

## CHEAT SHEET

# Naive Bayes Classifier

<b>Algorithm Name</b>	Naive Bayes Classifier
<b>Description</b>	<p>If our goal is to find the distribution for the label, namely <math>P(y \mathbf{x})</math>, we can use the naive Bayes classifier on this distribution to find the label of test points. To simplify the procedure for finding <math>P(y \mathbf{x})</math>, we assume that each feature is independent of the others given the label. Naive Bayes decomposes a d-dimensional probability estimation problem into d one-dimensional probability estimation problems, because MLE gets exponentially harder as d increases.</p> <p>We derive the naive Bayes classifier as follows:</p> $  \begin{aligned}  h(\mathbf{x}) &= \operatorname{argmax}_y P(y \mathbf{x}) \\  &= \operatorname{argmax}_y \frac{P(\mathbf{x} y)P(y)}{P(\mathbf{x})} && \text{(Bayes' rule)} \\  &= \operatorname{argmax}_y P(\mathbf{x} y)P(y) && (P(\mathbf{x}) \text{ does not depend on } y) \\  &= \operatorname{argmax}_y \prod_{\alpha=1}^d P(x_{\alpha} y)P(y) && \text{(by the naive Bayes assumption)} \\  &= \operatorname{argmax}_y \sum_{\alpha=1}^d \log(P(x_{\alpha} y)) + \log(P(y)) && \text{(as log is a monotonic function)}  \end{aligned}  $
<b>Applicability</b>	Classification problems where features can be assumed independent
<b>Assumptions</b>	Given the label, features are independent of one another.
<b>Underlying Mathematical Principles</b>	We assume the $\mathbf{x}_{\alpha} y$ follows some distribution (e.g., categorical distribution) and use MLE to learn the distribution from the data.
<b>Additional Details</b>	Optional +1 smoothing (Laplace smoothing)
<b>Example</b>	Email spam classification; features are words that appear in the emails, labels are spam/not spam.

