## Milestone\_4\_Raghuwanshi\_Prashant\_DSC540

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Term Project: Milestone 4, Data transformation or cleansing steps to API source data

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Course: DSC540-T301 Data Preparation (2221-1)

```
[1]: # Import common Data preparation libraries:
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

## API Data Source:

```
[2]: # import libraries for Api Data Source
from requests import Request, Session
from requests.exceptions import ConnectionError, Timeout, TooManyRedirects
import json
```

Fetching all crypto currency latest price data from coinmarket api

```
[3]: # Calling api request and storing the responce in dict
     url = 'https://pro-api.coinmarketcap.com/v1/cryptocurrency/listings/latest'
     parameters = {
       'start':'1',
       'limit':'100',
       'convert':'USD'
     }
     headers = {
       'Accepts': 'application/json',
       'X-CMC_PRO_API_KEY': 'c6d563eb-5020-4805-822e-422c3a9b018c',
     }
     session = Session()
     session.headers.update(headers)
     try:
      response = session.get(url, params=parameters)
     # storing jason to Dict
```

```
data = json.loads(response.text)
except (ConnectionError, Timeout, TooManyRedirects) as e:
   print(e)
```

```
Parsing nested Api Json data into Dataframe
[4]: # crearted the list -step 1
     cryptodata = data['data']
     # display the first element, with all columns in dataset
     cryptodata[0]
[4]: {'id': 1,
      'name': 'Bitcoin',
      'symbol': 'BTC',
      'slug': 'bitcoin',
      'num_market_pairs': 8294,
      'date added': '2013-04-28T00:00:00.000Z',
      'tags': ['mineable',
       'pow',
       'sha-256',
       'store-of-value',
       'state-channels',
       'coinbase-ventures-portfolio',
       'three-arrows-capital-portfolio',
       'polychain-capital-portfolio',
       'binance-labs-portfolio',
       'arrington-xrp-capital',
       'blockchain-capital-portfolio',
       'boostvc-portfolio',
       'cms-holdings-portfolio',
       'dcg-portfolio',
```

'dragonfly-capital-portfolio',
'electric-capital-portfolio',
'fabric-ventures-portfolio',

'galaxy-digital-portfolio',

'alameda-research-portfolio',

'placeholder-ventures-portfolio',
'pantera-capital-portfolio',
'multicoin-capital-portfolio',
'paradigm-xzy-screener'],
'max\_supply': 21000000,

'circulating\_supply': 18865700,

'1confirmation-portfolio',
'winklevoss-capital',
'usv-portfolio',

'framework-ventures',

'huobi-capital',

'a16z-portfolio',

```
'total_supply': 18865700,
     'platform': None,
     'cmc_rank': 1,
     'last_updated': '2021-11-06T18:25:02.000Z',
     'quote': {'USD': {'price': 60880.163530433216,
       'volume_24h': 28800647837.774776,
       'volume change 24h': -8.5717,
       'percent_change_1h': 0.22619363,
       'percent_change_24h': -0.42704839,
       'percent_change_7d': -0.92915866,
       'percent_change_30d': 12.63062007,
       'percent_change_60d': 30.79229688,
       'percent_change_90d': 39.45999401,
       'market_cap': 1148546901116.094,
       'market_cap_dominance': 42.6861,
       'fully_diluted_market_cap': 1278483434139.1,
       'last_updated': '2021-11-06T18:25:02.000Z'}}}
[5]: # Format data into a more readable format -- parsing the api data and writting
     \rightarrow it to list
    # parsing the nested Jason data present in quote collumns and creating
     → datafrane for data preparation requirment
    rows=[]
    for currency in cryptodata:
        currency_id = currency['id']
        slug = currency['slug']
        cmc_rank = currency['cmc_rank']
        total_supply = currency['total_supply']
        currency_name = currency['name']
        currency_symbol = currency['symbol']
        currenct_price = currency['quote']['USD']['price']
        last_updated = currency['quote']['USD']['last_updated']
        rows.append([currency_id, slug, currency_name, currency_symbol, cmc_rank,_
     [6]: # Created new Dataframe which contains required price quote columns
    # Replace Headers
    df_parse_nested_json = pd.DataFrame(rows, columns=["currency_id", "slug", __
     →"total_supply", "last_updated"])
[7]: # Display the new of data, use full for creating the lookup file..which
     →contains the currency name and its corresponding short name
    df_parse_nested_lookup = pd.DataFrame(df_parse_nested_json, columns = ['slug',_
     # writting the df to csv file for archiving the fetch data for future refrences
    df parse nested lookup.to csv(r'C:/Users/dell/Documents/docker/coin lookup.csv')
```

