

# Rajeev\_baby\_names\_bystate

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## 1 Pandas, Matplotlib, and Basemap: Coloring States by Baby Name Uniqueness

1.1 Here we will use Matplotlib and Basemap to visualize the degree of uniqueness each state has in giving baby names.

```
In [1]: import math
import csv
import pandas as pd
import os
import numpy as np
import matplotlib as mpl
import matplotlib.pyplot as plt
from mpl_toolkits.basemap import Basemap
from matplotlib.colors import rgb2hex
from matplotlib.patches import Polygon
```

1.1.1 Here we start with a file called "namebystate" that contains a text file of baby names for each state. We will use the `chdir()` method in the `os` module to change to the directory with the names data and print out all the files with `'.TXT'` extensions in the directory.

```
In [2]: data_path = "rajeev_data\states"
current_dir = os.chdir(data_path)

for file in os.listdir(current_dir):
    if file.endswith('.TXT'):
        print(file)
```

```
AK.TXT
AL.TXT
AR.TXT
AZ.TXT
CA.TXT
CO.TXT
CT.TXT
DC.TXT
DE.TXT
```

FL.TXT  
GA.TXT  
HI.TXT  
IA.TXT  
ID.TXT  
IL.TXT  
IN.TXT  
KS.TXT  
KY.TXT  
LA.TXT  
MA.TXT  
MD.TXT  
ME.TXT  
MI.TXT  
MN.TXT  
MO.TXT  
MS.TXT  
MT.TXT  
NC.TXT  
ND.TXT  
NE.TXT  
NH.TXT  
NJ.TXT  
NM.TXT  
NV.TXT  
NY.TXT  
OH.TXT  
OK.TXT  
OR.TXT  
PA.TXT  
RI.TXT  
SC.TXT  
SD.TXT  
TN.TXT  
TX.TXT  
UT.TXT  
VA.TXT  
VT.TXT  
WA.TXT  
WI.TXT  
WV.TXT  
WY.TXT

**1.1.2 We can then use the enumerate( ) function to see the format for each file. Enumerate returns a tuple with the first element being the index and the second number being the line. First line will have the index of one instead of zero**

```
In [3]: for lineno, line in enumerate(open('CA.TXT', 'r'), start=1):
        if lineno < 5:
            print(line)
```

CA,F,1910,Mary,295

CA,F,1910,Helen,239

CA,F,1910,Dorothy,220

CA,F,1910,Margaret,163

**1.1.3 Each text file is a comma delimited file with the following fields; state, gender, date, name, counts. Now that we know what we are dealing with we can get started. Let's use the walk( ) function of the os module to iterate over the list of files in the directory.**

```
In [4]: current_dir = os.getcwd()
        file_list = []
        for root, dirs, files in os.walk(current_dir):
            for filename in files:
                if filename.endswith('.TXT'):
                    file_list.append(filename)
        print(file_list)
        print(len(file_list))
```

```
['AK.TXT', 'AL.TXT', 'AR.TXT', 'AZ.TXT', 'CA.TXT', 'CO.TXT', 'CT.TXT', 'DC.TXT', 'DE.TXT', 'FL'
51
```

**1.1.4 Now we have a list containing all of the .TXT files in our data directory. The length of the list is 51 corresponding to the 50 states plus the District of Columbia.**

Next let's make a Pandas data frame for California in 2016. It will have columns for name and counts for 2016. We will then apply this to all 'TXT' files. We create a file object with open( ). We initialize an empty list (name\_list) outside of the loop. We will add info to this list as we go through the state files. We then use a for-loop to read each line as a string. We strip the string of new lines and spaces using the strip( ) method and convert the string to a list delimited by commas using the split( ) method of lists. The comma is the default delimiter but I like to specify it explicitly. Next, we only take the data from the females for the year of 2016 using indexing and Booleans.

Inside of the loop we make a temporary list called 'temp\_list' to store the counts (temp\_list.append(int(line[4]))), the name (temp\_list.append(line[3])) and the state (temp\_list.append(line[0])).

Finally, we can append the `temp_list` to the `name_list` to create a list of lists. Later we will want to sort our pandas data frame on births so we convert the elements in the births list from strings to integers using a list comprehension, `births = [int(element) for element in births]`. We then sort the lists in reverse so that they are in descending rather ascending order. By default Python sorts on the first element of each list. We then create a new "`name_list_top10`" which contains only the top10 names for California in 2016.

```
In [5]: name_list = []
        for line in open('CA.TXT', 'r'):
            line = line.strip().split(',')
            if line[1] == 'F' and line[2] == '2013':
                temp_list = []
                temp_list.append(int(line[4]))
                temp_list.append(line[3])
                temp_list.append(line[0])
                name_list.append(temp_list)
        name_list.sort(reverse=True)
        name_list_top10 = name_list[0:10]
        #close('CA.TXT')
        print(name_list_top10)
```

```
[[3460, 'Sophia', 'CA'], [2792, 'Isabella', 'CA'], [2599, 'Mia', 'CA'], [2488, 'Emma', 'CA'],
```

### 1.1.5 Creating a Pandas data frame is very easy. We just pass the list of lists and give it the column headings.

```
In [6]: name_df = pd.DataFrame(name_list_top10, columns=['births', 'name', 'state'])
        name_df.head()
```

```
Out[6]:
```

	births	name	state
0	3460	Sophia	CA
1	2792	Isabella	CA
2	2599	Mia	CA
3	2488	Emma	CA
4	2292	Emily	CA

We have made a Pandas data frame from one file ('CA.txt'). We can now apply this approach to all files in the `file_list` we created earlier. First we initialize an empty Pandas data frame. Then we iterate through the file list and repeat what we did with the California above. Except that we will append a new data frame for each state to the growing data frame called "`df`". Each Pandas data frame called "`data`" will be overwritten when with every new state file but that is o.k. because we are constantly adding this data to the growing data frame "`df`". Since we initialize it outside of the for-loop we won't overwrite it.

```
In [7]: df = pd.DataFrame()
        for file in file_list:
            name_list2 = []
            for line in open(file, 'r'):
```

```

line = line.strip().split(',')
if line[1] == 'F' and line[2] == '2016':
    temp_list2 = []
    temp_list2.append(int(line[4]))
    temp_list2.append(line[3])
    temp_list2.append(line[0])
    name_list2.append(temp_list2)
name_list2.sort(reverse=True)
name_list_top10 = name_list2[0:10]
data = pd.DataFrame(name_list_top10, columns = ['Births', 'Name', 'State'])
df = df.append(data)
df.head()

```

```

Out[7]:
   Births      Name State
0      47      Emma   AK
1      45    Olivia   AK
2      34  Charlotte   AK
3      34    Amelia   AK
4      33    Sophia   AK

```

You might notice some similarities to appending lists and appending a Pandas data frame. But there is one important difference. Python lists can be appended in place. This means you can initialize the empty list outside of the loop and build the list by going through the loop. Pandas Data Frames cannot be appended in place. Instead you have to store the output.

```

In [8]: df_example = pd.DataFrame()
        data2 = pd.DataFrame([[ 'A', 'B'],[1, 2]])
        df_example.append(data2)

```

```

Out[8]:
   0  1
0  A  B
1  1  2

```

```

In [9]: list = [1]
        df_example = pd.DataFrame()
        for i in list:
            data2 = pd.DataFrame([[ 'A', 'B'],[1,2]])
            df_example.append(data2)
        print(df_example)

```

```

Empty DataFrame
Columns: []
Index: []

```

```

In [10]: list = [1]
         df_example = pd.DataFrame()
         for i in list:
             data2 = pd.DataFrame([[ 'A', 'B'],[1,2]])

```

```
df_example = df_example.append(data2)
df_example.head()
```

```
Out[10]:    0  1
         0  A  B
         1  1  2
```

Now lets see if there are any top10 names that are unique to a particular state. First lets create a data frame of just the names using slicing. Before we dive to deeply we can use the nifty `describe()` function of Data Frames to quickly see if there are any unique names in the top ten.

```
In [11]: df_name = df.loc[:, 'Name']
         df_name.describe()
```

```
Out[11]: count      510
         unique       40
         top      Olivia
         freq        51
         Name: Name, dtype: object
```

**1.1.6** If we had sliced the a numerical column such as 'Births' are statistics would give the max and min number of births found etc. Since we don't have numerical data we get the max number of entries in the names column which is 510 for 10 names per state (including D.C). Here we can see that there are only 40 names that are represented in the top10 across all states.

There are a lot of ways you can filter data in a data frame. I have seen the name "Brooklyn" around a lot and I would like to know which states have baby girls with this name in 2016. You can slice a column using `df['name of column']`. You can also filter a column using a Boolean expression.

```
In [12]: col = df['Name']
         print(df[col == "Brooklyn"])
```

```
Births      Name State
4      113  Brooklyn  MS
9       56  Brooklyn  WV
```

We know from the `describe()` method function above that there are only 40 names in the Top10 across all states. We can use the `value_count()` method to quickly determine how many states have each name in their top10.

```
In [13]: name_state_counts = df['Name'].value_counts()
         name_state_counts.head()
```

```
Out[13]: Olivia      51
         Emma        51
         Ava         50
         Sophia      43
         Charlotte   40
         Name: Name, dtype: int64
```

So Olivia and Emma are rock stars. We can now use the `map( )` method to add a column containing the total number of states that have a particular name in the top10. The `map` method takes a dictionary so we will convert our state count series to a dictionary using the `to_dict( )` method.

```
In [14]: freq_to_name = name_state_counts.to_dict()
         print(freq_to_name)
```

```
{'Olivia': 51, 'Emma': 51, 'Ava': 50, 'Sophia': 43, 'Charlotte': 40, 'Isabella': 35, 'Harper':
```

Now we will use `map( )` which allows you to do a transformation from values in an array, Series or DataFrame column. We will call this new column 'name\_freq' for name frequency.

```
In [15]: df['name_freq'] = df['Name'].map(freq_to_name)
         df
```

```
Out[15]:
```

	Births	Name	State	name_freq
0	47	Emma	AK	51
1	45	Olivia	AK	51
2	34	Charlotte	AK	40
3	34	Amelia	AK	27
4	33	Sophia	AK	43
5	32	Elizabeth	AK	15
6	32	Ava	AK	50
7	32	Abigail	AK	29
8	31	Aurora	AK	1
9	29	Chloe	AK	2
0	330	Ava	AL	50
1	244	Emma	AL	51
2	238	Olivia	AL	51
3	216	Elizabeth	AL	15
4	181	Harper	AL	35
5	166	Madison	AL	11
6	160	Amelia	AL	27
7	157	Caroline	AL	1
8	156	Isabella	AL	35
9	152	Ella	AL	4
0	191	Ava	AR	50
1	164	Emma	AR	51
2	152	Olivia	AR	51
3	132	Abigail	AR	29
4	120	Harper	AR	35
5	107	Sophia	AR	43
6	97	Paisley	AR	3
7	95	Addison	AR	4
8	91	Isabella	AR	35
9	87	Mia	AR	22
..	...	...	...	...

0	343	Olivia	WI	51
1	319	Emma	WI	51
2	272	Ava	WI	50
3	264	Harper	WI	35
4	263	Charlotte	WI	40
5	242	Evelyn	WI	21
6	230	Amelia	WI	27
7	210	Sophia	WI	43
8	189	Nora	WI	5
9	183	Abigail	WI	29
0	102	Harper	WV	35
1	93	Olivia	WV	51
2	90	Ava	WV	50
3	88	Emma	WV	51
4	74	Isabella	WV	35
5	70	Addison	WV	4
6	68	Paisley	WV	3
7	66	Sophia	WV	43
8	61	Avery	WV	10
9	56	Brooklyn	WV	2
0	36	Emma	WY	51
1	29	Olivia	WY	51
2	24	Harper	WY	35
3	24	Ava	WY	50
4	23	Elizabeth	WY	15
5	21	Emily	WY	15
6	18	Piper	WY	1
7	18	Evelyn	WY	21
8	18	Avery	WY	10
9	17	Sophia	WY	43

[510 rows x 4 columns]

It is also easy to create a new data frame by pivoting our data using the `crosstab()` function.

```
In [16]: data = pd.crosstab([df.State, df.Name], df.name_freq)
data
```

```
Out[16]: name_freq      1   2   3   4   5   8  10  11  15  21  22  27  29  35  40  \
State Name
AK   Abigail      0   0   0   0   0   0   0   0   0   0   0   0   1   0   0
     Amelia      0   0   0   0   0   0   0   0   0   0   0   1   0   0   0
     Aurora      1   0   0   0   0   0   0   0   0   0   0   0   0   0   0
     Ava         0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
     Charlotte    0   0   0   0   0   0   0   0   0   0   0   0   0   0   1
     Chloe       0   1   0   0   0   0   0   0   0   0   0   0   0   0   0
     Elizabeth    0   0   0   0   0   0   0   0   1   0   0   0   0   0   0
     Emma        0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
```



AL	Olivia	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Sophia	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Amelia	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
	Ava	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Caroline	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Elizabeth	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
	Ella	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
	Emma	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Harper	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
	Isabella	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
AR	Madison	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
	Olivia	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Abigail	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
	Addison	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
	Ava	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Emma	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Harper	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
	Isabella	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
	Mia	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
	Olivia	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
...	Paisley	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
	Sophia	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	...	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
WI	Abigail	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
	Amelia	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
	Ava	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Charlotte	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
	Emma	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Evelyn	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
	Harper	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
	Nora	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
	Olivia	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Sophia	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WV	Addison	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
	Ava	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Avery	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
	Brooklyn	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
	Emma	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Harper	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
	Isabella	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
	Olivia	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Paisley	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
	Sophia	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WY	Ava	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Avery	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
	Elizabeth	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
	Emily	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
	Emma	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

	Evelyn	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
	Harper	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
	Olivia	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Piper	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Sophia	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
name_freq		43	50	51												
State Name																
AK	Abigail	0	0	0												
	Amelia	0	0	0												
	Aurora	0	0	0												
	Ava	0	1	0												
	Charlotte	0	0	0												
	Chloe	0	0	0												
	Elizabeth	0	0	0												
	Emma	0	0	1												
	Olivia	0	0	1												
	Sophia	1	0	0												
AL	Amelia	0	0	0												
	Ava	0	1	0												
	Caroline	0	0	0												
	Elizabeth	0	0	0												
	Ella	0	0	0												
	Emma	0	0	1												
	Harper	0	0	0												
	Isabella	0	0	0												
	Madison	0	0	0												
	Olivia	0	0	1												
AR	Abigail	0	0	0												
	Addison	0	0	0												
	Ava	0	1	0												
	Emma	0	0	1												
	Harper	0	0	0												
	Isabella	0	0	0												
	Mia	0	0	0												
	Olivia	0	0	1												
	Paisley	0	0	0												
	Sophia	1	0	0												
...		..	..	..												
WI	Abigail	0	0	0												
	Amelia	0	0	0												
	Ava	0	1	0												
	Charlotte	0	0	0												
	Emma	0	0	1												
	Evelyn	0	0	0												
	Harper	0	0	0												
	Nora	0	0	0												
	Olivia	0	0	1												

	Sophia	1	0	0
WV	Addison	0	0	0
	Ava	0	1	0
	Avery	0	0	0
	Brooklyn	0	0	0
	Emma	0	0	1
	Harper	0	0	0
	Isabella	0	0	0
	Olivia	0	0	1
	Paisley	0	0	0
	Sophia	1	0	0
WY	Ava	0	1	0
	Avery	0	0	0
	Elizabeth	0	0	0
	Emily	0	0	0
	Emma	0	0	1
	Evelyn	0	0	0
	Harper	0	0	0
	Olivia	0	0	1
	Piper	0	0	0
	Sophia	1	0	0

[510 rows x 18 columns]

Now we have created a data frame where the index is the state. Having a duplicate index is allowed but can make many other data manipulations more difficult.

I'm less interested in the particular names as I am in the frequency of novel names in each state. So I will reset the index followed by the `groupby()` function to group the states and sum the frequency of each name. If you try this without resetting the index you will get an error because you need a unique index for each color to do this.

```
In [17]: data_state = data.reset_index().groupby('State').sum()
data_state
```

```
Out[17]: name_freq  1   2   3   4   5   8  10  11  15  21  22  27  29  35  40  43  50  \
State
AK           1   1   0   0   0   0   0   0   1   0   0   1   1   0   1   1   1
AL           1   0   0   1   0   0   0   1   1   0   0   1   0   2   0   0   1
AR           0   0   1   1   0   0   0   0   0   0   1   0   1   2   0   1   1
AZ           0   0   0   0   0   1   0   0   1   0   1   0   1   1   1   1   1
CA           0   1   0   0   0   1   0   0   1   0   1   0   1   1   0   1   1
CO           0   0   0   0   0   0   0   0   0   1   1   0   1   2   1   1   1
CT           0   0   0   0   0   0   0   0   1   0   1   1   1   1   1   1   1
DC           1   0   0   1   0   1   0   0   1   0   0   0   1   1   1   0   1
DE           1   0   0   1   0   0   0   0   1   0   0   0   0   2   1   1   1
FL           0   0   0   0   0   1   0   0   1   0   1   1   1   1   0   1   1
GA           0   0   0   0   0   0   0   1   0   0   0   1   1   2   1   1   1
HI           1   0   1   1   0   0   0   0   0   0   1   1   0   1   0   1   1
```

IA	0	0	0	1	1	0	0	0	0	1	0	1	0	1	1	1	1
ID	0	0	0	0	0	0	0	0	2	1	0	1	1	1	1	0	1
IL	0	0	0	0	0	1	0	0	1	1	1	0	0	1	1	1	1
IN	0	0	0	0	0	0	0	0	0	1	0	1	1	2	1	1	1
KS	0	0	0	0	0	0	1	0	1	1	1	0	0	1	1	1	1
KY	0	0	0	0	0	0	0	0	0	0	1	1	1	2	1	1	1
LA	0	0	0	0	0	0	1	1	0	0	1	1	0	1	1	1	1
MA	0	0	1	0	0	0	0	0	0	0	1	1	1	1	1	1	1
MD	0	0	0	0	0	0	0	1	1	0	0	0	1	2	1	1	1
ME	1	0	0	0	0	0	0	0	0	1	0	1	1	1	1	1	1
MI	0	0	0	0	0	0	0	0	0	1	0	1	1	2	1	1	1
MN	0	0	1	0	1	0	0	0	0	1	0	1	0	1	1	1	1
MO	0	0	0	0	0	0	1	0	0	1	0	1	0	2	1	1	1
MS	0	3	1	0	0	0	0	1	0	0	0	0	0	2	0	0	1
MT	0	0	1	0	0	0	1	1	0	1	0	0	1	1	1	0	1
NC	0	0	0	0	0	0	0	1	1	0	0	0	1	2	1	1	1
ND	0	0	0	2	1	0	0	0	0	1	0	1	0	1	1	0	1
NE	0	0	0	0	0	0	1	0	1	1	1	0	0	1	1	1	1
NH	0	0	1	0	0	0	0	1	0	0	0	1	1	2	1	1	0
NJ	0	0	0	0	0	0	0	1	1	0	1	0	1	1	1	1	1
NM	2	0	0	0	0	1	0	0	1	0	1	0	0	1	0	1	1
NV	1	0	0	0	0	1	0	0	1	0	1	0	1	1	0	1	1
NY	0	0	0	0	0	0	0	1	1	0	1	0	1	1	1	1	1
OH	0	0	0	0	0	0	1	0	0	1	0	1	0	2	1	1	1
OK	0	0	0	0	0	0	0	0	1	0	1	0	1	2	1	1	1
OR	0	0	0	0	0	0	0	0	0	1	0	1	1	2	1	1	1
PA	0	0	0	0	0	0	0	0	1	0	1	0	1	2	1	1	1
RI	0	0	0	0	0	0	1	0	1	0	1	1	0	1	1	1	1
SC	0	1	0	1	0	0	0	1	1	0	0	0	0	2	1	0	1
SD	0	0	0	0	1	0	1	0	1	1	0	0	0	1	1	1	1
TN	0	0	0	1	0	0	0	0	1	0	0	1	0	2	1	1	1
TX	0	1	0	0	0	1	0	0	1	0	1	0	1	1	0	1	1
UT	3	0	0	0	0	0	0	0	0	1	0	1	0	1	1	0	1
VA	0	0	0	0	0	0	0	0	1	0	0	1	1	2	1	1	1
VT	0	0	1	1	0	0	0	0	0	1	0	1	0	1	1	1	1
WA	0	0	0	0	0	0	0	0	1	1	1	1	1	0	1	1	1
WI	0	0	0	0	1	0	0	0	0	1	0	1	1	1	1	1	1
WV	0	1	1	1	0	0	1	0	0	0	0	0	0	2	0	1	1
WY	1	0	0	0	0	0	1	0	2	1	0	0	0	1	0	1	1

name\_freq 51  
State  
AK 2  
AL 2  
AR 2  
AZ 2  
CA 2  
CO 2

CT	2
DC	2
DE	2
FL	2
GA	2
HI	2
IA	2
ID	2
IL	2
IN	2
KS	2
KY	2
LA	2
MA	2
MD	2
ME	2
MI	2
MN	2
MO	2
MS	2
MT	2
NC	2
ND	2
NE	2
NH	2
NJ	2
NM	2
NV	2
NY	2
OH	2
OK	2
OR	2
PA	2
RI	2
SC	2
SD	2
TN	2
TX	2
UT	2
VA	2
VT	2
WA	2
WI	2
WV	2
WY	2

This is great but now I want a way to rank each state for name uniqueness. I can create a new data series consisting of the sum of all name frequencies for each state. States with a lower score

are more unique than states with a higher score

```
In [18]: df_sum = df.groupby('State').name_freq.sum()  
df_sum
```

```
Out[18]: State  
AK      309  
AL      280  
AR      323  
AZ      344  
CA      306  
CO      377  
CT      363  
DC      284  
DE      325  
FL      331  
GA      372  
HI      287  
IA      327  
ID      334  
IL      336  
IN      382  
KS      338  
KY      383  
LA      340  
MA      351  
MD      360  
ME      348  
MI      382  
MN      326  
MO      363  
MS      242  
MT      301  
NC      360  
ND      288  
NE      338  
NH      325  
NJ      347  
NM      277  
NV      305  
NY      347  
OH      363  
OK      371  
OR      382  
PA      371  
RI      344  
SC      294  
SD      321
```

```

TN      351
TX      306
UT      278
VA      376
VT      325
WA      349
WI      352
WV      284
WY      292
Name: name_freq, dtype: int64

```

There are some nice built in Pandas functions that allow us to calculate some common statistics. For example we can compute the mean, max and min of our name frequencies:

```
In [19]: df_sum.mean(), df_sum.max(), df_sum.min()
```

```
Out[19]: (332.54901960784315, 383, 242)
```

Now I would like to normalize these values to a 0-1 scale and sort the new data frame from highest to lowest. We will use this later.

```
In [20]: unique_score = 1-((df_sum - df_sum.min()) / (df_sum.max() - df_sum.min()))
         unique_score
```

```
Out[20]: State
```

```

AK      0.524823
AL      0.730496
AR      0.425532
AZ      0.276596
CA      0.546099
CO      0.042553
CT      0.141844
DC      0.702128
DE      0.411348
FL      0.368794
GA      0.078014
HI      0.680851
IA      0.397163
ID      0.347518
IL      0.333333
IN      0.007092
KS      0.319149
KY      0.000000
LA      0.304965
MA      0.226950
MD      0.163121
ME      0.248227
MI      0.007092
MN      0.404255

```

```

MO      0.141844
MS      1.000000
MT      0.581560
NC      0.163121
ND      0.673759
NE      0.319149
NH      0.411348
NJ      0.255319
NM      0.751773
NV      0.553191
NY      0.255319
OH      0.141844
OK      0.085106
OR      0.007092
PA      0.085106
RI      0.276596
SC      0.631206
SD      0.439716
TN      0.226950
TX      0.546099
UT      0.744681
VA      0.049645
VT      0.411348
WA      0.241135
WI      0.219858
WV      0.702128
WY      0.645390
Name: name_freq, dtype: float64

```

Now we can Concatenate our "data\_state" data frame and our new "unique\_score" data series using the `concat()` function. The index values are our states. We can sort the states by the `name_frequency` value

```
In [21]: data_updated = pd.concat([data_state, unique_score], axis=1).sort_values(by='name_frequency')
data_updated
```

```

Out[21]:
   State  1  2  3  4  5  8 10 11 15 21 22 27 29 35 40 43 50 51 \
MS      0  3  1  0  0  0  0  1  0  0  0  0  0  2  0  0  1  2
NM      2  0  0  0  0  1  0  0  1  0  1  0  0  1  0  1  1  2
UT      3  0  0  0  0  0  0  0  0  1  0  1  0  1  1  0  1  2
AL      1  0  0  1  0  0  0  1  1  0  0  1  0  2  0  0  1  2
WV      0  1  1  1  0  0  1  0  0  0  0  0  0  2  0  1  1  2
DC      1  0  0  1  0  1  0  0  1  0  0  0  1  1  1  0  1  2
HI      1  0  1  1  0  0  0  0  0  0  1  1  0  1  0  1  1  2
ND      0  0  0  2  1  0  0  0  0  1  0  1  0  1  1  0  1  2
WY      1  0  0  0  0  0  1  0  2  1  0  0  0  1  0  1  1  2
SC      0  1  0  1  0  0  0  1  1  0  0  0  0  2  1  0  1  2

```



MT	0	0	1	0	0	0	1	1	0	1	0	0	1	1	1	0	1	2
NV	1	0	0	0	0	1	0	0	1	0	1	0	1	1	0	1	1	2
TX	0	1	0	0	0	1	0	0	1	0	1	0	1	1	0	1	1	2
CA	0	1	0	0	0	1	0	0	1	0	1	0	1	1	0	1	1	2
AK	1	1	0	0	0	0	0	0	1	0	0	1	1	0	1	1	1	2
SD	0	0	0	0	1	0	1	0	1	1	0	0	0	1	1	1	1	2
AR	0	0	1	1	0	0	0	0	0	0	1	0	1	2	0	1	1	2
VT	0	0	1	1	0	0	0	0	0	1	0	1	0	1	1	1	1	2
NH	0	0	1	0	0	0	0	1	0	0	0	1	1	2	1	1	0	2
DE	1	0	0	1	0	0	0	0	1	0	0	0	0	2	1	1	1	2
MN	0	0	1	0	1	0	0	0	0	1	0	1	0	1	1	1	1	2
IA	0	0	0	1	1	0	0	0	0	1	0	1	0	1	1	1	1	2
FL	0	0	0	0	0	1	0	0	1	0	1	1	1	1	0	1	1	2
ID	0	0	0	0	0	0	0	0	2	1	0	1	1	1	1	0	1	2
IL	0	0	0	0	0	1	0	0	1	1	1	0	0	1	1	1	1	2
NE	0	0	0	0	0	0	1	0	1	1	1	0	0	1	1	1	1	2
KS	0	0	0	0	0	0	1	0	1	1	1	0	0	1	1	1	1	2
LA	0	0	0	0	0	0	1	1	0	0	1	1	0	1	1	1	1	2
RI	0	0	0	0	0	0	1	0	1	0	1	1	0	1	1	1	1	2
AZ	0	0	0	0	0	1	0	0	1	0	1	0	1	1	1	1	1	2
NJ	0	0	0	0	0	0	0	1	1	0	1	0	1	1	1	1	1	2
NY	0	0	0	0	0	0	0	1	1	0	1	0	1	1	1	1	1	2
ME	1	0	0	0	0	0	0	0	0	1	0	1	1	1	1	1	1	2
WA	0	0	0	0	0	0	0	0	1	1	1	1	1	0	1	1	1	2
TN	0	0	0	1	0	0	0	0	1	0	0	1	0	2	1	1	1	2
MA	0	0	1	0	0	0	0	0	0	0	1	1	1	1	1	1	1	2
WI	0	0	0	0	1	0	0	0	0	1	0	1	1	1	1	1	1	2
MD	0	0	0	0	0	0	0	1	1	0	0	0	1	2	1	1	1	2
NC	0	0	0	0	0	0	0	1	1	0	0	0	1	2	1	1	1	2
CT	0	0	0	0	0	0	0	0	1	0	1	1	1	1	1	1	1	2
MO	0	0	0	0	0	0	1	0	0	1	0	1	0	2	1	1	1	2
OH	0	0	0	0	0	0	1	0	0	1	0	1	0	2	1	1	1	2
OK	0	0	0	0	0	0	0	0	1	0	1	0	1	2	1	1	1	2
PA	0	0	0	0	0	0	0	0	1	0	1	0	1	2	1	1	1	2
GA	0	0	0	0	0	0	0	1	0	0	0	1	1	2	1	1	1	2
VA	0	0	0	0	0	0	0	0	1	0	0	1	1	2	1	1	1	2
CO	0	0	0	0	0	0	0	0	0	1	1	0	1	2	1	1	1	2
OR	0	0	0	0	0	0	0	0	0	1	0	1	1	2	1	1	1	2
IN	0	0	0	0	0	0	0	0	0	1	0	1	1	2	1	1	1	2
MI	0	0	0	0	0	0	0	0	0	1	0	1	1	2	1	1	1	2
KY	0	0	0	0	0	0	0	0	0	0	1	1	1	2	1	1	1	2

name\_freq

State

MS	1.000000
NM	0.751773
UT	0.744681
AL	0.730496

WV	0.702128
DC	0.702128
HI	0.680851
ND	0.673759
WY	0.645390
SC	0.631206
MT	0.581560
NV	0.553191
TX	0.546099
CA	0.546099
AK	0.524823
SD	0.439716
AR	0.425532
VT	0.411348
NH	0.411348
DE	0.411348
MN	0.404255
IA	0.397163
FL	0.368794
ID	0.347518
IL	0.333333
NE	0.319149
KS	0.319149
LA	0.304965
RI	0.276596
AZ	0.276596
NJ	0.255319
NY	0.255319
ME	0.248227
WA	0.241135
TN	0.226950
MA	0.226950
WI	0.219858
MD	0.163121
NC	0.163121
CT	0.141844
MO	0.141844
OH	0.141844
OK	0.085106
PA	0.085106
GA	0.078014
VA	0.049645
CO	0.042553
OR	0.007092
IN	0.007092
MI	0.007092
KY	0.000000

We can see that Mississippi has the highest baby name uniqueness score. Let us see what the names are. To do this we can make a Pandas series from the df data frame and pass it into the df data frame as a boolean.

```
In [ ]: col = df['State']
        df[col=='MS']
```

It is a good idea to change the column name of the last column as it has the same name as our rows.

```
In [23]: data_updated = data_updated.rename(columns={'name_freq': 'unique score' })
        data_updated
```

```
Out[23]:
```

	1	2	3	4	5	8	10	11	15	21	22	27	29	35	40	43	50	51	\
State																			
MS	0	3	1	0	0	0	0	1	0	0	0	0	0	2	0	0	1	2	
NM	2	0	0	0	0	1	0	0	1	0	1	0	0	1	0	1	1	2	
UT	3	0	0	0	0	0	0	0	0	1	0	1	0	1	1	0	1	2	
AL	1	0	0	1	0	0	0	1	1	0	0	1	0	2	0	0	1	2	
WV	0	1	1	1	0	0	1	0	0	0	0	0	0	2	0	1	1	2	
DC	1	0	0	1	0	1	0	0	1	0	0	0	1	1	1	0	1	2	
HI	1	0	1	1	0	0	0	0	0	0	1	1	0	1	0	1	1	2	
ND	0	0	0	2	1	0	0	0	0	1	0	1	0	1	1	0	1	2	
WY	1	0	0	0	0	0	1	0	2	1	0	0	0	1	0	1	1	2	
SC	0	1	0	1	0	0	0	1	1	0	0	0	0	2	1	0	1	2	
MT	0	0	1	0	0	0	1	1	0	1	0	0	1	1	1	0	1	2	
NV	1	0	0	0	0	1	0	0	1	0	1	0	1	1	0	1	1	2	
TX	0	1	0	0	0	1	0	0	1	0	1	0	1	1	0	1	1	2	
CA	0	1	0	0	0	1	0	0	1	0	1	0	1	1	0	1	1	2	
AK	1	1	0	0	0	0	0	0	1	0	0	1	1	0	1	1	1	2	
SD	0	0	0	0	1	0	1	0	1	1	0	0	0	1	1	1	1	2	
AR	0	0	1	1	0	0	0	0	0	0	1	0	1	2	0	1	1	2	
VT	0	0	1	1	0	0	0	0	0	1	0	1	0	1	1	1	1	2	
NH	0	0	1	0	0	0	0	1	0	0	0	1	1	2	1	1	0	2	
DE	1	0	0	1	0	0	0	0	1	0	0	0	0	2	1	1	1	2	
MN	0	0	1	0	1	0	0	0	0	1	0	1	0	1	1	1	1	2	
IA	0	0	0	1	1	0	0	0	0	1	0	1	0	1	1	1	1	2	
FL	0	0	0	0	0	1	0	0	1	0	1	1	1	1	0	1	1	2	
ID	0	0	0	0	0	0	0	0	2	1	0	1	1	1	1	0	1	2	
IL	0	0	0	0	0	1	0	0	1	1	1	0	0	1	1	1	1	2	
NE	0	0	0	0	0	0	1	0	1	1	1	0	0	1	1	1	1	2	
KS	0	0	0	0	0	0	1	0	1	1	1	0	0	1	1	1	1	2	
LA	0	0	0	0	0	0	1	1	0	0	1	1	0	1	1	1	1	2	
RI	0	0	0	0	0	0	1	0	1	0	1	1	0	1	1	1	1	2	
AZ	0	0	0	0	0	1	0	0	1	0	1	0	1	1	1	1	1	2	
NJ	0	0	0	0	0	0	0	1	1	0	1	0	1	1	1	1	1	2	
NY	0	0	0	0	0	0	0	1	1	0	1	0	1	1	1	1	1	2	
ME	1	0	0	0	0	0	0	0	0	1	0	1	1	1	1	1	1	2	
WA	0	0	0	0	0	0	0	0	1	1	1	1	1	0	1	1	1	2	

TN	0	0	0	1	0	0	0	0	1	0	0	1	0	2	1	1	1	2
MA	0	0	1	0	0	0	0	0	0	0	1	1	1	1	1	1	1	2
WI	0	0	0	0	1	0	0	0	0	1	0	1	1	1	1	1	1	2
MD	0	0	0	0	0	0	0	1	1	0	0	0	1	2	1	1	1	2
NC	0	0	0	0	0	0	0	1	1	0	0	0	1	2	1	1	1	2
CT	0	0	0	0	0	0	0	0	1	0	1	1	1	1	1	1	1	2
MO	0	0	0	0	0	0	1	0	0	1	0	1	0	2	1	1	1	2
OH	0	0	0	0	0	0	1	0	0	1	0	1	0	2	1	1	1	2
OK	0	0	0	0	0	0	0	0	1	0	1	0	1	2	1	1	1	2
PA	0	0	0	0	0	0	0	0	1	0	1	0	1	2	1	1	1	2
GA	0	0	0	0	0	0	0	1	0	0	0	1	1	2	1	1	1	2
VA	0	0	0	0	0	0	0	0	1	0	0	1	1	2	1	1	1	2
CO	0	0	0	0	0	0	0	0	0	1	1	0	1	2	1	1	1	2
OR	0	0	0	0	0	0	0	0	0	1	0	1	1	2	1	1	1	2
IN	0	0	0	0	0	0	0	0	0	1	0	1	1	2	1	1	1	2
MI	0	0	0	0	0	0	0	0	0	1	0	1	1	2	1	1	1	2
KY	0	0	0	0	0	0	0	0	0	0	1	1	1	2	1	1	1	2

#### unique score

State	
MS	1.000000
NM	0.751773
UT	0.744681
AL	0.730496
WV	0.702128
DC	0.702128
HI	0.680851
ND	0.673759
WY	0.645390
SC	0.631206
MT	0.581560
NV	0.553191
TX	0.546099
CA	0.546099
AK	0.524823
SD	0.439716
AR	0.425532
VT	0.411348
NH	0.411348
DE	0.411348
MN	0.404255
IA	0.397163
FL	0.368794
ID	0.347518
IL	0.333333
NE	0.319149
KS	0.319149
LA	0.304965

RI	0.276596
AZ	0.276596
NJ	0.255319
NY	0.255319
ME	0.248227
WA	0.241135
TN	0.226950
MA	0.226950
WI	0.219858
MD	0.163121
NC	0.163121
CT	0.141844
MO	0.141844
OH	0.141844
OK	0.085106
PA	0.085106
GA	0.078014
VA	0.049645
CO	0.042553
OR	0.007092
IN	0.007092
MI	0.007092
KY	0.000000

```
In [24]: score_dict = unique_score.to_dict()
         score_dict
```

```
Out[24]: {'AK': 0.52482269503546097,
          'AL': 0.73049645390070927,
          'AR': 0.42553191489361697,
          'AZ': 0.27659574468085102,
          'CA': 0.54609929078014185,
          'CO': 0.042553191489361653,
          'CT': 0.14184397163120566,
          'DC': 0.7021276595744681,
          'DE': 0.41134751773049649,
          'FL': 0.36879432624113473,
          'GA': 0.078014184397163122,
          'HI': 0.68085106382978722,
          'IA': 0.3971631205673759,
          'ID': 0.34751773049645385,
          'IL': 0.33333333333333337,
          'IN': 0.0070921985815602939,
          'KS': 0.31914893617021278,
          'KY': 0.0,
          'LA': 0.30496453900709219,
          'MA': 0.22695035460992907,
          'MD': 0.16312056737588654,
```

```

'ME': 0.24822695035460995,
'MI': 0.0070921985815602939,
'MN': 0.4042553191489362,
'MO': 0.14184397163120566,
'MS': 1.0,
'MT': 0.58156028368794321,
'NC': 0.16312056737588654,
'ND': 0.67375886524822692,
'NE': 0.31914893617021278,
'NH': 0.41134751773049649,
'NJ': 0.25531914893617025,
'NM': 0.75177304964539005,
'NV': 0.55319148936170215,
'NY': 0.25531914893617025,
'OH': 0.14184397163120566,
'OK': 0.085106382978723416,
'OR': 0.0070921985815602939,
'PA': 0.085106382978723416,
'RI': 0.27659574468085102,
'SC': 0.63120567375886527,
'SD': 0.43971631205673756,
'TN': 0.22695035460992907,
'TX': 0.54609929078014185,
'UT': 0.74468085106382986,
'VA': 0.049645390070921946,
'VT': 0.41134751773049649,
'WA': 0.24113475177304966,
'WI': 0.21985815602836878,
'WV': 0.7021276595744681,
'WY': 0.64539007092198575}

```

First we make a list of all of the states including Washington D.C. Next we make a list of the state abbreviations using a list comprehension by iterating over the indices of the `unique_score` data series.

```

In [ ]: state_list = ['Alaska', 'Alabama', 'Arkansas', 'Arizona', 'California',
                      'Colorado', 'Connecticut', 'District of Columbia', 'Delaware',
                      'Florida', 'Georgia', 'Hawaii', 'Iowa', 'Idaho', 'Illinois',
                      'Indiana', 'Kansas', 'Kentucky', 'Louisiana', 'Massachusetts',
                      'Maryland', 'Maine', 'Michigan', 'Minnesota', 'Missouri',
                      'Mississippi', 'Montana', 'North Carolina', 'North Dakota',
                      'Nebraska', 'New Hampshire', 'New Jersey', 'New Mexico',
                      'Nevada', 'New York', 'Ohio', 'Oklahoma', 'Oregon',
                      'Pennsylvania', 'Rhode Island', 'South Carolina',
                      'South Dakota', 'Tennessee', 'Texas', 'Utah', 'Virginia',
                      'Vermont', 'Washington', 'Wisconsin', 'West Virginia',
                      'Wyoming']

```

```
state_abbrev = [i for i in unique_score.index]
print(state_abbrev)
```

Now we can use the Python Zip( ) function to make a list of tuples that we can pass the dict( ) function to give us our new dictionary.

```
In [26]: combine = zip(state_abbrev, state_list)
state_abbrev_dict = dict(combine)
print(state_abbrev_dict)
```

```
{'AK': 'Alaska', 'AL': 'Alabama', 'AR': 'Arkansas', 'AZ': 'Arizona', 'CA': 'California', 'CO':
```

We will create a new dictionary for Basemap with the spelled out states as keys and the scores as values. We first initialize an empty dictionary. Then we use the items( ) method of dictionaries to iterate over the keys and values in our score\_dict we made above. If the key matches the key in our state\_abbrev\_dict (The state abbreviations are the same) we use the value for that particular key (state name spelled out) as the new key for new\_dict. The value for score\_dict( ) (the score for that state) is then assigned as the value new\_dict.

```
In [27]: new_dict = {}
for key, value in score_dict.items():
    if key in state_abbrev_dict:
        new_dict[state_abbrev_dict[key]] = value

print(new_dict)
print(new_dict.get('Mississippi'))
print(score_dict.get('MS'))
```

```
{'Alaska': 0.52482269503546097, 'Alabama': 0.73049645390070927, 'Arkansas': 0.4255319148936169
1.0
1.0
```

To check our work. We can print out any score from our dictionary using the get( ) method of dictionaries. In the above example we printed out the score for Mississippi for the new\_dict and the score\_dict.

Now we are ready to pass our data into Basemap but first let us prep the maps. Briefly, "llcrnlon" is the longitude of the lower left corner, "llcrnlat" is the latitude of the lower left hand corner, "urcnrlon" is the longitude of the upper right hand corner and "urcnrlat" is the latitude of the upper right hand corner for the map. The 'llc' projection works well for square maps. Finally lon\_0 specifies the center longitude coordinate for the map. Finally, lat\_1 and lat\_2 allow you to define an oblique centerline. These coordinates were lifted from the Basemap example file, "fill\_states.py" that is distributed with the Basemap package.

```
In [29]: # Lambert Conformal map of lower 48 states.
from mpl_toolkits.basemap import Basemap
import math
import csv
```

```

import pandas as pd
import os
import numpy as np
import matplotlib as mpl
import matplotlib.pyplot as plt
from mpl_toolkits.basemap import Basemap
from matplotlib.colors import rgb2hex
from matplotlib.patches import Polygon

#map_lower_48 = Basemap(llcrnrlon=-119,llcrnrlat=22,urcrnrlon=-64,urcrnrlat=49,projec

map_lower_48 = Basemap(llcrnrlon=-121,llcrnrlat=20,urcrnrlon=-62,urcrnrlat=51,project

```

This lets Basemap know where in the world we want to focus on. But Basemap does not know anything about the shapes of the U.S states. For this need to provide a shape file. This is a little confusing because although it is referred to as a shape file, there are actually three files which provide the necessary information. They all have the 'st99\_d00' prefix with three different extensions, .dbf, .shp and .shx. The .shp file is a binary file containing geometric data and the .dbf and .shx are supporting files. These are maintained by the ESRI at <http://www.esri.com/>. Next we can use the Basemap readshapefile( ) function to read in these files. Do not include the extensions and make sure all three files are in the same directory.

```

In [34]: states_shp_info = map_lower_48.readshapefile('shapes\st99_d00', 'states', drawbounds='
plt.show()

```



Now we have a variable called "shp\_info" describing a map of the lower forty eight states. Now let us make the Alaska and Hawaii maps

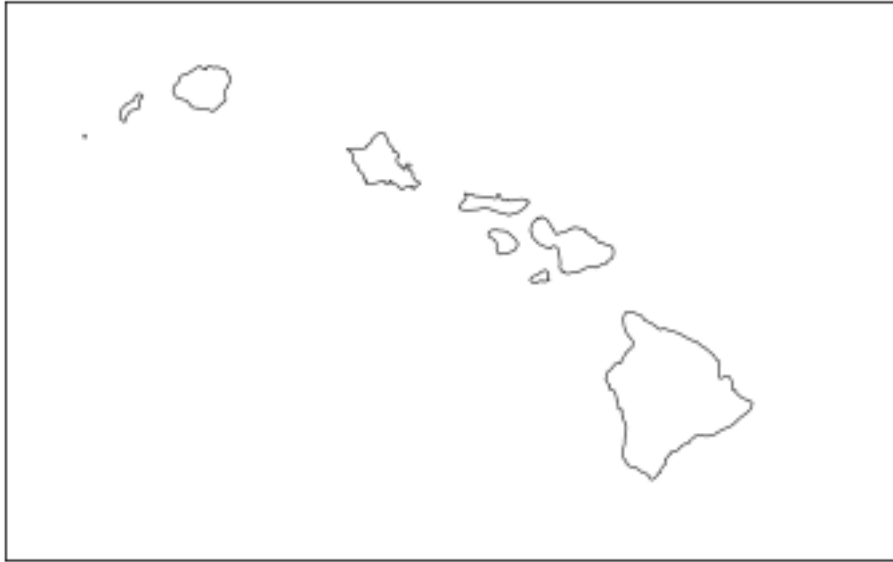


```
In [35]: m_alaska = Basemap(llcrnrlon=-173,llcrnrlat=51,urcrnrlon=-134.45,urcrnrlat=71.34,proj
In [37]: alaska_shp_info = m_alaska.readshapefile('shapes/st99_d00', 'states', drawbounds=True)
plt.show()
```



Hawaii has a very oblong shape so it will be hard to make a square like map. If we leave out the lower left hand and upper right hand corner longitude and latitude we can define a 'great circle' using two points.

```
In [38]: m_hawaii = Basemap(#llcrnrlon=-161,llcrnrlat=21,urcrnrlon=-154,urcrnrlat=22,
                             width=800000, height=500000,
                             projection='lcc',
                             lat_0=20.525, lon_0=-157.385,
                             lon_1=-158.115, lat_1=17.24,
                             lon_2=-153.479, lat_2=19.663,
                             )
In [39]: hawaii_shp_info = m_hawaii.readshapefile('shapes/st99_d00', 'states', drawbounds=True)
plt.show()
```



Now we are ready to color the maps. First we define the color map we are going to use with, `cmap=plt.cm.Blues`. This will give us a blue spectrum in which dark blues will be assigned a higher uniqueness score and light blues will have a lower uniqueness score. Next we can define the maximum and minimum values for our score, `vmin = 0; vmax = 1`. When we read the shape file into `basemap`, a dictionary called "shapedict" was created and stored in 'states\_shp\_info'. This is where the state names and corresponding shapes reside. for example if we pass the key "NAME" we will get back the state names as values. There are multiple entries for each state.

```
In [40]: for shapedict in map_lower_48.states_info:
          print(shapedict['NAME'])
```

```
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```

[illegible]

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Minnesota  
Washington  
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Montana  
Idaho  
North Dakota  
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Washington  
Michigan  
Washington  
Michigan  
Maine  
Wisconsin  
Wisconsin  
Wisconsin  
Wisconsin  
Oregon  
South Dakota  
Michigan  
Michigan  
Michigan  
Wisconsin  
New Hampshire  
Michigan  
Wisconsin  
Michigan

Vermont  
New York  
Wyoming  
Maine  
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Iowa  
Nebraska  
Massachusetts  
Illinois  
Pennsylvania  
Connecticut  
Rhode Island  
California  
Nevada  
Utah  
Ohio  
Indiana  
Ohio  
Ohio  
Rhode Island  
Ohio  
Rhode Island  
Rhode Island  
Ohio  
Massachusetts  
Rhode Island  
Rhode Island  
Massachusetts  
Massachusetts

New Jersey  
New York  
Rhode Island  
New York  
Colorado  
New York  
New York  
New York  
New York  
West Virginia  
Missouri  
Kansas  
Delaware  
Maryland  
Delaware  
Delaware  
Virginia  
Kentucky  
District of Columbia  
Maryland  
Maryland  
Virginia  
Virginia  
California  
Virginia  
California  
California  
Arizona  
Oklahoma  
New Mexico  
Tennessee  
North Carolina  
Kentucky  
Texas  
Arkansas  
North Carolina  
North Carolina  
South Carolina  
Alabama  
Georgia  
Mississippi  
California  
California  
California  
California  
California  
California  
California

[illegible]

```
Hawaii
Puerto Rico
Puerto Rico
Puerto Rico
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Puerto Rico
Puerto Rico
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Puerto Rico
```

We want to access shapedict using a for-loop. We initialize a new empty list called 'state\_names'. These names will be filled with the names from the shapedict dictionary in the order and frequency that they appear. We want to skip "Puerto Rico" so we add; if state\_name is not equal to "Puerto Rico", then the score is equal to our value of new\_dict for a particular state\_name key. So For every state\_name entry in shapedict we get a score which is the unique score taken from new\_dict. Next, we define the state\_name as a key in the new colors dictionary we are creating. With, 'colors[state\_name] = cmap(np.sqrt(score))' We let the key to be equal to the blues spectrum mapped onto the values for score. We use the numpy square root function to use the square root of the scores. This sepearates the valus more making it easier to see color differences.

```
In [41]: cmap = plt.cm.Blues
        vmin = 0; vmax = 1
        colors = {}
        state_names = []
        for shapedict in map_lower_48.states_info:
            state_name = shapedict['NAME']
            if state_name != 'Puerto Rico':
                score = new_dict[state_name]
                colors[state_name] = cmap(np.sqrt(score))
            state_names.append(state_name)
```

If we print the colors dictionary we can see that we have the state names as keys and RGB blue values that are scaled to the scores for each state. And we have a list of the state\_names.

```
In [42]: print(colors)
```

```
{'Alaska': (0.15478662053056519, 0.46851211072664356, 0.72287581699346404, 1.0), 'Minnesota':
```

```
In [43]: print(state_names)
```





axis properties for the mainland with "ax\_mainland = plt.subplot2grid((4,4),(0,0) colspan=4". This creates a four by four grid with a column span of 4. We will not be plotting this many figures but it creates the space we need. The mainland plot will be placed in the upper left hand corner and span the entire grid. Next, we repeat what we did above for the mainland, Alaska and Hawaii.

```
In [47]: import matplotlib.font_manager as fm
import math
cmap = plt.cm.Blues
vmin = 0; vmax = 1

fig = plt.figure(figsize = (15, 24), dpi=300)
prop = fm.FontProperties(fname='shapes/EBGaramond-Regular.ttf')

ax_mainland = plt.subplot2grid((4,4),(0,0), colspan=4)
plt.text(0.5, 1.05, "States Colored by Baby Name Uniqueness",
        horizontalalignment='center',
        fontproperties=prop, fontsize=25,
        transform = ax_mainland.transAxes)
ax_mainland.axis("off")

#map for the lower 48
colors = {}
state_names = []
for shapedict in map_lower_48.states_info:
    state_name = shapedict['NAME']
    if state_name != 'Puerto Rico':
        score = new_dict[state_name]
        colors[state_name] = cmap(np.sqrt(score))
        #maps the colors to the states in a dictionary called "colors"
        state_names.append(state_name)

for nshape, seg in enumerate(map_lower_48.states):
    if state_names[nshape] != 'Puerto Rico':
        color = rgb2hex(colors[state_names[nshape]])
        mainland_poly = Polygon(seg, facecolor=color, edgecolor=color)
        ax_mainland.add_patch(mainland_poly)
map_lower_48.drawstates(color=color, linewidth=0)

#Repeat for Alaska
colors = {}
ax_alaska = plt.subplot2grid((4,4), (1,1), colspan = 1)
ax_alaska.set_title('Alaska', fontproperties=prop, fontsize=25)
ax_alaska.axis("off")

for shapedict in m_alaska.states_info:
    score = new_dict['Alaska']
    colors['Alaska'] = cmap(math.sqrt(score))
```

```

state_names.append('Alaska')

for nshape, seg in enumerate(m_alaska.states):
    color_alaska = rgb2hex(colors['Alaska'])
    alaska_poly = Polygon(seg, facecolor=color_alaska, edgecolor=color_alaska)
    ax_alaska.add_patch(alaska_poly)
m_alaska.drawstates(color=color, linewidth=0)

#Repeat for Hawaii
colors = {}
ax_hawaii = plt.subplot2grid((4,4), (1,2), colspan = 1)
ax_hawaii.set_title('Hawaii', fontproperties=prop, fontsize=25)
ax_hawaii.axis("off")

for shapedict in m_hawaii.states_info:
    score = new_dict['Hawaii']
    colors['Hawaii'] = cmap(math.sqrt(score))
    state_names.append('Hawaii')

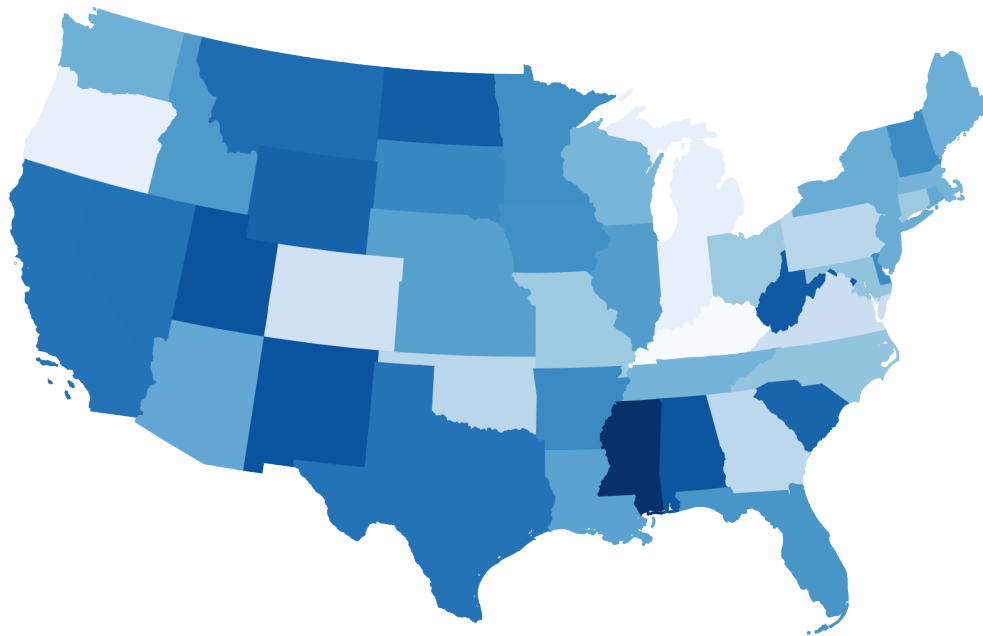
for nshape, seg in enumerate(m_hawaii.states):
    color_hawaii = rgb2hex(colors['Hawaii'])
    hawaii_poly = Polygon(seg, facecolor=color_hawaii, edgecolor=color_hawaii)
    ax_hawaii.add_patch(hawaii_poly)

m_hawaii.drawstates(color=color_hawaii, linewidth=0)

plt.savefig('shapes\state_name_scores.png', dpi=300) #bbox_inches='tight'
plt.show()

```

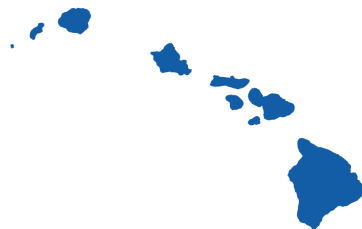
## States Colored by Baby Name Uniqueness



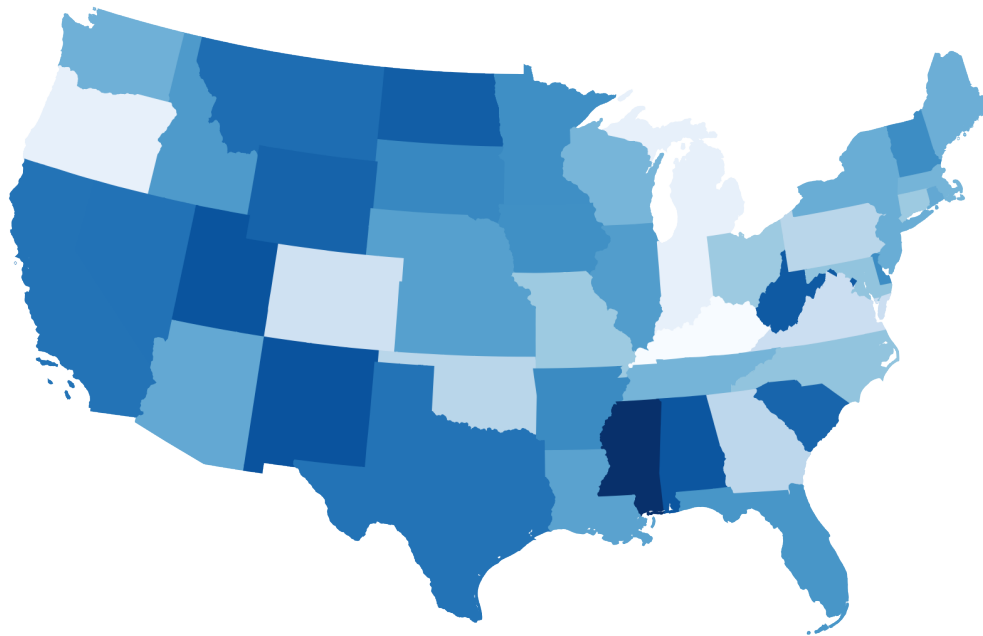
Alaska



Hawaii



## States Colored by Baby Name Uniqueness



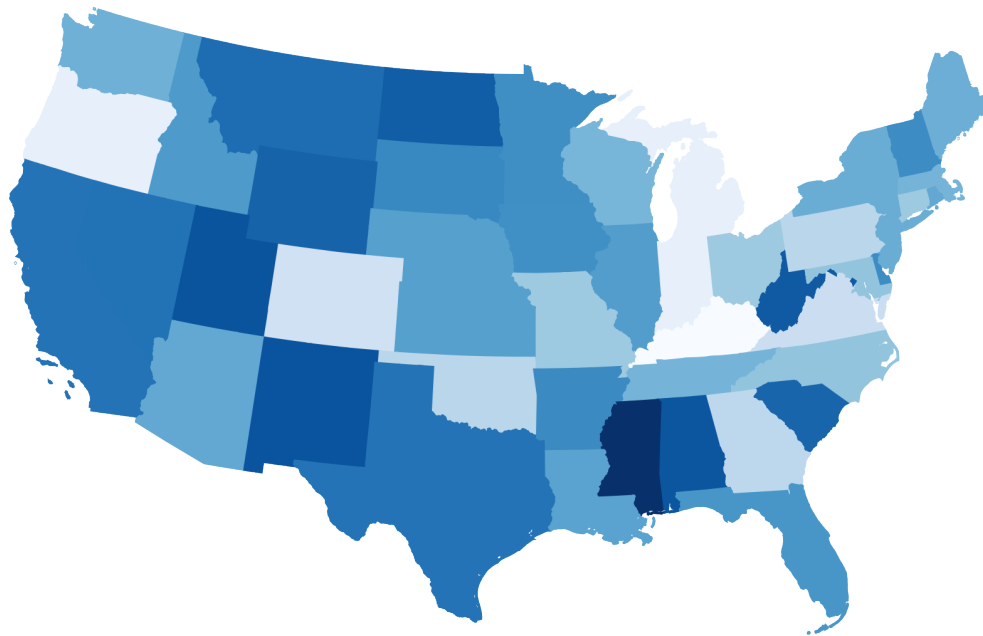
Alaska



Hawaii



## States Colored by Baby Name Uniqueness



Alaska



Hawaii

