Stage III

October 27, 2023

1 Stage 3

Through out this notebook, we are going to focus on three statistics:

- The average rate of new cases per week
- The maximum number of new cases in one week
- The ration between cases and deaths

All of these will be normalized with the population

```
[1]: FIRST_DATE = '2020-06-28'

LAST_DATE = '2020-12-27'

STATES = ['NC', 'SC', 'AL', 'CA', 'TX', 'NY']

FACTOR = 1000 # for normalisation

PICTURE_HEIGHT = 400

PICTURE_WIDTH = 1000
```

```
[2]: import pandas as pd
  import numpy as np
  import scipy.stats as stats
  import plotly.graph_objects as go
  import plotly.express as px
  from plotly.subplots import make_subplots
  from IPython.display import Image
  import os

if not os.path.exists("images"):
    os.mkdir("images")

raw_cases = pd.read_csv("../Team/covid_confirmed_usafacts.csv")
  raw_deaths = pd.read_csv("../Team/covid_deaths_usafacts.csv")
  county_population = pd.read_csv("../Team/covid_county_population_usafacts.csv")
```

1.1 Part I

Let's begin with the average new cases per week. For that we first normalize by population, then we differentiate the dataset to get the change in total cases.

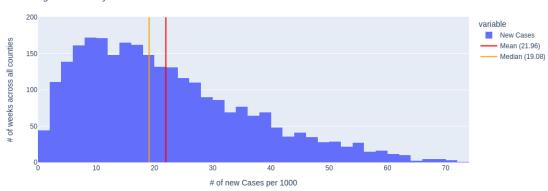
```
[3]: raw_cases = raw_cases.merge(county_population[['countyFIPS','population']],__
     ⇔on='countyFIPS')
    cases = raw_cases.drop(raw_cases[raw_cases.population == 0].index)
    for col in cases.columns:
        if FIRST_DATE <= col <= LAST_DATE:</pre>
            cases[col] = cases[col] / cases['population'] * FACTOR
    raw_deaths = raw_deaths.merge(county_population[['countyFIPS','population']],_
     ⇔on='countyFIPS')
    deaths = raw_deaths.drop(raw_cases[raw_deaths.population == 0].index)
    for col in deaths.columns:
        if FIRST_DATE <= col <= LAST_DATE:</pre>
            deaths[col] = deaths[col] / deaths['population'] * FACTOR
[4]: selected_date_columns = [col for col in cases.columns if FIRST_DATE <= col <=_u
     →LAST_DATE]
    additional_columns = ["countyFIPS", "County Name", "State", "StateFIPS"]
    selected_columns = additional_columns + selected_date_columns[0::7]
    selected_cases = cases[selected_columns]
    nc_cases = selected_cases.loc[selected_cases['State'] == 'NC']
    selected_deaths = deaths[selected_columns]
    nc_deaths = selected_deaths.loc[selected_deaths['State'] == 'NC']
[5]: data = np.reshape(nc_cases[selected_date_columns[0::7]].to_numpy(), -1)
    fig = px.histogram(data)
    mean = np.mean(data)
    fig.add_shape(go.layout.Shape(type='line', x0=mean, x1=mean, y0=0, y1=200, __
      ⇔line=dict(color='red', width=2)))
    fig.add_trace(go.Scatter(x=[None], y=[None], mode='lines', name=f'Mean ({mean:.
      median = np.median(data)
    fig.add_shape(go.layout.Shape(type='line', x0=median, x1=median, y0=0, y1=200, u
     →line=dict(color='orange', width=2)))
    fig.add_trace(go.Scatter(x=[None], y=[None], mode='lines', name=f'Median_
     for trace in fig.data:
        if trace.name == '0':
            trace.name = 'New Cases'
    fig.update_layout(
        title='Histogram of weekly new cases across North Carolina',
```

```
xaxis=dict(title=f'# of new Cases per {FACTOR}'),
  yaxis=dict(title='# of weeks across all counties'),
  showlegend=True,
  width=PICTURE_WIDTH,
  height=PICTURE_HEIGHT
)

fig.write_image("images/histo-cases.png")
Image(filename="images/histo-cases.png")
```

[5]:





```
[6]: print(f"The variance is {np.var(data)}")
    print(f"The skewness is {stats.skew(data)}")
    print(f"The kurtosis is {stats.kurtosis(data)}")
```

The variance is 208.7437899166838 The skewness is 0.8401691414226925 The kurtosis is 0.1810543779046978

The histogram is unimodal, and is skewed to the left.

