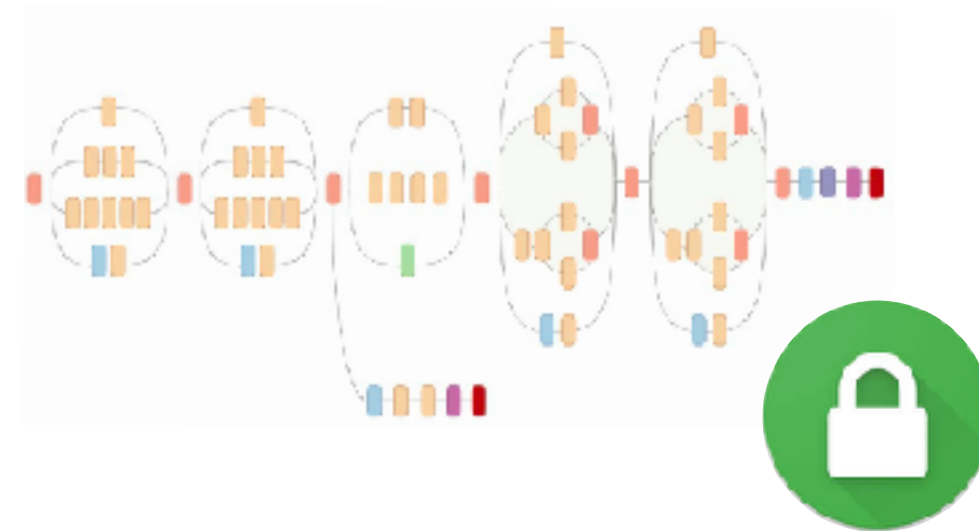


Cryptography behind Private Machine Learning



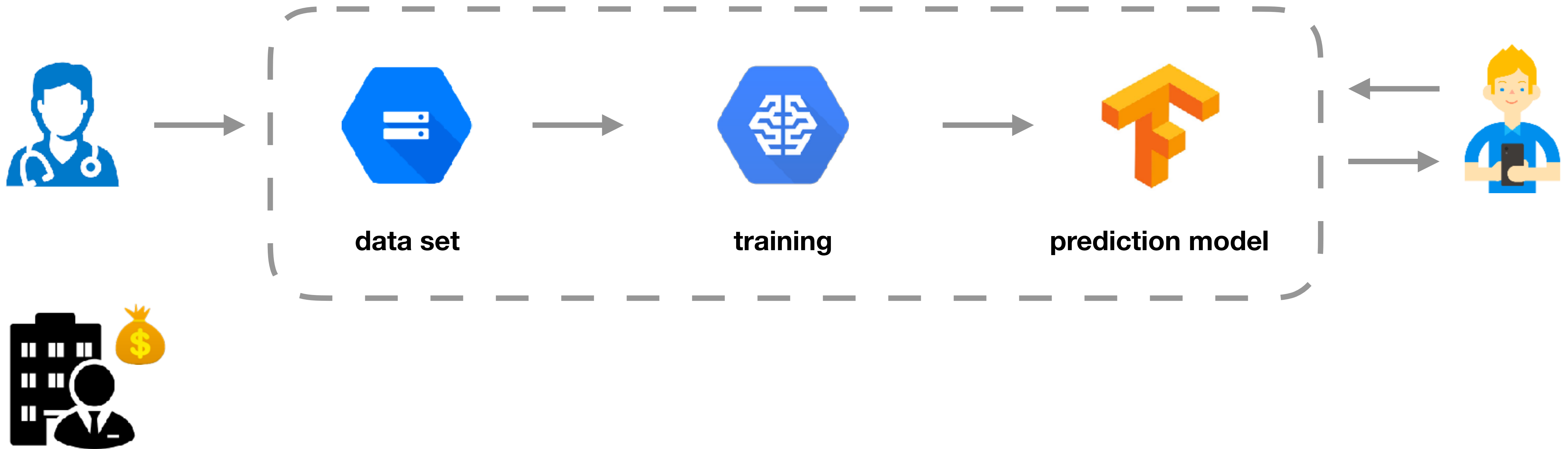
Morten Dahl

(Cyber)Security for Software Engineers meetup, June 2018

Why?

