In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn import linear_model
import seaborn as sns

import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
data = pd.read_csv('StudentsPerformance.csv')       # Dataset from kaggle
print(data.shape)
data.head()
```

```
(1000, 8)
```

Out[2]:

	gender	race/ethnicity	parental level of education	lunch	test preparation course	math score	reading score	writing score
0	female	group B	bachelor's degree	standard	none	72	72	74
1	female	group C	some college	standard	completed	69	90	88
2	female	group B	master's degree	standard	none	90	95	93
3	male	group A	associate's degree	free/reduced	none	47	57	44
4	male	group C	some college	standard	none	76	78	75

In [3]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 8 columns):
 #   Column                       Non-Null Count  Dtype 
---  ------                       --------------  ----- 
 0   gender                       1000 non-null   object
 1   race/ethnicity               1000 non-null   object
 2   parental level of education  1000 non-null   object
 3   lunch                        1000 non-null   object
 4   test preparation course      1000 non-null   object
 5   math score                   1000 non-null   int64 
 6   reading score                1000 non-null   int64 
 7   writing score                1000 non-null   int64 
dtypes: int64(3), object(5)
memory usage: 62.6+ KB
```

In [4]:
```
data.describe()
```

Out[4]:

	math score	reading score	writing score
count	1000.00000	1000.000000	1000.000000
mean	66.08900	69.169000	68.054000
std	15.16308	14.600192	15.195657
min	0.00000	17.000000	10.000000
25%	57.00000	59.000000	57.750000
50%	66.00000	70.000000	69.000000
75%	77.00000	79.000000	79.000000
max	100.00000	100.000000	100.000000

In [5]:
```
data.isnull().sum()
```

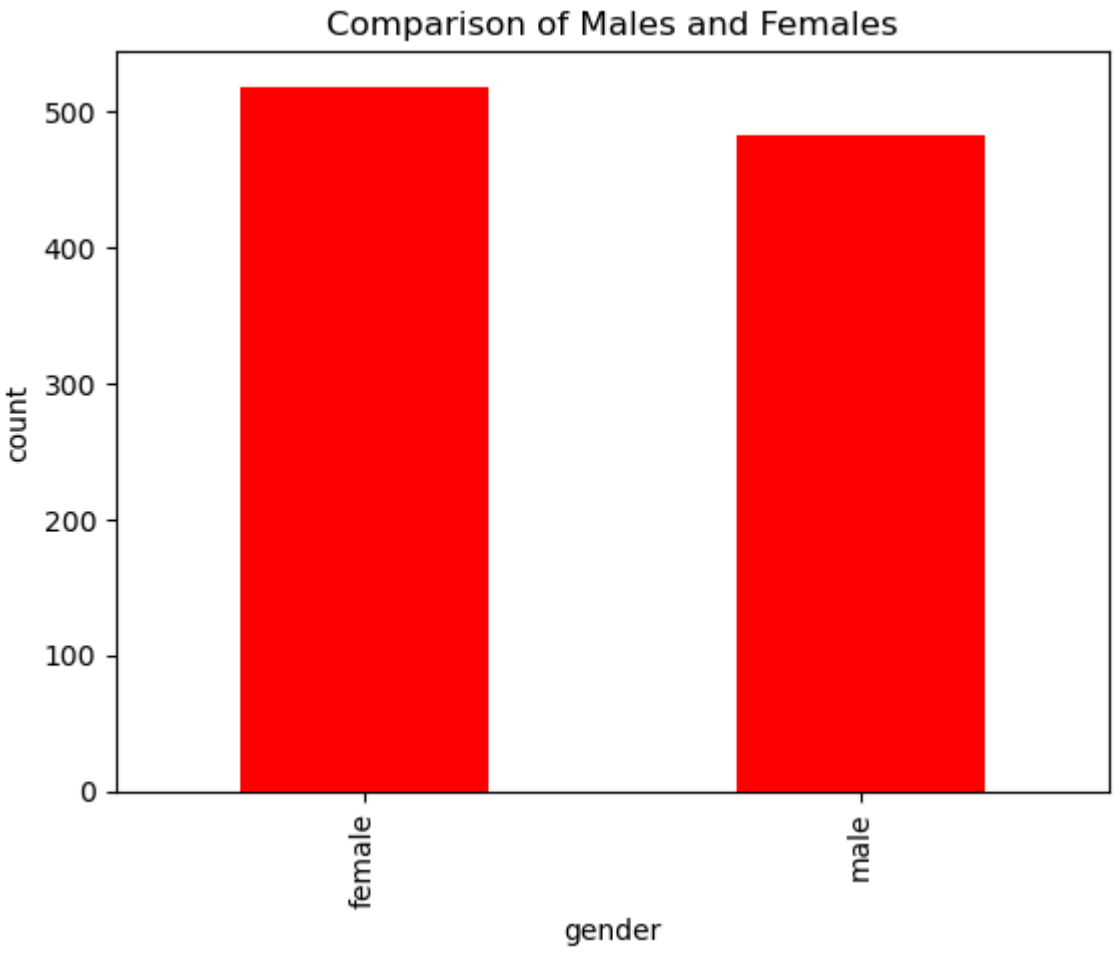
Out[5]:
```
gender                         0
race/ethnicity                 0
parental level of education    0
lunch                          0
test preparation course        0
math score                     0
reading score                  0
writing score                  0
dtype: int64
```

EXPLORING THE DATA FEATURES

In [6]:
```
data['gender'].value_counts(normalize = True)   # Counting the relative frequencies
```

Out[6]:
```
female    0.518
male      0.482
Name: gender, dtype: float64
```

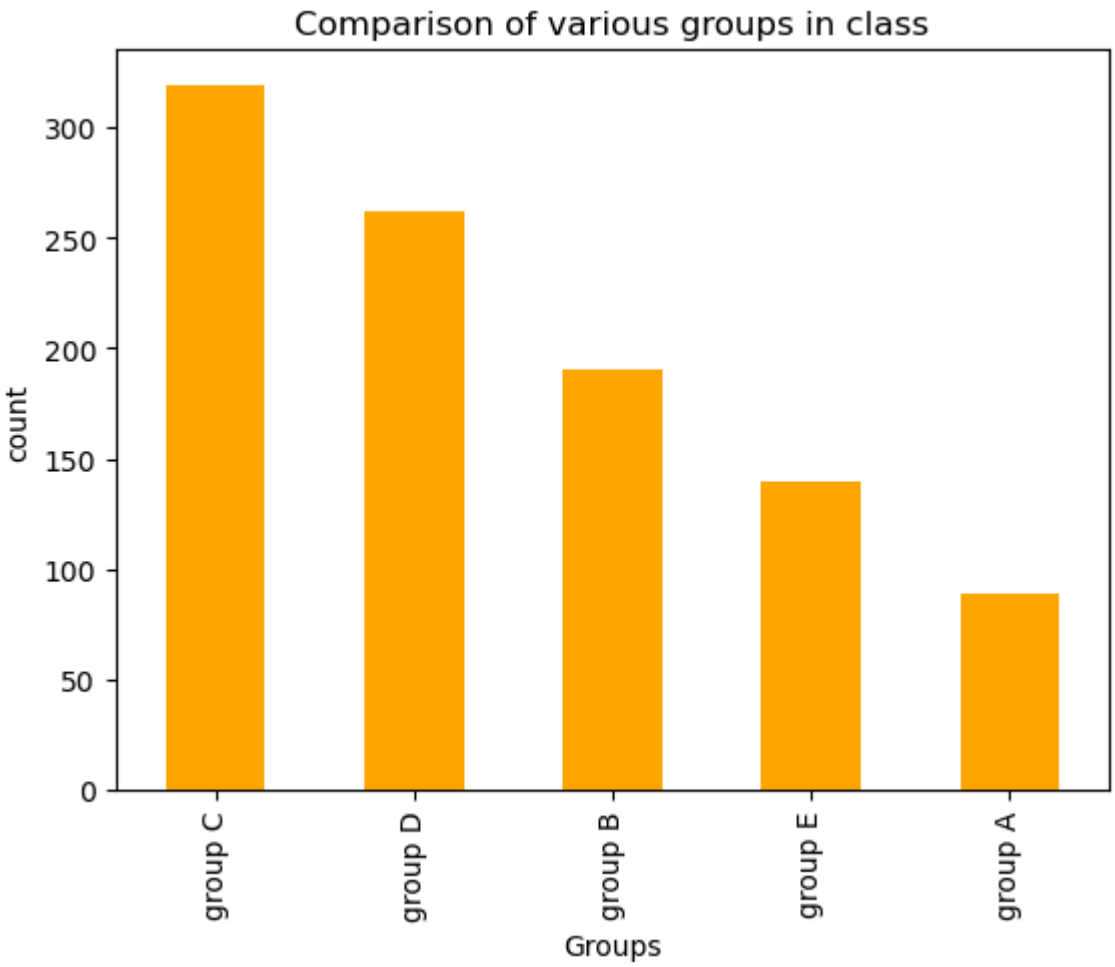
In [7]:
```
data['gender'].value_counts(dropna = False).plot.bar(color = 'red')
plt.title('Comparison of Males and Females')
plt.xlabel('gender')
plt.ylabel('count')
plt.show()              # Visualising the number of male and female in the dataset
```



In [8]:
```
print(data['race/ethnicity'].value_counts(normalize = True))
print()
print(data['race/ethnicity'].value_counts())
```