```
[8]: # display parsed and reshaped dataframe
      df_parse_nested_lookup. head()
 [8]:
                 slug currency_symbol
      0
              bitcoin
                                   BTC
      1
             ethereum
                                   ETH
        binance-coin
                                   BNB
      3
               solana
                                   SOL
      4
               tether
                                  USDT
 [9]: | #Fix Header casing, updating columns name in uppercase
      df_crypto_price = df_parse_nested_json.rename(columns=str.upper)
      df_crypto_price.head()
 [9]:
         CURRENCY ID
                               SLUG CURRENCY_NAME CURRENCY_SYMBOL
                                                                    CMC RANK
      0
                            bitcoin
                                          Bitcoin
                                                               BTC
                   1
                                                                            1
                1027
                                                               ETH
                                                                            2
      1
                           ethereum
                                         Ethereum
                                                                            3
      2
                1839
                      binance-coin
                                    Binance Coin
                                                               BNB
      3
                                                                            4
                5426
                             solana
                                           Solana
                                                               SOL
      4
                             tether
                                           Tether
                                                              USDT
                                                                            5
                 825
         CURRENCY PRICE TOTAL SUPPLY
                                                     LAST UPDATED
           60880.163530 1.886570e+07
      0
                                        2021-11-06T18:25:02.000Z
      1
            4441.364800 1.182345e+08 2021-11-06T18:25:02.000Z
             618.904122 1.668011e+08 2021-11-06T18:24:12.000Z
      3
             252.331559 5.083843e+08 2021-11-06T18:25:05.000Z
               1.000889 7.335785e+10 2021-11-06T18:24:20.000Z
      4
[10]: # transforming total supply value in millions
      # create function, convert counts in million
      def convert_to_million(total):
          total1 = total/1000000
          return total1
[11]: # call created function and update the date column value by using lambda,
       \hookrightarrow function
      df_crypto_price['TOTAL_SUPPLY'] = df_crypto_price['TOTAL_SUPPLY'].apply(lambda_
       →x: convert_to_million(x))
[12]: df_crypto_price.head()
[12]:
                               SLUG CURRENCY_NAME CURRENCY_SYMBOL CMC_RANK
         CURRENCY_ID
      0
                                                               BTC
                   1
                            bitcoin
                                          Bitcoin
                                                                            1
      1
                1027
                           ethereum
                                         Ethereum
                                                               ETH
                                                                            2
      2
                                                                            3
                1839
                      binance-coin
                                     Binance Coin
                                                               BNB
      3
                                           Solana
                                                                            4
                5426
                             solana
                                                               SOL
      4
                 825
                             tether
                                           Tether
                                                              USDT
```

```
CURRENCY_PRICE TOTAL_SUPPLY
                                                    LAST_UPDATED
      0
           60880.163530
                            18.865700 2021-11-06T18:25:02.000Z
            4441.364800
                           118.234458 2021-11-06T18:25:02.000Z
      1
      2
             618.904122
                           166.801148 2021-11-06T18:24:12.000Z
                           508.384251 2021-11-06T18:25:05.000Z
      3
             252.331559
      4
               1.000889 73357.845272 2021-11-06T18:24:20.000Z
[13]: # drop dublicate currency price entries from dataframe
      df_crypto_price_drop_dup = df_crypto_price.

¬drop_duplicates(subset=['CURRENCY_ID', 'CURRENCY_SYMBOL'], keep='first')

