edureka!
a Veranda Enterprise

ILLINOIS TECH

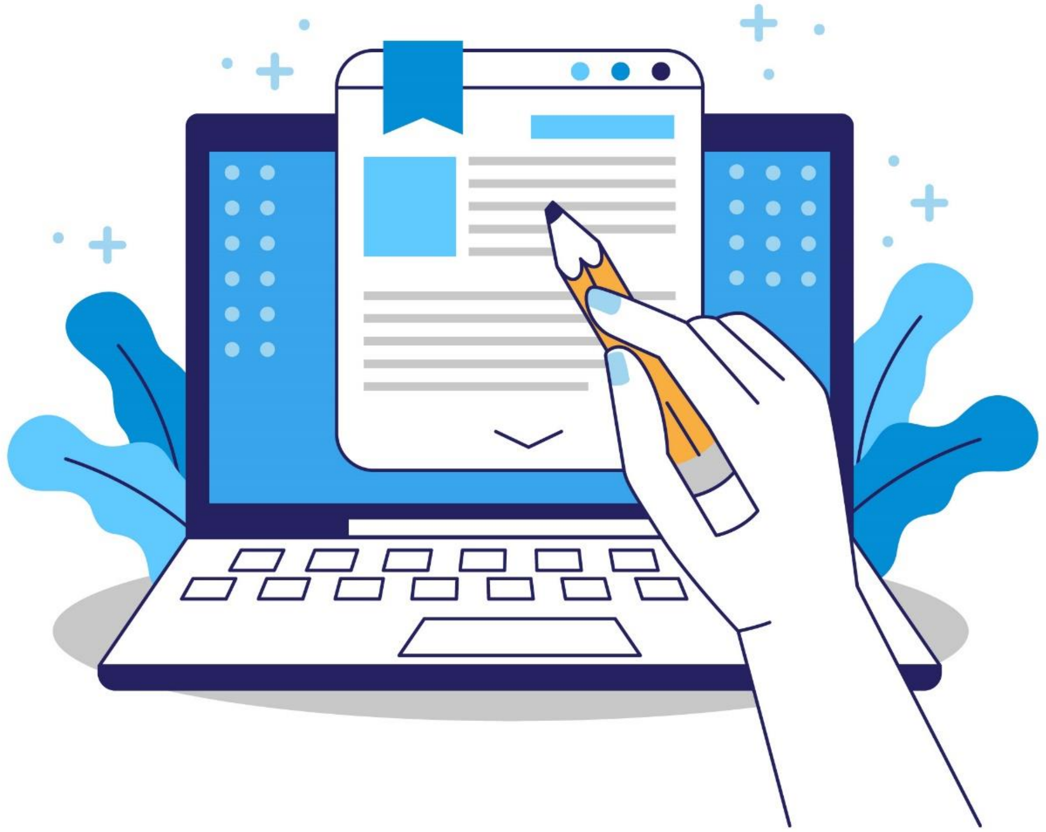
POST GRADUATE PROGRAM IN GENERATIVE AI AND ML

Natural Language Processing

Advanced Sentiment Analysis

Topics

- Introduction to Advanced Sentiment Analysis
- Sentiment Classification with Pretrained BERT Models
- Fine-Tuning Transformer Models
- State-of-the-Art Transformer Approaches
- Few-Shot and Zero-Shot Sentiment Classification
- Temporal and Event-Based Sentiment Analysis
- Aspect-Based Sentiment Analysis (ABSA)
- Multilingual and Cross-Lingual Sentiment Analysis
- Ethical Considerations in Sentiment Analysis



Learning Objectives

By the end of this lesson, you will be able to:

- Use pre-trained transformers, such as BERT, for sentiment classification.
- Fine-tune models for domain-specific sentiment tasks.
- Apply few-shot and zero-shot techniques with LLMs.
- Analyze sentiment trends, aspects, and multilingual data.
- Recognize and address ethical issues in sentiment analysis.

Sentiment Classification with Pretrained BERT Models

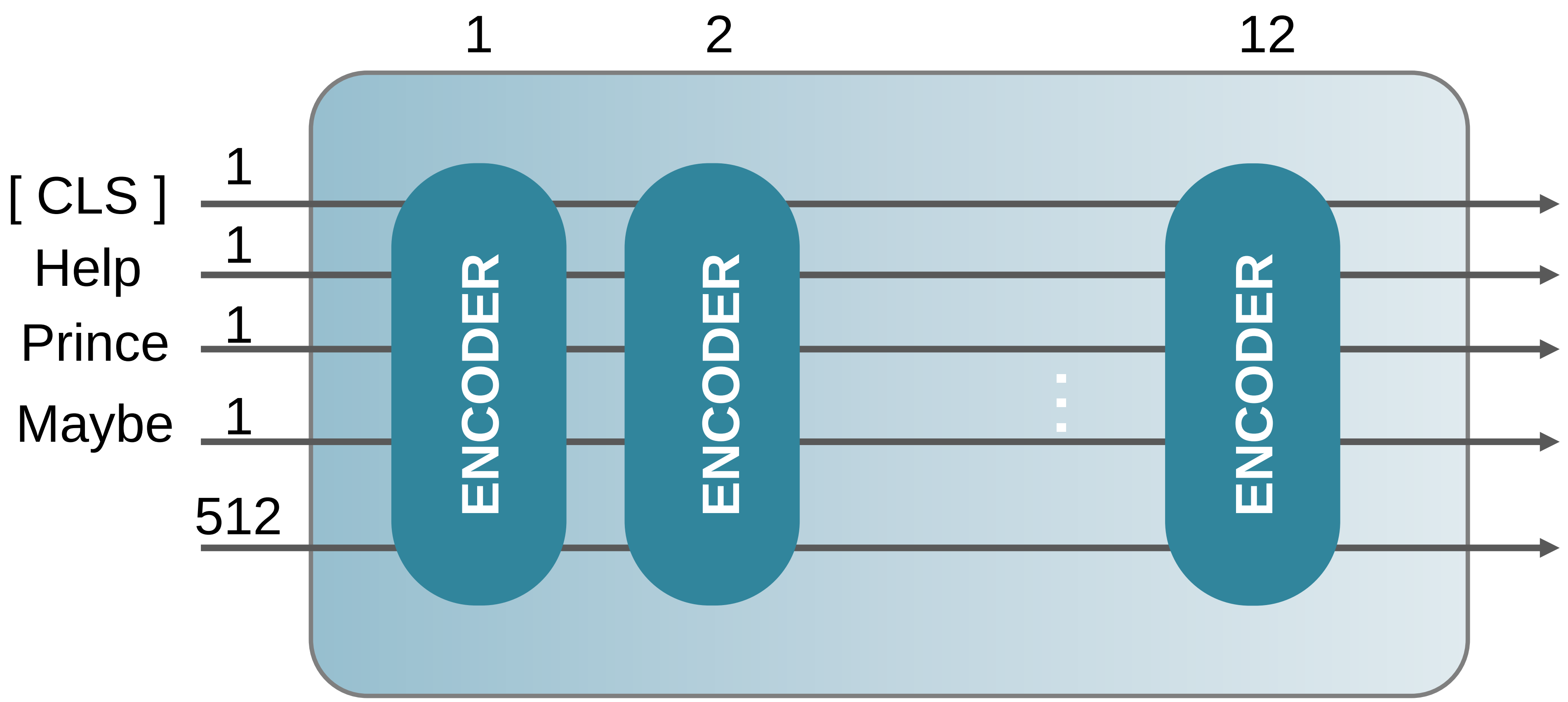
Why BERT for Sentiment Classification?

BERT Understands:

- **Context & tone** from both directions
- **Subtle sentiments** (negation, sarcasm, mixed reviews)

"It's not what I expected... it's better!"

BERT gets the positive sentiment.



How to Classify Sentiment using BERT

Input text

Tokenize with [CLS] and [SEP]

Pass through pretrained BERT

Use the [CLS] token embedding

Feed into a classifier (e.g., softmax layer)

Output sentiment: Positive / Negative / Neutral

Working Model

[Input Sentence]

[BERT Tokenizer]

[CLS], I loved the visuals, but not the plot. [SEP]

[BERT Encoder] — (Self-attention, Contextual Understanding)

[CLS] Vector

[Dense Layer + Softmax]

[Sentiment Label: Negative]

Sample Predictions from Pretrained BERT

Input Sentence	Prediction
"The movie was surprisingly good."	Positive
"It was okay, not great, not bad."	Neutral
"Terrible acting and worse editing. Don’t watch."	Negative

Fine-Tuning Transformer Models for Domain-Specific Sentiment Tasks

Why Fine-Tune for a Domain?

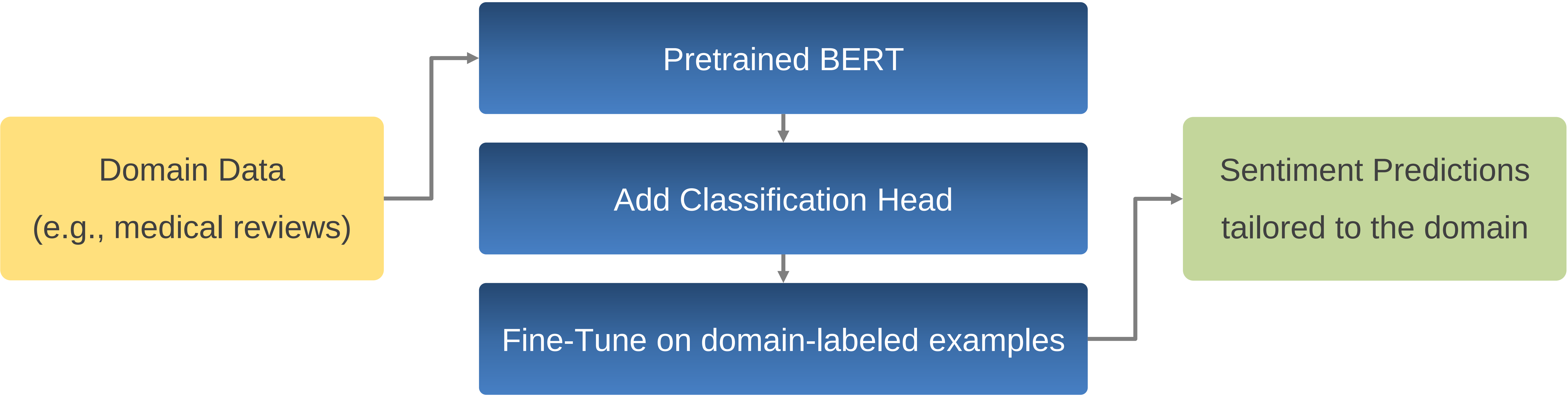
Models like BERT are trained on general text, but in the specialized fields, words can have specific meanings that the model may not understand.

"The app crashed after every push."

⬇

Tech Domain → Negative Sentiment

Fine-Tuning Process



Domains and Their Sentiment Language

Healthcare

"symptom improved", "worsened"

Finance

"plummeted", "rebounded"

Gaming

"laggy", "frame rate is smooth", "pay-to-win"

Before vs. After Fine-Tuning

Example Sentence	Generic BERT (Before Fine-Tuning)	Fine-Tuned Model (After Fine-Tuning)
“The app crashed after every push.”	Neutral → Doesn’t understand “push” context	Negative → Recognizes it as a deployment failure
“Patient’s symptoms worsened overnight.”	Neutral → Misses subtle medical deterioration	Negative → Flags it as serious medical concern
“Stock prices rebounded sharply.”	Negative → Thinks “sharply” = aggressive tone	Positive → Understands it's a financial recovery
“Frame rate is buttery smooth.”	Neutral → Doesn’t grasp gaming slang	Positive → Knows this means excellent performance

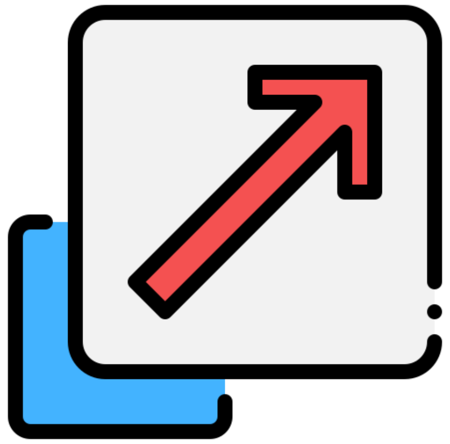
State-of-the-Art Transformers

Why Try Newer Models?

