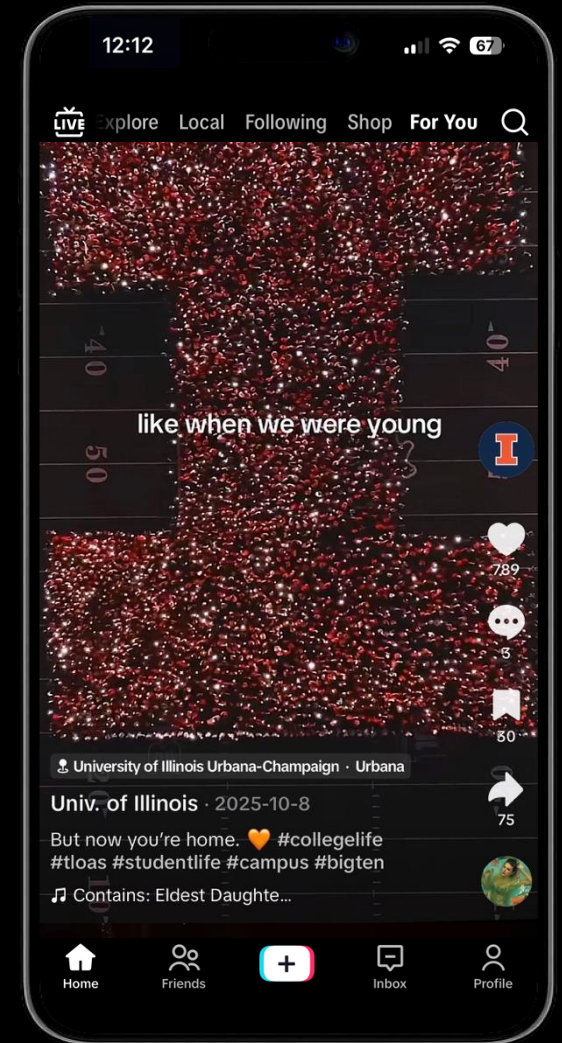


# QUANTIFYING TIKTOK USING VISION LANGUAGE MODELS

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**University of Illinois Urbana-Champaign**

[www.dprg.cs.uiuc.edu](http://www.dprg.cs.uiuc.edu)



# Can't Stop Watching TikTok?

**900M+**

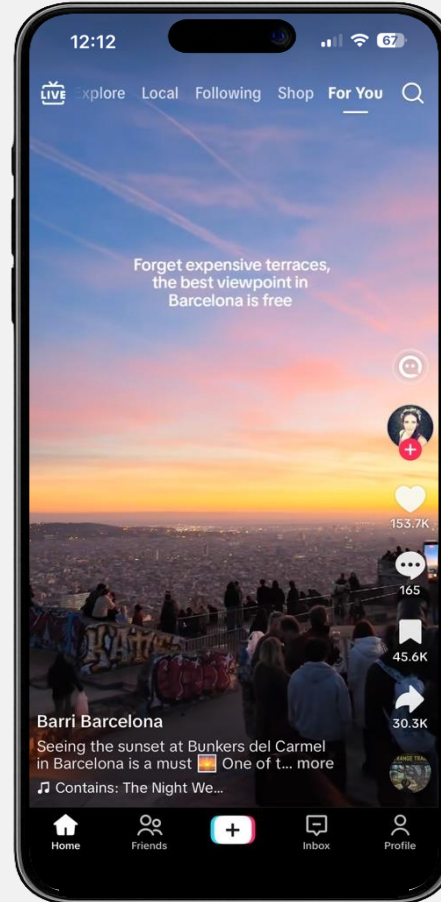
*Daily Active Users*

**19 Times**

*App Opened Daily*

**1 hr 37 min**

*Daily Watch Time*



**For You Page**

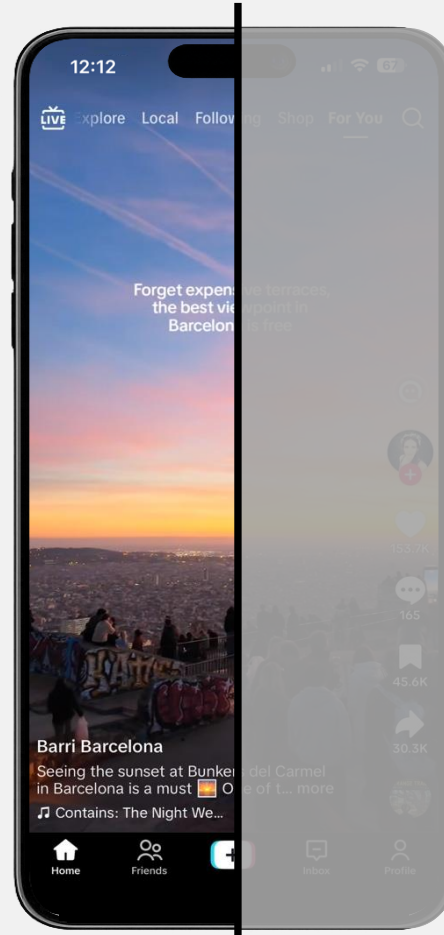
*driven by TikTok's Proprietary  
Recommendation System*

**Every day,  
TikTok's  
recommendation  
system helps  
determine what  
millions of people  
watch**

# Visible Feed, Invisible Logic

## Visible

- Videos
- Interactions



## Invisible

- Why this video?
- What mattered?
- What changed?

For You Page (FYP)

*driven by TikTok's Proprietary  
Recommendation Algorithm*

# Studying the Invisible Logic

## RQ1

*How Diverse Is My Feed?*

## RQ2

*Can A Like Reshape My Feed?*

## RQ3

*Am I Interested In The Past?*

## RQ4

*Does The Set of Videos Matter?*

## RQ5

*How Much Will I Like a Video?*

---

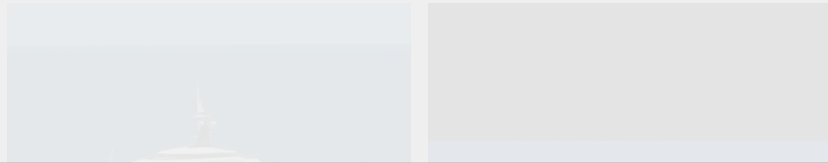
**Content**

**Action  
Response**

**Temporal  
Evolution**

# Existing Methods for Understanding TikTok

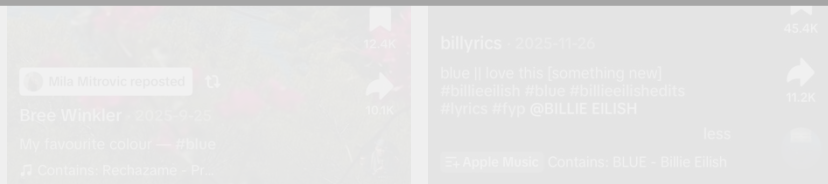
#blue



*"If there are things on the News Feed that I comment on or like, sometimes things [from that person] will start showing up more"* [1]



**We lack a scalable, content-aware measurement technique to measure the feed**



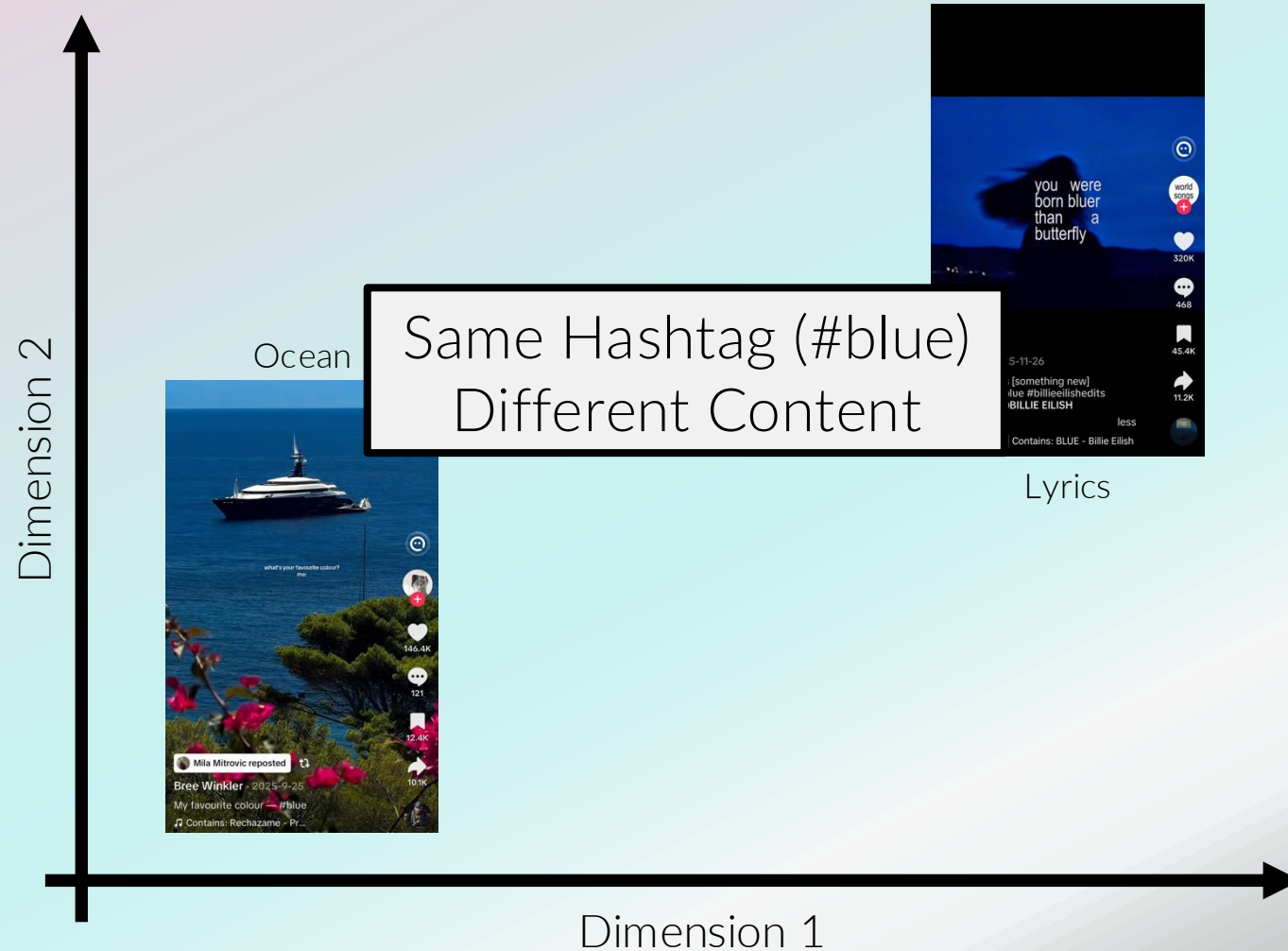
*"I might like one video, and then the next thing I know my explore page, I have a bunch of like posts of that type of stuff"* [2]

