

```
import pandas as pd
# Read data. This data represents the cumulative known cases to date (https://covidtracking.com/about-data/faq)
url = 'https://raw.githubusercontent.com/COVID19Tracking/covid-tracking-data/master/data/states_daily_4pm_et.csv'
df = pd.read_csv(url,index_col=0,parse_dates=[0])
```

```
df.head(5)
```

	state	positive	negative	pending	hospitalizedCurrently	hospitalizedCumulative	inIcuCurrently	inIcuCumulative	onVentilatorCur
date									
2020-05-02	AK	365.0	21034.0	NaN	10.0	NaN	NaN	NaN	
2020-05-02	AL	7434.0	84775.0	NaN	NaN	1023.0	NaN	335.0	
2020-05-02	AR	3372.0	48210.0	NaN	95.0	414.0	NaN	NaN	
2020-05-02	AS	0.0	57.0	NaN	NaN	NaN	NaN	NaN	
2020-05-02	AZ	8364.0	69633.0	NaN	718.0	1339.0	291.0	NaN	

Double-click (or enter) to edit

```
# Drop total, posNeg, and hospitalized columns as they are redundant
# Drop other columns that will not be used
#df_drop = df.drop(columns = [6, 7, 8, 9, 11, 12, 14, 15, 17, 18, 19, 20, 21, 22, 23])
df_drop = df.drop(columns = ['inIcuCurrently', 'inIcuCumulative',
                             'onVentilatorCurrently', 'onVentilatorCumulative',
                             'hash', 'dateChecked', 'hospitalized', 'total',
                             'posNeg', 'fips', 'deathIncrease',
                             'hospitalizedIncrease', 'negativeIncrease',
                             'positiveIncrease', 'totalTestResultsIncrease'])
df_drop.head()
```

	state	positive	negative	pending	hospitalizedCurrently	hospitalizedCumulative	recovered	death	totalTestResults
date									
2020-05-02	AK	365.0	21034.0	NaN	10.0	NaN	261.0	9.0	21399.0
2020-05-02	AL	7434.0	84775.0	NaN	NaN	1023.0	NaN	288.0	92209.0
2020-05-02	AR	3372.0	48210.0	NaN	95.0	414.0	1987.0	73.0	51582.0
2020-05-02	AS	0.0	57.0	NaN	NaN	NaN	NaN	0.0	57.0
2020-05-02	AZ	8364.0	69633.0	NaN	718.0	1339.0	1565.0	348.0	77997.0

```
# Create new features
# Divide positive by totalTestResults to get positive_percent
df_drop["percent_positive"] = ""
df_drop["percent_positive"] = 100*df_drop["positive"]/df_drop["totalTestResults"]
df_drop.head()
```

	state	positive	negative	pending	hospitalizedCurrently	hospitalizedCumulative	recovered	death	totalTestResults	percent_posi:
date										
2020-05-02	AK	365.0	21034.0	NaN	10.0	NaN	261.0	9.0	21399.0	1.70
2020-05-02	AL	7434.0	84775.0	NaN	NaN	1023.0	NaN	288.0	92209.0	8.00
2020-05-02	AR	3372.0	48210.0	NaN	95.0	414.0	1987.0	73.0	51582.0	6.50
2020-05-02	AS	0.0	57.0	NaN	NaN	NaN	NaN	0.0	57.0	0.00
2020-05-02	AZ	8364.0	69633.0	NaN	718.0	1339.0	1565.0	348.0	77997.0	10.70

```
# Divide hospitalized by positive to get hospitalized_percent
import numpy as np
df_drop["hospitalized_percent"] = ""
df_drop["hospitalized_percent"] = np.nanmax(df_drop[['hospitalizedCurrently','hospitalizedCumulative']], axis=1)
df_drop["hospitalized_percent"] = 100*df_drop["hospitalized_percent"]/df_drop["positive"]
df_drop.head()
```

⌘ /usr/local/lib/python3.6/dist-packages/ipykernel\_launcher.py:3: RuntimeWarning: All-NaN axis encountered  
This is separate from the ipykernel package so we can avoid doing imports until

	state	positive	negative	pending	hospitalizedCurrently	hospitalizedCumulative	recovered	death	totalTestResults	percent_posi:
date										
2020-05-02	AK	365.0	21034.0	NaN	10.0	NaN	261.0	9.0	21399.0	1.70
2020-05-02	AL	7434.0	84775.0	NaN	NaN	1023.0	NaN	288.0	92209.0	8.00
2020-05-02	AR	3372.0	48210.0	NaN	95.0	414.0	1987.0	73.0	51582.0	6.50
2020-05-02	AS	0.0	57.0	NaN	NaN	NaN	NaN	0.0	57.0	0.00
2020-05-02	AZ	8364.0	69633.0	NaN	718.0	1339.0	1565.0	348.0	77997.0	10.70

```
# Divide recovered by positive to get recovered_percent
df_drop["recovered_percent"] = ""
df_drop["recovered_percent"] = 100*df_drop["recovered"]/df_drop["positive"]
df_drop.head()
```

	state	positive	negative	pending	hospitalizedCurrently	hospitalizedCumulative	recovered	death	totalTestResults	percent_posi:
date										
2020-05-02	AK	365.0	21034.0	NaN	10.0	NaN	261.0	9.0	21399.0	1.70
2020-05-02	AL	7434.0	84775.0	NaN	NaN	1023.0	NaN	288.0	92209.0	8.00
2020-05-02	AR	3372.0	48210.0	NaN	95.0	414.0	1987.0	73.0	51582.0	6.50
2020-05-02	AS	0.0	57.0	NaN	NaN	NaN	NaN	0.0	57.0	0.00
2020-05-02	AZ	8364.0	69633.0	NaN	718.0	1339.0	1565.0	348.0	77997.0	10.70

```
# Divide death by positive to get death_percent
df_drop["death_percent"] = ""
df_drop["death_percent"] = 100*df_drop["death"]/df_drop["positive"]
df_drop.head()
```

⌘

	state	positive	negative	pending	hospitalizedCurrently	hospitalizedCumulative	recovered	death	totalTestResults	percent_pos:
date										
2020-05-02	AK	365.0	21034.0	NaN	10.0	NaN	261.0	9.0	21399.0	1.70
2020-05-02	AL	7434.0	84775.0	NaN	NaN	1023.0	NaN	288.0	92209.0	8.06
2020-05-02	AR	3372.0	48210.0	NaN	95.0	414.0	1987.0	73.0	51582.0	6.55
2020-05-02	AS	0.0	57.0	NaN	NaN	NaN	NaN	0.0	57.0	0.00
2020-05-02	AZ	8364.0	69633.0	NaN	718.0	1339.0	1565.0	348.0	77997.0	10.72

```
# Fetch the latest state population data (nst-est2019-01.csv)
from google.colab import files
uploaded = files.upload()

Choose Files nst-est2019-01.csv
• nst-est2019-01.csv(application/vnd.ms-excel) - 676 bytes, last modified: 4/13/2020 - 100% done
Saving nst-est2019-01.csv to nst-est2019-01.csv
```

```
# Load latest state population data
import io
df_state_pop = pd.read_csv(io.StringIO(uploaded['nst-est2019-01.csv'].decode('utf-8')))
df_state_pop["Population"] = pd.to_numeric(df_state_pop["Population"])
df_state_pop.head()
```

	State	Population
0	AK	731545.0
1	AL	4903185.0
2	AR	3017804.0
3	AS	NaN
4	AZ	7278717.0

```
# Add column of state populations (population) to df_drop_total_posNeg
# Need to sort rows by state using index numbering from state_list

df_drop["population"] = ""

for i in range(len(df_drop)):
    for index in range(len(df_state_pop)):
        if df_drop.iloc[i, 0] == df_state_pop.iloc[index, 0]:
            df_drop.iloc[i, 13] = df_state_pop.iloc[index, 1]

df_drop[["population"]] = df_drop["population"].apply(pd.to_numeric)

df_drop.head()
```

	state	positive	negative	pending	hospitalizedCurrently	hospitalizedCumulative	recovered	death	totalTestResults	percent_pos:
date										
2020-05-02	AK	365.0	21034.0	NaN	10.0	NaN	261.0	9.0	21399.0	1.70
2020-05-02	AL	7434.0	84775.0	NaN	NaN	1023.0	NaN	288.0	92209.0	8.06
2020-05-02	AR	3372.0	48210.0	NaN	95.0	414.0	1987.0	73.0	51582.0	6.55
2020-05-02	AS	0.0	57.0	NaN	NaN	NaN	NaN	0.0	57.0	0.00
2020-05-02	AZ	8364.0	69633.0	NaN	718.0	1339.0	1565.0	348.0	77997.0	10.72

```
# Normalize positive to state population
df_drop["positive_norm"] = ""
df_drop["positive_norm"] = df_drop["positive"]/df_drop["population"]
df_drop.head()
```

↗

	state	positive	negative	pending	hospitalizedCurrently	hospitalizedCumulative	recovered	death	totalTestResults	percent_posi
date										
2020-05-02	AK	365.0	21034.0	NaN	10.0	NaN	261.0	9.0	21399.0	1.70
2020-05-02	AL	7434.0	84775.0	NaN	NaN	1023.0	NaN	288.0	92209.0	8.00
2020-05-02	AR	3372.0	48210.0	NaN	95.0	414.0	1987.0	73.0	51582.0	6.50
2020-05-02	AS	0.0	57.0	NaN	NaN	NaN	NaN	0.0	57.0	0.00
2020-05-02	AZ	8364.0	69633.0	NaN	718.0	1339.0	1565.0	348.0	77997.0	10.70

```
# Normalize hospitalized to state population
df_drop["hospitalized_norm"] = ""
df_drop["hospitalized_norm"] = np.nanmax(df_drop[['hospitalizedCurrently','hospitalizedCumulative']], axis=1)
df_drop["hospitalized_norm"] = df_drop["hospitalized_norm"]/df_drop["population"]
df_drop.head()
```

↗

/usr/local/lib/python3.6/dist-packages/ipykernel\_launcher.py:2: RuntimeWarning: All-NaN axis encountered

	state	positive	negative	pending	hospitalizedCurrently	hospitalizedCumulative	recovered	death	totalTestResults	percent_posi
date										
2020-05-02	AK	365.0	21034.0	NaN	10.0	NaN	261.0	9.0	21399.0	1.70
2020-05-02	AL	7434.0	84775.0	NaN	NaN	1023.0	NaN	288.0	92209.0	8.00
2020-05-02	AR	3372.0	48210.0	NaN	95.0	414.0	1987.0	73.0	51582.0	6.50
2020-05-02	AS	0.0	57.0	NaN	NaN	NaN	NaN	0.0	57.0	0.00
2020-05-02	AZ	8364.0	69633.0	NaN	718.0	1339.0	1565.0	348.0	77997.0	10.70

```
# Normalize recovered to state population
df_drop["recovered_norm"] = ""
df_drop["recovered_norm"] = df_drop["recovered"]/df_drop["population"]
df_drop.head()
```

↗

	state	positive	negative	pending	hospitalizedCurrently	hospitalizedCumulative	recovered	death	totalTestResults	percent_posi
date										
2020-05-02	AK	365.0	21034.0	NaN	10.0	NaN	261.0	9.0	21399.0	1.70
2020-05-02	AL	7434.0	84775.0	NaN	NaN	1023.0	NaN	288.0	92209.0	8.00
2020-05-02	AR	3372.0	48210.0	NaN	95.0	414.0	1987.0	73.0	51582.0	6.50
2020-05-02	AS	0.0	57.0	NaN	NaN	NaN	NaN	0.0	57.0	0.00
2020-05-02	AZ	8364.0	69633.0	NaN	718.0	1339.0	1565.0	348.0	77997.0	10.70

```
# Normalize death to state population
df_drop["death_norm"] = ""
df_drop["death_norm"] = df_drop["death"]/df_drop["population"]
df_drop.head()
```

	state	positive	negative	pending	hospitalizedCurrently	hospitalizedCumulative	recovered	death	totalTestResults	percent_pos:
date										
2020-05-02	AK	365.0	21034.0	NaN	10.0	NaN	261.0	9.0	21399.0	1.70
2020-05-02	AL	7434.0	84775.0	NaN	NaN	1023.0	NaN	288.0	92209.0	8.00
2020-05-02	AR	3372.0	48210.0	NaN	95.0	414.0	1987.0	73.0	51582.0	6.50
2020-05-02	AS	0.0	57.0	NaN	NaN	NaN	NaN	0.0	57.0	0.00
2020-05-02	AZ	8364.0	69633.0	NaN	718.0	1339.0	1565.0	348.0	77997.0	10.70

```
df_drop.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 3265 entries, 2020-05-02 to 2020-01-22
Data columns (total 18 columns):
#   Column              Non-Null Count  Dtype
---  -
0   state                3265 non-null   object
1   positive             3250 non-null   float64
2   negative             3084 non-null   float64
3   pending              671 non-null    float64
4   hospitalizedCurrently 1152 non-null   float64
5   hospitalizedCumulative 1207 non-null   float64
6   recovered            997 non-null    float64
7   death                2538 non-null   float64
8   totalTestResults     3263 non-null   float64
9   percent_positive     3219 non-null   float64
10  hospitalized_percent   1822 non-null   float64
11  recovered_percent     997 non-null    float64
12  death_percent         2486 non-null   float64
13  population            3073 non-null   float64
14  positive_norm         3073 non-null   float64
15  hospitalized_norm     1783 non-null   float64
16  recovered_norm        913 non-null    float64
17  death_norm           2395 non-null   float64
dtypes: float64(17), object(1)
memory usage: 564.6+ KB
```

```
# Get the unique values of 'state' column
state_list = df.state.unique()
state_list
```

```
array(['AK', 'AL', 'AR', 'AS', 'AZ', 'CA', 'CO', 'CT', 'DC', 'DE', 'FL',
       'GA', 'GU', 'HI', 'IA', 'ID', 'IL', 'IN', 'KS', 'KY', 'LA', 'MA',
       'MD', 'ME', 'MI', 'MN', 'MO', 'MP', 'MS', 'MT', 'NC', 'ND', 'NE',
       'NH', 'NJ', 'NM', 'NV', 'NY', 'OH', 'OK', 'OR', 'PA', 'PR', 'RI',
       'SC', 'SD', 'TN', 'TX', 'UT', 'VA', 'VI', 'VT', 'WA', 'WI', 'WV',
       'WY'], dtype=object)
```

```
#create a data frame dictionary to store the state data frames
df_state_dict = {elem : pd.DataFrame for elem in state_list}
```

```
for key in df_state_dict.keys():
    df_state_dict[key] = df_drop[df_drop.state == key]
```

```
df_state_dict['AK'].head()
```

	state	positive	negative	pending	hospitalizedCurrently	hospitalizedCumulative	recovered	death	totalTestResults	percent_pos:
date										
2020-05-02	AK	365.0	21034.0	NaN	10.0	NaN	261.0	9.0	21399.0	1.7%
2020-05-01	AK	364.0	19961.0	NaN	25.0	NaN	254.0	9.0	20325.0	1.7%
2020-04-30	AK	355.0	18764.0	NaN	19.0	NaN	252.0	9.0	19119.0	1.8%
2020-04-29	AK	355.0	18764.0	NaN	14.0	NaN	240.0	9.0	19119.0	1.8%
2020-04-28	AK	351.0	16738.0	NaN	16.0	NaN	228.0	9.0	17089.0	2.0%

```
df_state_dict['CA'].head()
```

	state	positive	negative	pending	hospitalizedCurrently	hospitalizedCumulative	recovered	death	totalTestResults	percent_pos
date										
2020-05-02	CA	52197.0	634606.0	NaN	4722.0	NaN	NaN	2171.0	686803.0	7.5
2020-05-01	CA	50442.0	604543.0	NaN	4706.0	NaN	NaN	2073.0	654985.0	7.7
2020-04-30	CA	48917.0	576420.0	NaN	4981.0	NaN	NaN	1982.0	625337.0	7.8
2020-04-29	CA	46500.0	556639.0	NaN	5011.0	NaN	NaN	1887.0	603139.0	7.7
2020-04-28	CA	45031.0	532577.0	NaN	4983.0	NaN	NaN	1809.0	577608.0	7.7

