Assignment 2

Read all instructions carefully

Work Requirements

- You must work on Assignment 2 alone. You may not work with partners.
- You may use online resources (Stack Exchange, Googling, Regex cheat sheets), including documentation and everything on Canvas. However, you may not use an LLM (ChatGPT, Copilot, etc)
- Lightly document your code, especially any decisions you make along the way. You do not need extensive documentation. You do **NOT** need a separate README file. But a person should be able to read your submission top to bottom and understand what you're doing.

Submission Instructions

- This assignment is due on **Monday, October 6 at 6:59pm**.
- The assignment must be submitted on Canvas as a single PDF file together with a requirements.txt file (as a text file, not PDF). The two files must be submitted as separate files, not as a zip file.
- The PDF file you submit must be named with the following format "lastname_firstname_assignment2.pdf"
- The requirements.txt file should only include the libraries you need to run your code in a Jupyter notebook, with their versions properly specified (e.g., use pip freeze with your venv activated)

Recommendations and Resources

Recommendation: Complete the assignment in a Jupyter notebook, and then convert the notebook to a PDF. If you have too much trouble converting to PDF, then convert it to HTML, open it as HTML and export that page to PDF (but this is a less preferred option).

Recommendation: As always, start by examining the data you read in and understand it. What does each row represent in each dataframe?

Helpful Documentation:

- Pandas expanding: https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.expanding.html#pandas.DataFrame.expanding
- Python re library for Regex: https://docs.python.org/3/library/re.html
- Pareto: https://numpy.org/doc/stable/reference/random/generated/numpy.random.pareto.html#numpy.random.pareto

- Gaussian: https://numpy.org/doc/stable/reference/random/generated/numpy.random.normal.html#numpy-random-normal
- Seaborn Boxplot: https://seaborn.pydata.org/generated/seaborn.boxplot.html
- Seaborn Scatterplot: https://seaborn.pydata.org/generated/seaborn.scatterplot.html
- Matplotlib scatterplot: https://matplotlib.org/stable/api/_as_gen/matplotlib.pyplot.scatter.html
- Matplotlib boxplot: https://matplotlib.org/stable/api/_as_gen/matplotlib.pyplot.boxplot.html#

Part 0 - Imports and CoW

```
# Import libraries
from pathlib import Path
import numpy as np
import pandas as pd
import seaborn as sns
import re
from datetime import datetime
from matplotlib import pyplot as plt

# Enforce Copy-on-Write
pd.options.mode.copy_on_write = True
```

Part 1 - Regex, EDA, and Visualization

Load the Food Safety datasets (bus.csv, ins2vio.csv, ins.csv, and vio.csv) into pandas dataframes and answer the following questions based on the dataframes.

```
#Load the datasets into Pandas DataFrames
def load_dataset_to_df(file, na_values = None):
    cwd = Path.cwd()
    assignment2 = cwd.parent
    data = assignment2.joinpath('data')
    path = data.joinpath(file)
    if path.exists():
        print(f'Found the data file {path}')
    else:
        raise Exception('Could not find that file', path)
    return pd.read_csv(path, na_values = na_values)

bus_df = load_dataset_to_df('bus.csv', na_values = [-9999])
ins_df = load_dataset_to_df('ins.csv')
isn2vio_df = load_dataset_to_df('ins2vio.csv')
vio_df = load_dataset_to_df('vio.csv')
```

```
Found the data file /Users/Isaia/PycharmProjects/CS-577-07-Data-
Science-Fall-2025/Assignments/Assignment2/data/bus.csv
Found the data file /Users/Isaia/PycharmProjects/CS-577-07-Data-
Science-Fall-2025/Assignments/Assignment2/data/ins.csv
Found the data file /Users/Isaia/PycharmProjects/CS-577-07-Data-
Science-Fall-2025/Assignments/Assignment2/data/ins2vio.csv
Found the data file /Users/Isaia/PycharmProjects/CS-577-07-Data-
Science-Fall-2025/Assignments/Assignment2/data/vio.csv
```

Use the business dataset (bus) to answer the first few questions below

1.1) Examining the entries in `bus`, is the `bid` unique for each record (i.e. each row of data)?

Hint: use `value_counts()` or `unique()` to determine if the `bid` series has any duplicates.

```
bus_df.head()
```

```
   business id column                         name  
address  \
0                1000        HEUNG YUEN RESTAURANT            3279 
22nd St   
1              100010        ILLY CAFFE SF_PIER 39        PIER 39  K-
106-B   
2              100017  AMICI'S EAST COAST PIZZERIA             475 
06th St   
3              100026               LOCAL CATERING        1566 CARROLL 
AVE   
4              100030             OUI OUI! MACARON  2200 JERROLD AVE 
STE C   

            city state postal_code   latitude   longitude  
phone_number  
0  San Francisco    CA       94110  37.755282 -122.420493  
NaN  
1  San Francisco    CA       94133        NaN         NaN  
1.415483e+10  
2  San Francisco    CA       94103        NaN         NaN  
1.415528e+10  
3  San Francisco    CA       94124        NaN         NaN  
1.415586e+10  
4  San Francisco    CA       94124        NaN         NaN  
1.415970e+10
```

Im not sure what is bid is as there's no column named that, but business id column seems like thats what bid may be so im going to use that. Im curious what -9999 and -9999.0 means, but since there no documentation I have decided to interpret it as a NaN

```
ID = "business id column"
NAME = "name"
```

```
ADDRESS = "address"
POSTAL_CODE = "postal_code"

bid_has_duplicates = bus_df[ID].nunique() < bus_df.shape[0]
if bid_has_duplicates:
    print(f'{ID} has a duplicate ID')
else:
    print(f'{ID} has no duplicate ID')
```

```
business id column has no duplicate ID
```

1.2) In the two cells below create the following **two numpy arrays**:

1. Assign `top_names` to the top 5 most frequently used business names, from most frequent to least frequent.
2. Assign `top_addresses` to the top 5 addressses where businesses are located, from most popular to least popular.

Hint: you may find `value_counts()` helpful.

```
top_names_df =
bus_df[NAME].value_counts().sort_values(ascending=False).head(5).reset
_index()
top_names_df
```

```
                  name  count
0  Peet's Coffee & Tea     20
1     Starbucks Coffee     13
2           McDonald's     10
3          Jamba Juice     10
4            STARBUCKS      9
```

```
top_names = top_names_df[NAME].to_numpy()
top_names
```

```
array(["Peet's Coffee & Tea", 'Starbucks Coffee', "McDonald's",
       'Jamba Juice', 'STARBUCKS'], dtype=object)
```

```
top_addresses_df =
bus_df[ADDRESS].value_counts().sort_values(ascending=False).head(5).re
set_index()
top_addresses_df
```

```
          address  count
0    Off The Grid     39
1     428 11th St     34
2  2948 Folsom St     17
3   3251 20th Ave     17
4         Pier 41     16
```

```
top_addresses = top_addresses_df[ADDRESS].to_numpy()
top_addresses
```

```
array(['Off The Grid', '428 11th St', '2948 Folsom St', '3251 20th
Ave',
       'Pier 41'], dtype=object)
```

1.3) Look at the businesses that DO NOT have the special MISSING ZIP code value. Some of the invalid postal codes are just the full 9 digit code rather than the first 5 digits. Create a new column named `postal5` in the original bus dataframe which contains only the first 5 digits of the postal_code column. Finally, for any of the likely MISSING postal5 ZIP code entries set the entry to None.

```
bus_df[POSTAL_CODE].unique()
```

```
array(['94110', '94133', '94103', '94124', '94123', '94118', '94121',
       '94134', '94114', '94109', '94102', '94132', '94116', nan,
'94107',
       '94105', '94108', '94117', '94158', '94112', '94127', '94105-
1420',
       '94111', '94122', '94115', '94104', '94122-1909', '94131',
       '94117-3504', '94518', '95105', '94013', '94130', '941102019',
       '941', '941033148', 'CA', '92672', '94120', '94143', '94101',
       '94014', '94129', '94602', 'Ca', '94080', '00000', '94188',
       '64110', '94544', '94301', '94901', '95117', '95133', '95109',
       '95132', '95122', '94621', '94124-1917', '94102-5917',
       '94105-2907', '95112', '94123-3106'], dtype=object)
```

```
print(bus_df[POSTAL_CODE].value_counts().sort_values(ascending=True).t
o_string())
```

```
postal_code
94123-3106      1
94122-1909      1
94544           1
94901           1
95117           1
95133           1
95132           1
95109           1
95122           1
94621           1
94124-1917      1
94102-5917      1
94105-2907      1
95112           1
64110           1
00000           1
94117-3504      1
Ca              1
```

```
94602            1
94129            1
94014            1
94120            1
92672            1
941033148        1
941              1
941102019        1
94105-1420       1
95105            1
94080            1
94518            1
94188            2
CA               2
94013            2
94301            2
94101            2
94143            5
94130            8
94131           49
94127           67
94134           82
94158           90
94116           97
94132          132
94104          142
94121          157
94123          177
94117          189
94112          192
94114          200
94124          218
94108          229
94115          230
94118          231
94105          249
94122          255
94111          259
94109          382
94133          398
94107          408
94102          456
94110          555
94103          562
```

