

What is the Integrity Institute?

The Integrity Institute is a growing community of 500+ tech workers who believe in building integrity-first online platforms that help individuals, communities, and democracies thrive.

With years of experience mitigating harms to people and communities within 55+ online platform companies, we bring seasoned, insider knowledge to leaders theorizing, building, and governing online platforms and help them put integrity front and center.

- We build and empower a community of integrity professionals in tech, giving them the tools and research they need to make online platforms safer and healthier for people and societies
- We advise online platforms, policymakers, and academics to put integrity at the heart of company governance, compliance, and tech regulation.
- We educate the public about what an integrity-first future looks like for the social internet.

Outline

Paper in collaboration with EDMO

Matt Motyl, Spencer Gurley, Jeff Allen, Sofia Bonilla https://edmo.eu/publications/platform-datasets-challe nges-insights-and-examples-for-researchers-under-art icle-40-of-the-digital-services-act/



- What data do platforms collect?
 - And what don't they collect?
- How is data organized internally?
- Case Study: Mastodon
 - Comparisons Between Platforms
- Mapping data to systemic risks



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 - User provided
 - Extracted from user
 - Created by user
 - Behaviors
 - Received from other users
 - Inferred
 - Purchased

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 - **Purchased:** Data purchased from third parties. Income, consumer behavior, credit score...

Why do they collect all this data?

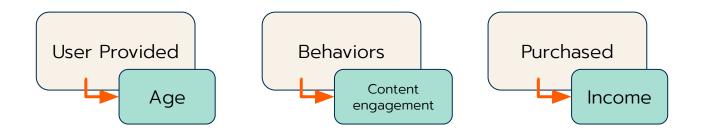
- It is in their business interests to!
- Broadly speaking, three big reasons
 - Inherently required for the platform experience
 - Advertising revenue!
 - More data -> more and better targeting options for advertisers
 - Leads to higher revenue per impression on ads
 - Tailoring the user experience
 - More data -> more customization and personalization for platform experience
 - Can lead to better overall experiences for users
 - Also leads to more time spent on platform, and thus more impressions on ads

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Why do they collect all this data?

• Example: Advertisers want to target wealthy new parents

- Age of user relevant
 - Mid 20's to early 30's age bucket most likely to be relevant
- Content the user engages with is relevant
 - Can identify interest in "baby" related or "parenting" related content
- External data sources
 - Can combine with external data around income or net worth, tied to email



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What don't they collect?

Perfect knowledge is hard to come by

- Not all platforms gather all details from users
 - Many platforms don't ask users age
 - And almost none verify ages outside of new regulation
 - "Age" might be a predicted thing
 - Predicted age
 - Probability of being in age range
 - \circ So asking for "Examples of content engaged with by users between 13 and 30"
 - If platform doesn't collect age, how do you map that to predicted ages?
- Some data platforms might explicitly avoid
 - Changing platform experience by political party affiliation might cause backlash
 - Platform may explicitly not collect or predict things around political party
 - So, "Examples of content engaged with by people in X political party" might not be meaningful

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What don't they collect?

Perfect knowledge is hard to come by

- Content topics might not be explicitly known, or might only be predictions
 - "Examples of most popular civic content": There may not be a topic classifier for that.
 - How to map that question to the predicted scores from the classifier?
- Inauthentic accounts or FIMI accounts
 - Inauthenticity can be a complicated assessment to make
 - Sometimes they use a known IP/device
 - But sometimes it's looser affiliations

APIII 24, 2025

Busting myths: do mobile devices listen to us all the time?

ov Sergev Korol



How is data organized internally?

Data Engineering 101

- Data internally can be very chaotic
- Will vary wildly between companies
- There will be entire company functions around data
 - Typically Data Engineering, Analytics, and Science teams
- But there are some useful principles in how it works
- Common framework: "Fact Tables" and "Dimension Tables"

Dimension Tables

- "Dimension" tables are data tables that
 - Collect a large amount of information
 - About entities or objects on the platform
- Each row will represent a single instance of an object
 - Represent "nouns" in the "language of data"
- For example, a user dimension table will collect
 - User id
 - Name
 - Email
 - Date created/joined
 - Any other user provided information

Dimension table data dictionary example

Variable	Description	Data Type	Retention	Restricted access?
user_id	Assigned numeric ID for each user	INTEGER	90	N
name	User's name	STRING	90	Υ
email	User's email address	STRING	90	Υ
date_joined	Date user created account	DATE	90	N
country	User's specified country	STRING	90	N
age	User's specified age	INTEGER	90	N

Dimension table data example

user_id	name	email	date_joined	country	age
12	John Doe	johndoe@example.com	2013-01-01	UK	45
53	Jane Doe	janedoe@example.com	2014-01-01	US	63
891	Fulano	fulano@example.com	2020-01-01	MX	32
156	Mengano	mengano@example.com	2010-01-01	со	22
932	Zutano	zutano@example.com	2025-01-01	ES	15

Fact Tables

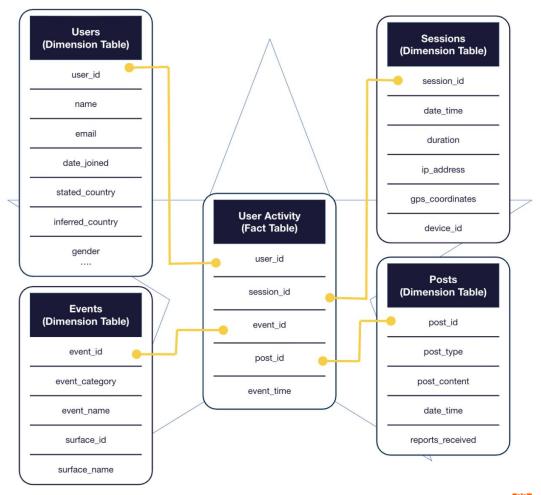
- "Fact" tables are data tables that
 - Collect facts about events on the platform
- Each row will represent an occurrence of something
 - Represent "verbs" in the "language of data"
- They will often take the form of "event logs"
 - Entity taking an action
 - Action taken
 - The entity that was acted upon
- So a content feed fact table will include
 - User ids of content feed users
 - An action they took (Viewed, engaged)
 - Content that was viewed/engaged with

Variable	Description	Data Type	Retention	Restricted access?
user_id	Assigned numeric ID for each user	INTEGER	30	N
session_id	Assigned numeric ID for each user session	INTEGER	30	N
event_id	Label for each event type	STRING	30	N
post_id	Assigned numeric ID for each post	INTEGER	30	N
event_time	The time when event occurred	TIMESTAMP	30	N

user_id	session_id	event_id	post_id	event_time
12	5021	LIKE	90	2025-01-01T00:10:10Z
12	5021	VIEW	93	2025-01-01T00:20:15Z
12	5022	LIKE	93	2025-01-01T00:20:20Z
53	5023	REPLY	143	2025-01-01T00:30:23Z
53	5023	SHARE	143	2025-01-01T00:30:24Z

"Star Schema"

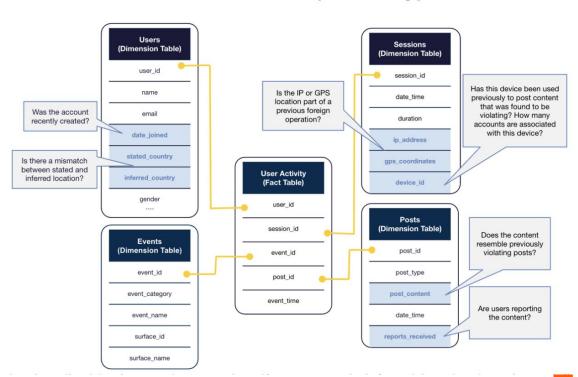
- Common jargon for this framework
- Involves core event logs as fact tables
- And unique ids to link to dimension tables



Example: Predicting Violating Posts

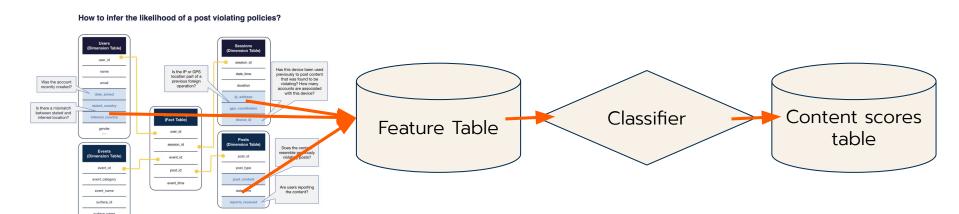
How to infer the likelihood of a post violating policies?

- Predicting is a post violates relies on lots of data
 - The content itself
 - Dimension table
 - Account that posted it
 - Dimension table
 - User responses
 - Fact table aggregations



Example: Predicting Violating Posts

- Data will be joined to feed the features of the classifier
- Classifier output will go to a dimension table



Case Study: Mastodon

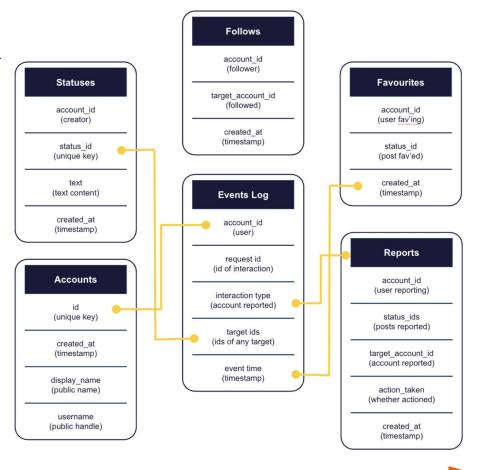
Data Tables in Mastodon

- Fun fact: There are open source platforms!
- And they generate data tables!
- Mastodon is a really great example
- Can act as a "minimalist" stand in for social media platforms
 - If Mastodon has the data, VLOPs almost certainly do
- Mastodon has "dimension" like tables and "fact" like tables



Data Tables in Mastodon

 Mastodon uses a "star schema" type framework



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Comparisons Between Platforms

APIs vs. Raw Data

 Not all platform APIs stack up against Mastodon or what we need

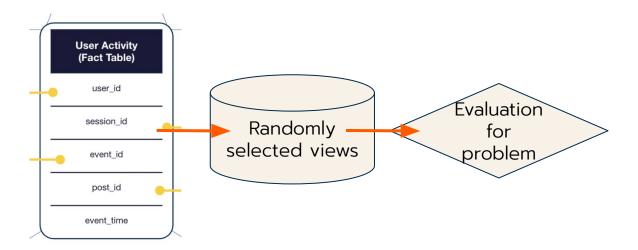
	Facebook	x	TikTok	Mastodon			
	FIMI						
Text	post_media_t ext	text	video_description hashtag_names region_code	statuses media_attachments			
Engagement	post_reaction s post_comme nts post_shares	organic_metrics nonpublic_metri cs promoted_metri cs	like_count comment_count share_count view_count favourites_count	favourites_count replies_count reblogs_count views (from event log)			
Reports				account_warnings reports report_notes			
Classifier		possibly_sensiti ve	video_label	follow_recommendat ion_suppressions global_follow_recom mendations			
Survey Data							
Manual review				account_moderation _notes account_notes admin_action_logs appeals			
User Controls				blocks conversation_mutes custom_filters follow_recommendat ion_mutes			
Creator Information			region_code	Location from IP of creator			

From Data to Systemic Risks

- How do we go from the core dimension and fact tables to a dataset that can answer questions around systemic risks?
- Key example: Can we produce a dataset that allows researchers to validate prevalence metrics for violating content? Or estimates prevalence for novel problems?

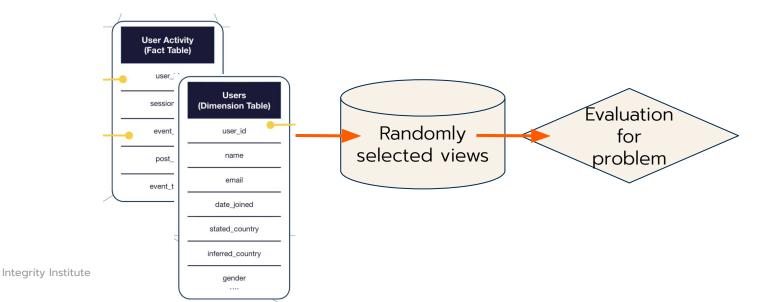
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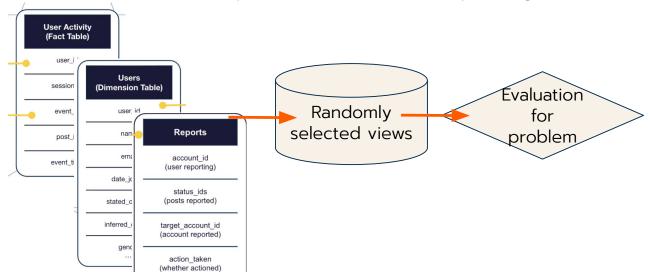
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- Can also combine with user attributes to filter to prevalence by country or age!



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- Key example: Can we produce a dataset that allows researchers to validate prevalence metrics for violating content? Or estimates prevalence for novel problems?
- Can also combine with user attributes to filter to prevalence by country or age!
- Can also combine with either predicted violation scores or reports to get stratified random sample!



Conclusion

Key Takeaways

- Platforms collect a lot of data! (But likely won't have perfect data for everything you want)
- Understanding how platform data is stored internally can help you
 - Determine the most likely datasets that will be useful
 - Help you navigate any conversation with platforms about data access
- There are open source example to learn from and point to!
 - If Mastodon has a data you need, every VLOP will
 - Other platforms to look to, like ElasticSearch for ranking systems
- Hopefully we get real access that lets us meaningfully answer questions about systemic risks
 - There are platform experts who can help! (Integrity Institute is one!)
- Check out our paper for more details!
 - Matt Motyl, Spencer Gurley, Jeff Allen, Sofia Bonilla
 - https://edmo.eu/publications/platform-datasets-challenges-insights-and-examples-for-researchers-under-article-40-of-the-digital-services-act/

