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A Measurement of Genuine Tor Traces for Realistic Website Fingerprinting

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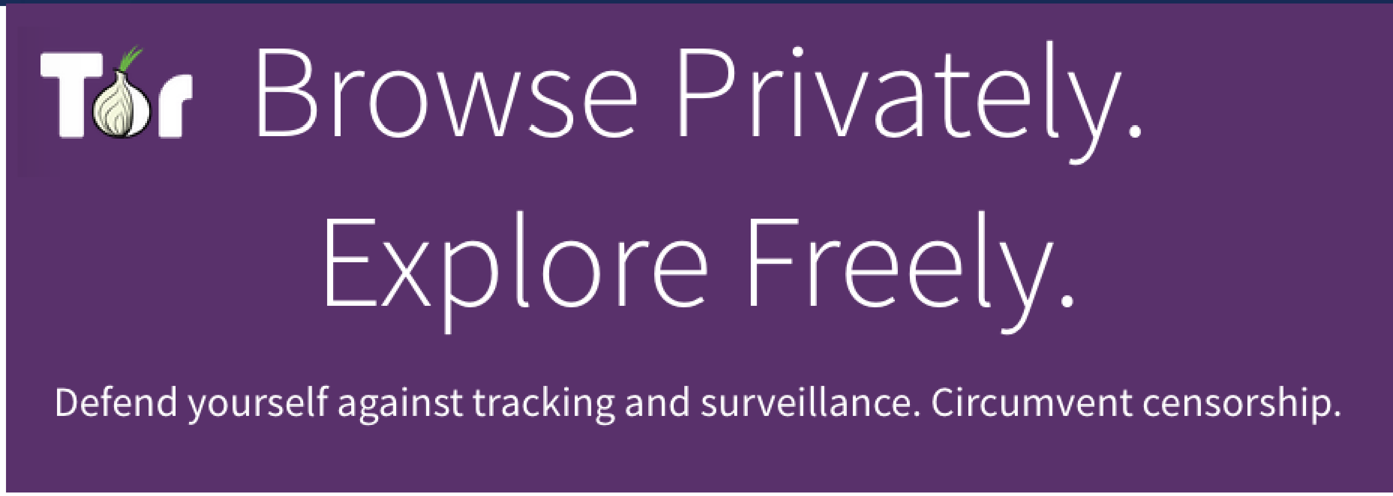
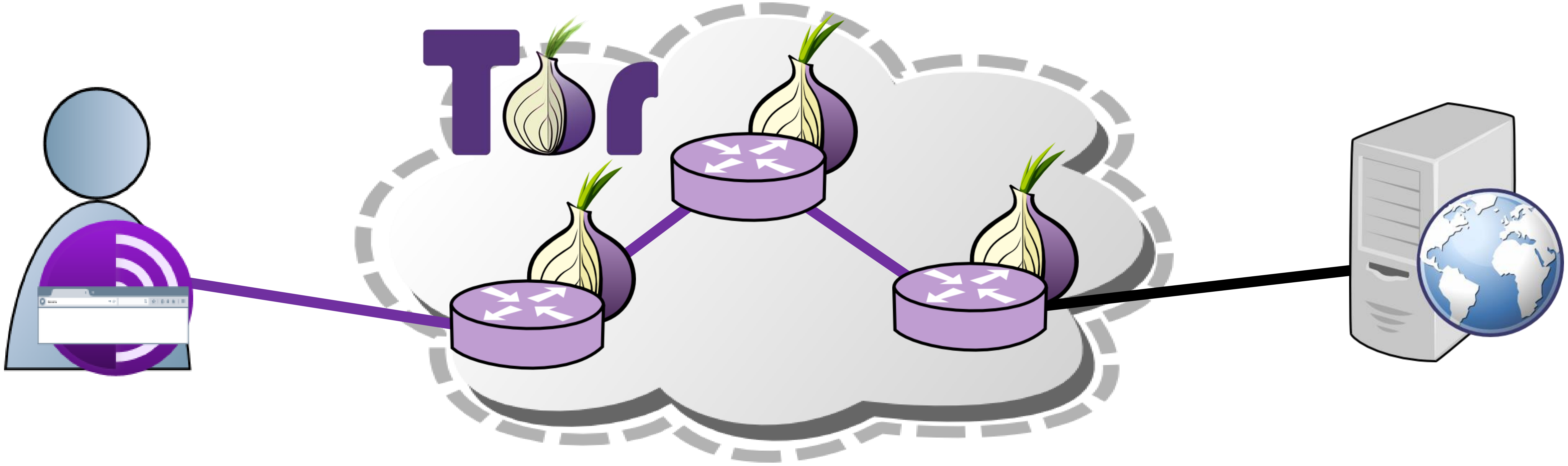
Anonymous Communication with Tor

- Separates *identification* from *routing*
- Provides unlinkable communication
- Promotes user safety and privacy online



Browse Privately.
Explore Freely.

Defend yourself against tracking and surveillance. Circumvent censorship.

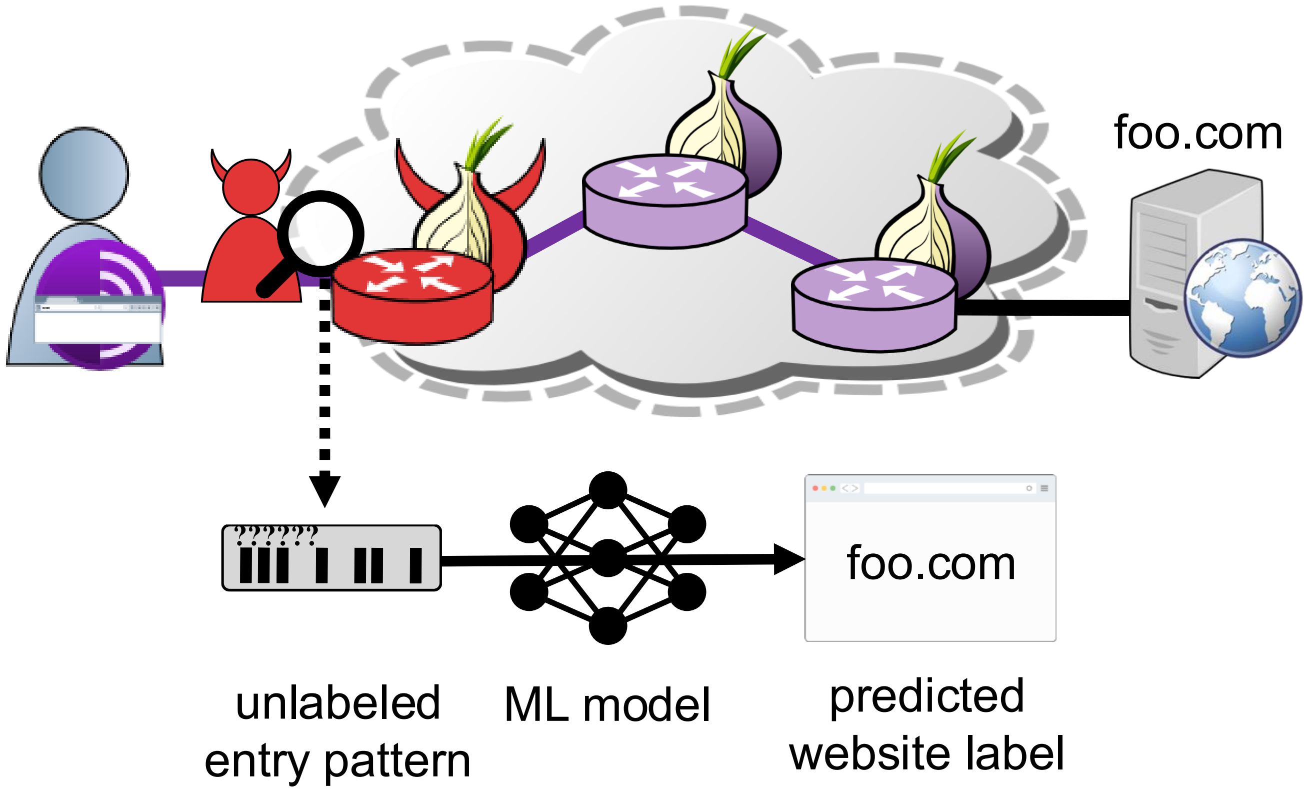


Website Fingerprinting Adversary Model

Website fingerprinting (WF) attacks can **link a source to its destination**, breaking Tor’s anonymity

Adversary can:

- Obtain entry-side vantage point
- Observe traffic patterns
- Predict website visited by user using **a trained ML model**