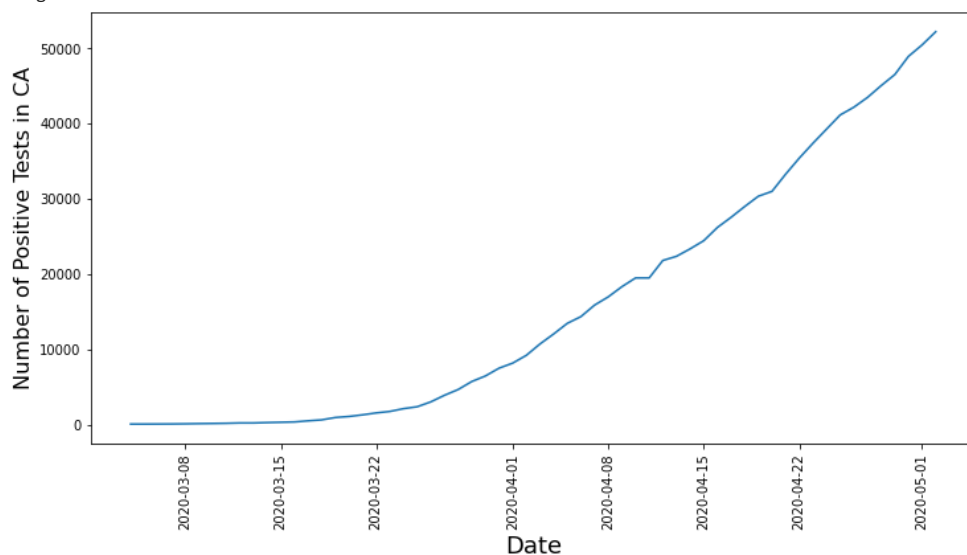
```
from matplotlib import pyplot as plt
```

```
fig = plt.figure()
fig, ax = plt.subplots(figsize=(12, 6))
plt.rcParams.update(plt.rcParamsDefault)

plt.plot(df_state_dict['CA'].positive)
plt.xticks(rotation='vertical')

plt.legend(frameon=False)
plt.xlabel('Date', fontsize=18)
plt.ylabel('Number of Positive Tests in CA', fontsize=16)
plt.show()
```

No handles with labels found to put in legend.  
<Figure size 432x288 with 0 Axes>

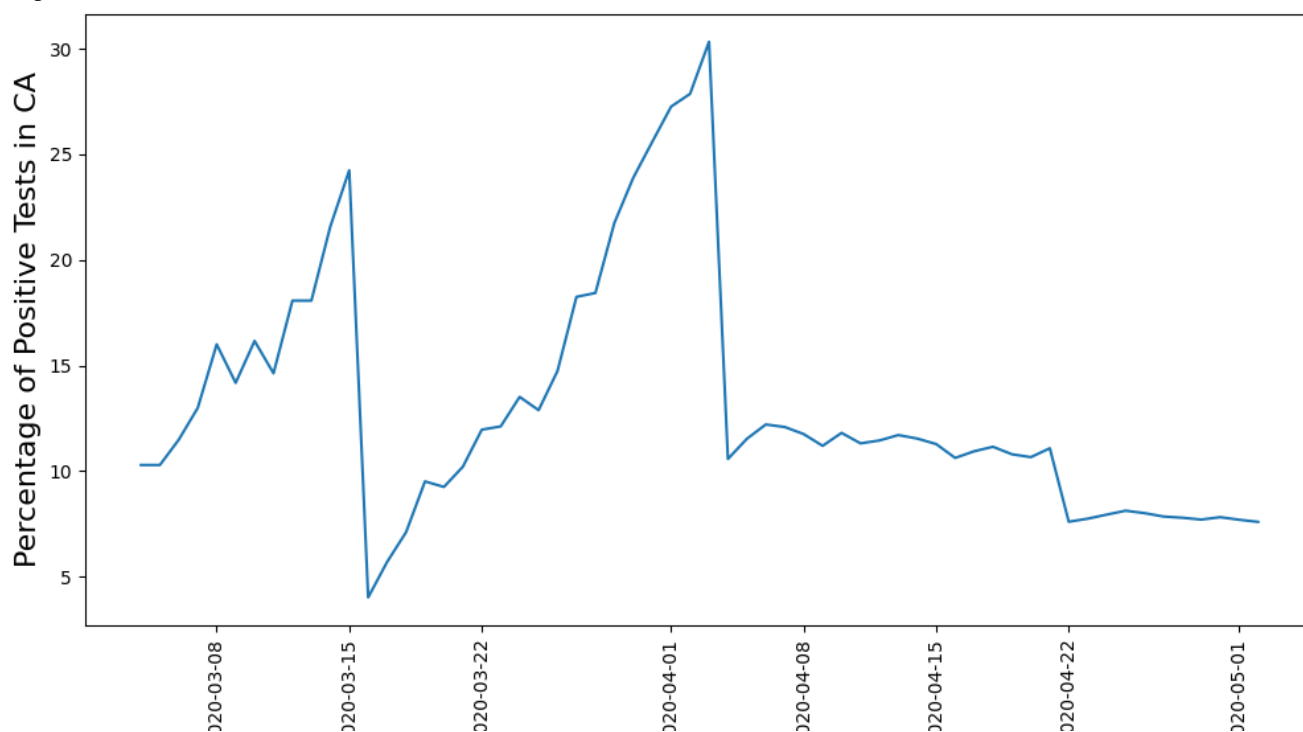


```
fig = plt.figure()
fig, ax = plt.subplots(figsize=(12, 6))
plt.rcParams.update(plt.rcParamsDefault)

plt.plot(df_state_dict['CA'].percent_positive)
plt.xticks(rotation='vertical')

plt.legend(frameon=False)
plt.xlabel('Date', fontsize=18)
plt.ylabel('Percentage of Positive Tests in CA', fontsize=16)
plt.show()
```

⌂ No handles with labels found to put in legend.  
<Figure size 640x480 with 0 Axes>

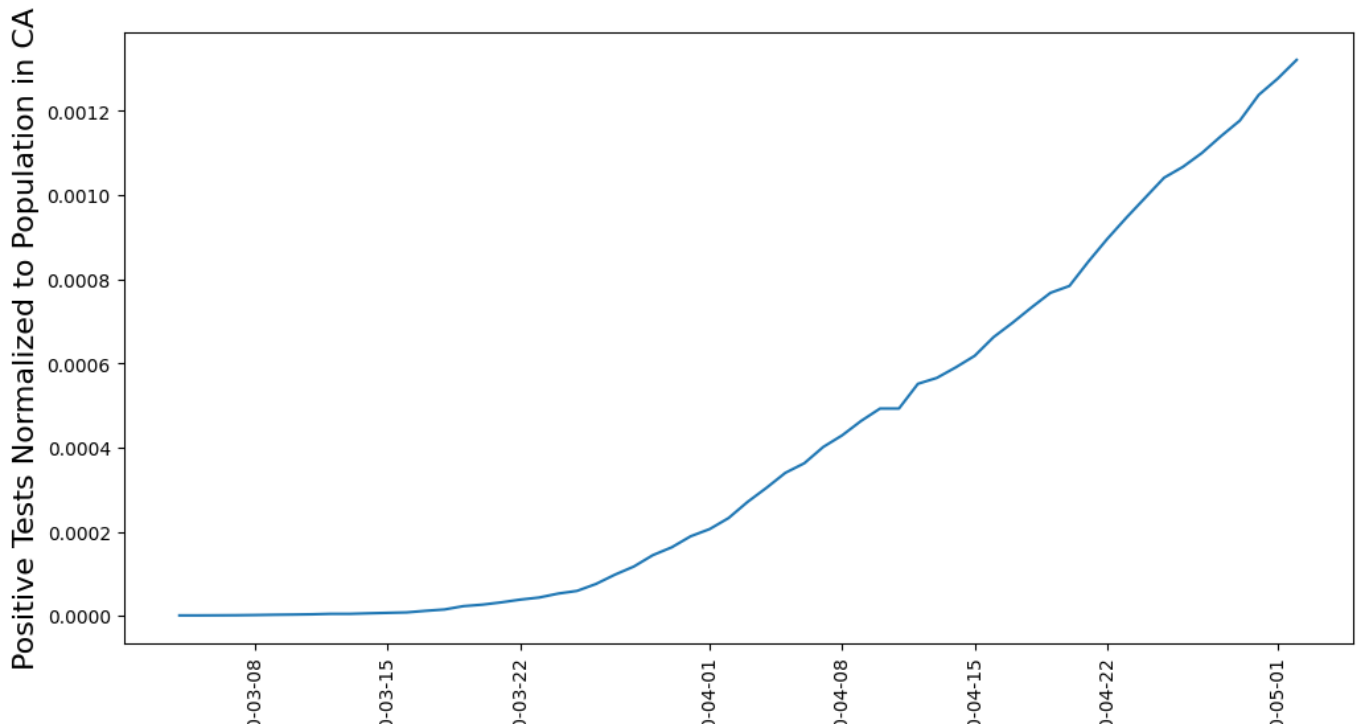


```
fig = plt.figure()
fig, ax = plt.subplots(figsize=(12, 6))
plt.rcParams.update(plt.rcParamsDefault)

plt.plot(df_state_dict['CA'].positive_norm)
plt.xticks(rotation='vertical')
```

```
plt.legend(frameon=False)
plt.xlabel('Date', fontsize=18)
plt.ylabel('Positive Tests Normalized to Population in CA', fontsize=16)
plt.show()
```

⏏ No handles with labels found to put in legend.  
<Figure size 640x480 with 0 Axes>



```
fig = plt.figure()
fig, ax = plt.subplots(figsize=(12, 6))
plt.rcParams.update(plt.rcParamsDefault)

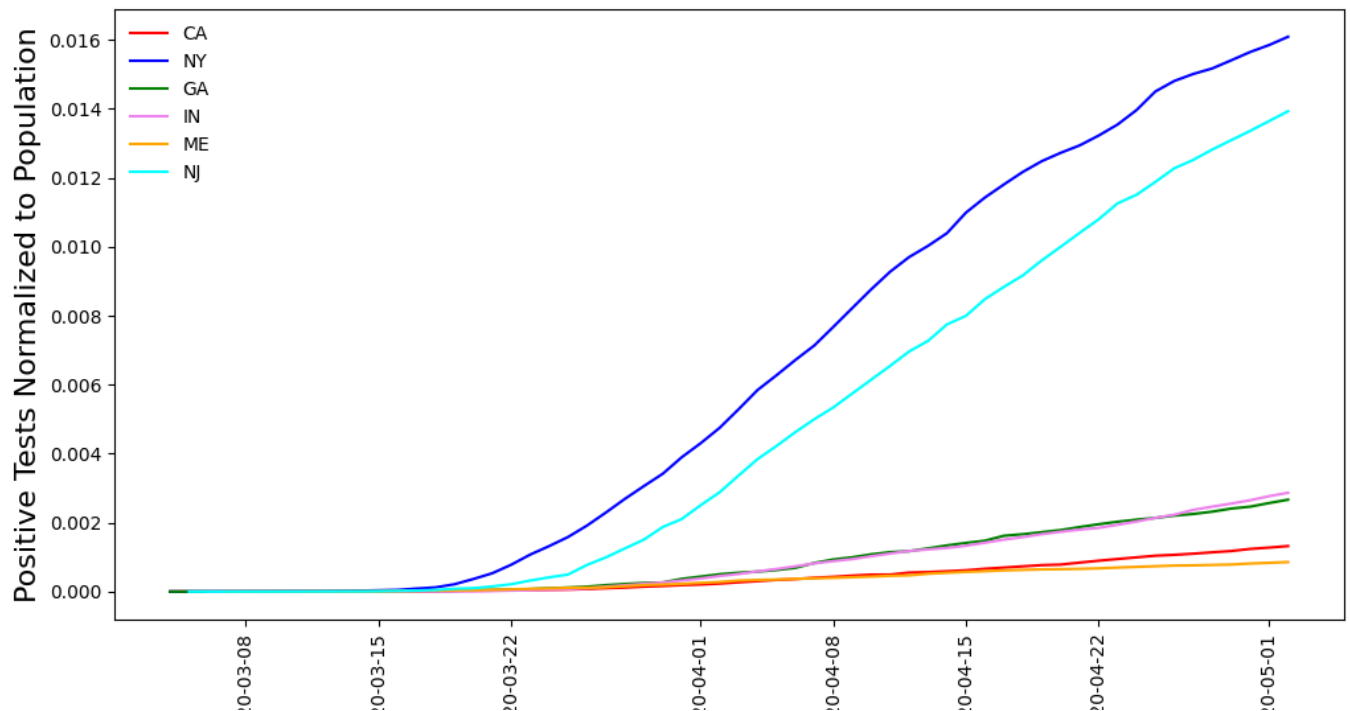
plt.plot(df_state_dict['CA'].positive_norm, color="red", label="CA")
plt.plot(df_state_dict['NY'].positive_norm, color="blue", label="NY")
plt.plot(df_state_dict['GA'].positive_norm, color="green", label="GA")
plt.plot(df_state_dict['IN'].positive_norm, color="violet", label="IN")
plt.plot(df_state_dict['ME'].positive_norm, color="orange", label="ME")
plt.plot(df_state_dict['NJ'].positive_norm, color="cyan", label="NJ")
plt.xticks(rotation='vertical')

plt.legend(frameon=False)
plt.xlabel('Date', fontsize=18)
plt.ylabel('Positive Tests Normalized to Population', fontsize=16)
plt.show()
```

⏏



&lt;Figure size 640x480 with 0 Axes&gt;

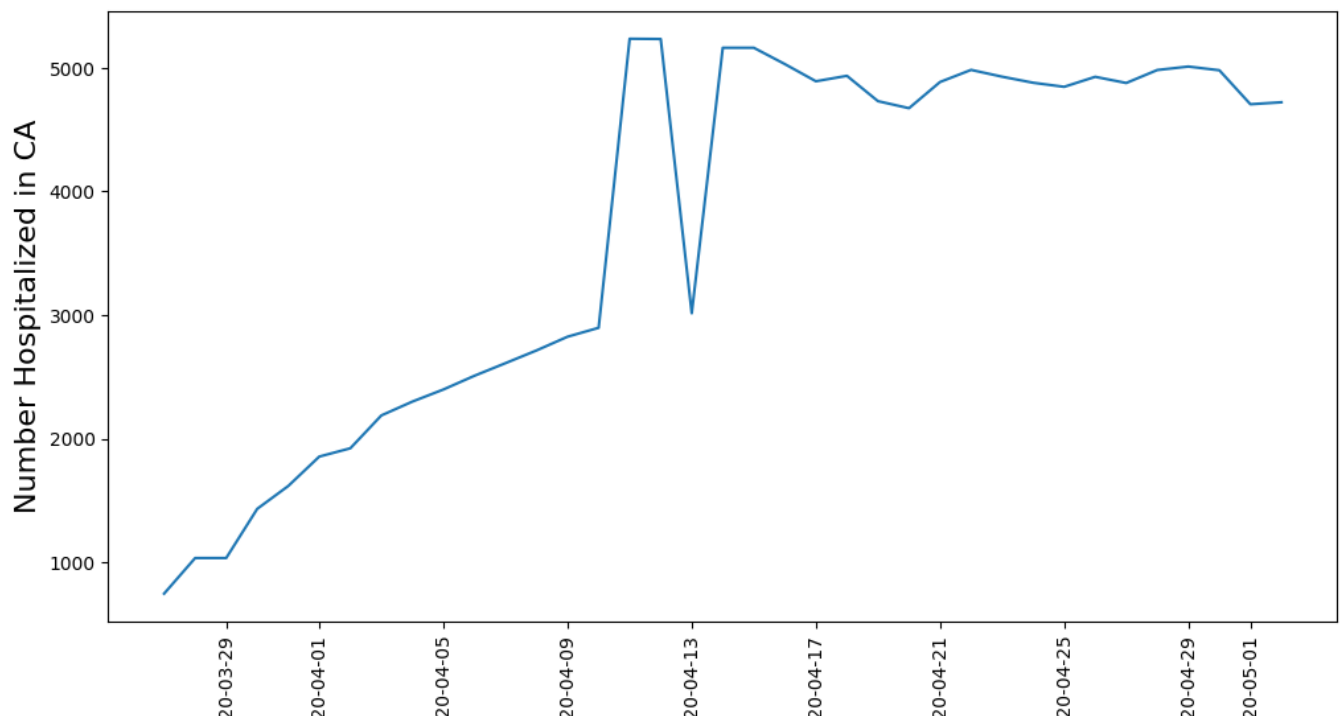


```
fig = plt.figure()
fig, ax = plt.subplots(figsize=(12, 6))
plt.rcParams.update(plt.rcParamsDefault)

plt.plot(df_state_dict['CA'].hospitalizedCurrently)
plt.xticks(rotation='vertical')

plt.legend(frameon=False)
plt.xlabel('Date', fontsize=18)
plt.ylabel('Number Hospitalized in CA', fontsize=16)
plt.show()
```

⚠ No handles with labels found to put in legend.  
<Figure size 640x480 with 0 Axes>

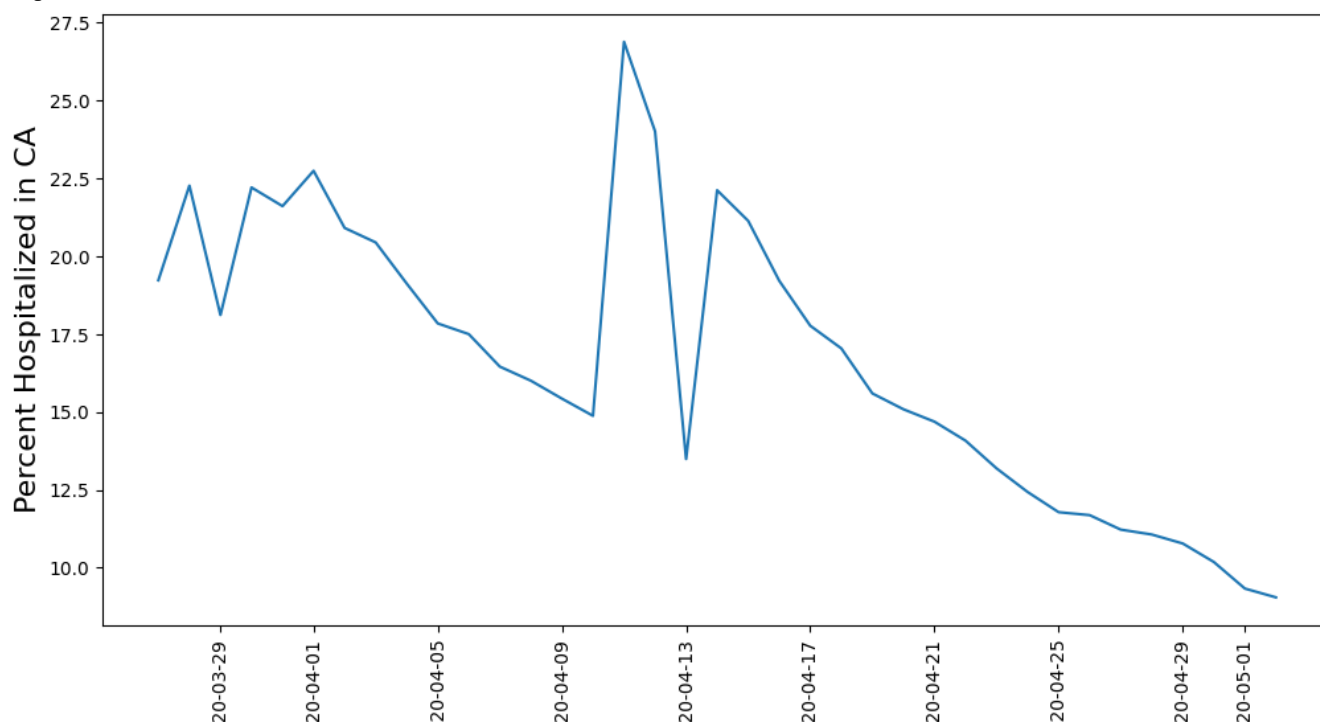


```
fig = plt.figure()
fig, ax = plt.subplots(figsize=(12, 6))
plt.rcParams.update(plt.rcParamsDefault)
```

```
plt.plot(df_state_dict['CA'].hospitalized_percent)
plt.xticks(rotation='vertical')

plt.legend(frameon=False)
plt.xlabel('Date', fontsize=18)
plt.ylabel('Percent Hospitalized in CA', fontsize=16)
plt.show()
```

⌵ No handles with labels found to put in legend.  
<Figure size 640x480 with 0 Axes>



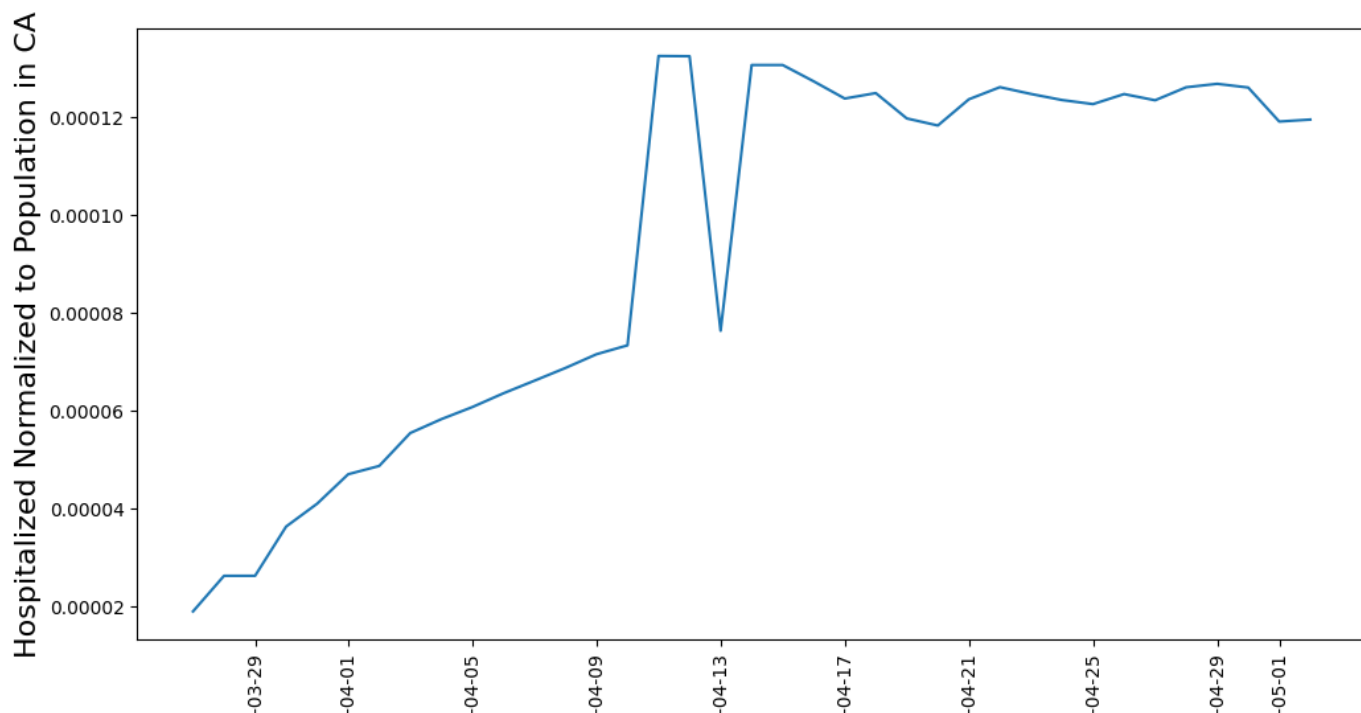
```
fig = plt.figure()
fig, ax = plt.subplots(figsize=(12, 6))
plt.rcParams.update(plt.rcParamsDefault)

plt.plot(df_state_dict['CA'].hospitalized_norm)
plt.xticks(rotation='vertical')

plt.legend(frameon=False)
plt.xlabel('Date', fontsize=18)
plt.ylabel('Hospitalized Normalized to Population in CA', fontsize=16)
plt.show()
```

⌵

No handles with labels found to put in legend.  
<Figure size 640x480 with 0 Axes>



```
fig = plt.figure()
fig, ax = plt.subplots(figsize=(12, 6))
plt.rcParams.update(plt.rcParamsDefault)

plt.plot(df_state_dict['CA'].hospitalized_norm, color="red", label="CA")
plt.plot(df_state_dict['NY'].hospitalized_norm, color="blue", label="NY")
plt.plot(df_state_dict['GA'].hospitalized_norm, color="green", label="GA")
plt.plot(df_state_dict['IN'].hospitalized_norm, color="violet", label="IN")
plt.plot(df_state_dict['ME'].hospitalized_norm, color="orange", label="ME")
plt.plot(df_state_dict['NJ'].hospitalized_norm, color="cyan", label="NJ")
plt.xticks(rotation='vertical')

plt.legend(frameon=False)
plt.xlabel('Date', fontsize=18)
plt.ylabel('Hospitalized Normalized to Population', fontsize=16)
plt.show()
```



```
<Figure size 640x480 with 0 Axes>
```

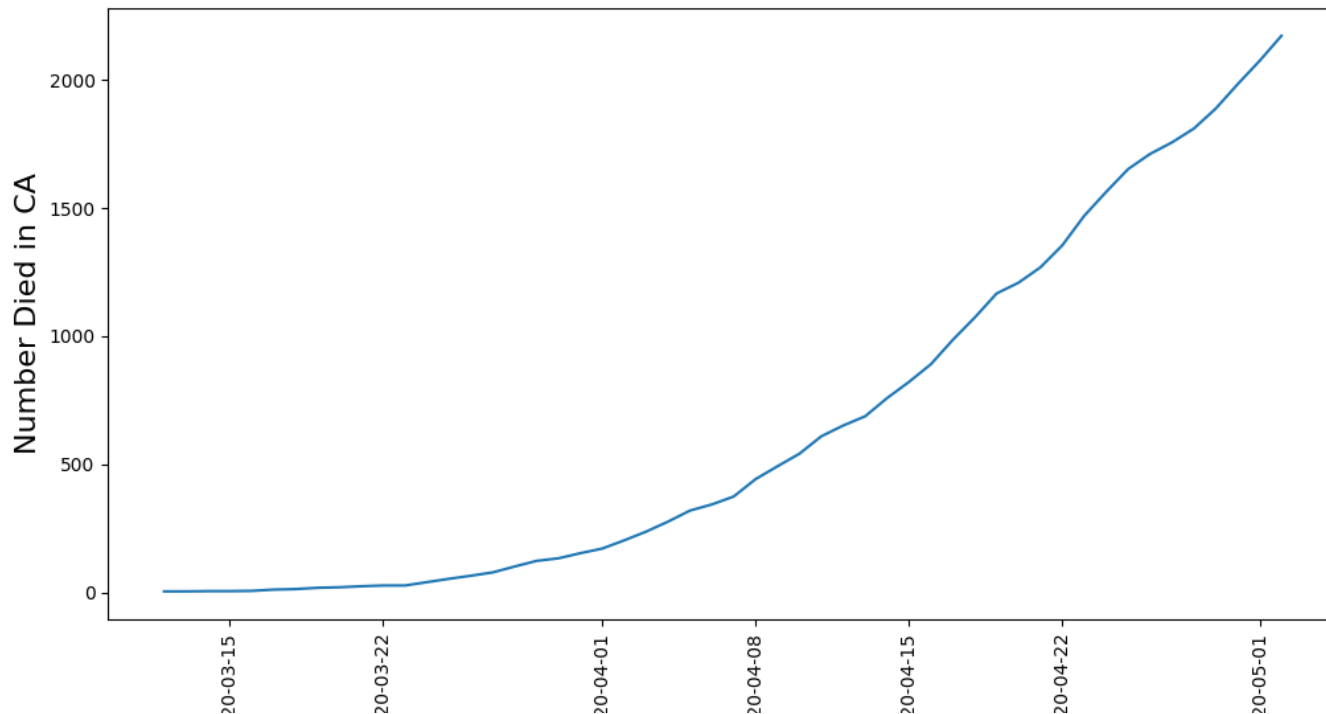
In several states, population normalized hospitalizations plateau, although population normalized death rate continues to grow.

```
fig = plt.figure()
fig, ax = plt.subplots(figsize=(12, 6))
plt.rcParams.update(plt.rcParamsDefault)

plt.plot(df_state_dict['CA'].death)
plt.xticks(rotation='vertical')

plt.legend(frameon=False)
plt.xlabel('Date', fontsize=18)
plt.ylabel('Number Died in CA', fontsize=16)
plt.show()
```

⌘ No handles with labels found to put in legend.  
<Figure size 640x480 with 0 Axes>



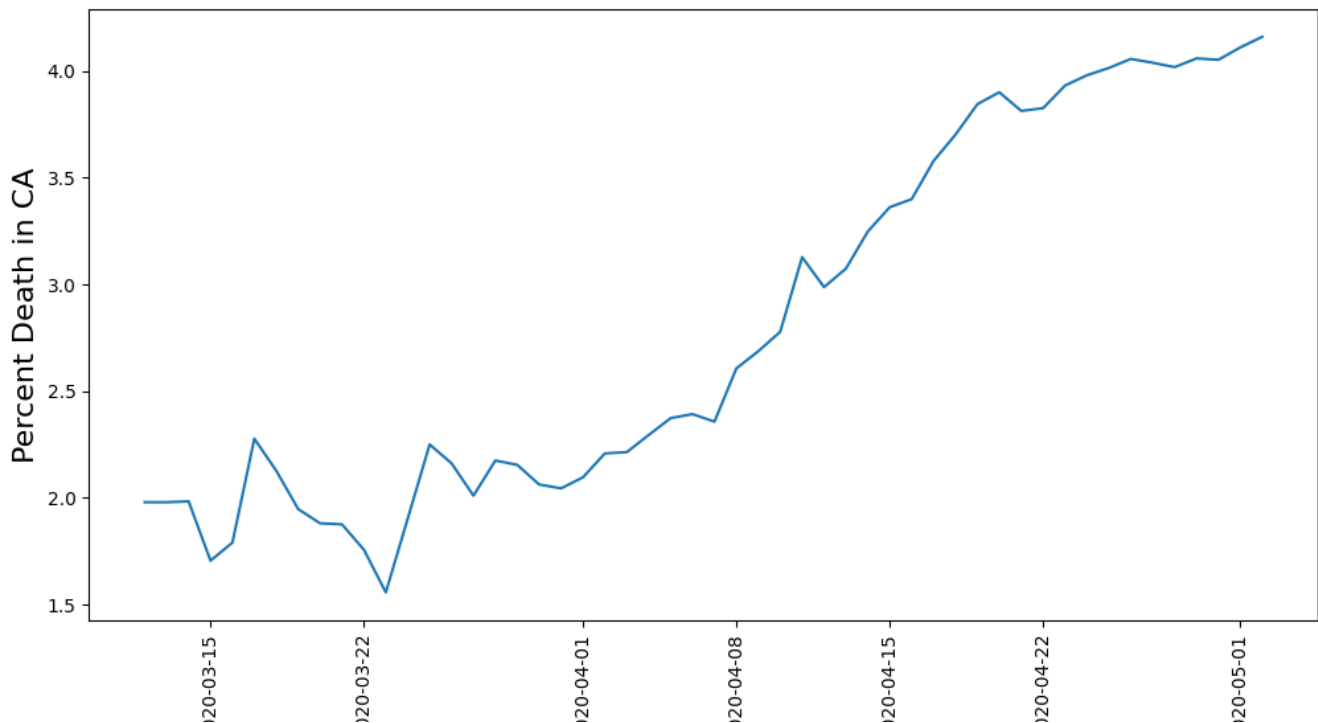
```
fig = plt.figure()
fig, ax = plt.subplots(figsize=(12, 6))
plt.rcParams.update(plt.rcParamsDefault)

plt.plot(df_state_dict['CA'].death_percent)
plt.xticks(rotation='vertical')

plt.legend(frameon=False)
plt.xlabel('Date', fontsize=18)
plt.ylabel('Percent Death in CA', fontsize=16)
plt.show()
```

⌘

No handles with labels found to put in legend.  
<Figure size 640x480 with 0 Axes>

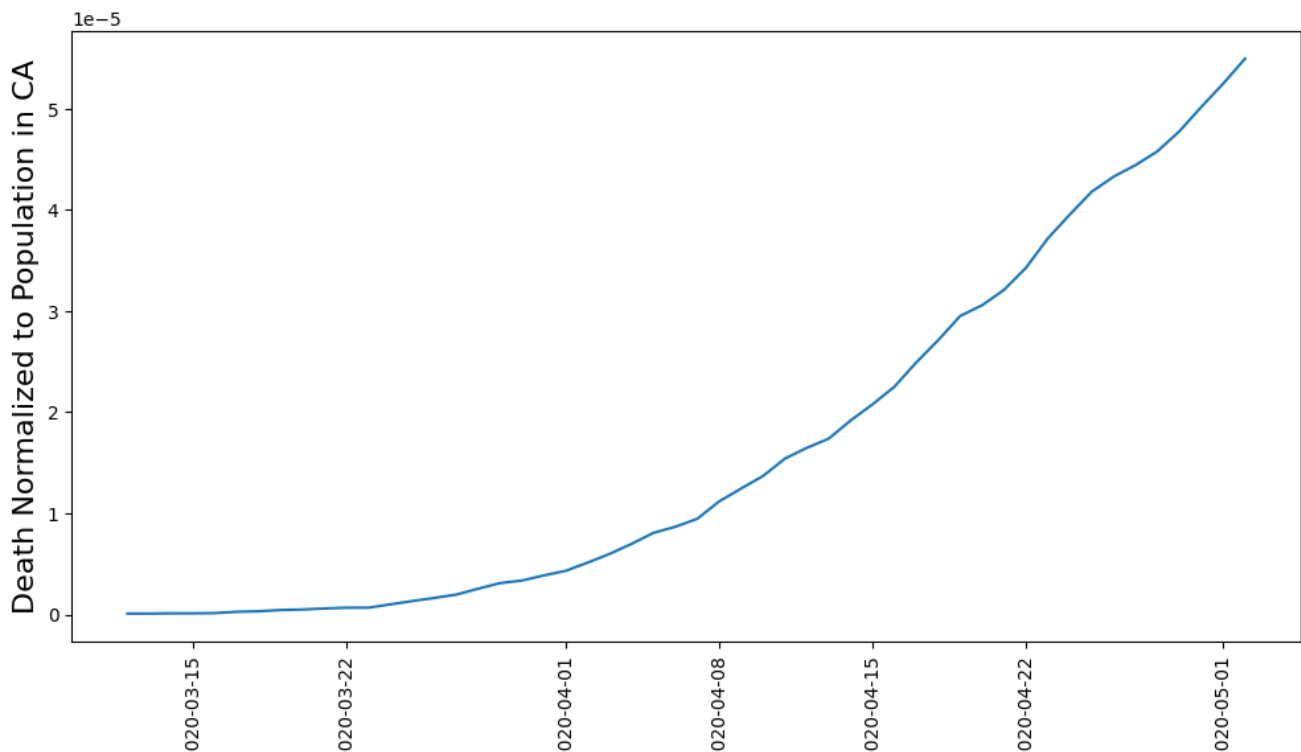


```
fig = plt.figure()
fig, ax = plt.subplots(figsize=(12, 6))
plt.rcParams.update(plt.rcParamsDefault)

plt.plot(df_state_dict['CA'].death_norm)
plt.xticks(rotation='vertical')

plt.legend(frameon=False)
plt.xlabel('Date', fontsize=18)
plt.ylabel('Death Normalized to Population in CA', fontsize=16)
plt.show()
```

No handles with labels found to put in legend.  
<Figure size 640x480 with 0 Axes>



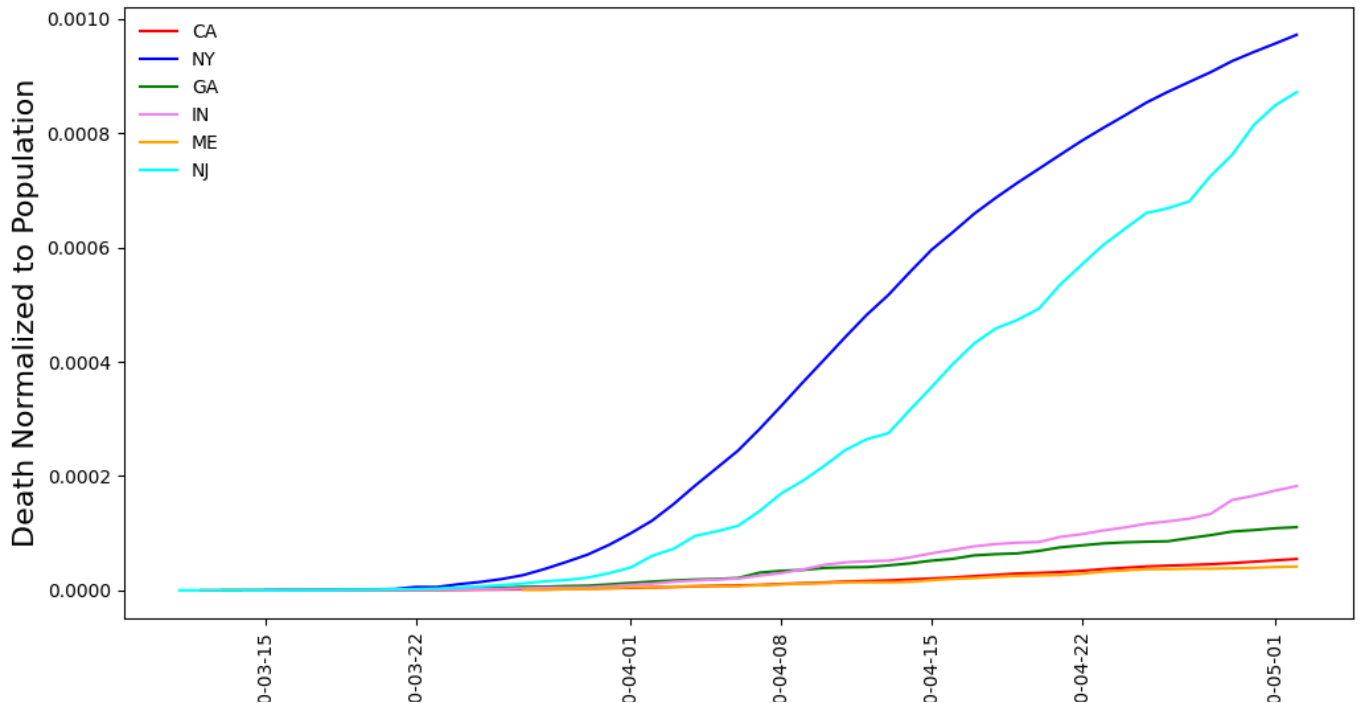
```
fig = plt.figure()
```

```
fig = plt.figure()
fig, ax = plt.subplots(figsize=(12, 6))
plt.rcParams.update(plt.rcParamsDefault)

plt.plot(df_state_dict['CA'].death_norm, color="red", label="CA")
plt.plot(df_state_dict['NY'].death_norm, color="blue", label="NY")
plt.plot(df_state_dict['GA'].death_norm, color="green", label="GA")
plt.plot(df_state_dict['IN'].death_norm, color="violet", label="IN")
plt.plot(df_state_dict['ME'].death_norm, color="orange", label="ME")
plt.plot(df_state_dict['NJ'].death_norm, color="cyan", label="NJ")
plt.xticks(rotation='vertical')

plt.legend(frameon=False)
plt.xlabel('Date', fontsize=18)
plt.ylabel('Death Normalized to Population', fontsize=16)
plt.show()
```

<Figure size 640x480 with 0 Axes>



Note how the population normalized death curves relate closely to population normalized positive test curves

# Curve fitting done at: <http://www.xuru.org/rt/NLR.asp#CopyPaste>

```
# Fetch the parameters for each state (AexpBx^-1.csv) that fit to positive_norm = a*exp(b/x)
# where x is the number of days from March 4, 2020
from google.colab import files
uploaded = files.upload()
```

Choose Files AexpBx^-1.csv

- AexpBx^-1.csv(application/vnd.ms-excel) - 1695 bytes, last modified: 4/14/2020 - 100% done

Saving AexpBx^-1.csv to AexpBx^-1.csv

```
# Load the parameters for each state (AexpBx^-1.csv) that fit to positive_norm = a*exp(b/x)
import io
df_state_params = pd.read_csv(io.StringIO(uploaded['AexpBx^-1.csv'].decode('utf-8')))
df_state_params.head()
```

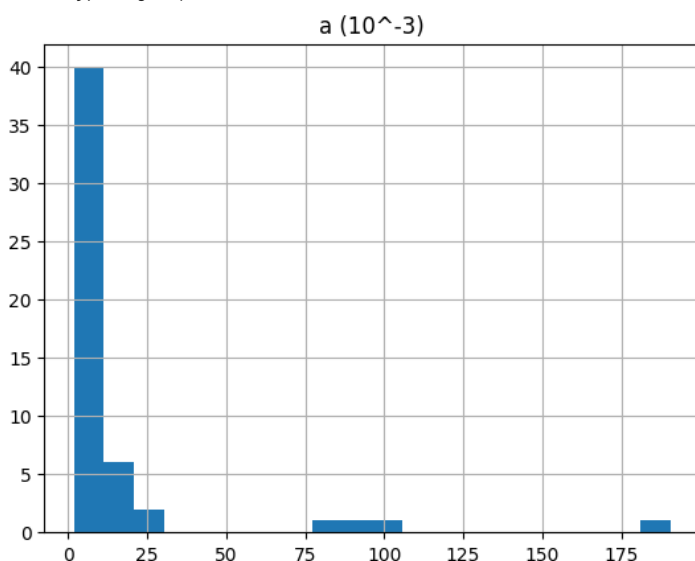
	State	a (10^-3)	b	fit rank
0	AK	2.593040	-75.366476	1.0
1	AL	12.121593	-111.222242	2.0
2	AR	2.941186	-75.356785	4.0
3	AS	NaN	NaN	NaN
4	AZ	4.984063	-90.295019	1.0

```
df_state_params.describe()
```

	a (10 <sup>-3</sup> )	b	fit rank
count	52.000000	52.000000	52.000000
mean	16.215254	-100.951881	1.769231
std	31.801661	25.545128	1.095720
min	1.952592	-185.986576	1.000000
25%	5.041013	-116.155268	1.000000
50%	7.113788	-99.476492	1.000000
75%	10.698133	-80.847333	2.000000
max	190.553218	-49.104858	5.000000

```
df_state_params.hist(column='a (10-3)', bins=20)
```

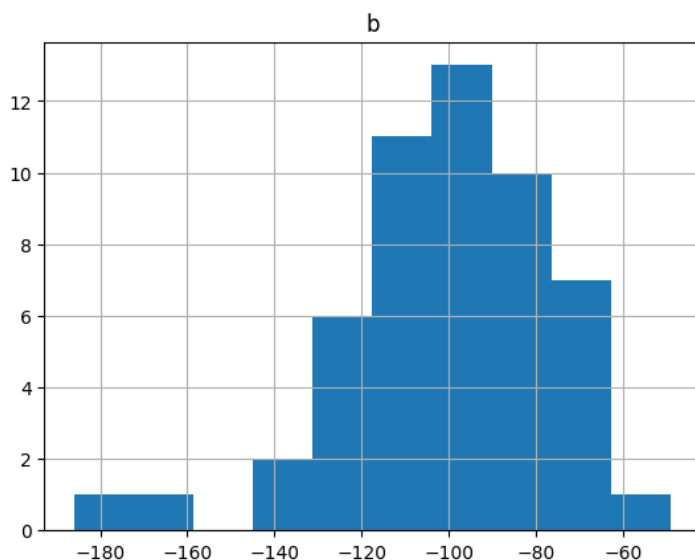
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7f7ce8cef748>]],
      dtype=object)
```



High value outliers here are NJ (fit rank 1), NY (fit rank 1), RI (fit rank 5), and SD (fit rank 4)

```
df_state_params.hist(column='b', bins=10)
```

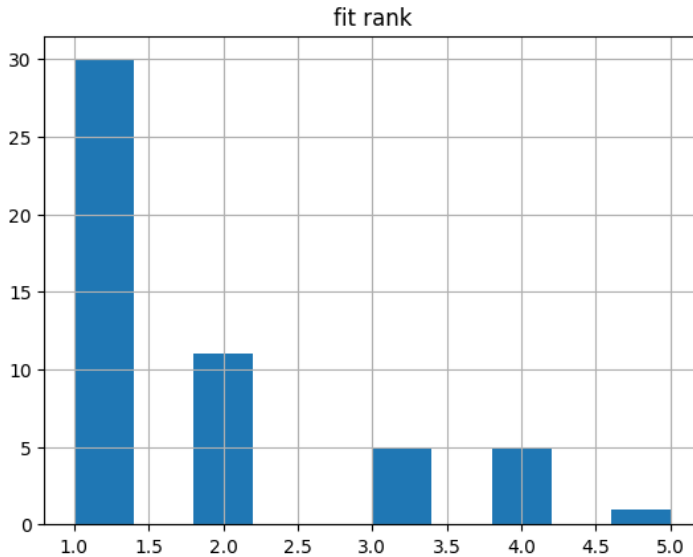
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7f7ce8ca6400>]],
      dtype=object)
```



Low value outliers here are RI (fit rank 5) and SD (fit rank 4).

```
df_state_params.hist(column='fit rank')
```

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7f7ce8bf2b70>]],
      dtype=object)
```



The  $A \cdot \exp(B/x)$  functional form works extremely well for thirty of the 52 states (57.7%).

```
# Fetch static data for each state (CovidCompleteStateData.csv)
from google.colab import files
uploaded = files.upload()
```

```
Choose Files CovidCompl...teData.csv
• CovidCompleteStateData.csv(application/vnd.ms-excel) - 60510 bytes, last modified: 4/20/2020 - 100% done
Saving CovidCompleteStateData.csv to CovidCompleteStateData.csv
```

```
# Load static data for each state (CovidCurrentStateData.csv)
import io
df_state_data = pd.read_csv(io.StringIO(uploaded['CovidCompleteStateData.csv'].decode('utf-8')))
df_state_data.head()
```

```
State      Sum of      Sum of      Sum of      Sum of      Sum of      Sum of      Sum of
NUM_Medicare_BEN  NUM_BEN_Age_Less_65  NUM_BEN_Age_65_to_74  NUM_BEN_Age_75_to_84  NUM_BEN_Age_Greater_84  NUM_Female_BEN  NUM_

0  AK      1820384.0      270970.0      809516.0      468255.0      175296.0      1034762.0
1  AL      10804823.0      2065353.0      4386595.0      2980828.0      1190504.0      6237445.0
2  AR      15892716.0      2818665.0      6370265.0      4555468.0      1848506.0      9275039.0
3  AS              NaN              NaN              NaN              NaN              NaN              NaN
4  AZ      10786064.0      886596.0      4861035.0      3377040.0      1294375.0      5944519.0

5 rows x 116 columns
```

```
# Feature Engineering
# Land Area/Water Area
df_state_data['State Area Ratio'] = df_state_data['Land Area']/df_state_data['Water Area']
df_state_data['State Area Ratio'] = df_state_data['Land Area'].divide(df_state_data['Water Area'], fill_value=0)

# Elevation Ratio = Highest Elevation/Mean Elevation
df_state_data['Elevation Ratio'] = df_state_data['Highest Elevation']/df_state_data['Mean Elevation']
df_state_data['Elevation Ratio'] = df_state_data['Highest Elevation'].divide(df_state_data['Mean Elevation'], fill_v.

# Capital Area Ratio = Capital Land Area/Capital Water Area
df_state_data['Capital Area Ratio'] = df_state_data['Capital Land Area']/df_state_data['Capital Water Area']
df_state_data['Capital Land Area'] = df_state_data['Capital Land Area'].astype(float)
df_state_data['Capital Area Ratio'] = df_state_data['Capital Land Area'].divide(df_state_data['Capital Water Area'],

# Boundaries = Number of boarding states + On Coast + Borders Another Country
df_state_data['Boundaries'] = df_state_data['Number of bordering states'] + df_state_data['On Coast'] + df_state_dat.
```



```
# Latitude Difference to State Capital = Latitude - Capital Latitude
df_state_data['Latitude Difference to State Capital'] = df_state_data['Latitude'] - df_state_data['Capital Latitude']

# Longitude Difference to State Capital = Capital Longitude - Longitude
df_state_data['Longitude Difference to State Capital'] = df_state_data['Capital Longitude'] - df_state_data['Longitude']

# Latitude Difference to DC = Latitude - DC Latitude
df_state_data['Latitude Difference to DC'] = df_state_data['Latitude'] - 38.904722

# Longitude Difference to DC = DC Longitude - Longitude
df_state_data['Longitude Difference to DC'] = -77.016389 - df_state_data['Longitude']

# Latitude Difference to US Center = Latitude - Center Latitude
df_state_data['Latitude Difference to Center'] = df_state_data['Latitude'] - 39.833333

# Longitude Different to US Center = Center Longitude - Longitude
df_state_data['Longitude Difference to Center'] = -98.585522 - df_state_data['Longitude']
```

```
df_state_data.head()
```

↗

	State	Sum of NUM_Medicare_BEN	Sum of NUM_BEN_Age_Less_65	Sum of NUM_BEN_Age_65_to_74	Sum of NUM_BEN_Age_75_to_84	Sum of NUM_BEN_Age_Greater_84	Sum of NUM_Female_BEN	NUM_
0	AK	1820384.0	270970.0	809516.0	468255.0	175296.0	1034762.0	
1	AL	10804823.0	2065353.0	4386595.0	2980828.0	1190504.0	6237445.0	4
2	AR	15892716.0	2818665.0	6370265.0	4555468.0	1848506.0	9275039.0	6
3	AS	NaN	NaN	NaN	NaN	NaN	NaN	
4	AZ	10786064.0	886596.0	4861035.0	3377040.0	1294375.0	5944519.0	4

5 rows × 126 columns

```
df_state_data.shape
```

↗ (56, 126)

```
# Define variables for regression
df_temp1 = df_state_data.drop(df_state_data.index[[3, 12, 27, 42, 50]])
X = df_temp1.drop('State', axis = 1)
df_temp2 = df_state_params.drop(df_state_data.index[[3, 12, 27, 42, 50]])
y = df_temp2['b']
```

```
# Look at correlation coefficients
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', 1000)
X.corr()
```

↗

	Sum of NUM_Medicare_BEN	Sum of NUM_BEN_Age_Less_65	Sum of NUM_BEN_Age_65_to_74	Sum of NUM_BEN_Age_75_to_84	Sum of NUM_BEN_Age_85_to_94
Sum of NUM_Medicare_BEN	1.000000	0.981404	0.998624	0.998100	0.998100
Sum of NUM_BEN_Age_Less_65	0.981404	1.000000	0.978099	0.969440	0.969440
Sum of NUM_BEN_Age_65_to_74	0.998624	0.978099	1.000000	0.996374	0.996374
Sum of NUM_BEN_Age_75_to_84	0.998100	0.969440	0.996374	1.000000	1.000000
Sum of NUM_BEN_Age_Greater_84	0.989961	0.960650	0.982712	0.992601	0.992601
Sum of NUM_Female_BEN	0.999917	0.982576	0.998372	0.997916	0.997916
Sum of NUM_Male_BEN	0.999897	0.979741	0.998636	0.998296	0.998296
Sum of NUM_Black_or_African_American_BEN	0.896692	0.926091	0.895722	0.884218	0.884218
Sum of NUM_Asian_Pacific_Islander_BEN	0.525530	0.475021	0.517514	0.530001	0.530001
Sum of NUM_Hispanic_BEN	0.893302	0.827878	0.902298	0.899556	0.899556
Sum of NUM_American_IndianAlaska_Native_BEN	0.082561	0.059858	0.091513	0.086836	0.086836
Sum of NUM_BEN_With_Race_Not_Elsewhere_Classified	0.823477	0.774080	0.803783	0.832225	0.832225
Sum of NUM_Non-Hispanic_White_BEN	0.996838	0.978894	0.994391	0.996119	0.996119
Sum of NUM_Minorities	0.958442	0.925721	0.961095	0.957721	0.957721
Sum of Average_Age_of_BEN	0.682483	0.730359	0.686432	0.663590	0.663590
Sum of NUM_BEN_Atrial_Fibrillation	0.990425	0.969550	0.985604	0.991418	0.991418
Sum of NUM_BEN_Asthma	0.995532	0.979588	0.991583	0.992903	0.992903
Sum of NUM_BEN_Cancer	0.994765	0.972149	0.992903	0.994874	0.994874
Sum of NUM_BEN_Heart_Failure	0.997133	0.985150	0.995371	0.993915	0.993915
Sum of NUM_BEN_Chronic_Kidney_Disease	0.997501	0.980301	0.997095	0.995430	0.995430
Sum of NUM_BEN_Chronic_Obstructive_Pulmonary_Disease	0.986234	0.980624	0.981625	0.983999	0.983999
Sum of NUM_BEN_Hyperlipidemia	0.996237	0.974348	0.994742	0.996423	0.996423
Sum of NUM_BEN_Diabetes	0.997754	0.981227	0.996544	0.995687	0.995687
Sum of NUM_BEN_Hypertension	0.998856	0.982300	0.998079	0.996943	0.996943
Sum of NUM_BEN_Ischemic_Heart_Disease	0.994006	0.975145	0.991547	0.994105	0.994105
Sum of NUM_BEN_Stroke	0.990547	0.972081	0.988818	0.990024	0.990024
Sum of PCT_MEDICARE	0.713702	0.762102	0.716971	0.696228	0.696228
% Urban Pop	0.246412	0.181090	0.240984	0.259055	0.259055
Density (P/mi2)	-0.095479	-0.105571	-0.096280	-0.092015	-0.092015
Children 0-18	0.886252	0.846604	0.876226	0.888481	0.888481
Adults 19-25	0.865749	0.826231	0.852680	0.868860	0.868860
Adults 26-34	0.848661	0.804492	0.835397	0.852982	0.852982
Adults 35-54	0.861684	0.820010	0.848035	0.865769	0.865769
Adults 55-64	0.840536	0.802214	0.822003	0.845654	0.845654
65+	0.842520	0.796154	0.822919	0.852028	0.852028
Latitude	-0.400391	-0.397373	-0.403138	-0.407192	-0.407192
Longitude	0.046601	0.092974	0.034115	0.040031	0.040031
Land Area	0.229013	0.193883	0.242084	0.230058	0.230058
Water Area	0.042895	0.056385	0.036723	0.038782	0.038782
Mean Elevation	-0.163276	-0.224740	-0.147730	-0.155029	-0.155029
Highest Elevation	-0.059881	-0.137582	-0.040603	-0.049835	-0.049835
Lowest elevation	-0.354394	-0.352655	-0.344053	-0.355481	-0.355481
Number of bordering states	0.077790	0.135863	0.075964	0.059448	0.059448
On Coast	0.471024	0.505115	0.442960	0.461862	0.461862
Bordering Another Country	0.258442	0.242648	0.262860	0.258845	0.258845

<b>Borders Another Country</b>	0.358143	0.310618	0.363869	0.358815
<b>Capital Latitude</b>	-0.388663	-0.393979	-0.394070	-0.392266
<b>Capital Longitude</b>	0.027375	0.076949	0.015075	0.019608
<b>Capital Land Area</b>	0.008902	-0.002410	0.018688	0.009403
<b>Capital Water Area</b>	-0.087670	-0.096352	-0.083610	-0.087193
<b>Capital Mean Elevation</b>	-0.194009	-0.217624	-0.182931	-0.190725
<b>Capital is the Largest City</b>	-0.171080	-0.147972	-0.165860	-0.173283
<b>Largest City Latitude</b>	-0.421170	-0.421496	-0.425109	-0.424938
<b>Largest City Longitude</b>	0.057094	0.102104	0.044423	0.050338
<b>Number of Counties</b>	0.663716	0.710105	0.670375	0.645677
<b>Became a State</b>	-0.140415	-0.200801	-0.128869	-0.126557
<b>DaysSinceStayatHomeOrder</b>	-0.020651	-0.019693	-0.030343	-0.027347
<b>DaysSinceFirstPositive</b>	0.368252	0.319941	0.366229	0.374653
<b>DaysSinceTestStart</b>	0.290649	0.242592	0.289428	0.297948
<b>15-49yearsAllcauses</b>	0.888203	0.856564	0.874919	0.889982
<b>15-49yearsAsthma</b>	0.824682	0.787879	0.807656	0.827220
<b>15-49yearsChronickidneydisease</b>	0.918864	0.893772	0.909568	0.918825
<b>15-49yearsChronicobstructivepulmonarydisease</b>	0.896769	0.878089	0.880516	0.897303
<b>15-49yearsDiabetesmellitus</b>	0.912330	0.881654	0.900896	0.914260
<b>15-49yearsInterstitiallungdiseaseandpulmonarysarcoidosis</b>	0.881251	0.864222	0.866766	0.880121
<b>15-49yearsIschemicheartdisease</b>	0.928387	0.927789	0.916634	0.923405
<b>15-49yearsNeoplasms</b>	0.887461	0.860138	0.873067	0.888685
<b>15-49yearsOtherchronicrespiratorydiseases</b>	0.906636	0.885246	0.892415	0.906637
<b>15-49yearsRheumaticheartdisease</b>	0.903473	0.893269	0.893364	0.898792
<b>15-49yearsStroke</b>	0.919789	0.898558	0.910295	0.919449
<b>50-69yearsAllcauses</b>	0.880146	0.855617	0.863069	0.881923
<b>50-69yearsAsthma</b>	0.801803	0.765502	0.781306	0.805925
<b>50-69yearsChronickidneydisease</b>	0.917312	0.898401	0.905572	0.916416
<b>50-69yearsChronicobstructivepulmonarydisease</b>	0.879259	0.872843	0.860771	0.878641
<b>50-69yearsDiabetesmellitus</b>	0.882501	0.857522	0.865414	0.884673
<b>50-69yearsInterstitiallungdiseaseandpulmonarysarcoidosis</b>	0.863191	0.840683	0.846169	0.863950
<b>50-69yearsIschemicheartdisease</b>	0.905979	0.901073	0.890019	0.902683
<b>50-69yearsNeoplasms</b>	0.872500	0.853408	0.854035	0.873415
<b>50-69yearsOtherchronicrespiratorydiseases</b>	0.885021	0.875159	0.867604	0.883457
<b>50-69yearsRheumaticheartdisease</b>	0.892519	0.890373	0.880528	0.886667
<b>50-69yearsStroke</b>	0.907993	0.892290	0.895108	0.907388
<b>70+yearsAllcauses</b>	0.849263	0.819400	0.828488	0.854118
<b>70+yearsAsthma</b>	0.791486	0.748032	0.769602	0.799338
<b>70+yearsChronickidneydisease</b>	0.877077	0.858325	0.859219	0.877628
<b>70+yearsChronicobstructivepulmonarydisease</b>	0.866728	0.842585	0.846829	0.871197
<b>70+yearsDiabetesmellitus</b>	0.845276	0.815442	0.823824	0.850785
<b>70+yearsInterstitiallungdiseaseandpulmonarysarcoidosis</b>	0.833832	0.799993	0.814083	0.839080
<b>70+yearsIschemicheartdisease</b>	0.841243	0.819787	0.818295	0.844148
<b>70+yearsNeoplasms</b>	0.837485	0.808405	0.816021	0.842466
<b>70+yearsOtherchronicrespiratorydiseases</b>	0.875916	0.859545	0.858192	0.875620
<b>70+yearsRheumaticheartdisease</b>	0.844465	0.839621	0.826738	0.839480
<b>70+yearsStroke</b>	0.871562	0.849583	0.854254	0.873252

AllAgesAllcauses	0.880003	0.851293	0.863399	0.882592
AllAgesAsthma	0.833253	0.794917	0.815812	0.836910
AllAgesChronicKidneydisease	0.905462	0.885503	0.891504	0.905307
AllAgesChronicobstructivepulmonarydisease	0.877214	0.860833	0.858127	0.879265
AllAgesDiabetesmellitus	0.879728	0.852121	0.862209	0.882908
AllAgesInterstitiallungdiseaseandpulmonarysarcoidosis	0.853912	0.826093	0.835749	0.856759
AllAgesIschemicheartdisease	0.883535	0.870954	0.864460	0.883069
AllAgesNeoplasms	0.865325	0.841450	0.846325	0.867726
AllAgesOtherchronicrespiratorydiseases	0.903592	0.885967	0.888445	0.902970
AllAgesRheumaticheartdisease	0.880357	0.875286	0.866144	0.875089
AllAgesStroke	0.895398	0.875735	0.880674	0.895978
AllAgesTotal	0.880507	0.853923	0.863463	0.882813
Airpollution	0.889229	0.888442	0.875092	0.882964
Highbody-massindex	0.893797	0.872739	0.877133	0.894624
Highfastingplasmaglucoese	0.886795	0.870124	0.868909	0.887417
HighLDLcholesterol	0.893215	0.882483	0.875398	0.892023
Highsystolicbloodpressure	0.897453	0.882631	0.880346	0.897131
Impairedkidneyfunction	0.889934	0.872693	0.873173	0.890034
Noaccesstohandwashingfacility	0.877603	0.857781	0.862453	0.876519
Smoking	0.881579	0.866726	0.862831	0.882612
Log10Pop	0.728494	0.737902	0.714057	0.722320
DaysSinceInfection	0.422525	0.373010	0.419727	0.431233
Children0-18	0.167133	0.180823	0.181296	0.159580
Allriskfactors	0.882815	0.860944	0.865530	0.884217
State Area Ratio	-0.141342	-0.180449	-0.126323	-0.134563
Elevation Ratio	0.020332	0.007311	0.029598	0.023691
Capital Area Ratio	-0.119284	-0.151665	-0.109968	-0.112407
Boundaries	0.499356	0.556393	0.479330	0.477960
Latitude Difference to State Capital	-0.268652	-0.211068	-0.252026	-0.293417
Longitude Difference to State Capital	-0.143646	-0.133106	-0.139285	-0.150250
Latitude Difference to DC	-0.400391	-0.397373	-0.403138	-0.407192
Longitude Difference to DC	-0.046601	-0.092974	-0.034115	-0.040031
Latitude Difference to Center	-0.400391	-0.397373	-0.403138	-0.407192
Longitude Difference to Center	-0.046601	-0.092974	-0.034115	-0.040031

```
# Note that there are many highly correlated features which need to be dropped
# Create absolute value correlation matrix
corr_matrix = X.corr().abs()

# Select upper triangle of correlation matrix
upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(np.bool))

# Find index of feature columns with correlation greater than 0.95
to_drop = [column for column in upper.columns if any(upper[column] > 0.95)]

# Drop features by index which were identified as being highly correlated
X = X.drop(X[to_drop], axis=1)
```

```
X.head()
```



	Sum of NUM_Medicare_BEN	Sum of NUM_Black_or_African_American_BEN	Sum of NUM_Asian_Pacific_Islander_BEN	Sum of NUM_Hispanic_BEN	Sum of NUM_American_IndianAlaska_Native	!
0	1820384.0	62311.0	76773.0	46525.0		14
1	10804823.0	1549811.0	30624.0	65500.0		
2	15892716.0	1334245.0	19642.0	108428.0		6
4	10786064.0	221183.0	61840.0	689880.0		17
5	42579588.0	2072012.0	3276415.0	5674776.0		11

```
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 51 entries, 0 to 55
Data columns (total 38 columns):
#   Column                                     Non-Null Count  Dtype
---  -
0   Sum of NUM_Medicare_BEN                   51 non-null     float64
1   Sum of NUM_Black_or_African_American_BEN 51 non-null     float64
2   Sum of NUM_Asian_Pacific_Islander_BEN    51 non-null     float64
3   Sum of NUM_Hispanic_BEN                   51 non-null     float64
4   Sum of NUM_American_IndianAlaska_Native_BEN 51 non-null     float64
5   Sum of NUM_BEN_With_Race_Not_Elsewhere_Classified 51 non-null     float64
6   Sum of Average_Age_of_BEN                 51 non-null     float64
7   Sum of PCT_MEDICARE                       51 non-null     float64
8   % Urban Pop                               51 non-null     float64
9   Density (P/mi2)                           51 non-null     float64
10  Children 0-18                             51 non-null     float64
11  Latitude                                   51 non-null     float64
12  Longitude                                  51 non-null     float64
13  Land Area                                 51 non-null     float64
14  Water Area                               51 non-null     float64
15  Mean Elevation                           51 non-null     float64
16  Highest Elevation                        51 non-null     float64
17  Lowest elevation                         51 non-null     float64
18  Number of bordering states               51 non-null     float64
19  On Coast                                 51 non-null     float64
20  Borders Another Country                  51 non-null     float64
21  Captial Land Area                        51 non-null     float64
22  Capital Water Area                       51 non-null     float64
23  Capital Mean Elevation                   51 non-null     float64
24  Capital is the Largest City               51 non-null     float64
25  Became a State                           51 non-null     float64
26  DaysSinceStayatHomeOrder                 51 non-null     float64
27  DaysSinceFirstPositive                   51 non-null     float64
28  DaysSinceTestStart                       51 non-null     float64
29  Log10Pop                                 51 non-null     float64
30  DaysSinceInfection                       51 non-null     float64
31  Children0-18                             51 non-null     float64
32  State Area Ratio                         51 non-null     float64
33  Elevation Ratio                          51 non-null     float64
34  Capital Area Ratio                       51 non-null     float64
35  Boundaries                               51 non-null     float64
36  Latitude Difference to State Capital      51 non-null     float64
37  Longitude Difference to State Capital     51 non-null     float64
dtypes: float64(38)
memory usage: 15.5 KB
```

```
X.describe()
```

	Sum of NUM_Medicare_BEN	Sum of NUM_Black_or_African_American_BEN	Sum of NUM_Asian_Pacific_Islander_BEN	Sum of NUM_Hispanic_BEN	Sum of NUM_American_IndianAlaska_I
<b>count</b>	5.100000e+01	5.100000e+01	5.100000e+01	5.100000e+01	
<b>mean</b>	1.038431e+07	9.464777e+05	1.411691e+05	5.310095e+05	38
<b>std</b>	1.311026e+07	1.274593e+06	4.722330e+05	1.629961e+06	87
<b>min</b>	1.655870e+05	2.960000e+02	1.660000e+02	4.130000e+02	
<b>25%</b>	2.252305e+06	5.366600e+04	6.445500e+03	3.101950e+04	2
<b>50%</b>	6.272609e+06	3.156040e+05	2.579200e+04	1.042170e+05	7
<b>75%</b>	1.471830e+07	1.547566e+06	7.063400e+04	2.005865e+05	28
<b>max</b>	7.644909e+07	7.011107e+06	3.276415e+06	1.007620e+07	560

```
# Train/validate split: random 75/25% train/validate split.
from sklearn.model_selection import train_test_split

X_train, X_val, y_train, y_val = train_test_split(X, y, test_size = 0.25, random_state = 42)

X_train.shape, y_train.shape, X_val.shape, y_val.shape
```

```
((38, 38), (38,), (13, 38), (13,))
```

```
X_train.describe()
```

	Sum of NUM_Medicare_BEN	Sum of NUM_Black_or_African_American_BEN	Sum of NUM_Asian_Pacific_Islander_BEN	Sum of NUM_Hispanic_BEN	Sum of NUM_American_IndianAlaska_I
<b>count</b>	3.800000e+01	3.800000e+01	3.800000e+01	3.800000e+01	
<b>mean</b>	1.014125e+07	9.685705e+05	1.623107e+05	3.942231e+05	37
<b>std</b>	9.963253e+06	1.001560e+06	5.333709e+05	1.021129e+06	93
<b>min</b>	3.472690e+05	2.689000e+03	4.580000e+02	2.622000e+03	
<b>25%</b>	2.518838e+06	4.934350e+04	1.427175e+04	3.676725e+04	4
<b>50%</b>	7.473651e+06	5.120990e+05	3.068000e+04	1.071920e+05	9
<b>75%</b>	1.563758e+07	1.560497e+06	9.455175e+04	1.983508e+05	27
<b>max</b>	4.257959e+07	3.265865e+06	3.276415e+06	5.674776e+06	560

```
# Optimizing Hyperparameters
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestRegressor

# Define classifier
forest = RandomForestRegressor(random_state = 1)

# Parameters to fit

max_depth = [0.95, 1.0, 1.05]
n_estimators = [16, 18, 20]
min_samples_split = [1.5, 2, 2.5]
min_samples_leaf = [3.5, 4, 4.5]
max_leaf_nodes = [None]
max_features = ['auto']
ccp_alpha = [0.0, 0.05, 0.1]
min_weight_fraction_leaf = [0.0, 0.05, 0.1]

hyperF = dict(n_estimators = n_estimators, max_depth = max_depth,
              min_samples_split = min_samples_split,
              min_samples_leaf = min_samples_leaf,
              max_leaf_nodes = max_leaf_nodes,
              max_features = max_features,
              ccp_alpha=ccp_alpha,
              min_weight_fraction_leaf=min_weight_fraction_leaf)
```

```

gridF = GridSearchCV(forest, hyperF, cv = 3, verbose = 10,
                    scoring='r2', return_train_score=True,
                    n_jobs = -1)
bestF = gridF.fit(X_train, y_train)

# Output best accuracy and best parameters
print('The score achieved with the best parameters = ', gridF.best_score_, '\n')
print('The parameters are:', gridF.best_params_)

```

```

Fitting 3 folds for each of 729 candidates, totalling 2187 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done 1 tasks      | elapsed: 1.3s
[Parallel(n_jobs=-1)]: Done 4 tasks      | elapsed: 1.4s
[Parallel(n_jobs=-1)]: Done 9 tasks      | elapsed: 1.5s
[Parallel(n_jobs=-1)]: Done 14 tasks     | elapsed: 1.5s
[Parallel(n_jobs=-1)]: Batch computation too fast (0.1900s.) Setting batch_size=2.
[Parallel(n_jobs=-1)]: Batch computation too fast (0.0551s.) Setting batch_size=4.
[Parallel(n_jobs=-1)]: Done 24 tasks     | elapsed: 1.6s
[Parallel(n_jobs=-1)]: Batch computation too fast (0.1051s.) Setting batch_size=8.
[Parallel(n_jobs=-1)]: Done 58 tasks     | elapsed: 2.0s
[Parallel(n_jobs=-1)]: Done 130 tasks    | elapsed: 3.1s
[Parallel(n_jobs=-1)]: Done 202 tasks    | elapsed: 3.9s
[Parallel(n_jobs=-1)]: Done 290 tasks    | elapsed: 4.7s
[Parallel(n_jobs=-1)]: Done 378 tasks    | elapsed: 5.9s
[Parallel(n_jobs=-1)]: Done 482 tasks    | elapsed: 7.0s
[Parallel(n_jobs=-1)]: Done 586 tasks    | elapsed: 8.1s
[Parallel(n_jobs=-1)]: Done 706 tasks    | elapsed: 9.6s
[Parallel(n_jobs=-1)]: Done 826 tasks    | elapsed: 10.8s
[Parallel(n_jobs=-1)]: Done 962 tasks    | elapsed: 12.5s
[Parallel(n_jobs=-1)]: Done 1098 tasks   | elapsed: 14.1s
[Parallel(n_jobs=-1)]: Done 1250 tasks   | elapsed: 15.6s
[Parallel(n_jobs=-1)]: Done 1402 tasks   | elapsed: 17.5s
[Parallel(n_jobs=-1)]: Done 1570 tasks   | elapsed: 19.3s
[Parallel(n_jobs=-1)]: Done 1738 tasks   | elapsed: 21.2s
[Parallel(n_jobs=-1)]: Done 1922 tasks   | elapsed: 23.4s
[Parallel(n_jobs=-1)]: Done 2106 tasks   | elapsed: 25.5s
The score achieved with the best parameters = 0.02626955110073052

The parameters are: {'ccp_alpha': 0.0, 'max_depth': 1.0, 'max_features': 'auto', 'max_leaf_nodes': None, 'min_samples_leaf': 4, 'min_samp
[Parallel(n_jobs=-1)]: Done 2187 out of 2187 | elapsed: 26.3s finished

```

```
!pip install category_encoders==2.0.0
```

```

Collecting category_encoders==2.0.0
  Downloading https://files.pythonhosted.org/packages/6e/a1/f7a22f144f33be78afeb06bfa78478e8284a64263a3c09b1ef54e673841e/category\_encoder-2.0.0-py3-none-any.whl (92kB)
    92kB 5.3MB/s
Requirement already satisfied: numpy>=1.11.3 in /usr/local/lib/python3.6/dist-packages (from category_encoders==2.0.0) (1.18.3)
Requirement already satisfied: scipy>=0.19.0 in /usr/local/lib/python3.6/dist-packages (from category_encoders==2.0.0) (1.4.1)
Requirement already satisfied: scikit-learn>=0.20.0 in /usr/local/lib/python3.6/dist-packages (from category_encoders==2.0.0) (0.22.2.post1)
Requirement already satisfied: patsy>=0.4.1 in /usr/local/lib/python3.6/dist-packages (from category_encoders==2.0.0) (0.5.1)
Requirement already satisfied: statsmodels>=0.6.1 in /usr/local/lib/python3.6/dist-packages (from category_encoders==2.0.0) (0.10.2)
Requirement already satisfied: pandas>=0.21.1 in /usr/local/lib/python3.6/dist-packages (from category_encoders==2.0.0) (1.0.3)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.6/dist-packages (from scikit-learn>=0.20.0->category_encoders==2.0.0) (0.12.0)
Requirement already satisfied: six in /usr/local/lib/python3.6/dist-packages (from patsy>=0.4.1->category_encoders==2.0.0) (1.12.0)
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.6/dist-packages (from pandas>=0.21.1->category_encoders==2.0.0) (2017.2)
Requirement already satisfied: python-dateutil>=2.6.1 in /usr/local/lib/python3.6/dist-packages (from pandas>=0.21.1->category_encoders==2.0.0) (2.6.1)
Installing collected packages: category-encoders
Successfully installed category-encoders-2.0.0

```

```

from sklearn.ensemble import RandomForestRegressor
from sklearn.pipeline import make_pipeline
import category_encoders as ce
from sklearn.impute import SimpleImputer

pipeline1 = make_pipeline(
    ce.OneHotEncoder(use_cat_names=True),
    SimpleImputer(strategy='mean'),
    RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                        max_depth=1, max_features='auto', max_leaf_nodes=None,
                        max_samples=None, min_impurity_decrease=0.0,
                        min_impurity_split=None, min_samples_leaf=4,
                        min_samples_split=2, min_weight_fraction_leaf=0.0,
                        n_estimators=18, n_jobs=None, oob_score=False,
                        random_state=0, verbose=0, warm_start=False))

pipeline1.fit(X_train, y_train)

# Get the model's training accuracy

```

```
print("Training Accuracy: R^2 = ", pipeline1.score(X_train,y_train))
```

```
# Get the model's validation accuracy
```

```
print('Validation Accuracy: R^2 = ', pipeline1.score(X_val, y_val))
```

```
☞ Training Accuracy: R^2 = 0.38074038406249433
   Validation Accuracy: R^2 = -0.18421766224718805
```

```
print("Feature Importances =")
```

```
#print(RandomForestRegressor.feature_importances_)
```

```
print(pipeline1.steps[2][1].feature_importances_)
```

```
☞ Feature Importances =
[0. 0. 0. 0. 0.11111111 0.
 0. 0. 0. 0.11111111 0.05555556 0.16666667
 0.16666667 0. 0.05555556 0.05555556 0.05555556 0.
 0. 0. 0. 0.11111111 0. 0.
 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0.
 0.05555556 0.05555556]
```

```
# Plot of feature importances from pure Random Forest Regressor
```

```
%matplotlib inline
```

```
import matplotlib.pyplot as plt
```

```
# Get feature importances
```

```
encoder = pipeline1.named_steps['onehotencoder']
```

```
encoded = encoder.transform(X_train)
```

```
rf = pipeline1.named_steps['randomforestregressor']
```

```
importances1 = pd.Series(rf.feature_importances_, encoded.columns)
```

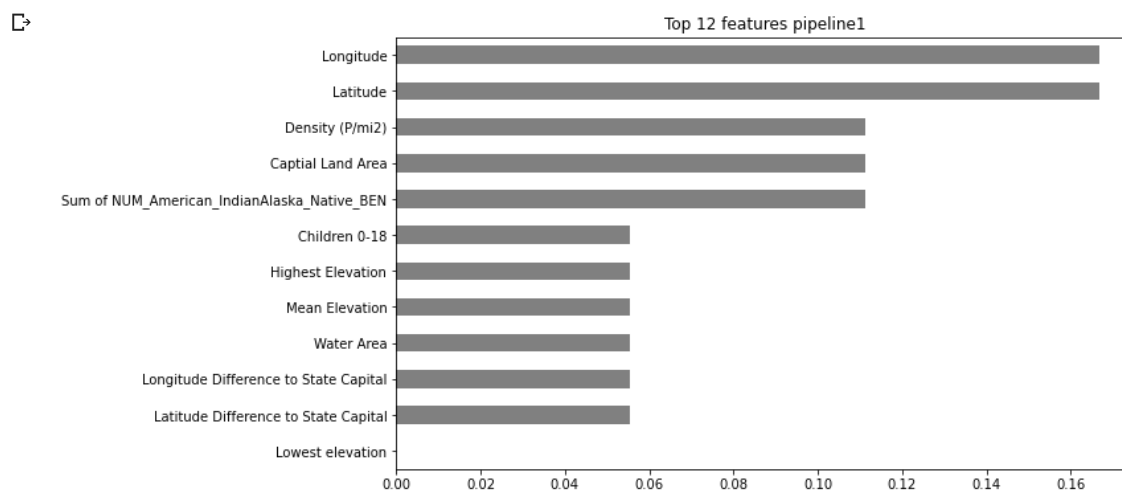
```
# Plot feature importances
```

```
n = 12
```

```
plt.figure(figsize=(10,n/2))
```

```
plt.title(f'Top {n} features pipeline1')
```

```
importances1.sort_values()[-n:].plot.barh(color='grey');
```



```
# Generate validation curves
```

```
%matplotlib inline
```

```
import numpy as np
```

```
import matplotlib.pyplot as plt
```

```
from sklearn.model_selection import validation_curve
```

```
pipeline2 = make_pipeline(
```

```
    ce.OrdinalEncoder(),
```

```
    SimpleImputer(),
```

```
    RandomForestRegressor()
```

```
)
```

```
depth = range(1, 10, 2)
```

```
train_scores, val_scores = validation_curve(
```

```
    pipeline2, X_train, y_train,
```

```
    param_name='randomforestregressor__max_depth',
```

```
    param_range=depth,
```

```
    cv=3,
```

```
    n_jobs=-1
```

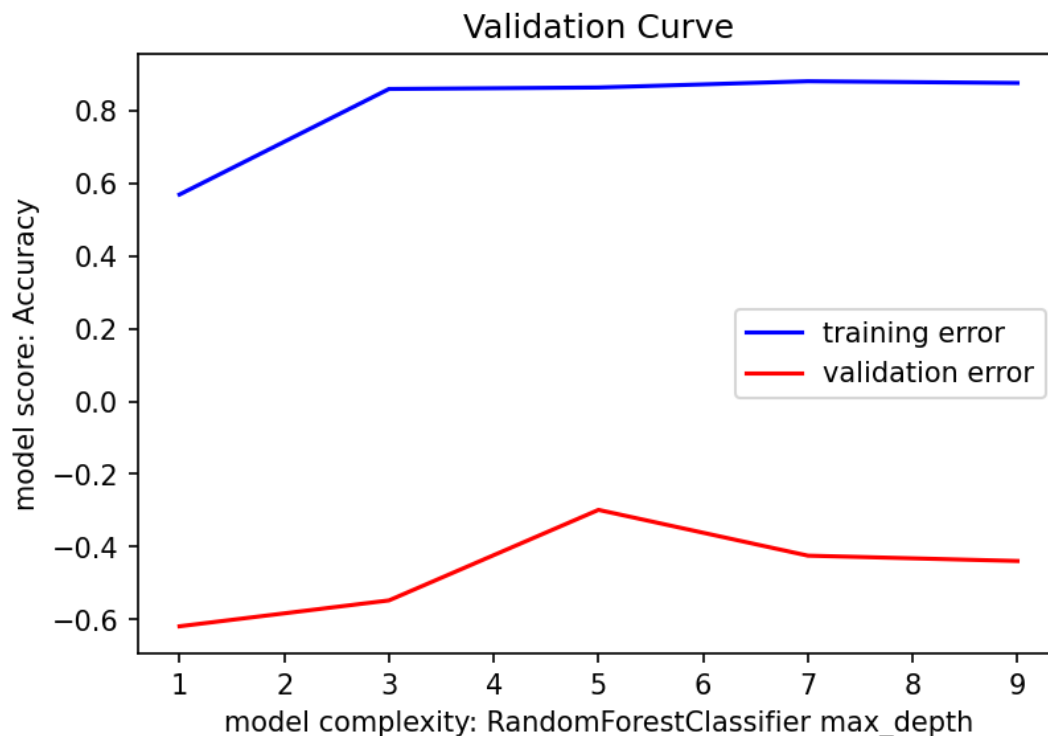
```
)
```

```
plt.figure(dpi=150)
```

```
plt.plot(depth, np.mean(train_scores, axis=1), color='blue', label='training error')
```



```
plt.plot(depth, np.mean(val_scores, axis=1), color='red', label='validation error')
plt.title('Validation Curve')
plt.xlabel('model complexity: RandomForestClassifier max_depth')
plt.ylabel('model score: Accuracy')
plt.legend();
```



```
# Get drop-column importances
column = 'Latitude'

pipeline3 = make_pipeline(
    ce.OneHotEncoder(use_cat_names=True),
    SimpleImputer(strategy = 'most_frequent'),
    RandomForestRegressor(bootstrap=True, ccp_alpha=0, criterion='mse',
        max_depth=1, max_features='auto', max_leaf_nodes=None,
        max_samples=None, min_impurity_decrease=0.0,
        min_impurity_split=None, min_samples_leaf=4,
        min_samples_split=2, min_weight_fraction_leaf=0,
        n_estimators=18, n_jobs=None, oob_score=False,
        random_state=0, verbose=0, warm_start=False))

# Fit without column
pipeline3.fit(X_train.drop(columns=column), y_train)
score_without = pipeline3.score(X_val.drop(columns=column), y_val)
print(f'Validation Accuracy without {column}: {score_without}')

# Fit with column
pipeline3.fit(X_train, y_train)
score_with = pipeline3.score(X_val, y_val)
print(f'Validation Accuracy with {column}: {score_with}')

# Compare the error with & without column
print(f'Drop-Column Importance for {column}: {score_with - score_without}')
```



```
Validation Accuracy without Latitude: -0.3777862174242266
Validation Accuracy with Latitude: -0.18421766224718805
Drop-Column Importance for Latitude: 0.19356855517703853
```

```
# Using Eli5 library which does not work with pipelines
transformers = make_pipeline(
    ce.OneHotEncoder(use_cat_names=True),
    SimpleImputer(strategy='most_frequent')
)

X_train_transformed = transformers.fit_transform(X_train)
X_val_transformed = transformers.transform(X_val)
```

```

model1 = RandomForestRegressor(bootstrap=True, ccp_alpha=0, criterion='mse',
                                max_depth=1, max_features='auto', max_leaf_nodes=None,
                                max_samples=None, min_impurity_decrease=0.0,
                                min_impurity_split=None, min_samples_leaf=4,
                                min_samples_split=2, min_weight_fraction_leaf=0,
                                n_estimators=18, n_jobs=None, oob_score=False,
                                random_state=0, verbose=0, warm_start=False)

model1.fit(X_train_transformed, y_train)

```

```

↳ RandomForestRegressor(bootstrap=True, ccp_alpha=0, criterion='mse', max_depth=1,
    max_features='auto', max_leaf_nodes=None,
    max_samples=None, min_impurity_decrease=0.0,
    min_impurity_split=None, min_samples_leaf=4,
    min_samples_split=2, min_weight_fraction_leaf=0,
    n_estimators=18, n_jobs=None, oob_score=False,
    random_state=0, verbose=0, warm_start=False)

```

```

# Get permutation importances
! pip install eli5
from eli5.sklearn import PermutationImportance
import eli5

permuter = PermutationImportance(
    model1,
    scoring='r2',
    n_iter=2,
    random_state=42
)

permuter.fit(X_val_transformed, y_val)
feature_names = X_val.columns.tolist()

eli5.show_weights(
    permuter,
    top=None, # show permutation importances for all features
    feature_names=feature_names
)

```

```

↳

```

Collecting eli5

Downloading <https://files.pythonhosted.org/packages/97/2f/c85c7d8f8548e460829971785347e14e45fa5c6617da374711dec8cb38cc/eli5-0.10.1-py2.7.tar.gz>

112kB 8.4MB/s

Requirement already satisfied: six in /usr/local/lib/python3.6/dist-packages (from eli5) (1.12.0)

Requirement already satisfied: attrs&gt;16.0.0 in /usr/local/lib/python3.6/dist-packages (from eli5) (19.3.0)

Requirement already satisfied: numpy&gt;=1.9.0 in /usr/local/lib/python3.6/dist-packages (from eli5) (1.18.3)

Requirement already satisfied: Jinja2 in /usr/local/lib/python3.6/dist-packages (from eli5) (2.11.2)

Requirement already satisfied: scikit-learn&gt;=0.18 in /usr/local/lib/python3.6/dist-packages (from eli5) (0.22.2.post1)

Requirement already satisfied: tabulate&gt;=0.7.7 in /usr/local/lib/python3.6/dist-packages (from eli5) (0.8.7)

Requirement already satisfied: scipy in /usr/local/lib/python3.6/dist-packages (from eli5) (1.4.1)

Requirement already satisfied: graphviz in /usr/local/lib/python3.6/dist-packages (from eli5) (0.10.1)

Requirement already satisfied: MarkupSafe&gt;=0.23 in /usr/local/lib/python3.6/dist-packages (from Jinja2-&gt;eli5) (1.1.1)

Requirement already satisfied: joblib&gt;=0.11 in /usr/local/lib/python3.6/dist-packages (from scikit-learn&gt;=0.18-&gt;eli5) (0.14.1)

Installing collected packages: eli5

Successfully installed eli5-0.10.1

/usr/local/lib/python3.6/dist-packages/sklearn/utils/deprecation.py:144: FutureWarning: The sklearn.metrics.scorer module is deprecated  
warnings.warn(message, FutureWarning)/usr/local/lib/python3.6/dist-packages/sklearn/utils/deprecation.py:144: FutureWarning: The sklearn.feature\_selection.base module is deprecated  
warnings.warn(message, FutureWarning)

Using TensorFlow backend.

Weight	Feature
0.1227 ± 0.0096	Latitude
0.0115 ± 0.0067	Water Area
0 ± 0.0000	Number of bordering states
0 ± 0.0000	Capital Water Area
0 ± 0.0000	Sum of NUM_Black_or_African_American_BEN
0 ± 0.0000	Sum of NUM_Asian_Pacific_Islander_BEN
0 ± 0.0000	Sum of NUM_Hispanic_BEN
0 ± 0.0000	Sum of NUM_BEN_With_Race_Not_Elsewhere_Classified
0 ± 0.0000	Sum of Average_Age_of_BEN
0 ± 0.0000	Sum of PCT_MEDICARE
0 ± 0.0000	% Urban Pop
0 ± 0.0000	Land Area
0 ± 0.0000	Lowest elevation
0 ± 0.0000	On Coast
0 ± 0.0000	Borders Another Country
0 ± 0.0000	Sum of NUM_Medicare_BEN
0 ± 0.0000	Boundaries
0 ± 0.0000	Capital Area Ratio
0 ± 0.0000	State Area Ratio
0 ± 0.0000	Children0-18
0 ± 0.0000	DaysSinceInfection
0 ± 0.0000	Log10Pop
0 ± 0.0000	Capital Mean Elevation
0 ± 0.0000	DaysSinceTestStart
0 ± 0.0000	Elevation Ratio
0 ± 0.0000	DaysSinceFirstPositive
0 ± 0.0000	DaysSinceStayatHomeOrder
0 ± 0.0000	Became a State
0 ± 0.0000	Capital is the Largest City
-0.0131 ± 0.0342	Children 0-18
-0.0139 ± 0.0013	Highest Elevation
-0.0252 ± 0.2914	Sum of NUM_American_IndianAlaska_Native_BEN
-0.0280 ± 0.0435	Mean Elevation
-0.0301 ± 0.0306	Density (P/mi2)
-0.0301 ± 0.0403	Latitude Difference to State Capital
-0.0384 ± 0.0006	Longitude Difference to State Capital
-0.1409 ± 0.0783	Longitude
-0.1920 ± 0.0820	Capital Land Area

```
from sklearn.metrics import mean_squared_error, r2_score
```

```
# Coefficient of determination r2 for the training set
pipeline_score = permutter.score(X_train_transformed,y_train)
print("Coefficient of determination r2 for the training set.: ", pipeline_score)
```

```
# Coefficient of determination r2 for the validation set
pipeline_score = permutter.score(X_val_transformed,y_val)
print("Coefficient of determination r2 for the validation set.: ", pipeline_score)
```

```
# The mean squared error
y_pred = permutter.predict(X_val_transformed)
print("Mean squared error: %.2f"% mean_squared_error(y_val, y_pred))
```

```
☐ Coefficient of determination r2 for the training set.: 0.38074038406249433
Coefficient of determination r2 for the validation set.: -0.18421766224718805
Mean squared error: 304.83
```

```
# Thus, Sum of NUM_American_IndianAlaska_Native_BEN is way more important according to feature permutation than acco
# Use importances for feature selection
print('Shape before removing features:', X_train.shape)
```

```
print('Shape before removing features:', X_train.shape)
```

```
↳ Shape before removing features: (38, 38)
```

```
# Remove features of 0 importance
zero_importance = 0.0
mask = permuted.feature_importances_ > zero_importance
features1 = X_train.columns[mask]
X_train = X_train[features1]
print('Shape after removing features:', X_train.shape)
```

```
↳ Shape after removing features: (38, 2)
```

```
# Random forest classifier with two features
X_val = X_val[features1]
pipeline4 = make_pipeline(
    ce.OneHotEncoder(use_cat_names=True),
    SimpleImputer(strategy='most_frequent'),
    RandomForestRegressor(bootstrap=True, ccp_alpha=0,
                        max_depth=1, max_features='auto', max_leaf_nodes=None,
                        max_samples=None, min_impurity_decrease=0.0,
                        min_impurity_split=None, min_samples_leaf=4,
                        min_samples_split=2, min_weight_fraction_leaf=0,
                        n_estimators=18, n_jobs=None, oob_score=False,
                        random_state=0, verbose=0, warm_start=False)
)

# Fit on train, score on val
pipeline4.fit(X_train, y_train);
```

```
from sklearn.metrics import mean_squared_error, r2_score

# Coefficient of determination r2 for the training set
pipeline_score = pipeline4.score(X_train, y_train)
print("Coefficient of determination r2 for the training set.: ", pipeline_score)

# Coefficient of determination r2 for the validation set
pipeline_score = pipeline4.score(X_val, y_val)
print("Coefficient of determination r2 for the validation set.: ", pipeline_score)

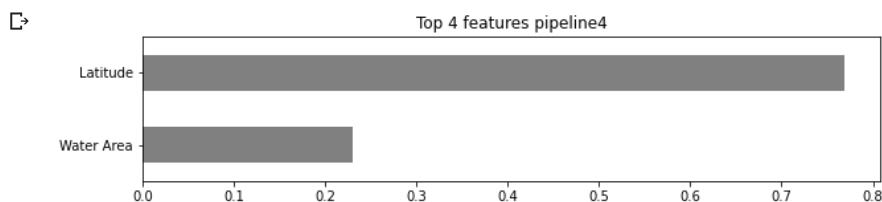
# The mean squared error
y_pred = pipeline4.predict(X_val)
print("Mean squared error: %.2f" % mean_squared_error(y_val, y_pred))
```

```
↳ Coefficient of determination r2 for the training set.: 0.27110557327427665
Coefficient of determination r2 for the validation set.: 0.1883085673181527
Mean squared error: 208.94
```

```
pipeline4.fit(X_val, y_val)
# Plot of features
%matplotlib inline
import matplotlib.pyplot as plt

# Get feature importances
encoder = pipeline4.named_steps['onehotencoder']
encoded = encoder.transform(X_val)
rf = pipeline4.named_steps['randomforestregressor']
importances2 = pd.Series(rf.feature_importances_, encoded.columns)

# Plot feature importances
n = 4
plt.figure(figsize=(10, n/2))
plt.title(f'Top {n} features pipeline4')
importances2.sort_values()[-n:].plot.barh(color='grey');
```



```
!pip install pdpbox
```

```
model2 = RandomForestRegressor(bootstrap=True, ccp_alpha=0,
                               max_depth=1, max_features='auto', max_leaf_nodes=None,
                               max_samples=None, min_impurity_decrease=0.0,
                               min_impurity_split=None, min_samples_leaf=4,
                               min_samples_split=2, min_weight_fraction_leaf=0,
                               n_estimators=18, n_jobs=None, oob_score=False,
                               random_state=0, verbose=0, warm_start=False)

model2.fit(X_train, y_train)
```

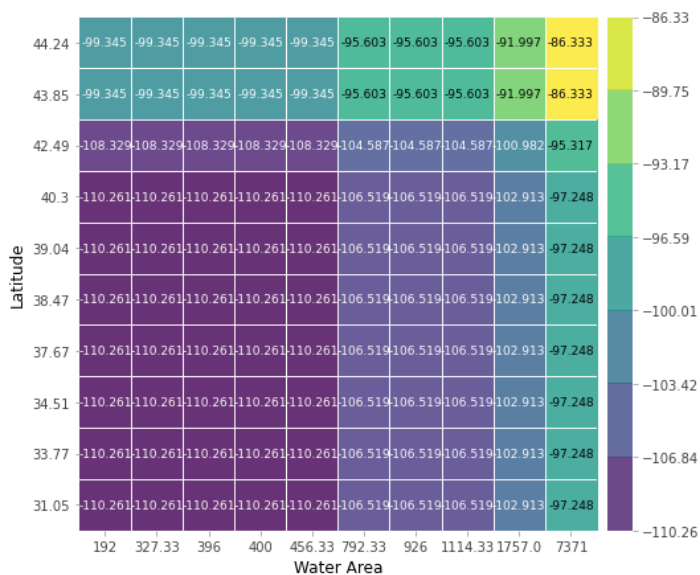
```
# Partial Dependence Plots with 2 features
from pdpbox.pdp import pdp_interact, pdp_interact_plot
features2 = ['Water Area', 'Latitude']
interaction = pdp_interact(
    #
    model=gb,
    model=model2,
    dataset=X_val,
    model_features=X_val.columns,
    features=features2
)
pdp_interact_plot(interaction, plot_type='grid', feature_names=features2);
```

→

findfont: Font family ['Arial'] not found. Falling back to DejaVu Sans.  
 findfont: Font family ['Arial'] not found. Falling back to DejaVu Sans.  
 findfont: Font family ['Arial'] not found. Falling back to DejaVu Sans.  
 findfont: Font family ['Arial'] not found. Falling back to DejaVu Sans.

### PDP interact for "Water Area" and "Latitude"

Number of unique grid points: (Water Area: 10, Latitude: 10)



```
# A two feature partical dependence plot in 3D
pdp = interaction.pdp.pivot_table(
    values='preds',
    columns=features2[0],
    index=features2[1]
)[::-1] # Slice notation to reverse index order so y axis is ascending

import plotly.graph_objs as go

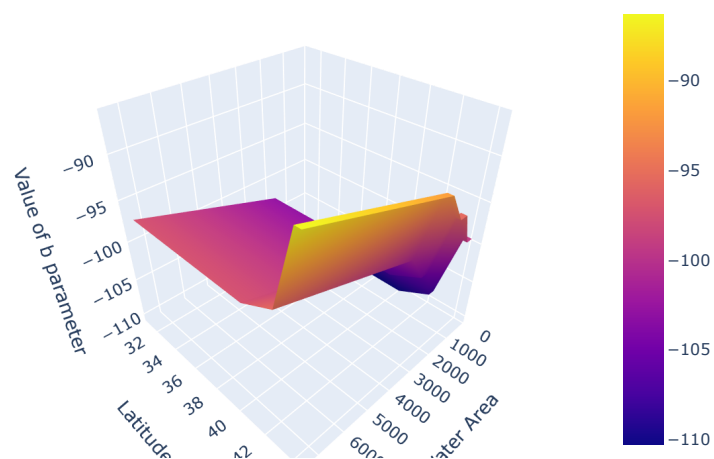
target = 'Value of b parameter'

surface = go.Surface(x=pdp.columns,
                    y=pdp.index,
                    z=pdp.values)

layout = go.Layout(
    scene=dict(
        xaxis=dict(title=features2[0]),
        yaxis=dict(title=features2[1]),
        zaxis=dict(title=target)
    )
)

fig = go.Figure(surface, layout)
fig.show()
```





```
! pip install shap==0.23.0
! pip install -I shap
```

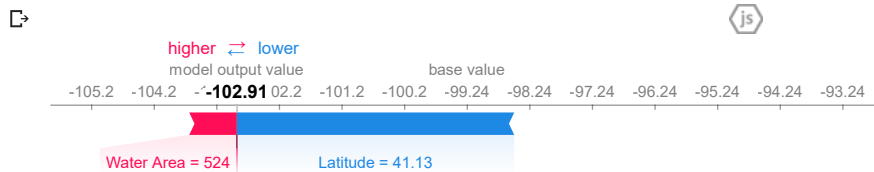


