Natural Language Processing (NLP)

Core of Modern NLP

Equipping You with Research Depth and Industry Skills – Data Science Oriented

By:

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Recommended Books

Speech and Language Processing

An Introduction to Natural Language Processing,
Computational Linguistics, and Speech Recognition
with Language Models

Third Edition draft

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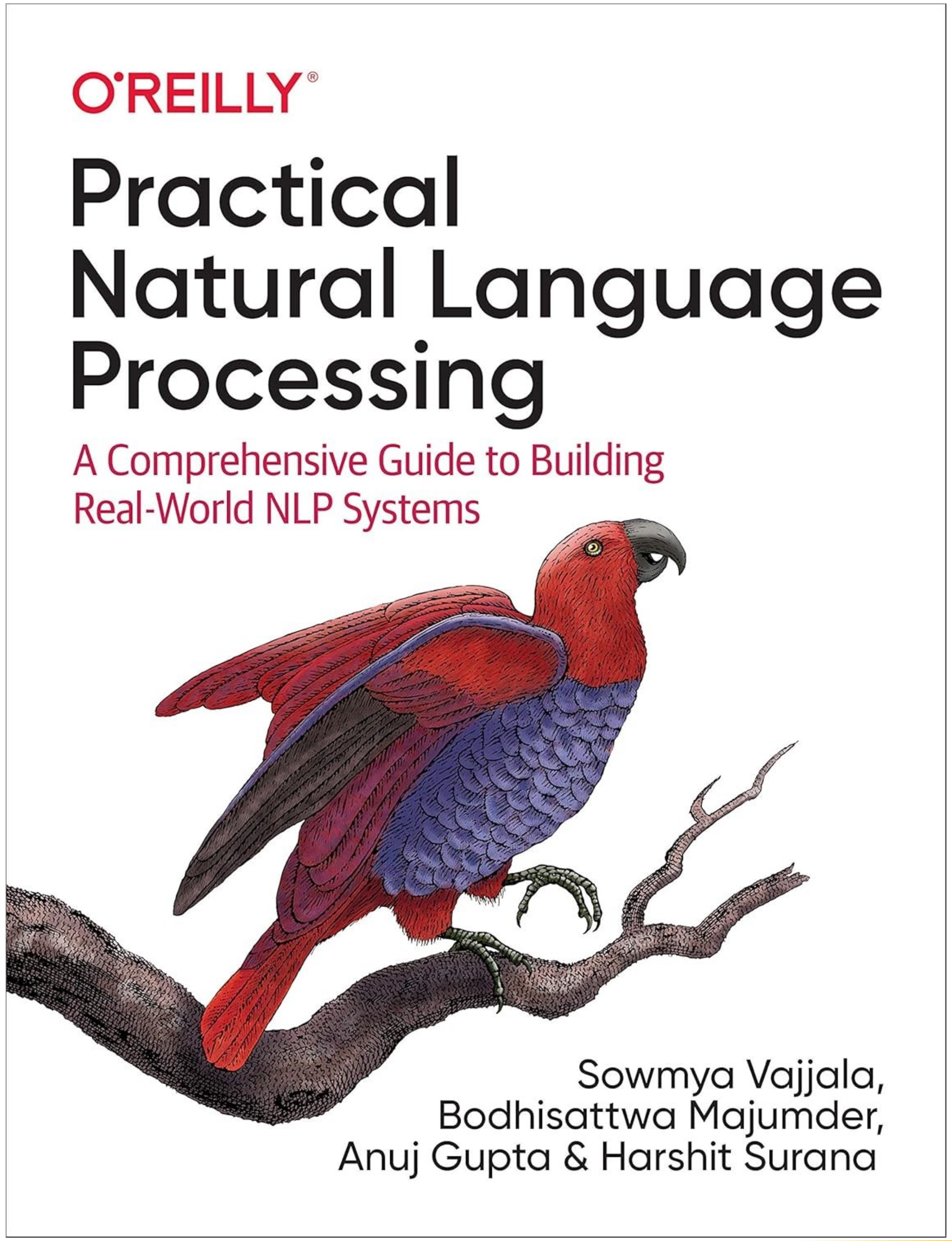

Natural Language Processing (NLP)

- **Natural Language Processing (NLP)** is a branch of artificial intelligence (AI) that focuses on helping computers understand, interpret, and respond to human language.
- Think of it like this:
- Humans speak in natural languages (like English, Arabic, Hindi, French).
- Computers “speak” in binary or programming languages.
- NLP acts as the **bridge** between the two.
- Some common **examples of NLP** you already interact with:
- Google Translate (language translation)
- Siri or Alexa (voice assistants)
- ChatGPT (text understanding and generation)
- Spam filters in email (detecting unwanted messages)

Real Time Use Cases

Common NLP Libraries

- **General NLP toolkits**
- **NLTK (Natural Language Toolkit)** – classic library, great for teaching basics: tokenization, stemming, POS tagging.
- **spaCy** – fast, industrial-strength, with built-in pipelines for tokenization, lemmatization, POS tagging, dependency parsing, and named entity recognition.
- **Deep Learning–based NLP**
- **Hugging Face Transformers** – the go-to for pretrained models like BERT, GPT, T5. Widely used in research & production.
- **AllenNLP** – built on PyTorch, good for experiments in academic NLP.
- **Fairseq (Meta AI)** – powerful for sequence-to-sequence models like translation and summarization.

