DSC680_Project1_Milestone3_BriggsC

June 27, 2021

[1]:
```
import pandas as pd
import numpy as np

from time import sleep
from random import randint
from urllib.request import Request, urlopen
from bs4 import BeautifulSoup as BS

from scipy import optimize

import matplotlib.pyplot as plt
import seaborn as sns
```

Strategy: get the n-day moving average; smooth enough to reveal the fall min. Then start fitting curves to the days from 1 to k starting at that min, and see how surprised the model is by k+1. Quantify the surprise (magnitude of error). Analyze the surprise between states, and see if it isn't anomalously high in late January.

Rather than try to come up with a reasonable k>1, I might just start with k=3 (or however many points are needed to determine my exponential curve), then look at the shape of the error curve. It should be a decreasing curve, so a sharp uptick later would indicate an anomaly. I might even model the error curves.

Probably just hand-pick the start date. Talk about why I would do this.

[2]:
```
states = ['Alabama', 'Alaska', 'Arizona', 'Arkansas', 'California', 'Colorado',␣
↪'Connecticut', 'Delaware',
          'District of Columbia', 'Florida', 'Georgia', 'Hawaii', 'Idaho',␣
↪'Illinois', 'Indiana',
          'Iowa', 'Kansas', 'Kentucky', 'Louisiana', 'Maine', 'Maryland',␣
↪'Massachusetts', 'Michigan',
          'Minnesota', 'Mississippi', 'Missouri', 'Montana', 'Nebraska',␣
↪'Nevada', 'New Hampshire',
          'New Jersey', 'New Mexico', 'New York', 'North Carolina', 'North␣
↪Dakota', 'Ohio',
          'Oklahoma', 'Oregon', 'Pennsylvania', 'Rhode Island', 'South␣
↪Carolina', 'South Dakota',
```

```
          'Tennessee', 'Texas', 'Utah', 'Vermont', 'Virginia', 'Washington',␣
↪'West Virginia',
          'Wisconsin', 'Wyoming']
```

I will now convert the list of states into a suitable format for the data scraping. Specifically, worldometers uses lowercase in its URL format, and replaces each space with a hyphen.

[3]:
```
states = [state.lower().replace(' ','-') for state in states]
```

The general format for the worldometer URL is

https://www.worldometers.info/coronavirus/usa/'+state+'/'

I loop through the list of states, substituting each in turn into the URL format, and use urllib to retrieve the HTML code.

With the HTML code in hand, I can find the list of daily case numbers. These daily case numbers begin on March 12, 2020 and continue to the present day. The data was harvested on June 24, 2021, so that is the last date for each of the records in this data frame.

[4]:
```
# # fetch the daily case numbers data from worldometers

# data = {}
# for state in states:
#     req = Request('https://www.worldometers.info/coronavirus/usa/'+state+'/',
#                                   headers={'User-Agent': 'Mozilla/5.0'})
#     webpage = urlopen(req).read()
#     html = webpage.decode("utf8")
#     soup = BS(html,'lxml')
#     ls = html.split('Novel Coronavirus Daily Cases')[1].split('data: [')[1].
↪split(']')[0]
#     data[state]=ls.split(',')
#     sleep(randint(5,13))

# # convert the data to a dataframe
# df_full = pd.DataFrame(data)

#  ''' The dataframe comes with strings instead of integers for entries. Also,␣
↪there are some "null"
#      entries. They don't contribute to the tallies in worldometers, so I␣
↪assume that null should
#      correspond to 0. I will now define a function and apply it to the data␣
↪frame which will handle
#      these cleanup steps.
# '''
# def convert_to_int(x):
#     res = []
#     for entry in x:
#         try: res.append(int(entry))
```

```
#         except: res.append(0)
#     return(np.asarray(res))

# df_full = df_full.apply(convert_to_int)

# # I will save a copy of the data, so that I don't have to keep hitting␣
 ↪worldometers with
# # request traffic each time I run the notebook.
# df_full.to_csv('data_full.csv')

# load the data from file
df_full = pd.read_csv('data_full.csv')
```

[ ]:

```

```

The last date of daily case numbers I am looking at for this study is January 31, 2021. So I will truncate the data frame at this date. January 31, 2021 is 325 days after March 12, 2020.

[5]:

```
df = df_full.iloc[:325,:]
```

[6]:

```
df.head()
```

[6]:

```
   Unnamed: 0  alabama  alaska  arizona  arkansas  california  colorado  \
0           0        0       0        0         0           0         0
1           1      316       0        0         3          45        28
2           2       64       0        3         3          77        24
3           3       77       0        1         4          67        30
4           4       67       0        5         6         134        29

   connecticut  delaware  district-of-columbia  …  south-dakota  tennessee  \
0            0         0                     0  …             0          0
1            6         0                     0  …             1        -17
2           12         2                     0  …             0          0
3            3         1                     8  …             0          5
4           15         1                     4  …             1          4

   texas  utah  vermont  virginia  washington  west-virginia  wisconsin  \
0      0     0        0         0           0              0          0
1     16     4        0        12         126              0          2
2     13     1        3        11          74              0         11
3     16    18        3         4         127              0         14
4     12    11        4         6         135              0         13

   wyoming
0        0
1        0
2        2
```

```
3         0
4         0

[5 rows x 54 columns]
```

