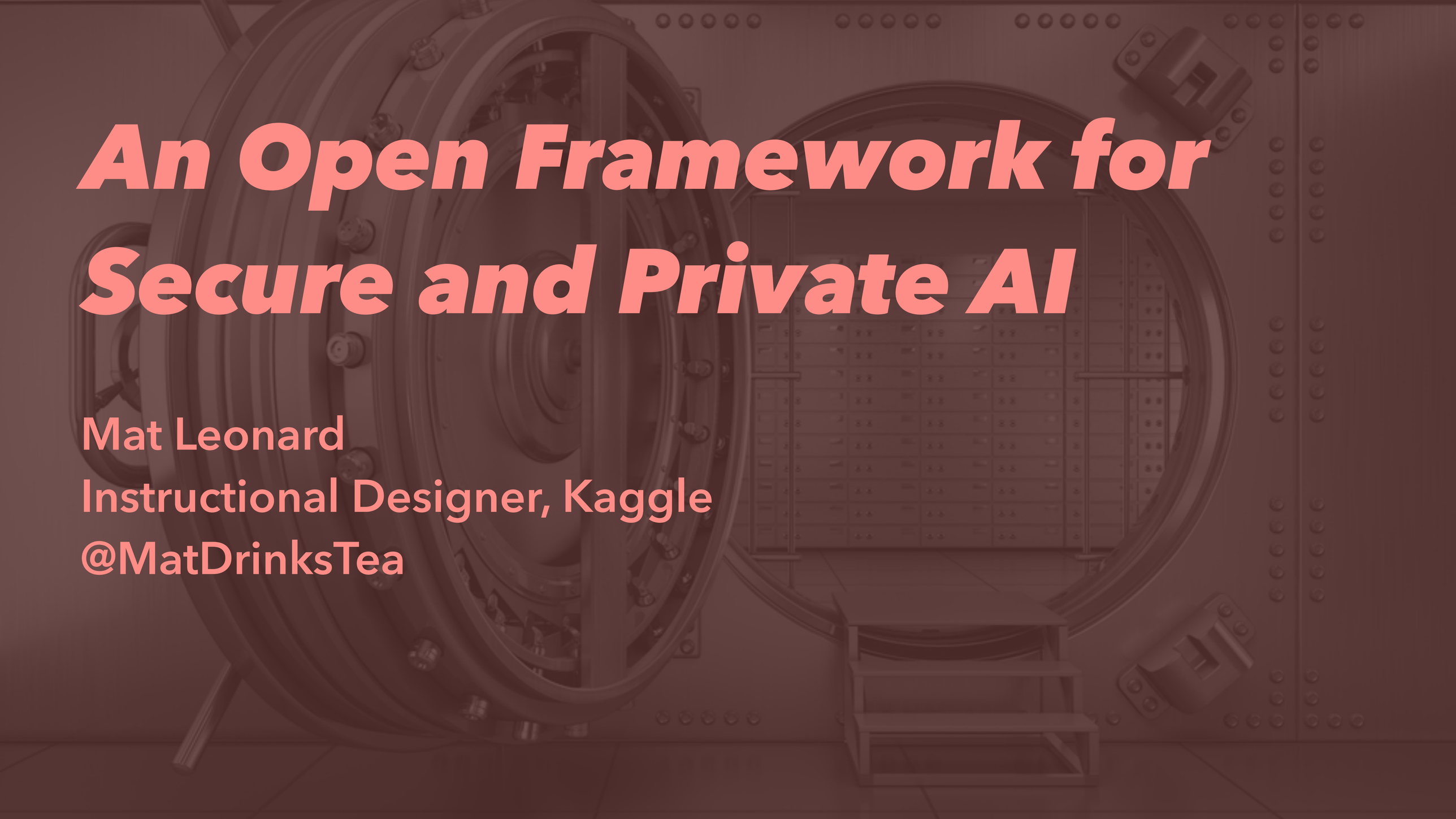
# OPEN DATA SCIENCE CONFERENCE

#ODSC

@ODSC

Boston | April 30 - May 4, 2019



# An Open Framework for Secure and Private AI

Mat Leonard
Instructional Designer, Kaggle
@MatDrinksTea

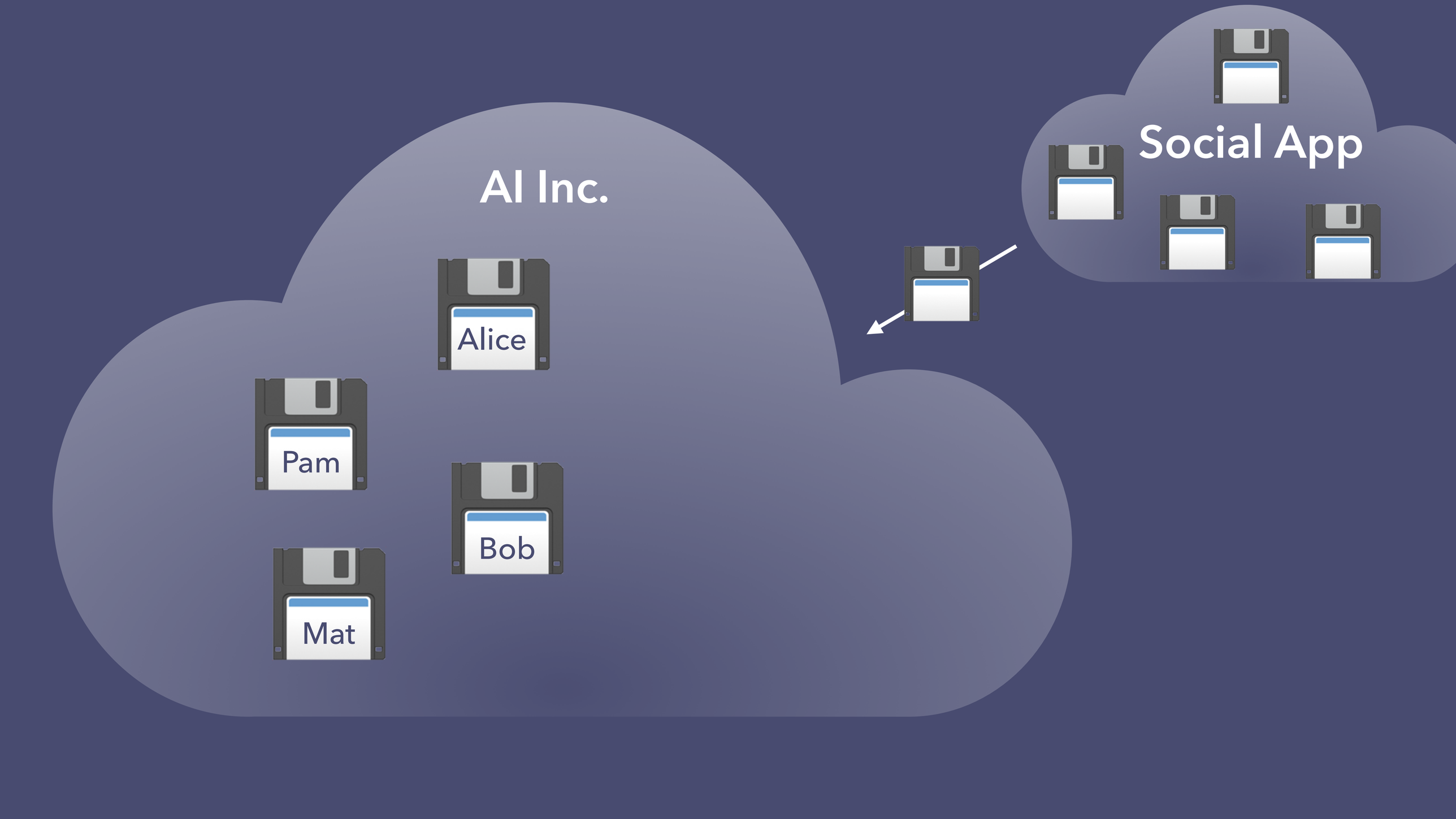
# Maintaining Privacy is an Ethical Obligation

# Maintaining Privacy is Good for Business

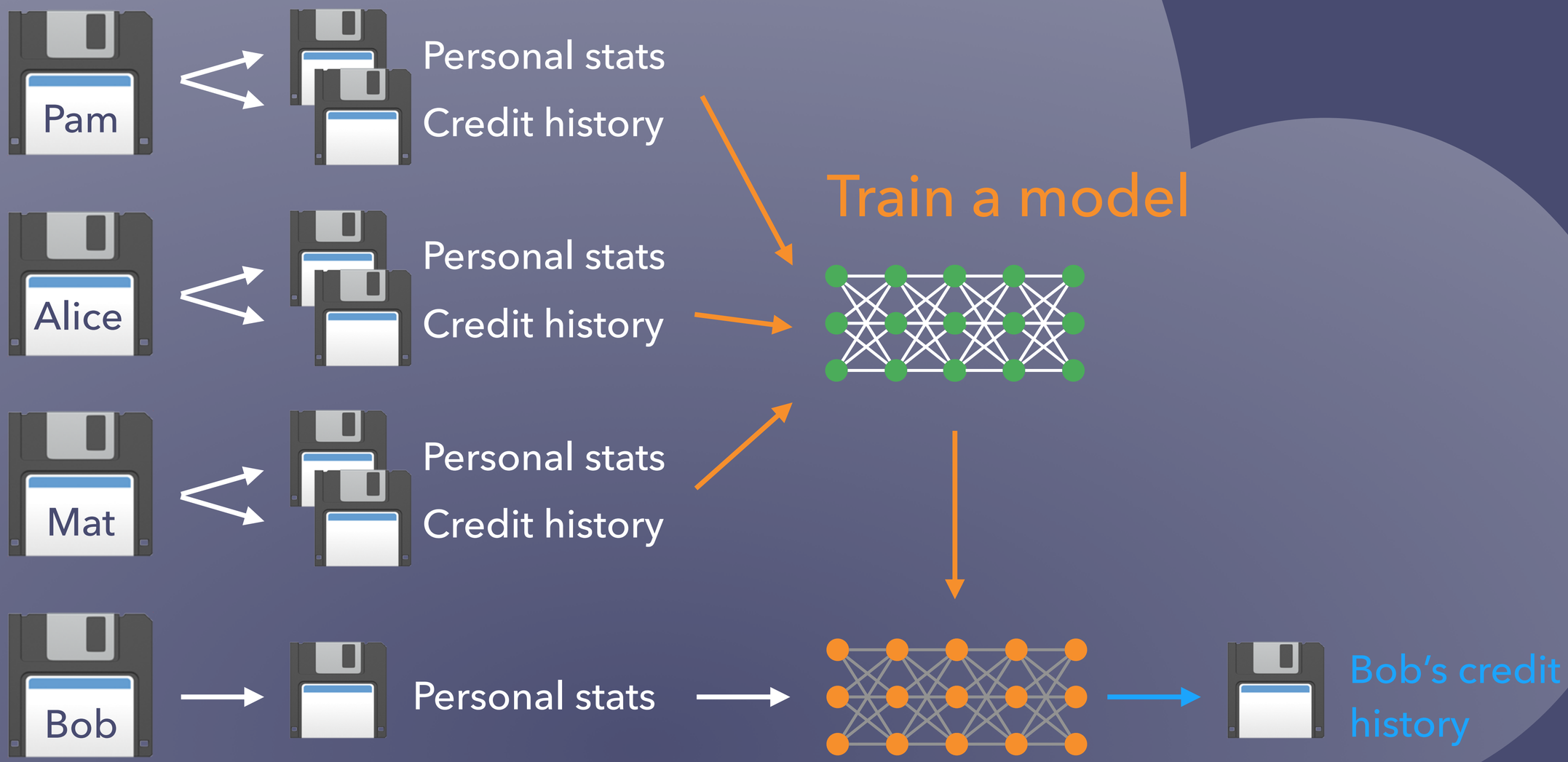
# *What Does Privacy Do For Us?*

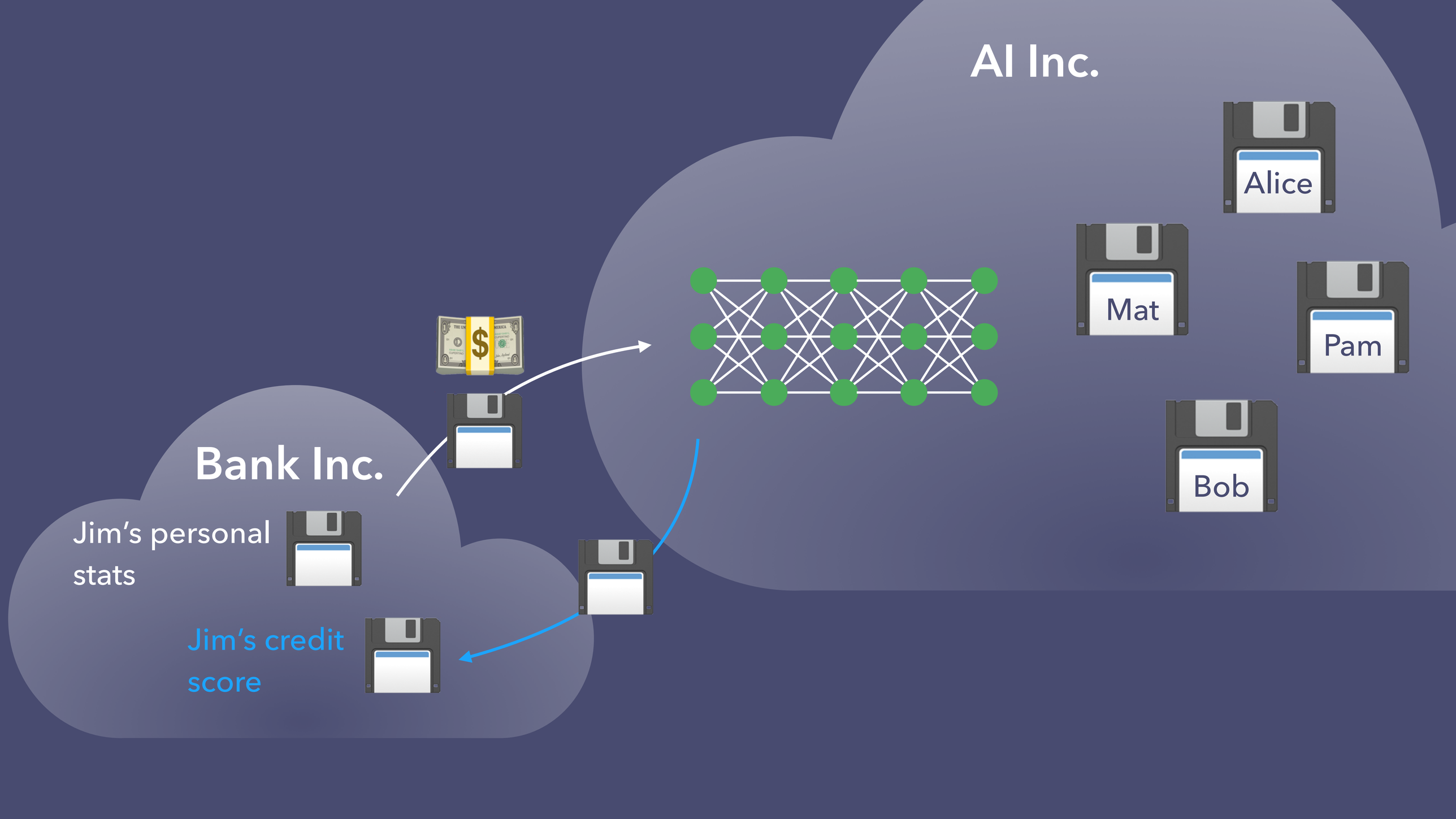
1. Builds user trust
2. More data with better quality
3. Innovative products
4. Compliance with GDPR and other regulations

# AI Inc.


AI Inc.
Alice
Pam
Bob
Mat
Social App

# AI Inc.


Pam
Alice
Mat
Bob
Personal stats
Credit history
Personal stats
Credit history
Personal stats
Credit history
Personal stats
Train a model
Bob's credit history


AI Inc.
Alice
Mat
Pam
Bob
Bank Inc.
Jim's personal stats
Jim's credit score

# *The AI Business Model*

1. Acquire data about people
2. Train a model that makes predictions
3. Sell the *use* of that model

# *Where this goes wrong*

1. Acquire data about people
   - **Privacy:** people lose control of their data
   - **Innovation:** “Sensitive Products” don’t get made
2. Train a model that makes predictions
   - **Privacy Loss:** models can leak private information from the training dataset
3. Sell the *use* of that model
   - **Lost Natural Income:** in practice, people are rarely compensated for their data

# How do we build machine learning products while preserving privacy?

1. Differential Privacy
2. Federated Learning
3. Multi-Party Computation

# Differential Privacy

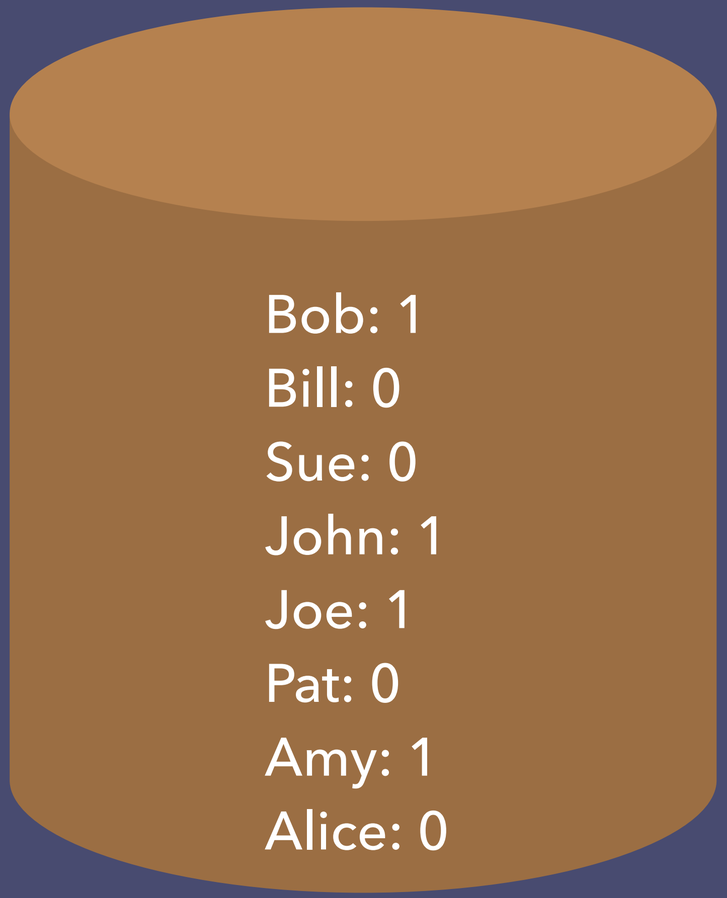
# Differential Privacy

- started with statistical database queries circa ‘03
- only more recently applied to Machine Learning
- Goal: ensure statistical analysis doesn’t compromise privacy

# *Privacy is preserved if...*

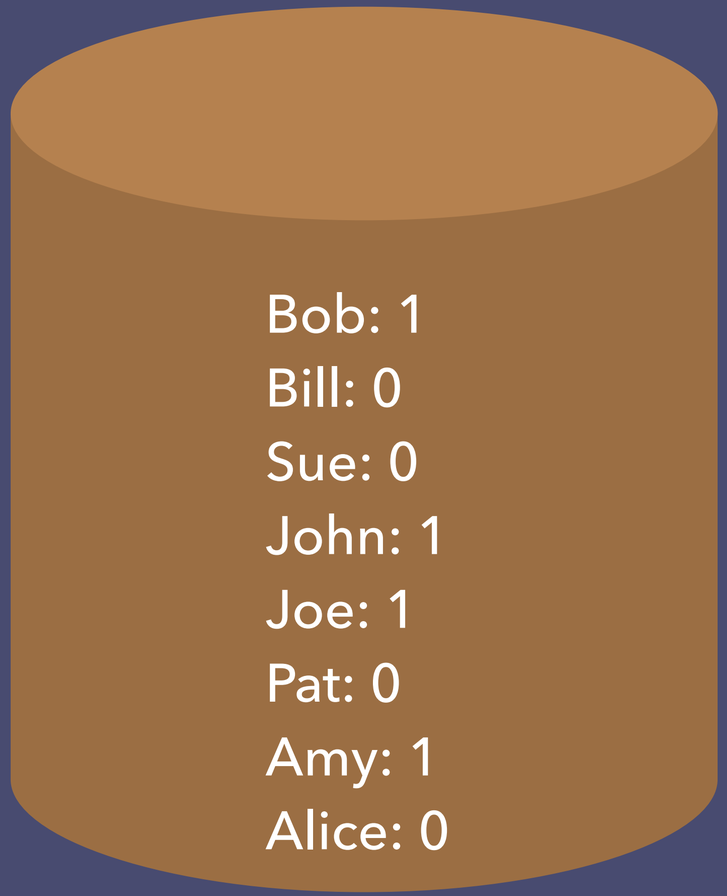
"You will **not be affected**, adversely or otherwise, by allowing your data to be used in any study or analysis, **no matter what other studies, data sets, or information sources, are available.**"

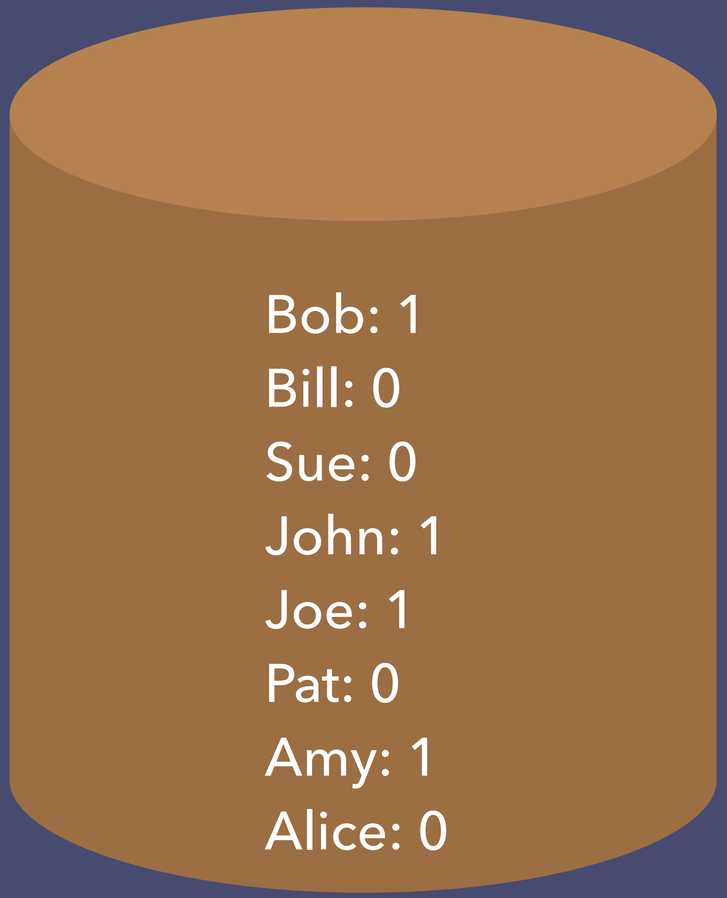
- Cynthia Dwork
  "The Algorithmic Foundations of Differential Privacy"



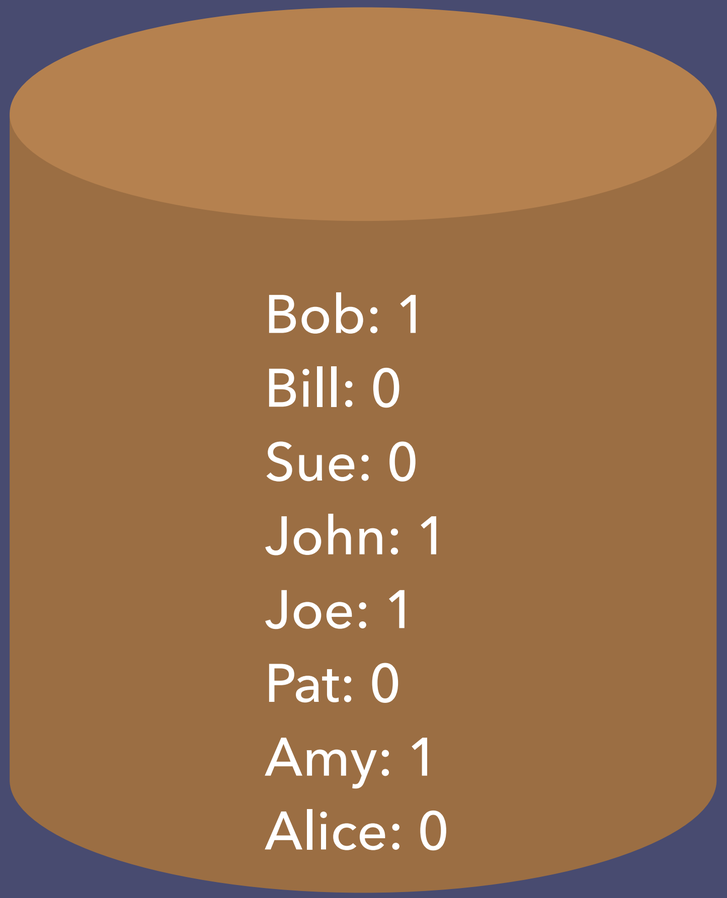

- **Query:** function(database)
- **Perfect Privacy:** the output of our query is the same between this database and any identical database with 1 person missing.
- **Exception:** you could still be affected by the results of the study even if you weren't included in the database (findings: smoking causes cancer)

# *Will your query be statistically different?*

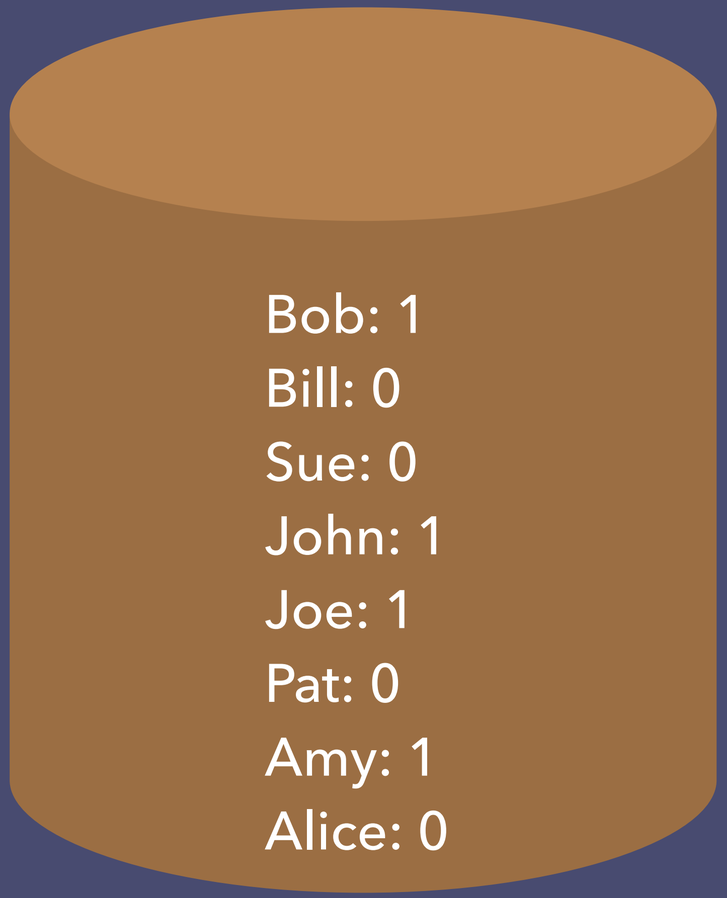


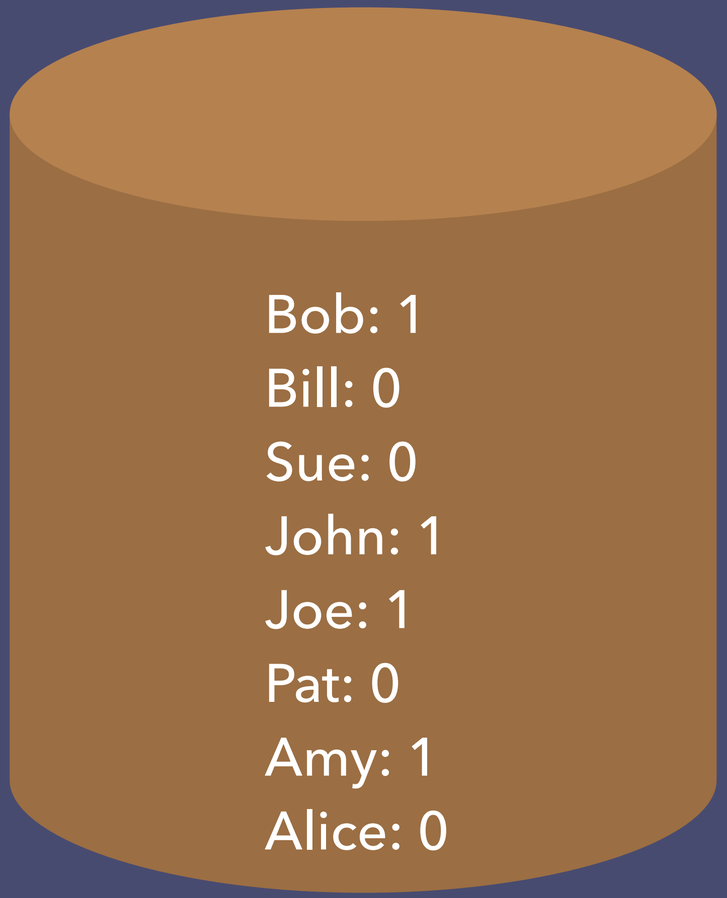

- **Query:** sum(database)
- **Perfect Privacy:** the output of our query is the same between this database and any identical database with 1 person missing.
- **Analysis:** query results are different if you remove a person from the study.




- **Query:** sum(database) + noise
- **Perfect Privacy:** the output of our query is the same between this database and any identical database with 1 person missing.
- **Analysis:** this one may work ok if the noise is great enough. How much is enough?




- **Query:** sum(database) > threshold
- **Perfect Privacy:** the output of our query is the same between this database and any identical database with 1 person missing.
- **Analysis:** this one may be perfect if the threshold is less than the max response by at least 1. Its success is dataset dependent.

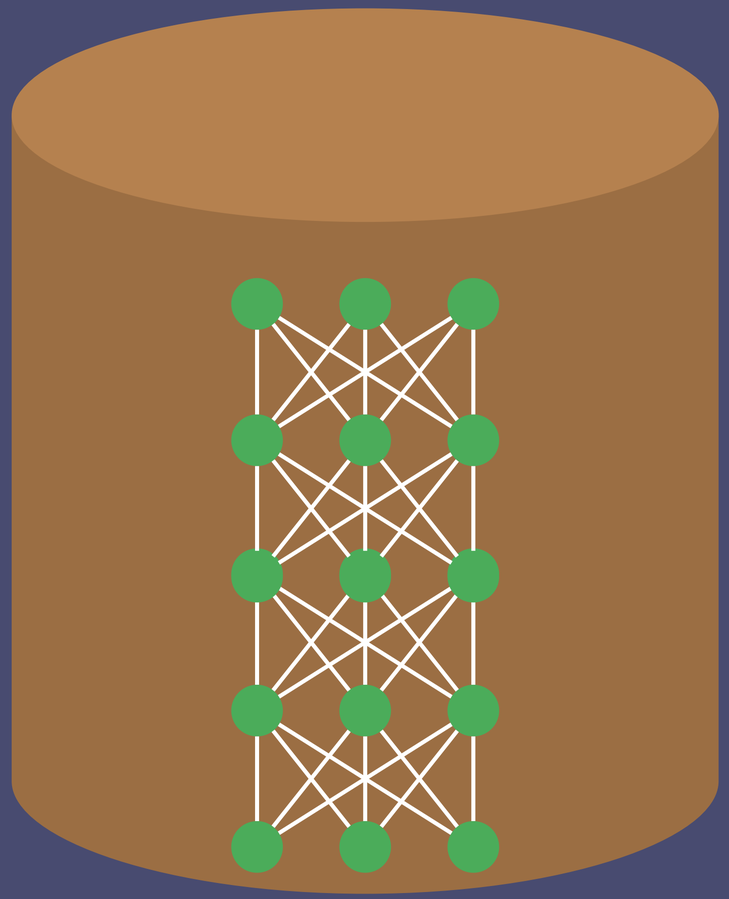



- **Query:** (sum(database) > threshold) + noise
- **Perfect Privacy:** the output of our query is the same between this database and any identical database with 1 person missing.
- **Analysis:** this one is likely to do well given that even if the threshold is equal to the max query, noise gives a “plausible explanation”

We will think of databases $x$ as being collections of records from a universe $\mathcal{X}$. It will often be convenient to represent databases by their histograms: $x \in \mathbb{N}^{|\mathcal{X}|}$, in which each entry $x_i$ represents the number of elements in the database $x$ of *type* $i \in \mathcal{X}$ (we abuse notation slightly, let-

**Definition 2.4** (Differential Privacy). A randomized algorithm $\mathcal{M}$ with domain $\mathbb{N}^{|\mathcal{X}|}$ is $(\varepsilon, \delta)$-differentially private if for all $\mathcal{S} \subseteq \text{Range}(\mathcal{M})$ and for all $x, y \in \mathbb{N}^{|\mathcal{X}|}$ such that $\|x - y\|_1 \leq 1$:

$$\Pr[\mathcal{M}(x) \in \mathcal{S}] \leq \exp(\varepsilon) \Pr[\mathcal{M}(y) \in \mathcal{S}] + \delta,$$



