

CS 481

***Artificial Intelligence Language
Understanding***

February 23, 2023

Announcements / Reminders

- Please follow the Week 07 To Do List instructions
- PA #01 due on ~~Monday (02/20/23) at 11:59 PM CST~~
Thursday (02/23/23) at 11:59 PM CST
- Written Assignment #02 due on Thursday (03/02/23) at 11:59 PM CST
- **Exam dates:**
 - **Midterm:** 03/02/2023 during Thursday lecture time
 - **Final:** 04/27/2023 during Thursday lecture time

Plan for Today

- Naïve Bayes classifier

Bag of Words: Document Vector

Pre-defined Vocabulary:

Word 1	Word 2	Word 3	Word 4	Word 5	Word 6	...	Word N
--------	--------	--------	--------	--------	--------	-----	--------

Document **A** **Non-binary** Vector [0-word absent | >0-word count]:

6	0	2	3	1	0	...	4
---	---	---	---	---	---	-----	---

Document **B** **Non-binary** Vector [0-word absent | >0-word count]:

4	2	0	0	5	0	...	1
---	---	---	---	---	---	-----	---

Document **C** **Non-binary** Vector [0-word absent | >0-word count]:

0	0	3	0	0	7	...	0
---	---	---	---	---	---	-----	---

Document vectors can be used to **compare documents**.

Bag of Words: Classification

category = **h**(

Learned Classifier model
(hypothesis)

6
5
4
3
3
2
1
1
1
...

)

Bayes' Rule

$$P(y \mid x) = \frac{P(x \mid y) * P(y)}{P(x)}$$

$$P(\textit{Category} \mid \textit{Document}) = \frac{P(\textit{Document} \mid \textit{Category}) * P(\textit{Category})}{P(\textit{Document})}$$

$$P(\textit{Category} \mid \textit{Instance}) = \frac{P(\textit{Instance} \mid \textit{Category}) * P(\textit{Category})}{P(\textit{Instance})}$$

$$P(\textit{Category} \mid \textit{Sample}) = \frac{P(\textit{Sample} \mid \textit{Category}) * P(\textit{Category})}{P(\textit{Sample})}$$

Classification: Conditional Probability

$$P(y | x) = \frac{P(x | y) * P(y)}{P(x)}$$

$\mathbf{X} = x_1, x_2, \dots, x_N$, **SO:**

How to
calculate?

$$P(y | x_1 \wedge x_2 \wedge \dots \wedge x_N) = \frac{P(x_1 \wedge x_2 \wedge \dots \wedge x_N | y) * P(y)}{P(x_1 \wedge x_2 \wedge \dots \wedge x_N)}$$

constant

Naive Bayes Assumption

$$\begin{aligned} P(x_1 \wedge x_2 \wedge \dots \wedge x_N \wedge y) &= \\ P(x_1 \mid x_2 \wedge \dots \wedge x_N \wedge y) * P(x_2 \wedge \dots \wedge x_N \wedge y) &= \\ P(x_1 \mid x_2 \wedge \dots \wedge x_N \wedge y) * P(x_2 \mid x_3 \wedge \dots \wedge x_N \wedge y) * P(x_3 \wedge \dots \wedge x_N \wedge y) &= \\ P(x_1 \mid x_2 \wedge \dots \wedge x_N \wedge y) * P(x_2 \mid x_3 \wedge \dots \wedge x_N \wedge y) * P(x_3 \mid x_4 \wedge \dots \wedge x_N \wedge y) * P(x_3 \wedge \dots \wedge x_N \wedge y) &= \\ \dots & \\ P(x_1 \mid x_2 \wedge \dots \wedge x_N \wedge y) * P(x_2 \mid x_3 \wedge \dots \wedge x_N \wedge y) * \dots * P(x_N \mid y) * P(y) & \end{aligned}$$

Now let's assume that all events x_1, x_2, \dots, x_N are **mutually independent** (not true in reality) and **conditionally independent given y** \rightarrow **Naive Bayes assumption**.

Under this assumption:

$$P(x_i \mid x_{i+1} \wedge \dots \wedge x_N \wedge y) = P(x_i \mid y)$$

Naive Bayes Assumption

Under Naive Bayes assumption:

$$\begin{aligned} P(x_1 \wedge x_2 \wedge \dots \wedge x_N \wedge y) &= \\ P(x_1 \mid x_2 \wedge \dots \wedge x_N \wedge y) * P(x_2 \wedge \dots \wedge x_N \wedge y) &= \\ P(x_1 \mid x_2 \wedge \dots \wedge x_N \wedge y) * P(x_2 \mid x_3 \wedge \dots \wedge x_N \wedge y) * P(x_3 \wedge \dots \wedge x_N \wedge y) &= \\ P(x_1 \mid x_2 \wedge \dots \wedge x_N \wedge y) * P(x_2 \mid x_3 \wedge \dots \wedge x_N \wedge y) * P(x_3 \mid x_4 \wedge \dots \wedge x_N \wedge y) * P(x_3 \wedge \dots \wedge x_N \wedge y) &= \\ \dots & \\ P(x_1 \mid x_2 \wedge \dots \wedge x_N \wedge y) * P(x_2 \mid x_3 \wedge \dots \wedge x_N \wedge y) * \dots * P(x_N \mid y) * P(y) & \end{aligned}$$

becomes:

$$\begin{aligned} P(x_1 \wedge x_2 \wedge \dots \wedge x_N \wedge y) &= \\ P(x_1 \mid y) * P(x_2 \mid y) * P(x_3 \mid y) * \dots * P(x_{N-1} \mid y) * P(x_N \mid y) * P(y) &= \\ P(y) * [P(x_1 \mid y) * P(x_2 \mid y) * P(x_3 \mid y) * \dots * P(x_{N-1} \mid y) * P(x_N \mid y)] &= \\ P(y) * \prod_{i=1}^N P(x_i \mid y) & \end{aligned}$$

Naive Bayes Classifier

Under Naive Bayes assumption:

$$y_{MAP} \propto \underset{y \in Y}{argmax} (P(x_1 \wedge x_2 \wedge \dots \wedge x_N \mid y) * P(y))$$

becomes:

$$y_{MAP} \propto \underset{y \in Y}{argmax} \left(P(y) * \prod_{i=1}^N P(x_i \mid y) \right)$$

MAP: Maximum a posteriori (corresponds to the most likely class).

Naive Bayes Classifier

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Naive Bayes Classifier

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How to
calculate?

$$y_{MAP} \propto \underset{y \in Y}{argmax} \left(P(y) * \prod_{i=1}^N P(x_i \mid y) \right)$$

MAP: Maximum a posteriori (corresponds to the most likely class).

Text Classification: Supervised ML

Input:

- a document \mathbf{x}
- a fixed set of classes $Y = \{y_1, y_2, \dots, y_J\}$
- a training set of N hand-labeled documents $(\mathbf{x}_1, y_1), \dots, (\mathbf{x}_N, y_N)$

Output:

- a learned classifier $h: \mathbf{x} \rightarrow y$ ($y = h(\mathbf{x})$)

Text Classification: Classifier

category/class = **h**(document)



Learned Classifier model
(hypothesis)

Text Classification: Classifier

$$y = \mathbf{h}(\mathbf{x})$$



**Learned Classifier model
(hypothesis)**

Text Classification: Supervised ML

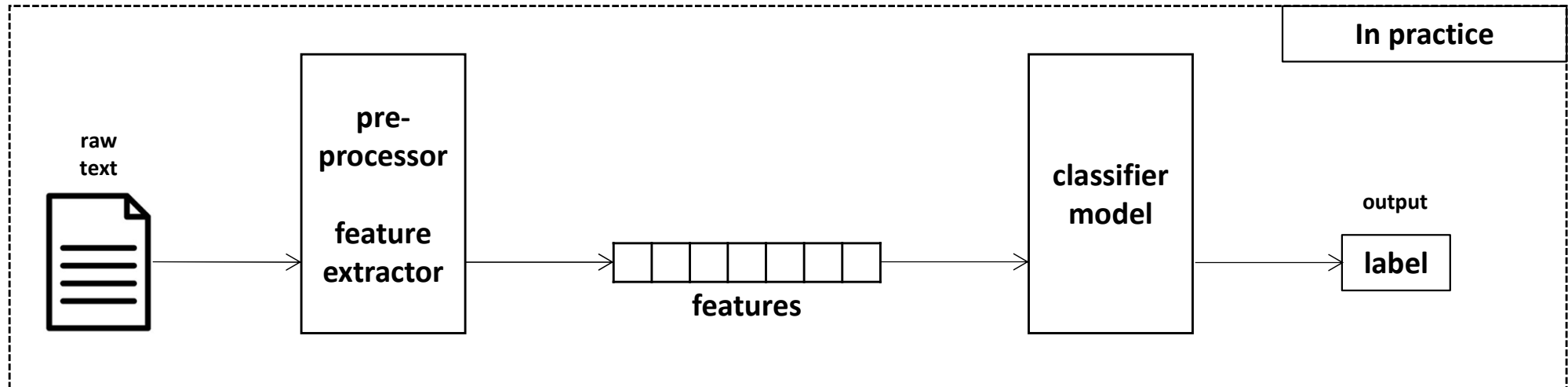
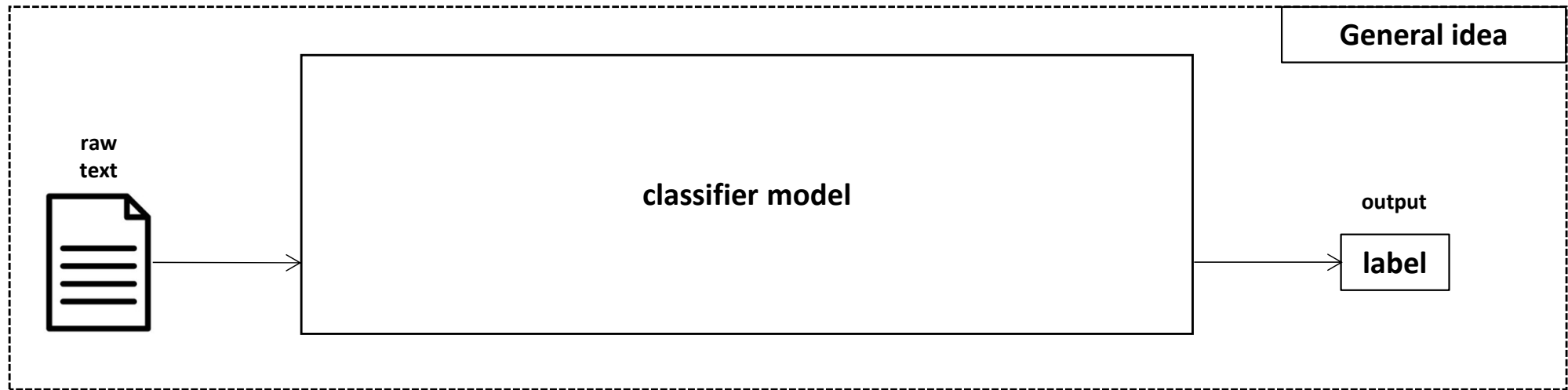
Input:

- a document \mathbf{x}
- a fixed set of classes $Y = \{y_1, y_2, \dots, y_J\}$
- a **training set** of N hand-labeled documents $(\mathbf{x}_1, y_1), \dots, (\mathbf{x}_N, y_N)$

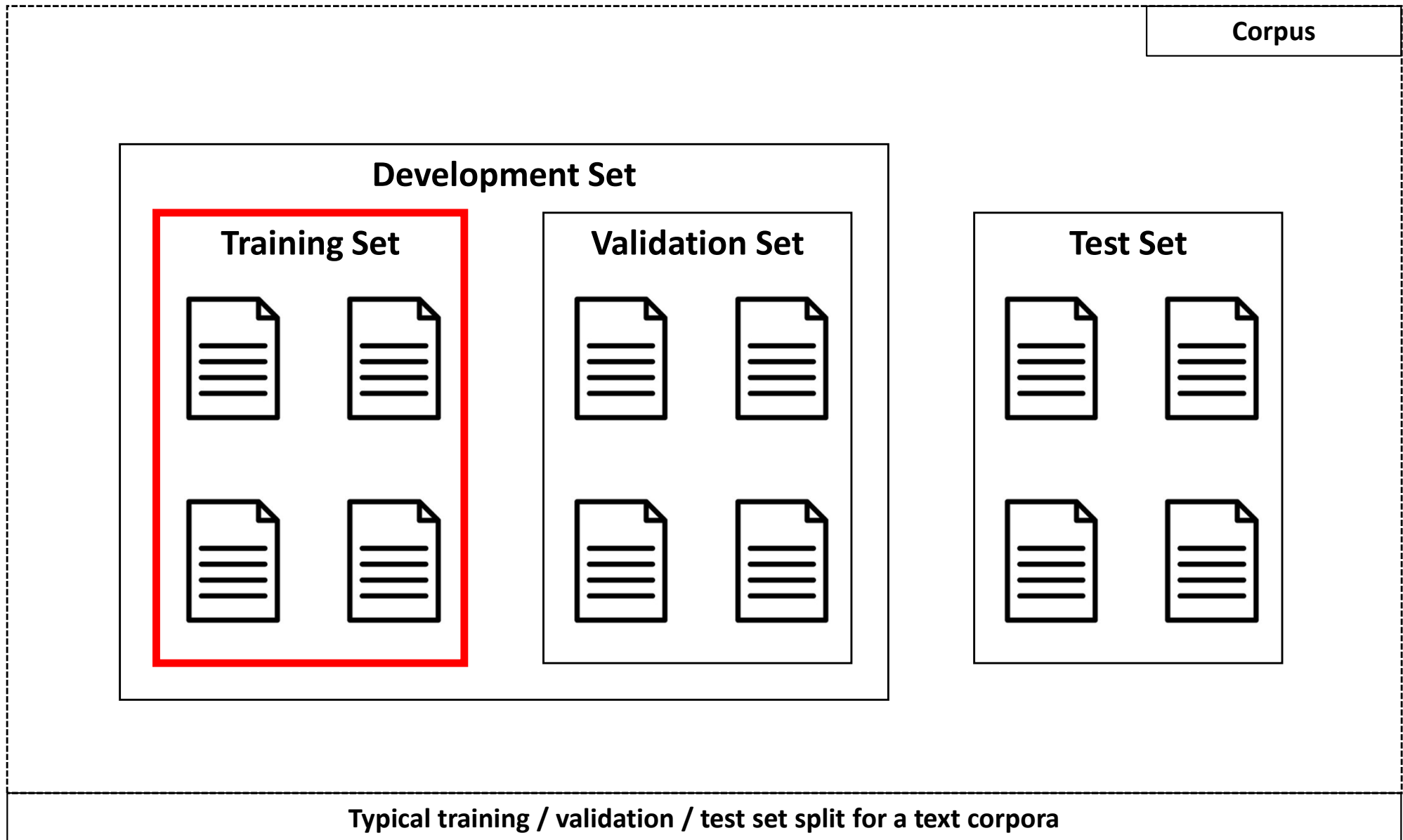
Output:

- a learned classifier $h: \mathbf{x} \rightarrow y$ ($y = h(\mathbf{x})$)