[14]: df_crypto_price_drop_dup.shape
[14]: (100, 8)
[15]: #created function to convert timestame to date
      def tstodate(ts):
          a2 = pd.to_datetime(ts)
          a3 = a2.strftime('%Y%m%d')
          return a3
[16]: # call created function and update the date column value by using lambda_
       \rightarrow function
      df_crypto_price_drop_dup['LAST_UPDATED'] =__
       →df_crypto_price_drop_dup['LAST_UPDATED'].apply(lambda x: tstodate(x))
[17]: df_crypto_price_drop_dup.head()
[17]:
         CURRENCY_ID
                              SLUG CURRENCY_NAME CURRENCY_SYMBOL CMC_RANK \
      0
                   1
                           bitcoin
                                          Bitcoin
                                                              BTC
                                                                          1
                                                                          2
      1
                1027
                          ethereum
                                        Ethereum
                                                              ETH
                                                              BNB
                                                                          3
      2
                1839 binance-coin Binance Coin
      3
                5426
                            solana
                                                              SOL
                                                                          4
                                           Solana
      4
                                                                          5
                 825
                            tether
                                           Tether
                                                             USDT
         CURRENCY_PRICE TOTAL_SUPPLY LAST_UPDATED
      0
           60880.163530
                            18.865700
                                           20211106
                                           20211106
      1
            4441.364800
                           118.234458
      2
             618.904122
                           166.801148
                                          20211106
      3
             252.331559
                           508.384251
                                           20211106
      4
               1.000889 73357.845272
                                           20211106
     Web Data Source Import libraries for Web Scraping
```

[18]: # import library to open urls and download htmls

# print out python data structures

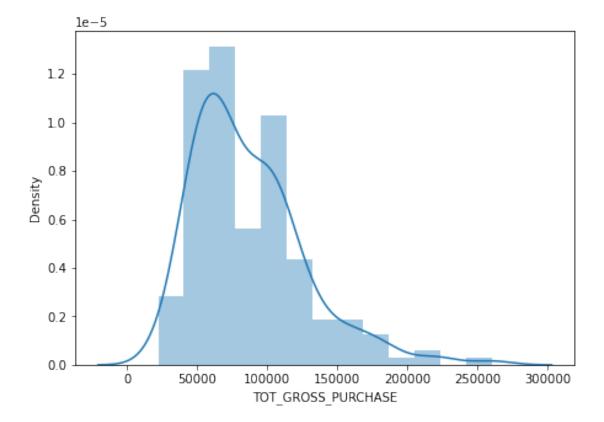
```
from pprint import pprint
      # for parsing all the tables present
      # on the website
      import urllib.request
      from html_table_parser.parser import HTMLTableParser
      # for converting the parsed data to pandas dataframe
      from bs4 import BeautifulSoup
[19]: # define function to pull the website html file
      def url load html(url):
          # request to the website
          req = urllib.request.Request(url=url)
          f = urllib.request.urlopen(req)
          # reading contents of the website
          return f.read()
[20]: # define the html contents of a URL.
      xhtml = url_load_html('https://www.moneycontrol.com/stocks/marketstats/
      →fii_dii_activity/index.php').decode('utf-8')
      # Defining the HTMLTableParser object
      par = HTMLTableParser()
      # feeding the html contents in the
      # HTMLTableParser object
      par.feed(xhtml)
[21]: # Format data into a more readable format
      #This step pulls the required table data from html file
      #pprint(par.tables[4])
      # converting the parsed web table data to dataframe
      df html data = pd.DataFrame(par.tables[4])
      # display the fetch table data in dataframe
      df html data.head()
[21]:
                                           FII Rs Crores DII Rs Crores
      0
      1
                                    Date Gross Purchase
                                                            Gross Sales
      2
             October 2021
                            October 2021
                                              185,566.83
                                                             211,139.02
      3 September 2021
                          September 2021
                                              217,636.41
                                                             216,722.64
                             August 2021
               August 2021
                                              175,168.36
                                                             177,736.88
                            3
                                                         5
                                                                               6
      0
                         None
                                         None
                                                      None
                                                                            None
      1 Net Purchase / Sales Gross Purchase Gross Sales Net Purchase / Sales
     2
                   -25,572.19
                                   151,607.74
                                               147,136.75
                                                                        4,470.99
      3
                                   144,147.33
                                               138,198.48
                                                                        5,948.85
                       913.77
                    -2,568.52
      4
                                   131,185.18
                                               124,290.49
                                                                        6,894.69
```

