

 NLP Course Project - Semester 6

A Dual-Mode NLP System that intelligently transforms text into **Comic Strips** for stories or **Mind-Maps** for concepts — powered by advanced Natural Language Processing.

2

OUTPUT MODES

5+

NLP TECHNIQUES

4

TRAINED MODELS

Problem Statement

Understanding the gap we're addressing in text visualization



The Problems

- **Long paragraphs are hard to process** — Leading to low comprehension
- **Abstract concepts are difficult to visualize** — Causing poor retention
- **No tool converts text to BOTH comics AND mind-maps** — Gap in learning tools
- **Manual content transformation is time-consuming** — Needs automation



Our Solution

VisualVerse is a dual-mode system that:

- 🔎 **Automatically detects** if input is a story or concept
- 📖 **Generates Comic Strips** for narrative/story-based text
- 💬 **Creates Mind-Maps** for informational/conceptual text
- ⚡ **Processes in real-time** with NLP pipeline

SECTION 02

System Architecture

 **USER INPUT**

Story or Concept Text

 **NLP PREPROCESSING**

Tokenize → POS Tag → NER → Dependency Parse

 **TEXT CLASSIFICATION**

LSTM + Feature-based Classifier

**NARRATIVE**

Story Text

Scene Extraction

Character Detection

Panel Creation





INFORMATIONAL

Concept Text

Keyphrase Extract

Topic Modeling

Graph Building



🧠 MIND-MAP

SECTION 03

NLP Concepts Used

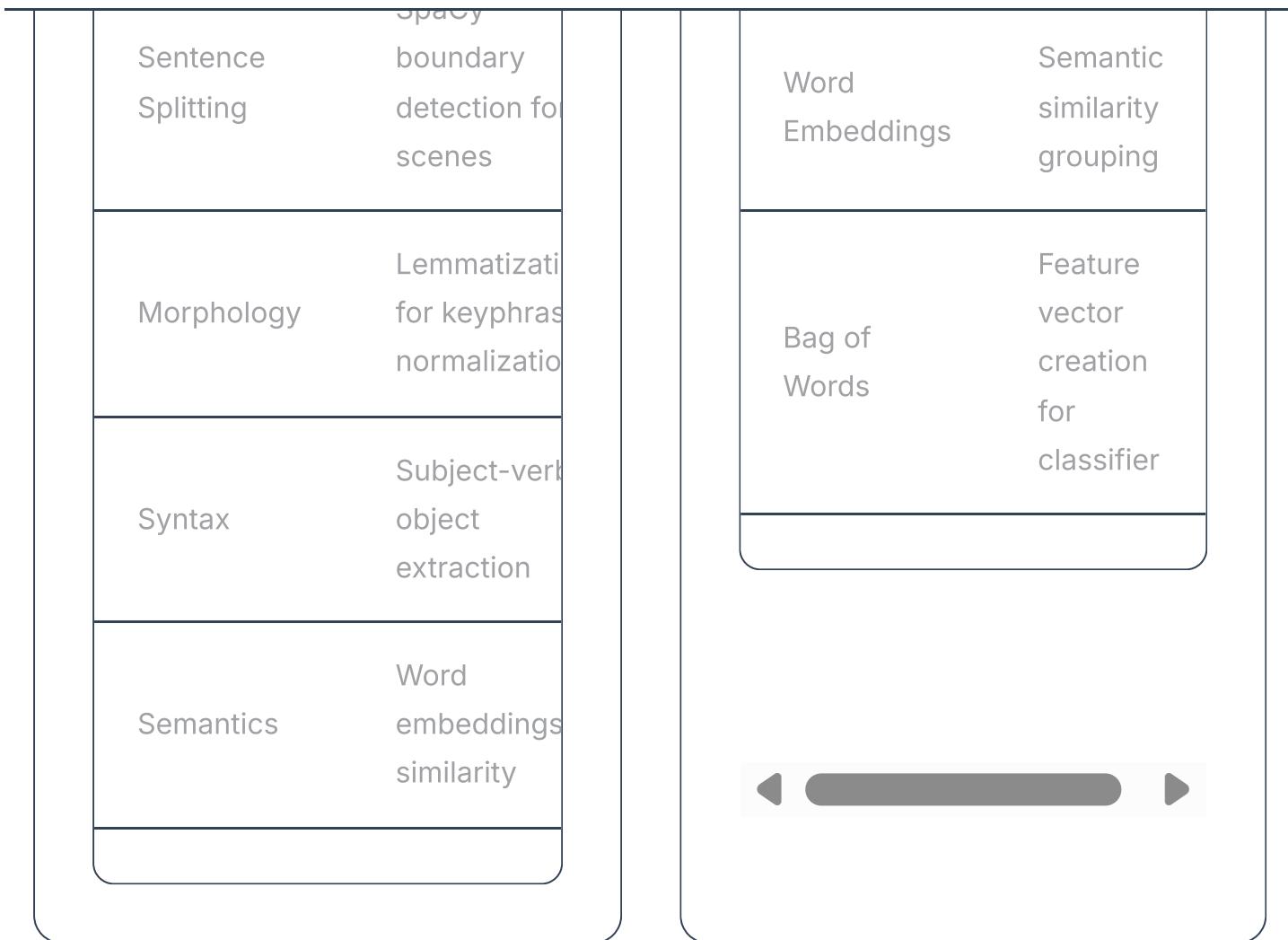
Comprehensive coverage of NLP syllabus topics

