Part 1:

1.
   a. Please find the code on this github link. Additionally, I have attached the code files in the email as well.
   b. As per the assignment, I used the state level dataset provided here. The reason why I used only state specific data is because it provided a good detailed to do some meaningful analysis, whereas the national and territory specific data did not provide a whole lot of details geography wise to do any detailed analysis in it.

2.
   a. Firstly there were multiple txt files by state in the raw dataset, and to be able to leverage the geography aspect of the data, I decided to read and combine these files into one csv file. Additionally, I decided to subset the data from 2000 (explained later).

```
with open(os.path.join(root_dir, 'output_file.csv'), 'w+') as csv_file:
    for path in glob.glob('./*.TXT'):
        with open(path) as txt_file:
            txt = txt_file.read() + '\n'
            csv_file.write(txt)

os.chdir(root_dir)

data = pd.read_csv('output_file.csv', header=None)
data.columns = ["state", "gender", "year", "name", "count"]
data = data[data["year"] > 2000]
```

   b. I then tried to understand the basics of my dataset, like how does the data look like, what the shape of the dataset is like, what are the column types and if it has any null values, the distribution of the numerical variables. During this exploration, I found that the all of the columns are object data types except year and count. I decided to change the year into a string column except the count column. The dataset has 21,469 rows and I found that the min value in this dataset is 5, and max value is 4170 and mean is 34. This tells me that the data is highly skewed due to the big range of the data.

```python
# Understanding the data
print(data.head())
print(data.shape)
print(data.info())

data["year"] = data["year"].astype(str)

print(data.describe())
print(data["name"].value_counts().shape)
```

```
      state gender  year     name  count
22227    ID      F  2001  Madison    143
22228    ID      F  2001    Emily    123
22229    ID      F  2001   Ashley    103
22230    ID      F  2001   Hannah    103
22231    ID      F  2001     Emma    101
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2023503 entries, 22227 to 6408040
Data columns (total 5 columns):
 #   Column  Dtype
---  ------  -----
 0   state   object
 1   gender  object
 2   year    int64
 3   name    object
 4   count   int64
dtypes: int64(2), object(3)
memory usage: 92.6+ MB
```

```
              count
count  2.023503e+06
mean   3.402511e+01
std    9.339381e+01
min    5.000000e+00
25%    7.000000e+00
50%    1.100000e+01
75%    2.600000e+01
max    4.170000e+03
(21469,)
```

c. According the readME provided in the raw dataset, there were some conditions like state code is always 2 digits, year is always 4 digits, hence I wanted to run some quality checks on the data as well. Therefore, I created some functions that does those checks for me.

```
# Data checks
def isnull(data):
    print(data.isnull().any())

isnull(data)

def check_state_length(data):
    state_length = data['state'].str.len()
    state_length = state_length.to_numpy()
    if((state_length[0] == state_length).all()) == True:
        print("Check pass")
    else:
        print("Data quality issue found")

check_state_length(data)
```

```
def check_year_length(data):
    year_length = data['state'].str.len()
    year_length = year_length.to_numpy()
    if((year_length[0] == year_length).all()) == True:
        print("Check pass")
    else:
        print("Data quality issue found")

check_year_length(data)
```

d. I was then interested in finding popular gender neutral names as well. How I defined popular gender neutral was if the name has more than 500 occurrences of it, and the absolute difference of female proportions and male proportions is < 0.3 (Range from 0 and 1 in which 0 is an equal split among the genders, and 1 being a name used only by 1 gender).

```python
# Function to create gender neutral names
def gender_neutral_names(data):
    """
    Returns gender neutral names

    data: dataframe
    """

    df_m=data[data['gender']=='M'].groupby(['name','gender'])['count'].sum()
    df_f=data[data['gender']=='F'].groupby(['name','gender'])['count'].sum()
    df_unisex=pd.merge(df_f,df_m,how='inner',on='name').reset_index()
    df_unisex["total"] = df_unisex['count_y']+ df_unisex['count_x']
    df_unisex['prop_x']=df_unisex['count_x']/df_unisex['total']
    df_unisex['prop_y']=df_unisex['count_y']/df_unisex['total']
    df_unisex['diff']=abs(df_unisex['prop_x']-df_unisex['prop_y'])
    df_unisex[(df_unisex['total']>=500) & (df_unisex['diff']<0.3)]
    print(df_unisex['name'])

gender_neutral_names(data)
```

Results:

```
0       Aaliyah
1         Aaron
2         Aarya
3         Aaryn
4          Abby
         ...
1705       Zuri
1706     Zuriel
1707     Zyaire
1708       Zyan
1709       Zyon
Name: name, Length: 1710, dtype: object
```

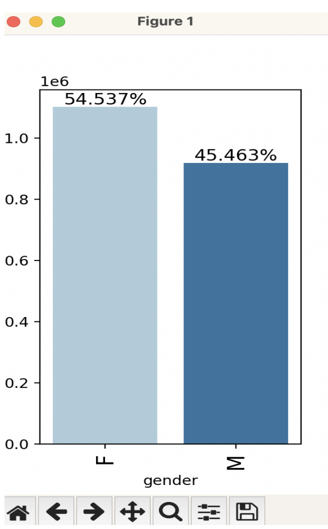
This tells me that there were 1710 gender neutral names that fits the conditions I specified above.

e. I then wanted to leverage matplotlib and seaborn to do some exploratory visualtion as well on the data. Hence I made a function so that I could visualize labelled barplots.

```python
# Function to create labeled barplots
def labeled_barplot(data, feature, perc=False, n=None):
    """
    Barplot with percentage at the top

    data: dataframe
    feature: dataframe column
    perc: whether to display percentages instead of count (default is False)
    n: displays the top n category levels (default is None, i.e., display all levels)
    """

    total = len(data[feature])  # length of the column
    count = data[feature].nunique()
    if n is None:
        plt.figure(figsize=(count + 1, 5))
    else:
        plt.figure(figsize=(n + 1, 5))

    plt.xticks(rotation=90, fontsize=15)
    ax = sns.countplot(
        data=data,
        x=feature,
        palette="Paired",
        order=data[feature].value_counts().index[:n].sort_values(),
    )

    for p in ax.patches:
        if perc == True:
            label = "{:.3f}%".format(
                100 * p.get_height() / total
            )  # percentage of each class of the category
        else:
            label = p.get_height()  # count of each level of the category

        x = p.get_x() + p.get_width() / 2  # width of the plot
        y = p.get_height()  # height of the plot

        ax.annotate(
            label,
            (x, y),
            ha="center",
            va="center",
            size=12,
            xytext=(0, 5),
            textcoords="offset points",
        )  # annotate the percentage

    plt.show()  # show the plot
```

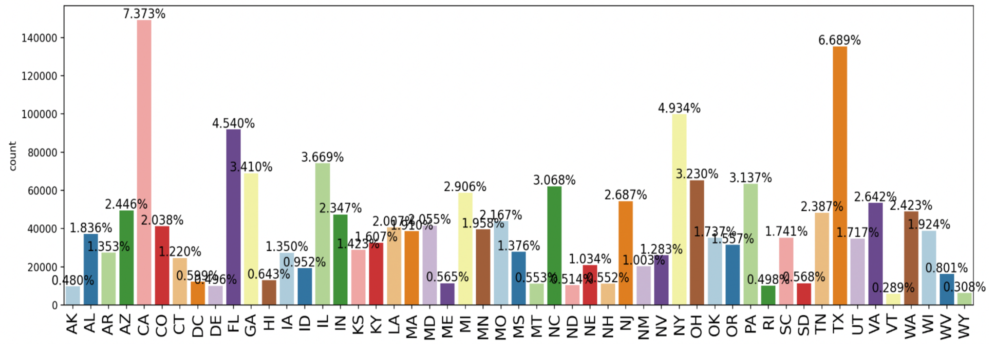
Here are the results for gender and state:

Gender:



This shows that 54.537% of the names in this dataset are female names.

State:



This shows that highest number of names are coming from California.

3. There were a couple errors that I encountered in steps 1 and 2:
    a. The first error was when I was combining the txt files, and in the loop where I was combing them as a csv file: `with open(os.path.join(root_dir, 'output_file.csv'), 'w+') as csv_file:`
    There is an argument “w+”, however, this was “a” before, in which it kept appending to “output_file.csv” instead of overwriting, hence it duplicating the results, and also increasing the file size immensely which resulted in the script running very slow.
    b. The next one was since the data is available for all states since 1910, the output file was relatively big, hence the python scripts were running slower and also models were becoming heavy in PowerBI as well. For the purpose of this assignment, I subsetted the data to start > 2000, so I can analyze the trend in last 2 decades and also make the analysis faster.
4. I believe if we had population data over the name data, I think it would have been very interesting to see the parallel trends between the population and name data. We could have a separate population table, and we could combine it on state and year. I would have personally loved to see that what infliction point was it when the number of distinct names increases and is at a point where population also increases.
5. Please find the [powerBI dashboard]() to see some of the trends and findings I found. I have determined top 10 trending names, top 10 female and male trending names, and it can be filtered on year and state. I have also found that average distinct names have increased over the years. Additionally, I have also found the male and female split in each state.

Part 2:

1.
    a. When we are building models in PowerBI, setting the storage mode is very important as it gives the developer control if they want to cache table data in memory or not. Setting storage provides many benefits such as boosting query performance, enable analysis over large datasets, get real time data to reduce data latency where needed. The schema provided shows us that its a Product and Store has a one to many relationship with Sales where Store/Product have one instance of a particular value, and the Sales table can have more than one instance of a value. Depending on how the storage mode is set for these tables, if it is a direct query for all tables, it is going to take a lot of time to query all the data in Product, Stores and Sales data, decrease query performance and interactivity with the visuals.
    b. To avoid any data issues, I have the following recommendations for each table:
        i. Sales: Report queries based on Sales tables should run in DirectQuery mode. These queries may take longer since they are closer to real time, no caching latency exists.
        ii. Storage and Product: These tables should store in Import mode. Queries based on Storage and Product tables will be returned from the in-memory cache and will be relatively fast.

2. There should be 2 dimension tables - Customer and Date, where the Customer Table, Date table and Sales table should have an extra field called “OrderID”, and these tables will join the sales on again a one-to-many relationship. These dimension tables should be stored in Dual mode, so load times of initial reports are fast when they retrieve slicer values to display.