st-analysis

July 3, 2024

1 Objective

This project is type analyze the factors Affecting the scoring of the students. In the the scores were taken as the depended variable and the remaining factors were taken as the independent and the analysis was performed each and very factor and the insights were drawn.

2 Steps

1. Dataset was downloaded for the kaggle with the kaggle API usage.
2. Correct the Column names.
3. Drop Unnamaed Column.
4. Change weekly_study_hours column
5. Analysis
    1. Gender Destribution
    2. Impact by Parent Eduction
    3. Impact by Parent Marital Status
    4. Impact by Test preparation
    5. Impact by Weekly Study Hours
    6. Impact by sport practice
    7. Impact by Transport means
    8. Impact by no of sibilings
    9. Impact of lunch type
    10. impact of first child or not
6. Distribution of the ethnic groups.
7. Insights

[31]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import kaggle
import re
```

[16]:
```
#!kaggle datasets download desalegngeb/students-exam-scores -f␣
↪Expanded_data_with_more_features.csv
```

[17]:
```
#as it is downloaded in the zip format we can unzip by using the below commands
#import zipfile
#zip_ref = zipfile.ZipFile('Expanded_data_with_more_features.csv.zip')
#zip_ref.extractall() # extract file to dir
#zip_ref.close() # close file
```

[18]:
```
st = pd.read_csv('Expanded_data_with_more_features.csv')
```

[19]:
```
st.head()
```

[19]:

	Unnamed: 0	Gender	EthnicGroup	ParentEduc	LunchType	TestPrep	ParentMaritalStatus	PracticeSport	IsFirstChild	NrSiblings	TransportMeans	WklyStudyHours	MathScore	ReadingScore	WritingScore
0	0	female	NaN	bachelor's degree	standard	none	married	regularly	yes	3.0	school_bus	< 5	71	71	74
1	1	female	group C	some college	standard	NaN	married	sometimes	yes	0.0	NaN	5 - 10	69	90	88
2	2	female	group B	master's degree	standard	none	single	sometimes	yes	4.0	school_bus	< 5	87	93	91
3	3	male	group A	associate's degree	free/reduced	none	married	never	no	1.0	NaN	5 - 10	45	56	42
4	4	male	group C	some college	standard	none	married	sometimes	yes	0.0	school_bus	5 - 10	76	78	75

3 Correct the Column names

[36]:
```
#function to add _ after the first instance in the column names
def add_space_before_capital(s):
    return re.sub(r'(?<=[A-Za-z])([A-Z])', r'_\1', s)
```

[37]:
```
st.columns = [add_space_before_capital(col) for col in st.columns]
```

[38]:
```
st.columns
```

[38]:
```
Index(['Unnamed: 0', 'Gender', 'Ethnic_Group', 'Parent_Educ', 'Lunch_Type',
       'Test_Prep', 'Parent_Marital_Status', 'Practice_Sport',
       'Is_First_Child', 'Nr_Siblings', 'Transport_Means', 'Wkly_Study_Hours',
       'Math_Score', 'Reading_Score', 'Writing_Score'],
      dtype='object')
```

[39]:
```
#rename columns names ..make them lower case
st.columns = st.columns.str.lower()
```

[41]:
```
st.columns
```

[41]:
```
Index(['unnamed: 0', 'gender', 'ethnic_group', 'parent_educ', 'lunch_type',
       'test_prep', 'parent_marital_status', 'practice_sport',
       'is_first_child', 'nr_siblings', 'transport_means', 'wkly_study_hours',
       'math_score', 'reading_score', 'writing_score'],
      dtype='object')
```

[42]:
```
st.describe()
```

[42]:

	unnamed: 0	nr_siblings	math_score	reading_score	writing_score
count	30641.000000	29069.000000	30641.000000	30641.000000	30641.000000
mean	499.556607	2.145894	66.558402	69.377533	68.418622
std	288.747894	1.458242	15.361616	14.758952	15.443525
min	0.000000	0.000000	0.000000	10.000000	4.000000
25%	249.000000	1.000000	56.000000	59.000000	58.000000
50%	500.000000	2.000000	67.000000	70.000000	69.000000
75%	750.000000	3.000000	78.000000	80.000000	79.000000
max	999.000000	7.000000	100.000000	100.000000	100.000000

[43]:
```
st.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30641 entries, 0 to 30640
Data columns (total 15 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   unnamed: 0             30641 non-null  int64
 1   gender                 30641 non-null  object
 2   ethnic_group           28801 non-null  object
 3   parent_educ            28796 non-null  object
 4   lunch_type             30641 non-null  object
 5   test_prep              28811 non-null  object
