

MITx: 6.008.1x Computational Probability and Inference

Heli



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The Naive Bayes Classifier: Prediction

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THE NAIVE BAYES CLASSIFIER: PREDICTION (PREFACE)

You should try to answer the following *before* watching the video below which presents the solution.

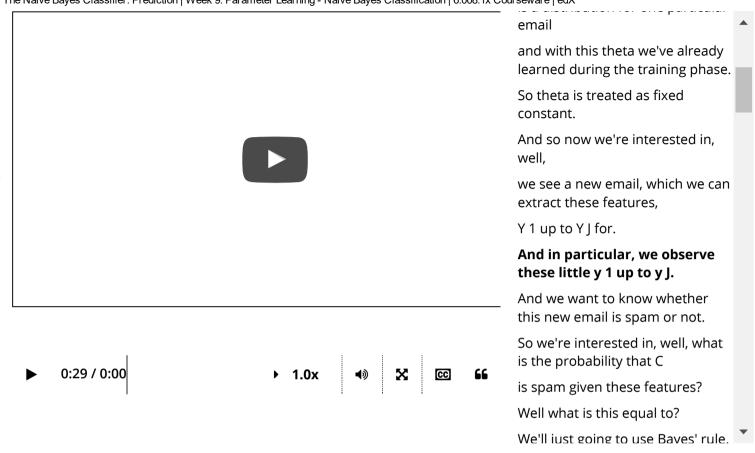
Practice problem: Once we learn the parameters θ , we can treat them as fixed and start doing prediction. Let's now look at classifying whether a new email that's not in our training data is spam or ham. This new email has random, unobserved label C, which we would like to infer, but we only get to see its features $Y_1=y_1,Y_2=y_2,\ldots,Y_J=y_J$. Assuming that θ is known and fixed, figure out what the MAP estimate for label C is given $Y_1=y_1,Y_2=y_2,\ldots,Y_J=y_J$.

The Naive Bayes Classifier: Prediction

Week 9: Parameter Learning - Naive Bayes Classification

Week 9: Mini-project on Email Spam Detection

Mini-projects due Nov 17, 2016 at 01:30 IST



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These notes cover roughly the same content as the video:

THE NAIVE BAYES CLASSIFIER: PREDICTION (COURSE NOTES)

Unleashing Bayes' rule,

$$\begin{split} & p_{C|Y_1,...,Y_J}(\text{``spam''} \mid y_1,...,y_J) \\ & = \frac{p_C(\text{``spam''})p_{Y_1,...,Y_J|C}(y_1,...,y_J|\text{``spam''})}{p_{Y_1,...,Y_J|C}(y_1,...,y_J|\text{``spam''})} \\ & = \frac{p_C(\text{``spam''})p_{Y_1,...,Y_J|C}(y_1,...,y_J|\text{``spam''})}{p_C(\text{``spam''})p_{Y_1,...,Y_J|C}(y_1,...,y_J|\text{``spam''})} \\ & = \frac{p_C(\text{``spam''})\prod_{j=1}^J p_{Y_j|X}(y_j|\text{``spam''})}{p_C(\text{``spam''})\prod_{j=1}^J p_{Y_j|C}(y_j|\text{``spam''}) + p_C(\text{``ham''})\prod_{j=1}^J p_{Y_j|X}(y_j|\text{``ham''})} \\ & = \frac{s\prod_{j=1}^J q_j^{y_j}(1-q_j)^{1-y_j}}{s\prod_{j=1}^J q_j^{y_j}(1-q_j)^{1-y_j}}, \end{split}$$

where for simplicity we've dropped the hats on the parameters even though the parameter values we use are estimated from training data.

Of course.

$$egin{aligned} &p_{C|Y_1,\ldots,Y_J}(ext{``ham ''}\;|y_1,\ldots,y_J)\ &=1-p_{C|Y_1,\ldots,Y_J}(ext{``spam ''}\;|y_1,\ldots,y_J)\ &=rac{(1-s)\prod_{j=1}^Jp_j^{y_j}(1-p_j)^{1-y_j}}{s\prod_{j=1}^Jq_j^{y_j}(1-q_j)^{1-y_j}+(1-s)\prod_{j=1}^Jp_j^{y_j}(1-p_j)^{1-y_j}}. \end{aligned}$$

The MAP estimate for $oldsymbol{C}$ is

$$\widehat{C}_{ ext{MAP}} = \left\{ egin{array}{ll} ext{``spam''} & ext{if } p_{C|Y_1,\ldots,Y_J} ext{(``spam''} & |y_1,\ldots,y_J) \geq p_{C|Y_1,\ldots,Y_J} ext{(``ham''} & |y_1,\ldots,y_J) \end{array}
ight.$$

Note that here we're breaking ties in favor of spam. The above is equivalent to looking at whether the *odds ratio*

$$rac{p_{C|Y_1,\ldots,Y_J}(ext{``spam"}|y_1,\ldots,y_J)}{p_{C|Y_1,\ldots,Y_J}(ext{``ham"}|y_1,\ldots,y_J)}$$

is at least 1, or whether the log odds ratio

$$\log rac{p_{C|Y_1,\ldots,Y_J}(ext{``spam "}|y_1,\ldots,y_J)}{p_{C|Y_1,\ldots,Y_J}(ext{``ham "}|y_1,\ldots,y_J)}$$

is at least 0. In practice the log odds ratio can be much more numerically stable to compute since, pushing in the log, we end up taking sums and differences of log probabilities rather than multiplying a large number of probabilities.

Discussion

Topic: Parameter Learning - Naive Bayes Classification / The Naive Bayes

Classifier: Prediction

Show Discussion

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