Connecting the Dots: An Investigative Study on Linking Private User Data Across Messaging Apps

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NDSS 2026

Messenger usage

- Billions of users on mainstream messaging platforms

WhatsApp
(2 billion)

Telegram
(950 million)

Tinder
(50 million)

KakaoTalk
(48.7 million)

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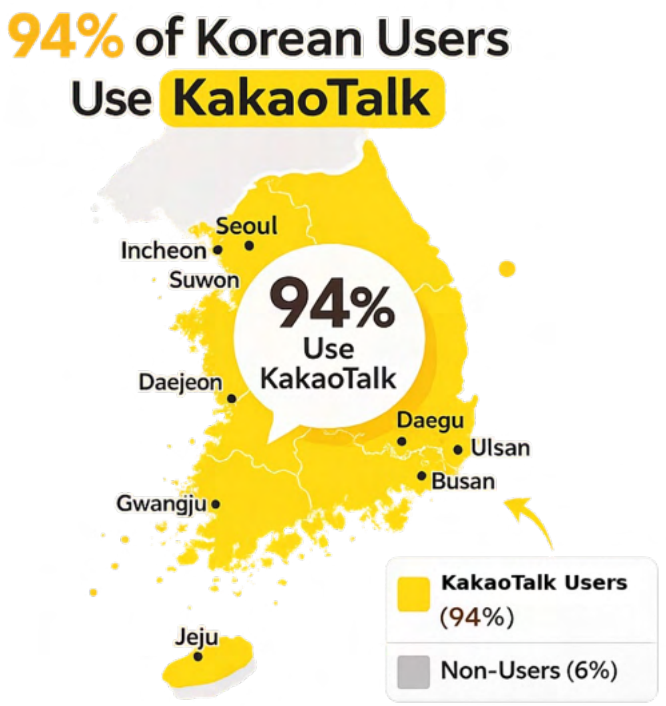

Privacy attacks targeting messengers

- Contact Discovery

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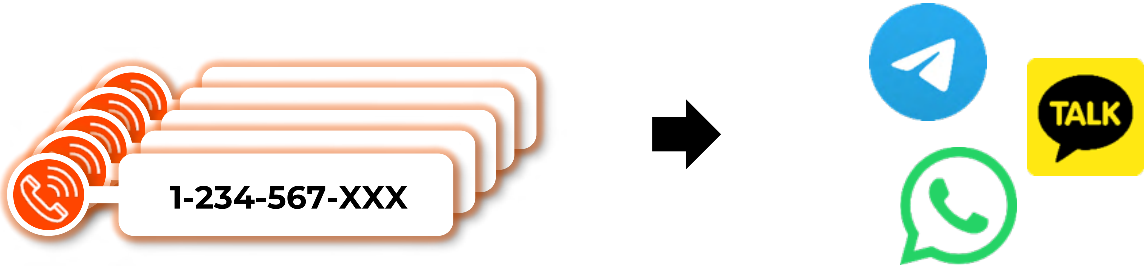

Phone numbers **Messenger apps**

Privacy attacks targeting messengers

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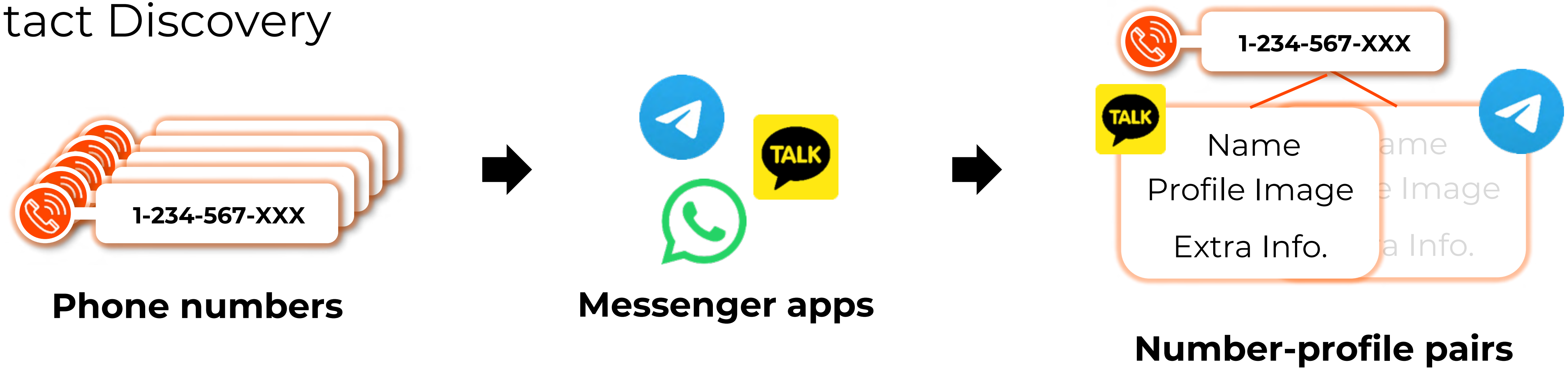
Phone numbers

Messenger apps

Number-profile pairs

Privacy attacks targeting messengers

- Contact Discovery



- Previous work

  - Targeting **WhatsApp**, **Signal**, and **Telegram**, enumerated **5M, 2.5M, and 908** profiles (Hagen *et al*., 2021)

  - Targeting **Facebook**, tested **200K** phone numbers (Kim *et al*., 2017)

  - Targeting **KakaoTalk**, enumerated over **50K** profiles (Kim *et al*., 2015)

Privacy attacks targeting messengers

- Location Inference

Privacy attacks targeting messengers

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Location-based Services (LBS)

Privacy attacks targeting messengers

- Location Inference

500m away

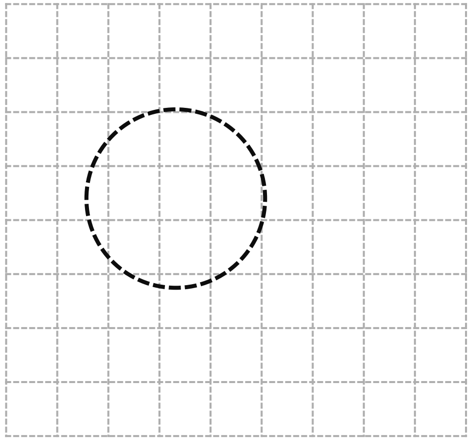
Location-based Services (LBS)

Nearby Signals

Privacy attacks targeting messengers

- Location Inference

500m away



Location-based Services (LBS)

Nearby Signals

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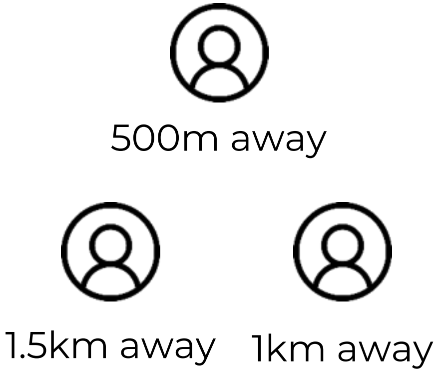
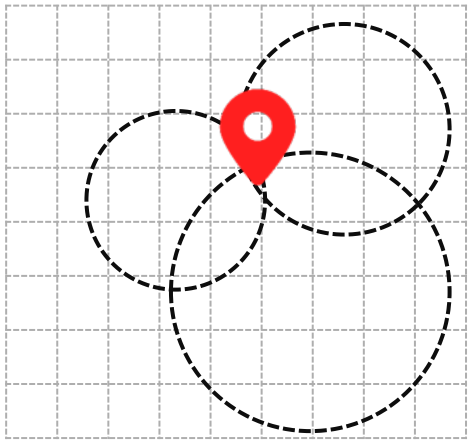


Nearby Signals



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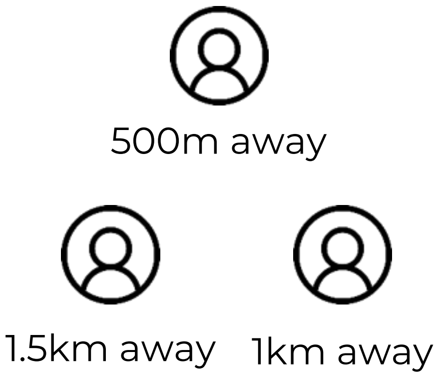

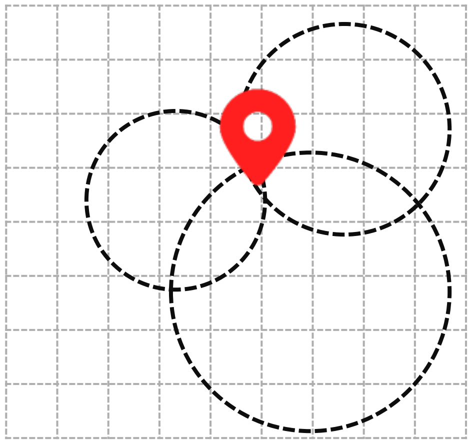

Location-based Services (LBS)

Nearby Signals

- Previous work

  - API traffic leakage of LBS application (Dhondt *et al.*, 2024)

  - Precise localization attacks targeting Tinder (Carman *et al.*, 2017)

  - Automated user location tracking on location-based social networks (Li *et al.*, 2014)

Social & Messenger apps

- Widely used services

KakaoTalk Telegram Tinder

Social & Messenger apps

- Widely used services

KakaoTalk

Telegram

Tinder

Friend Registration

SSO Login

Social & Messenger apps

- Widely used services

KakaoTalk

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Tinder

Friend Registration

Friend Registration

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Private Chatting

Social & Messenger apps

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Social Matching

SSO Login

Private Chatting

Location Service

Multi-platform usage in real-world

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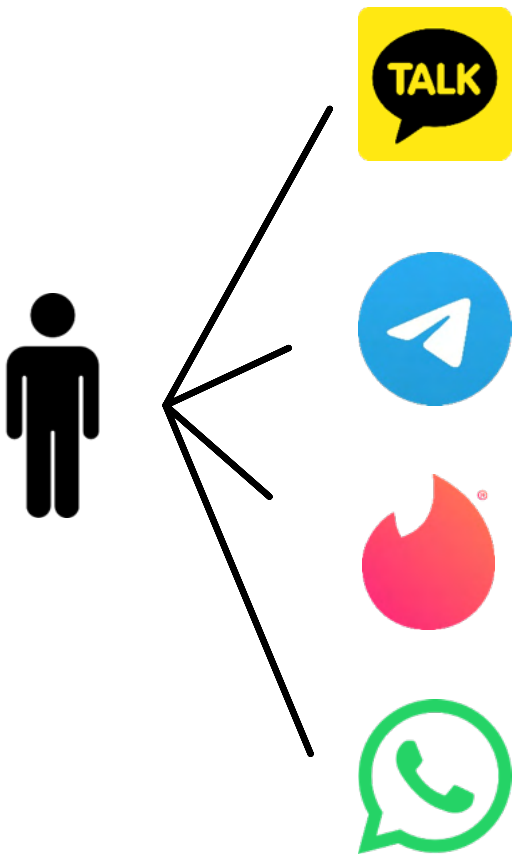

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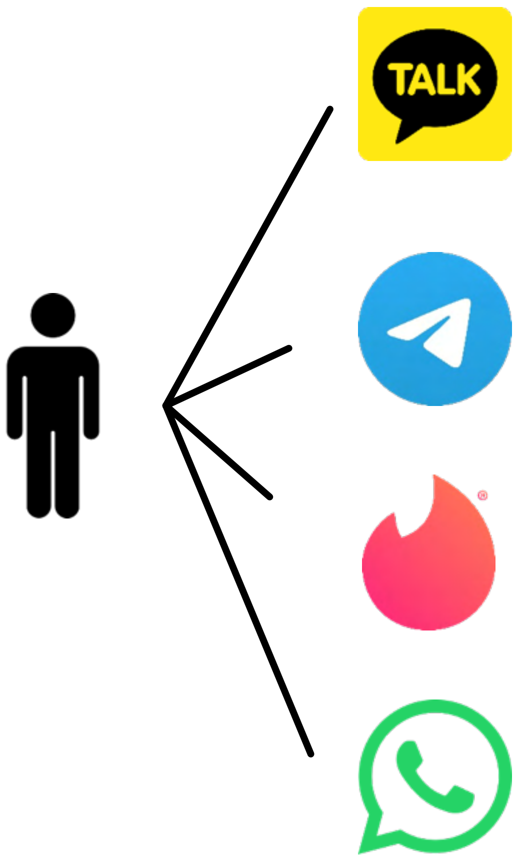
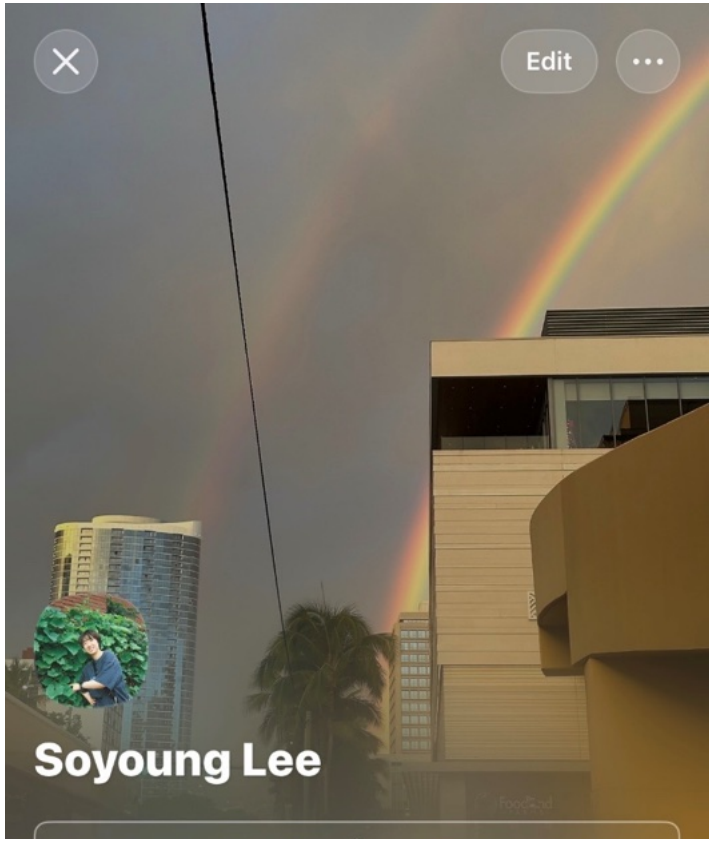
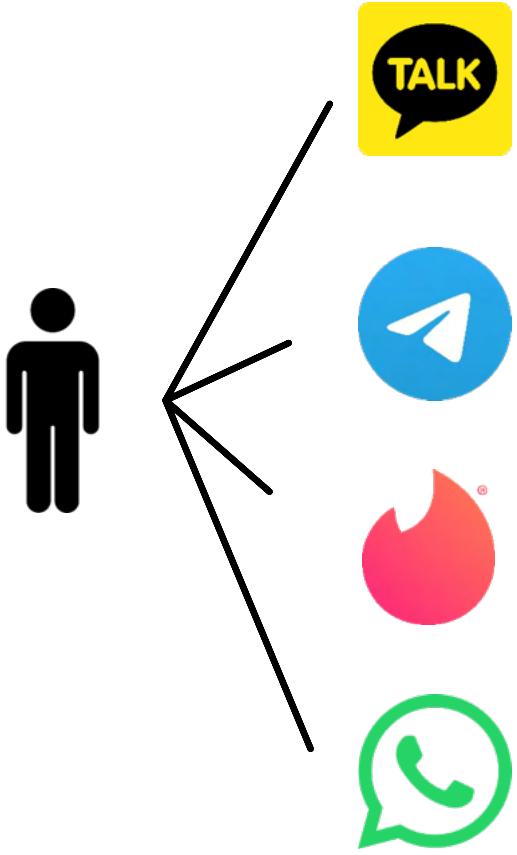
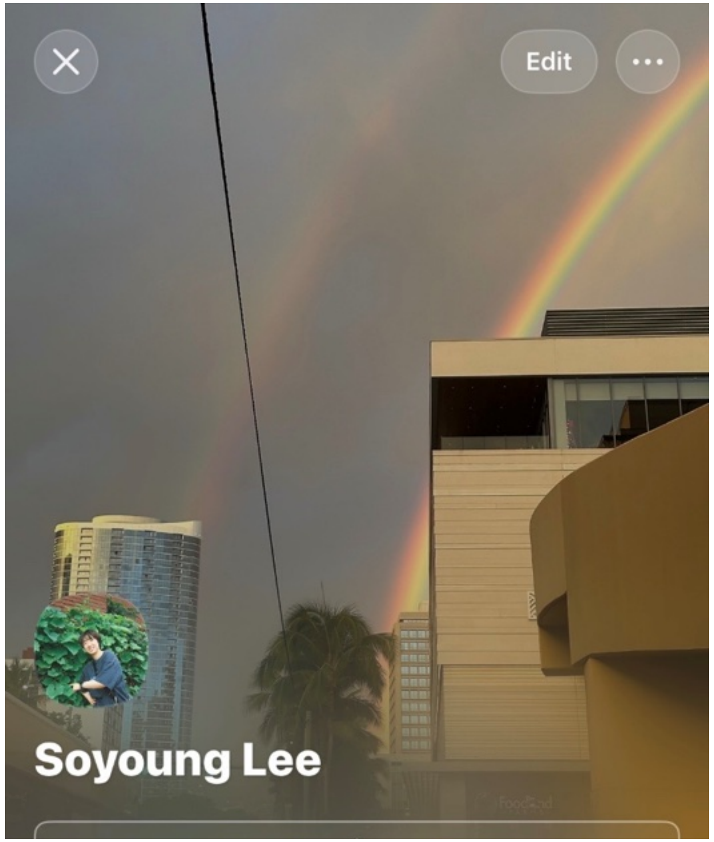


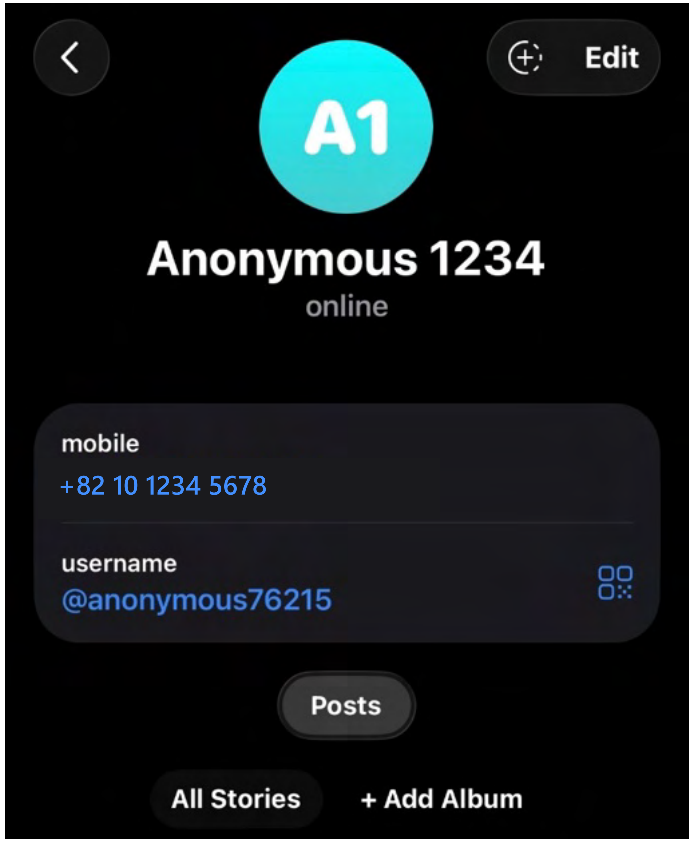


App A

Multi-platform usage in real-world



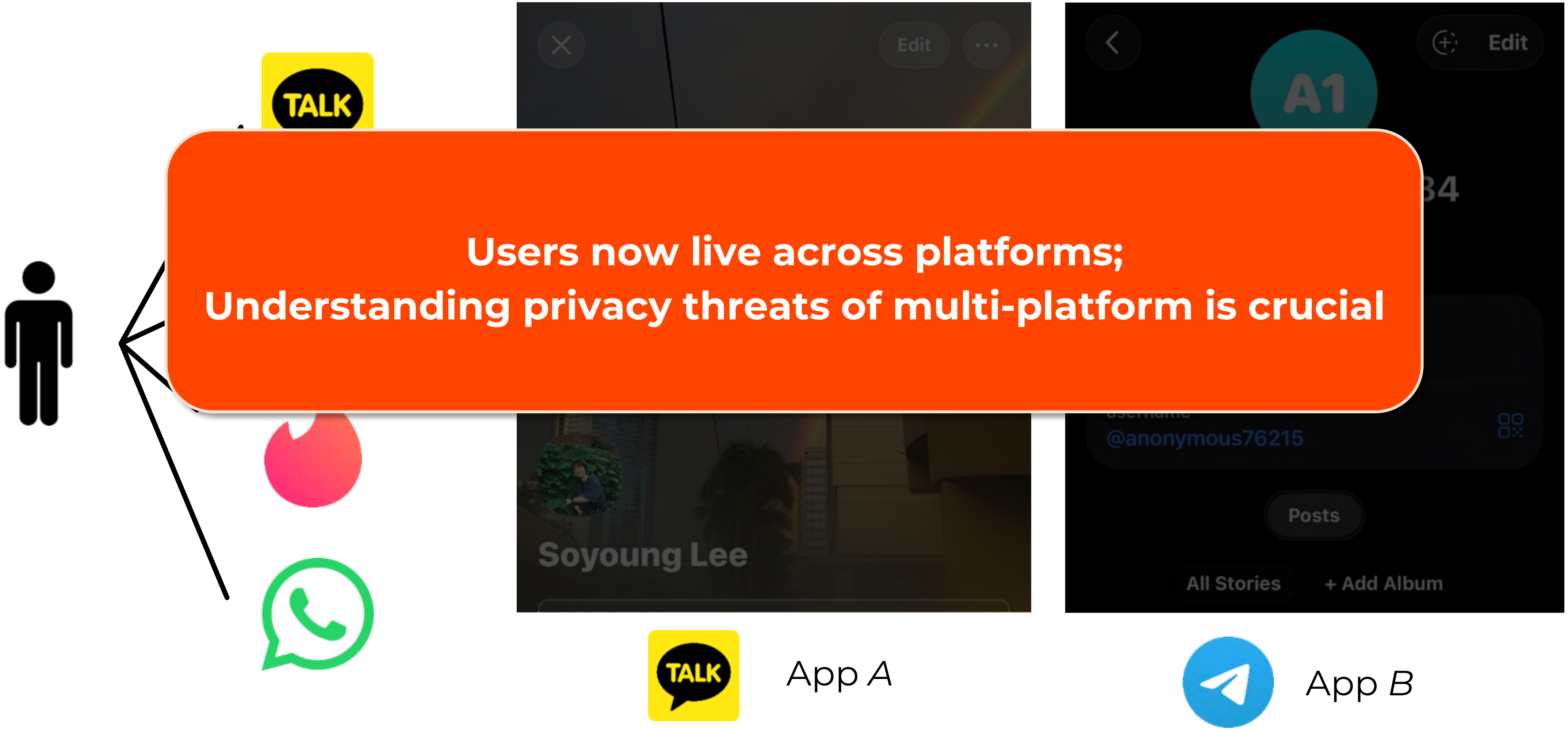




App *A*

App *B*

Multi-platform usage in real-world



Users now live across platforms;
Understanding privacy threats of multi-platform is crucial

Design: Apps, features, and pipeline

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Component-level Privacy Attacks

1. Contact Discovery

2. SSO Linking

3. Location Inference

Design: Apps, features, and pipeline

Component-level Privacy Attacks	1. Contact Discovery	2. SSO Linking	3. Location Inference
Threat Model			

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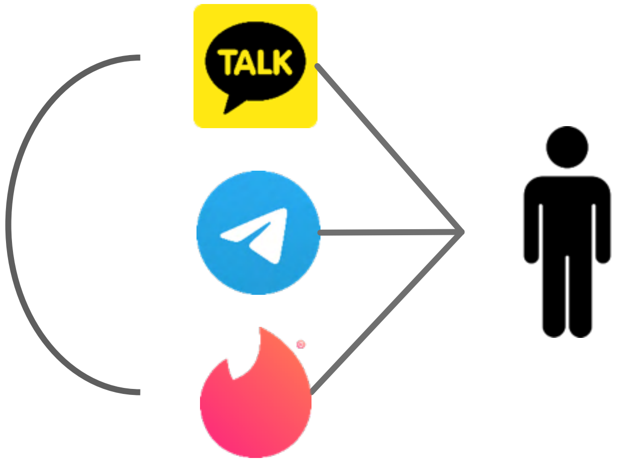

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Threat Model

Privacy-sensitive

Name, Profile image,
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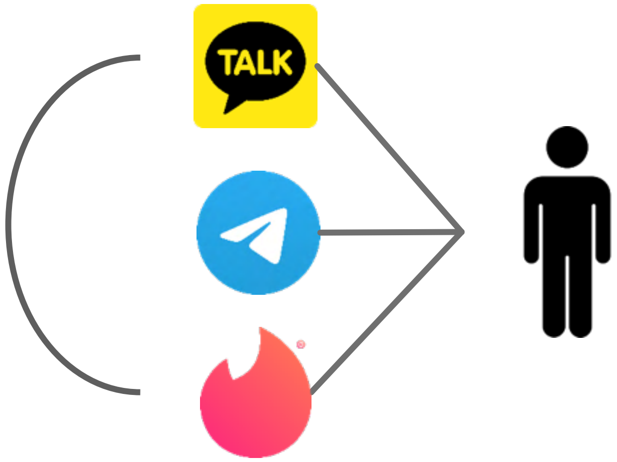

Design: Apps, features, and pipeline

Component-level Privacy Attacks

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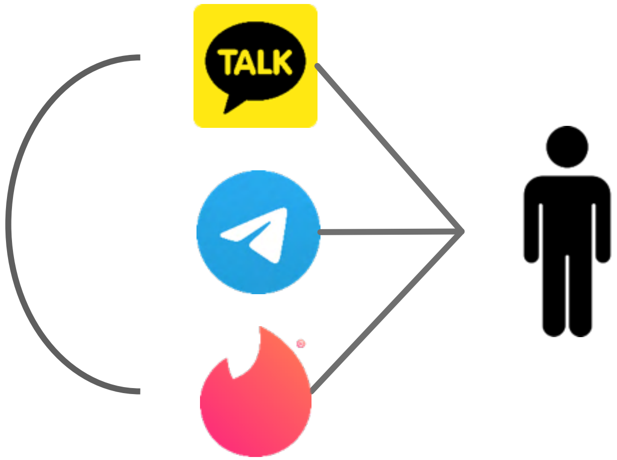
Threat Model

- ✓ Benign behaviors
- ✓ Same as regular users

Privacy-sensitive

Name, Profile image, Location, ..



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Design: Apps, features, and pipeline

Component-level Privacy Attacks

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Linking Keys

Phone numbers

Profile images

Design: Apps, features, and pipeline

Component-level Privacy Attacks

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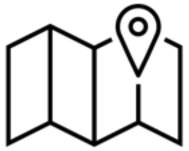
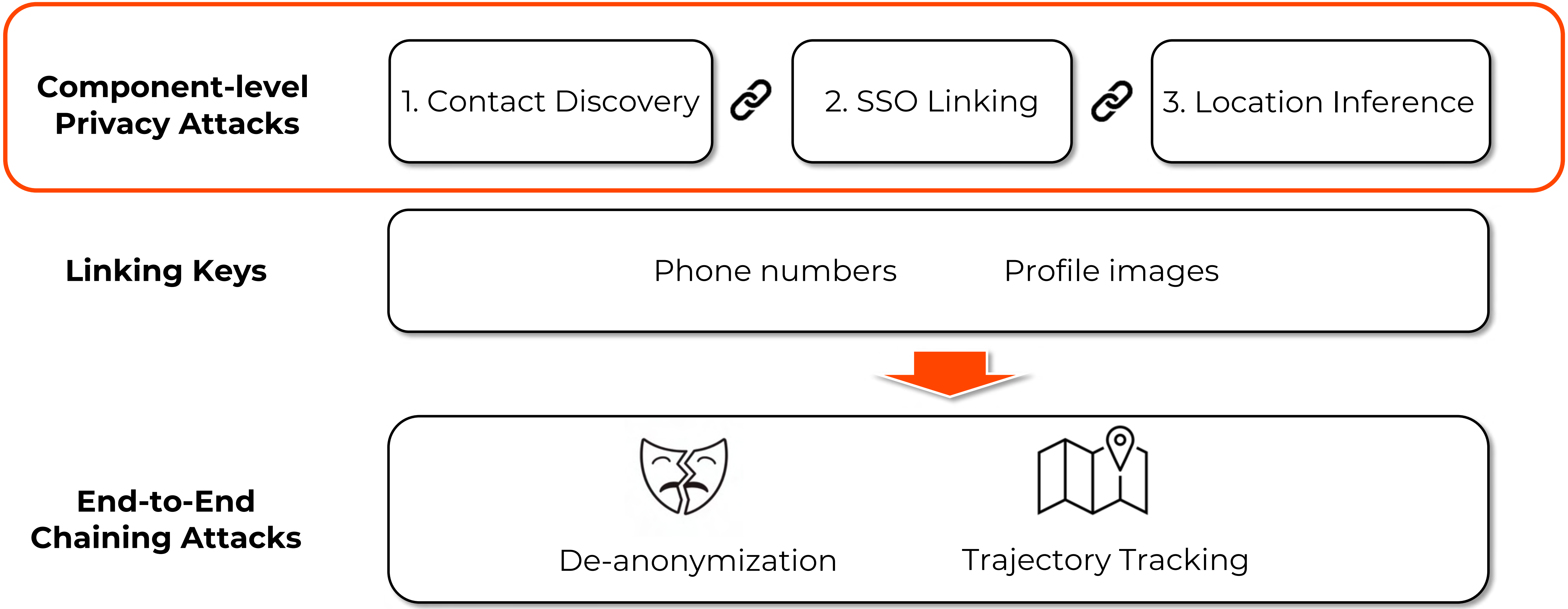
End-to-End Chaining Attacks

De-anonymization



Trajectory Tracking

Design: Apps, features, and pipeline



Attack 1: Contact discovery abuse

- Contact discovery attack

2015

Enumerated **50K** profiles
(Kim *et al.*, 2015)

2017

Tested **200K** numbers
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2021

5M, 2.5M, 908 profiles
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- Our Approach – Additional attack vectors
    - Address-book Syncing → **Still works!**

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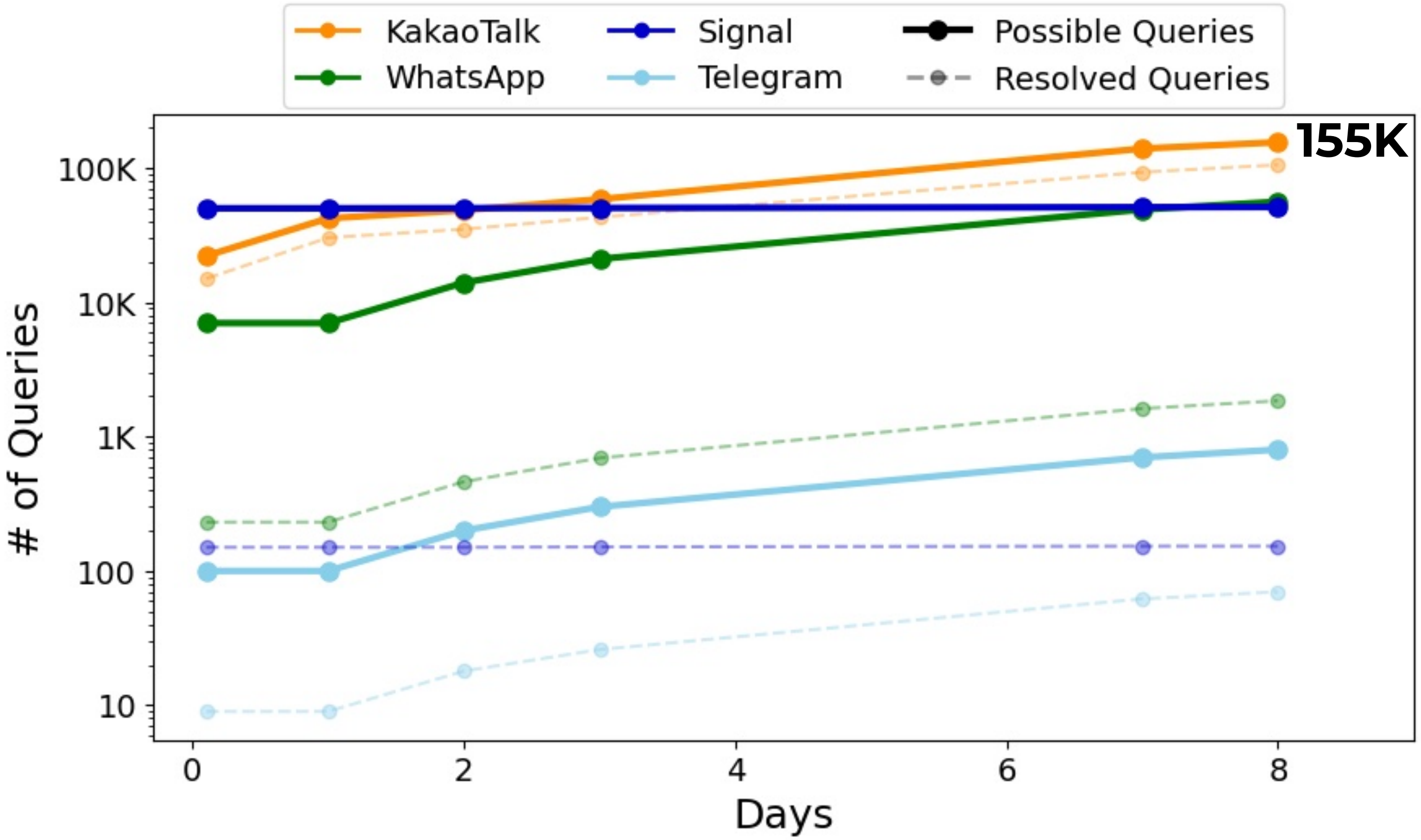
- Our Approach – Additional attack vectors
  - Address-book Syncing → **Still works!**
  - **Deleting Friends**
  - **Block/Unblocking Friends**

Attack 1: Contact discovery abuse

- Using only one account



18K queries / day

7K queries / day

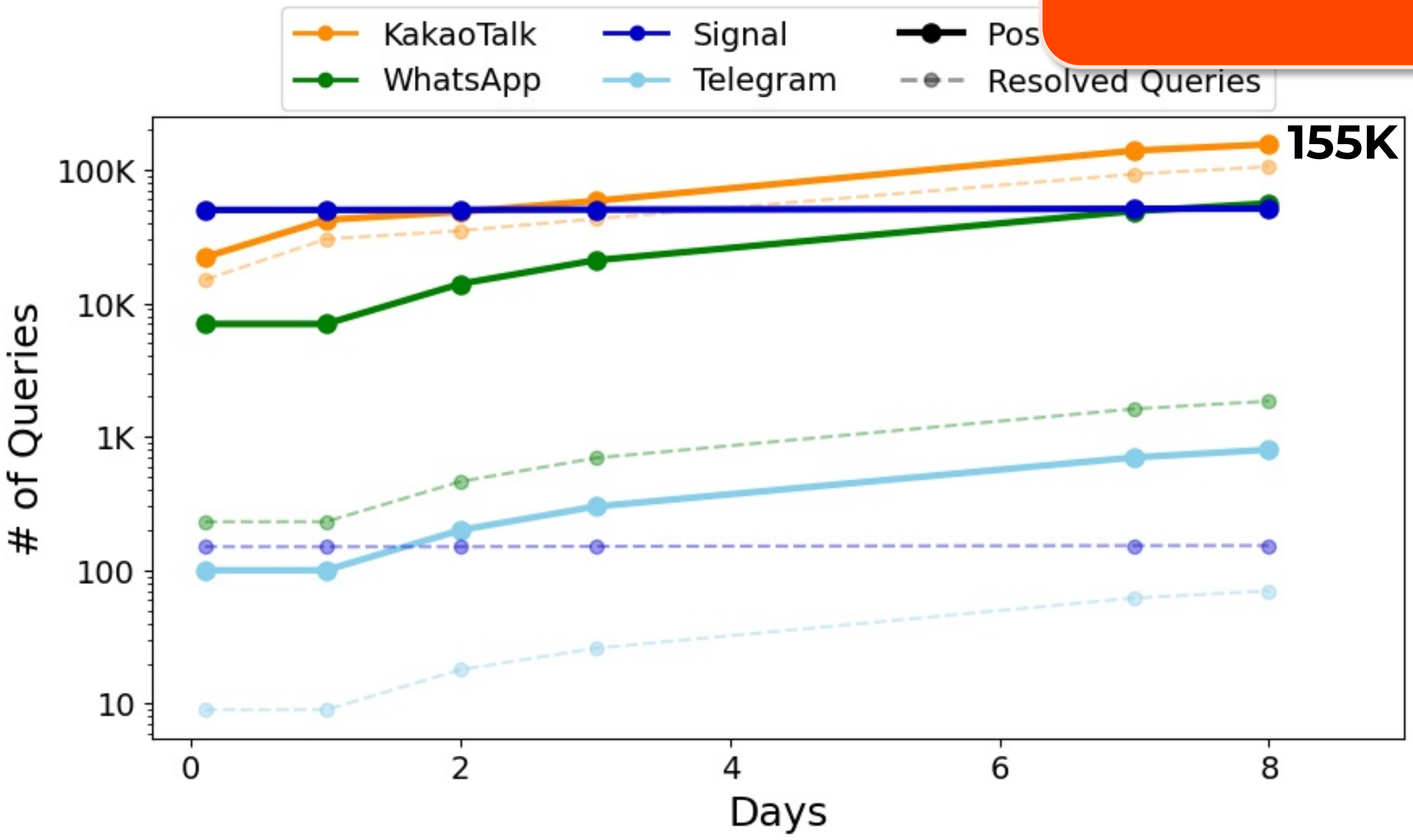
Initial 50K + 144 queries / day

100 queries / day

Attack 1: Contact discovery abuse

- Using only one account

Contact discovery still exists in modern messaging apps.



