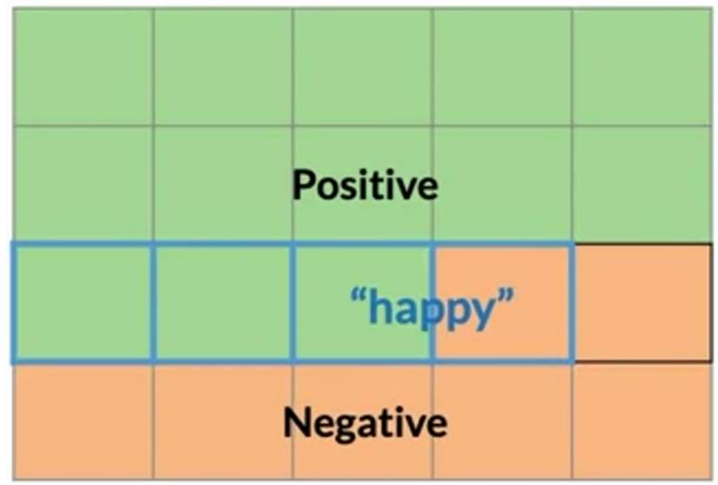
Procesamiento del Lenguaje Natural
NLP

Clasificador Bayesiano

Introduction

Corpus of tweets

Tweets containing the word "happy"



Probabilities

Corpus of tweets

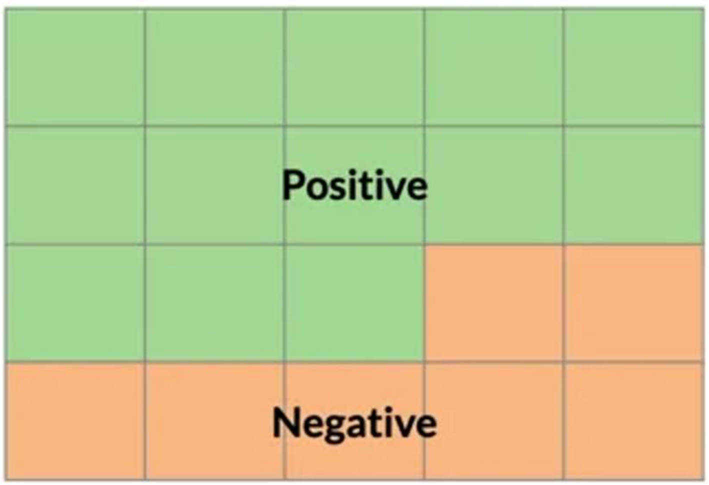
A → Positive tweet

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

Probablidad de que se presente un tweet como positivo vs negativo

Probabilities

Corpus of tweets



A → Positive tweet

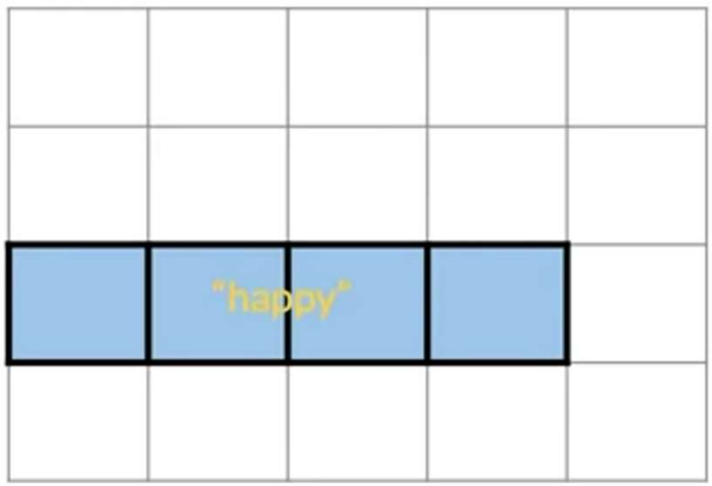
$P(A) = N_{pos} / N = 13 / 20 = 0.65$

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

Probablidad de que se presente un tweet como positivo vs negativo

Probabilities

Tweets containing the word "happy"



