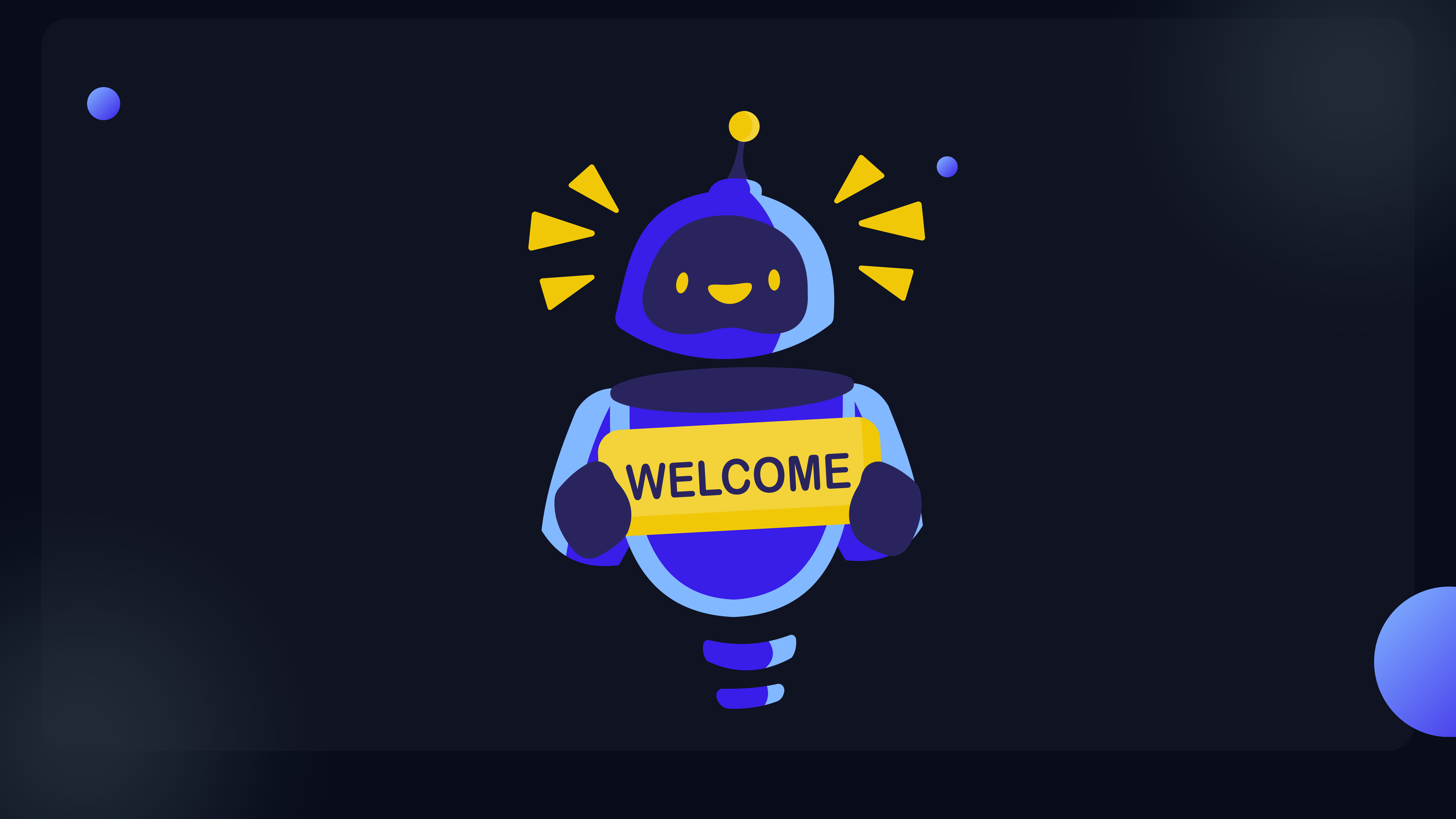
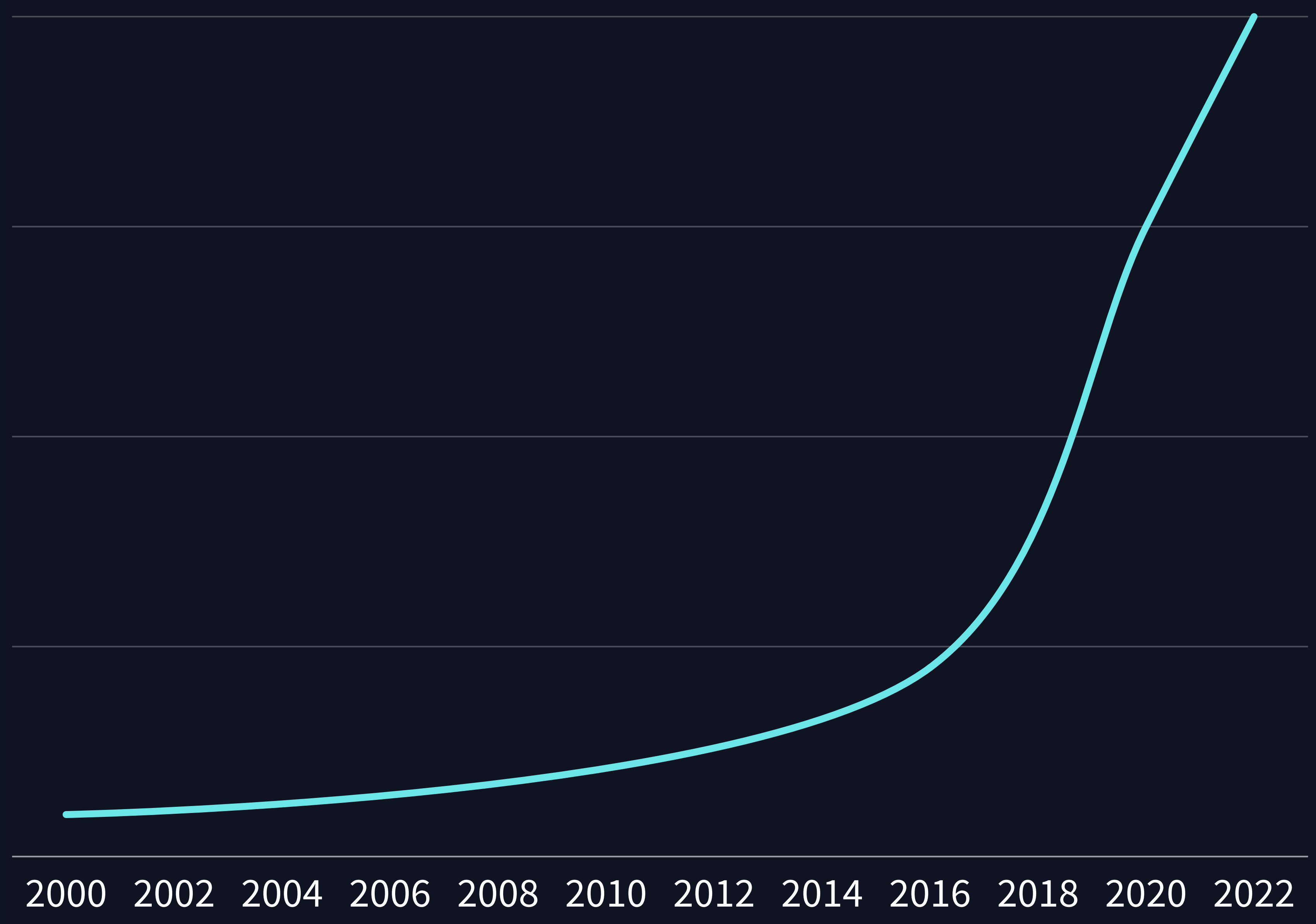
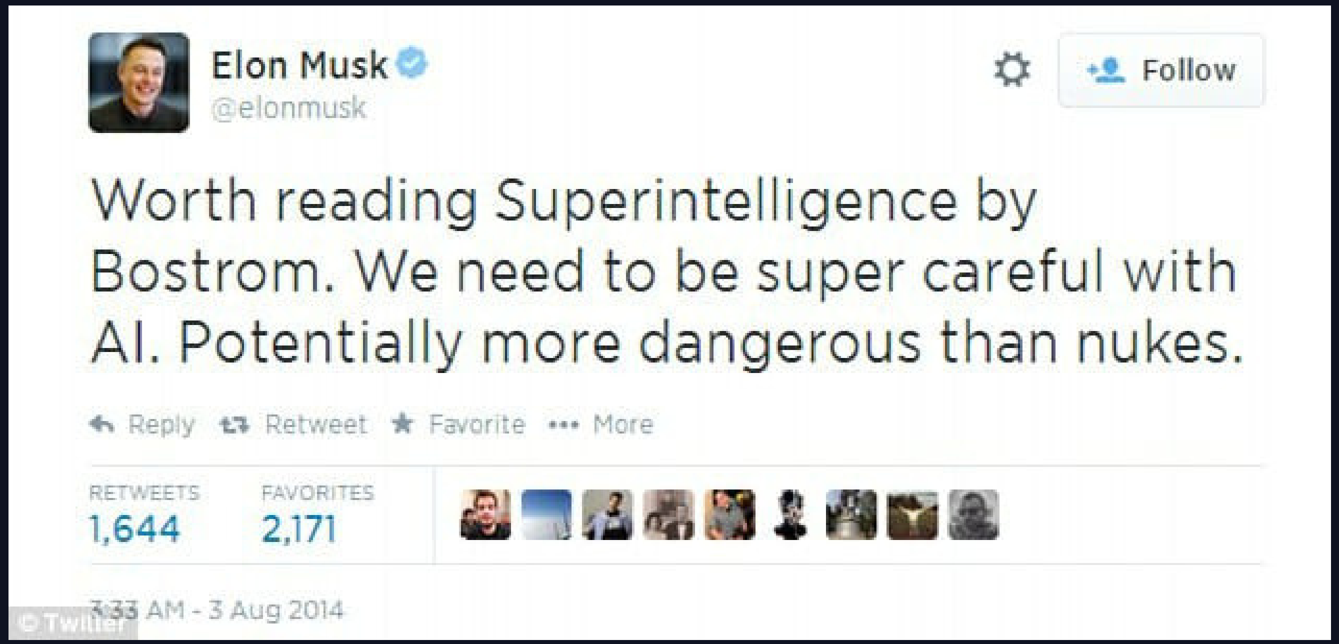

