Outline

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

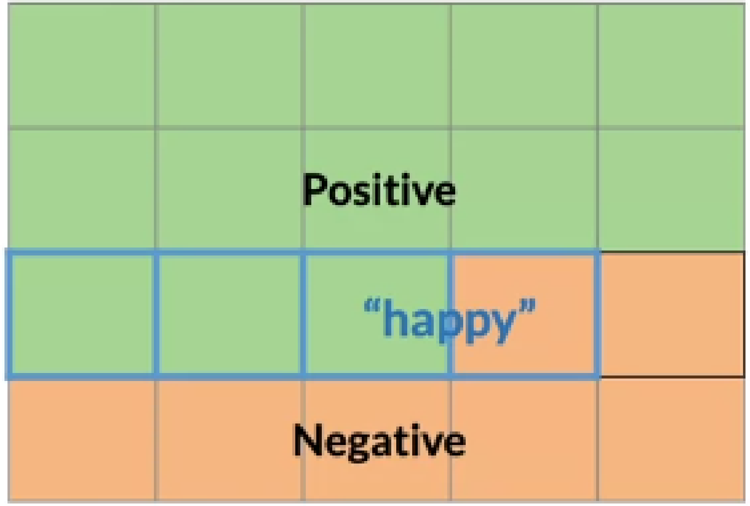
Introduction

Corpus of tweets

Introduction

Corpus of tweets

Tweets containing the word "happy"



Probabilities

Corpus of tweets

A → Positive tweet

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

Probabilities

Corpus of tweets

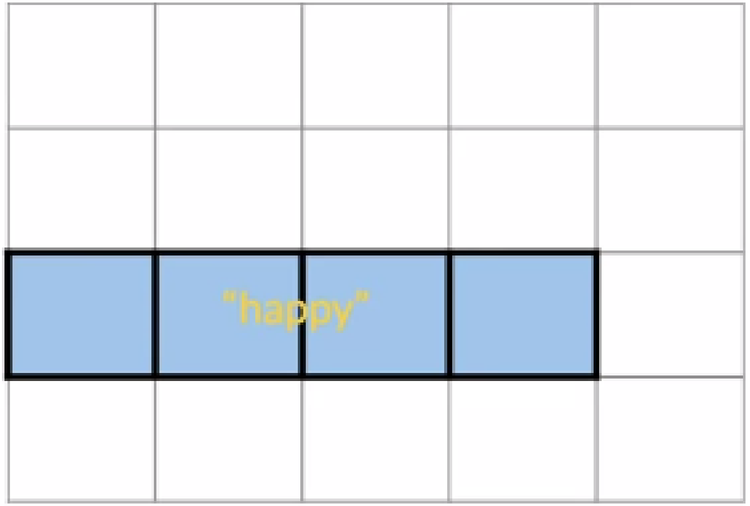
A → Positive tweet

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

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

Probabilities

Tweets containing the word "happy"

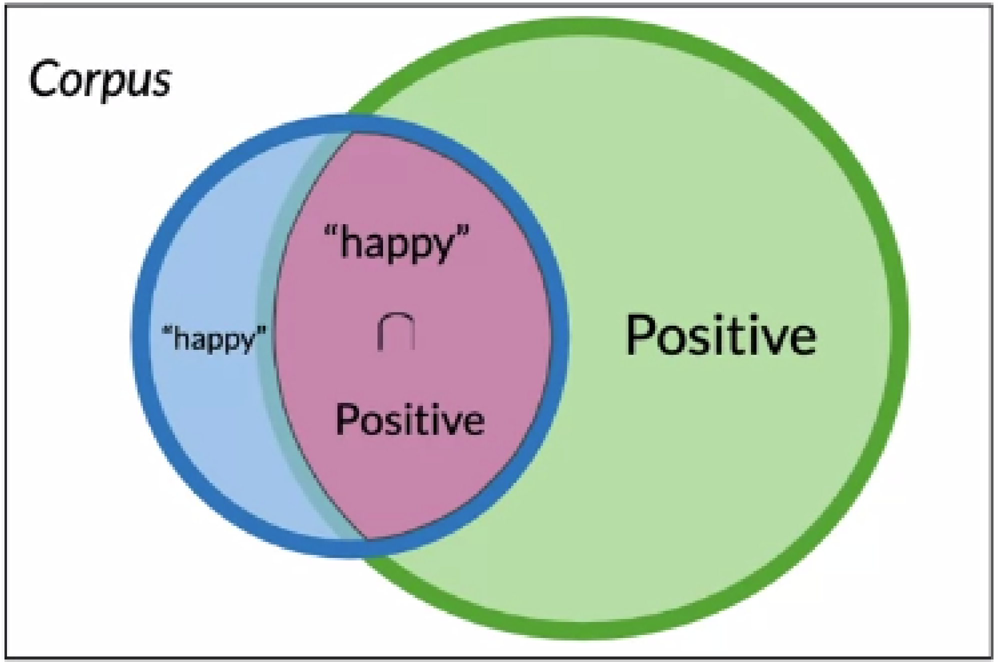


B → tweet contains "happy".

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

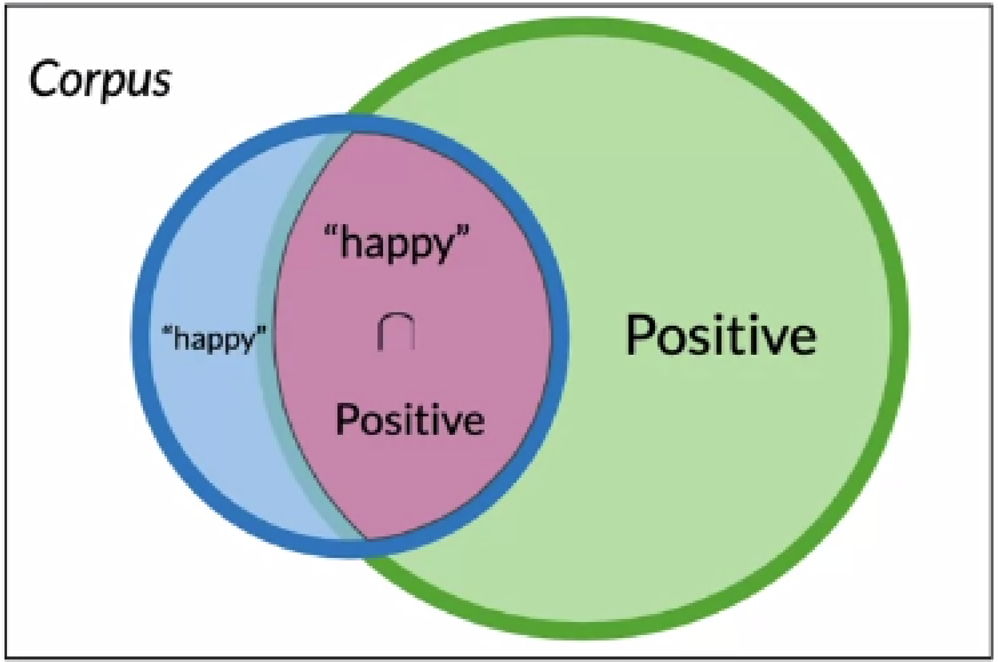
$P(B) = 4 / 20 = 0.2$

Probability of the intersection



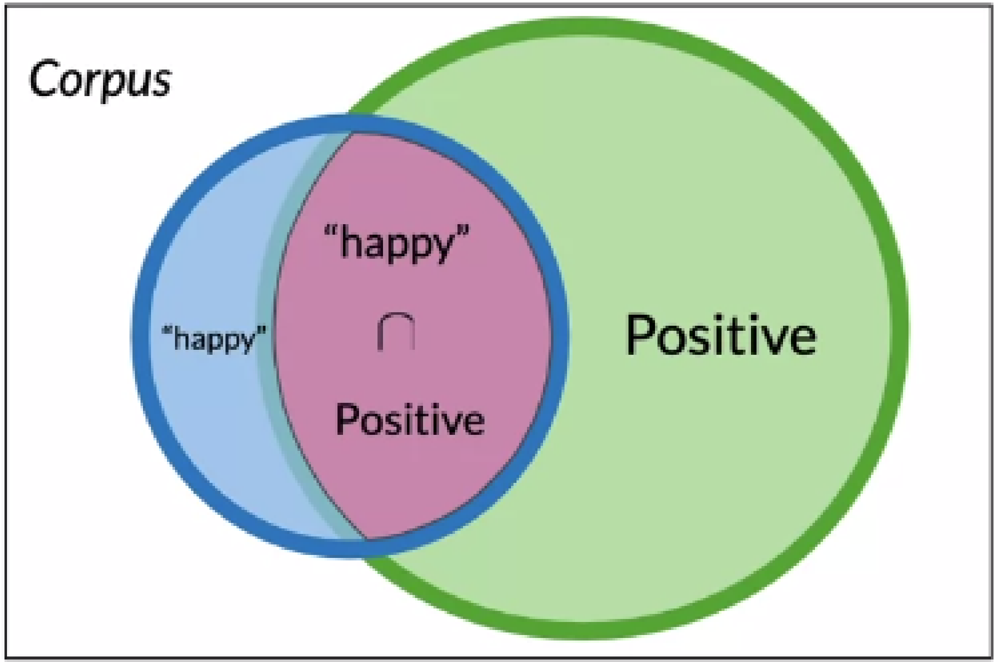
Probability of the intersection

$$P(A \cap B) = P(A, B) =$$



Probability of the intersection

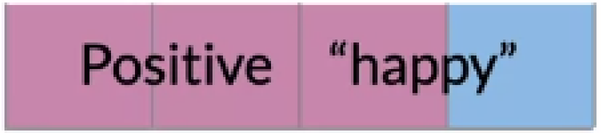
$$P(A \cap B) = P(A, B) = \frac{3}{20} = 0.15$$

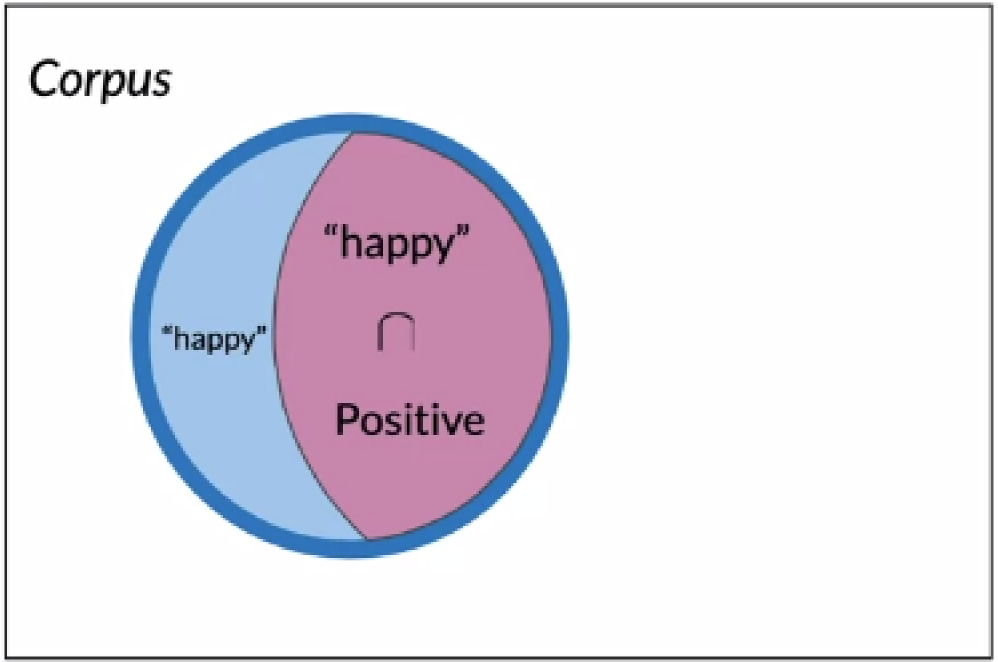


deeplearning.ai

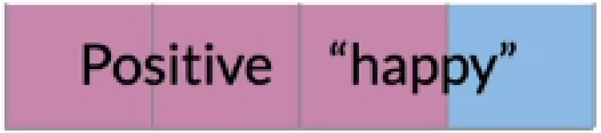
Bayes' Rule

Conditional Probabilities



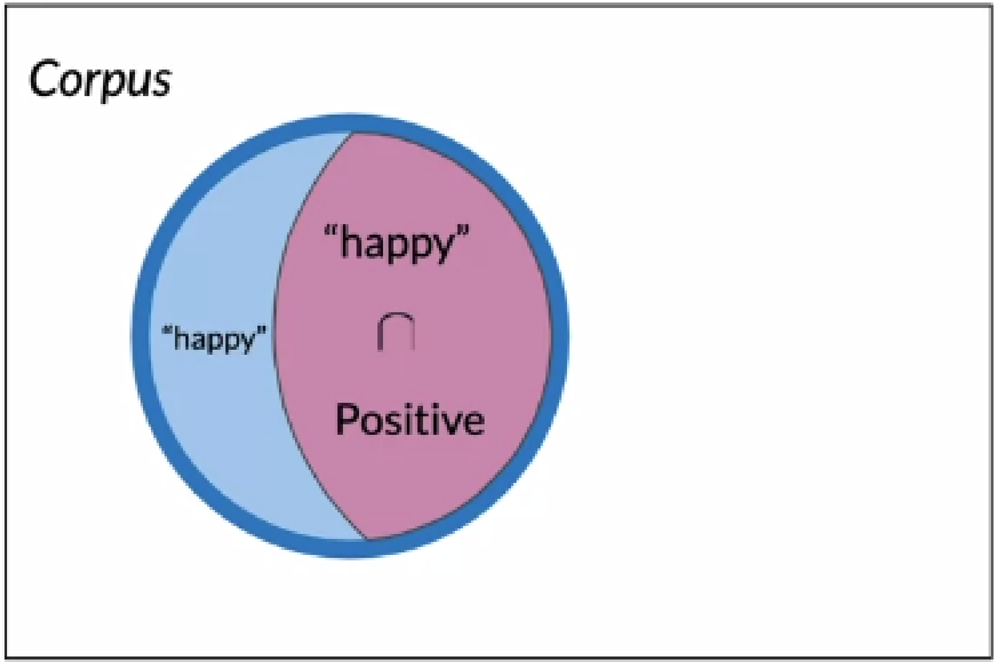


Conditional Probabilities

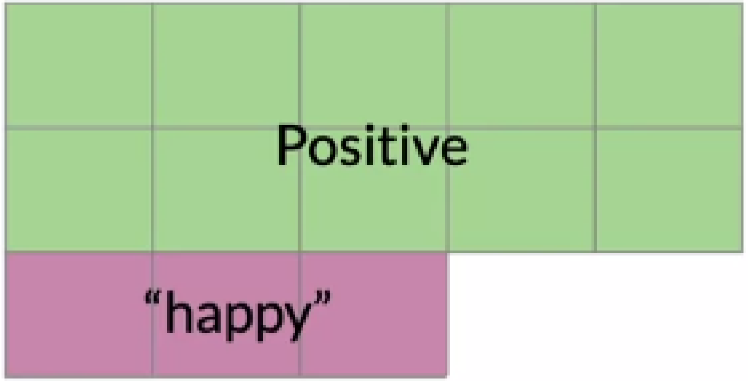


$P(A \mid B) = P(\text{Positive} \mid \text{“happy”})$

$P(A \mid B) = 3 / 4 = 0.75$

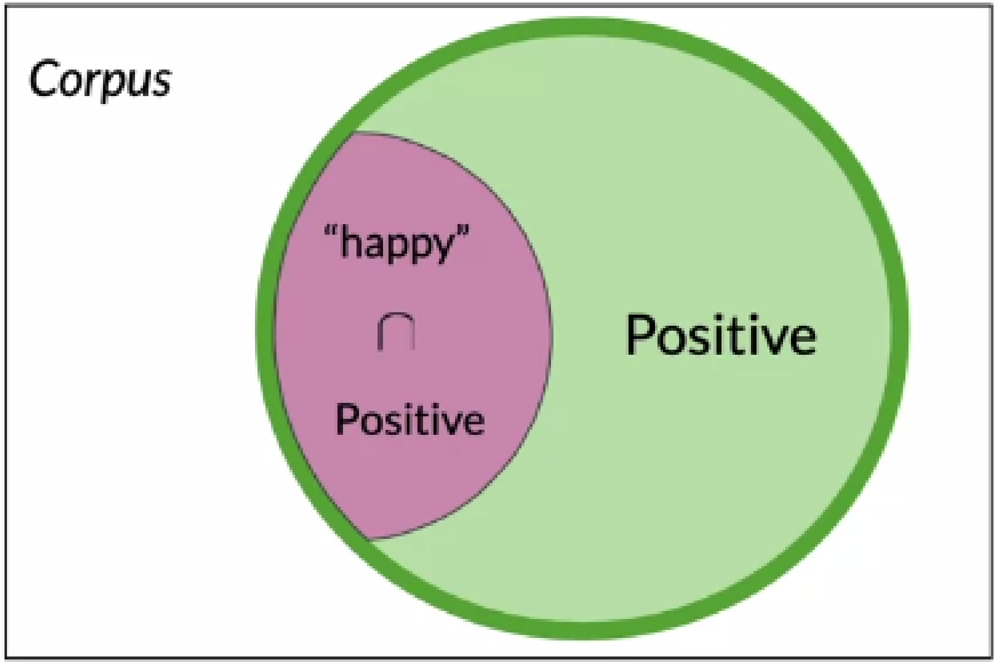


Conditional Probabilities



$P(B \mid A) = P(\text{"happy"} \mid \text{Positive})$

$P(B \mid A) = 3 / 13 = 0.231$



Conditional probabilities

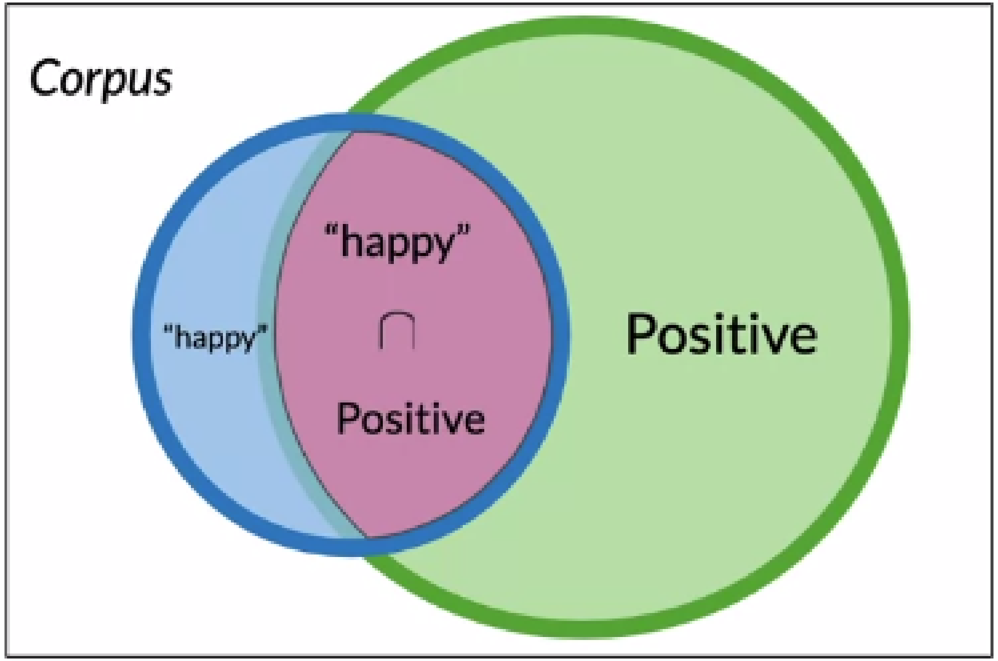
Probability of B, given A happened

Conditional probabilities

Probability of B, given A happened

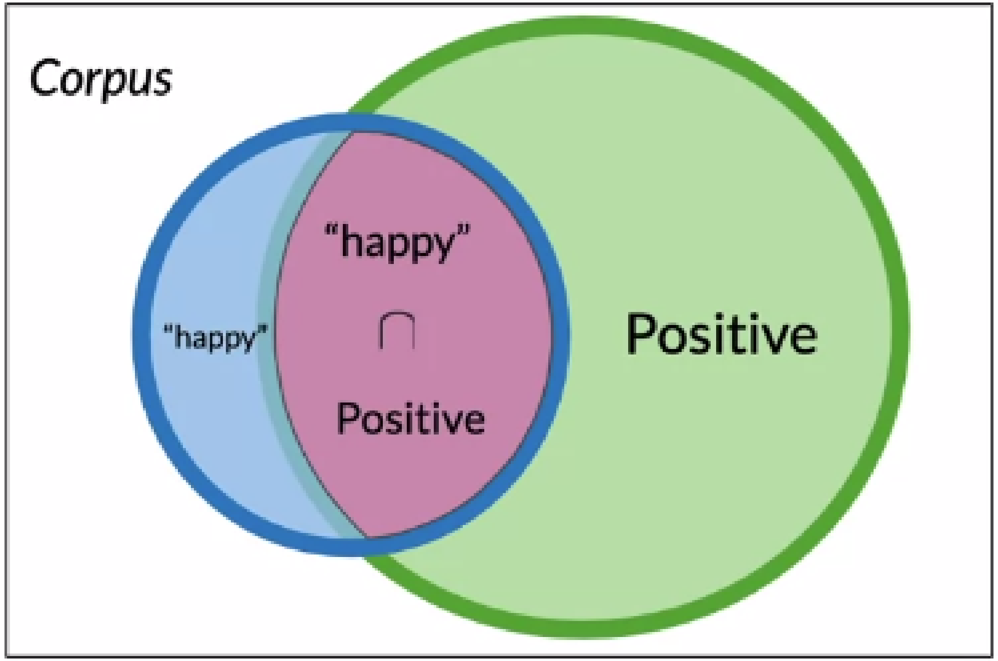
Looking at the elements of set A, the chance that one also belongs to set B

Conditional probabilities



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

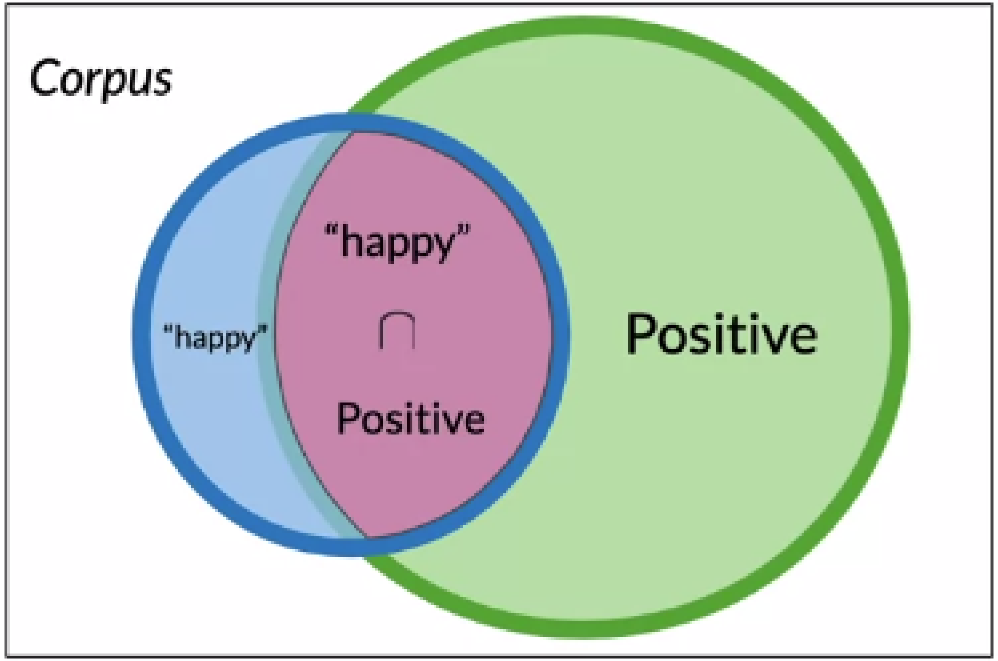
Conditional probabilities



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

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

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

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

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

Bayes' rule

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

Bayes' rule

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

$$\boxed{P(X|Y)}$$

Bayes' rule

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

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

Bayes' rule

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

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

Summary

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

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
I	3
am	3
happy	2
because	1
learning	1
NLP	1
sad	1
not	1

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

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

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

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	$\boxed{\mathbf{13}}$	**12**

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

word	Pos	Neg
I	0.24	

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

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**

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

word	Pos	Neg
I	0.24	

$P(w_i \mid class)$

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**

$$p(I|Neg) = \frac{3}{12}$$

word	Pos	Neg
I	0.24	0.25

$P(w_i \mid class)$

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

$P(w_i \mid class)$

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.

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.

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

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
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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
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
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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
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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
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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
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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Tweet: I am happy today; I am learning.

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

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

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
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Naïve Bayes

Tweet: I am happy today; I am learning.

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

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

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.

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

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

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

Naïve Bayes

Tweet: I am happy today; I am learning.

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

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

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

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

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 $P(w_i \mid class)$ 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**

word	Pos	Neg

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	**13**	**12**

$V = 8$

word	Pos	Neg
I		

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	**13**	**12**

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

V = 8

word	Pos	Neg
I		

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

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	$\boxed{\mathbf{13}}$	**12**

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

V = 8

word	Pos	Neg
I	0.19	

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

word	Pos	Neg
I	3	3
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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 $P(w_i \mid class)$ 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**	**$\boxed{12}$**

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

V = 8

word	Pos	Neg
I	0.19	0.20

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

word	Pos	Neg
I	3	3
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NLP	1	1
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Nclass	**13**	**12**

$V = 8$

word	Pos	Neg
I	0.19	0.20
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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

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	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
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	
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	

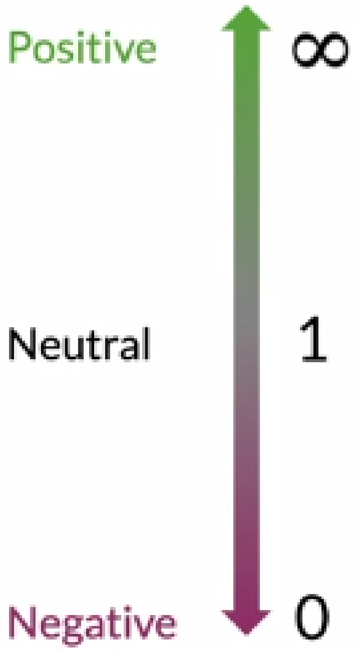
$$\text{ratio}(w_i) = \frac{P(w_i \mid \text{Pos})}{P(w_i \mid \text{Neg})}$$

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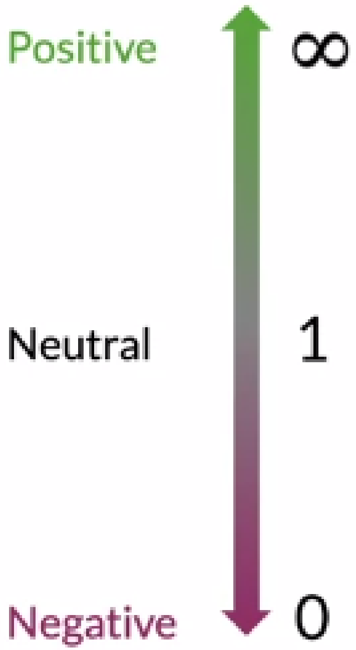
$$\text{ratio}(w_i) = \frac{P(w_i \mid \text{Pos})}{P(w_i \mid \text{Neg})}$$

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

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

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

Naïve Bayes' inference

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

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

Naïve Bayes' inference

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

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

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

- Products bring risk of underflow

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
- $log(a * b) = log(a) + log(b)$

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

Log Likelihood

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

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

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.

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

word	Pos	Neg
I	0.05	0.05
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.

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

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

word	Pos	Neg	λ
I	0.05	0.05	
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.

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

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

word	Pos	Neg	λ
I	0.05	0.05	
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

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

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

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.

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

$$\lambda(\text{am}) = log\frac{0.04}{0.04}$$

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.

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

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

word	Pos	Neg	λ
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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.

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

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

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	

Summing the Lambdas

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	
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	

Summing the Lambdas

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NLP	0.02	0.02	
sad	0.01	0.09	
not	0.02	0.03	

Summing the Lambdas

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

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

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

Summary

- Word sentiment $\begin{cases} ratio(w) = \dfrac{P(w|pos)}{P(w|neg)} \\ \\ \lambda(w) = log\dfrac{P(w|pos)}{P(w|neg)} \end{cases}$

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Log Likelihood, Part 2

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 =

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

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 $\boxed{\text{am}}$ 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

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

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
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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

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 $\boxed{\text{learning.}}$

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

log likelihood = 0 + 0 + 2.2 + 0 + 0 + 0 + 1.1

word	Pos	Neg	λ
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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.

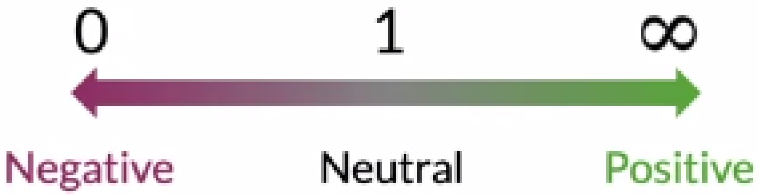
$$\sum_{i=1}^{m} log\frac{P(w_i|pos)}{P(w_i|neg)} = \sum_{i=1}^{m} \lambda(w_i)$$

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

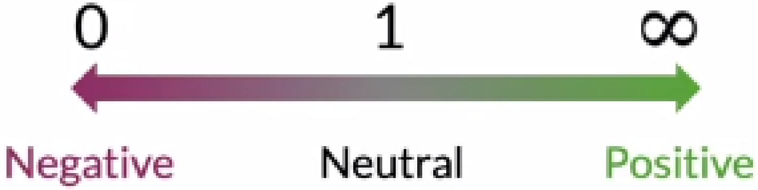
Log Likelihood

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

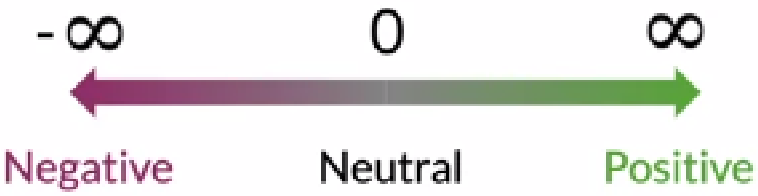


Log Likelihood

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



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



Log Likelihood

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

0 1 ∞

Negative Neutral Positive

3.3 > 0

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

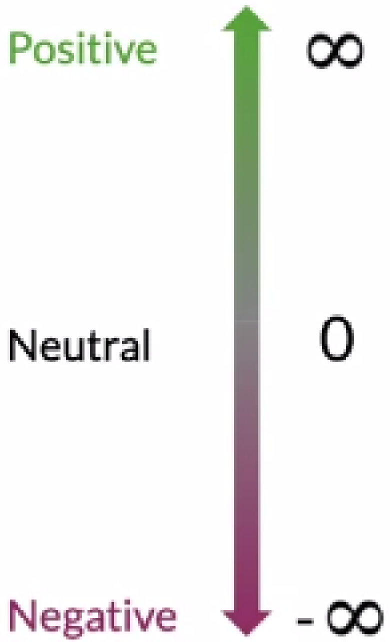
-∞ 0 ∞

Negative Neutral Positive

Summary

Tweet sentiment:

$$log \prod_{i=1}^{m} ratio(w_i) = \sum_{i=1}^{m} \lambda(w_i) \quad > 0$$



Outline

- Five steps for training a Naïve Bayes model

Training Naïve Bayes

Step 0: Collect and annotate corpus

Training Naïve Bayes

Step 0: Collect and annotate corpus

Positive tweets

I am happy because I am learning NLP

I am happy, not sad. @NLP

Negative tweets

I am sad, I am not learning NLP

I am sad, not happy!!

Training Naïve Bayes

Step 0: Collect and annotate corpus

Positive tweets

I am happy because I am learning NLP

I am happy, not sad. @NLP

Negative tweets

I am sad, I am not learning NLP

I am sad, not happy!!

Step 1: Preprocess

- Lowercase
- Remove punctuation, urls, names
- Remove stop words
- Stemming
- Tokenize sentences

Training Naïve Bayes

Step 0: Collect and annotate corpus

Positive tweets

I am happy because I am learning NLP

I am happy, not sad. @NLP

Negative tweets

I am sad, I am not learning NLP

I am sad, not happy!!

Step 1: Preprocess

- Lowercase
- Remove punctuation, urls, names
- Remove stop words
- Stemming
- Tokenize sentences

Positive tweets

[happi, because, learn, NLP]

[happi, not, sad]

Negative tweets

[sad, not, learn, NLP]

[sad, not, happi]

Training Naïve Bayes

Positive tweets

[happi, because, learn, NLP]

[happi, not, sad]

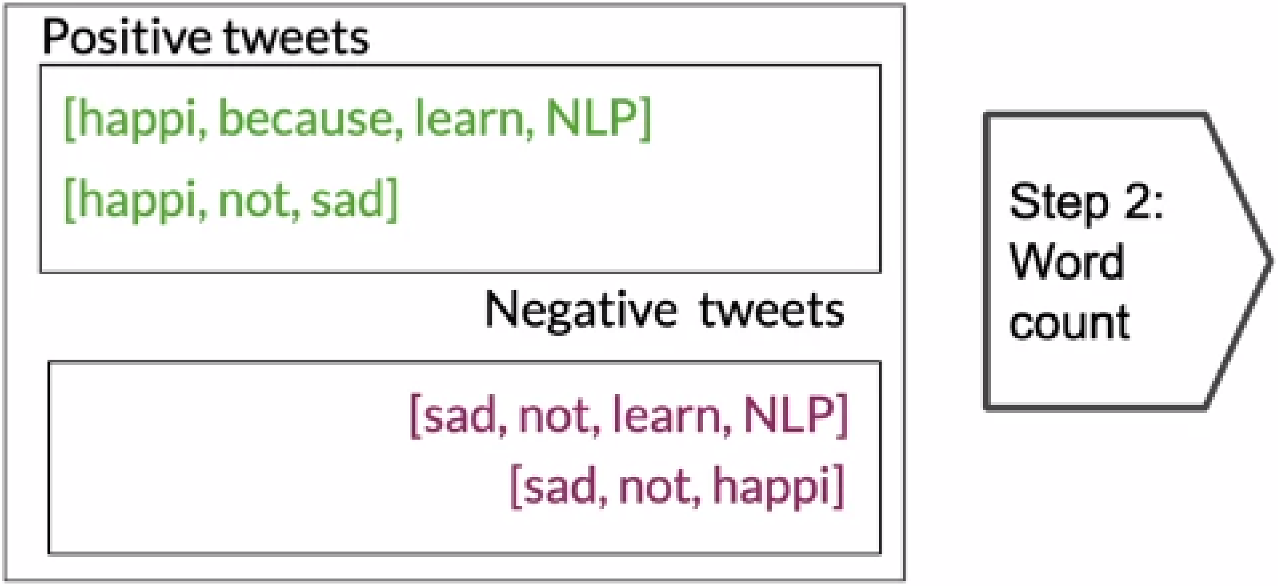
Negative tweets

[sad, not, learn, NLP]

[sad, not, happi]

Training Naïve Bayes

freq(w, class)



Training Naïve Bayes

Positive tweets

[happi, because, learn, NLP]

[happi, not, sad]

Negative tweets

[sad, not, learn, NLP]

[sad, not, happi]

Step 2: Word count

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

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

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

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

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

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

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

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

word	Pos	Neg
happy	0.23	0.15
because	0.15	0.07
learning	0.08	0.08
NLP	0.08	0.08
sad	0.08	0.17
not	0.08	0.17

Training Naïve Bayes

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

Step 4: Get lambda

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

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

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

word	Pos	Neg
happy	0.23	0.15
because	0.15	0.07
learning	0.08	0.08
NLP	0.08	0.08
sad	0.08	0.17
not	0.08	0.17

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

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

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

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

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

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

Training Naïve Bayes

Step 5:
Get the
log prior

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

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

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.

Summary

0. Get or annotate a dataset with positive and negative tweets
1. Preprocess the tweets: process_tweet(tweet) → $[w_1, w_2, w_3, \ldots]$
2. Compute freq(w, class)
3. Get $P(w \mid pos)$, $P(w \mid neg)$
4. Get $\lambda(w)$
5. Compute logprior = log(P(pos) / P(neg))

Outline

- Predict using a Näive Bayes Model
- Using your validation set to compute model accuracy

Predict using Naïve Bayes

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

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

Predict using Naïve Bayes

- log-likelihood dictionary $\lambda(w) = log\frac{P(w|pos)}{P(w|neg)}$
- $logprior = log\frac{D_{pos}}{D_{neg}} = 0$

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

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 passed the NLP interview.

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

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]

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

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]

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

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]

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

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

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Testing Naïve Bayes

- X_{val} Y_{val}

Testing Naïve Bayes

- X_{val} Y_{val} λ $logprior$

Testing Naïve Bayes

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

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

$$\begin{bmatrix} 0.5 \\ -1 \\ 1.3 \\ \vdots \\ score_m \end{bmatrix}$$

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

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Summary

- $X_{val}\ Y_{val} \longrightarrow$ Performance on unseen data
- Predict using λ and $logprior$ for each new tweet
- Accuracy $\longrightarrow \dfrac{1}{m}\sum_{i=1}^{m}(pred_i == Y_{val_i})$
- What about words that do not appear in λ(w)?

Applications of Naïve Bayes

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

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

Applications of Naïve Bayes

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

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

$$\frac{P(pos|tweet)}{P(neg|tweet)}$$

Applications of Naïve Bayes

Author identification:

$P($  $\mid \text{book})$

$P($  $\mid \text{book})$

Applications of Naïve Bayes

Author identification:

$P($  $|\,\text{book})$

―――

$P($  $|\,\text{book})$

Spam filtering:

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

Applications of Naïve Bayes

Word disambiguation:

Bank:

Applications of Naïve Bayes

Word disambiguation:

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

Bank:

Naïve Bayes Applications

- Sentiment analysis
- Author identification
- Information retrieval
- Word disambiguation
- Simple, fast and robust!

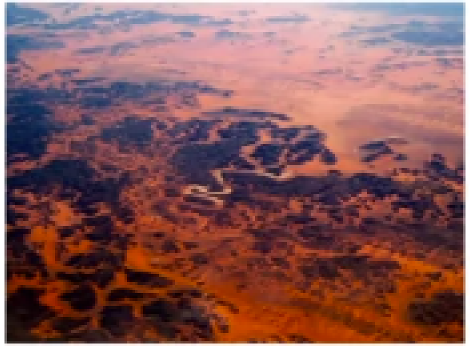
Outline

- Independence
- Relative frequency in corpus

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?? winter??

Naïve Bayes Assumptions

- Relative frequencies in corpus

Naïve Bayes Assumptions

- Relative frequencies in corpus

Summary

- Independence: Not true in NLP

- Relative frequency of classes affect the model

Outline

- Removing punctuation and stop words
- Word order
- Adversarial attacks

Processing as a Source of Errors: Punctuation

Tweet: My beloved grandmother ~~:(~~

processed_tweet: [belov, grandmoth]

Processing as a Source of Errors: Removing Words

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 Errors: Word Order

Tweet: I am happy because I did not go.

Tweet: I am not happy because I did go.

Processing as a Source of Errors: Word Order

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Adversarial attacks

Sarcasm, Irony and Euphemisms

Tweet: This is a ridiculously powerful movie. The plot was gripping and I cried right through until the ending!

Adversarial attacks

Sarcasm, Irony and Euphemisms

Tweet: This is a ridiculously powerful movie. The plot was gripping and I cried right through until the ending!

processed_tweet: [ridicul, power, movi, plot, grip, cry, end]