Privacy Preserving AI

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?

Source: Wikipedia Commons

- Step **1**: Download millions of tumor images.

What do tumors look like in humans?

Source: Wikipedia Commons

- Step **0**: Buy a dataset from a hospital.
- Step **1**: Download millions of tumor images.

What do tumors look like in humans?

Source: Wikipedia Commons

- Step **-1**: Persuade a VC.
- Step **0**: Buy a dataset from a hospital.
- Step **1**: Download millions of tumor images.

What do tumors look like in humans?

Source: Wikipedia Commons

- 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.

What do tumors look like in humans?

Source: Wikipedia Commons

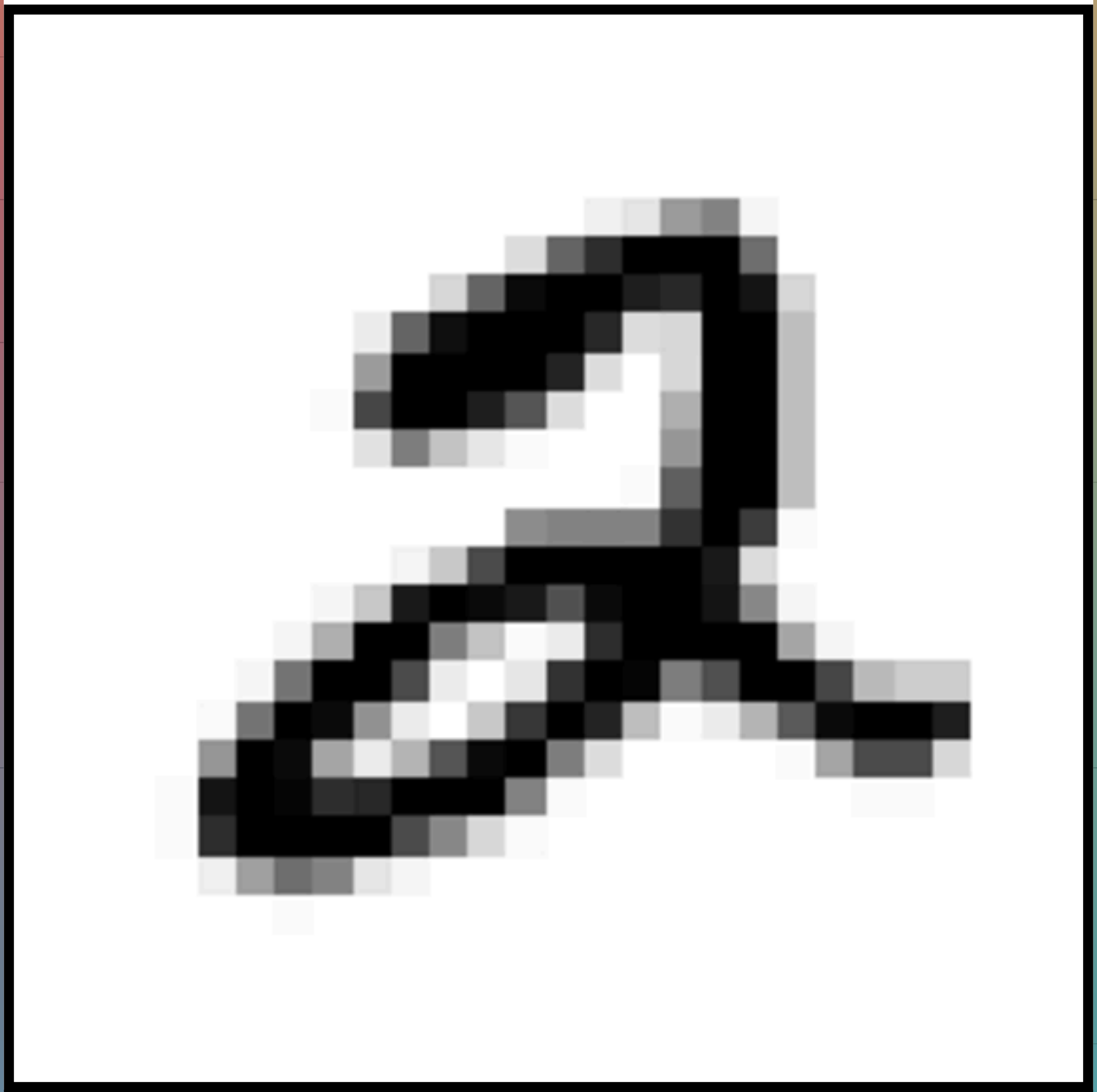
- Step **-3**: Find a business partner!
- Step **-2**: Create a business plan!
- Step **-1**: Persuade a VC.
- Step **0**: Buy a dataset from a hospital.
- Step **1**: Download millions of tumor images.