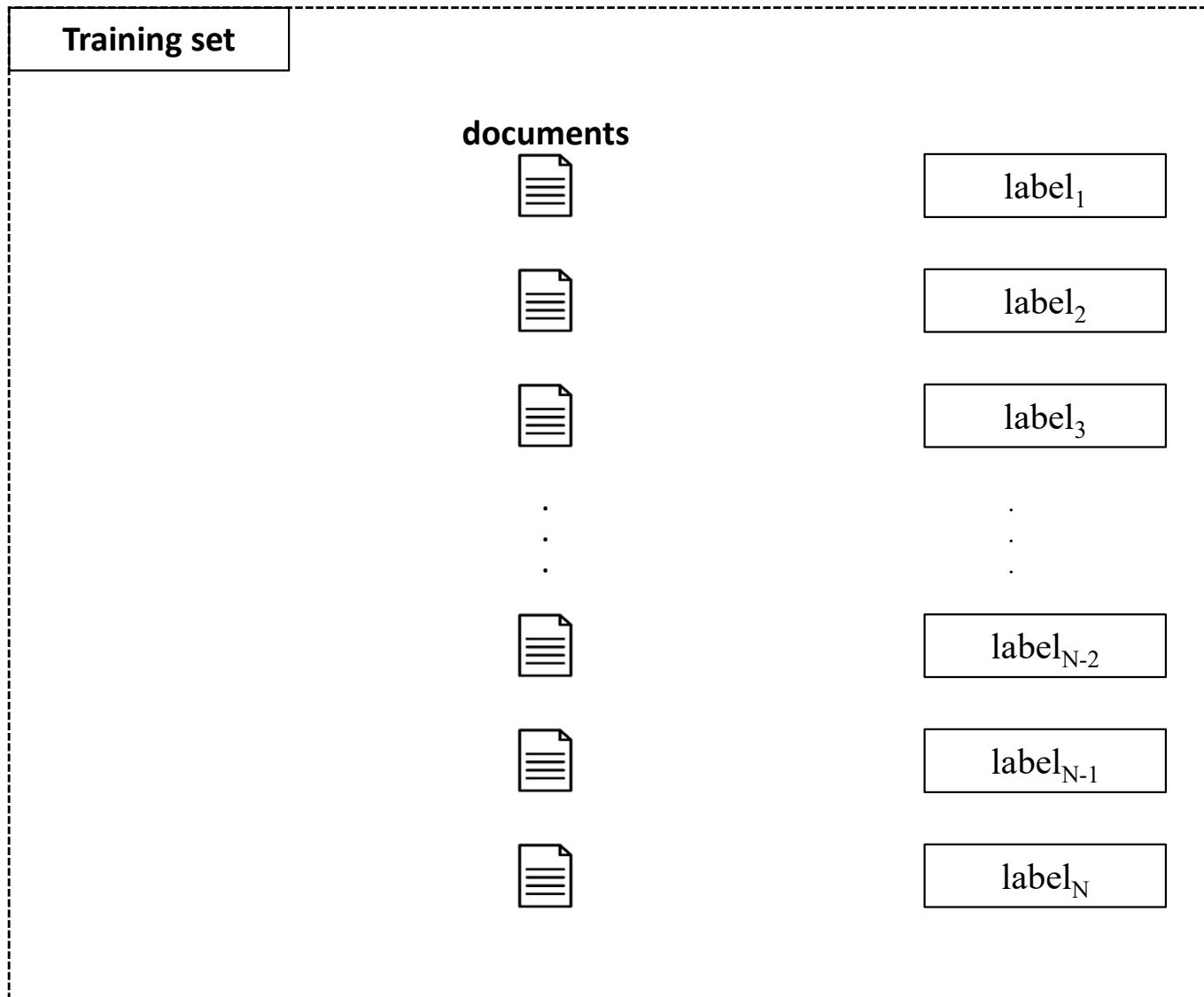
Text Classification: the Idea



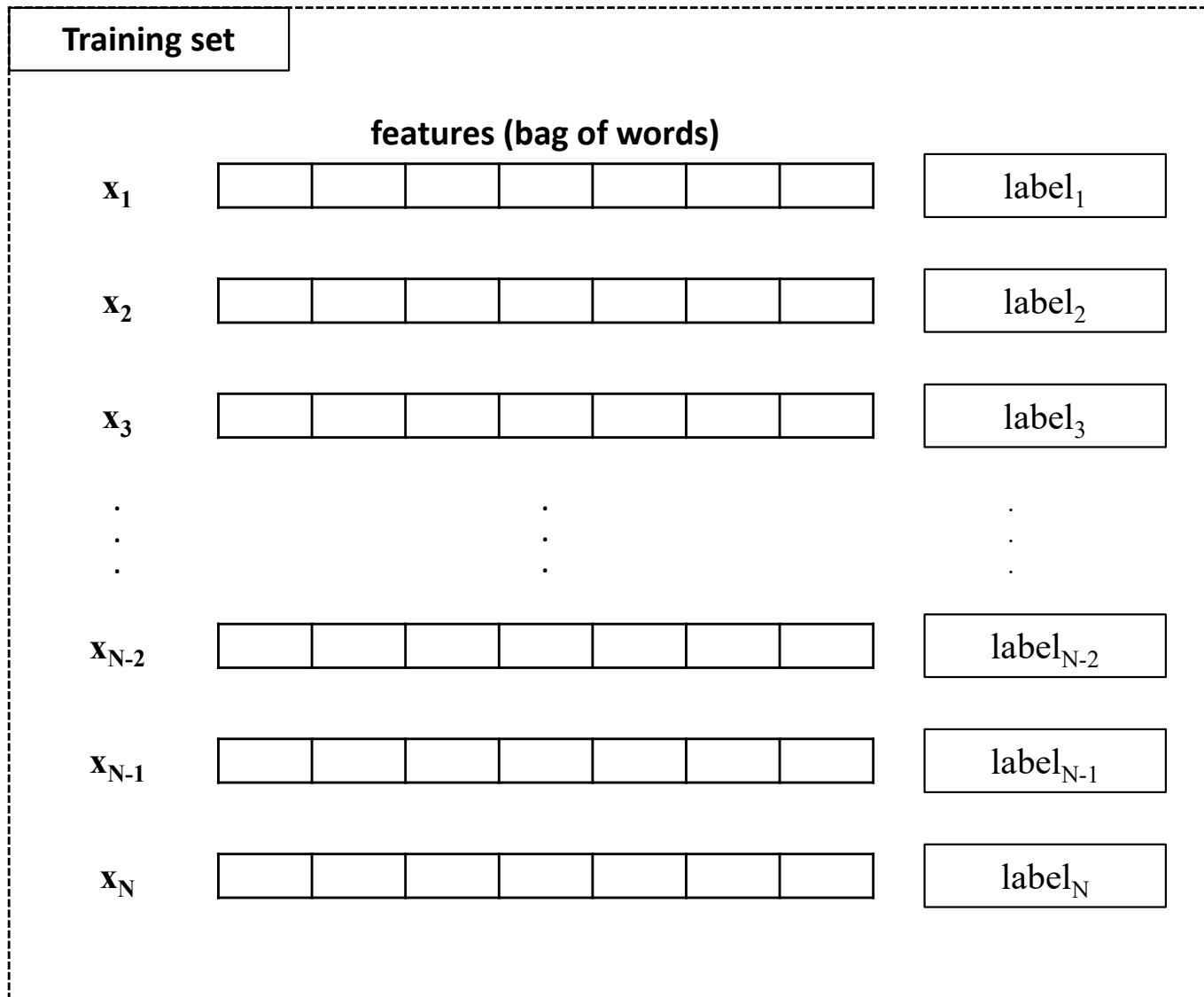
Corpus: Training / Validation / Test



Text Classification: Training Set

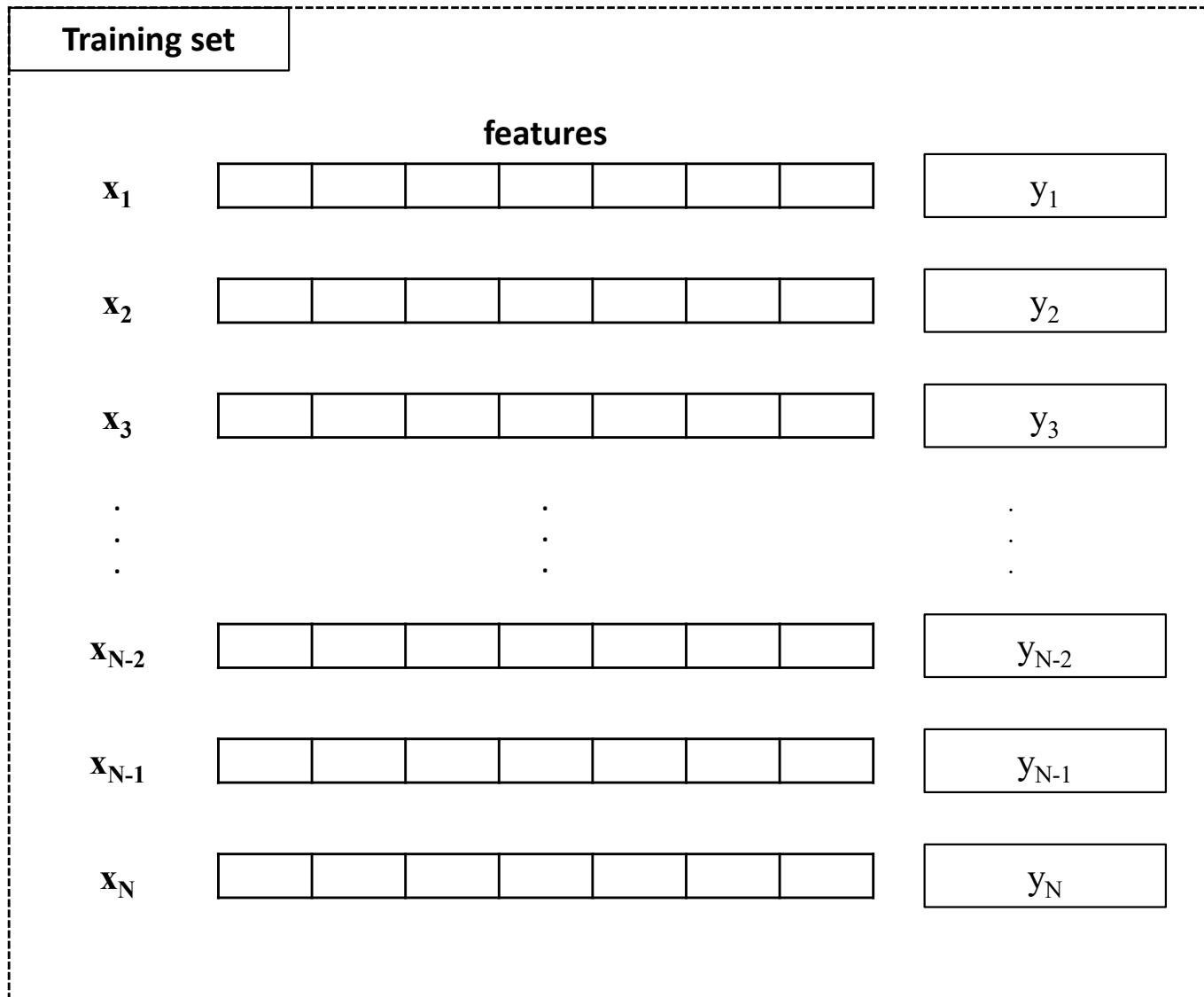


Text Classification: Training Set



$\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3, \dots, \mathbf{x}_{N-2}, \mathbf{x}_{N-1}, \mathbf{x}_N$ - feature vectors (in **bold**)

Text Classification: Training Set



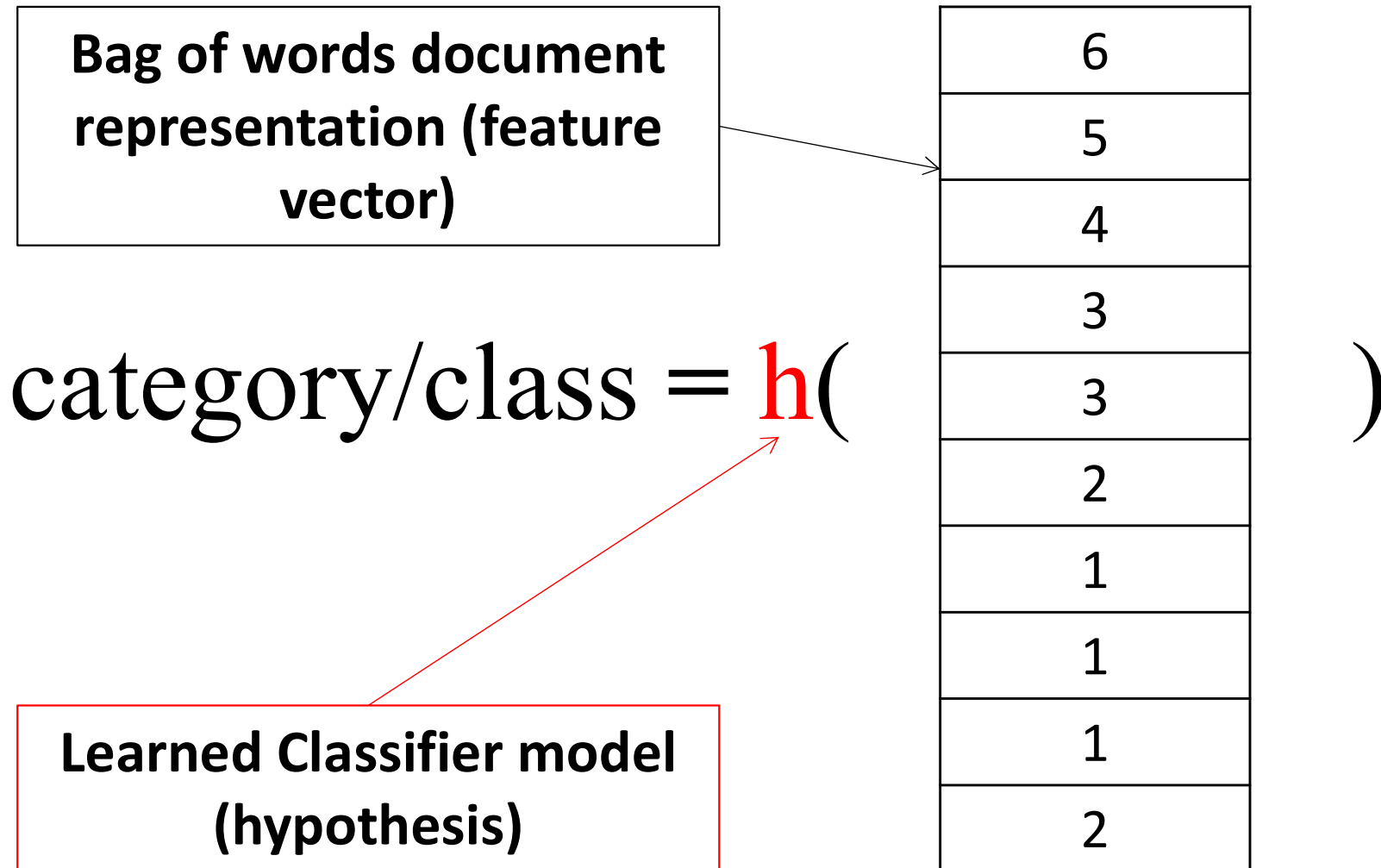
$\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3, \dots, \mathbf{x}_{N-2}, \mathbf{x}_{N-1}, \mathbf{x}_N$ - feature vectors (in **bold**) | $y_1, y_2, y_3, \dots, y_{N-2}, y_{N-1}, y_N$ - labels

Spam Detection: Training Set

Training set		Vocabulary V							
		word1	rolex	word3	replica	word5	word6	word7	
x_1		0	0	1	0	1	1	1	$y_1 = \text{HAM}$
x_2		1	0	1	1	0	1	1	$y_2 = \text{HAM}$
x_3		0	1	0	1	0	1	1	$y_3 = \text{SPAM}$
\vdots									\vdots
x_{N-2}		1	1	1	1	0	1	1	$y_{N-2} = \text{HAM}$
x_{N-1}		1	1	0	1	0	0	1	$y_{N-1} = \text{SPAM}$
x_N		1	0	0	1	0	0	1	$y_N = \text{HAM}$

$x_1, x_2, x_3, \dots, x_{N-2}, x_{N-1}, x_N$ - feature vectors (in **bold**) | $y_1, y_2, y_3, \dots, y_{N-2}, y_{N-1}, y_N$ - labels

Text Classification: Bag of Words

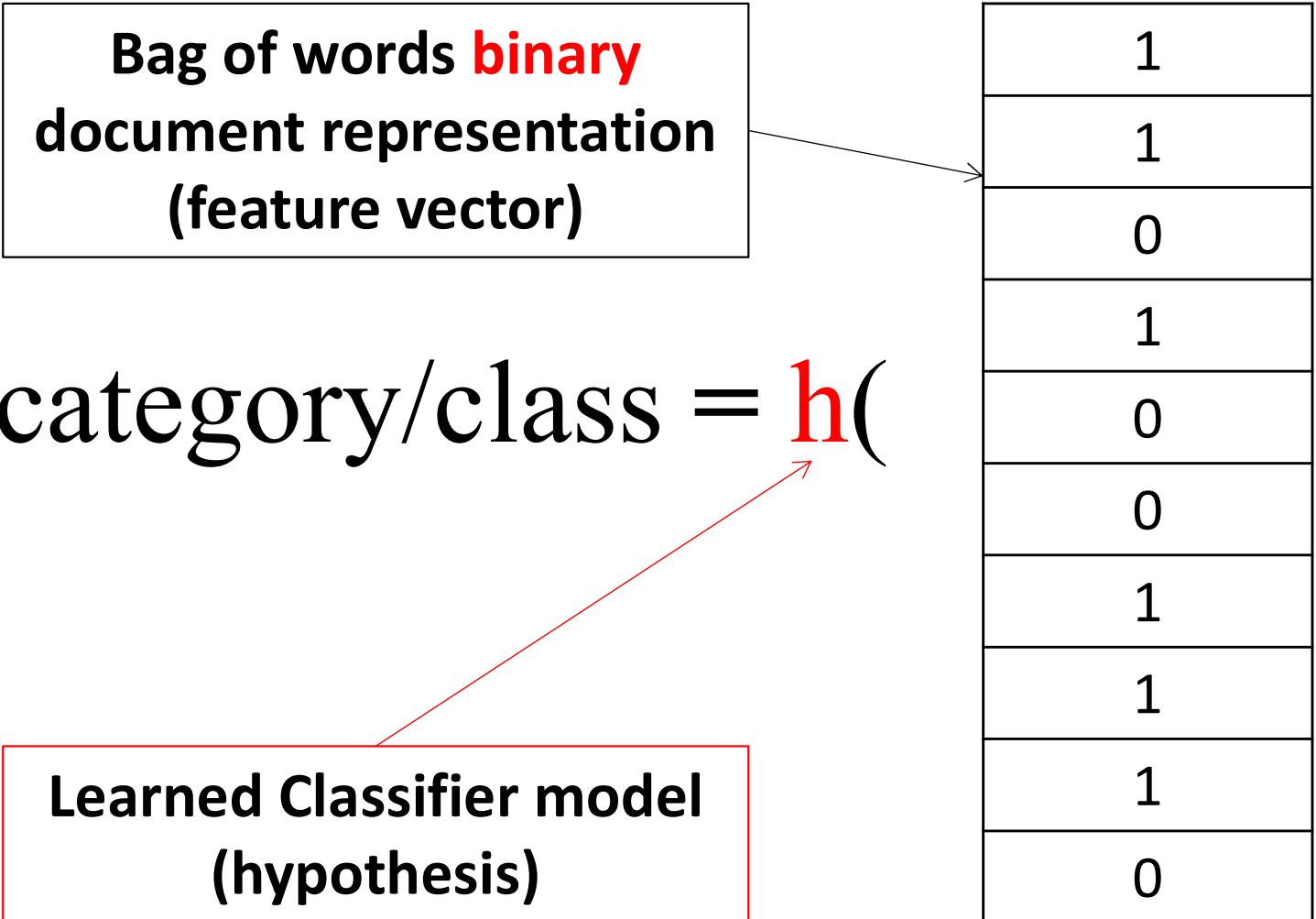


Text Classification: Bag of Words

Bag of words **binary**
document representation
(feature vector)

category/class = **h**()

Learned Classifier model
(hypothesis)



The diagram illustrates the process of text classification using a Bag of Words model. A box on the left describes the 'Bag of words binary document representation (feature vector)'. An arrow points from this box to a vertical table containing a binary vector. Below the table, the text 'category/class = h()' is shown, with a red arrow pointing from a box labeled 'Learned Classifier model (hypothesis)' to the 'h' in the function. The table itself contains the following values from top to bottom: 1, 1, 0, 1, 0, 0, 1, 1, 1, 0.

1
1
0
1
0
0
1
1
1
0

Text Classification: Bag of Words

Bag of words document
representation (feature
vector)

category/class = h (

--	--	--	--	--	--	--

)

Learned Classifier model
(hypothesis)

Spam Detection: Learning

Training set		Learning															
Vocabulary V																	
x_1	<table><tr><td>word1</td><td>rolex</td><td>word3</td><td>replica</td><td>word5</td><td>word6</td><td>word7</td></tr><tr><td>0</td><td>0</td><td>1</td><td>0</td><td>1</td><td>1</td><td>1</td></tr></table>	word1	rolex	word3	replica	word5	word6	word7	0	0	1	0	1	1	1	$y_1 = \text{HAM}$	
word1	rolex	word3	replica	word5	word6	word7											
0	0	1	0	1	1	1											
x_2	<table><tr><td>1</td><td>0</td><td>1</td><td>1</td><td>0</td><td>1</td><td>1</td></tr></table>	1	0	1	1	0	1	1	$y_2 = \text{HAM}$								
1	0	1	1	0	1	1											
x_3	<table><tr><td>0</td><td>1</td><td>0</td><td>1</td><td>0</td><td>1</td><td>1</td></tr></table>	0	1	0	1	0	1	1	$y_3 = \text{SPAM}$								
0	1	0	1	0	1	1											
\vdots	\vdots	\vdots															
x_{N-2}	<table><tr><td>1</td><td>1</td><td>1</td><td>1</td><td>0</td><td>1</td><td>1</td></tr></table>	1	1	1	1	0	1	1	$y_{N-2} = \text{HAM}$								
1	1	1	1	0	1	1											
x_{N-1}	<table><tr><td>1</td><td>1</td><td>0</td><td>1</td><td>0</td><td>0</td><td>1</td></tr></table>	1	1	0	1	0	0	1	$y_{N-1} = \text{SPAM}$								
1	1	0	1	0	0	1											
x_N	<table><tr><td>1</td><td>0</td><td>0</td><td>1</td><td>0</td><td>0</td><td>1</td></tr></table>	1	0	0	1	0	0	1	$y_N = \text{HAM}$								
1	0	0	1	0	0	1											

Naive Bayes Classifier:

$$y_{MAP} \propto \underset{y \in Y}{\operatorname{argmax}} \left(P(y) * \prod_{i=1}^N P(x_i | y) \right)$$

Probability estimates (Maximum Likelihood estimation):

$$P(y_k) = \frac{N_{\text{samples labeled } y_k}}{N}$$
$$P(x_i | y_k) = \frac{\text{count}(x_i, y_k)}{\sum_{x \in V} \text{count}(x, y_k)}$$

$\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3, \dots, \mathbf{x}_{N-2}, \mathbf{x}_{N-1}, \mathbf{x}_N$ - feature vectors (in **bold**) | $y_1, y_2, y_3, \dots, y_{N-2}, y_{N-1}, y_N$ - labels

Spam Detection: Learning

Training set

Vocabulary V

	word1	rolex	word3	replica	word5	word6	word7	
\mathbf{x}_1	0	0	1	0	1	1	1	$y_1 = \text{HAM}$
\mathbf{x}_2	1	0	1	1	0	1	1	$y_2 = \text{HAM}$
\mathbf{x}_3	0	1	0	1	0	1	1	$y_3 = \text{SPAM}$
\mathbf{x}_4	1	1	1	1	0	0	0	$y_4 = \text{HAM}$
\mathbf{x}_5	1	1	1	1	0	1	1	$y_5 = \text{HAM}$
\mathbf{x}_6	1	1	0	1	0	0	1	$y_6 = \text{SPAM}$
\mathbf{x}_7	1	0	0	1	0	0	1	$y_7 = \text{HAM}$

Learning

Naive Bayes Classifier:

$$y_{MAP} \propto \underset{y \in Y}{\operatorname{argmax}} \left(P(y) * \prod_{i=1}^N P(x_i | y) \right)$$

Probability estimates (Maximum Likelihood estimation):

$$P(y = \text{HAM}) = \frac{N_{\text{samples labeled HAM}}}{N} = \frac{5}{7}$$

$$P(y = \text{SPAM}) = \frac{N_{\text{samples labeled SPAM}}}{N} = \frac{2}{7}$$

$$P(x_i = \text{rolex} | y = \text{SPAM}) = \frac{\text{count}(x_i = \text{rolex}, y = \text{SPAM})}{\sum_{x \in V} \text{count}(x, y = \text{SPAM})} = \frac{2}{8}$$

and so on...

$\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3, \dots, \mathbf{x}_{N-2}, \mathbf{x}_{N-1}, \mathbf{x}_N$ - feature vectors (in **bold**) | $y_1, y_2, y_3, \dots, y_{N-2}, y_{N-1}, y_N$ - labels

Spam Detection: Learning

Training set

	word1	rolex	word3	replica	word5	word6	word7
\mathbf{x}_1	0	0	1	0	1	1	1
\mathbf{x}_2	1	0	1	1	0	1	1
\mathbf{x}_3	0	1	0	1	0	1	1
\vdots							
\mathbf{x}_{N-2}	1	1	1	1	0	1	1
\mathbf{x}_{N-1}	1	1	0	1	0	0	1
\mathbf{x}_N	1	0	0	1	0	0	1

Learning

Naive Bayes Classifier:

$$y_{MAP} \propto \underset{y \in Y}{\operatorname{argmax}} \left(P(y) * \prod_{i=1}^N P(x_i | y) \right)$$

Probability estimates:

$$P(y_k) = \frac{N_{\text{samples labeled } y_k}}{N}$$

or

- **equiprobable (all classes have equal probability)**

$$P(y = \text{HAM}) = P(y = \text{SPAM}) = 0.5$$

- **can be determined by experts in the area**

$x_1, x_2, x_3, \dots, x_{N-2}, x_{N-1}, x_N$ - feature vectors (in **bold**) | $y_1, y_2, y_3, \dots, y_{N-2}, y_{N-1}, y_N$ - labels

Classifier

$$y_{MAP} = \underset{y \in Y}{\operatorname{argmax}} (P(y | \mathbf{x})) = \underset{y \in Y}{\operatorname{argmax}} \left(\frac{P(\mathbf{x} | y) * P(y)}{P(\mathbf{x})} \right)$$

$\mathbf{X} = x_1, x_2, \dots, x_N$, **so:**

$$y_{MAP} = \underset{y \in Y}{\operatorname{argmax}} \left(\frac{P(x_1 \wedge x_2 \wedge \dots \wedge x_N | y) * P(y)}{P(x_1 \wedge x_2 \wedge \dots \wedge x_N)} \right)$$

constant | we can drop

$$y_{MAP} \propto \underset{y \in Y}{\operatorname{argmax}} (P(x_1 \wedge x_2 \wedge \dots \wedge x_N | y) * P(y))$$

MAP: Maximum a posteriori (corresponds to the most likely class).

Naive Bayes Classifier: Assumptions

- All events (words) x_1, x_2, \dots, x_N are **mutually independent**
 - Bag-of-words representation: the order of the words in a document d makes no difference (repetitions do)
- All events (words) x_1, x_2, \dots, x_N are **conditionally independent given y** (category / class)
 - **words appear independently** of each other, **given the document category / class y** (e.g. if you see word “*car*”, the word “*drive*” is no more likely to appear than if you saw “*dog*”)

Naive Bayes Classifier

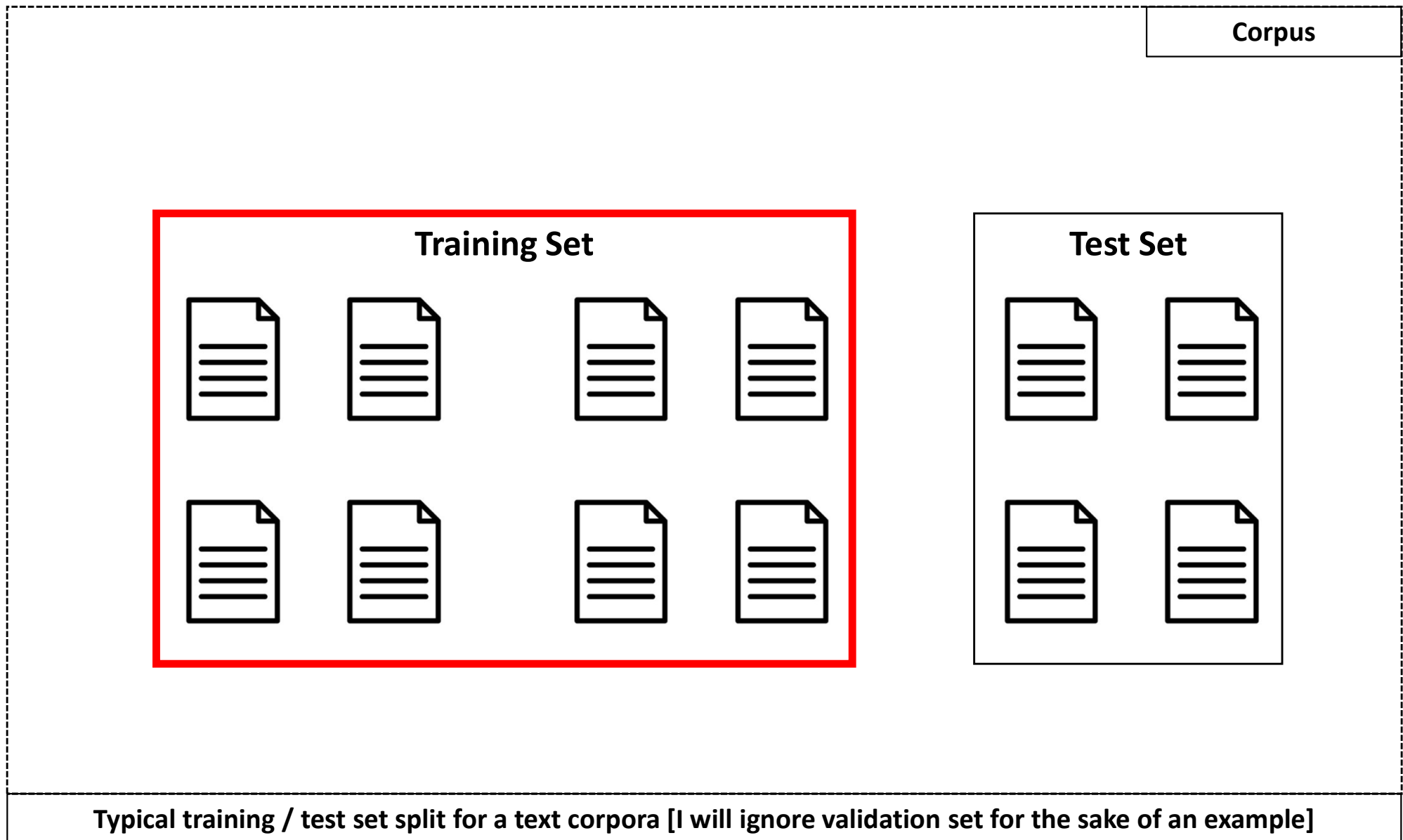
category/class = **h**(document)

Finding model / hypothesis **h** → Finding probabilities for y_{MAP}

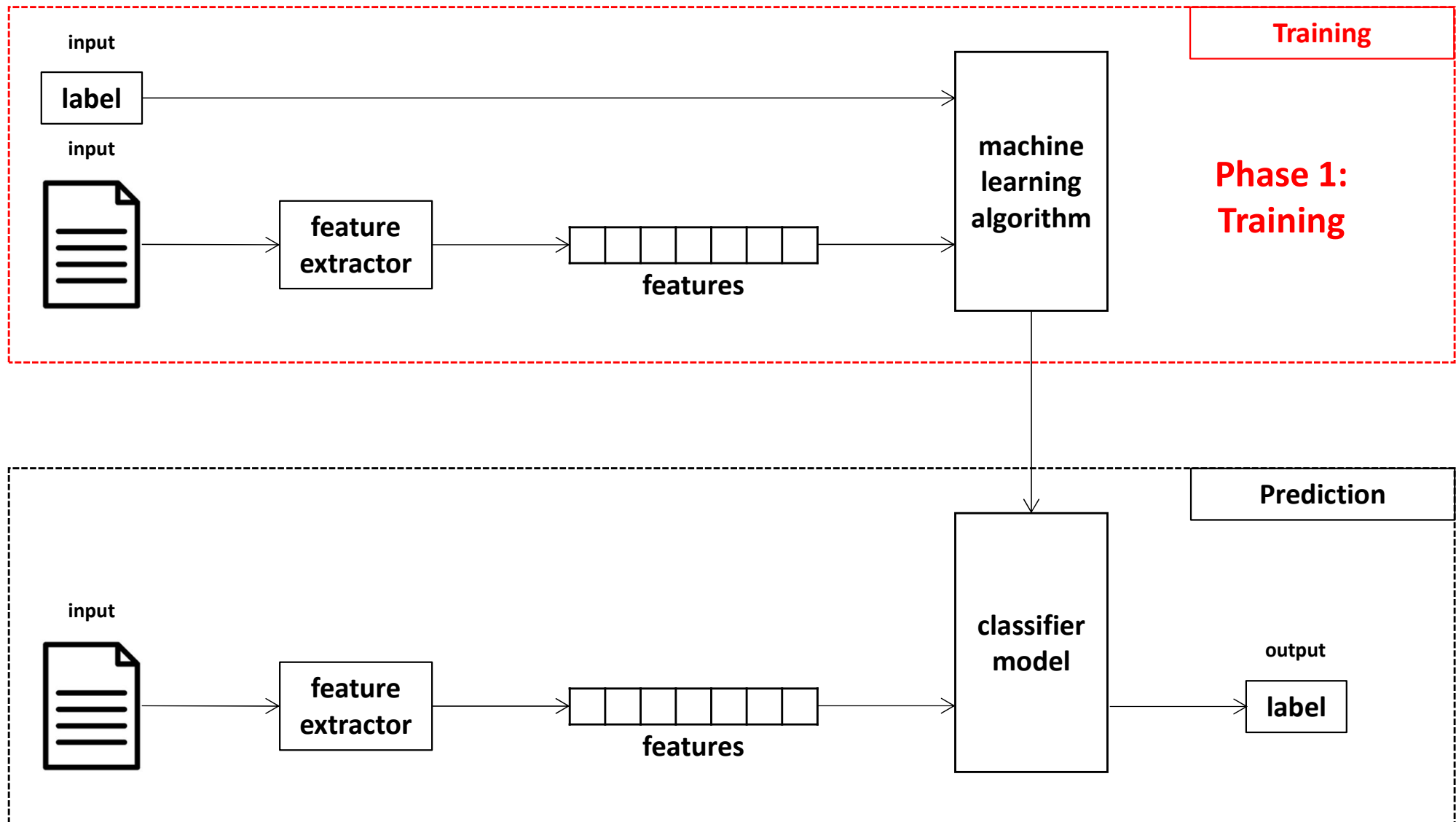
$$y_{MAP} \propto \underset{y \in Y}{argmax} \left(\boxed{P(y)} * \prod_{i=1}^N \boxed{P(x_i | y)} \right)$$

MAP: Maximum a posteriori (corresponds to the most likely class).

Corpus: Training / Test



Supervised Learning with ML



Spam Detection: Training Set

Training set		Vocabulary V						
		I	rolex	own	replica	watch	buy	cheap
x_1		1	1	1	0	1	0	0
		I own rolex watch						
x_2		1	0	1	0	1	0	0
		I own watch						
x_3		0	1	0	1	0	1	1
		buy cheap rolex replica						
x_4		1	0	1	0	0	0	0
		I own						
x_5		1	0	1	1	0	0	1
		I own cheap replica						
x_6		0	1	0	1	0	0	1
		cheap rolex replica						
x_7		1	0	0	0	1	0	0
		I watch						
		$y_1 = \text{HAM}$						
		$y_2 = \text{HAM}$						
		$y_3 = \text{SPAM}$						
		$y_4 = \text{HAM}$						
		$y_5 = \text{HAM}$						
		$y_6 = \text{SPAM}$						
		$y_7 = \text{HAM}$						

$x_1, x_2, x_3, \dots, x_{N-2}, x_{N-1}, x_N$ - feature vectors (in **bold**) | $y_1, y_2, y_3, \dots, y_{N-2}, y_{N-1}, y_N$ - labels

Spam Detection: Learning

Training set

Vocabulary V

	I	rolex	own	replica	watch	buy	cheap
x ₁	1	1	1	0	1	0	0
x ₂	1	0	1	0	1	0	0
x ₃	0	1	0	1	0	1	1
x ₄	1	0	1	0	0	0	0
x ₅	1	0	1	1	0	0	1
x ₆	0	1	0	1	0	0	1
x ₇	1	0	0	0	1	0	0

y₁=HAM

y₂=HAM

y₃=SPAM

y₄=HAM

y₅=HAM

y₆=SPAM

y₇=HAM

Learning

Probability estimates:

Naive Bayes Classifier:

$$y_{MAP} \propto \underset{y \in Y}{\operatorname{argmax}} \left(P(y) * \prod_{i=1}^N P(x_i | y) \right)$$

Probability estimates (Maximum Likelihood estimation):

$$P(y = \text{HAM}) = \frac{N_{\text{samples labeled HAM}}}{N}$$

$$P(y = \text{SPAM}) = \frac{N_{\text{samples labeled SPAM}}}{N}$$

$$P(x_i = \text{word} | y = \text{CLASS}) = \frac{\text{count}(x_i = \text{word}, y = \text{CLASS})}{\sum_{x \in V} \text{count}(x, y = \text{CLASS})}$$

x₁, x₂, x₃, ..., x_{N-2}, x_{N-1}, x_N - feature vectors (in **bold**) | y₁, y₂, y₃, ..., y_{N-2}, y_{N-1}, y_N - labels

Spam Detection: Learning

Training set

Vocabulary V

	I	rolex	own	replica	watch	buy	cheap
x_1	1	1	1	0	1	0	0
x_2	1	0	1	0	1	0	0
x_3	0	1	0	1	0	1	1
x_4	1	0	1	0	0	0	0
x_5	1	0	1	1	0	0	1
x_6	0	1	0	1	0	0	1
x_7	1	0	0	0	1	0	0

$y_1 = \text{HAM}$

$y_2 = \text{HAM}$

$y_3 = \text{SPAM}$

$y_4 = \text{HAM}$

$y_5 = \text{HAM}$

$y_6 = \text{SPAM}$

$y_7 = \text{HAM}$

Learning

$$P(y = \text{HAM}) = \frac{N_{\text{samples labeled HAM}}}{N} = \frac{5}{7}$$

$$P(y = \text{SPAM}) = \frac{N_{\text{samples labeled SPAM}}}{N} = \frac{2}{7}$$

$x_1, x_2, x_3, \dots, x_{N-2}, x_{N-1}, x_N$ - feature vectors (in **bold**) | $y_1, y_2, y_3, \dots, y_{N-2}, y_{N-1}, y_N$ - labels

Spam Detection: Learning

Training set		Learning															
Vocabulary V																	
x_1	<table><tr><th>I</th><th>rolex</th><th>own</th><th>replica</th><th>watch</th><th>buy</th><th>cheap</th></tr><tr><td>1</td><td>1</td><td>1</td><td>0</td><td>1</td><td>0</td><td>0</td></tr></table>	I	rolex	own	replica	watch	buy	cheap	1	1	1	0	1	0	0	$y_1 = \text{HAM}$	$P(x_i = I \mid y = \text{HAM}) = \frac{\text{count}(x_i = I, y = \text{HAM})}{\sum_{x \in V} \text{count}(x, y = \text{HAM})} = \frac{5}{15}$
I	rolex	own	replica	watch	buy	cheap											
1	1	1	0	1	0	0											
x_2	<table><tr><td>1</td><td>0</td><td>1</td><td>0</td><td>1</td><td>0</td><td>0</td></tr></table>	1	0	1	0	1	0	0	$y_2 = \text{HAM}$	$P(x_i = \text{rolex} \mid y = \text{HAM}) = \frac{\text{count}(x_i = \text{rolex}, y = \text{HAM})}{\sum_{x \in V} \text{count}(x, y = \text{HAM})} = \frac{1}{15}$							
1	0	1	0	1	0	0											
x_3	<table><tr><td>0</td><td>1</td><td>0</td><td>1</td><td>0</td><td>1</td><td>1</td></tr></table>	0	1	0	1	0	1	1	$y_3 = \text{SPAM}$	$P(x_i = \text{own} \mid y = \text{HAM}) = \frac{\text{count}(x_i = \text{own}, y = \text{HAM})}{\sum_{x \in V} \text{count}(x, y = \text{HAM})} = \frac{4}{15}$							
0	1	0	1	0	1	1											
x_4	<table><tr><td>1</td><td>0</td><td>1</td><td>0</td><td>0</td><td>0</td><td>0</td></tr></table>	1	0	1	0	0	0	0	$y_4 = \text{HAM}$	$P(x_i = \text{replica} \mid y = \text{HAM}) = \frac{\text{count}(x_i = \text{replica}, y = \text{HAM})}{\sum_{x \in V} \text{count}(x, y = \text{HAM})} = \frac{1}{15}$							
1	0	1	0	0	0	0											
x_5	<table><tr><td>1</td><td>0</td><td>1</td><td>1</td><td>0</td><td>0</td><td>1</td></tr></table>	1	0	1	1	0	0	1	$y_5 = \text{HAM}$	$P(x_i = \text{watch} \mid y = \text{HAM}) = \frac{\text{count}(x_i = \text{watch}, y = \text{HAM})}{\sum_{x \in V} \text{count}(x, y = \text{HAM})} = \frac{3}{15}$							
1	0	1	1	0	0	1											
x_6	<table><tr><td>0</td><td>1</td><td>0</td><td>1</td><td>0</td><td>0</td><td>1</td></tr></table>	0	1	0	1	0	0	1	$y_6 = \text{SPAM}$	$P(x_i = \text{buy} \mid y = \text{HAM}) = \frac{\text{count}(x_i = \text{buy}, y = \text{HAM})}{\sum_{x \in V} \text{count}(x, y = \text{HAM})} = \frac{0}{15}$							
0	1	0	1	0	0	1											
x_7	<table><tr><td>1</td><td>0</td><td>0</td><td>0</td><td>1</td><td>0</td><td>0</td></tr></table>	1	0	0	0	1	0	0	$y_7 = \text{HAM}$	$P(x_i = \text{cheap} \mid y = \text{HAM}) = \frac{\text{count}(x_i = \text{cheap}, y = \text{HAM})}{\sum_{x \in V} \text{count}(x, y = \text{HAM})} = \frac{1}{15}$							
1	0	0	0	1	0	0											

