Brokered Agreements in Multi-Party Machine Learning

10th ACM SIGOPS Asia-Pacific Workshop on Systems (APSys 2019)

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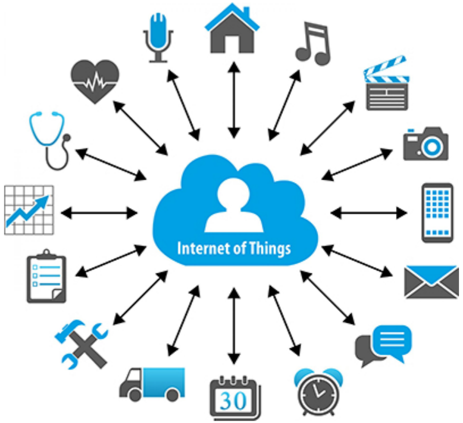
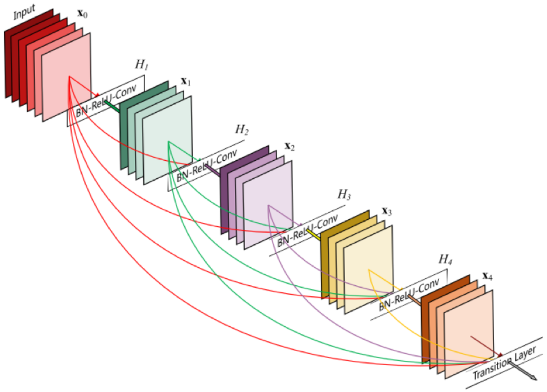
The emerging ML economy

- With the explosion of machine learning (ML), data is the new currency!
    - Good quality data is vital to the health of ML ecosystems
- Improve models with more data from more sources!





Actors in the ML economy

- Data providers:
  - Owners of potentially private datasets
  - Contribute data to the ML process

- Model owners:
  - Define model task and goals
  - Deploy and profit from trained model

UBER

- Infrastructure providers:
  - Host training process and model
  - Expose APIs for training and prediction

Google Cloud

Actors in today's ML economy

- Data providers supply data for model owners
- Model owners:
    - Manage infrastructure to host computation
    - Provide privacy and security for data providers
    - Use the model for profit once training is complete

In-House privacy solutions

ANDY GREENBERG SECURITY 06.13.16 07:02 PM

APPLE'S 'DIFFERENTIAL PRIVACY' IS ABOUT COLLECTING YOUR DATA—BUT NOT *YOUR* DATA

Senior vice president of software engineering Craig Federighi. JUSTIN KANEPS FOR WIRED

[1] Wired 2016.
[2] Apple. "*Learning with Privacy at Scale*" Apple Machine Learning Journal V1.8 2017.
[3] Wired 2017.

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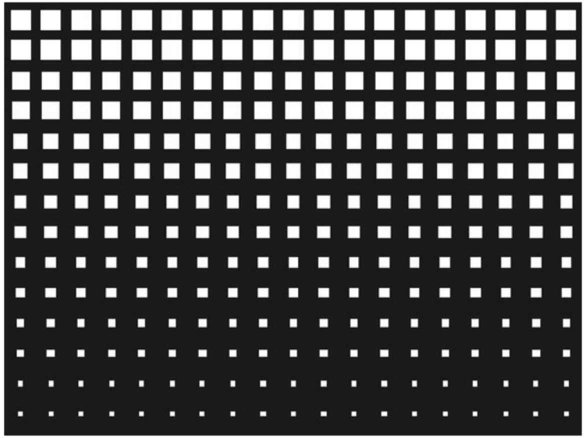
HOW ONE OF APPLE'S KEY PRIVACY SAFEGUARDS FALLS SHORT



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[2] Apple. "*Learning with Privacy at Scale*" Apple Machine Learning Journal V1.8 2017.
[3] Wired 2017.

Incentive trade-off in the ML economy

- Not only correctness, but there is an issue with incentives:
  - Data providers want to keep their data as private as possible
  - Model owners want to extract as much value from the data as possible
- Service providers **lack incentives to provide fairness** [1]
  - Need solutions that can work without cooperation from the system provider and are deployed from outside the system itself

[1] Overdorf et al. "*Questioning the assumptions behind fairness solutions.*" NeurIPS 2018.

Incentive trade-off in the ML economy

- Not only correctness, but there is an issue with incentives:
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We cannot trust model owners to control the ML incentive tradeoff!

