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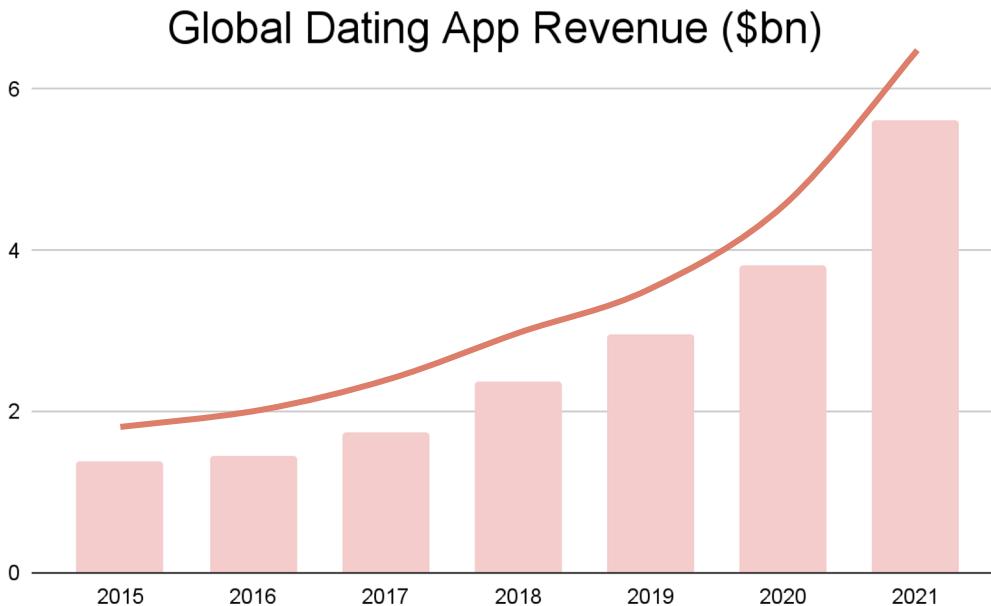


Business Recommendations



/01 Industry & Business Analysis

Dating App Industry: Business of Love

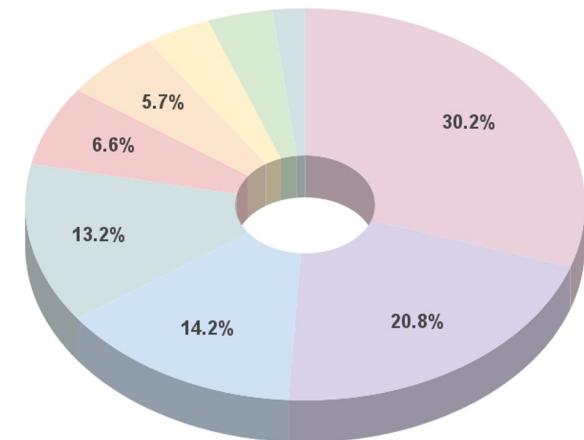


2021 global revenue : \$ 5.61 billion

5-year average growth rate : 33.8 %

US Dating App Market Share

- Tinder
- Bumble
- Hinge
- Plenty of Fish
- Gridr
- Badoo
- OK Cupid
- Match
- Zoosk



US Market leader : Tinder

Bumble and Hinge also catching up



Tinder: worldwide No.1 online dating app

Star Feature

Swipe to Match

Matching System

"Double Opt-In" System

Business Models

Tinder Plus*: 4.99\$/m

Tinder Gold*: 14.99\$/m

Tinder Platinum: 19.99\$/m

Sponsored Profiles*: 9\$

Boosts: 1.99~3.99\$/boost

*range depending on age or location

 tinder

Milestones

2015 – 5th highest-grossing mobile app

2020 – 75 million Monthly Active Users

2021 – 65 billion matches worldwide

Customer Acquisition

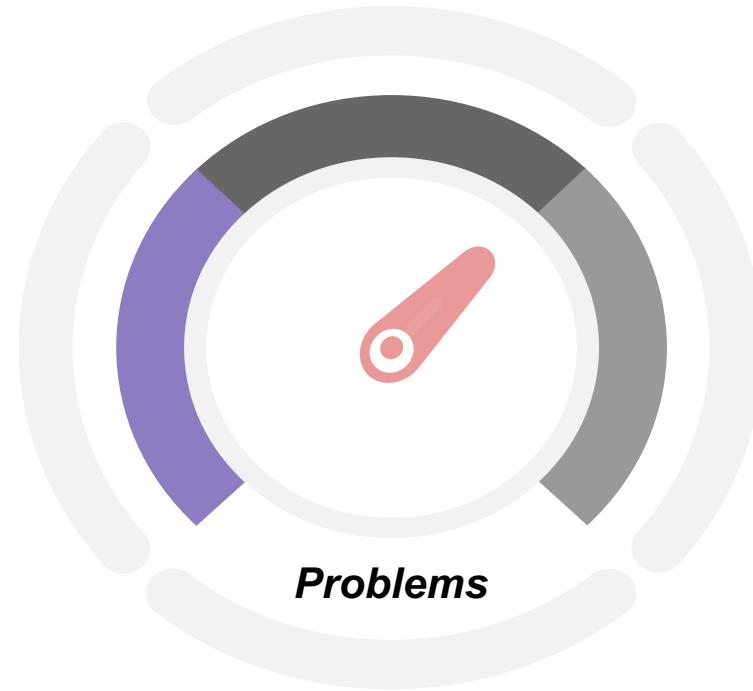
Start from

'Campus to Campus'

Expand by

'City to City '

Business Problems



Low Customer Growth Rate

Number of customers registered for the app is decreasing



Low Subscription Rate

Users are not willing to pay money to subscribe and enjoy member services



Low Retention Rate

Most people who go on Tinder don't stay on Tinder as consistent users



/02 Our Goals

Our Goals



What do we aim to achieve?