Speed

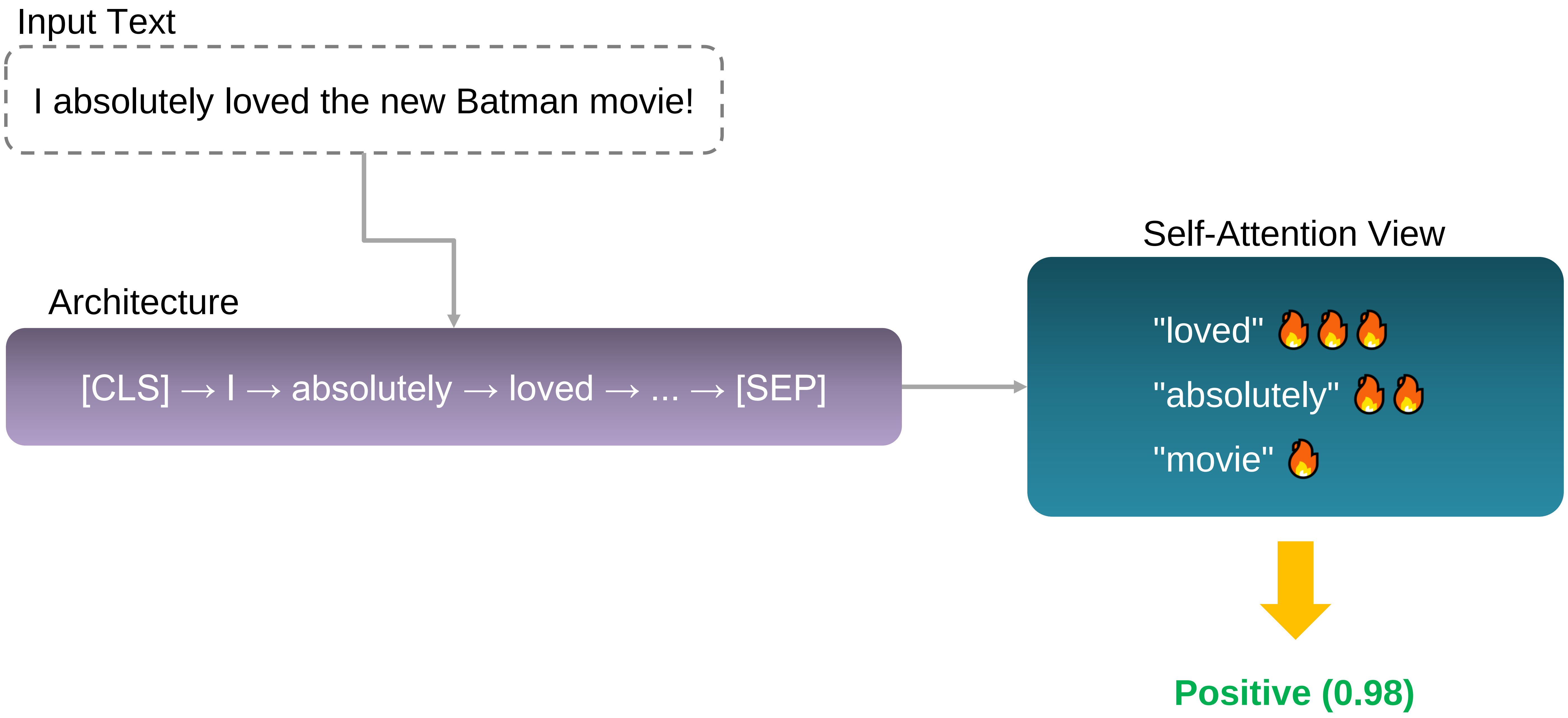
Accuracy

Size



Efficiency

RoBERTa


Input Text
I absolutely loved the new Batman movie!
Architecture
[CLS] → I → absolutely → loved → ... → [SEP]
Self-Attention View
"loved" 🔥🔥🔥
"absolutely" 🔥🔥
"movie" 🔥
Positive (0.98)

Distil BERT

Input Text

The product is okay but a bit overpriced.

Architecture

Fewer layers → faster inference

Self-Attention View

"okay" 🔥

"overpriced" 🔥🔥

Neutral (0.65)

GPT Based Approaches

Prompt: "Classify the sentiment: 'I hated the acting.'"

GPT RESPONSE:

"Sentiment: Negative"

PROMPT (FEW-SHOT STYLE):

1. I love this → Positive
2. It was awful → Negative
3. I hated the acting → ??

GPT RESPONSE:

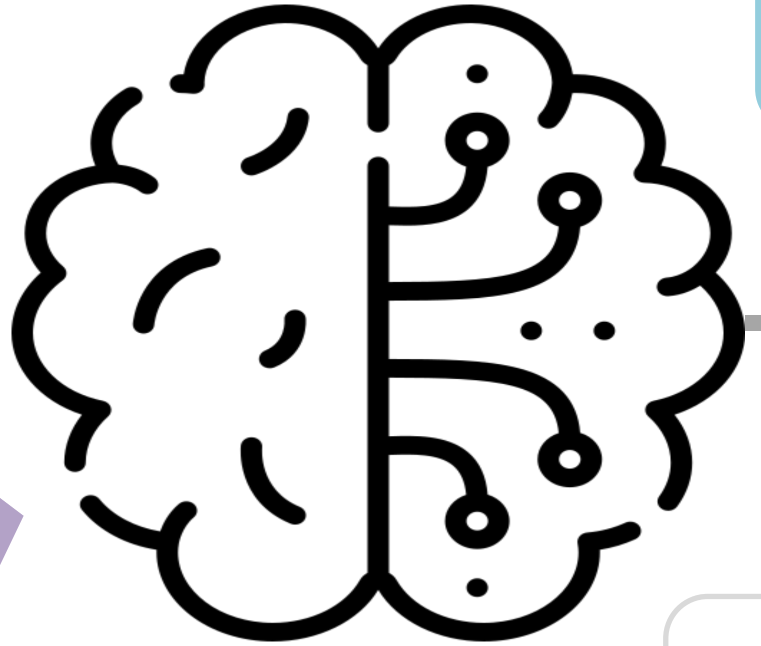
"Negative"

Few-Shot and Zero-Shot Sentiment Classification Using Instruction-Tuned LLMs

What Are Instruction-Tuned LLMs?

Classify this review as Positive, Neutral, or Negative

Translate this sentence into Spanish



Summarize task with

Completed the Task with understanding

INSTRUCTION-TUNING PIPELINE

BASE LLM

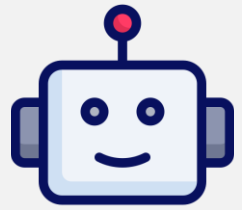
INSTRUCTION DATASET

FLAN

OpenAI Instruct

Self Instruct

INSTRUCTION-TUNED LLM



Zero-Shot Sentiment Classification

No labeled examples provided. Just a prompt and an input.

Classify the sentiment:

"I really hated the product. It broke in a day."

Negative

Few-Shot Sentiment Classification

The model is given a few labeled examples in the prompt to "learn from".

Classify the sentiment:

1. "Loved it!" → Positive
2. "Very slow service." → Negative
3. "It was fine." → Neutral
4. "The app crashes constantly." → ?

Negative

Few-Shot vs. Zero-Shot Classification

Feature	Zero-Shot	Few-Shot
Examples in Prompt	❌ None	✅ Yes (2–5)
Setup Time	🟢 Minimal	🟡 Low
Accuracy	⭐⭐	⭐⭐⭐⭐
Prompt Length	Short	Longer
Good For	Fast deployment	Slightly complex tasks

Real-World Instruction-Tuned Models

GPT-3.5 / GPT-4

Instruction-tuned; excels at high-quality zero- & few-shot tasks.

Mistral-Instruct

Efficient; ideal for lightweight inference.

FLAN-T5 / FLAN-UL2

Open-source; strong in few-shot sentiment tasks.

LLaMA 2 Chat

Research-focused; great for controlled experiments.

Tracking Sentiment Trends Over Time

Why Tracking Sentiments Over Time Matters?

Imagine you're managing a brand like Nike. In March, you launch a new eco-friendly sneaker line.

"How did public perception change before, during, and after the launch?"

How is it done?

Collect tweets, Instagram posts, and Reddit comments from Jan-Mar.

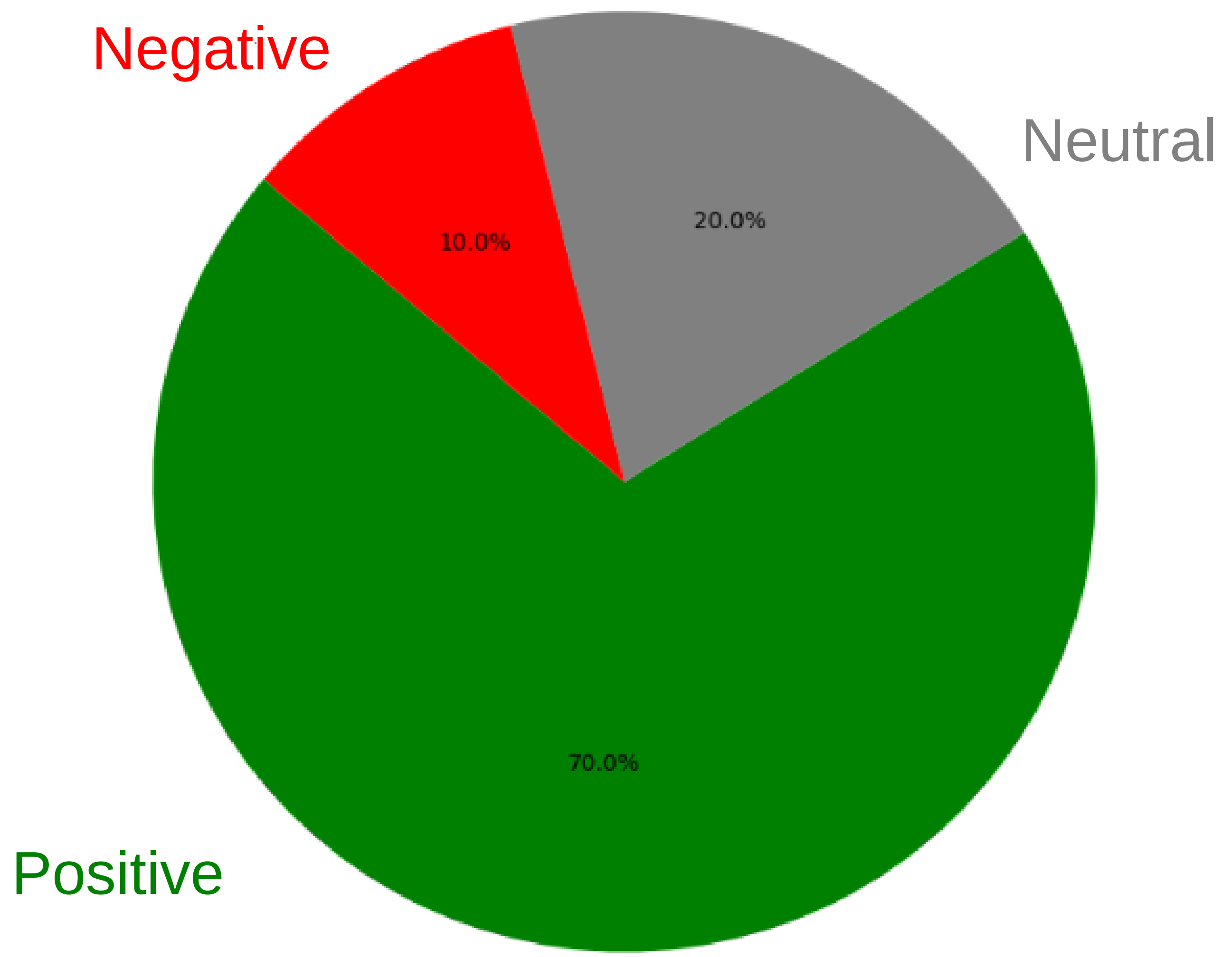
Tweet Text	Timestamp
Nike's new eco-sneakers are amazing! #NikeEco	2024-03-10 14:32:05
Just finished reading a fascinating article on AI.	2024-03-15 09:15:30
The weather in Bengaluru is beautiful today! 🌞	2024-03-20 11:00:12
Excited about the new movie release this weekend! 🎬	2024-03-25 18:45:55
Learning a new coding language is challenging but fun!	2024-03-30 16:20:40

How is it done? (Contd.)

