Anmol Agarwal ML project

June 18, 2020

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

[2]:
```
df = pd.read_csv('StudentsPerformance.csv')
# Renaming the columns
df=df.rename(columns={"race/ethnicity": "race", "parental level of education":␣
↪"parent_ed", "test preparation course": "course","math score":
↪"math","writing score":"write","reading score":"read"})
```

[3]:
```
df.dtypes
```

[3]:
```
gender        object
race          object
parent_ed     object
lunch         object
course        object
math           int64
read           int64
write          int64
dtype: object
```

0.0.1 Replacing "some high school" with "high school" as they both tend to mean the same thing.

[4]:
```
df.loc[df.parent_ed=="some high school", 'parent_ed'] = "high school"
```

0.0.2 Calculating aggregate total marks for analysis

[5]:
```
# calculating total marks
df["sum"]=df["math"]+df["read"]+df["write"]
```

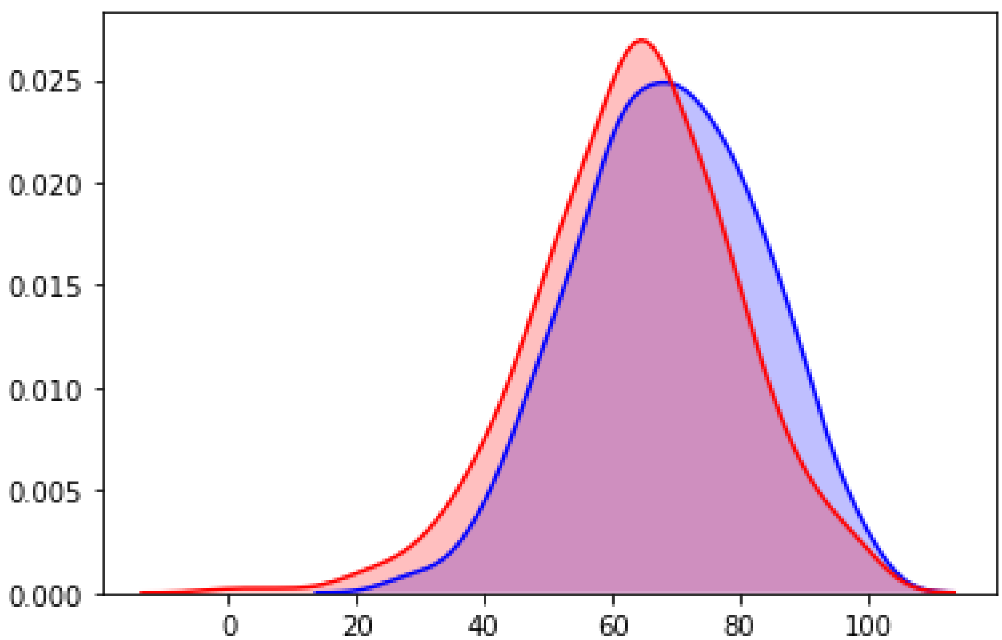
1 Effect of gender on marks

1.0.1 Effect on Maths

[6]:
```
sns.kdeplot(df.
 ↪loc[(df["gender"]=="male")]['math'],shade=True,color="b",legend=False)
sns.kdeplot(df.
 ↪loc[(df["gender"]=="female")]['math'],shade=True,color='r',legend=False)
df.groupby("gender")["math"].describe()
```

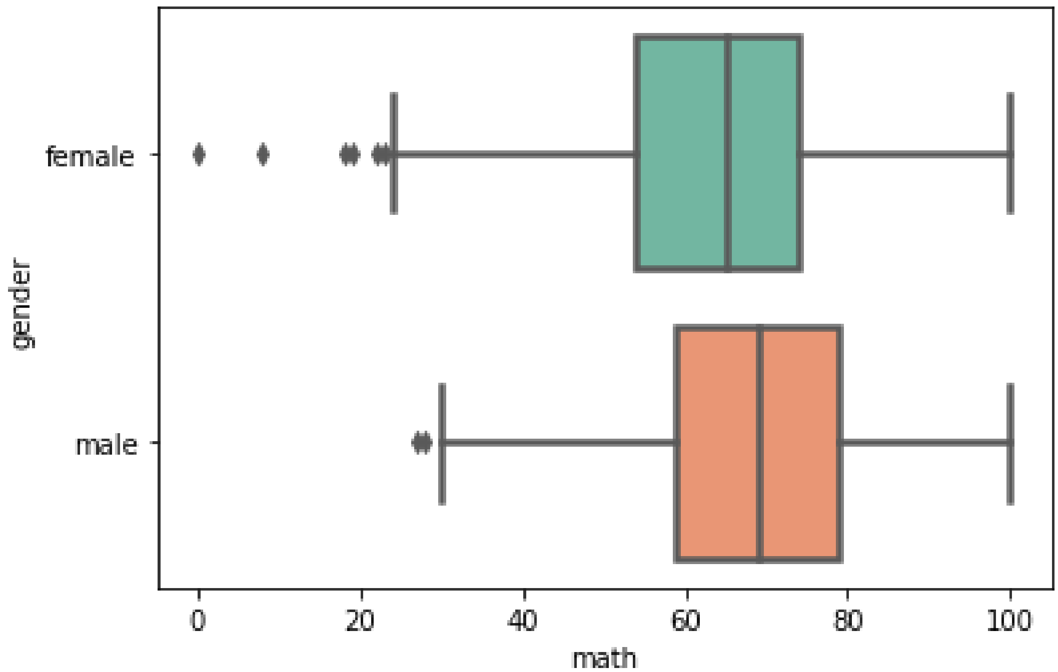
[6]:

	count	mean	std	min	25%	50%	75%	max
gender								
female	518.0	63.633205	15.491453	0.0	54.0	65.0	74.0	100.0
male	482.0	68.728216	14.356277	27.0	59.0	69.0	79.0	100.0



[7]:
```
sns.boxplot(x="math",y="gender",data=df,linewidth=2.5,palette="Set2")
```

[7]: <matplotlib.axes._subplots.AxesSubplot at 0x7f36c0a4cbd0>



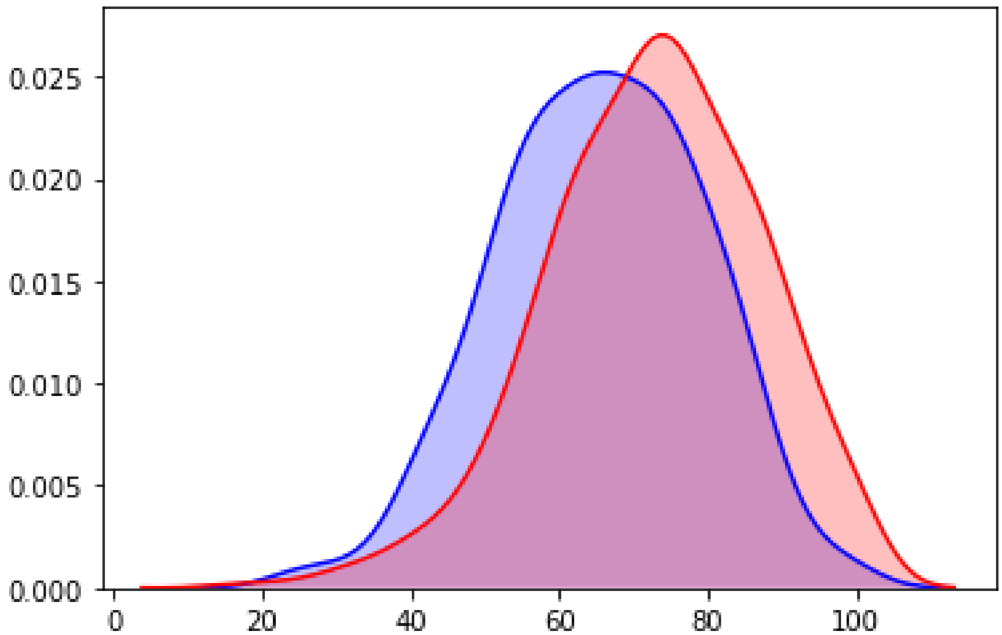
In the above KDE plot, the plot for females is by red color while plot for males is by red color. It is evident that **males are much better in a maths test than females.** The median of males scores is 69 whereas those of females is 65. Also, the mean for male scores is 68.72 whereas for females it is 63.63. **Also, the boy's plot in blue covers a larger portion in the right(towards higher marks) as compared to girls.**

1.0.2 Effect on Reading scores

[8]:
```
sns.kdeplot(df.
 ↪loc[(df["gender"]=="male")]['read'],shade=True,color="b",legend=False)
sns.kdeplot(df.
 ↪loc[(df["gender"]=="female")]['read'],shade=True,color='r',legend=False)
df.groupby("gender")["read"].describe()
```

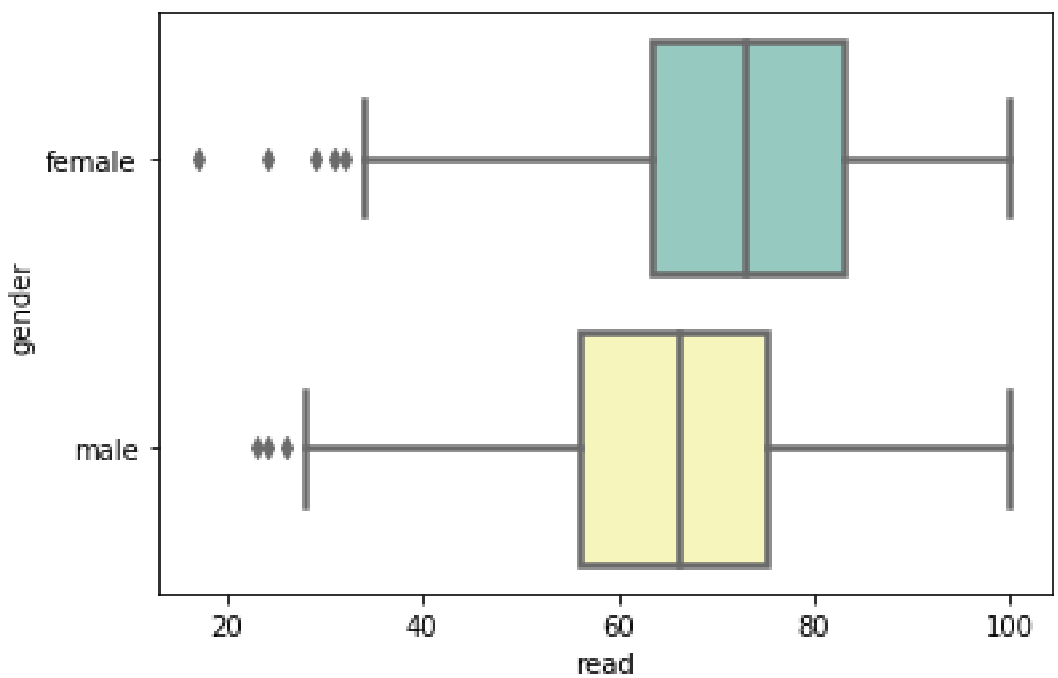
[8]:

	count	mean	std	min	25%	50%	75%	max
gender								
female	518.0	72.608108	14.378245	17.0	63.25	73.0	83.0	100.0
male	482.0	65.473029	13.931832	23.0	56.00	66.0	75.0	100.0



[9]:
```
sns.boxplot(x="read",y="gender",data=df,linewidth=2.5,palette="Set3")
```

[9]: <matplotlib.axes._subplots.AxesSubplot at 0x7f36c090ba90>



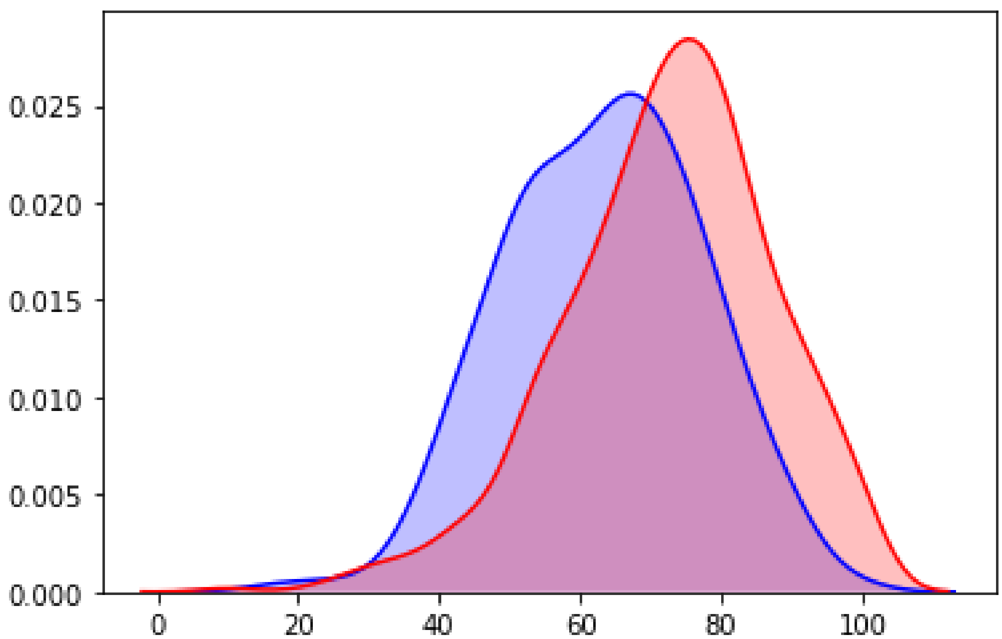
In the above KDE plot, the plot for females is by red color while plot for males is by red color. It is evident that **females are much better in a reading evaluation than males.** The median of males scores is 66 whereas those of females is 73. Also, the mean for male scores is 65.47 whereas for females it is 72.6. Also, **the female's plot in red covers a larger portion in the right(towards higher marks) as compared to males.**

1.0.3 Effect on Writing scores

[10]:
```
sns.kdeplot(df.
 ↪loc[(df["gender"]=="male")]['write'],shade=True,color="b",legend=False)
sns.kdeplot(df.
 ↪loc[(df["gender"]=="female")]['write'],shade=True,color='r',legend=False)
df.groupby("gender")["write"].describe()
```

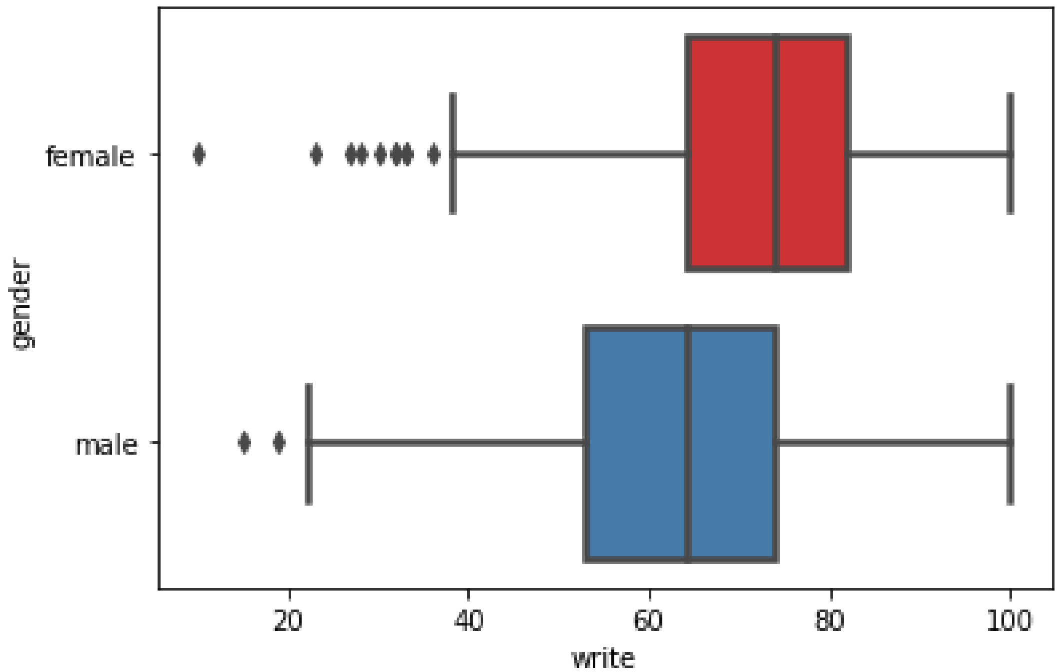
[10]:

gender	count	mean	std	min	25%	50%	75%	max
female	518.0	72.467181	14.844842	10.0	64.0	74.0	82.00	100.0
male	482.0	63.311203	14.113832	15.0	53.0	64.0	73.75	100.0



[11]:
```
sns.boxplot(x="write",y="gender",data=df,linewidth=2.5,palette="Set1")
```

