Cryptography for

Privacy-Preserving Machine Learning

Morten Dahl

The tf-encrypted Project and Dropout Labs

Applied ML Days, AI & Trust track, EPFL, January 2019

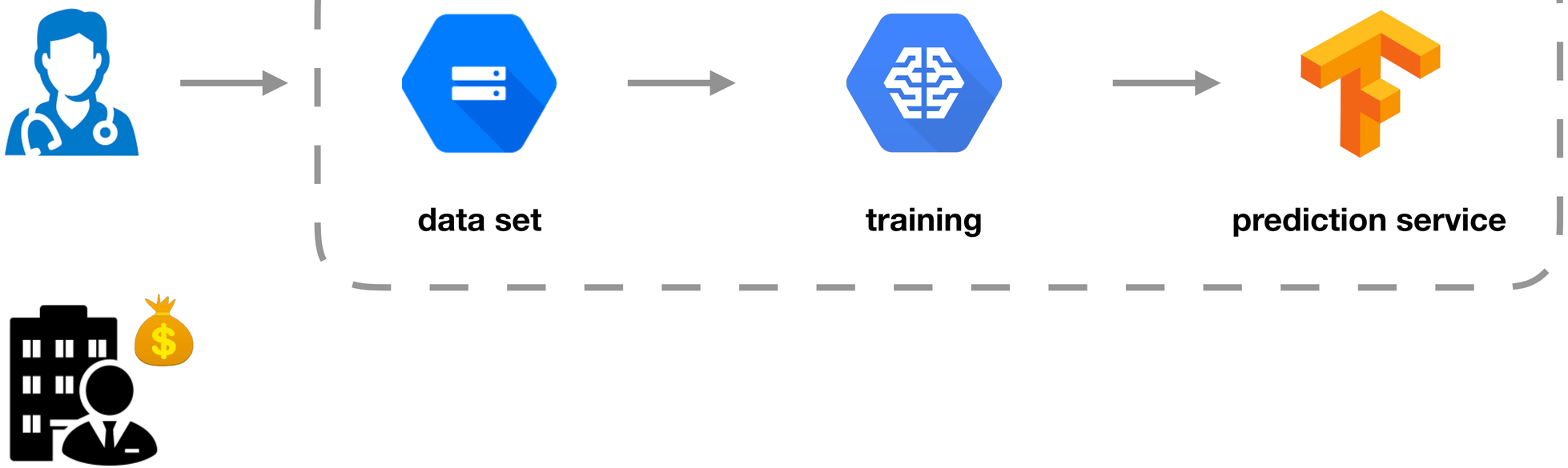
Why?

Machine Learning Process

data set **training** **prediction service**

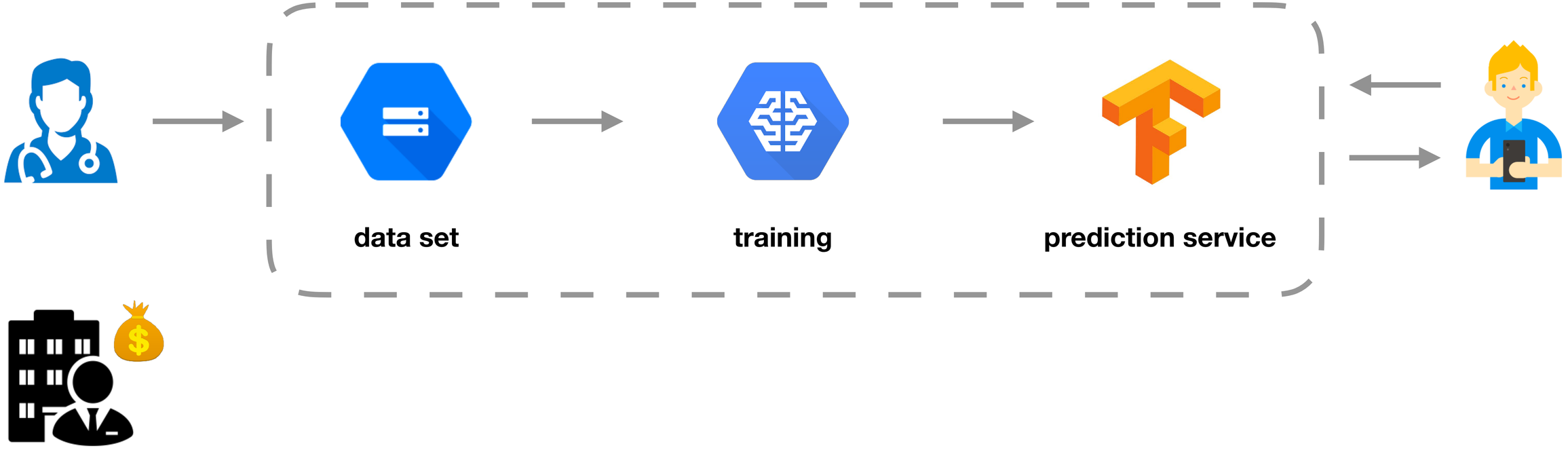
Machine Learning Process

IMAGENET



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.

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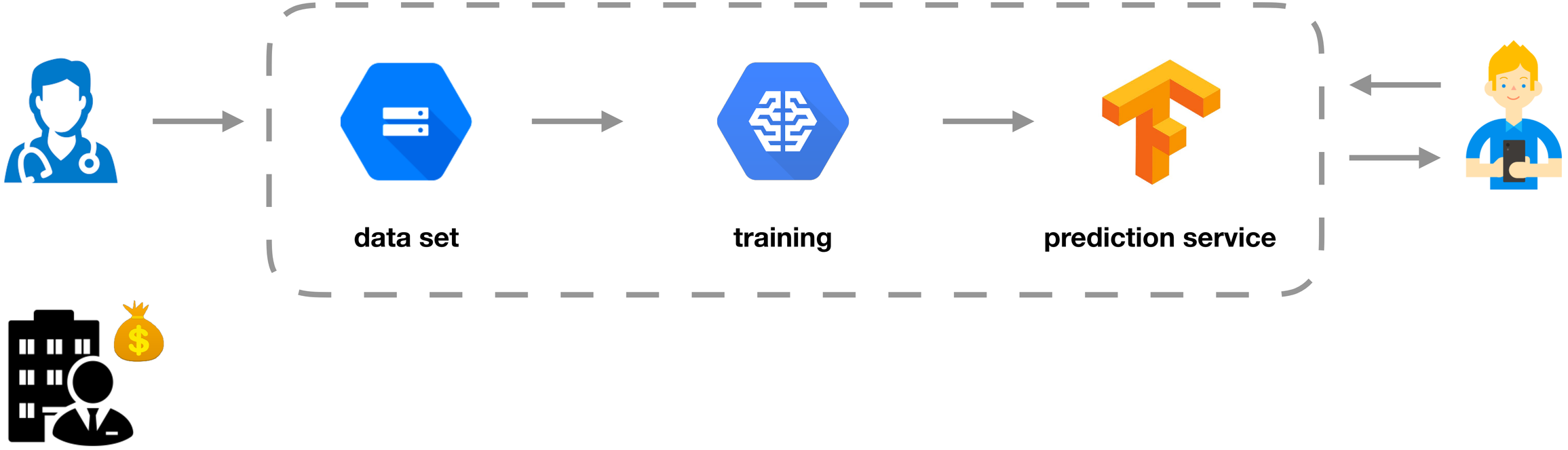
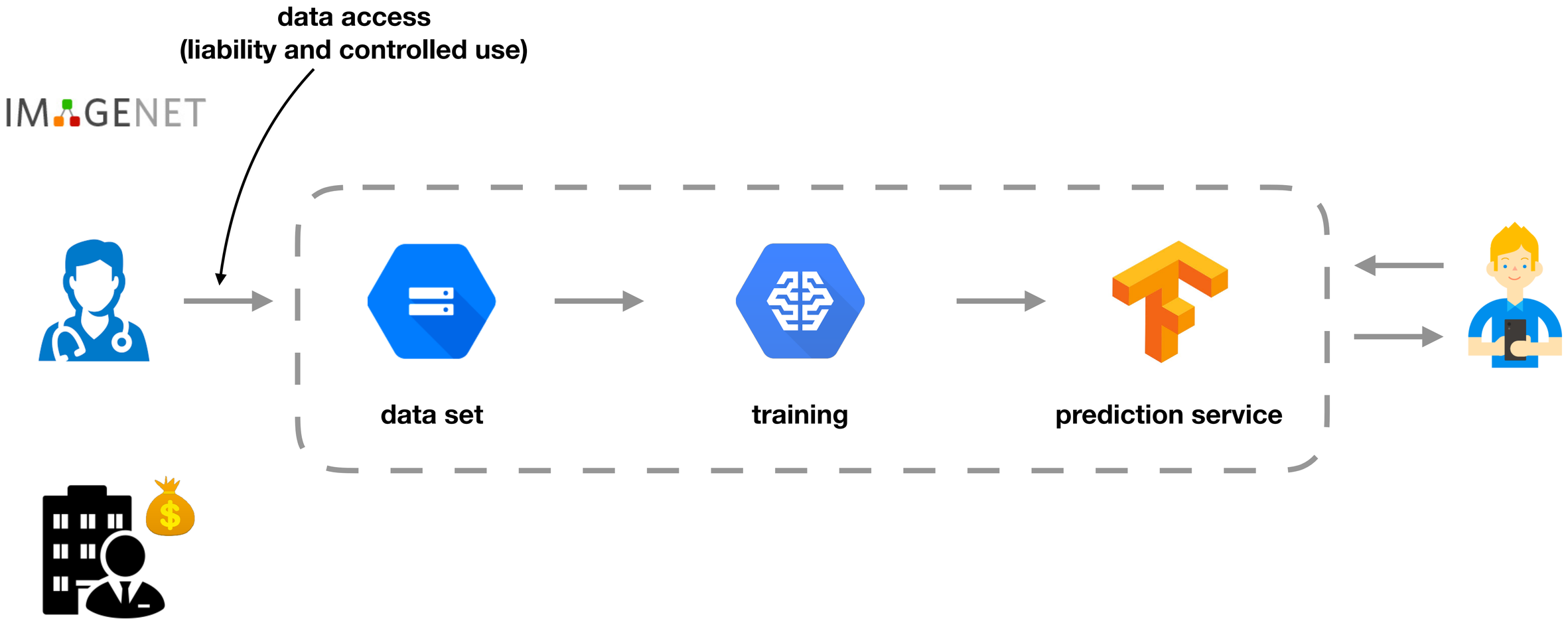
machine learning positioned to have huge impact on health care

Potential Bottlenecks

IMAGENET



Potential Bottlenecks



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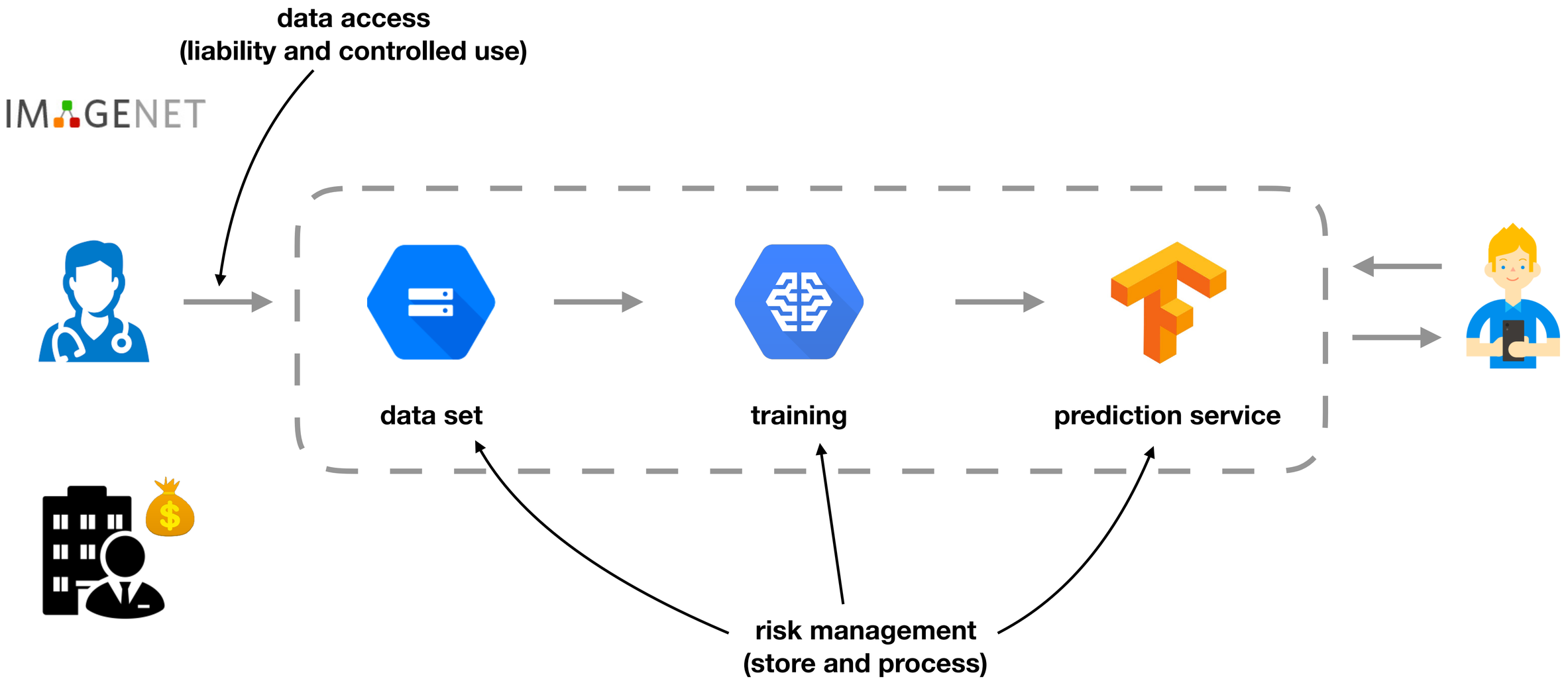

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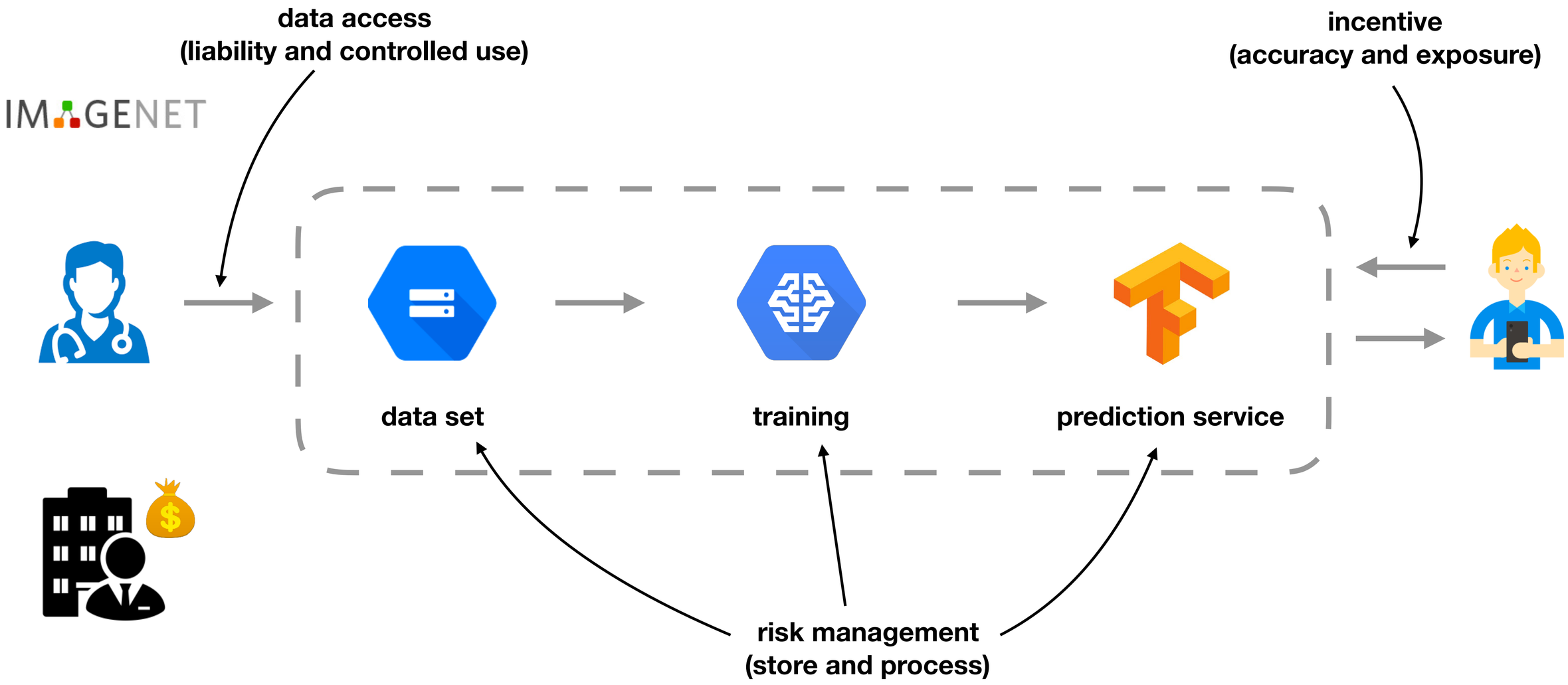