Let's compare this to other states

```
[7]: def getCasesArray(state):
    data = selected_cases.loc[selected_cases['State'] == state].copy()
    return np.reshape(data[selected_date_columns[0::7]].to_numpy(), -1)

def getDeathsArray(state):
    data = selected_deaths.loc[selected_deaths['State'] == state].copy()
    return np.reshape(data[selected_date_columns[0::7]].to_numpy(), -1)
```

```
fig = go.Figure()
fig.add_trace(go.Histogram(x=getCasesArray('NC'), name='North Carolina'))
fig.add_trace(go.Histogram(x=getCasesArray('SC'), name='South Carolina'))
```

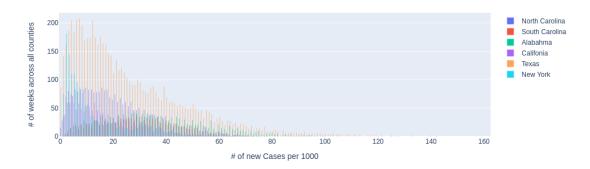
```
fig.add_trace(go.Histogram(x=getCasesArray('AL'), name='Alabahma'))
fig.add_trace(go.Histogram(x=getCasesArray('CA'), name='Califonia'))
fig.add_trace(go.Histogram(x=getCasesArray('TX'), name='Texas'))
fig.add_trace(go.Histogram(x=getCasesArray('NY'), name='New York'))

fig.update_layout(
   title='Histogram of weekly new cases across several states',
   xaxis=dict(title=f'# of new Cases per {FACTOR}'),
   yaxis=dict(title='# of weeks across all counties'),
   showlegend=True,
   width=PICTURE_WIDTH,
   height=PICTURE_HEIGHT
)

fig.write_image("images/histo-states.png")
Image(filename="images/histo-states.png")
```

[8]:

Histogram of weekly new cases across several states



Over all, all distribution are unimodal and skewed to the left. However, Texas sticks out with it's sheer number. We have to keep in mind that the data is not normalized over the number of counties in a given state. Knowing that, distrubutions that are more flat are more concerning, as that implies that covid was spreading there fast. An Example would Alabahma. New York has a very dense concentration in the lower numbers, this means that covid was not spreading fast there.

1.2 Part II

We are going to use North Carolina again

```
[9]: data = np.reshape(nc_cases[selected_date_columns[0::7]].to_numpy(), -1)

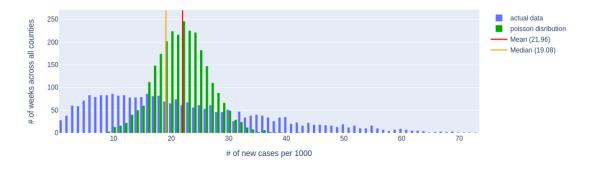
fig = go.Figure()
```

```
fig.add_trace(go.Histogram(x=data, name='actual data'))
fig.add_trace(go.Histogram(x=np.random.poisson(np.mean(data), len(data)),__

¬name='poisson disribution', marker_color='#00AA00'))
mean = np.mean(data)
fig.add shape(go.layout.Shape(type='line', x0=mean, x1=mean, y0=0, y1=270, 11
 ⇔line=dict(color='red', width=2)))
fig.add_trace(go.Scatter(x=[None], y=[None], mode='lines', name=f'Mean ({mean:.
 median = np.median(data)
fig.add_shape(go.layout.Shape(type='line', x0=median, x1=median, y0=0, y1=270, u
 →line=dict(color='orange', width=2)))
fig.add_trace(go.Scatter(x=[None], y=[None], mode='lines', name=f'Median_
 fig.update layout(
   title='Histogram of weekly new cases across North Carolina vs poisson∪
 ⇔distrbution',
   xaxis=dict(title=f'# of new cases per {FACTOR}'),
   yaxis=dict(title='# of weeks across all counties'),
   showlegend=True,
   width=PICTURE WIDTH,
   height=PICTURE_HEIGHT
)
fig.write_image("images/poisson-cases.png")
Image(filename="images/poisson-cases.png")
```