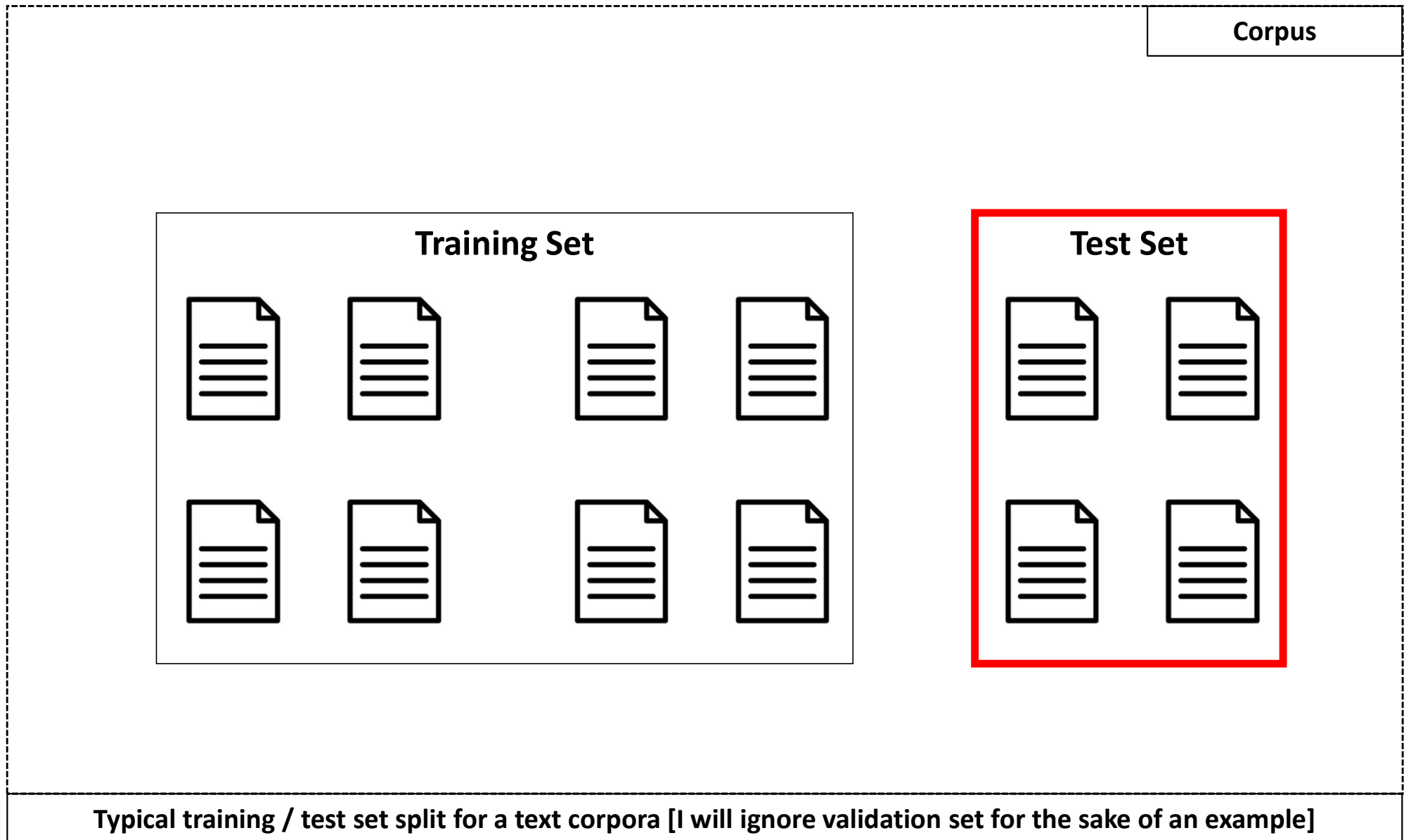
$x_1, x_2, x_3, \dots, x_{N-2}, x_{N-1}, x_N$ - feature vectors (in **bold**) | $y_1, y_2, y_3, \dots, y_{N-2}, y_{N-1}, y_N$ - labels

Spam Detection: Learning

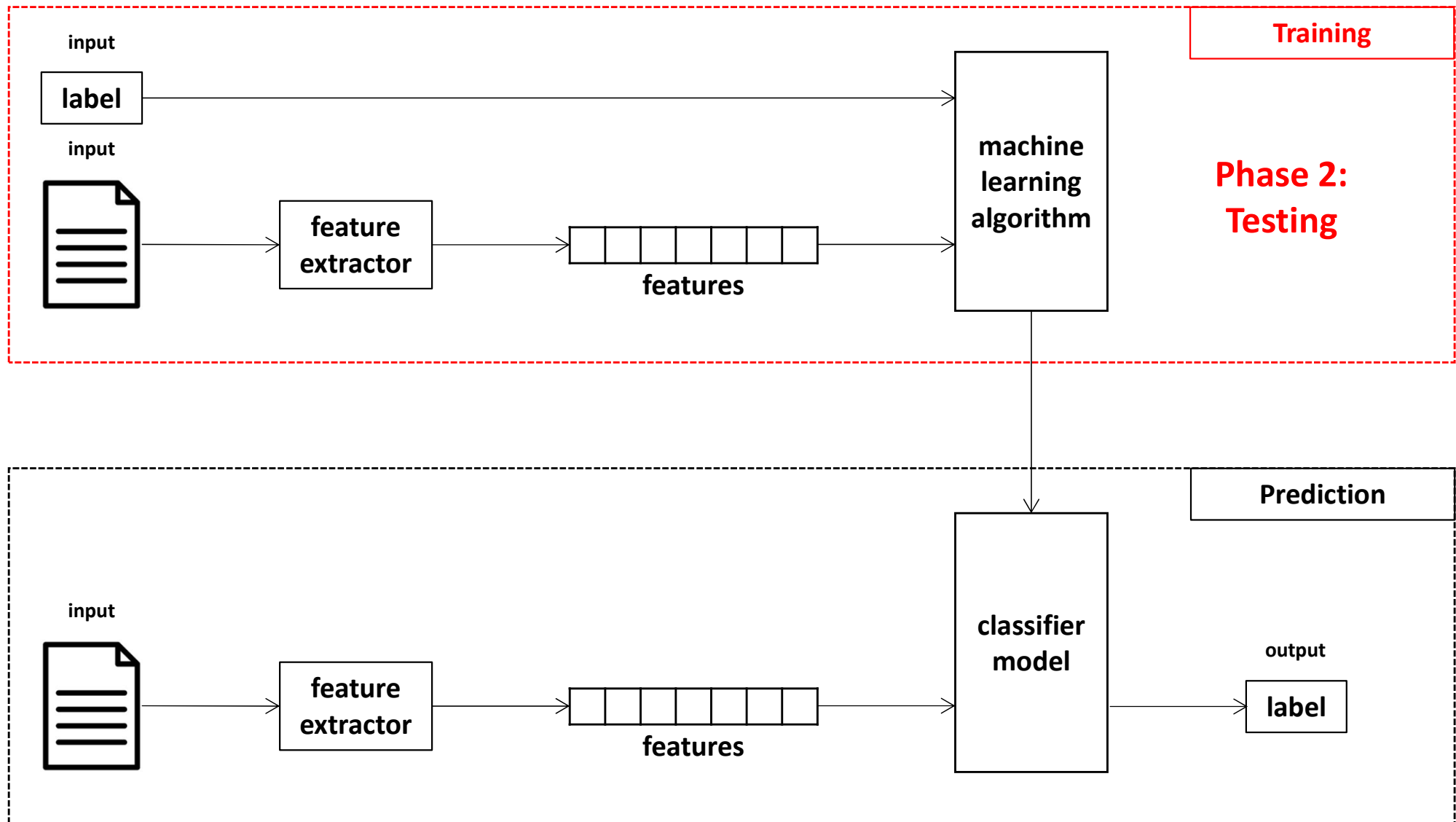
Training set		Vocabulary V								Learning	
		I	rolex	own	replica	watch	buy	cheap			
x_1		1	1	1	0	1	0	0	$y_1 = \text{HAM}$	$P(x_i = I \mid y = \text{SPAM}) = \frac{\text{count}(x_i = I, y = \text{SPAM})}{\sum_{x \in V} \text{count}(x, y = \text{SPAM})} = \frac{0}{7}$	
x_2		1	0	1	0	1	0	0	$y_2 = \text{HAM}$	$P(x_i = \text{rolex} \mid y = \text{SPAM}) = \frac{\text{count}(x_i = \text{rolex}, y = \text{SPAM})}{\sum_{x \in V} \text{count}(x, y = \text{SPAM})} = \frac{2}{7}$	
x_3		0	1	0	1	0	1	1	$y_3 = \text{SPAM}$	$P(x_i = \text{own} \mid y = \text{SPAM}) = \frac{\text{count}(x_i = \text{own}, y = \text{SPAM})}{\sum_{x \in V} \text{count}(x, y = \text{SPAM})} = \frac{0}{7}$	
x_4		1	0	1	0	0	0	0	$y_4 = \text{HAM}$	$P(x_i = \text{replica} \mid y = \text{SPAM}) = \frac{\text{count}(x_i = \text{replica}, y = \text{SPAM})}{\sum_{x \in V} \text{count}(x, y = \text{SPAM})} = \frac{2}{7}$	
x_5		1	0	1	1	0	0	1	$y_5 = \text{HAM}$	$P(x_i = \text{watch} \mid y = \text{SPAM}) = \frac{\text{count}(x_i = \text{watch}, y = \text{SPAM})}{\sum_{x \in V} \text{count}(x, y = \text{SPAM})} = \frac{0}{7}$	
x_6		0	1	0	1	0	0	1	$y_6 = \text{SPAM}$	$P(x_i = \text{buy} \mid y = \text{SPAM}) = \frac{\text{count}(x_i = \text{buy}, y = \text{SPAM})}{\sum_{x \in V} \text{count}(x, y = \text{SPAM})} = \frac{1}{7}$	
x_7		1	0	0	0	1	0	0	$y_7 = \text{HAM}$	$P(x_i = \text{cheap} \mid y = \text{SPAM}) = \frac{\text{count}(x_i = \text{cheap}, y = \text{SPAM})}{\sum_{x \in V} \text{count}(x, y = \text{SPAM})} = \frac{2}{7}$	

$x_1, x_2, x_3, \dots, x_{N-2}, x_{N-1}, x_N$ - feature vectors (in **bold**) | $y_1, y_2, y_3, \dots, y_{N-2}, y_{N-1}, y_N$ - labels

Corpus: Training / Test



Supervised Learning with ML



Spam Detection: Test Set

Test set		Vocabulary V							
		I	rolex	own	replica	watch	buy	cheap	
x_8		0	1	0	1	0	1	1	$y_8 = \text{SPAM}$
		buy cheap rolex replica rolex							
x_9		1	1	1	0	1	0	1	$y_9 = \text{HAM}$
		I own cheap rolex watch							
x_{10}		0	0	0	1	0	0	0	$y_{10} = \text{HAM}$
		replica							

$x_1, x_2, x_3, \dots, x_{N-2}, x_{N-1}, x_N$ - feature vectors (in **bold**) | $y_1, y_2, y_3, \dots, y_{N-2}, y_{N-1}, y_N$ - labels

Spam Detection: Testing Classifier

Test set	Vocabulary V							Learned $h()$
x_8	I	rolex	own	replica	watch	buy	cheap	$y_8 = \text{SPAM}$
	0	1	0	1	0	1	1	
	buy cheap rolex replica rolex							
x_9	1	1	1	0	1	0	1	$y_9 = \text{HAM}$
	I own cheap rolex watch							
x_{10}	0	0	0	1	0	0	0	$y_{10} = \text{HAM}$
	replica							
Testing	$y_{MAP} \propto \underset{y \in Y}{\operatorname{argmax}} \left(P(y) * \prod_{i=1}^N P(x_i y) \right)$ category/class = $h(\text{document})$							$P(y = \text{HAM}) = \frac{5}{7} \quad P(y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = I y = \text{HAM}) = \frac{5}{15}$ $P(x_i = \text{rolex} y = \text{HAM}) = \frac{1}{15}$ $P(x_i = \text{own} y = \text{HAM}) = \frac{4}{15}$ $P(x_i = \text{replica} y = \text{HAM}) = \frac{1}{15}$ $P(x_i = \text{watch} y = \text{HAM}) = \frac{3}{15}$ $P(x_i = \text{buy} y = \text{HAM}) = \frac{0}{15}$ $P(x_i = \text{cheap} y = \text{HAM}) = \frac{1}{15}$ $P(x_i = I y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = \text{rolex} y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = \text{own} y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = \text{replica} y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = \text{watch} y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = \text{buy} y = \text{SPAM}) = \frac{1}{7}$ $P(x_i = \text{cheap} y = \text{SPAM}) = \frac{2}{7}$

$x_1, x_2, x_3, \dots, x_{N-2}, x_{N-1}, x_N$ - feature vectors (in **bold**) | $y_1, y_2, y_3, \dots, y_{N-2}, y_{N-1}, y_N$ - labels

Spam Detection: Testing Classifier

Test set	Vocabulary V						Learned $h()$
	I	rolex	own	replica	watch	buy	cheap
x_8	0	1	0	1	0	1	1
	buy cheap rolex replica rolex						$y_8 = \text{SPAM}$
x_9	1	1	1	0	1	0	1
	I own cheap rolex watch						$y_9 = \text{HAM}$
x_{10}	0	0	0	1	0	0	0
	replica						$y_{10} = \text{HAM}$
Testing	$y_{MAP} \propto \underset{y \in Y}{\operatorname{argmax}} \left(P(y) * \prod_{i=1}^N P(x_i y) \right)$ <p>category/class = $h(x_8)$</p>						$P(y = \text{HAM}) = \frac{5}{7} \quad P(y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = I y = \text{HAM}) = \frac{5}{15}$ $P(x_i = rolex y = \text{HAM}) = \frac{1}{15}$ $P(x_i = own y = \text{HAM}) = \frac{4}{15}$ $P(x_i = replica y = \text{HAM}) = \frac{1}{15}$ $P(x_i = watch y = \text{HAM}) = \frac{3}{15}$ $P(x_i = buy y = \text{HAM}) = \frac{0}{15}$ $P(x_i = cheap y = \text{HAM}) = \frac{1}{15}$ $P(x_i = I y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = rolex y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = own y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = replica y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = watch y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = buy y = \text{SPAM}) = \frac{1}{7}$ $P(x_i = cheap y = \text{SPAM}) = \frac{2}{7}$

$x_1, x_2, x_3, \dots, x_{N-2}, x_{N-1}, x_N$ - feature vectors (in **bold**) | $y_1, y_2, y_3, \dots, y_{N-2}, y_{N-1}, y_N$ - labels

Spam Detection: Testing Classifier

Test set	Vocabulary V							Learned $h()$
	I	rolex	own	replica	watch	buy	cheap	
x_8	0	1	0	1	0	1	1	$y_8 = \text{SPAM}$
	buy cheap rolex replica rolex							
x_9	1	1	1	0	1	0	1	$y_9 = \text{HAM}$
	I own cheap rolex watch							
x_{10}	0	0	0	1	0	0	0	$y_{10} = \text{HAM}$
	replica							
Testing								
$y_{MAP} \propto \underset{y \in Y}{\operatorname{argmax}} \left(P(y) * \prod_{i=1}^N P(x_i y) \right)$								
category/class = $h(\text{buy cheap rolex replica rolex})$								
$P(y = \text{HAM}) = \frac{5}{7} \quad P(y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = I y = \text{HAM}) = \frac{5}{15}$ $P(x_i = \text{rolex} y = \text{HAM}) = \frac{1}{15}$ $P(x_i = \text{own} y = \text{HAM}) = \frac{4}{15}$ $P(x_i = \text{replica} y = \text{HAM}) = \frac{1}{15}$ $P(x_i = \text{watch} y = \text{HAM}) = \frac{3}{15}$ $P(x_i = \text{buy} y = \text{HAM}) = \frac{0}{15}$ $P(x_i = \text{cheap} y = \text{HAM}) = \frac{1}{15}$ $P(x_i = I y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = \text{rolex} y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = \text{own} y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = \text{replica} y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = \text{watch} y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = \text{buy} y = \text{SPAM}) = \frac{1}{7}$ $P(x_i = \text{cheap} y = \text{SPAM}) = \frac{2}{7}$								

$x_1, x_2, x_3, \dots, x_{N-2}, x_{N-1}, x_N$ - feature vectors (in **bold**) | $y_1, y_2, y_3, \dots, y_{N-2}, y_{N-1}, y_N$ - labels

Spam Detection: Testing Classifier

Test set

Vocabulary V

	I	rolex	own	replica	watch	buy	cheap
x_8	0	1	0	1	0	1	1

buy cheap **rolex replica rolex**

$y_8 = \text{SPAM}$

x_9	1	1	1	0	1	0	1
-------	---	---	---	---	---	---	---

I own cheap **rolex** watch

$y_9 = \text{HAM}$

x_{10}	0	0	0	1	0	0	0
----------	---	---	---	---	---	---	---

replica

$y_{10} = \text{HAM}$

Learned $h()$

$P(y = \text{HAM}) = \frac{5}{7}$ $P(y = \text{SPAM}) = \frac{2}{7}$

$P(x_i = I | y = \text{HAM}) = \frac{5}{15}$
 $P(x_i = \text{rolex} | y = \text{HAM}) = \frac{1}{15}$
 $P(x_i = \text{own} | y = \text{HAM}) = \frac{4}{15}$
 $P(x_i = \text{replica} | y = \text{HAM}) = \frac{1}{15}$
 $P(x_i = \text{watch} | y = \text{HAM}) = \frac{3}{15}$
 $P(x_i = \text{buy} | y = \text{HAM}) = \frac{0}{15}$
 $P(x_i = \text{cheap} | y = \text{HAM}) = \frac{1}{15}$

$P(x_i = I | y = \text{SPAM}) = \frac{0}{7}$
 $P(x_i = \text{rolex} | y = \text{SPAM}) = \frac{2}{7}$
 $P(x_i = \text{own} | y = \text{SPAM}) = \frac{0}{7}$
 $P(x_i = \text{replica} | y = \text{SPAM}) = \frac{2}{7}$
 $P(x_i = \text{watch} | y = \text{SPAM}) = \frac{0}{7}$
 $P(x_i = \text{buy} | y = \text{SPAM}) = \frac{1}{7}$
 $P(x_i = \text{cheap} | y = \text{SPAM}) = \frac{2}{7}$

Testing

$$y_{MAP} \propto \underset{y \in Y}{\operatorname{argmax}} \left(P(y) * \prod_{i=1}^N P(x_i | y) \right)$$

category/class = $h(\text{0, 1, 0, 1, 0, 1, 1})$

$x_1, x_2, x_3, \dots, x_{N-2}, x_{N-1}, x_N$ - feature vectors (in **bold**) | $y_1, y_2, y_3, \dots, y_{N-2}, y_{N-1}, y_N$ - labels

Spam Detection: Testing Classifier

Test set								Learned h()
	Vocabulary V							
	I	rolex	own	replica	watch	buy	cheap	
x₈	0	1	0	1	0	1	1	y₈=SPAM
	buy cheap rolex replica rolex							
x₉	1	1	1	0	1	0	1	y₉=HAM
	I own cheap rolex watch							
x₁₀	0	0	0	1	0	0	0	y₁₀=HAM
	replica							
Testing								
Which probability is higher? Which y maximizes P())?								
$P(y = \text{HAM} \mid x_8) \propto P(y = \text{HAM}) * \prod_{i=1}^5 P(x_i \mid y = \text{HAM})$								
$P(y = \text{SPAM} \mid x_8) \propto P(y = \text{SPAM}) * \prod_{i=1}^5 P(x_i \mid y = \text{SPAM})$								
$P(y = \text{HAM}) = \frac{5}{7} \quad P(y = \text{SPAM}) = \frac{2}{7}$								
$P(x_i = I \mid y = \text{HAM}) = \frac{5}{15}$								
$P(x_i = \text{rolex} \mid y = \text{HAM}) = \frac{1}{15}$								
$P(x_i = \text{own} \mid y = \text{HAM}) = \frac{4}{15}$								
$P(x_i = \text{replica} \mid y = \text{HAM}) = \frac{1}{15}$								
$P(x_i = \text{watch} \mid y = \text{HAM}) = \frac{3}{15}$								
$P(x_i = \text{buy} \mid y = \text{HAM}) = \frac{0}{15}$								
$P(x_i = \text{cheap} \mid y = \text{HAM}) = \frac{1}{15}$								
$P(x_i = I \mid y = \text{SPAM}) = \frac{0}{7}$								
$P(x_i = \text{rolex} \mid y = \text{SPAM}) = \frac{2}{7}$								
$P(x_i = \text{own} \mid y = \text{SPAM}) = \frac{0}{7}$								
$P(x_i = \text{replica} \mid y = \text{SPAM}) = \frac{2}{7}$								
$P(x_i = \text{watch} \mid y = \text{SPAM}) = \frac{0}{7}$								
$P(x_i = \text{buy} \mid y = \text{SPAM}) = \frac{1}{7}$								
$P(x_i = \text{cheap} \mid y = \text{SPAM}) = \frac{2}{7}$								

x₁, x₂, x₃, ..., x_{N-2}, x_{N-1}, x_N - feature vectors (in **bold**) | **y₁, y₂, y₃, ..., y_{N-2}, y_{N-1}, y_N** - labels

Spam Detection: Testing Classifier

Test set	Vocabulary V							Learned $h()$
	I	rolex	own	replica	watch	buy	cheap	
x_8	0	1	0	1	0	1	1	$y_8 = \text{SPAM}$
	buy cheap rolex replica rolex							
x_9	1	1	1	0	1	0	1	$y_9 = \text{HAM}$
	I own cheap rolex watch							
x_{10}	0	0	0	1	0	0	0	$y_{10} = \text{HAM}$
	replica							
Testing								$P(y = \text{HAM}) = \frac{5}{7}$ $P(y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = I y = \text{HAM}) = \frac{5}{15}$ $P(x_i = \text{rolex} y = \text{HAM}) = \frac{1}{15}$ $P(x_i = \text{own} y = \text{HAM}) = \frac{4}{15}$ $P(x_i = \text{replica} y = \text{HAM}) = \frac{1}{15}$ $P(x_i = \text{watch} y = \text{HAM}) = \frac{3}{15}$ $P(x_i = \text{buy} y = \text{HAM}) = \frac{0}{15}$ $P(x_i = \text{cheap} y = \text{HAM}) = \frac{1}{15}$ $P(x_i = I y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = \text{rolex} y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = \text{own} y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = \text{replica} y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = \text{watch} y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = \text{buy} y = \text{SPAM}) = \frac{1}{7}$ $P(x_i = \text{cheap} y = \text{SPAM}) = \frac{2}{7}$
<p>Which probability is higher? Which y maximizes $P()$?</p> $P(y = \text{HAM} x_8) \propto P(y = \text{HAM}) * \prod_{i=1}^5 P(x_i y = \text{HAM}) =$ $P(y = \text{HAM}) * P(x_1 = \text{buy} y = \text{HAM}) * P(x_2 = \text{cheap} y = \text{HAM}) * P(x_3 = \text{rolex} y = \text{HAM}) * P(x_4 = \text{replica} y = \text{HAM}) * P(x_5 = \text{rolex} y = \text{HAM})$								

$x_1, x_2, x_3, \dots, x_{N-2}, x_{N-1}, x_N$ - feature vectors (in **bold**) | $y_1, y_2, y_3, \dots, y_{N-2}, y_{N-1}, y_N$ - labels

Spam Detection: Testing Classifier

Test set	Vocabulary V							Learned $h()$
	I	rolex	own	replica	watch	buy	cheap	
x_8	0	1	0	1	0	1	1	$y_8 = \text{SPAM}$
	buy cheap rolex replica rolex							
x_9	1	1	1	0	1	0	1	$y_9 = \text{HAM}$
	I own cheap rolex watch							
x_{10}	0	0	0	1	0	0	0	$y_{10} = \text{HAM}$
	replica							
Testing	Which probability is higher? Which y maximizes $P()$?							
	$P(y = \text{HAM} \mid x_8) \propto P(y = \text{HAM}) * \prod_{i=1}^5 P(x_i \mid y = \text{HAM}) =$ $\frac{5}{7} * \frac{0}{15} * \frac{1}{15} * \frac{1}{15} * \frac{1}{15} * \frac{1}{15} = 0$							
	$P(y = \text{SPAM} \mid x_8) \propto P(y = \text{SPAM}) * \prod_{i=1}^5 P(x_i \mid y = \text{SPAM}) =$ $\frac{2}{7} * \frac{5}{7} * \frac{1}{7} * \frac{2}{7} * \frac{0}{7} * \frac{2}{7} = \frac{20}{7^5}$							

$x_1, x_2, x_3, \dots, x_{N-2}, x_{N-1}, x_N$ - feature vectors (in bold) | $y_1, y_2, y_3, \dots, y_{N-2}, y_{N-1}, y_N$ - labels

Spam Detection: Testing Classifier

Test set	Vocabulary V							Learned $h()$
	I	rolex	own	replica	watch	buy	cheap	
x_8	0	1	0	1	0	1	1	$y_8 = \text{SPAM}$
	buy cheap rolex replica rolex							
x_9	1	1	1	0	1	0	1	$y_9 = \text{HAM}$
	I own cheap rolex watch							
x_{10}	0	0	0	1	0	0	0	$y_{10} = \text{HAM}$
	replica							

Testing
Which probability is higher? Which y maximizes $P()$?
$P(y = \text{SPAM} \mid x_8) \propto P(y = \text{SPAM}) * \prod_{i=1}^5 P(x_i \mid y = \text{SPAM}) =$ $P(y = \text{SPAM}) * P(x_1 = \text{buy} \mid y = \text{SPAM}) * P(x_2 = \text{cheap} \mid y = \text{SPAM}) * P(x_3 = \text{rolex} \mid y = \text{SPAM}) * P(x_4 = \text{replica} \mid y = \text{SPAM}) * P(x_5 = \text{rolex} \mid y = \text{SPAM})$

$P(y = \text{HAM}) = \frac{5}{7} \quad P(y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = I \mid y = \text{HAM}) = \frac{5}{15}$ $P(x_i = \text{rolex} \mid y = \text{HAM}) = \frac{1}{15}$ $P(x_i = \text{own} \mid y = \text{HAM}) = \frac{4}{15}$ $P(x_i = \text{replica} \mid y = \text{HAM}) = \frac{1}{15}$ $P(x_i = \text{watch} \mid y = \text{HAM}) = \frac{3}{15}$ $P(x_i = \text{buy} \mid y = \text{HAM}) = \frac{0}{15}$ $P(x_i = \text{cheap} \mid y = \text{HAM}) = \frac{1}{15}$ $P(x_i = I \mid y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = \text{rolex} \mid y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = \text{own} \mid y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = \text{replica} \mid y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = \text{watch} \mid y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = \text{buy} \mid y = \text{SPAM}) = \frac{1}{7}$ $P(x_i = \text{cheap} \mid y = \text{SPAM}) = \frac{2}{7}$
--

$x_1, x_2, x_3, \dots, x_{N-2}, x_{N-1}, x_N$ - feature vectors (in **bold**) | $y_1, y_2, y_3, \dots, y_{N-2}, y_{N-1}, y_N$ - labels

Spam Detection: Testing Classifier

Test set

Vocabulary V

	I	rolex	own	replica	watch	buy	cheap
x_8	0	1	0	1	0	1	1
	buy cheap rolex replica rolex						
x_9	1	1	1	0	1	0	1
	I own cheap rolex watch						
x_{10}	0	0	0	1	0	0	0
	replica						

$y_8 = \text{SPAM}$

$y_9 = \text{HAM}$

$y_{10} = \text{HAM}$

Learned $h()$

$P(y = \text{HAM}) = \frac{5}{7}$ $P(y = \text{SPAM}) = \frac{2}{7}$

$P(x_i = I | y = \text{HAM}) = \frac{5}{15}$
 $P(x_i = \text{rolex} | y = \text{HAM}) = \frac{1}{15}$
 $P(x_i = \text{own} | y = \text{HAM}) = \frac{4}{15}$
 $P(x_i = \text{replica} | y = \text{HAM}) = \frac{1}{15}$
 $P(x_i = \text{watch} | y = \text{HAM}) = \frac{3}{15}$
 $P(x_i = \text{buy} | y = \text{HAM}) = \frac{0}{15}$
 $P(x_i = \text{cheap} | y = \text{HAM}) = \frac{1}{15}$

$P(x_i = I | y = \text{SPAM}) = \frac{0}{7}$
 $P(x_i = \text{rolex} | y = \text{SPAM}) = \frac{2}{7}$
 $P(x_i = \text{own} | y = \text{SPAM}) = \frac{0}{7}$
 $P(x_i = \text{replica} | y = \text{SPAM}) = \frac{2}{7}$
 $P(x_i = \text{watch} | y = \text{SPAM}) = \frac{0}{7}$
 $P(x_i = \text{buy} | y = \text{SPAM}) = \frac{1}{7}$
 $P(x_i = \text{cheap} | y = \text{SPAM}) = \frac{2}{7}$

Testing

Which probability is higher? Which y maximizes $P()$?

$$P(y = \text{SPAM} | x_8) \propto P(y = \text{SPAM}) * \prod_{i=1}^5 P(x_i | y = \text{SPAM}) =$$

$$\frac{2}{7} * \frac{1}{7} * \frac{2}{7} * \frac{2}{7} * \frac{2}{7} * \frac{2}{7} \approx 0.00027$$

$x_1, x_2, x_3, \dots, x_{N-2}, x_{N-1}, x_N$ - feature vectors (in **bold**) | $y_1, y_2, y_3, \dots, y_{N-2}, y_{N-1}, y_N$ - labels

Spam Detection: Testing Classifier

Test set	Vocabulary V							Learned $h()$
	I	rolex	own	replica	watch	buy	cheap	
x_8	0	1	0	1	0	1	1	$y_8 = \text{SPAM}$
	buy cheap rolex replica rolex							
x_9	1	1	1	0	1	0	1	$y_9 = \text{HAM}$
	I own cheap rolex watch							
x_{10}	0	0	0	1	0	0	0	$y_{10} = \text{HAM}$
	replica							
Testing	Which probability is higher? Which y maximizes $P()$?							
	$P(y = \text{HAM} \mid x_8) = 0$							
	$P(y = \text{SPAM} \mid x_8) \approx 0.00027$							
	For document x_8 $y = \text{SPAM}$ maximizes $P()$. Class = SPAM .							
	$P(y = \text{HAM}) = \frac{5}{7}$ $P(y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = I \mid y = \text{HAM}) = \frac{5}{15}$ $P(x_i = \text{rolex} \mid y = \text{HAM}) = \frac{1}{15}$ $P(x_i = \text{own} \mid y = \text{HAM}) = \frac{4}{15}$ $P(x_i = \text{replica} \mid y = \text{HAM}) = \frac{1}{15}$ $P(x_i = \text{watch} \mid y = \text{HAM}) = \frac{3}{15}$ $P(x_i = \text{buy} \mid y = \text{HAM}) = \frac{0}{15}$ $P(x_i = \text{cheap} \mid y = \text{HAM}) = \frac{1}{15}$ $P(x_i = I \mid y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = \text{rolex} \mid y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = \text{own} \mid y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = \text{replica} \mid y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = \text{watch} \mid y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = \text{buy} \mid y = \text{SPAM}) = \frac{1}{7}$ $P(x_i = \text{cheap} \mid y = \text{SPAM}) = \frac{2}{7}$							

$x_1, x_2, x_3, \dots, x_{N-2}, x_{N-1}, x_N$ - feature vectors (in **bold**) | $y_1, y_2, y_3, \dots, y_{N-2}, y_{N-1}, y_N$ - labels

Spam Detection: Testing Classifier

Test set

Vocabulary V

	I	rolex	own	replica	watch	buy	cheap
x_8	0	1	0	1	0	1	1
	buy cheap rolex replica rolex						
x_9	1	1	1	0	1	0	1
	I own cheap rolex watch						
x_{10}	0	0	0	1	0	0	0
	replica						

$y_8 = \text{SPAM}$

$y_9 = \text{HAM}$

$y_{10} = \text{HAM}$

Learned $h()$

$$P(y = \text{HAM}) = \frac{5}{7} \quad P(y = \text{SPAM}) = \frac{2}{7}$$

$$P(x_i = I | y = \text{HAM}) = \frac{5}{15}$$

$$P(x_i = rolex | y = \text{HAM}) = \frac{1}{15}$$

$$P(x_i = own | y = \text{HAM}) = \frac{4}{15}$$

$$P(x_i = replica | y = \text{HAM}) = \frac{1}{15}$$

$$P(x_i = watch | y = \text{HAM}) = \frac{3}{15}$$

$$P(x_i = buy | y = \text{HAM}) = \frac{0}{15}$$

$$P(x_i = cheap | y = \text{HAM}) = \frac{1}{15}$$

$$P(x_i = I | y = \text{SPAM}) = \frac{0}{7}$$

$$P(x_i = rolex | y = \text{SPAM}) = \frac{2}{7}$$

$$P(x_i = own | y = \text{SPAM}) = \frac{0}{7}$$

$$P(x_i = replica | y = \text{SPAM}) = \frac{2}{7}$$

$$P(x_i = watch | y = \text{SPAM}) = \frac{0}{7}$$

$$P(x_i = buy | y = \text{SPAM}) = \frac{1}{7}$$

$$P(x_i = cheap | y = \text{SPAM}) = \frac{2}{7}$$

Testing

Which probability is higher? Which y maximizes $P()$?

For document x_8 $y = \text{SPAM}$ maximizes $P()$. Class = **SPAM**.

Correct classification!

$x_1, x_2, x_3, \dots, x_{N-2}, x_{N-1}, x_N$ - feature vectors (in **bold**) | $y_1, y_2, y_3, \dots, y_{N-2}, y_{N-1}, y_N$ - labels

Spam Detection: Testing Classifier

Test set	Vocabulary V						Learned $h()$
	I	rolex	own	replica	watch	buy	cheap
x_8	0	1	0	1	0	1	1
	buy cheap rolex replica rolex						$y_8 = \text{SPAM}$
x_9	1	1	1	0	1	0	1
	I own cheap rolex watch						$y_9 = \text{HAM}$
x_{10}	0	0	0	1	0	0	0
	replica						$y_{10} = \text{HAM}$
Testing	$y_{MAP} \propto \underset{y \in Y}{\operatorname{argmax}} \left(P(y) * \prod_{i=1}^N P(x_i y) \right)$ <p>category/class = $h(x_9)$</p>						$P(y = \text{HAM}) = \frac{5}{7} \quad P(y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = I y = \text{HAM}) = \frac{5}{15}$ $P(x_i = rolex y = \text{HAM}) = \frac{1}{15}$ $P(x_i = own y = \text{HAM}) = \frac{4}{15}$ $P(x_i = replica y = \text{HAM}) = \frac{1}{15}$ $P(x_i = watch y = \text{HAM}) = \frac{3}{15}$ $P(x_i = buy y = \text{HAM}) = \frac{0}{15}$ $P(x_i = cheap y = \text{HAM}) = \frac{1}{15}$ $P(x_i = I y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = rolex y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = own y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = replica y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = watch y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = buy y = \text{SPAM}) = \frac{1}{7}$ $P(x_i = cheap y = \text{SPAM}) = \frac{2}{7}$

$x_1, x_2, x_3, \dots, x_{N-2}, x_{N-1}, x_N$ - feature vectors (in **bold**) | $y_1, y_2, y_3, \dots, y_{N-2}, y_{N-1}, y_N$ - labels

Spam Detection: Testing Classifier

Test set	Vocabulary V						Learned $h()$
	I	rolex	own	replica	watch	buy	cheap
x_8	0	1	0	1	0	1	1
	buy cheap rolex replica rolex						$y_8 = \text{SPAM}$
x_9	1	1	1	0	1	0	1
	I own cheap rolex watch						$y_9 = \text{HAM}$
x_{10}	0	0	0	1	0	0	0
	replica						$y_{10} = \text{HAM}$
Testing	$y_{MAP} \propto \underset{y \in Y}{\operatorname{argmax}} \left(P(y) * \prod_{i=1}^N P(x_i y) \right)$ <p>category/class = $h(\text{I own cheap rolex watch})$</p>						$P(y = \text{HAM}) = \frac{5}{7} \quad P(y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = I y = \text{HAM}) = \frac{5}{15}$ $P(x_i = rolex y = \text{HAM}) = \frac{1}{15}$ $P(x_i = own y = \text{HAM}) = \frac{4}{15}$ $P(x_i = replica y = \text{HAM}) = \frac{1}{15}$ $P(x_i = watch y = \text{HAM}) = \frac{3}{15}$ $P(x_i = buy y = \text{HAM}) = \frac{0}{15}$ $P(x_i = cheap y = \text{HAM}) = \frac{1}{15}$ $P(x_i = I y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = rolex y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = own y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = replica y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = watch y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = buy y = \text{SPAM}) = \frac{1}{7}$ $P(x_i = cheap y = \text{SPAM}) = \frac{2}{7}$

$x_1, x_2, x_3, \dots, x_{N-2}, x_{N-1}, x_N$ - feature vectors (in **bold**) | $y_1, y_2, y_3, \dots, y_{N-2}, y_{N-1}, y_N$ - labels

Spam Detection: Testing Classifier

Test set	Vocabulary V						Learned $h()$
	I	rolex	own	replica	watch	buy	cheap
x_8	0	1	0	1	0	1	1
	buy cheap rolex replica rolex						$y_8 = \text{SPAM}$
x_9	1	1	1	0	1	0	1
	I own cheap rolex watch						$y_9 = \text{HAM}$
x_{10}	0	0	0	1	0	0	0
	replica						$y_{10} = \text{HAM}$
Testing	$y_{MAP} \propto \underset{y \in Y}{\operatorname{argmax}} \left(P(y) * \prod_{i=1}^N P(x_i y) \right)$						$\text{category/class} = h(\text{1, 1, 1, 0, 1, 0, 1})$
	1	1	1	0	1	0	1

$x_1, x_2, x_3, \dots, x_{N-2}, x_{N-1}, x_N$ - feature vectors (in **bold**) | $y_1, y_2, y_3, \dots, y_{N-2}, y_{N-1}, y_N$ - labels

Spam Detection: Testing Classifier

Test set	Vocabulary V							Learned $h()$
x_8	I	rolex	own	replica	watch	buy	cheap	$y_8 = \text{SPAM}$
	0	1	0	1	0	1	1	
	buy cheap rolex replica rolex							
x_9	1	1	1	0	1	0	1	$y_9 = \text{HAM}$
	I own cheap rolex watch							
x_{10}	0	0	0	1	0	0	0	$y_{10} = \text{HAM}$
	replica							
Testing	Which probability is higher? Which y maximizes $P()$?							
	$P(y = \text{HAM} \mid x_9) \propto P(y = \text{HAM}) * \prod_{i=1}^1 P(x_i \mid y = \text{HAM})$							
	$P(y = \text{SPAM} \mid x_9) \propto P(y = \text{SPAM}) * \prod_{i=1}^1 P(x_i \mid y = \text{SPAM})$							
	$P(y = \text{HAM}) = \frac{5}{7} \quad P(y = \text{SPAM}) = \frac{2}{7}$							
	$P(x_i = I \mid y = \text{HAM}) = \frac{5}{15}$							
	$P(x_i = \text{rolex} \mid y = \text{HAM}) = \frac{1}{15}$							
	$P(x_i = \text{own} \mid y = \text{HAM}) = \frac{4}{15}$							
	$P(x_i = \text{replica} \mid y = \text{HAM}) = \frac{1}{15}$							
	$P(x_i = \text{watch} \mid y = \text{HAM}) = \frac{3}{15}$							
	$P(x_i = \text{buy} \mid y = \text{HAM}) = \frac{0}{15}$							
	$P(x_i = \text{cheap} \mid y = \text{HAM}) = \frac{1}{15}$							
	$P(x_i = I \mid y = \text{SPAM}) = \frac{0}{7}$							
	$P(x_i = \text{rolex} \mid y = \text{SPAM}) = \frac{2}{7}$							
	$P(x_i = \text{own} \mid y = \text{SPAM}) = \frac{0}{7}$							
	$P(x_i = \text{replica} \mid y = \text{SPAM}) = \frac{2}{7}$							
	$P(x_i = \text{watch} \mid y = \text{SPAM}) = \frac{0}{7}$							
	$P(x_i = \text{buy} \mid y = \text{SPAM}) = \frac{1}{7}$							
	$P(x_i = \text{cheap} \mid y = \text{SPAM}) = \frac{2}{7}$							

$x_1, x_2, x_3, \dots, x_{N-2}, x_{N-1}, x_N$ - feature vectors (in **bold**) | $y_1, y_2, y_3, \dots, y_{N-2}, y_{N-1}, y_N$ - labels

Spam Detection: Testing Classifier

Test set	Vocabulary V							Learned $h()$
	I	rolex	own	replica	watch	buy	cheap	
x_8	0	1	0	1	0	1	1	$y_8 = \text{SPAM}$
	buy cheap rolex replica rolex							
x_9	1	1	1	0	1	0	1	$y_9 = \text{HAM}$
	I own cheap rolex watch							
x_{10}	0	0	0	1	0	0	0	$y_{10} = \text{HAM}$
	replica							
Testing								
Which probability is higher? Which y maximizes $P()$?								
$P(y = \text{HAM} \mid x_9) \propto P(y = \text{HAM}) * \prod_{i=1}^5 P(x_i \mid y = \text{HAM}) =$ $P(y = \text{HAM}) * P(x_1 = I \mid y = \text{HAM}) * P(x_2 = \text{own} \mid y = \text{HAM}) * P(x_3 = \text{cheap} \mid y = \text{HAM}) * P(x_4 = \text{rolex} \mid y = \text{HAM}) * P(x_5 = \text{watch} \mid y = \text{HAM})$								

$P(y = \text{HAM}) = \frac{5}{7}$	$P(y = \text{SPAM}) = \frac{2}{7}$
$P(x_i = I \mid y = \text{HAM}) = \frac{5}{15}$	
$P(x_i = \text{rolex} \mid y = \text{HAM}) = \frac{1}{15}$	
$P(x_i = \text{own} \mid y = \text{HAM}) = \frac{4}{15}$	
$P(x_i = \text{replica} \mid y = \text{HAM}) = \frac{1}{15}$	
$P(x_i = \text{watch} \mid y = \text{HAM}) = \frac{3}{15}$	
$P(x_i = \text{buy} \mid y = \text{HAM}) = \frac{0}{15}$	
$P(x_i = \text{cheap} \mid y = \text{HAM}) = \frac{1}{15}$	
$P(x_i = I \mid y = \text{SPAM}) = \frac{0}{7}$	
$P(x_i = \text{rolex} \mid y = \text{SPAM}) = \frac{2}{7}$	
$P(x_i = \text{own} \mid y = \text{SPAM}) = \frac{0}{7}$	
$P(x_i = \text{replica} \mid y = \text{SPAM}) = \frac{2}{7}$	
$P(x_i = \text{watch} \mid y = \text{SPAM}) = \frac{0}{7}$	
$P(x_i = \text{buy} \mid y = \text{SPAM}) = \frac{1}{7}$	
$P(x_i = \text{cheap} \mid y = \text{SPAM}) = \frac{2}{7}$	

$x_1, x_2, x_3, \dots, x_{N-2}, x_{N-1}, x_N$ - feature vectors (in **bold**) | $y_1, y_2, y_3, \dots, y_{N-2}, y_{N-1}, y_N$ - labels

Spam Detection: Testing Classifier

Test set		Learned h()																
	Vocabulary V																	
	<table border="1" style="margin: auto;"> <tr> <th></th> <th>I</th> <th>rolex</th> <th>own</th> <th>replica</th> <th>watch</th> <th>buy</th> <th>cheap</th> </tr> <tr> <td>x₈</td> <td>0</td> <td>1</td> <td>0</td> <td>1</td> <td>0</td> <td>1</td> <td>1</td> </tr> </table> <p style="text-align: center;">buy cheap rolex replica rolex</p>		I	rolex	own	replica	watch	buy	cheap	x₈	0	1	0	1	0	1	1	<div style="border: 1px solid black; padding: 5px; display: inline-block;">y₈=SPAM</div>
	I	rolex	own	replica	watch	buy	cheap											
x₈	0	1	0	1	0	1	1											
	<table border="1" style="margin: auto;"> <tr> <th></th> <th>1</th> <th>1</th> <th>1</th> <th>0</th> <th>1</th> <th>0</th> <th>1</th> </tr> <tr> <td>x₉</td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> </tr> </table> <p style="text-align: center;">I own cheap rolex watch</p>		1	1	1	0	1	0	1	x₉								<div style="border: 1px solid black; padding: 5px; display: inline-block;">y₉=HAM</div>
	1	1	1	0	1	0	1											
x₉																		
	<table border="1" style="margin: auto;"> <tr> <th></th> <th>0</th> <th>0</th> <th>0</th> <th>1</th> <th>0</th> <th>0</th> <th>0</th> </tr> <tr> <td>x₁₀</td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> </tr> </table> <p style="text-align: center;">replica</p>		0	0	0	1	0	0	0	x₁₀								<div style="border: 1px solid black; padding: 5px; display: inline-block;">y₁₀=HAM</div>
	0	0	0	1	0	0	0											
x₁₀																		
Testing	<p>Which probability is higher? Which y maximizes P()?</p> $P(y = \text{HAM} \mid x_9) \propto P(y = \text{HAM}) * \prod_{i=1}^5 P(x_i \mid y = \text{HAM}) =$ $\frac{5}{7} * \frac{5}{15} * \frac{4}{15} * \frac{1}{15} * \frac{1}{15} * \frac{3}{15} \approx 0.000056$																	

Learned h()

$P(y = \text{HAM}) = \frac{5}{7}$ $P(y = \text{SPAM}) = \frac{2}{7}$

$P(x_i = I \mid y = \text{HAM}) = \frac{5}{15}$ $P(x_i = I \mid y = \text{SPAM}) = \frac{0}{7}$

$P(x_i = rolex \mid y = \text{HAM}) = \frac{1}{15}$ $P(x_i = rolex \mid y = \text{SPAM}) = \frac{2}{7}$

$P(x_i = own \mid y = \text{HAM}) = \frac{4}{15}$ $P(x_i = own \mid y = \text{SPAM}) = \frac{0}{7}$

$P(x_i = replica \mid y = \text{HAM}) = \frac{1}{15}$ $P(x_i = replica \mid y = \text{SPAM}) = \frac{2}{7}$

$P(x_i = watch \mid y = \text{HAM}) = \frac{3}{15}$ $P(x_i = watch \mid y = \text{SPAM}) = \frac{0}{7}$

$P(x_i = buy \mid y = \text{HAM}) = \frac{0}{15}$ $P(x_i = buy \mid y = \text{SPAM}) = \frac{1}{7}$

$P(x_i = cheap \mid y = \text{HAM}) = \frac{1}{15}$ $P(x_i = cheap \mid y = \text{SPAM}) = \frac{2}{7}$

x₁, x₂, x₃, ..., x_{N-2}, x_{N-1}, x_N - feature vectors (in **bold**) | **y₁, y₂, y₃, ..., y_{N-2}, y_{N-1}, y_N** - labels

Spam Detection: Testing Classifier

Test set

Vocabulary V

	I	rolex	own	replica	watch	buy	cheap
x_8	0	1	0	1	0	1	1

buy cheap rolex replica rolex

$y_8 = \text{SPAM}$

x_9	1	1	1	0	1	0	1
-------	---	---	---	---	---	---	---

I own cheap rolex watch

$y_9 = \text{HAM}$

x_{10}	0	0	0	1	0	0	0
----------	---	---	---	---	---	---	---

replica

$y_{10} = \text{HAM}$

Testing

Which probability is higher? Which y maximizes $P()$?

$$P(y = \text{SPAM} | x_9) \propto P(y = \text{SPAM}) * \prod_{i=1}^5 P(x_i | y = \text{SPAM}) =$$

$$P(y = \text{SPAM}) * P(x_1 = I | y = \text{SPAM}) * P(x_2 = \text{own} | y = \text{SPAM}) * P(x_3 = \text{cheap} | y = \text{SPAM}) * P(x_4 = \text{rolex} | y = \text{SPAM}) * P(x_5 = \text{watch} | y = \text{SPAM})$$

Learned $h()$

$$P(y = \text{HAM}) = \frac{5}{7} \quad P(y = \text{SPAM}) = \frac{2}{7}$$

$$P(x_i = I | y = \text{HAM}) = \frac{5}{15}$$

$$P(x_i = \text{rolex} | y = \text{HAM}) = \frac{1}{15}$$

$$P(x_i = \text{own} | y = \text{HAM}) = \frac{4}{15}$$

$$P(x_i = \text{replica} | y = \text{HAM}) = \frac{1}{15}$$

$$P(x_i = \text{watch} | y = \text{HAM}) = \frac{3}{15}$$

$$P(x_i = \text{buy} | y = \text{HAM}) = \frac{0}{15}$$

$$P(x_i = \text{cheap} | y = \text{HAM}) = \frac{1}{15}$$

$$P(x_i = I | y = \text{SPAM}) = \frac{0}{7}$$

$$P(x_i = \text{rolex} | y = \text{SPAM}) = \frac{2}{7}$$

$$P(x_i = \text{own} | y = \text{SPAM}) = \frac{0}{7}$$

$$P(x_i = \text{replica} | y = \text{SPAM}) = \frac{2}{7}$$

$$P(x_i = \text{watch} | y = \text{SPAM}) = \frac{0}{7}$$

$$P(x_i = \text{buy} | y = \text{SPAM}) = \frac{1}{7}$$

$$P(x_i = \text{cheap} | y = \text{SPAM}) = \frac{2}{7}$$

$x_1, x_2, x_3, \dots, x_{N-2}, x_{N-1}, x_N$ - feature vectors (in **bold**) | $y_1, y_2, y_3, \dots, y_{N-2}, y_{N-1}, y_N$ - labels

Spam Detection: Testing Classifier

Test set

Vocabulary V

	I	rolex	own	replica	watch	buy	cheap
x_8	0	1	0	1	0	1	1
	buy cheap rolex replica rolex						
x_9	1	1	1	0	1	0	1
	I own cheap rolex watch						
x_{10}	0	0	0	1	0	0	0
	replica						

$y_8 = \text{SPAM}$

$y_9 = \text{HAM}$

$y_{10} = \text{HAM}$

Learned $h()$

$$P(y = \text{HAM}) = \frac{5}{7} \quad P(y = \text{SPAM}) = \frac{2}{7}$$

$$P(x_i = I | y = \text{HAM}) = \frac{5}{15}$$

$$P(x_i = \text{rolex} | y = \text{HAM}) = \frac{1}{15}$$

$$P(x_i = \text{own} | y = \text{HAM}) = \frac{4}{15}$$

$$P(x_i = \text{replica} | y = \text{HAM}) = \frac{1}{15}$$

$$P(x_i = \text{watch} | y = \text{HAM}) = \frac{3}{15}$$

$$P(x_i = \text{buy} | y = \text{HAM}) = \frac{0}{15}$$

$$P(x_i = \text{cheap} | y = \text{HAM}) = \frac{1}{15}$$

$$P(x_i = I | y = \text{SPAM}) = \frac{0}{7}$$

$$P(x_i = \text{rolex} | y = \text{SPAM}) = \frac{2}{7}$$

$$P(x_i = \text{own} | y = \text{SPAM}) = \frac{0}{7}$$

$$P(x_i = \text{replica} | y = \text{SPAM}) = \frac{2}{7}$$

$$P(x_i = \text{watch} | y = \text{SPAM}) = \frac{0}{7}$$

$$P(x_i = \text{buy} | y = \text{SPAM}) = \frac{1}{7}$$

$$P(x_i = \text{cheap} | y = \text{SPAM}) = \frac{2}{7}$$

Testing

Which probability is higher? Which y maximizes $P()$?

$$P(y = \text{SPAM} | x_9) \propto P(y = \text{SPAM}) * \prod_{i=1}^5 P(x_i | y = \text{SPAM}) =$$

$$\frac{2}{7} * \frac{0}{7} * \frac{0}{7} * \frac{2}{7} * \frac{2}{7} * \frac{0}{7} = 0$$

$x_1, x_2, x_3, \dots, x_{N-2}, x_{N-1}, x_N$ - feature vectors (in **bold**) | $y_1, y_2, y_3, \dots, y_{N-2}, y_{N-1}, y_N$ - labels

Spam Detection: Testing Classifier

Test set	Vocabulary V							Learned $h()$
	I	rolex	own	replica	watch	buy	cheap	
x_8	0	1	0	1	0	1	1	$y_8 = \text{SPAM}$
	buy cheap rolex replica rolex							
x_9	1	1	1	0	1	0	1	$y_9 = \text{HAM}$
	I own cheap rolex watch							
x_{10}	0	0	0	1	0	0	0	$y_{10} = \text{HAM}$
	replica							
Testing	Which probability is higher? Which y maximizes $P()$?							
	$P(y = \text{HAM} \mid x_9) \approx 0.000056$							
	$P(y = \text{SPAM} \mid x_9) = 0$							
	For document x_8 $y = \text{HAM}$ maximizes $P()$. Class = HAM .							
	$P(y = \text{HAM}) = \frac{5}{7} \quad P(y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = I \mid y = \text{HAM}) = \frac{5}{15}$ $P(x_i = \text{rolex} \mid y = \text{HAM}) = \frac{1}{15}$ $P(x_i = \text{own} \mid y = \text{HAM}) = \frac{4}{15}$ $P(x_i = \text{replica} \mid y = \text{HAM}) = \frac{1}{15}$ $P(x_i = \text{watch} \mid y = \text{HAM}) = \frac{3}{15}$ $P(x_i = \text{buy} \mid y = \text{HAM}) = \frac{0}{15}$ $P(x_i = \text{cheap} \mid y = \text{HAM}) = \frac{1}{15}$ $P(x_i = I \mid y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = \text{rolex} \mid y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = \text{own} \mid y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = \text{replica} \mid y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = \text{watch} \mid y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = \text{buy} \mid y = \text{SPAM}) = \frac{1}{7}$ $P(x_i = \text{cheap} \mid y = \text{SPAM}) = \frac{2}{7}$							

$x_1, x_2, x_3, \dots, x_{N-2}, x_{N-1}, x_N$ - feature vectors (in **bold**) | $y_1, y_2, y_3, \dots, y_{N-2}, y_{N-1}, y_N$ - labels

Spam Detection: Testing Classifier

Test set

Vocabulary V

	I	rolex	own	replica	watch	buy	cheap
x_8	0	1	0	1	0	1	1
	buy cheap rolex replica rolex						
x_9	1	1	1	0	1	0	1
	I own cheap rolex watch						
x_{10}	0	0	0	1	0	0	0
	replica						

$y_8 = \text{SPAM}$

$y_9 = \text{HAM}$

$y_{10} = \text{HAM}$

Learned $h()$

$$P(y = \text{HAM}) = \frac{5}{7} \quad P(y = \text{SPAM}) = \frac{2}{7}$$

$$P(x_i = I | y = \text{HAM}) = \frac{5}{15}$$

$$P(x_i = \text{rolex} | y = \text{HAM}) = \frac{1}{15}$$

$$P(x_i = \text{own} | y = \text{HAM}) = \frac{4}{15}$$

$$P(x_i = \text{replica} | y = \text{HAM}) = \frac{1}{15}$$

$$P(x_i = \text{watch} | y = \text{HAM}) = \frac{3}{15}$$

$$P(x_i = \text{buy} | y = \text{HAM}) = \frac{0}{15}$$

$$P(x_i = \text{cheap} | y = \text{HAM}) = \frac{1}{15}$$

$$P(x_i = I | y = \text{SPAM}) = \frac{0}{7}$$

$$P(x_i = \text{rolex} | y = \text{SPAM}) = \frac{2}{7}$$

$$P(x_i = \text{own} | y = \text{SPAM}) = \frac{0}{7}$$

$$P(x_i = \text{replica} | y = \text{SPAM}) = \frac{2}{7}$$

$$P(x_i = \text{watch} | y = \text{SPAM}) = \frac{0}{7}$$

$$P(x_i = \text{buy} | y = \text{SPAM}) = \frac{1}{7}$$

$$P(x_i = \text{cheap} | y = \text{SPAM}) = \frac{2}{7}$$

Testing

Which probability is higher? Which y maximizes $P()$?

For document x_9 , $y = \text{HAM}$ maximizes $P()$. **Class = HAM.**

Correct classification!

$x_1, x_2, x_3, \dots, x_{N-2}, x_{N-1}, x_N$ - feature vectors (in **bold**) | $y_1, y_2, y_3, \dots, y_{N-2}, y_{N-1}, y_N$ - labels

Spam Detection: Testing Classifier

Test set	Vocabulary V						Learned $h()$
	I	rolex	own	replica	watch	buy	cheap
x_8	0	1	0	1	0	1	1
	buy cheap rolex replica rolex						$y_8 = \text{SPAM}$
x_9	1	1	1	0	1	0	1
	I own cheap rolex watch						$y_9 = \text{HAM}$
x_{10}	0	0	0	1	0	0	0
	replica						$y_{10} = \text{HAM}$
Testing	$y_{MAP} \propto \underset{y \in Y}{\operatorname{argmax}} \left(P(y) * \prod_{i=1}^N P(x_i y) \right)$ <p>category/class = $h(x_{10})$</p>						$P(y = \text{HAM}) = \frac{5}{7} \quad P(y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = I y = \text{HAM}) = \frac{5}{15}$ $P(x_i = rolex y = \text{HAM}) = \frac{1}{15}$ $P(x_i = own y = \text{HAM}) = \frac{4}{15}$ $P(x_i = replica y = \text{HAM}) = \frac{1}{15}$ $P(x_i = watch y = \text{HAM}) = \frac{3}{15}$ $P(x_i = buy y = \text{HAM}) = \frac{0}{15}$ $P(x_i = cheap y = \text{HAM}) = \frac{1}{15}$ $P(x_i = I y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = rolex y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = own y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = replica y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = watch y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = buy y = \text{SPAM}) = \frac{1}{7}$ $P(x_i = cheap y = \text{SPAM}) = \frac{2}{7}$

$x_1, x_2, x_3, \dots, x_{N-2}, x_{N-1}, x_N$ - feature vectors (in **bold**) | $y_1, y_2, y_3, \dots, y_{N-2}, y_{N-1}, y_N$ - labels

Spam Detection: Testing Classifier

Test set	Vocabulary V						Learned $h()$
	I	rolex	own	replica	watch	buy	cheap
x_8	0	1	0	1	0	1	1
	buy cheap rolex replica rolex						$y_8 = \text{SPAM}$
x_9	1	1	1	0	1	0	1
	I own cheap rolex watch						$y_9 = \text{HAM}$
x_{10}	0	0	0	1	0	0	0
	replica						$y_{10} = \text{HAM}$
Testing	$y_{MAP} \propto \underset{y \in Y}{\operatorname{argmax}} \left(P(y) * \prod_{i=1}^N P(x_i y) \right)$ <p>category/class = $h(\text{replica})$</p>						$P(y = \text{HAM}) = \frac{5}{7} \quad P(y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = I y = \text{HAM}) = \frac{5}{15}$ $P(x_i = rolex y = \text{HAM}) = \frac{1}{15}$ $P(x_i = own y = \text{HAM}) = \frac{4}{15}$ $P(x_i = replica y = \text{HAM}) = \frac{1}{15}$ $P(x_i = watch y = \text{HAM}) = \frac{3}{15}$ $P(x_i = buy y = \text{HAM}) = \frac{0}{15}$ $P(x_i = cheap y = \text{HAM}) = \frac{1}{15}$ $P(x_i = I y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = rolex y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = own y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = replica y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = watch y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = buy y = \text{SPAM}) = \frac{1}{7}$ $P(x_i = cheap y = \text{SPAM}) = \frac{2}{7}$

$x_1, x_2, x_3, \dots, x_{N-2}, x_{N-1}, x_N$ - feature vectors (in **bold**) | $y_1, y_2, y_3, \dots, y_{N-2}, y_{N-1}, y_N$ - labels

Spam Detection: Testing Classifier

Test set	Vocabulary V							Learned $h()$
	I	rolex	own	replica	watch	buy	cheap	
x_8	0	1	0	1	0	1	1	$y_8 = \text{SPAM}$
	buy cheap rolex replica rolex							
x_9	1	1	1	0	1	0	1	$y_9 = \text{HAM}$
	I own cheap rolex watch							
x_{10}	0	0	0	1	0	0	0	$y_{10} = \text{HAM}$
	replica							
Testing								
$y_{MAP} \propto \underset{y \in Y}{\operatorname{argmax}} \left(P(y) * \prod_{i=1}^N P(x_i y) \right)$								
category/class = $h(\begin{array}{ c c c c c c c } \hline 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ \hline \end{array})$								

$P(y = \text{HAM}) = \frac{5}{7}$	$P(y = \text{SPAM}) = \frac{2}{7}$
$P(x_i = I y = \text{HAM}) = \frac{5}{15}$	
$P(x_i = \text{rolex} y = \text{HAM}) = \frac{1}{15}$	
$P(x_i = \text{own} y = \text{HAM}) = \frac{4}{15}$	
$P(x_i = \text{replica} y = \text{HAM}) = \frac{1}{15}$	
$P(x_i = \text{watch} y = \text{HAM}) = \frac{3}{15}$	
$P(x_i = \text{buy} y = \text{HAM}) = \frac{0}{15}$	
$P(x_i = \text{cheap} y = \text{HAM}) = \frac{1}{15}$	
$P(x_i = I y = \text{SPAM}) = \frac{0}{7}$	
$P(x_i = \text{rolex} y = \text{SPAM}) = \frac{2}{7}$	
$P(x_i = \text{own} y = \text{SPAM}) = \frac{0}{7}$	
$P(x_i = \text{replica} y = \text{SPAM}) = \frac{2}{7}$	
$P(x_i = \text{watch} y = \text{SPAM}) = \frac{0}{7}$	
$P(x_i = \text{buy} y = \text{SPAM}) = \frac{1}{7}$	
$P(x_i = \text{cheap} y = \text{SPAM}) = \frac{2}{7}$	

$x_1, x_2, x_3, \dots, x_{N-2}, x_{N-1}, x_N$ - feature vectors (in **bold**) | $y_1, y_2, y_3, \dots, y_{N-2}, y_{N-1}, y_N$ - labels

Spam Detection: Testing Classifier

Test set	Vocabulary V							Learned $h()$
	I	rolex	own	replica	watch	buy	cheap	
x_8	0	1	0	1	0	1	1	$y_8 = \text{SPAM}$
	buy cheap rolex replica rolex							
x_9	1	1	1	0	1	0	1	$y_9 = \text{HAM}$
	I own cheap rolex watch							
x_{10}	0	0	0	1	0	0	0	$y_{10} = \text{HAM}$
	replica							
Testing	Which probability is higher? Which y maximizes $P()$?							
	$P(y = \text{HAM} \mid x_{10}) \propto P(y = \text{HAM}) * \prod_{i=1}^1 P(x_i \mid y = \text{HAM})$							
	$P(y = \text{SPAM} \mid x_{10}) \propto P(y = \text{SPAM}) * \prod_{i=1}^1 P(x_i \mid y = \text{SPAM})$							
								$P(y = \text{HAM}) = \frac{5}{7} \quad P(y = \text{SPAM}) = \frac{2}{7}$
								$P(x_i = I \mid y = \text{HAM}) = \frac{5}{15}$
								$P(x_i = \text{rolex} \mid y = \text{HAM}) = \frac{1}{15}$
								$P(x_i = \text{own} \mid y = \text{HAM}) = \frac{4}{15}$
								$P(x_i = \text{replica} \mid y = \text{HAM}) = \frac{1}{15}$
								$P(x_i = \text{watch} \mid y = \text{HAM}) = \frac{3}{15}$
								$P(x_i = \text{buy} \mid y = \text{HAM}) = \frac{0}{15}$
								$P(x_i = \text{cheap} \mid y = \text{HAM}) = \frac{1}{15}$
								$P(x_i = I \mid y = \text{SPAM}) = \frac{0}{7}$
								$P(x_i = \text{rolex} \mid y = \text{SPAM}) = \frac{2}{7}$
								$P(x_i = \text{own} \mid y = \text{SPAM}) = \frac{0}{7}$
								$P(x_i = \text{replica} \mid y = \text{SPAM}) = \frac{2}{7}$
								$P(x_i = \text{watch} \mid y = \text{SPAM}) = \frac{0}{7}$
								$P(x_i = \text{buy} \mid y = \text{SPAM}) = \frac{1}{7}$
								$P(x_i = \text{cheap} \mid y = \text{SPAM}) = \frac{2}{7}$

$x_1, x_2, x_3, \dots, x_{N-2}, x_{N-1}, x_N$ - feature vectors (in **bold**) | $y_1, y_2, y_3, \dots, y_{N-2}, y_{N-1}, y_N$ - labels

Spam Detection: Testing Classifier

Test set		Learned h()							
	Vocabulary V <table border="1" style="margin: 10px auto; border-collapse: collapse;"> <tr> <td style="padding: 2px 10px;">I</td> <td style="padding: 2px 10px; color: red;">rolex</td> <td style="padding: 2px 10px;">own</td> <td style="padding: 2px 10px; color: red;">replica</td> <td style="padding: 2px 10px;">watch</td> <td style="padding: 2px 10px;">buy</td> <td style="padding: 2px 10px;">cheap</td> </tr> </table>	I	rolex	own	replica	watch	buy	cheap	
I	rolex	own	replica	watch	buy	cheap			
x₈	<table border="1" style="margin: 10px auto; border-collapse: collapse;"> <tr> <td style="padding: 2px 10px;">0</td> <td style="padding: 2px 10px; color: red;">1</td> <td style="padding: 2px 10px;">0</td> <td style="padding: 2px 10px; color: red;">1</td> <td style="padding: 2px 10px;">0</td> <td style="padding: 2px 10px;">1</td> <td style="padding: 2px 10px;">1</td> </tr> </table> <p style="text-align: center; color: red;">buy cheap rolex replica rolex</p>	0	1	0	1	0	1	1	y ₈ =SPAM
0	1	0	1	0	1	1			
x₉	<table border="1" style="margin: 10px auto; border-collapse: collapse;"> <tr> <td style="padding: 2px 10px;">1</td> <td style="padding: 2px 10px; color: red;">1</td> <td style="padding: 2px 10px;">1</td> <td style="padding: 2px 10px;">0</td> <td style="padding: 2px 10px;">1</td> <td style="padding: 2px 10px;">0</td> <td style="padding: 2px 10px;">1</td> </tr> </table> <p style="text-align: center; color: red;">I own cheap rolex watch</p>	1	1	1	0	1	0	1	y ₉ =HAM
1	1	1	0	1	0	1			
x₁₀	<table border="1" style="margin: 10px auto; border-collapse: collapse;"> <tr> <td style="padding: 2px 10px;">0</td> <td style="padding: 2px 10px;">0</td> <td style="padding: 2px 10px;">0</td> <td style="padding: 2px 10px; color: red;">1</td> <td style="padding: 2px 10px;">0</td> <td style="padding: 2px 10px;">0</td> <td style="padding: 2px 10px;">0</td> </tr> </table> <p style="text-align: center; color: red;">replica</p>	0	0	0	1	0	0	0	y ₁₀ =HAM
0	0	0	1	0	0	0			

Testing	
	<p>Which probability is higher? Which y maximizes P()?</p> $P(y = \text{HAM} x_{10}) \propto P(y = \text{HAM}) * \prod_{i=1}^1 P(x_i y = \text{HAM}) =$ $P(y = \text{HAM}) * P(x_1 = \text{replica} y = \text{HAM}) = \frac{5}{7} * \frac{1}{15} \approx 0.048$

Learned h()	
	$P(y = \text{HAM}) = \frac{5}{7} \quad P(y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = I y = \text{HAM}) = \frac{5}{15}$ $P(x_i = rolex y = \text{HAM}) = \frac{1}{15}$ $P(x_i = own y = \text{HAM}) = \frac{4}{15}$ $P(x_i = replica y = \text{HAM}) = \frac{1}{15}$ $P(x_i = watch y = \text{HAM}) = \frac{3}{15}$ $P(x_i = buy y = \text{HAM}) = \frac{0}{15}$ $P(x_i = cheap y = \text{HAM}) = \frac{1}{15}$ $P(x_i = I y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = rolex y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = own y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = replica y = \text{SPAM}) = \frac{2}{7}$ $P(x_i = watch y = \text{SPAM}) = \frac{0}{7}$ $P(x_i = buy y = \text{SPAM}) = \frac{1}{7}$ $P(x_i = cheap y = \text{SPAM}) = \frac{2}{7}$

x₁, x₂, x₃, ..., x_{N-2}, x_{N-1}, x_N - feature vectors (in **bold**) | **y₁, y₂, y₃, ..., y_{N-2}, y_{N-1}, y_N** - labels

Spam Detection: Testing Classifier

Test set		Learned h()							
	Vocabulary V <table border="1" style="margin: auto;"> <tr> <td>I</td> <td>rolex</td> <td>own</td> <td>replica</td> <td>watch</td> <td>buy</td> <td>cheap</td> </tr> </table>	I	rolex	own	replica	watch	buy	cheap	
I	rolex	own	replica	watch	buy	cheap			
x₈	<table border="1" style="margin: auto;"> <tr> <td>0</td> <td>1</td> <td>0</td> <td>1</td> <td>0</td> <td>1</td> <td>1</td> </tr> </table> <p style="text-align: center;">buy cheap rolex replica rolex</p>	0	1	0	1	0	1	1	y ₈ = SPAM
0	1	0	1	0	1	1			
x₉	<table border="1" style="margin: auto;"> <tr> <td>1</td> <td>1</td> <td>1</td> <td>0</td> <td>1</td> <td>0</td> <td>1</td> </tr> </table> <p style="text-align: center;">I own cheap rolex watch</p>	1	1	1	0	1	0	1	y ₉ = HAM
1	1	1	0	1	0	1			
x₁₀	<table border="1" style="margin: auto;"> <tr> <td>0</td> <td>0</td> <td>0</td> <td>1</td> <td>0</td> <td>0</td> <td>0</td> </tr> </table> <p style="text-align: center;">replica</p>	0	0	0	1	0	0	0	y ₁₀ = HAM
0	0	0	1	0	0	0			

Testing	
	<p>Which probability is higher? Which y maximizes P()? </p> $P(y = \text{SPAM} \mid x_{10}) \propto P(y = \text{SPAM}) * \prod_{i=1}^1 P(x_i \mid y = \text{SPAM}) =$ $P(y = \text{SPAM}) * P(x_1 = \text{replica} \mid y = \text{SPAM}) = \frac{2}{7} * \frac{2}{7} \approx \mathbf{0.082}$

$P(y = \text{HAM}) = \frac{5}{7}$ $P(y = \text{SPAM}) = \frac{2}{7}$
$P(x_i = I \mid y = \text{HAM}) = \frac{5}{15}$
$P(x_i = \text{rolex} \mid y = \text{HAM}) = \frac{1}{15}$
$P(x_i = \text{own} \mid y = \text{HAM}) = \frac{4}{15}$
$P(x_i = \text{replica} \mid y = \text{HAM}) = \frac{1}{15}$
$P(x_i = \text{watch} \mid y = \text{HAM}) = \frac{3}{15}$
$P(x_i = \text{buy} \mid y = \text{HAM}) = \frac{0}{15}$
$P(x_i = \text{cheap} \mid y = \text{HAM}) = \frac{1}{15}$
$P(x_i = I \mid y = \text{SPAM}) = \frac{0}{7}$
$P(x_i = \text{rolex} \mid y = \text{SPAM}) = \frac{2}{7}$
$P(x_i = \text{own} \mid y = \text{SPAM}) = \frac{0}{7}$
$P(x_i = \text{replica} \mid y = \text{SPAM}) = \frac{2}{7}$
$P(x_i = \text{watch} \mid y = \text{SPAM}) = \frac{0}{7}$
$P(x_i = \text{buy} \mid y = \text{SPAM}) = \frac{1}{7}$
$P(x_i = \text{cheap} \mid y = \text{SPAM}) = \frac{2}{7}$

x₁, x₂, x₃, ..., x_{N-2}, x_{N-1}, x_N - feature vectors (in **bold**) | **y₁, y₂, y₃, ..., y_{N-2}, y_{N-1}, y_N** - labels

Spam Detection: Testing Classifier

Test set	Vocabulary V						Learned $h()$
	I	rolex	own	replica	watch	buy	cheap
x_8	0	1	0	1	0	1	1
	buy cheap rolex replica rolex						$y_8 = \text{SPAM}$
x_9	1	1	1	0	1	0	1
	I own cheap rolex watch						$y_9 = \text{HAM}$
x_{10}	0	0	0	1	0	0	0
	replica						$y_{10} = \text{HAM}$
Testing	Which probability is higher? Which y maximizes $P()$?						
	$P(y = \text{HAM} x_{10}) \approx 0.048$						
	$P(y = \text{SPAM} x_{10}) \approx 0.082$						
	For document x_{10} $y = \text{SPAM}$ maximizes $P()$. Class = SPAM .						

$$P(y = \text{HAM}) = \frac{5}{7} \quad P(y = \text{SPAM}) = \frac{2}{7}$$

$$P(x_i = I | y = \text{HAM}) = \frac{5}{15}$$

$$P(x_i = \text{rolex} | y = \text{HAM}) = \frac{1}{15}$$

$$P(x_i = \text{own} | y = \text{HAM}) = \frac{4}{15}$$

$$P(x_i = \text{replica} | y = \text{HAM}) = \frac{1}{15}$$

$$P(x_i = \text{watch} | y = \text{HAM}) = \frac{3}{15}$$

$$P(x_i = \text{buy} | y = \text{HAM}) = \frac{0}{15}$$

$$P(x_i = \text{cheap} | y = \text{HAM}) = \frac{1}{15}$$

$$P(x_i = I | y = \text{SPAM}) = \frac{0}{7}$$

$$P(x_i = \text{rolex} | y = \text{SPAM}) = \frac{2}{7}$$

$$P(x_i = \text{own} | y = \text{SPAM}) = \frac{0}{7}$$

$$P(x_i = \text{replica} | y = \text{SPAM}) = \frac{2}{7}$$

$$P(x_i = \text{watch} | y = \text{SPAM}) = \frac{0}{7}$$

$$P(x_i = \text{buy} | y = \text{SPAM}) = \frac{1}{7}$$

$$P(x_i = \text{cheap} | y = \text{SPAM}) = \frac{2}{7}$$

$x_1, x_2, x_3, \dots, x_{N-2}, x_{N-1}, x_N$ - feature vectors (in **bold**) | $y_1, y_2, y_3, \dots, y_{N-2}, y_{N-1}, y_N$ - labels

Spam Detection: Testing Classifier

Test set		Learned h()							
	Vocabulary V <table border="1" style="margin: 10px auto; border-collapse: collapse;"> <tr> <td>I</td> <td>rolex</td> <td>own</td> <td>replica</td> <td>watch</td> <td>buy</td> <td>cheap</td> </tr> </table>	I	rolex	own	replica	watch	buy	cheap	
I	rolex	own	replica	watch	buy	cheap			
x₈	<table border="1" style="margin: 10px auto; border-collapse: collapse;"> <tr> <td>0</td> <td>1</td> <td>0</td> <td>1</td> <td>0</td> <td>1</td> <td>1</td> </tr> </table> <p style="text-align: center;">buy cheap rolex replica rolex</p>	0	1	0	1	0	1	1	y ₈ = SPAM
0	1	0	1	0	1	1			
x₉	<table border="1" style="margin: 10px auto; border-collapse: collapse;"> <tr> <td>1</td> <td>1</td> <td>1</td> <td>0</td> <td>1</td> <td>0</td> <td>1</td> </tr> </table> <p style="text-align: center;">I own cheap rolex watch</p>	1	1	1	0	1	0	1	y ₉ = HAM
1	1	1	0	1	0	1			
x₁₀	<table border="1" style="margin: 10px auto; border-collapse: collapse;"> <tr> <td>0</td> <td>0</td> <td>0</td> <td>1</td> <td>0</td> <td>0</td> <td>0</td> </tr> </table> <p style="text-align: center;">replica</p>	0	0	0	1	0	0	0	y ₁₀ = HAM
0	0	0	1	0	0	0			
Testing	<p style="text-align: center;">Which probability is higher? Which y maximizes P()? </p> <p style="text-align: center;">For document x₁₀ y = SPAM maximizes P(). Class = SPAM.</p> <p style="text-align: center; color: red;"><u>Incorrect classification! Misclassification.</u></p>								

$$P(y = \text{HAM}) = \frac{5}{7} \quad P(y = \text{SPAM}) = \frac{2}{7}$$

$$P(x_i = I | y = \text{HAM}) = \frac{5}{15}$$

$$P(x_i = rolex | y = \text{HAM}) = \frac{1}{15}$$

$$P(x_i = own | y = \text{HAM}) = \frac{4}{15}$$

$$P(x_i = replica | y = \text{HAM}) = \frac{1}{15}$$

$$P(x_i = watch | y = \text{HAM}) = \frac{3}{15}$$

$$P(x_i = buy | y = \text{HAM}) = \frac{0}{15}$$

$$P(x_i = cheap | y = \text{HAM}) = \frac{1}{15}$$

$$P(x_i = I | y = \text{SPAM}) = \frac{0}{7}$$

$$P(x_i = rolex | y = \text{SPAM}) = \frac{2}{7}$$

$$P(x_i = own | y = \text{SPAM}) = \frac{0}{7}$$

$$P(x_i = replica | y = \text{SPAM}) = \frac{2}{7}$$

$$P(x_i = watch | y = \text{SPAM}) = \frac{0}{7}$$

$$P(x_i = buy | y = \text{SPAM}) = \frac{1}{7}$$

$$P(x_i = cheap | y = \text{SPAM}) = \frac{2}{7}$$

x₁, x₂, x₃, ..., x_{N-2}, x_{N-1}, x_N - feature vectors (in **bold**) | **y₁, y₂, y₃, ..., y_{N-2}, y_{N-1}, y_N** - labels

Classifier Evaluation: Confusion Matrix

		Predicted class		
		Positive	Negative	
Actual class	Positive	True Positive (TP)	False Negative (FN) Type II Error	Sensitivity (Recall) $\frac{TP}{TP+FN}$
	Negative	False Positive (FP) Type I Error	True Negative (TN)	Specificity $\frac{TN}{TN+FP}$
		Precision $\frac{TP}{TP+FP}$	Negative Predictive Value $\frac{TN}{TN+FN}$	Accuracy $\frac{TP+TN}{TP+TN+FP+FN}$

Classifier Evaluation: Confusion Matrix

		Predicted class		
		SPAM	HAM	
Actual class	SPAM	True Positive (TP)	False Negative (FN) Type II Error	Sensitivity (Recall) $\frac{TP}{TP+FN}$
	HAM	False Positive (FP) Type I Error	True Negative (TN)	Specificity $\frac{TN}{TN+FP}$
		Precision $\frac{TP}{TP+FP}$	Negative Predictive Value $\frac{TN}{TN+FN}$	Accuracy $\frac{TP+TN}{TP+TN+FP+FN}$

Spam Detection: Evaluating Classifier

Test set		Vocabulary V							Testing results													
x_8	<table><tr><td>I</td><td>rolex</td><td>own</td><td>replica</td><td>watch</td><td>buy</td><td>cheap</td></tr><tr><td>0</td><td>1</td><td>0</td><td>1</td><td>0</td><td>1</td><td>1</td></tr></table>	I	rolex	own	replica	watch	buy	cheap	0	1	0	1	0	1	1	buy cheap rolex replica rolex					$y_8 = \text{SPAM}$	$y_8 = \text{SPAM}$ correct
I	rolex	own	replica	watch	buy	cheap																
0	1	0	1	0	1	1																
x_9	<table><tr><td>1</td><td>1</td><td>1</td><td>0</td><td>1</td><td>0</td><td>1</td></tr></table>	1	1	1	0	1	0	1	I own cheap rolex watch					$y_9 = \text{HAM}$	$y_9 = \text{HAM}$ correct							
1	1	1	0	1	0	1																
x_{10}	<table><tr><td>0</td><td>0</td><td>0</td><td>1</td><td>0</td><td>0</td><td>0</td></tr></table>	0	0	0	1	0	0	0	replica					$y_{10} = \text{HAM}$	$y_{10} = \text{SPAM}$ incorrect							
0	0	0	1	0	0	0																

Evaluation		Confusion matrix	
$y_8 = \text{SPAM}$	$y_8 = \text{SPAM}$	true positive	
$y_9 = \text{HAM}$	$y_9 = \text{HAM}$	true negative	
$y_{10} = \text{HAM}$	$y_{10} = \text{SPAM}$	false positive	
No false negatives in this example.			

	SPAM	HAM
SPAM	True Positive (TP)	False Negative (FN) Type II Error
HAM	False Positive (FP) Type I Error	True Negative (TN)

$x_1, x_2, x_3, \dots, x_{N-2}, x_{N-1}, x_N$ - feature vectors (in **bold**) | $y_1, y_2, y_3, \dots, y_{N-2}, y_{N-1}, y_N$ - labels

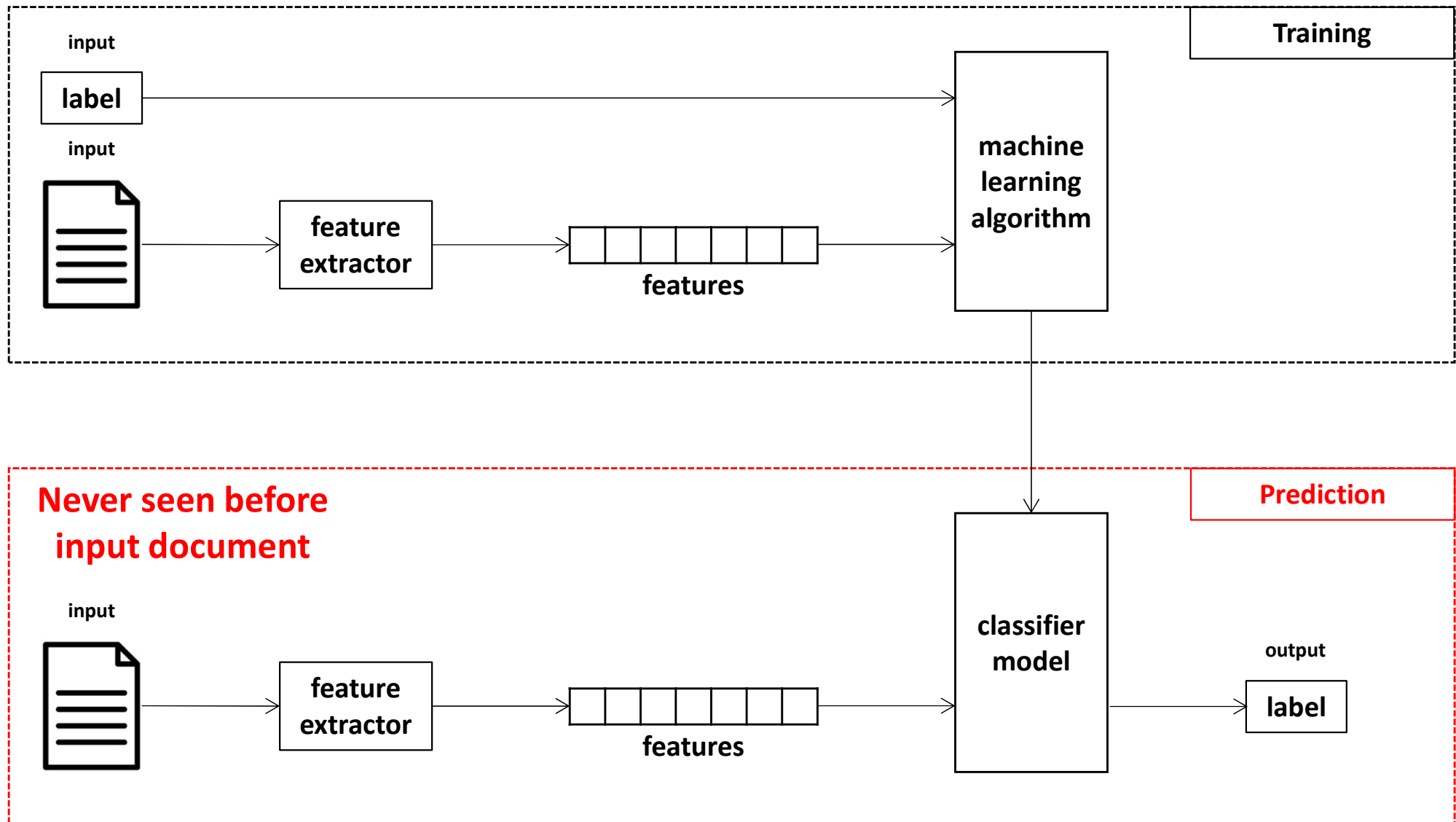
Classifier Evaluation: Confusion Matrix

		Predicted class		
		SPAM	HAM	
Actual class	SPAM	TP = 1 (x_8)	FN = 0	Sensitivity (Recall) $\frac{1}{1+0} = 1.0$
	HAM	FP = 1 (x_{10})	TN = 1 (x_9)	Specificity $\frac{1}{1+1} = 0.5$
		Precision $\frac{1}{1+1} = 0.5$	Negative Predictive Value $\frac{1}{1+0} = 1.0$	Accuracy $\frac{1+1}{1+1+1+0} = \frac{2}{3}$

Confusion Matrix Explained

- **Accuracy $(TP+TN)/(TP+TN+FP+FN)$:**
 - Overall, how often is the classifier correct?
- **Misclassification rate [Error Rate] $(FP+FN)/(TP+TN+FP+FN)$:**
 - Overall, how often is the classifier incorrect?
- **Sensitivity [Recall | True Positive Rate] $(TP)/(TP+FN)$:**
 - When it's actually yes, how often does it predict yes?
- **Specificity [True Negative Rate] $(TN)/(TN+FP)$**
 - When it's actually no, how often does it predict no?
- **Precision $(TP)/(TP+FP)$**
 - When it predicts yes, how often is it correct?
- **Negative Predictive Value $(TN)/(TN+FN)$**
 - When it predicts no, how often is it correct?

Supervised Learning with ML



Spam Detection: Prediction

Unseen x

Vocabulary V

	I	rolex	own	replica	watch	buy	cheap
x_?	0	1	0	0	0	1	0

buy rolex

Label needs to be decided

y_? = ????

Learned h()

$P(y = \text{HAM}) = \frac{5}{7}$ $P(y = \text{SPAM}) = \frac{2}{7}$

$P(x_i = I | y = \text{HAM}) = \frac{5}{15}$
 $P(x_i = \text{rolex} | y = \text{HAM}) = \frac{1}{15}$
 $P(x_i = \text{own} | y = \text{HAM}) = \frac{4}{15}$
 $P(x_i = \text{replica} | y = \text{HAM}) = \frac{1}{15}$
 $P(x_i = \text{watch} | y = \text{HAM}) = \frac{3}{15}$
 $P(x_i = \text{buy} | y = \text{HAM}) = \frac{0}{15}$
 $P(x_i = \text{cheap} | y = \text{HAM}) = \frac{1}{15}$

$P(x_i = I | y = \text{SPAM}) = \frac{0}{7}$
 $P(x_i = \text{rolex} | y = \text{SPAM}) = \frac{2}{7}$
 $P(x_i = \text{own} | y = \text{SPAM}) = \frac{0}{7}$
 $P(x_i = \text{replica} | y = \text{SPAM}) = \frac{2}{7}$
 $P(x_i = \text{watch} | y = \text{SPAM}) = \frac{0}{7}$
 $P(x_i = \text{buy} | y = \text{SPAM}) = \frac{1}{7}$
 $P(x_i = \text{cheap} | y = \text{SPAM}) = \frac{2}{7}$

Prediction

Which probability is higher? Which **y** maximizes P()?

$$P(y = \text{HAM} | x_?) \propto P(y = \text{HAM}) * \prod_{i=1}^2 P(x_i | y = \text{HAM}) =$$

$$P(y = \text{HAM}) * P(x_1 = \text{buy} | y = \text{HAM}) * P(x_2 = \text{rolex} | y = \text{HAM})$$

$$= \frac{5}{7} * \frac{0}{15} * \frac{1}{15} = 0$$

$$P(y = \text{SPAM} | x_?) \propto P(y = \text{SPAM}) * \prod_{i=1}^2 P(x_i | y = \text{SPAM}) =$$

$$P(y = \text{SPAM}) * P(x_1 = \text{buy} | y = \text{SPAM}) * P(x_2 = \text{rolex} | y = \text{SPAM})$$

$$= \frac{2}{7} * \frac{1}{7} * \frac{2}{7} \approx 0.012$$

For document **x_?**, **y = SPAM** maximizes P(). Class = **SPAM**

x₁, x₂, x₃, ..., x_{N-2}, x_{N-1}, x_N - feature vectors (in bold) | **y₁, y₂, y₃, ..., y_{N-2}, y_{N-1}, y_N** - labels

Classifier Problems: Zero Counts

$$P(\mathbf{x}_i = \text{word} \mid \mathbf{y} = \text{CLASS}) = \frac{\text{count}(\mathbf{x}_i = \text{word}, \mathbf{y} = \text{CLASS})}{\sum_{\mathbf{x} \in V} \text{count}(\mathbf{x}, \mathbf{y} = \text{CLASS})}$$

- **Unseen words:**
 - $\text{count}(\mathbf{x}_i = \text{word}, \mathbf{y} = \text{CLASS})$ can be zero
- **Words NOT present in samples for one class (see: example):**
 - $\text{count}(\mathbf{x}_i = \text{word}, \mathbf{y} = \text{CLASS})$ can be zero
- **Solution: smoothing (e.g. Laplace smoothing)**

$$P(\mathbf{x}_i = \text{word} \mid \mathbf{y} = \text{CLASS}) = \frac{\text{count}(\mathbf{x}_i = \text{word}, \mathbf{y} = \text{CLASS}) + \alpha}{\sum_{\mathbf{x} \in V} \text{count}(\mathbf{x}, \mathbf{y} = \text{CLASS}) + \alpha * |V|}$$

where: α - pseudo-occurrence (typically “add 1”), $|V|$ - vocabulary size

Classifier Problems: Underflow

$$P(\mathbf{y} | \mathbf{x}) \propto P(\mathbf{y}) * \prod_{i=1}^N P(x_i | y)$$

- N can be large (100 and more):
 - long, “wordy”, documents
- some $P(x_i | y)$ can be very small (< 0.1)
 - the product $\prod_{i=1}^N P(x_i | y)$ may lead to underflow
- Solution: use logarithms

$$\log(P(\mathbf{y} | \mathbf{x})) \propto \log(P(\mathbf{y})) + \sum_{i=1}^N \log(P(x_i | y))$$

Naive Bayes Classifier

category/class = **h**(document)

Finding model / hypothesis **h** → Finding probabilities for y_{MAP}

$$y_{MAP} \propto \underset{y \in Y}{argmax} \left(\log(P(\mathbf{y})) + \sum_{i=1}^N \log(P(\mathbf{x}_i | \mathbf{y})) \right)$$

MAP: Maximum a posteriori (corresponds to the most likely class).

Naive Bayes Classifier

category/class = **h**(document)

Finding model / hypothesis **h** → Finding probabilities for y_{MAP}

$$y_{MAP} \propto \underset{y \in Y}{argmax} \left(\log(P(\mathbf{y})) + \sum_{i=1}^N \log(P(\mathbf{x}_i | \mathbf{y})) \right)$$

- Taking log doesn't change the ranking of classes!
 - The class with highest probability also has highest log probability!
- It's a linear model:
 - Just a max of a sum of weights: a linear function of the inputs
 - So Naive Bayes is a linear classifier

Naive Bayes: Training/Testing

```
function TRAIN NAIVE BAYES(D, C) returns  $\log P(c)$  and  $\log P(w|c)$ 

for each class  $c \in C$            # Calculate  $P(c)$  terms
     $N_{doc}$  = number of documents in D
     $N_c$  = number of documents from D in class c
     $\text{logprior}[c] \leftarrow \log \frac{N_c}{N_{doc}}$ 
     $V \leftarrow$  vocabulary of D
     $\text{bigdoc}[c] \leftarrow \text{append}(d)$  for  $d \in D$  with class c
    for each word  $w$  in  $V$            # Calculate  $P(w|c)$  terms
         $\text{count}(w, c) \leftarrow$  # of occurrences of  $w$  in  $\text{bigdoc}[c]$ 
         $\text{loglikelihood}[w, c] \leftarrow \log \frac{\text{count}(w, c) + 1}{\sum_{w' \in V} (\text{count}(w', c) + 1)}$ 
return  $\text{logprior}$ ,  $\text{loglikelihood}$ ,  $V$ 

function TEST NAIVE BAYES( $\text{testdoc}$ ,  $\text{logprior}$ ,  $\text{loglikelihood}$ , C, V) returns best c

for each class  $c \in C$ 
     $\text{sum}[c] \leftarrow \text{logprior}[c]$ 
    for each position  $i$  in  $\text{testdoc}$ 
         $\text{word} \leftarrow \text{testdoc}[i]$ 
        if  $\text{word} \in V$ 
             $\text{sum}[c] \leftarrow \text{sum}[c] + \text{loglikelihood}[\text{word}, c]$ 
return  $\text{argmax}_c \text{sum}[c]$ 
```

Naive Bayes: Summary

- **Pros:**

- Very fast and easy-to-implement
- Well-understood formally & experimentally
 - see “Naive (Bayes) at Forty”, Lewis, ECML98

- **Cons:**

- Seldom gives the very best performance (baseline)
- “Probabilities” $P(y | x)$ are not accurate
- Probabilities tend to be close to zero or one

Naive Bayes: Stop Words

- **Some systems ignore stop words**
 - **Stop words: very frequent words like the and a.**
 - Sort the vocabulary by word frequency in training set
 - Call the top 10 or 50 words the stopword list.
 - Remove all stop words from both training and test sets
 - As if they were never there!
- **But removing stop words doesn't usually help**
 - So **in practice** most NB algorithms use all words and don't use stopword lists

Naive Bayes: Unknown Words

- What about unknown words
 - that appear in our test data
 - but not in our training data or vocabulary?
- We **ignore** them
 - Remove them from the test document!
 - Pretend they weren't there!
 - Don't include any probability for them at all!
- Why don't we build an unknown word model?
 - It doesn't help: knowing which class has more unknown words is not generally helpful!

Naive Bayes: More Than Two Classes

- Dealing with **any-of** or **multivalued** classification
 - A document can belong to 0, 1, or more than 1 classes.
 - For each class $c \in C$
 - Build a classifier h_c to distinguish c from all other classes $c' \in C$
 - Given test document d ,
 - Evaluate it for membership in each class using each h_c
 - d belongs to **any** class for which h_c returns true

Naive Bayes: More Than Two Classes

- Dealing with **one-of** or **multinomial** classification
 - Classes are mutually exclusive: each document in exactly one class
- For each class $c \in C$
 - Build a classifier h_c to distinguish c from all other classes $c' \in C$
- Given test document d ,
 - Evaluate it for membership in each class using each h_c
 - d belongs to the **one** class with maximum score