Untitled

September 18, 2020

1 Project Overview

This project has two parts that demonstrate the importance and value of data visualization techniques in the data analysis process. In the first part, you will use Python visualization libraries to systematically explore a selected dataset, starting from plots of single variables and building up to plots of multiple variables. In the second part, you will produce a short presentation that illustrates interesting properties, trends, and relationships that you discovered in your selected dataset. The primary method of conveying your findings will be through transforming your exploratory visualizations from the first part into polished, explanatory visualizations.

1.1 Table of Contents

Why this project?

Data visualization is an important skill that is used in many parts of the data analysis process.

Exploratory data visualization generally occurs during and after the data wrangling process, and is the main method that you will use to understand the patterns and relationships present in your data. This understanding will help you approach any statistical analyses and will help you build conclusions and findings. This process might also illuminate additional data cleaning tasks to be performed.

Explanatory data visualization techniques are used after generating your findings, and are used to help communicate your results to others. Understanding design considerations will make sure that your message is clear and effective. In addition to being a good producer of visualizations, going through this project will also help you be a good consumer of visualizations that are presented to you by others.

For this project I choose to analyse the results of the OECD **Programme for International Student Assessment (PISA)** in 2012.

From OECD website: *PISA is an international study that was launched by the OECD in 1997, first administered in 2000 and now covers over 80 countries. Every 3 years the PISA survey provides comparative data on 15-year-olds' performance in reading, mathematics, and science. In addition, each cycle explores a distinct "innovative domain" such as Collaborative Problem Solving (PISA 2015) and Global Competence (PISA 2018). The results have informed education policy discussions at the national and global level since its inception.*
https://www.oecd.org/pisa/aboutpisa/pisa-based-test-for-schools-faq.htm

The PISA goals are:

- Empower school leaders and teachers by providing them with evidence-based analysis of their students' performance.
- Measure students' knowledge, skills and competencies that will equip them for success in education and the world of work.
- Provide valuable information on the learning climate within a school, students' socioeconomic background and motivation for learning.
- Help schools measure a wider range of 21st century skills beyond maths, reading and science.
- Provide opportunities for global peer-learning among teachers and school leaders.

Based on the objectives of the PISA, using the data, the following questions can be answered:

1. What is students' performance at schools in different countries (including whether country is a OECD member).
2. What are the characteristics of students participated in PICA 2012:
* gender,
* age,
* whether a student passed the test in the country of birth or not,
* international grade and grade compared to modal grade in country.
3. What's a relationship between students performance and highest parental education measured in years as well as mother's and father's highest schooling?
4. Whether there exist a correlation between family wealth (measured in the number of telephones, computers, etc.) and students performance?
5. How do student possessions such as own room and desk, etc. affect his/her performance?
6. Last but not least, whether total time learning and out of school lessons on math, science, and reading affect student performance?

[1]:
```
# Import libraries

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

%matplotlib inline

pd.set_option('display.max_columns', 700)
```

[2]:
```
FOLDER = 'C:/Sasha/udacity/Data Analyst Nanodegree Program/5. Data␣
 ↪Visualization/8. Communicate Data Findings'

FILE_NAME = 'pisa2012.csv'
DICT_NAME = 'pisadict2012.csv'

file_path = os.path.join(FOLDER, FILE_NAME)
dict_path = os.path.join(FOLDER, DICT_NAME)
```

[3]:
```
DTYPES = {'SCHOOLID': 'str', 'STIDSTD': 'str'}
```

[4]:
```
# Load in data

df = pd.read_csv(file_path, dtype=DTYPES, encoding='ISO-8859-1')
df.head(2)
```

```
C:\ProgramData\Anaconda3\lib\site-
packages\IPython\core\interactiveshell.py:3057: DtypeWarning: Columns (15,16,17,
21,22,23,24,25,26,30,31,36,37,45,65,123,155,156,157,158,159,160,161,162,163,164,
165,166,167,168,169,170,171,284,285,286,287,288,289,290,291,292,293,294,295,296,
297,298,299,300,301,302,303,307,308,309,310,311,312,313,314,315,316,317,318,319,
320,321,322,323,324,325,326,327,328,329,330,331,332,333,334,335,336,337,338,339,
340,341,342,343,344,345,346,347,348,349,350,351,352,353,354,355,356,357,376,377,
378,379,380,381,382,383,384,385,386,387,388,389,390,391,392,393,394,395,396,397,
398,399,400,401,402,403,475) have mixed types. Specify dtype option on import or
set low_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)
```

[4]:

	Unnamed: 0	CNT	SUBNATIO	STRATUM	OECD	NC	SCHOOLID	STIDSTD	\
0	1	Albania	80000	ALB0006	Non-OECD	Albania	0000001	00001	
1	2	Albania	80000	ALB0006	Non-OECD	Albania	0000001	00002	

	ST01Q01	ST02Q01	ST03Q01	ST03Q02	ST04Q01	ST05Q01	\
0	10	1.0	2	1996	Female	No	
1	10	1.0	2	1996	Female	Yes, for more than one year	

	ST06Q01	ST07Q01	ST07Q02	ST07Q03	ST08Q01	ST09Q01	\
0	6.0	No, never	No, never	No, never	None	None	
1	7.0	No, never	No, never	No, never	One or two times	None	

	ST115Q01	ST11Q01	ST11Q02	ST11Q03	ST11Q04	ST11Q05	ST11Q06	\
0	1.0	Yes	Yes	Yes	Yes	NaN	NaN	
1	1.0	Yes	Yes	NaN	Yes	NaN	NaN	

	ST13Q01	ST14Q01	ST14Q02	ST14Q03	ST14Q04	\
0	<ISCED level 3A>	No	No	No	No	
1	<ISCED level 3A>	Yes	Yes	No	No	

	ST15Q01	ST17Q01	ST18Q01	ST18Q02	\
0	Other (e.g. home duties, retired)	<ISCED level 3A>	NaN	NaN	
1	Working full-time <for pay>	<ISCED level 3A>	No	No	

	ST18Q03	ST18Q04	ST19Q01	ST20Q01	\
0	NaN	NaN	Working part-time <for pay>	Country of test	
1	No	No	Working full-time <for pay>	Country of test	

	ST20Q02	ST20Q03	ST21Q01	ST25Q01	ST26Q01	\
0	Country of test	Country of test	NaN	Language of the test	Yes	

```
1  Country of test  Country of test      NaN  Language of the test     Yes

  ST26Q02 ST26Q03 ST26Q04 ST26Q05 ST26Q06 ST26Q07 ST26Q08 ST26Q09 ST26Q10  \
0      No     Yes      No      No      No      No     Yes      No     Yes
1     Yes     Yes     Yes     Yes     Yes     Yes     Yes     Yes     Yes

  ST26Q11 ST26Q12 ST26Q13 ST26Q14  ST26Q15  ST26Q16  ST26Q17        ST27Q01  \
0      No     Yes      No     Yes     8002     8001     8002            Two
1     Yes     Yes     Yes     Yes     8001     8001     8002  Three or more

        ST27Q02        ST27Q03 ST27Q04 ST27Q05         ST28Q01   ST29Q01  \
0           One           None    None    None     0-10 books      Agree
1  Three or more  Three or more     Two     Two  201-500 books   Disagree

         ST29Q02   ST29Q03   ST29Q04 ST29Q05 ST29Q06   ST29Q07  \
0  Strongly agree     Agree     Agree   Agree   Agree     Agree
1  Strongly agree  Disagree  Disagree   Agree   Agree  Disagree

         ST29Q08         ST35Q01         ST35Q02   ST35Q03 ST35Q04   ST35Q05  \
0  Strongly agree        Disagree           Agree  Disagree   Agree     Agree
1        Disagree  Strongly agree  Strongly agree  Disagree   Agree  Disagree

  ST35Q06               ST37Q01             ST37Q02         ST37Q03  \
0   Agree  Not at all confident  Not very confident       Confident
1   Agree             Confident      Very confident  Very confident

    ST37Q04         ST37Q05               ST37Q06         ST37Q07  \
0  Confident       Confident  Not at all confident       Confident
1  Confident  Very confident             Confident  Very confident

             ST37Q08 ST42Q01   ST42Q02 ST42Q03 ST42Q04 ST42Q05 ST42Q06  \
0      Very confident   Agree  Disagree   Agree   Agree   Agree   Agree
1  Not very confident     NaN       NaN     NaN     NaN     NaN     NaN

  ST42Q07   ST42Q08   ST42Q09   ST42Q10         ST43Q01         ST43Q02  \
0   Agree  Disagree  Disagree  Disagree           Agree        Disagree
1     NaN       NaN       NaN       NaN  Strongly agree  Strongly agree

            ST43Q03   ST43Q04 ST43Q05   ST43Q06 ST44Q01          ST44Q03  \
0          Disagree     Agree     NaN  Disagree  Likely  Slightly likely
1  Strongly disagree  Disagree   Agree  Disagree  Likely  Slightly likely

          ST44Q04        ST44Q05          ST44Q07        ST44Q08 ST46Q01  \
0          Likely         Likely           Likely  Very   Likely   Agree
1  Slightly likely  Very   Likely  Slightly likely         Likely   Agree

  ST46Q02         ST46Q03         ST46Q04         ST46Q05 ST46Q06 ST46Q07  \
```

```
0   Agree           Agree           Agree           Agree   Agree   Agree
1   Agree  Strongly agree  Strongly agree  Strongly agree   Agree   Agree

    ST46Q08 ST46Q09                            ST48Q01  \
0     Agree   Agree  Courses after school Test Language
1  Disagree   Agree           Courses after school Math

                   ST48Q02                      ST48Q03  \
0  Major in college Science  Study harder Test Language
1  Major in college Science           Study harder Math

                  ST48Q04                     ST48Q05    ST49Q01    ST49Q02  \
0  Maximum classes Science     Pursuing a career Math      Often  Sometimes
1  Maximum classes Science  Pursuing a career Science  Sometimes      Often

                  ST49Q03    ST49Q04                  ST49Q05  \
0               Sometimes  Sometimes                Sometimes
1  Always or almost always  Sometimes  Always or almost always

         ST49Q06          ST49Q07          ST49Q09            ST53Q01  \
0  Never or rarely  Never or rarely  Never or rarely                NaN
1  Never or rarely  Never or rarely            Often  relating to known

                ST53Q02      ST53Q03          ST53Q04  \
0                   NaN          NaN              NaN
1  Improve understanding  in my sleep  Repeat examples

                                           ST55Q01  \
0                                              NaN
1  I do not attend <out-of-school time lessons> i...

                                ST55Q02  \
0                                   NaN
1  2 or more but less than 4 hours a week

                                ST55Q03                   ST55Q04  ST57Q01  \
0                                   NaN                       NaN      NaN
1  2 or more but less than 4 hours a week  Less than 2 hours a week      NaN

   ST57Q02  ST57Q03  ST57Q04  ST57Q05  ST57Q06  ST61Q01  ST61Q02     ST61Q03  \
0      NaN      NaN      NaN      NaN      NaN      NaN      NaN         NaN
1      NaN      6.0      0.0      0.0      2.0  Rarely   Rarely   Frequently

     ST61Q04     ST61Q05    ST61Q06     ST61Q07 ST61Q08     ST61Q09  \
0        NaN         NaN        NaN         NaN     NaN         NaN
1  Sometimes  Frequently  Sometimes  Frequently  Never   Frequently
```

```
                                ST62Q01  \
0                                   NaN
1  Know it well,  understand the concept

                                ST62Q02                    ST62Q03  \
0                                   NaN                       NaN
1  Know it well,  understand the concept  Heard of it once or twice

                                ST62Q04  \
0                                   NaN
1  Know it well,  understand the concept

                                ST62Q06  \
0                                   NaN
1  Know it well,  understand the concept

                                ST62Q07            ST62Q08  \
0                                   NaN                NaN
1  Know it well,  understand the concept  Never heard of it

                                ST62Q09  \
0                                   NaN
1  Know it well,  understand the concept

                                ST62Q10            ST62Q11  \
0                                   NaN                NaN
1  Know it well,  understand the concept  Never heard of it

                                ST62Q12                    ST62Q13  \
0                                   NaN                       NaN
1  Know it well,  understand the concept  Heard of it once or twice

                                ST62Q15  \
0                                   NaN
1  Know it well,  understand the concept

                                ST62Q16            ST62Q17  \
0                                   NaN                NaN
1  Know it well,  understand the concept  Never heard of it

            ST62Q19  ST69Q01  ST69Q02  ST69Q03  ST70Q01  ST70Q02  ST70Q03  \
0               NaN      NaN      NaN      NaN      NaN      NaN      NaN
1  Heard of it often     45.0     45.0     45.0      7.0      6.0      2.0

   ST71Q01  ST72Q01     ST73Q01    ST73Q02     ST74Q01     ST74Q02    ST75Q01  \
0      NaN      NaN         NaN        NaN         NaN         NaN        NaN
1      NaN     30.0  Frequently  Sometimes  Frequently  Frequently  Sometimes
```

```
     ST75Q02    ST76Q01    ST76Q02       ST77Q01       ST77Q02       ST77Q04  \
0        NaN        NaN        NaN  Every Lesson  Every Lesson  Every Lesson
1  Sometimes  Sometimes  Sometimes           NaN           NaN           NaN

       ST77Q05       ST77Q06               ST79Q01       ST79Q02  \
0  Every Lesson  Every Lesson  Never or Hardly Ever  Most Lessons
1           NaN           NaN                   NaN           NaN

               ST79Q03       ST79Q04       ST79Q05       ST79Q06  \
0  Never or Hardly Ever  Every Lesson  Most Lessons  Every Lesson
1                   NaN           NaN           NaN           NaN

       ST79Q07       ST79Q08               ST79Q10       ST79Q11  \
0  Every Lesson  Every Lesson  Never or Hardly Ever  Most Lessons
1           NaN           NaN                   NaN           NaN

       ST79Q12       ST79Q15       ST79Q17                   ST80Q01  \
0  Every Lesson  Every Lesson  Every Lesson  Always or almost always
1           NaN           NaN           NaN                     NaN

     ST80Q04          ST80Q05                  ST80Q06  \
0  Sometimes  Never or rarely  Always or almost always
1        NaN              NaN                     NaN

                  ST80Q07                   ST80Q08                   ST80Q09  \
0  Always or almost always  Always or almost always  Always or almost always
1                      NaN                       NaN                       NaN

  ST80Q10 ST80Q11               ST81Q01               ST81Q02  \
0   Often   Often  Never or Hardly Ever  Never or Hardly Ever
1     NaN     NaN                   NaN                   NaN

               ST81Q03               ST81Q04               ST81Q05  \
0  Never or Hardly Ever  Never or Hardly Ever  Never or Hardly Ever
1                   NaN                   NaN                   NaN

            ST82Q01           ST82Q02           ST82Q03           ST83Q01  \
0  Strongly disagree  Strongly disagree  Strongly disagree  Strongly disagree
1               NaN               NaN               NaN               NaN

  ST83Q02 ST83Q03 ST83Q04         ST84Q01         ST84Q02   ST84Q03 ST85Q01  \
0   Agree   Agree   Agree  Strongly agree  Strongly agree  Disagree   Agree
1     NaN     NaN     NaN             NaN             NaN       NaN     NaN

            ST85Q02   ST85Q03 ST85Q04 ST86Q01            ST86Q02 ST86Q03  \
0  Strongly disagree  Disagree   Agree   Agree  Strongly disagree   Agree
```

```
1                NaN       NaN     NaN     NaN                 NaN     NaN

  ST86Q04   ST86Q05 ST87Q01 ST87Q02            ST87Q03         ST87Q04  \
0   Agree  Disagree   Agree   Agree  Strongly disagree  Strongly agree
1     NaN       NaN     NaN     NaN                NaN             NaN

          ST87Q05            ST87Q06 ST87Q07            ST87Q08 ST87Q09  \
0  Strongly agree  Strongly disagree   Agree  Strongly disagree   Agree
1             NaN                NaN     NaN                NaN     NaN

  ST88Q01         ST88Q02            ST88Q03            ST88Q04 ST89Q02  \
0   Agree  Strongly agree  Strongly disagree  Strongly disagree   Agree
1     NaN             NaN                NaN                NaN     NaN

          ST89Q03         ST89Q04         ST89Q05         ST91Q01  \
0  Strongly agree  Strongly agree  Strongly agree  Strongly agree
1             NaN             NaN             NaN             NaN

          ST91Q02         ST91Q03            ST91Q04   ST91Q05  \
0  Strongly agree  Strongly agree  Strongly disagree  Disagree
1             NaN             NaN                NaN       NaN

            ST91Q06             ST93Q01             ST93Q03  \
0  Strongly disagree   Very much like me   Very much like me
1               NaN  Not at all like me  Not at all like me

            ST93Q04           ST93Q06            ST93Q07           ST94Q05  \
0  Very much like me  Somewhat like me  Very much like me  Somewhat like me
1    Mostly like me  Somewhat like me  Very much like me  Somewhat like me

           ST94Q06           ST94Q09         ST94Q10           ST94Q14  \
0   Mostly like me    Mostly like me  Mostly like me  Somewhat like me
1  Not much like me  Not much like me  Mostly like me  Not much like me

              ST96Q01             ST96Q02              ST96Q03  \
0   definitely do this  definitely do this    definitely do this
1  probably not do this    probably do this  probably not do this

             ST96Q05  ST101Q01  ST101Q02  ST101Q03  ST101Q05  ST104Q01  \
0  definitely do this       4.0       2.0       1.0       1.0       1.0
1   probably do this        1.0       2.0       3.0       2.0       2.0

   ST104Q04  ST104Q05  ST104Q06 IC01Q01 IC01Q02 IC01Q03 IC01Q04 IC01Q05  \
0       2.0       1.0       1.0     NaN     NaN     NaN     NaN     NaN
1       3.0       1.0       1.0     NaN     NaN     NaN     NaN     NaN

  IC01Q06 IC01Q07 IC01Q08 IC01Q09 IC01Q10 IC01Q11 IC02Q01 IC02Q02 IC02Q03  \
```

```
0     NaN     NaN     NaN     NaN     NaN     NaN     NaN     NaN     NaN
1     NaN     NaN     NaN     NaN     NaN     NaN     NaN     NaN     NaN

  IC02Q04 IC02Q05 IC02Q06 IC02Q07 IC03Q01 IC04Q01  IC05Q01  IC06Q01  IC07Q01  \
0     NaN     NaN     NaN     NaN     NaN     NaN       99       99       99
1     NaN     NaN     NaN     NaN     NaN     NaN       99       99       99

  IC08Q01 IC08Q02 IC08Q03 IC08Q04 IC08Q05 IC08Q06 IC08Q07 IC08Q08 IC08Q09  \
0     NaN     NaN     NaN     NaN     NaN     NaN     NaN     NaN     NaN
1     NaN     NaN     NaN     NaN     NaN     NaN     NaN     NaN     NaN

  IC08Q11 IC09Q01 IC09Q02 IC09Q03 IC09Q04 IC09Q05 IC09Q06 IC09Q07 IC10Q01  \
0     NaN     NaN     NaN     NaN     NaN     NaN     NaN     NaN     NaN
1     NaN     NaN     NaN     NaN     NaN     NaN     NaN     NaN     NaN

  IC10Q02 IC10Q03 IC10Q04 IC10Q05 IC10Q06 IC10Q07 IC10Q08 IC10Q09 IC11Q01  \
0     NaN     NaN     NaN     NaN     NaN     NaN     NaN     NaN     NaN
1     NaN     NaN     NaN     NaN     NaN     NaN     NaN     NaN     NaN

  IC11Q02 IC11Q03 IC11Q04 IC11Q05 IC11Q06 IC11Q07 IC22Q01 IC22Q02 IC22Q04  \
0     NaN     NaN     NaN     NaN     NaN     NaN     NaN     NaN     NaN
1     NaN     NaN     NaN     NaN     NaN     NaN     NaN     NaN     NaN

  IC22Q06 IC22Q07 IC22Q08 EC01Q01 EC02Q01 EC03Q01 EC03Q02 EC03Q03 EC03Q04  \
0     NaN     NaN     NaN     NaN     NaN     NaN     NaN     NaN     NaN
1     NaN     NaN     NaN     NaN     NaN     NaN     NaN     NaN     NaN

  EC03Q05 EC03Q06 EC03Q07 EC03Q08 EC03Q09 EC03Q10  EC04Q01A  EC04Q01B  \
0     NaN     NaN     NaN     NaN     NaN     NaN       NaN       NaN
1     NaN     NaN     NaN     NaN     NaN     NaN       NaN       NaN

   EC04Q01C  EC04Q02A  EC04Q02B  EC04Q02C  EC04Q03A  EC04Q03B  EC04Q03C  \
0       NaN       NaN       NaN       NaN       NaN       NaN       NaN
1       NaN       NaN       NaN       NaN       NaN       NaN       NaN

   EC04Q04A  EC04Q04B  EC04Q04C  EC04Q05A  EC04Q05B  EC04Q05C  EC04Q06A  \
0       NaN       NaN       NaN       NaN       NaN       NaN       NaN
1       NaN       NaN       NaN       NaN       NaN       NaN       NaN

   EC04Q06B  EC04Q06C EC05Q01 EC06Q01 EC07Q01 EC07Q02 EC07Q03 EC07Q04 EC07Q05  \
0       NaN       NaN     NaN     NaN     NaN     NaN     NaN     NaN     NaN
1       NaN       NaN     NaN     NaN     NaN     NaN     NaN     NaN     NaN

  EC08Q01 EC08Q02 EC08Q03 EC08Q04 EC09Q03 EC10Q01 EC11Q02 EC11Q03 EC12Q01  \
0     NaN     NaN     NaN     NaN     NaN     NaN     NaN     NaN     NaN
1     NaN     NaN     NaN     NaN     NaN     NaN     NaN     NaN     NaN
```

```
  ST22Q01 ST23Q01 ST23Q02 ST23Q03 ST23Q04 ST23Q05 ST23Q06 ST23Q07 ST23Q08  \
0     NaN     NaN     NaN     NaN     NaN     NaN     NaN     NaN     NaN
1     NaN     NaN     NaN     NaN     NaN     NaN     NaN     NaN     NaN

  ST24Q01 ST24Q02 ST24Q03             CLCUSE1  CLCUSE301  CLCUSE302  DEFFORT  \
0     NaN     NaN     NaN  A Simple calculator         99         99       99
1     NaN     NaN     NaN  A Simple calculator         99         99       99

      QUESTID     BOOKID                       EASY    AGE  GRADE  \
0  StQ Form B  booklet 7  Standard set of booklets  16.17    0.0
1  StQ Form A  booklet 9  Standard set of booklets  16.17    0.0

                                PROGN  ANXMAT  ATSCHL  ATTLNACT  BELONG  \
0  Albania: Upper secondary education    0.32   -2.31    0.5206   -1.18
1  Albania: Upper secondary education     NaN     NaN       NaN     NaN

   BFMJ2  BMMJ1  CLSMAN   COBN_F   COBN_M   COBN_S  COGACT  CULTDIST  CULTPOS  \
0  76.49  79.74 -1.3771  Albania  Albania  Albania  0.6994       NaN    -0.48
1  15.35  23.47     NaN  Albania  Albania  Albania     NaN       NaN     1.27

   DISCLIMA  ENTUSE  ESCS  EXAPPLM  EXPUREM  FAILMAT  FAMCON  FAMCONC  \
0      1.85     NaN   NaN      NaN      NaN   0.6400     NaN      NaN
1       NaN     NaN   NaN  -0.0681   0.7955   0.1524  0.6387    -0.08

   FAMSTRUC             FISCED  HEDRES  HERITCUL             HISCED  HISEI  \
0       2.0  ISCED 3A, ISCED 4   -1.29       NaN  ISCED 3A, ISCED 4    NaN
1       2.0  ISCED 3A, ISCED 4    1.12       NaN        ISCED 5A, 6    NaN

   HOMEPOS  HOMSCH  HOSTCUL  ICTATTNEG  ICTATTPOS  ICTHOME  ICTRES  ICTSCH  \
0    -2.61     NaN      NaN        NaN        NaN      NaN   -3.16     NaN
1     1.41     NaN      NaN        NaN        NaN      NaN    1.15     NaN

    IMMIG  INFOCAR  INFOJOB1  INFOJOB2  INSTMOT  INTMAT ISCEDD         ISCEDL  \
0  Native      NaN       NaN       NaN     0.80    0.91      A  ISCED level 3
1  Native      NaN       NaN       NaN    -0.39    0.00      A  ISCED level 3

    ISCEDO  LANGCOMM      LANGN  LANGRPPD  LMINS  MATBEH  MATHEFF  MATINTFC  \
0  General       NaN  Albanian       NaN    NaN  0.6426    -0.77   -0.7332
1  General       NaN  Albanian       NaN  315.0  1.4702     0.34   -0.2514

   MATWKETH             MISCED  MMINS   MTSUP  \
0    0.2882  ISCED 3A, ISCED 4    NaN -0.9508
1    0.6490        ISCED 5A, 6  270.0     NaN

                                     OCOD1  \
0                     Building architects
1  Tailors, dressmakers, furriers and hatters
```

```
                              OCOD2  OPENPS  OUTHOURS  PARED  PERSEV  \
0          Primary school teachers  0.0521       NaN   12.0 -0.3407
1  Building construction labourers -0.9492       8.0   16.0  1.3116

                     REPEAT  SCMAT  SMINS  STUDREL  SUBNORM  TCHBEHFA  \
0  Did not repeat a <grade>   0.41    NaN    -1.04  -0.0455    1.3625
1  Did not repeat a <grade>    NaN   90.0      NaN   0.6602       NaN

   TCHBEHSO  TCHBEHTD  TEACHSUP   TESTLANG  TIMEINT  USEMATH  USESCH  WEALTH  \
0    0.9374    0.4297      1.68  Albanian       NaN      NaN     NaN   -2.92
1       NaN       NaN       NaN  Albanian       NaN      NaN     NaN    0.69

   ANCATSCHL  ANCATTLNACT  ANCBELONG  ANCCLSMAN  ANCCOGACT  ANCINSTMOT  \
0    -1.8636      -0.6779    -0.7351    -0.7808    -0.0219     -0.1562
1        NaN          NaN        NaN        NaN        NaN         NaN

   ANCINTMAT  ANCMATWKETH  ANCMTSUP  ANCSCMAT  ANCSTUDREL  ANCSUBNORM  \
0     0.0486      -0.2199   -0.5983   -0.0807     -0.5901     -0.3346
1        NaN          NaN       NaN       NaN         NaN         NaN

    PV1MATH   PV2MATH   PV3MATH   PV4MATH   PV5MATH   PV1MACC   PV2MACC  \
0  406.8469  376.4683  344.5319  321.1637  381.9209  325.8374  324.2795
1  486.1427  464.3325  453.4273  472.9008  476.0165  325.6816  419.9330

    PV3MACC   PV4MACC   PV5MACC   PV1MACQ   PV2MACQ   PV3MACQ   PV4MACQ  \
0  279.8800  267.4170  312.5954  409.1837  388.1524  373.3525  389.7102
1  378.6493  359.9548  384.1019  373.1968  444.0801  456.5431  401.2385

    PV5MACQ   PV1MACS   PV2MACS   PV3MACS   PV4MACS   PV5MACS   PV1MACU  \
0  415.4152  351.5423  375.6894  341.4161  386.5945  426.3203  396.7207
1  461.2167  366.9653  459.6588  426.1645  423.0488  443.3011  389.5544

    PV2MACU   PV3MACU   PV4MACU   PV5MACU   PV1MAPE   PV2MAPE   PV3MAPE  \
0  334.4057  328.9531  339.8582  354.6580  324.2795  345.3108  381.1419
1  438.6275  417.5962  379.4283  438.6275  440.1854  456.5431  486.9216

   PV4MAPE   PV5MAPE   PV1MAPF   PV2MAPF   PV3MAPF   PV4MAPF   PV5MAPF  \
0  380.363  346.8687  319.6059  345.3108  360.8895  390.4892  322.7216
1  458.101  444.0801  411.3647  437.8486  457.3220  454.2063  460.4378

    PV1MAPI   PV2MAPI   PV3MAPI   PV4MAPI   PV5MAPI   PV1READ   PV2READ  \
0  290.7852  345.3108  326.6163  407.6258  367.1210  249.5762  254.3420
1  434.7328  448.7537  494.7110  429.2803  434.7328  406.2936  349.8975

    PV3READ   PV4READ   PV5READ   PV1SCIE   PV2SCIE   PV3SCIE   PV4SCIE  \
0  406.8496  175.7053  218.5981  341.7009  408.8400  348.2283  367.8105
```

```
1  400.7334  369.7553  396.7618  548.9929  471.5964  471.5964  443.6218

    PV5SCIE  W_FSTUWT  W_FSTR1  W_FSTR2  W_FSTR3  W_FSTR4  W_FSTR5  W_FSTR6  \
0  392.9877    8.9096  13.1249  13.0829   4.5315  13.0829  13.9235  13.1249
1  454.8116    8.9096  13.1249  13.0829   4.5315  13.0829  13.9235  13.1249

   W_FSTR7  W_FSTR8  W_FSTR9  W_FSTR10  W_FSTR11  W_FSTR12  W_FSTR13  \
0  13.1249   4.3389   4.3313   13.7954    4.5315    4.3313   13.7954
1  13.1249   4.3389   4.3313   13.7954    4.5315    4.3313   13.7954

   W_FSTR14  W_FSTR15  W_FSTR16  W_FSTR17  W_FSTR18  W_FSTR19  W_FSTR20  \
0   13.9235    4.3389    4.3313    4.5084    4.5084   13.7954    4.5315
1   13.9235    4.3389    4.3313    4.5084    4.5084   13.7954    4.5315

   W_FSTR21  W_FSTR22  W_FSTR23  W_FSTR24  W_FSTR25  W_FSTR26  W_FSTR27  \
0   13.1249   13.0829    4.5315   13.0829   13.9235   13.1249   13.1249
1   13.1249   13.0829    4.5315   13.0829   13.9235   13.1249   13.1249

   W_FSTR28  W_FSTR29  W_FSTR30  W_FSTR31  W_FSTR32  W_FSTR33  W_FSTR34  \
0    4.3389    4.3313   13.7954    4.5315    4.3313   13.7954   13.9235
1    4.3389    4.3313   13.7954    4.5315    4.3313   13.7954   13.9235

   W_FSTR35  W_FSTR36  W_FSTR37  W_FSTR38  W_FSTR39  W_FSTR40  W_FSTR41  \
0    4.3389    4.3313    4.5084    4.5084   13.7954    4.5315    4.5084
1    4.3389    4.3313    4.5084    4.5084   13.7954    4.5315    4.5084

   W_FSTR42  W_FSTR43  W_FSTR44  W_FSTR45  W_FSTR46  W_FSTR47  W_FSTR48  \
0    4.5315   13.0829    4.5315    4.3313    4.5084    4.5084   13.7954
1    4.5315   13.0829    4.5315    4.3313    4.5084    4.5084   13.7954

   W_FSTR49  W_FSTR50  W_FSTR51  W_FSTR52  W_FSTR53  W_FSTR54  W_FSTR55  \
0   13.9235    4.3389   13.0829   13.9235    4.3389    4.3313   13.7954
1   13.9235    4.3389   13.0829   13.9235    4.3389    4.3313   13.7954

   W_FSTR56  W_FSTR57  W_FSTR58  W_FSTR59  W_FSTR60  W_FSTR61  W_FSTR62  \
0   13.9235   13.1249   13.1249    4.3389   13.0829    4.5084    4.5315
1   13.9235   13.1249   13.1249    4.3389   13.0829    4.5084    4.5315

   W_FSTR63  W_FSTR64  W_FSTR65  W_FSTR66  W_FSTR67  W_FSTR68  W_FSTR69  \
0   13.0829    4.5315    4.3313    4.5084    4.5084   13.7954   13.9235
1   13.0829    4.5315    4.3313    4.5084    4.5084   13.7954   13.9235

   W_FSTR70  W_FSTR71  W_FSTR72  W_FSTR73  W_FSTR74  W_FSTR75  W_FSTR76  \
0    4.3389   13.0829   13.9235    4.3389    4.3313   13.7954   13.9235
1    4.3389   13.0829   13.9235    4.3389    4.3313   13.7954   13.9235

   W_FSTR77  W_FSTR78  W_FSTR79  W_FSTR80  WVARSTRR  VAR_UNIT  SENWGT_STU  \
```

```
0   13.1249   13.1249    4.3389   13.0829        19         1      0.2098
1   13.1249   13.1249    4.3389   13.0829        19         1      0.2098

   VER_STU
0  22NOV13
1  22NOV13
```

Let's first drop unused columns that could slow down our work.

[5]:
```
cols_to_keep = ['CNT', 'OECD', 'SCHOOLID', 'STIDSTD', 'AGE', 'ST04Q01',␣
↪'ST20Q01', 'ST01Q01', 'GRADE',
                'ST11Q01', 'ST11Q02', 'ST11Q05', 'PARED', 'ST13Q01', 'ST17Q01',␣
↪'ST27Q01', 'ST27Q02', 'ST27Q03',
                'ST27Q04', 'ST27Q05', 'ST28Q01', 'ST26Q01', 'ST26Q02',␣
↪'ST26Q03', 'ST26Q04', 'ST26Q05', 'ST26Q06',
                'ST55Q01', 'ST55Q02', 'ST55Q03', 'LMINS', 'SMINS', 'MMINS',
                'PV1MATH', 'PV2MATH', 'PV3MATH', 'PV4MATH', 'PV5MATH',␣
↪'PV1SCIE', 'PV2SCIE', 'PV3SCIE',
                'PV4SCIE', 'PV5SCIE', 'PV1READ', 'PV2READ', 'PV3READ',␣
↪'PV4READ', 'PV5READ']

df = df[cols_to_keep]
df.head(2)
```

[5]:
```
       CNT      OECD SCHOOLID STIDSTD    AGE ST04Q01          ST20Q01  \
0  Albania  Non-OECD  0000001   00001  16.17  Female  Country of test
1  Albania  Non-OECD  0000001   00002  16.17  Female  Country of test

   ST01Q01  GRADE ST11Q01 ST11Q02 ST11Q05  PARED           ST13Q01  \
0       10    0.0     Yes     Yes     NaN   12.0  <ISCED level 3A>
1       10    0.0     Yes     Yes     NaN   16.0  <ISCED level 3A>

             ST17Q01        ST27Q01        ST27Q02        ST27Q03 ST27Q04  \
0  <ISCED level 3A>            Two            One           None    None
1  <ISCED level 3A>   Three or more  Three or more  Three or more     Two

  ST27Q05         ST28Q01 ST26Q01 ST26Q02 ST26Q03 ST26Q04 ST26Q05 ST26Q06  \
0    None     0-10 books      Yes      No     Yes      No      No      No
1     Two  201-500 books      Yes     Yes     Yes     Yes     Yes     Yes

                                          ST55Q01  \
0                                             NaN
1  I do not attend <out-of-school time lessons> i...

                                ST55Q02  \
0                                   NaN
1  2 or more but less than 4 hours a week
```

```
                                    ST55Q03  LMINS  SMINS  MMINS   PV1MATH  \
0                                       NaN    NaN    NaN    NaN  406.8469
1  2 or more but less than 4 hours a week  315.0   90.0  270.0  486.1427

    PV2MATH   PV3MATH   PV4MATH   PV5MATH   PV1SCIE   PV2SCIE   PV3SCIE  \
0  376.4683  344.5319  321.1637  381.9209  341.7009  408.8400  348.2283
1  464.3325  453.4273  472.9008  476.0165  548.9929  471.5964  471.5964

    PV4SCIE   PV5SCIE   PV1READ   PV2READ   PV3READ   PV4READ   PV5READ
0  367.8105  392.9877  249.5762  254.3420  406.8496  175.7053  218.5981
1  443.6218  454.8116  406.2936  349.8975  400.7334  369.7553  396.7618
```

We can look at meaning of columns using PISA dictionary data.

[6]:
```
# Load in dict data

dict_df = pd.read_csv(dict_path, header=None, names=['value', 'meaning'],␣
 ↪skiprows=1, encoding='ISO-8859-1')
dict_df.head()
```

[6]:
```
      value                                            meaning
0       CNT                          Country code 3-character
1  SUBNATIO  Adjudicated sub-region code 7-digit code (3-di...
2   STRATUM  Stratum ID 7-character (cnt + region ID + orig...
3      OECD                                        OECD country
4        NC                      National Centre 6-digit Code
```

[7]:
```
dict_df[dict_df['value'].isin(df.columns)]
```

[7]:
```
        value                                            meaning
0         CNT                          Country code 3-character
3        OECD                                        OECD country
5    SCHOOLID  School ID 7-digit (region ID + stratum ID + 3-...
6     STIDSTD                                        Student ID
7     ST01Q01                                 International Grade
11    ST04Q01                                            Gender
20    ST11Q01                                At Home - Mother
21    ST11Q02                                At Home - Father
24    ST11Q05                             At Home - Grandparents
26    ST13Q01                          Mother<Highest Schooling>
32    ST17Q01                          Father<Highest Schooling>
38    ST20Q01              Country of Birth International - Self
43    ST26Q01                                 Possessions - desk
44    ST26Q02                             Possessions - own room
45    ST26Q03                          Possessions - study place
46    ST26Q04                             Possessions - computer
47    ST26Q05                             Possessions - software
48    ST26Q06                             Possessions - Internet
60    ST27Q01                          How many - cellular phones
61    ST27Q02                             How many - televisions
```

```
62    ST27Q03                                How many - computers
63    ST27Q04                                     How many - cars
64    ST27Q05                   How many - rooms bath or shower
65    ST28Q01                             How many books at home
136   ST55Q01               Out of school lessons - <test lang>
137   ST55Q02                   Out of school lessons - <maths>
138   ST55Q03                 Out of school lessons - <science>
410       AGE                                      Age of student
411     GRADE          Grade compared to modal grade in country
460     LMINS  Learning time (minutes per week)  - <test lang...
466     MMINS    Learning time (minutes per week)- <Mathematics>
472     PARED               Highest parental education in years
476     SMINS       Learning time (minutes per week) - <Science>
500   PV1MATH                   Plausible value 1 in mathematics
501   PV2MATH                   Plausible value 2 in mathematics
502   PV3MATH                   Plausible value 3 in mathematics
503   PV4MATH                   Plausible value 4 in mathematics
504   PV5MATH                   Plausible value 5 in mathematics
540   PV1READ                       Plausible value 1 in reading
541   PV2READ                       Plausible value 2 in reading
542   PV3READ                       Plausible value 3 in reading
543   PV4READ                       Plausible value 4 in reading
544   PV5READ                       Plausible value 5 in reading
545   PV1SCIE                       Plausible value 1 in science
546   PV2SCIE                       Plausible value 2 in science
547   PV3SCIE                       Plausible value 3 in science
548   PV4SCIE                       Plausible value 4 in science
549   PV5SCIE                       Plausible value 5 in science
```

1.1.1 General Properties

[8]:
```
print('Shape:', df.shape[0], 'rows and', df.shape[1], 'columns')
```

```
Shape: 485490 rows and 48 columns
```

There're 1471 schools with 33806 students in the dataset.

[9]:
```
df.SCHOOLID.nunique(), df.STIDSTD.nunique()
```

[9]:
```
(1471, 33806)
```

Schools and students identifiers were loaded as integers first time, so their types were specified directly when loading data.

[10]:
```
df.dtypes
```

[10]:
```
CNT          object
OECD         object
SCHOOLID     object
STIDSTD      object
```

```
AGE         float64
ST04Q01      object
ST20Q01      object
ST01Q01       int64
GRADE       float64
ST11Q01      object
ST11Q02      object
ST11Q05      object
PARED       float64
ST13Q01      object
ST17Q01      object
ST27Q01      object
ST27Q02      object
ST27Q03      object
ST27Q04      object
ST27Q05      object
ST28Q01      object
ST26Q01      object
ST26Q02      object
ST26Q03      object
ST26Q04      object
ST26Q05      object
ST26Q06      object
ST55Q01      object
ST55Q02      object
ST55Q03      object
LMINS       float64
SMINS       float64
MMINS       float64
PV1MATH     float64
PV2MATH     float64
PV3MATH     float64
PV4MATH     float64
PV5MATH     float64
PV1SCIE     float64
PV2SCIE     float64
PV3SCIE     float64
PV4SCIE     float64
PV5SCIE     float64
PV1READ     float64
PV2READ     float64
PV3READ     float64
PV4READ     float64
PV5READ     float64
dtype: object
```

[11]:
```
# First, I think, "ST55Q.." clumns should be numeric

df.ST55Q01.unique()
```

[11]:
```
array([nan,
       'I do not attend <out-of-school time lessons> in this subject',
       'Less than 2 hours a week',
       '4 or more but less than 6 hours a week',
       '2 or more but less than 4 hours a week', '6 or more hours a week'],
      dtype=object)
```

Most rows have some missing values.

[12]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 485490 entries, 0 to 485489
Data columns (total 48 columns):
CNT         485490 non-null object
OECD        485490 non-null object
SCHOOLID    485490 non-null object
STIDSTD     485490 non-null object
AGE         485374 non-null float64
ST04Q01     485490 non-null object
ST20Q01     476363 non-null object
ST01Q01     485490 non-null int64
GRADE       484617 non-null float64
ST11Q01     460559 non-null object
ST11Q02     441036 non-null object
ST11Q05     348180 non-null object
PARED       473091 non-null float64
ST13Q01     457979 non-null object
ST17Q01     443261 non-null object
ST27Q01     477079 non-null object
ST27Q02     476548 non-null object
ST27Q03     473459 non-null object
ST27Q04     472499 non-null object
ST27Q05     469643 non-null object
ST28Q01     473765 non-null object
ST26Q01     473079 non-null object
ST26Q02     469693 non-null object
ST26Q03     472020 non-null object
ST26Q04     473877 non-null object
ST26Q05     463178 non-null object
ST26Q06     473182 non-null object
ST55Q01     307761 non-null object
ST55Q02     308171 non-null object
ST55Q03     306090 non-null object
LMINS       282866 non-null float64
```

```
SMINS       270914 non-null float64
MMINS       283303 non-null float64
PV1MATH     485490 non-null float64
PV2MATH     485490 non-null float64
PV3MATH     485490 non-null float64
PV4MATH     485490 non-null float64
PV5MATH     485490 non-null float64
PV1SCIE     485490 non-null float64
PV2SCIE     485490 non-null float64
PV3SCIE     485490 non-null float64
PV4SCIE     485490 non-null float64
PV5SCIE     485490 non-null float64
PV1READ     485490 non-null float64
PV2READ     485490 non-null float64
PV3READ     485490 non-null float64
PV4READ     485490 non-null float64
PV5READ     485490 non-null float64
dtypes: float64(21), int64(1), object(26)
memory usage: 177.8+ MB
```

[13]:
```
# Check missing data

df_missing = df.isnull().sum().sort_values(ascending=False)
df_missing[df_missing > 0] / df.shape[0]
```

[13]:
```
SMINS      0.441978
LMINS      0.417360
MMINS      0.416460
ST55Q03    0.369524
ST55Q01    0.366082
ST55Q02    0.365237
ST11Q05    0.282828
ST11Q02    0.091565
ST17Q01    0.086982
ST13Q01    0.056666
ST11Q01    0.051352
ST26Q05    0.045958
ST27Q05    0.032641
ST26Q02    0.032538
ST26Q03    0.027745
ST27Q04    0.026759
ST26Q01    0.025564
PARED      0.025539
ST26Q06    0.025352
ST27Q03    0.024781
ST28Q01    0.024151
ST26Q04    0.023920
ST20Q01    0.018800
```

```
ST27Q02    0.018419
ST27Q01    0.017325
GRADE      0.001798
AGE        0.000239
dtype: float64
```

[14]:
```
df[['SMINS', 'LMINS', 'MMINS']].head(10)
```

[14]:
```
   SMINS  LMINS  MMINS
0    NaN    NaN    NaN
1   90.0  315.0  270.0
2    NaN  300.0    NaN
3   90.0  135.0  135.0
4    NaN    NaN    NaN
5    NaN    NaN    NaN
6   90.0  135.0  225.0
7    NaN    NaN    NaN
8    NaN    NaN    NaN
9  270.0  240.0   90.0
```

Columns SMINS, LMINS, and MMINS (that's Learning time (minutes per week)) have more than 40% missing values. So, last 7th question could be modified as follows:
Whether absense of data about learning time on math, science, and reading, affect students performance? And if a student report info about total time learning, how these influence each grade in assesment?

The same could be applied to ST55Q03, ST55Q01, and ST55Q02 (Out of school lessons) because of high percent (about 36%) of missingvalues.

Finally, it's also more than a quater missig values in ST11Q05 column (At Home - Grandparents). He we can asume, NaN in ST11Q05 could be also considered as missing data.

[15]:
```
df.ST11Q05.unique()
```

[15]:
```
array([nan, 'No', 'Yes'], dtype=object)
```

In all other columns share of missing data isn't exceed than 10%. So, for explanatory data analysis, we could ignore this distortions, and drop missing values.

[16]:
```
for column in df_missing.index:
    if column not in ('SMINS', 'LMINS', 'MMINS', 'ST55Q03', 'ST55Q01',␣
 ↪'ST55Q02', 'ST11Q05'):
        df[column].fillna(df[column].mode()[0], inplace=True)


# Check NaN
df_missing = df.isnull().sum().sort_values(ascending=False)
df_missing[df_missing > 0] / df.shape[0]
```

[16]:
```
SMINS      0.441978
LMINS      0.417360
MMINS      0.416460
ST55Q03    0.369524
```

```
ST55Q01    0.366082
ST55Q02    0.365237
ST11Q05    0.282828
dtype: float64
```

[17]:
```
# Check duplicated rows

df.duplicated().sum() # => there's no duplicated rows
```

[17]:
```
0
```

[18]:
```
# Summary statistics of numeric columns

df.describe()
```

[18]:
```
                AGE        ST01Q01          GRADE          PARED  \
count  485490.000000  485490.000000  485490.000000  485490.000000
mean       15.784234       9.813323      -0.162671      12.969808
std         0.290203       3.734726       0.655005       3.358615
min        15.170000       7.000000      -3.000000       3.000000
25%        15.580000       9.000000       0.000000      12.000000
50%        15.750000      10.000000       0.000000      13.000000
75%        16.000000      10.000000       0.000000      16.000000
max        16.330000      96.000000       3.000000      18.000000

               LMINS          SMINS          MMINS        PV1MATH  \
count  282866.000000  270914.000000  283303.000000  485490.000000
mean      219.276636     211.122460     226.007056     469.621653
std        97.997730     131.368322      97.448421     103.265391
min         0.000000       0.000000       0.000000      19.792800
25%       165.000000     120.000000     180.000000     395.318600
50%       200.000000     180.000000     220.000000     466.201900
75%       250.000000     270.000000     250.000000     541.057800
max      2400.000000    2975.000000    3000.000000     962.229300

             PV2MATH        PV3MATH        PV4MATH        PV5MATH  \
count  485490.000000  485490.000000  485490.000000  485490.000000
mean      469.648358     469.648930     469.641832     469.695396
std       103.382077     103.407631     103.392286     103.419170
min         6.473000      42.226200      24.622200      37.085200
25%       395.318600     395.240700     395.396500     395.240700
50%       466.124000     466.201900     466.279800     466.435600
75%       541.447300     541.291500     541.447300     541.447300
max       957.010400     935.745400     943.456900     907.625800

             PV1SCIE        PV2SCIE        PV3SCIE       PV4SCIE  \
count  485490.000000  485490.000000  485490.000000  485490.00000
mean      475.769824     475.813674     475.851549     475.78524
std       101.464426     101.514649     101.495072     101.51220
```

```
min         2.648300       2.834800      11.879900       8.42970
25%       404.457300     404.457300     404.550500     404.45730
50%       475.699400     475.606100     475.699400     475.97910
75%       547.780700     547.873900     547.967200     547.78070
max       903.338300     900.540800     867.624000     926.55730

             PV5SCIE        PV1READ        PV2READ        PV3READ  \
count  485490.000000  485490.000000  485490.000000  485490.000000
mean      475.820184     472.004640     472.068052     472.022059
std       101.566347     102.505523     102.626198     102.640489
min        17.754600       0.083400       0.703500       0.703500
25%       404.457300     403.600700     403.360100     403.360100
50%       475.885900     475.455000     475.535200     475.455000
75%       547.780700     544.502500     544.503500     544.503500
max       880.958600     904.802600     881.239200     884.447000

             PV4READ        PV5READ
count  485490.000000  485490.000000
mean      471.926562     472.013506
std       102.576066     102.659989
min         4.134400       2.307400
25%       403.354600     403.360100
50%       475.535200     475.535200
75%       544.502500     544.503500
max       881.159000     901.608600
```

Part I - Data Wrangling and Data Exploration

[19]:
```
# Check values of object columns , and simplify where possible

cat_cols = df.select_dtypes(include='object').columns
cat_cols = cat_cols.drop(['SCHOOLID', 'STIDSTD', 'CNT'])
print('Number of string columns', cat_cols.shape[0])
cat_cols
```

```
Number of string columns 23
```

[19]:
```
Index(['OECD', 'ST04Q01', 'ST20Q01', 'ST11Q01', 'ST11Q02', 'ST11Q05',
       'ST13Q01', 'ST17Q01', 'ST27Q01', 'ST27Q02', 'ST27Q03', 'ST27Q04',
       'ST27Q05', 'ST28Q01', 'ST26Q01', 'ST26Q02', 'ST26Q03', 'ST26Q04',
       'ST26Q05', 'ST26Q06', 'ST55Q01', 'ST55Q02', 'ST55Q03'],
      dtype='object')
```

There's a lot of categories in CNT column (countries). Look at them seperately.

[20]:
```
for column in cat_cols:
    print(column, df[column].nunique(), df[column].unique())
```

```
OECD 2 ['Non-OECD' 'OECD']
ST04Q01 2 ['Female' 'Male']
```

```
ST20Q01 2 ['Country of test' 'Other country']
ST11Q01 2 ['Yes' 'No']
ST11Q02 2 ['Yes' 'No']
ST11Q05 2 [nan 'No' 'Yes']
ST13Q01 5 ['<ISCED level 3A> ' '<ISCED level 3B, 3C> '
 'She did not complete <ISCED level 1> ' '<ISCED level 2> '
 '<ISCED level 1> ']
ST17Q01 5 ['<ISCED level 3A> ' '<ISCED level 3B, 3C> ' '<ISCED level 2> '
 'He did not complete <ISCED level 1> ' '<ISCED level 1> ']
ST27Q01 4 ['Two' 'Three or more' 'One' 'None']
ST27Q02 4 ['One' 'Three or more' 'Two' 'None']
ST27Q03 4 ['None' 'Three or more' 'Two' 'One']
ST27Q04 4 ['None' 'Two' 'One' 'Three or more']
ST27Q05 4 ['None' 'Two' 'One' 'Three or more']
ST28Q01 6 ['0-10 books ' '201-500 books ' 'More than 500 books' '11-25 books '
 '101-200 books ' '26-100 books ']
ST26Q01 2 ['Yes' 'No']
ST26Q02 2 ['No' 'Yes']
ST26Q03 2 ['Yes' 'No']
ST26Q04 2 ['No' 'Yes']
ST26Q05 2 ['No' 'Yes']
ST26Q06 2 ['No' 'Yes']
ST55Q01 5 [nan 'I do not attend <out-of-school time lessons> in this subject'
 'Less than 2 hours a week' '4 or more but less than 6 hours a week'
 '2 or more but less than 4 hours a week' '6 or more hours a week']
ST55Q02 5 [nan '2 or more but less than 4 hours a week'
 'I do not attend <out-of-school time lessons> in this subject'
 'Less than 2 hours a week' '6 or more hours a week'
 '4 or more but less than 6 hours a week']
ST55Q03 5 [nan '2 or more but less than 4 hours a week'
 '4 or more but less than 6 hours a week' 'Less than 2 hours a week'
 'I do not attend <out-of-school time lessons> in this subject'
 '6 or more hours a week']
```

For column "How many properties are at home?" replace "None" and NaN values with zeros.

[21]:
```
cols_with_none = 'ST27Q01', 'ST27Q02', 'ST27Q03', 'ST27Q04', 'ST27Q05'
for column in cols_with_none:
    df[column] = df[column].replace(['None', np.nan], 'Zero')
```

[22]:
```
print('Number of unique countries', df['CNT'].nunique())
df.CNT.unique()
```

```
Number of unique countries 68
```

[22]:
```
array(['Albania', 'United Arab Emirates', 'Argentina', 'Australia',
       'Austria', 'Belgium', 'Bulgaria', 'Brazil', 'Canada',
       'Switzerland', 'Chile', 'Colombia', 'Costa Rica', 'Czech Republic',
       'Germany', 'Denmark', 'Spain', 'Estonia', 'Finland', 'France',
```

```
       'United Kingdom', 'Greece', 'Hong Kong-China', 'Croatia',
       'Hungary', 'Indonesia', 'Ireland', 'Iceland', 'Israel', 'Italy',
       'Jordan', 'Japan', 'Kazakhstan', 'Korea', 'Liechtenstein',
       'Lithuania', 'Luxembourg', 'Latvia', 'Macao-China', 'Mexico',
       'Montenegro', 'Malaysia', 'Netherlands', 'Norway', 'New Zealand',
       'Peru', 'Poland', 'Portugal', 'Qatar', 'China-Shanghai',
       'Perm(Russian Federation)', 'Florida (USA)', 'Connecticut (USA)',
       'Massachusetts (USA)', 'Romania', 'Russian Federation',
       'Singapore', 'Serbia', 'Slovak Republic', 'Slovenia', 'Sweden',
       'Chinese Taipei', 'Thailand', 'Tunisia', 'Turkey', 'Uruguay',
       'United States of America', 'Vietnam'], dtype=object)
```

Some change could be made: 1. Hong Kong-China -> Hong Kong 2. China-Shanghai -> China 3. Perm(Russian Federation) -> Russian Federation (since Perm is just a city in RF) 4. Florida (USA) -> United States of America 5. Connecticut (USA) -> United States of America 6. Massachusetts (USA) -> United States of America 7. Chinese Taipei -> Taiwan 8. Macao-China -> Macao

[23]:
```
# Implement changes in NCT column

df['CNT'] = (df['CNT'].replace('Hong Kong-China', 'Hong Kong')
                      .replace('China-Shanghai', 'China')
                      .replace('Perm(Russian Federation)', 'Russian␣
 ↪Federation')
                      .replace('Florida (USA)', 'United States of America')
                      .replace('Connecticut (USA)', 'United States of␣
 ↪America')
                      .replace('Connecticut (USA)', 'United States of␣
 ↪America')
                      .replace('Massachusetts (USA)', 'United States of␣
 ↪America')
                      .replace('Chinese Taipei', 'Taiwan')
                      .replace('Macao-China', 'Macao'))
```

[24]:
```
# Check changes

print('Number of unique countries', df['CNT'].nunique())
df['CNT'].unique()
```

```
Number of unique countries 64
```

[24]:
```
array(['Albania', 'United Arab Emirates', 'Argentina', 'Australia',
       'Austria', 'Belgium', 'Bulgaria', 'Brazil', 'Canada',
       'Switzerland', 'Chile', 'Colombia', 'Costa Rica', 'Czech Republic',
       'Germany', 'Denmark', 'Spain', 'Estonia', 'Finland', 'France',
       'United Kingdom', 'Greece', 'Hong Kong', 'Croatia', 'Hungary',
       'Indonesia', 'Ireland', 'Iceland', 'Israel', 'Italy', 'Jordan',
       'Japan', 'Kazakhstan', 'Korea', 'Liechtenstein', 'Lithuania',
       'Luxembourg', 'Latvia', 'Macao', 'Mexico', 'Montenegro',
```

```
       'Malaysia', 'Netherlands', 'Norway', 'New Zealand', 'Peru',
       'Poland', 'Portugal', 'Qatar', 'China', 'Russian Federation',
       'United States of America', 'Romania', 'Singapore', 'Serbia',
       'Slovak Republic', 'Slovenia', 'Sweden', 'Taiwan', 'Thailand',
       'Tunisia', 'Turkey', 'Uruguay', 'Vietnam'], dtype=object)
```

Finally, the independent variables "PV..." - plausible values in math, science, and reading - will be summed and diveded by 5 (number of column of each subject).

[25]:
```
df['PV_MATH'] = (df.PV1MATH + df.PV2MATH + df.PV3MATH + df.PV4MATH + df.
 ↪PV5MATH) / 5
df['PV_SCIE'] = (df.PV1SCIE + df.PV2SCIE + df.PV3SCIE + df.PV4SCIE + df.
 ↪PV5SCIE) / 5
df['PV_READ'] = (df.PV1READ + df.PV2READ + df.PV3READ + df.PV4READ + df.
 ↪PV5READ) / 5

df[['PV_MATH', 'PV_SCIE', 'PV_READ']].describe()
```

[25]:

	PV_MATH	PV_SCIE	PV_READ
count	485490.000000	485490.000000	485490.000000
mean	469.651234	475.808094	472.006964
std	100.786610	97.998470	98.863310
min	54.767080	25.158540	6.445400
25%	396.019620	405.762800	405.044200
50%	465.734520	475.512860	475.477980
75%	540.123060	546.381920	542.831195
max	903.107960	857.832900	849.359740

[26]:
```
# Drop initial "PV..." columns

df.drop(['PV1MATH', 'PV2MATH', 'PV3MATH', 'PV4MATH', 'PV5MATH', 'PV1SCIE',␣
 ↪'PV2SCIE', 'PV3SCIE', 'PV4SCIE',
         'PV5SCIE', 'PV1READ', 'PV2READ', 'PV3READ', 'PV4READ', 'PV5READ'],␣
 ↪axis=1, inplace=True)
```

Part II - Explanatory Data Analysis

[27]:
```
df.head(3)
```

[27]:

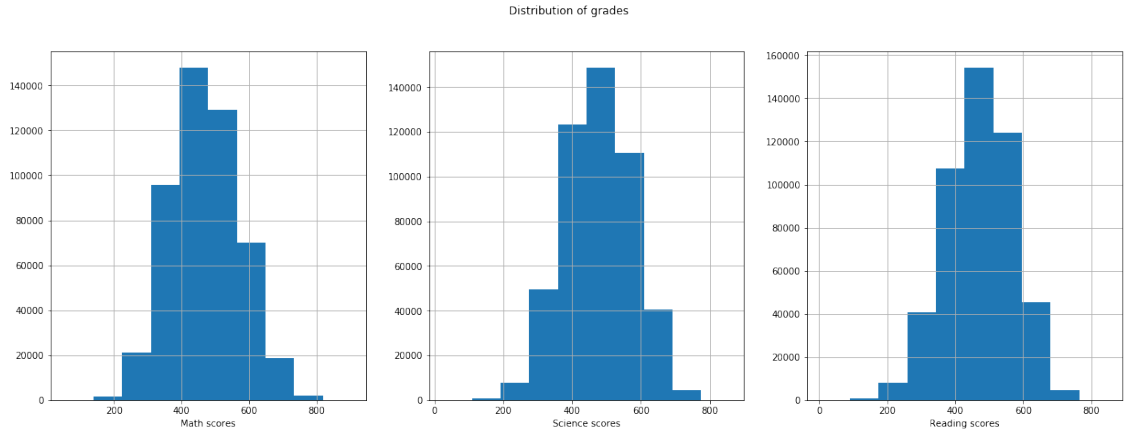
	CNT	OECD	SCHOOLID	STIDSTD	AGE	ST04Q01	ST20Q01	ST01Q01	GRADE	ST11Q01	ST11Q02	ST11Q05	PARED	ST13Q01	ST17Q01	ST27Q01	ST27Q02	ST27Q03	ST27Q04
0	Albania	Non-OECD	0000001	00001	16.17	Female	Country of test	10	0.0	Yes	Yes	NaN	12.0	<ISCED level 3A>	<ISCED level 3A>	Two	One	Zero	Zero
1	Albania	Non-OECD	0000001	00002	16.17	Female	Country of test	10	0.0	Yes	Yes	NaN	16.0	<ISCED level 3A>					
2	Albania	Non-OECD	0000001	00003	15.58	Female	Country of test	9	-1.0	Yes	Yes	No	16.0	<ISCED level 3B, 3C>					

```
1  <ISCED level 3A>   Three or more  Three or more  Three or more     Two
2  <ISCED level 3A>   Three or more            Two            Two     One

  ST27Q05              ST28Q01 ST26Q01 ST26Q02 ST26Q03 ST26Q04 ST26Q05  \
0    Zero           0-10 books      Yes      No     Yes      No      No
1     Two       201-500 books      Yes     Yes     Yes     Yes     Yes
2     Two  More than 500 books      Yes     Yes     Yes     Yes      No

  ST26Q06                                            ST55Q01  \
0      No                                               NaN
1     Yes  I do not attend <out-of-school time lessons> i...
2     Yes                            Less than 2 hours a week

                                  ST55Q02  \
0                                    NaN
1  2 or more but less than 4 hours a week
2  2 or more but less than 4 hours a week

                                  ST55Q03  LMINS  SMINS  MMINS    PV_MATH  \
0                                    NaN    NaN    NaN    NaN  366.18634
1  2 or more but less than 4 hours a week  315.0   90.0  270.0  470.56396
2  4 or more but less than 6 hours a week  300.0    NaN    NaN  505.53824

     PV_SCIE    PV_READ
0  371.91348  261.01424
1  478.12382  384.68832
2  486.60946  405.18154
```

1. What is students' performance at schools in different countries (including whether country is a OECD member).

[28]:
```
base_color = sns.color_palette()[0]
```

[29]:
```
fig, ax = plt.subplots(nrows=1, ncols=3, figsize=(21,7))
df['PV_MATH'].hist(ax=ax[0])
df['PV_SCIE'].hist(ax=ax[1])
df['PV_READ'].hist(ax=ax[2])
ax[0].set_xlabel('Math scores')
ax[1].set_xlabel('Science scores')
ax[2].set_xlabel('Reading scores')
plt.suptitle('Distribution of grades')
plt.show()
```

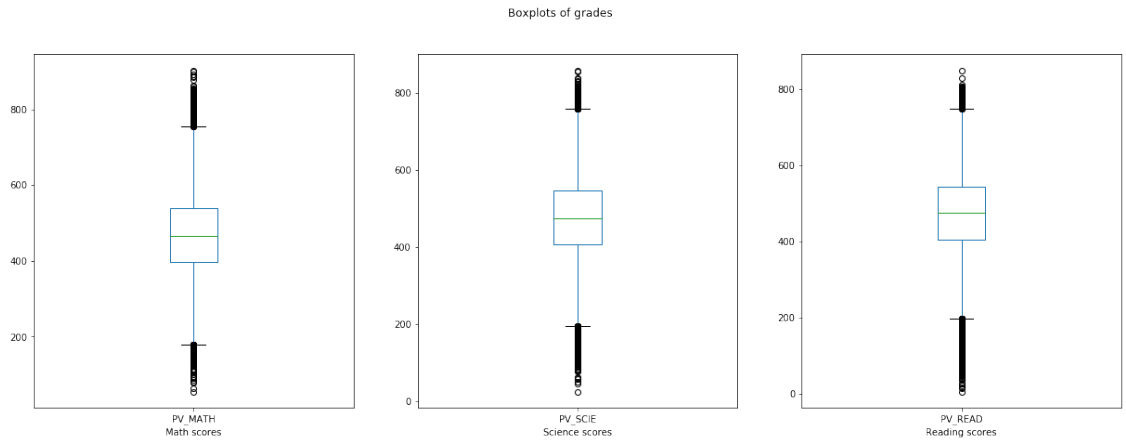


[30]:
```
df['PV_MATH'].mean(), df['PV_SCIE'].mean(), df['PV_READ'].mean()
```

[30]:
```
(469.65123385442615, 475.80809403002854, 472.0069640898506)
```

If we plot all the grades by subject, then scores in each subject looks normally distributed. Mean scores of science are about 3 points higher than average reading scores. In its turn, avearge reading scores are about 3 poits higher than avearge math scores. So scores in those 3 subjects are very similar.
So, let's look at their boxplots.

[31]:
```
fig, ax = plt.subplots(nrows=1, ncols=3, figsize=(21,7))
df['PV_MATH'].plot(kind='box', ax=ax[0])
df['PV_SCIE'].plot(kind='box', ax=ax[1])
df['PV_READ'].plot(kind='box', ax=ax[2])
ax[0].set_xlabel('Math scores')
ax[1].set_xlabel('Science scores')
ax[2].set_xlabel('Reading scores')
plt.suptitle('Boxplots of grades')
plt.show()
```



In general, there're outliers in every Series of scores. Moreover, math scores have approximately equal tails of outliers, but science and reading scores have outliers with lower scores more, than outliers with higher scores. let's go deepper, and look at students perormance in the context of countries, OECD membership, and other columns.

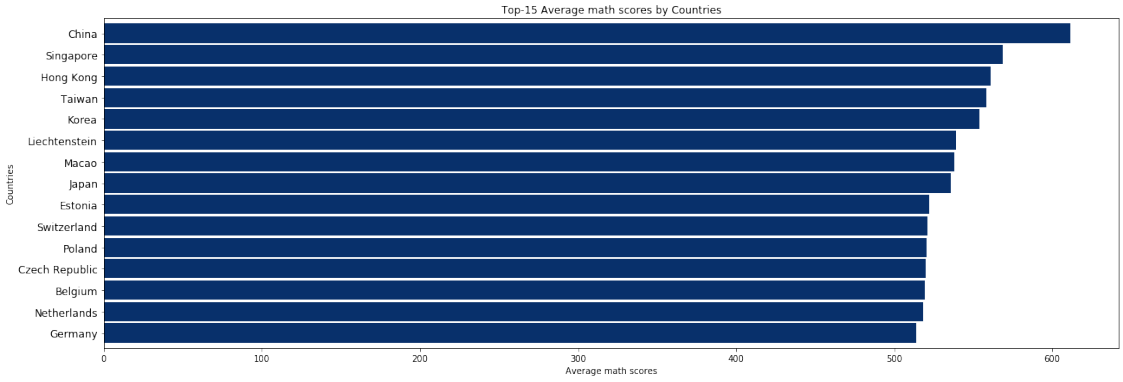
[32]:
```
df_plot1 = df.groupby('CNT').agg({'PV_MATH': 'mean', 'PV_SCIE': 'mean',␣
 ↪'PV_READ': 'mean', 'STIDSTD': 'nunique'})

print('Shape', df_plot1.shape)
df_plot1.head()
```

```
Shape (64, 4)
```

[32]:

CNT	PV_MATH	PV_SCIE	PV_READ	STIDSTD
Albania	394.878912	398.916529	396.250245	4743
Argentina	395.635711	410.478404	403.596060	5908
Australia	493.268939	511.638212	501.056931	14481
Austria	507.778785	508.036810	491.485551	4755
Belgium	519.668410	510.302595	512.281728	8597

[33]:
```
df_plot1[['PV_MATH']].sort_values('PV_MATH').iloc[-15:].plot.
 ↪barh(figsize=(21,7), width=.9, legend=False,
                                                                  ␣
 ↪cmap='Blues_r')
plt.yticks(fontsize=12)
plt.xlabel('Average math scores')
plt.ylabel('Countries')
plt.title('Top-15 Average math scores by Countries')
plt.show()
```

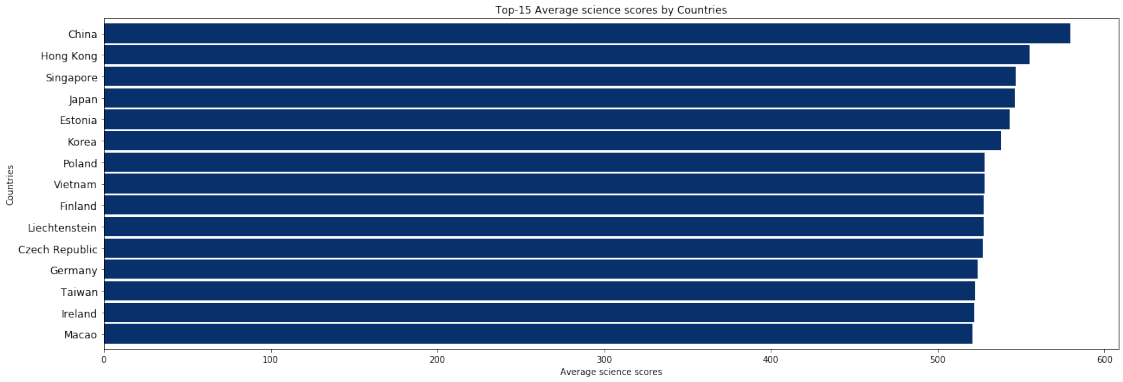


[34]:
```
df[df.CNT == 'China'].PV_MATH.mean(), df[df.CNT == 'Peru'].PV_MATH.mean()
```

[34]:
```
(611.4389329882152, 367.8596761126761)
```

Except Liechtenstein which is on the 6th position, on average, students from Asia countries receive the highest scores on math. China, Singapore, Hong Kong, Taiwan, and Korea are in Top-5. Macao and Japan follow immediately behind Liechtenstein.
Chinese students receive on average 611 points. In comparison, in Peru average math scores are equal 368. This's 1.7 times less than in China.

[35]:
```
df_plot1[['PV_SCIE']].sort_values('PV_SCIE').iloc[-15:].plot.
 ↪barh(figsize=(21,7), width=.9, legend=False,
                                                                 ␣
 ↪cmap='Blues_r')
plt.yticks(fontsize=12)
plt.xlabel('Average science scores')
plt.ylabel('Countries')
plt.title('Top-15 Average science scores by Countries')
plt.show()
```

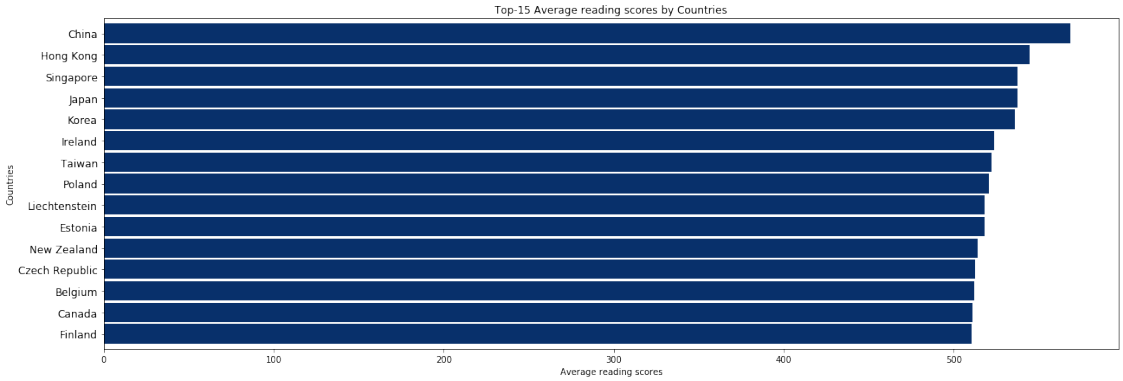


[36]:
```
(df[df.CNT == 'China'].PV_SCIE.mean(), df[df.CNT == 'Hong Kong'].PV_SCIE.mean(),
            df[df.CNT == 'Singapore'].PV_SCIE.mean())
```

[36]:
```
(579.5565404481328, 554.9864334004274, 546.8229195961078)
```

Average science scores are less than math scores by about 6 points. And this is becoming noticeable for countries with the highest average scores in science. China, Gang Kong and Singapore are also in the Top-3 with an average score of 547 to 579. For China, this difference is 32 points or 5.2%.

[37]:
```
df_plot1[['PV_READ']].sort_values('PV_READ').iloc[-15:].plot.
 ↪barh(figsize=(21,7), width=.9, legend=False,
                                                                 ␣
 ↪cmap='Blues_r')
plt.yticks(fontsize=12)
plt.xlabel('Average reading scores')
plt.ylabel('Countries')
plt.title('Top-15 Average reading scores by Countries')
plt.show()
```



[38]:
```
df[df.CNT == 'China'].PV_READ.mean()
```

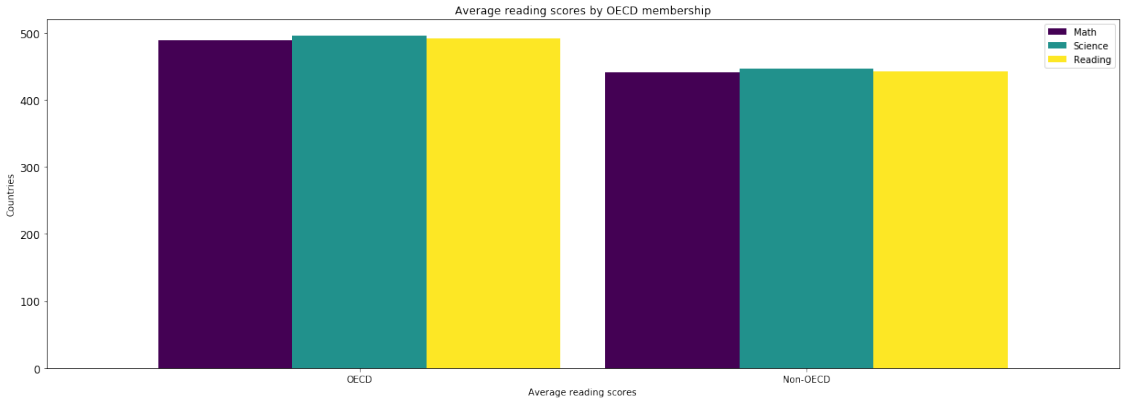
[38]:
```
568.6292328568668
```

For average reading scores, China, Hong Kong, Singapore, Japan, Korea and Taiwan continue to be the leaders with a maximum average of 569 points for China. This average score is the lowest for China in three subjects, possibly also because English is not a native language for a large population of the country.

[39]:
```
df_plot2 = df.groupby('OECD').agg({'PV_MATH': 'mean', 'PV_SCIE': 'mean',␣
 ↪'PV_READ': 'mean', 'STIDSTD': 'nunique'})
print(df_plot2)
```

```
             PV_MATH     PV_SCIE     PV_READ  STIDSTD
OECD
Non-OECD  440.509684  446.101570  442.803610    19204
OECD      488.401237  494.921608  490.796733    33806
```

[40]:
```
df_plot2[['PV_MATH', 'PV_SCIE', 'PV_READ']].sort_values('PV_READ',␣
 ↪ascending=False).plot.bar(
                    figsize=(21,7), width=.9, legend=True, cmap='viridis',␣
 ↪rot=0)
plt.legend(['Math', 'Science', 'Reading'])
plt.yticks(fontsize=12)
plt.xlabel('Average reading scores')
plt.ylabel('Countries')
plt.title('Average reading scores by OECD membership')
plt.show()
```

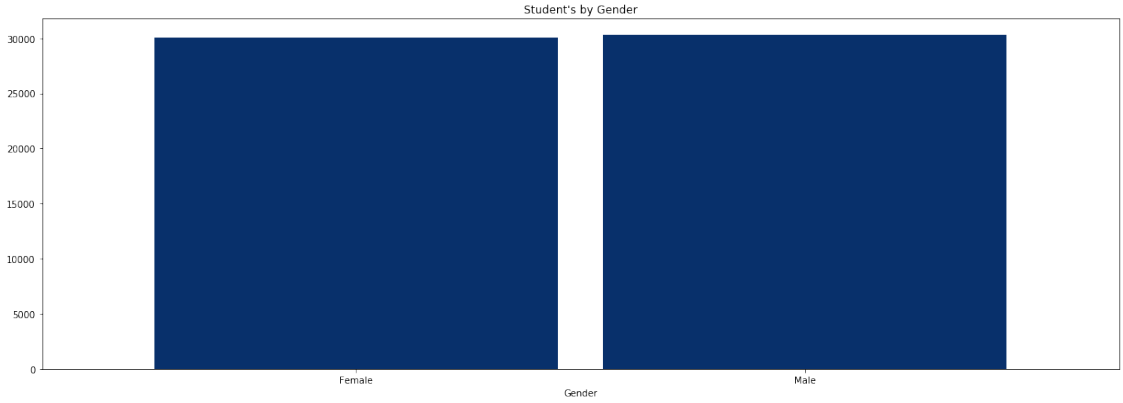


The difference is noticeable in all three subjects at once: average scores in mathematics, science and reading are higher in OSCE countries than in non-OSCE countries. The difference is about 48 points for each subject.

2. What are the characteristics of students participated in PICA 2012:

- gender,
- age,
- whether a student passed the test in the country of birth or not,
- international grade and grade compared to modal grade in country.

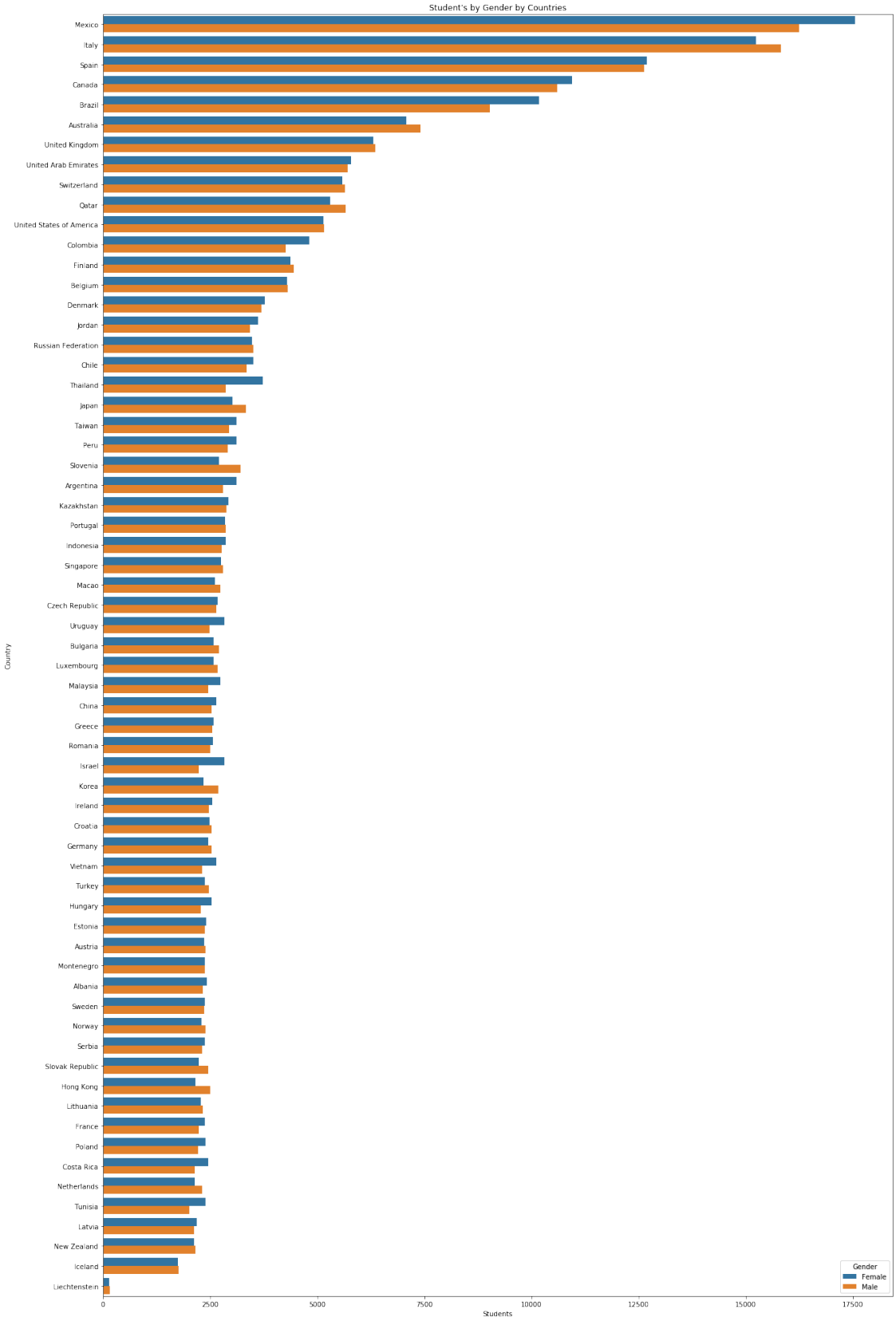
[41]:
```
df.groupby('ST04Q01').STIDSTD.nunique().sort_index().plot.bar(figsize=(21,7),␣
↪width=.9, legend=False,
                                                                ␣
↪cmap='Blues_r', rot=0)
plt.xlabel('Gender')
plt.title('Student\'s by Gender')
plt.show()
```



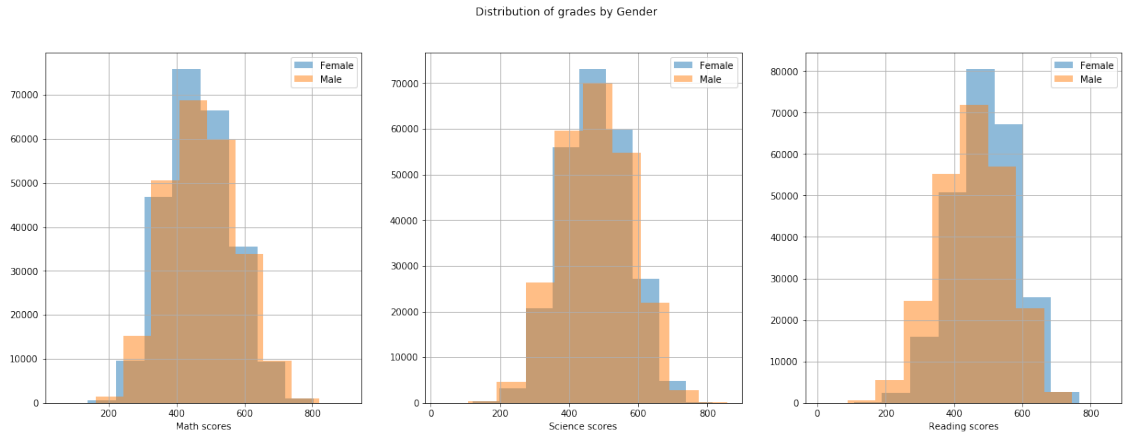
Number of female students is little more (by 0.6%) than number of male students. Let's look at gender by countries.

The largest number of students are in Mexico, Italy, Spain, Canada and Brazil. Except for Italy, the number of the females is greater than that of the male. In Brazil, there are 8% fewer males than females. The number of students in Mexico is 1.8 times higher than in Brazil, which is in 5th place, the number of males is 2.8 times less and the number of females is 2.7.

[42]:
```
fig, ax = plt.subplots(figsize=(21,35))
df.sort_values(by=['ST04Q01', 'CNT'])
sns.countplot(data=df, y='CNT', hue='ST04Q01', ax=ax, order=df['CNT'].
 ↪value_counts().index)
ax.legend(title='Gender', loc='best')
plt.xlabel('Students')
plt.ylabel('Country')
plt.title('Student\'s by Gender by Countries')
plt.show()
```


Student's by Gender by Countries
Mexico
Italy
Spain
Canada
Brazil
Australia
United Kingdom
United Arab Emirates
Switzerland
Qatar
United States of America
Colombia
Finland
Belgium
Denmark
Jordan
Russian Federation
Chile
Thailand
Japan
Taiwan
Peru
Slovenia
Argentina
Kazakhstan
Portugal
Indonesia
Singapore
Macao
Czech Republic
Uruguay
Bulgaria
Luxembourg
Malaysia
China
Greece
Romania
Israel
Korea
Ireland
Croatia
Germany
Vietnam
Turkey
Hungary
Estonia
Austria
Montenegro
Albania
Sweden
Norway
Serbia
Slovak Republic
Hong Kong
Lithuania
France
Poland
Costa Rica
Netherlands
Tunisia
Latvia
New Zealand
Iceland
Liechtenstein
Country
0
2500
5000
7500
10000
12500
15000
17500
Students
Gender
Female
Male

[43]:
```
fig, ax = plt.subplots(nrows=1, ncols=3, figsize=(21,7))
df[df.ST04Q01 == 'Female']['PV_MATH'].hist(ax=ax[0], alpha=.5, label='Female')
df[df.ST04Q01 == 'Male']['PV_MATH'].hist(ax=ax[0], alpha=.5, label='Male')
ax[0].set_xlabel('Math scores')
ax[0].legend()

df[df.ST04Q01 == 'Female']['PV_SCIE'].hist(ax=ax[1], alpha=.5, label='Female')
df[df.ST04Q01 == 'Male']['PV_SCIE'].hist(ax=ax[1], alpha=.5, label='Male')
ax[1].set_xlabel('Science scores')
ax[1].legend()

df[df.ST04Q01 == 'Female']['PV_READ'].hist(ax=ax[2], alpha=.5, label='Female')
df[df.ST04Q01 == 'Male']['PV_READ'].hist(ax=ax[2], alpha=.5, label='Male')
ax[2].set_xlabel('Reading scores')
ax[2].legend()

plt.suptitle('Distribution of grades by Gender')
plt.show()
```

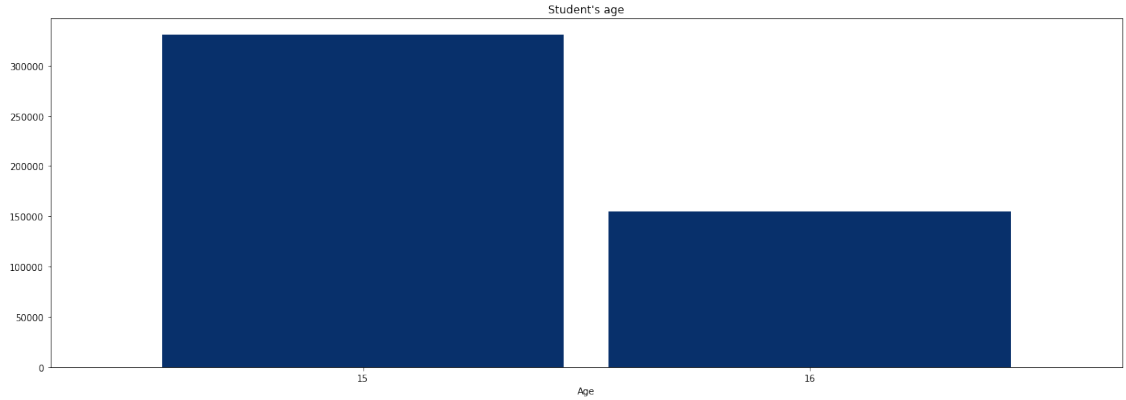


Distriution of males and females math and science score are distributed approximately normal. However, there's slight difference of reading scores: female have aslightly higher grades than males.

Since student age is between 15 and 16 year old, and number of students who are 15 years old are twice larger than students who are 16 years old, there would be interesting to compare whether there's some biases due to the different age.

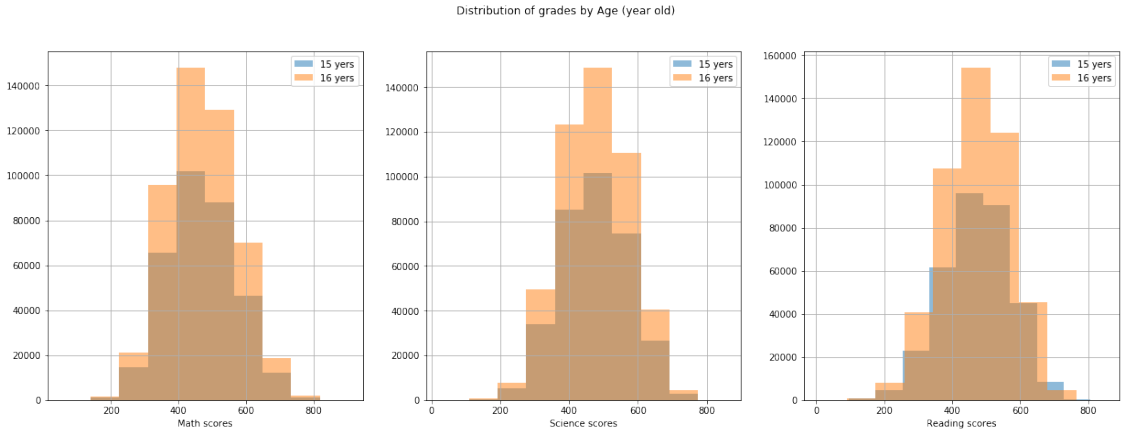
[44]:
```
df.AGE.astype(int).value_counts().sort_index().plot.bar(figsize=(21,7), width=.
↪9, legend=False,

↪cmap='Blues_r', rot=0)
plt.xlabel('Age')
plt.title('Student\'s age')
```

```
plt.show()
```

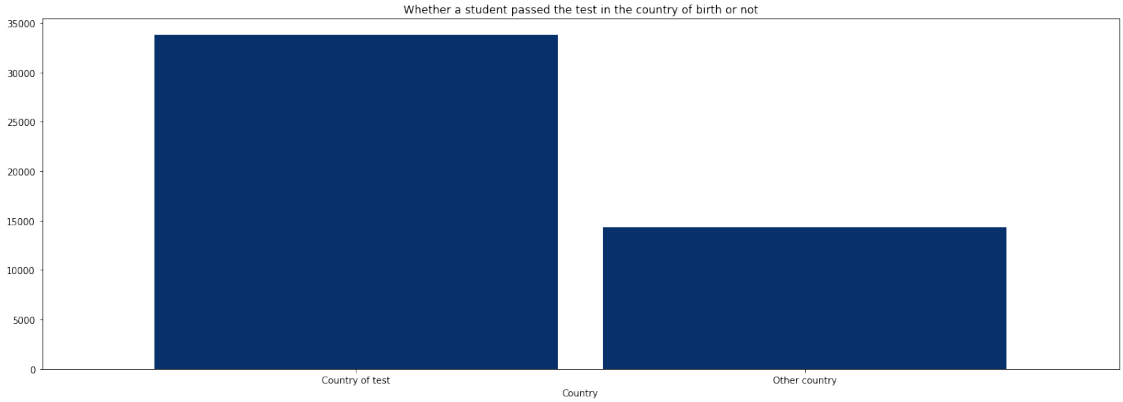


Distribution of scores of students from 15 and 16 years old groups is distributed normally, and I think, there's no significant difference between these students.

[45]:
```
fig, ax = plt.subplots(nrows=1, ncols=3, figsize=(21,7))
df[df.AGE < 16]['PV_MATH'].hist(ax=ax[0], alpha=.5, label='15 yers')
df[df.AGE > 15]['PV_MATH'].hist(ax=ax[0], alpha=.5, label='16 yers')
ax[0].set_xlabel('Math scores')
ax[0].legend()

df[df.AGE < 16]['PV_SCIE'].hist(ax=ax[1], alpha=.5, label='15 yers')
df[df.AGE > 15]['PV_SCIE'].hist(ax=ax[1], alpha=.5, label='16 yers')
ax[1].set_xlabel('Science scores')
ax[1].legend()

df[df.AGE < 16]['PV_READ'].hist(ax=ax[2], alpha=.5, label='15 yers')
df[df.AGE > 15]['PV_READ'].hist(ax=ax[2], alpha=.5, label='16 yers')
ax[2].set_xlabel('Reading scores')
ax[2].legend()

plt.suptitle('Distribution of grades by Age (year old)')
plt.show()
```

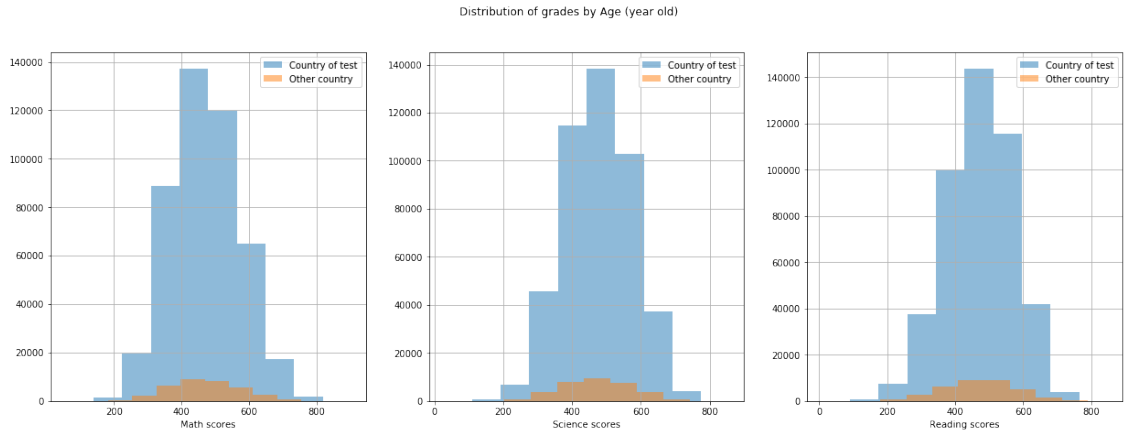


[46]:
```
df.groupby('ST20Q01').STIDSTD.nunique().sort_index().plot.bar(figsize=(21,7),␣
 ↪width=.9, legend=False,

                                                                  ␣
 ↪cmap='Blues_r', rot=0)
plt.xlabel('Country')
plt.title('Whether a student passed the test in the country of birth or not')
plt.show()
```



[52]:
```
# Whether a student passed the test in the country of birth or not

fig, ax = plt.subplots(nrows=1, ncols=3, figsize=(21,7))
df[df.ST20Q01 == 'Country of test']['PV_MATH'].hist(ax=ax[0], alpha=.5,␣
 ↪label='Country of test')
df[df.ST20Q01 == 'Other country']['PV_MATH'].hist(ax=ax[0], alpha=.5,␣
 ↪label='Other country')
ax[0].set_xlabel('Math scores')
ax[0].legend()
```

```
df[df.ST20Q01 == 'Country of test']['PV_SCIE'].hist(ax=ax[1], alpha=.5,␣
 ↪label='Country of test')
df[df.ST20Q01 == 'Other country']['PV_SCIE'].hist(ax=ax[1], alpha=.5,␣
 ↪label='Other country')
ax[1].set_xlabel('Science scores')
ax[1].legend()

df[df.ST20Q01 == 'Country of test']['PV_READ'].hist(ax=ax[2], alpha=.5,␣
 ↪label='Country of test')
df[df.ST20Q01 == 'Other country']['PV_READ'].hist(ax=ax[2], alpha=.5,␣
 ↪label='Other country')
ax[2].set_xlabel('Reading scores')
ax[2].legend()

plt.suptitle('Distribution of grades by Age (year old)')
plt.show()
```



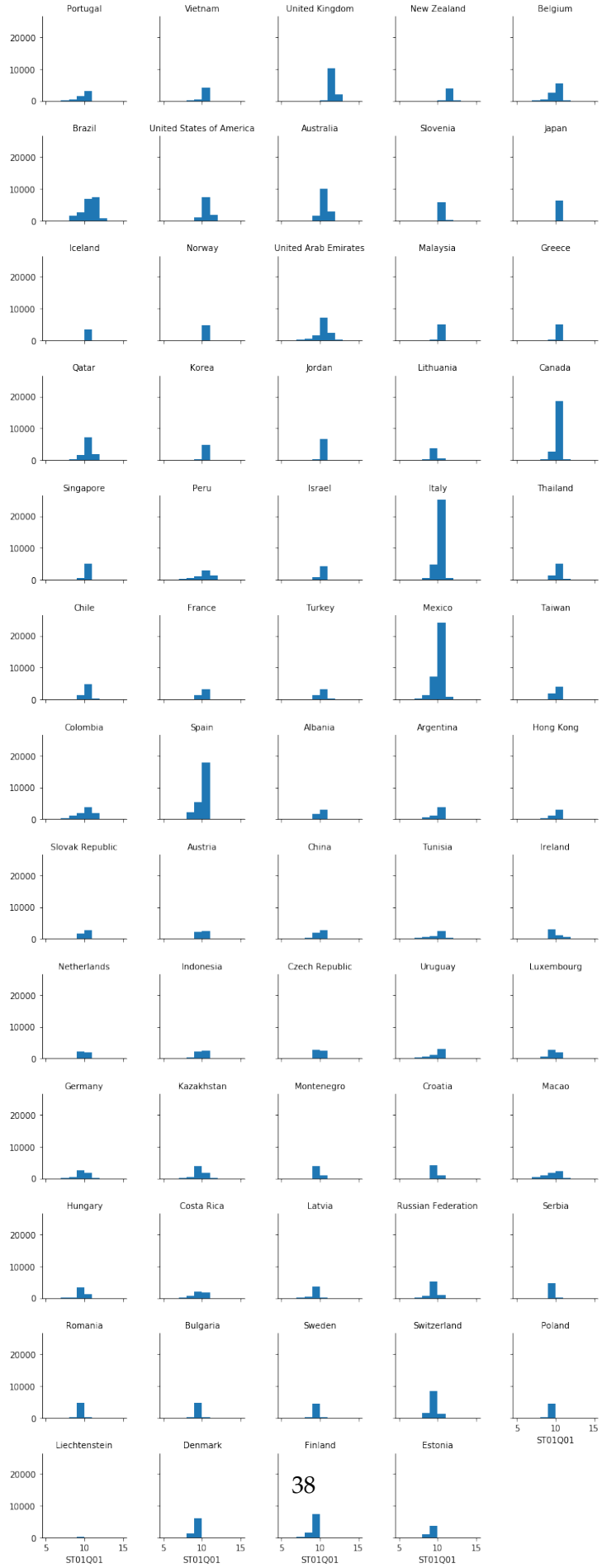
An average international grade of students is 9.8 points, and on the same time, the mean grade compared to modal grade in country is equal -0.16 points.
Among all 64 countries represented in the dataset, students from Canada, Italy, Mexico, and Spain have the highest average international rate.

[51]:
```
# International grade and grade compared to modal grade in country

df[['ST01Q01', 'GRADE']].mean()
```

[51]:
```
ST01Q01    9.813323
GRADE     -0.162671
dtype: float64
```

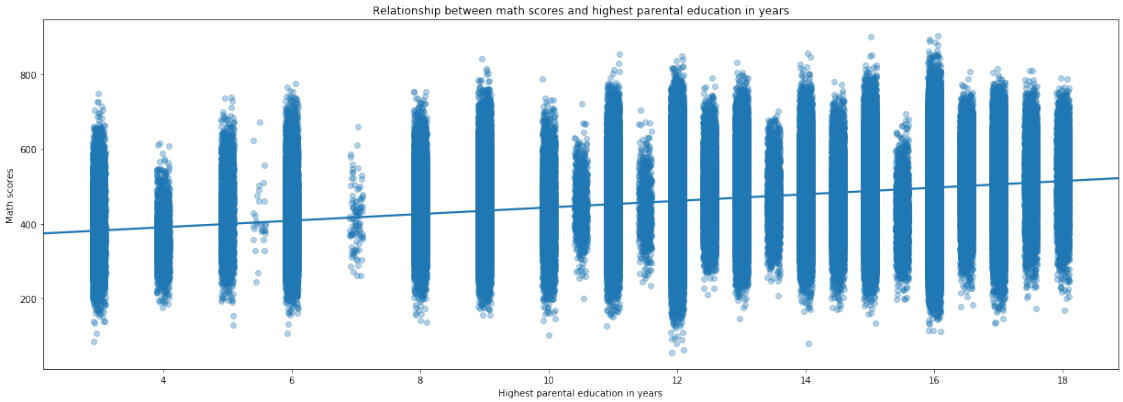
[49]:
```
group_means = df.groupby(['CNT']).mean()
group_order = group_means.sort_values(['ST01Q01'], ascending = False).index

g = sns.FacetGrid(data = df, col = 'CNT', col_wrap = 5, height = 2,
```

```
                  col_order = group_order)
g.map(plt.hist, 'ST01Q01', bins = np.arange(5, 15+1, 1))
g.set_titles('{col_name}')
plt.show()
```


Portugal
Vietnam
United Kingdom
New Zealand
Belgium
Brazil
United States of America
Australia
Slovenia
Japan
Iceland
Norway
United Arab Emirates
Malaysia
Greece
Qatar
Korea
Jordan
Lithuania
Canada
Singapore
Peru
Israel
Italy
Thailand
Chile
France
Turkey
Mexico
Taiwan
Colombia
Spain
Albania
Argentina
Hong Kong
Slovak Republic
Austria
China
Tunisia
Ireland
Netherlands
Indonesia
Czech Republic
Uruguay
Luxembourg
Germany
Kazakhstan
Montenegro
Croatia
Macao
Hungary
Costa Rica
Latvia
Russian Federation
Serbia
Romania
Bulgaria
Sweden
Switzerland
Poland
Liechtenstein
Denmark
Finland
Estonia
0
10000
20000
5
10
15
ST01Q01

3. What's a relationship between students performance and highest parental education measured in years as well as mother's and father's highest schooling?

[54]:
```
plt.subplots(figsize=(21,7))
sns.regplot(df['PARED'], df['PV_MATH'], fit_reg=True, x_jitter=0.1, y_jitter=0.
 ↪1, scatter_kws={'alpha': 1/3})
plt.xlabel('Highest parental education in years')
plt.ylabel('Math scores')
plt.title('Relationship between math scores and highest parental education in␣
 ↪years')
plt.show()
```

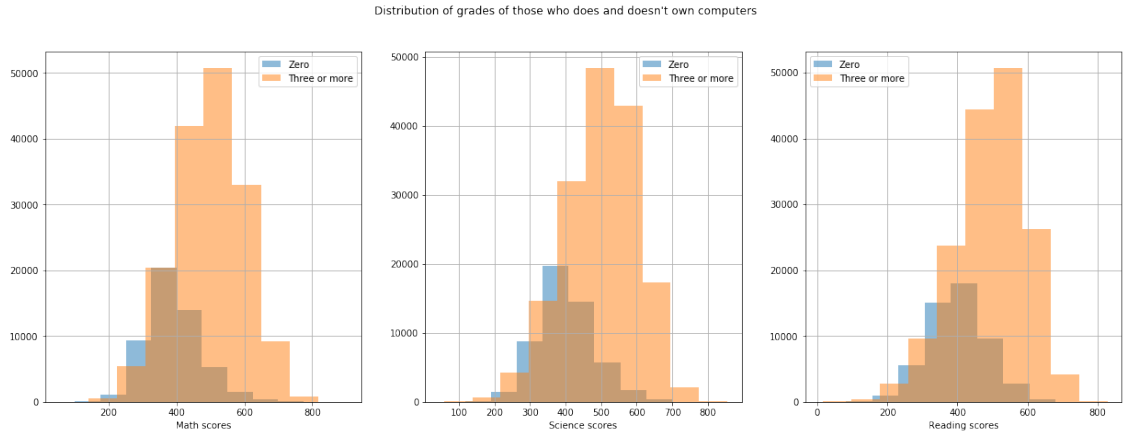


There exist a positive weak relationship between highest parental education in years and students math scores. To check whether this relationship is significant, linear regression can be fitted to determine if increase in parental education affects increases students math scores.

4. Whether there exist a correlation between family wealth (measured in the number of telephones, computers, etc.) and students performance?

[56]:
```
# How many - computers (here we'll look at 2 extreme - no computer vs. 3 or␣
 ↪more computers)

fig, ax = plt.subplots(nrows=1, ncols=3, figsize=(21,7))
df[df.ST27Q03 == 'Zero']['PV_MATH'].hist(ax=ax[0], alpha=.5, label='Zero')
df[df.ST27Q03 == 'Three or more']['PV_MATH'].hist(ax=ax[0], alpha=.5,␣
 ↪label='Three or more')
ax[0].set_xlabel('Math scores')
ax[0].legend()

df[df.ST27Q03 == 'Zero']['PV_SCIE'].hist(ax=ax[1], alpha=.5, label='Zero')
```

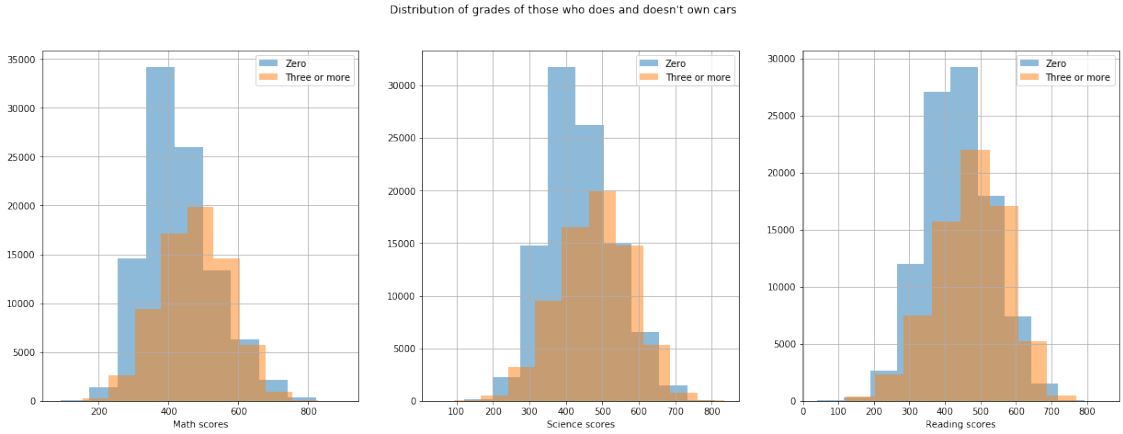
```
df[df.ST27Q03 == 'Three or more']['PV_SCIE'].hist(ax=ax[1], alpha=.5,␣
 ↪label='Three or more')
ax[1].set_xlabel('Science scores')
ax[1].legend()

df[df.ST27Q03 == 'Zero']['PV_READ'].hist(ax=ax[2], alpha=.5, label='Zero')
df[df.ST27Q03 == 'Three or more']['PV_READ'].hist(ax=ax[2], alpha=.5,␣
 ↪label='Three or more')
ax[2].set_xlabel('Reading scores')
ax[2].legend()

plt.suptitle('Distribution of grades of those who does and doesn\'t own␣
 ↪computers')
plt.show()
```



More than half of all students don't have a computer at all. Therefore, we can observe, that distribution of score of those students who doesn't have a computer is skewed to the right for two subjects - mathematics and science.

[57]:
```
# How many - cars (here we'll look at 2 extreme - no car vs. 3 or more cars)

fig, ax = plt.subplots(nrows=1, ncols=3, figsize=(21,7))
df[df.ST27Q04 == 'Zero']['PV_MATH'].hist(ax=ax[0], alpha=.5, label='Zero')
df[df.ST27Q04 == 'Three or more']['PV_MATH'].hist(ax=ax[0], alpha=.5,␣
 ↪label='Three or more')
ax[0].set_xlabel('Math scores')
ax[0].legend()

df[df.ST27Q04 == 'Zero']['PV_SCIE'].hist(ax=ax[1], alpha=.5, label='Zero')
df[df.ST27Q04 == 'Three or more']['PV_SCIE'].hist(ax=ax[1], alpha=.5,␣
 ↪label='Three or more')
ax[1].set_xlabel('Science scores')
ax[1].legend()
```

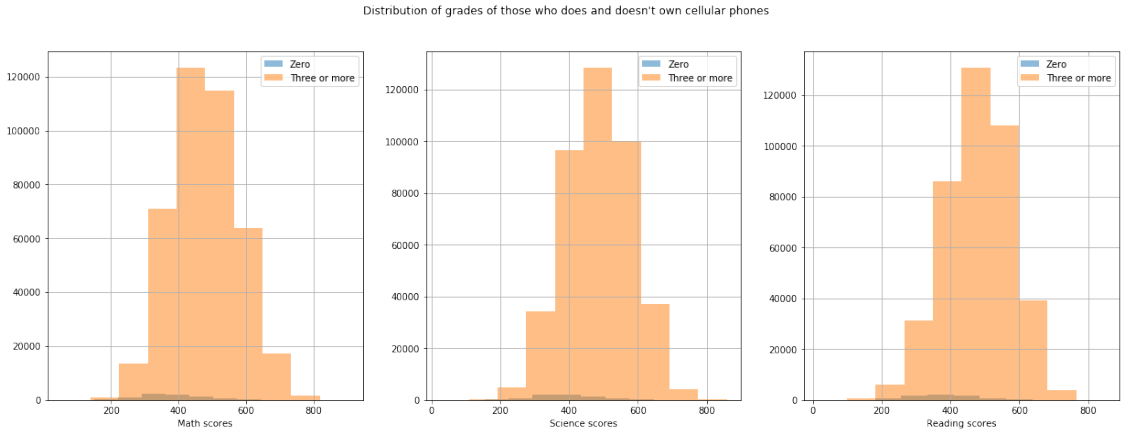
```
df[df.ST27Q04 == 'Zero']['PV_READ'].hist(ax=ax[2], alpha=.5, label='Zero')
df[df.ST27Q04 == 'Three or more']['PV_READ'].hist(ax=ax[2], alpha=.5,␣
 ↪label='Three or more')
ax[2].set_xlabel('Reading scores')
ax[2].legend()

plt.suptitle('Distribution of grades of those who does and doesn\'t own cars')
plt.show()
```



A half of all students don't have a car in family. And we can observe, that distribution of score of those students who has no car in the family is skewed to the right for all 3 subjects - math, science, and reading.

[59]:
```
# How many - cellular phones (here we'll look at 2 extreme - no cellular phone␣
 ↪vs. 3 or more cellular phones)

fig, ax = plt.subplots(nrows=1, ncols=3, figsize=(21,7))
df[df.ST27Q01 == 'Zero']['PV_MATH'].hist(ax=ax[0], alpha=.5, label='Zero')
df[df.ST27Q01 == 'Three or more']['PV_MATH'].hist(ax=ax[0], alpha=.5,␣
 ↪label='Three or more')
ax[0].set_xlabel('Math scores')
ax[0].legend()

df[df.ST27Q01 == 'Zero']['PV_SCIE'].hist(ax=ax[1], alpha=.5, label='Zero')
df[df.ST27Q01 == 'Three or more']['PV_SCIE'].hist(ax=ax[1], alpha=.5,␣
 ↪label='Three or more')
ax[1].set_xlabel('Science scores')
ax[1].legend()

df[df.ST27Q01 == 'Zero']['PV_READ'].hist(ax=ax[2], alpha=.5, label='Zero')
df[df.ST27Q01 == 'Three or more']['PV_READ'].hist(ax=ax[2], alpha=.5,␣
 ↪label='Three or more')
```

```
ax[2].set_xlabel('Reading scores')
ax[2].legend()

plt.suptitle('Distribution of grades of those who does and doesn\'t own␣
 ↪cellular phones')
plt.show()
```



[107]:
```
df[df.ST27Q01 == 'Zero'].shape[0] / df.shape[0]
```

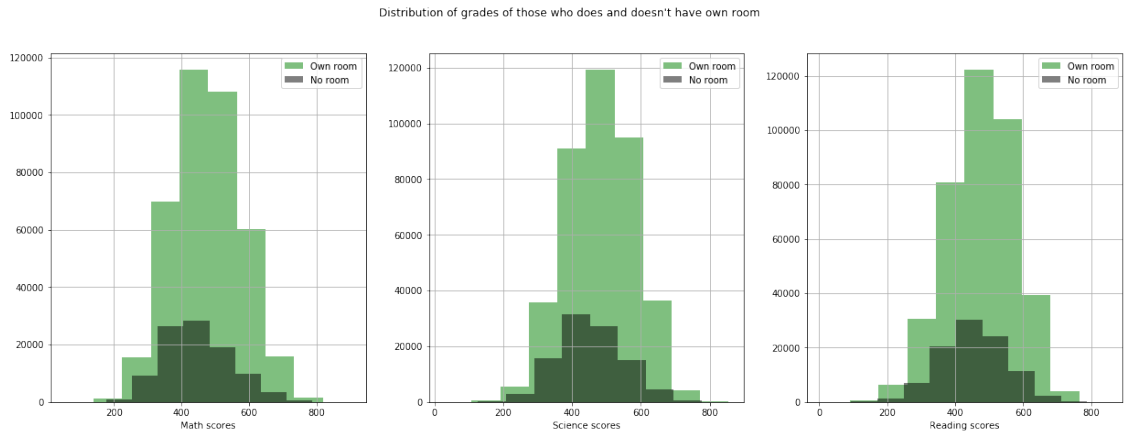
[107]:
```
0.014589383921399
```

Almost every student in the dataset has at least one cellular phone. And it is almost impossible to determine what the distribution of grades looks like for those students who do not have a cell phone, since the number of such guys in the dataset is very small (about 1.5%).

5. How do student possessions such as own room and desk, etc. affect his/her performance?

[95]:
```
# Possessions - own room

fig, ax = plt.subplots(nrows=1, ncols=3, figsize=(21,7))
df[df.ST26Q02 == 'Yes']['PV_MATH'].hist(ax=ax[0], alpha=.5, label='Own room',␣
 ↪color='green')
df[df.ST26Q02 == 'No']['PV_MATH'].hist(ax=ax[0], alpha=.5, label='No room',␣
 ↪color='black')
ax[0].set_xlabel('Math scores')
ax[0].legend()

df[df.ST26Q02 == 'Yes']['PV_SCIE'].hist(ax=ax[1], alpha=.5, label='Own room',␣
 ↪color='green')
df[df.ST26Q02 == 'No']['PV_SCIE'].hist(ax=ax[1], alpha=.5, label='No room',␣
 ↪color='black')
ax[1].set_xlabel('Science scores')
ax[1].legend()
```

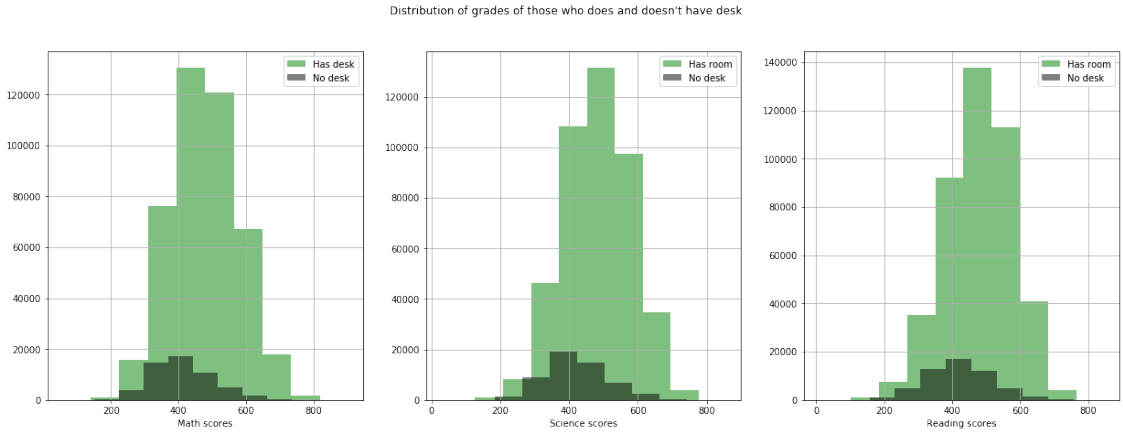
```
df[df.ST26Q02 == 'Yes']['PV_READ'].hist(ax=ax[2], alpha=.5, label='Own room',␣
 ↪color='green')
df[df.ST26Q02 == 'No']['PV_READ'].hist(ax=ax[2], alpha=.5, label='No room',␣
 ↪color='black')
ax[2].set_xlabel('Reading scores')
ax[2].legend()

plt.suptitle('Distribution of grades of those who does and doesn\'t have own␣
 ↪room')
plt.show()
```



About a quater of students doesn't have their own rooms. This affects their preparation to the exam. And as the result, the distribution of math and science scores of those students who don't have their own room is skewed to the right

[97]:
```
# Possessions - has desk

fig, ax = plt.subplots(nrows=1, ncols=3, figsize=(21,7))
df[df.ST26Q01 == 'Yes']['PV_MATH'].hist(ax=ax[0], alpha=.5, label='Has desk',␣
 ↪color='green')
df[df.ST26Q01 == 'No']['PV_MATH'].hist(ax=ax[0], alpha=.5, label='No desk',␣
 ↪color='black')
ax[0].set_xlabel('Math scores')
ax[0].legend()

df[df.ST26Q01 == 'Yes']['PV_SCIE'].hist(ax=ax[1], alpha=.5, label='Has room',␣
 ↪color='green')
df[df.ST26Q01 == 'No']['PV_SCIE'].hist(ax=ax[1], alpha=.5, label='No desk',␣
 ↪color='black')
ax[1].set_xlabel('Science scores')
ax[1].legend()
```

```
df[df.ST26Q01 == 'Yes']['PV_READ'].hist(ax=ax[2], alpha=.5, label='Has room',␣
 ↪color='green')
df[df.ST26Q01 == 'No']['PV_READ'].hist(ax=ax[2], alpha=.5, label='No desk',␣
 ↪color='black')
ax[2].set_xlabel('Reading scores')
ax[2].legend()

plt.suptitle('Distribution of grades of those who does and doesn\'t have desk')
plt.show()
```



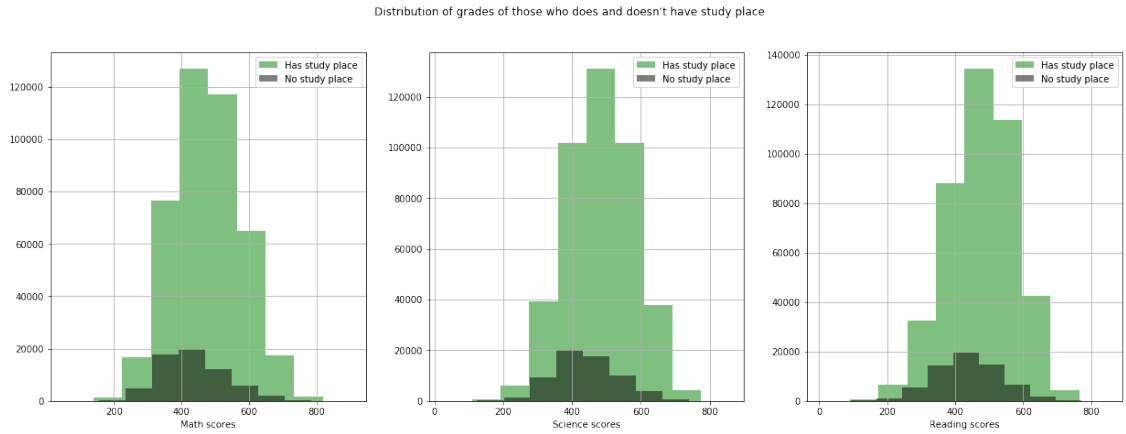
[112]:
```
df[df.ST26Q01 == 'No'].shape[0] / df.shape[0]
```

[112]:
```
0.11132258130960473
```

11.1% of students don't have a desk, therefore, on average their math and science scores are lower than scores of students who has a table. Both, the distribution of reading scores of those who have and who doesn't have a desk ia normally distributed without any skewednes.

[99]:
```
# Possessions - has study place

fig, ax = plt.subplots(nrows=1, ncols=3, figsize=(21,7))
df[df.ST26Q03 == 'Yes']['PV_MATH'].hist(ax=ax[0], alpha=.5, label='Has study␣
 ↪place', color='green')
df[df.ST26Q03 == 'No']['PV_MATH'].hist(ax=ax[0], alpha=.5, label='No study␣
 ↪place', color='black')
ax[0].set_xlabel('Math scores')
ax[0].legend()

df[df.ST26Q03 == 'Yes']['PV_SCIE'].hist(ax=ax[1], alpha=.5, label='Has study␣
 ↪place', color='green')
df[df.ST26Q03 == 'No']['PV_SCIE'].hist(ax=ax[1], alpha=.5, label='No study␣
 ↪place', color='black')
ax[1].set_xlabel('Science scores')
ax[1].legend()
```

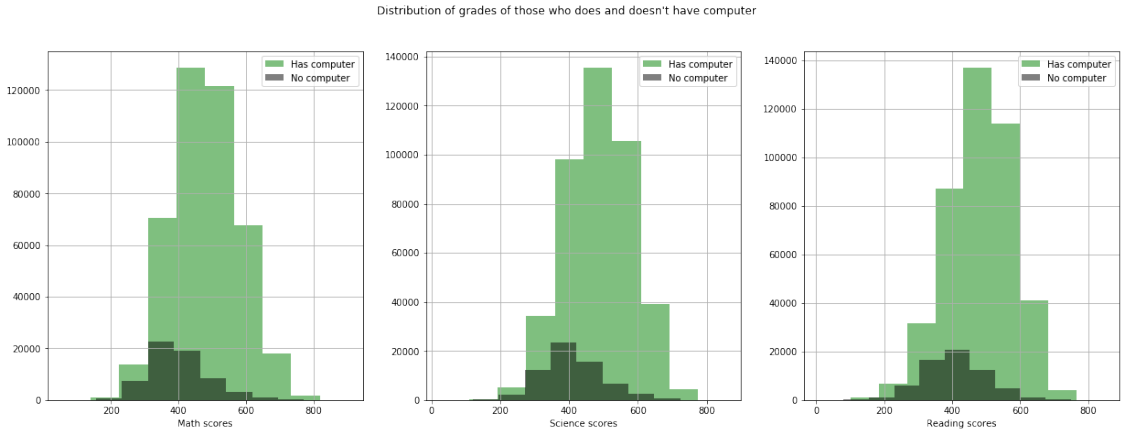
```
df[df.ST26Q03 == 'Yes']['PV_READ'].hist(ax=ax[2], alpha=.5, label='Has study␣
 ↪place', color='green')
df[df.ST26Q03 == 'No']['PV_READ'].hist(ax=ax[2], alpha=.5, label='No study␣
 ↪place', color='black')
ax[2].set_xlabel('Reading scores')
ax[2].legend()

plt.suptitle('Distribution of grades of those who does and doesn\'t have study␣
 ↪place')
plt.show()
```



It's really difficult to prepare to the assessment if you dont have study place at home. As a result the distribution of scores of those students who don't have a study place on average receive lower scores on math and science.

[100]:
```
# Possessions - has computer

fig, ax = plt.subplots(nrows=1, ncols=3, figsize=(21,7))
df[df.ST26Q04 == 'Yes']['PV_MATH'].hist(ax=ax[0], alpha=.5, label='Has␣
 ↪computer', color='green')
df[df.ST26Q04 == 'No']['PV_MATH'].hist(ax=ax[0], alpha=.5, label='No computer',␣
 ↪color='black')
ax[0].set_xlabel('Math scores')
ax[0].legend()