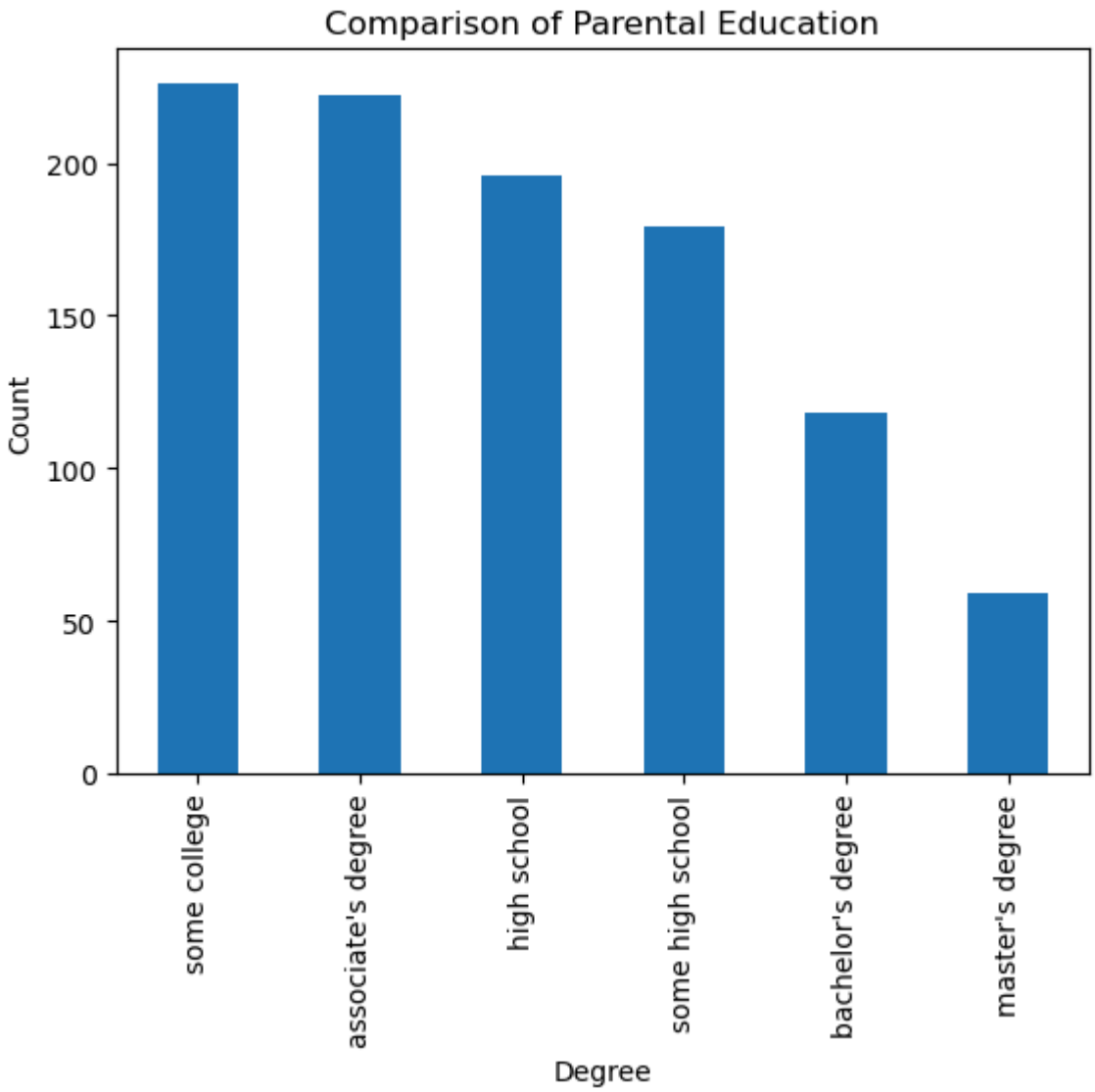
```
group C    0.319
group D    0.262
group B    0.190
group E    0.140
group A    0.089
Name: race/ethnicity, dtype: float64

group C    319
group D    262
group B    190
group E    140
group A     89
Name: race/ethnicity, dtype: int64
```

In [9]:
```
data['race/ethnicity'].value_counts(dropna = False).plot.bar(color = 'orange')
plt.title('Comparison of various groups in class')
plt.xlabel('Groups')
plt.ylabel('count')
plt.show()                    # Visualizing the different groups in the dataset
```



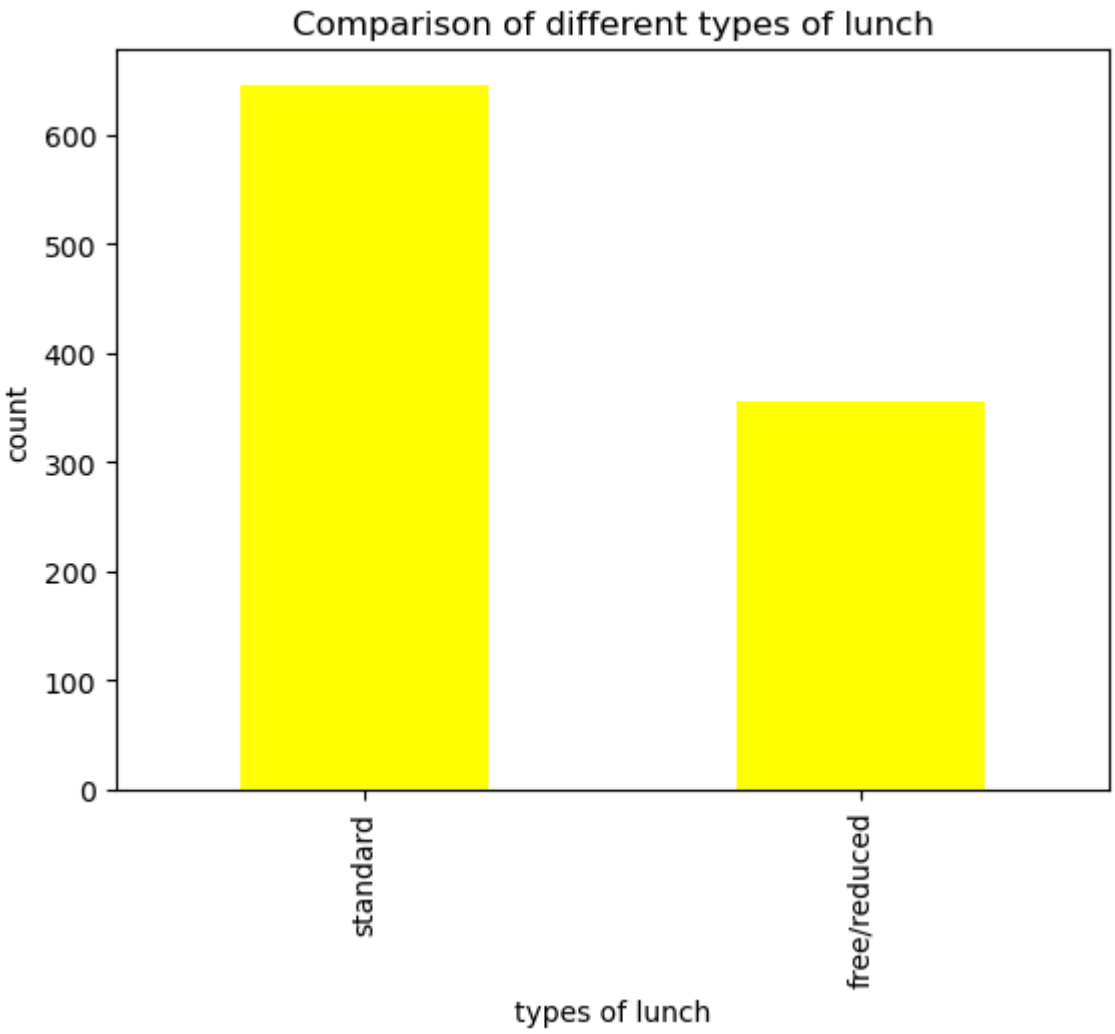
In [10]:
```
print(data['parental level of education'].value_counts(normalize = True))
print()
data['parental level of education'].value_counts(dropna = False).plot.bar()
plt.title('Comparison of Parental Education')
plt.xlabel('Degree')
plt.ylabel('Count')
plt.show()              # Visualizing the different parental education levels
```

```
some college          0.226
associate's degree    0.222
high school           0.196
some high school      0.179
bachelor's degree     0.118
master's degree       0.059
Name: parental level of education, dtype: float64
```



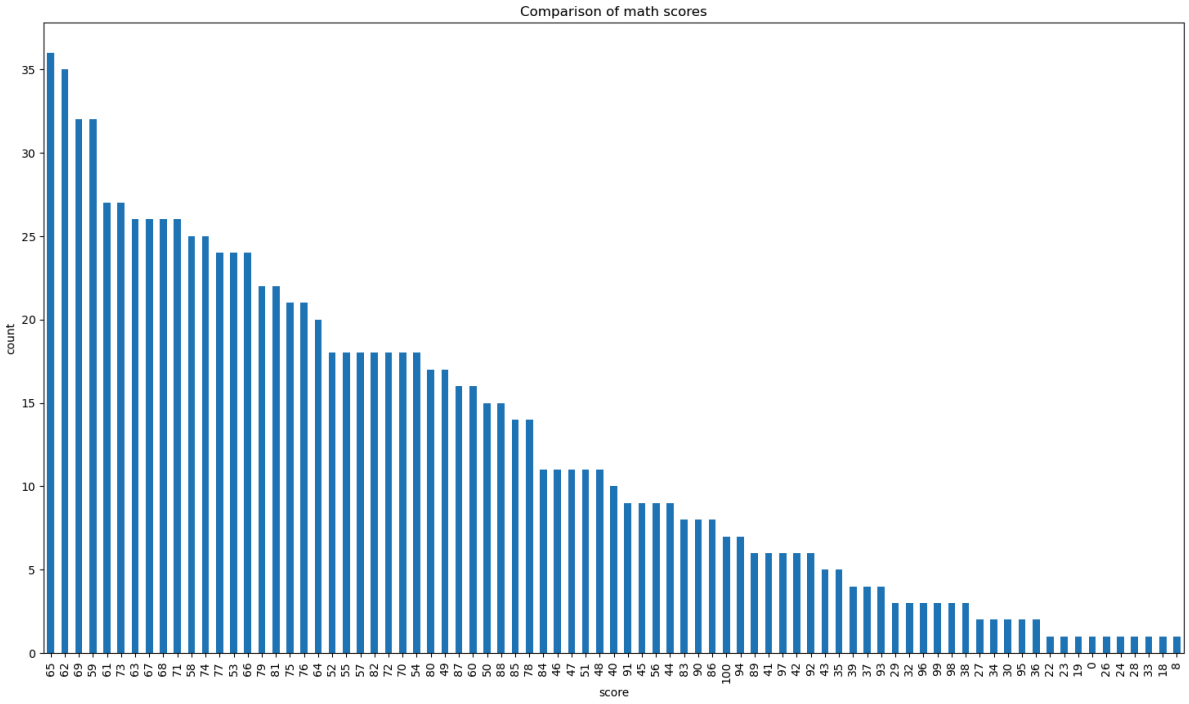
In [11]:
```
print(data['lunch'].value_counts(normalize = True))
print()
data['lunch'].value_counts(dropna = False).plot.bar(color = 'yellow')
plt.title('Comparison of different types of lunch')
plt.xlabel('types of lunch')
plt.ylabel('count')
plt.show()                  # Visualizing different types of lunches
```

```
standard        0.645
free/reduced    0.355
Name: lunch, dtype: float64
```



