Understanding Feature Engineering (Part 1) — Continuous Numeric Data

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Strategies for working with continuous, numerical data

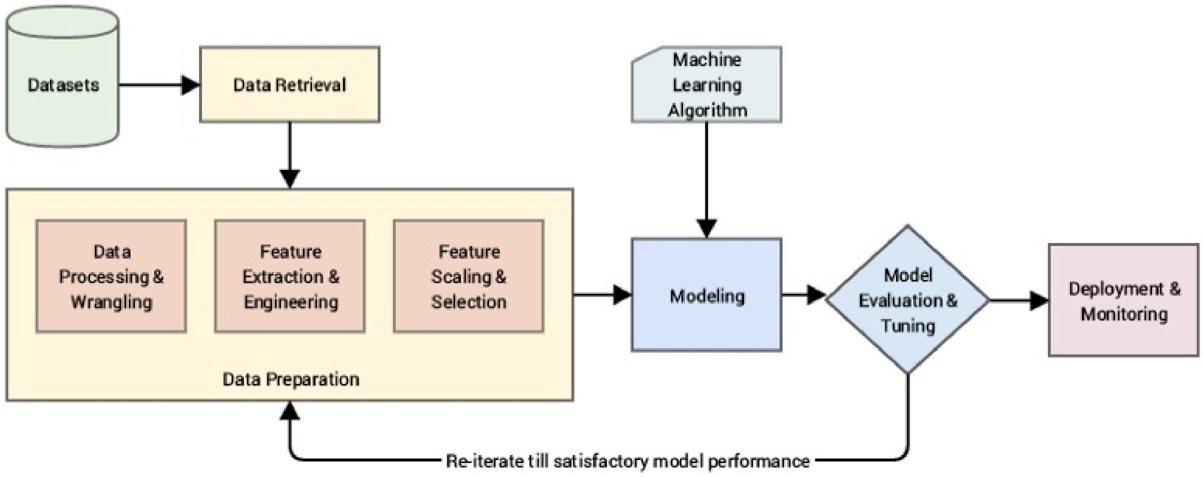
Source: https://pixabay.com

Introduction

> **"Money makes the world go round"** is something which you cannot ignore whether to choose to agree or disagree with it. A more apt saying in today's digital revolutionary age would be **"Data makes the world go round"**. Indeed data has become a first class asset for businesses, corporations and organizations irrespective of their size and scale. Any intelligent system regardless of their complexity needs to be powered by data. At the heart of any intelligent system, we have one or more algorithms based on machine learning, deep learning or statistical methods which consume this data to gather knowledge and provide intelligent insights over a period of time. Algorithms are pretty naive by themselves and cannot work out of the box on raw data. Hence the need for engineering meaningful features from raw data is of utmost importance which can be understood and consumed by these algorithms.

A gentle refresher of the machine learning pipeline

Any intelligent system basically consists of an end-to-end pipeline starting from ingesting raw data, leveraging data processing techniques to wrangle, process and engineer meaningful features and attributes from this data. Then we usually leverage techniques like statistical models or machine learning models to model on these features and then deploy this model if necessary for future usage based on the problem to be solved at hand. A typical standard machine learning pipeline based on the CRISP-DM industry standard process model is depicted below.



A standard machine learning pipeline (source: Practical Machine Learning with Python, Apress/Springer)

Ingesting raw data and building models on top of this data directly would be foolhardy since we wouldn't get desired results or performance and also algorithms are not intelligent enough to automatically extract meaningful features from raw data (there are automated feature extraction techniques which are enabled nowadays with deep learning methodologies to some extent, but more on that later!).

Our main area of focus falls under the data preparation aspect as pointed out in the figure above, where we deal with various methodologies to extract meaningful attributes or features from the raw data after it has gone through necessary wrangling and pre-processing.

Motivation

Feature engineering is an essential part of building any intelligent system. Even though you have a lot of newer methodologies coming in like deep learning and meta-heuristics which aid in automated machine learning, each problem is domain specific and better features (suited to the problem) is often the deciding factor of the performance of your system. Feature Engineering is an art as well as a science and this is the reason Data Scientists often spend 70% of their time in the data preparation phase before modeling. Let's look at a few quotes relevant to feature engineering from several renowned people in the world of Data Science.

> "Coming up with features is difficult, time-consuming, requires expert knowledge. 'Applied machine learning' is basically feature engineering."

> — Prof. Andrew Ng.

This basically reinforces what we mentioned earlier about data scientists spending close to 80% of their time in engineering features which is a difficult and time-consuming process, requiring both domain knowledge and mathematical computations.

> "Feature engineering is the process of transforming **raw data** into **features** that better represent **the underlying problem** to **the predictive models**, resulting in improved **model accuracy** on **unseen data**."

> — Dr. Jason Brownlee

This gives us an idea about feature engineering being the process of transforming data into features to act as inputs for machine learning models such that *good quality features* help in *improving* the overall *model performance*. Features are also very much dependent on the underlying problem. Thus, even though the machine learning task might be same in different scenarios, like classification of emails into spam and non-spam or classifying handwritten digits, the features extracted in each scenario will be very different from the other.

Prof. Pedro Domingos from the University of Washington, in his paper titled, *"A Few Useful Things to Know about Machine Learning"* tells us the following.

> "At the end of the day, some machine learning projects succeed and some fail. What makes the difference? Easily the most important factor is the features used."

> — Prof. Pedro Domingos

The final quote which should motivate you about feature engineering is from renowned Kaggler, Xavier Conort. Most of you already know that tough real-world machine learning problems are often posted on Kaggle regularly which is usually open to everyone.

