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INF1340H: Programming for Data Science
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Midterm Project – Data Cleaning Writeup
Nov 15, 2022

## Introduction

Data cleansing is a key component of data analysis and modeling. It can be handled by using a variety of tools, such as Python, Excel, Tableau, etc. Inconsistencies can arise when transferring data from a well-formatted excel spreadsheet into Python. Restructuring the data frame and controlling the data type of variables allows data users to work with a well-organized data frame in further analysis. Additionally, controlling the data type of variables prevents errors in data entry and allows for more accurate data analysis.

In this project, I managed to reorganize the provided excel spreadsheet in python through multiple steps and to align the final output with five tidy data principles. In general, most tables require similar operations:

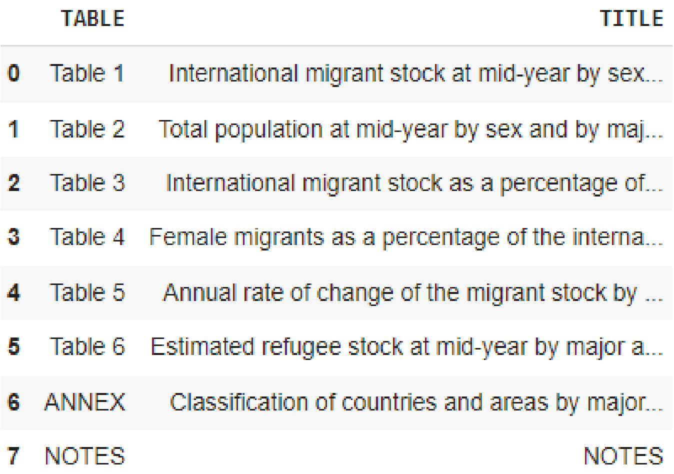
1. Stacking dataframe: transform multi-column variables to single-column variables
2. Handling missing values: replace with NaN
3. Splitting dataset: into multiple small datasets with logical meanings
4. Formatting output and unifying column data type

Details of each steps will be discussed in the following paragraphs

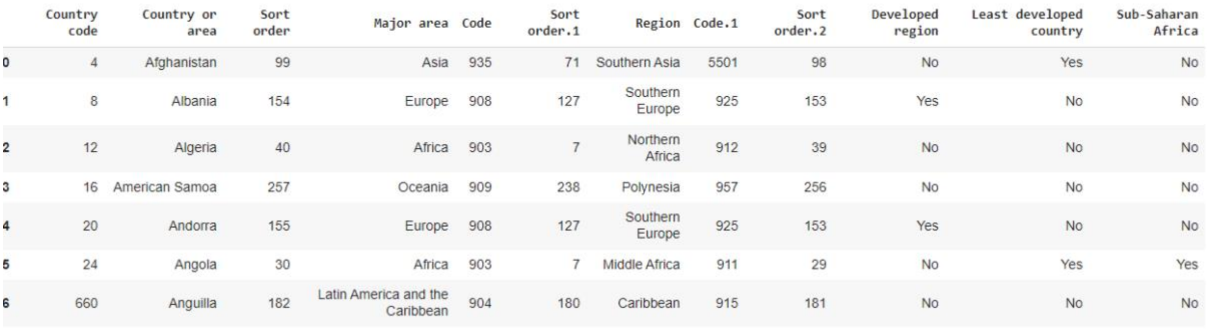
## Methods and Results

### Appendix Table

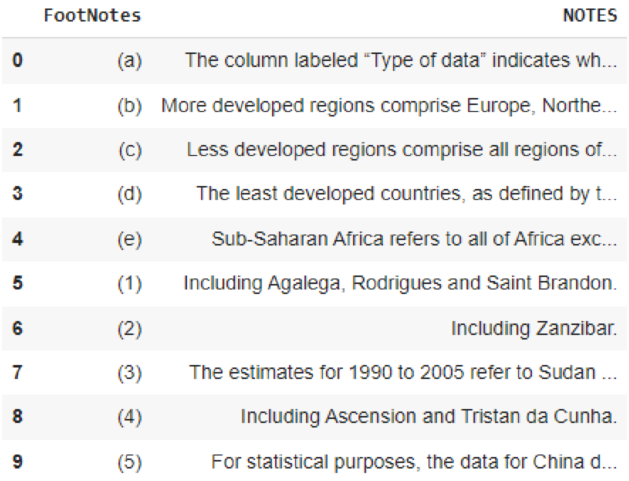
The three appendix tables (CONTENTS, ANNEX, NOTES) are simple. These tables only require direct import from excel spreadsheet. One thing to notice is that original data contains a formatted title page for all tabs, ie. row 1 to row 15. I use “skiprows” under pd.read_excel to exclude these rows from the importing process. The reason for exclusion of these rows is that they are simply text and are not considered as a dataset.