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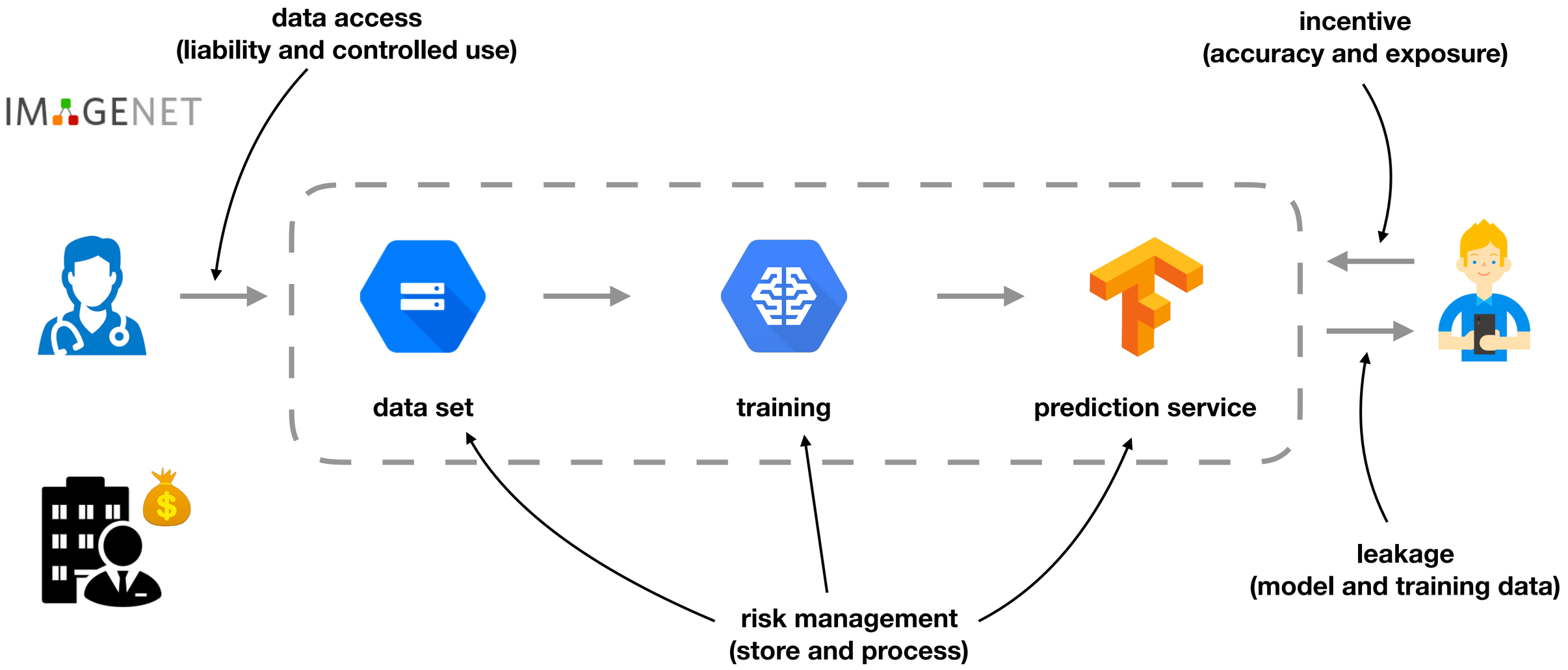
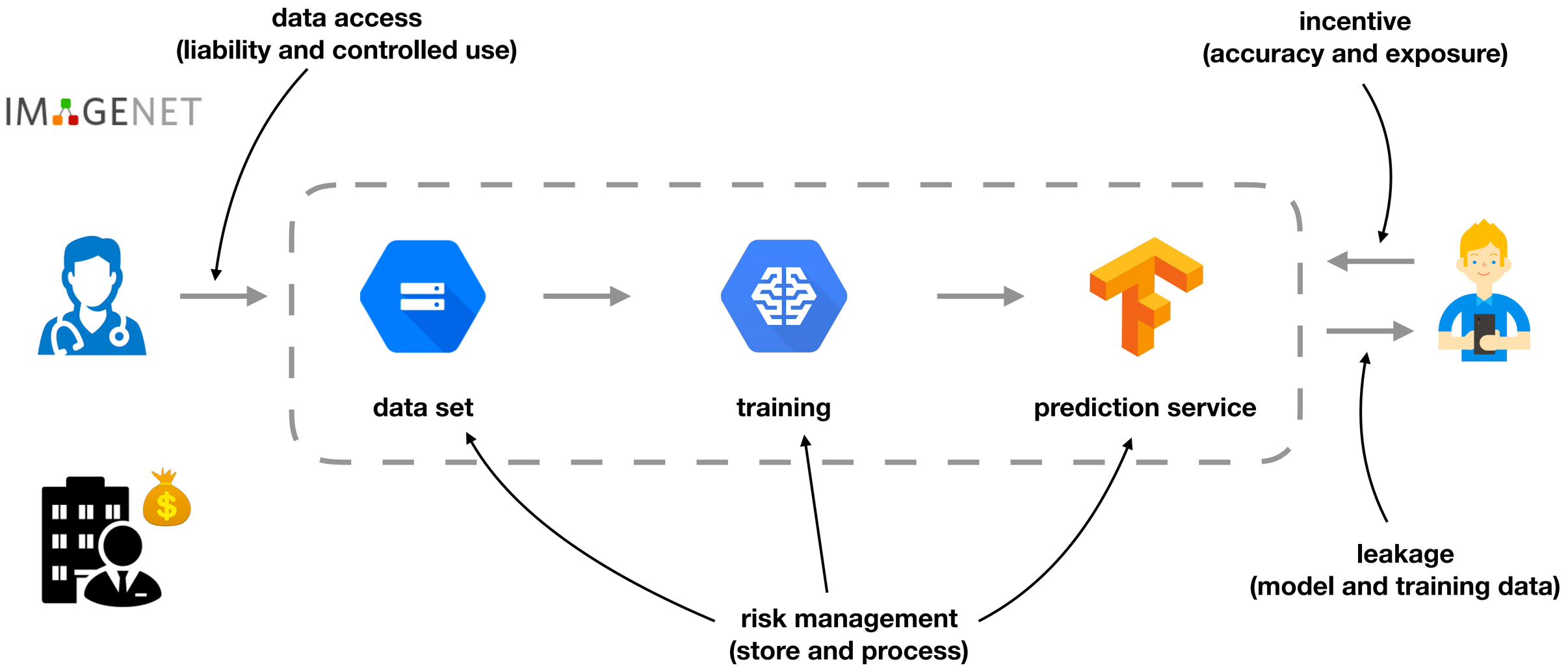


Differential Privacy



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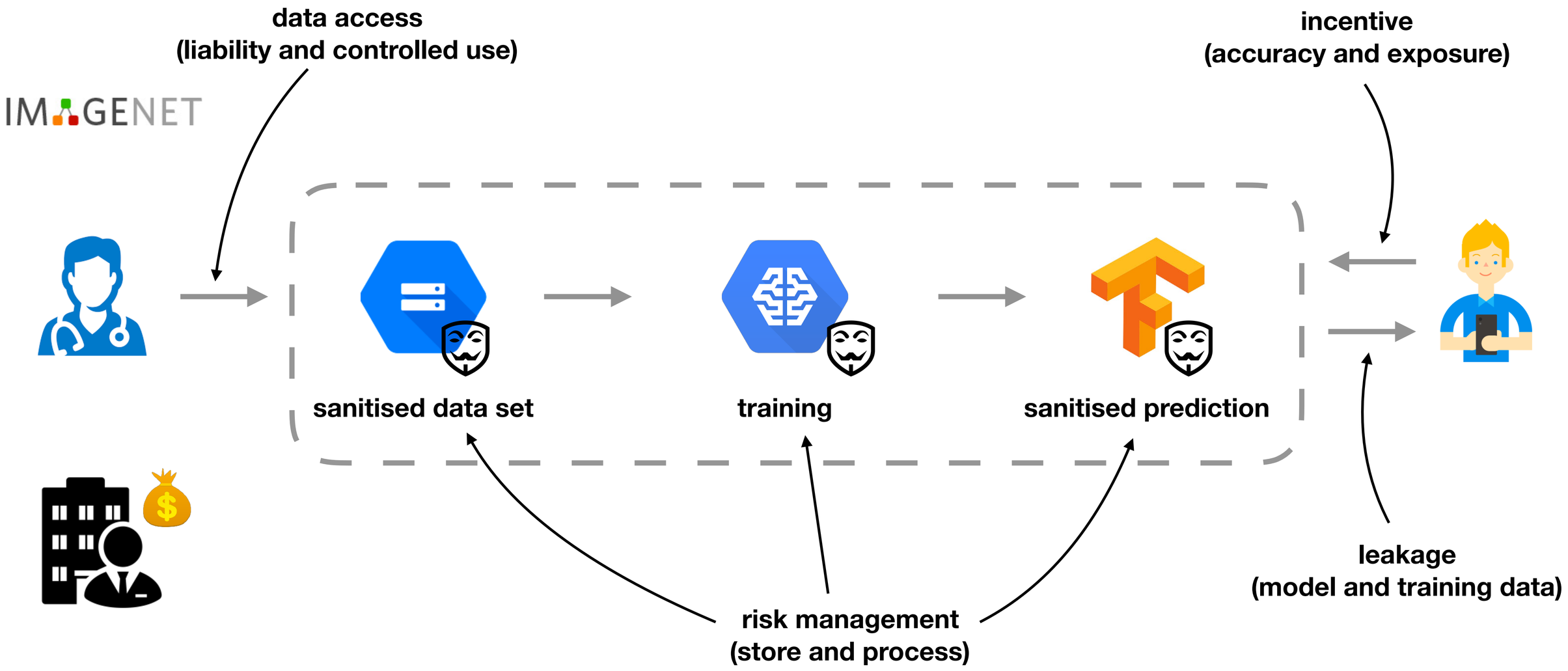

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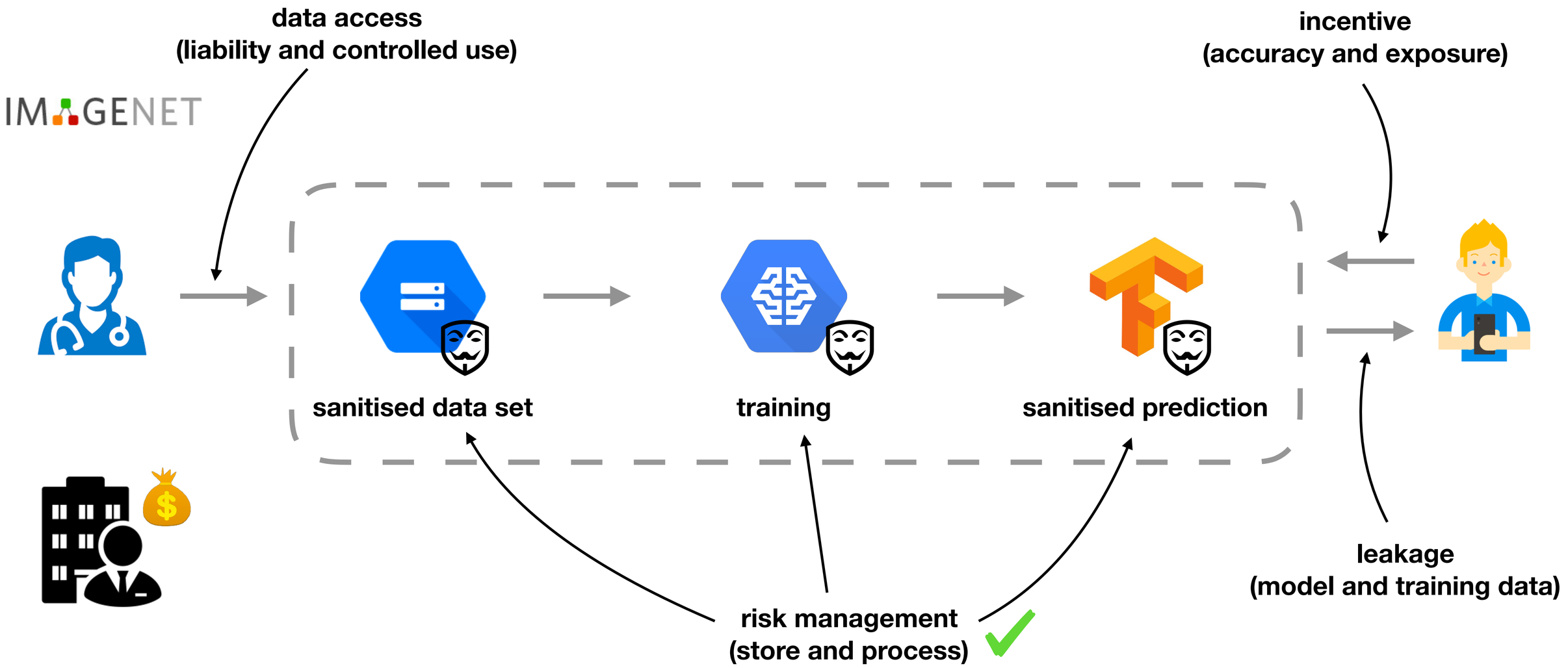

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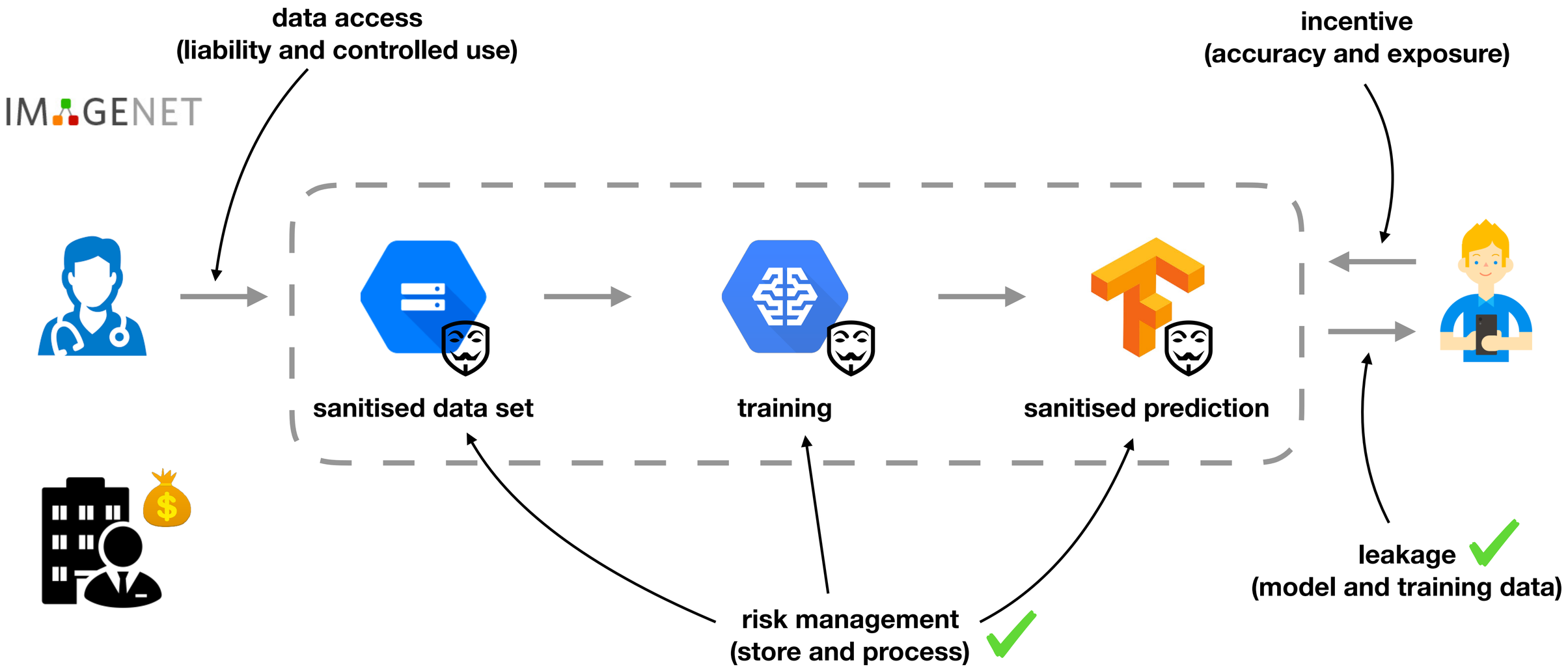

