Google Cloud

A Tutorial on Remote Data Science

Google Cloud Applied ML Summit

Solving for the future.

06/10/21

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Research Scientist
Google DeepMind

Is it possible to:

answer questions using data we cannot see?

What do tumors look like in humans?

Source: Wikipedia Commons

What do tumors look like in humans?

Step 1: Download millions of tumor images.

Source: Wikipedia Commons

What do tumors look like in humans?

Step 0: Buy a dataset from a hospital.

Step 1: Download millions of tumor images.

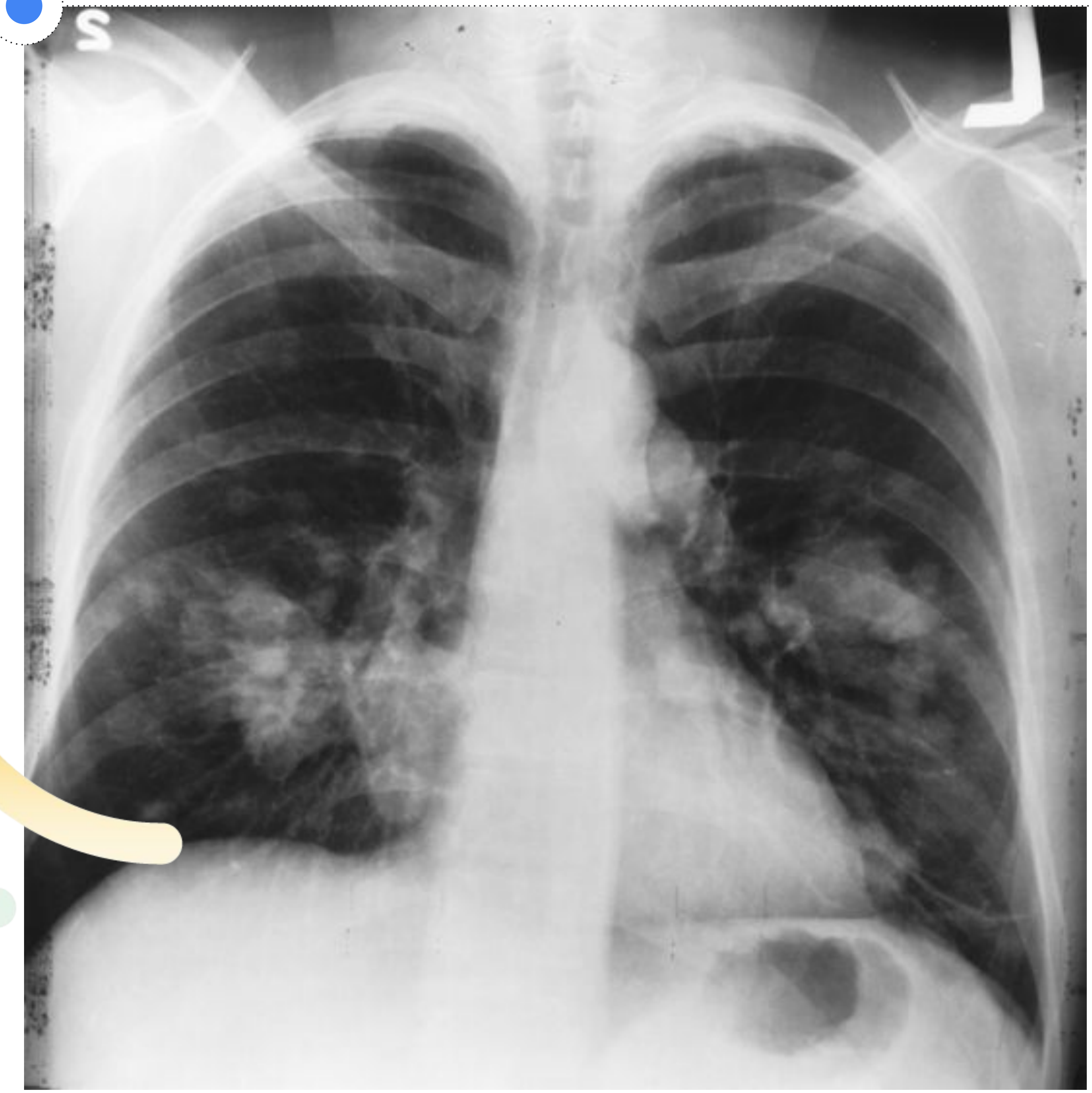
Source: Wikipedia Commons

What do tumors look like in humans?

Step -1: Persuade a VC.

Step 0: Buy a dataset from a hospital.

Step 1: Download millions of tumor images.



Source: Wikipedia Commons

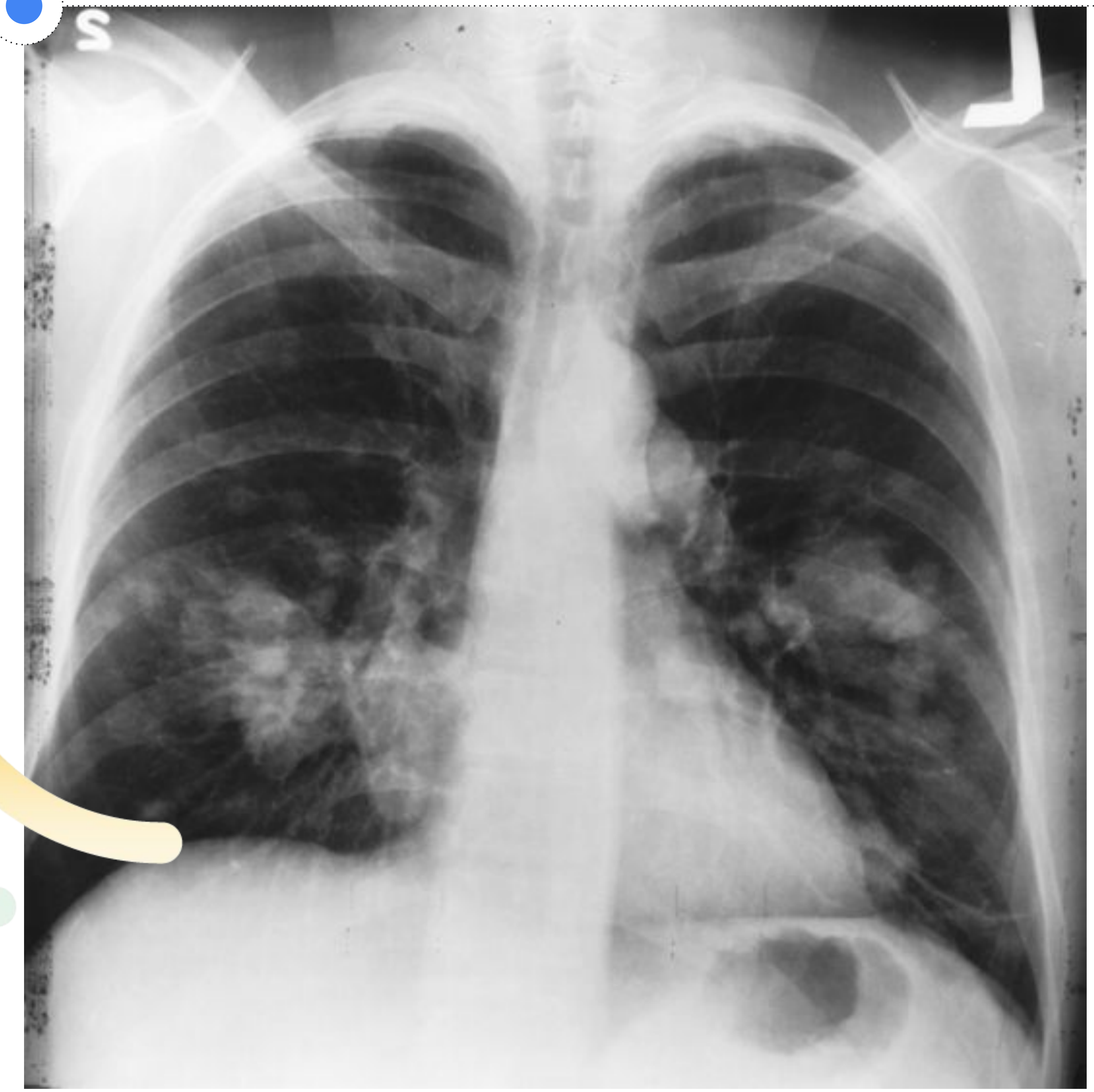
What do tumors look like in humans?

