Data Mining 2

Topic 02 : Feature Engineering

Lecture 05 : Automatic Feature Engineering

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Outline

- Walk-through of Featuretools

Motivation

- Typically, feature engineering is a drawn-out manual process, relying on domain knowledge, intuition, and data manipulation.
- This process can be extremely tedious and the final features will be limited both by human subjectivity and time.
- While each individual new feature may be easy to create/develop the process is not scalable and often not applicable across datasets.

$\Rightarrow$ Automated feature engineering* aims to help the data scientist by automatically creating many candidate features out of a dataset from which the best can be selected and used for training.,

featuretools is an attempt to automate the feature generation using their Deep Feature Synthesis (DFS) process which performs feature engineering on relational and temporal data.

*Note that this is the trend in all stages of the data mining pipeline — e.g. model selection, hyper-parameter training — more and more of the process is being automated.

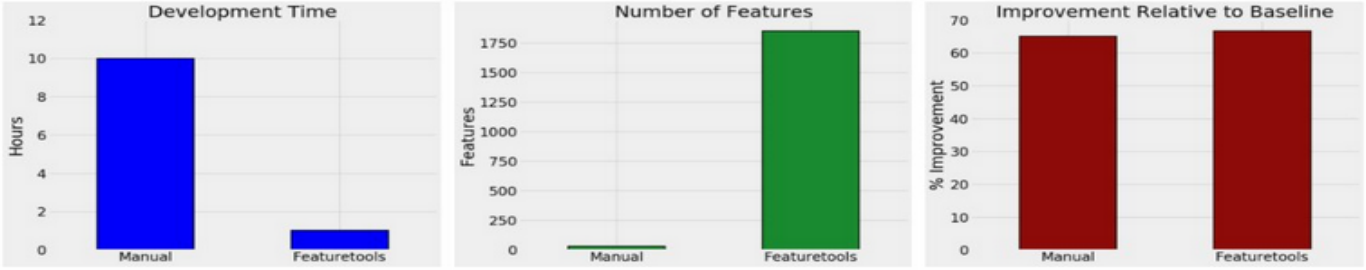
Why (Learn Yet Another Library)?

KDnuggets: Why Automated Feature Engineering Will Change the Way You Do Machine Learning

After a little feature selection and model optimization, these features did slightly better in a predictive model compared to the manual features with an overall development time of **1 hour**, a 10x reduction compared to the manual process. Featuretools is much faster both because it requires less domain knowledge and because there are considerably fewer lines of code to write.

I'll admit that there is a slight time cost to learning Featuretools but it's an investment that will pay off. After taking an hour or so to learn Featuretools, you can apply it *to any machine learning* problem.

The following graphs sum up my experience for the loan repayment problem:



Comparison between automated and manual feature engineering on time, number of features, and performance.

- Development time: accounts for everything required to make the final feature engineering code: **10 hours manual vs 1 hour automated**
- Number of features produced by the method: **30 features manual vs 1820 automated**
- Improvement relative to baseline is the % gain over the baseline compared to the top public leaderboard score using a model trained on the features: **65% manual vs 66% automated**

> My takeaway is that automated feature engineering will not replace the data scientist, but rather by significantly increasing efficiency, it will free her to spend more time on other aspects of the machine learning pipeline.

Furthermore, the Featuretools code I wrote for this first project could be applied to any dataset while the manual engineering code would have to be thrown away and entirely rewritten for the next dataset!

Example Applications of Featuretools

There exists online a number of guides covering the application of featuretools. In particular:

- A Hands-On Guide to Automated Feature Engineering using Featuretools in Python
  Which uses data from Analytics Vidhya BigMart Sales challenge is to build a predictive model to estimate the sales of each product at a particular store.
  - This is a single table dataset, but featuretools created 29 new features resulting in a model RMSE score of 1155.12, compared to initial model of 1183 (lower is better).
- Predicting a customer's next purchase using automated feature engineering
  Uses Instacart's multi-table dataset of 3 million online grocery orders to predict what product a customer buys next.
  - Generate 150+ features using Deep Feature Synthesis and select the 20 most important features for predictive modeling.
  - Develop a model on a subset of the data and validate on the entire dataset in a scalable manner using Dask.
- Automated Feature Engineering in Python
  Small multi-table, loan repayment dataset — not real data but demonstrates the potential explosion of features when merging tables.

source for this lecture

Loan Repayment Dataset

client_id	joined	income	credit_score
46109	2002-04-16	172677	527
49545	2007-11-14	104564	770
41480	2013-03-11	122607	585
46180	2001-11-06	43851	562
25707	2006-10-06	211422	621

Clients

Basic information about clients at a credit union. Each client appears in exactly one row.

1-*

client_id	loan_type	loan_amount	repaid	loan_id	loan_start	loan_end	rate
25707	other	9942	1	10438	2009-03-26	2010-10-22	2.39
39384	other	13131	1	10579	2012-08-12	2014-06-17	2.95
49624	other	2572	1	10578	2004-05-04	2005-12-16	2.28
29841	credit	10537	1	10157	2010-08-04	2013-03-11	3.43
39505	other	6484	1	10407	2011-02-14	2012-12-07	1.14
44601	home	4475	1	10362	2005-07-29	2007-07-06	6.58
39384	credit	1770	1	10868	2013-08-03	2016-04-28	2.64
48177	other	1383	0	11264	2009-08-08	2012-01-03	5.69
32885	home	11783	0	10301	2000-08-10	2003-03-12	2.64
49068	cash	6473	1	11546	2002-09-01	2004-10-23	5.18

Loans

loans made to the clients. Each loan has exactly one row, but clients may have multiple loans.

*-1

loan_id	payment_amount	payment_date	missed
10302	489	2006-06-17	1
11652	1896	2014-08-17	0
11827	2755	2005-02-26	1
10078	624	2005-05-28	1
10177	1474	2002-05-03	0
10660	701	2005-09-22	1
11251	568	2000-08-27	0
10826	2538	2005-03-20	0
11896	1055	2004-06-02	0
10742	437	2005-06-04	1

Payments

Payments made on the loans. Each payment has exactly one row, but each loan will have multiple payments.

Transformations versus Aggregations

New features can be organised into two categories — transformations and aggregations.

Transformation

Transformations act on a single table by creating new features out of one or more of the existing columns.

In the clients table, features showing the month of the joined column or the natural log of the income column are transformations.

client_id	joined	income	credit_score	join_month	log_income
46109	2002-04-16	172677	527	4	12.059178
49545	2007-11-14	104564	770	11	11.557555
41480	2013-03-11	122607	585	3	11.716739
46180	2001-11-06	43851	562	11	10.688553
25707	2006-10-06	211422	621	10	12.261611

Aggregations

Aggregations are performed across tables, and use a one-to-many relationship to group observations and then calculate statistics.

Combining the clients and loans tables, where each client may have multiple loans, we can calculate statistics such as the average, maximum, and minimum of loans for each client.

client_id	joined	income	credit_score	join_month	log_income	mean_loan_amount	max_loan_amount	min_loan_amount
46109	2002-04-16	172677	527	4	12.059178	8951.600000	14049	559
49545	2007-11-14	104564	770	11	11.557555	10289.300000	14971	3851
41480	2013-03-11	122607	585	3	11.716739	7894.850000	14399	811
46180	2001-11-06	43851	562	11	10.688553	7700.850000	14081	1607
25707	2006-10-06	211422	621	10	12.261611	7963.950000	13913	1212
39505	2011-10-14	153873	610	10	11.943883	7424.050000	14575	904
32726	2006-05-01	235705	730	5	12.370336	6633.263158	14802	851
35089	2010-03-01	131176	771	3	11.784295	6939.200000	13194	773
35214	2003-08-08	95849	696	8	11.470529	7173.555556	14767	667
48177	2008-06-09	190632	769	6	12.158100	7424.368421	14740	659

Featuretools Concepts/Termonology

Featuretools Feature engineering means building additional features out of existing data which is often spread across multiple related tables. Feature engineering requires extracting the relevant information from the data and getting it into a single table which can then be used to train a machine learning model.

Entity / Entityset

- An Entity can be considered as a representation of a Pandas DataFrame (or a single table in a relational database). A collection of multiple entities is called an Entityset.

Deep Feature Synthesis (DFS)

- DFS is the automatic feature engineering method at the core of Featuretools. It enables the creation of new features from single, as well as multiple dataframes.
- 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.

Walk-Through — Step 1: Create an empty EntitySet

Step 0: Load data into Pandas DataFrames

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

clients = pd.read_csv("data/clients.csv", parse_dates = ["joined"])
loans = pd.read_csv("data/loans.csv", parse_dates = ["loan_start", "loan_end"])
payments = pd.read_csv("data/payments.csv", parse_dates = ["payment_date"])
```

Step 1 — Create an empty EntitySet

An EntitySet is a collection of tables and the relationships between them.

```
es = ft.EntitySet(id="clients")
```

Walk-Through: Step 2 — Create each Entity

Step 2 — Create each Entity

- Each entity must have an index, which is a column with all unique elements. (Primary key in traditional database terms.)
- The index in the clients dataframe is the `client_id` because each client has only one row in this dataframe.

We add an entity with an existing index to an entityset using the following syntax:

```
# Create an entity from the client dataframe
# This dataframe already has an index and a time index
es = es.entity_from_dataframe(entity_id = "clients",
    dataframe = clients,
    index = "client_id",
    time_index = "joined")
print(es)
```

```
Entityset: clients
  Entities:
    clients [Rows: 25, Columns: 4]
  Relationships:
    No relationships
```

Walk-Through: Step 2 — Create each Entity II

- The `loans` dataframe also has a unique index,`loan_id`.
- Although featuretools will automatically infer the data type of each column in an entity, we can override this by passing in a dictionary of column types to the parameter `variable_types`.

```
# Create an entity from the loans dataframe
# This dataframe already has an index and a time index
es = es.entity_from_dataframe(entity_id = "loans",
    dataframe = loans,
    variable_types = {"repaid": ft.variable_types.Categorical},
    index = "loan_id",
    time_index = "loan_start")
print(es)
```

```
Entityset: clients
  Entities:
    clients [Rows: 25, Columns: 4]
    loans [Rows: 443, Columns: 8]
  Relationships:
    No relationships
```

Walk-Through: Step 2 — Create each Entity III

- For the payments dataframe, there is no unique index. Hence we need to pass in the parameter `make_index=True` and specify the name of the index.
- For this dataframe, even though `missed` is an integer, this is not a numeric variable since it can only take on 2 discrete values, so we tell featuretools to treat is as a categorical variable.

```
# Create an entity from the payments dataframe
# This does not yet have a unique index
es = es.entity_from_dataframe(entity_id = "payments",
    dataframe = payments,
    variable_types = {"missed": ft.variable_types.Categorical},
    time_index = "payment_date",
    make_index = True,
    index = "payment_id")
print(es)
```

```
Entityset: clients
  Entities:
    clients [Rows: 25, Columns: 4]
    loans [Rows: 443, Columns: 8]
    payments [Rows: 3456, Columns: 5]
  Relationships:
    No relationships
```

Walk-Through: Step 2 — Create each Entity IV

We can access any of the entities in the entityset using Python dictionary syntax.

```
print(es["clients"])
print(es["loans"])
print(es["payments"])
```

```
Entity: clients
  Variables:
    client_id (dtype: index)
    joined (dtype: datetime_time_index)
    income (dtype: numeric)
    credit_score (dtype: numeric)
  Shape:
    (Rows: 25, Columns: 4)
Entity: loans
  Variables:
    loan_id (dtype: index)
    client_id (dtype: numeric)
    loan_type (dtype: categorical)
    loan_amount (dtype: numeric)
    loan_start (dtype: datetime_time_index)
    loan_end (dtype: datetime)
    rate (dtype: numeric)
    repaid (dtype: categorical)
  Shape:
    (Rows: 443, Columns: 8)
Entity: payments
  Variables:
    payment_id (dtype: index)
    loan_id (dtype: numeric)
    payment_amount (dtype: numeric)
    payment_date (dtype: datetime_time_index)
    missed (dtype: categorical)
  Shape:
    (Rows: 3456, Columns: 5)
```

Walk-Through: Step 3 — Create Table Relationships I

Step 3 — Create Table Relationships

New we need to define the relationship between tables and its multiplicity, i.e., one-to-many.[†] In our dataset:

- `clients` dataframe is a parent of the `loans` dataframe.
  Each client has only one row in clients but may have multiple rows in loans.
- `loans` is the parent of `payments` since each loan will have multiple payments.
  The parents are linked to their children by a shared variable. When we perform aggregations, we group the child table by the parent variable and calculate statistics across the children of each parent.

To formalise a relationship in featuretools, we only need to specify the variable that links two tables together. The clients and the loans table are linked via the `client_id` variable and loans and payments are linked with the `loan_id`.

[†]The best way to think of a relationship between two tables is the analogy of parent to child. This is a one-to-many relationship: each parent can have multiple children. In the realm of tables, a parent table has one row for every parent, but the child table may have multiple rows corresponding to multiple children of the same parent.

Walk-Through: Step 3 — Create Table Relationships II

```
# Relationship between clients and previous loans
r_client_previous = ft.Relationship(
    es["clients"]["client_id"], es["loans"]["client_id"])

# Add the relationship to the entity set
es = es.add_relationship(r_client_previous)

print(es)
```

```
Entityset: clients
  Entities:
    clients [Rows: 25, Columns: 4]
    loans [Rows: 443, Columns: 8]
    payments [Rows: 3456, Columns: 5]
  Relationships:
    loans.client_id -> clients.client_id
```

Walk-Through: Step 3 — Create Table Relationships III

```
# Relationship between previous loans and previous payments
r_payments = ft.Relationship(
    es["loans"]["loan_id"], es["payments"]["loan_id"])

# Add the relationship to the entity set
es = es.add_relationship(r_payments)

print(es)
```

```
Entityset: clients
  Entities:
    clients [Rows: 25, Columns: 4]
    loans [Rows: 443, Columns: 8]
    payments [Rows: 3456, Columns: 5]
  Relationships:
    loans.client_id -> clients.client_id
    payments.loan_id -> loans.loan_id
```

Walk-Through: Step 4 — Create Feature Primitives

New features are created in featuretools using primitives either by themselves or stacking multiple primitives. Below is a list of some of the feature primitives in featuretools[‡]:

	name	type	dask_compatible	koalas_compatible	description
0	all	aggregation	True	False	Calculates if all values are 'True' in a list.
1	min	aggregation	True	True	Calculates the smallest value, ignoring `NaN` ...
2	last	aggregation	False	False	Determines the last value in a list.
3	mean	aggregation	True	True	Computes the average for a list of values.
4	percent_true	aggregation	True	False	Determines the percent of `True` values.
...	...	...	...	...	...
74	cum_count	transform	False	False	Calculates the cumulative count.
75	hour	transform	True	True	Determines the hour value of a datetime.
76	age	transform	True	False	Calculates the age in years as a floating poin...
77	modulo_by_feature	transform	True	True	Return the modulo of a scalar by each element ...
78	add_numeric	transform	True	True	Element-wise addition of two lists.

79 rows × 5 columns

[‡] We can also define custom primitives.

Walk-Through: Step 4 — Generate Feature Primitives I

Step 4 — Generate Feature Primitives

To make features with specified primitives we use the `ft.dfs` function (standing for deep feature synthesis). We pass in the `entityset`, the `target_entity`, which is the table where we want to add the features, the selected `trans_primitives` (transformations), and `agg_primitives` (aggregations):

```
# Create new features using specified primitives
features, feature_names = ft.dfs(
    entityset = es,
    target_entity = "clients",
    agg_primitives = ["mean", "max", "last"],
    trans_primitives = ["year", "month", "subtract_numeric", "divide_numeric"])

print("Number of features", len(features.columns))
```

```
Number of features 218
```

The result is a dataframe of new features for each client (because we made clients the `target_entity`).

Walk-Through: Step 4 — Generate Feature Primitives II

To see the generated features (218 features) use

```
pd.DataFrame(features["MONTH(joined)"].head())
```

client_id	MONTH(joined)
42320	4
39384	6
26945	11
41472	11
46180	11

```
pd.DataFrame(features['MEAN(payments.payment_amount)'].head())
```

client_id	MEAN(payments.payment_amount)
42320	1021.483333
39384	1193.630137
26945	1109.473214
41472	1129.076190
46180	1186.550336

Walk-Through: Step 4 — Generate Feature Primitives II

Or look at the entire feature dataframe using

```
features.head()
```

Even though we specified only a few feature primitives, featuretools created many new features by combining and stacking these primitives.

client_id	income	credit_score	LAST(loans.loan_amount)	LAST(loans.loan_id)	LAST(loans.loan_type)	LAST(loans.rate)	LAST(loans.repaid)	MAX(loans.loan_
42320	229481	563	8090	10156	home	3.18	0	13887
39384	191204	617	14654	11735	other	2.26	0	14654
26945	214516	806	9249	11482	cash	2.86	1	14593
41472	152214	638	10122	11936	cash	1.03	0	13657
46180	43851	562	3834	10887	other	1.38	0	14081

5 rows × 218 columns

Deep Feature Synthesis

- Now that we have covered process, let's look at the last step — deep feature synthesis (DFS) — a little closer.
- A deep feature is simply a feature made of stacking multiple primitives and DFS is the name of process that makes these features. The depth of a deep feature is the number of primitives required to make the feature.
  - For example, the

    `MEAN(payments.payment_amount)`

    column is a deep feature with a depth of 1 because it was created using a single aggregation.
  - A feature with a depth of two is

    `LAST(loans(MEAN(payments.payment_amount))`

    This is made by stacking two aggregations: LAST (most recent) on top of MEAN. This represents the average payment size of the most recent loan for each client.
- We can stack features to any depth we want, but in practice, a max depth of 2 is recommended. After this point, the features are difficult to interpret.
- We do not have to manually specify the feature primitives, but can let featuretools automatically choose features for us. To do this, we call `ft.dfs` but do not pass in any feature primitives and set `max_depth`.

Final Comments

- This dataset is incomplete (no target) and was synthetic, but we (you) will look at a real dataset in week 6 practical.
- However, generation of features is trivial and scalable, (think about the InstaCart dataset).
- Also — just in case you were thinking about it — it is probably of little use in the Churn dataset, The number of observations is so small that manual engineering would be more effective.