The postal codes look suspicious:

1. NaN (-9999)
2. 94518

3. 95105
4. 94013
5. 941
6. CA
7. 92672
8. 94101
9. 94014
10. 94602
11. Ca
12. 00000
13. 94188
14. 64110
15. 94544
16. 94301
17. 94901
18. 95117
19. 95133
20. 95109
21. 95132
22. 95122
23. 94621
24. 95112

According to USPS, postal codes in San Francisco, CA and South Francisco, CA are:

1. 94080
2. 94083
3. 94102 - 94112
4. 94114- 94134
5. 94137
6. 94139 - 94147
7. 94151
8. 94158 - 94161
9. 94163 - 94164
10. 94172
11. 94177

The pairs with a dash 'zipcode 1 - zipcode 2' are interpolated for example 0-9 is 0,2,3,4,5,6,7,8,0 and one can use USPS tool below to verify these zip codes

https://tools.usps.com/zip-code-lookup.htm?bycitystate

and the 9 digit numbers seem to be "valid" as defined below

1. 94122-1909 -> 94122
2. 94124-1917 -> 94124

3. 94102-5917 -> 94102
4. 94105-1420 -> 94105
5. 94117-3504 -> 94117
6. 941033148 -> 94103
7. 941102019 -> 94110
8. 94105-2907 -> 94105
9. 94123-3106 -> 94123

From looking at bus_df from bus.csv, all rows say that the city is in San Francisco, however there some entries that have incorrect/invalid zip codes for San Francisco or South San Francisco, zip codes must be included in bullet points 1-11.

if the zip code is not numerical or doesnt contain at least 5 numbers or the first 5 digits are invalid San Francisco or South San Francisco (excluded in bullet points 1-11), then I will store None for postal5

if the zip code is numerical and contains at least 5 numbers and the first 5 digits San Francisco or South San Francisco is valid (included in bullet points 1-11), then I will keep the zip code for postal5

```
def is_valid(postal_code, pattern):
    if(len(str(postal_code)) >= 5) and re.fullmatch(pattern,
postal_code[:5]):
        return postal_code[:5]
    else:
        return None

sf_postal_code_pattern = r'941(0[2-9]|1[^3]|2[0-9]|3[^5,6,8]|4[0-7]|
5[1,8,9]|6[0,1,3]|7[2,7])|940(8[0,3])'
POSTAL5 = 'postal5'
bus_df[POSTAL5] = bus_df[POSTAL_CODE].map(lambda x: is_valid(x,
sf_postal_code_pattern))

bus_df.head(5)

   business id column                         name
address  \
0                1000        HEUNG YUEN RESTAURANT            3279
22nd St
1              100010        ILLY CAFFE SF_PIER 39        PIER 39  K-
106-B
2              100017  AMICI'S EAST COAST PIZZERIA             475
06th St
3              100026               LOCAL CATERING        1566 CARROLL
AVE
4              100030             OUI OUI! MACARON  2200 JERROLD AVE
STE C

            city state postal_code   latitude   longitude
phone_number  \
```

```
0  San Francisco     CA        94110  37.755282 -122.420493
NaN
1  San Francisco     CA        94133        NaN         NaN
1.415483e+10
2  San Francisco     CA        94103        NaN         NaN
1.415528e+10
3  San Francisco     CA        94124        NaN         NaN
1.415586e+10
4  San Francisco     CA        94124        NaN         NaN
1.415970e+10

  postal5
0   94110
1   94133
2   94103
3   94124
4   94124
```

Here we can we see that all of our values were mapped correctly based on the is_valid method

```
print(bus_df[POSTAL5].value_counts(dropna=False).sort_values(ascending
=True).to_string())

postal5
94080      1
94120      1
94129      1
94143      5
94130      8
94131     49
94127     67
94134     82
94158     90
94116     97
94132    132
94104    142
94121    157
94123    178
94117    190
94112    192
94114    200
94124    219
None     222
94108    229
94115    230
94118    231
94105    251
94122    256
94111    259
```

```
94109     382
94133     398
94107     408
94102     457
94110     556
94103     563
```

Now using the four Food Safety datasets bus.csv, ins2vio.csv, ins.csv, and vio.csv:

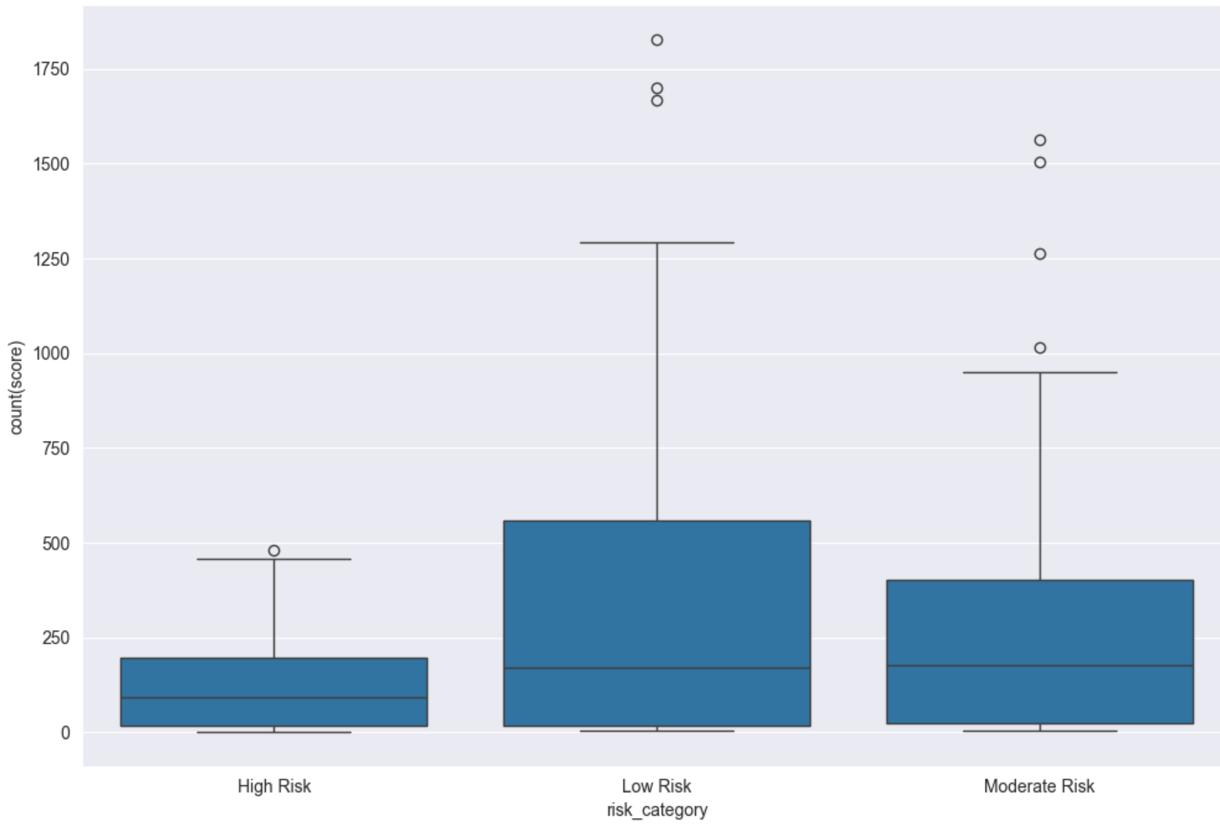
1.5) Create a side-by-side boxplot that shows the distribution of the restaurant scores for each different risk category from 2017 to 2019. Use a figure size of at least 12 by 8.