WELCOME

WHAT IS MACHINE LEARNING

WHY ML IS GETTING DEMAND NOW?



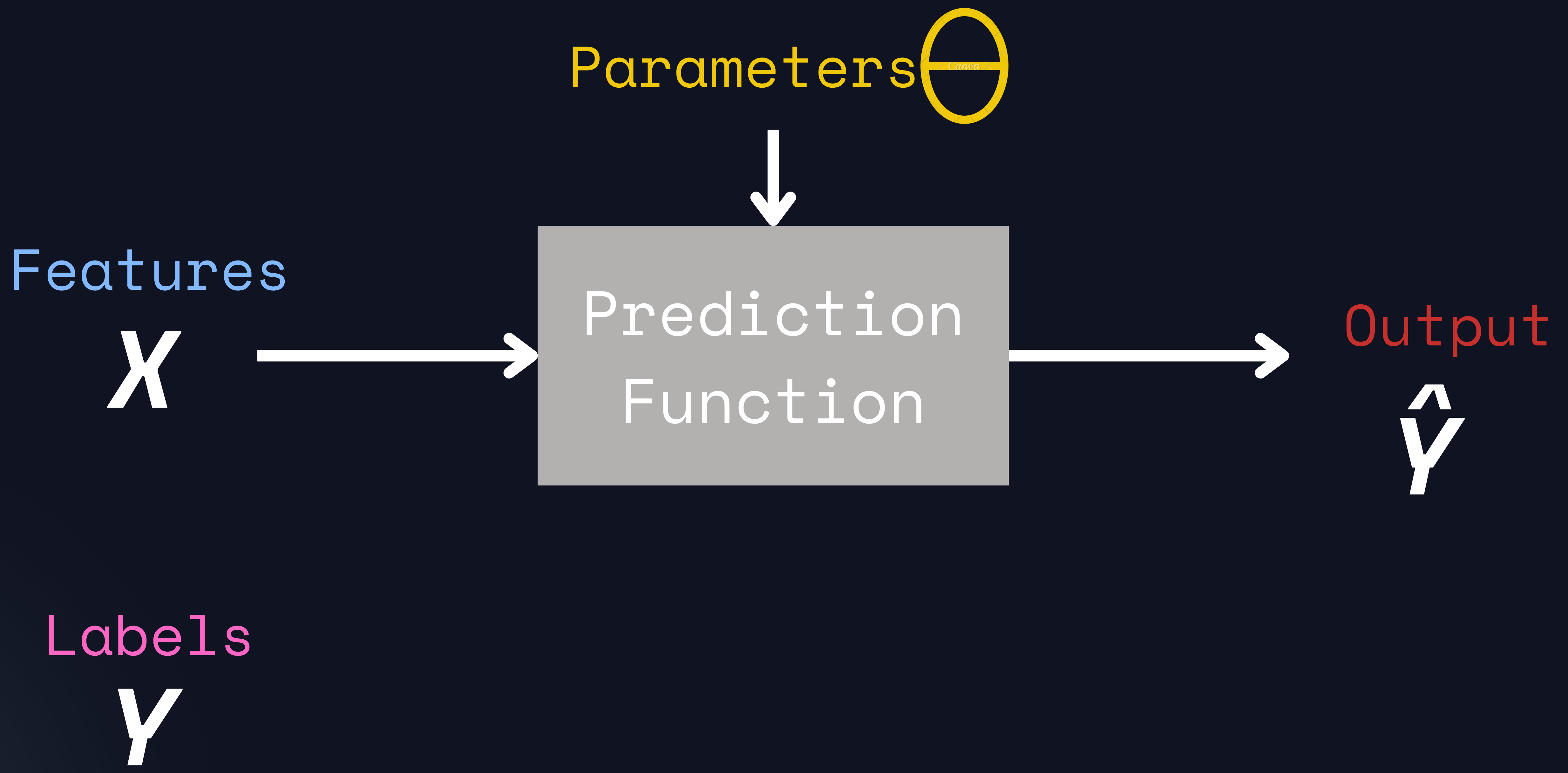
NATURAL LANGUGE PROCESSING


Elon Musk
@elonmusk
Follow
Worth reading Superintelligence by Bostrom. We need to be super careful with AI. Potentially more dangerous than nukes.
Reply Retweet Favorite More
RETWEETS
1,644
FAVORITES
2,171
7:33 AM - 3 Aug 2014
© Twitter


Elon Musk
@elonmusk · Follow
He's fired
9:02 PM · Nov 14, 2022
40.3K
Reply
Share
Read 7.1K replies

SUPERVISED ML &
SENTIMENT ANALYSIS

SUPERVISED ML (TRAINING)



SENTIMENT ANALYSIS

Tweet: I am happy I am learning NLP

Positive

< 0 <

Negative

SENTIMENT ANALYSIS

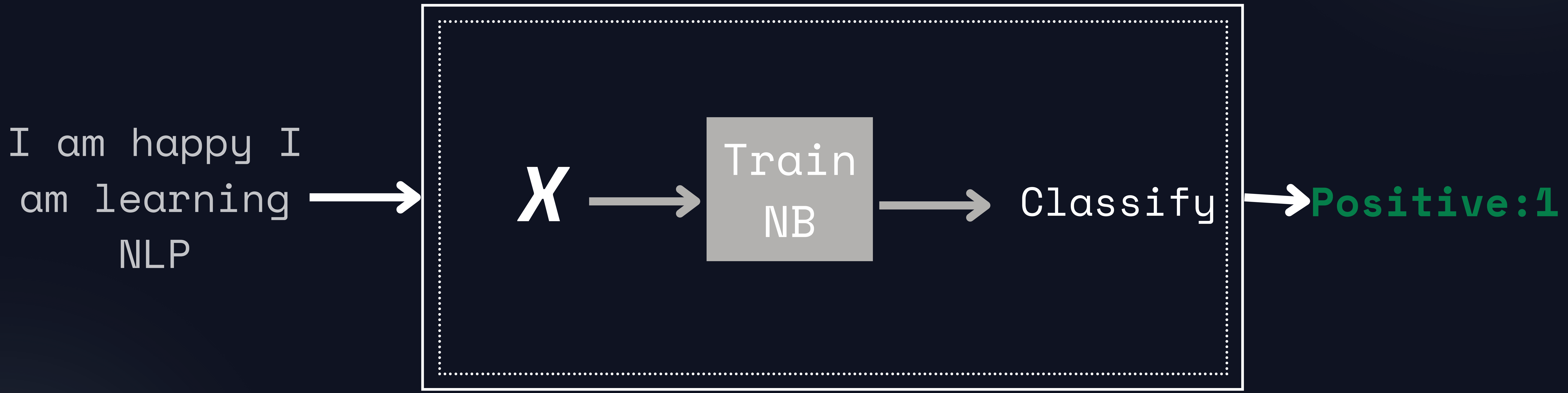
Positive:1

Tweet: I am happy I am learning NLP

Negative:0

Naive Bayes

SENTIMENT ANALYSIS



VOCABULARY & FEATURE EXTRACTION

VOCABULARY

Tweets:

[tweet_1,tweet2, ..., tweet_m]

```
I am happy I am learning NLP
...
...
...
I hate the movie
```

$V=$

[I,am, happy, learning, NLP,..., hate, the, movie]

FEATURE EXTRACTION

I am happy I am learning NLP

FEATURE EXTRACTION

I am happy I am learning NLP

[I, am, happy, learning, NLP,..., hate, the, movie]

[1, 1

FEATURE EXTRACTION

I am happy I am learning NLP

[I, am, happy, learning, NLP,..., hate, the, movie]

[1, 1 1

FEATURE EXTRACTION

I am happy I am learning NLP

[I, am, happy, learning, NLP,..., hate, the, movie]

[1, 1 1 1,

FEATURE EXTRACTION

I am happy I am learning NLP

[I, am, happy, learning, NLP,..., hate, the, movie]

[1, 1, 1, 1, 1,

FEATURE EXTRACTION

I am happy I am learning NLP

[I, am, happy, learning, NLP,..., hate, the, movie]

[1, 1, 1, 1, 1, ..., 0, 0, 0]

FEATURE EXTRACTION

I am happy I am learning NLP

[I, am, happy, learning, NLP,..., hate, the, movie]

$$\begin{array}{cccccccc} I, & am, & happy, & learning, & NLP, \ldots, & hate, & the, & movie \\ \downarrow & \downarrow & \downarrow & \downarrow & \downarrow & \downarrow & \downarrow & \downarrow \\ 1, & 1, & 1, & 1, & 1, \ldots, & 0, & 0, & 0 \end{array}$$

[1, 1, 1, 1, 1, ..., 0, 0, 0]

FEATURE EXTRACTION

I am happy I am learning NLP

[I, am, happy, learning, NLP,..., hate, the, movie]

[1, 1, 1, 1, 1, ..., 0, 0, 0]

VOCABULARY

I am happy I am learning NLP

VOCABULARY

I am happy I am learning NLP

[1, 1, 1, 1, ..., 0, 0, 0]

VOCABULARY

I am happy I am learning NLP

[1, 1, 1, 1, ..., 0, 0, 0]

$1 \longleftrightarrow |V|$

VOCABULARY

I am happy I am learning NLP

All Zeros

[1, 1, 1, 1, ..., 0, 0, 0]

1 $\longleftrightarrow$ $|V|$

VOCABULARY

I am happy I am learning NLP

All Zeros

[1, 1, 1, 1, ..., 0, 0, 0]

$1 \longleftrightarrow |V|$

$$[\theta_1, \theta_2, \theta_3, \ldots, \theta_n]$$

VOCABULARY

I am happy I am learning NLP

All Zeros

[1, 1, 1, 1, . . . , 0, 0, 0]

$1 \longleftrightarrow |V|$

$$[\theta_1, \theta_2, \theta_3, \ldots, \theta_n]$$

$$n = |V|$$

VOCABULARY

I am happy I am learning NLP

All Zeros

[1, 1, 1, 1, ..., 0, 0, 0]

$1 \longleftrightarrow |V|$

$$[\theta_1, \theta_2, \theta_3, \ldots, \theta_n]$$

1) Large Traning Time
2) Large Prediction Time

$$n = |V|$$

POSITIVE & NEGATIVE FREQUENCE

POSITIVE & NEGATIVE COUNT

Corpos:

I am happy because I am learning NLP

I am happy

I am sad I am not Learning NLP

I am sad

POSITIVE & NEGATIVE COUNT

Corpos:

I am happy because I am learning NLP

I am happy

I am sad I am not Learning NLP

I am sad

VOCABULARY

I
am
happy
because
learning
NLP
sad
not

POSITIVE & NEGATIVE COUNT

Positive:

```
I am happy becaues I am

learning NLP

I am happy
```

POSITIVE & NEGATIVE COUNT

Positive:

I am happy becaues I am learning NLP

I am happy

Negative:

I am sad I am not Learning NLP

I am sad

POSITIVE & NEGATIVE COUNT

Positive:

I am happy becaues I am

learning NLP

I am happy

VOCABULARY
I
am
happy
because
learning
NLP
sad
not

POSITIVE & NEGATIVE COUNT

Positive:

I am happy becaues I am learning NLP

I am happy

VOCABULARY	PosFreq(1)
I	
am	
happy	
because	
learning	
NLP	
sad	
not	

POSITIVE & NEGATIVE COUNT

Positive:

I am happy becaues I am learning NLP

I am happy

VOCABULARY	PosFreq(1)
I	
am	
happy	2
because	
learning	
NLP	
sad	
not	

POSITIVE & NEGATIVE COUNT

Positive:

I am happy becaues I am

learning NLP

I am happy

VOCABULARY	PosFreq(1)
I	3
am	3
happy	2
because	1
learning	1
NLP	1
sad	0
not	0

POSITIVE & NEGATIVE COUNT

Negative:

I am sad I am not Learning NLP

I am sad

VOCABULARY	NegFreq(0)
I	3
am	3
happy	0
because	0
learning	1
NLP	1
sad	2
not	1

POSITIVE & NEGATIVE COUNT

VOCABULARY	PosFreq(1)	NegFreq(0)
I	3	3
am	3	3
happy	2	0
because	1	0
learning	1	1
NLP	1	1
sad	0	2
not	0	1

FEATURE EXTRACTION WITH FREQUENCIES

WORD FREQUENCE IN CLASSES

WORD FREQUENCE IN CLASSES

VOCABULARY	PosFreq(1)	NegFreq(0)
I	3	3
am	3	3
happy	2	0
because	1	0
learning	1	1
NLP	1	1
sad	0	2
not	0	1

WORD FREQUENCE IN CLASSES

VOCABULARY	PosFreq(1)	NegFreq(0)
I	3	3
am	3	3
happy	2	0
because	1	0
learning	1	1
NLP	1	1
sad	0	2
not	0	1

Freq: Dictionary mapping from (word, class) to frequency

FEATURE EXTRACTION

FEATURE EXTRACTION

Freq: Dictionary mapping from (word, class) to frequency

FEATURE EXTRACTION

Freq: Dictionary mapping from (word, class) to frequency

$$X_m = [\quad]$$

Features of tweets m

FEATURE EXTRACTION

Freq: Dictionary mapping from (word, class) to frequency

$$X_m = [\ 1, \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad]$$

Features of tweets m

Bias

FEATURE EXTRACTION

Freq: Dictionary mapping from (word, class) to frequency

$$X_m = [\ 1,\ \sum freqs(w,1),\ \ ]$$

Features of tweets m

Bias

Sum Pos Frequence

FEATURE EXTRACTION

Freq: Dictionary mapping from (word, class) to frequency

$$X_m = [\ 1, \sum freqs(w,1), \sum freqs(w,0)\ ]$$

Features of tweets m

Bias

Sum Pos Frequencies

Sum Neg Frequencies

FEATURE EXTRACTION

I am sad, I am not Learning NLP

FEATURE EXTRACTION

VOCABULARY	PosFreq(1)
I	3
am	3
happy	2
because	1
learning	1
NLP	1
sad	0
not	0

I am sad, I am not Learning NLP

FEATURE EXTRACTION

VOCABULARY	PosFreq(1)
I	3
am	3
happy	2
because	1
learning	1
NLP	1
sad	0
not	0

I am sad, I am not Learning NLP

FEATURE EXTRACTION

VOCABULARY	PosFreq(1)
I	3
am	3
happy	2
because	1
learning	1
NLP	1
sad	0
not	0

I am sad, I am not Learning NLP

$$X_m = [\ 1, \sum freqs(w,1), \sum freqs(w,0)\ ]$$

FEATURE EXTRACTION

VOCABULARY	PosFreq(1)
I	3
am	3
happy	2
because	1
learning	1
NLP	1
sad	0
not	0

I am sad, I am not Learning NLP

$$X_m = [\ 1, \sum freqs(w,1), \sum freqs(w,0)\ ]$$

FEATURE EXTRACTION

VOCABULARY	PosFreq(1)
I	3
am	3
happy	2
because	1
learning	1
NLP	1
sad	0
not	0

I am sad, I am not Learning NLP

$$X_m = [\ 1, \sum freqs(w,1), \sum freqs(w,0)\ ]$$

8

FEATURE EXTRACTION

VOCABULARY	NegFreq(0)
I	3
am	3
happy	0
because	0
learning	1
NLP	1
sad	2
not	1

I am sad, I am not Learning NLP

$$X_m = [\ 1, \sum freqs(w,1), \sum freqs(w,0)\ ]$$

FEATURE EXTRACTION

VOCABULARY	NegFreq(0)
I	3
am	3
happy	0
because	0
learning	1
NLP	1
sad	2
not	1

I am sad, I am not Learning NLP

$$X_m = [\ 1, \sum freqs(w,1), \underbrace{\sum freqs(w,0)}_{11}\ ]$$

FEATURE EXTRACTION

I am sad, I am not Learning NLP

$$X_m = [\ 1, \sum freqs(w,1), \sum freqs(w,0)\ ]$$

$$\downarrow$$

$$X_m = [1, 8, 11]$$

PREPROCESSING

PREPROCESSING: STOP WORD & PUNCTUATION

PREPROCESSING: STOP WORD & PUNCTUATION

@PSGiTech is conducting YUKTA

to register https://yuktaha.psgitech.ac.in/

PREPROCESSING: STOP WORD & PUNCTUATION

@PSGiTech is conducting YUKTA!!!