Machine Learning Process

IMAGENET



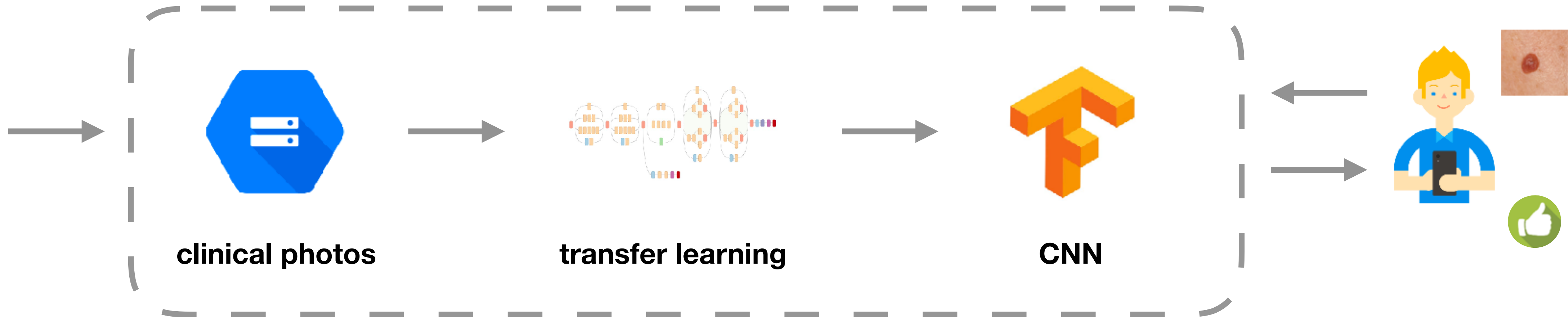


Skin Cancer Image Classification

Brett Kuprel

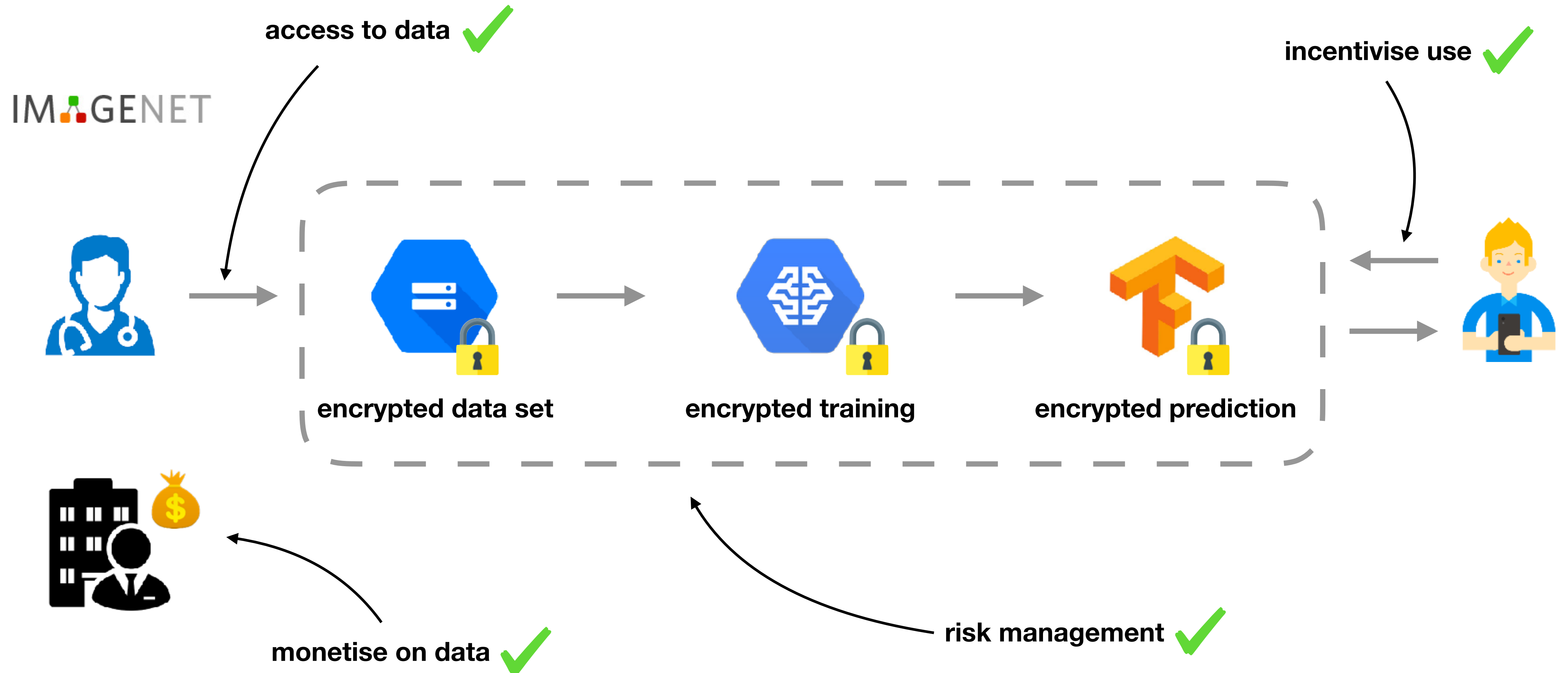
12:30-12:40pm

Join Brett Kuprel, and see how TensorFlow was used by the artificial intelligence lab and medical school of Stanford to classify skin cancer images. He'll describe the project steps: from acquiring a dataset, training a deep network, and evaluating of the results. To wrap up, Brett will give his take on the future of skin cancer image classification.



