ALMA MATER STUDIORUM
UNIVERSITÀ DI BOLOGNA
CAMPUS DI FORLÌ

# 91258 / B0385
# Natural Language Processing

## Lesson 4. Rule-based Sentiment Analysis (+ Naïve Bayes)

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10/10/2024

# Previously

- Pre-processing (e.g., tokenisation, stemming, stopwording)

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- Pre-processing (e.g., tokenisation, stemming, stopwording)
- BoW representation

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- Pre-processing (e.g., tokenisation, stemming, stopwording)
- BoW representation
- Dot product

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## Sentiment Analysis (with VADER)

# Sentiment Analysis

It does not refer to actual sentiment (e.g., love or hate)[1]
It is about positive and negative perceptions (plus neutral)

From (Lane et al., 2019, p. 62–65)

---

[1] That's emotion analysis; e.g., 📕 Fernicola et al. (2020); 📕 Zhang et al. (2022)

# Sentiment Analysis

It does not refer to actual sentiment (e.g., love or hate)[1]
It is about positive and negative perceptions (plus neutral)

This monitor is definitely a good value. Does it have superb color and contrast? No. Does it boast the best refresh rate on the market? No. But if you're tight on money, this thing looks and preforms great for the money. It has a Matte screen which does a great job at eliminating glare. The chassis it's enclosed within is absolutely stunning.

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His [ssa] didnt concede until July 12, 2016. Because he was throwing a tantrum. I can't say this enough: [kcuF] Bernie Sanders.

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NEGATIVE

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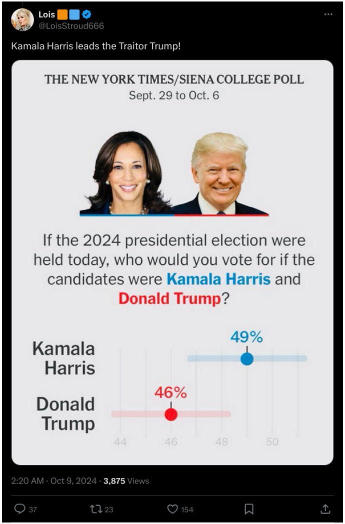
# Sentiment Analysis



**Lois** 🟧🟦
@LoisStroud666

Kamala Harris leads the Traitor Trump!

THE NEW YORK TIMES/SIENA COLLEGE POLL
Sept. 29 to Oct. 6

If the 2024 presidential election were held today, who would you vote for if the candidates were **Kamala Harris** and **Donald Trump**?

2:20 AM · Oct 9, 2024 · **3,875** Views

https://x.com/LoisStroud666/status/1843808652802801745

Valence Aware Dictionary for sEntiment Reasoning
(Hutto and Gilbert, 2014)[2]

---

[2] `http://comp.social.gatech.edu/papers/icwsm14.vader.hutto.pdf`
`https://github.com/cjhutto/vaderSentiment`

Valence Aware Dictionary for sEntiment Reasoning
(Hutto and Gilbert, 2014)[2]

- It has a lexicon packed with tokens and their associated "sentiment" score
- It counts all tokens belonging to each category: [pos, neu, neg]
  . . . and combine them to determine the sentiment

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  ...and combine them to determine the sentiment

</> Let us see it working

---

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# Into ML

# Machine Learning

"[. . . ] an umbrella term for **solving problems** for which development of algorithms by human programmers would be cost-prohibitive"

`https://en.wikipedia.org/wiki/Machine_learning`

# Machine Learning

"[. . . ] an umbrella term for **solving problems** for which development of algorithms by human programmers would be cost-prohibitive"

"[. . . ] the problems are solved by helping machines **"discover" their "own" algorithms**, without needing to be explicitly told what to do by any human-developed algorithms."

`https://en.wikipedia.org/wiki/Machine_learning`

# Machine Learning

## A change of paradigm

From hand-crafted rules

# Machine Learning

## A change of paradigm

From hand-crafted rules

To training

Diagrams borrowed from L. Moroney's Introduction to TensorFlow for Artificial Intelligence, Machine Learning, and Deep Learning

# Supervised vs Unsupervised

**Supervised** The algorithms build a mathematical model of a set of data including. . .

- the inputs
- desired outputs

# Supervised vs Unsupervised

**Supervised** The algorithms build a mathematical model of a set of data including. . .

- the inputs
- desired outputs

**Unsupervised** The algorithms take a set of data that contains. . .

- only inputs

. . . and find structure in the data

https://en.wikipedia.org/wiki/Machine_learning

# Naïve Bayes

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1. Introduced in the IR community by Maron (1961)

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3. It is a supervised model

# Naïve Bayes

1. Introduced in the IR community by Maron (1961)
2. First machine learning approach
3. It is a supervised model
4. It applies Bayes' theorem with strong (naïve) independence assumptions between the features
    - they are independent
    - they contribute "the same"

