NAS Exploration

November 4, 2017

1 Gramener Data Science Entry Level Position Use Case 1

1.1 Introduction

For use case 1, we're examining the National Acheivement Survey for class VIII students from 2014. In an effort to answer the following questions - 1. What influences student performance the most? 2. How do girls and boys perform across states? 3. Do students from South India really excel at Math and Science

```
In [16]: #imports
         import pandas as pd
         import seaborn as sns
         import matplotlib.pyplot as plt
         import numpy as np
```

```
In [17]: datapath = './'
         filename = 'nas-pupil-marks.csv'
         Data = pd.read_csv(datapath+filename)
         Data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 185348 entries, 0 to 185347
Data columns (total 64 columns):
STUID                    185348 non-null int64
State                    185348 non-null object
District                 185348 non-null int64
Gender                   185348 non-null int64
Age                      185348 non-null int64
Category                 185348 non-null int64
Same language            185348 non-null int64
Siblings                 185348 non-null int64
Handicap                 185348 non-null int64
Father edu               185348 non-null int64
Mother edu               185348 non-null int64
Father occupation        185348 non-null int64
Mother occupation        185348 non-null int64
Below poverty            185348 non-null int64
Use calculator           185348 non-null int64
```

```
Use computer               166186 non-null object
Use Internet               185348 non-null int64
Use dictionary             185348 non-null int64
Read other books           185348 non-null int64
# Books                    185348 non-null int64
Distance                   185348 non-null int64
Computer use               185348 non-null int64
Library use                185348 non-null int64
Like school                185348 non-null int64
Subjects                   185348 non-null object
Give Lang HW               185348 non-null int64
Give Math HW               185348 non-null int64
Give Scie HW               185348 non-null int64
Give SoSc HW               185348 non-null int64
Correct Lang HW            185348 non-null int64
Correct Math HW            185348 non-null int64
Correct Scie HW            185348 non-null int64
Correct SocS HW            185348 non-null int64
Help in Study              185348 non-null int64
Private tuition            185348 non-null int64
English is difficult       185348 non-null int64
Read English               185348 non-null int64
Dictionary to learn        185348 non-null int64
Answer English WB          185348 non-null int64
Answer English aloud       185348 non-null int64
Maths is difficult         185348 non-null int64
Solve Maths                185348 non-null int64
Solve Maths in groups      185348 non-null int64
Draw geometry              185348 non-null int64
Explain answers            185348 non-null int64
SocSci is difficult        185348 non-null int64
Historical excursions      185348 non-null int64
Participate in SocSci      185348 non-null int64
Small groups in SocSci     185348 non-null int64
Express SocSci views       185348 non-null int64
Science is difficult       185348 non-null int64
Observe experiments        185348 non-null int64
Conduct experiments        185348 non-null int64
Solve science problems     185348 non-null int64
Express science views      185348 non-null int64
Watch TV                   185348 non-null int64
Read magazine              185348 non-null int64
Read a book                185348 non-null int64
Play games                 185348 non-null int64
Help in household          185348 non-null int64
Maths %                    92681 non-null float64
Reading %                  93271 non-null float64
Science %                  90992 non-null float64
```

```
Social %                  89571 non-null float64
dtypes: float64(4), int64(57), object(3)
memory usage: 90.5+ MB
```

1.2 Data Cleaning

From our info function, we can see there are a few null entries in our dataset, thus it becomes important to try and handle those first. The rows which have the most nulls are our metrics of performance, the maths, science, social science and reading scores.

```
In [18]: NullsDropped = Data.dropna(axis=0,how='all',inplace=False)
         NullsDropped.shape
```

```
Out[18]: (185348, 64)
```

Immediately, there are no rows such that all values are null. The fact that our nulls are in our target variables, presents a problem as we can't easily replace them with a statistical measure without tainting the spread of features.

Dropping all the rows with nulls would also not be ideal, as we'd reduce our current number of data points by ~96% as is evidenced below.

```
In [19]: NullsDropped = Data.dropna(axis=0,how='any',inplace=False)
         NullsDropped.shape
```

```
Out[19]: (8044, 64)
```

In order to preserve the majority of our dataset, we split our target variables - we seperate our current dataset to 5 different ones, one each for our four performance metrics and one for Maths and Science.

Moreover, our dataset also has zeroes in our dataset for columns that don't have valid 0 levels. This also needs to be fixed.

```
In [20]: Maths = Data.drop(['Reading %','Science %','Social %'],axis=1)
```

Similarly, we create a dataset for each metric of performance

```
In [21]: Reading = Data.drop(['Maths %','Science %','Social %'],axis=1)
         Science = Data.drop(['Maths %','Reading %','Social %'],axis=1)
         Social = Data.drop(['Maths %','Reading %','Science %'],axis=1)
         Maths_and_Science = Data.drop(['Reading %','Social %'],axis=1)
```

```
In [22]: filename = 'nas-labels.csv'
         labels = pd.read_csv(datapath+filename)
         labels.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 241 entries, 0 to 240
Data columns (total 4 columns):
Column    241 non-null object
```

```
Name      241 non-null object
Level     241 non-null object
Rename    241 non-null object
dtypes: object(4)
memory usage: 7.6+ KB
```

```
In [23]: # We use the labels.csv file to figure out which columns in our dataset are allowed t

         zero_allowed = pd.DataFrame(labels.loc[labels['Level'].astype(str) == '0'])

         #Slightly janky, but I didn't want to drop the states and can't convert characters to

         zero_allowed = zero_allowed['Column'].tolist()


         #Gives me the list of the columns which shouldn't have zeroes.
         def remove_zeroes(df):
             '''Helper function that first removes nulls and then removes 0's from rows that sh
             df.dropna(axis=0,how='any',inplace=True)
             zero_not_allowed = [item for item in df.columns.values.tolist() if item not in zer
             df = df.replace(0,np.nan)
             #Since the dropna function has a subset parameter, casting 0's to  np.nan

             df.dropna(axis =0, how='any',inplace=True,subset = zero_not_allowed)
             df.fillna(value=0,inplace=True)

             #Convert object types to categories and categories to cat codes.
             objects = df.select_dtypes(include=['O']).columns.tolist()
             for col in objects:
                 df[col] = df[col].astype('category')

             return df
```

```
In [24]: Maths=remove_zeroes(Maths)
         Science=remove_zeroes(Science)
         Social=remove_zeroes(Social)
         Reading=remove_zeroes(Reading)
         Maths_and_Science=remove_zeroes(Maths_and_Science)
         NullsDropped=remove_zeroes(NullsDropped)
```

```
/home/karmanya/anaconda3/envs/MLIntel/lib/python3.5/site-packages/ipykernel/__main__.py:13: Se
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
```

Finally we should take the average of the performance metrics for the frames with multiple metrics

```
In [25]: ## Maths and Science
         Maths_and_Science['Avg %'] = (Maths_and_Science['Maths %']+Maths_and_Science['Science
         Maths_and_Science.drop(['Maths %','Science %'],axis=1,inplace=True)

         NullsDropped['Avg %'] = (NullsDropped['Maths %']+NullsDropped['Science %']+NullsDroppe
         NullsDropped.drop(['Maths %','Science %','Social %','Reading %'],axis=1,inplace=True)
```

```
In [26]: Science.isnull().values.any()
```

```
Out[26]: False
```

```
In [27]: Maths.describe()
```

```
Out[27]:               STUID      District        Gender           Age      Category  \
         count  5.054200e+04  50542.000000  50542.000000  50542.000000  50542.000000
         mean   2.714830e+10      5.114222      1.520894      3.644870      2.654901
         std    9.808741e+09      4.030791      0.499568      0.946113      1.211942
         min    1.101100e+10      1.000000      1.000000      1.000000      0.000000
         25%    1.808118e+10      2.000000      1.000000      3.000000      2.000000
         50%    2.607110e+10      4.000000      2.000000      4.000000      3.000000
         75%    3.601103e+10      7.000000      2.000000      4.000000      4.000000
         max    4.502103e+10     28.000000      2.000000      6.000000      4.000000

                Same language      Siblings      Handicap    Father edu    Mother edu  \
         count   50542.000000  50542.000000  50542.000000  50542.000000  50542.000000
         mean        1.305647      3.465039      1.895374      2.213090      1.885363
         std         0.531592      1.209956      0.380640      1.222056      1.176629
         min         0.000000      1.000000      0.000000      0.000000      0.000000
         25%         1.000000      2.000000      2.000000      1.000000      1.000000
         50%         1.000000      3.000000      2.000000      2.000000      2.000000
         75%         2.000000      5.000000      2.000000      3.000000      3.000000
         max         2.000000      5.000000      2.000000      5.000000      5.000000

                    ...        Observe experiments  Conduct experiments  \
         count      ...               50542.000000         50542.000000
         mean       ...                   2.646769             2.082941
         std        ...                   0.692864             0.930929
         min        ...                   1.000000             1.000000
         25%        ...                   3.000000             1.000000
         50%        ...                   3.000000             2.000000
         75%        ...                   3.000000             3.000000
         max        ...                   3.000000             3.000000

                Solve science problems  Express science views      Watch TV  \
         count            50542.000000           50542.000000  50542.000000
         mean                 2.426833               2.349828      3.556587
         std                  0.813011               0.822457      0.798879
         min                  1.000000               1.000000      1.000000
         25%                  2.000000               2.000000      3.000000
```

```
50%                    3.000000                 3.000000      4.000000
75%                    3.000000                 3.000000      4.000000
max                    3.000000                 3.000000      4.000000

       Read magazine   Read a book    Play games  Help in household  \
count   50542.000000  50542.000000  50542.000000       50542.000000
mean        3.168850      3.096019      3.445333           3.511456
std         1.017827      0.922589      0.882576           1.012895
min         1.000000      1.000000      1.000000           1.000000
25%         3.000000      3.000000      3.000000           4.000000
50%         3.000000      3.000000      4.000000           4.000000
75%         4.000000      4.000000      4.000000           4.000000
max         4.000000      4.000000      4.000000           4.000000

            Maths %
count  50542.000000
mean      32.903478
std       15.862777
min        1.670000
25%       22.030000
50%       28.810000
75%       38.980000
max      100.000000

[8 rows x 58 columns]
```

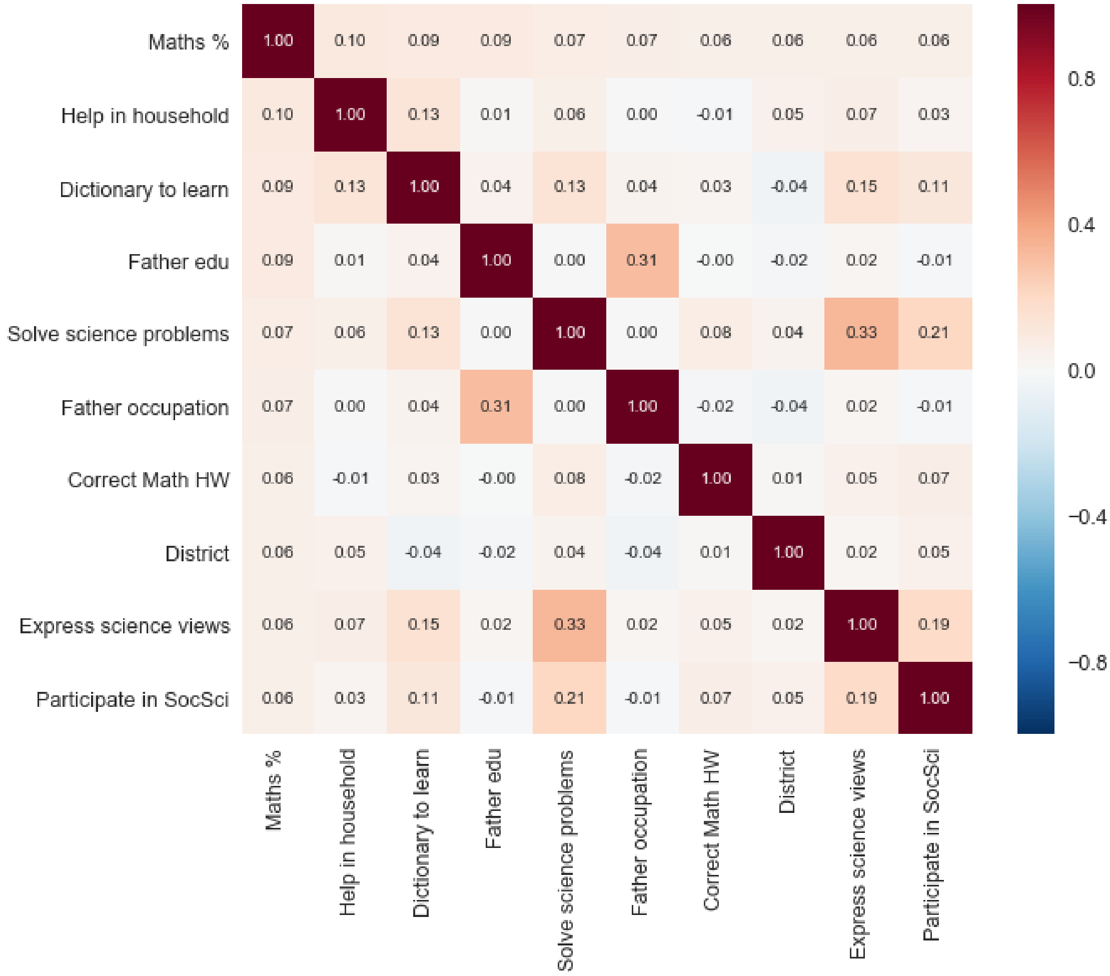
We can see now that our datasets are relatively clean. This has resulted in a rather large reduction in our dataset - each of our target variables has approximately 30% of the total samples which is less than ideal, but it's perhaps the safest way to ensure there's no tainting of our data.

1.3 Exploring Student Performance

The First Question, attempts to answer which of the features affect student performance the most. We can examine both linear and non linear correlations using various feature selection techniques. First via a correlation matrix and then using random forests for feature selection.

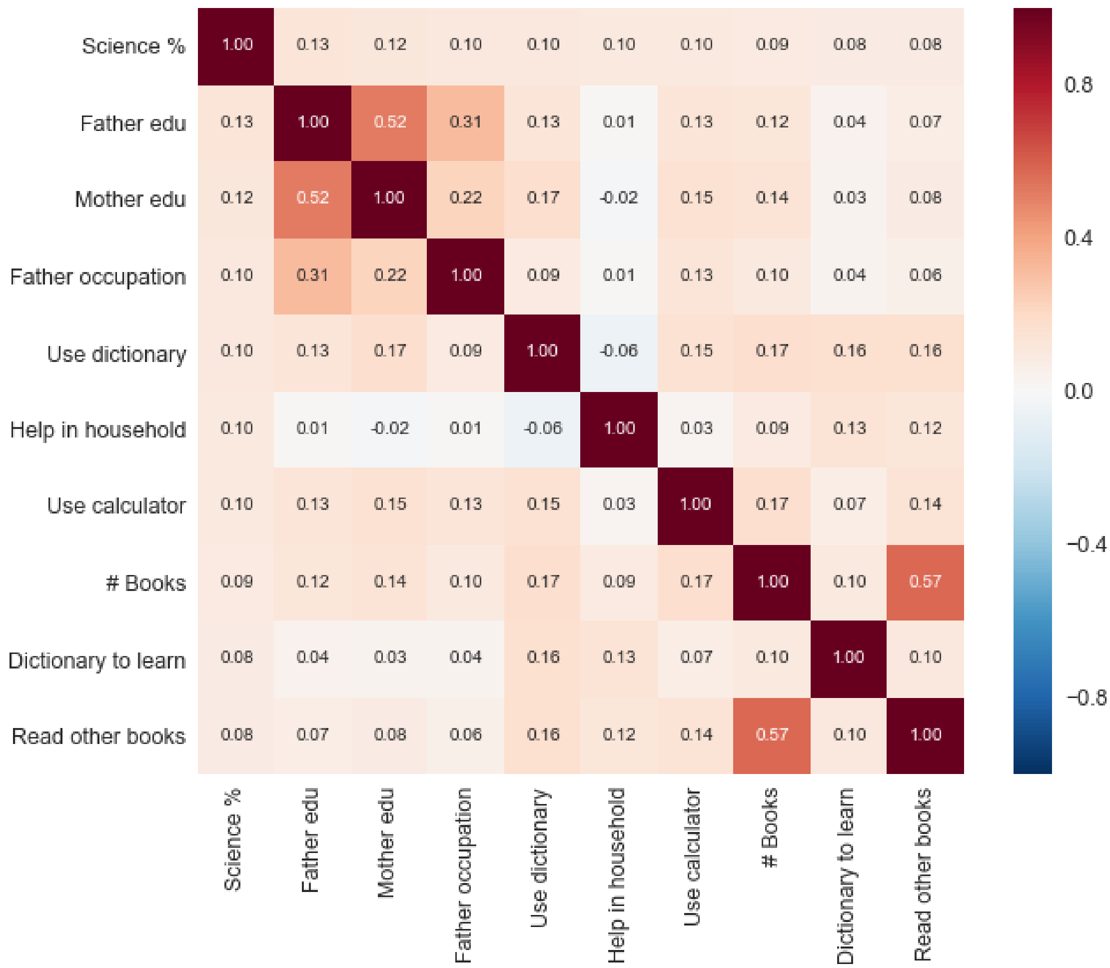
```
In [28]: def correlation_matrix(df,target):
             '''Helper function for correlation matrix'''
             k = 10 #number of variables for heatmap
             corrmat = df.corr() #Create a correlation matrix
             cols = corrmat.nlargest(k, target)[target].index #Find the 10 highest correlation
             cm = np.corrcoef(df[cols].values.T)
             fig, ax = plt.subplots() #Plot this as a heatmap
             fig.set_size_inches(10,8)
             sns.set(font_scale=1.25)
             hm = sns.heatmap(cm, cbar=True, annot=True, square=True, fmt='.2f', annot_kws={'s
                              yticklabels=cols.values, xticklabels=cols.values,ax=ax)
             plt.show()
```

In [29]: correlation_matrix(Maths,'Maths %')



We can see from the plot that the Father's Education is quite important, as is the presence of a Dictionary, the extent to which they help in the household and the work they put into doing their homework.

In [30]: correlation_matrix(Science,'Science %')

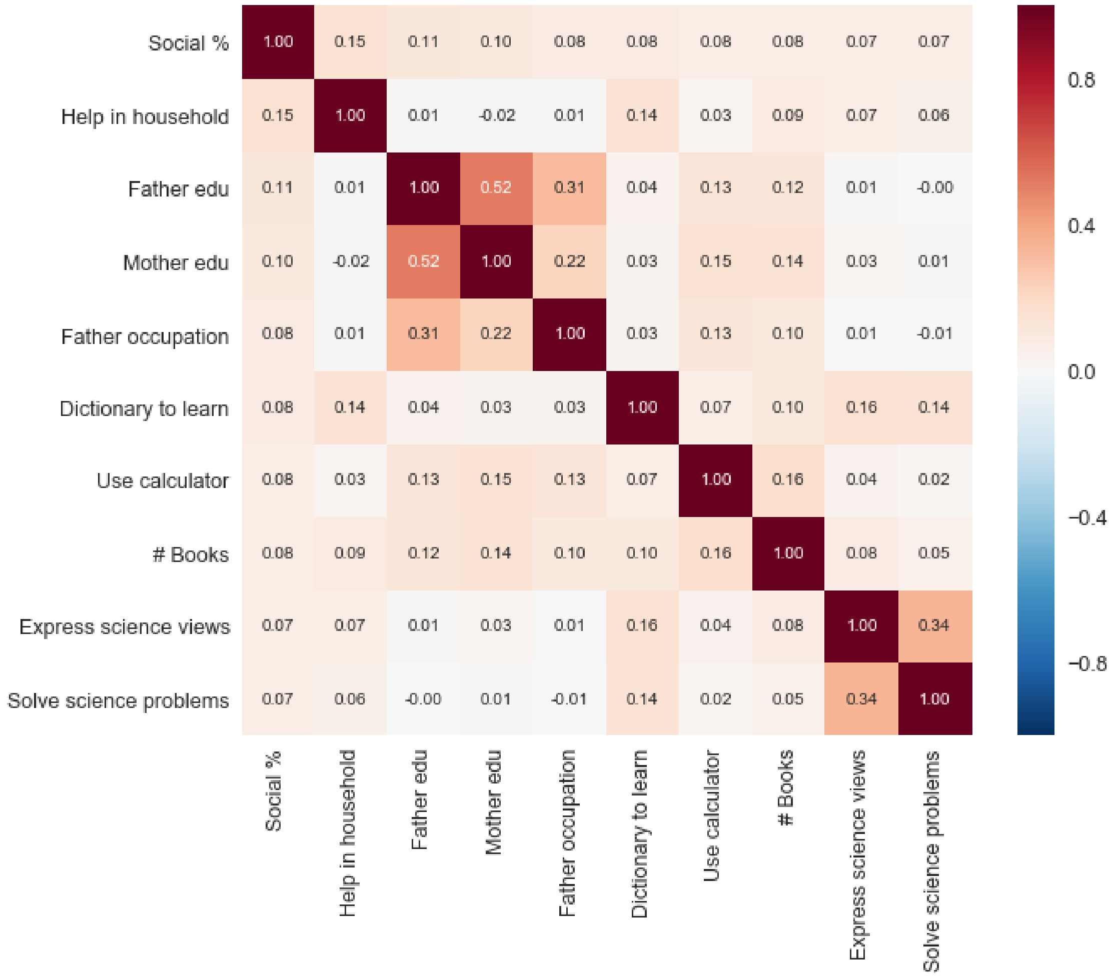


Again, Father's Education, and Mother's Education show up as important features, as does the presence of having a dictionary and the extent to which they help in the household. How much they read, also plays an important role

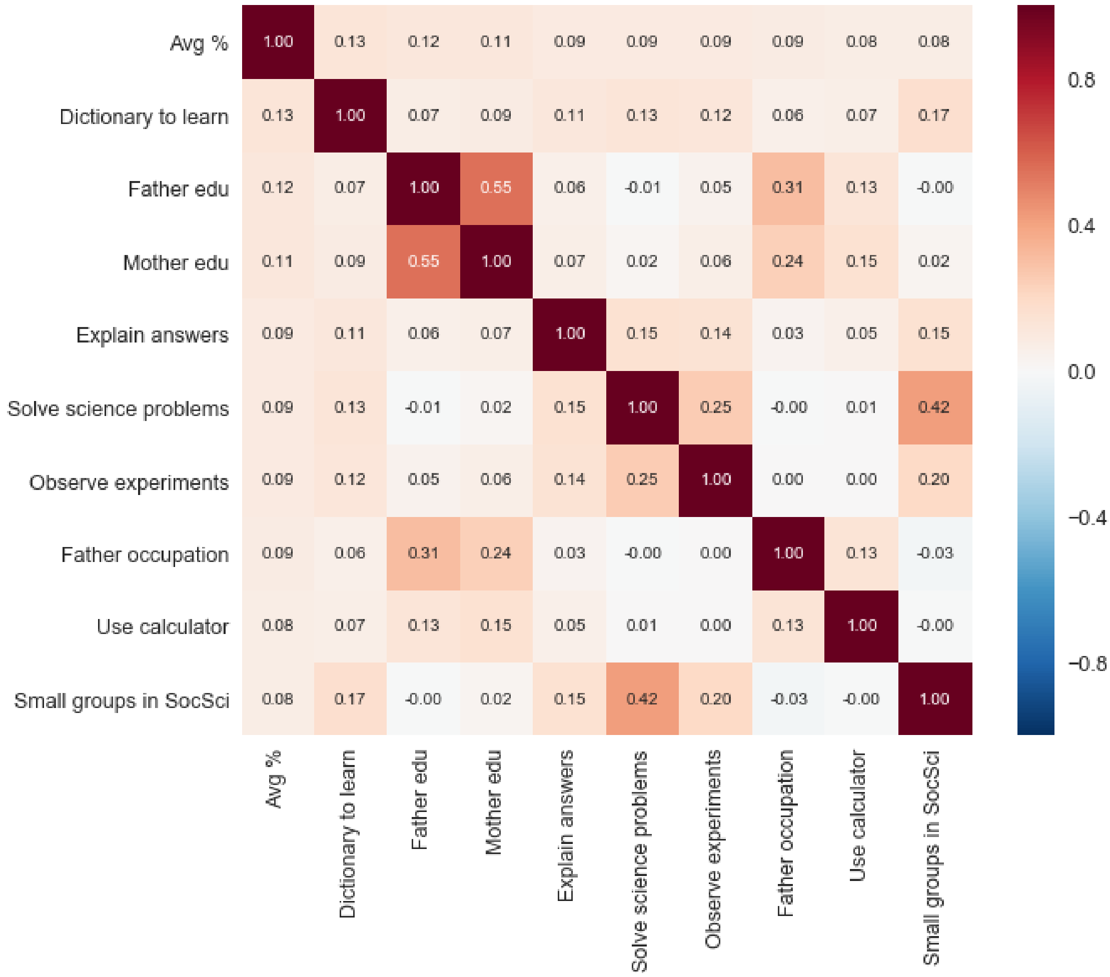
```
In [31]: correlation_matrix(Reading,'Reading %')
```

Unsurprisingly, the extent to which people read either magazines, other books etc are important towards their Reading ability. The dictionary and the parent's education is also important.

```
In [32]: correlation_matrix(Social,'Social %')
```




```
In [33]: correlation_matrix(Maths_and_Science,'Avg %')
```




```
In [34]: correlation_matrix(NullsDropped,'Avg %')
```

Analysis In terms of a linear correlation of features, across all the datasets, the parent's education and the ability to read a dictionary is very important. How much effort the student puts in towards studies, whether it's in solving maths problems, explaining science answers, reading books and magazines, are all very important. Hard work does pay off apparently.

Now we should attempt to check for non linear correlations -

```
In [35]: from sklearn.ensemble import RandomForestRegressor
         Mcopy = Maths.copy()
         cat_columns = Mcopy.select_dtypes(['category']).columns
         Mcopy[cat_columns] = Mcopy[cat_columns].apply(lambda x: x.cat.codes) #Encoding Catego
         features = Mcopy.drop('Maths %',axis=1)
         target = Mcopy['Maths %']
         tree = RandomForestRegressor()
         tree.fit(features,target)
         sorted(zip(tree.feature_importances_,Mcopy.columns.values),reverse=True)[:10]
```

```
Out[35]: [(0.16741771951059425, 'STUID'),
          (0.045822058846183962, 'State'),
```

```
(0.043747338741231746, 'District'),
(0.029811571045266709, 'Computer use'),
(0.026936486831861457, 'Father occupation'),
(0.026748832874502877, 'Father edu'),
(0.024952413896465034, 'Mother occupation'),
(0.024674615988126355, 'Library use'),
(0.024400337640052634, 'Mother edu'),
(0.022614412104687547, 'Siblings')]
```

Analysis The non linear correlations follow the linear ones, so there isn't much reason to do this for each dataset.

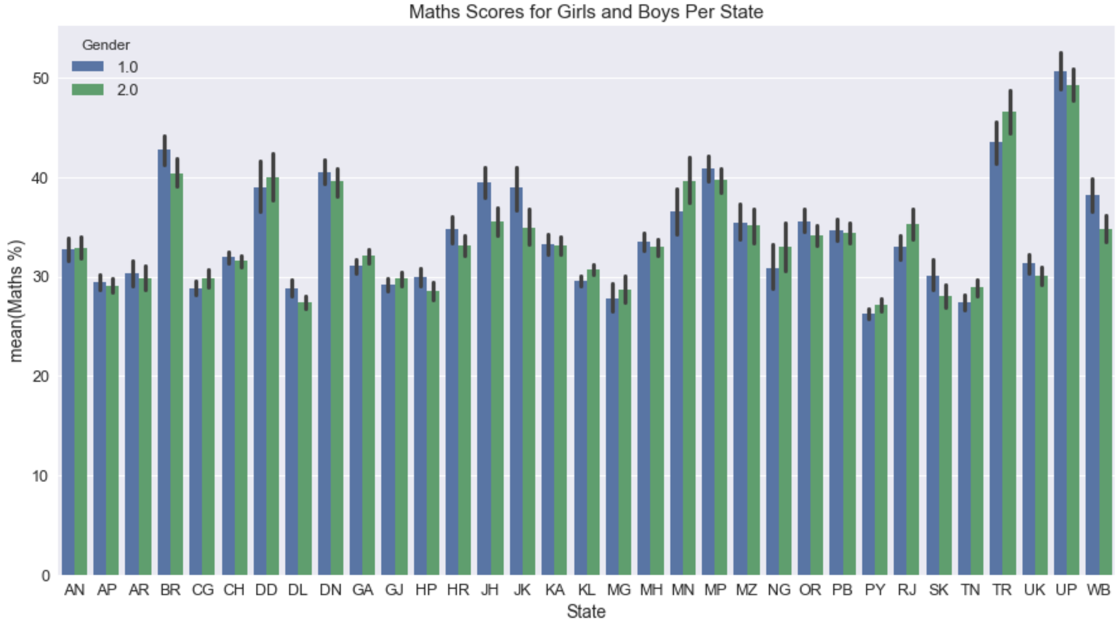
1.4 Girls vs Boys Across States

So, lets start by a simple metric, looking at the average of scores of boys and girls

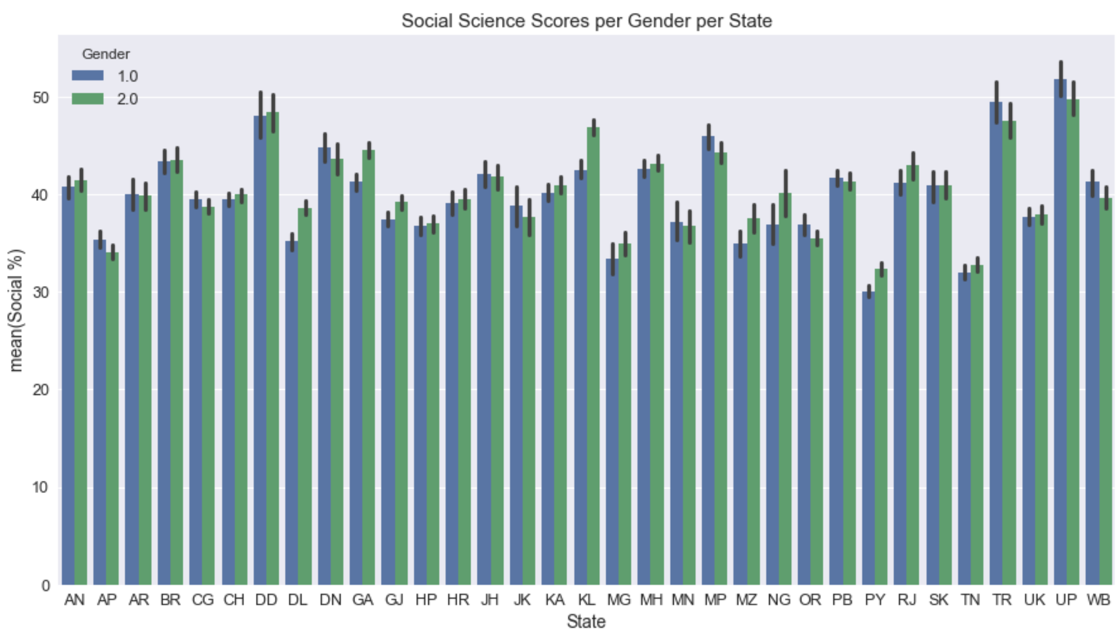
```
In [36]: def split_girl_boy(df,target):
             boys=df.loc[df['Gender']==1].groupby('State',as_index=False)[target].mean()
             girls=df.loc[df['Gender']==2].groupby('State',as_index=False)[target].mean()
             return (boys,girls)
```

```
In [37]: (boys_maths_score,girls_maths_score) = split_girl_boy(Maths,'Maths %')
         (boys_science_score,girls_science_score) = split_girl_boy(Science,'Science %')
         (boys_reading_score,girls_reading_score) = split_girl_boy(Reading,'Reading %')
         (boys_social_score,girls_social_score) = split_girl_boy(Social,'Social %')
         (boys_mathsandscience_score,girls_mathsandscience_score) = split_girl_boy(Maths_and_Sc
         (boys_overall_score,girls_overall_score) = split_girl_boy(NullsDropped,'Avg %')
```

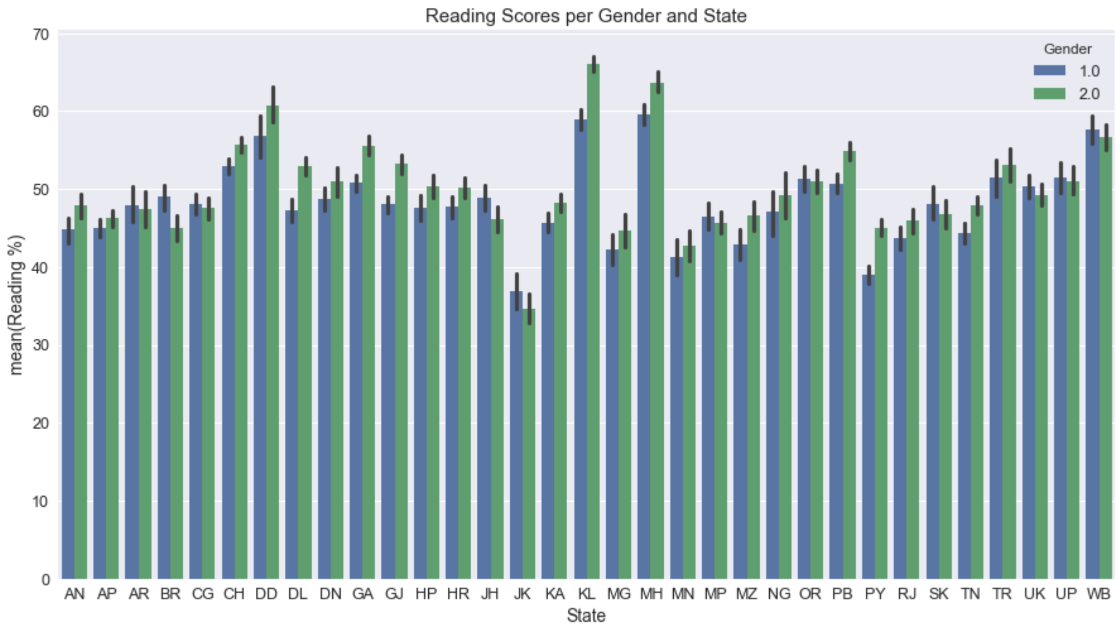
```
In [38]: fig, ax = plt.subplots()
         fig.set_size_inches(15,8)
         sns.barplot(x='State',y='Maths %',hue='Gender',data=Maths, ax=ax)\
         .set_title("Maths Scores for Girls and Boys Per State")
         plt.show()
```



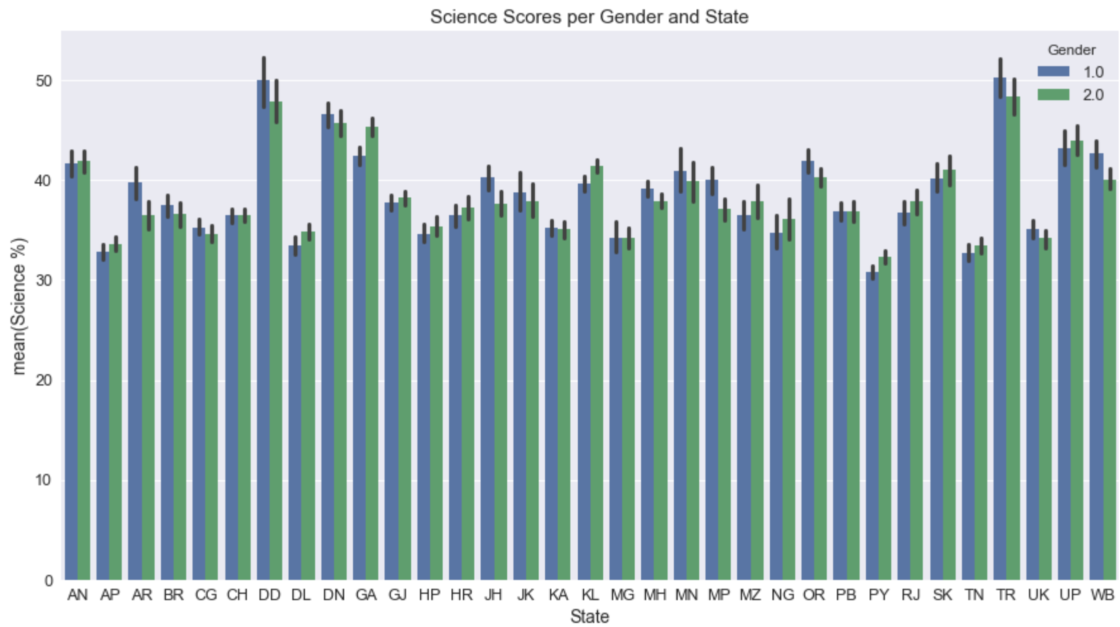

```
In [39]: fig, ax = plt.subplots()
         fig.set_size_inches(15,8)
         sns.barplot(x='State',y='Social %',hue='Gender',data=Social, ax=ax)\
         .set_title("Social Science Scores per Gender per State")
         plt.show()
```



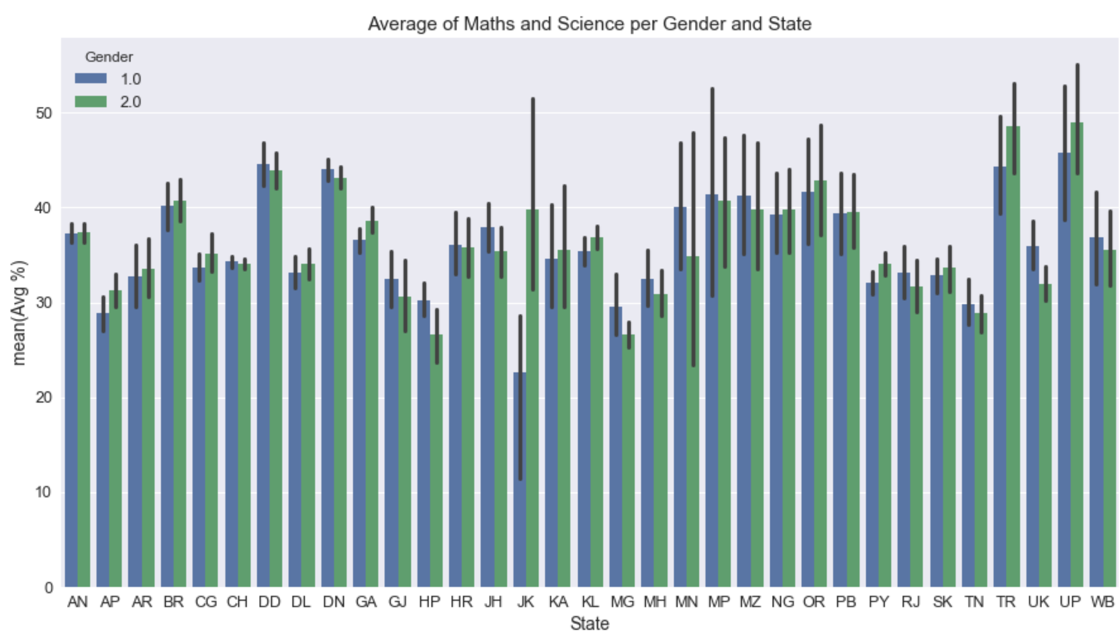
In [40]:
```python
fig, ax = plt.subplots()
fig.set_size_inches(15,8)
sns.barplot(x='State',y='Reading %',hue='Gender',data=Reading, ax=ax)\
.set_title("Reading Scores per Gender and State")
plt.show()
```



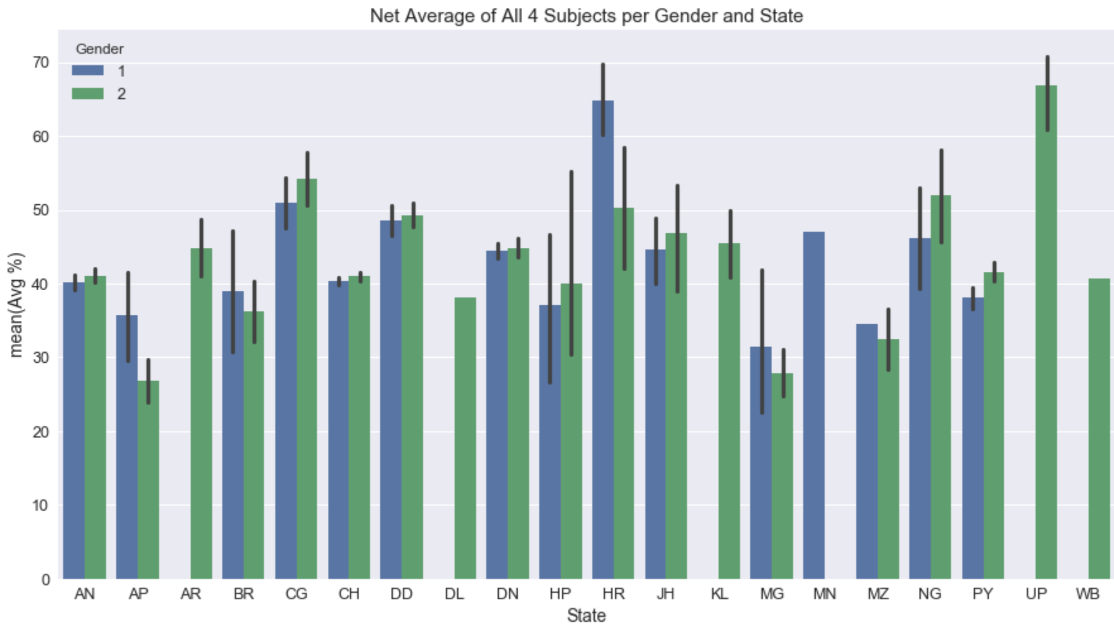
In [41]:
```python
fig, ax = plt.subplots()
fig.set_size_inches(15,8)
sns.barplot(x='State',y='Science %',hue='Gender',data=Science, ax=ax)\
.set_title("Science Scores per Gender and State")
plt.show()
```




```
In [42]: fig, ax = plt.subplots()
         fig.set_size_inches(15,8)
         sns.barplot(x='State',y='Avg %',hue='Gender',data=Maths_and_Science, ax=ax)\
         .set_title("Average of Maths and Science per Gender and State")
         plt.show()
```

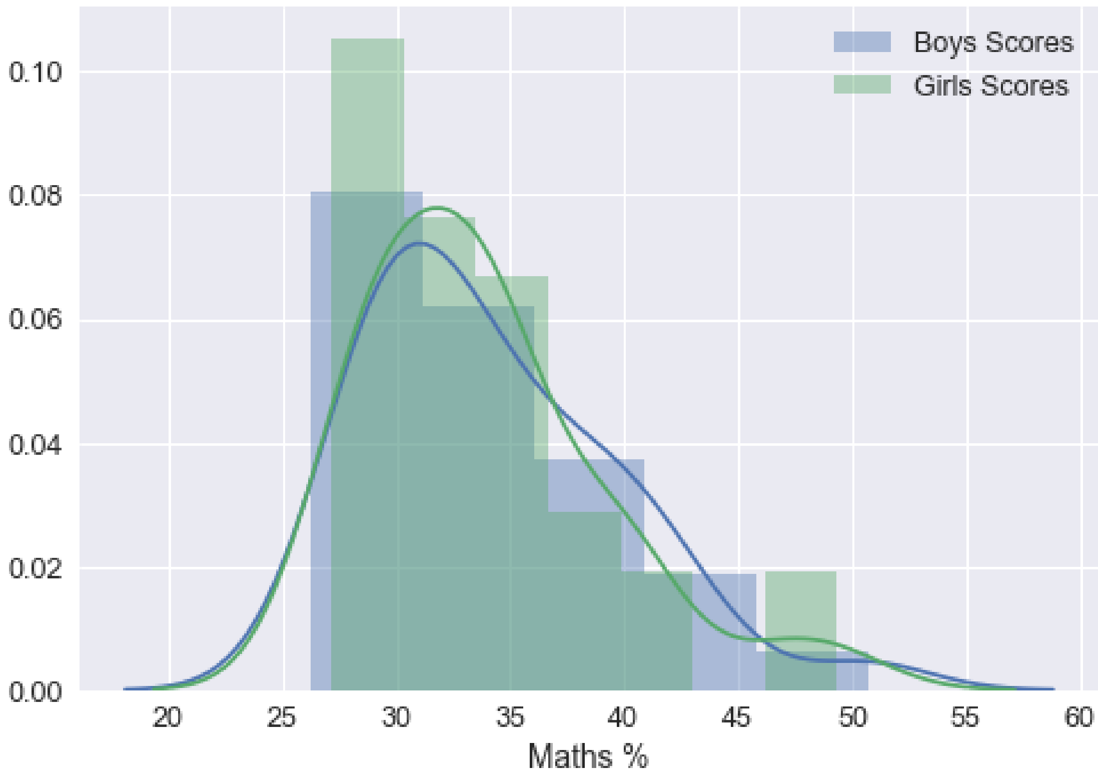


```
In [43]: fig, ax = plt.subplots()
         fig.set_size_inches(15,8)
         sns.barplot(x='State',y='Avg %',hue='Gender',data=NullsDropped, ax=ax)\
         .set_title("Net Average of All 4 Subjects per Gender and State")
         plt.show()
```

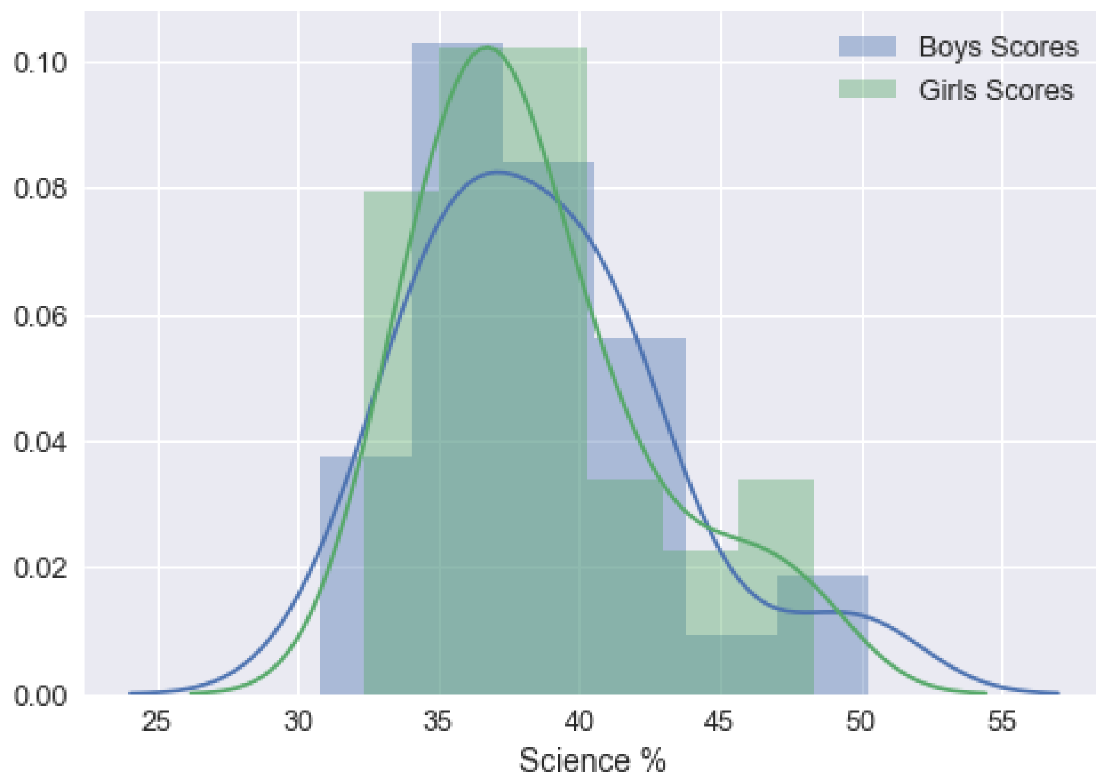


Analysis Primarily, we can see that girls and boys have fairly comparable performance, except in certain standout cases. In maths for example, except for a few standout states, girls and boys do about the same. However, in Science, boys seem to do a lot better. Which is perhaps why Maths and Science shows the same trend as Science. Conversely girls do a lot better than boys in both reading and social science. Our data seems to back up commonly held stereotypes. As somewhat expected just taking an average of all three is such a small dataset that it doesn't seem worth to try and extrapolate information from. Contrary to most stereotypes, students from UP score very highly relative to other states. Students in Kerala perform significantly better than most other states in Reading, which lends some credence to the notion that Kerala has the highest literacy rates. Tripura and Daman and Diu have the best Science scores Overall, across all states, ther average scores in Maths, Social Sciences and Science are roughly similar, and significantly lower than Reading scores. Just to get a better idea of the distribution marks over all the states, lets plot some distributions

```
In [44]: fig, ax = plt.subplots()
         sns.distplot(a=boys_maths_score['Maths %'],ax=ax,label='Boys Scores')
         sns.distplot(a=girls_maths_score['Maths %'],ax=ax,label='Girls Scores')
         ax.legend()
         plt.show()
```

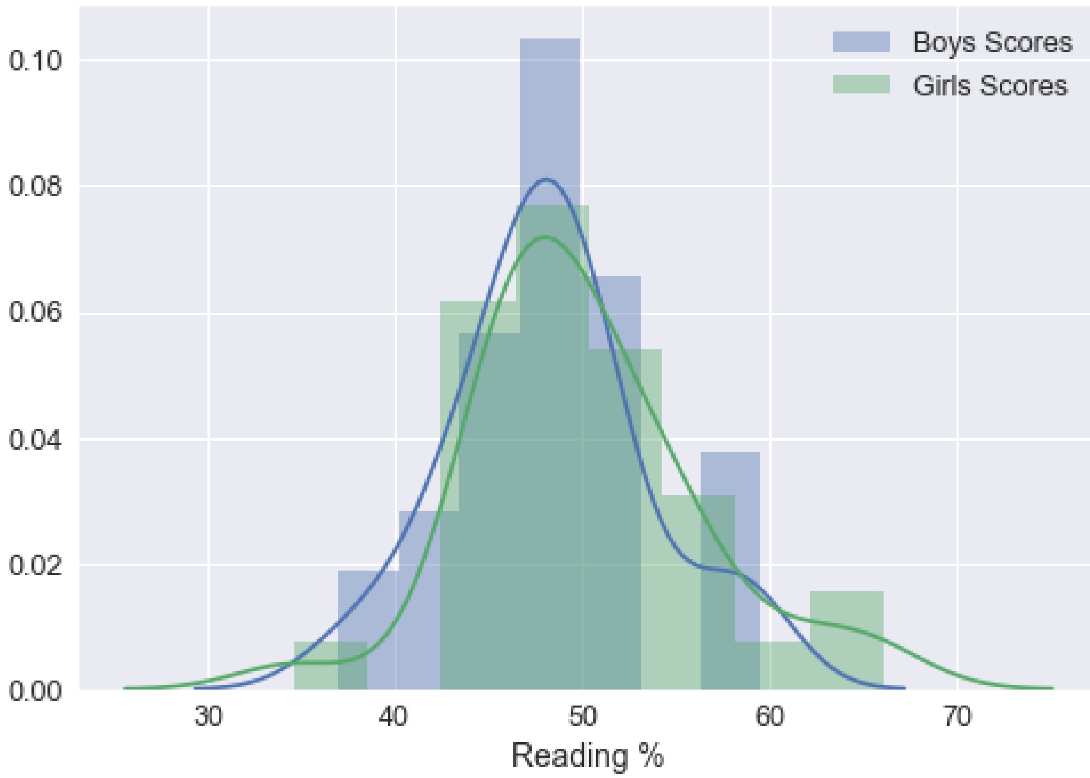



```
In [45]: fig, ax = plt.subplots()
         sns.distplot(a=boys_science_score['Science %'],ax=ax,label='Boys Scores')
         sns.distplot(a=girls_science_score['Science %'],ax=ax,label='Girls Scores')
         ax.legend()
         plt.show()
```

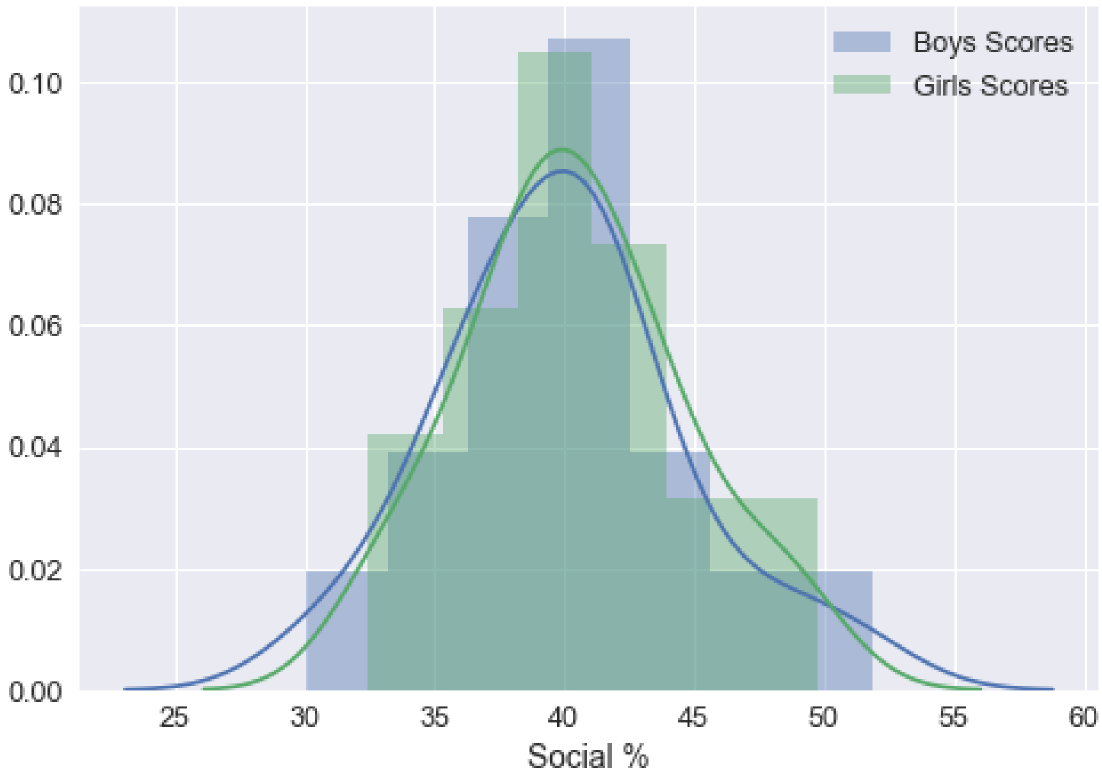


This is probably the only dataset where girls do significantly worse in terms of performance. Just looking at the peak around the 35-40% average score for girls across states is indicative of the fact that girls don't have the best marks in science.

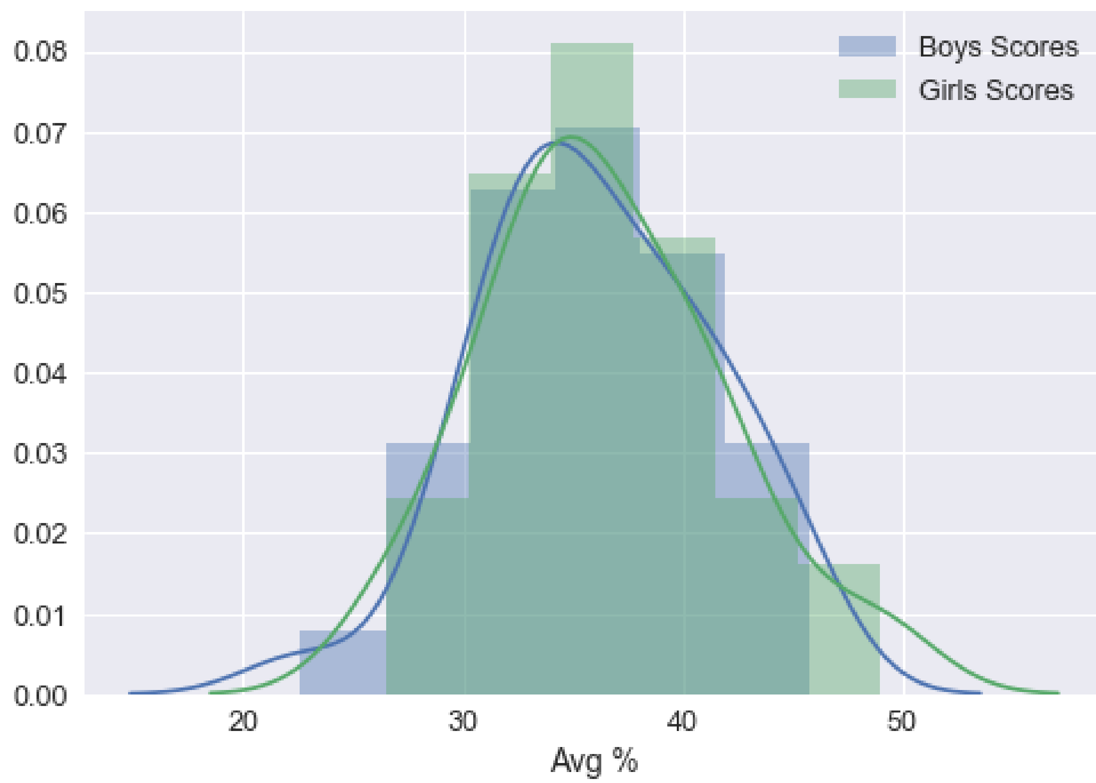
```
In [46]: fig, ax = plt.subplots()
         sns.distplot(a=boys_reading_score['Reading %'],ax=ax,label='Boys Scores')
         sns.distplot(a=girls_reading_score['Reading %'],ax=ax, label='Girls Scores')
         ax.legend()
         plt.show()
```




```
In [47]: fig, ax = plt.subplots()
         sns.distplot(a=boys_social_score['Social %'],ax=ax,label='Boys Scores')
         sns.distplot(a=girls_social_score['Social %'],ax=ax,label='Girls Scores')
         ax.legend()
         plt.show()
```




```
In [48]: fig, ax = plt.subplots()
         sns.distplot(a=boys_mathsandscience_score['Avg %'],ax=ax,label='Boys Scores')
         sns.distplot(a=girls_mathsandscience_score['Avg %'],ax=ax,label='Girls Scores')
         ax.legend()
         plt.show()
```



Analysis Looking at the average score of the math and science scores for girls and boys across all states, it seems like they seems to perform similarly, despite the fact that girls do relatively worse in science. Girls do significantly better in Reading, and slightly better in Social Science subjects.

1.5 Examining Performance for South Indian States

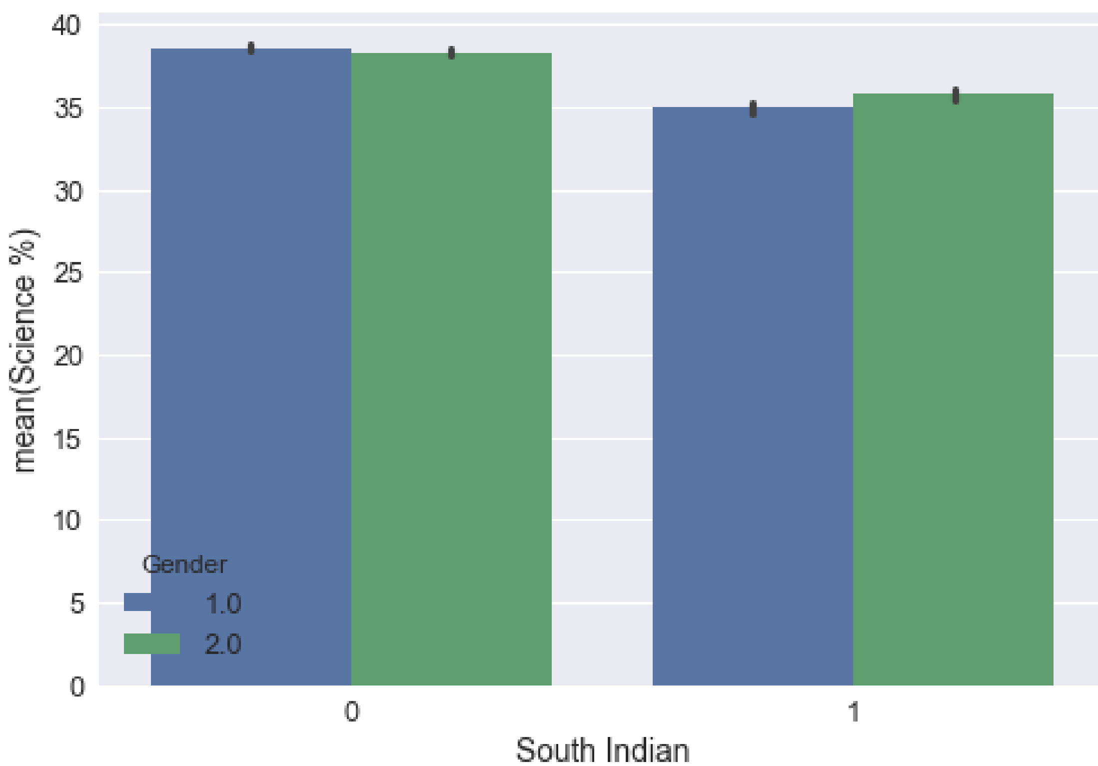
For this final question, we transform our dataset slightly. We already have some small idea about this is, as in our state wise plots we could see certain states do significantly better than others in certain subjects. let's change our levels for the state column by manufacturing another feature which aggregates whether people are in South Indian States or not. South Indian States and their respective labels in our dataset are- 1. Andaman and Nicobar (AN) 2. Andhra Pradesh (AP) 3. Karnataka (KA) 4. Kerala (KL) 5. Puducherry (PY) 6. Tamil Nadu (TN) 7. Telangana -Not in Dataset 8. Lakshwadeep -Not in Dataset

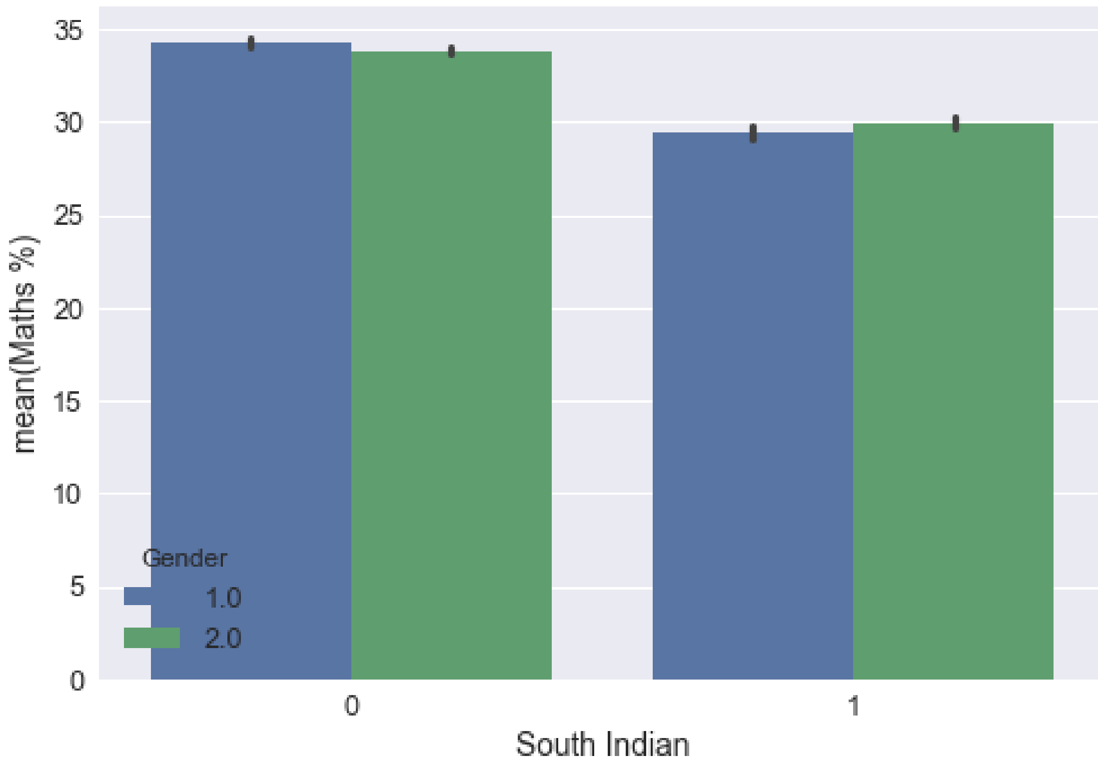
Then we can use the same charts as we did previously to try and answer this question.

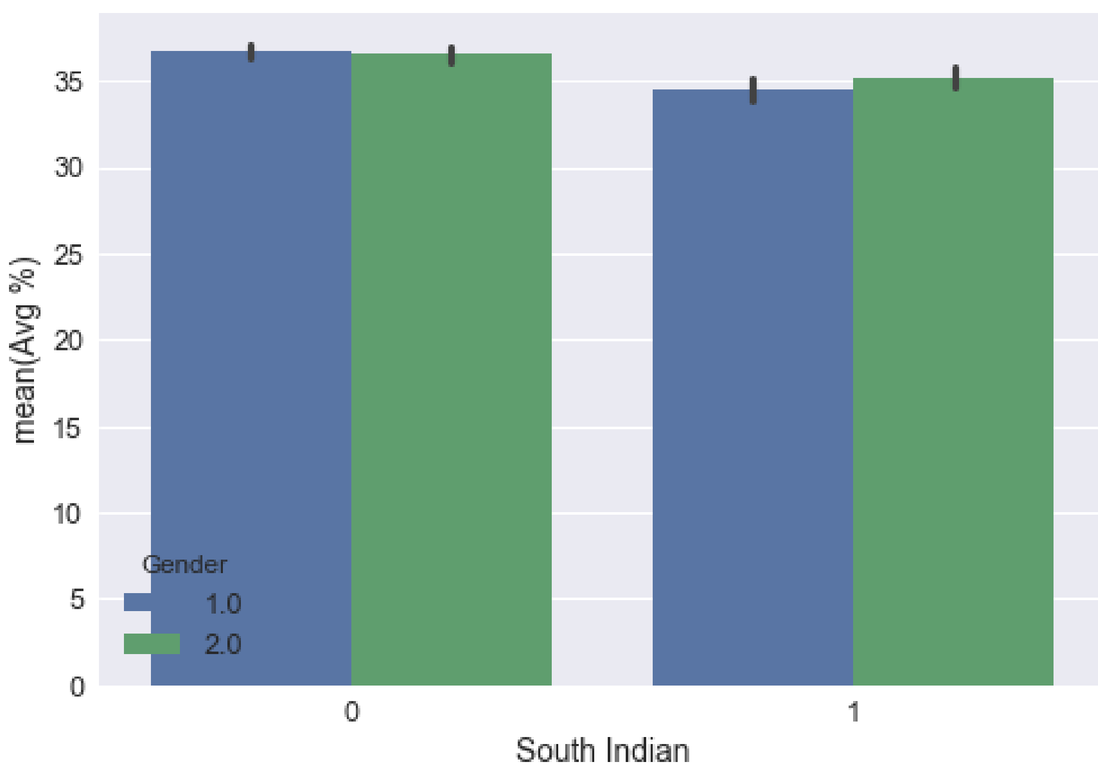
```
In [49]: def create_south_indian_column(df):
             south_indian_states = ['AN','AP','KA','KL','PY','TN']
             df['South Indian'] = [1 if x in south_indian_states else 0 for x in df['State']]
             return df

In [50]: Maths = create_south_indian_column(Maths)
         Science = create_south_indian_column(Science)
```

```
Maths_and_Science = create_south_indian_column(Maths_and_Science)
Reading = create_south_indian_column(Reading)
Social = create_south_indian_column(Social)
```

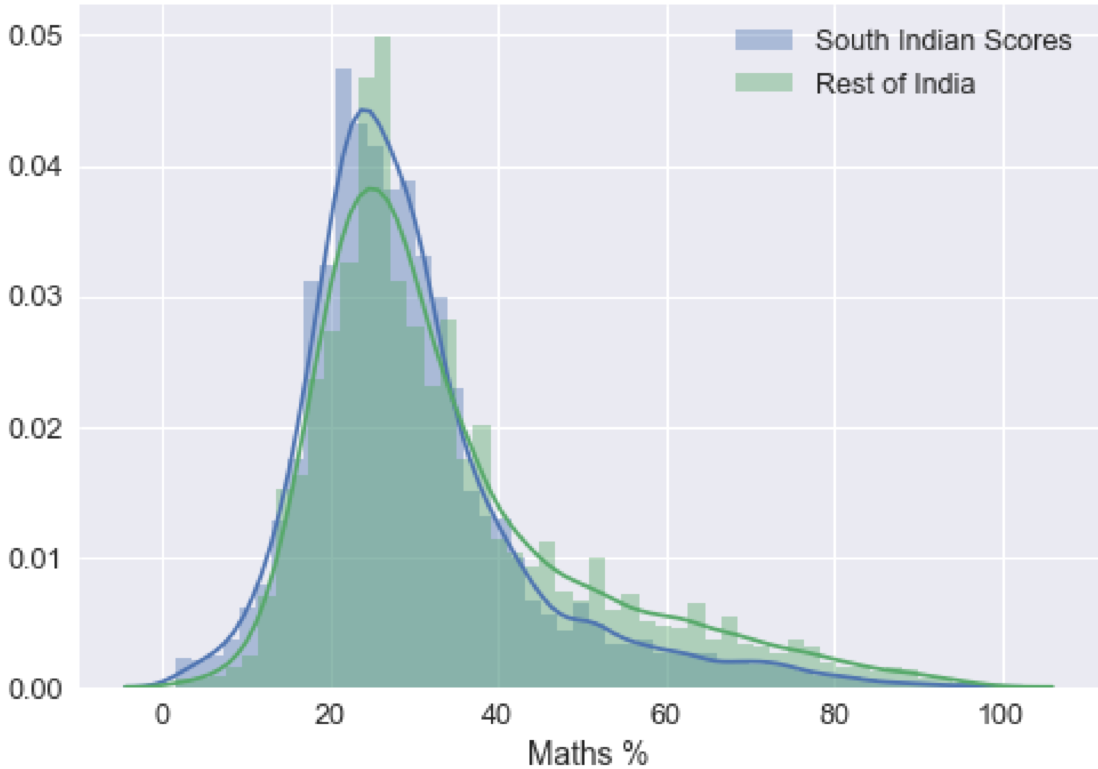
In [51]:
```
fig, ax = plt.subplots()
sns.barplot(x='South Indian',y='Science %',hue='Gender',data=Science, ax=ax)
plt.show()
fig, ax = plt.subplots()
sns.barplot(x='South Indian',hue='Gender',y='Maths %',data=Maths, ax=ax)
plt.show()
fig, ax = plt.subplots()
sns.barplot(x='South Indian',hue='Gender',y='Avg %',data=Maths_and_Science, ax=ax)
plt.show()
```



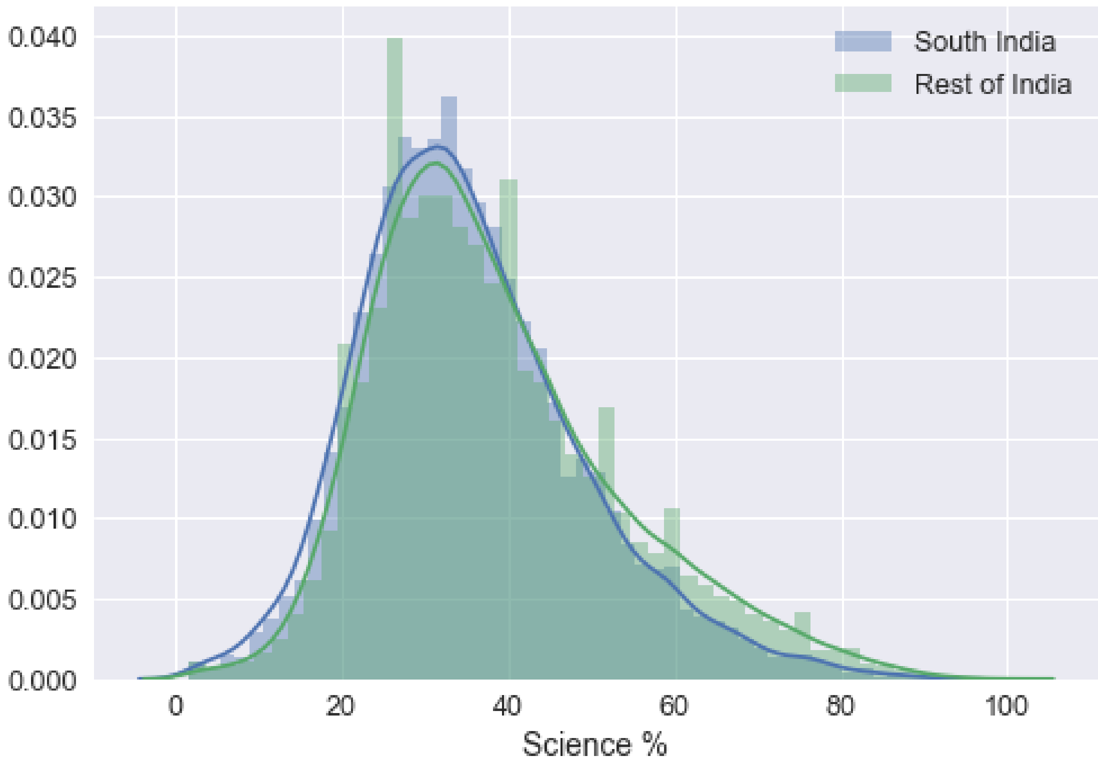

mean(Maths %)
35
30
25
20
15
10
5
0
Gender
1.0
2.0
0
1
South Indian


mean(Avg %)
35
30
25
20
15
10
5
0
Gender
1.0
2.0
0
1
South Indian

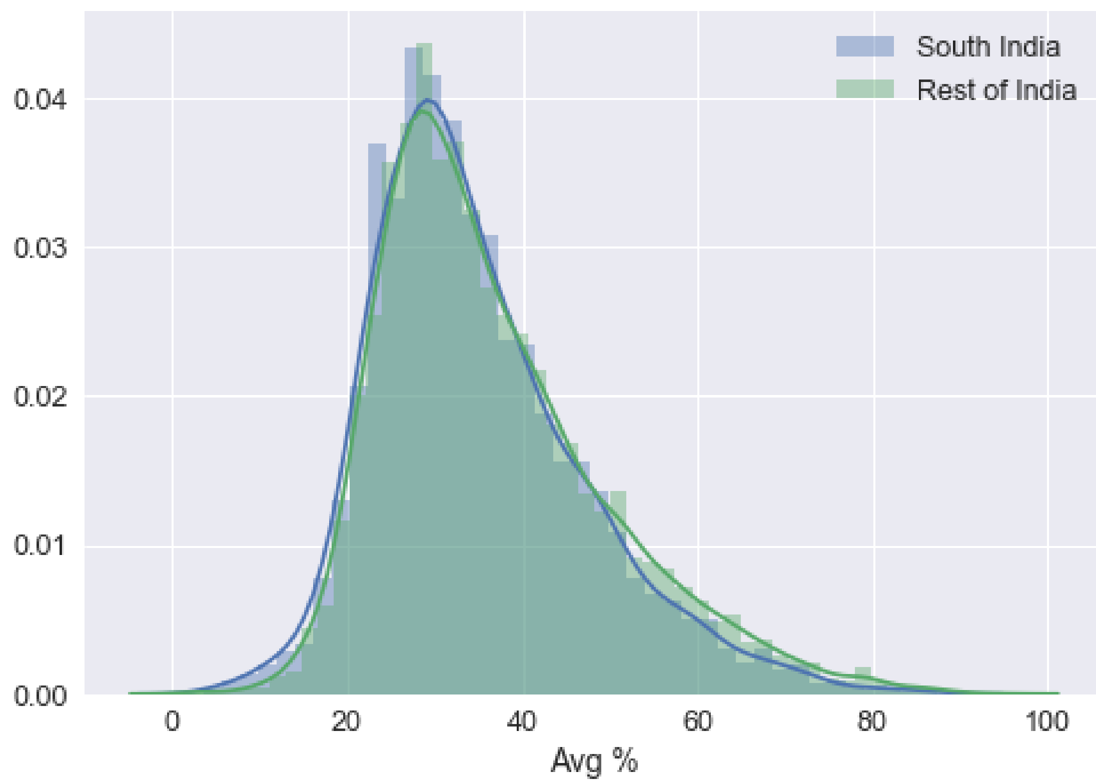
In [52]:
```
fig, ax = plt.subplots()
sns.distplot(a=Maths.loc[Maths['South Indian']==1]['Maths %'],ax=ax,label = 'South Inc
sns.distplot(a=Maths.loc[Maths['South Indian']==0]['Maths %'],ax=ax,label='Rest of Inc
ax.legend()
plt.show()
```



In [53]:
```
fig, ax = plt.subplots()
sns.distplot(a=Science.loc[Science['South Indian']==1]['Science %'],ax=ax,label='South
sns.distplot(a=Science.loc[Science['South Indian']==0]['Science %'],ax=ax,label='Rest
ax.legend()
plt.show()
```




```
In [54]: fig, ax = plt.subplots()
         sns.distplot(a=Maths_and_Science.loc[Maths_and_Science['South Indian']==1]['Avg %'],ax
         sns.distplot(a=Maths_and_Science.loc[Maths_and_Science['South Indian']==0]['Avg %'],ax
         ax.legend()
         plt.show()
```



From these graphs, I don't think we can conclude that students in South Indian States are extraordinarily gifted or perform significantly better in maths and science, in fact the opposite seems to be the case in maths, even if the science scores are very similar.