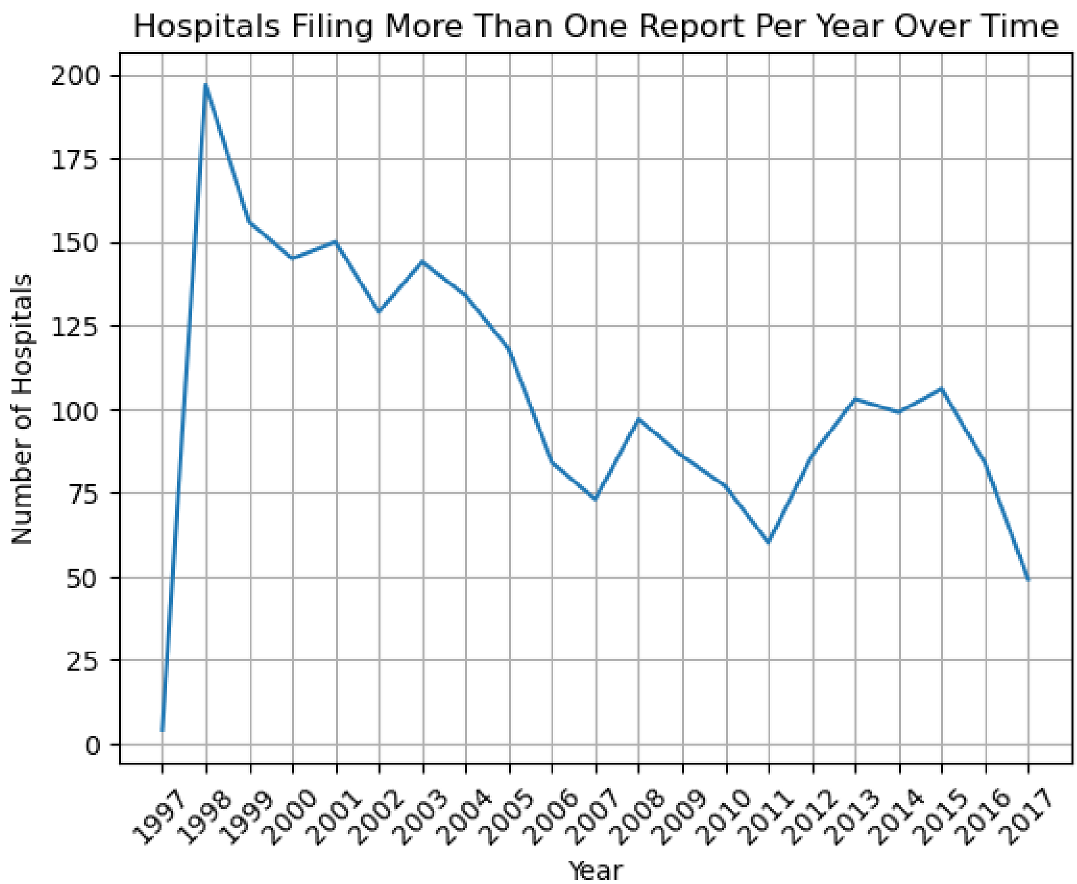
Homework 2

Question 1



Question 2

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#Question 2
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```
#Removing duplicate reports
unique_hospitals = HCRIS.drop_duplicates(subset=['provider_number', 'year'])

#Count of number of unique hospital IDs
unique_hospital_count = unique_hospitals['provider_number'].nunique()

print(f"Number of Unique Hospital IDs: {unique_hospital_count}")
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```
Number of Unique Hospital IDs: 9323
```

#Question 3

```
#Question 3
HCRIS['tot_charges'] = pd.to_numeric(HCRIS['tot_charges'], errors='coerce')

# Convert tot_charges to numeric
HCRIS['tot_charges'] = pd.to_numeric(HCRIS['tot_charges'], errors='coerce')

#Remove rows with missing charges or years, negative values, and outliers
charges_by_year = HCRIS[['year', 'tot_charges']].dropna()
charges_by_year = charges_by_year[charges_by_year['tot_charges'] >= 0]

