```
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)
```

date	state	positive	negative	pending	hospitalizedCurrently	hospitalizedCumulative	inIcuCurrently	inIcuCumulative	onVentilatorCurrently	onVentilatorCumulative	recovered	hash	dateChecked	death	hospitalized	total	totalTestResults	
2020-05-03	AK	368.0	21210.0	NaN	12.0	NaN	NaN	NaN	NaN	NaN	262.0	d15bb8087806f8dded75fb6165d7bed1bcface44	2020-05-03T20:00:00Z	9.0	NaN	21578.0	21578.0	2
2020-05-03	AL	7725.0	84775.0	NaN	NaN	1035.0	NaN	403.0	NaN	242.0	NaN	aa4e1102894dd9528461e4d910fab397cc40d31b	2020-05-03T20:00:00Z	290.0	1035.0	92500.0	92500.0	9
2020-05-03	AR	3431.0	49459.0	NaN	100.0	427.0	NaN	NaN	20.0	88.0	1999.0	6b15aab296af49161db3f9fc69eef7c6ca244994	2020-05-03T20:00:00Z	76.0	427.0	52890.0	52890.0	5
2020-05-03	AS	0.0	57.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	ccae2e571ac93c5836a22158f57c12313127810d	2020-05-03T20:00:00Z	0.0	NaN	57.0	57.0	
2020-05-03	AZ	8640.0	72479.0	NaN	732.0	1348.0	282.0	NaN	192.0	NaN	1597.0	c687661dcf3f892bcc23c38ddcb46fe809b006f1	2020-05-03T20:00:00Z	362.0	1348.0	81119.0	81119.0	8

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()
```

date	state	positive	negative	pending	hospitalizedCurrently	hospitalizedCumulative	recovered	death	totalTestResults
2020-05-03	AK	368.0	21210.0	NaN	12.0	NaN	262.0	9.0	21578.0
2020-05-03	AL	7725.0	84775.0	NaN	NaN	1035.0	NaN	290.0	92500.0
2020-05-03	AR	3431.0	49459.0	NaN	100.0	427.0	1999.0	76.0	52890.0
2020-05-03	AS	0.0	57.0	NaN	NaN	NaN	NaN	0.0	57.0
2020-05-03	AZ	8640.0	72479.0	NaN	732.0	1348.0	1597.0	362.0	81119.0

```
# 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()
```

date	state	positive	negative	pending	hospitalizedCurrently	hospitalizedCumulative	recovered	death	totalTestResults	percent_positive
2020-05-03	AK	368.0	21210.0	NaN	12.0	NaN	262.0	9.0	21578.0	1.705441
2020-05-03	AL	7725.0	84775.0	NaN	NaN	1035.0	NaN	290.0	92500.0	8.351351
2020-05-03	AR	3431.0	49459.0	NaN	100.0	427.0	1999.0	76.0	52890.0	6.487049
2020-05-03	AS	0.0	57.0	NaN	NaN	NaN	NaN	0.0	57.0	0.000000
2020-05-03	AZ	8640.0	72479.0	NaN	732.0	1348.0	1597.0	362.0	81119.0	10.651019

```
# 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
```

date	state	positive	negative	pending	hospitalizedCurrently	hospitalizedCumulative	recovered	death	totalTestResults	percent_positive	hospitalized_percent
2020-05-03	AK	368.0	21210.0	NaN	12.0	NaN	262.0	9.0	21578.0	1.705441	3.260870
2020-05-03	AL	7725.0	84775.0	NaN	NaN	1035.0	NaN	290.0	92500.0	8.351351	13.398058
2020-05-03	AR	3431.0	49459.0	NaN	100.0	427.0	1999.0	76.0	52890.0	6.487049	12.445351
2020-05-03	AS	0.0	57.0	NaN	NaN	NaN	NaN	0.0	57.0	0.000000	NaN
2020-05-03	AZ	8640.0	72479.0	NaN	732.0	1348.0	1597.0	362.0	81119.0	10.651019	15.601852

```
# 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()
```

date	state	positive	negative	pending	hospitalizedCurrently	hospitalizedCumulative	recovered	death	totalTestResults	percent_positive	hospitalized_percent	recovered_percent
2020-05-03	AK	368.0	21210.0	NaN	12.0	NaN	262.0	9.0	21578.0	1.705441	3.260870	71.195652
2020-05-03	AL	7725.0	84775.0	NaN	NaN	1035.0	NaN	290.0	92500.0	8.351351	13.398058	NaN
2020-05-03	AR	3431.0	49459.0	NaN	100.0	427.0	1999.0	76.0	52890.0	6.487049	12.445351	58.262897
2020-05-03	AS	0.0	57.0	NaN	NaN	NaN	NaN	0.0	57.0	0.000000	NaN	NaN
2020-05-03	AZ	8640.0	72479.0	NaN	732.0	1348.0	1597.0	362.0	81119.0	10.651019	15.601852	18.483796

```
# 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()
```

```
# 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()
```

date	state	positive	negative	pending	hospitalizedCurrently	hospitalizedCumulative	recovered	death	totalTestResults	percent_positive	hospitalized_percent	recovered_percent	death_percent	population
2020-05-03	AK	368.0	21210.0	NaN	12.0	NaN	262.0	9.0	21578.0	1.705441	3.260870	71.195652	2.445652	731545.0
2020-05-03	AL	7725.0	84775.0	NaN	NaN	1035.0	NaN	290.0	92500.0	8.351351	13.398058	NaN	3.754045	4903185.0
2020-05-03	AR	3431.0	49459.0	NaN	100.0	427.0	1999.0	76.0	52890.0	6.487049	12.445351	58.262897	2.215098	3017804.0
2020-05-03	AS	0.0	57.0	NaN	NaN	NaN	NaN	0.0	57.0	0.000000	NaN	NaN	NaN	NaN
2020-05-03	AZ	8640.0	72479.0	NaN	732.0	1348.0	1597.0	362.0	81119.0	10.651019	15.601852	18.483796	4.189815	7278717.0

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

date	state	positive	negative	pending	hospitalizedCurrently	hospitalizedCumulative	recovered	death	totalTestResults	percent_positive	hospitalized_percent	recovered_percent	death_percent	population	positive_norm
2020-05-03	AK	368.0	21210.0	NaN	12.0	NaN	262.0	9.0	21578.0	1.705441	3.260870	71.195652	2.445652	731545.0	0.000503
2020-05-03	AL	7725.0	84775.0	NaN	NaN	1035.0	NaN	290.0	92500.0	8.351351	13.398058	NaN	3.754045	4903185.0	0.001576
2020-05-03	AR	3431.0	49459.0	NaN	100.0	427.0	1999.0	76.0	52890.0	6.487049	12.445351	58.262897	2.215098	3017804.0	0.001137
2020-05-03	AS	0.0	57.0	NaN	NaN	NaN	NaN	0.0	57.0	0.000000	NaN	NaN	NaN	NaN	NaN
2020-05-03	AZ	8640.0	72479.0	NaN	732.0	1348.0	1597.0	362.0	81119.0	10.651019	15.601852	18.483796	4.189815	7278717.0	0.001187

```
# 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
```

date	state	positive	negative	pending	hospitalizedCurrently	hospitalizedCumulative	recovered	death	totalTestResults	percent_positive	hospitalized_percent	recovered_percent	death_percent	population	positive_norm	hospitalized_norm
2020-05-03	AK	368.0	21210.0	NaN	12.0	NaN	262.0	9.0	21578.0	1.705441	3.260870	71.195652	2.445652	731545.0	0.000503	0.000016
2020-05-03	AL	7725.0	84775.0	NaN	NaN	1035.0	NaN	290.0	92500.0	8.351351	13.398058	NaN	3.754045	4903185.0	0.001576	0.000211
2020-05-03	AR	3431.0	49459.0	NaN	100.0	427.0	1999.0	76.0	52890.0	6.487049	12.445351	58.262897	2.215098	3017804.0	0.001137	0.000141
2020-05-03	AS	0.0	57.0	NaN	NaN	NaN	NaN	0.0	57.0	0.000000	NaN	NaN	NaN	NaN	NaN	NaN
2020-05-03	AZ	8640.0	72479.0	NaN	732.0	1348.0	1597.0	362.0	81119.0	10.651019	15.601852	18.483796	4.189815	7278717.0	0.001187	0.000185

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

date	state	positive	negative	pending	hospitalizedCurrently	hospitalizedCumulative	recovered	death	totalTestResults	percent_positive	hospitalized_percent	recovered_percent	death_percent	population	positive_norm	hospitalized_norm	recovered_norm
2020-05-03	AK	368.0	21210.0	NaN	12.0	NaN	262.0	9.0	21578.0	1.705441	3.260870	71.195652	2.445652	731545.0	0.000503	0.000016	0.000358
2020-05-03	AL	7725.0	84775.0	NaN	NaN	1035.0	NaN	290.0	92500.0	8.351351	13.398058	NaN	3.754045	4903185.0	0.001576	0.000211	NaN
2020-05-03	AR	3431.0	49459.0	NaN	100.0	427.0	1999.0	76.0	52890.0	6.487049	12.445351	58.262897	2.215098	3017804.0	0.001137	0.000141	0.000662
2020-05-03	AS	0.0	57.0	NaN	NaN	NaN	NaN	0.0	57.0	0.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2020-05-03	AZ	8640.0	72479.0	NaN	732.0	1348.0	1597.0	362.0	81119.0	10.651019	15.601852	18.483796	4.189815	7278717.0	0.001187	0.000185	0.000219

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

date	state	positive	negative	pending	hospitalizedCurrently	hospitalizedCumulative	recovered	death	totalTestResults	percent_positive	hospitalized_percent	recovered_percent	death_percent	population	positive_norm	hospitalized_norm	recovered_norm	death_norm
2020-05-03	AK	368.0	21210.0	NaN	12.0	NaN	262.0	9.0	21578.0	1.705441	3.260870	71.195652	2.445652	731545.0	0.000503	0.000016	0.000358	0.000012
2020-05-03	AL	7725.0	84775.0	NaN	NaN	1035.0	NaN	290.0	92500.0	8.351351	13.398058	NaN	3.754045	4903185.0	0.001576	0.000211	NaN	0.000059
2020-05-03	AR	3431.0	49459.0	NaN	100.0	427.0	1999.0	76.0	52890.0	6.487049	12.445351	58.262897	2.215098	3017804.0	0.001137	0.000141	0.000662	0.000025
2020-05-03	AS	0.0	57.0	NaN	NaN	NaN	NaN	0.0	57.0	0.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2020-05-03	AZ	8640.0	72479.0	NaN	732.0	1348.0	1597.0	362.0	81119.0	10.651019	15.601852	18.483796	4.189815	7278717.0	0.001187	0.000185	0.000219	0.000050