- **Query:** model(database)
- **Perfect Privacy:** our model is identical regardless of whether a person is removed from the training dataset.
- **Best Case:** the model could still adversely affect people who weren't included in the dataset (recommendation systems)

# Options for DP in Machine Learning

- Train on the output of a differentially private query
  - Pro: removes private information
  - Con: removes lots of other information too

- Generate dataset from model - then perform DP-query on that dataset and retrain model
  - Pro: removes private information

"Semi-supervised Knowledge Transfer for Deep Learning from Private Training Data" - Papernot et al. 2016

# *Private Aggregation of Teacher Ensembles (PATE)*

- **Step 1:** split data into buckets
- **Step 2:** train model on each bucket
- **Step 3:** predict models on public, unlabeled dataset
  - Sum the predictions over labels, take the max label, add noise
- **Step 4:** Train final model on public dataset with generated labels

"Semi-supervised Knowledge Transfer for Deep Learning from Private Training Data" - Papernot et al. 2016

# Federated Learning

# Non-federated Learning

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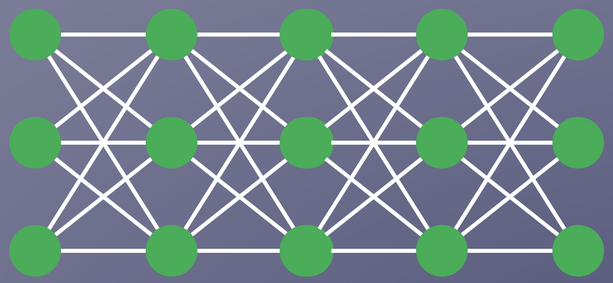
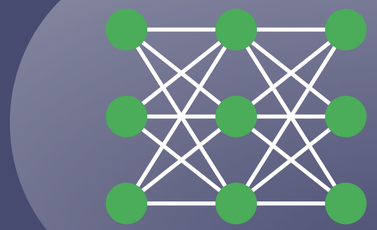


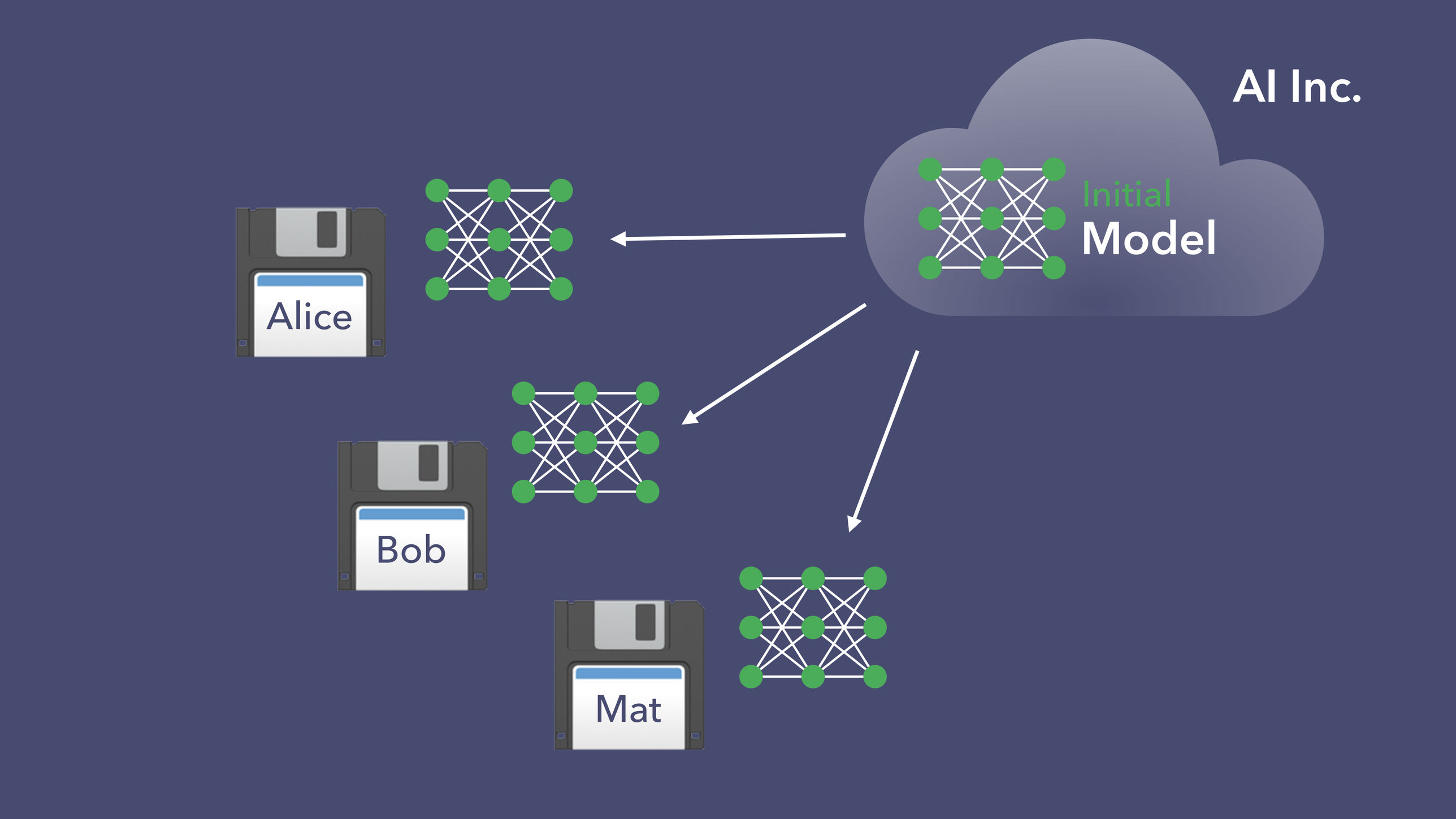



AI Inc.

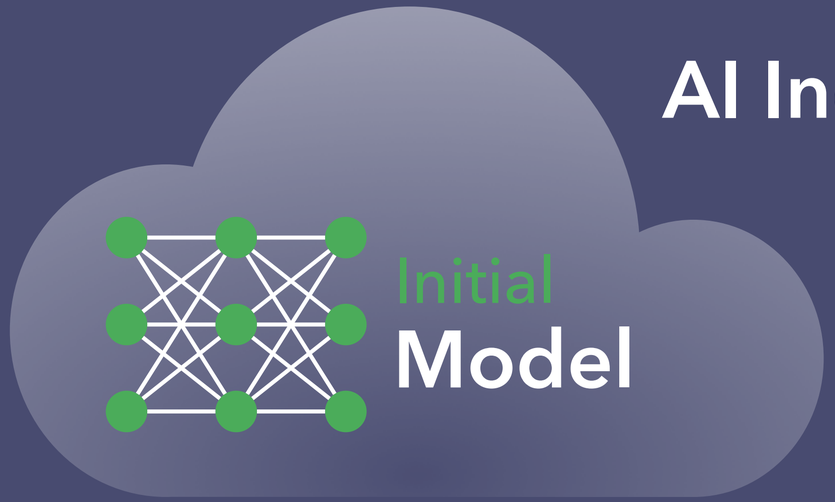


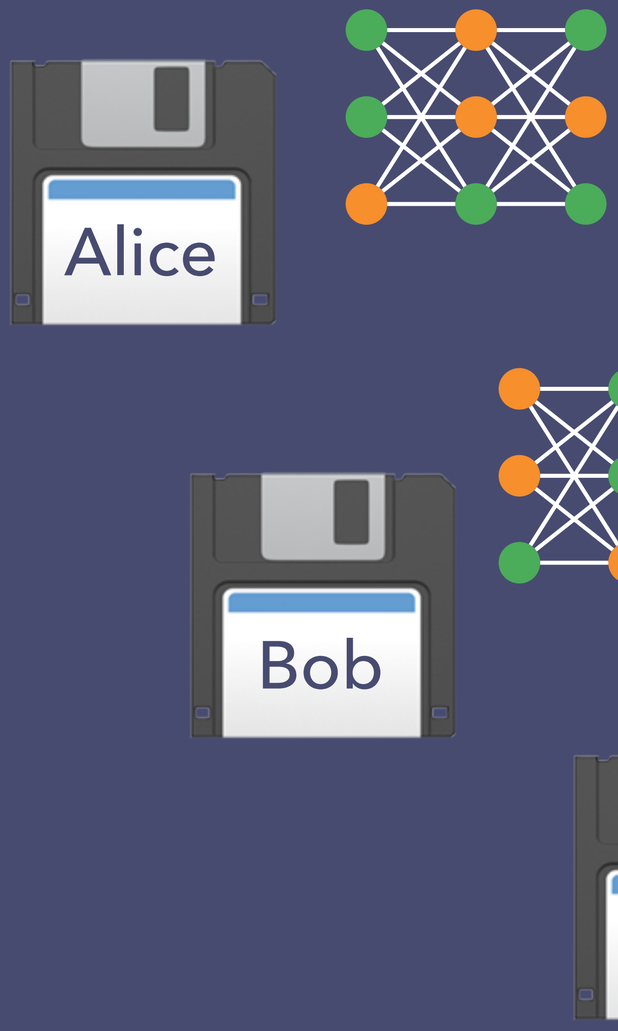
Initial
Model

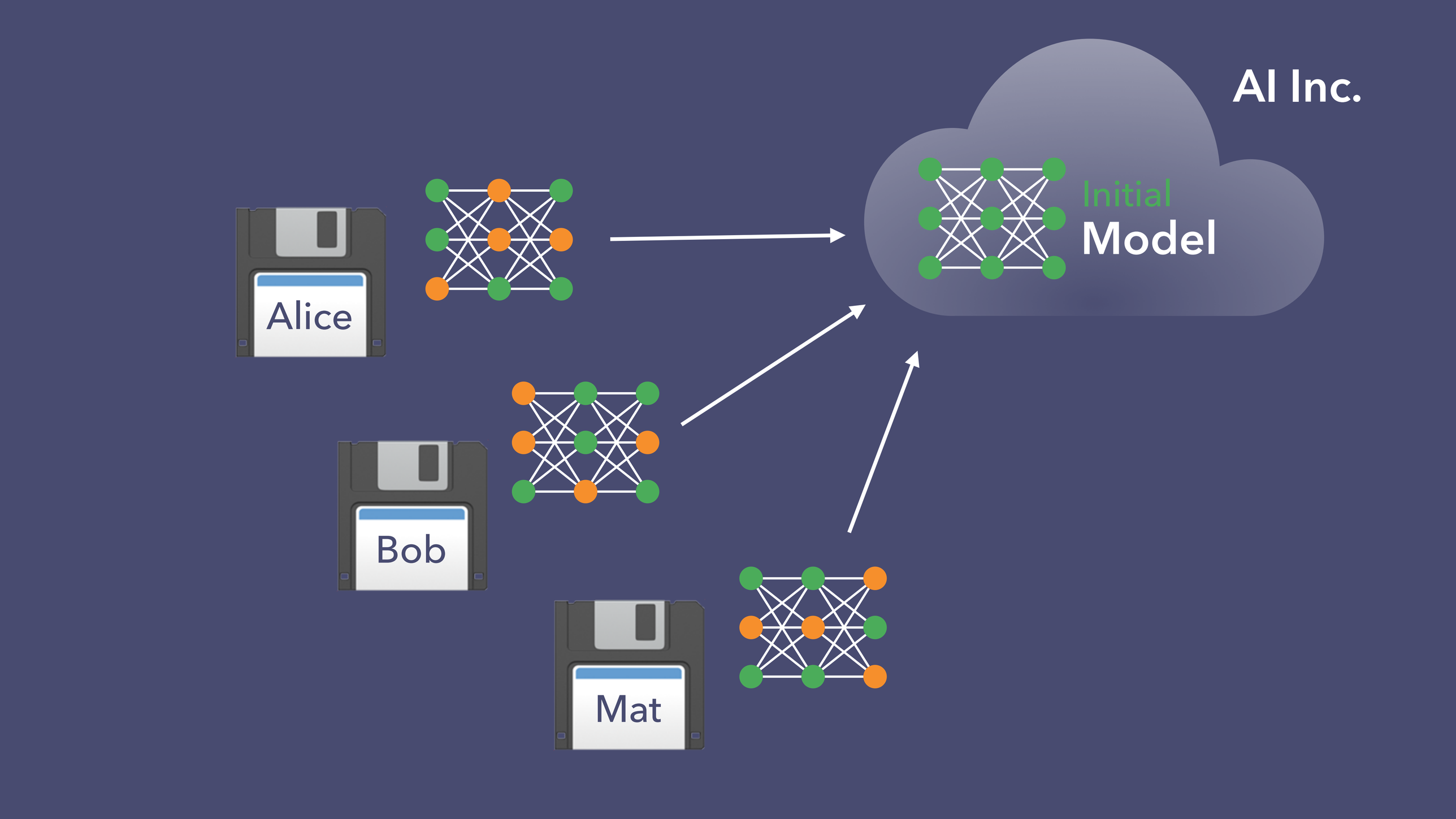



AI Inc.
Initial
Model
Alice
Bob
Mat

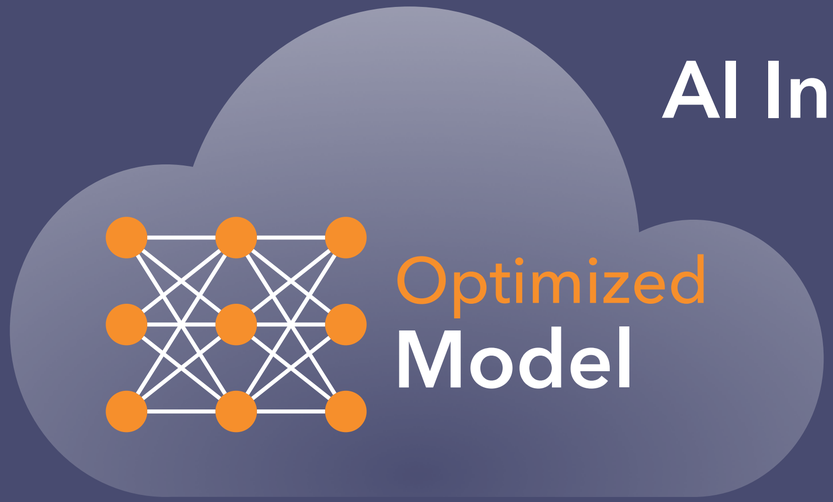
AI Inc.



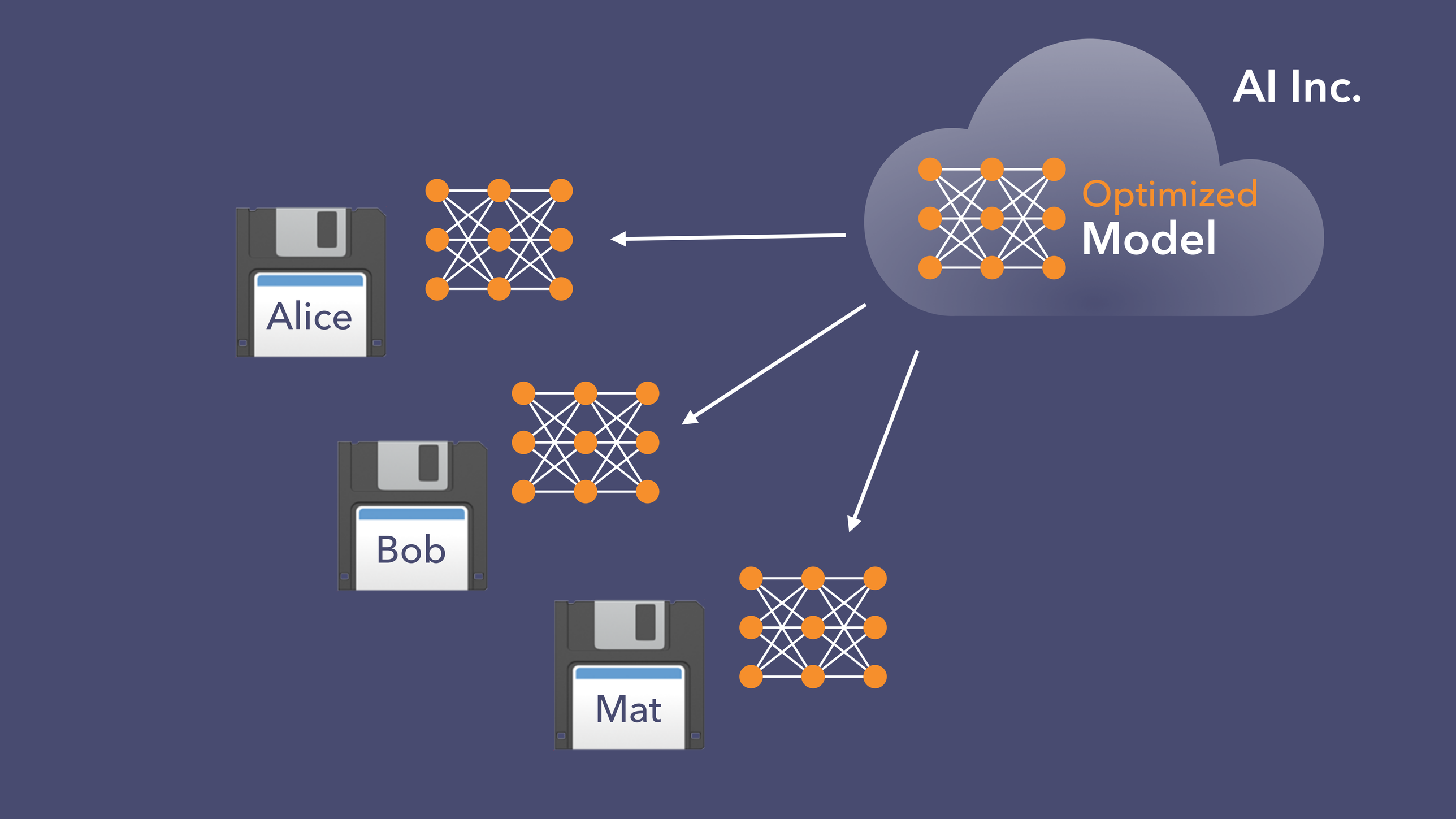




AI Inc.
Initial
Model
Alice
Bob
Mat

AI Inc.

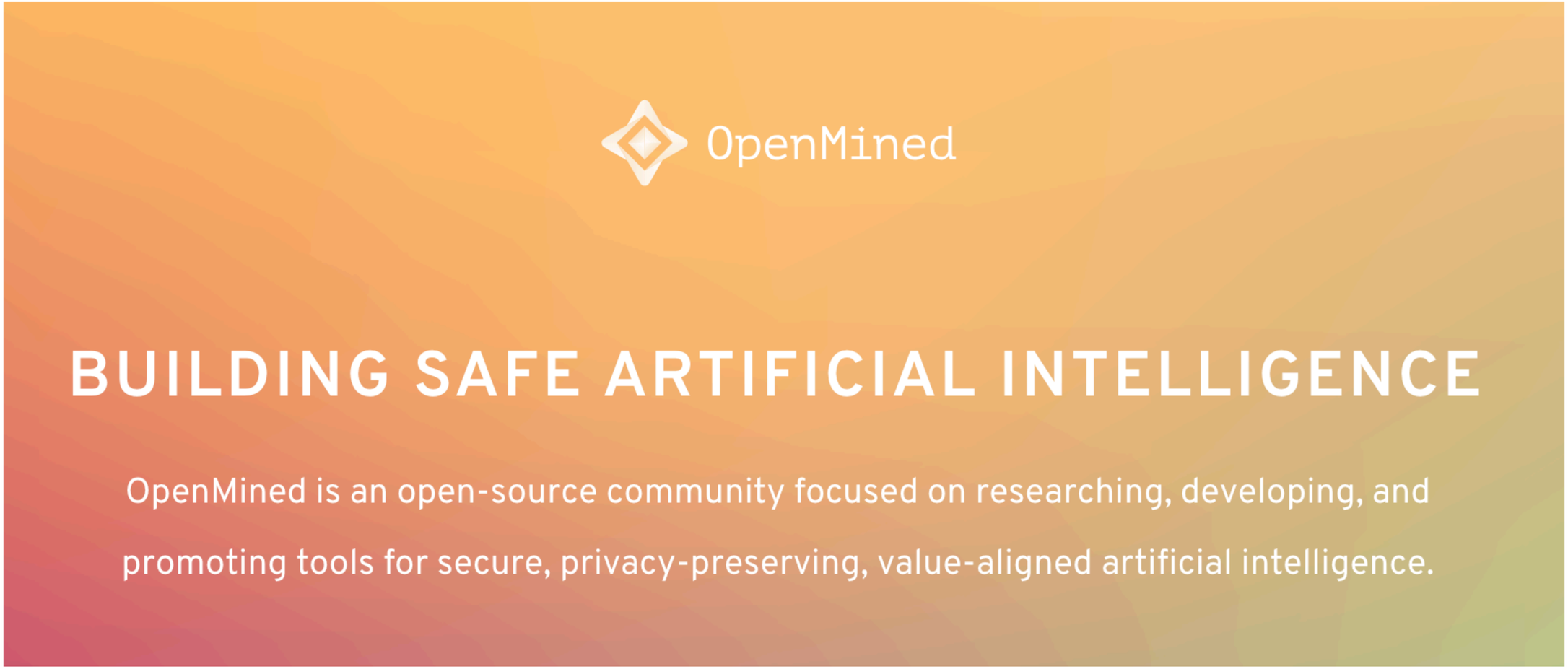






AI Inc.
Optimized
Model
Alice
Bob
Mat

# Demo!

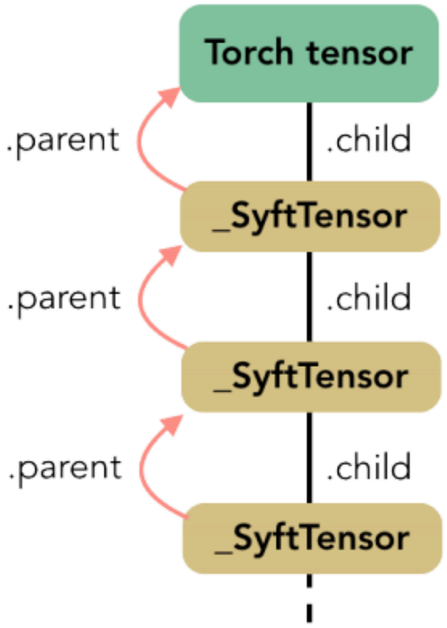
# OpenMined.org

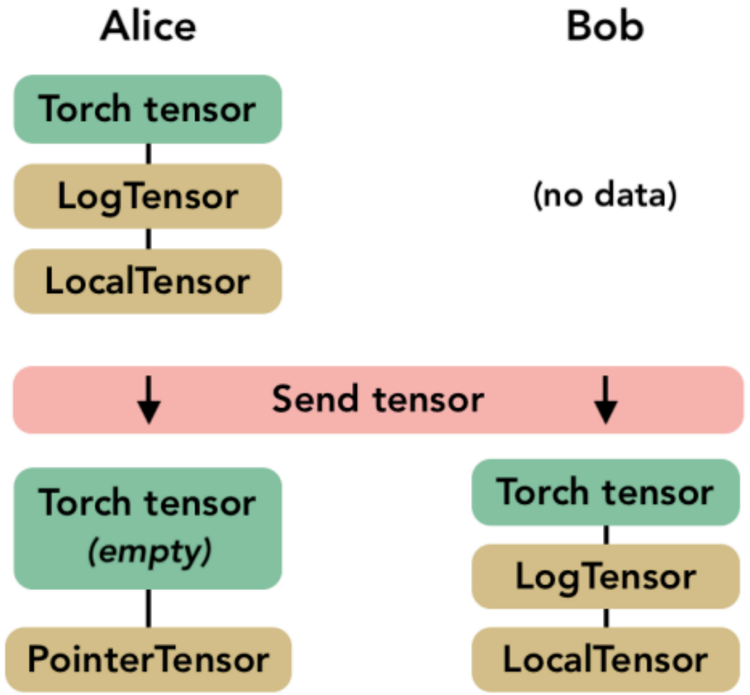



## Join the community at slack.openmined.org

# PySyft extends PyTorch

(and TensorFlow eventually)



# Demo!

# Great!

# Private data remains private

# But!

We're transmitting insecure models and gradients

# Secure Multi-party Computation

# Multi-Party Computation

# Multi-Party Computation

$a = 5$ → Share Splitter → $\text{shares}_a = [1, -3, 5, 0, 2]$

$b = 3$ → Share Splitter → $\text{shares}_b = [2, -5, 8, -3, 1]$

# Multi-Party Computation

$a = 5$ → Share Splitter → $\text{shares}_a = [1, -3, 5, 0, 2]$

$b = 3$ → Share Splitter → $\text{shares}_b = [2, -5, 8, -3, 1]$

| Alice | Bob | Chuck | Dora | Erika |
|---|---|---|---|---|
| $s_a = 1$ | $s_a = -3$ | $s_a = 5$ | $s_a = 0$ | $s_a = 2$ |
| $s_b = 2$ | $s_b = -5$ | $s_b = 8$ | $s_b = -3$ | $s_b = 1$ |
| $s_c = 3$ | $s_c = -8$ | $s_c = 13$ | $s_c = -3$ | $s_c = 3$ |

# Multi-Party Computation

| Alice | Bob | Chuck | Dora | Erika |
|---|---|---|---|---|
| $s_a = 1$ | $s_a = -3$ | $s_a = 5$ | $s_a = 0$ | $s_a = 2$ |
| $s_b = 2$ | $s_b = -5$ | $s_b = 8$ | $s_b = -3$ | $s_b = 1$ |
| $s_c = 3$ | $s_c = -8$ | $s_c = 13$ | $s_c = -3$ | $s_c = 3$ |

$$\text{shares}_c = [3, -8, 13, -3, 3] \longrightarrow \boxed{\text{Share Combiner}} \longrightarrow c = 8$$

# Demo!

# *Multi-Party Computation + Federated Learning*

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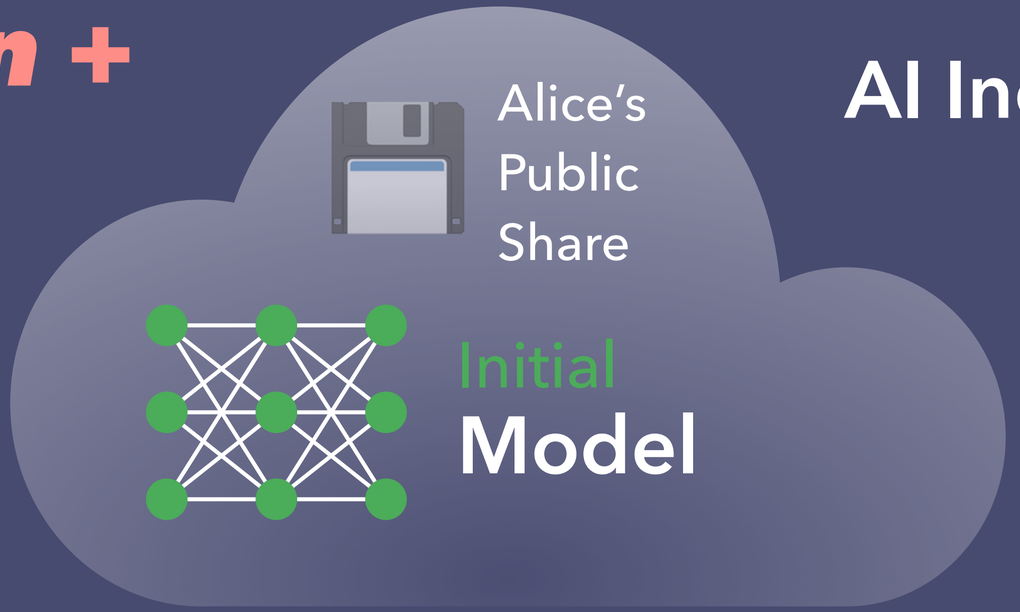
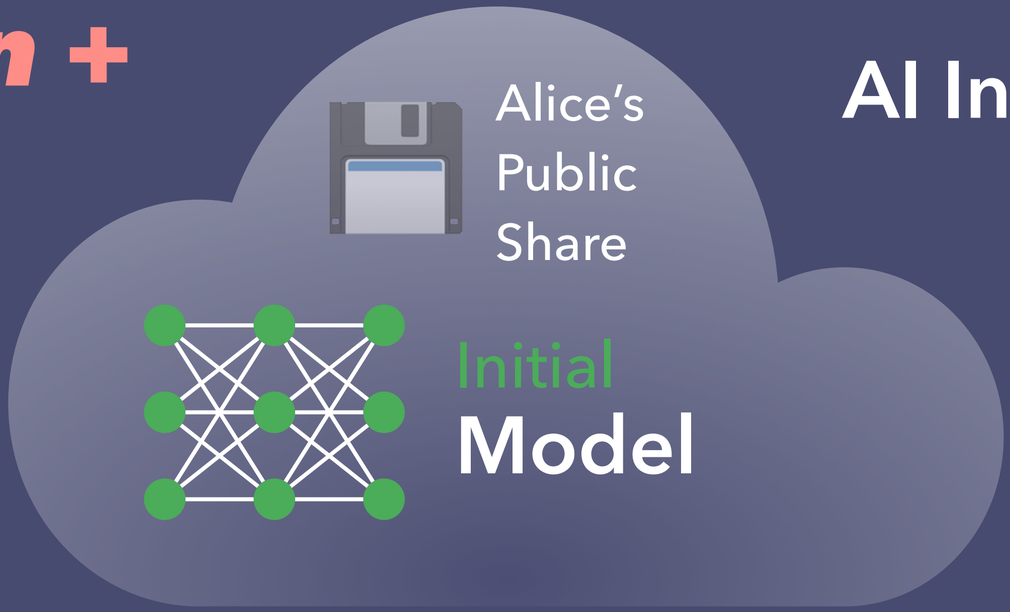
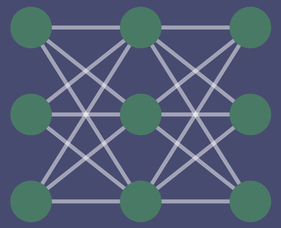





# *Multi-Party Computation + Federated Learning*

AI Inc.

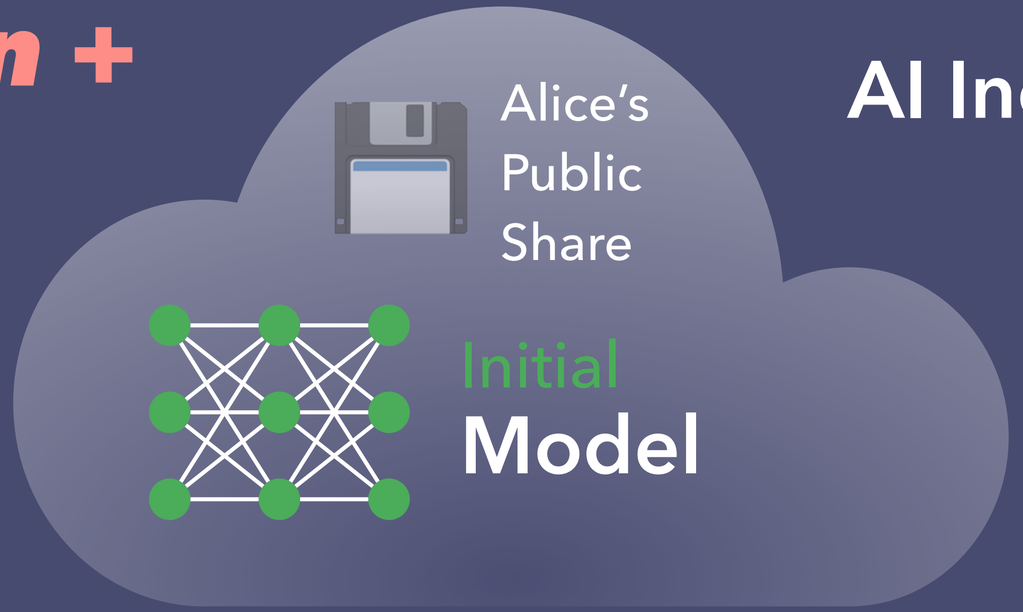


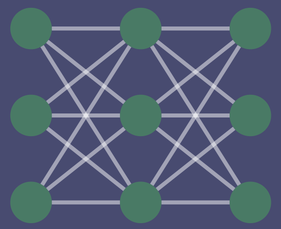



Model's
Public
Share



# *Multi-Party Computation + Federated Learning*

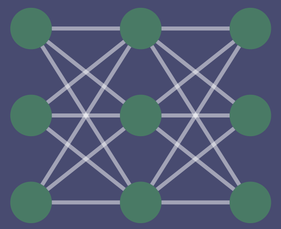


Model's
Public
Share


Training
Ensues


# *Multi-Party Computation + Federated Learning + Secure Aggregation*



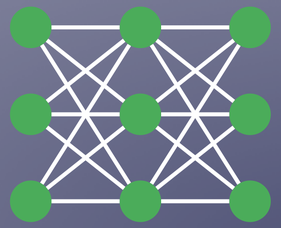
Model's Public Share


Training Ensues



AI Inc.

Alice's Public Share



Initial **Model**

# Udacity Free Course

FREE COURSE

## Secure and Private AI

by facebook Artificial Intelligence

Learn how to extend PyTorch with the tools necessary to train AI models that preserve user privacy.

NOTIFY ME

http://udacity.com/private-ai

### Course Leads

**Andrew Trask**

Leader of OpenMined, Research Scientist at DeepMind Oxford, PhD Student

# Thank you!

# Questions?