```
[22]: # setting second row as header
      # step-1 extracting the header information
      new_header = df_html_data.iloc[1] #qrab the first row for the header
[23]: new_header[1] = 'Tot_Gross_Purchase'
      new_header[2] = 'Gross_Sales'
      new header[3] = 'net purchase'
      new header
[23]: 0
                           Date
      1
             Tot_Gross_Purchase
      2
                    Gross_Sales
      3
                   net_purchase
      4
                 Gross Purchase
      5
                    Gross Sales
           Net Purchase / Sales
      Name: 1, dtype: object
[24]: df_html_data1 = df_html_data[2:] #take out the data less the header row
[25]: df_html_data1.head()
[25]:
                                                               2
                                                                           3 \
                                                   1
             October 2021
                            October 2021 185,566.83 211,139.02
                                                                  -25,572.19
      2
      3 September 2021
                          September 2021 217,636.41
                                                      216,722.64
                                                                      913.77
                             August 2021
                                         175,168.36
                                                      177,736.88
      4
               August 2021
                                                                   -2,568.52
      5
                   July 2021
                               July 2021
                                          125,896.68
                                                      149,090.07
                                                                  -23,193.39
                   June 2021
                               June 2021 170,188.95
                                                      170,214.84
                                                                      -25.89
                              5
      2 151,607.74 147,136.75
                                  4,470.99
      3 144,147.33 138,198.48
                                  5,948.85
      4 131,185.18 124,290.49
                                  6,894.69
      5 117,910.10
                      99,516.18
                                 18,393.92
      6 114,289.67
                     107,246.16
                                  7,043.51
[26]: df_html_data1.columns = new_header #set the header row as the df header
      df_html_data1.head()
                                    Date Tot Gross Purchase Gross Sales \
[26]: 1
      2
             October 2021
                            October 2021
                                                 185,566.83
                                                             211,139.02
                          September 2021
                                                 217,636.41
                                                             216,722.64
         September 2021
      4
               August 2021
                             August 2021
                                                 175,168.36
                                                             177,736.88
      5
                   July 2021
                               July 2021
                                                 125,896.68
                                                             149,090.07
                   June 2021
                               June 2021
                                                 170,188.95
                                                             170,214.84
      1 net_purchase Gross Purchase Gross Sales Net Purchase / Sales
          -25,572.19
                         151,607.74 147,136.75
                                                            4,470.99
```

```
3
              913.77
                         144,147.33
                                     138,198.48
                                                             5,948.85
      4
           -2,568.52
                         131,185.18
                                     124,290.49
                                                             6,894.69
                                      99,516.18
      5
          -23,193.39
                         117,910.10
                                                            18,393.92
              -25.89
      6
                         114,289.67
                                     107,246.16
                                                             7,043.51
[27]: # renaming the columns names
      df html data2 = df html data1.rename(columns={"Gross Purchase":
       _{\hookrightarrow} "Int_Gross_Purchase", "Gross Sales": "Int_Gross_Sales", "Net Purchase /_{\sqcup}
       df_html_data2.head()
[27]: 1
                                    Date Tot_Gross_Purchase Gross_Sales \
                                                  185,566.83
                                                              211,139.02
      2
             October 2021
                            October 2021
                          September 2021
      3
         September 2021
                                                  217,636.41
                                                              216,722.64
                                                              177,736.88
      4
               August 2021
                             August 2021
                                                  175,168.36
      5
                   July 2021
                               July 2021
                                                  125,896.68
                                                              149,090.07
      6
                   June 2021
                               June 2021
                                                  170,188.95
                                                              170,214.84
      1 net_purchase Int_Gross_Purchase Int_Gross_Sales int_Net_Purchase
      2
          -25,572.19
                             151,607.74
                                              147,136.75
                                                                 4,470.99
      3
              913.77
                             144,147.33
                                              138,198.48
                                                                 5,948.85
      4
           -2,568.52
                             131,185.18
                                              124,290.49
                                                                 6,894.69
      5
          -23,193.39
                             117,910.10
                                               99,516.18
                                                                18,393.92
              -25.89
                             114,289.67
                                              107,246.16
                                                                 7,043.51
[28]: #Fix Header casing
      # updating columns name in uppercase
      df_html_data3 = df_html_data2.rename(columns=str.upper)
      df_html_data3.head()
[28]: 1
                                    DATE TOT_GROSS_PURCHASE GROSS_SALES
      2
             October 2021
                            October 2021
                                                  185,566.83
                                                              211,139.02
         September 2021
                          September 2021
                                                  217,636.41
                                                              216,722.64
      3
      4
               August 2021
                             August 2021
                                                  175,168.36
                                                              177,736.88
      5
                   July 2021
                               July 2021
                                                  125,896.68
                                                              149,090.07
      6
                   June 2021
                               June 2021
                                                  170,188.95
                                                              170,214.84
      1 NET PURCHASE INT GROSS PURCHASE INT GROSS SALES INT NET PURCHASE
      2
          -25,572.19
                             151,607.74
                                              147,136.75
                                                                 4,470.99
      3
              913.77
                             144,147.33
                                              138,198.48
                                                                 5,948.85
      4
           -2,568.52
                             131,185.18
                                              124,290.49
                                                                 6,894.69
          -23,193.39
                             117,910.10
                                               99,516.18
                                                                18,393.92
      5
                             114,289.67
              -25.89
                                              107,246.16
                                                                 7,043.51
[29]: # create lambda function to fix the date inconsistent values
      # input -- September 2021 September 2021 --> out put : 2021-09-01
      import re
```

