Sentiment Analysis: Corpus-based approaches

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Autumn Semester 2024

Learning objectives

- Explain the Naïve Bayes model for sentiment analysis
- Explain the Laplace smoothing technique
- Explain the Binary Naïve Bayes model
- Identify other tasks for which the same approach is applicable

Sentiment Analysis: 2 main approaches

- **Lexicon based**
  - **Binary**
  - **Gradable**
- **Corpus based**
  - **Naive Bayes**
  - Deep Learning

Corpus-based approaches: Naive Bayes

Principle

Assign the **sentiment** or **class** having the highest **posterior probability**.
Namely, determine the sentiment $\mathbf{s}^*$ of text T such that:

$$\mathbf{s}^* = \underset{s_i}{\operatorname{argmax}}\, p(s_i|T) \text{ for } s_i \in \{\textbf{negative}, \textbf{positive}, \textbf{neutral}\}$$

$p(s_i|T)$ cannot be directly estimated...

Corpus-based approaches: Naive Bayes

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$p(s_i|T)$ cannot be directly estimated...
$\rightarrow$ use the **Bayes rule**:

$$p(s_i|T) = \frac{p(T|s_i)p(s_i)}{p(T)}$$

Corpus-based approaches: Naive Bayes

Bayes classifier:

$$\mathbf{s}^* = \underset{s_i}{\operatorname{argmax}} \frac{p(T|s_i)p(s_i)}{p(T)}$$

Corpus-based approaches: Naive Bayes

Bayes classifier:

$$\mathbf{s}^* = \operatorname*{argmax}_{s_i} \frac{p(T|s_i)p(s_i)}{\mathbf{p(T)}}$$

Since **evidence p(T)** is independent of s_i, we can ignore it

$$\mathbf{s}^* = \operatorname*{argmax}_{s_i} p(T|s_i)p(s_i)$$

Corpus-based approaches: Naive Bayes

Bayes classifier:

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$$\mathbf{s}^* = \operatorname*{argmax}_{s_i} p(T|s_i)p(s_i)$$

- $p(s_i|T)$ is the **posterior probability**
- $p(T|s_i)$ is the **likelihood**
- $p(s_i)$ is the **prior probability**

Corpus-based approaches: Naive Bayes

How to compute the likelihood?

Assume that T is described by a number of **features** or attributes $t_1, t_2, ..., t_N$

Corpus-based approaches: Naive Bayes

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Naive assumption: **features** are **independent**

$$p(T|s_i) = p(t_1, t_2, ..., t_N|s_i) \approx \prod_{j=1}^{N} p(t_j|s_i)$$

Corpus-based approaches: Naive Bayes

How to compute the likelihood?

Assume that T is described by a number of **features** or attributes $t_1, t_2, ..., t_N$

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$$p(T|s_i) = p(t_1, t_2, ..., t_N|s_i) \approx \prod_{j=1}^{N} p(t_j|s_i)$$

$\Rightarrow$ product of probabilities of each **feature** value of text occurring with class s_i

Corpus-based approaches: Naive Bayes

How to compute the prior probability?

$\rightarrow$ corresponds to the safest decision when no other information is given $\sim$ majority voting

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Requires an **annotated corpus** (text along with their sentiment)

Corpus-based approaches: Naive Bayes

How to compute the prior probability?

$\rightarrow$ corresponds to the safest decision when no other information is given $\sim$ majority voting

Requires an **annotated corpus** (text along with their sentiment)
Compute **prior probability** by simple relative frequency

$$p(s_i) = \frac{count(s_i)}{\sum_{j=0}^{J} count(s_j)}$$

with J the number of different classes and $count(.)$ is the counting function

Digression: corpus-based machine learning

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  - input data along with the ground truth (correct labels)

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  - e.g. feature selection, set meta-parameters (could be some weights)
  - ground truth (correct labels) available
  - used to select the best model

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- **training** set $\rightarrow$ used to **estimate probabilities**
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  - e.g. feature selection, set meta-parameters (could be some weights)
  - ground truth (correct labels) available
  - used to select the best model
- **test** set $\rightarrow$ used to **evaluate generalisation** power
  - unseen examples
  - best case: no access to the ground truth

Naive Bayes classifier

Final decision

$$\mathbf{s}^* = \underset{s_i}{\operatorname{argmax}}\, p(s_i) \prod_{j=1}^{N} p(t_j|s_i)$$

Naive Bayes classifier

Final decision

$$\mathbf{s}^* = \underset{s_i}{\operatorname{argmax}}\, p(s_i) \prod_{j=1}^{N} p(t_j|s_i)$$

1. Compute **prior probability** of each class

Naive Bayes classifier

Final decision

$$\mathbf{s}^* = \operatorname*{argmax}_{s_i} p(s_i) \prod_{j=1}^{N} p(t_j|s_i)$$

1. Compute **prior probability** of each class
2. For each class:
   - Compute **likelihood** of each feature

Naive Bayes classifier

Final decision

$$\mathbf{s}^* = \underset{s_i}{\operatorname{argmax}}\, p(s_i) \prod_{j=1}^{N} p(t_j|s_i)$$

1. Compute **prior probability** of each class
2. For each class:
   - Compute **likelihood** of each feature
3. Calculate the **posterior probability** by product of previous components

Naive Bayes classifier

Final decision

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1. Compute **prior probability** of each class
2. For each class:
   - Compute **likelihood** of each feature
3. Calculate the **posterior probability** by product of previous components
4. Select sentiment having maximum posterior probability

$\rightarrow$ **negative**, **positive** or **neutral**

Naive Bayes for Sentiment Analysis - Example

Consider the following dummy **training** corpus of 7 movie reviews:

Doc	Words	Class
1	great movie, excellent plot, renowned actors	**positive**
2	I had not seen a fantastic plot like this in good 5 years. amazing!!!	**positive**
3	lovely plot, amazing cast, somehow I am in love with the bad guy	**positive**
4	bad movie with great cast, but very poor plot and unimaginative ending	**negative**
5	I hate this film, it has nothing original	**negative**
6	great movie, but not...	**negative**
7	very bad movie, I have no words to express how I dislike it	**negative**

Naive Bayes for Sentiment Analysis - Example

Compute prior probability of each class by relative frequency

$$p(\textbf{positive}) = \frac{count(\textbf{positive})}{\sum_{s \in \{\textbf{positive},\textbf{negative}\}} count(s)} = \frac{3}{7} = 0.43$$

$$p(\textbf{negative}) = \frac{count(\textbf{negative})}{\sum_{s \in \{\textbf{positive},\textbf{negative}\}} count(s)} = \frac{4}{7} = 0.57$$

Naive Bayes for Sentiment Analysis - Example

What **features** should we consider?

- could use **all** words
  - but some might not be relevant $\rightarrow$ we are interested in the **emotion words**
- in this example: focus on **adjectives** (**bag-of-word** representation)

Doc	Words	Class
1	**great** movie, **excellent** plot, **renowned** actors	**positive**
2	I had not seen a **fantastic** plot like this in **good** 5 years. **amazing !!!**	**positive**
3	**Lovely** plot, **amazing** cast, somehow I am in love with the **bad** guy	**positive**
4	**bad** movie with **great** cast, but very **poor** plot and **unimaginative** ending	**negative**
5	I hate this film, it has nothing **original**	**negative**
6	**great** movie, but **bad** casting...	**negative**
7	Very **bad** movie, I have no words to express how I dislike it	**negative**

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Doc	Words	Class
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Naive Bayes for Sentiment Analysis - Example

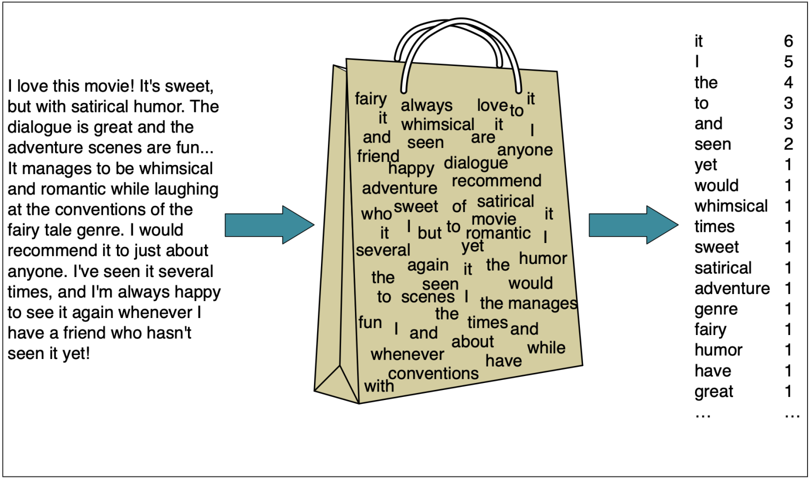

Figure 4.1 Intuition of the multinomial naive Bayes classifier applied to a movie review. The position of the words is ignored (the *bag of words* assumption) and we make use of the frequency of each word.

[Jurafsky and Martin, 2021]

Naive Bayes for Sentiment Analysis - Example

Compute the likelihoods for all features in a given each class

Important

Assume **standard pre-processing**: tokenisation, lowercasing, punctuation removal (but keep special punctuation, e.g. "!!!")

Examples:

- GOOD = GooD = Good = good
- I'll = I will (though not relevant here)
- aren't = are not

Naive Bayes for Sentiment Analysis - Example

Compute the likelihoods for all features in a given each class

$$p(t_j|s_i) = \frac{count(t_j, s_i)}{\sum_f count(t_f, s_i)} \quad \rightarrow \textbf{relative frequency}$$

p(amazing|**positive**)	$= 2/10$	p(amazing|**negative**)	$= 0/8$
p(bad|**positive**)	$= 1/10$	p(bad|**negative**)	$= 3/8$
p(excellent|**positive**)	$= 1/10$	p(excellent|**negative**)	$= 0/8$
p(fantastic|**positive**)	$= 1/10$	p(fantastic|**negative**)	$= 0/8$
p(good|**positive**)	$= 1/10$	p(good|**negative**)	$= 0/8$
p(great|**positive**)	$= 1/10$	p(great|**negative**)	$= 2/8$
p(lovely|**positive**)	$= 1/10$	p(lovely|**negative**)	$= 0/8$
p(original|**positive**)	$= 0/10$	p(original|**negative**)	$= 1/8$
p(poor|**positive**)	$= 0/10$	p(poor|**negative**)	$= 1/8$
p(renowned|**positive**)	$= 1/10$	p(renowned|**negative**)	$= 0/8$
p(unimaginative|**positive**)	$= 0/10$	p(unimaginative|**negative**)	$= 1/8$
p(!!!|**positive**)	$= 1/10$	p(!!!|**negative**)	$= 0/8$

Naive Bayes for Sentiment Analysis - Example

Relative frequencies for prior and likelihoods make the model in a Naive Bayes classifier
$\rightarrow$ features are supposed to be **independent** (no covariance taken into account)
$\rightarrow$ this is an approximation of course

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Naive Bayes for Sentiment Analysis - Example

Relative frequencies for prior and likelihoods make the model in a Naive Bayes classifier
$\rightarrow$ features are supposed to be **independent** (no covariance taken into account)
$\rightarrow$ this is an approximation of course

What is the model?
$\rightarrow$ the set of all prior probabilities and likelihoods

At **test** time, this model is used to find the most likely class (sentiment) for the unknown text

$$\mathbf{s}^* = \operatorname*{argmax}_{s_i} p(s_i) \prod_{j=1}^{N} p(t_j | s_i)$$

Naive Bayes for Sentiment Analysis - Text Ex. 1

Consider the following **test segment** to classify:

Doc	Words	Class
8	This was a fantastic story, great, lovely	?

Naive Bayes for Sentiment Analysis - Text Ex. 1

Consider the following **test segment** to classify:

1. Extract features

Doc	Words	Class
8	This was a **fantastic** story, **great**, **lovely**	?

Naive Bayes for Sentiment Analysis - Text Ex. 1

Consider the following **test segment** to classify:

1. Extract features
2. Build representation

Doc	Words	Class
8	**fantastic great lovely**	?

Naive Bayes for Sentiment Analysis - Text Ex. 1

Consider the following **test segment** to classify:

1. Extract features
2. Build representation

Doc	Words	Class
8	**fantastic great lovely**	?

3. Get **likelihoods**

$$\begin{aligned} p(\text{fantastic}|\textbf{positive}) &= 1/10 \\ p(\text{great}|\textbf{positive}) &= 1/10 \\ p(\text{lovely}|\textbf{positive}) &= 1/10 \end{aligned} \quad \left| \quad \begin{aligned} p(\text{fantastic}|\textbf{negative}) &= 0/8 \\ p(\text{great}|\textbf{negative}) &= 2/8 \\ p(\text{lovely}|\textbf{negative}) &= 0/8 \end{aligned} \right.$$

Naive Bayes for Sentiment Analysis - Text Ex. 1

$$\begin{aligned} p(\textbf{positive}|text) &= p(\textbf{positive}) * p(fantastic|\textbf{positive}) * p(great|\textbf{positive}) * p(lovely|\textbf{positive}) \\ &= 3/7 * 1/10 * 1/10 * 1/10 \\ &= \textbf{0.00043} \end{aligned}$$

$$\begin{aligned} p(\textbf{negative}|text) &= p(\textbf{negative}) * p(fantastic|\textbf{negative}) * p(great|\textbf{negative}) * p(lovely|\textbf{negative}) \\ &= 4/7 * 0/8 * 2/8 * 0/8 \\ &= \textbf{0} \end{aligned}$$

Final decision: sentiment is **positive**

Naive Bayes for Sentiment Analysis - Text Ex. 2

Doc	Words	Class
1	great movie, excellent plot, renowned actors	positive
2	I had not seen a fantastic plot like this in good 5 years. amazing!!!	positive
3	lovely plot, amazing cast, somehow I am in love with the bad guy	positive
4	bad movie with great cast, but very poor plot and unimaginative ending	negative
5	I hate this film, it has nothing original	negative
6	great movie, but not...	negative
7	very bad movie, I have no words to express how I dislike it	negative

Doc	Words	Class
1	**great excellent renowned**	**positive**
2	**fantastic good amazing !!!**	**positive**
3	**lovely amazing bad**	**positive**
4	**bad great poor unimaginative**	**negative**
5	**original**	**negative**
6	**great bad**	**negative**
7	**bad**	**negative**

Consider the following **test segment** to classify:

Doc	Words	Class
9	**Great great great**	?

Naive Bayes for Sentiment Analysis - Text Ex. 2

Consider the following **test segment** to classify:

Doc	Words	Class
9	Great plot, great cast, great everything	?

Naive Bayes for Sentiment Analysis - Text Ex. 2

Consider the following **test segment** to classify:

1. Extract features
2. Build representation

Doc	Words	Class
9	**Great great great**	?

Naive Bayes for Sentiment Analysis - Text Ex. 2

Consider the following **test segment** to classify:

1. Extract features
2. Build representation

Doc	Words	Class
9	**Great great great**	?

3. Get likelihoods:

$$p(\text{great}|\textbf{positive}) = 1/10 \mid p(\text{great}|\textbf{negative}) = 2/8$$

Naive Bayes for Sentiment Analysis - Text Ex. 2

Consider the following **test segment** to classify:

1. Extract features
2. Build representation

Doc	Words	Class
9	**Great great great**	?

3. Get likelihoods:
   p(great|**positive**) $= 1/10$ | p(great|**negative**) $= 2/8$
4. Compute posteriors

$$p(\textbf{positive}|text) = 3/7 * 1/10 * 1/10 * 1/10 = \textbf{0.00043}$$
$$p(\textbf{negative}|text) = 4/7 * 2/8 * 2/8 * 2/8 = \textbf{0.00893}$$

Final decision: sentiment is **negative**

Naive Bayes for Sentiment Analysis - Text Ex. 2

Consider the following **test segment** to classify:

1. Extract featur
2. Build represen

Doc	Words	Class
9	**Great gr**	?

Training data should be representative!

3. Get likelihoods:
   p(great|**positive**) $= 1/10$ | p(great|**negative**) $= 2/8$
4. Compute posteriors

$$p(\textbf{positive}|text) = 3/7 * 1/10 * 1/10 * 1/10 = \textbf{0.00043}$$
$$p(\textbf{negative}|text) = 4/7 * 2/8 * 2/8 * 2/8 = \textbf{0.00893}$$

Final decision: sentiment is **negative**

Naive Bayes for Sentiment Analysis - Text Ex. 3

Doc	Words	Class
1	great movie, excellent plot, renowned actors	**positive**
2	I had not seen a fantastic plot like this in good 5 years. amazing!!!	**positive**
3	lovely plot, amazing cast, somehow I am in love with the bad guy	**positive**
4	bad movie with great cast, but very poor plot and unimaginative ending	**negative**
5	I hate this film, it has nothing original	**negative**
6	great movie, but not...	**negative**
7	very bad movie, I have no words to express how I dislike it	**negative**

Doc	Words	Class
1	**great excellent renowned**	**positive**
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4	**bad great poor unimaginative**	**negative**
5	**original**	**negative**
6	**great bad**	**negative**
7	**bad**	**negative**

Consider the following **test segment** to classify:

Doc	Words	Class
10	Excellent cast, unimaginative ending	?

Naive Bayes for Sentiment Analysis - Text Ex. 3

Consider the following **test segment** to classify:

Doc	Words	Class
10	Excellent cast, unimaginative ending	?

Naive Bayes for Sentiment Analysis - Text Ex. 3

Consider the following **test segment** to classify:

1. Extract features
2. Build representation

Doc	Words	Class
10	**Excellent unimaginative**	?

Naive Bayes for Sentiment Analysis - Text Ex. 3

Consider the following **test segment** to classify:

1. Extract features
2. Build representation

Doc	Words	Class
10	**Excellent unimaginative**	?

3. Get likelihoods:

$$\begin{array}{rl|rl} p(\text{excellent}|\textbf{positive}) & = 1/10 & p(\text{excellent}|\textbf{negative}) & = 0/8 \\ p(\text{unimaginative}|\textbf{positive}) & = 0/10 & p(\text{unimaginative}|\textbf{negative}) & = 1/8 \end{array}$$

Naive Bayes for Sentiment Analysis - Text Ex. 3

Consider the following **test segment** to classify:

1. Extract features
2. Build representation

Doc	Words	Class
10	**Excellent unimaginative**	?

3. Get likelihoods:

$$\begin{array}{rl|rl} \text{p(excellent}|\textbf{positive}) & = 1/10 & \text{p(excellent}|\textbf{negative}) & = 0/8 \\ \text{p(unimaginative}|\textbf{positive}) & = 0/10 & \text{p(unimaginative}|\textbf{negative}) & = 1/8 \end{array}$$

4. Compute posteriors

$$p(\textbf{positive}|text) = 3/7 * 1/10 * 0/10 \quad = \quad \mathbf{0.0}$$

$$p(\textbf{negative}|text) = 4/7 * 0/8 * 1/8 \quad = \quad \mathbf{0.0}$$

Final decision: sentiment is **???**

Naive Bayes for Sentiment Analysis - Text Ex. 3

Consider the following **test segment** to classify:

1. Extract featur
2. Build represen

Training data should be large!

Doc	Words	Class
10	**Excellent unimaginative**	?

3. Get likelihoods:

$$\begin{aligned} p(\text{excellent}|\textbf{positive}) &= 1/10 \quad & p(\text{excellent}|\textbf{negative}) &= 0/8 \\ p(\text{unimaginative}|\textbf{positive}) &= 0/10 \quad & p(\text{unimaginative}|\textbf{negative}) &= 1/8 \end{aligned}$$

4. Compute posteriors

$$p(\textbf{positive}|text) = 3/7 * 1/10 * 0/10 \quad = \quad \textbf{0.0}$$
$$p(\textbf{negative}|text) = 4/7 * 0/8 * 1/8 \quad = \quad \textbf{0.0}$$

Final decision: sentiment is **???**

Exercise

Doc	Words	Class
1	A **sensitive**, **moving**, **brilliant** work	Positive
2	An **edgy** thriller that delivers a **surprising** punch	Positive
3	A **sensitive**, **insightful**, **flamboyant** film	Positive
4	Neither **revelatory** nor truly **edgy** – merely crassly **flamboyant** and comedically **labored**	Negative
5	**Unlikable**, **uninteresting**, **unfunny**, and completely, utterly **inept**	Negative
6	A sometimes **incisive** and **sensitive** portrait, targeting **sensitive** topics, that is undercut by its **awkward** structure	Negative
7	It's a sometimes **interesting** remake that doesn't compare to the **brilliant** original	Negative

Classify the following sentence using a Naive Bayes classifier based on the above training data (without smoothing).

Doc	Words	Class
8	A **flamboyant** romcom, **sensitive** but **awkward** at times.	???

Naive Bayes for Sentiment Analysis

We cannot ensure that all possible words appear in the training corpus

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$\rightarrow$ apply a **smoothing** technique

$$p(t_j|s_i) = \frac{count(t_j, s_i) + 1}{\sum_f (count(t_f, s_i) + 1)}$$

Naive Bayes for Sentiment Analysis

We cannot ensure that all possible words appear in the training corpus

→ apply a **smoothing** technique

$$p(t_j|s_i) = \frac{count(t_j, s_i) + \mathbf{1}}{(\sum_f count(t_f, s_i)) + |\mathbf{V}|}$$

→ **Laplace** smoothing, also called **add-1** smoothing

where $|\mathbf{V}|$ is the number of **distinct features** or **types** (also called **vocabulary**)
→ **12 in our example**

great, excellent, renowned, fantastic, good, amazing, !!!, lovely, bad, poor, unimaginative, original

Naive Bayes for Sentiment Analysis - Text Ex. 3

Consider the following **test segment** to classify:

1. Extract features
2. Build representation

Doc	Words	Class
10	**Excellent unimaginative**	?

Naive Bayes for Sentiment Analysis - Text Ex. 3

Consider the following **test segment** to classify:

1. Extract features
2. Build representation

Doc	Words	Class
10	**Excellent unimaginative**	?

3. **Get new likelihoods:**

p(excellent|**positive**)	$= (1+1)/(10+12) = 2/22$	p(excellent|**negative**)	$= (0+1)/(8+12) = 1/20$
p(unimaginative|**positive**)	$= (0+1)/(10+12) = 1/22$	p(unimaginative|**negative**)	$= (1+1)/(8+12) = 2/20$

Naive Bayes for Sentiment Analysis - Text Ex. 3

Consider the following **test segment** to classify:

1. Extract features
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Doc	Words	Class
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3. **Get new likelihoods:**

p(excellent|**positive**)	= (1+1)/(10+12) = 2/22	p(excellent|**negative**)	= (0+1)/(8+12) = 1/20
p(unimaginative|**positive**)	= (0+1)/(10+12) = 1/22	p(unimaginative|**negative**)	= (1+1)/(8+12) = 2/20

4. Compute posteriors

$$p(\textbf{positive}|text) = 3/7 * 2/22 * 1/22 = \textbf{0.00176}$$
$$p(\textbf{negative}|text) = 4/7 * 1/20 * 2/20 = \textbf{0.00286}$$

Final decision: sentiment is **negative**

Exercise

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1	A **sensitive**, **moving**, **brilliant** work	Positive
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7	It's a sometimes **interesting** remake that doesn't compare to the **brilliant** original	Negative

Classify the following sentence using a Naive Bayes classifier based on the above training data **with smoothing: Laplace (add-1)**.

Doc	Words	Class
8	A **flamboyant** romcom, **sensitive** but **awkward** at times.	???

Naive Bayes for Sentiment Analysis - Questions

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- reminder: safest decision **when no other information is given** $\sim$ majority voting
- important especially on biased cases

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Can we extend to a non-binary classification?

- Naive Bayes can be easily extended by considering more than 2 classes
- ... but beware of the **curse of dimensionality** $\rightarrow$ sparsity

Naive Bayes for Sentiment Analysis - Questions

How can we improve this solution?

1. Consider other **features**?
   - using all words in Naive Bayes works well for some tasks
   - subsets of words may help → use the **development** set to decide
   - previous examples consider only adjectives, this is limiting
     - **verbs**: hate, dislike
     - **intensifiers**: very, much, a lot
     - **negation**: not ← **very important!**

     → *didn't like this movie*

     → *didn't NOT_like NOT_this NOT_movie*
     - **nouns**: love, creativity

     → possibly people tend to mostly talk of those **nouns** in a **positive** or **negative** way
   - pre-built polarity lexicons can be helpful

Naive Bayes for Sentiment Analysis - Questions

How can we improve this solution?

1. Consider other **features**?
   - **pre-built polarity lexicons** can be helpful
   - → add a feature that is counted whenever a word from a lexicon occurs
   - → "word appears in positive/negative lexicon"
   - → simple approach → can be effective when the data is sparse

Naive Bayes for Sentiment Analysis - Questions

How can we improve this solution?

2. Consider other **feature representations**?
   - Instead of frequencies → binary count
   - 1 if feature appears in a segment, 0 otherwise

Four original documents:

- − it was pathetic the worst part was the boxing scenes
- − no plot twists or great scenes
- + and satire and great plot twists
- + great scenes great film

After per-document binarization:

- − it was pathetic the worst part boxing scenes
- − no plot twists or great scenes
- + and satire great plot twists
- + great scenes film

	NB Counts +	NB Counts −	Binary Counts +	Binary Counts −
and	2	0	1	0
boxing	0	1	0	1
film	1	0	1	0
great	3	1	2	1
it	0	1	0	1
no	0	1	0	1
or	0	1	0	1
part	0	1	0	1
pathetic	0	1	0	1
plot	1	1	1	1
satire	1	0	1	0
scenes	1	2	1	2
the	0	2	0	1
twists	1	1	1	1
was	0	2	0	1
worst	0	1	0	1

Figure 4.3 An example of binarization for the binary naive Bayes algorithm.

[Jurafsky and Martin, 2021]

Naive Bayes for Sentiment Analysis - Binary example

Consider the following **training set**:

doc	"good"	"poor"	"great"	(class)
d1.	3	0	3	pos
d2.	0	1	2	pos
d3.	1	3	0	neg
d4.	1	5	2	neg
d5.	0	2	0	neg

[Jurafsky and Martin, 2021]

Predict the sentiment of the text:

"A **good**, **good** plot and **great** characters, but **poor** acting."

Naive Bayes for Sentiment Analysis - Binary example

Consider the following **training set**:

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d5.	0	2	0	neg

[Jurafsky and Martin, 2021]

Predict the sentiment of the text:

"A **good**, **good** plot and **great** characters, but **poor** acting."

Standard NB:

p(good|**positive**)	$= 3/9 = 1/3$	p(good|**negative**)	$= 1/14$
p(great|**positive**)	$= 5/9$	p(great|**negative**)	$= 2/14 = 1/7$

Naive Bayes for Sentiment Analysis - Binary example

Consider the following **training set**:

doc	"good"	"poor"	"great"	(class)
d1.	3	0	3	pos
d2.	0	1	2	pos
d3.	1	3	0	neg
d4.	1	5	2	neg
d5.	0	2	0	neg

[Jurafsky and Martin, 2021]

Predict the sentiment of the text:

"A **good**, **good** plot and **great** characters, but **poor** acting."

Binary NB:

$$\begin{aligned} p(\text{good}|\textbf{positive}) &= 1/4 \\ p(\text{great}|\textbf{positive}) &= 2/4 = 1/2 \end{aligned} \quad \Bigg| \quad \begin{aligned} p(\text{good}|\textbf{negative}) &= 2/6 = 1/3 \\ p(\text{great}|\textbf{negative}) &= 1/6 \end{aligned}$$

Exercise

Doc	Words	Class
1	A **sensitive**, **moving**, **brilliant** work	Positive
2	An **edgy** thriller that delivers a **surprising** punch	Positive
3	A **sensitive**, **insightful**, **flamboyant** film	Positive
4	Neither **revelatory** nor truly **edgy** – merely crassly **flamboyant** and comedically **labored**	Negative
5	**Unlikable**, **uninteresting**, **unfunny**, and completely, utterly **inept**	Negative
6	A sometimes **incisive** and **sensitive** portrait, targeting **sensitive** topics, that is undercut by its **awkward** structure	Negative
7	It's a sometimes **interesting** remake that doesn't compare to the **brilliant** original	Negative

Classify the following sentence using a **Binary Naive Bayes** classifier based on the above training data **without smoothing**.

Doc	Words	Class
8	A **flamboyant** romcom, **sensitive** but **awkward** at times.	???

Naive Bayes for Sentiment Analysis - Questions

How can we improve this solution?

3. Consider other **algorithms**?
   - Maximum Entropy (MaxEnt), Support Vector Machines (SVM), neural networks

   → no assumption of statistical independence among features

   → more complex but tend to do better

→ Take a look at Chapter 5 of [Jurafsky and Martin, 2021] for **Text Classification with Logistic Regression**

Learning objectives

- Explain the Naïve Bayes model for sentiment analysis
- Explain the Laplace smoothing technique
- Explain the Binary Naïve Bayes model
- Identify other tasks for which the same approach is applicable

Extra reading (optional)

Geriska Isabelle, Warih Maharani and Ibnu Asror (2018).
Analysis on Opinion Mining Using Combining Lexicon-Based Method and Multinomial Naive Bayes.
International Conference on Industrial Enterprise and System Engineering

Hanhoon Kang, Seong Joon Yoo and Dongil Han (2012).
Senti-lexicon and improved Naïve Bayes algorithms for sentiment analysis of restaurant reviews.
Expert Systems with Applications, v.39, issue 5.
`https://www.sciencedirect.com/science/article/pii/S0957417411016538`

References I

Jurafsky, D. and Martin, J. H. (2021).
Speech and Language Processing, see chapter 4: Naive Bayes and Sentiment Classification.