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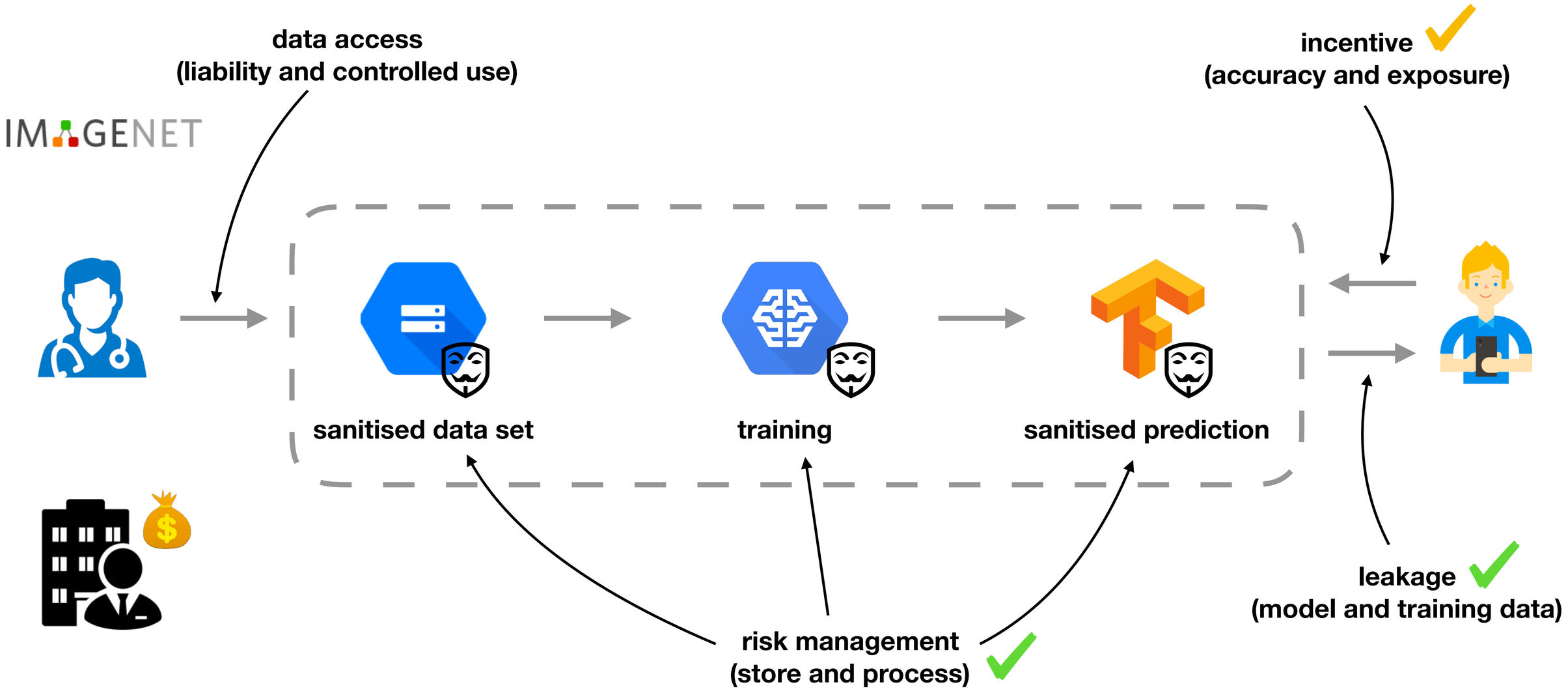

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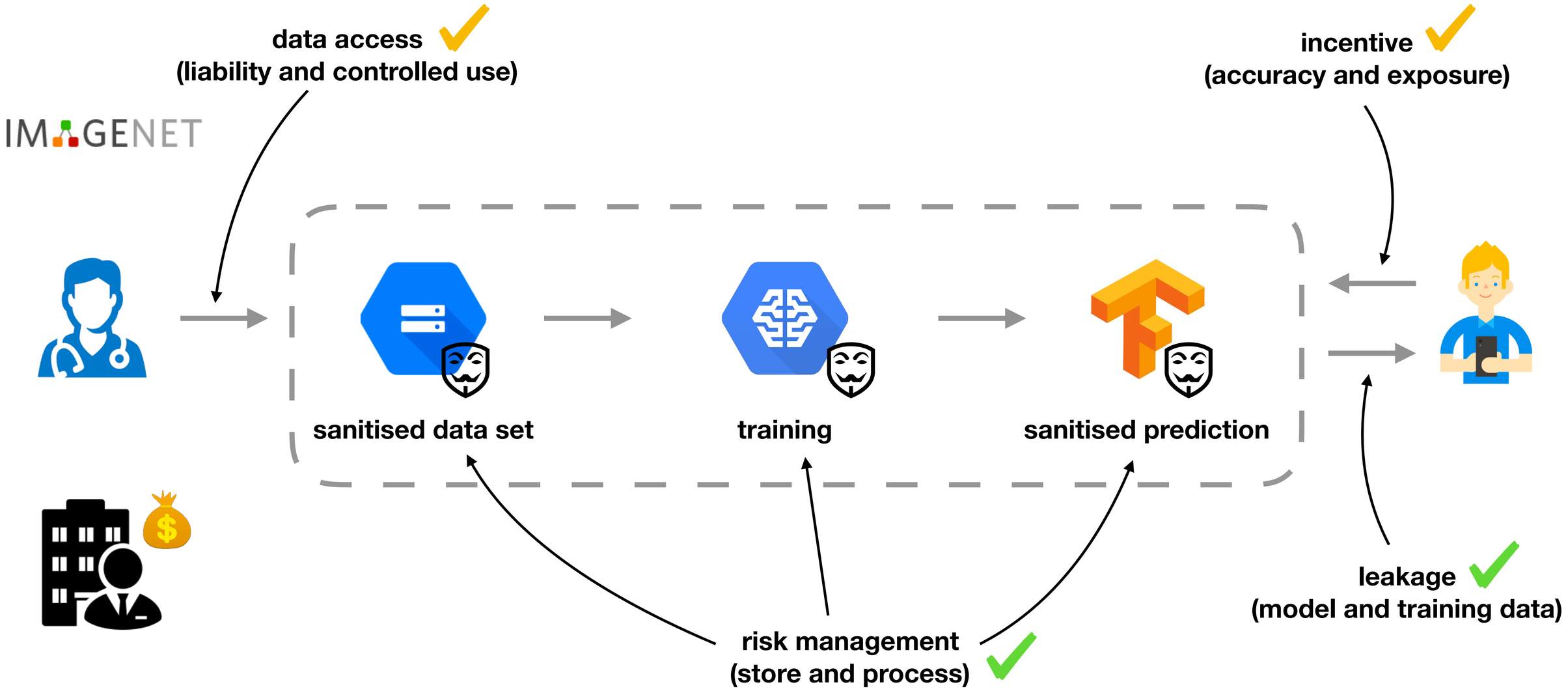
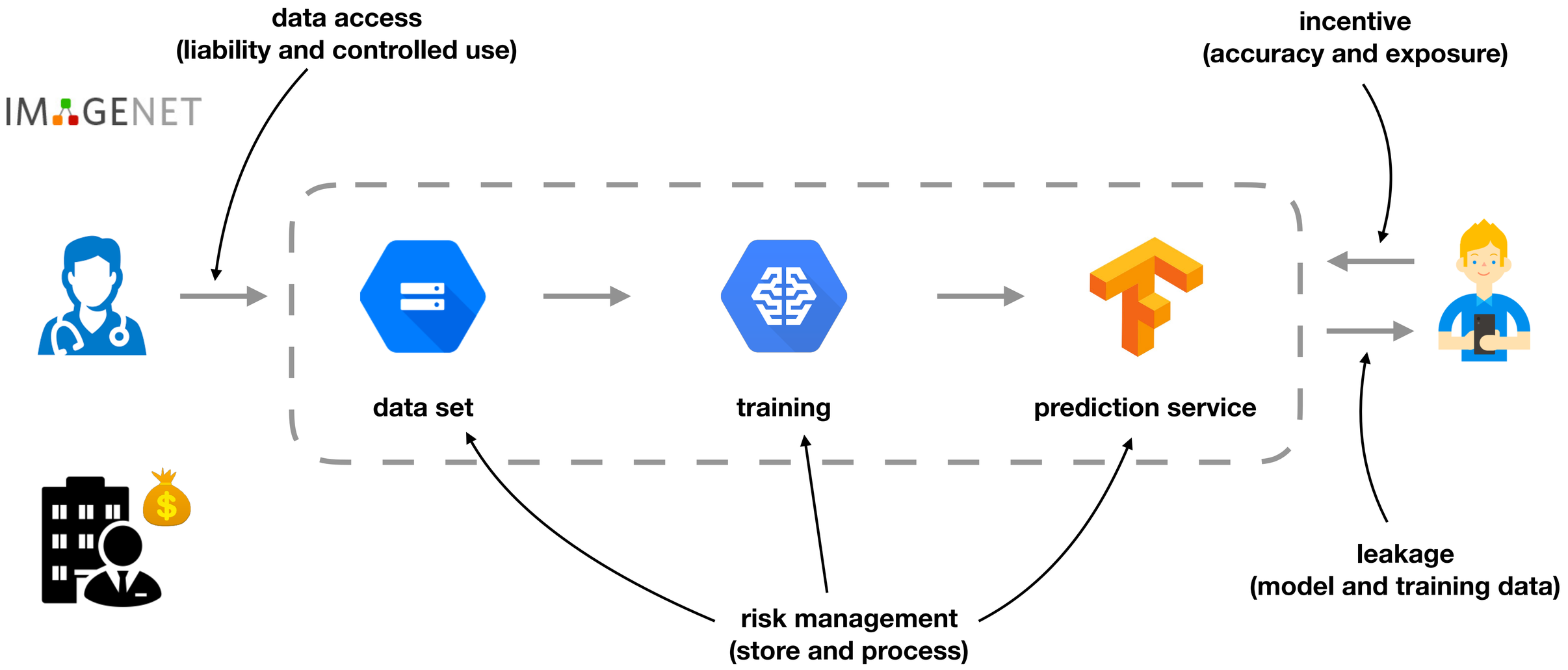


Secure Computation



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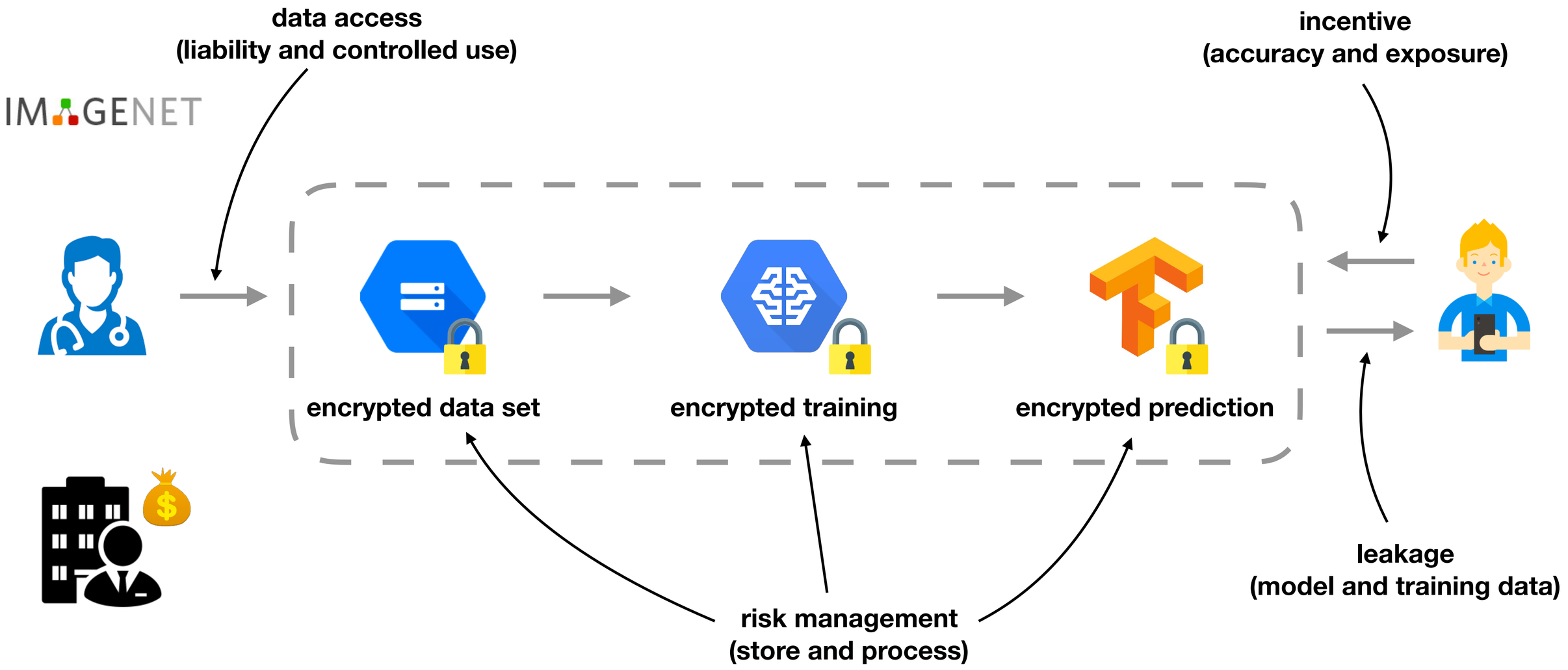

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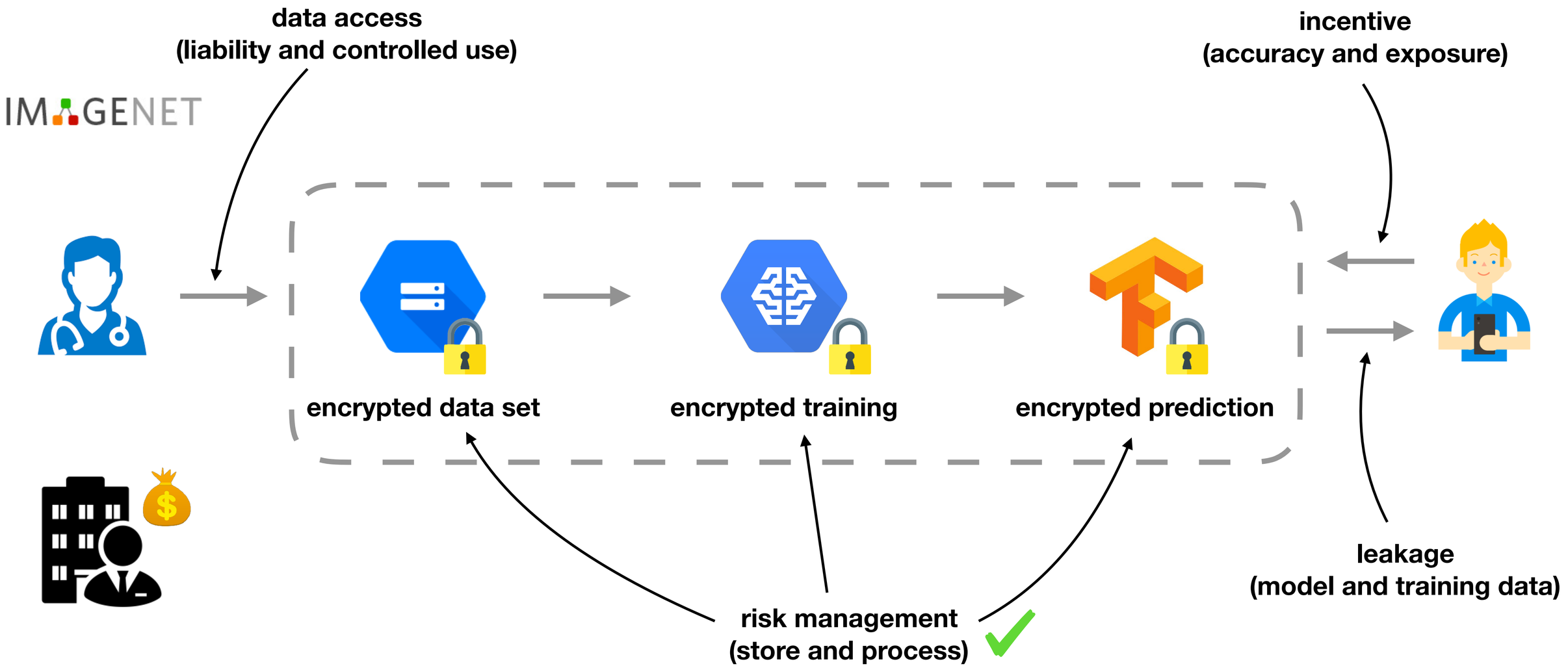