```
def remove_dup_date(row):
              k = re.split("
                              ", row)
              k1 = re.split(" ", k[1])
              a = pd.to_datetime(k1[1] + k1[0], format='%Y%B')
              #print(a)
              return a
[30]: # fixing inconsistent values for date columns -- date values are populting.
       \rightarrow twice
      # step 1 create function and update the date column value by using lambda_{f L}
      \hookrightarrow function
      df_html_data3['DATE'] = df_html_data3['DATE'].apply(lambda x:__
       \rightarrowremove dup date(x))
[31]: # create lambda function to fix the amount inconsistent values
      # input -- '175,168.36' --> out put : 175168.36
      import re
      def fix_amount_value(row):
              b = row.replace(',', '')
              b2 = float(b)
              #print(b2)
              return b
[32]: # displaying df after fixing date value
      df_html_data3.head()
              DATE TOT_GROSS_PURCHASE GROSS_SALES_NET_PURCHASE_INT_GROSS_PURCHASE_\
[32]: 1
      2 2021-10-01
                           185,566.83 211,139.02
                                                    -25,572.19
                                                                       151,607.74
                           217,636.41 216,722.64
                                                                       144,147.33
      3 2021-09-01
                                                        913.77
     4 2021-08-01
                           175,168.36 177,736.88
                                                     -2,568.52
                                                                       131,185.18
                                                                       117,910.10
      5 2021-07-01
                           125,896.68 149,090.07
                                                    -23,193.39
      6 2021-06-01
                                                                       114,289.67
                           170,188.95 170,214.84
                                                        -25.89
      1 INT_GROSS_SALES INT_NET_PURCHASE
             147,136.75
                                4,470.99
     2
      3
                                5,948.85
             138,198.48
      4
             124,290.49
                                6,894.69
              99,516.18
                               18,393.92
      6
             107,246.16
                               7,043.51
[33]: df_html_data3['TOT_GROSS_PURCHASE'] = df_html_data3['TOT_GROSS_PURCHASE'].
       →apply(lambda x: fix_amount_value(x))
[34]: # Remove duplicates based on second and third columns value
      df_html_data3_rm_dup = df_html_data3.drop_duplicates(['TOT_GROSS_PURCHASE',_
      df_html_data3_rm_dup.head()
```

```
[34]: 1
              DATE TOT_GROSS_PURCHASE GROSS_SALES NET_PURCHASE INT_GROSS_PURCHASE \
      2 2021-10-01
                                       211,139.02
                                                     -25,572.19
                                                                        151,607.74
                            185566.83
                            217636.41 216,722.64
      3 2021-09-01
                                                         913.77
                                                                        144,147.33
      4 2021-08-01
                            175168.36 177,736.88
                                                      -2,568.52
                                                                        131,185.18
      5 2021-07-01
                            125896.68
                                       149,090.07
                                                     -23,193.39
                                                                        117,910.10
      6 2021-06-01
                            170188.95
                                       170,214.84
                                                         -25.89
                                                                        114,289.67
      1 INT_GROSS_SALES INT_NET_PURCHASE
      2
             147,136.75
                                4,470.99
      3
             138,198.48
                                5,948.85
      4
             124,290.49
                                6,894.69
      5
              99,516.18
                               18,393.92
      6
             107,246.16
                                7,043.51
```



```
[36]: # Finding the Outliers
     df_html_data3_rm_dup[(df_html_data3_rm_dup['TOT_GROSS_PURCHASE'] > '250000') |

