



Naive Bayes' classifier prediction step



$$\hat{\mathbf{y}} = \operatorname{argmax}_y \log P(\mathbf{x}, y; \boldsymbol{\mu}, \boldsymbol{\phi})$$

$$= \operatorname{argmax}_y \log P(\mathbf{x} | y; \boldsymbol{\mu}, \boldsymbol{\phi}) + \log P(y; \boldsymbol{\mu})$$

$$= \operatorname{argmax}_y \log \left[ B(\mathbf{x}) \prod_{j=1}^N \phi_j^{\mathbf{x}_j} \right] + \log \mu_y$$

$$= \operatorname{argmax}_y \log B(\mathbf{x}) + \sum_{j=1}^N x_j \log \phi_{y,j} + \log \mu_y$$

$$= \operatorname{argmax}_y \sum_{j=1}^N x_j \log \phi_{y,j} + \log \mu_y$$

This ends up being the label  
with the highest log posterior  
probability

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$$\begin{aligned}\hat{y} &= \operatorname{argmax}_y \log P(\mathbf{x}, y; \boldsymbol{\mu}, \boldsymbol{\phi}) \\ &= \operatorname{argmax}_y \log P(\mathbf{x} | y; \boldsymbol{\mu}, \boldsymbol{\phi}) + \log P(y; \boldsymbol{\mu}) \\ &= \operatorname{argmax}_y \log \left[ B(\mathbf{x}) \prod_{j=1}^N \phi_j^{\mathbf{x}_j} \right] + \log \mu_y \\ &= \operatorname{argmax}_y \log B(\mathbf{x}) + \sum_{j=1}^N x_j \log \phi_{y,j} + \log \mu_y \\ &= \operatorname{argmax}_y \sum_{j=1}^N x_j \log \phi_{y,j} + \log \mu_y\end{aligned}$$

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# Naive Bayes' classifier estimation step

Maximum likelihood estimate of  $\phi_y$

$$\hat{\phi}_{y,j} = \frac{\sum_{i: y^{(i)}=y}^M x_j^{(i)}}{\sum_{j'=1}^N \sum_{i: y^{(i)}=y}^M x_{j'}}$$

i.e., the ratio between the number of times label  $y$  appears in conjunction with word  $x_j$ , and the number of times label  $y$  appears in total.