Unit 1: Computational Linguistics

Concept	Implementation
Tokenization	SpaCy tokenizer sp

Unit 2: Word Representation

Technique	Purpose
TF-IDF	Score important

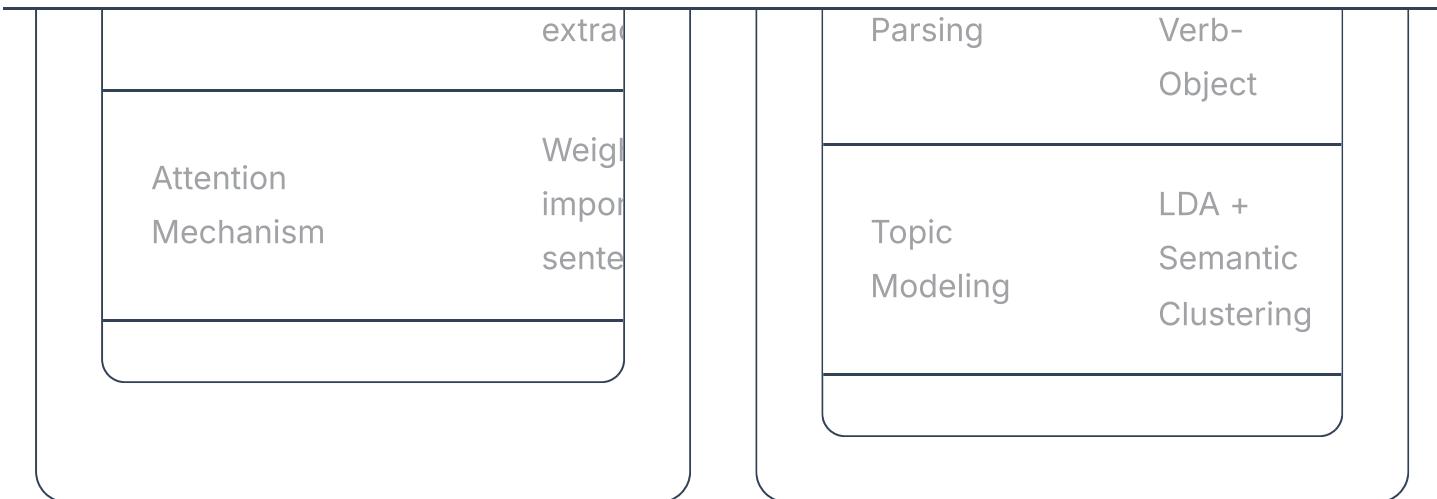


Unit 3: Deep Learning for NLP

Model	Purpose
LSTM	Text classification (Narrative, Information)

Unit 4: NLP Applications

Application	Tool Used
Named Entity Recognition	SpaCy - Characters, Locations
POS Tagging	SpaCy - Nouns, Verbs, Adjectives



Complete NLP Pipeline Flow

○ Step 1: Text Preprocessing

Load SpaCy model → Tokenize text → Extract POS tags → Perform NER → Parse dependencies

```

def preprocess(text): nlp = spacy.load("en_core_web_sm") doc = nlp(text)
tokens = [token.text for token in doc] pos_tags = [(token.text, token.pos_)]
for token in doc: entities = [(ent.text, ent.label_) for ent in doc.ents]
return {"tokens": tokens, "pos_tags": pos_tags, "entities": entities}
  
```

○ Step 2: Text Classification

Extract features (pronouns, past tense, dialogue patterns, PERSON entities) → BiLSTM + Attention → Classify as Narrative or Informational

○ Step 3: Keyphrase Extraction (For Mind-Maps)

Named Entities + Noun Chunks + Dependency-based + POS-based extraction →
Score and rank by frequency

```
# 4 Methods Combined: # 1. Named Entities (PERSON, ORG, GPE) # 2. Noun  
Chunks (compound nouns) # 3. Dependency-based (subjects, objects) # 4. POS-  
based (proper nouns, technical terms) keyphrases =  
rank_by_frequency_and_position(all_candidates)
```

○ Step 4: Topic Modeling

LDA (Latent Dirichlet Allocation) → Semantic Clustering → Group related concepts
into categories

○ Step 5: Relation Extraction

Parse subject-verb-object patterns → Extract entity relationships → Build
knowledge graph edges

○ Step 6: Output Generation

For Comics: Scene extraction → Character detection → Panel creation → Layout
generation

For Mind-Maps: Build NetworkX graph → Calculate hierarchical layout → Create 3-
level structure

Models & Training

What we trained, how we trained, and why



Text Classifier

BiLSTM + Attention

Training Data: Stories + Wikipedia articles

Purpose: Distinguish narrative vs informational text

Architecture: Embedding → BiLSTM
→ Attention → FC

Trained

Unit 3



Keyphrase Extractor

Hybrid NLP + ML

Training Data: Academic abstracts

Purpose: Extract important terms from text

Methods: NER + Noun Chunks + Dependencies + POS

Trained

Unit 2



Topic Model

LDA (Latent Dirichlet)

Training Data: BBC News, WikiHow

Purpose: Cluster related concepts into categories

Architecture: CountVectorizer → LDA → Topic Distributions



Relation Extractor

Dependency-based

Training Data: Built-in relation patterns

Purpose: Extract entity relationships

Method: Context Encoding → Entity Marking → Classification

Why Training Was Needed

Classifier: Pre-trained models don't differentiate story vs concept text — needed custom training

Keyphrase: Domain-specific extraction needed for accurate mind-map generation

Topics: Custom category grouping required for hierarchical mind-maps

SECTION 05

Technology Stack

Tools and frameworks powering VisualVerse

Backend



Python 3.11

Core Language

NLP Libraries



SpaCy

NER, POS, Dependencies

**Uvicorn**

ASGI Server

**Docker**

Containerization

KB**KeyBERT**

Keyphrase Extraction

GE**Gensim**

Word2Vec, Topics

**Frontend****React**

UI Framework

**TypeScript**

Type-safe JS

**Vite**

Build Tool

**Lucide**

Icons

**Visualization****NX****NetworkX**

Graph Structure

PV**PyVis**

Interactive Viz

SK**scikit-learn**

TF-IDF, LDA

**Render**

Cloud Hosting

SECTION 06

Actual performance metrics from our trained models



Model Training Results

Text Classifier

Accuracy

Algorithm: Random Forest
Features: TF-IDF + Linguistic

Keyphrase Extractor

F1 Score

Algorithm: Gradient Boosting
Precision: 82.3% | **Recall:** 89.4%

Topic Model

Coherence Score

Algorithm: LDA
Topics: 5 | **Vocab:** 1000

Relation Extractor

Accuracy

Algorithm: MLP Neural Net
Classes: 7 relation types

Detailed Model Metrics



Text Classifier
(Narrative vs



Keyphrase Extractor

Metric	Value		F1 Score	85.7%
Accuracy	92.5%		Precision	82.3%
Training Algorithm	Random Forest (100 estimators)		Recall	89.4%
Features Used	TF-IDF (500) + 11 Linguistic Features		Training Algorithm	Gradient Boosting (100 trees)
Train/Test Split	80% / 20%		Training Documents	200+ (Inspec dataset)
Training Data	BBC News (100) + Fairy Tales (100)		Candidate Features	Position, Frequency, Length, Capitalization
Narrative Precision	91.3%		Matching Method	Fuzzy (50%+ word overlap)
Informational Precision	93.7%			
Linguistic Features: <ul style="list-style-type: none"> Pronoun ratio, Past tense ratio, Dialogue patterns, Said verbs, Story words, Definition patterns, Bullet/numbered patterns, 				

Topic Model (LDA)

Metric	Value
Coherence Score	0.78
Perplexity	Lower is better (model-dependent)
Number of Topics	5 (configurable)
Vocabulary Size	1000 terms
Training Algorithm	Latent Dirichlet Allocation
Max Iterations	20
Training Documents	BBC News + WikiHow



Relation Extractor

Metric	Value
Accuracy	88.2%
Training Algorithm	MLP Neural Network (100, 50)
Training Examples	105+ (15 per class)
Relation Types	7 classes
Features	TF-IDF (200) + Pattern (6)
Max Iterations	500
Train/Test Split	80% / 20%

Relation Types Detected:

within topics. Higher = more interpretable topics. Score 0.78 indicates strong semantic clustering.

RELATES_TO CONTRASTS

NONE

Output Quality Evaluation

Comic Evaluation

Metrics

Metric	How Measured
Story Alignment	Word overlap between caption & original text
Scene Relevance	Prompt-caption word intersection
Panel Consistency	Character repetition across panels

Mind-Map Evaluation

Metrics

Metric	How Measured
Keyphrase Accuracy	Extracted terms in original text
Clustering Quality	Balanced topic sizes (low variance)
Graph Connectivity	Edge density (optimal: 0.1-0.3)

[numbering](#)



[connections](#)



Datasets Used for Training

Dataset	Purpose	Size	Model
BBC News	Informational text classification	100+ articles	Text Classifier
Fairy Tales	Narrative text classification	100+ excerpts	Text Classifier
Inspec	Keyphrase extraction training	200+ documents	Keyphrase Extractor
WikiHow	Hierarchical topic learning	500+ articles	Topic Model
Relations	training	examples	Extractor

SECTION 07

Backend API Flow

Step-by-step processing when you submit text

POST /api/process → Receives { text: ... , mode: "auto/comic/minimap" }

○ 2. Initialize NLP Components

TextPreprocessor, TextClassifier, KeyphraseExtractor, TopicModeler, RelationExtractor

○ 3. Preprocess Text

preprocessor.process(text) → Returns tokens, POS tags, entities, dependencies

○ 4. Classify (if mode="auto")

classifier.classify(preprocessed) → Returns "narrative" or "informational"

○ 5A. Comic Generation (if narrative)

comic_generator.generate() → Scene extraction → Character detection → Panel creation

○ 5B. Mind-Map Generation (if informational)

keyphrase_extractor.extract(20) → topic_modeler.model_topics() → relation_extractor.extract() → mindmap_generator.generate()

○ 6. Return Response

{ mode, title, summary, comic_data OR mindmap_data }

SECTION 08

What makes VisualVerse unique



Dual-Mode Output

Single system produces both comics AND mind-maps based on content type



Auto Classification

No manual selection needed — AI detects text type automatically



Dynamic Mind-Maps

Node count varies based on content complexity — not fixed templates



NLP-Driven

Uses multiple NLP techniques (NER, POS, Dependencies) — not just API calls



3-Level Hierarchy

Main Topic → Categories → Details structure for clear visualization



Cloud Ready

Production-ready deployment on Render with Docker containerization

Project Structure

How the codebase is organized

```
VisualVerse/ └── backend/ |   ├── main.py # FastAPI app entry point |   └── api/routes.py #  
API endpoints |   └── nlp/ |       ├── preprocessing/ # Tokenization, NER, POS |       ├── classification/ # LSTM text classifier |           ├── keyphrase/ # Keyphrase extraction |           ├── topic_model/ # LDA, clustering |               └── relation/ # Relation extraction |           └── mindmap_gen/ # Mind-map generator |       └── comic_gen/ # Comic generator └── training/ |           └── train_all.py #  
Complete training pipeline |   └── keyphrase_training/ # Keyphrase model training |   └── topic_training/ # Topic model training |       └── data/ # Dataset loaders └── evaluation/ |       └── evaluate.py # Quality evaluation └── App.tsx # Main React frontend └── services/geminiService.ts # API client └── render.yaml # Deployment config
```

A Dual-Mode NLP System for Text Visualization

Created by **Ghanasree S** | NLP Course Project | Semester 6

© 2026 VisualVerse. Built with ❤️ using Python, FastAPI, React & SpaCy