| | TABLE | TITLE |
|---|---|---|
| 0 | Table 1 | International migrant stock at mid-year by sex... |
| 1 | Table 2 | Total population at mid-year by sex and by maj... |
| 2 | Table 3 | International migrant stock as a percentage of... |
| 3 | Table 4 | Female migrants as a percentage of the interna... |
| 4 | Table 5 | Annual rate of change of the migrant stock by ... |
| 5 | Table 6 | Estimated refugee stock at mid-year by major a... |
| 6 | ANNEX | Classification of countries and areas by major... |
| 7 | NOTES | NOTES |



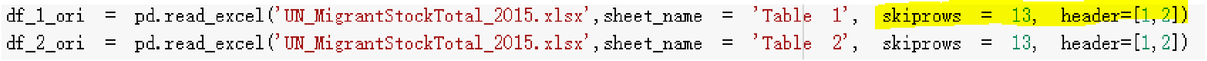
| | Country code | Country or area | Sort order | Major area | Code | Sort order.1 | Region | Code.1 | Sort order.2 | Developed region | Least developed country | Sub-Saharan Africa |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 4 | Afghanistan | 99 | Asia | 935 | 71 | Southern Asia | 5501 | 98 | No | Yes | No |
| 1 | 8 | Albania | 154 | Europe | 908 | 127 | Southern Europe | 925 | 153 | Yes | No | No |
| 2 | 12 | Algeria | 40 | Africa | 903 | 7 | Northern Africa | 912 | 39 | No | No | No |
| 3 | 16 | American Samoa | 257 | Oceania | 909 | 238 | Polynesia | 957 | 256 | No | No | No |
| 4 | 20 | Andorra | 155 | Europe | 908 | 127 | Southern Europe | 925 | 153 | Yes | No | No |
| 5 | 24 | Angola | 30 | Africa | 903 | 7 | Middle Africa | 911 | 29 | No | Yes | Yes |
| 6 | 660 | Anguilla | 182 | Latin America and the Caribbean | 904 | 180 | Caribbean | 915 | 181 | No | No | No |



| | FootNotes | NOTES |
|---|---|---|
| 0 | (a) | The column labeled “Type of data” indicates wh... |
| 1 | (b) | More developed regions comprise Europe, Northe... |
| 2 | (c) | Less developed regions comprise all regions of... |
| 3 | (d) | The least developed countries, as defined by t... |
| 4 | (e) | Sub-Saharan Africa refers to all of Africa exc... |
| 5 | (1) | Including Agalega, Rodrigues and Saint Brandon. |
| 6 | (2) | Including Zanzibar. |
| 7 | (3) | The estimates for 1990 to 2005 refer to Sudan ... |
| 8 | (4) | Including Ascension and Tristan da Cunha. |
| 9 | (5) | For statistical purposes, the data for China d... |

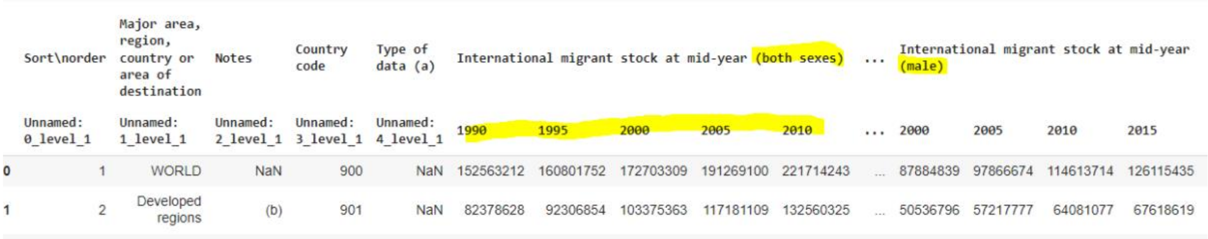
## Table 1-3, 5

Table 1, 2, 3, 5 have similar structures and I write one function melt_df to handle these tables. In the importing stage, I use “skiprows” to exclude the title page and use header = [1,2] to set multi-index column names. It will be easier in the later unstacking process.



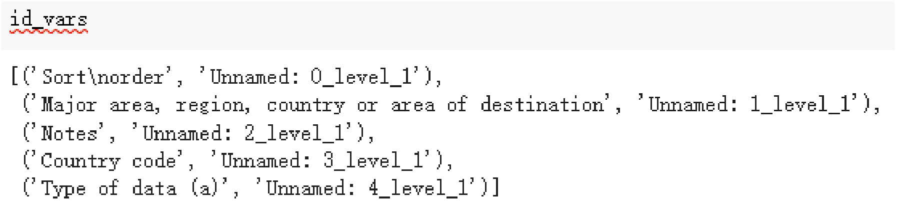
```
df_1_ori = pd.read_excel('UN_MigrantStockTotal_2015.xlsx',sheet_name = 'Table 1', skiprows = 13, header=[1,2])
df_2_ori = pd.read_excel('UN_MigrantStockTotal_2015.xlsx',sheet_name = 'Table 2', skiprows = 13, header=[1,2])
```

Use Table 1 as an example, both year information and original column names are set as headers. I noticed that “International migrant stock at mid-year” is splitted into 3 large sections: Both sexes, male, and female. Therefore, I performed a multi-level melt to group value variables into “Gender” and “Year”.



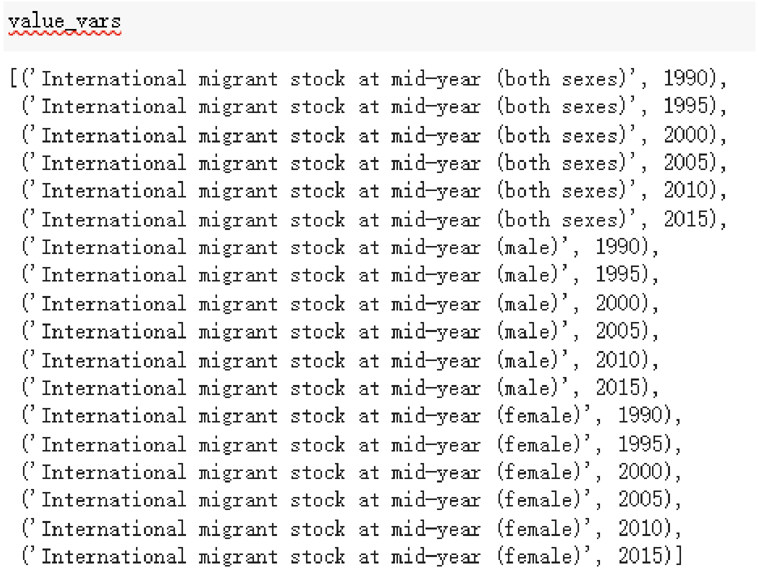
| | Sort\norder | Major area, region, country or area of destination | Notes | Country code | Type of data (a) | International migrant stock at mid-year (both sexes) | | | | | ... | International migrant stock at mid-year (male) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Unnamed: 0_level_1 | Unnamed: 1_level_1 | Unnamed: 2_level_1 | Unnamed: 3_level_1 | Unnamed: 4_level_1 | 1990 | 1995 | 2000 | 2005 | 2010 | ... | 2000 | 2005 | 2010 | 2015 |
| 0 | 1 | WORLD | NaN | 900 | NaN | 152563212 | 160801752 | 172703309 | 191269100 | 221714243 | ... | 87884839 | 97866674 | 114613714 | 126115435 |
| 1 | 2 | Developed regions | (b) | 901 | NaN | 82378628 | 92306854 | 103375363 | 117181109 | 132560325 | ... | 50536796 | 57217777 | 64081077 | 67618619 |

By looping through columns, I grouped columns into id_vars and value_vars. Id_vars are general variables and will not be changed in the “pd.melt” process. Value_vars are used to stack values into one single column.



```
id_vars
```

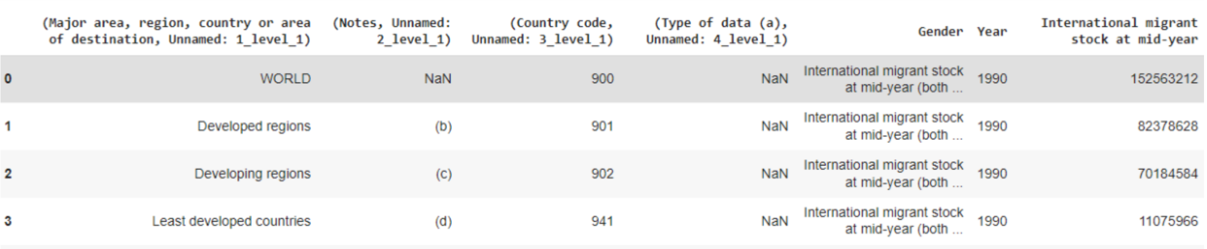
```
[('Sort\norder', 'Unnamed: 0_level_1'),
 ('Major area, region, country or area of destination', 'Unnamed: 1_level_1'),
 ('Notes', 'Unnamed: 2_level_1'),
 ('Country code', 'Unnamed: 3_level_1'),
 ('Type of data (a)', 'Unnamed: 4_level_1')]
```



```
value_vars
```

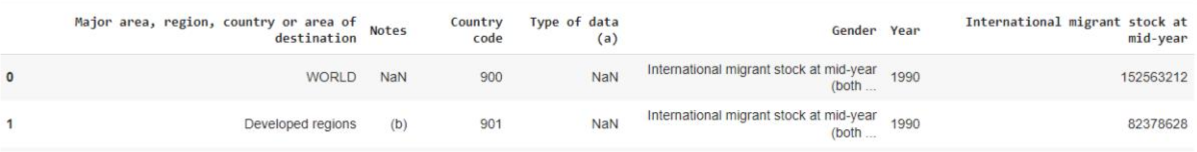
```
[('International migrant stock at mid-year (both sexes)', 1990),
 ('International migrant stock at mid-year (both sexes)', 1995),
 ('International migrant stock at mid-year (both sexes)', 2000),
 ('International migrant stock at mid-year (both sexes)', 2005),
 ('International migrant stock at mid-year (both sexes)', 2010),
 ('International migrant stock at mid-year (both sexes)', 2015),
 ('International migrant stock at mid-year (male)', 1990),
 ('International migrant stock at mid-year (male)', 1995),
 ('International migrant stock at mid-year (male)', 2000),
 ('International migrant stock at mid-year (male)', 2005),
 ('International migrant stock at mid-year (male)', 2010),
 ('International migrant stock at mid-year (male)', 2015),
 ('International migrant stock at mid-year (female)', 1990),
 ('International migrant stock at mid-year (female)', 1995),
 ('International migrant stock at mid-year (female)', 2000),
 ('International migrant stock at mid-year (female)', 2005),
 ('International migrant stock at mid-year (female)', 2010),
 ('International migrant stock at mid-year (female)', 2015)]
```

After “pd.melt”, I changed year and gender information from column names to 2 individual columns.



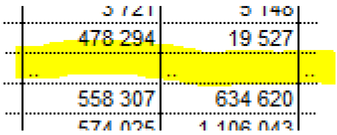
| | (Major area, region, country or area of destination, Unnamed: 1_level_1) | (Notes, Unnamed: 2_level_1) | (Country code, Unnamed: 3_level_1) | (Type of data (a), Unnamed: 4_level_1) | Gender | Year | International migrant stock at mid-year |
|---|---|---|---|---|---|---|---|
| 0 | WORLD | NaN | 900 | NaN | International migrant stock at mid-year (both ... | 1990 | 152563212 |
| 1 | Developed regions | (b) | 901 | NaN | International migrant stock at mid-year (both ... | 1990 | 82378628 |
| 2 | Developing regions | (c) | 902 | NaN | International migrant stock at mid-year (both ... | 1990 | 70184584 |
| 3 | Least developed countries | (d) | 941 | NaN | International migrant stock at mid-year (both ... | 1990 | 11075966 |

Next, I changed the column names to be more meaningful and removed “Unnamed”.



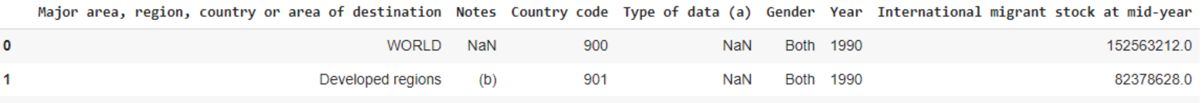
| | Major area, region, country or area of destination | Notes | Country code | Type of data (a) | Gender | Year | International migrant stock at mid-year |
|---|---|---|---|---|---|---|---|
| 0 | WORLD | NaN | 900 | NaN | International migrant stock at mid-year (both ... | 1990 | 152563212 |
| 1 | Developed regions | (b) | 901 | NaN | International migrant stock at mid-year (both ... | 1990 | 82378628 |

Going through the original data, I noticed some cells contain “..” to indicate missing value. However, when importing the dataset into python, “..” will be considered as string and other numbers will be considered as float. Thus the data type within one column is not consistent. I replaced all “..” with np.nan (read as float type and indicate missing value).



| | | |
|---|---|---|
| | 5 721 | 5 146 |
| | 478 294 | 19 527 |
| .. | .. | .. |
| | 558 307 | 634 620 |
| | 574 025 | 1 106 043 |

Lastly, “Gender” column contains too much information. By searching “both sexes”, “male”, “female” as indicators, I replace the gender column with “Both”, “M”, “F” to make sure each column only contains one variable. I also split the “Gender == “Both" records into a separate dataframe. Thus for each table, I have one for both gender and one for M/F. In this way, it is easier to retrieve data needed. This process only applies to table 1,2,3 and 5. Table 4 & 6 don’t have gender classification.



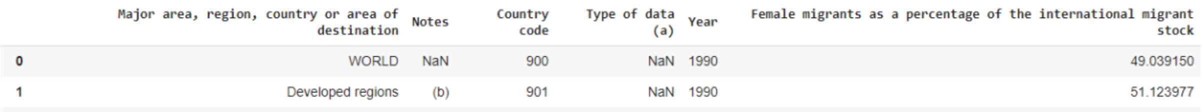
| | Major area, region, country or area of destination | Notes | Country code | Type of data (a) | Gender | Year | International migrant stock at mid-year |
|---|---|---|---|---|---|---|---|
| 0 | WORLD | NaN | 900 | NaN | Both | 1990 | 152563212.0 |
| 1 | Developed regions | (b) | 901 | NaN | Both | 1990 | 82378628.0 |

I also clean the index for each dataset since when I separate the dataset, the index for each row will stick to the original index. It will be a little bit messy to see index jumps from 6 to 100. However, I don’t think this process is required since I am not performing any operations on the index column, it is totally for presenting consideration.

Up to this step, I have changed the original dataset to align with most of the tidy data principles. Each column name is informative and doesn’t contain values. Each column contains only one variable and has a singular data type. All variables are in cells.

## Table 4

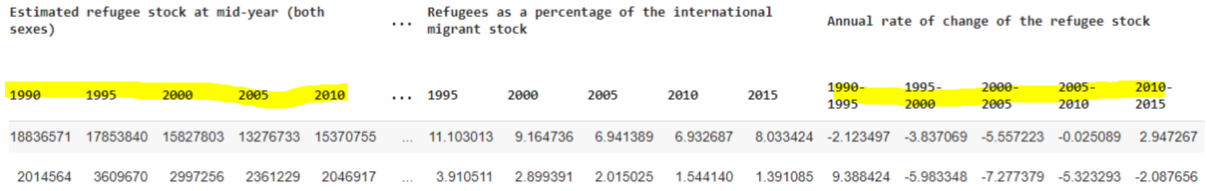
For Table 4, since original data doesn’t have gender classification, thus I only stacked data based on year information.



| | Major area, region, country or area of destination | Notes | Country code | Type of data (a) | Year | Female migrants as a percentage of the international migrant stock |
|---|---|---|---|---|---|---|
| 0 | WORLD | NaN | 900 | NaN | 1990 | 49.039150 |
| 1 | Developed regions | (b) | 901 | NaN | 1990 | 51.123977 |

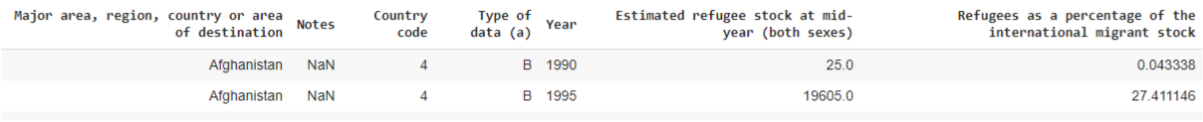
## Table 6

For Table 6, there are three types of value variables and no gender classification. The “year” information also has two formats. It is important to split the two “year” type into two tables, otherwise the year column will have different data type.



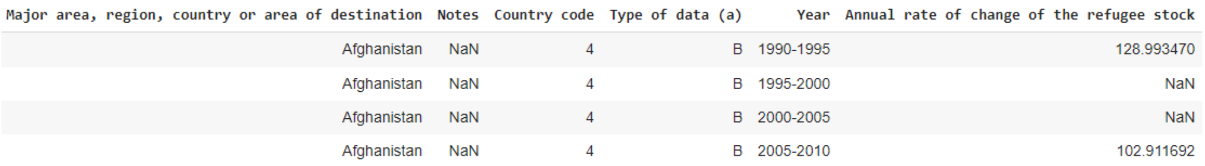
| Estimated refugee stock at mid-year (both sexes) | | | | | ... | Refugees as a percentage of the international migrant stock | | | | | Annual rate of change of the refugee stock | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1990 | 1995 | 2000 | 2005 | 2010 | ... | 1995 | 2000 | 2005 | 2010 | 2015 | 1990-1995 | 1995-2000 | 2000-2005 | 2005-2010 | 2010-2015 |
| 18836571 | 17853840 | 15827803 | 13276733 | 15370755 | ... | 11.103013 | 9.164736 | 6.941389 | 6.932687 | 8.033424 | -2.123497 | -3.837069 | -5.557223 | -0.025089 | 2.947267 |
| 2014564 | 3609670 | 2997256 | 2361229 | 2046917 | ... | 3.910511 | 2.899391 | 2.015025 | 1.544140 | 1.391085 | 9.388424 | -5.983348 | -7.277379 | -5.323293 | -2.087656 |

I created one specific function melt6_df for Table 6 and it split the dataset into two individual datasets based on “Year”.



| Major area, region, country or area of destination | Notes | Country code | Type of data (a) | Year | Estimated refugee stock at mid-year (both sexes) | Refugees as a percentage of the international migrant stock |
|---|---|---|---|---|---|---|
| Afghanistan | NaN | 4 | B | 1990 | 25.0 | 0.043338 |
| Afghanistan | NaN | 4 | B | 1995 | 19605.0 | 27.411146 |

## Country & Major Area split



| Major area, region, country or area of destination | Notes | Country code | Type of data (a) | Year | Annual rate of change of the refugee stock |
|---|---|---|---|---|---|
| Afghanistan | NaN | 4 | B | 1990-1995 | 128.993470 |
| Afghanistan | NaN | 4 | B | 1995-2000 | NaN |
| Afghanistan | NaN | 4 | B | 2000-2005 | NaN |
| Afghanistan | NaN | 4 | B | 2005-2010 | 102.911692 |

The original data use color code and indention to separate major area and country data. This information disappeared when imported into python. To reduce the information loss through the data cleansing process, I decided to split each table into “Country” and “Major Area”. The main idea for this split is to check whether the “major area, region, country or area” column in each table exists in “Country or area” from “ANNEX”. If it does, then that row will be classified as a country and vice versa, as a major area.

After the split, the original column name is not informative anymore. I changed the column name to “Country” or “Major Area” correspondingly.

The value variables for all tables are either number of count or rate of change (%). Therefore, I formatted the final output for better visual experience. The submitted workbook will contain all tables and please check for more details.

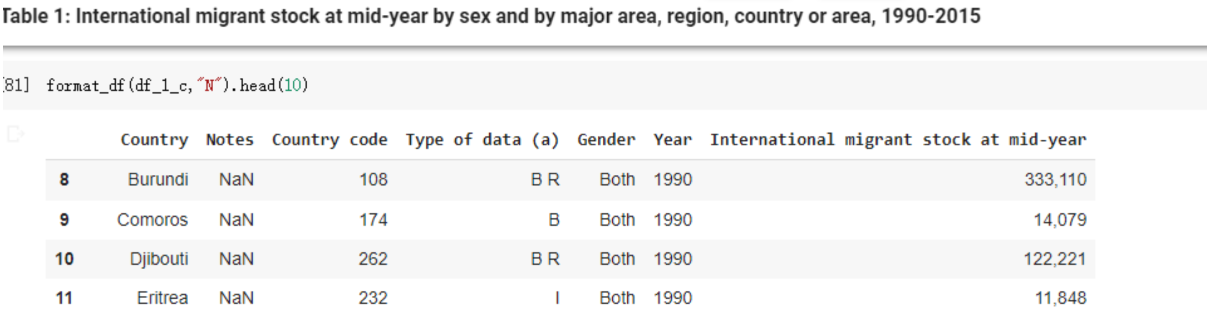
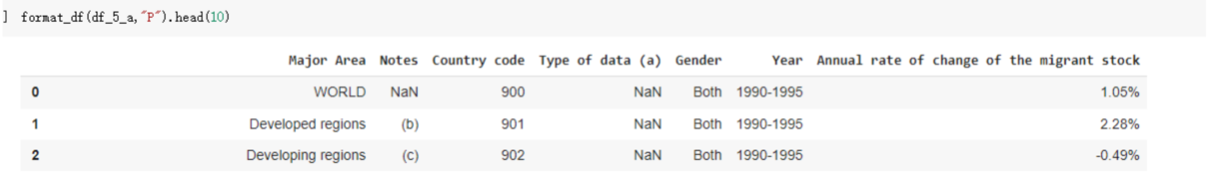


