



# **AUTOMATED TICKECT CLASSIFICATIO N**

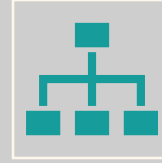
GROUP 2



# BUSINESS UNDERSTANDING



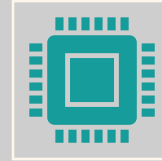
Financial institutions receive thousands of customer complaints daily.



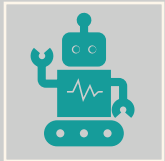
Manual complaint classification is slow and inefficient.



Customer complaints are submitted as unstructured text, requiring automation for faster processing.



**Solution:** Implement **Natural Language Processing (NLP)** to classify complaints automatically.



**Objective:** Automate complaint categorization using NLP & ML.

# Business Objective

- ❖ Develop an automated ticket classification model for customer complaints.
- ❖ Categorize complaints into 5 key service areas using Topic Modeling:
  1. Credit Card / Prepaid Card
  2. Bank Account Services
  3. Theft / Dispute Reporting
  4. Mortgages / Loans
  5. Others
- ❖ Train a supervised learning model (e.g. LSTM,)
- ❖ Key Benefits:
  1. Faster complaint resolution.
  2. Improved customer experience
  3. Better resource allocation

# **DATA PREPARATION**

## **❖ Handling Missing Data:**

- Removed or imputed missing values to maintain data integrity.

## **❖ Text Cleaning:**

- Removed stopwords, punctuation, and special characters.
- Converted text to lowercase for consistency.

## **❖ Tokenization & Vectorization:**

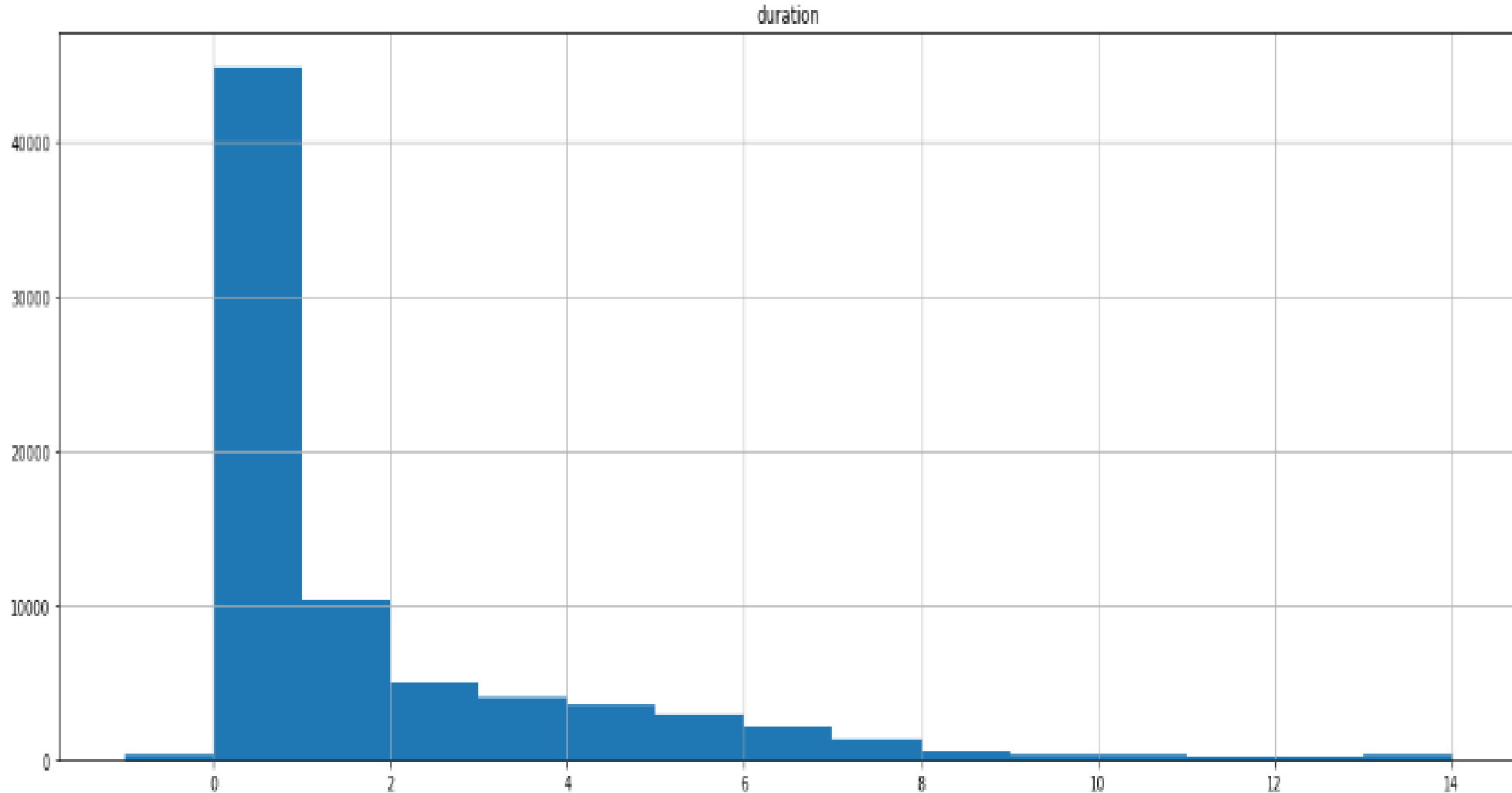
- Applied **TF-IDF** and **Word2Vec** to transform text into numerical representations.

## **❖ Feature Engineering:**

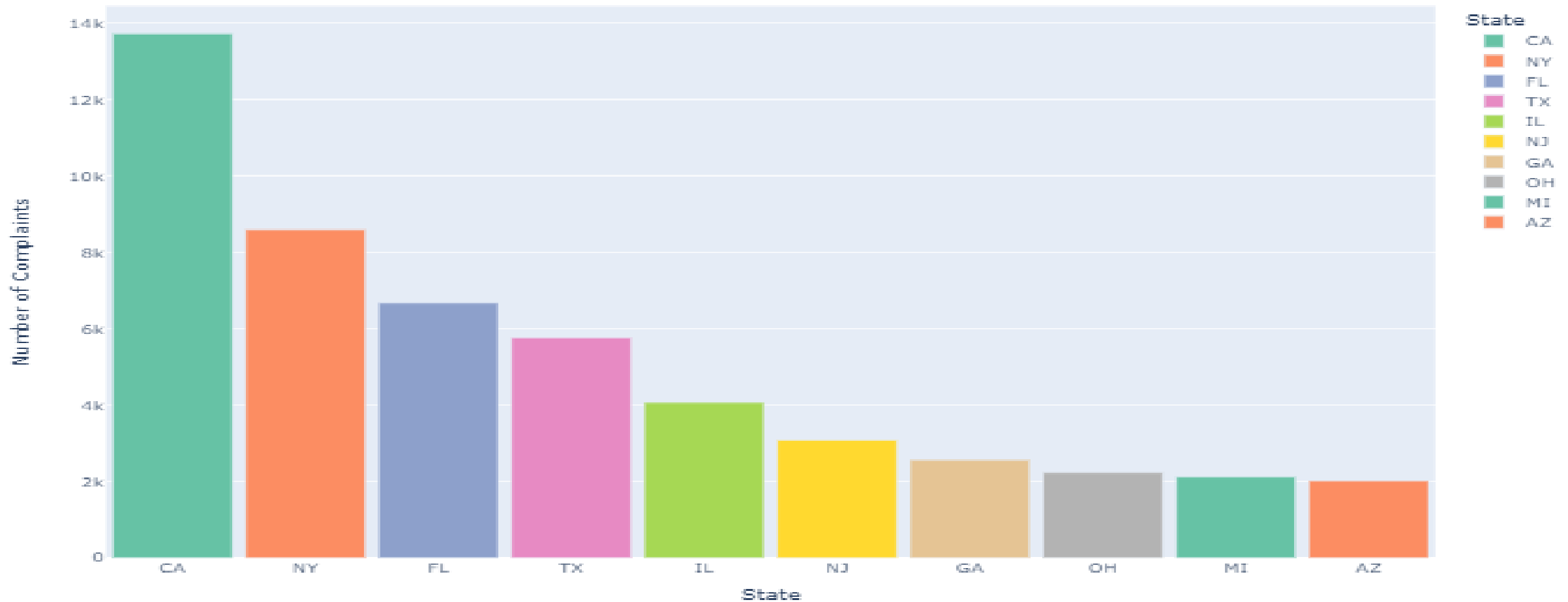
- Extracted key terms and phrases for better model performance.

## Observations

- The histogram shows a right-skewed distribution, with most complaints resolved within a few days (0-1) days. A small number of cases take significantly longer, faster complaints resolution.



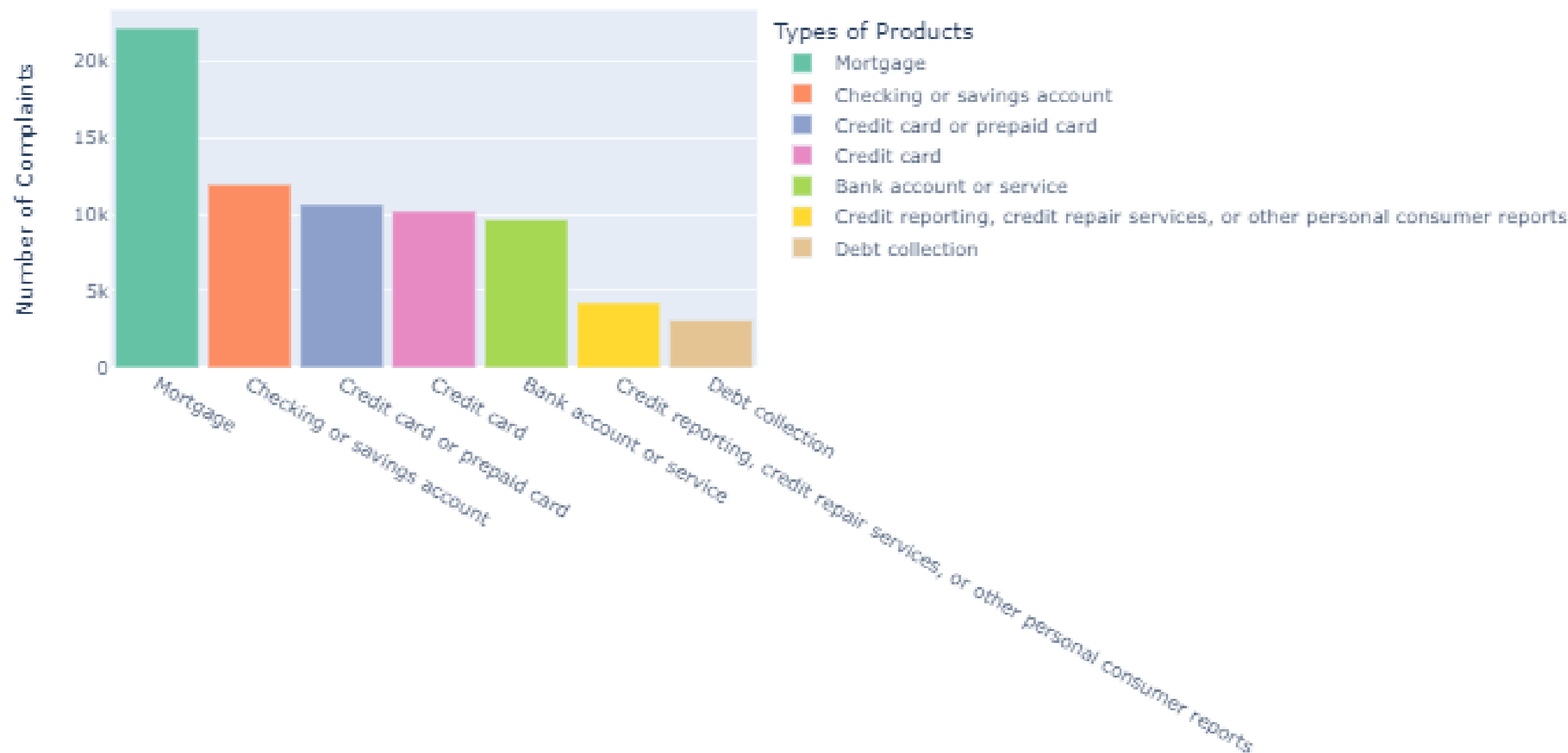
Frequency Distribution of States



### **Observations :**

Most complaints originate from CA, NY, FL. These are the three states with most complains

# Frequency Distribution of Products



## Observation on Distribution of product

Mortgage-related complaints are the highest, exceeding 20,000 cases.

Checking/savings accounts, credit cards, and prepaid cards also have a significant number of complaints, each around 10,000.

Bank account services, credit reporting, and debt collection have fewer complaints in comparison.

The distribution is uneven, with mortgage-related issues being the most frequent concern.



# MODELING APPROACH

## ❖ Data Preprocessing:

- Cleaned text data.
- Tokenized text and TF-IDF vectorization for feature selection.

## ❖ Unsupervised Learning: Topic Modeling (LDA & NMF)

## ❖ Supervised Learning: (LSTM)

# Topic Modeling with NMF.

**Topic 1:** Bank Account Services

**Topic 2:** Credit Card / Prepaid Card

**Topic 3:** Mortgages/Loans

**Topic 4:** Theft/Dispute Reporting

**Topic 5:** Others

	Word 1	Word 2	Word 3	Word 4	Word 5	Word 6	Word 7	Word 8	Word 9	Word 10
Topic 1	account	bank	check	money	fund	chase	wa	deposit	branch	day
Topic 2	credit	card	report	inquiry	chase	account	score	company	limit	bureau
Topic 3	loan	mortgage	home	chase	modification	property	year	wa	rate	letter
Topic 4	charge	card	chase	transaction	dispute	wa	fraud	claim	merchant	purchase
Topic 5	payment	balance	fee	month	statement	wa	day	time	date	auto

# Topic Modeling with LDA

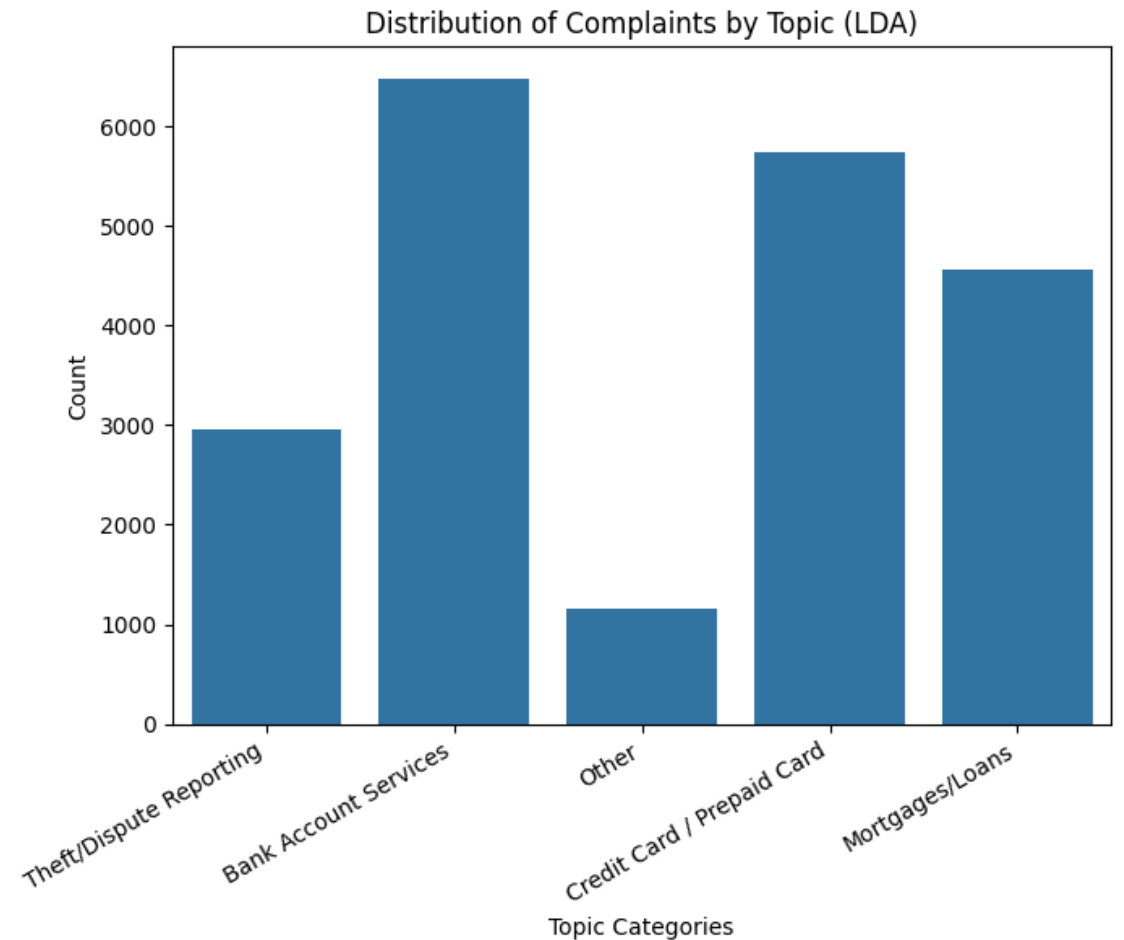
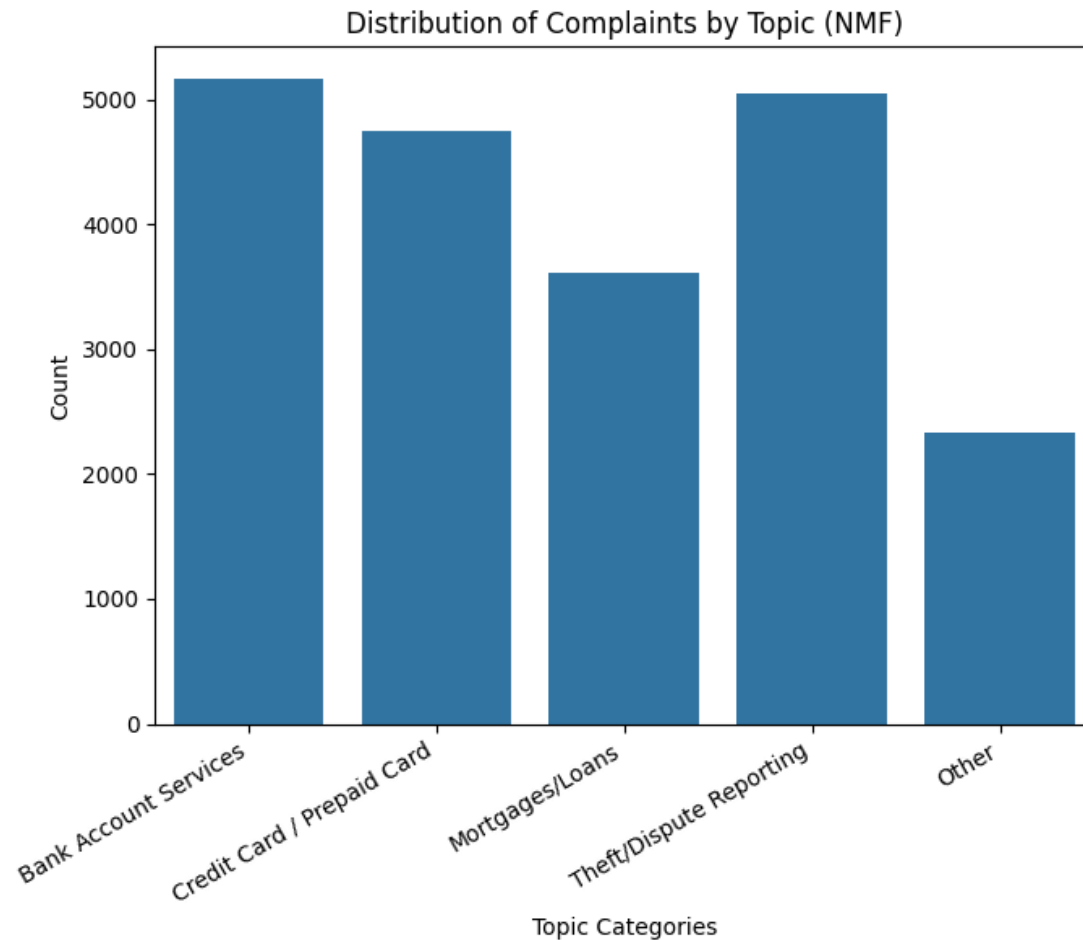
## LDA Topics Identified:

- Similar to NMF with slight variations
- **Main Difference:** "Others" category was less defined

**Comparison:** NMF had better topic separability

	Word 1	Word 2	Word 3	Word 4	Word 5	Word 6	Word 7	Word 8	Word 9	Word 10
Topic 1	card	chase	charge	wa	credit	fraud	transaction	account	claim	number
Topic 2	loan	chase	mortgage	payment	wa	home	bank	time	year	property
Topic 3	account	bank	chase	wa	check	money	fund	day	branch	time
Topic 4	credit	card	account	chase	payment	balance	report	wa	month	time
Topic 5	chase	wa	dispute	fee	time	charge	car	day	merchant	company

# DISTRIBUTION OF COMPLAINTS BY LDA & NMF



# Observations on Topic Consistencies Between NMF and LDA

From the two distribution plots, we can observe some consistencies despite the differences in the topic modeling approaches:

- Bank Account Services – This topic is the most dominant in both NMF and LDA, suggesting strong clustering around banking-related complaints.

- Credit Card / Prepaid Card – This category also appears as a significant topic in both models, showing consistent identification of credit card-related issues.

- Mortgages/Loans – Both models assign a comparable number of complaints to this topic, reflecting a shared pattern in complaint distribution.

- Theft/Dispute Reporting – While there is some variation in frequency, this category is clearly identified in both models.

- Other Category – The "Other" category differs in size between the models, but it still represents a smaller portion of the dataset in both cases.

# Topic Consistency Observations

## Similarities:

- Bank Account Services & Credit Cards were strong topics in both models
- Mortgages/Loans & Theft/Dispute categories were consistent

## Differences:

- "Others" category was more ambiguous in LDA



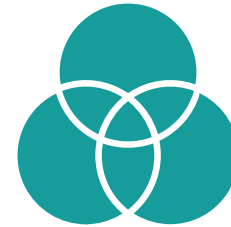
# Model performance Metrics



## LSTM Classification Results:

**NMF-Based Model:** 90% Accuracy

**LDA-Based Model:** 88% Accuracy

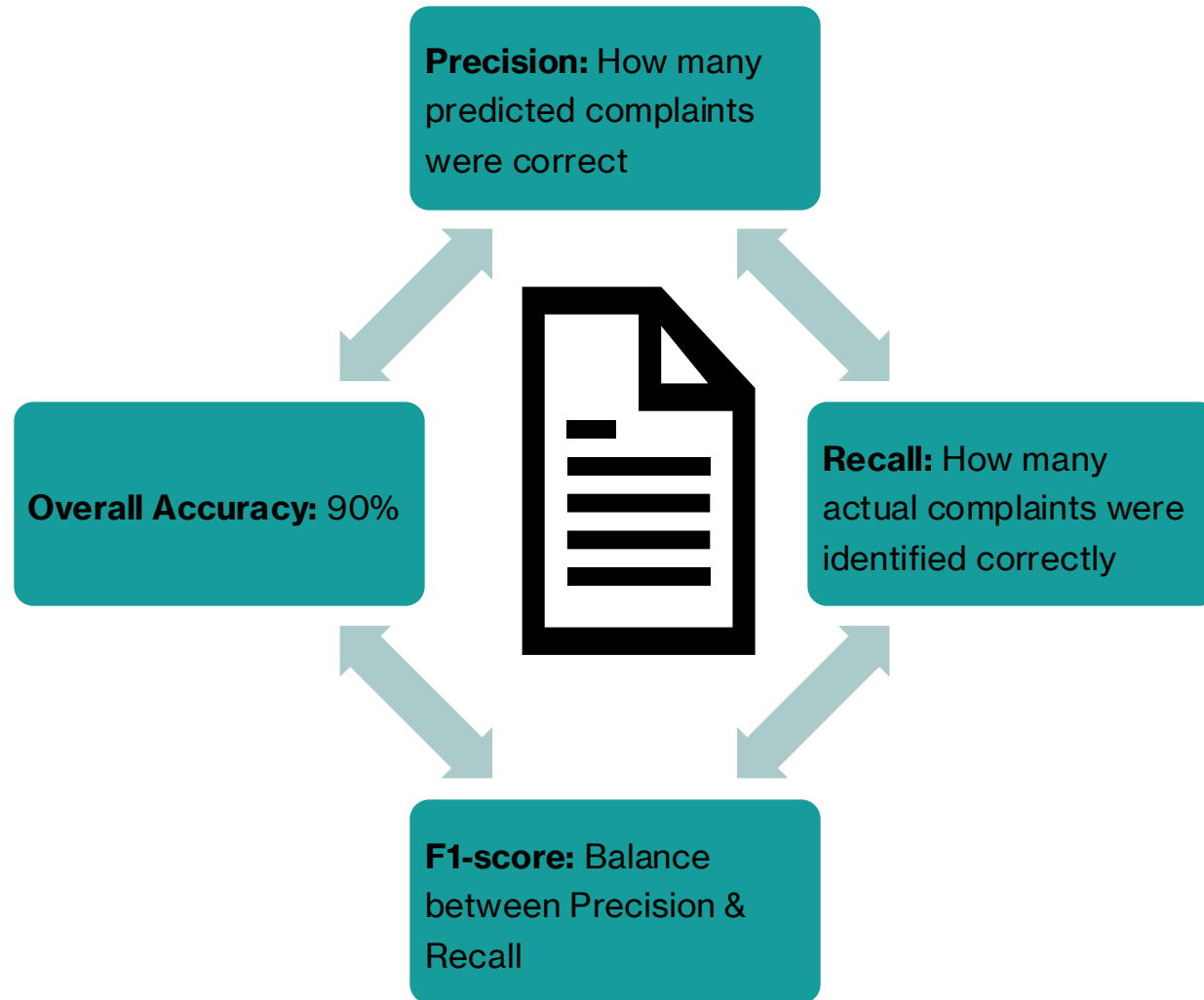


## Key Observations:

NMF-based model performed better due to clearer topic clusters

"Others" category had the lowest performance in both models

# Model Evaluation





# CONCLUSION

- **Best Approach:** NMF + LSTM for automated classification
- **Key Takeaways:**
  - NMF produced clearer topic separation, leading to better classification
  - LDA struggled with overlapping categories

# RECOMENDATION

**Use NMF for Topic Extraction**  
(Better coherence, clearer clusters)



**Improve "Others" Category Labeling** (Refine definitions for better classification)



**Deploy NMF-based BiLSTM Model** (Automate complaint classification)



**Implement Continuous Learning**  
(Retrain model periodically for accuracy improvement)

# Next Steps

## **Implementation**

**Plan:** Integrate the model into customer service workflows

## **Monitor**

### **Performance:**

Regular evaluation & retraining

**Q&A:** Open for discussion