Prapemrosesan & Rekayasa Data - IBDA3111

UTS - Students Performance in Exams

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Description:

1. Masalah yang akan diselesaikan
   A. How effective is the test preparation course?
   B. Which major factors contribute to test outcomes?
   C. What would be the best way to improve student scores on each test?
   D. What patterns and interactions in the data can you find?

2. Deskripsi singkat dataset
   Students Performance in Exams dataset adalah sebuah dataset yang menggambarkan tentang peforma ujian siswa. Dalam dataset berisikan tentang nilai-nilai ujian siswa di sekolah. Adapun tabel-tabel yang terdapat di dalam dataset. (exams.csv)

   Terdapat 8 kolom, 5 string 3 integers dan 1000 baris data. Dataset ini ingin memberikan gambaran, apakah pengaruh latar belakang orang tua, persiapan ujian, dan lain-lain terhadap kinerja ujian siswa.

3. Sumber dataset
   Dataset diperoleh dari kaggle.com
   https://www.kaggle.com/datasets/whenamancodes/students-performance-in-exams

4. Cara memperoleh dataset
   Dataset diperoleh dengan cara mengunduh dari website.

Library

In [ ]:
```
# Import library needed

import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

from numpy import mean
from numpy import std
from sklearn.model_selection import train_test_split
from sklearn.datasets import make_classification
from sklearn.model_selection import cross_val_score
from sklearn.preprocessing import OneHotEncoder
from sklearn.feature_selection import VarianceThreshold
from sklearn.feature_selection import RFE
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import RepeatedStratifiedKFold
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import Perceptron
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.pipeline import Pipeline
from sklearn import linear_model
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2

from matplotlib import pyplot
```

Load and check dataset

In [ ]:
```
# Load dataset
df = pd.read_csv('exams.csv', delimiter=',')

# Show dataset
# pd.set_option('display.max_rows', None) # display all rows dataset
display(df.head(5))

# Dataset shape
print(f"Rows    : {df.shape[0]}\nColumns: {df.shape[1]}")
```

	gender	race/ethnicity	parental level of education	lunch	test preparation course	math score	reading score	writing score
0	male	group A	high school	standard	completed	67	67	63
1	female	group D	some high school	free/reduced	none	40	59	55
2	male	group E	some college	free/reduced	none	59	60	50
3	male	group B	high school	standard	none	77	78	68
4	male	group E	associate's degree	standard	completed	78	73	68

```
Rows    : 1000
Columns: 8
```

In [ ]:
```
# Check the datatype for all the column values
df.dtypes
```

Out[ ]:
```
gender                        object
race/ethnicity                object
parental level of education    object
lunch                         object
test preparation course       object
math score                     int64
reading score                  int64
writing score                  int64
dtype: object
```

In [ ]:
```
# Check unique values columns
df.nunique()
```

Out[ ]:
```
gender                        2
race/ethnicity                5
parental level of education    6
lunch                         2
test preparation course       2
math score                   77
reading score                73
writing score                76
dtype: int64
```

In [ ]:
```
# Let's check if the data has some missing values
print(f"Check if the data has some missing values")
df.isnull().sum()
```

```
Check if the data has some missing values
```

Out[ ]:
```
gender                       0
race/ethnicity               0
parental level of education    0
lunch                        0
test preparation course      0
math score                   0
reading score                0
writing score                0
dtype: int64
```

↑ There are no missing values in the dataset* ↑

In [ ]:
```
# Let's check if the values of the first 5 columns numerical or categirical
for i in range(5):
    print(f"{df[df.columns[i]].value_counts()}\n")
```

```
male      517
female    483
Name: gender, dtype: int64

group C    323
group D    262
group B    205
group E    131
group A     79
Name: race/ethnicity, dtype: int64

some college          222
associate's degree    203
high school           202
some high school      191
bachelor's degree     112
master's degree        70
Name: parental level of education, dtype: int64

standard        652
free/reduced    348
Name: lunch, dtype: int64

none         665
completed    335
Name: test preparation course, dtype: int64
```

↑↑↑ We can see from the output above that the first 5 columns are categorical variables. Then, the rest columns are numerical variables.

In [ ]:
```
df.iloc[:, 5:].describe()
```

Out[ ]:

	math score	reading score	writing score
count	1000.000000	1000.000000	1000.000000
mean	66.396000	69.002000	67.738000
std	15.402871	14.737272	15.600985
min	13.000000	27.000000	23.000000
25%	56.000000	60.000000	58.000000
50%	66.500000	70.000000	68.000000
75%	77.000000	79.000000	79.000000
max	100.000000	100.000000	100.000000

↑↑ Let's see the statistic presentation using .describe()

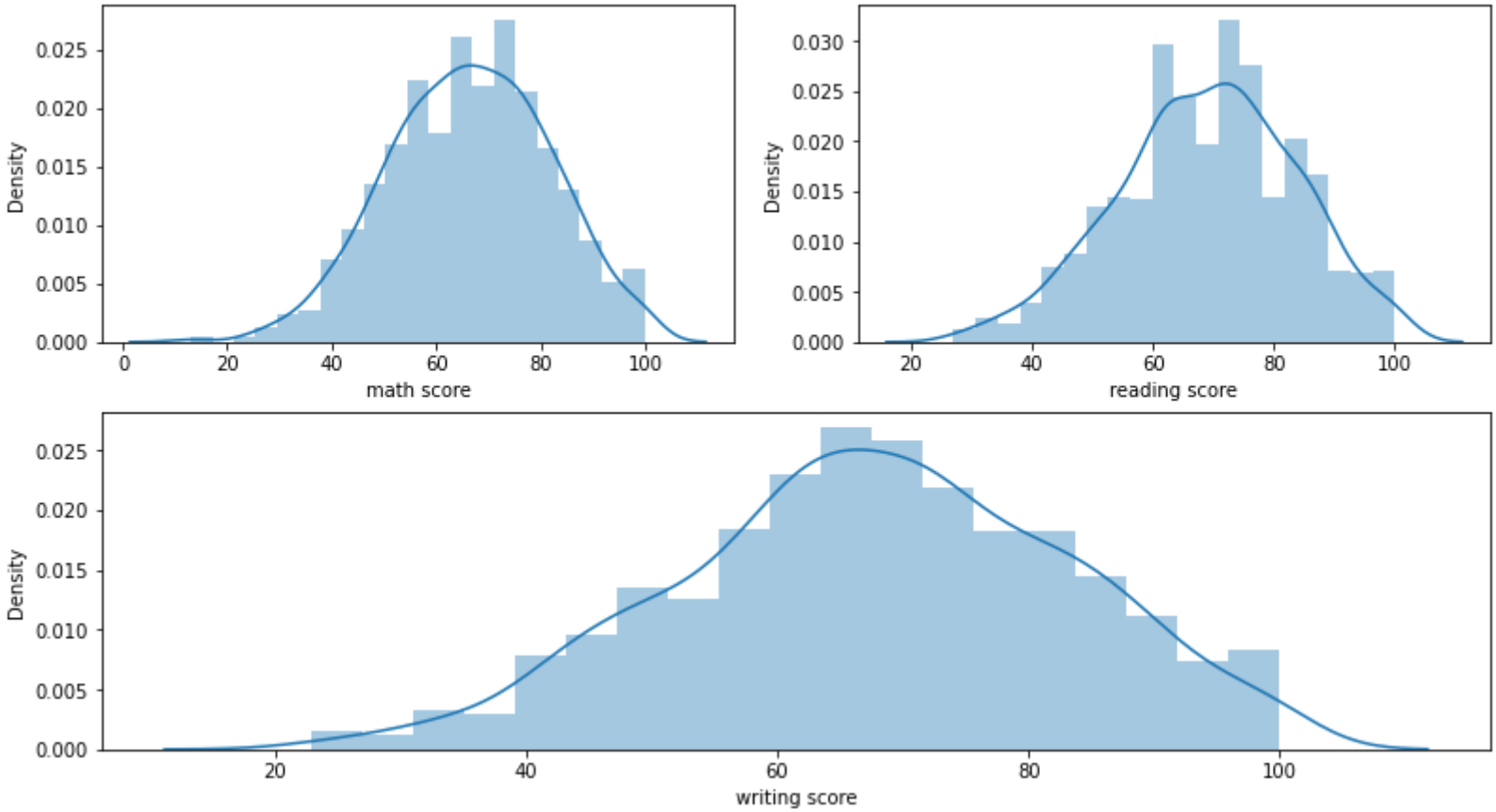
In [ ]:

```
figure, ax = plt.subplots(2,2, constrained_layout=True, figsize=(11, 6))

plt.subplot(2, 2, 1)
sns.distplot(df['math score'])

plt.subplot(2, 2, 2)
sns.distplot(df['reading score'])

plt.subplot(2, 2, (3, 4))
sns.distplot(df['writing score'])
```

```
c:\Python 3.10.2\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
c:\Python 3.10.2\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
c:\Python 3.10.2\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[ ]:

```
<AxesSubplot:xlabel='writing score', ylabel='Density'>
```



↑ ↑ Let's see the distribution

↑ ↑ Let's see the distribution of the scores.

1. Data cleaning

1. Delete duplicated rows

In [ ]:
```
# Delete duplicated rows
dups = df.duplicated()
print(f"Duplicated rows:")
print(dups.any())
print(df[dups])

print(f"\nShape before delete:  {df.shape}")
df.drop_duplicates(inplace=True)
print(f"Shape after delete :  {df.shape}\n")
```

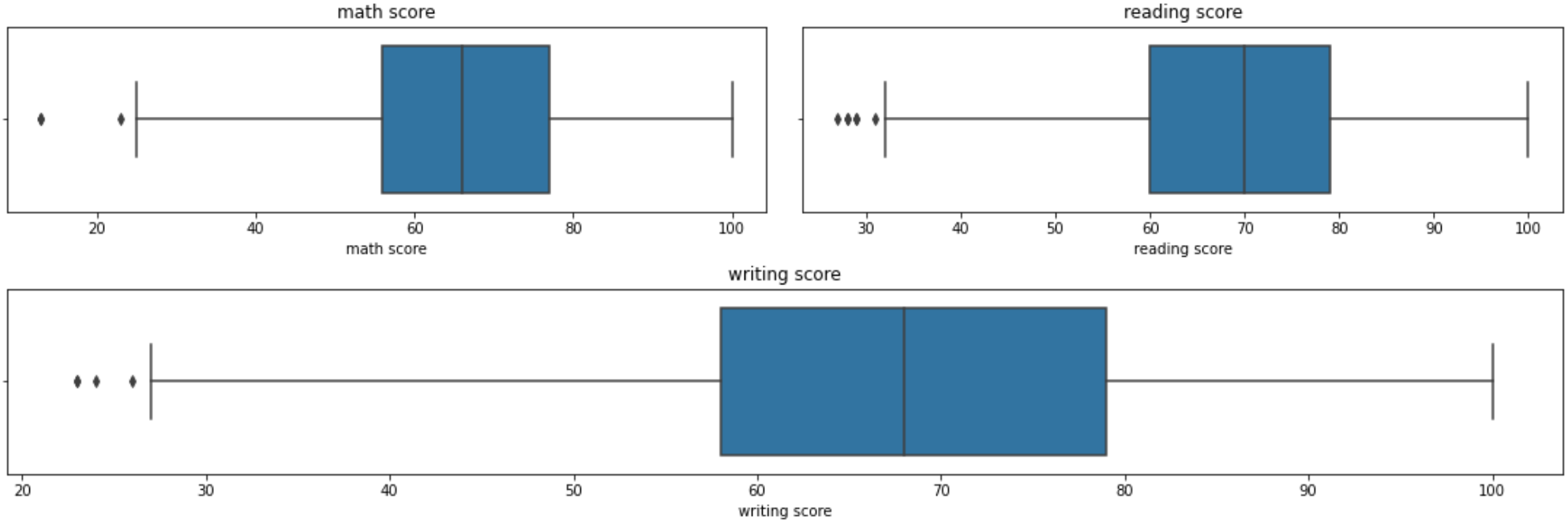
```
Duplicated rows:
True
    gender race/ethnicity parental level of education     lunch  \
825   male        group E          associate's degree  standard

    test preparation course  math score  reading score  writing score
825               completed         100            100            100

Shape before delete:  (1000, 8)
Shape after delete :  (999, 8)
```

2. Identifikasi Pencilan lalu diimputasi ke nilai lower bound

In [ ]:

```
# This func return upper & lower bound from dataset column
def identify_outlier(datacolumn):
    Q1, Q3 = np.percentile(datacolumn, [25, 75])
    IQR = Q3 - Q1
    lower_range = Q1 - (1.5 * IQR)
    upper_range = Q3 + (1.5 * IQR)

    return lower_range, upper_range


# Plot to boxplot so we can see the outlier data
def display_boxplot():
    figure, ax = plt.subplots(2,2, constrained_layout=True, figsize=(15, 5))

    s = 1
    for i in range(len(df.columns)):
        if i == 7:
            plt.subplot(2, 2, (s, s+1))
            plt.title(df.columns[i])
            sns.boxplot(x=df.iloc[:, i])
            s += 1
            continue

        if i >= 5:
            plt.subplot(2, 2, s)
            plt.title(df.columns[i])
            sns.boxplot(x=df.iloc[:, i])
            s += 1


# Take the bounderies value
math_score = identify_outlier(df.iloc[:, 5])
reading_score = identify_outlier(df.iloc[:, 6])
writing_score = identify_outlier(df.iloc[:, 7])

# Capture outlier (lower bound)
outlier_ms = [x for x in df.iloc[:, 5] if x < math_score[0]]
outlier_rs = [x for x in df.iloc[:, 6] if x < reading_score[0]]
outlier_ws = [x for x in df.iloc[:, 7] if x < writing_score[0]]

print(f"Outlier")
print(f"    Math score    = {outlier_ms}")
print(f"    Writing score = {outlier_rs}")
print(f"    Reading score = {outlier_ws}")

display_boxplot()
```

```
Outlier
    Math score    = [23, 13, 13]
    Writing score = [28, 29, 27, 28, 31, 29]
    Reading score = [24, 23, 26, 23]
```

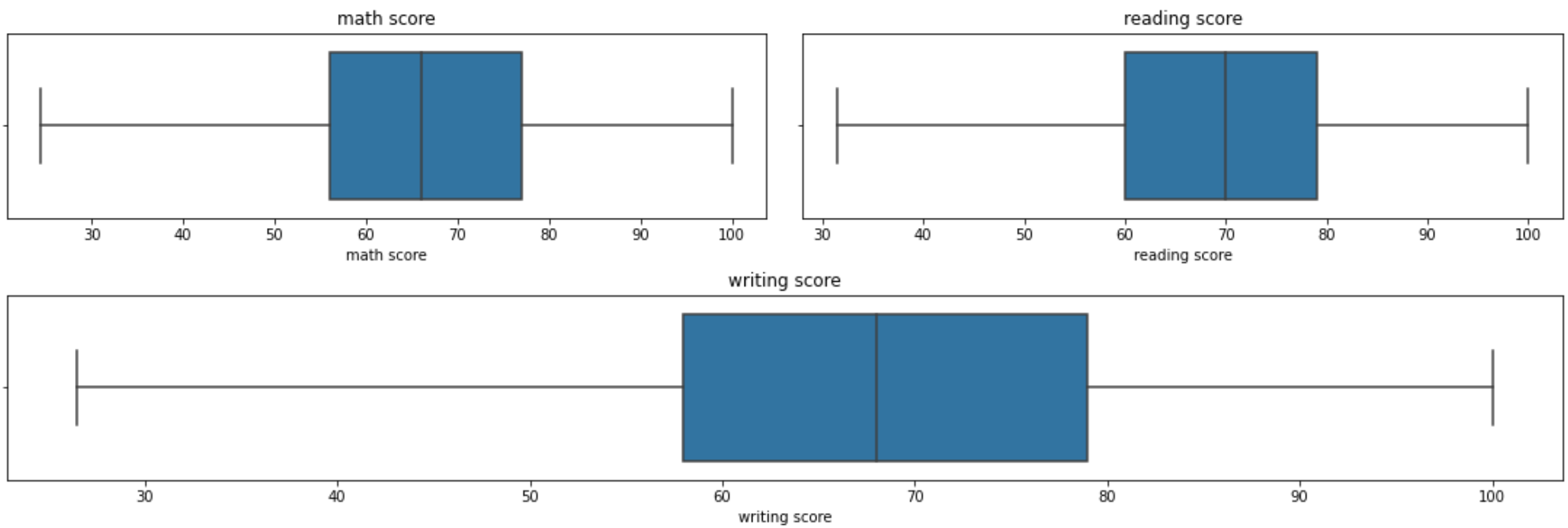


↑↑ From boxplot above.. we can see that there is an outlier in our dataset

In [ ]:

```python
# Function to impute to our dataset
def impute_outlier_to_lower_bound_value(df: pd.DataFrame, bounderies: tuple, n_col: int):
    for i in range(df.shape[0]):
        if df.iloc[i, n_col] <= bounderies[0]:
            df.iloc[i, n_col] = bounderies[0]
    return

impute_outlier_to_lower_bound_value(df, math_score, 5)
impute_outlier_to_lower_bound_value(df, reading_score, 6)
impute_outlier_to_lower_bound_value(df, writing_score, 7)

# Take the bounderies value
math_score = identify_outlier(df.iloc[:, 5])
reading_score = identify_outlier(df.iloc[:, 6])
writing_score = identify_outlier(df.iloc[:, 7])

# Capture outlier (lower bound)
outlier_ms = [x for x in df.iloc[:, 5] if x < math_score[0]]
outlier_rs = [x for x in df.iloc[:, 6] if x < reading_score[0]]
outlier_ws = [x for x in df.iloc[:, 7] if x < writing_score[0]]

print(f"Outlier")
print(f"    Math score    = {outlier_ms}")
print(f"    Writing score = {outlier_rs}")
print(f"    Reading score = {outlier_ws}")

display_boxplot()
```

```
Outlier
    Math score    = []
    Writing score = []
    Reading score = []
```



↑ ↑ Now, we have done imputing the outlier data to it's lower bound value (so no more outlier)

We impute the outlier to it's lower bound because there are just a few outlier and we need it, so we don't delete the outlier data

2. Features selection

1. RFE

↓↓ Adding columns “total” and “average” to the dataset

In [ ]:
```
# Display dataset before one hot encoding (after data cleaning)
display(df.head(2))
print(df.shape)

# Adding columns “total” and “average” to the dataset
df['total'] = df['math score'] + df['reading score'] + df['writing score']
df['average'] = df['total'] / 3
df.drop(["total"], axis=1, inplace=True)

print()
display(df.head(2))
print(df.shape)
```

	gender	race/ethnicity	parental level of education	lunch	test preparation course	math score	reading score	writing score
0	male	group A	high school	standard	completed	67.0	67.0	63.0
1	female	group D	some high school	free/reduced	none	40.0	59.0	55.0

```
(999, 8)
```

	gender	race/ethnicity	parental level of education	lunch	test preparation course	math score	reading score	writing score	average
0	male	group A	high school	standard	completed	67.0	67.0	63.0	65.666667
1	female	group D	some high school	free/reduced	none	40.0	59.0	55.0	51.333333

```
(999, 9)
```

↓↓ One hot encoding

In [ ]:

```
# Create a function for one hot encoding (only variable input)
def one_hot_encoding(df):
    encoded = pd.get_dummies(df.iloc[:, :-4])
    ms = df.iloc[:, -4]
    rs = df.iloc[:, -3]
    ws = df.iloc[:, -2]
    avg = df.iloc[:, -1]

    encoded["math score"] = ms
    encoded["reading score"] = rs
    encoded["writing score"] = ws
    encoded["average"] = avg

    return encoded


# ----- Save it for later -----
# Original output
saved_mathscore = df.iloc[:, -4]
save_readingscore = df.iloc[:, -3]
save_writingscore = df.iloc[:, -2]
save_average = df.iloc[:, -1]

# before one hot encoding
display(df.head(3))
df.shape

# Make sure to run it just ONCE otherwise, you need to run it all again from begining
df_encoded = one_hot_encoding(df)

# after one hot encoding
display(df_encoded.head(3))
df_encoded.shape

# Adding new column indicates pass or not the exams
# if it's under 60, it's fail else they pass the test
df_encoded['math_PassStatus'] = np.where(df_encoded['math score']<60, 0, 1)
df_encoded['read_PassStatus'] = np.where(df_encoded['reading score']<60, 0, 1)
df_encoded['write_PassStatus'] = np.where(df_encoded['writing score']<60, 0, 1)
df_encoded['overall_PassStatus'] = np.where(df_encoded['average']<60, 0, 1)

# After added, we drop the column
df_encoded.drop(['math score'], axis=1, inplace=True)
df_encoded.drop(['reading score'], axis=1, inplace=True)
df_encoded.drop(['writing score'], axis=1, inplace=True)
df_encoded.drop(['average'], axis=1, inplace=True)

# FINAL DATASET
```

```
display(df_encoded.head(3))
df_encoded.shape
```

	gender	race/ethnicity	parental level of education	lunch	test preparation course	math score	reading score	writing score	average
0	male	group A	high school	standard	completed	67.0	67.0	63.0	65.666667
1	female	group D	some high school	free/reduced	none	40.0	59.0	55.0	51.333333
2	male	group E	some college	free/reduced	none	59.0	60.0	50.0	56.333333

	gender_female	gender_male	race/ethnicity_group A	race/ethnicity_group B	race/ethnicity_group C	race/ethnicity_group D	race/ethnicity_group E	parental level of education_associate's degree	edu
0	0	1	1	0	0	0	0	0	
1	1	0	0	0	0	1	0	0	
2	0	1	0	0	0	0	1	0	

3 rows × 21 columns

	gender_female	gender_male	race/ethnicity_group A	race/ethnicity_group B	race/ethnicity_group C	race/ethnicity_group D	race/ethnicity_group E	parental level of education_associate's degree	edu
0	0	1	1	0	0	0	0	0	
1	1	0	0	0	0	1	0	0	
2	0	1	0	0	0	0	1	0	

3 rows × 21 columns

Out[ ]: (999, 21)

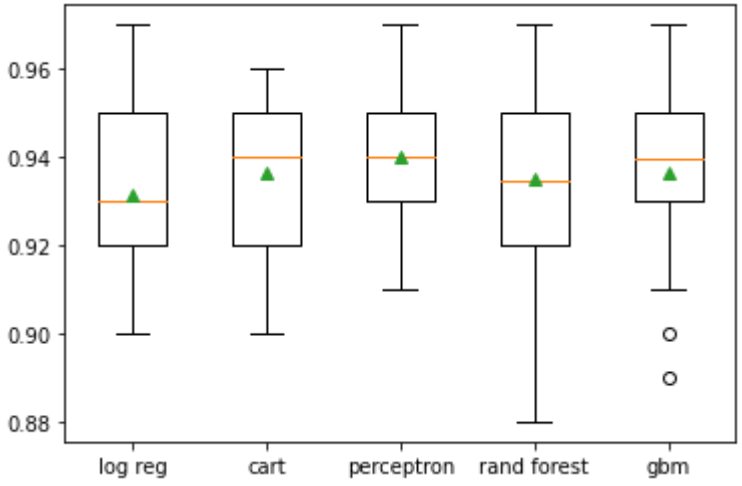
↑↑ Done One Hot Encoding ✔

In [ ]:

```
"""
This templates function is given from my teacher's jupyter notebook "RFE.ipynb" / from books "Data Preparation for
Machine Learning - Jason Brownlee"
"""

# get a list of models to evaluate
def get_models(X, y, n: int):
    models = dict()
    # lr
    rfe = RFE(estimator=LogisticRegression(), n_features_to_select=n)
    model = DecisionTreeClassifier()
    models['log reg'] = Pipeline(steps=[('s',rfe),('m',model)])
    # cart
    rfe = RFE(estimator=DecisionTreeClassifier(), n_features_to_select=n)
    model = DecisionTreeClassifier()
    models['cart'] = Pipeline(steps=[('s',rfe),('m',model)])
    # perceptron
    rfe = RFE(estimator=Perceptron(), n_features_to_select=n)
    model = DecisionTreeClassifier()
    models['perceptron'] = Pipeline(steps=[('s',rfe),('m',model)])
    # rf
    rfe = RFE(estimator=RandomForestClassifier(), n_features_to_select=n)
    model = DecisionTreeClassifier()
    models['rand forest'] = Pipeline(steps=[('s',rfe),('m',model)])
    # gbm
    rfe = RFE(estimator=GradientBoostingClassifier(), n_features_to_select=n)
    model = DecisionTreeClassifier()
    models['gbm'] = Pipeline(steps=[('s',rfe),('m',model)])
    return models