# Display summary statistics to find  cutoff values
summary_stats = charges_by_year['tot_charges'].describe()
print(summary_stats)

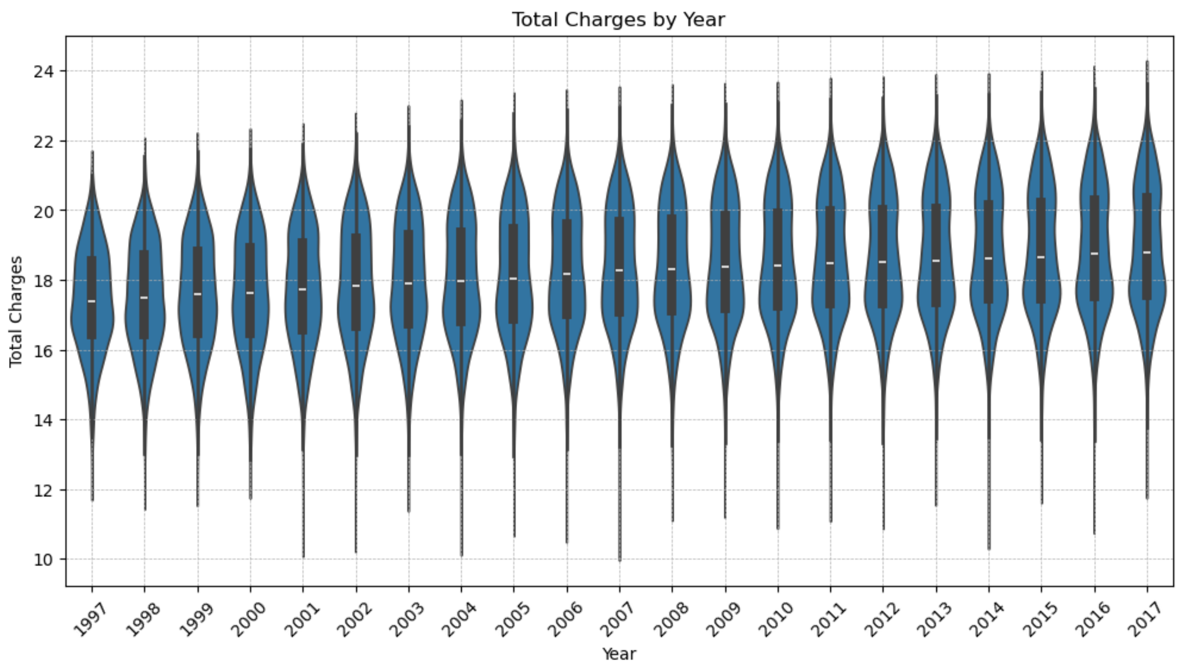
#creating upper bound limit
upper_bound = summary_stats['95%'] if '95%' in summary_stats else summary_stats['max']
charges_by_year = charges_by_year[charges_by_year['tot_charges'] <= upper_bound]
charges_by_year['log_tot_charges'] = np.log(charges_by_year['tot_charges'] + 1)
charges_by_year = charges_by_year[charges_by_year['log_tot_charges'] >= 10]



# Plot violin plot
plt.figure(figsize=(12, 6))
sns.violinplot(x='year', y='log_tot_charges', data=charges_by_year)
plt.title("Total Charges by Year")
plt.xlabel("Year")
plt.ylabel("Total Charges")
```

```
plt.xticks(rotation=45)
plt.grid(True, which='both', linestyle='--', linewidth=0.5)
plt.show()
```

```
count    1.192340e+05
mean     3.226221e+08
std      6.867871e+08
min      1.000000e+00
25%      2.456732e+07
50%      7.782326e+07
75%      3.215973e+08
max      1.863371e+10
Name: tot_charges, dtype: float64
```



Question 4

```
#Question 4

#Converting columns to numeric
numeric_columns = [
    'tot_discounts', 'tot_charges', 'ip_charges', 'icu_charges', 'ancillary_charges',
    'tot_mcare_payment', 'tot_discharges', 'mcare_discharges'
```

