

Data Wrangling

Steps involved

- [1. Importing necessary packages](#)
- [2. Importing data from a csv file in its raw form](#)
- [3. Examine the imported dataframe](#)
- [4. Identifying and choosing the appropriate Index](#)
- [5. Verify the correctness of data types for each column](#)
 - [\(i\). Span the use of category type](#)
 - [\(ii\). Deal with coerced types](#)
 - [\(iii\). Handling datetime objects](#)
- [6. Handle "null" values](#)
- [7. Handling duplicates](#)
- [8. Normalize embedded json values](#)
- [9. Joining Dataframes](#)

1. Importing necessary packages :

This allows us to use the underlying functions and methods and easily just by using the alias created.

For ex: Importing pandas package can be done as follows -

```
import pandas as pd
```

2. Importing data from a csv file in its raw form :

The first step involved was to import the raw data from file to a dataframe using pandas `read_csv()` utility.

```
sample_dataframe = pd.read_csv("../data/sample.csv")
```

```
flipkart_df=  
pd.read_csv("../data/flipkart_com-ecommerce_sample.csv")
```

3. Examine the imported dataframe:

`.info()` - This gives a high level summary of the data that lies in the dataframe. For example - the type of data in each column, the number of non null entries, coerced data types, etc.

```
sample_dataframe.info()
```

```
flipkart_df.info()
```

`.head()` - examine the first few rows, to get the gist of type of values for each column. For example, null values can be identified at early stages.

```
sample_dataframe.head()
```

```
flipkart_df.head()
```

`.columns` - can get details on the column names and the no.of columns in the dataset. This was useful to clean up the column names - for example - If the column names have unnecessary spaces or can reassign new column names to be precise on what kind of info is depicted by that column.

```
sample_dataframe.columns
```

```
flipkart_df.columns
```

`.describe()` - this gives a high level summary statistics of all quantitative columns.

```
sample_dataframe.describe()
```

```
flipkart_df.describe()
```

.value_counts() - to identify frequency counts for categorical data

```
sample_dataframe.sample_categorical_column.value_counts()
```

```
flipkart_df.product_category_tree.value_counts()
```

.unique() - To get the unique values of a particular column. For instance, if a column has null values and we are not sure about how the null values are stored, we can identify it using this.

```
sample_dataframe.column_categorical.unique()
```

```
flipkart_df.product_name.unique()
```

4. Identifying and choosing the appropriate Index:

After examining the raw dataset using the above methods, if a particular column has a unique identifier for each row/case/observation/subject and describes an appropriate meaning to each observation, then this column can be conveniently used to set as index leveraging pandas `set_index()` method or can be performed while doing the `read_csv()` import with `index_col` attribute.

Reference: flipkart_df Index - "uniq_id"

```
# Setting the index using the index_col attribute of read_csv()
utility
flipkart_df =
pd.read_csv("../data/flipkart_com-ecommerce_sample.csv", index_col=0
)

# Setting the index using set_index() dataframe method
```

```
# Using inplace as True, so it alters the dataframe, without having  
to create a new dataframe  
flipkart_df.set_index('uniq_id',inplace=True)
```

After examining the dataframe in step 3, the most appropriate unique identifier for this dataset would be “product identifier (pid)” column, as this uniquely identifies each observation. So, we can re-set the index to “pid” column (*after removing any duplicates - explained in later part of this document*).

Reference: flipkart_df new Index - "pid"

```
# Setting the index using set_index() dataframe method  
# Using inplace as True, so it alters the dataframe, without having  
to create a new dataframe  
# This automatically drops any existing index  
flipkart_df.set_index('pid',inplace=True)
```

5. Verify the correctness of data type for each column:

examine using the `info()` method.

(i). *Span the use of category type:*

If a column has categorical data and its datatype is 'object', this can be changed to 'category' type - as its good to use for memory efficiency. This can be done easily using `.astype('category')`.

Reference: flipkart_df column: "product_category_tree"

```
flipkart_df.product_category_tree =  
flipkart_df.product_category_tree.astype('category')
```

(ii). *Deal with coerced types :*

If a numeric column (for eg: price) is of dtype: object then it means - the data of that column needs to be examined further. This is often the case that some of the missing values may be set to some string(eg: 'missing') instead of NaN, as a result the data type is *coerced* to 'object' in other words, string. This can be handled by using `.to_numeric()` method on the

column. But, before using this conversion "null" values need to be handled using any of the techniques above

Reference: flipkart_df column: "overall_rating"

```
# If errors= 'coerce' then invalid parsing will be set as NaN
flipkart_df.overall_rating
=pd.to_numeric(flipkart_df['overall_rating'],errors='coerce')
```

(iii). Handling datetime objects :

Date columns need to be imported as pandas datetime objects as it would make the dataset easier to access for further analysis of data. We can do this using pandas `to_datetime()` method or can be performed while doing the `read_csv()` import with `parse_dates` attribute.

Reference: flipkart_df column : "crawl_timestamp"

```
# Using the parse_dates attribute if read_csv() utility
pd.read_csv("../data/flipkart_com-ecommerce_sample.csv",index_col=0
,
              parse_dates=['crawl_timestamp'])

# Using to_datetime()
flipkart_df.crawl_timestamp=pd.to_datetime(flipkart_df['crawl_times
tamp']).dt.strftime('%Y-%m-%d %H:%M:%S')
```

6. Handle "null" values :

These can often be represented as - empty strings, NaN's, NA, 'missing' or in any other format. Can be examined by using `head()`, `unique()`, `isnull()`, `values` etc.,

Following can be used to handle null/empty values :

1. `dropna()` - Delete records with null entries, not a great choice since most of the data is lost.
2. `fillna()` - Broadcast null entries with a particular value.
3. Custom Python functions - Impute using custom generated values
4. `{ }` - Broadcast using Dict comprehensions
5. `.map()` - Using other column data as a basis to fill in the null entries.

Reference: flipkart_df column : "brand"

```
flipkart_df['brand']=[str(k).split()[0] if v is np.NaN else k for  
k,v in zip(flipkart_df['product_name'],flipkart_df['brand'])]
```

Example for using .map()

```
dataframe['name']= dataframe['code'].map({k: v for k, v in  
zip(dataframe['code'], dataframe['name']) if v is not ''})
```

7. Handling duplicates :

Duplicates are removed using `drop_duplicates()` method. If dropping is based only on a particular column, that column name can be provided as a value to the subset attribute.

For example: In `flipkart_df` - "pid" column has duplicate entries (meaning has the same product details). In this case we can safely discard the duplicate entries retaining one entry and removing the duplicate entry.

Reference: flipkart_df column : "pid"

```
flipkart_df  
flipkart_df.drop_duplicates(subset='pid',keep='first') =
```

8. Normalize embedded json values :

Some of the column values may contain embedded json as their which is required to normalize to make the dataset tidy and ready for analysis.

Reference: flipkart_df column : `product_specifications[0]`

```
json_data = {'product_specification': [{'key': 'Number of Contents  
in Sales Package',  
    'value': 'Pack of 3'},  
    {'key': 'Fabric', 'value': 'Cotton Lycra'},  
    {'key': 'Type', 'value': 'Cycling Shorts'},
```

```
{'key': 'Pattern', 'value': 'Solid'},
{'key': 'Ideal For', 'value': "Women's"},
{'value': 'Gentle Machine Wash in Lukewarm Water, Do Not Bleach'},
{'key': 'Style Code', 'value': 'ALTHT_3P_21'},
{'value': '3 shorts'}}

json_normalize(json_data)
```

9. Joining dataframes :

After retrieving the json data as columns, it needs to be joined back onto the original dataframe on which the analysis will be performed.

Reference: flipkart_df and product_specifications join

```
flipkart_df=flipkart_df.join(product_specification,how='left')
```

10. Reindex columns :

To reorder the columns in a dataframe we can use the `.reindex()` method of dataframe.

Reference: flipkart_df

```
flipkart_df = flipkart_df.reindex(columns=['crawl_timestamp',
'product_category','brand', 'product_name','retail_price',
'discounted_price','final_price', 'is_FK_Advantage_product',
'description','product_url','image', 'product_rating',
'product_color', 'product_ideal_for', 'product_occasion'])
```