What do tumors look like in humans?

Source: Wikipedia Commons

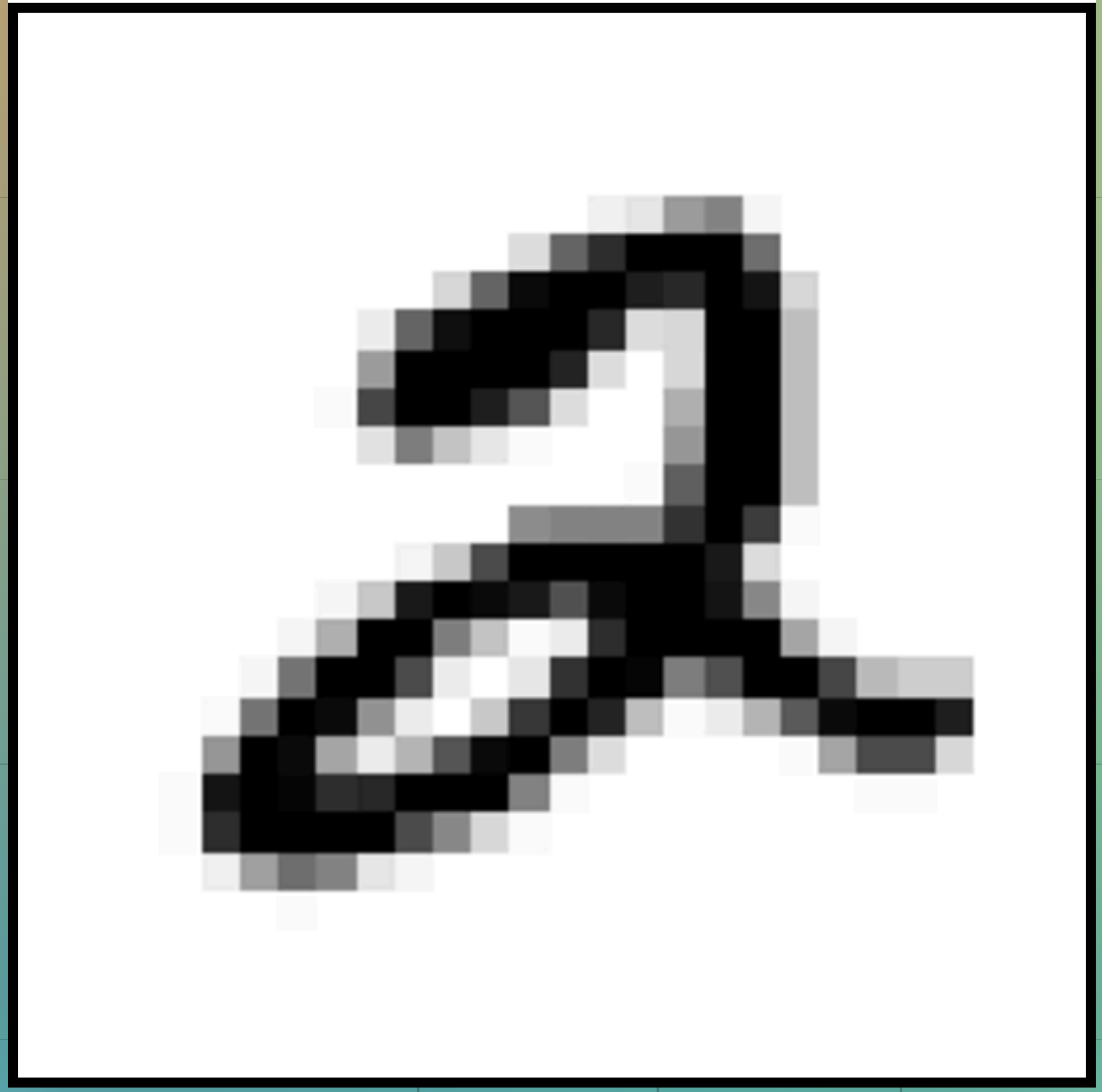
- Step **-4**: Spam all my classmates on LinkedIn!
- Step **-3**: Find a business partner!
- Step **-2**: Create a business plan!
- Step **-1**: Persuade a VC.
- Step **0**: Buy a dataset from a hospital.
- Step **1**: Download millions of tumor images.

What do handwritten digits look like?



- Step **1**: Download data
- Step **2**: Download SOTA training script
- Step **3**: Run script.