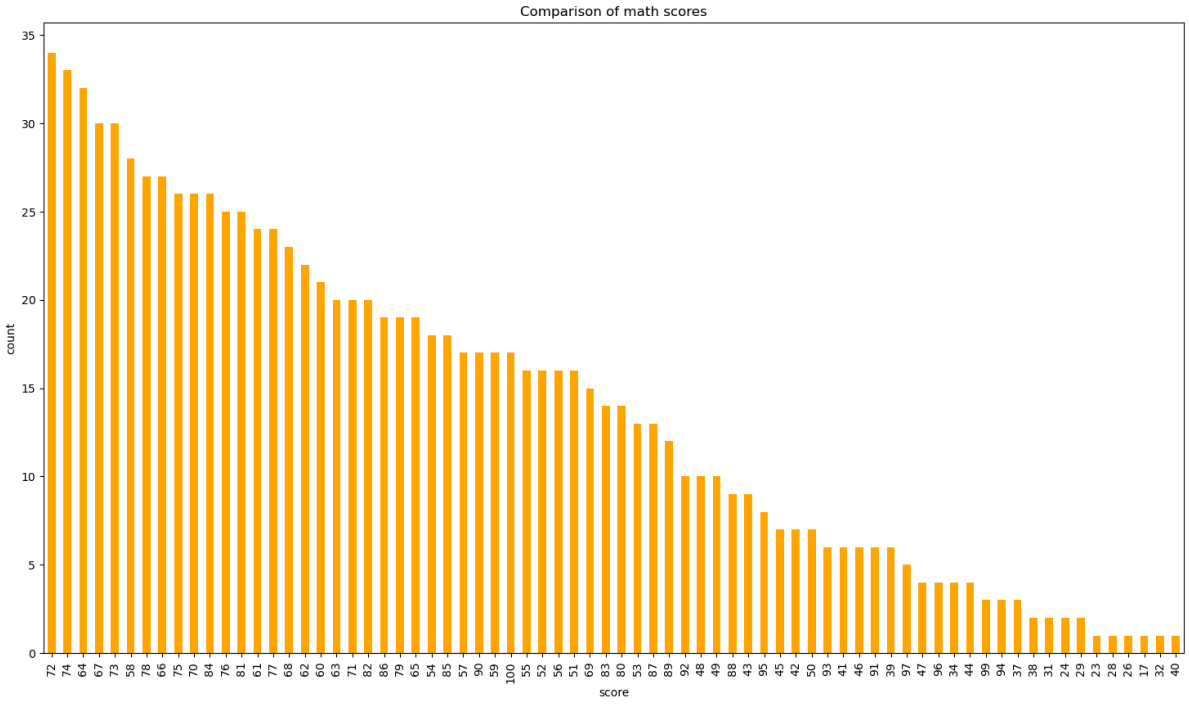
In [12]:
```
print(data['math score'].value_counts(normalize = True).unique())
print()
print(data['math score'].value_counts(normalize = True))
print()
data['math score'].value_counts(dropna = False).plot.bar(figsize = (18, 10))
plt.title('Comparison of math scores')
plt.xlabel('score')
plt.ylabel('count')
plt.show()                # Visualizing maths score of students
```

```
[0.036 0.035 0.032 0.027 0.026 0.025 0.024 0.022 0.021 0.02  0.018 0.017
 0.016 0.015 0.014 0.011 0.01  0.009 0.008 0.007 0.006 0.005 0.004 0.003
 0.002 0.001]

65    0.036
62    0.035
69    0.032
59    0.032
61    0.027
      ...
24    0.001
28    0.001
33    0.001
18    0.001
8     0.001
Name: math score, Length: 81, dtype: float64
```



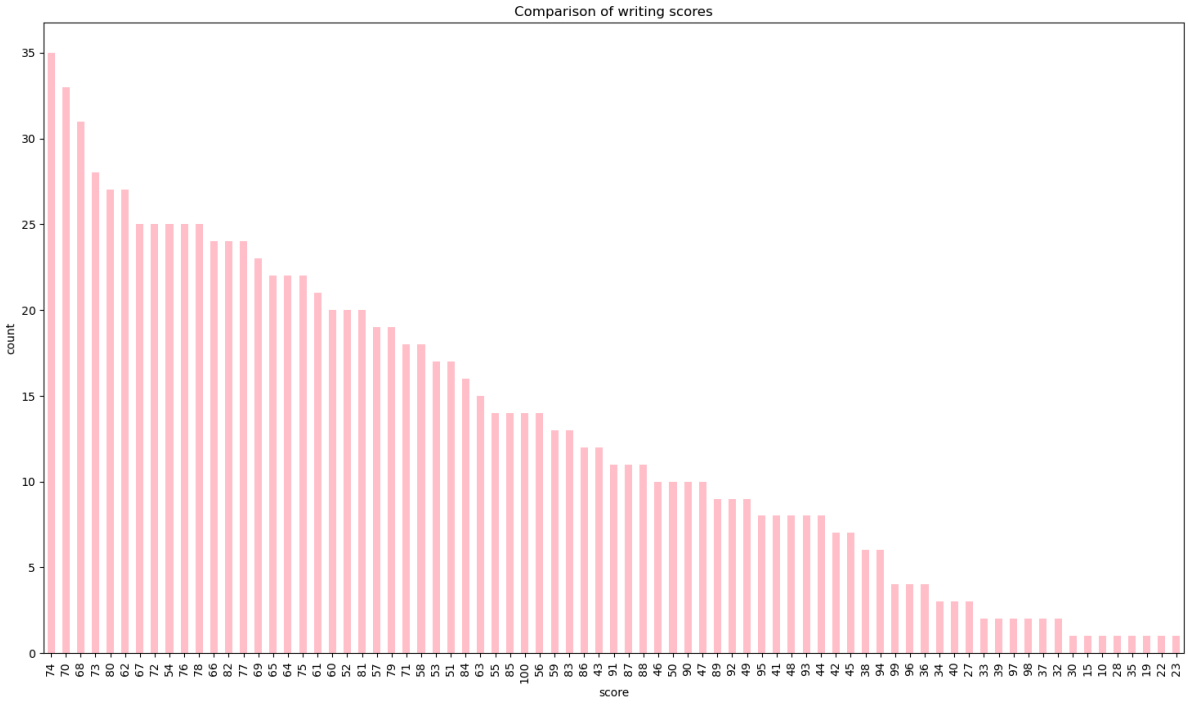
In [13]:
```
print(data['reading score'].value_counts(normalize = True))
print()
data['reading score'].value_counts(dropna = False).plot.bar(figsize = (18, 10), col
plt.title('Comparison of math scores')
plt.xlabel('score')
plt.ylabel('count')
plt.show()                    # Visualizing reading score
```

```
72    0.034
74    0.033
64    0.032
67    0.030
73    0.030
      ...
28    0.001
26    0.001
17    0.001
32    0.001
40    0.001
Name: reading score, Length: 72, dtype: float64
```



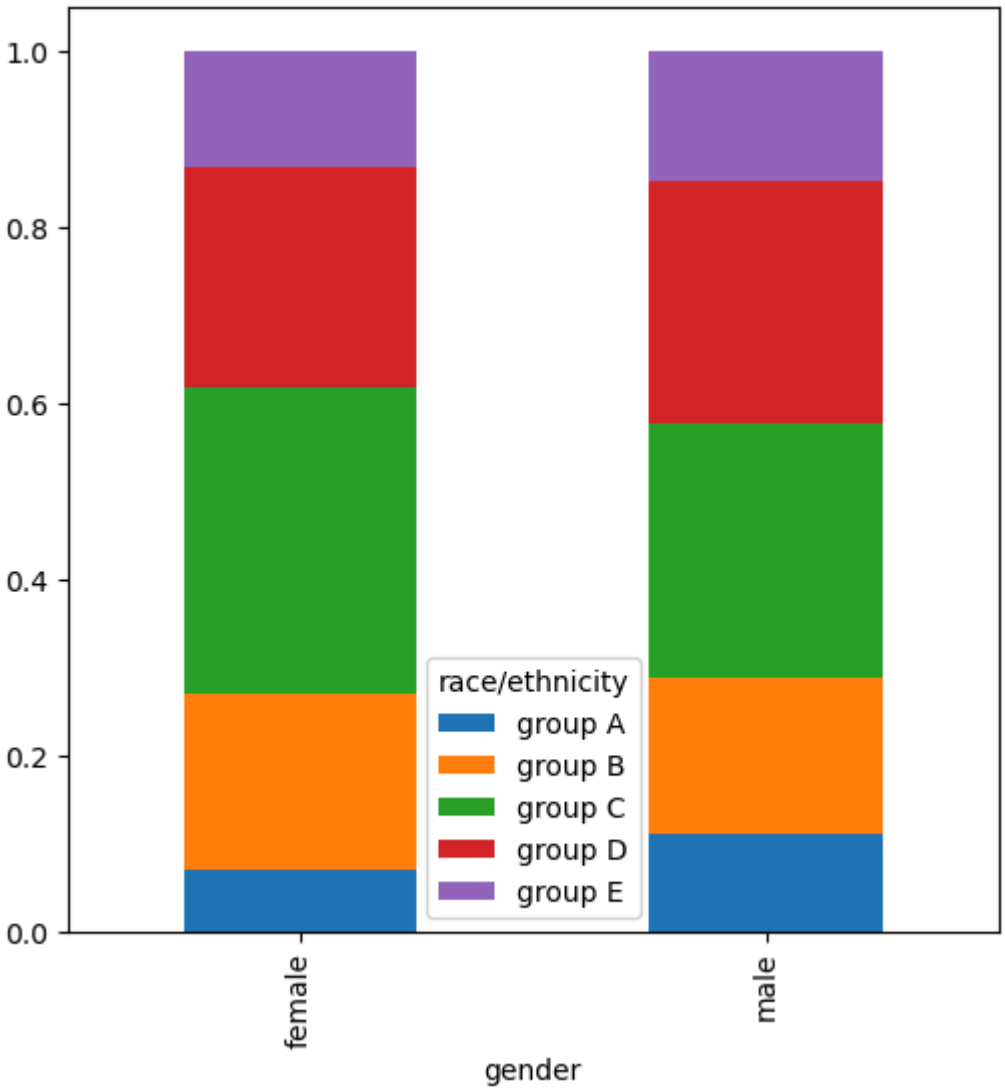
In [14]:
```
print((data['writing score'].value_counts(normalize = True)))
print()
data['writing score'].value_counts(dropna = False).plot.bar(figsize = (18, 10), col
plt.title('Comparison of writing scores')
plt.xlabel('score')
plt.ylabel('count')
plt.show()                          # Visualizing writing score
```

```
74    0.035
70    0.033
68    0.031
73    0.028
80    0.027
      ...
28    0.001
35    0.001
19    0.001
22    0.001
23    0.001
Name: writing score, Length: 77, dtype: float64
```