Step -2: Create a business plan!

Step -1: Persuade a VC.

Step 0: Buy a dataset from a hospital.

Step 1: Download millions of tumor images.



Source: Wikipedia Commons

What do tumors look like in humans?

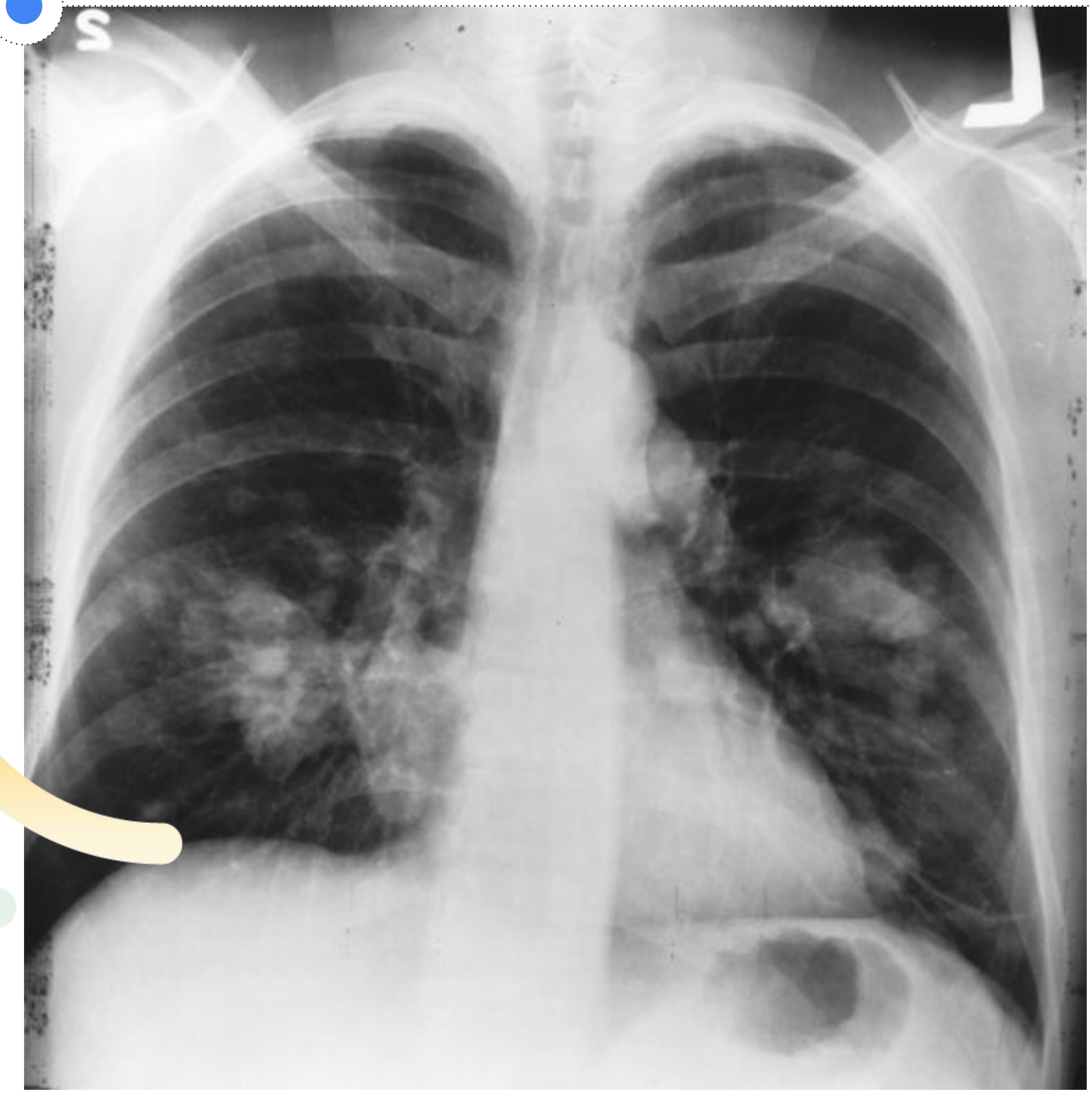
Step -3: Find a business partner!

Step -2: Create a business plan!

Step -1: Persuade a VC.

Step 0: Buy a dataset from a hospital.

Step 1: Download millions of tumor images.



Source: Wikipedia Commons

What do tumors look like in humans?

Step -4: Spam all my classmates on LinkedIn!

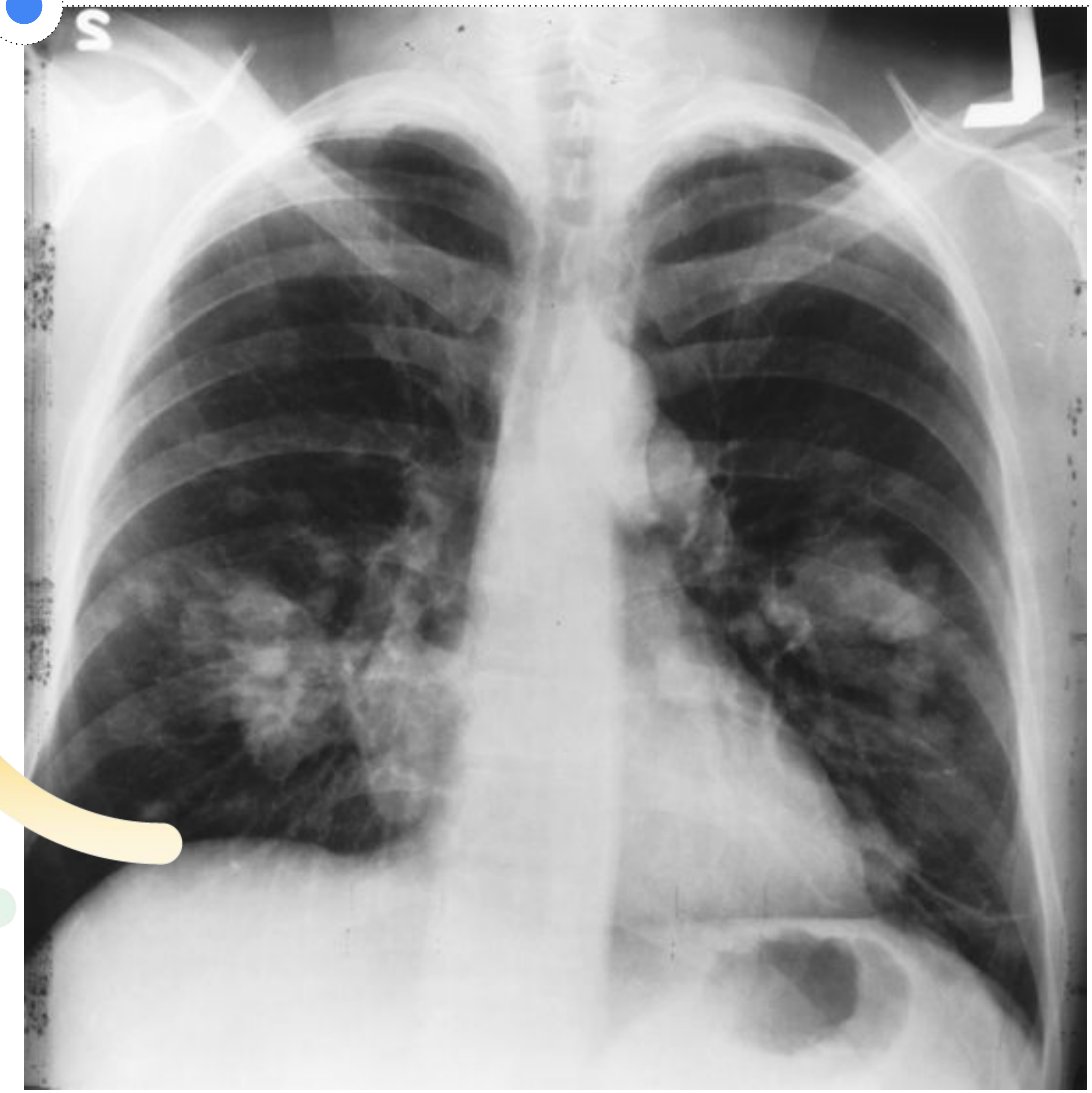
Step -3: Find a business partner!

Step -2: Create a business plan!

Step -1: Persuade a VC.

Step 0: Buy a dataset from a hospital.

Step 1: Download millions of tumor images.



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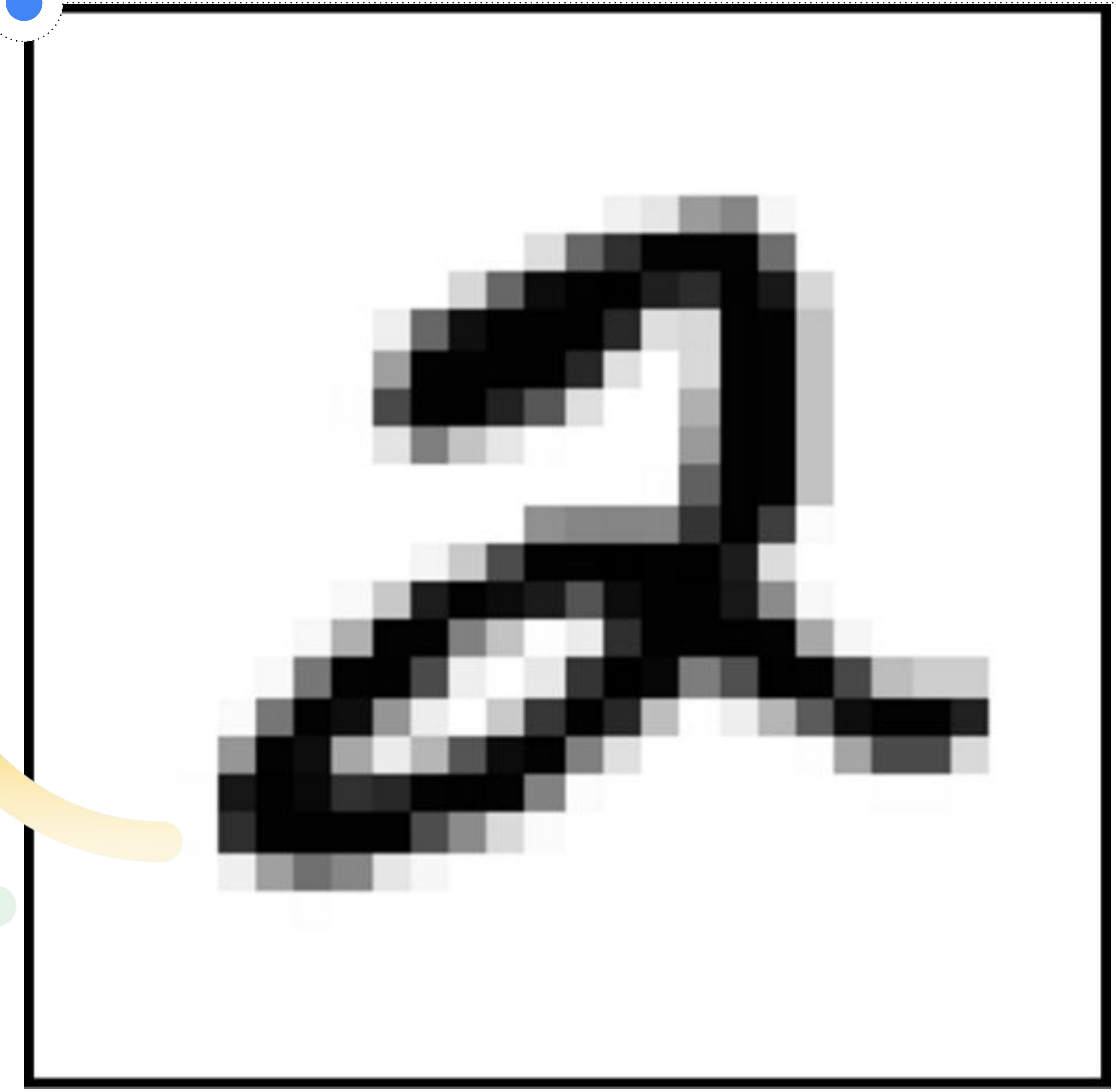
What do handwritten digits look like?

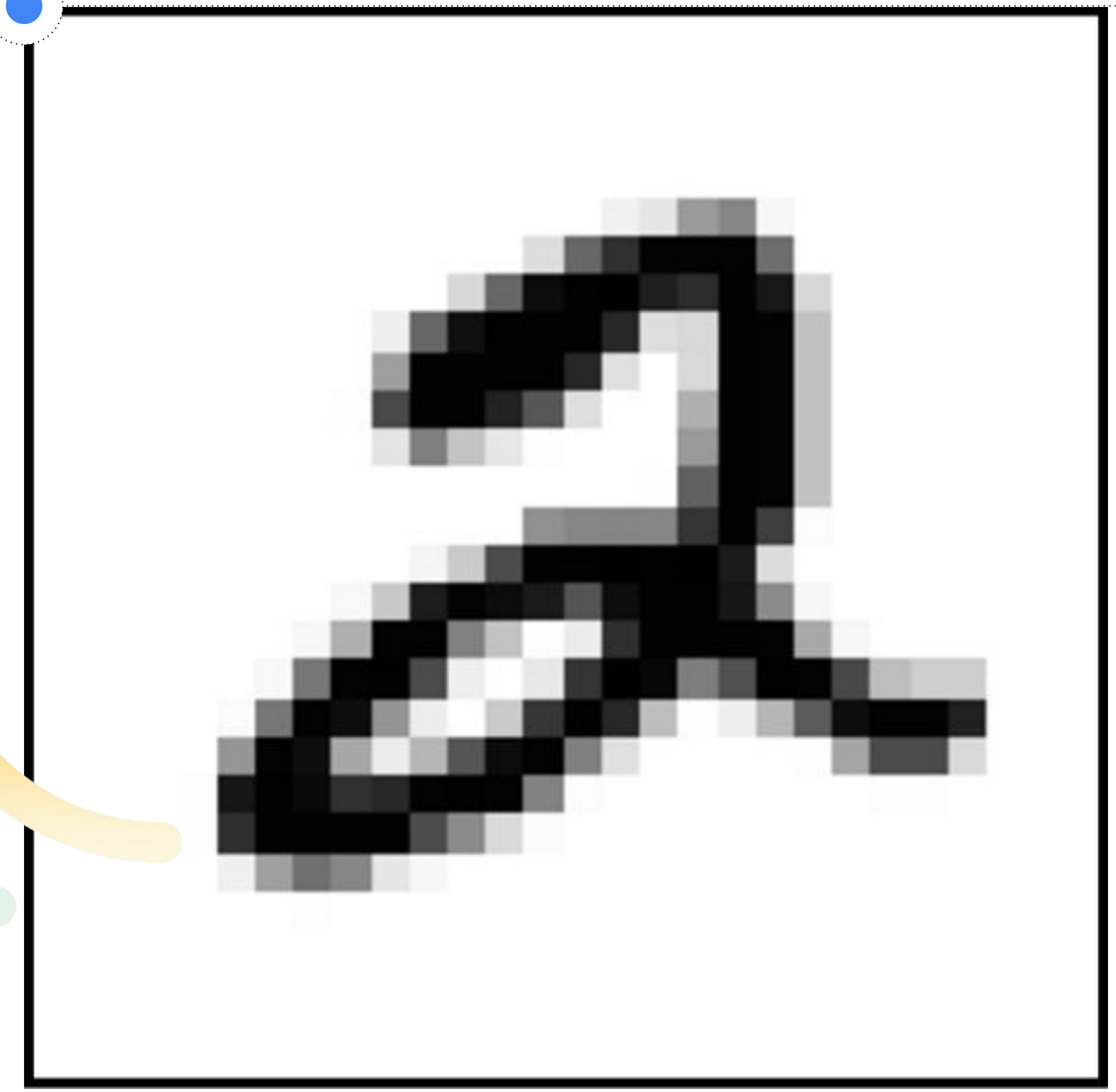


What do handwritten digits look like?

Step 1: Download data

Step 2: Download SOTA training script

Step 3: Run script.



Getting access to private data is HARD!

We SOLVE tasks which are accessible:

ImageNet

MNIST

CIFAR-10

Librispeech

WikiText-103

WMT

We SOLVE tasks which are accessible:

ImageNet

MNIST

CIFAR-10

Librispeech

WikiText-103

WMT

... but what about?

Cancer

Alzheimer’s

Dementia

Depression

Anxiety

... the Common Cold?

Is it possible to:

answer questions using data we cannot see?

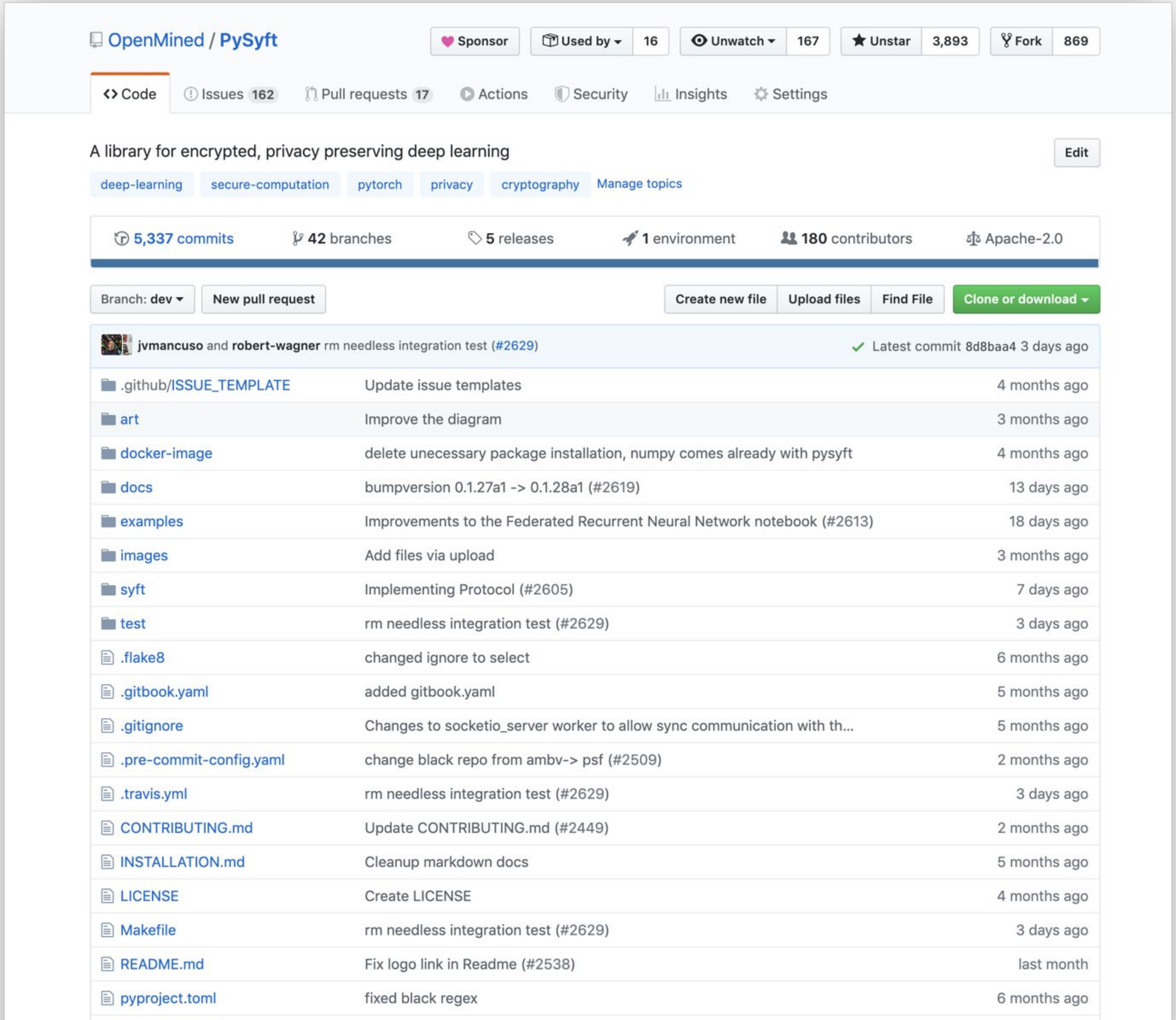
```
atrask:~  pip install the-worlds-data
```