# evaluate a given model using cross-validation
def evaluate_model(model, X, y):
    cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
    scores = cross_val_score(model, X, y, scoring='accuracy', cv=cv, n_jobs=-1)
    return scores
```

In [ ]:
```
# Split dataset
X = df_encoded.iloc[:, :-1]
y = df_encoded.iloc[:, -1]

# evaluate the models and store results

# We select n features to 15 because we think that from 20 features...
# there are redundant features after one hot encoding, like we can drop 1 column but it's still represent the dataset itself
# (Column: gender, race/ethnicity, parental level of education, lunch, test preparation course) = 5 columns
n_features_to_select = 15

models = get_models(X, y, n_features_to_select)

results, names = list(), list()
for name, model in models.items():
    scores = evaluate_model(model, X, y)
    results.append(scores)
    names.append(name)
    print('> %s %.3f (%.3f)' % (name, mean(scores), std(scores)))

# plot model performance for comparison
pyplot.boxplot(results, labels=names, showmeans=True)
pyplot.show()
```

```
> log reg 0.932 (0.020)
> cart 0.936 (0.019)
> perceptron 0.940 (0.017)
> rand forest 0.935 (0.018)
> gbm 0.937 (0.019)
```



↑ ↑ As we can see.. "perceptron" has the highest accuracy, so we take "perception" model as our estimator

In [ ]:
```
def get_model_perceptron(X, y, n: int):
    models = dict()
    rfe = RFE(estimator=Perceptron(), n_features_to_select=n)
    model = DecisionTreeClassifier()
    models['perceptron'] = Pipeline(steps=[('s',rfe),('m',model)])
    rfe.fit(X, y)
    return models, rfe.support_, rfe.ranking_

# Ranking the features
percp = get_model_perceptron(X, y, n_features_to_select)
print(f"Selected feat. :{percp[1]}")
print(f"Features rank  : {percp[2]}")
```

```
Selected feat. :[ True  True False False  True  True  True  True False False  True False
  True  True  True  True  True  True  True  True]
Features rank  : [1 1 5 4 1 1 1 1 2 6 1 3 1 1 1 1 1 1 1 1]
```

In [ ]:
```
selected_fetures = [i for i, s in enumerate(percp[1]) if s]
print(f"Selected features: {selected_fetures}")

df_RFE = df_encoded.iloc[:, selected_fetures]
df_RFE["average"] = y

# Let's see the final dataset after features selection (RFE)
display(df_RFE.head(2))
print(df_RFE.shape)
```

```
Selected features: [0, 1, 4, 5, 6, 7, 10, 12, 13, 14, 15, 16, 17, 18, 19]
C:\Users\victo\AppData\Local\Temp\ipykernel_19276\2196618856.py:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_RFE["average"] = y
```

	gender_female	gender_male	race/ethnicity_group C	race/ethnicity_group D	race/ethnicity_group E	parental level of education_associate's degree	parental level of education_master's degree	parental level of education_some high school	lunch_free
0	0	1	0	0	0	0	0	0	
1	1	0	0	1	0	0	0	1	

```
(999, 16)
```

↑ ↑ Final dataset after features selection (RFE)

2. Features selection chi-square

In [ ]:
```
# Display datase after one hot encoding
df_encoded.head(2)
```

Out[ ]:

	gender_female	gender_male	race/ethnicity_group A	race/ethnicity_group B	race/ethnicity_group C	race/ethnicity_group D	race/ethnicity_group E	parental level of education_associate's degree	edu
0	0	1	1	0	0	0	0	0	
1	1	0	0	0	0	1	0	0	

2 rows × 21 columns

In [ ]:
```
# Split dataset
X = df_encoded.iloc[:, :-1]
y = df_encoded.iloc[:, -1]

# Features selection based on chi-square score
fs = SelectKBest(score_func=chi2, k='all')
fs.fit(X, y)
X_train_fs = fs.transform(X)

# Get chi-square score for all columns
features_score = fs.scores_
features_score = features_score.tolist()

print(f"Features score:\n{features_score}")
```

```
Features score:
[1.646292313558209, 1.5410061772260017, 0.10517193147122977, 0.6211477202956669, 8.859720493179172, 8.432822006776183, 3.2824830828256424,
6.214337849241212, 5.446751250342558, 0.09983407905054674, 3.5271481283661714, 2.2988294248913577, 17.45630466477532, 44.049242183903544, 2
3.547060337939232, 23.342219507272105, 11.72376137658479, 180.74431188914133, 172.26055207393418, 192.1720486724545]
```

↑ ↑ Done features selection chi-square ✔

In [ ]:
```
def selection_sort_and_keep_track_the_original_index(features_score):
    temp = [i for i in range(len(features_score))]
    for i in range(0, len(features_score)-1):
        for j in range(i+1, len(features_score)):
            if features_score[i] > features_score[j]:
                features_score[i], features_score[j] = features_score[j], features_score[i]
                temp[i], temp[j] = temp[j], temp[i]

    return list(zip(temp, features_score))


final_features = selection_sort_and_keep_track_the_original_index(features_score)
print(final_features)
```

```
[(9, 0.09983407905054674), (2, 0.10517193147122977), (3, 0.6211477202956669), (1, 1.5410061772260017), (0, 1.646292313558209), (11, 2.2988294248913577), (6, 3.2824830828256424), (10, 3.5271481283661714), (8, 5.446751250342558), (7, 6.214337849241212), (5, 8.432822006776183), (4, 8.859720493179172), (16, 11.72376137658479), (12, 17.45630466477532), (15, 23.342219507272105), (14, 23.547060337939232), (13, 44.049242183903544), (18, 172.26055207393418), (17, 180.74431188914133), (19, 192.1720486724545)]
```

↑ ↑ We sort the chi-square features socre but keep tracking the original index (Don't run it twice)

In [ ]:
```
# We select best of 15 features out of 20 based on our RFE above
final_features = [g[0] for g in (final_features[5:])]

df_cs = df_encoded.iloc[:, final_features]
df_cs["average"] = y

display(df_cs)
```

```
C:\Users\victo\AppData\Local\Temp\ipykernel_19276\2541747963.py:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_cs["average"] = y
```

	parental level of education_some college	race/ethnicity_group E	parental level of education_master's degree	parental level of education_bachelor's degree	parental level of education_associate's degree	race/ethnicity_group D	race/ethnicity_group C	test preparation course_none	e
0	0	0	0	0	0	0	0	0	
1	0	0	0	0	0	1	0	1	
2	1	1	0	0	0	0	0	1	
3	0	0	0	0	0	0	0	1	
4	0	1	0	0	1	0	0	0	
...	...	...	...	...	...	...	...	...	
995	0	0	0	0	0	0	1	1	
996	0	0	0	0	1	1	0	0	
997	0	0	0	0	0	0	1	1	
998	1	0	0	0	0	0	1	1	
999	1	0	0	0	0	0	0	0	

999 rows × 16 columns

↑ ↑ Final dataset after features selection (chi-square)

Summary (answering the problem define description above)

In [ ]:
```
# Display original dataset (but with new column "average")
df
```

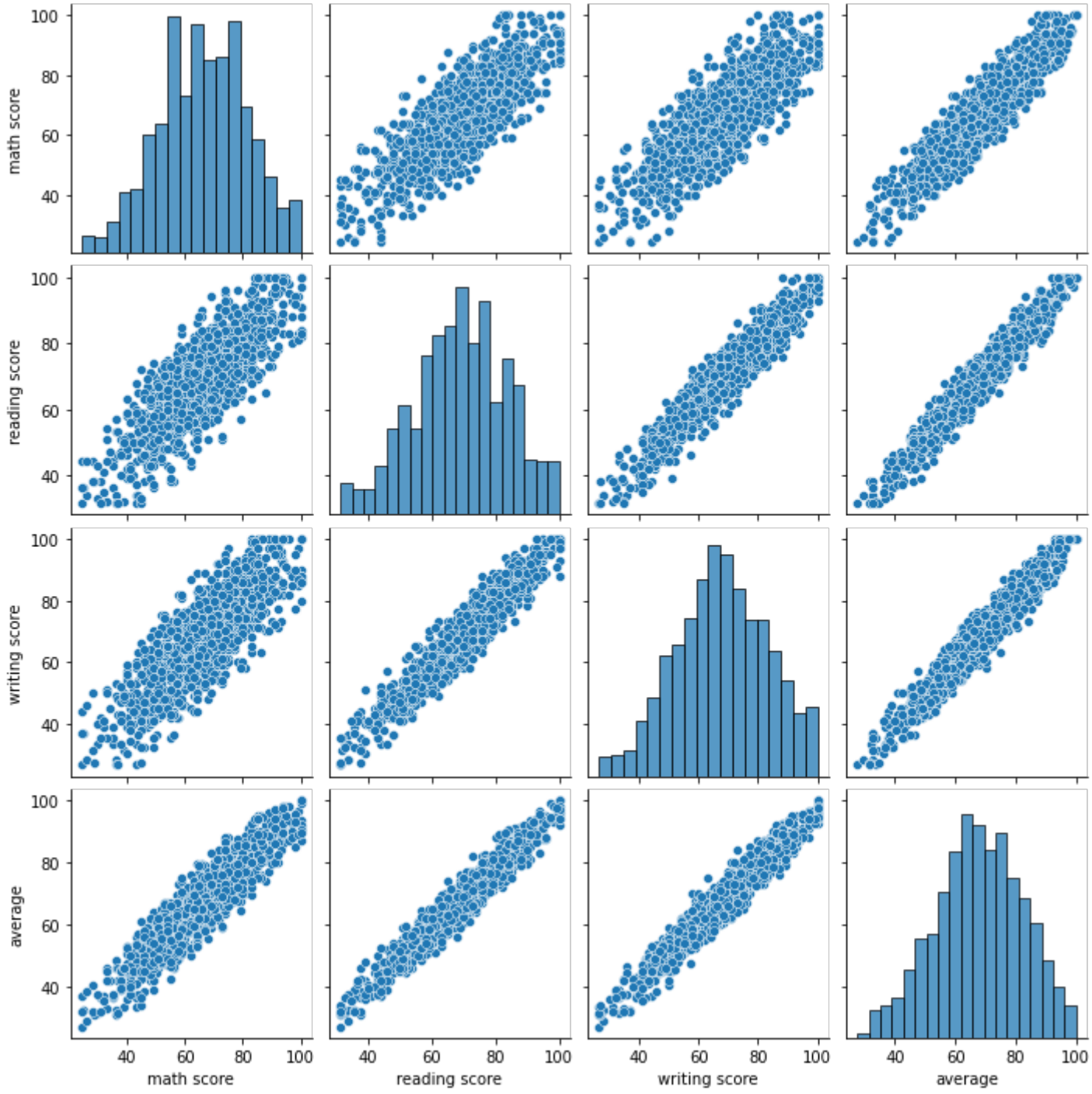
Out[ ]:

	gender	race/ethnicity	parental level of education	lunch	test preparation course	math score	reading score	writing score	average
0	male	group A	high school	standard	completed	67.0	67.0	63.0	65.666667
1	female	group D	some high school	free/reduced	none	40.0	59.0	55.0	51.333333
2	male	group E	some college	free/reduced	none	59.0	60.0	50.0	56.333333
3	male	group B	high school	standard	none	77.0	78.0	68.0	74.333333
4	male	group E	associate's degree	standard	completed	78.0	73.0	68.0	73.000000
...	...	...	...	...	...	...	...	...	...
995	male	group C	high school	standard	none	73.0	70.0	65.0	69.333333
996	male	group D	associate's degree	free/reduced	completed	85.0	91.0	92.0	89.333333
997	female	group C	some high school	free/reduced	none	32.0	35.0	41.0	36.000000
998	female	group C	some college	standard	none	73.0	74.0	82.0	76.333333
999	male	group A	some college	standard	completed	65.0	60.0	62.0	62.333333

999 rows × 9 columns

In [ ]:
```
# Let's see the distribution
sns.pairplot(df)
```

Out[ ]:
```
<seaborn.axisgrid.PairGrid at 0x1d04b692050>
```

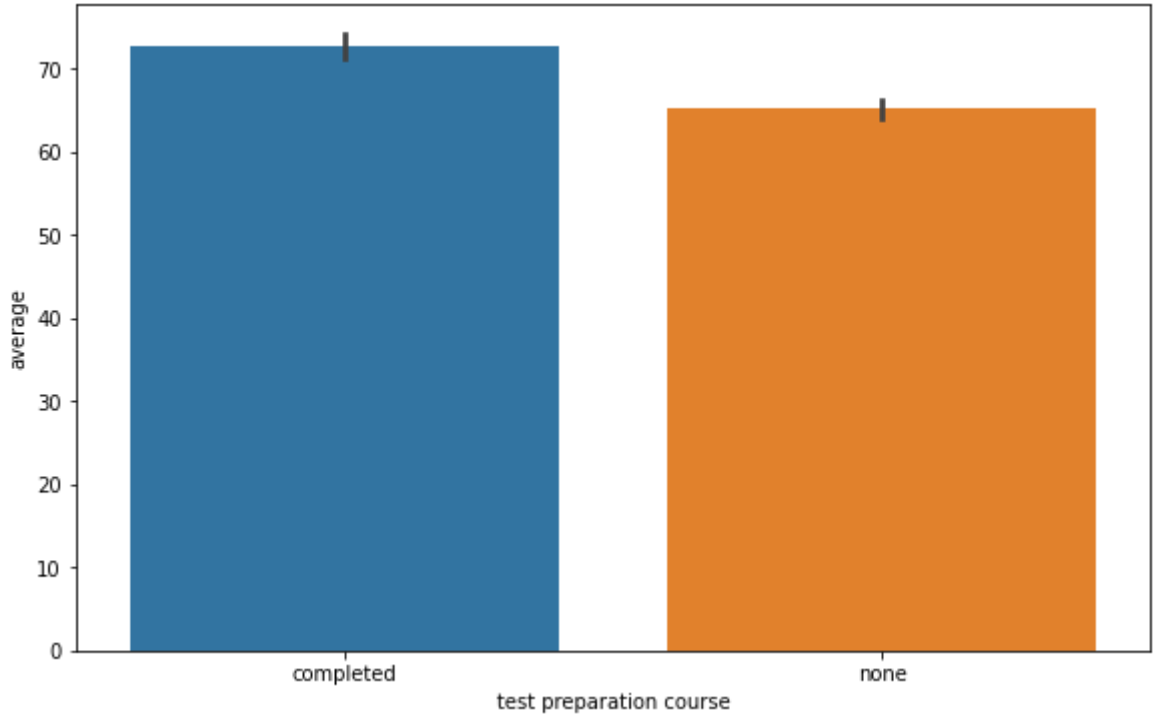


a. How effective is the test preparation course?

In [ ]:
```
# We plot to barplot so we can see the corelation
figure, ax = plt.subplots(1,1, constrained_layout=True, figsize=(8, 5))
plt.subplot(1, 1, 1)
sns.barplot(df['test preparation course'], df['average'])
```

```
c:\Python 3.10.2\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From versi
on 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error
or misinterpretation.
  warnings.warn(
```

Out[ ]:
```
<AxesSubplot:xlabel='test preparation course', ylabel='average'>
```



In [ ]:
```
# Let's see value counts for "test preparation course"
df['test preparation course'].value_counts()
```

Out[ ]:
```
none         665
completed    334
Name: test preparation course, dtype: int64
```

↑ ↑ From barplot above... we can see that the "test preparation course" is quite effective in peforming student's exams score

There is a different between "completed" and "none"

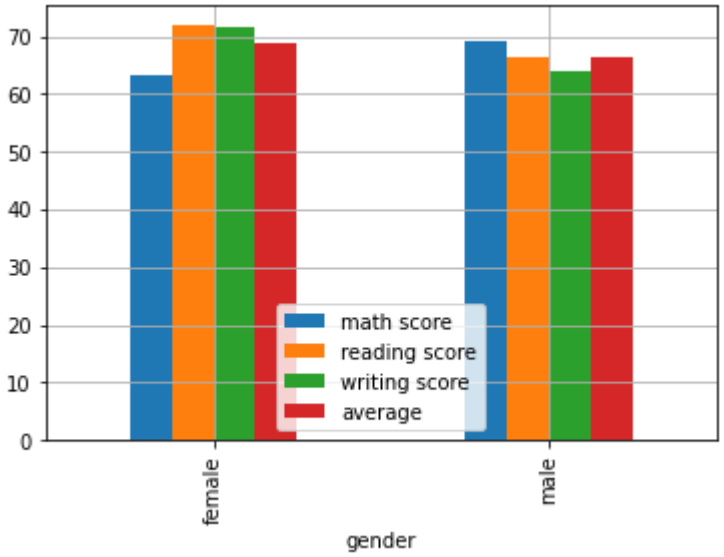
The average of exams score of the completed "test preparation course" is higher than those who not (none) completed "test preparation course"

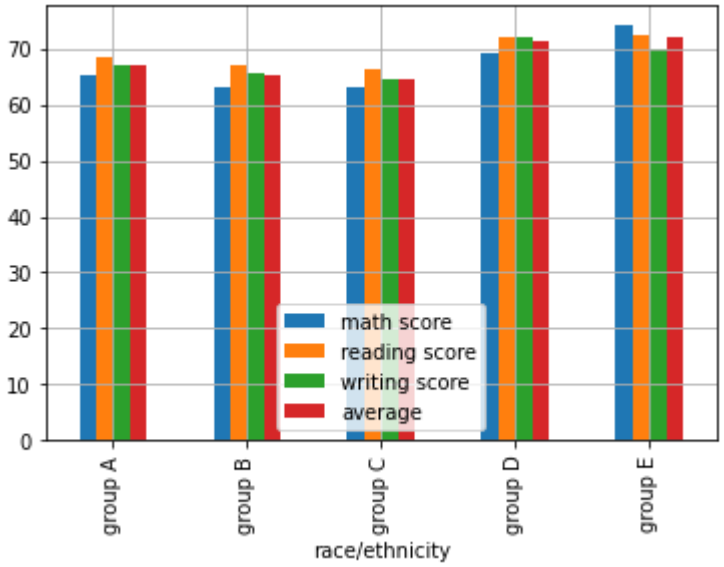
So we can say that "test preparation course" is quite effective ✔

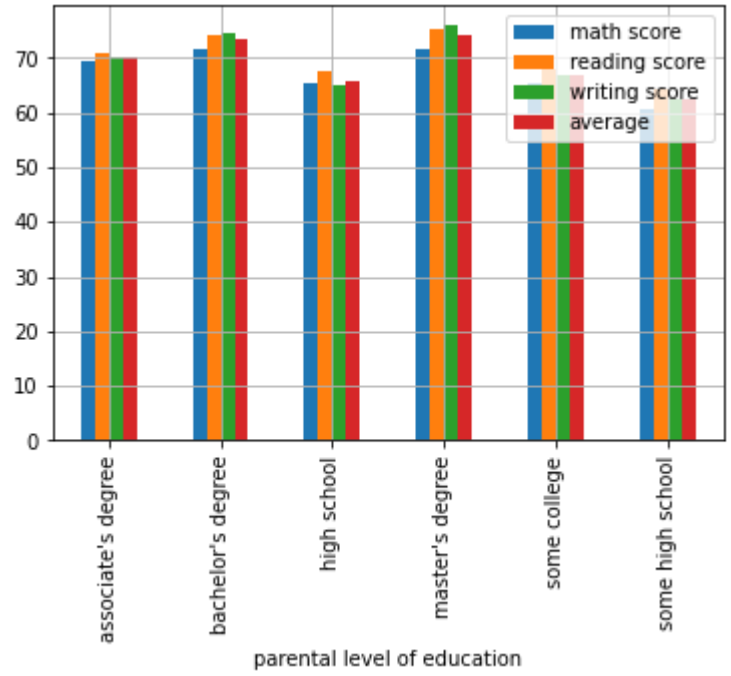
b. Which major factors contribute to test outcomes?

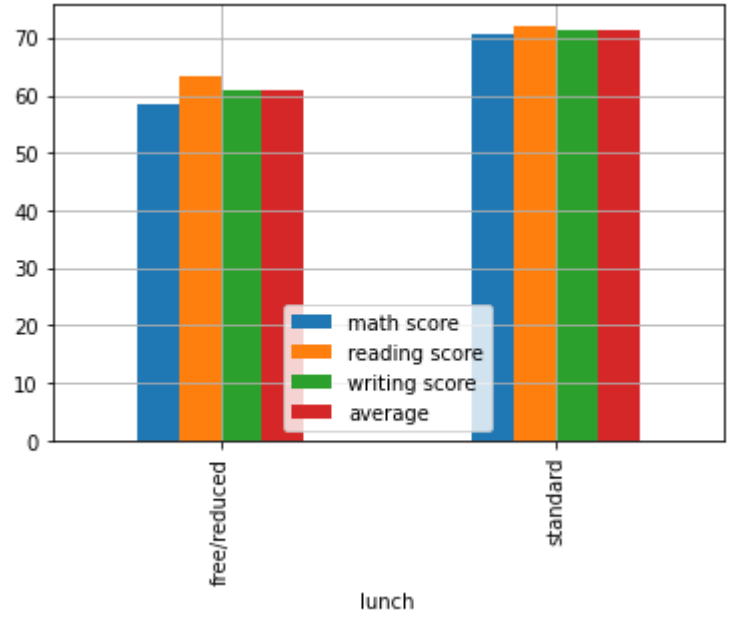
In [ ]:
```
# Let's bar plot 5 input columns and check which has the most significant difference
output = ['math score','reading score','writing score','average']

for x in df.columns[:-4]:
    scores=df.groupby(x)[output].mean()
    print(scores)
    scores.plot(kind='bar',grid=True )
```

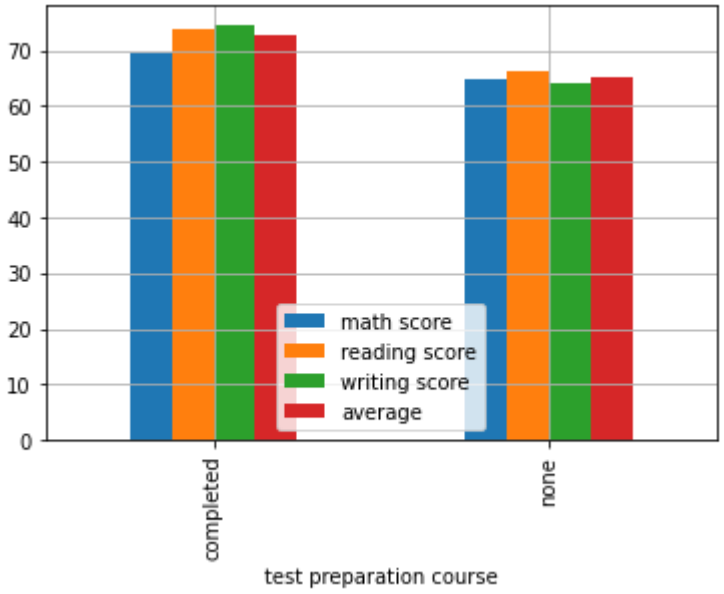
```
        math score  reading score  writing score    average
gender
female   63.247412      71.898551      71.715321  68.953761
male     69.325581      66.263566      63.971899  66.520349
                math score  reading score  writing score    average
race/ethnicity
group A          65.215190      68.556962      66.974684  66.915612
group B          63.170732      67.148780      65.765854  65.361789
group C          63.170279      66.407121      64.535604  64.704334
group D          69.311069      72.087786      72.259542  71.219466
group E          74.269231      72.315385      69.984615  72.189744
                            math score  reading score  writing score  \
parental level of education
associate's degree            69.393564      70.841584      69.965347
bachelor's degree             71.491071      74.008929      74.410714
high school                   65.207921      67.418317      64.863861
master's degree               71.585714      75.428571      75.885714
some college                  65.400901      68.103604      66.763514
some high school              60.701571      64.410995      62.539267