# Naïve Bayes

## A conditional probability model

Given an instance represented by a vector

$$\mathbf{x} = (x_1, \ldots, x_n) \tag{1}$$

representing $n$ independent features $x_1, x_2, x_3, \ldots, x_{n-2}, x_{n-1}, x_n$

From `https://en.wikipedia.org/wiki/Naive_Bayes_classifier`

# Naïve Bayes

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$n$ could be $|V|$ (the size of the vocabulary)

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$n$ could be $|V|$ (the size of the vocabulary)

The model assigns to instance $\mathbf{x}$ the probability

$$p(C_k \mid \mathbf{x}) = p(C_k \mid x_1, \ldots, x_n) \tag{2}$$

for each of the $k$ possible outcomes $C_k$

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# Naïve Bayes

## A conditional probability model

Given an instance represented by a vector

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The model assigns to instance $\mathbf{x}$ the probability

$$p(C_k \mid \mathbf{x}) = p(C_k \mid x_1, \dots, x_n) \tag{2}$$

for each of the $k$ possible outcomes $C_k$

where $C_k = \{c_1, \dots, c_k\}$

From `https://en.wikipedia.org/wiki/Naive_Bayes_classifier`

# Naïve Bayes'

## Using Bayes' Theorem

The conditional probability $p(C_k \mid x_1, \ldots, x_n)$ can be decomposed as

$$p(C_k \mid \mathbf{x}) = \frac{p(C_k)\ p(\mathbf{x} \mid C_k)}{p(\mathbf{x})} \tag{3}$$

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Which can be read as

$$\text{posterior} = \frac{\text{prior} \times \text{likelihood}}{\text{evidence}}$$

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The conditional probability $p(C_k \mid x_1, \ldots, x_n)$ can be decomposed as

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Which can be read as

$$\text{posterior} = \frac{\text{prior} \times \text{likelihood}}{\text{evidence}}$$

But $p(x)$ does not depend on the class (since it is constant):

$$p(C_k \mid \mathbf{x}) \sim p(C_k)\ p(\mathbf{x} \mid C_k) \tag{4}$$

From `https://en.wikipedia.org/wiki/Naive_Bayes_classifier`

# Naïve Bayes

## Going deeper (assuming a binary classifier)

$$p(C \mid \mathbf{x}) = \frac{p(C)\ p(\mathbf{x} \mid C)}{p(\mathbf{x})} \tag{5}$$

$$\text{posterior probability} = \frac{\text{class prior probability} \times \text{likelihood}}{\text{predictor prior probability}}$$

---

[3] Symbol $\mid$ means "given": the probability of the class given the representation vector

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$p(C \mid \mathbf{x})$ Posterior probability of the class given the input[3]

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$p(C \mid \mathbf{x})$ Posterior probability of the class given the input[3]

```
if p > 0.5:
    class = positive
else:
    class = negative
```

---

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# Naïve Bayes

## Going deeper (assuming a binary classifier)

$$p(C \mid \mathbf{x}) = \frac{p(C)\ p(\mathbf{x} \mid C)}{p(\mathbf{x})} \tag{6}$$

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$p(C)$ Class prior probability

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$p(C)$ Class prior probability

How many positive instances I have seen (during training)?

# Naïve Bayes

## Going deeper (assuming a binary classifier)

$$p(C \mid \mathbf{x}) = \frac{p(C)\ p(\mathbf{x} \mid C)}{p(\mathbf{x})} \tag{7}$$

$$\text{posterior probability} = \frac{\text{class prior probability} \times \text{likelihood}}{\text{predictor prior probability}}$$

# Naïve Bayes

## Going deeper (assuming a binary classifier)

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$p(\mathbf{x} \mid C)$ Likelihood

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$$\text{posterior probability} = \frac{\text{class prior probability} \times \text{likelihood}}{\text{predictor prior probability}}$$

$p(\mathbf{x} \mid C)$ Likelihood

The probability of the document given the class

# Rough Idea

- The value of a particular feature is independent of the value of any other feature, given the class variable

From (Lane et al., 2019, p. 65–68)

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- The value of a particular feature is independent of the value of any other feature, given the class variable
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- Naïve Bayes' tries to find keywords in a set of documents that are predictive of the target (output) variable

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- The internal coefficients will try to map tokens to scores

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# Rough Idea

- The value of a particular feature is independent of the value of any other feature, given the class variable
- All features contribute the same to the classification

- Naïve Bayes' tries to find keywords in a set of documents that are predictive of the target (output) variable
- The internal coefficients will try to map tokens to scores
- Same as VADER, but without manually-created rules
  the machine will *estimate* them!

From (Lane et al., 2019, p. 65–68)

# Naïve Bayes

## A toy example: Should I ride my bike today?

One single factor: *zone (flag)*

sunny

🚩

overcast

🚩

rainy

🚩

(here come some dense slides)

# Naïve Bayes

## A toy example: Should I ride my bike today?

Dataset

| **Flag** | 🚲 |
|---|---|
| 🟨 | yes |
| 🟧 | yes |
| 🟨 | no |
| 🟥 | yes |
| 🟨 | yes |
| 🟧 | yes |
| 🟨 | yes |
| 🟧 | yes |
| 🟥 | yes |
| 🟨 | no |
| 🟥 | no |
| 🟧 | yes |
| 🟥 | no |
| 🟥 | no |

Adapted from `http://www.saedsayad.com/naive bayesian.htm`

# Naïve Bayes

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|---|---|
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| 🟧 | yes |
| 🟥 | no |
| 🟥 | no |

Computing all the probabilities by "counting"

Adapted from `http://www.saedsayad.com/naive_bayesian.htm`

# Naïve Bayes

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| 🟥 | no |
| 🟧 | yes |
| 🟥 | no |
| 🟥 | no |

Computing all the probabilities by “counting”

Frequency table

|  | 🚲 |  |
|---|---|---|
| **Flag** | **yes** | **no** |
| 🟨 | 3 | 2 |
| 🟧 | 4 | 0 |
| 🟥 | 2 | 3 |

Adapted from `http://www.saedsayad.com/naive bayesian.htm`

# Naïve Bayes

## A toy example: Should I ride my bike today?

**Dataset**

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Computing all the probabilities by “counting”

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|---|---|---|
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| 🟨 | 3 | 2 |
| 🟧 | 4 | 0 |
| 🟥 | 2 | 3 |

**Likelihood table**

|  | 🚲 |  |
|---|---|---|
| **Flag** | **yes** | **no** |
| 🟨 | $3/9$ | $2/5$ |
| 🟧 | $4/9$ | $0/5$ |
| 🟥 | $2/9$ | $3/5$ |

Adapted from `http://www.saedsavad.com/naive bayesian.htm`

# Naïve Bayes

## A toy example: Should I ride my bike today?

### Likelihood table

| | 🚲 | |
|---|---|---|
| **Flag** | **yes** | **no** |
| 🟨 | 3/9 | 2/5 |
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| | 9/14 | 5/14 |

# Naïve Bayes

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[1] $p(x \mid c) = p($🟨$\mid \text{yes}) = 3/9 = 0.33$

# Naïve Bayes

## A toy example: Should I ride my bike today?

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[1] $p(x \mid c) = p(\text{🟨} \mid \text{yes}) = 3/9 = 0.33$

[2] $p(c) = p(\text{yes}) = 9/14 = 0.64$

# Naïve Bayes

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$p(x) = p(🟨) = 5/14 = 0.36$

# Naïve Bayes

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What is the Naïve Bayes' probability of yes if 🟨?

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What is the Naïve Bayes' probability of yes if 🟨?

$$p(c \mid x) \quad = \quad p(c)p(x \mid c)/p(x)$$

# Naïve Bayes

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What is the Naïve Bayes' probability of yes if 🟨?

$$
\begin{aligned}
p(c \mid x) &= p(c)p(x \mid c)/p(x) \\
p(\text{yes} \mid \text{🟨}) &= p(\text{yes})p(\text{🟨} \mid \text{yes})/p(\text{🟨})
\end{aligned}
$$

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p(\text{yes} \mid \text{🟨}) &= 0.64 * 0.33/0.36
\end{aligned}
$$

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What is the Naïve Bayes' probability of yes if 🟨?

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p(\text{yes} \mid \text{🟨}) &= 0.64 * 0.33/0.36 \\
p(\text{yes} \mid \text{🟨}) &= 0.59
\end{aligned}
$$

# Naïve Bayes

## A toy example: Should I ride my bike today?

If. . . 🚩 let's ride 🚲!

# Naïve Bayes

## A toy example: Should I ride my bike today?

### Considering more data

| Flag | Temp | Humidity | Windy | 🚲 |
|---|---|---|---|---|
| 🟥 | hot | high | false | no |
| 🟥 | hot | high | true | no |
| 🟧 | hot | high | false | yes |
| 🟧 | mild | high | false | yes |
| 🟨 | cool | normal | false | yes |
| 🟨 | cool | normal | true | no |
| 🟧 | cool | normal | true | yes |
| 🟥 | mild | high | false | no |
| 🟥 | cool | normal | false | yes |
| 🟨 | mild | normal | false | yes |
| 🟥 | mild | normal | true | yes |
| 🟧 | mild | high | true | yes |
| 🟧 | hot | normal | false | yes |
| 🟨 | mild | high | true | no |