OpenMined


OpenMind is a Community
Google Cloud

PySyft

PySyft


OpenMined / PySyft
Sponsor
Used by 16
Unwatch 167
Unstar 3,893
Fork 869
Code
Issues 162
Pull requests 17
Actions
Security
Insights
Settings
A library for encrypted, privacy preserving deep learning
Edit
deep-learning
secure-computation
pytorch
privacy
cryptography
Manage topics
5,337 commits
42 branches
5 releases
1 environment
180 contributors
Apache-2.0
Branch: dev
New pull request
Create new file
Upload files
Find File
Clone or download
jvmancuso and robert-wagner rm needless integration test (#2629)
Latest commit 8d8baa4 3 days ago
.github/ISSUE_TEMPLATE	Update issue templates	4 months ago
art	Improve the diagram	3 months ago
docker-image	delete unecessary package installation, numpy comes already with pysyft	4 months ago
docs	bumpversion 0.1.27a1 -> 0.1.28a1 (#2619)	13 days ago
examples	Improvements to the Federated Recurrent Neural Network notebook (#2613)	18 days ago
images	Add files via upload	3 months ago
syft	Implementing Protocol (#2605)	7 days ago
test	rm needless integration test (#2629)	3 days ago
.flake8	changed ignore to select	6 months ago
.gitbook.yaml	added gitbook.yaml	5 months ago
.gitignore	Changes to socketio_server worker to allow sync communication with th...	5 months ago
.pre-commit-config.yaml	change black repo from ambv-> psf (#2509)	2 months ago
.travis.yml	rm needless integration test (#2629)	3 days ago
CONTRIBUTING.md	Update CONTRIBUTING.md (#2449)	2 months ago
INSTALLATION.md	Cleanup markdown docs	5 months ago
LICENSE	Create LICENSE	4 months ago
Makefile	rm needless integration test (#2629)	3 days ago
README.md	Fix logo link in Readme (#2538)	last month
pyproject.toml	fixed black regex	6 months ago

TOOL

01

Remote Execution

Tool 1: Remote Execution

Tool 1: Remote Execution

```
In [1]: import syft as sy
        import torch as th
        hook = sy.TorchHook(th)
```

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In [1]: import syft as sy
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In [2]: hospital_datacenter = sy.VirtualWorker(hook, id="May Clinic")
```

Tool 1: Remote Execution

```
In [1]: import syft as sy
        import torch as th
        hook = sy.TorchHook(th)

In [2]: hospital_datacenter = sy.VirtualWorker(hook, id="May Clinic")

In [5]: x = th.tensor([1,3,4,5])
        x = x.send(hospital_datacenter)
        x

Out[5]: (Wrapper)>[PointerTensor | me:20069769489 -> May Clinic:27535193014]
```

Tool 1: Remote Execution

```
In [1]: import syft as sy
        import torch as th
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Out[5]: (Wrapper)>[PointerTensor | me:20069769489 -> May Clinic:27535193014]

In [ ]: x.
        x.abs
        x.abs_
        x.acos
        x.acos_
        x.add
        x.add_
        x.addbmm
        x.addbmm_
        x.addcdiv

In [
```

Tool 1: Remote Execution

```
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In [6]: y = x + x
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Out[5]: (Wrapper)>[PointerTensor | me:20069769489 -> May Clinic:27535193014]

In [6]: y = x + x

In [7]: y

Out[7]: (Wrapper)>[PointerTensor | me:52194974528 -> May Clinic:13992236415]
```

Tool 1: Remote Execution

```
In [1]: import syft as sy
        import torch as th
        hook = sy.TorchHook(th)

In [2]: hospital_datacenter = sy.VirtualWorker(hook, id="May Clinic")

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In [6]: y = x + x

In [7]: y

Out[7]: (Wrapper)>[PointerTensor | me:52194974528 -> May Clinic:13992236415]

In [8]: y.get()

Out[8]: tensor([ 2,  6,  8, 10])
```

Tool 1: Remote Execution

Pros:

RPC: Data remains on remote machine

Cons:

How do we do data science without seeing the data?

Top Contributors

TOOL

02

Search and Example Data

Tool 2: Search and Example Data

```
In [3]: grid = GridClient(url="http://data.bighospital.org",
                          username="atrask",
                          password="*********")

        Connecting to grid... Connected!
```

PyGrid

Tool 2: Search and Example Data

```
In [3]: grid = GridClient(url="http://data.bighospital.org",
                          username="atrask",
                          password="*********")

        Connecting to grid... Connected!

In [5]: diabetes_datasets = grid.search("#diabetes")

        Found 12 results in total.

        Tag Profile:
                dataset found 12
                diabetes found 12
                #diabetes found 12
                #data found 6
                #target found 6
```

Tool 2: Search and Example Data

```
In [3]: grid = GridClient(url="http://data.bighospital.org",
                          username="atrask",
                          password="*********")

        Connecting to grid... Connected!

In [5]: diabetes_datasets = grid.search("#diabetes")

        Found 12 results in total.

        Tag Profile:
                dataset found 12
                diabetes found 12
                #diabetes found 12
                #data found 6
                #target found 6

In [10]: dataset = diabetes_datasets[0]
         dataset

Out[10]: (Wrapper)>[PointerTensor | me:42698983859 -> andy:47710699917]
                Tags: #data dataset diabetes #diabetes
                Shape: torch.Size([73, 10])
                Description: Diabetes dataset...
```

Tool 2: Search and Example Data

```
In [12]: print(dataset.description)

         Diabetes dataset
         ================

         Notes
         -----

         Ten baseline variables, age, sex, body mass index, average blood
         pressure, and six blood serum measurements were obtained for each of n =
         442 diabetes patients, as well as the response of interest, a
         quantitative measure of disease progression one year after baseline.

         Data Set Characteristics:

           :Number of Instances: 442

           :Number of Attributes: First 10 columns are numeric predictive values
```

Tool 2: Search and Example Data

```
For more information see:
Bradley Efron, Trevor Hastie, Iain Johnstone and Robert Tibshirani (2004) "Le
ast Angle Regression," Annals of Statistics (with discussion), 407-499.
(http://web.stanford.edu/~hastie/Papers/LARS/LeastAngle_2002.pdf)
```

In [14]:
```
dataset.sample()
```

Out[14]:
```
tensor([[ 9.0156e-03, -4.4642e-02, -2.2373e-02, -3.2066e-02, -4.9727e-02,
         -6.8641e-02,  7.8093e-02, -7.0859e-02, -6.2913e-02, -3.8357e-02],
        [-7.0900e-02, -4.4642e-02,  9.2953e-02,  1.2691e-02,  2.0446e-02,
          4.2527e-02,  7.7881e-04,  3.5983e-04, -5.4544e-02, -1.0777e-03],
        [ 2.3546e-02,  5.0680e-02, -3.0996e-02, -5.6706e-03, -1.6704e-02,
          1.7788e-02, -3.2356e-02, -2.5923e-03, -7.4089e-02, -3.4215e-02],
        [-5.2738e-02,  5.0680e-02,  3.9062e-02, -4.0099e-02, -5.6968e-03,
         -1.2900e-02,  1.1824e-02, -3.9493e-02,  1.6305e-02,  3.0644e-03],
        [ 6.7136e-02, -4.4642e-02, -6.1174e-02, -4.0099e-02, -2.6336e-02,
         -2.4487e-02,  3.3914e-02, -3.9493e-02, -5.6158e-02, -5.9067e-02],
        [ 1.7505e-03, -4.4642e-02, -8.3616e-03, -6.4199e-02, -3.8720e-02,
         -2.4487e-02,  4.4604e-03, -3.9493e-02, -6.4683e-02, -5.4925e-02],
```

Tool 2: Search and Example Data

Pros:

RPC: Data remains on remote machine

Search/Sample: We feature engineer w/ sample data

Cons:

We can steal data using PointerTensor.get()

Top Contributors

TOOL

03

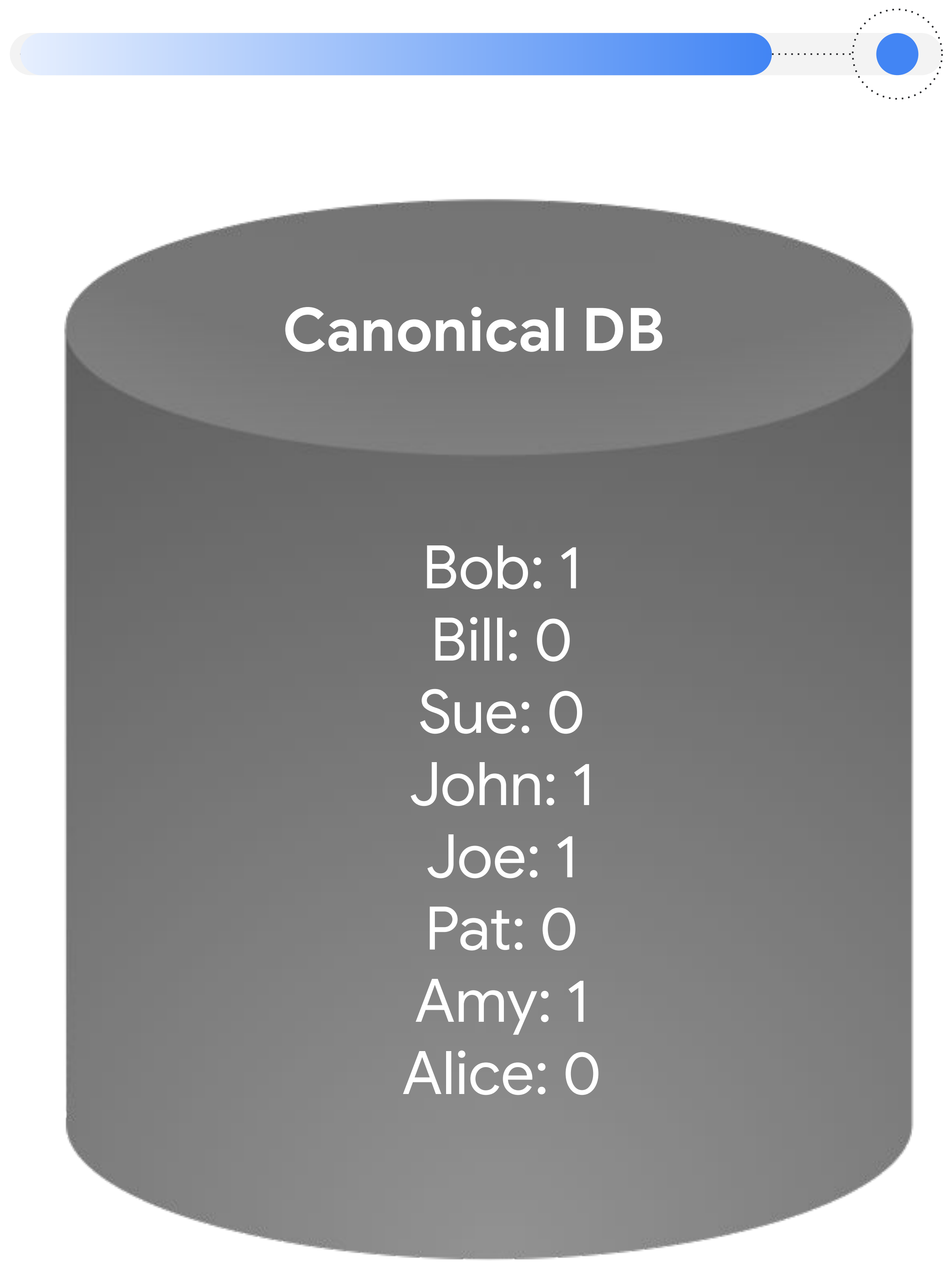
Differential Privacy

Tool 3: Differential Privacy

Goal: ensure statistical analysis doesn't compromise privacy

Query: function(database)

Perfect Privacy: the output of our query is the same between this database and any identical database with one row removed or replaced



Tool 3: Differential Privacy

Tool 3: Differential Privacy

```
In [4]: dataset

Out[4]: (Wrapper)>[PointerTensor | me:74628800218 -> alice:72083270314]
                Tags: diabetes #data #diabetes dataset
                Shape: torch.Size([73, 10])
                Description: Diabetes dataset...
```

Feature in Development

Tool 3: Differential Privacy

Feature in Development

```
In [4]: dataset

Out[4]: (Wrapper)>[PointerTensor | me:74628800218 -> alice:72083270314]
                Tags: diabetes #data #diabetes dataset
                Shape: torch.Size([73, 10])
                Description: Diabetes dataset...

In [5]: dataset.get()

---------------------------------------------------------------------------
CannotRequestPrivateData                  Traceback (most recent call last)
<ipython-input-5-c3af7bfad554> in <module>()
      1 # dataset.get()
----> 2 raise CannotRequestPrivateData()

CannotRequestPrivateData: You just requsted a datapoint which is private or which
depends on data which is private. You can only query private data if noise is add
ed.

Use .get(epsilon) to add appropriate noise.
```

Tool 3: Differential Privacy

Feature in Development

```
In [5]: dataset.get()

---------------------------------------------------------------------------
CannotRequestPrivateData                  Traceback (most recent call last)
<ipython-input-5-c3af7bfad554> in <module>()
      1 # dataset.get()
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CannotRequestPrivateData: You just requsted a datapoint which is private or which
depends on data which is private. You can only query private data if noise is add
ed.

Use .get(epsilon) to add appropriate noise.

In [6]: dataset.get(epsilon=0.1)

Out[6]: tensor([[-0.0891, -0.0446, -0.0418, -0.0194, -0.0662, -0.0743,  0.0081, -0.0395,
                   0.0011, -0.0301],
                 [ 0.0235,  0.0507, -0.0396, -0.0057, -0.0484, -0.0333,  0.0118, -0.0395,
                  -0.1016, -0.0674],
```

Tool 2: Search and Example Data

Pros:

Remote: Data remains on remote machine

Search/Sample: We feature engineer using toy data

DP: formal, rigorous privacy budgeting

Cons:

The data is safe, but the model is put at risk!

What if we need to do a join/computation across multiple data owners?

Feature in Development

Top Contributors

TOOL

04

Secure Multi-party Computation

Tool 4: Secure Multi-Party Computation

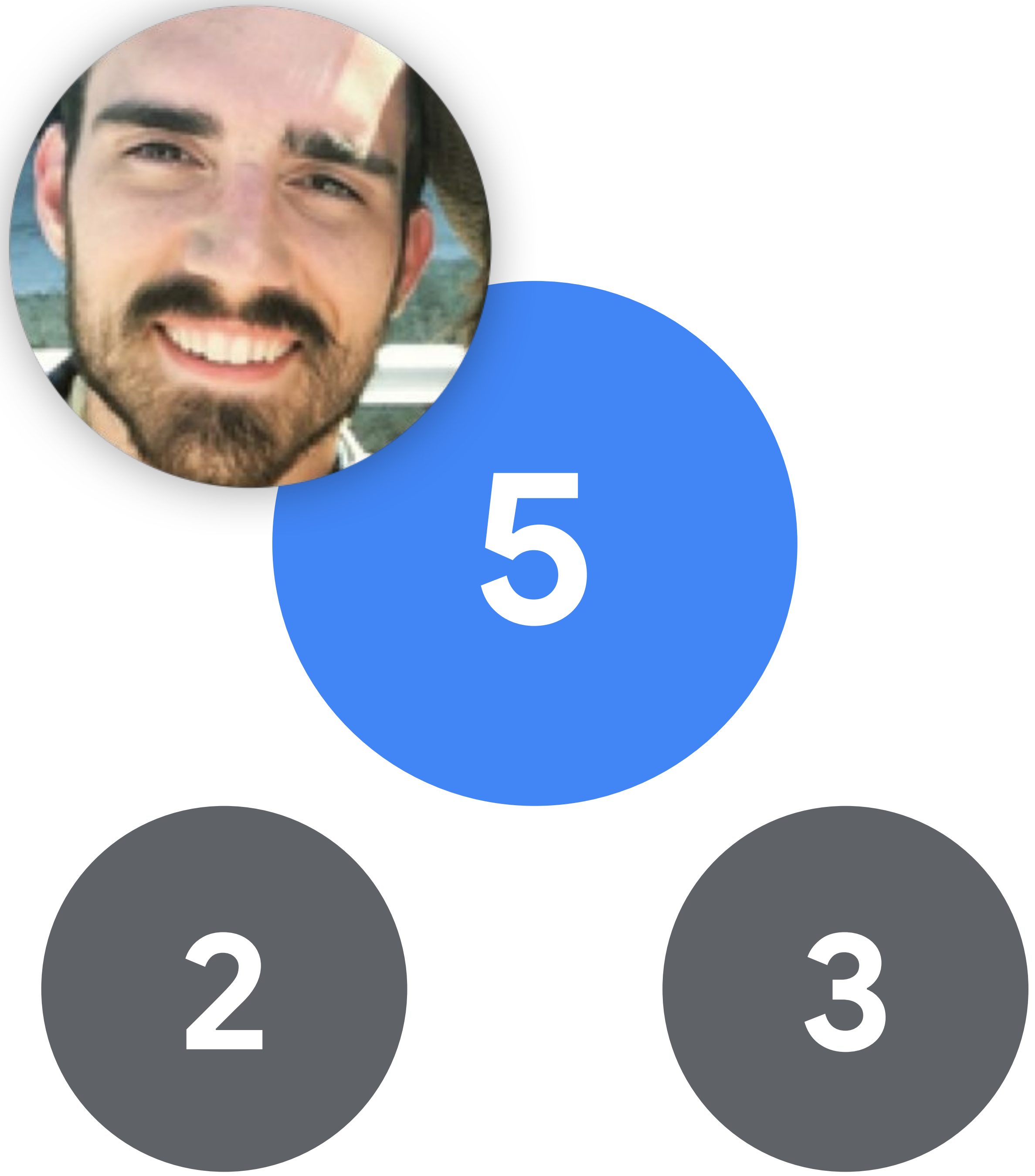
Definition: multiple people can combine their private inputs to compute a function, without revealing their inputs to each other.

Implication: multiple people can:

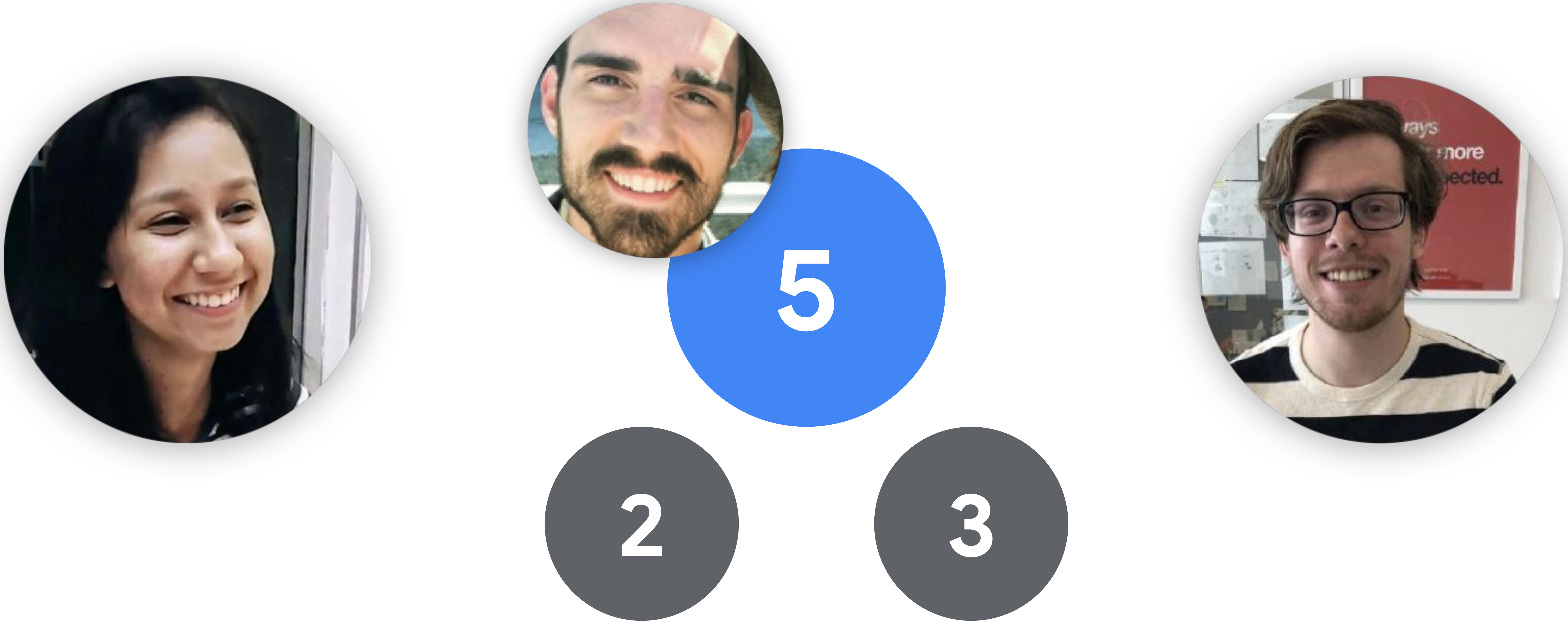
SHARE OWNERSHIP OF A NUMBER

Tool 4: Secure Multi-Party Computation

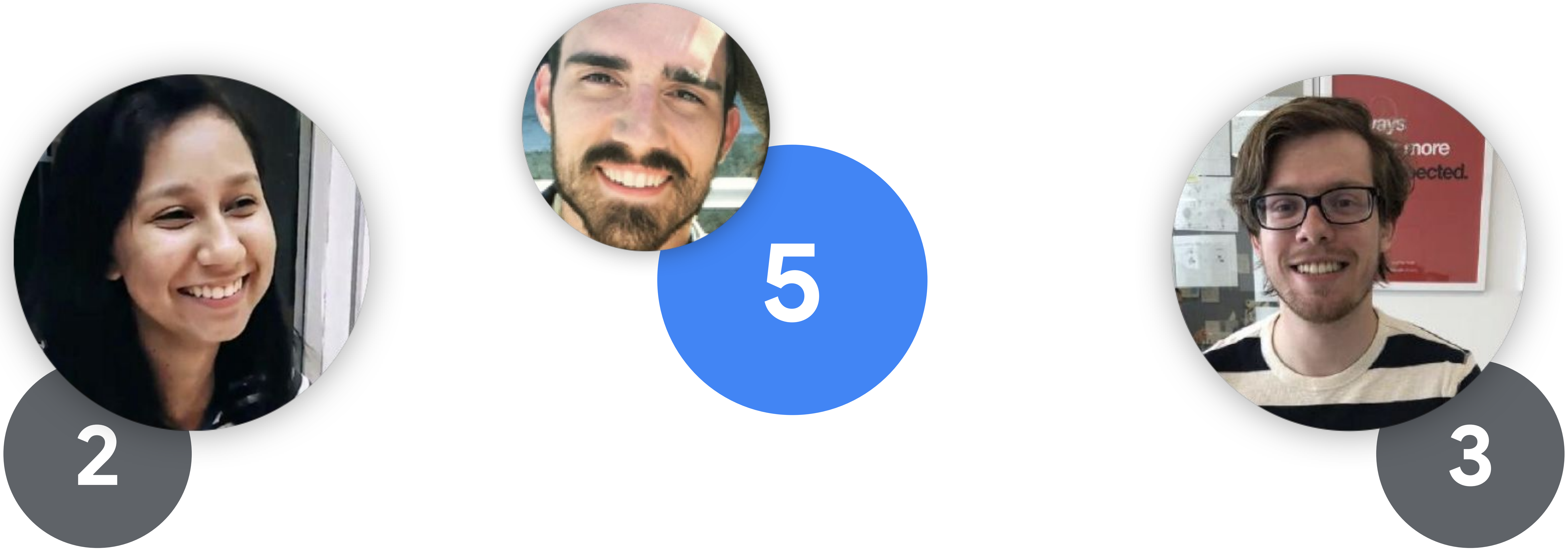
Tool 4: Secure Multi-Party Computation



Tool 4: Secure Multi-Party Computation



Tool 4: Secure Multi-Party Computation



Tool 4: Secure Multi-Party Computation

2

5

3

Encryption: neither knows the hidden value

Shared Governance: the number can only be used if everyone agrees

Tool 4: Secure Multi-Party Computation

2

5

3

Tool 4: Secure Multi-Party Computation

2

x

2

4

5

3

x

2

6

Models and datasets are just large collections of numbers which we can encrypt

Tool 4: Secure Multi-Party Computation

2

x

2

4

5

10

3

x

2

6

Tool 4: Secure Multi-Party Computation

