

Unnamed Project 1 Writeup

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Abstract

This paper describes the Naïve Bayes algorithm, used for classification of data. This algorithm builds its model by finding the average value for each attribute of a given class, then classifies an input by finding the class it most closely matches. In this experiment, we run ten-fold cross-validation of our models build from 5 different datasets acquired from (whatever that repository is) to test the accuracy of the algorithm

Keywords: Naïve Bayes, Classification,

1. Introduction

Probabilistic inference has become a core technology in AI, largely due to developments in graph-theoretic methods for the representation and manipulation of complex probability distributions (?). Whether in their guise as directed graphs (Bayesian networks) or as undirected graphs (Markov random fields), *probabilistic graphical models* have a number of virtues as representations of uncertainty and as inference engines. Graphical models allow a separation between qualitative, structural aspects of uncertain knowledge and the quantitative, parametric aspects of uncertainty...

Remainder omitted in this sample. See <http://www.jmlr.org/papers/> for full paper.

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Appendix A.

In this appendix we prove the following theorem from Section 6.2:

Theorem *Let u, v, w be discrete variables such that v, w do not co-occur with u (i.e., $u \neq 0 \Rightarrow v = w = 0$ in a given dataset \mathcal{D}). Let N_{v0}, N_{w0} be the number of data points for which $v = 0, w = 0$ respectively, and let I_{uv}, I_{uw} be the respective empirical mutual information values based on the sample \mathcal{D} . Then*

$$N_{v0} > N_{w0} \Rightarrow I_{uv} \leq I_{uw}$$

with equality only if u is identically 0. ■

Proof. We use the notation:

$$P_v(i) = \frac{N_v^i}{N}, \quad i \neq 0; \quad P_{v0} \equiv P_v(0) = 1 - \sum_{i \neq 0} P_v(i).$$

These values represent the (empirical) probabilities of v taking value $i \neq 0$ and 0 respectively. Entropies will be denoted by H . We aim to show that $\frac{\partial I_{uv}}{\partial P_{v0}} < 0 \dots$

Remainder omitted in this sample. See <http://www.jmlr.org/papers/> for full paper.

References