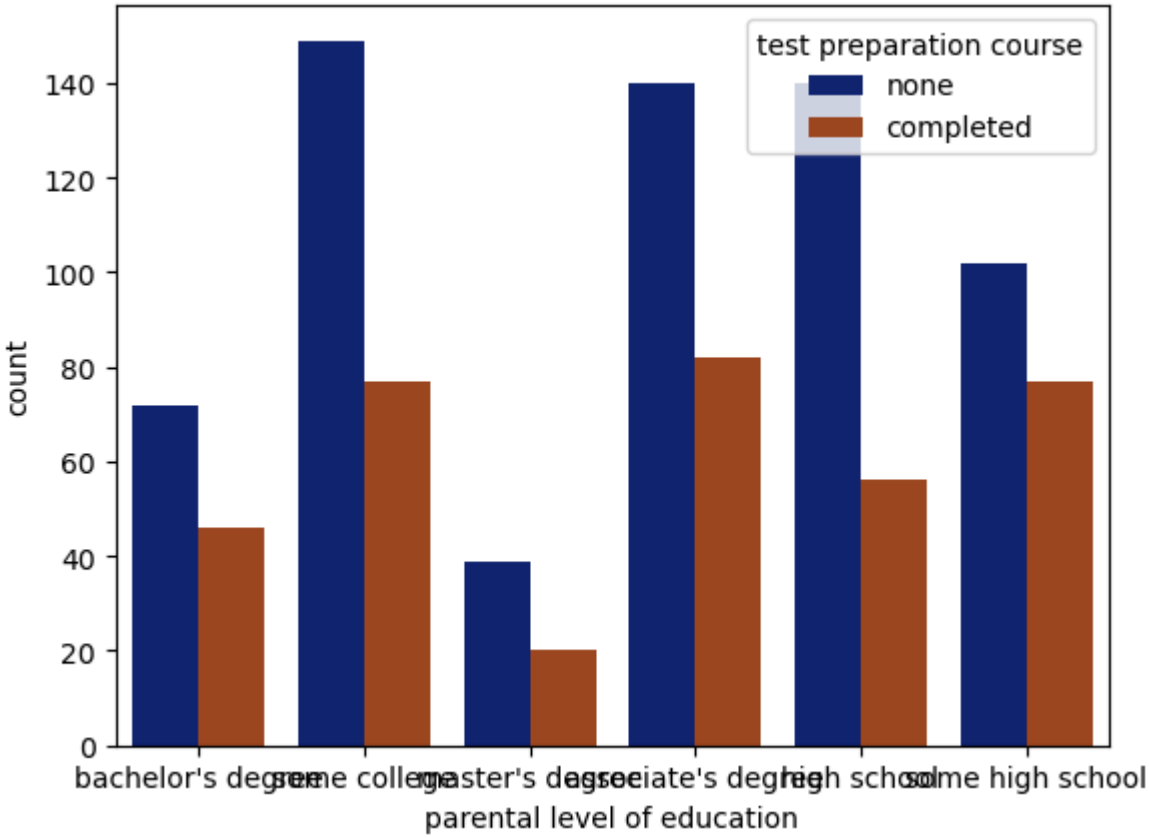


In [15]:
```
# Gender vs Etnicity
x = pd.crosstab(data['gender'], data['race/ethnicity'])
x.div(x.sum(1).astype(float), axis = 0).plot(kind = 'bar', stacked = True, figsize
```

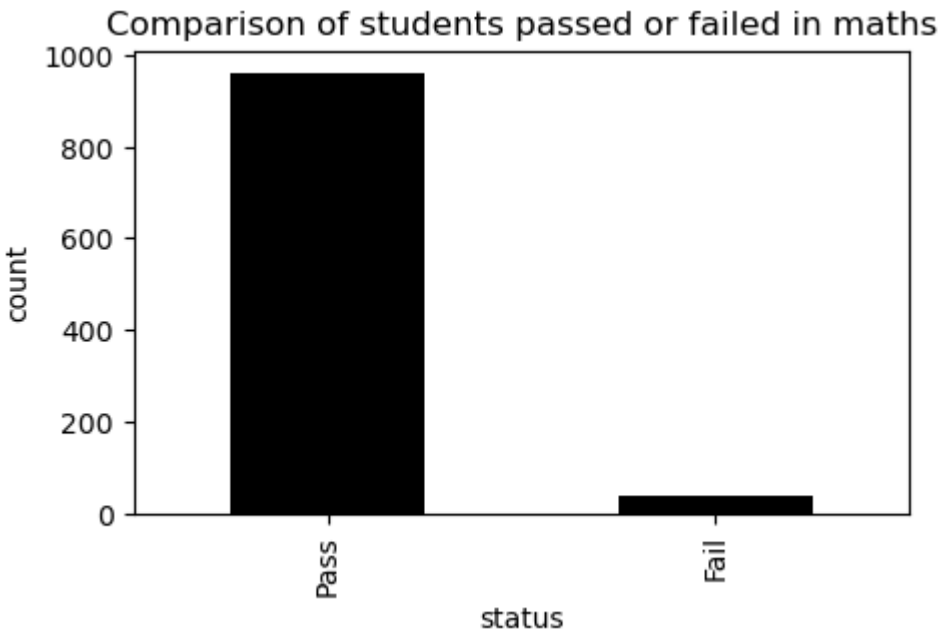
Out[15]:
```
<Axes: xlabel='gender'>
```



In [16]:
```
# Comparison of parental degree and test course
sns.countplot(x = 'parental level of education', data = data, hue = 'test preparati
plt.show()
```

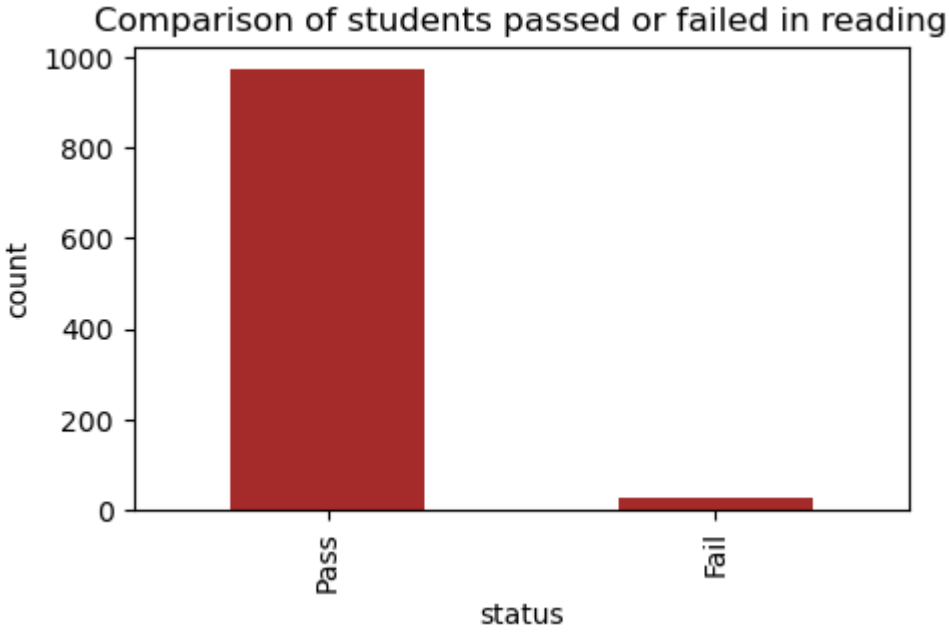


In [17]:
```
# Feature Engineering on the data to visualize and solve the dataset more accuratel
# Setting a passing mark for the students to pass on the three subjects individuall
passmarks = 40
# creating a new column pass_math, this column will tell us whether the students ar
data['pass_math'] = np.where(data['math score']< passmarks, 'Fail', 'Pass')
data['pass_math'].value_counts(dropna = False).plot.bar(color = 'black', figsize =
plt.title('Comparison of students passed or failed in maths')
plt.xlabel('status')
plt.ylabel('count')
plt.show()
print()
print(data['pass_math'].value_counts())
```




```
Pass    960
Fail     40
Name: pass_math, dtype: int64
```

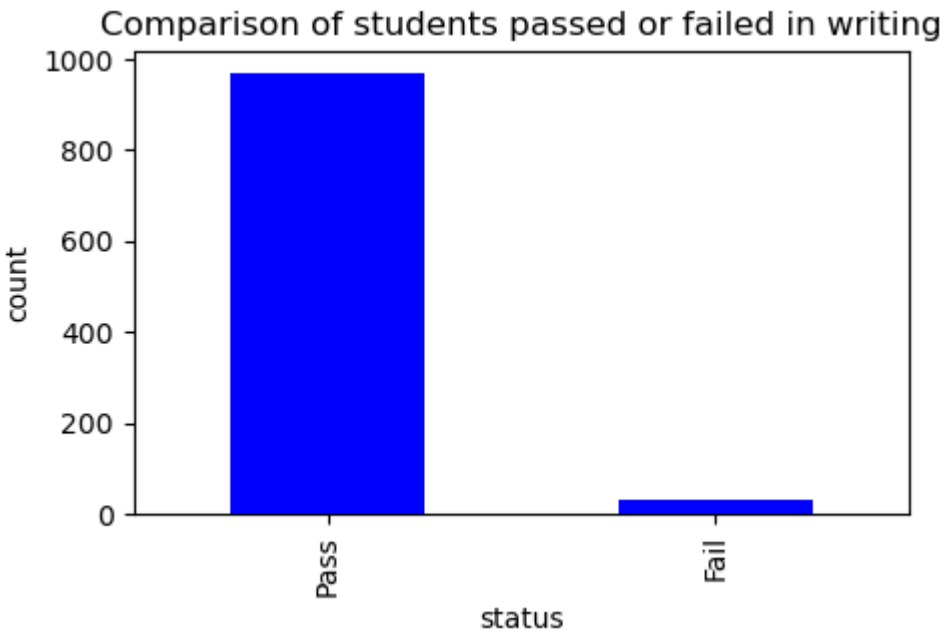
In [18]:
```
# creating a new column pass_math, this column will tell us whether the students ar
data['pass_reading'] = np.where(data['reading score']< passmarks, 'Fail', 'Pass')
data['pass_reading'].value_counts(dropna = False).plot.bar(color = 'brown', figsize
plt.title('Comparison of students passed or failed in reading')
plt.xlabel('status')
plt.ylabel('count')
plt.show()
print()
print(data['pass_reading'].value_counts(dropna = False))
```




```
Pass    974
Fail     26
Name: pass_reading, dtype: int64
```

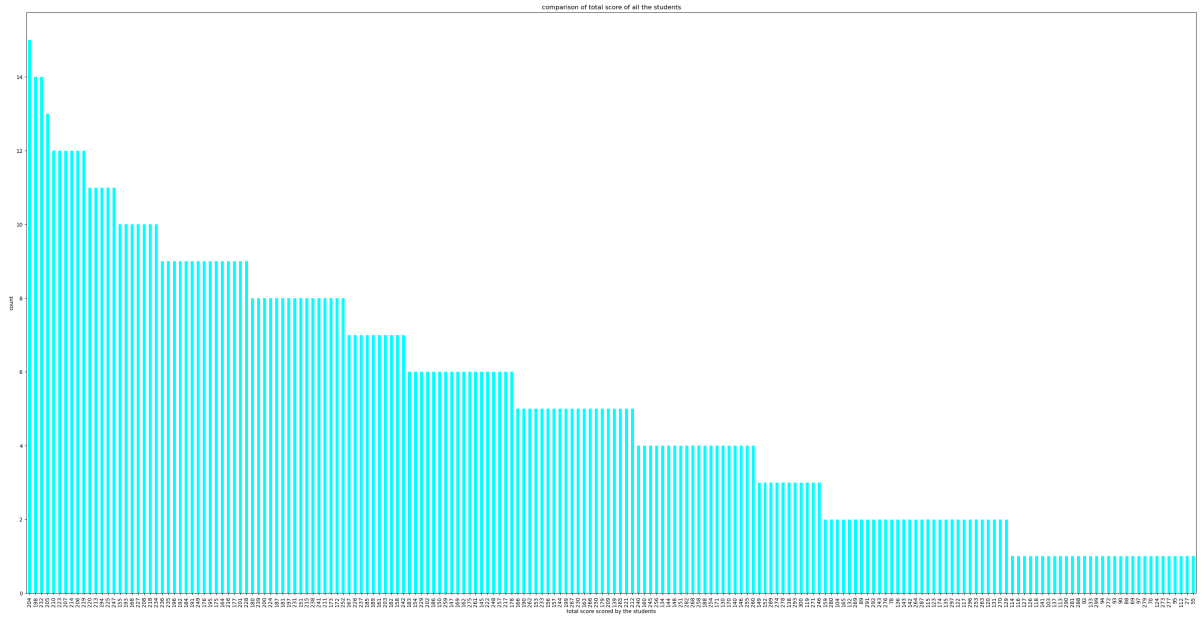
In [19]:
```
# creating a new column pass_math, this column will tell us whether the students ar
data['pass_writing'] = np.where(data['writing score']< passmarks, 'Fail', 'Pass')
data['pass_writing'].value_counts(dropna = False).plot.bar(color = 'blue', figsize

plt.title('Comparison of students passed or failed in writing')
```

```
plt.xlabel('status')
plt.ylabel('count')
plt.show()
print()
print(data['pass_writing'].value_counts(dropna = False))
```



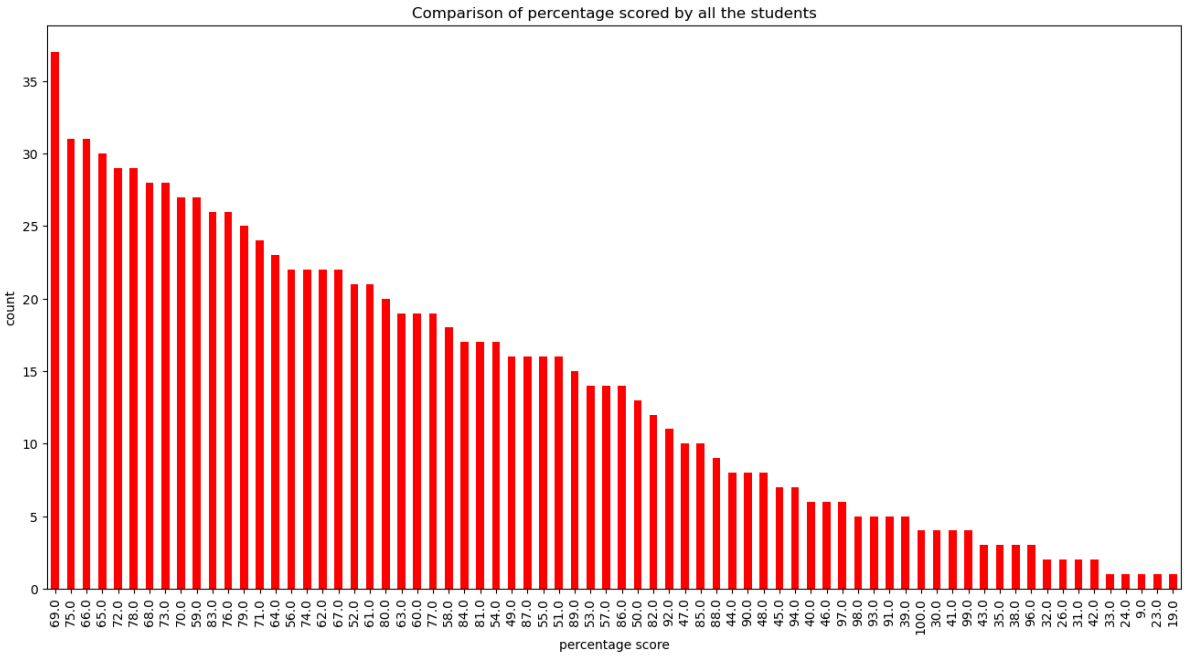

```
Pass    968
Fail     32
Name: pass_writing, dtype: int64
```

In [20]:
```
# computing the total score for each student
data['total_score'] = data['math score'] + data['reading score'] + data['writing sc
data['total_score'].value_counts(normalize = True)
data['total_score'].value_counts(dropna = True).plot.bar(color = 'cyan', figsize =
plt.title('comparison of total score of all the students')
plt.xlabel('total score scored by the students')
plt.ylabel('count')
plt.show()
```

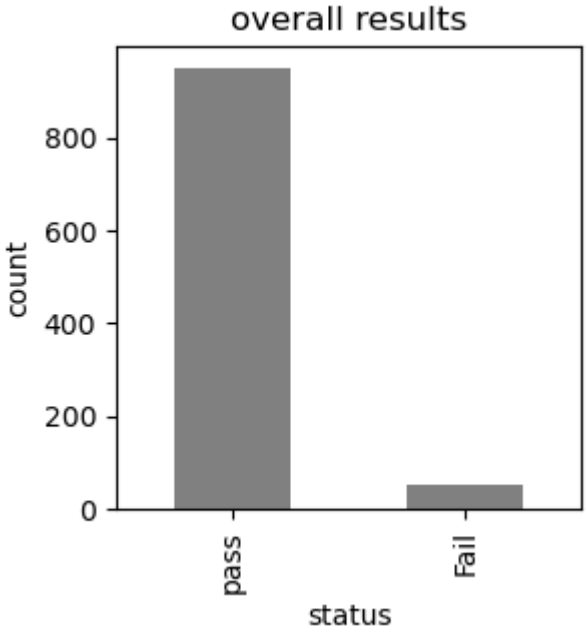


In [21]:
```
# computing percentage for each of the students
from math import *
data['percentage'] = data['total_score']/3
for i in range(0, 1000):
  data['percentage'][i] = ceil(data['percentage'][i])
```

```
data['percentage'].value_counts(normalize = True)
data['percentage'].value_counts(dropna = False).plot.bar(figsize = (16, 8), color =
plt.title('Comparison of percentage scored by all the students')
plt.xlabel('percentage score')
plt.ylabel('count')
plt.show()
```



In [22]:
```
# checking which student is fail overall

data['status'] = data.apply(lambda x : 'Fail' if x['pass_math'] == 'Fail' or
                            x['pass_reading'] == 'Fail' or x['pass_writing'] == 'Fai
                            else 'pass', axis = 1)

data['status'].value_counts(dropna = False).plot.bar(color = 'gray', figsize = (3,
plt.title('overall results')
plt.xlabel('status')
plt.ylabel('count')
plt.show()
```

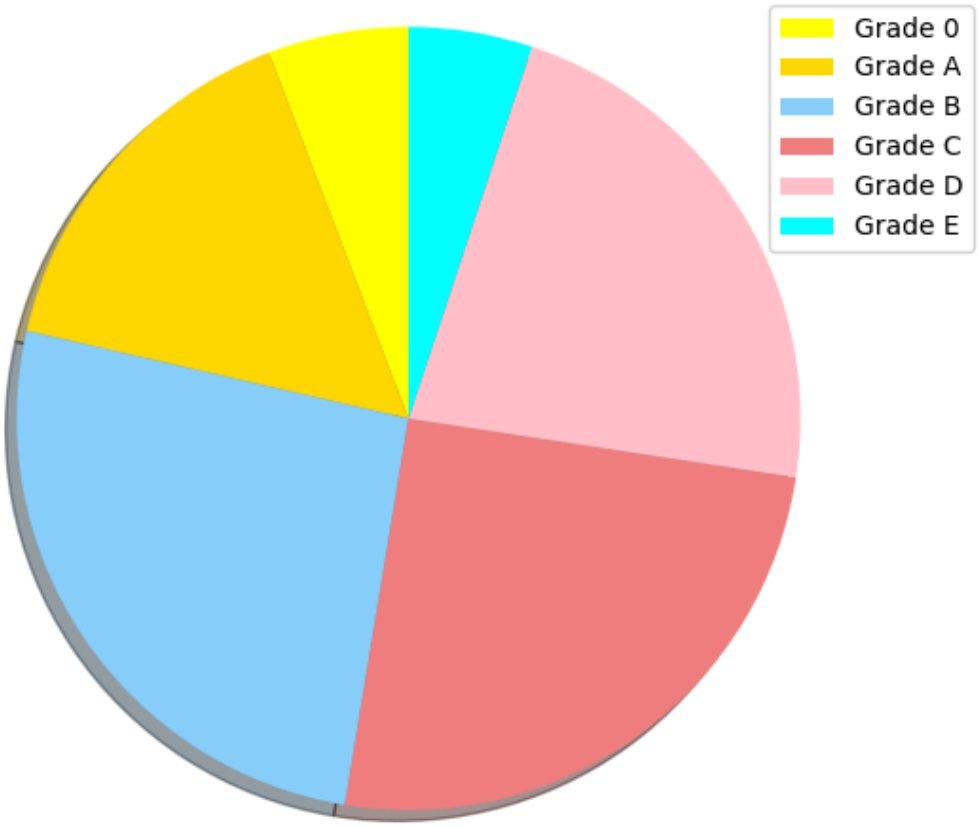


In [23]:
```
# Assigning grades to the grades according to the following criteria :
# 0  - 40 marks : grade E
```

```
# 41 - 60 marks : grade D
# 60 - 70 marks : grade C
# 70 - 80 marks : grade B
# 80 - 90 marks : grade A
# 90 - 100 marks : grade O

def getgrade(percentage, status):
  if status == 'Fail':
    return 'E'
  if(percentage >= 90):
    return 'O'
  if(percentage >= 80):
    return 'A'
  if(percentage >= 70):
    return 'B'
  if(percentage >= 60):
    return 'C'
  if(percentage >= 40):
    return 'D'
  else :
    return 'E'
data['grades'] = data.apply(lambda x: getgrade(x['percentage'], x['status']), axis
data['grades'].value_counts()
```

Out[23]:
```
B    260
C    252
D    223
A    156
O     58
E     51
Name: grades, dtype: int64
```

In [24]:
```
# plotting a pie chart for the distribution of various grades amongst the students

labels = ['Grade 0', 'Grade A', 'Grade B', 'Grade C', 'Grade D', 'Grade E']
sizes = [58, 156, 260, 252, 223, 51]
colors = ['yellow', 'gold', 'lightskyblue', 'lightcoral', 'pink', 'cyan']
explode = (0.0001, 0.0001, 0.0001, 0.0001, 0.0001, 0.0001)

patches, texts = plt.pie(sizes, colors=colors, shadow=True, startangle=90)
plt.legend(patches, labels)
plt.axis('equal')
plt.tight_layout()
plt.show()
```



FEATURE ENGINERRING

In [25]:
```
print(data['test preparation course'].value_counts())
print()
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
data['test preparation course'] = le.fit_transform(data['test preparation course'])
data['test preparation course'].value_counts()
```

```
none         642
completed    358
Name: test preparation course, dtype: int64
```

Out[25]:
```
1    642
0    358
Name: test preparation course, dtype: int64
```

In [26]:
```
data['lunch'] = le.fit_transform(data['lunch'])
data['lunch'].value_counts()
```

Out[26]:
```
1    645
0    355
Name: lunch, dtype: int64
```

In [27]:
```
# label encoding for race/ethnicity

data['race/ethnicity'] = data['race/ethnicity'].replace('group A', 1)
data['race/ethnicity'] = data['race/ethnicity'].replace('group B', 2)
data['race/ethnicity'] = data['race/ethnicity'].replace('group C', 3)
data['race/ethnicity'] = data['race/ethnicity'].replace('group D', 4)
data['race/ethnicity'] = data['race/ethnicity'].replace('group E', 5)
data['race/ethnicity'].value_counts()
```

Out[27]:
```
3    319
4    262
2    190
5    140
1     89
Name: race/ethnicity, dtype: int64
```

In [28]:
```
data['parental level of education'] = le.fit_transform(data['parental level of educ
data['parental level of education'].value_counts()
```

Out[28]:
```
4    226
0    222
2    196
5    179
1    118
3     59
Name: parental level of education, dtype: int64
```

In [29]:
```
data['gender'] = le.fit_transform(data['gender'])
data['gender'].value_counts()
```

Out[29]:
```
0    518
1    482
Name: gender, dtype: int64
```

In [30]:
```
data['pass_math'] = le.fit_transform(data['pass_math'])
data['pass_math'].value_counts()
```

Out[30]:
```
1    960
0     40
Name: pass_math, dtype: int64
```

In [31]:
```
data['pass_reading'] = le.fit_transform(data['pass_reading'])
data['pass_reading'].value_counts()
```

Out[31]:
```
1    974
0     26
Name: pass_reading, dtype: int64
```

In [32]:
```
data['pass_writing'] = le.fit_transform(data['pass_writing'])
data['pass_writing'].value_counts()
```

Out[32]:
```
1    968
0     32
Name: pass_writing, dtype: int64
```

In [33]:
```
data['status'] = le.fit_transform(data['status'])
data['status'].value_counts()
```

Out[33]:
```
1    949
0     51
Name: status, dtype: int64
```

In [34]:
```
# label encoding for grades

data['grades'] = data['grades'].replace('O', 0)
data['grades'] = data['grades'].replace('A', 1)
data['grades'] = data['grades'].replace('B', 2)
data['grades'] = data['grades'].replace('C', 3)
data['grades'] = data['grades'].replace('D', 4)
data['grades'] = data['grades'].replace('E', 5)
data['race/ethnicity'].value_counts()
```

Out[34]:
```
3    319
4    262
2    190
5    140
1     89
Name: race/ethnicity, dtype: int64
```

In [35]:
```
data.shape
```

Out[35]:
```
(1000, 15)
```

In [36]:
```
# Splitting the dependent and independent variables
x = data.iloc[:,:14]
y = data.iloc[:,14]
print(x.shape)
print(y.shape)
```

```
(1000, 14)
(1000,)
```

In [37]:
```
# Splitting the dataset into training and test sets
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.25, random_
print(x_train.shape)
print(y_train.shape)
print(x_test.shape)
print(y_test.shape)
```

```
(750, 14)
(750,)
(250, 14)
(250,)
```

In [38]:
```
from sklearn.preprocessing import MinMaxScaler
mm = MinMaxScaler()
x_train = mm.fit_transform(x_train)
x_test = mm.transform(x_test)
```

Logistic Regression

In [39]:
```
from sklearn.linear_model import  LogisticRegression
model = LogisticRegression()
model.fit(x_train, y_train)
y_pred = model.predict(x_test)
print("Training Accuracy :", model.score(x_train, y_train))
print("Testing Accuracy :", model.score(x_test, y_test))
```

```
Training Accuracy : 0.8533333333333334
Testing Accuracy : 0.812
```

In [40]:
```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
print(cm)
```

```
[[ 3  8  0  0  0  0]
 [ 2 17 13  0  0  0]
 [ 0  0 60 12  0  0]
 [ 0  0  3 51  4  0]
 [ 0  0  0  4 57  0]
 [ 0  0  0  0  1 15]]
```

In [41]:
```
from sklearn.ensemble import RandomForestClassifier
model = RandomForestClassifier()
model.fit(x_train, y_train)
y_pred = model.predict(x_test)
print("Training Accuracy :", model.score(x_train, y_train))
print("Testing Accuracy :", model.score(x_test, y_test))
```

```
Training Accuracy : 1.0
Testing Accuracy : 1.0
```

In [42]:
```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
print(cm)
```

```
[[11  0  0  0  0  0]
 [ 0 32  0  0  0  0]
 [ 0  0 72  0  0  0]
 [ 0  0  0 58  0  0]
 [ 0  0  0  0 61  0]
 [ 0  0  0  0  0 16]]
```

In [43]:
```
from sklearn.tree import DecisionTreeClassifier
model = DecisionTreeClassifier()
model.fit(x_train, y_train)
y_pred = model.predict(x_test)
print("Training Accuracy :", model.score(x_train, y_train))
print("Testing Accuracy :", model.score(x_test, y_test))
```

```
Training Accuracy : 1.0
Testing Accuracy : 1.0
```

In [44]:
```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
print(cm)
```

```
[[11  0  0  0  0  0]
 [ 0 32  0  0  0  0]
 [ 0  0 72  0  0  0]
 [ 0  0  0 58  0  0]
 [ 0  0  0  0 61  0]
 [ 0  0  0  0  0 16]]
```

CREATING A DATASET

In [45]:
```
import pandas as pd
import random

num_rows = 120
student_ids = [1, 2, 3, 4, 5,6,7,8,9,10]
names = ['Alice', 'Bob', 'Charlie', 'David', 'Emily']
ages = [20, 18, 19,17,]
genders = ['Female', 'Male']
grades = [12, 11, 12, 10, 11,19,17,16,'',None]
studying_class=['Tenth','Twelfth']
course=['completed',None]
phone_numbers = ['123-456-7890', '234-567-8901', '(345) 678-9012', '4567890123', '5

stud_data = {
    'student_ID': [random.choice(student_ids) for _ in range(num_rows)],
    'name': [random.choice(names) for _ in range(num_rows)],
    'age': [random.choice(ages) for _ in range(num_rows)],
    'gender': [random.choice(genders) for _ in range(num_rows)],
```

```
    'grade': [random.choice(grades) for _ in range(num_rows)],
    'class': [random.choice(studying_class) for _ in range(num_rows)],
    'course':[random.choice(course) for _ in range(num_rows)],
    'Phone Number': [random.choice(phone_numbers) for _ in range(num_rows)]

df = pd.DataFrame(stud_data)
df.to_csv('C:\just folder\studfile.csv', index=False)
```