```
]
HCRIS[numeric_columns] = HCRIS[numeric_columns].apply(pd.to_numeric, errors='coerce')


# Remove missing values
hcris_clean = HCRIS[['year'] + numeric_columns].dropna()

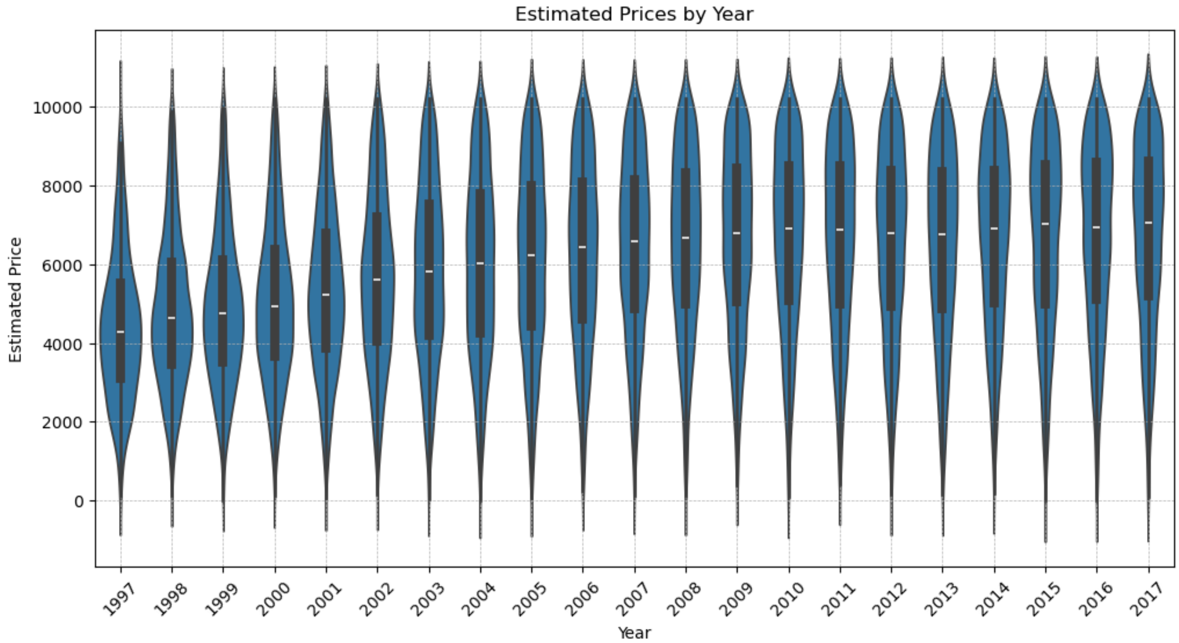
# Calculate estimated price based on the formula
discount_factor = 1 - hcris_clean['tot_discounts'] / hcris_clean['tot_charges']
price_num = (hcris_clean['ip_charges'] + hcris_clean['icu_charges'] + hcris_clean['ancillary_
price_denom = hcris_clean['tot_discharges'] - hcris_clean['mcare_discharges']
hcris_clean['estimated_price'] = price_num / price_denom

#removing outliers and negatives
hcris_clean = hcris_clean[hcris_clean['estimated_price'] > 0]
summary_stats = hcris_clean['estimated_price'].describe()
print(summary_stats)

upper_bound = summary_stats['75%'] if '75%' in summary_stats else summary_stats['max']
hcris_clean = hcris_clean[hcris_clean['estimated_price'] <= upper_bound]

#Plot violin plot
plt.figure(figsize=(12, 6))
sns.violinplot(x='year', y='estimated_price', data=hcris_clean)
plt.title("Estimated Prices by Year")
plt.xlabel("Year")
plt.ylabel("Estimated Price")
plt.xticks(rotation=45)
plt.grid(True, which='both', linestyle='--', linewidth=0.5)
plt.show()
```

```
count    5.882500e+04
mean              inf
std               NaN
min      1.953267e+00
25%      4.789842e+03
50%      7.109387e+03
75%      1.022331e+04
max               inf
Name: estimated_price, dtype: float64
```



Question 5

