

Trust and Technology: Growing Gaps and Urgent Opportunities

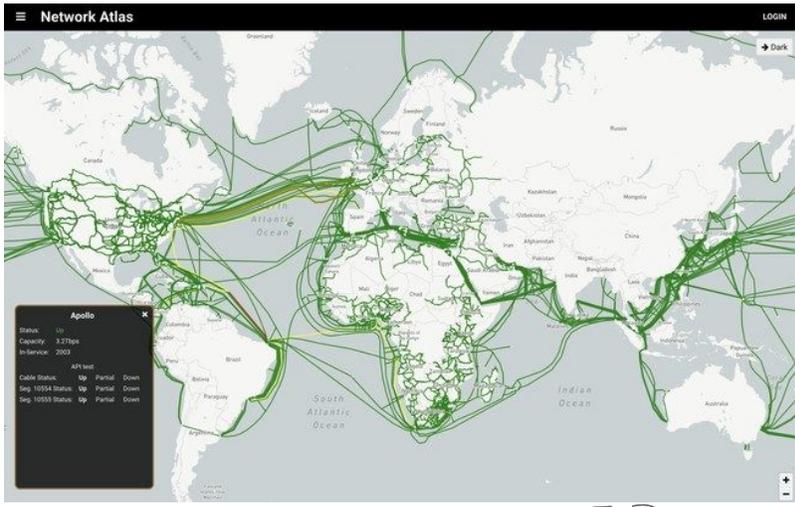
MIT Future of Data Initiative
January 21, 2021

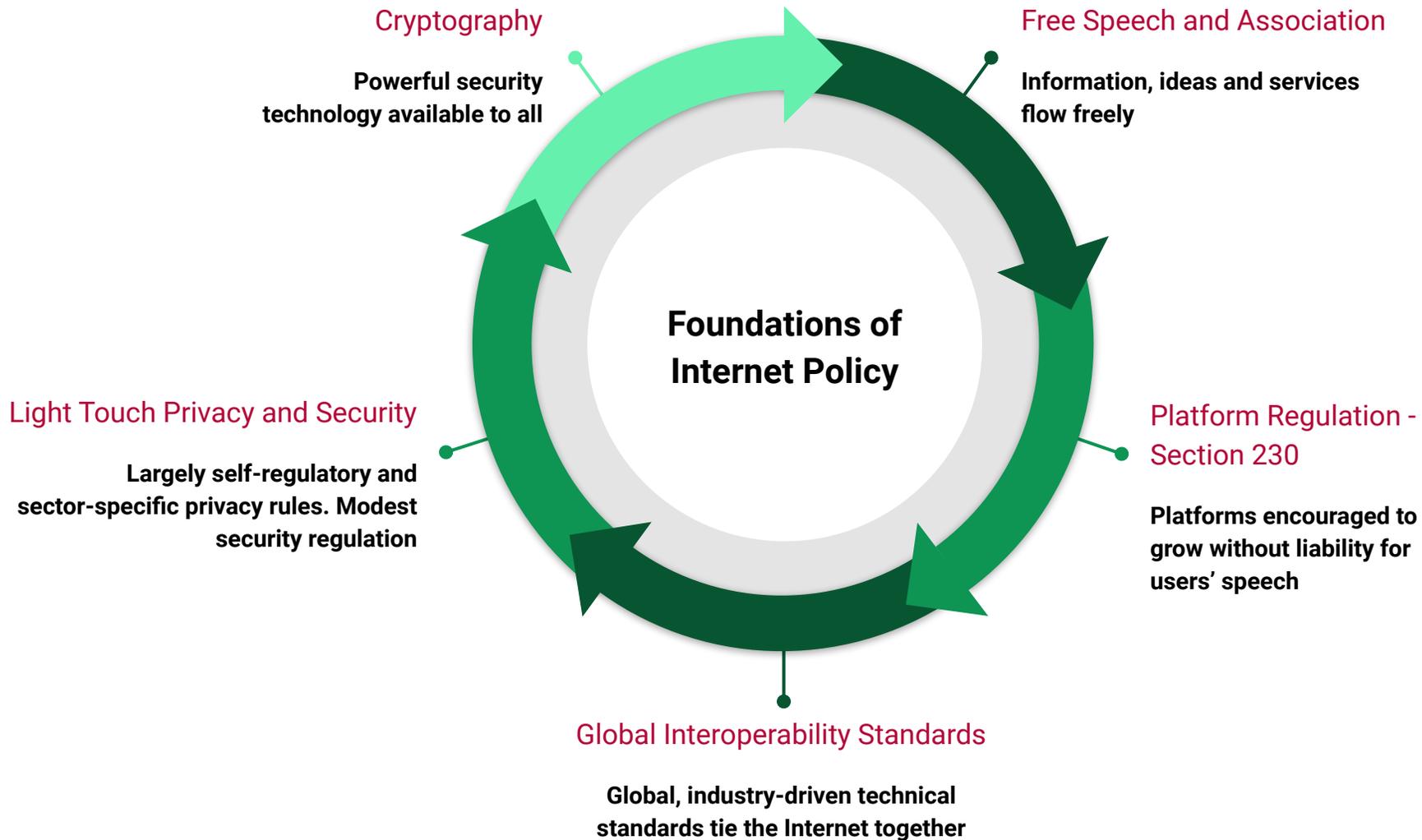
Daniel J. Weitzner

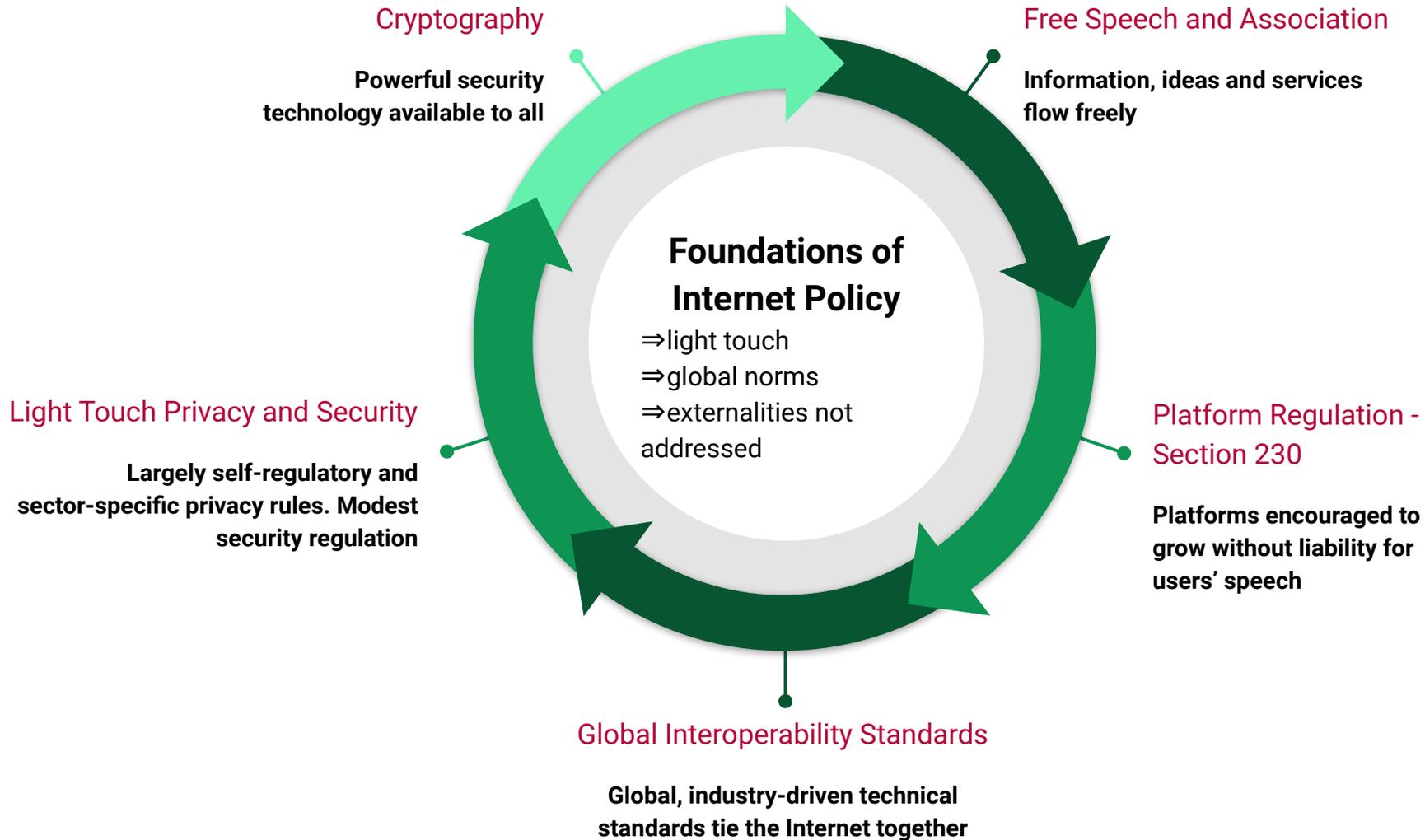
3Com Founders Principal Research Scientist, MIT CSAIL
Founding Director, MIT Internet Policy Research Initiative