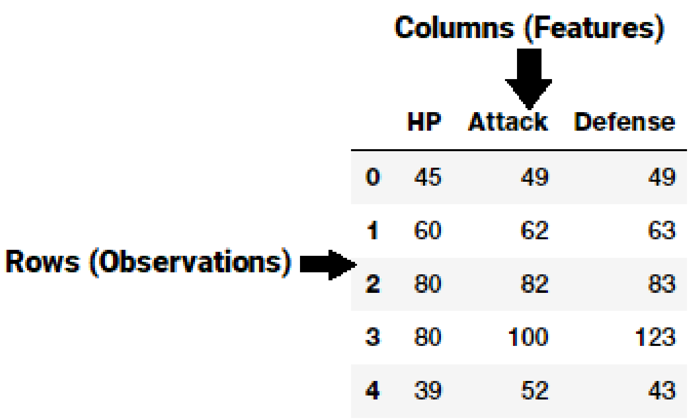
> "The algorithms we used are very standard for Kagglers. …We spent most of our efforts in feature engineering. … We were also very careful to discard features likely to expose us to the risk of over-fitting our model."

> — Xavier Conort

Understanding Features

A ***feature*** is typically a specific representation on top of ***raw data***, which is an individual, measurable attribute, typically depicted by a column in a dataset. Considering a generic two-dimensional dataset, each *observation* is depicted by a *row* and each *feature* by a *column*, which will have a specific value for an observation.

A generic dataset snapshot



	HP	Attack	Defense
0	45	49	49
1	60	62	63
2	80	82	83
3	80	100	123
4	39	52	43

Thus like in the example in the figure above, each row typically indicates a feature vector and the entire set of features across all the observations forms a two-dimensional feature matrix also known as a feature-set. This is akin to data frames or spreadsheets representing two-dimensional data. Typically machine learning algorithms work with these numeric matrices or tensors and hence most feature engineering techniques deal with converting raw data into some numeric representations which can be easily understood by these algorithms.

Features can be of two major types based on the dataset. Inherent ***raw features*** are obtained directly from the dataset with no extra data manipulation or engineering. ***Derived features*** are usually obtained from feature engineering, where we extract features from existing data attributes. A simple example would be creating a new feature *"Age"* from an employee dataset containing *"Birthdate"* by just subtracting their birth date from the current date.

There are diverse types and formats of data including structured and unstructured data. In this article, we will discuss various feature engineering strategies for dealing with structured continuous numeric data. All these examples are a part of one of my recent books *'Practical Machine Learning with Python'* and you can access relevant datasets and code used in this article on **GitHub.** A big shout out also goes to Gabriel Moreira who helped me by providing some excellent pointers on feature engineering techniques.

Feature Engineering on Numeric Data

Numeric data typically represents data in the form of scalar values depicting observations, recordings or measurements. Here, by numeric data, we mean ***continuous data*** and not discrete data which is typically represented as categorical data. Numeric data can also be represented as a vector of values where each value or entity in the vector can represent a specific feature. Integers and floats are the most common and widely used numeric data types for continuous numeric data. Even though numeric data can be directly fed into machine learning models, you would still need to engineer features which are relevant to the scenario, problem and domain before building a model. Hence the need for feature engineering still remains. Let's leverage python and look at some strategies for feature engineering on numeric data. We load up the following necessary dependencies first (typically in a Jupyter notebook).

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import scipy.stats as spstats

%matplotlib inline
```

Raw Measures

Like we mentioned earlier, raw numeric data can often be fed directly to machine learning models based on the context and data format. Raw measures are typically indicated using numeric variables directly as features without any form of transformation or engineering. Typically these features can indicate values or counts. Let's load up one of our datasets, the ***Pokémon dataset*** also available on Kaggle.

```
poke_df = pd.read_csv('datasets/Pokemon.csv', encoding='utf-8') poke_df.head()
```

	#	Name	Type 1	Type 2	Total	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation	Legendary
0	1	Bulbasaur	Grass	Poison	318	45	49	49	65	65	45	Gen 1	False
1	2	Ivysaur	Grass	Poison	405	60	62	63	80	80	60	Gen 1	False
2	3	Venusaur	Grass	Poison	525	80	82	83	100	100	80	Gen 1	False
3	3	VenusaurMega Venusaur	Grass	Poison	625	80	100	123	122	120	80	Gen 1	False
4	4	Charmander	Fire	NaN	309	39	52	43	60	50	65	Gen 1	False

Snapshot of our Pokemon dataset

Pokémon is a huge media franchise surrounding fictional characters called Pokémon which stands for pocket monsters. In short, you can think of them as fictional animals with superpowers! This dataset consists of these characters with various statistics for each character.

Values

If you closely observe the data frame snapshot in the above figure, you can see that several attributes represent numeric raw values which can be used directly. The following snippet depicts some of these features with more emphasis.

```
poke_df[['HP', 'Attack', 'Defense']].head()
```

Features with (continuous) numeric data

	HP	Attack	Defense
0	45	49	49
1	60	62	63
2	80	82	83
3	80	100	123
4	39	52	43

Thus, you can directly use these attributes as features which are depicted in the above data frame. These include each Pokémon's HP (Hit Points), Attack and Defense stats. In fact, we can also compute some basic statistical measures on these fields.

```
poke_df[['HP', 'Attack', 'Defense']].describe()
```

Basic descriptive statistics on numeric features

	HP	Attack	Defense
count	800.000000	800.000000	800.000000
mean	69.258750	79.001250	73.842500
std	25.534669	32.457366	31.183501
min	1.000000	5.000000	5.000000
25%	50.000000	55.000000	50.000000
50%	65.000000	75.000000	70.000000
75%	80.000000	100.000000	90.000000
max	255.000000	190.000000	230.000000

With this you can get a good idea about statistical measures in these features like count, average, standard deviation and quartiles.

Counts

Another form of raw measures include features which represent frequencies, counts or occurrences of specific attributes. Let's look at a sample of data from the ***millionsong dataset*** which depicts counts or frequencies of songs which have been heard by various users.

```
popsong_df = pd.read_csv('datasets/song_views.csv',
                          encoding='utf-8')
popsong_df.head(10)
```

	user_id	song_id	title	listen_count
0	b6b799f34a204bd928ea014c243ddad6d0be4f8f	SOBONKR12A58A7A7E0	You're The One	2
1	b41ead730ac14f6b6717b9cf8859d5579f3f8d4d	SOBONKR12A58A7A7E0	You're The One	0
2	4c84359a164b161496d05282707cecbd50adbfc4	SOBONKR12A58A7A7E0	You're The One	0
3	779b5908593756abb6ff7586177c966022668b06	SOBONKR12A58A7A7E0	You're The One	0
4	dd88ea94f605a63d9fc37a214127e3f00e85e42d	SOBONKR12A58A7A7E0	You're The One	0
5	68f0359a2f1cedb0d15c98d88017281db79f9bc6	SOBONKR12A58A7A7E0	You're The One	0
6	116a4c95d63623a967edf2f3456c90ebbf964e6f	SOBONKR12A58A7A7E0	You're The One	17
7	45544491ccfcdc0b0803c34f201a6287ed4e30f8	SOBONKR12A58A7A7E0	You're The One	0
8	e701a24d9b6c59f5ac37ab28462ca82470e27cfb	SOBONKR12A58A7A7E0	You're The One	68
9	edc8b7b1fd592a3b69c3d823a742e1a064abec95	SOBONKR12A58A7A7E0	You're The One	0

Song listen counts as a numeric feature

It is quite evident from the above snapshot that the `listen_count` field can be used directly as a frequency\count based numeric feature.

Binarization

Often raw frequencies or counts may not be relevant for building a model based on the problem which is being solved. For instance if I'm building a recommendation system for song recommendations, I would just want to know if a person is interested or has listened to a particular song. This doesn't require the number of times a song has been listened to since I am more concerned about the various songs he\she has listened to. In this case, a binary feature is preferred as opposed to a count based feature. We can binarize our `listen_count` field as follows.

```
watched = np.array(popsong_df['listen_count'])
watched[watched >= 1] = 1
popsong_df['watched'] = watched
```

You can also use `scikit-learn's` `Binarizer` class here from its `preprocessing` module to perform the same task instead of `numpy` arrays.

```
from sklearn.preprocessing import Binarizer

bn = Binarizer(threshold=0.9)
pd_watched = bn.transform([popsong_df['listen_count']])[0]
popsong_df['pd_watched'] = pd_watched
popsong_df.head(11)
```

	user_id	song_id	title	listen_count	watched	pd_watched
0	b6b799f34a204bd928ea014c243ddad6d0be4f8f	SOBONKR12A58A7A7E0	You're The One	2	1	1
1	b41ead730ac14f6b6717b9cf8859d5579f3f8d4d	SOBONKR12A58A7A7E0	You're The One	0	0	0
2	4c84359a164b161496d05282707cecbd50adbfc4	SOBONKR12A58A7A7E0	You're The One	0	0	0
3	779b5908593756abb6ff7586177c966022668b06	SOBONKR12A58A7A7E0	You're The One	0	0	0
4	dd88ea94f605a63d9fc37a214127e3f00e85e42d	SOBONKR12A58A7A7E0	You're The One	0	0	0
5	68f0359a2f1cedb0d15c98d88017281db79f9bc6	SOBONKR12A58A7A7E0	You're The One	0	0	0
6	116a4c95d63623a967edf2f3456c90ebbf964e6f	SOBONKR12A58A7A7E0	You're The One	17	1	1
7	45544491ccfcdc0b0803c34f201a6287ed4e30f8	SOBONKR12A58A7A7E0	You're The One	0	0	0
8	e701a24d9b6c59f5ac37ab28462ca82470e27cfb	SOBONKR12A58A7A7E0	You're The One	68	1	1
9	edc8b7b1fd592a3b69c3d823a742e1a064abec95	SOBONKR12A58A7A7E0	You're The One	0	0	0
10	fb41d1c374d093ab643ef3bcd70eeb258d479076	SOBONKR12A58A7A7E0	You're The One	1	1	1

Binarizing song counts

You can clearly see from the above snapshot that both the methods have produced the same result. Thus we get a binarized feature indicating if the song was listened to or not by each user which can be then further used in a relevant model.

Rounding

Often when dealing with continuous numeric attributes like proportions or percentages, we may not need the raw values having a high amount of precision. Hence it often makes sense to round off these high precision percentages into numeric integers. These integers can then be directly used as raw values or even as categorical (discrete-class based) features. Let’s try applying this concept in a dummy dataset depicting store items and their popularity percentages.

```
items_popularity = pd.read_csv('datasets/item_popularity.csv',
                               encoding='utf-8')

items_popularity['popularity_scale_10'] = np.array(
                   np.round((items_popularity['pop_percent'] * 10)),
                   dtype='int')
items_popularity['popularity_scale_100'] = np.array(
                  np.round((items_popularity['pop_percent'] * 100)),
                  dtype='int')
items_popularity
```

	item_id	pop_percent	popularity_scale_10	popularity_scale_100
0	it_01345	0.98324	10	98
1	it_03431	0.56123	6	56
2	it_04572	0.12098	1	12
3	it_98021	0.35476	4	35
4	it_01298	0.92101	9	92
5	it_90120	0.81212	8	81
6	it_10123	0.56502	6	57

Rounding popularity to different scales

Based on the above ouputs, you can guess that we tried two forms of rounding. The features depict the item popularities now both on a scale of **1–10** and on a scale of **1–100**. You can use these values both as numerical or categorical features based on the scenario and problem.

Interactions

Supervised machine learning models usually try to model the output responses (discrete classes or continuous values) as a function of the input feature variables. For example, a simple linear regression equation can be depicted as

$$y = c_1x_1 + c_2x_2 + \cdots + c_nx_n$$

where the input features are depicted by variables

$\{x_1, x_2, \ldots, x_n\}$

having weights or coefficients denoted by

$\{c_1, c_2, \ldots, c_n\}$

respectively and the goal is to predict the response ***y*.**

In this case, this simple linear model depicts the relationship between the output and inputs, purely based on the individual, separate input features.

However, often in several real-world scenarios, it makes sense to also try and capture the interactions between these feature variables as a part of the input feature set. A simple depiction of the extension of the above linear regression formulation with interaction features would be

$$y = c_1x_1 + c_2x_2 + \cdots + c_nx_n + c_{11}x_1^2 + c_{22}x_2^2 + c_{12}x_1x_2 + \cdots$$

where the features represented by

$\{x_1x_2, x_1^2, \ldots\}$

denote the interaction features. Let's try engineering some interaction features on our Pokémon dataset now.

```
atk_def = poke_df[['Attack', 'Defense']]
atk_def.head()
```

	Attack	Defense
0	49	49
1	62	63
2	82	83
3	100	123
4	52	43

From the output data frame, we can see that we have two numeric (continuous) features, `Attack` and `Defence`. We will now build features up to the 2nd degree by leveraging `scikit-learn`.

```
from sklearn.preprocessing import PolynomialFeatures

pf = PolynomialFeatures(degree=2, interaction_only=False,
                        include_bias=False)
res = pf.fit_transform(atk_def)
res

Output
------
```

```
array([[   49.,    49.,  2401.,  2401.,  2401.],
       [   62.,    63.,  3844.,  3906.,  3969.],
       [   82.,    83.,  6724.,  6806.,  6889.],
       ...,
       [  110.,    60., 12100.,  6600.,  3600.],
       [  160.,    60., 25600.,  9600.,  3600.],
       [  110.,   120., 12100., 13200., 14400.]])
```

The above feature matrix depicts a total of five features including the new interaction features. We can see the degree of each feature in the above matrix as follows.

```
pd.DataFrame(pf.powers_, columns=['Attack_degree',
                                  'Defense_degree'])
```

Looking at this output, we now know what each feature actually represents from the degrees depicted here. Armed with this knowledge, we can assign a name to each feature now as follows. This is just for ease of understanding and you should name your features with better, easy to access and simple names.

	Attack_degree	Defense_degree
0	1	0
1	0	1
2	2	0
3	1	1
4	0	2

```
intr_features = pd.DataFrame(res, columns=
['Attack', 'Defense',
                                           'Attack^2',
                                           'Attack x Defense',
                                           'Defense^2'])
intr_features.head(5)
```

	Attack	Defense	Attack^2	Attack x Defense	Defense^2
0	49.0	49.0	2401.0	2401.0	2401.0
1	62.0	63.0	3844.0	3906.0	3969.0
2	82.0	83.0	6724.0	6806.0	6889.0
3	100.0	123.0	10000.0	12300.0	15129.0
4	52.0	43.0	2704.0	2236.0	1849.0

Numeric features with their interactions

Thus the above data frame represents our original features along with their interaction features.

Binning

The problem of working with raw, continuous numeric features is that often the distribution of values in these features will be skewed. This signifies that some values will occur quite frequently while some will be quite rare. Besides this, there is also another problem of the varying range of values in any of these features. For instance view counts of specific music videos could be abnormally large (*Despacito* we're looking at you!) and some could be really small. Directly using these features can cause a lot of issues and adversely affect the model. Hence there are strategies to deal with this, which include binning and transformations.

Binning, also known as quantization is used for transforming continuous numeric features into discrete ones (categories). These discrete values or numbers can be thought of as categories or bins into which the raw, continuous numeric values are binned or grouped into. Each bin represents a specific degree of intensity and hence a specific range of continuous numeric values fall into it. Specific strategies of binning data include fixed-width and adaptive binning. Let's use a subset of data from a dataset extracted from the **2016 FreeCodeCamp Developer\Coder survey** which talks about various attributes pertaining to coders and software developers.

```
fcc_survey_df = pd.read_csv('datasets/fcc_2016_coder_survey_subset.csv',
encoding='utf-8')
```

```
fcc_survey_df[['ID.x', 'EmploymentField', 'Age', 'Income']].head()
```

	ID.x	EmploymentField	Age	Income
0	cef35615d61b202f1dc794ef2746df14	office and administrative support	28.0	32000.0
1	323e5a113644d18185c743c241407754	food and beverage	22.0	15000.0
2	b29a1027e5cd062e654a63764157461d	finance	19.0	48000.0
3	04a11e4bcb573a1261eb0d9948d32637	arts, entertainment, sports, or media	26.0	43000.0
4	9368291c93d5d5f5c8cdb1a575e18bec	education	20.0	6000.0

Sample attributes from the FCC coder survey dataset

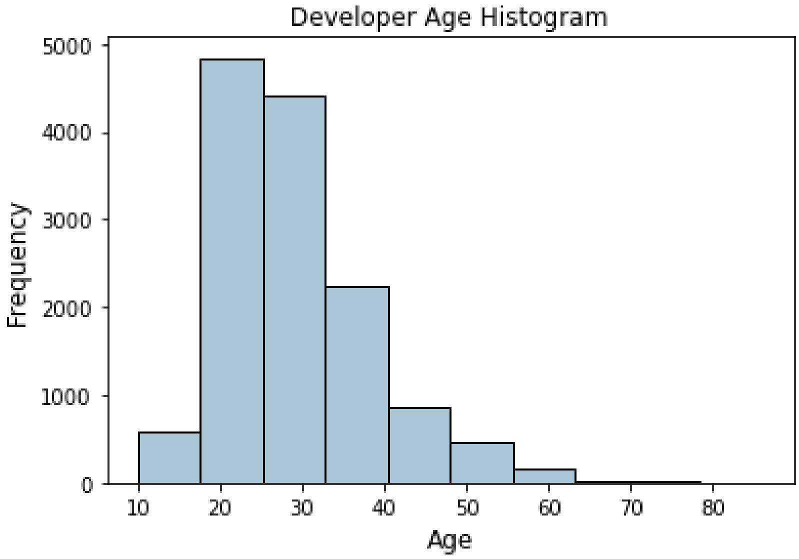
The `ID.x` variable is basically a unique identifier for each coder\developer who took the survey and the other fields are pretty self-explanatory.

Fixed-Width Binning

Just like the name indicates, in fixed-width binning, we have specific fixed widths for each of the bins which are usually pre-defined by the user analyzing the data. Each bin has a pre-fixed range of values which should be assigned to that bin on the basis of some domain knowledge, rules or constraints. Binning based on rounding is one of the ways, where you can use the rounding operation which we discussed earlier to bin raw values.

Let's now consider the `Age` feature from the coder survey dataset and look at its distribution.

```
fig, ax = plt.subplots()
fcc_survey_df['Age'].hist(color='#A9C5D3', edgecolor='black',
                          grid=False)
ax.set_title('Developer Age Histogram', fontsize=12)
ax.set_xlabel('Age', fontsize=12)
ax.set_ylabel('Frequency', fontsize=12)
```



Histogram depicting developer age distribution

The above histogram depicting developer ages is slightly right skewed as expected (lesser aged developers). We will now assign these raw age values into specific bins based on the following scheme

```
Age Range: Bin
---------------
 0 -  9  : 0
10 - 19  : 1
20 - 29  : 2
30 - 39  : 3
40 - 49  : 4
50 - 59  : 5
60 - 69  : 6
  ... and so on
```

We can easily do this using what we learnt in the *Rounding* section earlier where we round off these raw age values by taking the floor value after dividing it by 10.

```
fcc_survey_df['Age_bin_round'] = np.array(np.floor(
                              np.array(fcc_survey_df['Age']) / 10.))

fcc_survey_df[['ID.x', 'Age', 'Age_bin_round']].iloc[1071:1076]
```

	ID.x	Age	Age_bin_round
1071	6a02aa4618c99fdb3e24de522a099431	17.0	1.0
1072	f0e5e47278c5f248fe861c5f7214c07a	38.0	3.0
1073	6e14f6d0779b7e424fa3fdd9e4bd3bf9	21.0	2.0
1074	c2654c07dc929cdf3dad4d1aec4ffbb3	53.0	5.0
1075	f07449fc9339b2e57703ec7886232523	35.0	3.0

Binning by rounding

You can see the corresponding bins for each age have been assigned based on rounding. But what if we need more flexibility? What if we want to decide and fix the bin widths based on our own rules\logic? Binning based on custom ranges will help us achieve this. Let's define some custom age ranges for binning developer ages using the following scheme.

```
Age Range : Bin
---------------
 0 -  15  : 1
16 -  30  : 2
31 -  45  : 3
46 -  60  : 4
61 -  75  : 5
75 - 100  : 6
```

Based on this custom binning scheme, we will now label the bins for each developer age value and we will store both the bin range as well as the corresponding label.

```
bin_ranges = [0, 15, 30, 45, 60, 75, 100]
bin_names = [1, 2, 3, 4, 5, 6]

fcc_survey_df['Age_bin_custom_range'] = pd.cut(
                                           np.array(
                                              fcc_survey_df['Age']),
                                              bins=bin_ranges)
fcc_survey_df['Age_bin_custom_label'] = pd.cut(
                                           np.array(
                                              fcc_survey_df['Age']),
                                              bins=bin_ranges,
                                              labels=bin_names)
# view the binned features
fcc_survey_df[['ID.x', 'Age', 'Age_bin_round',
               'Age_bin_custom_range',
               'Age_bin_custom_label']].iloc[10a71:1076]
```

	ID.x	Age	Age_bin_round	Age_bin_custom_range	Age_bin_custom_label
1071	6a02aa4618c99fdb3e24de522a099431	17.0	1.0	(15, 30]	2
1072	f0e5e47278c5f248fe861c5f7214c07a	38.0	3.0	(30, 45]	3
1073	6e14f6d0779b7e424fa3fdd9e4bd3bf9	21.0	2.0	(15, 30]	2
1074	c2654c07dc929cdf3dad4d1aec4ffbb3	53.0	5.0	(45, 60]	4
1075	f07449fc9339b2e57703ec7886232523	35.0	3.0	(30, 45]	3

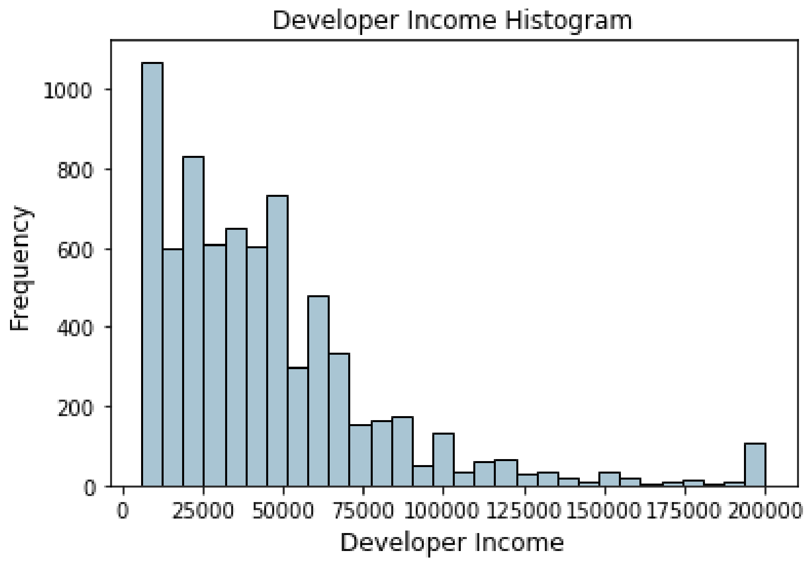
Custom binning scheme for developer ages

Adaptive Binning

The drawback in using fixed-width binning is that due to us manually deciding the bin ranges, we can end up with irregular bins which are not uniform based on the number of data points or values which fall in each bin. Some of the bins might be densely populated and some of them might be sparsely populated or even empty! Adaptive binning is a safer strategy in these scenarios where we let the data speak for itself! That's right, we use the data distribution itself to decide our bin ranges.

Quantile based binning is a good strategy to use for adaptive binning. Quantiles are specific values or cut-points which help in partitioning the continuous valued distribution of a specific numeric field into discrete contiguous bins or intervals. Thus, *q-Quantiles* help in partitioning a numeric attribute into *q* equal partitions. Popular examples of quantiles include the *2-Quantile* known as the *median* which divides the data distribution into two equal bins, *4-Quantiles* known as the *quartiles* which divide the data into 4 equal bins and *10-Quantiles* also known as the *deciles* which create 10 equal width bins. Let’s now look at the data distribution for the developer `Income` field.

```
fig, ax = plt.subplots()
fcc_survey_df['Income'].hist(bins=30, color='#A9C5D3',
                             edgecolor='black', grid=False)
ax.set_title('Developer Income Histogram', fontsize=12)
ax.set_xlabel('Developer Income', fontsize=12)
ax.set_ylabel('Frequency', fontsize=12)
```



Histogram depicting developer income distribution

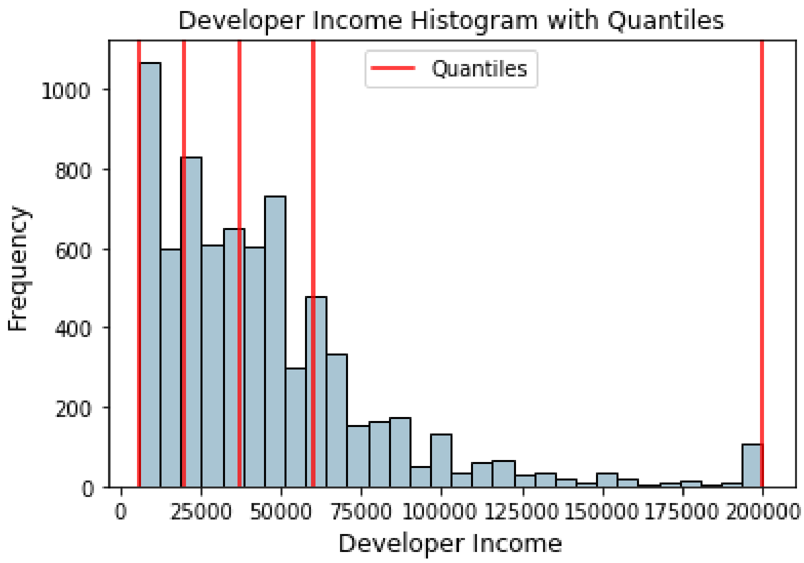
The above distribution depicts a right skew in the income with lesser developers earning more money and vice versa. Let’s take a *4-Quantile* or a *quartile* based adaptive binning scheme. We can obtain the quartiles easily as follows.

```
quantile_list = [0, .25, .5, .75, 1.]
quantiles = fcc_survey_df['Income'].quantile(quantile_list)
quantiles


Output
------
0.00      6000.0
0.25     20000.0
0.50     37000.0
0.75     60000.0
1.00    200000.0
Name: Income, dtype: float64
```

Let’s now visualize these quantiles in the original distribution histogram!

```
fig, ax = plt.subplots()
fcc_survey_df['Income'].hist(bins=30, color='#A9C5D3',
                             edgecolor='black', grid=False)
```

```
for quantile in quantiles:
    qvl = plt.axvline(quantile, color='r')
ax.legend([qvl], ['Quantiles'], fontsize=10)

ax.set_title('Developer Income Histogram with Quantiles',
             fontsize=12)
ax.set_xlabel('Developer Income', fontsize=12)
ax.set_ylabel('Frequency', fontsize=12)
```



Histogram depicting developer income distribution with quartile values

The red lines in the distribution above depict the quartile values and our potential bins. Let's now leverage this knowledge to build our quartile based binning scheme.

```
quantile_labels = ['0-25Q', '25-50Q', '50-75Q', '75-100Q']
fcc_survey_df['Income_quantile_range'] = pd.qcut(
                                            fcc_survey_df['Income'],
                                            q=quantile_list)
fcc_survey_df['Income_quantile_label'] = pd.qcut(
                                            fcc_survey_df['Income'],
                                            q=quantile_list,
                                            labels=quantile_labels)

fcc_survey_df[['ID.x', 'Age', 'Income', 'Income_quantile_range',
               'Income_quantile_label']].iloc[4:9]
```

	ID.x	Age	Income	Income_quantile_range	Income_quantile_label
4	9368291c93d5d5f5c8cdb1a575e18bec	20.0	6000.0	(5999.999, 20000.0]	0-25Q
5	dd0e77eab9270e4b67c19b0d6bbf621b	34.0	40000.0	(37000.0, 60000.0]	50-75Q
6	7599c0aa0419b59fd11ffede98a3665d	23.0	32000.0	(20000.0, 37000.0]	25-50Q
7	6dff182db452487f07a47596f314bddc	35.0	40000.0	(37000.0, 60000.0]	50-75Q
8	9dc233f8ed1c6eb2432672ab4bb39249	33.0	80000.0	(60000.0, 200000.0]	75-100Q

Quantile based bin ranges and labels for developer incomes

This should give you a good idea of how quantile based adaptive binning works. An important point to remember here is that the resultant outcome of binning leads to discrete valued categorical features and you might need an additional step of feature engineering on the categorical data before using it in any model. We will cover feature engineering strategies for categorical data shortly in the next part!

Statistical Transformations

We talked about the adverse effects of skewed data distributions briefly earlier. Let's look at a different strategy of feature engineering now by making use of statistical or mathematical transformations.We will look at the Log transform as well as the Box-Cox transform. Both of these transform functions belong to the Power Transform family of functions, typically used to create monotonic data transformations. Their main significance is that they help in stabilizing variance, adhering closely to the normal distribution and making the data independent of the mean based on its distribution

Log Transform

The log transform belongs to the power transform family of functions. This function can be mathematically represented as

$$y = \log_b(x)$$

which reads as *log* of *x* to the base *b* is equal to *y*. This can then be translated into

$$b^y = x$$

which indicates as to what power must the base *b* be raised to in order to get *x*. The natural logarithm uses *b=e* where *e* = 2.71828 popularly known as Euler's number. You can also use base *b*=10 used popularly in the decimal system.

Log transforms are useful when applied to skewed distributions as they tend to expand the values which fall in the range of lower magnitudes and tend to compress or reduce the values which fall in the range of higher magnitudes. This tends to make the skewed distribution as normal-like as possible. Let's use log transform on our developer `Income` feature which we used earlier.

```
fcc_survey_df['Income_log'] = np.log((1+ fcc_survey_df['Income']))
fcc_survey_df[['ID.x', 'Age', 'Income', 'Income_log']].iloc[4:9]
```

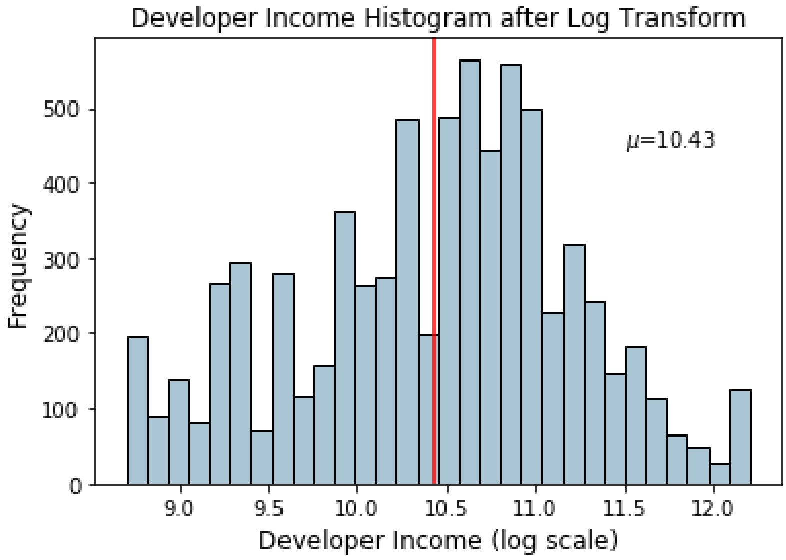
	ID.x	Age	Income	Income_log
4	9368291c93d5d5f5c8cdb1a575e18bec	20.0	6000.0	8.699681
5	dd0e77eab9270e4b67c19b0d6bbf621b	34.0	40000.0	10.596660
6	7599c0aa0419b59fd11ffede98a3665d	23.0	32000.0	10.373522
7	6dff182db452487f07a47596f314bddc	35.0	40000.0	10.596660
8	9dc233f8ed1c6eb2432672ab4bb39249	33.0	80000.0	11.289794

Log transform on developer income

The `Income_log` field depicts the transformed feature after log transformation. Let's look at the data distribution on this transformed field now.

```
income_log_mean = np.round(np.mean(fcc_survey_df['Income_log']), 2)
```

```
fig, ax = plt.subplots()
fcc_survey_df['Income_log'].hist(bins=30, color='#A9C5D3',
                                 edgecolor='black', grid=False)
plt.axvline(income_log_mean, color='r')
ax.set_title('Developer Income Histogram after Log Transform',
             fontsize=12)
ax.set_xlabel('Developer Income (log scale)', fontsize=12)
ax.set_ylabel('Frequency', fontsize=12)
ax.text(11.5, 450, r'$\mu$='+str(income_log_mean), fontsize=10)
```



Histogram depicting developer income distribution after log transform

Based on the above plot, we can clearly see that the distribution is more normal-like or gaussian as compared to the skewed distribution on the original data.

Box-Cox Transform

The Box-Cox transform is another popular function belonging to the power transform family of functions. This function has a pre-requisite that the numeric values to be transformed must be positive (similar to what *log* transform expects). In case they are negative, shifting using a constant value helps. Mathematically, the Box-Cox transform function can be denoted as follows.

$$y = f(x, \lambda) = x^{\lambda} = \left\{ \begin{array}{ll} \frac{x^{\lambda} - 1}{\lambda} & for\ \lambda > 0 \\ \log_e(x) & for\ \lambda = 0 \end{array} \right\}$$

Such that the resulted transformed output *y* is a function of input *x* and the transformation parameter λ such that when λ = 0, the resultant transform is the natural *log* transform which we discussed earlier.
The optimal value of λ is usually determined using a maximum likelihood or log-likelihood estimation. Let's now apply the Box-Cox transform on our developer income feature. First we get the optimal lambda value from the data distribution by removing the non-null values as follows.

```
income = np.array(fcc_survey_df['Income'])
income_clean = income[~np.isnan(income)]
l, opt_lambda = spstats.boxcox(income_clean)
print('Optimal lambda value:', opt_lambda)
```

```
Output
------
Optimal lambda value: 0.117991239456
```

Now that we have obtained the optimal λ value, let us use the Box-Cox transform for two values of λ such that λ = 0 and λ = λ(optimal) and transform the developer `Income` feature.

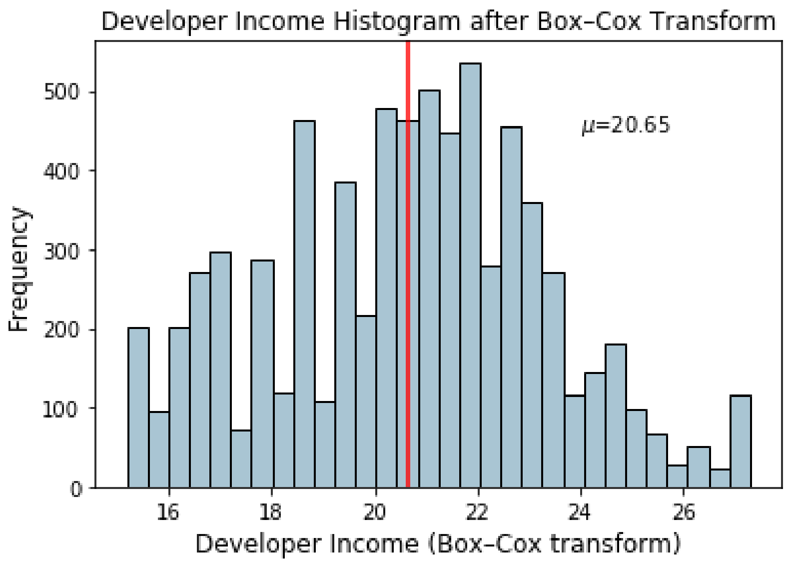
```
fcc_survey_df['Income_boxcox_lambda_0'] = spstats.boxcox(
                                        (1+fcc_survey_df['Income']),
                                          lmbda=0)
fcc_survey_df['Income_boxcox_lambda_opt'] = spstats.boxcox(
                                            fcc_survey_df['Income'],
                                              lmbda=opt_lambda)

fcc_survey_df[['ID.x', 'Age', 'Income', 'Income_log',
               'Income_boxcox_lambda_0',
               'Income_boxcox_lambda_opt']].iloc[4:9]
```

	ID.x	Age	Income	Income_log	Income_boxcox_lambda_0	Income_boxcox_lambda_opt
4	9368291c93d5d5f5c8cdb1a575e18bec	20.0	6000.0	8.699681	8.699681	15.181133
5	dd0e77eab9270e4b67c19b0d6bbf621b	34.0	40000.0	10.596660	10.596660	21.115429
6	7599c0aa0419b59fd11ffede98a3665d	23.0	32000.0	10.373522	10.373522	20.346526
7	6dff182db452487f07a47596f314bddc	35.0	40000.0	10.596660	10.596660	21.115429
8	9dc233f8ed1c6eb2432672ab4bb39249	33.0	80000.0	11.289794	11.289794	23.637178

Developer income distribution after Box-Cox transform

The transformed features are depicted in the above data frame. Just like we expected, `Income_log` and `Income_boxcox_lamba_0` have the same values. Let's look at the distribution of the transformed `Income` feature after transforming with the optimal λ.

```
income_boxcox_mean = np.round(
                      np.mean(
                       fcc_survey_df['Income_boxcox_lambda_opt']),2)

fig, ax = plt.subplots()
fcc_survey_df['Income_boxcox_lambda_opt'].hist(bins=30,
                     color='#A9C5D3', edgecolor='black', grid=False)
plt.axvline(income_boxcox_mean, color='r')
ax.set_title('Developer Income Histogram after Box-Cox Transform',
             fontsize=12)
ax.set_xlabel('Developer Income (Box-Cox transform)', fontsize=12)
ax.set_ylabel('Frequency', fontsize=12)
ax.text(24, 450, r'$\mu$='+str(income_boxcox_mean), fontsize=10)
```



Histogram depicting developer income distribution after Box-Cox transform

The distribution looks more normal-like similar to what we obtained after the *log* transform.

Conclusion

Feature engineering is a very important aspect of machine learning and data science and should never be ignored. While we have automated feature engineering methodologies like deep learning as well as automated machine learning frameworks like AutoML (which still stresses that it requires good features to work well!). Feature engineering is here to stay and even some of these automated methodologies often require specific engineered features based on the data type, domain and the problem to be solved.

We looked at popular strategies for feature engineering on continuous numeric data in this article. In the next part, we will look at popular strategies for dealing with discrete, categorical data and then move on to unstructured data types in future articles. Stay tuned!

All the code and datasets used in this article can be accessed from my **GitHub**

The code is also available as a **Jupyter notebook**