```
Collecting shap==0.23.0
  Downloading https://files.pythonhosted.org/packages/60/0d/8bd076821f7230edb2892ad982ea91ca25f2f925466563272e61eae891c6/shap-0.23.0.tar.gz
    184kB 8.7MB/s
Requirement already satisfied: numpy in /usr/local/lib/python3.6/dist-packages (from shap==0.23.0) (1.18.3)
Requirement already satisfied: scipy in /usr/local/lib/python3.6/dist-packages (from shap==0.23.0) (1.4.1)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.6/dist-packages (from shap==0.23.0) (0.22.2.post1)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.6/dist-packages (from shap==0.23.0) (3.2.1)
Requirement already satisfied: pandas in /usr/local/lib/python3.6/dist-packages (from shap==0.23.0) (1.0.3)
Requirement already satisfied: tqdm in /usr/local/lib/python3.6/dist-packages (from shap==0.23.0) (4.38.0)
Requirement already satisfied: ipython in /usr/local/lib/python3.6/dist-packages (from shap==0.23.0) (5.5.0)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.6/dist-packages (from shap==0.23.0) (0.14.1)
Requirement already satisfied: parsim==2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr/local/lib/python3.6/dist-packages (from matplotlib->shap==0.23.0) (2.0.4)
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.6/dist-packages (from matplotlib->shap==0.23.0) (2.8.1)
Requirement already satisfied: cyclus>=0.10 in /usr/local/lib/python3.6/dist-packages (from matplotlib->shap==0.23.0) (0.10.0)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.6/dist-packages (from matplotlib->shap==0.23.0) (1.2.0)
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.6/dist-packages (from pandas->shap==0.23.0) (2018.9)
Requirement already satisfied: decorator in /usr/local/lib/python3.6/dist-packages (from ipython->shap==0.23.0) (4.4.2)
Requirement already satisfied: pickleshare in /usr/local/lib/python3.6/dist-packages (from ipython->shap==0.23.0) (0.7.5)
Requirement already satisfied: simplegeneric>0.8 in /usr/local/lib/python3.6/dist-packages (from ipython->shap==0.23.0) (0.8.1)
Requirement already satisfied: setuptools>=18.5 in /usr/local/lib/python3.6/dist-packages (from ipython->shap==0.23.0) (46.1.3)
Requirement already satisfied: prompt-toolkit<2.0.0,>=1.0.4 in /usr/local/lib/python3.6/dist-packages (from ipython->shap==0.23.0) (1.0.1)
Requirement already satisfied: traitlets>=4.2 in /usr/local/lib/python3.6/dist-packages (from ipython->shap==0.23.0) (4.3.3)
Requirement already satisfied: pexpect; sys_platform != "win32" in /usr/local/lib/python3.6/dist-packages (from ipython->shap==0.23.0) (4.0.1)
Requirement already satisfied: pygments in /usr/local/lib/python3.6/dist-packages (from ipython->shap==0.23.0) (2.1.1)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.6/dist-packages (from python-dateutil>=2.1->matplotlib->shap==0.23.0) (1.12.0)
Requirement already satisfied: wcwidth in /usr/local/lib/python3.6/dist-packages (from prompt-toolkit<2.0.0,>=1.0.4->ipython->shap==0.23.0) (0.1.9)
Requirement already satisfied: ipython-genutils in /usr/local/lib/python3.6/dist-packages (from traitlets>=4.2->ipython->shap==0.23.0) (0.2.0)
Requirement already satisfied: ptyprocess>=0.5 in /usr/local/lib/python3.6/dist-packages (from pexpect; sys_platform != "win32"->ipython->shap==0.23.0) (0.6.0)
Building wheels for collected packages: shap
  Building wheel for shap (setup.py) ... done
  Created wheel for shap: filename=shap-0.23.0-cp36-cp36m-linux_x86_64.whl size=235673 sha256=d7b19f033dda0f93a8e92001ec7f7969c37a80aa117
  Stored in directory: /root/.cache/pip/wheels/c1/2c/aa/10d1782fe066536fcd564a2f8adea4dd05f57768236038855b
Successfully built shap
Installing collected packages: shap
Successfully installed shap-0.23.0
Collecting shap
  Downloading https://files.pythonhosted.org/packages/a8/77/b504e43e21a2ba543a1ac4696718beb500cfa708af2fb57cb54ce299045c/shap-0.35.0.tar.gz
    276kB 9.6MB/s
Collecting numpy
  Downloading https://files.pythonhosted.org/packages/03/27/e35e7c6e6a52fab9fcc64fc2b20c6b516eba930bb02b10ace3b3820d3ab/numpy-1.18.4-cp36-cp36m-linux_x86_64.whl
    20.2MB 67.9MB/s
Collecting scipy
  Downloading https://files.pythonhosted.org/packages/dc/29/162476fd44203116e7980cfbd9352eef9db37c49445d1fec35509022f6aa/scipy-1.4.1-cp36-cp36m-linux_x86_64.whl
    26.1MB 1.5MB/s
Collecting scikit-learn
  Downloading https://files.pythonhosted.org/packages/5e/d8/312e03adf4c78663e17d802fe2440072376fee46cada1404f1727ed77a32/scikit_learn-0.22.2.post1-cp36-cp36m-linux_x86_64.whl
    7.1MB 49.5MB/s
Collecting pandas
  Downloading https://files.pythonhosted.org/packages/bb/71/8f53dbdbcb67c912b888b40def255767e475402e9df64050019149b1a943/pandas-1.0.3-cp36-cp36m-linux_x86_64.whl
    10.0MB 47.6MB/s
Collecting tqdm>4.25.0
  Downloading https://files.pythonhosted.org/packages/c9/40/058b12e8ba10e35f89c9b1fd4c2d4c7f8c05947df2d5eb3c7b258019fda0/tqdm-4.46.0-py2.py3-none-any.whl
    71kB 9.3MB/s
Collecting joblib>=0.11
  Downloading https://files.pythonhosted.org/packages/28/5c/cf6a2b65a321c4a209efc6df64c2689efae2cb62661f8f6f4bb28547cf1bf/joblib-0.14.1-py2.py3-none-any.whl
    296kB 37.8MB/s
Collecting python-dateutil>=2.6.1
  Downloading https://files.pythonhosted.org/packages/d4/70/d60450c3dd48ef87586924207ae8907090de0b306af2bce5d134d78615cb/python_dateutil-2.8.1-py2.py3-none-any.whl
    235kB 52.0MB/s
Collecting pytz>=2017.2
  Downloading https://files.pythonhosted.org/packages/4f/a4/879454d49688e2fad93e59d7d4efda580b783c745fd2ec2a3adf87b0808d/pytz-2020.1-py2.py3-none-any.whl
    512kB 25.6MB/s
Collecting six>=1.5
  Downloading https://files.pythonhosted.org/packages/65/eb/1f97cb97bfc2390a276969c6fae16075da282f5058082d4cb10c6c5c1dba/six-1.14.0-py2.py3-none-any.whl
    4.9kB 12.5MB/s
Building wheels for collected packages: shap
  Building wheel for shap (setup.py) ... done
  Created wheel for shap: filename=shap-0.35.0-cp36-cp36m-linux_x86_64.whl size=394119 sha256=a99f99f9e861b9a391c9d681aee8f92cdf6bbe4b57
  Stored in directory: /root/.cache/pip/wheels/e7/f7/0f/b57055080cf8894906b3bd3616d2fc2bfd0b12d5161bcb24ac
Successfully built shap
ERROR: google-colab 1.0.0 has requirement six<=1.12.0, but you'll have six 1.14.0 which is incompatible.
ERROR: datascience 0.10.6 has requirement folium==0.2.1, but you'll have folium 0.8.3 which is incompatible.
ERROR: convertdate 2.2.0 has requirement pytz<2020,>=2014.10, but you'll have pytz 2020.1 which is incompatible.
ERROR: alumentations 0.1.12 has requirement imgaug<0.2.7,>=0.2.5, but you'll have imgaug 0.2.9 which is incompatible.
Installing collected packages: numpy, scipy, joblib, scikit-learn, six, python-dateutil, pytz, pandas, tqdm, shap
Successfully installed joblib-0.14.1 numpy-1.18.4 pandas-1.0.3 python-dateutil-2.8.1 pytz-2020.1 scikit-learn-0.22.2.post1 scipy-1.4.1 shap-0.35.0
WARNING: The following packages were previously imported in this runtime:
[dateutil,joblib,numpy,pandas,pytz,scipy,six,sklearn,tqdm]
You must restart the runtime in order to use newly installed versions.
```

RESTART RUNTIME



```
# Local Interpretation using SHAP (for prediction at State # = 4, row 32)
import shap
shap.initjs()
explainer = shap.TreeExplainer(model2)
shap_values = explainer.shap_values(X_train)
i = 32
shap.force_plot(explainer.expected_value, shap_values[i], features=X_train.loc[i], feature_names=X_train.columns)
```



```
# Find Shapley Forces across the training sample i (i = 0 - 37)
processor = make_pipeline(
    ce.OrdinalEncoder(),
    SimpleImputer(strategy='median')
)

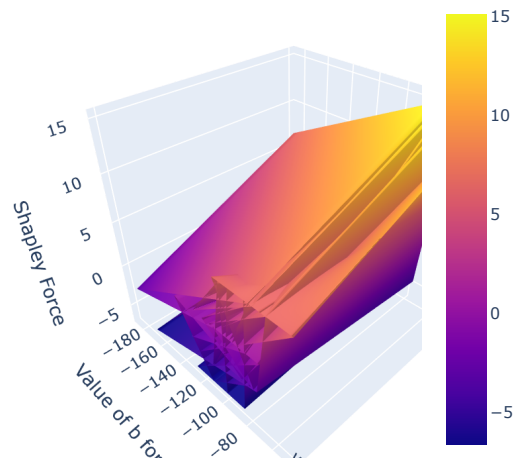
X_train_processed = processor.fit_transform(X_train)
column_names = X_train.columns
shap_values_array = pd.DataFrame(columns = column_names)

for i in range(len(y_train)):
    row = X_train.iloc[[i]]
    explainer = shap.TreeExplainer(model2)
    row_processed = processor.transform(row)
    shap_values_input = explainer.shap_values(row_processed)
    shap_values_array = np.concatenate((shap_values_array, shap_values_input), axis=0)
```

```
# Create a 3D plot of force as a function of state curve displacement from mean curve and features for validation set
# A two feature partial dependence plot in 3D
import plotly.graph_objs as go
surface = go.Surface(x=column_names,
                    y=y_train,
                    z=shap_values_array)

layout = go.Layout(
    scene=dict(
        xaxis=dict(title= ''),
        yaxis=dict(title= 'Value of b for state'),
        zaxis=dict(title= 'Shapley Force')
    )
)
fig = go.Figure(surface, layout)
fig.show()
```





```
# Recursive Feature Elimination
from sklearn.feature_selection import RFE, f_regression
from sklearn.model_selection import StratifiedKFold

rfr = RandomForestRegressor(bootstrap=True, ccp_alpha=0,
                           max_depth=1, max_features='auto', max_leaf_nodes=None,
                           max_samples=None, min_impurity_decrease=0.0,
                           min_impurity_split=None, min_samples_leaf=4,
                           min_samples_split=2, min_weight_fraction_leaf=0,
                           n_estimators=18, n_jobs=None, oob_score=False,
                           random_state=0, verbose=0, warm_start=False)

#Selecting 2 features turns out to give maximum validation accuracy
number_selected_features = 2
rfe = RFE(rfr, n_features_to_select=number_selected_features, verbose =3)
rfe.fit(X_train,y_train)

RFE(estimator=RandomForestRegressor(bootstrap=True, ccp_alpha=0,
                                     criterion='mse', max_depth=1,
                                     max_features='auto', max_leaf_nodes=None,
                                     max_samples=None, min_impurity_decrease=0.0,
                                     min_impurity_split=None, min_samples_leaf=4,
                                     min_samples_split=2,
                                     min_weight_fraction_leaf=0, n_estimators=18,
                                     n_jobs=None, oob_score=False,
                                     random_state=0, verbose=0,
                                     warm_start=False),
    n_features_to_select=2, step=1, verbose=3)
```

```
rfe_support = rfe.get_support()
rfe_feature = X_train.loc[:,rfe_support].columns.tolist()
print(str(len(rfe_feature)), 'selected features')
```

```
2 selected features
```

```
from sklearn.metrics import mean_squared_error, r2_score

# Coefficient of determination r2 for the training set
pipeline_score = rfe.score(X_train,y_train)
print("Coefficient of determination r2 for the training set.: ", pipeline_score)

# Coefficient of determination r2 for the validation set
pipeline_score = rfe.score(X_val,y_val)
print("Coefficient of determination r2 for the validation set.: ", pipeline_score)

# The mean squared error
y_pred = rfe.predict(X_val)
print("Mean squared error: %.2f"% mean_squared_error(y_val, y_pred))
```

```

↳ Coefficient of determination r2 for the training set.: 0.27110557327427665
   Coefficient of determination r2 for the validation set.: 0.1883085673181527
   Mean squared error: 208.94

```

```

# Retain only features with highest importance from RFE
X_train_rfe_select = X_train[rfe_feature]
X_val_rfe_select = X_val[rfe_feature]
print('Shape after removing features:', X_train_rfe_select.shape, X_val_rfe_select.shape)

```

```

↳ Shape after removing features: (38, 2) (13, 2)

```

```

# Random forest classifier after RFE Feature Selection on Reduced Feature Set

```

```

pipeline5 = make_pipeline(
    ce.OneHotEncoder(use_cat_names=True),
    SimpleImputer(strategy = 'most_frequent'),
    RandomForestRegressor(bootstrap=True, ccp_alpha=0,
                          max_depth=1, max_features='auto', max_leaf_nodes=None,
                          max_samples=None, min_impurity_decrease=0.0,
                          min_impurity_split=None, min_samples_leaf=4,
                          min_samples_split=2, min_weight_fraction_leaf=0,
                          n_estimators=18, n_jobs=None, oob_score=False,
                          random_state=0, verbose=0, warm_start=False)
)

```

```

# Fit on train, score on val
pipeline5.fit(X_train_rfe_select, y_train);

```

```

# Coefficient of determination r2 for the training set
pipeline_score = pipeline5.score(X_train_rfe_select,y_train)
print("Coefficient of determination r2 for the training set.: ", pipeline_score)

```

```

# Coefficient of determination r2 for the validation set
pipeline_score = pipeline5.score(X_val_rfe_select,y_val)
print("Coefficient of determination r2 for the validation set.: ", pipeline_score)

```

```

# The mean squared error
y_pred = pipeline5.predict(X_val_rfe_select)
print("Mean squared error: %.2f"% mean_squared_error(y_val, y_pred))

```

```

↳ Coefficient of determination r2 for the training set.: 0.27110557327427665
   Coefficient of determination r2 for the validation set.: 0.1883085673181527
   Mean squared error: 208.94

```

```

pipeline5.fit(X_val_rfe_select, y_val)
# Plot of features
%matplotlib inline
import matplotlib.pyplot as plt

# Get feature importances
encoder = pipeline5.named_steps['onehotencoder']
encoded = encoder.transform(X_val_rfe_select)
rf = pipeline5.named_steps['randomforestregressor']
importances3 = pd.Series(rf.feature_importances_, encoded.columns)

# Plot feature importances
n = number_selected_features
plt.figure(figsize=(10,n/2))
plt.title(f'Top {n} features pipeline5')
importances3.sort_values()[-n:].plot.barh(color='grey');

```