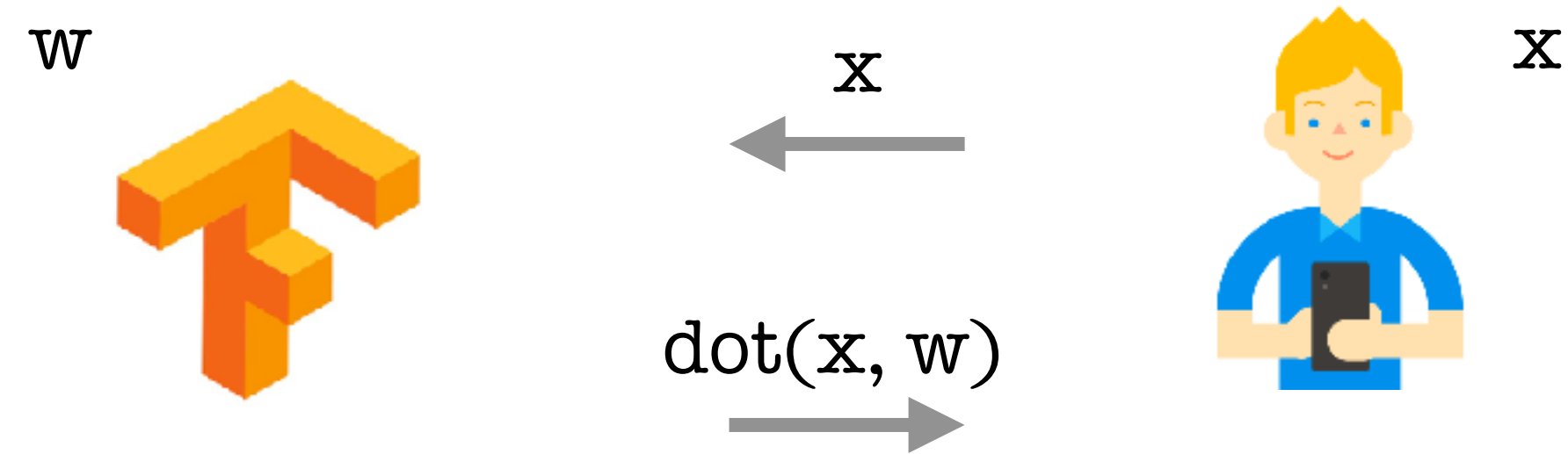
machine learning on sensitive information could make a big impact

Potential Bottlenecks



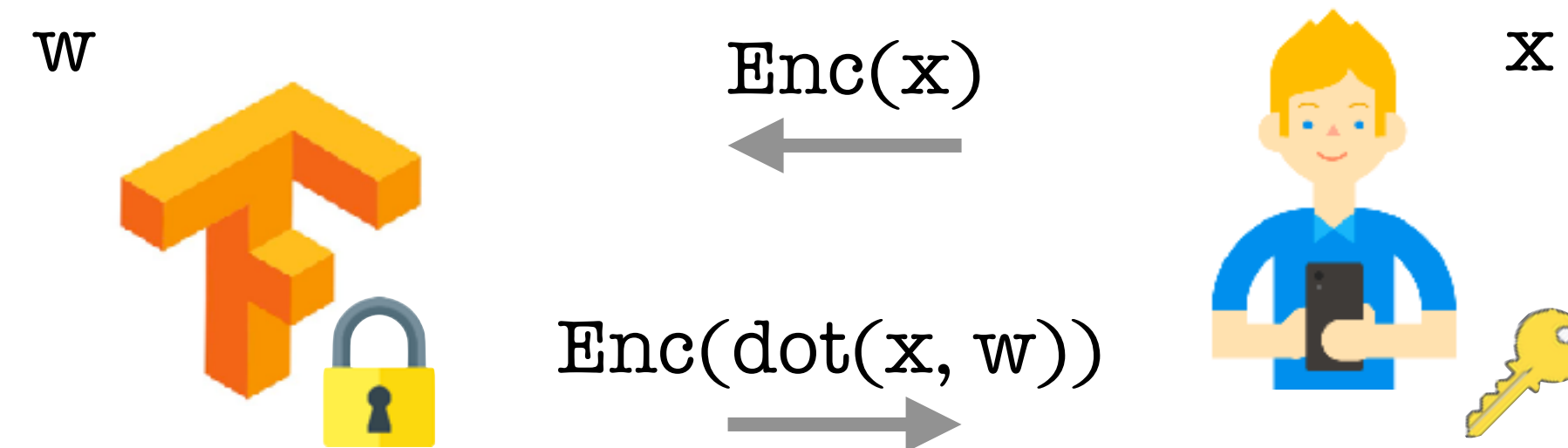
Prediction

Unencrypted Prediction



$$\text{dot}\left(\begin{array}{|c|c|c|} \hline x_0 & x_1 & x_2 \\ \hline \end{array}, \begin{array}{|c|} \hline w_0 \\ w_1 \\ w_2 \\ \hline \end{array} \right) = \begin{array}{|c|} \hline x_0 * w_0 + x_1 * w_1 + x_2 * w_2 \\ \hline \end{array}$$

