# Project Step 3: Data Cleaning

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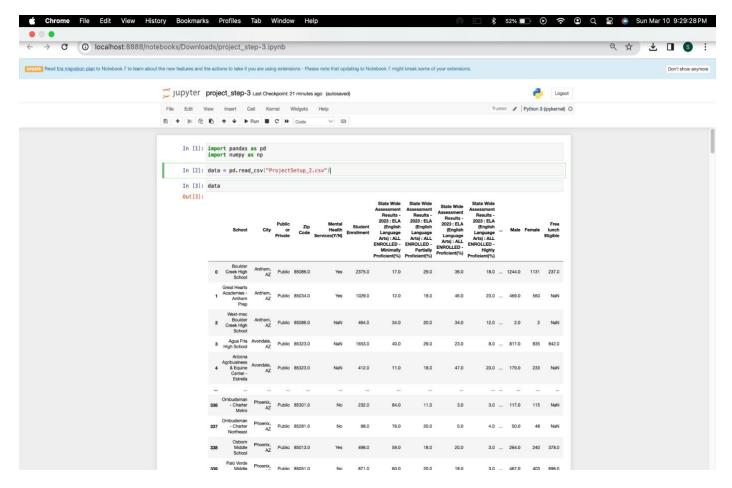
IFT 511: Analyzing Big Data

Professor: Asmaa Elbadrawy

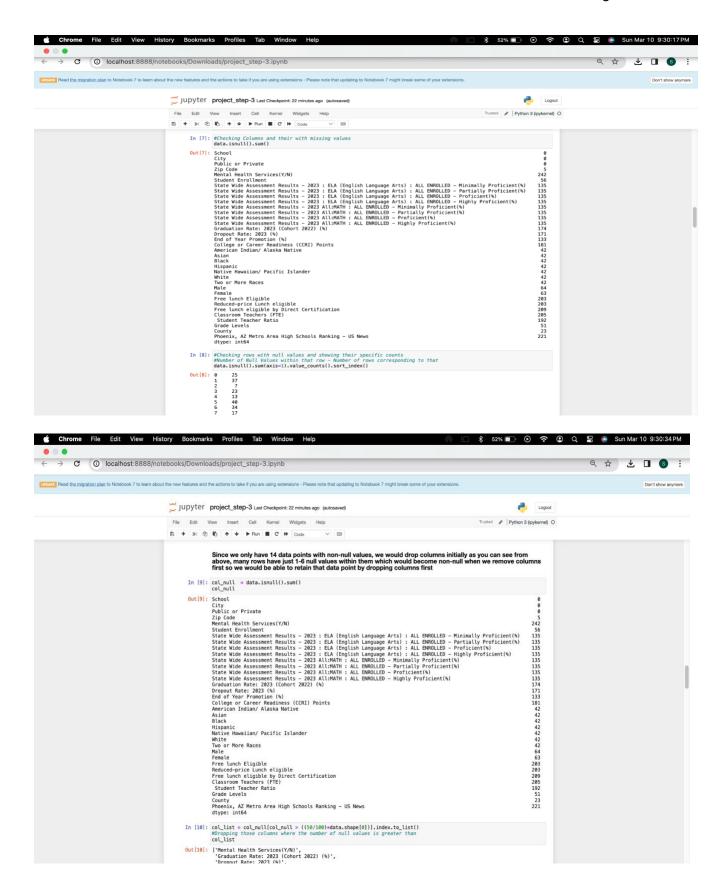
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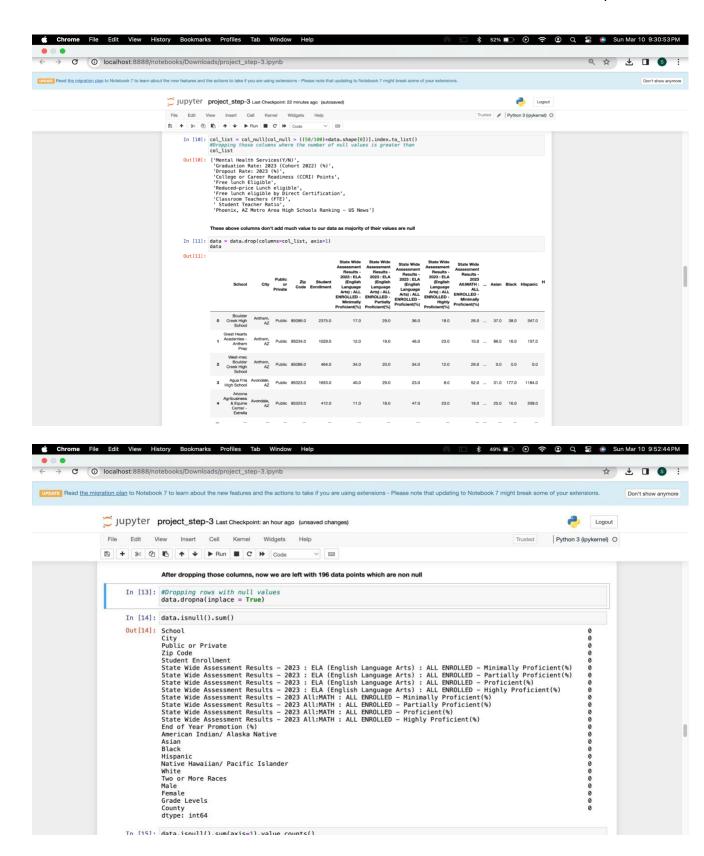
### 1. Data cleaning steps:

1) The provided Python code uses the pandas library to perform comprehensive data cleaning and transformation on a dataset read from a CSV file named "ProjectSetup\_2.csv."

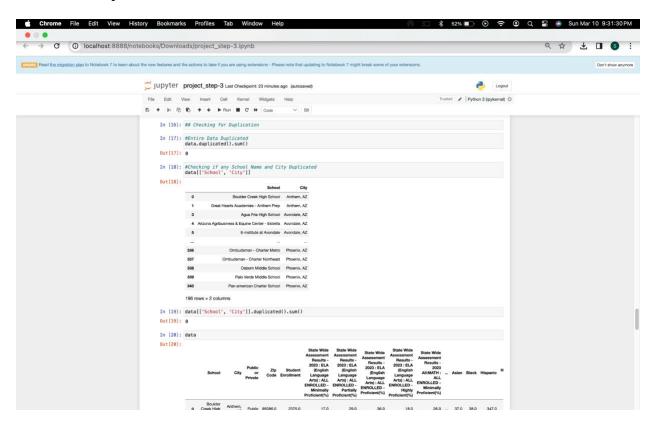


2) The initial exploration of the data includes checking its shape, information, and descriptive statistics. Subsequently, missing values are addressed by first identifying columns with more than 50% null values, which are then dropped to retain valuable data points. Rows with any remaining null values are removed as well.



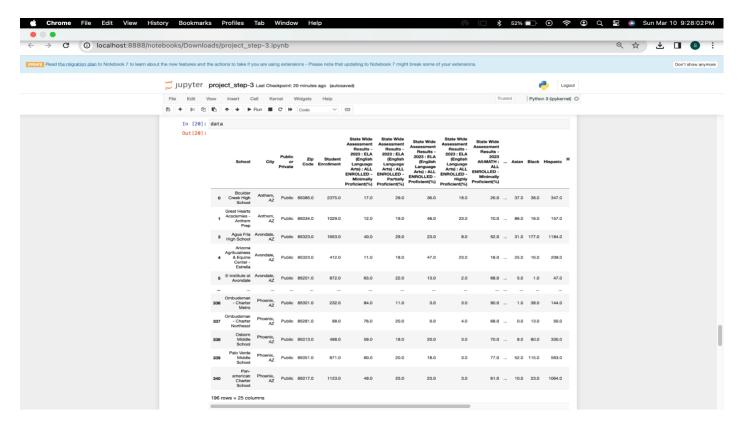


3) Then we proceed further and investigate and handle duplicate records in the dataset, checking for duplicates in both the entire dataset and specific columns (for example - 'School' and 'City'). Duplicate records are addressed by combining them into a single record if multiple entries exist for a particular school. But in this dataset, as we can see there are no duplicate entries.



- 4) In the next step, we move on to data transformation. This phase focuses on cleaning and standardizing specific columns. For instance, the 'City' column has trailing ", AZ" removed, and numeric columns like 'Zip Code,' 'Student Enrollment,' and demographic categories are appropriately converted to integers after removing non-numeric characters.
- 5) The final data-cleaning procedure involves systematically addressing missing values, handling duplicates, and ensuring uniformity in data types. The code's outcome is a cleaned

and transformed dataset ready for further analysis. After performing all the data cleaning steps, we are left with **196 rows \* 25 columns** of data. Attaching screenshot below shows data after data cleaning:



### 2. Data description and transformation methods used:

After Cleaning, we have 25 columns. Here's a description of attributes for each column:

Categorical: School, City, Public or Private, Zip Code, County

**Ordinal:** Grade Levels

All the remaining columns are of Ratio type.

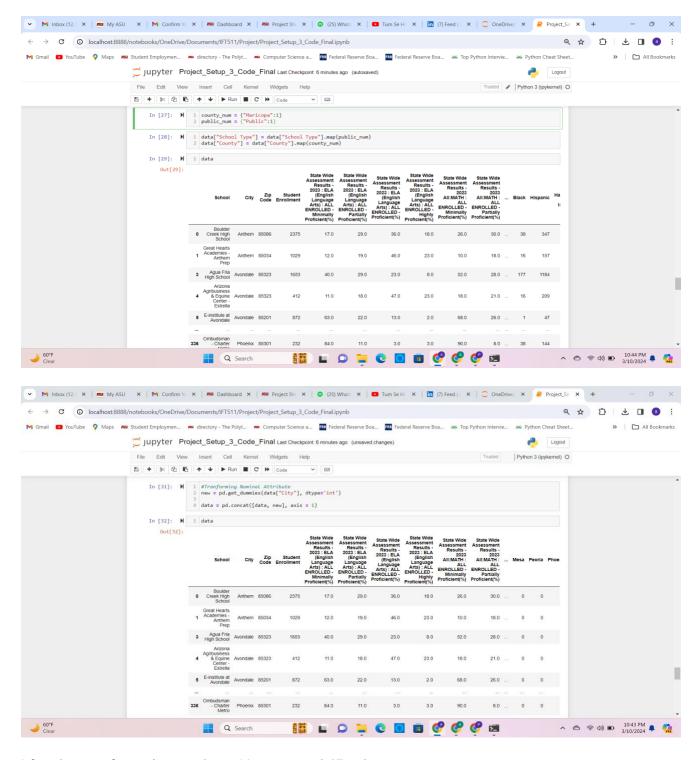
Ratio: Student Enrollment, State Wide Assessment Results - 2023: ELA (English Language Arts)
: ALL ENROLLED - Minimally Proficient(%), State Wide Assessment Results - 2023: ELA
(English Language Arts): ALL ENROLLED - Partially Proficient(%), State Wide Assessment

Results - 2023 : ELA (English Language Arts) : ALL ENROLLED - Proficient(%), State Wide Assessment Results - 2023 : ELA (English Language Arts) : ALL ENROLLED - Highly Proficient(%), State Wide Assessment Results - 2023 All:MATH : ALL ENROLLED - Minimally Proficient(%), State Wide Assessment Results - 2023, All:MATH : ALL ENROLLED - Partially Proficient(%), State Wide Assessment Results - 2023 All:MATH : ALL ENROLLED - Proficient(%), State Wide Assessment Results - 2023 All:MATH : ALL, ENROLLED - Highly Proficient(%), End of Year Promotion (%), American Indian/ Alaska Native, Asian, Black, Hispanic, Native Hawaiian/ Pacific Islander, White, Two or More Races Races, Male, Female.

We have opted not to undergo any transformations on School and Zip codes as we believe their numerical values are unnecessary for model training at this stage. Should the need arise, any required transformations will be performed in subsequent steps.

#### **Transformation Methods for each type:**

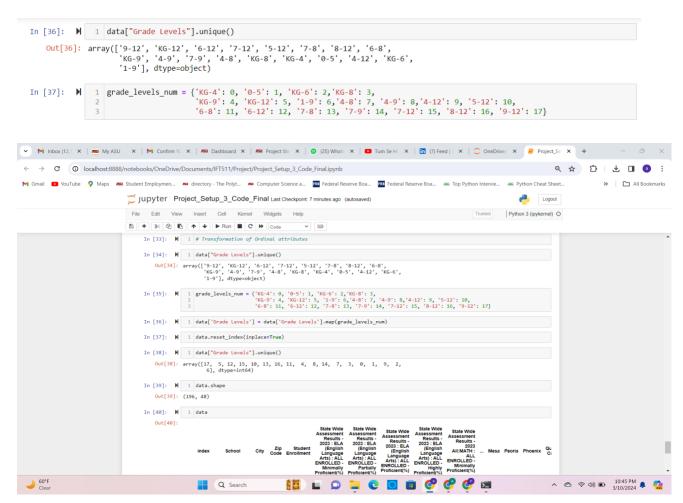
- 1. Ratio attributes do not need any transformation, as it is already in a numerical form and we can perform operations on it easily.
- 2. Categorical attributes need to be converted using One-Hot Encoding. By creating binary columns for every category and designating if a category exists with a 1 or 0, one-hot encoding is done.



After the transformation, we have 196 rows and 47 columns.

25 previous columns and 22 cities, which we have added.

3. For transforming ordinal attributes, we can do Label Encoding. Label encoding with a customized mapping can be used if the ordinal attribute has a distinct order. Refer following screenshot for mentioning the order for each category explicitly.



#### The code for the Cleaning and Transformation:

```
import pandas as pd
import numpy as np
data = pd.read_csv("Project_Setup_Data.csv")
data
data.shape
data.info()
data
data.describe()
#Checking Columns and their with missing values
data.isnull().sum()
#Checking rows with null values and showing their specific counts
#Number of Null Values within that row - Number of rows corresponding to that
data.isnull().sum(axis=1).value_counts().sort_index()
col_null = data.isnull().sum()
col_null
col_list = col_null[col_null > ((50/100)*data.shape[0])].index.to_list()
#Dropping those columns where the number of null values is greater than
col_list
data = data.drop(columns=col_list, axis=1)
data
data.isnull().sum(axis=1).value_counts().sort_index()#Dropping rows with null values
data.dropna(inplace = True)
```

```
data.isnull().sum()
data.isnull().sum()
data.isnull().sum(axis=1).value_counts()
# Checking whether there are any duplication
data.duplicated().sum()
# Checking if any School Name and City has duplicates
data[['School', 'City']]
data[['School', 'City']].duplicated().sum()
data["School Type"] = data['Public or Private'].str.replace(" ","")
data.drop(columns=["Public or Private"], axis=1, inplace=True)
print(data['County'].unique())
print(data['School Type'].unique())
print(data['City'].unique())
data['City'] = data['City'].str.replace(", AZ","")
data['Zip Code'] = data['Zip Code'].astype("int").astype("str")
int_con = ['Student Enrollment', 'American Indian/ Alaska Native', 'Asian', 'Black', 'Hispanic',
'Native Hawaiian/ Pacific Islander', 'White', 'Two or More Races', 'Male', 'Female']
for v_ in int_con:
  data[v] = data[v].astype("int")
data.columns
county_num = {"Maricopa":1}
public_num = {"Public":1}
data["School Type"] = data["School Type"].map(public_num)
```

```
data["County"] = data["County"].map(county_num)
data
data["City"].unique()
#Transforming Nominal Attribute
new = pd.get_dummies(data["City"], dtype='int')
data = pd.concat([data, new], axis = 1)
data
data["Grade Levels"].unique()grade_levels_num = {'KG-4': 0, '0-5': 1, 'KG-6': 2, 'KG-8': 3,
            'KG-9': 4, 'KG-12': 5, '1-9': 6,'4-8': 7, '4-9': 8,'4-12': 9, '5-12': 10,
            '6-8': 11, '6-12': 12, '7-8': 13, '7-9': 14, '7-12': 15, '8-12': 16, '9-12': 17}
data.reset_index(inplace=True)
data["Grade Levels"].unique()
data.shape
data
```