 6   parent_marital_status  29451 non-null  object
 7   practice_sport         30010 non-null  object
 8   is_first_child         29737 non-null  object
 9   nr_siblings            29069 non-null  float64
 10  transport_means        27507 non-null  object
 11  wkly_study_hours       29686 non-null  object
 12  math_score             30641 non-null  int64
 13  reading_score          30641 non-null  int64
 14  writing_score          30641 non-null  int64
dtypes: float64(1), int64(4), object(10)
memory usage: 3.5+ MB
```

[44]:
```
st.isnull().sum()
```

[44]:
```
unnamed: 0                 0
gender                     0
ethnic_group            1840
parent_educ             1845
lunch_type                 0
test_prep               1830
parent_marital_status   1190
practice_sport           631
is_first_child           904
nr_siblings             1572
transport_means         3134
wkly_study_hours         955
math_score                 0
reading_score              0
writing_score              0
dtype: int64
```

As the score columns are not having any null values there is no need to remove the null values.

4 Drop Unnamaed Column

[46]:
```
st = st.drop('unnamed: 0', axis =1)
st.head()
```

[46]:

	gender	ethnic_group	parent_educ	lunch_type	test_prep	\
0	female	NaN	bachelor's degree	standard	none	
1	female	group C	some college	standard	NaN	
2	female	group B	master's degree	standard	none	
3	male	group A	associate's degree	free/reduced	none	
4	male	group C	some college	standard	none	

	parent_marital_status	practice_sport	is_first_child	nr_siblings	\
0	married	regularly	yes	3.0	
1	married	sometimes	yes	0.0	
2	single	sometimes	yes	4.0	
3	married	never	no	1.0	
4	married	sometimes	yes	0.0	

	transport_means	wkly_study_hours	math_score	reading_score	writing_score
0	school_bus	< 5	71	71	74
1	NaN	5 - 10	69	90	88
2	school_bus	< 5	87	93	91
3	NaN	5 - 10	45	56	42
4	school_bus	5 - 10	76	78	75

5 Change wkly_study_hours column

[47]:
```
st['wkly_study_hours'].value_counts()
```

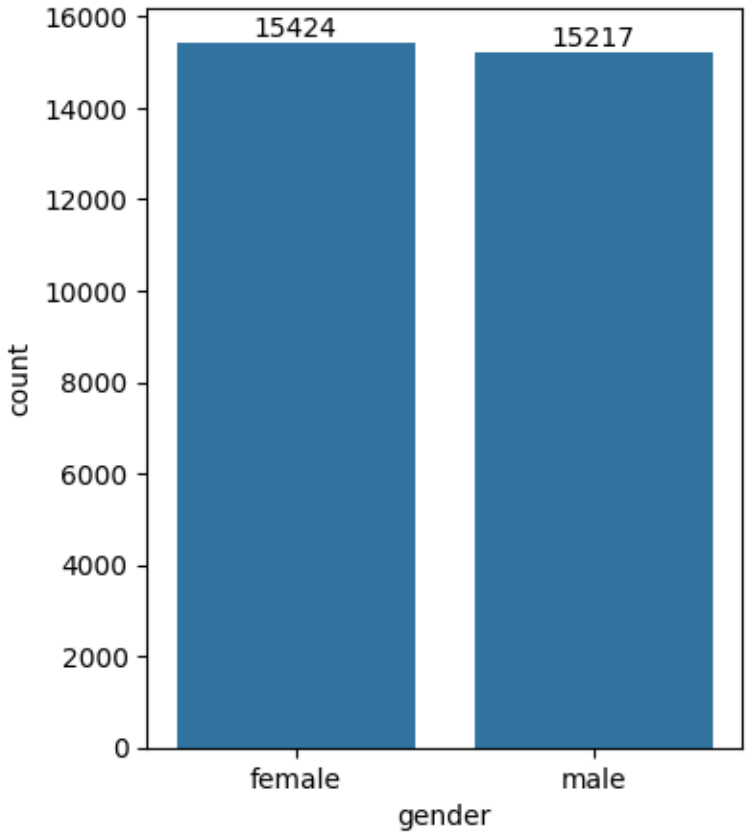
[47]:
```
wkly_study_hours
5 - 10    16246
< 5        8238
> 10       5202
Name: count, dtype: int64
```

as there is no anamoly their no need to change the wkly hours

6 Analysis

6.0.1 Gender Destribution

[51]:
```
plt.figure(figsize= (4,5))
ax = sns.countplot(x= 'gender', data = st)
ax.bar_label(ax.containers[0])
plt.savefig('gender distribution.jpg')
plt.show()
```



From the a bove data we can say that the number of females werer more when compared to males in the data set.

[52]:
```
st.columns
```

[52]:
```
Index(['gender', 'ethnic_group', 'parent_educ', 'lunch_type', 'test_prep',
       'parent_marital_status', 'practice_sport', 'is_first_child',
       'nr_siblings', 'transport_means', 'wkly_study_hours', 'math_score',
       'reading_score', 'writing_score'],
      dtype='object')
```

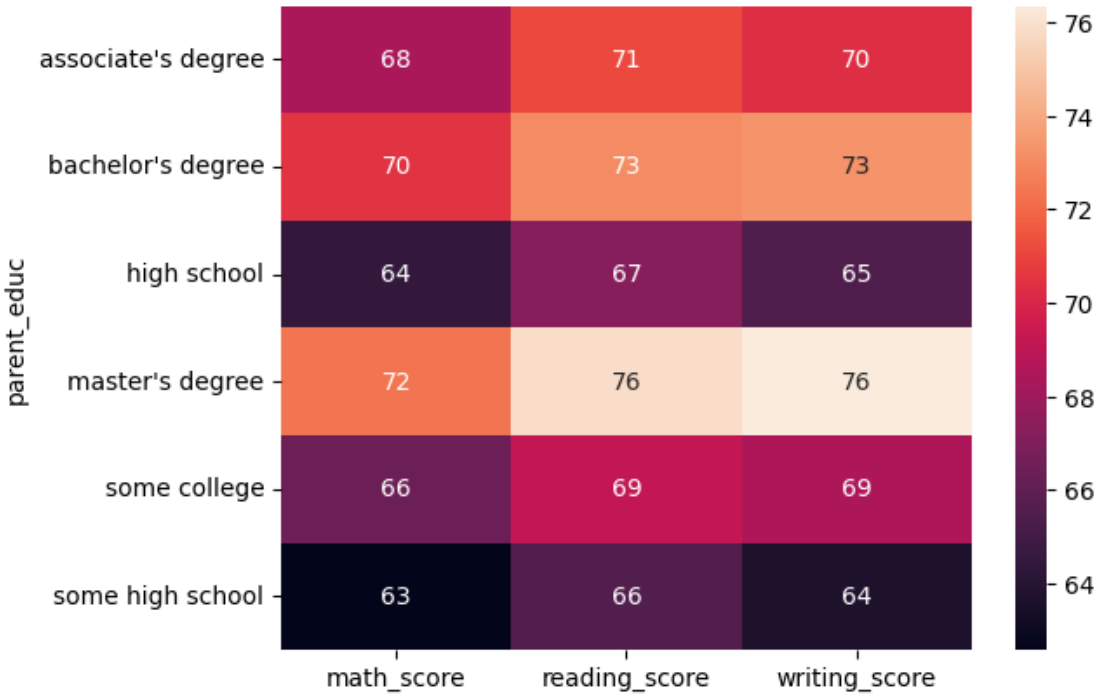
7 Impact by Parent Eduction

[54]:
```
gb = st.groupby('parent_educ').agg({"math_score":'mean',"reading_score":
 ↪'mean',"writing_score":'mean'})
gb
```

[54]:

parent_educ	math_score	reading_score	writing_score
associate's degree	68.365586	71.124324	70.299099
bachelor's degree	70.466627	73.062020	73.331069
high school	64.435731	67.213997	65.421136
master's degree	72.336134	75.832921	76.356896
some college	66.390472	69.179708	68.501432
some high school	62.584013	65.510785	63.632409

[56]:
```
sns.heatmap(gb, annot= True)
plt.show()
```



From the a bove chart we can conclude that the eduction of the parents has a good impact on the student scores.

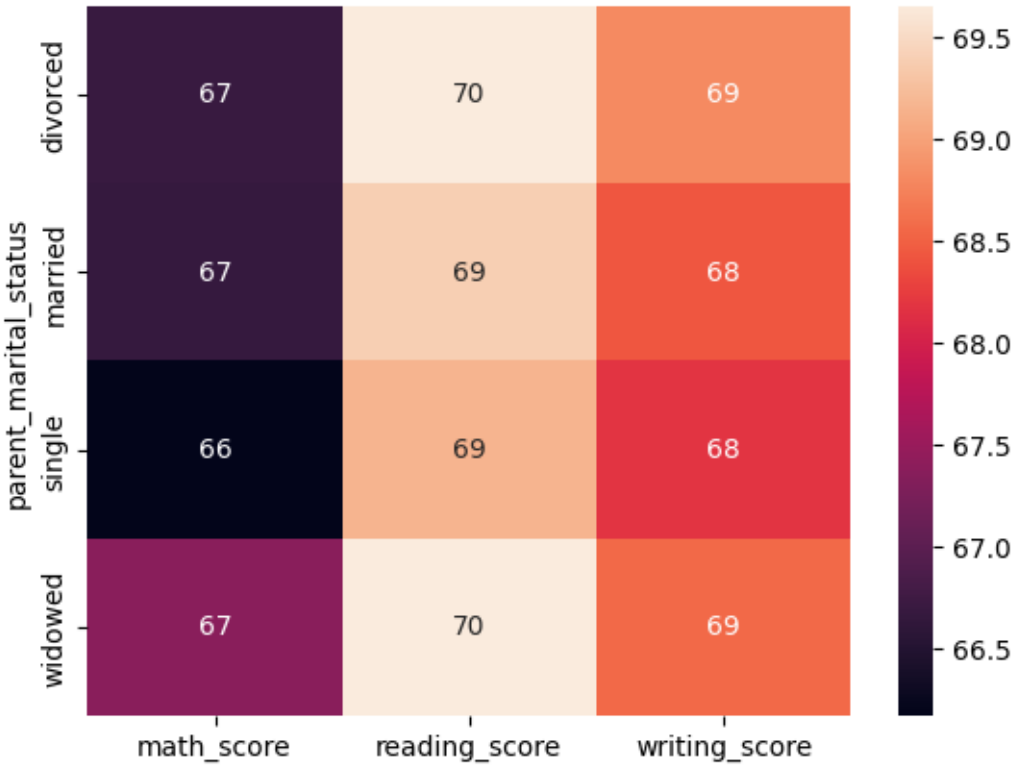
8 Impact by Parent Marital Status

[59]:
```
gb1 = st.groupby('parent_marital_status').agg({"math_score":
  ↪'mean',"reading_score":'mean',"writing_score":'mean'})
gb1
```

[59]:

parent_marital_status	math_score	reading_score	writing_score
divorced	66.691197	69.655011	68.799146
married	66.657326	69.389575	68.420981
single	66.165704	69.157250	68.174440
widowed	67.368866	69.651438	68.563452

[60]:
```
sns.heatmap(gb1, annot= True)
plt.show()
```



So from the above chart we can say parent_marital_status does not have any impact on student scores

[75]:
```
st.columns
```

[75]:
```
Index(['gender', 'ethnic_group', 'parent_educ', 'lunch_type', 'test_prep',
       'parent_marital_status', 'practice_sport', 'is_first_child',
       'nr_siblings', 'transport_means', 'wkly_study_hours', 'math_score',
       'reading_score', 'writing_score'],
      dtype='object')
```

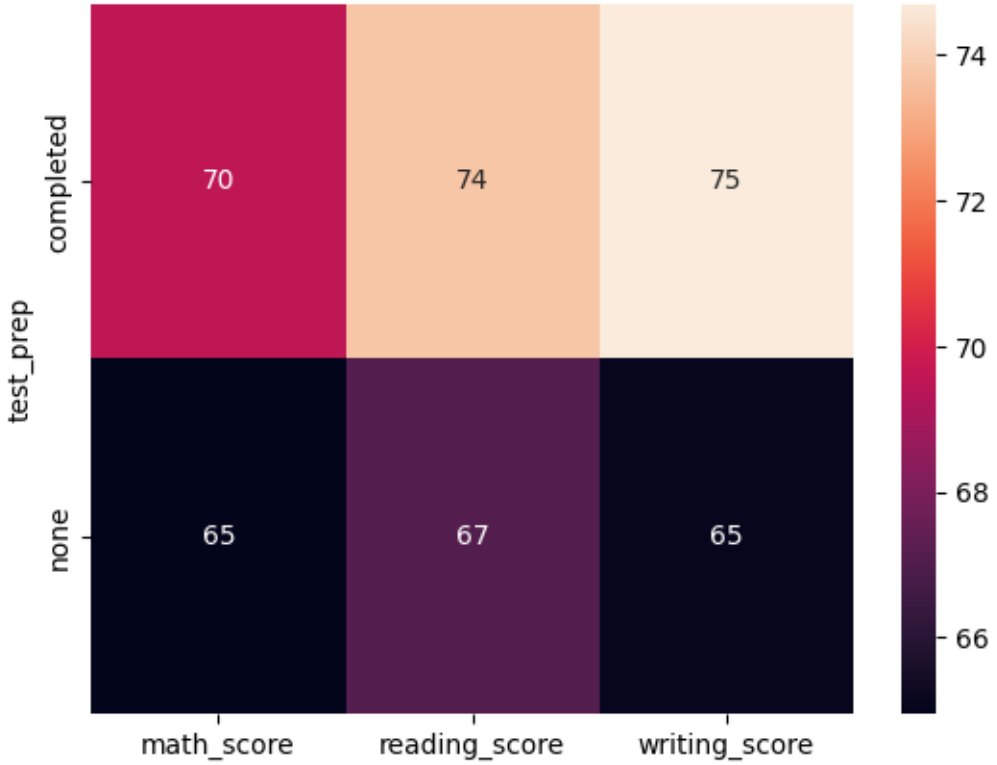
9 Impact by Test preparation

[76]:
```
gb2 = st.groupby('test_prep').agg({"math_score":'mean',"reading_score":
  ↪'mean',"writing_score":'mean'})
gb2
```

[76]:

test_prep	math_score	reading_score	writing_score
completed	69.54666	73.732998	74.703265
none	64.94877	67.051071	65.092756

[77]:
```
sns.heatmap(gb2, annot= True)
plt.show()
```



The students who were prepared for the exams were scored higher than the students who are not.

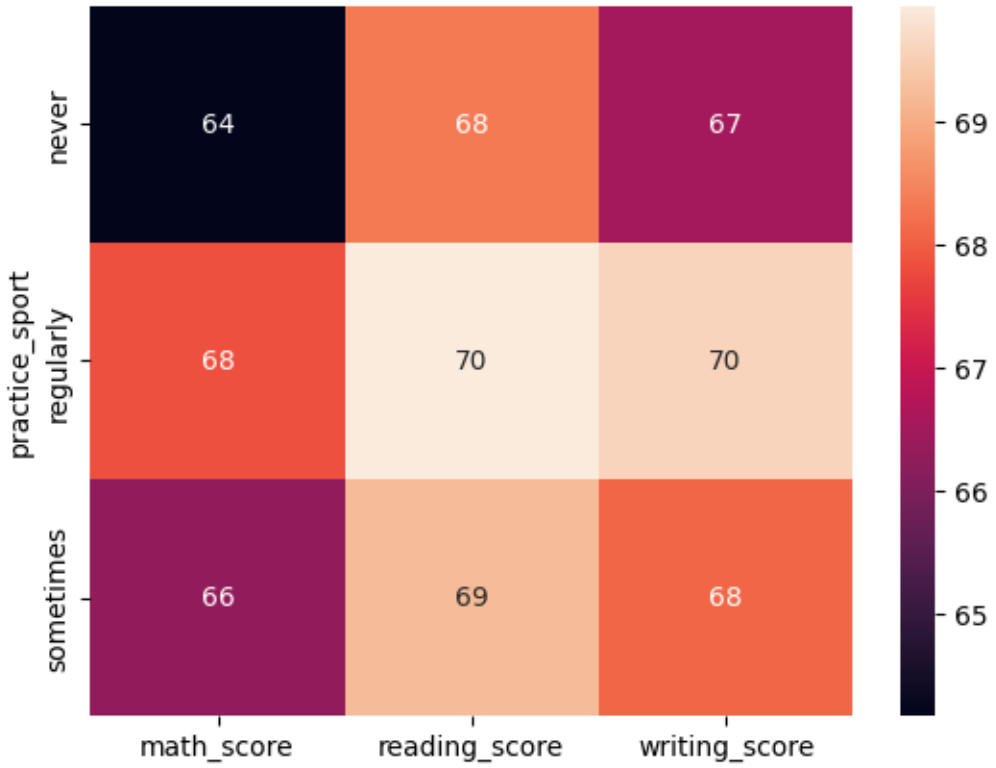
10 Impact by sport practice

[78]:
```
gb3 = st.groupby('practice_sport').agg({"math_score":'mean',"reading_score":
  ↪'mean',"writing_score":'mean'})
gb3
```

[78]:

practice_sport	math_score	reading_score	writing_score
never	64.171079	68.337662	66.522727
regularly	67.839155	69.943019	69.604003
sometimes	66.274831	69.241307	68.072438

[79]:
```
sns.heatmap(gb3, annot= True)
plt.show()
```



This shows that the students who practice sports daily were the ones with the highest avg scores.

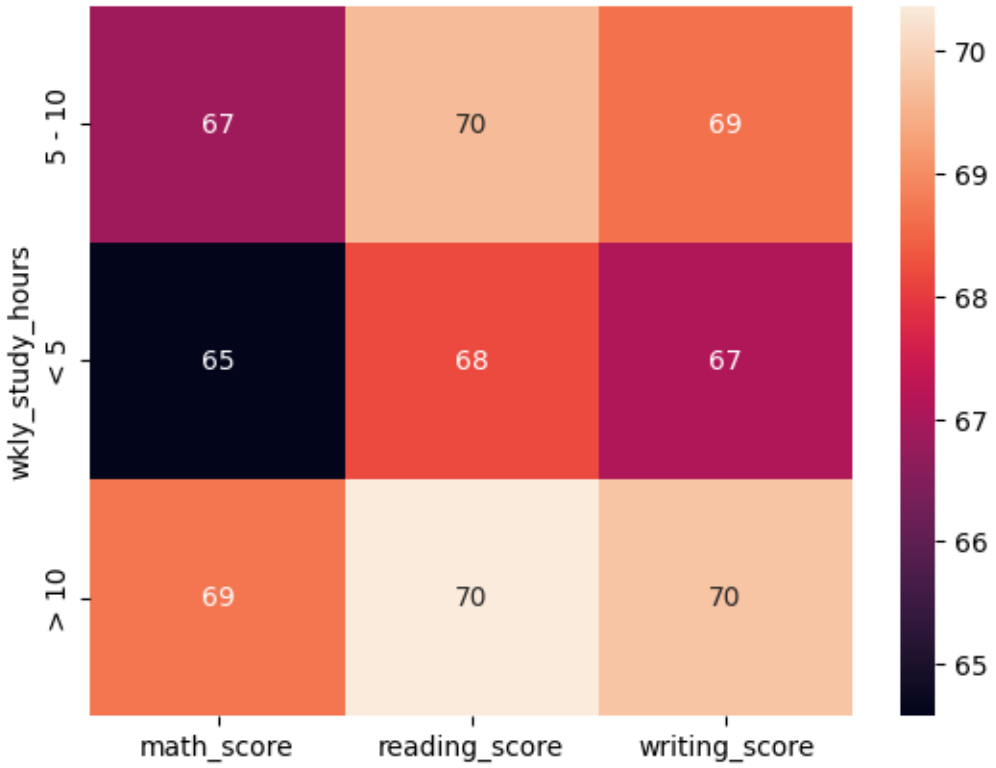
11 Impact by weekly study hours

[80]:
```
gb4 = st.groupby('wkly_study_hours').agg({"math_score":'mean',"reading_score":
  ↪'mean',"writing_score":'mean'})
gb4
```

[80]:

wkly_study_hours	math_score	reading_score	writing_score
5 - 10	66.870491	69.660532	68.636280
< 5	64.580359	68.176135	67.090192
> 10	68.696655	70.365436	69.777778

[81]:
```
sns.heatmap(gb4, annot= True)
plt.show()
```



This shows that the number of weekly study hours does have the impact on the scores of the students were the $>$ 10 hours had highest average scores in the subjects

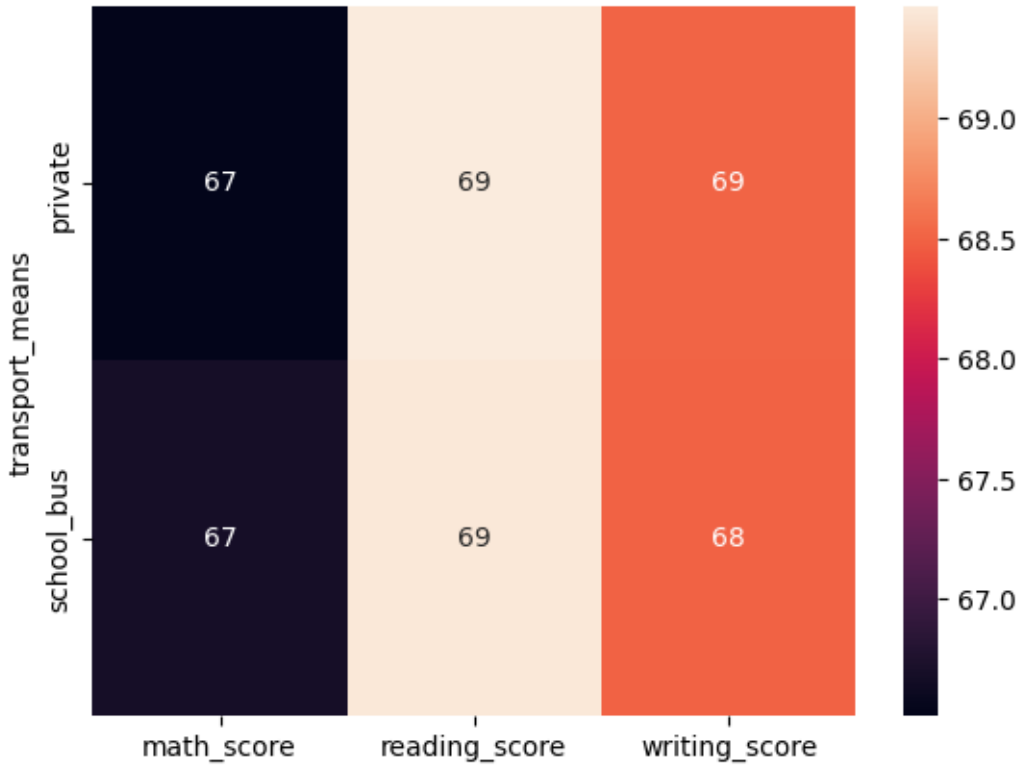
12 Impact by Transport means

[119]:
```
gb5 = st.groupby('transport_means').agg({"math_score":'mean',"reading_score":
  ↪'mean',"writing_score":'mean'})
gb5
```

[119]:

transport_means	math_score	reading_score	writing_score
private	66.511354	69.472364	68.509593
school_bus	66.674636	69.446206	68.492351

[120]:
```
sns.heatmap(gb5, annot= True)
plt.show()
```



this shows that the mode of transport does not impact the scores

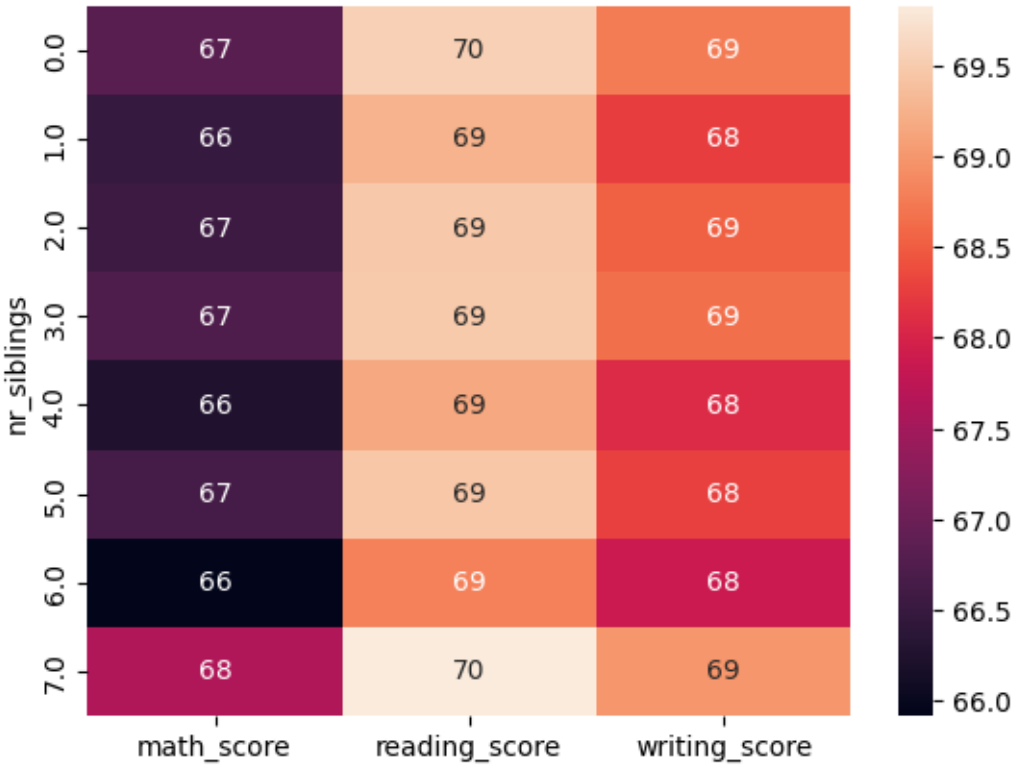
13 Impact by no of sibilings

[103]:
```
gb6 = st.groupby('nr_siblings').agg({"math_score":'mean',"reading_score":
  ↪'mean',"writing_score":'mean'})
gb6
```

[103]:

nr_siblings	math_score	reading_score	writing_score
0.0	66.819449	69.547812	68.746515
1.0	66.473896	69.259097	68.245345
2.0	66.554934	69.472018	68.522533
3.0	66.719092	69.488159	68.650498
4.0	66.245495	69.144169	68.073444
5.0	66.630303	69.453788	68.282576
6.0	65.917219	68.801325	67.860927
7.0	67.615120	69.828179	68.986254

[104]:
```
sns.heatmap(gb6, annot= True)
plt.show()
```



These show that the sibilings number does not impact the scores.

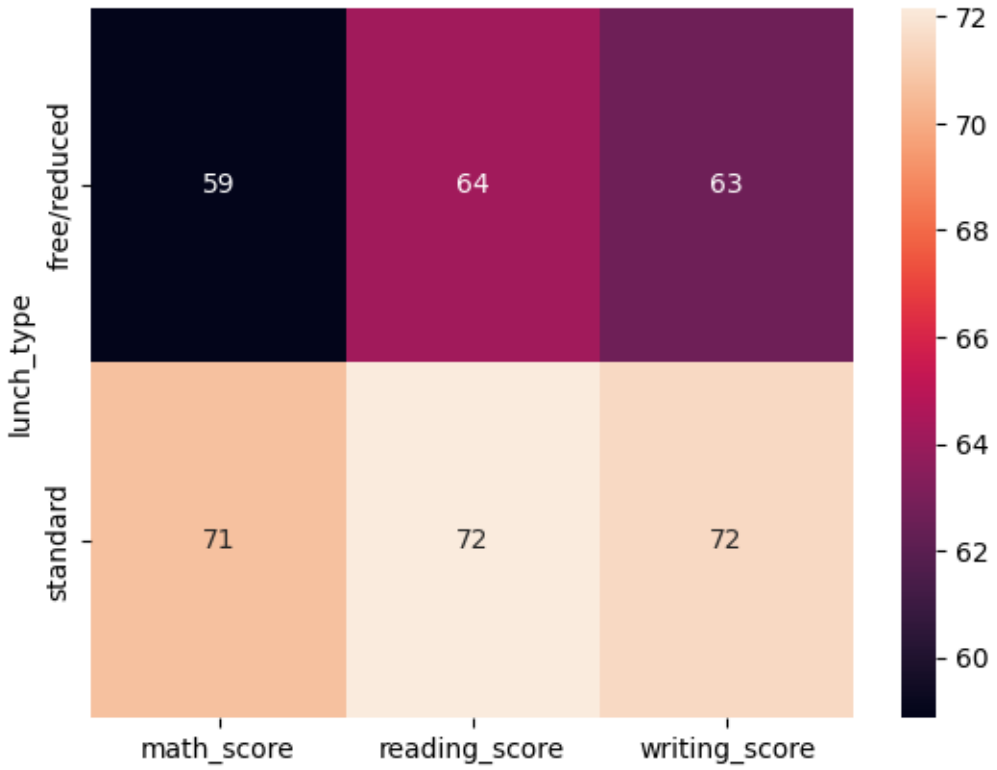
14 Impact of lunch type

[112]:
```
gb7 = st.groupby('lunch_type').agg({"math_score":'mean',"reading_score":
  ↪'mean',"writing_score":'mean'})
gb7
```

[112]:

lunch_type	math_score	reading_score	writing_score
free/reduced	58.862332	64.189735	62.650522
standard	70.709370	72.175634	71.529716

[115]:
```
sns.heatmap(gb7, annot= True)
plt.show()
```



Their is a clear difference in scores the students who get the standard food and who are not and the difference is significant.

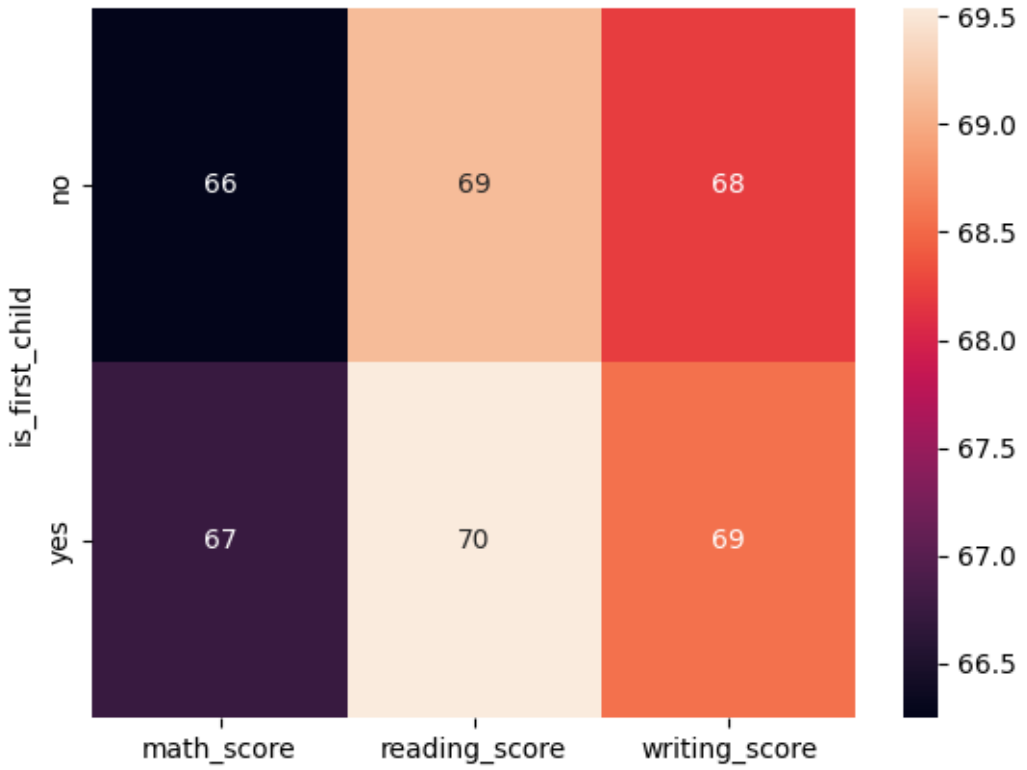
15 impact of first child or not

[113]:
```
gb8 = st.groupby('is_first_child').agg({"math_score":'mean',"reading_score":
↪'mean',"writing_score":'mean'})
gb8
```

[113]:

is_first_child	math_score	reading_score	writing_score
no	66.246832	69.132614	68.210887
yes	66.740646	69.542553	68.558484

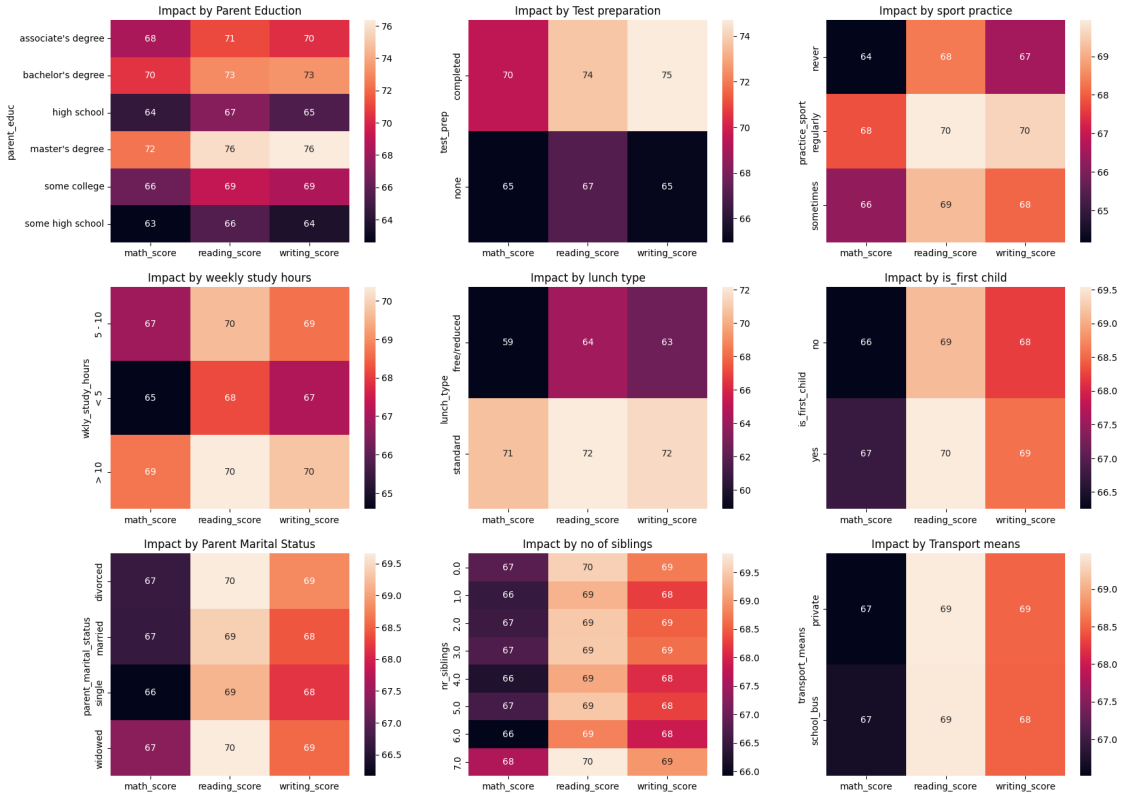
[114]:
```
sns.heatmap(gb8, annot= True)
plt.show()
```



No impact is their in the score by whether he is a first child or not

[121]:
```
plt.figure(figsize= (20,15))

plt.subplot(3,3,7)
sns.heatmap(gb1, annot= True)
plt.title("Impact by Parent Marital Status")


plt.subplot(3,3,2)
sns.heatmap(gb2, annot= True)
plt.title("Impact by Test preparation")

plt.subplot(3,3,3)
sns.heatmap(gb3, annot= True)
plt.title("Impact by sport practice")

plt.subplot(3,3,4)
sns.heatmap(gb4, annot= True)
plt.title("Impact by weekly study hours")

plt.subplot(3,3,9)
```

```
sns.heatmap(gb5, annot= True)
plt.title("Impact by Transport means")

plt.subplot(3,3,1)
sns.heatmap(gb, annot= True)
plt.title("Impact by Parent Eduction")

plt.subplot(3,3,8)
sns.heatmap(gb6, annot= True)
plt.title("Impact by no of siblings")

plt.subplot(3,3,5)
sns.heatmap(gb7, annot= True)
plt.title("Impact by lunch type")

plt.subplot(3,3,6)
sns.heatmap(gb8, annot= True)
plt.title("Impact by is_first child")

plt.savefig("Relationship_representation.jpg")
```



16 Insights

1. From the a bove chart we can conclude that the eduction of the parents has a good impact on the student scores.
2. So from the above chart we can say parent_marital_status does not have any impact on student scores
3. The students who were prepared for the exams were scored higher than the students who are not.
4. This shows that the students who practice sports daily were the ones with the highest avg scores.
5. This shows that the number of weekly study hours does have the impact on the scores of the students were the $>$ 10 hours had highest average scores in the subjects.
6. this shows that the mode of transport does not impact the scores.
7. These show that the sibilings number does not impact the scores.
8. Their is a clear difference in scores the students who get the standard food and who are not and the difference is significant.
9. No impact is their in the score by whether he is a first child or not.

17 This is further reprented by the pair plot

[139]:
```
sc = st.drop(['nr_siblings'], axis = 1)
```

[133]:
```
st.columns
```

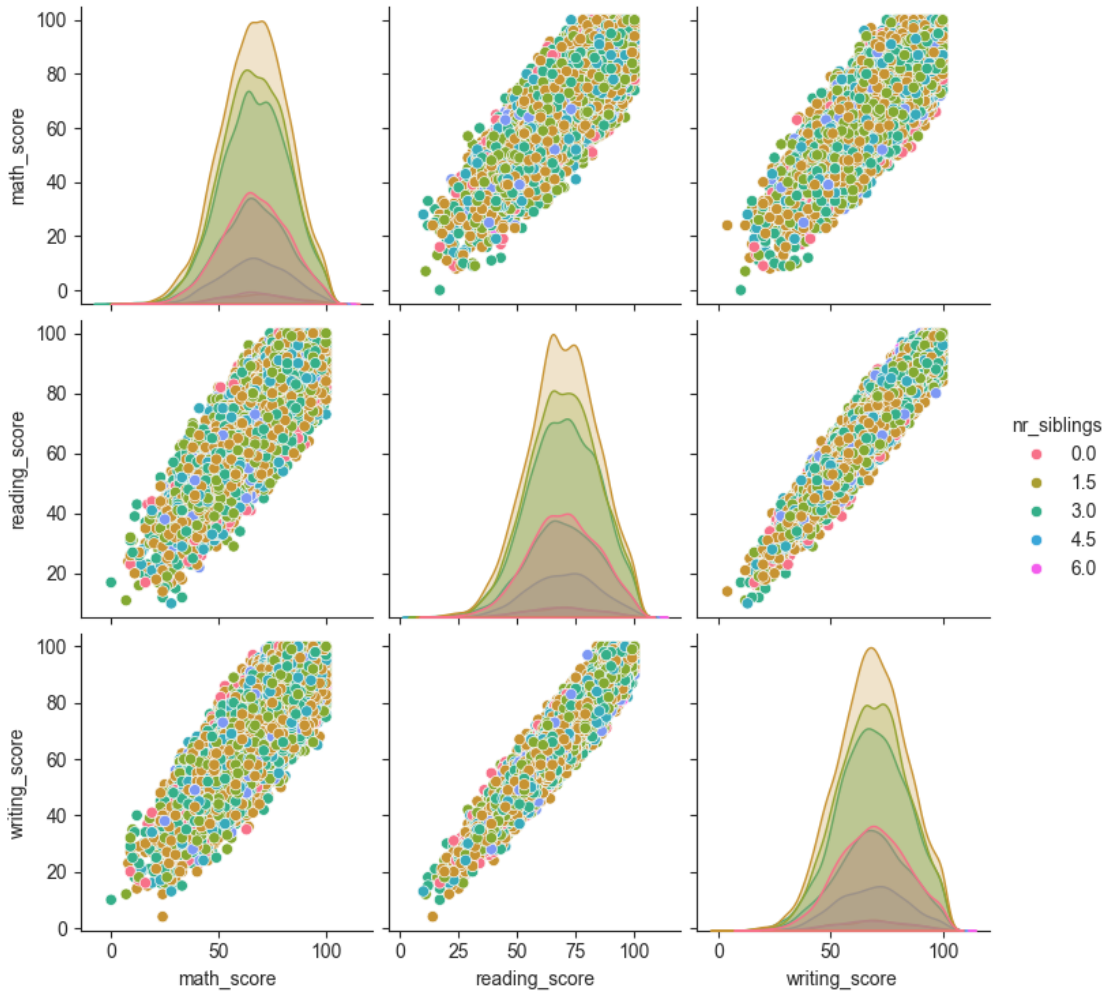
[133]:
```
Index(['gender', 'ethnic_group', 'parent_educ', 'lunch_type', 'test_prep',
       'parent_marital_status', 'practice_sport', 'is_first_child',
       'nr_siblings', 'transport_means', 'wkly_study_hours', 'math_score',
       'reading_score', 'writing_score'],
      dtype='object')
```

[140]:
```
sc.columns
```

[140]:
```
Index(['gender', 'ethnic_group', 'parent_educ', 'lunch_type', 'test_prep',
       'parent_marital_status', 'practice_sport', 'is_first_child',
       'transport_means', 'wkly_study_hours', 'math_score', 'reading_score',
       'writing_score'],
      dtype='object')
```

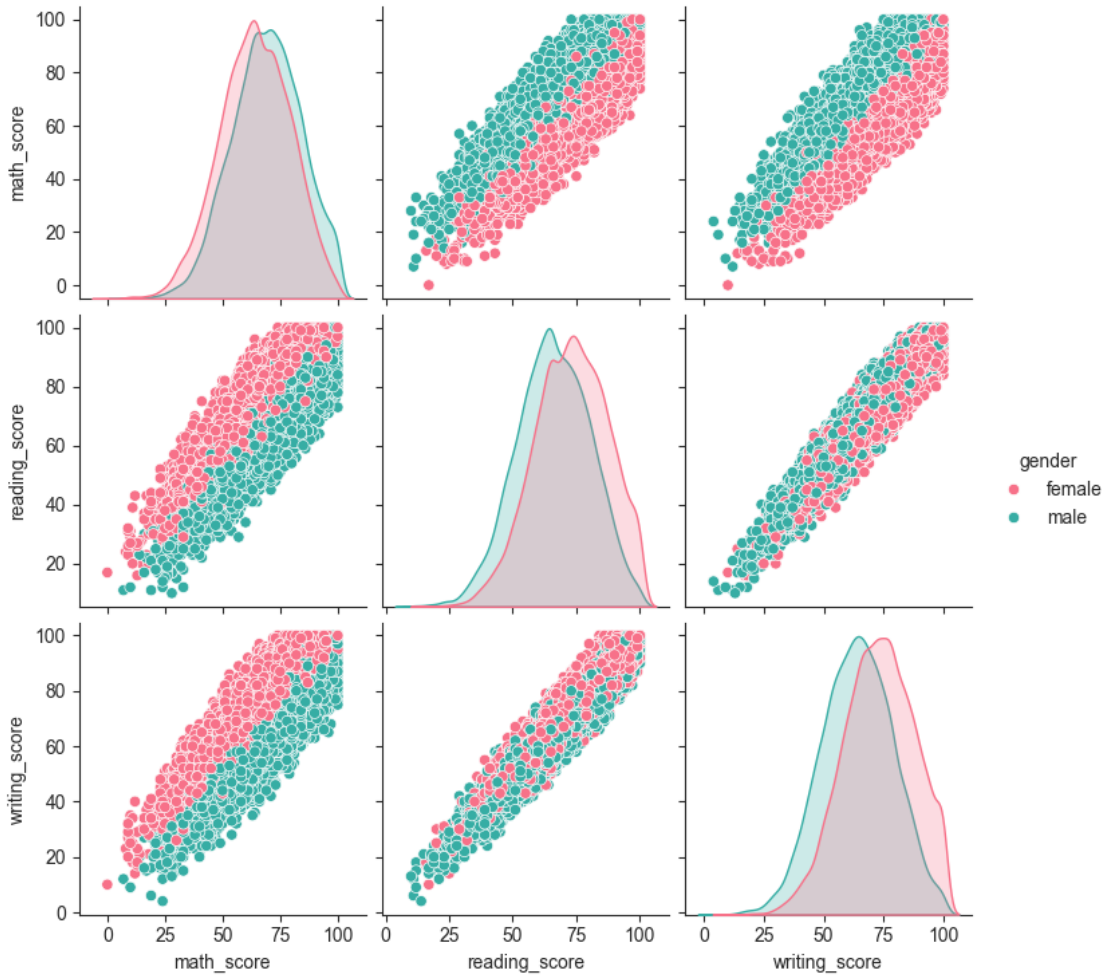
[135]:
```
sns.set_style('ticks')
sns.pairplot(st, hue = 'nr_siblings', diag_kind= 'kde', kind= 'scatter',␣
 ↪palette= 'husl')
```

[135]:
```
<seaborn.axisgrid.PairGrid at 0x1d62701b380>
```



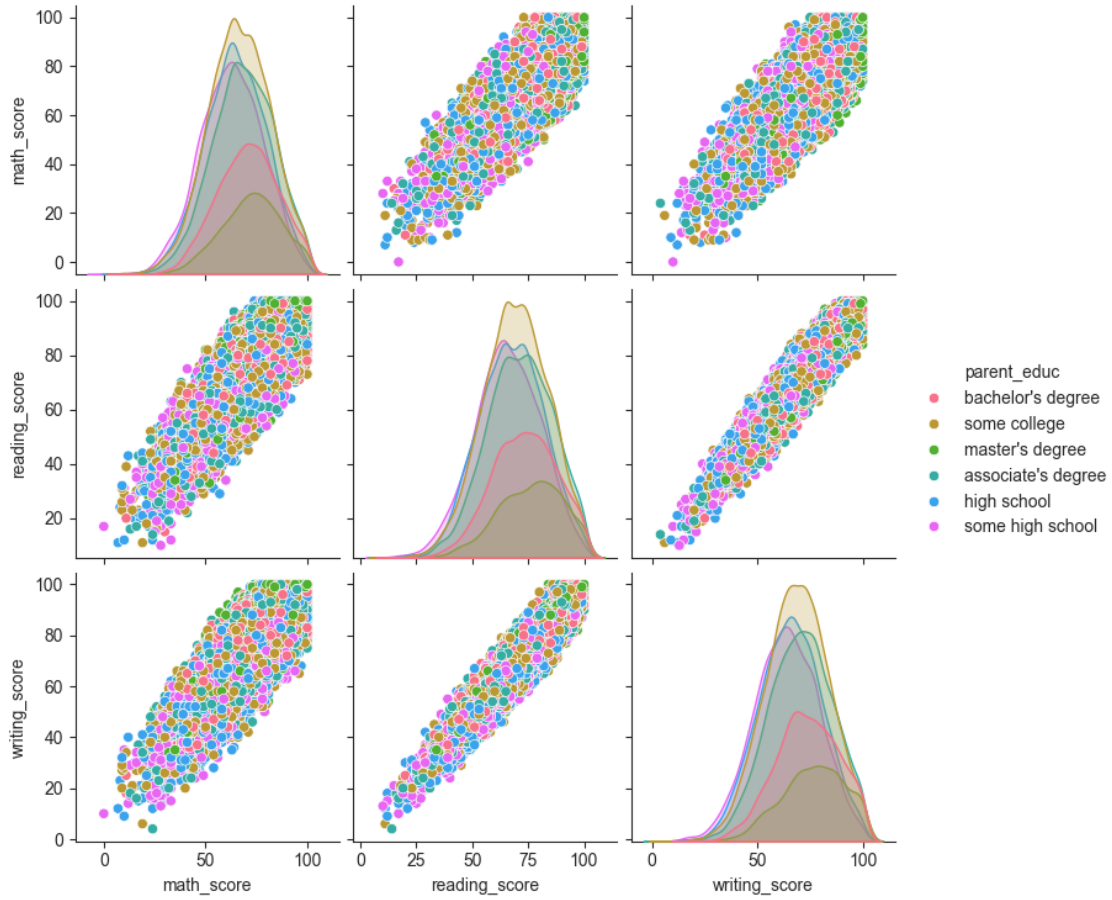
[142]:
```
sns.set_style('ticks')
sns.pairplot(sc, hue = 'gender', diag_kind= 'kde', kind= 'scatter', palette=␣
↪'husl')
```

[142]: <seaborn.axisgrid.PairGrid at 0x1d625f277a0>



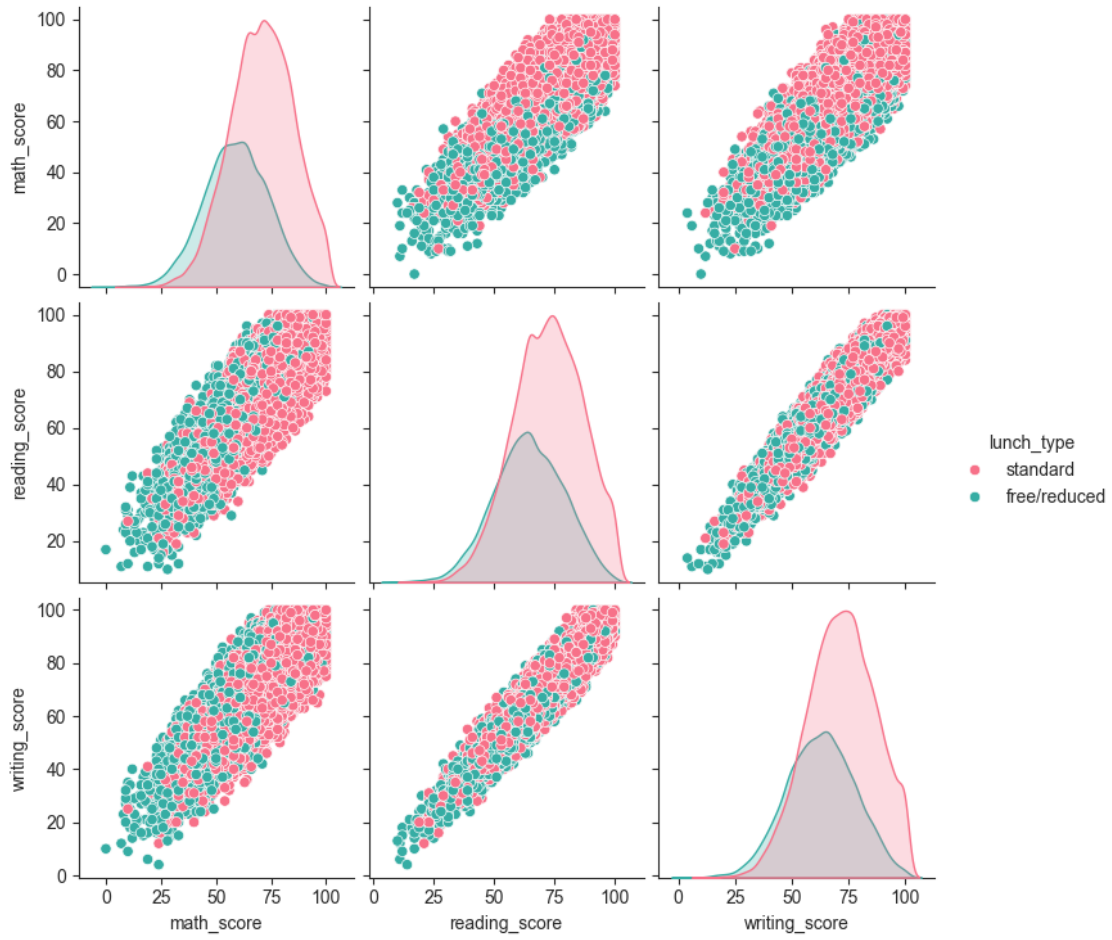
[144]:
```
sns.set_style('ticks')
sns.pairplot(sc, hue = 'parent_educ', diag_kind= 'kde', kind= 'scatter',␣
↪palette= 'husl')
```

[144]: <seaborn.axisgrid.PairGrid at 0x1d62bf4a300>



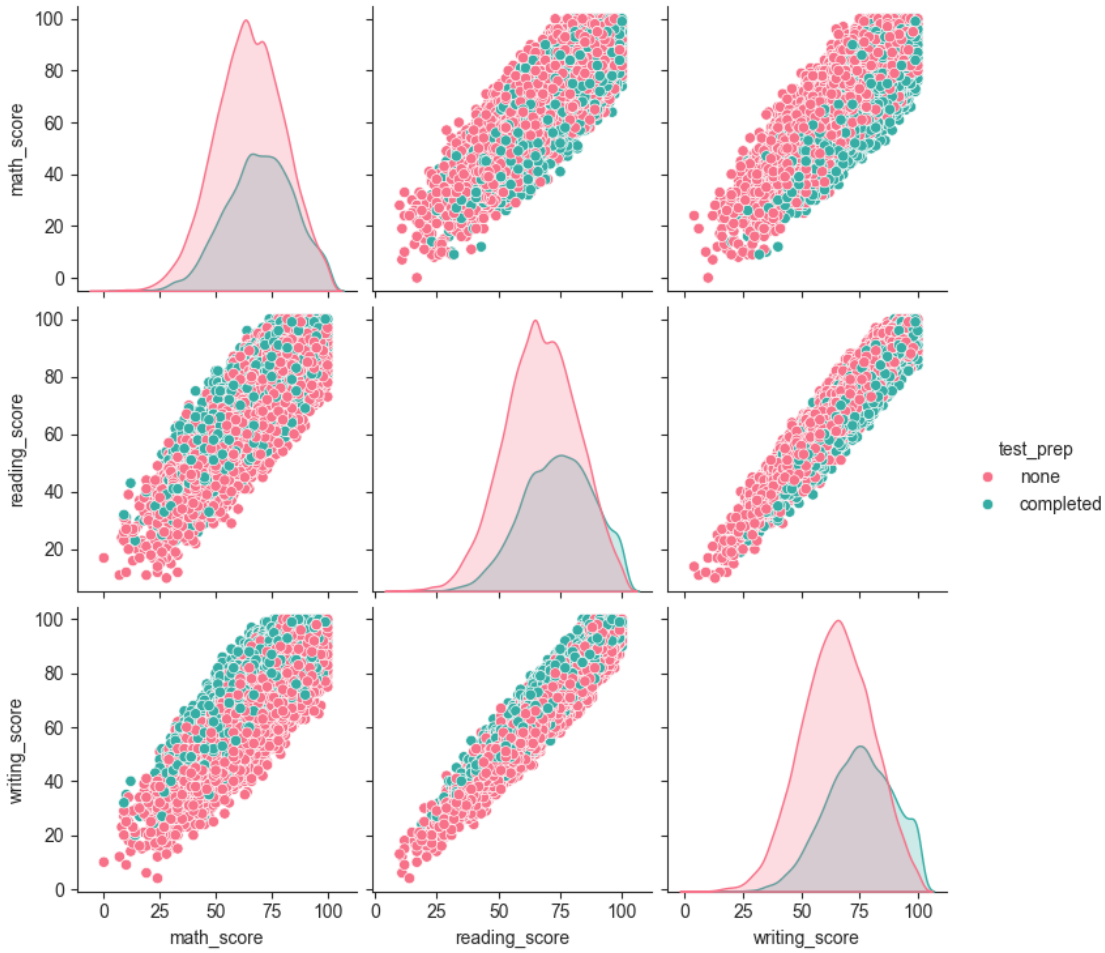
[148]:
```
sns.set_style('ticks')
sns.pairplot(sc, hue = 'lunch_type', diag_kind= 'kde', kind= 'scatter',␣
 ↪palette= 'husl')
```

[148]: <seaborn.axisgrid.PairGrid at 0x1d62bd7baa0>



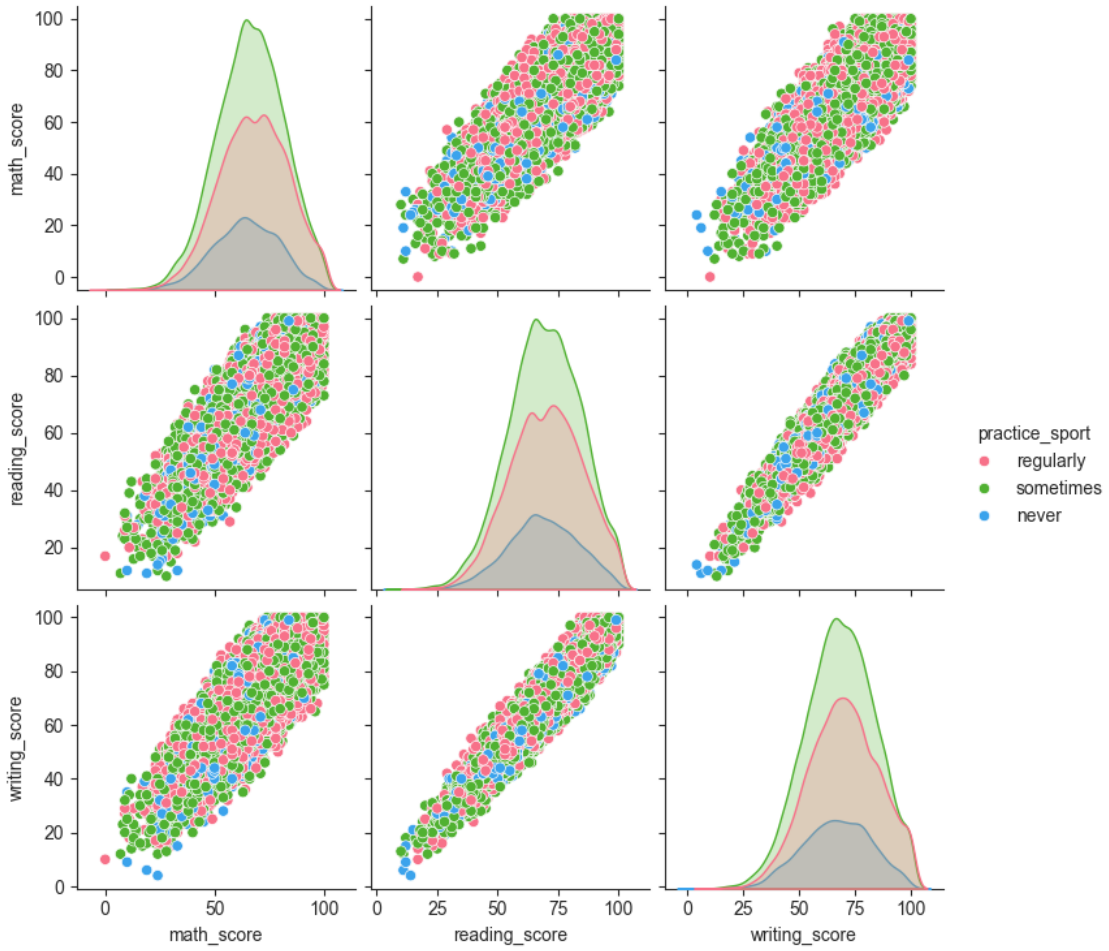
[149]:
```
sns.set_style('ticks')
sns.pairplot(sc, hue = 'test_prep', diag_kind= 'kde', kind= 'scatter', palette=␣
↪'husl')
```

[149]: <seaborn.axisgrid.PairGrid at 0x1d636411100>



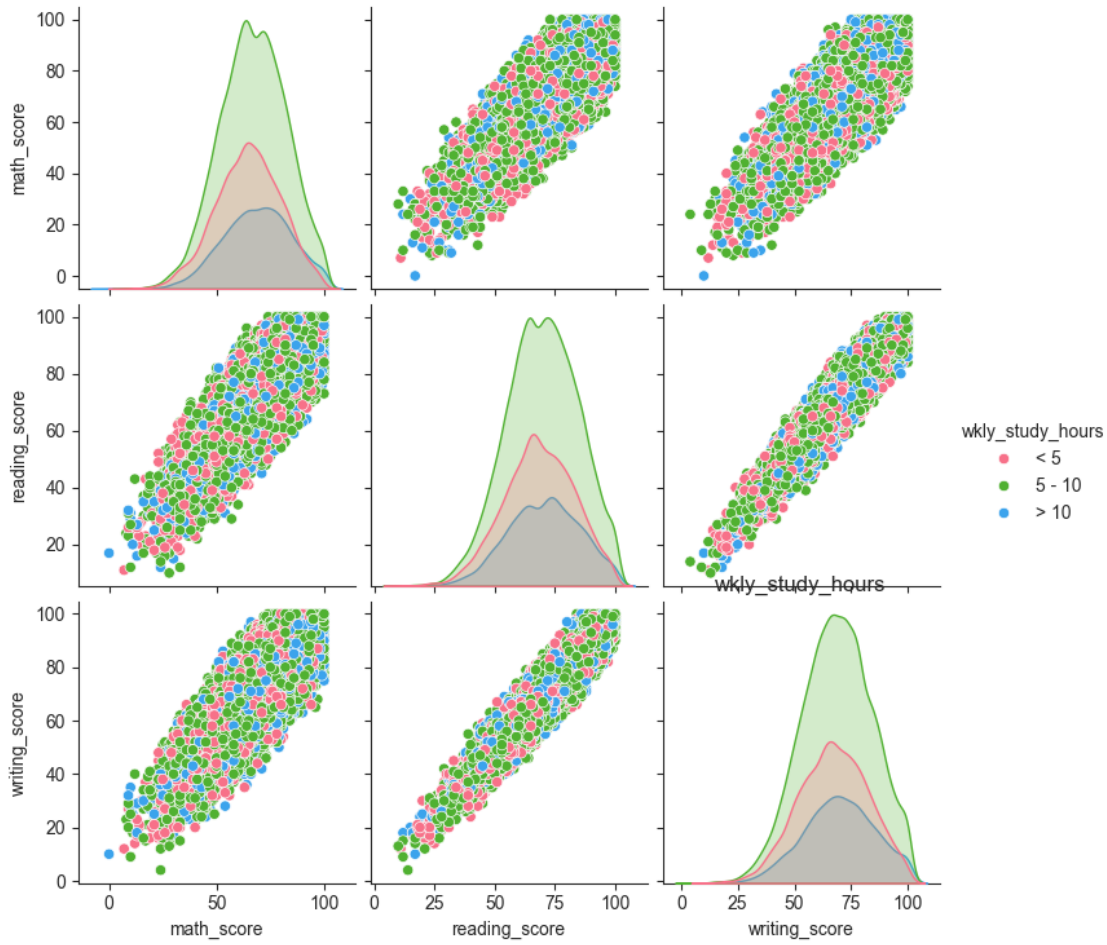
[150]:
```
sns.set_style('ticks')
sns.pairplot(sc, hue = 'practice_sport', diag_kind= 'kde', kind= 'scatter',␣
 ↪palette= 'husl')
```

[150]: <seaborn.axisgrid.PairGrid at 0x1d636761df0>



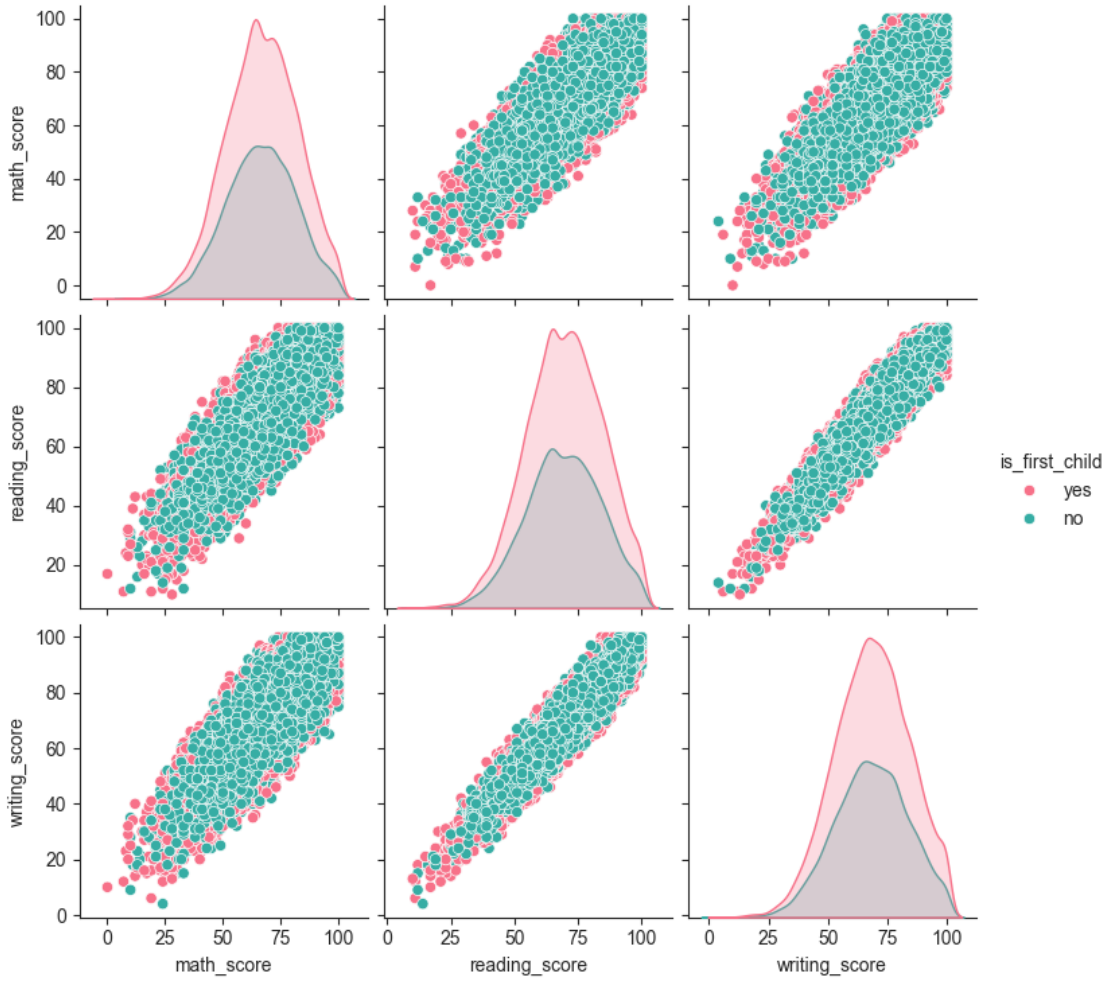
[153]:
```
sns.set_style('ticks')
sns.pairplot(sc, hue = 'wkly_study_hours', diag_kind= 'kde', kind= 'scatter',␣
↪palette= 'husl')
```

[153]: Text(0.5, 1.0, 'wkly_study_hours')



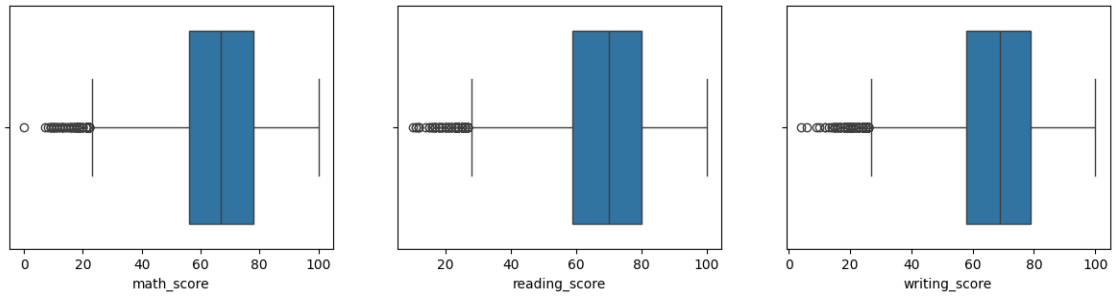
[147]:
```
sns.set_style('ticks')
sns.pairplot(sc, hue = 'is_first_child', diag_kind= 'kde', kind= 'scatter',␣
↪palette= 'husl')
```

[147]: <seaborn.axisgrid.PairGrid at 0x1d627fdf0b0>



[64]:
```
plt.figure(figsize= (20,15))
plt.subplot(4,4,1)
sns.boxplot(data = st, x = 'math_score')

plt.subplot(4,4,2)
sns.boxplot(data = st, x = 'reading_score')

plt.subplot(4,4,3)
sns.boxplot(data = st, x = 'writing_score')
```

[64]:
```
<Axes: xlabel='writing_score'>
```



This shows that the students maths scores are low when comapred with the other two.

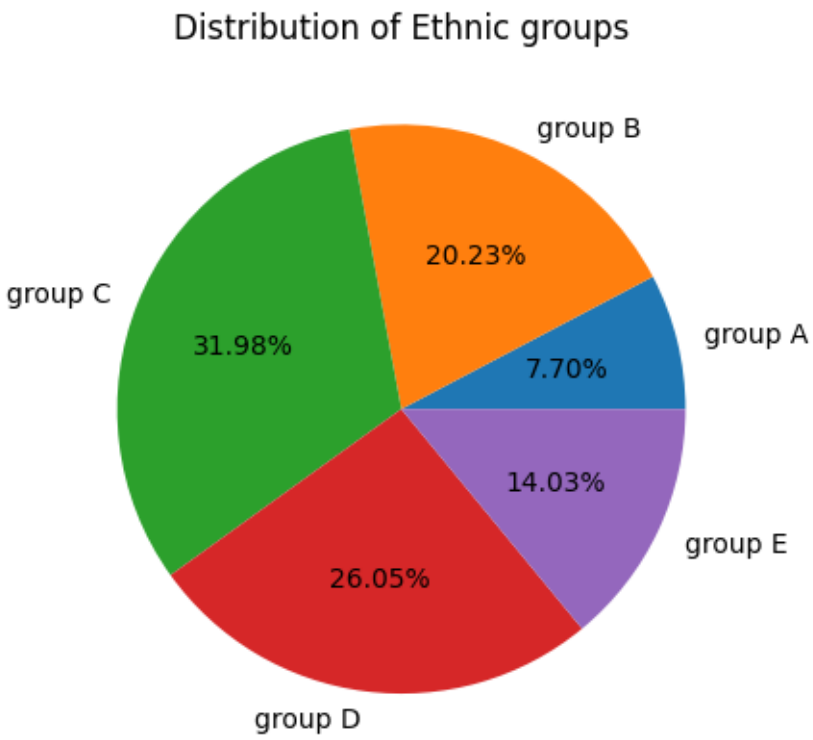
18 Distribution of Ethnic groups

[65]:
```
st['ethnic_group'].unique()
```

[65]:
```
array([nan, 'group C', 'group B', 'group A', 'group D', 'group E'],
      dtype=object)
```

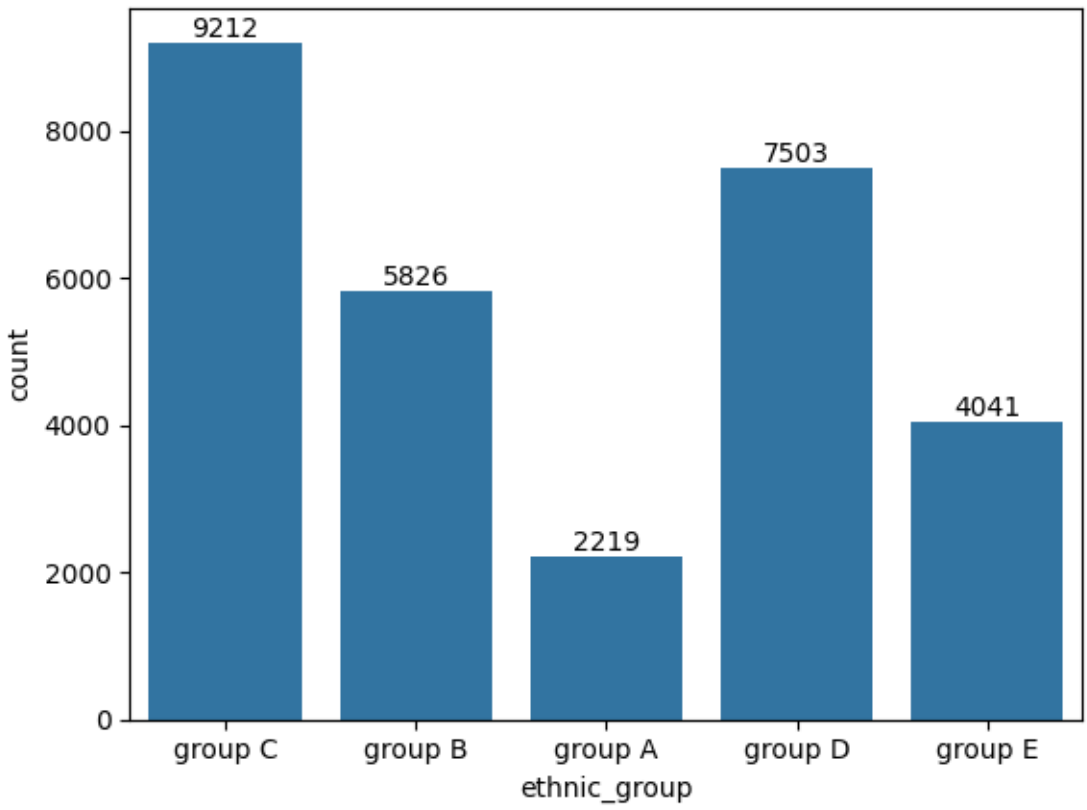
[67]:
```
groupA = st.loc[(st['ethnic_group'] == "group A")].count()
groupB = st.loc[(st['ethnic_group'] == "group B")].count()
groupC = st.loc[(st['ethnic_group'] == "group C")].count()
groupD = st.loc[(st['ethnic_group'] == "group D")].count()
groupE = st.loc[(st['ethnic_group'] == "group E")].count()