Hint: Consider using appropriate JOIN operations.

```
IID ='iid'
VID ='vid'
INNER = 'inner'
food_safety_df = ins_df.merge(isn2vio_df, on=IID,
how=INNER).merge(vio_df, on=VID, how=INNER)
food_safety_df[ID] =
food_safety_df[IID].str.split('_').str[0].astype('int64')
food_safety_df = food_safety_df.merge(bus_df, on=ID, how=INNER)
food_safety_df.head()

               iid                    date  score
type  \
0  100017_20190816  08/16/2019 12:00:00 AM     91  Routine -
Unscheduled
1  100017_20190816  08/16/2019 12:00:00 AM     91  Routine -
Unscheduled
2  100030_20190612  06/12/2019 12:00:00 AM     -1          New
Ownership
3  100030_20190612  06/12/2019 12:00:00 AM     -1          New
Ownership
4  100030_20190826  08/26/2019 12:00:00 AM     -1          New
Ownership

      vid                                  description
risk_category  \
0  103105                     Improper cooling methods     High
Risk
1  103139                        Improper food storage      Low
Risk
2  103142              Unclean nonfood contact surfaces      Low
Risk
3  103154       Unclean or degraded floors walls or ceilings      Low
Risk
4  103149  Wiping cloths not clean or properly stored or ...      Low
Risk
```

```
   business id column                              name
address  \
0              100017  AMICI'S EAST COAST PIZZERIA            475
06th St
1              100017  AMICI'S EAST COAST PIZZERIA            475
06th St
2              100030             OUI OUI! MACARON  2200 JERROLD AVE
STE C
3              100030             OUI OUI! MACARON  2200 JERROLD AVE
STE C
4              100030             OUI OUI! MACARON  2200 JERROLD AVE
STE C

            city state postal_code  latitude  longitude  phone_number
postal5
0  San Francisco    CA       94103       NaN        NaN  1.415528e+10
94103
1  San Francisco    CA       94103       NaN        NaN  1.415528e+10
94103
2  San Francisco    CA       94124       NaN        NaN  1.415970e+10
94124
3  San Francisco    CA       94124       NaN        NaN  1.415970e+10
94124
4  San Francisco    CA       94124       NaN        NaN  1.415970e+10
94124

DATETIME = 'datetime'
DATE = 'date'
RISK_CATEGORY = 'risk_category'
SCORE = 'score'

food_safety_df[DATETIME] = pd.to_datetime(food_safety_df[DATE],
format='%m/%d/%Y %I:%M:%S %p')

COUNT_SCORE = f'count({SCORE})'
scores_df = food_safety_df[
    (datetime(year=2017, month=1, day=1) <= food_safety_df[DATETIME])
&
    (food_safety_df[DATETIME] <= datetime(year=2019, month=12,
day=31))
].groupby([RISK_CATEGORY, SCORE])[SCORE].count().reset_index(name=
COUNT_SCORE)

scores_df.head()

  risk_category  score  count(score)
0     High Risk     -1           457
1     High Risk     45             5
2     High Risk     46             4
```

```
3     High Risk     48              2
4     High Risk     51              3

plt.figure(figsize=(12, 8))
plot = sns.boxplot(data=scores_df, x=RISK_CATEGORY, y=COUNT_SCORE)
```



All risk categories look skewed top. High risk has the smallest median and IQR. low risk and moderate risk have a roughly similar median, but low risk has a larger iqr range compared to moderate risk. low risk has the outlier whisker wider than all risks, followed by moderate and high. They all have outliers, but moderate has most then low risk then high risk. but these are in respect to their outlier band.

Part II - Making a Synthetic Dataset

In this part you're going to be create a synthetic dataset (dataframe) with 1000 observations (rows). You are going to use random number generators to create the data for you.

You can use either the numpy or scipy library, whichever you find easier. Be sure to import any libraries you use at the top of the ntoebook (not down here).

```
n = 10000
```

```
#Optional: set random seed for reproducibility (how you do it depends
on whether you use numpy or scipy to generate the random numbers)
np.random.seed(n)
```

2.1) Create a variable "v1" of 10,000 numbers where y = 3x+4 is the value of the element at index x, i.e., [4, 7, 10, ...] (Done for you)

```
v1 = 3 * np.arange(n) + 4
```

2.2) Create a list of 10,000 samples from a normal (Gaussian) distribution with mean = 0 and variance = 10.

HINT: Pay attention to whether the argument to your number generator is variance or standard deviation. (It doesn't have to be a python list, it can be an array or dataframe, or whatever dtype is most convenient for you.)

```
mean = 0
variance = 10
standard_deviation = np.sqrt(variance)
noise = np.random.normal(mean, standard_deviation, n)
```

2.3) Create a variable v2 = v1 + Gaussian noise, using the noise your created above

```
v2 = v1 + noise
```

2.4) Create a variable v3 = exp(v1) that exponentiates the libear variable in v1, also sometimes denoted e^(v1), e.g., v3[0] = e^4

```
v3 = np.exp(v1)

/var/folders/2p/bfr58x5j3q7bhsbb77vmqxbw0000gn/T/
ipykernel_1670/706569660.py:1: RuntimeWarning: overflow encountered in
exp
  v3 = np.exp(v1)
```

2.5) Create a list v4 = exp(v1) + Gaussian noise, using the same noise variable you created earlier

```
v4 = v3 + noise
```

2.6) Create a list v5 = exp(v1 + Gaussian noise), using the same noise variable you created earlier

```
v5 = np.exp(v2)

/var/folders/2p/bfr58x5j3q7bhsbb77vmqxbw0000gn/T/
ipykernel_1670/3036182197.py:1: RuntimeWarning: overflow encountered
in exp
  v5 = np.exp(v2)
```

v3 and v5 have overflows, This is not good, the random numbers that are generated from np.arrange(0,n) are being passed to these functions(v1,v2,v3,v4,v5), where they may to be big to represent. I will come up with a theoretical better values for np.arrange

We know

- v1 = 3x + 4
- v2 = v1 + noise
  - v2 = 3x + 4 + noise
- v5 = e^(v2)
  - v5 = e^(3x + 4 + noise)

to prevent an overflow

- v5 <= float64.max
  - e^(3x + 4 + noise) <= float64.max
    - 3x + (4 + noise) <= ln(float64.max)
    - 3x <= ln(float64.max) - (4 + noise)
    - x <= (ln(float64.max) - (4 + noise) / 3
- Due to the 68-95-99.7 rule
- μ = mean
  - μ = 0
- variance = 10
- σ = standard deviation =
  - σ = sqrt(variance)
    - σ = sqrt(10)
- z = z score
- % of samples
  - confidence interval
    - μ +- zσ

we will use the z score of 3.9 to get 99.995%

- Range
  - lower noise
    - 0 - 3.9 * sqrt(10)
  - upper noise
    - 0 + 3.9 * sqrt(10)

Our stop value in np arrange must be

- stop = x
  - stop = (ln(float64.max) - (4 + noise) / 3
    - noise must be the upper bound of noise to account of 99.995% of data
  - stop = (ln(float64.max) - (4 + upper_noise) / 3

```
z_score = 3
upper_noise = mean + (z_score * standard_deviation)
max_float64 = np.finfo(np.float64).max

#scaling stop parameter in np.arrange
stop = ((np.log(max_float64) - (4 + upper_noise)) / 3)
print(stop)
# updating the v1,v2,v3,v4,v5
v1 = 3 * np.arange(start=0, stop=stop, step=stop / n) + 4
v2 = v1 + noise
v3 = np.exp(v1)
v4 = v3 + noise
v5 = np.exp(v2)
```

```
232.09862663762627
```

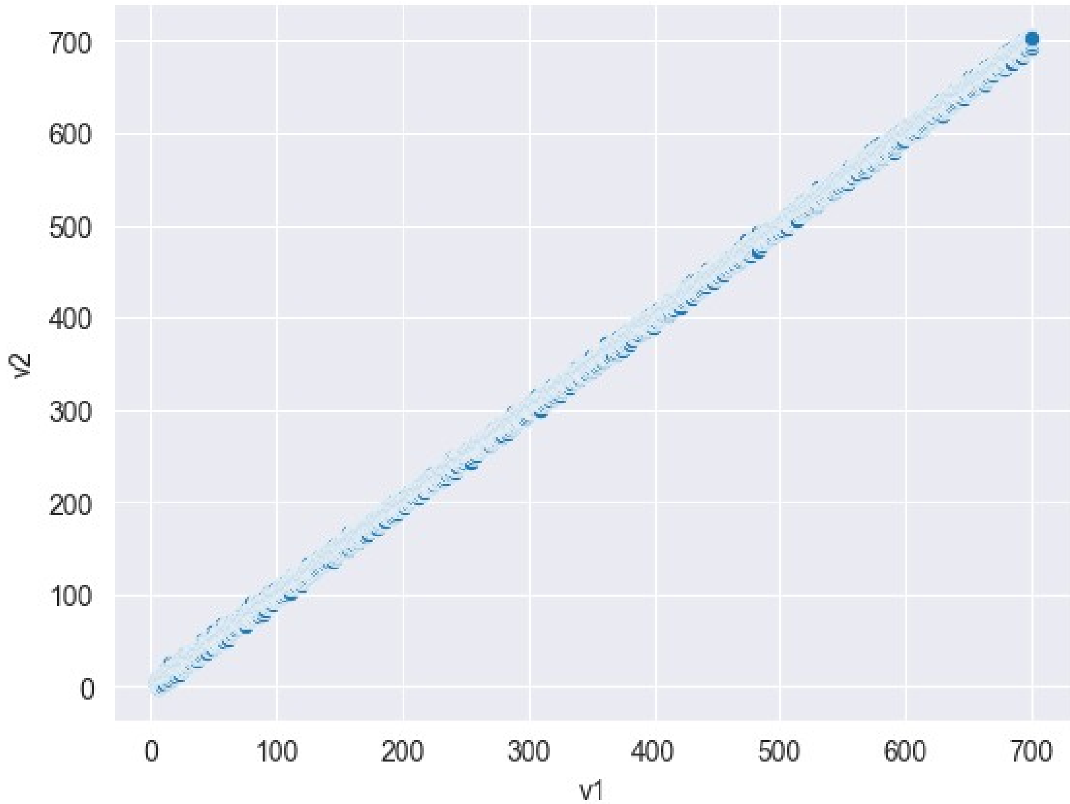
2.7) Create a dataframe with 10,000 rows and columns = [v1, v2, v3, v4, v5, noise]

```
V1 = 'v1'
V2 = 'v2'
V3 = 'v3'
V4 = 'v4'
V5 = 'v5'
NOISE = 'noise'
df_full = pd.DataFrame({V1: v1, V2: v2, V3: v3, V4: v4, V5: v5, NOISE: noise})
```