[9]:

Histogram of weekly new cases across North Carolina vs poisson distrbution



We can see that the actual data cannot be represented as a poisson distribution. That is because

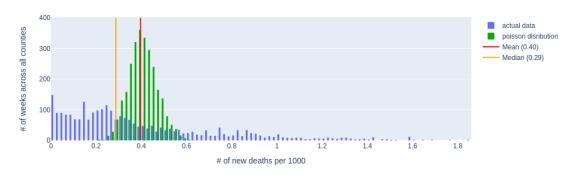
the varience is not equal to the mean. Which shows in the difference of mean and median.

```
[10]: data = np.reshape(nc_deaths[selected_date_columns[0::7]].to_numpy(), -1)
     fig = go.Figure()
     fig.add_trace(go.Histogram(x=data, name='actual data'))
     fig.add_trace(go.Histogram(x=(np.random.poisson(np.mean(data) *100, len(data)) /
      ⇔100), name='poisson disribution', marker_color='#00AA00'))
     mean = np.mean(data)
     fig.add_shape(go.layout.Shape(type='line', x0=mean, x1=mean, y0=0, y1=400, ___
      ⇒line=dict(color='red', width=2)))
     fig.add_trace(go.Scatter(x=[None], y=[None], mode='lines', name=f'Mean ({mean:.
      →2f})', line=dict(color='red', width=2)))
     median = np.median(data)
     fig.add_shape(go.layout.Shape(type='line', x0=median, x1=median, y0=0, y1=400, u
      →line=dict(color='orange', width=2)))
     fig.add_trace(go.Scatter(x=[None], y=[None], mode='lines', name=f'Median_
      fig.update_layout(
         title='Histogram of weekly new deaths across North Carolina vs poisson_

→distrbution',
         xaxis=dict(title=f'# of new deaths per {FACTOR}'),
         yaxis=dict(title='# of weeks across all counties'),
         showlegend=True,
         width=PICTURE_WIDTH,
         height=PICTURE_HEIGHT
     )
     fig.write_image("images/poisson-cases.png")
     Image(filename="images/poisson-cases.png")
```

Γ107:

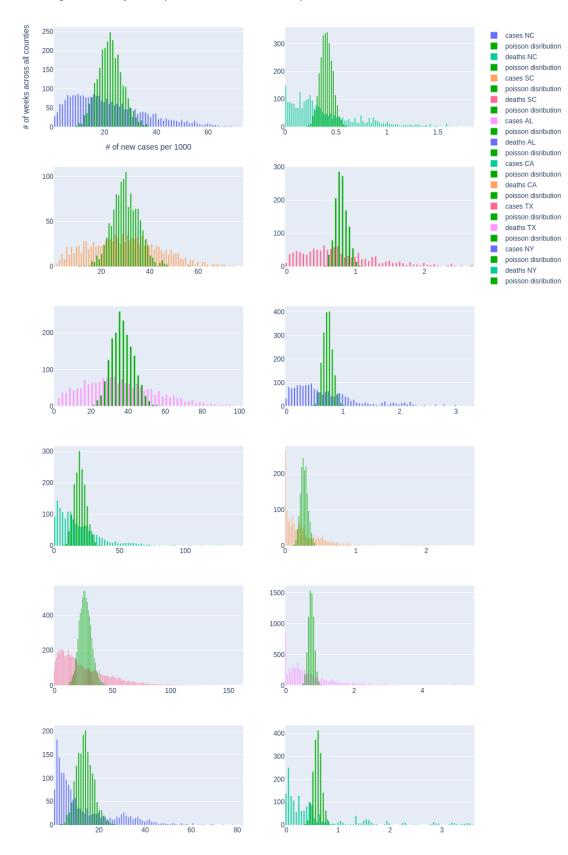
Histogram of weekly new deaths across North Carolina vs poisson distrbution



