Outline

- Probabilities
- Bayes' rule (Applied in different fields, including NLP)
- Build your own Naive-Bayes tweet classifier!

Introduction

Corpus of tweets

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Tweets containing the word "happy"

Probabilities

Corpus of tweets

A → Positive tweet

$P(A) = P(\text{Positive}) = N_{pos} / N$

Probabilities

Corpus of tweets

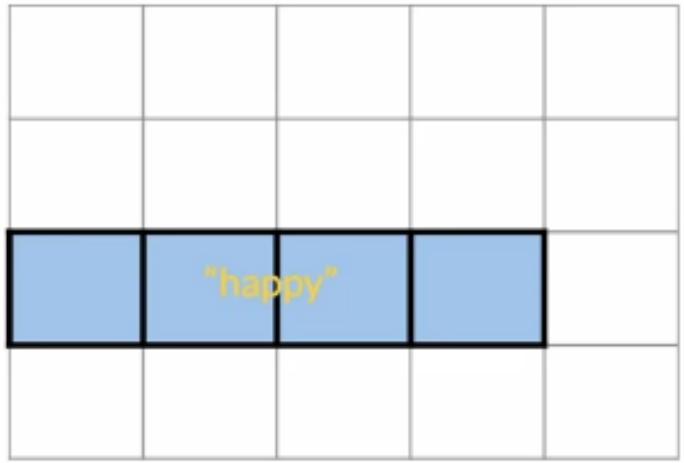
A → Positive tweet

$P(A) = N_{pos} / N = 13 / 20 = 0.65$

P(Negative) = 1 - P(Positive) = 0.35

Probabilities

Tweets containing the word "happy"

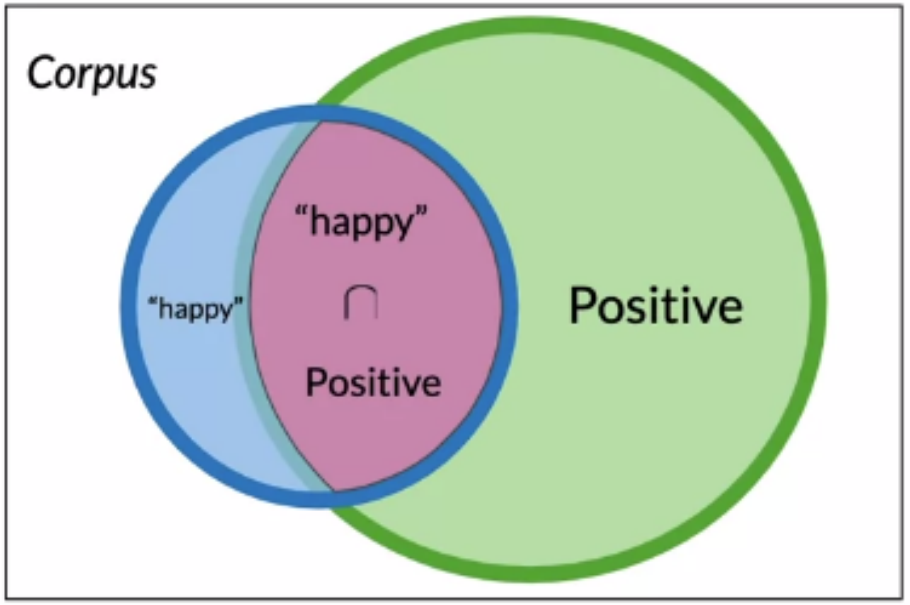


B → tweet contains "happy".

$P(B) = P(happy) = N_{happy} / N$

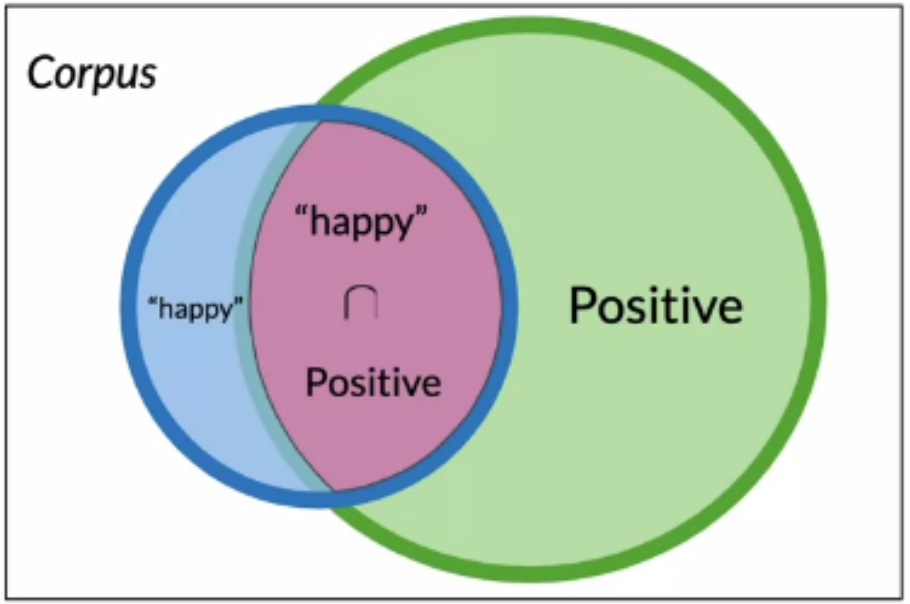
$P(B) = 4 / 20 = 0.2$

Probability of the intersection

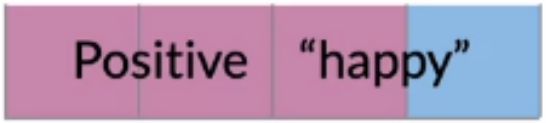


Probability of the intersection

$$P(A \cap B) = P(A, B) = \frac{3}{20} = 0.15$$

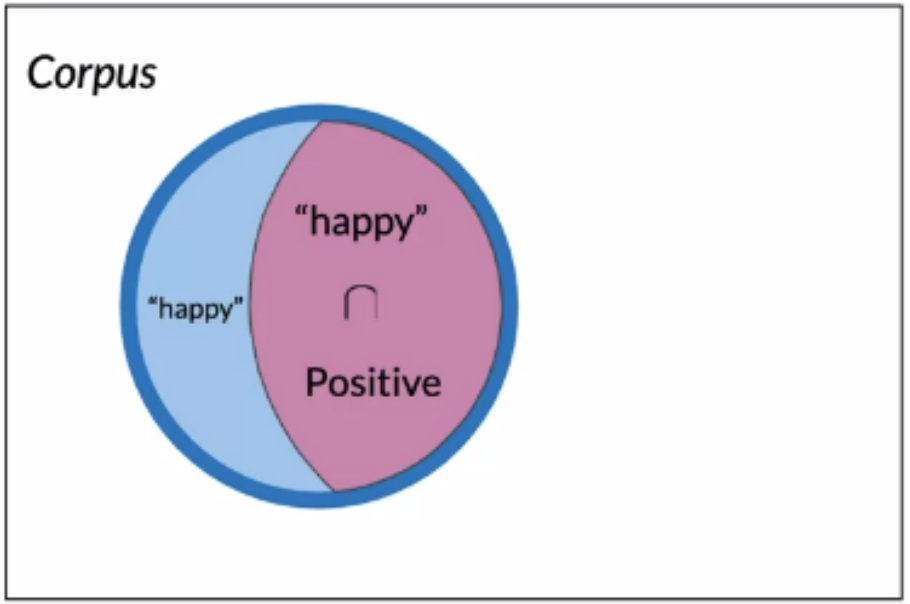


Conditional Probabilities

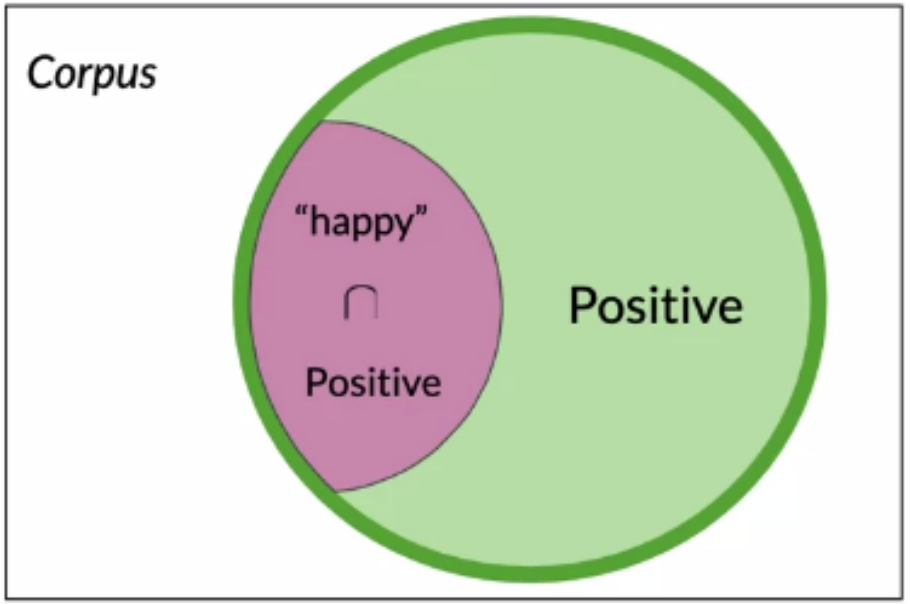


P(A | B) = P(Positive | “happy”)

P(A | B) = 3 / 4 = 0.75



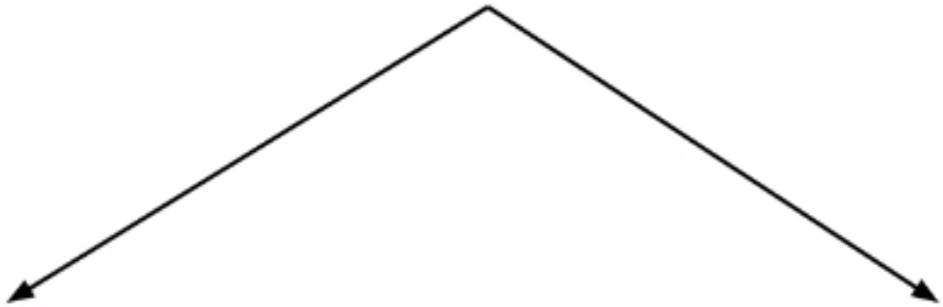
Conditional Probabilities



P(B | A) = P(“happy”| Positive)

P(B | A) = 3 / 13 = 0.231

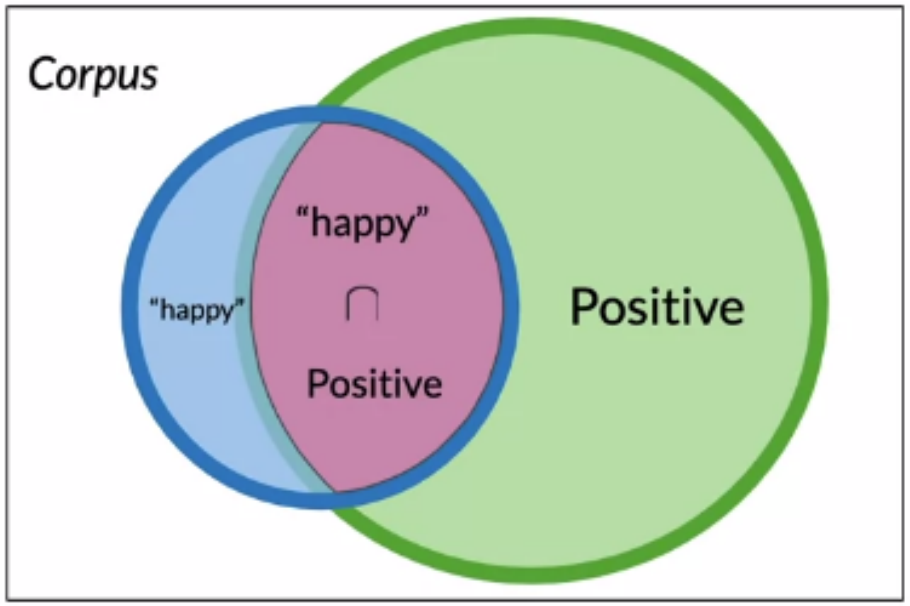
Conditional probabilities



Probability of B, given A happened

Looking at the elements of set A, the chance that one also belongs to set B

Conditional probabilities



$$P(\text{Positive}|\text{“happy”}) = \frac{P(\text{Positive} \cap \text{“happy”})}{P(\text{“happy”})}$$

Bayes' rule

$$P(\text{Positive}|\text{“happy”}) = \frac{P(\text{Positive} \cap \text{“happy”})}{P(\text{“happy”})}$$

Bayes' rule

$$P(\text{Positive}|\text{“happy”}) = \frac{P(\text{Positive} \cap \text{“happy”})}{P(\text{“happy”})}$$

$$P(\text{“happy”}|\text{Positive}) = \frac{P(\text{“happy”} \cap \text{Positive})}{P(\text{Positive})}$$

Bayes' rule

$$P(\text{Positive}|\text{“happy”}) = P(\text{“happy”}|\text{Positive}) \times \frac{P(\text{Positive})}{P(\text{“happy”})}$$

$$P(X|Y) = P(Y|X) \times \frac{P(X)}{P(Y)}$$

Summary

- Conditional probabilities $\longrightarrow$ Bayes' Rule
- $P(X|Y) = P(Y|X) \times \frac{P(X)}{P(Y)}$

Naïve Bayes for Sentiment Analysis

Positive tweets

I am happy because I am learning NLP

I am happy, not sad.

Negative tweets

I am sad, I am not learning NLP

I am sad, not happy

Naïve Bayes for Sentiment Analysis

Positive tweets

I am happy because I am learning NLP

I am happy, not sad.

Negative tweets

I am sad, I am not learning NLP

I am sad, not happy

word
I
am
happy
because
learning
NLP
sad
not

Naïve Bayes for Sentiment Analysis

Positive tweets

I am happy because I am learning NLP

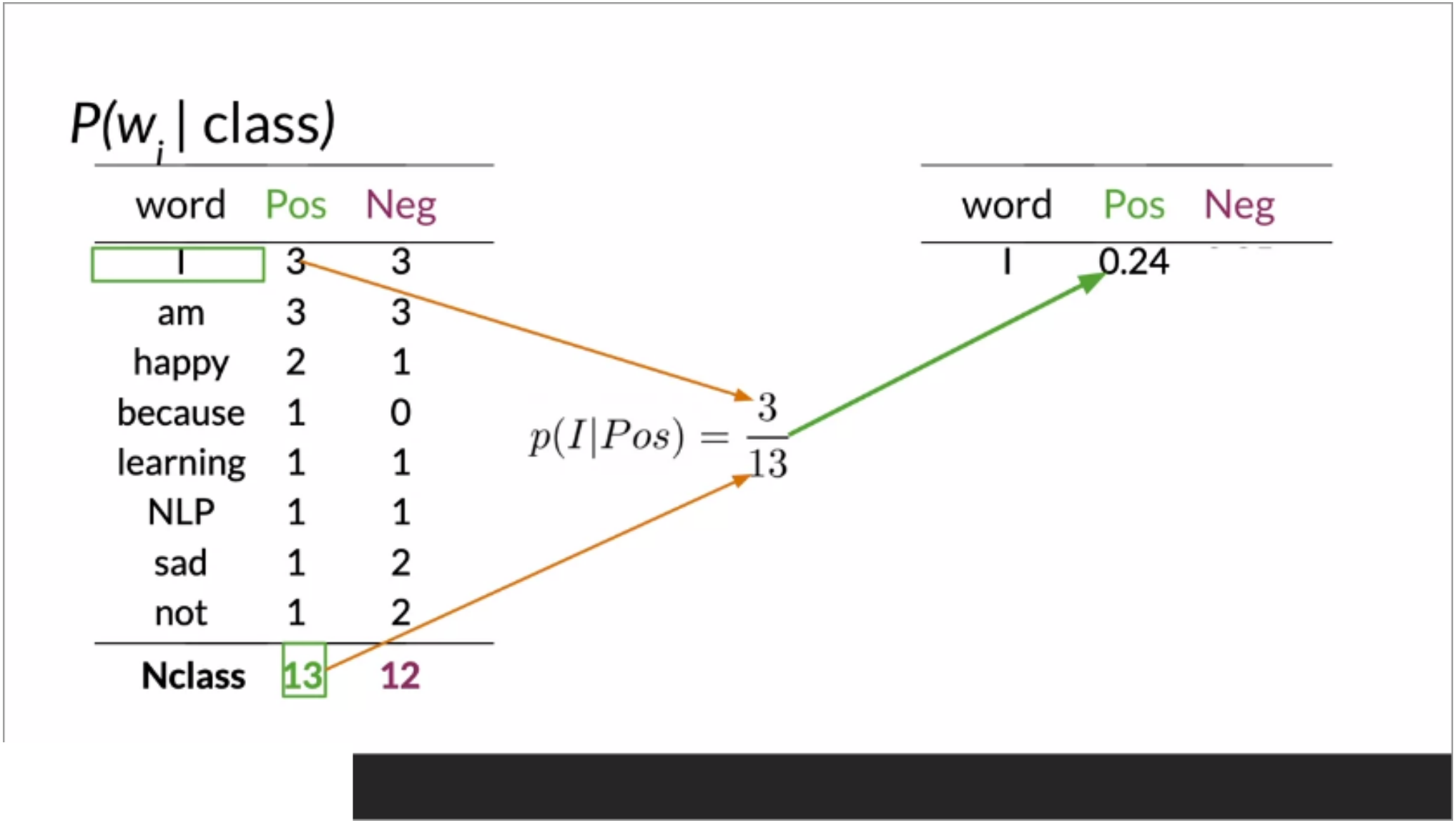
I am happy, not sad.

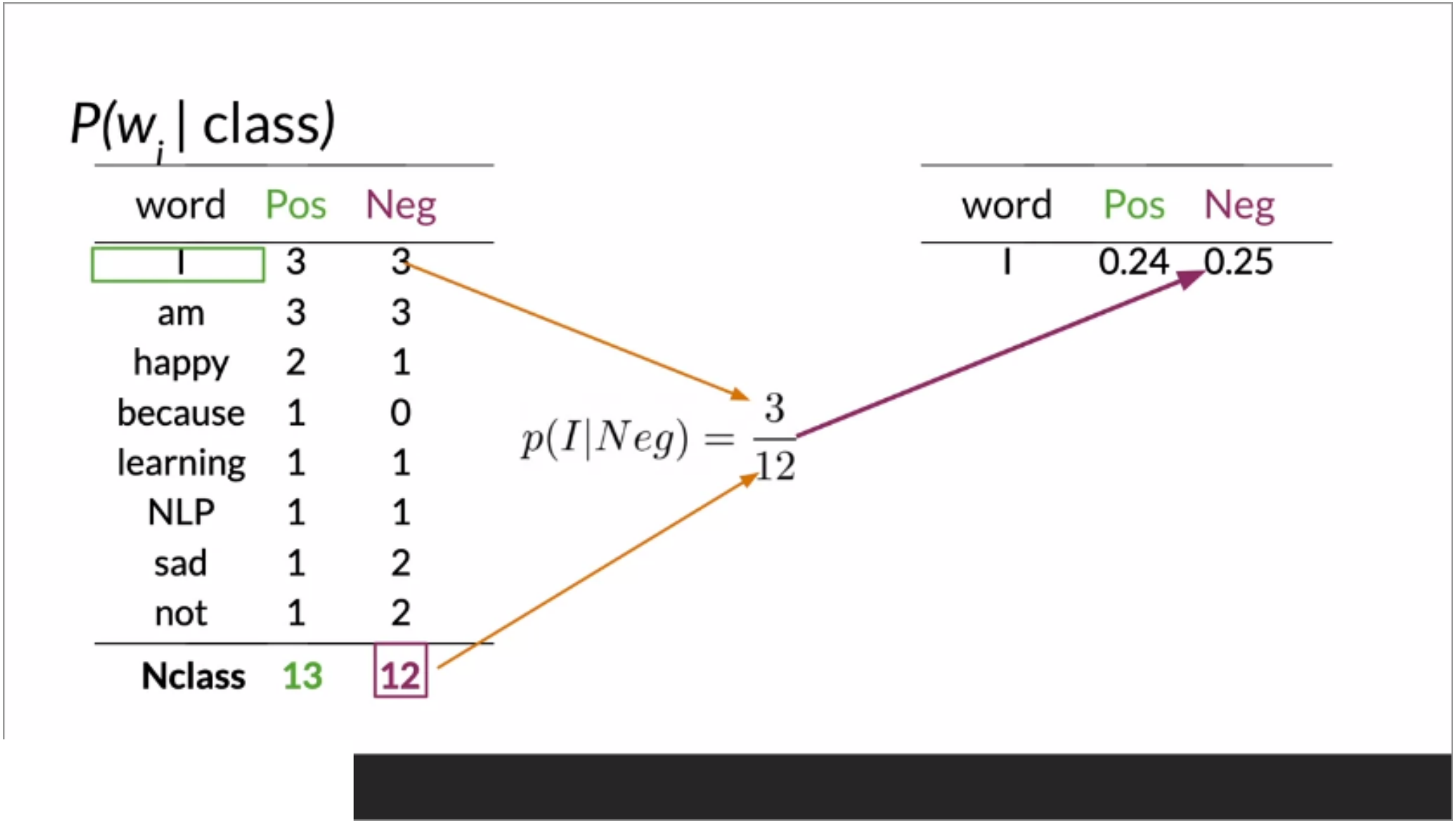
Negative tweets

I am sad, I am not learning NLP

I am sad, not happy

word	Pos	Neg
I	3	3
am	3	3
happy	2	1
because	1	0
learning	1	1
NLP	1	1
sad	1	2
not	1	2
N_{class}	13	12


P(w_i | class)
word Pos Neg
I 3 3
am 3 3
happy 2 1
because 1 0
learning 1 1
NLP 1 1
sad 1 2
not 1 2
Nclass 13 12
p(I|Pos) = 3/13
word Pos Neg
I 0.24


P(w_i | class)
word Pos Neg
I 3 3
am 3 3
happy 2 1
because 1 0
learning 1 1
NLP 1 1
sad 1 2
not 1 2
Nclass 13 12
p(I|Neg) = 3/12
word Pos Neg
I 0.24 0.25

$P(w_i \mid \text{class})$

word	Pos	Neg
I	3	3
am	3	3
happy	2	1
because	1	0
learning	1	1
NLP	1	1
sad	1	2
not	1	2
Nclass	**13**	**12**

word	Pos	Neg
I	0.24	0.25
am	0.24	0.25
happy	0.15	0.08
because	0.08	0.00
learning	0.08	0.08
NLP	0.08	0.08
sad	0.08	0.17
not	0.08	0.17
Sum	**1**	**1**

$P(w_i \mid class)$

word	Pos	Neg
I	0.24	0.25
am	0.24	0.25
happy	0.15	0.08
because	0.08	0
learning	0.08	0.08
NLP	0.08	0.08
sad	0.08	0.17
not	0.08	0.17

Naïve Bayes

Tweet: I am happy today; I am learning.

$$\prod_{i=1}^{m} \frac{P(w_i|pos)}{P(w_i|neg)}$$

word	Pos	Neg
I	0.20	0.20
am	0.20	0.20
happy	0.14	0.10
because	0.10	0.05
learning	0.10	0.10
NLP	0.10	0.10
sad	0.10	0.15
not	0.10	0.15

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$$\prod_{i=1}^{m} \frac{P(w_i|pos)}{P(w_i|neg)}$$

$$\frac{0.20}{0.20}$$

word	Pos	Neg
I	0.20	0.20
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because	0.10	0.05
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NLP	0.10	0.10
sad	0.10	0.15
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$$\frac{0.20}{0.20} * \frac{0.20}{0.20}$$

word	Pos	Neg
I	0.20	0.20
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happy	0.14	0.10
because	0.10	0.05
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NLP	0.10	0.10
sad	0.10	0.15
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$$\prod_{i=1}^{m} \frac{P(w_i|pos)}{P(w_i|neg)}$$

$$\frac{0.20}{0.20} * \frac{0.20}{0.20} * \frac{0.14}{0.10}$$

word	Pos	Neg
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$$\prod_{i=1}^{m} \frac{P(w_i|pos)}{P(w_i|neg)}$$

$$\frac{0.20}{0.20} * \frac{0.20}{0.20} * \frac{0.14}{0.10}$$

word	Pos	Neg
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am	0.20	0.20
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learning	0.10	0.10
NLP	0.10	0.10
sad	0.10	0.15
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$$\prod_{i=1}^{m} \frac{P(w_i|pos)}{P(w_i|neg)}$$

$$\frac{0.20}{0.20} * \frac{0.20}{0.20} * \frac{0.14}{0.10} * \frac{0.20}{0.20}$$

word	Pos	Neg
I	0.20	0.20
am	0.20	0.20
happy	0.14	0.10
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NLP	0.10	0.10
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$$\prod_{i=1}^{m} \frac{P(w_i|pos)}{P(w_i|neg)}$$

$$\frac{0.20}{0.20} * \frac{0.20}{0.20} * \frac{0.14}{0.10} * \frac{0.20}{0.20} * \frac{0.20}{0.20}$$

word	Pos	Neg
I	0.20	0.20
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because	0.10	0.05
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Naïve Bayes

Tweet: I am happy today; I am learning.

$$\prod_{i=1}^{m} \frac{P(w_i|pos)}{P(w_i|neg)}$$

$$\frac{0.20}{0.20} * \frac{0.20}{0.20} * \frac{0.14}{0.10} * \frac{0.20}{0.20} * \frac{0.20}{0.20} * \frac{0.10}{0.10}$$

word	Pos	Neg
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am	0.20	0.20
happy	0.14	0.10
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NLP	0.10	0.10
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Naïve Bayes

Tweet: I am happy today; I am learning.

$$\prod_{i=1}^{m} \frac{P(w_i|pos)}{P(w_i|neg)}$$

$$\frac{0.20}{0.20} * \frac{0.20}{0.20} * \frac{0.14}{0.10} * \frac{0.20}{0.20} * \frac{0.20}{0.20} * \frac{0.10}{0.10}$$

word	Pos	Neg
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am	0.20	0.20
happy	0.14	0.10
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learning	0.10	0.10
NLP	0.10	0.10
sad	0.10	0.15
not	0.10	0.15

Naïve Bayes

Tweet: I am happy today; I am learning.

$$\prod_{i=1}^{m} \frac{P(w_i|pos)}{P(w_i|neg)} = \frac{0.14}{0.10} = 1.4$$

$$\frac{0.20}{0.20} * \frac{0.20}{0.20} * \boxed{\frac{0.14}{0.10}} * \frac{0.20}{0.20} * \frac{0.20}{0.20} * \frac{0.10}{0.10}$$

word	Pos	Neg
I	0.20	0.20
am	0.20	0.20
happy	0.14	0.10
because	0.10	0.05
learning	0.10	0.10
NLP	0.10	0.10
sad	0.10	0.15
not	0.10	0.15

Naïve Bayes

Tweet: I am happy today; I am learning.

$$\prod_{i=1}^{m} \frac{P(w_i|pos)}{P(w_i|neg)} = \frac{0.14}{0.10} = 1.4 \quad > 1$$

$$\frac{0.20}{0.20} * \frac{0.20}{0.20} * \frac{0.14}{0.10} * \frac{0.20}{0.20} * \frac{0.20}{0.20} * \frac{0.10}{0.10}$$

word	Pos	Neg
I	0.20	0.20
am	0.20	0.20
happy	0.14	0.10
because	0.10	0.05
learning	0.10	0.10
NLP	0.10	0.10
sad	0.10	0.15
not	0.10	0.15

Summary

- Naive Bayes inference condition rule for binary classification

$$\prod_{i=1}^{m} \frac{P(w_i|pos)}{P(w_i|neg)}$$

- Table of probabilities

Laplacian Smoothing

$$P(\mathrm{w_i}|\mathrm{class}) = \frac{\mathrm{freq}(\mathrm{w_i}, \mathrm{class})}{\mathrm{N_{class}}}$$

class $\in$ {Positive, Negative}

N_{class} = frequency of all words in class

V = number of unique words in vocabulary

Laplacian Smoothing

$$P(\mathrm{w_i}|\mathrm{class}) = \frac{\mathrm{freq}(\mathrm{w_i}, \mathrm{class})}{\mathrm{N_{class}}}$$

class ∈ {Positive, Negative}

$$P(\mathrm{w_i}|\mathrm{class}) = \frac{\mathrm{freq}(\mathrm{w_i}, \mathrm{class}) + 1}{\mathrm{N_{class}} + \mathrm{V}}$$

N_{class} = frequency of all words in class

V = number of unique words in vocabulary

Introducing $P(w_i \mid \text{class})$ with smoothing

word	Pos	Neg
I	3	3
am	3	3
happy	2	1
because	1	0
learning	1	1
NLP	1	1
sad	1	2
not	1	2
Nclass	**13**	**12**

$V = 8$

word	Pos	Neg
I		

Introducing $P(w_i \mid \text{class})$ with smoothing

word	Pos	Neg
I	3	3
am	3	3
happy	2	1
because	1	0
learning	1	1
NLP	1	1
sad	1	2
not	1	2
Nclass	**13**	**12**

$$P(I|Pos) = \frac{3+1}{13+8}$$

V = 8

word	Pos	Neg
I		

Introducing $P(w_i \mid \text{class})$ with smoothing

word	Pos	Neg
I	3	3
am	3	3
happy	2	1
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Nclass	**13**	**12**

$$P(I|Pos) = \frac{3+1}{13+8}$$

V = 8

word	Pos	Neg
I	0.19	

Introducing $P(w_i \mid \text{class})$ with smoothing

word	Pos	Neg
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happy	2	1
because	1	0
learning	1	1
NLP	1	1
sad	1	2
not	1	2
Nclass	**13**	**12**

$$P(I|Neg) = \frac{3+1}{12+8}$$

V = 8

word	Pos	Neg
I	0.19	

Introducing $P(w_i \mid \text{class})$ with smoothing

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Nclass	**13**	**12**

$$P(I|Neg) = \frac{3+1}{12+8}$$

V = 8

word	Pos	Neg
I	0.19	0.20

Introducing $P(w_i \mid \text{class})$ with smoothing

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Introducing $P(w_i \mid \text{class})$ with smoothing

word	Pos	Neg
I	3	3
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NLP	1	1
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$V = 8$

word	Pos	Neg
I	0.19	0.20
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happy	0.14	0.10
because	0.10	0.05
learning	0.10	0.10
NLP	0.10	0.10
sad	0.10	0.15
not	0.10	0.15
Sum	**1**	**1**

Summary

- Laplacian smoothing to avoid $P(w_i|class) = 0$
- Naïve Bayes formula

$$\prod_{i=1}^{m} \frac{P(w_i|pos)}{P(w_i|neg)}$$

Ratio of probabilities

word	Pos	Neg	ratio
I	0.20	0.20	
am	0.20	0.20	
happy	0.14	0.10	
because	0.10	0.10	
learning	0.10	0.10	
NLP	0.10	0.10	
sad	0.10	0.15	
not	0.10	0.15	

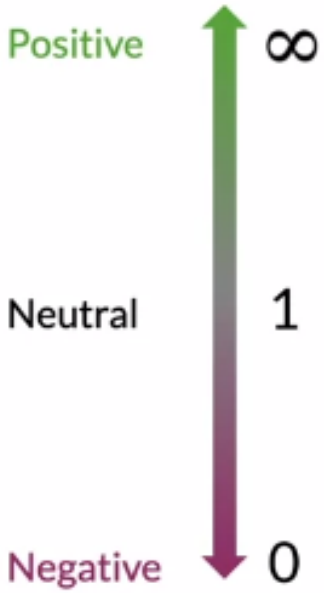
$$\text{ratio}(w_i) = \frac{P(w_i \mid \text{Pos})}{P(w_i \mid \text{Neg})}$$

Ratio of probabilities

word	Pos	Neg	ratio
I	0.20	0.20	1
am	0.20	0.20	1
happy	0.14	0.10	1.4
because	0.10	0.10	1
learning	0.10	0.10	1
NLP	0.10	0.10	1
sad	0.10	0.15	0.6
not	0.10	0.15	0.6

$$\text{ratio}(w_i) = \frac{P(w_i \mid \text{Pos})}{P(w_i \mid \text{Neg})}$$

Ratio of probabilities



word	Pos	Neg	ratio
I	0.20	0.20	1
am	0.20	0.20	1
happy	0.14	0.10	1.4
because	0.10	0.10	1
learning	0.10	0.10	1
NLP	0.10	0.10	1
sad	0.10	0.15	0.6
not	0.10	0.15	0.6

$$\text{ratio}(w_i) = \frac{P(w_i \mid \text{Pos})}{P(w_i \mid \text{Neg})}$$

$$\approx \frac{freq(w_i, 1) + 1}{freq(w_i, 0) + 1}$$

Naïve Bayes' inference

class $\in$ *{pos, neg}*
w -> *Set of m words in a tweet*

$$\frac{P(pos)}{P(neg)} \prod_{i=1}^{m} \frac{P(w_i|pos)}{P(w_i|neg)} > 1$$

- A simple, fast, and powerful baseline
- A probabilistic model used for classification