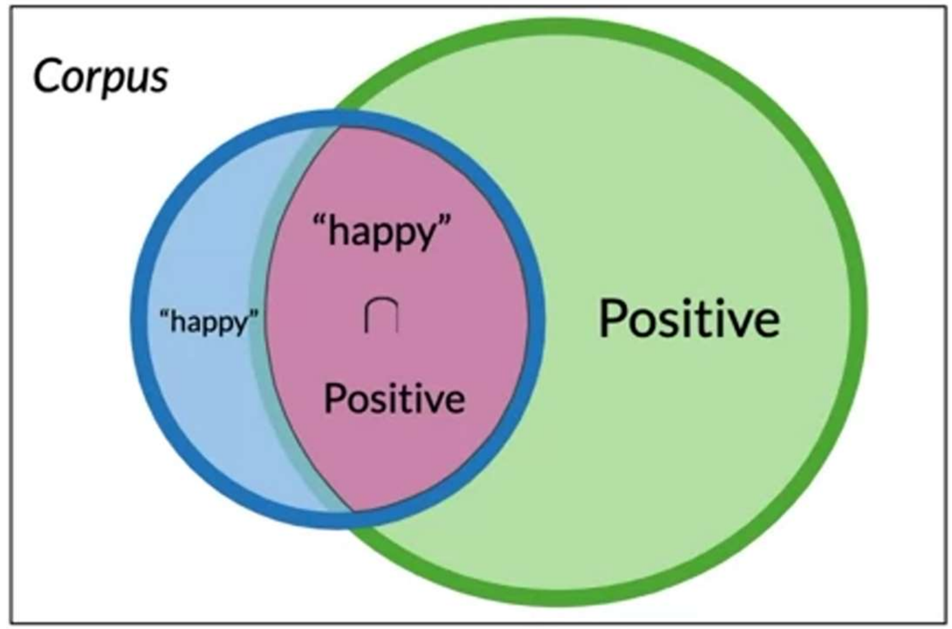
B → tweet contains "happy".

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

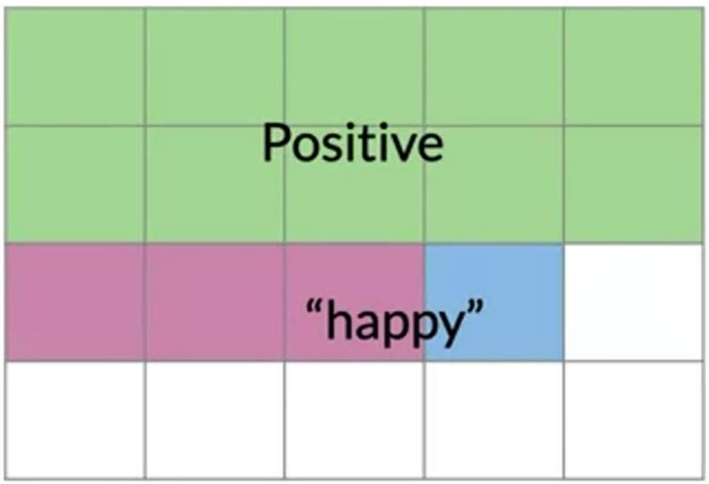
$$P(B) = 4 / 20 = 0.2$$

Probablidad de encontrar la palabra "happy" en un tweet (ya sea positivo o negativo)

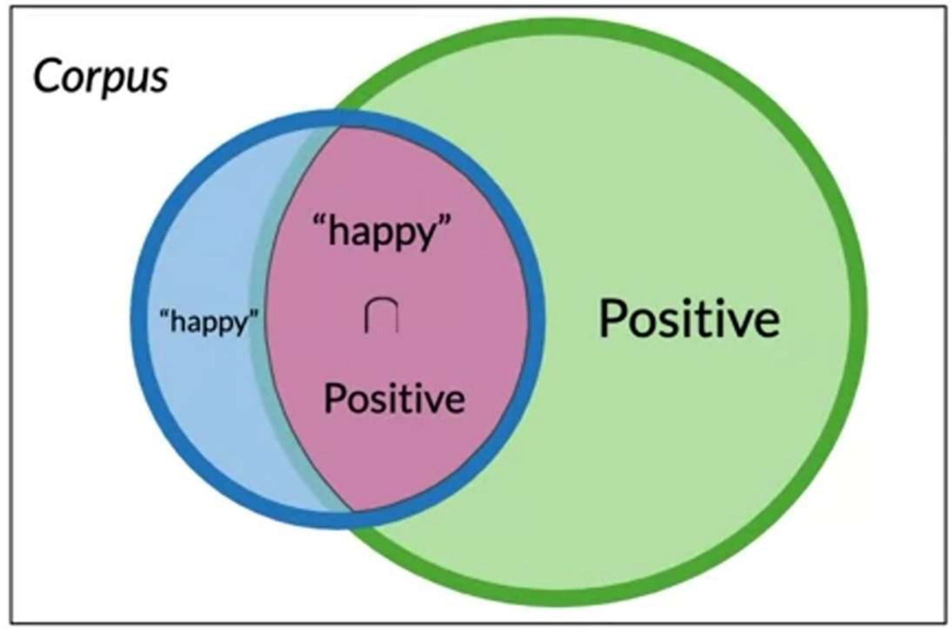
Probability of the intersection



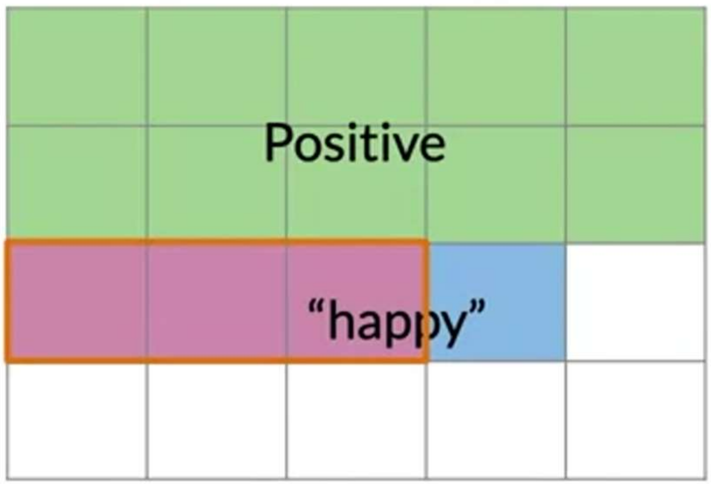
Probability of the intersection



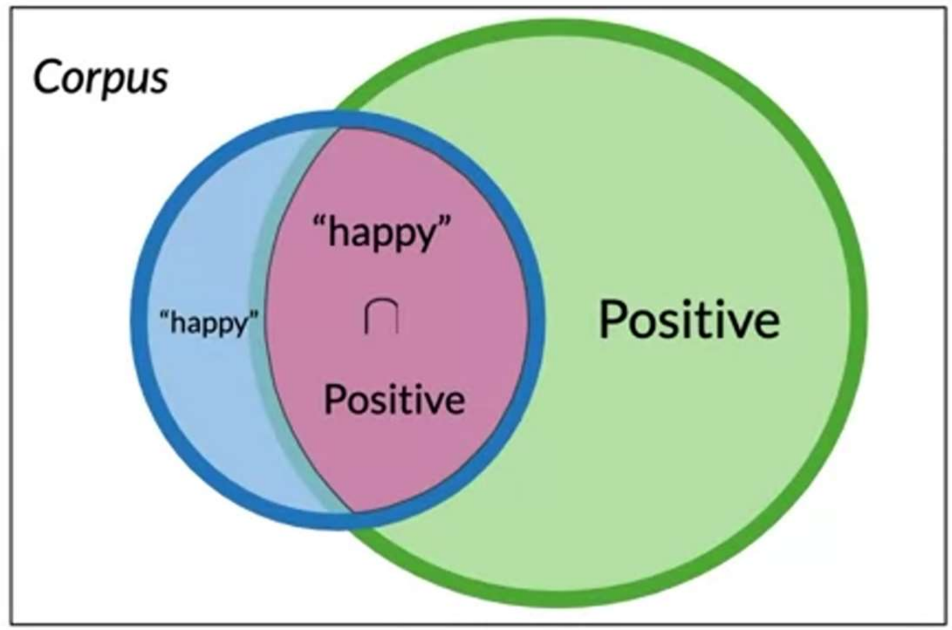
$$P(A \cap B) = P(A, B) =$$



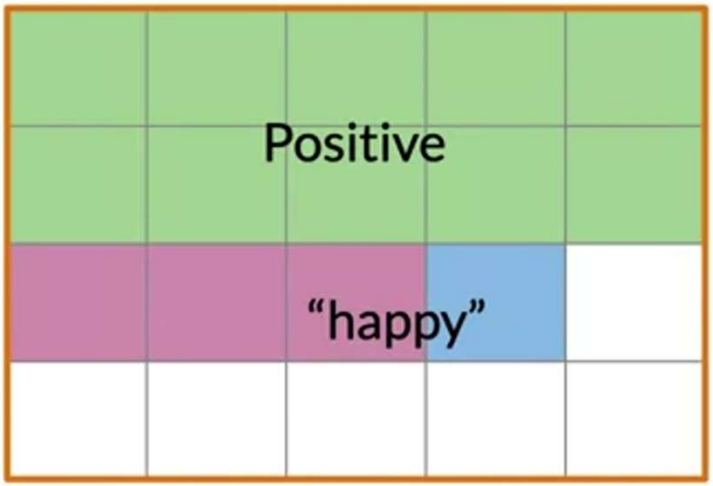
