



# Sentiment Analysis with CNN

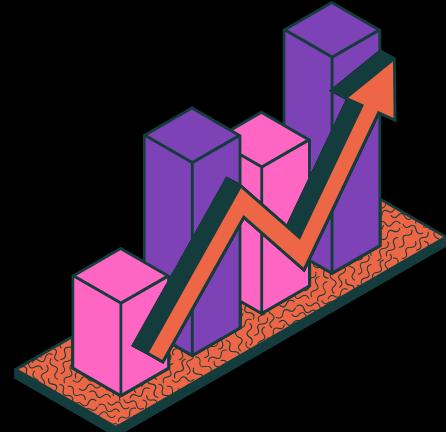


Connect over  
conversation



# Threads, Customer Feedback

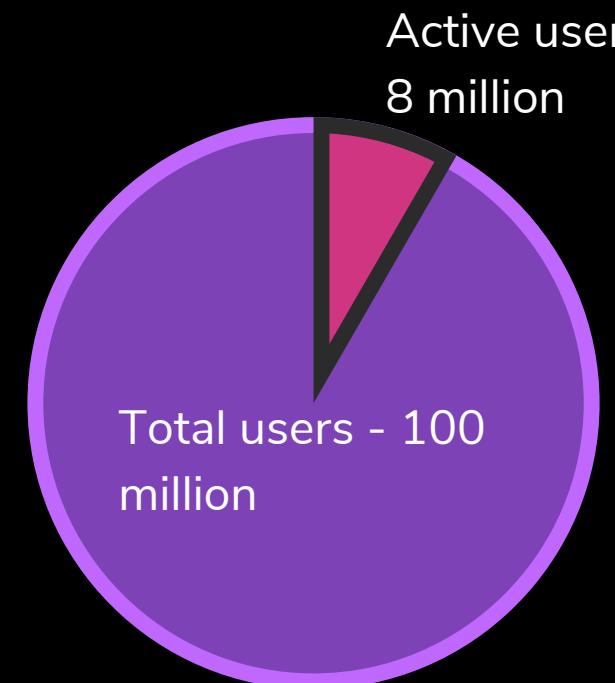
**While being the fastest-growing social media app**



**100 million users**

in the first 5 days

**... Threads struggles to retain customers**



8% sustained active  
daily users  
**long-term**

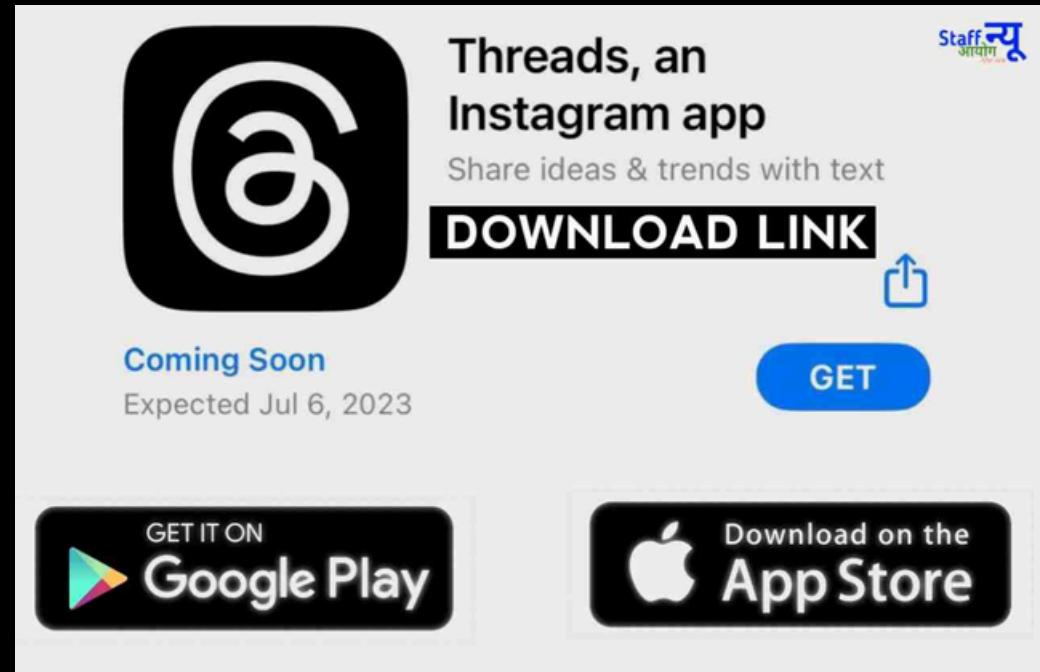
The need to analyze customer feedback to innovate the Threads app:

- fix bugs and inconveniences when using the app
- add additional features to meet customers' demands and attract customers



# From the original dataset

No.	Variable name	Type of data	Value
1	source	label	Google Play or App Store
2	review_id	string	id generated after each review done by users
3	user_name	string	
4	review_title	string	title about review (2000 unique values, accounting for 5% only)
5	review_description	string	main review text
6	rating	index	corresponding ratings
7	thumbs_up	index	validation provided by other users
8	review_date	date	date each review was published
9	developer_response	string	100% no response
10	language_code	label	the corresponding language that the review was written in
11	appVersion	label	corresponding version for reviews
12	country_code	geographic role	1 value only: "us"



**37,000 text-based reviews**

# to a more selected dataset

Redundant features are removed

No.	Variable name
1	source
2	review_id
3	user_name
4	review_title
5	review_description
6	rating
7	thumbs_up
8	review_date
9	developer_response
10	language_code
11	appVersion
12	country_code

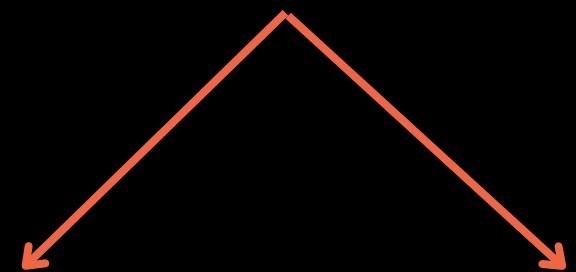
So that remaining features are below

- **review\_text:** Analyze user experiences and identify improvement areas.
- **rating:** Gauge user satisfaction and train sentiment recognition models.
- **review\_likes (thumbs\_up):** Understand user sentiment resonance and potential widespread issues.
- **appVersion:** Track sentiment changes linked to specific app versions.
- **review\_date:** Monitor sentiment trends over time.
- **language\_code:** Filter for English reviews for the best training of BERT model.

# What is Convolutional Neural Network?

## A CNN

is a special type of computer program that can learn to find patterns in data, like images or text



### Convolution:

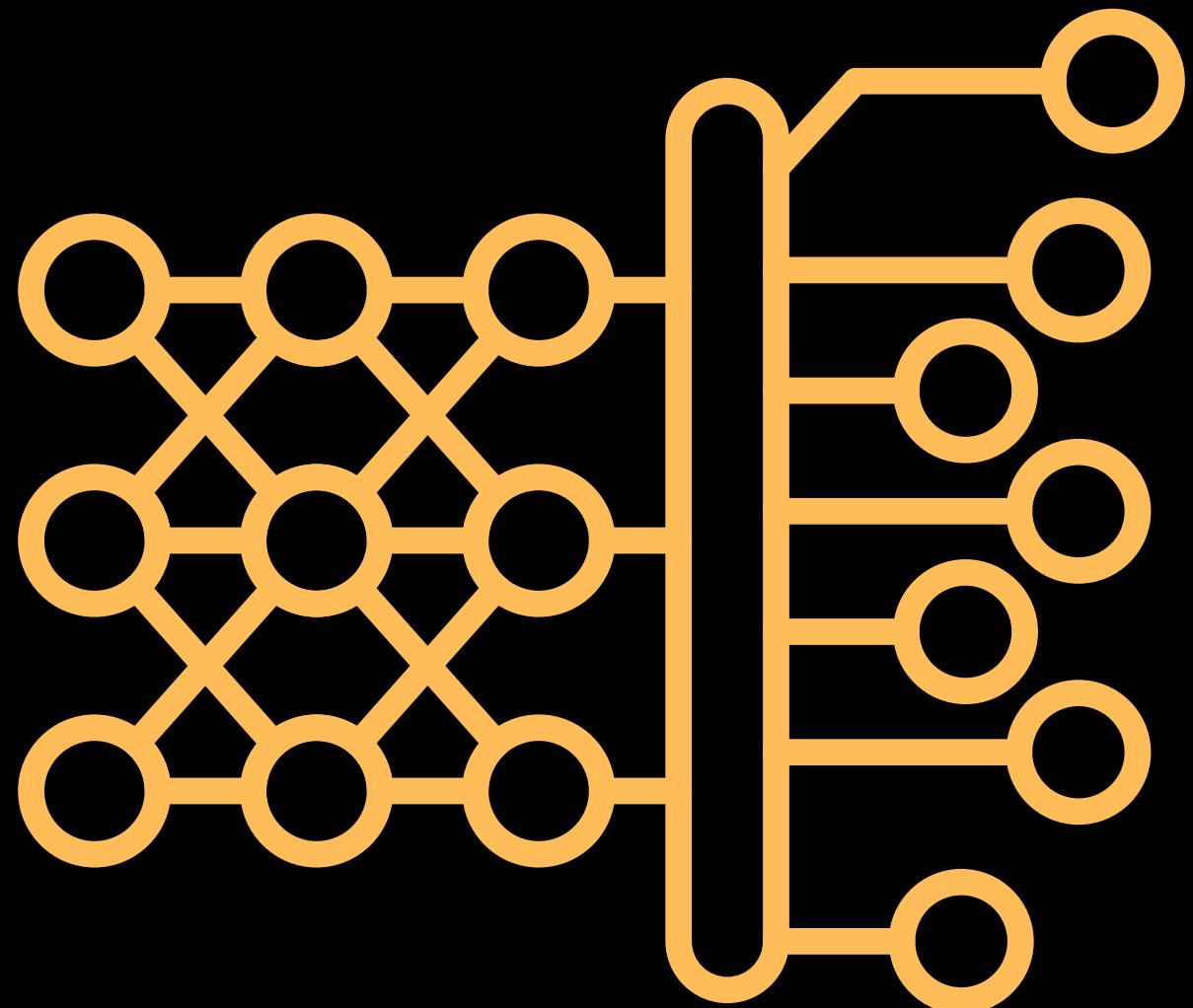
A process where a small tool (filter) moves over the data to look for specific patterns