2.8) For each variable (v2, v3, v4, v5) create a separate scatter plot with v1 on the x-axis. Remark on your general observations.

```
# Code for plots here, and remarks and observations here
sns.scatterplot(data=df_full, x=V1, y=V2)
```

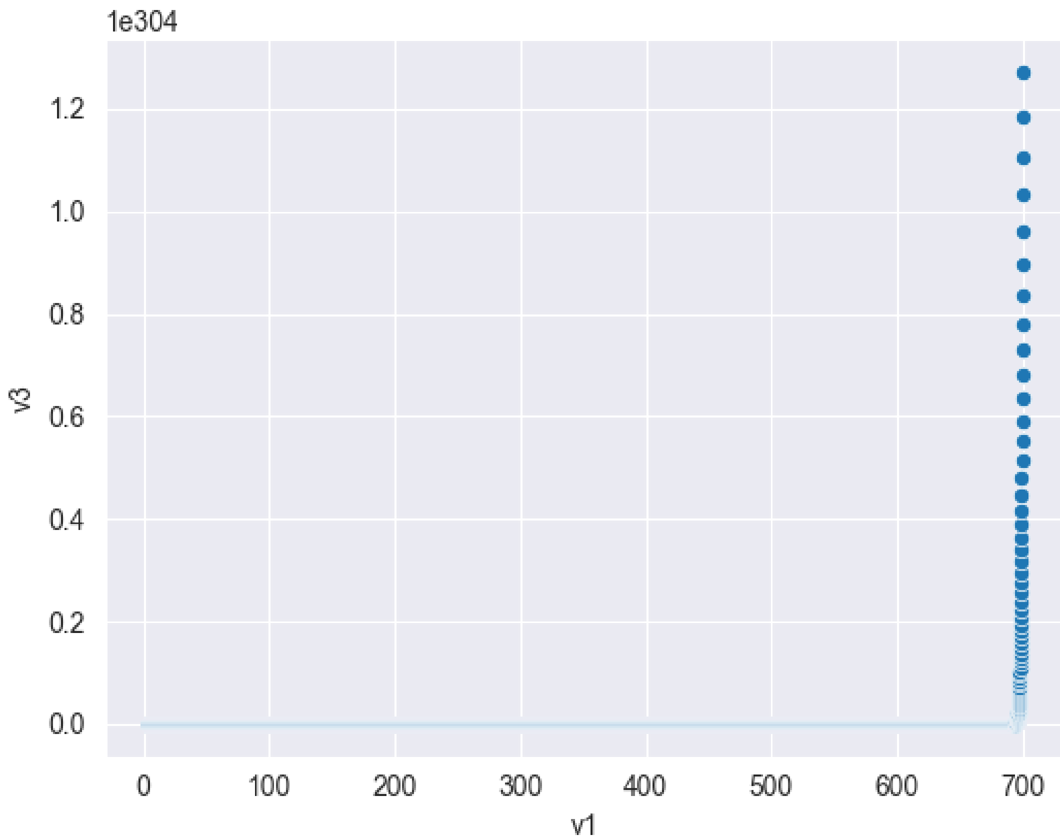
```
<Axes: xlabel='v1', ylabel='v2'>
```



Will make observation later, with different view of this graph

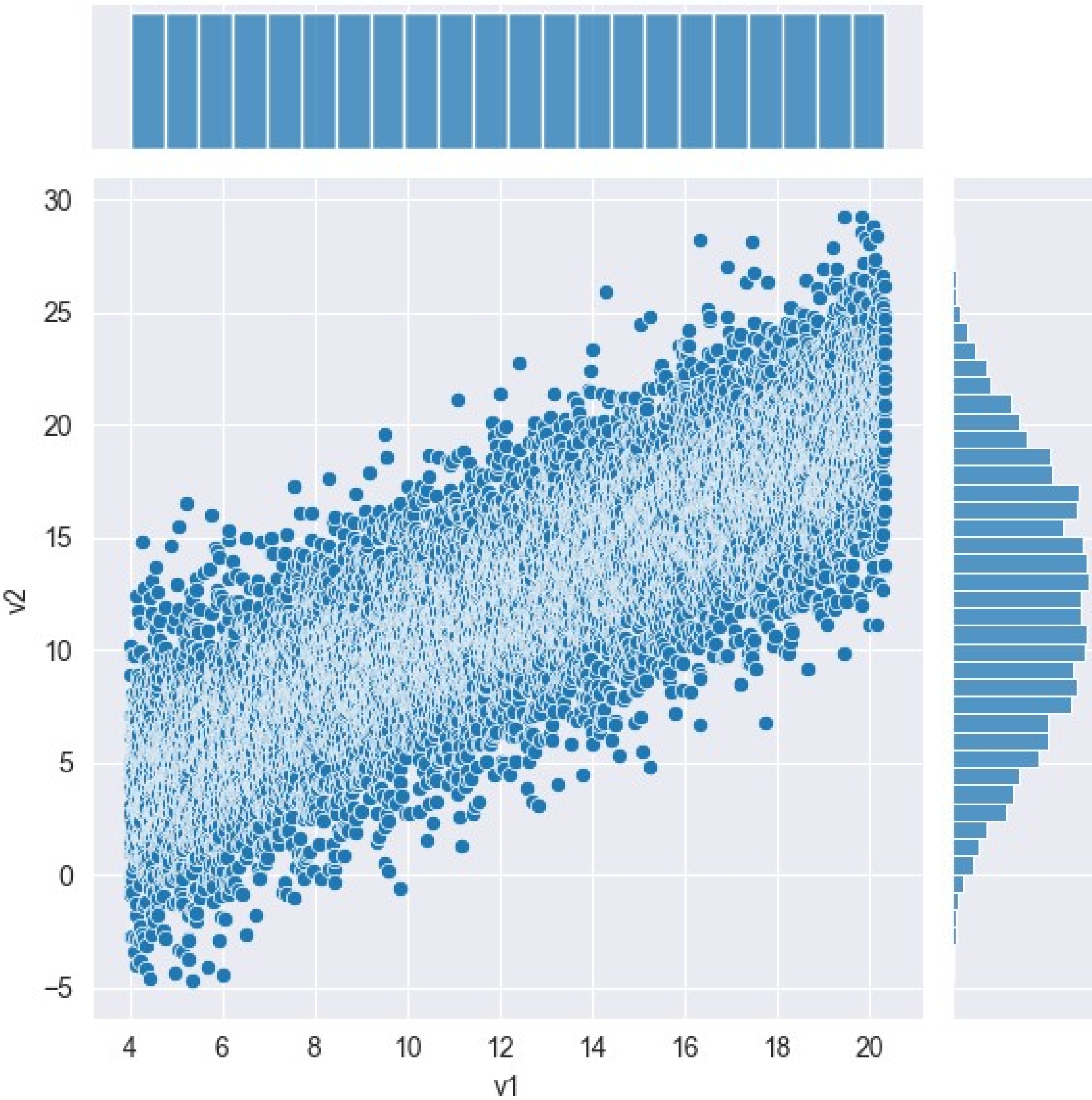
```
sns.scatterplot(data=df_full, x=V1, y=V3)
```

```
<Axes: xlabel='v1', ylabel='v3'>
```