                              average
parental level of education
associate's degree           70.066832
bachelor's degree            73.303571
high school                  65.830033
master's degree              74.300000
some college                 66.756006
some high school             62.550611
             math score  reading score  writing score    average
lunch
free/reduced   58.576149      63.238506      60.954023  60.922893
standard       70.562212      72.061444      71.330261  71.317972
                         math score  reading score  writing score    average
test preparation course
completed                 69.595808      74.019461      74.595808  72.737026
none                      64.775188      66.460902      64.260150  65.165414
```


70
60
50
40
30
20
10
0
math score
reading score
writing score
average
female
male
gender


70
60
50
40
30
20
10
0
math score
reading score
writing score
average
group A
group B
group C
group D
group E
race/ethnicity


math score
reading score
writing score
average
0
10
20
30
40
50
60
70
associate's degree
bachelor's degree
high school
master's degree
some college
some high school
parental level of education


math score
reading score
writing score
average
0
10
20
30
40
50
60
70
free/reduced
standard
lunch



↑ ↑ From 5 barplot above... we can observe that the most significant to test outcome is "lunch"

Which major factors contribute to test outcomes? The answer is "lunch" ✔

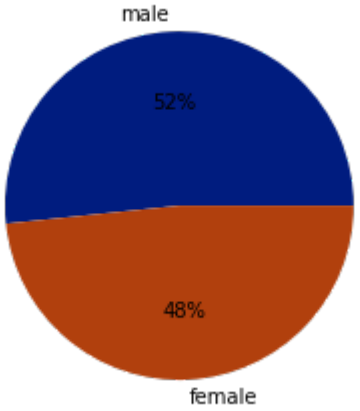
c. What would be the best way to improve student scores on each test?

It's easy after we see all the 5 barplot above in cell "b". The "lunch" is a key and a simple problem and solution to improve student scores (based on each test/average)

d. What patterns and interactions in the data can you find?

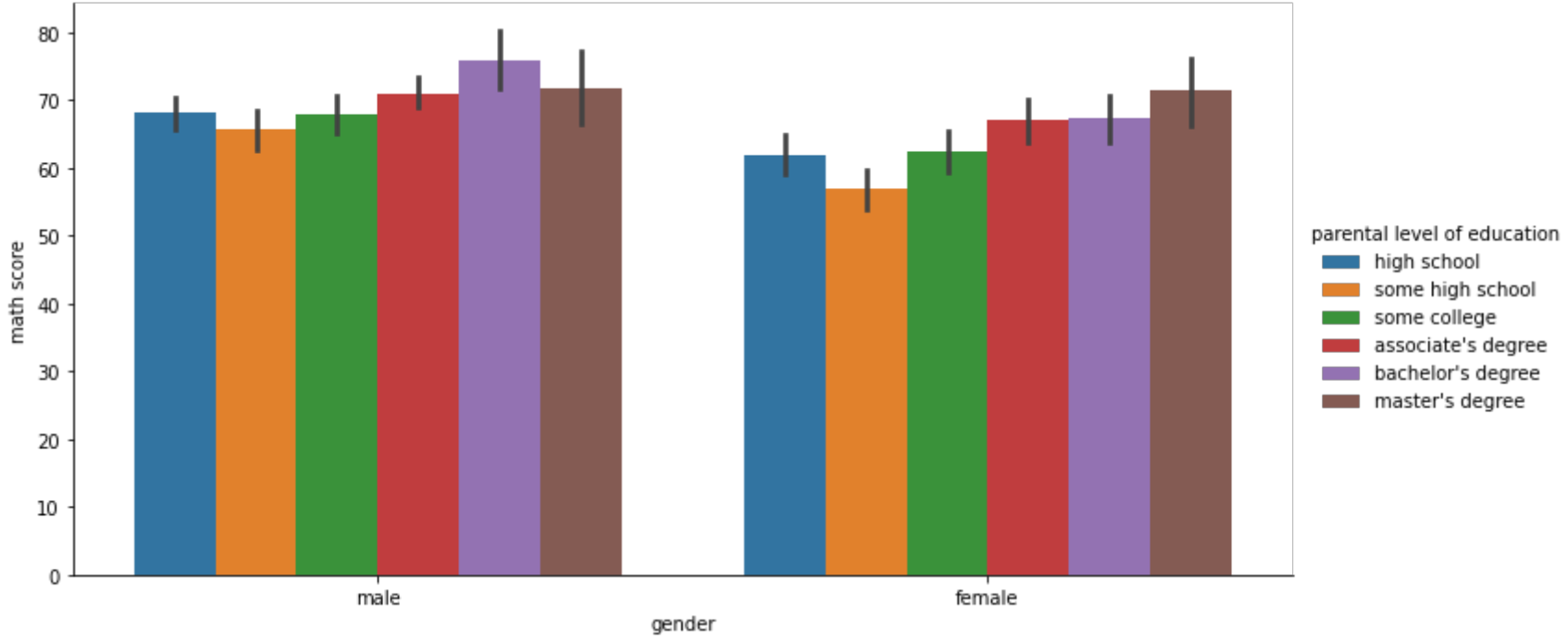
In [ ]:
```
palette_color = sns.color_palette('dark')