Probability of the intersection



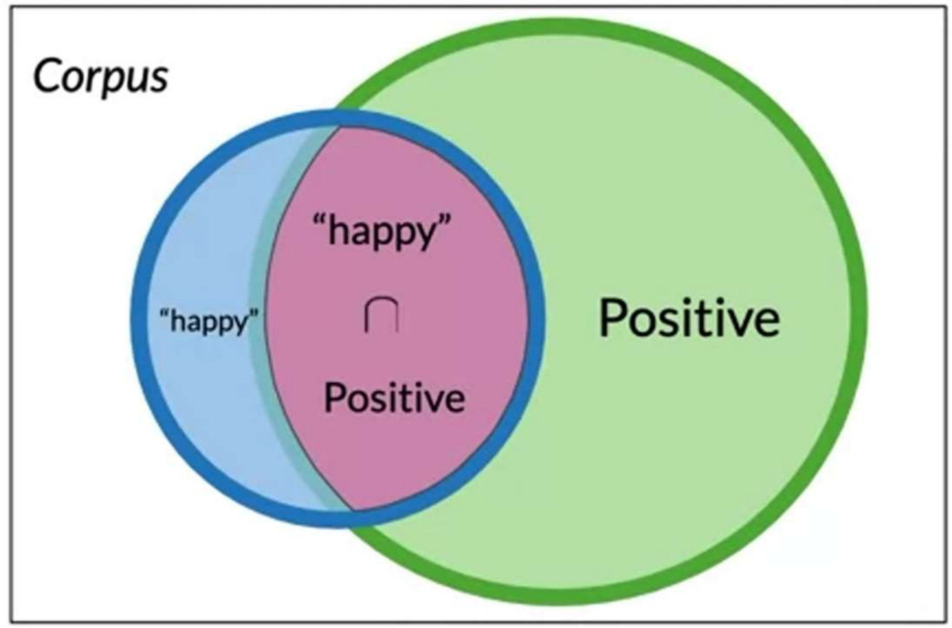
$$P(A \cap B) = P(A, B) = \frac{3}{}$$



Probability of the intersection



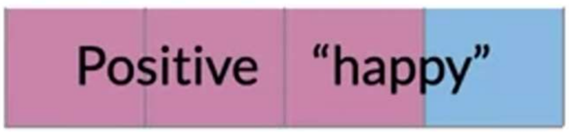
$$P(A \cap B) = P(A, B) = \frac{3}{20}$$

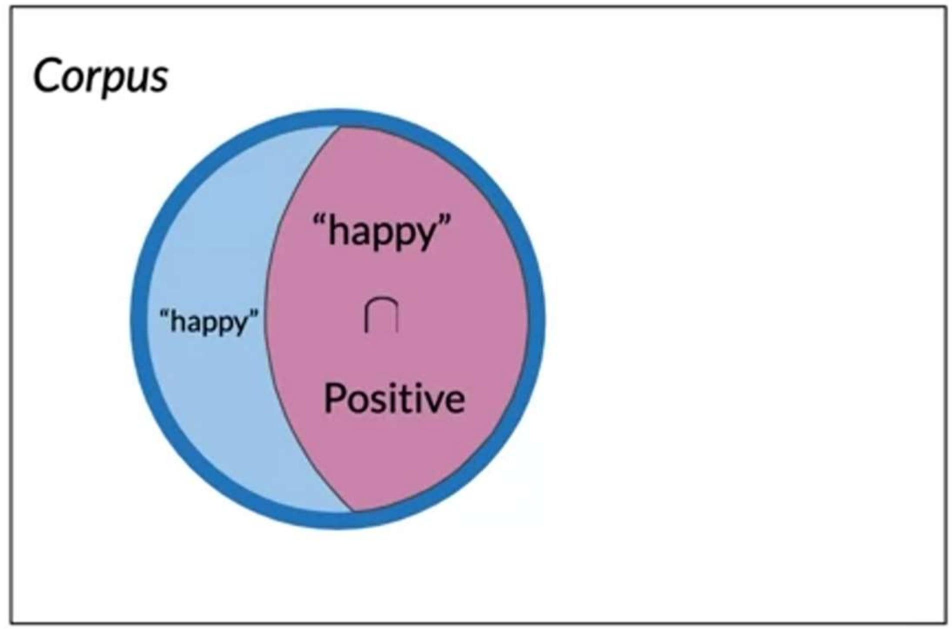


Probablidad que en un tweet aparezca la palabra "happy" deeplearning.ai

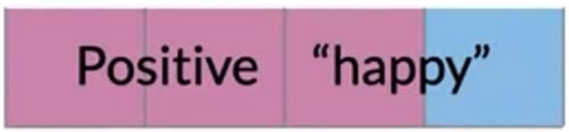
Bayes' Rule

Conditional Probabilities



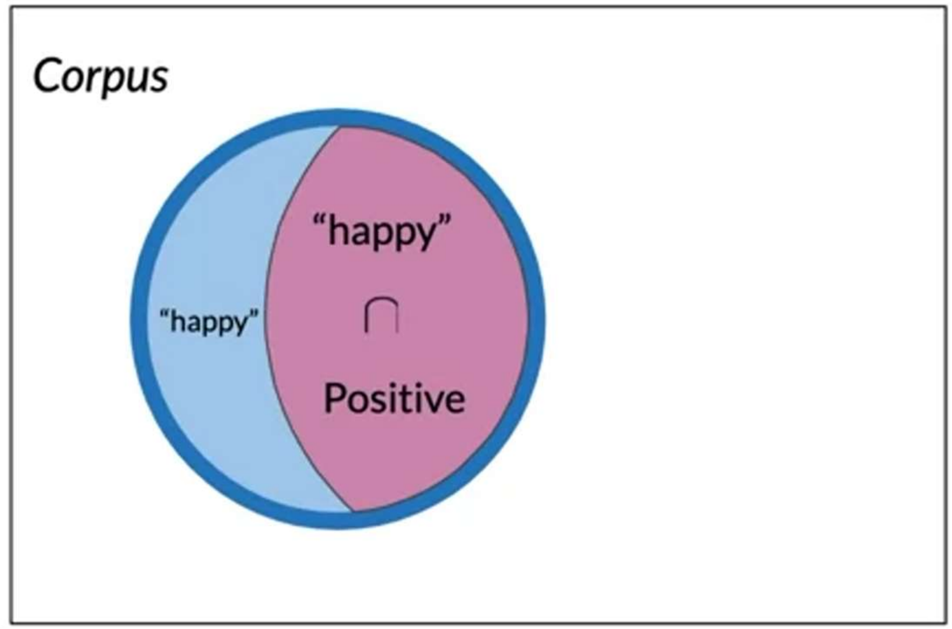


Conditional Probabilities



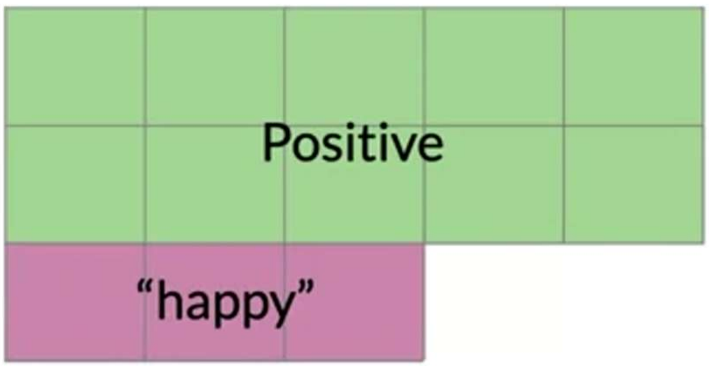
$$P(A \mid B) = P(\text{Positive} \mid \text{"happy"})$$

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



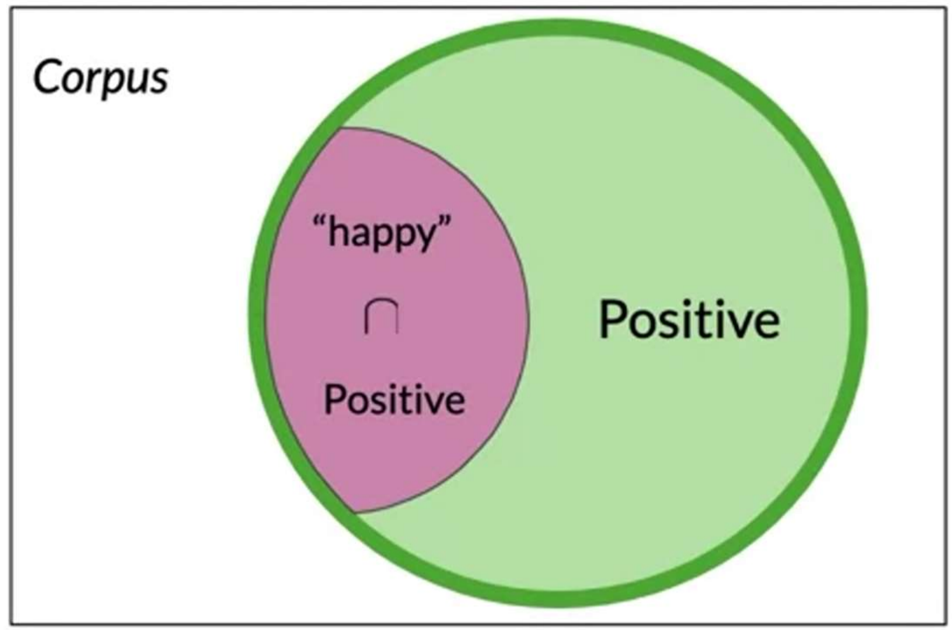
Probabilidad condicional

Conditional Probabilities



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

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



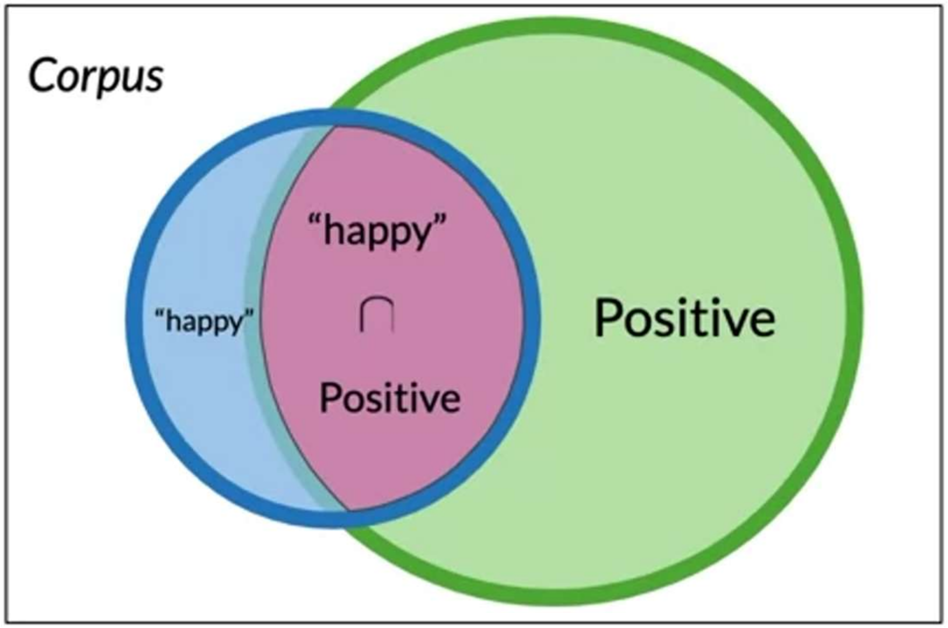
Probabilidad condicional

Conditional probabilities

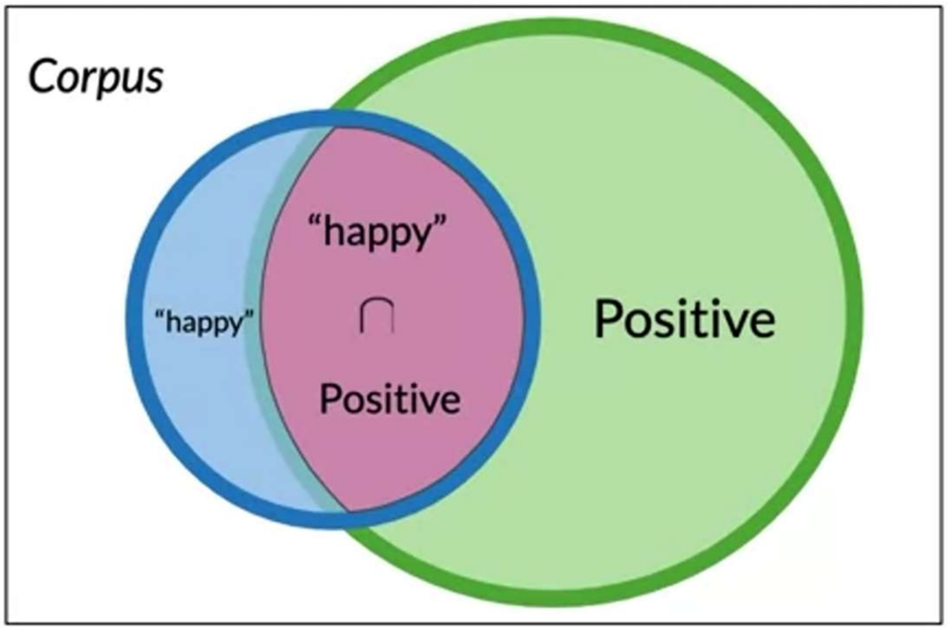
Probability of B, given A happened

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

Conditional probabilities

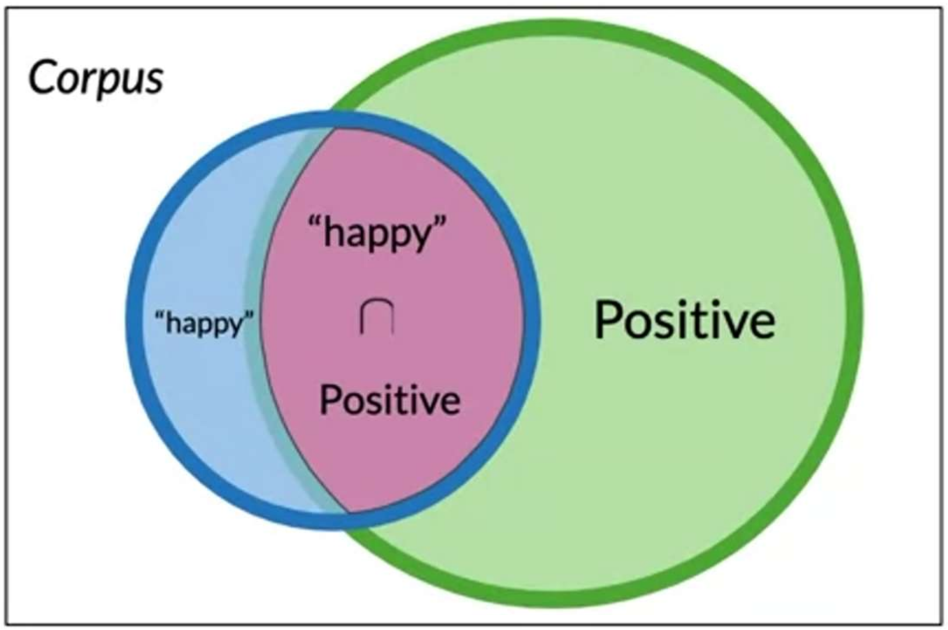


Conditional probabilities



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

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

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

Bayes' rule

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

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

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

Tablas de Frecuencia: Contar la cantidad de apariciones de una palabra en el corpus positivo, y hacer lo mismo con el corpus negativo

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

Tablas de Frecuencia: Contar la cantidad de apariciones de una palabra en el corpus positivo, y hacer lo mismo con el corpus negativo

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

Tablas de Frecuencia: Contar la cantidad de apariciones de una palabra en el corpus positivo, y hacer lo mismo con el corpus negativo

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

Tablas de Frecuencia: Contar la cantidad de apariciones de una palabra en el corpus positivo, y hacer lo mismo con el corpus negativo

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

Tablas de Frecuencia: Contar la cantidad de apariciones de una palabra en el corpus positivo, y hacer lo mismo con el corpus negativo

$P(w_i \mid class)$

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

Calcular probabilidad de una palabra en la clase positiva

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

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		

Calcular probabilidad de una palabra en la clase positiva

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

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	

Calcular probabilidad de una palabra en la clase positiva

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

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

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

word	Pos	Neg
I	0.24	

Calcular probabilidad de una palabra en la clase positiva

$P(w_i \mid class)$

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

Calcular probabilidad de una palabra en la clase positiva

$P(w_i \mid class)$

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	0.01
learning	0.08	0.08
NLP	0.08	0.08
sad	0.08	0.17
not	0.08	0.17

Calcular probabilidad de una palabra en la clase positiva

$P(w_i \mid class)$

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	0.01
learning	0.08	0.08
NLP	0.08	0.08
sad	0.08	0.17
not	0.08	0.17
Sum	**1**	**1**

Calcular probabilidad de una palabra en la clase positiva

$P(w_i \mid class)$

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

$P(w_i \mid class)$

word	Pos	Neg
$\boxed{\text{I}}$	0.24	0.25
$\boxed{\text{am}}$	0.24	0.25
happy	0.15	0.08
because	0.08	0
$\boxed{\text{learning}}$	0.08	0.08
$\boxed{\text{NLP}}$	0.08	0.08
sad	0.08	0.17
not	0.08	0.17

Probabilidades iguales tanto en positivo como negativo, no aportan mucho para descifrar un sentimiento.

$P(w_i \mid class)$

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

Las que difieren serán mejor para la clasificación

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
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.

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

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

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.

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

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

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

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.

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

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

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

Naive Bayes:
Laplacian Smoothing

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	**13**	**12**

$V = 8$

word	Pos	Neg

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

word	Pos	Neg
$\boxed{I}$	3	3
am	3	3
happy	2	1
because	1	0
learning	1	1
NLP	1	1
sad	1	2
not	1	2
Nclass	$\boxed{13}$	**12**

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

$V = 8$

word	Pos	Neg
I	0.19	

Calcular la probabilidad por cada palabra según la fórmula de Laplacian Smoothing

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

word	Pos	Neg
$\boxed{I}$	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**	$\boxed{\mathbf{12}}$

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

$V = 8$

word	Pos	Neg
I	0.19	0.20

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

word	Pos	Neg
I	3	3
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
am	0.19	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
Sum	**1**	**1**

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

Laplacian Smoothing

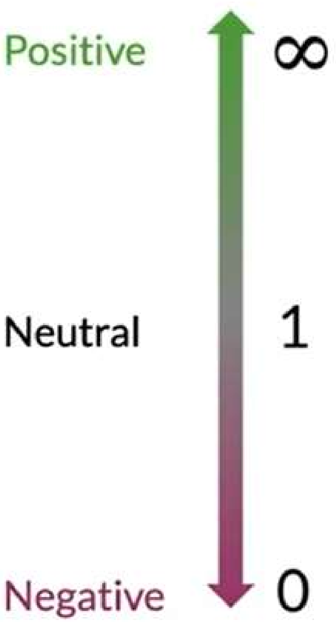
$V = 8$

word	Pos	Neg
I	0.19	0.20
am	0.19	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
Sum	1	1

Con el método anterior este dato antes daba 0

Log Likelihood

Ratio of probabilities

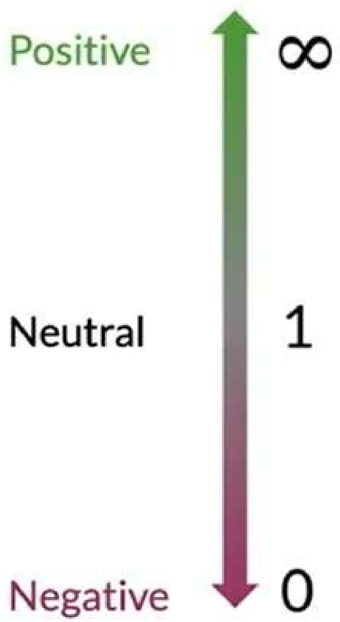


word	Pos	Neg	ratio
I	0.20	0.20	1
am	0.20	0.20	1
happy	0.14	0.10	1.4
because	0.10	0.10	1
learning	0.10	0.10	1
NLP	0.10	0.10	1
sad	0.10	0.15	0.6
not	0.10	0.15	0.6

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

Obtener la relación entre las categorías “ratio” para obtener una nueva categoría “neutral”

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*

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

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

Probabilidad de twits positivos y probabilidad de negativos. Para estos ejemplos los datasets están equilibrados por lo que será 1

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	

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	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	

Sentimiento positivo

Summary

- Word sentiment

$$
\begin{cases}
ratio(w) = \dfrac{P(w|pos)}{P(w|neg)} \\[2ex]
\lambda(w) = \ log\dfrac{P(w|pos)}{P(w|neg)}
\end{cases}
$$

doc: I am happy because I am learning.

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

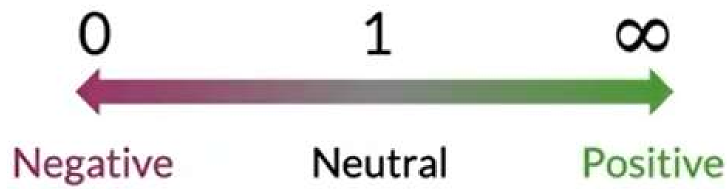
log likelihood = 0 + 0 + 2.2 + 0 + 0 + 0 + 1.1 = **3.3**

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

Dado un documento sumar todas las lambdas. Si es mayor que 0 entonces es positivo, de lo contrario negativo

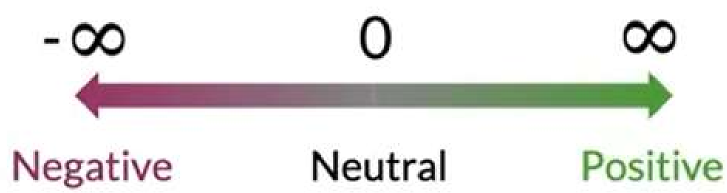
Log Likelihood

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



3.3 > 0

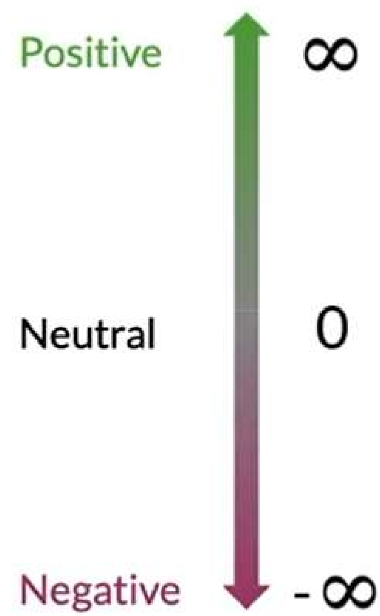
$$\sum_{i=1}^{m} log \frac{P(w_i|pos)}{P(w_i|neg)} > 0$$



Summary

Tweet sentiment:

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



Entrenamiento del modelo

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

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

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

[redacted]

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

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

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

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

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

of your conditional

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, ...]
2. Compute freq(w, class)
3. Get P(w | pos), P(w | neg)
4. Get λ(w)
5. Compute logprior = log(P(pos) / P(neg))

Prueba

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

Ante una nueva frase verificar el valor de lambda y en caso que una palabra no exista dejarla con un valor neutral (ósea 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

Logprior ayuda a balancear la predicción en caso que el dataset está desbalanceado

Applications of Naïve Bayes

Author identification:

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

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

Spam filtering:

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

Posibles errores

Processing as a Source of Errors: Word Order

Tweet: I am happy because I do not go.

Tweet: I am not happy because I did go.

Una negación que es una stop Word puede cambiar el significado de la oración

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]