What do handwritten digits look like?



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:

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… but what about?

- ◆ Cancer
- ◆ Alzheimers
- ◆ Dementia
- ◆ Depression
- ◆ Anxiety
- ◆ … the Common Cold?

IS IT POSSIBLE TO:

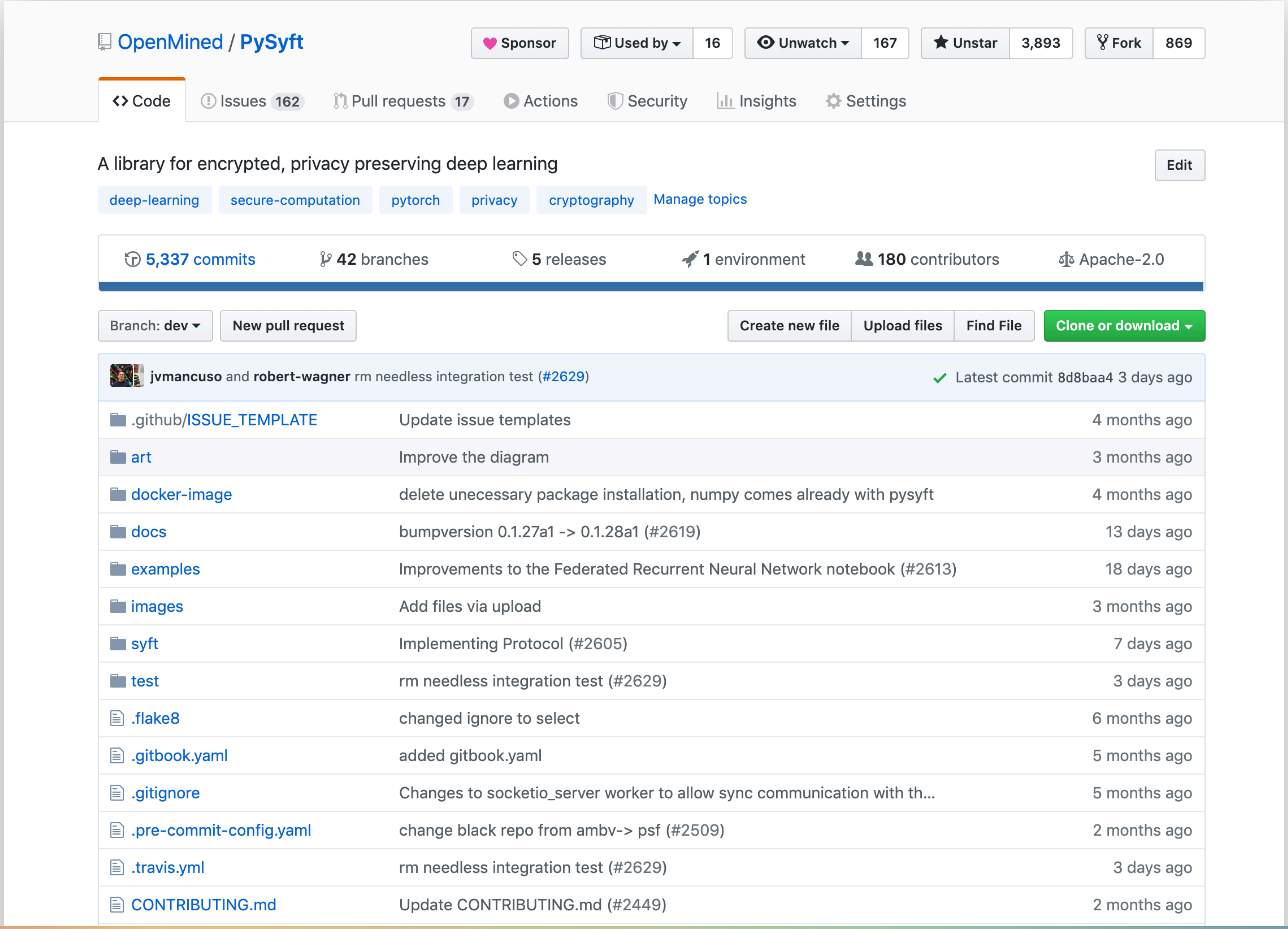
answer questions using data we cannot see?

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

OpenMined


OpenMind is a Community

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

PySyft

Tool 1: Remote Execution

Tool 1: Remote Execution






Tool 1: Remote Execution

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






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")
```

Tool 1: Remote Execution

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

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

In [5]:
```python
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
        hook = sy.TorchHook(th)

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

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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

In [
```

Tool 1: Remote Execution

```
In [1]: import syft as sy
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In [6]: y = x + x
```






Tool 1: Remote Execution

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In [1]: import syft as sy
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        x = x.send(hospital_datacenter)
        x

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")

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

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]

In [8]: y.get()

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

Tool 1: Remote Execution

Pros:

- **RPC:** Data remains on remote machine

Cons:

- How can we do good data science without seeing the data?

Top Contributors

Tool 2: 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

```
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

```
Description: Diabetes dataset...
```

```
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

```
  :Number of Instances: 442

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

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

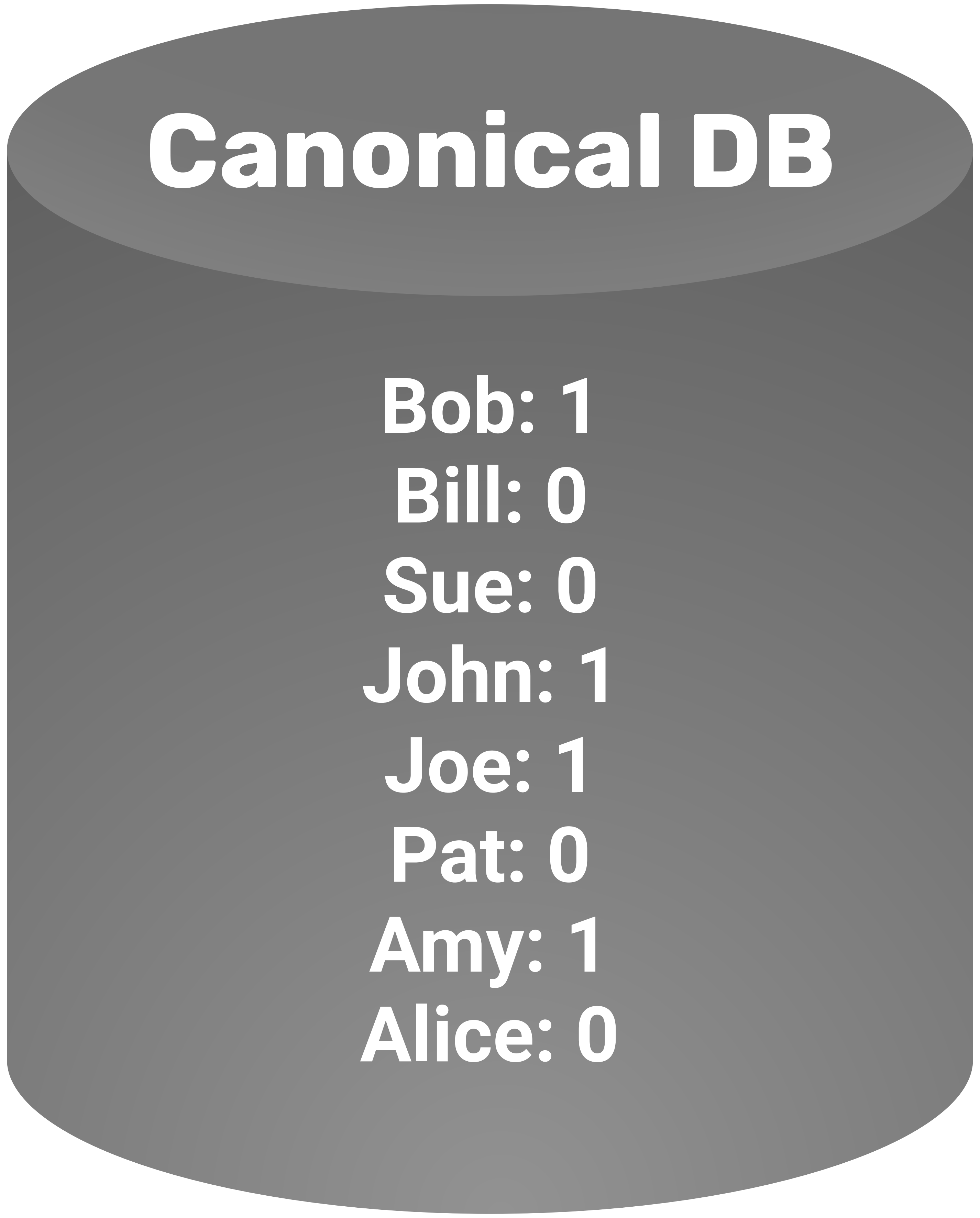
Cons:

- We can steal data using PointerTensor.get()

Top Contributors

Tool 3: 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

FEATURE IN DEVELOPMENT

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

```
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.
```

FEATURE IN DEVELOPMENT

Tool 3: Differential Privacy

```
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 added.

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],
```

FEATURE IN DEVELOPMENT

Tool 3: Differential Privacy

- **Pros:**
  - **Remote:** Data remains on remote machine
  - **Search/Sample:** We can 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?

