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Automated Data Cleaning with Python

How to automate data preparation and save time on your next data science project

Image from Unsplash.

It is commonly known among Data Scientists that data cleaning and preprocessing make up a major part of a data science project. And, you will probably agree with me that it is

So, (let's ask ourselves): can we automate this process?

Well, automating data cleaning is easier said than done, since the required steps are highly **dependent** on the **shape of the data** and the domain-specific **use case**. Nevertheless, there are ways to **automate** at least a considerable **part of it** in a standardized way.

In this article, I will show you how you can build your own **automated data cleaning pipeline** in **Python 3.8**.

View the AutoClean project on Github.

1 | What do we want to Automate?

The first and most important question we should ask ourselves before diving into this project is: which steps of the data cleaning process **can** we actually **standardize** and **automate**?

Steps that can most likely be automated or standardized, are steps which are **performed over and over again**, in each cleaning process of almost every data science project. And, since we want to build a "**one size fits all**" pipeline, we want to make sure that our processing steps are fairly generic and can adapt to various types of datasets.

For example, some of the common questions that are repeatedly asked during the majority of projects include for example:

- What **format** does my data come in? CSV, JSON, text? Or another format? How am I going to handle this format?
- What **data types** do our data features come in? Does our dataset contain categorical and/or numerical data? How do we deal with each? Do we want to **one-hot encode** our data, and/or perform data **type transformations**?




- Does our data contain **outliers**? If yes, do we apply a **regularization technique**, or do we leave them as they are? …and wait, what do we even consider as an "outlier"?

No matter what use case our project will be targeted at, these are questions that will very likely need to be addressed, and therefore can be a great subject of **automation**.

The answers to these questions, as well as their implementation will be discussed and shown in the next few chapters.

2 | Building Blocks of the Pipeline

First off, let's start by importing the libraries we will be using. Those will be mainly the Python **Pandas**, **Sklearn** and **Numpy** library, as these are very helpful when it comes to manipulating data.

```
import numpy as np
import pandas as pd
from math import isnan
from sklearn import preprocessing
from sklearn.impute import KNNImputer, SimpleImputer
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import LogisticRegression
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler
```

AutoClean_libraries.py hosted with ❤ by GitHub view raw

We will define that our script will take a **Pandas dataframe as input**, which means that we need to at least transform the data into a Pandas dataframe format before it can be processed by our pipeline.

Now let's look at the building blocks of our pipeline. The below chapters will go through the following processing steps:

[Block 1] Missing Values

[Block 2] Outliers

[Block 1] Missing Values

It is fairly common that a project starts with a dataset that contains missing values and there are various methods of dealing with them. We could simply delete the observations containing missing values, or we can use an imputation technique. It is also common practice to predict missing values in our data with the help of various regression or classification models.

> 💡 *Imputation techniques replace missing data by certain values, like the mean, or by a value similar to other sample values in the feature space (f. e. K-NN).*

The choice of how we handle missing values will depend mostly on:

- the data type (numerical or categorical) and
- how many missing values we have relative to the number of total samples we have (deleting 1 observation out of 100k will have a different impact than deleting 1 out of 100)

Our pipeline will follow the strategy **imputation > deletion**, and will support the following techniques: prediction with Linear and Logistic Regression, imputation with K-NN, mean, median and mode, as well as deletion.

Good, now we can start writing the function for our first building block. We will first create a separate class for handling missing values. The function *handle* below will handle **numerical** and **categorical** missing values in a different manner: some imputation techniques might be applicable only for numerical data, whereas some only for categorical data. Let's look at the **first part** of it which handles numerical features:

```
1  class MissingValues:
2      # Function for handling missing values in the data
3      def handle(df, missing_num='auto', missing_categ='auto', _n_neighbors=3):
4          count_missing = df.isna().sum().sum()
5          if count_missing != 0:
6              # drop rows containing only missing values
```

```
                if missing_num == 'auto':
                    missing_num = 'linreg'
                    lr = LinearRegression()
                    df = MissingValues._lin_regression_impute(self, df, lr)
                    missing_num = 'knn'
                    imputer = KNNImputer(n_neighbors=_n_neighbors)
                    df = MissingValues._impute(self, df, imputer, type='num')
                # linear regression imputation
                elif missing_num == 'linreg':
                    lr = LinearRegression()
                    df = MissingValues._lin_regression_impute(self, df, lr)
                # knn imputation
                elif missing_num == 'knn':
                    imputer = KNNImputer(n_neighbors=_n_neighbors)
                    df = MissingValues._impute(self, df, imputer, type='num')
                # mean, median or mode imputation
                elif missing_num in ['mean', 'median', 'most_frequent']:
                    imputer = SimpleImputer(strategy=self.missing_num)
                    df = MissingValues._impute_missing(self, df, imputer, type='num')
                # delete missing values
                elif missing_num == 'delete':
                    df = MissingValues._delete(self, df, type='num')

            if missing_categ:
                ...
        else:
            pass
        return df
```

MissingValues.handle_pt1.py hosted with ❤ by GitHub view raw

View the full source code here

This function checks which handling method has been chosen for numerical and categorical features. The default setting is set to *'auto'* which means that:

- **numerical** missing values will first be imputed through prediction with **Linear Regression**, and the remaining values will be imputed with K-NN
- **categorical** missing values will first be imputed through prediction with **Logistic**

For categorical features, the same principle as above applies, except that we will support only imputation with Logistic Regression, K-NN and mode imputation. When using K-NN, we will first label encode our categorical features to integers, use these labels to predict our missing values, and finally map the labels back to their original values.

Depending on the handling method chosen, the *handle* function calls the required functions from within its class to then manipulate the data with the help of various Sklearn packages: the *_impute* function will be in charge of K-NN, mean, median and mode imputation, *_lin_regression_impute* and *log_regression_impute* will perform imputation through prediction, and I assume that the role of *_delete* is self-explanatory.

Our final *MissingValues* class structure will look as following:




View the full source code here

I will not go more into detail on the code within the remaining functions of the class, but I invite you to check out the full source code in the AutoClean repository.

After we have finished all the required steps, our function then outputs the processed input data.

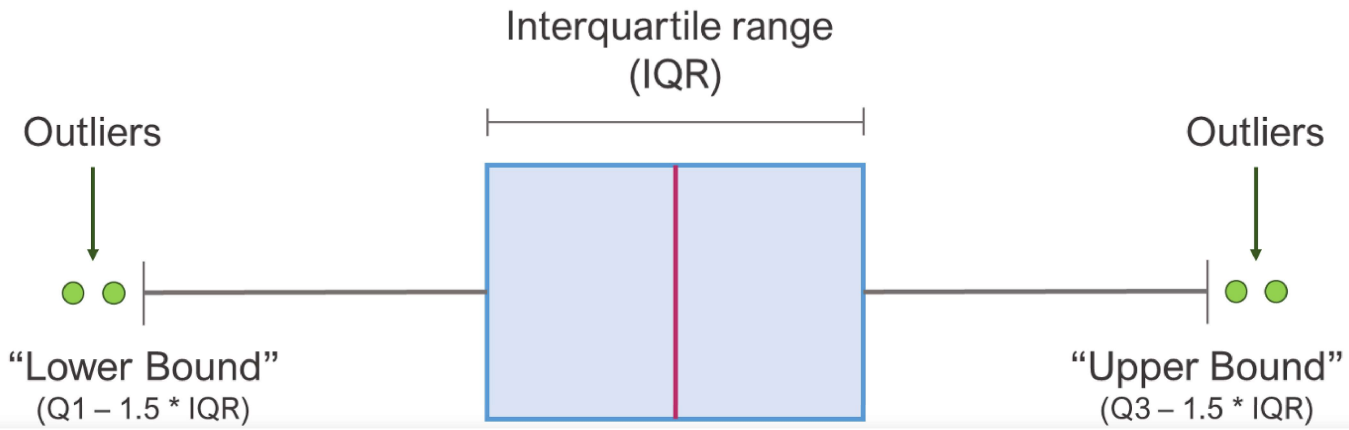
Cool, we made it through the first block of our pipeline 🥕. Now let's think about how we will handle outliers in our data.

[Block 2] Outliers

Our second block will focus on the handling of outliers in our data. First we need to ask ourselves: when do we consider a value to be an outlier? For our pipeline, we will use a commonly applied rule that says that a data point can be considered an outlier if is **outside** the following range:

*[Q1 — 1.5 * IQR ; Q3 + 1.5 * IQR]*

…where Q1 and Q3 are the 1st and the 3rd quartiles and IQR is the interquartile range. Below you can see this nicely visualized with a boxplot:



Now that we have defined what an outlier is, we now have to decide how we handle these. There are again various strategies to do so, and for our use-case we will focus on the following two: winsorization and deletion.

> 💡 *Winsorization is used in statistics to limit extreme values in the data and reduce the effect of outliers by replacing them with a specific percentile of the data.*

When using winsorization, we will again use our above defined range to replace outliers:

- values > upper bound will be replaced by the **upper range value** and
- values < lower bound will be replaced by the **lower range value**.

The final structure of our *Outliers* class will look as following:

View the full source code here

We arrived at the end of the second block — now let's have a look at how we can encode categorical data.

[Block 3] Categorical Encoding

In order to be able to perform computations with categorical data, in most cases we need our data to be of a numeric type i. e. numbers, or integers. Therefore, common techniques consist of **one-hot encoding** data, or **label encoding** data.

> 💡 *One-hot encoding of data represents each unique value of a feature as a binary vector, whereas label encoding assigns a unique integer to each value.*

Fruit	Label
Apple	1
Orange	2
Banana	3
Orange	2

Label Encoding

Fruit	Apple	Orange	Banana
Apple	1	0	0
Orange	0	1	0
Banana	0	0	1
Orange	0	1	0

One-Hot Encoding

Image by author.

There are various **pros and cons** for each of the methods, like f. e. the fact that one-hot encoding produces a lot of additional features. Also, if we label encode, the labels might be interpreted by certain algorithms as mathematically dependent: 1 apple + 1 orange = 1 banana, which is obviously a wrong interpretation of this type of categorical data.

For our pipeline, we will set the default strategy *'auto'* to perform the encoding according to the following rules:

- if the feature contains > 20 unique values, it will **not** be encoded

This is quite a primitive and quick way of handling the encoding process which might come in handy, but might also lead to encodings not fully appropriate for our data. Even though automation is great, we still want to make sure that we can also **define manually** which features should be encoded, and how. This is implemented in the *handle* function of the *EncodeCateg* class:

The *handle* function takes a **list** as input, whereas the features we want to manually encode can be defined by column names or indexes as following:

```
encode_categ = ['onehot', ['column_name', 2]]
```

Now that we've defined how to handle outliers, we can move on to our fourth block, which will cover the extraction of **datetime** features.

[Block 4] Extraction of DateTime features

If our dataset contains a feature that has **datetime** values, like timestamps or dates, we will very likely want to extract these so they become easier to handle when processing or visualizing later on.

We can also do this in an automated fashion: we will let our pipeline search through the features and check whether one of these can be converted into the **datetime** type. If yes, then we can safely assume that this feature holds **datetime** values.

View the full source code here

We can define the granularity at which the **datetime** features are extracted, whereas the default is set to *'s'* for seconds. After the extraction, the function checks whether the entries for dates and times are valid meaning: if the extracted columns *'Day'*, *'Month'* and *'Year'* **all** contain 0's, all three will be deleted. The same happens for *'Hour'*, *'Minute'* and *'Sec'*.

Now that we are done with **datetime** extraction we can move on to the last building block of our pipeline which will consist of some final adjustment to polish our output dataframe.

[Block 5] Dataframe Polishing

Now that we've processed our dataset, we still need to do a few adjustments to make our dataframe 'look good'. What do I mean by that?

Firstly, some features that were originally of type **integer** could have been converted to **floats**, due to imputation techniques or other processing steps that were applied. Before outputting our final dataframe we will **convert these values back to integers**.

Secondly, we want to **round** all the **float** features in our dataset to the **same number of decimals** as they had in our original input dataset. This is to avoid on one hand unnecessary trailing 0's in the float decimals, and on the other hand make sure not to round our values more than our original values.




3 | Putting it all Together

First of all, congrats for sticking with me this far!

We've now arrived at the part where we want to put all of our building blocks together so we can actually start using our pipeline. Instead of posting the full code here, you will find the full **AutoClean** code in my **GitHub repository**:

GitHub - elisemercury/AutoClean: Package for automated data cleaning in Python.

AutoClean automates the preprocessing & cleaning for your next Data Science project in Python.

github.com

Let's look at a visual example of how AutoClean processes the sample dataset below:

	int	float	str_cat_1	str_cat_2	str_num	datetime
0	1.0	NaN	a	a	5	10-10-2020
1	NaN	500.57	b	b	5	11-10-2020
2	3.0	100.00	NaN	c	7	NaN
3	100.0	3.20	a	d	NaN	12-10-2020
4	7.0	5.70	b	e	5	10-10-2020
5	1.0	34.20	c	f	5	10-10-2020
6	3.0	3.10	c	g	NaN	17-12-2020
7	2.0	500.00	b	h	7	NaN
8	10.0	80.50	a	i	5	13-10-2020
9	1.0	NaN	b	j	5	11-10-2020
10	12.0	2.73	c	k	7	12-10-2020

Sample dataset. Image by author.

I generated a random dataset, and as you can see, I made it fairly varying when it comes to the different data types and I added a few random NaN values in the dataset.

The resulting cleaned output dataframe looks as below:

	int	float	str_cat_1	str_cat_2	str_num	datetime	Day	Month	Year	str_num_5	str_num_7	str_cat_2_lab	str_cat_1_a	str_cat_1_b	str_cat_1_c
0	1	173.31	a	a	5	2020-10-10	10	10	2020	1	0	0	1	0	0
1	0	334.97	b	b	5	2020-11-10	10	11	2020	1	0	1	0	1	0
2	3	100.00	b	c	7	2020-11-10	10	11	2020	0	1	2	0	1	0
3	19	3.20	a	d	7	2020-12-10	10	12	2020	0	1	3	1	0	0
4	7	5.70	b	e	5	2020-10-10	10	10	2020	1	0	4	0	1	0
5	1	34.20	c	f	5	2020-10-10	10	10	2020	1	0	5	0	0	1

Processed sample dataset. Image by author.

In the image above you will see visualized which changes AutoClean made to our data. The imputed missing values are marked in **yellow**, the outliers in **green**, the extracted datetime values in **blue** and the categorical encodings in **orange**.

I hope this article was informative for you and that AutoClean will help you save some valuable minutes of your time. 🚀

Feel free to leave comment if you have any questions or feedback. Contributions on GitHub are also welcome!

References:

[1] N. Tamboli, All You Need To Know About Different Types Of Missing Data Values And How To Handle It (2021)

[2] C. Tylor, What Is the Interquartile Range Rule? (2018)

[3] J. Brownlee, Ordinal and One-Hot Encodings for Categorical Data (2020)