```
#Q5
hcris_2012 = HCRIS[HCRIS['year'] == 2012]

#Calculating estimated price for 2012
hcris_2012['discount_factor'] = 1 - hcris_2012['tot_discounts'] / hcris_2012['tot_charges']
hcris_2012['price_num'] = (
    (hcris_2012['ip_charges'] + hcris_2012['icu_charges'] + hcris_2012['ancillary_charges'])
    * hcris_2012['discount_factor'] - hcris_2012['tot_mcare_payment'])
hcris_2012['price_denom'] = hcris_2012['tot_discharges'] - hcris_2012['mcare_discharges']
hcris_2012['price'] = hcris_2012['price_num'] / hcris_2012['price_denom']

#NA payments
hcris_2012['hvbp_payment'] = hcris_2012['hvbp_payment'].fillna(0)
hcris_2012['hrrp_payment'] = hcris_2012['hrrp_payment'].fillna(0).abs()

#Defining penalty
hcris_2012['penalty'] = (hcris_2012['hvbp_payment'] + hcris_2012['hrrp_payment'] < 0).astype

# Clean data
hcris_2012 = hcris_2012[(hcris_2012['price_denom'] > 100) & (hcris_2012['price_num'] > 0) &
hcris_2012 = hcris_2012[hcris_2012['beds'] > 30]
hcris_2012 = hcris_2012[hcris_2012['price'] < 100000]
```

```python
# Calculate average price for penalized vs non-penalized hospitals
mean_penalized = round(hcris_2012.loc[hcris_2012['penalty'] == 1, 'price'].mean(), 2)
mean_non_penalized = round(hcris_2012.loc[hcris_2012['penalty'] == 0, 'price'].mean(), 2)

print(f"Average price for penalized hospitals in 2012: {mean_penalized}")
print(f"Average price for non-penalized hospitals in 2012: {mean_non_penalized}")
```

```
Average price for penalized hospitals in 2012: 10087.73
Average price for non-penalized hospitals in 2012: 9388.11
```

Question 6

```python
#Question 6
hcris_2012['beds_quartile'] = pd.qcut(hcris_2012['beds'], 4, labels=[1, 2, 3, 4])

# Create indicator variables for each quartile
for i in range(1, 5):
    hcris_2012[f'quartile_{i}'] = (hcris_2012['beds_quartile'] == i).astype(int)


# Calculate average price for treated and control groups within each quartile
Avg_per_group = []
for i in range(1, 5):
    treated_mean = hcris_2012.loc[(hcris_2012[f'quartile_{i}'] == 1) & (hcris_2012['penalty']
    control_mean = hcris_2012.loc[(hcris_2012[f'quartile_{i}'] == 1) & (hcris_2012['penalty']
    Avg_per_group.append({'Quartile': i, 'Penalized_Mean_Price': round(treated_mean, 2), 'Non

results_df = pd.DataFrame(Avg_per_group)
print(results_df)
```

```
   Quartile  Penalized_Mean_Price  Non_Penalized_Mean_Price
0         1               7558.71                   7408.88
1         2               9444.01                   8387.51
2         3              10956.85                   9429.43
3         4              12678.08                  12308.15
```

Question 7

```
from causalinference import CausalModel
# penalized/non-penalized groups
hcris_2012['treated'] = (hcris_2012['penalty'] > 0).astype(int)
treated_df = hcris_2012[hcris_2012['treated'] == 1]
control_df = hcris_2012[hcris_2012['treated'] == 0]

covariate = 'beds_quartile'

variance_quartiles = control_df.groupby(covariate)['beds'].var().fillna(1)
inverse_weights = 1 / variance_quartiles

#erform nearest neighbor matching using inverse variance distance
matched_pairs = []
for _, treated_row in treated_df.iterrows():
    quartile = treated_row[covariate]
    control_candidates = control_df[control_df[covariate] == quartile]

    if not control_candidates.empty:
        # Compute distance: absolute difference in beds * inverse variance weight
        distances = np.abs(control_candidates['beds'] - treated_row['beds']) * inverse_weigh

        # Get the best match (hospital with minimum distance)
        best_match_idx = distances.idxmin()
        best_match = control_candidates.loc[best_match_idx]

        # Store matched pair (treated price, control price)
        matched_pairs.append((treated_row['price'], best_match['price']))

#Calculate ATE
treated_prices, control_prices = zip(*matched_pairs)
ate_nn_inverse_variance = np.mean(np.array(treated_prices) - np.array(control_prices))

X = hcris_2012[[covariate]].values
y = hcris_2012['price'].values
treatment = hcris_2012['treated'].values

causal_model = CausalModel(Y=y, D=treatment, X=X)
causal_model.est_via_matching(matches=1, bias_adj=True)

#Printing
print(f"ATE using Nearest Neighbor Matching (Inverse Variance Distance): {ate_nn_inverse_vari
```

```
print(causal_model.estimates)
```

```
ATE using Nearest Neighbor Matching (Inverse Variance Distance): 43.7439

Treatment Effect Estimates: Matching

                     Est.       S.e.          z      P>|z|      [95% Conf. int.]
--------------------------------------------------------------------------------
           ATE    774.169    249.738      3.100      0.002    284.683   1263.654
           ATC    780.816    249.892      3.125      0.002    291.028   1270.604
           ATT    748.376    249.572      2.999      0.003    259.215   1237.537
```

```
from causalinference import CausalModel
#Question 7 - Nearest Neighbor Match - Mahalanobis

# Select relevant variables
X = hcris_2012[['beds_quartile']].values
y = hcris_2012['price'].values
treatment = hcris_2012['penalty'].values

# Create Causal Model
causal_model = CausalModel(Y=y, D=treatment, X=X)

# Perform Nearest Neighbor Matching (1-to-1) with Inverse Variance Distance
causal_model.est_via_matching(matches=1, bias_adj=True)

# Print the Average Treatment Effect (ATE)
print("ATE using Nearest Neighbor Matching (Inverse Variance Distance):")
print(causal_model.estimates)
```

```
ATE using Nearest Neighbor Matching (Inverse Variance Distance):

Treatment Effect Estimates: Matching

                     Est.       S.e.          z      P>|z|      [95% Conf. int.]
--------------------------------------------------------------------------------
           ATE    774.169    249.738      3.100      0.002    284.683   1263.654
           ATC    780.816    249.892      3.125      0.002    291.028   1270.604
           ATT    748.376    249.572      2.999      0.003    259.215   1237.537
```

```
# Question 7 - Inverse Propensity Weighting
X = hcris_2012[['beds_quartile']].values
y = hcris_2012['price'].values
treatment = hcris_2012['penalty'].values

pw_model = CausalModel(Y=y, D=treatment, X=X)
pw_model.est_via_matching(matches=1, bias_adj=True)

# Print
print("ATE using Propensity Score Matching:")
print(pw_model.estimates)
```

```
ATE using Propensity Score Matching:

Treatment Effect Estimates: Matching

                     Est.       S.e.          z       P>|z|      [95% Conf. int.]
--------------------------------------------------------------------------------
           ATE    774.169    249.738      3.100       0.002    284.683   1263.654
           ATC    780.816    249.892      3.125       0.002    291.028   1270.604
           ATT    748.376    249.572      2.999       0.003    259.215   1237.537
```

```
#Question 7 - Simple Liner Regression
```

Question 8 - The different treatment effect estimators are exactly identical. This is expected.

Question 9 - No I do not think we've estimated a causal effect. We have purely adjusted our model for bed size. There are lots of other factors that would need to be controlled for in order to estimate a causal effect of the penalty

Question 10 - Overall, I had a difficult experience working with this data, but learned a lot of valuable lessons along the way. When I have worked with data in other classes in the past, I have always been given a nice, clean dataset and am able to begin analyzing the dataset easily. When working with this data, the bulk of the work is cleaning and merging the data, which I definitely found to be challenging. However, I definitely recognize how important these skills are. When working with data in the real world, it is rarely ever clean, so I am really happy to be getting experience with this.