[11]: <matplotlib.axes._subplots.AxesSubplot at 0x7f36c087a090>



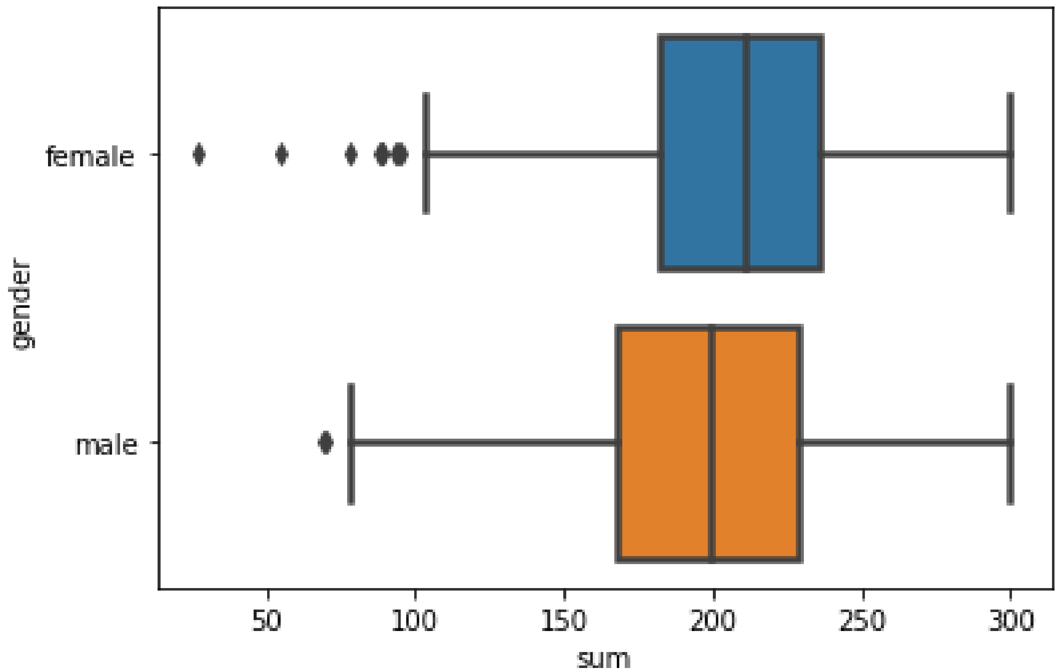
In the above KDE plot, the plot for females is by red color while plot for males is by red color. It is evident that **females are significantly better in a writing evaluation than males.** The median of males scores is 64 whereas those of females is 74 (a huge difference of 10 marks). Also, the mean for male scores is 63.31 whereas for females it is 72.46. **Also, the female's plot in red covers a larger portion in the right(towards higher marks) as compared to males.**

1.0.4 Effect of gender on overall marks

[12]:
```
sns.boxplot(x="sum",y="gender",data=df,linewidth=2.5)
df.groupby("gender")["sum"].describe()
```

[12]:

gender	count	mean	std	min	25%	50%	75%	max
female	518.0	208.708494	43.625427	27.0	182.0	211.0	236.00	300.0
male	482.0	197.512448	41.096520	69.0	168.0	199.0	228.75	300.0



1.1 Analysis

From the above plot, we can derive that the median scores of females is much higher than that of males. Also, mean for females is 208,.7 whereas mean for males is 197.5

2 Effect of parent's education

[13]:
```
df["parent_ed"].unique()
```

[13]:
```
array(["bachelor's degree", 'some college', "master's degree",
       "associate's degree", 'high school'], dtype=object)
```

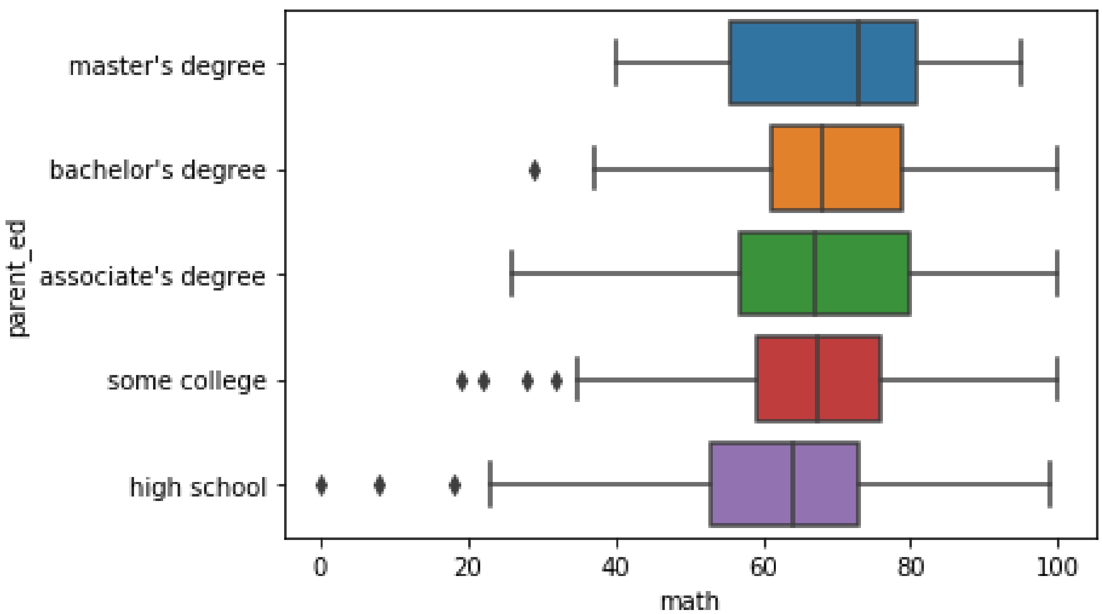
[14]:
```
asc=["master's degree","bachelor's degree","associate's degree", 'some␣
↪college','high school']
```

2.0.1 Effect on maths scores

[15]:
```
sns.boxplot(x="math",y="parent_ed",data=df,order=asc)
df.groupby("parent_ed")["math"].describe()
```

[15]:

parent_ed	count	mean	std	min	25%	50%	75%	max
associate's degree	222.0	67.882883	15.112093	26.0	57.0	67.0	80.0	100.0
bachelor's degree	118.0	69.389831	14.943789	29.0	61.0	68.0	79.0	100.0
high school	375.0	62.786667	15.212833	0.0	53.0	64.0	73.0	99.0
master's degree	59.0	69.745763	15.153915	40.0	55.5	73.0	81.0	95.0
some college	226.0	67.128319	14.312897	19.0	59.0	67.5	76.0	100.0



2.0.2 Effect on reading scores

[16]:

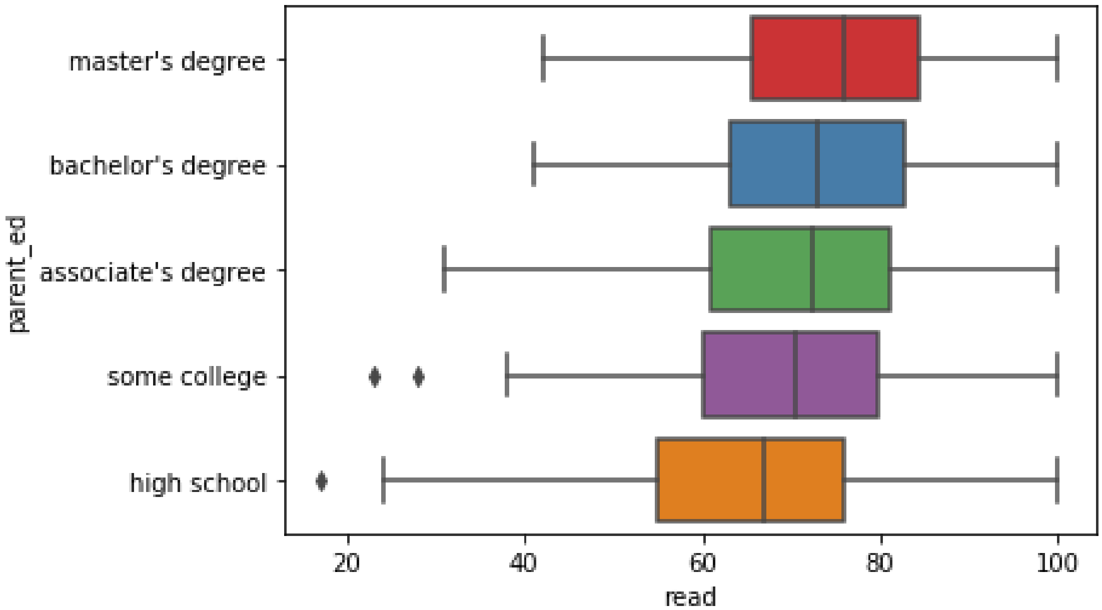
```
sns.boxplot(x="read", y="parent_ed", data=df,order=asc,palette="Set1")
df.groupby("parent_ed")["read"].describe()
```

[16]:

parent_ed	count	mean	std	min	25%	50%	75% \
associate's degree	222.0	70.927928	13.868948	31.0	61.0	72.5	81.00
bachelor's degree	118.0	73.000000	14.285250	41.0	63.0	73.0	82.75
high school	375.0	65.770667	14.812760	17.0	55.0	67.0	76.00
master's degree	59.0	75.372881	13.775163	42.0	65.5	76.0	84.50
some college	226.0	69.460177	14.057049	23.0	60.0	70.5	79.75

parent_ed	max
associate's degree	100.0
bachelor's degree	100.0

```
high school         100.0
master's degree     100.0
some college        100.0
```

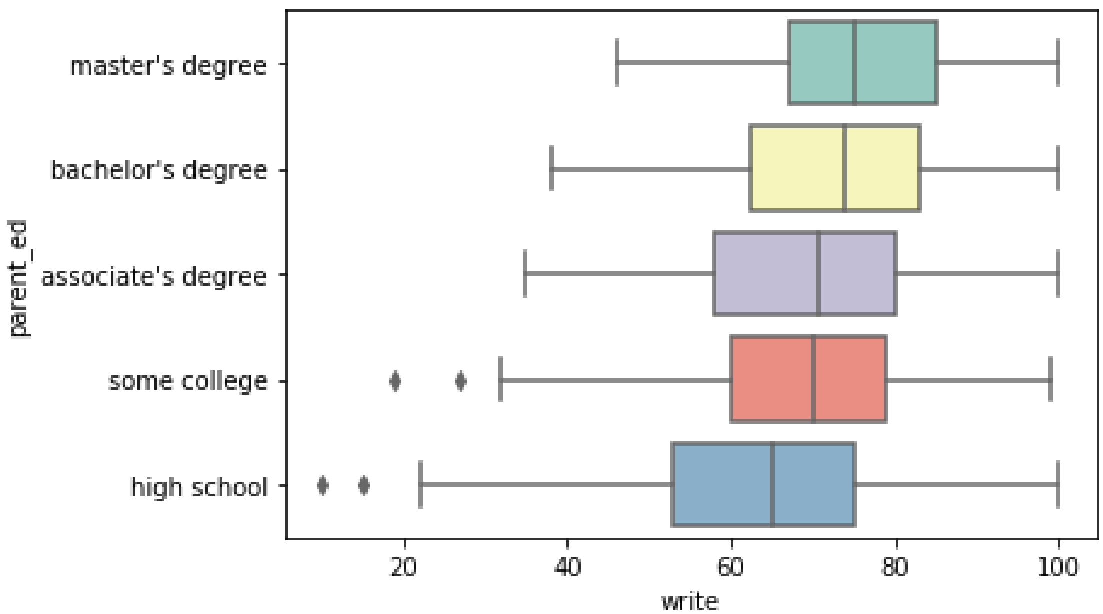


2.0.3 Effect on writing scores

[17]:
```python
sns.boxplot(x="write", y="parent_ed", data=df,order=asc,palette="Set3")
df.groupby("parent_ed")["write"].describe()
```

[17]:

parent_ed	count	mean	std	min	25%	50%	75%	max
associate's degree	222.0	69.896396	14.311122	35.0	58.0	70.5	80.0	100.0
bachelor's degree	118.0	73.381356	14.728262	38.0	62.5	74.0	83.0	100.0
high school	375.0	63.613333	14.926284	10.0	53.0	65.0	75.0	100.0
master's degree	59.0	75.677966	13.730711	46.0	67.0	75.0	85.0	100.0
some college	226.0	68.840708	15.012331	19.0	60.0	70.0	79.0	99.0

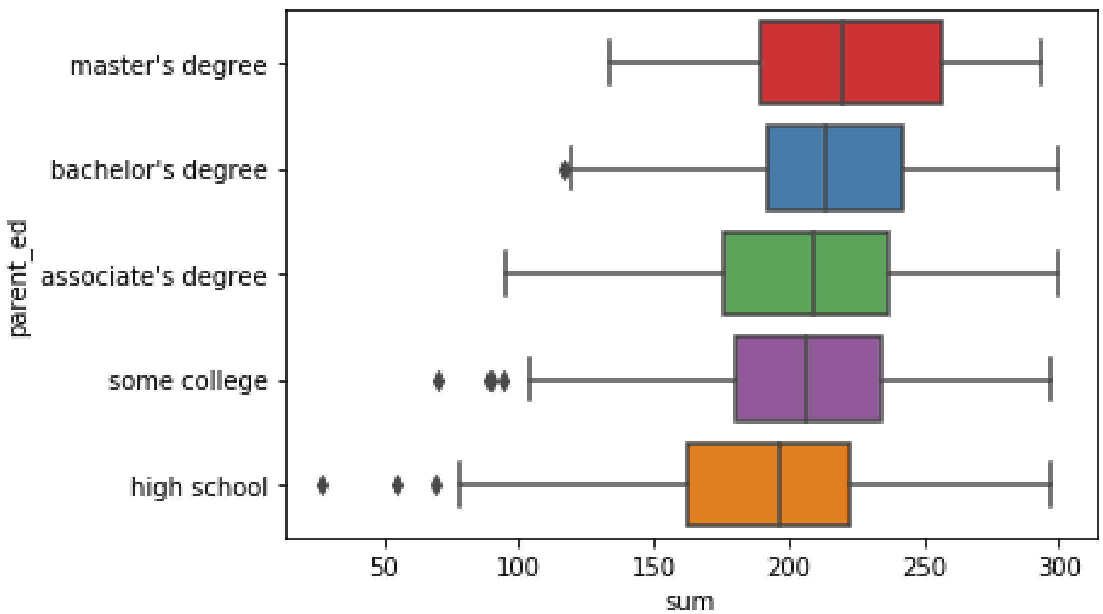


2.1 Effect on total scores

[18]:
```
sns.boxplot(x="sum", y="parent_ed", data=df,order=asc,palette="Set1")
df.groupby("parent_ed")["sum"].describe()
```

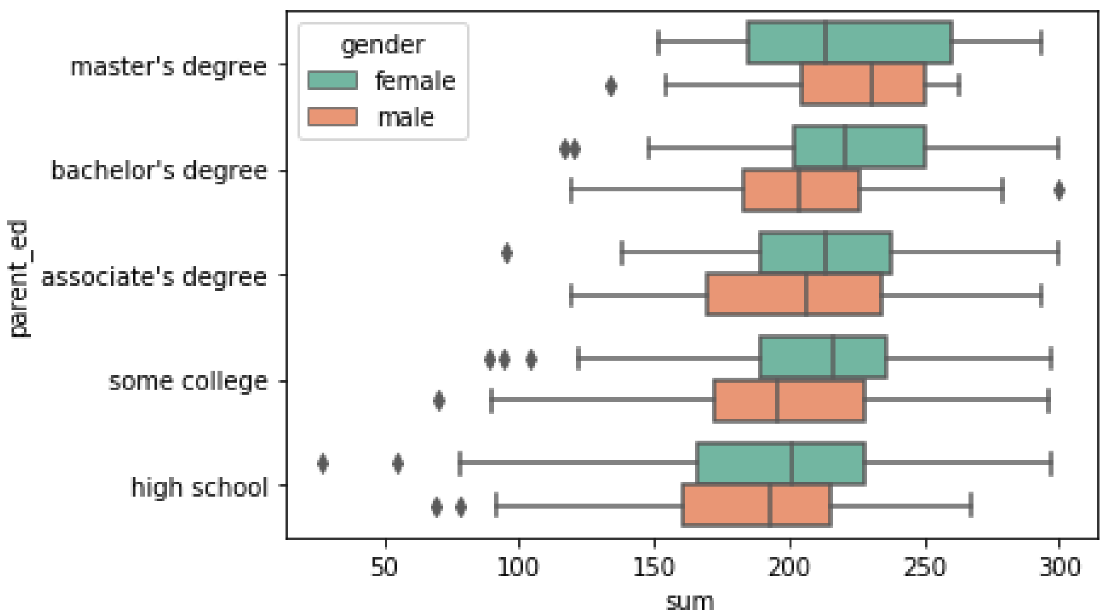
[18]:
```
                    count        mean        std    min     25%    50%    75%  \
parent_ed
associate's degree  222.0  208.707207  41.012743   95.0  176.00  209.0  237.0
bachelor's degree   118.0  215.771186  41.839827  117.0  192.25  213.5  242.0
high school         375.0  192.170667  42.747895   27.0  162.50  197.0  223.0
master's degree      59.0  220.796610  40.803051  134.0  189.50  220.0  256.5
some college        226.0  205.429204  41.132921   70.0  180.00  206.0  234.0

                      max
parent_ed
associate's degree  300.0
bachelor's degree   300.0
high school         297.0
master's degree     293.0
some college        297.0
```



[19]:
```
sns.boxplot(x="sum", y="parent_ed",␣
 ↪data=df,order=asc,palette="Set2",hue="gender")
#df.groupby(["gender","parent_ed"])["write"].describe()
```

[19]: <matplotlib.axes._subplots.AxesSubplot at 0x7f36c05da510>

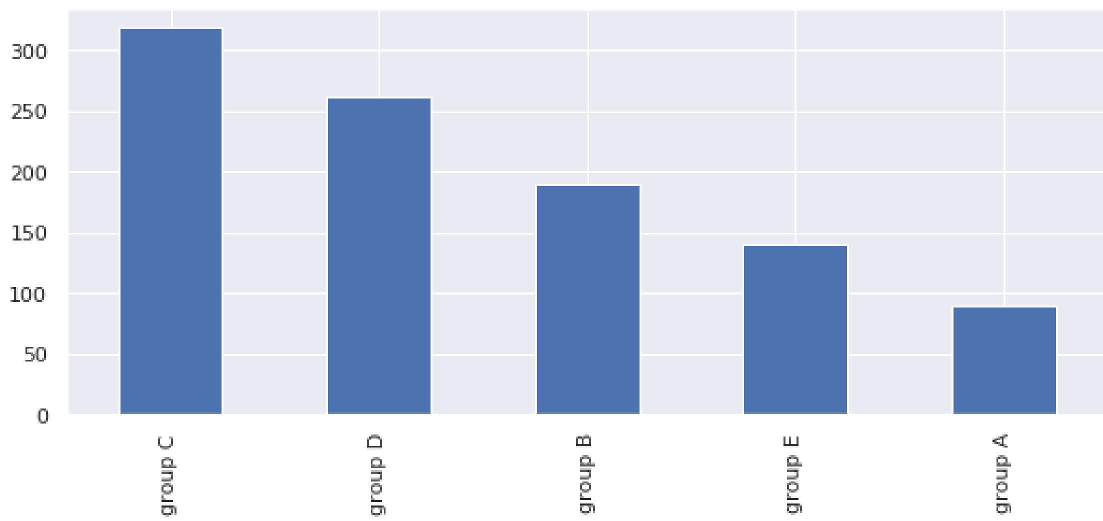


2.2 Analysis of effect of parent's education level on children's marks

An **expected trend** which can be inferred from the above data is that **children whose parent's level of education is higher, perform better than the ones whose parents' education is comparitively lower. This trend is observed across all subjects and also in total aggregate marks.** The mean total for students shose parent''s have a master's degree is 220.79 whereas for students whose parents' are just high school graduates is 189.29.