Use VADER or BERT to score sentiment: Positive, Negative, Neutral

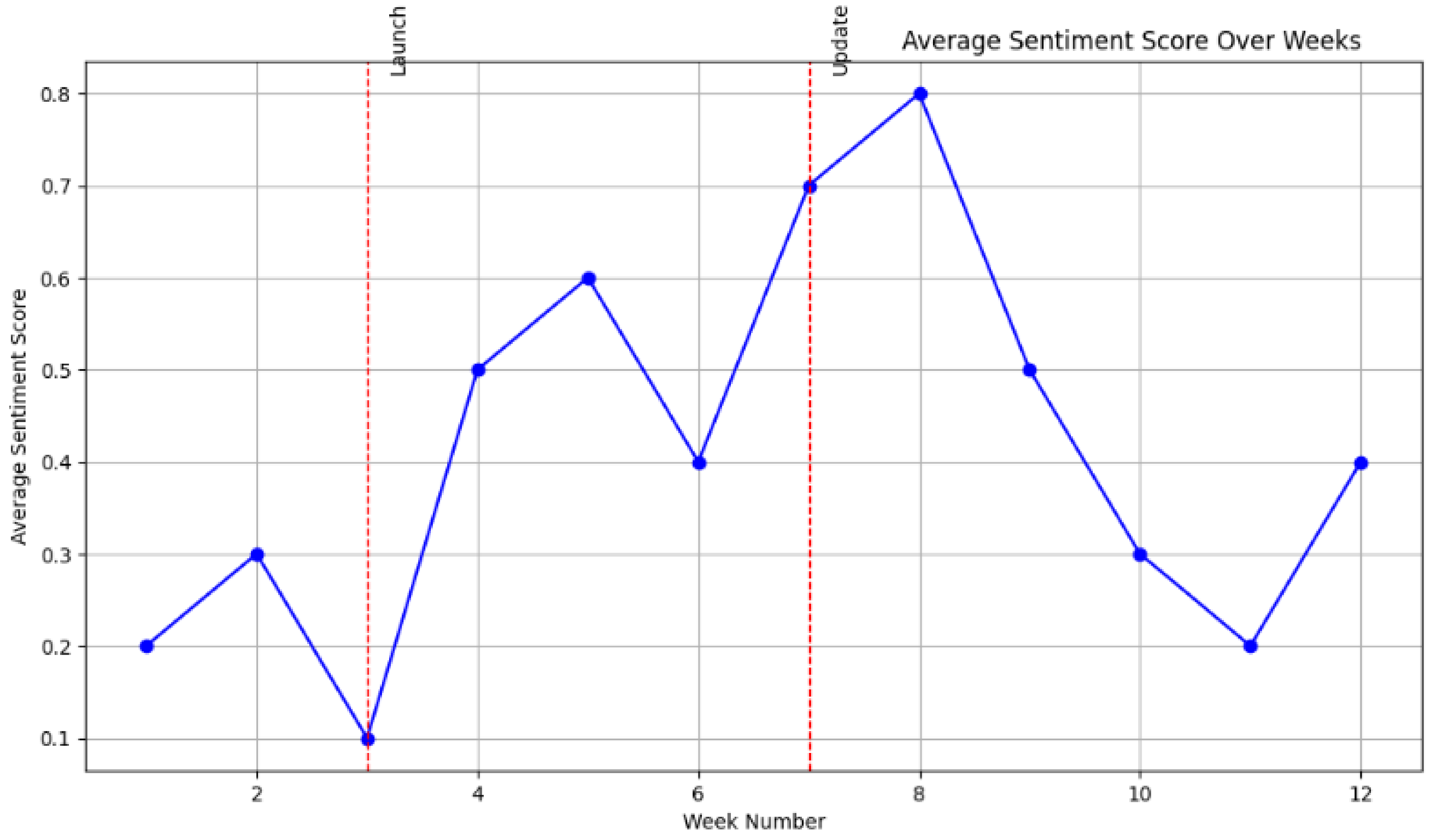
“Love these shoes!” → Positive

“These are overpriced.” → Negative



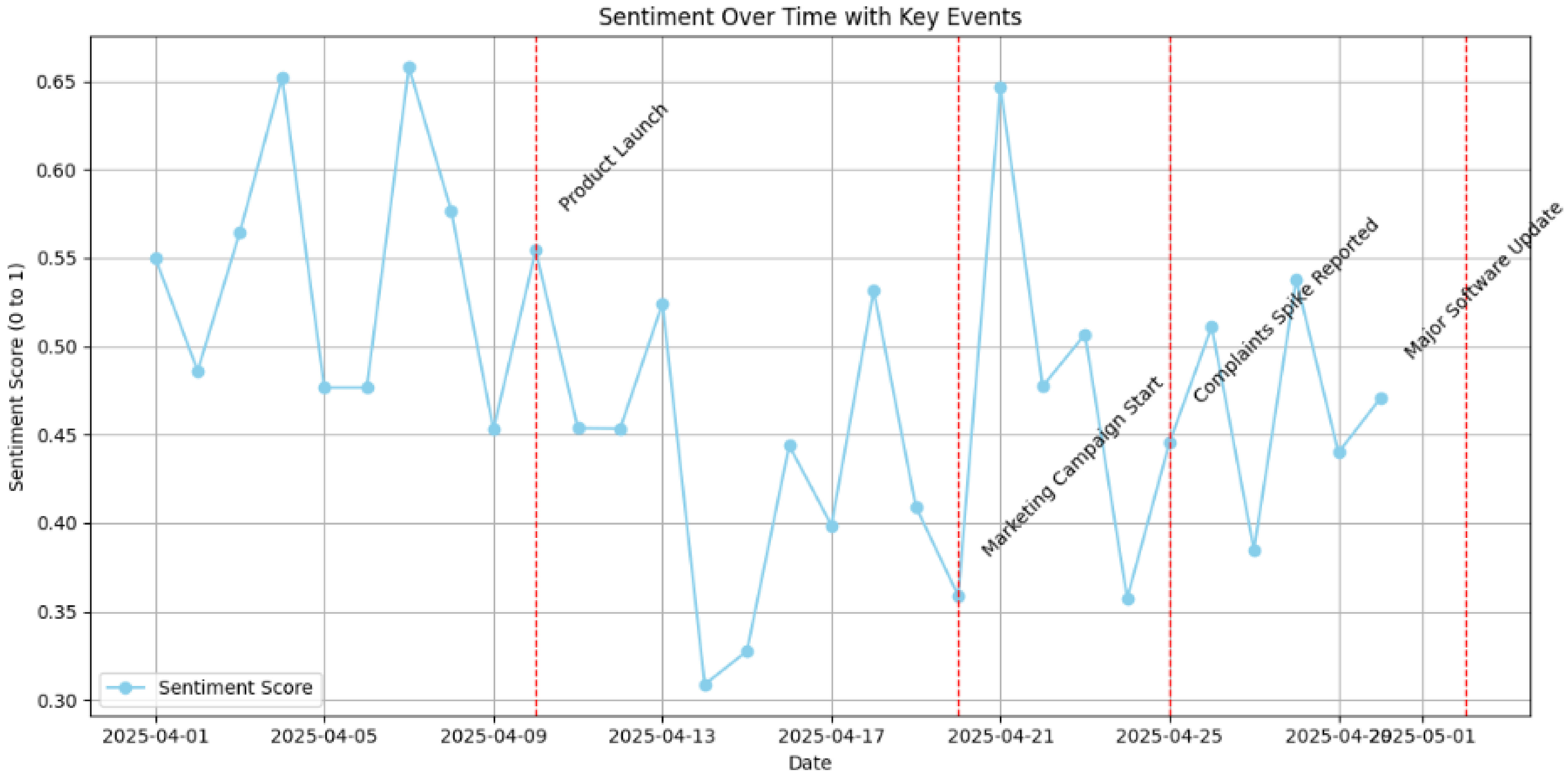
How is it done? (Contd.)

Group posts by week and calculate the average sentiment score.



How is it done? (Contd.)

Create charts to track changes in sentiment.



Detecting Sudden Shifts in Opinion

What Are Sudden Opinion Shifts?

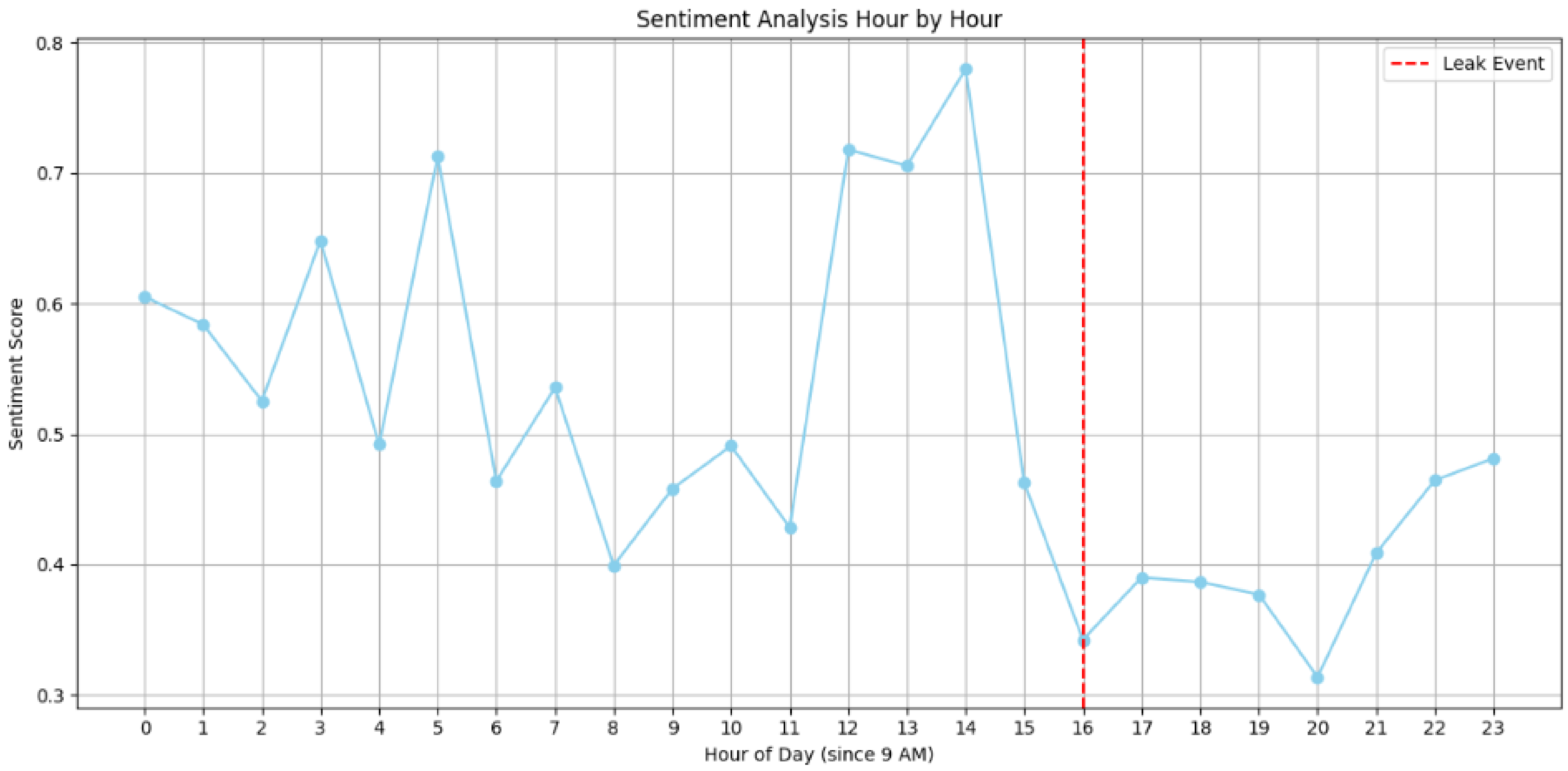
A new data privacy policy is announced.

Panel 1: “Excited about new policy!”

Panel 2: “This is a betrayal. #Boycott”

How to Track Shifts in Real-Time

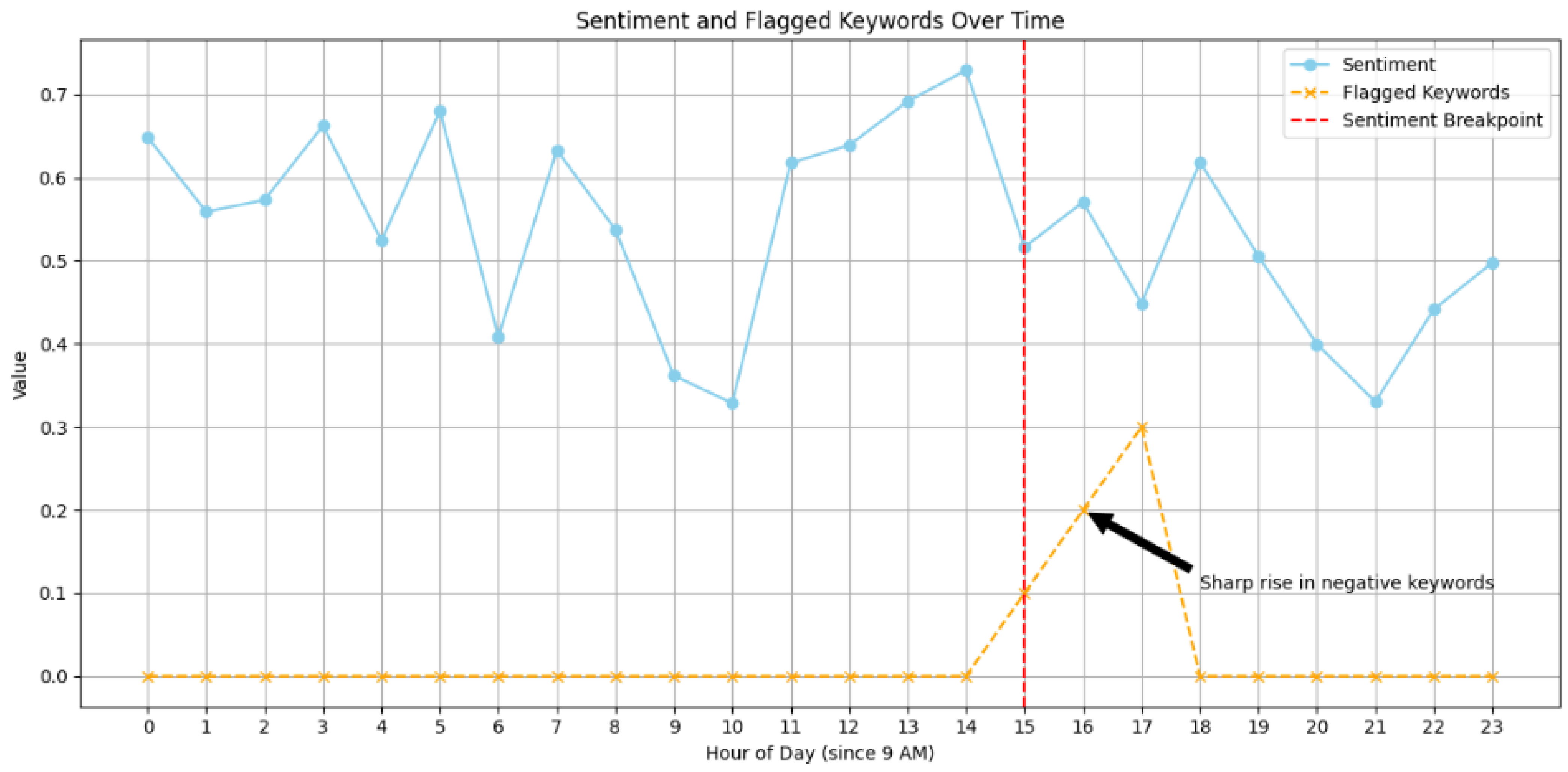
Monitor posts hourly or in short intervals to capture early sentiment volatility.



Detecting the Moment Sentiment Breaks

Use statistical anomaly detection to automatically flag the sentiment shifts.

- Z-score on sentiment score delta
- Sudden keyword frequency spikes
- Time-series changepoint detection

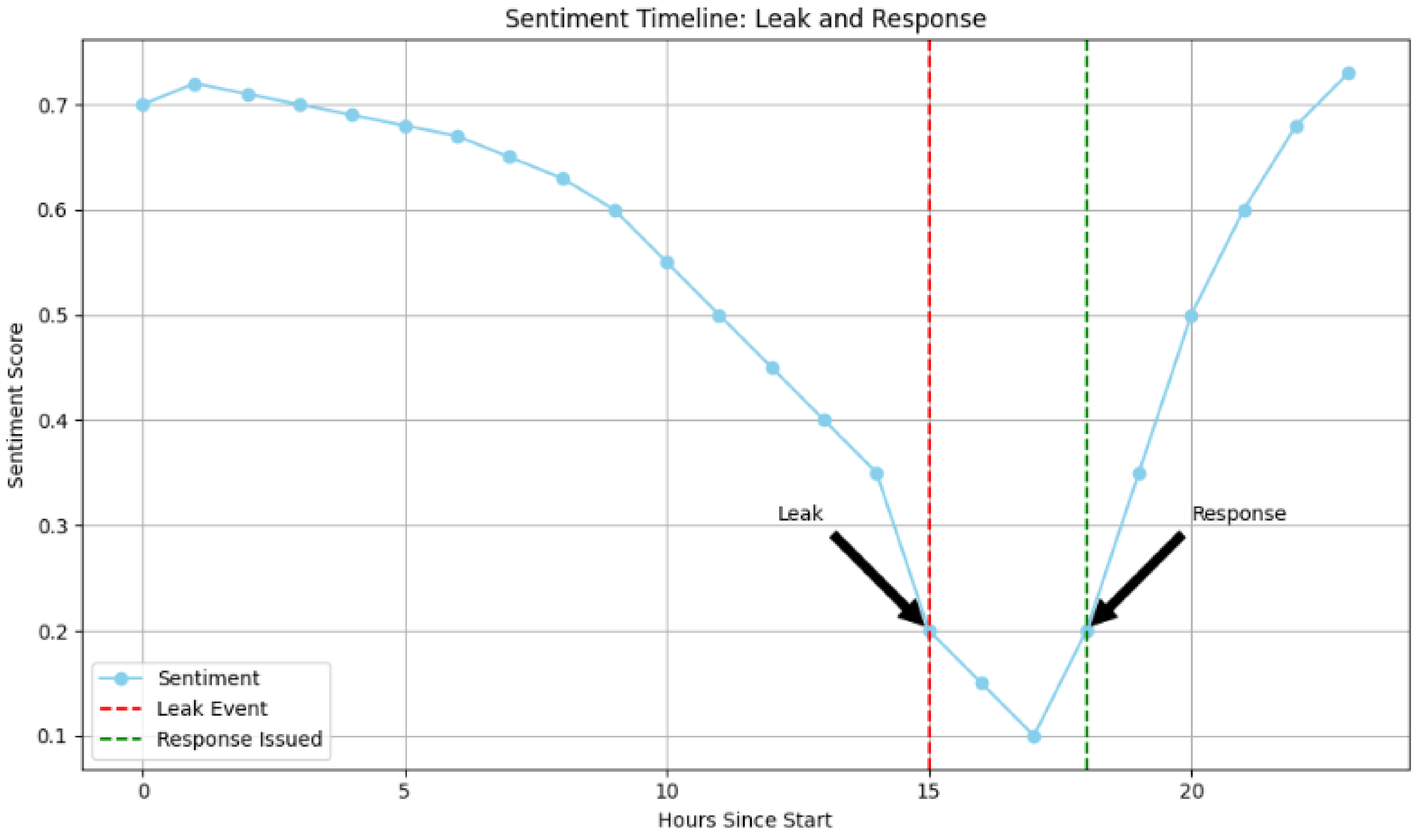


Responding to Shifts Quickly

The government issues a clarification post. Public sentiment begins to stabilize.

Early detection allows real-time response:

- Public clarifications
- Policy revision messaging
- Controlled narrative



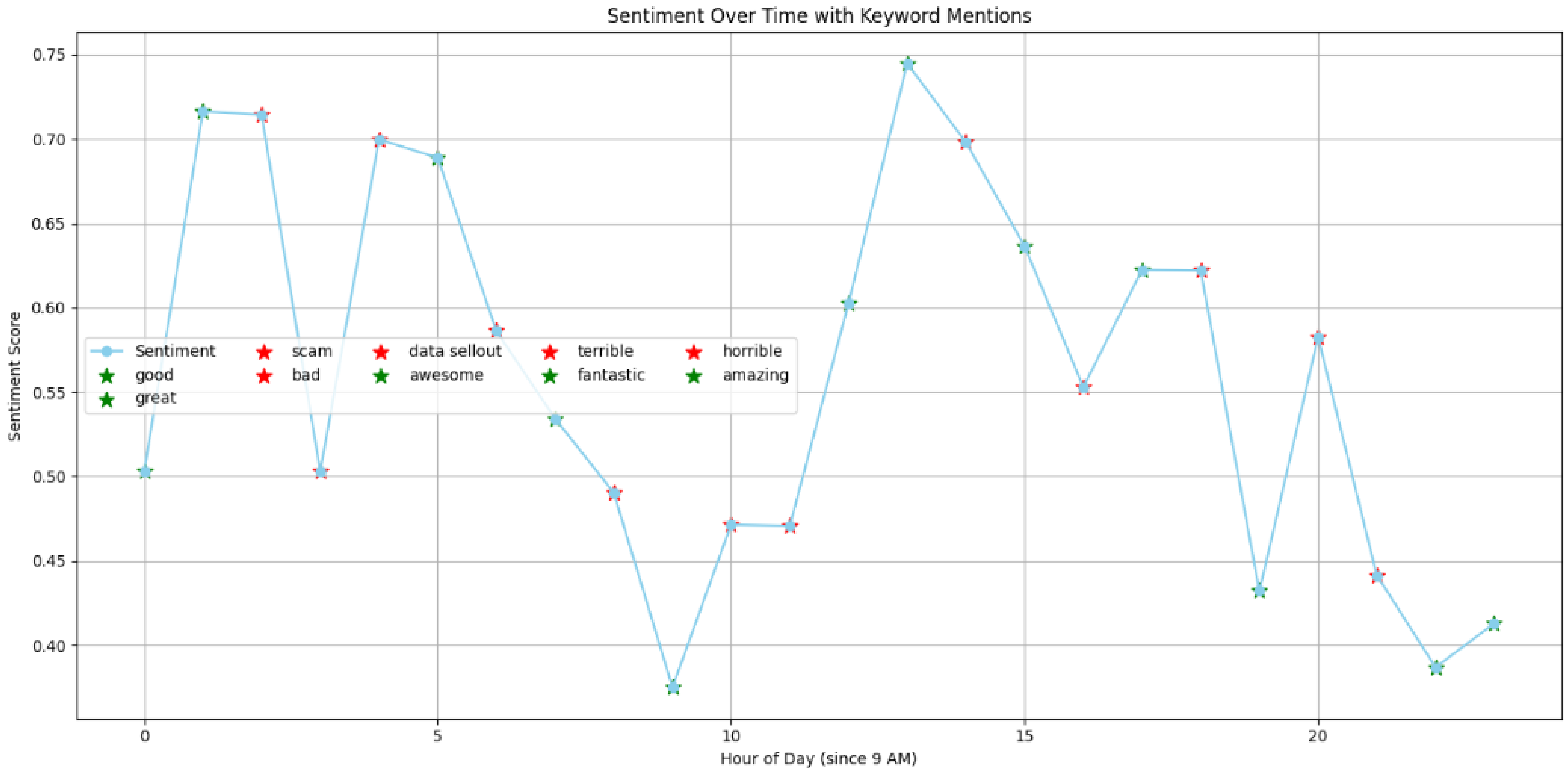
Sentiment Analysis for Public Discourse and Crisis Events

Why Sentiment Analysis in Public Discourse?

Lockdown announcement floods Twitter and local forums.

Monitoring Sentiment During the Crisis

In the 24 hours after the lockdown, there's a spike in posts mentioning “income loss,” “panic buying,” and “safety.”



Tools and Techniques Used

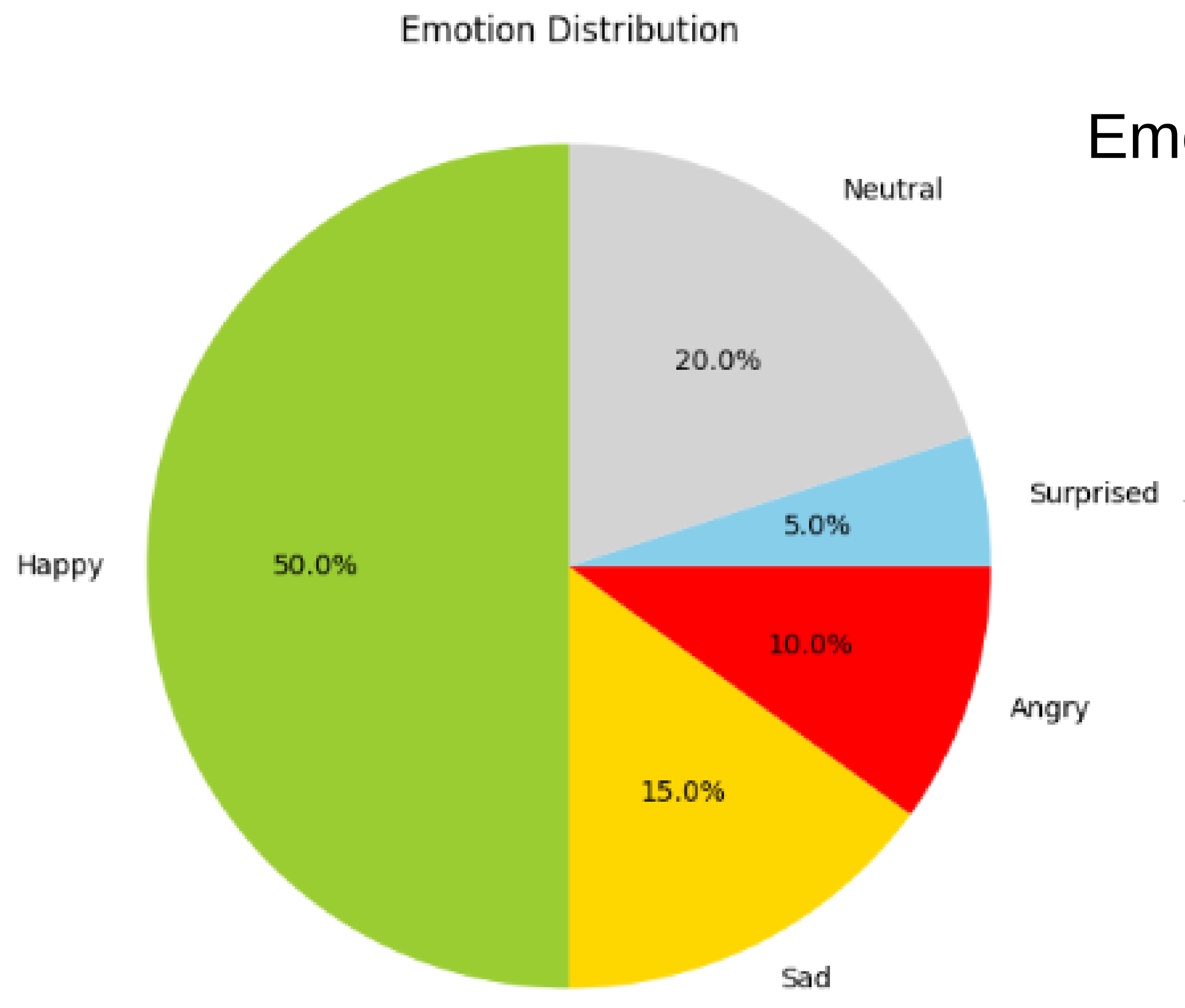
NLP tools are used to break down thousands of posts by sentiment and topic.

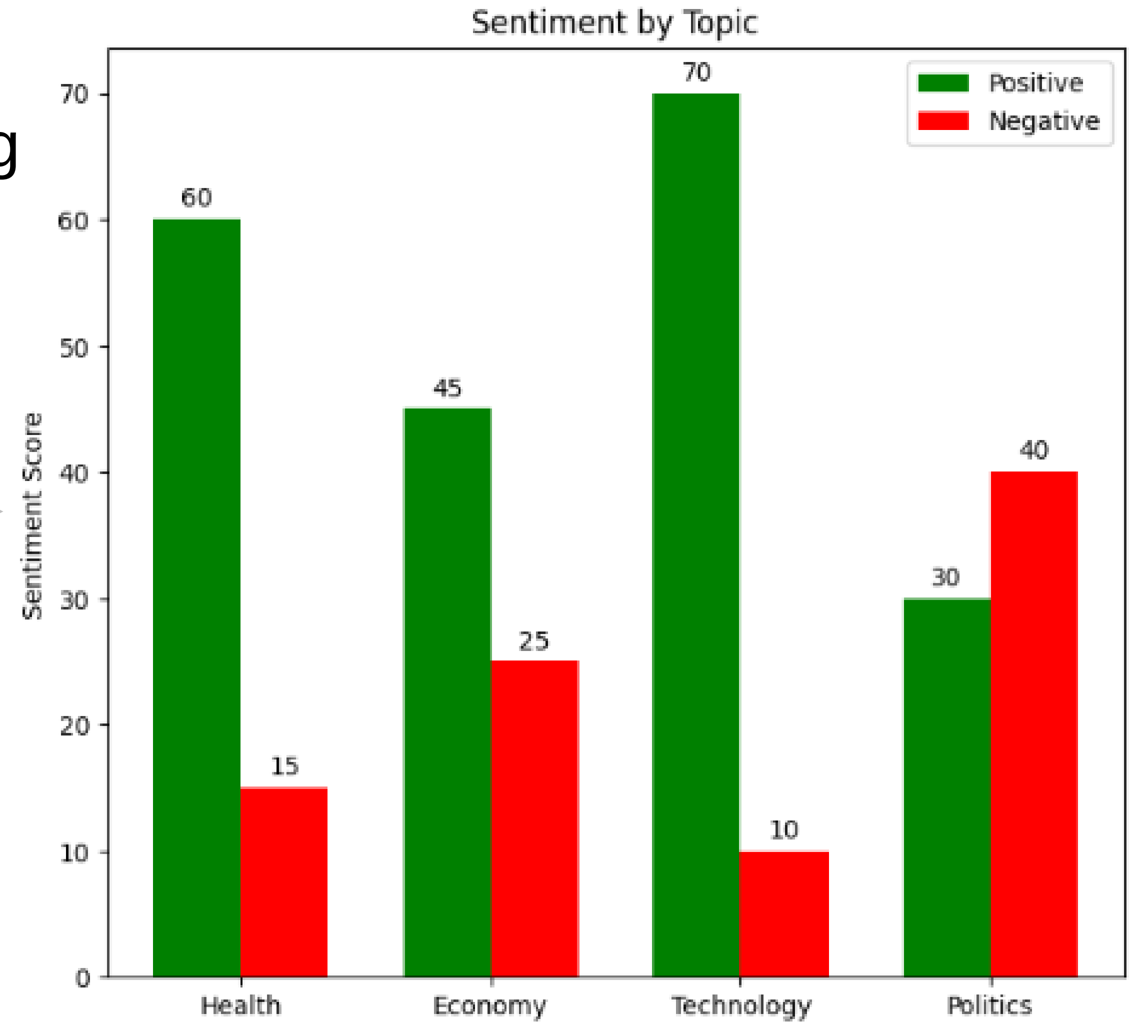
Sentiment Analysis

+

Emotion Tagging

Topic Modelling





From Insights to Action

City officials see rising frustration over job loss within 48 hours, they announce financial aid measures.

01 Sentiment Spike

02 Insight

03 Response Tweet

04 Public Sentiment Rebound

Introduction to ABSA and Fine-Grained Sentiment

Why Fine-Grained Sentiment Matters?

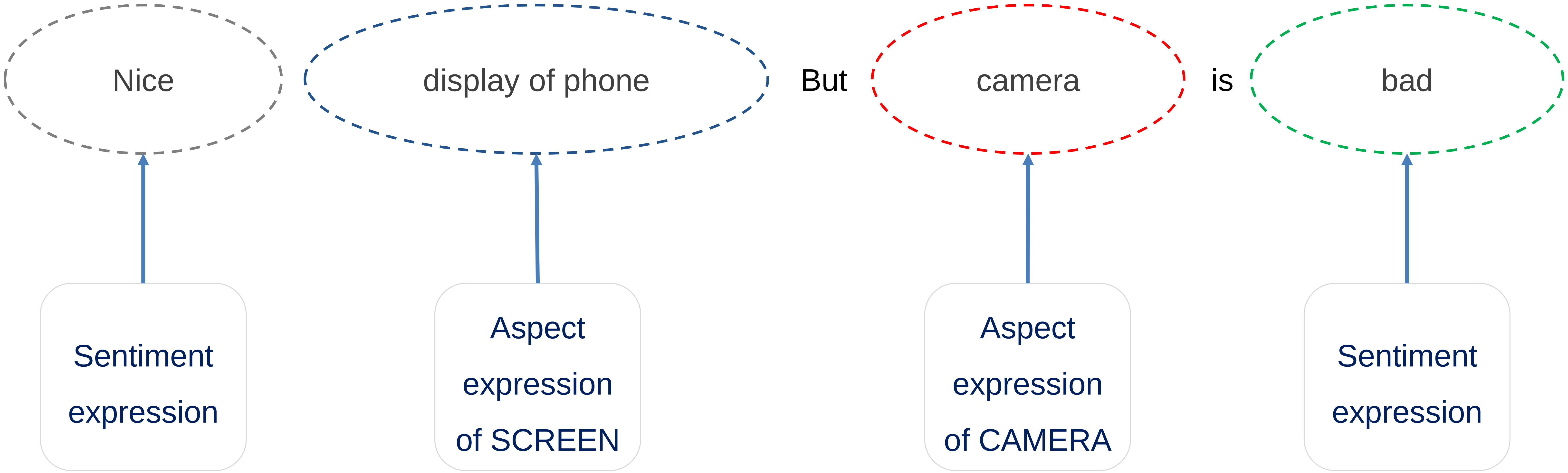
The display is gorgeous, but the battery is awful.

Coarse Sentiment → Mixed/Neutral

Display = 'gorgeous' → Positive

Battery = 'awful' → Negative

What is ABSA?


Nice
display of phone
But
camera
is
bad
Sentiment expression
Aspect expression of SCREEN
Aspect expression of CAMERA
Sentiment expression

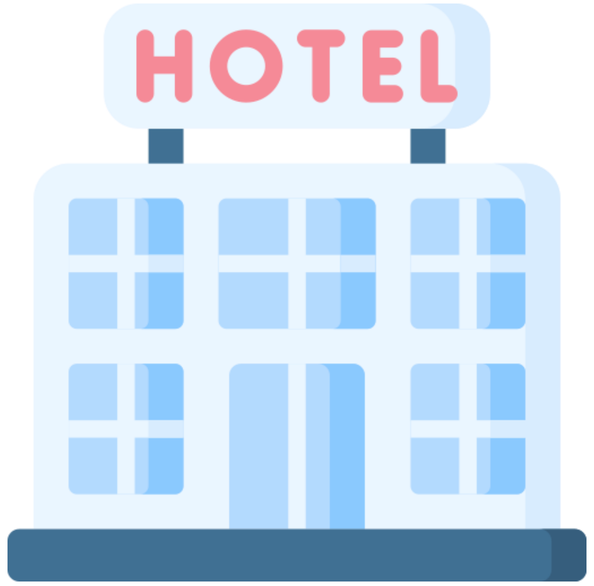
Use Case of Fine-Grained Sentiment

E-Commerce

Image Quality = “Great”

Battery life = “Bad”

Hotels



Cleanliness = “Excellent”

Staff = “Rude”

Support

UI = “Smooth”

Login = “Buggy”

ABSA vs. Traditional SA

“The performance is impressive,
but the UI is confusing.”

Traditional Sentiment	ABSA – Fined-Grained Sentiment
Mixed/Neutral	Performance – positive UI - negative

Aspect Extraction Using Machine Learning

Why General Sentiment Isn't Enough?

- Overall sentiment analysis says: Neutral
- But the product team wants to know what to fix (e.g., battery)

“The camera is outstanding, but the battery life is terrible.”

Understand the Text Structure

The Battery is good.

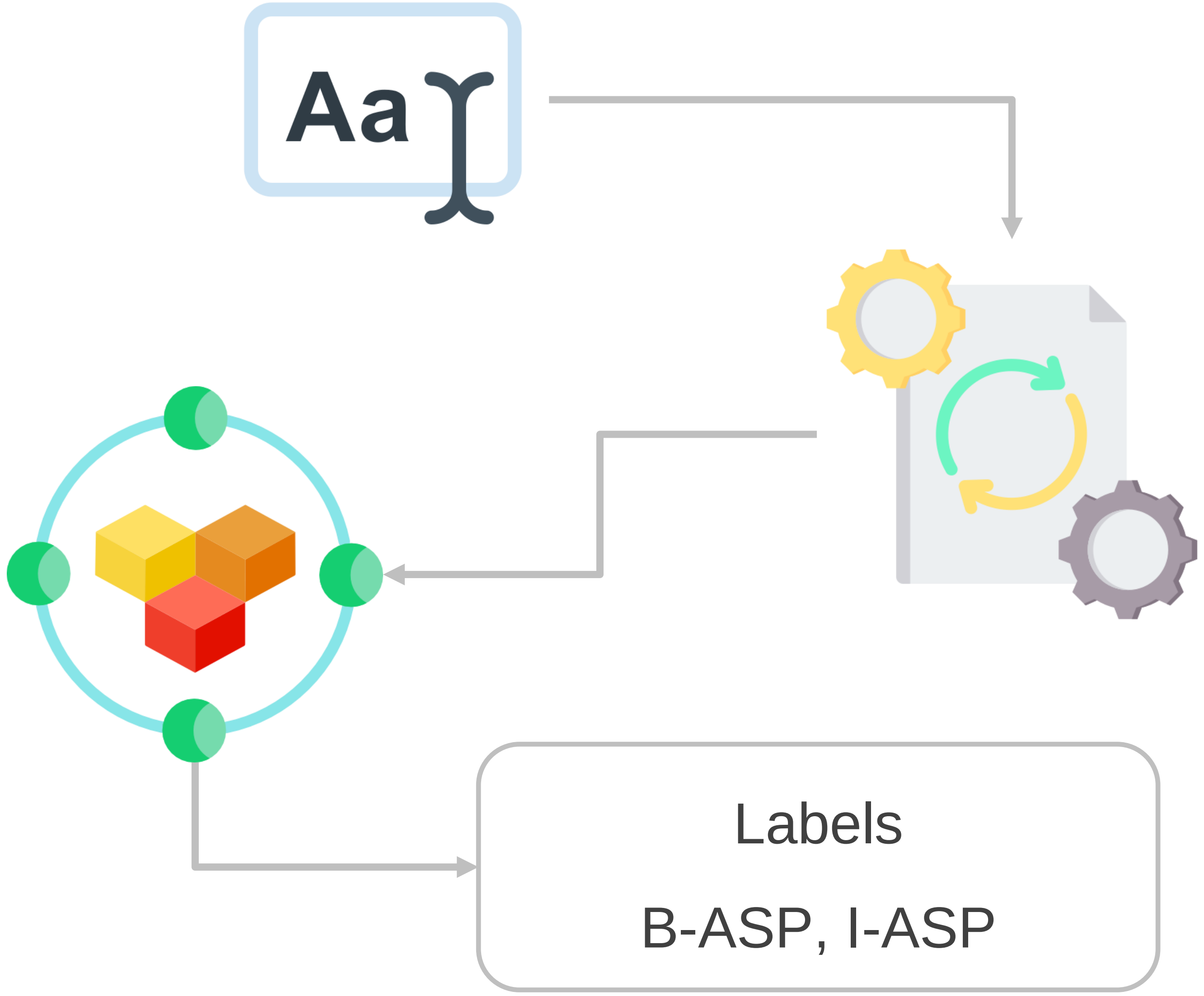
Battery ⟷ Good

Detect Aspect Terms Using ML

Demonstrates how machine learning models detect and label aspects in text.

The battery is good.

Battery → B-ASP



Aggregate Results & Enable Action

Positive Sentiment

Aspect	Sentiment	Sentiment Score	Trend
Battery	Positive	+0.75	↑
Service	Negative	-0.60	↓
Price	Neutral	0.00	→

Aspect-Level Sentiment Classification Techniques

Traditional ML Techniques

"The screen is bright, but the battery drains fast."

Aspect	Battery
Context	“drains fast”
Predicted	Negative

Text 01

Vector Features 02

ML Model 03

Sentiment Model 04

LSTM-Based Deep Learning

Tokens: [The | battery | lasts | really | long | in | this | device]

Attention on "lasts":

→ The: 0.1

→ battery: 0.2

→ lasts: 0.4 <-- most focus

→ really: 0.15

→ long: 0.15

→ (others ~0)

Attention on "long":

→ lasts: 0.3

→ really: 0.2

→ long: 0.4 <-- most focus

→ device: 0.1

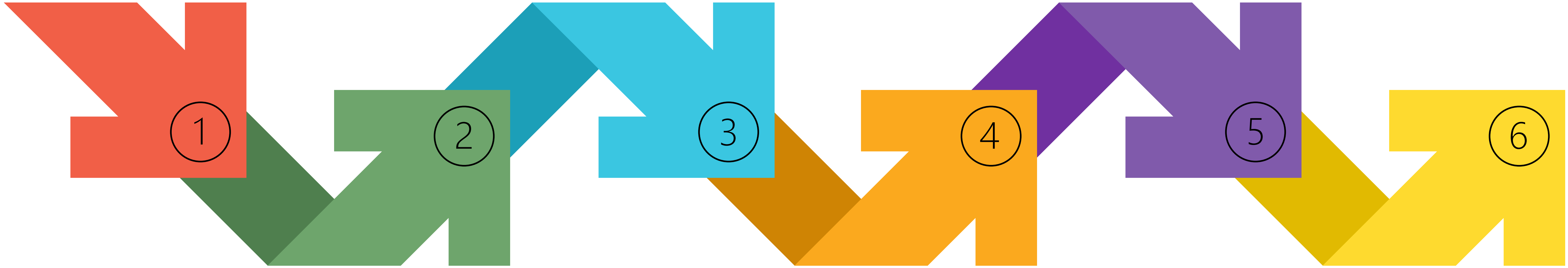
→ (others ~0)

Transformer-Based Models

Input Format
[CLS] battery [SEP] The battery dies quickly [SEP]

BERT Blocks (stacked)
Multi-Head Attention
Feed-Forward Networks

Softmax Classifier
(outputs class label or probability)



Embeddings
(Token + Position)

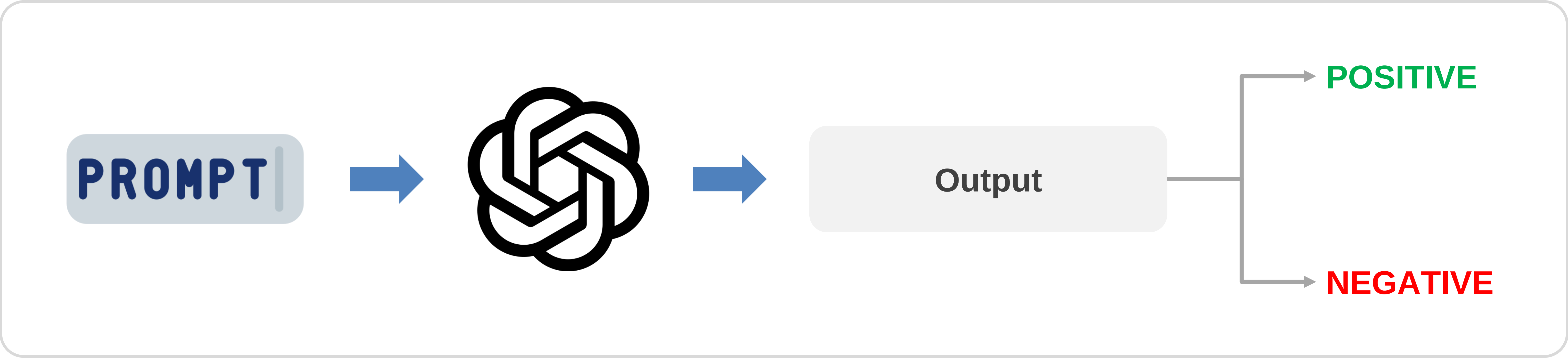
[Final [CLS] Vector]
(Representation of full input)

[Prediction]
(e.g., "Battery Problem" / "Camera Issue")

Prompt-Based LLMs

“What is the sentiment toward ‘screen’ in: ‘The screen is extremely vibrant’?”

POSITIVE

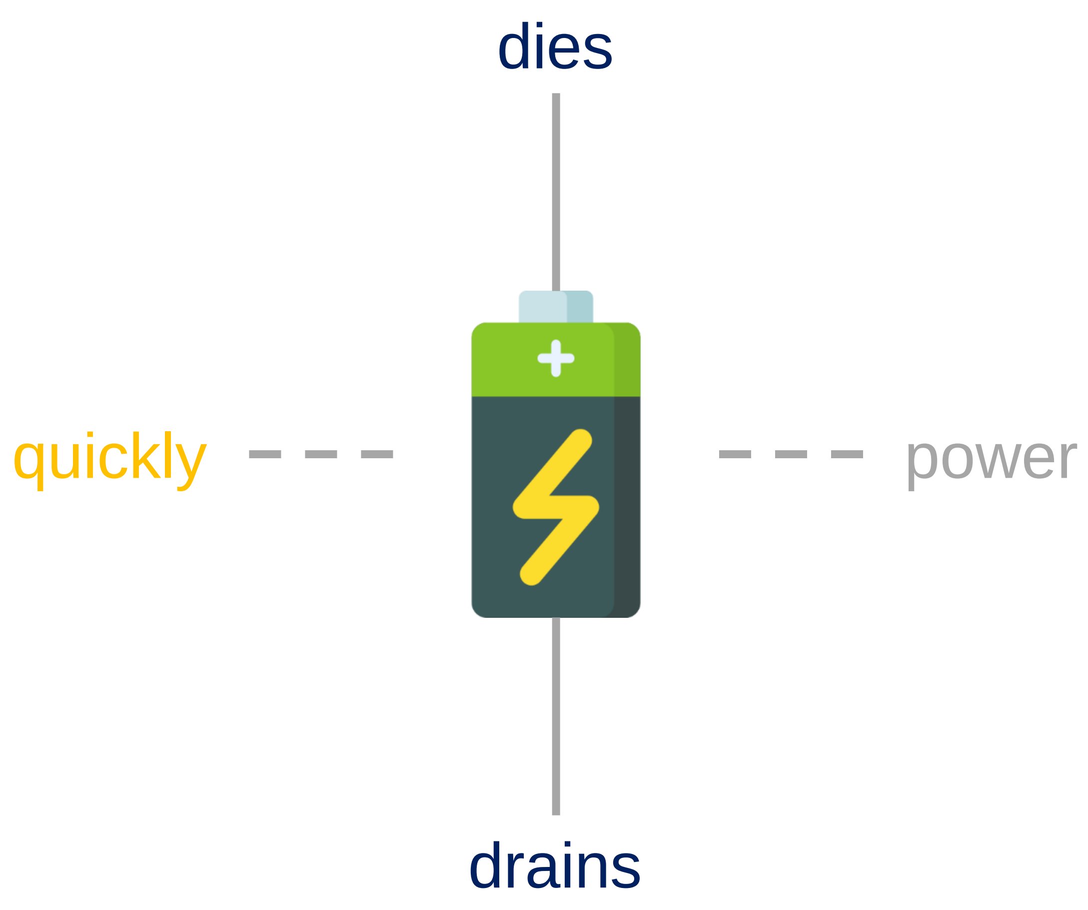


Hybrid and Knowledge-Based Models

The battery dies quickly after charging.

Aspect: Battery

Context words: dies, quickly, charging



Integrating NER with ABSA for Enhanced Precision

Why NER with ABSA?

"Samsung's display is stunning, but I prefer Apple's camera quality."

- Contains multiple brands
- Multiple aspects with distinct sentiments
- Needs entity-aware sentiment attribution

ABSA + NER

Without NER

- Fail to distinguish between Apple and Samsung
- Assign sentiments to the wrong aspects or brands

With NER

- Samsung → display
- Apple → camera quality

Precision Improvements with NER

Low Precision

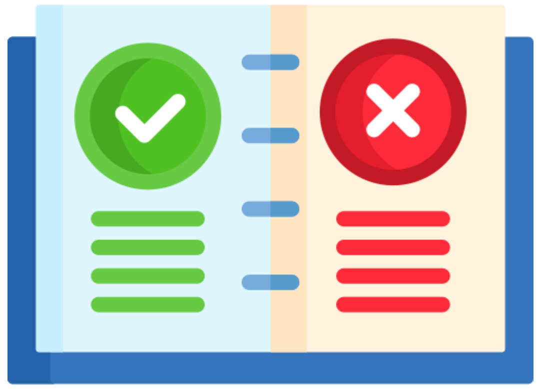
- ABSA might confuse aspects — assigns "camera quality" to Samsung
- Can't distinguish which brand each sentiment refers to

High Precision

- Samsung → display → Positive
- Apple → camera quality → Positive (but preferred)

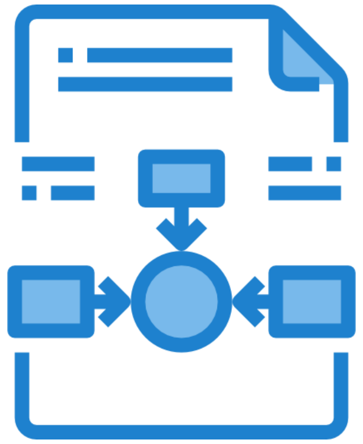
Brand	Aspect	Sentiment
Samsung	display	Positive
Apple	camera quality	Positive (preferable)

Techniques to Combine NER with ABSA



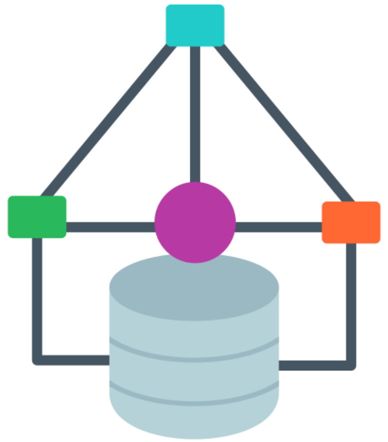
Rule-Based

Use the proximity between named entities and aspects



Joint Models

Co-train NER & ABSA in models like BERT



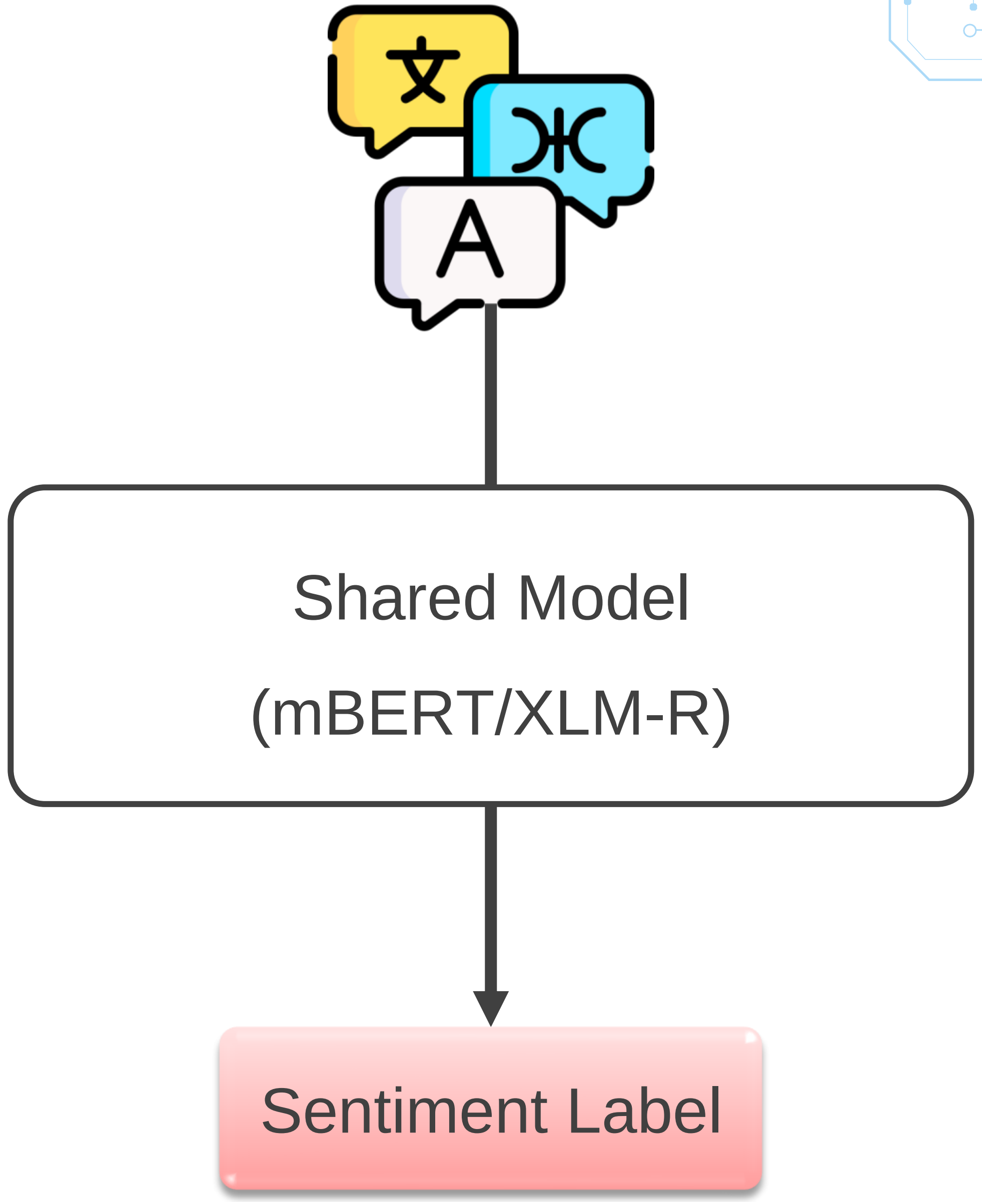
Graph-Based

Use dependency trees or knowledge graphs

Fine-Tuning mBERT and XLM-R for Multilingual Tasks

Fine-Tune for Sentiment Across Languages

Language	Input Sentence	Label
French	"Ce téléphone est incroyable."	Positive
English	"This phone is amazing."	Positive
Hindi	"यह फोन शानदार है।"	Positive



Tokenization and Preprocessing

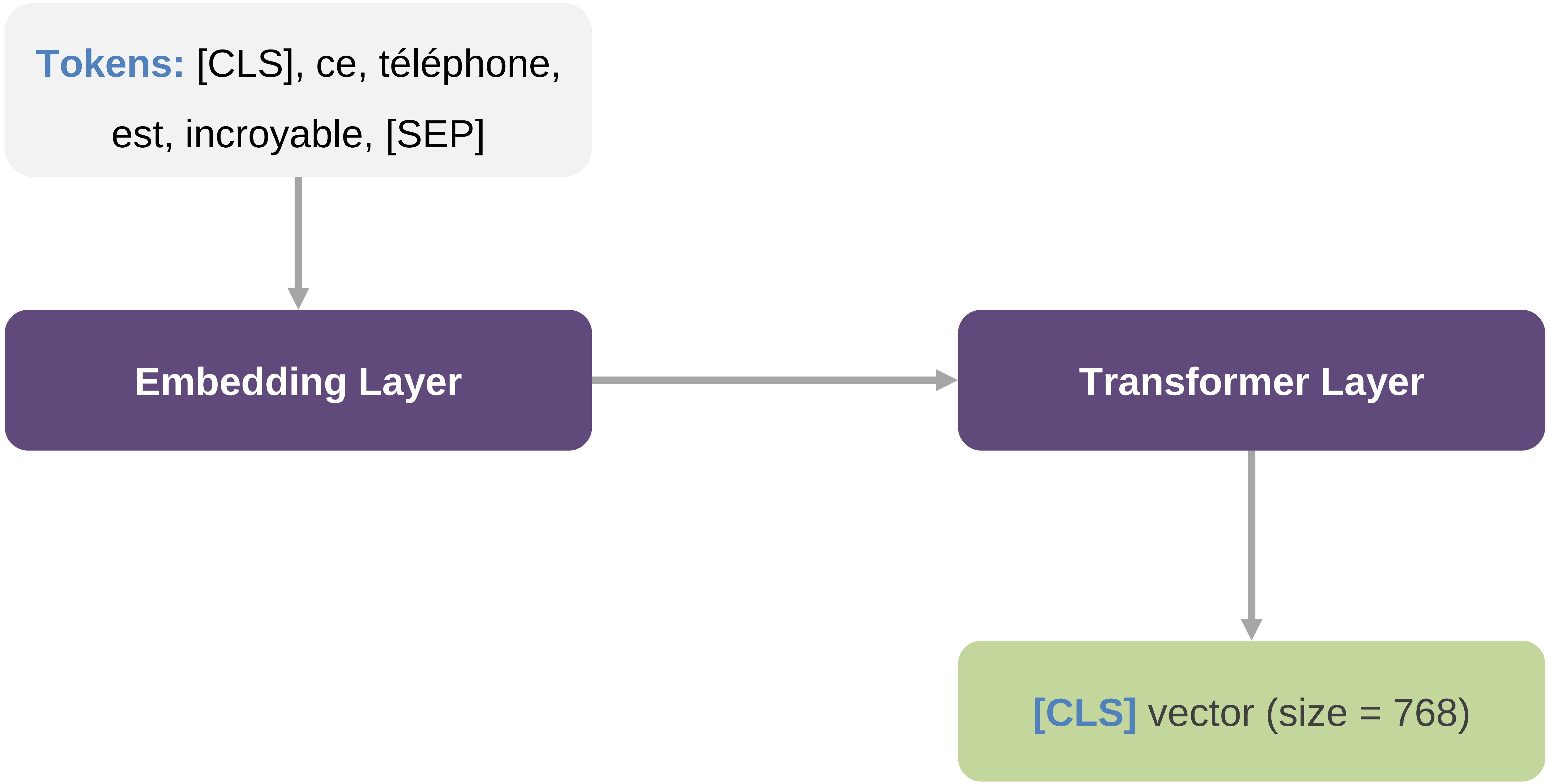
Input: "Ce téléphone est incroyable."

Tokens: [CLS], ce, téléphone, est, incroyable, [SEP]

IDs: [101, 2025, 6013, 3111, 7234, 102]

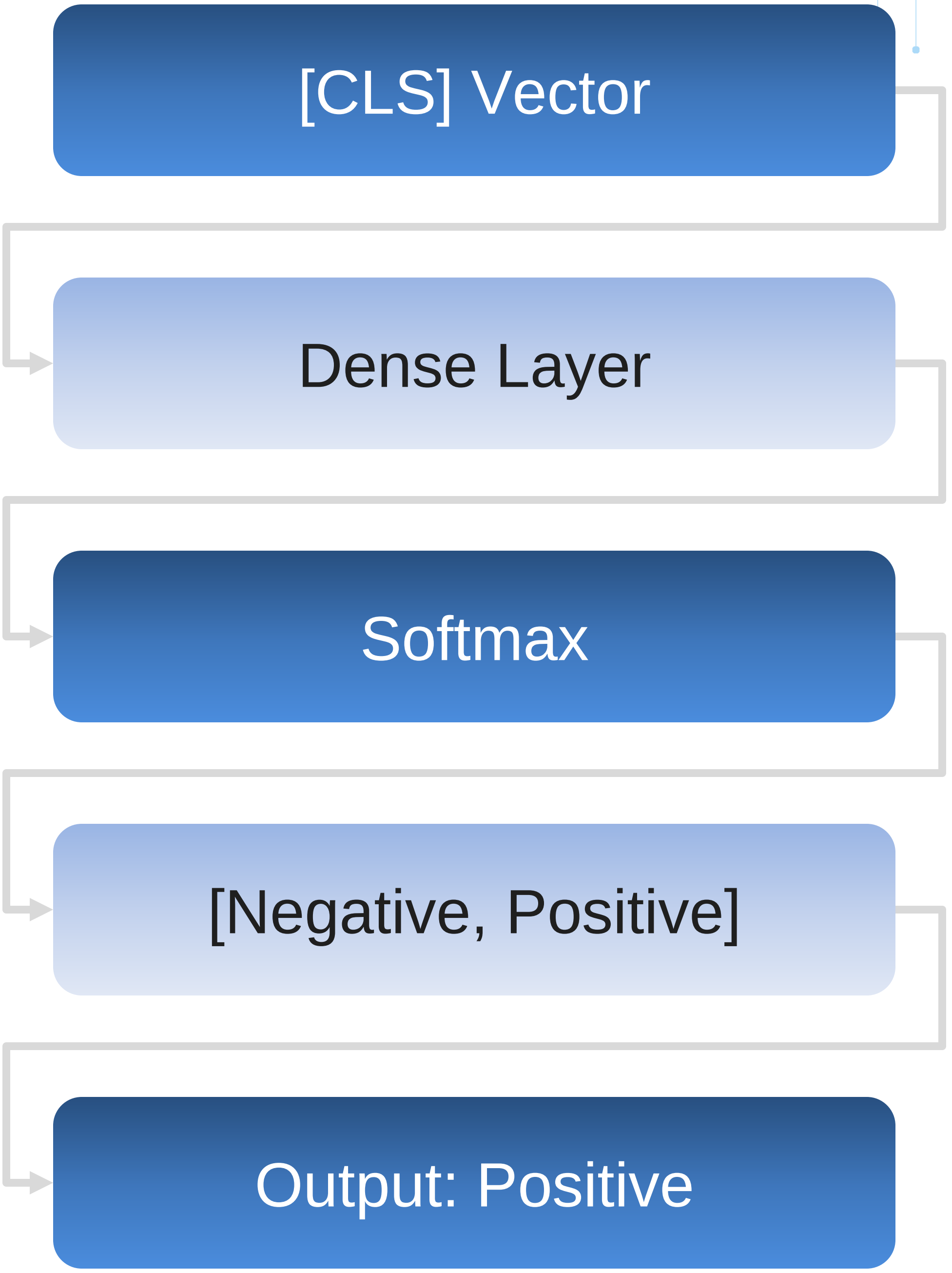
Raw Text
↓
Tokenizer
↓
Tokens
↓
IDs
↓
Attention Mask

Transformer and CLS Vector



Add Head and Fine-Tune

1. Forward pass
2. Loss computed (Cross-Entropy)
3. Backpropagation
4. Update the entire model



Zero-Shot and Few-Shot Multilingual Sentiment Transfer

Zero-Shot Transfer

Language	Text	Trained On?	Prediction
English	"I love this phone."	✅ Yes	Positive ✅
Swahili	"Ninapenda simu hii."	❌ No	Positive ✅

English Sentiment Data

Multilingual Model (mBERT/XLM-R)

(Shared Language Knowledge)

Swahili/Hindi Input

Prediction (Positive/Negative)

Few-Shot Transfer

Language	Text	Trained On?	Prediction
English	"Great service!"	✅ Yes	Positive ✅
Hindi	"सेवा शानदार है।"	✅ Few-Shot	Positive ✅

English Sentiment Data

↓

Multilingual Model (mBERT/XLM-R)

↓

Add Few Hindi Labeled Samples

↓ (Shared Language Knowledge)

Much Better Predictions

Working Process

Pretrain (e.g., mBERT / XLM-R)

Fine-tune on English Sentiment Data

Zero-Shot

Evaluate directly in the target language

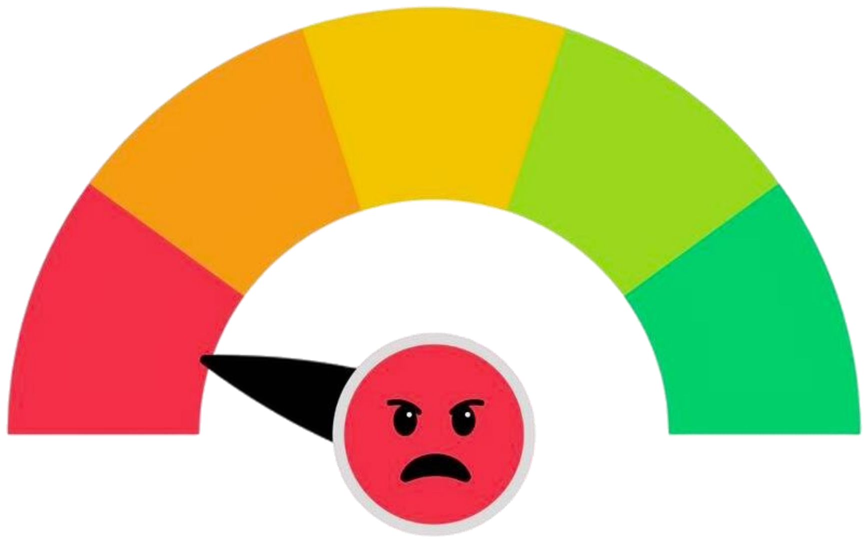
Few-Shot

Add a few target language samples, fine-tune again

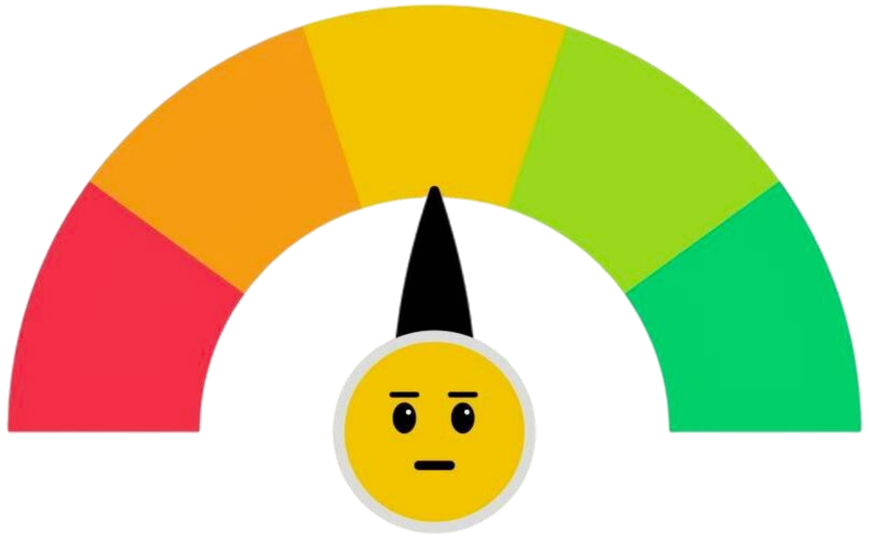
Bias in Sentiment Models

Why Is Bias a Problem in Sentiment Models?

She is aggressive



He is aggressive



Types of Bias in Sentiment Models

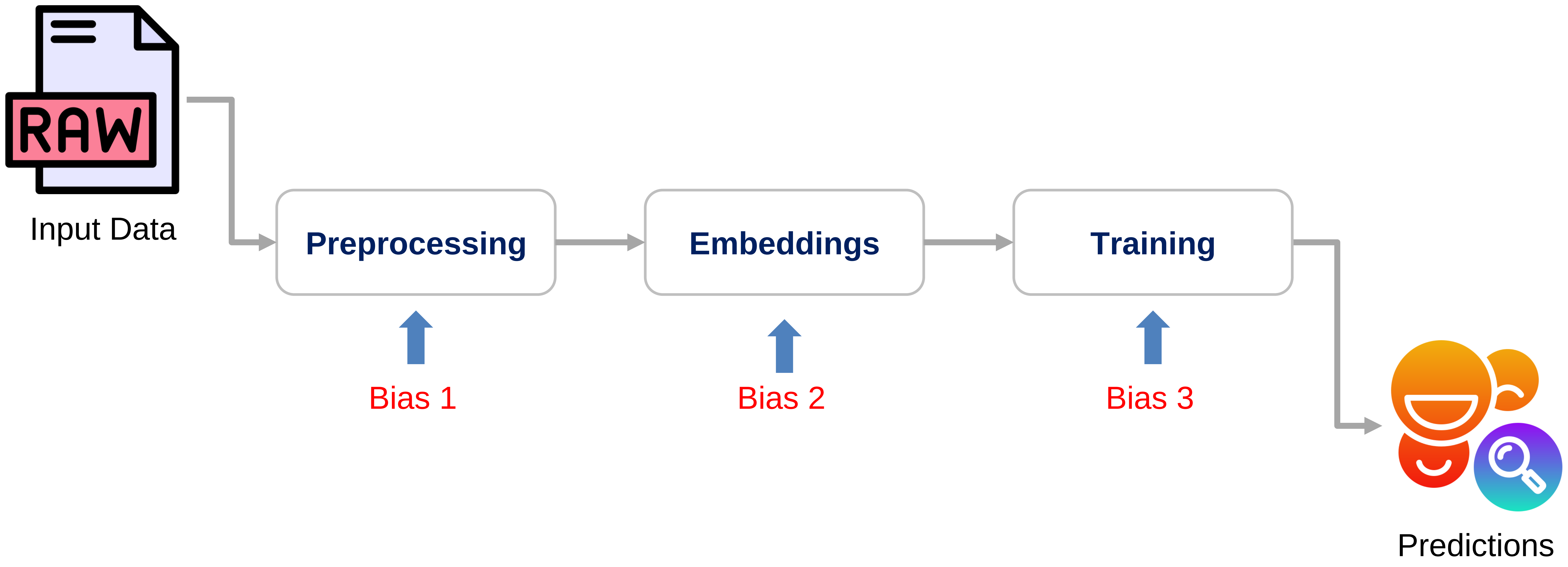
Bias in Sentiment Models

01
Gender Bias
Example: “bossy” (female) → more negative than “assertive” (male).

02
Racial Bias
Tweets from minority dialects get lower sentiment scores.

03
Cultural Bias
Positive sentiment is misunderstood in non-Western phrase styles.

How Bias Enters Models



Reducing False Negatives and Positives in High-Risk Applications

Why False Predictions Are Dangerous?

HR

A false negative on a complaint email → ignored harassment report

Healthcare

Misinterpreting “I’m fine” (actually distressed) → no help offered

Justice

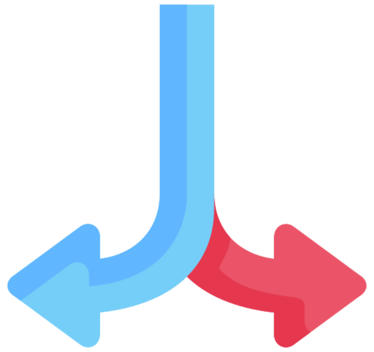
Overestimating aggression in minority speech → flagged unfairly

Understanding False Positives vs. Negatives

- False Positive = Model says “negative” but it’s actually “neutral/positive”
- False Negative = Model says “neutral/positive” but it’s actually “negative”

I feel okay, just numb.

Model Output: **Positive** ✅

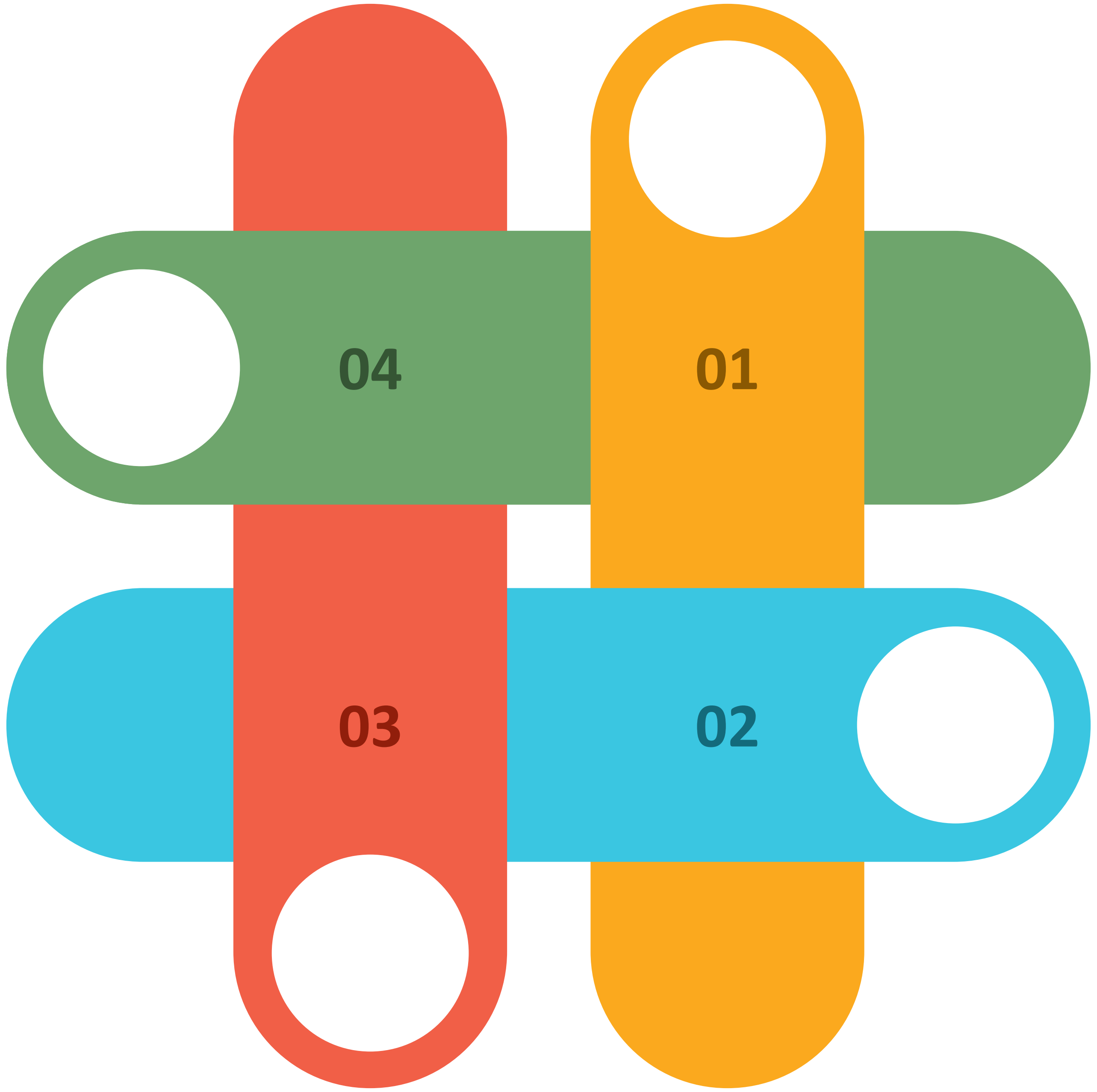


Ground Truth: **Negative** ❌

Techniques to Reduce Errors

Calibrate with class-weighted loss functions to penalize false predictions more

Add confidence thresholds before triggering action



Use domain-specific sentiment data

Incorporate context-aware models (e.g., BERT with full sentence history)

Aspect-Based Sentiment Analysis ABSA (Demonstration)

Note: Refer to Module 6: Demo 1 on LMS for detailed steps.

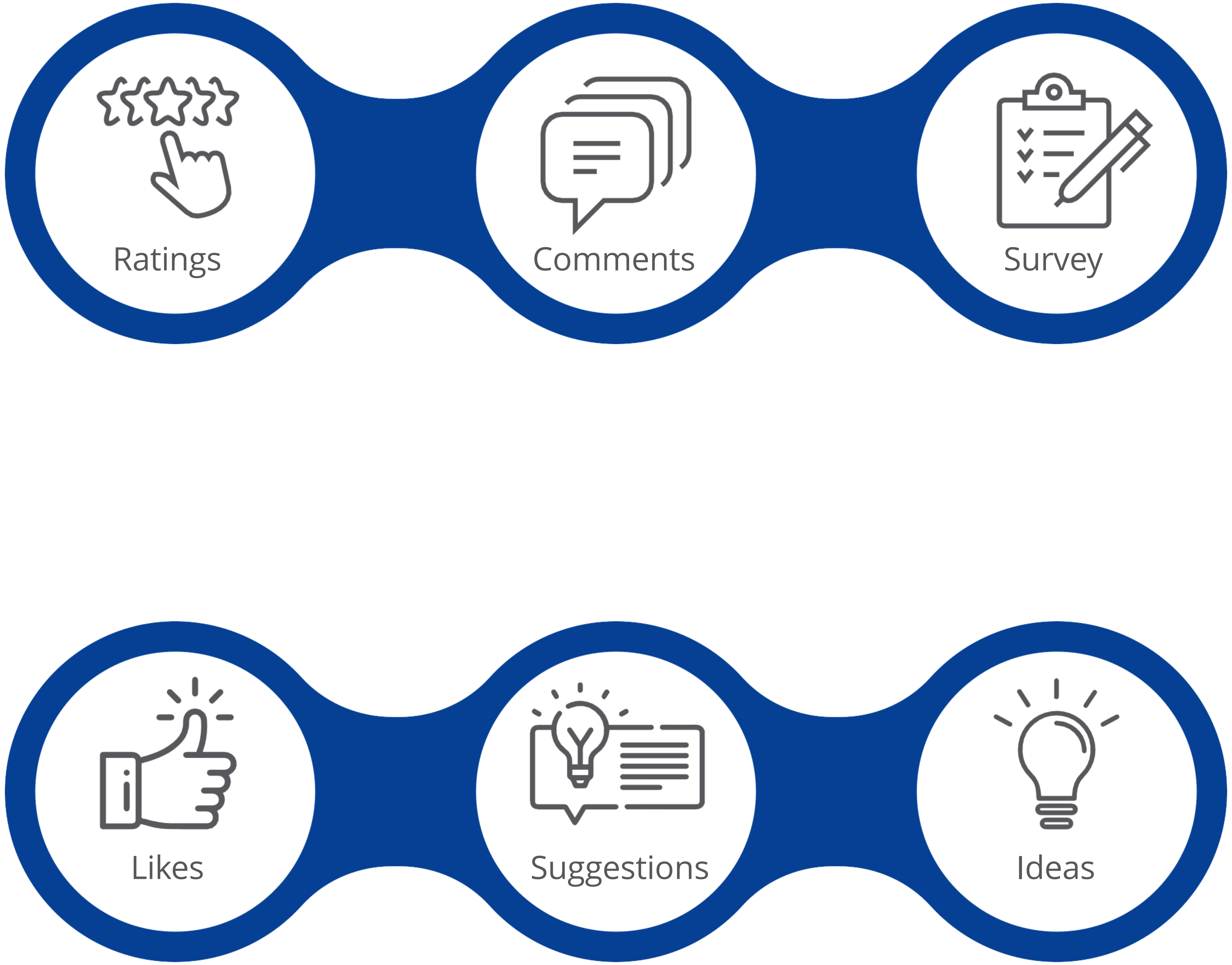
Summary

In this lesson, you have learned to:

- Leverage pre-trained transformer models, such as BERT, for effective sentiment classification.
- Learned how to fine-tune models for specific domains and datasets.
- Apply few-shot and zero-shot learning for low-resource sentiment tasks.
- Analyze sentiment across time, aspects, and multiple languages.
- Discuss ethical concerns and strategies for fair and responsible sentiment modeling.

Questions

Feedback



Thank You

For information, Please Visit our Website
www.edureka.co