Text Classification and Document Categorization

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Understanding Text with Machine Learning

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- **Machine learning approaches include supervised, unsupervised, and deep learning techniques.**
- **AI models combine data and algorithms to identify patterns and generate actionable insights.**

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- **Applications include spam filtering, sentiment analysis, and news or topic categorization.**
- **Effective classification relies on sufficient labeled data to train predictive models.**

Supervised vs. Unsupervised

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- **Supervised: documents have labels (e.g., spam, non-spam).**
- **Unsupervised: documents grouped by similarity without labels.**
- **Document classification is a general problem applicable to many use cases.**

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- **Consider documents as sequences of sentences or paragraphs.**
- **Our task: classify each document into categories.**
- **This involves:**
  - **Preprocessing text**
  - **Extracting features**
  - **Training a classification model**
  - **Evaluating performance**

Concept of Text Classification

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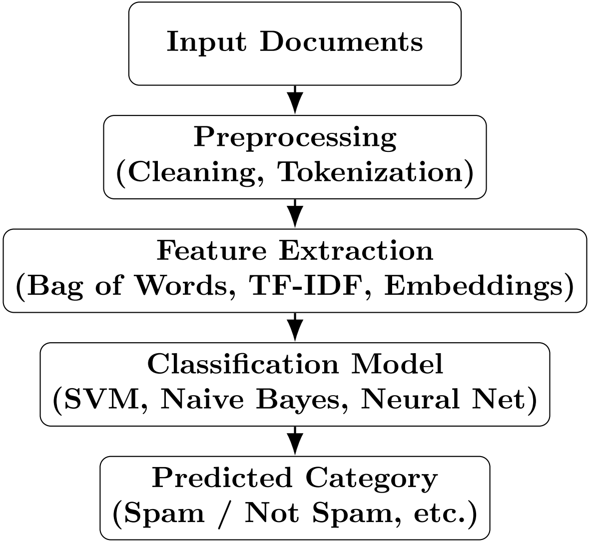
- **Represent documents as features (words, phrases, embeddings).**
- **Use these features to assign documents to predefined categories.**
- **Examples: spam detection, sentiment analysis, topic categorization.**
- **Process: Preprocessing $\rightarrow$ Feature Extraction $\rightarrow$ Classification.**

Simple Diagram of Text Classification



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- **Features represent text documents in a structured form for ML algorithms.**
- **Example: words, phrases, or even TF-IDF scores.**

Feature Extraction

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Feature Extraction

- **Process of converting raw text into structured features.**
- **Usually involves transforming documents into numerical vectors.**
- **Helps ML algorithms detect patterns and make predictions.**
- **Challenge: finding the best way to represent unstructured text.**

Vector Space Model

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- **Vector space enables algorithms to process and compare documents.**

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- where w_{iD} = weight of word i in document D.
- Weight can be frequency, average occurrence, or TF-IDF.

Common Feature Extraction Models

- **Bag of Words (BoW)**

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- **TF-IDF (Term Frequency–Inverse Document Frequency)**

Common Feature Extraction Models

- **Bag of Words (BoW)**
- **TF-IDF (Term Frequency–Inverse Document Frequency)**
- **Advanced word vectorization models (Word2Vec, GloVe, BERT embeddings)**

Movie Review Dataset (New 10 Sentences)

Positive Reviews:

- **I absolutely loved this movie. I loved the story and the characters.**

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- Such a disappointing movie, I regret watching it.
- This was the worst movie I have seen. Truly the worst experience.
- Poor storyline and bad performances throughout.

BoW Vector Representation with Features and Class

Review	loved (x_1)	movie (x_2)	fantastic (x_3)	boring (x_4)	terrible (x_5)	great (x_6)	excellent (x_7)	worst (x_8)	acting (x_9)	story (x_{10})	Class
1	2	1	0	0	0	0	0	0	0	1	Positive
2	0	0	0	0	0	0	0	0	1	1	Positive
3	0	0	0	0	0	2	0	0	0	0	Positive
4	0	1	0	0	0	0	0	0	0	0	Positive
5	0	0	0	0	0	0	1	0	0	0	Positive
6	0	1	0	1	0	0	0	0	0	0	Negative
7	0	0	0	0	1	0	0	0	1	0	Negative
8	0	0	0	0	0	0	0	0	0	0	Negative
9	0	1	0	0	0	0	0	2	0	0	Negative
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- **Each column x_i represents the count of the corresponding word in the review.**

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- **Each column x_i represents the count of the corresponding word in the review.**
- **Last column shows the class label (Positive/Negative).**

Use of Bag of Words in Classification

- **Positive words: {loved, fantastic, great, excellent}**

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- **New unseen reviews can be classified as Positive or Negative.**

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- **Formula for predicting the class y:**

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

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- Here, $P(y)$ = prior probability of class y, $P(x_i \mid y)$ = likelihood of word x_i in class y.

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- **BoW vector representation: $x = [2, 1, 0, 0, 0, 0, 0, 0, 0, 1]$**

Naive Bayes: Compute Probability for Positive Class

- **Positive word counts (sum from all Positive reviews): loved=2, movie=3, story=2, fantastic=0, great=2, excellent=1, acting=1, boring=0, terrible=0, worst=0**

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- **Positive word counts (sum from all Positive reviews): loved=2, movie=3, story=2, fantastic=0, great=2, excellent=1, acting=1, boring=0, terrible=0, worst=0**
- **Total words in Positive reviews = 11**

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- **Total words in Positive reviews = 11**
- **Probabilities for words in Review 1 (Positive):**

$$P(x_1 = 2 \mid Positive) = \frac{2}{11} \approx 0.182, \quad P(x_2 = 1 \mid Positive) = \frac{3}{11} \approx 0.273, \quad P(x_{10} = 1 \mid Positive) = \frac{2}{11} \approx 0.182$$

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- **Joint probability for Review 1 (Positive):**

$$P(x \mid Positive) \approx 0.182^2 \cdot 0.273 \cdot 0.182 \approx 0.00166$$

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- **Multiply by prior $P(Positive) = 0.5$:**

$$P(Positive \mid x) \propto 0.5 \cdot 0.00166 \approx 0.00083$$

Naive Bayes: Compute Probability for Negative Class

- **Negative word counts (sum from all Negative reviews): loved=0, movie=3, story=0, fantastic=0, great=0, excellent=0, acting=1, boring=1, terrible=1, worst=2**

Naive Bayes: Compute Probability for Negative Class

- **Negative word counts (sum from all Negative reviews): loved=0, movie=3, story=0, fantastic=0, great=0, excellent=0, acting=1, boring=1, terrible=1, worst=2**
- **Total words in Negative reviews = 8**

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- **Probabilities for words in Review 1 (Negative):**

$$P(x_1 = 2 \mid Negative) = 0, \quad P(x_2 = 1 \mid Negative) = \frac{3}{8} = 0.375, \quad P(x_{10} = 1 \mid Negative) = 0$$

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- Compare: $P(Positive \mid x) > P(Negative \mid x)$

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- Compare: $P(Positive \mid x) > P(Negative \mid x)$
- Conclusion: Review 1 is classified as Positive.

Reach PostNetwork Academy

Website

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www.postnetwork.co

YouTube Channel

www.youtube.com/@postnetworkacademy

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Website

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GitHub Repositories

www.github.com/postnetworkacademy

Thank You!