3 Effect of group/race on education

[62]:
```
df.race.value_counts().plot(kind="bar")
asc=["group A","group B","group C","group D","group E"]
```

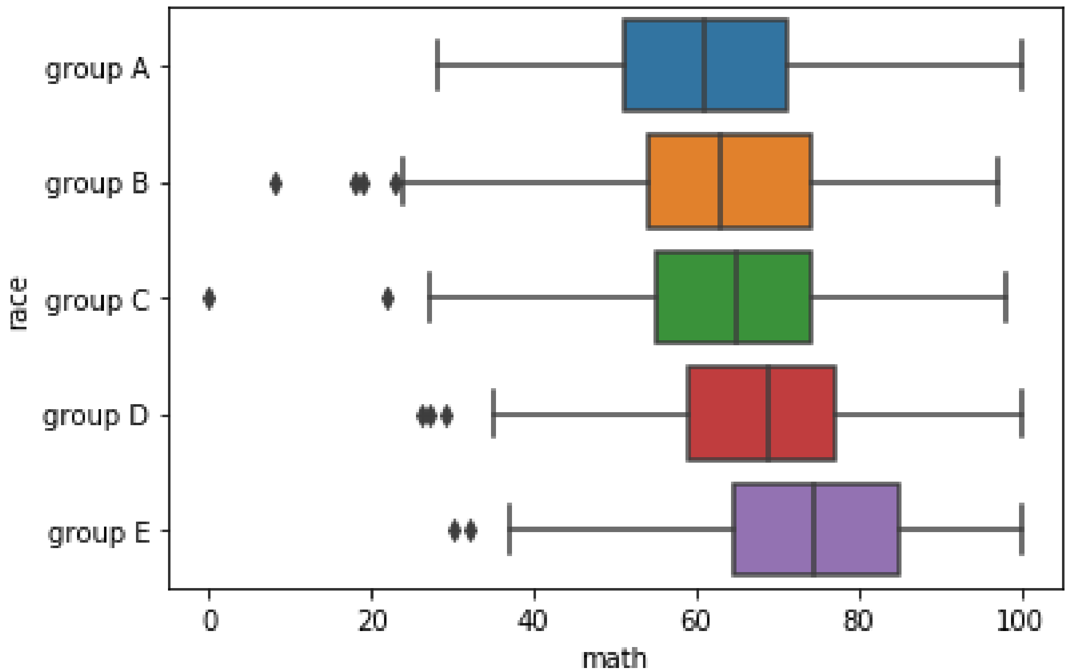


3.0.1 Effect on math scores

[21]:
```
sns.boxplot(x="math",y="race",data=df,order=asc)
df.groupby("race")["math"].describe()
```

[21]:

race	count	mean	std	min	25%	50%	75%	max
group A	89.0	61.629213	14.523008	28.0	51.00	61.0	71.0	100.0
group B	190.0	63.452632	15.468191	8.0	54.00	63.0	74.0	97.0
group C	319.0	64.463950	14.852666	0.0	55.00	65.0	74.0	98.0
group D	262.0	67.362595	13.769386	26.0	59.00	69.0	77.0	100.0
group E	140.0	73.821429	15.534259	30.0	64.75	74.5	85.0	100.0

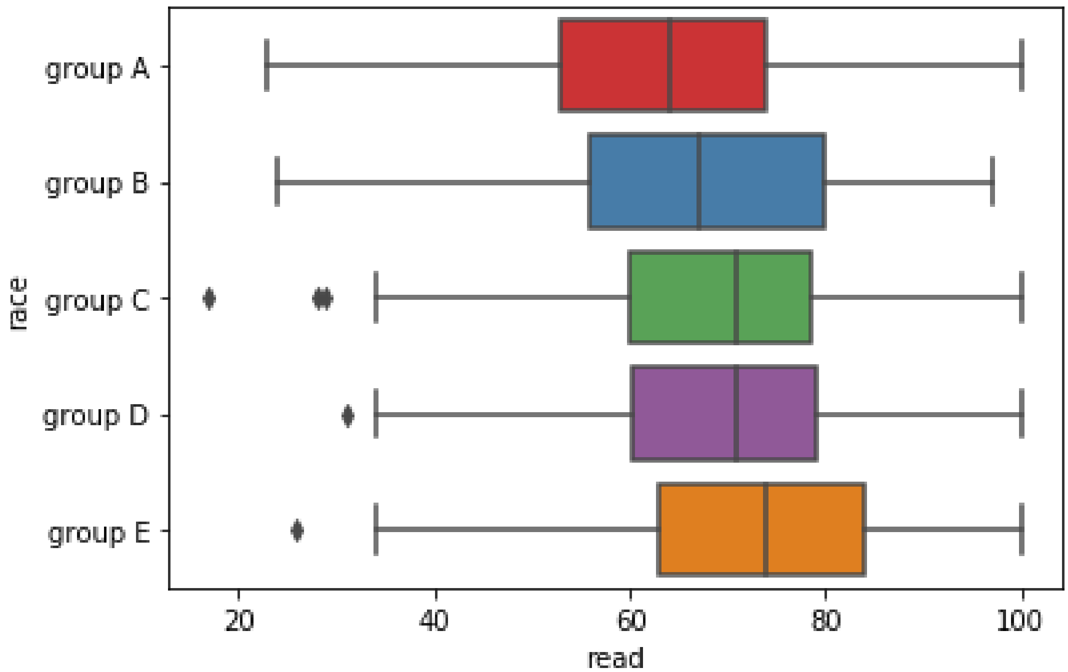


3.0.2 Effect on reading scores

[22]:
```
sns.boxplot(x="read", y="race", data=df,order=asc,palette="Set1")
df.groupby("race")["read"].describe()
```

[22]:

race	count	mean	std	min	25%	50%	75%	max
group A	89.0	64.674157	15.543762	23.0	53.00	64.0	74.00	100.0
group B	190.0	67.352632	15.177499	24.0	56.00	67.0	79.75	97.0
group C	319.0	69.103448	13.997033	17.0	60.00	71.0	78.50	100.0
group D	262.0	70.030534	13.895306	31.0	60.25	71.0	79.00	100.0
group E	140.0	73.028571	14.874024	26.0	63.00	74.0	84.00	100.0

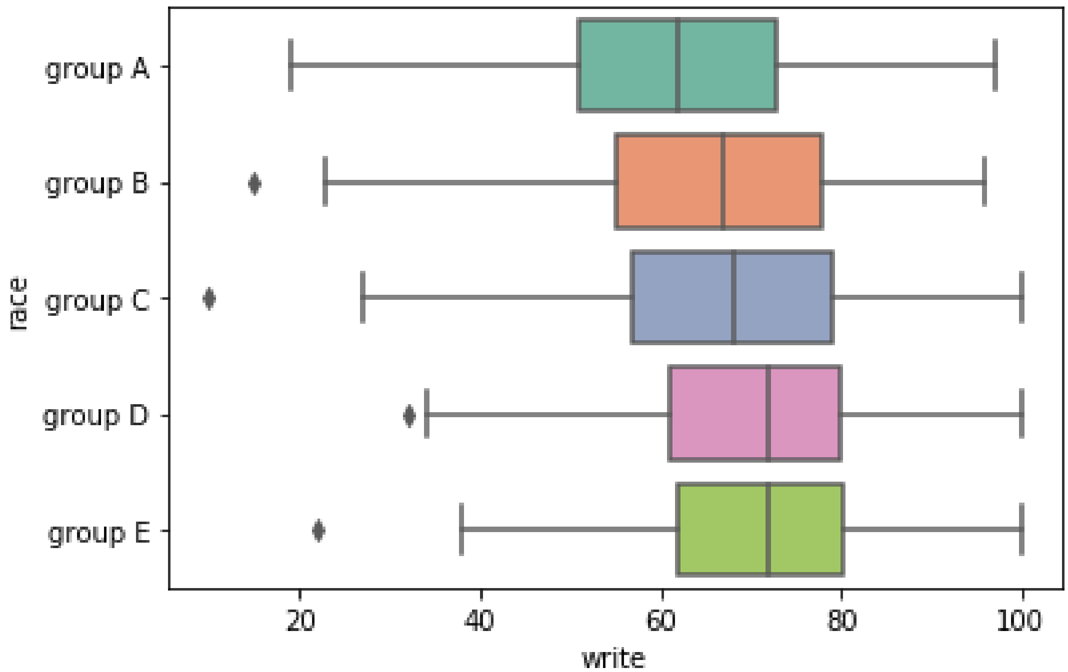


3.0.3 Effect on writing scores

[23]:
```
sns.boxplot(x="write", y="race", data=df,order=asc,palette="Set2")
df.groupby("race")["write"].describe()
```

[23]:

race	count	mean	std	min	25%	50%	75%	max
group A	89.0	62.674157	15.468278	19.0	51.00	62.0	73.00	97.0
group B	190.0	65.600000	15.625173	15.0	55.25	67.0	78.00	96.0
group C	319.0	67.827586	14.983378	10.0	57.00	68.0	79.00	100.0
group D	262.0	70.145038	14.367707	32.0	61.00	72.0	80.00	100.0
group E	140.0	71.407143	15.113906	22.0	62.00	72.0	80.25	100.0

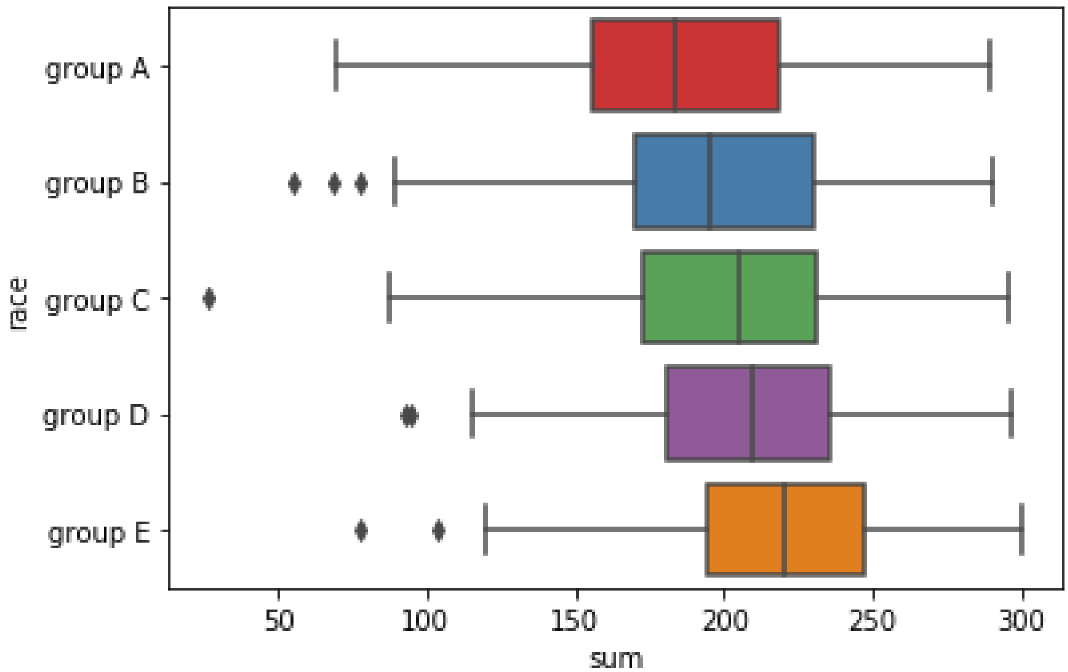


3.0.4 Effect on total aggregate scores

[24]:
```
sns.boxplot(x="sum", y="race", data=df,order=asc,palette="Set1")
df.groupby("race")["sum"].describe()
```

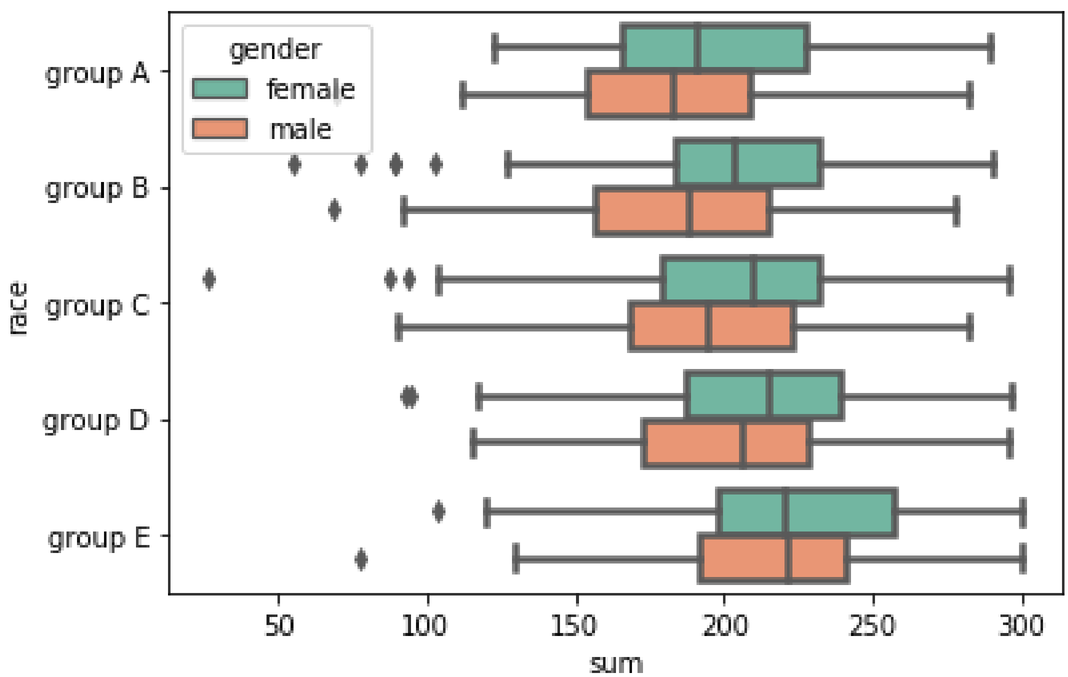
[24]:

race	count	mean	std	min	25%	50%	75%	max
group A	89.0	188.977528	43.333794	70.0	156.0	184.0	219.00	289.0
group B	190.0	196.405263	44.196399	55.0	170.0	195.0	230.50	290.0
group C	319.0	201.394984	41.616633	27.0	173.0	205.0	231.00	296.0
group D	262.0	207.538168	39.758327	93.0	181.0	210.0	235.75	297.0
group E	140.0	218.257143	43.695047	78.0	194.0	220.5	247.25	300.0



[25]:
```
# girls of all races performing better
sns.boxplot(x="sum", y="race",␣
↪data=df,order=asc,palette="Set2",hue="gender",linewidth=2.5)
```

[25]: <matplotlib.axes._subplots.AxesSubplot at 0x7f36c00ec150>



3.1 Analysis of effect of race

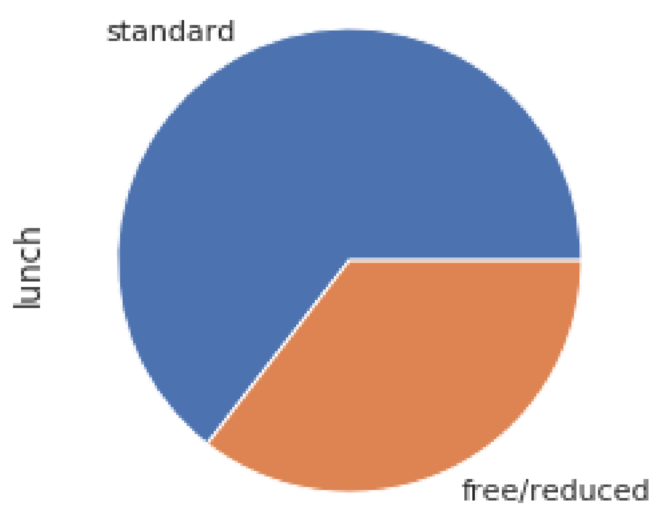
It is quite evident from above plots that the average performance of children in any subject (be it maths,reading,writing or in aggregate) is in the following order (from best to worst) : **gr E > gr D > gr C > gr B > gr A. The median as well as the mean of scores of children in all subjects decreases alphabetically from E to A.** This leads to the conclusion that technique, strategy etc of the groups are variable.

Also, from the boxplot involving "gender" and "race" together, it would be fair to conclude that females of a race on average perform better than the males of the same race.

4 Effect of lunch on marks

[61]:
```
df.lunch.value_counts().plot(kind="pie")
```

[61]: <matplotlib.axes._subplots.AxesSubplot at 0x7f36c0a88050>



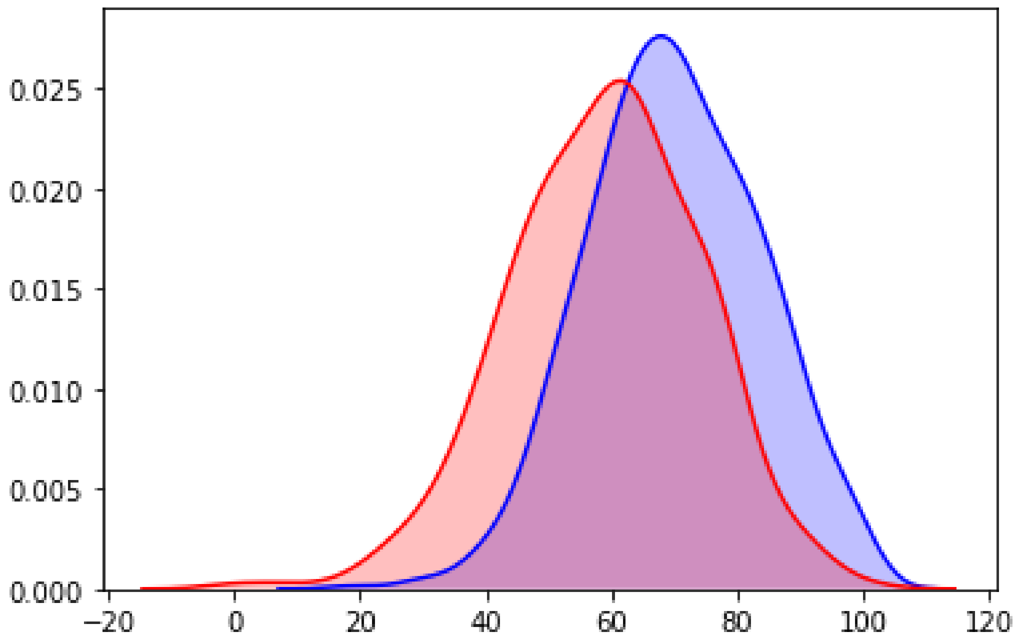
Effect on math marks

[27]:
```
sns.kdeplot(df.
 ↪loc[(df["lunch"]=="standard")]['math'],shade=True,color="b",legend=False)
```

```
sns.kdeplot(df.loc[(df["lunch"]=="free/
 ↪reduced")]['math'],shade=True,color='r',legend=False)
df.groupby("lunch")["math"].describe()
```

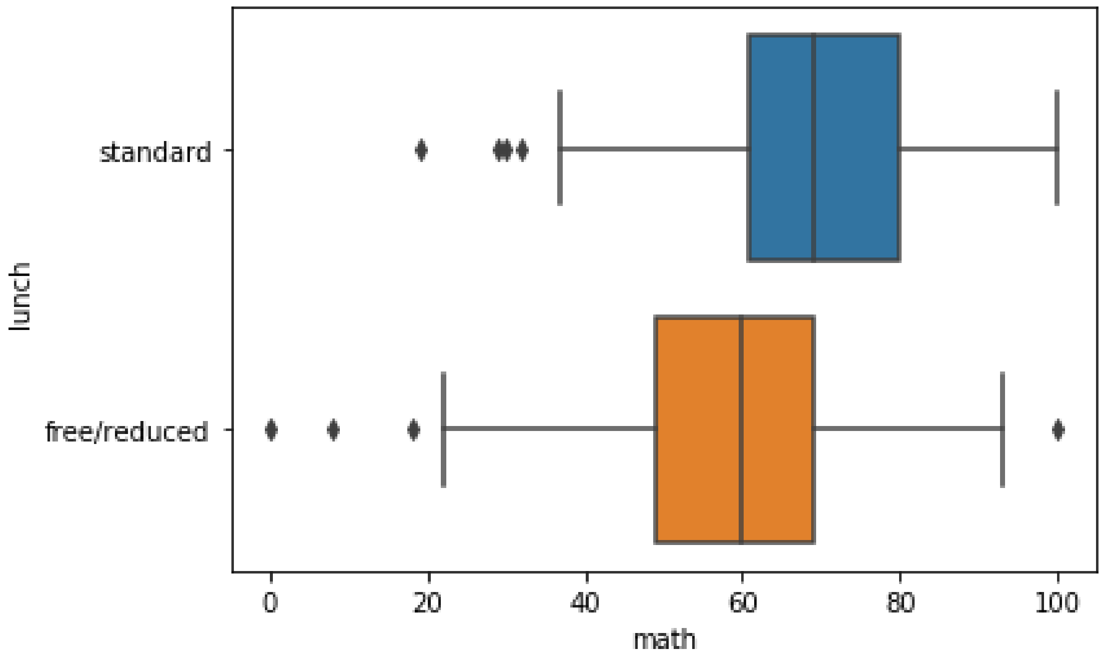
[27]:

	count	mean	std	min	25%	50%	75%	max
lunch								
free/reduced	355.0	58.921127	15.159956	0.0	49.0	60.0	69.0	100.0
standard	645.0	70.034109	13.653501	19.0	61.0	69.0	80.0	100.0



[28]:
```
sns.boxplot(x="math",y="lunch",data=df)
```

[28]: <matplotlib.axes._subplots.AxesSubplot at 0x7f36c06e55d0>

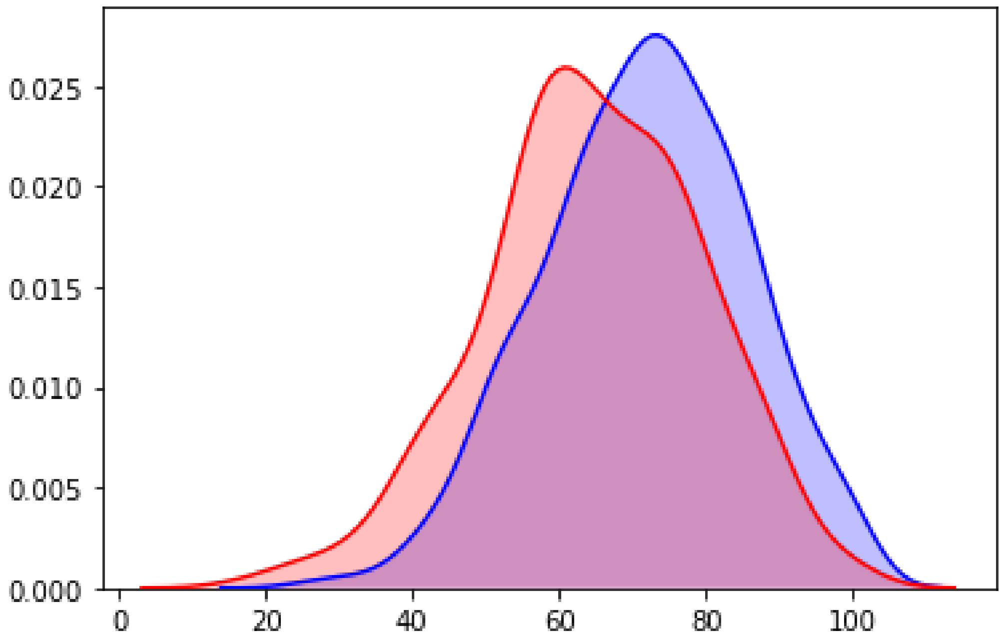


Effect on reading marks

```
[29]: sns.kdeplot(df.
      ↪loc[(df["lunch"]=="standard")]['read'],shade=True,color="b",legend=False)
      sns.kdeplot(df.loc[(df["lunch"]=="free/
      ↪reduced")]['read'],shade=True,color='r',legend=False)
      df.groupby("lunch")["read"].describe()
```

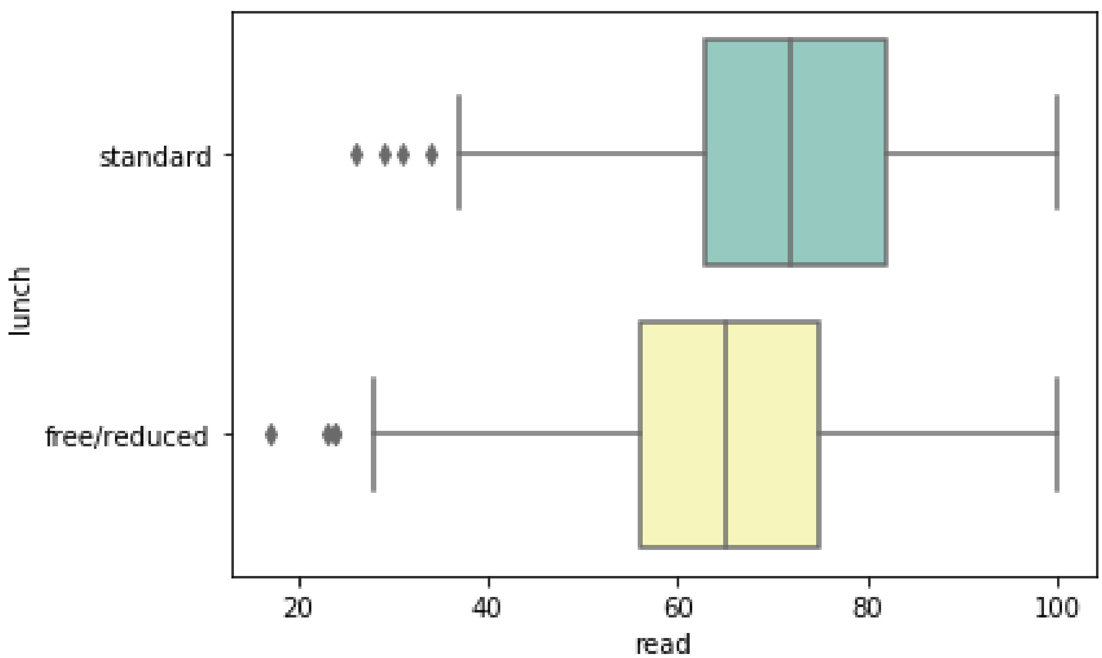
[29]:

lunch	count	mean	std	min	25%	50%	75%	max
free/reduced	355.0	64.653521	14.895339	17.0	56.0	65.0	75.0	100.0
standard	645.0	71.654264	13.830602	26.0	63.0	72.0	82.0	100.0



[30]:
```
sns.boxplot(x="read",y="lunch",data=df,palette="Set3")
```

[30]: <matplotlib.axes._subplots.AxesSubplot at 0x7f36c08ac310>

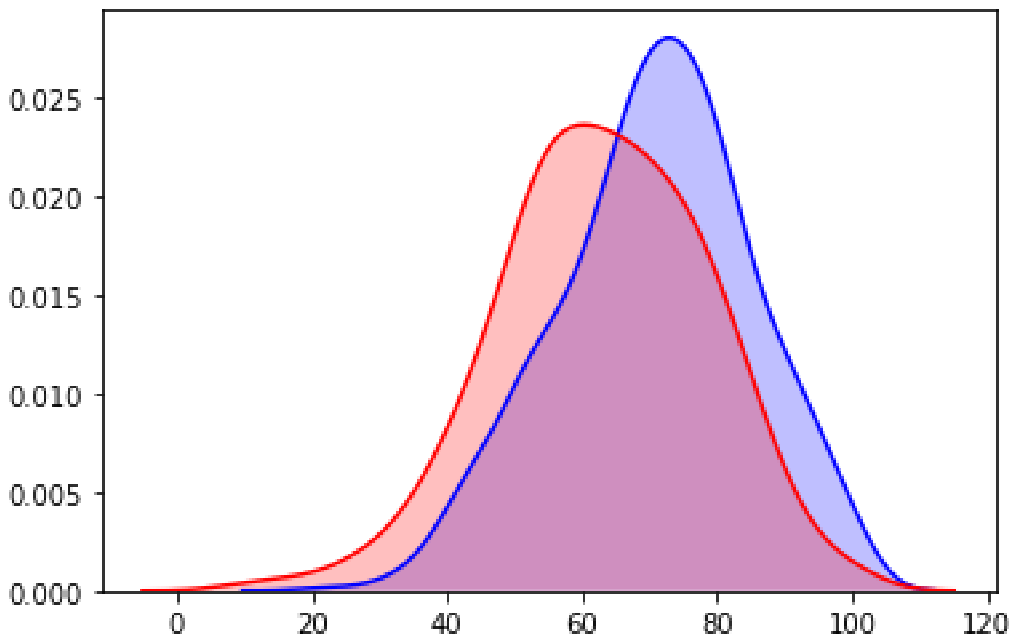


Effect on writing marks

[31]:
```
sns.kdeplot(df.
→loc[(df["lunch"]=="standard")]['write'],shade=True,color="b",legend=False)
sns.kdeplot(df.loc[(df["lunch"]=="free/
→reduced")]['write'],shade=True,color='r',legend=False)
df.groupby("lunch")["write"].describe()
```

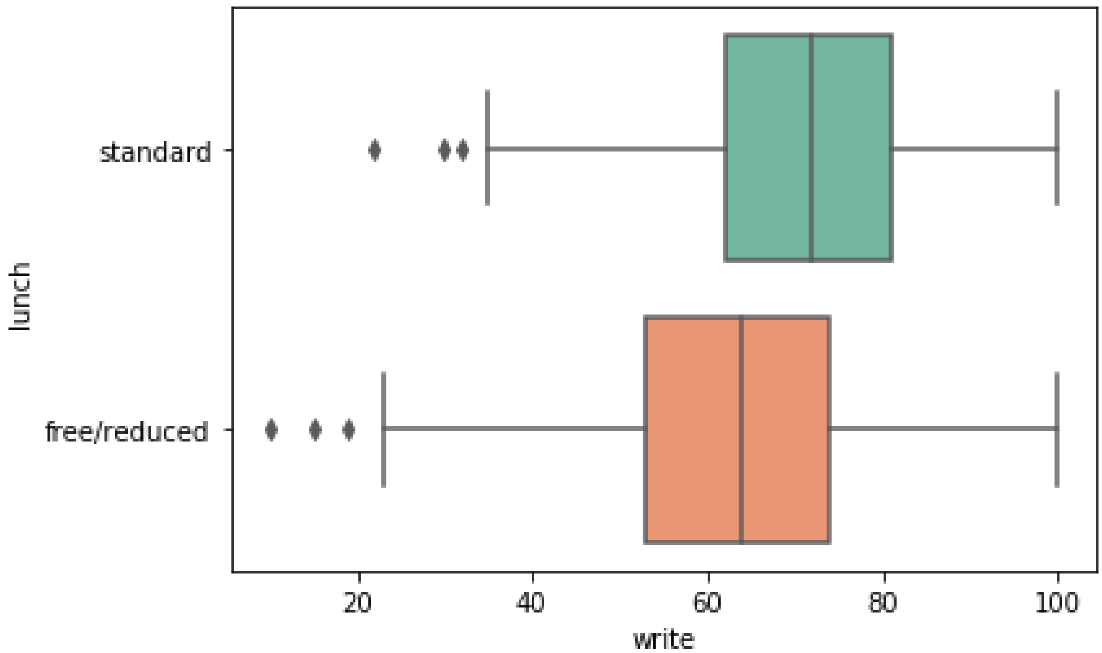
[31]:

	count	mean	std	min	25%	50%	75%	max
lunch								
free/reduced	355.0	63.022535	15.433823	10.0	53.0	64.0	74.0	100.0
standard	645.0	70.823256	14.339487	22.0	62.0	72.0	81.0	100.0



[32]:
```
sns.boxplot(x="write",y="lunch",data=df,palette="Set2")
```

[32]: <matplotlib.axes._subplots.AxesSubplot at 0x7f36c019e810>

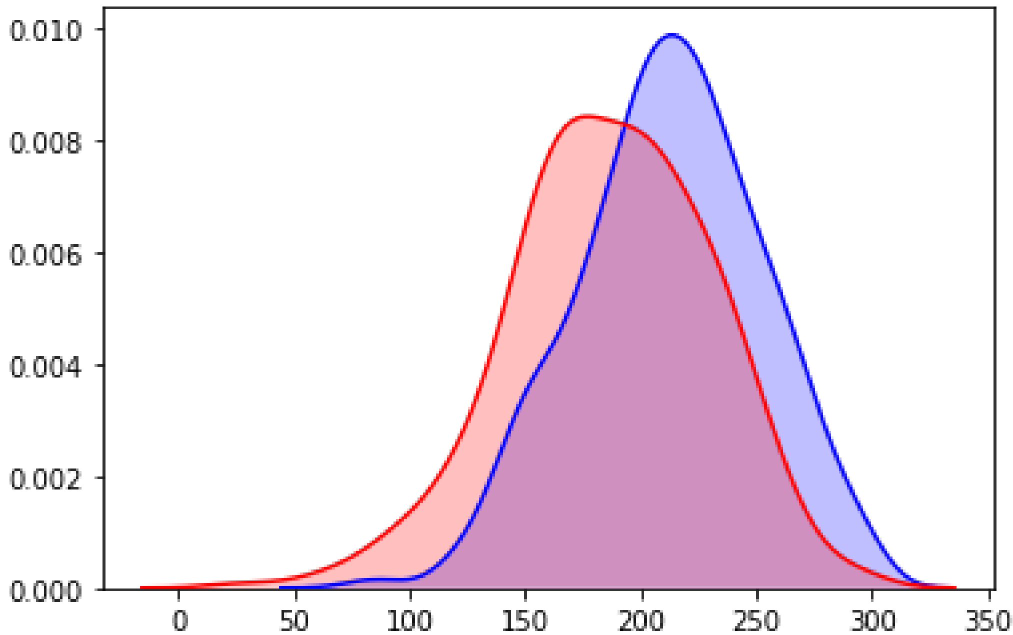


Effect on overall marks

[33]:
```
sns.kdeplot(df.
 ↪loc[(df["lunch"]=="standard")]['sum'],shade=True,color="b",legend=False)
sns.kdeplot(df.loc[(df["lunch"]=="free/
 ↪reduced")]['sum'],shade=True,color='r',legend=False)
df.groupby("lunch")["sum"].describe()
```

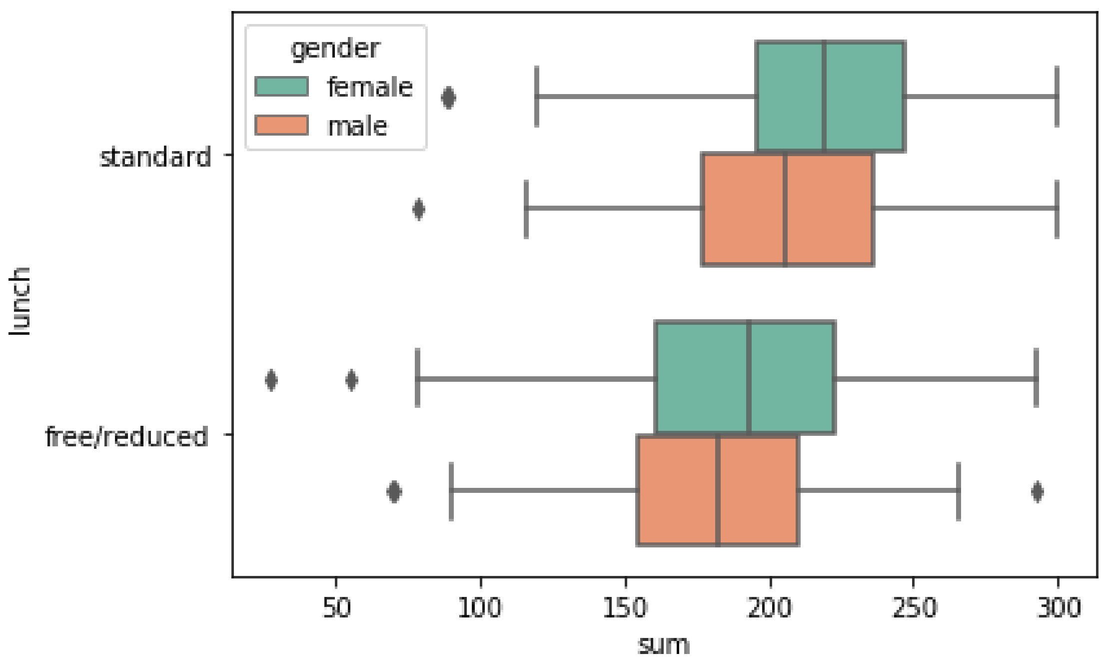
[33]:

	count	mean	std	min	25%	50%	75%	max
lunch								
free/reduced	355.0	186.597183	43.374971	27.0	158.5	188.0	217.5	293.0
standard	645.0	212.511628	39.559515	78.0	187.0	214.0	239.0	300.0



[34]:
```
sns.boxplot(x="sum",y="lunch",data=df,palette="Set2",hue="gender")
```

[34]: <matplotlib.axes._subplots.AxesSubplot at 0x7f36c0168750>



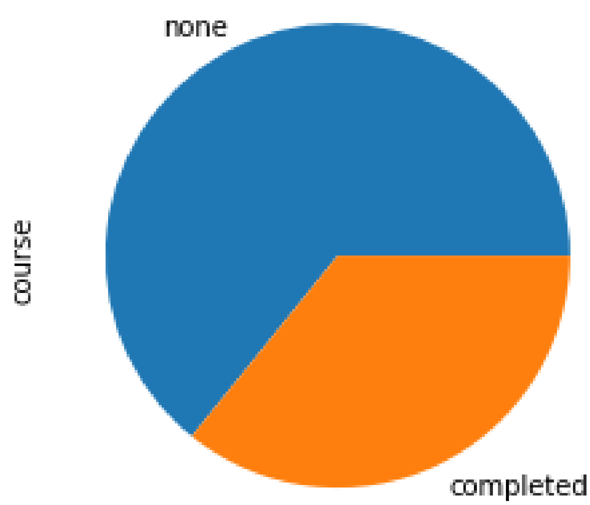
4.1 Analysis of effect of lunch on performance of students

It is quite evident from the above graph that **children who have a "standard lunch" perform much better** than the ones with "free/reduced lunch" in all 3 subjects. The mean total for those **having *free/reduced lunch* is 186.5** while for those with ***standard lunch" is 212.51.***

5 Effect of course status on marks

[35]:
```
df.course.value_counts().plot(kind="pie")
```

[35]: <matplotlib.axes._subplots.AxesSubplot at 0x7f36c0135b10>

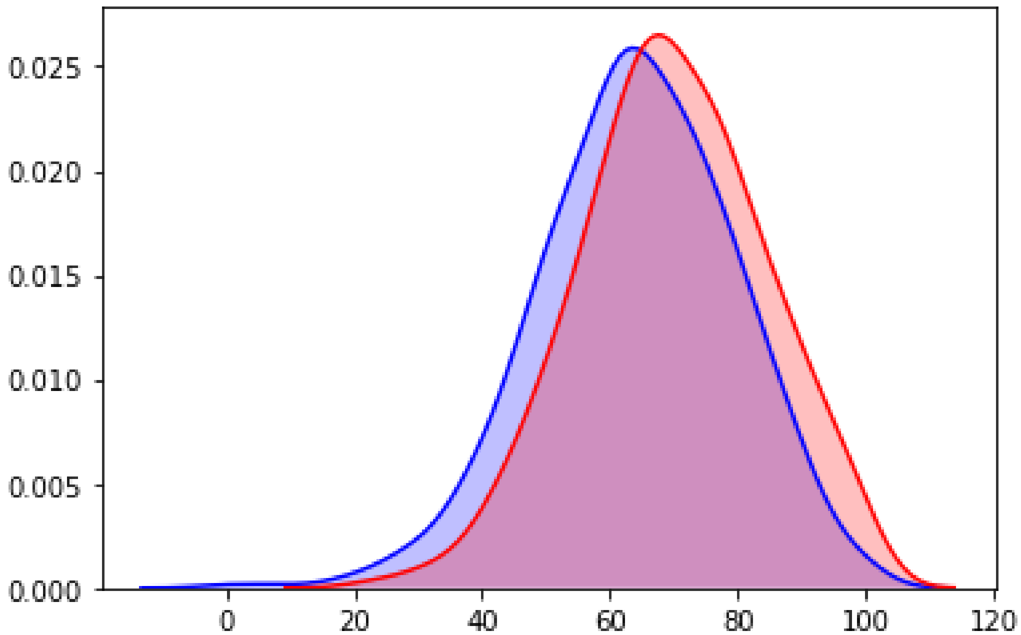


Effect on math marks

[36]:
```
sns.kdeplot(df.
 ↪loc[(df["course"]=="none")]['math'],shade=True,color="b",legend=False)
sns.kdeplot(df.
 ↪loc[(df["course"]=="completed")]['math'],shade=True,color='r',legend=False)
df.groupby("course")["math"].describe()
```

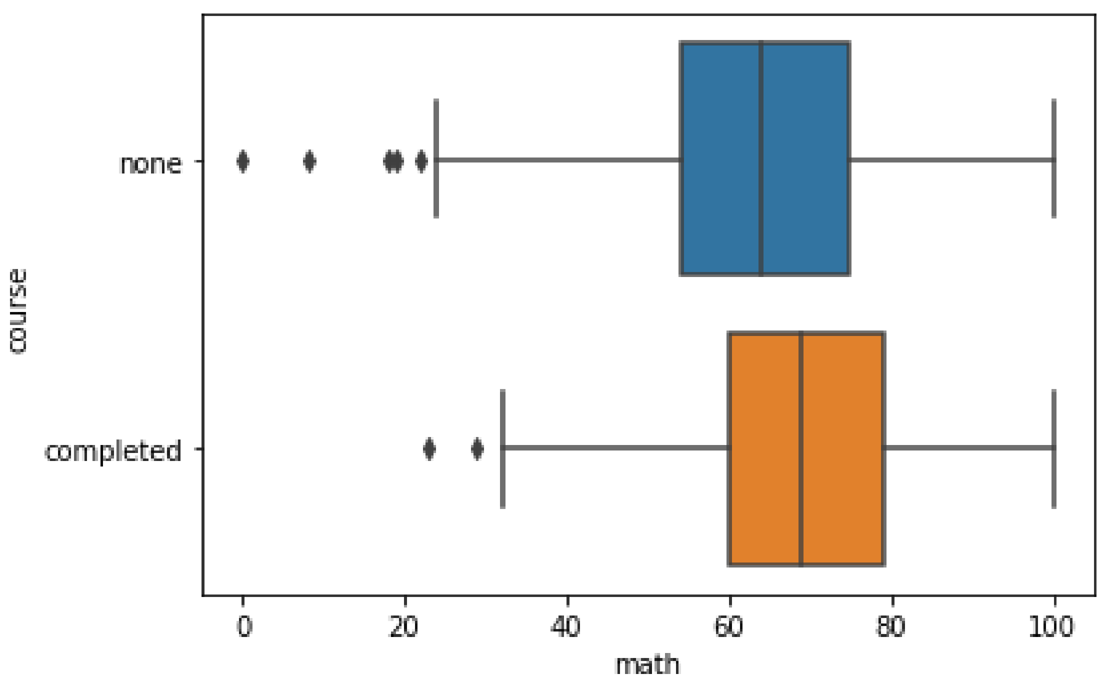
[36]:

course	count	mean	std	min	25%	50%	75%	max
completed	358.0	69.695531	14.444699	23.0	60.0	69.0	79.00	100.0
none	642.0	64.077882	15.192376	0.0	54.0	64.0	74.75	100.0




```
[37]: sns.boxplot(x="math",y="course",data=df)
```

```
[37]: <matplotlib.axes._subplots.AxesSubplot at 0x7f36c076a750>
```

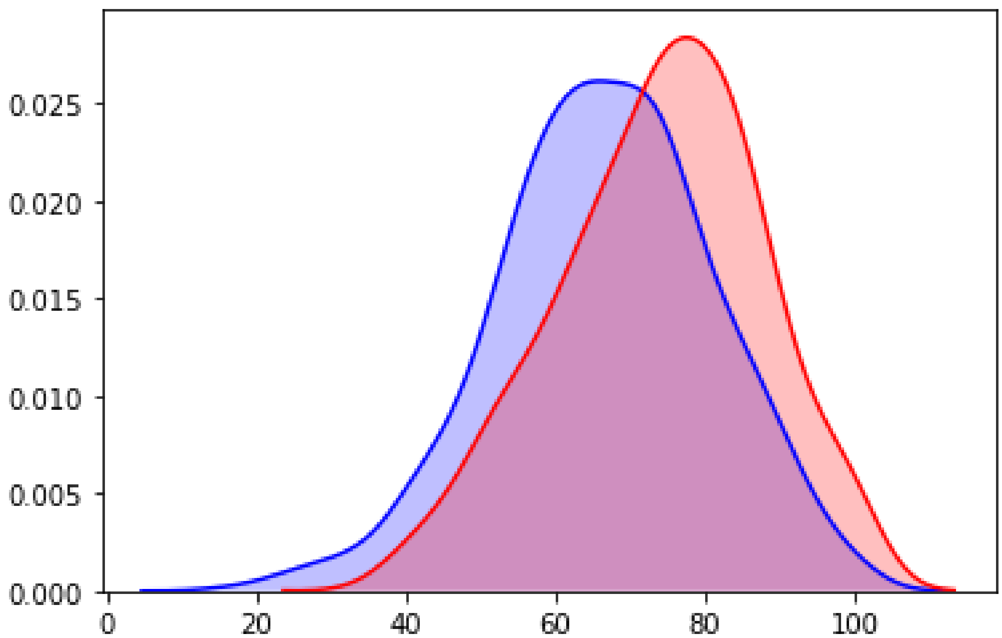


Effect on reading marks

[38]:
```
sns.kdeplot(df.
 ↪loc[(df["course"]=="none")]['read'],shade=True,color="b",legend=False)
sns.kdeplot(df.
 ↪loc[(df["course"]=="completed")]['read'],shade=True,color='r',legend=False)
df.groupby("course")["read"].describe()
```

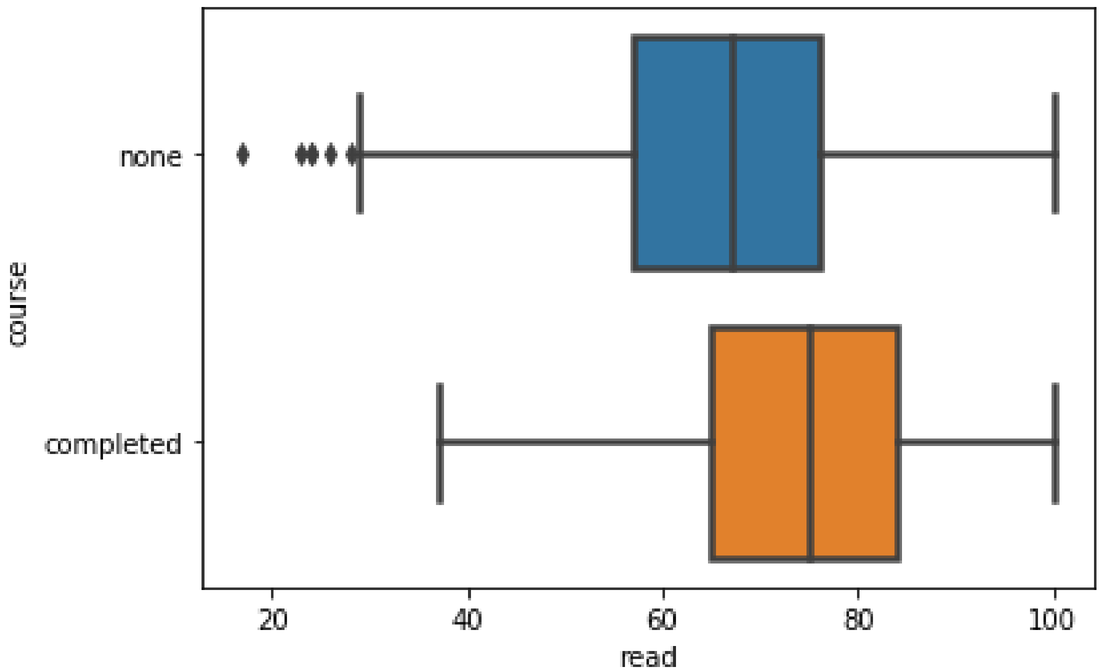
[38]:

	count	mean	std	min	25%	50%	75%	max
course								
completed	358.0	73.893855	13.638384	37.0	65.0	75.0	84.0	100.0
none	642.0	66.534268	14.463885	17.0	57.0	67.0	76.0	100.0



[39]:
```
sns.boxplot(x="read",y="course",data=df,linewidth=2.5          )
```

[39]: <matplotlib.axes._subplots.AxesSubplot at 0x7f36c08a4ed0>

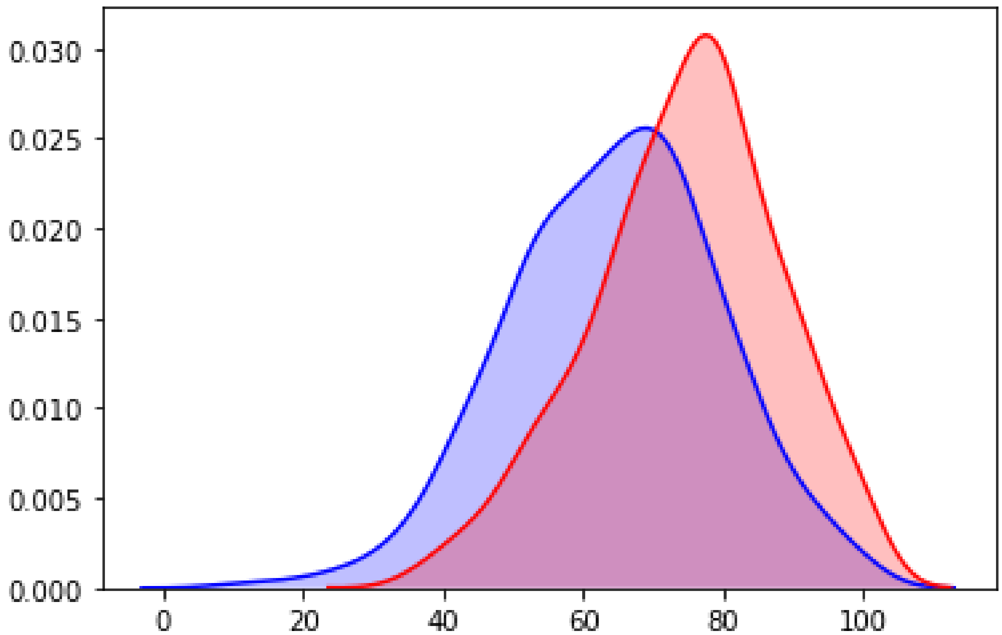


Effect on writing marks

[40]:
```
sns.kdeplot(df.
 ↪loc[(df["course"]=="none")]['write'],shade=True,color="b",legend=False)
sns.kdeplot(df.
 ↪loc[(df["course"]=="completed")]['write'],shade=True,color='r',legend=False)
df.groupby("course")["write"].describe()
```

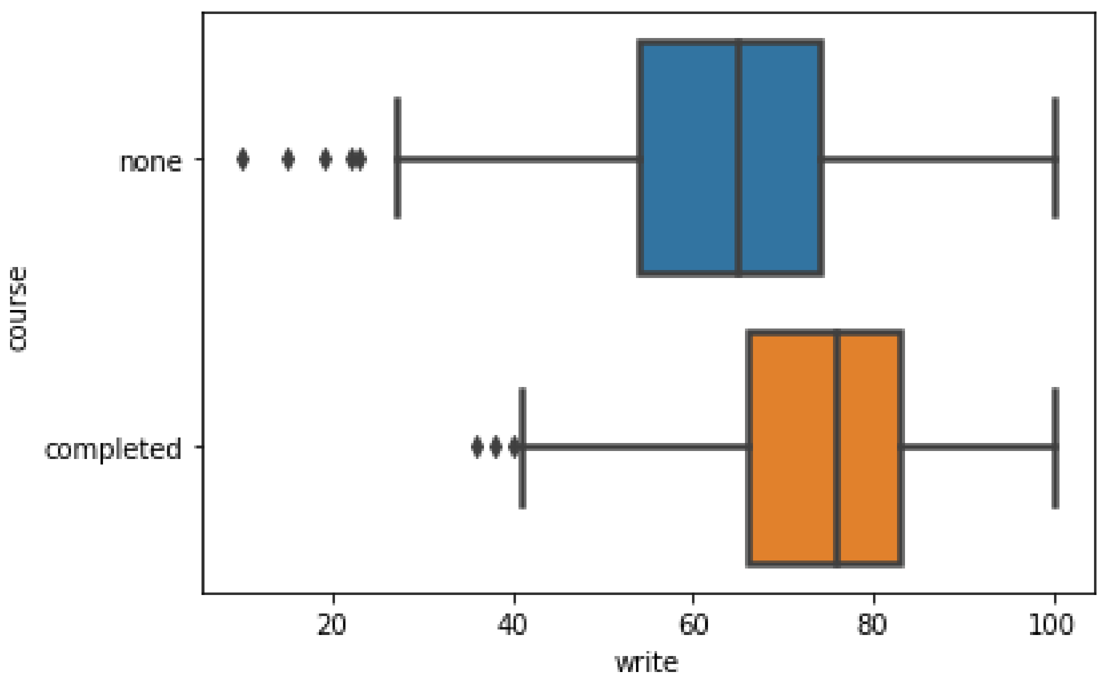
[40]:

	count	mean	std	min	25%	50%	75%	max
course								
completed	358.0	74.418994	13.375335	36.0	66.0	76.0	83.0	100.0
none	642.0	64.504673	14.999661	10.0	54.0	65.0	74.0	100.0




```
[41]: sns.boxplot(x="write",y="course",data=df,linewidth=2.5)
```

```
[41]: <matplotlib.axes._subplots.AxesSubplot at 0x7f36c039f610>
```

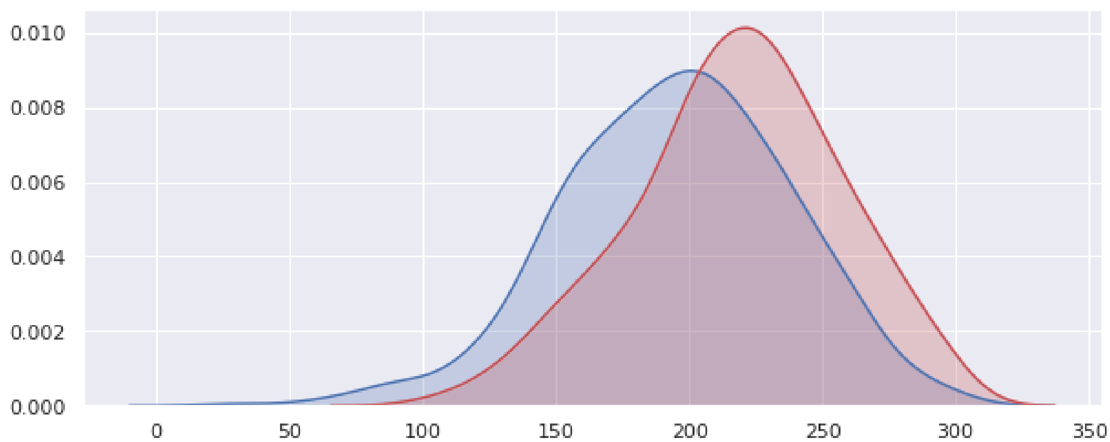


Effect on total marks

[63]:
```
sns.kdeplot(df.
 ↪loc[(df["course"]=="none")]['sum'],shade=True,color="b",legend=False)
sns.kdeplot(df.
 ↪loc[(df["course"]=="completed")]['sum'],shade=True,color='r',legend=False)
df.groupby("course")["sum"].describe()
```

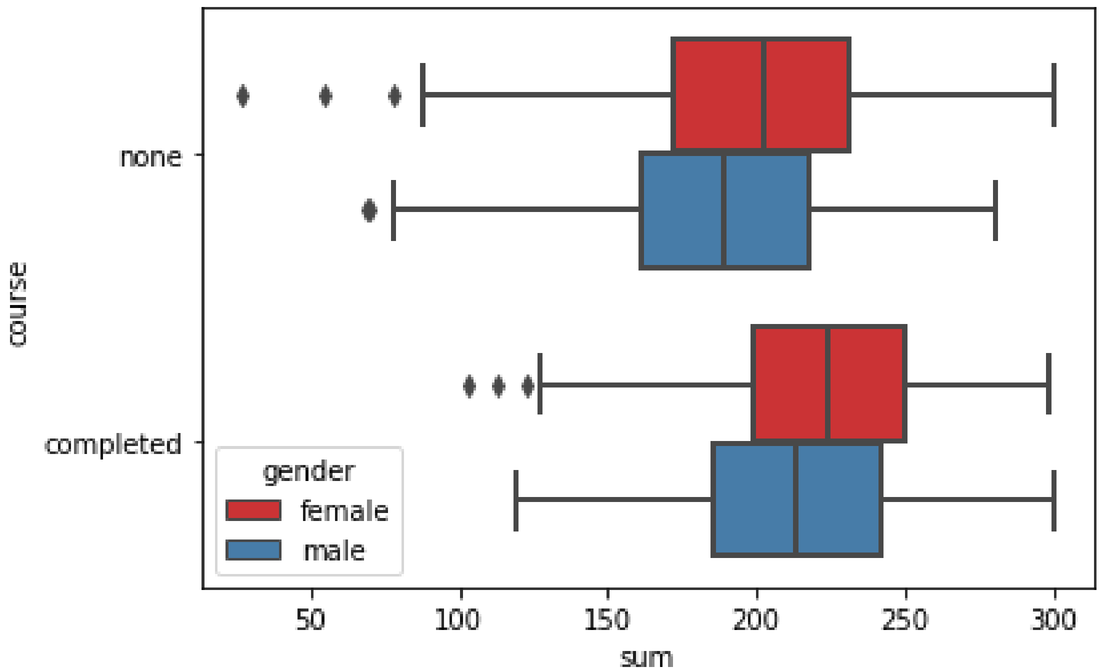
[63]:

	count	mean	std	min	25%	50%	75%	max
course								
completed	358.0	218.008380	39.110881	103.0	195.00	220.5	246.5	300.0
none	642.0	195.116822	42.560121	27.0	166.25	196.0	225.0	300.0



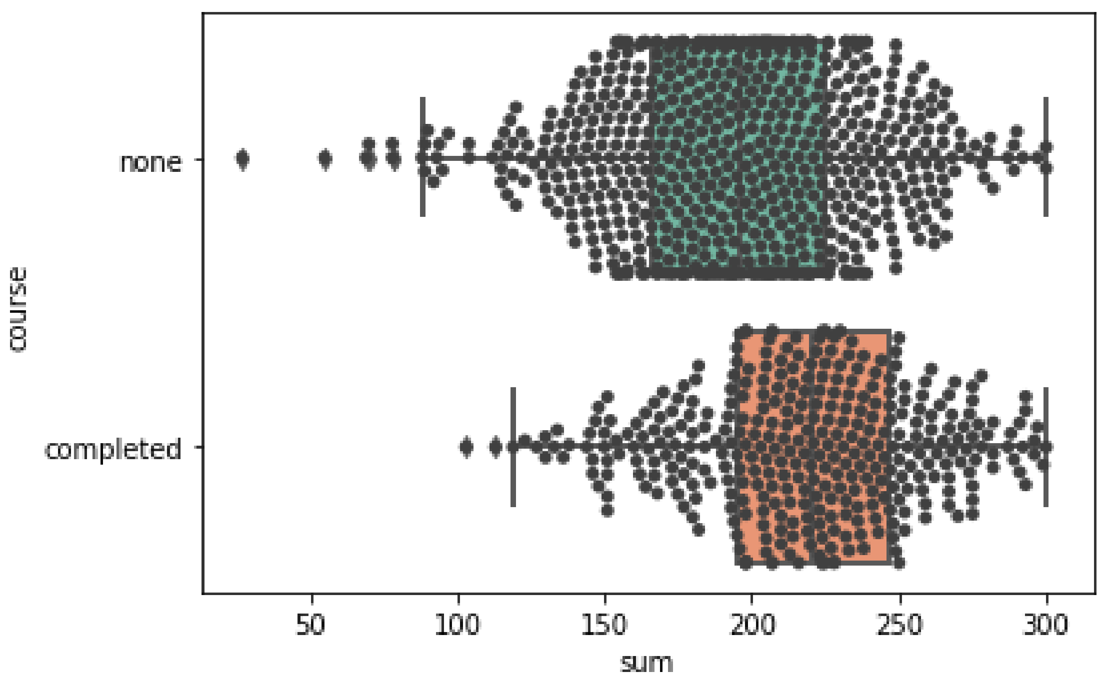
[43]:
```
sns.boxplot(x="sum",y="course",data=df,hue="gender",palette="Set1",linewidth=2)
```

[43]: <matplotlib.axes._subplots.AxesSubplot at 0x7f36c0039290>



[44]:
```
sns.swarmplot(x="sum",y="course",data=df,color=".25")
sns.boxplot(x="sum",y="course",data=df,palette="Set2",linewidth=2)
```

[44]: <matplotlib.axes._subplots.AxesSubplot at 0x7f36bff69a10>



5.1 Contrast in peformance in people who have completed the course Vs those who didn't

It is evident from the above plot that **people who have completed the course perform better on average, than those who didn't .** However, surprisingly, **the difference in marks is not as much as we would expect.** So, we can infer that the course is not well-designed enough to improve students' performance. **The difference in corrsponding means in maths is about 5, that for reading scores is just 7 and that for writing scores is only 9.** However, the difference in scores increases in the sequence "maths","reading scores" and "writing scores".

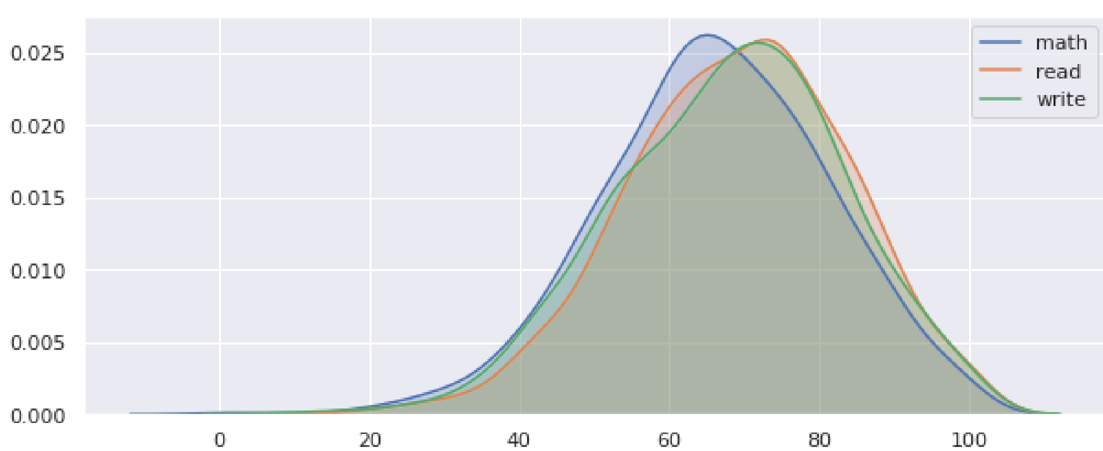
6 General Observations

7 Relationship between marks in different subjects

7.1 Insight 1: No subject liked or disliked unanimously by all students together

[60]:
```
sns.kdeplot(df['math'],shade=True)
sns.kdeplot(df['read'],shade=True)
sns.kdeplot(df['write'],shade=True)
```

[60]: <matplotlib.axes._subplots.AxesSubplot at 0x7f36c09f3110>



As can be seen above, there is no major difference in the curves of the 3 subjects. This shows that on average, all subjects are favoured equally by the students. There are certainly cases where a particular student may like one subject ad does not like the other. But there is no subject which is unanimously liked or disliked by all the students.

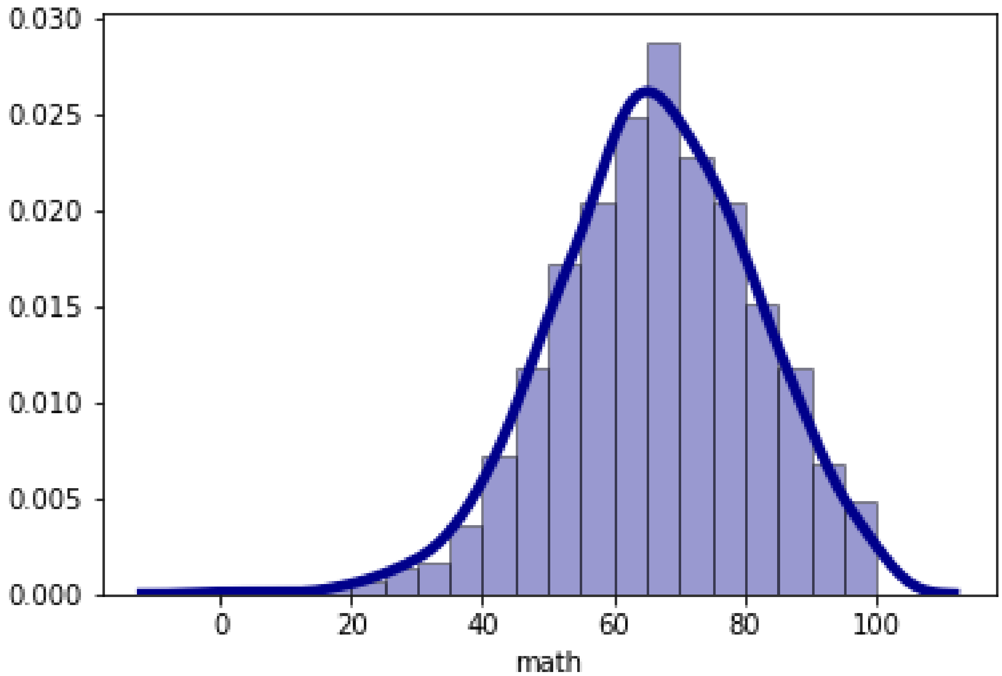
7.2 Insight 2: Analysis of histograms

7.2.1 Histogram for math marks

The distribution can be classified as a **"normal distribution"**. In a normal or "typical" distribution, points are as likely to occur on one side of the average as on the other.

[46]:
```
# Density Plot and Histogram of all arrival delays
sns.distplot(df["math"], hist=True, kde=True,
             bins=20, color = 'darkblue',
             hist_kws={'edgecolor':'black'},
             kde_kws={'linewidth': 4})
```

[46]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f36bfefb290>
```

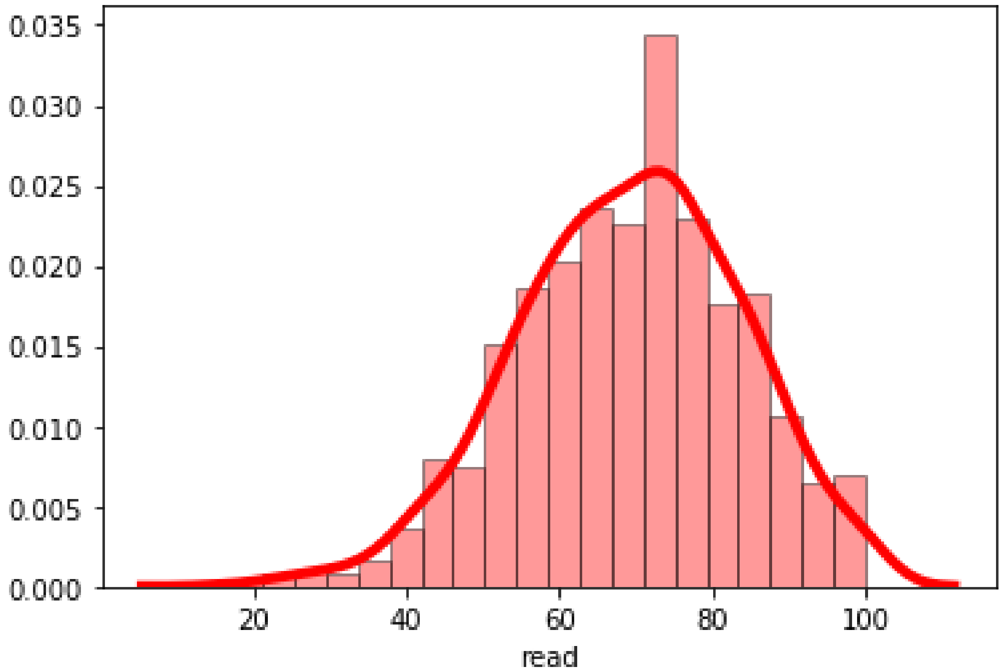


7.2.2 Histogram for Reading marks

The distribution can be classified as a **"normal distribution"**. In a normal or "typical" distribution, points are as likely to occur on one side of the average as on the other.

[47]:
```
sns.distplot(df["read"], hist=True, kde=True,
             bins=20, color = 'red',
             hist_kws={'edgecolor':'black'},
             kde_kws={'linewidth': 4})
```

[47]: <matplotlib.axes._subplots.AxesSubplot at 0x7f36be5b4b50>

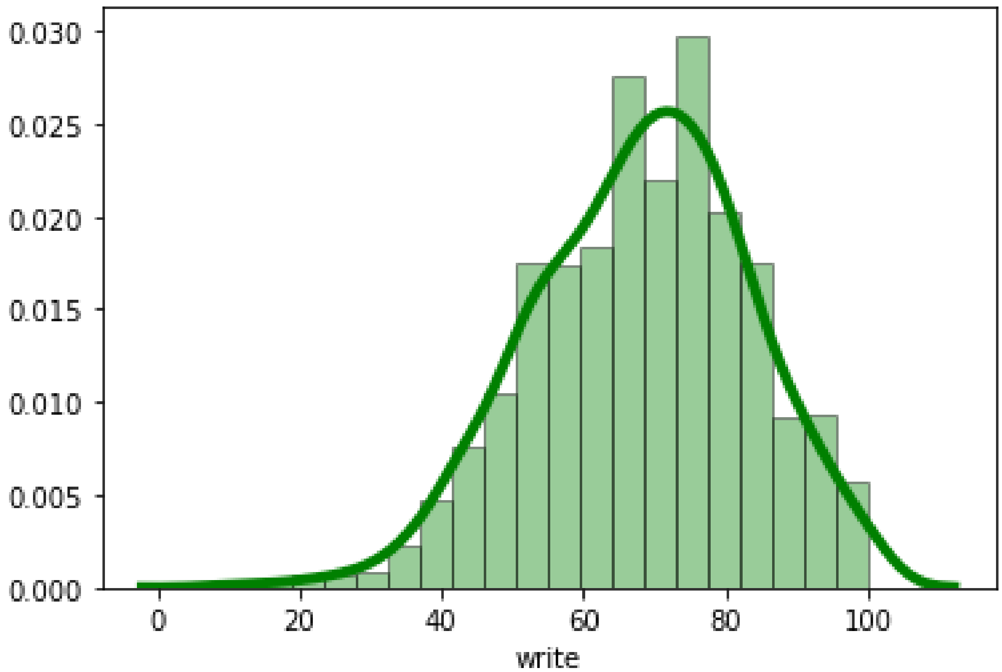


7.2.3 Histogram for Writing marks

The histogram may be classified as a ***"bimodal" or "double peaked" distribution***.This indicates outcomes of two processes with different distributions are combined in one set of data. #### In this situation, it is likely that the Writing paper was conducted in 2 sets of paper with questions of varying difficulty ie paper A had easy questions while paper B had comparitively tougher questions and hence, the peaks of the two papers do not coincide.

[48]:
```
sns.distplot(df["write"], hist=True, kde=True,bins=20, color =␣
↪'green',hist_kws={'edgecolor':'black'},
             kde_kws={'linewidth': 4})
```

[48]: <matplotlib.axes._subplots.AxesSubplot at 0x7f36be4e3090>



7.3 Insight 3: Pattern of marks of a particular student in all 3 subjects

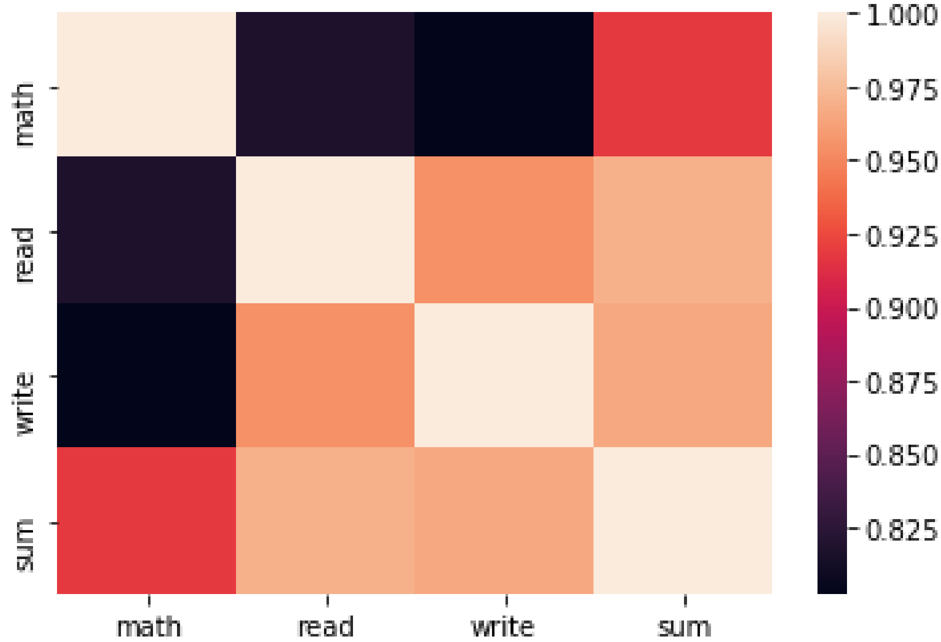
[49]:
```
df.corr()
```

[49]:

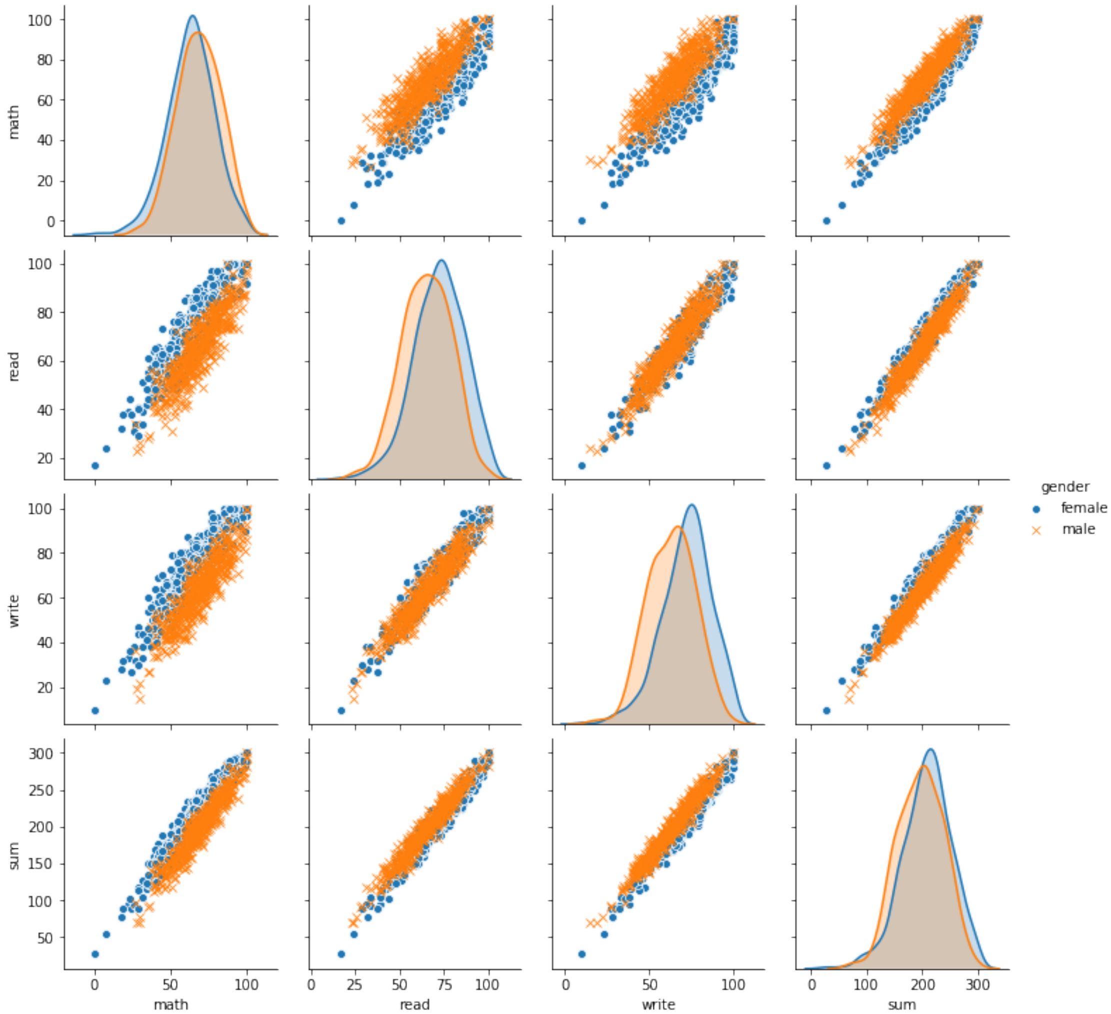
	math	read	write	sum
math	1.000000	0.817580	0.802642	0.918746
read	0.817580	1.000000	0.954598	0.970331
write	0.802642	0.954598	1.000000	0.965667
sum	0.918746	0.970331	0.965667	1.000000

[50]:
```
sns.heatmap(df.corr())
sns.pairplot(df, hue="gender", markers=["o", "x"])
```

[50]: <seaborn.axisgrid.PairGrid at 0x7f36be3fff50>



math
read
write
sum
math
read
write
sum
1.000
0.975
0.950
0.925
0.900
0.875
0.850
0.825

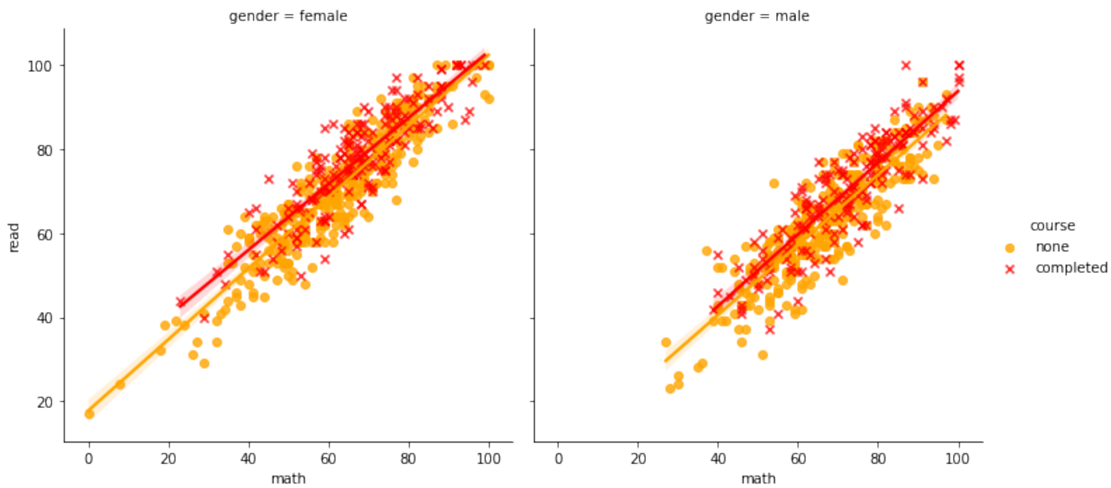


7.3.1 Analysis:

From the heatmap, we can observe that the slopes for all possible correlations between the 3 subjects is **close to 1.** ****This shows that when a student performs well in one subject, he is likely to give a similar performance in another subject and vice-versa.**** In the below plots, we can see that all data points are very close to a hypothetical **y=x** line. Also, there are **no data points at all which are very far away from the *y=x* line.** #### So, we conclude that there is not a single instance of a student who has performed extremely well in one subject but has performed badly in another.

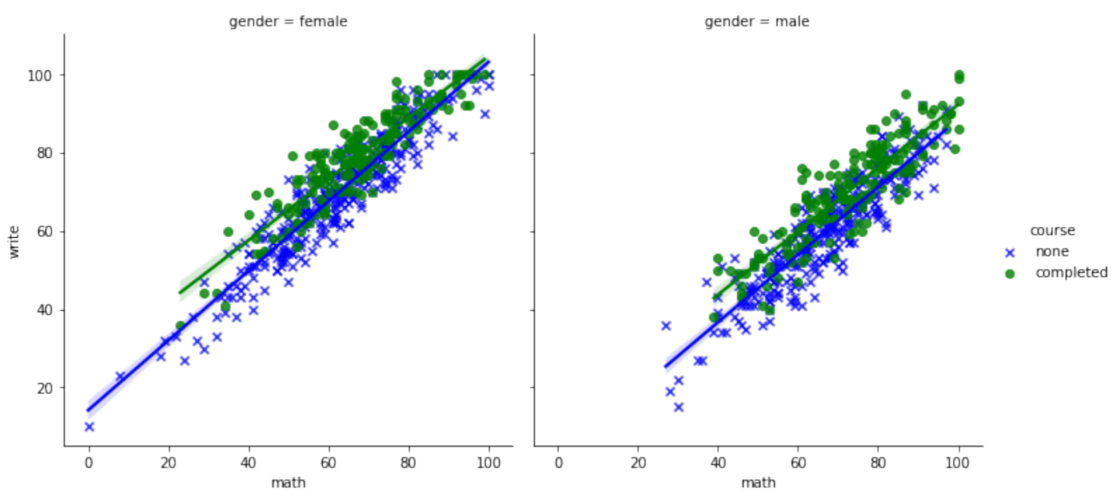
[51]:
```
sns.
↪lmplot('math','read',data=df,order=1,col="gender",hue="course",scatter=True,palette=dict(co
↪none="orange"),markers=["o", "x"])
```

[51]:
```
<seaborn.axisgrid.FacetGrid at 0x7f36bdcc4310>
```



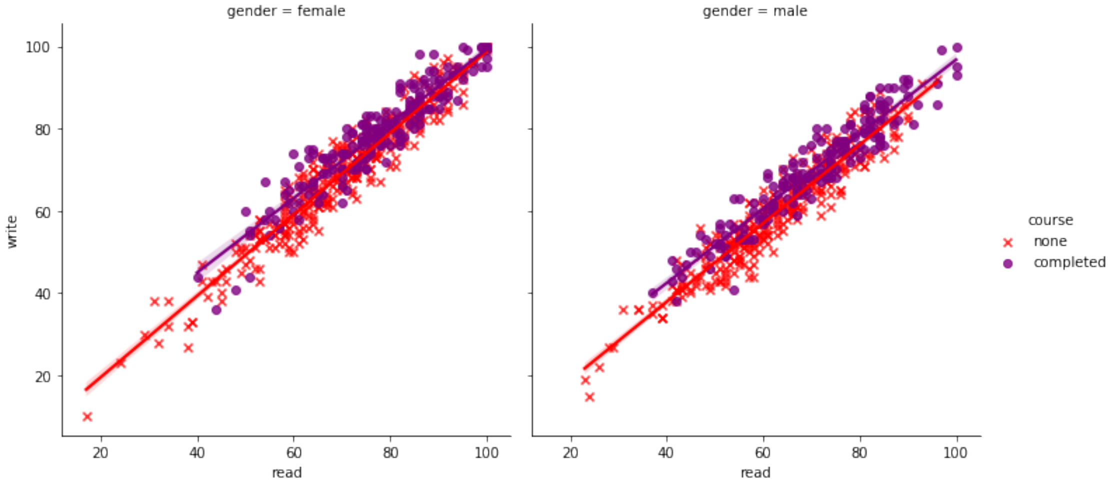

```
[52]: sns.
      ↪lmplot('math','write',data=df,order=1,col="gender",hue="course",scatter=True,palette=dict(c
      ↪none="blue"),markers=["x", "o"])
```

```
[52]: <seaborn.axisgrid.FacetGrid at 0x7f36bdc1bc50>
```



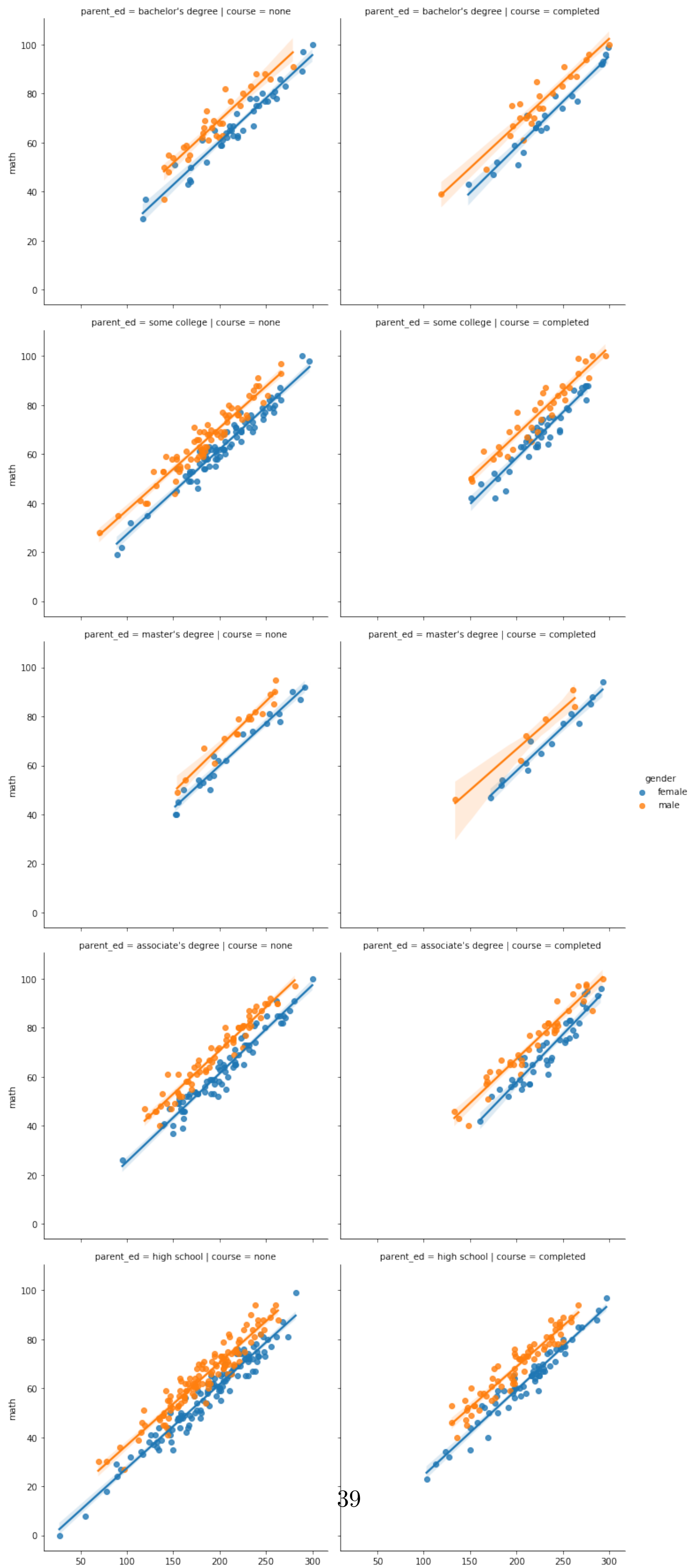

```
[53]: sns.
      ↪lmplot('read','write',data=df,order=1,col="gender",hue="course",scatter=True,palette=dict(c
      ↪none="red"),markers=["x", "o"])
```

```
[53]: <seaborn.axisgrid.FacetGrid at 0x7f36bda84e50>
```




```
[54]: sns.
       ↪lmplot('sum','math',data=df,order=1,row="parent_ed",col="course",hue="gender")
```

```
[54]: <seaborn.axisgrid.FacetGrid at 0x7f36bc70a9d0>
```


parent_ed = bachelor's degree | course = none
parent_ed = bachelor's degree | course = completed
parent_ed = some college | course = none
parent_ed = some college | course = completed
parent_ed = master's degree | course = none
parent_ed = master's degree | course = completed
parent_ed = associate's degree | course = none
parent_ed = associate's degree | course = completed
parent_ed = high school | course = none
parent_ed = high school | course = completed
math
sum
gender
female
male

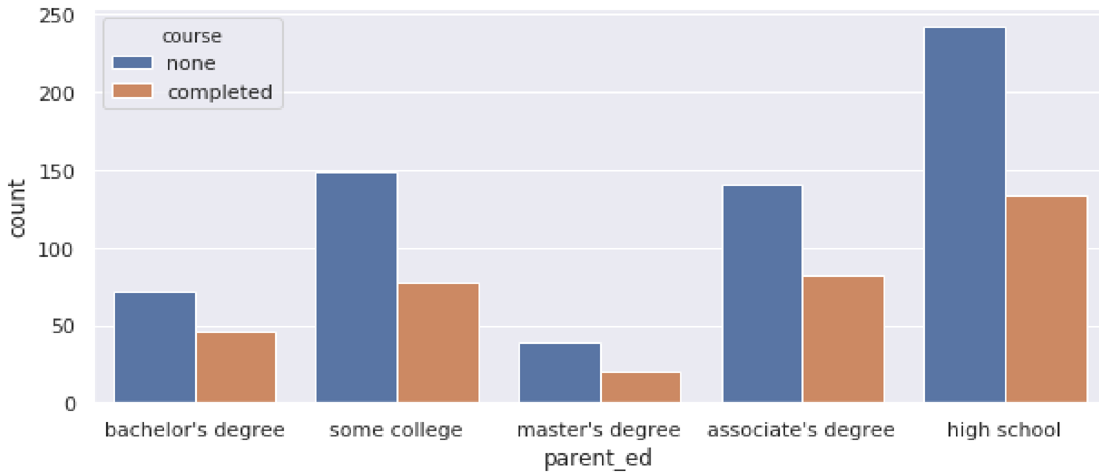
7.4 Insight 4: Relation bewteen two variable factors

7.5 Relation between parents' education and course completion rates

[55]:
```
sns.set(rc={'figure.figsize':(10,4)})
sns.countplot(x="parent_ed",data=df,hue="course")
df.groupby(['parent_ed','course'])["sum"].describe()
```

[55]:
```
                             count        mean        std    min     25%  \
parent_ed         course
associate's degree completed   82.0  224.817073  37.146400  133.0  202.50
                   none       140.0  199.271429  40.341856   95.0  166.75
bachelor's degree  completed   46.0  228.717391  40.469831  119.0  204.75
                   none        72.0  207.500000  40.850121  117.0  181.75
high school        completed  133.0  205.015038  38.824583  103.0  179.00
                   none       242.0  185.111570  43.233900   27.0  157.00
master's degree    completed   20.0  228.950000  41.456985  134.0  208.75
                   none        39.0  216.615385  40.359317  152.0  186.00
some college       completed   77.0  223.961039  34.857017  151.0  201.00
                   none       149.0  195.852349  40.954057   70.0  175.00

                                50%     75%    max
parent_ed         course
associate's degree completed  229.0  253.00  293.0
                   none       199.5  227.25  300.0
bachelor's degree  completed  224.5  256.25  300.0
                   none       206.5  236.75  300.0
high school        completed  207.0  233.00  297.0
                   none       188.5  215.00  282.0
master's degree    completed  229.0  261.50  293.0
                   none       219.0  252.50  292.0
some college       completed  226.0  248.00  296.0
                   none       195.0  223.00  297.0
```



Firstly, we notice that for any category of parents' education, children who have completed the course on average score better than the ones who didn't take the course. **However, an unexpected trend is that irrespective of parents' educational background, the proportion of students' completing the course VS the ones who didn't take the course stays fairly constant; even though we expected that children of parents' having a higher educational background were more likely to have a higher course completion rate**

7.6 Relation between race and course completion rates

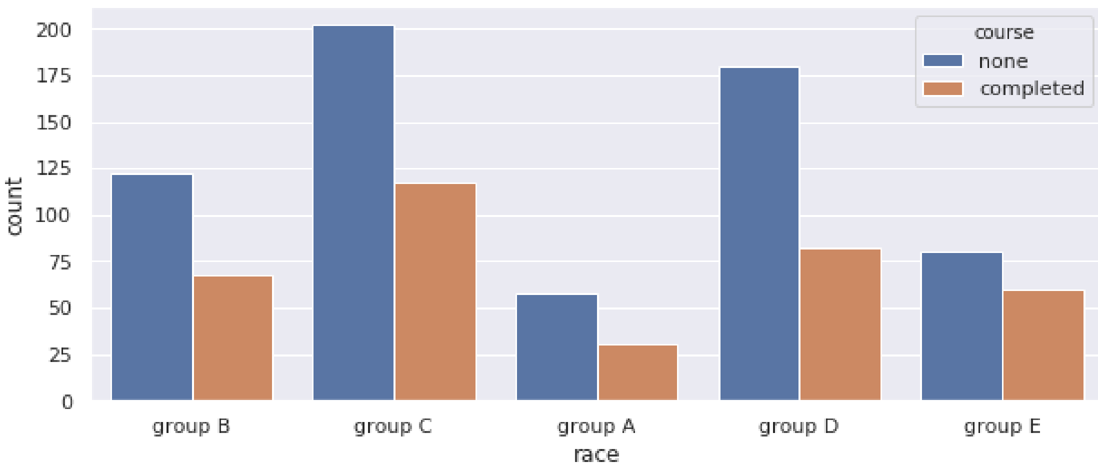
[56]:
```
sns.set(rc={'figure.figsize':(10,4)})
sns.countplot(x="race",data=df,hue="course")
df.groupby(['race','course'])["sum"].describe()
```

[56]:

race	course	count	mean	std	min	25%	50%	75%	\
group A	completed	31.0	210.193548	45.908909	123.0	174.50	219.0	241.50	
	none	58.0	177.637931	37.605383	70.0	154.25	178.0	201.00	
group B	completed	68.0	211.926471	38.625765	103.0	190.75	212.0	243.25	
	none	122.0	187.754098	44.878589	55.0	157.25	188.5	219.75	
group C	completed	117.0	215.606838	39.623434	113.0	193.00	218.0	242.00	
	none	202.0	193.163366	40.599831	27.0	168.25	197.0	219.75	
group D	completed	82.0	220.597561	35.473468	119.0	198.00	223.0	240.25	
	none	180.0	201.588889	40.270425	93.0	171.00	206.0	229.75	
group E	completed	60.0	230.083333	37.837427	133.0	205.00	230.5	254.00	
	none	80.0	209.387500	45.871724	78.0	182.50	212.0	237.25	

race	course	max
group A	completed	289.0
	none	279.0

```
group B completed  278.0
        none       290.0
group C completed  296.0
        none       281.0
group D completed  297.0
        none       297.0
group E completed  300.0
        none       300.0
```



Firstly, we notice irrespective of race, children who have completed the course on average score better than the ones who didn't take the course. However, an unexpected trend is that irrespective parents' educational background, the proportion of students' completing the course VS the ones who didn't take the course stays fairly constant. ### Group E is the only group where the difference in the students who complete the course and those who don't is not very high.###

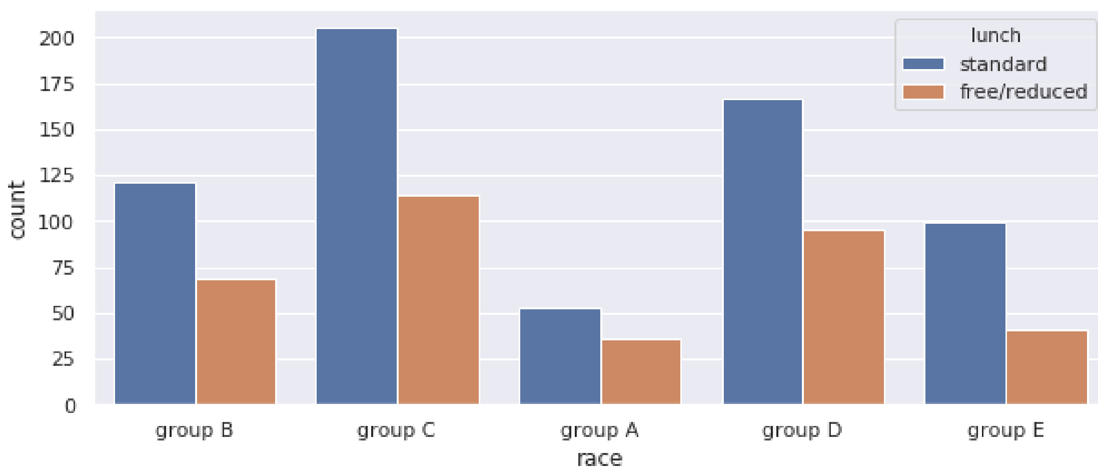
8 Miscellaneous plots

[57]:
```
sns.set(rc={'figure.figsize':(10,4)})
sns.countplot(x="race",data=df,hue="lunch")
df.groupby(['race','lunch'])["sum"].describe()
```

[57]:
```
                        count        mean        std    min     25%    50%  \
race    lunch
group A free/reduced     36.0  172.972222  41.189101   70.0  147.00  168.0
        standard         53.0  199.849057  41.690894  118.0  168.00  195.0
group B free/reduced     69.0  182.927536  47.807617   55.0  157.00  186.0
        standard        121.0  204.090909  40.215876   89.0  178.00  203.0
group C free/reduced    114.0  181.236842  39.564510   27.0  160.25  183.5
        standard        205.0  212.604878  38.462421   88.0  185.00  214.0
```

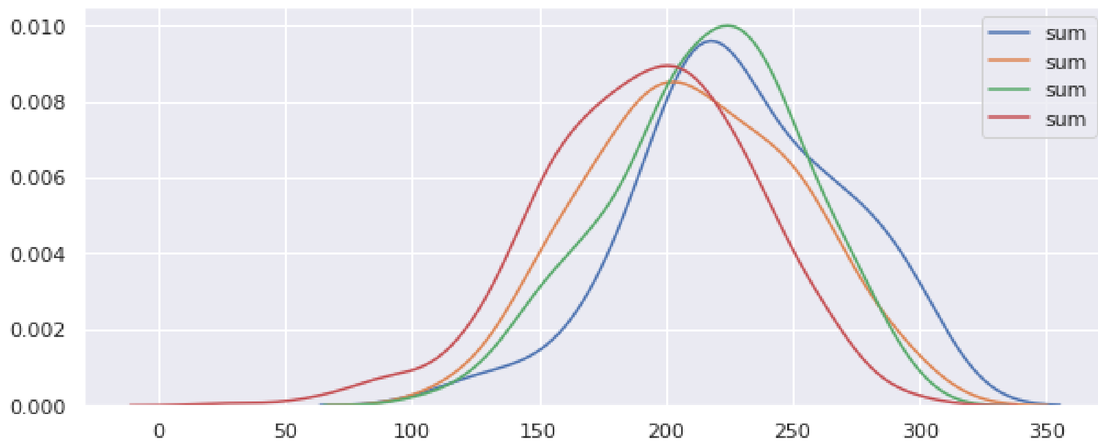
```
group D free/reduced   95.0  194.000000  41.273349   93.0  163.50  195.0
        standard      167.0  215.239521  36.826230  116.0  194.00  218.0
group E free/reduced   41.0  202.487805  46.838618  104.0  167.00  210.0
        standard       99.0  224.787879  40.809981   78.0  202.00  226.0

                         75%    max
race    lunch
group A free/reduced  201.75  250.0
        standard      224.00  289.0
group B free/reduced  220.00  268.0
        standard      236.00  290.0
group C free/reduced  208.75  268.0
        standard      237.00  296.0
group D free/reduced  224.00  293.0
        standard      239.00  297.0
group E free/reduced  235.00  293.0
        standard      255.00  300.0
```



[58]:
```
#Blue
sns.kdeplot(df.loc[(df["course"]=="completed")&((df["parent_ed"]=="master's␣
↪degree")|(df["parent_ed"]=="bachelor's degree"))]["sum"],legend=True)
#Orange
sns.kdeplot(df.loc[(df["course"]=="none")&((df["parent_ed"]=="master's␣
↪degree")|(df["parent_ed"]=="bachelor's degree"))]["sum"],legend=True)
#Green
sns.kdeplot(df.loc[(df["course"]=="completed")&((df["parent_ed"]!="master's␣
↪degree")&(df["parent_ed"]!="bachelor's degree"))]["sum"],legend=True)
#Yellow
sns.kdeplot(df.loc[(df["course"]=="none")&((df["parent_ed"]!="master's␣
↪degree")&(df["parent_ed"]!="bachelor's degree"))]["sum"],legend=True)
```

[58]: <matplotlib.axes._subplots.AxesSubplot at 0x7f36bc0a65d0>



[59]:
```
sns.countplot(x="parent_ed",data=df,hue="race")
```

[59]: <matplotlib.axes._subplots.AxesSubplot at 0x7f36bc0f9150>