# Naïve Bayes

## A toy example: Should I ride my bike today?

### Frequency tables

| Flag | yes | no |
|---|---|---|
| 🟨 | 3 | 2 |
| 🟧 | 4 | 0 |
| 🟥 | 2 | 3 |

### Likelihood tables

| Flag | yes | no |
|---|---|---|
| 🟨 | $3/9$ | $2/5$ |
| 🟧 | $4/9$ | $0/5$ |
| 🟥 | $2/9$ | $3/5$ |

# Naïve Bayes

## A toy example: Should I ride my bike today?

### Frequency tables

| **Flag** | **yes** | **no** |
|---|---|---|
| 🟨 | 3 | 2 |
| 🟧 | 4 | 0 |
| 🟥 | 2 | 3 |

| **Humidity** | **yes** | **no** |
|---|---|---|
| high | 3 | 4 |
| normal | 6 | 1 |

### Likelihood tables

| **Flag** | **yes** | **no** |
|---|---|---|
| 🟨 | $3/9$ | $2/5$ |
| 🟧 | $4/9$ | $0/5$ |
| 🟥 | $2/9$ | $3/5$ |

| **Humidity** | **yes** | **no** |
|---|---|---|
| high | $3/9$ | $4/5$ |
| normal | $6/9$ | $1/5$ |

# Naïve Bayes

## A toy example: Should I ride my bike today?

### Frequency tables

| **Flag** | **yes** | **no** |
|---|---|---|
| 🟨 | 3 | 2 |
| 🟧 | 4 | 0 |
| 🟥 | 2 | 3 |

| **Humidity** | **yes** | **no** |
|---|---|---|
| high | 3 | 4 |
| normal | 6 | 1 |

| **Temp** | **yes** | **no** |
|---|---|---|
| hot | 2 | 2 |
| mild | 4 | 2 |
| cool | 3 | 1 |

### Likelihood tables

| **Flag** | **yes** | **no** |
|---|---|---|
| 🟨 | 3/9 | 2/5 |
| 🟧 | 4/9 | 0/5 |
| 🟥 | 2/9 | 3/5 |

| **Humidity** | **yes** | **no** |
|---|---|---|
| high | 3/9 | 4/5 |
| normal | 6/9 | 1/5 |

| **Temp** | **yes** | **no** |
|---|---|---|
| hot | 2/9 | 2/5 |
| mild | 4/9 | 2/5 |
| cool | 3/9 | 1/5 |

# Naïve Bayes

## A toy example: Should I ride my bike today?

### Frequency tables

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|---|---|---|
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| 🟧 | 4 | 0 |
| 🟥 | 2 | 3 |

| **Humidity** | **yes** | **no** |
|---|---|---|
| high | 3 | 4 |
| normal | 6 | 1 |

| **Temp** | **yes** | **no** |
|---|---|---|
| hot | 2 | 2 |
| mild | 4 | 2 |
| cool | 3 | 1 |

| **Windy** | **yes** | **no** |
|---|---|---|
| false | 6 | 2 |
| true | 3 | 3 |

### Likelihood tables

| **Flag** | **yes** | **no** |
|---|---|---|
| 🟨 | 3/9 | 2/5 |
| 🟧 | 4/9 | 0/5 |
| 🟥 | 2/9 | 3/5 |

| **Humidity** | **yes** | **no** |
|---|---|---|
| high | 3/9 | 4/5 |
| normal | 6/9 | 1/5 |

| **Temp** | **yes** | **no** |
|---|---|---|
| hot | 2/9 | 2/5 |
| mild | 4/9 | 2/5 |
| cool | 3/9 | 1/5 |

| **Windy** | **yes** | **no** |
|---|---|---|
| false | 6/9 | 2/5 |
| true | 3/9 | 3/5 |

# Naïve Bayes

## Likelihood tables

| **Flag** | **yes** | **no** |
|---|---|---|
| 🟨 | 3/9 | 2/5 |
| 🟧 | 4/9 | 0/5 |
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| **Humidity** | **yes** | **no** |
|---|---|---|
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| normal | 6/9 | 1/5 |

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|---|---|---|
| hot | 2/9 | 2/5 |
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| cool | 3/9 | 1/5 |

| **Windy** | **yes** | **no** |
|---|---|---|
| false | 6/9 | 2/5 |
| true | 3/9 | 3/5 |

