California State University, Dominguez Hills
Department of Computer Science
CSC 595

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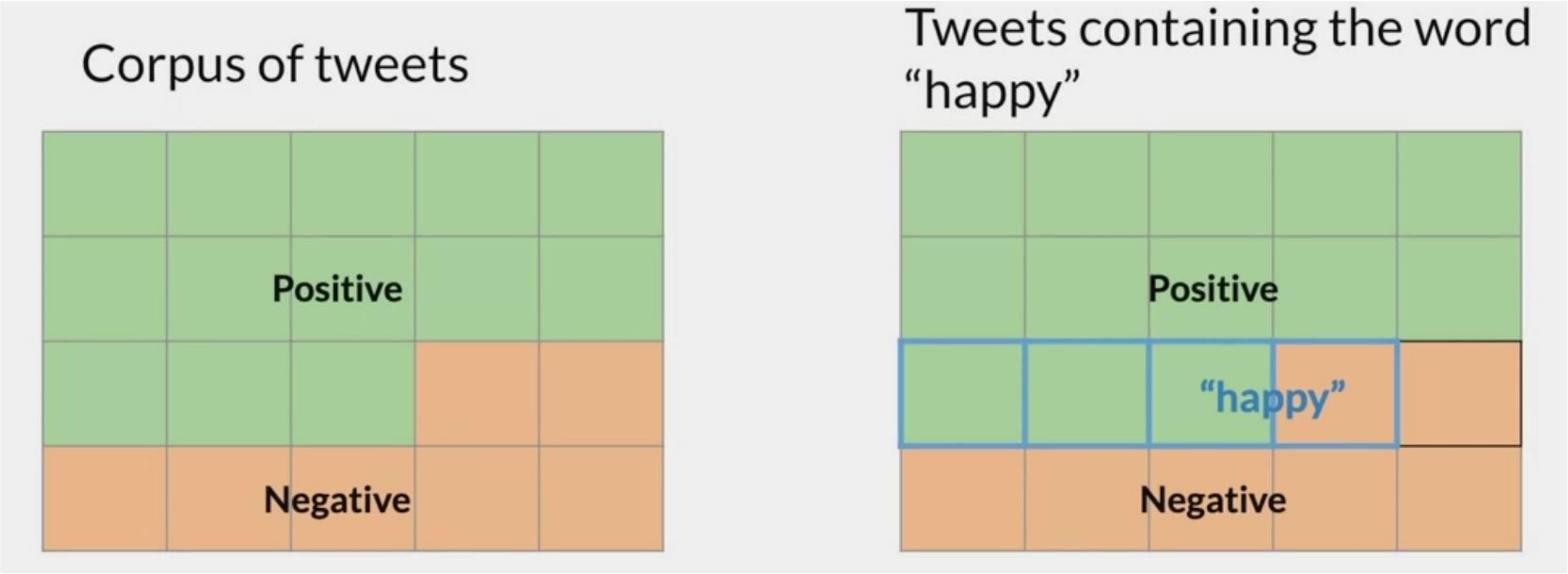
Lecture 2

Sentiment Analysis with Naïve Bayes

Introduction



Probabilities

Corpus of tweets

A → Positive tweet

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

Probabilities

Corpus of tweets

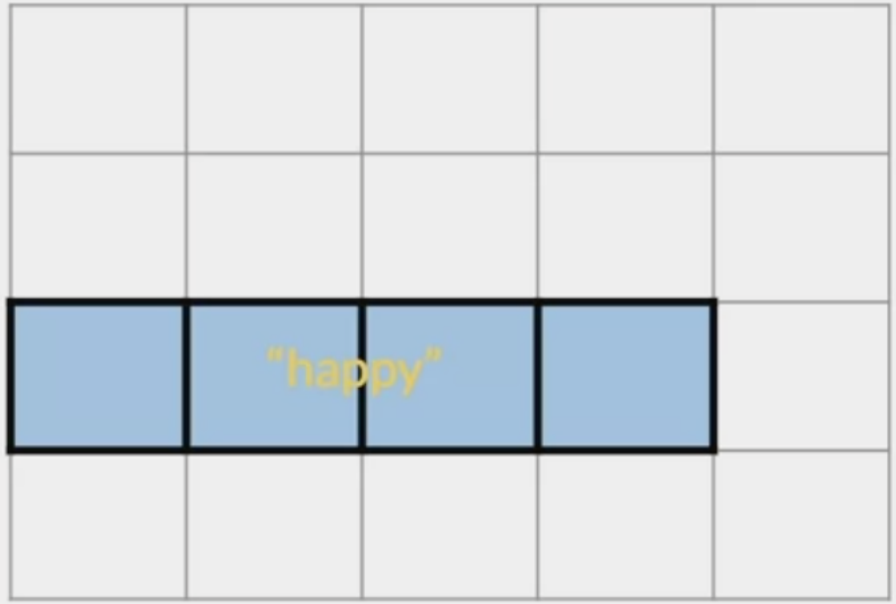
$A \rightarrow$ Positive tweet

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

$P(\text{Negative}) = 1 - P(\text{Positive}) = 0.35$

Probabilities

Tweets containing the word "happy"