Is the review
positive or negative?

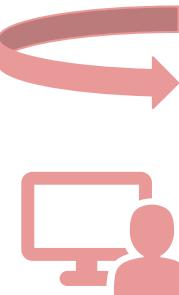
What are customers
complaining about?

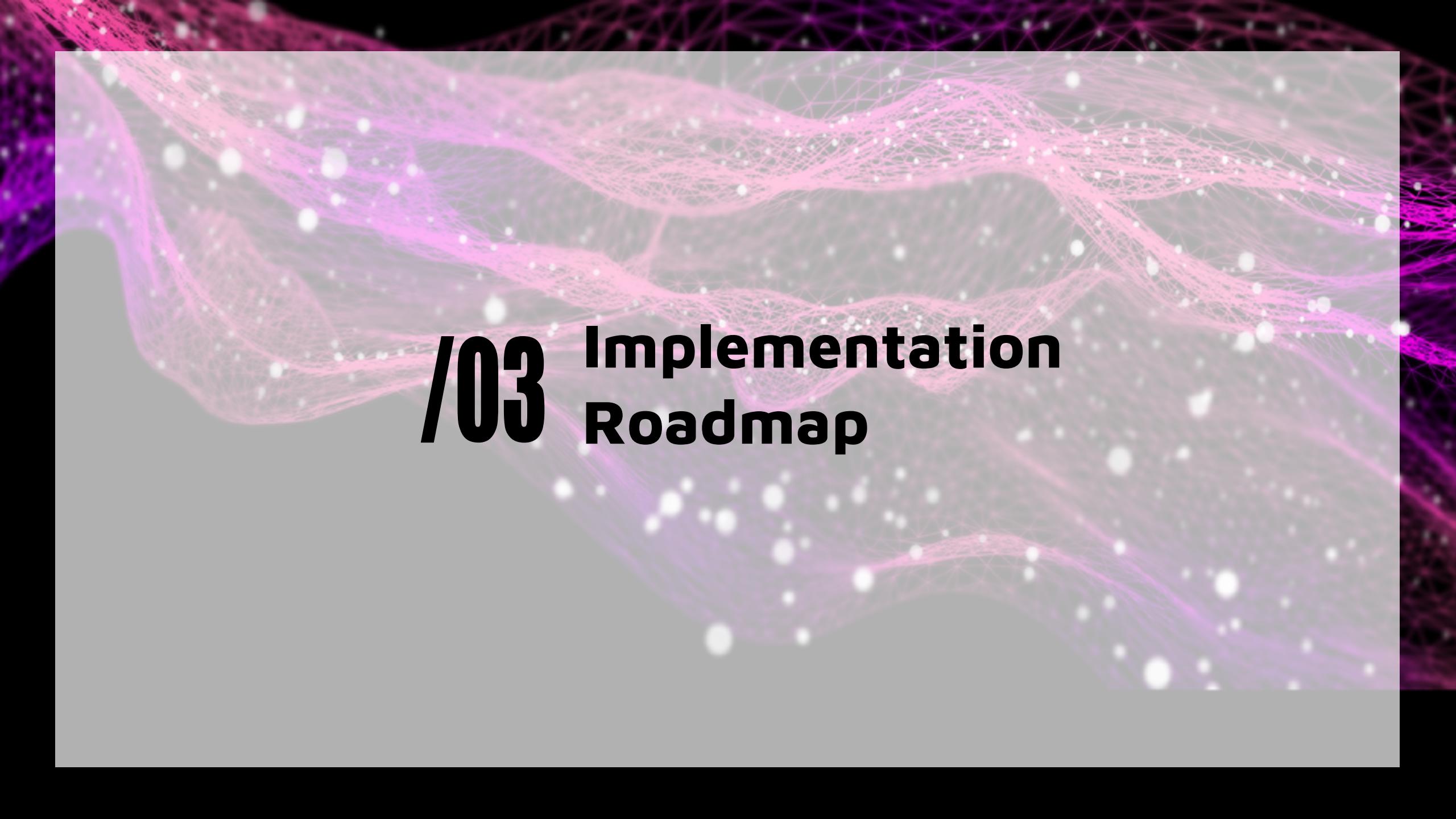
**Customer
Review**

Prediction and classification for
future reviews

Based on identified problems, what
improvement can tinder make?

