In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
```

Objectives

The objectives of this analysis are to find an accurate machine learning model that is not opaque and to determine what features contribute the most significantly to covid death from the CSV file provided.

Importing Data

In [2]:
```
# Import CSV file to a dataframe and format the columns
df = pd.read_csv("data/COVID-19_Reported_Patient_Impact_and_Hospital_Capacity_by_State_Timeseries__RAW_.csv")
df['date'] = pd.to_datetime(df['date'])
```

Describing Data

The dataset is extremely wide with 133 columns, each with different levels of data completeness. All data is numeric except for state and date.

There are 64703 entries from the years 2020 to 2023.

In [3]:
```
df.head()
```

Out[3]:

	state	date	critical_staffing_shortage_today_yes	critical_staffing_shortage_today_no	critical_staffing_shortage_today_not_reported	critical_staffing_shortage_
0	RI	2021-02-26	4	10	1	
1	MA	2021-02-24	10	90	1	
2	NE	2021-02-17	10	90	1	
3	ME	2021-01-30	2	29	8	
4	NH	2021-01-30	6	23	1	

5 rows × 135 columns

In [4]:
```
# Print initial dataframe info
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 64703 entries, 0 to 64702
Columns: 135 entries, state to total_staffed_pediatric_icu_beds_coverage
dtypes: datetime64[ns](1), float64(77), int64(56), object(1)
memory usage: 66.6+ MB
```

In [5]:
```
# Print initial dataframe description
df.describe()
```

Out[5]:

	date	critical_staffing_shortage_today_yes	critical_staffing_shortage_today_no	critical_staffing_shortage_today_not_reported	critical_staffing
count	64703	64703.000000	64703.000000	64703.000000	
mean	2021-10-23 20:33:20.105095424	9.334343	55.179404	39.791323	
min	2020-01-01 00:00:00	0.000000	0.000000	0.000000	
25%	2020-12-26 00:00:00	0.000000	6.000000	3.000000	
50%	2021-10-26 00:00:00	3.000000	37.000000	14.000000	
75%	2022-08-22 00:00:00	12.000000	87.000000	47.000000	
max	2023-06-17 00:00:00	191.000000	494.000000	523.000000	
std	NaN	16.287815	62.544193	66.802128	

8 rows × 134 columns

In [6]:

```
# Create null_df showing null value counts
null_df = (df
           .isnull()
           .sum()
           .to_frame()
           .reset_index()
           .rename(columns={'index':'column', 0:'null_values'})
           .sort_values(by='null_values', ascending=False)
           .reset_index(drop=True)
           .set_index('column')
          )

# Filter null_df to only columns that have null values
null_df = null_df[null_df['null_values'] != 0]

# Print top 30 null value counts
null_df.head(30)
```

Out[6]:

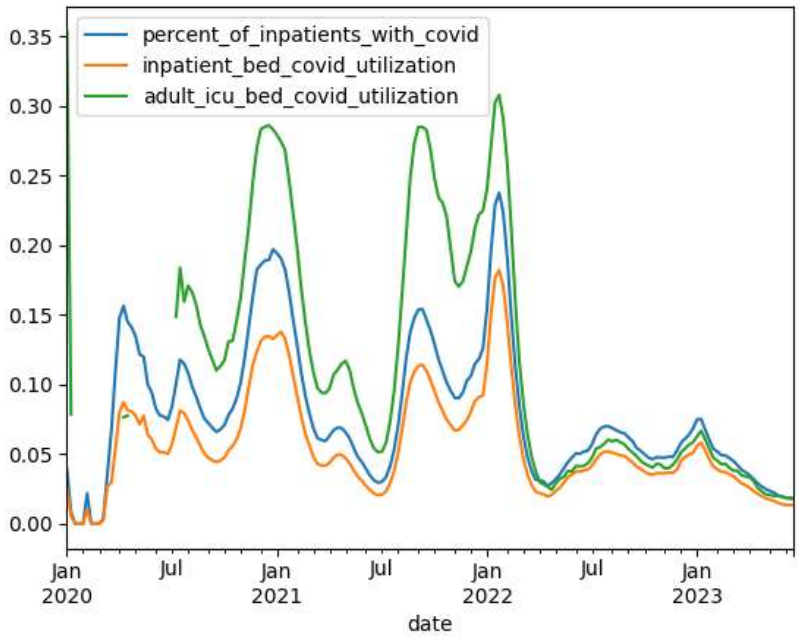
column	null_values
geocoded_state	64703
previous_day_admission_pediatric_covid_confirmed_12_17	37040
previous_day_admission_pediatric_covid_confirmed_5_11	37026
previous_day_admission_pediatric_covid_confirmed_0_4	36410
previous_day_admission_pediatric_covid_confirmed_unknown	36296
staffed_icu_pediatric_patients_confirmed_covid	30149
on_hand_supply_therapeutic_c_bamlanivimab_etesevimab_courses	21210
previous_week_therapeutic_c_bamlanivimab_etesevimab_courses_used	21193
on_hand_supply_therapeutic_b_bamlanivimab_courses	17718
previous_week_therapeutic_b_bamlanivimab_courses_used	17686
on_hand_supply_therapeutic_a_casirivimab_imdevimab_courses	16528
previous_week_therapeutic_a_casirivimab_imdevimab_courses_used	16527
previous_day_deaths_covid_and_influenza	12888
total_patients_hospitalized_confirmed_influenza_and_covid	12884
previous_day_deaths_influenza	12746
total_patients_hospitalized_confirmed_influenza	11766
icu_patients_confirmed_influenza	11710
previous_day_admission_influenza_confirmed	11709
total_staffed_pediatric_icu_beds	8316
all_pediatric_inpatient_beds	8314
all_pediatric_inpatient_bed_occupied	8303
staffed_pediatric_icu_bed_occupancy	8303
previous_day_admission_adult_covid_suspected_80+	8158
previous_day_admission_adult_covid_suspected_50-59	8156
previous_day_admission_adult_covid_suspected_40-49	8154
previous_day_admission_adult_covid_suspected_70-79	8151
previous_day_admission_adult_covid_suspected_60-69	8150
previous_day_admission_adult_covid_suspected_20-29	8146
previous_day_admission_adult_covid_suspected_30-39	8145
previous_day_admission_adult_covid_confirmed_40-49	8127

Visualizing Data

The data clearly has holes in it, as demonstrated in the two following line charts. This is going to be fixed later through fixing NaN values in the dataframe.

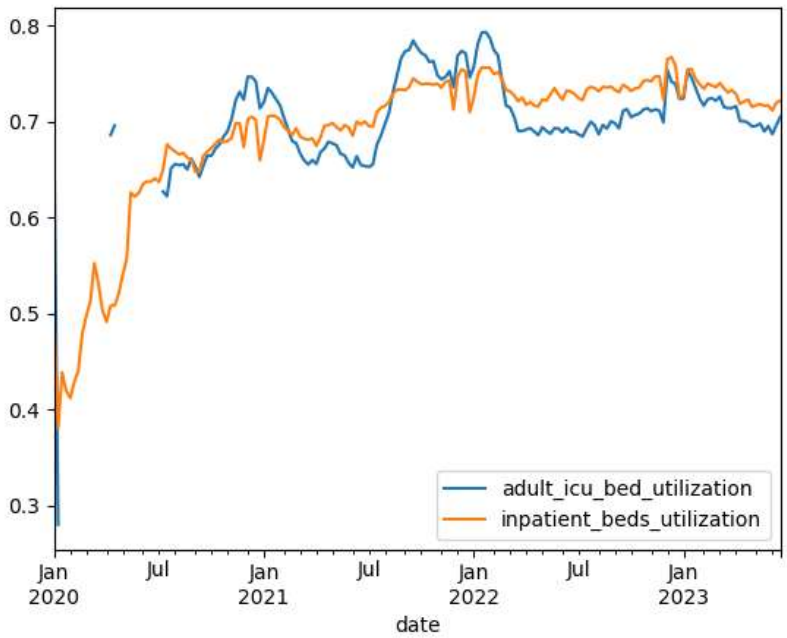
In [7]:
```
# Plots with similar trends showing missing values
df[['date', 'percent_of_inpatients_with_covid', 'inpatient_bed_covid_utilization', 'adult_icu_bed_covid_utilization']].grou
```

Out[7]: <Axes: xlabel='date'>



In [8]:
```
# Adult ICU Bed Utilization and Inpatient Beds Utilization line charts
df[['date', 'adult_icu_bed_utilization', 'inpatient_beds_utilization']].groupby('date').mean().resample('W').mean().plot()
```

Out[8]: <Axes: xlabel='date'>



Preprocessing Data

In [9]:
```
# Drop geocoded_state as it is empty
df.drop(columns='geocoded_state', inplace=True)
```

In [10]:
```
# Create a mask and remove the beginning days of pandemic with little information
start_date = '2020-01-01'
end_date = '2020-08-01'
mask = (df['date'] >= start_date) & (df['date'] <= end_date)

# Apply mask to dataframe to filter by date
df = df.loc[~mask].reset_index(drop=True)
```

Fix NaN Values

In [11]:
```
# Forward fill all null values and remove the rest
df = df.fillna(method='ffill').dropna().reset_index(drop=True)
```

In [12]:
```
# Create null_df showing null value counts
null_df = (df
           .isnull()
           .sum()
           .to_frame()
           .reset_index()
           .rename(columns={'index':'column', 0:'null_values'})
           .sort_values(by='null_values', ascending=False)
           .reset_index(drop=True)
           .set_index('column')
          )

# Filter null_df to only columns that have null values
null_df = null_df[null_df['null_values'] != 0]
```

In [13]:
```
# Print null values
# There are no more null values
null_df
```

Out[13]:

column	null_values

Model Training

I chose two different models here including:

- Random Forest
- Decision Tree
- Linear Regression

Each of these models are first analyzed using a .20 test and .80 train split.

The results are shown under the Accuracy Results section. Each model showed improvement, especially decision trees which shot up by 8% accuracy.

In [14]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_squared_error
```

In [15]:
```
# Remove unnecessary columns and the result variable
X = df.drop(columns={'state', 'date', 'deaths_covid'})

# Extract result variable
y = df['deaths_covid']

# Set random_state constant
random_state = 42
```

In [16]:
```
# Split data into train/test splits
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = random_state)
```

In [17]:
```
# Scale data using StandardScaler()
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

Random Forest

In [18]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [19]:
```
# Define classifier
rfc = RandomForestClassifier(random_state=random_state)

# Run predictions using random forest classifier
rfc.fit(X_train, y_train)
pred_rfc = rfc.predict(X_test)
```

In [20]:
```
# Calculate mean squared error
mse_rf = mean_squared_error(y_test, pred_rfc)

# Calculate root mean squared error
rmse_rf = np.sqrt(mse_rf)

# Print RMSE
print("Random Forest Root Mean Squared Error:", rmse_rf)
```

```
Random Forest Root Mean Squared Error: 10.288897409494494
```

In [21]:
```
# Add random forest importances to dataframe
Random_Forest_Importances = pd.DataFrame({
    "Feature": X.columns,
    "Importance": rfc.feature_importances_
}).sort_values("Importance", ascending=False).reset_index(drop=True)

# Print top 20 values of the dataframe
Random_Forest_Importances.head(20)
```

Out[21]:

	Feature	Importance
0	staffed_icu_adult_patients_confirmed_covid	0.026500
1	staffed_icu_adult_patients_confirmed_and_suspe...	0.025898
2	adult_icu_bed_covid_utilization_numerator	0.023353
3	percent_of_inpatients_with_covid_numerator	0.020792
4	total_adult_patients_hospitalized_confirmed_covid	0.019461
5	total_adult_patients_hospitalized_confirmed_an...	0.019099
6	deaths_covid_coverage	0.018980
7	inpatient_bed_covid_utilization_numerator	0.018109
8	previous_day_admission_adult_covid_confirmed_5...	0.016019
9	inpatient_beds_used_covid	0.015906
10	adult_icu_bed_covid_utilization	0.015842
11	previous_day_admission_adult_covid_confirmed	0.014609
12	inpatient_beds_utilization	0.013619
13	inpatient_bed_covid_utilization	0.013484
14	adult_icu_bed_utilization	0.013188
15	percent_of_inpatients_with_covid	0.013176
16	previous_day_admission_adult_covid_confirmed_4...	0.012333
17	adult_icu_bed_covid_utilization_denominator	0.012239
18	critical_staffing_shortage_today_no	0.012147
19	previous_day_admission_adult_covid_suspected	0.012105

Decision Trees

In [22]:
```
from sklearn.tree import DecisionTreeRegressor
```

In [23]:
```
# Define classification
dt = DecisionTreeRegressor(random_state=random_state)

# Run prediction using decision trees
dt.fit(X_train, y_train)
pred_dt = dt.predict(X_test)
```

In [24]:
```
# Calculate mean squared error
mse_dt = mean_squared_error(y_test, pred_dt)

# Calculate root mean squared error
rmse_dt = np.sqrt(mse_dt)

# Print RMSE
print("Random Forest Root Mean Squared Error:", rmse_dt)
```

```
Random Forest Root Mean Squared Error: 11.982188903538527
```

In [25]:
```
# Add decision tree importances to dataframe
Decision_Tree_Importances = pd.DataFrame({
    "Feature": X.columns,
    "Importance": dt.feature_importances_
}).sort_values("Importance", ascending=False).reset_index(drop=True)

# Print top 20 values of the dataframe
Decision_Tree_Importances.head(20)
```

Out[25]:

	Feature	Importance
0	staffed_icu_adult_patients_confirmed_covid	0.619773
1	inpatient_beds_coverage	0.067250
2	adult_icu_bed_covid_utilization_numerator	0.046706
3	total_adult_patients_hospitalized_confirmed_an...	0.036031
4	previous_day_admission_adult_covid_confirmed_u...	0.029505
5	previous_day_admission_adult_covid_suspected_6...	0.024762
6	previous_day_admission_adult_covid_suspected_7...	0.023170
7	deaths_covid_coverage	0.012864
8	staffed_pediatric_icu_bed_occupancy	0.010547
9	total_adult_patients_hospitalized_confirmed_covid	0.007443
10	previous_day_admission_adult_covid_suspected_5...	0.007377
11	critical_staffing_shortage_today_not_reported	0.006928
12	adult_icu_bed_covid_utilization	0.006112
13	critical_staffing_shortage_today_yes	0.005054
14	adult_icu_bed_utilization_denominator	0.004770
15	staffed_adult_icu_bed_occupancy	0.004643
16	staffed_icu_pediatric_patients_confirmed_covid...	0.004381
17	total_staffed_pediatric_icu_beds	0.004099
18	staffed_icu_adult_patients_confirmed_and_suspe...	0.003889
19	inpatient_beds_used_covid	0.003455

Linear Regression

In [26]:
```
from sklearn.linear_model import LinearRegression
```

In [27]:
```
# Define classification
lr = LinearRegression()

# Run prediction using linear regression
lr.fit(X_train, y_train)
pred_lr = lr.predict(X_test)
```

In [28]:
```
# Calculate mean squared error
mse_lr = mean_squared_error(y_test, pred_lr)

# Calculate root mean squared error
rmse_lr = np.sqrt(mse_lr)

# Print RMSE
print("Linear Regression Root Mean Squared Error:", rmse_lr)
```

```
Linear Regression Root Mean Squared Error: 11.579237777122788
```

In [29]:

```
# Add linear regression coefficients to dataframe
Linear_Regression_Coefficients = pd.DataFrame({
    'Feature': X.columns,
    'Coefficient': lr.coef_
}).sort_values(by='Coefficient', ascending=False).reset_index(drop=True)

# Create an absolute value column and sort by that column
Linear_Regression_Coefficients['Abs_Coefficient'] = Linear_Regression_Coefficients['Coefficient'].apply(lambda x: abs(float
Linear_Regression_Coefficients = Linear_Regression_Coefficients.sort_values(by='Abs_Coefficient', ascending=False).head(20)

# Print top 20 values of the dataframe
Linear_Regression_Coefficients.head(20)
```

Out[29]:

	Feature	Coefficient	Abs_Coefficient
0	critical_staffing_shortage_today_no	-1.407022e+12	1.407022e+12
1	critical_staffing_shortage_today_not_reported	-1.399735e+12	1.399735e+12
2	critical_staffing_shortage_anticipated_within_...	1.342986e+12	1.342986e+12
3	critical_staffing_shortage_anticipated_within_...	1.129891e+12	1.129891e+12
4	critical_staffing_shortage_anticipated_within_...	4.675849e+11	4.675849e+11
5	critical_staffing_shortage_today_yes	-3.752257e+11	3.752257e+11
6	inpatient_beds_coverage	1.577878e+02	1.577878e+02
7	inpatient_bed_covid_utilization_coverage	-1.557128e+02	1.557128e+02
8	adult_icu_bed_utilization_numerator	1.069342e+02	1.069342e+02
9	staffed_adult_icu_bed_occupancy	-1.059861e+02	1.059861e+02
10	percent_of_inpatients_with_covid_coverage	1.012391e+02	1.012391e+02
11	previous_day_admission_adult_covid_confirmed_5...	-1.000766e+02	1.000766e+02
12	all_pediatric_inpatient_beds_coverage	-8.345058e+01	8.345058e+01
13	inpatient_beds_utilization_coverage	-8.208582e+01	8.208582e+01
14	icu_patients_confirmed_influenza_coverage	-7.412975e+01	7.412975e+01
15	staffed_icu_adult_patients_confirmed_and_suspe...	-7.337561e+01	7.337561e+01
16	staffed_icu_adult_patients_confirmed_covid_cov...	7.295163e+01	7.295163e+01
17	previous_day_admission_adult_covid_suspected_7...	-7.136121e+01	7.136121e+01
18	staffed_pediatric_icu_bed_occupancy_coverage	7.107138e+01	7.107138e+01
19	adult_icu_bed_covid_utilization_numerator	-7.093283e+01	7.093283e+01

Results

Key Findings and Optimal Model

The results show the reliability of the models as follow:

- The Decision Tree model is the most reliable, with a root mean squared error of 11.2
- The Random Forest model is next with a RMSE of 12.3
- The Linear Regression model is last with a RMSE of 15.7.

The most common features among the algorithms are the following:

- staffed_icu_adult_patients_confirmed_covid
- adult_icu_bed_covid_utilization_numerator
- total_adult_patients_hospitalized_confirmed_covid
- total_adult_patients_hospitalized_confirmed_and_suspected_covid
- deaths_covid_coverage
- inpatient_beds_coverage

One potential issue is that the features extracted from Linear Regression are assumed to be more important the higher the coefficient is. This is not necessarily the case and can skew the results. More research may be needed.

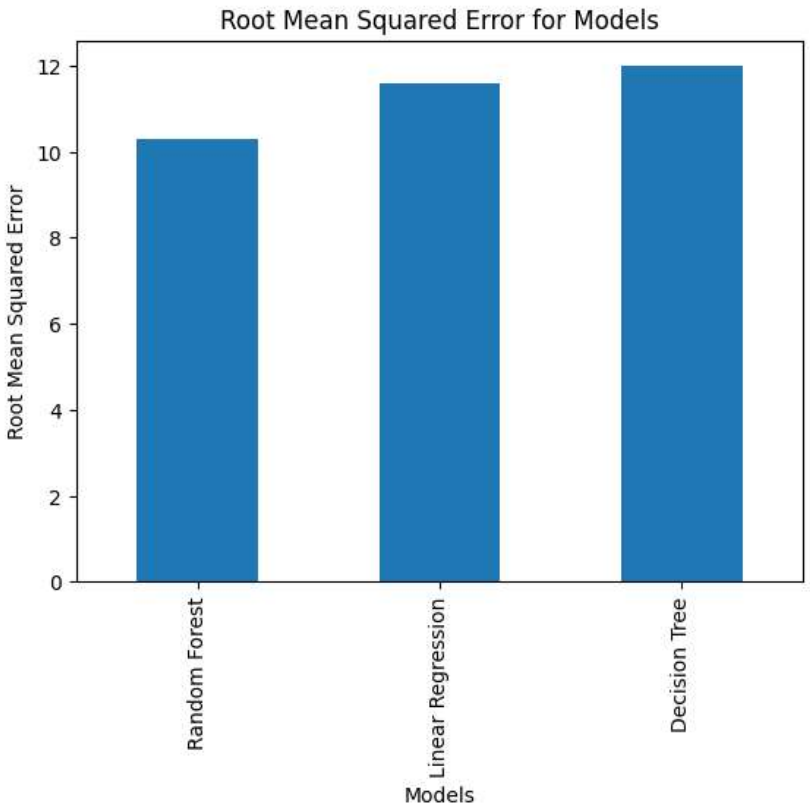
Model Accuracy

In [30]:
```
# Create dataframe using model results
result_models = ['Random Forest', 'Decision Tree', 'Linear Regression']
result_stats = [rmse_rf, rmse_dt, rmse_lr]
results = pd.DataFrame([result_models, result_stats])
results = results.T.rename(columns={0:'Models', 1:'RMSE'}).set_index('Models').sort_values(by='RMSE')
```

In [31]:
```
# Plot the results dataframe with appropriate labels
ax = results.plot(kind='bar', legend=False)

ax.set_title('Root Mean Squared Error for Models')
ax.set_xlabel('Models')
ax.set_ylabel('Root Mean Squared Error')

plt.show()
```



Top Features

In [32]:
```
from collections import Counter
```

In [33]:
```
# Create temporary dataframes with top 10 features from each
RF_top10 = Random_Forest_Importances[['Feature']].rename(columns={'Feature':'Random Forest'}).head(10)
DT_top10 = Decision_Tree_Importances[['Feature']].rename(columns={'Feature':'Decision Tree'}).head(10)
LR_top10 = Linear_Regression_Coefficients[['Feature']].rename(columns={'Feature':'Linear Regression'}).head(10)

# Combine dataframes into a top 10 list for each
top10 = RF_top10.merge(DT_top10, left_index=True, right_index=True, how='outer')
top10 = top10.merge(LR_top10, left_index=True, right_index=True, how='outer')
```

In [34]:
```
# Print significant features on models
top10
```

Out[34]:

	Random Forest	Decision Tree	Linear Regression
0	staffed_icu_adult_patients_confirmed_covid	staffed_icu_adult_patients_confirmed_covid	critical_staffing_shortage_today_no
1	staffed_icu_adult_patients_confirmed_and_suspe...	inpatient_beds_coverage	critical_staffing_shortage_today_not_reported
2	adult_icu_bed_covid_utilization_numerator	adult_icu_bed_covid_utilization_numerator	critical_staffing_shortage_anticipated_within_...
3	percent_of_inpatients_with_covid_numerator	total_adult_patients_hospitalized_confirmed_an...	critical_staffing_shortage_anticipated_within_...
4	total_adult_patients_hospitalized_confirmed_covid	previous_day_admission_adult_covid_confirmed_u...	critical_staffing_shortage_anticipated_within_...
5	total_adult_patients_hospitalized_confirmed_an...	previous_day_admission_adult_covid_suspected_6...	critical_staffing_shortage_today_yes
6	deaths_covid_coverage	previous_day_admission_adult_covid_suspected_7...	inpatient_beds_coverage
7	inpatient_bed_covid_utilization_numerator	deaths_covid_coverage	inpatient_bed_covid_utilization_coverage
8	previous_day_admission_adult_covid_confirmed_5...	staffed_pediatric_icu_bed_occupancy	adult_icu_bed_utilization_numerator
9	inpatient_beds_used_covid	total_adult_patients_hospitalized_confirmed_covid	staffed_adult_icu_bed_occupancy

In [35]:
```
# Combine top10 dataframes into a single dataframe
all_entries = pd.concat([top10['Random Forest'], top10['Decision Tree'], top10['Linear Regression']])

# Count the frequency of each entry
counter = Counter(all_entries)

# Sort counter by value in descending order and get the most common entries
most_common_entries = counter.most_common()

# Get the highest count (the count of the first entry in the sorted list)
highest_count = most_common_entries[0][1]

# Print only the most common entries (those with a count equal to highest_count)
for entry, count in most_common_entries:
    if count == highest_count:
        print(entry)
```

```
staffed_icu_adult_patients_confirmed_covid
adult_icu_bed_covid_utilization_numerator
total_adult_patients_hospitalized_confirmed_covid
total_adult_patients_hospitalized_confirmed_and_suspected_covid
deaths_covid_coverage
inpatient_beds_coverage
```

In [ ]:
```

```