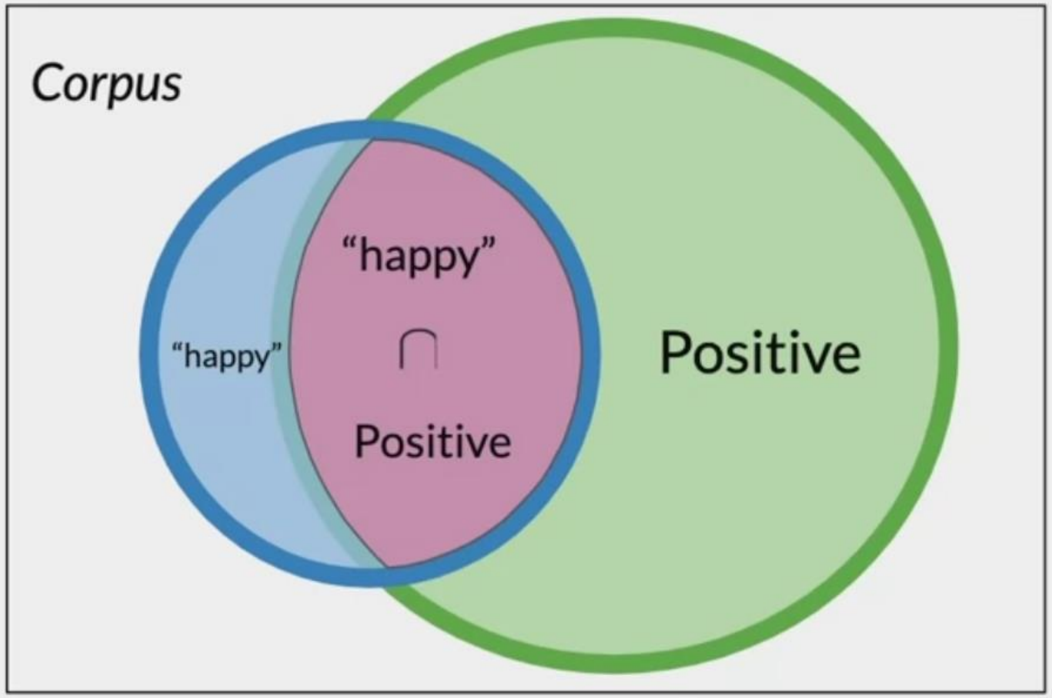
B → tweet contains "happy".

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

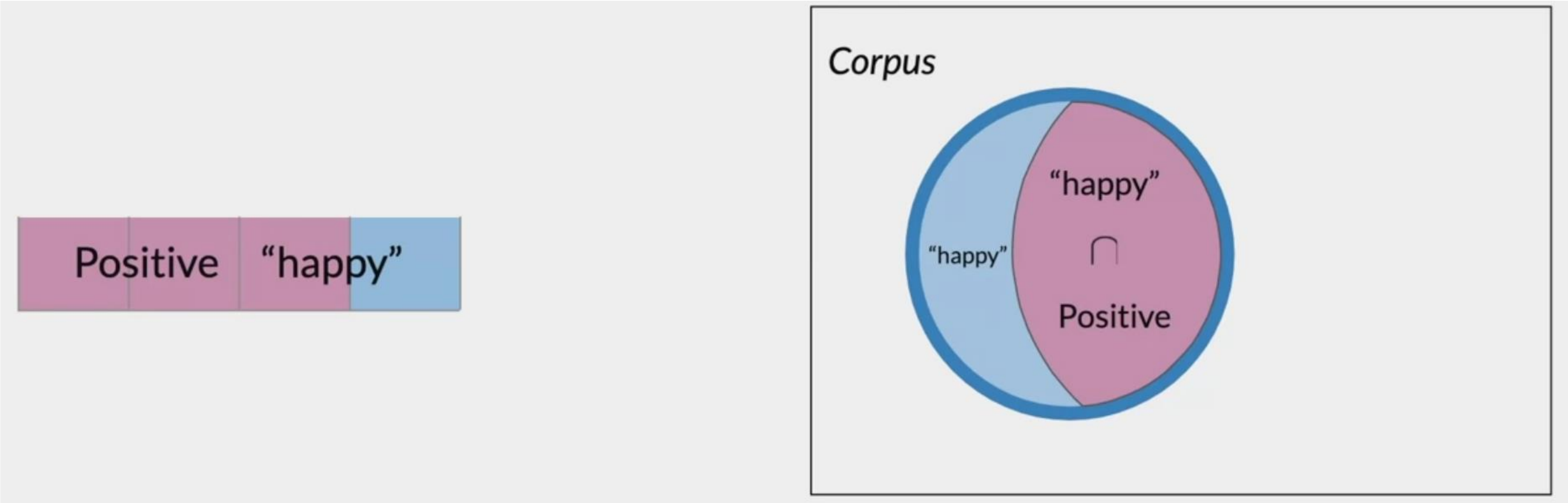
$P(B) = 4 / 20 = 0.2$

Probability of the Intersection

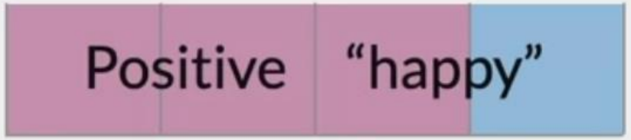
$$P(A \cap B) = P(A, B) = \frac{3}{20} = 0.15$$

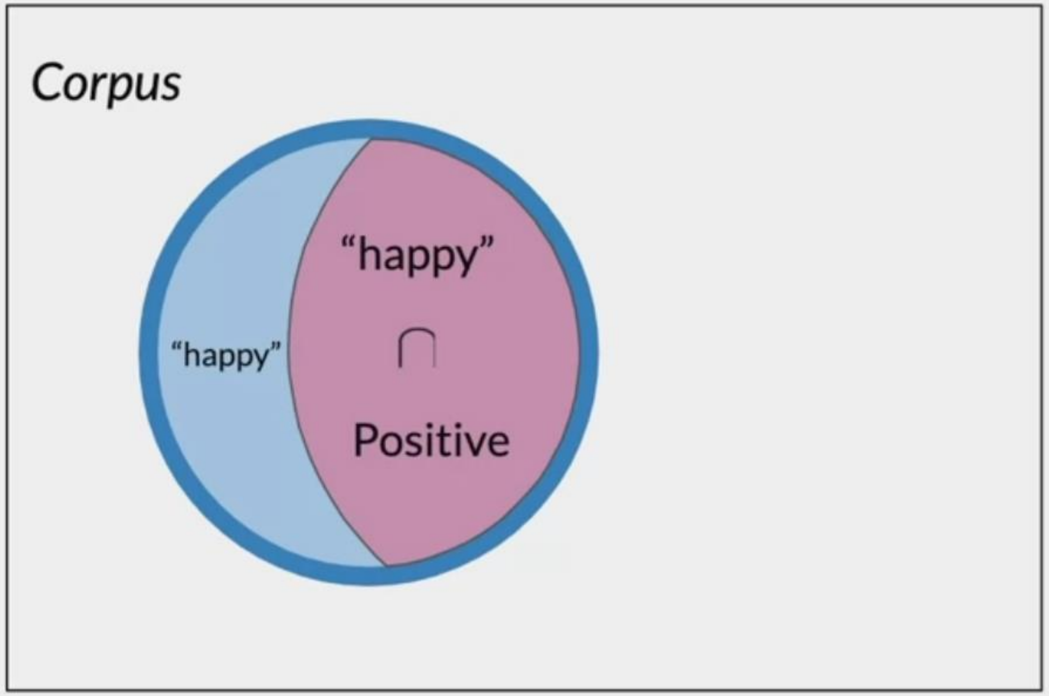


Conditional Probability



Conditional Probability





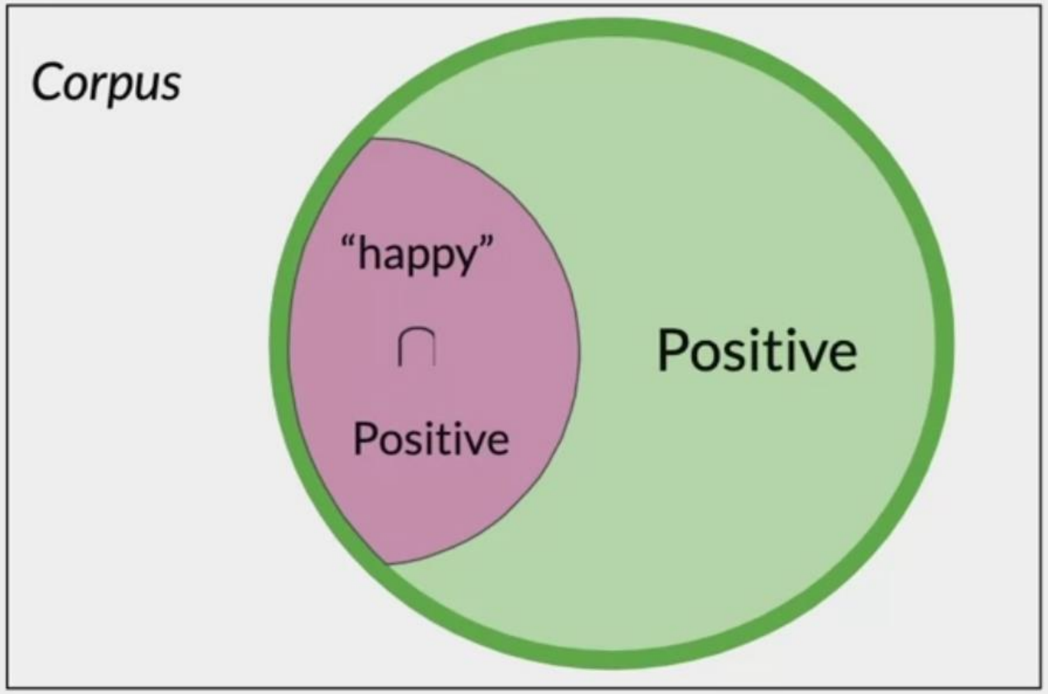
P(A | B) = P(Positive | "happy")

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

Conditional Probability

P(B | A) = P(“happy”| Positive)

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

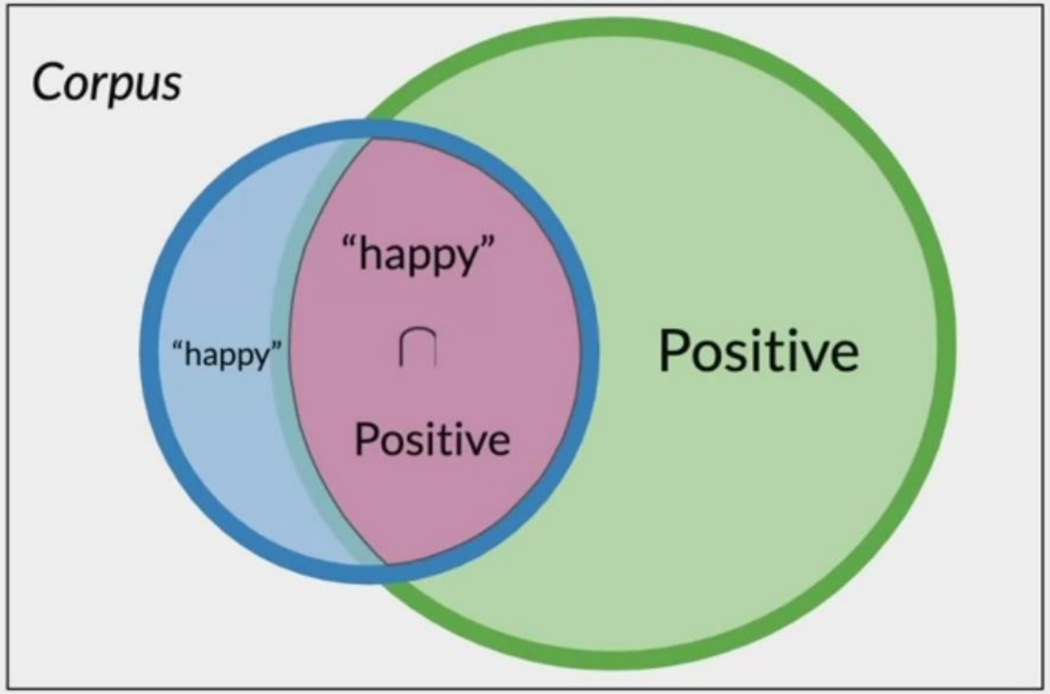


Conditional Probability

Probability of B, given A happened

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

Conditional Probability



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

Bayes' Rule

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

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

Bayes' Rule

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

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

Bayes' Rule

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

Bayes' Rule

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

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

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

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}		

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

word	Pos	Neg
$\boxed{\text{I}}$	3	3
am	3	3
happy	2	1
because	1	0
learning	1	1
NLP	1	1
sad	1	2
not	1	2
Nclass	$\boxed{13}$	

$$p(I|Pos) = \frac{3}{13}$$

word	Pos	Neg
I	0.24	

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

Naïve Bayes

Tweet: I am happy today; I am learning.

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

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

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.

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

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

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.

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

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

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.

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

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

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.

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

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

word	Pos	Neg
I	0.20	0.20
am	0.20	0.20
happy	0.14	0.10
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.

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

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

word	Pos	Neg
I	0.20	0.20
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.

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

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

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

Naïve Bayes

Tweet: I am happy today; I am learning.

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

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

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

Laplacian Smoothing

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

class ∈ {Positive, Negative}

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

N_{class} = frequency of all words in class

V_{class} = number of unique words in class

Introducing $P(w_i \mid class)$ with Smoothing

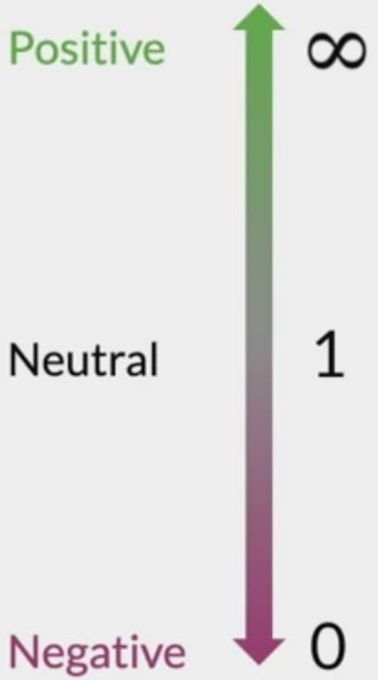
word	Pos	Neg
I	3	3
am	3	3
happy	2	1
because	1	0
learning	1	1
NLP	1	1
sad	1	2
not	1	2
Nclass	$\boxed{13}$	

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

V = 8

word	Pos	Neg
I	0.19	

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

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

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

Naïve Bayes' Inference

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

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

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

Log Likelihood

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

- Products bring risk of underflow
- $log(a * b) = log(a) + log(b)$
- $log(\frac{P(pos)}{P(neg)} \prod_{i=1}^{n} \frac{P(w_i|pos)}{P(w_i|neg)}) \Rightarrow log \frac{P(pos)}{P(neg)} + \sum_{i=1}^{n} log \frac{P(w_i|pos)}{P(w_i|neg)}$

log prior + log likelihood

Calculating Lambda

tweet: I am happy because I am learning.

$$\lambda(w) = log\frac{P(w|pos)}{P(w|neg)}$$

$$\lambda(I) = log\frac{0.05}{0.05} = log(1) = 0$$

word	Pos	Neg	λ
I	0.05	0.05	0
am	0.04	0.04	
happy	0.09	0.01	
because	0.01	0.01	
learning	0.03	0.01	
NLP	0.02	0.02	
sad	0.01	0.09	
not	0.02	0.03	

Calculating Lambda

tweet: I am happy because I am learning.

$$\lambda(w) = log\frac{P(w|pos)}{P(w|neg)}$$

$$\lambda(\mathrm{am}) = log\frac{0.04}{0.04} = log(1) = 0$$

word	Pos	Neg	λ
I	0.05	0.05	0
am	0.04	0.04	0
happy	0.09	0.01	
because	0.01	0.01	
learning	0.03	0.01	
NLP	0.02	0.02	
sad	0.01	0.09	
not	0.02	0.03	

Calculating Lambda

doc: I am happy because I am learning.

$$\lambda(w) = log\frac{P(w|pos)}{P(w|neg)}$$

$$\lambda(\text{happy}) = log\frac{0.09}{0.01} \approx 2.2$$

word	Pos	Neg	λ
I	0.05	0.05	0
am	0.04	0.04	0
happy	0.09	0.01	2.2
because	0.01	0.01	
learning	0.03	0.01	
NLP	0.02	0.02	
sad	0.01	0.09	
not	0.02	0.03	

Calculating Lambda

doc: I am happy because I am learning.

$$\lambda(w) = log\frac{P(w|pos)}{P(w|neg)}$$

$$\lambda(\text{happy}) = log\frac{0.09}{0.01} \approx 2.2$$

word	Pos	Neg	λ
I	0.05	0.05	0
am	0.04	0.04	0
happy	0.09	0.01	2.2
because	0.01	0.01	0
learning	0.03	0.01	1.1
NLP	0.02	0.02	0
sad	0.01	0.09	-2.2
not	0.02	0.03	-0.4

Log Likelihood

doc: I am happy because I am learning.

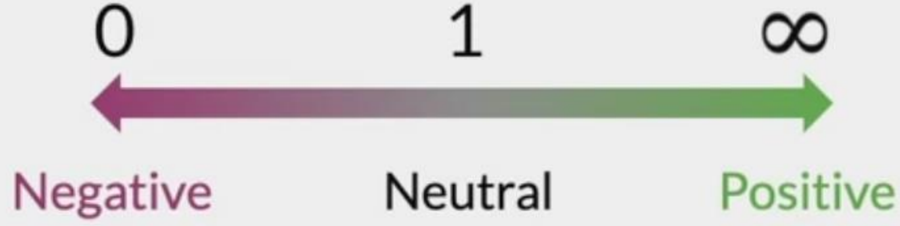
$$\sum_{i=1}^{m} log \frac{P(w_i|pos)}{P(w_i|neg)} = \sum_{i=1}^{m} \lambda(w_i)$$

log likelihood = 0 + 0 + 2.2 + 0 + 0 + 0 + 1.1 = **3.3**

word	Pos	Neg	λ
I	0.05	0.05	0
am	0.04	0.04	0
happy	0.09	0.01	2.2
because	0.01	0.01	0
learning	0.03	0.01	1.1
NLP	0.02	0.02	0
sad	0.01	0.09	-2.2
not	0.02	0.03	-0.4

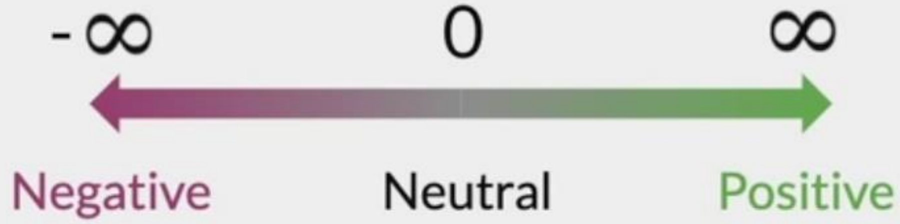
Log Likelihood

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

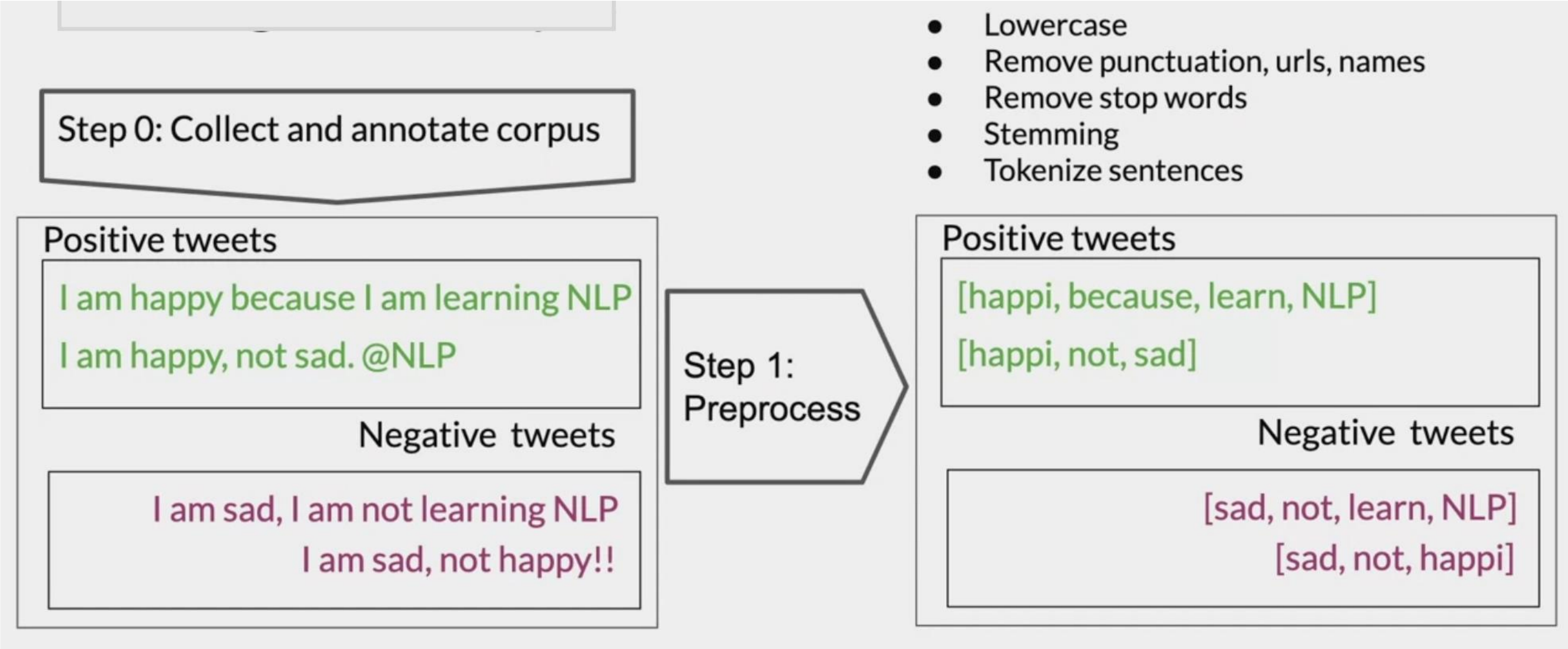


3.3 > 0

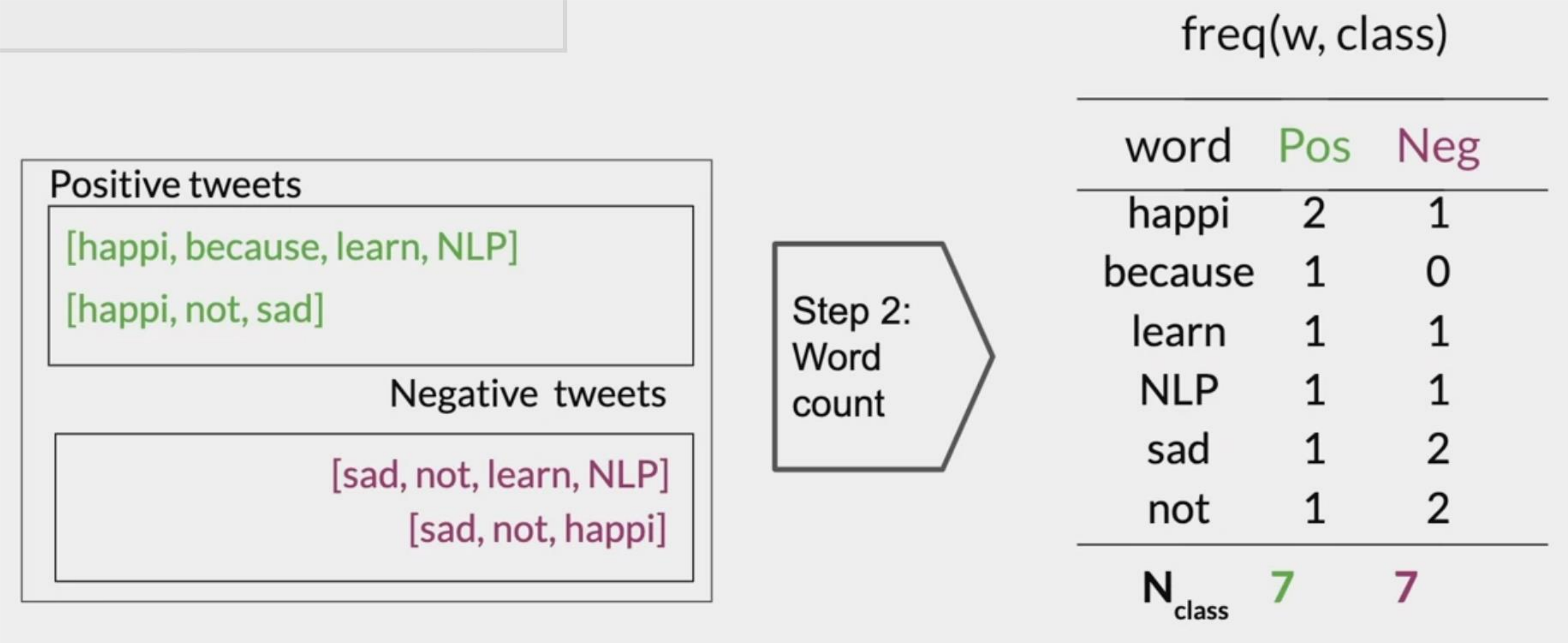
$$\sum_{i=1}^{m} log \frac{P(w_i|pos)}{P(w_i|neg)} > 0$$



Training Naïve Bayes



Training Naïve Bayes



word	Pos	Neg
happi	2	1
because	1	0
learn	1	1
NLP	1	1
sad	1	2
not	1	2
N_{class}	7	7

Training Naïve Bayes

freq(w, class)

word	Pos	Neg
happi	2	1
because	1	0
learn	1	1
NLP	1	1
sad	1	2
not	1	2
N_{class}	7	7

Step 3: $P(\mathrm{w}|\mathrm{class})$

$$V_{\mathrm{class}} = 6$$

$$\frac{\mathrm{freq}(\mathrm{w}, \mathrm{class}) + 1}{N_{\mathrm{class}} + V_{\mathrm{class}}}$$

$$\lambda(w) = log\frac{P(\mathrm{w}|\mathrm{pos})}{P(\mathrm{w}|\mathrm{neg})}$$

Step 4: Get lambda

word	Pos	Neg	λ
happy	0.23	0.15	0.43
because	0.15	0.07	0.6
learning	0.08	0.08	0
NLP	0.08	0.08	0
sad	0.08	0.17	-0.75
not	0.08	0.17	-0.75

Training Naïve Bayes

Step 5: Get the log prior

D_{pos} = Number of positive tweets
D_{neg} = Number of negative tweets

$$\text{logprior} = log\frac{D_{pos}}{D_{neg}}$$

If dataset is balanced, $D_{pos} = D_{neg}$ and logprior = 0

Predict using Naïve Bayes

- log-likelihood dictionary $\lambda(w) = log\frac{P(w|pos)}{P(w|neg)}$
- $logprior = log\frac{D_{pos}}{D_{neg}} = 0$
- Tweet: [I, pass, the, NLP, interview]

$$score = -0.01 + 0.5 - 0.01 + 0 + logprior = 0.48$$

$$pred = score > 0$$

word	λ
I	-0.01
the	-0.01
happi	0.63
because	0.01
pass	0.5
NLP	0
sad	-0.75
not	-0.75

Testing Naïve Bayes

- X_{val} Y_{val} λ $logprior$

$$score = predict(X_{val}, \lambda, logprior)$$

$$pred = score > 0 \qquad \begin{bmatrix} 0.5 \\ -1 \\ 1.3 \\ \vdots \\ score_m \end{bmatrix} > 0 = \begin{bmatrix} 0.5 > 0 \\ -1 > 0 \\ 1.3 > 0 \\ \vdots \\ score_m > 0 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \\ 1 \\ \vdots \\ pred_m \end{bmatrix}$$

Testing Naïve Bayes

- X_{val} Y_{val} λ $logprior$

$$score = predict(X_{val}, \lambda, logprior)$$

$$pred = score > 0$$

$$\frac{1}{m}\sum_{i=1}^{m}(pred_i == Y_{val_i})$$

$$\begin{bmatrix} 0 \\ 1 \\ 1 \\ \vdots \\ pred_m \end{bmatrix} == \begin{bmatrix} 0 \\ 0 \\ 1 \\ \vdots \\ Y_{val_m} \end{bmatrix}$$

$$\begin{bmatrix} 1 \\ 0 \\ 1 \\ \vdots \\ pred_m == Y_{val_m} \end{bmatrix}$$

Testing Naïve Bayes

- $X_{val}\ Y_{val}\ \lambda\ logprior$

$$score = predict(X_{val}, \lambda, logprior)$$

$$pred = score > 0$$

$$\frac{1}{m}\sum_{i=1}^{m}(pred_i == Y_{val_i})$$

$$\begin{bmatrix} 1 \\ 0 \\ 1 \\ \vdots \\ pred_m == Y_{val_m} \end{bmatrix}$$

Applications of Naïve Bayes

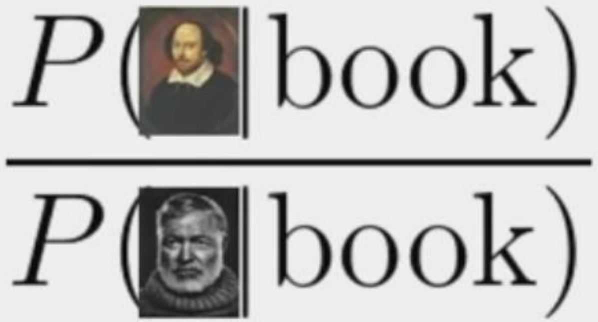
$$P(pos|tweet) \approx P(pos)P(tweet|pos)$$

$$P(neg|tweet) \approx P(neg)P(tweet|neg)$$

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

Applications of Naïve Bayes

Author identification:



Spam filtering:

$$\frac{P(\text{spam}|\text{email})}{P(\text{nonspam}|\text{email})}$$

Applications of Naïve Bayes

Information retrieval:

$$P(\text{document}_\text{k}|\text{query}) \propto \prod_{i=0}^{|query|} P(\text{query}_\text{i}|\text{document}_\text{k})$$

Retrieve document if $P(\text{document}_\text{k}|\text{query}) > \text{threshold}$

Applications of Naïve Bayes

Word disambiguation:

$$\frac{P(\text{river}|\text{text})}{P(\text{money}|\text{text})}$$

Bank:

Naïve Bayes Assumptions

- Independence

"It is sunny and hot in the Sahara desert."

Naïve Bayes Assumptions

"It's always cold and snowy in ___."

spring?? summer? fall?? $\boxed{\text{winter}}$??

Naïve Bayes Assumptions

- Relative frequencies in corpus

Processing as a Source of Error: Punctuation

Tweet: My beloved grandmother ~~:(~~

processed_tweet: [belov, grandmoth]

Processing as a Source of Error: Removing Word

Tweet: This is not good, because your attitude is not even close to being nice.

processed_tweet: [good, attitude, close, nice]

Processing as a Source of Error: Word Order