# Naïve Bayes

## Likelihood tables

| **Flag** | **yes** | **no** |
|---|---|---|
| 🟨 | 3/9 | 2/5 |
| 🟧 | 4/9 | 0/5 |
| 🟥 | 2/9 | 3/5 |

| **Temp** | **yes** | **no** |
|---|---|---|
| hot | 2/9 | 2/5 |
| mild | 4/9 | 2/5 |
| cool | 3/9 | 1/5 |

| **Humidity** | **yes** | **no** |
|---|---|---|
| high | 3/9 | 4/5 |
| normal | 6/9 | 1/5 |

| **Windy** | **yes** | **no** |
|---|---|---|
| false | 6/9 | 2/5 |
| true | 3/9 | 3/5 |

| **flag** | **temp** | **humidity** | **windy** | ride |
|---|---|---|---|---|
| 🟥 | cool | high | true | ? |

# Naïve Bayes

## Likelihood tables

| **Flag** | **yes** | **no** |
|---|---|---|
| 🟨 | 3/9 | 2/5 |
| 🟧 | 4/9 | 0/5 |
| 🟥 | 2/9 | 3/5 |

| **Temp** | **yes** | **no** |
|---|---|---|
| hot | 2/9 | 2/5 |
| mild | 4/9 | 2/5 |
| cool | 3/9 | 1/5 |

| **Humidity** | **yes** | **no** |
|---|---|---|
| high | 3/9 | 4/5 |
| normal | 6/9 | 1/5 |

| **Windy** | **yes** | **no** |
|---|---|---|
| false | 6/9 | 2/5 |
| true | 3/9 | 3/5 |

| **flag** | **temp** | **humidity** | **windy** | ride |
|---|---|---|---|---|
| 🟥 | cool | high | true | ? |

$$p(\text{yes} \mid x) = \frac{p(\text{yes})p(\text{🟥} \mid \text{yes})p(\text{cool} \mid \text{yes})p(\text{high} \mid \text{yes})p(\text{true} \mid \text{yes})}{p(\text{🟥})p(\text{cool})p(\text{high})p(\text{true})}$$

# Naïve Bayes

## Likelihood tables

| **Flag** | **yes** | **no** |
|---|---|---|
| 🟨 | 3/9 | 2/5 |
| 🟧 | 4/9 | 0/5 |
| 🟥 | 2/9 | 3/5 |

| **Temp** | **yes** | **no** |
|---|---|---|
| hot | 2/9 | 2/5 |
| mild | 4/9 | 2/5 |
| cool | 3/9 | 1/5 |

| **Humidity** | **yes** | **no** |
|---|---|---|
| high | 3/9 | 4/5 |
| normal | 6/9 | 1/5 |

| **Windy** | **yes** | **no** |
|---|---|---|
| false | 6/9 | 2/5 |
| true | 3/9 | 3/5 |

| **flag** | **temp** | **humidity** | **windy** | ride |
|---|---|---|---|---|
| 🟥 | cool | high | true | ? |

$$
\begin{aligned}
p(\text{yes} \mid x) &= \frac{p(\text{yes})p(\text{🟥} \mid \text{yes})p(\text{cool} \mid \text{yes})p(\text{high} \mid \text{yes})p(\text{true} \mid \text{yes})}{p(\text{🟥})p(\text{cool})p(\text{high})p(\text{true})} \\
&= \frac{9/14 \times 2/9 \times 3/9 \times 3/9 \times 3/9}{5/14 \times 4/14 \times 7/14 \times 6/14}
\end{aligned}
$$

# Naïve Bayes

## Likelihood tables

| **Flag** | **yes** | **no** |
|---|---|---|
| 🟨 | 3/9 | 2/5 |
| 🟧 | 4/9 | 0/5 |
| 🟥 | 2/9 | 3/5 |

| **Temp** | **yes** | **no** |
|---|---|---|
| hot | 2/9 | 2/5 |
| mild | 4/9 | 2/5 |
| cool | 3/9 | 1/5 |

| **Humidity** | **yes** | **no** |
|---|---|---|
| high | 3/9 | 4/5 |
| normal | 6/9 | 1/5 |

| **Windy** | **yes** | **no** |
|---|---|---|
| false | 6/9 | 2/5 |
| true | 3/9 | 3/5 |

| **flag** | **temp** | **humidity** | **windy** | ride |
|---|---|---|---|---|
| 🟥 | cool | high | true | ? |

$$
\begin{aligned}
p(\text{yes} \mid x) &= \frac{p(\text{yes})p(\text{🟥} \mid \text{yes})p(\text{cool} \mid \text{yes})p(\text{high} \mid \text{yes})p(\text{true} \mid \text{yes})}{p(\text{🟥})p(\text{cool})p(\text{high})p(\text{true})} \\
&= \frac{9/14 \times 2/9 \times 3/9 \times 3/9 \times 3/9}{5/14 \times 4/14 \times 7/14 \times 6/14} \\
&= 0.00529/0.02811
\end{aligned}
$$