Director, CSAIL Computing and Society Community of Research

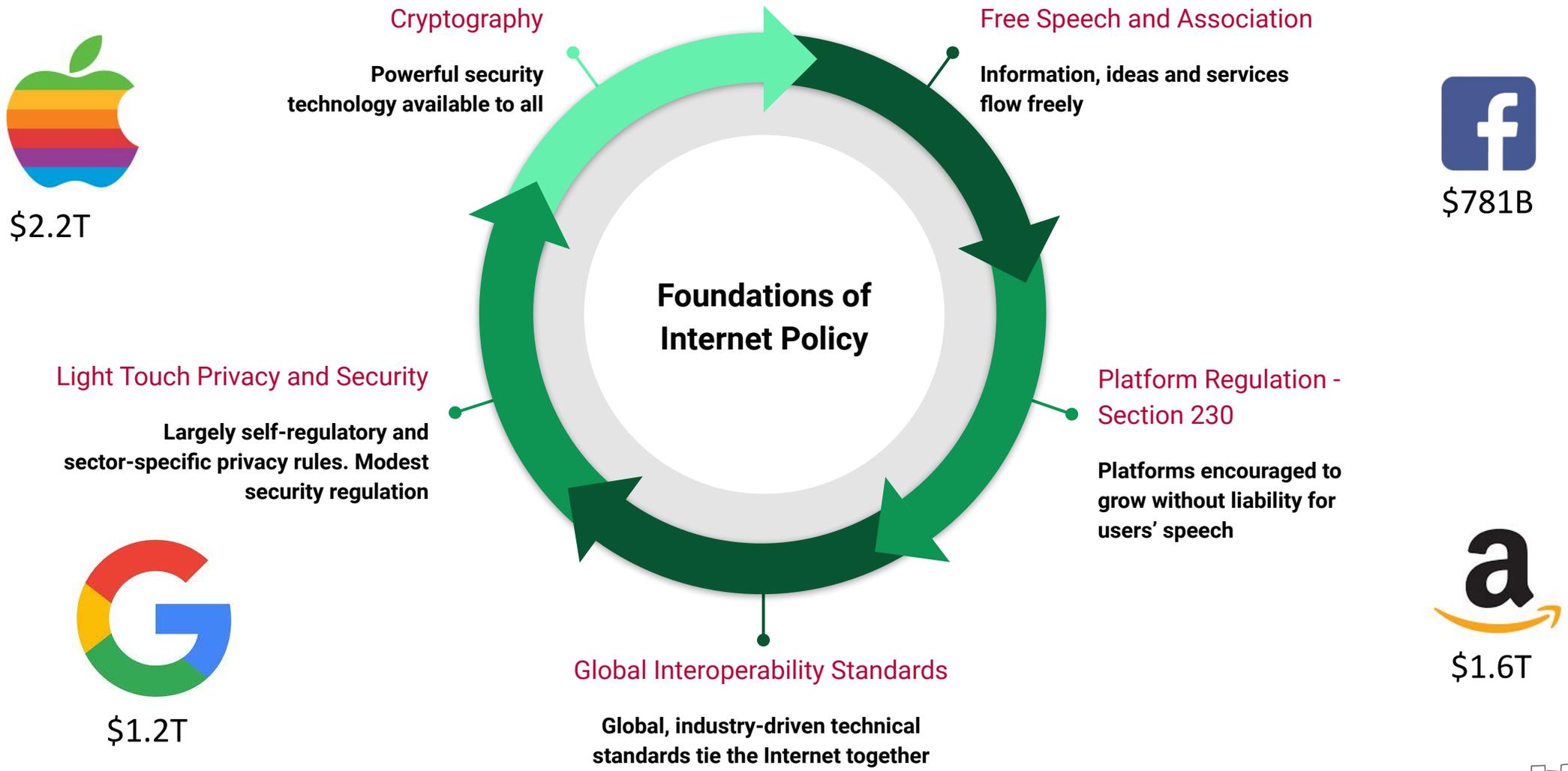
Four Decades of Computing Leadership: 1982 - 2018



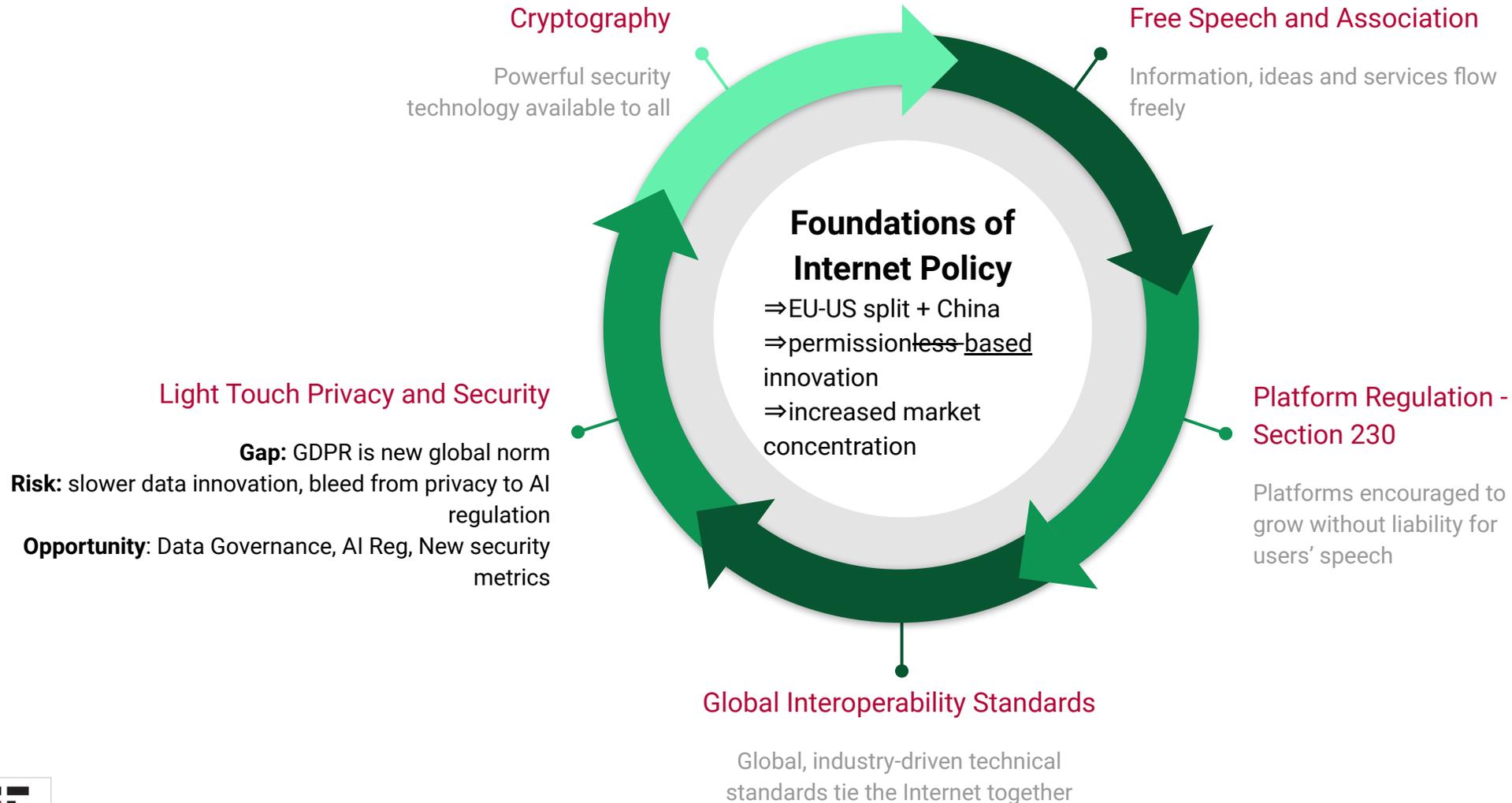




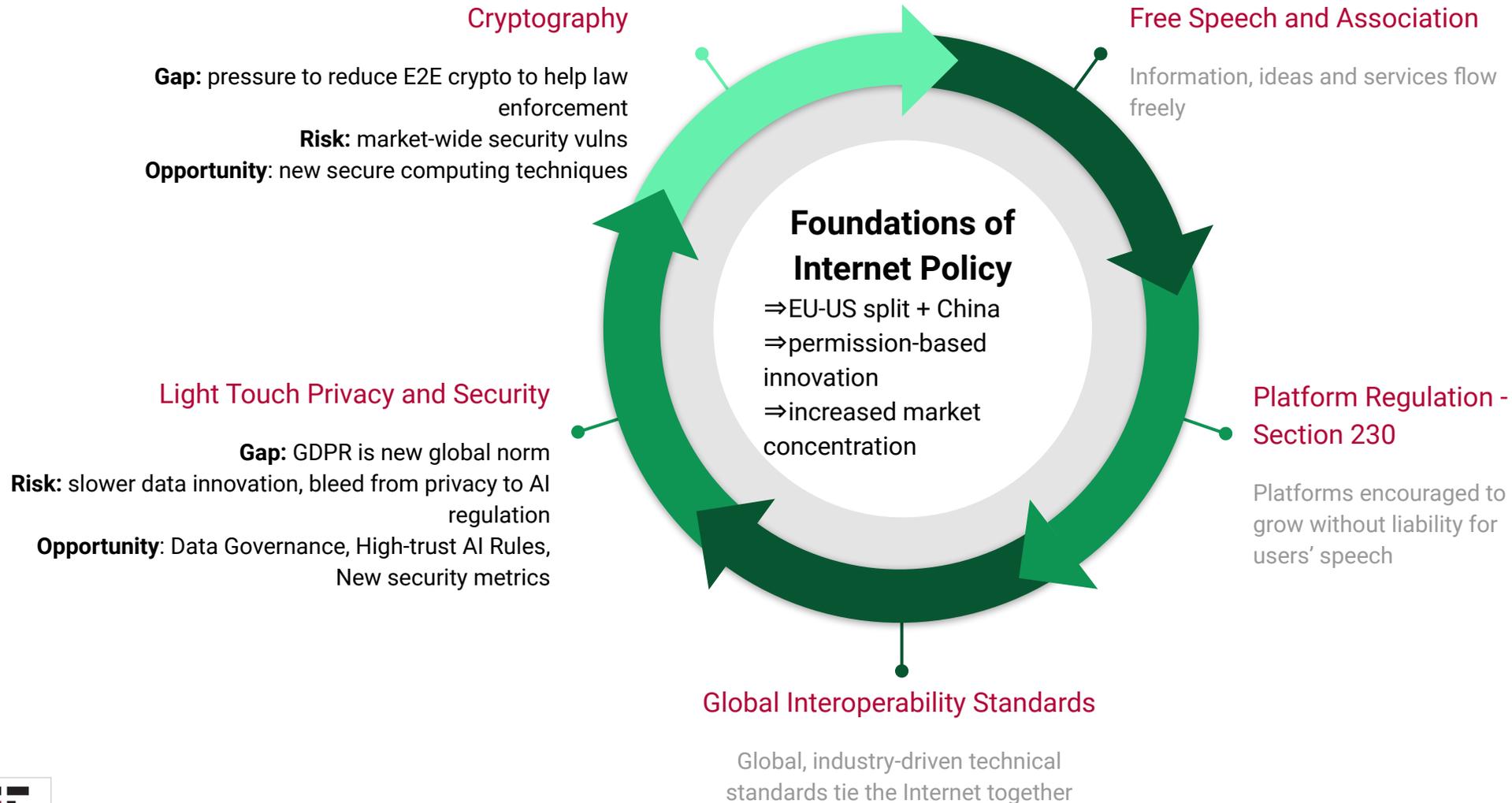
\$6T+/3B Person-enabling Internet Policy framework



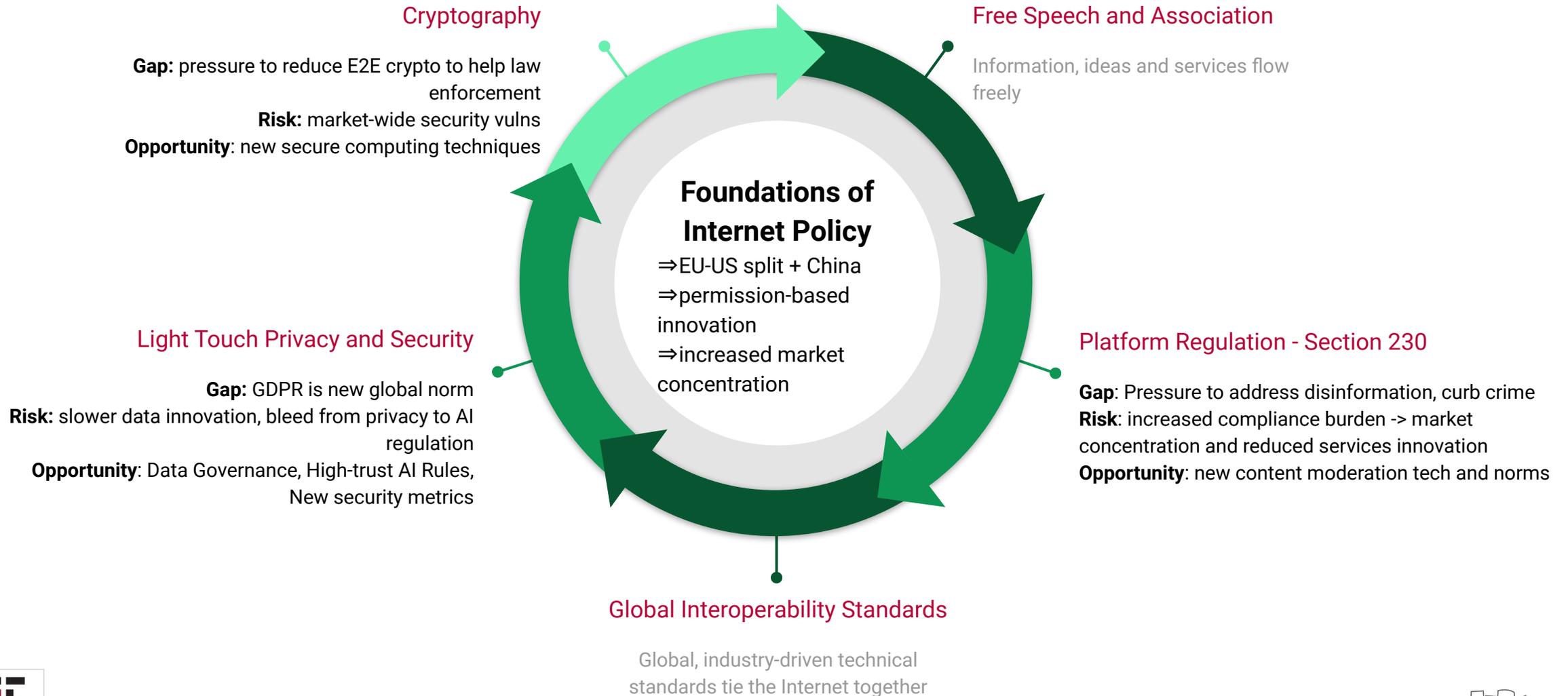
Gaps Emerge, Opportunities too.



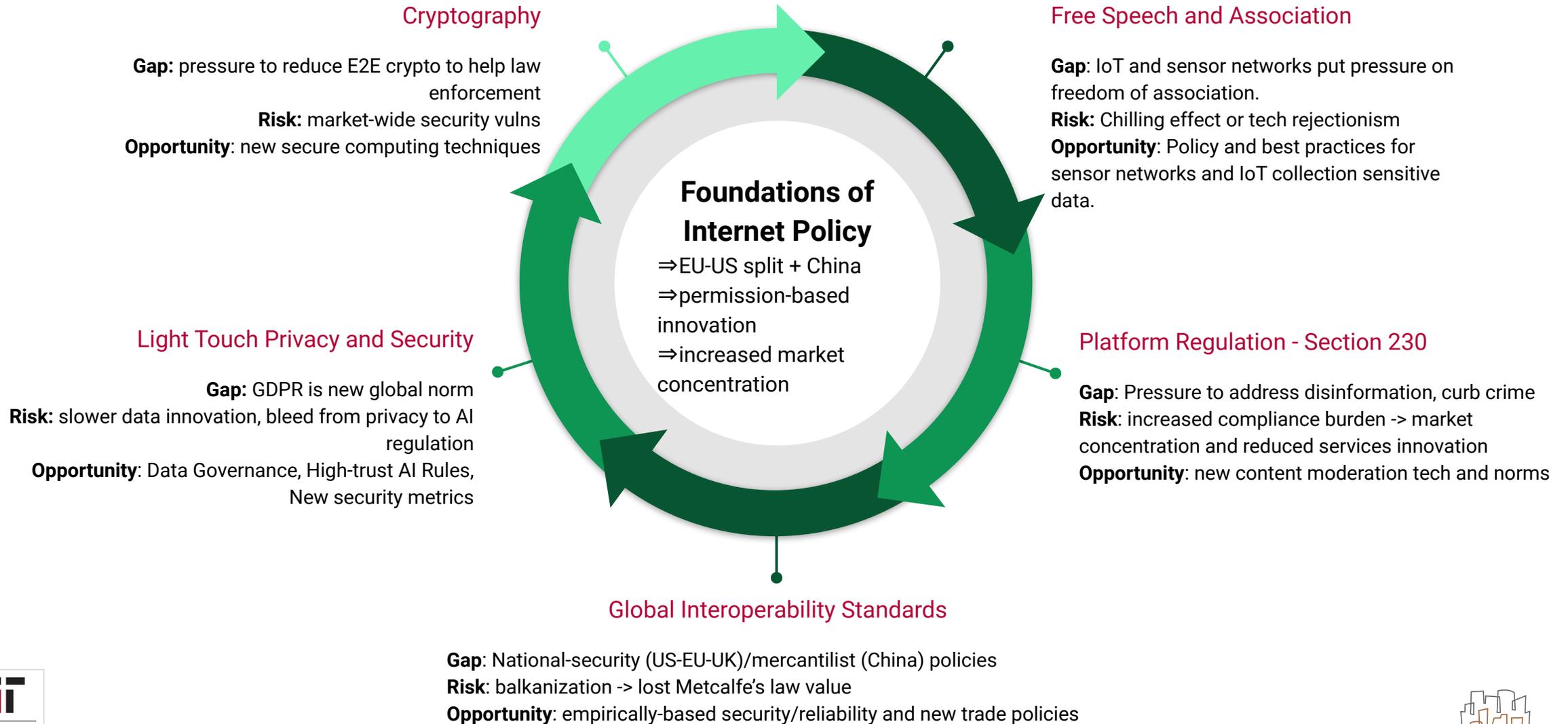
Gaps Emerge, Opportunities too.



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Gaps Emerge, Opportunities too.



Frontiers of Computing no longer purely technical

M.I.T. Plans College for Artificial Intelligence, Backed by \$1 Billion



The Massachusetts Institute of Technology is taking a particularly ambitious step in preparing students to develop, and consider the implications of, artificial intelligence. It is creating a new college, backed by a planned investment of \$1 billion. Cody O'Loughlin for The New York Times

“The MIT Schwarzman College of Computing will seek to be not only a center of advances in computing, but also a place for teaching and research on relevant policy and ethics to better ensure that the groundbreaking technologies of the future are responsibly implemented in support of the greater good.”
-MIT President Rafael Reif

By Steve Lohr

Oct. 15, 2018

Future of Data: Research Agenda



SCRAM

Secure Cyber Risk Aggregation and Measurement

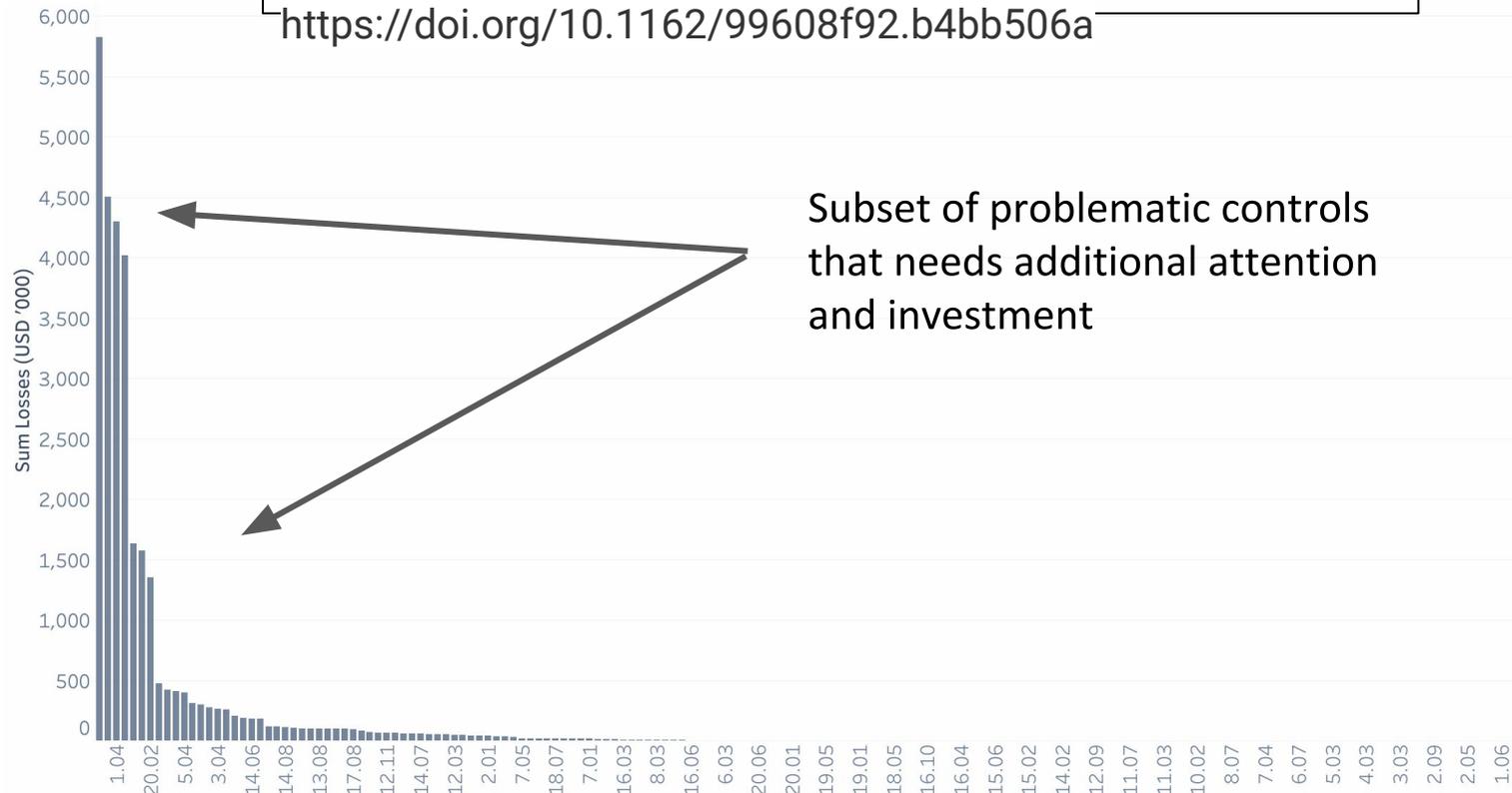
Problem: Cyber attacks happen all the time, but we collectively learn very little from them because firms are reluctant to disclose how they were attacked and the magnitude of their losses.

Gap: Lack of cyber risk pricing models:

- Impair CISO investment and prioritization decisions
- Limit quality and efficiency of cyber insurance
- Leave policymakers and regulators making uninformed choices in setting security standards
- Sow public distrust

de Castro, L., Lo, A. W., Reynolds, T., Susan, F., Vaikuntanathan, V., Weitzner, D., & Zhang, N. (2020). SCRAM: A Platform for Securely Measuring Cyber Risk . Harvard Data Science Review.

<https://doi.org/10.1162/99608f92.b4bb506a>



<https://scram.mit.edu>

We built a solution

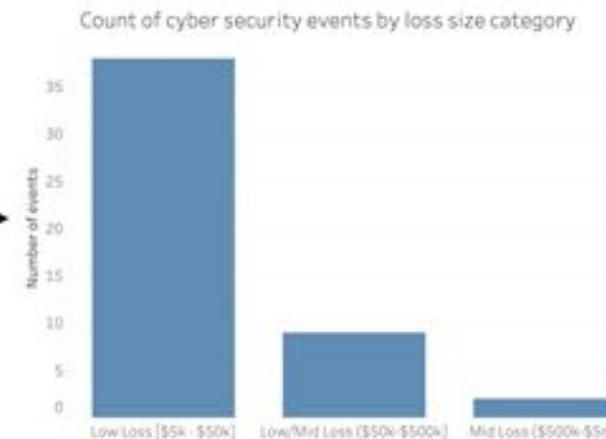
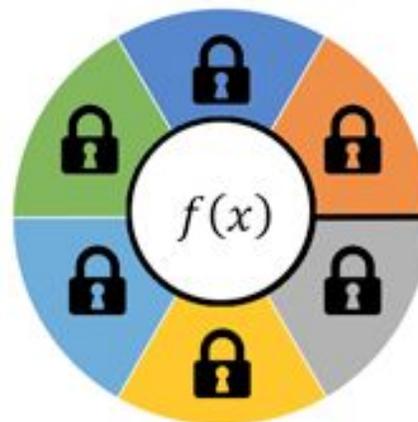
Using our new cryptographic platform (multi-party computation), firms can securely and privately contribute sensitive data for calculating aggregate frequency and loss data without disclosure to anyone - including MIT!

Homomorphic encryption →

Elegant way of computing on encrypted data

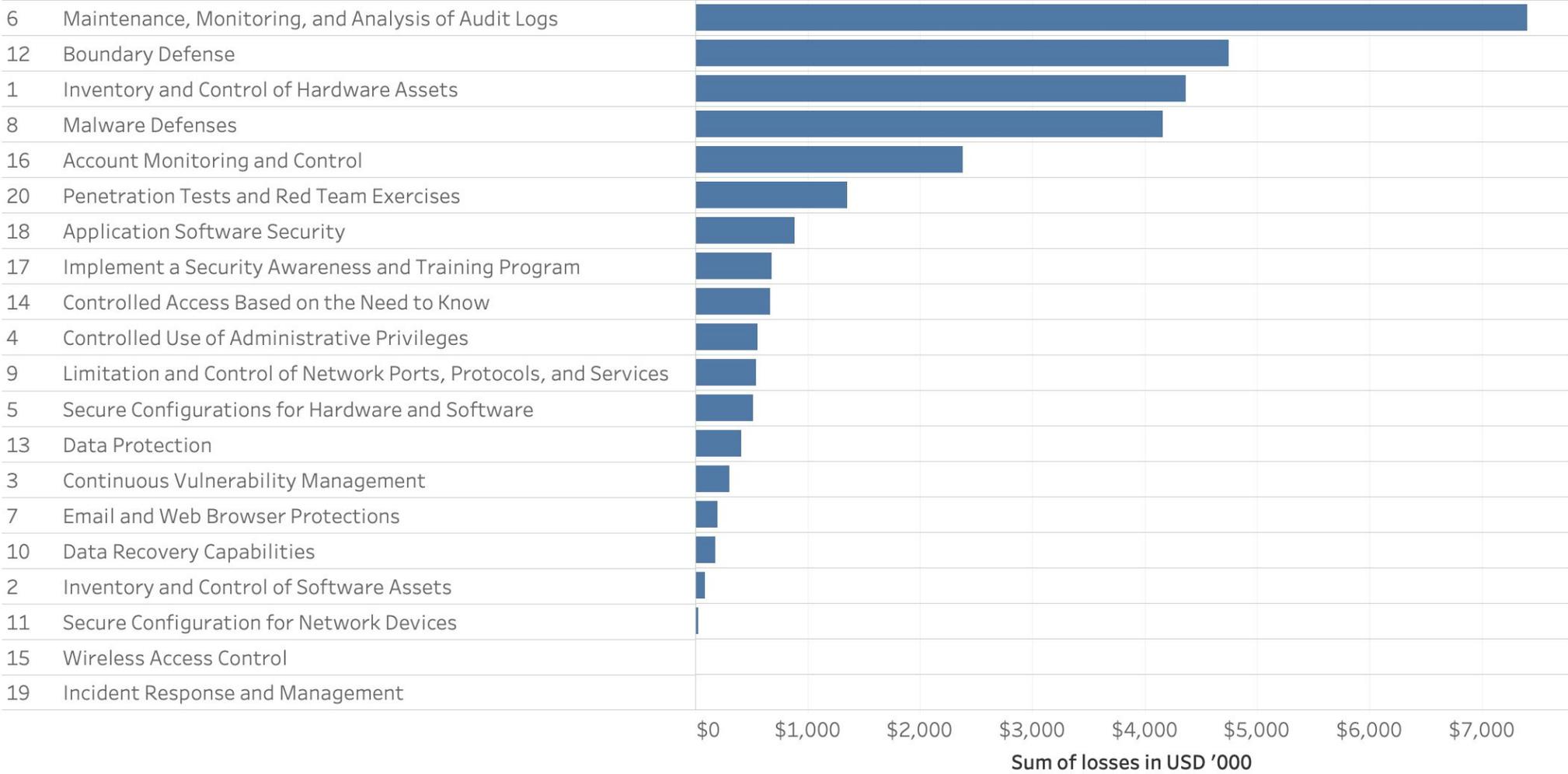


SCRAM
Secure Cyber Risk Aggregation and Measurement



scram.mit.edu

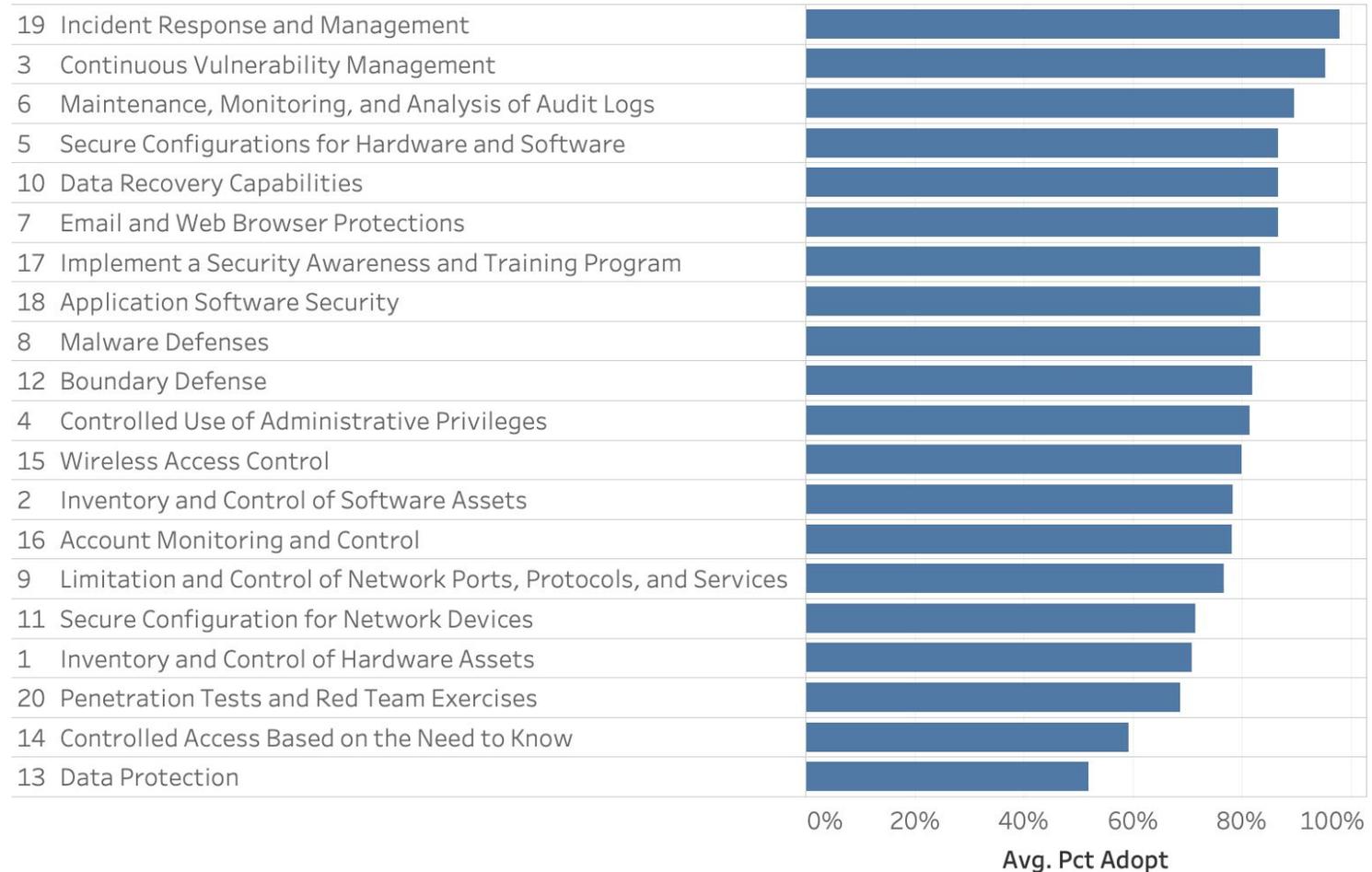
Early results: Losses by category



“Implemented” does not mean protected

Correlation
of control
adoption
with losses

10.3%



Tools: GDPR-aware database architecture

- unsolved problems

GDPR	Consumer Privacy Bill of Rights	Cal. Consumer Privacy Act	Apple proposal
Lawful basis - Consent, etc.	Right individual control		
legitimate interest, etc	Right to respect for context		
Right to be informed	Right to transparency	Right to know	Right to know
Right of access	Right to access		Right to access
Right to rectification	Right to accurate		
Right to erasure		Right to be deleted	
Right to restrict processing		No discrimination for exercise	Right to minimization
Right to portability	Machine-readable		
Right to object	Right to control		
Right to avoid automated decisionmaking & explanation			
Data Breach Notification	Security & Breach Notification		Privacy
Accountability	Accountability		
Fines < 4% annual revenue	Fines	\$7500/incident, 30 day cure	

Purpose limitation enforcement

Effective Notice - HCI/UX

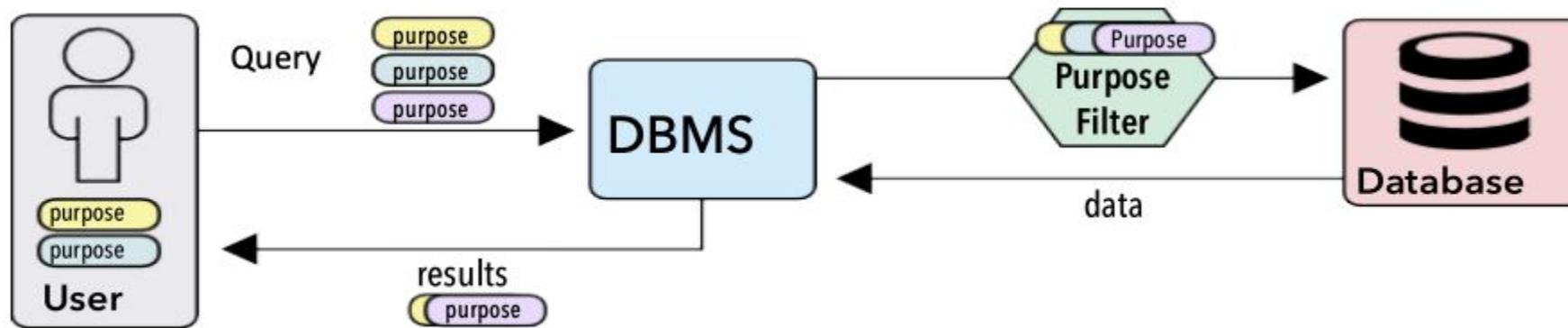
Hard Delete

Graph privacy

ML explanation

Policy-Aware Event Logging

Purpose-Aware Database Architecture



Stonebraker, M., Brodie, M., Kraska, T., Servan-Schreiber, S., Weitzner, D. J., SchengenDB: A Data Protection Database., VLBD Workshop Poly'19