### Neural network:

Connected unit work together to make decisions

Automated learning

Efficiency



# CNN Input

**Text data -> Number**

(CNN can only understand numbers, not words)

Sentence: I love using Threads

	Feature 1	Feature 2	Feature 3
I	1.0	0.0	0.0
love	0.0	1.0	0.0
using	0.0	0.0	1.0
Threads	0.5	0.5	0.0

# CNN Layer Types (Feature Extraction)

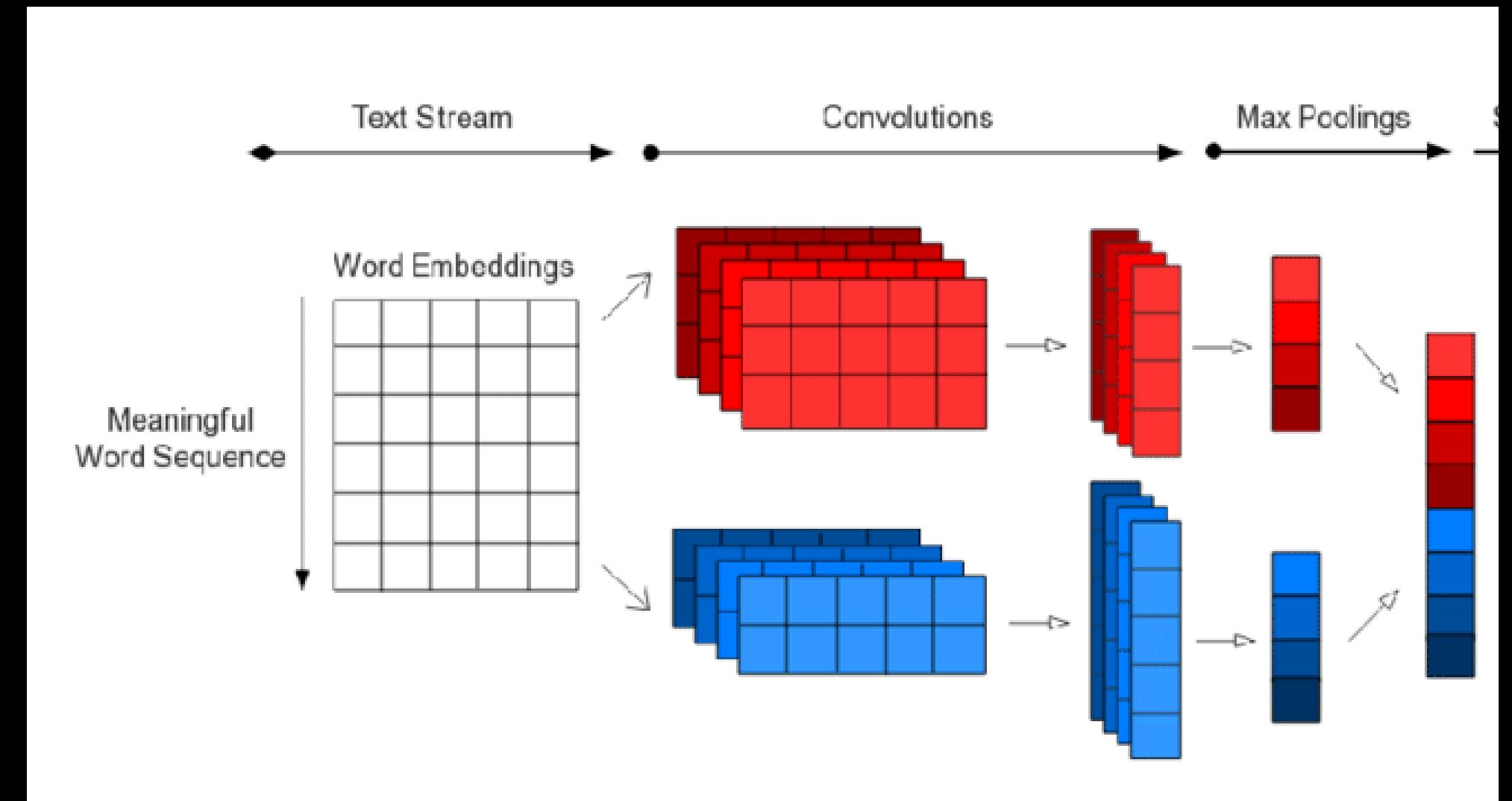
## 1. Convolutional Layer

Detects important words/phrases in text data



## 2. Max Pooling Layer

Reduces the size data, keeping only the most important information



# CNN Layer Types (Classification)

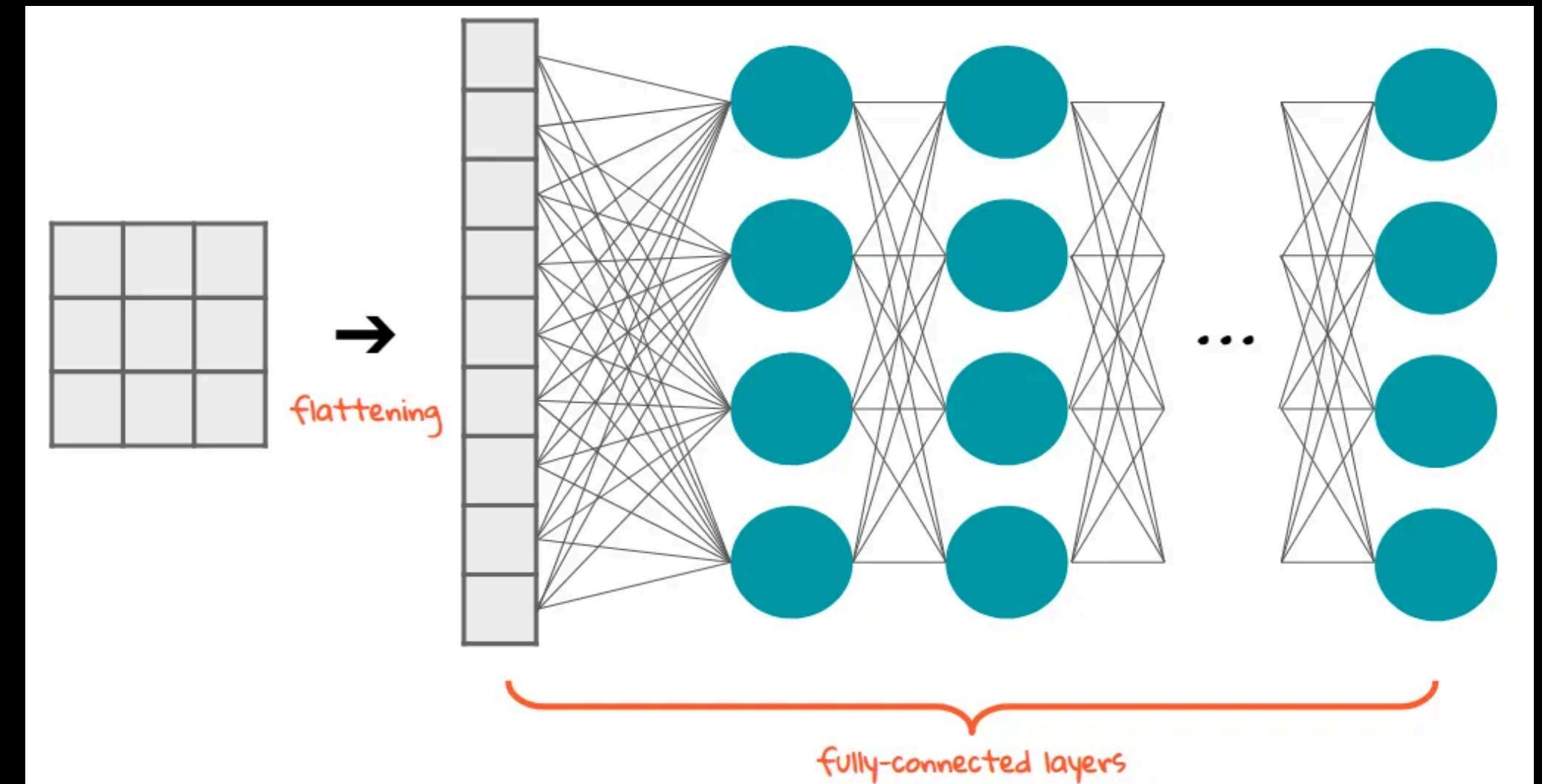
## 3. Flatten Layer

Converts the data from multiple dimensions into a single list of numbers



## 4. Fully Connected Layer

Combines all features to determine the overall sentiment (classifying a review as positive or negative)



# CNN Output

Probability distribution for Positive, Negative, and Neutral sentiments

=> Indicates the model's confidence in each sentiment

## Example of Interpreting Results:

- Highest Probability: Positive (50%)

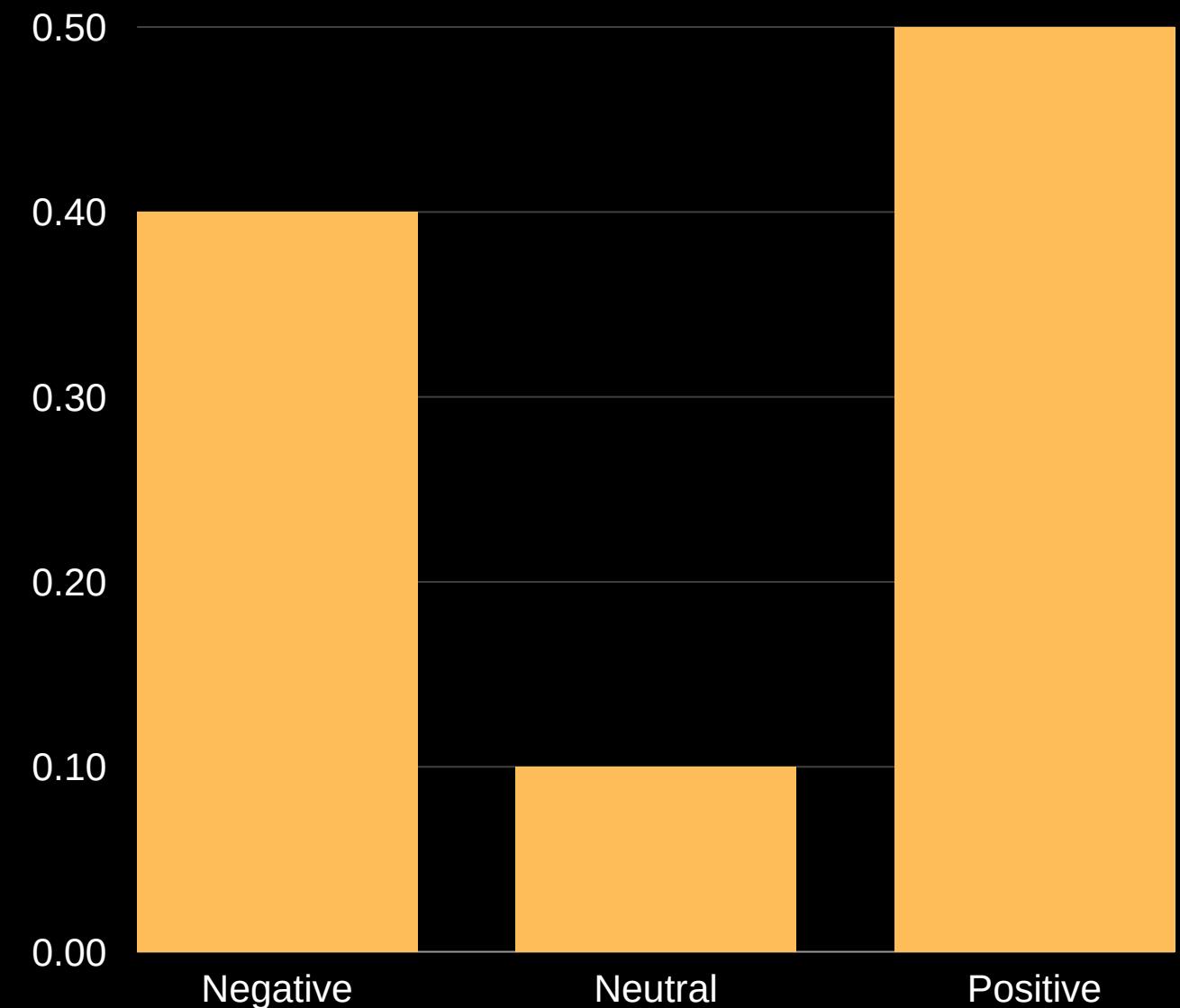
=> Most confident in **Positive sentiment**.

- Other Classes: Negative at 40%; Neutral at 10%

=> Some evidence for Negative and Neutral.

Sentiment Determination: **Positive sentiment is most likely.**

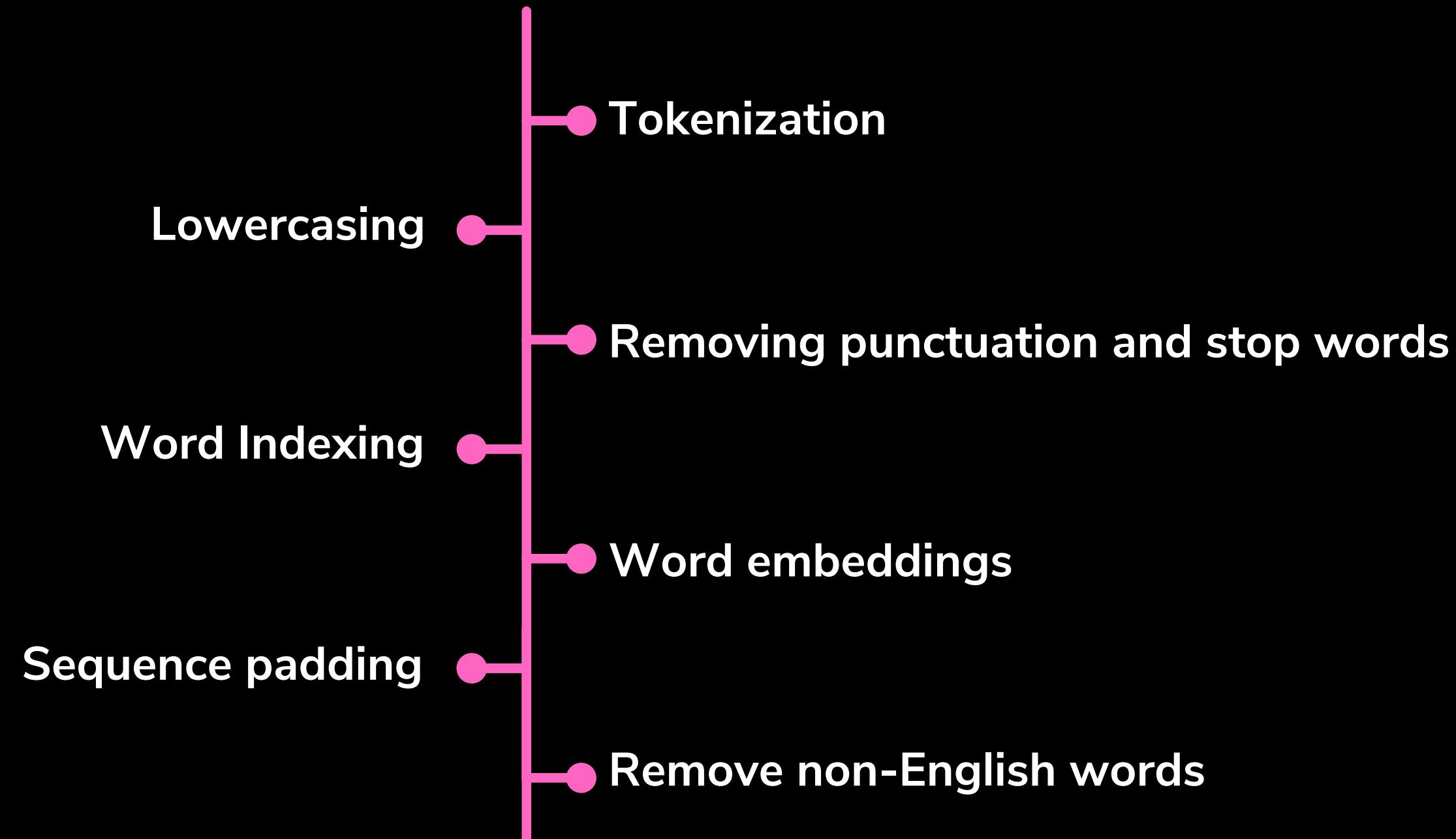
## Output Probabilities



# Final cleaning steps



Ensure  
***consistency***  
***focus***  
***accuracy***

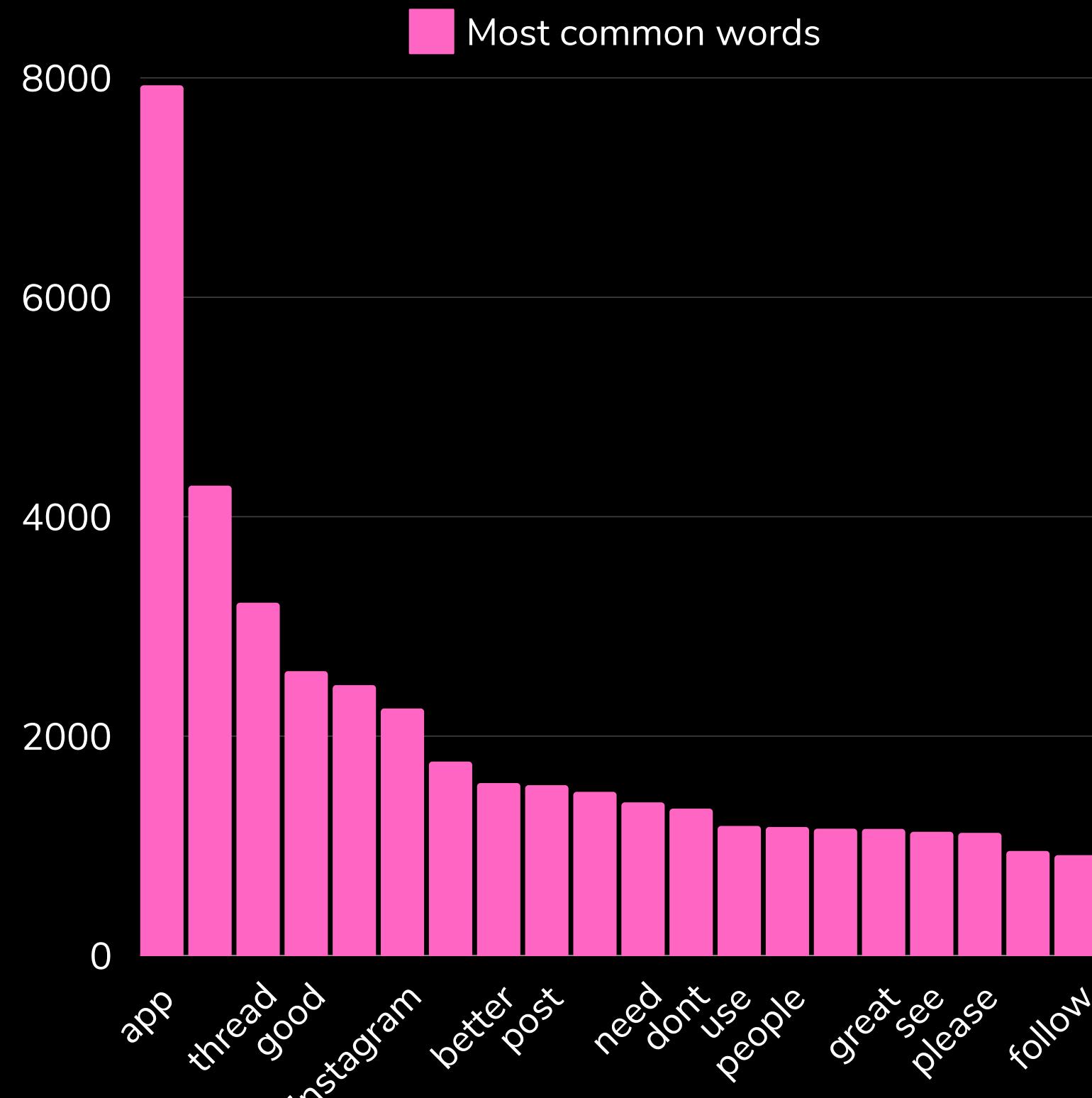


# Distribution of Review Ratings



- Higher number of positive reviews (scores 4 and 5) than negative reviews (scores 1 and 2)
- The number of extreme scores (lowest - 1 and highest - 5) is 2-3 times the number of review scores of 2, 3, and 4
- Few 3 “neutral” scores = challenges in training the model to identify “moderate” feedback

# Identification of Most Common Words



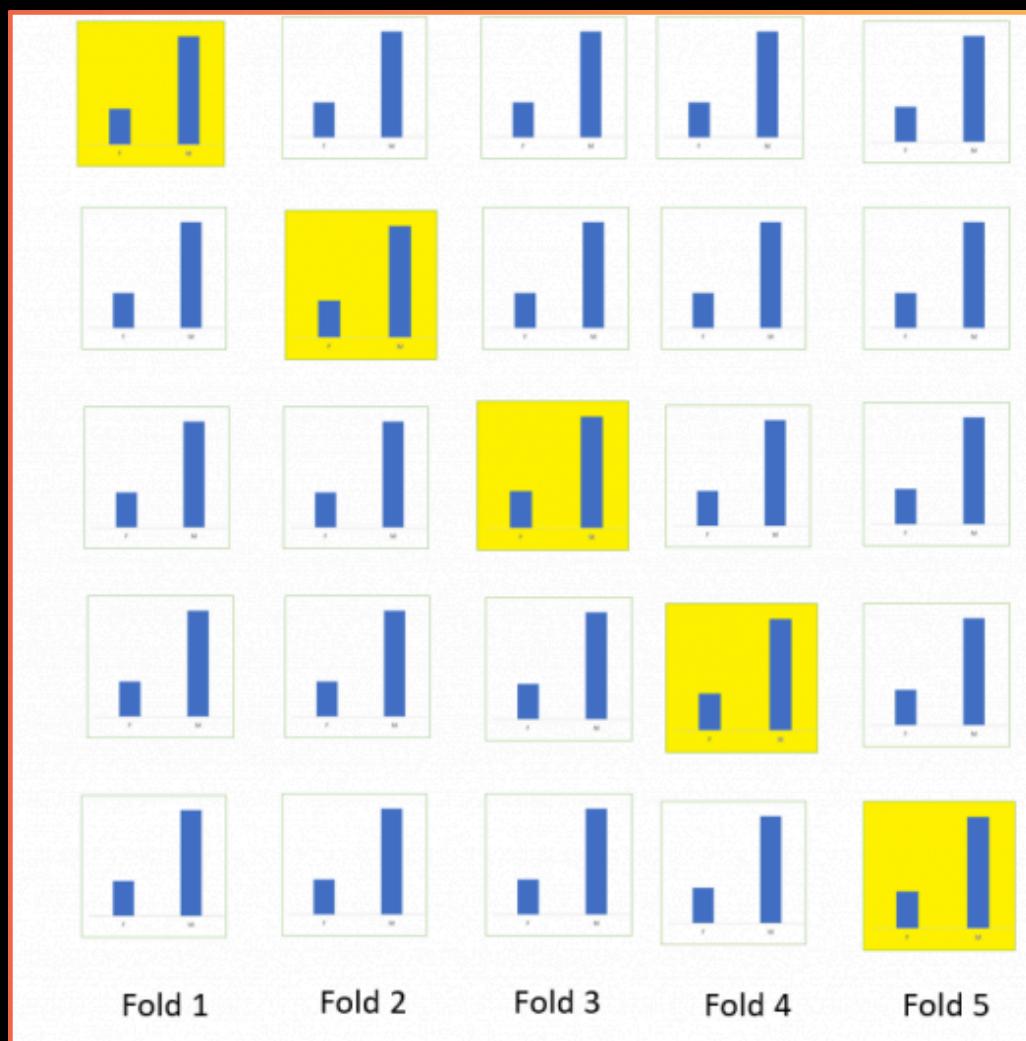
- Top most common words in the dataset are **mostly positive** words (“good”, “like”, “great”, and “nice”).
- However, there are still areas for improvement
  - “better” (the app can be updated to become better next time)
  - “can’t” (users are unable to use certain app functions)
  - “don’t” (suggest a negative experience)

# CNN Model's Architecture

Model: "sequential"		
Layer (type)	Output Shape	Param #
embedding (Embedding)	(None, 490, 128)	640000
conv1d (Conv1D)	(None, 488, 32)	12320
max_pooling1d (MaxPooling1D)	(None, 244, 32)	0
flatten (Flatten)	(None, 7808)	0
dense (Dense)	(None, 3)	23427
Total params: 675747 (2.58 MB)		
Trainable params: 675747 (2.58 MB)		
Non-trainable params: 0 (0.00 Byte)		

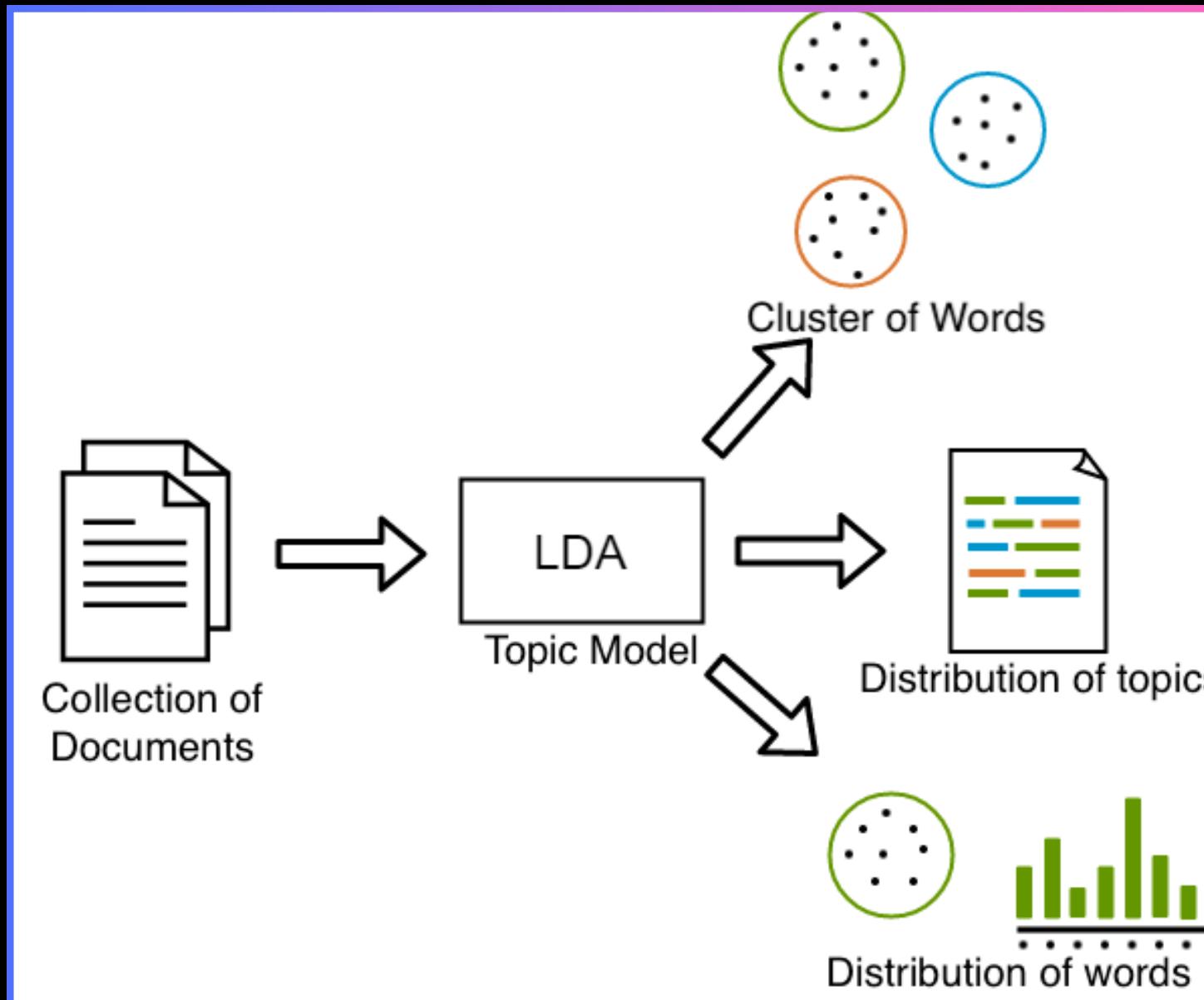
- 5-layers neural networks
- Over 600,000 trainable parameters
- Relu & Softmax activation function for non-linear patterns and multi-class classification

# Stratified k-fold



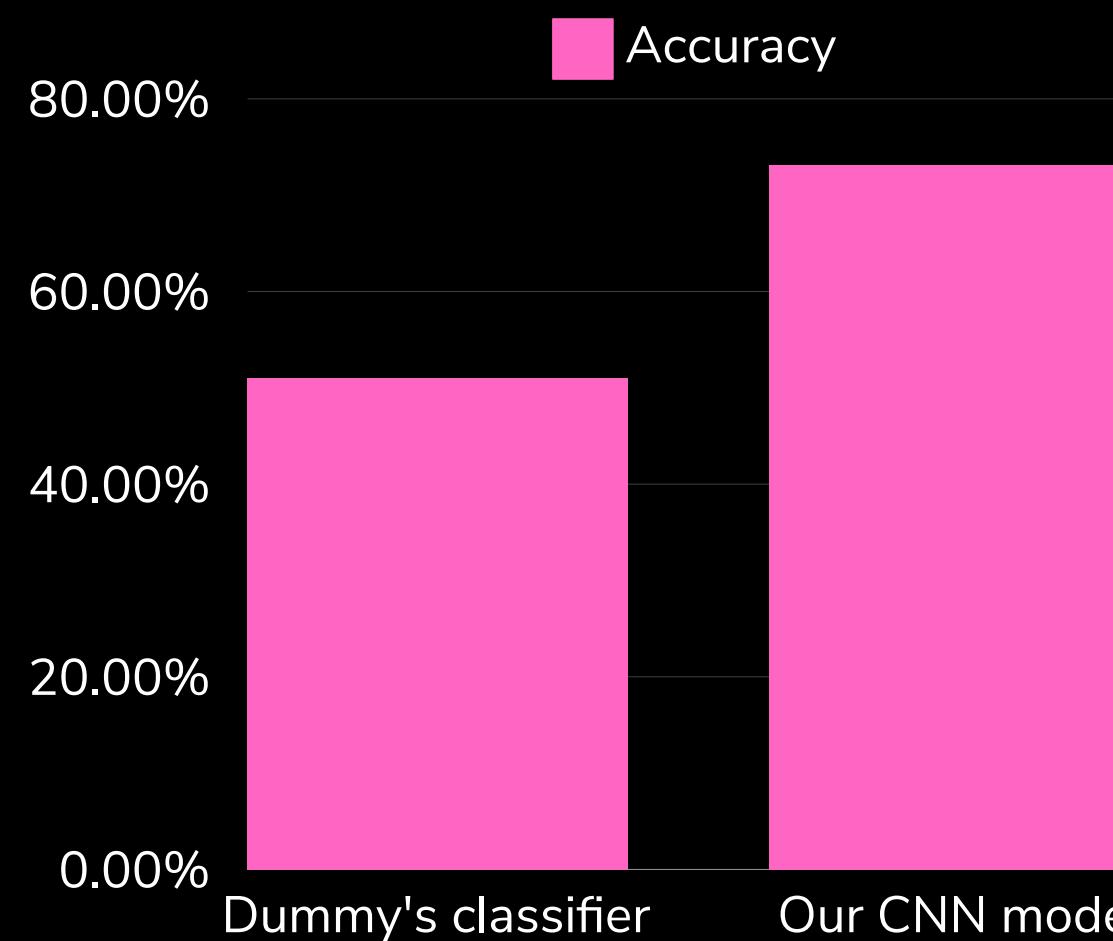
- Preserve same ratio between negative, neutral, positive classes for each fold (3.6 : 1 : 4.8).
- Cross-validate on 5 folds ( $k = 5$ )

# Latent Dirichlet Allocation

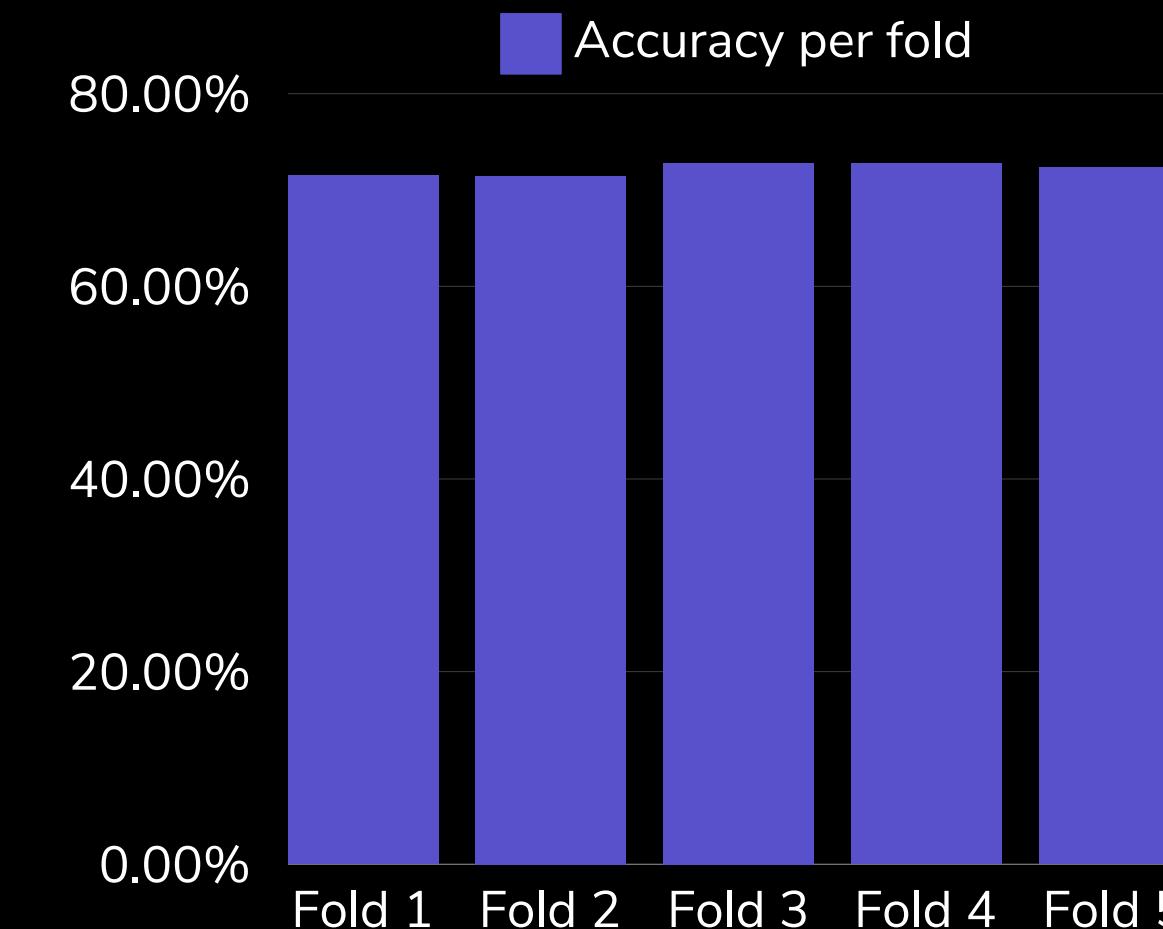


- A method for unsupervised classification of documents.
- Extract the top 5 most common topics mentioned in the positive and negative reviews.

# CNN's overall performance

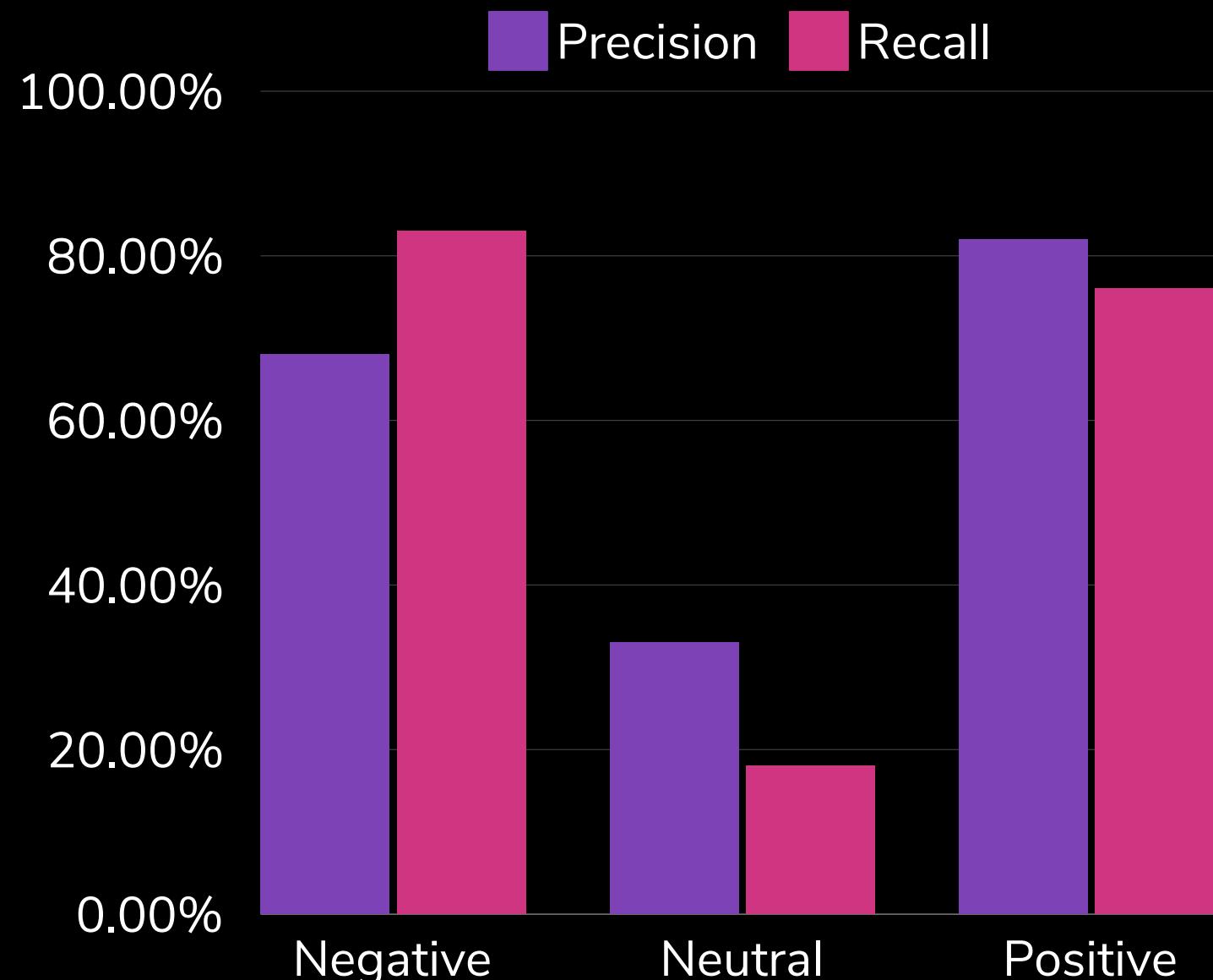


Our model outperforms the dummy classifier in accuracy (>20%), which can capture meaningful patterns in the data.



Model shows consistent performance across 5 data subsets, indicating reliability and generalization

# CNN's performance by class



### Class-Wise Performance Metrics

- Most positive reviews are correctly identified with few false positives.
- Many negative reviews are correctly identified, but there are some false positives.
- The model struggles to distinguish neutral reviews from positive and negative ones

### Keyword Analysis:

- Positive and Negative Reviews contain extreme keywords such as “poor”, “horrible”, “irrelevant”, “copycat”, “pointless”, and “excellent”.
- Neutral Reviews: Lack of clear, distinct keywords makes them harder to classify.

# Topic Modelling using LDA

Topic	Content
1	<u>lovely interface</u> fun beat <u>twitter</u> good wonderful app one amazing
2	think app way alternative thread much review first better <u>twitter</u>
3	follow like option please feature easy use add need thread
4	im friendly like instagram good thread user wow app top
5	instagram smooth like thread really experience best nice app good

## Positive Feedback:

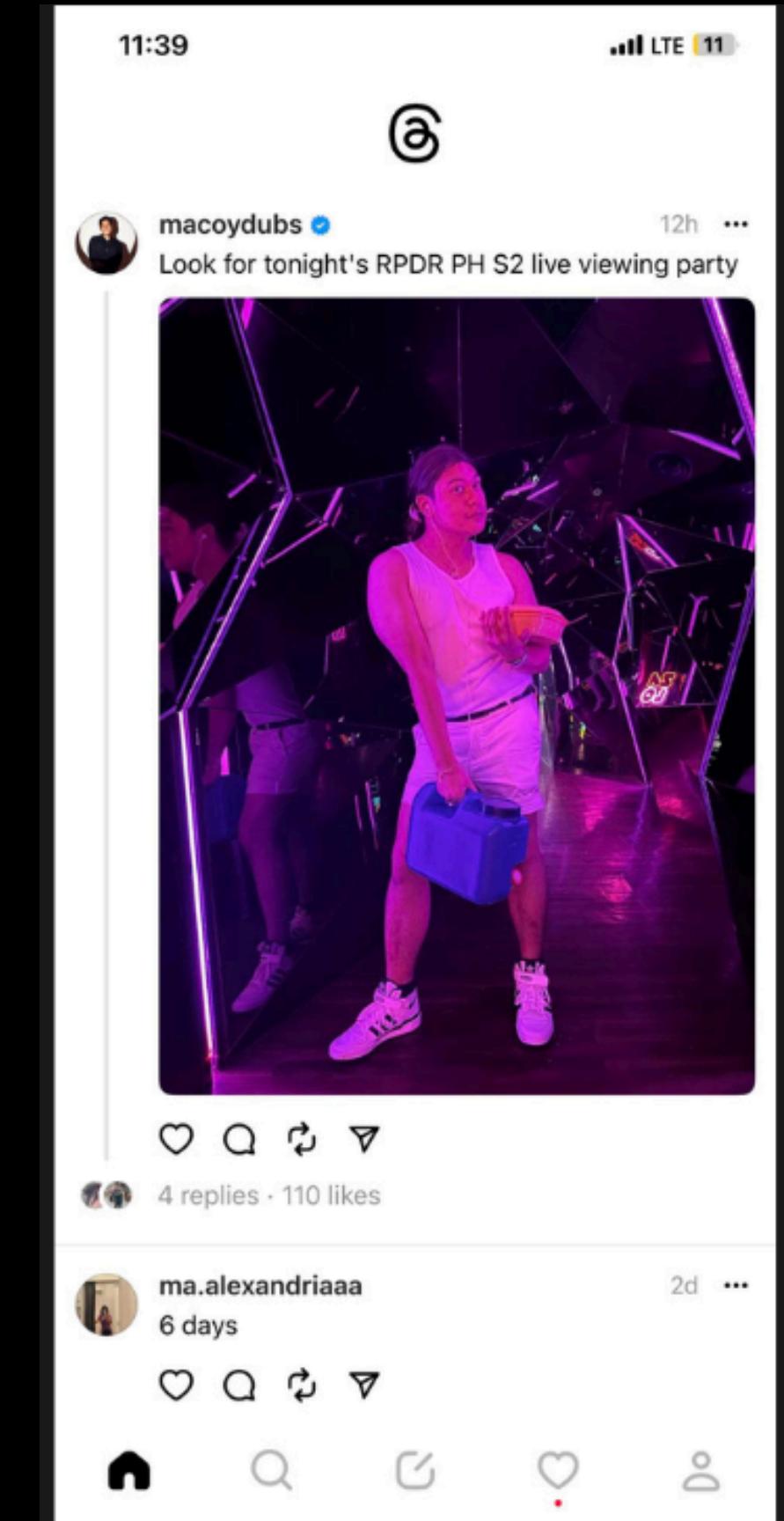
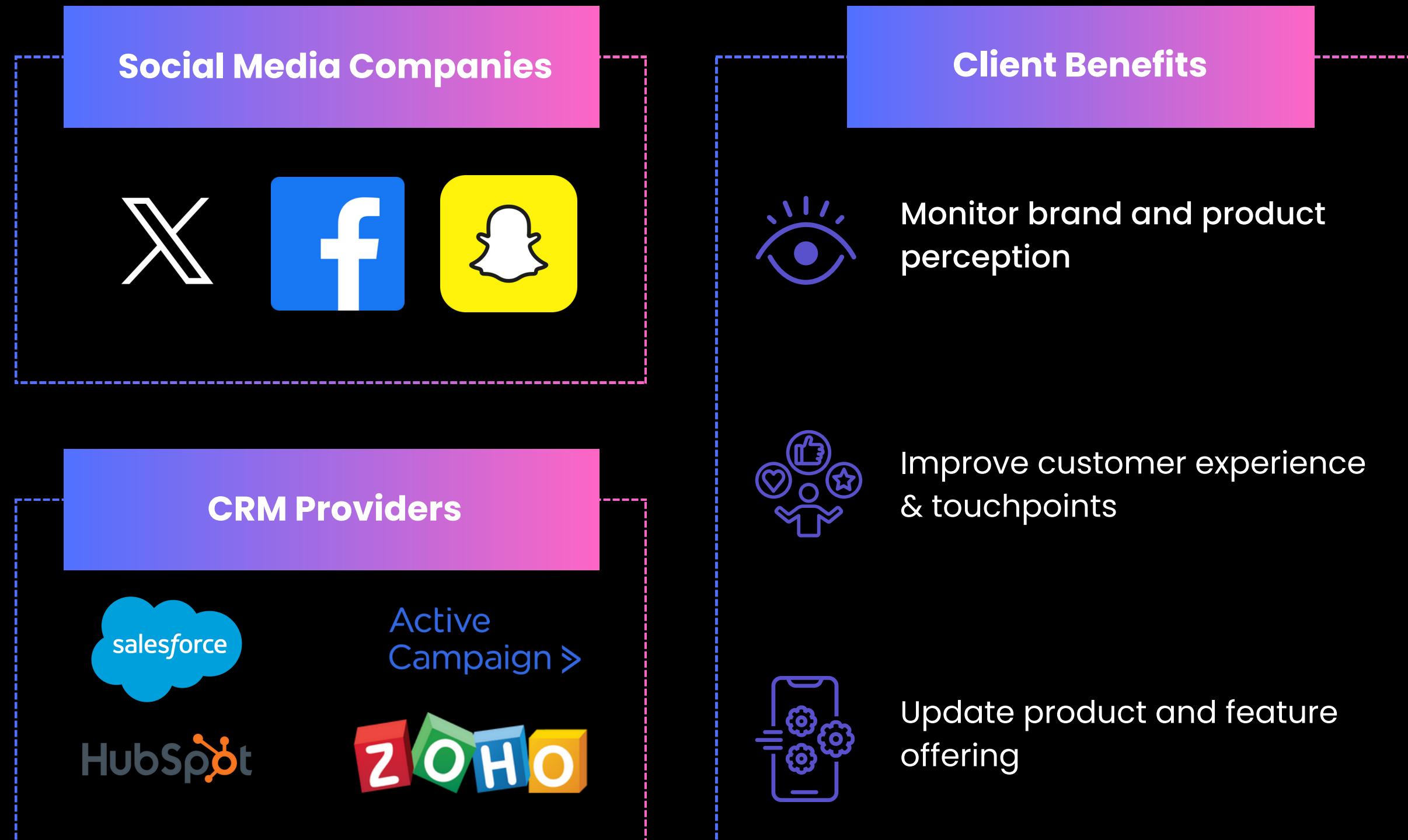
Users appreciate the interface, community, and perceive Threads as a better alternative to Twitter.

Topic	Content
1	<u>racist opinion</u> time truth waste support free boring speech freedom
2	better new clone work app doesnt twitter nothing properly working
3	app search poor following dont see feed post people follow
4	want without login app dont thread cant delete instagram account
5	worse don't suck version best good paste app twitter copy

## Negative Feedback:

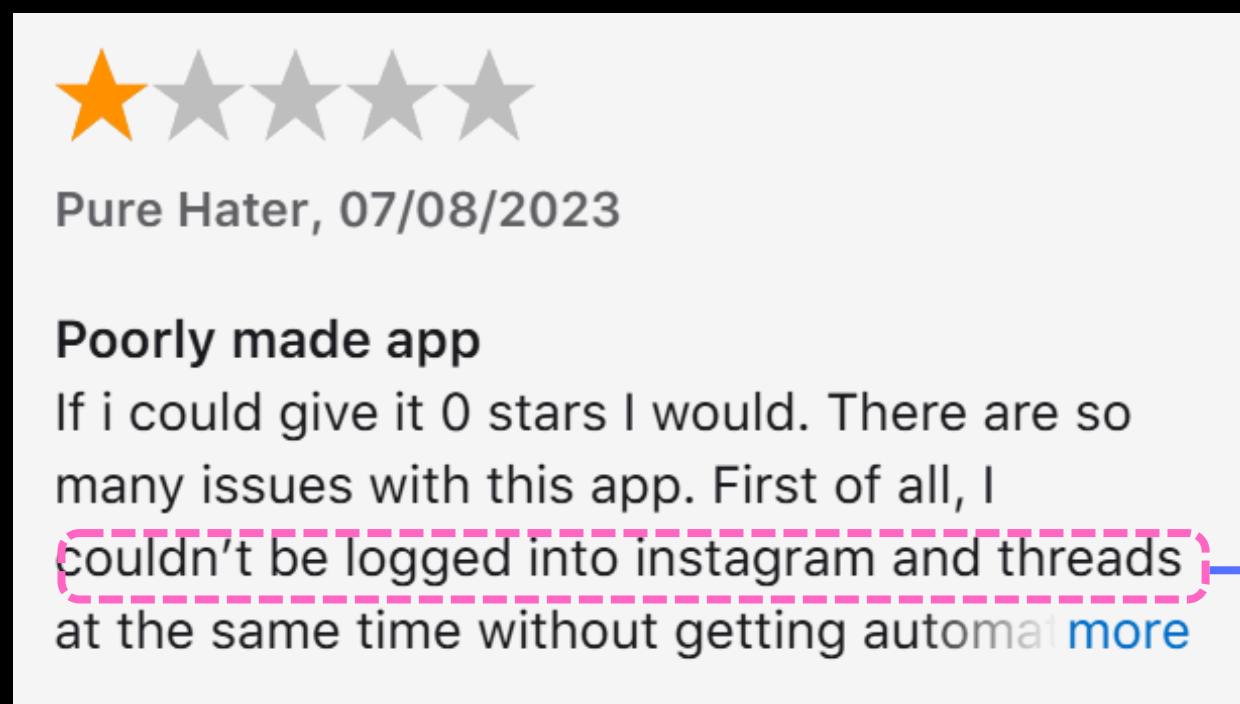
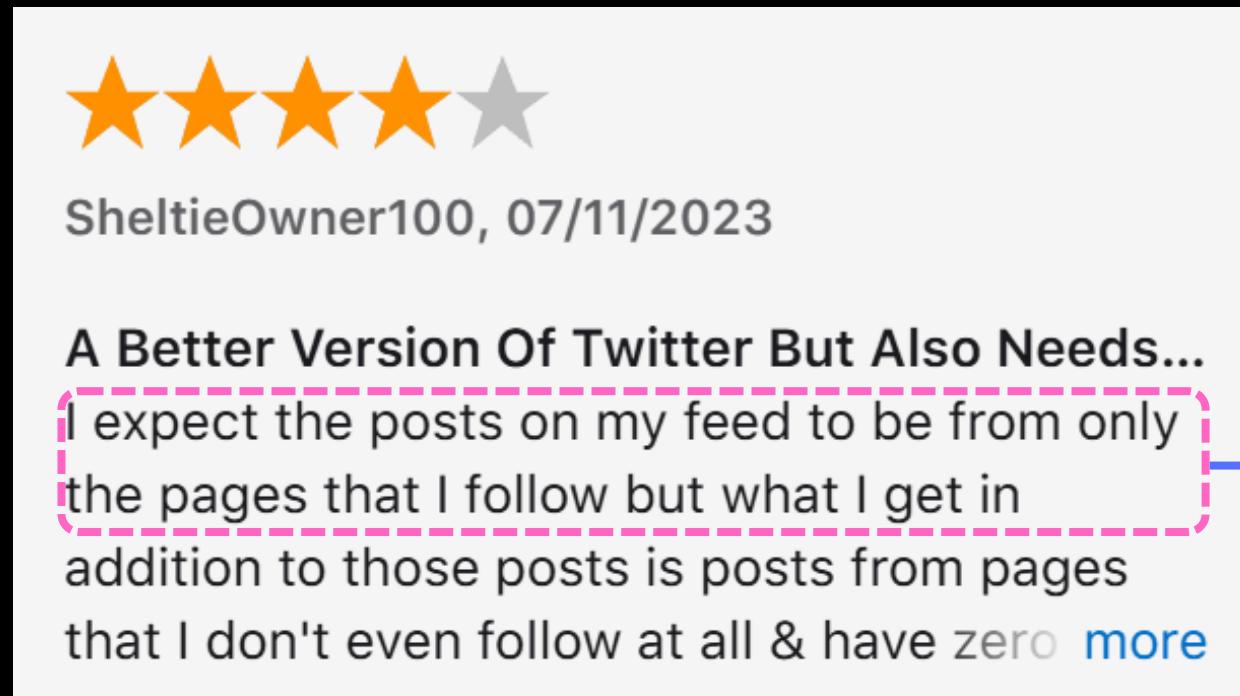
Users are frustrated with content moderation, customer service, and account management issues.

# Business Insights

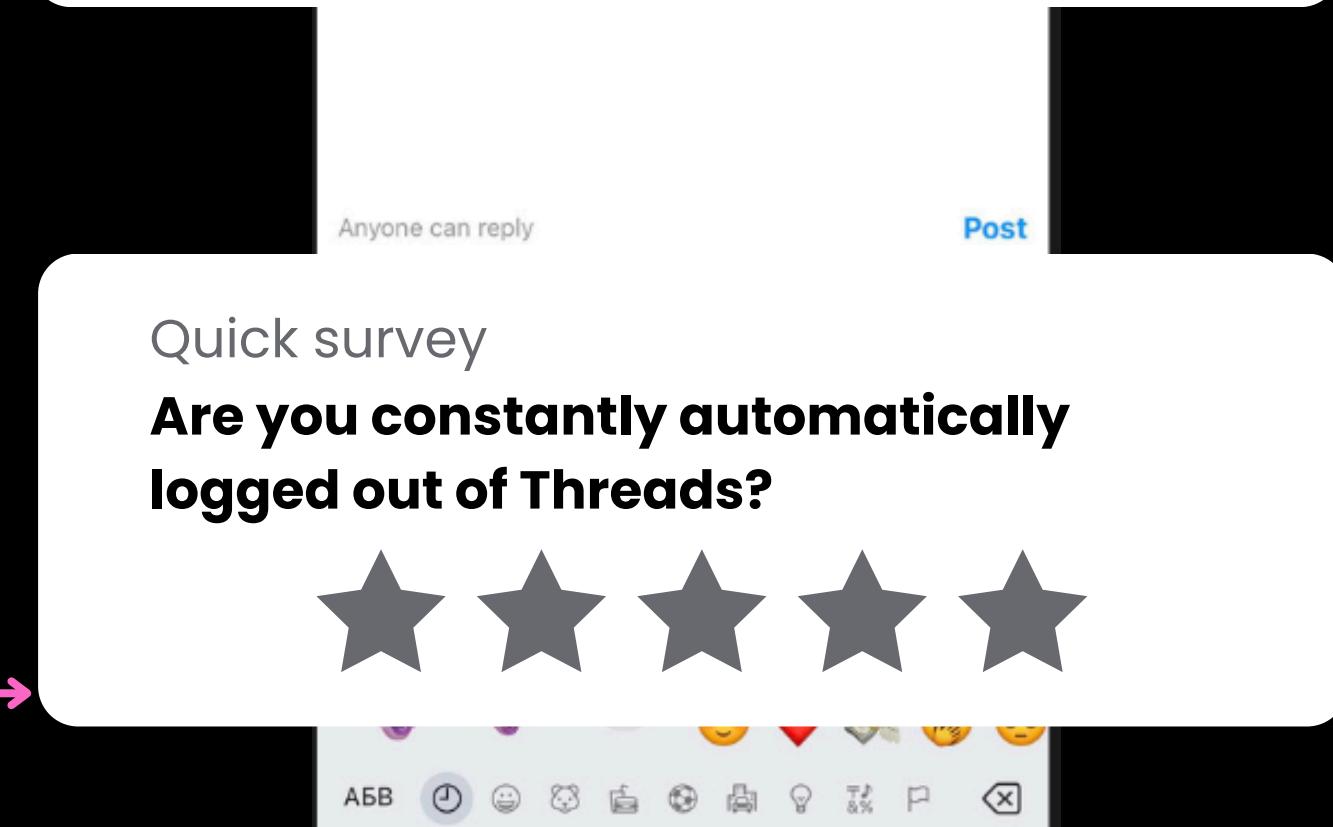
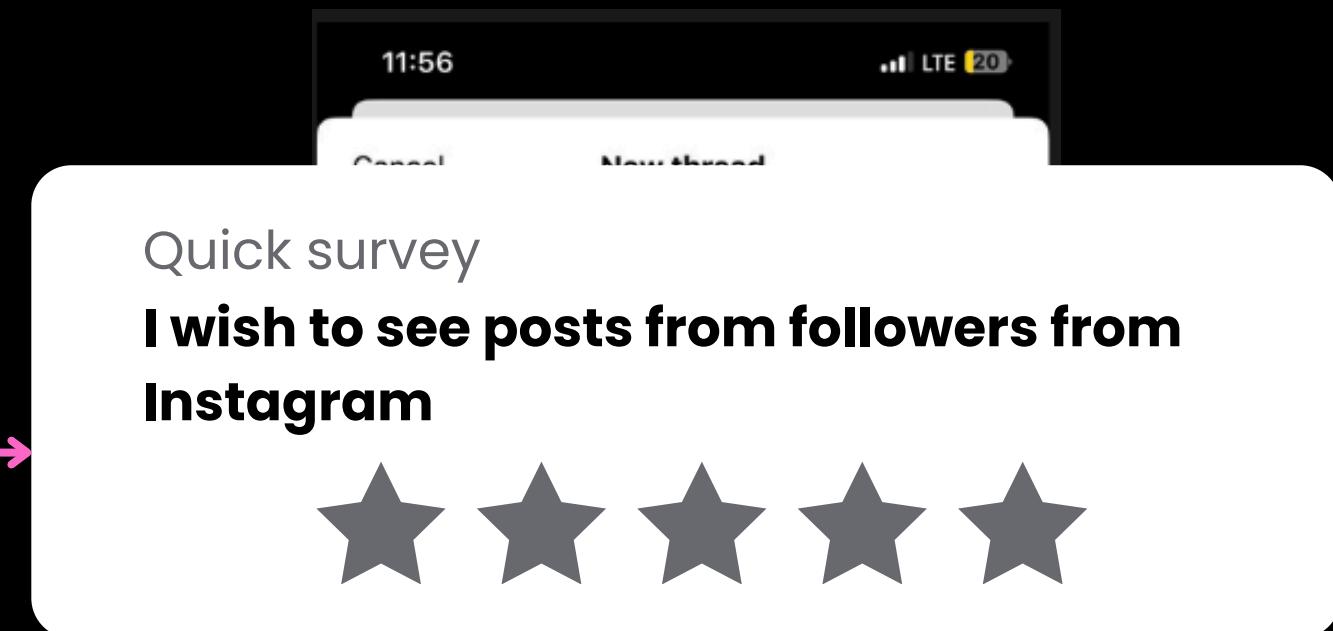


# Integrate automated surveys

From specific feedback in reviews



to feature-specific surveys for improving



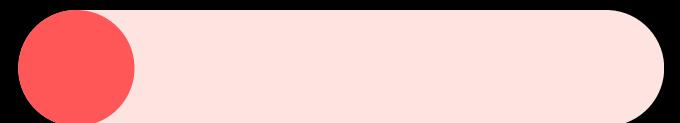
# Technical & Operational Concerns

Generally, resources are not an issue for large tech companies

Concern level

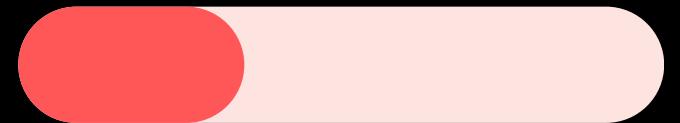
## Integration Cost

- ✓ Cloud computing, CPU generators, system adaptation processes
- ✓ Integration into legacy systems



## Latency Issues

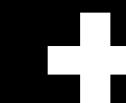
- ✓ Batch Processing: general sentiments - monthly
- ✓ Real-time Processing: feature launch + event shock



# Constraints and Potential for Expansion

## 1. Genuinity of reviews input

Double-sentiment reviews  
Sarcasm



## 2. Language Accuracy Gap

Languages with high-context  
Low resources



### Irony Detection & Subjectivity Classification

Filter out un-genuine content as part of preprocessing



### Multi-lingual models Multi-label Scenarios

Normalize noise sources  
Assign weights to emotional states