# COMP 333 Data Analytics

## Exploratory Data Analysis

Greg Butler

Data Science Research Centre

and

Centre for Structural and Functional Genomics

and

Computer Science and Software Engineering
Concordia University, Montreal, Canada

gregb@cs.concordia.ca

# Feature Engineering

## Feature

A feature is an attribute or property shared by all of the independent units on which analysis or prediction is to be done. Any attribute could be a feature, as long as it is useful to the model.

## Process of Feature Engineering

- Brainstorming or Testing features;
- Deciding what features to create;
- Creating features;
- Checking how the features work with your model;
- Improving your features if needed;
- Go back to brainstorming/creating more features until the work is done.

See video 3, Ryan Baker, Coursera, Big Data Week 3 Feature Engineering

`https://www.youtube.com/watch?v=drUToKxEAUA`

# Feature Engineering

## FE is a Representation Problem

What is the best representation of the sample data
in order to learn a solution to your problem?

Machine learning algorithms learn a solution to a problem from sample data.

You have to turn your inputs into things the algorithm can understand

## FE is an Art

like engineering, like programming, like medicine is an art.

The data is variable and is different every time.

You get good at deciding which procedures to use and when, by practice.

# Feature Importance

You can objectively estimate the usefulness of features.

A feature may be important if it is *highly correlated*
with the dependent variable (the thing being predicted).

Correlation coefficients can provide feature importance scores.

Features with the highest scores can be selected
for inclusion in the training dataset,
whereas those remaining can be ignored.

Important features can guide you
to extract or construct new features,
similar but different to those that have been estimated to be useful.

# Approaches to Feature Engineering

The key approaches to feature engineering are:

- feature selection
- feature extraction
- feature construction

## Feature Learning

Deep learning is feature learning where the set of features is *learnt* from the raw data, by the early layers of the network.

# Feature Selection

Feature selection selects a subset of features that are most useful to the problem.

Feature selection algorithms may use a scoring method
to rank and choose features,
such as correlation or other feature importance methods.

More advanced methods may search subsets of features
by trial and error,
creating and evaluating models automatically in pursuit of
the objectively most predictive sub-group of features.

Some machine learning algorithms, such as random forests,
will incorporate feature selection as part of their algorithm.

# Feature Extraction

Feature extraction is a process of automatically reducing the dimensionality of these types of observations into a much smaller set that can be modelled.

For tabular data, this might include projection methods like Principal Component Analysis and unsupervised clustering methods.

Examples include
Images into colours, textures, contours, etc
Signals into frequency, phase, samples, spectrum, etc
Time series into ticks, trends, self-similarities, etc
Biomed into dna sequence, genes, etc

Text into words, POS (part-of-speech) tags, grammatical dependencies, etc

# Feature Construction

Feature construction is the manual construction of new features from raw data

This requires spending a lot of time with actual sample data (not aggregates) and thinking about
the underlying form of the problem,
the structures in the data, and
how best to expose them to predictive modeling algorithms.

With tabular data, it often means a mixture of
aggregating or combining features to create new features,
and decomposing or splitting features to create new features.

# Feature Creation

## Aggregation

Basic aggregation operators

- sum
- mean, media, mode
- frequency

Other

- binning

## Transformation

Apply a transformation to features

- normalization, unification, resolution, regularization
- log
- feature split
- scaling

# Feature Creation: Binning

## Numerical Data to Categorical Data

## Example: Age

Define **bins**:

`Infant` for *age* between 0 – 4
`Child` for *age* between 5 – 12
`Teen` for *age* between 13 – 19
`YoungAdult` for *age* between 20 – 29
`Adult` for *age* between 30 – 44
`Mature` for *age* between 45 – 64
`Senior` for *age* between 65 – 79
`Elderly` for *age* 80 and over

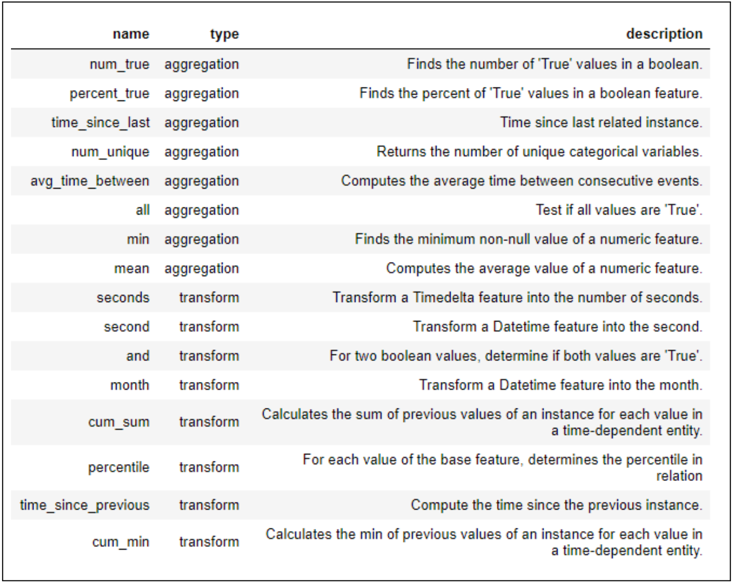
# Feature Creation: Splitting

## Feature Splitting

Example: Name split to FirstName, LastName

Example: Date 2019-06-21 split to Year, Month, Day

# Python featuretools



| name | type | description |
|---|---|---|
| num_true | aggregation | Finds the number of 'True' values in a boolean. |
| percent_true | aggregation | Finds the percent of 'True' values in a boolean feature. |
| time_since_last | aggregation | Time since last related instance. |
| num_unique | aggregation | Returns the number of unique categorical variables. |
| avg_time_between | aggregation | Computes the average time between consecutive events. |
| all | aggregation | Test if all values are 'True'. |
| min | aggregation | Finds the minimum non-null value of a numeric feature. |
| mean | aggregation | Computes the average value of a numeric feature. |
| seconds | transform | Transform a Timedelta feature into the number of seconds. |
| second | transform | Transform a Datetime feature into the second. |
| and | transform | For two boolean values, determine if both values are 'True'. |
| month | transform | Transform a Datetime feature into the month. |
| cum_sum | transform | Calculates the sum of previous values of an instance for each value in a time-dependent entity. |
| percentile | transform | For each value of the base feature, determines the percentile in relation |
| time_since_previous | transform | Compute the time since the previous instance. |
| cum_min | transform | Calculates the min of previous values of an instance for each value in a time-dependent entity. |

# Feature Creation: Other

## Clusters

## PCA Components

## Flags

flag variables indicating missing values
flag variables indicating outliers
etc

# Feature Contribution

## Correlation Example

$r^2$ measures how much of variation is explained by linear regression

## Contribution to Model

When building a model from your dataset,
does the technique allow you
to know the contribution of each feature?

## Compare with PCA

PCA finds principal orthogonal components
components are ranked by contribution
components are defined as combinations of features