Common NLP Libraries

- **Text Processing & Utilities**
- **TextBlob** – simple API for sentiment analysis, part-of-speech tagging, and translation (good for quick demos).
- **Gensim** – specializes in topic modeling and word embeddings (e.g., Word2Vec, Doc2Vec, LDA).
- **Stanford CoreNLP** – Java-based, but very strong for parsing and linguistic features.
- **Speech & Multimodal NLP**
- **SpeechRecognition** – for converting speech to text.
- **OpenAI Whisper** (and Hugging Face integration) – state-of-the-art speech recognition.

Why NLP is Popular right now

- **Why is NLP Booming Today?**
- NLP has existed in academia for decades.
- Real industry applications rushed in the last 7–10 years.

Reason 1 – Pre-trained Models & APIs

- Training NLP models needs **huge data + compute**.
- Big companies (Google, Facebook, OpenAI, Amazon) provide **pre-trained models**:
  - **fastText (Facebook)**
  - **TensorFlow Hub (Google)** – BERT, USE, etc.
  - **GPT-3 (OpenAI)** – $4M training cost, now accessible.
- **Transfer learning** makes NLP accessible to small companies.

Reason 2 – Open-Source Ecosystem

- Earlier: coding from scratch in C++
- Now: Python + open-source libraries = rapid prototyping
  - **spaCy**
  - **Gensim**
  - **NLTK**
- Backed by community, continuously improving.

Reason 3 – Affordable Hardware & Cloud

- Past: costly GPUs & infrastructure.
- Present:
  - Cheaper GPUs.
  - Cloud platforms: **AWS, Azure, Google Cloud**.
  - Rent resources instead of buying.

Reason 4 – Learning Resources

- **Reason 4 – Learning Resources**
- Before: limited access (only universities).
- Now: global accessibility.
  - Free content: **YouTube, blogs, Kaggle, StackOverflow**
  - Courses: **Coursera, Udemy, bootcamps**
  - Communities: **Discord, Zoom, competitions**
- Anyone can learn NLP quickly.

Reason 5 – Big Tech Investments

- Tech giants building ecosystem:
  - Google: TensorFlow, Google Home
  - Amazon: Alexa, Echo devices
  - Meta: fastText, FAIR research
- Heavy investments → smaller companies follow (FOMO effect).
- FOMO = Fear of Missing Out
- When big tech companies (Google, Amazon, Meta, etc.) invest in NLP
- Smaller companies feel pressure to adopt it too, because they don't want to miss opportunities, market share, or innovation trends.

NLP is booming

- Free pre-trained models
- Open-source libraries
- Cloud & cheap hardware
- Easy learning resources
- Big tech investments
- Future: **More rapid advancements, wider adoption**.

Techniques to Solve NLP Problems

- **Techniques to Solve NLP Problems**
- NLP has many approaches.
- **3 broad categories of techniques**.

Technique 1 – Rules & Heuristics

- Based on **patterns, rules, and regex**.
- Example: Gmail flight ticket → auto-extracted summary.
- **Regex approach:**
  – “Booking Ref: XXXXX” → extract confirmation number.
- Pros: Simple, precise.
- Cons: Not scalable, hard for complex text.
- **Example – Rules in Action**
- Search “Elon Musk” → Google sidebar info.
- Likely uses **pattern-based extraction**.
- **Key idea:** Rules can solve information extraction tasks without ML.

Technique 2 – Statistical / Machine Learning

- **Spam Detection**
  - Raw email text → Number vector → Classifier.
- Common workflow:
  - Raw text
  - Preprocessing (cleaning, lemmatization, etc.)
  - Convert text → numbers (e.g., CountVectorizer, TF-IDF)
  - Classification (e.g., Naïve Bayes)
- Pros: More general than rules.
- Cons: Struggles with unseen words/phrases.

- **Example – Spam Email**
- Text: *"Urgent business assistance… 55 million USD…"*
- Suspicious keywords trigger spam detection.
- **Pipeline:**
  - CountVectorizer → numeric representation.
  - Naïve Bayes → spam/not spam.

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What is CountVectorizer?

- **CountVectorizer** is a technique to convert text into a **numeric representation** that machine learning models can understand. It essentially counts how often each word appears in a document. This is also known as **Bag of Words** (BoW).

What is CountVectorizer?

- **Step 1 – Tokenization**
  - Split text into individual words (tokens).
  - **Sentence 1:** "I love NLP." → Tokens: ["I", "love", "NLP"]
  - **Sentence 2:** "NLP is amazing!" → Tokens: ["NLP", "is", "amazing"]
- **Step 2 - Build Vocabulary**
  - Create a vocabulary of unique words from the entire text.
  - Vocabulary: ["I", "love", "NLP", "is", "amazing"]
- Step 3 - Count Word Occurrences
  - Count how often each word appears in each document.
  - **Sentence 1:** ["I", "love", "NLP"] → Word counts: I:1, love:1, NLP:1
  - **Sentence 2:** ["NLP", "is", "amazing"] → Word counts: NLP:1, is:1, amazing:1
- Step 4 - Create Vectors
  - Convert the word counts into vectors (numeric form).
  - Sentence 1 Vector: [1, 1, 1, 0, 0]
  - Sentence 2 Vector: [0, 0, 1, 1, 1]

Word	I	love	NLP	is	amazing
Sentence 1	1	1	1	0	0
Sentence 2	0	0	1	1	1

Challenge with Statistical ML

- Example:
  - Training: *“Hurry up to win cash”*, *“You won a laptop”*.
  - New text: *“Rush for this great deal to win money”*.
- CountVectorizer fails if words are unseen.
- **Solution:** Use embeddings that capture semantic meaning.

Technique 3 – Deep Learning

- Uses **word embeddings / sentence embeddings**.
- Example: **BERT (Google)**, Hugging Face Transformers.
- Embeddings allow similar sentences to have similar vectors.
- Example:
  - “Win cash fast” ≈ “Hurry up to win money”
  - Embedding vectors → Cosine similarity.
- **Hugging Face Sentence Transformers**
- Input: “I love baby yoda!” vs. spam sentences.
- Output: Similarity scores (cosine similarity).
- Shows how embeddings capture **semantic meaning**
- https://huggingface.co/sentence-transformers

Cosine Similarity

- Imagine two arrows (vectors) starting at the same point.
- If they point in **exactly the same direction**, they are **very similar**.
- If they point in **opposite directions**, they are **very different**.
- If they are **at a right angle**, they are **not similar at all**.
- Cosine similarity just measures **the angle between two vectors**.

- For two vectors **A** and **B**:
- Cosine Similarity= $\frac{\boldsymbol{A}.\boldsymbol{B}}{||\boldsymbol{A}||\,||\boldsymbol{B}||}$
- ||A||= length (magnitude) of vector A.
- ||B||= length (magnitude) of vector B.
- Cosine similarity **high** (**close** meaning).
- Cosine similarity **low** (**different** meaning).

Naive Bayes

- **Naive Bayes** is a simple but effective **probabilistic machine learning algorithm** based on **Bayes' Theorem**, and it's particularly well-suited for **classification tasks** like **text classification** (e.g., spam detection, sentiment analysis).
- It’s called "Naive" because it assumes that all features (words, in this case) are **independent** of each other, which is often **not true** in real-world scenarios. However, this simplification works surprisingly well in practice.

Bayes' Theorem:

- Bayes' Theorem is the foundation of Naive Bayes. It calculates the **probability** of a class C given some features X (in NLP, the features are words in the document).

$$P(C|X) = \frac{P(X|C) \cdot P(C)}{P(X)}$$

- Where:
- P(C|X) = Posterior: Probability of class C given the features X.
- P(X|C) = Likelihood: Probability of features X given the class C.
- P(C) = Prior: The probability of class C occurring in the dataset.
- P(X) = Evidence: The probability of features X occurring, independent of the class.

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Bayes' Theorem:

Email	Class
"Win money now"	Spam
"Cheap offer, win now"	Spam
"Meeting schedule"	Not Spam
"Lunch at noon"	Not Spam

- **Class Priors:**
- $\mathrm{P}(\text{Spam}) = \frac{2}{4} = 0.5\,;\ P(\text{Not Spam}) = \frac{2}{4} = 0.5$
- **Likelihoods:**
- Let's say we are given the new email: **"win money".**
- **P(win|Spam):** From the training data, "win" appears 2 times in 2 spam emails (out of 2 total spam emails). So,
- $P(\text{win}|\text{Spam}) = \frac{2}{2} = 1$
- **P(money|Spam):** "money" appears 1 time in 2 spam emails (out of 2 total spam emails). So,
- $P(\text{money}|\text{Spam}) = \frac{1}{2} = 0.5$
- Similarly, we calculate for the Not Spam class.

- **Posterior Calculation:**
- **For Spam:**
- $P(\text{Spam}|\text{win, money}) \propto P(\text{win}|\text{Spam}) \cdot P(\text{money}|\text{Spam}) \cdot P(\text{Spam}) = 1 \cdot 0.5 \cdot 0.5 = 0.25$
- **For Not Spam:**
- $P(\text{Not Spam}|\text{win, money}) \propto P(\text{win}|\text{Not Spam}) \cdot P(\text{money}|\text{Not Spam}) \cdot P(\text{Not Spam}) = 0.25 \cdot 0.25 \cdot 0.5 = 0.03125$
- **Prediction:**
- Since the posterior probability of Spam is higher (0.25 vs. 0.03125), the algorithm classifies the email as Spam.