Naïve Bayes classifier

- ► This movie is disappointing.
- ► This movie does not disappoint.
- ► I would love to have that two hours of my life back.
- This is one of my favorite if not favorite films.
- I have seen so many bad low budget films lately, but I love this one.

Deterministic model

f(I love, love this movie.) = 0 or 1

Probabilistic model

f(I love, love this movie.)= $\mathbb{P}(y = 1 | I \text{ love, love this movie.})$

Naïve Bayes

Simple (naïve) classifier based on Bayes rule:
For a document d = {w₁, w₂, ..., w_n} and a class y = 0 or 1

$$\mathbb{P}(y = 1 | w_1, w_2, \dots, w_n) = \frac{\mathbb{P}(w_1, w_2, \dots, w_n | y = 1) \mathbb{P}(y = 1)}{\mathbb{P}(w_1, w_2, \dots, w_n)}$$
$$\mathbb{P}(y = 0 | w_1, w_2, \dots, w_n) = \frac{\mathbb{P}(w_1, w_2, \dots, w_n | y = 0) \mathbb{P}(y = 0)}{\mathbb{P}(w_1, w_2, \dots, w_n)}$$

- Compute $\mathbb{P}(w_1, w_2, \dots, w_n | y)$ and $\mathbb{P}(y)$ from the (labeled) data.
- What about $\mathbb{P}(w_1, w_2, \ldots, w_n)$?

Conditional independence

We assume that $\mathbb{P}(w_i|y)$ are independent given the class *y*.

$$\mathbb{P}(w_1, w_2, \ldots, w_n | y) = \mathbb{P}(w_1 | y) \mathbb{P}(w_2 | y) \ldots \mathbb{P}(w_n | y).$$

Graphical model

$$\mathbb{P}(w_1, w_2, \ldots, w_n | y) \mathbb{P}(y) = \mathbb{P}(y) \mathbb{P}(w_1 | y) \mathbb{P}(w_2 | y) \ldots \mathbb{P}(w_n | y)$$

where

$$\mathbb{P}(w_i|y) = \frac{count(w_i, y)}{\sum_{w \in V} count(w, y)}$$

and

$$\mathbb{P}(y) = \frac{countdoc(Y = y)}{count(\mathsf{Documents})}$$

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$\mathbb{P}(\mathsf{Positive}) =$

- This movie is disappointing.
- This movie does not disappoint.
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- This is one of my favorite if not favorite films.
- ► I have seen so many bad low budget films lately, but I love this one.

$\mathbb{P}(\mathsf{favorite}|\mathsf{Positive}) =$

- This movie is disappointing.
- This movie does not disappoint.
- I would love to have that two hours of my life back.
- This is one of my favorite if not favorite films.
- ► I have seen so many bad low budget films lately, but I love this one.

$\mathbb{P}(disappoint | Positive) =$

$$\mathbb{P}(y = 1 | I \text{ love, love this movie.})$$

$$\mathbb{P}(y = 0 | I \text{ love, love this movie.})$$

What if there is a word slept in the test set, but not in the training set?

$$\mathbb{P}(\operatorname{slept}|y) = \frac{\operatorname{count}(\operatorname{slept}, y)}{\sum_{w \in V} \operatorname{count}(w, y)} = 0.$$

► There is no best *y* in this case.

$$\mathbb{P}(y|slept,...) = \mathbb{P}(y)\mathbb{P}(slept|y)... = 0$$

Laplace smoothing

Fix $\alpha > 0$.

$$\mathbb{P}(w_i|y) = \frac{count(w_i, y) + \alpha}{\sum_{w \in V} (count(w, y) + \alpha)}$$

$$= \frac{count(w_i, y) + \alpha}{\sum_{w \in V} count(w, y) + \alpha |V|}$$

In the previous example, if we choose $\alpha = 1$,

$$\mathbb{P}(\mathsf{slept}|y) = \frac{\alpha}{\sum_{w \in V} \mathsf{count}(w, y) + \alpha |V|}$$

From the training corpus, extract the **Vocabulary**.

- For each class y, calculate $\mathbb{P}(y)$
 - Count number of documents in class y.

$$\mathbb{P}(\mathbf{y}) = \frac{\operatorname{countdoc}(\mathbf{Y}=\mathbf{y})}{\sqrt{2}}$$

 $\blacktriangleright \mathbb{P}(y) = \frac{1}{count(Documents)}$

- ► For each word *w_i* and class *y*
 - Merge all documents in class y
 - *n_i* ← # of occurrence of each word in class *y*

•
$$\mathbb{P}(w_i|y) = \frac{n_i + \alpha}{\sum_i n_i + \alpha |Vocab|}$$