# Naïve Bayes

## Likelihood tables

| **Flag** | **yes** | **no** |
|---|---|---|
| 🟨 | 3/9 | 2/5 |
| 🟧 | 4/9 | 0/5 |
| 🟥 | 2/9 | 3/5 |

| **Temp** | **yes** | **no** |
|---|---|---|
| hot | 2/9 | 2/5 |
| mild | 4/9 | 2/5 |
| cool | 3/9 | 1/5 |

| **Humidity** | **yes** | **no** |
|---|---|---|
| high | 3/9 | 4/5 |
| normal | 6/9 | 1/5 |

| **Windy** | **yes** | **no** |
|---|---|---|
| false | 6/9 | 2/5 |
| true | 3/9 | 3/5 |

| **flag** | **temp** | **humidity** | **windy** | ride |
|---|---|---|---|---|
| 🟥 | cool | high | true | ? |

$$
\begin{aligned}
p(\text{yes} \mid x) &= \frac{p(\text{yes})p(\text{🟥} \mid \text{yes})p(\text{cool} \mid \text{yes})p(\text{high} \mid \text{yes})p(\text{true} \mid \text{yes})}{p(\text{🟥})p(\text{cool})p(\text{high})p(\text{true})} \\
&= \frac{9/14 \times 2/9 \times 3/9 \times 3/9 \times 3/9}{5/14 \times 4/14 \times 7/14 \times 6/14} \\
&= 0.00529/0.02811 = 0.188 \sim 0.2
\end{aligned}
$$

# Naïve Bayes

## Likelihood tables

| **Flag** | **yes** | **no** |
|---|---|---|
| 🟨 | 3/9 | 2/5 |
| 🟧 | 4/9 | 0/5 |
| 🚩 | 2/9 | 3/5 |

| **Temp** | **yes** | **no** |
|---|---|---|
| hot | 2/9 | 2/5 |
| mild | 4/9 | 2/5 |
| cool | 3/9 | 1/5 |

| **Humidity** | **yes** | **no** |
|---|---|---|
| high | 3/9 | 4/5 |
| normal | 6/9 | 1/5 |

| **Windy** | **yes** | **no** |
|---|---|---|
| false | 6/9 | 2/5 |
| true | 3/9 | 3/5 |

| **flag** | **temp** | **humidity** | **windy** | ride |
|---|---|---|---|---|
| 🚩 | cool | high | true | ? |

$$
\begin{aligned}
p(\text{yes} \mid x) &= \frac{p(\text{yes})p(\text{🚩} \mid \text{yes})p(\text{cool} \mid \text{yes})p(\text{high} \mid \text{yes})p(\text{true} \mid \text{yes})}{p(\text{🚩})p(\text{cool})p(\text{high})p(\text{true})} \\
&= \frac{9/14 \times 2/9 \times 3/9 \times 3/9 \times 3/9}{5/14 \times 4/14 \times 7/14 \times 6/14} \\
&= 0.00529/0.02811 = 0.188 \sim 0.2
\end{aligned}
$$

no 🚲

# Naïve Bayes

## Back to the definition. . .

$$p(C \mid \mathbf{x}) = \frac{p(C)\ p(\mathbf{x} \mid C)}{p(\mathbf{x})} \tag{8}$$

# Naïve Bayes

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$$p(C \mid \mathbf{x}) = \frac{p(C)\ p(\mathbf{x} \mid C)}{p(\mathbf{x})} \tag{8}$$

The probability $p(\mathbf{x})$ is constant for any given input

# Naïve Bayes

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$$p(C \mid \mathbf{x}) = \frac{p(C)\ p(\mathbf{x} \mid C)}{p(\mathbf{x})} \tag{8}$$

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$$p(C \mid \mathbf{x}) = \frac{p(C)\ p(\mathbf{x} \mid C)}{\cancel{p(\mathbf{x})}} \tag{9}$$

# Naïve Bayes

## Back to the definition. . .

$$p(C \mid \mathbf{x}) = \frac{p(C)\ p(\mathbf{x} \mid C)}{p(\mathbf{x})} \tag{8}$$

The probability $p(\mathbf{x})$ is constant for any given input

$$p(C \mid \mathbf{x}) = \frac{p(C)\ p(\mathbf{x} \mid C)}{\cancel{p(\mathbf{x})}} \tag{9}$$

$$p(c \mid \mathbf{x}) \propto p(c)p(\mathbf{x} \mid c) \tag{10}$$

# Naïve Bayes

## Back to the definition. . .

$$p(c \mid \mathbf{x}) \propto p(c)p(\mathbf{x} \mid c) \tag{11}$$

# Naïve Bayes

## Back to the definition. . .

$$p(c \mid \mathbf{x}) \propto p(c)p(\mathbf{x} \mid c) \tag{11}$$

Remember that **x** is a vector

# Naïve Bayes

## Back to the definition...

$$p(c \mid \mathbf{x}) \propto p(c)p(\mathbf{x} \mid c) \tag{11}$$

Remember that **x** is a vector

$$p(c \mid x_1 \dots x_n) \propto p(c)p(x_1 \mid c) \times p(x_2 \mid c) \times \cdots \times p(x_n \mid c) \tag{12}$$

# Naïve Bayes

## Back to the definition. . .

$$p(c \mid \mathbf{x}) \propto p(c)p(\mathbf{x} \mid c) \tag{11}$$

Remember that **x** is a vector

$$p(c \mid x_1 \dots x_n) \propto p(c)p(x_1 \mid c) \times p(x_2 \mid c) \times \cdots \times p(x_n \mid c) \tag{12}$$

Eq. (12) can be rewritten as

$$p(c \mid x_1 \dots x_n) \propto p(c) \prod_{i=1}^{n} p(x_i \mid c) \tag{13}$$

# Naïve Bayes

## The classification process

### Back to the toy example

$$p(\text{yes} \mid x) \quad \propto \quad p(\text{yes})p(\text{🚩} \mid \text{yes})p(\text{cool} \mid \text{yes})p(\text{high} \mid \text{yes})p(\text{true} \mid \text{yes})$$

# Naïve Bayes

## The classification process

### Back to the toy example

$$\begin{aligned} p(\text{yes} \mid x) &\propto p(\text{yes})p(\text{🚩} \mid \text{yes})p(\text{cool} \mid \text{yes})p(\text{high} \mid \text{yes})p(\text{true} \mid \text{yes}) \\ &\propto 9/14 \times 2/9 \times 3/9 \times 3/9 \times 3/9 \end{aligned}$$

# Naïve Bayes

## The classification process

### Back to the toy example

$$
\begin{aligned}
p(\text{yes} \mid x) &\propto p(\text{yes})p(\text{🚩} \mid \text{yes})p(\text{cool} \mid \text{yes})p(\text{high} \mid \text{yes})p(\text{true} \mid \text{yes}) \\
&\propto 9/14 \times 2/9 \times 3/9 \times 3/9 \times 3/9 \\
&\propto 0.00529
\end{aligned}
$$

# Naïve Bayes

## The classification process

### Back to the toy example

$$\begin{aligned} p(\text{yes} \mid x) &\propto p(\text{yes})p(\text{🚩} \mid \text{yes})p(\text{cool} \mid \text{yes})p(\text{high} \mid \text{yes})p(\text{true} \mid \text{yes}) \\ &\propto 9/14 \times 2/9 \times 3/9 \times 3/9 \times 3/9 \\ &\propto 0.00529\text{, which is not a probability} \end{aligned}$$

# Naïve Bayes

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### Back to the toy example

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### Classification: the maximum for all the classes

$$c \propto \arg\max_{c} p(c) \prod_{i=1}^{n} p(x_i \mid c) \tag{14}$$

# Naïve Bayes

## The classification process

### Back to the toy example

$$\begin{aligned} p(\text{yes} \mid x) &\propto p(\text{yes})p(\text{🚩} \mid \text{yes})p(\text{cool} \mid \text{yes})p(\text{high} \mid \text{yes})p(\text{true} \mid \text{yes}) \\ &\propto 9/14 \times 2/9 \times 3/9 \times 3/9 \times 3/9 \\ &\propto 0.00529\text{, which is not a probability} \end{aligned}$$

### Classification: the maximum for all the classes

$$c \propto \arg\max_{c} p(c) \prod_{i=1}^{n} p(x_i \mid c) \tag{14}$$

```
compute p(yes|x)
compute p(no|x)
if p(yes|x) > p(no|x):
    yes
else:
    no
```

# Naïve Bayes

## Classification process

$$p(C \mid \mathbf{x}) = \frac{p(C)\ p(\mathbf{x} \mid C)}{p(\mathbf{x})} \tag{15}$$

# Naïve Bayes

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# Naïve Bayes

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$$p(C \mid \mathbf{x}) = \frac{p(C)\ p(\mathbf{x} \mid C)}{\cancel{p(\mathbf{x})}} \tag{16}$$

# Naïve Bayes

## Classification process

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$$p(C \mid \mathbf{x}) = \frac{p(C)\ p(\mathbf{x} \mid C)}{\cancel{p(\mathbf{x})}} \tag{16}$$

Back to the toy example, using Eq. (16). . .

$$p(\text{yes} \mid x) \;=\; p(\text{yes})p(\text{rainy} \mid \text{yes})p(\text{cool} \mid \text{yes})p(\text{high} \mid \text{yes})p(\text{true} \mid \text{yes})$$

# Naïve Bayes

## Classification process

$$p(C \mid \mathbf{x}) = \frac{p(C)\ p(\mathbf{x} \mid C)}{p(\mathbf{x})} \tag{15}$$

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Back to the toy example, using Eq. (16)...

$$\begin{aligned} p(\text{yes} \mid x) &= p(\text{yes})p(\text{rainy} \mid \text{yes})p(\text{cool} \mid \text{yes})p(\text{high} \mid \text{yes})p(\text{true} \mid \text{yes}) \\ &= 9/14 \times 2/9 \times 3/9 \times 3/9 \times 3/9 \end{aligned}$$

# Naïve Bayes

## Classification process

$$p(C \mid \mathbf{x}) = \frac{p(C)\ p(\mathbf{x} \mid C)}{p(\mathbf{x})} \tag{15}$$

The probability $p(\mathbf{x})$ is constant for any given input!

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Back to the toy example, using Eq. (16)...

$$\begin{aligned} p(\text{yes} \mid x) &= p(\text{yes})p(\text{rainy} \mid \text{yes})p(\text{cool} \mid \text{yes})p(\text{high} \mid \text{yes})p(\text{true} \mid \text{yes}) \\ &= 9/14 \times 2/9 \times 3/9 \times 3/9 \times 3/9 \\ &= 0.00529 \end{aligned}$$

# Naïve Bayes

## Classification process

$$p(C \mid \mathbf{x}) = \frac{p(C)\ p(\mathbf{x} \mid C)}{p(\mathbf{x})} \tag{15}$$

The probability $p(\mathbf{x})$ is constant for any given input!

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Back to the toy example, using Eq. (16)...

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# Training a Machine Learning Model

# The dataset

We need a bunch of items (documents) with their associated class

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| **kind** | **examples** |
|---|---|

# The dataset

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| **kind** | **examples** |
|---|---|
| binary | {positive, negative} |
| | {0, 1} |
| | {-1, 1} |

# The dataset

We need a bunch of items (documents) with their associated class

| **kind** | **examples** |
|---|---|
| binary | {positive, negative}<br>{0, 1}<br>{-1, 1} |
| multiclass | {positive, neutral, negative}<br>{0,1,2} |

# The dataset

We need a bunch of items (documents) with their associated class

| **kind** | **examples** |
|---|---|
| binary | {positive, negative}<br>{0, 1}<br>{-1, 1} |
| multiclass | {positive, neutral, negative}<br>{0,1,2} |

In our case, we need the sentiment:

| | | | | | |
|---|---|---|---|---|---|
| $d_1$ | pos | $d_5$ | neg | $d_9$ | neu |
| $d_2$ | neu | $d_6$ | neg | $d_{10}$ | pos |
| $d_3$ | pos | $d_7$ | neg | $d_{11}$ | neu |
| $d_4$ | pos | $d_8$ | pos | $d_{12}$ | neg |

# The dataset

Option 1 Use a corpus created by somebody else

---

[4] Stay tuned: a course on this topic will start in November

# The dataset

**Option 1** Use a corpus created by somebody else

**Option 2** Build your own corpus[4]

---

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Option 1 Use a corpus created by somebody else

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  (a) You have/hire experts to do it

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Option 1 Use a corpus created by somebody else

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  (a) You have/hire experts to do it
  (b) You engage non-experts through gamification

---

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# The dataset

Option 1 Use a corpus created by somebody else

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  (a) You have/hire experts to do it
  (b) You engage non-experts through gamification
  (c) You hire non-experts through explicit crowdsourcing

---

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Option 1 Use a corpus created by somebody else

Option 2 Build your own corpus[4]

- (a) You have/hire experts to do it
- (b) You engage non-experts through gamification
- (c) You hire non-experts through explicit crowdsourcing
- (d) There are many other ways to get annotated data

---

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# The dataset

Option 1 Use a corpus created by somebody else

Option 2 Build your own corpus[4]

(a) You have/hire experts to do it
(b) You engage non-experts through gamification
(c) You hire non-experts through explicit crowdsourcing
(d) There are many other ways to get annotated data

---

[4] Stay tuned: a course on this topic will start in November

Let us go and build a classifier with a corpus built by Hutto and Gilbert (2014)[5]

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[5] http://comp.social.gatech.edu/papers/icwsm14.vader.hutto.pdf

Let us go and build a classifier with a corpus built by Hutto and Gilbert (2014)[5]

For this, you have to download and install the software companion of NLP in Action:

`https://github.com/totalgood/nlpia`

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[5] http://comp.social.gatech.edu/papers/icwsm14.vader.hutto.pdf

# What I did on OsX and GNU Linux

I use pipenv[6]

```
$ pipenv install --skip-lock nlpia
```

On Github they explain how to install it with conda or pip if you plan to contribute to the project

</> Let us see it working

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[6] `https://pipenv.readthedocs.io/en/latest/`

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