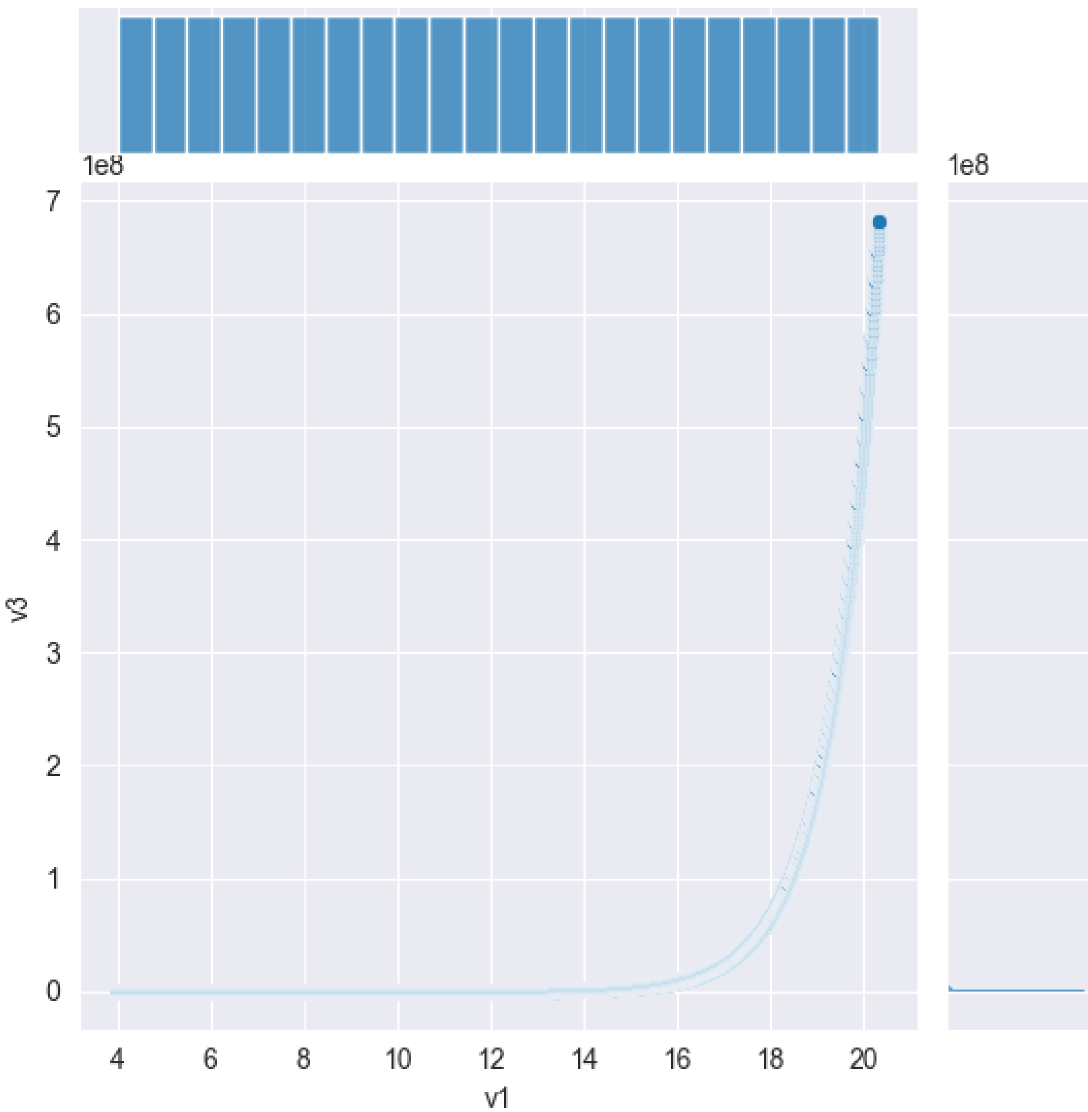
Its hard to make an observation since e^1.2e304 is close to float64.max, making the axis large, so i will scale stop down another log().

```
#scaling stop parameter in np.arrange again
stop = np.log(stop)
# updating the v1,v2,v3,v4,v5
v1 = 3 * np.arange(start=0, stop=stop, step=stop / n) + 4
v2 = v1 + noise
v3 = np.exp(v1)
v4 = v3 + noise
v5 = np.exp(v2)
#updating df full
df_full = pd.DataFrame({V1: v1, V2: v2, V3: v3, V4: v4, V5: v5, NOISE:
noise})

sns.jointplot(data=df_full, x=V1 , y=V2, kind='scatter')

<seaborn.axisgrid.JointGrid at 0x1105b1f70>
```



There appears to be a uniform spread across the positive linear pattern and moderate to strong relationship.

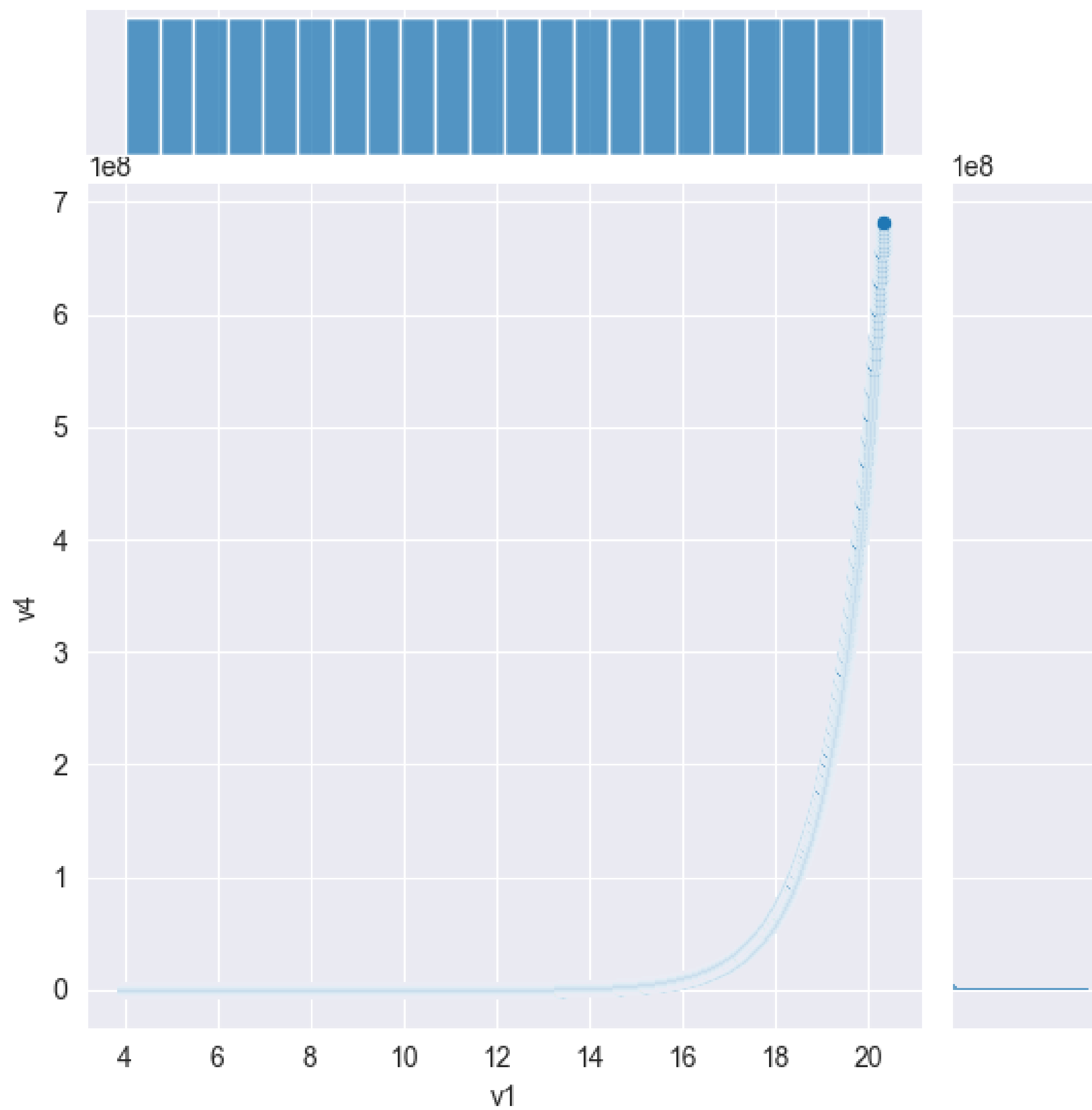
```
sns.jointplot(data=df_full, x=V1 , y=V3, kind='scatter')

<seaborn.axisgrid.JointGrid at 0x1106c28e0>
```



There appears positive exponential trend, but when you look at the where most the density is, trend begins to look slightly constant then skyrockets around (19e8,1e8). there appears to be a strong relationship as all the points are packed tightly, and the points are spread evenly across x = 4e8 through x=20e8 according to distribution at the top margin. it looks like y=+0e8 might be outliers, there arent many points around that area. and lastly the variability is minimal until (16e8 ,0e8)

```
sns.jointplot(data=df_full, x=V1 , y=V4, kind='scatter')
```

