

# NLP: Solutions for Real-World Problems

COMP8460: ARTIFICIAL INTELLIGENCE FOR NATURAL LANGUAGE PROCESSING APPLICATIONS

**Group F**

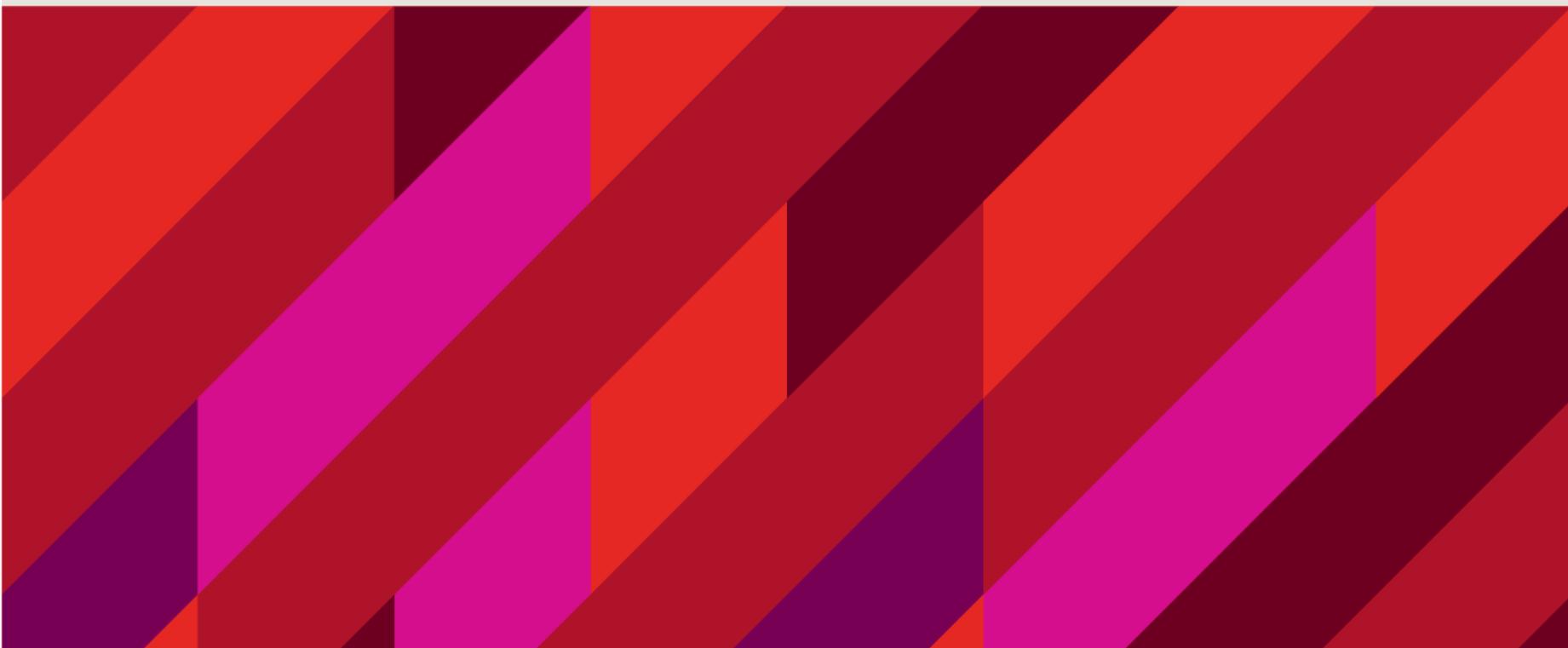
**Use Case 6: E-commerce Intelligent System**

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# Use Case: E-commerce Intelligent System



## GOAL OF THE SYSTEM

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Goal:

To build an intelligent E-commerce review analysis system that can:

- Extract key product aspects
- Determine sentiment expressed towards each aspect
- Analyze and summarize customer reviews at scale
- Detect fake or unreliable reviews to improve trust
- Generate concise product descriptions automatically
- Provide actionable business insights for product improvement and marketing decisions

# Dataset

## AMAZON PRODUCT REVIEWS (KAGGLE)

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- **Source:** Kaggle – Consumer reviews of Amazon products
- Combined 3 CSV files into one dataset
- Total reviews before cleaning: 67,992
- Dataset included around 15–20 attributes
- **Key fields used:** *product\_name, review\_text, rating, review\_date*

# Data processing

## DATA CLEANING AND PRE-PROCESSING WORKFLOW

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### 1. Data Cleaning

- Removed duplicates and missing entries
- Standardized key columns (`product_name`, `review_text`, `rating`, `review_date`)
- Corrected inconsistent text formatting and casing
- Final cleaned dataset size: **64,037 reviews**

### 2. Text Pre-processing

- Removed punctuation, numbers, and stop-words
- Converted all text to lowercase
- Tokenized and lemmatized using *spaCy(en\_core\_web\_sm)*

### 3. Feature Preparation

- Encoded sentiment labels: **0 = Negative, 1 = Positive, 2 = Neutral**
- Label distribution: Positive: **91.9%**, Neutral: **4.3%**, Negative: **3.8%**

# Basic Technique: Product Aspect Extraction (NER)

## SPACY CUSTOM NAMED ENTITY RECOGNITION

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### Goal:

Identify key product features (*e.g., battery, display, sound, price*) mentioned in customer reviews.

### Method:

- Created aspect keyword patterns using regex
- Trained a custom **spaCy NER** model using these aspect labels
- Evaluated performance using **Precision, Recall, and F1-Score**

### Process Steps:

1. Loaded the preprocessed review dataset
2. Defined aspect terms and patterns (battery, display, sound, price, quality)
3. Trained and fine-tuned spaCy NER model
4. Visualized extracted aspects using `spacy.displacy.render()`
5. Saved final model for downstream sentiment and summarization tasks

### Results:

- **F1-Score:** 0.75 – 0.85 (varies by aspect)
- Successfully extracts the most relevant product attributes from user reviews

# Basic Technique: Sentiment Classification

## TF-IDF FEATURES + LOGISTIC REGRESSION

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### Goal:

Classify each review as **Positive, Negative, or Neutral**.

### Method:

- Converted review text into TF-IDF weighted features (unigrams + bigrams)
- Trained a **Logistic Regression** classifier with class balancing
- Evaluated using **Accuracy, Precision, Recall, and Confusion Matrix**

### Process Steps:

- Vectorized cleaned text using TF-IDF
- Split dataset into train and test sets
- Trained Logistic Regression model
- Identified top predictive words for each sentiment class
- Saved the trained model and vectorizer for reuse

### Results:

- Accuracy:** 0.88 – 0.92 on test set
- Model highlights sentiment-defining terms (e.g., *great, poor, expensive*)

# Advanced Techniques : RAG + LLM- Based Summarization

## SECTION 1: RAG PIPELINE (RETRIEVAL-AUGMENTED GENERATION)

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### Goal:

Retrieve the most relevant reviews to answer product-related queries.

### Method:

- Encoded reviews using **SentenceTransformer** embeddings
- Built a **FAISS** index for fast similarity search
- Retrieved **top-K** semantically similar reviews for each query
- Injected retrieved text into the **LLM prompt** to ground responses in real data

# Advanced Techniques : RAG + LLM- Based Summarization

## SECTION 2: LLM SUMMARIZATION & EVALUATION

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### Approach:

- Used **few-shot prompting** with structured templates
- Generated **aspect-wise summaries** (e.g., Battery, Screen, Price) with sentiment
- Model used: ***Microsoft Phi-2***

### Output:

- Final summaries and product descriptions **with cited review snippets**

### Quality Check:

- Evaluated summaries using ***ROUGE-L*** to measure factual consistency and improvement

### Results:

- Rough-L=0.288



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**Thank You**