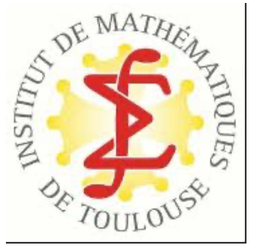
Make Your Training Loop Private: A Hands-On Introduction to Differential Privacy

Clément Lalanne - ANITI Days 2026



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How can someone recover user data from the model?

- Directly from the weights (e.g., memorization of the dataset in the weights of overparameterized models).
- Simply through black-box access to the model (e.g., “Hey GPT, can you tell me surprising anecdotes that happened to your users?”).

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To understand what the model learns from you, ask a *counterfactual*: **would the trained model look essentially the same if your data were someone else's?**

Differential privacy makes this precise by requiring training to be **stable to the inclusion/removal of any single user**.

As a result, the model captures patterns shared across many users and *filters out information that is unique to one person*.

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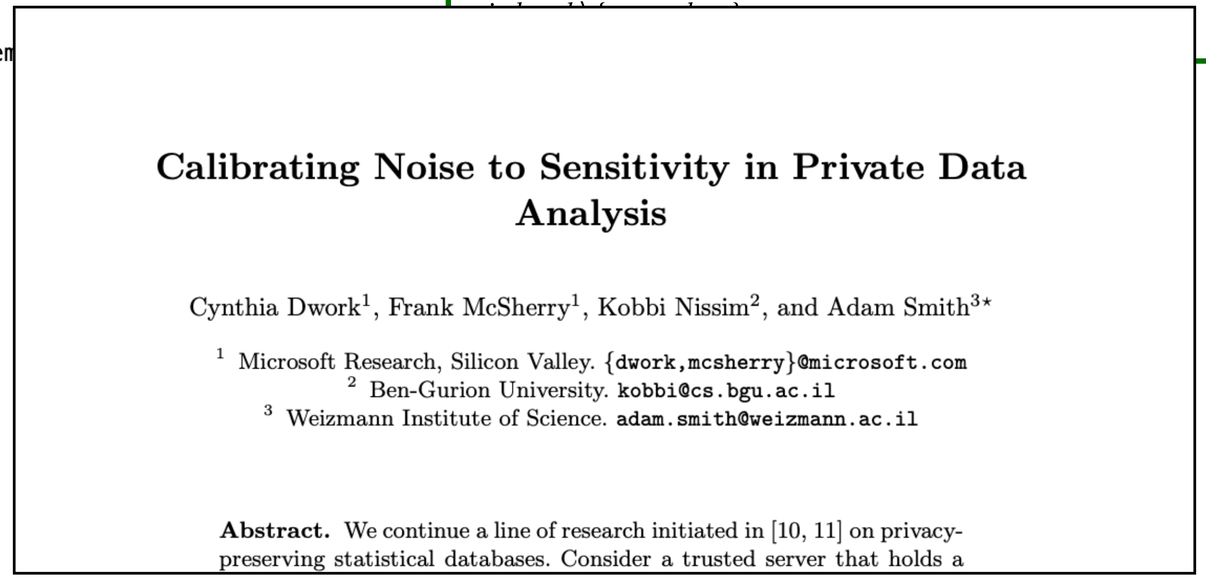

Calibrating Noise to Sensitivity in Private Data Analysis

Cynthia Dwork[1], Frank McSherry[1], Kobbi Nissim[2], and Adam Smith[3⋆]

[1] Microsoft Research, Silicon Valley. {dwork,mcsherry}@microsoft.com
[2] Ben-Gurion University. kobbi@cs.bgu.ac.il
[3] Weizmann Institute of Science. adam.smith@weizmann.ac.il

Abstract. We continue a line of research initiated in [10, 11] on privacy-preserving statistical databases. Consider a trusted server that holds a

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2017 Gödel Prize:

The 2017 Gödel Prize is awarded to **Cynthia Dwork, Frank McSherry, Kobbi Nissim and Adam Smith** for their work on Differential Privacy in the paper:

Calibrating Noise to Sensitivity in Private Data Analysis,
Journal of Privacy and Confidentiality, Volume 7, Issue 3, 2016
(preliminary version in *Theory of Cryptography, TCC 2006*).

Cynthia Dwork, Frank McSherry, Kobbi Nissim and Adam Smith will receive the 2017 Gödel Prize at the 49th Annual ACM Symposium on Theory of Computing, to be held from 19-23 June, 2017 in Montreal, Canada.

Differential privacy is a powerful theoretical model for dealing with the privacy of statistical data. By

Calibrating Noise to

Cynthia Dwork[1], Frank McSh

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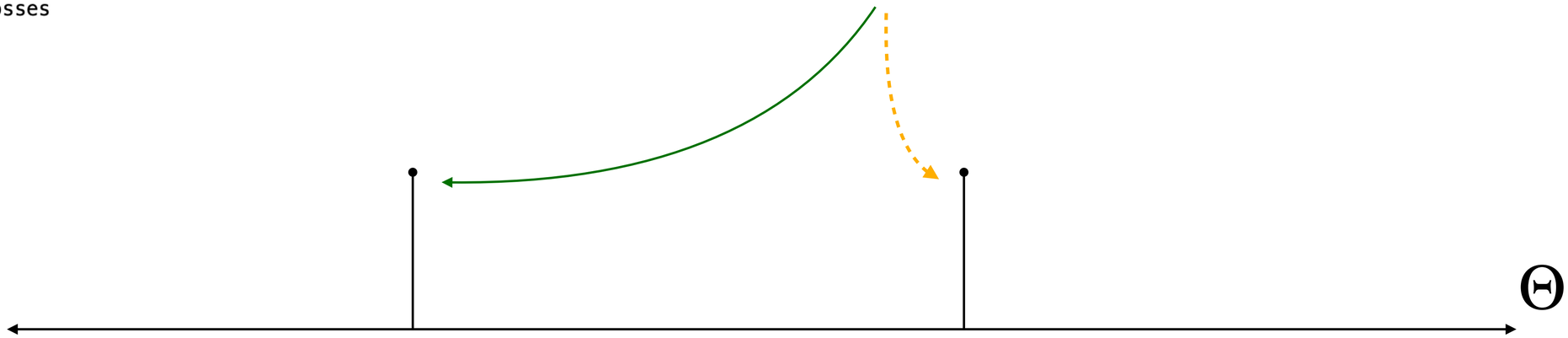

Update direction with your data

Update direction if your data were replaced by Chuck Norris's data

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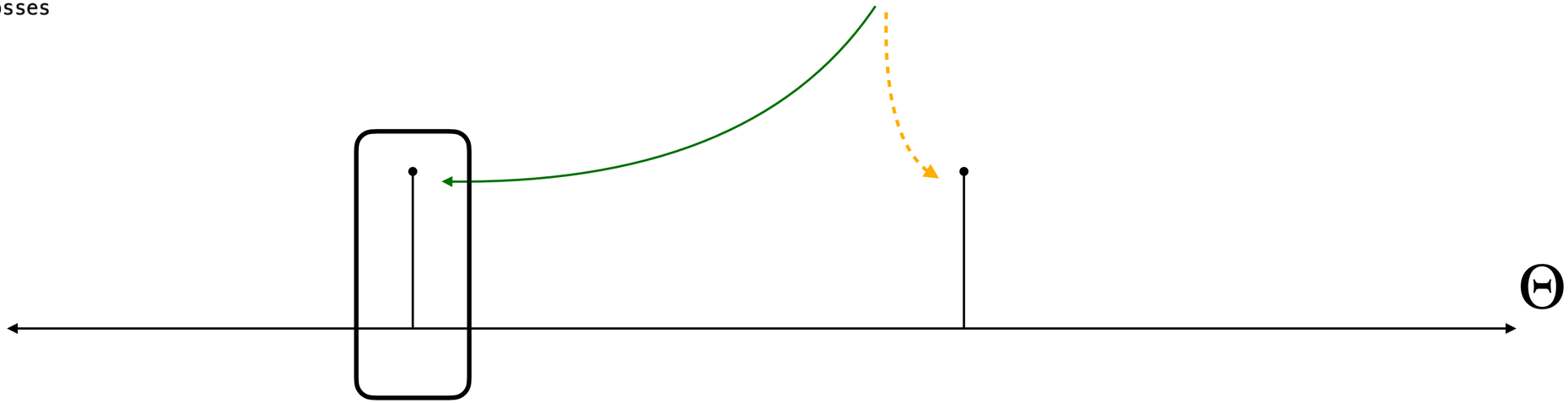

If this is the update direction, I know for a fact that your data was part of the training set.

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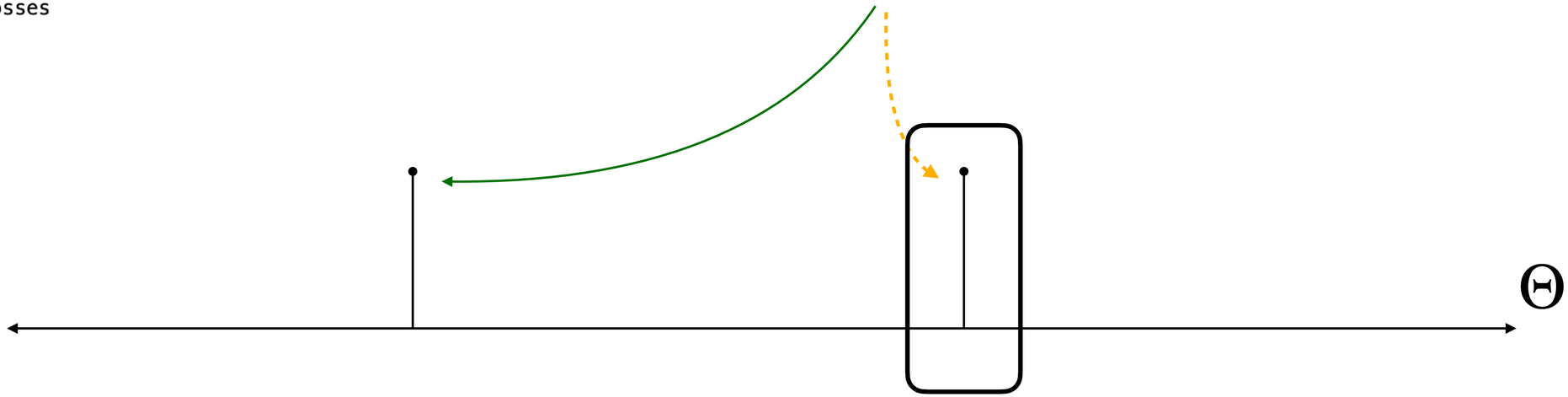

If this is the update direction, I know for a fact that it was Chuck Norris's instead.

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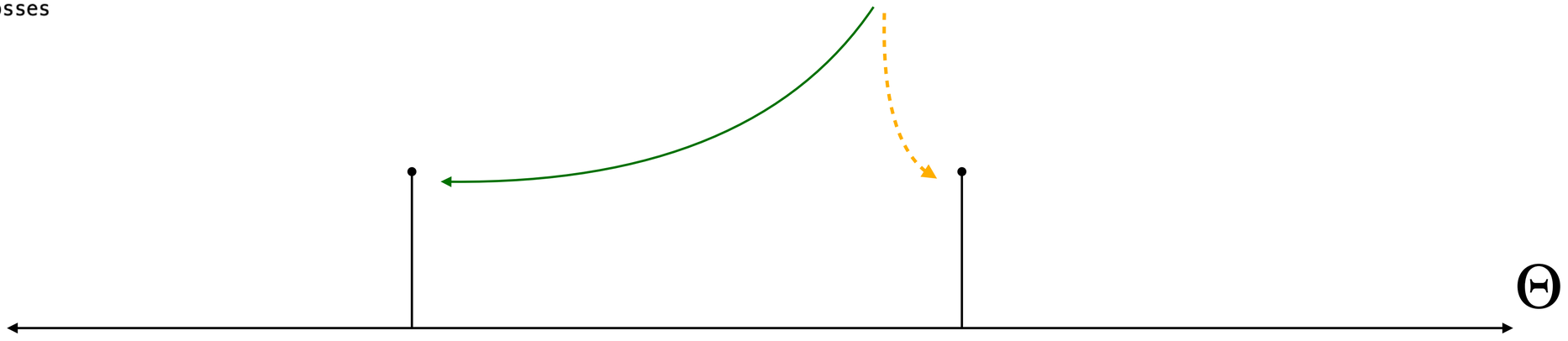

This is problematic: the model has learned **too much user-specific noise**.

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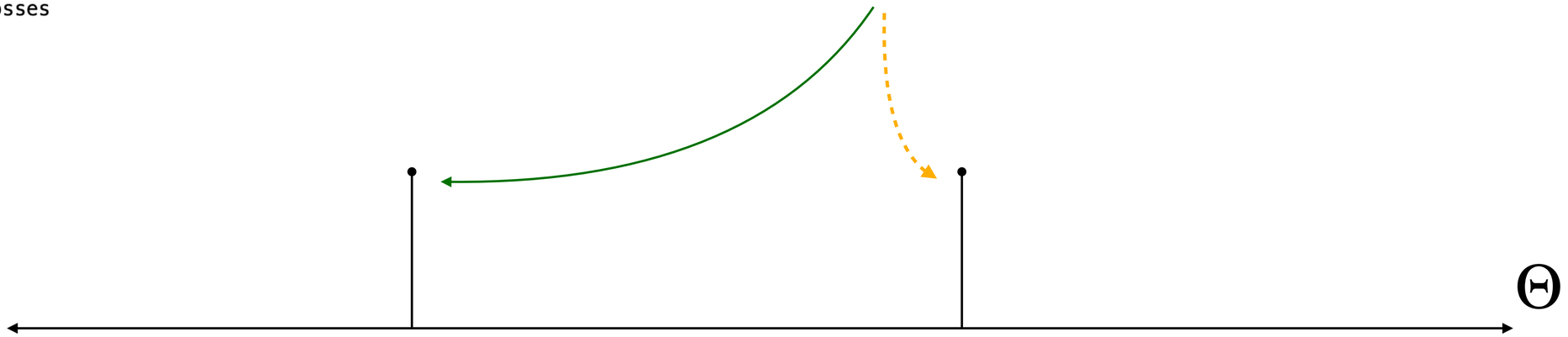

Differential privacy enforces stability by **perturbing the update direction** so that it **cannot depend strongly on any individual user's data**.

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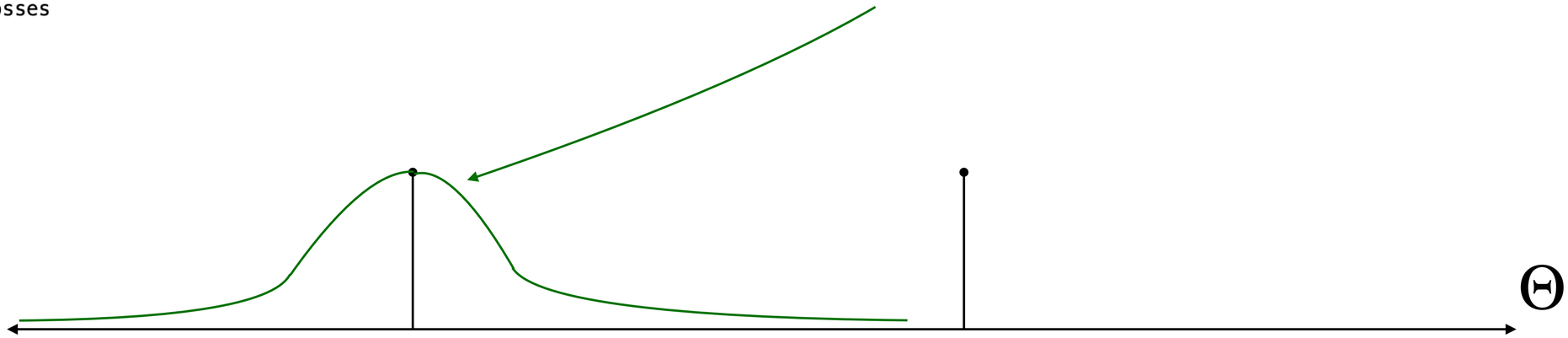

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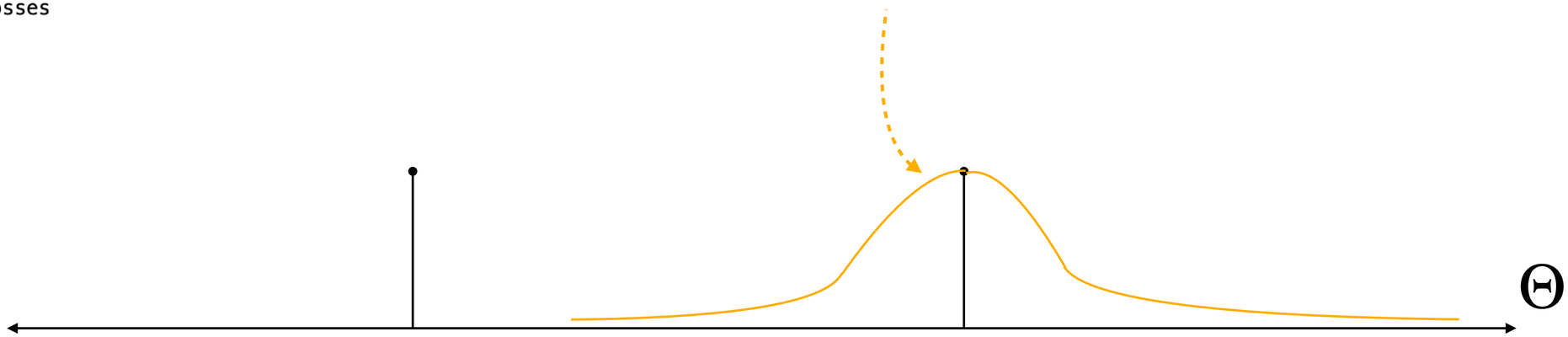

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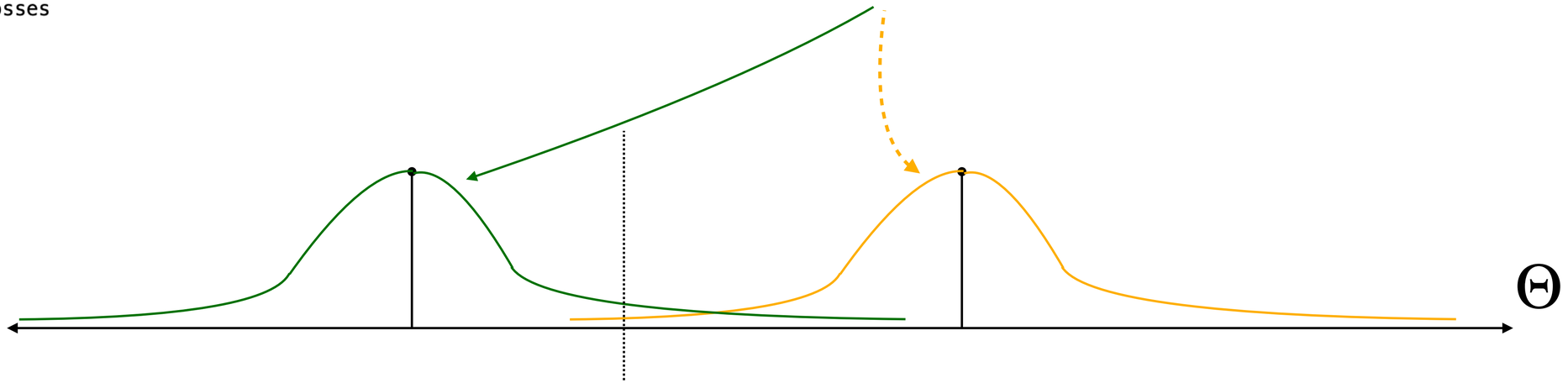

From the observed update direction, it is **impossible to determine exactly** whether your data or Chuck Norris's data was used.

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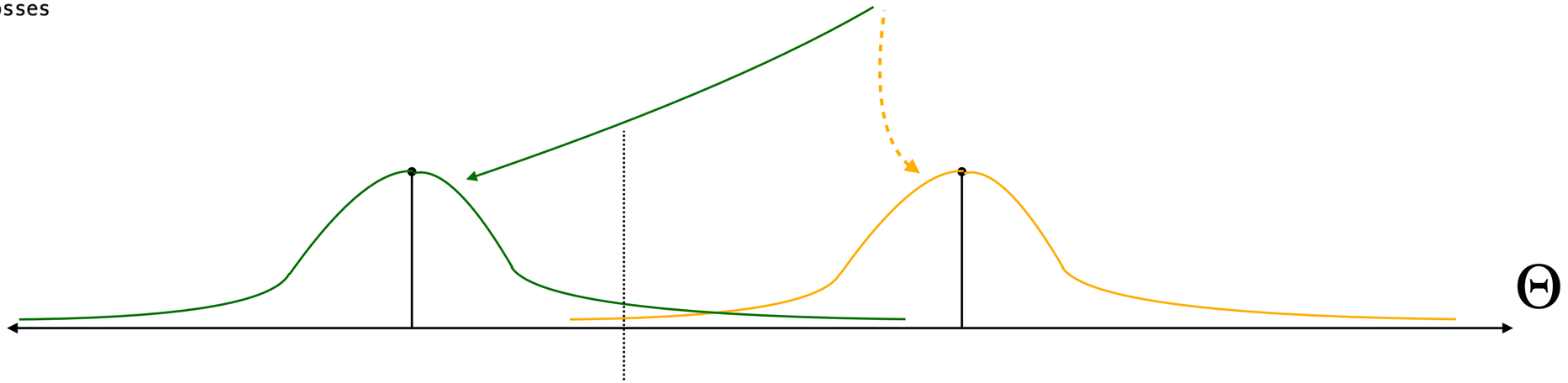

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The most I can do is **update a prior belief via the likelihood ratio**, yielding explicit and quantifiable bounds.

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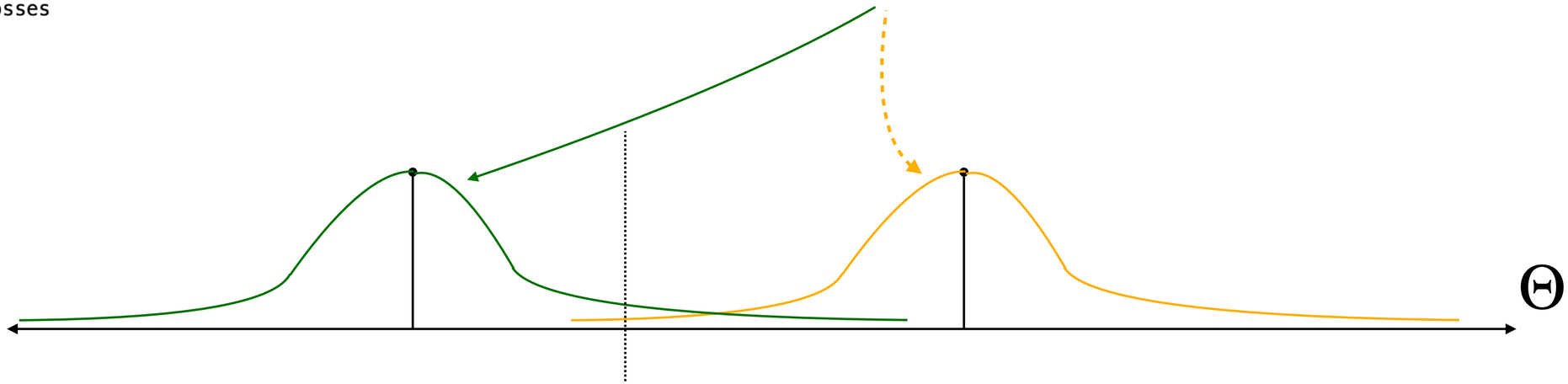
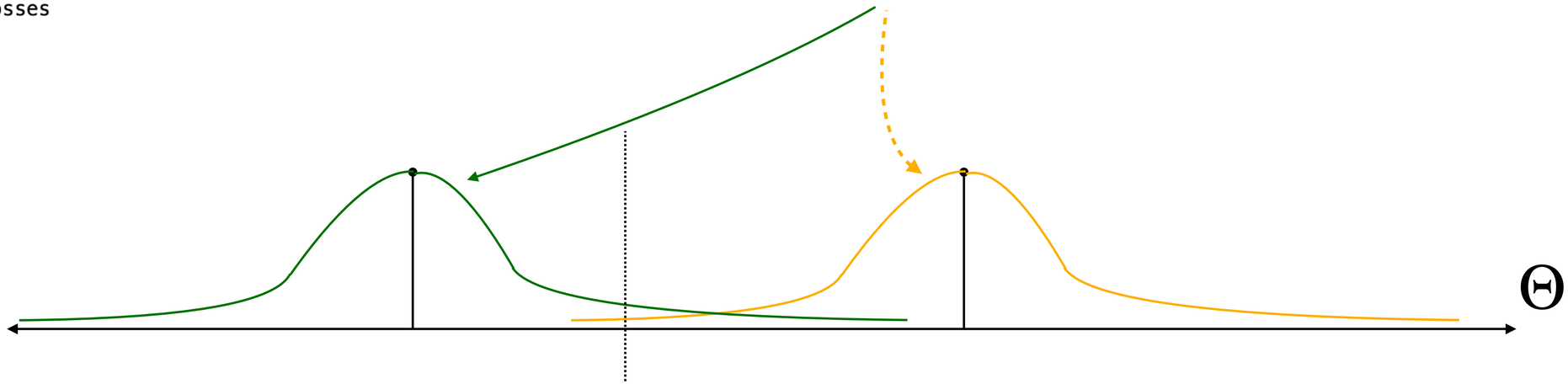


Let's identify the key control knobs and understand how they shape the privacy-utility tradeoff.

```python
def train_nonprivate(model, epochs=epochs, bs=batch_size, lr=lr):
    opt = optim.SGD(model.parameters(), lr=lr)
    losses = []
    for _ in range(epochs):
        idx = torch.randperm(n)
        for i in range(0, n, bs):
            b = idx[i:i+bs]
            xb, yb = X[b], y[b]
            opt.zero_grad()
            loss = loss_fn(model(xb), yb)
            loss.backward()
            opt.step()
            losses.append(loss.item())
    return losses
```

$$\theta \leftarrow \theta - lr \times \left\{ \frac{1}{batch\_size} \left(\sum_{j \in batch} \nabla l(y_j, model(x_j)) + \sigma \mathcal{N}(0,I) \right) \right\}$$

$$\sum_{j \in batch \setminus \{your\_data\}} \nabla l(y_j, model(x_j)) + \mathbf{1}_{your\_data \in batch} \nabla l(y_{your\_data}, model(x_{your\_data})) + \sigma \mathcal{N}(0,I)$$



The noise level σ

```python
def train_nonprivate(model, epochs=epochs, bs=batch_size, lr=lr):
    opt = optim.SGD(model.parameters(), lr=lr)
    losses = []
    for _ in range(epochs):
        idx = torch.randperm(n)
        for i in range(0, n, bs):
            b = idx[i:i+bs]
            xb, yb = X[b], y[b]
            opt.zero_grad()
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            loss.backward()
            opt.step()
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    return losses
```

$$\theta \leftarrow \theta - lr \times \left\{ \frac{1}{batch\_size} \left(\sum_{j \in batch} \nabla l(y_j, model(x_j)) + \sigma \mathcal{N}(0,I) \right) \right\}$$

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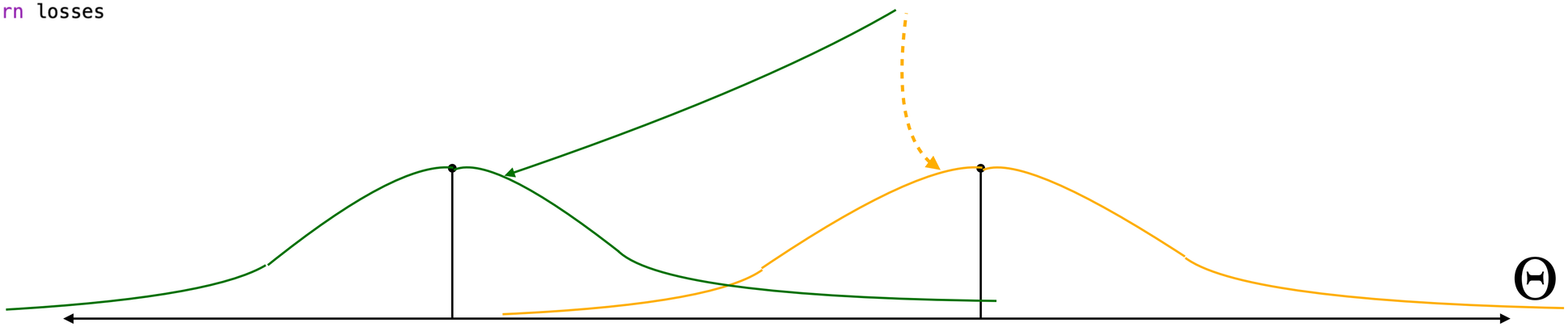


The noise level σ

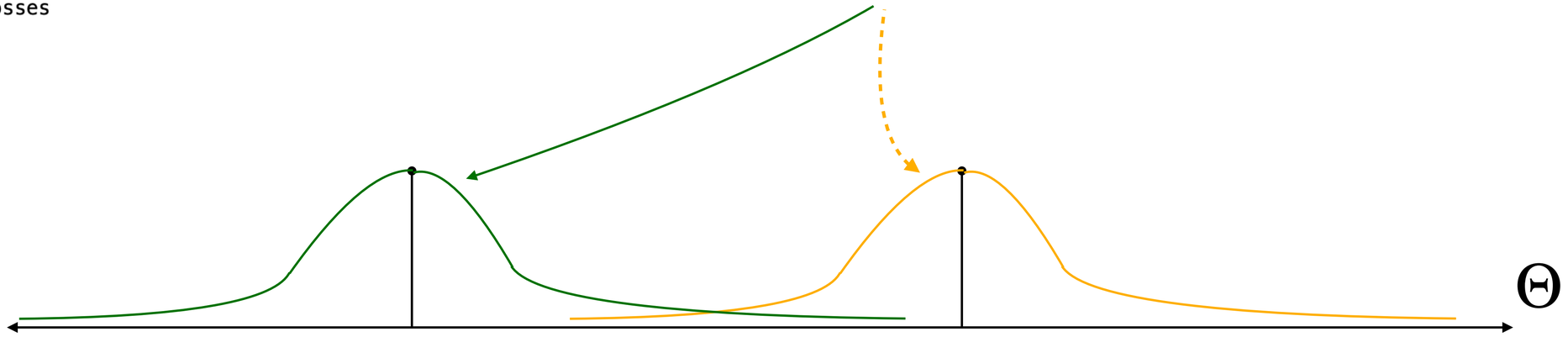
- Increasing σ makes it **harder** to guess if your data was in the training set -> **Increased Privacy**

- But it also means that the **dynamic is noisier** -> **Reduced Utility**

```python
def train_nonprivate(model, epochs=epochs, bs=batch_size, lr=lr):
    opt = optim.SGD(model.parameters(), lr=lr)
    losses = []
    for _ in range(epochs):
        idx = torch.randperm(n)
        for i in range(0, n, bs):
            b = idx[i:i+bs]
            xb, yb = X[b], y[b]
            opt.zero_grad()
            loss = loss_fn(model(xb), yb)
            loss.backward()
            opt.step()
            losses.append(loss.item())
    return losses
```

$$\theta \leftarrow \theta - lr \times \left\{ \frac{1}{batch\_size} \left(\sum_{j \in batch} \nabla l(y_j, model(x_j)) + \sigma \mathcal{N}(0, I) \right) \right\}$$

$$\sum_{j \in batch \setminus \{your\_data\}} \nabla l(y_j, model(x_j)) + \mathbf{1}_{your\_data \in batch} \nabla l(y_{your\_data}, model(x_{your\_data})) + \sigma \mathcal{N}(0, I)$$



How much the gradients can change

```python
def train_nonprivate(model, epochs=epochs, bs=batch_size, lr=lr):
    opt = optim.SGD(model.parameters(), lr=lr)
    losses = []
    for _ in range(epochs):
        idx = torch.randperm(n)
        for i in range(0, n, bs):
            b = idx[i:i+bs]
            xb, yb = X[b], y[b]
            opt.zero_grad()
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            loss.backward()
            opt.step()
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    return losses
```
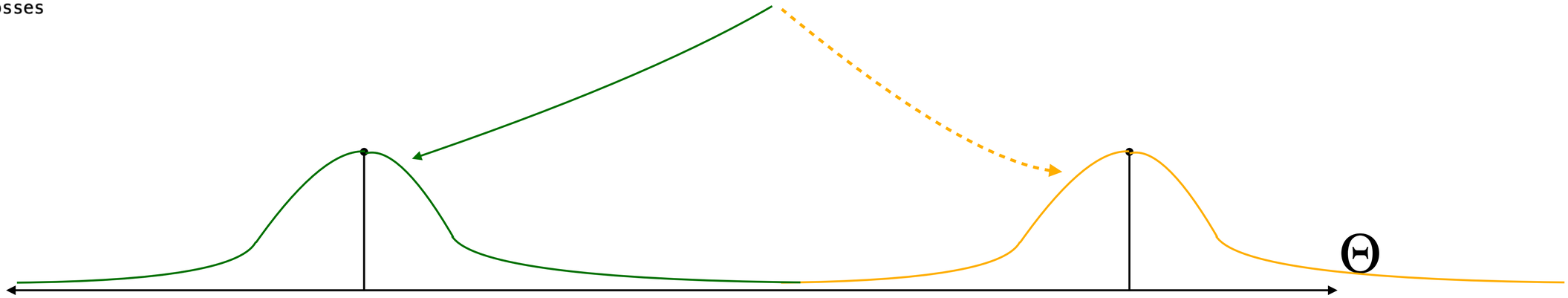

$$\theta \leftarrow \theta - lr \times \left\{ \frac{1}{batch\_size} \left(\sum_{j \in batch} \nabla l(y_j, model(x_j)) + \sigma \mathcal{N}(0,I) \right) \right\}$$

$$\sum_{j \in batch \setminus \{your\_data\}} \nabla l(y_j, model(x_j)) + \mathbf{1}_{your\_data \in batch} \nabla l(y_{your\_data}, model(x_{your\_data})) + \sigma \mathcal{N}(0,I)$$



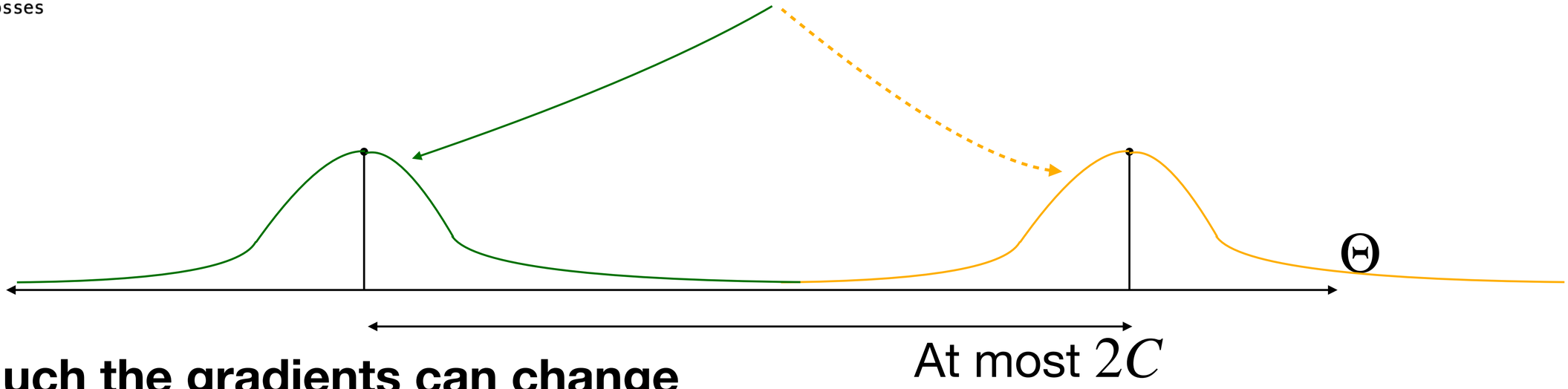
How much the gradients can change

If the **difference between** your gradient and Chuck Norris's **gradient is large**, determining whether your data was included in the training set becomes easy.

```python
def train_nonprivate(model, epochs=epochs, bs=batch_size, lr=lr):
    opt = optim.SGD(model.parameters(), lr=lr)
    losses = []
    for _ in range(epochs):
        idx = torch.randperm(n)
        for i in range(0, n, bs):
            b = idx[i:i+bs]
            xb, yb = X[b], y[b]
            opt.zero_grad()
            loss = loss_fn(model(xb), yb)
            loss.backward()
            opt.step()
            losses.append(loss.item())
    return losses
```

$$\theta \leftarrow \theta - lr \times \left\{ \frac{1}{batch\_size} \left(\sum_{j \in batch} clip_C(\nabla l(y_j, model(x_j))) + \sigma \mathcal{N}(0, I) \right) \right\}$$

$$\sum_{j \in batch \setminus \{your\_data\}} clip_C(\nabla l(y_j, model(x_j))) + \mathbf{1}_{your\_data \in batch}\, clip_C(\nabla l(y_{your\_data}, model(x_{your\_data}))) + \sigma \mathcal{N}(0, I)$$



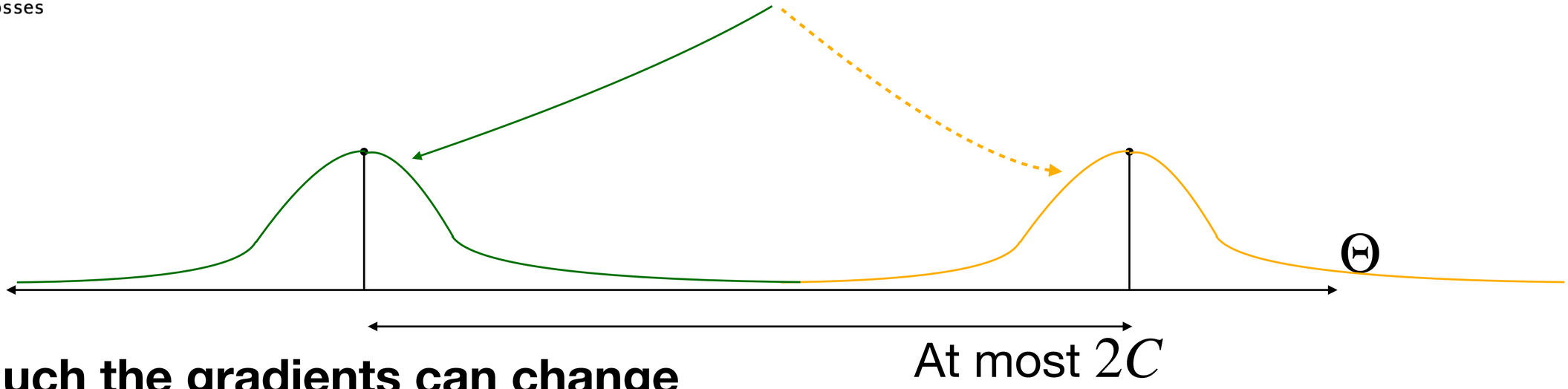
How much the gradients can change

In practice, we make sure that **this difference is not too large** by *clipping* the values of the gradients.

```python
def train_nonprivate(model, epochs=epochs, bs=batch_size, lr=lr):
    opt = optim.SGD(model.parameters(), lr=lr)
    losses = []
    for _ in range(epochs):
        idx = torch.randperm(n)
        for i in range(0, n, bs):
            b = idx[i:i+bs]
            xb, yb = X[b], y[b]
            opt.zero_grad()
            loss = loss_fn(model(xb), yb)
            loss.backward()
            opt.step()
            losses.append(loss.item())
    return losses
```

$$\theta \leftarrow \theta - lr \times \left\{ \frac{1}{batch\_size} \left(\sum_{j \in batch} clip_C(\nabla l(y_j, model(x_j))) + \sigma \mathcal{N}(0, I) \right) \right\}$$

$$\sum_{j \in batch \setminus \{your\_data\}} clip_C(\nabla l(y_j, model(x_j))) + \mathbf{1}_{your\_data \in batch}\, clip_C(\nabla l(y_{your\_data}, model(x_{your\_data}))) + \sigma \mathcal{N}(0, I)$$



How much the gradients can change

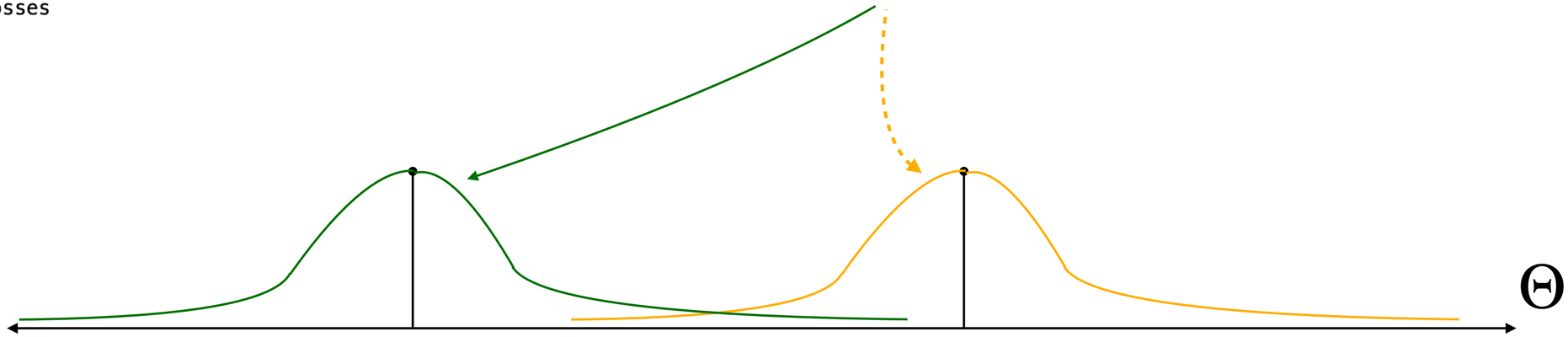
- A lower clipping threshold **reduces the influence of your data** -> **Higher Privacy**.

- However, it **alters the standard SGD dynamics** -> **Reduced Utility**.

```python
def train_nonprivate(model, epochs=epochs, bs=batch_size, lr=lr):
    opt = optim.SGD(model.parameters(), lr=lr)
    losses = []
    for _ in range(epochs):
        idx = torch.randperm(n)
        for i in range(0, n, bs):
            b = idx[i:i+bs]
            xb, yb = X[b], y[b]
            opt.zero_grad()
            loss = loss_fn(model(xb), yb)
            loss.backward()
            opt.step()
            losses.append(loss.item())
    return losses
```

$$\theta \leftarrow \theta - lr \times \left\{ \frac{1}{batch\_size} \left(\sum_{j \in batch} \nabla l(y_j, model(x_j)) + \sigma \mathcal{N}(0, I) \right) \right\}$$

$$\sum_{j \in batch \setminus \{your\_data\}} \nabla l(y_j, model(x_j)) + \mathbf{1}_{your\_data \in batch} \nabla l(y_{your\_data}, model(x_{your\_data})) + \sigma \mathcal{N}(0, I)$$



The number of epochs

```python
def train_nonprivate(model, epochs=epochs, bs=batch_size, lr=lr):
    opt = optim.SGD(model.parameters(), lr=lr)
    losses = []
    for _ in range(epochs):
        idx = torch.randperm(n)
        for i in range(0, n, bs):
            b = idx[i:i+bs]
            xb, yb = X[b], y[b]
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            loss = loss_fn(model(xb), yb)
            loss.backward()
            opt.step()
            losses.append(loss.item())
    return losses
```
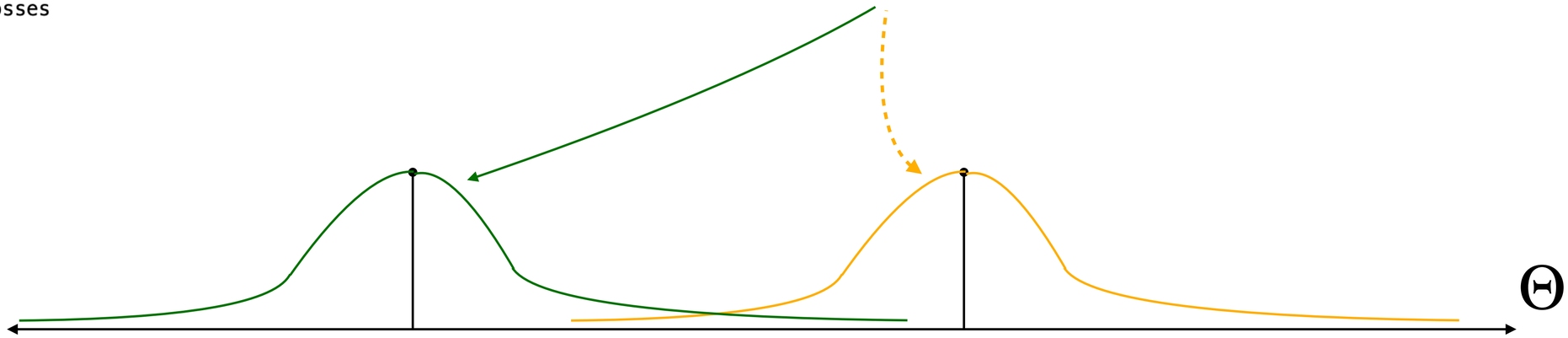

$$\theta \leftarrow \theta - lr \times \left\{ \frac{1}{batch\_size} \left(\sum_{j \in batch} \nabla l(y_j, model(x_j)) + \sigma \mathcal{N}(0,I) \right) \right\}$$

$$\sum_{j \in batch \setminus \{your\_data\}} \nabla l(y_j, model(x_j)) + \mathbf{1}_{your\_data \in batch} \nabla l(y_{your\_data}, model(x_{your\_data})) + \sigma \mathcal{N}(0,I)$$



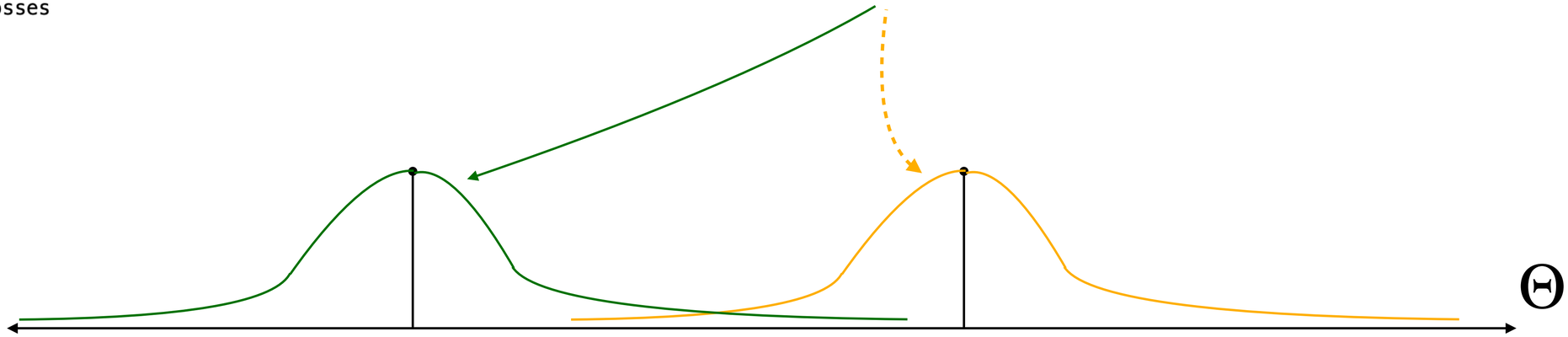
The number of epochs

- **More epochs** -> better optimization and **higher utility**.
- But **more exposure to each user's data** -> **weaker privacy** guarantees.

```python
def train_nonprivate(model, epochs=epochs, bs=batch_size, lr=lr):
    opt = optim.SGD(model.parameters(), lr=lr)
    losses = []
    for _ in range(epochs):
        idx = torch.randperm(n)
        for i in range(0, n, bs):
            b = idx[i:i+bs]
            xb, yb = X[b], y[b]
            opt.zero_grad()
            loss = loss_fn(model(xb), yb)
            loss.backward()
            opt.step()
            losses.append(loss.item())
    return losses
```

$$\theta \leftarrow \theta - lr \times \left\{ \frac{1}{batch\_size} \left(\sum_{j \in batch} \nabla l(y_j, model(x_j)) + \sigma \mathcal{N}(0,I) \right) \right\}$$

$$\sum_{j \in batch \setminus \{your\_data\}} \nabla l(y_j, model(x_j)) + \mathbf{1}_{your\_data \in batch} \nabla l(y_{your\_data}, model(x_{your\_data})) + \sigma \mathcal{N}(0,I)$$



The batching mechanism

```python
def train_nonprivate(model, epochs=epochs, bs=batch_size, lr=lr):
    opt = optim.SGD(model.parameters(), lr=lr)
    losses = []
    for _ in range(epochs):
        idx = torch.randperm(n)
        for i in range(0, n, bs):
            b = idx[i:i+bs]
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```
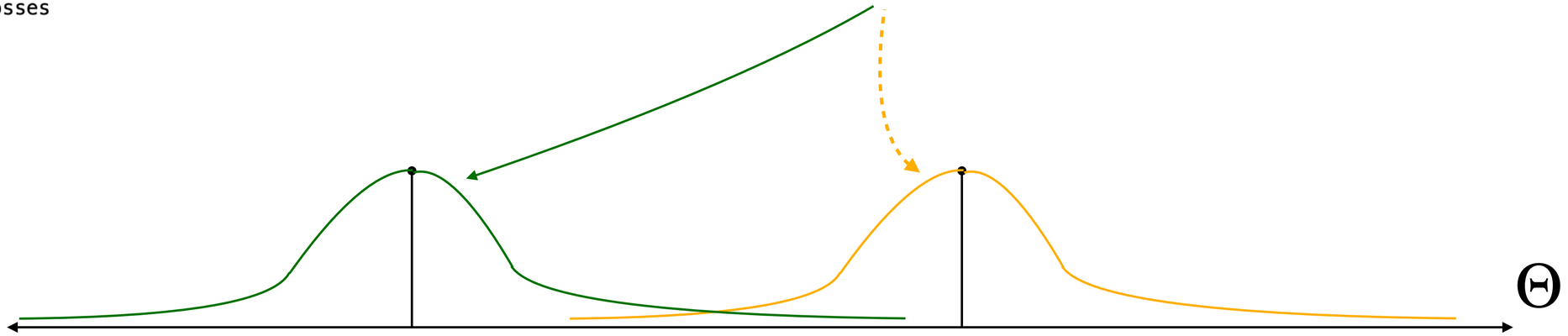

$$\theta \leftarrow \theta - lr \times \left\{ \frac{1}{batch\_size} \left(\sum_{j \in batch} \nabla l(y_j, model(x_j)) + \sigma \mathcal{N}(0,I) \right) \right\}$$

$$\sum_{j \in batch \setminus \{your\_data\}} \nabla l(y_j, model(x_j)) + \mathbf{1}_{your\_data \in batch} \nabla l(y_{your\_data}, model(x_{your\_data})) + \sigma \mathcal{N}(0,I)$$



The batching mechanism

Outside of the scope of this presentation, but it is possible to play with “smarter” batching mechanisms to shape the privacy-utility tradeoff.

```
def train_nonprivate(model, epochs=epochs, bs=batch_size, lr=lr):
    opt = optim.SGD(model.parameters(), lr=lr)
    losses = []
    for _ in range(epochs):
        idx = torch.randperm(n
        for i in range(0, n, b
            b = idx[i:i+bs]
            xb, yb = X[b], y[b
            opt.zero_grad()
            loss = loss_fn(mod
            loss.backward()
            opt.step()
            losses.append(loss
    return losses
```

$$\theta \leftarrow \theta - lr \times \left\{ \frac{1}{\text{batch\_size}} \left(\sum \nabla l(y_j, model(x_j)) + \sigma \mathcal{N}(0,I) \right) \right\}$$

$$\ldots del(x_{your\_data})) + \sigma \mathcal{N}(0,I)$$

A preliminary version of this paper appears in the proceedings of the *23rd ACM Conference on Computer and Communications Security (CCS 2016)*. This is a full version.

Deep Learning with Differential Privacy

October 25, 2016

Martín Abadi* Andy Chu* Ian Goodfellow†
H. Brendan McMahan* Ilya Mironov* Kunal Talwar*
Li Zhang*

ABSTRACT

Machine learning techniques based on neural networks are achieving remarkable results in a wide variety of domains. Often, the training of models requires large, representative datasets, which may be crowdsourced and contain sensitive information. The models should not expose private information in these datasets. Addressing this goal, we develop new algorithmic techniques for learning and a refined analysis of privacy costs within the framework of differential privacy.

1. We demonstrate that, by tracking detailed information (higher moments) of the privacy loss, we can obtain much tighter estimates on the overall privacy loss, both asymptotically and empirically.
2. We improve the computational efficiency of differentially private training by introducing new techniques. These techniques include efficient algorithms for computing gradients for individual training examples, sub-

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The batching mechanism

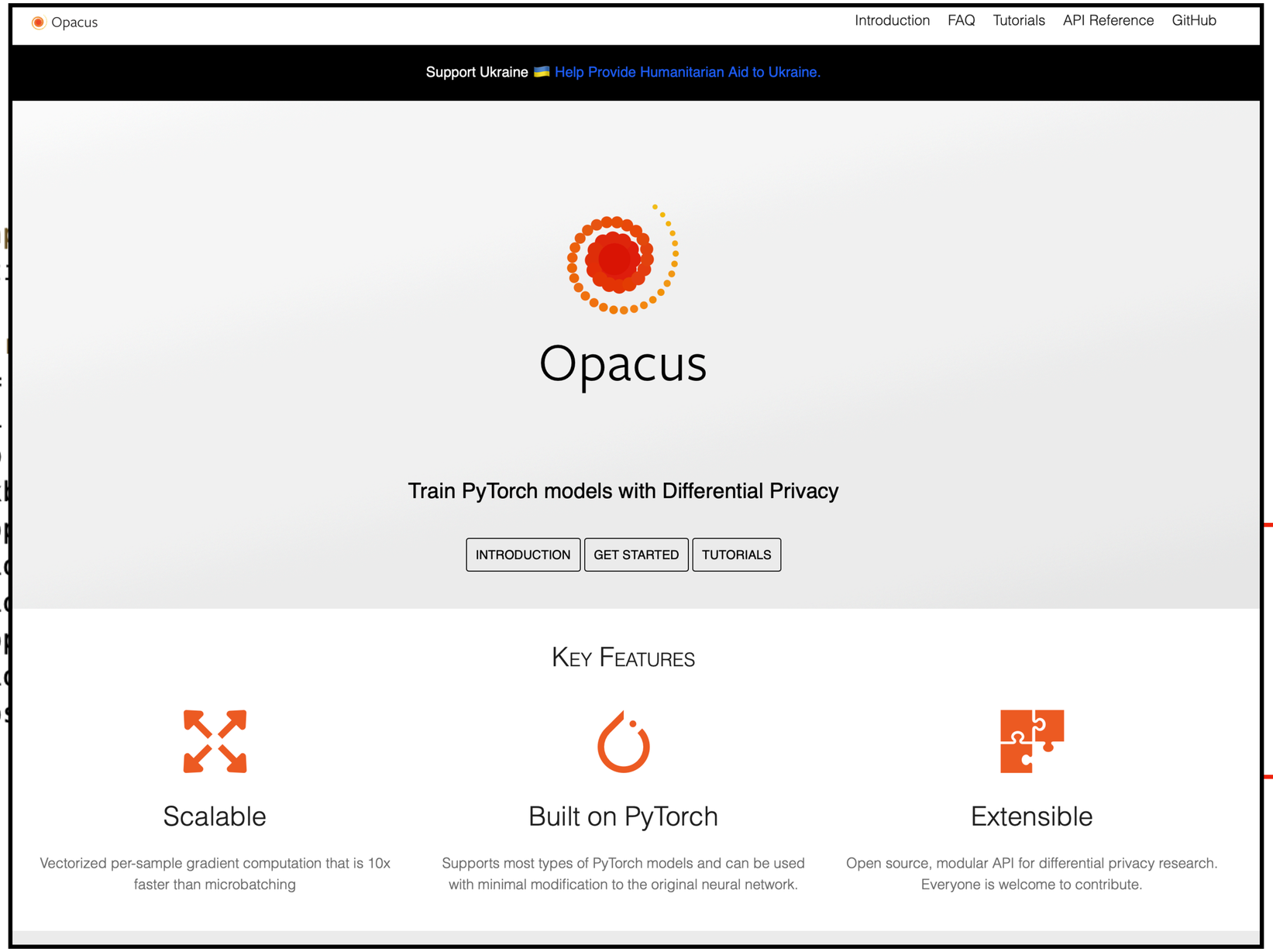
Outside of the scope of this presentation, but it is possible to play with “smarter” batching mechanisms to shape the privacy-utility tradeoff.

ANITI

```python
def train_nonprivate(model, epochs=epochs, bs=batch_size, lr=lr):
    opt = optim.SGD(model.parameters(), lr=lr)
    losses = []
    for _ in range(epochs):
        idx = torch.randperm(n)
        for i in range(0, n, bs):
            b = idx[i:i+bs]
            xb, yb = X[b], y[b]
            opt.zero_grad()
            loss = loss_fn(model(xb), yb)
            loss.backward()
            opt.step()
            losses.append(loss.item())
    return losses
```

Clément, enough theory, we just want to make this private already!

```
def train_nonp
    opt = opti
    losses =
    for _ in
        idx =
        for i
            b
            xb
            op
            lo
            lo
            op
            lo
    return los
```



just

```python
def train_nonprivate(model, epochs=epochs, bs=batch_size, lr=lr):
    opt = optim.SGD(model.parameters(), lr=lr)
    losses = []
    for _ in range(epochs):
        idx = torch.randperm(n)
        for i in range(0, n, bs):
            b = idx[i:i+bs]
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            opt.zero_grad()
            loss = loss_fn(model(xb), yb)
            loss.backward()
            opt.step()
            losses.append(loss.item())
    return losses
```

```python
def train_opacus(model, epochs=epochs, bs=batch_size, lr=lr, max_grad_norm=1.0, noise_multiplier=1.0, delta=1e-5):
    from opacus import PrivacyEngine

    loader = torch.utils.data.DataLoader(
        torch.utils.data.TensorDataset(X, y),
        batch_size=bs,
        shuffle=True,
    )
    opt = optim.SGD(model.parameters(), lr=lr)
    privacy_engine = PrivacyEngine()

    model, opt, loader = privacy_engine.make_private(
        module=model,
        optimizer=opt,
        data_loader=loader,
        noise_multiplier=noise_multiplier,
        max_grad_norm=max_grad_norm,
    )

    losses = []
    for _ in range(epochs):
        for xb, yb in loader:
            opt.zero_grad()
            loss = loss_fn(model(xb), yb)
            loss.backward()
            opt.step()
            losses.append(loss.item())

    eps = privacy_engine.get_epsilon(delta=delta)
    return losses, eps
```

```python
def train_nonprivate(model, epochs=epochs, bs=batch_size, lr=lr):
    opt = optim.SGD(model.parameters(), lr=lr)
    losses = []
    for _ in range(epochs):
        idx = torch.randperm(n)
        for i in range(0, n, bs):
            b = idx[i:i+bs]
            xb, yb = X[b], y[b]
            opt.zero_grad()
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            loss.backward()
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    return losses
```

```python
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        shuffle=True,
    )
    opt = optim.SGD(model.parameters(), lr=lr)
    privacy_engine = PrivacyEngine()

    model, opt, loader = privacy_engine.make_private(
        module=model,
        optimizer=opt,
        data_loader=loader,
        noise_multiplier=noise_multiplier,
        max_grad_norm=max_grad_norm,
    )

    losses = []
    for _ in range(epochs):
        for xb, yb in loader:
            opt.zero_grad()
            loss = loss_fn(model(xb), yb)
            loss.backward()
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            losses.append(loss.item())

    eps = privacy_engine.get_epsilon(delta=delta)
    return losses, eps
```

Extra code to handle Privacy

```python
def train_nonprivate(model, epochs=epochs, bs=batch_size, lr=lr):
    opt = optim.SGD(model.parameters(), lr=lr)
    losses = []
    for _ in range(epochs):
        idx = torch.randperm(n)
        for i in range(0, n, bs):
            b = idx[i:i+bs]
            xb, yb = X[b], y[b]
            opt.zero_grad()
            loss = loss_fn(model(xb), yb)
            loss.backward()
            opt.step()
            losses.append(loss.item())
    return losses
```

Same training loop

```python
def train_opacus(model, epochs=epochs, bs=batch_size, lr=lr, max_grad_norm=1.0, noise_multiplier=1.0, delta=1e-5):
    from opacus import PrivacyEngine

    loader = torch.utils.data.DataLoader(
        torch.utils.data.TensorDataset(X, y),
        batch_size=bs,
        shuffle=True,
    )
    opt = optim.SGD(model.parameters(), lr=lr)
    privacy_engine = PrivacyEngine()

    model, opt, loader = privacy_engine.make_private(
        module=model,
        optimizer=opt,
        data_loader=loader,
        noise_multiplier=noise_multiplier,
        max_grad_norm=max_grad_norm,
    )

    losses = []
    for _ in range(epochs):
        for xb, yb in loader:
            opt.zero_grad()
            loss = loss_fn(model(xb), yb)
            loss.backward()
            opt.step()
            losses.append(loss.item())

    eps = privacy_engine.get_epsilon(delta=delta)
    return losses, eps
```

Extra code to handle Privacy

```python
def train_opacus(model, epochs=epochs, bs=batch_size, lr=lr, max_grad_norm=1.0, noise_multiplier=1.0, delta=1e-5):
    from opacus import PrivacyEngine

    loader = torch.utils.data.DataLoader(
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        shuffle=True,
    )
    opt = optim.SGD(model.parameters(), lr=lr)
    privacy_engine = PrivacyEngine()

    model, opt, loader = privacy_engine.make_private(
        module=model,
        optimizer=opt,
        data_loader=loader,
        noise_multiplier=noise_multiplier,
        max_grad_norm=max_grad_norm,
    )

    losses = []
    for _ in range(epochs):
        for xb, yb in loader:
            opt.zero_grad()
            loss = loss_fn(model(xb), yb)
            loss.backward()
            opt.step()
            losses.append(loss.item())

    eps = privacy_engine.get_epsilon(delta=delta)
    return losses, eps
```
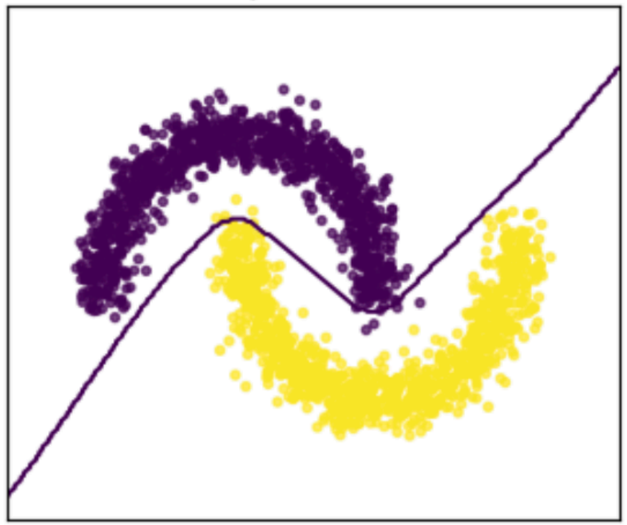
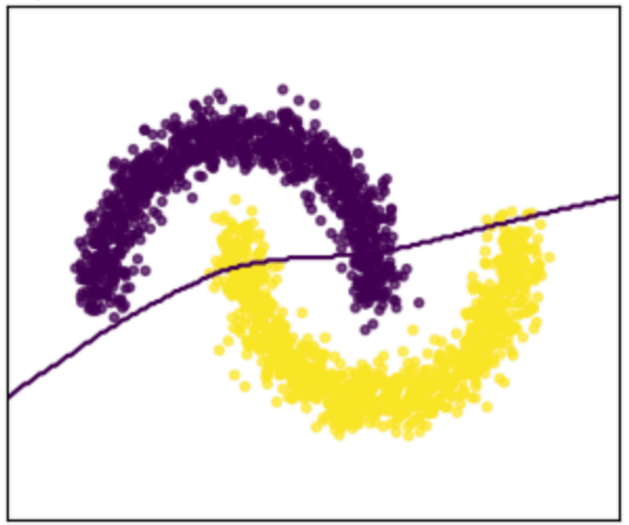
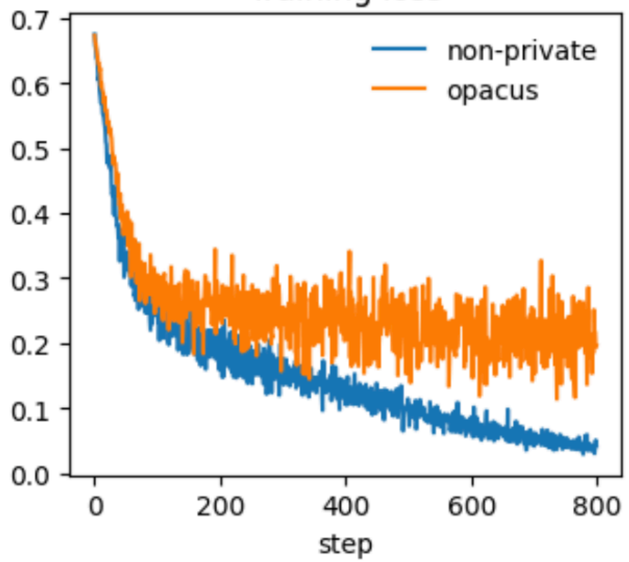

```
n = 2000
lr = 0.05
batch_size = 256
epochs = 100
max_grad_norm = 1.0
noise_multiplier= 1.0
```



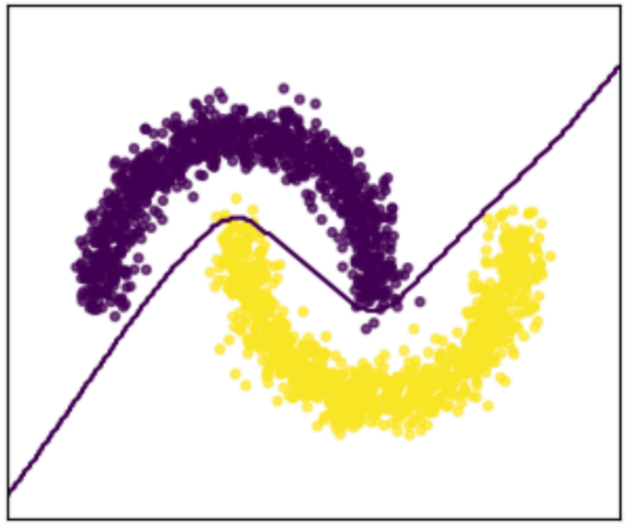


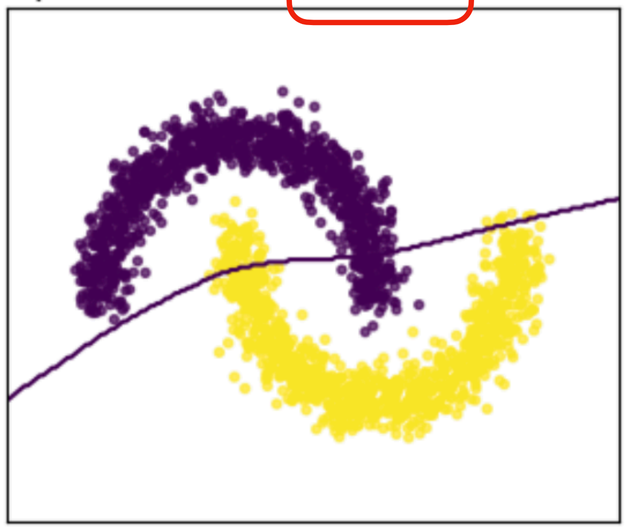


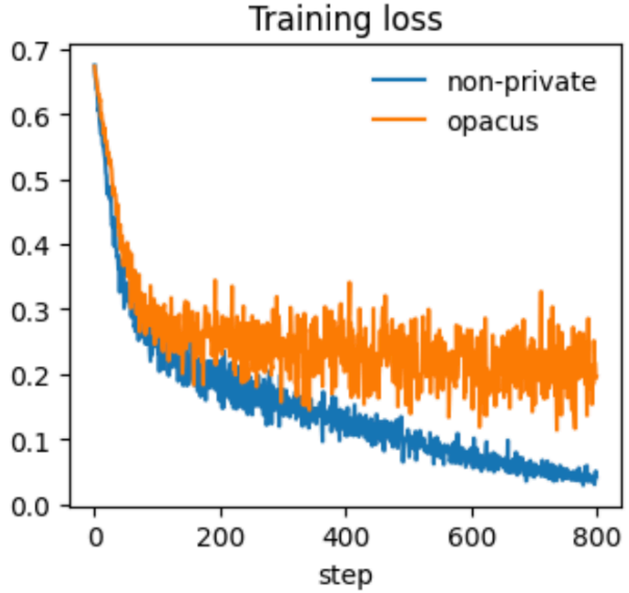
```python
def train_opacus(model, epochs=epochs, bs=batch_size, lr=lr, max_grad_norm=1.0, noise_multiplier=1.0, delta=1e-5):
    from opacus import PrivacyEngine

    loader = torch.utils.data.DataLoader(
        torch.utils.data.TensorDataset(X, y),
        batch_size=bs,
        shuffle=True,
    )
    opt = optim.SGD(model.parameters(), lr=lr)
    privacy_engine = PrivacyEngine()

    model, opt, loader = privacy_engine.make_private(
        module=model,
        optimizer=opt,
        data_loader=loader,
        noise_multiplier=noise_multiplier,
        max_grad_norm=max_grad_norm,
    )

    losses = []
    for _ in range(epochs):
        for xb, yb in loader:
            opt.zero_grad()
            loss = loss_fn(model(xb), yb)
            loss.backward()
            opt.step()
            losses.append(loss.item())

    eps = privacy_engine.get_epsilon(delta=delta)
    return losses, eps
```

Privacy Budget: The smaller, the more private.

```
n = 2000
lr = 0.05
batch_size = 256
epochs = 100
max_grad_norm = 1.0
noise_multiplier= 1.0
```

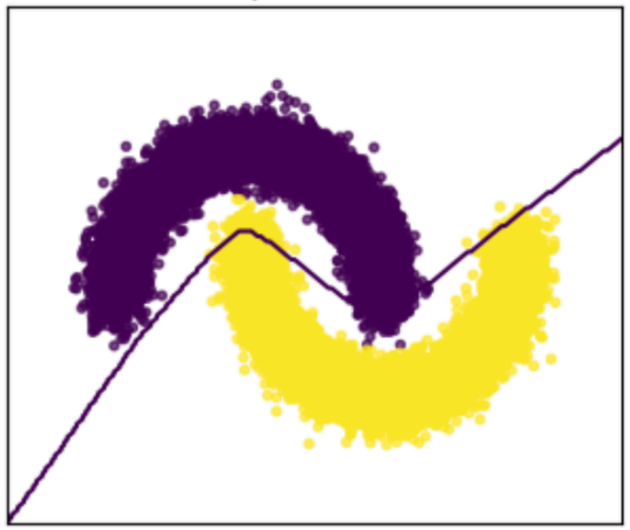


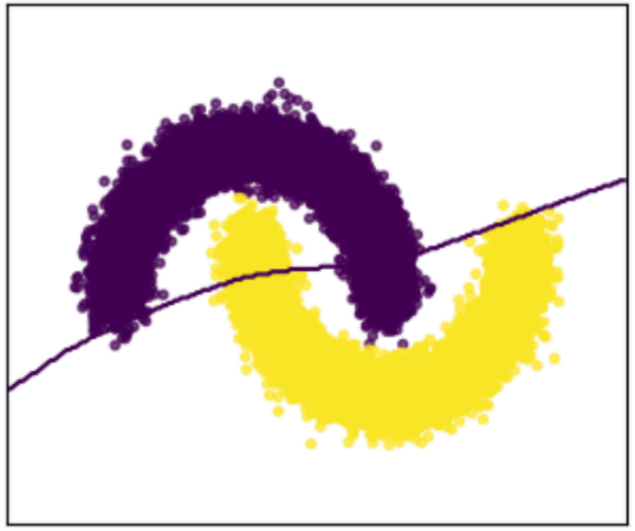


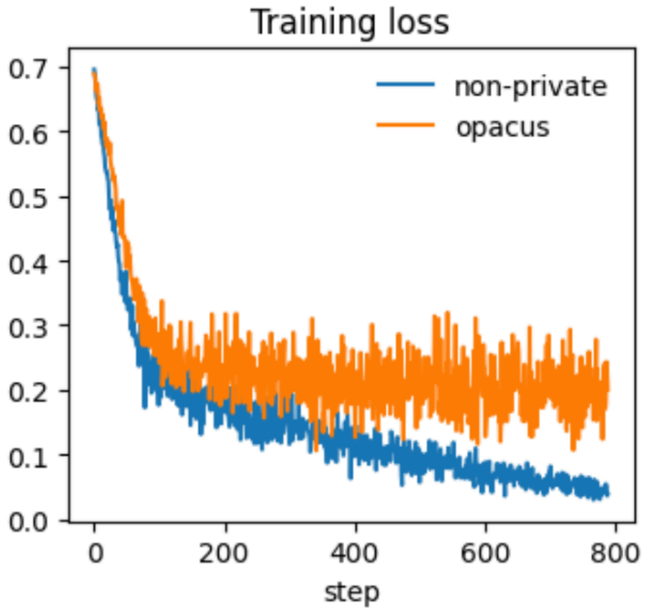


```python
def train_opacus(model, epochs=epochs, bs=batch_size, lr=lr, max_grad_norm=1.0, noise_multiplier=1.0, delta=1e-5):
    from opacus import PrivacyEngine

    loader = torch.utils.data.DataLoader(
        torch.utils.data.TensorDataset(X, y),
        batch_size=bs,
        shuffle=True,
    )
    opt = optim.SGD(model.parameters(), lr=lr)
    privacy_engine = PrivacyEngine()

    model, opt, loader = privacy_engine.make_private(
        module=model,
        optimizer=opt,
        data_loader=loader,
        noise_multiplier=noise_multiplier,
        max_grad_norm=max_grad_norm,
    )

    losses = []
    for _ in range(epochs):
        for xb, yb in loader:
            opt.zero_grad()
            loss = loss_fn(model(xb), yb)
            loss.backward()
            opt.step()
            losses.append(loss.item())

    eps = privacy_engine.get_epsilon(delta=delta)
    return losses, eps
```

```
n = 20000
lr = 0.05
batch_size = 256
epochs = 10
max_grad_norm = 1.0
noise_multiplier= 1.0
```

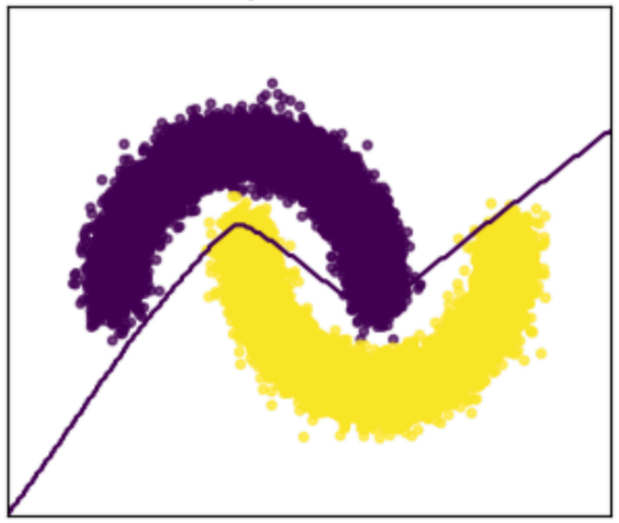


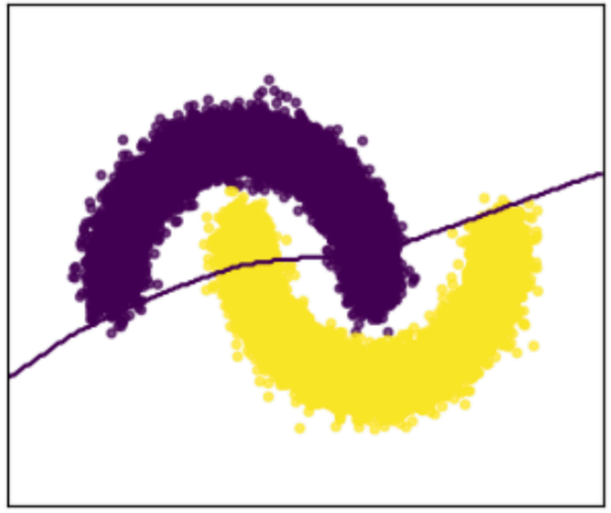


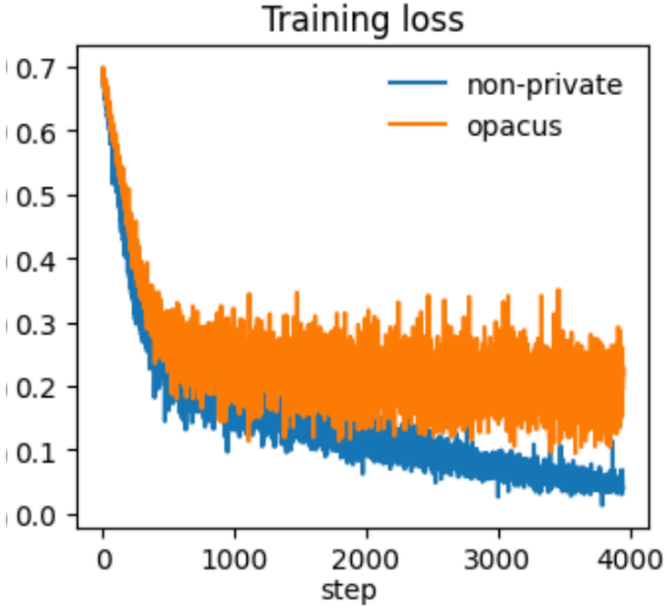


```python
def train_opacus(model, epochs=epochs, bs=batch_size, lr=lr, max_grad_norm=1.0, noise_multiplier=1.0, delta=1e-5):
    from opacus import PrivacyEngine

    loader = torch.utils.data.DataLoader(
        torch.utils.data.TensorDataset(X, y),
        batch_size=bs,
        shuffle=True,
    )
    opt = optim.SGD(model.parameters(), lr=lr)
    privacy_engine = PrivacyEngine()

    model, opt, loader = privacy_engine.make_private(
        module=model,
        optimizer=opt,
        data_loader=loader,
        noise_multiplier=noise_multiplier,
        max_grad_norm=max_grad_norm,
    )

    losses = []
    for _ in range(epochs):
        for xb, yb in loader:
            opt.zero_grad()
            loss = loss_fn(model(xb), yb)
            loss.backward()
            opt.step()
            losses.append(loss.item())

    eps = privacy_engine.get_epsilon(delta=delta)
    return losses, eps
```

```
n = 20000
lr = 0.01
batch_size = 256
epochs = 50
max_grad_norm = 1.0
noise_multiplier= 1.0
```

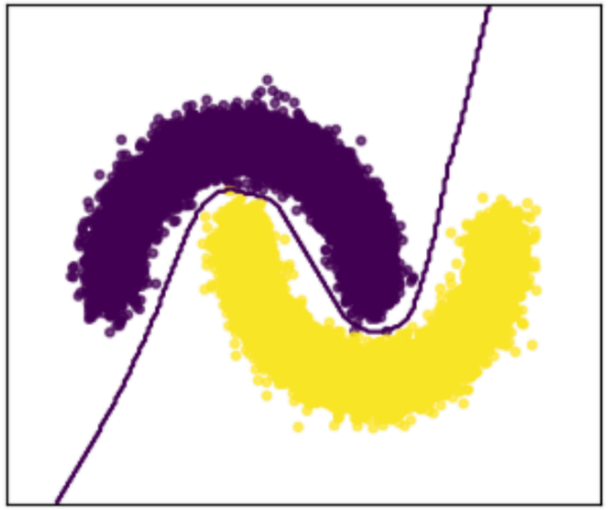


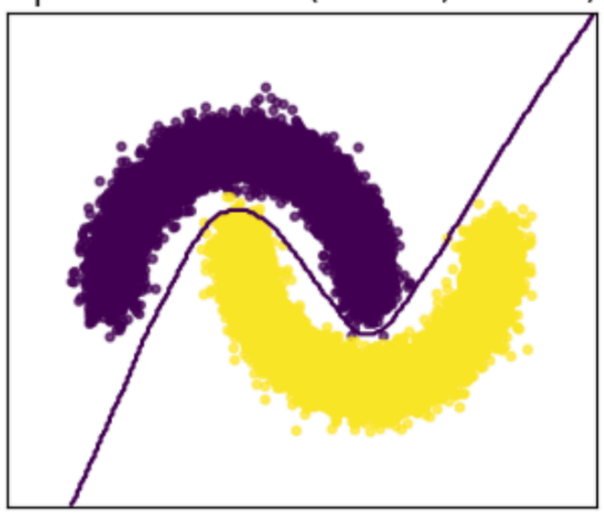


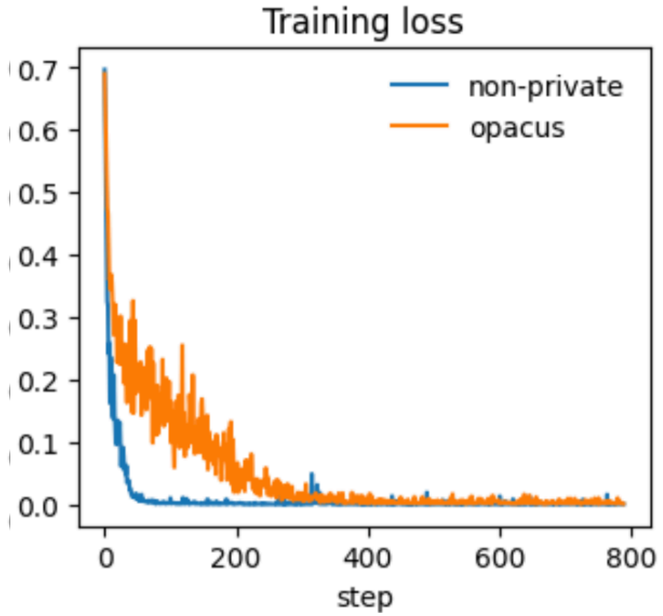


```python
def train_opacus(model, epochs=epochs, bs=batch_size, lr=lr, max_grad_norm=1.0, noise_multiplier=1.0, delta=1e-5):
    from opacus import PrivacyEngine

    loader = torch.utils.data.DataLoader(
        torch.utils.data.TensorDataset(X, y),
        batch_size=bs,
        shuffle=True,
    )
    opt = optim.Adam(model.parameters(), lr=lr)
    privacy_engine = PrivacyEngine()

    model, opt, loader = privacy_engine.make_private(
        module=model,
        optimizer=opt,
        data_loader=loader,
        noise_multiplier=noise_multiplier,
        max_grad_norm=max_grad_norm,
    )

    losses = []
    for _ in range(epochs):
        for xb, yb in loader:
            opt.zero_grad()
            loss = loss_fn(model(xb), yb)
            loss.backward()
            opt.step()
            losses.append(loss.item())

    eps = privacy_engine.get_epsilon(delta=delta)
    return losses, eps
```

```
n = 20000
lr = 0.01
batch_size = 256
epochs = 10
max_grad_norm = 1.0
noise_multiplier= 2.5
```







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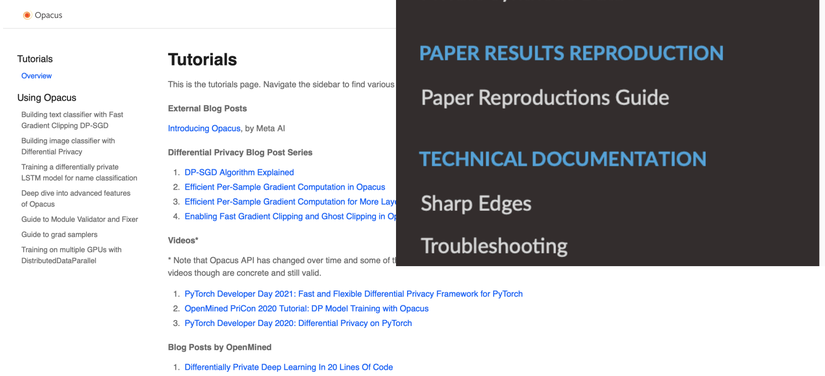

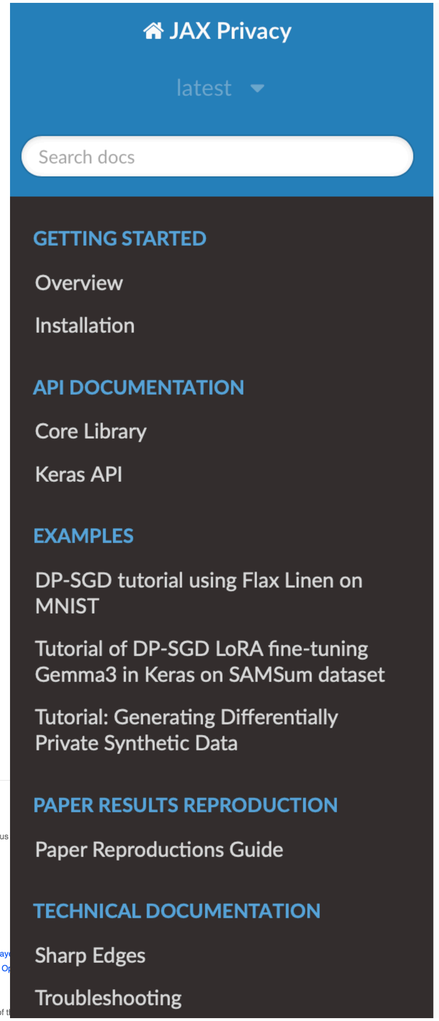

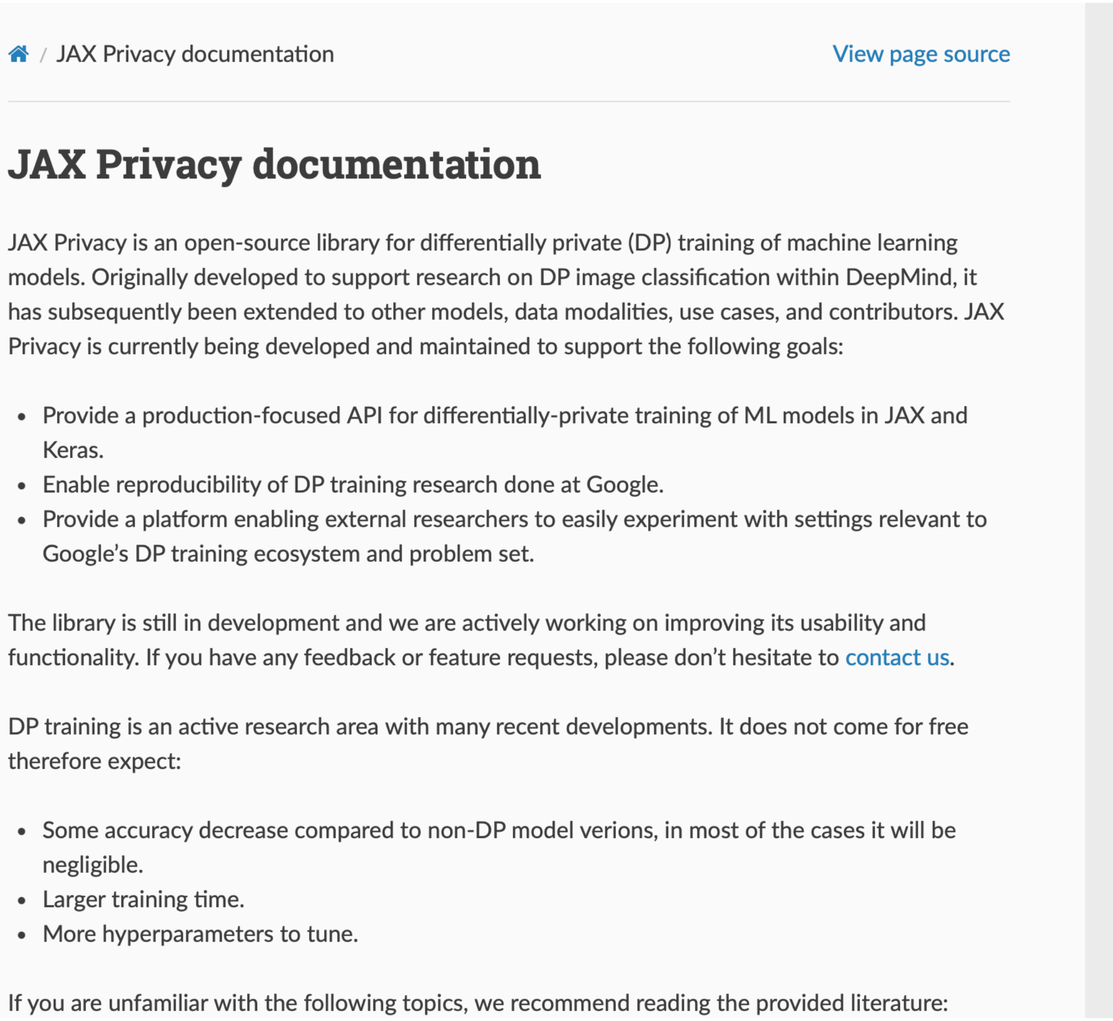

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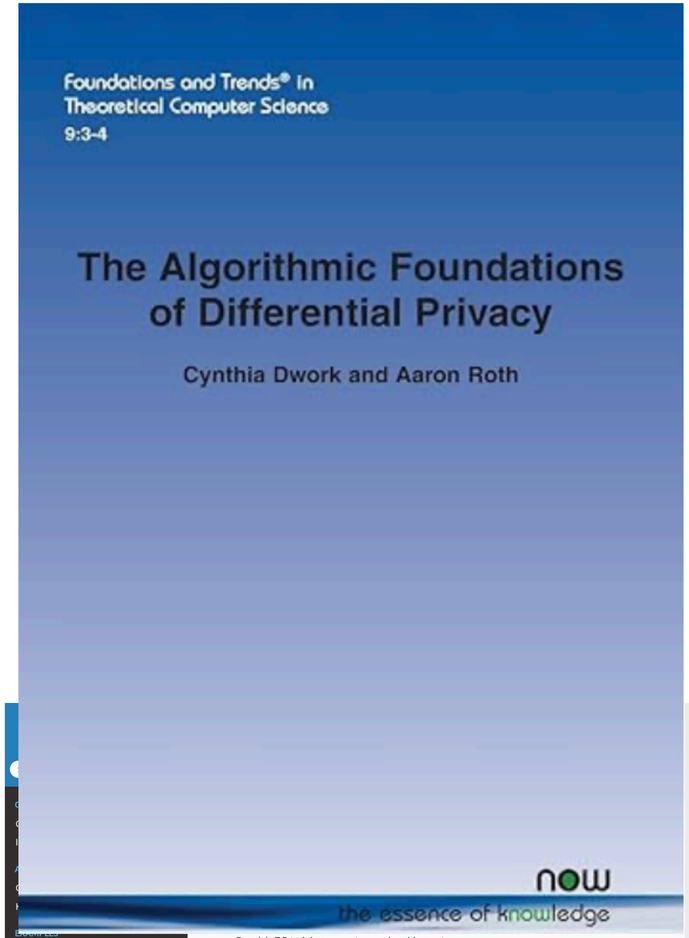

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Tutorial: Generating Differentially Private Synthetic Data

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Troubleshooting

Google's DP training ecosystem and problem set.

The library is still in development and we are actively working on improving its usability and functionality. If you have any feedback or feature requests, please don't hesitate to contact us.

DP training is an active research area with many recent developments. It does not come for free therefore expect:

- Some accuracy decrease compared to non-DP model verions, in most of the cases it will be negligible.
- Larger training time.
- More hyperparameters to tune.

If you are unfamiliar with the following topics, we recommend reading the provided literature:

Going further

Gaussian Differential Privacy

Jinshuo Dong* Aaron Roth† Weijie J. Su‡

May 24, 2019

Abstract

In the past decade, differential privacy has seen remarkable success as a rigorous and practical formalization of data privacy. This privacy definition and its divergence based relaxations, however, have several acknowledged weaknesses, either in handling composition of private algorithms or in analyzing important primitives like privacy amplification by subsampling. Inspired

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Keras API

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- Provide a production-focused API for differentially-private training of ML models in JAX and Keras.
- Enable reproducibility of DP training research done at Google.
- Provide a platform enabling external researchers to easily experiment with settings relevant to Google's DP training ecosystem and problem set.

The library is still in development and we are actively working on improving its usability and functionality. If you have any feedback or feature requests, please don't hesitate to contact us.

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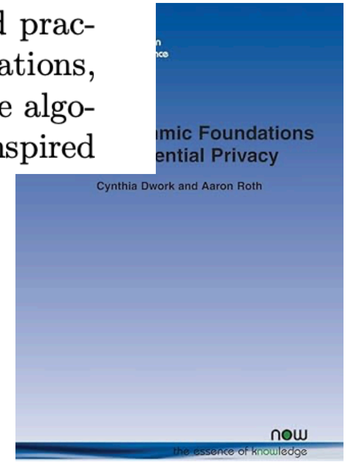

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Thank you!

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Thank you!

Contact: clement.lalanne@math.univ-toulouse.fr