mtlist = [groupA['ethnic_group'],groupB['ethnic_group'],groupC['ethnic_group'],
          groupD['ethnic_group'],groupE['ethnic_group']]
```

[70]:
```
l = ["group A", "group B", "group C", "group D", "group E"]
plt.pie(mtlist, labels=l, autopct= "%1.2f%%")
plt.title("Distribution of Ethnic groups")
plt.show()
```



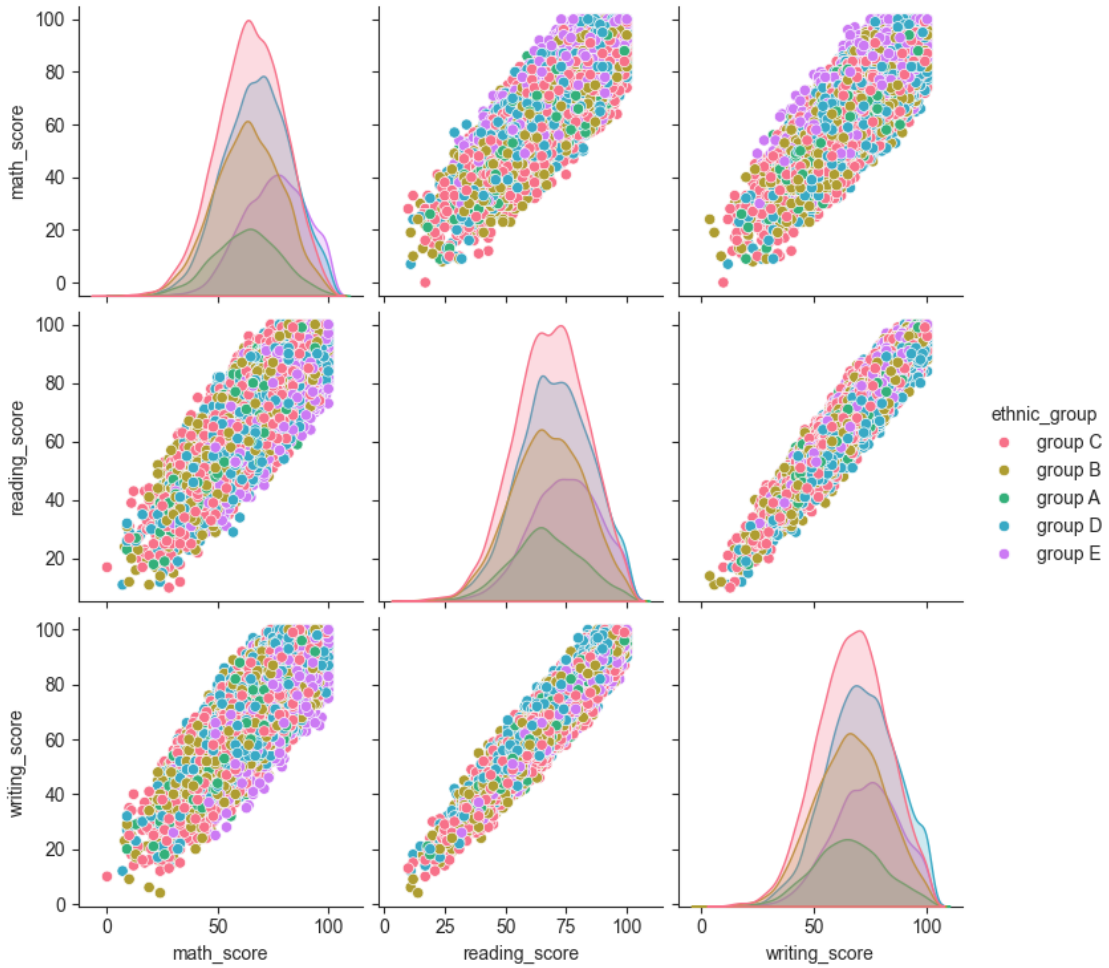
[74]:
```
ax = sns.countplot(data=st, x = 'ethnic_group')
ax.bar_label(ax.containers[0])
```

[74]:
```
[Text(0, 0, '9212'),
 Text(0, 0, '5826'),
 Text(0, 0, '2219'),
 Text(0, 0, '7503'),
 Text(0, 0, '4041')]
```



[152]:
```
sns.set_style('ticks')
sns.pairplot(sc, hue = 'ethnic_group', diag_kind= 'kde', kind= 'scatter',␣
↪palette= 'husl')
```

[152]: <seaborn.axisgrid.PairGrid at 0x1d63a7a3080>



Group c has the highest percentage distribution in the ethnic groups

19 Conclusion

The student scores on an average mostly effected by the food they are provided, Physical activity they are involved, Time they allocate for studies and the level of there parent education.