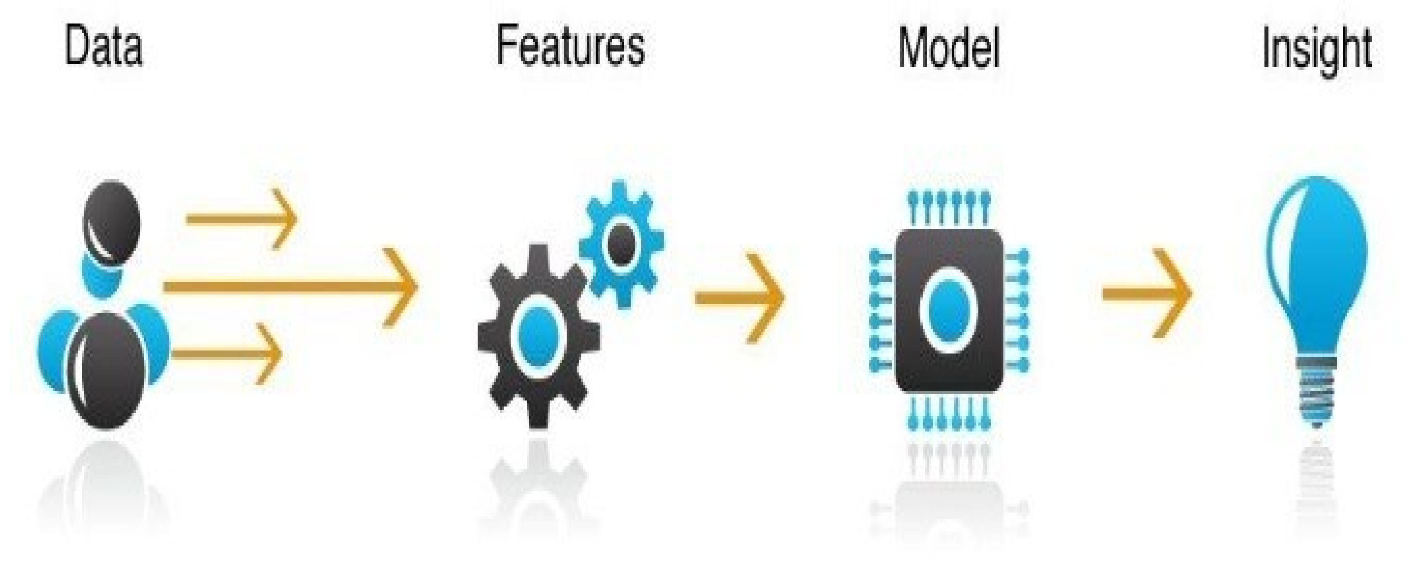


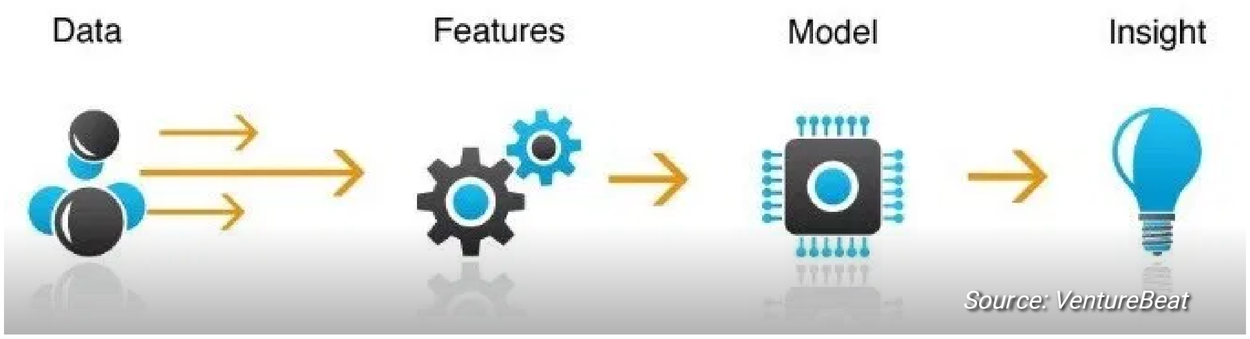
A Hands-On Guide to Automated Feature Engineering using Featuretools in Python

PRATEEK JOSHI

Introduction

Anyone who has participated in machine learning hackathons and competitions can attest to how crucial feature engineering can be. It is often the difference between getting into the top 10 of the leaderboard and finishing outside the top 50!

I have been a huge advocate of feature engineering ever since I realized it's immense potential. But it can be a slow and arduous process when done manually. I have to spend time brainstorming over what features to come up, and analyze their usability them from different angles. Now, this entire FE process can be automated and I'm going to show you how in this article.



We will be using the Python feature engineering library called Featuretools to do this. But before we get into that, we will first look at the basic building blocks of FE, understand them with intuitive examples, and then finally dive into the awesome world of automated feature engineering using the BigMart Sales dataset.

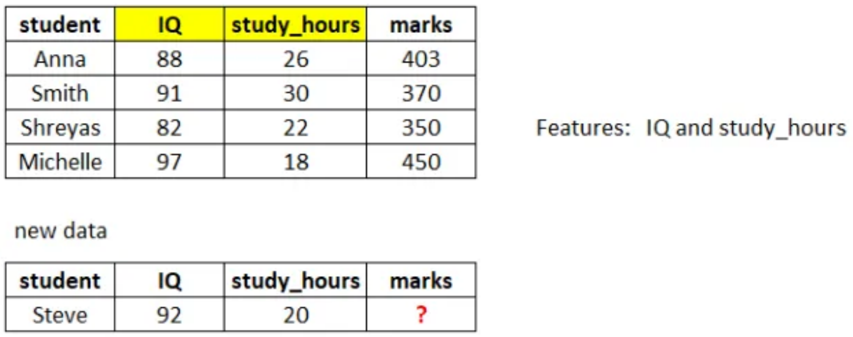
Table of Contents

1. What is a feature?

In the context of machine learning, a feature can be described as a characteristic, or a set of characteristics, that explains the occurrence of a phenomenon. When these characteristics are converted into some measurable form, they are called features.

For example, assume you have a list of students. This list contains the name of each student, number of hours they studied, their IQ, and their total marks in the previous examinations. Now you are given information about a new student— the number of hours he/she studied and his IQ, but his/her marks are missing. You have to estimate his/her probable marks.

Here, you'd use IQ and study_hours to build a predictive model to estimate these missing marks. So, IQ and study_hours are called the features for this model.



student	IQ	study_hours	marks
Anna	88	26	403
Smith	91	30	370
Shreyas	82	22	350
Michelle	97	18	450

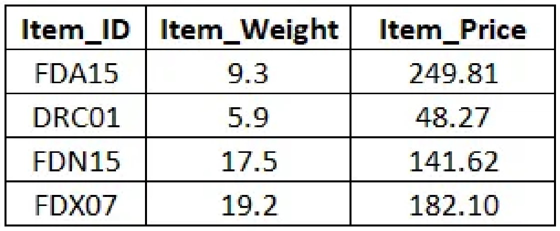
Features: IQ and study_hours

new data

student	IQ	study_hours	marks
Steve	92	20	?

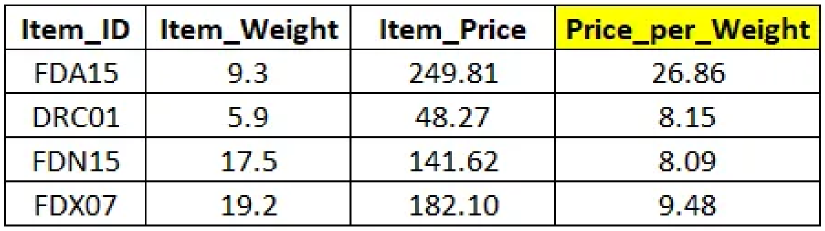
2. What is Feature Engineering?

Feature Engineering can simply be defined as the process of creating new features from the existing features in a dataset. Let's consider a sample data that has details about a few items, such as their weight and price.



Item_ID	Item_Weight	Item_Price
FDA15	9.3	249.81
DRC01	5.9	48.27
FDN15	17.5	141.62
FDX07	19.2	182.10

Now, to create a new feature we can use Item_Weight and Item_Price. So, let's create a feature called Price_per_Weight. It is nothing but the price of the item divided by the weight of the item. This process is called feature engineering.



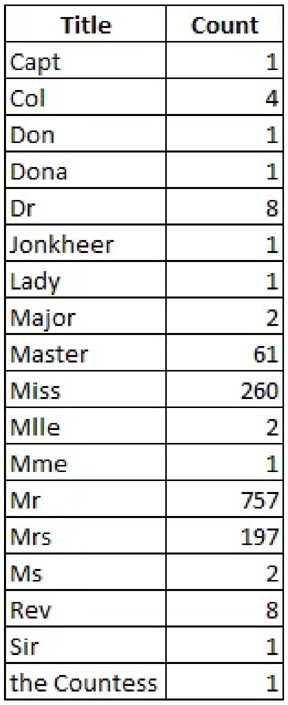
Item_ID	Item_Weight	Item_Price	Price_per_Weight
FDA15	9.3	249.81	26.86
DRC01	5.9	48.27	8.15
FDN15	17.5	141.62	8.09
FDX07	19.2	182.10	9.48

This was just a simple example to create a new feature from existing ones, but in practice, when we have quite a lot of features, feature engineering can become quite complex and cumbersome.

Let's take another example. In the popular Titanic dataset, there is a passenger name feature and below are some of the names in the dataset:

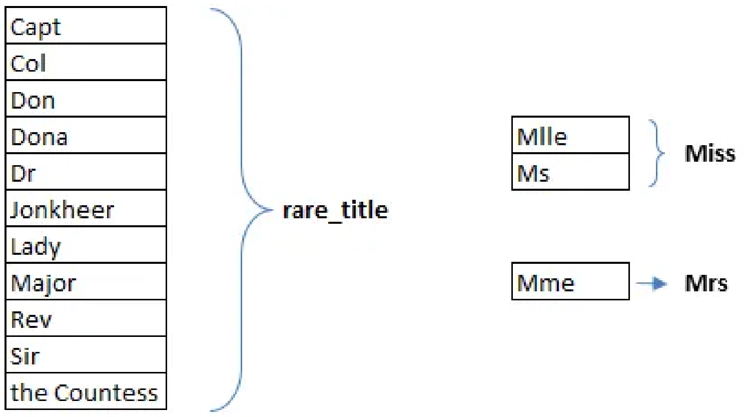
- Montvila, Rev. Juozas
- Graham, Miss. Margaret Edith
- Johnston, Miss. Catherine Helen "Carrie"
- Behr, Mr. Karl Howell
- Dooley, Mr. Patrick

These names can actually be broken down into additional meaningful features. For example, we can extract and group similar titles into single categories. Let's have a look at the unique number of titles in the passenger names.

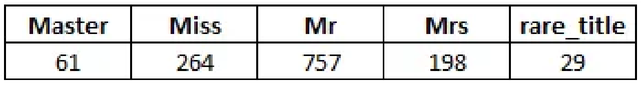


Title	Count
Capt	1
Col	4
Don	1
Dona	1
Dr	8
Jonkheer	1
Lady	1
Major	2
Master	61
Miss	260
Mlle	2
Mme	1
Mr	757
Mrs	197
Ms	2
Rev	8
Sir	1
the Countess	1

It turns out that titles like 'Dona', 'Lady', 'the Countess', 'Capt', 'Col', 'Don', 'Dr', 'Major', 'Rev', 'Sir', and 'Jonkheer' are quite rare and can be put under a single label. Let's call it *rare_title*. Apart from this, the titles 'Mlle' and 'Ms' can be placed under 'Miss', and 'Mme' can be replaced with 'Mrs'.



Hence, the new title feature would have only 5 unique values as shown below:



Master	Miss	Mr	Mrs	rare_title
61	264	757	198	29

So, this is how we can extract useful information with the help of feature engineering, even from features like passenger names which initially seemed fairly pointless.

3. Why is Feature Engineering required?

The performance of a predictive model is heavily dependent on the quality of the features in the dataset used to train that model. If you are able to create new features which help in providing more information to the model about the target variable, it's performance will go up. Hence, when we don't have enough quality features in our dataset, we have to lean on feature engineering.

In one of the most popular Kaggle competitions, Bike Sharing Demand Prediction, the participants are asked to forecast the rental demand in Washington, D.C based on historical usage patterns in relation with weather, time and other data.

As explained in this article, smart feature engineering was instrumental in securing a place in the top 5 percentile of the leaderboard. Some of the features created are given below:

1. **Hour Bins**: A new feature was created by binning the *hour* feature with the help of a decision tree
2. **Temp Bins**: Similarly, a binned feature for the temperature variable
3. **Year Bins**: 8 quarterly bins were created for a period of 2 years
4. **Day Type**: Days were categorized as "weekday", "weekend" or "holiday"

Creating such features is no cakewalk – it takes a great deal of brainstorming and extensive data exploration. Not everyone is good at feature engineering because it is not something that you can learn by reading books or watching videos. This is why feature engineering is also called an art. If you are good at it, then you have a major edge over the competition. Quite like Roger Federer, the master of feature engineering when it comes to Tennis shots.

4. Automating Feature Engineering

Analyze the two images shown above. The left one shows a car being assembled by a group of men during early 20th century, and the right picture shows robots doing the same job in today's world. Automating any process has the potential to make it much more efficient and cost-effective. For similar reasons, feature engineering can, and has been, automated in machine learning.

Building machine learning models can often be a painstaking and tedious process. It involves many steps so if we are able to automate a certain percentage of feature engineering tasks, then the data scientists or the domain experts can focus on other aspects of the model. Sounds too good to be true, right?

Now that we have understood that automating feature engineering is the need of the hour, the next question to ask is – how is it going to happen? Well, we have a great tool to address this issue and it's called Featuretools.

5. Introduction to Featuretools

Featuretools is an open source library for performing automated feature engineering. It is a great tool designed to fast-forward the feature generation process, thereby giving more time to focus on other aspects of machine learning model building. In other words, it makes your data "machine learning ready".

Before taking Featuretools for a spin, there are three major components of the package that we should be aware of:

- Entities
- Deep Feature Synthesis (DFS)
- Feature primitives

a) An **Entity** can be considered as a representation of a Pandas DataFrame. A collection of multiple entities is called an **Entityset**.

b) **Deep Feature Synthesis** (DFS) has got nothing to do with deep learning. Don't worry. DFS is actually a Feature Engineering method and is the backbone of Featuretools. It enables the creation of new features from single, as well as multiple dataframes.

c) DFS create features by applying **Feature primitives** to the Entity-relationships in an EntitySet. These primitives are the often-used methods to generate features manually. For example, the primitive "mean" would find the mean of a variable at an aggregated level.

The best way to understand and become comfortable with Featuretools is by applying it on a dataset. So, we will use the dataset from our BigMart Sales practice problem in the next section to solidify our concepts.

6. Implementation of Featuretools

The objective of the BigMart Sales challenge is to build a predictive model to estimate the sales of each product at a particular store. This would help the decision makers at BigMart to find out the properties of any product or store, which play a key role in increasing the overall sales. Note that there are 1559 products across 10 stores in the given dataset.

The below table shows the features provided in our data:

Variable	Description
Item_Identifier	Unique product ID

Item_Weight	Weight of product
Item_Fat_Content	Whether the product is low fat or not
Item_Visibility	The % of total display area of all products in a store allocated to the particular product
Item_Type	The category to which the product belongs
Item_MRP	Maximum Retail Price (list price) of the product
Outlet_Identifier	Unique store ID
Outlet_Establishment_Year	The year in which store was established
Outlet_Size	The size of the store in terms of ground area covered
Outlet_Location_Type	The type of city in which the store is located
Outlet_Type	Whether the outlet is just a grocery store or some sort of supermarket
Item_Outlet_Sales	Sales of the product in the particulat store. This is the outcome variable to be predicted.

You can download the data from here.

6.1. Installation

Featuretools is available for Python 2.7, 3.5, and 3.6. You can easily install Featuretools using pip.

```
python -m pip install featuretools
```

6.2. Loading required Libraries and Data

```
import featuretools as ft
import numpy as np
import pandas as pd

train = pd.read_csv("Train_UWu5bXk.csv")
test = pd.read_csv("Test_u94Q5KV.csv")
```

6.3. Data Preparation

To start off, we'll just store the target Item_Outlet_Sales in a variable called sales and id variables in test_Item_Identifier and test_Outlet_Identifier.

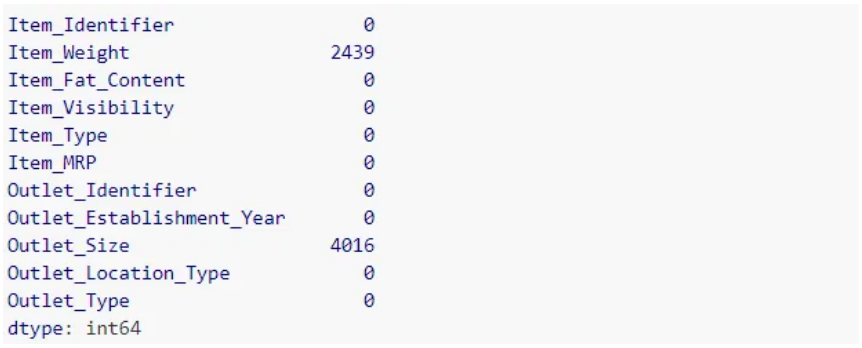
```
# saving identifiers
test_Item_Identifier = test['Item_Identifier']
test_Outlet_Identifier = test['Outlet_Identifier']
sales = train['Item_Outlet_Sales']
train.drop(['Item_Outlet_Sales'], axis=1, inplace=True)
```

Then we will combine the train and test set as it saves us the trouble of performing the same step(s) twice.

```
combi = train.append(test, ignore_index=True)
```

Let's check the missing values in the dataset.

```
combi.isnull().sum()
```



```
Item_Identifier                0
Item_Weight                 2439
Item_Fat_Content               0
Item_Visibility                0
Item_Type                      0
Item_MRP                       0
Outlet_Identifier              0
Outlet_Establishment_Year      0
Outlet_Size                 4016
Outlet_Location_Type           0
Outlet_Type                    0
dtype: int64
```

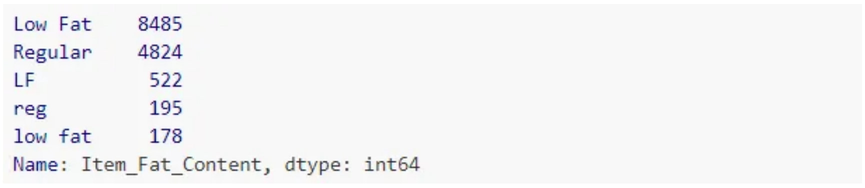
Quite a lot of missing values in the Item_Weight and Outlet_size variables. Let's quickly deal with them:

```
# imputing missing data
combi['Item_Weight'].fillna(combi['Item_Weight'].mean(), inplace = True)
combi['Outlet_Size'].fillna("missing", inplace = True)
```

6.4. Data Preprocessing

I will not do an extensive preprocessing operation since the objective of this article is to get you started with Featuretools.

```
combi['Item_Fat_Content'].value_counts()
```



```
Low Fat    8485
Regular    4824
LF          522
reg         195
low fat     178
Name: Item_Fat_Content, dtype: int64
```

It seems Item_Fat_Content contains only two categories, i.e., “Low Fat” and “Regular” – the rest of them we will consider redundant. So, let’s convert it into a binary variable.

```
# dictionary to replace the categories
fat_content_dict = {'Low Fat':0, 'Regular':1, 'LF':0, 'reg':1, 'low fat':0}


combi['Item_Fat_Content'] = combi['Item_Fat_Content'].replace(fat_content_dict, regex=True)
```

6.5. Feature Engineering using Featuretools

Now we can start using Featuretools to perform automated feature engineering! It is necessary to have a unique identifier feature in the dataset (our dataset doesn’t have any right now). So, we will create one unique ID for our combined dataset. If you notice, we have two IDs in our data—one for the item and another for the outlet. So, simply concatenating both will give us a unique ID.

```
combi['id'] = combi['Item_Identifier'] + combi['Outlet_Identifier']
combi.drop(['Item_Identifier'], axis=1, inplace=True)
```

Please note that I have dropped the feature *Item_Identifier* as it is no longer required. However, I have retained the feature *Outlet_Identifier* because I plan to use it later.

Now before proceeding, we will have to create an EntitySet. An EntitySet is a structure that contains multiple dataframes and relationships between them. So, let’s create an EntitySet and add the dataframe combination to it.

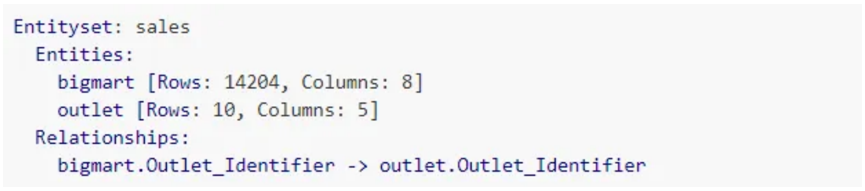
```
# creating and entity set 'es'
es = ft.EntitySet(id = 'sales')


# adding a dataframe
es.entity_from_dataframe(entity_id = 'bigmart', dataframe = combi, index = 'id')
```

Our data contains information at two levels—item level and outlet level. Featuretools offers a functionality to split a dataset into multiple tables. We have created a new table ‘outlet’ from the BigMart table based on the outlet ID *Outlet_Identifier*.

```
es.normalize_entity(base_entity_id='bigmart', new_entity_id='outlet', index = 'Outlet_Identifie
r',
additional_variables = ['Outlet_Establishment_Year', 'Outlet_Size', 'Outlet_Location_Type', 'Outl
et_Type'])
```

Let's check the summary of our EntitySet.

```
print(es)
```

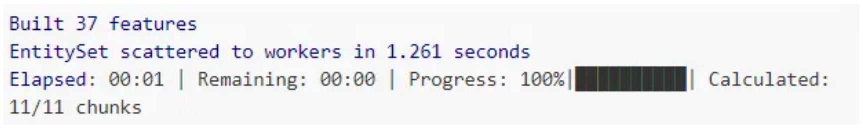


```
Entityset: sales
  Entities:
    bigmart [Rows: 14204, Columns: 8]
    outlet [Rows: 10, Columns: 5]
  Relationships:
    bigmart.Outlet_Identifier -> outlet.Outlet_Identifier
```

As you can see above, it contains two entities – bigmart and outlet. There is also a relationship formed between the two tables, connected by Outlet_Identifier. This relationship will play a key role in the generation of new features.

Now we will use **Deep Feature Synthesis** to create new features automatically. Recall that DFS uses Feature Primitives to create features using multiple tables present in the EntitySet.

```
feature_matrix, feature_names = ft.dfs(entityset=es,
target_entity = 'bigmart',
max_depth = 2,
verbose = 1,
n_jobs = 3)
```



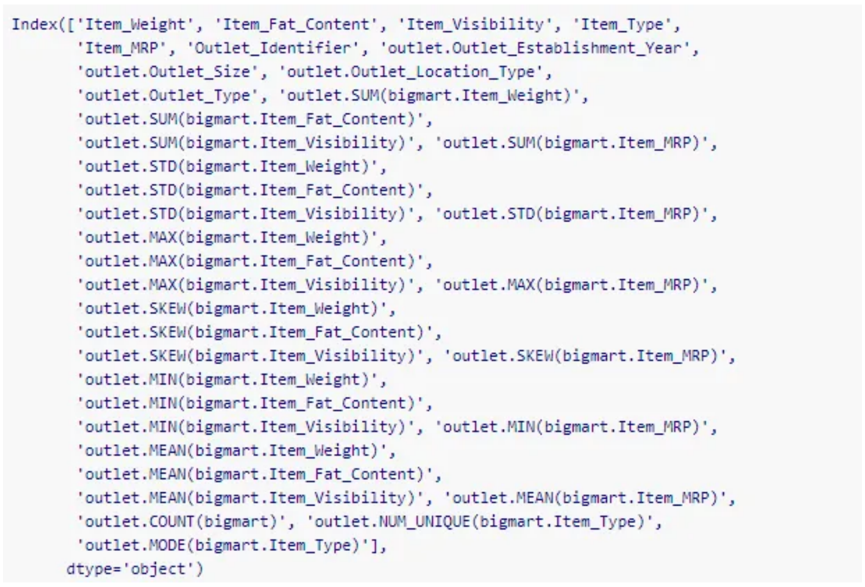
```
Built 37 features
EntitySet scattered to workers in 1.261 seconds
Elapsed: 00:01 | Remaining: 00:00 | Progress: 100%|██████████| Calculated:
11/11 chunks
```

target_entity is nothing but the entity ID for which we wish to create new features (in this case, it is the entity 'bigmart'). The parameter *max_depth* controls the complexity of the features being generated by stacking the primitives. The parameter *n_jobs* helps in parallel feature computation by using multiple cores.

That's all you have to do with Featuretools. It has generated a bunch of new features on its own.

Let's have a look at these newly created features.

```
feature_matrix.columns
```

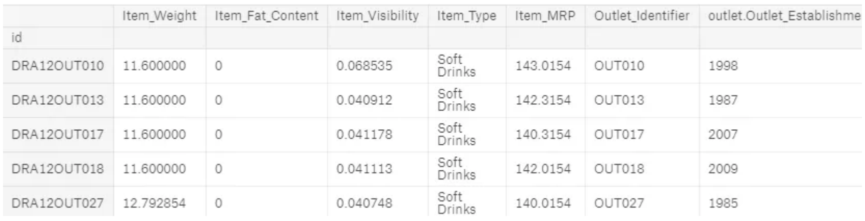


```
Index(['Item_Weight', 'Item_Fat_Content', 'Item_Visibility', 'Item_Type',
       'Item_MRP', 'Outlet_Identifier', 'outlet.Outlet_Establishment_Year',
       'outlet.Outlet_Size', 'outlet.Outlet_Location_Type',
       'outlet.Outlet_Type', 'outlet.SUM(bigmart.Item_Weight)',
       'outlet.SUM(bigmart.Item_Fat_Content)',
       'outlet.SUM(bigmart.Item_Visibility)', 'outlet.SUM(bigmart.Item_MRP)',
       'outlet.STD(bigmart.Item_Weight)',
       'outlet.STD(bigmart.Item_Fat_Content)',
       'outlet.STD(bigmart.Item_Visibility)', 'outlet.STD(bigmart.Item_MRP)',
       'outlet.MAX(bigmart.Item_Weight)',
       'outlet.MAX(bigmart.Item_Fat_Content)',
       'outlet.MAX(bigmart.Item_Visibility)', 'outlet.MAX(bigmart.Item_MRP)',
       'outlet.SKEW(bigmart.Item_Weight)',
       'outlet.SKEW(bigmart.Item_Fat_Content)',
       'outlet.SKEW(bigmart.Item_Visibility)', 'outlet.SKEW(bigmart.Item_MRP)',
       'outlet.MIN(bigmart.Item_Weight)',
       'outlet.MIN(bigmart.Item_Fat_Content)',
       'outlet.MIN(bigmart.Item_Visibility)', 'outlet.MIN(bigmart.Item_MRP)',
       'outlet.MEAN(bigmart.Item_Weight)',
       'outlet.MEAN(bigmart.Item_Fat_Content)',
       'outlet.MEAN(bigmart.Item_Visibility)', 'outlet.MEAN(bigmart.Item_MRP)',
       'outlet.COUNT(bigmart)', 'outlet.NUM_UNIQUE(bigmart.Item_Type)',
       'outlet.MODE(bigmart.Item_Type)'],
      dtype='object')
```

DFS has created 29 new features in such a quick time. It is phenomenal as it would have taken much longer to do it manually. If you have datasets with multiple interrelated tables, Featuretools would still work. In that case, you wouldn't have to normalize a table as multiple tables will already be available.

Let's print the first few rows of feature_matrix.

```
feature_matrix.head()
```



	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier	outlet.Outlet_Establishme
id							
DRA12OUT010	11.600000	0	0.068535	Soft Drinks	143.0154	OUT010	1998
DRA12OUT013	11.600000	0	0.040912	Soft Drinks	142.3154	OUT013	1987
DRA12OUT017	11.600000	0	0.041178	Soft Drinks	140.3154	OUT017	2007
DRA12OUT018	11.600000	0	0.041113	Soft Drinks	142.0154	OUT018	2009
DRA12OUT027	12.792854	0	0.040748	Soft Drinks	140.0154	OUT027	1985

There is one issue with this dataframe – it is not sorted properly. We will have to sort it based on the *id* variable from the *combi* dataframe.

```
feature_matrix = feature_matrix.reindex(index=combi['id'])

feature_matrix = feature_matrix.reset_index()
```

Now the dataframe feature_matrix is in proper order.

6.6. Model Building

It is time to check how useful these generated features actually are. We will use them to build a model and predict Item_Outlet_Sales. Since our final data (feature_matrix) has many categorical features, I decided to use the CatBoost algorithm. It can use categorical features directly and is scalable in nature. You can refer to this article to read more about CatBoost.

```
from catboost import CatBoostRegressor
```

CatBoost requires all the categorical variables to be in the string format. So, we will convert the categorical variables in our data to string first:

```
categorical_features = np.where(feature_matrix.dtypes == 'object')[0]


for i in categorical_features:
    feature_matrix.iloc[:,i] = feature_matrix.iloc[:,i].astype('str')
```

Let's split feature_matrix back into train and test sets.

```
feature_matrix.drop(['id'], axis=1, inplace=True)
train = feature_matrix[:8523]
test = feature_matrix[8523:]
```

```
# removing uneccesary variables
train.drop(['Outlet_Identifier'], axis=1, inplace=True)
test.drop(['Outlet_Identifier'], axis=1, inplace=True)
```

```
# identifying categorical features
categorical_features = np.where(train.dtypes == 'object')[0]
```

Split the train data into training and validation set to check the model's performance locally.

```
from sklearn.model_selection import train_test_split


# splitting train data into training and validation set
xtrain, xvalid, ytrain, yvalid = train_test_split(train, sales, test_size=0.25, random_state=11)
```

Finally, we can now train our model. The evaluation metric we will use is RMSE (Root Mean Squared Error).

```
model_cat = CatBoostRegressor(iterations=100, learning_rate=0.3, depth=6, eval_metric='RMSE', ran
dom_seed=7)

# training model
model_cat.fit(xtrain, ytrain, cat_features=categorical_features, use_best_model=True)
```

```
# validation score
model_cat.score(xvalid, yvalid)
```

1091.244

The RMSE score on the validation set is ~1092.24.

The same model got a score of 1155.12 on the public leaderboard. Without any feature engineering, the scores were ~1103 and ~1183 on the validation set and the public leaderboard, respectively. Hence, the features created by Featuretools are not just random features, they are valuable and useful. Most importantly, the amount of time it saves in feature engineering is incredible.

7. Featuretools Interpretability

Making our data science solutions interpretable is a very important aspect of performing machine learning. Features generated by Featuretools can be easily explained even to a non-technical person because they are based on the primitives, which are easy to understand.

For example, the features *outlet.SUM(bigmart.Item_Weight)* and *outlet.STD(bigmart.Item_MRP)* mean outlet-level sum of weight of the items and standard deviation of the cost of the items, respectively.

This makes it possible for those people who are not machine learning experts, to contribute as well in terms of their domain expertise.

End Notes

The featuretools package is truly a game-changer in machine learning. While it's applications are understandably still limited in industry use cases, it has quickly become ultra popular in hackathons and ML competitions. The amount of time it saves, and the usefulness of feature it generates, has truly won me over.

Try it out next time you work on any dataset and let me know how it went in the comments section!