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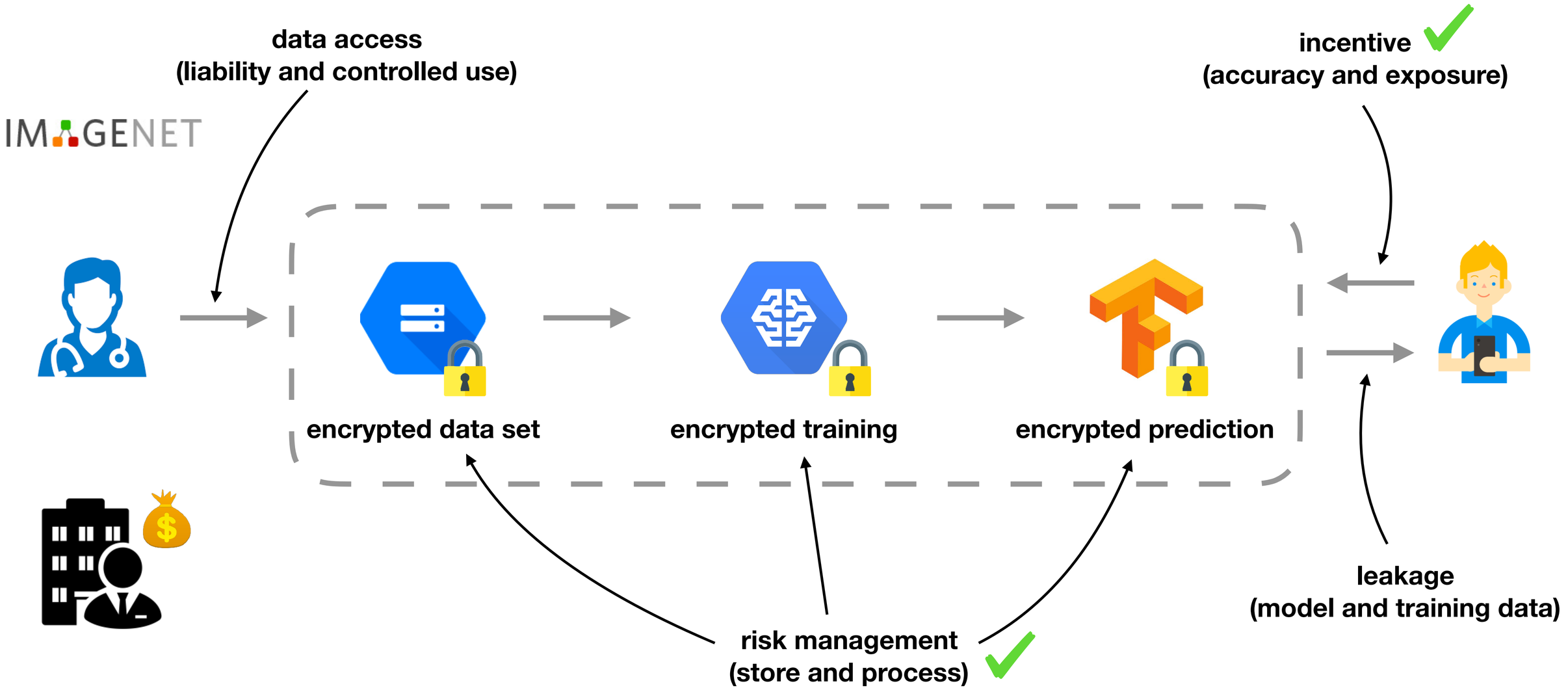

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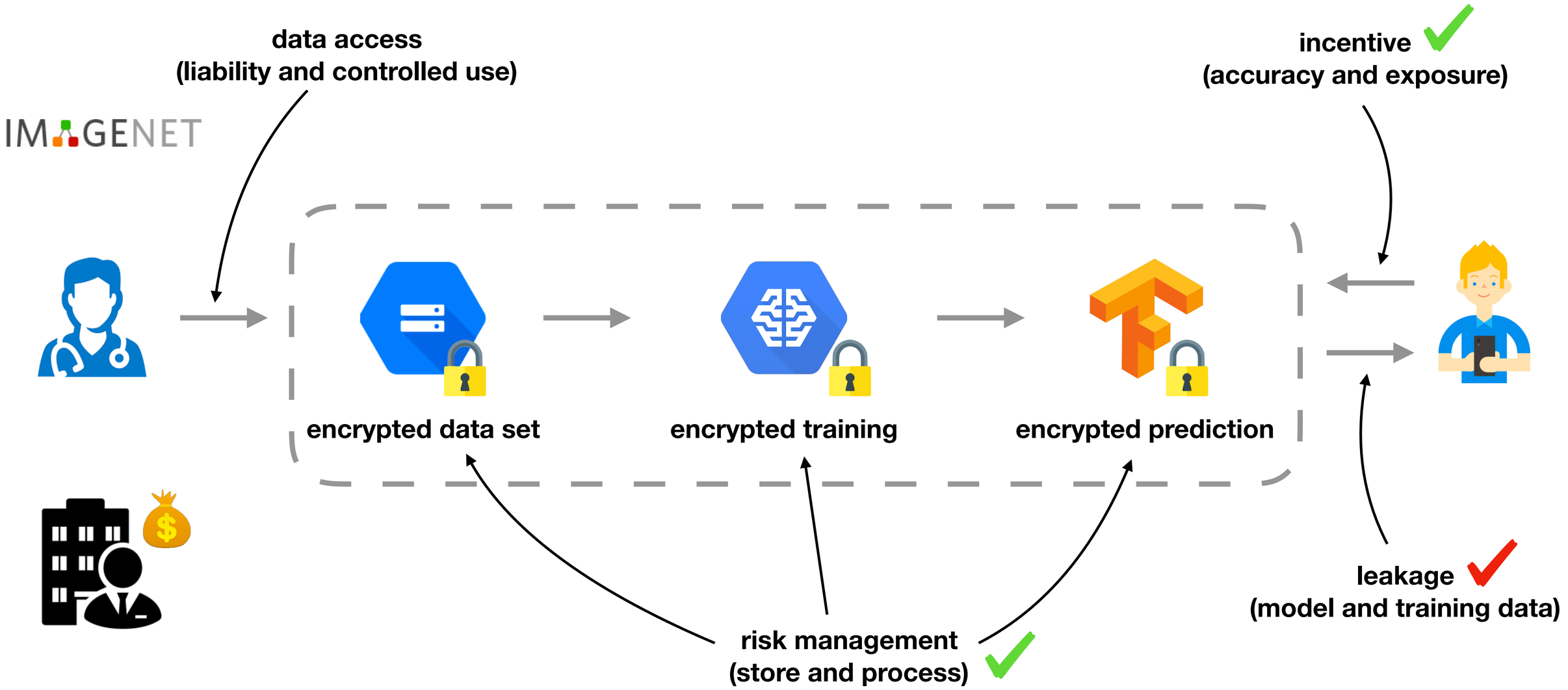

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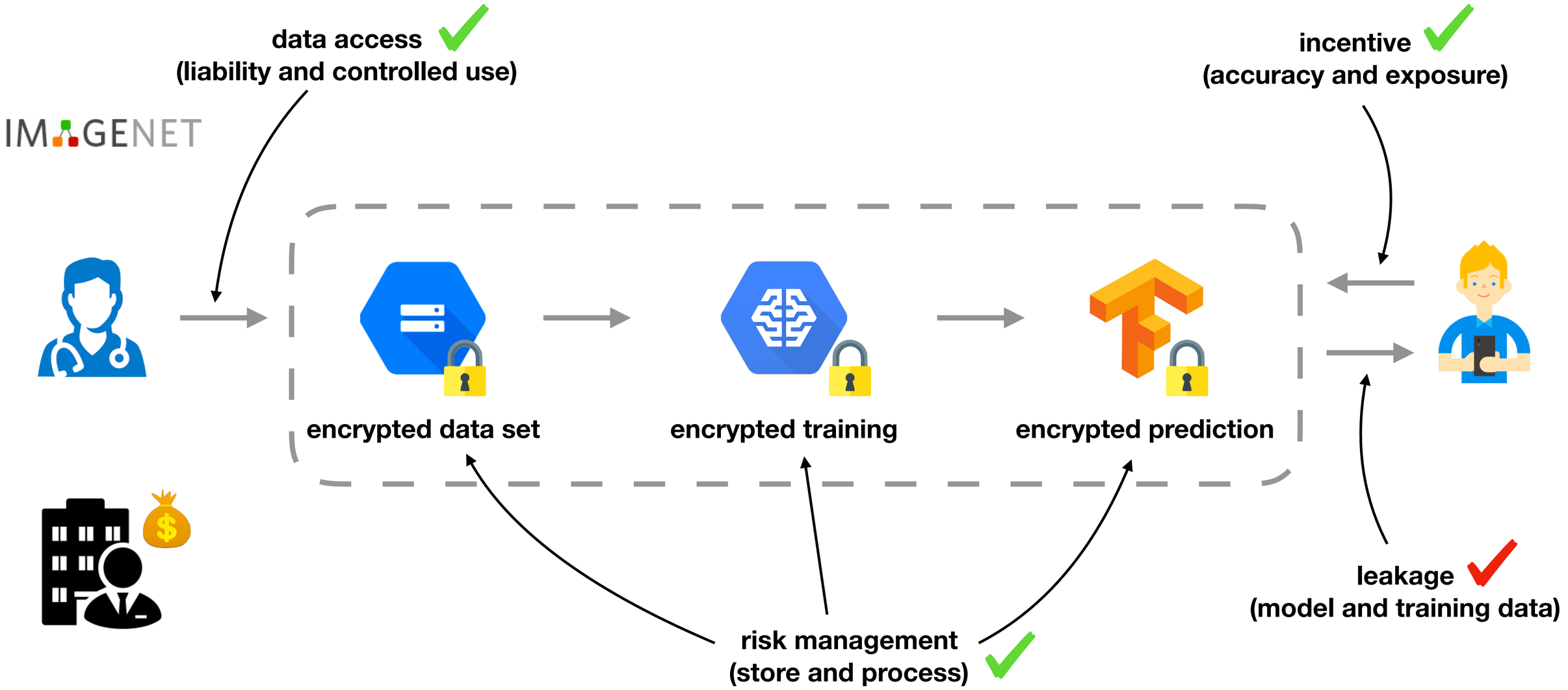
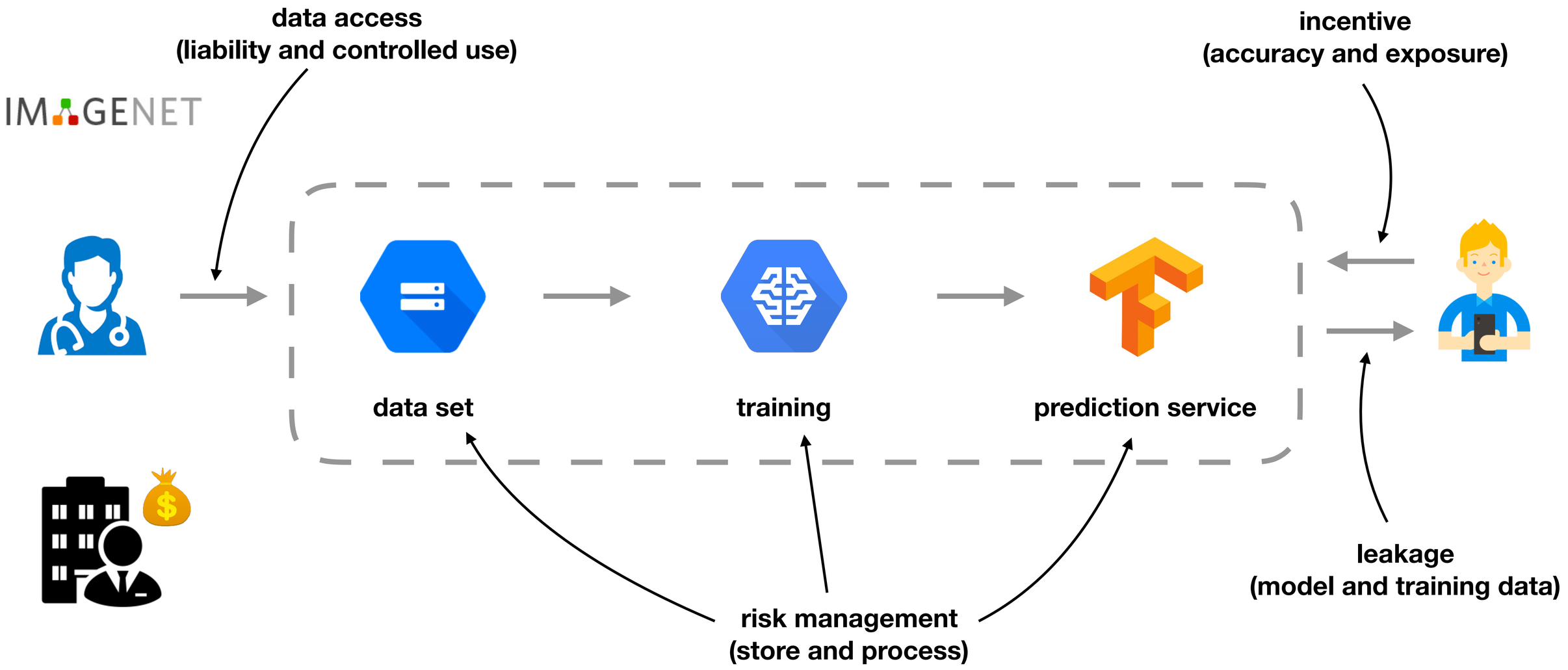
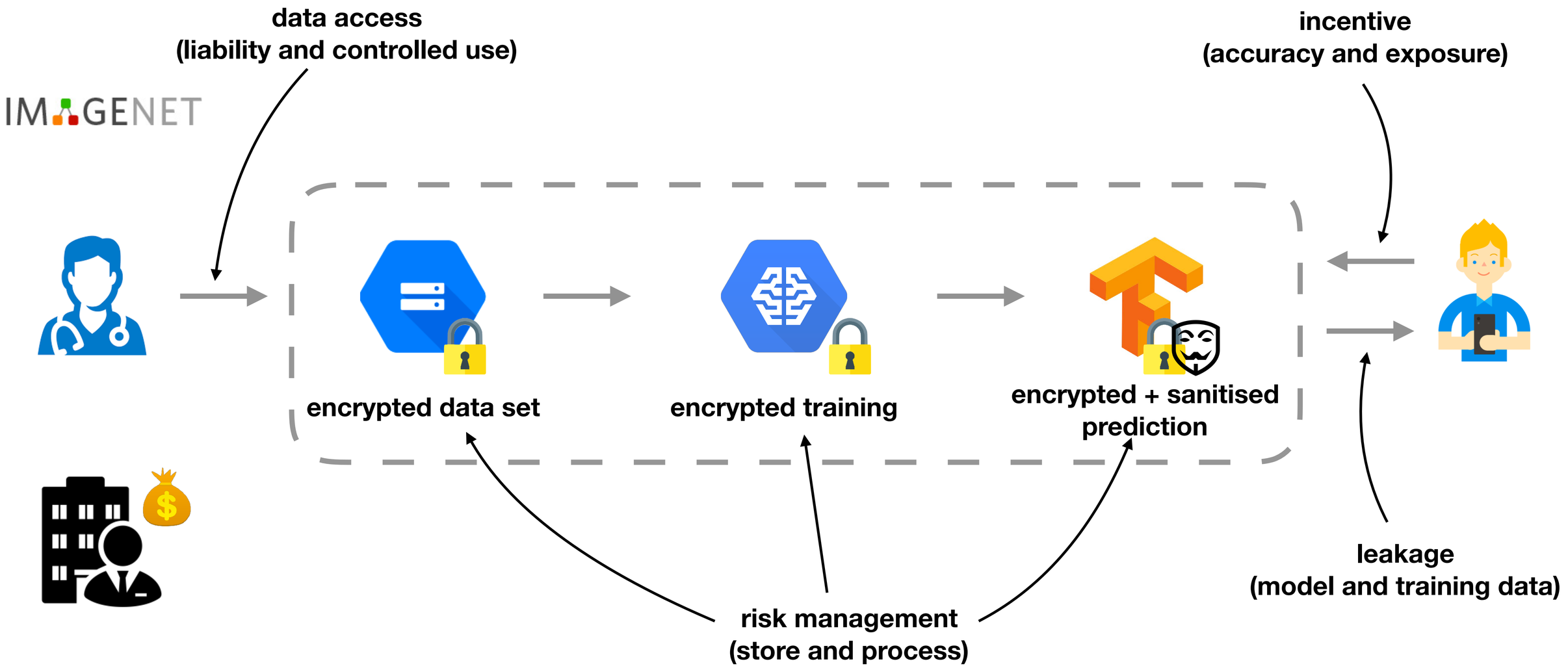


Hybrid


data access
(liability and controlled use)
IMAGENET
incentive
(accuracy and exposure)
data set
training
prediction service
leakage
(model and training data)
risk management
(store and process)

Hybrid


data access
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encrypted training
encrypted + sanitised
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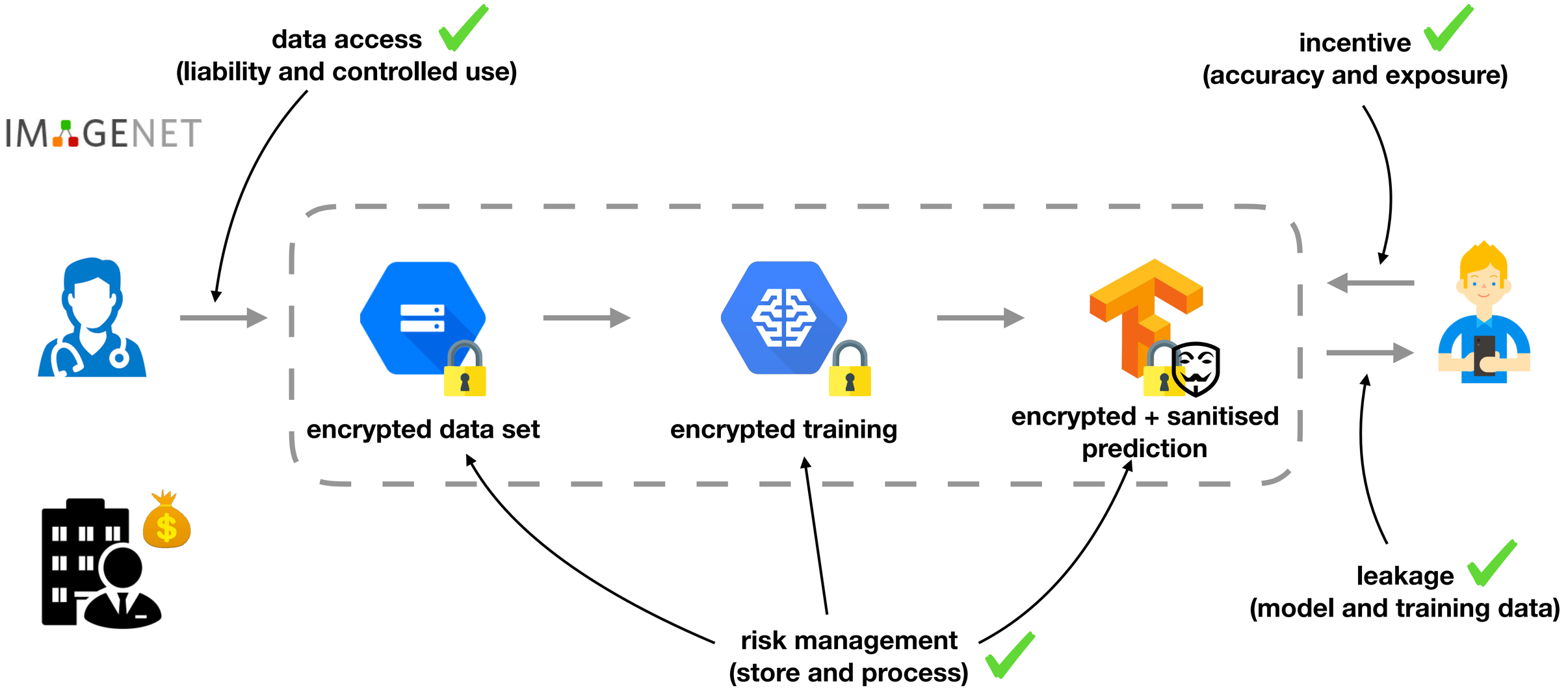
(store and process)

Hybrid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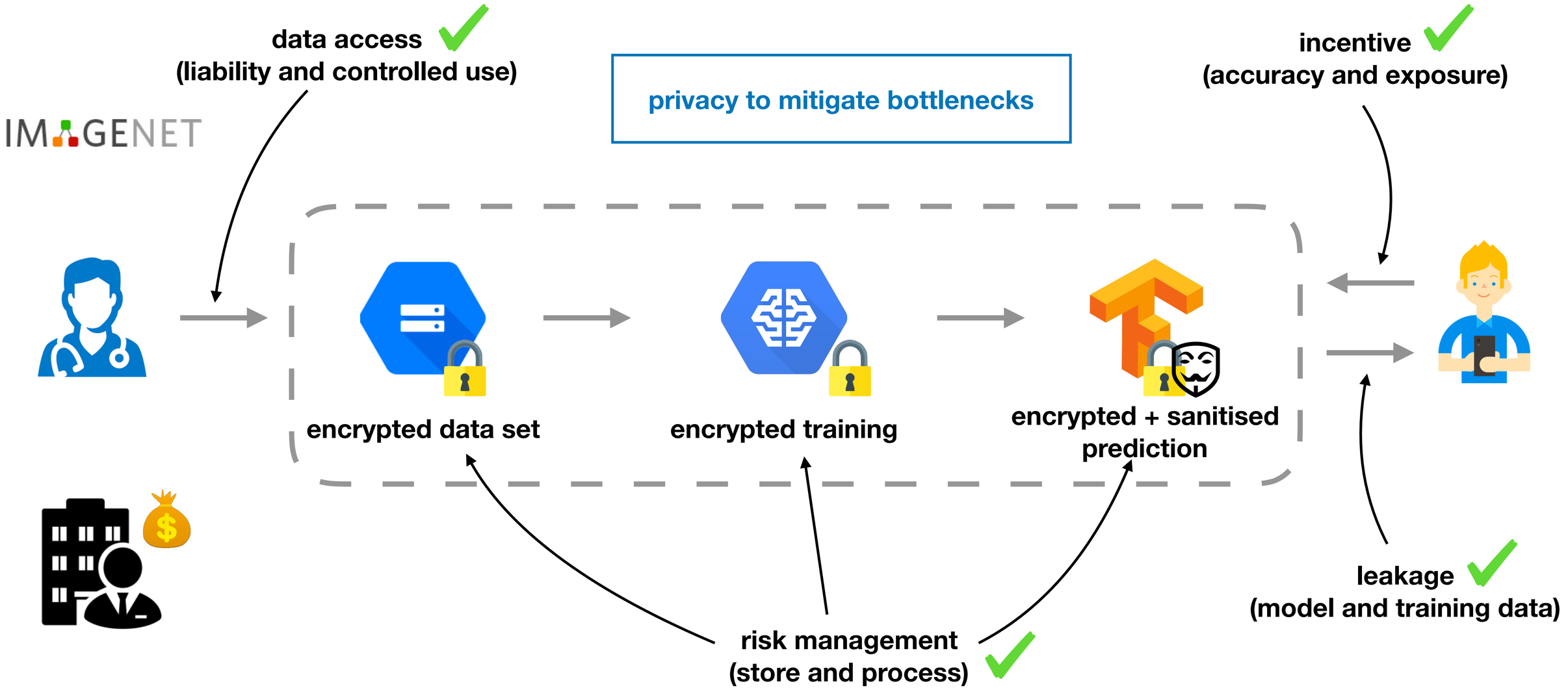
data access
(liability and controlled use)
IMAGENET
privacy to mitigate bottlenecks
incentive
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encrypted data set
encrypted training
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prediction
leakage
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risk management
(store and process)

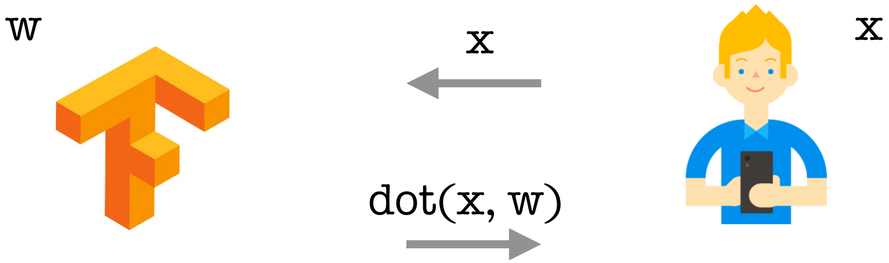
Prediction

Prediction with Linear Model

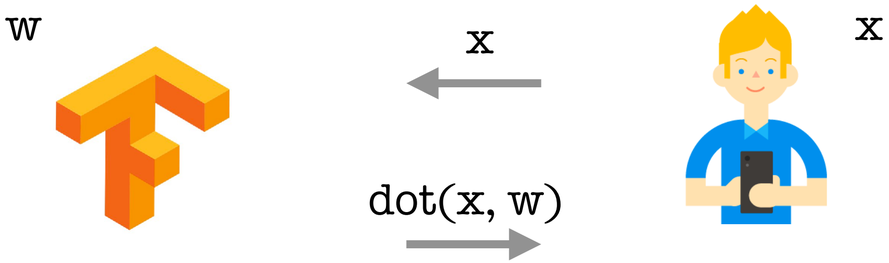
$\mathbf{w}$

$\mathbf{x}$

Prediction with Linear Model



Prediction with Linear Model



dot(x1 x2 x3 , w1 w2 w3) = x1*w1 + x2*w2 + x3*w3

… using Homomorphic Encryption

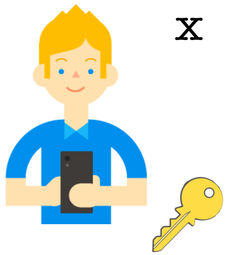
w

x

… using Homomorphic Encryption

$\mathbf{w}$

$\mathbf{x}$



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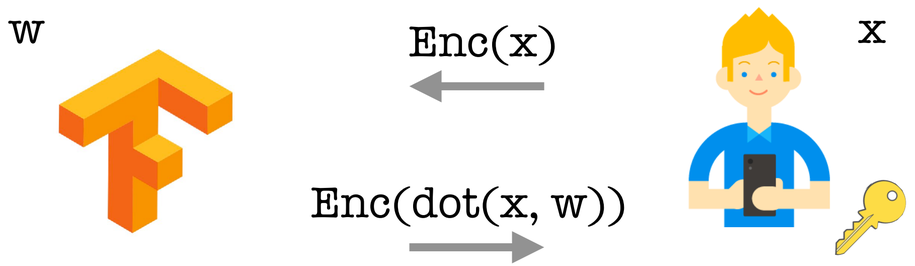

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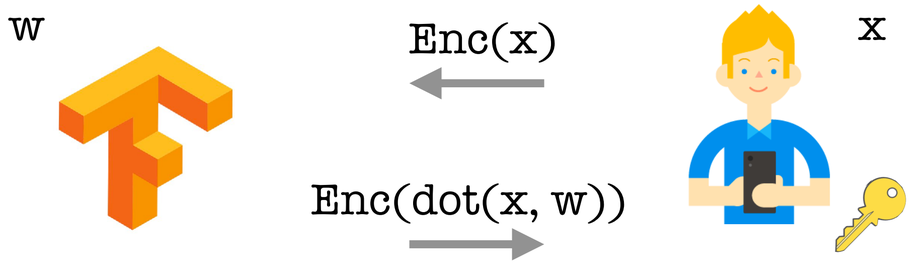
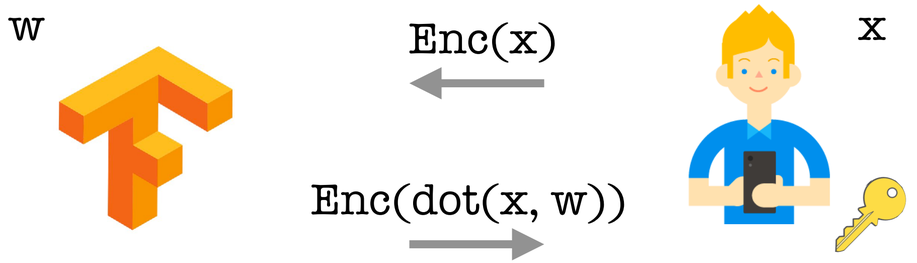


dot(Enc(x1) Enc(x2) Enc(x3) , w1 w2 w3) = Enc(x1)*w1 + Enc(x2)*w2 + Enc(x3)*w3

… using Homomorphic Encryption

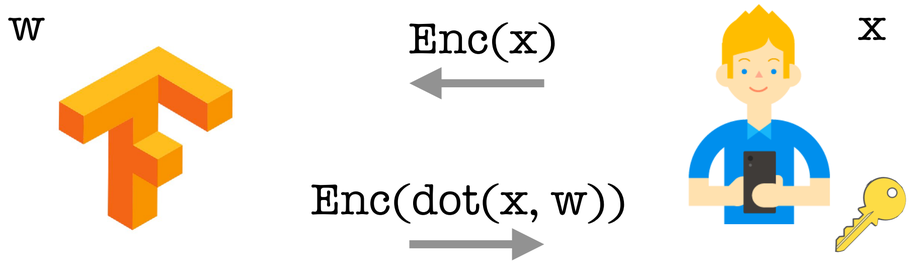


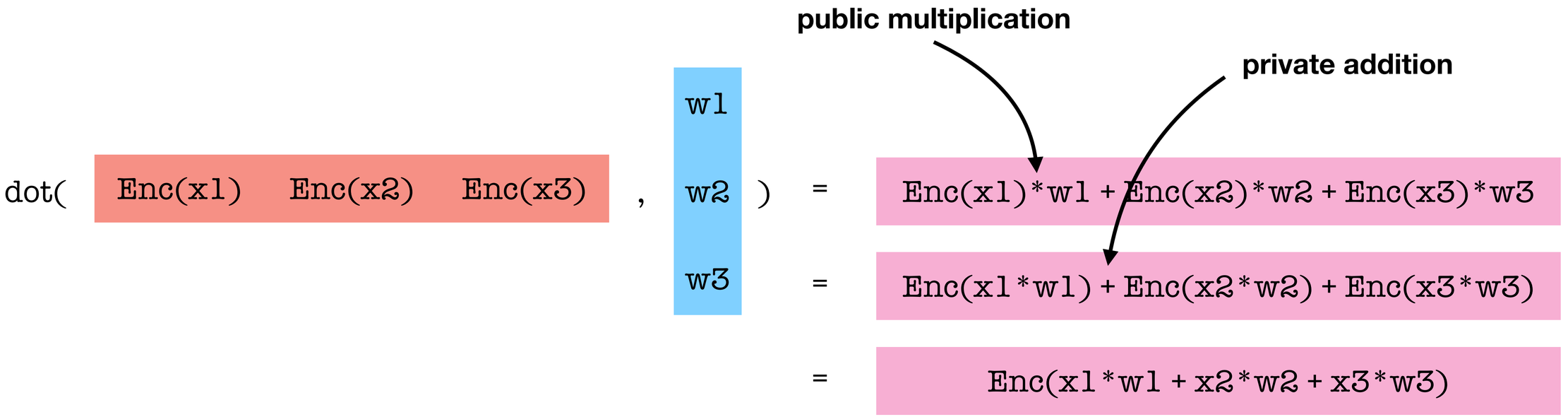
public multiplication

dot(Enc(x1) Enc(x2) Enc(x3) , w1 w2 w3) = Enc(x1)*w1 + Enc(x2)*w2 + Enc(x3)*w3

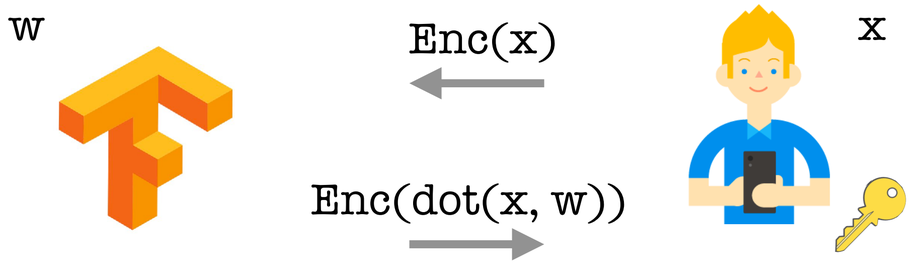
= Enc(x1*w1) + Enc(x2*w2) + Enc(x3*w3)

… using Homomorphic Encryption





… using Homomorphic Encryption



homomorphic encryption scheme

public multiplication

private addition

dot(Enc(x1) Enc(x2) Enc(x3) , w1 w2 w3) = Enc(x1)*w1 + Enc(x2)*w2 + Enc(x3)*w3

= Enc(x1*w1) + Enc(x2*w2) + Enc(x3*w3)

= Enc(x1*w1 + x2*w2 + x3*w3)

… using Secret Sharing

w

x

---

w

… using Secret Sharing

w

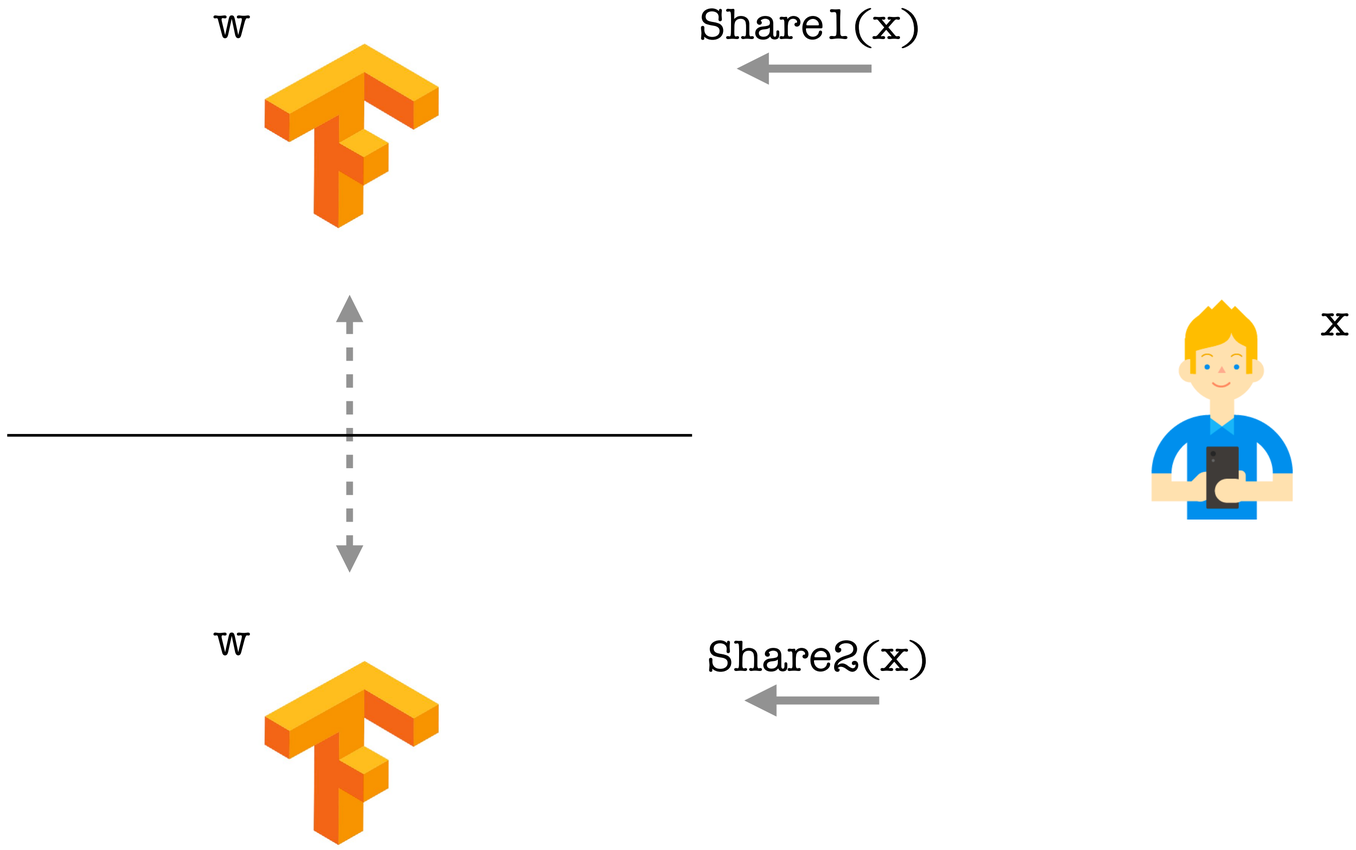
Share1(x)

x

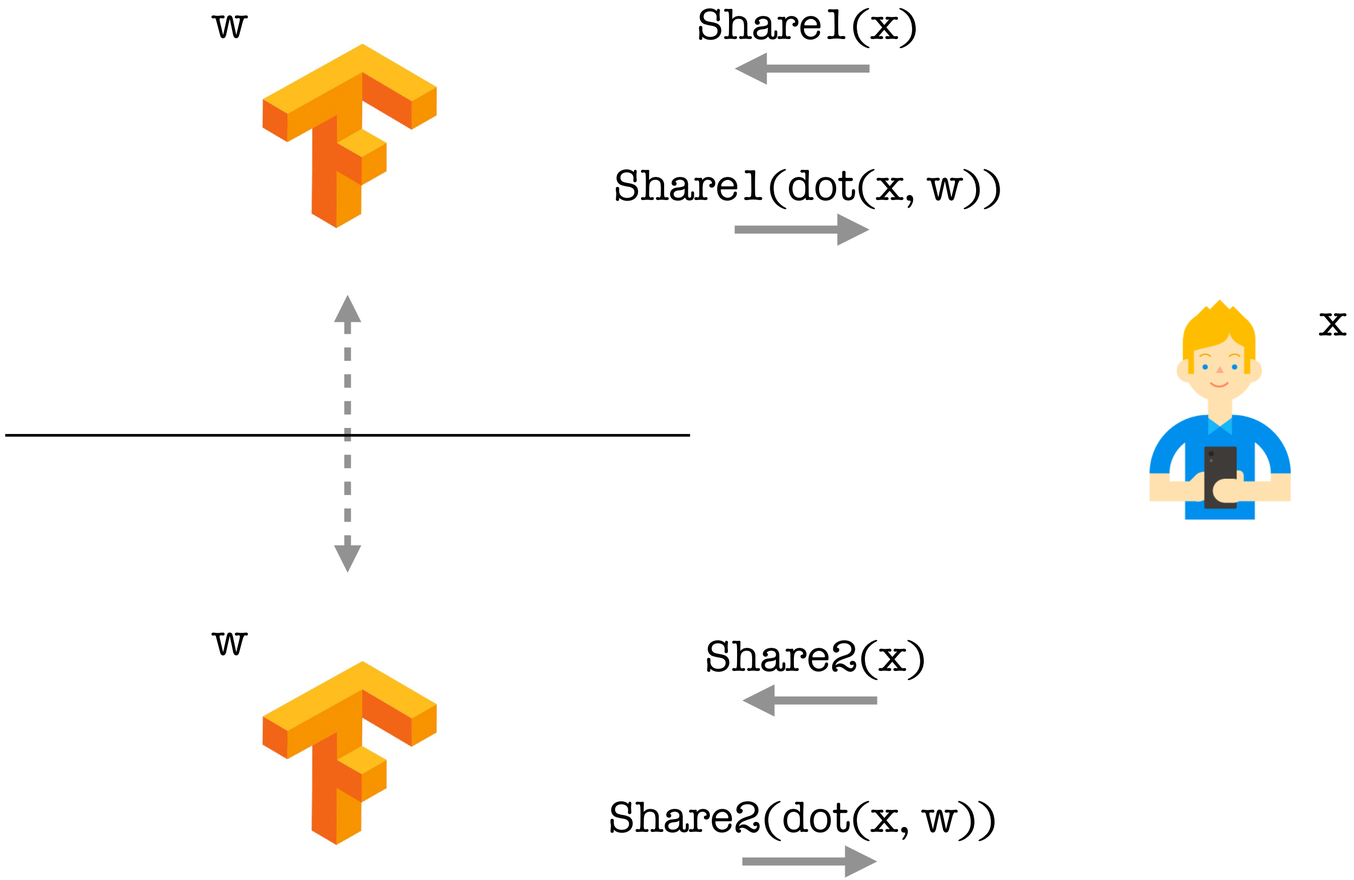
w

Share2(x)

… using Secret Sharing



… using Secret Sharing



… using Secret Sharing

w

Sharel(x)

Sharel(dot(x,w))

homomorphic secret sharing

public multiplication

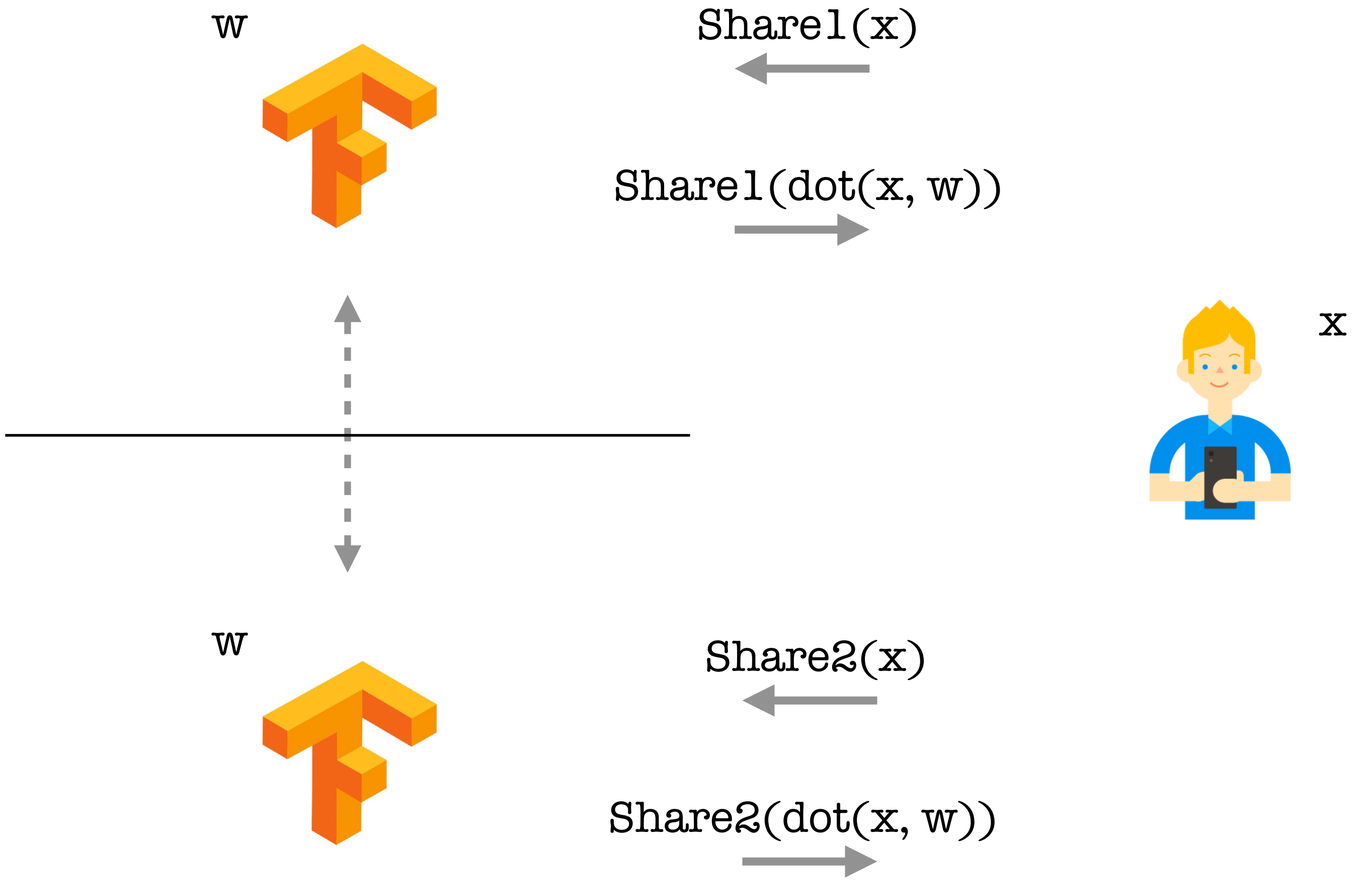
private addition

dot(Sharel(x0) Sharel(x1) Sharel(x2) , w0 w1 w2) = Sharel(x0)*w0 + Sharel(x1)*w1 + Sharel(x2)*w2

= Sharel(x0*w0) + Sharel(x1*w1) + Sharel(x2*w2)

= Sharel(x0*w0 + x1*w1 + x2*w2)

… using Secret Sharing



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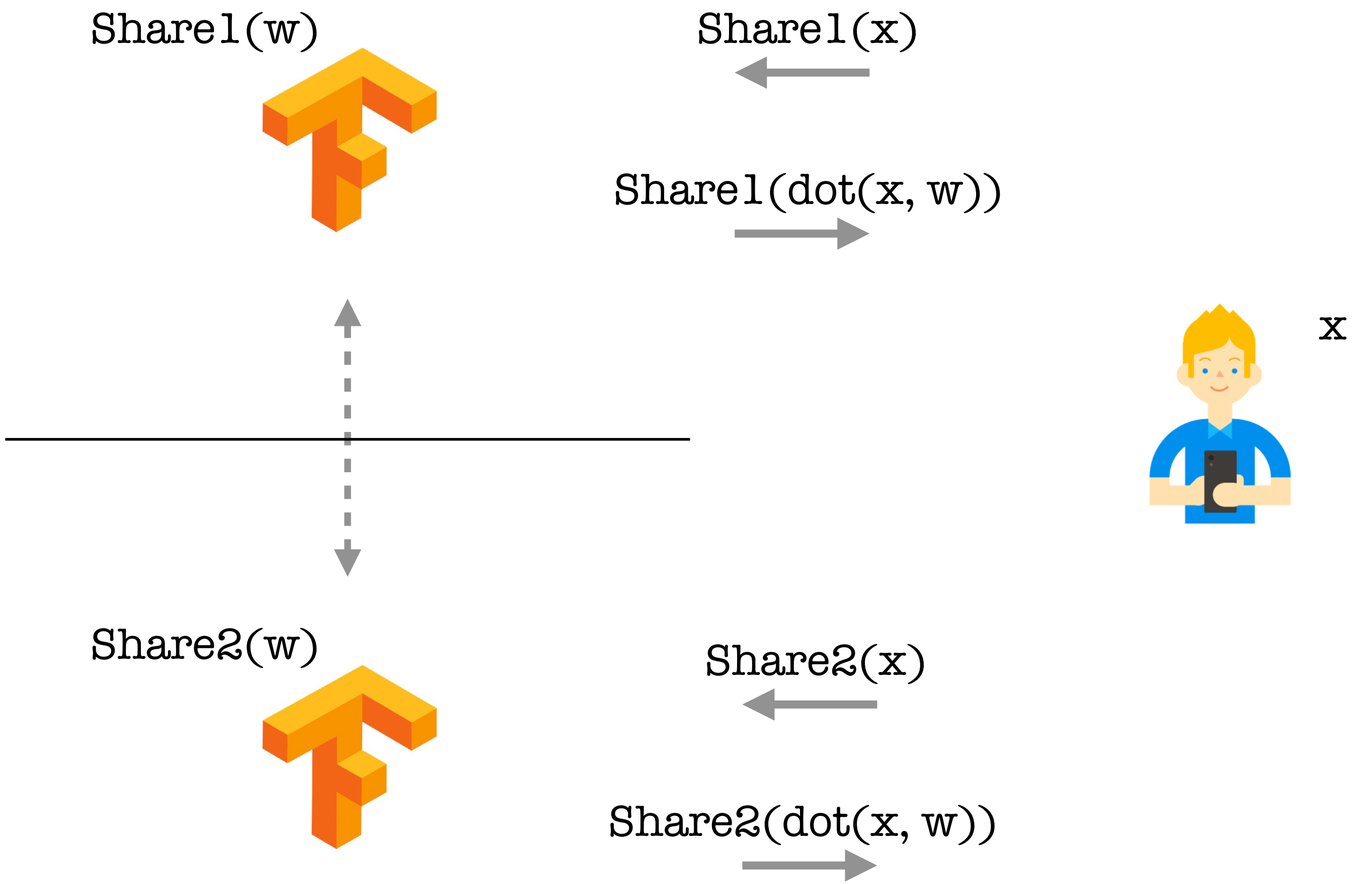


… using Secret Sharing

Sharel(w)

Sharel(x)

Sharel(dot(x, w))

x

private multiplication

dot(Sharel(x0) Sharel(x1) Sharel(x2) , Share(w0) Share(w1) Share(w2)) =

Sharel(x0)*Share(w0) + …

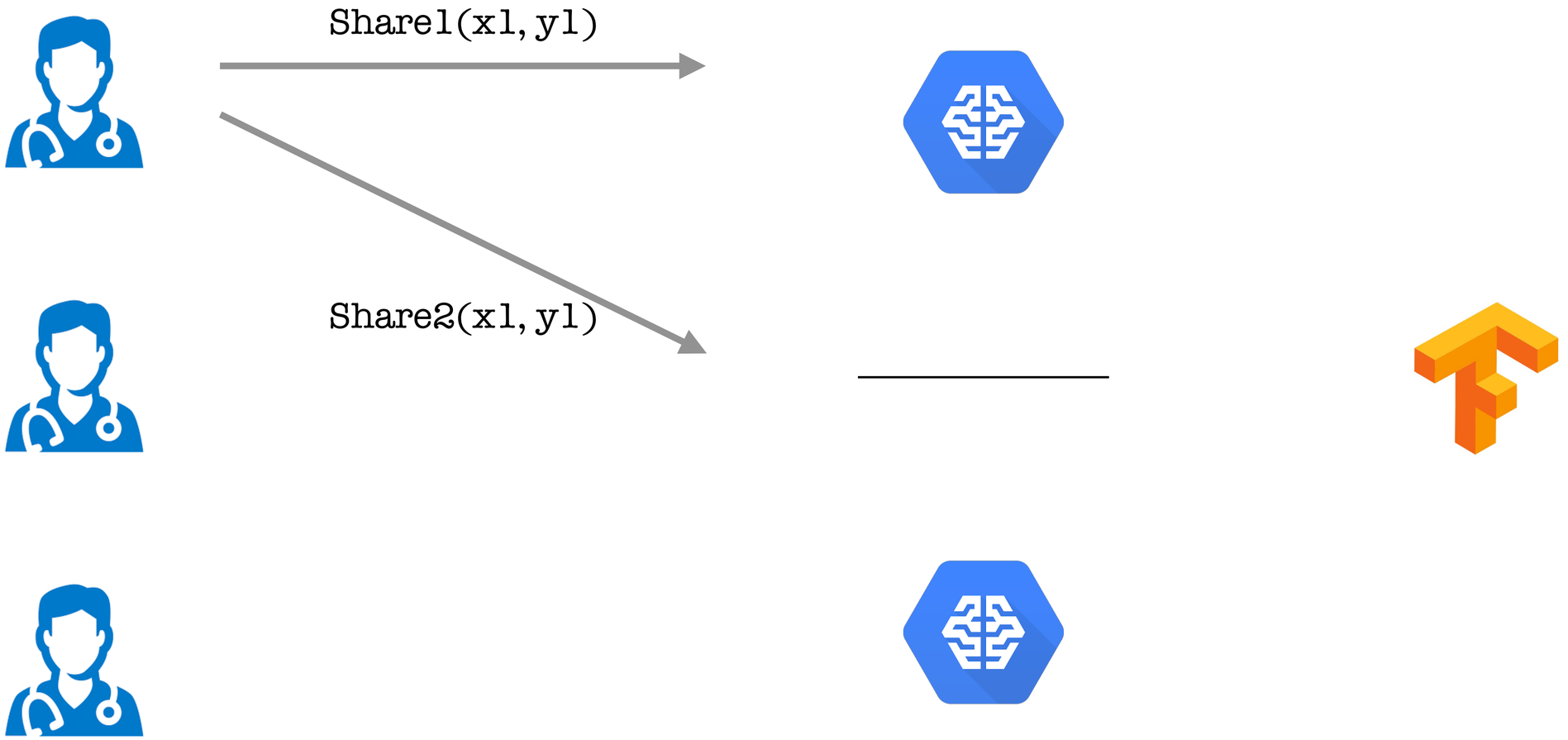
= Sharel(x0*w0) + …

= Sharel(x0*w0 + x1*w1 + x2*w2)

Training

Server-Aided

Server-Aided



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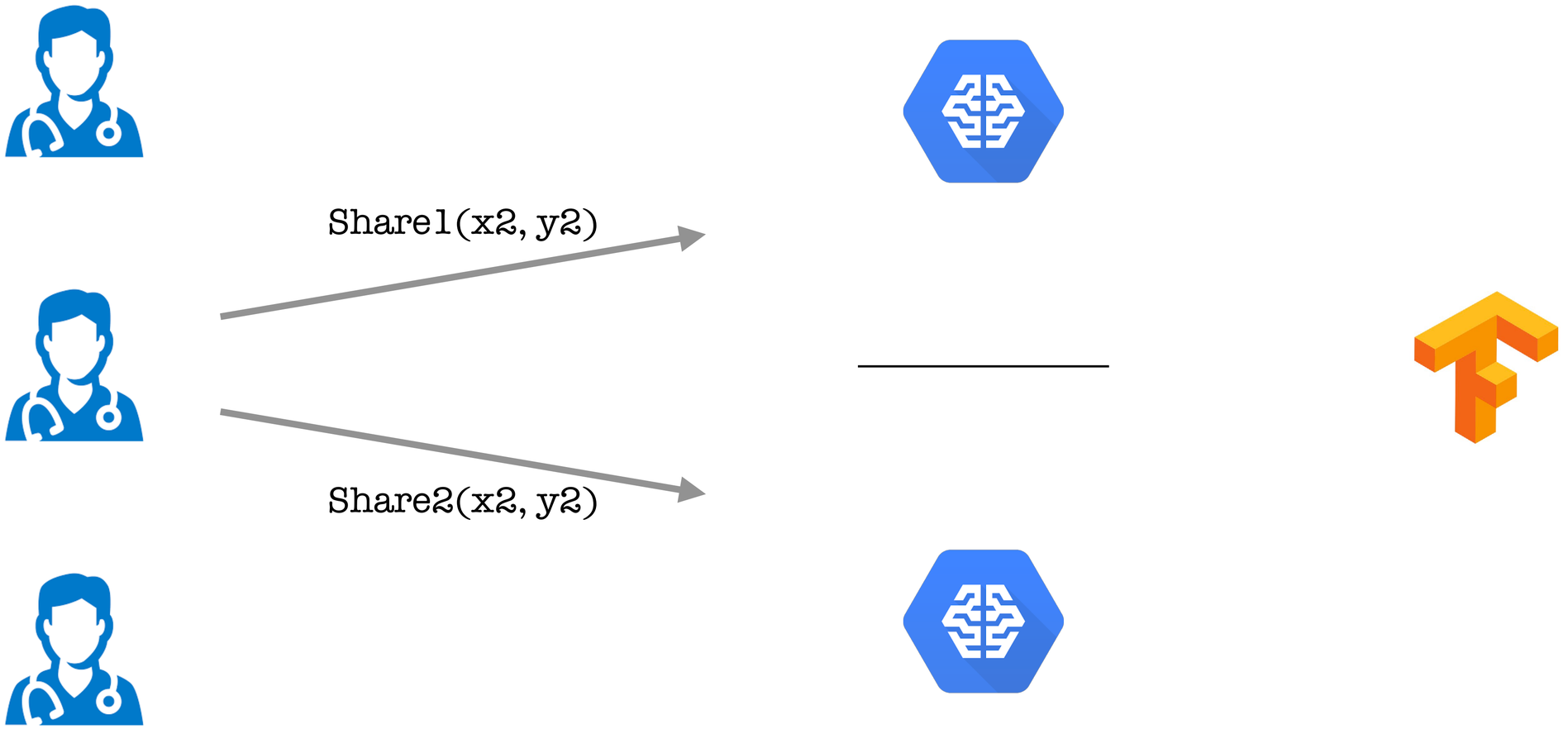

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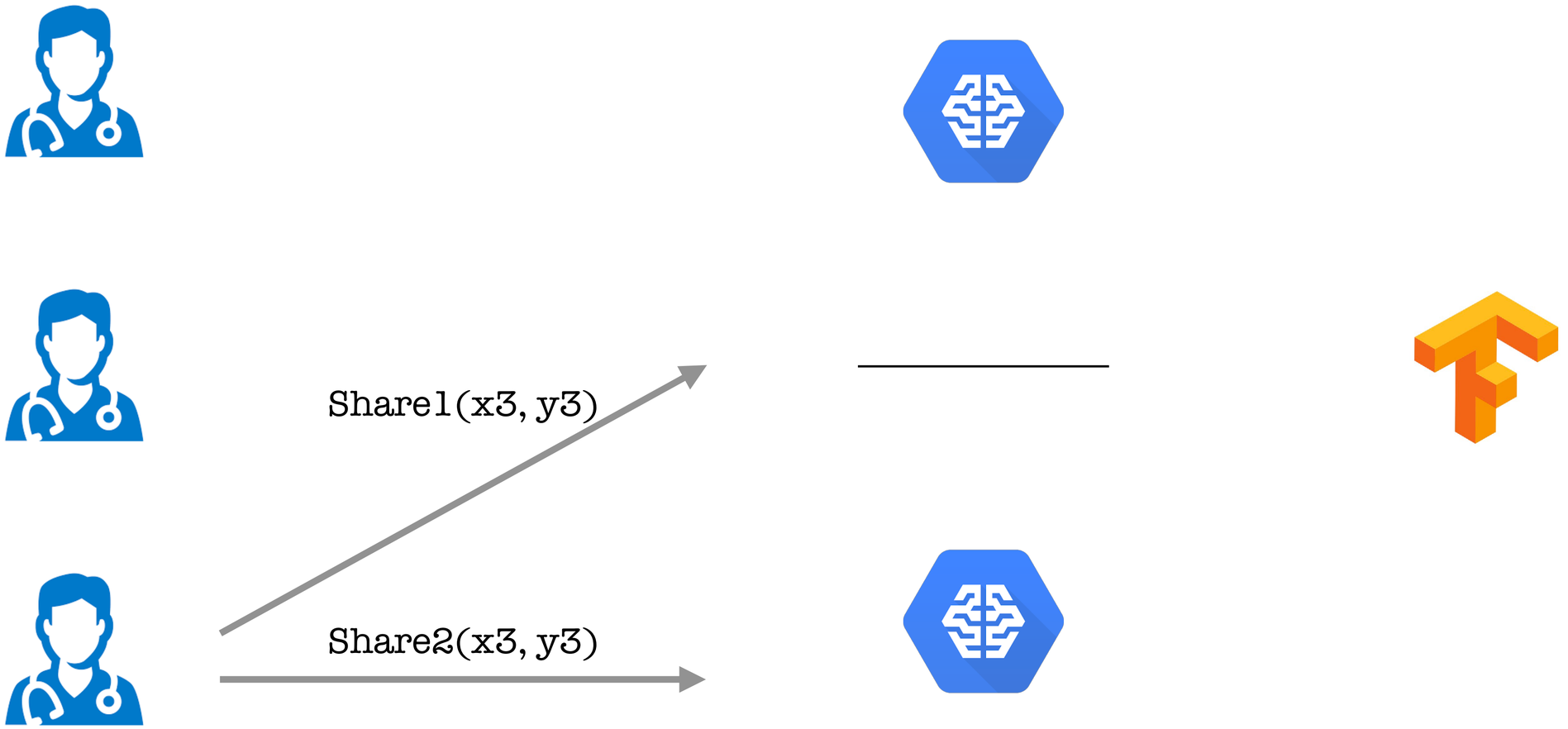

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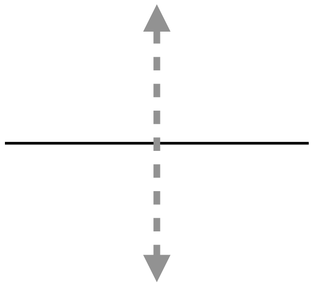

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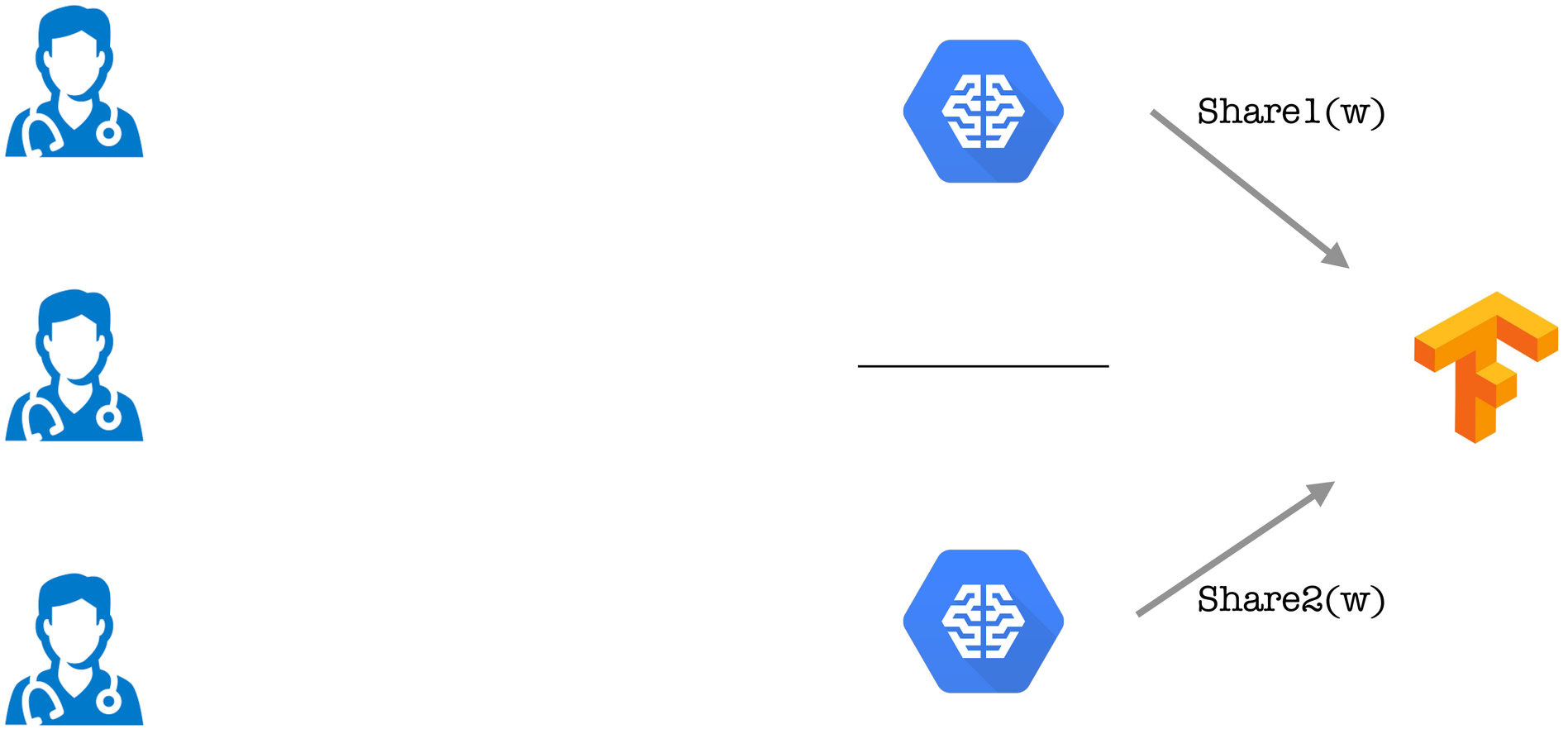

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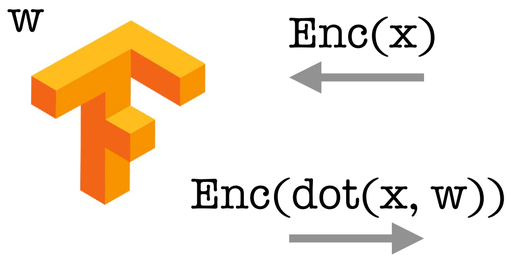

Server-Aided

Server-Aided

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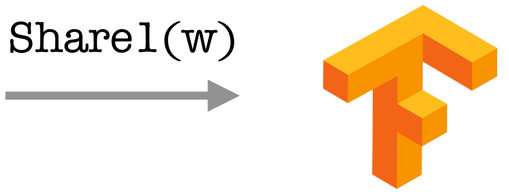
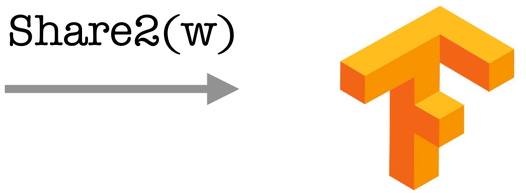
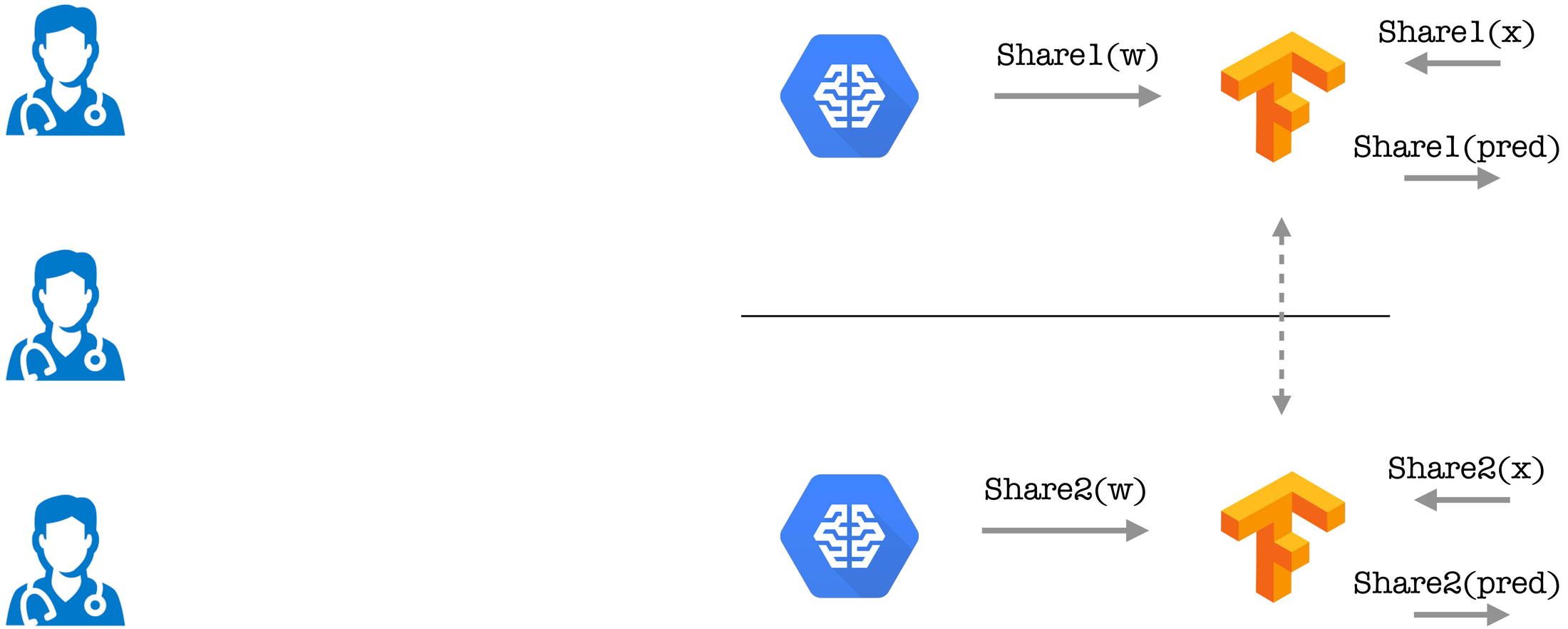


Share2(w)



Server-Aided



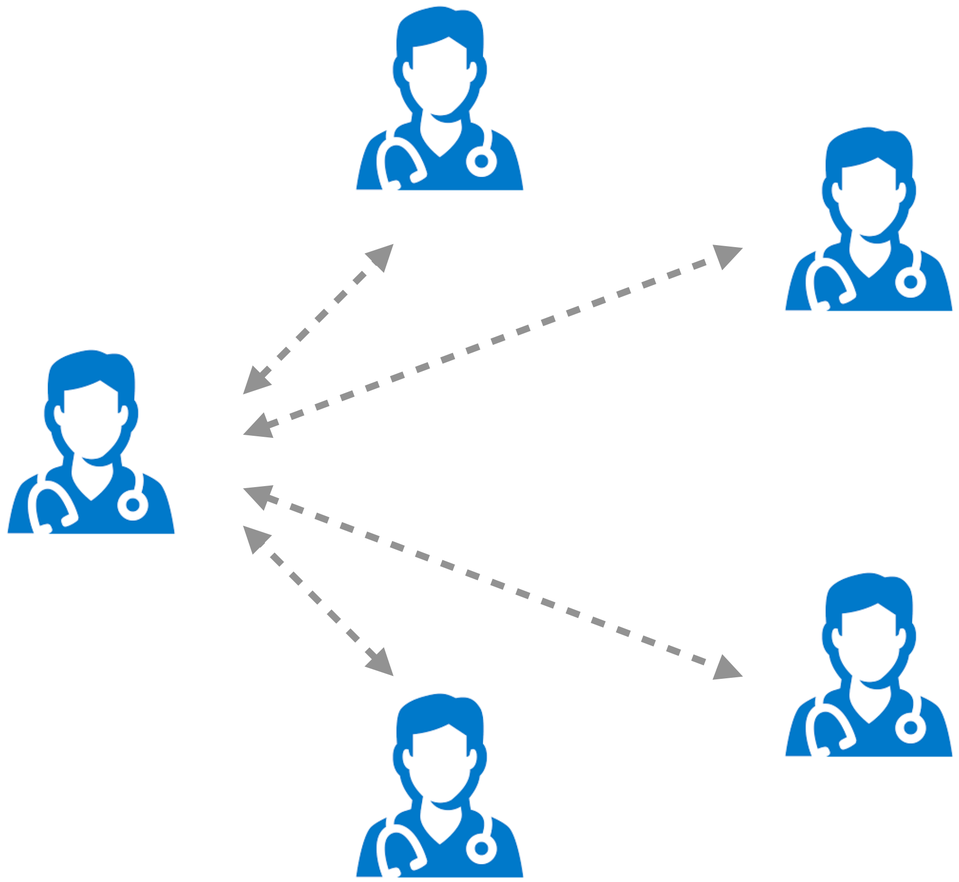
Multi-Party



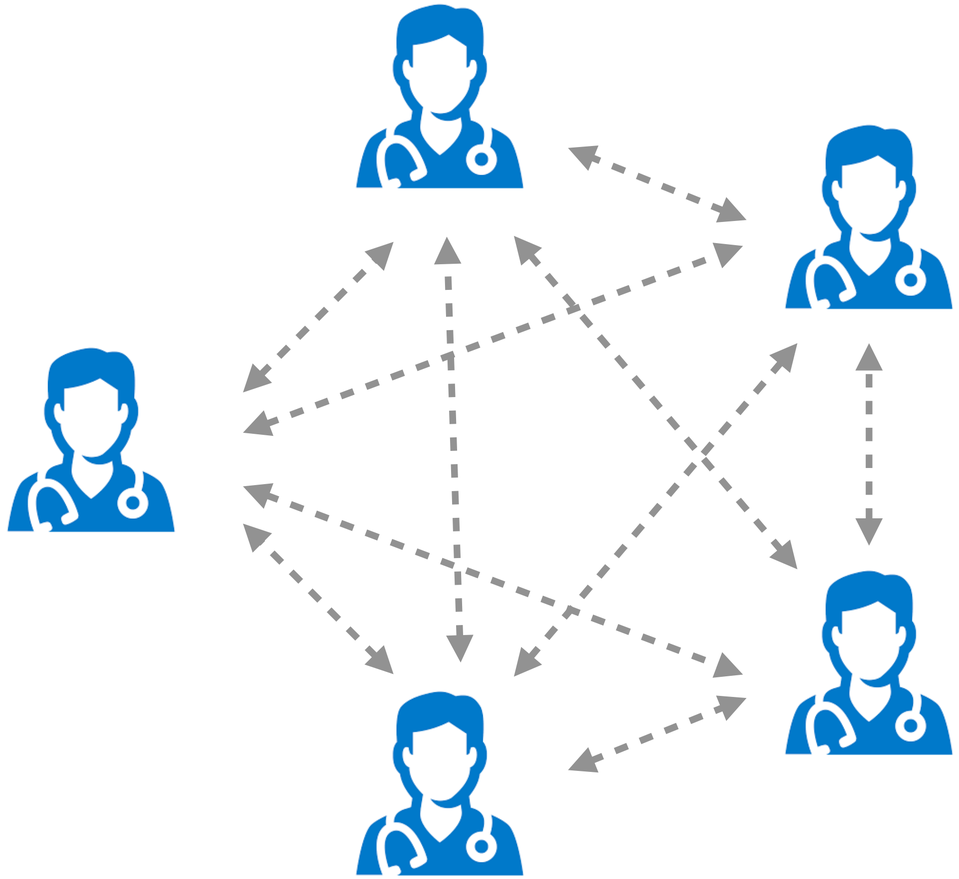




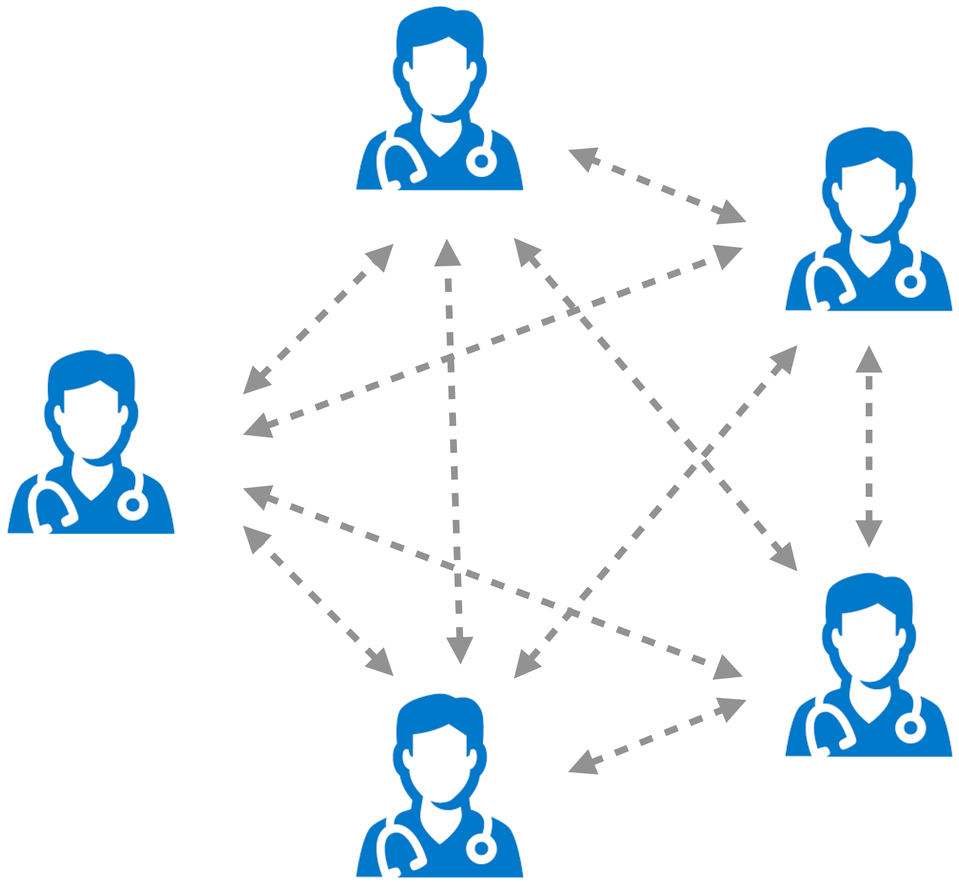
Multi-Party



Multi-Party



Multi-Party



Share1(w)

Share2(w)

Making It Accessible

Projects and Literature

Projects and Literature

Recent research papers using secure computation

***CryptoNets**: Applying Neural Networks to Encrypted Data with High Throughput and Accuracy*, Dowlin et al.

***SecureML**: A System for Scalable Privacy-Preserving Machine Learning*, Mohassel and Zhang

***DeepSecure**: Scalable Provably-Secure Deep Learning*, Rouhani et al.

***Gazelle**: A Low Latency Framework for Secure Neural Network Inference*, Juvekar et al.

***ABY3**: A Mixed Protocol Framework for Machine Learning*, Mohassel and Rindal

***SecureNN**: Efficient and Private Neural Network Training*, Wagh et al.

***Blind Justice**: Fairness with Encrypted Sensitive Attributes*, Kilbertus et al.

(also great summary in https://eprint.iacr.org/2017/1190)

Projects and Literature

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(also great summary in https://eprint.iacr.org/2017/1190)

Secure computation frameworks

***SCALE-MAMBA** (https://homes.esat.kuleuven.be/~nsmart/SCALE/)*

***MP-SPDZ** (https://github.com/n1analytics/MP-SPDZ)*

***ABY** (https://github.com/encryptogroup/ABY)*

***OblivC** (http://oblivc.org/)*

(much more at https://github.com/rdragos/awesome-mpc)

Projects and Literature

Recent research papers using secure computation

***CryptoNets**: Applying Neural Networks to Encrypted Data with High Throughput and Accuracy*, Dowlin et al.

***SecureML**: A System for Scalable Privacy-Preserving Machine Learning*, Mohassel and Zhang

***DeepSecure**: Scalable Provably-Secure Deep Learning*, Rouhani et al.

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Specialised projects

***tf-encrypted** (https://github.com/mortendahl/tf-encrypted)*

***PySyft** (https://github.com/OpenMined/PySyft)*

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(techniques, protocols, trust)

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need for common language

tf-encrypted

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open source project for exploring and experimenting with
privacy-preserving machine learning in TensorFlow

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separate concerns, take expertise out of equation,
and provide tight integration with ecosystem

Private Prediction with tf-encrypted

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import tensorflow as tf

def provide_weights():""" Load from disk """
def provide_input(): """ Pre-process """
def receive_output(logits): return tf.Print([], [tf.argmax(logits)])

# get model weights
w0, b0, w1, b1, w2, b2 = provide_weights()

# get prediction input
x = provide_input()

# compute prediction
layer0 = tf.nn.relu((tf.matmul(x, w0) + b0))
layer1 = tf.nn.relu((tf.matmul(layer0, w1) + b1))
logits = tf.matmul(layer2, w2) + b2

# process result of prediction
prediction_op = receive_output(logits)

# run graph execution in a tf.Session
with tf.Session() as sess:
    sess.run(tf.global_variables_initializer())
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# get model weights as private tensors from owner
w0, b0, w1, b1, w2, b2 = tfe.define_private_input("model-owner", provide_weights)

# get prediction input as private tensors from client
x = tfe.define_private_input("prediction-client", provide_input)

# compute private prediction on servers
layer0 = tfe.relu((tfe.matmul(x, w0) + b0))
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Privacy-preserving ML mitigate **bottlenecks** and
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Focus on **usability** and **integration**

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Thank you!