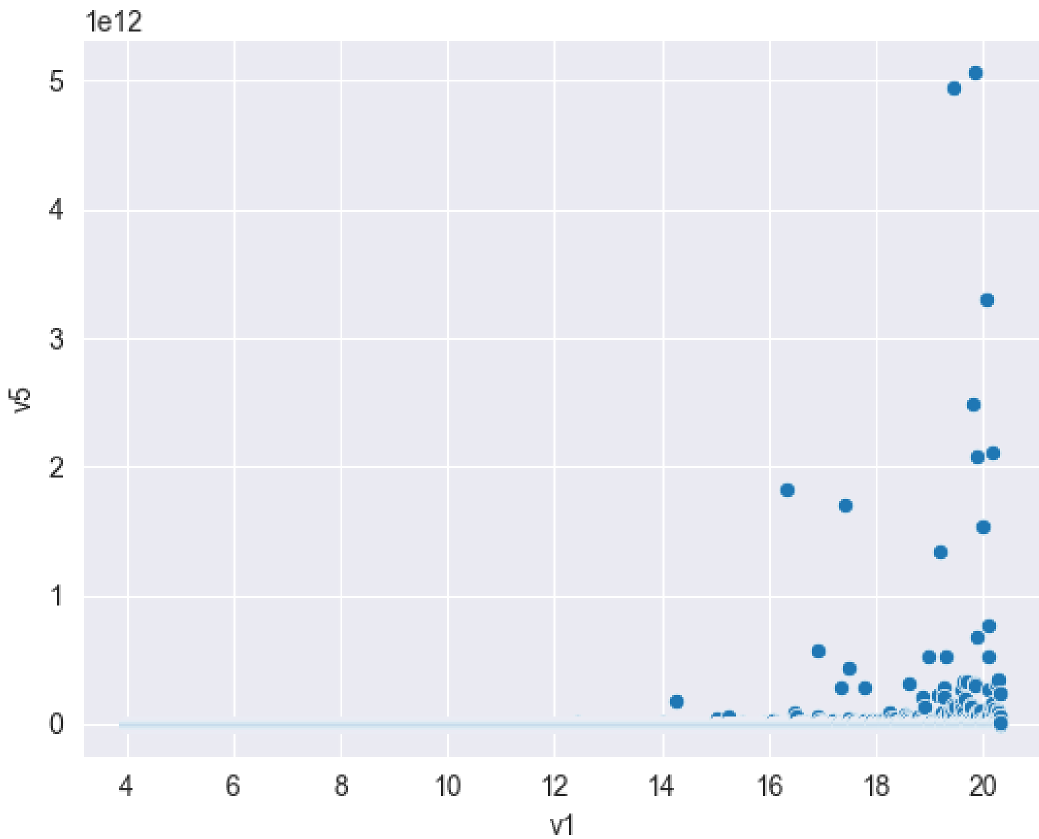
```
<seaborn.axisgrid.JointGrid at 0x110c4bfd0>
```



There appears positive exponential trend, but when you look at the where most the density is, trend begins to look slightly constant then skyrockets around (19e8,1e8). there appears to be a strong relationship as all the points are packed tightly, and the points are spread evenly across x = 4e8 through x=20e8 according to distribution at the top margin. it looks like y=+0e8 might be outliers, there arent many points around that area. and lastly the variability is minimal until (16e8 ,0e8)

```
sns.scatterplot(data=df_full, x=V1 , y=V5)
```

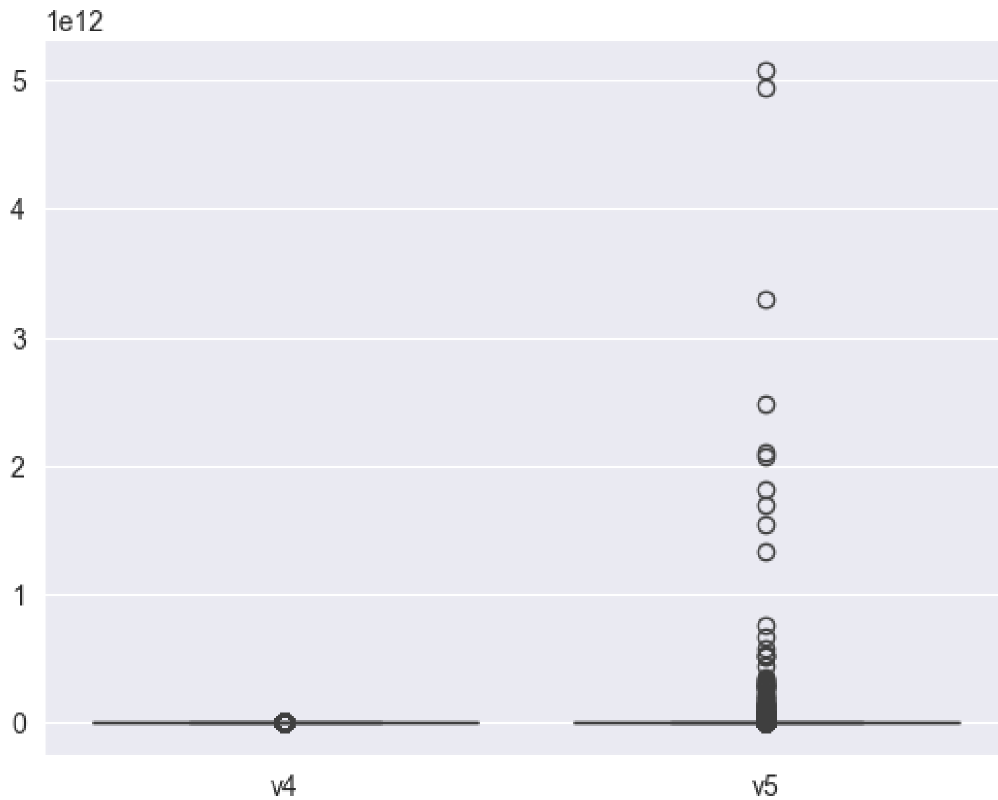
```
<Axes: xlabel='v1', ylabel='v5'>
```



There appears constant trend, strong relationship as all the points are packed tightly, however the variability starts to increases after 14e12, sort of heteroscedasicity

2.9) Create pair of boxplots with v4 and v5 next to each other. Remark on how v4 and v5 compare, based on the violin plots and the scatter plots. You may use other plots or tools if helpful.

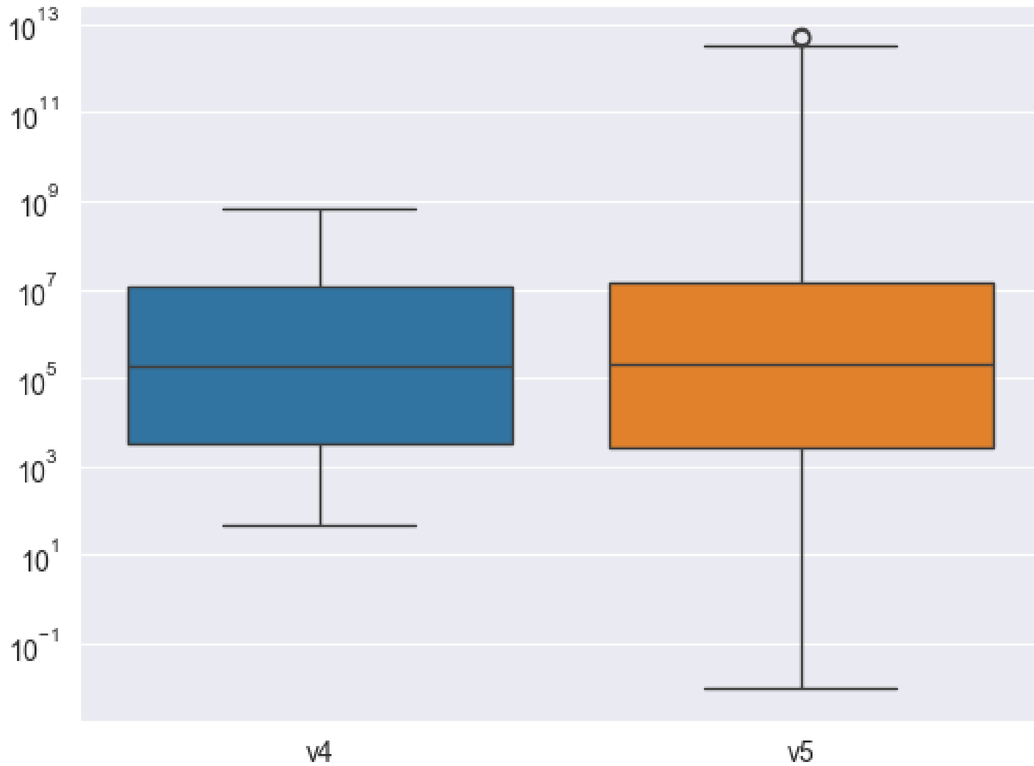
```
# Pair of boxplots
sns.boxplot(data=df_full[[V4, V5]])

<Axes: >
```



This is hard to interpret so i will log the scale

```
sns.boxplot(data=df_full[[V4, V5]], log_scale=True)
```

