FP-Fed: Privacy-Preserving Federated Detection of Browser Fingerprinting

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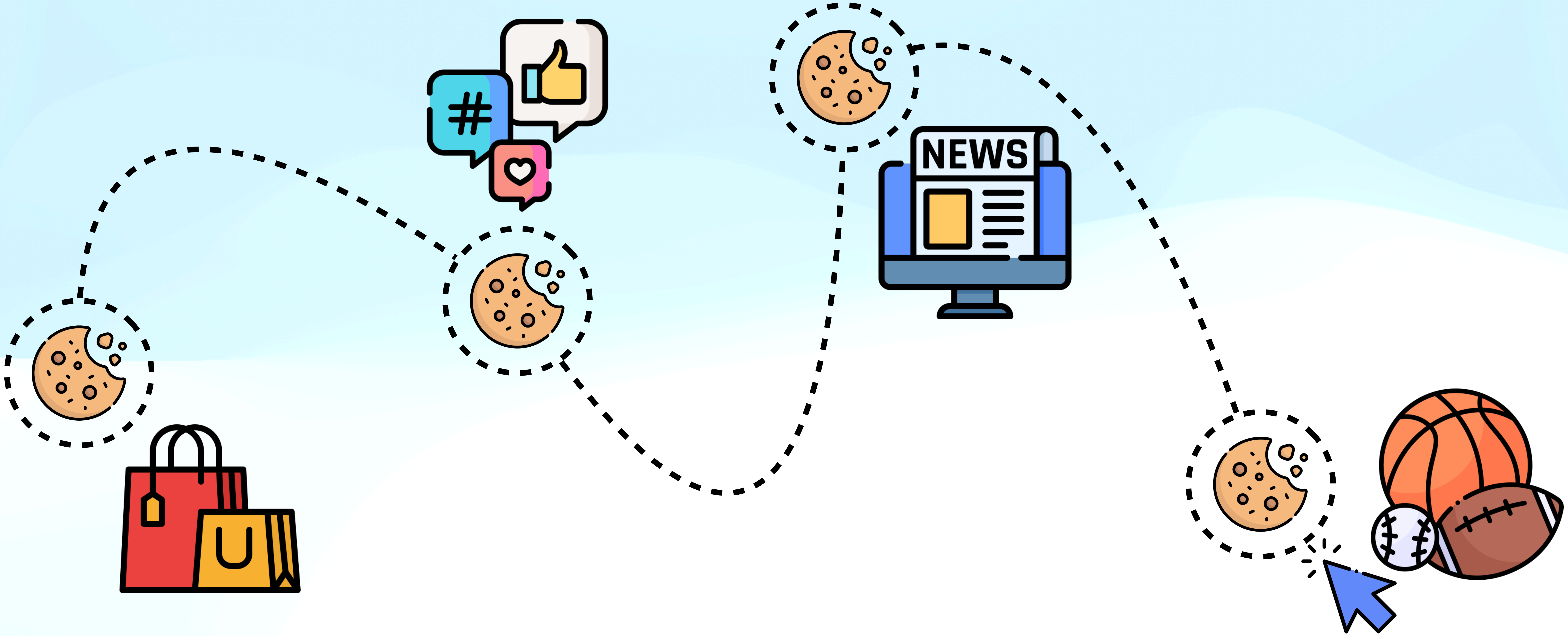
What is Browser Fingerprinting?

Tracking on the Web

Third-party cookies



Tracking on the Web

Browsers block/restrict third-party cookies

Source: https://developer.mozilla.org/en-US/blog/goodbye-third-party-cookies/

What is Browser Fingerprinting?

Definition

- Collects set of information related to a user’s device that can be **uniquely identifiable**
    - Hardware (# CPU cores, screen size, etc.)
    - Software (Browser extensions installed, Version of flash installed, etc.)

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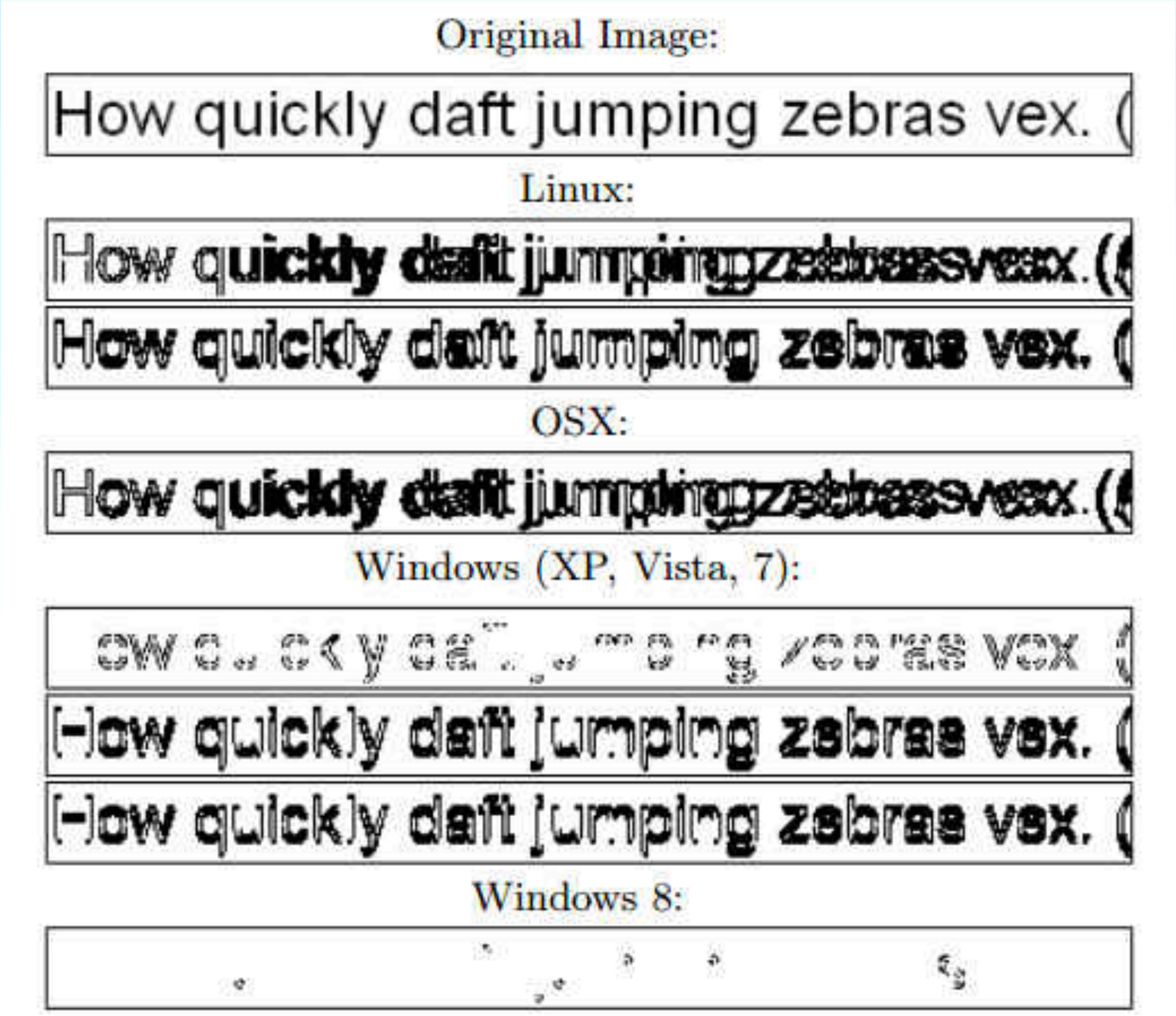
    - Hardware (# CPU cores, screen size, etc.)
    - Software (Browser extensions installed, Version of flash installed, etc.)
- Deployed via **JS script** that runs in browser (e.g. `fingerprintjs`)
- **Invasive** tracking technique
    - Stateless: no information stored in browser (e.g., cookies)
    - Hard to prevent and less transparent

What is Browser Fingerprinting?

Example: Canvas Fingerprinting



Source: https://www.i-programmer.info/news/149-security/7583-the-canvas-fingerprint-how.html

Exploits differences in how different devices render images

Challenges of Browser Fingerprinting Detection

Prior Work

Browser Fingerprinting Detection

Manually curated blocklists / heuristics

- Hard to maintain
- Narrowly defined

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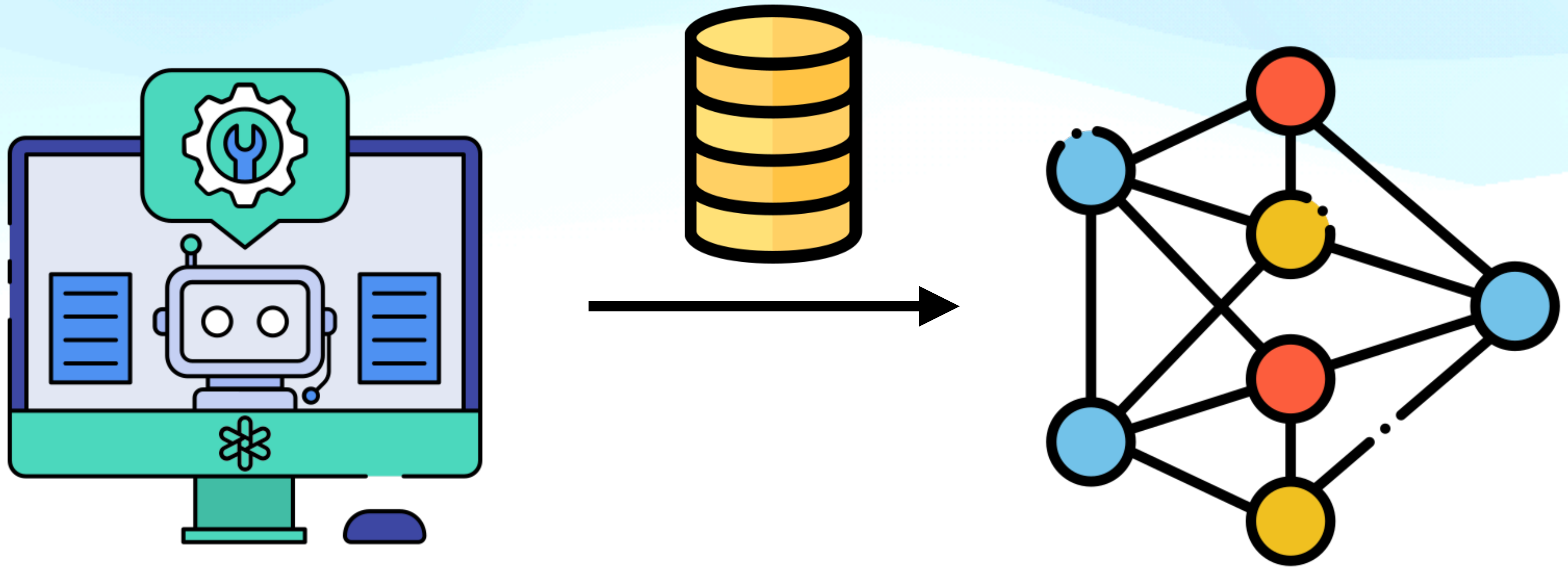
<u>Centralized Machine Learning + Automated Web Crawl</u>



- Cannot replicate real human interactions
- Blocked by bot detectors, CAPTCHAs, login pages, and paywalls
- Large number of features (~2000)

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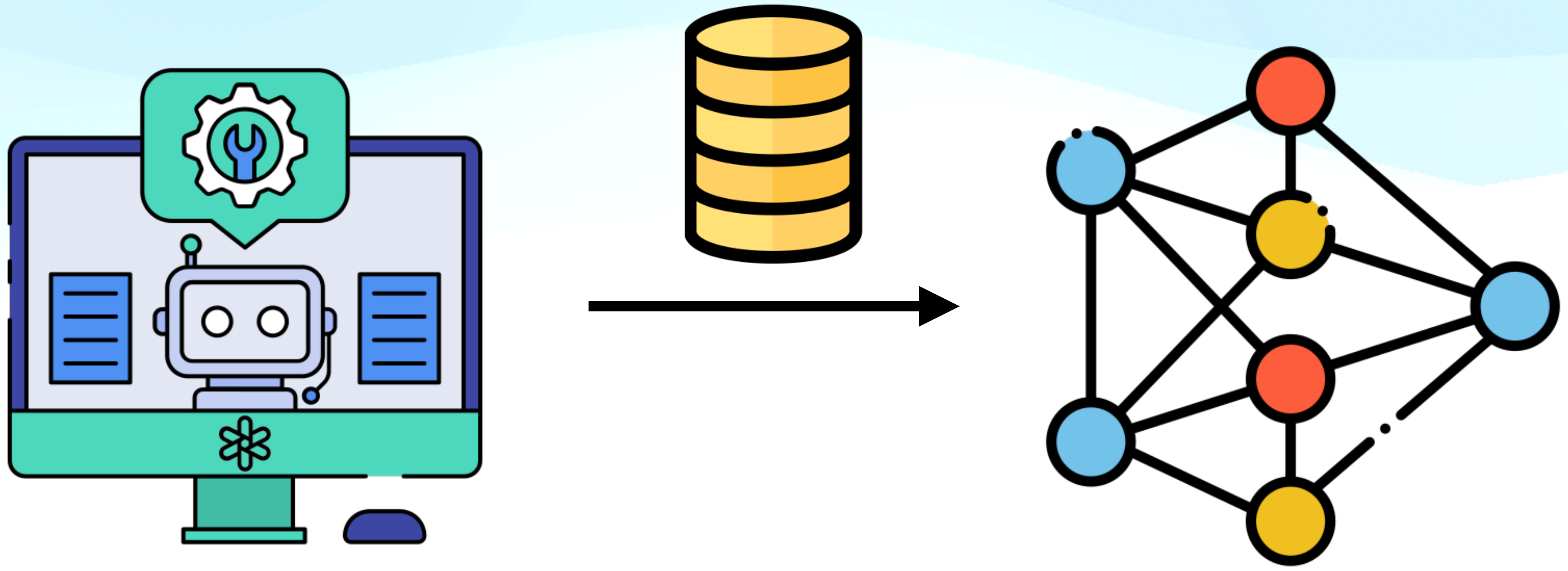

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Might miss fingerprinting scripts

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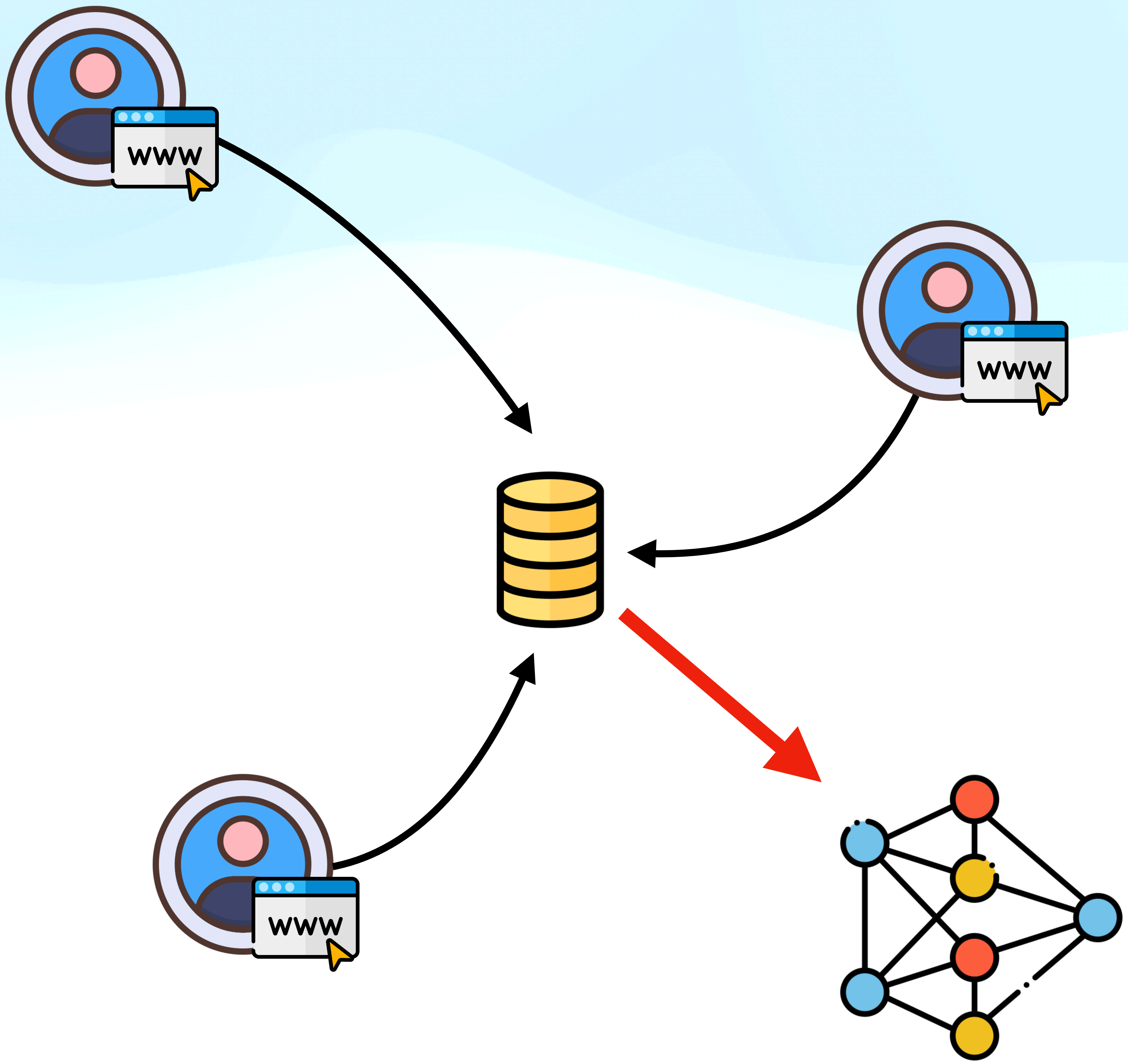
Naive solution