```
df_drop.info()
```

```
df_drop.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 3321 entries, 2020-05-03 to 2020-01-22
Data columns (total 18 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   state                  3321 non-null   object 
 1   positive               3306 non-null   float64
 2   negative               3140 non-null   float64
 3   pending                677 non-null    float64
 4   hospitalizedCurrently  1191 non-null   float64
 5   hospitalizedCumulative 1239 non-null   float64
 6   recovered              1037 non-null   float64
 7   death                  2594 non-null   float64
 8   totalTestResults       3319 non-null   float64
 9   percent_positive       3275 non-null   float64
 10  hospitalized_percent   1870 non-null   float64
 11  recovered_percent      1037 non-null   float64
 12  death_percent          2541 non-null   float64
 13  population             3125 non-null   float64
 14  positive_norm          3125 non-null   float64
 15  hospitalized_norm      1831 non-null   float64
 16  recovered_norm         950 non-null    float64
 17  death_norm             2447 non-null   float64
dtypes: float64(17), object(1)
memory usage: 573.0+ 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()
```

date	state	positive	negative	pending	hospitalizedCurrently	hospitalizedCumulative	recovered	death	totalTestResults	percent_positive	hospitalized_percent	recovered_percent	death_percent	population	positive_norm	hospitalized_norm	recovered_norm	death_norm
2020-05-03	AK	368.0	21210.0	NaN	12.0	NaN	262.0	9.0	21578.0	1.705441	3.260870	71.195652	2.445652	731545.0	0.000503	0.000016	0.000358	0.000012
2020-05-02	AK	365.0	21034.0	NaN	10.0	NaN	261.0	9.0	21399.0	1.705687	2.739726	71.506849	2.465753	731545.0	0.000499	0.000014	0.000357	0.000012
2020-05-01	AK	364.0	19961.0	NaN	25.0	NaN	254.0	9.0	20325.0	1.790898	6.868132	69.780220	2.472527	731545.0	0.000498	0.000034	0.000347	0.000012
2020-04-30	AK	355.0	18764.0	NaN	19.0	NaN	252.0	9.0	19119.0	1.856792	5.352113	70.985915	2.535211	731545.0	0.000485	0.000026	0.000344	0.000012
2020-04-29	AK	355.0	18764.0	NaN	14.0	NaN	240.0	9.0	19119.0	1.856792	3.943662	67.605634	2.535211	731545.0	0.000485	0.000019	0.000328	0.000012

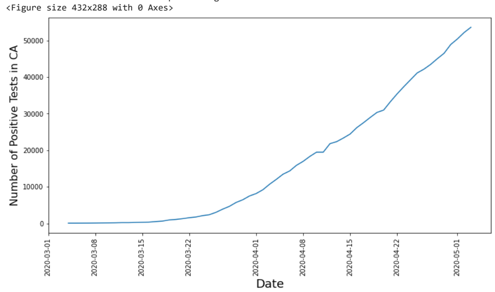
```
df_state_dict['CA'].head()
```

date	state	positive	negative	pending	hospitalizedCurrently	hospitalizedCumulative	recovered	death	totalTestResults	percent_positive	hospitalized_percent	recovered_percent	death_percent	population	positive_norm	hospitalized_norm	recovered_norm	death_norm
2020-05-03	CA	53616.0	662135.0	NaN	4734.0	NaN	NaN	2215.0	715751.0	7.490873	8.829454	NaN	4.131229	39512223.0	0.001357	0.000120	NaN	0.000056
2020-05-02	CA	52197.0	634606.0	NaN	4722.0	NaN	NaN	2171.0	686803.0	7.599996	9.046497	NaN	4.159243	39512223.0	0.001321	0.000120	NaN	0.000055
2020-05-01	CA	50442.0	604543.0	NaN	4706.0	NaN	NaN	2073.0	654985.0	7.701245	9.329527	NaN	4.109671	39512223.0	0.001277	0.000119	NaN	0.000052
2020-04-30	CA	48917.0	576420.0	NaN	4981.0	NaN	NaN	1982.0	625337.0	7.822502	10.182554	NaN	4.051761	39512223.0	0.001238	0.000126	NaN	0.000050
2020-04-29	CA	46500.0	556639.0	NaN	5011.0	NaN	NaN	1887.0	603139.0	7.709666	10.776344	NaN	4.058065	39512223.0	0.001177	0.000127	NaN	0.000048

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

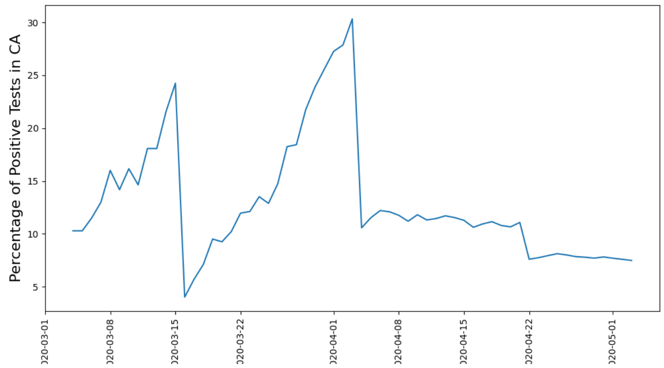
```
fig = plt.figure()
fig, ax = plt.subplots(figsize=(12, 6))
plt.rcParams.update(plt.rcParamsDefault)

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>
```



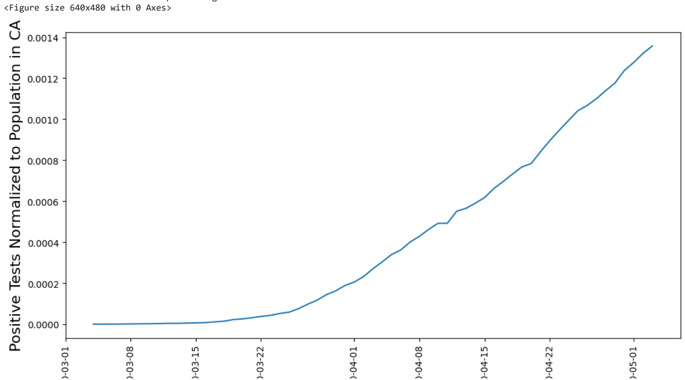

```
fig = plt.figure()
fig, ax = plt.subplots(figsize=(12, 6))
plt.rcParams.update(plt.rcParamsDefault)

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>
```



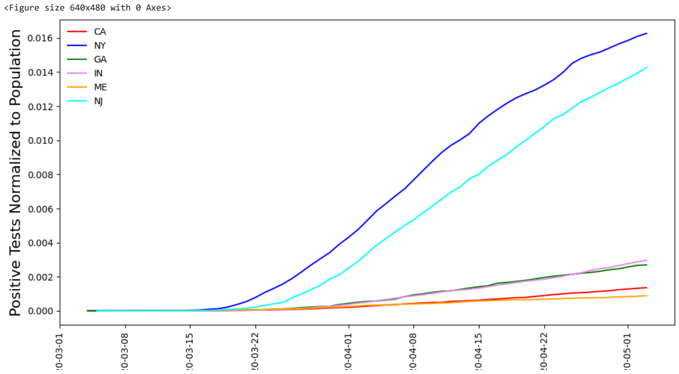

```
fig = plt.figure()
fig, ax = plt.subplots(figsize=(12, 6))
plt.rcParams.update(plt.rcParamsDefault)

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>
```



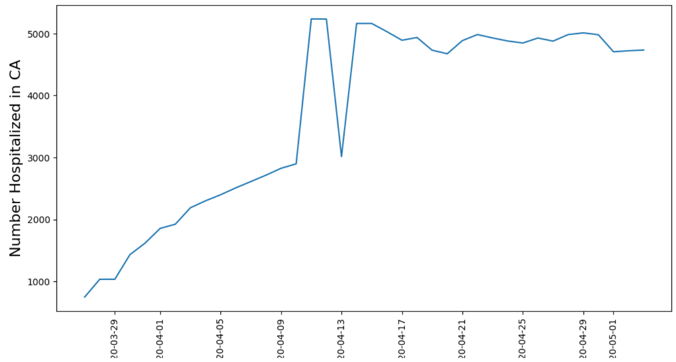

```
fig = plt.figure()
fig, ax = plt.subplots(figsize=(12, 6))
plt.rcParams.update(plt.rcParamsDefault)

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()
```

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



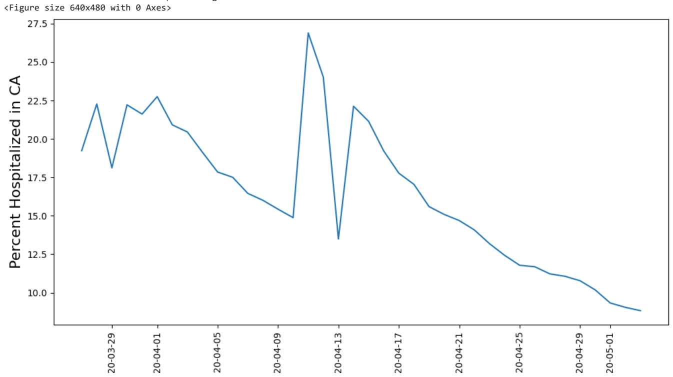

```
fig = plt.figure()
fig, ax = plt.subplots(figsize=(12, 6))
plt.rcParams.update(plt.rcParamsDefault)

plt.plot(df_state_dict['CA'].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>
```



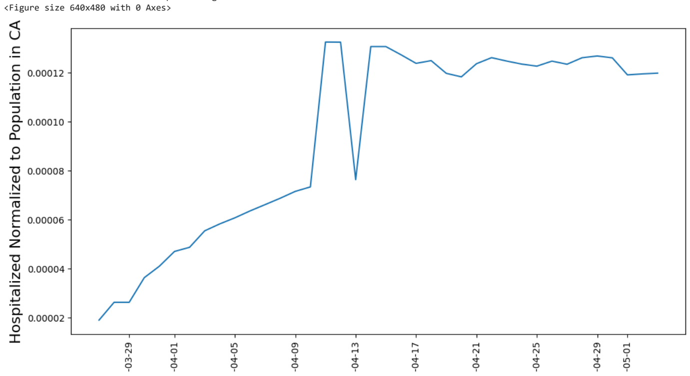

```
fig = plt.figure()
fig, ax = plt.subplots(figsize=(12, 6))
plt.rcParams.update(plt.rcParamsDefault)

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>
```



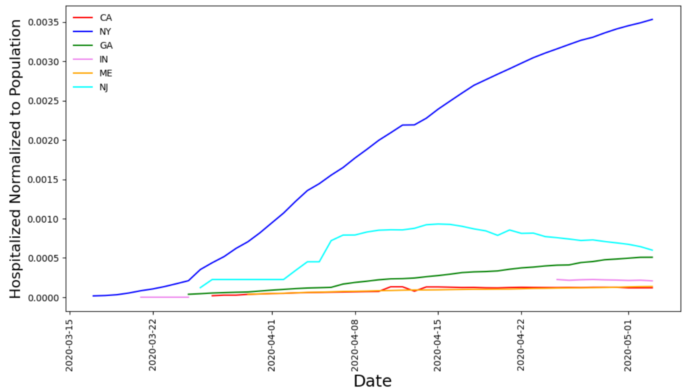

```
fig = plt.figure()
fig, ax = plt.subplots(figsize=(12, 6))
plt.rcParams.update(plt.rcParamsDefault)

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()
```

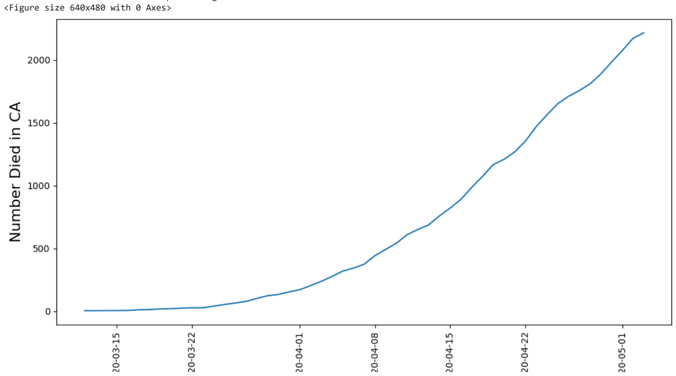
```
<Figure size 640x480 with 0 Axes>
```



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

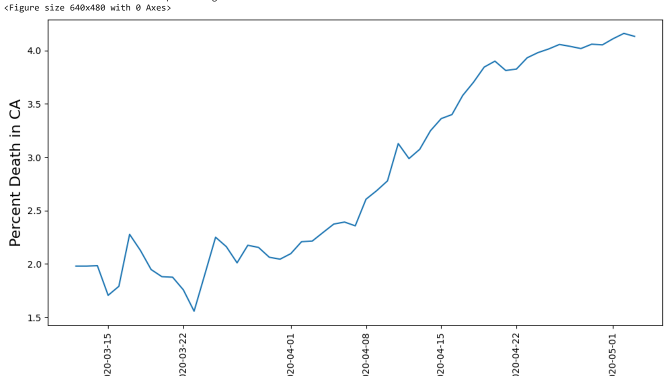
```
fig = plt.figure()
fig, ax = plt.subplots(figsize=(12, 6))
plt.rcParams.update(plt.rcParamsDefault)

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>
```



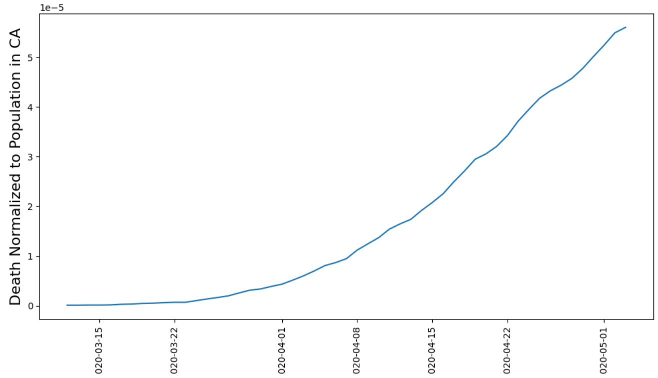

```
fig = plt.figure()
fig, ax = plt.subplots(figsize=(12, 6))
plt.rcParams.update(plt.rcParamsDefault)

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>
```



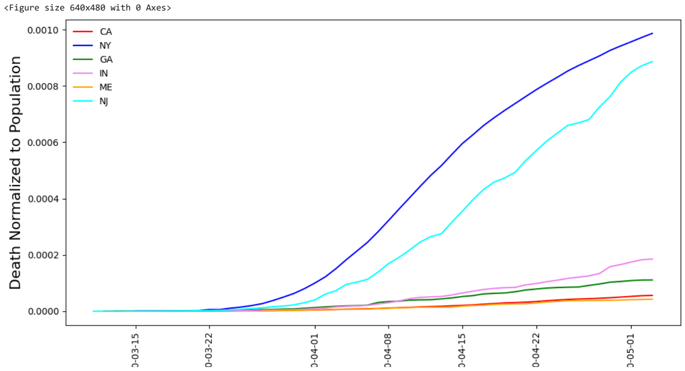

```
fig = plt.figure()
fig, ax = plt.subplots(figsize=(12, 6))
plt.rcParams.update(plt.rcParamsDefault)

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, 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 postive test curves

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

```
# Fetch the parameters for each state (CexpDx^-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 CexpDx^-1.csv

- **CexpDx^-1.csv**(application/vnd.ms-excel) - 2367 bytes, last modified: 5/3/2020 - 100% done

```
Saving CexpDx^-1.csv to CexpDx^-1.csv
```

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

	State	c (10^-4)	d	fit rank	r^2
0	AK	1.331139	-95.882596	2.0	0.975010
1	AL	8.124937	-145.096536	1.0	0.986827
2	AR	1.444874	-108.708991	3.0	0.991505
3	AS	NaN	NaN	NaN	NaN
4	AZ	4.374538	-129.204382	1.0	0.997129

```
df_state_params.describe()
```

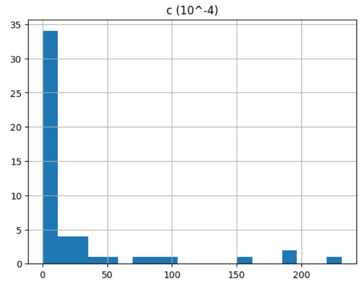
	c (10^-4)	d	fit rank	r^2
count	51.000000	51.000000	51.000000	51.000000
mean	28.922502	-142.879078	2.098039	0.984584
std	53.235594	33.811201	2.156431	0.021142
min	0.516899	-215.115296	1.000000	0.889521
25%	3.745253	-165.040649	1.000000	0.982796
50%	7.421743	-145.096536	1.000000	0.989768
75%	20.958221	-123.240757	2.500000	0.995856
max	231.216701	-47.945262	15.000000	0.998705

```
df_state_params.hist(column='r^2')
```

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7f1a65eee7b8>]],
```

```
df_state_params.hist(column='c (10^-4)', bins=20)
```

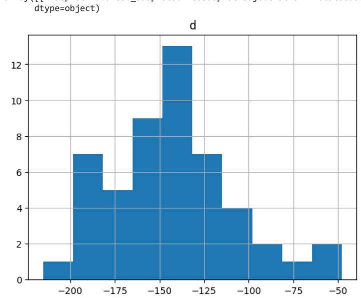
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7f1a67a37dd8>]],
      dtype=object)
```



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='d', bins=10)
```

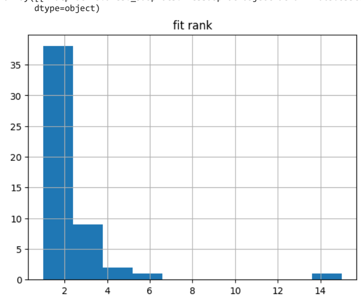
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7f1a65e3bda0>]],
      dtype=object)
```



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 0x7f1a65db53c8>]],
      dtype=object)
```



The A*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 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	Sum of NUM_Male_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_BEN	NUM_BEN_With_
0	AK	1820384.0	270970.0	809516.0	468255.0	175296.0	1034762.0	760009.0	62311.0	76773.0	46525.0	147917.0	
1	AL	10804823.0	2065353.0	4386595.0	2980828.0	1190504.0	6237445.0	4514041.0	1549811.0	30624.0	65500.0	5556.0	
2	AR	15892716.0	2818665.0	6370265.0	4555468.0	1848506.0	9275039.0	6507151.0	1334245.0	19642.0	108428.0	62782.0	
3	AS	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
4	AZ	10786064.0	886596.0	4861035.0	3377040.0	1294375.0	5944519.0	4747801.0	221183.0	61840.0	689880.0	179818.0	

5 rows × 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['Captial Land Area']/df_state_data['Capital Water Area']
df_state_data['Captial Land Area'] = df_state_data['Captial Land Area'].astype(float)
df_state_data['Capital Area Ratio'] = df_state_data['Captial 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['Longitu

# 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	Sum of NUM_Male_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_BEN	NUM_BEN_With_
0	AK	1820384.0	270970.0	809516.0	468255.0	175296.0	1034762.0	760009.0	62311.0	76773.0	46525.0	147917.0	
1	AL	10804823.0	2065353.0	4386595.0	2980828.0	1190504.0	6237445.0	4514041.0	1549811.0	30624.0	65500.0	5556.0	
2	AR	15892716.0	2818665.0	6370265.0	4555468.0	1848506.0	9275039.0	6507151.0	1334245.0	19642.0	108428.0	62782.0	
3	AS	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
4	AZ	10786064.0	886596.0	4861035.0	3377040.0	1294375.0	5944519.0	4747801.0	221183.0	61840.0	689880.0	179818.0	

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, 55]])
X = df_temp1.drop('State', axis = 1)
df_temp2 = df_state_params.drop(df_state_data.index[[3, 12, 27, 42, 50, 55]])
y = df_temp2['c (10^-4)']
```

