

### **Feature Learning**

Finding the diamonds in the rough

## High Dimensionality

#### **Higher Dimensionality**

More Data

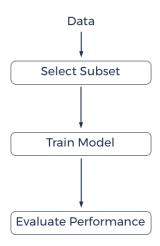
| Feature 1  | Feature 2  | Feature 3  | Feature 4  |
|------------|------------|------------|------------|
| Value 1, 1 | Value 1, 2 | Value 1, 3 | Value 1, 4 |
| Value 2, 1 | Value 2, 2 | Value 2, 3 | Value 2, 4 |
| Value 3, 1 | Value 3, 2 | Value 3, 3 | Value 3, 4 |
| Value 4, 1 | Value 4, 2 | Value 4, 3 | Value 4, 4 |
| Value 5, 1 | Value 5, 2 | Value 5, 3 | Value 5, 4 |
| Value 6, 1 | Value 6, 2 | Value 6, 3 | Value 6, 4 |

## Feature Learning

- Feature Selection
- Feature Extraction

## Feature Selection

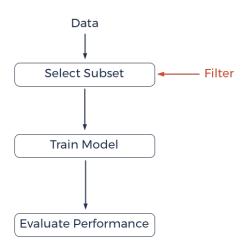
#### Feature Selection



#### Feature Selection Methods

- Filter methods
- Wrapper methods
- Embedded methods

#### Filter Methods



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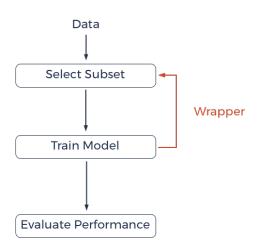
#### Mutual Information Score

Mutual information between two vectors of discrete values,  $\mathbf{x}$  and  $\mathbf{y}$  is,

$$MI(\mathbf{x}, \mathbf{y}) = \sum_{x_i \in \mathbf{x}} \sum_{y_i \in \mathbf{y}} p(x_i, y_i) \log \left( \frac{p(x_i, y_j)}{p(x_i) \times p(y_j)} \right).$$

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## Wrapper Methods



#### Recursive Feature Elimination

#### **Algorithm 1:** Recursive Feature Elimination

**Input:** Features from data

**Parameter:** *r* features to select from the data **Parameter:** *k* features to remove per iteration **Output:** Subset of *r* features from the data

Train a model on all features and obtain feature coefficients

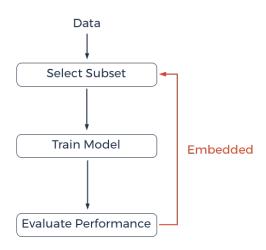
**while** selected features count > r **do** 

Remove up to k features with the lowest feature coefficients

Train a model on the new subset of features

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#### Embedded Methods



## Regularization Based methods

$$\min_{\mathbf{w}} f(\mathbf{x}, \mathbf{w}) + g(\mathbf{w}),$$

where f is a core objective function with learned parameters  $\mathbf{w}$  and g is a regularization function applied to the learned parameters.

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### Linear Regression Based Regularization

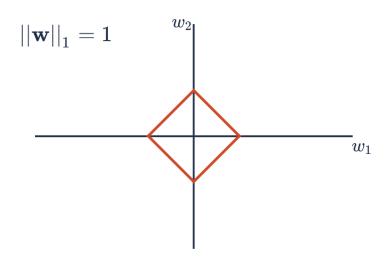
$$\min_{\mathbf{w}} ||\mathbf{y}^T - \mathbf{w}^T \mathbf{X}||_2^2 + g(\mathbf{w}).$$

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#### Lasso

$$\min_{\mathbf{w}} ||\mathbf{y}^T - \mathbf{w}^T \mathbf{X}||_2^2 + \alpha ||\mathbf{w}||_1.$$

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### Feature Selection Summary

- Filter methods
  - Pros: Low computation time
  - Cons: May select redundant data, not as effective as other methods, greedy
- Wrapper methods
  - Pros: Incorporate information from learned model
  - Cons: Potentially high computation time, prone to overfitting, greedy
- Embedded methods
  - Pros: Improve on both Filter and Wrapper in terms of performance
  - Cons: High computation time

## Feature Extraction

$$\min_{\mathbf{U},\mathbf{V}} ||\mathbf{X} - \mathbf{U}\mathbf{V}^T||_F^2,$$
 s.t.  $\mathbf{U}^T\mathbf{U} = \mathbf{I}$ .

## Demo



# Questions

These slides are designed for educational purposes, specifically the CSCI-470 Introduction to Machine Learning course at the Colorado School of Mines as part of the Department of Computer Science.

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