionage    2020.0       5.0
       ..    …                     …         …       …
       519  2020               Malware    2020.0       NaN
       520  2020  Other cyber incident    2020.0       NaN
       521  2020              Phishing    2020.0       NaN
       522  2020            Ransomware    2020.0       NaN
       523  2020   Unauthorised access    2020.0       NaN

       [524 rows x 4 columns]
```

```
[164]: big_df.isnull().sum()
       big_df.dropna(inplace=True)
       big_df.isnull().sum()
       big_df
```

```
[164]:      Year                                Type  Year_int  Type_Num
       0    2020                           Espionage    2020.0       5.0
       1    2020                           Espionage    2020.0       5.0
       2    2020                    Data destruction    2020.0       1.0
       3    2020                           Espionage    2020.0       5.0
       4    2020                           Espionage    2020.0       5.0
       ..    …                                   …         …       …
       488  2019                         Brute Force    2019.0       8.0
       489  2019  Hardware/software misconfiguration    2019.0       9.0
       490  2019                             Malware    2019.0      10.0
       491  2019                Other cyber incident    2019.0      11.0
       492  2019                            Phishing    2019.0      13.0

       [462 rows x 4 columns]
```

```
[165]: big_df.Year.unique()
```

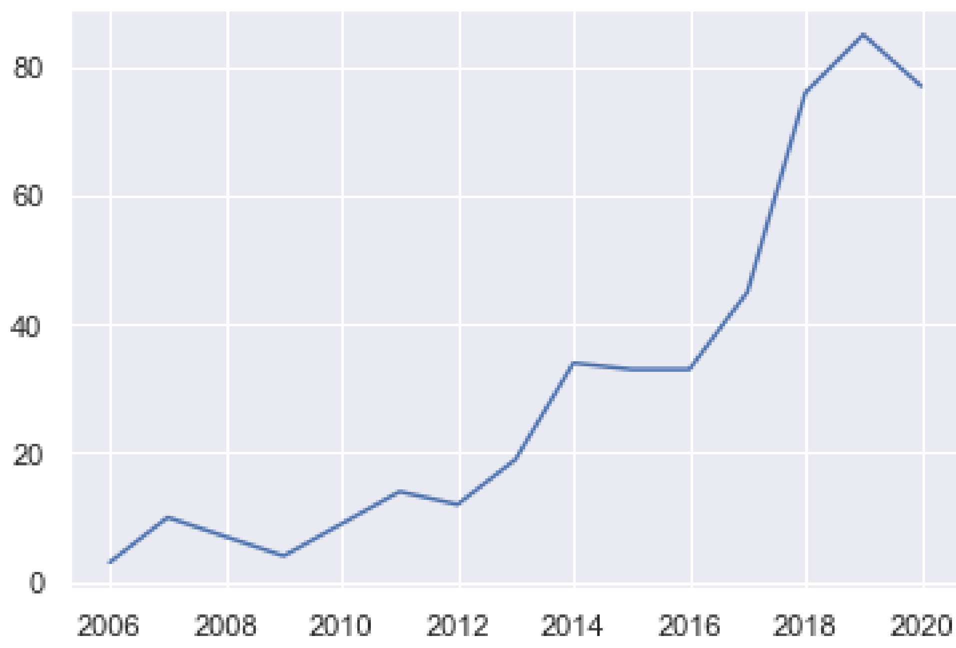
```
[165]: array(['2020', '2019', '2018', '2017', '2016', '2015', '2014', '2013',
              '2012', '2011', '2010', '2009', '2008', '2007', '2006', '2005'],
             dtype=object)
```

```
[166]: grouped_df = big_df.groupby(['Year_int']).size().reset_index(name="Count")
       grouped_df
```

```
[166]:     Year_int  Count
       0     2005.0      1
       1     2006.0      3
       2     2007.0     10
```

```
3      2008.0      7
4      2009.0      4
5      2010.0      9
6      2011.0     14
7      2012.0     12
8      2013.0     19
9      2014.0     34
10     2015.0     33
11     2016.0     33
12     2017.0     45
13     2018.0     76
14     2019.0     85
15     2020.0     77
```

[156]:
```
#Hypothesis Testing:Onthe combined dataset:
import matplotlib
from matplotlib import pyplot
%matplotlib inline