Hashtags are weak proxy for content

Interviews captures beliefs, not feed behaviour

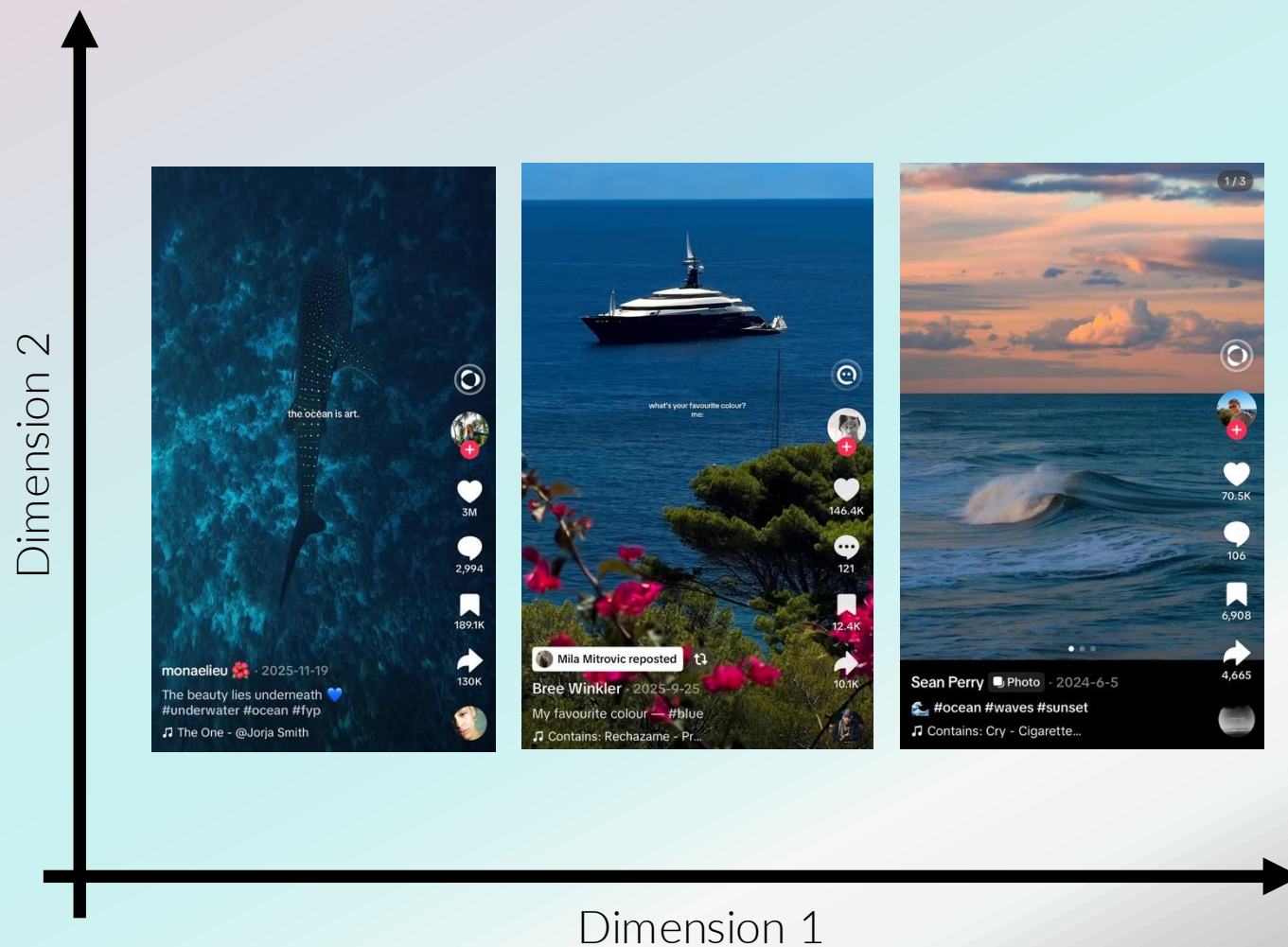
# New Measurement Tool: Video Content Analysis

Content Embedding Space



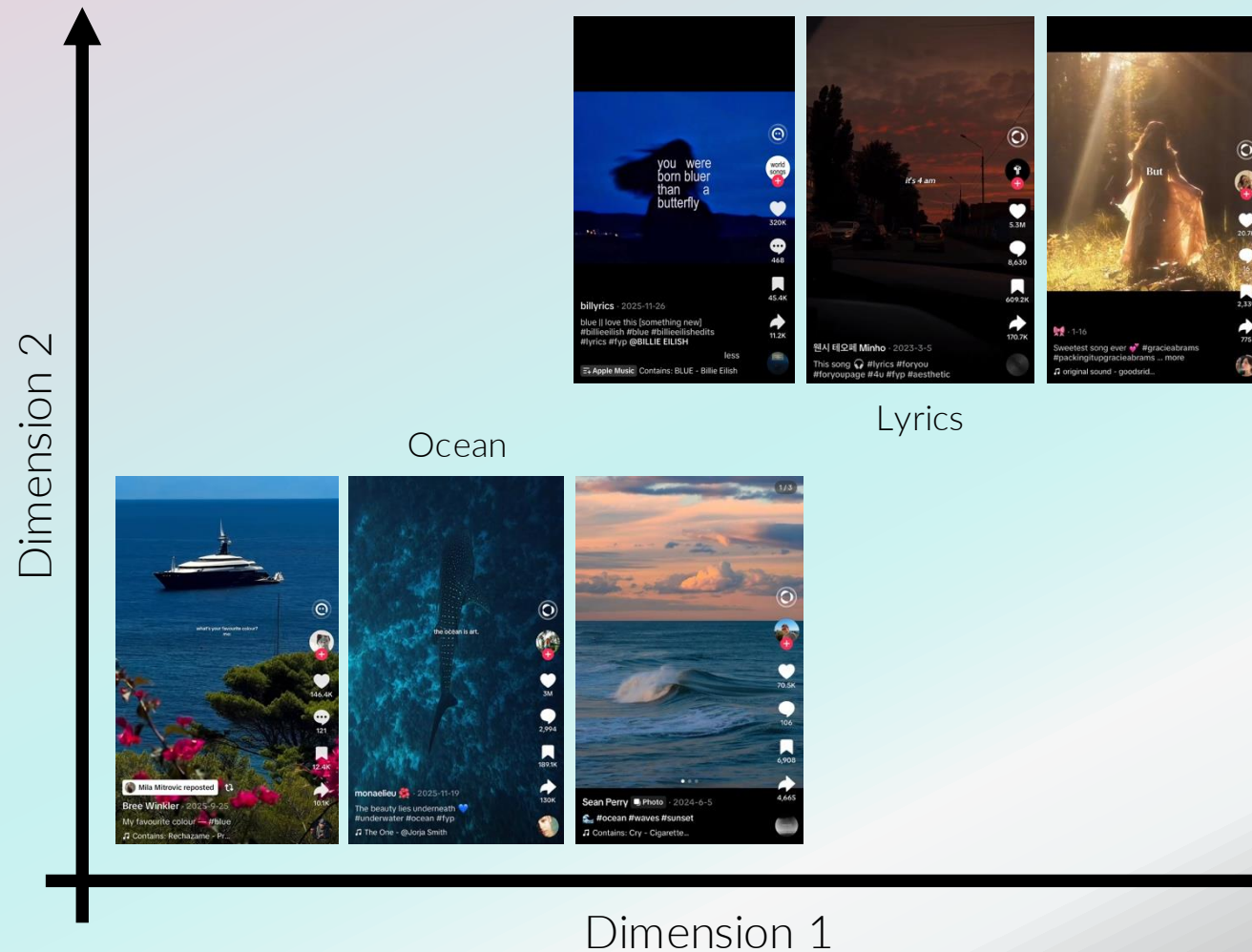
# New Measurement Tool: Video Content Analysis

Content Embedding Space



# New Measurement Tool: Video Content Analysis

## Content Embedding Space



# How We Measure TikTok's For You Page

## Video Content Analysis Tool

Content-aware Analysis Of Recommended  
Videos



### User Study

Link User Experiences To  
Observed Feeds



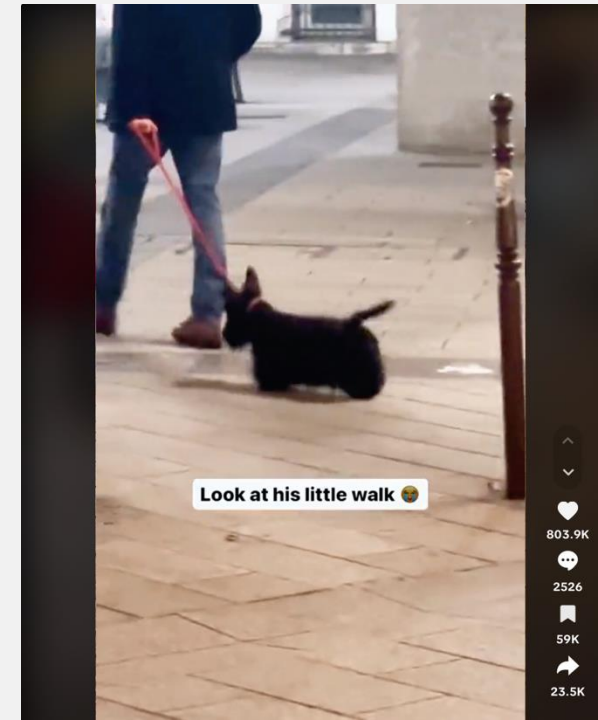
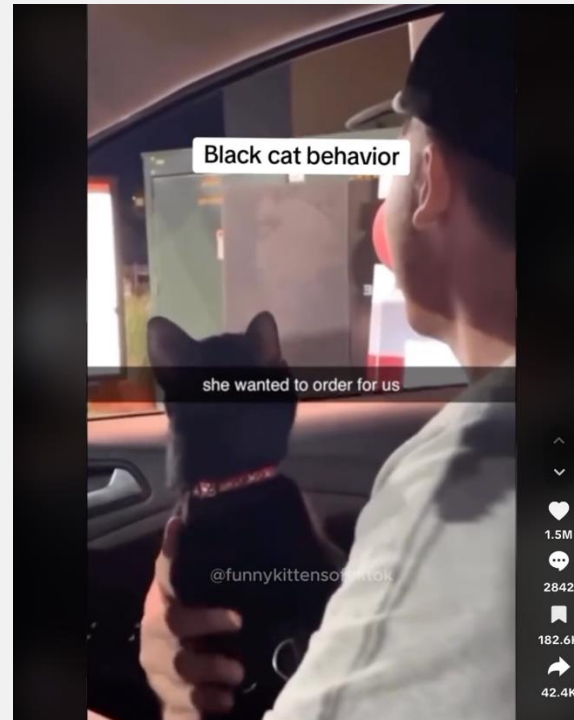
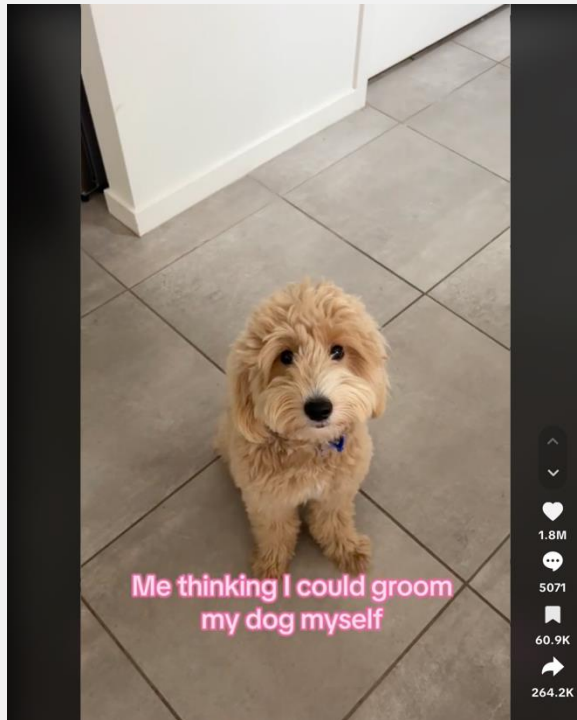
### Data Donation

Longitudinal Traces From  
100 Users (2.5M Videos)

# RQ1: How Diverse Is My Feed?

2.5M Videos  $\xrightarrow{\text{using KMeans}}$  100 Clusters

Cluster 48



# RQ1: How Diverse Is My Feed?

Feed stays broad

~52.5  
clusters/day



Time

Narrow attention

50% Time → Top 5 Clusters



Time

Rapid Churn

4 out of Top  
5

Change Daily



Time

# RQ1: How Diverse Is My Feed?

Feed stays broad

~52.5  
clusters/day

Narrow attention

50% Time → Top 5  
Clusters

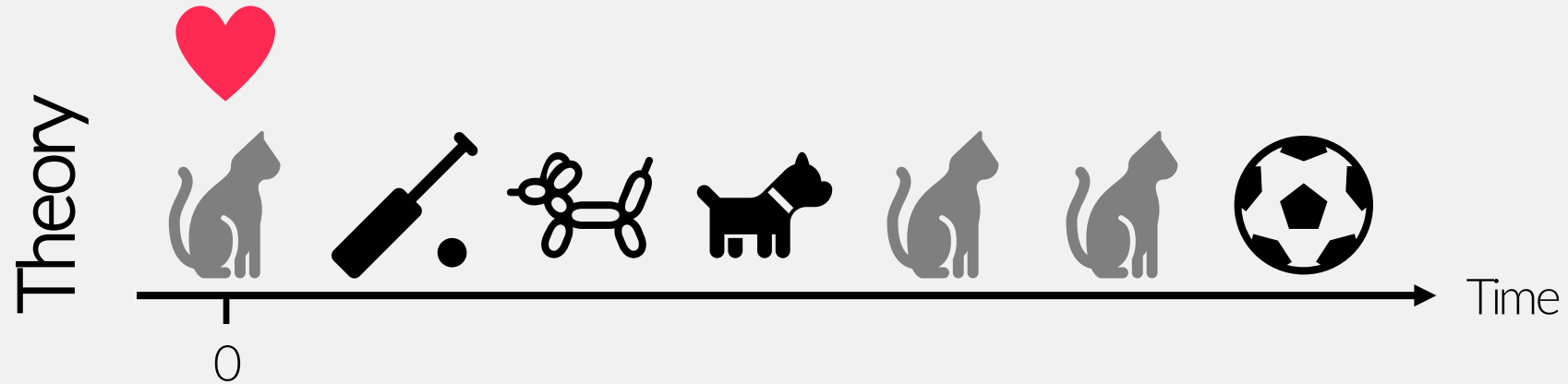
Rapid Churn

4 out of Top  
5  
Change Daily

TikTok recommends *broadly*,  
but your interests are *narrow* and *dynamic*

Implication: TikTok does not keep users in a traditional *filter bubble*

# RQ2: Can A Like Reshape My Feed?



*Post Interaction Anticipation  
(PIA) Theory [1,2,3]*

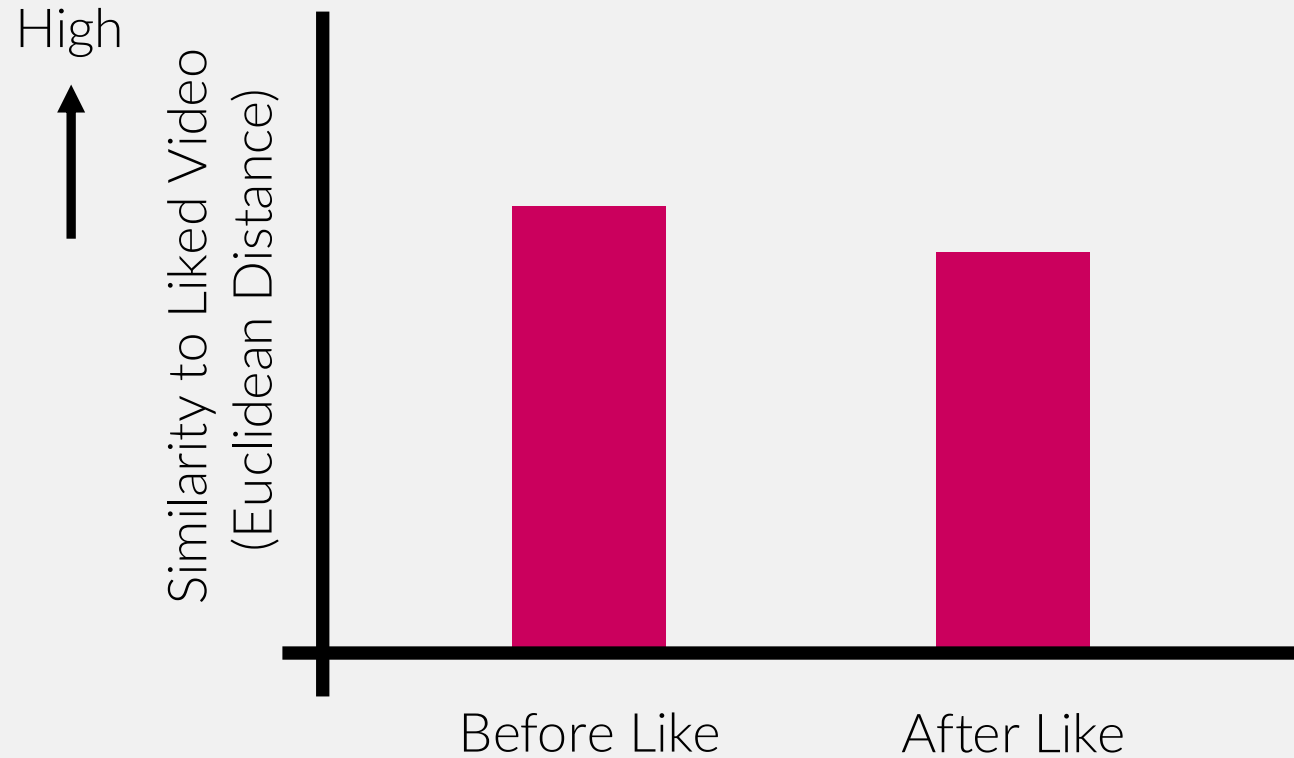
Sources:

[1] First I "like" it, then I hide it: Folk Theories of Social Feeds - CHI '16

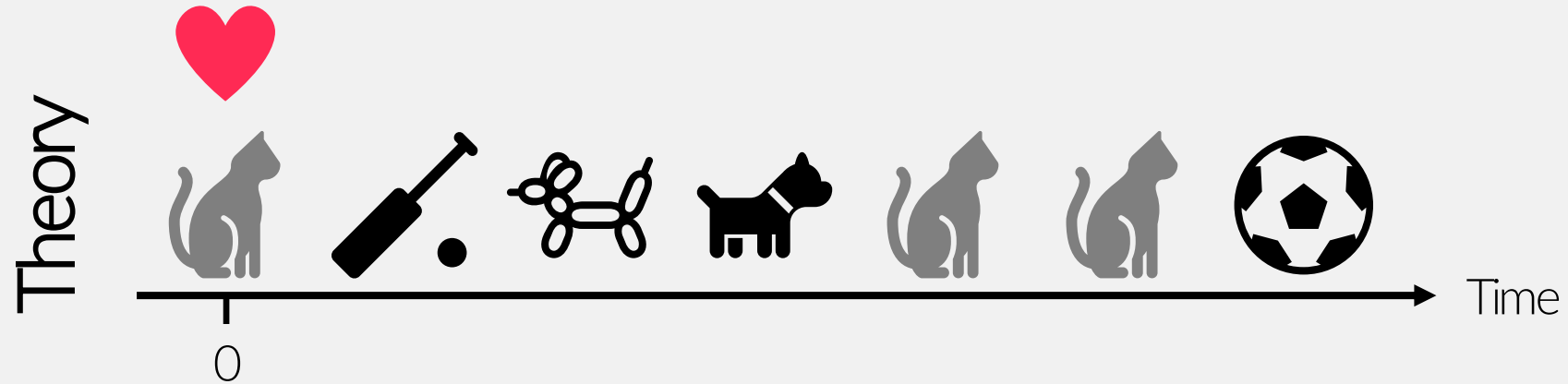
[2] How People Form Folk Theories of Social Media Feeds and What it Means for How We Study Self-Presentation - CHI '18

[3] For Me or Not for Me? The Ease With Which Teens Navigate Accurate and Inaccurate Personalized Social Media Content - CHI '24

# RQ2: Can A Like Reshape My Feed?



# RQ2: Can A Like Reshape My Feed?



*Post Interaction Anticipation  
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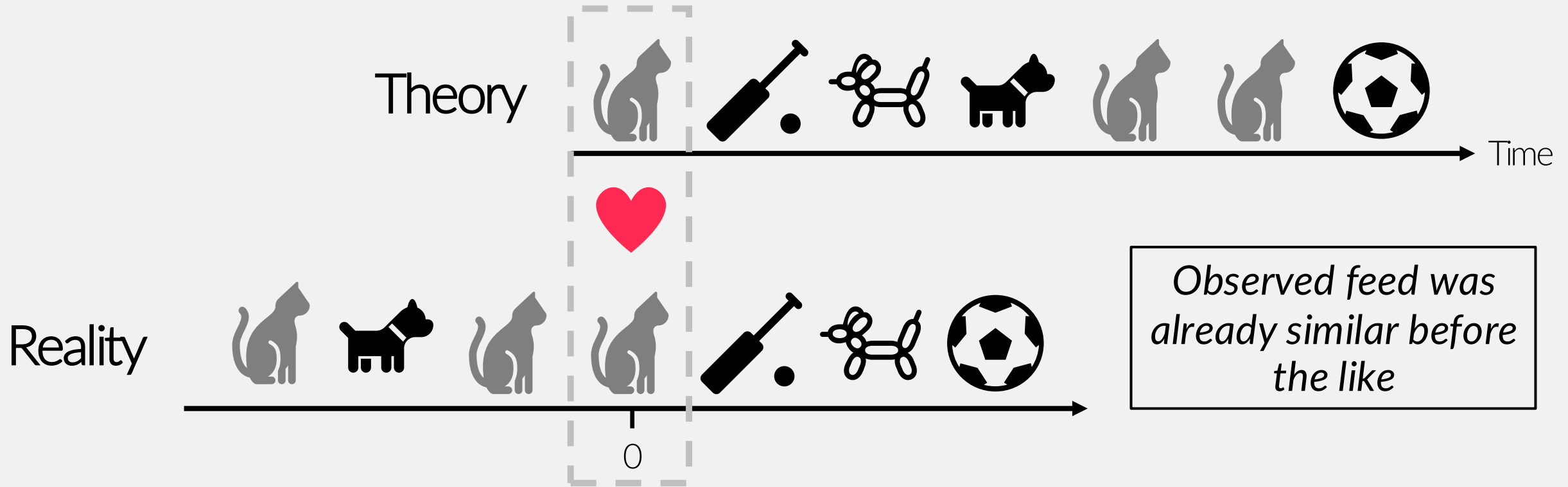
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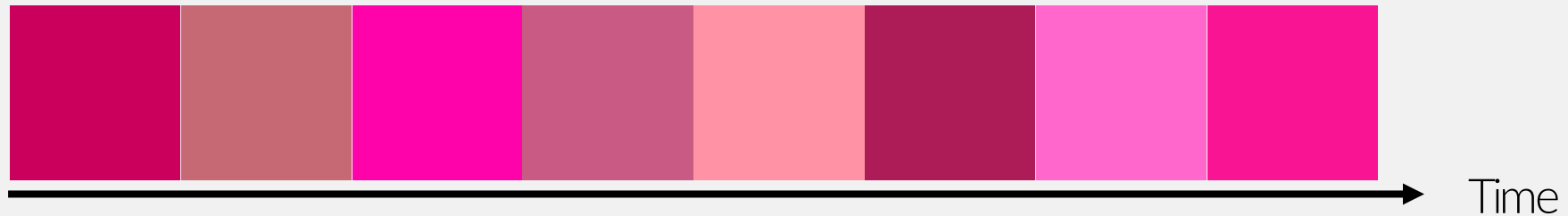
# RQ2: Can A Like Reshape My Feed?



Likes *are* influenced by the past, but do *not* influence the future

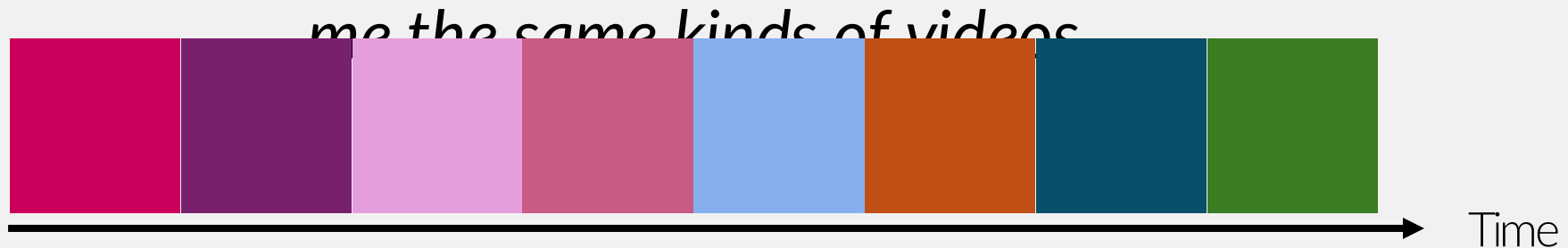
# RQ3: Am I Interested In The Past?

Theory



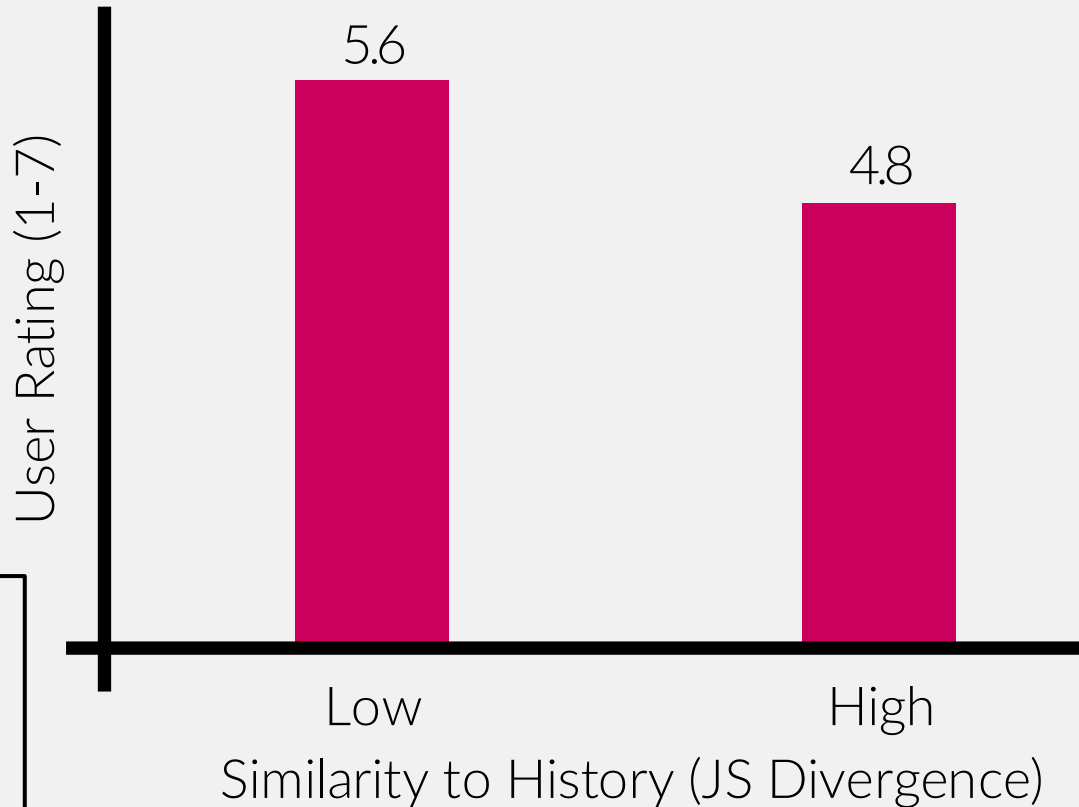
*Theory: If the feed knows what I like from my past, it should keep showing*

Reality



*Reality: The feed explores interests instead of repeating them*

# RQ3: Am I Interested In The Past?

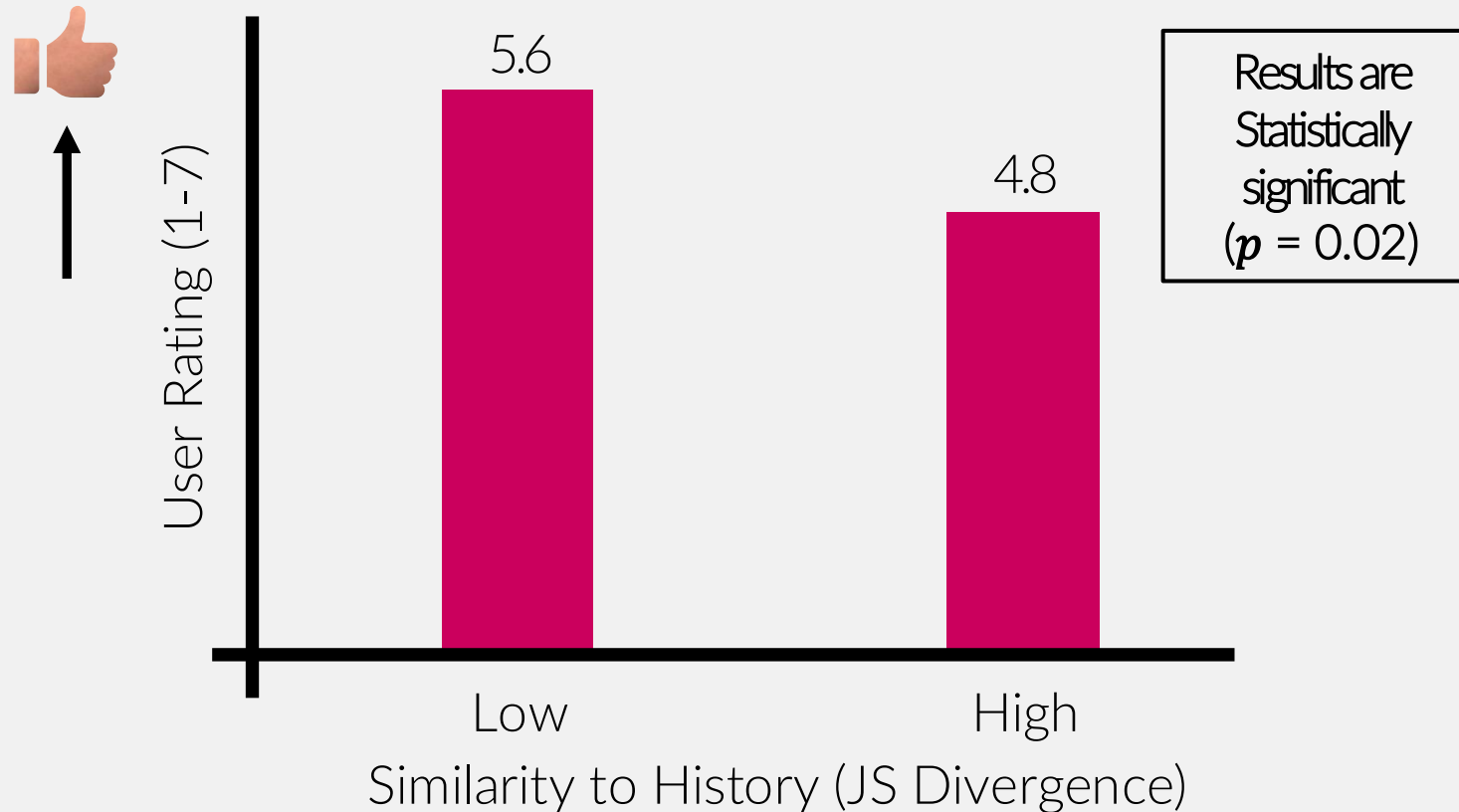


Results are  
Statistically  
significant  
( $p = 0.02$ )

## User Study

- N = 60
- Participants watch their own For You Pages
- Content Rating provided using 1-7 Likert Scale (1 = Very Dissatisfied and 7 = Very Satisfied)

# RQ3: Am I Interested In The Past?



Feeds are *relevant* and *not repetitive*

Implication: Diversity in recommendations *improves* user experience

# Beyond Today's Talk

*See the paper for more complete discussions*

- **Additional Results**

RQ4: Sequence continuity

RQ5: Predicting watch behavior

- **Limitations**
- **Discussion**
- **Implications**

*Explore more ways to use our VCA Tool*

- An evolutionary study of recommender systems
- Auditing recommendation systems beyond metadata
  - Comparing platforms
    - Content-aware accountability tools

# From User Questions to Measured Feed Behaviour

1. We introduce a content-aware framework to quantify what actually appears on the FYP
2. Common assumptions about the FYP are only partially right the feed is not as immediately responsive or as repetitive as users may believe

*Video Content Analysis Lets Us Move Beyond Hashtags And Begin Quantitatively Verifying How The For You Page Behaves and, opens the door to many deeper insights*



Paper



Website