→ (df_html_data3_rm_dup['TOT_GROSS_PURCHASE'] < '25000')].head(5)
[36]: 1
             DATE TOT GROSS PURCHASE GROSS SALES NET PURCHASE INT GROSS PURCHASE \
     2 2021-10-01
                           185566.83 211,139.02
                                                  -25,572.19
                                                                     151,607.74
     3 2021-09-01
                           217636.41 216,722.64
                                                      913.77
                                                                     144,147.33
     4 2021-08-01
                           175168.36 177,736.88
                                                   -2,568.52
                                                                     131,185.18
     5 2021-07-01
                           125896.68 149,090.07
                                                  -23,193.39
                                                                     117,910.10
     6 2021-06-01
                           170188.95 170,214.84
                                                      -25.89
                                                                     114,289.67
     1 INT_GROSS_SALES INT_NET_PURCHASE
     2
            147,136.75
                               4,470.99
     3
            138,198.48
                               5,948.85
     4
            124,290.49
                               6,894.69
     5
             99,516.18
                              18,393.92
     6
            107,246.16
                               7,043.51
[37]: #Trimming of Outliers
     df_html_data_trim_out =_
      →df html data3 rm_dup[(df html data3 rm_dup['TOT_GROSS_PURCHASE'] < '250000')
      df html data trim out.head()
[37]: 1
             DATE TOT GROSS PURCHASE GROSS SALES NET PURCHASE INT GROSS PURCHASE
                           185566.83 211,139.02
     2 2021-10-01
                                                  -25,572.19
                                                                     151,607.74
     3 2021-09-01
                           217636.41 216,722.64
                                                      913.77
                                                                     144,147.33
     4 2021-08-01
                                     177,736.88
                                                   -2,568.52
                                                                     131,185.18
                           175168.36
     5 2021-07-01
                           125896.68
                                    149,090.07
                                                  -23,193.39
                                                                     117,910.10
     6 2021-06-01
                           170188.95 170,214.84
                                                      -25.89
                                                                     114,289.67
     1 INT GROSS SALES INT NET PURCHASE
     2
            147,136.75
                               4,470.99
     3
            138,198.48
                               5,948.85
     4
            124,290.49
                               6,894.69
     5
             99,516.18
                              18,393.92
     6
            107,246.16
                               7,043.51
```

Flat File Source Data: Data Source: https://www.kaggle.com/danielbethell/adult-incomes-in-the-united-states

 $\label{lem:crypto_income} \ \text{crypto\_income} \ \text{for adult}, \ \text{updated the dataset by adding additional columns} \ \text{crypto\_slang} \ \& \ \text{crypto} \ \text{symbol}$ 

Data Set Details: Dataset columns details: age: continuous.

workclass: Private, Self-emp-not-inc, Self-emp-inc, Federal-gov, Local-gov, State-gov, Without-pay, Never-worked.

fnlwgt: continuous.

education: Bachelors, Some-college, 11th, HS-grad, Prof-school, Assoc-acdm, Assoc-voc, 9th, 7th-8th, 12th, Masters, 1st-4th, 10th, Doctorate, 5th-6th, Preschool.

education-num: continuous.

marital-status: Married-civ-spouse, Divorced, Never-married, Separated, Widowed, Married-spouse-absent, Married-AF-spouse.

relationship: Wife, Own-child, Husband, Not-in-family, Other-relative, Unmarried.

sex: Female, Male.

capital-gain: continuous. capital-loss: continuous.

hours-per-week: continuous.

native-country: United-States, Cambodia, England, Puerto-Rico, Canada, Germany, Outlying-US(Guam-USVI-etc), India, Japan, Greece, South, China, Cuba, Iran, Honduras, Philippines, Italy, Poland, Jamaica, Vietnam, Mexico, Portugal, Ireland, France, Dominican-Republic, Laos, Ecuador, Taiwan, Haiti, Columbia, Hungary, Guatemala, Nicaragua, Scotland, Thailand, Yugoslavia, El-Salvador, Trinadad&Tobago, Peru, Hong, Holand-Netherlands. crypto\_slang: 20 crypto currencires name like bitcoins crypto\_symbol:

[38]:		age	workclass	fnlwgt	education	education-num	\
	0	39	State-gov	77516	Bachelors	13	
	1	50	Self-emp-not-inc	83311	Bachelors	13	
	2	38	Private	215646	HS-grad	9	
	3	53	Private	234721	11th	7	
	4	28	Private	338409	Bachelors	13	

marital-status	relationship	sex	capital-gain	capital-loss	\
Never-married	Not-in-family	Male	2174	0	
Married-civ-spouse	Husband	Male	0	0	
Divorced	Not-in-family	Male	0	0	
Married-civ-spouse	Husband	Male	0	0	
Married-civ-spouse	Wife	Female	0	0	
	Never-married Married-civ-spouse	Divorced Not-in-family Married-civ-spouse Husband	Never-married Not-in-family Male Married-civ-spouse Husband Male Divorced Not-in-family Male Married-civ-spouse Husband Male	Never-married Not-in-family Male 2174  Married-civ-spouse Husband Male 0  Divorced Not-in-family Male 0  Married-civ-spouse Husband Male 0	Never-marriedNot-in-familyMale21740Married-civ-spouseHusbandMale00DivorcedNot-in-familyMale00Married-civ-spouseHusbandMale00

hours-per-week native-country total-income crypto\_slang crypto\_symbol 0 40 United-States <=50K bitcoin BTC