FirstSample = grouped_df[1:100]['Year_int']
SecondSample = grouped_df[1:100]['Count']
pyplot.plot(FirstSample, SecondSample)
pyplot.show()
```



[167]:
```
#Hypothesis testing using Pearson Correlation between teh Year and Type␣
↪variables for the combined dataset
from scipy.stats import pearsonr
stat, p = pearsonr(FirstSample, SecondSample)
print('stat=%3f, p=%5f' % (stat, p))

if p > 0.05:
    print('Independent Samples')
else:
    print('Dependent Samples')
```

```
stat=0.913623, p=0.000002
Dependent Samples
```

[168]:
```
#correlation of combined file

grouped_df.head()

grouped_df.corr()
```

[168]:

	Year_int	Count
Year_int	1.000000	0.910558
Count	0.910558	1.000000

[169]:
```
#covariance of combined file
grouped_df.cov()
```

[169]:

	Year_int	Count
Year_int	22.666667	122.133333
Count	122.133333	793.716667

[170]:
```
##### Regression Analysis for variables in the combined dataset.  This includes␣
↪Incident Type Independent variable and
#Year Dependent variable

import pandas as pd
from statsmodels.formula.api import ols
from scipy import stats
import statsmodels.api as sm

grouped_df.head()
```

[170]:

	Year_int	Count
0	2005.0	1
1	2006.0	3
2	2007.0	10
3	2008.0	7
4	2009.0	4

[173]:
```
reg=ols("Year_int ~ Count", grouped_df).fit()
reg.summary()
```

```
C:\Users\saima\anaconda3\envs\srahmanzaiDSC530\lib\site-
packages\scipy\stats\stats.py:1541: UserWarning: kurtosistest only valid for
n>=20 … continuing anyway, n=16
  warnings.warn("kurtosistest only valid for n>=20 … continuing "
```

[173]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:               Year_int   R-squared:                       0.829
Model:                            OLS   Adj. R-squared:                  0.817
Method:                 Least Squares   F-statistic:                     67.93
Date:                Fri, 04 Mar 2022   Prob (F-statistic):           9.67e-07
Time:                        00:50:56   Log-Likelihood:                -33.020
No. Observations:                  16   AIC:                             70.04
Df Residuals:                      14   BIC:                             71.58
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept   2008.0569      0.742   2707.646      0.000    2006.466    2009.647
Count          0.1539      0.019      8.242      0.000       0.114       0.194
==============================================================================
Omnibus:                        3.229   Durbin-Watson:                   0.528
Prob(Omnibus):                  0.199   Jarque-Bera (JB):                1.295
Skew:                          -0.238   Prob(JB):                        0.523
Kurtosis:                       1.690   Cond. No.                         57.9
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
"""
```

[ ]:
```
#PMF, CDF etc. on Combined file below.  It was done earlier on Dataset2
```

[ ]:
```
#PMF:  Comvined dataset on field Type
#Type_category=cyberopsfinal_df.groupby(['Type']).count()
#Type_category
```

[191]:
```
df_1 = big_df["Type"].value_counts()
df_1
```

[191]:
```
Espionage                              371
Sabotage                                22
Denial of service                       18
Data destruction                        14
Financial Theft                          7
Doxing                                   6
Defacement                               5
Brute Force                              3
Hardware/software misconfiguration       3
Malware                                  3
Other cyber incident                     3
Phishing                                 3
Unauthorised access                      2
Ransomware                               2
Name: Type, dtype: int64
```

[192]:
```
sum1 = len(big_df["Type"].value_counts())
sum1
```

[192]:
```
14
```

[193]:
```
df_2=pd.DataFrame(df_1)
```

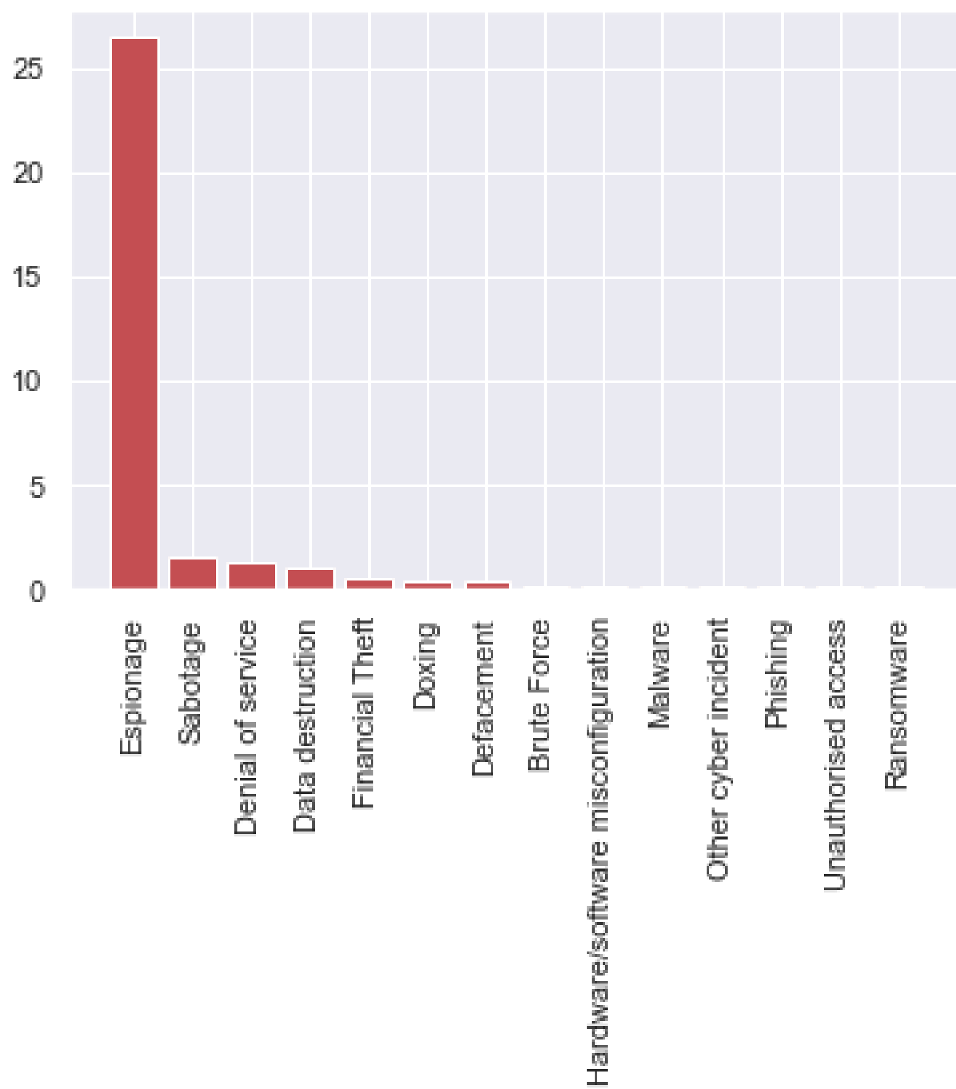
[194]:
```
df_2["item"]=df_2.index
```

[195]:
```
df_2['probability']=df_2['Type']/sum1
df_2
```

[195]:
```
                                    Type                                item  \
Espionage                            371                           Espionage
Sabotage                              22                            Sabotage
Denial of service                     18                   Denial of service
Data destruction                      14                    Data destruction
Financial Theft                        7                     Financial Theft
Doxing                                 6                              Doxing
Defacement                             5                          Defacement
Brute Force                            3                         Brute Force
Hardware/software misconfiguration     3  Hardware/software misconfiguration
Malware                                3                             Malware
Other cyber incident                   3                Other cyber incident
Phishing                               3                            Phishing
Unauthorised access                    2                 Unauthorised access
Ransomware                             2                          Ransomware

                                    probability
Espionage                             26.500000
Sabotage                               1.571429
```

```
Denial of service                       1.285714
Data destruction                        1.000000
Financial Theft                         0.500000
Doxing                                  0.428571
Defacement                              0.357143
Brute Force                             0.214286
Hardware/software misconfiguration      0.214286
Malware                                 0.214286
Other cyber incident                    0.214286
Phishing                                0.214286
Unauthorised access                     0.142857
Ransomware                              0.142857
```

[197]:
```python
plt.bar(df_2['item'], df_2['probability'], color='r')
plt.xticks(rotation=90)
plt.show()
```

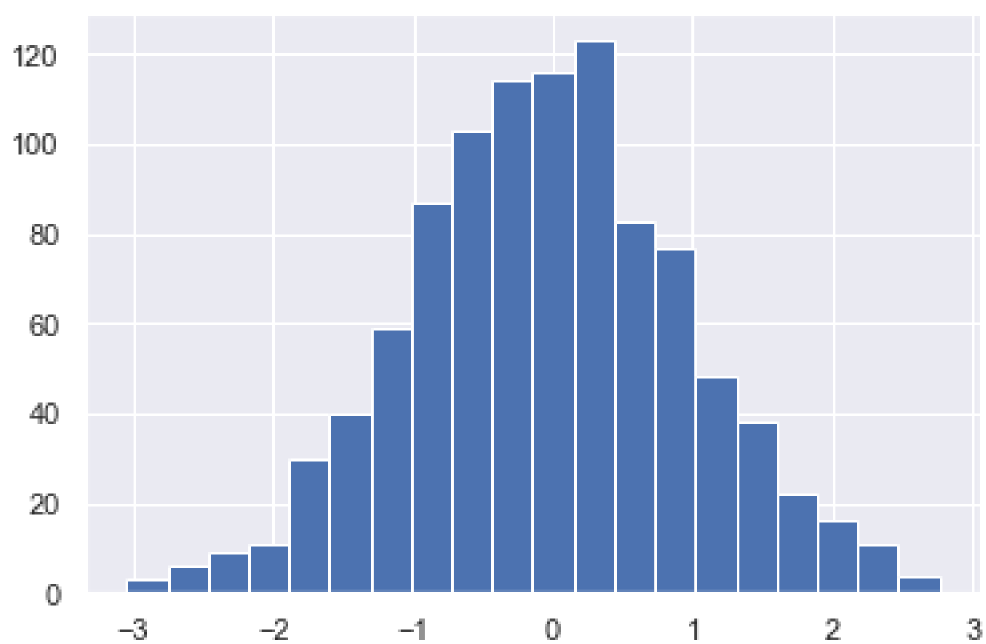


[198]:
```
#CDF:  Combined Dataset on field Type
import seaborn as sns
sns.set()
```

[199]:
```
#first create normal distribution and generate random values
np.random.seed(0)
X_rand = np.random.normal(loc=0, scale=1.0, size=1000)
```

[200]:
```
#Now visualize the above
plt.hist(X_rand, bins=20)
```

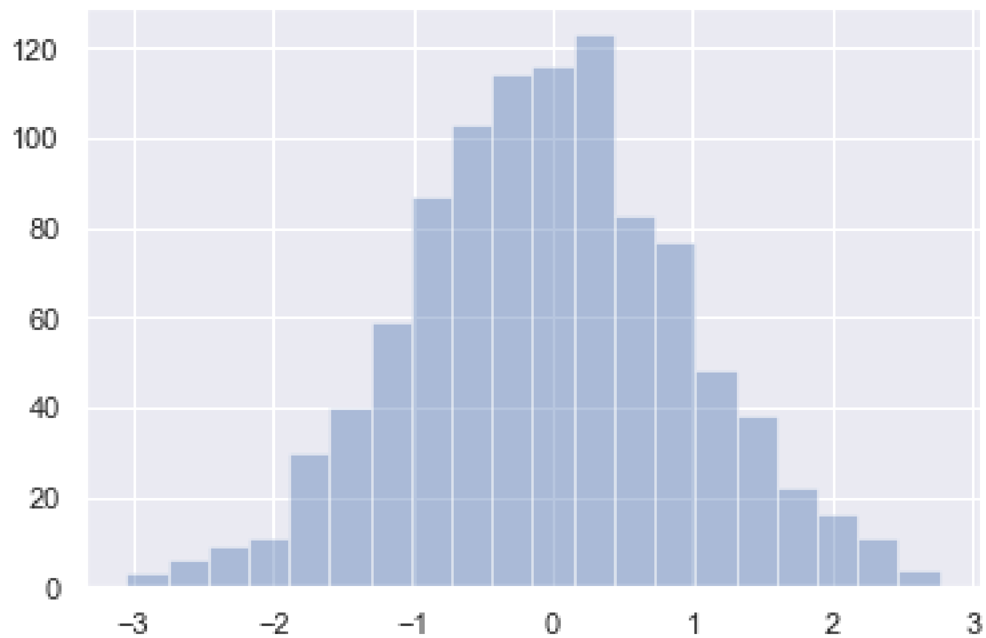
[200]:
```
(array([  3.,    6.,    9.,   11.,   30.,   40.,   59.,   87., 103., 114., 116.,
        123.,   83.,   77.,   48.,   38.,   22.,   16.,   11.,    4.]),
 array([-3.04614305, -2.75586815, -2.46559324, -2.17531833, -1.88504342,
        -1.59476851, -1.3044936 , -1.0142187 , -0.72394379, -0.43366888,
        -0.14339397,  0.14688094,  0.43715585,  0.72743075,  1.01770566,
         1.30798057,  1.59825548,  1.88853039,  2.1788053 ,  2.46908021,
         2.75935511]),
 <BarContainer object of 20 artists>)
```



[201]:
```
#Or
sns.distplot(X_rand, bins=20, kde=False)
```

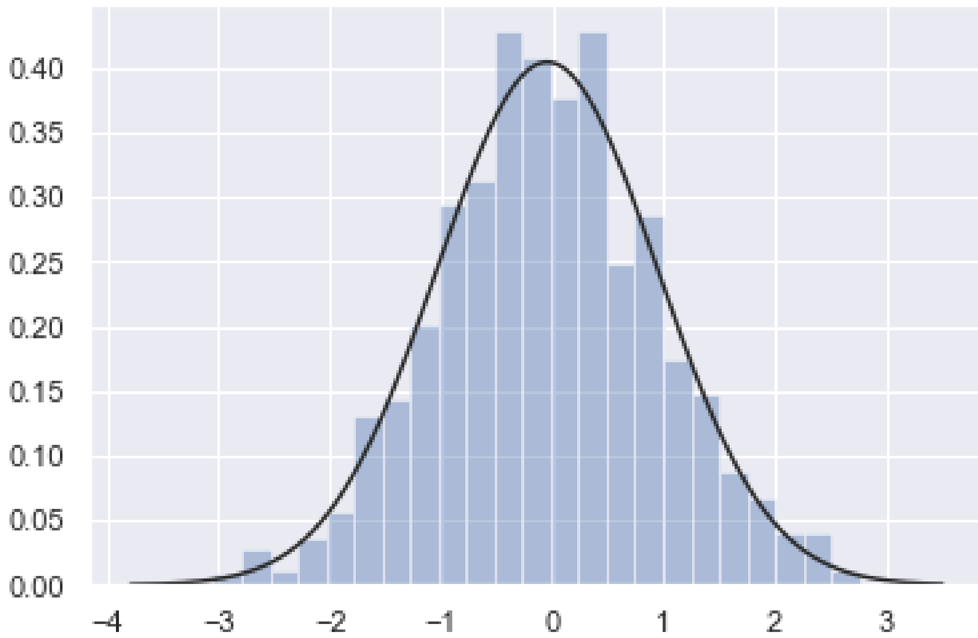
```
C:\Users\saima\anaconda3\envs\srahmanzaiDSC530\lib\site-
packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a
deprecated function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar flexibility)
or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

[201]: <AxesSubplot:>



[202]:
```
sns.distplot(X_rand, fit=stats.norm, kde=False)
```

[202]: <AxesSubplot:>



[203]:
```
#Distribution fitting
```

[204]:
```
loc, scale=stats.norm.fit(X_rand)
loc, scale
```

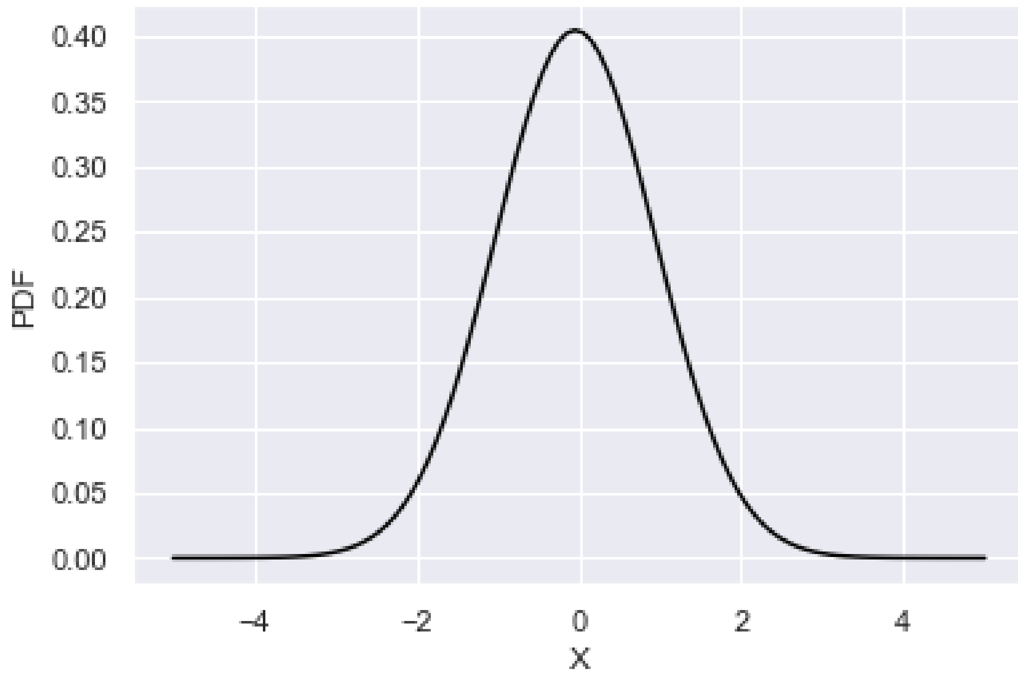
[204]: (-0.045256707490195384, 0.9870331586690257)

[206]:
```
#Calculate PDF
#linear space value of x

x=np.linspace(start=-5, stop=5, num=100)
```

[207]:
```
#pdf
pdf=stats.norm.pdf(x, loc=loc, scale=scale)
```

[208]:
```
#plot
plt.plot(x,pdf,color='black')
plt.xlabel('X')
plt.ylabel('PDF')
```

[208]: Text(0, 0.5, 'PDF')



[209]:
```
#CDF

#cdf=stats.norm.cdf(x, loc=loc, scale=scale)
#cdf = stats.norm.cdf(df_1, loc=loc, scale=scale)

#cdf1=stats.norm.cdf(df_1, loc=loc, scale=scale)
#cdf1
```

[210]:
```
mu=df_1.mean()
mu
#where df_1 is cyberopsfinal_df["Type"].value_counts()
```

[210]: 33.0

[211]:
```
sigma=df_1.std()
sigma
```

[211]: 97.4924060159007

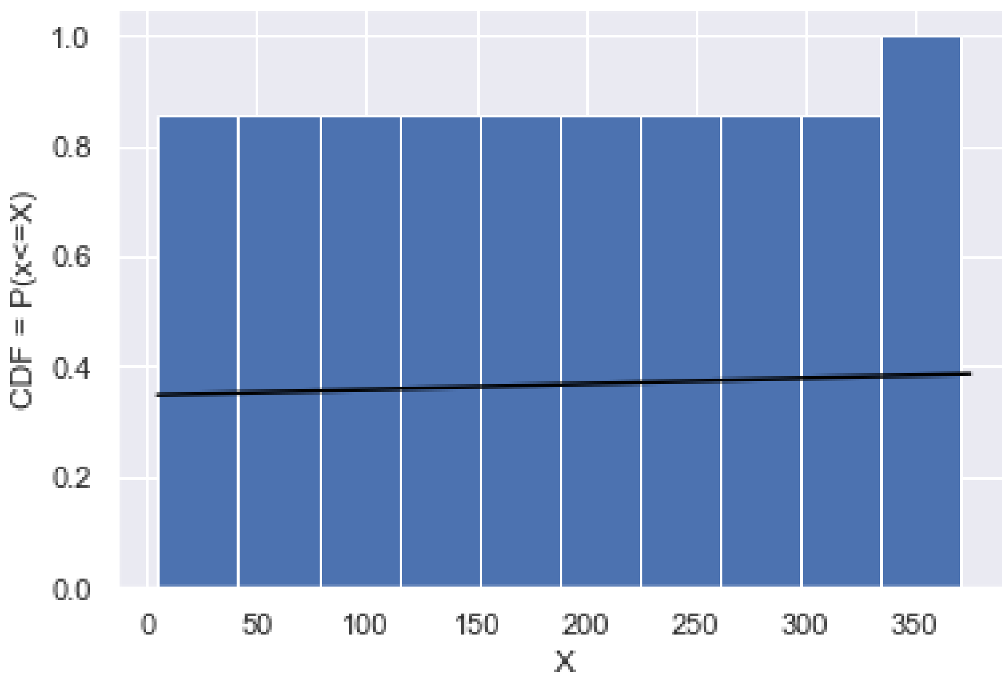
[212]:
```
cdf=stats.norm.cdf(x, loc=mu, scale=sigma)
```

[213]:
```
x=np.linspace(start=5, stop=375, num=100)
```

[214]:
```
df_1 = cyberopsfinal_df["Type"].value_counts()
df_1
```

[214]:
```
Espionage           371
Sabotage             22
Denial of service    18
Data destruction     14
Financial Theft       7
Doxing                6
Defacement            5
Name: Type, dtype: int64
```

[215]:
```
#plot
plt.hist(df_1, density=True, cumulative= True)
plt.plot(x,cdf,color='black')

plt.xlabel('X')
plt.ylabel('CDF = P(x<=X)')
plt.show()
```



[216]:
```
#For Analytics Distribution, I will create a pareto chart of variable Type in
↪the dataframe cyberopsfinal_df
```

[217]:
```
df_1 = big_df["Type"].value_counts()
```

[218]:
```
df_2=pd.DataFrame(df_1)
```

[219]:
```
df_2["item"]=df_2.index
```

[220]:
```
df_3=df_2.sort_values(by='Type', ascending=False)
df_3
```

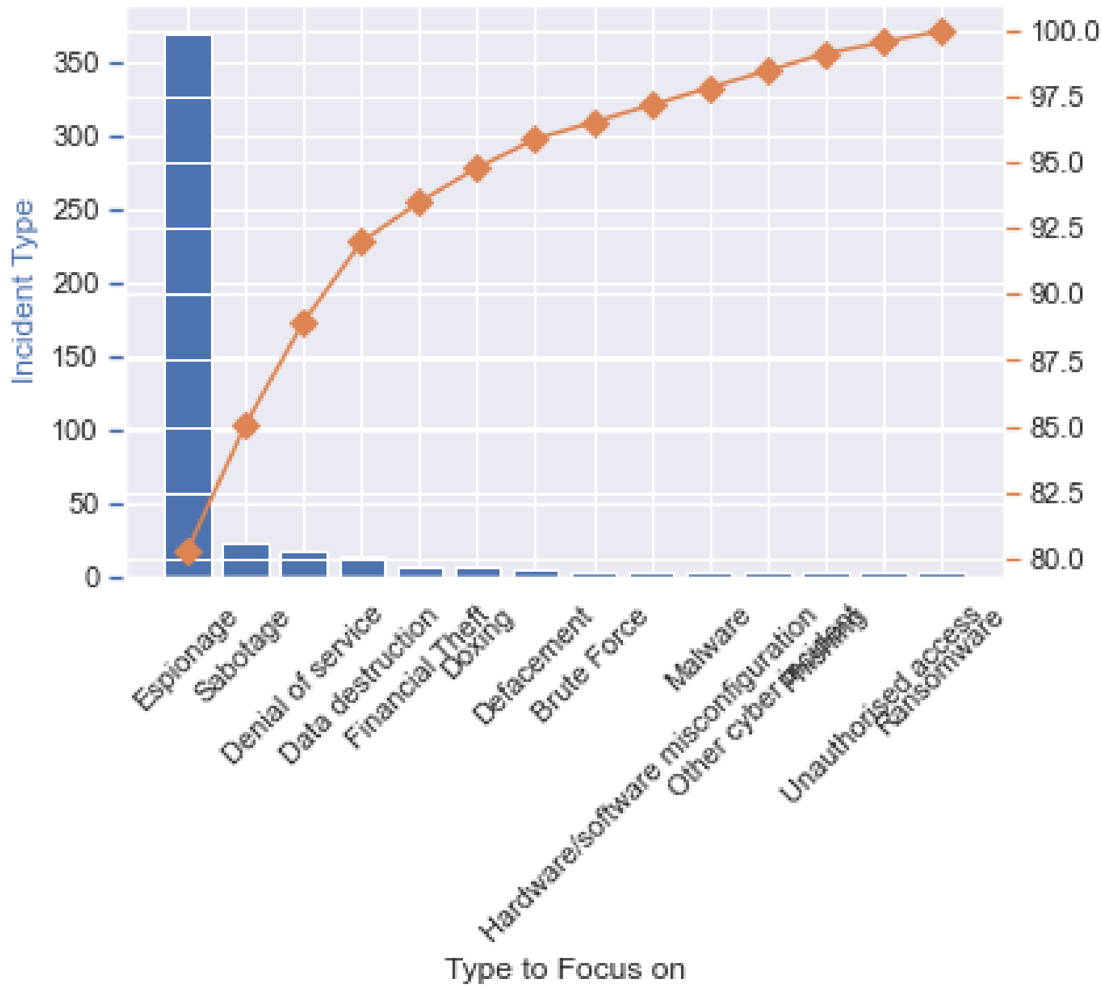
[220]:

	Type	item
Espionage	371	Espionage
Sabotage	22	Sabotage
Denial of service	18	Denial of service
Data destruction	14	Data destruction
Financial Theft	7	Financial Theft
Doxing	6	Doxing
Defacement	5	Defacement
Brute Force	3	Brute Force
Hardware/software misconfiguration	3	Hardware/software misconfiguration
Malware	3	Malware
Other cyber incident	3	Other cyber incident
Phishing	3	Phishing
Unauthorised access	2	Unauthorised access
Ransomware	2	Ransomware

[221]:
```
df_3["cumpercentage"]=df_3["Type"].cumsum()/df_3["Type"].sum()*100
```

[222]:
```
fig, ax1=plt.subplots()
ax1.bar(df_3.item, df_3["Type"], color="C0")
ax1.set_ylabel("Incident Type", color="C0")
ax1.tick_params(axis="y", color="C0")
ax1.set_xlabel("Type to Focus on")
ax1.set_xticklabels(df_3["item"], rotation=45)
ax2=ax1.twinx()
ax2.plot(df_3.item, df_3["cumpercentage"], color="C1", marker="D", ms=7)
#ax2.yaxis.set_major_formatter(formatter)
ax2.tick_params(axis="y", color="C1")
plt.show()
```

```
C:\Users\saima\AppData\Local\Temp/ipykernel_21752/542301559.py:6: UserWarning:
FixedFormatter should only be used together with FixedLocator
  ax1.set_xticklabels(df_3["item"], rotation=45)
```




```
[ ]: #Based on the above Paretto Distribution, Espionage Type, even for the combined
     ↪dataset is significant and
     #need to be addressed to tackle this Cyber Incident Type
```

```
[ ]:
```