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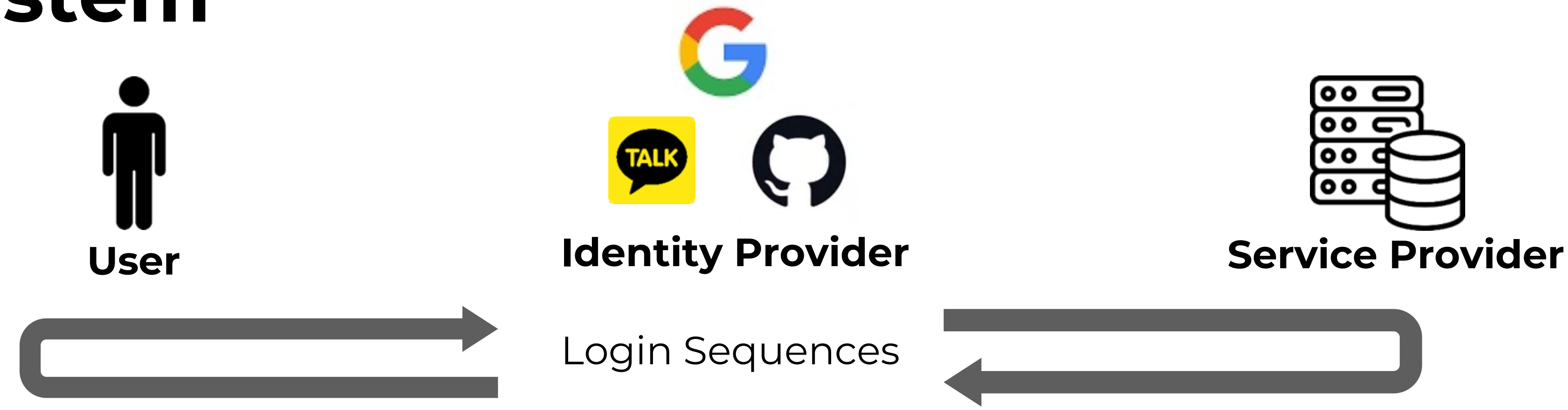

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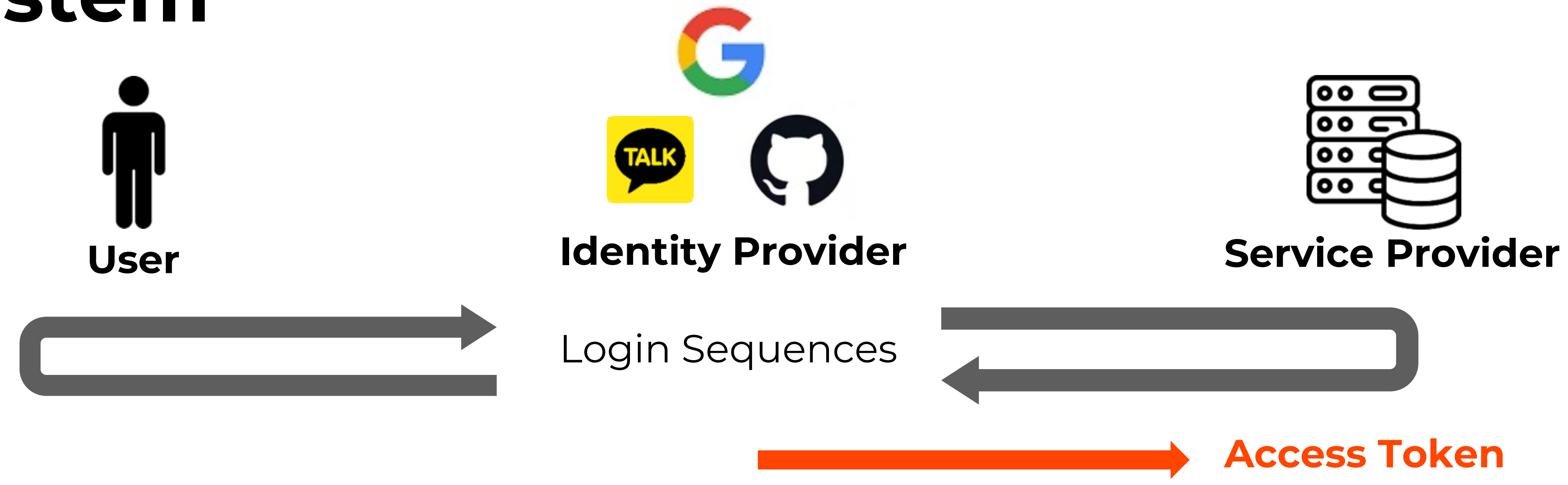

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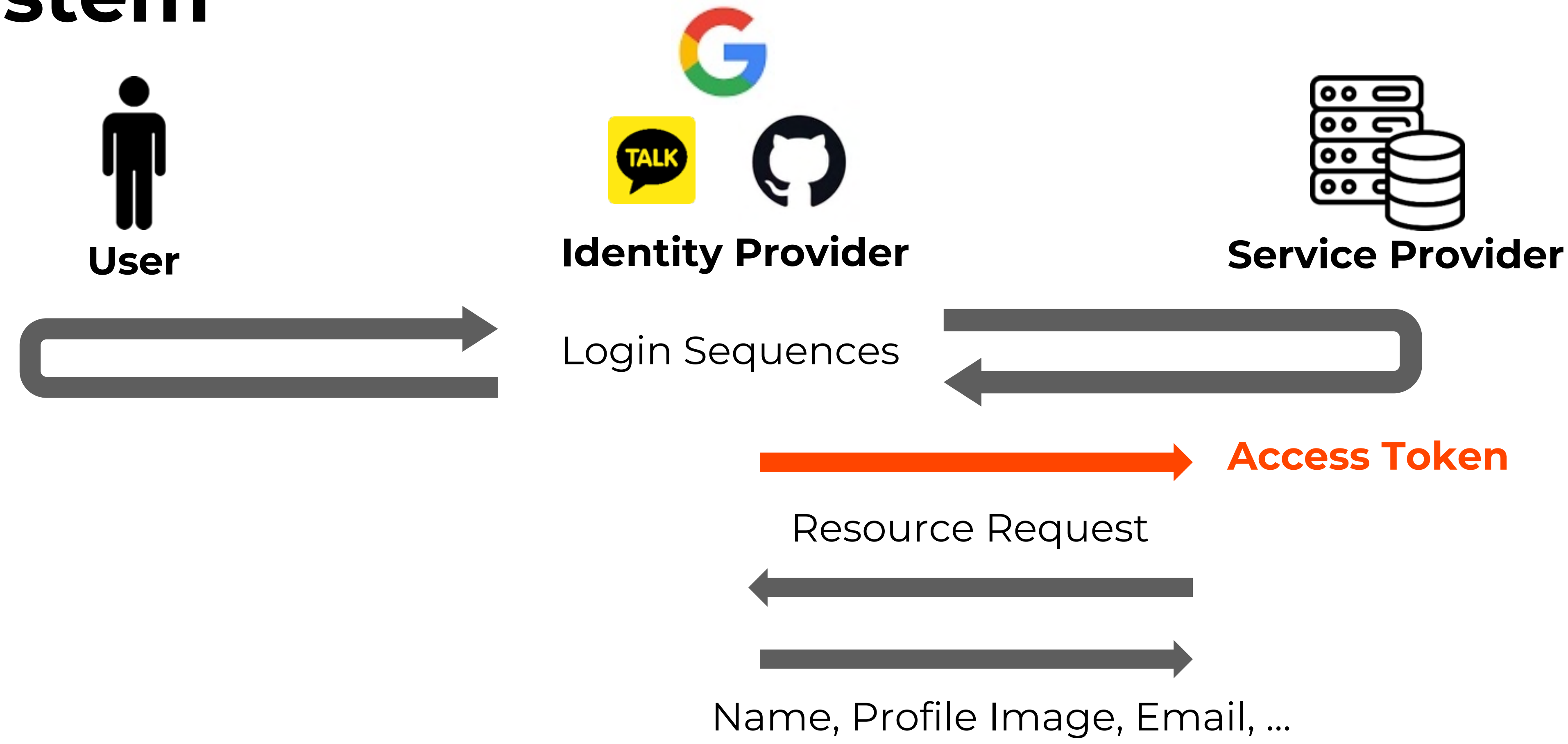

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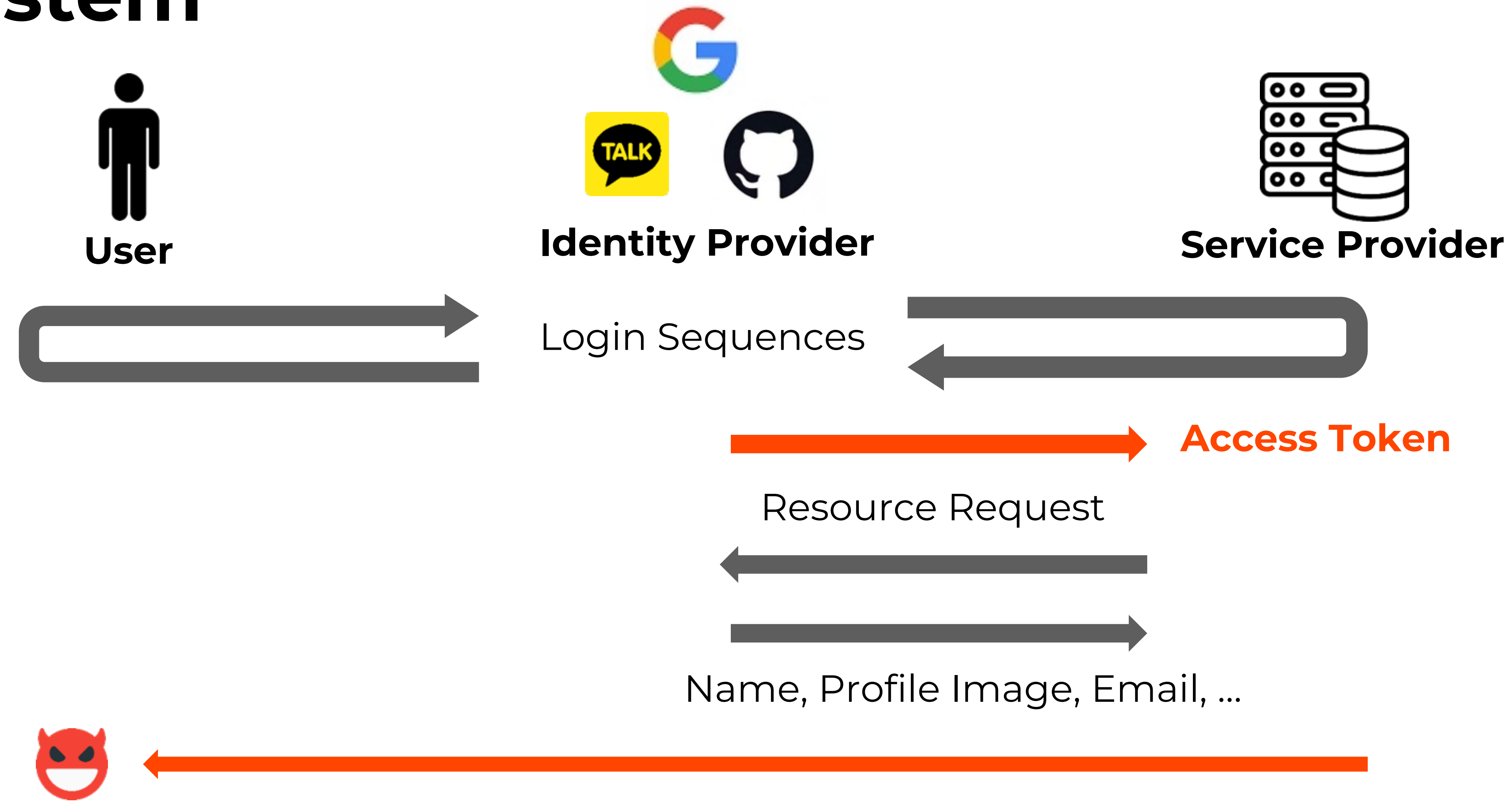

Attack 2: OAuth token exposure in KakaoTalk SSO ecosystem

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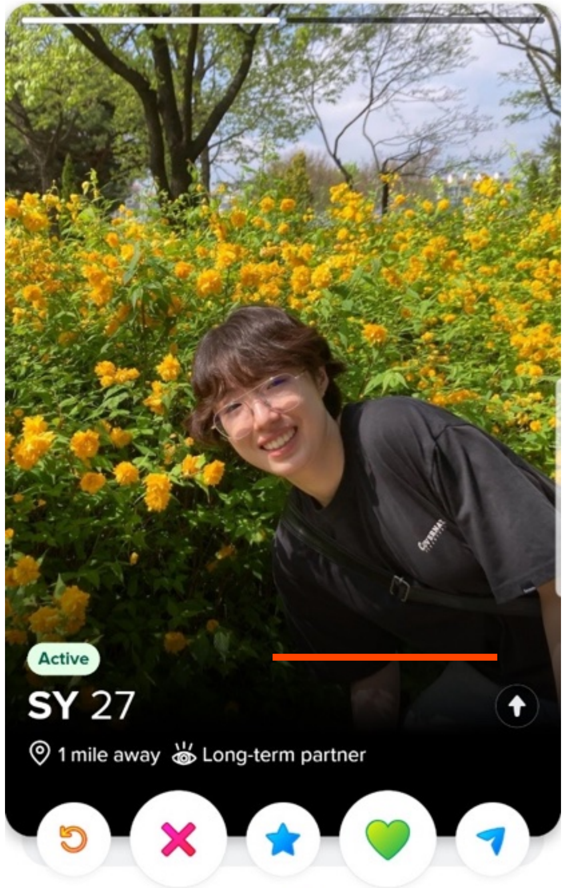
Token exposure is exploitable in the real world.

Attack 3: Efficient location inference from Tinder "nearby" signals



Tinder profile card

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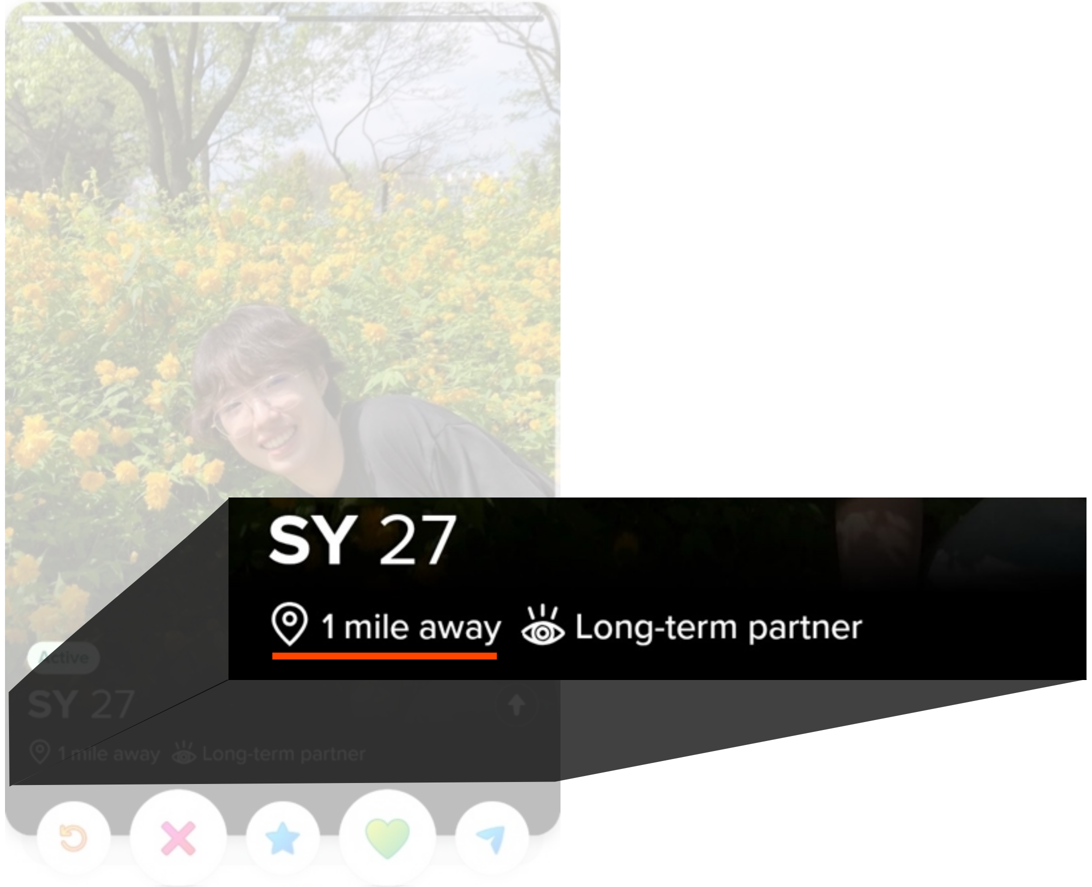

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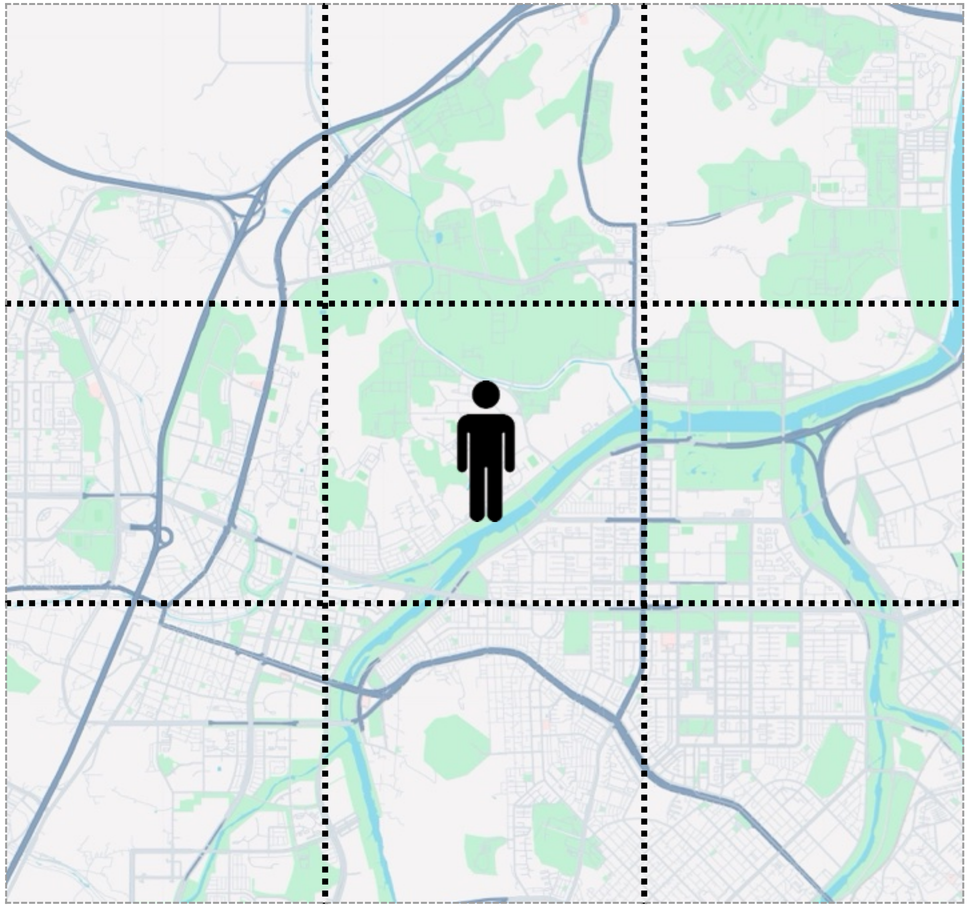

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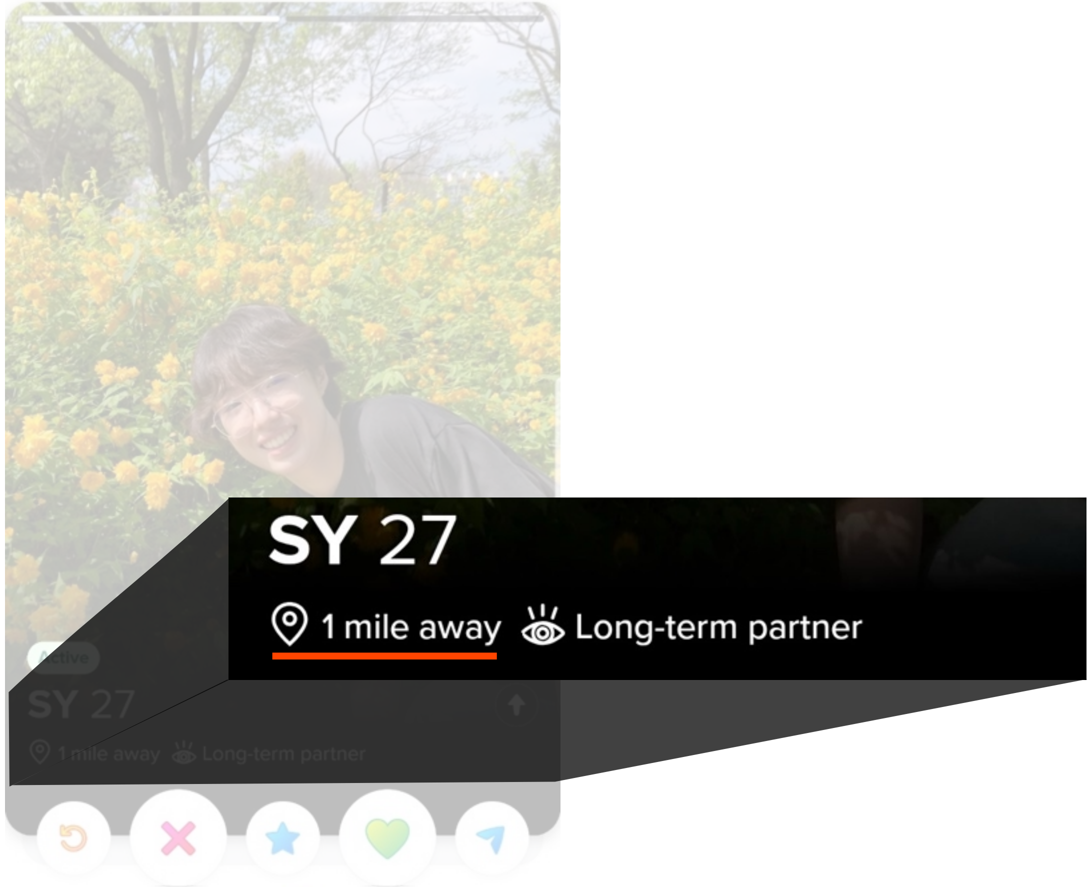

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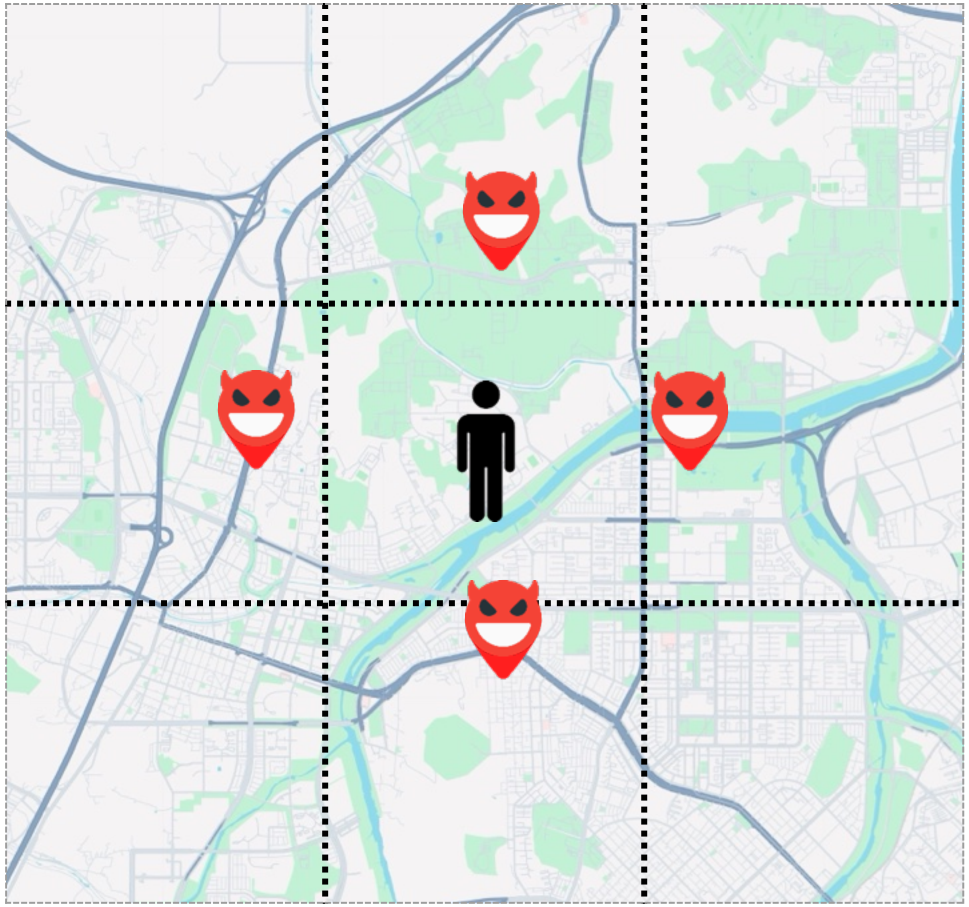

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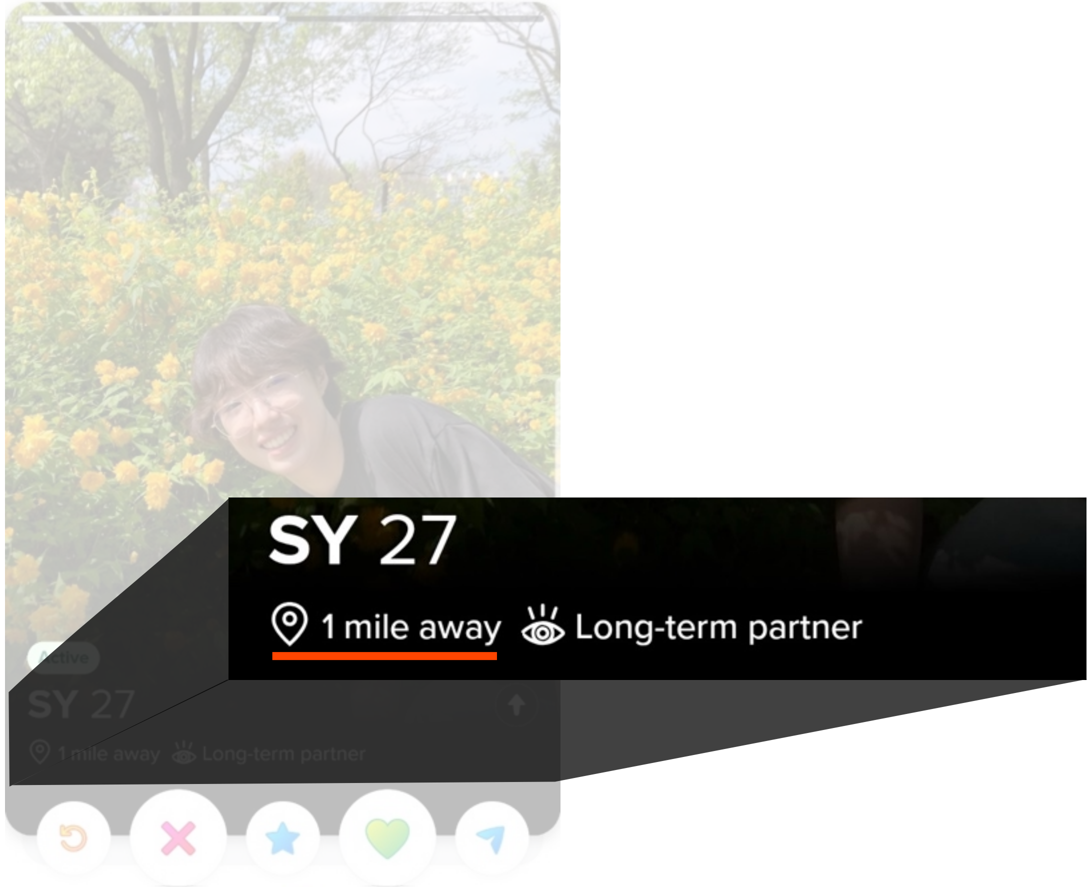

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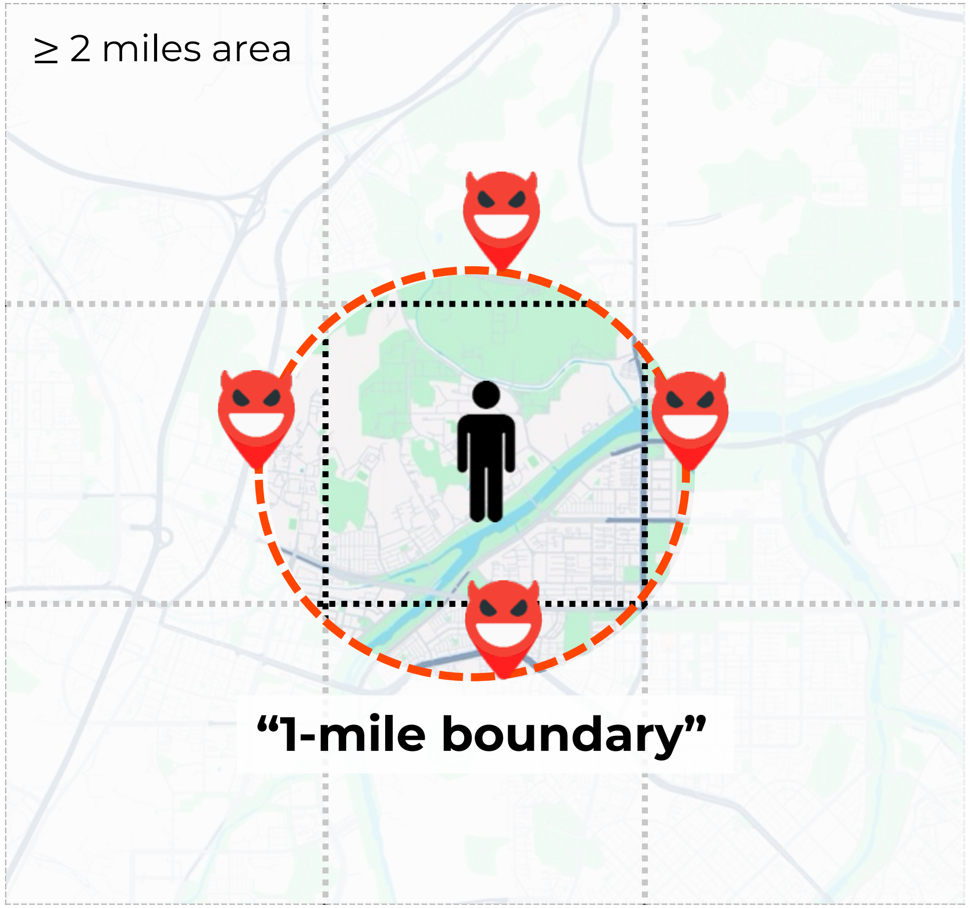

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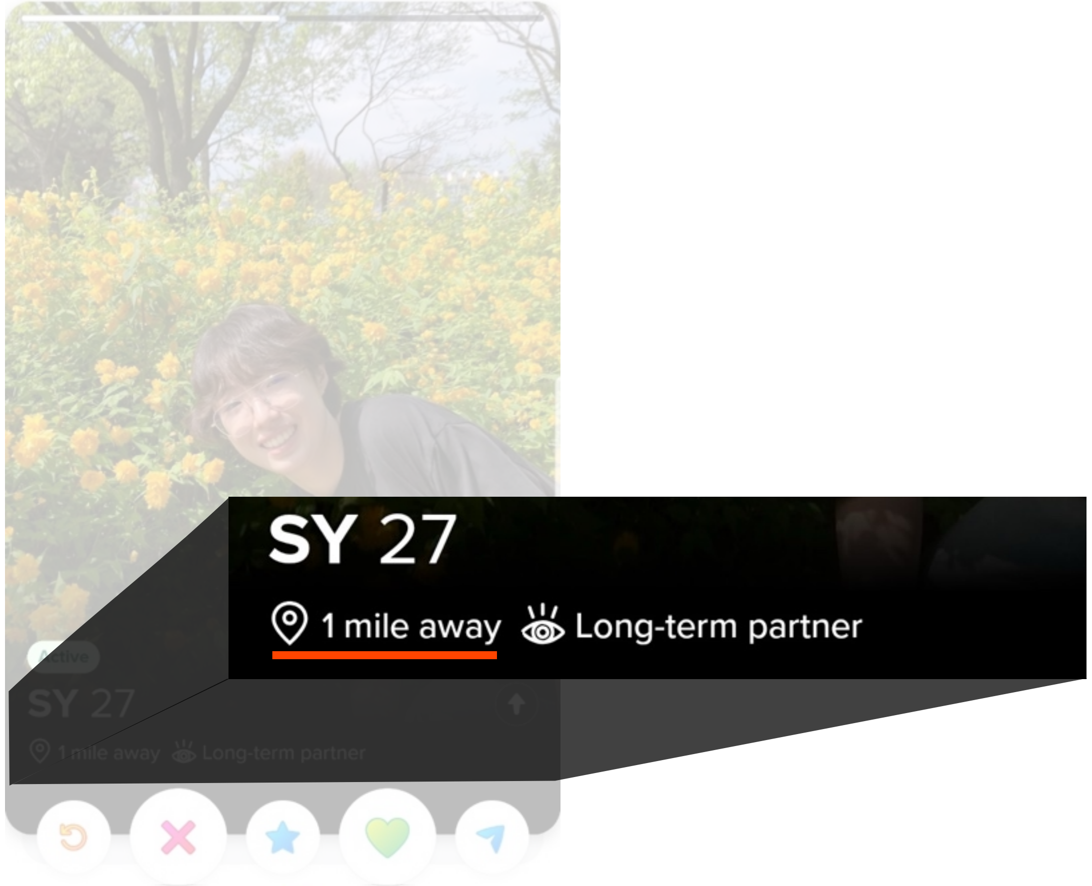

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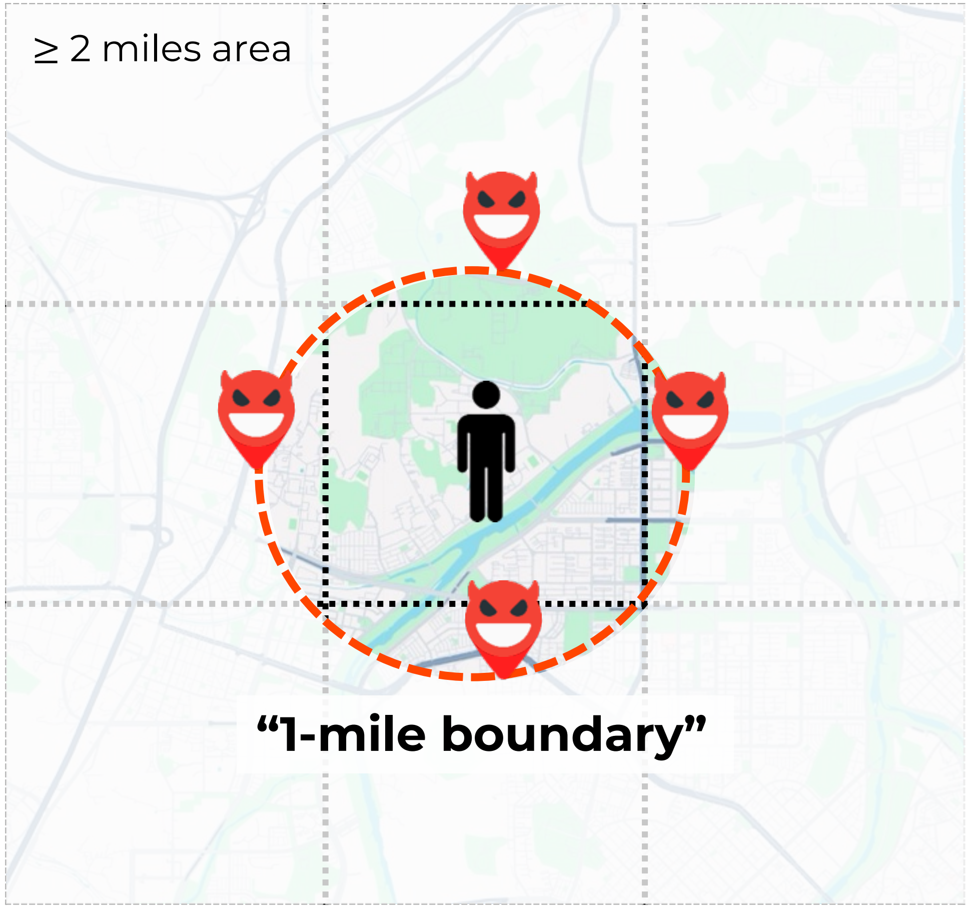


Attack 3: Efficient location inference from Tinder “nearby” signals

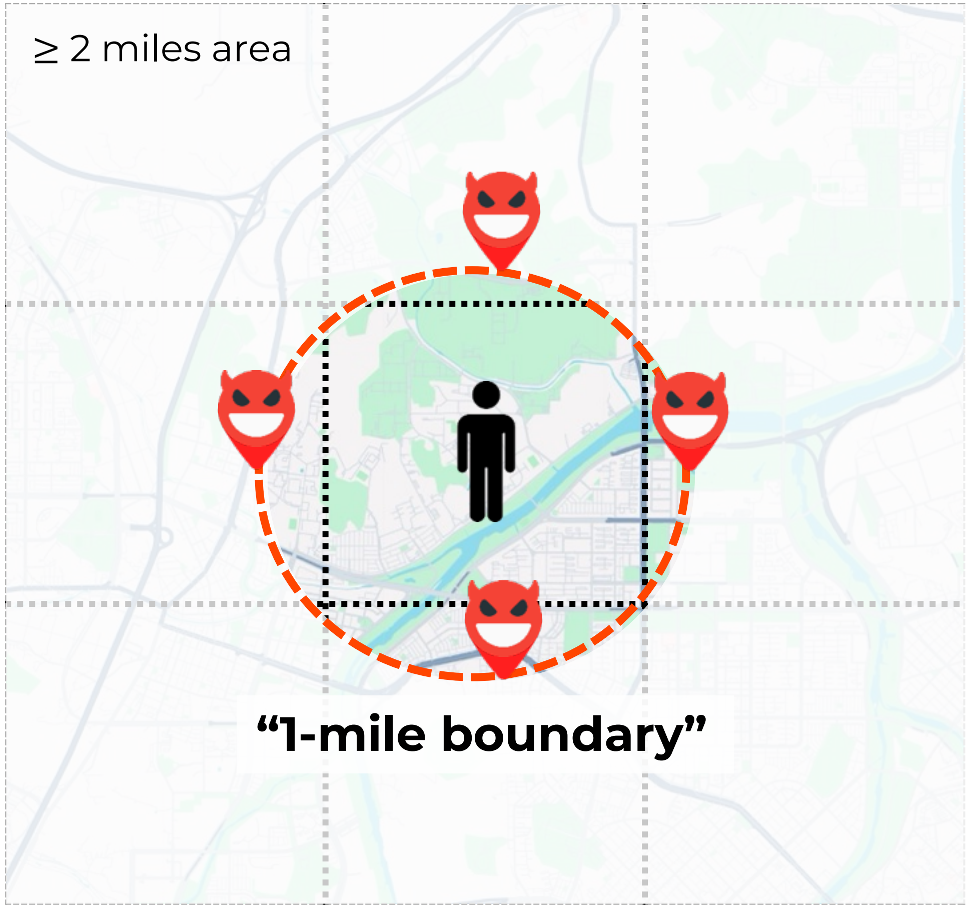
- Targeting 10 sampled locations
  - Previous work (Heaton, 2018)