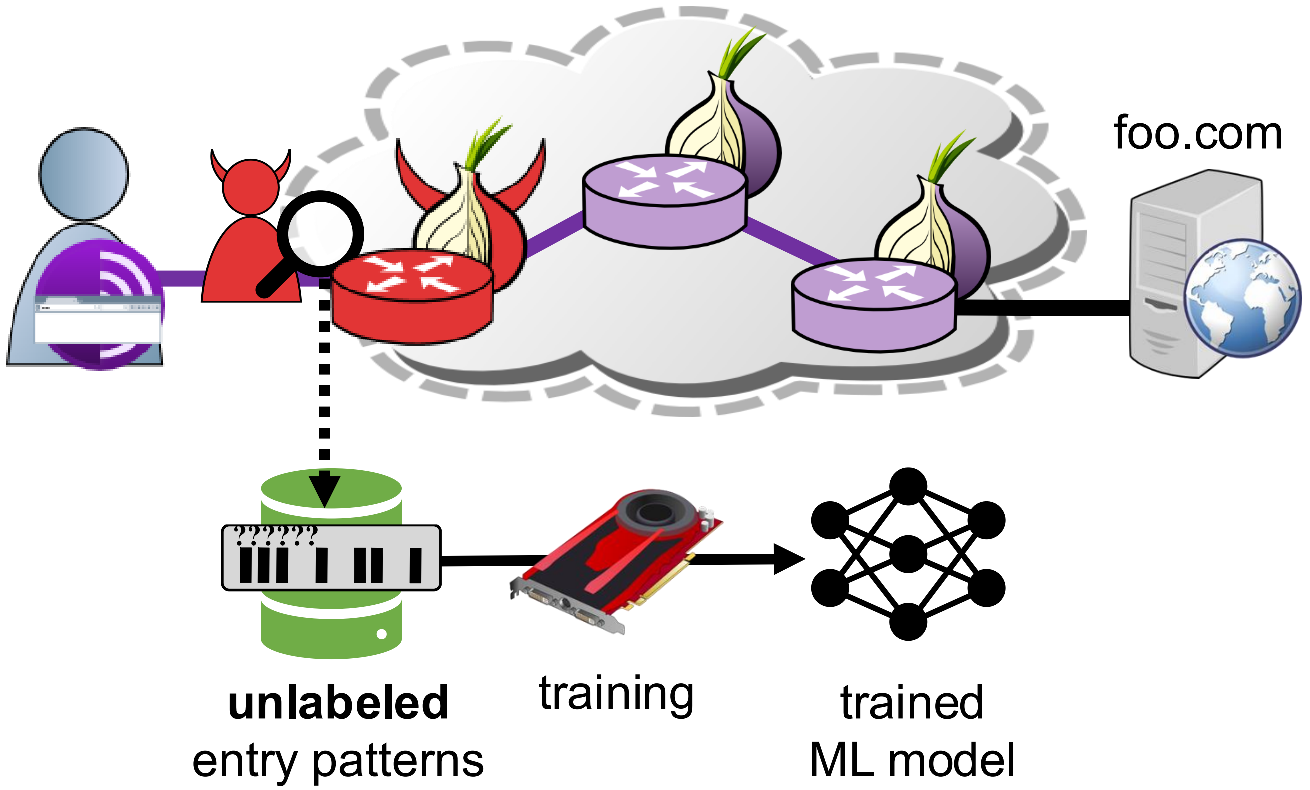


How Might Adversary Train ML Models?

Non-option: use **entry examples**

- Need **labeled** examples of patterns
- **Onion-encryption** hides labels
- Observed examples are **unlabeled**

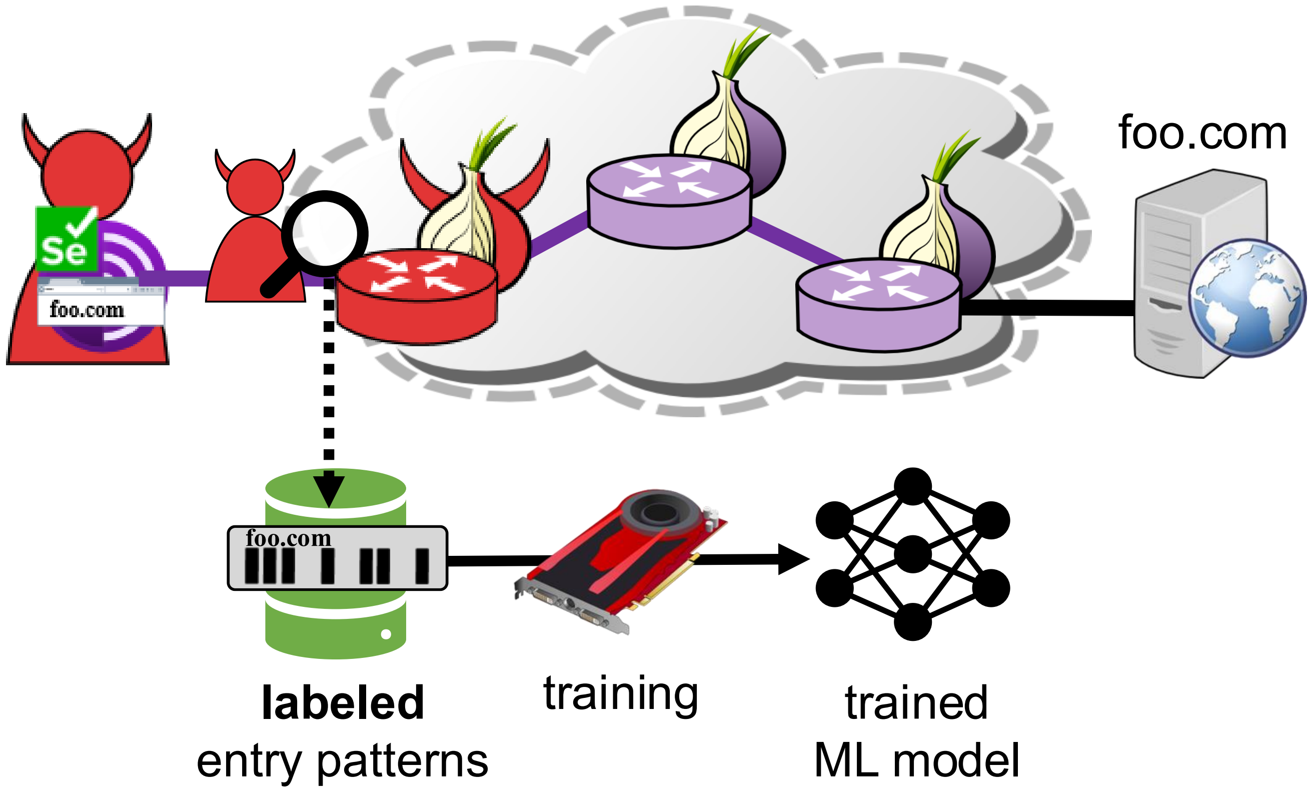
☒



How Might Adversary Train ML Models?

Option 1: **synthetic data**

- Use **automated browser** (selenium) to **replicate users'** behavior/diversity
  - Usually by crawling frontpages of top sites…



Problems

- Modeling WF with synthetic user data **oversimplifies the ML task** [CCS'14, USENIX'22, PoPETs'23]
  - Browser version, configuration
  - URL choice, fetch order, usage of tabs
  - # of sites/pages, world size dynamics
  - Geo-location, concept drift
  - Tor network variation: relay churn, software versions, congestion, location…

How Might Adversary Train ML Models?

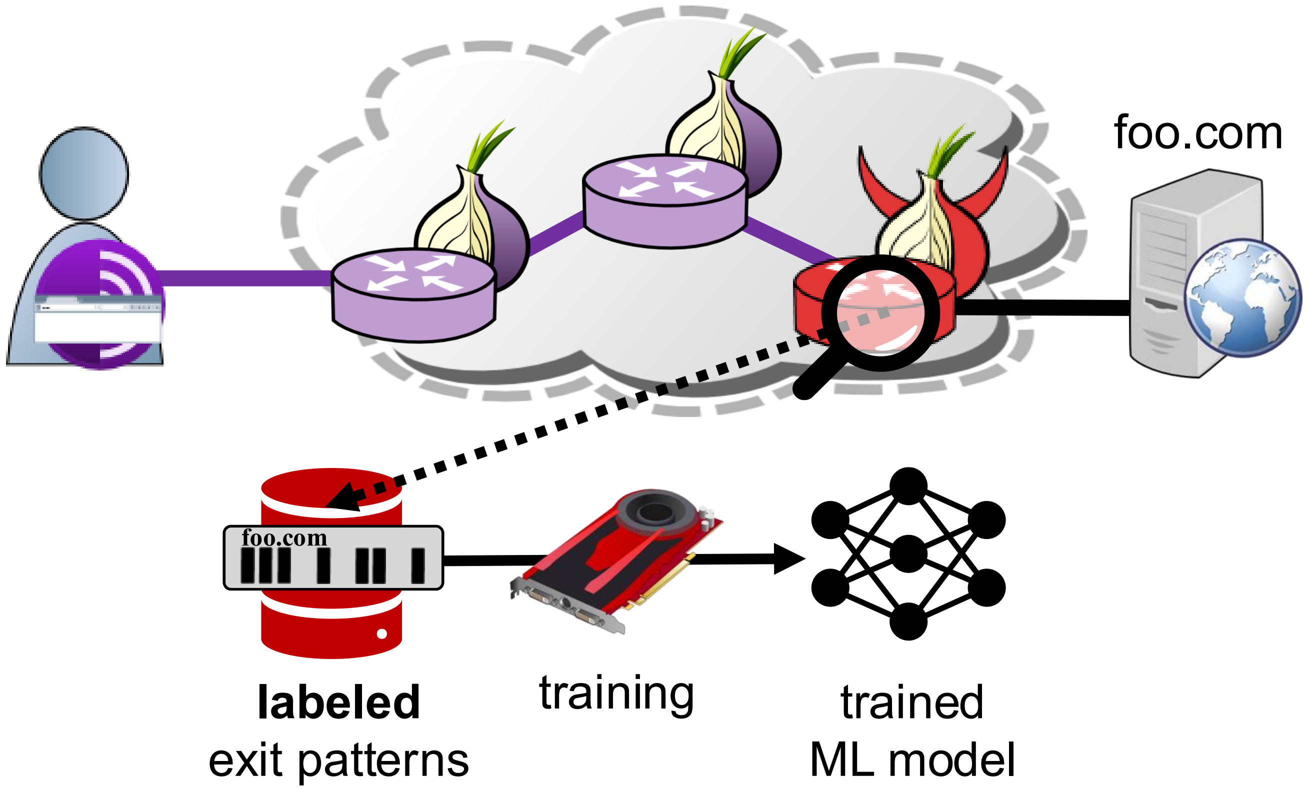
Option 2: **real Tor user data**

- Run **exit relay**, observe traffic [USENIX'22]
  - Traffic patterns from **real Tor users**
  - Website **labels** observed in DNS requests

Problems

- Study done in **online** setting [USENIX'22]
  - Data was **not persistently stored**
  - Results cannot be replicated
  - Difficult to build on the methodology without **new measurements**

- Exit-entry position mismatch
  - **Train** on **exit** side, **predict** on **entry** side
  - Position "distortion" reduces performance
    - 5-18% [USENIX'22]
    - 17% median, 93% worse-case [WPES'24]

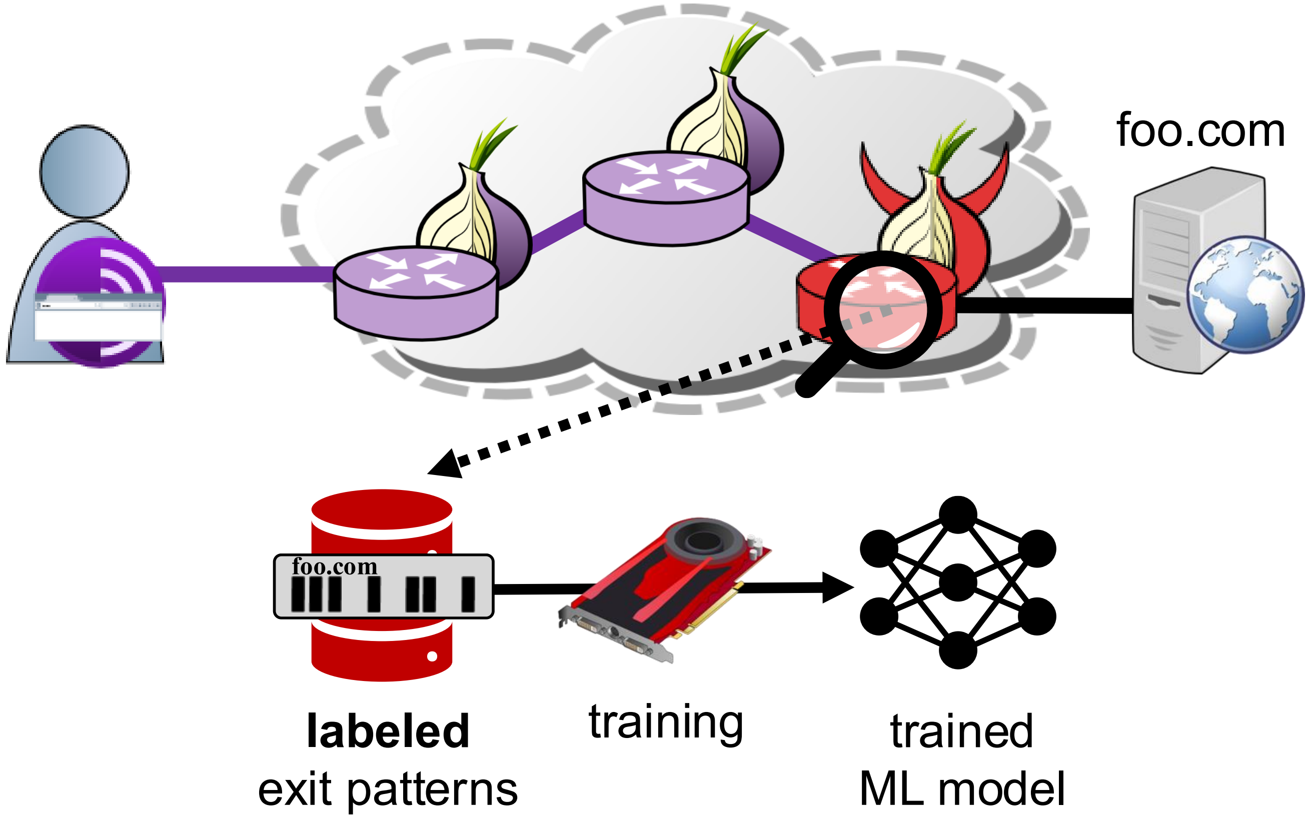


Our Research Direction: Key Insights

Key insights:

- If adversary would **test** on real user data, they should **train** on it too
- The **real network** is the best place to get traffic patterns of **real users**
- Easier to **mitigate** entry-exit distortion than **accurately replicate users**

	Synthetic client	Real Tor exit
Ground-truth labels	✓	✓
Entry-side examples	✓	✗
Real Tor user data	✗	✓

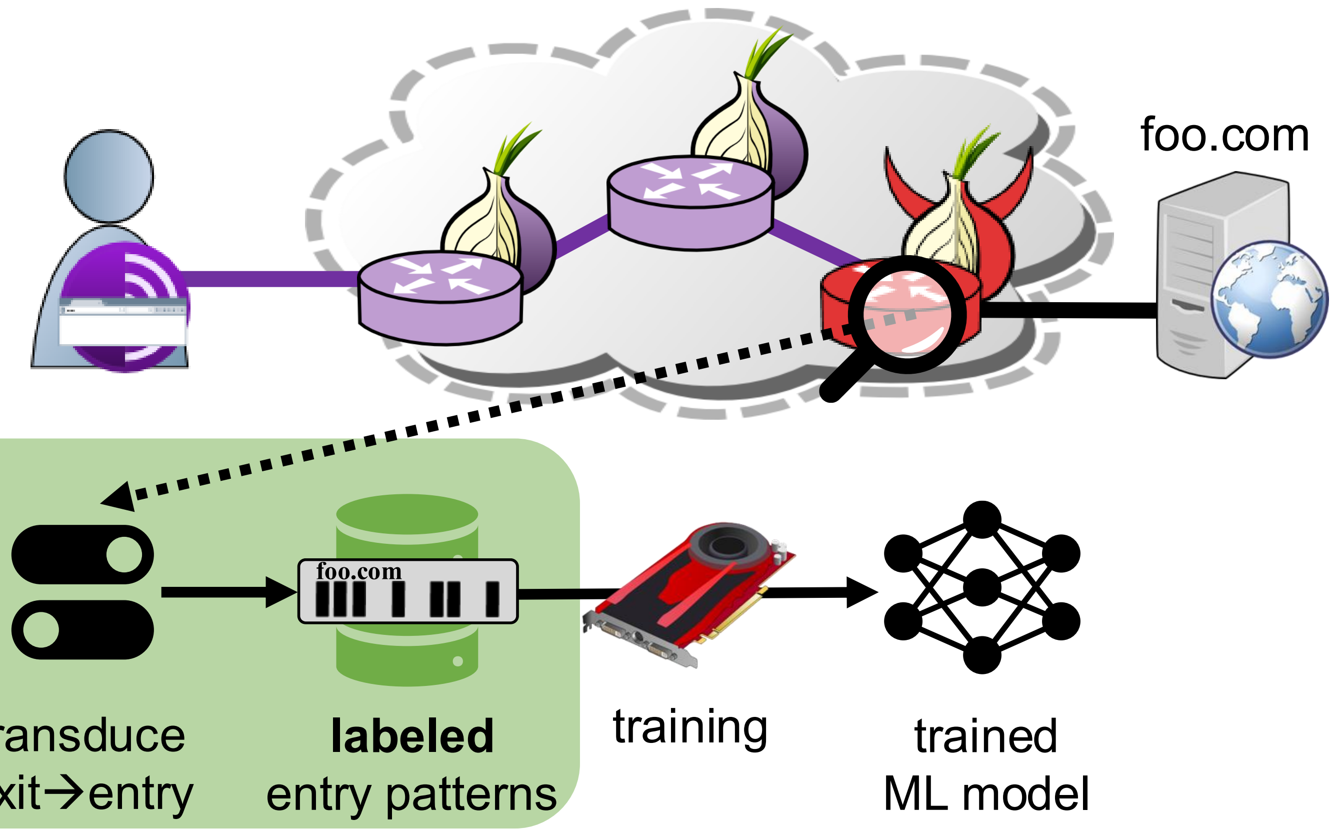


Our Research Direction: Key Insights

Key insights:

- If adversary would **test** on real user data, they should **train** on it too
- The **real network** is the best place to get traffic patterns of **real users**
- Easier to **mitigate** entry-exit distortion than **accurately replicate users**
  - **Now mitigated** with exit→entry **transducers**:
    - **Retracer**: using network simulation [WPES'24]
    - **CellShift**: using cell RTTs and math [NDSS'26]

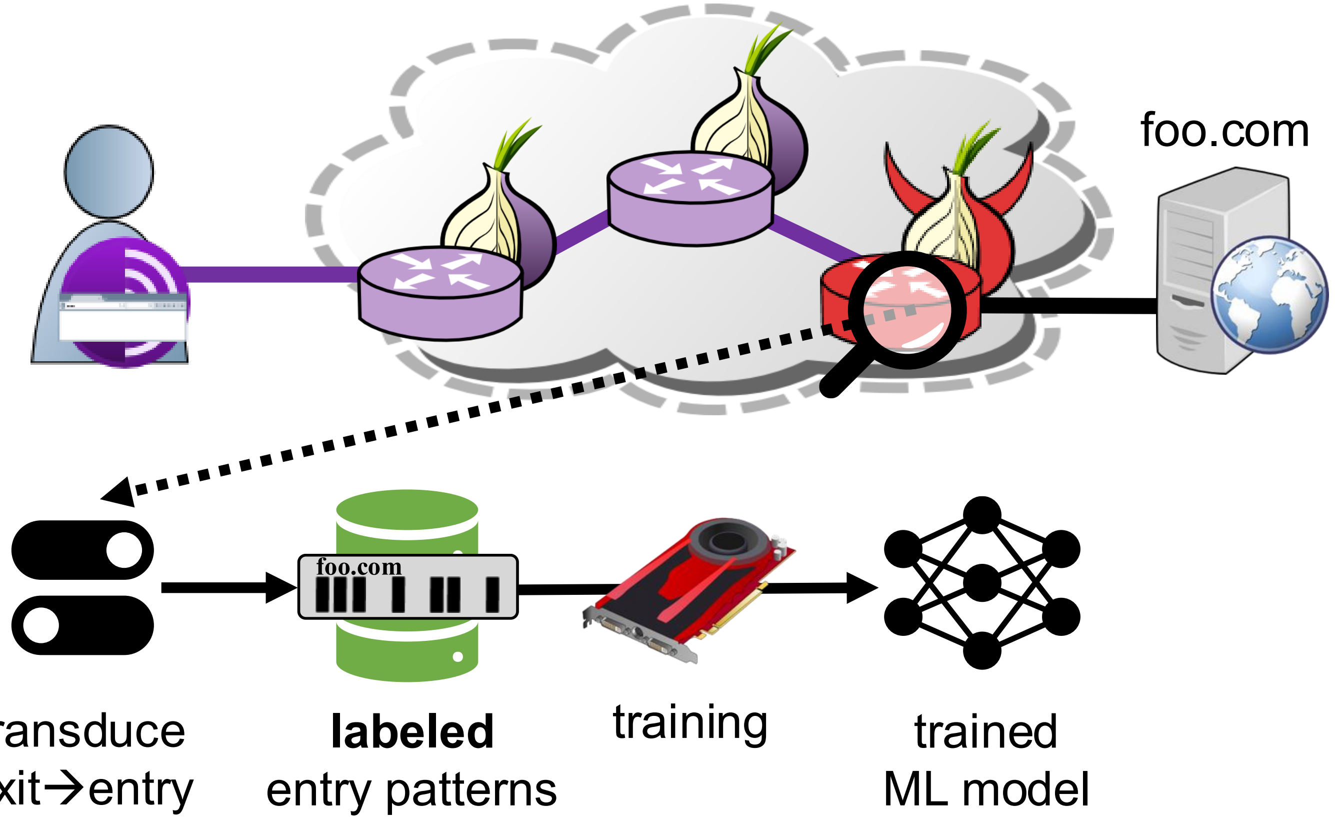
	Synthetic client	Real Tor exit
Ground-truth labels	✓	✓
Entry-side examples	✓	✗ → ✓
Real Tor user data	✗	✓



Our Goals in this Work

- Goals:
  - Create a **persistent dataset** to improve the study of real-world WF
  - Understand **disparities** between **synthetic** datasets and **real** data
  - Inform/prioritize WF **defenses**
- Non-Goals:
  - Develop new WF attacks
  - Improve attacks to benefit adversary

	Synthetic client	Real Tor exit
Ground-truth labels	✓	✓
Entry-side examples	✓	✗ → ✓
Real Tor user data	✗	✓

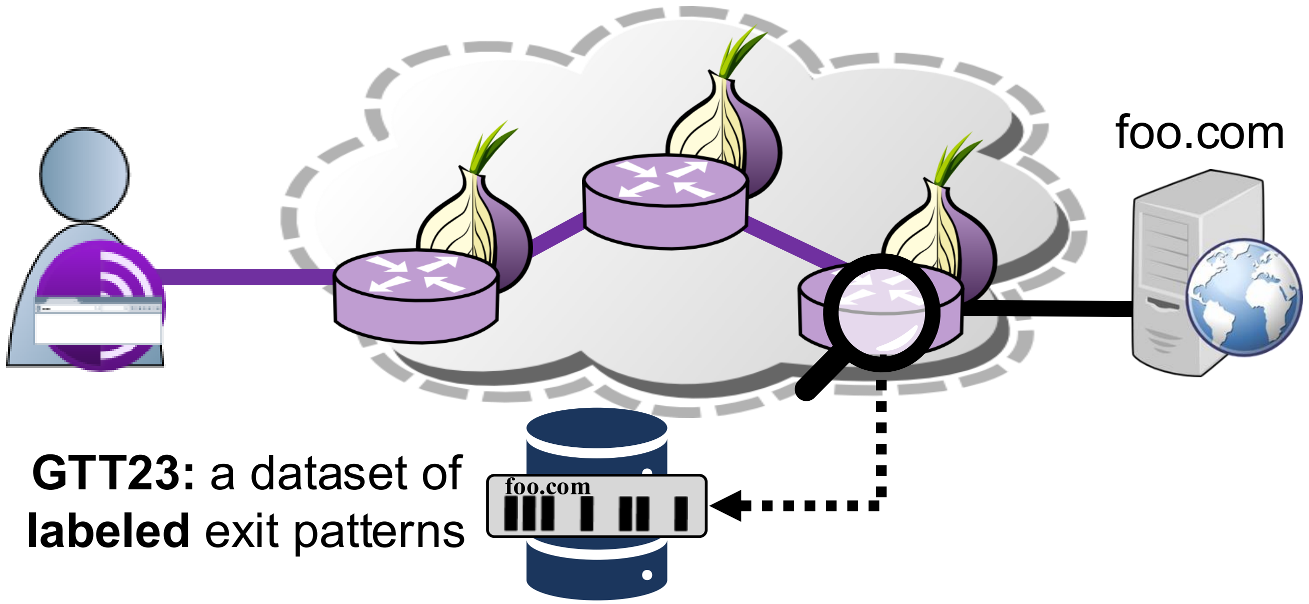


GTT23: A dataset of Genuine Tor Traces

Introducing **GTT23**

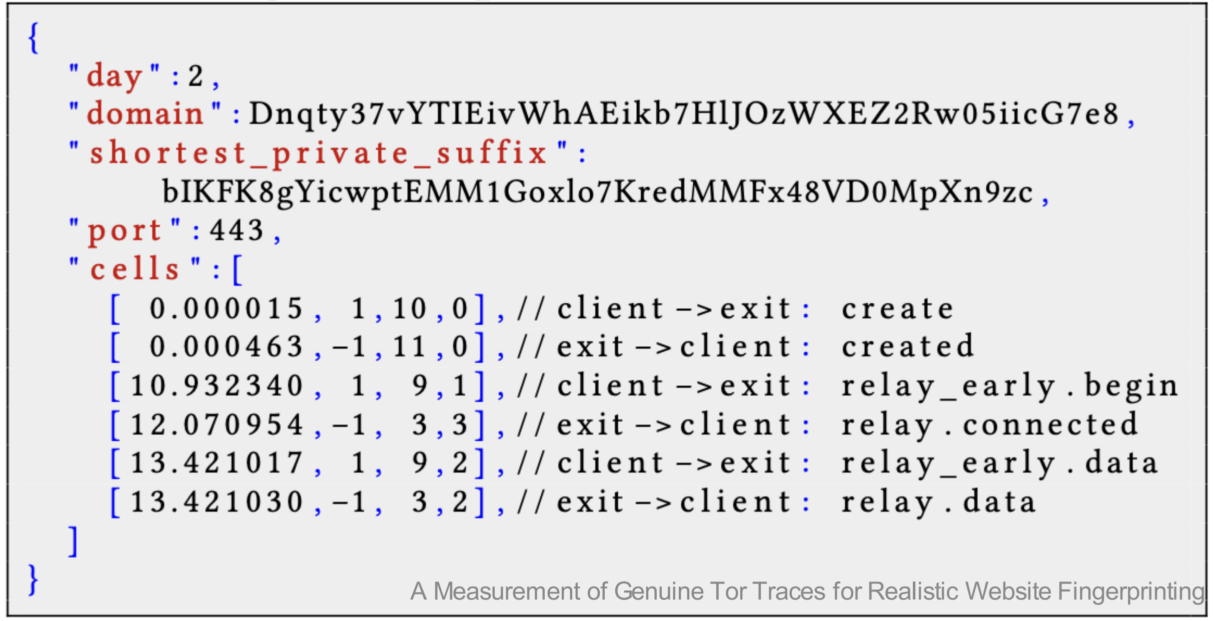
- A dataset of **genuine Tor traces** of real Tor user traffic patterns
    - **13.9M** traces to **1.1M** unique domains measured over **13 weeks**

- Measured from Tor **exit relays**
    - Traffic **traces** of normal activities
        - The first **5,000 cells** on a Tor circuit
        - **Natural**, real-world website **base rates**
        - No **PII** is recorded, website labels are **protected** with HMAC
    - Measurement plan **reviewed** by IRB, Tor Research Safety Board



GTT23: a dataset of **labeled** exit patterns

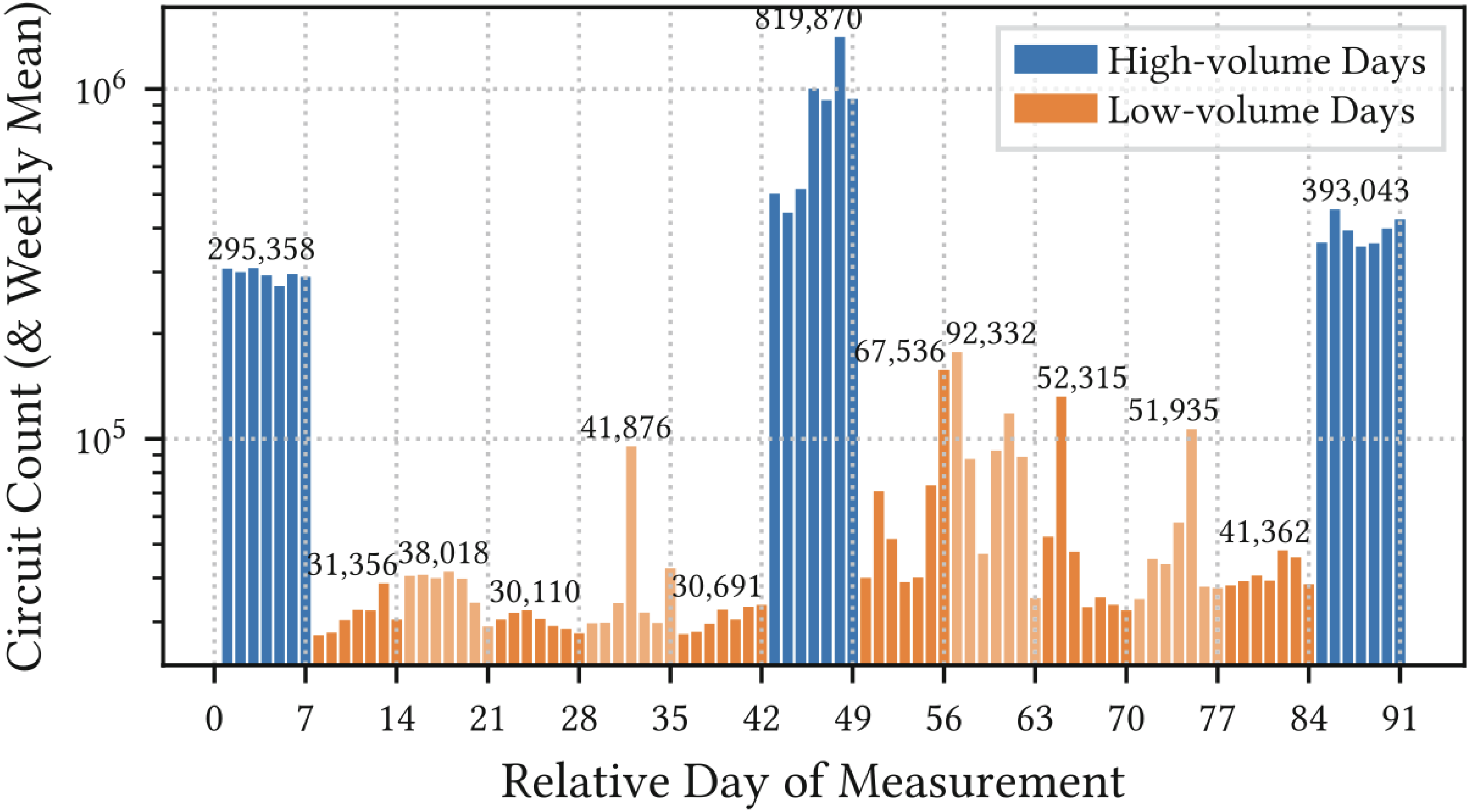
Listing 1: Example circuit metadata record.



```
{
  "day":2,
  "domain":Dnqty37vYTIEivWhAEikb7HlJOzWXEZ2Rw05iicG7e8,
  "shortest_private_suffix":
       bIKFK8gYicwptEMM1Goxlo7KredMMFx48VD0MpXn9zc,
  "port":443,
  "cells":[
    [ 0.000015, 1,10,0],//client->exit: create
    [ 0.000463,-1,11,0],//exit->client: created
    [10.932340, 1, 9,1],//client->exit: relay_early.begin
    [12.070954,-1, 3,3],//exit->client: relay.connected
    [13.421017, 1, 9,2],//client->exit: relay_early.data
    [13.421030,-1, 3,2],//exit->client: relay.data
  ]
}
```

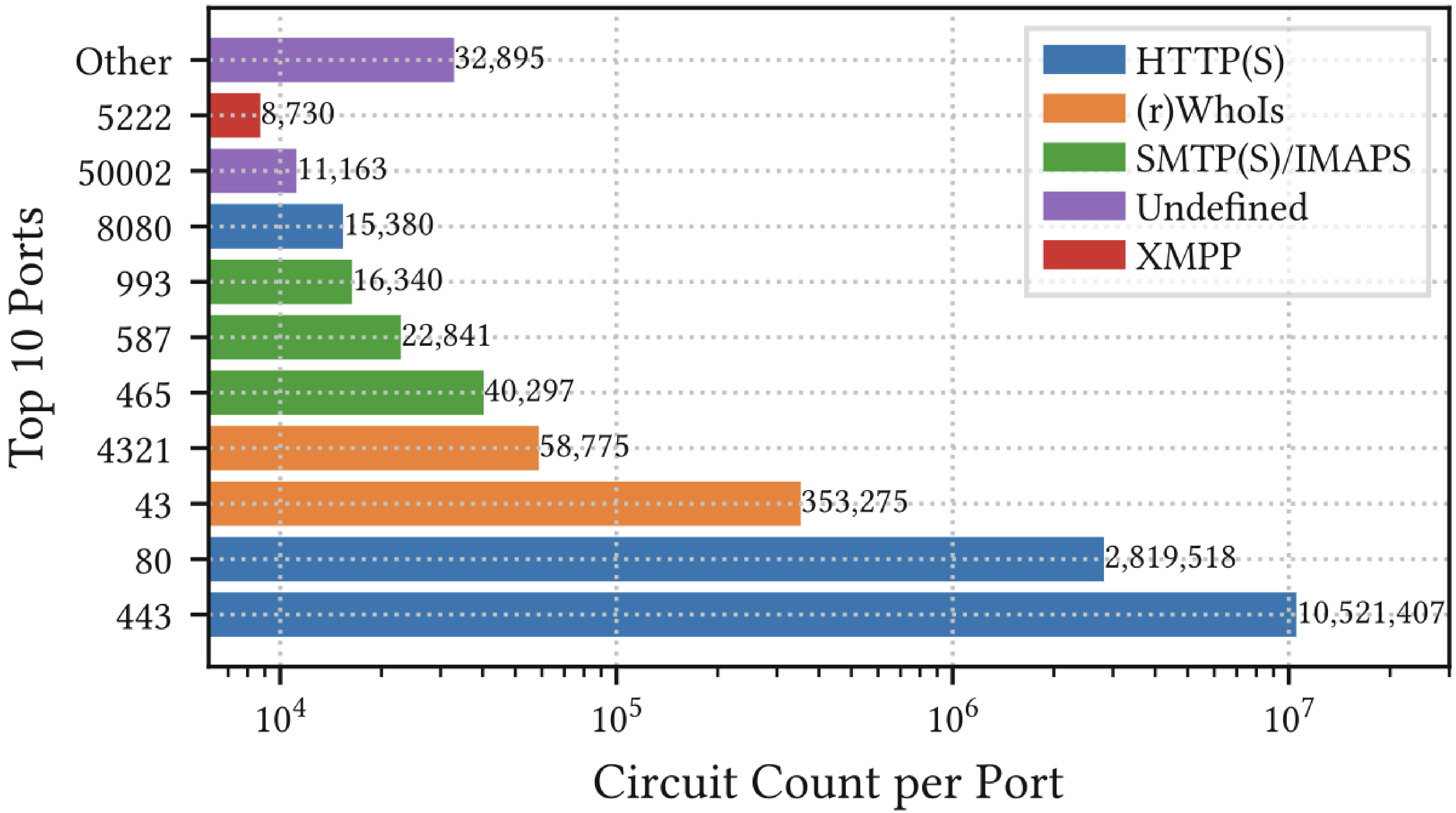
Temporal Composition of GTT23

13.9M traces across the **13 week** measurement



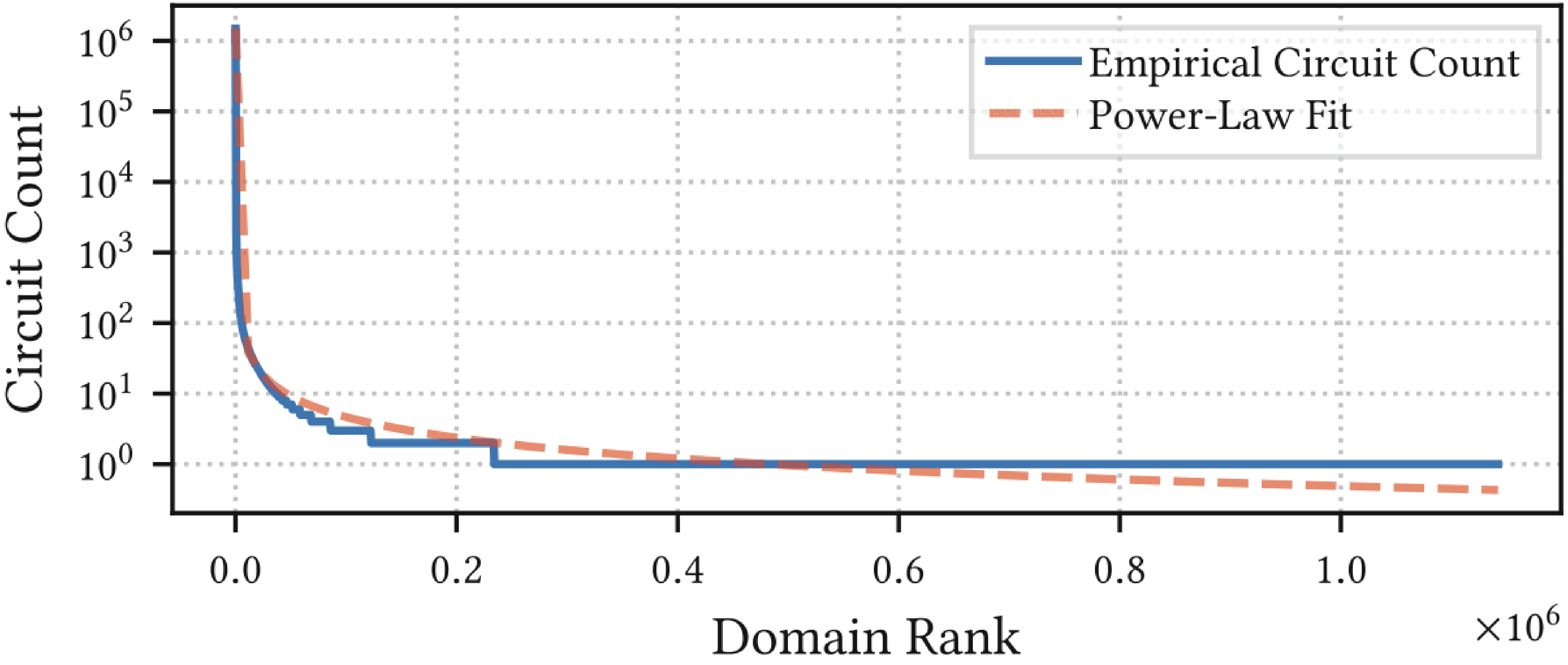
IANA-assigned Service (Port) Composition

68 unique destination service **ports**



Circuit Count per Domain is Similar to Internet Traffic

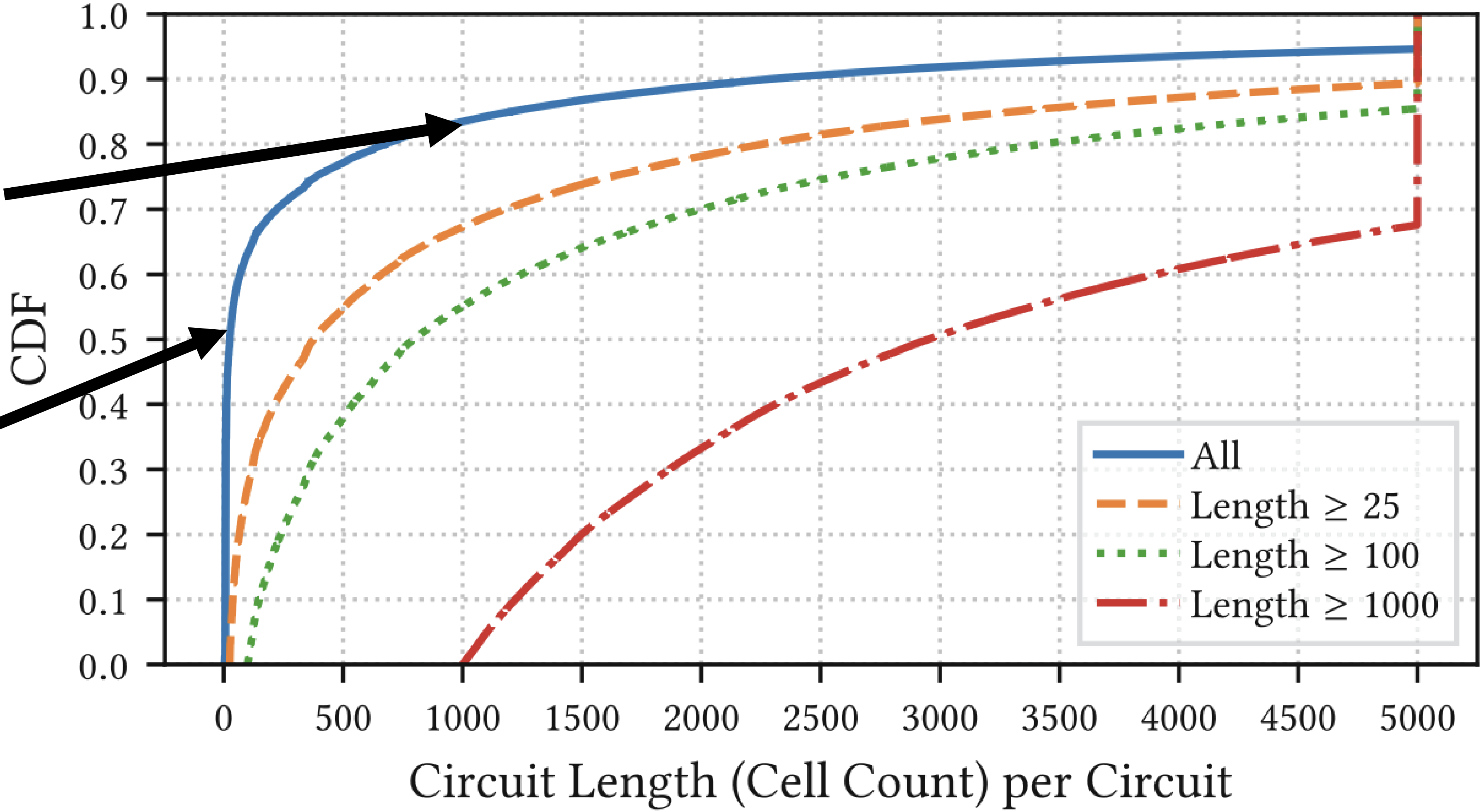
1.1M unique destination **domains**



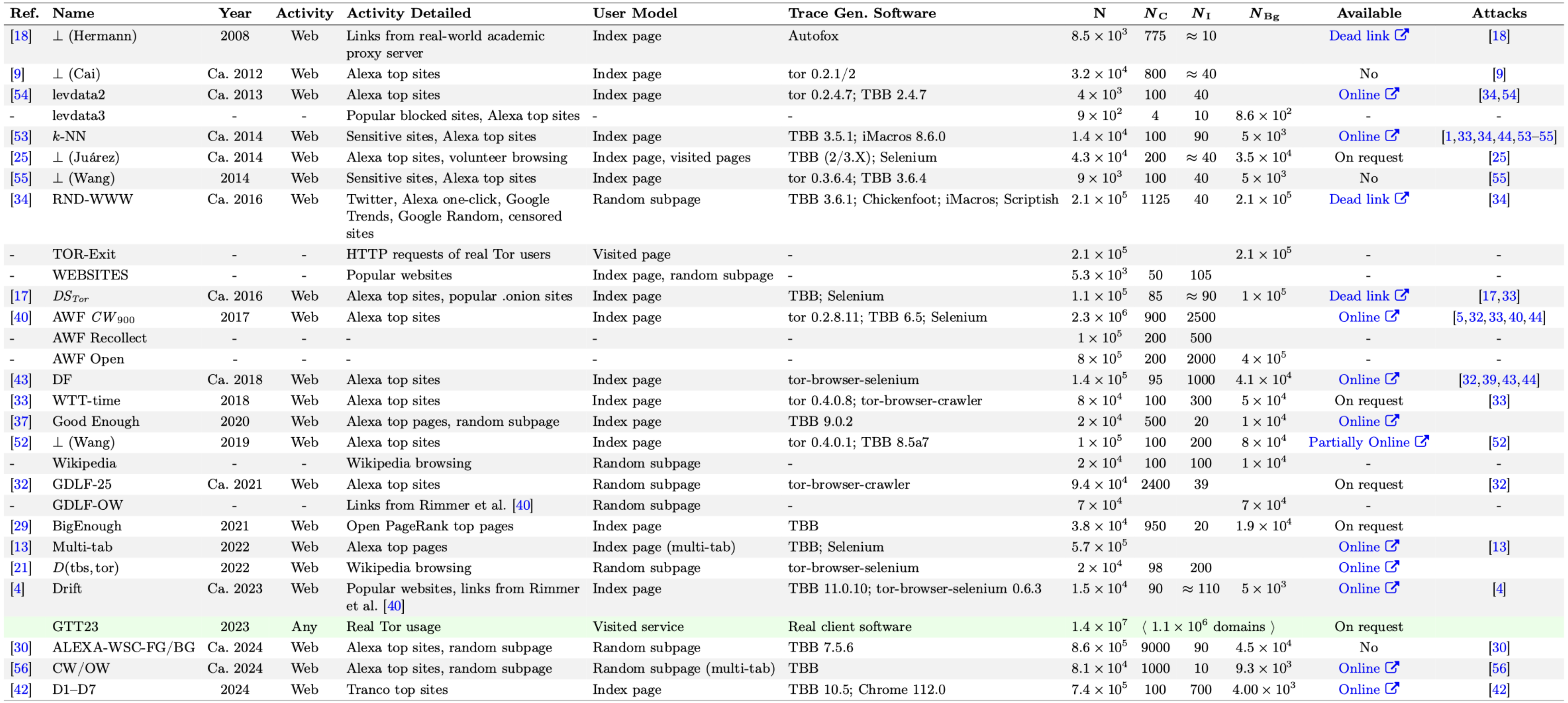
Most Circuits are Much Shorter than Expected

HTTP Archive:
90% of webpages are > **450 KB**

Median circuit is **10.5 KB** (25 cells)



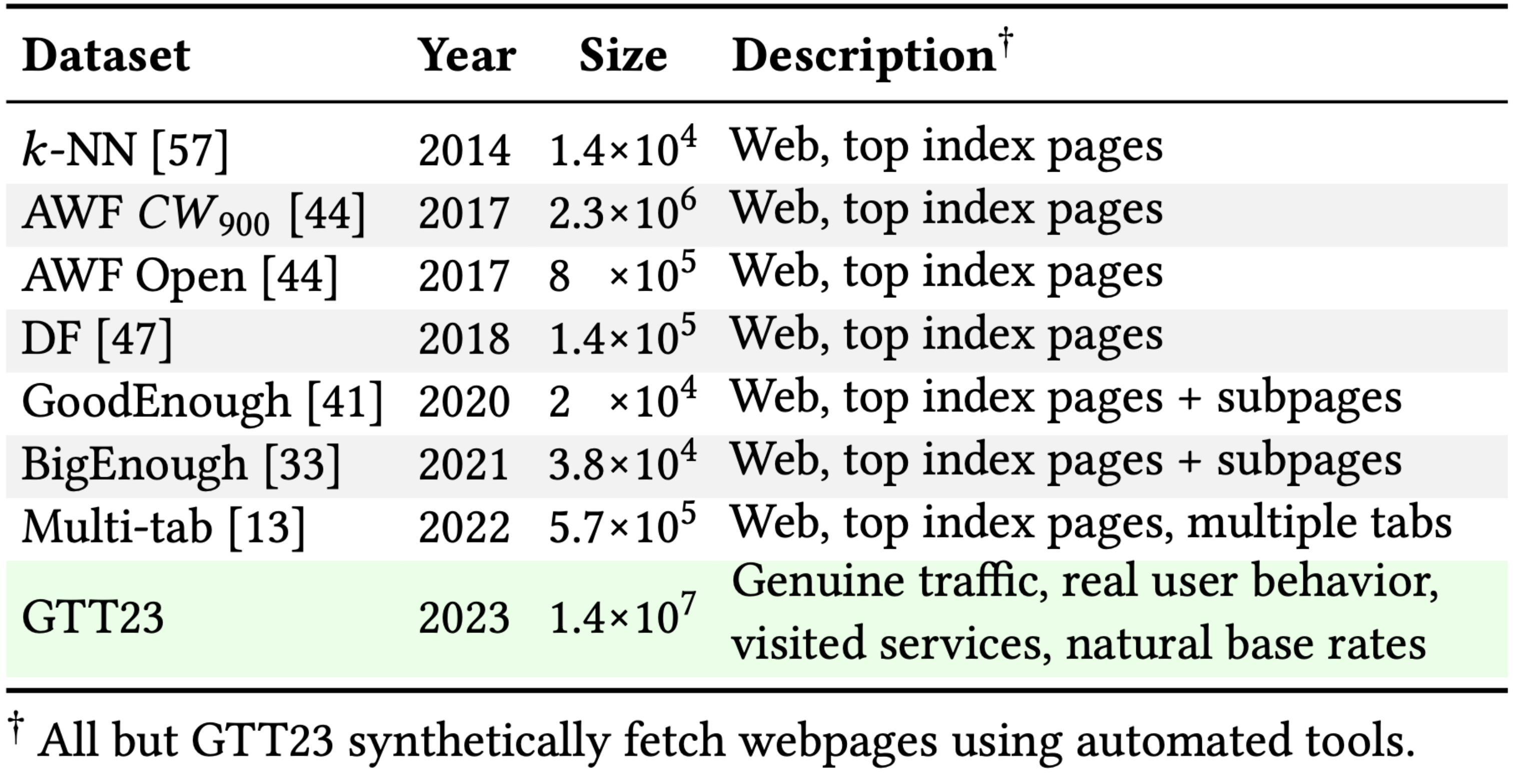
We surveyed 28 WF datasets published since 2008



Ref.	Name	Year	Activity	Activity Detailed	User Model	Trace Gen. Software	N	N_{C}	N_{I}	N_{Bg}	Available	Attacks
[18]	⊥ (Hermann)	2008	Web	Links from real-world academic proxy server	Index page	Autofox	8.5×10^3	775	≈ 10		Dead link ↗	[18]
[9]	⊥ (Cai)	Ca. 2012	Web	Alexa top sites	Index page	tor 0.2.1/2	3.2×10^4	800	≈ 40		No	[9]
[54]	levdata2	Ca. 2013	Web	Alexa top sites	Index page	tor 0.2.4.7; TBB 2.4.7	4×10^3	100	40		Online ↗	[34,54]
-	levdata3	-	-	Popular blocked sites, Alexa top sites	-	-	9×10^2	4	10	8.6×10^2	-	-
[53]	*k*-NN	Ca. 2014	Web	Sensitive sites, Alexa top sites	Index page	TBB 3.5.1; iMacros 8.6.0	1.4×10^4	100	90	5×10^3	Online ↗	[1,33,34,44,53–55]
[25]	⊥ (Juárez)	Ca. 2014	Web	Alexa top sites, volunteer browsing	Index page, visited pages	TBB (2/3.X); Selenium	4.3×10^4	200	≈ 40	3.5×10^4	On request	[25]
[55]	⊥ (Wang)	2014	Web	Sensitive sites, Alexa top sites	Index page	tor 0.3.6.4; TBB 3.6.4	9×10^3	100	40	5×10^3	No	[55]
[34]	RND-WWW	Ca. 2016	Web	Twitter, Alexa one-click, Google Trends, Google Random, censored sites	Random subpage	TBB 3.6.1; Chickenfoot; iMacros; Scriptish	2.1×10^5	1125	40	2.1×10^5	Dead link ↗	[34]
-	TOR-Exit	-	-	HTTP requests of real Tor users	Visited page	-	2.1×10^5			2.1×10^5	-	-
-	WEBSITES	-	-	Popular websites	Index page, random subpage	-	5.3×10^3	50	105		-	-
[17]	DS_{Tor}	Ca. 2016	Web	Alexa top sites, popular .onion sites	Index page	TBB; Selenium	1.1×10^5	85	≈ 90	1×10^5	Dead link ↗	[17,33]
[40]	AWF CW_{900}	2017	Web	Alexa top sites	Index page	tor 0.2.8.11; TBB 6.5; Selenium	2.3×10^6	900	2500		Online ↗	[5, 32, 33, 40, 44]
-	AWF Recollect	-	-	-	-	-	1×10^5	200	500		-	-
-	AWF Open	-	-	-	-	-	8×10^5	200	2000	4×10^5	-	-
[43]	DF	Ca. 2018	Web	Alexa top sites	Index page	tor-browser-selenium	1.4×10^5	95	1000	4.1×10^4	Online ↗	[32,39,43,44]
[33]	WTT-time	2018	Web	Alexa top sites	Index page	tor 0.4.0.8; tor-browser-crawler	8×10^4	100	300	5×10^4	On request	[33]
[37]	Good Enough	2020	Web	Alexa top pages, random subpage	Index page	TBB 9.0.2	2×10^4	500	20	1×10^4	Online ↗	
[52]	⊥ (Wang)	2019	Web	Alexa top sites	Index page	tor 0.4.0.1; TBB 8.5a7	1×10^5	100	200	8×10^4	Partially Online ↗	[52]
-	Wikipedia	-	-	Wikipedia browsing	Random subpage	-	2×10^4	100	100	1×10^4	-	-
[32]	GDLF-25	Ca. 2021	Web	Alexa top sites	Random subpage	tor-browser-crawler	9.4×10^4	2400	39		On request	[32]
-	GDLF-OW	-	-	Links from Rimmer et al. [40]	Random subpage	-	7×10^4			7×10^4	-	-
[29]	BigEnough	2021	Web	Open PageRank top pages	Index page	TBB	3.8×10^4	950	20	1.9×10^4	On request	
[13]	Multi-tab	2022	Web	Alexa top pages	Index page (multi-tab)	TBB; Selenium	5.7×10^5				Online ↗	[13]
[21]	$D(\mathrm{tbs}, \mathrm{tor})$	2022	Web	Wikipedia browsing	Random subpage	tor-browser-selenium	2×10^4	98	200		Online ↗	
[4]	Drift	Ca. 2023	Web	Popular websites, links from Rimmer et al. [40]	Index page	TBB 11.0.10; tor-browser-selenium 0.6.3	1.5×10^4	90	≈ 110	5×10^3	Online ↗	[4]
	GTT23	2023	Any	Real Tor usage	Visited service	Real client software	1.4×10^7	$\langle$ 1.1×10^6 domains $\rangle$			On request	
[30]	ALEXA-WSC-FG/BG	Ca. 2024	Web	Alexa top sites, random subpage	Random subpage	TBB 7.5.6	8.6×10^5	9000	90	4.5×10^4	No	[30]
[56]	CW/OW	Ca. 2024	Web	Alexa top sites, random subpage	Random subpage (multi-tab)	TBB	8.1×10^4	1000	10	9.3×10^3	Online ↗	[56]
[42]	D1–D7	2024	Web	Tranco top sites	Index page	TBB 10.5; Chrome 112.0	7.4×10^5	100	700	4.00×10^3	Online ↗	[42]

Summary of Comparisons to Synthetic Datasets

- Most synthetic datasets contain traces of **index pages** fetched with automated tools
- GTT23 is **larger** than any existing WF dataset by an **order of magnitude**
- No other WF dataset contains **genuine** traces of **real Tor user behavior**

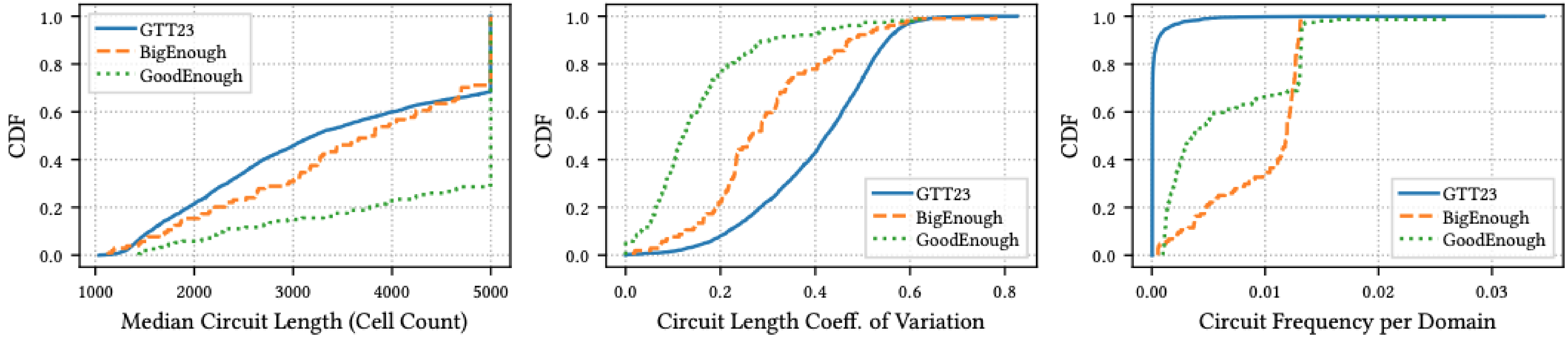


Dataset	Year	Size	Description[†]
k-NN [57]	2014	1.4×10^4	Web, top index pages
AWF CW_{900} [44]	2017	2.3×10^6	Web, top index pages
AWF Open [44]	2017	$8\ \times10^5$	Web, top index pages
DF [47]	2018	1.4×10^5	Web, top index pages
GoodEnough [41]	2020	$2\ \times10^4$	Web, top index pages + subpages
BigEnough [33]	2021	3.8×10^4	Web, top index pages + subpages
Multi-tab [13]	2022	5.7×10^5	Web, top index pages, multiple tabs
GTT23	2023	1.4×10^7	Genuine traffic, real user behavior, visited services, natural base rates

[†] All but GTT23 synthetically fetch webpages using automated tools.

Disparities between GTT23 and Synthetic Datasets

- BigEnough and GoodEnough have 10 pages per website
  - Highest web*site* **diversity** among synthetic datasets
- Compared to GTT23, data is still too homogeneous
  - **Chosen domains** are over-represented, **traffic variation** is still too low



A Measurement of Genuine Tor Traces for Realistic Website Fingerprinting

Contributions – GTT23

- The first dataset of labeled genuine Tor traces
  - **13.9M** traces, **1.1M** unique domains, **68** unique ports
  - An order-of-magnitude **larger** than existing WF datasets
- Analysis of its statistical **properties**
- Analysis of **disparities** between characteristics of **genuine** and **synthetic** datasets

Impact and Future Work

- Already has ~30 approved users
  - E.g., used to study **trace transduction** [WPES'24, NDSS'26]
- Genuine traces could inform the study of:
  - **WF** attacks/defenses, **end-to-end correlation** attacks/defenses, Tor **user** patterns, Tor **performance** characteristics, …

Read the Paper!

Access the Dataset!

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