In [46]:
```
df=pd.read_csv("studfile.csv")
df
```

Out[46]:

	student_ID	name	age	gender	grade	class	course	Phone Number
0	3	Charlie	20	Female	19.0	Tenth	NaN	(345) 678-9012
1	5	David	20	Male	10.0	Twelfth	NaN	NaN
2	7	Charlie	20	Male	12.0	Twelfth	completed	NaN
3	3	David	19	Female	12.0	Twelfth	NaN	567-890-1234
4	7	Charlie	19	Male	11.0	Twelfth	NaN	4567890123
...	...	...	...	...	...	...	...	...
115	7	Bob	19	Female	11.0	Twelfth	completed	234-567-8901
116	5	Emily	20	Male	12.0	Tenth	NaN	(345) 678-9012
117	3	Alice	20	Female	NaN	Twelfth	NaN	4567890123
118	6	Bob	20	Female	11.0	Twelfth	completed	NaN
119	8	Charlie	18	Female	NaN	Twelfth	NaN	123-456-7890

120 rows × 8 columns

In [47]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 120 entries, 0 to 119
Data columns (total 8 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   student_ID    120 non-null    int64
 1   name          120 non-null    object
 2   age           120 non-null    int64
 3   gender        120 non-null    object
 4   grade         99 non-null     float64
 5   class         120 non-null    object
 6   course        59 non-null     object
 7   Phone Number  101 non-null    object
dtypes: float64(1), int64(2), object(5)
memory usage: 7.6+ KB
```

In [48]:
```
df.describe()
```

Out[48]:

	student_ID	age	grade
count	120.000000	120.000000	99.000000
mean	5.516667	18.583333	13.363636
std	2.725489	1.065765	3.166968
min	1.000000	17.000000	10.000000
25%	3.000000	18.000000	11.000000
50%	6.000000	19.000000	12.000000
75%	8.000000	19.250000	16.000000
max	10.000000	20.000000	19.000000

In [49]:
```
print(df.shape)
```

```
(120, 8)
```

In [50]:
```
for i in df.columns:
    print(i,df[i].unique())
    print ("--------------------------------------------------------------------------------")
```

```
student_ID [ 3  5  7  9  2  4  6  8 10  1]
--------------------------------------------------------------------------------
name ['Charlie' 'David' 'Alice' 'Bob' 'Emily']
--------------------------------------------------------------------------------
age [20 19 18 17]
--------------------------------------------------------------------------------
gender ['Female' 'Male']
--------------------------------------------------------------------------------
grade [19. 10. 12. 11. 16. 17. nan]
--------------------------------------------------------------------------------
class ['Tenth' 'Twelfth']
--------------------------------------------------------------------------------
course [nan 'completed']
--------------------------------------------------------------------------------
Phone Number ['(345) 678-9012' nan '567-890-1234' '4567890123' '234-567-8901'
 '123-456-7890']
--------------------------------------------------------------------------------
```

In [51]:
```
df.isnull().sum()
```

Out[51]:
```
student_ID       0
name             0
age              0
gender           0
grade           21
class            0
course          61
Phone Number    19
dtype: int64
```

FEATURE ENGINERRING

In [52]:
```
print(df['course'].value_counts())
print()
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
```

```
df['course'] = le.fit_transform(df['course'])
df['course'].value_counts()
```

```
completed    59
Name: course, dtype: int64
```

Out[52]:
```
1    61
0    59
Name: course, dtype: int64
```

In [53]:
```
print(df['gender'].value_counts())
print()
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
df['gender'] = le.fit_transform(df['gender'])
print(df['gender'].value_counts())
```

```
Male      62
Female    58
Name: gender, dtype: int64

1    62
0    58
Name: gender, dtype: int64
```

In [54]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 120 entries, 0 to 119
Data columns (total 8 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   student_ID    120 non-null    int64
 1   name          120 non-null    object
 2   age           120 non-null    int64
 3   gender        120 non-null    int32
 4   grade         99 non-null     float64
 5   class         120 non-null    object
 6   course        120 non-null    int32
 7   Phone Number  101 non-null    object
dtypes: float64(1), int32(2), int64(2), object(3)
memory usage: 6.7+ KB
```

In [55]:
```
df['class'].replace(['Tenth'], 10, inplace=True)
df['class'].replace(['Twelfth'], 11, inplace=True)
df
```

Out[55]:

	student_ID	name	age	gender	grade	class	course	Phone Number
0	3	Charlie	20	0	19.0	10	1	(345) 678-9012
1	5	David	20	1	10.0	11	1	NaN
2	7	Charlie	20	1	12.0	11	0	NaN
3	3	David	19	0	12.0	11	1	567-890-1234
4	7	Charlie	19	1	11.0	11	1	4567890123
...	...	...	...	...	...	...	...	...
115	7	Bob	19	0	11.0	11	0	234-567-8901
116	5	Emily	20	1	12.0	10	1	(345) 678-9012
117	3	Alice	20	0	NaN	11	1	4567890123
118	6	Bob	20	0	11.0	11	0	NaN
119	8	Charlie	18	0	NaN	11	1	123-456-7890

120 rows × 8 columns

In [56]:
```
df.describe()
```

Out[56]:

	student_ID	age	gender	grade	class	course
count	120.000000	120.000000	120.000000	99.000000	120.000000	120.000000
mean	5.516667	18.583333	0.516667	13.363636	10.558333	0.508333
std	2.725489	1.065765	0.501817	3.166968	0.498668	0.502027
min	1.000000	17.000000	0.000000	10.000000	10.000000	0.000000
25%	3.000000	18.000000	0.000000	11.000000	10.000000	0.000000
50%	6.000000	19.000000	1.000000	12.000000	11.000000	1.000000
75%	8.000000	19.250000	1.000000	16.000000	11.000000	1.000000
max	10.000000	20.000000	1.000000	19.000000	11.000000	1.000000

In [57]:
```
df['grade'].fillna(df['grade'].median(), inplace=True)
df['grade'].isnull().sum()
```

Out[57]:
```
0
```

In [58]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 120 entries, 0 to 119
Data columns (total 8 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   student_ID    120 non-null    int64
 1   name          120 non-null    object
 2   age           120 non-null    int64
 3   gender        120 non-null    int32
 4   grade         120 non-null    float64
 5   class         120 non-null    int64
 6   course        120 non-null    int32
 7   Phone Number  101 non-null    object
dtypes: float64(1), int32(2), int64(3), object(2)
memory usage: 6.7+ KB
```

In [59]:
```
new_df=df.drop(columns=['student_ID','name','Phone Number'])
new_df.head()
```

Out[59]:

	age	gender	grade	class	course
0	20	0	19.0	10	1
1	20	1	10.0	11	1
2	20	1	12.0	11	0
3	19	0	12.0	11	1
4	19	1	11.0	11	1

In [60]:
```
new_df1=new_df.drop('grade',axis='columns')
new_df1.head()
```

Out[60]:

	age	gender	class	course
0	20	0	10	1
1	20	1	11	1
2	20	1	11	0
3	19	0	11	1
4	19	1	11	1

In [61]:
```
grade=df.grade
grade
```

Out[61]:
```
0      19.0
1      10.0
2      12.0
3      12.0
4      11.0
       ...
115    11.0
116    12.0
117    12.0
118    11.0
119    12.0
Name: grade, Length: 120, dtype: float64
```

REGRESSION

In [62]:
```
reg=linear_model.LinearRegression()
reg.fit(new_df1,grade)
```

Out[62]:
```
LinearRegression
LinearRegression()
```

In [63]:
```
#PREDICT THE GRADE OF THE STUDENT WITH age=19,gender=0(MALE),class=10

reg.predict([[19,0,10,1]])
```

Out[63]:
```
array([12.90130647])
```

In [64]:
```
reg.coef_
```

Out[64]:
```
array([ 0.1844531 ,  0.00571867,  0.4145057 , -0.13456677])
```

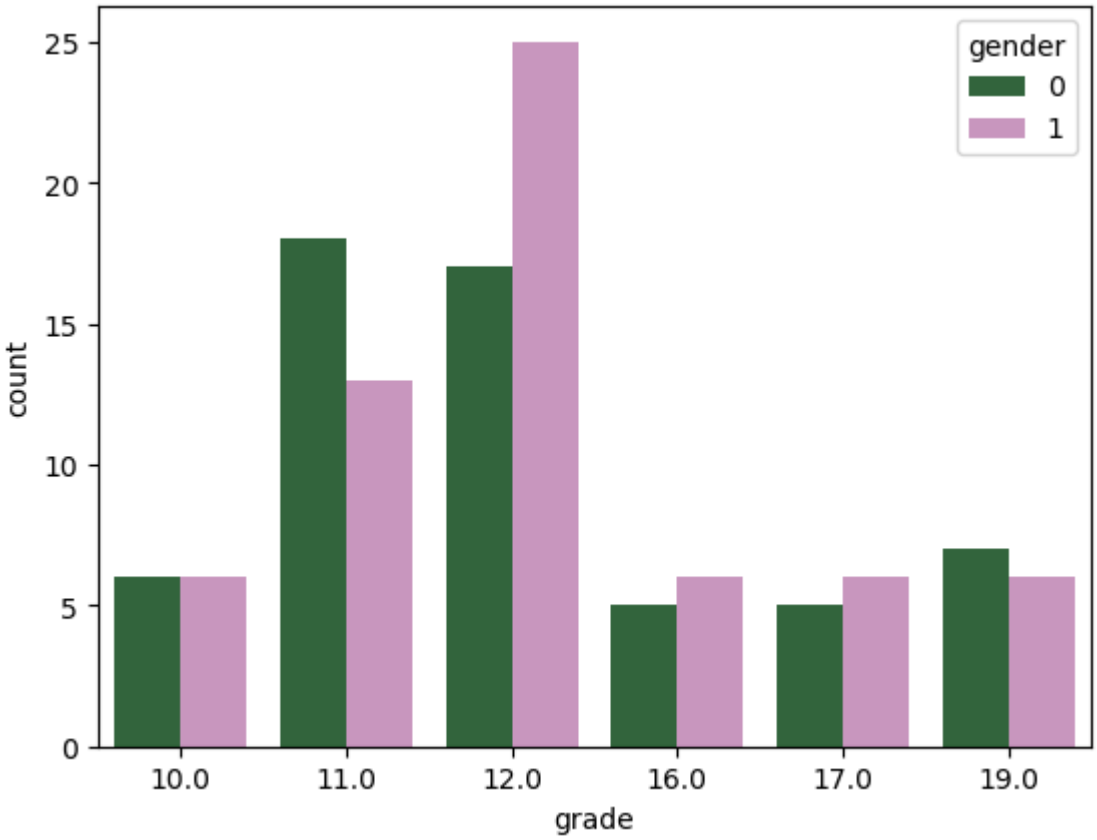
In [65]:
```
reg.intercept_
```

Out[65]:
```
5.386207378120808
```

In [66]:
```
19*(0.1844531) + 0*(-0.00571867) + 10* 0.4145057 + 1*(-0.13456677) +5.3919260432389
```

Out[66]:
```
12.907025173238933
```

In [67]:
```
# Comparing the distribution of grades among males and females
# MALE-0 ,FEMALE-1
sns.countplot(x = df['grade'], data = df, hue = df['gender'], palette = 'cubehelix'
plt.show()
```



In [68]:
```
df.head()
```

Out[68]:

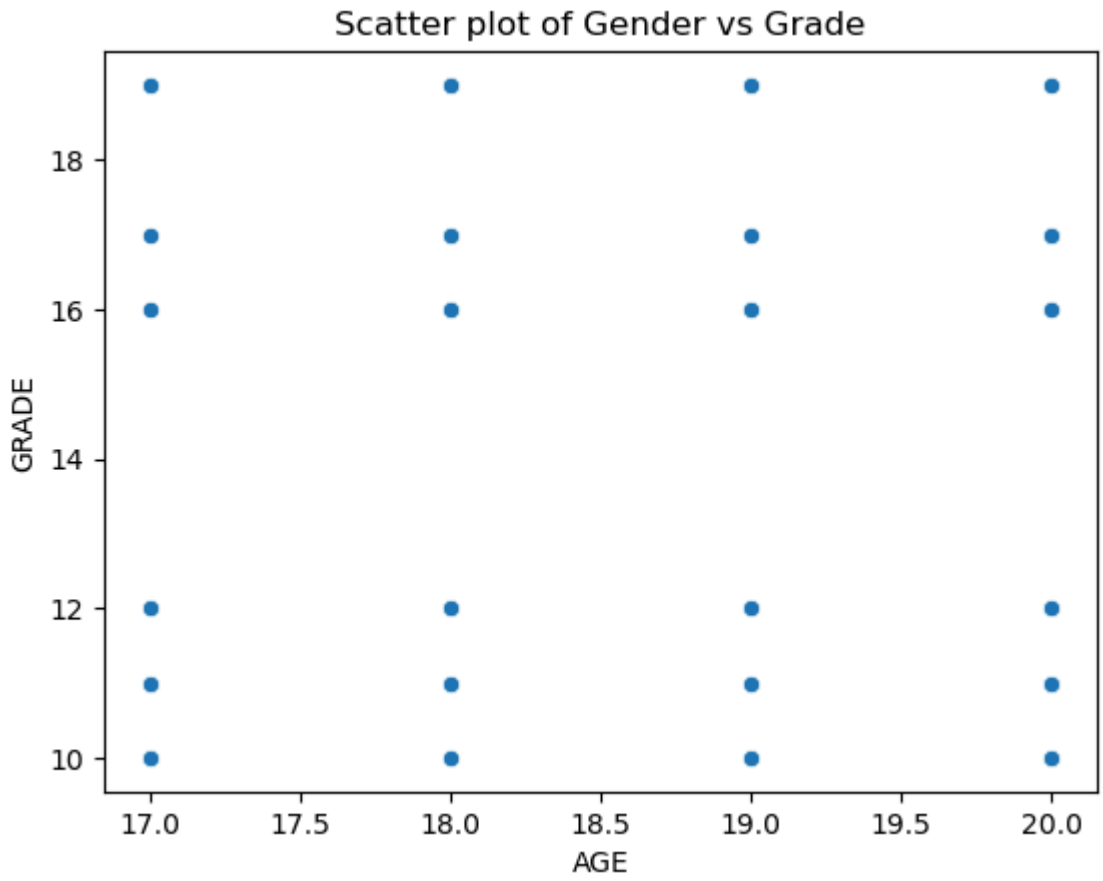
	student_ID	name	age	gender	grade	class	course	Phone Number
0	3	Charlie	20	0	19.0	10	1	(345) 678-9012
1	5	David	20	1	10.0	11	1	NaN
2	7	Charlie	20	1	12.0	11	0	NaN
3	3	David	19	0	12.0	11	1	567-890-1234
4	7	Charlie	19	1	11.0	11	1	4567890123

In [69]:
```
df.describe()
```

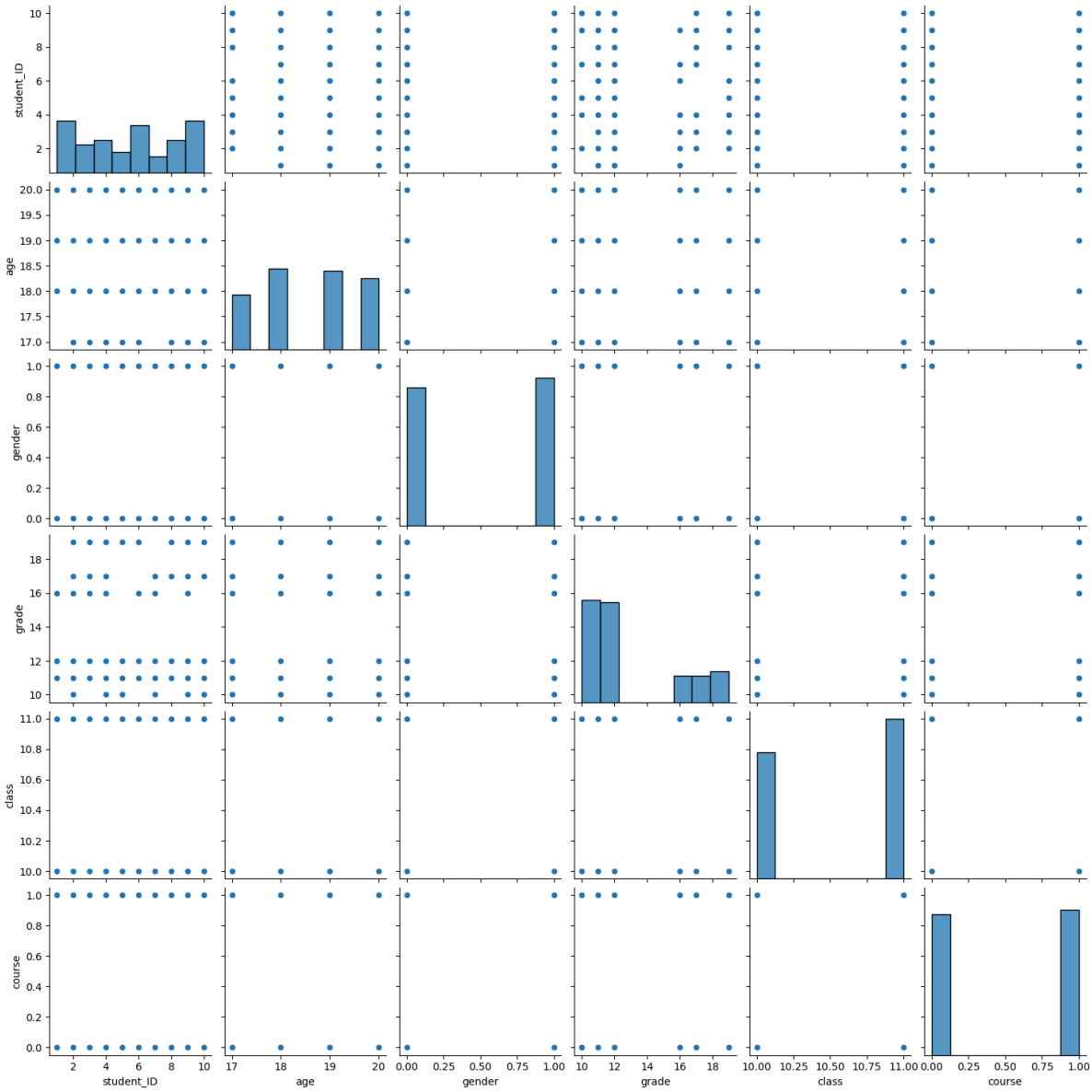
Out[69]:

	student_ID	age	gender	grade	class	course
count	120.000000	120.000000	120.000000	120.000000	120.000000	120.000000
mean	5.516667	18.583333	0.516667	13.125000	10.558333	0.508333
std	2.725489	1.065765	0.501817	2.920695	0.498668	0.502027
min	1.000000	17.000000	0.000000	10.000000	10.000000	0.000000
25%	3.000000	18.000000	0.000000	11.000000	10.000000	0.000000
50%	6.000000	19.000000	1.000000	12.000000	11.000000	1.000000
75%	8.000000	19.250000	1.000000	16.000000	11.000000	1.000000
max	10.000000	20.000000	1.000000	19.000000	11.000000	1.000000

In [70]:
```
sns.scatterplot(x='age', y='grade', data=df)
plt.title('Scatter plot of Gender vs Grade')
plt.xlabel('AGE')
plt.ylabel('GRADE')
plt.show()
```



In [71]:
```
sns.pairplot(df)
plt.show()
```



In [72]:
```
df.columns
```

Out[72]:
```
Index(['student_ID', 'name', 'age', 'gender', 'grade', 'class', 'course',
       'Phone Number'],
      dtype='object')
```

In [73]:
```
data=df[['name', 'age','gender','class','grade','course']]
corr = data.corr()
sns.heatmap(corr, annot=True, cmap='coolwarm')
plt.show()
```


age
gender
class
grade
course
1
0.15
0.094
0.074
0.022
0.15
1
-0.054
0.0072
0.016
0.094
-0.054
1
0.079
-0.069
0.074
0.0072
0.079
1
-0.027
0.022
0.016
-0.069
-0.027
1
age
gender
class
grade
course
1.0
0.8
0.6
0.4
0.2
0.0

In [ ]: