

# NATURAL LANGUAGE PROCESSING (NLP)

## PMDS606L

MODULE 1 LECTURE 4

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### REAL LIFE APPLICATIONS OF NLP

- Spell Checking
- Grammar Checking
- Information Extraction
- Information Retrieval
- Question Answering
- Machine Translation

## **Types of Errors**

Non-word errors

Word does not exist in the dictionary

**Example**: "recieve" → "receive"

Real-word errors

Word is valid but incorrect in the context

**Example**: "Their going to the store" →

"They're going to the store"

## Components of Spell Checking

- Error Detection
- Candidate Generation

**Edit Distance Methods** 

Phonetic Algorithms

**Keyboard Distance** 

Candidate Ranking and Selection

- Input Text → Tokenization → For each token:
  - → Error Detection (dictionary lookup)
  - → If misspelled:
- → Generate Candidates (edit distance, phonetics)
  - → Rank Candidates (frequency, context)
  - → Replace with Best Candidate

## **Applications of Spell Checking in NLP**

- Text Editors (MS Word, Google Docs)
- Search Engines ("Did you mean?" suggestions)
- Autocorrect in Smartphones
- Voice Assistants (after speech-to-text conversion)
- Chatbots and Email Filters
- Assistive Tools for Language Learners

## **GRAMMAR CHECKING**

- Modern grammar checkers go beyond rulebased correction and use deep learning, contextual understanding, and large corpora to detect even subtle issues.
- Grammar checkers aim to ensure syntactic and semantic correctness by analyzing sentence structure, agreement rules, and contextual usage.

Error Type	Example	Correction
Subject-verb agreement	He go to school	He <b>goes</b> to school
Tense errors	She eat yesterday	She <b>ate</b> yesterday
Article misuse	She has <b>a</b> idea	She has <b>an</b> idea
Preposition errors	He arrived <b>to</b> the airport	He arrived <b>at</b> the airport
Word order	Beautifully she sings	She sings beautifully
Pronoun errors	Me went there	I went there
Run-on sentences	I went home I slept	I went home, and I slept
Fragment sentences	Because he was late.	He was late, so

## APPROCHES IN GRAMMAR CHECKING

- Rule-Based Grammar Checking
- Statistical Grammar Checking
- Machine Learning-Based Grammar Checking
- Deep Learning-Based Grammar Correction

### RULE-BASED GRAMMAR CHECKING

- Uses hand-crafted grammar rules and regular expressions.
- Simple but rigid and language-specific.
- Examples

**Grammarly** (initial versions)

LanguageTool

Ginger (initially rule-based)

### STATISTICAL GRAMMAR CHECKING

- Use of n-gram language models (e.g., trigram models)
- Detect errors by measuring how likely a sentence is based on training data
- "He go to school" has a lower probability than "He goes to school"
- Examples

Grammarly (older hybrid systems)

Microsoft Word's statistical checker (predeep learning)

## **ML-BASED GRAMMAR CHECKING**

- Supervised classification (Is this word/phrase grammatically correct?)
- Features: POS tags, dependency trees, context windows
- Examples

Google's early grammar checker
CoNLL Shared Tasks on Grammatical
Error Correction (GEC)

### **DL-BASED GRAMMAR CHECKING**

- Treat grammar correction as a sequence-tosequence (seq2seq) task
- LSTM Encoder-Decoder, Transformer Encoder-Decoder, BERT-based models (e.g., RoBERTa, T5, BART, GECToR)
- Examples
- **GECToR** (Efficient Transformer-based model for grammar correction)
  - Gingerlt
  - **Grammarly (Advanced)**
  - **DeepL Write**
  - ChatGPT, Google's grammar checker

## **GRAMMAR CHECKING**

## **Applications of Grammar Checkers**

- Word processors (Google Docs, MS Word)
- Writing assistants (Grammarly, Quillbot, DeepL Write)
- Language learning apps (Duolingo, HelloTalk)
- Chatbots (to ensure correct replies)
- Speech-to-text systems (after ASR)

### **GRAMMAR CHECKING**

Input: "She not goes to college."

#### Steps:

- Tokenization: [She, not, goes, to, college, .]
- POS Tagging: PRON, ADV, VERB, PREP, NOUN, PUNCT
- Parse Tree: Detected mismatch in negation and verb form
- Error Detection: "not goes" is ungrammatical
- Candidate Generation: "does not go", "doesn't go", "is not going"
- Ranking: Based on language model → "does not go"
- Correction: "She does not go to college."

## INFORMATION EXTRACTION (IE)

Task	Example

Template Filling

Named Entity Recognition (NER)

"Barack Obama was born in Hawaii." → Entities: Barack
Obama (Person), Hawaii (Location)

Relation Extraction "Google acquired YouTube in 2006." → (Google, acquired, YouTube, 2006)

Event Extraction

"An earthquake struck Japan on Monday." → Event:
earthquake, Location: Japan, Date: Monday

Coreference Resolution "Mary said she would help." → Mary = she

"John works at Microsoft." → Fill: {Person: John, Organization: Microsoft, Job: employee}

## IE TECHNIQUES AND MODELS

Technique	Description	Example Tools	
Rule-Based	Manually defined grammar and pattern-matching rules	GATE, spaCy Matcher	
Statistical Models	CRF, HMM, MaxEnt	Stanford NER	
Neural Models	BiLSTM-CRF, CNN, RNN	Flair, AllenNLP	
Transformer-based	Pretrained language models with fine-tuning	BERT, RoBERTa, spaCy 3+, T5, GPT, REBEL	

### OTHER IE APPROACHES

- Distant Supervision
- Open Information Extraction (OpenIE)
   OpenIE5
   Stanford OpenIE
   MinIE
- Zero-Shot IE
- Few-Shot IE

## APPLICATIONS OF IE

Domain Use Case

Search Engines Enhancing result snippets with extracted facts

Chatbots / QA Systems Answering fact-based queries

Healthcare Extracting patient data from clinical notes

Finance Extracting company earnings, merger news

Legal Contract clause identification

Social Media Analysis Entity and trend detection from tweets/posts

## **INFORMATION RETRIEVAL (IR)**

- Information Retrieval (IR) is the process of obtaining information system resources (e.g., documents, paragraphs, sentences) that are relevant to an information need (query) from a large corpus.
- It is the foundation of search engines, question answering systems, and document recommendation tools.

## INFORMATION RETRIEVAL (IR)

Task Example

**Document Retrieval** "Jurafsky" → Return documents written by Jurafsky

Passage Retrieval "Where was Gandhi born?" → Return relevant sentence

Ad-hoc Retrieval User poses novel, unstructured queries

Question Answering Extract answer phrases from retrieved docs

Semantic Search Match queries based on meaning, not just keywords

## **APPLICATIONS OF IR**

Domain Use Case

Search Engines Google, Bing, DuckDuckGo

**E-commerce** Product search and ranking

Chatbots Retrieve relevant FAQs

**Legal/Medical NLP** Find related case laws or symptoms

**Document Recommendation**Suggest papers, news, or books

Question Answering (QA) Retrieve evidence for answering queries

## IR MODELS

Model	Description
BERT (re-ranker)	Contextual ranking of documents after initial retrieval (not suitable for large-scale retrieval)
Siamese BERT / Sentence-BERT (SBERT)	Converts queries and documents into fixed-length semantic vectors for fast search
Dense Passage Retrieval (DPR)	Dual BERT encoders for questions and passages; used in QA
ColBERT (Contextual Late Interaction)	Efficient dense retrieval using token-level interactions
TAS-B (Token-Aware SBERT)	Hybrid model combining BERT and interaction layers for better performance
ANCE (Approximate Nearest Neighbor Negative Contrastive Estimation)	Learns better dense representations for fast retrieval
RAG (Retrieval-Augmented Generation)	Combines dense retrieval and text generation (e.g., BART + FAISS)

## **QUESTION ANSWERING (QA)**

Туре	Description	Example
Closed-domain QA	Focused on a specific subject area (e.g., medicine, law)	"What is the normal blood pressure?"
Open-domain QA	Answers any general question from a large corpus like Wikipedia	"Who discovered penicillin?"
Factoid QA	Provides a factual answer (name, date, location)	"When did World War II end?" → "1945"
Yes/No QA	Returns binary responses	"Is Mount Everest the tallest mountain?"
List QA	Returns a list of answers	"Name the continents"
Generative QA	Produces natural language answers (beyond span extraction)	"Why is the sky blue?" → "Because molecules in the air scatter blue light more."

## **QUESTION ANSWERING (QA) PIPELINE**

```
User Question
[1] Information Retrieval (IR)
Top-k Relevant Passages or
Documents
[2] Machine Reading Comprehension
(MRC)
Extracted or Generated Answer
```

## **QUESTION ANSWERING (QA) MODELS**

Model	Use Case	Туре
BERT	Extractive QA from short passages	Span-based
RoBERTa / XLNet	Improved versions of BERT	Span-based
T5 (Text-to-Text Transfer Transformer)	Generative QA	Seq2Seq
RAG (Retrieval-Augmented Generation)	Combines retrieval + generation	Hybrid
GPT-3 / GPT-4 / Claude / LLaMA	Zero-shot QA, open-domain	Generative

**DPR (Dense Passage Retrieval)** 

Open-domain retrieval

**Dual Encoder** 

## **QA SYSTEMS**

System Platform

Google Search Snippets Open-domain QA

Alexa / Siri / Google Assistant Voice-based QA

IBM Watson Domain-specific QA

ChatGPT / Claude / Bard Large Language Model-based QA

Haystack QA Pipelines End-to-end Python QA systems

## MACHINE TRANSLATION (MT) PIPELINE

Source Language Text

- 1. Text Preprocessing
- 2. Tokenization & Subword Segmentation
- 3. Embedding Layer (Encoder Input)
- 4. Encoder (e.g., Transformer)
- 5. Attention Mechanism
- 6. Decoder (Auto-regressive)
- 7. Target Language Generation
- 8. Postprocessing (Detokenization, Grammar Fixes)

**Target Language Text** 

### **DL-BASED MT**

Feature Description

**Uses** Neural networks (especially Transformers)

**Models** Encoder–Decoder architecture

Handles Context, long dependencies, fluency

**Examples** Google Translate (Transformer), DeepL (custom NMT), OpenNMT

Frameworks OpenNMT, Fairseq, MarianNMT, HuggingFace Transformers

#### **APPLICATIONS OF MACHINE TRANSLATION**

Domain Use

Web Translation Google Translate, DeepL

**E-commerce** Translate reviews, product listings

Healthcare Cross-lingual patient communication

Legal / Policy Document translation between jurisdictions

News & Media Multilingual publishing

**Government** Translation of official documents

Social Media Facebook auto-translation of posts

#### **TOOLS AND LIBRARIES FOR MT**

Tool Description

**OpenNMT** Open-source NMT toolkit (PyTorch, TensorFlow)

MarianNMT Fast NMT framework used by Microsoft

Fairseq Facebook's NLP toolkit for sequence modeling

**Transformers (HuggingFace)** Pretrained MT models like T5, mBART, MarianMT

Google Translate API Commercial translation service

DeepL API High-quality translations in European languages

Bergamot / Firefox Translator Offline NMT in browser (privacy-preserving)