```
bob = GridClient("http://bob-cloud.herokuapp.com")
alice = GridClient("http://alice-cloud.herokuapp.com")
theo = GridClient("http://sue-cloud.herokuapp.com")

crypto = GridClient("http://openmined.herokuapp.com")
```

Tool 4: Secure Multi-Party Computation

```
bob = GridClient("http://bob-cloud.herokuapp.com")
alice = GridClient("http://alice-cloud.herokuapp.com")
theo = GridClient("http://sue-cloud.herokuapp.com")

crypto = GridClient("http://openmined.herokuapp.com")
```

```
x = th.tensor([1,2,3,4,5]).share(bob, alice, theo,
                                 crypto_provider=openmined)
x
```

```
(Wrapper)>[AdditiveSharingTensor]
        -> [PointerTensor | me:75100832451 -> bob:61109349352]
        -> [PointerTensor | me:24508960736 -> alice:58174473186]
        -> [PointerTensor | me:23291943380 -> theo:84520473722]
        *crypto provider: openmined*
```

Tool 4: Secure Multi-Party Computation

```
                                crypto_provider=openmined)
x
```

```
(Wrapper)>[AdditiveSharingTensor]
        -> [PointerTensor | me:75100832451 -> bob:61109349352]
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        *crypto provider: openmined*
```

```
y = x + x
y
```

```
(Wrapper)>[AdditiveSharingTensor]
        -> [PointerTensor | me:61688667118 -> bob:47353472328]
        -> [PointerTensor | me:66053589763 -> alice:2058066939]
        -> [PointerTensor | me:63817030862 -> theo:90586760070]
        *crypto provider: openmined*
```

```
y.get()
```

```
tensor([ 2,  4,  6,  8, 10])
```

Tool 4: Secure Multi-Party Computation

```
In [9]:  encrypted_model = model.share(bob, alice, theo)

         encrypted_data = data.share(bob, alice, theo)
         encrypted_target = target.share(bob, alice, theo)

In [10]: encrypted_pred = encrypted_model(encrypted_data)

In [11]: encrypted_loss = ((encrypted_pred - encrypted_target)**2).sum()

In [12]: encrypted_loss.backward()
```

Tool 4: Secure Multi-Party Computation

Pros:

Remote: Data remains on remote machine

Search/Sample: We feature engineer using toy data

DP: formal, rigorous privacy budgeting

MPC: The model can be encrypted during training!

MPC: We can do joins / functions across data owners!

Top Contributors

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Remote Execution

TOOL 02

Example Data

TOOL 03

Differential Privacy

TOOL 04

Secure Multi-party Computation

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atrask:~  pip install the-worlds-data
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ImageNet

MNIST

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Librispeech

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Let's solve these!

Cancer

Alzheimer's

Dementia

Depression

Anxiety

… the Common Cold?

courses.openmined.org

Google Cloud

Thank you.