    Average error: 371m with 676 queries

  - 1-mile boundary algorithm

    Average error: 385m with **12 queries (56x fewer)**

    Average error: 324m with **40 queries (17x fewer)**



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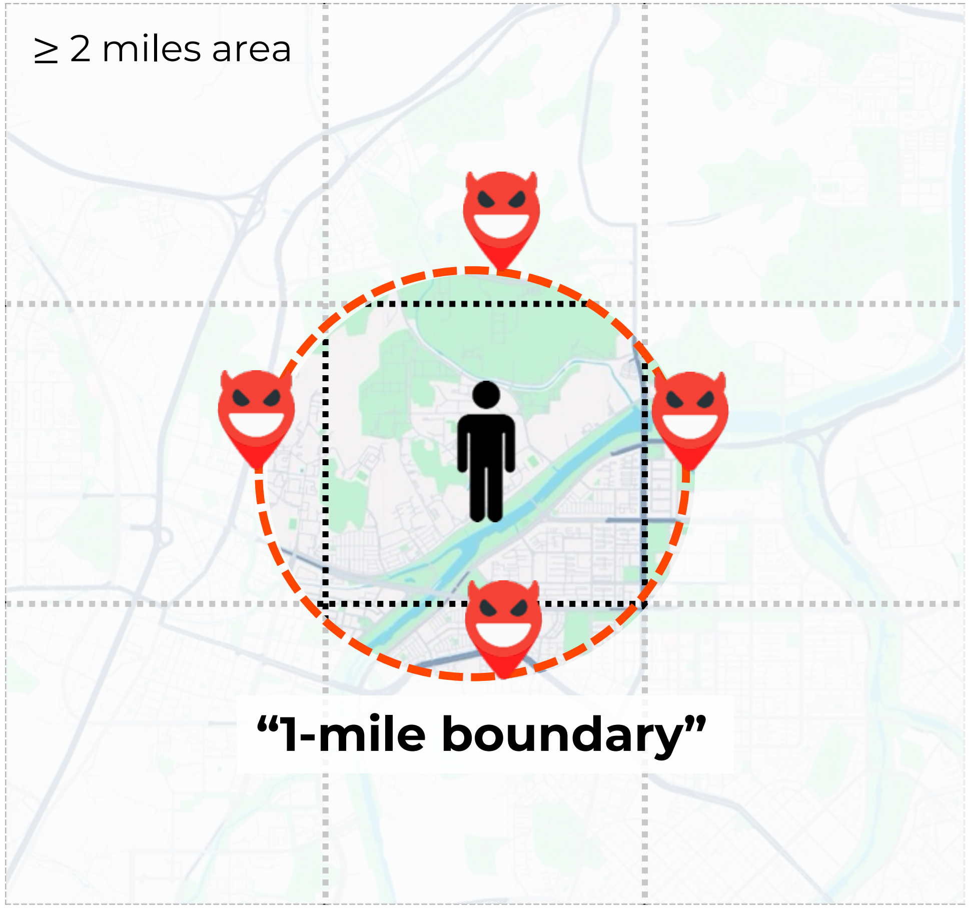
More precise location with fewer queries



“Linking keys” enable cross-platform chaining

1. Contact Discovery

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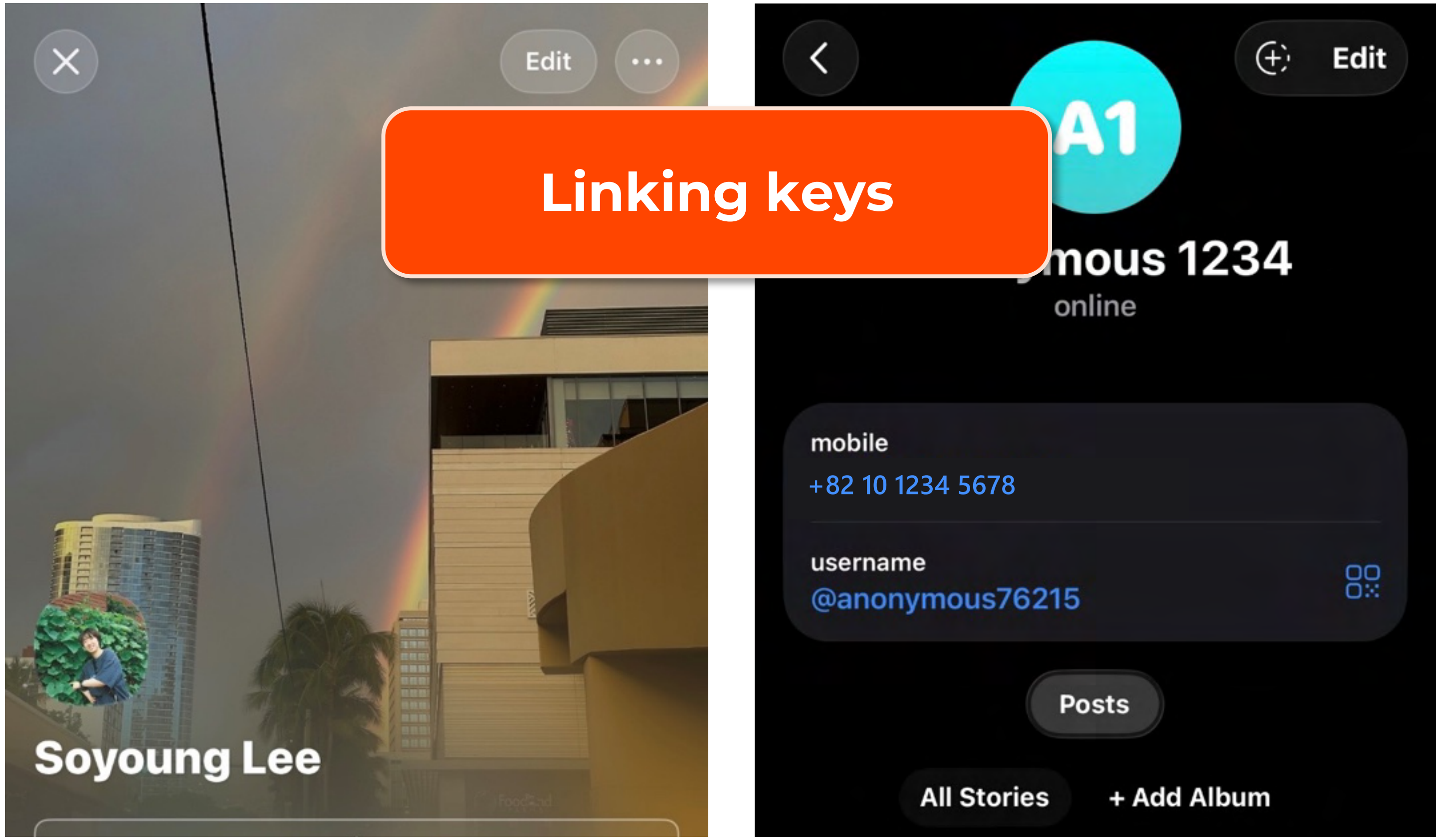

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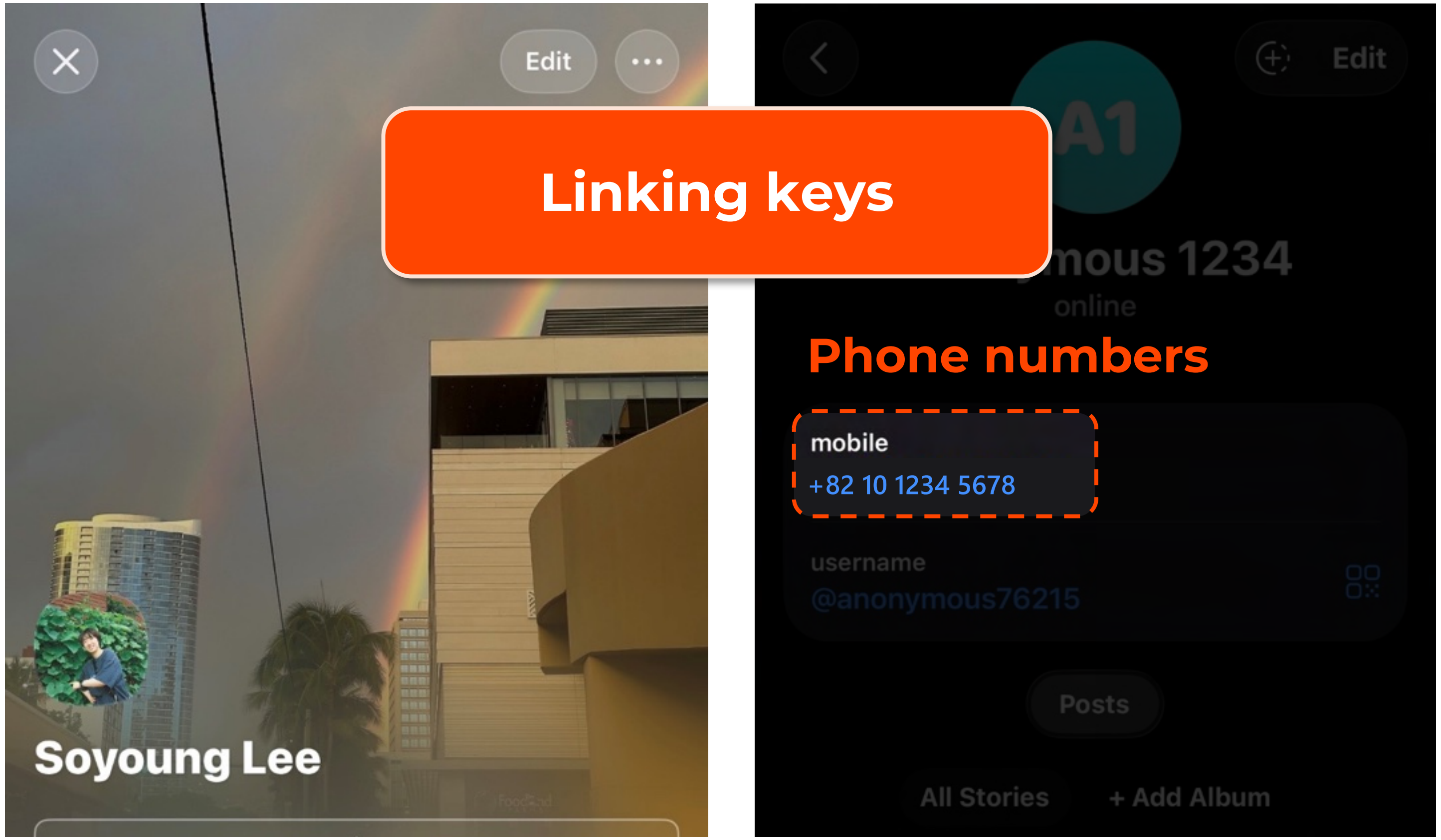

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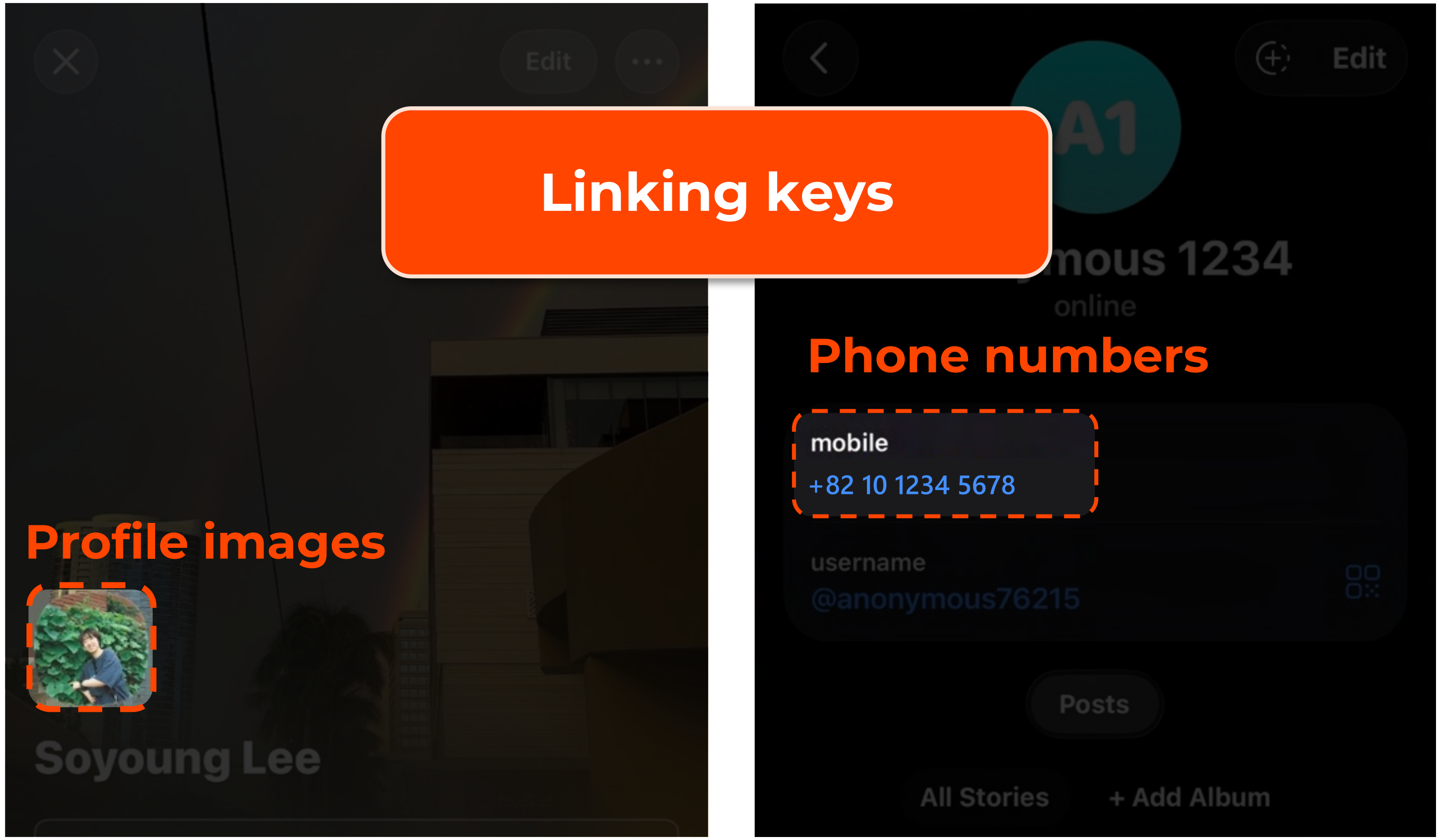

Chain 1: De-anonymization via cross-platform linking

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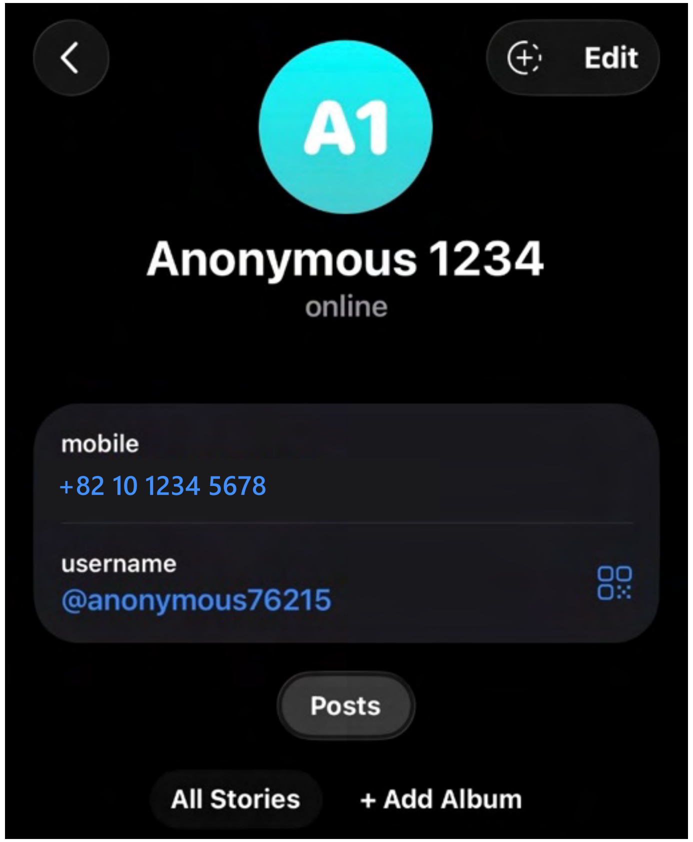
Who is this in App *B*?:
+82 10 1234 5678

App *B*



App *B*

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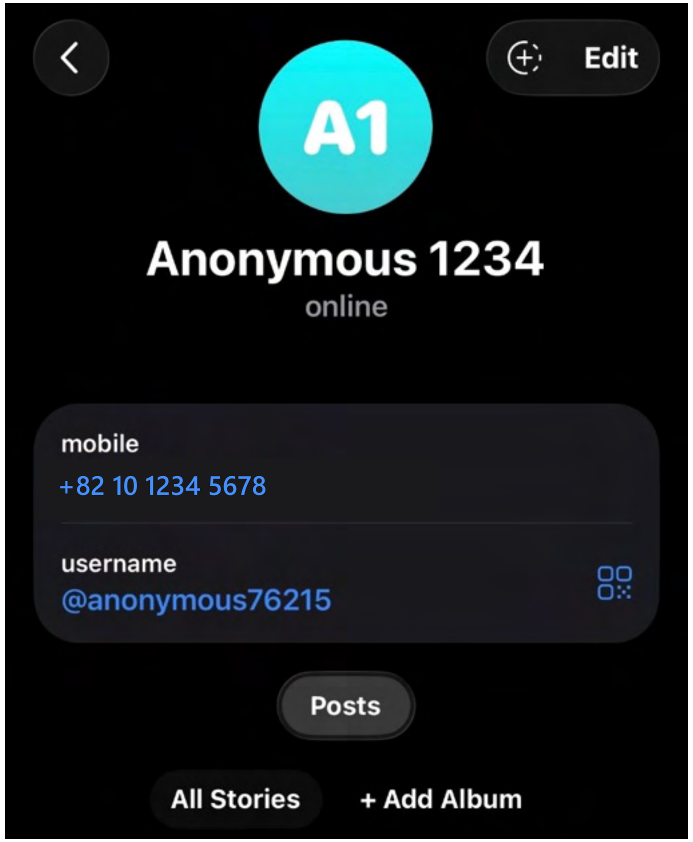

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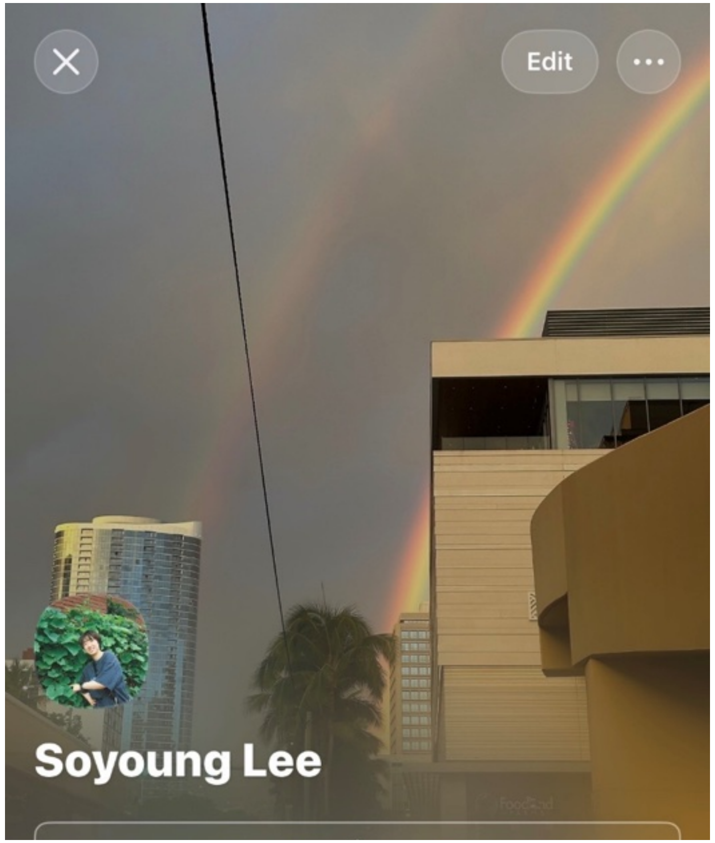

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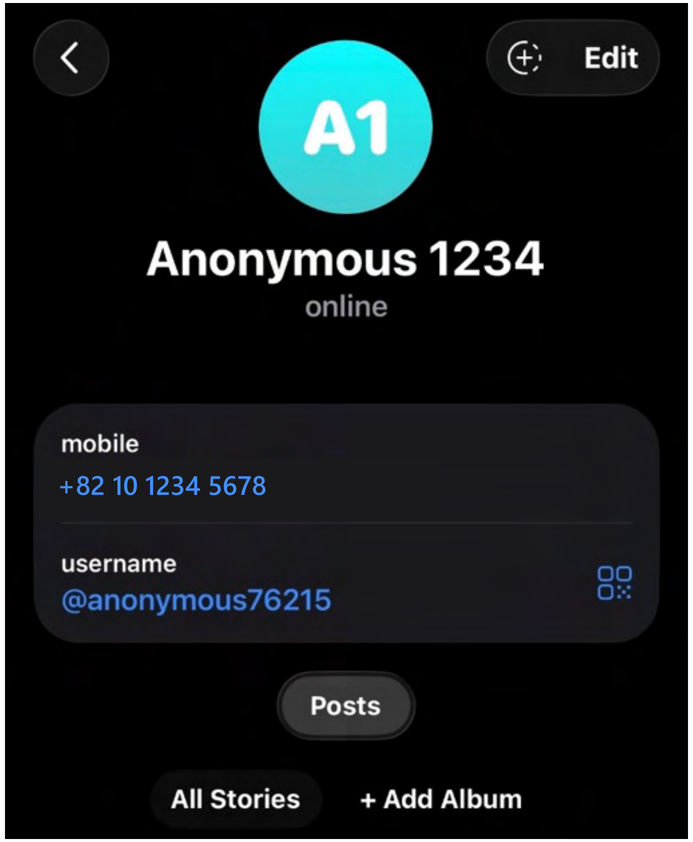

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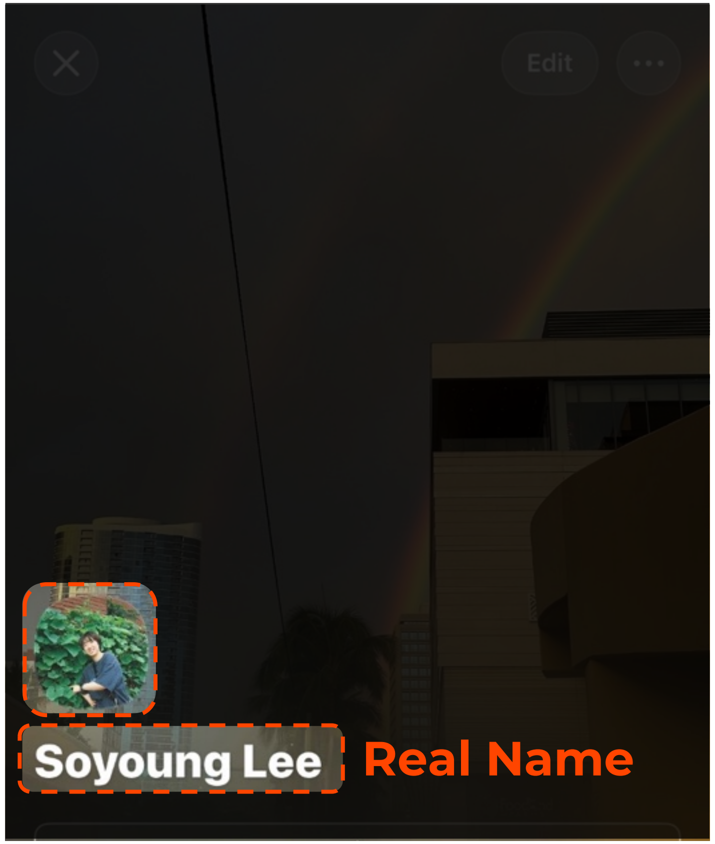

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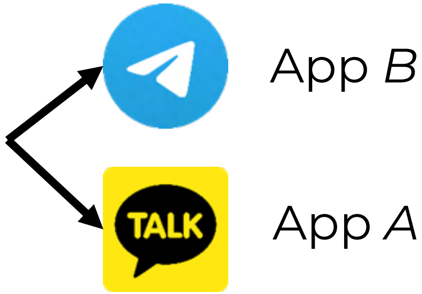
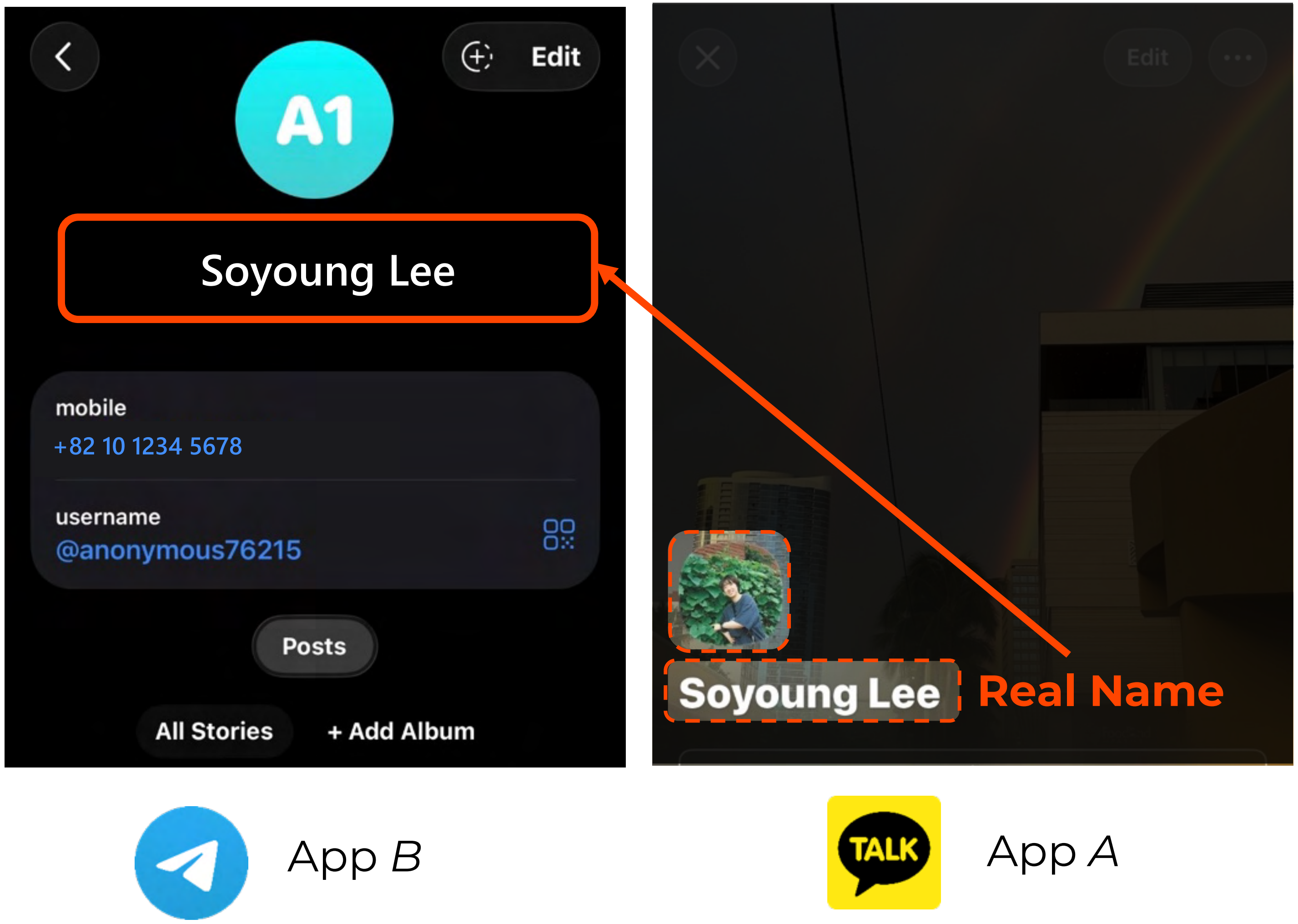
Soyoung's Account!





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- Random samples 1,000 phone numbers

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88 profiles

40 anonymous (45%)

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→

22 real-name profiles
(**55%** success rate)

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42 hidden profiles

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40 anonymous (45%) → 22 real-name profiles (**55%** success rate)

42 hidden profiles → 30 real-name profiles (**71%** success rate)

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Why?

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- Random samples 1,000 phone numbers

88 profiles
40 anonymous (45%) → 22 real-name profiles (**55%** success rate)

42 hidden profiles → 30 real-name profiles (**71%** success rate)

5 hidden profiles → 4 real-name profiles (**80%** success rate)

Why?

Chain 1: De-anonymization via cross-platform linking

- Random samples 1,000 phone numbers

When a platform dominates a country, attacks become highly effective

Why?

88 pro

40 anony

42 hidden profiles

(**71%** success rate)

5 hidden profiles

4 real-name profiles
(**80%** success rate)

Chain 2: Untargeted tracking campaign

- Targeting 5,000 phone numbers
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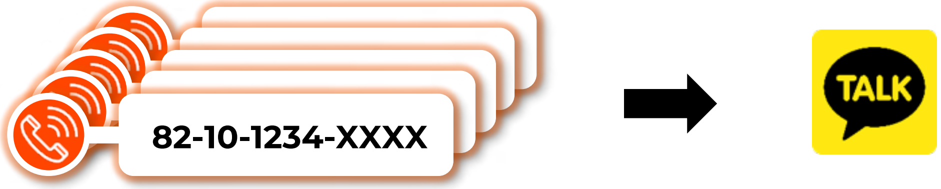

5,000 phone numbers

KakaoTalk

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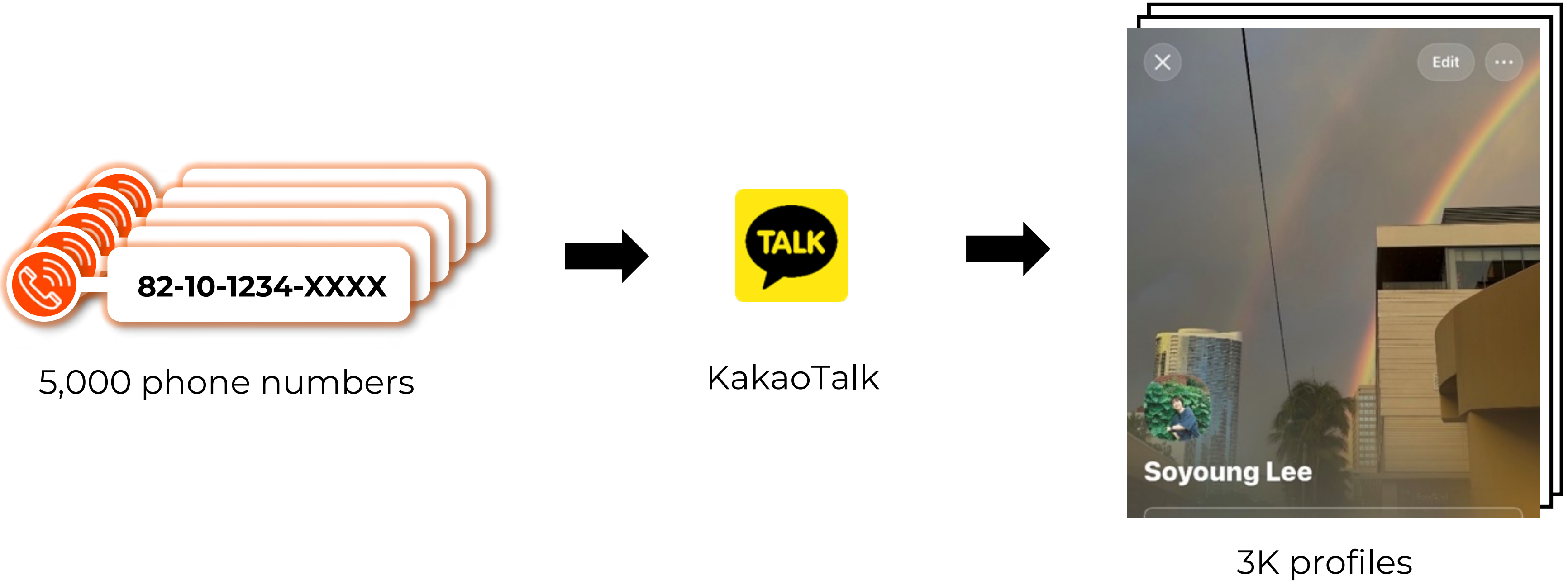

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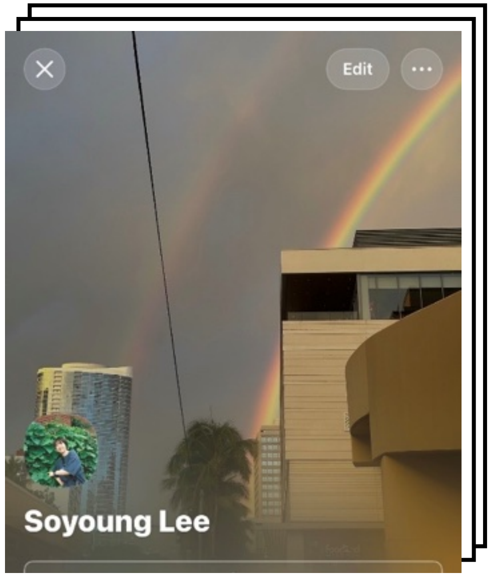

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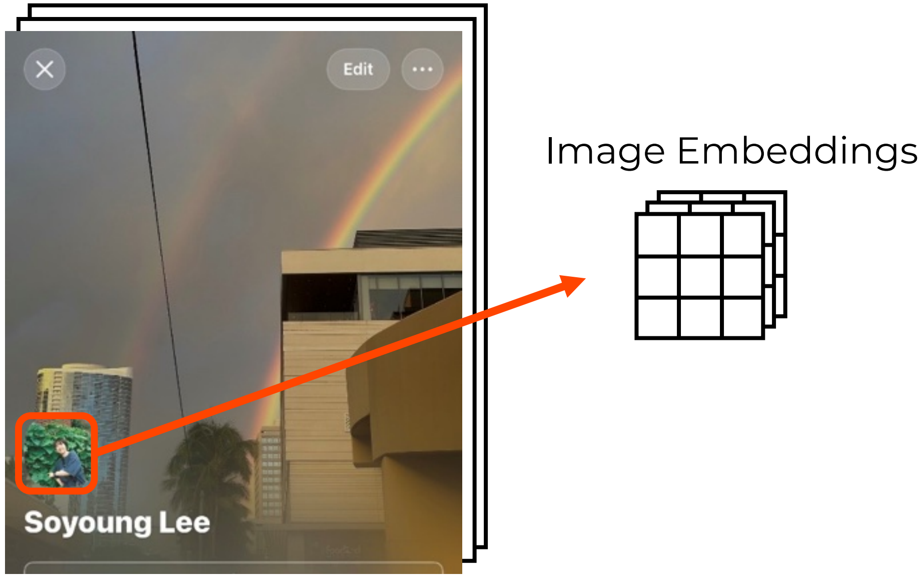

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Find target

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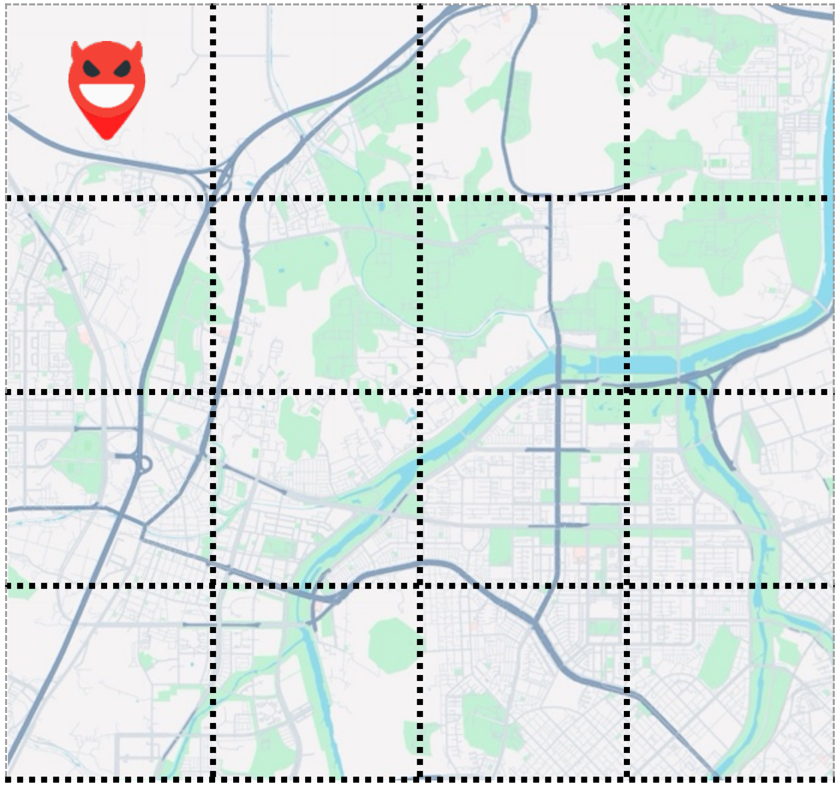

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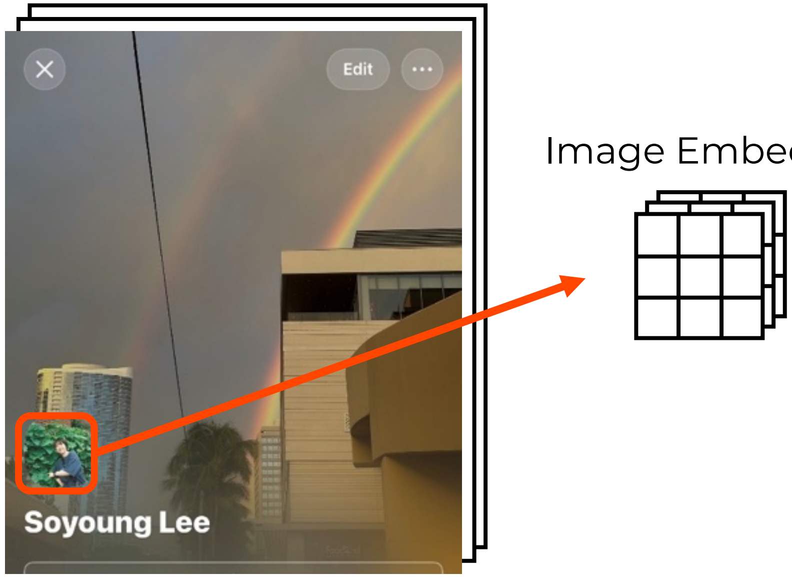

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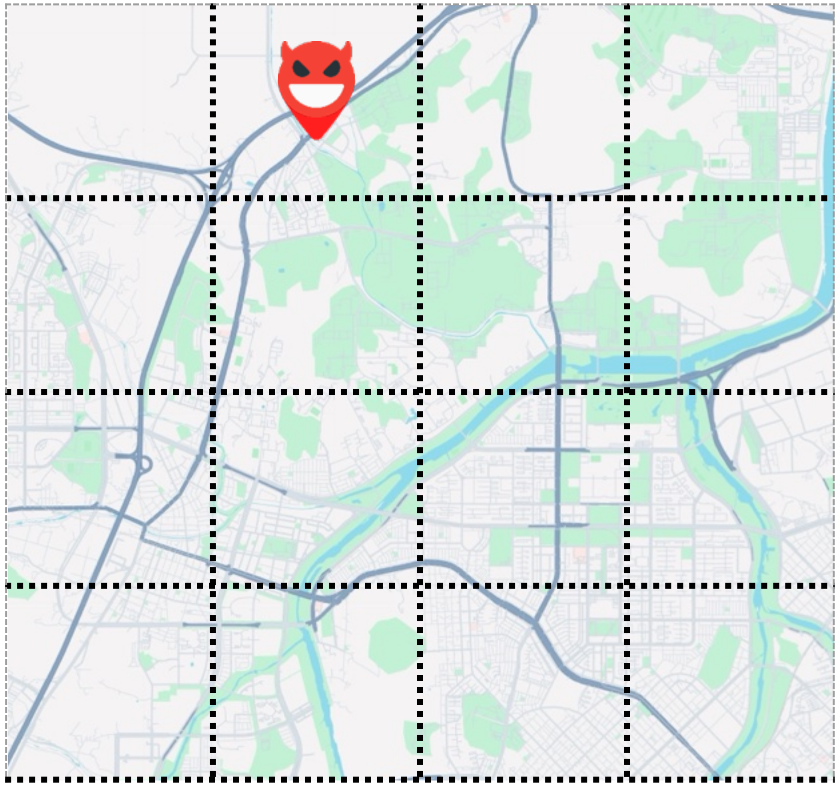

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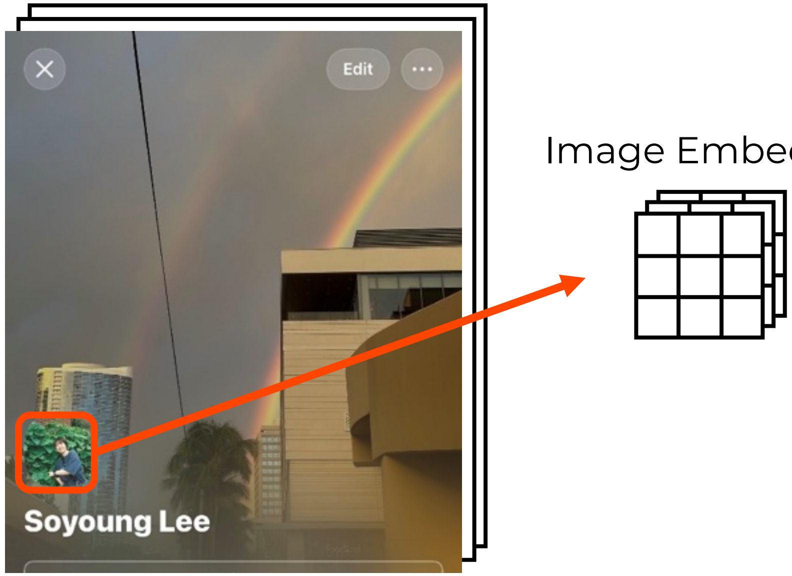

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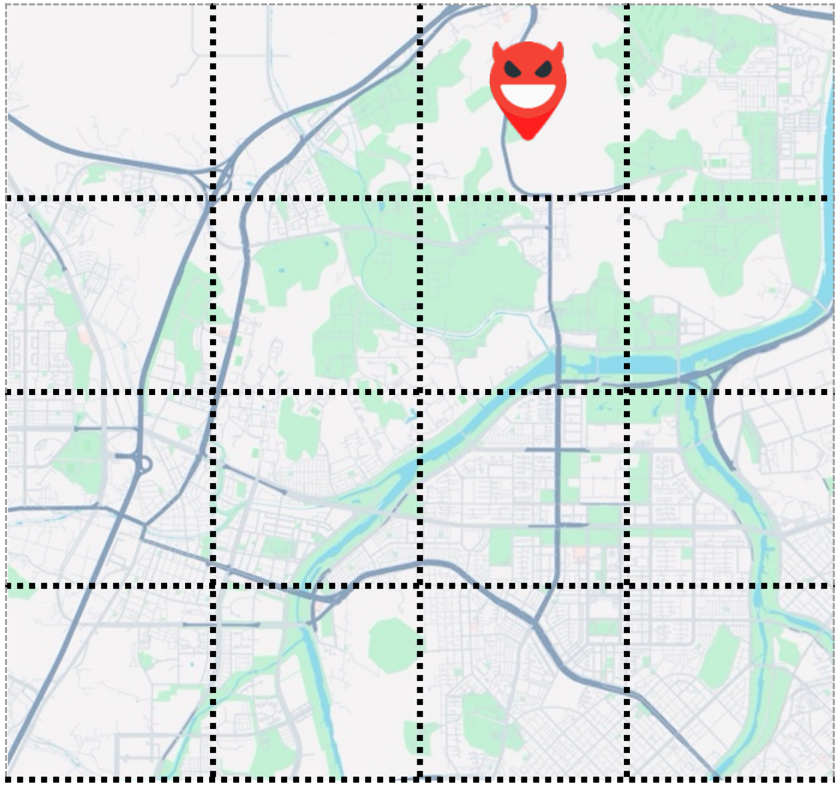

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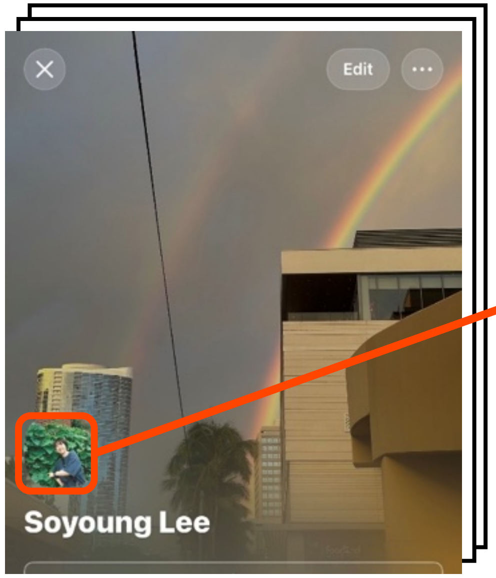

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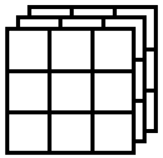
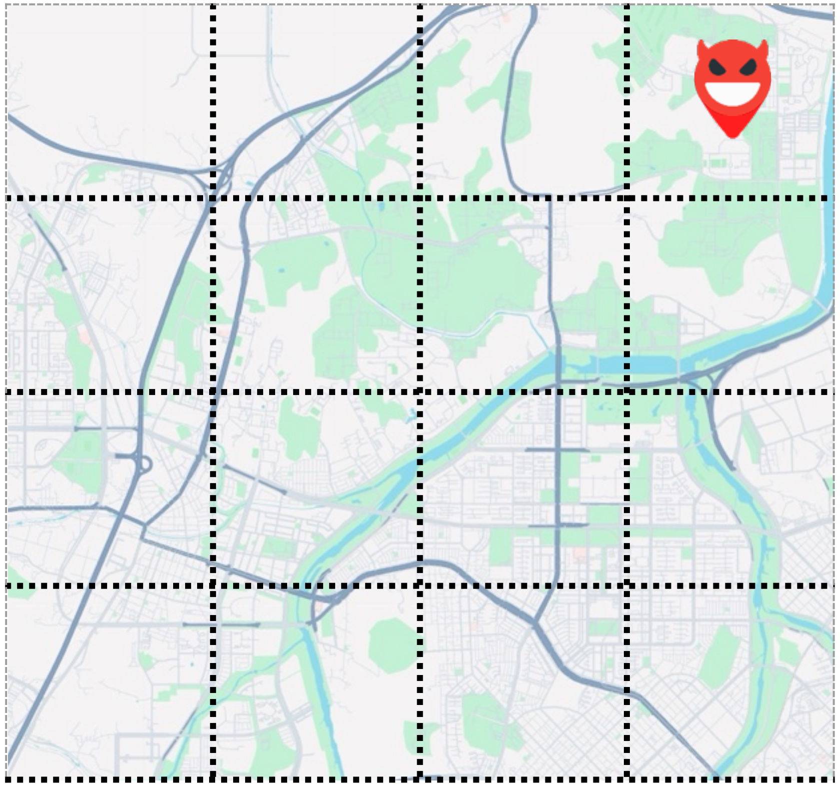
Image Embeddings





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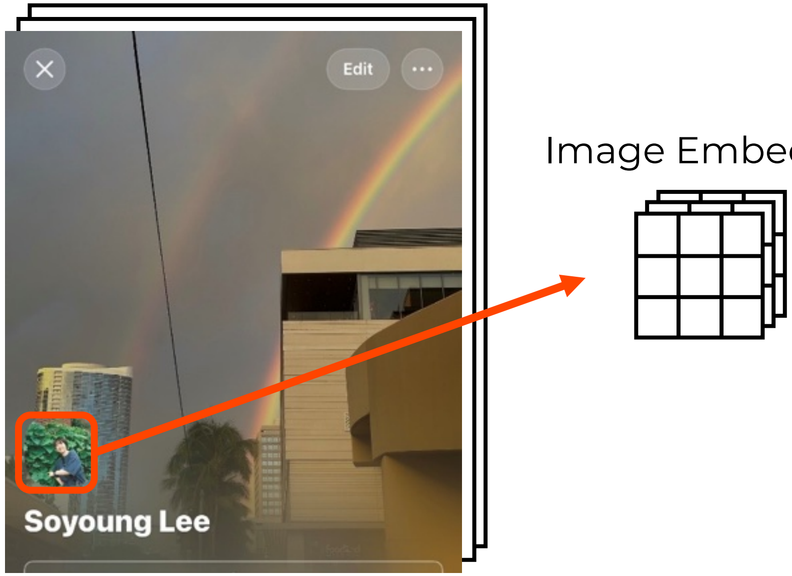

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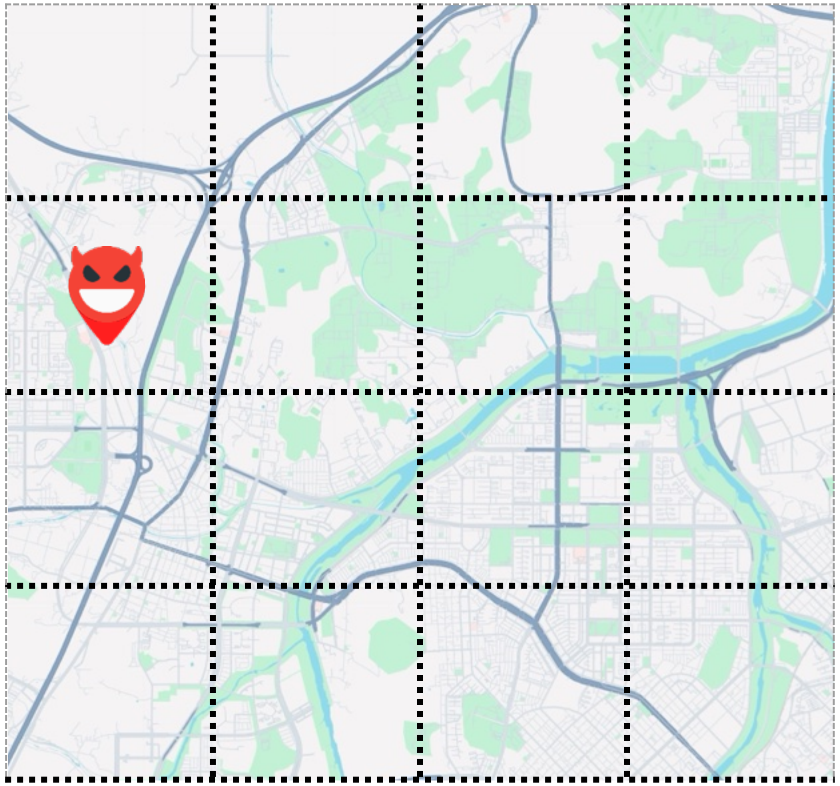

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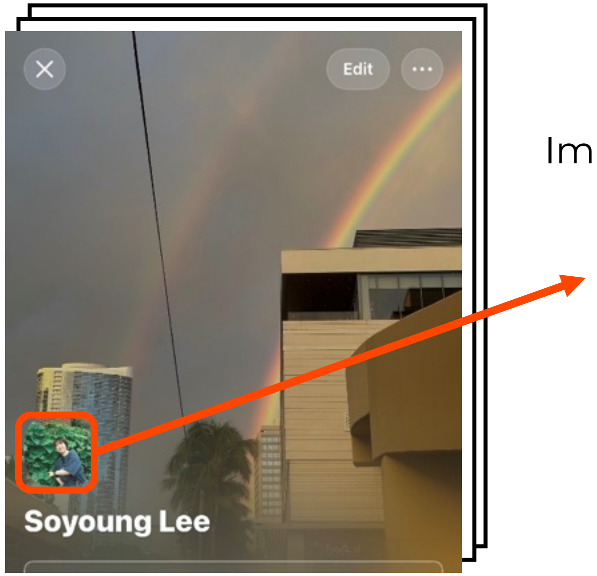

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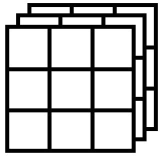

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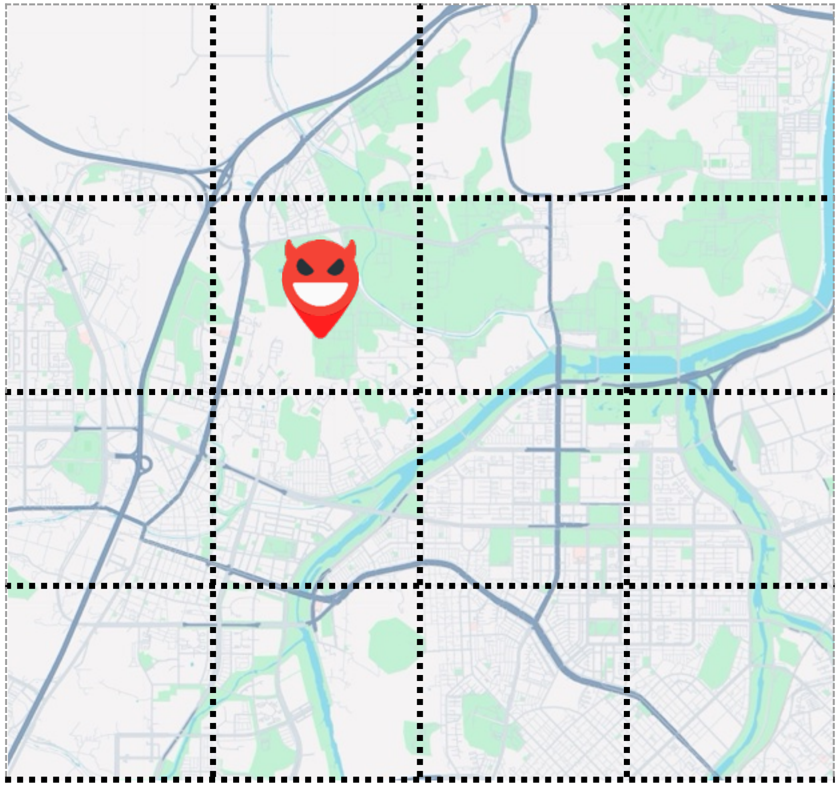

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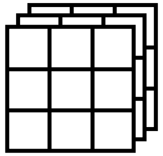

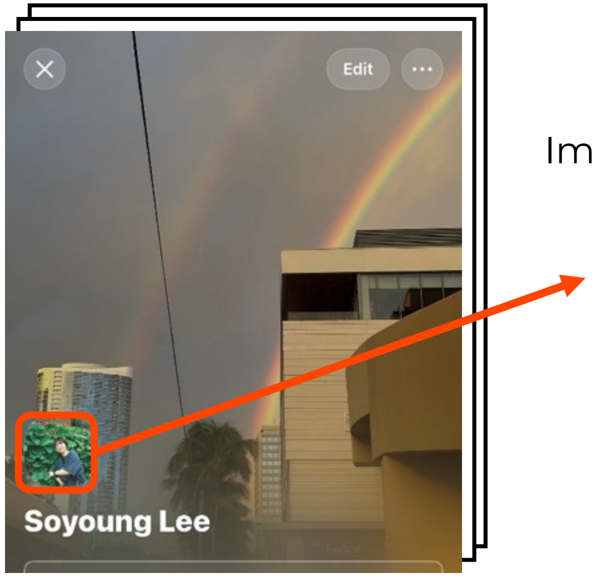

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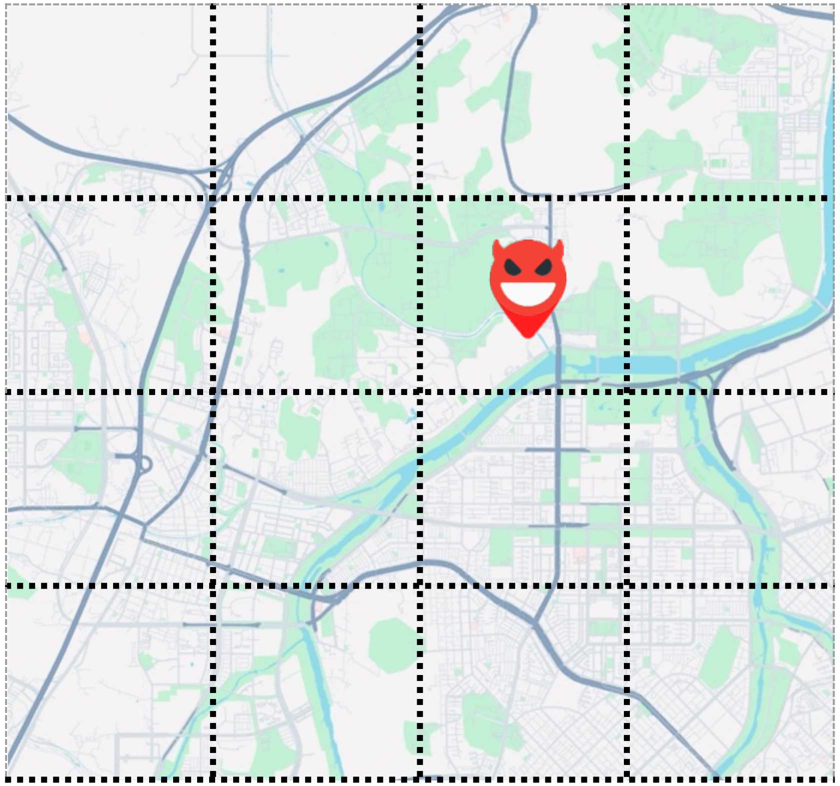

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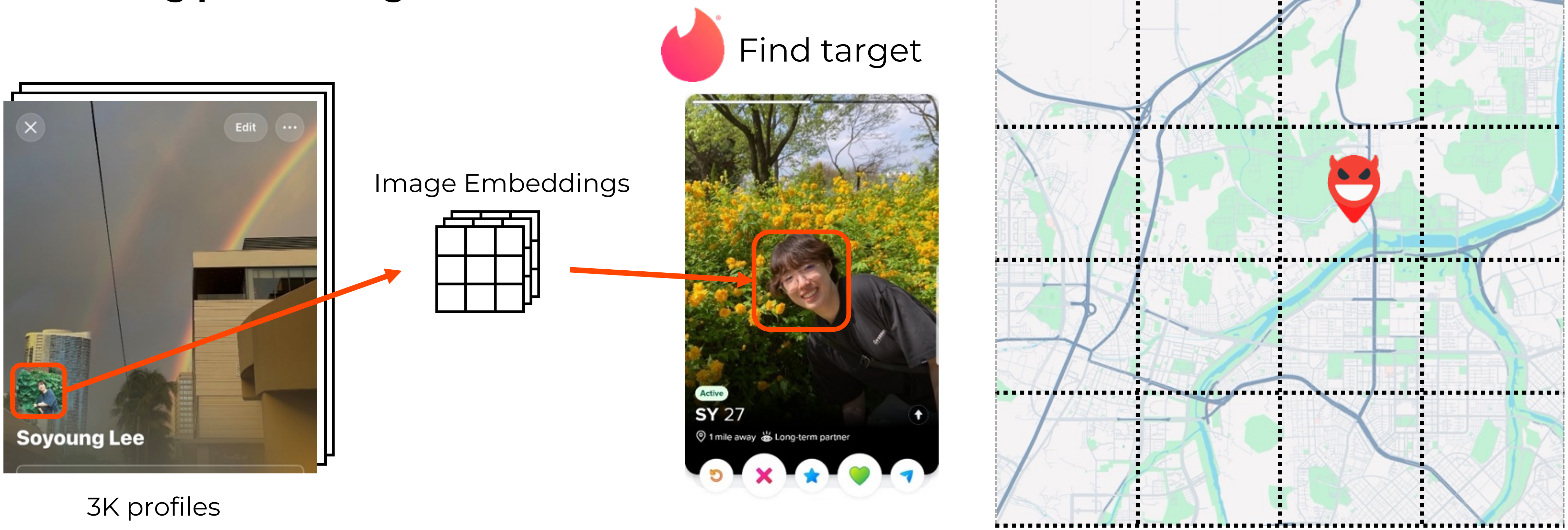

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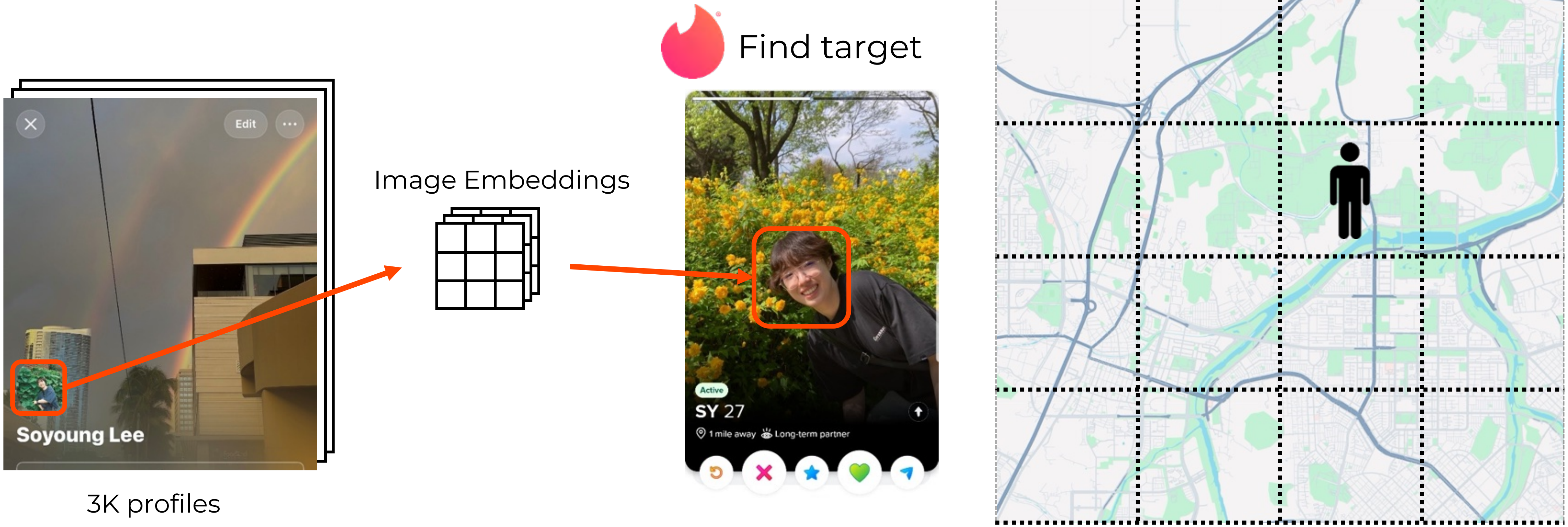

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- Goal: Finding people in a certain area, two victims in City A

(two authors)

3. Location Inference

Find target

Chain 2: Untargeted tracking campaign

- Targeting 5,000 phone numbers
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3. Location Inference

- 1-mile boundary algorithm

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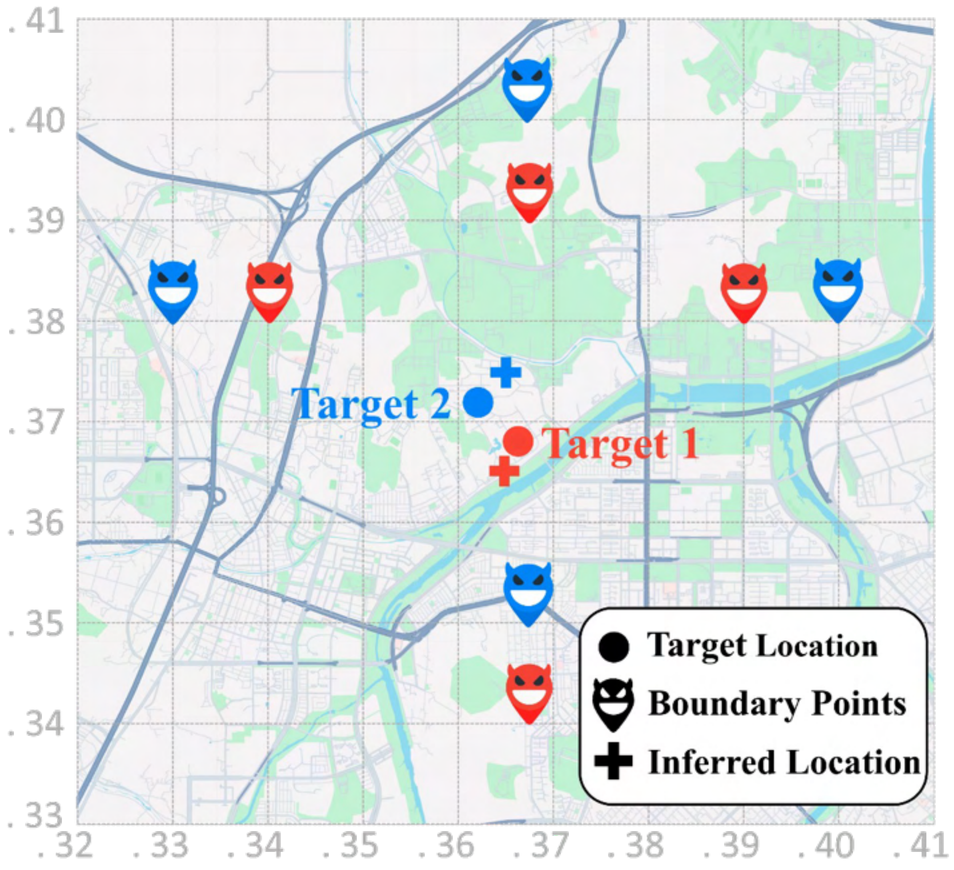

Chain 2: Untargeted tracking campaign

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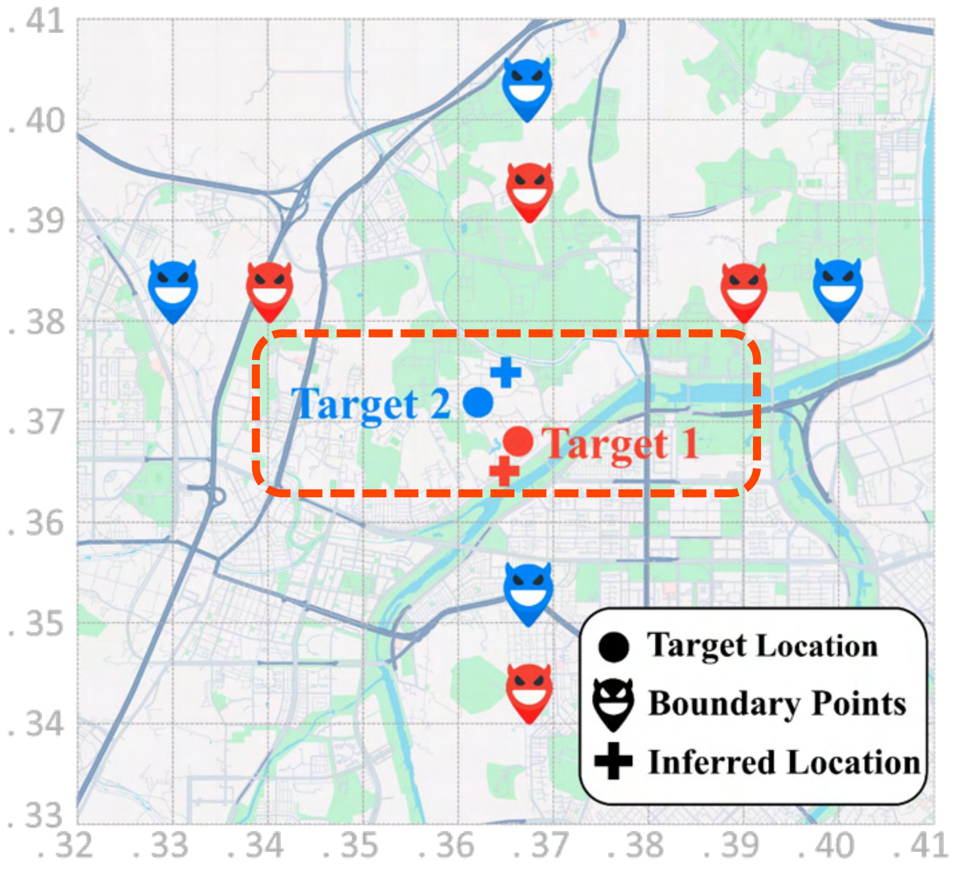
3. Location Inference

- 1-mile boundary algorithm
- Successfully find two target users (336m and 418m errors)



Mitigation – Contact Discovery

1. Query throttling
    - Set a strict daily limit (e.g., under 100 registrations)
        → Disrupt the service (address-book sync)
        → Adversaries can easily bypass this using multiple accounts

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Brute-force **contact discovery** attempts

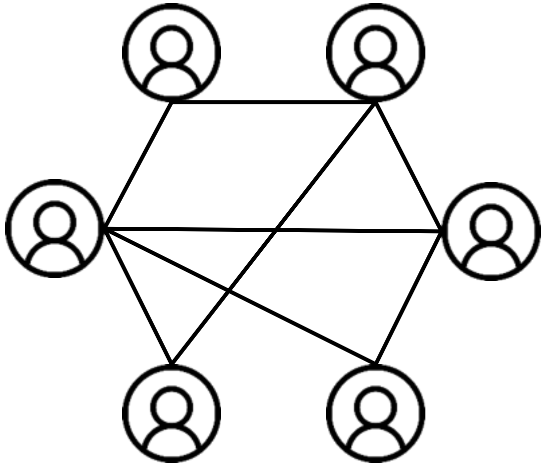
vs.

Registration attempts from **benign users**

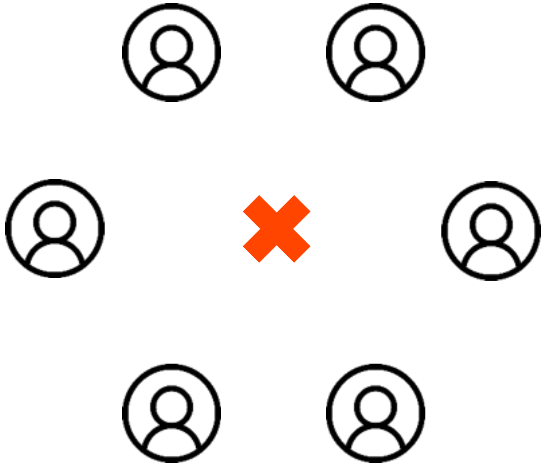
Mitigation – Contact Discovery

2. Social Circles

- Structural difference in social relationships



Benign user's address book



Adversary's address book
(Random generated)

Mitigation – Contact Discovery

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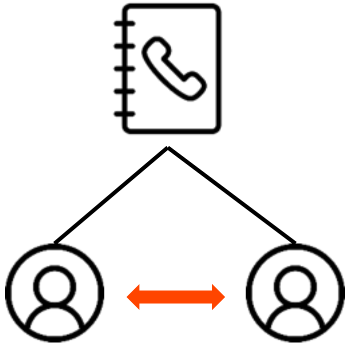

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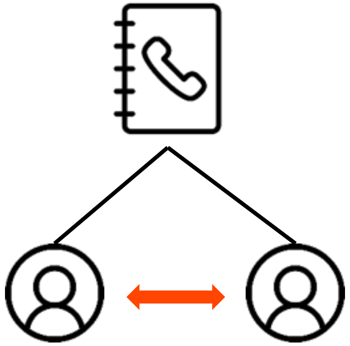

24%
(Mislove *et al.*, 2007)

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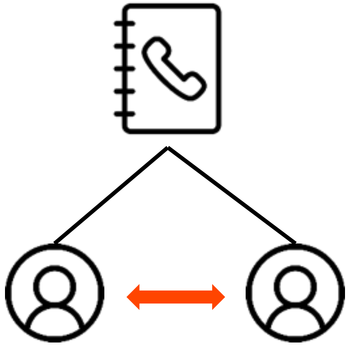

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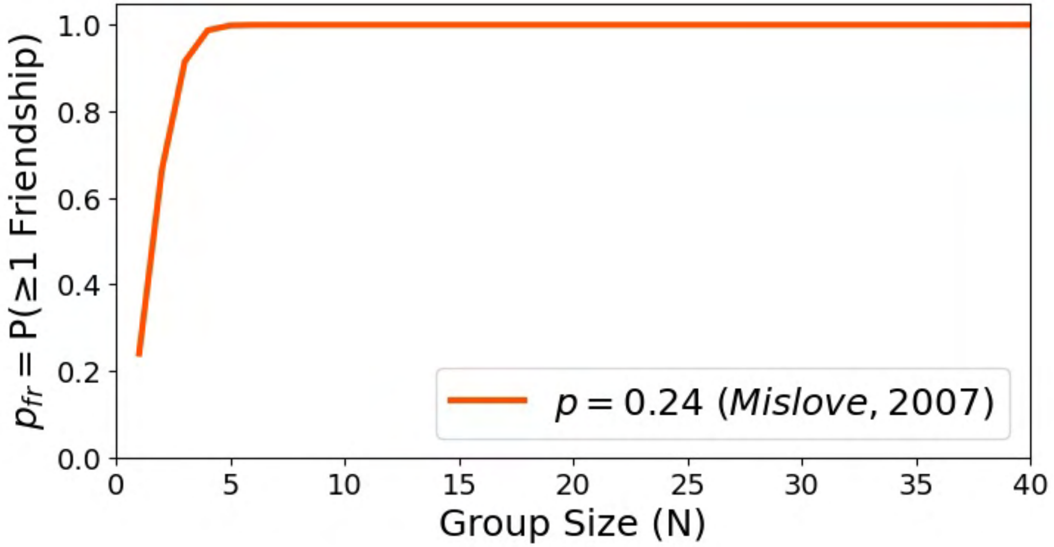

Simulation Results

Mitigation – Contact Discovery

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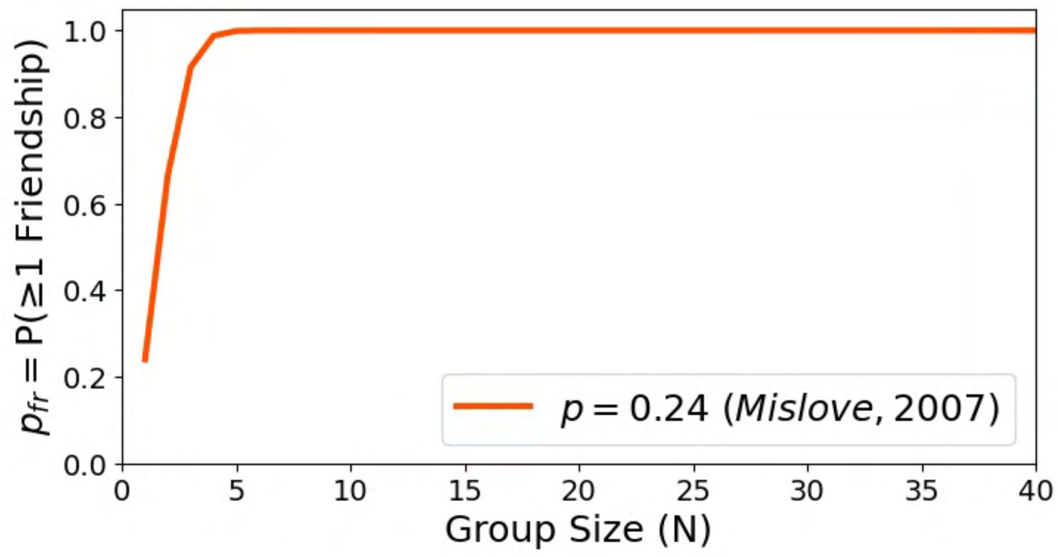

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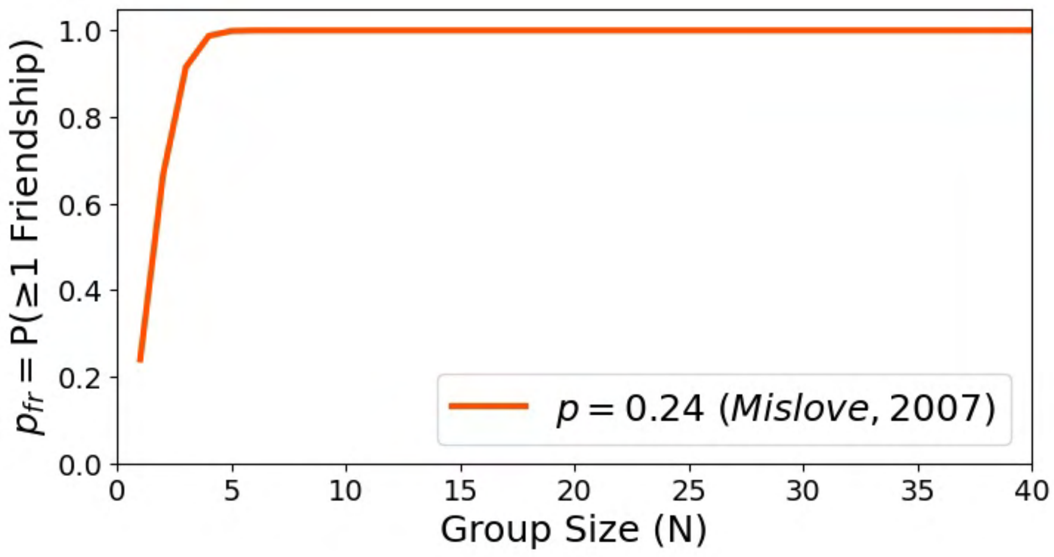

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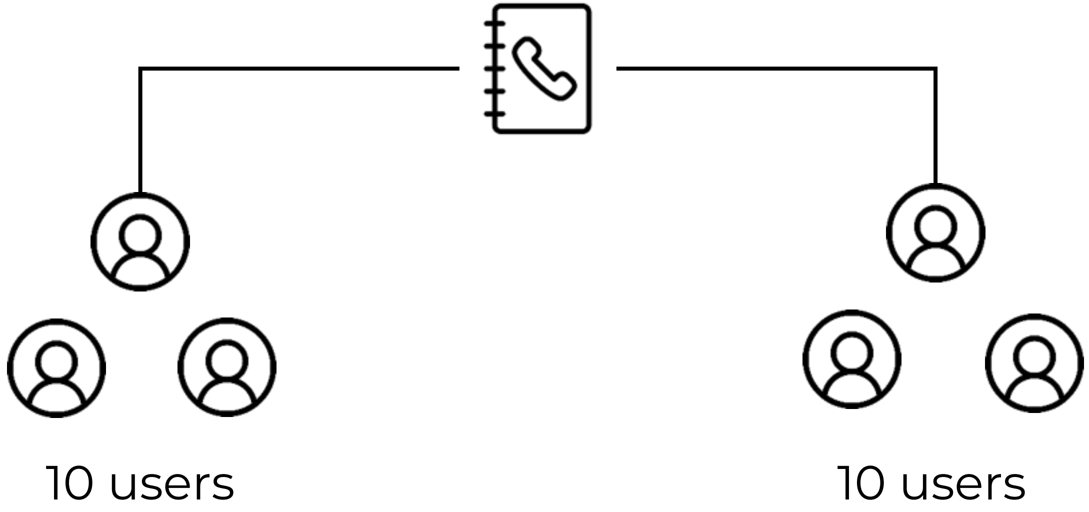

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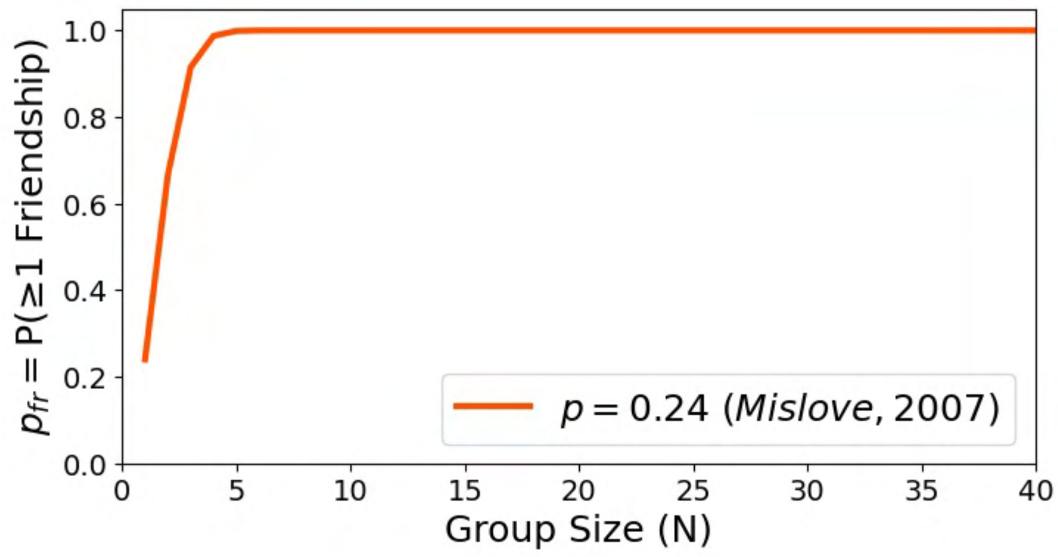

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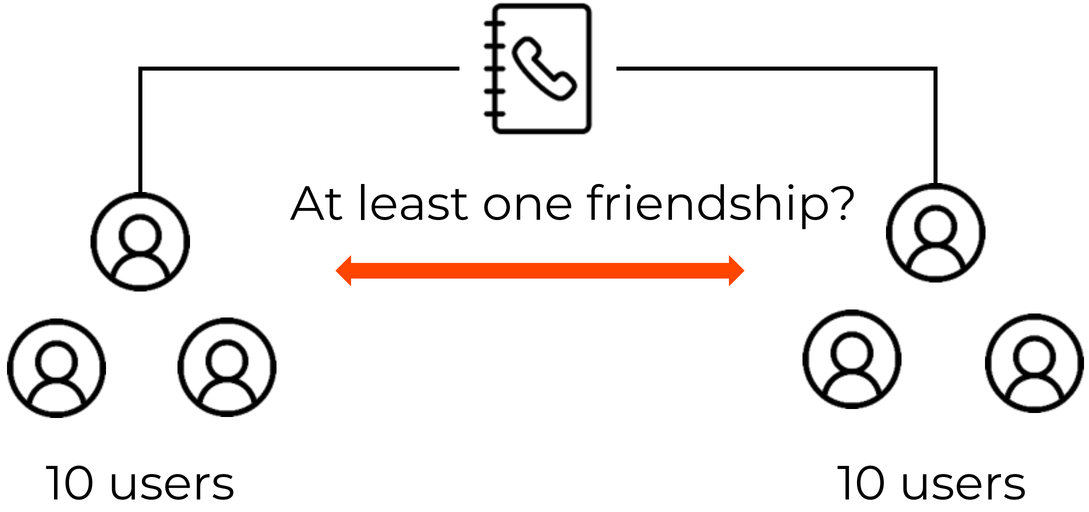

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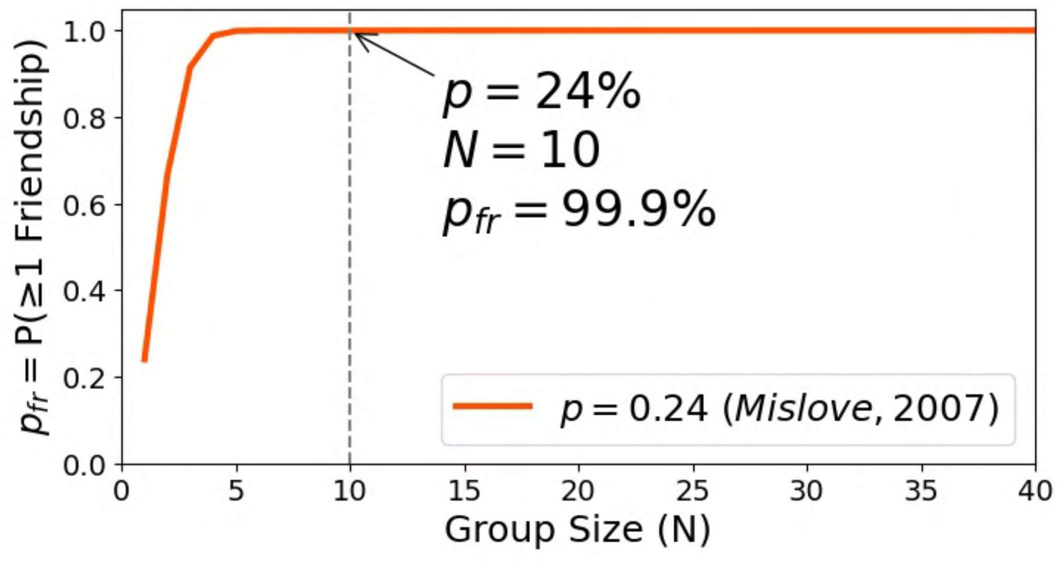

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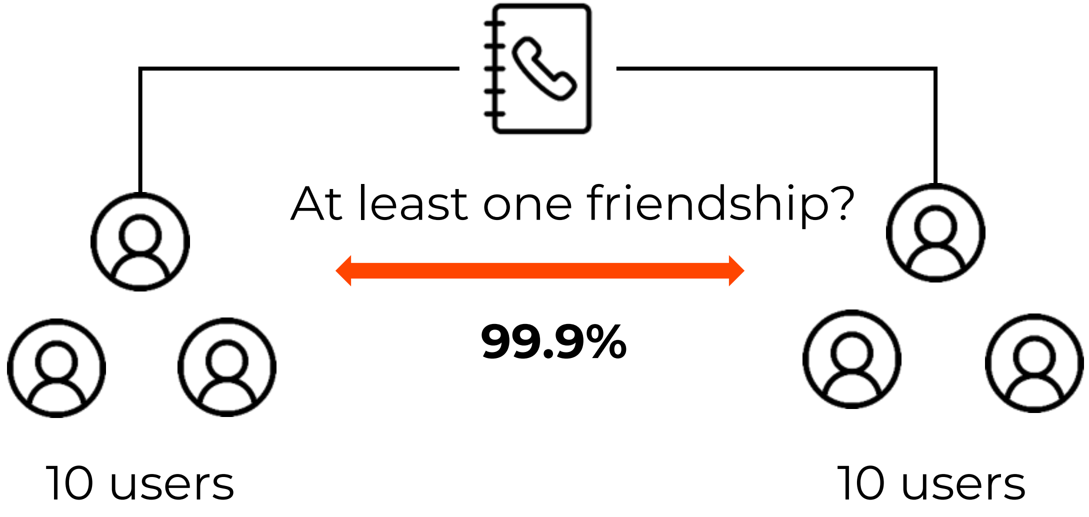

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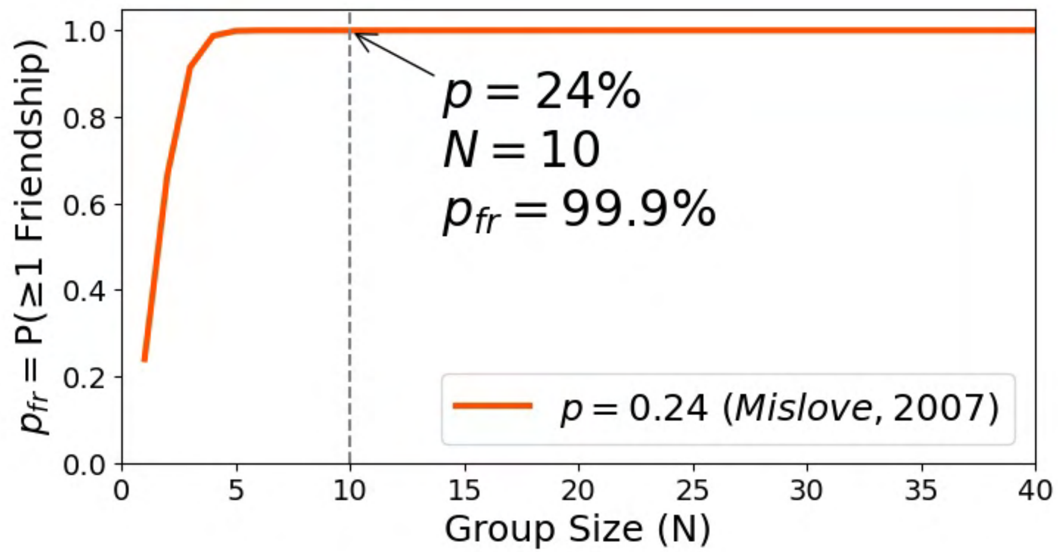
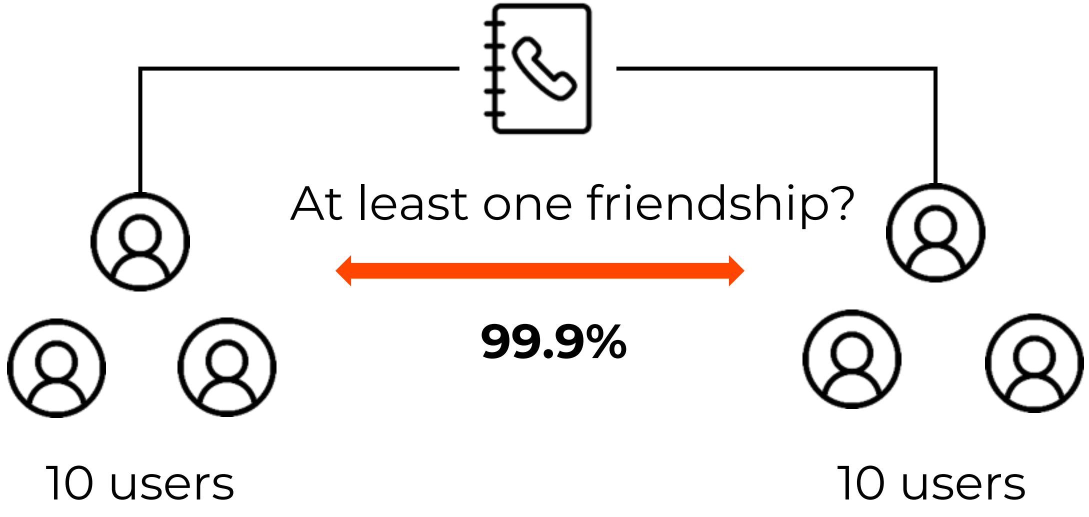
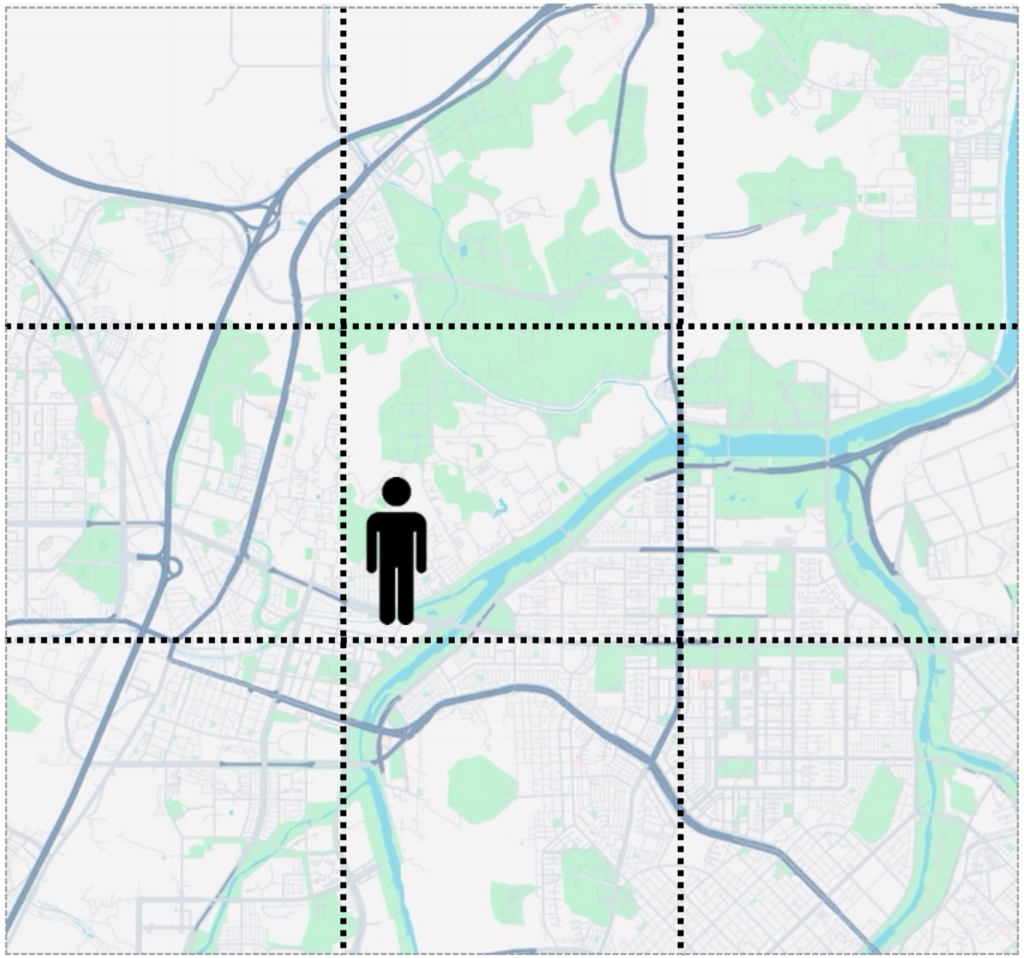




Identifying malicious attempts is possible by leveraging social circles

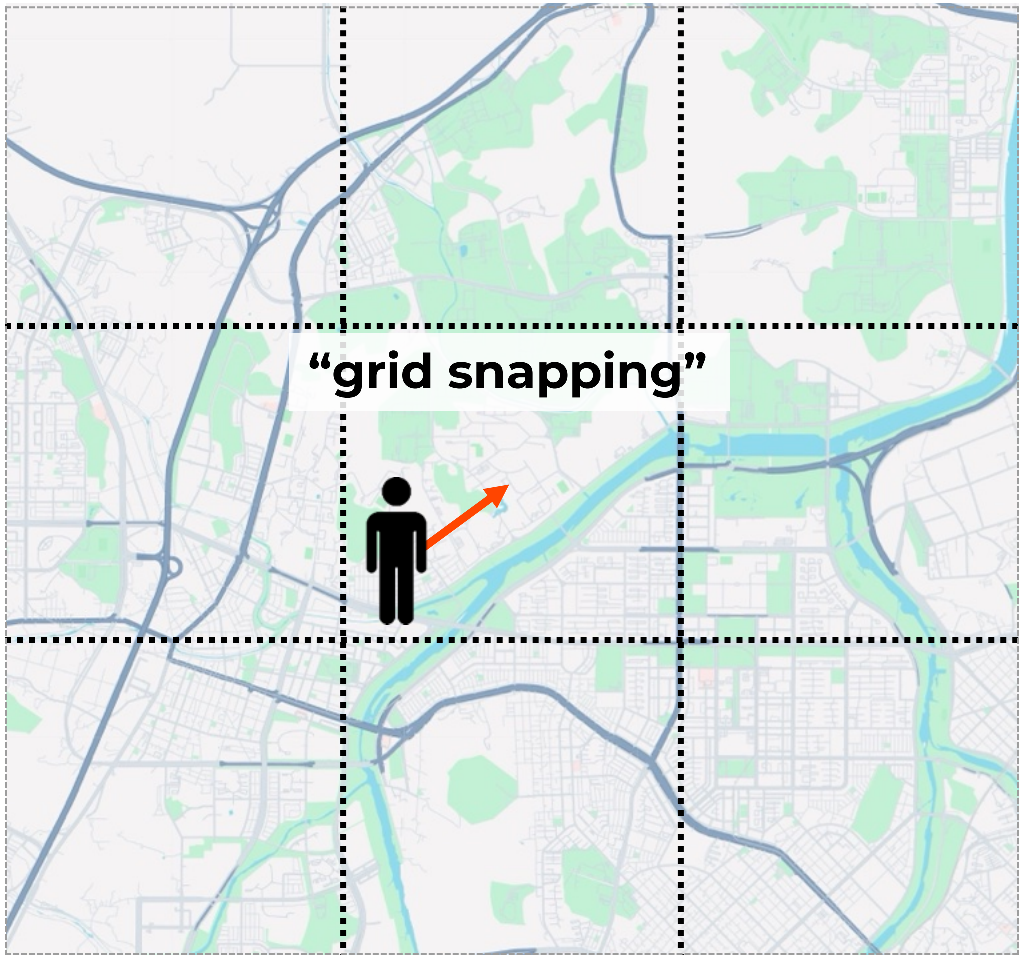
Mitigation – Location Inference

- Grid snapping



Mitigation – Location Inference

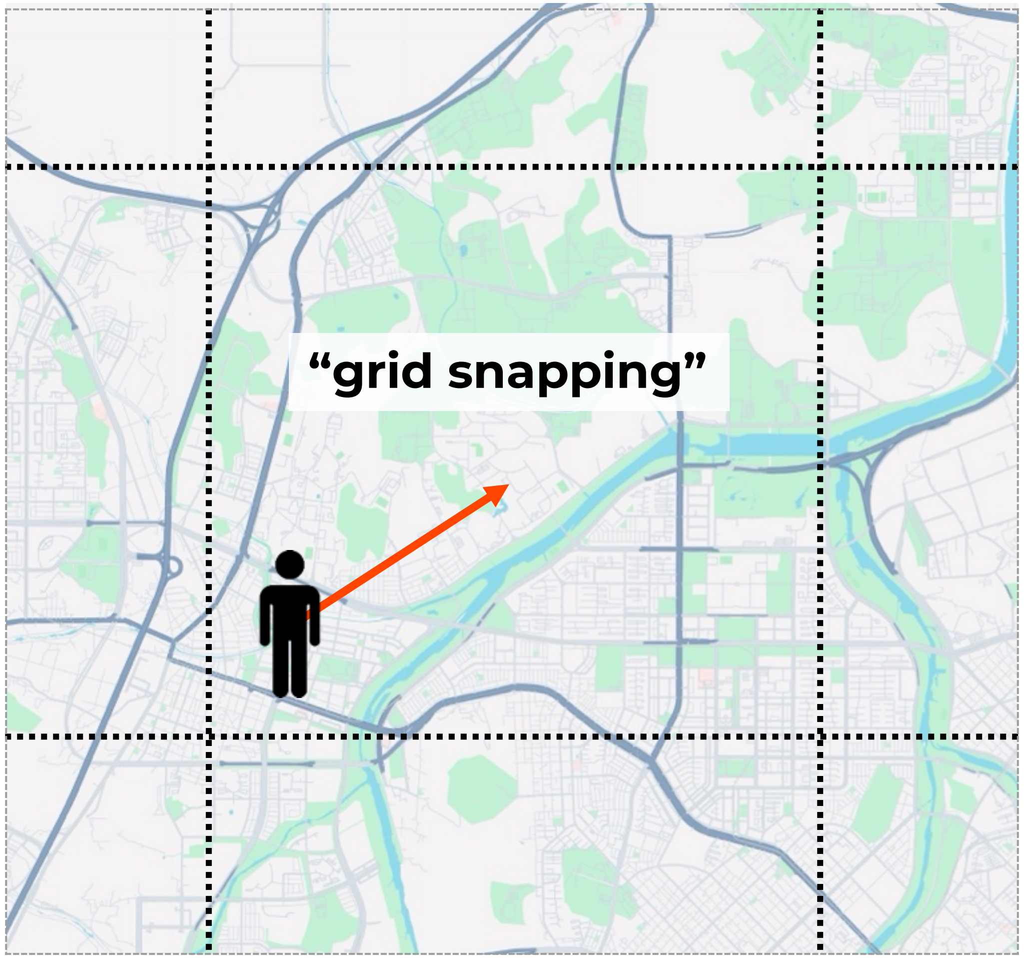
- Grid snapping
  - Mapping to the center point



Mitigation – Location Inference

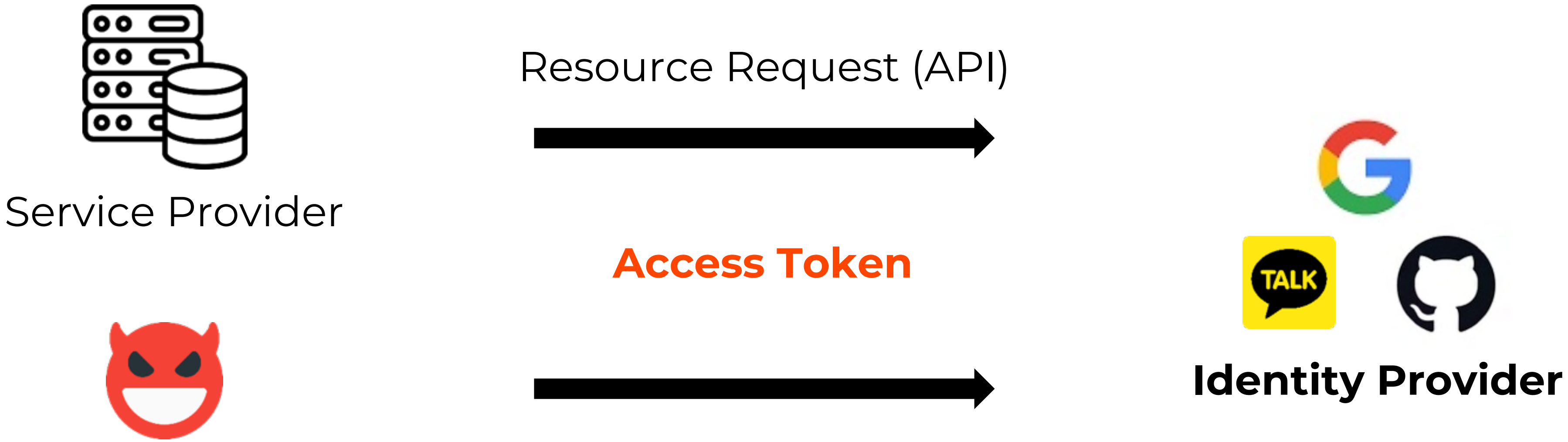
- Grid snapping
  - Mapping to the center point
  - Increasing the grid size increases the error margin

Tradeoff: Privacy vs. Usability



Mitigation – OAuth Token

- Using Mutual TLS protocol



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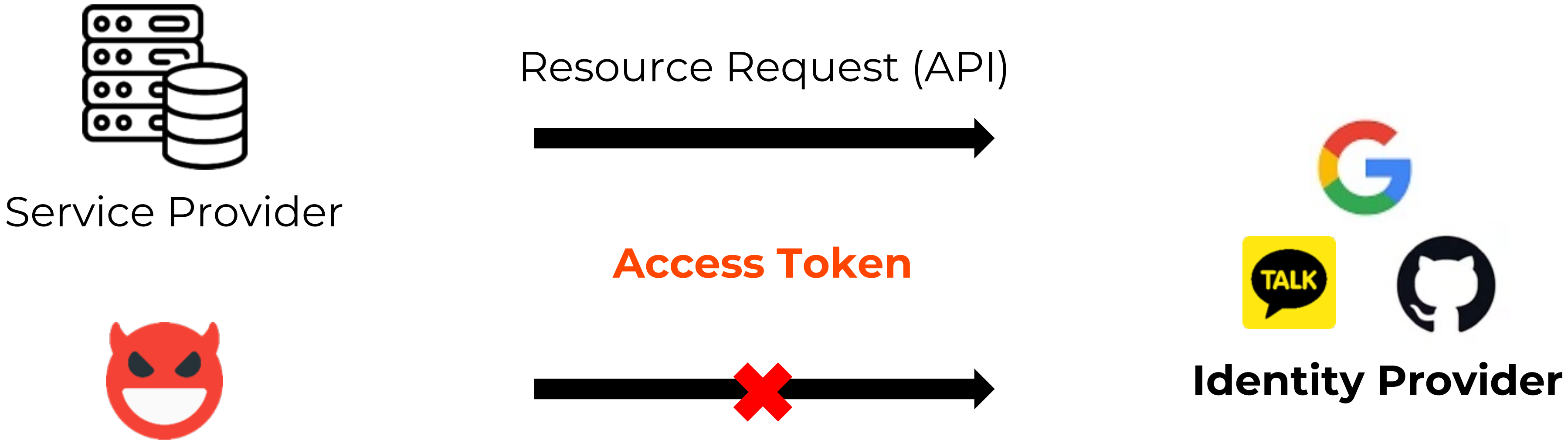

Conclusion

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Evaluate **privacy attacks** and propose concrete **end-to-end attacks**

1. Contact Discovery
2. SSO Linking
3. Location Inference

De-anonymization

Trajectory Tracking

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Privacy can fail by **composition** when attacks combine across apps

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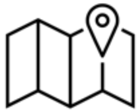

Trajectory Tracking

Privacy can fail by **composition** when attacks combine across apps

Geographically dominant messengers pose **privacy risks**.

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Trajectory Tracking

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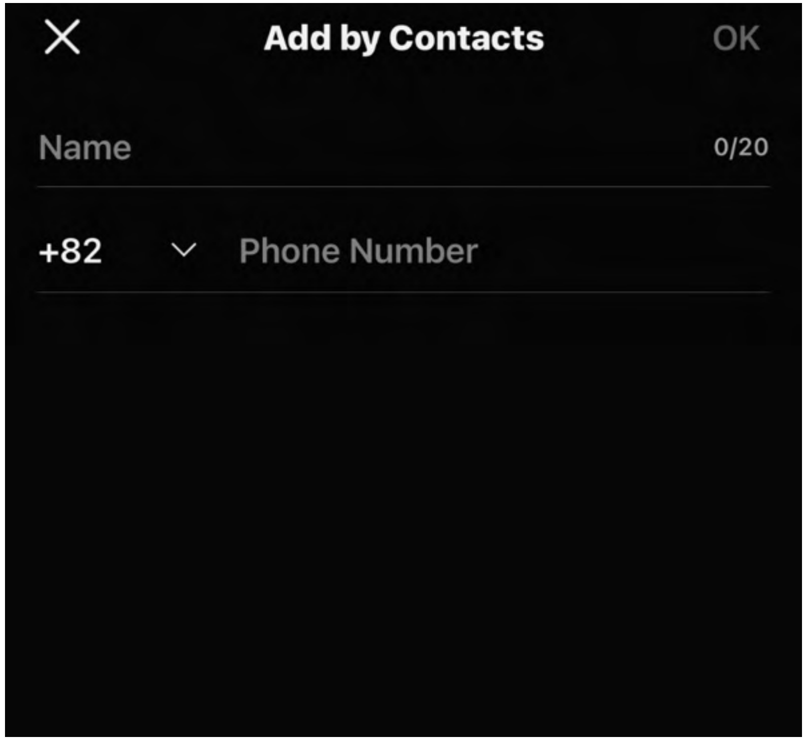
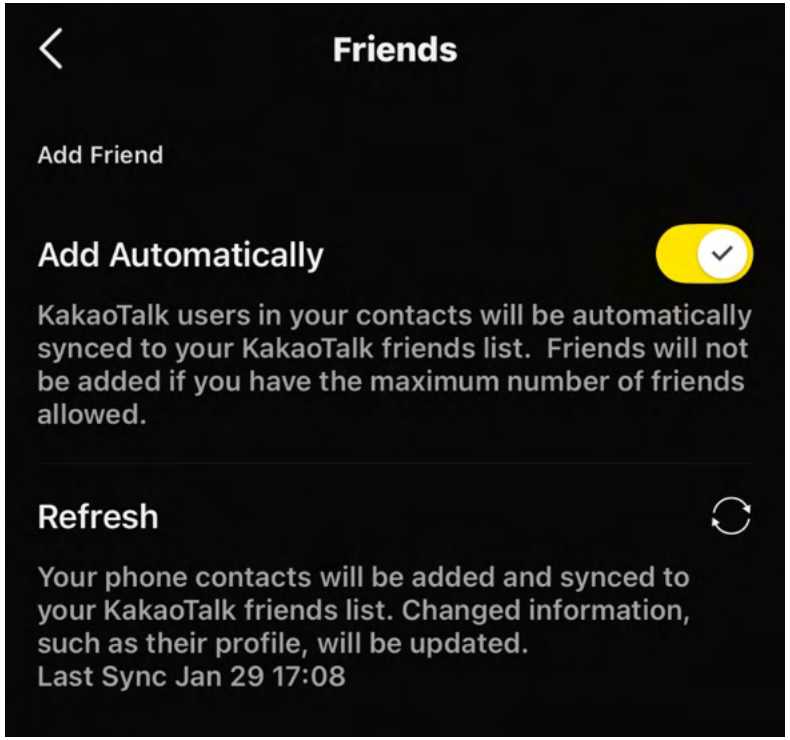
Extra slides

Attack 1: Contact discovery abuse (KakaoTalk)

- Friend Registration



1. Manual Registration



2. Address-book syncing

Attack 1: Contact discovery abuse (KakaoTalk)

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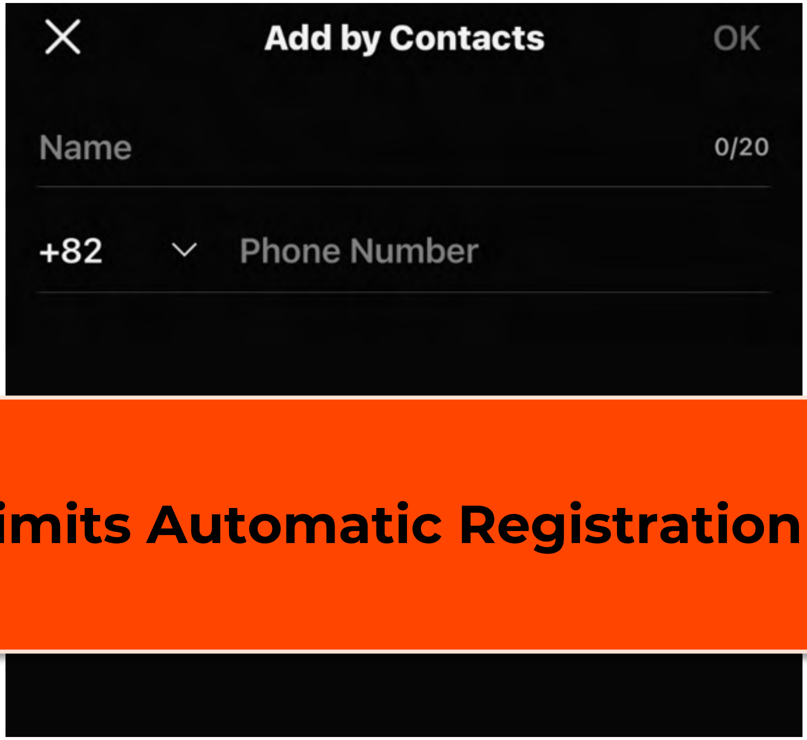

Limits Automatic Registration

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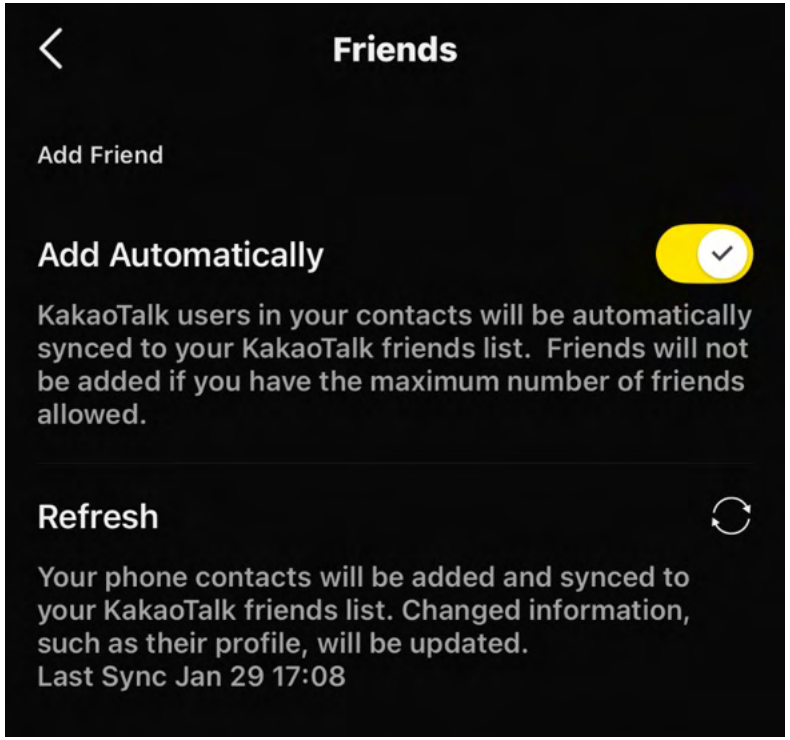

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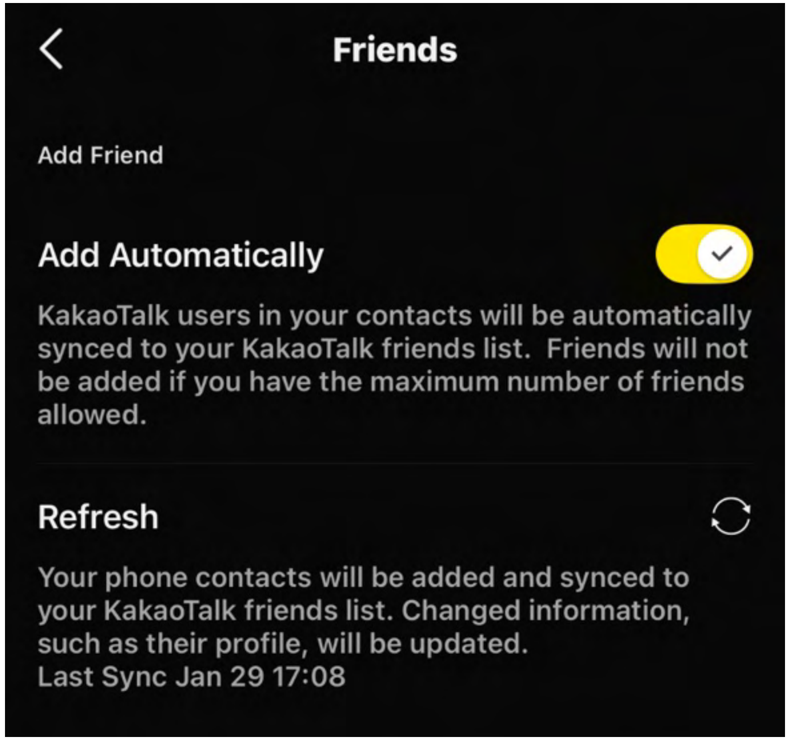

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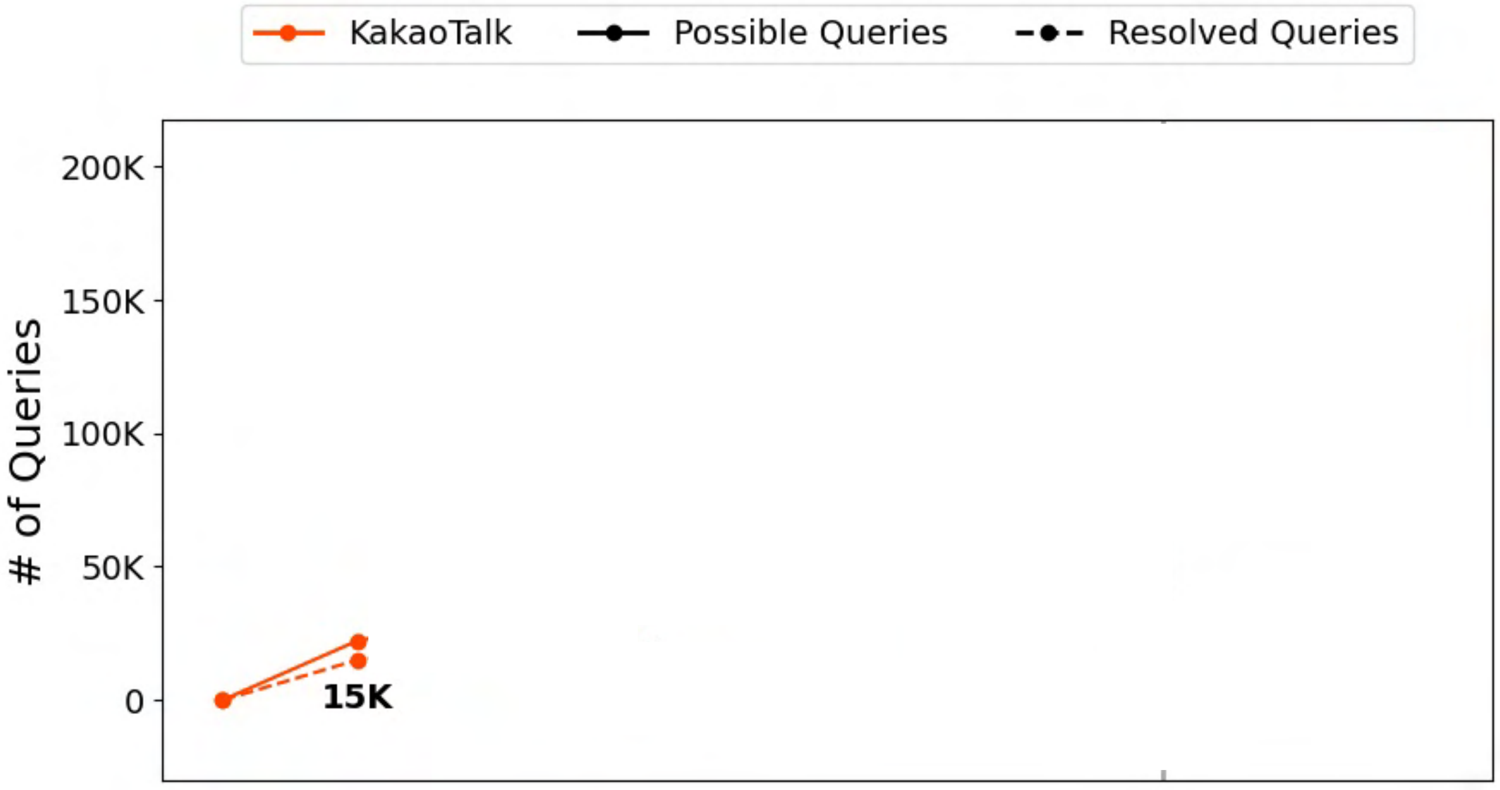

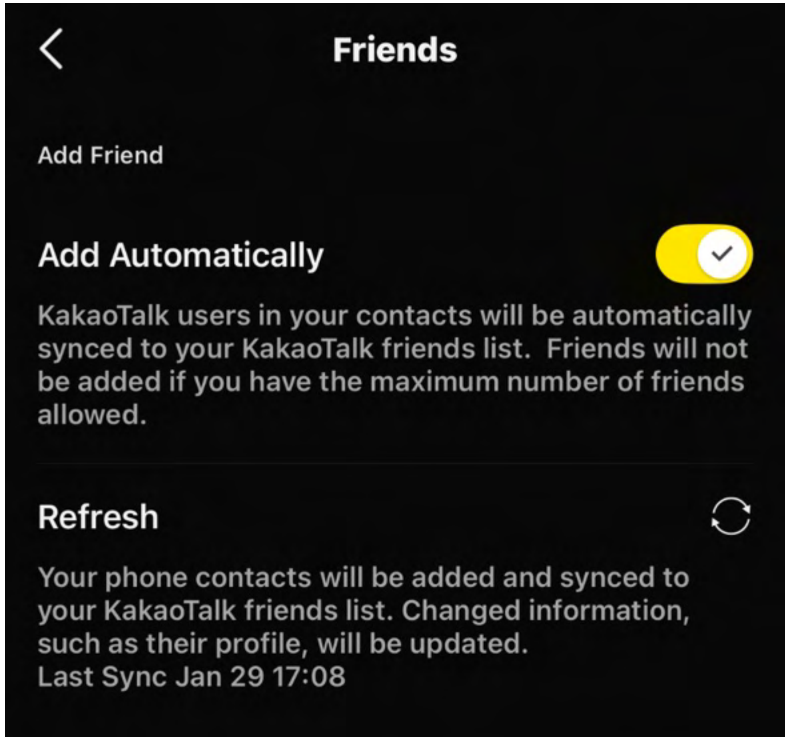

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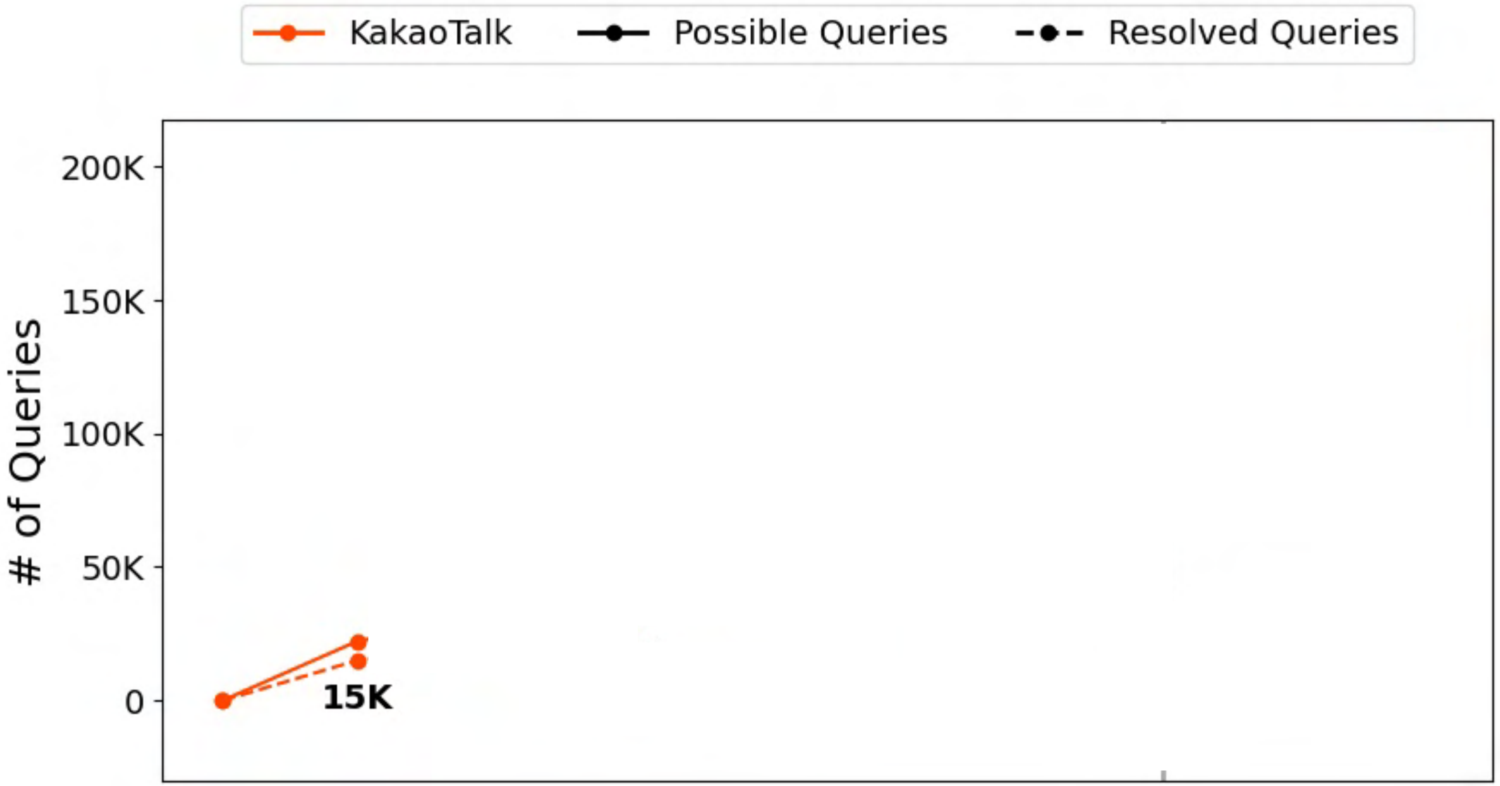

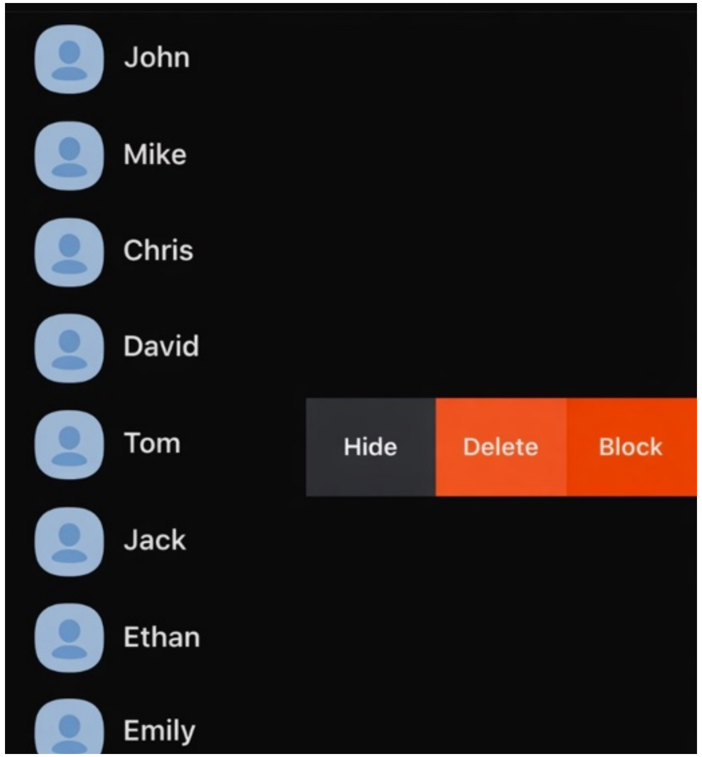

2. Deleting Friends

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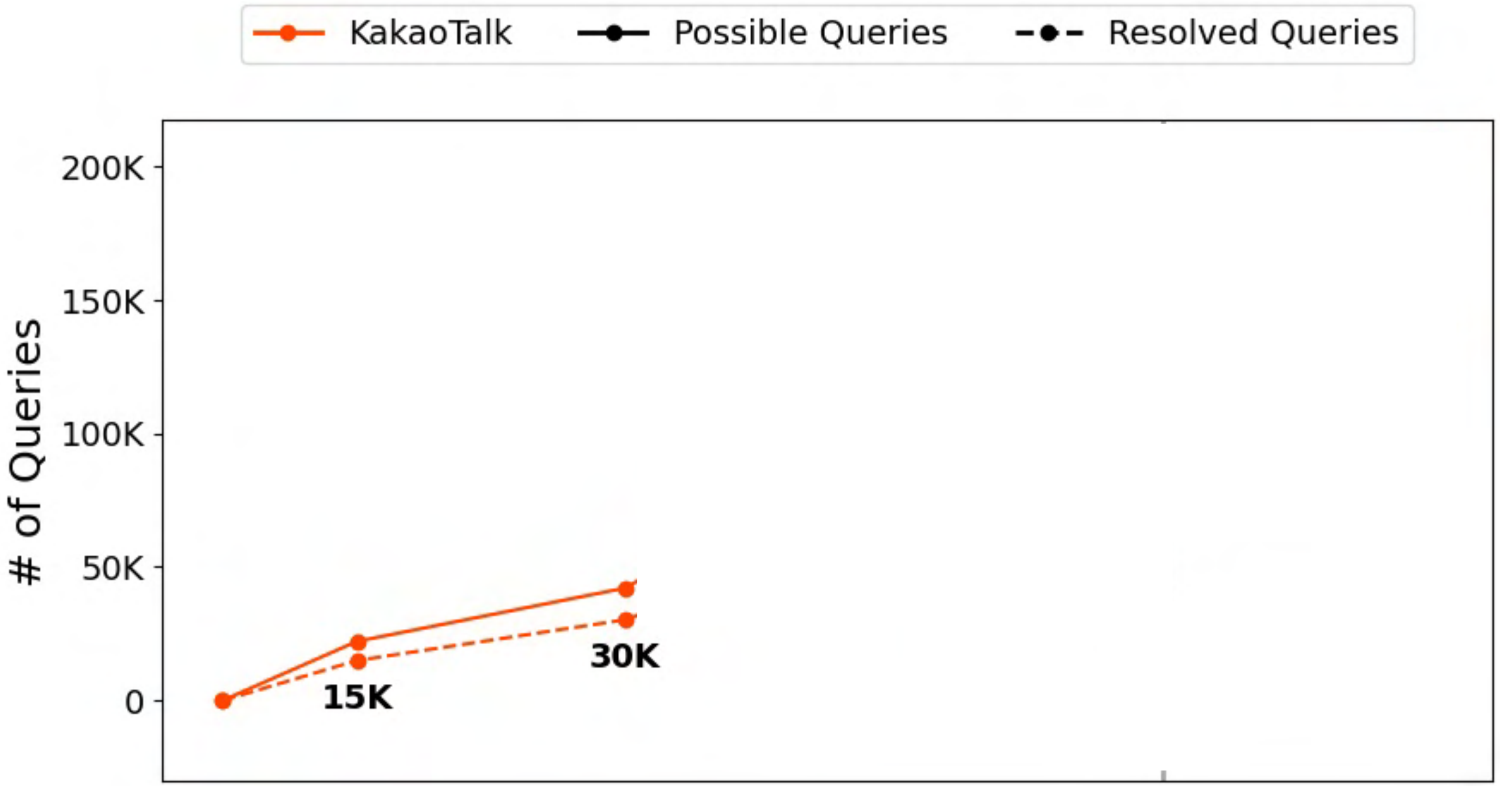

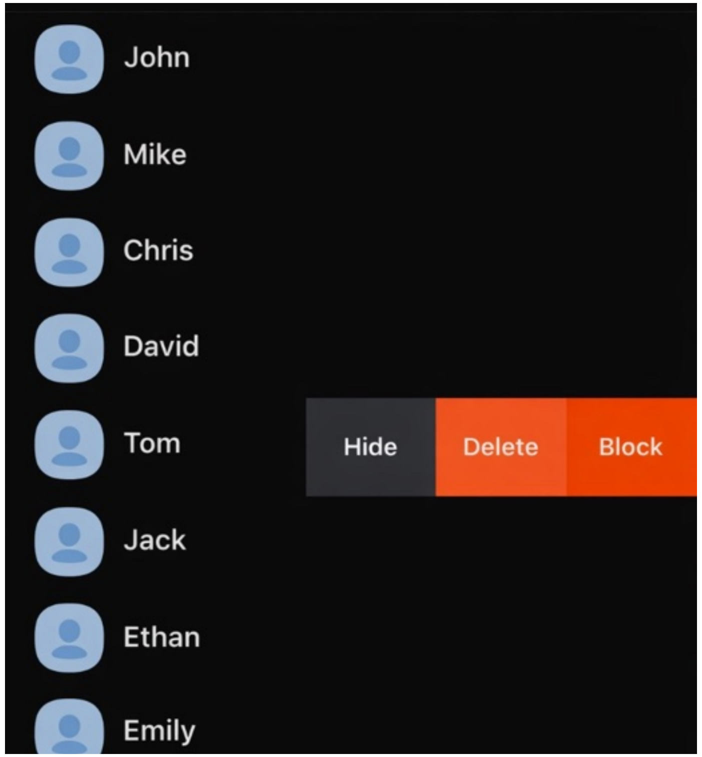

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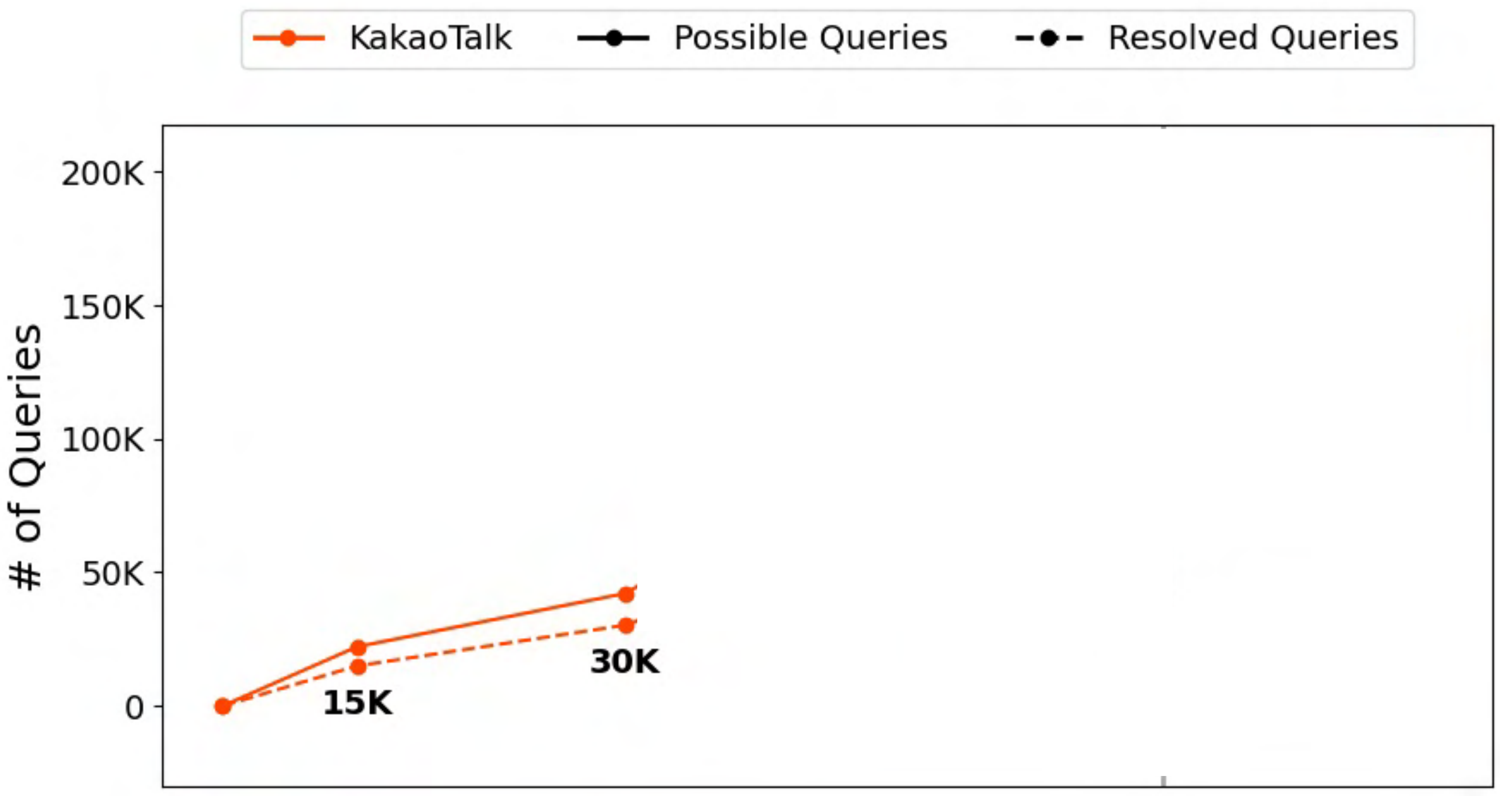

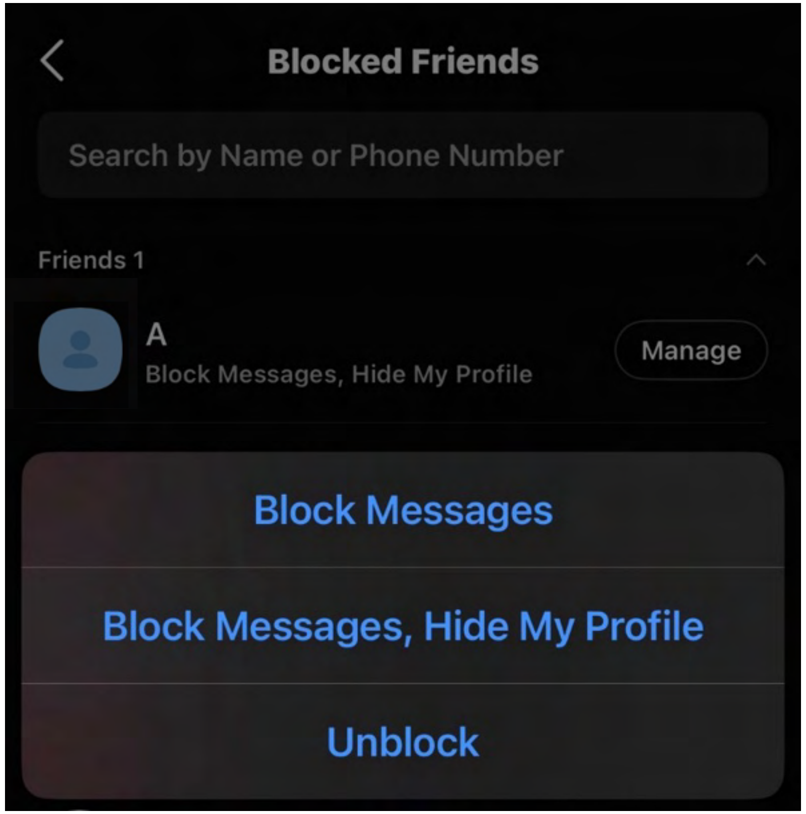

3. Block & Unblock Friends

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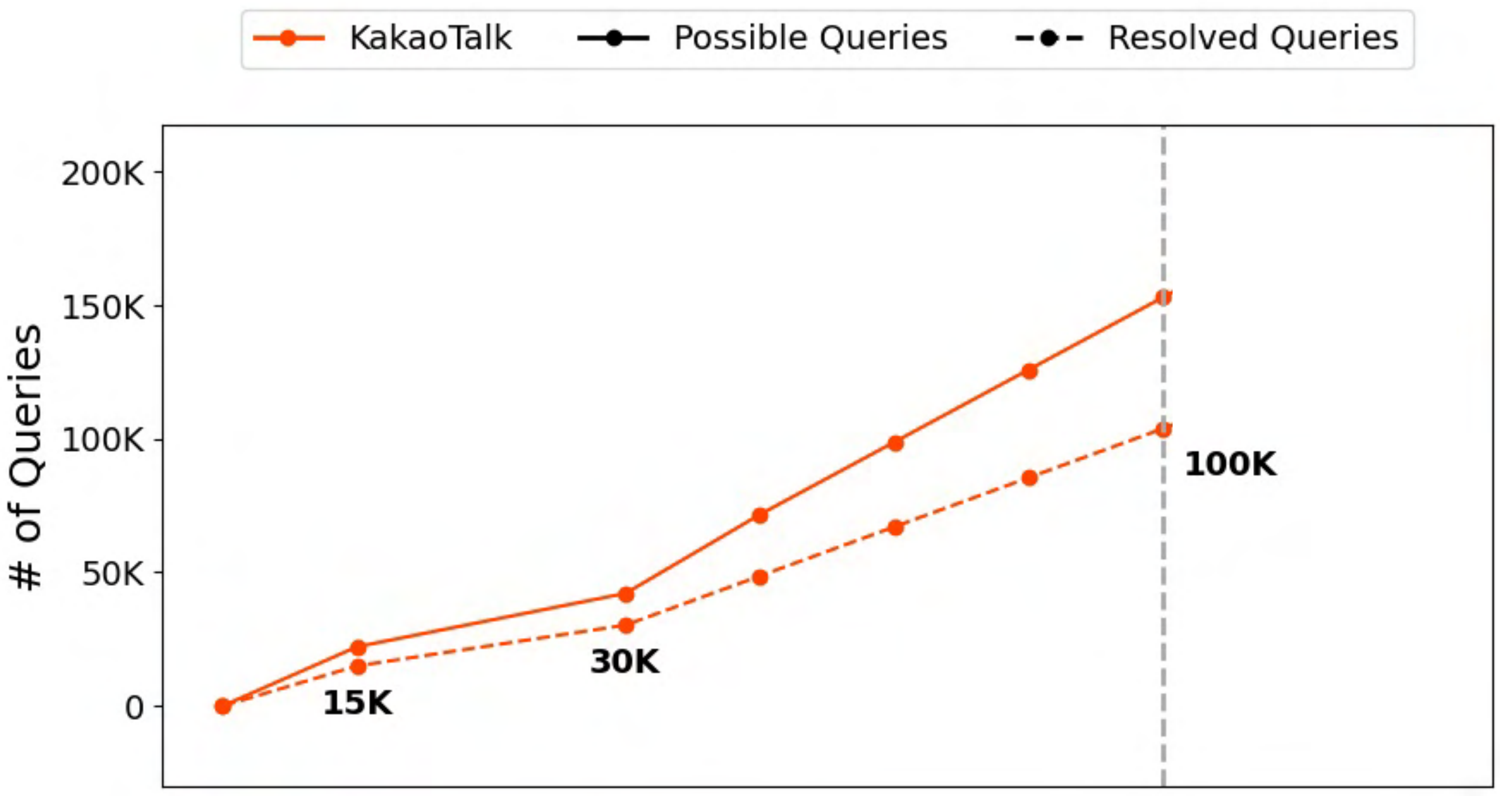

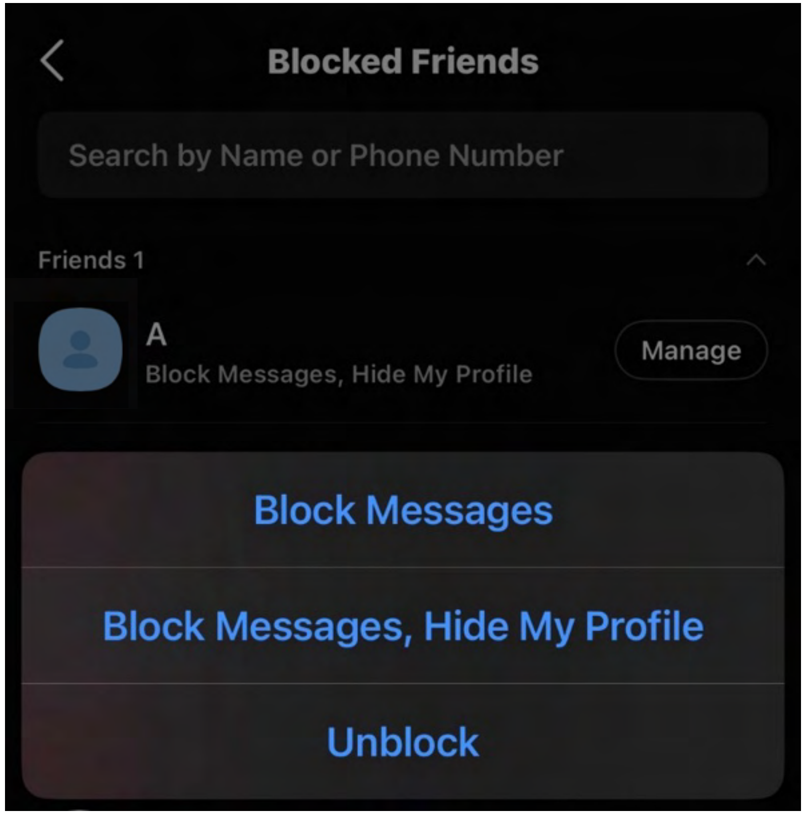

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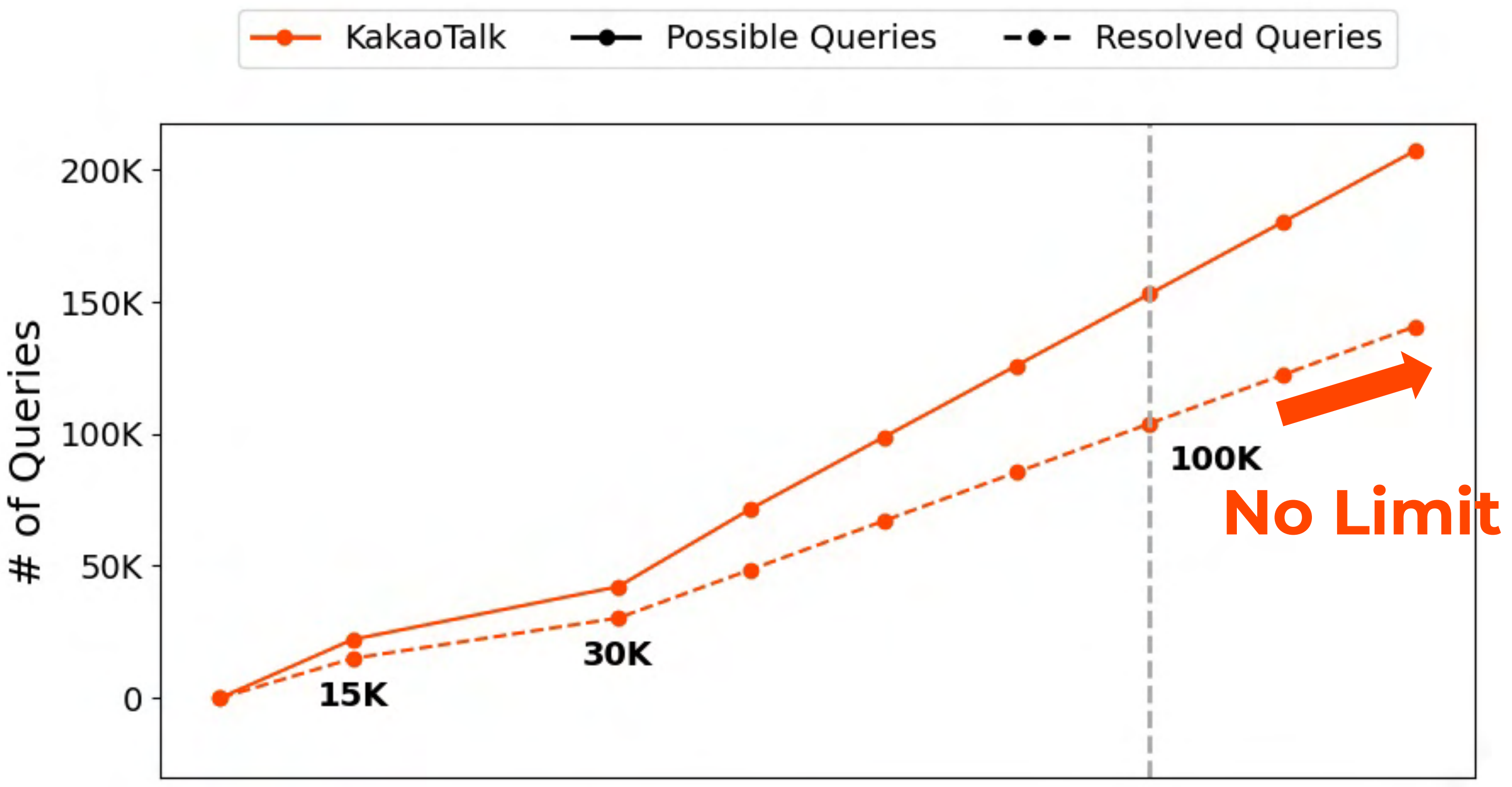
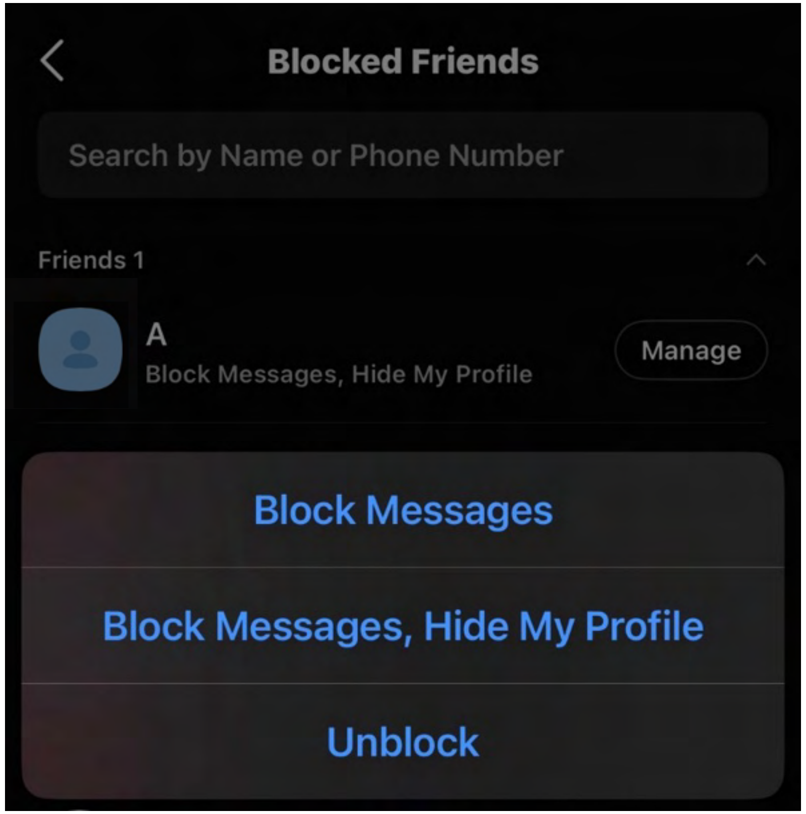
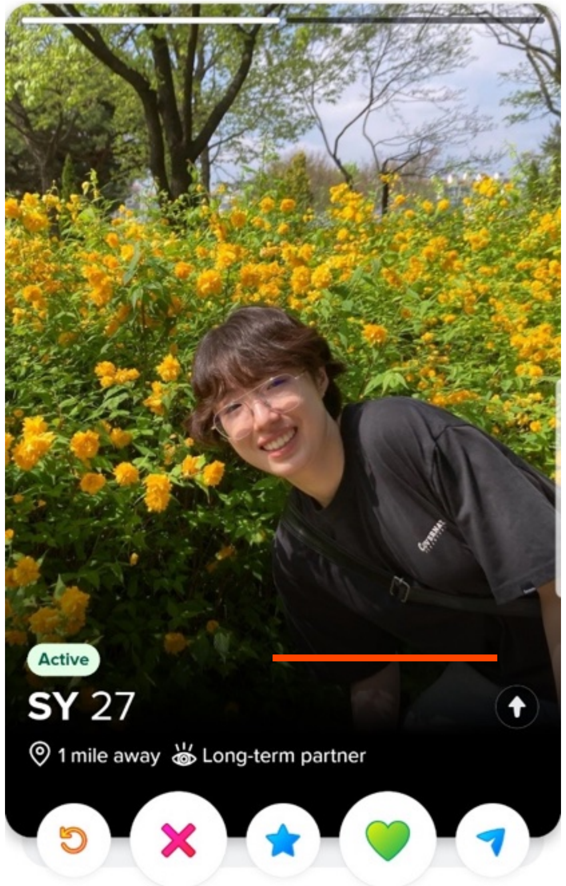




3. Block & Unblock Friends

Attack 3: Efficient location inference from Tinder “nearby” signals



Tinder profile card

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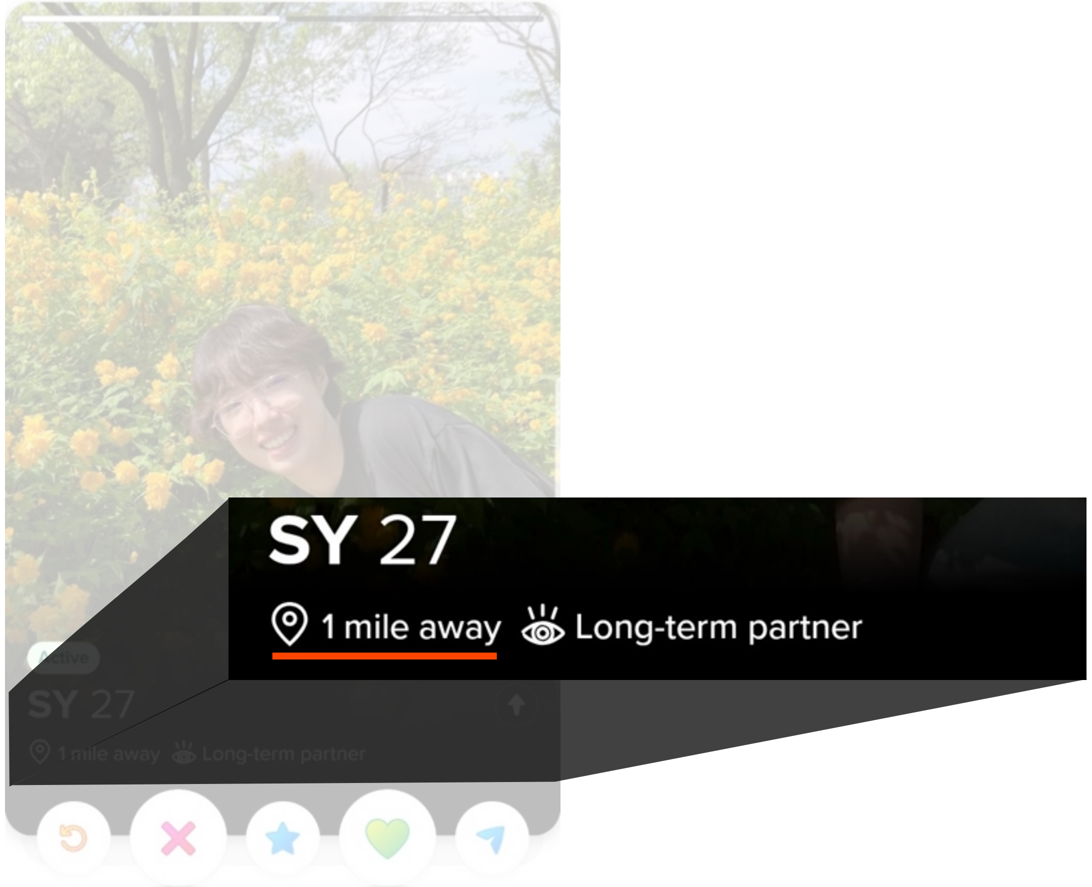

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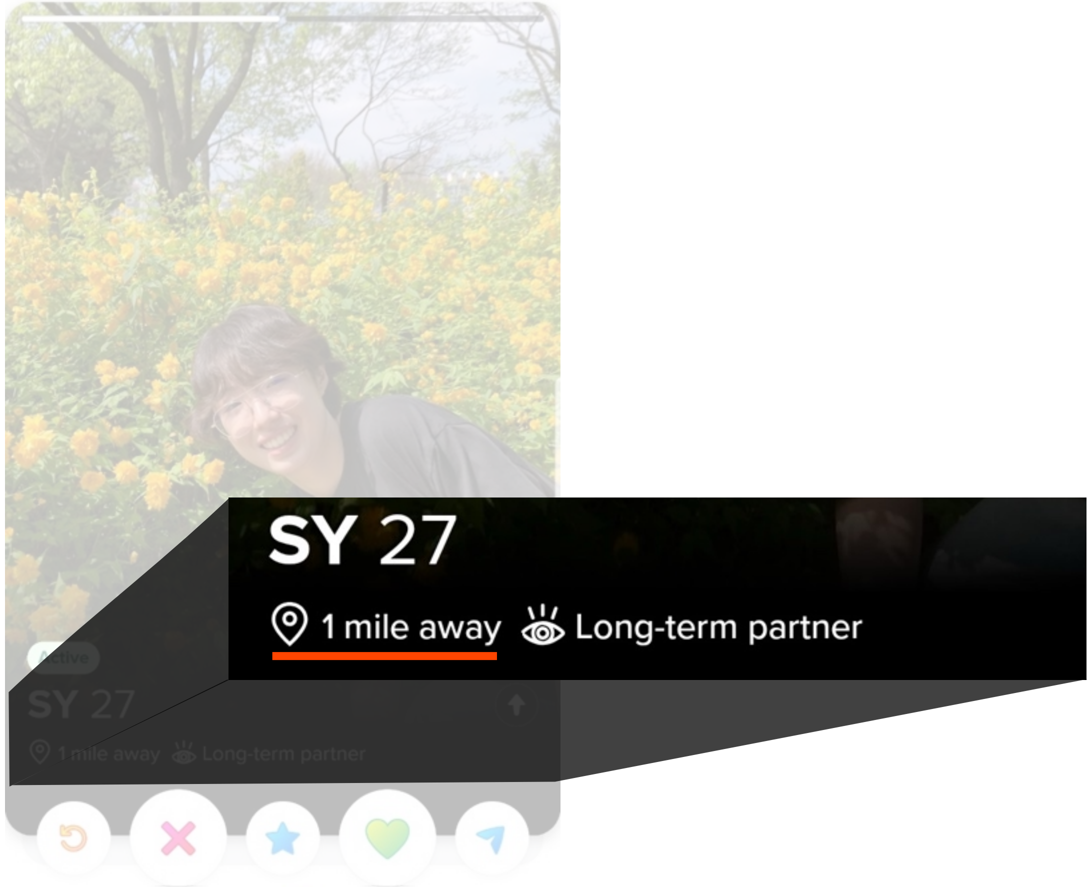

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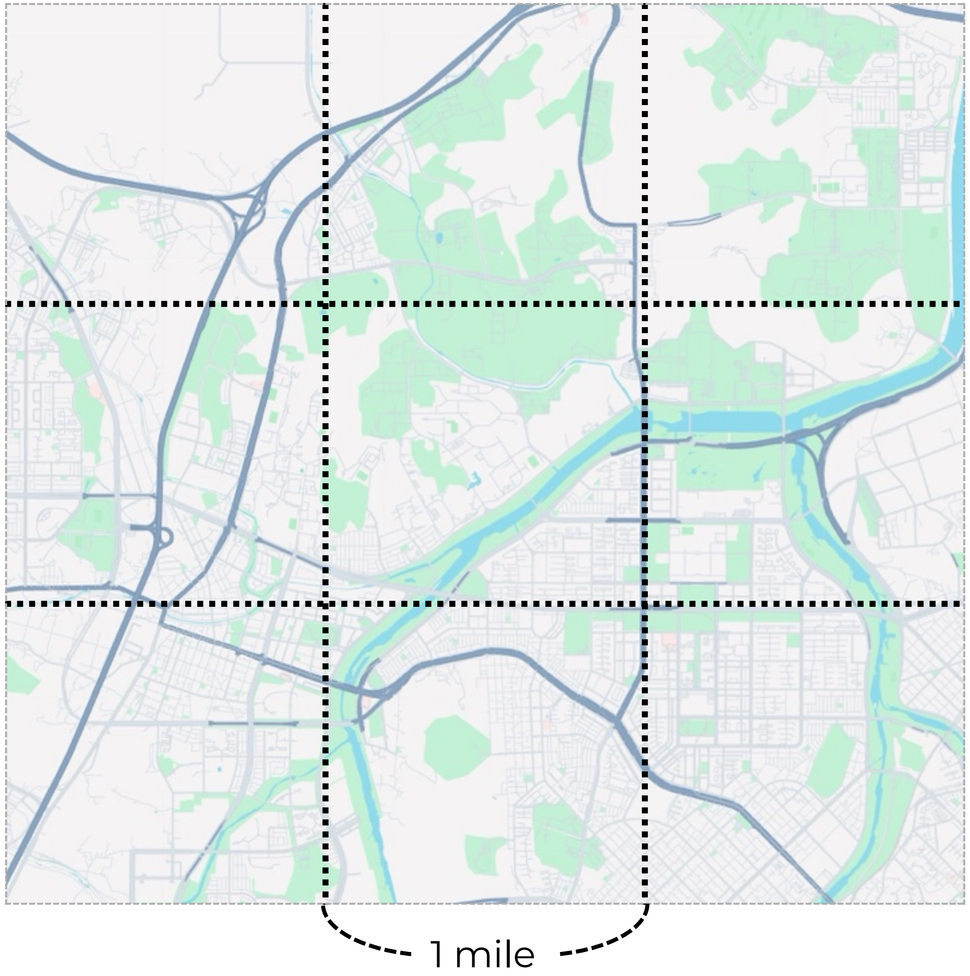

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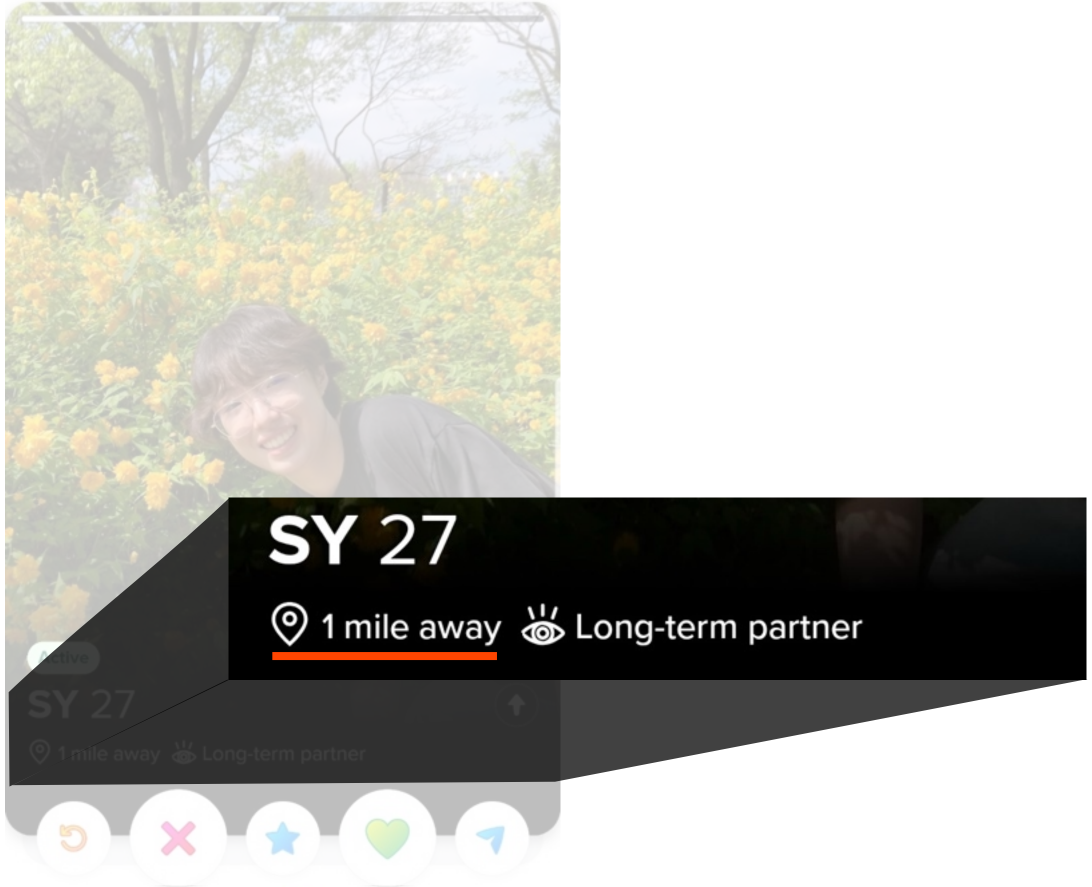

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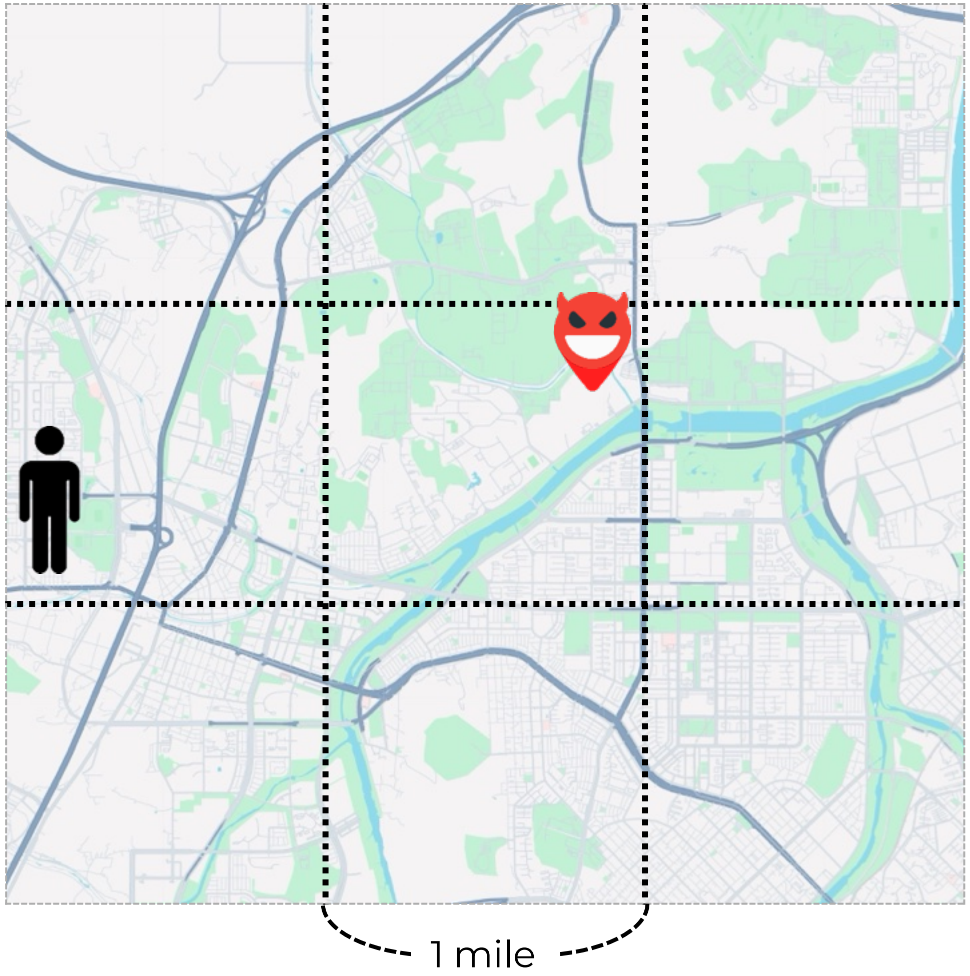

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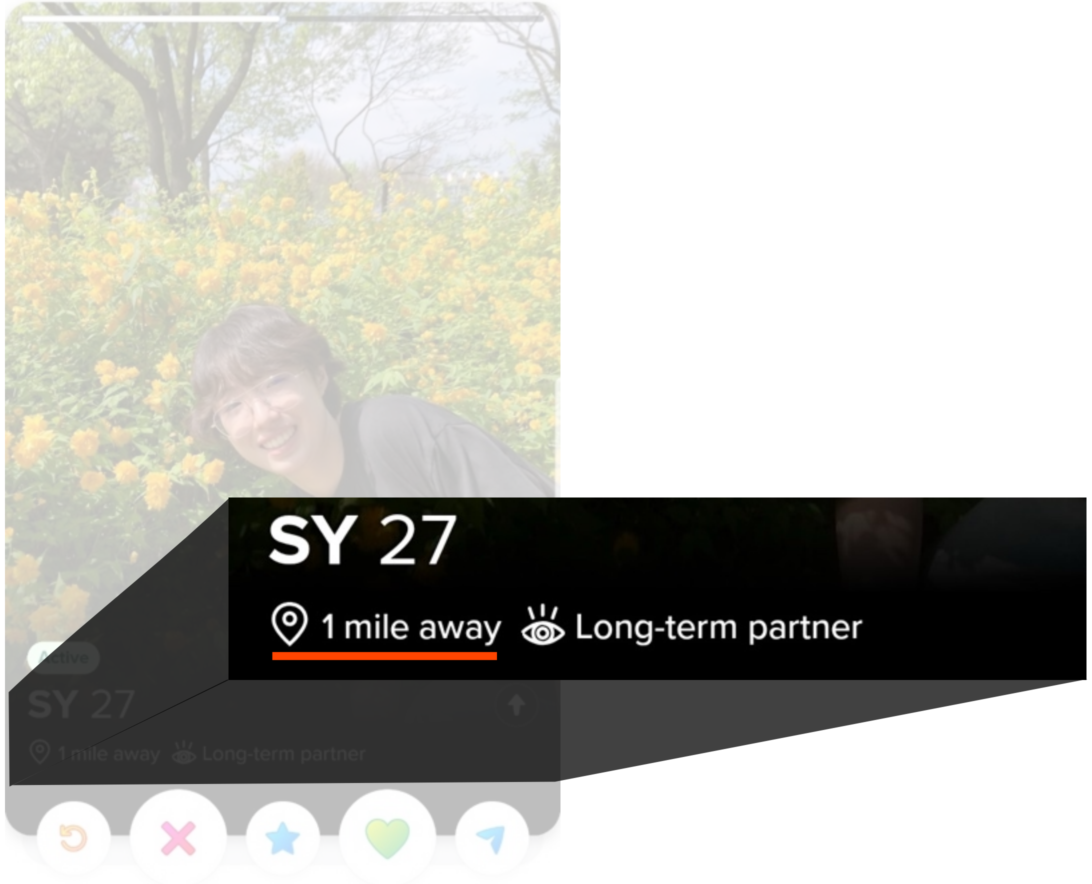

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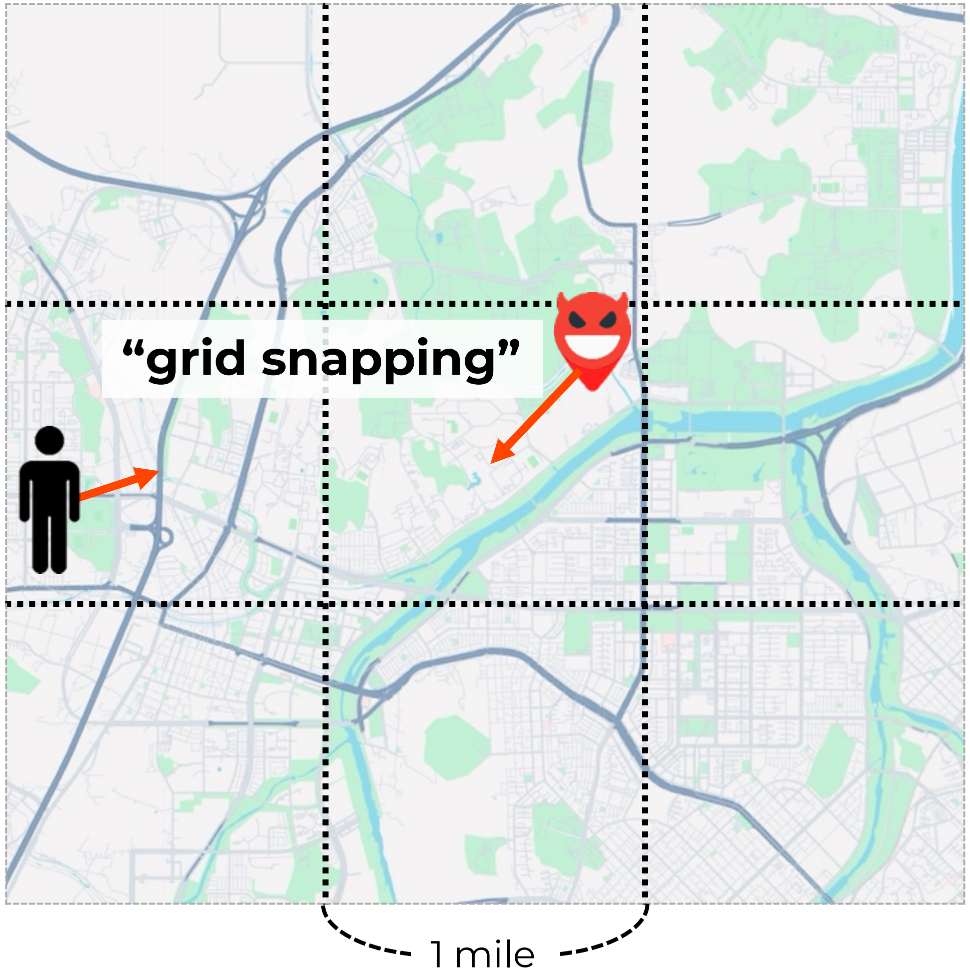

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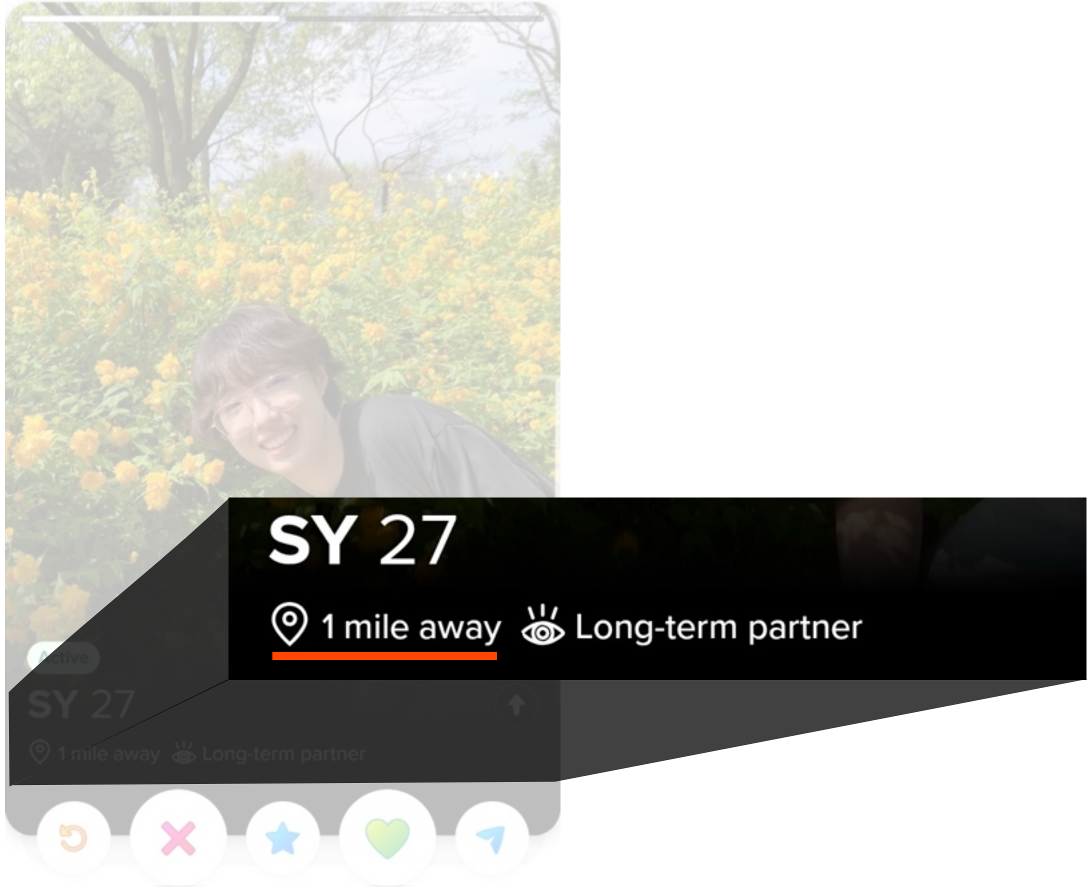

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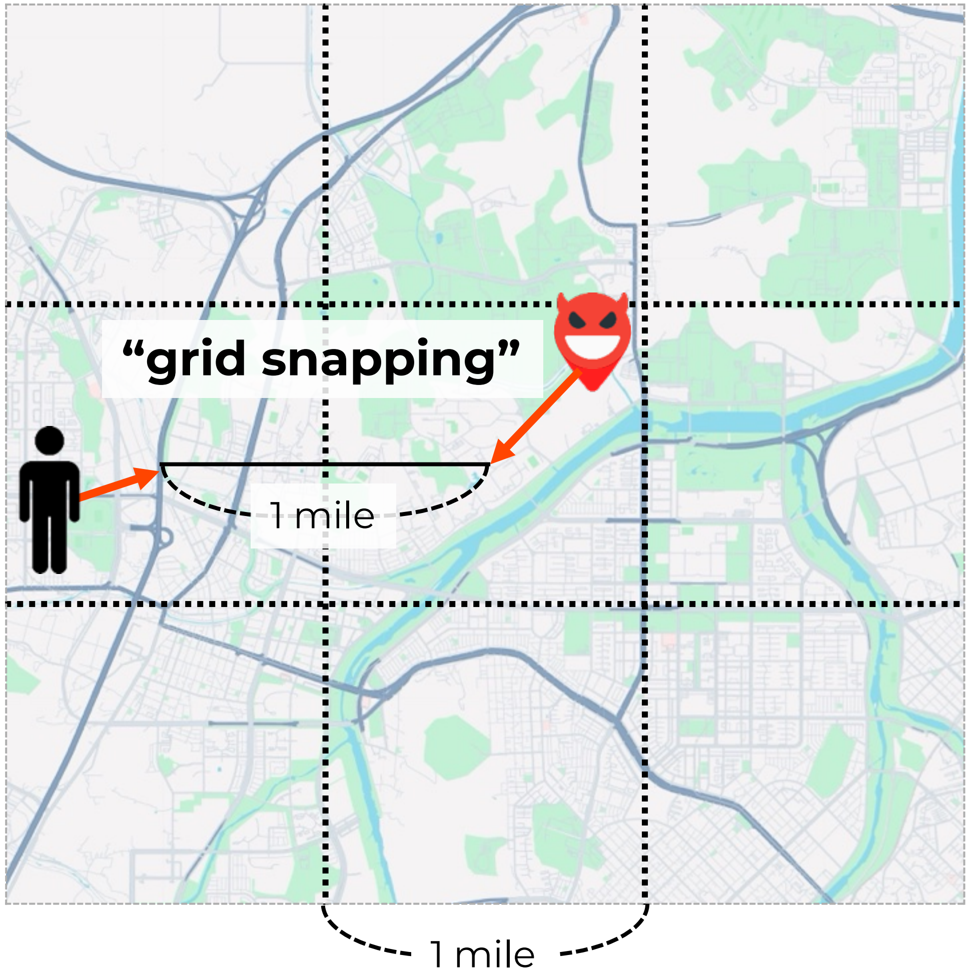
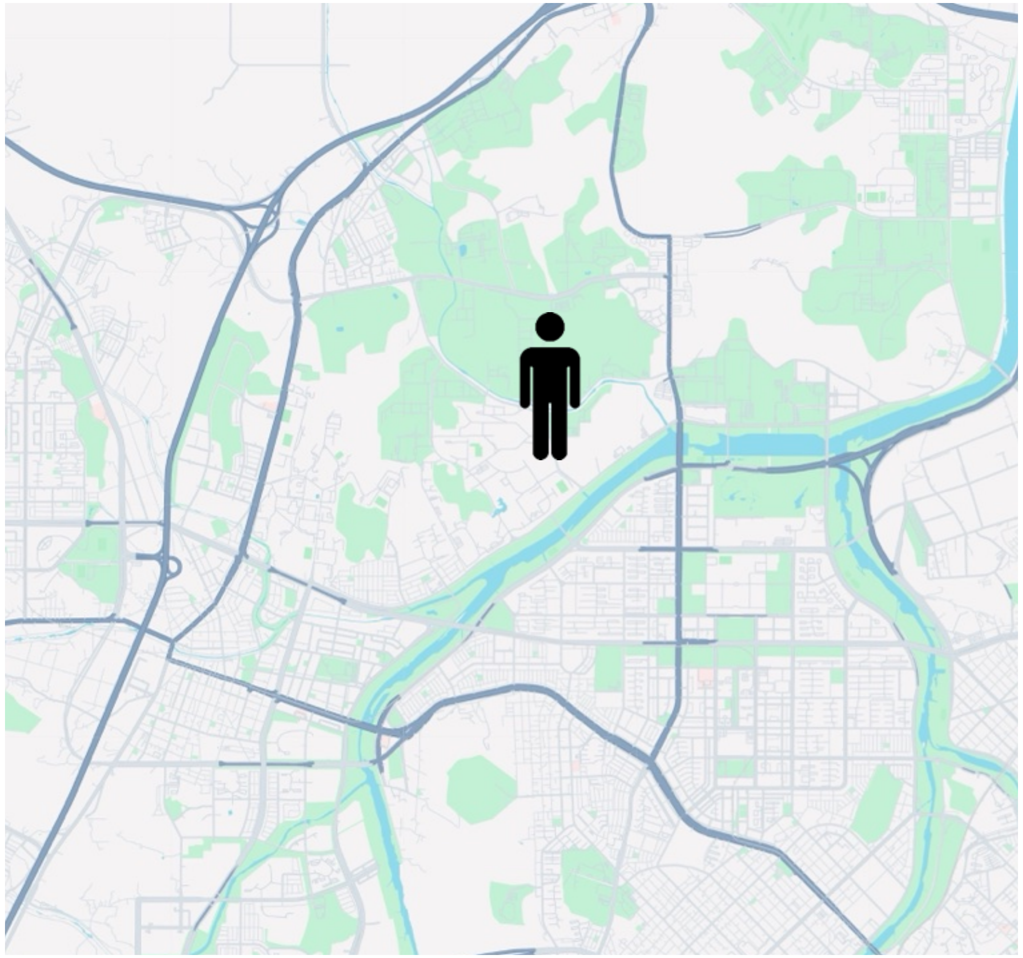


Attack 3: Efficient location inference from Tinder “nearby” signals

1. Create 2 miles x 2miles grid



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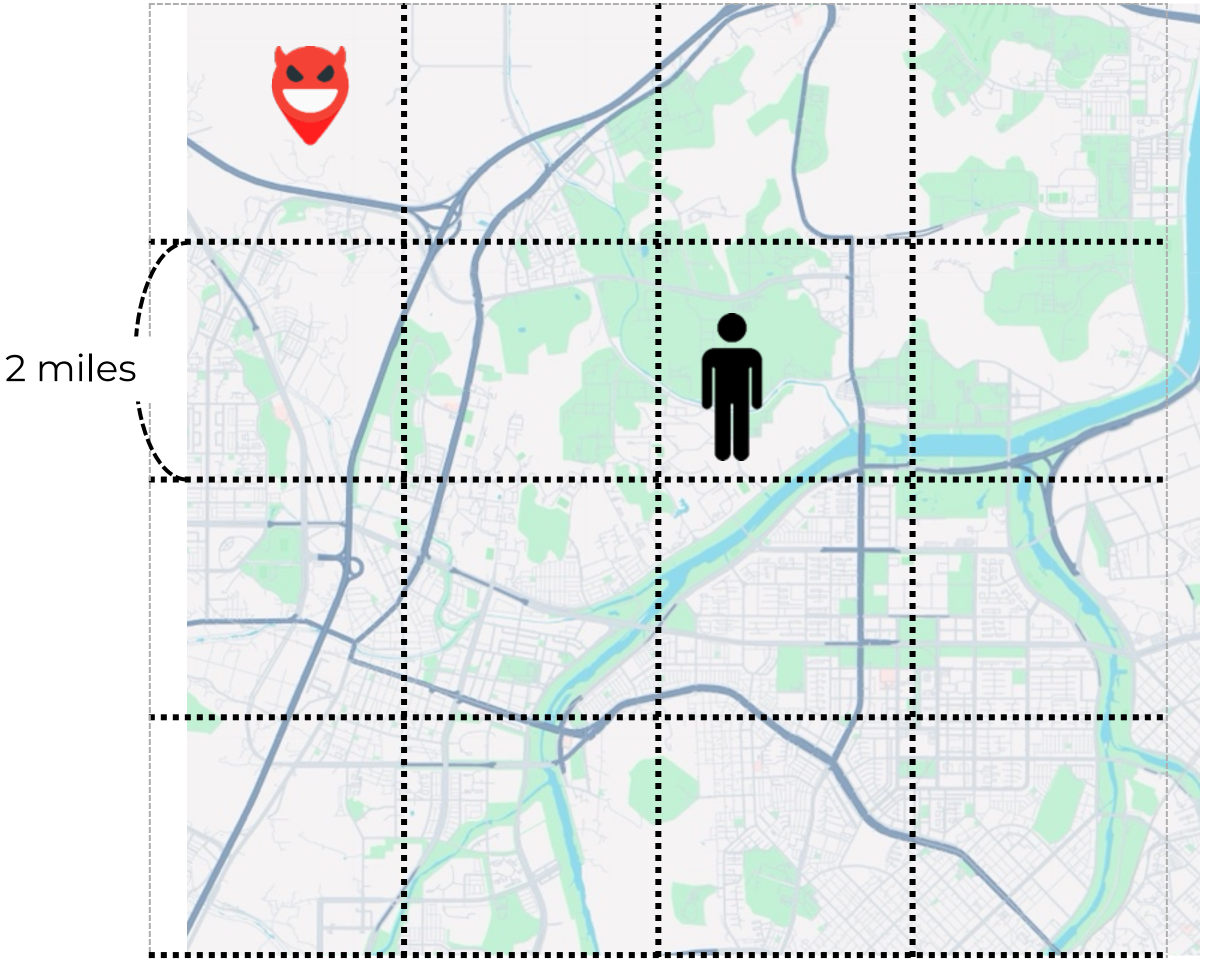
2. Search grid cells



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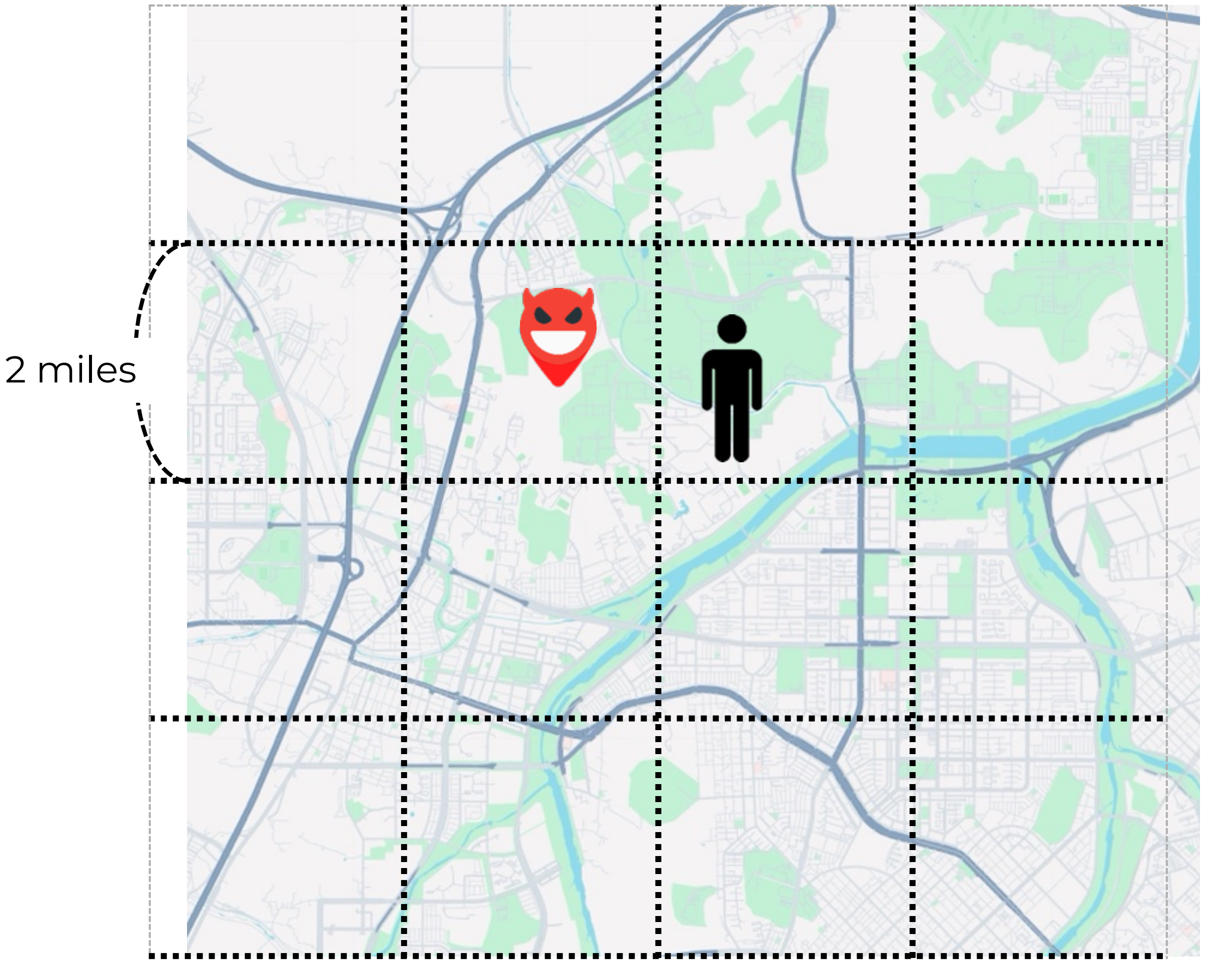

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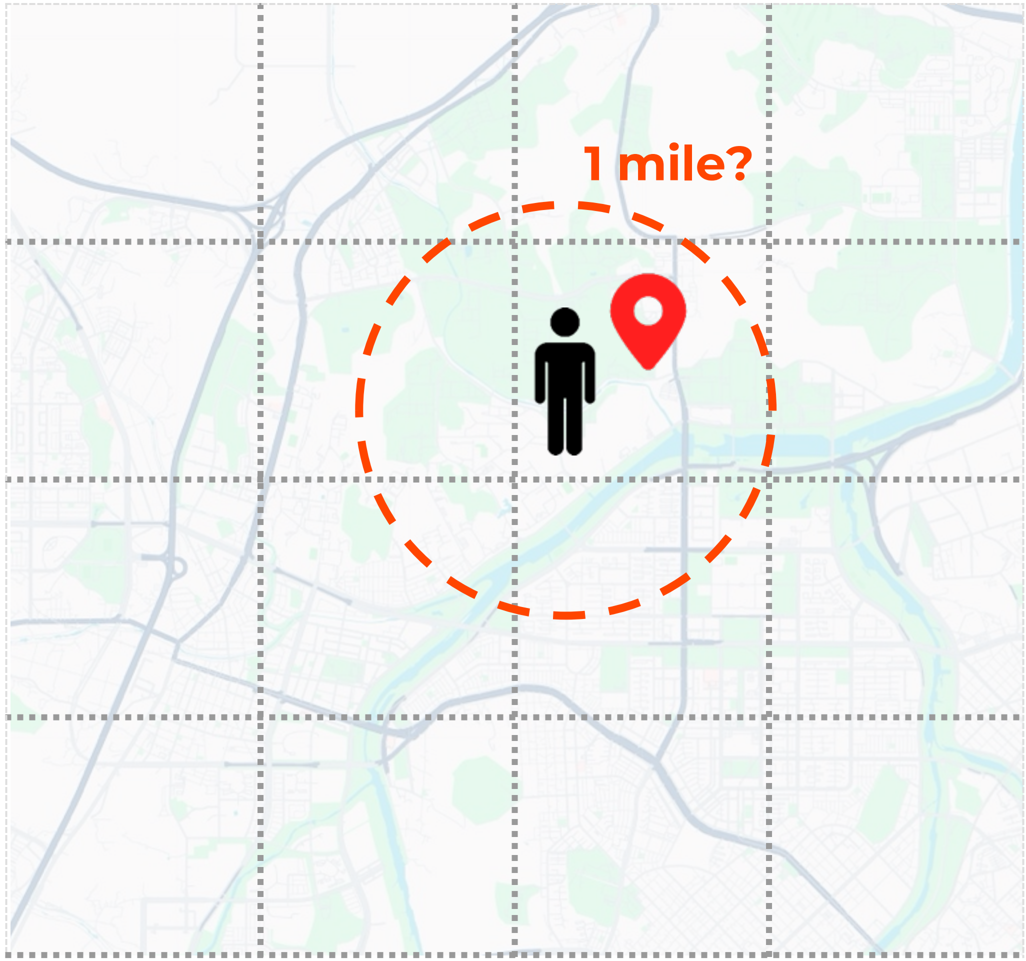
3. Find 1-mile boundary points (East, West, North, South)
   - Binary Search
   - Stop when *high – low* < $epsilon$ *(9 meters)*



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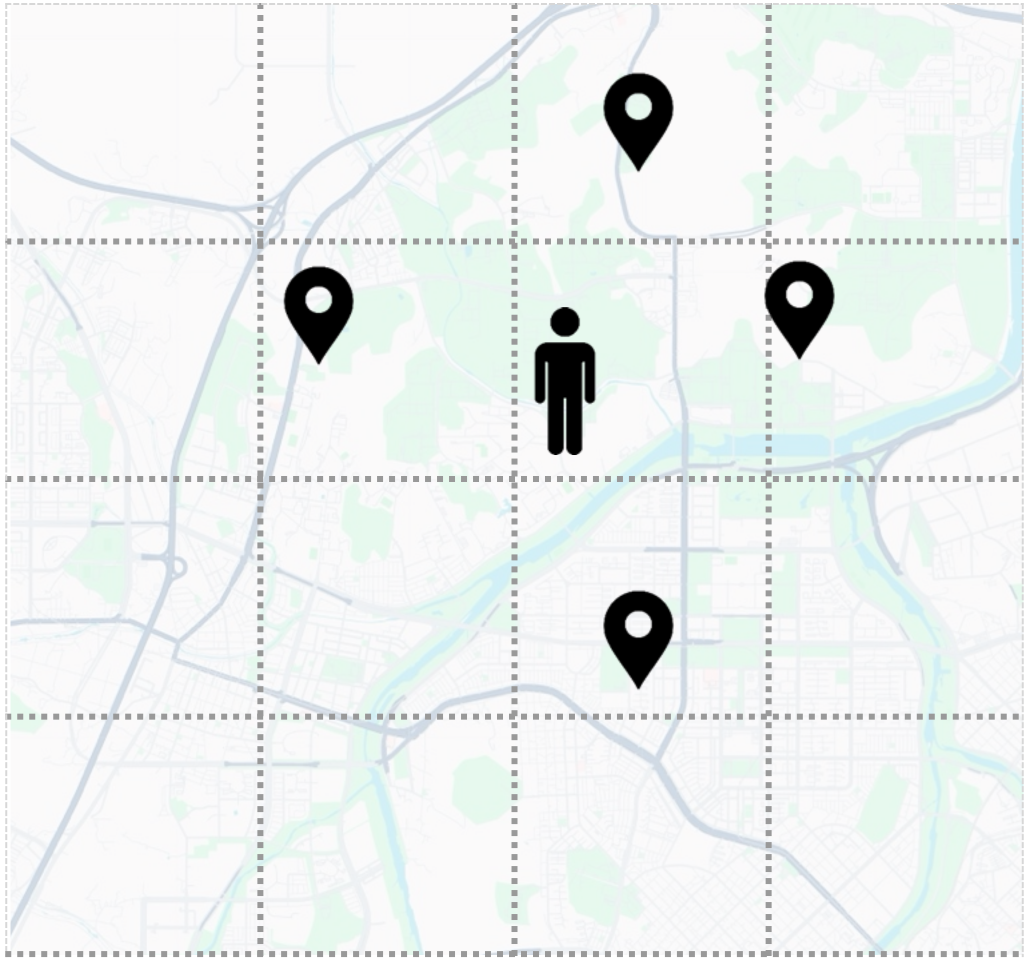

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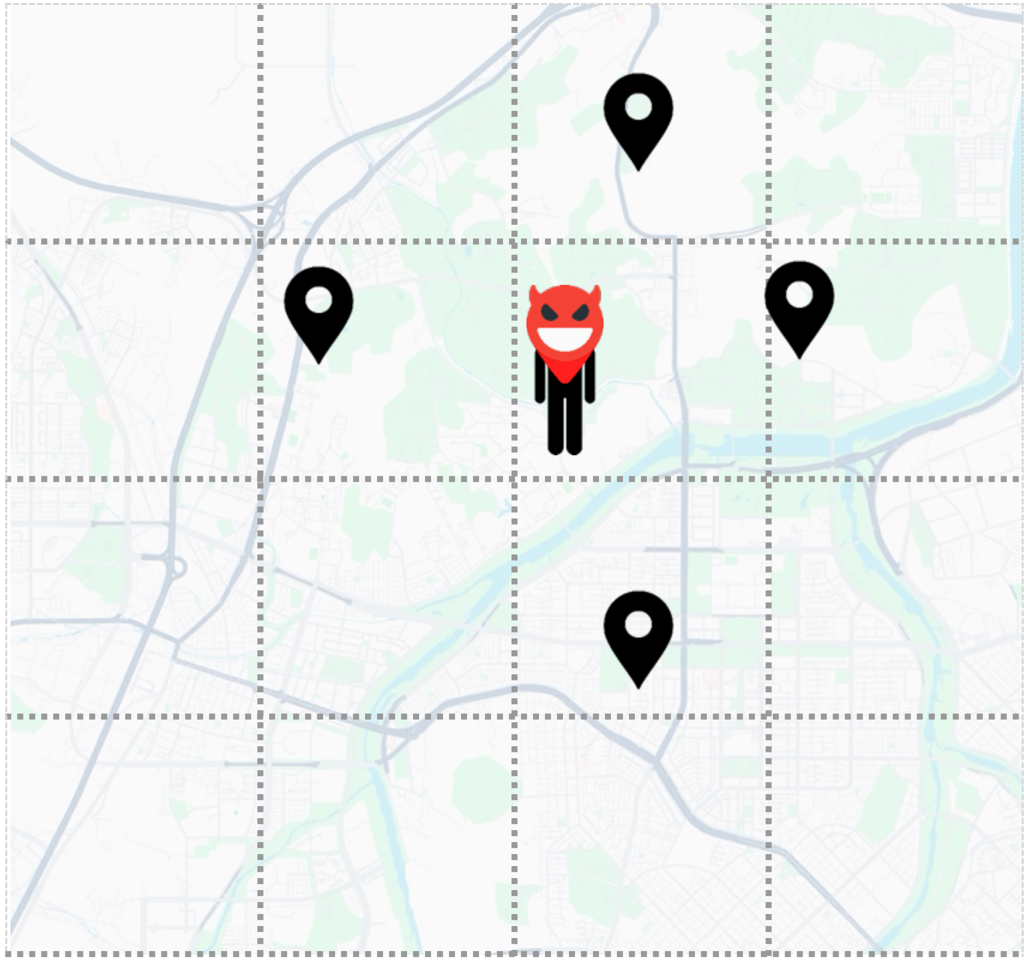

Chain 3: Targeted trajectory tracking

- Tracking specific user

1. Access token exposure

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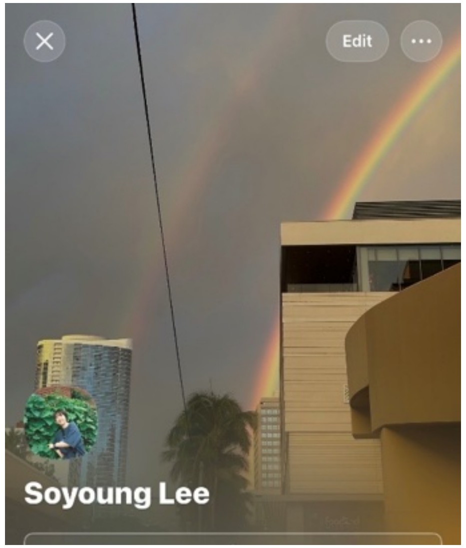
- Tracking specific user

1. Access token exposure

TALK → Profile image

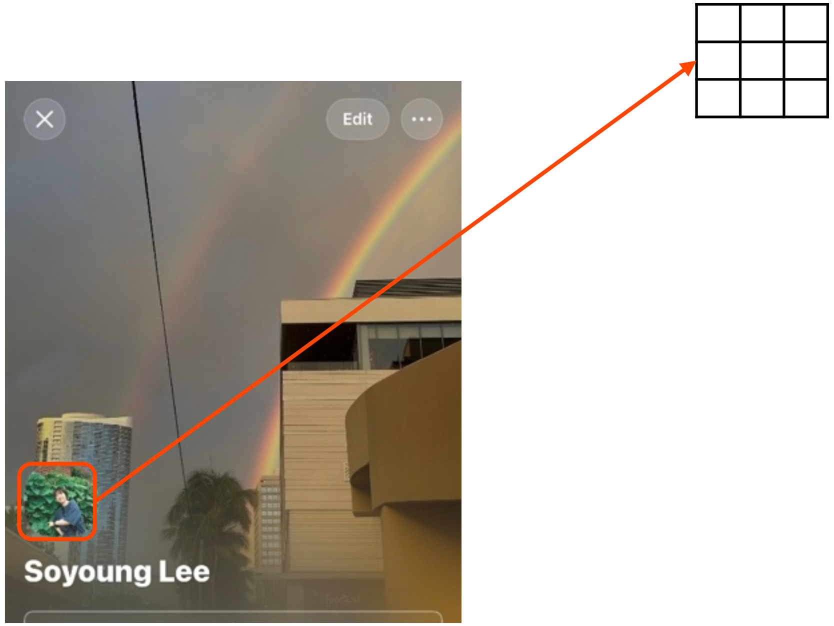


Chain 3: Targeted trajectory tracking

- Tracking specific user

1. Access token exposure

TALK → Profile image → Image Embeddings

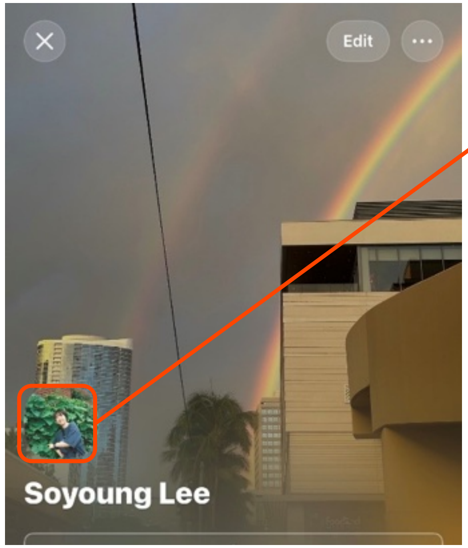


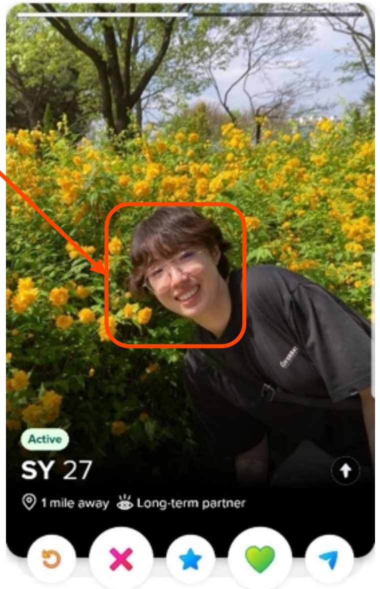
Chain 3: Targeted trajectory tracking

- Tracking specific user

1. Access token exposure

Profile image → Image Embeddings → Find target



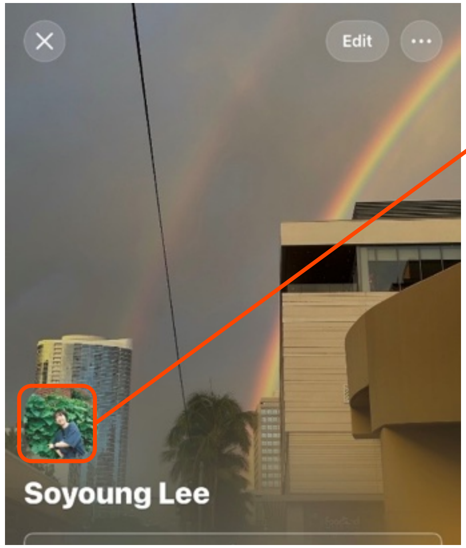


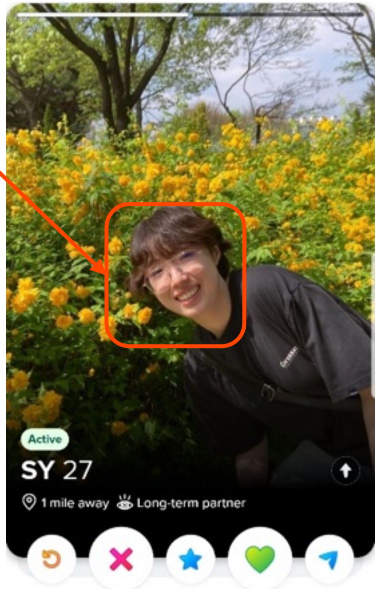
Chain 3: Targeted trajectory tracking

- Tracking specific user

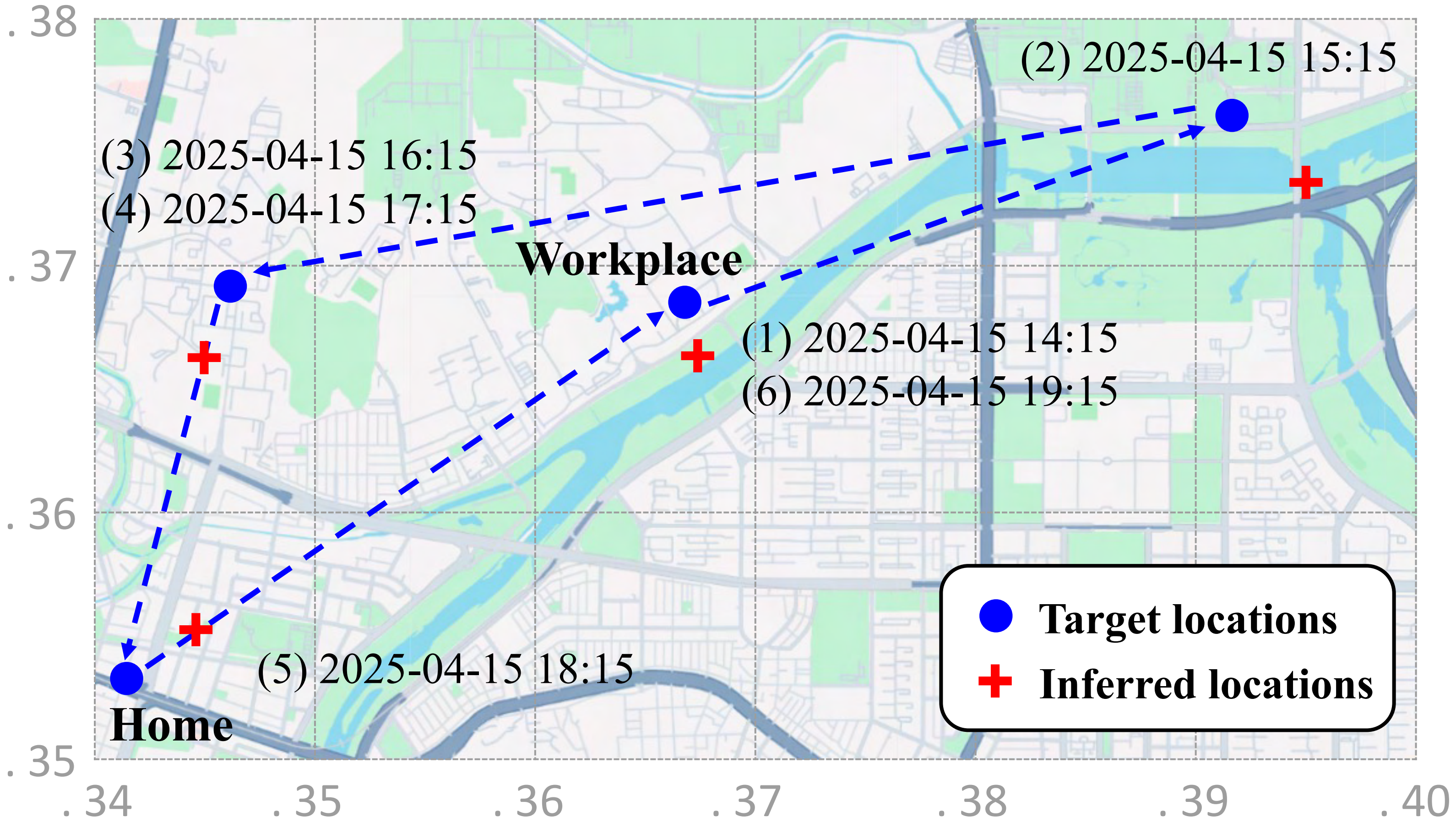
1. Access token exposure

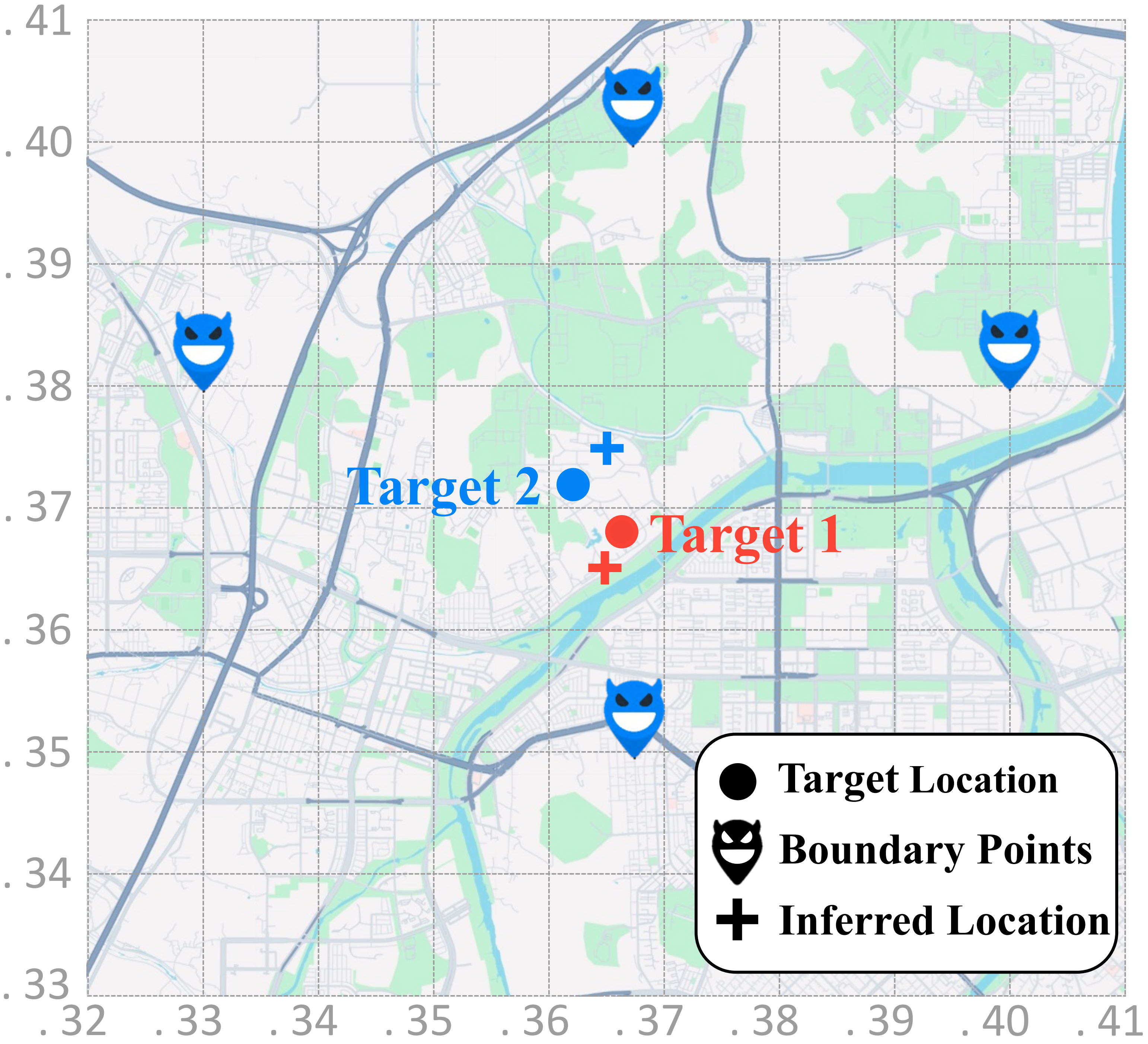
TALK → Profile image → Image Embeddings → Find target → **2. Trajectory Tracking (Location Inference)**





Chain 3: Targeted trajectory tracking (token → profile → Tinder)





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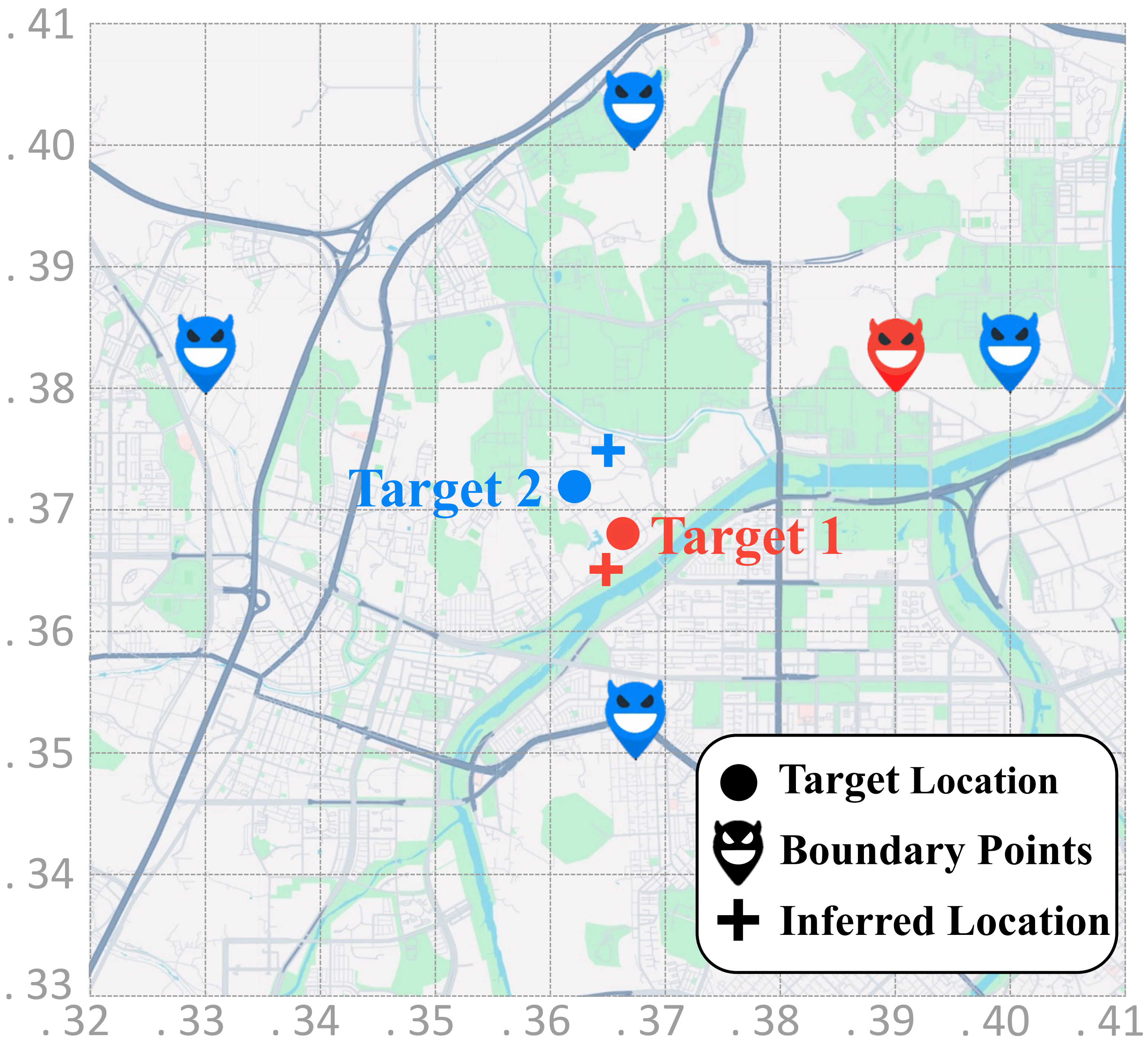
Target 2
Target 1
Target Location
Boundary Points
Inferred Location



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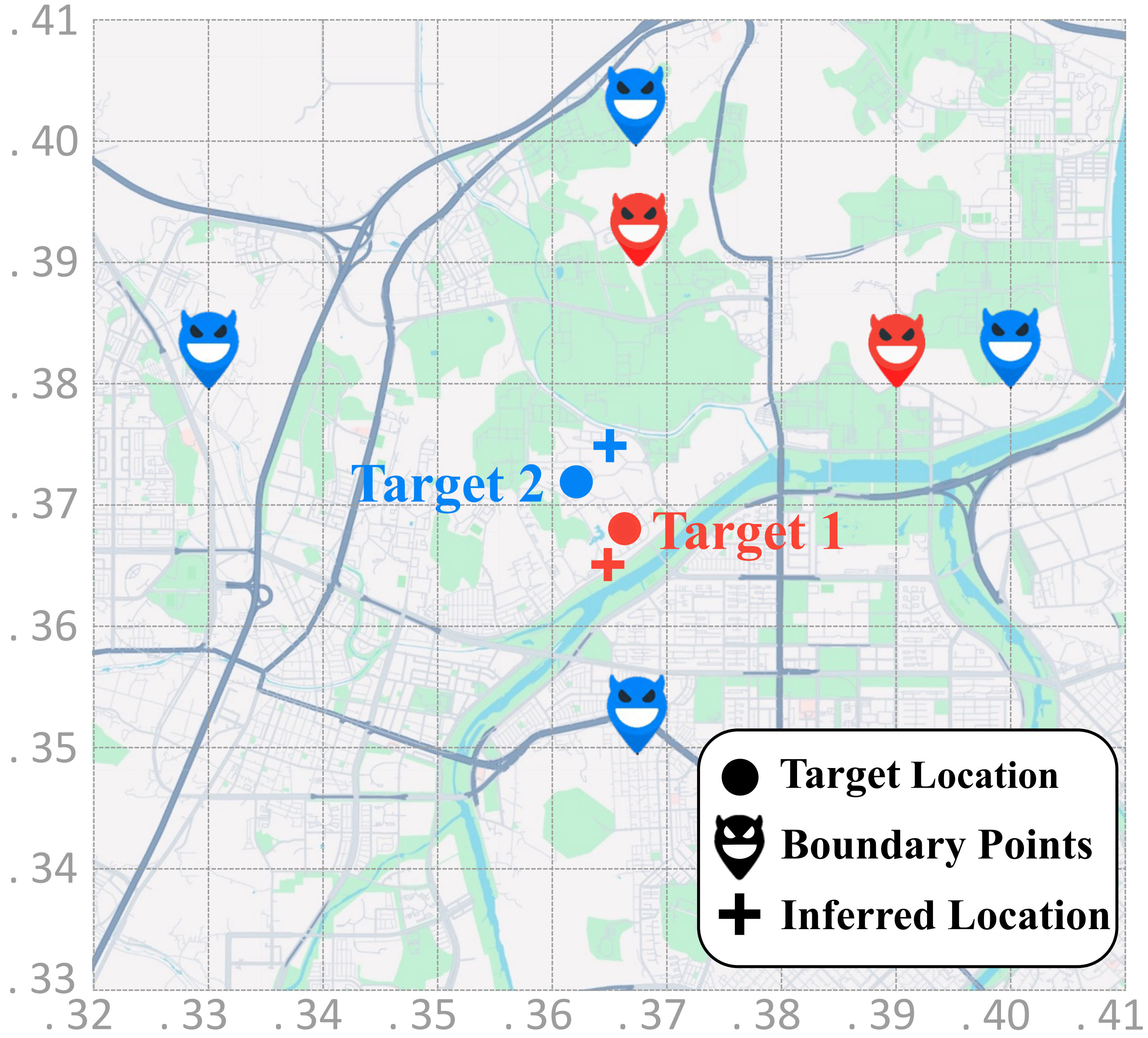

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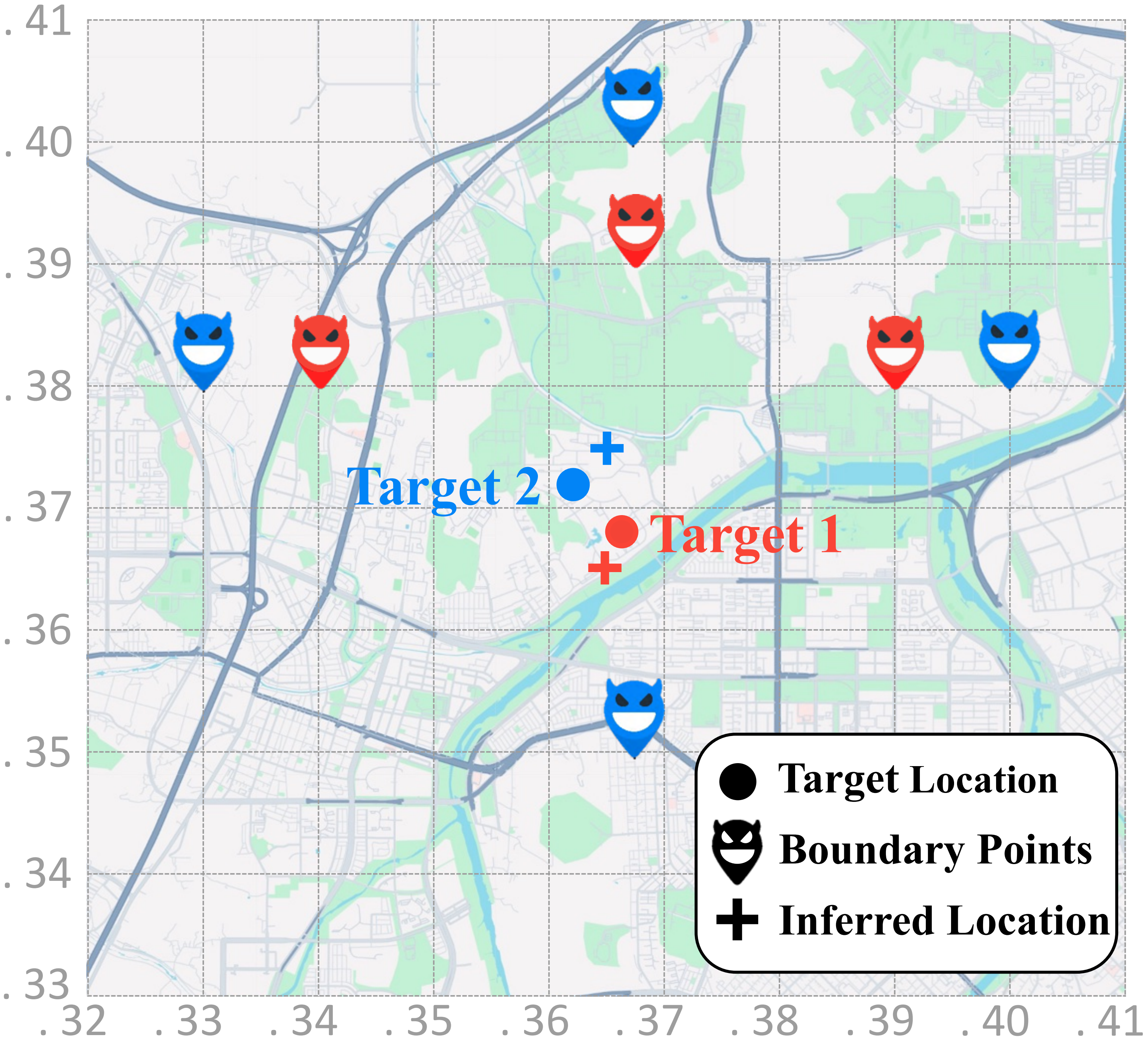

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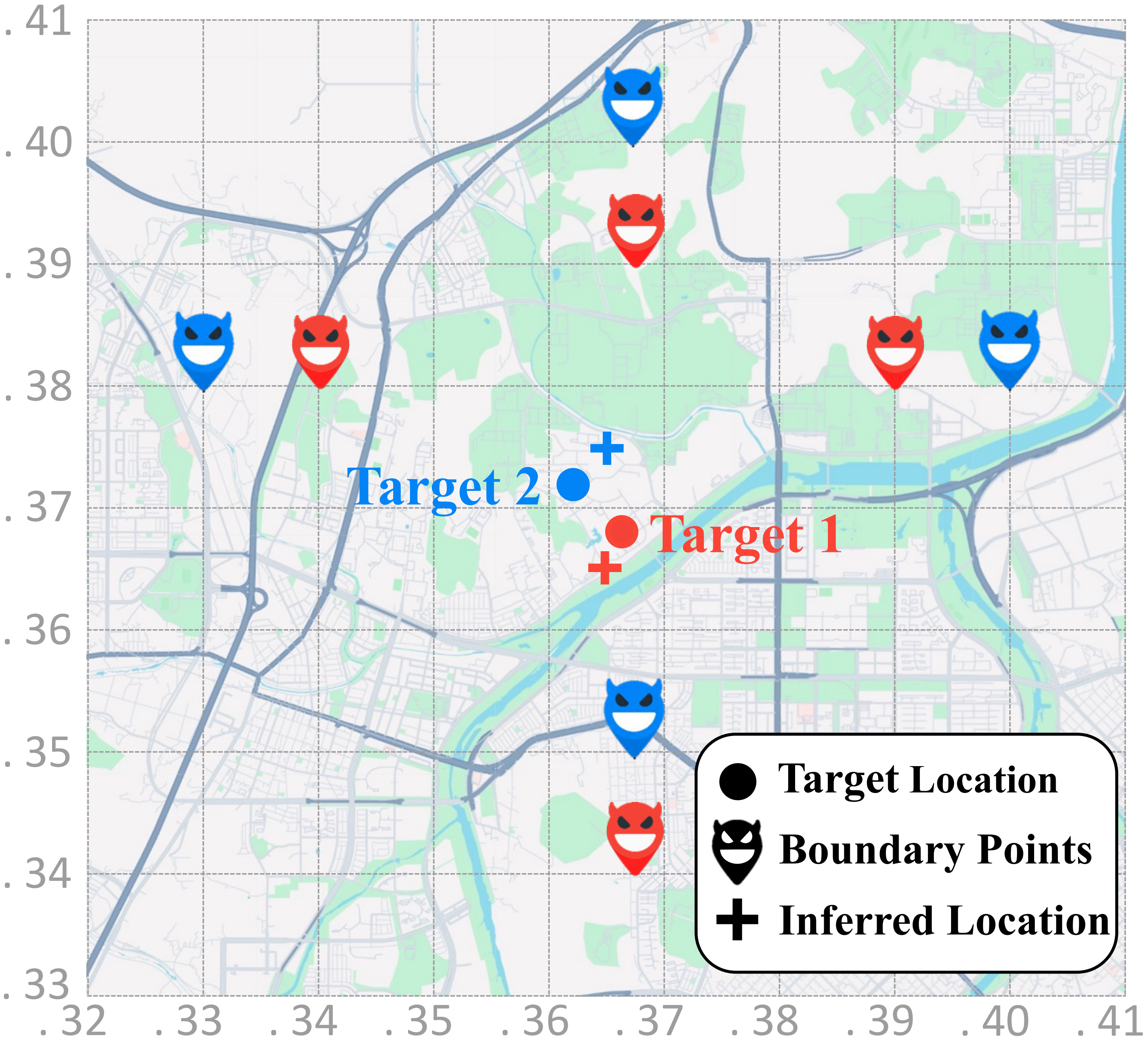
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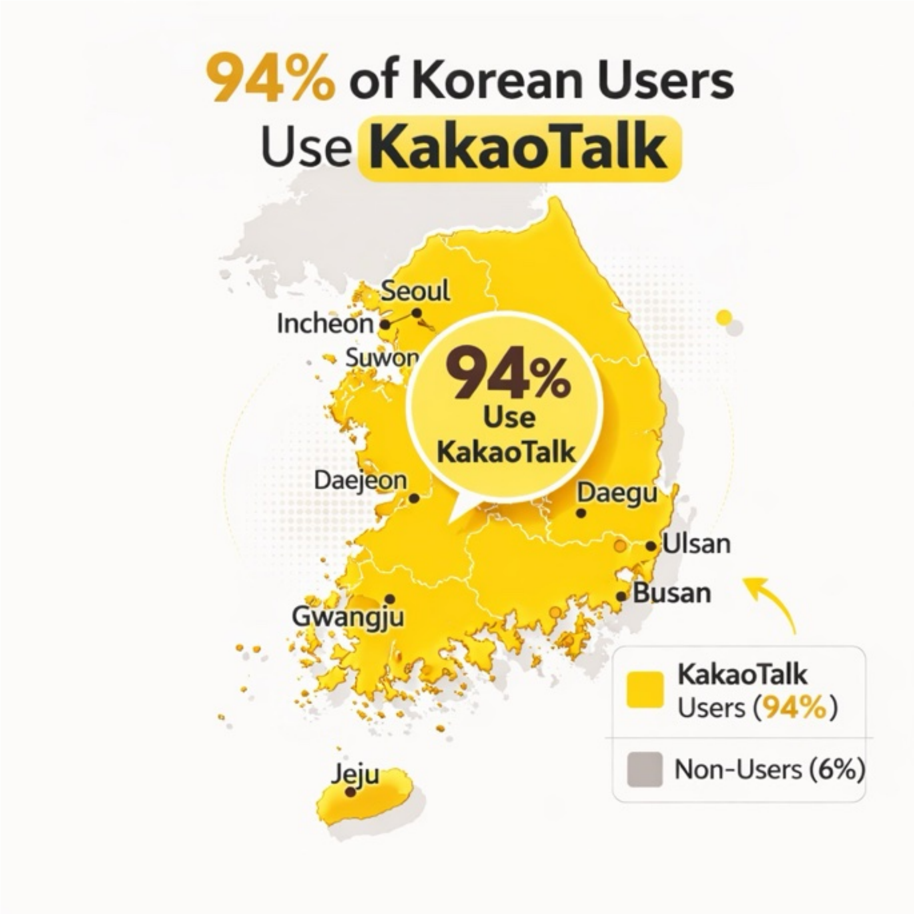
94% of Korean Users
Use KakaoTalk
Seoul
Incheon
Suwon
94%
Use
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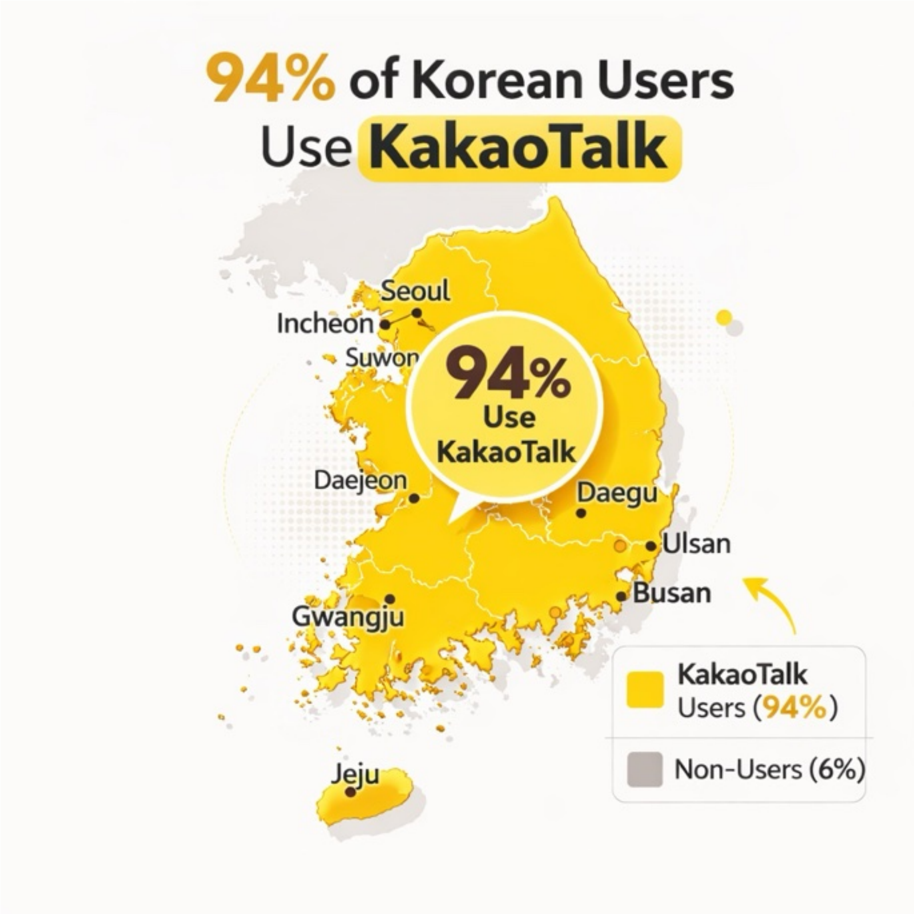
Daejeon
Daegu
Ulsan
Busan
Gwangju
Jeju
KakaoTalk
Users (94%)
Non-Users (6%)



KakaoTalk in S. Korea