to register

https://yuktaha.psgitech.ac.in/

STOPWORD
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PREPROCESSING: STOP WORD & PUNCTUATION

@PSGiTech ~~is~~ conducting YUKTA!!!

~~to~~ register

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PREPROCESSING: STOP WORD & PUNCTUATION

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~~to~~ register

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PREPROCESSING: STOP WORD & PUNCTUATION

@PSGiTech conducting YUKTA!!!

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PREPROCESSING: STOP WORD & PUNCTUATION

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https://yuktaha.psgitech.ac.in/

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PREPROCESSING: STOP WORD & PUNCTUATION

@PSGiTech conducting YUKTA!~~!~~!

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@PSGiTech conducting YUKTA

register

https://yuktaha.psgitech.ac.in/

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PREPROCESSING: STOP WORD & PUNCTUATION

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PREPROCESSING: HANDLES AND URLS

~~@PSGiTech~~ conducting YUKTA register

~~https://yuktaha.psgitech.ac.in/~~

↓

conducting YUKTA register

PREPROCESSING: STEMMING & LOWERCASE

conducting YUKTA register

PREPROCESSING: STEMMING & LOWERCASE

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PREPROCESSING: STEMMING & LOWERCASE

conduct~~ing~~ YUKTA register

conduct

conductivity

PREPROCESSING: STEMMING & LOWERCASE

conduct~~ing~~ YUKTA register

conduct

conductivity

conducted

PREPROCESSING: STEMMING & LOWERCASE

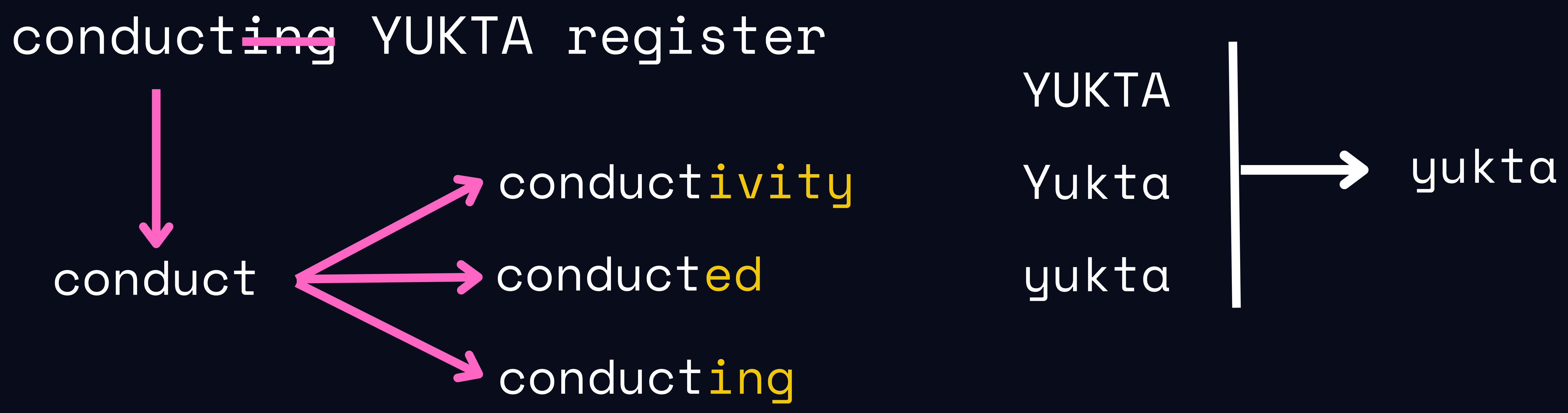
conduct~~ing~~ YUKTA register

conduct → conductivity

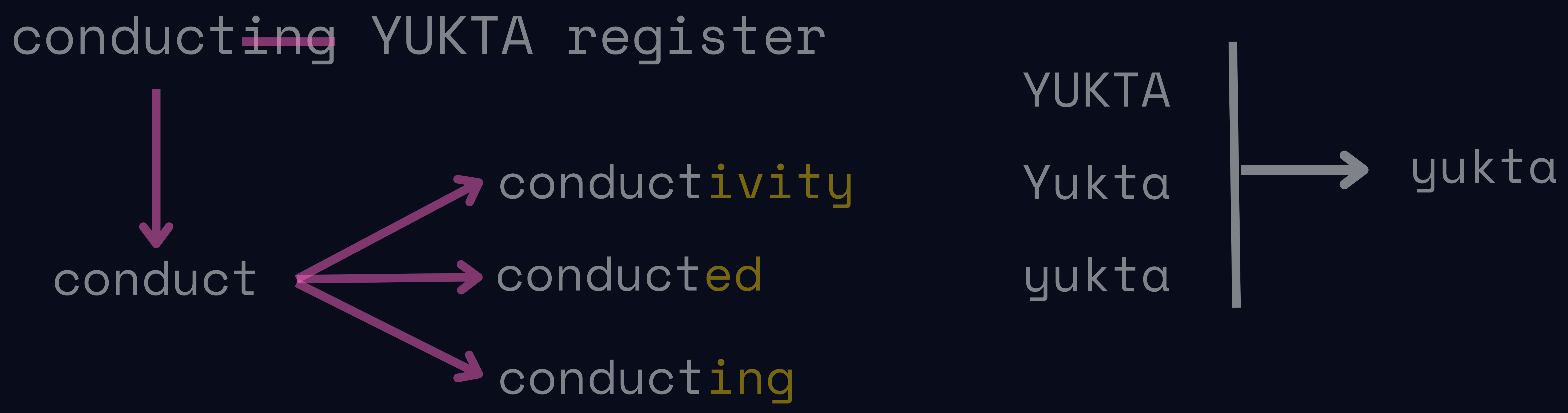
conduct → conducted

conduct → conducting

PREPROCESSING: STEMMING & LOWERCASE



PREPROCESSING: STEMMING & LOWERCASE



PROCESSED TWEET:

conduct yukta register

NAIVEE BAYES FOR SENTIMENT ANALAYSIS

NAIVEE BAYES FOR SENTIMENT ANALAYSIS

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

NAIVEE BAYES FOR SENTIMENT ANALAYSIS

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

NAIVEE BAYES FOR SENTIMENT ANALAYSIS

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	13

NAIVEE BAYES FOR SENTIMENT ANALAYSIS

$P(w_i | class)$

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
N_{class}	13	13

WORD	Pos	Neg

NAIVEE BAYES FOR SENTIMENT ANALAYSIS

$P(w_i \mid class)$

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
N_{class}	13	13

WORD	Pos	Neg
I		

NAIVEE BAYES FOR SENTIMENT ANALAYSIS

$P(w_i | class)$

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
N_{class}	13	13

$$P(I|pos) = \frac{3}{13}$$

WORD	Pos	Neg
I	0.24	

NAIVEE BAYES FOR SENTIMENT ANALAYSIS

$P(w_i \mid class)$

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
N_{class}	13	13

$P(I|pos) = \frac{3}{13}$

WORD	Pos	Neg
I	0.24	0.24

NAIVEE BAYES FOR SENTIMENT ANALAYSIS

$P(w_i \mid class)$

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
N_{class}	13	13

WORD	Pos	Neg
I	0.24	0.24
am	0.24	0.24
happy	0.15	0.08
because	0.08	0
learning	0.08	0.08
NLP	0.08	0.08
sad	0.08	0.15
not	0.08	0.15

NAIVEE BAYES FOR SENTIMENT ANALAYSIS

$P(w_i \mid class)$

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
N_{class}	13	13

WORD	Pos	Neg
I	0.24	0.24
am	0.24	0.24
happy	0.15	0.08
because	0.08	0
learning	0.08	0.08
NLP	0.08	0.08
sad	0.08	0.15
not	0.08	0.15
Sum	1	1

NAIVEE BAYES FOR SENTIMENT ANALAYSIS

$P(w_i | class)$

WORD	Pos	Neg
I	0.24	0.24
am	0.24	0.24
happy	0.15	0.08
because	0.08	0
learning	0.08	0.08
NLP	0.08	0.08
sad	0.08	0.15
not	0.08	0.15

NAIVEE BAYES FOR SENTIMENT ANALAYSIS

$P(w_i \mid class)$

WORD	Pos	Neg
I	0.24	0.24
am	0.24	0.24
happy	0.15	0.08
because	0.08	0
learning	0.08	0.08
NLP	0.08	0.08
sad	0.08	0.15
not	0.08	0.15

NAIVEE BAYES FOR SENTIMENT ANALAYSIS

$P(w_i \mid class)$

WORD	Pos	Neg
I	0.24	0.24
am	0.24	0.24
happy	0.15	0.08
because	0.08	0
learning	0.08	0.08
NLP	0.08	0.08
sad	0.08	0.15
not	0.08	0.15

NAIVEE BAYES FOR SENTIMENT ANALAYSIS

$P(w_i \mid class)$

WORD	Pos	Neg
I	0.24	0.24
am	0.24	0.24
happy	0.15	0.08
because	0.08	0
learning	0.08	0.08
NLP	0.08	0.08
sad	0.08	0.15
not	0.08	0.15

NAIVEE BAYES

Tweet: I am happy today; I am learning

NAIVEE 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	0.14
not	0.10	0.14

NAIVEE 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	0.14
not	0.10	0.14

NAIVEE 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	0.14
not	0.10	0.14

NAIVEE 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	0.14
not	0.10	0.14

NAIVEE 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	0.14
not	0.10	0.14

NAIVEE 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	0.14
not	0.10	0.14

NAIVEE 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	0.14
not	0.10	0.14

NAIVEE 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	0.14
not	0.10	0.14

NAIVEE 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	0.14
not	0.10	0.14

NAIVEE 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	0.14
not	0.10	0.14

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

NAIVEE 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	0.14
not	0.10	0.14

NAIVEE BAYES

Tweet: I am happy today; I am learning

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

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

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	0.14
not	0.10	0.14

NAIVEE BAYES

Tweet: I am happy today; I am learning

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

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	0.14
not	0.10	0.14

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

LAPLACIAN SMOOTHING

LAPLACIAN SMOOTHING

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

class - {Positive,Negative}

N_{class} = frequency of all words in class

V_{class} = number of unique words in class

LAPLACIAN SMOOTHING

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

class - {Positive,Negative}

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

N_{class} = frequency of all words in class

V_{class} = number of unique words in class

LAPLACIAN SMOOTHING

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

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

N_{class} = frequency of all words in class

V_{class} = number of unique words in class

LAPLACIAN SMOOTHING

Introducing $P(w_i|class)$ 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
N_{class}	13	13

WORD	Pos	Neg

LAPLACIAN SMOOTHING

Introducing $P(w_i|class)$ 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
N_{class}	13	13

$V = 8$

WORD	Pos	Neg
I		

LAPLACIAN SMOOTHING

Introducing $P(w_i|class)$ 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
N_{class}	13	13

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

WORD	Pos	Neg
I	0.20	

$V = 8$

LAPLACIAN SMOOTHING

Introducing $P(w_i|class)$ 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
N_{class}	13	13

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

$V = 8$

WORD	Pos	Neg
I	0.20	0.20

LAPLACIAN SMOOTHING

Introducing $P(w_i|class)$ with smoothing

WORD	Pos	Neg
I	3	3
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sad	1	2
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$V = 8$

WORD	Pos	Neg
I	0.20	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	0.14
not	0.10	0.14

LAPLACIAN SMOOTHING

Introducing $P(w_i|class)$ with smoothing

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I	3	3
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learning	1	1
NLP	1	1
sad	1	2
not	1	2
N_{class}	13	13

$V = 8$

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	0.14
not	0.10	0.14
Sum	1	1

LAPLACIAN SMOOTHING

Introducing $P(w_i|class)$ 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
N_{class}	13	13

$V = 8$

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	0.14
not	0.10	0.14
Sum	1	1

LOG LIKELIHOOD

Ratio of Probabilities

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

LOG LIKELIHOOD

Ratio of Probabilities

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I	0.20	0.20
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because	0.10	0.05
learning	0.10	0.10
NLP	0.10	0.14
sad	0.10	0.14
not	0.10	0.14

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

LOG LIKELIHOOD

Ratio of Probabilities

WORD	Pos	Neg	ratio
I	0.20	0.20	
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$$\text{ratio}(w_i) = \frac{P(w_i \mid \text{Pos})}{P(w_i \mid \text{Neg})}$$

LOG LIKELIHOOD

Ratio of Probabilities

WORD	Pos	Neg	ratio
I	0.20	0.20	1
am	0.20	0.20	
happy	0.14	0.10	
because	0.10	0.05	
learning	0.10	0.10	
NLP	0.10	0.14	
sad	0.10	0.14	
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$$\text{ratio}(w_i) = \frac{P(w_i \mid \text{Pos})}{P(w_i \mid \text{Neg})}$$

LOG LIKELIHOOD

Ratio of Probabilities

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NLP	0.10	0.14	
sad	0.10	0.14	
not	0.10	0.14	

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

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	0.05	
learning	0.10	0.10	
NLP	0.10	0.14	
sad	0.10	0.14	
not	0.10	0.14	

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

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
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learning	0.10	0.10	
NLP	0.10	0.14	
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not	0.10	0.14	

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

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	0.05	2
learning	0.10	0.10	1
NLP	0.10	0.14	
sad	0.10	0.14	
not	0.10	0.14	

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

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	0.05	2
learning	0.10	0.10	1
NLP	0.10	0.14	0.6
sad	0.10	0.14	
not	0.10	0.14	

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

LOG LIKELIHOOD

Ratio of Probabilities

Neutral 1

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	0.05	2
learning	0.10	0.10	1
NLP	0.10	0.14	0.6
sad	0.10	0.14	0.6
not	0.10	0.14	0.6

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

LOG LIKELIHOOD

Ratio of Probabilities

Pos ∞

Neutral 1

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	0.05	2
learning	0.10	0.10	1
NLP	0.10	0.14	0.6
sad	0.10	0.14	0.6
not	0.10	0.14	0.6

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

LOG LIKELIHOOD

Ratio of Probabilities

Pos ∞

Neutral 1

Neg 0

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	0.05	2
learning	0.10	0.10	1
NLP	0.10	0.14	0.6
sad	0.10	0.14	0.6
not	0.10	0.14	0.6

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

LOG LIKELIHOOD

Naive Bayes' inference

LOG LIKELIHOOD

Naive Bayes' inference

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

LOG LIKELIHOOD

Naive Bayes' inference

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

LOG LIKELIHOOD

- Products bring the risk of underflow
- log(a * b) = log(a) + log(b)

LOG LIKELIHOOD

- Products bring the 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

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

- Products bring the risk of underflow
- $\log(a * b) = \log(a) + \log(b)$
- $\log\left(\frac{P(Pos)}{P(Neg)} \prod_{i=1}^{m} \frac{P(w_i|Pos)}{P(w_i|Neg)}\right)$

LOG LIKELIHOOD

- Products bring the risk of underflow $\frac{P(Pos)}{P(Neg)} \prod_{i=1}^{m} \frac{P(w_i|Pos)}{P(w_i|Neg)}$
- log(a * b) = log(a) + log(b)
- $\log\left(\frac{P(Pos)}{P(Neg)} \prod_{i=1}^{m} \frac{P(w_i|Pos)}{P(w_i|Neg)}\right) \Rightarrow \log \frac{P(Pos)}{P(Neg)} + \sum_{i=1}^{n} \log \frac{P(w_i|Pos)}{P(w_i|Neg)}$

LOG LIKELIHOOD

- Products bring the risk of underflow

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

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

- $$\log\left(\frac{P(Pos)}{P(Neg)} \prod_{i=1}^{m} \frac{P(w_i|Pos)}{P(w_i|Neg)}\right) \Rightarrow \log \frac{P(Pos)}{P(Neg)} + \sum_{i=1}^{n} \log \frac{P(w_i|Pos)}{P(w_i|Neg)}$$

log prior + log likelihood

LOG LIKELIHOOD

Calculating Lambda

tweet: I am happy because I am learning.

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

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

LOG LIKELIHOOD

Calculating Lambda

tweet: I am happy because I am learning.

$$\lambda(w) = \log \frac{P(w|Pos)}{P(w|Neg)}$$

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

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	

LOG LIKELIHOOD

Calculating Lambda

tweet: I am happy because I am learning.

$$\lambda(w) = \log \frac{P(w|Pos)}{P(w|Neg)}$$

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

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	

LOG LIKELIHOOD

Calculating Lambda

tweet: I am happy because I am learning.

$$\lambda(w) = \log \frac{P(w|Pos)}{P(w|Neg)}$$

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

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	

LOG LIKELIHOOD

Calculating Lambda

tweet: I am happy because I am learning.

$$\lambda(w) = \log \frac{P(w|Pos)}{P(w|Neg)}$$

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

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	

LOG LIKELIHOOD

Calculating Lambda

tweet: I am happy because I am learning.

$$\lambda(w) = \log \frac{P(w|Pos)}{P(w|Neg)}$$

$$\lambda(\text{because}) = \log \frac{0.01}{0.01} = 0$$

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	
NLP	0.02	0.02	
sad	0.01	0.09	
not	0.02	0.03	

LOG LIKELIHOOD

Calculating Lambda

tweet: I am happy because I am learning.

$$\lambda(w) = \log \frac{P(w|Pos)}{P(w|Neg)}$$

$$\lambda(\text{learning}) = \log \frac{0.03}{0.01} = 1.1$$

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	
sad	0.01	0.09	
not	0.02	0.03	

LOG LIKELIHOOD

Calculating Lambda

tweet: I am happy because I am learning.

$$\lambda(w) = \log \frac{P(w|Pos)}{P(w|Neg)}$$

$$\lambda(NLP) = \log \frac{0.02}{0.02} = 0$$

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	
not	0.02	0.03	0

LOG LIKELIHOOD

Calculating Lambda

tweet: I am happy because I am learning.

$$\lambda(w) = \log \frac{P(w|Pos)}{P(w|Neg)}$$

$$\lambda(sad) = \log \frac{0.01}{0.08} = -2.2$$

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- 0

LOG LIKELIHOOD

Calculating Lambda

tweet: I am happy because I am learning.

$$\lambda(w) = \log \frac{P(w|Pos)}{P(w|Neg)}$$

$$\lambda(\text{not}) = \log \frac{0.02}{0.03} = -0.4$$

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

$$\text{Word sentiment} \begin{cases} \text{ratio}(w) = \dfrac{P(w|Pos)}{P(w|Neg)} \\[2em] \lambda(w) = \log \dfrac{P(w|Pos)}{P(w|Neg)} \end{cases}$$

LOG LIKELIHOOD

tweet: I am happy because I am learning.

$$\sum_{i=1}^{n} \log \frac{P(w_i|Pos)}{P(w_i|Neg)} = \sum_{i=1}^{n} \lambda(w_i)$$

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

total log likelihood =

LOG LIKELIHOOD

tweet: I am happy because I am learning.

$$\sum_{i=1}^{n} \log \frac{P(w_i|Pos)}{P(w_i|Neg)} = \sum_{i=1}^{n} \lambda(w_i)$$

total 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

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$$\sum_{i=1}^{n} \log \frac{P(w_i|Pos)}{P(w_i|Neg)} = \sum_{i=1}^{n} \lambda(w_i)$$

total 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

tweet: I am happy because I am learning.

$$\sum_{i=1}^{n} \log \frac{P(w_i|Pos)}{P(w_i|Neg)} = \sum_{i=1}^{n} \lambda(w_i)$$

total 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
not	0.02	0.03	-0.4

LOG LIKELIHOOD

tweet: I am happy because I am learning.

$$\sum_{i=1}^{n} \log \frac{P(w_i|Pos)}{P(w_i|Neg)} = \sum_{i=1}^{n} \lambda(w_i)$$

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

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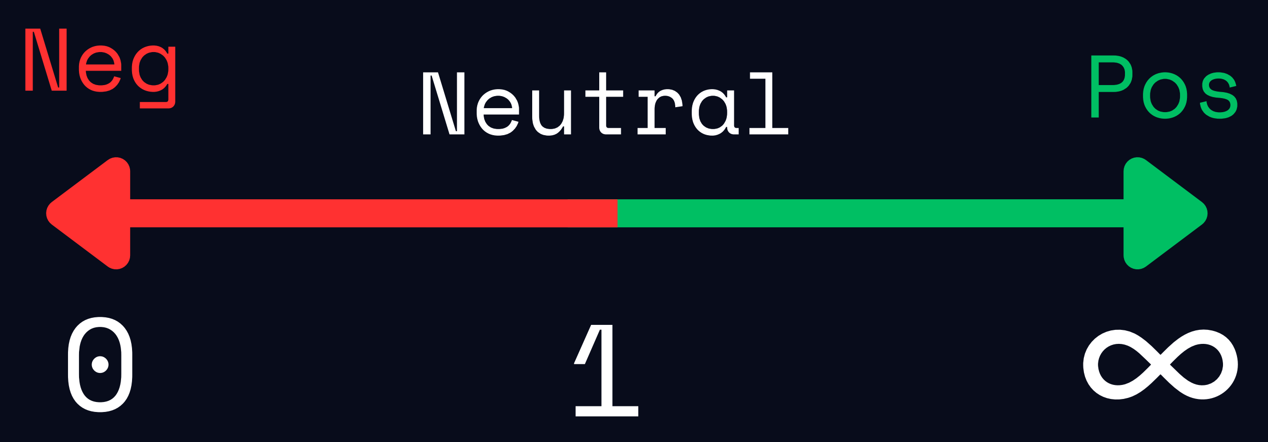
sad	0.01	0.09	-2.2
not	0.02	0.03	-0.4

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

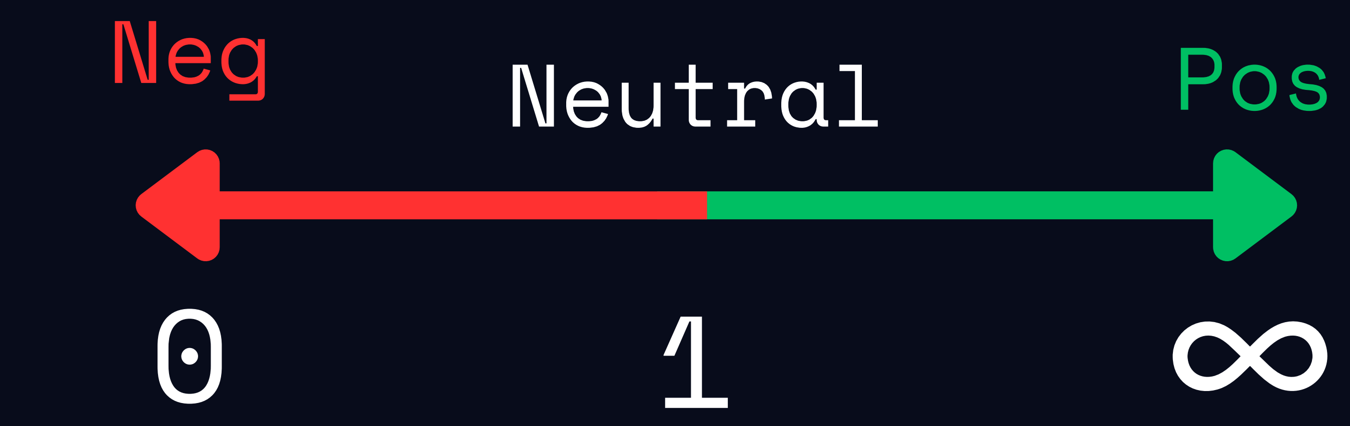
LOG LIKELIHOOD

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

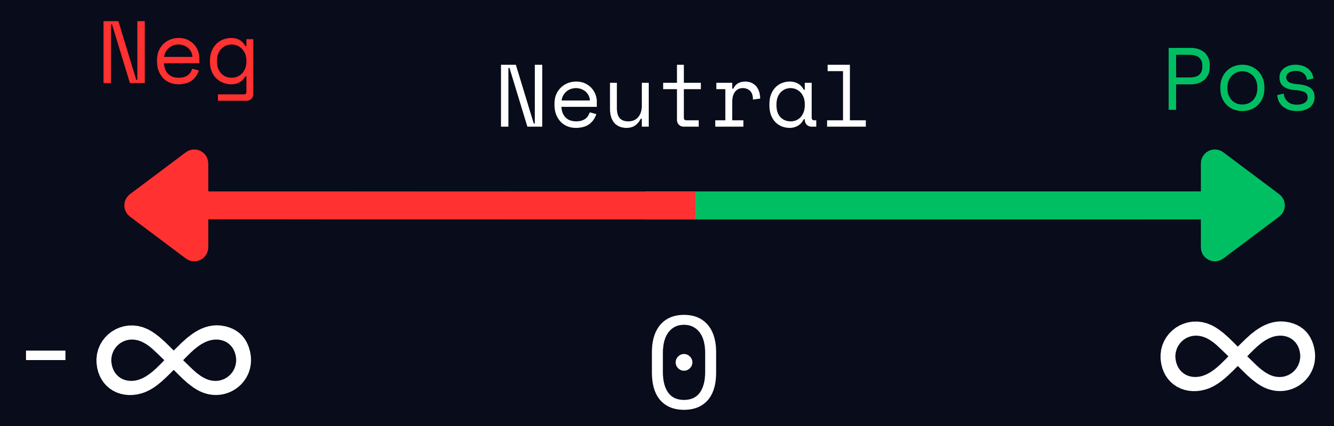


LOG LIKELIHOOD

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

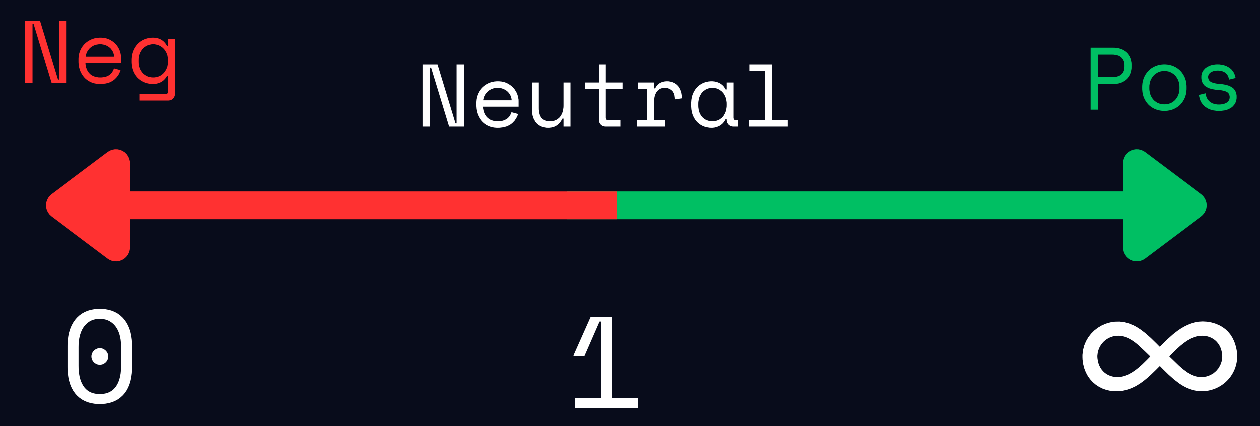


$$\sum_{i=1}^{n} \log \frac{P(w_i|Pos)}{P(w_i|Neg)} > 0$$



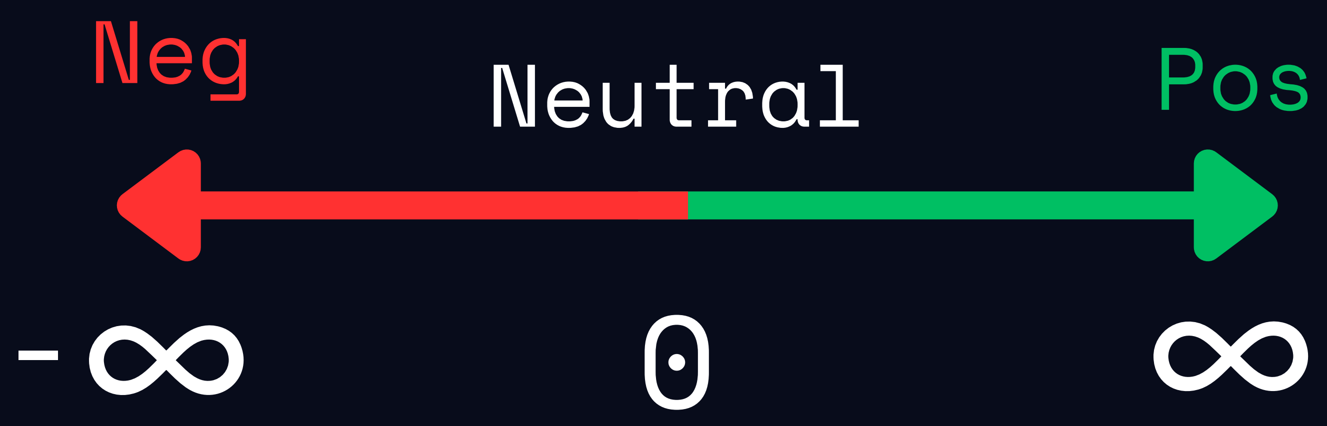
LOG **LIKELIHOOD**

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



$$\sum_{i=1}^{n} \log \frac{P(w_i|Pos)}{P(w_i|Neg)} > 0$$

$3.3 > 0$



LOG LIKELIHOOD

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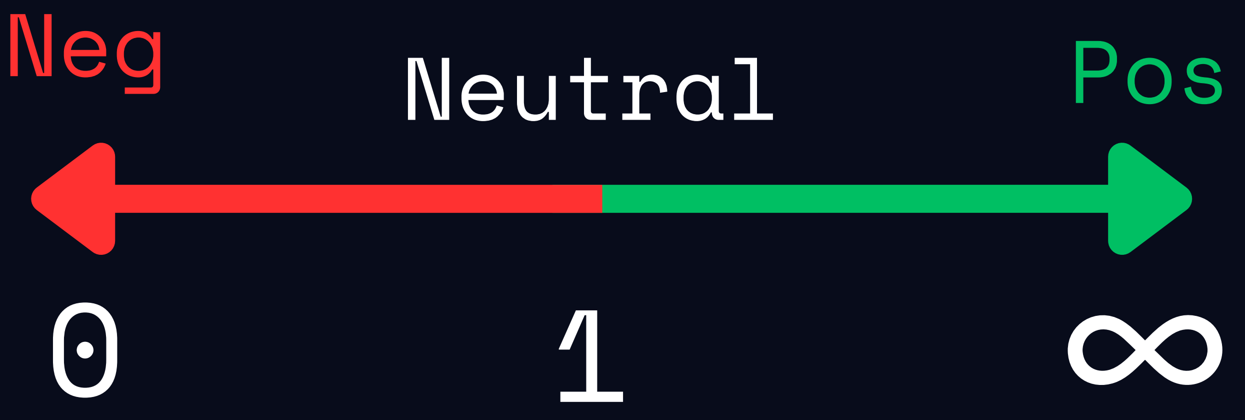
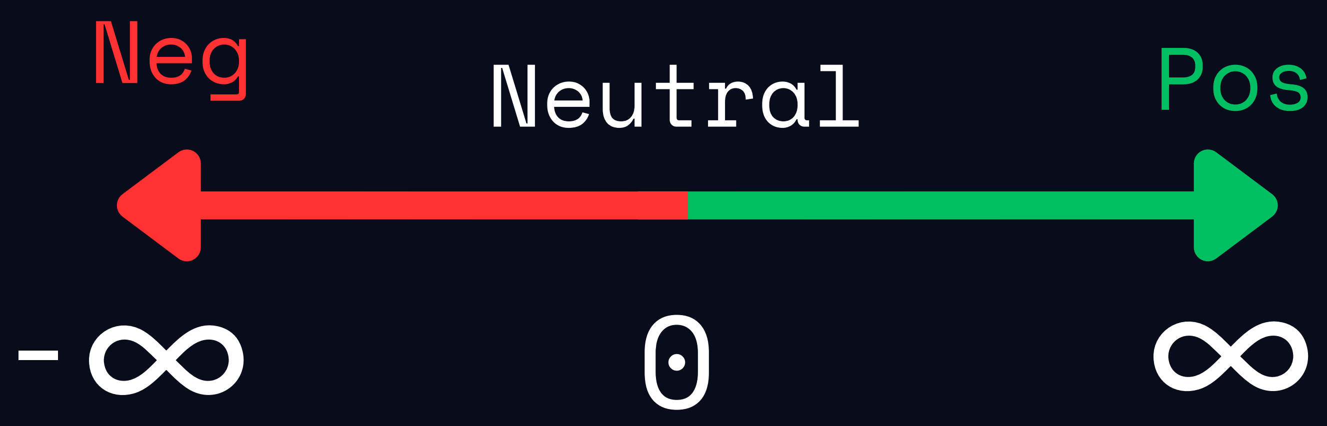


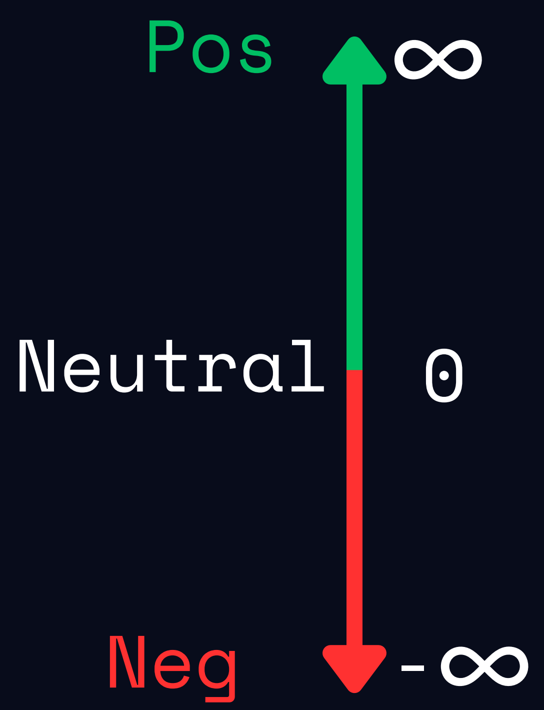
$$3.3 > 0$$

$$\sum_{i=1}^{n} \log \frac{P(w_i|Pos)}{P(w_i|Neg)} > 0$$



LOG LIKELIHOOD

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



TRAINING NAIVE BAYES

Step 0: Collect and annotate corpus

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

TRAINING NAIVE BAYES

Step 0: Collect and annotate corpus

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I am happy, not sad

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Step 1: Preprocess

TRAINING NAIVE BAYES

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Step 1: Preprocess

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

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Step 1: Preprocess

Positive tweets

[happi, because, learn, NLP]

[happi, not, sad]

Negative tweets

[sad, not, learn, NLP]

[sad, not, happi]

TRAINING NAIVE BAYES

Positive tweets

[happi, because, learn, NLP]

[happi, not, sad]

Negative tweets

[sad, not, learn, NLP]

[sad, not, happi]

TRAINING NAIVE BAYES

freq(w, class)

Positive tweets

[happi, because, learn, NLP]

[happi, not, sad]

Negative tweets

[sad, not, learn, NLP]

[sad, not, happi]

TRAINING NAIVE BAYES

Positive tweets

[happi, because, learn, NLP]

[happi, not, sad]

Negative tweets

[sad, not, learn, NLP]

[sad, not, happi]

Step 2: Word coun

freq(w, class)

WORD	Pos	Neg
happi	2	1
beacuse	1	0
learn	1	1
NLP	1	1
sad	1	2
not	1	2
N_{class}	7	7

TRAINING NAIVE BAYES

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WORD	Pos	Neg
happi	2	1
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not	1	2
N_{class}	7	7

Step 3:
$P(w|class)$

$$V_{class} = 6$$

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

TRAINING NAIVE BAYES

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happi	2	1
beacuse	1	0
learn	1	1
NLP	1	1
sad	1	2
not	1	2
N_{class}	7	7

Step 3:
$P(w|class)$

$V_{class} = 6$

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

WORD	Pos	Neg
happi	0.23	0.15
beacuse	0.15	0.07
learn	0.08	0.08
NLP	0.08	0.08
sad	0.08	0.17
not	0.08	0.17

TRAINING NAIVE BAYES

$freq(w, class)$

WORD	Pos	Neg
happi	2	1
beacuse	1	0
learn	1	1
NLP	1	1
sad	1	2
not	1	2
N_{class}	7	7

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

$$\lambda(w) = \log \frac{P(w|Pos)}{P(w|Neg)}$$

WORD	Pos	Neg
happi	0.23	0.15
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TRAINING NAIVE BAYES

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NLP	1	1
sad	1	2
not	1	2
N_{class}	7	7

Step 3:
P(w|class)

$V_{class} = 6$

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

$$\lambda(w) = \log \frac{P(w|Pos)}{P(w|Neg)}$$

Step 4:
Get lambda

WORD	Pos	Neg
happi	0.23	0.15
beacuse	0.15	0.07
learn	0.08	0.08
NLP	0.08	0.08
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TRAINING NAIVE BAYES

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WORD	Pos	Neg
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learn	1	1
NLP	1	1
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not	1	2
N_{class}	7	7

Step 3:
P(w|class)

$$V_{class} = 6$$

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

$$\lambda(w) = \log \frac{P(w|Pos)}{P(w|Neg)}$$

Step 4:
Get lambda

WORD	Pos	Neg	λ
happi	0.23	0.15	0.43
beacuse	0.15	0.07	0.6
learn	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 NAIVE BAYES

Step 5:
Get the
log prior

TRAINING NAIVE BAYES

D_{pos} = Number of positive tweets

D_{neg} = Number of negative tweets

Step 5:
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TRAINING NAIVE BAYES

D_{pos} = Number of positive tweets

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Step 5:
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log prior

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

TRAINING NAIVE BAYES.

D_{pos} = Number of positive tweets

D_{neg} = Number of negative tweets

Step 5:
Get the
log prior

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

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

TRAINING NAIVE BAYES

0. Get or annotate a dataset with positive and negative tweets
1. Preprocess the tweets: process_tweet(tweet)-->[W1, W2, W3,..]
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))

TESTING NAIVE BAYES

Outline

- Predicting using a Naive Bayes Model

TESTING NAIVE BAYES

Predicting using a Naive Bayes Model

- Log-liklihood dictionary $\lambda(w) = \log \frac{P(w|Pos)}{P(w|Neg)}$

WORD	λ
happi	0.43
beacuse	0.6
learn	0
NLP	0
sad	-0.75
not	-0.75

TESTING NAIVE BAYES

Predicting using a Naive Bayes Model

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

WORD	λ
happi	0.43
beacuse	0.6
learn	0
NLP	0
sad	-0.75
not	-0.75

TESTING NAIVE BAYES

Predicting using a Naive Bayes Model

- Log-liklihood dictionary $\lambda(w) = \log \frac{P(w|Pos)}{P(w|Neg)}$
- logprior = $\log \frac{D_{pos}}{D_{neg}} = 0$
- Tweet: **I am happy because I am learning NLP**

WORD	λ
happi	0.43
beacuse	0.6
learn	0
NLP	0
sad	-0.75
not	-0.75

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- Log-liklihood dictionary $\lambda(w) = \log \frac{P(w|Pos)}{P(w|Neg)}$
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- Tweet: **[happi, because, learn, NLP]**

WORD	λ
happi	0.43
because	0.6
learn	0
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TESTING NAIVE BAYES

Outline

- Log-liklihood dictionary $\lambda(w) = \log \frac{P(w|Pos)}{P(w|Neg)}$
- logprior $= \log \frac{D_{pos}}{D_{neg}} = 0$
- Tweet: **[happi, because, learn, NLP]**

score = 0.43 + 0.6 + 0 + 0 + logprior = 1.03

WORD	λ
happi	0.43
because	0.6
learn	0
NLP	0
sad	-0.75
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TESTING NAIVE BAYES

Predicting using a Naive Bayes Model

- Log-liklihood dictionary $\lambda(w) = \log \frac{P(w|Pos)}{P(w|Neg)}$
- $\text{logprior} = \log \frac{D_{pos}}{D_{neg}} = 0$
- Tweet: **[happi, because, learn, NLP]**

$$\textit{score} = 0.43 + 0.6 + 0 + 0 + \text{logprior} = 1.03$$

$$\textit{pred} = \textit{score} > 0$$

WORD	λ
happi	0.43
because	0.6
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NLP	0
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TESTING NAIVE BAYES

Predicting using a Naive Bayes Model

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happi	0.43
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$$score = 0.43 + 0.6 + 0 + 0 + \text{logprior} = 1.03$$

$$pred = score > 0$$

Karthik @iamnkarthik · 08 Feb

Even though there are so many workshops in this world, why did I participate in this workshop?

1 2 5 420