```
1
                     13 United-States
                                              <=50K
                                                          ethereum
                                                                             ETH
      2
                     40 United-States
                                                                             ADA
                                              <=50K
                                                           cardano
      3
                     40 United-States
                                               <=50K
                                                     binance-coin
                                                                             BNB
      4
                                                                            USDT
                     40
                                  Cuba
                                               <=50K
                                                            tether
[39]: # Headers, updating columns name in uppercase
      crypto_income_df = crypto_income_df.rename(columns=str.upper)
      crypto_income_df.head()
[39]:
         AGE
                     WORKCLASS FNLWGT EDUCATION EDUCATION-NUM
      0
          39
                     State-gov
                                 77516 Bachelors
                                                               13
              Self-emp-not-inc
                                 83311 Bachelors
                                                               13
      1
          50
      2
          38
                       Private 215646
                                          HS-grad
                                                                9
      3
          53
                       Private 234721
                                             11th
                                                                7
      4
          28
                       Private 338409 Bachelors
                                                               13
                              RELATIONSHIP
             MARITAL-STATUS
                                               SEX CAPITAL-GAIN
                                                                   CAPITAL-LOSS
      0
                                                             2174
              Never-married Not-in-family
                                              Male
        Married-civ-spouse
                                   Husband
                                              Male
                                                                0
                                                                              0
      1
                   Divorced Not-in-family
                                              Male
                                                                0
                                                                              0
      2
      3 Married-civ-spouse
                                   Husband
                                              Male
                                                                0
                                                                              0
                                      Wife Female
                                                                0
                                                                              0
        Married-civ-spouse
         HOURS-PER-WEEK NATIVE-COUNTRY TOTAL-INCOME CRYPTO_SLANG CRYPTO_SYMBOL
                     40 United-States
                                              <=50K
                                                           bitcoin
      0
                                                                             BTC
      1
                     13 United-States
                                              <=50K
                                                          ethereum
                                                                             ETH
      2
                     40 United-States
                                              <=50K
                                                           cardano
                                                                             ADA
      3
                     40 United-States
                                              <=50K
                                                     binance-coin
                                                                             BNB
                     40
                                  Cuba
                                              <=50K
                                                            tether
                                                                            USDT
     Performing the transformation operation on File data source:
[40]: # renaming the columns names
      crypto_income_df2 = crypto_income_df.rename(columns={"EDUCATION-NUM":
       → "EDUCATION NUM", "CAPITAL-GAIN": "CAPITAL GAIN", "HOURS-PER-WEEK":
       →"HOURS_PER_WEEK", "NATIVE-COUNTRY": "NATIVE_COUNTRY", "TOTAL-INCOME":
       →"TOTAL_INCOME"})
[41]: crypto_income_df2.head()
         AGE
[41]:
                     WORKCLASS FNLWGT EDUCATION EDUCATION NUM
      0
          39
                     State-gov
                                 77516 Bachelors
      1
          50
              Self-emp-not-inc
                                 83311
                                        Bachelors
                                                               13
      2
          38
                       Private 215646
                                          HS-grad
                                                                9
                                                                7
      3
          53
                       Private 234721
                                             11th
          28
                       Private 338409 Bachelors
                                                               13
             MARITAL-STATUS
                              RELATIONSHIP
                                               SEX CAPITAL_GAIN CAPITAL-LOSS \
```