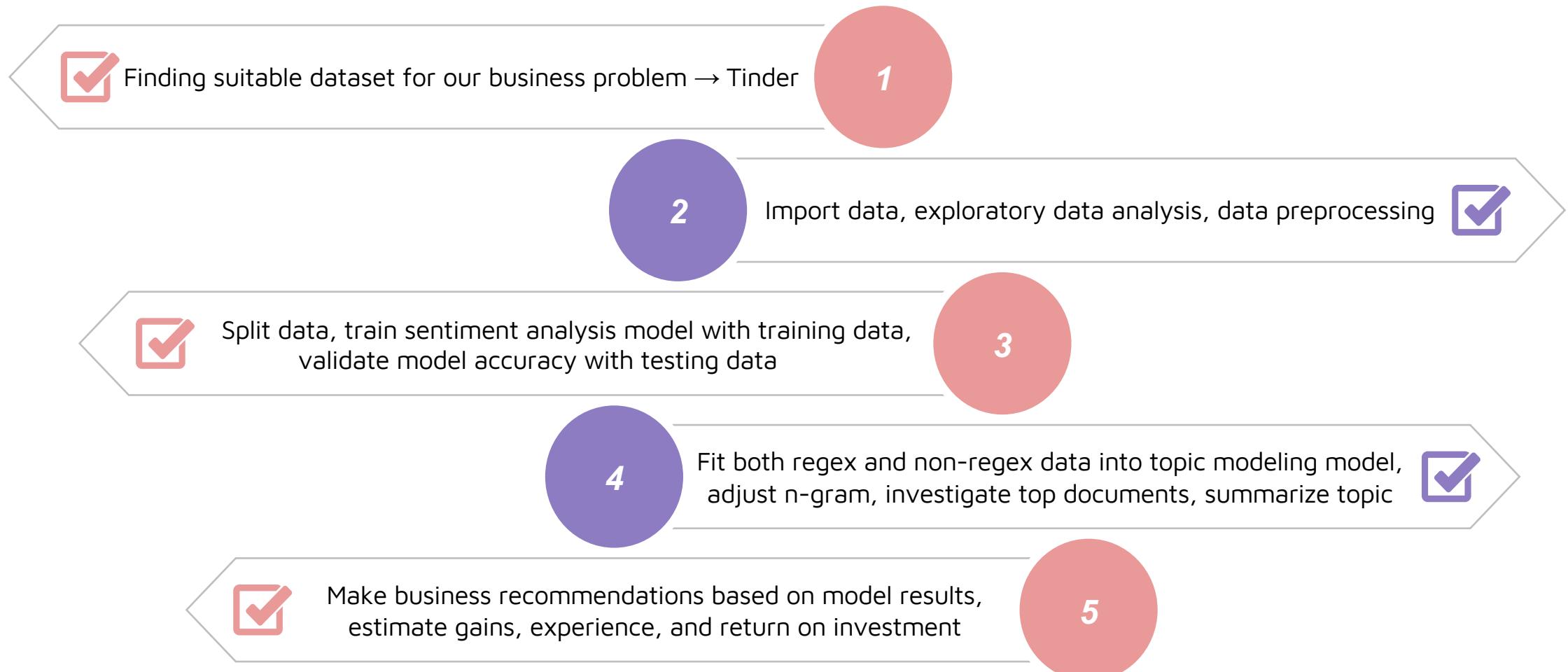
**Business
Improvement**





/03 Implementation Roadmap

Implementation Roadmap



Our Dataset

Columns:

- **userName**: Name of a user
- **userImage**: Profile image that a user has
- **content**: Comments made by a user
- **score**: Scores/Rating between 1 to 5
- **thumbsUpCount**: Number of Thumbs up received by a person
- **reviewCreatedVersion**: Version number on which the review is created
- **at**: Time when review was created
- **replyContent**: Reply to the comment by the Company
- **repliedAt**: Date and time of the above reply
- **reviewId**: Unique identifier

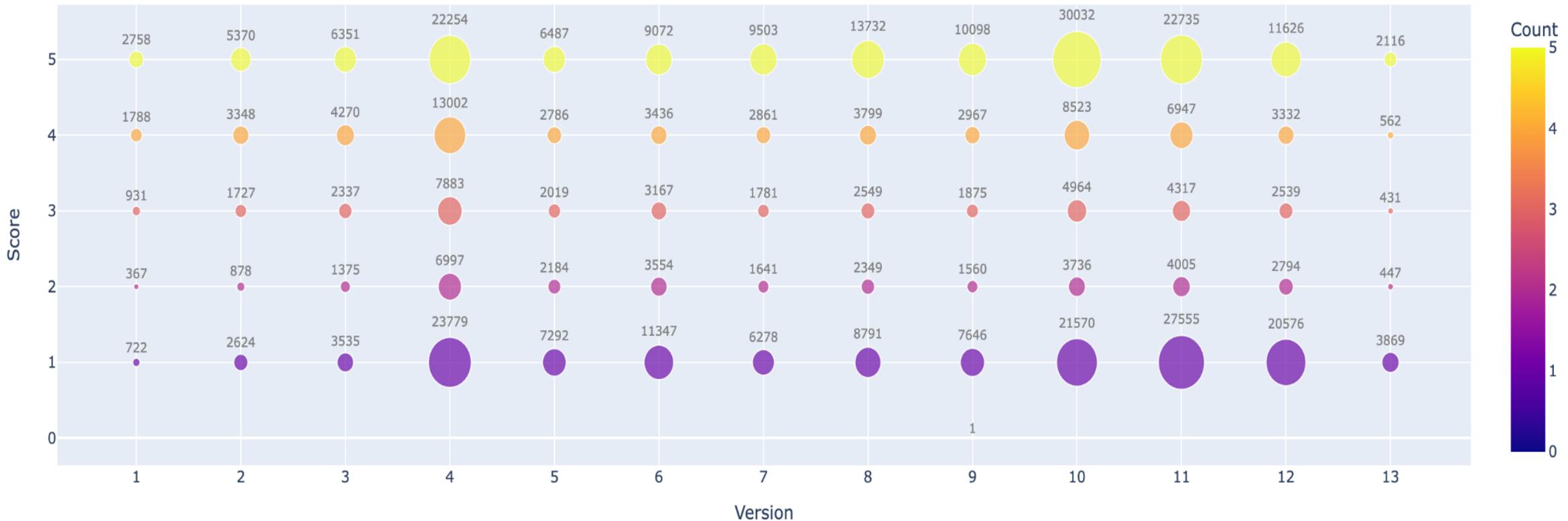
Our Dataset



reviewId	userName	userImage	content	score	thumbsUpCount	reviewCreatedVersion	at	replyContent	repliedAt
gp:AOqpTOG	Yatin Raval	https://play-	Excellent	5	0	13.6.1	5/7/22 04:58		
gp:AOqpTOF	T 1000	https://play-	Messages co	1	0		5/7/22 04:49		
gp:AOqpTOF	Richard Mist	https://play-	Should be on	1	0	13.6.1	5/7/22 04:45		
gp:AOqpTOH	Shubham Sa	https://play-	Most of the a	1	0	13.6.1	5/7/22 04:38		
gp:AOqpTOE	swaggy jatt	https://play-	Better than c	4	1		5/7/22 04:37		
gp:AOqpTOF	Mpumi nxum	https://play-	The last upda	2	0	13.6.1	5/7/22 04:33		
gp:AOqpTOH	Danny Japan	https://play-	I meet with s	5	0		5/7/22 04:28		
gp:AOqpTOG	Will_i_am E	https://play-	I keep gettin	1	0		5/7/22 04:15		
gp:AOqpTOF	Bone Daddy	https://play-	Mostly bots.	1	0	13.6.1	5/7/22 04:11		
gp:AOqpTOG	A F	https://play-	I can't stand	1	0	13.6.1	5/7/22 04:10		
gp:AOqpTOE	Trek Sisters	https://play-	Blocked and	1	0		5/7/22 04:05		
gp:AOqpTOF	Debashish Sa	https://play-	Only money	1	0		5/7/22 03:39		
gp:AOqpTOH	Sutria Utama	https://play-	bad apps. i've	1	0		5/7/22 03:36		
gp:AOqpTOG	Jason Simps	https://play-	T E R R I B L	1	0	8.1.0	5/7/22 03:31		
gp:AOqpTOF	Tanzeelur Ra	https://play-	Worst app	1	0	7.2.1	5/7/22 03:30		
gp:AOqpTOE	Sam Cayen	https://play-	Permanently	1	0		5/7/22 03:17		
gp:AOqpTOG	Boyko Chelik	https://play-	Money and n	1	0		5/7/22 03:17		
gp:AOqpTOH	Orion Rutley	https://play-	Where's my	1	0	13.6.1	5/7/22 02:58		
gp:AOqpTOF	†††û†††£†††`	https://play-	Terrible	1	0	13.6.1	5/7/22 02:52		
gp:AOqpTOF	John Henry	https://play-	Fun times ar	5	0	13.6.1	5/7/22 02:15		

Exploratory Data Analysis

App version vs Score review

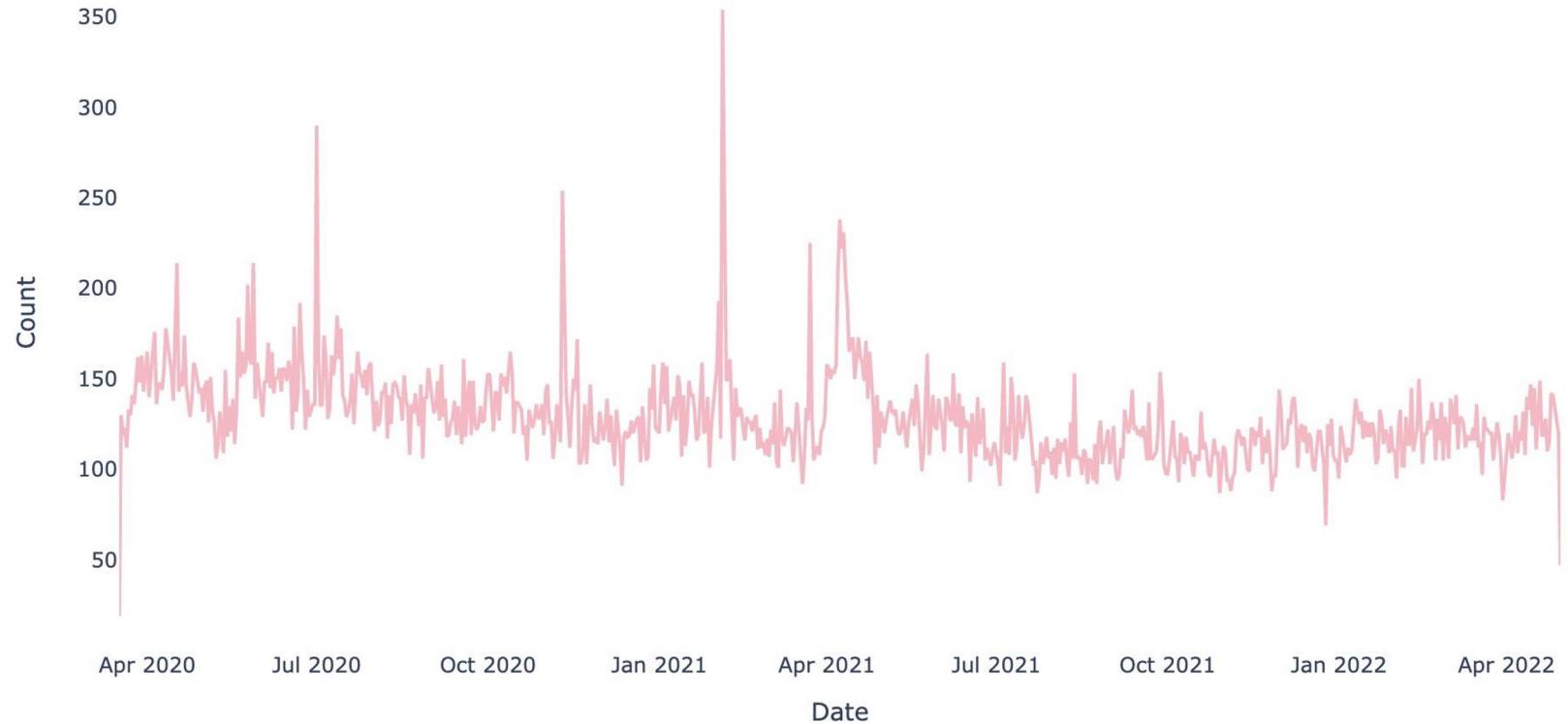


Exploratory Data Analysis

“

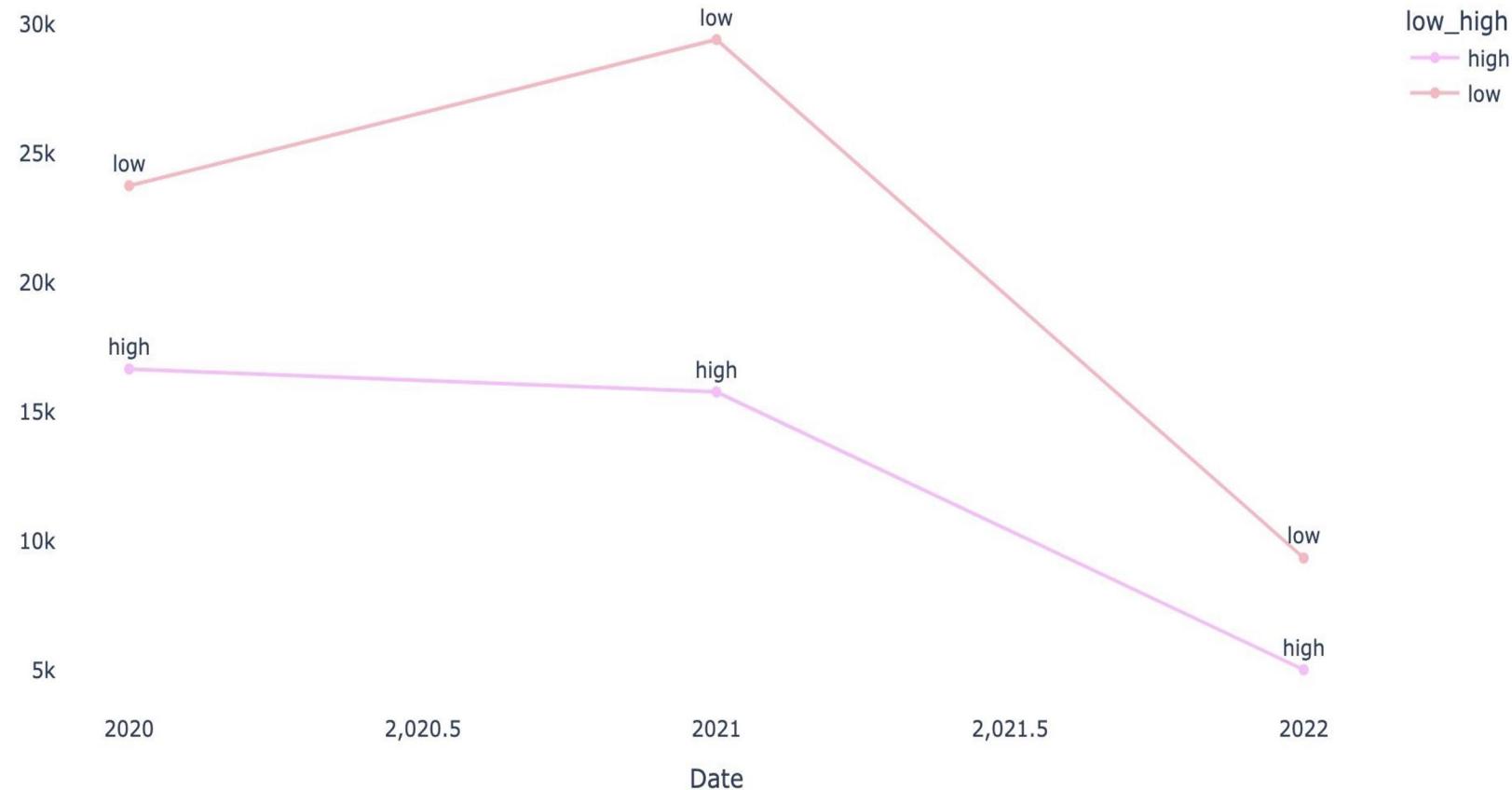
Number of daily
customer reviews
from April 2020 to
April 2022

”



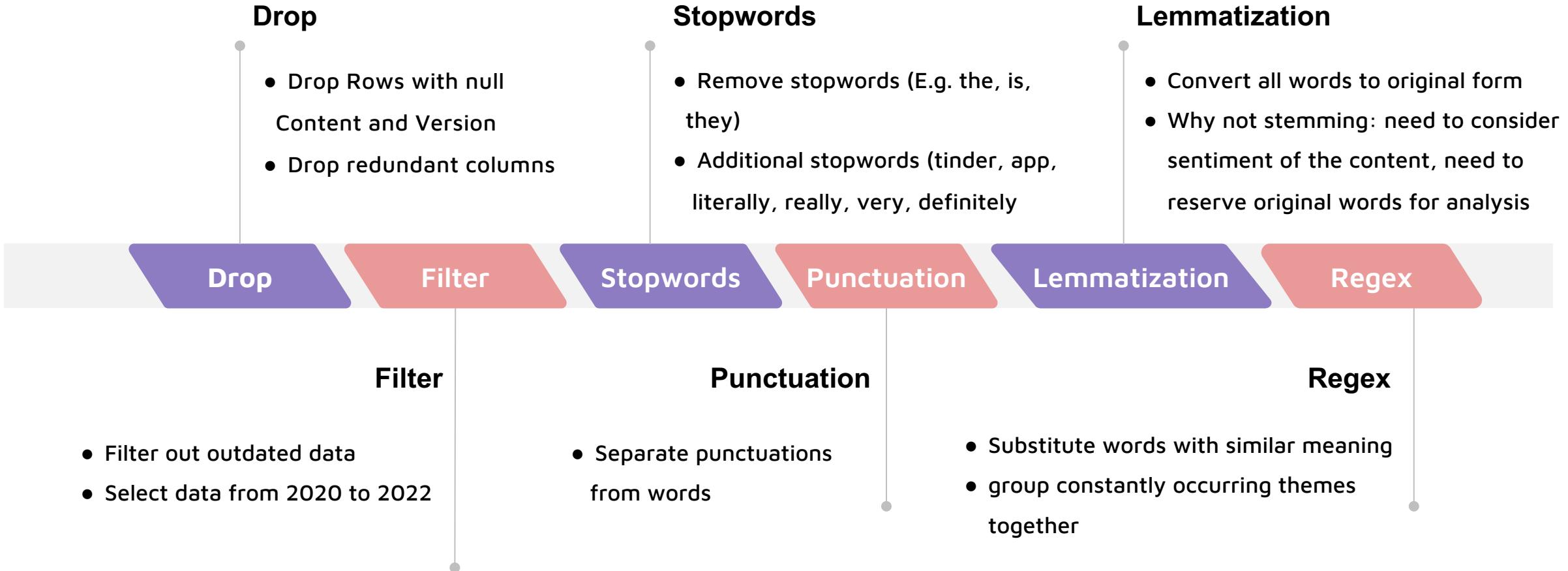
tinder

Exploratory Data Analysis



Number of semi-annual
low-score and high-
score customer reviews
from April 2020 to April
2022

Data Preprocessing





/04 Models



Models

Business Recommendation

Business Recommendation

Business improvement recommendation based on problems and topics discussed in reviews

Topic Modeling

Topic Modeling

Used Non-Negative Matrix Factorization Model to perform clustering based on topic in content

Sentiment Analysis

Sentiment Analysis

Used Long Short-Term Memory Model to categorize and classify reviews



Why Sentiment Analysis?

Classification

- LSTM algorithm can help customer support department to classify whether comments are positive and negative based on the accuracy of algorithm

Increase Efficiency

- Machine learning still under the guidance of domain experts
- Domain experts have more time to think about how to corporate with algorithm and improve it



Reduce Cost

- With the help of LSTM classification algorithm, customer support department can reduce the cost from labors who need to manually check the comments

Automation

- Streaming the classification of positive comments and negative comments by utilizing algorithm, reduce manual intervention

Sentiment Analysis - Long Short Term Memory

01

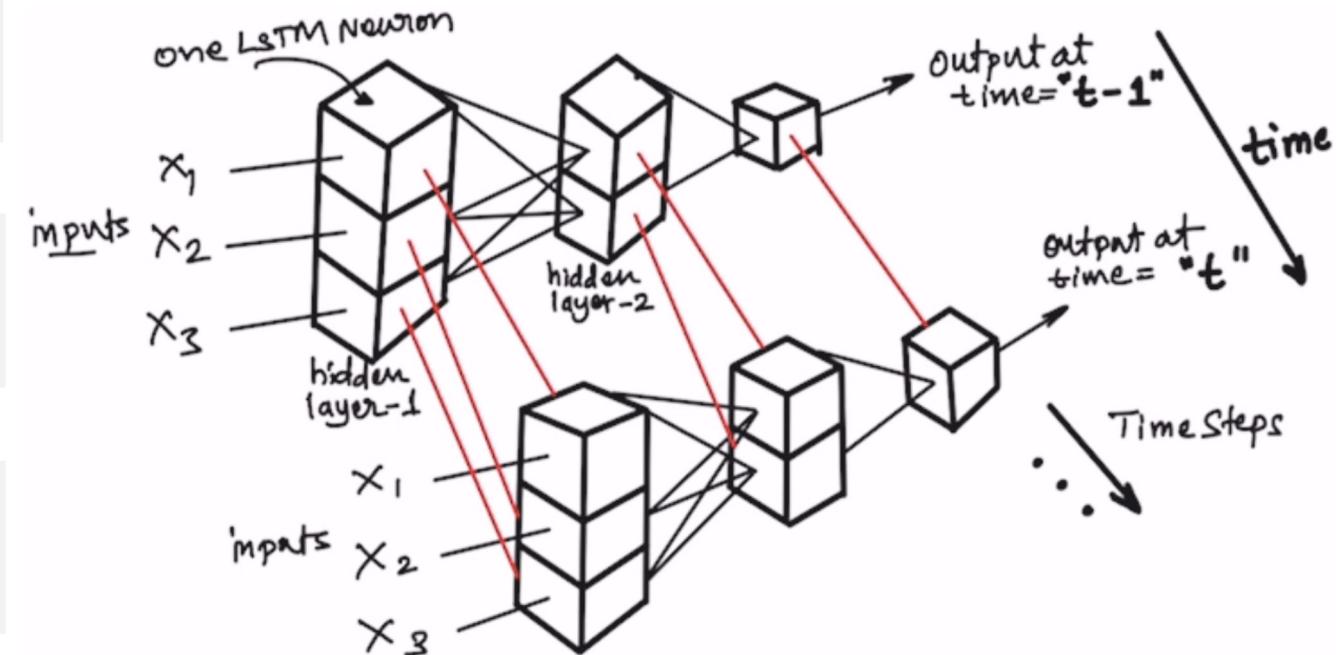
LSTM is artificial neural networks used in the fields of AI and deep learning

02

LSTM networks are well-suited to classifying, processing, and making predictions

03

LSTM is better solutions for gradient disappearance and gradient explosion in the process of long sequence training



Sentiment Analysis - Long Short Term Memory

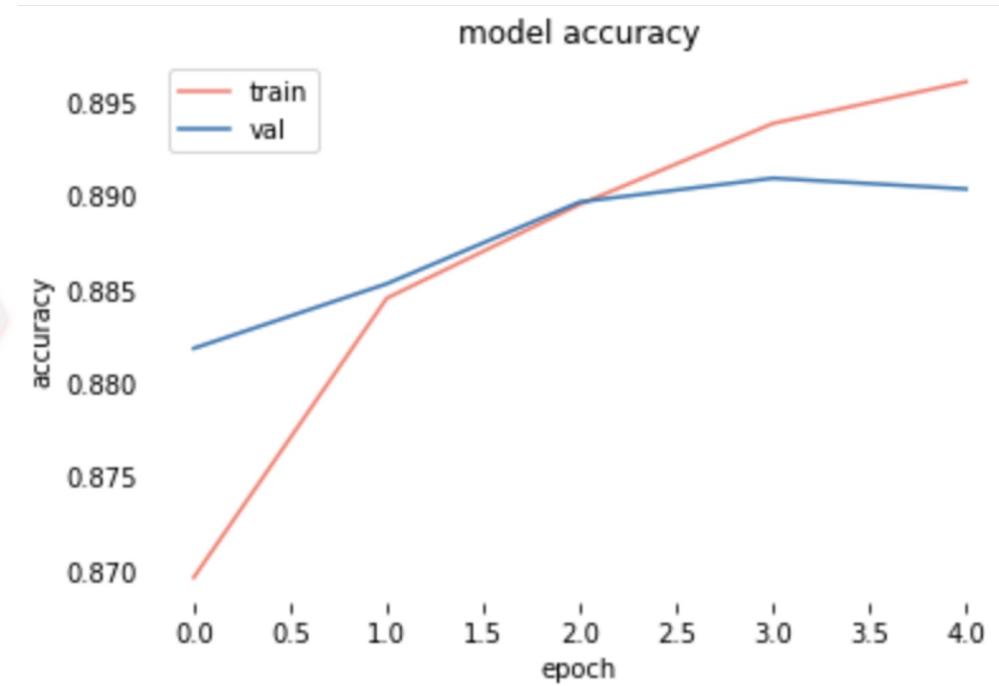
Testing dataset accuracy : 89.21%

```
loss, accuracy = model.evaluate(X_test, y_test, verbose=1)
```

```
loss: 0.2785 - accuracy: 0.8921
```

”

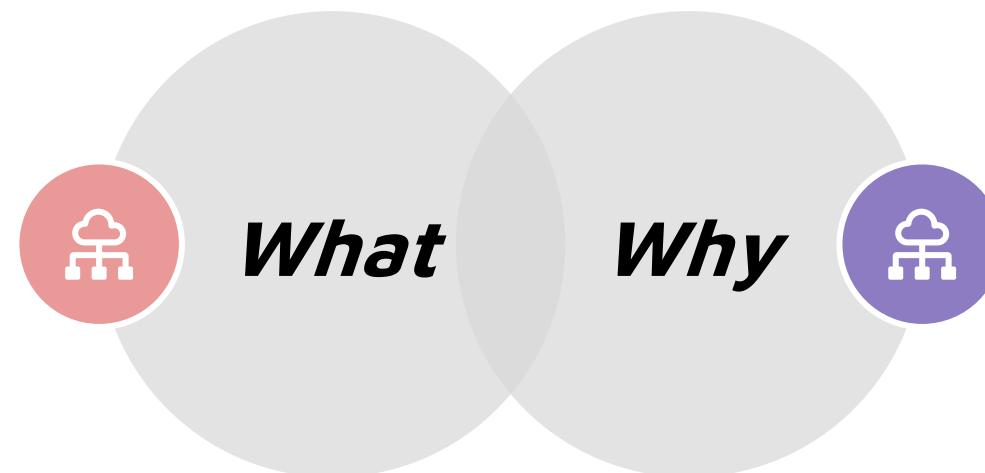
“



Why Topic Modeling?

Identify product issues by reviewing comments on Google Play Store

What are the product
features that our customers
are complaining about?



Why are our customers
complaining these product
features?

Topic Modeling - Non-Negative Matrix Factorization

01

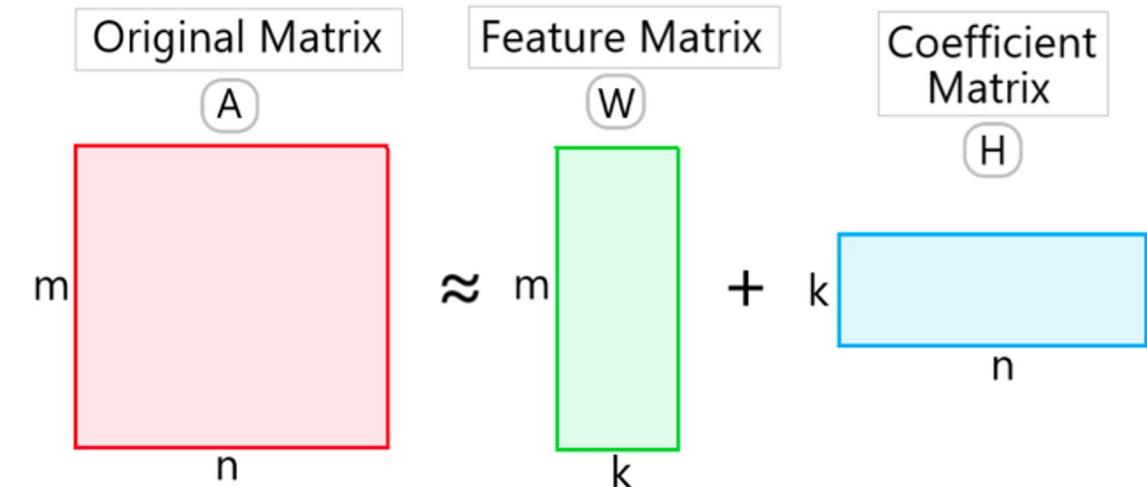
NMF is a group of algorithms in multivariate analysis and linear algebra where a matrix V is factorized into (usually) two matrices W and H , with the property that all three matrices have no negative elements.

02

NMF extracts topics and discovers the underlying relationships between texts.

03

We utilize NMF to help identify major product issues from Google Play Store reviews.



Topic Modeling - Topic Summary

Topic 0

not _waste_ time (58.8%)
ban without reason (1.2%)
fake not _waste_ (1.1%)
please not _waste_ (1.1%)
waste time not (0.8%)

Topic 1

account _ban_ reason (52.8%)
ban reason not (6.4%)
ban reason give (1.8%)
say account _ban_ (1.4%)
got _ban_ reason (1.2%)

Topic 2

number mile away (37.5%)
show _number_ mile (4.3%)
number _number_ mile (3.6%)
matching _number_ mile (3.5%)
set _number_ mile (2.8%)

Topic 3

waste time money (63.0%)
dont _waste_ time (3.6%)
complete _waste_ time (1.8%)
time money not (1.6%)
total _waste_ time (1.5%)

The background features a complex, abstract design composed of numerous thin, translucent pink lines forming a grid-like, wavy pattern. Interspersed among these lines are numerous small, semi-transparent white circular dots of varying sizes, creating a sense of depth and motion.

/05 Business Recommendations

Major Complaints



Banned Account for No Reason

- "It banned me for doing nothing"

.....



Distance

- "Matching with people who were 1-2 miles away and when i match with the person they will be 2,000-9,000 miles away"

.....

Waste of Money

- "I paid for the gold service and literally for 50 dollars you get nothing."

.....

Fake Accounts

- "You guys definitely need to start verifying your users you have so many fake profiles it's ridiculous!!!"

.....

Business Recommendations

Banned Account for No Reason

- Improve fraud detection algorithm
- Add appeal service for users



Distance

- Increase frequency of updating user location
- Add a filter to only match people within certain distance

Waste of Money

- Provide advice from experts for users with subscription to increase matching chance
- Filter by personal tags for members only

Fake Accounts

- Give users the option to perform facial recognition and increase exposure rate for these users
- Adopt report service for fake matching
- Based on report system to improve fraud detection algorithm

Return on Investment

Earnings and Revenues

For each business model (m\$):

Revenue = MAU * (Retention Rate + Expansion Rate + Upgrade Rate)

$$\begin{aligned} \text{Rev(Total)} &= \text{Rev(Platinum)} + \text{Rev(Gold)} + \text{Rev(plus)} \\ &= 0.57 + 0.50 + 0.43 = \underline{\underline{1.50}} \end{aligned}$$

\$ 1.50 Million

Expenditures

For all business models (m\$):

Capital expenditure = 0.7

Direct Labor expenditure (domain expert team) = $0.04 * 12 = 0.48$

$$\text{Expenditure (Total)} = 0.7 + 0.48 = \underline{\underline{1.18}}$$

\$ 1.18 Million

Return on Investment

Total Earnings (1.5) - Total Expenditures (1.18)

Total Expenditures (1.18)

= Return on investment (0.27)

ROI =
27%

Conclusions

“Swipe Right”

Through google play reviews for Tinder, we aim to identify the root causes behind Tinder's business problems.



Advanced NLP techniques allow us to investigate deeply into review contents, classify reviews, and then automatically summarize topics covered in reviews;



By adopting Sentiment Analysis, Tinder can use the classification model as an automatic tool for splitting reviews and therefore reduce the labor costs and achieve automation in its initial screening process;



With Topic Modeling, Tinder will be able to extract major complaints and root problems behind its low customer growth, retention, and subscription rates. Tinder can therefore timely adjust their business model and app functions to address the problems and increase profit margin.