

[10-701] Introduction to Machine Learning(PhD)

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Spring 2018

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4 Classification

4.1 Naive Bayes, Generative vs Discriminative

Conditional Independence

X is conditionally independent of Y given Z:

$P(X \perp Y, Z) = P(X \perp Z)$. Also, $P(X, Y \perp Z) = P(X \perp Z)P(Y \perp Z)$.

For example, $P(\text{Thunder} \perp \text{Rain}, \text{Lightning}) = P(\text{Thunder} \perp \text{Lightning})$. Thunder is not independent of rain. However, thunder is **conditionally independent** of rain given lightning. If you see lightning, thunder and rain are independent. Seeing rain does not give you information about thunder in that case.

Naive Assumption: features are independent given class

$P(X_1, X_2 | Y) = P(X_1 | X_2, Y)P(X_2 | Y) = P(X_1 | Y)P(X_2 | Y)$. More generally, $P(X_1 \dots X_d | Y) = \prod_{i=1}^d P(X_i | Y)$.

Note: if conditional independence assumption hold, Naive Bayes is the optimal classifier. But worse otherwise.

4.1.1 Generative vs Discriminative Model

Generative(Model-BASED) Approach

Discriminative(Model-FREE) Approach

4.2 Support Vector Machines (SVM)

4.3 Boosting, Surrogate Losses

5 Decision Tree

6 Neural Networks and Deep Learning

For each neuron,

Weight tells you what pattern this neuron in the second layer is picking up on **Bias** tells you how high the weighted sum needs to be before the neuron starts getting meaningfully active

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7.1 K-Nearest Neighbors, Kernel Density Estimation

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