```
2174
      0
              Never-married Not-in-family
                                              Male
                                                                             0
                                              Male
      1 Married-civ-spouse
                                   Husband
                                                                             0
                                              Male
                   Divorced Not-in-family
                                                               0
                                                                             0
      3 Married-civ-spouse
                                   Husband
                                              Male
                                                               0
                                                                              0
      4 Married-civ-spouse
                                      Wife Female
                                                               0
                                                                              0
         HOURS_PER_WEEK NATIVE_COUNTRY TOTAL_INCOME CRYPTO_SLANG CRYPTO_SYMBOL
     0
                     40 United-States
                                                          bitcoin
                                              <=50K
                                                                             BTC
                                                                            ETH
      1
                     13 United-States
                                              <=50K
                                                         ethereum
      2
                     40 United-States
                                              <=50K
                                                          cardano
                                                                            ADA
      3
                     40 United-States
                                              <=50K binance-coin
                                                                            BNB
      4
                     40
                                  Cuba
                                              <=50K
                                                           tether
                                                                           USDT
[42]: #5. Look at summary information about your data (total, mean, min, max, )
      #freq, unique, etc.) Does this present any more questions for you? Does it_{\sqcup}
      #lead you to a conclusion yet?
      print("\nDescribe Data\n")
      print(crypto_income_df.describe())
      print("\nSummarized Data\n")
      print(crypto_income_df.describe(include=['0']))
     Describe Data
```

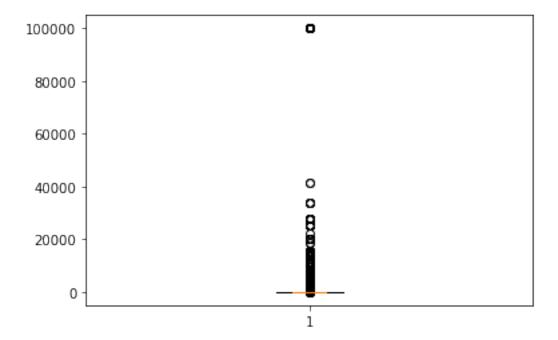
	AGE	FNLWGT	EDUCATION-NUM	CAPITAL-GAIN	CAPITAL-LOSS	\
count	32561.000000	3.256100e+04	32561.000000	32561.000000	32561.000000	
mean	38.581647	1.897784e+05	10.080679	1077.648844	87.303830	
std	13.640433	1.055500e+05	2.572720	7385.292085	402.960219	
min	17.000000	1.228500e+04	1.000000	0.000000	0.000000	
25%	28.000000	1.178270e+05	9.000000	0.000000	0.000000	
50%	37.000000	1.783560e+05	10.000000	0.000000	0.000000	
75%	48.000000	2.370510e+05	12.000000	0.000000	0.000000	
max	90.000000	1.484705e+06	16.000000	99999.000000	4356.000000	

## HOURS-PER-WEEK 32561.000000 count 40.437456 mean std 12.347429 min 1.000000 25% 40.000000 50% 40.000000 75% 45.000000 99.000000 max

## Summarized Data

	WURKCLASS	EDUCATION	MARITAL-STATUS	RELATIONSHIP	SEX	\
count	32561	32561	32561	32561	32561	

```
unique
                              16
                        HS-grad Married-civ-spouse
     top
              Private
                                                          Husband
                                                                    Male
     freq
                22696
                           10501
                                               14976
                                                            13193 21790
            NATIVE-COUNTRY TOTAL-INCOME CRYPTO SLANG CRYPTO SYMBOL
                     32561
                                   32561
                                                32561
                                                              32561
     count
     unique
                        42
                                                   47
                                                                 47
     top
             United-States
                                   <=50K
                                              bitcoin
                                                                BTC
                     29170
                                   24720
                                                 9710
                                                               9710
     freq
[43]: # find out the null present in required columns
      print(f"is null is present in AGE -- {crypto income df.AGE.isnull().values.
      \rightarrowany()}")
      print(f"is null is present in CRYPTO_SYMBOL -- {crypto_income_df.CRYPTO_SYMBOL.
       →isnull().values.any()}")
      print(f"is null is present in CRYPTO_SLANG -- {crypto_income_df.CRYPTO_SLANG.
       →isnull().values.any()}")
      print(f"is null is present in CAPITAL_GAIN -- {crypto_income_df2.CAPITAL_GAIN.
       →isnull().values.any()}")
     is null is present in AGE -- False
     is null is present in CRYPTO SYMBOL -- False
     is null is present in CRYPTO_SLANG -- False
     is null is present in CAPITAL_GAIN -- False
[44]: from fuzzywuzzy import fuzz
      from fuzzywuzzy import process
      df_crypto_price['name_from_df2'] = df_crypto_price['CURRENCY_NAME'].
      →apply(lambda x: process.extractOne(x, crypto_income_df2['CRYPTO_SLANG'].
      →to_list(),score_cutoff=80))
      name_from_df2_list = df_crypto_price['name_from_df2'].to_list()
      name_from_df2_list = [_[0] if _ != None else None for _ in name_from_df2_list]
      df_crypto_price['name_from_df2'] = name_from_df2_list
      df_crypto_price = df_crypto_price.merge(crypto_income_df2, left_on = __
      → 'name from df2', right on = 'CRYPTO SLANG', suffixes=('',' 2'))
      df_crypto_price.drop(['CURRENCY_NAME', 'name_from_df2'], axis=1, inplace=True)
[45]: # identifying outliers
      # load libraries
      import numpy as np
      import matplotlib.pyplot as plt
      %matplotlib inline
[46]: #plot boxplot to find outliers data
      plt.boxplot(crypto_income_df2.CAPITAL_GAIN, notch=True)
```



```
'boxes': [<matplotlib.lines.Line2D at 0x1b6113b2310>],
'medians': [<matplotlib.lines.Line2D at 0x1b6113be430>],
'fliers': [<matplotlib.lines.Line2D at 0x1b6113be790>],
'means': []}
```