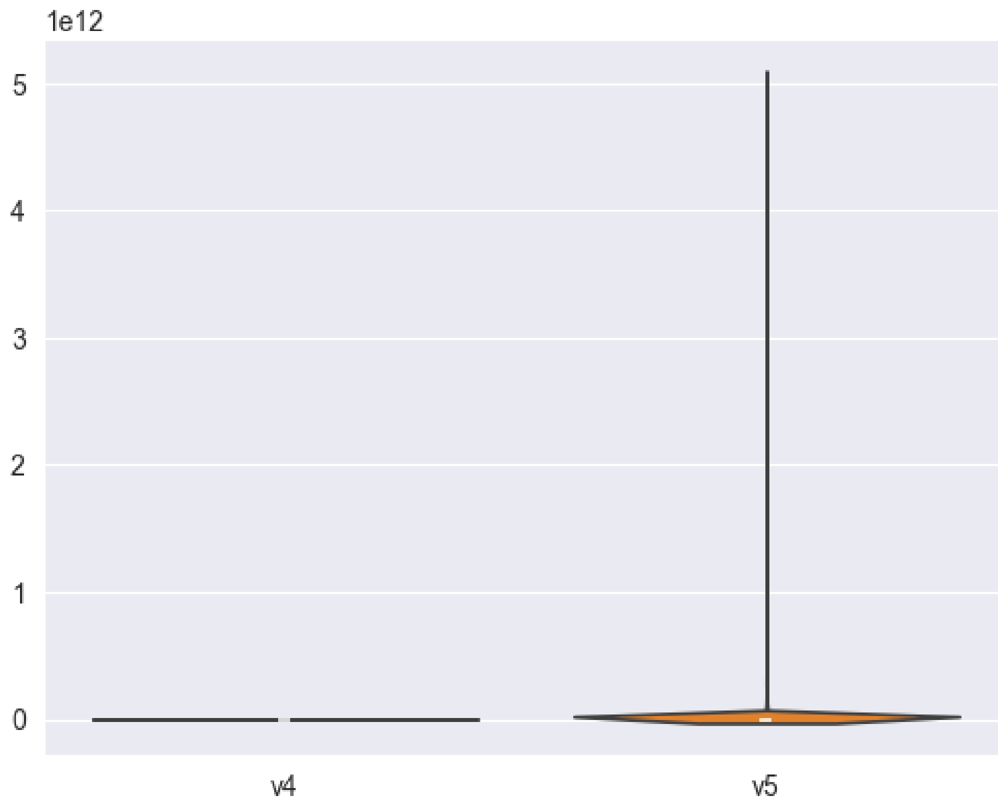
```
<Axes: >
```



The IQR and mean seem to be roughly the same but with v5 IQR range slightly larger. There are different in a sense that v5 outlier whiskers are way larger or smaller than v4. and v5 has outliers where v4 does not.

```
# Violin plots
sns.violinplot(data=df_full[[V4, V5]])
```

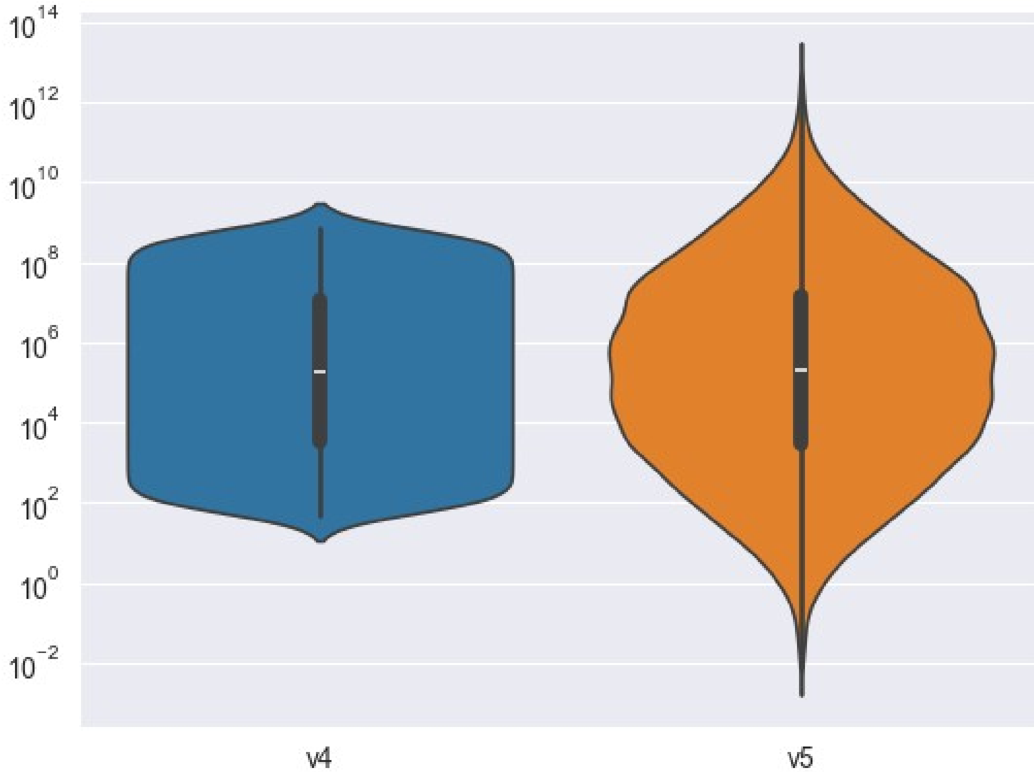
```
<Axes: >
```



Again hard to interpret will use log scale

```
sns.violinplot(data=df_full[[V4, V5]], log_scale=True)
```

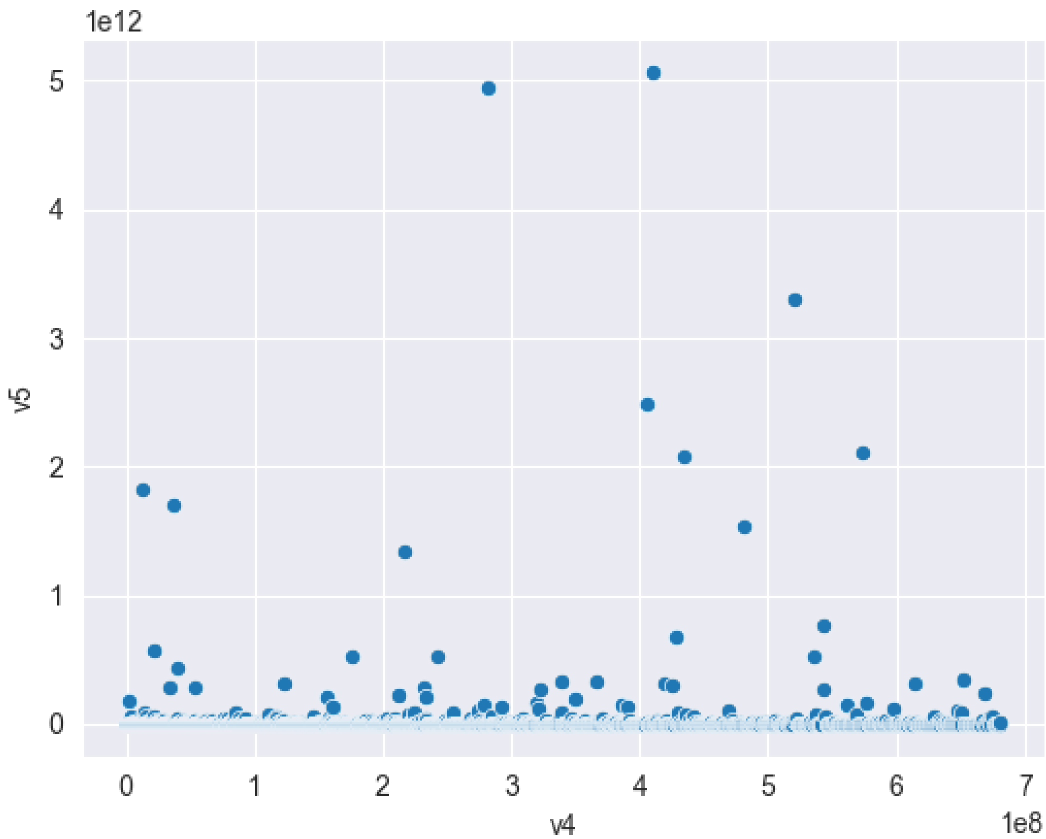
```
<Axes: >
```



v4 looks more dense than v5 in smaller range, as the outlier whiskers are wider in v5 than v4. they both look symmetric. but v5 has 3 minor modes(bumps)

```
# Scatter plot to see relationship
sns.scatterplot(data=df_full, x=V4, y=V5)
```

```
<Axes: xlabel='v4', ylabel='v5'>
```



There looks like theres a constant not positive not negative linear trend and somewhat uniform variability.

Part III - Sampling and Convergence

3.1) Create a variable "pareto" that is a list of 10,000 samples from a Pareto distribution with shape parameter = 1.2 (usually denoted a or alpha). Add this list "pareto" as a column to your dataframe from Part II

```
alpha = 1.2
pareto = np.random.pareto(a=alpha, size=n)
PARETO = 'pareto'
df_full[PARETO] = pareto
df_full.head()
```

```
          v1        v2         v3         v4          v5     noise
pareto
0   4.000000 -0.019542  54.598150  50.578608    0.980648 -4.019542
0.718339
1   4.001634  4.558628  54.687444  55.244439   95.452475  0.556994
1.062391
2   4.003268  3.066550  54.776885  53.840167   21.467708 -0.936718
0.184718
```

```
3  4.004902  5.038742  54.866472  55.900311  154.275835  1.033840
0.457977
4  4.006537  0.928314  54.956205  51.877982    2.530240 -3.078222
0.318868
```

3.2) Add two more columns to your dataframe labeled "running_avg_normal" and "running_avg_pareto". In the "running_avg_normal" column put the running average of the (unsorted) values in the noise column. For example, if the values in the noise column are [0.1, 0.3, 0.5, ...] then the running average should be [0.1, 0.2, 0.3, ...]. Do the same for the Pareto column.

HINT: Check out the .expanding() and .mean() methods for pandas Series objects

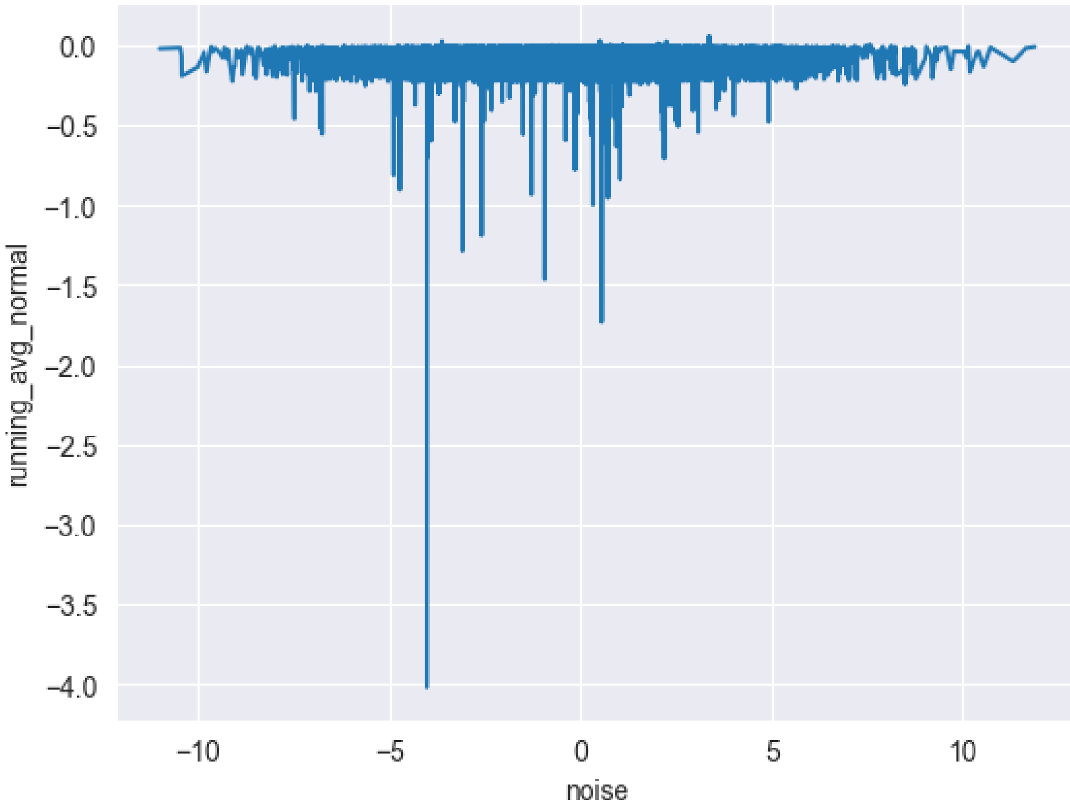
```
RUNNING_AVG_NORMAL = 'running_avg_normal'
RUNNING_AVG_PARETO = 'running_avg_pareto'
df_full[RUNNING_AVG_NORMAL] = df_full[NOISE].expanding().mean()
df_full[RUNNING_AVG_PARETO] = df_full[PARETO].expanding().mean()
df_full.head()
```

```
         v1        v2         v3         v4          v5     noise
pareto  \
0  4.000000 -0.019542  54.598150  50.578608    0.980648 -4.019542
0.718339
1  4.001634  4.558628  54.687444  55.244439   95.452475  0.556994
1.062391
2  4.003268  3.066550  54.776885  53.840167   21.467708 -0.936718
0.184718
3  4.004902  5.038742  54.866472  55.900311  154.275835  1.033840
0.457977
4  4.006537  0.928314  54.956205  51.877982    2.530240 -3.078222
0.318868

   running_avg_normal  running_avg_pareto
0           -4.019542            0.718339
1           -1.731274            0.890365
2           -1.466422            0.655149
3           -0.841356            0.605856
4           -1.288730            0.548459
```

3.3) Create a lineplot for running_avg_normal and a lineplot for running_avg_Pareto. Remark on your observations.

```
sns.lineplot(data=df_full, x=NOISE, y=RUNNING_AVG_NORMAL)
```

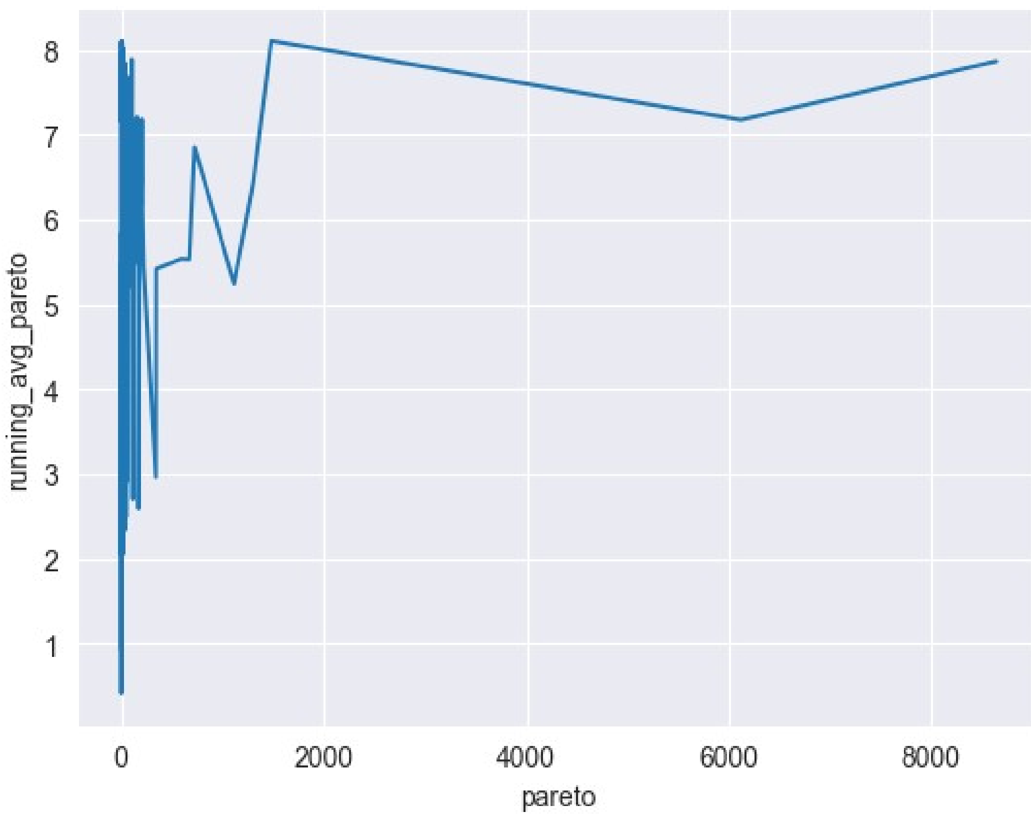
```
<Axes: xlabel='noise', ylabel='running_avg_normal'>
```



Overall the trend is constant like with medium amount of fluctuation about the trend. The fluctuation is minimal on the edges and grows toward the center then minimizes

```
sns.lineplot(data=df_full, x=PARETO, y=RUNNING_AVG_PARETO)
```

```
<Axes: xlabel='pareto', ylabel='running_avg_pareto'>
```



There's overall a growth trend in the beginning then it stabilizes. Id also point out that there was much fluctuation and variation in the growth section of the trend.