Creating Python Functions for Exploratory Data Analysis and Data Cleaning

Automating the Boring Stuff for Data Scientists

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Update (2021–02–05): The Python library used in this blog post is now published on PyPi. The package also includes new features: it provides a class that includes methods to streamline the modeling process for Scikit-Learn models. Part II of this blog post is coming up and will cover how to utilize OOP in Python to automate your modeling process.

Exploratory Data Analysis and Data Cleaning are two essential steps before we start to develop Machine Learning Models, and they can be time-consuming, especially for people who are still familiarizing themselves with this whole process.

EDA and Data Cleaning is rarely a one-time, linear process: you might find yourself going back to earlier sections and modifying the way you treat the dataset quite often. One way to speed up this process is to recycle some of the code you find yourself using over and over again. This is why we should create functions to automate the repetitive parts of EDA and Data Cleaning. Another benefit of using functions in the EDA and Data Cleaning is to eliminate the inconsistency of results caused by accidental differences in the code.

In this blog post, I will walk you through a few useful python functions that I created for EDA and Data Cleaning. The library containing all these functions can be cloned from my repository `eda_and_beyond`. Special thanks to all the people who contributed to this small (but growing) library.

Functions for Handling Missing Values

One important step in the EDA is to inspect missing values, study if there are any patterns in the missing values, and make a decision about how to deal with them accordingly.

The first function here is to give you a general idea of the total and percentage of missing data in each column:

```
def intitial_eda_checks(df):
    '''
    Takes df
    Checks nulls
    '''
    if df.isnull().sum().sum() > 0:
        mask_total = df.isnull().sum().sort_value
        total = mask_total[mask_total > 0]

        mask_percent = df.isnull().mean().sort_va
        percent = mask_percent[mask_percent > 0]

        missing_data = pd.concat([total, percent

        print(f'Total and Percentage of NaN:\n {r
    else:
        print('No NaN found.')
```

After the initial inspection, you can decide if you want to have a closer inspection on those columns with excessive missing values. With specification of the threshold of the missing value percentage, the following function will give you a list of columns that have missing values over that threshold:

```
def view_columns_w_many_nans(df, missing_percent
    '''
    Checks which columns have over specified perc
    Takes df, missing percentage
    Returns columns as a list
    '''
    mask_percent = df.isnull().mean()
    series = mask_percent[mask_percent > missing_
    columns = series.index.to_list()
    print(columns)
    return columns
```

There are many ways to deal with missing values. If you decide to drop the columns with too many missing values (over a certain threshold you specify), you can use this function to accomplish the task:

```
def drop_columns_w_many_nans(df, missing_percent
    '''
    Takes df, missing percentage
    Drops the columns whose missing value is bigg
    Returns df
    '''
    series = view_columns_w_many_nans(df, missing
    list_of_cols = series.index.to_list()
    df.drop(columns=list_of_cols)
    print(list_of_cols)
    return df
```

However, there are many downsides of deleting missing values from your dataset, such as reduced statistical power. If you decide to impute the missing values instead, check out Sklearn's `SimpleImputer` module, which is an easy-to-use tool to impute missing values whichever way strikes your fancy.

In addition, if you'd like to read more about how to deal with missing values, check out this helpful slide created by Melissa Humphries at Population Research Center.

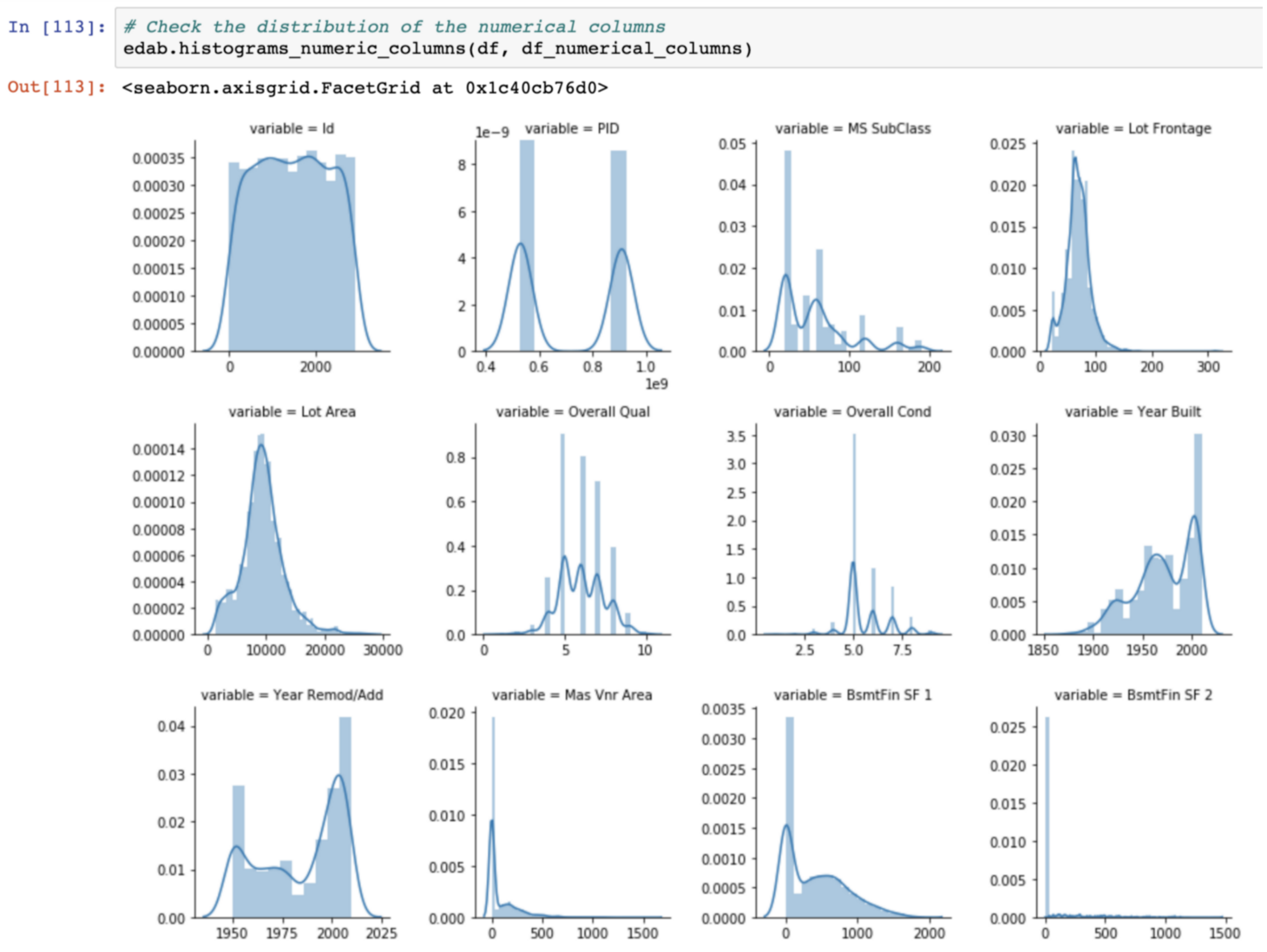
Functions for Data Visualization

The human brain is very good at identify patterns, and this is why visualizing your dataset during the EDA process and identifying the patterns can be very beneficial. For instance, histograms make analyzing the distribution of the data an easier task; Boxplot is great for identifying outliers; Scatter plot is very useful when it comes to checking the correlations between two variables. Matplotlib and Seaborn are your best friends when it comes to data visualization. However, creating individual plot(s) for each features can become tedious if you have a large number of features. In this section, I will walk you through a few functions for creating group plots that can help you to kill many birds with one function.

We often want to look at the distributions of columns with numerical values. The following function will create a group of plots for all numerical columns in your dataset. (This function is adapted from Dominik Gawlik's blog post, which is a great read for the entire EDA process with a real dataset):

```
def histograms_numeric_columns(df, numerical_colu
    '''
    Takes df, numerical columns as list
    Returns a group of histagrams
    '''
    f = pd.melt(df, value_vars=numerical_columns
    g = sns.FacetGrid(f, col='variable',  col_wra
    g = g.map(sns.distplot, 'value')
    return g
```

Here is what the output looks like:

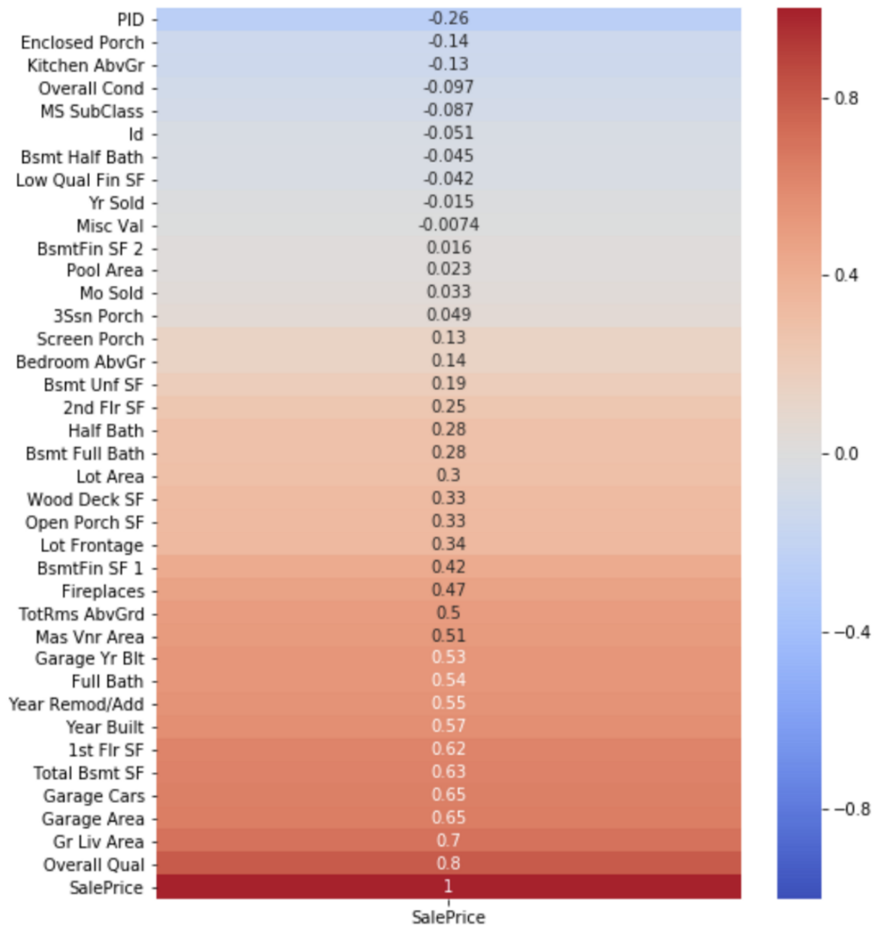


```
In [113]: # Check the distribution of the numerical columns
          edab.histograms_numeric_columns(df, df_numerical_columns)

Out[113]: <seaborn.axisgrid.FacetGrid at 0x1c40cb76d0>
```

Another helpful visualization tool is a heatmap. Heatmaps come in very handy when you want to check the correlation between your dependent and independent variables. Oftentimes, heatmaps can be visually cluttered if you have too many features. One way to avoid it is to create a heatmap just for the dependent variable (target) and independent variables (features). The following function will assist you with this task:

```
def heatmap_numeric_w_dependent_variable(df, depe
    '''
    Takes df, a dependant variable as str
    Returns a heatmap of all independent variabl
    '''
    plt.figure(figsize=(8, 10))
    g = sns.heatmap(df.corr()[[dependent_variabl
                    annot=True,
                    cmap='coolwarm',
                    vmin=-1,
                    vmax=1)
    return g
```

```
In [16]: #Check correlation between independent varibles and dependent varible 'SalePrice'

         edab.heatmap_numeric_w_dependent_variable(df, 'SalePrice');
```



As you can see in the output, the correlations become easier to read since the values are sorted.

Functions for Changing Data Types

Ensuring your features are of the correct datatypes is another important step during the EDA and Data Cleaning process. It happens quite often that Pandas' `.read_csv()` method would interpret datatypes differently than the original data file. Reading the data dictionary is very illuminating during this step. Additionally, if you are planning to do some feature engineering, changing data types is required. The following two functions work hand in hand to transform categorical features into numerical (ordinal) features:

The first function is to output a function, i.e. a transformer, that will transform each `str` in a list into a `int`, where the `int` is the index of that element in the list.

```
def categorical_to_ordinal_transformer(categorie
    '''
    Returns a function that will map categories 
    order of the list of `categories` given. Ex.

    If categories is ['A', 'B', 'C'] then the tra
    'A' -> 0, 'B' -> 1, 'C' -> 2.
    '''
    return lambda categorical_value: categories.
```

The second function has two parts: first, it takes a dictionary of the following form:

```
categorical_numerical_mapping = {
    'Utilities': ['ELO', 'NoSeWa', 'NoSewr', 'Al
    'Exter Qual': ['Po', 'Fa', 'TA', 'Gd', 'Ex'],
    'Exter Cond': ['Po', 'Fa', 'TA', 'Gd', 'Ex']
}
```

Using the previous function we define earlier, it turns the dictionary into this:

```
transformers = {'Utilities': <utilties_transform
                'Exter Qual': <exter_qual_transf
                'Exter Cond': <exter_cond_transf
```

The second part of the function uses the `.map()` method to map each transformer function onto the dataframe. Note that a copy of the original dataframe will be created during this function.

```
def transform_categorical_to_numercial(df, categ
    '''
    Transforms categorical columns to numerical
    Takes a df, a dictionary
    Returns df
    '''
    transformers = {k: categorical_to_ordinal_tr
                    for k, v in categorical_nume
    new_df = df.copy()
    for col, transformer in transformers.items()
        new_df[col] = new_df[col].map(transforme
    return new_df
```

This will conclude my blog post. I aim to create an open source library to make the EDA and Data Cleaning process more streamlined. As always, I'd love to hear your feedback. If you have any corrections or want to contribute to this small open source project, please make a pull request. Thank you for reading!

Resources: Check out this awesome (and free!) textbook on Python Programming: Automate the Boring Stuff with Python by Al Sweigart.

Originally published at https://github.com.