```
# 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_Greater_84	Sum of NUM_Female_BEN	Sum of NUM_Male_BEN	Sum of NUM_Black_or_African_American_BEN	Sum of NUM_Asian_Pacific_Islander_BEN	Sum of NUM_Hispanic_BEN	NUM_Ameri
Sum of NUM_Medicare_BEN	1.000000	0.981244	0.998612	0.998085	0.989852	0.999917	0.999896	0.895536	0.524429	0.894417	
Sum of NUM_BEN_Age_Less_65	0.981244	1.000000	0.977935	0.969186	0.960258	0.982419	0.979571	0.925224	0.473716	0.829126	
Sum of NUM_BEN_Age_65_to_74	0.998612	0.977935	1.000000	0.996336	0.982527	0.998360	0.998622	0.894585	0.516336	0.903356	
Sum of NUM_BEN_Age_75_to_84	0.998085	0.969186	0.996336	1.000000	0.992524	0.997902	0.998281	0.882970	0.528889	0.900554	
Sum of NUM_BEN_Age_Greater_84	0.989852	0.960258	0.982527	0.992524	1.000000	0.989495	0.990300	0.863288	0.560359	0.880694	
Sum of NUM_Female_BEN	0.999917	0.982419	0.998360	0.997902	0.989495	1.000000	0.999655	0.898089	0.522516	0.891099	
Sum of NUM_Male_BEN	0.999896	0.979571	0.998622	0.998281	0.990300	0.999655	1.000000	0.892308	0.525905	0.896619	
Sum of NUM_Black_or_African_American_BEN	0.895536	0.925224	0.894585	0.882970	0.863288	0.898089	0.892308	1.000000	0.300440	0.726598	
Sum of NUM_Asian_Pacific_Islander_BEN	0.524429	0.473716	0.516336	0.528889	0.560359	0.522516	0.525905	0.300440	1.000000	0.633176	
Sum of NUM_Hispanic_BEN	0.894417	0.829126	0.903356	0.900554	0.880694	0.891099	0.896619	0.726598	0.633176	1.000000	
Sum of NUM_American_IndianAlaska_Native_BEN	0.077349	0.053905	0.086472	0.081806	0.060473	0.076938	0.078057	-0.041752	0.116101	0.128504	
Sum of NUM_BEN_With_Race_Not_Elsewhere_Classified	0.821569	0.771437	0.801707	0.830466	0.877807	0.819981	0.822968	0.634906	0.740095	0.734077	
Sum of NUM_Non-Hispanic_White_BEN	0.996809	0.978655	0.994347	0.996101	0.988772	0.997015	0.996718	0.887564	0.484280	0.866806	
Sum of NUM_Minorities	0.958404	0.925675	0.961032	0.957614	0.944932	0.957333	0.958539	0.867684	0.645007	0.959572	
Sum of Average_Age_of_BEN	0.678752	0.726826	0.682844	0.659778	0.633311	0.681583	0.674831	0.688783	0.128621	0.515698	
Sum of NUM_BEN_Atrial_Fibrillation	0.990319	0.969220	0.985453	0.991337	0.990274	0.990298	0.990716	0.888630	0.458859	0.852899	
Sum of NUM_BEN_Asthma	0.995489	0.979353	0.991510	0.992852	0.991685	0.995193	0.995563	0.892110	0.525949	0.882032	
Sum of NUM_BEN_Cancer	0.994721	0.971958	0.992833	0.994822	0.987275	0.994401	0.994876	0.899492	0.462638	0.884760	
Sum of NUM_BEN_Heart_Failure	0.997108	0.985088	0.995323	0.993852	0.984794	0.997149	0.996815	0.912205	0.483209	0.885584	
Sum of NUM_BEN_Chronic_Kidney_Disease	0.997480	0.980181	0.997065	0.995383	0.984109	0.997259	0.997594	0.906086	0.484030	0.894095	
Sum of NUM_BEN_Chronic_Obstructive_Pulmonary_Disease	0.986081	0.980417	0.981434	0.983841	0.977815	0.986841	0.985732	0.905511	0.428114	0.834249	
Sum of NUM_BEN_Hyperlipidemia	0.996199	0.974138	0.994686	0.996386	0.987456	0.996064	0.996454	0.902110	0.475920	0.885160	
Sum of NUM_BEN_Diabetes	0.997736	0.981117	0.996508	0.995642	0.985749	0.997730	0.997434	0.911839	0.493440	0.893757	
Sum of NUM_BEN_Hypertension	0.998843	0.982162	0.998059	0.996914	0.985866	0.998953	0.998618	0.907127	0.491385	0.887840	
Sum of NUM_BEN_Ischemic_Heart_Disease	0.993954	0.974989	0.991463	0.994045	0.985698	0.994069	0.993920	0.905308	0.456240	0.877711	
Sum of NUM_BEN_Stroke	0.990470	0.971925	0.988713	0.989929	0.980696	0.990390	0.990562	0.918281	0.446318	0.880341	
Sum of PCT_MEDICARE	0.710503	0.759188	0.713882	0.692945	0.667920	0.714560	0.706037	0.750005	0.138118	0.483164	
% Urban Pop	0.239324	0.172542	0.233998	0.252295	0.279217	0.235109	0.243800	0.173856	0.309518	0.280539	
Density (P/mi2)	-0.099963	-0.110703	-0.100658	-0.096325	-0.092020	-0.100642	-0.099698	-0.022034	-0.030915	-0.043443	
Children 0-18	0.884945	0.844648	0.874846	0.887257	0.911738	0.883447	0.886079	0.720117	0.776658	0.840977	
Adults 19-25	0.864191	0.823977	0.851022	0.867408	0.899146	0.862807	0.865269	0.694892	0.785158	0.809783	
Adults 26-34	0.846985	0.802138	0.833617	0.851409	0.884954	0.845326	0.848432	0.664003	0.812162	0.808332	
Adults 35-54	0.860076	0.817671	0.846322	0.864281	0.897686	0.858614	0.861368	0.692402	0.776687	0.803974	
Adults 55-64	0.838622	0.799478	0.819933	0.843902	0.887867	0.837386	0.840024	0.674409	0.735657	0.748042	
65+	0.840633	0.793344	0.820862	0.850354	0.895448	0.839427	0.842748	0.668530	0.692069	0.734700	
Latitude	-0.395637	-0.392189	-0.398492	-0.402613	-0.376290	-0.399287	-0.394167	-0.444864	-0.181758	-0.282176	
Longitude	0.036162	0.081918	0.023777	0.029848	0.047659	0.039383	0.032672	0.180157	-0.278308	-0.102843	
Land Area	0.235431	0.200886	0.248419	0.236252	0.212046	0.232714	0.237349	0.134233	0.203781	0.344879	
Water Area	0.038411	0.051521	0.032297	0.034407	0.046226	0.038427	0.038074	0.075830	0.047097	0.042598	
Mean Elevation	-0.133770	-0.196098	-0.117766	-0.126100	-0.141332	-0.139240	-0.128028	-0.298543	0.122569	0.060713	
Highest Elevation	-0.038246	-0.115800	-0.018904	-0.028611	-0.050574	-0.043899	-0.033001	-0.216534	0.306550	0.170534	
Lowest elevation	-0.344113	-0.337087	-0.333651	-0.346722	-0.365999	-0.345830	-0.342548	-0.297556	-0.559828	-0.292318	
Number of bordering states	0.092703	0.153356	0.090523	0.073651	0.071016	0.094695	0.089368	0.058746	-0.143034	-0.069825	
On Coast	0.464164	0.497887	0.435913	0.455132	0.512184	0.464668	0.463205	0.505677	0.168436	0.270946	
Borders Another Country	0.351913	0.303223	0.357825	0.350755	0.353612	0.345594	0.357028	0.180434	0.421510	0.499260	
Capital Latitude	-0.386561	-0.391908	-0.392011	-0.390199	-0.357046	-0.390466	-0.384523	-0.462045	-0.135382	-0.268392	
Capital Longitude	0.018177	0.067248	0.005968	0.010624	0.028374	0.021534	0.014318	0.173452	-0.302807	-0.121403	
Captial Land Area	0.003972	-0.007988	0.013931	0.004629	-0.017430	0.003967	0.003985	-0.025204	-0.015016	0.020859	
Capital Water Area	-0.091118	-0.100314	-0.086948	-0.090518	-0.095998	-0.091883	-0.090783	-0.100670	-0.021996	-0.041502	
Capital Mean Elevation	-0.166033	-0.186941	-0.154788	-0.163860	-0.181086	-0.169042	-0.162464	-0.226755	-0.114759	-0.033818	
Capital is the Largest City	-0.154074	-0.128106	-0.149158	-0.156946	-0.178305	-0.151938	-0.155487	-0.115770	-0.123610	-0.183826	
Largest City Latitude	-0.419120	-0.419459	-0.423088	-0.422919	-0.395974	-0.422660	-0.417371	-0.465860	-0.233447	-0.316075	
Largest City Longitude	0.048321	0.092830	0.035728	0.041774	0.061209	0.051430	0.044859	0.194353	-0.267233	-0.086233	
Number of Counties	0.659574	0.706073	0.666432	0.641478	0.607276	0.662444	0.655389	0.681011	0.096573	0.501717	
Became a State	-0.126570	-0.186422	-0.115157	-0.112935	-0.129547	-0.130157	-0.122258	-0.297191	0.083847	0.043321	
DaysSinceStayatHomeOrder	-0.021086	-0.020186	-0.030817	-0.027800	0.007419	-0.024088	-0.019335	-0.046409	0.222069	0.052387	
DaysSinceFirstPositive	0.357249	0.306142	0.355519	0.364255	0.380604	0.354390	0.360064	0.274180	0.255767	0.299965	
DaysSinceTestStart	0.273593	0.219953	0.272942	0.282120	0.296656	0.271182	0.275880	0.213147	0.187346	0.237754	
15-49yearsAllcauses	0.886884	0.854562	0.873498	0.888773	0.918524	0.885981	0.887769	0.736622	0.737674	0.796260	
15-49yearsAsthma	0.822646	0.785134	0.805485	0.825296	0.867899	0.821129	0.823386	0.663701	0.757688	0.750738	
15-49yearsChronickidneydisease	0.917925	0.892317	0.908566	0.917956	0.934714	0.917697	0.918009	0.803582	0.715805	0.829422	
15-49yearsChronicobstructivepulmonarydisease	0.895564	0.876357	0.879172	0.896199	0.927893	0.895413	0.895782	0.768727	0.635855	0.750723	
15-49yearsDiabetesmellitus	0.911319	0.879991	0.899800	0.913356	0.936198	0.910686	0.911822	0.779288	0.693258	0.813431	
15-49yearsInterstitiallungdiseaseandpulmonarysarcoidosis	0.879916	0.862208	0.865322	0.878905	0.908126	0.879919	0.879735	0.780069	0.644763	0.739273	
15-49yearsIschemicheartdisease	0.927678	0.926759	0.915842	0.922736	0.939065	0.928593	0.926497	0.847540	0.595987	0.766226	
15-49yearsNeoplasms	0.886136	0.858150	0.871628	0.887471	0.918495	0.885565	0.886670	0.745343	0.730821	0.786369	
15-49yearsOtherchronicrespiratorydiseases	0.905560	0.883613	0.891223	0.905653	0.934091	0.905184	0.905799	0.782455	0.653038	0.776105	
15-49yearsRheumaticheartdisease	0.902424	0.891711	0.892262	0.897798	0.916013	0.902292	0.902447	0.789490	0.691629	0.786644	
15-49yearsStroke	0.918867	0.897147	0.909310	0.918599	0.934170	0.918952	0.918838	0.805987	0.703053	0.816330	
50-69yearsAllcauses	0.878744	0.853509	0.861522	0.880659	0.917334	0.878249	0.879628	0.741745	0.678456	0.746293	
50-69yearsAsthma	0.799440	0.762340	0.778773	0.803715	0.854143	0.798097	0.800517	0.636677	0.742056	0.706594	
50-69yearsChronickidneydisease	0.916387	0.896945	0.904561	0.915572	0.937636	0.916311	0.916688	0.807095	0.676156	0.795122	
50-69yearsChronicobstructivepulmonarydisease	0.877906	0.870963	0.859255	0.877419	0.911277	0.878288	0.878455	0.762080	0.542320	0.678790	
50-69yearsDiabetesmellitus	0.881134	0.855438	0.863901	0.883450	0.919693	0.880643	0.882016	0.750770	0.653836	0.744109	
50-69yearsInterstitiallungdiseaseandpulmonarysarcoidosis	0.861583	0.838312	0.844421	0.862487	0.900025	0.861105	0.862351	0.735721	0.674419	0.726896	
50-69yearsIschemicheartdisease	0.904978	0.899635	0.888882	0.901757	0.930901	0.905480	0.904633	0.804866	0.618552	0.737135	
50-69yearsNeoplasms	0.871034	0.851227	0.852407	0.872097	0.911177	0.870768	0.871794	0.742697	0.651344	0.720355	
50-69yearsOtherchronicrespiratorydiseases	0.883753	0.873315	0.866185	0.882303	0.916676	0.883761	0.884109	0.777456	0.570326	0.702496	
50-69yearsRheumaticheartdisease	0.891423	0.888783	0.879360	0.885632	0.907455	0.891577	0.891644	0.791210	0.641520	0.739209	
50-69yearsStroke	0.906978	0.890724	0.893997	0.906473	0.929829	0.907205	0.907337	0.798197	0.657305	0.765372	
70+yearsAllcauses	0.847442	0.816751	0.826481	0.852488	0.898736	0.846808	0.848827	0.697071	0.654330	0.704089	
70+yearsAsthma	0.789028	0.744699	0.766961	0.797072	0.850124	0.787734	0.790683	0.607592	0.747748	0.697495	
70+yearsChronickidneydisease	0.875670	0.856224	0.857657	0.876360	0.914685	0.875402	0.876558	0.748543	0.643668	0.724464	
70+yearsChronicobstructivepulmonarydisease	0.865156	0.840259	0.845077	0.869812	0.910486	0.864851	0.866648	0.717738	0.599882	0.699384	
70+yearsDiabetesmellitus	0.843401	0.812744	0.821754	0.849108	0.896105	0.842866	0.844798	0.698870	0.638607	0.695980	
70+yearsInterstitiallungdiseaseandpulmonarysarcoidosis	0.831802	0.797053	0.811884	0.837251	0.883211	0.830937	0.833566	0.671418	0.689938	0.706600	
70+yearsIschemicheartdisease	0.839315	0.817188	0.816155	0.842376	0.892450	0.839017	0.840006	0.702589	0.634217	0.681467	
70+yearsNeoplasms	0.835509	0.805555	0.813851	0.840697	0.888696	0.834904	0.836996	0.685194	0.648382	0.686885	
70+yearsOtherchronicrespiratorydiseases	0.874566	0.857451	0.856689	0.874418	0.912408	0.874057	0.875635	0.748794	0.586877	0.705416	
70+yearsRheumaticheartdisease	0.842665	0.837198	0.824793	0.837776	0.877986	0.842106	0.843753	0.716967	0.626865	0.680450	
70+yearsStroke	0.870071	0.847350	0.852618	0.871917	0.909247	0.869793	0.871222	0.729313	0.660317	0.721808	

AllAgesAllcauses	0.878588	0.849145	0.861845	0.881318	0.917774	0.877905	0.879599	0.733191	0.695871	0.758571
AllAgesAsthma	0.831304	0.792231	0.813720	0.835086	0.877936	0.829823	0.832271	0.670182	0.749293	0.755115
AllAgesChronickidneydisease	0.904402	0.883840	0.890334	0.904351	0.932451	0.904221	0.904913	0.786269	0.672518	0.775388
AllAgesChronicobstructivepulmonarydisease	0.875803	0.858774	0.856544	0.878011	0.915264	0.875795	0.876810	0.742655	0.580530	0.697110
AllAgesDiabetesmellitus	0.878317	0.849967	0.860647	0.881652	0.919029	0.877785	0.879297	0.742684	0.658751	0.744450
AllAgesInterstitiallungdiseaseandpulmonarysarcoidosis	0.852165	0.823512	0.833849	0.855184	0.896166	0.851536	0.853348	0.710857	0.681959	0.721415
AllAgesIschemicheartdisease	0.882192	0.869062	0.862943	0.881839	0.920162	0.882348	0.882268	0.765407	0.628781	0.718536
AllAgesNeoplasms	0.863741	0.839097	0.844574	0.866307	0.907502	0.863308	0.864731	0.725375	0.663557	0.720556
AllAgesOtherchronicrespiratorydiseases	0.902524	0.884302	0.887253	0.902007	0.932378	0.902199	0.902973	0.782928	0.623094	0.754060
AllAgesRheumaticheartdisease	0.879079	0.873449	0.864765	0.873886	0.903225	0.878847	0.879647	0.764366	0.648372	0.728889
AllAgesStroke	0.894221	0.873914	0.879380	0.894925	0.924402	0.894172	0.894932	0.768243	0.667366	0.753694
AllAgesTotal	0.879105	0.851798	0.861916	0.881553	0.918458	0.878539	0.880046	0.737330	0.684312	0.751284
Airpollution	0.887961	0.886816	0.873716	0.881728	0.909727	0.888331	0.887745	0.777358	0.655261	0.730312
Highbody-massindex	0.892574	0.870891	0.875767	0.893521	0.928006	0.892269	0.893140	0.768343	0.661265	0.754688
Highfastingplasmaglucose	0.885519	0.868208	0.867475	0.886276	0.922271	0.885469	0.886040	0.770273	0.617289	0.725192
HighLDLcholesterol	0.892016	0.880761	0.874040	0.890927	0.925614	0.892300	0.891950	0.780580	0.627540	0.728204
Highsystolicbloodpressure	0.896298	0.880918	0.879042	0.896085	0.929809	0.896363	0.896543	0.785586	0.638860	0.742184
Impairedkidneyfunction	0.888684	0.870825	0.871779	0.888904	0.923102	0.888693	0.889102	0.770201	0.658349	0.741125
Noaccesstohandwashingfacility	0.876183	0.855685	0.860915	0.875209	0.908573	0.875653	0.876553	0.753540	0.668494	0.745193
Smoking	0.880256	0.864750	0.861340	0.881441	0.918294	0.880406	0.880814	0.757828	0.604253	0.706722
Log10Pop	0.730625	0.738162	0.716041	0.724834	0.750347	0.731527	0.730121	0.665876	0.425752	0.516893
DaysSinceInfection	0.412821	0.360632	0.410278	0.422147	0.434949	0.410914	0.414835	0.354265	0.259813	0.349814
Children0-18	0.170467	0.184747	0.184614	0.162743	0.122101	0.172944	0.167407	0.173000	0.050826	0.150062
Allriskfactors	0.881460	0.858902	0.864027	0.883001	0.919342	0.881097	0.882336	0.747372	0.661101	0.738270
State Area Ratio	-0.128550	-0.166800	-0.113602	-0.122087	-0.145833	-0.130919	-0.125230	-0.249270	-0.098980	-0.021322
Elevation Ratio	0.006435	-0.008386	0.016149	0.010278	-0.014214	0.007719	0.004657	0.117476	0.047721	0.006349
Capital Area Ratio	-0.107958	-0.139494	-0.098783	-0.101355	-0.113882	-0.109206	-0.106482	-0.160284	-0.071880	-0.046967
Boundaries	0.500872	0.558822	0.480645	0.479234	0.518677	0.501040	0.498998	0.456575	0.125069	0.276862
Latitude Difference to State Capital	-0.251296	-0.188306	-0.234552	-0.277897	-0.313035	-0.251254	-0.254554	-0.091516	-0.409883	-0.230231
Longitude Difference to State Capital	-0.132644	-0.120676	-0.128482	-0.139685	-0.144345	-0.132468	-0.134362	-0.089151	-0.102664	-0.103498
Latitude Difference to DC	-0.395637	-0.392189	-0.398492	-0.402613	-0.376290	-0.399287	-0.394167	-0.444864	-0.181758	-0.282176
Longitude Difference to DC	-0.036162	-0.081918	-0.023777	-0.029848	-0.047659	-0.039383	-0.032672	-0.180157	0.278308	0.102843
Latitude Difference to Center	-0.395637	-0.392189	-0.398492	-0.402613	-0.376290	-0.399287	-0.394167	-0.444864	-0.181758	-0.282176
Longitude Difference to Center	-0.036162	-0.081918	-0.023777	-0.029848	-0.047659	-0.039383	-0.032672	-0.180157	0.278308	0.102843

```
#  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_BEN	Sum of NUM_BEN_With_Race_Not_Elsewhere_Classified	Sum of Average_Age_of_BEN	Sum of PCT_MEDICARE	% Urban Pop	Density (P/mi2)	Children 0-18	Latitude	Longitude	Land Area
0	1820384.0	62311.0	76773.0	46525.0	147917.0	23372.0	996.298679	10.069041	66.0	1.2863	181405.17	61.370716	-152.404419	570665.0
1	10804823.0	1549811.0	30624.0	65500.0	5556.0	58660.0	3967.220634	51.254704	59.0	96.9221	1105570.08	32.806671	-86.791130	50644.0
2	15892716.0	1334245.0	19642.0	108428.0	62782.0	61250.0	3928.834167	94.570949	56.2	58.4030	686482.50	34.969704	-92.373123	52030.0
4	10786064.0	221183.0	61840.0	689880.0	179818.0	114903.0	1009.367955	14.075942	89.8	64.9550	1744612.56	33.729759	-111.431221	113595.0
5	42579588.0	2072012.0	3276415.0	5674776.0	113871.0	562214.0	4001.853612	63.398334	95.0	256.3727	9481941.36	36.116203	-119.681564	155766.0

```
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 50 entries, 0 to 54
Data columns (total 38 columns):
 #   Column                                             Non-Null Count  Dtype  
---  ------                                             --------------  -----  
 0   Sum of NUM_Medicare_BEN                            50 non-null     float64
 1   Sum of NUM_Black_or_African_American_BEN           50 non-null     float64
 2   Sum of NUM_Asian_Pacific_Islander_BEN              50 non-null     float64
 3   Sum of NUM_Hispanic_BEN                            50 non-null     float64
 4   Sum of NUM_American_IndianAlaska_Native_BEN        50 non-null     float64
 5   Sum of NUM_BEN_With_Race_Not_Elsewhere_Classified  50 non-null     float64
 6   Sum of Average_Age_of_BEN                          50 non-null     float64
 7   Sum of PCT_MEDICARE                                50 non-null     float64
 8   % Urban Pop                                        50 non-null     float64
 9   Density (P/mi2)                                    50 non-null     float64
 10  Children 0-18                                      50 non-null     float64
 11  Latitude                                           50 non-null     float64
 12  Longitude                                          50 non-null     float64
 13  Land Area                                          50 non-null     float64
 14  Water Area                                         50 non-null     float64
 15  Mean Elevation                                     50 non-null     float64
 16  Highest Elevation                                  50 non-null     float64
 17  Lowest elevation                                   50 non-null     float64
 18  Number of bordering states                         50 non-null     float64
 19  On Coast                                           50 non-null     float64
 20  Borders Another Country                            50 non-null     float64
 21  Captial Land Area                                  50 non-null     float64
 22  Captial Water Area                                 50 non-null     float64
 23  Capital Mean Elevation                             50 non-null     float64
 24  Capital is the Largest City                        50 non-null     float64
 25  Became a State                                     50 non-null     float64
 26  DaysSinceStayatHomeOrder                           50 non-null     float64
 27  DaysSinceFirstPositive                             50 non-null     float64
 28  DaysSinceTestStart                                 50 non-null     float64
 29  Log10Pop                                           50 non-null     float64
 30  DaysSinceInfection                                 50 non-null     float64
 31  Children0-18                                       50 non-null     float64
 32  State Area Ratio                                   50 non-null     float64
 33  Elevation Ratio                                    50 non-null     float64
 34  Capital Area Ratio                                 50 non-null     float64
 35  Boundaries                                         50 non-null     float64
 36  Latitude Difference to State Capital               50 non-null     float64
 37  Longitude Difference to State Capital              50 non-null     float64
dtypes: float64(38)
memory usage: 15.2 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_Native_BEN	Sum of NUM_BEN_With_Race_Not_Elsewhere_Classified	Sum of Average_Age_of_BEN	Sum of PCT_MEDICARE	% Urban Pop	Density (P/mi2)	Children 0-18	Latitude	Longit
count	5.000000e+01	5.000000e+01	5.000000e+01	5.000000e+01	50.000000	50.000000	50.000000	50.000000	50.000000	50.000000	5.000000e+01	50.000000	50.000
mean	1.057661e+07	9.653450e+05	1.439833e+05	5.412557e+05	39027.080000	88021.940000	3574.438430	52.910339	74.294000	440.074918	1.513864e+06	39.399000	-93.060
std	1.317051e+07	1.280319e+06	4.765951e+05	1.644850e+06	88090.522177	115323.411288	2527.939135	46.730862	14.976518	1662.815407	1.772177e+06	6.112752	19.379
min	1.655870e+05	2.960000e+02	1.660000e+02	4.130000e+02	0.000000	1693.000000	70.002893	0.972106	38.700000	1.286300	1.160123e+05	21.094318	-157.498
25%	2.518838e+06	6.328700e+04	6.770500e+03	3.269350e+04	2929.750000	19717.000000	1529.891773	13.039638	66.025000	56.532925	4.596994e+05	35.659511	-99.697
50%	6.848160e+06	3.978665e+05	2.777200e+04	1.050865e+05	7558.000000	58749.500000	3752.318846	52.406965	74.400000	110.435050	1.059542e+06	39.583974	-89.301
75%	1.479523e+07	1.548688e+06	7.370350e+04	2.012818e+05	28748.250000	100639.500000	5216.766839	79.721735	87.725000	226.003700	1.728603e+06	43.052506	-78.579
max	7.644909e+07	7.011107e+06	3.276415e+06	1.007620e+07	560433.000000	562214.000000	13644.965980	219.756971	100.000000	11814.541000	9.481941e+06	61.370716	-69.381

```
# 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
```

```
((37, 38), (37,), (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_Native_BEN	Sum of NUM_BEN_With_Race_Not_Elsewhere_Classified	Sum of Average_Age_of_BEN	Sum of PCT_MEDICARE	% Urban Pop	Density (P/mi2)	Children 0-18	Latitude	Longitu
count	3.700000e+01	3.700000e+01	37.000000	3.700000e+01	37.000000	37.000000	37.000000	37.000000	37.000000	37.000000	3.700000e+01	37.000000	37.0000
mean	1.157925e+07	1.130874e+06	98436.675676	5.365955e+05	41090.810811	90806.621622	3662.637363	54.022267	74.981081	514.205595	1.534385e+06	38.957733	-92.7059
std	1.384476e+07	1.398898e+06	171362.519286	1.696478e+06	97224.502922	103467.502844	2692.872668	45.920797	15.241297	1924.750858	1.503167e+06	6.614804	19.8657
min	1.655870e+05	2.960000e+02	166.000000	4.130000e+02	0.000000	1693.000000	70.002893	1.702566	38.700000	1.286300	1.160123e+05	21.094318	-157.4983
25%	3.242760e+06	1.057920e+05	12709.000000	4.230000e+04	3527.000000	20656.000000	1517.642713	12.694204	66.200000	57.654700	4.774097e+05	35.565342	-98.2680
50%	8.517210e+06	5.217080e+05	30624.000000	1.112130e+05	7061.000000	63452.000000	3926.277651	54.780620	74.600000	112.820400	1.140729e+06	39.063946	-86.7911
75%	1.629170e+07	1.693845e+06	76800.000000	2.027260e+05	28990.000000	101294.000000	5219.433901	81.425494	87.900000	228.024300	2.042904e+06	41.597782	-79.8064
max	7.644909e+07	7.011107e+06	793067.000000	1.007620e+07	560433.000000	441947.000000	13644.965980	219.756971	100.000000	11814.541000	7.650584e+06	61.370716	-69.3819

```
# 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 = [2, 3, 4]
n_estimators = [13, 14, 15]
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, 0.00625, 0.0125]
min_weight_fraction_leaf = [0.0, 0.00625, 0.0125]

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:    1.4s
[Parallel(n_jobs=-1)]: Done  14 tasks      | elapsed:    1.5s
[Parallel(n_jobs=-1)]: Batch computation too fast (0.1779s.) Setting batch_size=2.
[Parallel(n_jobs=-1)]: Batch computation too fast (0.0530s.) Setting batch_size=4.
[Parallel(n_jobs=-1)]: Done  24 tasks      | elapsed:    1.6s
[Parallel(n_jobs=-1)]: Batch computation too fast (0.0891s.) Setting batch_size=8.
[Parallel(n_jobs=-1)]: Done  58 tasks      | elapsed:    1.9s
[Parallel(n_jobs=-1)]: Done 130 tasks      | elapsed:    2.9s
[Parallel(n_jobs=-1)]: Done 202 tasks      | elapsed:    3.5s
[Parallel(n_jobs=-1)]: Done 290 tasks      | elapsed:    4.2s
[Parallel(n_jobs=-1)]: Done 378 tasks      | elapsed:    5.3s
[Parallel(n_jobs=-1)]: Done 482 tasks      | elapsed:    6.2s
[Parallel(n_jobs=-1)]: Done 586 tasks      | elapsed:    7.1s
[Parallel(n_jobs=-1)]: Done 706 tasks      | elapsed:    8.4s
[Parallel(n_jobs=-1)]: Done 826 tasks      | elapsed:    9.5s
[Parallel(n_jobs=-1)]: Done 962 tasks      | elapsed:   10.9s
[Parallel(n_jobs=-1)]: Done 1098 tasks      | elapsed:   12.4s
[Parallel(n_jobs=-1)]: Done 1250 tasks      | elapsed:   13.7s
[Parallel(n_jobs=-1)]: Done 1402 tasks      | elapsed:   15.4s
[Parallel(n_jobs=-1)]: Done 1570 tasks      | elapsed:   16.9s
[Parallel(n_jobs=-1)]: Done 1738 tasks      | elapsed:   18.5s
[Parallel(n_jobs=-1)]: Done 1922 tasks      | elapsed:   20.5s
[Parallel(n_jobs=-1)]: Done 2106 tasks      | elapsed:   22.4s
The score achieved with the best parameters =  -5.7456180073156355

The parameters are: {'ccp_alpha': 0.0, 'max_depth': 3, 'max_features': 'auto', 'max_leaf_nodes': None, 'min_samples_leaf': 4, 'min_samples_split': 2, 'min_weight_fraction_leaf': 0.0, 'n_estimators': 14}
[Parallel(n_jobs=-1)]: Done 2187 out of 2187 | elapsed:   23.0s finished
```

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

```
Collecting category_encoders==2.0.0
  Downloading https://files.pythonhosted.org/packages/6e/a1/f7a22f144f33be78afeb06bfa78478e8284a64263a3c09b1ef54e673841e/category_encoders-2.0.0-py2.py3-none-any.whl (87kB)
     |████████████████████████████████| 92kB 2.4MB/s
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: numpy>=1.11.3 in /usr/local/lib/python3.6/dist-packages (from category_encoders==2.0.0) (1.18.3)
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: pandas>=0.21.1 in /usr/local/lib/python3.6/dist-packages (from category_encoders==2.0.0) (1.0.3)
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: joblib>=0.11 in /usr/local/lib/python3.6/dist-packages (from scikit-learn>=0.20.0->category_encoders==2.0.0) (0.14.1)
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) (2018.9)
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) (2.8.1)
Installing collected packages: category-encoders
Successfully installed category-encoders-2.0.0
```

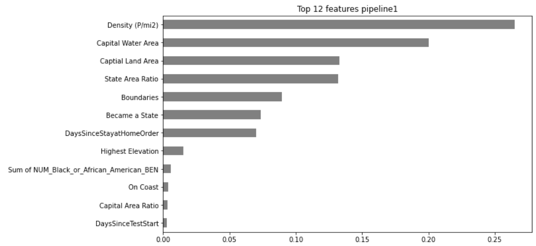
```
from sklearn.ensemble import RandomForestRegressor
from sklearn.pipeline import make_pipeline
import category_encoders as ce
from sklearn.impute import SimpleImputer

pipeline1 = make_pipeline(
    ce.OneHotEncoder(use_cat_names=True),
    SimpleImputer(strategy='mean'),
    RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                    max_depth=3, 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=14, 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 Accurary:  R^2 = ", pipeline1.score(X_train,y_train))

# Get the model's validation accuracy
ce.OneHotEncoder(use_cat_names=True),
print('Validation Accuracy:  R^2 = ', pipeline1.score(X_val, y_val))
```

```
Training Accurary:  R^2 =  0.6583151537360081
Validation Accuracy:  R^2 =  0.433396906882795
```

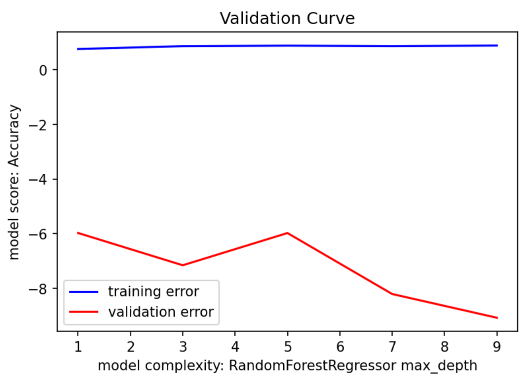
```
print("Feature Importances =")
#print(RandomForestRegressor.feature_importances_)
print(pipeline1.steps[2][1].feature_importances_)
```

```
Feature Importances =
[0.         0.00567273 0.         0.00249142 0.         0.00069529
 0.         0.         0.         0.264967   0.         0.
 0.         0.         0.00084393 0.         0.01535011 0.
 0.         0.00376275 0.         0.132861   0.20003276 0.
 0.00059546 0.07368697 0.06985453 0.         0.0025562  0.
 0.         0.         0.13198829 0.00219718 0.00310825 0.08933613
 0.         0.        ]
```

```
# 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: RandomForestRegressor max_depth')
plt.ylabel('model score: Accuracy')
plt.legend();
```




```
# Get drop-column importances
column = 'Density (P/mi2)'

pipeline3 = make_pipeline(
    ce.OneHotEncoder(use_cat_names=True),
    SimpleImputer(strategy = 'most_frequent'),
    RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                  max_depth=3, 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=14, 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 Density (P/mi2): 0.23757628259873162
Validation Accuracy with Density (P/mi2): 0.433396906882795
Drop-Column Importance for Density (P/mi2): 0.19582062428406335
```

```
# 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=0.15, criterion='mse',
                  max_depth=3, 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=14, 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=0.15, criterion='mse',
                      max_depth=3, 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=14, 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.py3-none-any.whl (105kB)
     |████████████████████████████████| 112kB 2.8MB/s
Requirement already satisfied: jinja2 in /usr/local/lib/python3.6/dist-packages (from eli5) (2.11.2)
Requirement already satisfied: attrs>16.0.0 in /usr/local/lib/python3.6/dist-packages (from eli5) (19.3.0)
Requirement already satisfied: scikit-learn>=0.18 in /usr/local/lib/python3.6/dist-packages (from eli5) (0.22.2.post1)
Requirement already satisfied: numpy>=1.9.0 in /usr/local/lib/python3.6/dist-packages (from eli5) (1.18.3)
Requirement already satisfied: tabulate>=0.7.7 in /usr/local/lib/python3.6/dist-packages (from eli5) (0.8.7)
Requirement already satisfied: six in /usr/local/lib/python3.6/dist-packages (from eli5) (1.12.0)
Requirement already satisfied: graphviz in /usr/local/lib/python3.6/dist-packages (from eli5) (0.10.1)
Requirement already satisfied: scipy in /usr/local/lib/python3.6/dist-packages (from eli5) (1.4.1)
Requirement already satisfied: MarkupSafe>=0.23 in /usr/local/lib/python3.6/dist-packages (from jinja2->eli5) (1.1.1)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.6/dist-packages (from scikit-learn>=0.18->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 in version 0.22 and will be removed in version 0.24. The corresponding classes / functions should instead be imported from sklearn.metrics. Anythi
  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 in version 0.22 and will be removed in version 0.24. The corresponding classes / functions should instead be imported from sklearn.feature
  warnings.warn(message, FutureWarning)
Using TensorFlow backend.
```

Weight	Feature
0.4793 ± 0.2232	Density (P/mi2)
0.1685 ± 0.0511	Became a State
0.1509 ± 0.0306	State Area Ratio
0.0270 ± 0.0581	Highest Elevation
0.0130 ± 0.0060	Capital Area Ratio
0.0111 ± 0.0073	Sum of NUM_BEN_With_Race_Not_Elsewhere_Classified
0.0043 ± 0.0137	Sum of NUM_Hispanic_BEN
0.0022 ± 0.0006	Capital is the Largest City
0.0020 ± 0.0025	Water Area
0.0014 ± 0.0039	DaysSinceStayatHomeOrder
0.0001 ± 0.0032	On Coast
0 ± 0.0000	% Urban Pop
0 ± 0.0000	Mean Elevation
0 ± 0.0000	Sum of PCT_MEDICARE
0 ± 0.0000	Sum of Average_Age_of_BEN
0 ± 0.0000	Sum of NUM_American_IndianAlaska_Native_BEN
0 ± 0.0000	Children 0-18
0 ± 0.0000	Latitude
0 ± 0.0000	Longitude
0 ± 0.0000	Land Area
0 ± 0.0000	Sum of NUM_Asian_Pacific_Islander_BEN
0 ± 0.0000	Longitude Difference to State Capital
0 ± 0.0000	Number of bordering states
0 ± 0.0000	Lowest elevation
0 ± 0.0000	Latitude Difference to State Capital
0 ± 0.0000	Borders Another Country
0 ± 0.0000	Capital Mean Elevation
0 ± 0.0000	DaysSinceFirstPositive
0 ± 0.0000	Log10Pop
0 ± 0.0000	DaysSinceInfection
0 ± 0.0000	Children0-18
0 ± 0.0000	Sum of NUM_Medicare_BEN
-0.0003 ± 0.0060	Elevation Ratio
-0.0004 ± 0.0009	DaysSinceTestStart
-0.0005 ± 0.0019	Boundaries
-0.0035 ± 0.0000	Sum of NUM_Black_or_African_American_BEN
-0.0063 ± 0.0126	Captial Land Area
-0.0657 ± 0.1535	Capital Water Area

```
from sklearn.metrics import mean_squared_error, r2_score

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

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

```
Coefficient of determination r2 for the training set.:  0.6583151537360081
Coefficient of determination r2 for the validation set.:  0.433396906882795
Mean squared error: 1063.44
```

```
# Thus, Density remains important according to feature permutation than according to feature importance in the Randoı
# Use importances for feature selection
print('Shape before removing features:', X_train.shape)
```

```
Shape before removing features: (37, 38)
```

```
# Remove features of 0 importance
zero_importance = 0.0
mask = permuter.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: (37, 11)
```

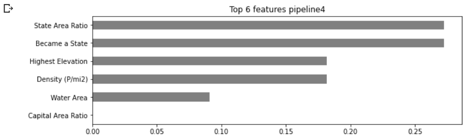
```
# Random forest classifier with eleven features
X_val = X_val[features1]
pipeline4 = make_pipeline(
    ce.OneHotEncoder(use_cat_names=True),
    SimpleImputer(strategy = 'most_frequent'),
    RandomForestRegressor(bootstrap=True, ccp_alpha=0,
                      max_depth=3, max_features='auto', 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=14, 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);
```

```
# 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.:  0.6369330994170446
Coefficient of determination r2 for the validation set.:  0.6746768878502091
Mean squared error: 610.59
```

```
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 = 6
plt.figure(figsize=(10,n/2))
plt.title(f'Top {n} features pipeline4')
```

```
importances2.sort_values()[-n:].plot.barh(color='grey');
```




```
# Gradient boosting using XGboost with 45 estimators
from xgboost import XGBRegressor
pipeline5 = make_pipeline(
    ce.OrdinalEncoder(),
    XGBRegressor(n_estimators=13,
                max_depth=3, # try deeper trees because of high cardinality categoricals
                learning_rate=0.25, # try a higher learning rate
                random_state=42,
                n_jobs=-1)
)
pipeline5.fit(X_train, y_train);
```

```
[05:28:00] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.
```

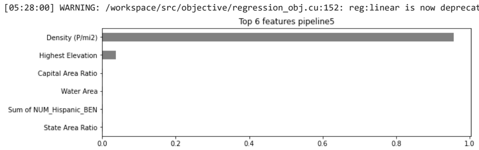
```
# Coefficient of determination r2 for the training set
pipeline_score = pipeline5.score(X_train,y_train)
print("Coefficient of determination r2 for the training set.: ", pipeline_score)

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

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

```
Coefficient of determination r2 for the training set.:  0.9816891241240165
Coefficient of determination r2 for the validation set.:  0.5216622294565731
Mean squared error: 897.78
```

The best validation score (0.52166) and lowest MSE (897.78) comes from using Gradient Boosting with 45 parameters.

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

# Get feature importances
encoder = pipeline5.named_steps['ordinalencoder']
encoded = encoder.transform(X_val)
rf = pipeline5.named_steps['xgbregressor']
importances3 = pd.Series(rf.feature_importances_, encoded.columns)

# Plot feature importances
n = 6
plt.figure(figsize=(10,n/2))
plt.title(f'Top {n} features pipeline5')
importances3.sort_values()[-n:].plot.barh(color='grey');
```

```
[05:28:00] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.
```



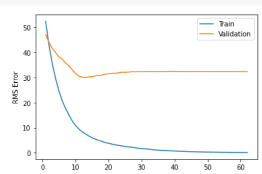

```
# Gradient boosting using XGboost with 1000 estimators
encoder = ce.OrdinalEncoder()
X_train_encoded = encoder.fit_transform(X_train)
X_val_encoded = encoder.transform(X_val)
X_train.shape, X_val.shape, X_train_encoded.shape, X_val_encoded.shape
```

```
((37, 11), (13, 11), (37, 11), (13, 11))
```

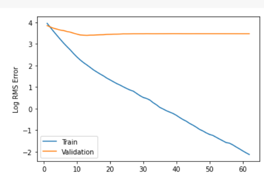
```
eval_set = [(X_train_encoded, y_train),
            (X_val_encoded, y_val)]

model2 = XGBRegressor(
          n_estimators=1000, # <= 1000 trees, depends on early stopping
          max_depth=3, # try deeper trees because of high cardinality categoricals
          learning_rate=0.25,
          n_jobs=-1)

model2.fit(X_train_encoded, y_train, eval_set=eval_set, eval_metric='rmse',
          early_stopping_rounds=50)
```

```
[05:28:01] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.
[0]	validation_0-rmse:52.3781	validation_1-rmse:47.1529
Multiple eval metrics have been passed: 'validation_1-rmse' will be used for early stopping.

Will train until validation_1-rmse hasn't improved in 50 rounds.
[1]	validation_0-rmse:43.1199	validation_1-rmse:44.0964
[2]	validation_0-rmse:35.6563	validation_1-rmse:41.6354
[3]	validation_0-rmse:29.6914	validation_1-rmse:39.9172
[4]	validation_0-rmse:24.814	validation_1-rmse:38.26
[5]	validation_0-rmse:20.8448	validation_1-rmse:37.4253
[6]	validation_0-rmse:17.7565	validation_1-rmse:35.8079
[7]	validation_0-rmse:15.2326	validation_1-rmse:34.7899
[8]	validation_0-rmse:12.835	validation_1-rmse:33.1101
[9]	validation_0-rmse:10.9878	validation_1-rmse:31.7264
[10]	validation_0-rmse:9.55471	validation_1-rmse:30.563
[11]	validation_0-rmse:8.44929	validation_1-rmse:30.1642
[12]	validation_0-rmse:7.58771	validation_1-rmse:29.963
[13]	validation_0-rmse:6.77693	validation_1-rmse:30.2651
[14]	validation_0-rmse:6.0322	validation_1-rmse:30.2984
[15]	validation_0-rmse:5.4796	validation_1-rmse:30.625
[16]	validation_0-rmse:4.98416	validation_1-rmse:30.8223
[17]	validation_0-rmse:4.57179	validation_1-rmse:30.9203
[18]	validation_0-rmse:4.12728	validation_1-rmse:31.3629
[19]	validation_0-rmse:3.79802	validation_1-rmse:31.4719
[20]	validation_0-rmse:3.48454	validation_1-rmse:31.6666
[21]	validation_0-rmse:3.20129	validation_1-rmse:31.7125
[22]	validation_0-rmse:2.98495	validation_1-rmse:31.8522
[23]	validation_0-rmse:2.75047	validation_1-rmse:32.1235
[24]	validation_0-rmse:2.5478	validation_1-rmse:32.0904
[25]	validation_0-rmse:2.37349	validation_1-rmse:32.1687
[26]	validation_0-rmse:2.25188	validation_1-rmse:32.2998
[27]	validation_0-rmse:2.02664	validation_1-rmse:32.2823
[28]	validation_0-rmse:1.83008	validation_1-rmse:32.3191
[29]	validation_0-rmse:1.67982	validation_1-rmse:32.3075
[30]	validation_0-rmse:1.60264	validation_1-rmse:32.3992
[31]	validation_0-rmse:1.49057	validation_1-rmse:32.3636
[32]	validation_0-rmse:1.31788	validation_1-rmse:32.3428
[33]	validation_0-rmse:1.19508	validation_1-rmse:32.3274
[34]	validation_0-rmse:1.05979	validation_1-rmse:32.3784
[35]	validation_0-rmse:0.984212	validation_1-rmse:32.3686
[36]	validation_0-rmse:0.907694	validation_1-rmse:32.3994
[37]	validation_0-rmse:0.851577	validation_1-rmse:32.4227
[38]	validation_0-rmse:0.799215	validation_1-rmse:32.4612
[39]	validation_0-rmse:0.733846	validation_1-rmse:32.4421
[40]	validation_0-rmse:0.662806	validation_1-rmse:32.4362
[41]	validation_0-rmse:0.603196	validation_1-rmse:32.398
[42]	validation_0-rmse:0.558525	validation_1-rmse:32.3853
[43]	validation_0-rmse:0.504073	validation_1-rmse:32.3657
[44]	validation_0-rmse:0.465015	validation_1-rmse:32.3978
[45]	validation_0-rmse:0.423969	validation_1-rmse:32.4056
[46]	validation_0-rmse:0.381959	validation_1-rmse:32.4076
[47]	validation_0-rmse:0.35554	validation_1-rmse:32.3895
[48]	validation_0-rmse:0.325552	validation_1-rmse:32.4004
[49]	validation_0-rmse:0.302503	validation_1-rmse:32.4023
[50]	validation_0-rmse:0.28915	validation_1-rmse:32.3975
[51]	validation_0-rmse:0.265711	validation_1-rmse:32.3974
[52]	validation_0-rmse:0.244267	validation_1-rmse:32.3964
[53]	validation_0-rmse:0.225414	validation_1-rmse:32.3959
[54]	validation_0-rmse:0.2075	validation_1-rmse:32.3828
[55]	validation_0-rmse:0.201813	validation_1-rmse:32.38
[56]	validation_0-rmse:0.186793	validation_1-rmse:32.3687
[57]	validation_0-rmse:0.169785	validation_1-rmse:32.363
[58]	validation_0-rmse:0.155332	validation_1-rmse:32.355
[59]	validation_0-rmse:0.141339	validation_1-rmse:32.3448
[60]	validation_0-rmse:0.12925	validation_1-rmse:32.3393
[61]	validation_0-rmse:0.119124	validation_1-rmse:32.3441
[62]	validation_0-rmse:0.107996	validation_1-rmse:32.3361
Stopping. Best iteration:
[12]	validation_0-rmse:7.58771	validation_1-rmse:29.963

XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0,
             importance_type='gain', learning_rate=0.25, max_delta_step=0,
             max_depth=3, min_child_weight=1, missing=None, n_estimators=1000,
             n_jobs=-1, nthread=None, objective='reg:linear', random_state=0,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
             silent=None, subsample=1, verbosity=1)
```

```
# Plot the results
results = model2.evals_result()
train_error = results['validation_0']['rmse']
val_error = results['validation_1']['rmse']
epoch = range(1, len(train_error)+1)
plt.plot(epoch, train_error, label='Train')
plt.plot(epoch, val_error, label='Validation')
plt.ylabel('RMS Error')
plt.xlabel('Model Complexity (n_estimators)')
# plt.ylim((0.18, 0.22)) # Zoom in
plt.legend();
```




```
# Plot log classification error versus model complexity
import numpy as np
results = model2.evals_result()
log_train_error = np.log(results['validation_0']['rmse'])
log_val_error = np.log(results['validation_1']['rmse'])
epoch = range(1, len(train_error)+1)
plt.plot(epoch, log_train_error, label='Train')
plt.plot(epoch, log_val_error, label='Validation')
plt.ylabel('Log RMS Error')
plt.xlabel('Model Complexity (n_estimators)')
# plt.ylim((0.18, 0.22)) # Zoom in
plt.legend();
```



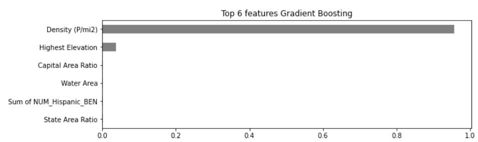

```
#Gradient Boosting R^2

gb = make_pipeline(
                ce.OrdinalEncoder(),
                XGBRegressor(n_estimators=13,
                            objective='reg:squarederror',
                            max_depth=3, # try deeper trees because of high cardinality categoricals
                            learning_rate=0.25,
                            random_state=42,
                            n_jobs=-1)
                )
gb.fit(X_train, y_train)
```

```
Pipeline(memory=None,
         steps=[('ordinalencoder',
                 OrdinalEncoder(cols=[], drop_invariant=False,
                                handle_missing='value', handle_unknown='value',
                                mapping=[], return_df=True, verbose=0)),
                ('xgbregressor',
                 XGBRegressor(base_score=0.5, booster='gbtree',
                              colsample_bylevel=1, colsample_bynode=1,
                              colsample_bytree=1, gamma=0,
                              importance_type='gain', learning_rate=0.25,
                              max_delta_step=0, max_depth=3, min_child_weight=1,
                              missing=None, n_estimators=13, n_jobs=-1,
                              nthread=None, objective='reg:squarederror',
                              random_state=42, reg_alpha=0, reg_lambda=1,
                              scale_pos_weight=1, seed=None, silent=None,
                              subsample=1, verbosity=1))],
         verbose=False)
```

```
# Coefficient of determination r2 for the training set
y_train_pred = gb.predict(X_train)
pipeline_score = r2_score(y_train, y_train_pred)
print("Coefficient of determination r2 for the training set.: ", pipeline_score)

# Coefficient of determination r2 for the validation set
y_val_pred = gb.predict(X_val)
pipeline_score = r2_score(y_val, y_val_pred)
print("Coefficient of determination r2 for the validation set.: ", pipeline_score)

# The mean squared error
print("Mean squared error: %.2f"% mean_squared_error(y_val, y_val_pred))
```

```
Coefficient of determination r2 for the training set.:  0.9816891241240167
Coefficient of determination r2 for the validation set.:  0.5216622294565731
Mean squared error: 897.78
```

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

# Get feature importances
encoder = gb.named_steps['ordinalencoder']
encoded = encoder.transform(X_val)
rf = gb.named_steps['xgbregressor']
importances4 = pd.Series(rf.feature_importances_, encoded.columns)

# Plot feature importances
n = 6
plt.figure(figsize=(10,n/2))
plt.title(f'Top {n} features Gradient Boosting')
importances4.sort_values()[-n:].plot.barh(color='grey');
```

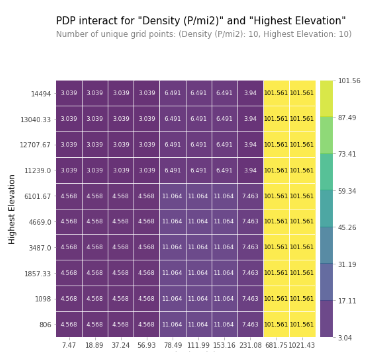



```
!pip install pdpbox
```

```
Collecting pdpbox
  Downloading https://files.pythonhosted.org/packages/87/23/ac7da5ba1c6c03a87c412e7e7b6e91a10d6ecf4474906c3e736f93940d49/PDPbox-0.2.0.tar.gz (57.7MB)
     |████████████████████████████████| 57.7MB 73kB/s
Requirement already satisfied: pandas in /usr/local/lib/python3.6/dist-packages (from pdpbox) (1.0.3)
Requirement already satisfied: numpy in /usr/local/lib/python3.6/dist-packages (from pdpbox) (1.18.3)
Requirement already satisfied: scipy in /usr/local/lib/python3.6/dist-packages (from pdpbox) (1.4.1)
Requirement already satisfied: matplotlib>=2.1.2 in /usr/local/lib/python3.6/dist-packages (from pdpbox) (3.2.1)
Requirement already satisfied: joblib in /usr/local/lib/python3.6/dist-packages (from pdpbox) (0.14.1)
Requirement already satisfied: psutil in /usr/local/lib/python3.6/dist-packages (from pdpbox) (5.4.8)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.6/dist-packages (from pdpbox) (0.22.2.post1)
Requirement already satisfied: python-dateutil>=2.6.1 in /usr/local/lib/python3.6/dist-packages (from pandas->pdpbox) (2.8.1)
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.6/dist-packages (from pandas->pdpbox) (2018.9)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.6/dist-packages (from matplotlib>=2.1.2->pdpbox) (0.10.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr/local/lib/python3.6/dist-packages (from matplotlib>=2.1.2->pdpbox) (2.4.7)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.6/dist-packages (from matplotlib>=2.1.2->pdpbox) (1.2.0)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.6/dist-packages (from python-dateutil>=2.6.1->pandas->pdpbox) (1.12.0)
Building wheels for collected packages: pdpbox
  Building wheel for pdpbox (setup.py) ... done
  Created wheel for pdpbox: filename=PDPbox-0.2.0-cp36-none-any.whl size=57690722 sha256=4343d517325585065865a1bbbc3fc82be1b36d7c3dfcf40d41cced44b9f4a3fb
  Stored in directory: /root/.cache/pip/wheels/7d/08/51/63fd122b04a2c87d780464eeffb94867c75bd96a64d500a3fe
Successfully built pdpbox
Installing collected packages: pdpbox
Successfully installed pdpbox-0.2.0
```

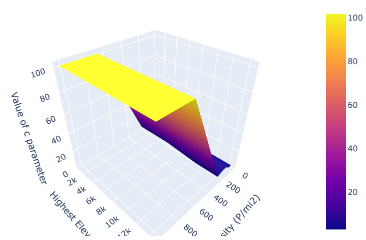
```
# Partial Dependence Plots with 2 features
from pdpbox.pdp import pdp_interact, pdp_interact_plot
features2 = ['Density (P/mi2)', 'Highest Elevation']
interaction = pdp_interact(
                    model=gb,
                    dataset=X_val,
                    model_features=X_val.columns,
                    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.
```




```
# 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 c 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()
```



In order to establish feature importances, Shapley Force Plots are used. SHAP is both consistent and accurate as a way to allocate feature importances. The details are in a recent paper by Lundberg and Lee (papers.nips.cc/paper/7062-a-unified-approach-to-interpreting-model-predictions.pdf)

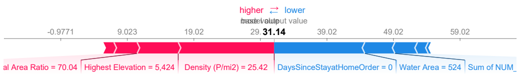
```
! pip install shap==0.23.0
! pip install -I shap
```

```
Collecting shap==0.23.0
  Downloading https://files.pythonhosted.org/packages/60/0d/8bd076821f7230edb2892ad982ea91ca25f2f925466563272e61eae891c6/shap-0.23.0.tar.gz (182kB)
     |████████████████████████████████| 184kB 2.8MB/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 scikit-learn->shap==0.23.0) (0.14.1)
Requirement already satisfied: pyparsing!=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) (2.4.7)
Requirement already satisfied: cycler>=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: python-dateutil>=2.1 in /usr/local/lib/python3.6/dist-packages (from matplotlib->shap==0.23.0) (2.8.1)
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: simplegeneric>0.8 in /usr/local/lib/python3.6/dist-packages (from ipython->shap==0.23.0) (0.8.1)
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: decorator in /usr/local/lib/python3.6/dist-packages (from ipython->shap==0.23.0) (4.4.2)
Requirement already satisfied: pygments in /usr/local/lib/python3.6/dist-packages (from ipython->shap==0.23.0) (2.1.3)
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: pexpect; sys_platform != "win32" in /usr/local/lib/python3.6/dist-packages (from ipython->shap==0.23.0) (4.8.0)
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) (1.0.18)
Requirement already satisfied: pickleshare in /usr/local/lib/python3.6/dist-packages (from ipython->shap==0.23.0) (0.7.5)
Requirement already satisfied: six in /usr/local/lib/python3.6/dist-packages (from cycler>=0.10->matplotlib->shap==0.23.0) (1.12.0)
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)
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)
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=235675 sha256=d961021556233d28986114b96c6b790616c19fc96c5d872b30b460584341ef5b
  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 (273kB)
     |████████████████████████████████| 276kB 2.8MB/s
Collecting numpy
  Downloading https://files.pythonhosted.org/packages/03/27/e35e7c6e6a52fab9fcc64fc2b20c6b516eba930bb02b10ace3b38200d3ab/numpy-1.18.4-cp36-cp36m-manylinux1_x86_64.whl (20.2MB)
     |████████████████████████████████| 20.2MB 1.2MB/s
Collecting scipy
  Downloading https://files.pythonhosted.org/packages/dc/29/162476fd44203116e7980cfbd9352eef9db37c49445d1fec35509022f6aa/scipy-1.4.1-cp36-cp36m-manylinux1_x86_64.whl (26.1MB)
     |████████████████████████████████| 26.1MB 1.3MB/s
Collecting scikit-learn
  Downloading https://files.pythonhosted.org/packages/5e/d8/312e03adf4c78663e17d802fe2440072376fee46cada1404f1727ed77a32/scikit_learn-0.22.2.post1-cp36-cp36m-manylinux1_x86_64.whl (7.1MB)
     |████████████████████████████████| 7.1MB 36.6MB/s
Collecting pandas
  Downloading https://files.pythonhosted.org/packages/bb/71/8f53bdbcbc67c912b888b40def255767e475402e9df64050019149b1a943/pandas-1.0.3-cp36-cp36m-manylinux1_x86_64.whl (10.0MB)
     |████████████████████████████████| 10.0MB 38.0MB/s
Collecting tqdm>4.25.0
  Downloading https://files.pythonhosted.org/packages/c9/40/058b12e8ba10e35f89c9b1fdfc2d4c7f8c05947df2d5eb3c7b258019fda0/tqdm-4.46.0-py2.py3-none-any.whl (63kB)
     |████████████████████████████████| 71kB 10.1MB/s
Collecting joblib>=0.11
  Downloading https://files.pythonhosted.org/packages/28/5c/cf6a2b65a321c4a209efcdf64c2689efae2cb62661f8f6f4bb28547cf1bf/joblib-0.14.1-py2.py3-none-any.whl (294kB)
     |████████████████████████████████| 296kB 48.8MB/s
Collecting pytz>=2017.2
  Downloading https://files.pythonhosted.org/packages/4f/a4/879454d49688e2fad93e59d7d4efda580b783c745fd2ec2a3adf87b0808d/pytz-2020.1-py2.py3-none-any.whl (510kB)
     |████████████████████████████████| 512kB 34.5MB/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 (227kB)
     |████████████████████████████████| 235kB 51.0MB/s
Collecting six>=1.5
  Downloading https://files.pythonhosted.org/packages/65/eb/1f97cb97bfc2390a276969c6fae16075da282f5058082d4cb10c6c5c1dba/six-1.14.0-py2.py3-none-any.whl
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=394134 sha256=3a9811210f0b91f5eae1f6e71344c90cf60e7c414427527859e1b073953f5e3b
  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: albumentations 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, pytz, six, python-dateutil, 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 six-1.14.0 tqdm-4.46.0
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

model_shap =     XGBRegressor(n_estimators=13,
                              objective='reg:squarederror',
                              max_depth=3, # try deeper trees because of high cardinality categoricals
                              learning_rate=0.25, # try a higher learning rate
                              random_state=42,
                              n_jobs=-1)

eval_set = [(X_train, y_train),
            (X_val, y_val)]

model_shap.fit(X_train,
               y_train,
               eval_set=eval_set,
               eval_metric='rmse',
               early_stopping_rounds=50)

shap.initjs()
explainer = shap.TreeExplainer(model_shap)
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)
```

```
[0]     validation_0-rmse:52.3781       validation_1-rmse:47.1529
Multiple eval metrics have been passed: 'validation_1-rmse' will be used for early stopping.

Will train until validation_1-rmse hasn't improved in 50 rounds.
[1]     validation_0-rmse:43.1199       validation_1-rmse:44.0964
[2]     validation_0-rmse:35.6563       validation_1-rmse:41.6354
[3]     validation_0-rmse:29.6914       validation_1-rmse:39.9172
[4]     validation_0-rmse:24.814        validation_1-rmse:38.26
[5]     validation_0-rmse:20.8448       validation_1-rmse:37.4253
[6]     validation_0-rmse:17.7565       validation_1-rmse:35.8079
[7]     validation_0-rmse:15.2326       validation_1-rmse:34.7899
[8]     validation_0-rmse:12.835        validation_1-rmse:33.1101
[9]     validation_0-rmse:10.9878       validation_1-rmse:31.7264
[10]    validation_0-rmse:9.55471       validation_1-rmse:30.563
[11]    validation_0-rmse:8.44929       validation_1-rmse:30.1642
[12]    validation_0-rmse:7.58771       validation_1-rmse:29.963
```




```
# 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(model_shap)
        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 sa
# A two feature partical 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 c for state'),
                zaxis=dict(title= 'Shapley Force')
)
)
fig = go.Figure(surface, layout)
fig.show()
```