Browser Fingerprinting Detection

- Gather real-world observations from users as they browse websites



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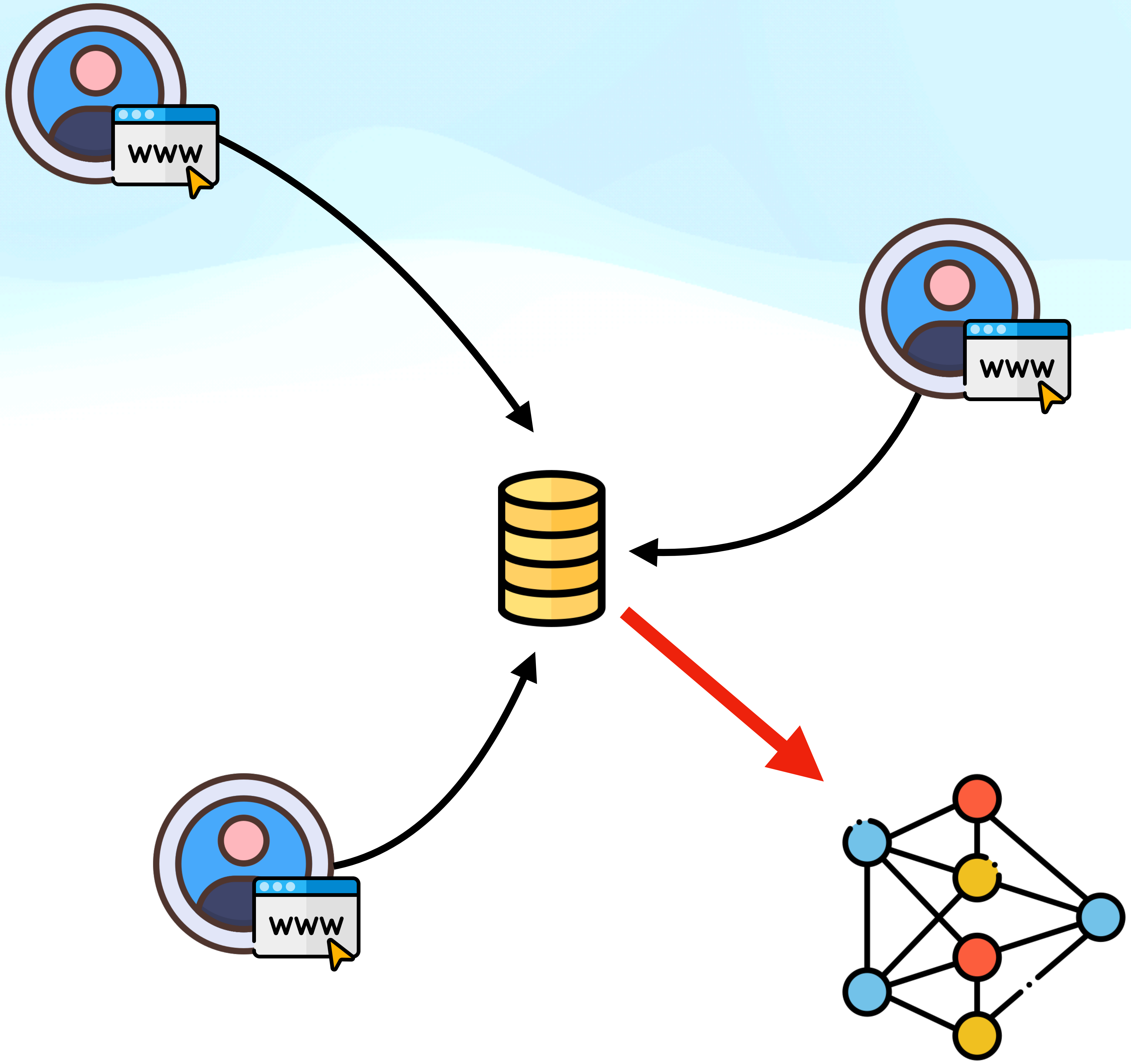
Naive solution

Browser Fingerprinting Detection

- Gather real-world observations from users as they browse websites
- Data collected from websites **might reveal sensitive information** (e.g., medical conditions)



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Naive solution

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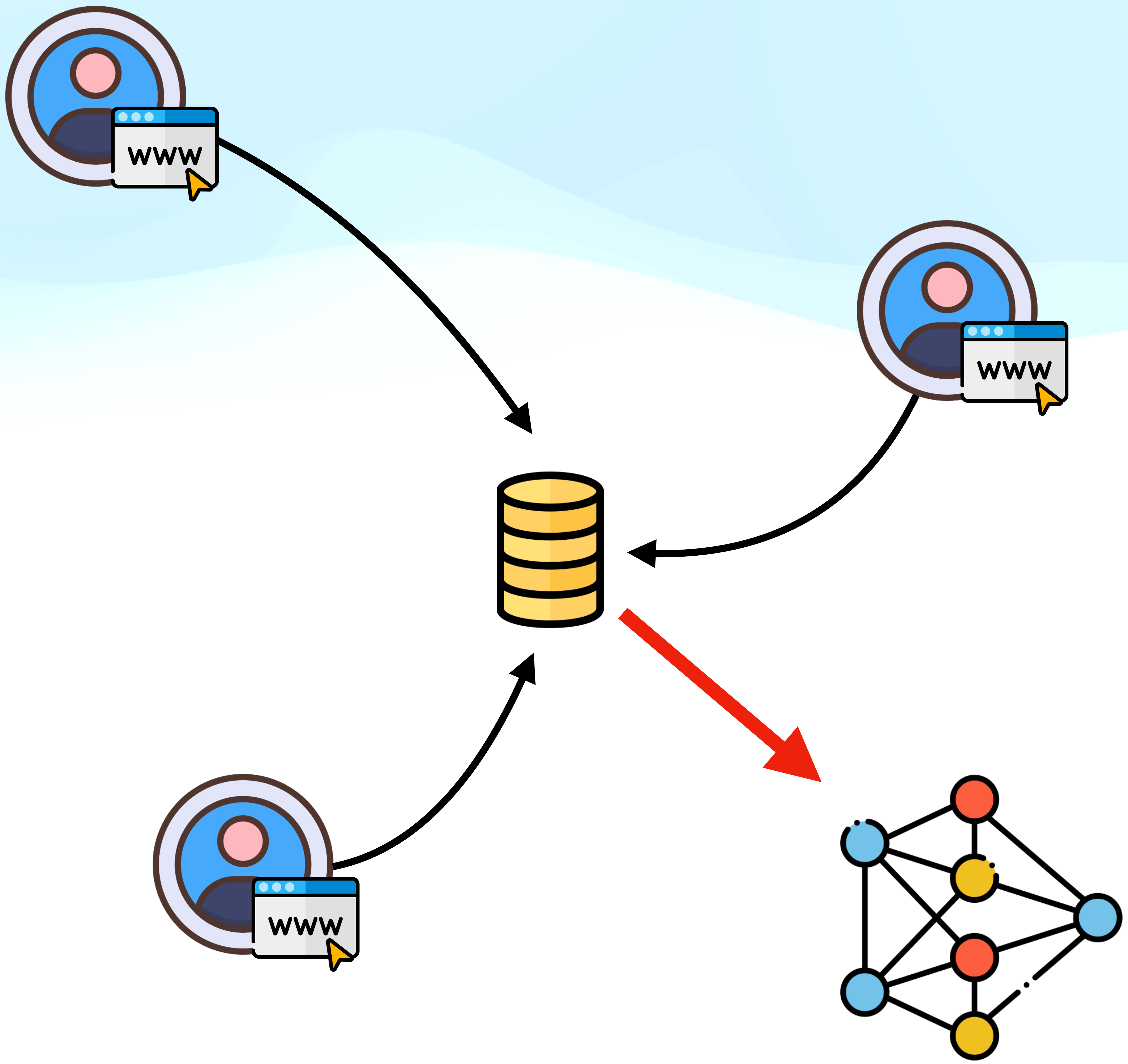
➡**Affect user's privacy**



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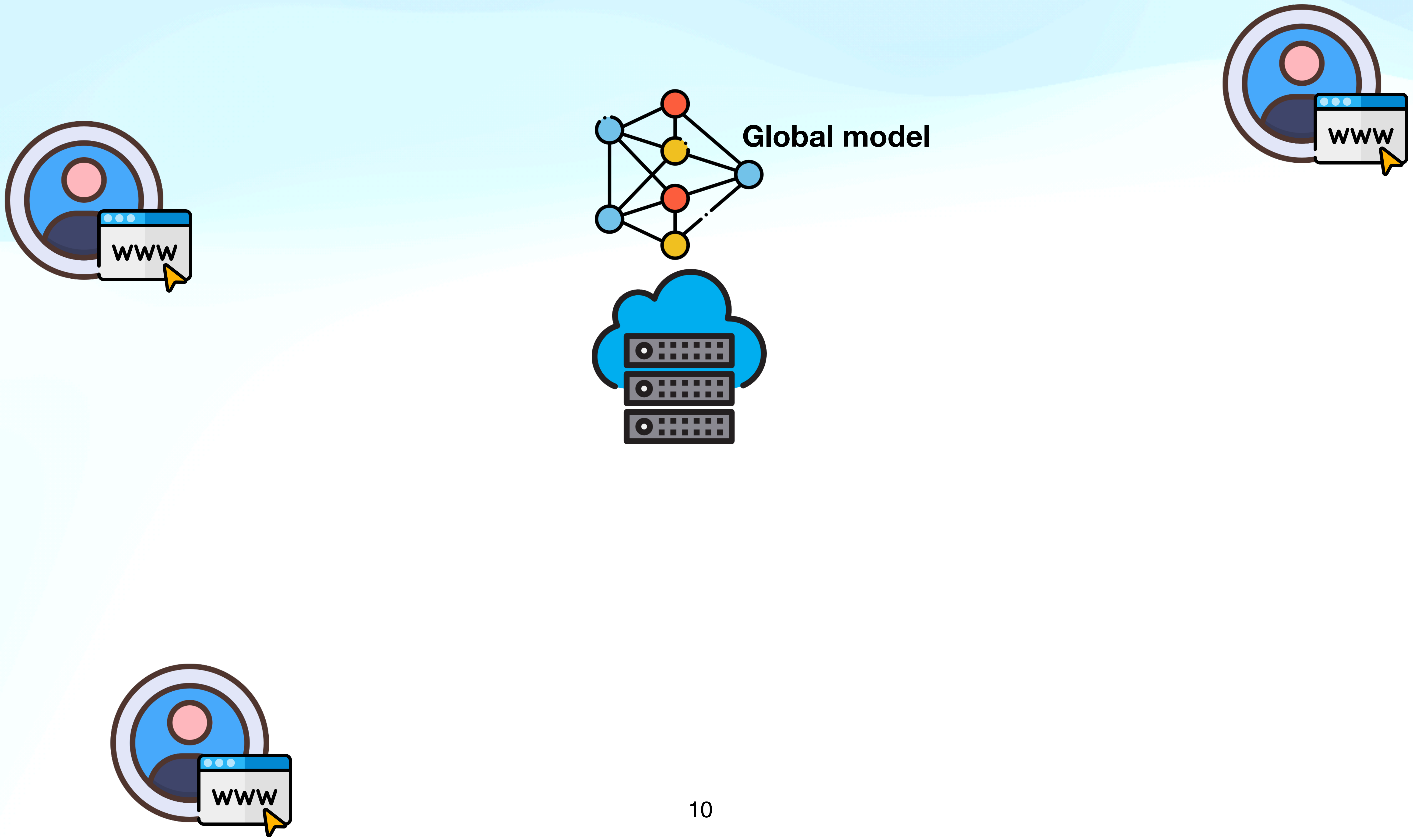
Differentially Private Federated Learning (DP-FL)

DP-FedAvg



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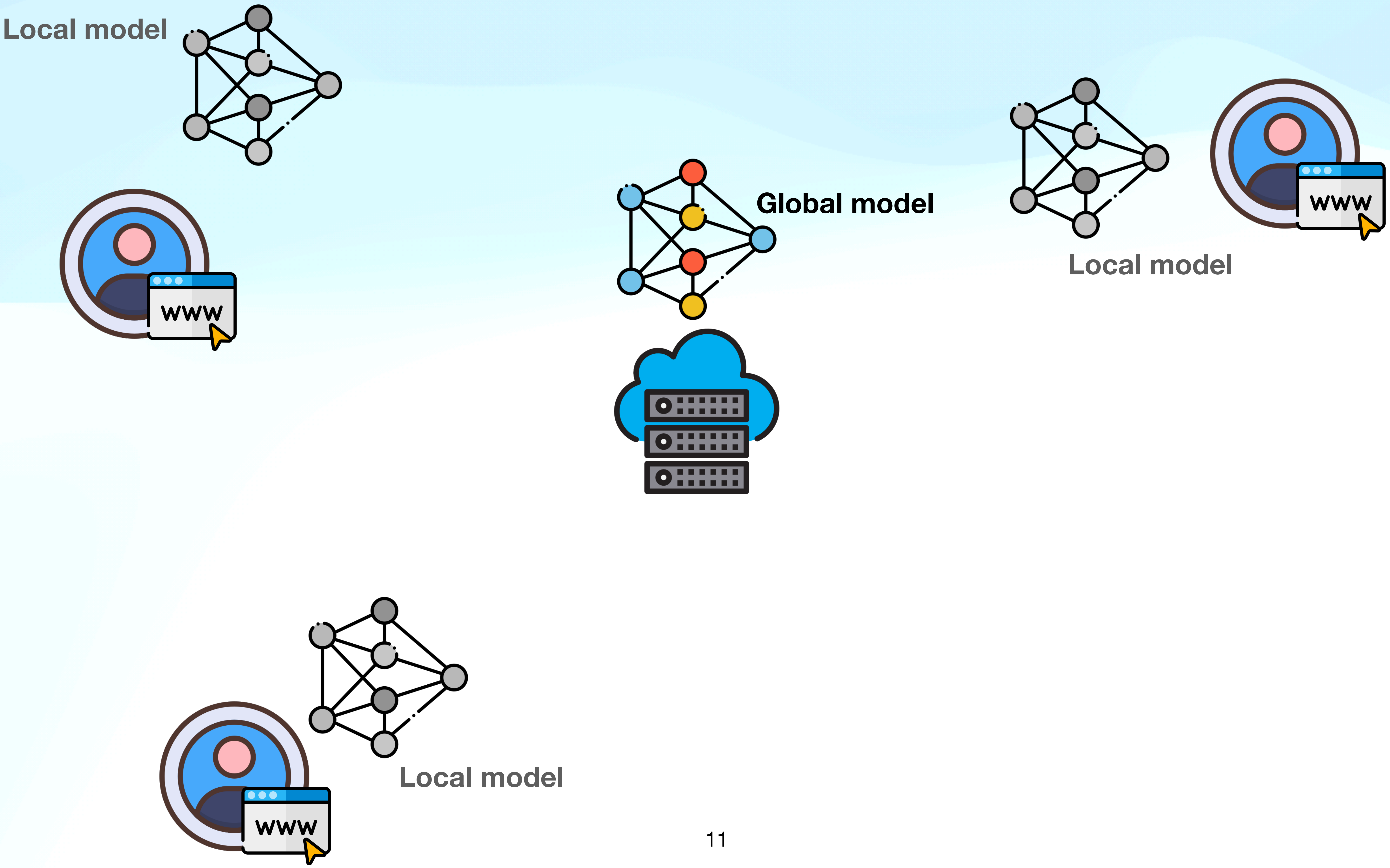
DP-FedAvg

Each user trains local model



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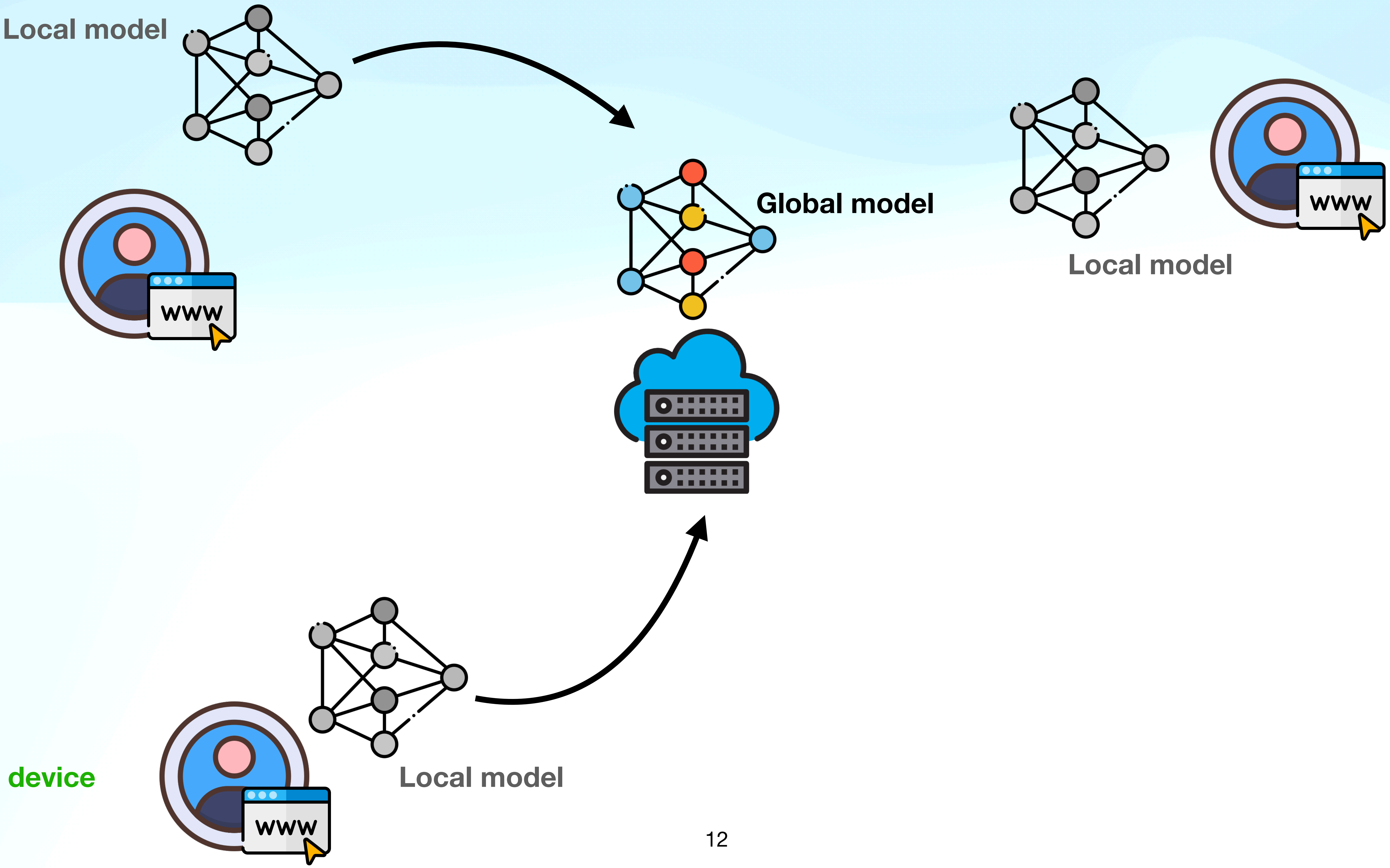
DP-FedAvg

Model updates are shared with the server



Raw data remains on device

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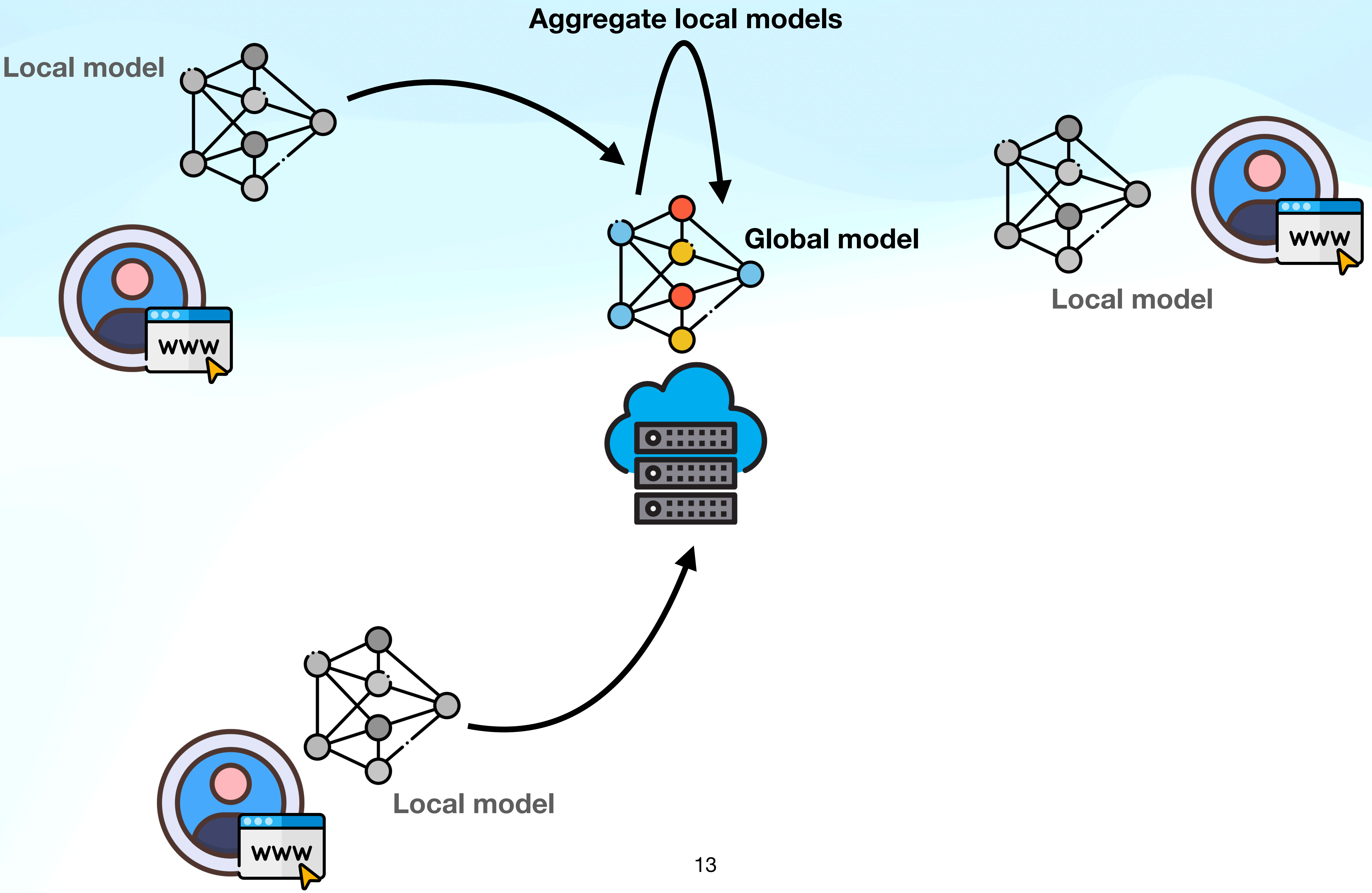
DP-FedAvg

Server aggregates model updates



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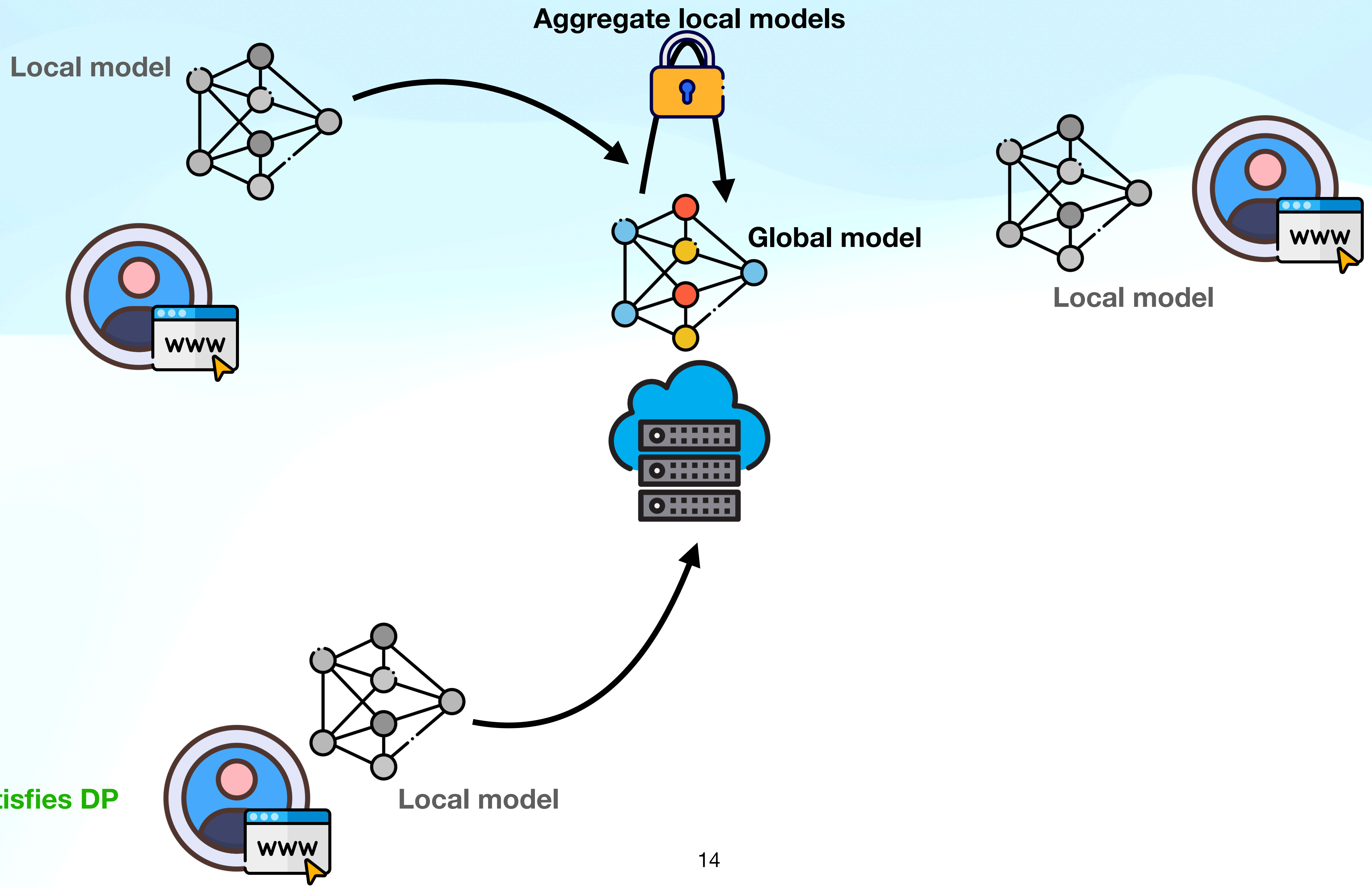
DP-FedAvg

Server adds statistical noise for privacy



Aggregated model satisfies DP

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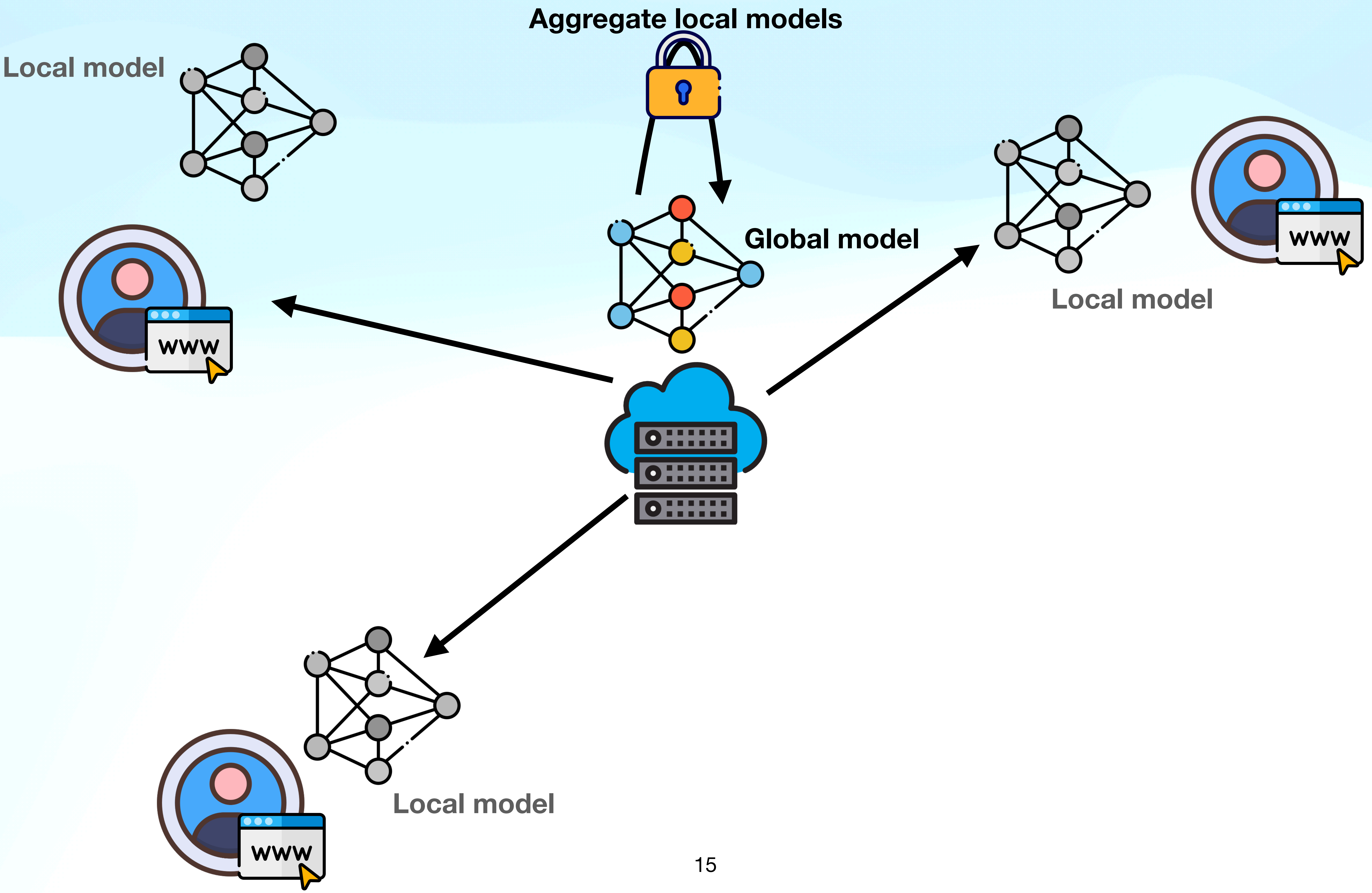
DP-FedAvg

Updated model is shared with users



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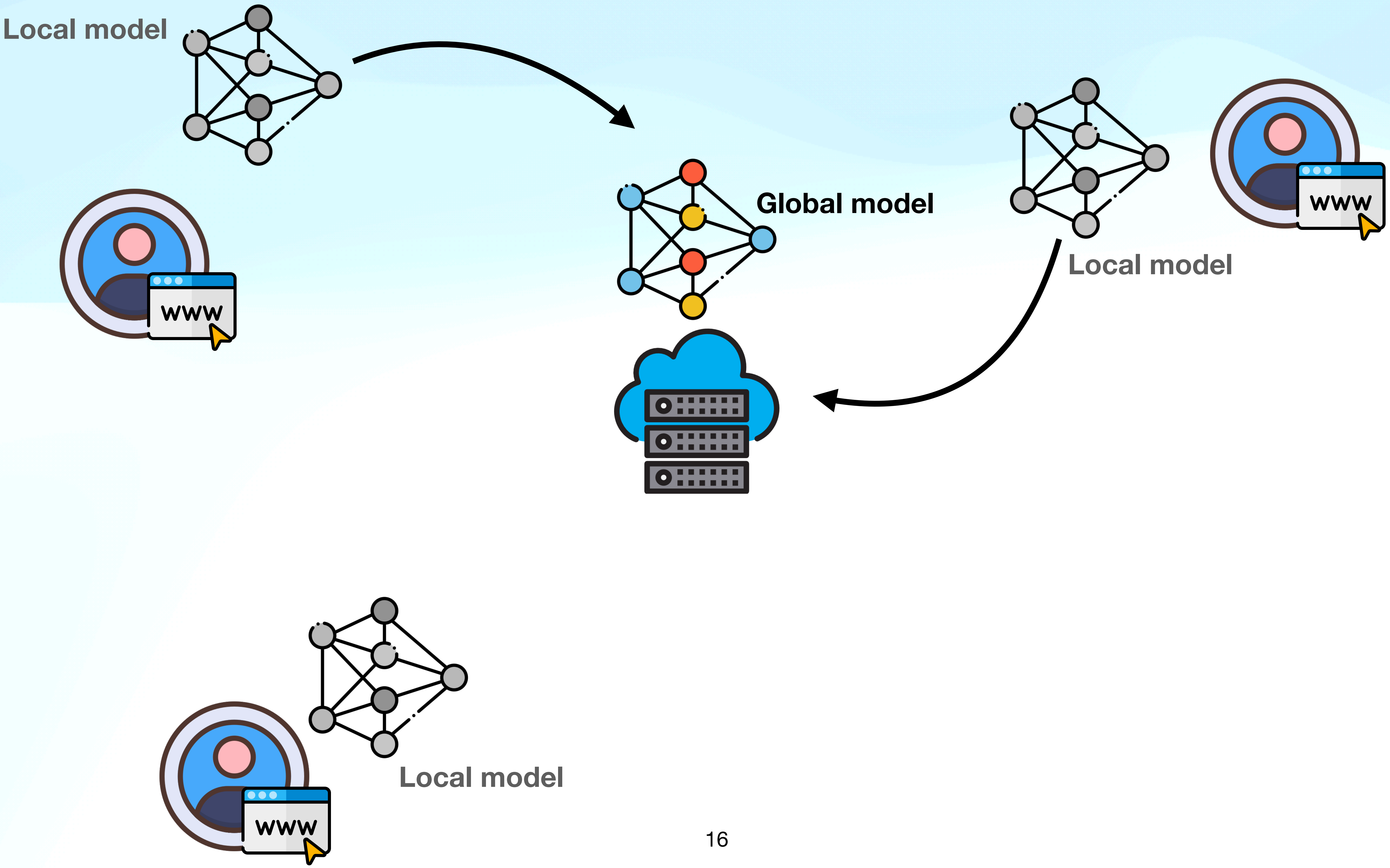
DP-FedAvg

Repeats until convergence



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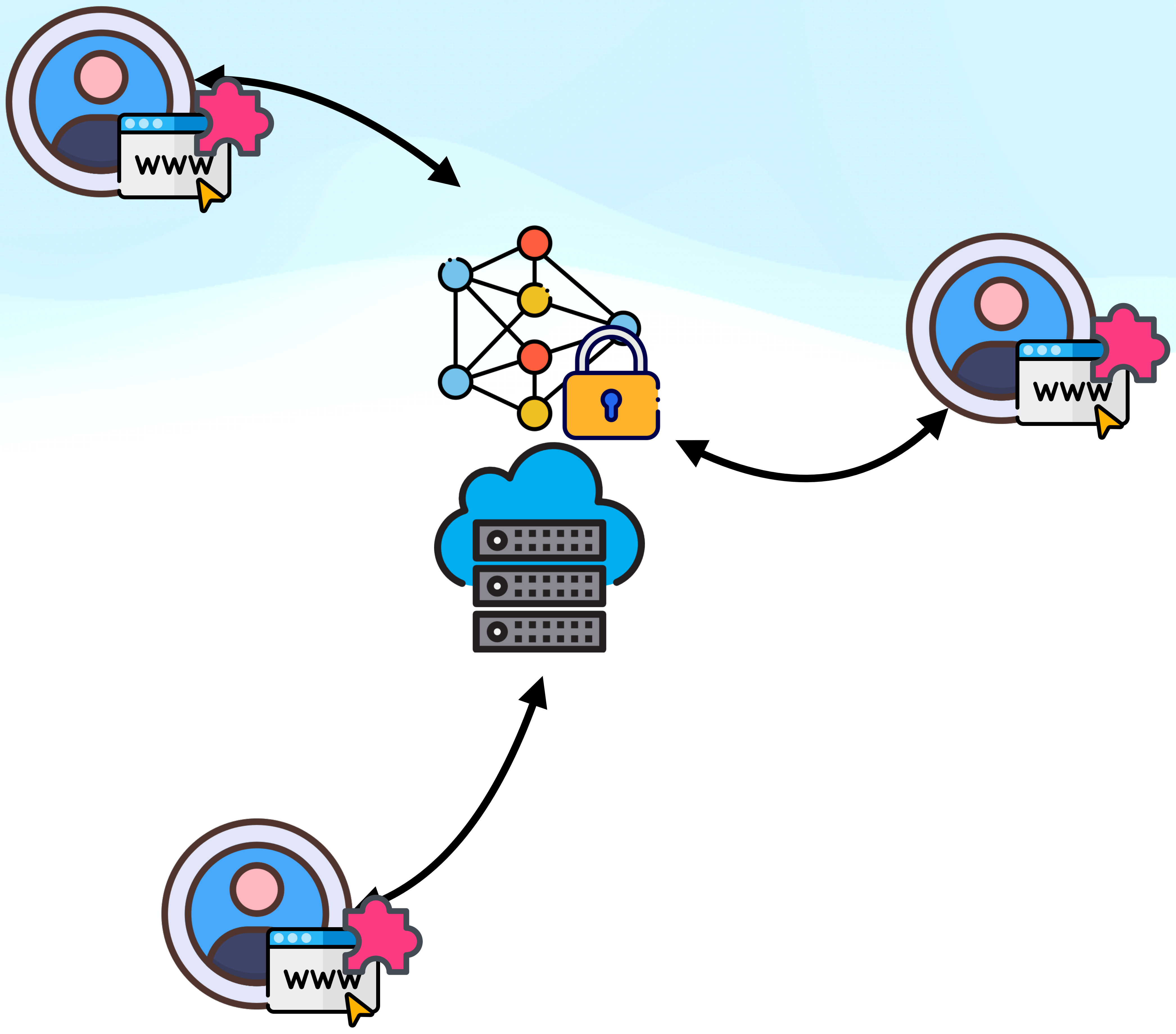
Applying DP-FL to Browser FP

Challenges

- Not trivial to federate existing classifiers **efficiently**



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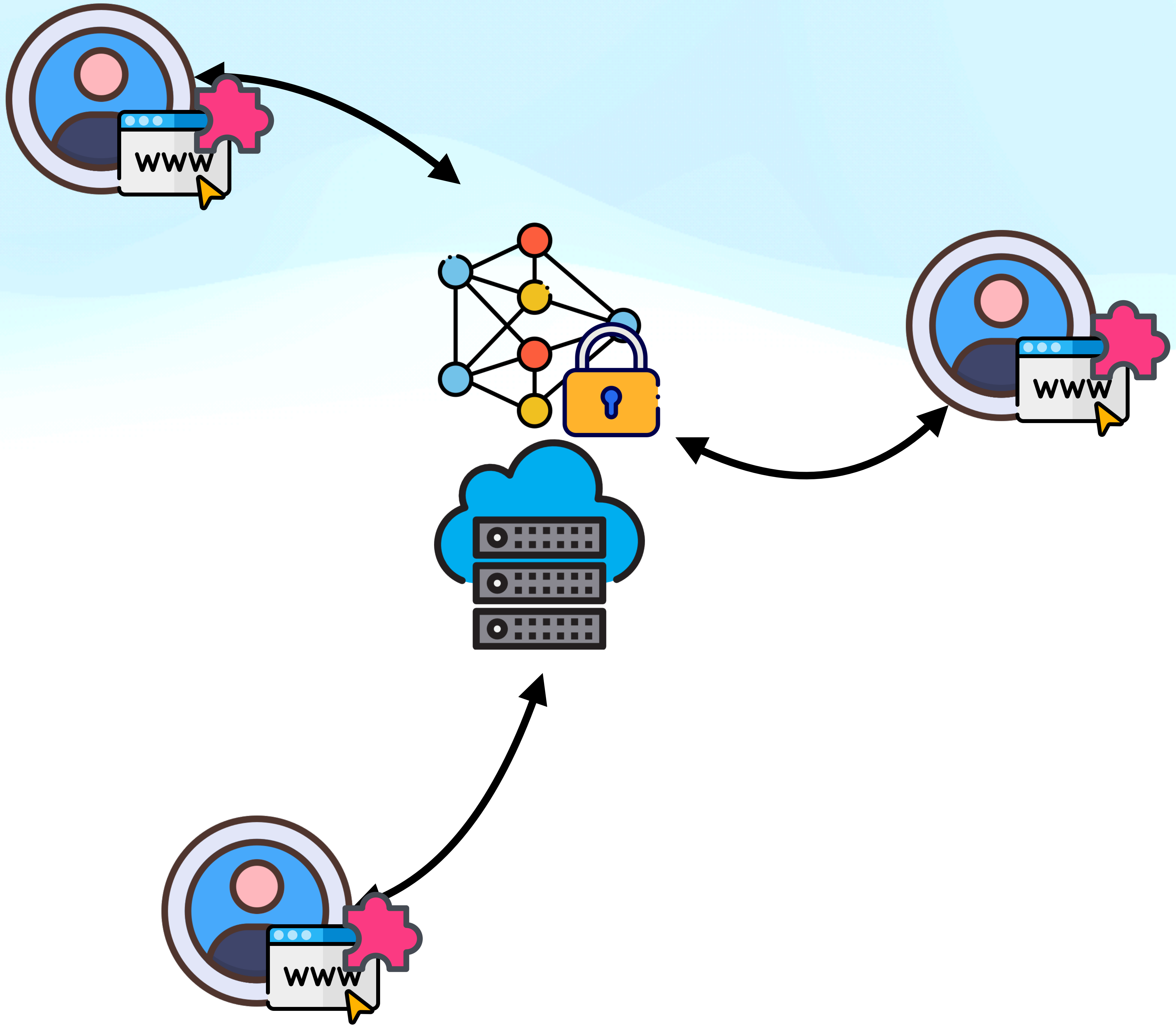

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Applying DP-FL to Browser FP

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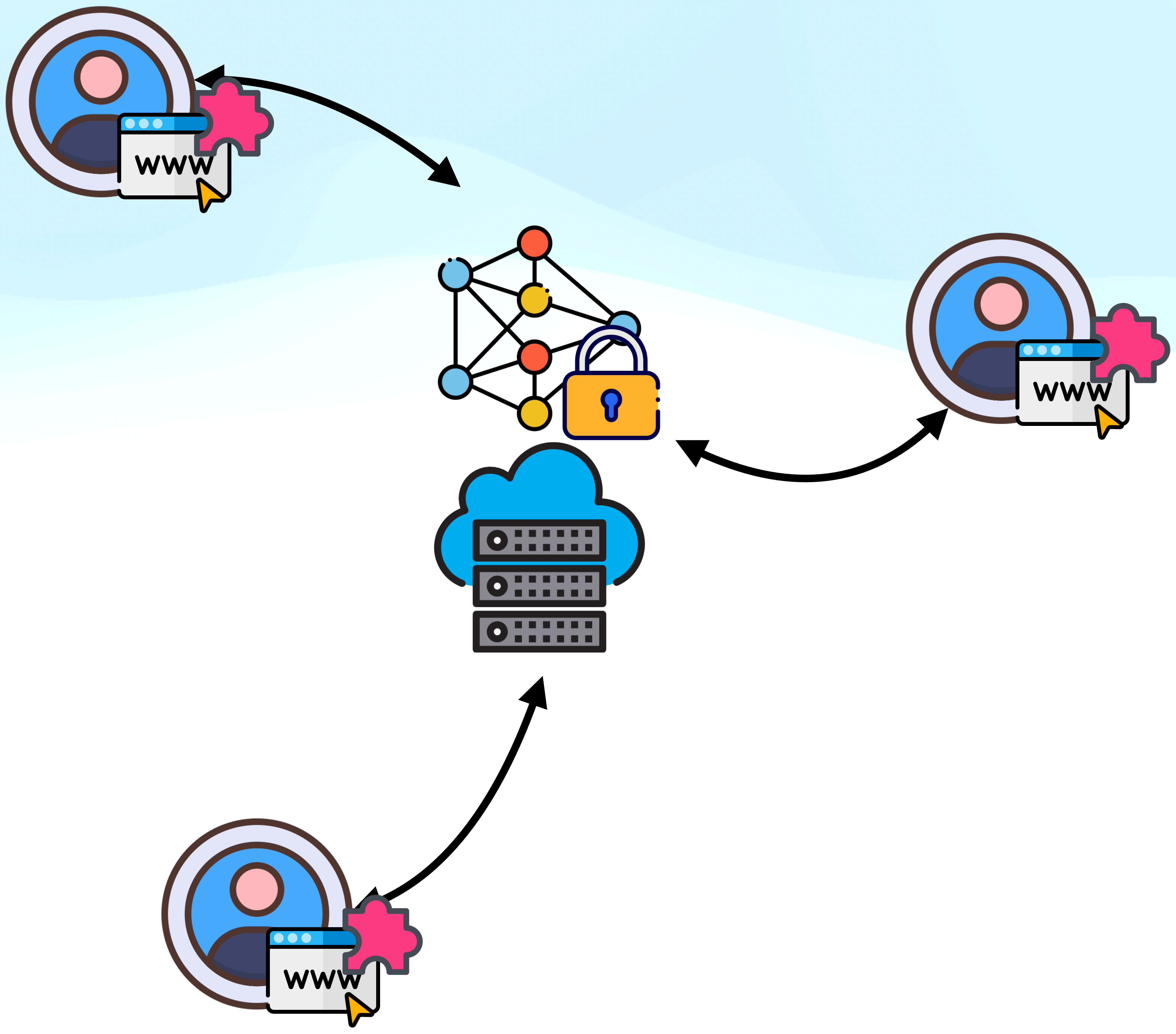
- Not trivial to federate existing classifiers **efficiently**
- **Intensive feature extraction** and **complex algorithms** may impact browser performance
- DP introduces **privacy-utility tradeoff**



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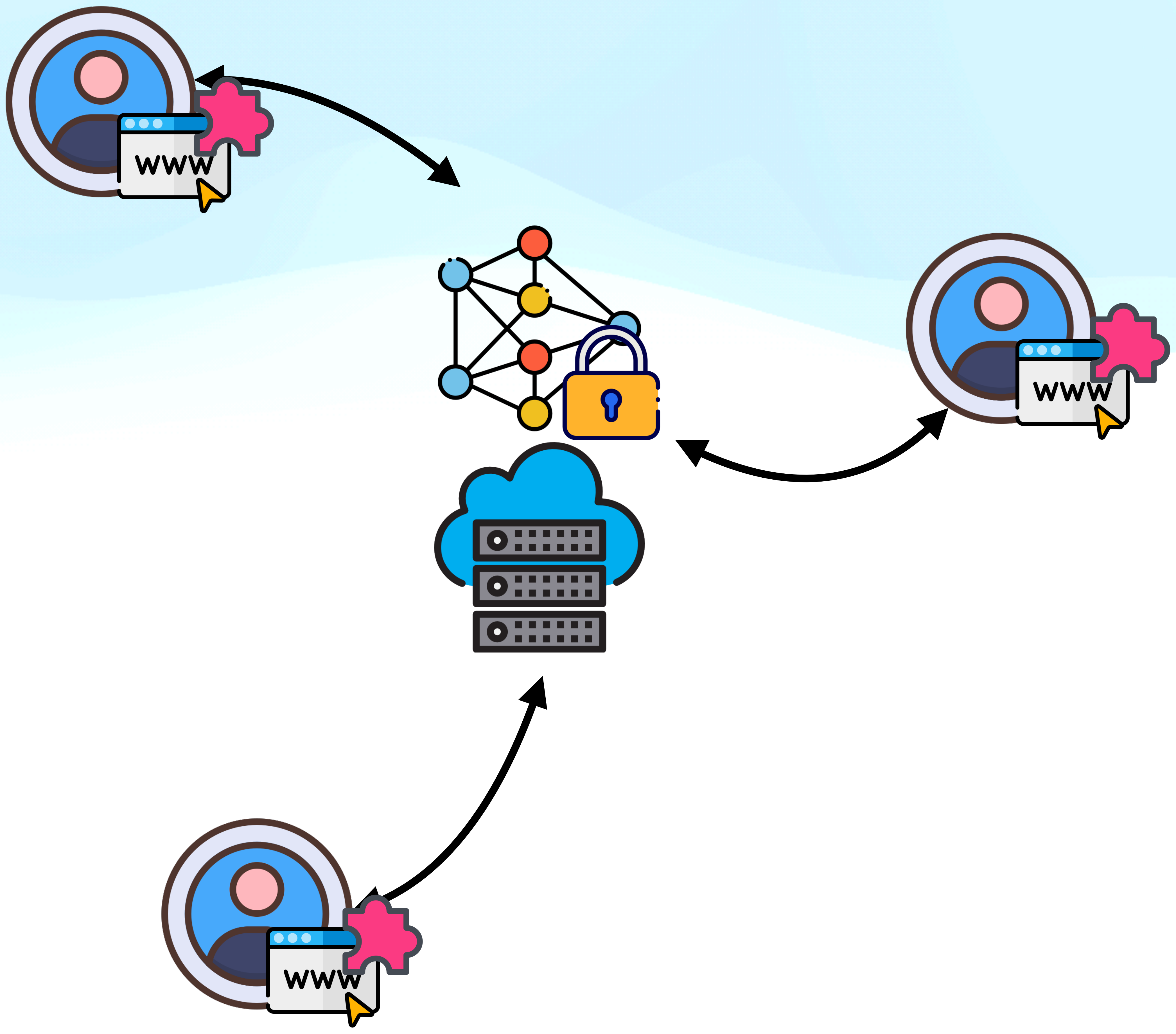
Our Work

FP-Fed

- **Distributed system (DP-FL)** for detecting browser fingerprinting in the wild



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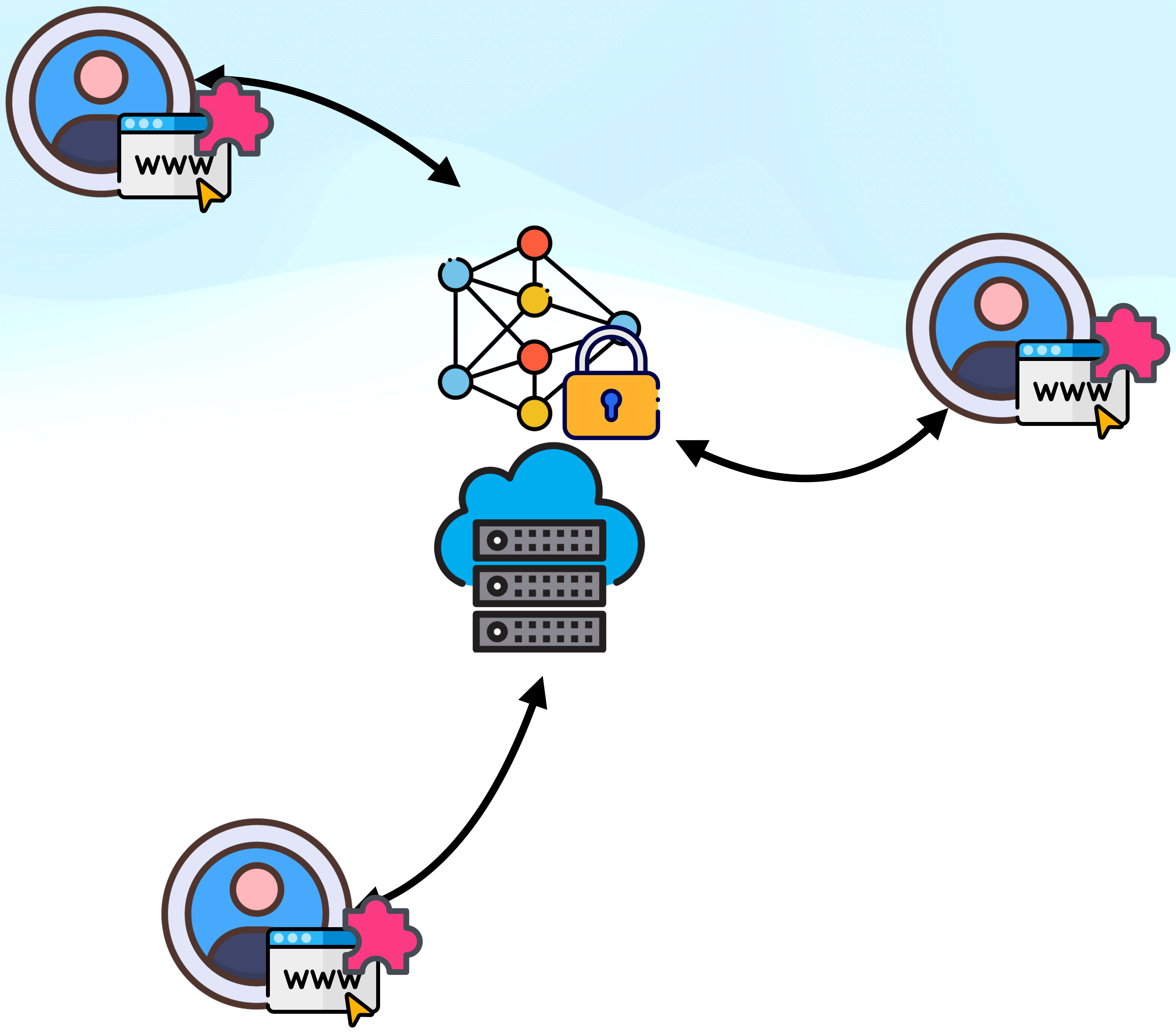

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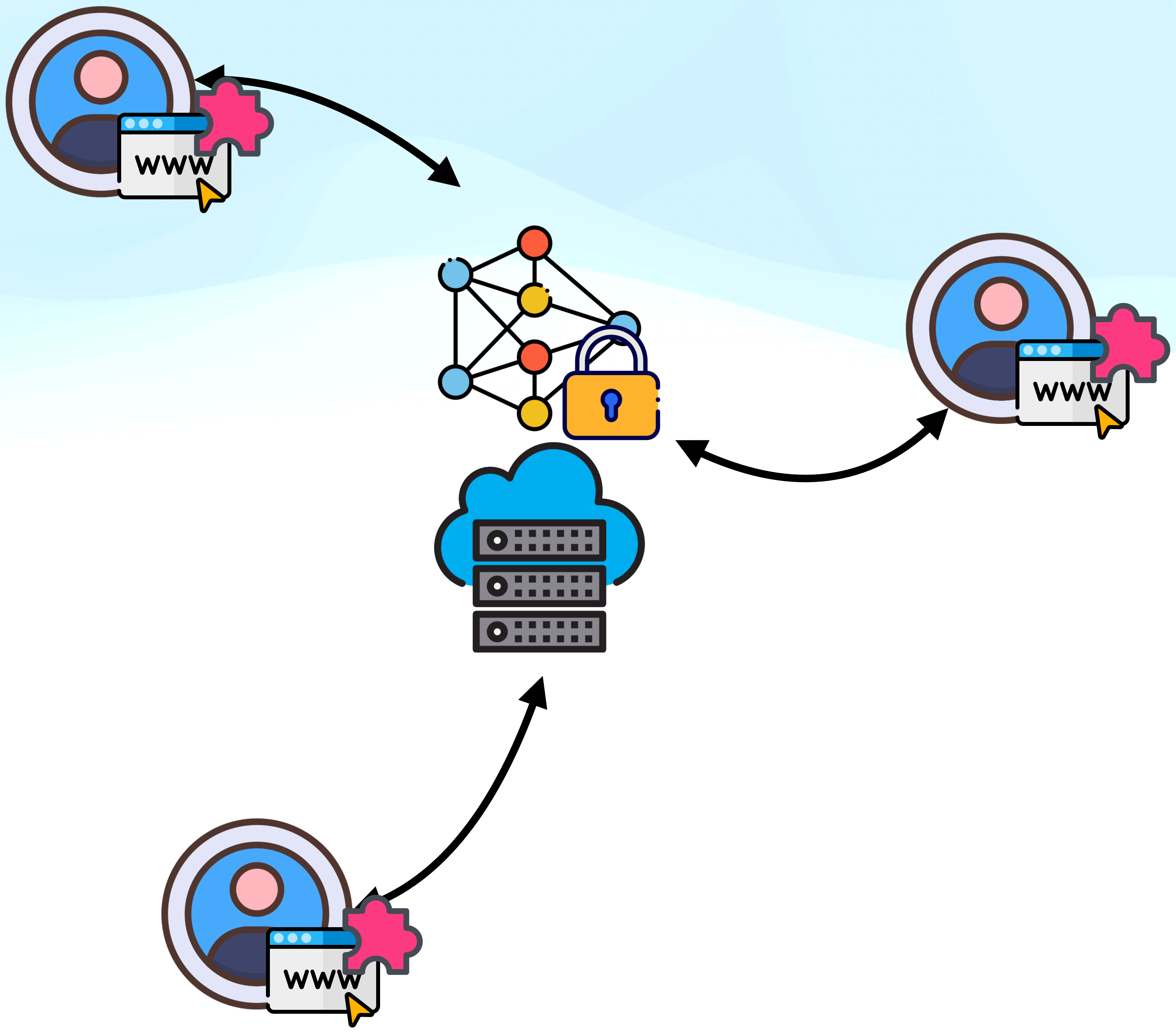

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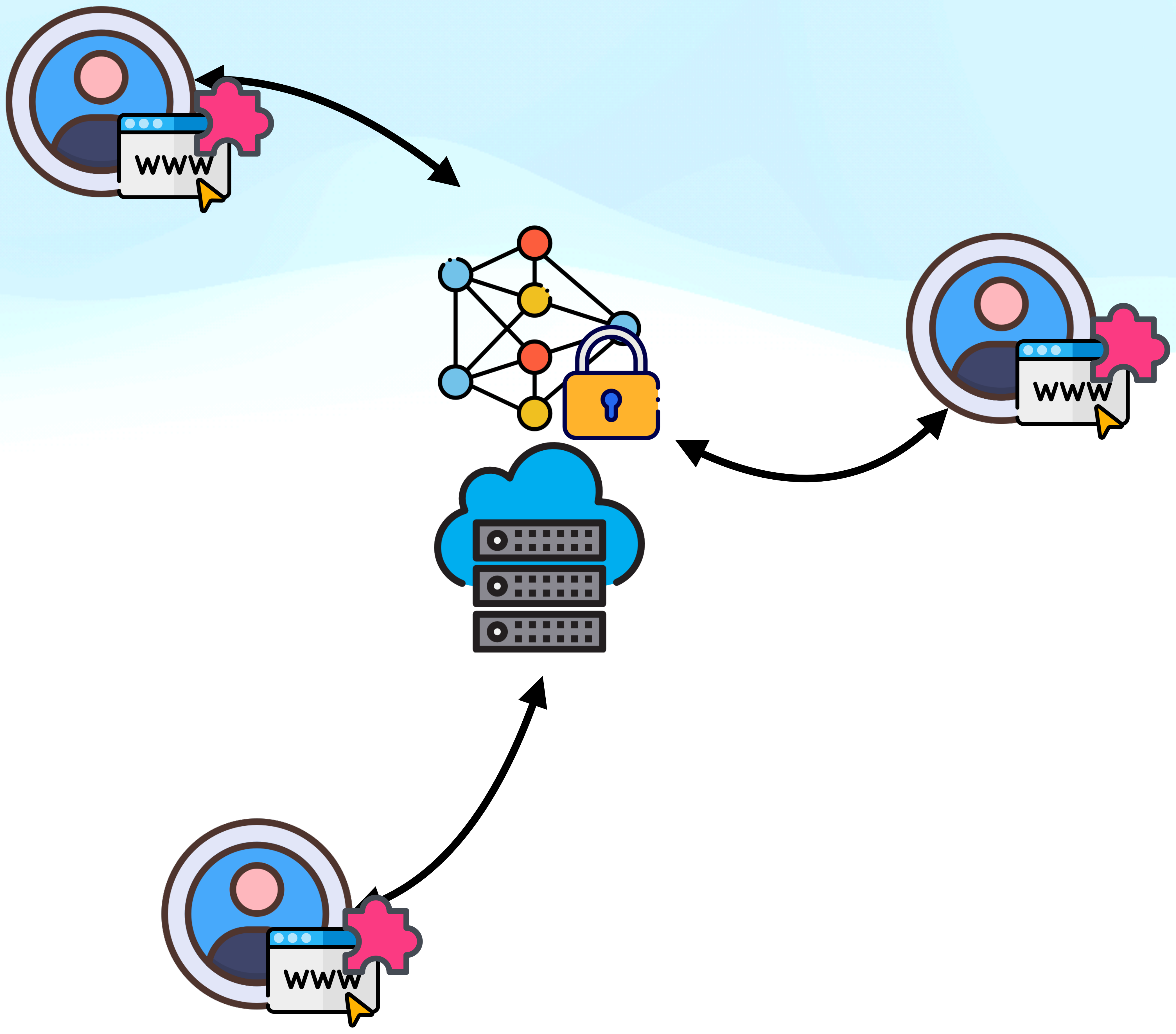
➡ Enables use of **real-world browsing patterns** instead of automated crawls



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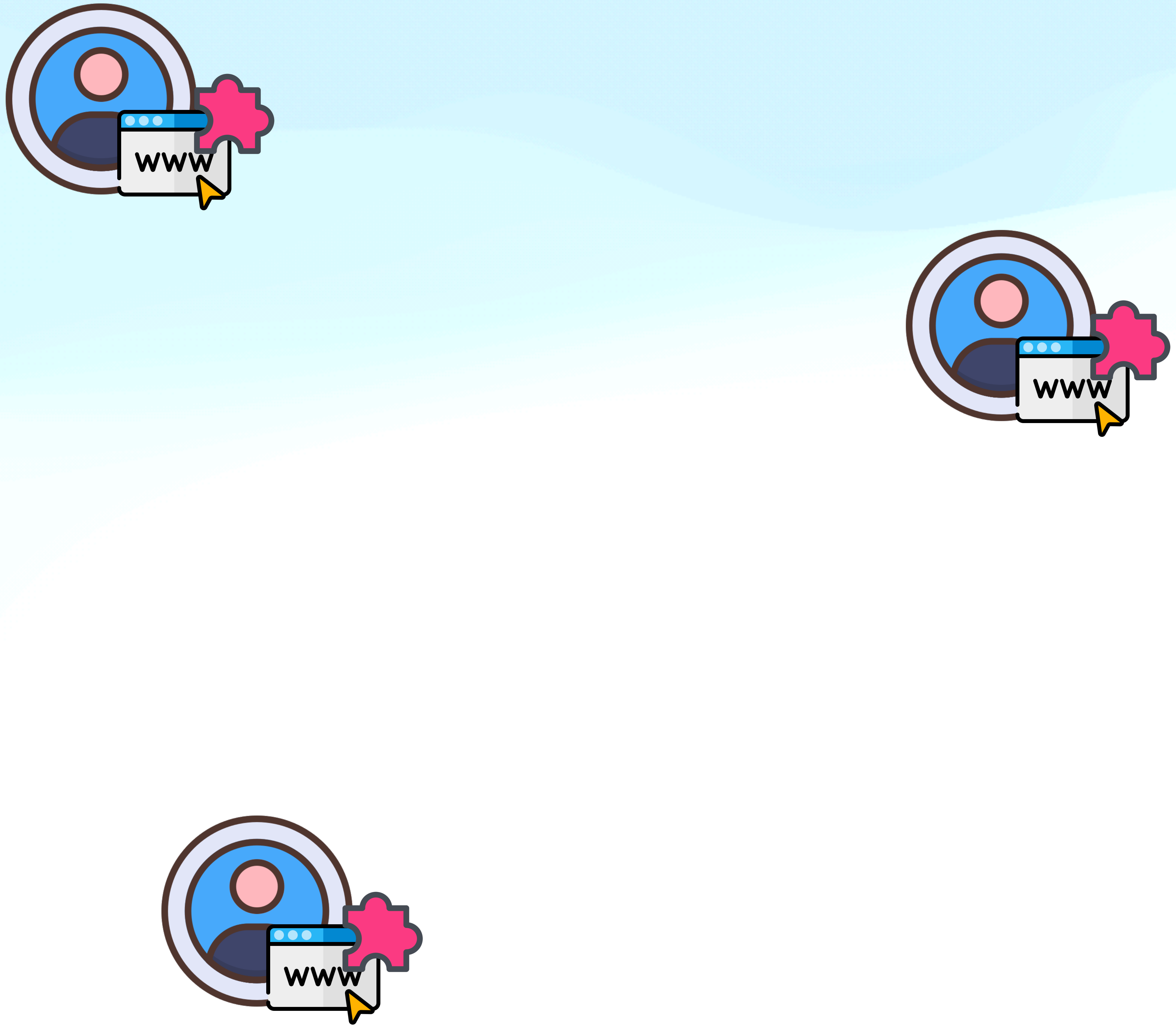
FP-Fed

FP-Fed

Step 1: Participants build local dataset



Step 1: Participants build local dataset

a) Feature Extraction

- API Call Counts (684)
  - # times **monitored APIs** are called
  - e.g., `CanvasRenderingContext2D.measureText` is called 50 times ⇒ Canvas Font fingerprinting

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- Custom features (830)
  - Processed from **arguments and return values of API calls**

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➡ Total features: 1514 (684 + 830)

Step 1: Participants build local dataset

b) Assign Ground Truth

- High-precision ground-truth heuristic defined by Iqbal et al.[1]
- Types of fingerprinting: Canvas, Canvas Font, WebRTC & Audio Context

[1] *Iqbal, U., Englehardt, S., & Shafiq, Z. (2021, May). Fingerprinting the Fingerprinters: Learning to Detect Browser Fingerprinting Behaviors. In IEEE S&P*

Step 1: Participants build local dataset
c) DP Federated Feature Pre-processing

- Feature normalization
  - Normalize each feature to have **mean 0 and variance 1**

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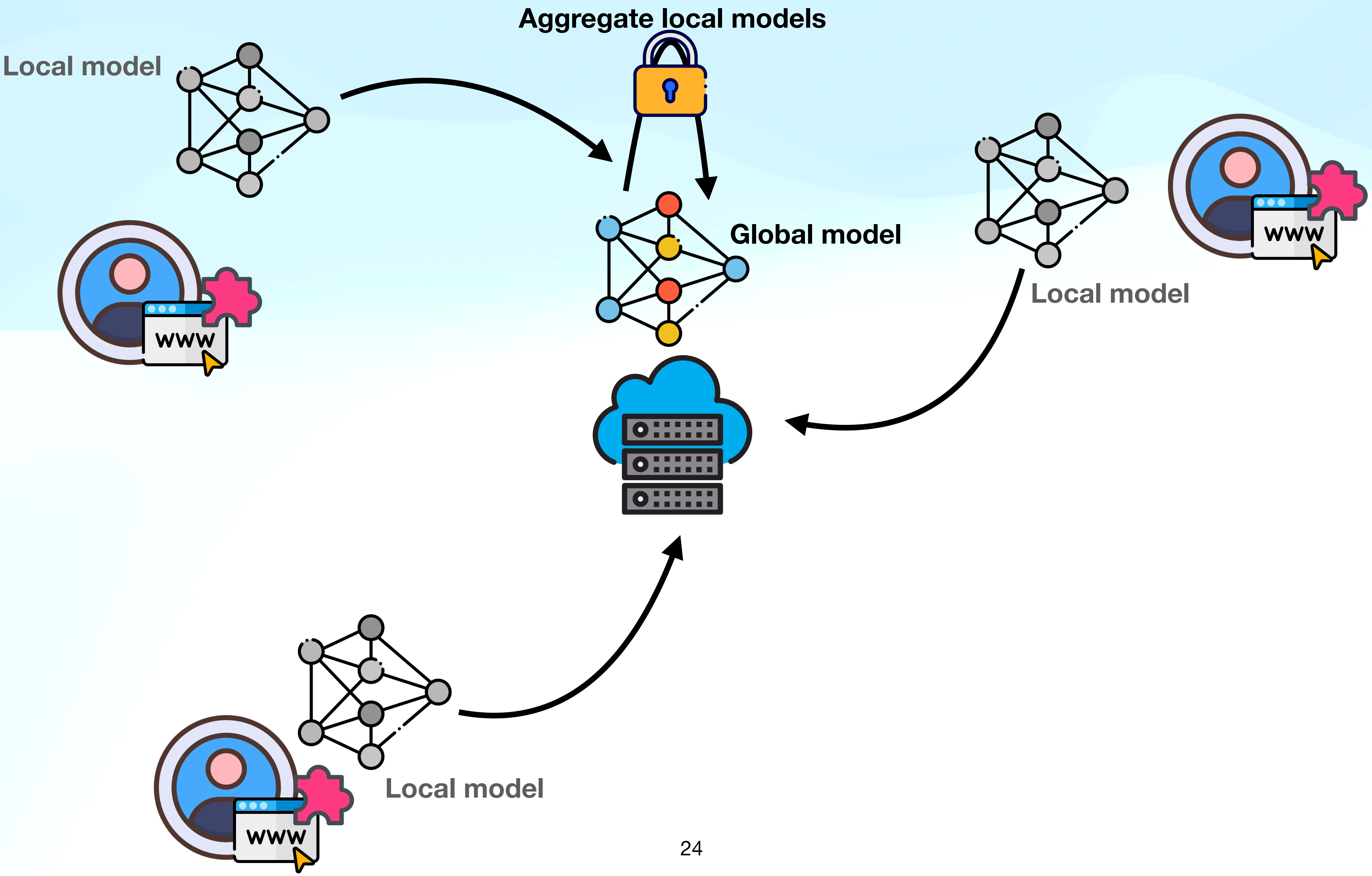
- **DP-FedNorm:** Federate + Add DP noise to normalisation

FP-Fed

Step 2: Participants run DP-FedAvg



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Experimental Setup

Experimental Setup
Dataset

- Ideally real-world browsing sessions will be collected
- For the purposes of this work, **automated crawl of 20k popular websites** sampled from Chrome User Experience Reports
- 18k successfully visited, 181k unique scripts, **752 fingerprinting**

Experimental Setup

Simulating Participants

- Each participant **samples 100 domains** according to Zipf's law over popularity of websites from Tranco ranking
- Assign **scripts loaded by domain** to participant

Experimental Setup
Model

- Logistic Regression, LBFGS solver
- Report Area-Under-Precision-Recall-Curve (AUPRC)
  - Threshold can be adjusted, allowing precision-recall to be tuned
  - AUPRC summarizes model performance across variety of thresholds

Experimental Setup

Minimal Feature Set

- Collecting all 1514 features may be **computationally intensive** and raise **privacy concerns**
- Experiment with smaller feature sets (e.g., APIs that are natively tracked by Google Chrome — High Entropy APIs)

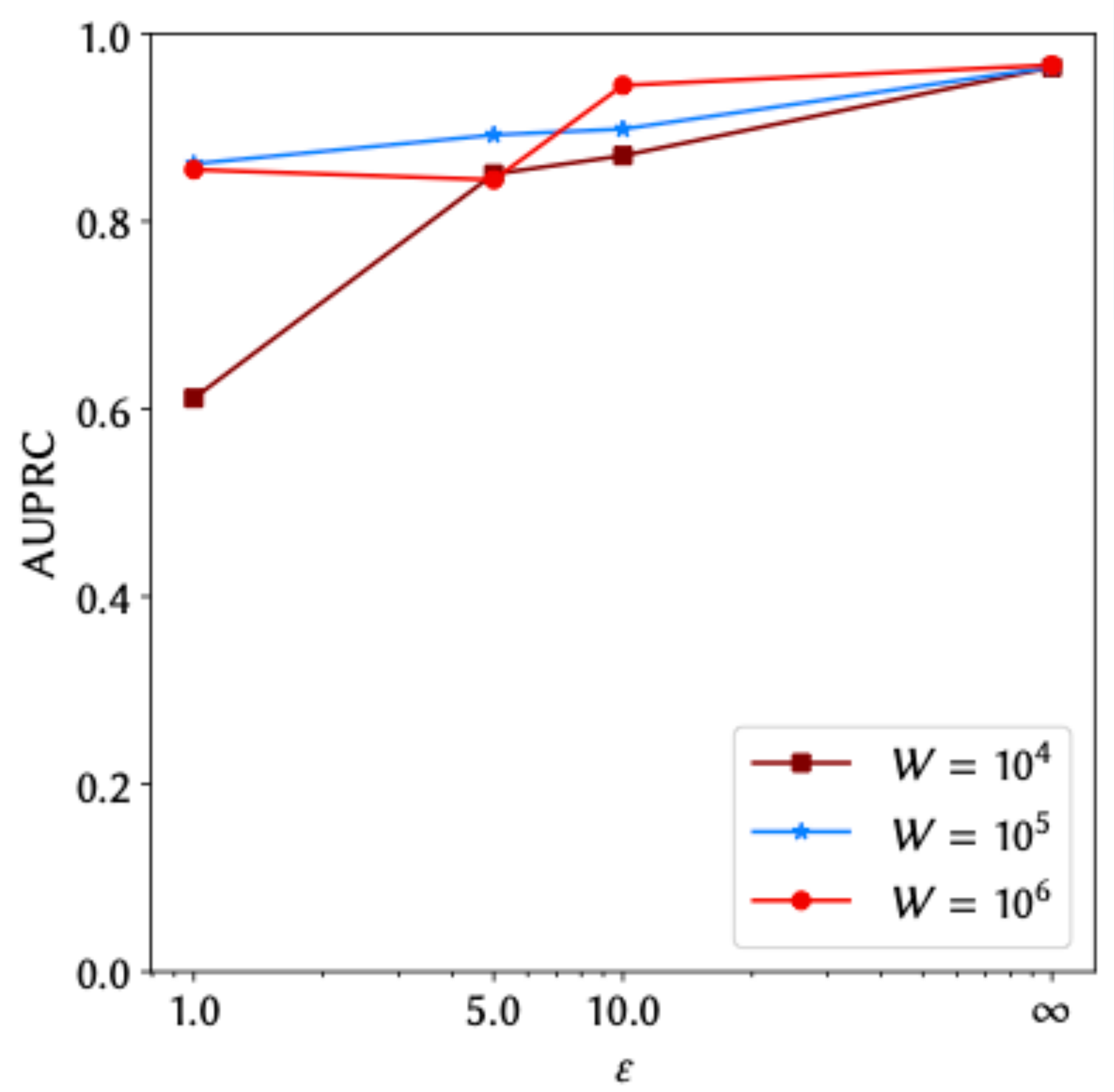
Feature Set	# API Call Counts	# Custom
API	684	830
FP-Inspector	500	830
JShelter	96	492
High Entropy APIs	109	0

Results

FP-Fed

Impact of ε (privacy parameter)

- *All* feature set
- 100 participants sampled per round



FP-Fed

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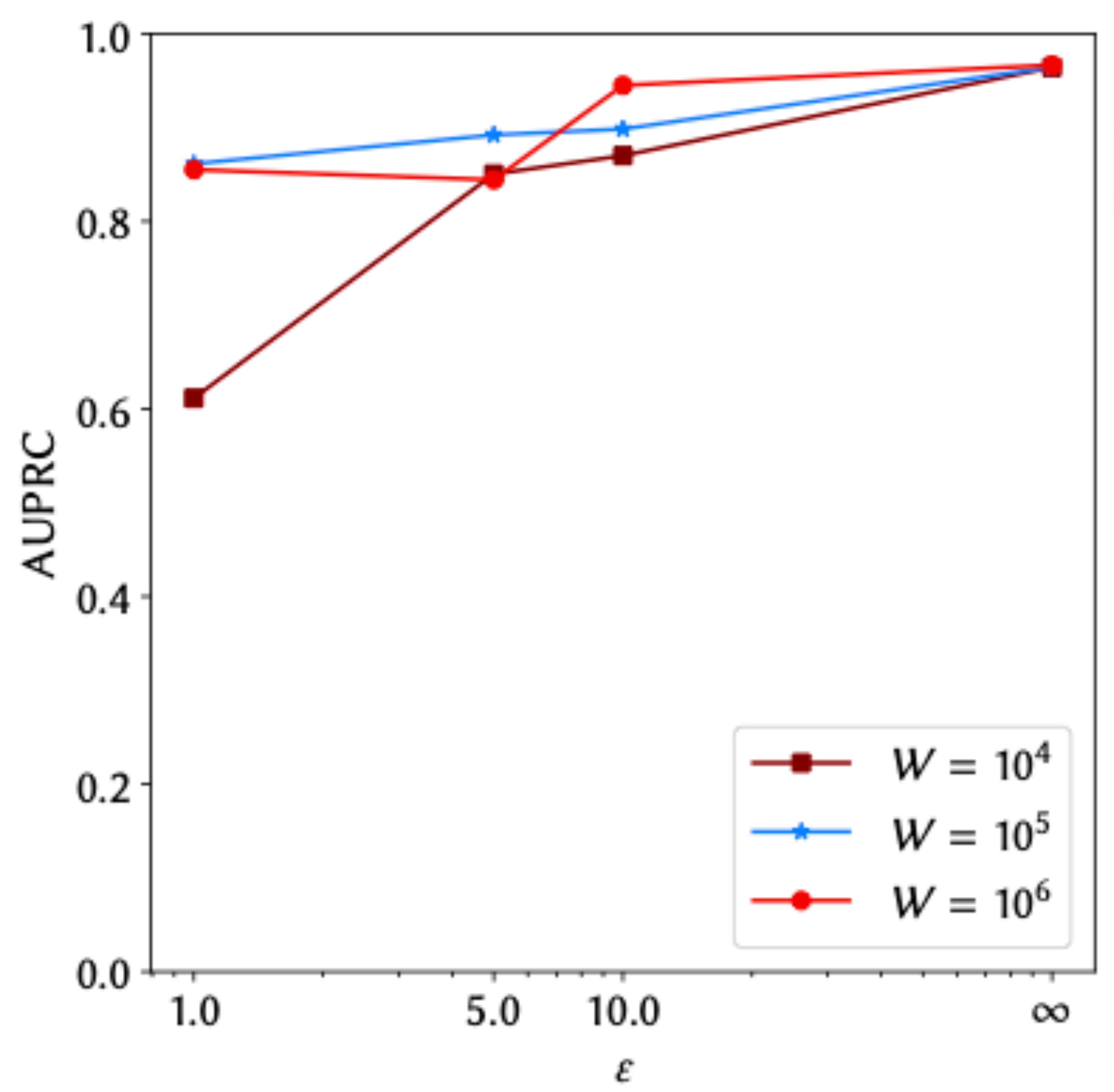
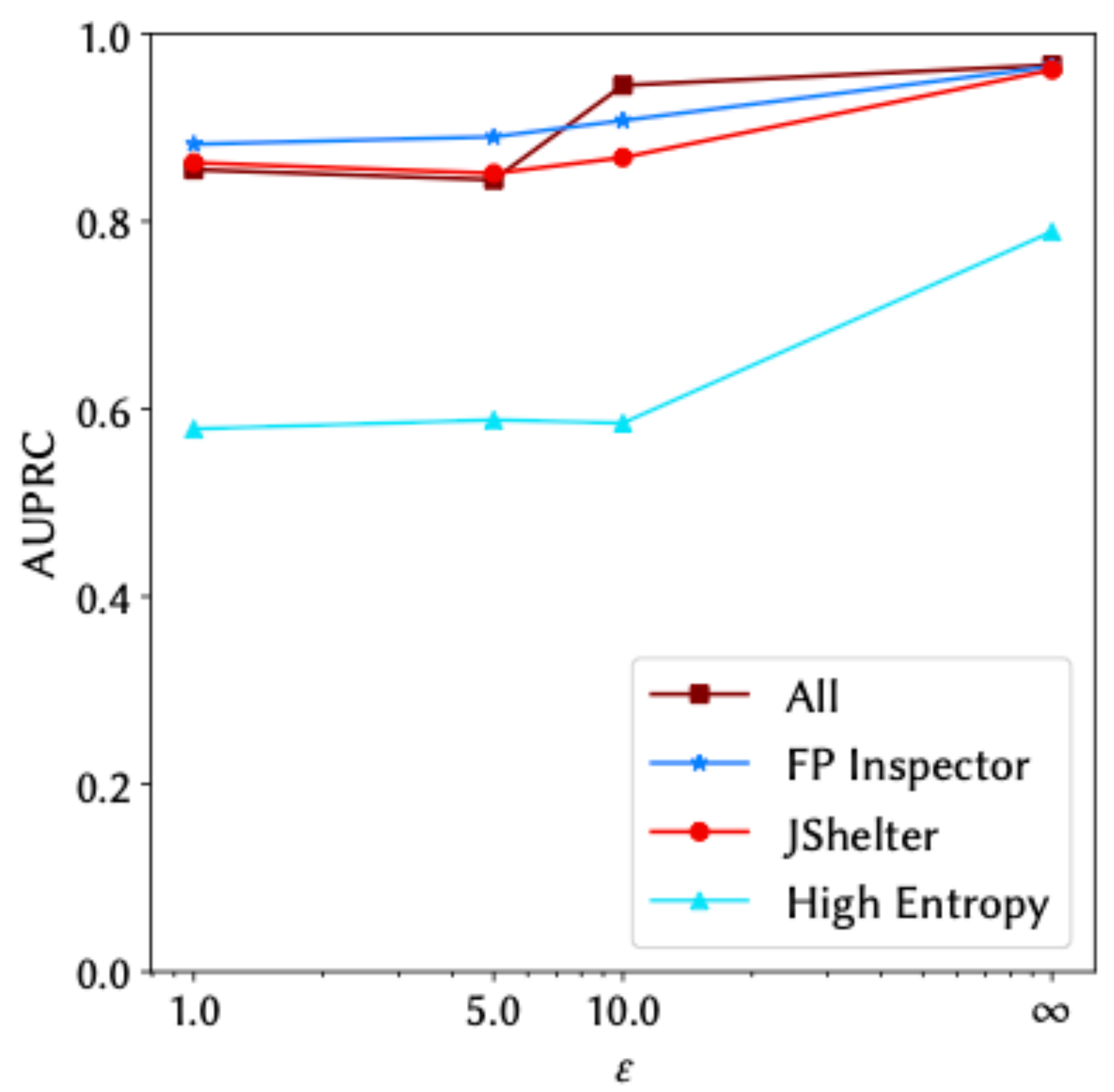
➡ **Having large number of participants is beneficial** even if not all are participating in each round



FP-Fed

Impact of feature set (*All*, *FP-Inspector*, *JShelter*, *High Entropy*)

- 1M total participants



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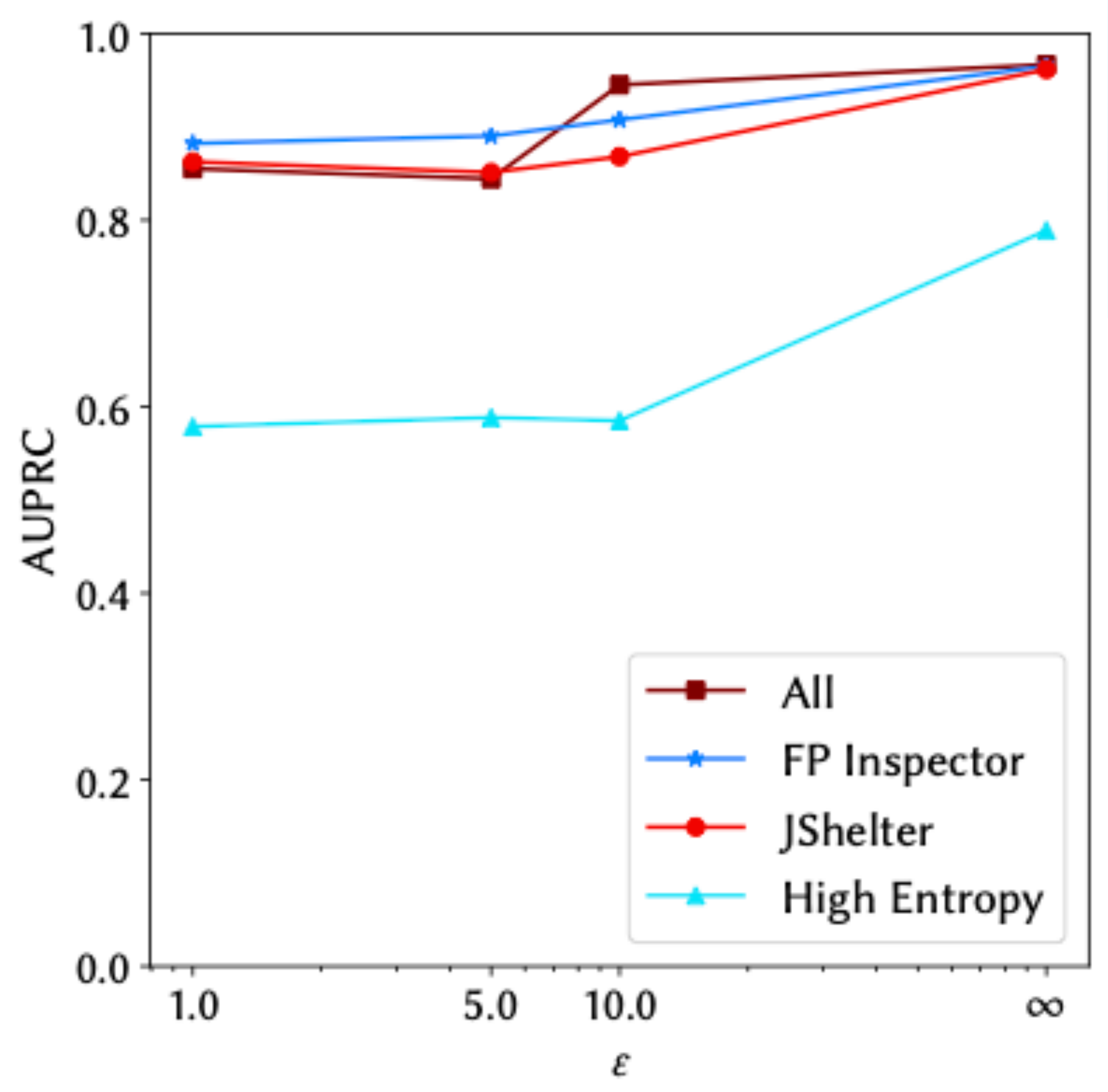
➡ *JShelter* **performs similarly** to *All* and *FP-Inspector* even though it **only contains 40% of features**



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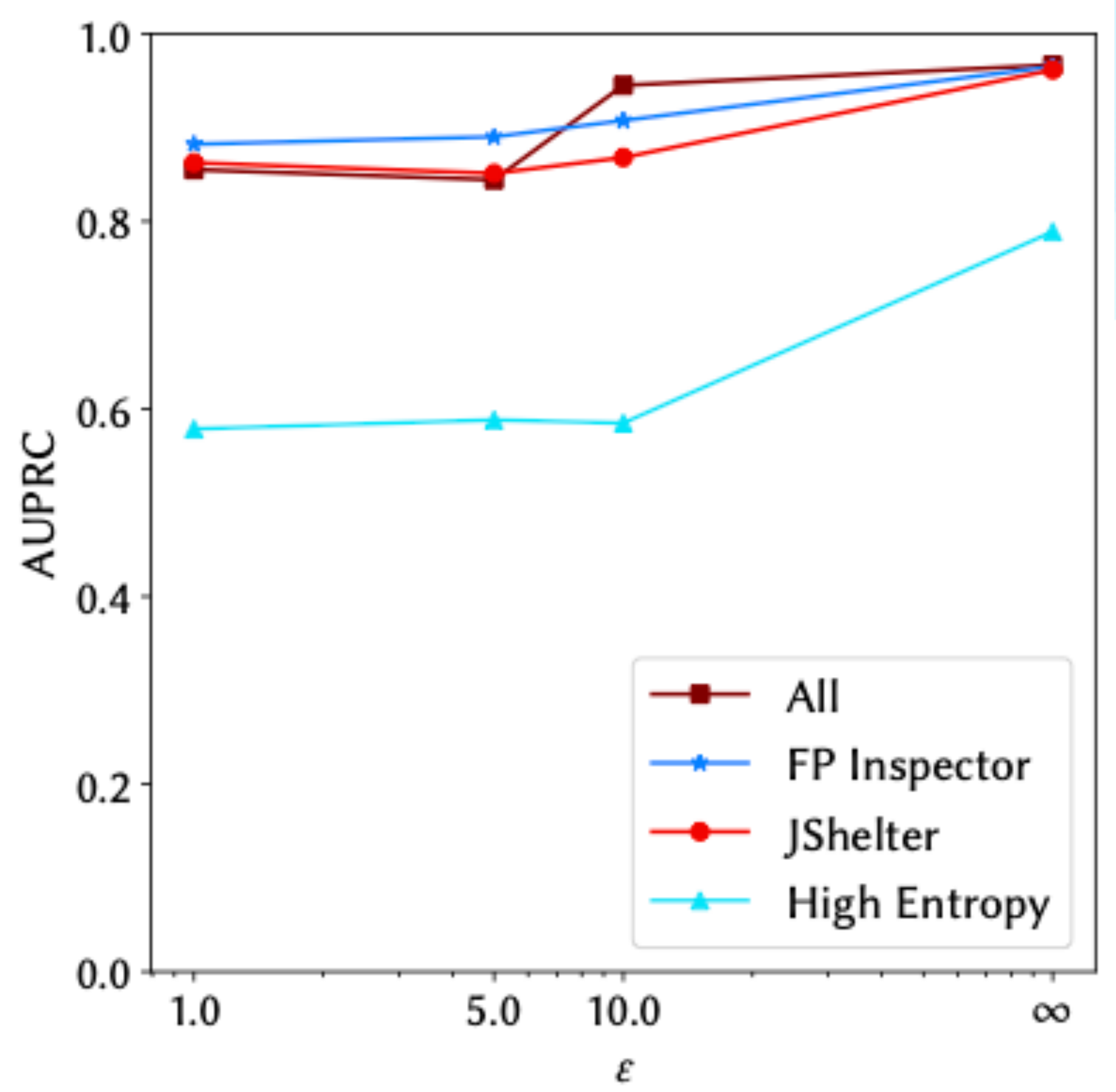
➡ *High Entropy* is **ineffective even without DP**



Working towards a “minimal” feature set

Research Questions

- High Entropy APIs **have too little features** to reliably detect Browser FP

Working towards a “minimal” feature set

Research Questions

- High Entropy APIs **have too little features** to reliably detect Browser FP
- RQ: **How many features** does FP-Fed need to perform well?
  - RQ1: How many API call counts?
  - RQ2: How many custom features?

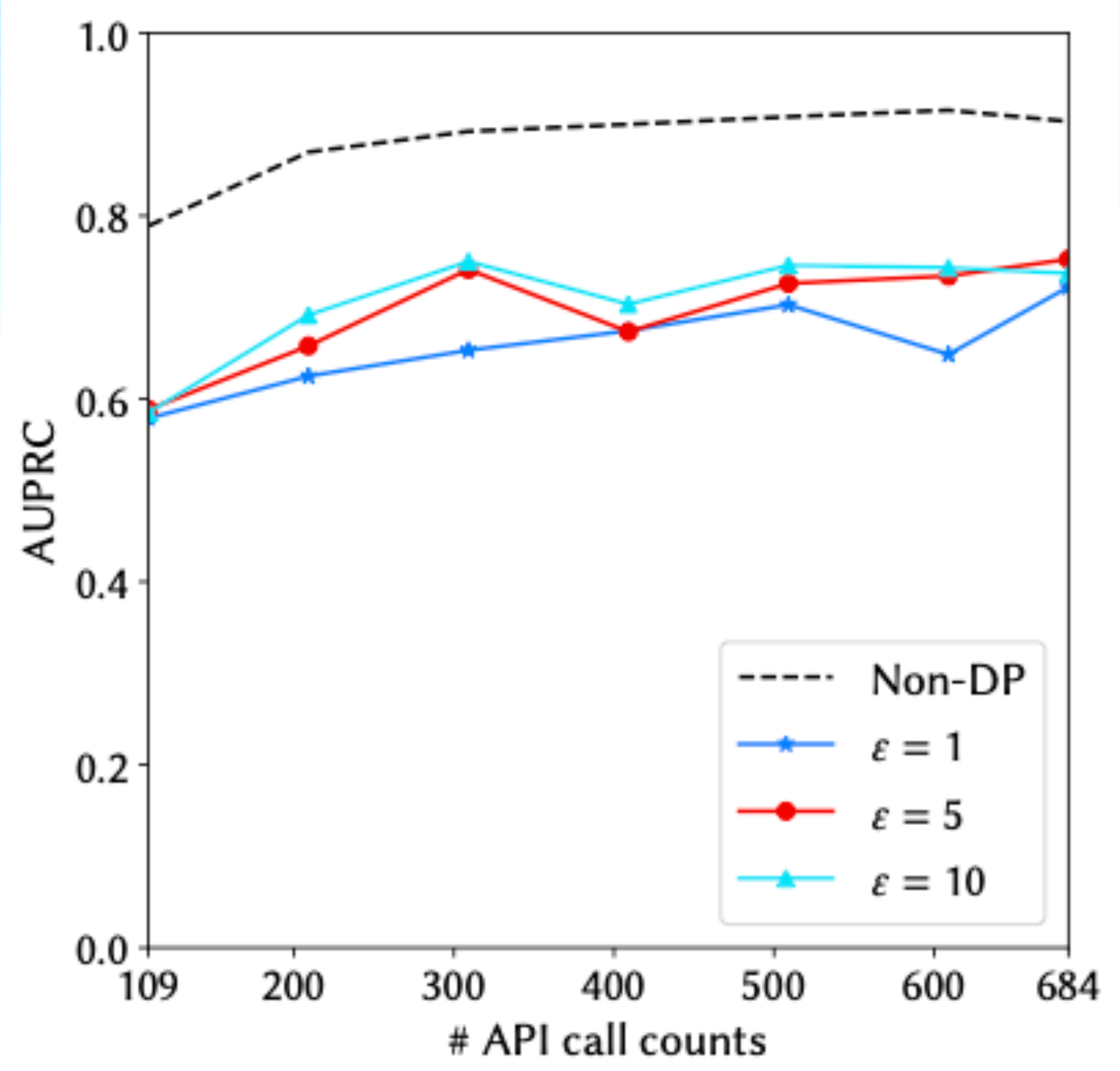
Working towards a “minimal” feature set

Methodology

- Model parameters are used as **“feature importance” score**
- Sort features according to score and **add features to *High Entropy* incrementally**

Working towards a “minimal” feature set

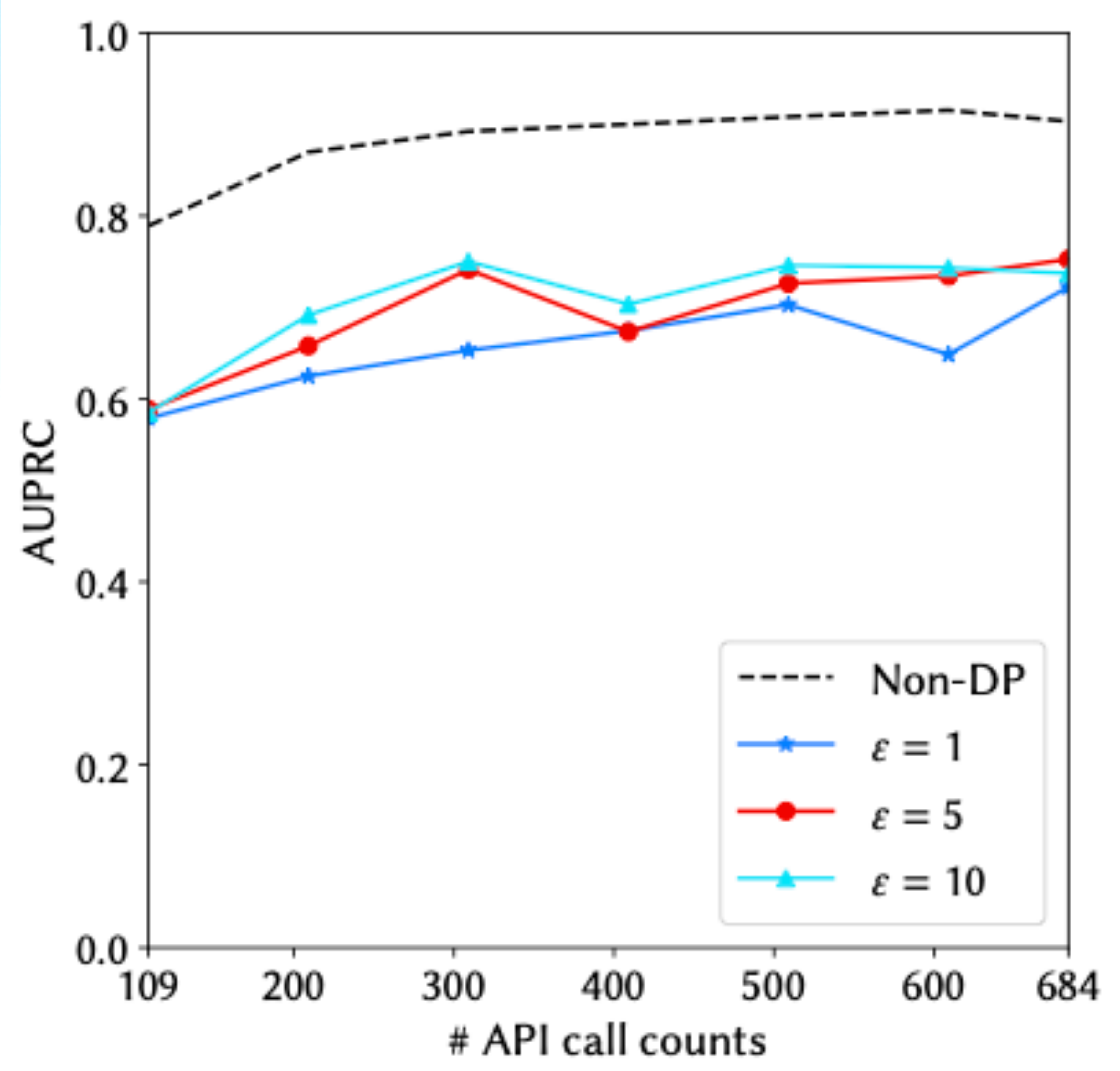
RQ1: How many API Call Counts necessary?



Working towards a “minimal” feature set

RQ1: How many API Call Counts necessary?

➡ API call counts by themselves are not enough to reliably detect fingerprinting



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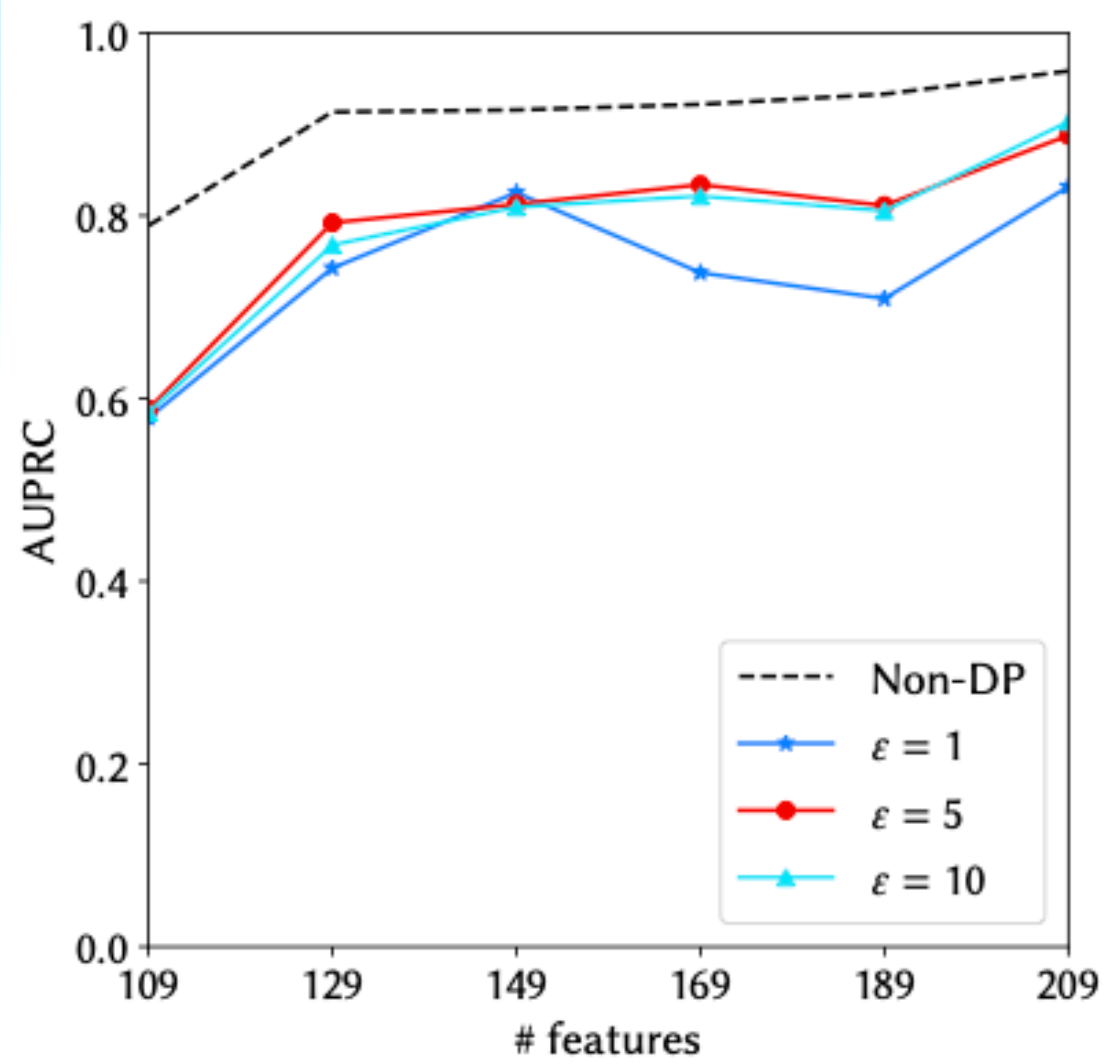
RQ2: How many custom features necessary?



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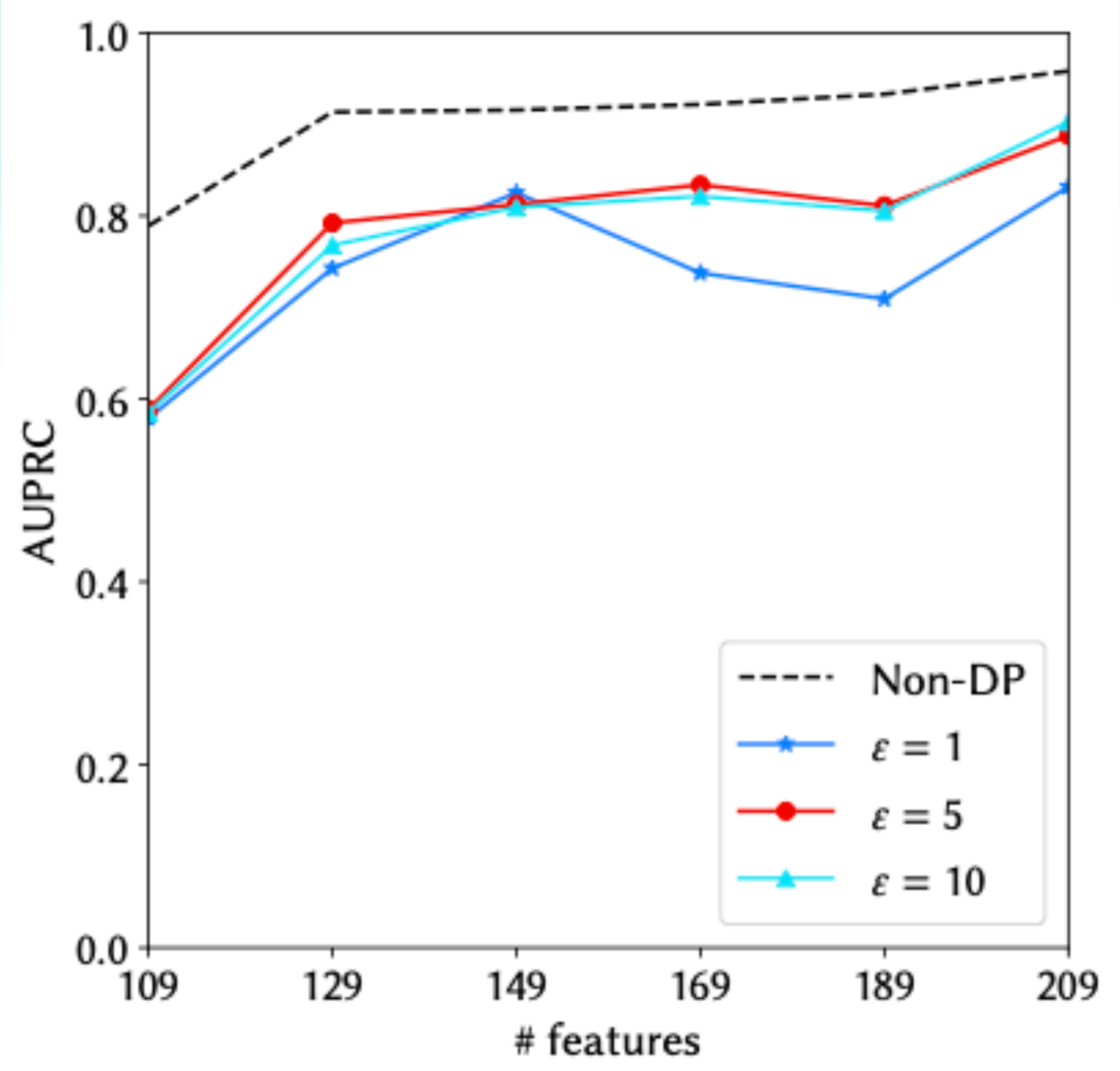
RQ2: How many custom features necessary?

➡ DP-FedNorm might cause **momentary drops** even with **more features** especially at **high privacy levels**



Working towards a “minimal” feature set

RQ2: How many custom features necessary?

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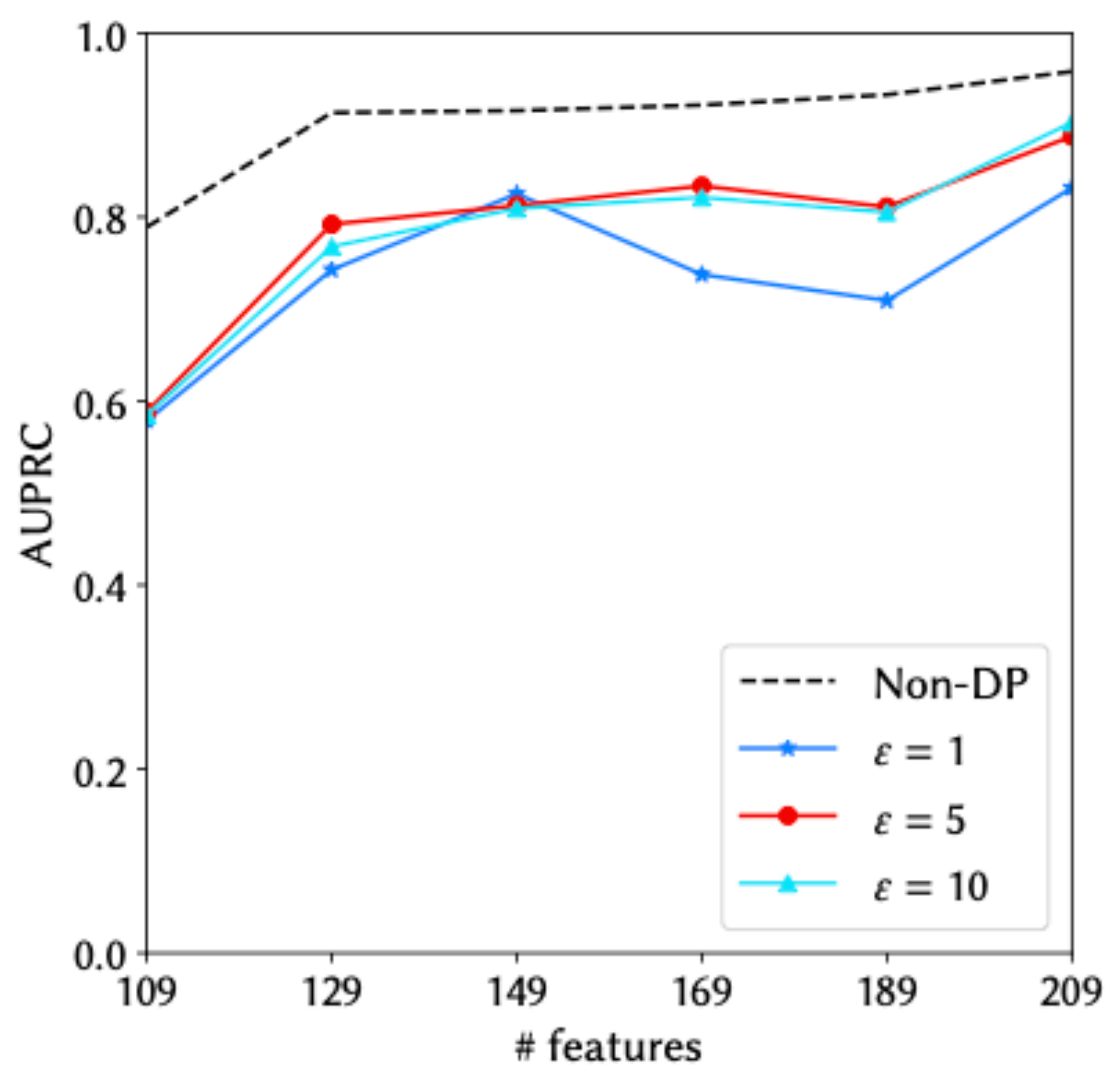
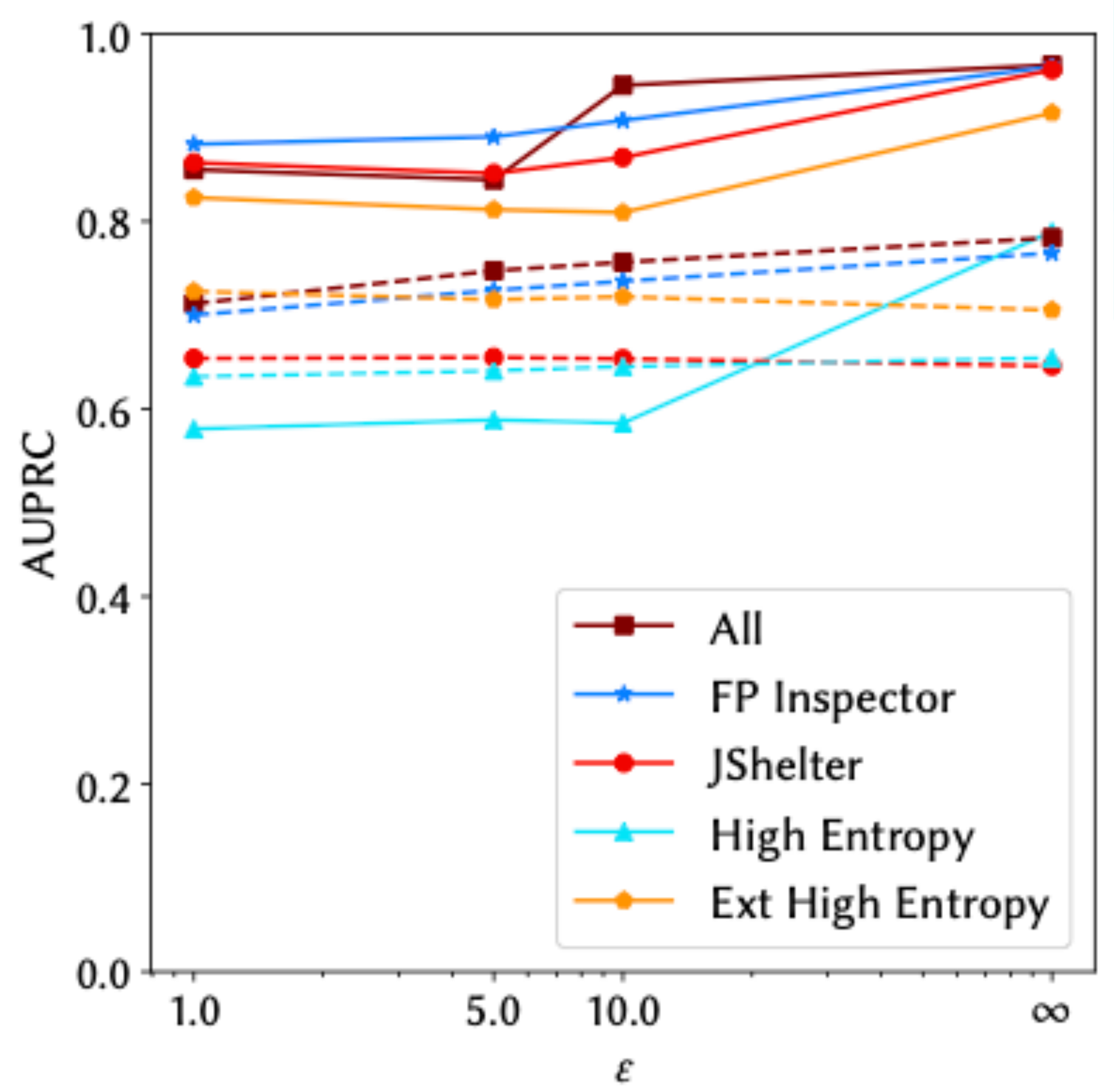
➡ **40 additional features (API call counts + custom) are optimal**



FP-Fed

Impact of DP-FedNorm

- Dotted line ⇒ Train with DP-FedAvg but **without DP-FedNorm**
- First work to consider using **differentially private feature pre-processing** in federated setting



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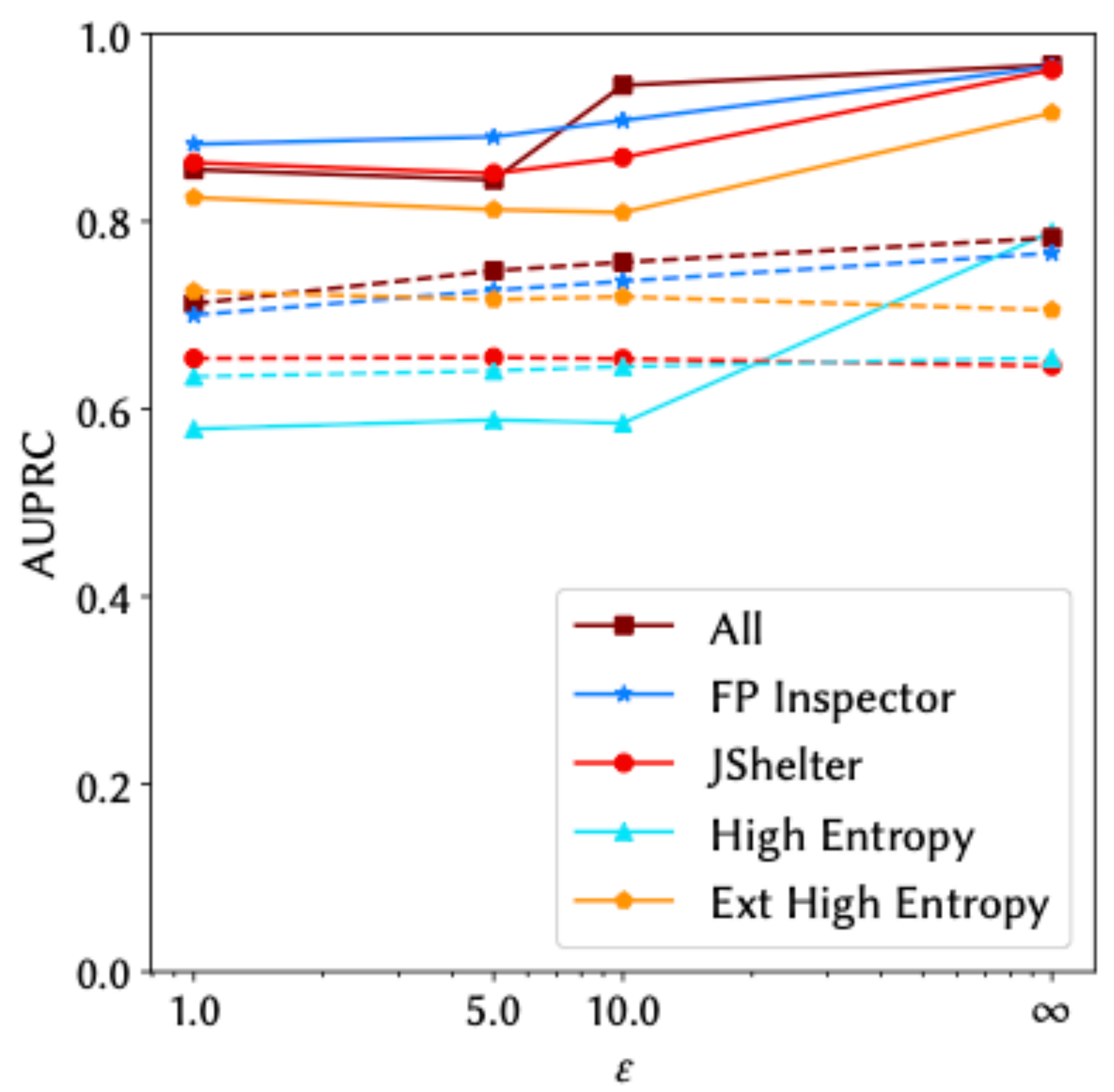
➡ **DP-FedNorm improves model-performance by up to 20.8%**



Conclusion

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Limitations

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3. Real world considerations

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3. Real world considerations

4. Ground truth heuristic

Conclusion

Summary

- Introduced FP-Fed: Applying DP-FL to solve problem of detecting browser fingerprinting
  - Does not require automated crawl
  - Efficient system: Minimal feature set (149 API Call counts + custom features)
  - Acceptable utility with strong privacy guarantees (AUPRC > 0.8 at $\varepsilon = 1$)

Credits

- Icons are made by Andrean Probowo, iconixar, Freepik, Jesus Chavarria, Iconfromus, Uniconlabs, Paul J., zafdesign, setiawanap, srip, manshagraphics, Good Ware, and IdeaGrafc from www.flaticon.com

Thank you!