The effect is even stronger with more skewed deaths statistic. Let's have a look at the other states

```
[11]: fig = make_subplots(rows=6, cols=2)
      for i, state in enumerate(STATES):
          data = getCasesArray(state)
          fig.add_trace(go.Histogram(x=data, name='cases '+state), row=(i+1), col=1)
          fig.add_trace(go.Histogram(x=np.random.poisson(np.mean(data), len(data)),__
       name='poisson disribution', marker_color='#00AA00'), row=(i+1), col=1)
          data = getDeathsArray(state)
          fig.add_trace(go.Histogram(x=data, name='deaths '+state), row=(i+1), col=2)
          fig.add_trace(go.Histogram(x=(np.random.poisson(np.mean(data) * 100,__
       ⇔len(data))/100), name='poisson disribution', marker_color='#00AA00'),⊔
       \rightarrowrow=(i+1), col=2)
      fig.update_layout(
          title='Histograma of weekly data vs poisson distribution across multiple_
       ⇔states',
          xaxis=dict(title=f'# of new cases per {FACTOR}'),
          yaxis=dict(title='# of weeks across all counties'),
          showlegend=True,
          width=PICTURE_WIDTH,
          height=(PICTURE HEIGHT *4)
      )
      fig.write_image("images/poisson-cases.png")
      Image(filename="images/poisson-cases.png")
```

「111]:



We can see that the actual data cannot be represented as a poisson distribution. That is because the variance is not equal to the mean. Thus the poisson distribution should not be assumed for the distribution of cases or deaths.

1.3 Part III

```
[12]: housing = pd.read_csv("./data/ACSDP1Y2022.DP04-Data.csv", low_memory=False)
economics = pd.read_csv("./data/ACSDP1Y2022.DP03-Data.csv", low_memory=False)
housing['GE0_ID'] = pd.to_numeric(housing['GE0_ID'].str.slice(start=9))
economics['GE0_ID'] = pd.to_numeric(economics['GE0_ID'].str.slice(start=9))
```

to compare individual variables, we need a single indicator for the spread of covid. We'll focus on the average number of new cases a week and the maximum spread in one week.

```
[13]:
         countyFIPS
                           County Name State
                                                StateFIPS
                                                            2020-06-28
                                                                         2020-07-05
                       Baldwin County
                                                                           3.946531
      0
                1003
                                           AL
                                                         1
                                                              2.575773
                       Calhoun County
      1
                1015
                                            ΑL
                                                         1
                                                              2.156595
                                                                           3.186479
      2
                       Cullman County
                1043
                                           AL
                                                         1
                                                              4.560214
                                                                           5.491357
      3
                1049
                        DeKalb County
                                           ΑL
                                                         1
                                                              7.607009
                                                                          10.179967
      4
                1051
                        Elmore County
                                           ΑL
                                                              9.715672
                                                                          11.538130
         2020-07-12
                       2020-07-19
                                    2020-07-26
                                                 2020-08-02
                                                                 DP04 0142PM
      0
            5.796608
                         8.676994
                                     12.130769
                                                  14.437765
                                                                          9.2
      1
            4.630078
                         6.909907
                                                                          8.8
                                      9.797104
                                                  13.907839
      2
                         9.812816
            7.461083
                                     11.651227
                                                  14.062649
                                                                         14.3
                                     21.170976
      3
          13.661852
                        18.234447
                                                  23.939703
                                                                         12.6
          13.372902
                        15.774114
                                     18.323092
                                                  20.256376
                                                                          9.9
         DP04_0142PMA
                         DP04_0143PE
                                       DP04_0143PEA
                                                      DP04_0143PM
                                                                    DP04_0143PMA \
      0
                   NaN
                                  (X)
                                                 (X)
                                                               (X)
                                                                               (X)
                                  (X)
                                                 (X)
                                                               (X)
                                                                               (X)
      1
                   NaN
      2
                                  (X)
                                                 (X)
                                                                (X)
                                                                               (X)
                   NaN
      3
                   NaN
                                  (X)
                                                 (X)
                                                                (X)
                                                                               (X)
      4
                   NaN
                                  (X)
                                                 (X)
                                                                (X)
                                                                               (X)
```

Unnamed: 1146 population average max

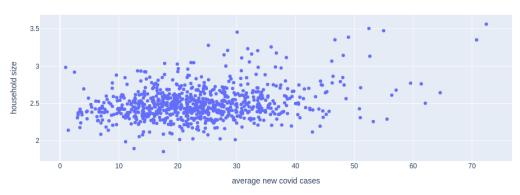
```
0
              {\tt NaN}
                        223234 25.904059
                                              57.450926
              NaN
                                              81.264029
1
                        113605
                                 33.573770
2
              {\tt NaN}
                         83768
                                 30.095909
                                              80.603572
3
              {\tt NaN}
                         71513
                                 42.264266
                                              94.038846
              NaN
                         81209
                                 34.875718
                                              73.809553
```

[5 rows x 2280 columns]

Let's check the realtion between average house hold size and covid spread

[14]:

Household size vs cases



```
[15]: print(f"The correlation of household size is {np.

corrcoef(selected_cases['average'],selected_cases['population'] /

(selected_cases['DP04_0002E'].astype(float)))[0, 1]}")
```

The correlation of household size is 0.277828419859136

Let's check some other variables from the housing and economics dataset

0.08106336532189166

[16]:

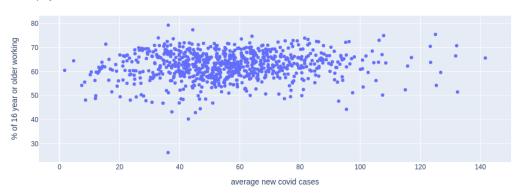
Households with zero vehicles vs cases



0.11276115691267607

[17]:

Employment rate vs cases



```
[18]: selected_cases['DP03_0037E'] = pd.to_numeric(selected_cases['DP03_0037E'],__
      ⇔errors='coerce')
      data = selected_cases.dropna(subset=['DP03_0037E'])
      print(np.corrcoef(data['max'],(data['DP03_0037E'].astype(float) /__

data['DP03_0001E'].astype(float)))[0, 1])

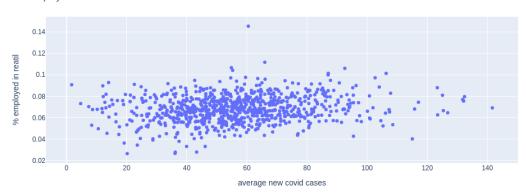
      fig = px.scatter(x=data['max'], y=(data['DP03_0037E'].astype(float)/

data['DP03_0001E'].astype(float)))
      fig.update_layout(
          title='Employment in Retail vs cases',
          xaxis=dict(title=f'average new covid cases'),
          yaxis=dict(title=f'% employed in reatil'),
          showlegend=True,
          width=PICTURE_WIDTH,
          height=PICTURE_HEIGHT
      fig.write image("images/cases-retail.png")
      Image(filename="images/cases-retail.png")
```

0.17242015943941838

[18]:

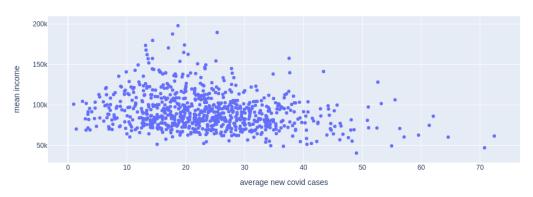
Employment in Retail vs cases



-0.23924435962550658

[19]:





1.4 Part IV

With most of these Variable we have low correlation. I hypothesize that covid was a society-wide phenomenon, disregarding economic and social factors. In particular I want to answer the following questions:

- Does an increased average household size lead to more cases?
- Does decreased mobility lead to fewer cases? (based on the number of vehicles)
- Does increased mean income lead to a lower mortality rate?

[0]: