Review: Naïve Bayes

CS114B Lab 1

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Suppose we observe a movie review d = "predictable with no fun". Is the review positive or negative?

► Training data:

document	class	
just plain boring	negative	
entirely predictable and lacks energy	negative	
no surprises and very few laughs	negative	
very powerful	positive	
the most fun film of the summer	positive	

Naïve Bayes models are generative

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 - Assume the data are generated according to an underlying distribution

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 - "rolling a |V|-sided die n times"
 - ightharpoonup V = vocabulary, n = length of document

- ▶ *c* = negative
- ightharpoonup d = "predictable with no fun"

- ightharpoonup c = negative
- ▶ d = "predictable with no fun"
 - w_1 = predictable
 - \triangleright $w_2 = \text{with}$
 - $\sim w_3 = no$
 - $w_4 = \text{fun}$

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- $\hat{c} = \operatorname*{argmax}_{c \in C} P(d|c)P(c)$
- ▶ What about P(d)?
 - ightharpoonup P(d) is the same for each class

$$\hat{c} = \operatorname*{argmax}_{c \in \mathcal{C}} P(c) P(d|c)$$

$$\hat{c} = \underset{c \in C}{\operatorname{argmax}} P(c)P(d|c) \\
= \underset{c \in C}{\operatorname{argmax}} P(c)P(w_1, ..., w_n|c)$$

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► Chain Rule:
$$\hat{c} = \underset{c \in C}{\operatorname{argmax}} P(c) \prod_{i=1}^{n} P\left(w_{i} \middle| \bigcap_{j=1}^{i-1} w_{j}, c\right)$$

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$$\prod_{i=1}^n P\left(w_i \middle| \bigcap_{j=1}^{i-1} w_j, c\right) = \prod_{i=1}^n P(w_i | c)$$

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 - ightharpoonup argmax(0,0)=?

Smoothing

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$$\hat{P}(w_i|c) = \frac{\text{wordcount}(w_i, c) + 1}{\sum_{w \in V} (\text{wordcount}(w, c) + 1)}$$

$$= \frac{\text{wordcount}(w_i, c) + 1}{\left(\sum_{w \in V} \text{wordcount}(w, c)\right) + |V|}$$

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- $\hat{P}(\text{negative}) = 3/5$
- $\hat{P}(positive) = 2/5$



	wordcount(w, c)		w			
	VVC	rucount(w,c)	predictable	no	fun	
		negative	1	1	0	
	C	positive	0	0	1	

C	wordcount(w,c)+1		w			
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	_	negative	1 + 1	1 + 1	0 + 1	
	C	positive	0 + 1	0+1	1 + 1	

	wordcount(w,c)+1		w				
			predictable	no	fun		
	с	negative	2	2	1		
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- ► |V| = 20

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$\hat{P}(w c)$		W					
		predictable	no	fun			
С	negative	2/(14+20)	2/(14+20)	1/(14+20)			
	positive	1/(9+20)	1/(9+20)	2/(9+20)			

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	$\hat{P}(w c)$		w				
			predictable	no	fun		
	С	negative	1/17	1/17	1/34		
		positive	1/29	1/29	2/29		

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- ▶ Importantly, V should still be the entire vocabulary
 - ▶ The other words are still there, even if we are not using them

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- Avoid floating-point underflow
 - (You will need to do this for PA, but not for HW)