df[df.ST26Q04 == 'Yes']['PV_SCIE'].hist(ax=ax[1], alpha=.5, label='Has␣
 ↪computer', color='green')
df[df.ST26Q04 == 'No']['PV_SCIE'].hist(ax=ax[1], alpha=.5, label='No computer',␣
 ↪color='black')
ax[1].set_xlabel('Science scores')
ax[1].legend()
```

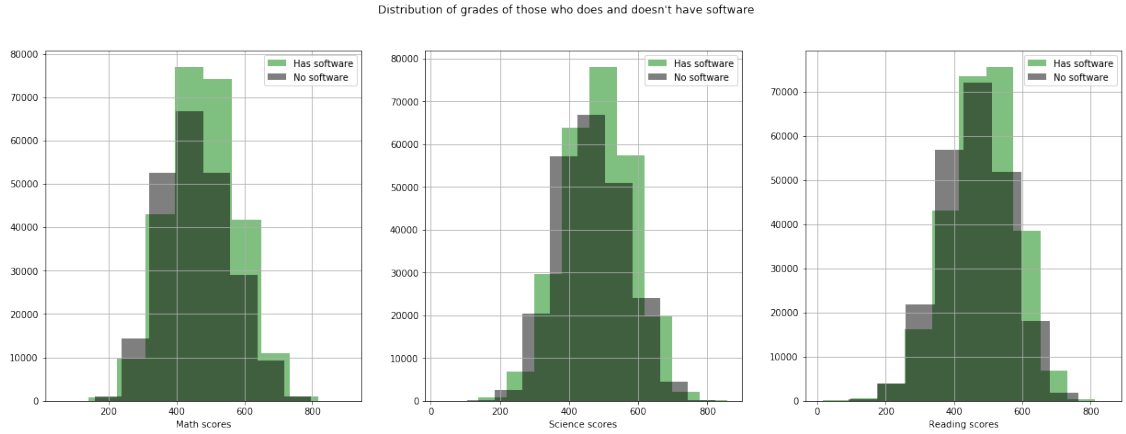
```
df[df.ST26Q04 == 'Yes']['PV_READ'].hist(ax=ax[2], alpha=.5, label='Has␣
 ↪computer', color='green')
df[df.ST26Q04 == 'No']['PV_READ'].hist(ax=ax[2], alpha=.5, label='No computer',␣
 ↪color='black')
ax[2].set_xlabel('Reading scores')
ax[2].legend()

plt.suptitle('Distribution of grades of those who does and doesn\'t have␣
 ↪computer')
plt.show()
```



Absense of computer significantly complicates the preparation not only for the exam, but also for the homework. Because for example, not all students have large-screen tablets or smartphones that can partially replace a computer. As a result, the distribution of math scores is significantly skewed to the right. Distributions of reading and science scores are also slightly skewed to theright.

[104]:
```
# Possessions - has software

fig, ax = plt.subplots(nrows=1, ncols=3, figsize=(21,7))
df[df.ST26Q05 == 'Yes']['PV_MATH'].hist(ax=ax[0], alpha=.5, label='Has␣
 ↪software', color='green')
df[df.ST26Q05 == 'No']['PV_MATH'].hist(ax=ax[0], alpha=.5, label='No software',␣
 ↪color='black')
ax[0].set_xlabel('Math scores')
ax[0].legend()

df[df.ST26Q05 == 'Yes']['PV_SCIE'].hist(ax=ax[1], alpha=.5, label='Has␣
 ↪software', color='green')
df[df.ST26Q05 == 'No']['PV_SCIE'].hist(ax=ax[1], alpha=.5, label='No software',␣
 ↪color='black')
ax[1].set_xlabel('Science scores')
ax[1].legend()
```

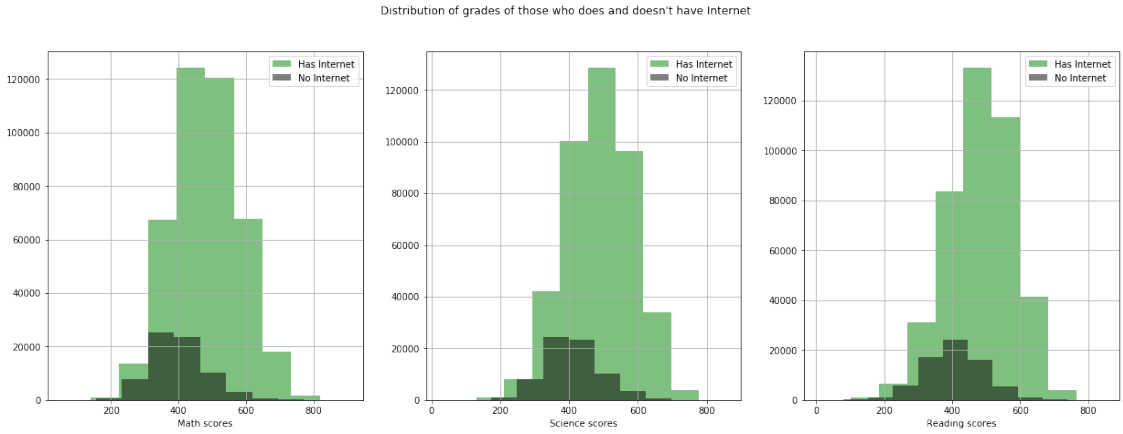
```
df[df.ST26Q05 == 'Yes']['PV_READ'].hist(ax=ax[2], alpha=.5, label='Has␣
 ↪software', color='green')
df[df.ST26Q05 == 'No']['PV_READ'].hist(ax=ax[2], alpha=.5, label='No software',␣
 ↪color='black')
ax[2].set_xlabel('Reading scores')
ax[2].legend()

plt.suptitle('Distribution of grades of those who does and doesn\'t have␣
 ↪software')
plt.show()
```



I can assume that the lack of software does not affect the distribution of grades in any way, since not all students pay money for software, thus, the lack of a computer worsens the average grade for the test more significantly.

[105]:
```
# Possessions - has Internet

fig, ax = plt.subplots(nrows=1, ncols=3, figsize=(21,7))
df[df.ST26Q06 == 'Yes']['PV_MATH'].hist(ax=ax[0], alpha=.5, label='Has␣
 ↪Internet', color='green')
df[df.ST26Q06 == 'No']['PV_MATH'].hist(ax=ax[0], alpha=.5, label='No Internet',␣
 ↪color='black')
ax[0].set_xlabel('Math scores')
ax[0].legend()

df[df.ST26Q06 == 'Yes']['PV_SCIE'].hist(ax=ax[1], alpha=.5, label='Has␣
 ↪Internet', color='green')
df[df.ST26Q06 == 'No']['PV_SCIE'].hist(ax=ax[1], alpha=.5, label='No Internet',␣
 ↪color='black')
ax[1].set_xlabel('Science scores')
ax[1].legend()
```

```
df[df.ST26Q06 == 'Yes']['PV_READ'].hist(ax=ax[2], alpha=.5, label='Has␣
 ↪Internet', color='green')
df[df.ST26Q06 == 'No']['PV_READ'].hist(ax=ax[2], alpha=.5, label='No Internet',␣
 ↪color='black')
ax[2].set_xlabel('Reading scores')
ax[2].legend()

plt.suptitle('Distribution of grades of those who does and doesn\'t have␣
 ↪Internet')
plt.show()
```

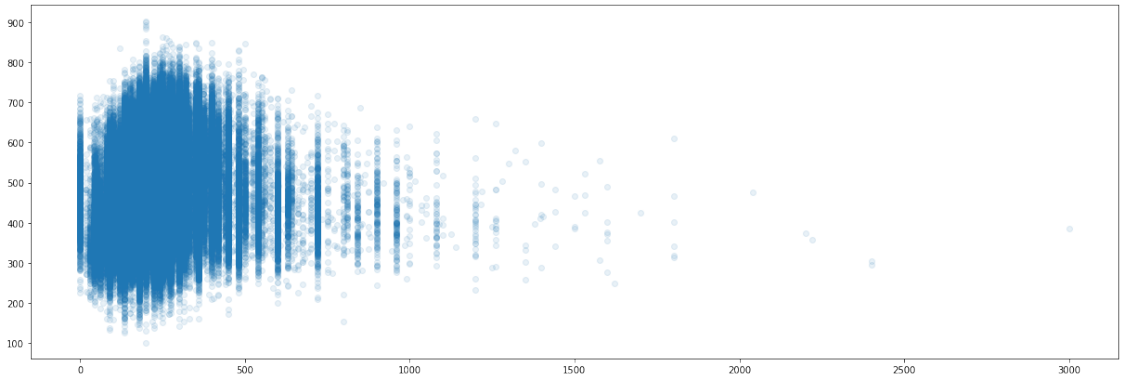


The lack of the Internet affects the distribution of grades in mathematics and science, since the process of obtaining the necessary information is either very slow or not at all. But it is worth noting that the presence of the Internet affects the distribution of reading grades in such a way that for those students who have the Internet, the opportunity to obtain additional information leads to a distortion of the distribution of grades to the left.

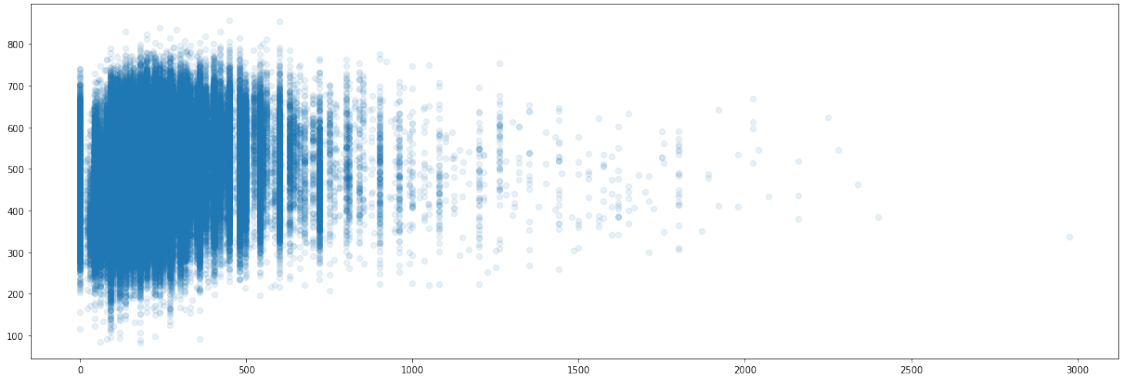
Summing up, I would like to say that for a student who prepares and takes the exam, any help, whether it be a computer, the Internet, a place for preparation, or his own team, positively correlates with higher grades in both mathematics and science and reading. This is a very interesting study that can be done by collecting additional missing data and adding information from other sources, for example, information on income and / or expenses of students' families.

6. Whether total time learning and out of school lessons on math, science, and reading affect student performance?

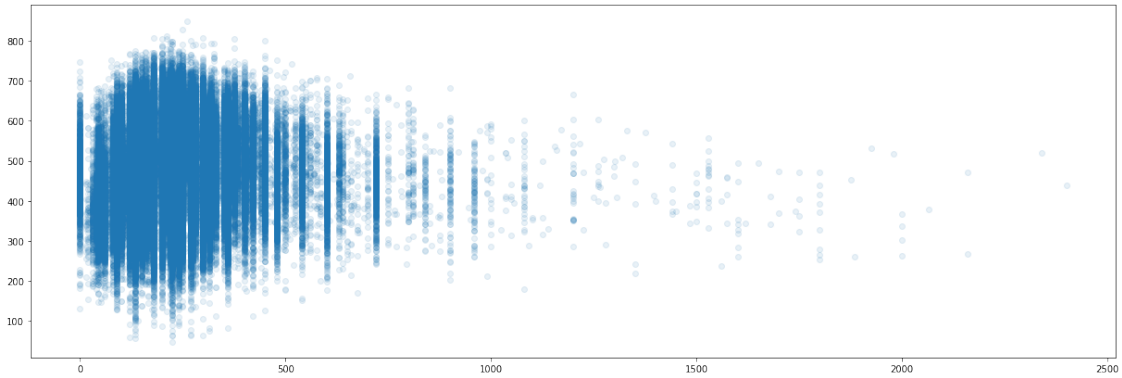
[254]:
```
plt.subplots(figsize=(21,7))
plt.scatter(df['MMINS'], df['PV_MATH'], alpha=.1, cmap='Blues_r')
plt.xlabel('')
plt.ylabel('')
plt.title('')
plt.show()
```



[255]:
```
plt.subplots(figsize=(21,7))
plt.scatter(df['SMINS'], df['PV_SCIE'], alpha=.1, cmap='Blues_r')
plt.xlabel('')
plt.ylabel('')
plt.title('')
plt.show()
```



[256]:
```
plt.subplots(figsize=(21,7))
plt.scatter(df['LMINS'], df['PV_READ'], alpha=.1, cmap='Blues_r')
plt.xlabel('')
plt.ylabel('')
plt.title('')
plt.show()
```



[263]:
```
print(df[['MMINS', 'PV_MATH']].corr().iloc[0,1])
print(df[['SMINS', 'PV_SCIE']].corr().iloc[0,1])
print(df[['LMINS', 'PV_READ']].corr().iloc[0,1])
```

```
0.07118616777216413
0.1497322691619717
0.030070040120862448
```

Probably, the answer is obvious to the question whether there is a positive correlation between the number of hours of preparation for a particular subject and the grade for the exam after such preparation. But according to the schedules of preparing students for both mathematics and science and literature, one cannot say that there is a moderated relationship between this action and the result.
In order to understand whether there really is no relationship between the preparation time for the exam and the grade for it. I calculated the Pearson correlation coefficient. And indeed the highest correlation coefficient is 15%.

Part III - Conclusions

1. What is students' performance at schools in different countries (including whether country is a OECD member) If we plot all the grades by subject, then scores in each subject looks normally distributed. Mean scores of science are about 3 points higher than average reading scores. In its turn, avearge reading scores are about 3 poits higher than avearge math scores. So scores in those 3 subjects are very similar.
   So, let's look at their boxplots.
   In general, there're outliers in every Series of scores. Moreover, math scores have approximately equal tails of outliers, but science and reading scores have outliers with lower scores more, than outliers with higher scores. let's go deepper, and look at students perormance in the context of countries, OECD membership, and other columns.
   Except Liechtenstein which is on the 6th position, on average, students from Asia countries receive the highest scores on math. China, Singapore, Hong Kong, Taiwan, and Korea are in Top-5. Macao and Japan follow immediately behind Liechtenstein.
   Chinese students receive on average 611 points. In comparison, in Peru average math scores are equal 368. This's 1.7 times less than in China.
   Average science scores are less than math scores by about 6 points. And this is becoming

noticeable for countries with the highest average scores in science. China, Gang Kong and Singapore are also in the Top-3 with an average score of 547 to 579. For China, this difference is 32 points or 5.2%.
For average reading scores, China, Hong Kong, Singapore, Japan, Korea and Taiwan continue to be the leaders with a maximum average of 569 points for China. This average score is the lowest for China in three subjects, possibly also because English is not a native language for a large population of the country.
The difference is noticeable in all three subjects at once: average scores in mathematics, science and reading are higher in OSCE countries than in non-OSCE countries. The difference is about 48 points for each subject.

2. What are the characteristics of students participated in PICA 2012:

- gender:
  Number of female students is little more (by 0.6%) than number of male students. Let's look at gender by countries. The largest number of students are in Mexico, Italy, Spain, Canada and Brazil. Except for Italy, the number of the females is greater than that of the male. In Brazil, there are 8% fewer males than females. The number of students in Mexico is 1.8 times higher than in Brazil, which is in 5th place, the number of males is 2.8 times less and the number of females is 2.7.
  Distriution of males and females math and science score are distributed approximately normal. However, there's slight difference of reading scores: female have aslightly higher grades than males.

- age:
  Since student age is between 15 and 16 year old, and number of students who are 15 years old are twice larger than students who are 16 years old, there would be interesting to compare whether there's some biases due to the different age.
  Distribution of scores of students from 15 and 16 years old groups is distributed normally, and I think, there's no significant difference between these students.

- international grade and grade compared to modal grade in country:
  An average international grade of students is 9.8 points, and on the same time, the mean grade compared to modal grade in country is equal -0.16 points.
  Among all 64 countries represented in the dataset, students from Canada, Italy, Mexico, and Spain have the highest average international rate.

3. What's a relationship between students performance and highest parental education measured in years as well as mother's and father's highest schooling?
   There exist a positive weak relationship between highest parental education in years and students math scores. To check whether this relationship is significant, linear regression can be fitted to determine if increase in parental education affects increases students math scores.

4. Whether there exist a correlation between family wealth (measured in the number of telephones, computers, etc.) and students performance?
   More than half of all students don't have a computer at all. Therefore, we can observe, that distribution of score of those students who doesn't have a computer is skewed to the right for two subjects - mathematics and science.

A half of all students don't have a car in family. And we can observe, that distribution of score of those students who has no car in the family is skewed to the right for all 3 subjects - math, science, and reading.
Almost every student in the dataset has at least one cellular phone. And it is almost impossible to determine what the distribution of grades looks like for those students who do not have a cell phone, since the number of such guys in the dataset is very small (about 1.5%).

5. How do student possessions such as own room and desk, etc. affect his/her performance?
   About a quater of students doesn't have their own rooms. This affects their preparation to the exam. And as the result, the distribution of math and science scores of those students who don't have their own room is skewed to the right
   11.1% of students don't have a desk, therefore, on average their math and science scores are lower than scores of students who has a table. Both, the distribution of reading scores of those who have and who doesn't have a desk ia normally distributed without any skewednes.
   It's really difficult to prepare to the assessment if you dont have study place at home. As a result the distribution of scores of those students who don't have a study place on average receive lower scores on math and science.
   Absense of computer significantly complicates the preparation not only for the exam, but also for the homework. Because for example, not all students have large-screen tablets or smartphones that can partially replace a computer. As a result, the distribution of math scores is significantly skewed to the right. Distributions of reading and science scores are also slightly skewed to theright.
   I can assume that the lack of software does not affect the distribution of grades in any way, since not all students pay money for software, thus, the lack of a computer worsens the average grade for the test more significantly.

Summing up, I would like to say that for a student who prepares and takes the exam, any help, whether it be a computer, the Internet, a place for preparation, or his own team, positively correlates with higher grades in both mathematics and science and reading.
This is a very interesting study that can be done by collecting additional missing data and adding information from other sources, for example, information on income and / or expenses of students' families.

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[ ]: