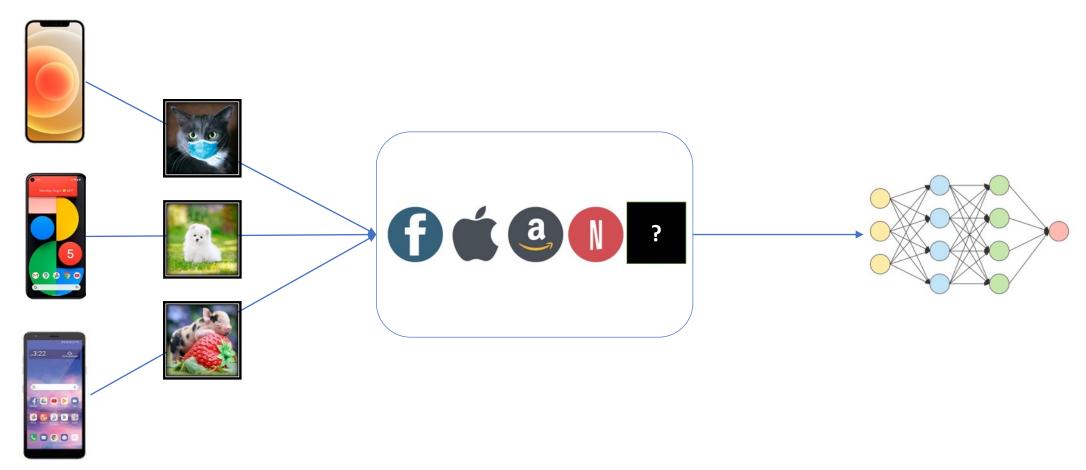
### What is (and isn't) private learning?

Florian Tramèr

Stanford University



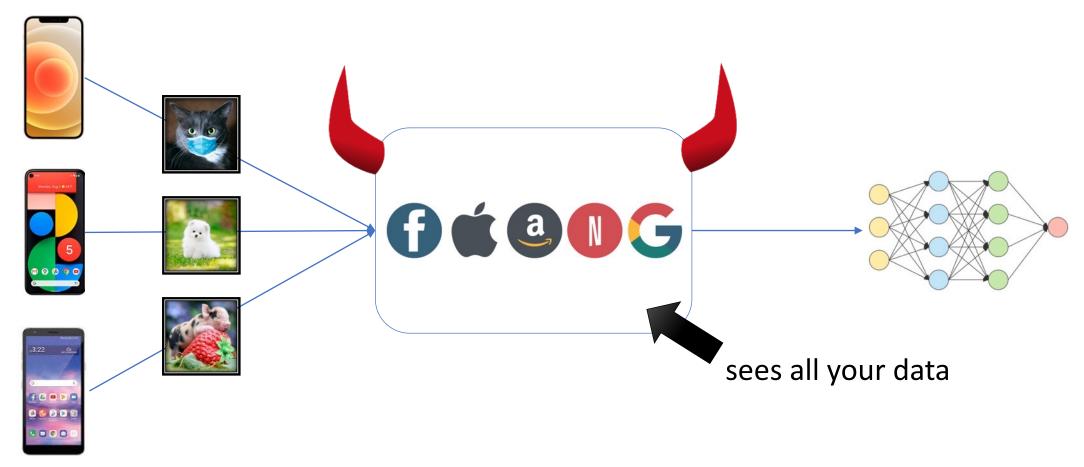
> what does this mean?

how can we achieve this?

> what's next?

> what does this mean?

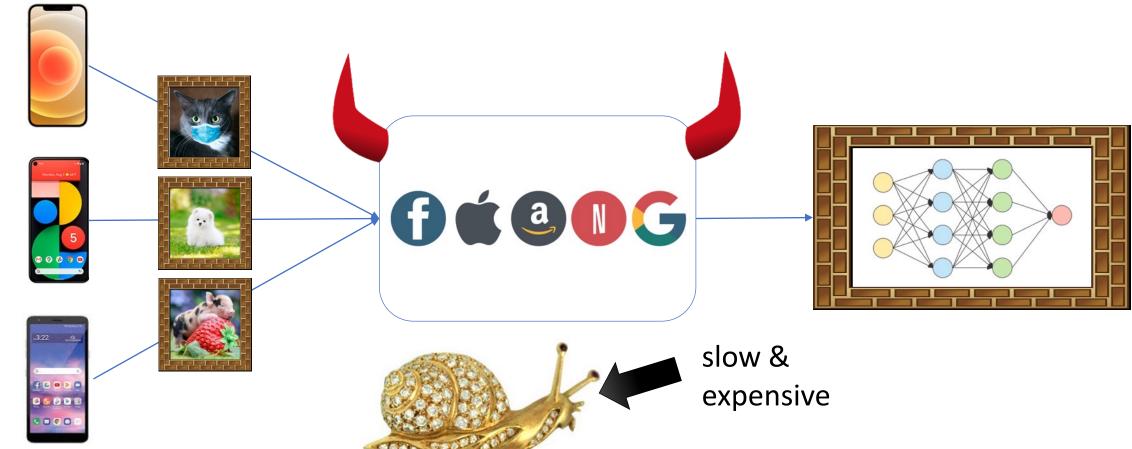
data secrecy



- > what does this mean?
- how can we achieve this?

data secrecy

federated ML, MPC, FHE, ...

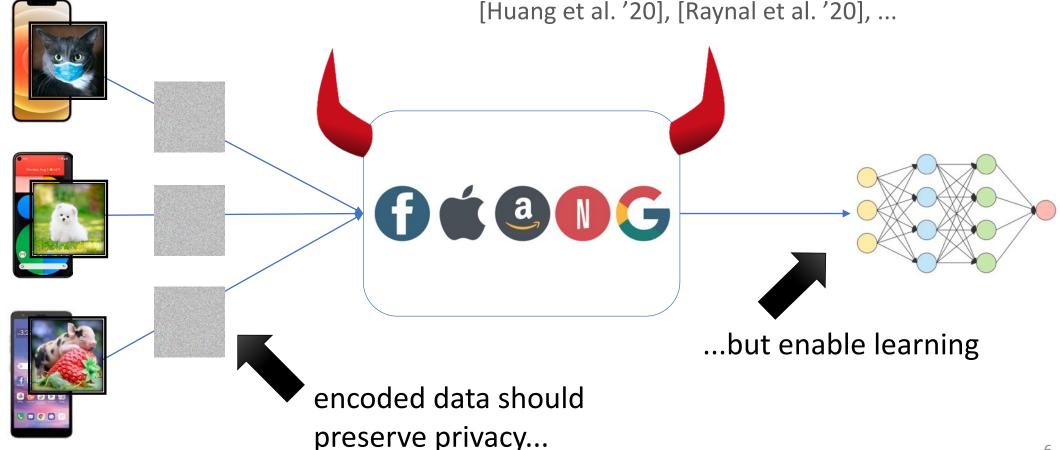


- > what does this mean?
- how (else) can we achieve this?

data secrecy

learning on "encoded" data

[Huang et al. '20], [Raynal et al. '20], ...



### Goal: private learning on "encoded" data

Example: InstaHide [Huang et al. ICML '20]

*private* data public data Encode(

no formal privacy guarantee... 1) Mixing:



map pixel space [0, 255] to [-1, 1]

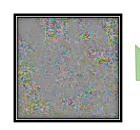


 $\in$  [-1, 1]<sup>d</sup>

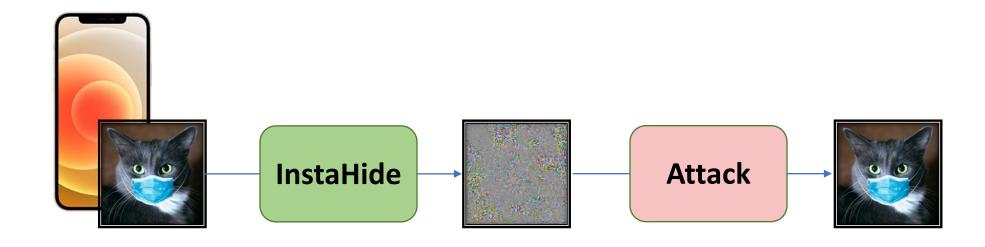
2) "high-order bit flip":  $\sigma \leftarrow^R \{-1, 1\}^d$ 



⊙ σ =



learning still works!



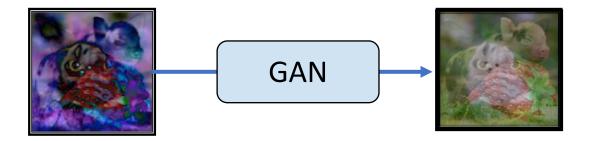
#### 1. Undo the random bit flip



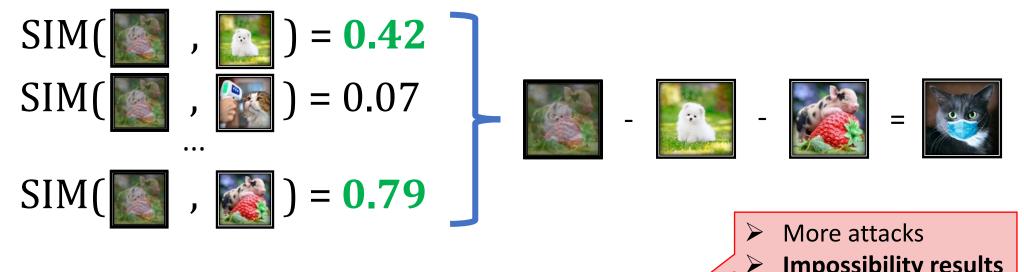
this is clearly **not** private!!!



- 1. Undo the random bit flip
- 2. Learn to "recolor" mixed images



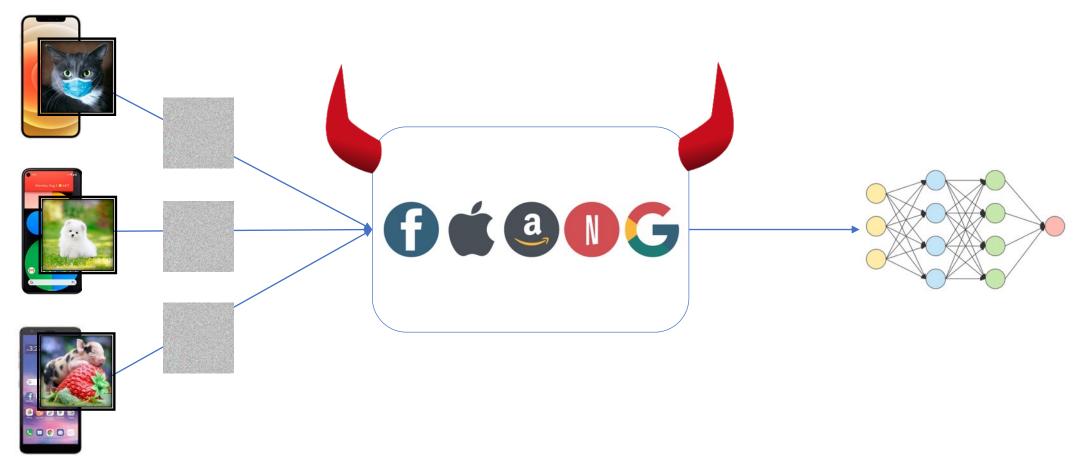
- 1. Undo the random bit flip
- 2. Learn to "recolor" mixed images
- 3. Undo the mixing by finding the most similar public images



- > what does this mean?
- ➤ how (else) can we achieve this?

data secrecy

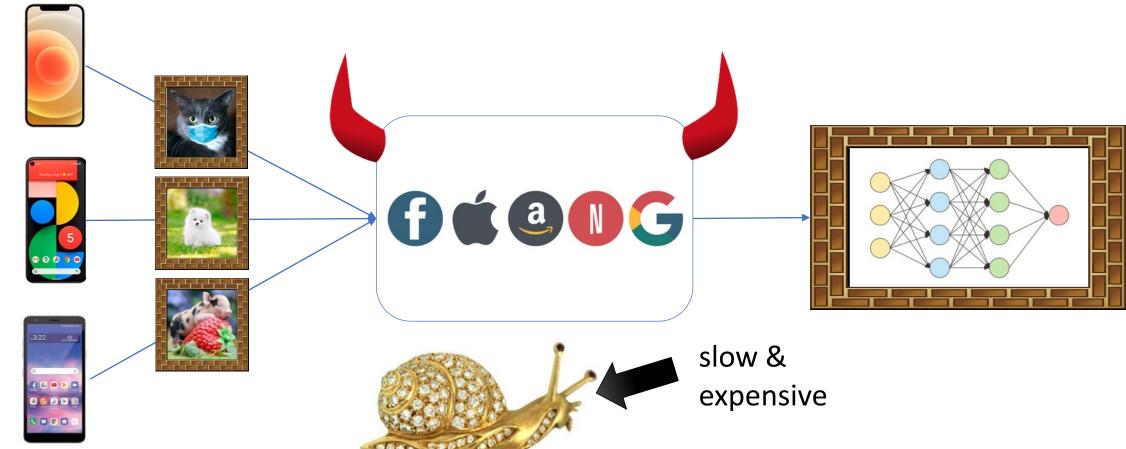
learning on "encoded" data



- > what does this mean?
- how can we achieve this?

data secrecy

federated ML, MPC, FHE, ...



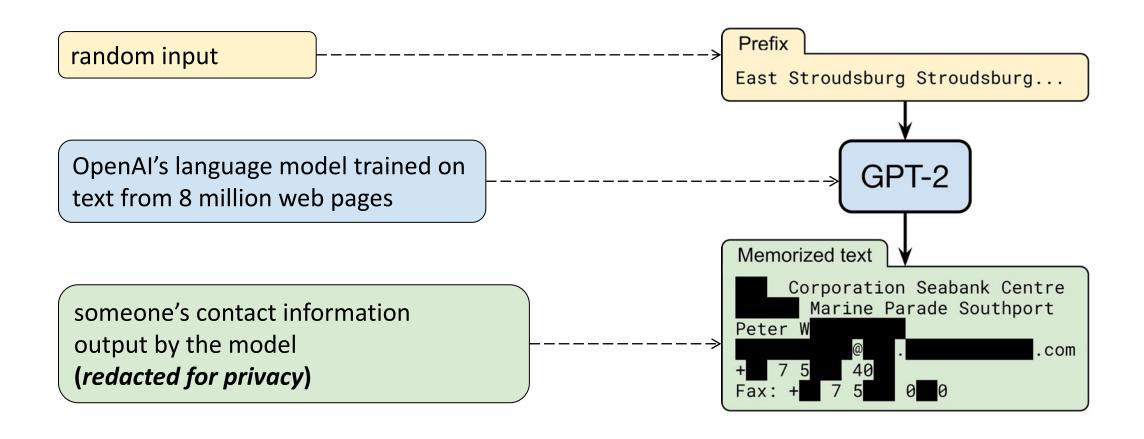
#### Is data secrecy *sufficient?*

No! The ideal functionality itself can be non-private

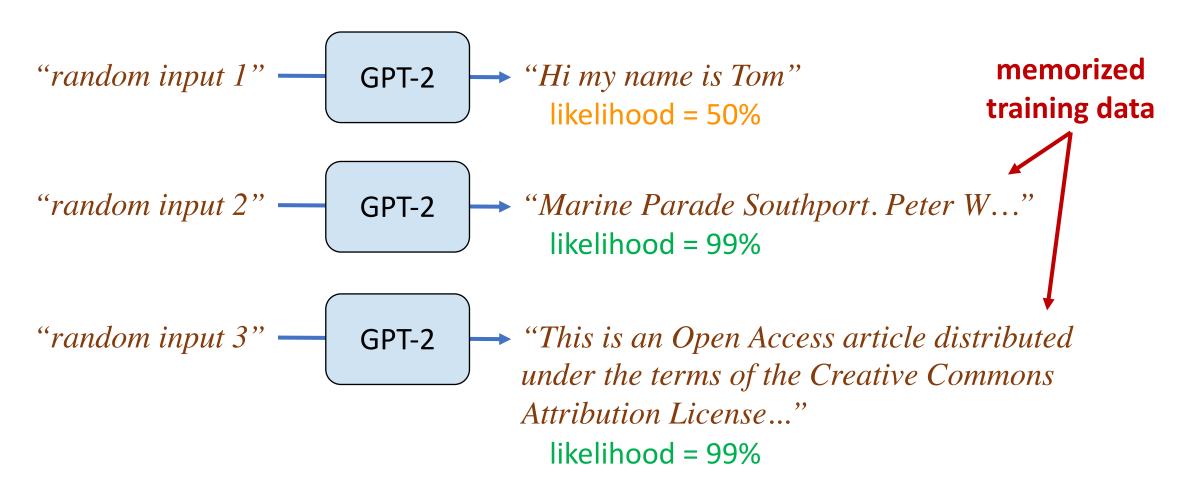


WHEN YOU TRAIN PREDICTIVE MODELS ON INPUT FROM YOUR USERS, IT CAN LEAK INFORMATION IN UNEXPECTED WAYS.

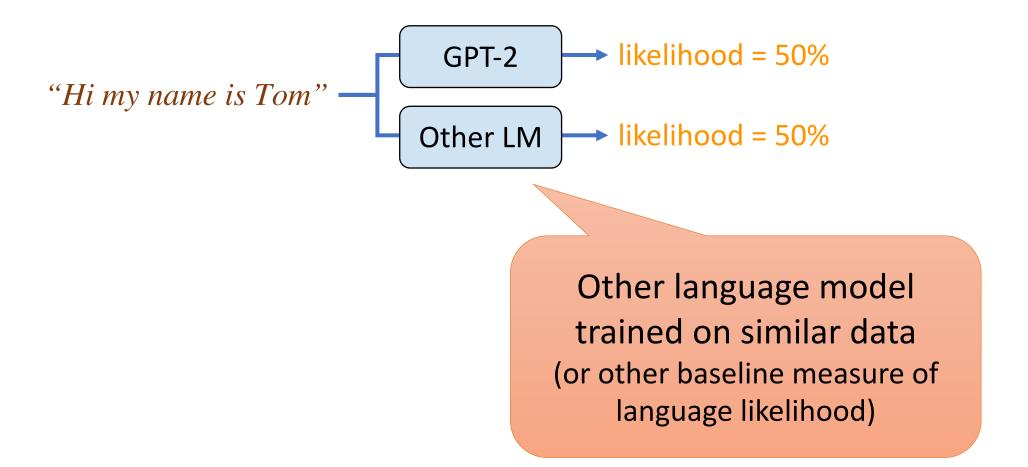
#### Models memorize their training data.



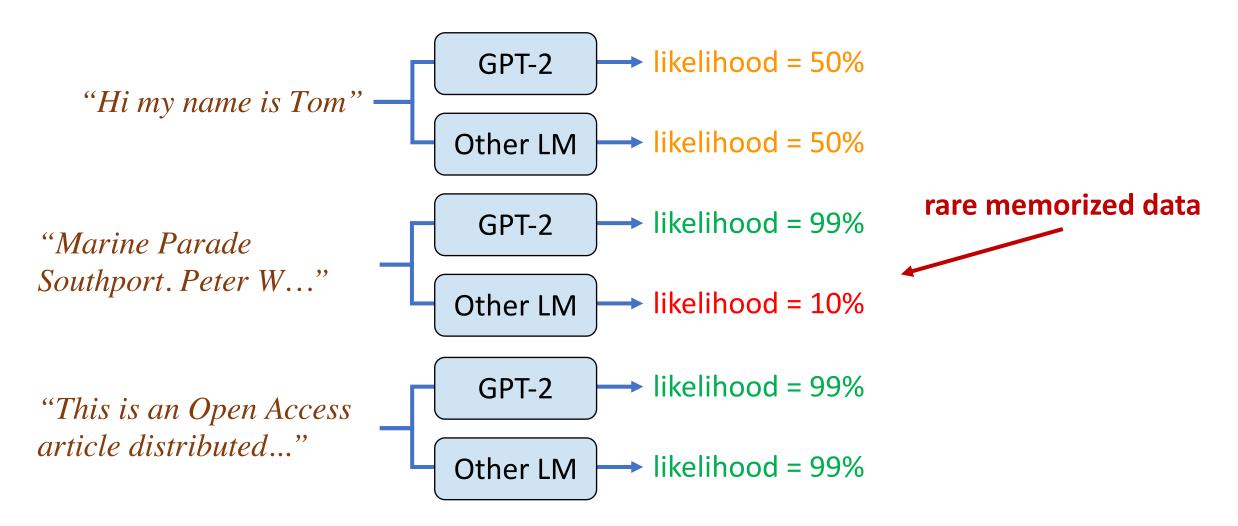
# Extracting memorized training data by generating high-likelihood outputs.



#### Extracting rare memorized training data.



#### Extracting rare memorized training data.



	Occurrences		Memorized?		
URL (trimmed)	Docs	Total	XL	M	S
/r/ 51y/milo_evacua	1	359	<b>√</b>	✓	1/2
/r/zin/hi_my_name	1	113	✓	$\checkmark$	
/r/ 7ne/for_all_yo	1	76	1	1/2	
/r/ 5mj/fake_news	1	72	✓		
/r/ 5wn/reddit_admi	1	64	✓	$\checkmark$	
/r/ lp8/26_evening	1	56	$\checkmark$	$\checkmark$	
/r/ jla/so_pizzagat	1	51	$\checkmark$	1/2	
/r/ ubf/late_night	1	51	$\checkmark$	1/2	
/r/ eta/make_christ	1	35	✓	1/2	
/r/ 6ev/its_officia	1	33	✓		
/r/ 3c7/scott_adams	1	17			
/r/k2o/because_his	1	17			
/r/ tu3/armynavy_ga	1	8			

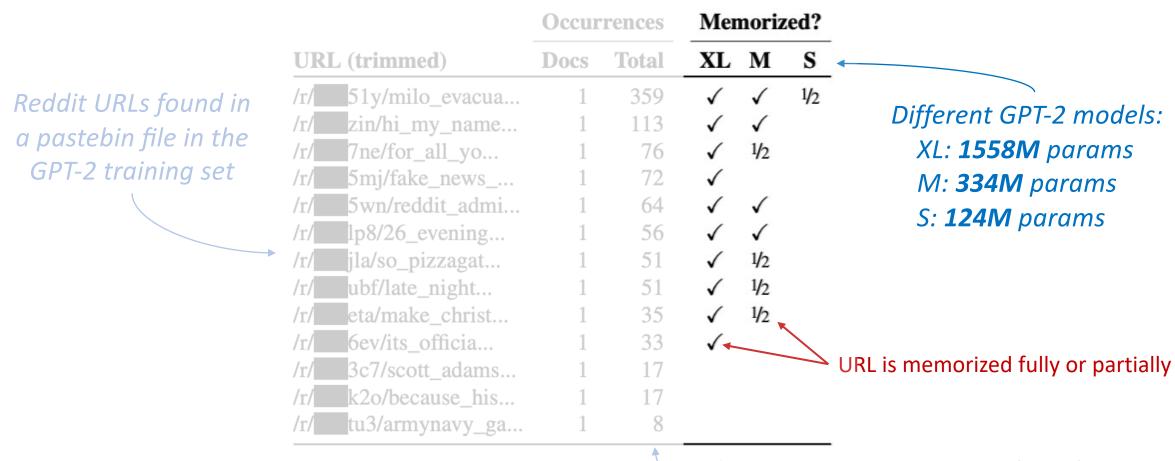
Reddit URLs found in a pastebin file in the GPT-2 training set

	Occurrences		Memorized?		
URL (trimmed)	Docs	Total	XL	M	S
/r/ 51y/milo_evacua	1	359	$\checkmark$	$\checkmark$	1/2
/r/ zin/hi_my_name	1	113	$\sqrt{}$	$\sqrt{}$	
/r/ 7ne/for_all_yo	1	76	$\sqrt{}$	1/2	
/r/ 5mj/fake_news	1	72	$\sqrt{}$		
/r/ 5wn/reddit_admi	1	64	$\sqrt{}$	$\sqrt{}$	
/r/ lp8/26_evening	1	56	$\sqrt{}$	$\sqrt{}$	
/r/jla/so_pizzagat	1	51	$\sqrt{}$	1/2	
/r/ ubf/late_night	1	51	$\sqrt{}$	1/2	
/r/ eta/make_christ	1	35	$\sqrt{}$	1/2	
/r/ 6ev/its_officia	1	33	$\sqrt{}$		
/r/ 3c7/scott_adams	1	17			
/r/k2o/because_his	1	17			
/r/ tu3/armynavy_ga	1	8			

Reddit URLs found in a pastebin file in the GPT-2 training set

Memorized?		
M	S	
<b>√</b>	1/2	
$\checkmark$		
1/2		
$\checkmark$		
$\checkmark$		
1/2		
1/2		
1/2		

Some URLs appear many times in this pastebin file



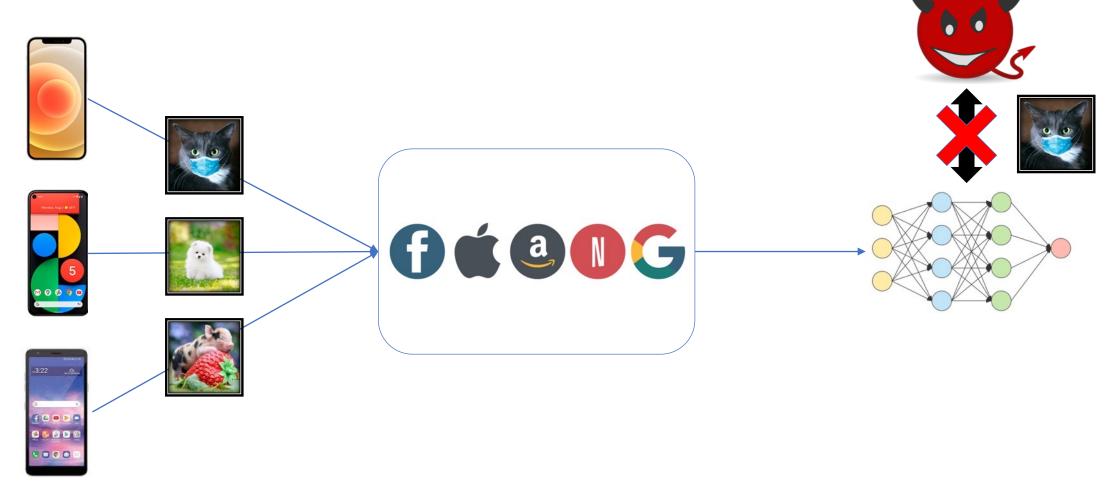
Some URLs appear many times in this pastebin file

URL (trimmed)         Docs         Total         XL           /r/■51y/milo_evacua         1         359         ✓           /r/■zin/hi_my_name         1         113         ✓	M
/r/ zin/hi my name 1 113	<b>√</b>
717 Zilly in _ inty_iname	$\checkmark$
/r/ 7ne/for_all_yo 1 76 ✓	1/2
/r/ 5mj/fake_news 1 72 ✓	
/r/ 5wn/reddit_admi 1 64 ✓	$\checkmark$
/r/ lp8/26_evening 1 56 ✓	$\checkmark$
/r/ jla/so_pizzagat 1 51 ✓	1/2
/r/ ubf/late_night 1 51 ✓	1/2
/r/ eta/make_christ 1 35 ✓	1/2
/r/ 6ev/its_officia 1 33 ✓	
/r/ 3c7/scott_adams 1 17	
/r/ k2o/because_his 1 17	
/r/tu3/armynavy_ga 1 8	

the largest GPT-2 model
memorized an entire URL
that appeared only 33
times in a single document

> what does this mean?

no training data leakage



#### Preventing data leakage with decade-old ML

- provably prevent leakage of training data. using differential privacy
- better accuracy than with deep learning methods. using domain-specific feature engineering

- > what does this mean?
- how can we achieve this?

no training data leakage

differential privacy

intuition: randomized training algorithm is not influenced (too much) by any individual data point

for any two datasets that differ in a single element

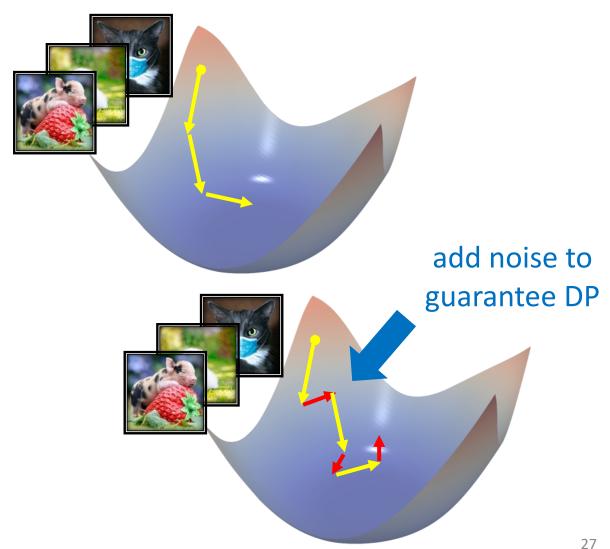
$$\frac{\Pr[A_{\text{train}}(\text{w}) = \text{w}]}{\Pr[A_{\text{train}}(\text{w}) = \text{w}]} \leq e^{\varepsilon}$$

#### How? Private Gradient Descent

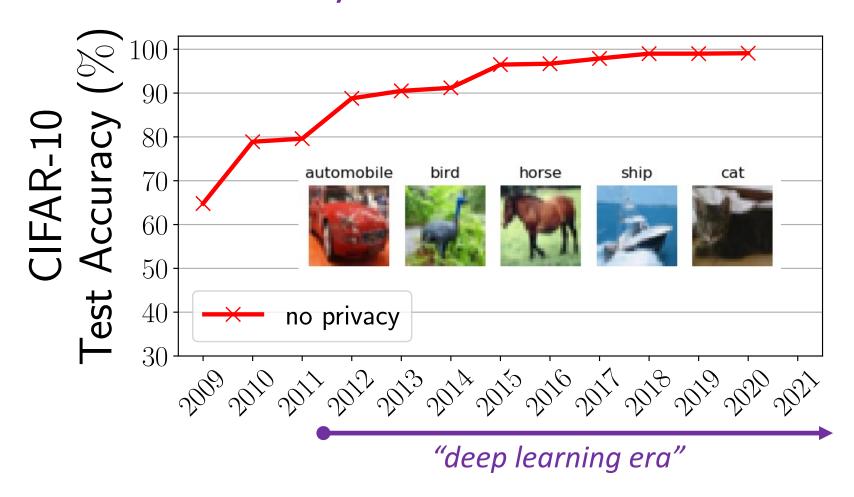
gradient descent (SGD)

### *private* gradient descent (DP-SGD)

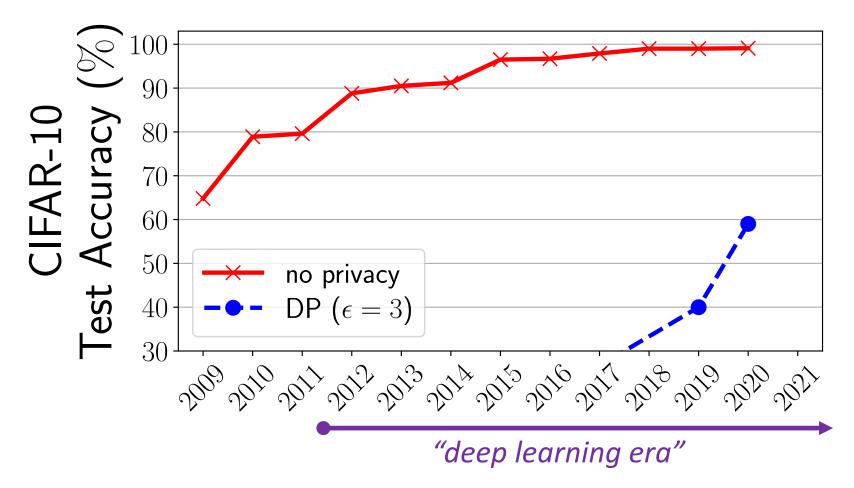
Chaudhuri et al., '11; Bassily et al. '14; Shokri & Shmatikov '15; Abadi et al. '16



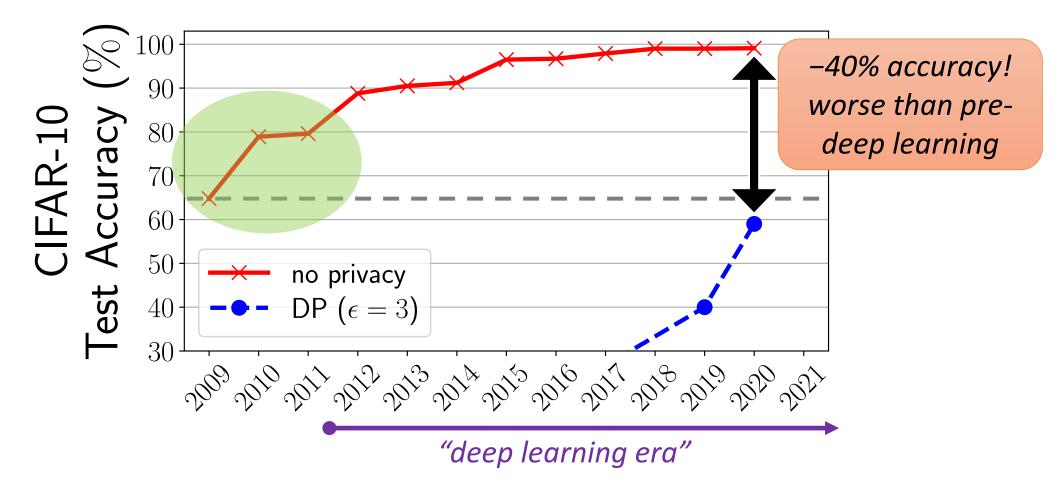
# Non-private deep learning can achieve near-perfect accuracy.



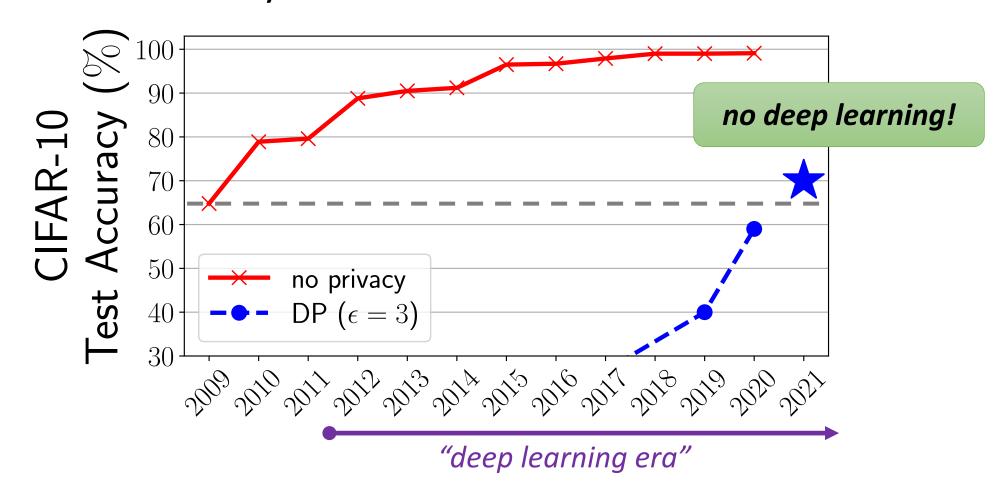
# Differentially private deep learning lowers accuracy significantly.



# Differentially private deep learning lowers accuracy significantly.

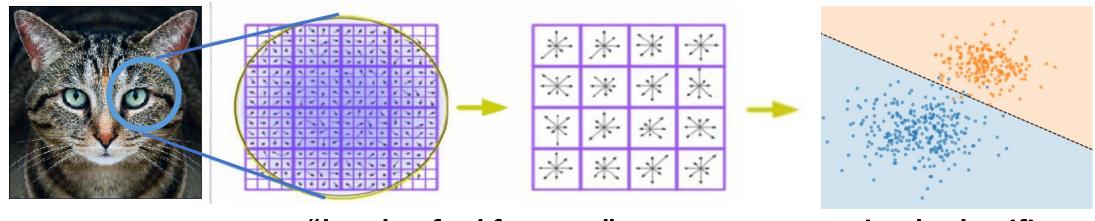


# Differential privacy without deep learning improves accuracy.



# Privacy-free features from "old-school" image recognition.

SIFT [Lowe '99, '04], HOG [Dalal & Triggs '05], SURF [Bay et al. '06], ORB [Rublee et al. '11], ... Scattering transforms [Bruna & Mallat '11], [Oyallon & Mallat '14], ...



"handcrafted features"

(no learning involved)

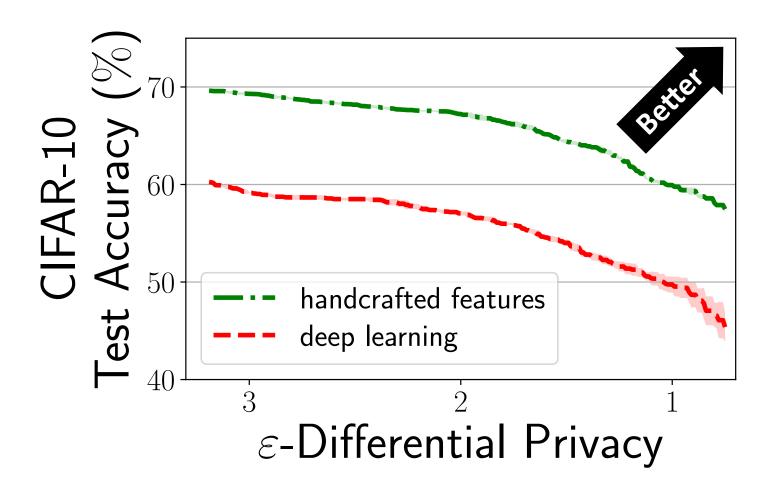
simple classifier (e.g., logistic regression)





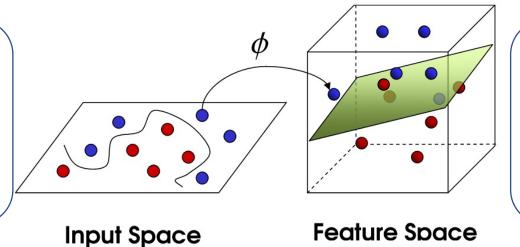
captures some *prior* about the domain: e.g., invariance under rotation & scaling

### Handcrafted features lead to a better tradeoff between accuracy and privacy.



### Handcrafted features lead to an *easier* learning task (for noisy gradient descent).

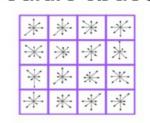
high accuracy classifier exists but learning takes many gradient steps



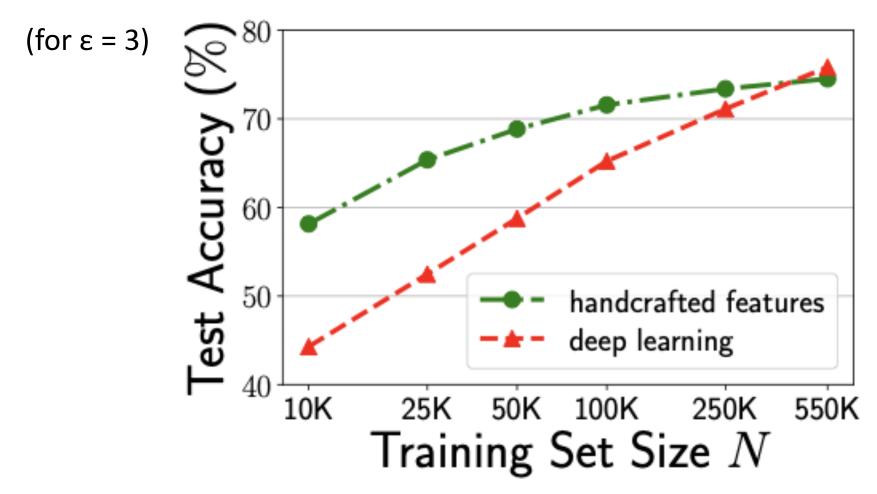
in feature space,
maximal accuracy is
reduced but *learning*progresses faster

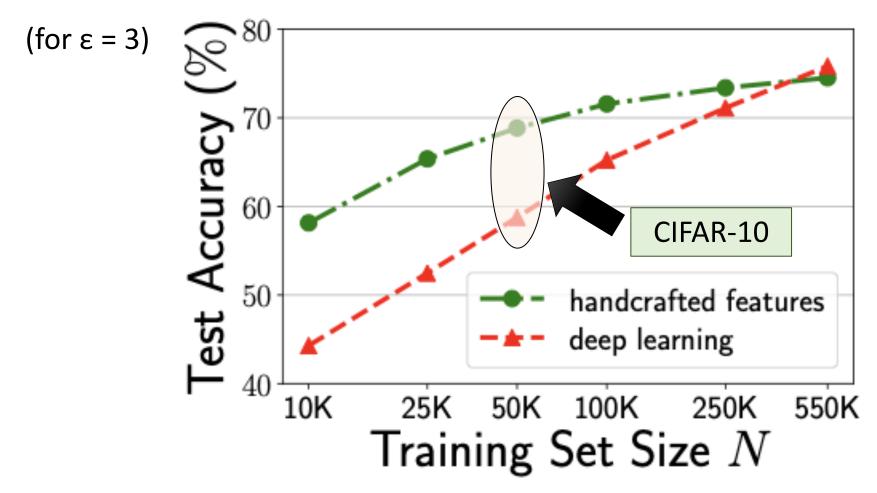
bad for privacy

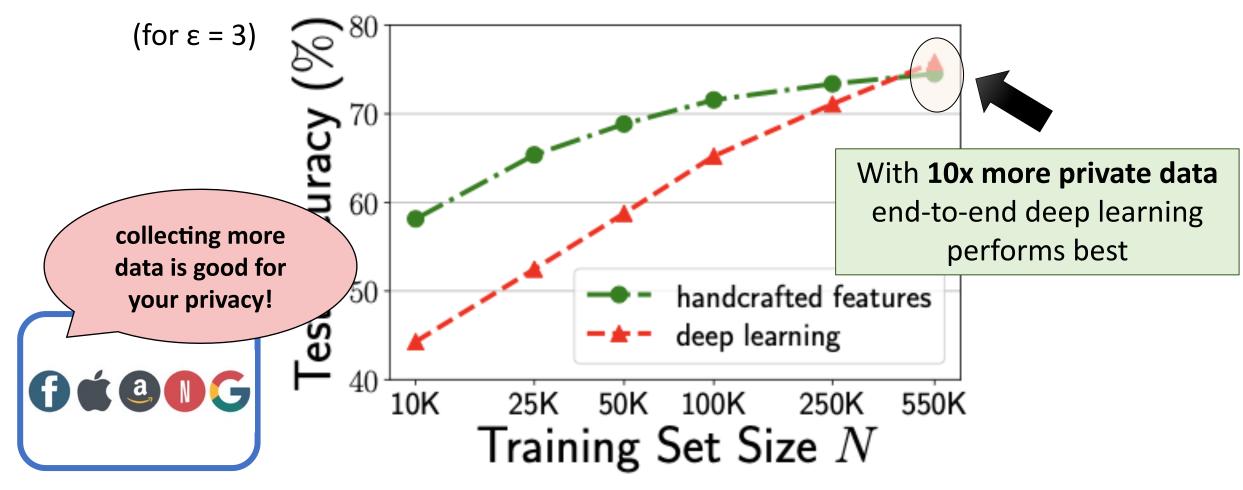


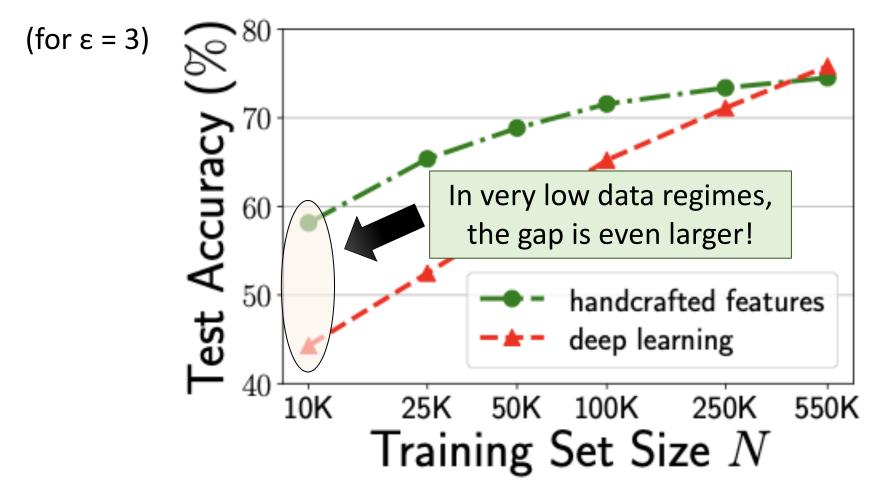


good for privacy



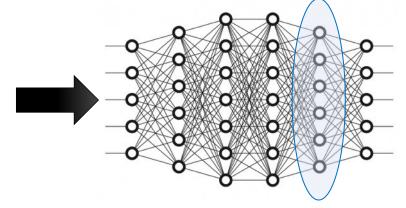






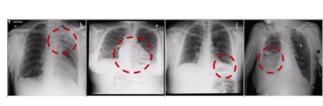


public data

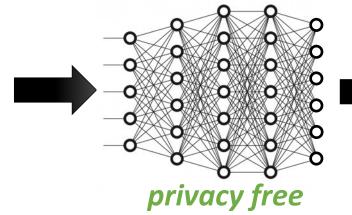


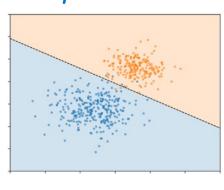
train a feature extractor on public data...

...transfer and fine-tune on private data

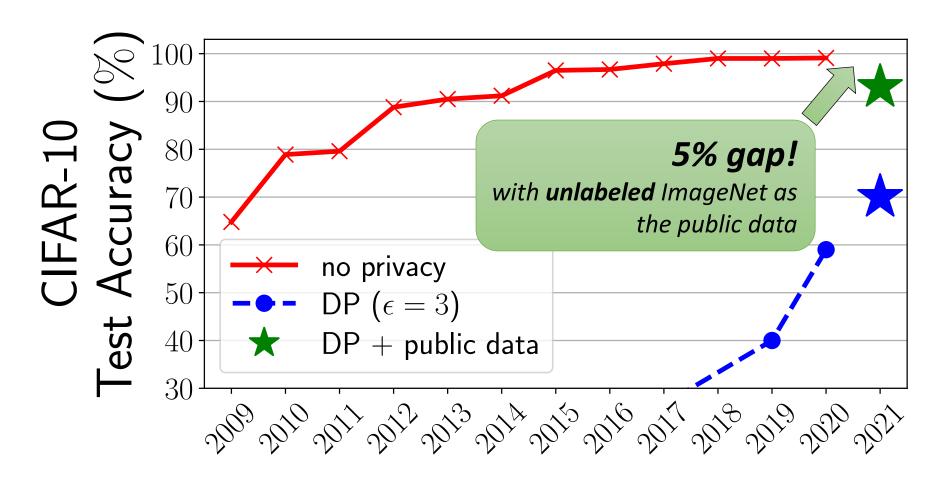


private data



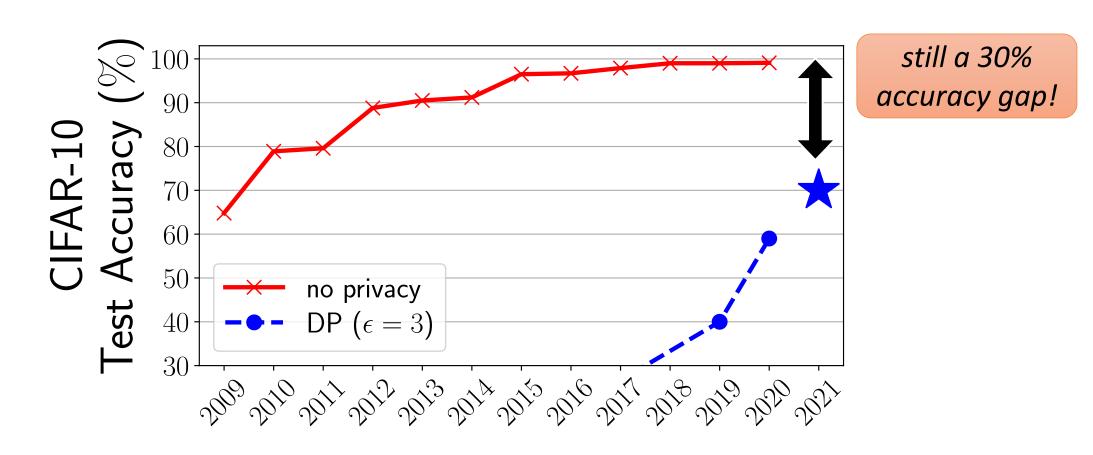


# With access to a public dataset, privacy comes almost for free!

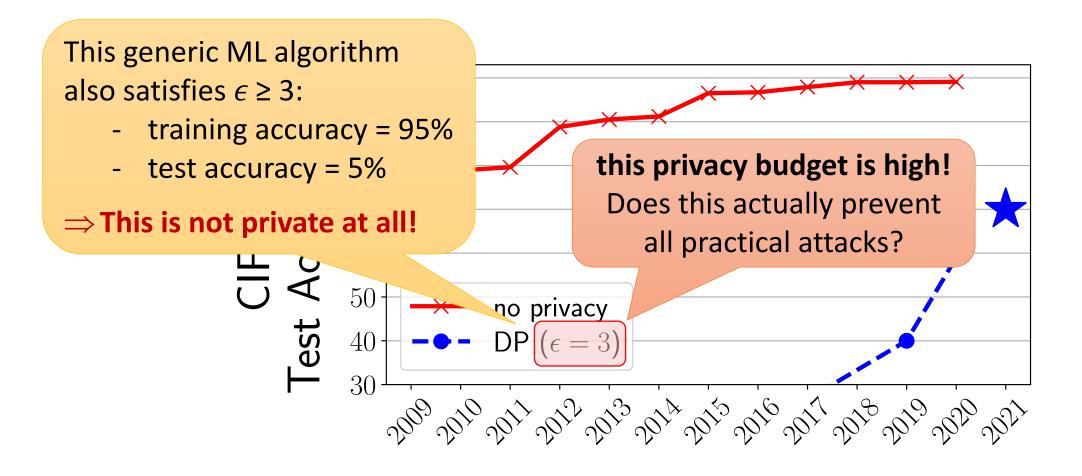


- > what does this mean?
  - data secrecy
  - no training data leakage
- > how can we achieve this?
  - > (strong) cryptography
  - differential privacy (+ feature engineering!)
- > what's next?

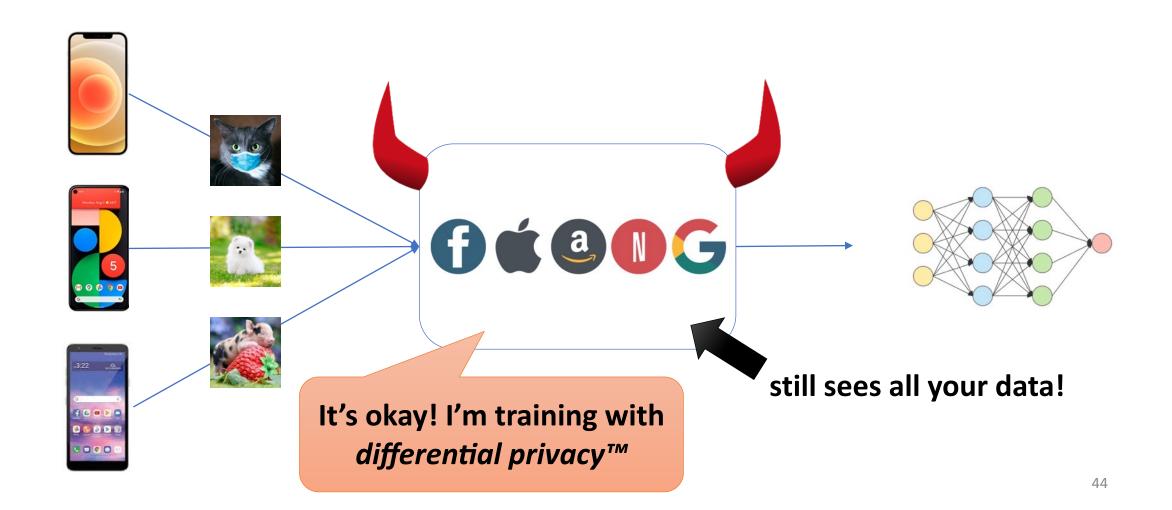
# Can we bridge the accuracy gap in differentially private learning?



#### How much privacy do we really get from DP-SGD?



### Is differential privacy sufficient? No! We also need secure decentralized training



#### Conclusion

- Machine learning is not private "by default"!
  - > Without (strong) cryptography, you must trust someone with your data
  - > Trained models leak rare training data

- > Solutions exist but we need to make them more efficient!
  - Secure decentralized learning has high overhead
  - Differential privacy needs good features or a lot more data!
  - > Privacy guarantees must be rigorously defined!

Thank you!