Table 1: International migrant stock at mid-year by sex and by major area, region, country or area, 1990-2015

```
81]  format_df(df_1_c,"N").head(10)
```

|  | Country | Notes | Country code | Type of data (a) | Gender | Year | International migrant stock at mid-year |
|---|---|---|---|---|---|---|---|
| 8 | Burundi | NaN | 108 | B R | Both | 1990 | 333,110 |
| 9 | Comoros | NaN | 174 | B | Both | 1990 | 14,079 |
| 10 | Djibouti | NaN | 262 | B R | Both | 1990 | 122,221 |
| 11 | Eritrea | NaN | 232 | I | Both | 1990 | 11,848 |



```
]  format_df(df_5_a,"P").head(10)
```

|  | Major Area | Notes | Country code | Type of data (a) | Gender | Year | Annual rate of change of the migrant stock |
|---|---|---|---|---|---|---|---|
| 0 | WORLD | NaN | 900 | NaN | Both | 1990-1995 | 1.05% |
| 1 | Developed regions | (b) | 901 | NaN | Both | 1990-1995 | 2.28% |
| 2 | Developing regions | (c) | 902 | NaN | Both | 1990-1995 | -0.49% |

## Discussion

This project helped to deepen my understanding of tidy data principles and to practice how to use python to accomplish basic data cleansing. I need to review the excel sheets multiple times to plan what steps are needed to create the desired outcome, what that outcome should look like, and how many manual steps are involved. I also need to identify any potential risks or problems that could occur during the process. The process of thinking and planning is more valuable than the final mark on this project. By taking the time to think about my long-term goals, I can make better decisions and plans. This process also allows me to develop relationships and connections that will be valuable down the road, and it allows me to learn new things.

I did a lot of syntax searches on google to write efficient and clean code. Although the primary goal of this project is to cleanse the data, I have been thinking about ways to make further analysis easier in the future. Documenting the data cleansing process can ensure that the data is clean and that any step can be repeated if necessary. After changing the column names and moving all variables into cells, users can read the dataset without further clarification. A singular data type column dataframe is easier for row or column operation. For example, if the column consists of a string and an integer, it is impossible to find the sum of the whole column.

In general, I am satisfied with what I have done on the project but there are still several improvements that can be done additionally. For example, the dataset can be further divided into the country, regions, major areas, and others. Gender “Both” can be separated from “M” and “F” and into an individual dataframe. Table 6 can be split into three separate tables based on value variables instead of two. Add-in one more step to format the columns of each table, and manually set the data type for each column. By making all of these improvements, the final results will more closely match the five principles.

## Conclusion

Achieving a satisfactory result in data preparation requires clear thinking and design. Data cleansing is an important step in that process. It is important to identify and correct errors in the data, to ensure that the data is complete and accurate. Data cleansing can be a time-consuming and difficult process, but it is essential to ensure that the data is of high quality.

Following the tidy data principle is a good start, but there are other things to think about such as missing values, duplicates, and choosing which data to use. In reality, data can be way more complicated and messy than project data. Data can be unstructured, with many different formats and sources. It can be difficult to clean and normalize. But with the right tools and techniques, it is possible to make sense of even the most complex data sets. Finding the pattern within a large chunk of data and organizing the dataset into input for the next step are crucial skills. I learned a lot from this project and am willing to use what I have learned in my future career.