Feature Selection

Lesson 6 – Section 3

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Overview

- Why feature selection?
- 3 types of feature selection methods
- Mutual information

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Feature Selection

- Process of selecting a subset of features that are good predictors of the target
- Useful for
  - –Controlling complexity of model
  - –Speed up model learning without reducing accuracy
  - –Improve generalization capability

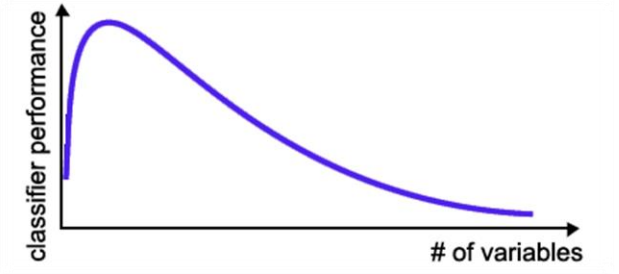
Model Selection vs Feature Selection

- Model selection includes selecting:
  - –Model algorithm
  - –Model algorithm hyperparameters
  - –Features to be used to train the models
- Feature selection
  - –Select features to be used to train the models

Why We Need Feature Selection?

Curse of Dimensionality

- The required number of samples (to achieve the same accuracy) grows exponentially with the number of variables!
- In practice: number of training examples is fixed!
  the classifier's performance will degrade for a large number of features!



In many cases the information lost by discarding variables is made up for by a more accurate mapping/sampling in the lower-dimensional space !

Problems of High-Dimensional Data

- High-dimensional data is often notorious to tackle due to the curse of dimensionality
  - –Increase storage and running time
  - –Overfit the machine learning models
  - –Require more data

- The intrinsic dimension of data may be small
  - –The number of genes responsible for a certain disease

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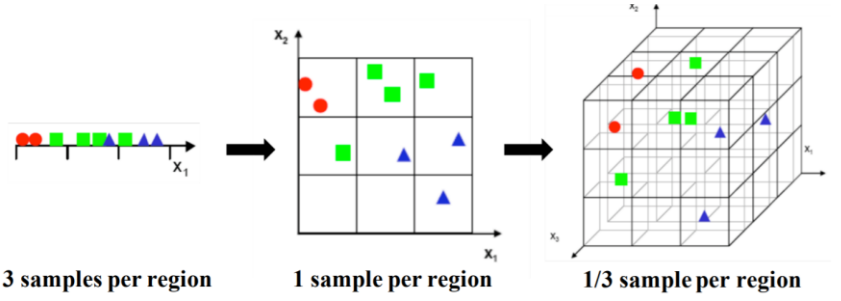
Curse of Dimensionality – Required Samples

- Data sparsity becomes exponentially worse as feature dimension increases
  - –Conventional distance metrics become ineffective
  - –All points in the high-dimensional space look equally distant



http://nikhilbuduma.com/2015/03/10/the-curse-of-dimensionality/

Feature Selection, 3 types of methods (1)

Filter Methods, select a subset of features before training a model, e.g.

- –Correlation with target,
- –Mutual Information between feature and target
- *Simple to implement, and have reasonable performance*

Feature Selection, 3 types of methods (2)

Wrapper Methods, search combination of feature space by training and evaluating model using a subset of features, e.g.

- –Forward, backward, step-wise feature selection,
- –Genetic algorithms.

• *Computationally expensive and prone to over-fitting*

Feature Selection, 3 types of methods (3)

Embedded Methods, feature subset is chosen as part of model training, e.g.

- –LASSO (L-1) regression, Regularized **decision trees, random forests**

• *Typically robust to over-fitting, but has hyper parameters that will need to be fit using a validation data*

Filter-Based Feature Selection

Filter-based Feature Selection

- Correlation with target variable
  - –A good starting point
  - –If Y is categorical variable (classification):
    - Use chi-square test to decide the correlation between each categorical X variable and Y variable
    - Use ANOVA test to decide the correlation between each numerical X variable and Y variable
  - –If Y is continuous variable (regression):
    - Use ANOVA test to decide the correlation between each categorical X variable and Y variable
    - Use correlation between each numerical X variable and Y variable

Filter-based Feature Selection

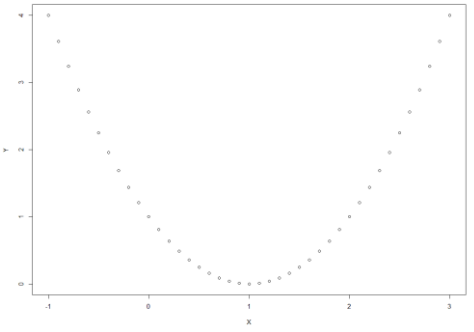
Alert:

If x1 and x2 are highly correlated, and x1 and Y are highly correlated, both x1 and x2 will be selected based on correlation with Y.

- Strong correlations in X will bring some challenge for some machine learning models, such as linear regression model.

Is Correlation Always a Good Choice?

- It makes sense for linear regression (logistic regression) model.
  - Since linear regression model only looks at linear relationship
- Does not make sense for nonlinear models such as tree-based models
- Cannot capture nonlinear relationship between X and Y



Mutual Information

- Captures Statistical Dependency between Two Variables $\Pr(X, Y) = \Pr(X) \times \Pr(Y)$
  - –If two variables are statistically independent

$$I(X;Y) = \sum_{y \in Y} \sum_{x \in X} p(x,y) \log \left(\frac{p(x,y)}{p(x)\,p(y)} \right)$$

$$\hat{f}(x) = \frac{1}{Nh\sqrt{2\pi}} \sum_{i=1}^{N} \exp\left(\frac{-(x-x_i)^2}{2h^2}\right).$$

  - –Estimate Pr(X) from observations by using a kernel function

Summary

Feature Selection to avoid high-dimension sparse data

>Filter Methods

–Subset of data before splitting based on correlation or mutual information

>Mutual Information

–Captures the statistical dependency between 2 variables