

What is Feature Selection?

When you build machine learning models you compile data from multiple sources

You collect many variables that could potentially describe the output of interest

A parameter may have several surrogates

Soil properties related to sand fraction, clay fraction

Which parameters should you use as inputs?

Approaches to Feature Selection

There are many approaches to selecting features

They can be classified into three broad categories

Filter Methods

Filter out redundant or non important inputs Wrapper Methods

Make use of a model and optimize for best set of subsets

Best set of subsets maximize the performance of the model

Searching over all features is computationally expensive

Make use of heuristics

Embedded Methods

Embed feature selection as part of the model training

Both Wrapper & Embedded methods require a model to select optimal subsets



Filter methods are the first step to feature selection

Can be used to identify a smaller subset of features

Can be used to eliminate variables for use with wrapper or embedded methods

Filter methods are model independent so useful with any model

They use statistical concepts but often in an *ad hoc* manner.

Filter Methods

Filter Methods seek to "remove" irrelevant variables

They may rank or order variables according to their relevance

A suitable cut-off can be used to select a subset

How do we define relevance?

The Feature should be correlated to the output variable

The Feature should explain the variability noted in the output

The Feature should contain information about the output variable

Feature selection methods use different relevance criterion

Feature Relevance

Spearman Rank Correlation and Kendall-Tau are two common rank correlation measures

The Pearson Product Moment Correlation (R) is widely used when the inputs (features) and output are continuous

R varies between -1 to +1

Sign of R denotes the nature of the relationship

Magnitude of |R| denotes the strength of the relationship

When the output is not continuous then other correlation measures have to be used

Integer data can be treated as continuous data

Rank Correlation coefficients can be used as well

Less sensitive to outliers

Measures ordinal correlation and not linear correlation

Useful when the relationship is suspected to be nonlinear

Binary Variable Correlations

Serial, Biserial and Tetrachoric correlations

- Sometimes the output is binary
 - Input can be continuous
 - Input can be binary
- If the output is truly binary and input is continuous then "point biserial correlation" can be used
 - This value can be greater than 1
- If the output is made binary (by discretizing a continuous variable) and the input is continuous then "biserial correlation" can be used
- If both input and output are binary, then "tetrachoric Correlation" can be used

Multinomial Variables

- The correlations can only used for multinomial variables that are ordered
- When the output is ordered multinomial and input is continuous then 'polyserial' correlation coefficient is used
 - Generalization of the biserial correlation
- If both input and output variables are ordinal multinomial
 - Polychoric correlation
 - Assumed the underlying variables (latent variables) are continuous

Other Approaches

Contingency table measures can be used to evaluate variables

Most useful for categorical variables

Continuous variables can be categorized

The values may be affected by binning

Accuracy is the ratio of sum of diagonal elements to the total elements

Entropy Based Methods

- Entropy is a measure of information content (or lack thereof) in a variable
- Conditional Entropy of y is the information content of y given x is known
- Mutual Information (MI) is the reduction in uncertainty of y due to knowledge of x

$$H(y|x) = -\sum_{y} p(y)log(p(y))$$

$$H(y|x) = -\sum_{x} \sum_{y} p(x, y) log(p(y|x))$$

$$MI(y,x) = H(y) - H(y|x)$$

Use MI to rank variables

While Entropy can be computed using continuous variables it is common to use discrete versions presented here

Computing Entropy

Entropy computations require discretization

Continuous variables have to be discretized

Use one of the binning method for discretization

Sturges rule for symmetric data

Doane's formula or Freedman-Diaconis choice for skewed data

```
Square-root choice [edit]
   k = \lceil \sqrt{n} \rceil
which takes the square root of the number of data points in the
Sturges' formula [edit]
Sturges' formula[12] is derived from a binomial distribution and
   k = \lceil \log_2 n \rceil + 1,
It implicitly bases the bin sizes on the range of the data and ca
trends in the data well. It may also perform poorly if the data a
Rice Rule [edit]
   k = [2\sqrt[3]{n}],
```

Both R and Python Provide Methods to compute Entropy & Mutual Information



MultiCollinearity

While an input must be strongly correlated with an output it should not be with other inputs

Inputs that are strongly correlated to each other are redundant

Add little additional information
 Correlation and MI can be used to remove highly correlated variables

Physical understanding of the system and other practical considerations must be borne in mind to decide which variables to remove

Ease of measurement, data availability

Points to Consider

Identify Use Use physical basis to identify features Identify those features that have strong correlation to the output •Use appropriate correlation measures •Use mutual information measures •Remove variables that cause multicollinearity

Model Free Feature Selection

It is simple and model agnostic

However it is subjective

 The cut-offs for correlation and MI has to be subjectively assigned

Can be used for initial model selection or exclusion of certain variables

Always use a combination of physical considerations and statistical criteria

You Should Know