Prediction on Encrypted Data



homomorphic
encryption scheme

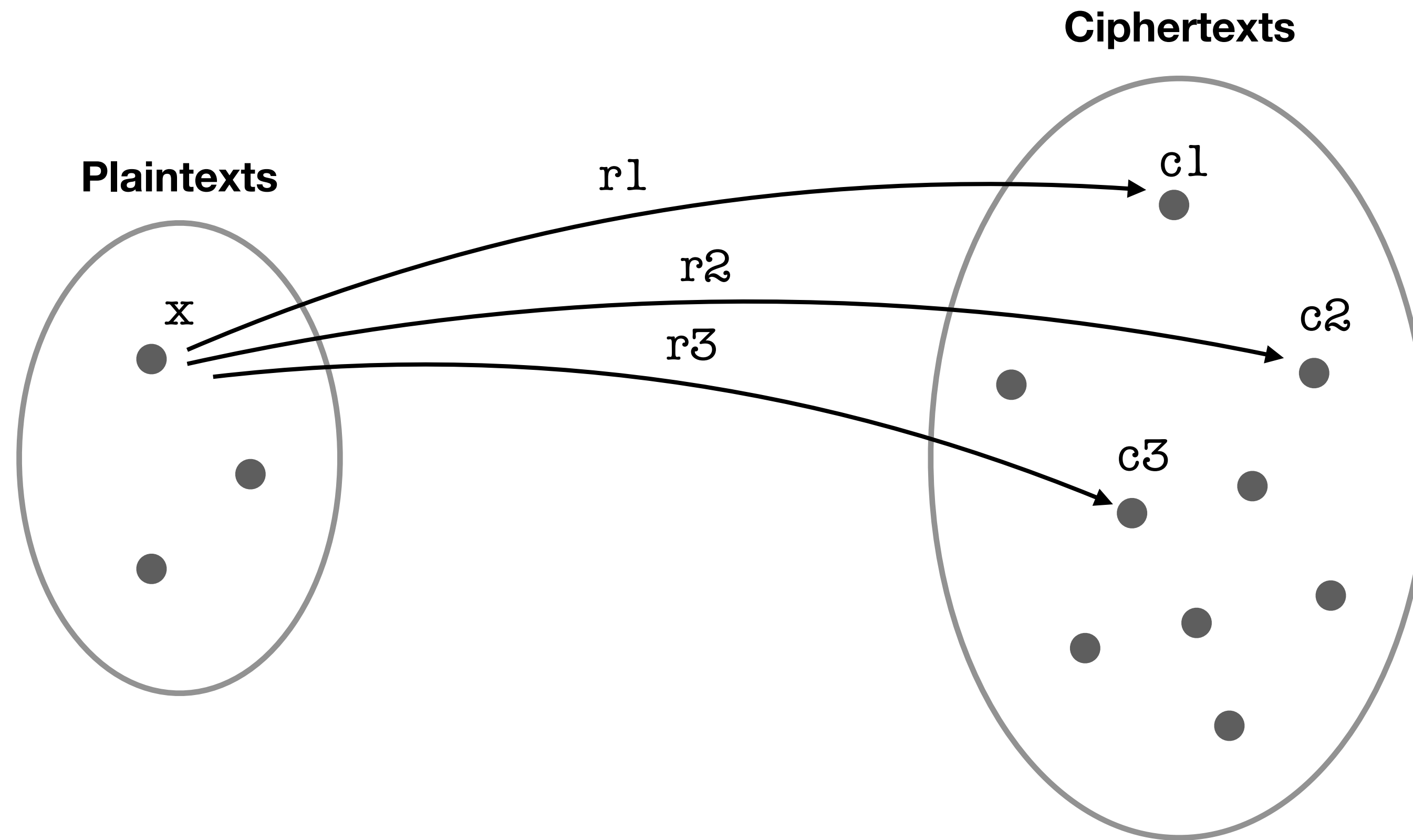
public multiplication

private addition

$$\begin{aligned}
 \text{dot}(\text{Enc}(x_0) \quad \text{Enc}(x_1) \quad \text{Enc}(x_2), \begin{matrix} w_0 \\ w_1 \\ w_2 \end{matrix}) &= \text{Enc}(x_0) * w_0 + \text{Enc}(x_1) * w_1 + \text{Enc}(x_2) * w_2 \\
 &= \text{Enc}(x_0 * w_0) + \text{Enc}(x_1 * w_1) + \text{Enc}(x_2 * w_2) \\
 &= \text{Enc}(x_0 * w_0 + x_1 * w_1 + x_2 * w_2)
 \end{aligned}$$

Paillier Encryption

$$c = \text{Enc}(x, r)$$



Paillier Encryption

public encryption key

$$c = \text{Enc}(x, r) = g^x * r^n \bmod n^2$$

$$\begin{aligned}g &= 36 \\n &= 35 \\n^2 &= 1225\end{aligned}$$

$$\text{Enc}(5, 2) = 36^5 * 2^{35} \bmod 1225 = 718$$

$$\text{Enc}(5, 4) = 36^5 * 4^{35} \bmod 1225 = 674$$

Private Addition

$$\begin{aligned} & \text{Enc}(x, r) * \text{Enc}(y, s) \\ &= (g^x * r^n \bmod n^2) * (g^y * s^n \bmod n^2) \\ &= g^{(x+y)} * (r * s)^n \bmod n^2 \\ &= \text{Enc}(x+y, r*s) \end{aligned}$$

$$\begin{aligned} & \text{Enc}(5, 2) * \text{Enc}(5, 4) \\ &= 718 * 674 \\ &= 5^7 \\ &= 36^{10} * 8^{35} \\ &= \text{Enc}(10, 8) \end{aligned}$$

Public Multiplication

$$\begin{aligned} & \text{Enc}(\mathbf{x}, \mathbf{r})^w \\ &= (g^{\mathbf{x}} * \mathbf{r}^n \bmod n^2)^w \\ &= g^{(\mathbf{x} * w)} * (\mathbf{r}^w)^n \bmod n^2 \\ &= \text{Enc}(\mathbf{x} * w, \mathbf{r}^w) \end{aligned}$$

$$\begin{aligned} & \text{Enc}(5, 2)^2 \\ &= 718 * 718 \\ &= 1024 \\ &= 36^{10} * 4^{35} \\ &= \text{Enc}(10, 4) \end{aligned}$$

What's Next?

computationally expensive

4096 bit modulus

data expansion

available operations

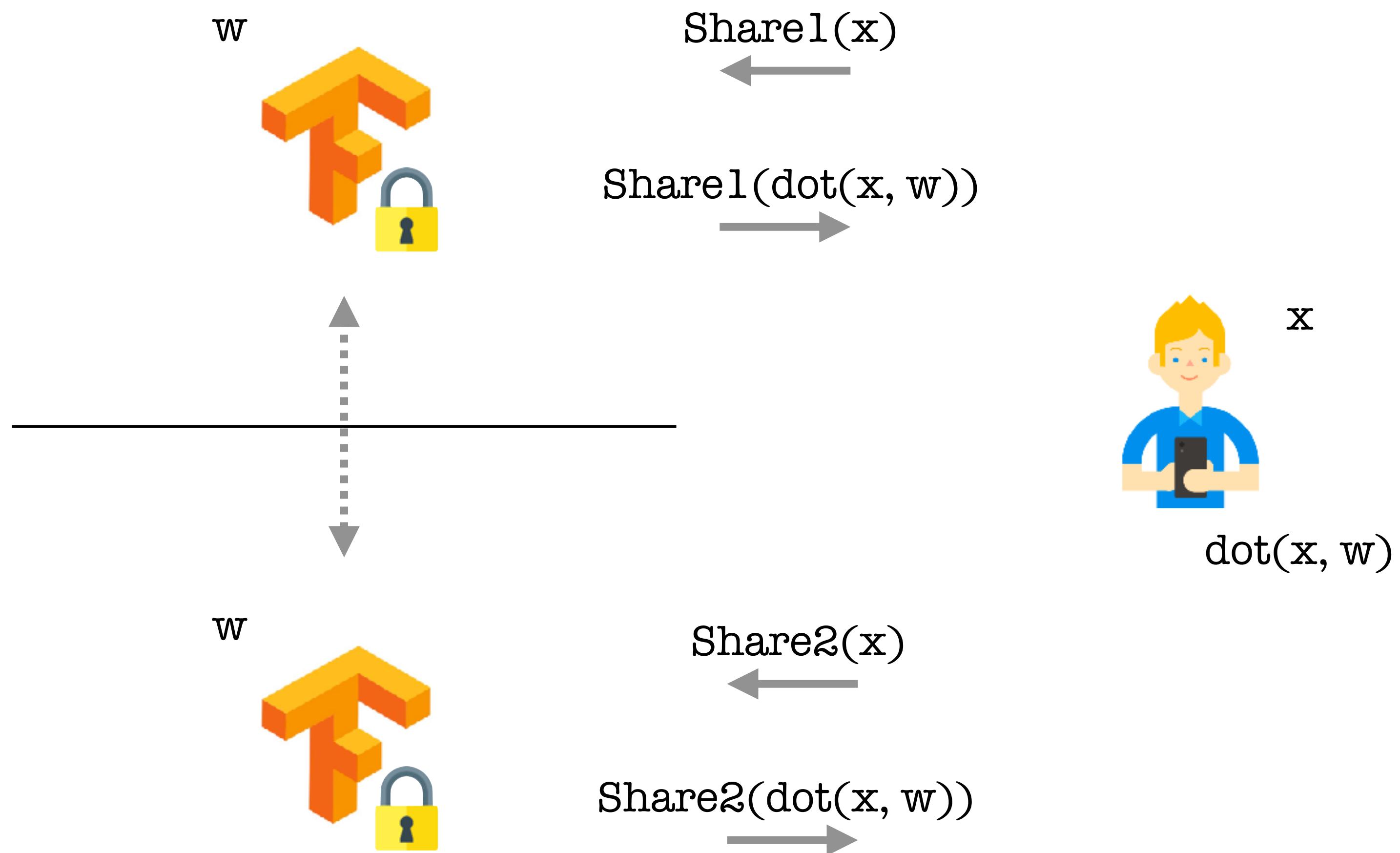
private multiplication

...

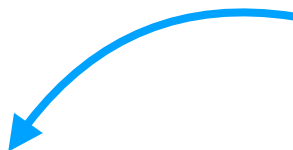
Secret Sharing

replace computation with communication

Prediction on Secret Shared Data



Secret Sharing in SPDZ

$$x_1 = \text{Share}_1(x, r) = r \bmod m$$


public parameter

$$x_2 = \text{Share}_2(x, r) = x - r \bmod m$$

$$x_1 + x_2 = x \bmod m$$

$$m = 10$$

$$\text{Share}_1(5, 7) = 7 \bmod 10 = 7$$

$$\text{Share}_2(5, 7) = 5 - 7 \bmod 10 = 8$$

Private Addition



$x1$

$y1$

$$z1 = x1 + y1$$



$x2$

$y2$

$$z2 = x2 + y2$$

$$x1 + x2 = x$$

$$y1 + y2 = y$$

$$\begin{aligned} z1 + z2 &= (x1 + y1) + (x2 + y2) \\ &= (x1 + x2) + (y1 + y2) \\ &= x + y \end{aligned}$$

Public Multiplication



$x1$

w

$$z1 = x1 * w$$



$x2$

w

$$z2 = x2 * w$$

$$x1 + x2 = x$$

$$\begin{aligned} z1 + z2 &= (x1 * w) + (x2 * w) \\ &= (x1 + x2) * w \\ &= x * w \end{aligned}$$

Private Multiplication



random triple

(a_1 , b_1 , c_1)

x_1

y_1

$x - a$

$y - b$

$$\begin{aligned} z_1 &= (x - a) * (y - b) \\ &+ (x - a) * b_1 \\ &+ (y - b) * a_1 \\ &+ c_1 \end{aligned}$$



(a_2 , b_2 , c_2)

x_2

y_2

$x - a$

$y - b$

$$\begin{aligned} z_2 &= (x - a) * b_2 \\ &+ (y - b) * a_2 \\ &+ c_2 \end{aligned}$$

$$a_1 + a_2 = a$$

$$b_1 + b_2 = b$$

$$c_1 + c_2 = a * b$$

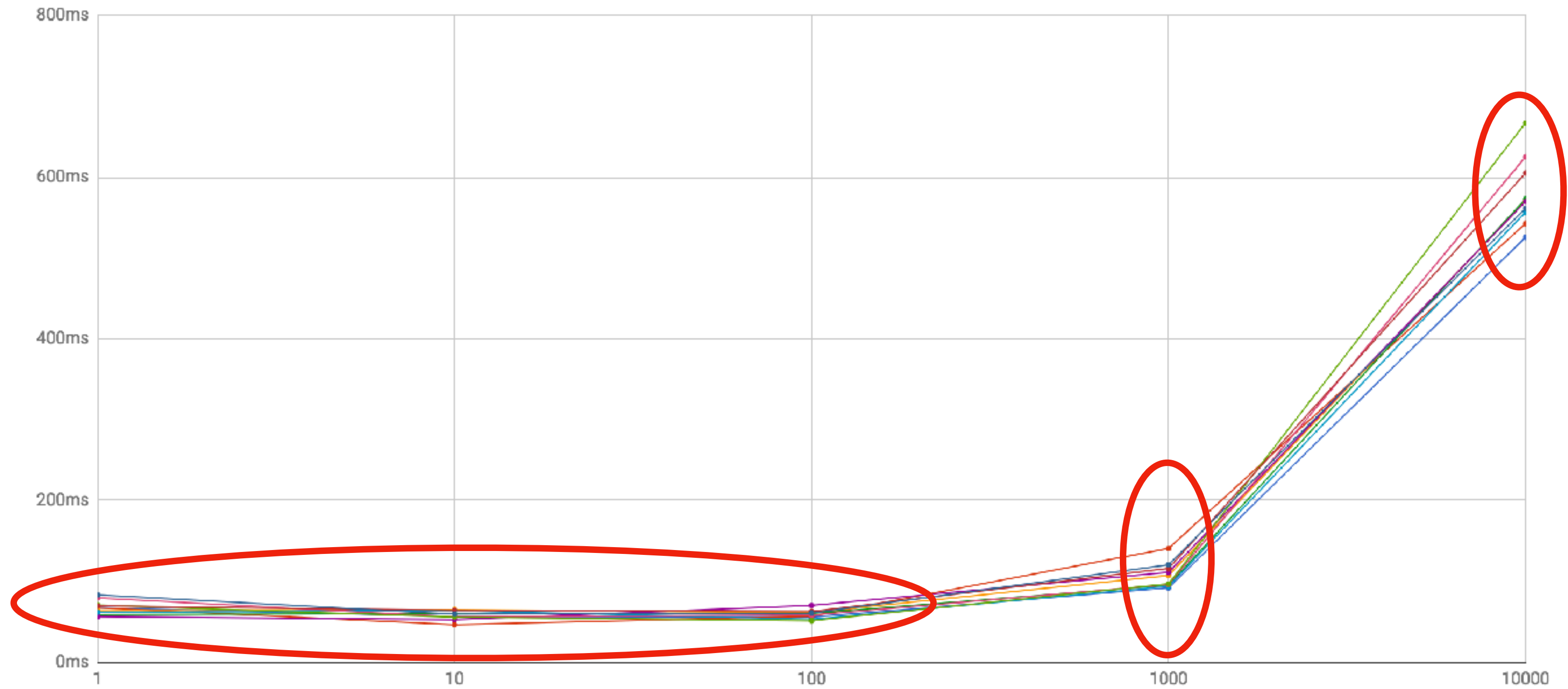
$$x_1 + x_2 = x \quad y_1 + y_2 = y$$

$$\begin{aligned} z_1 + z_2 &= \dots \\ &= x * y \end{aligned}$$

Performance

logistic regression

Sigmoid evaluation, 100 features, servers on Google cloud (2 vCPU, 10 GB)



Getting Involved

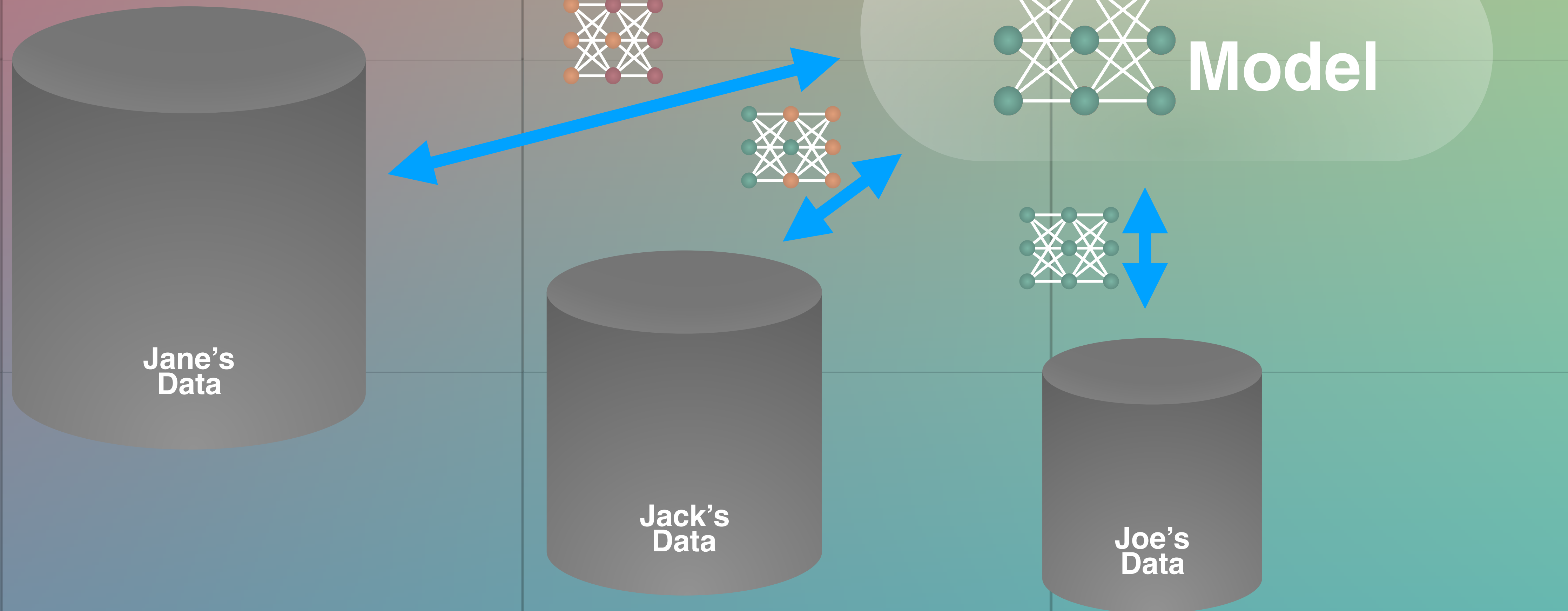
Tools for Safe AI

- ◆ Federated Learning
- ◆ Homomorphic Encryption
- ◆ Multi-Party Computation
- ◆ Gradient Validation Markets



OpenMined

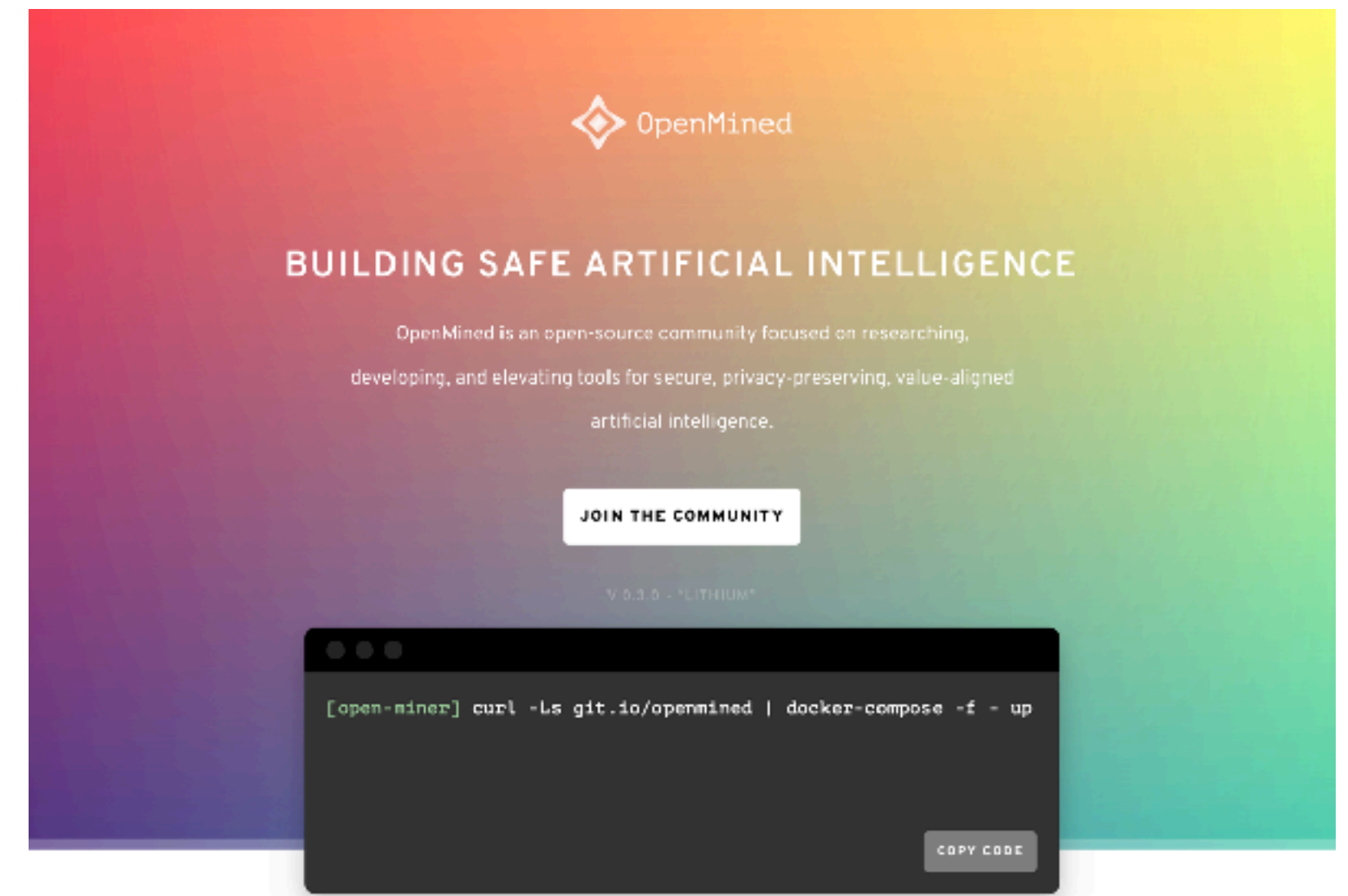
Multi-Party Computation + Federated Learning



Federated Learning for Safe AI



@mortendahlcs
mortendahl.github.io



@openminedorg
openmined.org

Thank you