plt.pie(df["gender"].value_counts(), labels=["male", "female"], colors=palette_color, autopct='%.0f%%')
```

Out[ ]:
```
([<matplotlib.patches.Wedge at 0x1d04d8ae5c0>,
  <matplotlib.patches.Wedge at 0x1d04d8aece0>],
 [Text(-0.057051340946565506, 1.0985195239485728, 'male'),
  Text(0.05705134094656561, -1.0985195239485728, 'female')],
 [Text(-0.03111891324358118, 0.5991924676083124, '52%'),
  Text(0.031118913243581237, -0.5991924676083124, '48%')])
```

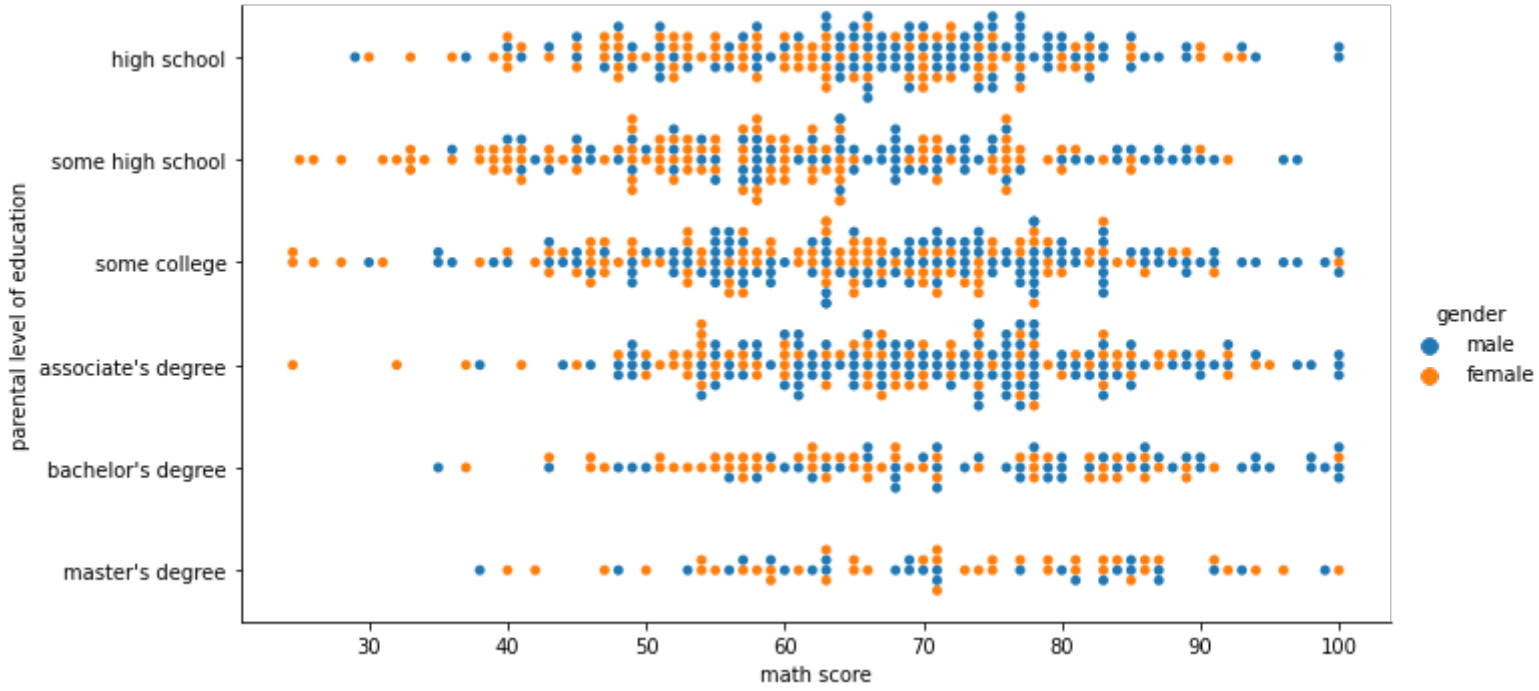


In [ ]:
```
plt.figure(figsize=(10,10))
sns.catplot(x="gender", y="math score", hue="parental level of education", data=df, kind='bar', height=5, aspect=2)
plt.show()
sns.catplot(data=df, x="math score", y="parental level of education", hue="gender", kind="swarm" ,height=5, aspect=2)
plt.figure(figsize=(10,10))
sns.catplot(data=df, x="reading score", y="parental level of education", hue="gender", kind="swarm" ,height=5, aspect=2)
plt.figure(figsize=(10,10))
sns.catplot(data=df, x="writing score", y="parental level of education", hue="gender", kind="swarm" ,height=5, aspect=2)
plt.figure(figsize=(10,10))
```

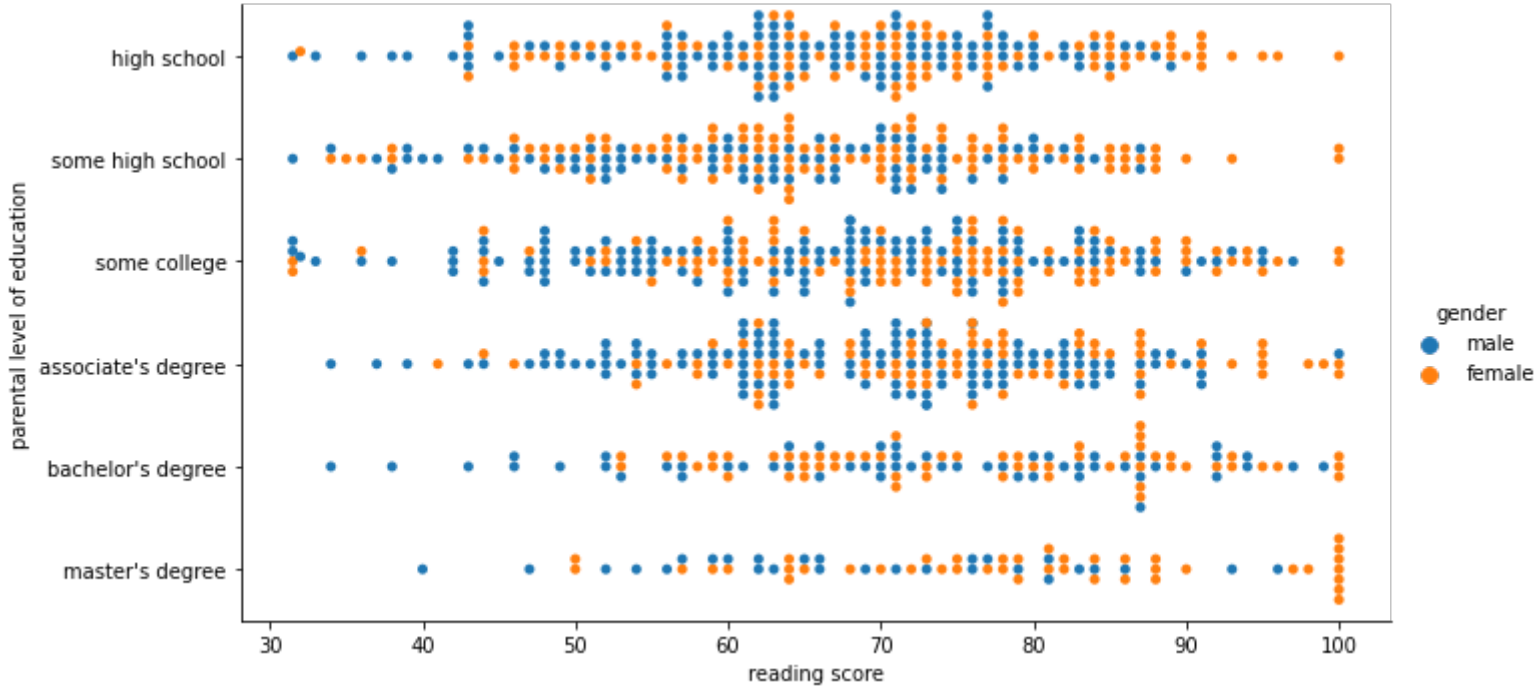
```
<Figure size 720x720 with 0 Axes>
```



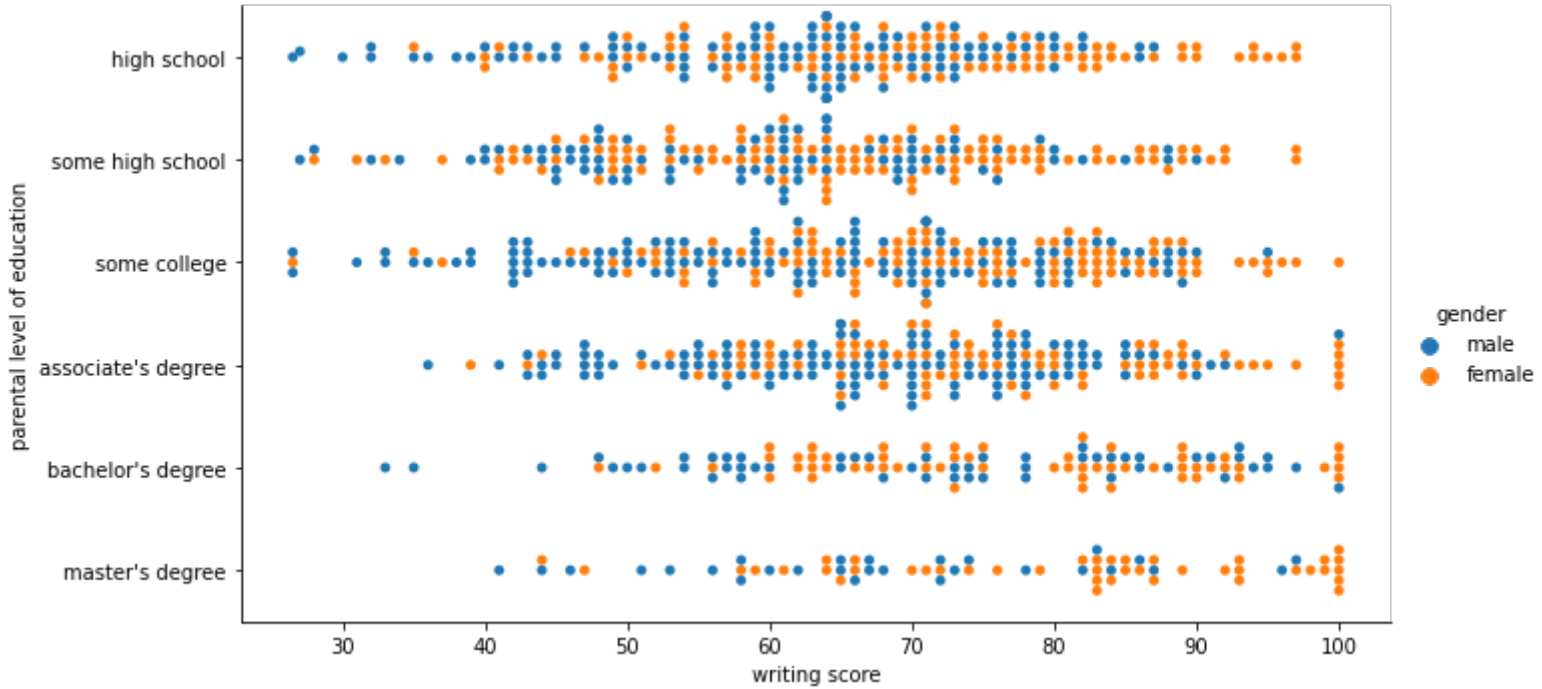
Out[ ]: <Figure size 720x720 with 0 Axes>



<Figure size 720x720 with 0 Axes>



<Figure size 720x720 with 0 Axes>




```
<Figure size 720x720 with 0 Axes>
```

From barplot before and chart above, we can observe...

- Students with a higher parental's degrees have more chances to achieve a higher scores
- Based on gender, female have higher score average than male
- The females dominate the higher scores in reading and writing
- Male outperform female in ONLY math
- Along this dataset female and male students are equally distributed
- "Lunch" is quite influential in performing student's exams score

In [ ]: