Gramener Task

December 13, 2017

0.1 Programming Task in Python

1 1:Given two lists L1 = ['a', 'b', 'c'], L2 = ['b', 'd'], find common elements, find elements present in L1

and not in L2?

```
In [108]: L1 = ['a','b','c']
          L2 = ['b','d']
```

Find common elements

```
In [109]: def common_elements(l1,l2) :
              # Using set property and take intersection
              return set(l1) & set(l2);

In [110]: common_elements(L1,L2)

Out[110]: {'b'}
```

Elements present in L1 and not in L2

```
In [111]: def l1_not_l2(l1,l2) :
              # Using set property and Subtraction
              return set(l1)-set(l2) ;

In [112]: l1_not_l2(L1,L2)

Out[112]: {'a', 'c'}
```

2 2: Thrusday Count between 1990-2000

```
In [113]: from datetime import date  ## for data and weekday;

          def thrusday_count(year_range) :

              min_thr = 52    ## 52 weeks in a year
              count = 0       ## Count for Thrusday
```

```
    for i in range(year_range[0],year_range[1]+1):

        if (i%100==0) :         ### Check for a decade

            if (i%400==0) :     ### Check for a leap year

                        ### Checking Last two Days
                if ((date(1990, 12, 31).weekday()==3) or (date(1990, 12, 30).weekday()
                    count += (min_thr+1)
                else :
                    count += min_thr

        elif(i%4==0) :    ###  Check for a leap year

                        ### Checking Last two Days
            if ((date(1990, 12, 31).weekday()==3) or (date(1990, 12, 31).weekday()==3)
                count += (min_thr+1)
            else :
                count += min_thr

        else :
                ### Checking Last Day
            if ((date(1990, 12, 31).weekday()==3)) :
                count += (min_thr+1)
            else :
                count += min_thr
    return count
```

In [114]:
```
thrusday_count([1990,2000])
```

Out[114]:
```
572
```

2.1 Data Analysis Part

3 Use case 2 - 2011 India Census

In [115]:
```
## Loading libraries
import pandas as pd     ## for data manipulation
import numpy as np      ## for array and matrices operations
import matplotlib.pyplot as plt          ## For interactive visualizations
import geopandas as gpd                  # For plotting maps
```

Setting Matplotlib plot style and figure size

In [116]:
```
plt.style.use(['ggplot'])
plt.rcParams['figure.figsize'] = (10,8)
```

Reading Data and Print it's first 5 rows

```
In [117]: census_data = pd.read_csv('india_2011.csv')

In [118]: census_data.head()      ##Printing Head Data

Out[118]:    District code        State name District name  Population    Male  Female  \
          0              1  JAMMU & KASHMIR       Kupwara      870354  474190  396164
          1              2  JAMMU & KASHMIR        Badgam      753745  398041  355704
          2              3  JAMMU & KASHMIR   Leh(Ladakh)      133487   78971   54516
          3              4  JAMMU & KASHMIR        Kargil      140802   77785   63017
          4              5  JAMMU & KASHMIR         Punch      476835  251899  224936

             Literate  Male_Literate  Female_Literate    SC          ...            \
          0    439654         282823           156831  1048          ...
          1    335649         207741           127908   368          ...
          2     93770          62834            30936   488          ...
          3     86236          56301            29935    18          ...
          4    261724         163333            98391   556          ...

             Power_Parity_Rs_90000_150000  Power_Parity_Rs_45000_150000  \
          0                            94                           588
          1                           126                           562
          2                            46                           122
          3                            27                           114
          4                            78                           346

             Power_Parity_Rs_150000_240000  Power_Parity_Rs_240000_330000  \
          0                             71                            101
          1                             72                             89
          2                             15                             22
          3                             12                             18
          4                             35                             50

             Power_Parity_Rs_150000_330000  Power_Parity_Rs_330000_425000  \
          0                            172                             74
          1                            161                             96
          2                             37                             20
          3                             30                             19
          4                             85                             59

             Power_Parity_Rs_425000_545000  Power_Parity_Rs_330000_545000  \
          0                             10                             84
          1                             28                            124
          2                             14                             34
          3                              3                             22
          4                              8                             67

             Power_Parity_Above_Rs_545000  Total_Power_Parity
```

```
0                            15               1119
1                            18               1066
2                            17                242
3                             7                214
4                            12                629

[5 rows x 118 columns]
```

Showing Data Property

```
In [119]: census_data.describe()     ## Describing Data
```

```
Out[119]:       District code   Population          Male        Female      Literate  \
          count    640.000000  6.400000e+02  6.400000e+02  6.400000e+02  6.400000e+02
          mean     320.500000  1.891961e+06  9.738598e+05  9.181011e+05  1.193186e+06
          std      184.896367  1.544380e+06  8.007785e+05  7.449864e+05  1.068583e+06
          min        1.000000  8.004000e+03  4.414000e+03  3.590000e+03  4.436000e+03
          25%      160.750000  8.178610e+05  4.171682e+05  4.017458e+05  4.825982e+05
          50%      320.500000  1.557367e+06  7.986815e+05  7.589200e+05  9.573465e+05
          75%      480.250000  2.583551e+06  1.338604e+06  1.264277e+06  1.602260e+06
          max      640.000000  1.106015e+07  5.865078e+06  5.195070e+06  8.227161e+06

                Male_Literate  Female_Literate            SC       Male_SC  \
          count  6.400000e+02     6.400000e+02  6.400000e+02  6.400000e+02
          mean   6.793182e+05     5.138675e+05  3.146537e+05  1.617739e+05
          std    5.924144e+05     4.801816e+05  3.129818e+05  1.611216e+05
          min    2.614000e+03     1.822000e+03  0.000000e+00  0.000000e+00
          25%    2.764365e+05     2.008920e+05  8.320850e+04  4.230700e+04
          50%    5.483525e+05     4.038590e+05  2.460160e+05  1.255485e+05
          75%    9.188582e+05     6.641550e+05  4.477078e+05  2.284602e+05
          max    4.591396e+06     3.635765e+06  2.464032e+06  1.266504e+06

                   Female_SC          ...        Power_Parity_Rs_90000_150000  \
          count 6.400000e+02          ...                          640.000000
          mean  1.528798e+05          ...                          786.046875
          std   1.520336e+05          ...                         1038.854733
          min   0.000000e+00          ...                            0.000000
          25%   4.267175e+04          ...                          236.750000
          50%   1.178550e+05          ...                          518.000000
          75%   2.140502e+05          ...                          941.250000
          max   1.197528e+06          ...                        10334.000000

                Power_Parity_Rs_45000_150000 Power_Parity_Rs_150000_240000  \
          count                   640.000000                    640.000000
          mean                   1696.456250                    294.000000
          std                    1720.535151                    638.345281
          min                       0.000000                      0.000000
          25%                     589.000000                     59.000000
```

```
50%                      1220.500000                     149.000000
75%                      2233.250000                     296.500000
max                     13819.000000                   10835.000000

       Power_Parity_Rs_240000_330000  Power_Parity_Rs_150000_330000  \
count                     640.000000                     640.000000
mean                      215.300000                     509.300000
std                       362.684243                     968.538748
min                         0.000000                       0.000000
25%                        24.750000                      95.000000
50%                       118.500000                     278.000000
75%                       262.000000                     564.500000
max                      3595.000000                   14430.000000

       Power_Parity_Rs_330000_425000  Power_Parity_Rs_425000_545000  \
count                     640.000000                     640.000000
mean                      194.204688                     261.245313
std                       424.108001                     587.279450
min                         0.000000                       0.000000
25%                        19.000000                      21.000000
50%                        84.000000                      85.500000
75%                       213.250000                     293.000000
max                      5027.000000                    7597.000000

       Power_Parity_Rs_330000_545000  Power_Parity_Above_Rs_545000  \
count                     640.000000                    640.000000
mean                      455.450000                    279.631250
std                      1007.364839                   1050.934537
min                         0.000000                      0.000000
25%                        44.000000                     18.000000
50%                       186.500000                     60.500000
75%                       497.000000                    215.500000
max                     12624.000000                  18289.000000

       Total_Power_Parity
count          640.000000
mean          3315.412500
std           4638.568719
min              9.000000
25%           1024.250000
50%           2238.500000
75%           3959.000000
max          60163.000000

[8 rows x 116 columns]
```

3.0.1 understanding the data column

```
In [120]: for i in census_data.columns:
              print('{}: {}\n'.format(i, census_data[i].dtype))
```

```
District code: int64

State name: object

District name: object

Population: int64

Male: int64

Female: int64

Literate: int64

Male_Literate: int64

Female_Literate: int64

SC: int64

Male_SC: int64

Female_SC: int64

ST: int64

Male_ST: int64

Female_ST: int64

Workers: int64

Male_Workers: int64

Female_Workers: int64

Main_Workers: int64

Marginal_Workers: int64

Non_Workers: int64

Cultivator_Workers: int64
```

Agricultural_Workers: int64

Household_Workers: int64

Other_Workers: int64

Hindus: int64

Muslims: int64

Christians: int64

Sikhs: int64

Buddhists: int64

Jains: int64

Others_Religions: int64

Religion_Not_Stated: int64

LPG_or_PNG_Households: int64

Housholds_with_Electric_Lighting: int64

Households_with_Internet: int64

Households_with_Computer: int64

Rural_Households: int64

Urban_Households: int64

Households: int64

Below_Primary_Education: int64

Primary_Education: int64

Middle_Education: int64

Secondary_Education: int64

Higher_Education: int64

Graduate_Education: int64

Other_Education: int64

Literate_Education: int64

Illiterate_Education: int64

Total_Education: int64

Age_Group_0_29: int64

Age_Group_30_49: int64

Age_Group_50: int64

Age not stated: int64

Households_with_Bicycle: int64

Households_with_Car_Jeep_Van: int64

Households_with_Radio_Transistor: int64

Households_with_Scooter_Motorcycle_Moped: int64

Households_with_Telephone_Mobile_Phone_Landline_only: int64

Households_with_Telephone_Mobile_Phone_Mobile_only: int64

Households_with_TV_Computer_Laptop_Telephone_mobile_phone_and_Scooter_Car: int64

Households_with_Television: int64

Households_with_Telephone_Mobile_Phone: int64

Households_with_Telephone_Mobile_Phone_Both: int64

Condition_of_occupied_census_houses_Dilapidated_Households: int64

Households_with_separate_kitchen_Cooking_inside_house: int64

Having_bathing_facility_Total_Households: int64

Having_latrine_facility_within_the_premises_Total_Households: int64

Ownership_Owned_Households: int64

Ownership_Rented_Households: int64

Type_of_bathing_facility_Enclosure_without_roof_Households: int64

Type_of_fuel_used_for_cooking_Any_other_Households: int64

Type_of_latrine_facility_Pit_latrine_Households: int64

Type_of_latrine_facility_Other_latrine_Households: int64

Type_of_latrine_facility_Night_soil_disposed_into_open_drain_Households: int64

Type_of_latrine_facility_Flush_pour_flush_latrine_connected_to_other_system_Households: int64

Not_having_bathing_facility_within_the_premises_Total_Households: int64

Not_having_latrine_facility_within_the_premises_Alternative_source_Open_Households: int64

Main_source_of_drinking_water_Un_covered_well_Households: int64

Main_source_of_drinking_water_Handpump_Tubewell_Borewell_Households: int64

Main_source_of_drinking_water_Spring_Households: int64

Main_source_of_drinking_water_River_Canal_Households: int64

Main_source_of_drinking_water_Other_sources_Households: int64

Main_source_of_drinking_water_Other_sources_Spring_River_Canal_Tank_Pond_Lake_Other_sources__Hou

Location_of_drinking_water_source_Near_the_premises_Households: int64

Location_of_drinking_water_source_Within_the_premises_Households: int64

Main_source_of_drinking_water_Tank_Pond_Lake_Households: int64

Main_source_of_drinking_water_Tapwater_Households: int64

Main_source_of_drinking_water_Tubewell_Borehole_Households: int64

Household_size_1_person_Households: int64

Household_size_2_persons_Households: int64

Household_size_1_to_2_persons: int64

Household_size_3_persons_Households: int64

Household_size_3_to_5_persons_Households: int64

Household_size_4_persons_Households: int64

Household_size_5_persons_Households: int64

Household_size_6_8_persons_Households: int64

Household_size_9_persons_and_above_Households: int64

Location_of_drinking_water_source_Away_Households: int64

Married_couples_1_Households: int64

Married_couples_2_Households: int64

Married_couples_3_Households: int64

Married_couples_3_or_more_Households: int64

Married_couples_4_Households: int64

Married_couples_5__Households: int64

Married_couples_None_Households: int64

Power_Parity_Less_than_Rs_45000: int64

Power_Parity_Rs_45000_90000: int64

Power_Parity_Rs_90000_150000: int64

Power_Parity_Rs_45000_150000: int64

Power_Parity_Rs_150000_240000: int64

Power_Parity_Rs_240000_330000: int64

Power_Parity_Rs_150000_330000: int64

Power_Parity_Rs_330000_425000: int64

Power_Parity_Rs_425000_545000: int64

Power_Parity_Rs_330000_545000: int64

Power_Parity_Above_Rs_545000: int64

Total_Power_Parity: int64

3.0.2 list of all the categorical Variables

```
In [121]: cat_var = [i for i in census_data.columns if census_data[i].dtype==object]
          cat_var
```

```
Out[121]: ['State name', 'District name']
```

```
In [122]: census_data[cat_var[0]] = census_data[cat_var[0]].astype('category')
          census_data[cat_var[1]] = census_data[cat_var[1]].astype('category')
```

3.0.3 Calculating the literacy rate statewise

calculate total number of literate people statewise

```
In [123]: lit_pop = census_data.groupby('State name')['Literate'].agg('sum')      ## Sum of Liter
          tot_pop = census_data.groupby('State name')['Population'].agg('sum')    ## Sum of Popul
          lit_rate = (lit_pop/tot_pop)*100                                        ## Percentage o
```

Printing top 10 states with lowest literacy rate

```
In [124]: lit_rate.sort_values().head(10)
```

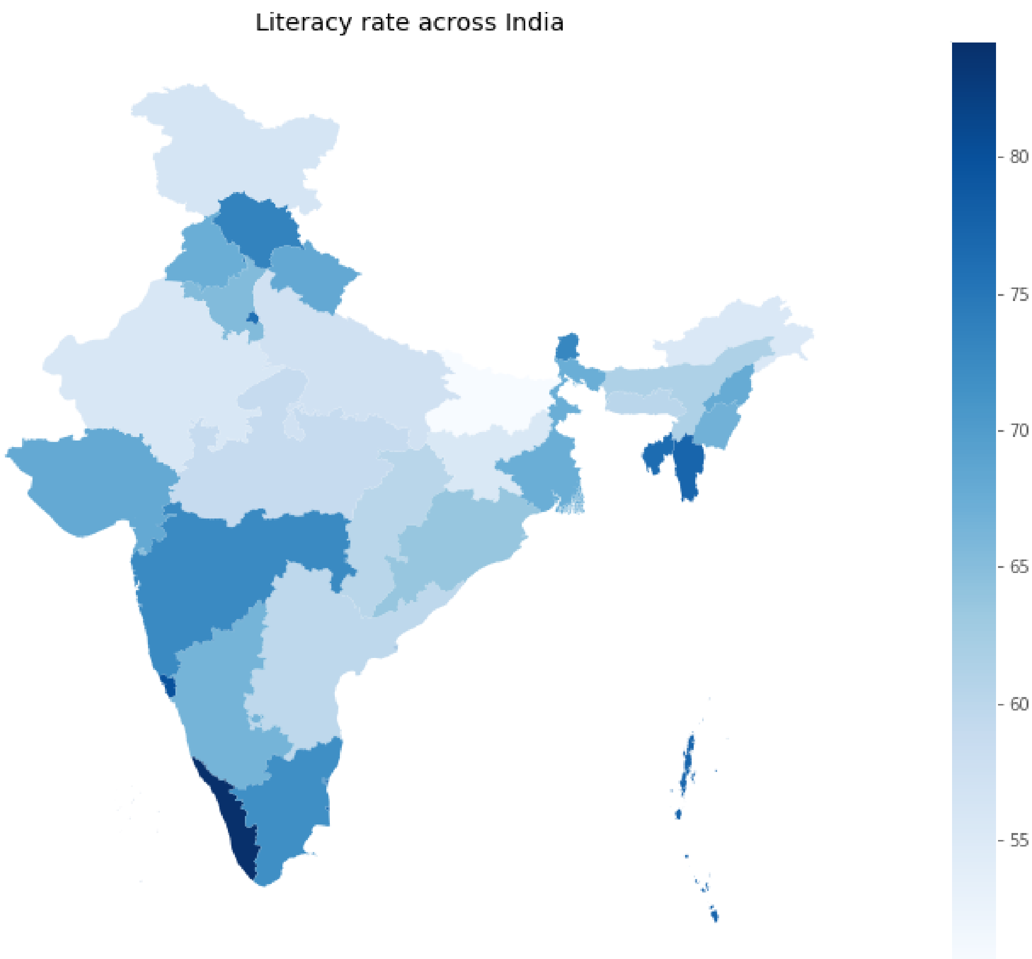
```
Out[124]: State name
          BIHAR                 50.436916
          ARUNACHAL PRADESH     55.358102
          JHARKHAND             55.559581
          RAJASTHAN             55.836841
          JAMMU & KASHMIR       56.351669
          UTTAR PRADESH         57.252497
          MADHYA PRADESH        59.001861
          ANDHRA PRADESH        59.773345
          MEGHALAYA             60.164199
          CHHATTISGARH          60.206705
          dtype: float64
```

```
In [125]: ## Reading the shape files for plotting state boundaries of India.
          india = gpd.read_file('INDIA.shp')
```

```
In [126]: india.head(2)    ## Printing 1st 2 Location data
```

```
Out[126]:
                                                      geometry
          0  (POLYGON ((92.898888 12.915831, 92.89917 12.91...
          1   POLYGON ((83.943192 18.214308, 83.942359999999...
```

```
In [127]: ## Ploting Literacy Rate data
          india['lit_rate'] = lit_rate.values      ## Adding Column of %Litercy in India Datafra
          india.plot(column = 'lit_rate', figsize=(20,10),cmap='Blues',legend=True)    ## Setting
          plt.axis('off')
          plt.title('Literacy rate across India')
          plt.show()
```



3.1 Finding the most simillar districts based on the given parameter

The given below code will display all the districts in Bihar simillar to districts in Tamilnadu. Based on any one numerical parameter, it will display simillar districs by measuring just the absolute difference between the numbers. For example i have taken our parameter as the Total_Power_parity to display the simillar districts. We can use other parameters like population to display the simillarity.

```
In [128]: # Here is the function to calculate absolute simillarity between Bihar and TamilNadu b


          def Simillarity(param):

              B_dist = census_data[census_data['State name']== 'BIHAR']   ## Select all the distr
              B_dist_p = B_dist[['District name',param]]
```

```python
    T_dist = census_data[census_data['State name']=='TAMIL NADU']  #Select all the dis
    T_dist_p = T_dist[['District name',param]]


    simillar = []

    for l,i in enumerate(T_dist_p[param].values):
        temp = np.zeros(len(B_dist_p))
        for k,j in enumerate(B_dist_p[param].values):
            temp[k] = abs(i-j)
        m = np.argmin(temp)     ### chosing the index having minimum absolute differen

        simillar.append((l,m))

    d2 = B_dist_p['District name']
    d1 = T_dist_p['District name']

    simillar_dist = [(d1.iloc[i[0]], d2.iloc[i[1]]) for i in simillar]  ## Displaying

    return simillar_dist



Simillarity('Total_Power_Parity')
```

Out[128]:
```
[('Thiruvallur', 'Patna'),
 ('Chennai', 'Patna'),
 ('Kancheepuram', 'Patna'),
 ('Vellore', 'Patna'),
 ('Tiruvannamalai', 'Muzaffarpur'),
 ('Viluppuram', 'Muzaffarpur'),
 ('Salem', 'Patna'),
 ('Namakkal', 'Saran'),
 ('Erode', 'Patna'),
 ('The Nilgiris', 'Araria'),
 ('Dindigul', 'Muzaffarpur'),
 ('Karur', 'Aurangabad'),
 ('Tiruchirappalli', 'Patna'),
 ('Perambalur', 'Jehanabad'),
 ('Ariyalur', 'Khagaria'),
 ('Cuddalore', 'Muzaffarpur'),
 ('Nagapattinam', 'Siwan'),
 ('Thiruvarur', 'Aurangabad'),
 ('Thanjavur', 'Muzaffarpur'),
 ('Pudukkottai', 'Bhagalpur'),
 ('Sivaganga', 'Katihar'),
 ('Madurai', 'Patna'),
```

```
('Theni', 'Purnia'),
('Virudhunagar', 'Muzaffarpur'),
('Ramanathapuram', 'Begusarai'),
('Thoothukkudi', 'Saran'),
('Tirunelveli', 'Patna'),
('Kanniyakumari', 'Muzaffarpur'),
('Dharmapuri', 'Gopalganj'),
('Krishnagiri', 'Pashchim Champaran'),
('Coimbatore', 'Patna'),
('Tiruppur', 'Patna')]
```

3.2 Mobile Penetration Variation with regions (districts or states) with high or low agricultural workers

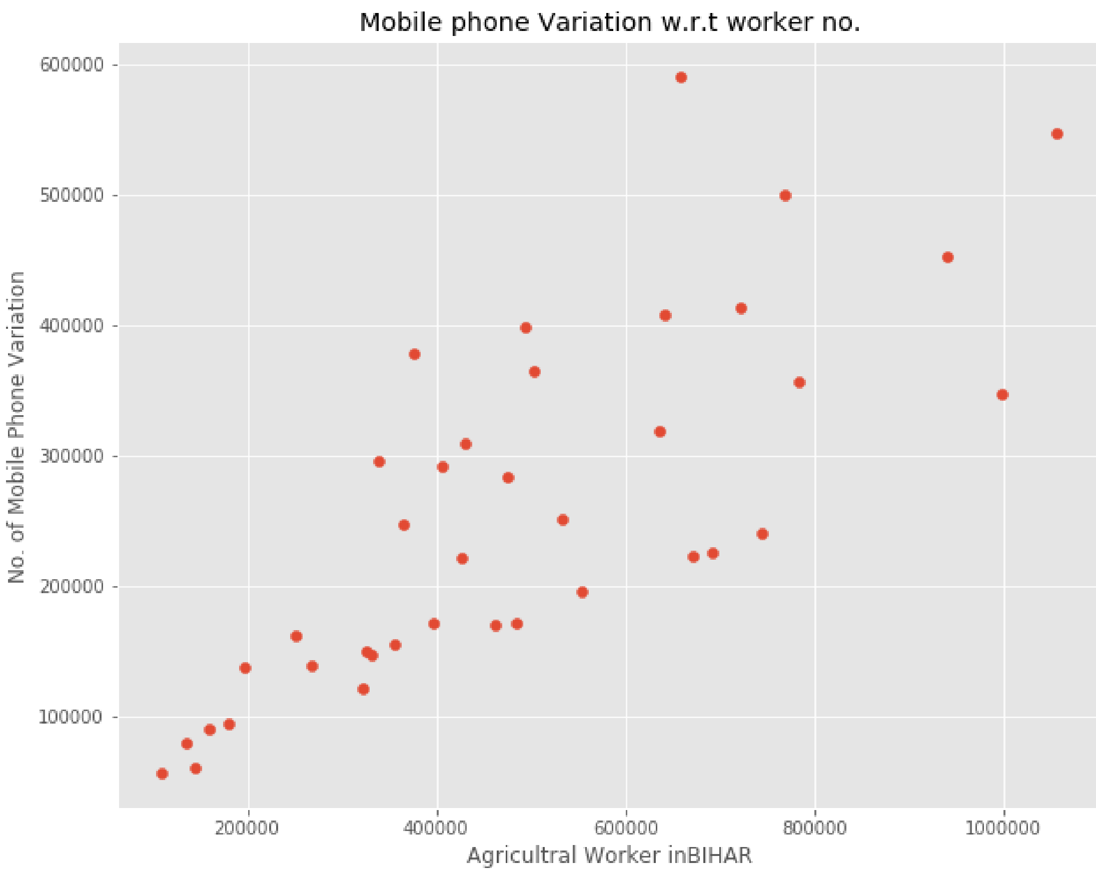
```
In [129]: state_list = list(census_data['State name'].unique())   ## Accessing State List
```

In worker_mobile_scatter plot method we do scatterplot between Agricultural_Workers number and number of mobiles phones they and see if there any trend exist i.e with increasing no. of Agricultural_Workers is mobile increases

```
In [130]: def worker_mobile_scatter(state) :
              state = state.upper() ;      ## Changing state name into capital

              ## Ending Function with message if state not in list
              if state not in state_list :
                  print(state,'Not Found')
                  return ;

                 ### Subsetting of data of Particular State and Columns
              df1 = census_data[census_data['State name']==state]
              df = df1[['District name','Agricultural_Workers','Households_with_Telephone_Mobile

               ### Renaming the Columns
              df.rename(columns={'Agricultural_Workers':'Worker','Households_with_Telephone_Mobi


              df.reset_index(inplace=True)

              ## Sorting values on Worker_count column
              df2 = df.sort_values('Worker',ascending=True)

              ## Plotting Scatter Plot
              fig = plt.figure();
              plt.scatter(df2['Worker'],df2['Mobile'])
              plt.xlabel('Agricultral Worker in'+state)
              plt.ylabel('No. of Mobile Phone Variation')
              plt.title('Mobile phone Variation w.r.t worker no.')
              plt.show()
```

```
In [131]: ## Calling Functio for Bihar State
          worker_mobile_scatter('bihar')
```

```
/home/bhumihar/anaconda3/envs/geopandas/lib/python3.6/site-packages/pandas/core/frame.py:3027: S
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#
  return super(DataFrame, self).rename(**kwargs)
```



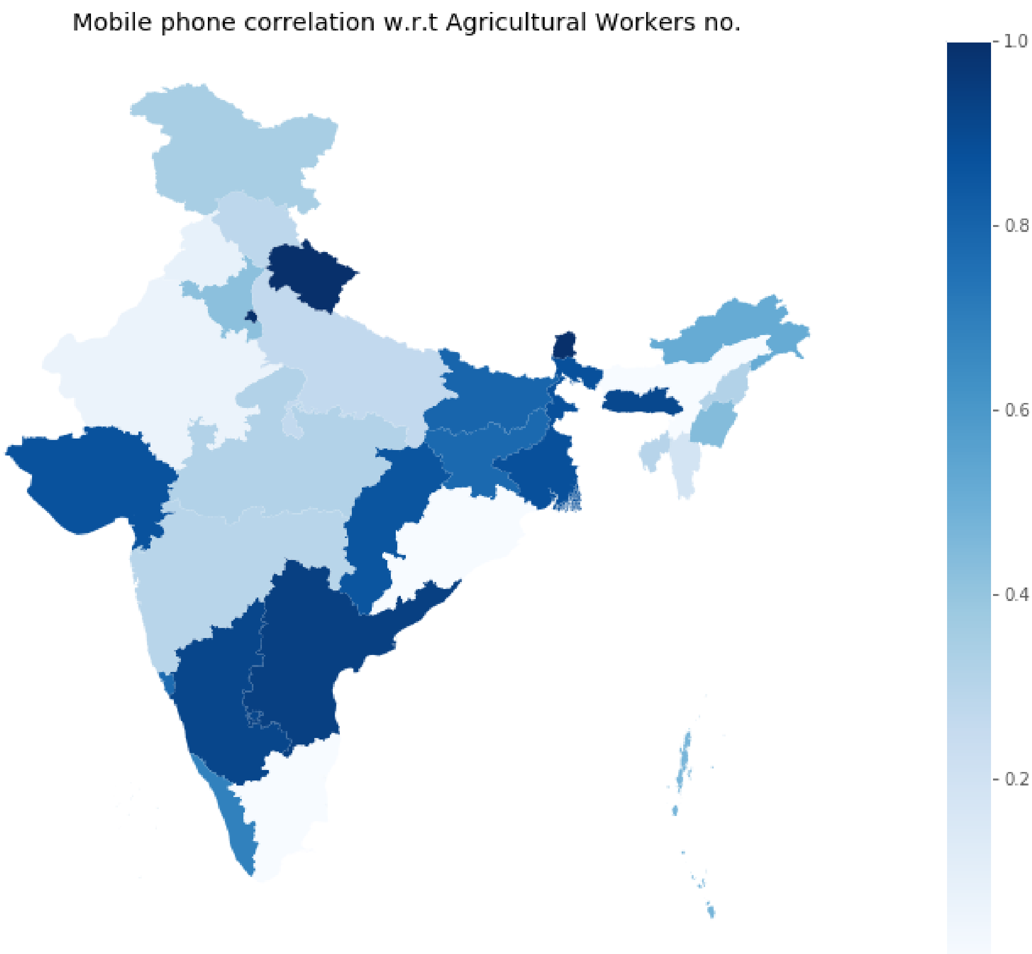
In worker_phone_corr method we find correlation between Agricultural_Workers number and number of mobiles phones for each region in state and pass them in corr_mat_plot method and plot map and visulise correlation between them using intensity plot.

```
In [132]: def worker_phone_corr() :
              corr_val = []
              i=0

              for state in state_list :
```

```
            ### Subsetting of data of Particular State and Columns
            df1 = census_data[census_data['State name']==state]
            df = df1[['District name','Agricultural_Workers','Households_with_Telephone_Mo

            ### Renaming the Columns
            df.rename(columns={'Agricultural_Workers':'Worker','Households_with_Telephone_

             ## Resetting the index
            df.reset_index(inplace=True)
            df2 = df.sort_values('Worker',ascending=True)

            ## If state has only one Region then some default value
            if df2.shape[0] >1:
                corr_val.append(df2['Worker'].corr(df2['Mobile']))
            else :
                corr_val.append(0.001)
            i +=1
        return corr_val

    def corr_mat_plot(corr_val) :
            ## Reading Data
        india = gpd.read_file('INDIA.shx')
        india['corr'] = corr_val

         ## Ploting Intensity Map
        india.plot(column = 'corr', figsize=(20,10),cmap='Blues',legend=True)
        plt.axis('off')
        plt.title('Mobile phone correlation w.r.t Agricultural Workers no.')
        plt.show()
```

In [133]:
```
     ## Calling Function
    corr_val = worker_phone_corr()
    corr_mat_plot(corr_val)
```

```
/home/bhumihar/anaconda3/envs/geopandas/lib/python3.6/site-packages/pandas/core/frame.py:3027: S
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#
  return super(DataFrame, self).rename(**kwargs)
```

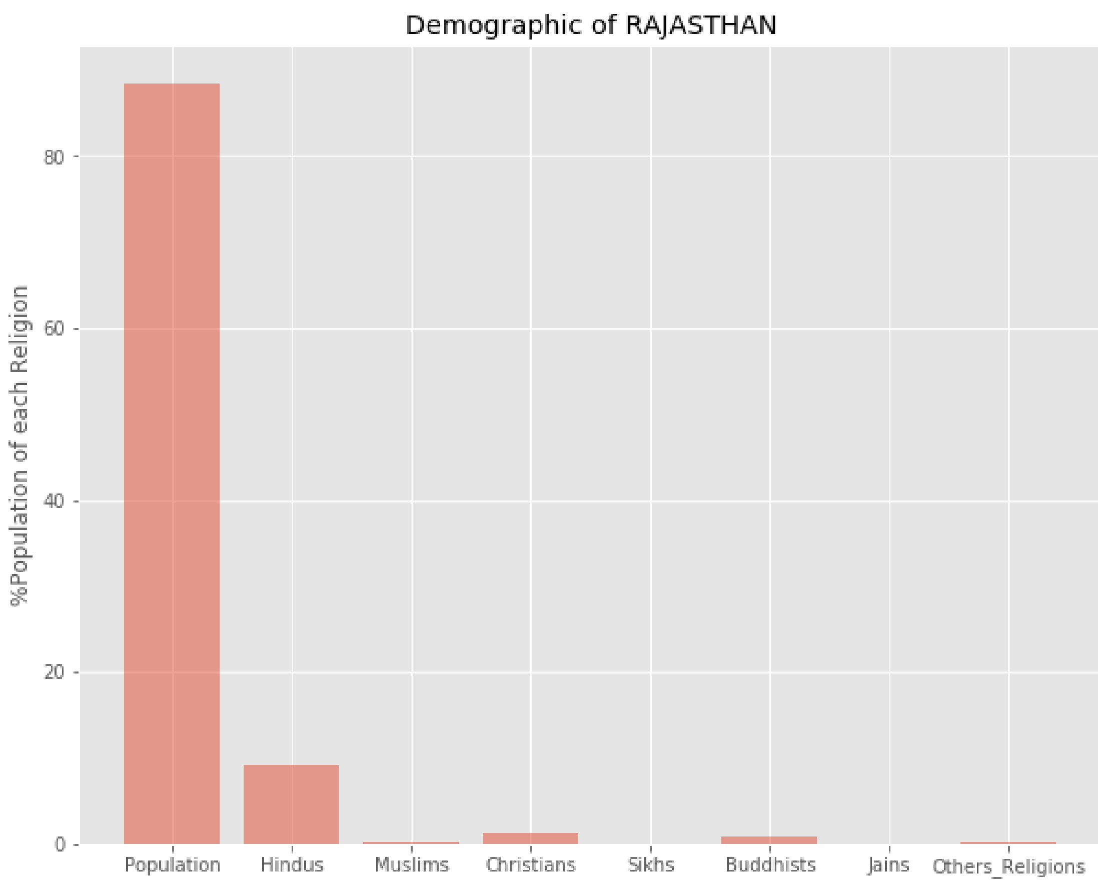


3.2.1 Demographics of India and its state

In [134]:
```
def state_demography(state) :
    state = state.upper()          ## Changing state name into capital

    ## Ending Function with message if state not in list
    if state not in state_list :
        print(state,'Not Found')
        return ;

    col_name = ['Population','Hindus', 'Muslims', 'Christians', 'Sikhs', 'Buddhists',

    ## Calculating State PoPulation
    state_pol = census_data.groupby('State name')[col_name].agg('sum')

    ## Calculating % of each religion of State PoPulation
```

```
    pop_val = (state_pol.loc[state][1:].values*100)/state_pol.loc[state][0]
    x_pos = np.arange(len(col_name[1:]))

    ## bar plot
    plt.bar(x_pos,pop_val,align='center',alpha=0.5)
    plt.xticks(x_pos,col_name)
    plt.ylabel('%Population of each Religion')
    plt.title('Demographic of '+state)
    plt.show()
```

```
In [135]: state_demography('Rajasthan')
```



3.2.2 Select any Religion number which propotion across india you want to Show on Map

3.2.3 1:Hindus

3.2.4 2:Muslims

3.2.5 3:Christians

3.2.6 4:Sikhs

3.2.7 5:Buddhists

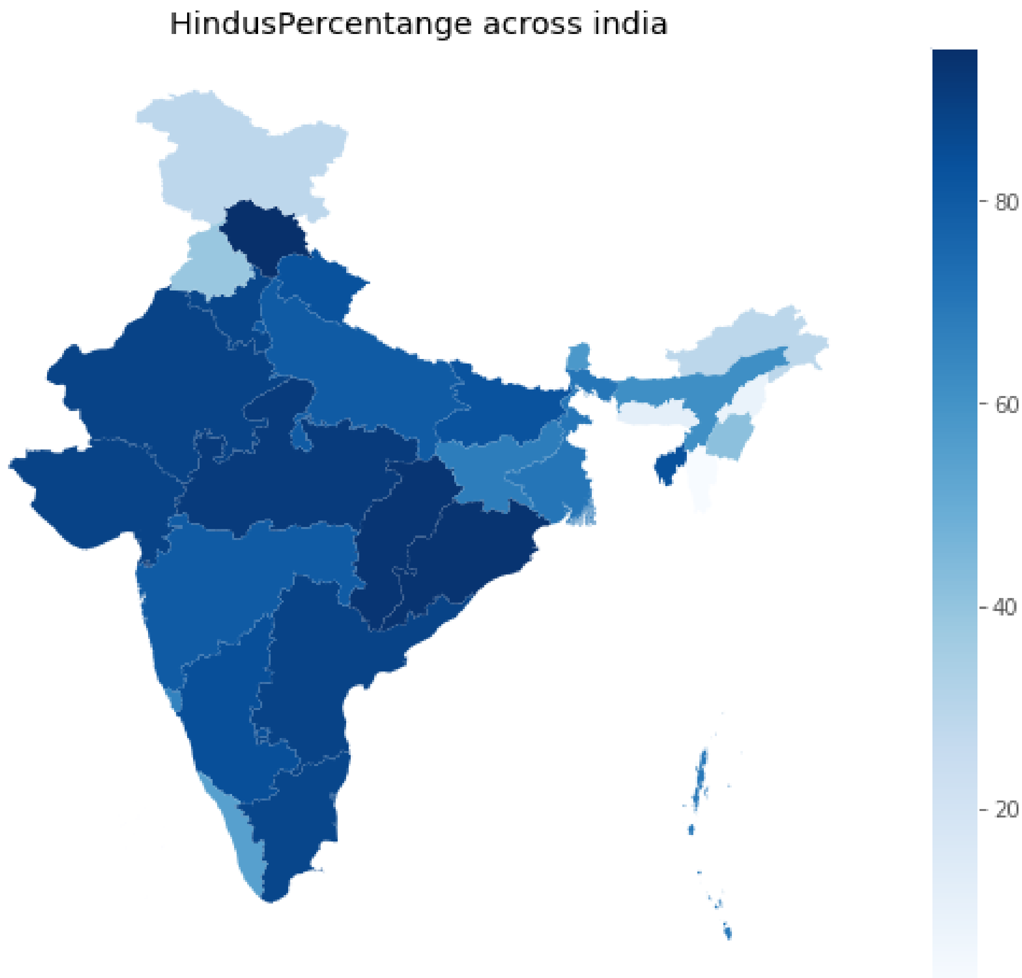
3.2.8 6:Jains

3.2.9 7:Others_Religions

3.2.10 8:Religion_Not_Stated

In [136]:
```
def religion_propotion(val):

            ## Religion Name
         col_name = ['Hindus', 'Muslims', 'Christians', 'Sikhs', 'Buddhists', 'Jains','Othe

         ## if val in range of religion_column_size
         if (val <= 0 or val>8) :
             print('Please Enter valid Value')
             return ;

         rel_pol = census_data.groupby('State name')[col_name[val-1]].agg('sum')  ## Count
         tot_pop = census_data.groupby('State name')['Population'].agg('sum')    ## Count o
         rel_per = (rel_pol/tot_pop)*100                                  ## calculating of % for each

          ### Intensity Plot
         india = gpd.read_file('INDIA.shx')
         india['Rel_per'] = rel_per.values
         india.plot(column = 'Rel_per',cmap='Blues',legend=True)
         plt.axis('off')
         plt.title(col_name[val-1]+'Percentange across india')
         plt.show()
```

In [137]:
```
religion_propotion(1)
```



4 Thank You