Bringing Technical Rigor to Policy Debates

The New York Times

Voting on Your Phone: New Elections App Ignites Security Debate

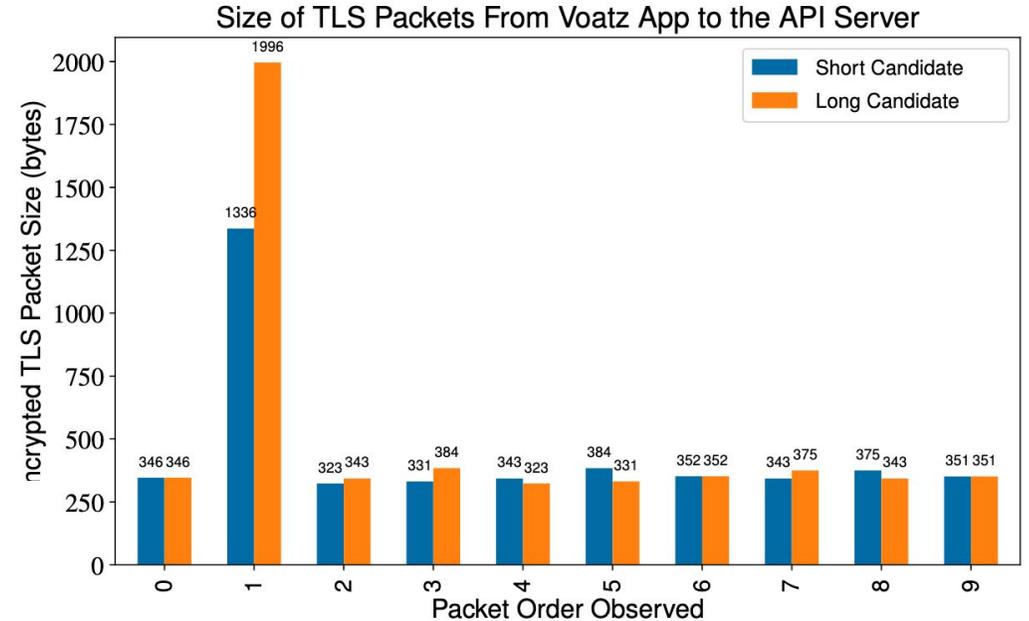


New Hampshire residents voting in the presidential primary on Tuesday. A smartphone app could let some absentee voters this year cast ballots from home. Alyssa Schukar for The New York Times

By Matthew Rosenberg

Feb. 13, 2020

In the new paper, the M.I.T. researchers, Michael A. Specter, James Koppel and Daniel J. Weitzner, go beyond speculation and detail how they found serious security issues by reverse-engineering Voatz's app and recreating what they could of the company's server from publicly available information.



Specter, Michael A., James Koppel, and Daniel Weitzner. "The Ballot is Busted Before the Blockchain: A Security Analysis of Voatz, the First Internet Voting Application Used in US Federal Elections." In *29th {USENIX} Security Symposium ({USENIX} Security 20)*, pp. 1535-1553. 2020.

Findings on mobile voting security

- 5 high-severity vulnerabilities & a serious privacy issue
- Many basic implementation failures, e.g.:
 - Mandated use of weak passwords
 - Anti-tamper/AV solution was easily circumventable
 - Sends a photo of user's ID, and location to a third party *without alerting the user*
- API Server has complete control
 - No proofs of inclusion (where's the Blockchain?)
 - Weak receipt validation, not E2E-V

Adversary	Attacker Capability				
	Suppress Ballot	Learn Secret Vote	Alter Ballot	Learn User's Identity	Learn User IP
Passive Network (§5.3)		✓			✓
Active Network (§5.3)	✓	✓			✓
3rd-Party ID Svc. (§5.4)	✓			✓	✓
Root On-Device (§5.1)	✓	✓	✓	✓	✓
Voatz API Server (§5.2)	✓	✓	✓	✓	✓

Future of Data: Engagement and Education

Tools: Engagement

"All the News That's Fit to Print"

The New York Times

VOL. CLXIV ... No. 56,923 © 2015 The New York Times NEW YORK, WEDNESDAY, JULY 8, 2015

Security Experts Oppose Government Access to Encrypted Communication

By NICOLE PERLROTH JULY 7, 2015

SAN FRANCISCO — An elite group of security technologists has concluded that the American and British governments cannot demand special access to encrypted communications without putting the world's most confidential data and critical infrastructure in danger.



The New York Times

A.I. Policy Is Tricky. From Around the World, They Came to Hash It Out.



Nicolas Mialhe, a co-founder of the Future Society, asking a question during a gathering of global policymakers last week at the Massachusetts Institute of Technology. Kayana Szymczak for The New York Times

By Steve Lohr

Jan. 20, 2019



MIT News

ON CAMPUS AND AROUND THE WORLD

[Browse](#)

AI, the law, and our future

MIT "Policy Congress" examines the complex terrain of AI regulation.

Peter Dizikes | MIT News Office
January 18, 2019

[Press Inquiries](#)

Scientists and policymakers converged at MIT on Tuesday to discuss one of the hardest problems in artificial intelligence: How to govern it.

The first MIT AI Policy Congress featured seven panel discussions sprawling across a variety of AI applications, and 25 speakers — including two former White House chiefs of staff, former cabinet secretaries, homeland security and defense policy chiefs, industry and civil society leaders, and leading researchers.



Computing & Society CoR Student Research



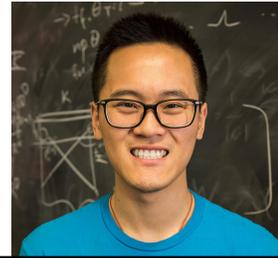
ML : Diagnosing bias in predictive modeling



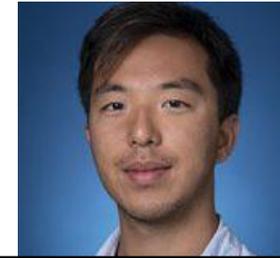
Creating and democratizing conversational AI



Neural networks, technology policy, and the Lottery Ticket Hypothesis



App Inventor voice-based conversational programming system



ML Bias in Predictive Policing



Differential Privacy for Machine Learning



How organizations develop structures for technology policy decision making



Efficient two-party computation from plaintext-ciphertext homomorphic operations



Personal audio classifier for App Inventor



The impact of vulnerabilities and benefits of security in the Internet's core routing protocols



Cybersecurity policy, trust, and privacy online



International security, the political economy of technology, and Chinese foreign policy



Denial of Service vulnerabilities, network protocols, Linux performance bottlenecks, and Future Internet Architectures



Evaluating the quasi-voluntary public-private partnership approach to critical infrastructure cybersecurity



AI policy and predictive policing



Systems security and applied cryptography, particularly in areas relevant to public policy

<https://internetpolicy.mit.edu/>

Techniques for Data Privacy: “Old” and New

Srini Devadas

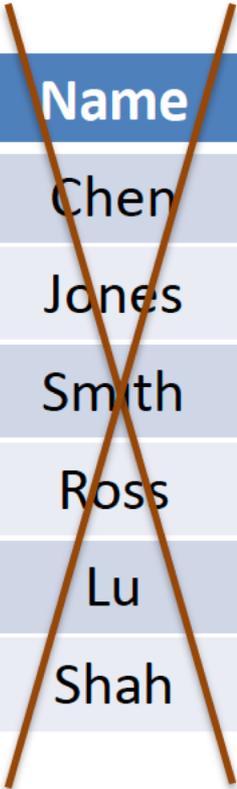
MIT CSAIL



Motivation

- Being able to compute on private data is essential
- Many questions:
 - What is the privacy guarantee? Does it conform to applicable laws governing use and sharing of data?
 - What is the computational cost of “private” computation?
 - What is the utility or accuracy cost of “private” computation?
- Not surprisingly, there are many approaches with differing tradeoffs

Approach 1: “Anonymize” the Data

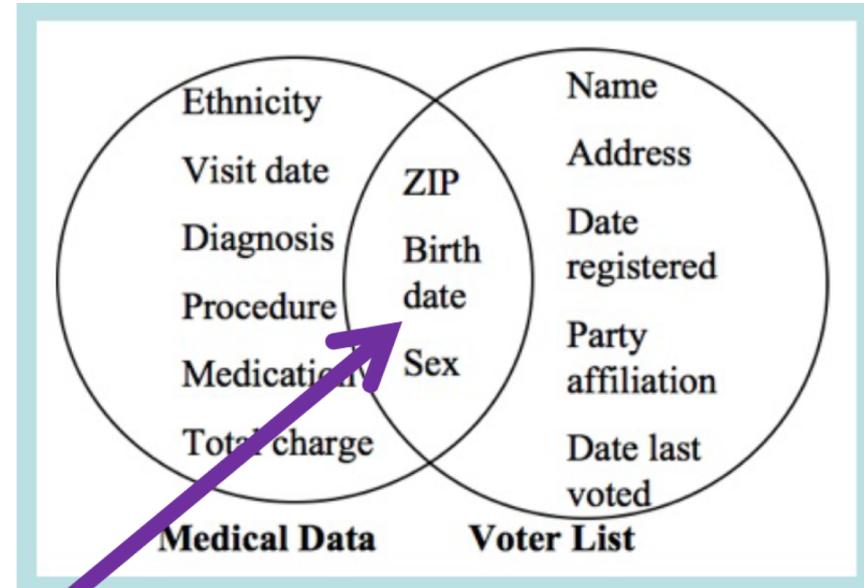


Name	Sex	Blood	...	HIV?
Chen	F	B	...	Y
Jones	M	A	...	N
Smith	M	O	...	N
Ross	M	O	...	Y
Lu	F	A	...	N
Shah	M	B	...	Y

Problems?

Reidentification via Linkage

Name	Sex	Blood	...	HIV?
Chen	F	B	...	Y
Jones	M	A	...	N
Smith	M	O	...	N
Ross	M	O	...	Y
Lu	F	A	...	N
Shah	M	B	...	Y



[Sweeney '97]

Uniquely identify > 60% of the US population [Sweeney '00, Golle '06]

All it takes is a knowledge of a small number of attributes to identify/name the person!

Approach 2: Encrypt the Data

Name	Sex	Blood	...	HIV?
Chen	F	B	...	Y
Jones	M	A	...	N
Smith	M	O	...	N
Ross	M	O	...	Y
Lu	F	A	...	N
Shah	M	B	...	Y



Name	Sex	Blood	...	HIV?
100101	001001	110101	...	110111
101010	111010	111111	...	001001
001010	100100	011001	...	110101
001110	010010	110101	...	100001
110101	000000	111001	...	010010
111110	110010	000101	...	110101

Challenges: How to search over data or compute statistics? How efficient/general is this?

Ongoing work on Fully Homomorphic Encryption and Secure Multiparty Computation

- Secure processors, such as Intel SGX, provide attested execution inside enclaves
 - Encrypted data from user is decrypted inside the enclave and processed

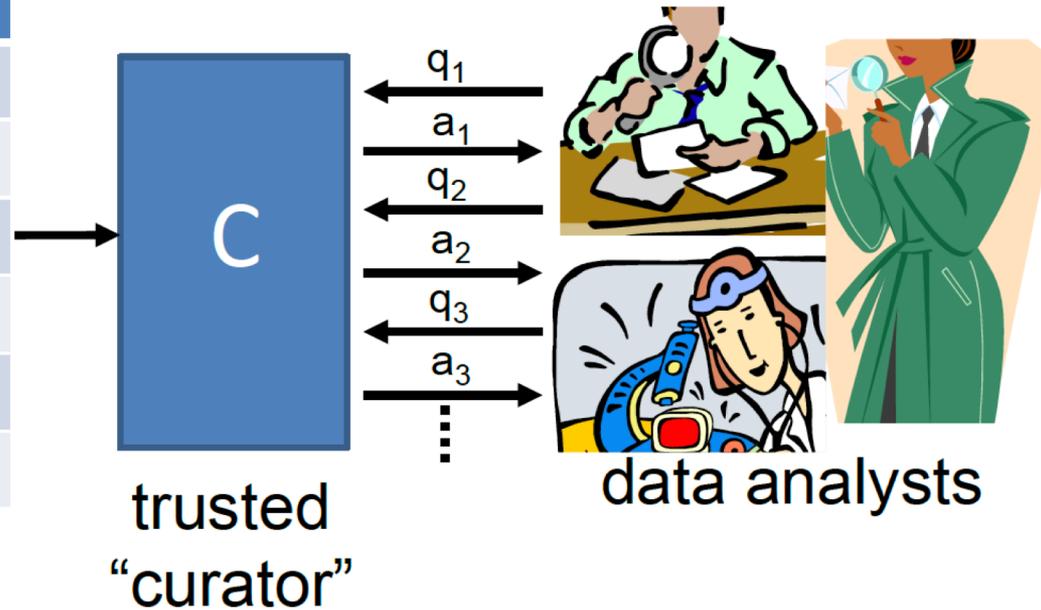


Challenges: Side Channel attacks! Spectre, Meltdown, Foreshadow, ...

Ongoing work on RISC-V based secure enclaves

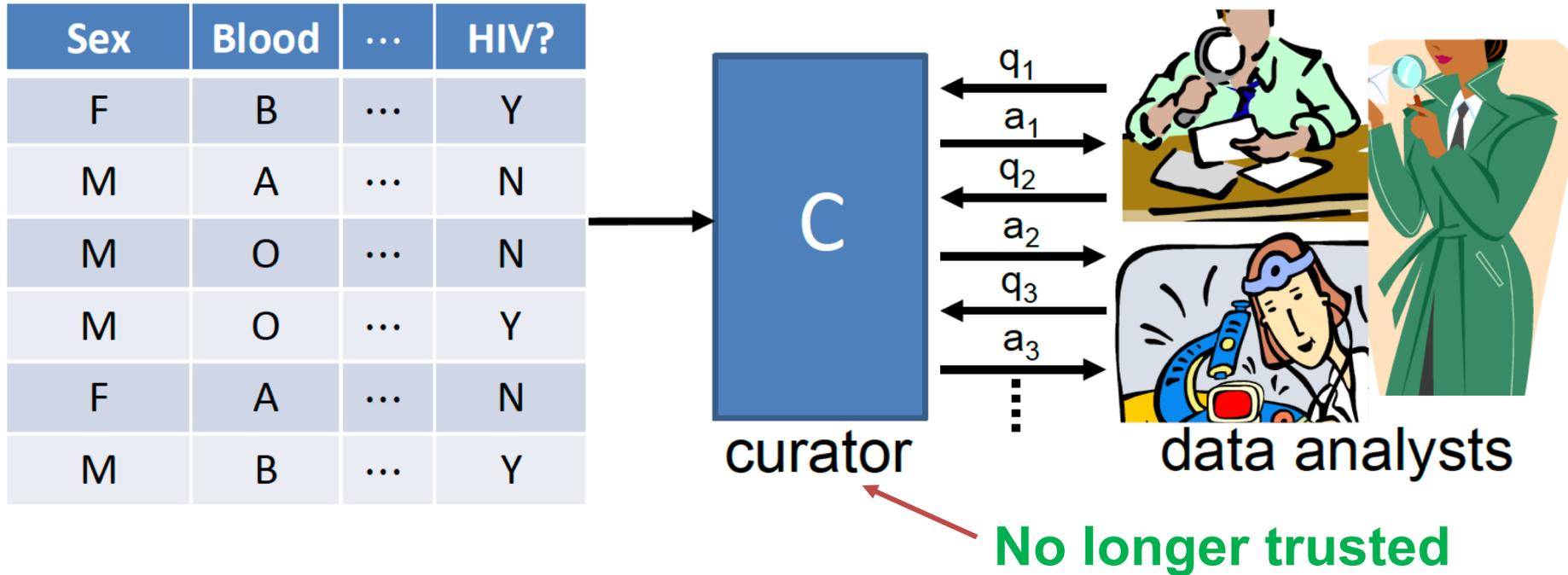
Approach 4: Mediate Access

Name	Sex	Blood	...	HIV?
Chen	F	B	...	Y
Jones	M	A	...	N
Smith	M	O	...	N
Ross	M	O	...	Y
Lu	F	A	...	N
Shah	M	B	...	Y



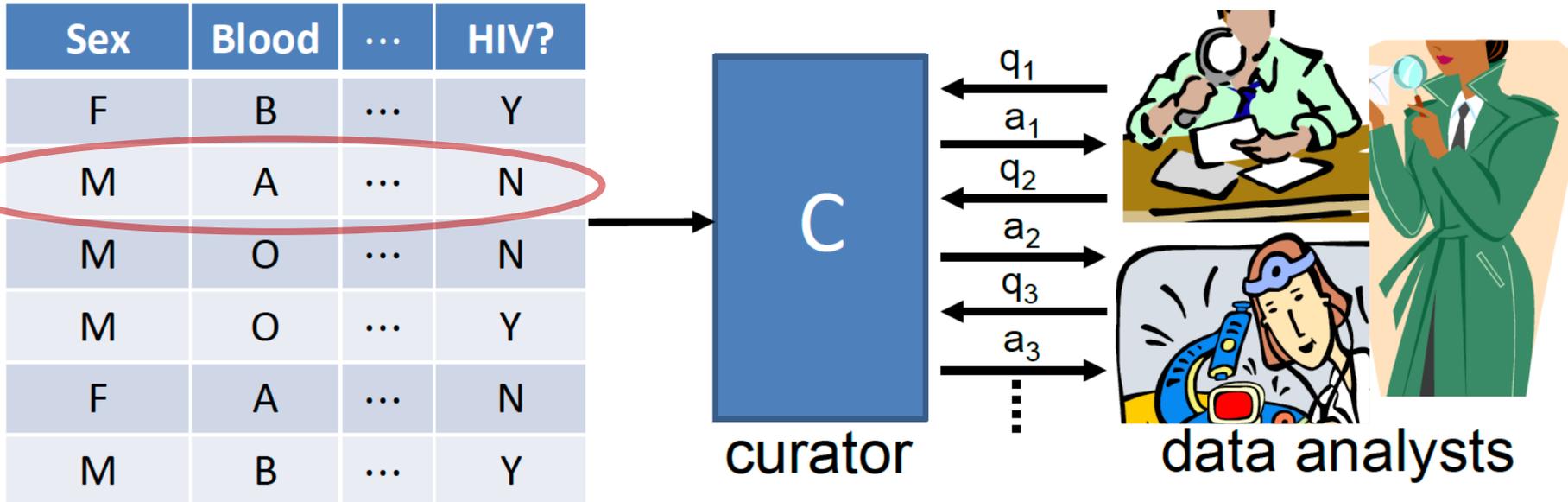
Problems: Curator sees all the data. What queries are allowed? How much do they leak?

Differential privacy



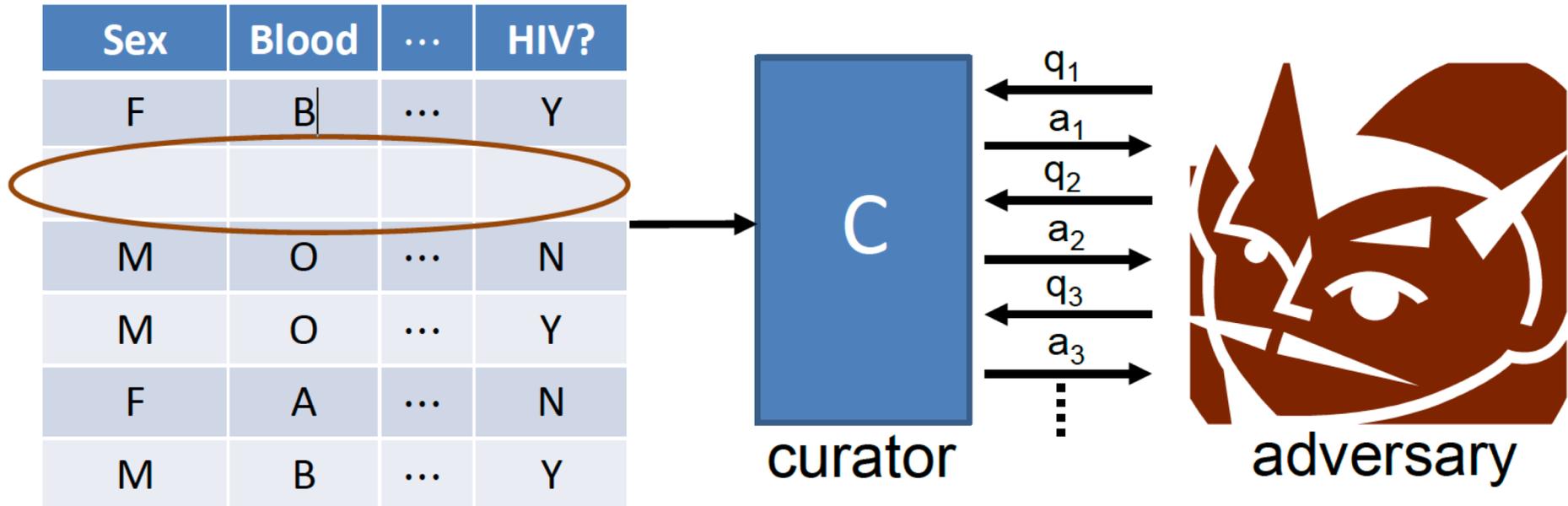
- **Requirement:** effect of each individual should be “hidden”

Differential privacy



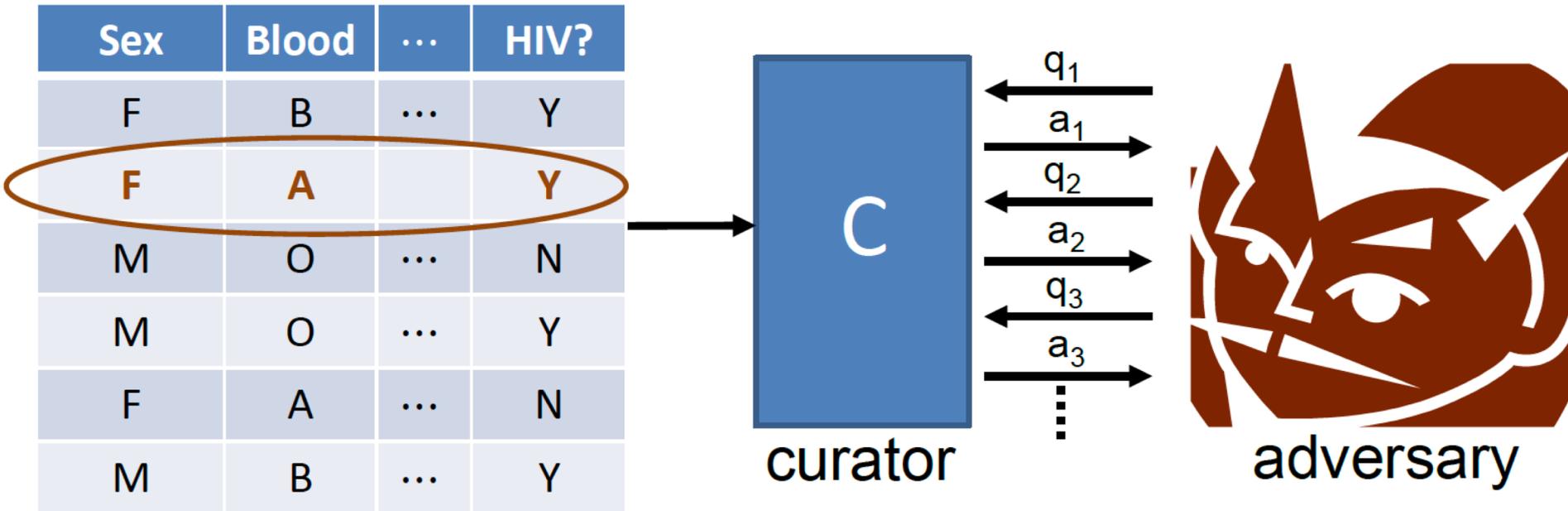
- **Requirement:** Adversary should not be able to tell if any one person's data were changed arbitrarily

Differential privacy



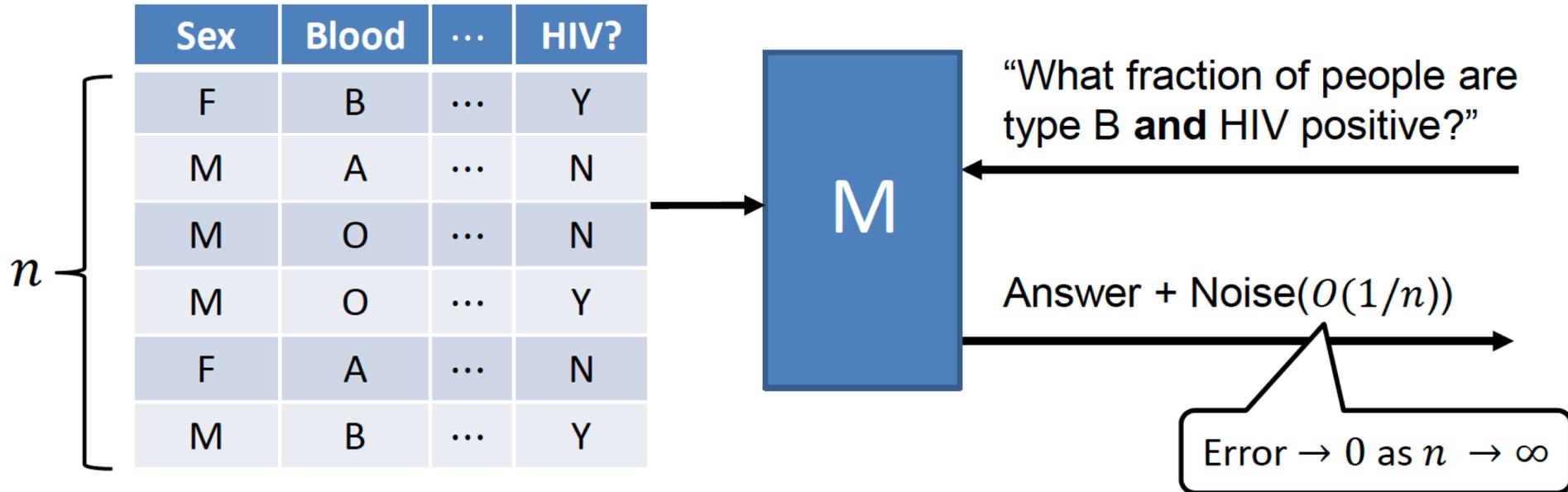
- **Requirement:** Adversary should not be able to tell if any one person's data were changed arbitrarily

Differential privacy



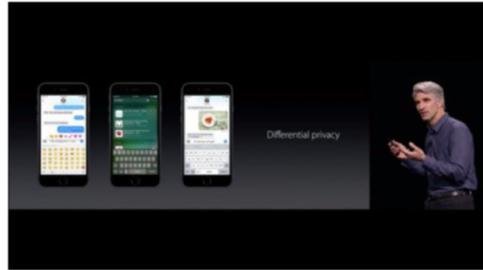
- **Requirement:** Adversary should not be able to tell if any one person's data were changed arbitrarily

Simple approach: random noise



- Very little noise needed to hide each person as $n \rightarrow \infty$
- This is just for one query

Differential Privacy Deployed



Apple

Google Security Blog

The latest news and insights from Google on security and safety on the Internet

Learning statistics with privacy, aided by the flip of a coin
October 30, 2014

Cross-posted on the [Research Blog](#) and the [Chromium Blog](#)

At Google, we are constantly trying to improve the techniques we use to [protect our users' security and privacy](#). One such project, RAPPOR (Randomized Aggregatable Privacy-Preserving Ordinal Response), provides a new state-of-the-art, privacy-

Google



Census Bureau



Uber

mostly focused on count and average statistics

- Accuracy for “small data” (small n)
- Modeling and managing privacy loss over time
- Analysts are used to working with raw data, not querying (slightly) noisy data
- Matching guarantees with privacy law and regulation
- Significant work at CSAIL addressing these challenges

- Dataset X belongs to **Owner**
- **Owner** transforms X using a **private transform** T to $T(X)$ and shares with untrusted entity U
- U learns model M based on $T(X)$ and returns M to Owner
- To predict using M , owner queries $M(T(x_{\text{new}}))$
- Key questions:
 - How much does $T(X)$ leak about X ?
 - How accurate is M relative to model based on X ?

Data Augmentation

- **Mixup** is a popular data augmentation strategy
- Given two samples X and Y , choose random r , $0 < r < 1$ and generate a new sample
$$r X + (1 - r) Y$$
- + Can increase the number of training samples
- + Data augmentation can hide private Y with secret r , even if one sample X is public

- How to choose the transform T so we can show a privacy property?
 - What is the resultant utility of learning/computing on the transformed data?
- + One-time transformation of data is computationally efficient
- + Positive preliminary results for Support Vector Machines, fully connected neural networks for transform with bounded leakage

Summary

- Being able to legally and efficiently compute on private data is essential
- This is a rich area of research with new technologies constantly being developed
- We look forward to working with you to address research challenges!