Top Contributors

Tool 4: Secure Multi-Party Computation

Tool 4: Secure Multi-Party Computation

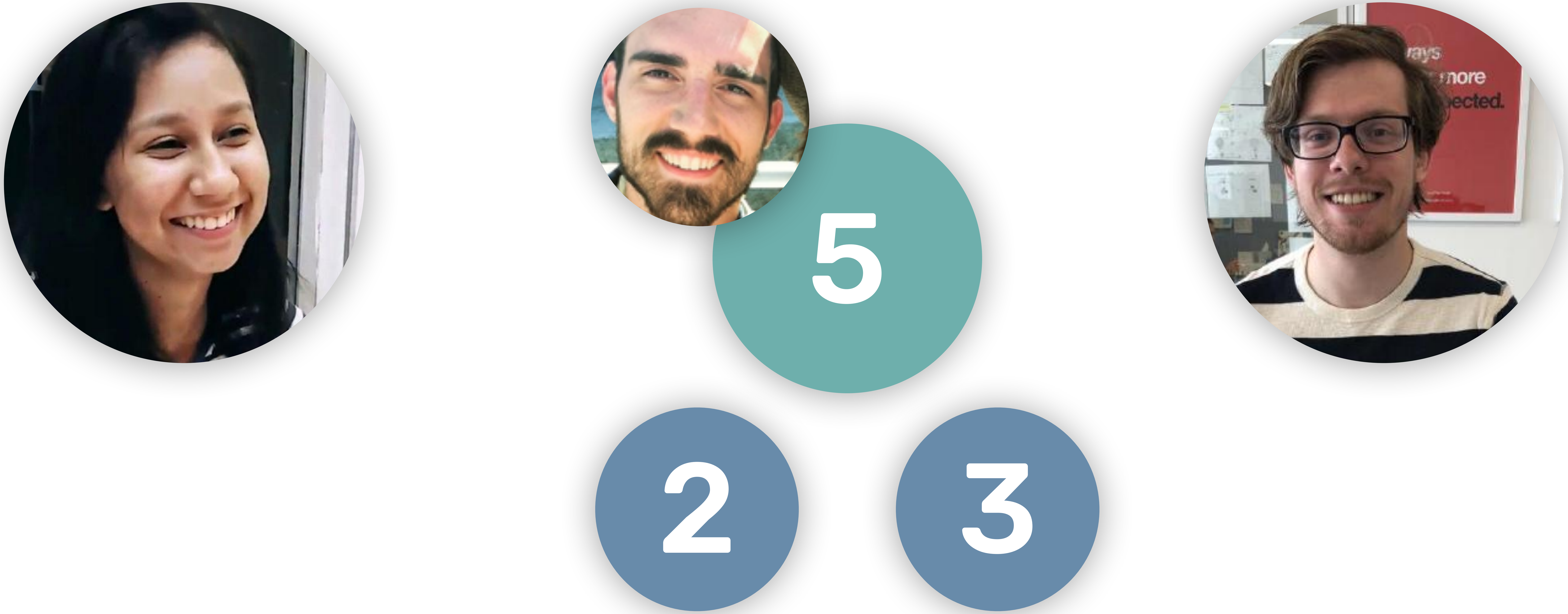
- **Definition:** multiple people can combine their private inputs to compute a function, without revealing their inputs to each other.
- **Implication:** multiple people can:

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

Tool 4: Secure Multi-Party Computation

2

5

3

x

2

4

x

2

6

Tool 4: Secure Multi-Party Computation

2

5

3

x

2

4

10

x

2

6

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

Tool 4: Secure Multi-Party Computation

```python
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]
        -> [PointerTensor | me:24508960736 -> alice:58174473186]
        -> [PointerTensor | me:23291943380 -> theo:84520473722]
        *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 can 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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Tool 1

Remote Execution

Tool 2

Example Data

Tool 3

Differential Privacy

Tool 4

Secure Multi-party Computation

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

Lets forget these

- ImageNet
- MNIST
- CIFAR-10
- Librispeech
- WikiText-103
- WMT

Lets solve these!

- ✓ Cancer
- ✓ Alzheimers
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- ✓ Anxiety
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udacity.com/private-ai

Part 2: AI, Privacy & Society