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Incentives in today's ML economy

- Data providers supply data for model owners
- Model owners:
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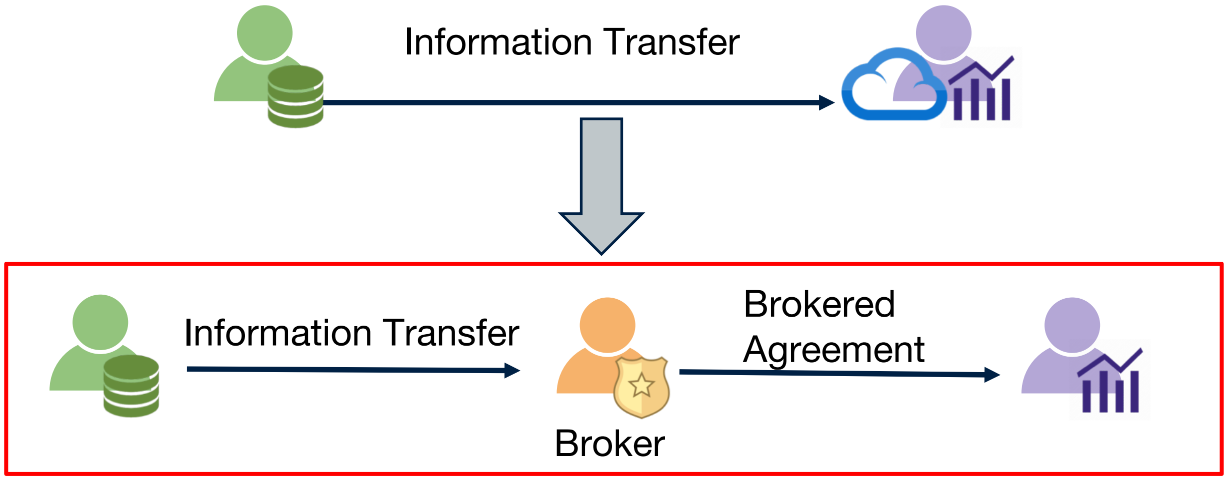
  - Provide privacy and security for data providers
  - Use the model for profit once training is complete

Incentives in today's ML economy

- Data providers supply data for model owners
- Model owners have incentive to:
  - ~~Manage infrastructure to host computation~~
  - ~~Provide privacy and security for data providers~~
  - Use the model for profit once training is complete

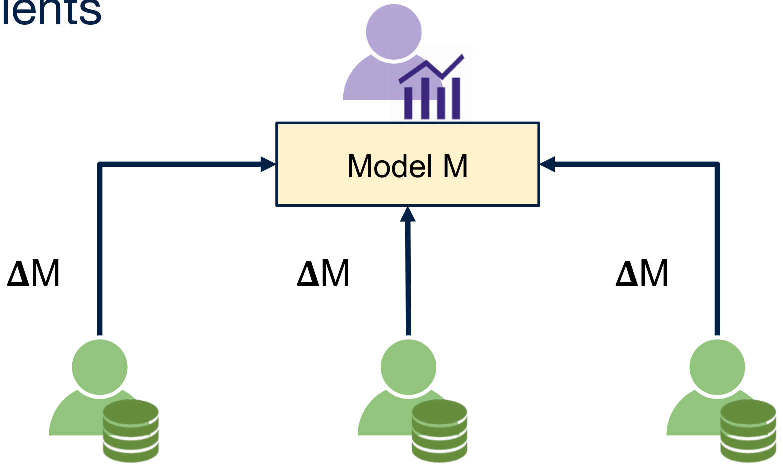
Our contribution: Brokered learning

- Introduce a broker as a neutral infrastructure provider:
  - Manage infrastructure to host ML computation
  - Provide privacy and security **for data providers and model owners**



Federated learning

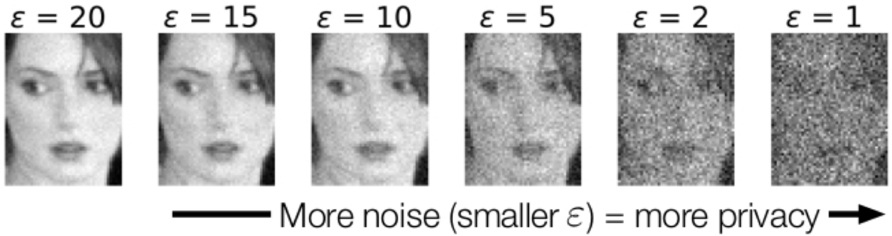
- A recent push for privacy-preserving multi-party ML [1]:
  - Send model updates over network
  - Aggregate updates across multiple clients
  - Client-side differential privacy [2]
  - Better speed, no data transfer
  - State of the art in multi-party ML
- Brokered learning builds on federated learning



[1] McMahan et al. "*Communication-Efficient Learning of Deep Networks from Decentralized Data*" AISTATS 2017.
[2] Geyer et al. "*Differentially Private Federated Learning: A Client Level Perspective*" NIPS 2017.

Data providers are not to be trusted

- Giving data providers unmonitored control over compute:
  - Providers can maximize privacy, **give zero utility or attack system**
  - Providers can attack ML model, compromising integrity [1]
  - Providers can attack other providers, compromising privacy [2]



[1] Bagdasaryan et al. "*How To Backdoor Federated Learning*" arXiv 2018.
[2] Hitaj et al. "*Deep Models Under the GAN: Information Leakage from Collaborative Deep Learning*" CCS 2017.

Data providers are not to be trusted

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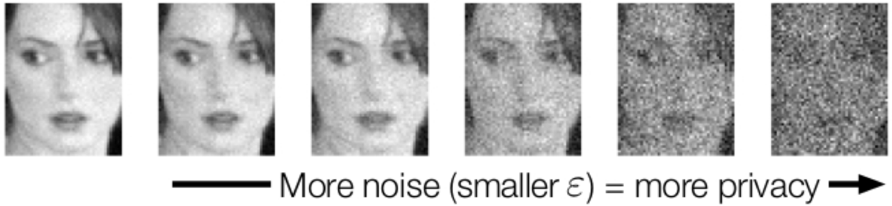
We <u>also</u> cannot trust data providers to control the ML incentive tradeoff!



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Putting it all together

- The state of the art in multi-party ML
  - Gives too much control to model owners
  - **Not privacy focused and vulnerable**
- State of the art in private multi-party ML (federated learning)
  - Require trust in model owners or data providers
  - **But there is no incentive for either to do so**
- Data marketplaces (blockchains) [1]
  - Security and system overkill
  - **Much too slow for modern use cases**

[1] Hynes et al. "*A Demonstration of Sterling: A Privacy-Preserving Data Marketplace*" VLDB 2018.

Putting it all together

More Centralized
Less Private/Secure

Less Centralized
More Private/Secure

Putting it all together

Centralized
Parameter Server

More Centralized
Less Private/Secure

Less Centralized
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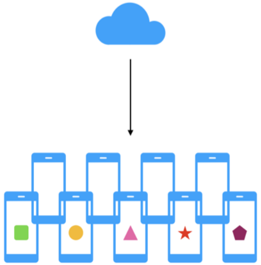
Putting it all together



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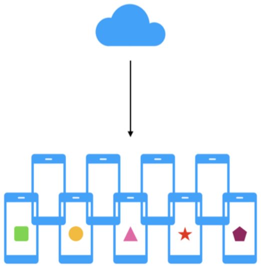

Federated
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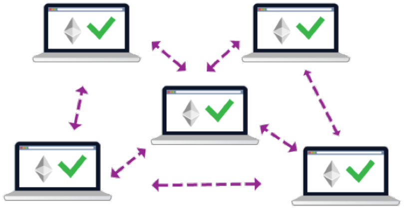

Blockchain-based
Multi-party ML

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Putting it all together

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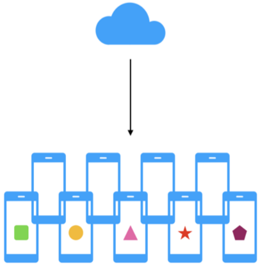

Federated
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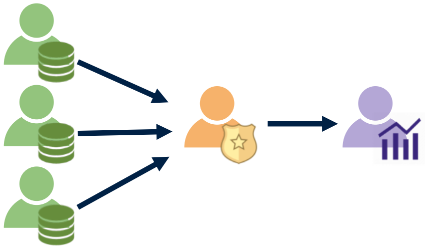
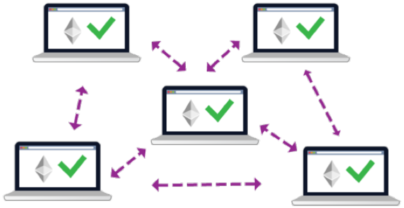


Brokered
Learning



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Our contributions

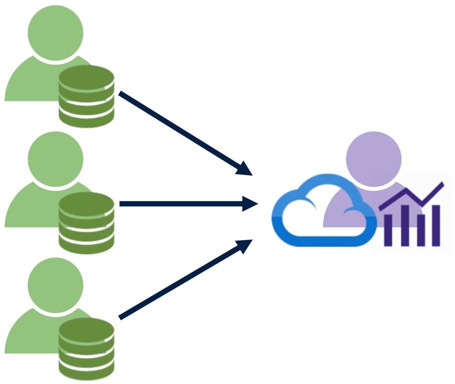
- Current multi-party ML systems use unsophisticated threat/incentive model:
  - Trust the model owner
- New brokered learning setting for privacy-preserving ML
- New defences against known ML attacks for this setting
- TorMentor: A brokered learning example of an anonymous ML system

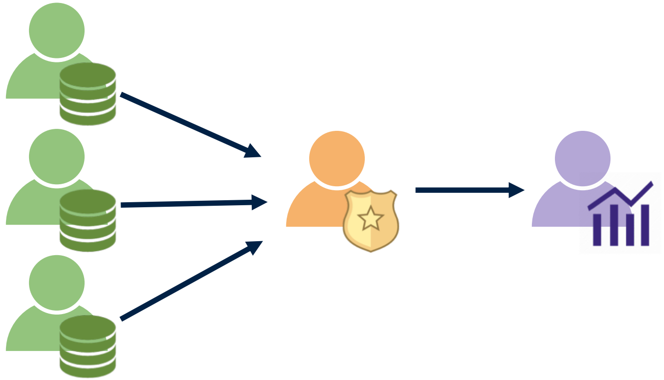
Brokered Learning: A new standard for incentives in secure ML

Brokered Learning

Brokered agreements in the ML economy

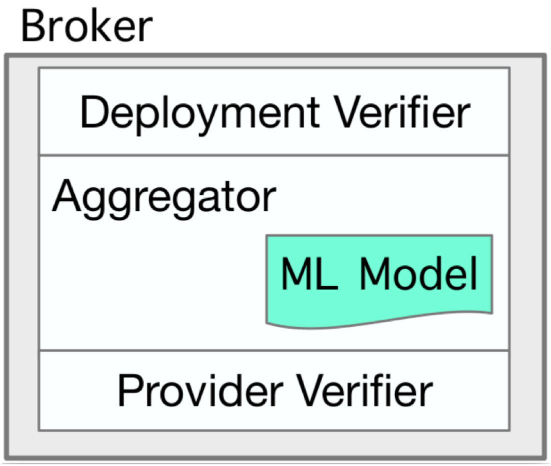
- Federated learning:
  - Communicate with model owner
  - Trust that model owner is not malicious
  - Model owners have full control over model and process
- Brokered learning
  - Communicate with neutral broker
  - Broker executes model owner’s validation services
  - **Decouple model owners and infrastructure**





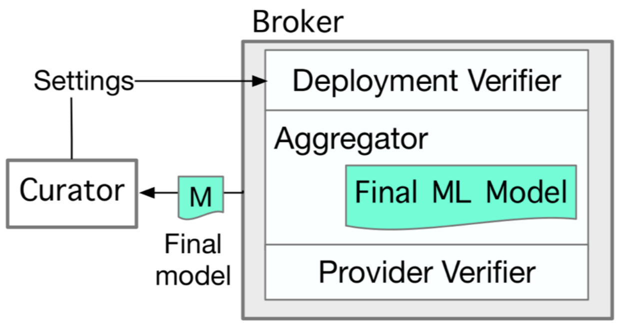
Brokered learning components

- Deployment verifier
  - Interface for model owners (“curators”)
- Provider verifier
  - Interface for data providers
- Aggregator
  - Host ML deployments
  - Collect and aggregate model updates
  - Same as federated learning



Deployment verifier API

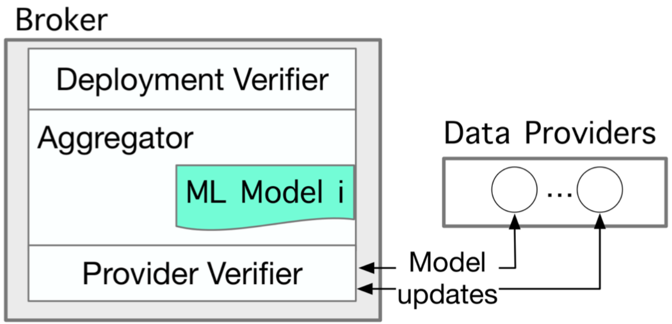
- Serves as model owner interface
  - `curate()`: Launch curator deployment
    - Set provider verifier parameters
  - `fetch()`: Access to model once trained
- Protects the ML model from abuse from curator during training
- E.g. Blockchain smart contracts [1]



[1] Szabo, Nick. "*Formalizing and Securing Relationships on Public Networks*" 1997.

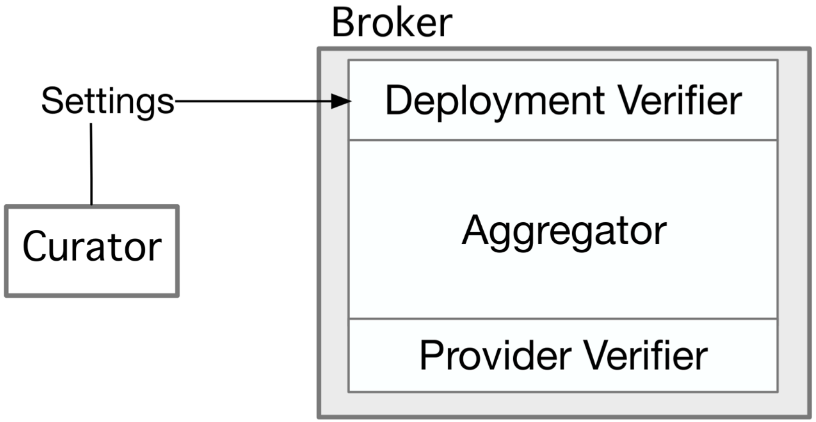
Provider verifier API

- Serves as data provider interface
  - Defined by curator
  - `join()`: Verify identity and allow provider join
  - `update()`: Verify and allow model update
- Protect model from malicious data providers
- E.g. Access tokens and statistical tests



Brokered learning workflow

- Curator: Create deployment
  - Define model and provide deployment parameters
  - Define verification services



Brokered learning workflow

- Curator: Create deployment
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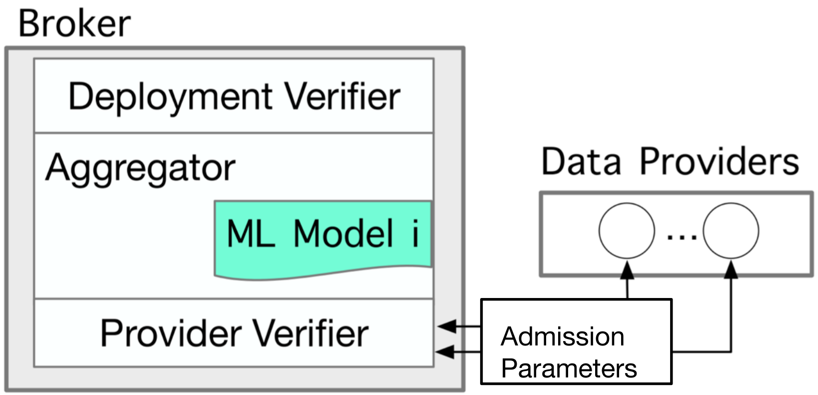
- Data providers: Join model
  - Define personal privacy preferences (ε)
  - Pass verification on join



Brokered learning workflow

- Curator: Create deployment
  - Define model and provide deployment parameters
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- Data providers: Join model and train
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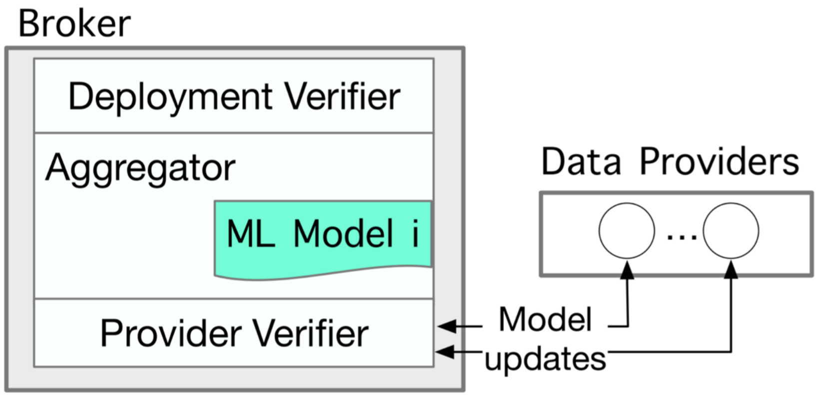
  - Iterative model updates
  - Pass verification on model update



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- Data providers: Join model and train
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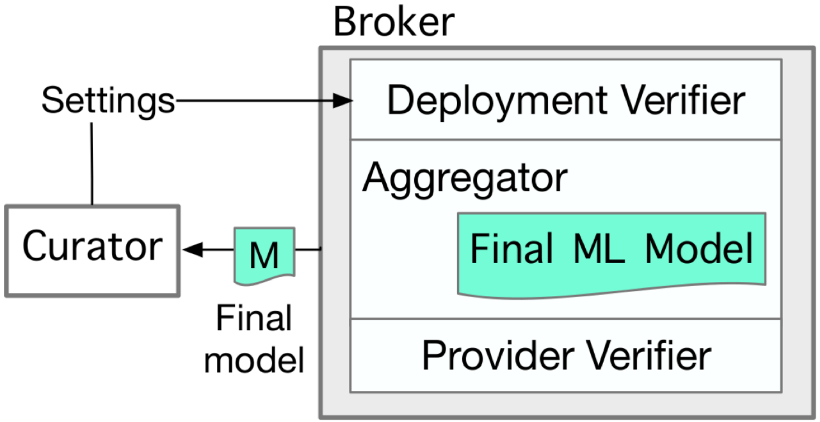
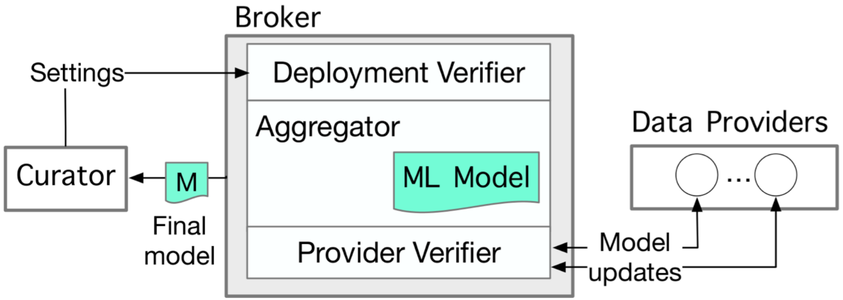
  - Iterative model updates
  - Pass verification on model update
- Complete training
  - Return model to curator



Threat model



- Assume:
  - Broker honours verifier parameters
  - Users adhere to the given APIs for joining and model updates
  - Curators and data providers can collaborate
- Trust is **based on incentives**: broker is neutral to ML incentive trade-off
  - If broker attacks clients or violates curator specifications, reputation lost
  - Governments, large organizations, blockchains

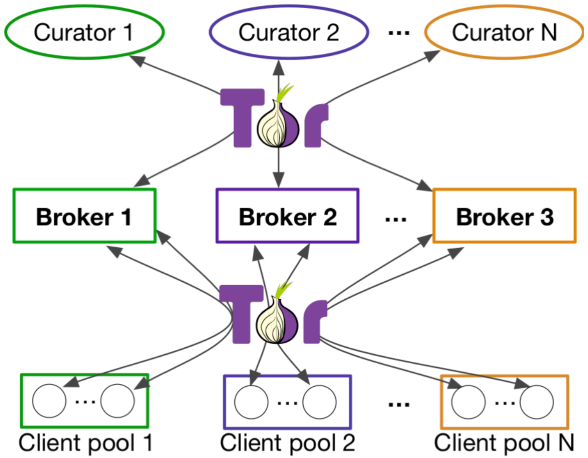
TorMentor : An Example Brokered Learning System

TorMentor system goals

- Use brokered learning to **build the first anonymous ML system**:
    - Further support privacy in multi-party ML
    - Data provider and curator identity are hidden:
        - From each other and from the broker
- Meet defined learning objectives in reasonable time
    - Compared to WAN federated learning baseline

Implementation on Tor

- Onion routing protocols (Tor) [1]
  - Hide source and destination of messages by communicating through chain of random nodes in system
  - Hide identity of users in distributed ML!
  - Deploy broker as hidden Tor service



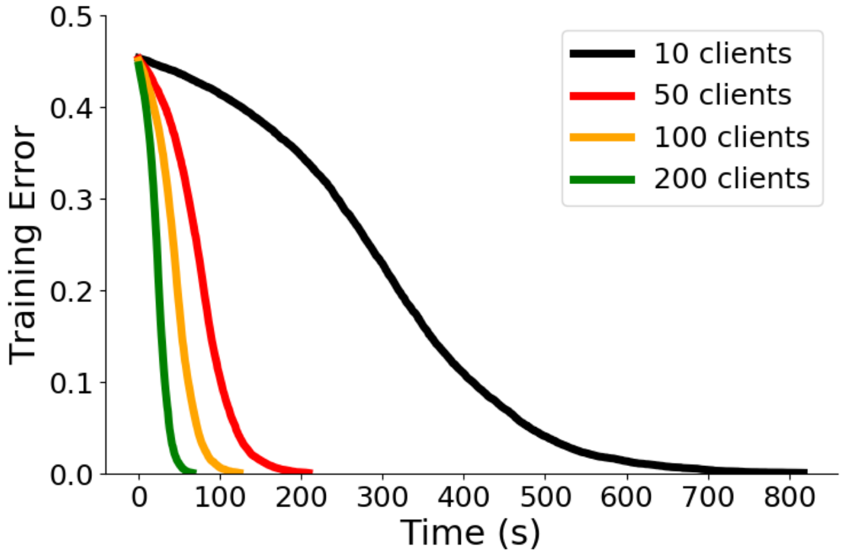
[1] Dingledine et al. "*Tor: The Second-Generation Onion Router*" Usenix Security 2014.

Implementation

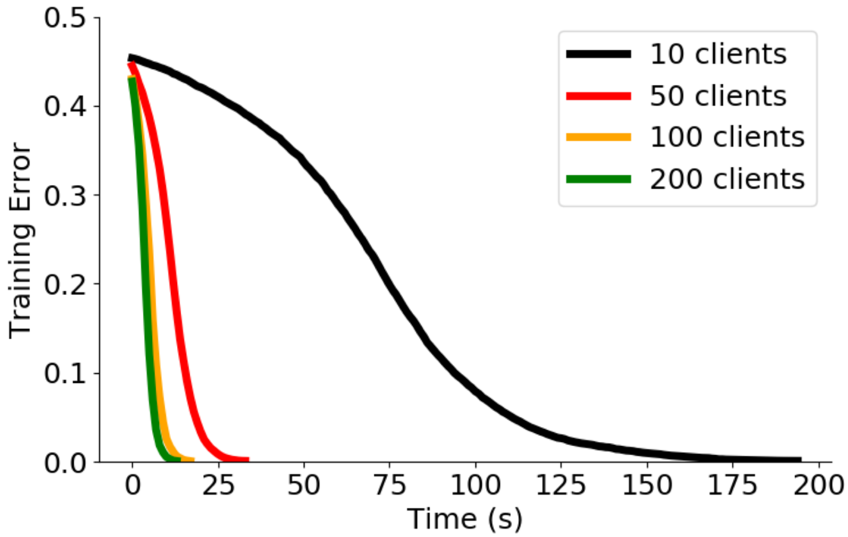
- Libraries written in Python and Go
  - 1500 LOC Python, 600 LOC Go
- Tested on “credit card default” UCI dataset
  - Logistic classifier
  - 30000 examples, 24 features (14 MB / client)
- Deployment at scale on Azure (8 data centres)
  - Deploy curators and data providers as users over wide area network

Convergence at scale over Tor

With Tor



Without Tor



Convergence at scale over Tor

With Tor

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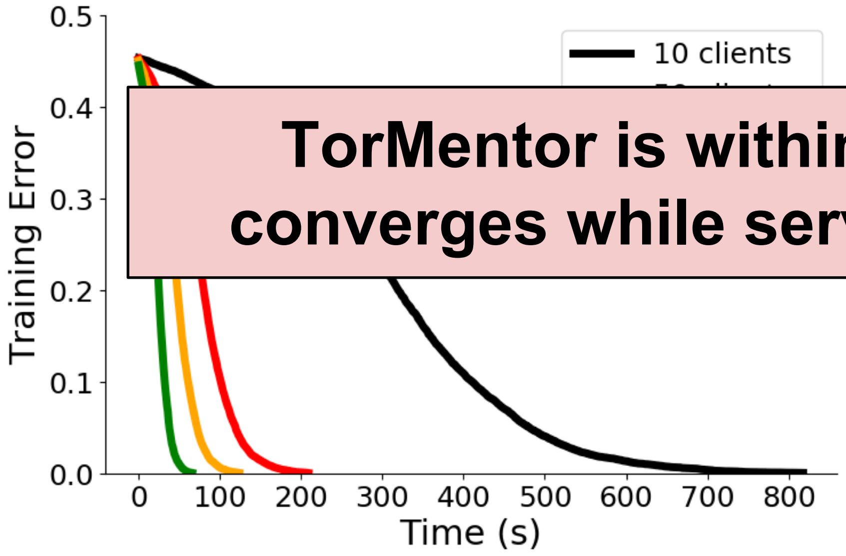
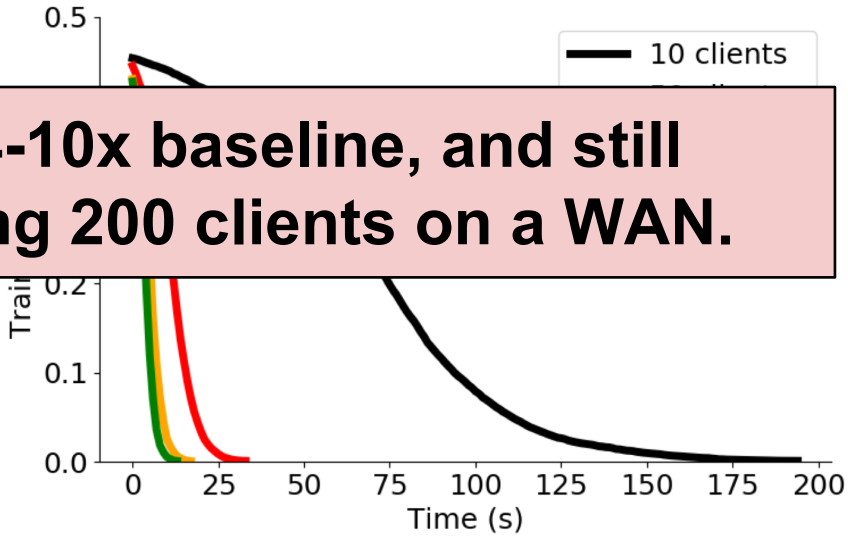




TorMentor is within 4-10x baseline, and still converges while serving 200 clients on a WAN.

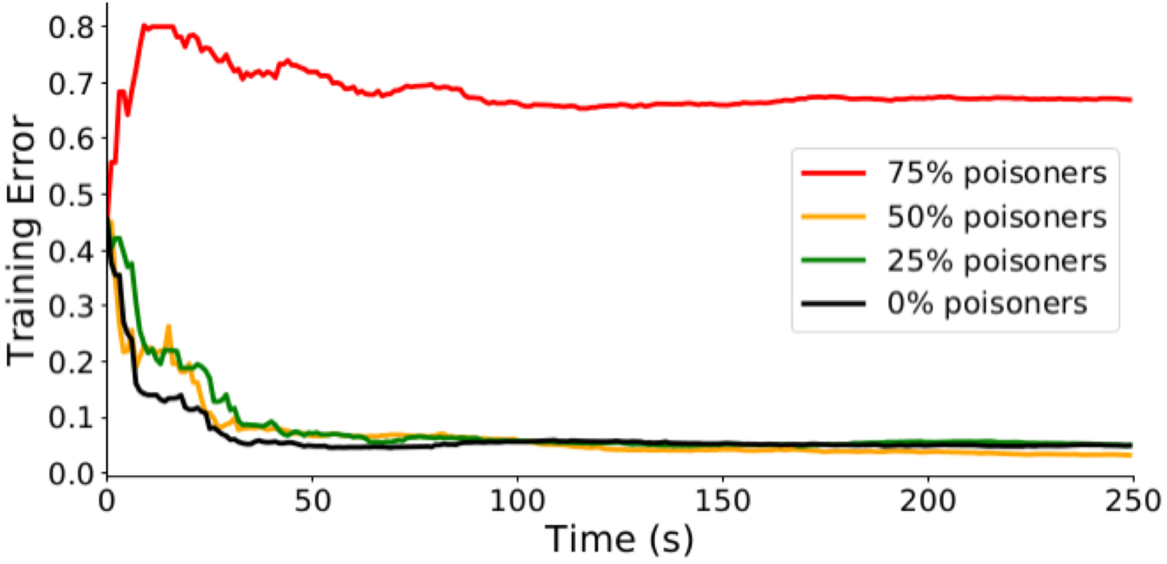
Provider verifier

- Reject on Negative Influence (RONI) [1]
  - Reject datasets with negative impact on “influence” metric
    - Typically, just use validation error

- Model curator defines a distributed RONI:
  - Evaluate influence of model updates instead of data
  - Use curator provided validation set
  - Tune using data provider proof-of-work [2]

[1] Barreno et al. “*The Security of Machine Learning.*” Machine Learning 81:2, 2010.
[2] Nakamoto, Satoshi. “*Bitcoin: A peer-to-peer electronic cash system*” 2008.

Evaluation: Provider verifier



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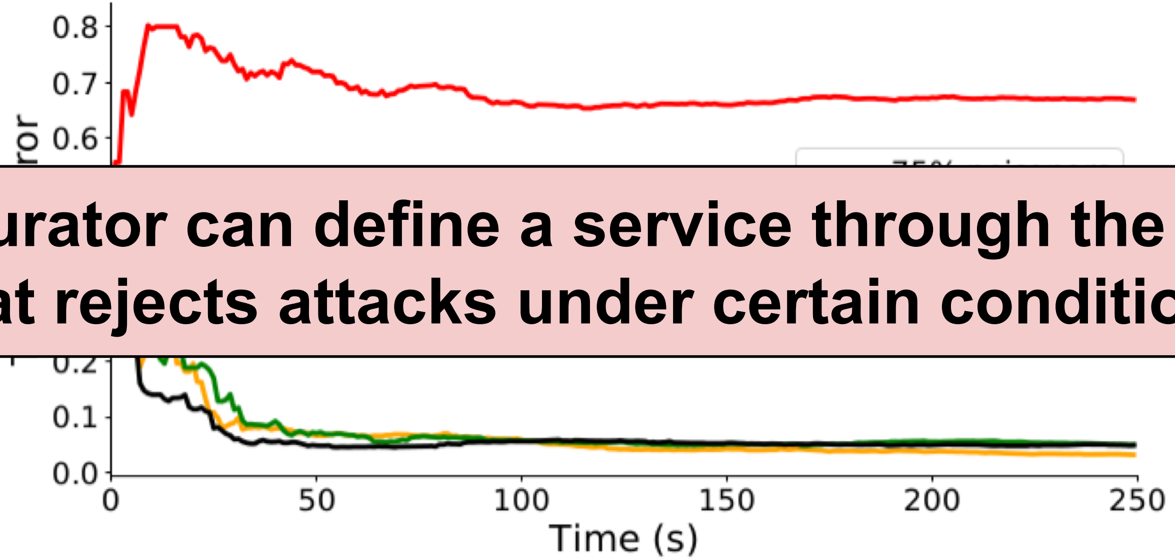


The curator can define a service through the broker that rejects attacks under certain conditions.

Brokered learning opportunities and limitations

- Modern use cases:
    - Blockchain-based data marketplaces
    - Standardizing “ML as a service”
    - GDPR Compliance
- Limitations
    - Moving from 2 actors to 3
    - Adoption from big players

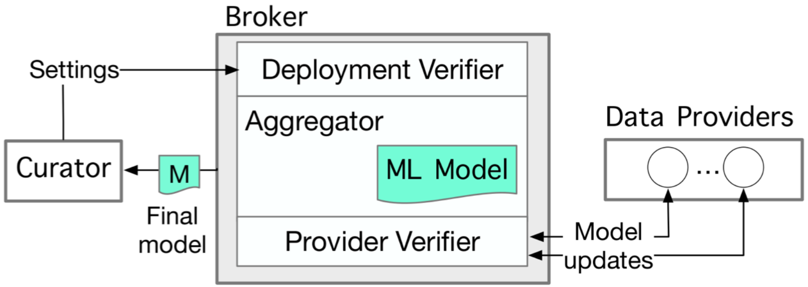
Datapace

H2O.ai

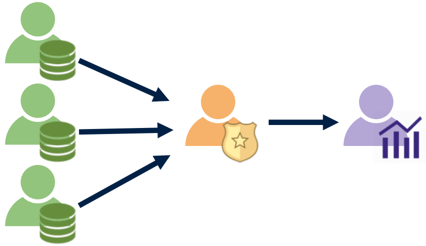
Amazon SageMaker

DataAgora

Summary of contributions



- Existing ML systems do not provide:
  - Incentives, privacy, security
- We propose **brokered learning** as an alternative to federated learning
  - APIs to protect process from **model owners and data providers**
- TorMentor prototype
  - Supports anonymous ML between data providers and curators
  - Allows curator defined process to reject malicious data providers



https://github.com/DistributedML/TorML