[7]:
```
# do some summary statistics
df.describe()
```

[7]:
```
       Unnamed: 0      alabama      alaska      arizona     arkansas  \
count  325.000000   325.000000  325.000000   325.000000   325.000000
mean   162.000000  1465.430769  162.156923  2318.061538   914.089231
std     93.963645  1324.627164  200.618834  2747.456065   870.146717
min      0.000000     0.000000    0.000000     0.000000     0.000000
25%     81.000000   523.000000   13.000000   402.000000   255.000000
50%    162.000000  1061.000000   79.000000  1030.000000   704.000000
75%    243.000000  2066.000000  224.000000  3476.000000  1178.000000
max    324.000000  6812.000000  885.000000 17234.000000  4344.000000

         california     colorado  connecticut     delaware  \
count    325.000000   325.000000   325.000000   325.000000
mean   10193.144615  1215.283077   769.286154   242.255385
std    12596.337772  1439.598420  1336.451315   257.503121
min        0.000000     0.000000   -15.000000     0.000000
25%     2560.000000   300.000000    29.000000    75.000000
50%     4938.000000   459.000000   220.000000   134.000000
75%    10328.000000  1689.000000   796.000000   336.000000
max    61869.000000  6439.000000  8457.000000  1240.000000

       district-of-columbia  …  south-dakota    tennessee         texas  \
count            325.000000  …    325.000000   325.000000    325.000000
mean             112.775385  …    332.498462  2208.843077   7390.095385
std               89.518441  …    401.022240  2299.368282   6628.768258
min                0.000000  …      0.000000   -17.000000      0.000000
25%               49.000000  …     61.000000   472.000000   1649.000000
50%               80.000000  …    133.000000  1532.000000   5803.000000
75%              155.000000  …    452.000000  2759.000000  10736.000000
max              492.000000  …   2138.000000 11806.000000  32055.000000

              utah     vermont     virginia   washington  west-virginia  \
count   325.000000  325.000000   325.000000   325.000000     325.000000
mean   1062.846154   36.396923  1545.240000   967.596923     370.283077
std    1087.257614   51.385489  1528.028922  1028.099653     475.430494
min       0.000000    0.000000     0.000000     0.000000       0.000000
25%     244.000000    4.000000   645.000000   316.000000      34.000000
50%     567.000000   10.000000   951.000000   563.000000     143.000000
75%    1735.000000   51.000000  1551.000000  1160.000000     543.000000
max    4707.000000  245.000000  9914.000000  6621.000000    2148.000000
```

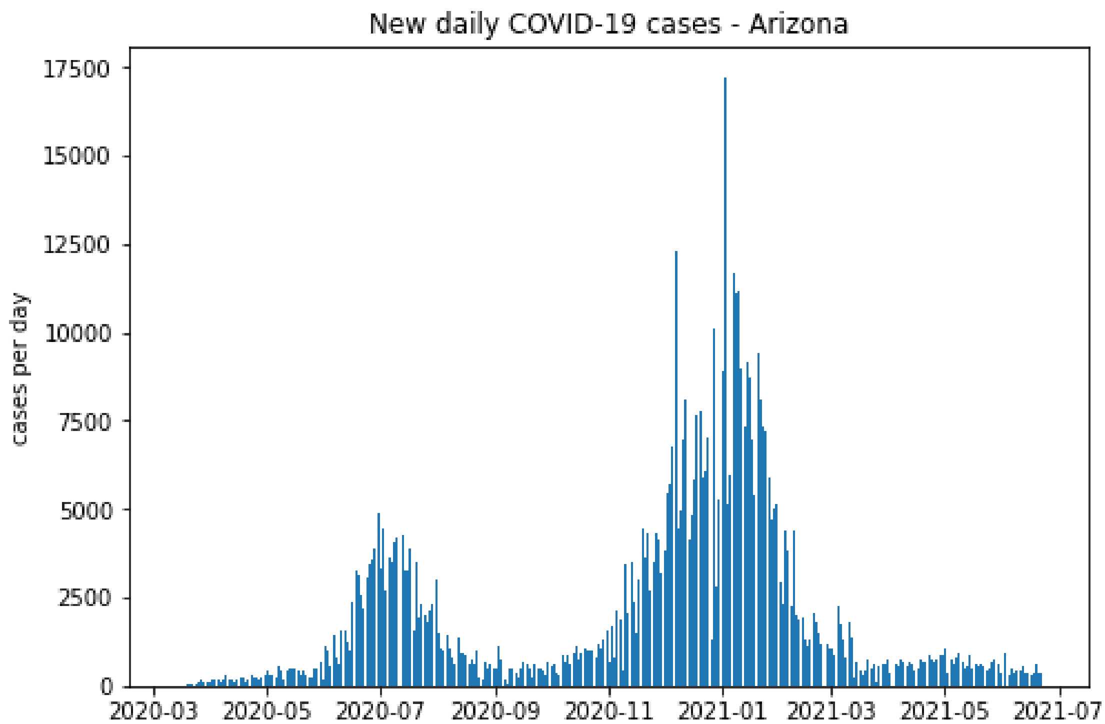
```
       wisconsin     wyoming
count   325.000000   325.000000
mean   1811.003077   159.086154
std    1940.831179   240.195173
min       0.000000     0.000000
25%     358.000000    13.000000
50%     919.000000    42.000000
75%    2882.000000   213.000000
max    8520.000000  1262.000000

[8 rows x 54 columns]
```

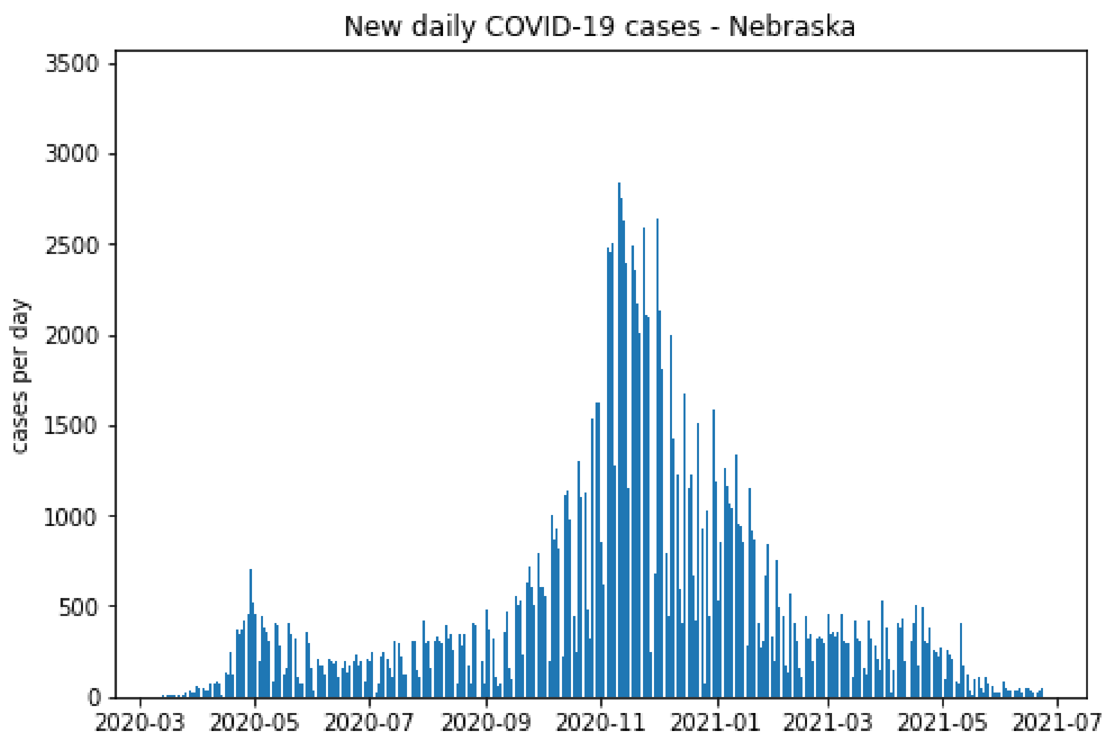
[8]:
```
# a function to graph the daily new cases for a state
def show_cases(state):
    ys = np.asarray(df_full[state])
    xs = pd.date_range(periods=len(ys),start="2020-03-12")
    fig = plt.figure()
    ax = fig.add_axes([0,0,1,1])
    ax.set_ylabel('cases per day')
    ax.set_title('New daily COVID-19 cases - {}{}'.format(state[0].
 ↪upper(),state[1:]))
    ax.bar(xs,ys)
    plt.show()
```

The daily new coronavirus cases shows a multiple wave behavior. The following examples are typical.

[9]:
```
show_cases('arizona')
```



[10]:
```
show_cases('nebraska')
```



There are exceptions to this rule, but on average, there is a "winter wave" which will be the focus of my analysis.

[11]:
```python
# identifying by hand the start date of the winter wave in each state

''' data offsets:
    Mar 12 = 0
    Apr 00 = 20
    May 00 = 50
    Jun 00 = 81
    Jul 00 = 111
    Aug 00 = 142
    Sep 00 = 173
    Oct 00 = 203
    Nov 00 = 234
    Dec 00 = 264
'''
months = {'mar':-12,'apr':20,'may':50,'jun':81,'jul':111,
          'aug':142,'sep':173,'oct':203,'nov':234,'dec':264}

start_dates = {'alabama': 'oct 15','alaska': 'sep 15','arizona': 'oct␣
↪15','arkansas': 'nov 01',
               'california': 'nov 01','colorado': 'oct 15','connecticut': 'oct␣
↪01','delaware': 'nov 01',
               'district-of-columbia': 'nov 01','florida': 'oct 15','georgia':␣
↪'nov 01','hawaii': 'nov 01',
               'idaho': 'sep 15','illinois': 'oct 01','indiana': 'oct␣
↪01','iowa': 'oct 01',
               'kansas': 'oct 01','kentucky': 'oct 01','louisiana': 'oct␣
↪15','maine': 'oct 15',
               'maryland': 'oct 15','massachusetts': 'oct 15','michigan': 'oct␣
↪01','minnesota': 'oct 01',
               'mississippi': 'oct 01','missouri': 'oct 15','montana': 'sep␣
↪15','nebraska': 'oct 01',
               'nevada': 'oct 01','new-hampshire': 'oct 15','new-jersey': 'oct␣
↪15','new-mexico': 'sep 15',
               'new-york': 'oct 15','north-carolina': 'nov 01','north-dakota':␣
↪'sep 01','ohio': 'oct 01',
               'oklahoma': 'nov 01','oregon': 'oct 15','pennsylvania': 'oct␣
↪01','rhode-island': 'sep 15',
               'south-carolina': 'nov 01','south-dakota': 'sep 15','tennessee':␣
↪'nov 01','texas': 'oct 21',
               'utah': 'sep 01','vermont': 'oct 15','virginia': 'nov␣
↪01','washington': 'oct 21',
```

```
               'west-virginia': 'oct 15','wisconsin': 'sep 01','wyoming': 'sep␣
↪01'
              }

# convert the offset to number of days since 3/12/20
def get_offset(state):
    date_str = start_dates[state]
    offset = months[date_str.split()[0]]+int(date_str.split()[1])
    return(offset)
```

I will now create a function which will accept as input a date (measured in days since the beginning of the truncated data for the particular state) and will return the predicted number of cases for that day.

[12]:
```
# define the generic model function
def model_f(x,a,b,c):
    y = a*np.exp(-np.abs((x-b)/c))
    return(y)

def predict(x,params):
    a = params[0]
    b = params[1]
    c = params[2]
    y = model_f(x,a,b,c)
    return(int(y))
```

[13]:
```
prediction_data = []

# Create a list of dictionaries to convert to a dataframe. Each row will be a␣
↪state.
for state in states:
    dct = {'state':state}
    offset = get_offset(state)
    daily_cases = df[state][offset:].values

    # predicting for the first half of January
    num = 31
    # I stopped the training data two weeks early so as to avoid the Christmas␣
↪holiday effects
    data = daily_cases[:-num-14]
    params, cov = optimize.curve_fit(model_f,
                                     xdata=np.arange(len(data)),
                                     ydata=data,
                                     maxfev=20000,
                                     p0=[np.max(data), 1, 1])

    ls = []
```

```
    # make predictions for January 1, 2, ..., 16
    for i in range(num,num-16,-1):
        ls.append(predict(len(daily_cases)-i,params))
    early_pred = [_ for _ in ls]
    early_actual = [_ for _ in daily_cases[-31:-15]]
    early_error = [j-i for (i,j) in zip(early_pred,early_actual)]

    # predicting for the second half of January
    num = 15
    data = daily_cases[:-num]
    params, cov = optimize.curve_fit(model_f,
                                     xdata=np.arange(len(data)),
                                     ydata=data,
                                     maxfev=20000,
                                     p0=[np.max(data), 1, 1])

    ls = []
    # make predictions for January 17, 18, ..., 31
    for i in range(num,num-15,-1):
        ls.append(predict(len(daily_cases)-i,params))
    late_pred = [_ for _ in ls]
    late_actual = [_ for _ in daily_cases[-15:]]
    late_error = [j-i for (i,j) in zip(late_pred,late_actual)]

    # assemble the early and late january pieces into a single piece for each␣
 ↪of prediction, actual, error
    predicted = early_pred + late_pred
    actual = early_actual + late_actual
    error = early_error + late_error
    pct_error = [round(i/j,3) if j!= 0 else np.nan for (i,j) in␣
 ↪zip(error,actual)]
    dct['predicted'] = predicted
    dct['actual'] = actual
    dct['error'] = error
    dct['pct_error'] = pct_error

    prediction_data.append(dct)

# convert the list of dictionaries into a dataframe
pred_df = pd.DataFrame(prediction_data)
```

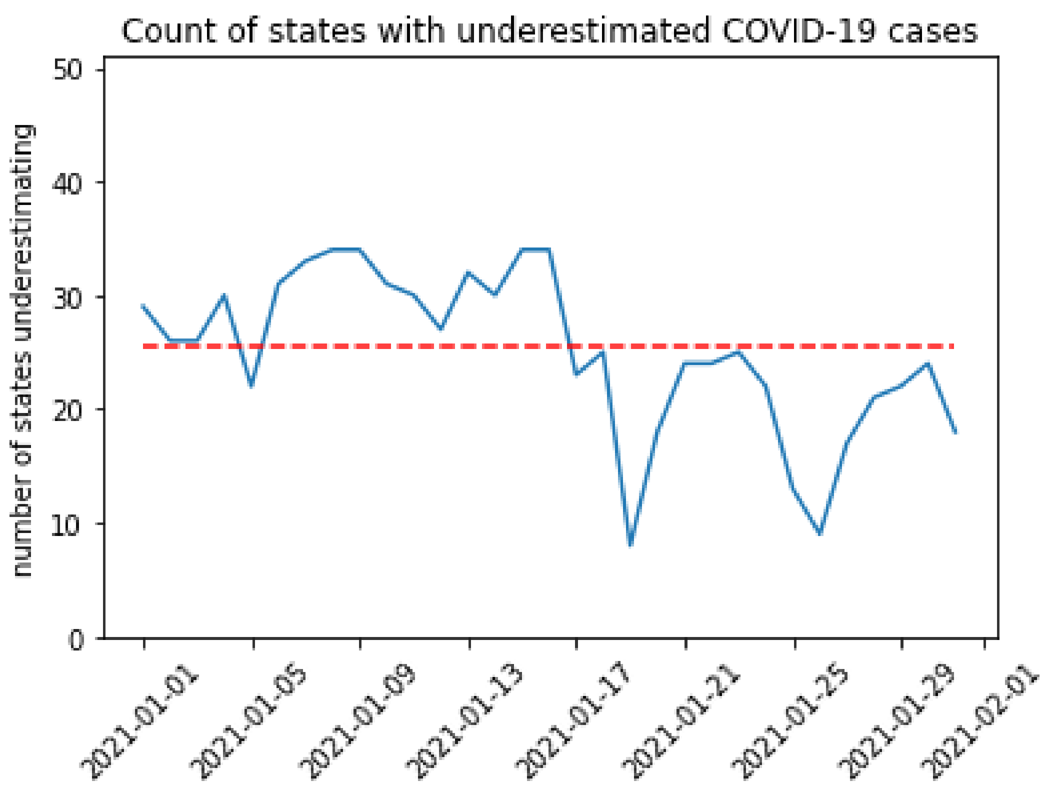
[14]:
```
# declare a vector of 31 zeros, to hold the count of positive errors over all␣
 ↪states per day of January
pos_error_count = [0 for i in range(31)]

for state in states:
    ls = pred_df[pred_df['state']==state]['error'].values[0]
```

```
    for i in range(31):
        if ls[i]>0: pos_error_count[i]+=1

pos_error_pct = [_/len(states) for _ in pos_error_count]
```

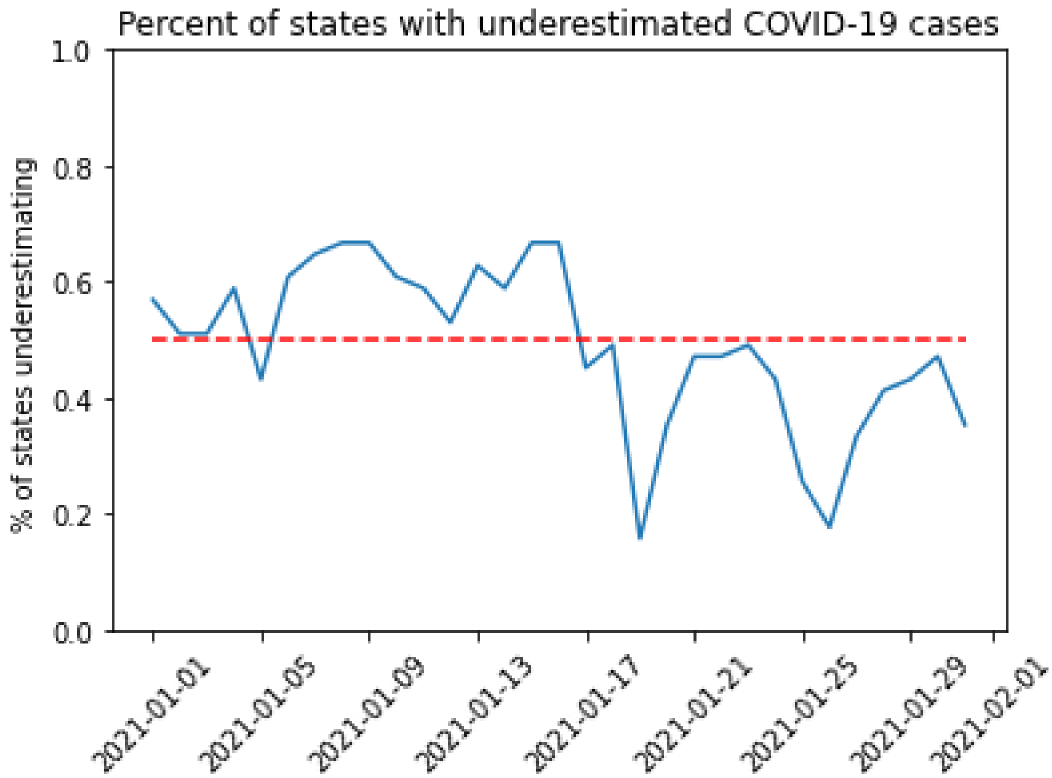
[15]:
```
x = pd.date_range(periods=31,end="2021-01-31")
y = pos_error_count
horiz_line = [25.5 for _ in range(31)]
plt.plot(x, y, label = "things")
plt.plot(x, horiz_line, 'r--')
plt.ylim(0,51)
plt.xticks(rotation = 45)
plt.ylabel('number of states underestimating')
plt.title('Count of states with underestimated COVID-19 cases')
plt.show()
```



[16]:
```
x = pd.date_range(periods=31,end="2021-01-31")
y = pos_error_pct
horiz_line = [0.5 for _ in range(31)]
plt.plot(x, y, label = "things")
plt.plot(x, horiz_line, 'r--')
plt.ylim(0,1)
```

```
plt.xticks(rotation = 45)
plt.ylabel('% of states underestimating')
plt.title('Percent of states with underestimated COVID-19 cases')

plt.show()
```



Two main things about the graph:

1. The graph appears to be rather above the red line for the first half of the month. This is not necessarily unexpected, as the first half of January follows the winter holidays. In addition to fewer people being diagnosed due to business closures / travel, more people were also probably infected.

2. The graph appears to be rather below the red line for the second half of the month. This is unexpected, all else being equal, as it follows on the heels of a high case load. Remember, the fact that the graph has dropped below the middle line does *not* simply indicate that the case numbers have dropped, even a lot. It indicates that the case numbers have droppped off at a rate *faster* than predicted by the exponential model as trained on the past several months of data. That is, this graph dropping significantly below the red line indicates that there has been a much sharper than expected decline in the case numbers.

[17]:
```
# now graph the percentage overestimates by date in January
```

```
state = 'hawaii'

np.asarray(pred_df[pred_df['state']==state]['pct_error'])
```

```
[17]: array([list([0.437, 0.557, 0.367, 0.282, -0.204, 0.124, 0.242, 0.665, 0.592,
0.562, 0.452, 0.367, 0.05, -0.036, 0.372, 0.268, -0.046, -0.346, -0.37, -1.791,
-1.423, -0.528, -0.409, -0.403, -0.247, -0.567, -2.0, -0.88, -0.971, -0.719,
-0.736])],
      dtype=object)
```

I will create a heatmap with states as rows and dates as columns. The color will correspond to the % error, from -100% to 100%.

```
[18]: # generating data for the heatmap

heatmap_data = []
for state in states:
    heatmap_data.append([x for x in␣
↪pred_df[pred_df['state']==state]['pct_error']][0])
np.asarray(heatmap_data)
```

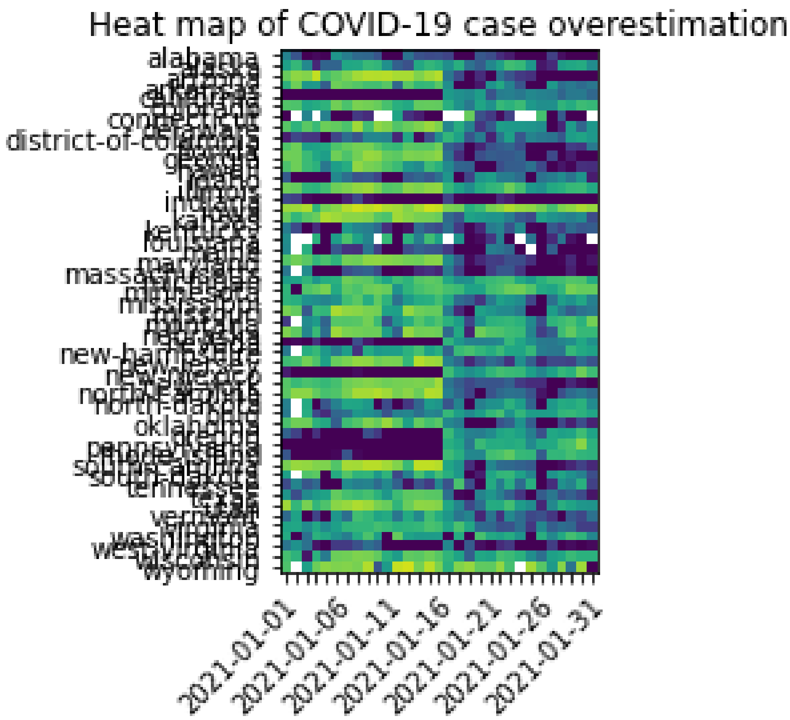
```
[18]: array([[-0.116, -0.484, -1.895, …, -1.159, -1.342, -1.733],
       [ 0.134,  0.332, -0.055, …,  0.195,  0.232, -0.031],
       [ 0.537,  0.658,  0.627, …, -1.877, -1.727, -1.734],
       …,
       [-0.228,  0.023, -0.256, …, -0.933, -1.024, -0.949],
       [ 0.414,  0.291, -0.883, …,  0.358,  0.278,  0.274],
       [ 0.442,    nan,  0.134, …, -0.242,  0.715, -4.071]])
```

```
[19]: # now create a dataframe where the rows are states and the columns are
# % over/underestimate on each day of January.
# use it to graph a heat map

# custom label list for the heatmap
x_labels_spaced = ['2021-01-01', ' ', ' ', ' ', ' ',
                   '2021-01-06', ' ', ' ', ' ', ' ',
                   '2021-01-11', ' ', ' ', ' ', ' ',
                   '2021-01-16', ' ', ' ', ' ', ' ',
                   '2021-01-21', ' ', ' ', ' ', ' ',
                   '2021-01-26', ' ', ' ', ' ', ' ',
                   '2021-01-31'
                  ]

# uniform_data = np.random.rand(10, 12)
fig, ax = plt.subplots()
im = ax.imshow(heatmap_data, vmin=-1, vmax=1)
```

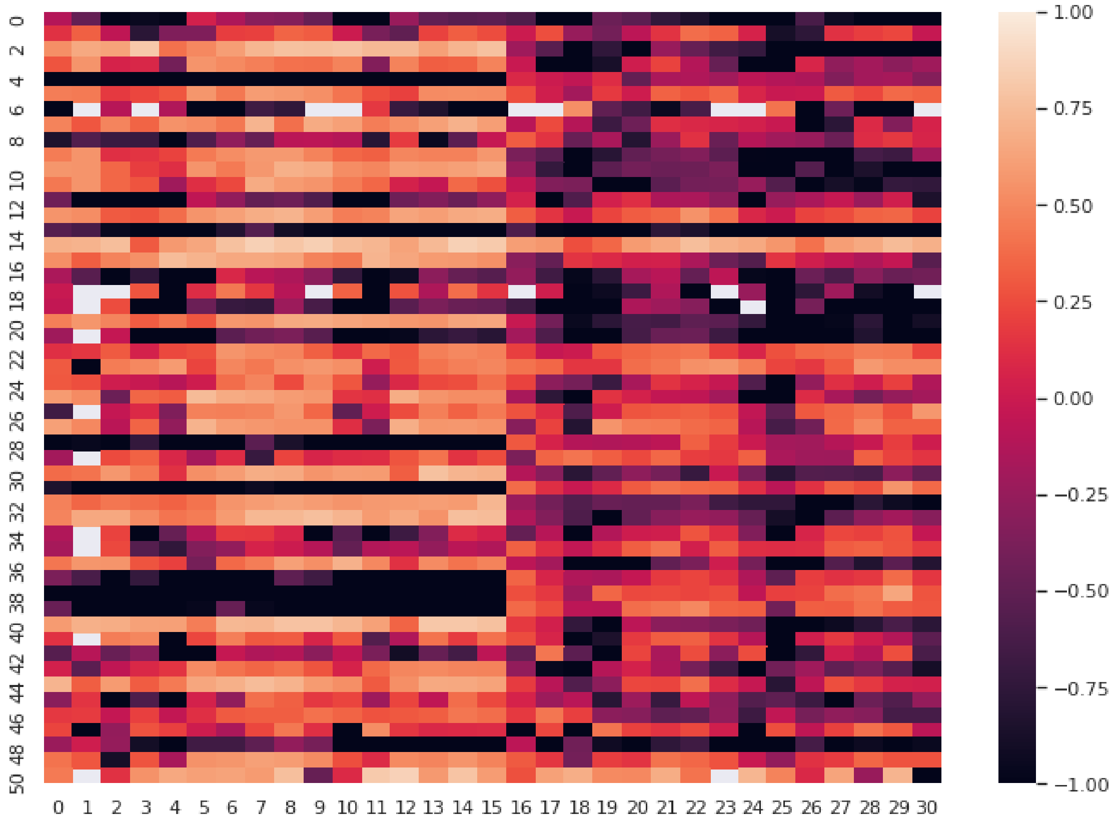
```
ax.set_xticks(np.arange(len(x_labels_spaced)))
ax.set_yticks(np.arange(len(states)))
ax.set_yticklabels(states)
ax.set_xticklabels(x_labels_spaced)
plt.setp(ax.get_xticklabels(), rotation=45, ha="right",
         rotation_mode="anchor")
ax.set_title("Heat map of COVID-19 case overestimation")
fig.tight_layout()
plt.show()
```



The labels above are good, but they are slightly misaligned to the rows, and I don't like the white lines in the heatmap. I will create a cleaner heatmap, and add on the labels in image editing software for inclusion in the report.

[20]:
```
# generating a better view of the heatmap

sns.set(rc={'figure.figsize':(11.7,8.27)})
ax = sns.heatmap(heatmap_data, vmin=-1, vmax=1)
```



Appendix: put in the full data table? From Nov 1 to Feb 1? Technical details on function fitting? Technical details on the prediction method? Leave the most technical details out of the report, and put them in the appendix.

A standard Gaussian curve is a function of the form

$f(x) = a \cdot \exp\left(-\frac{1}{2}\left(\frac{x-b}{c}\right)^2\right).$

The center of the curve is at $x = b$. As x is removed from b in either direction (to the right or left), the negativeexponent on e increases rapidly. This rapid increase is largely due to the square in $\left(\frac{x-b}{c}\right)^2$. Another importantfeature of the square is that it gives the curve symmetry over $x = b$.

If we wish to fatten the tails of the distribution, we might take the absolute value instead of squaring. Our functionthen has the form

$g(x) = a \cdot \exp\left(-\frac{1}{2}\left|\frac{x-b}{c}\right|\right).$

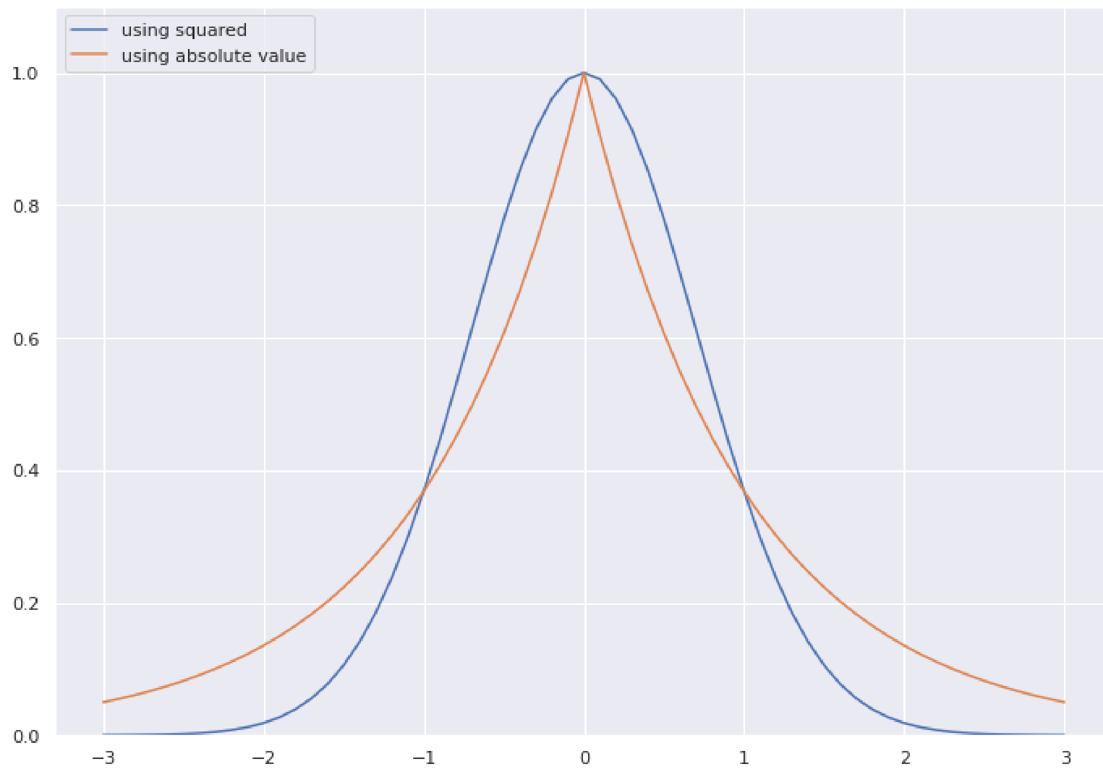
For comparison, here are plots of f and g using the parameters $a = c = 1, b = 0$:

[21]:
```
# a typical Gaussian function
def gauss_f(x):
    return(np.exp(-x*x))

# a function of the sort used to model the winter 2020-21 COVID-19 wave
```

```
def abs_g(x):
    return(np.exp(-np.abs(x)))

xs = np.linspace(-3,3,61)
y1 = [gauss_f(x) for x in xs]
y2 = [abs_g(x) for x in xs]
plt.plot(xs, y1, label = "using squared")
plt.plot(xs, y2, label = "using absolute value")
plt.ylim(0,1.1)
plt.legend(loc="upper left")
plt.show()
```



For inclusion in Appendix B, I generate an aggregated dataframe of the January predictions, observations, and errors.

[22]:
```
# a function to add two lists componentwise
def add_lists(ls1,ls2):
    res = [ls1[i]+ls2[i] for i in range(len(ls1))]
    return(res)

# get aggregate numbers
pred = [0 for _ in range(31)]
act = [0 for _ in range(31)]
```

```
err = [0 for _ in range(31)]

# populate the aggregate dataframe column vectors
for state in states:
    pred =␣
 ↪add_lists(pred,list(pred_df[pred_df['state']==state]['predicted'])[0])
    act = add_lists(act,list(pred_df[pred_df['state']==state]['actual'])[0])
    err = add_lists(err,list(pred_df[pred_df['state']==state]['error'])[0])
```

[23]:

```
df_aggregate = pd.DataFrame(list(zip(pred, act, err)),
               columns =['predicted', 'actual', 'error'])
df_aggregate.set_index(pd.date_range(periods=31,end="2021-01-31"))
```

[23]:

	predicted	actual	error
2021-01-01	278458	243566	-34892
2021-01-02	282631	221741	-60890
2021-01-03	287129	230621	-56508
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2021-01-07	307598	257252	-50346
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2021-01-10	327755	257623	-70132
2021-01-11	335074	219580	-115494
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2021-01-14	359242	230754	-128488
2021-01-15	368513	233786	-134727
2021-01-16	371900	239546	-132354
2021-01-17	222700	203937	-18763
2021-01-18	223231	179829	-43402
2021-01-19	223851	146818	-77033
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2021-01-21	225348	181710	-43638
2021-01-22	225913	193083	-32830
2021-01-23	226523	188172	-38351
2021-01-24	227162	171233	-55929
2021-01-25	227849	140955	-86894
2021-01-26	228609	143956	-84653
2021-01-27	229110	150957	-78153
2021-01-28	229400	153835	-75565
2021-01-29	229655	164933	-64722
2021-01-30	229995	164571	-65424
2021-01-31	230418	144399	-86019