# Differential Privacy Has Disparate Impact on Model Accuracy

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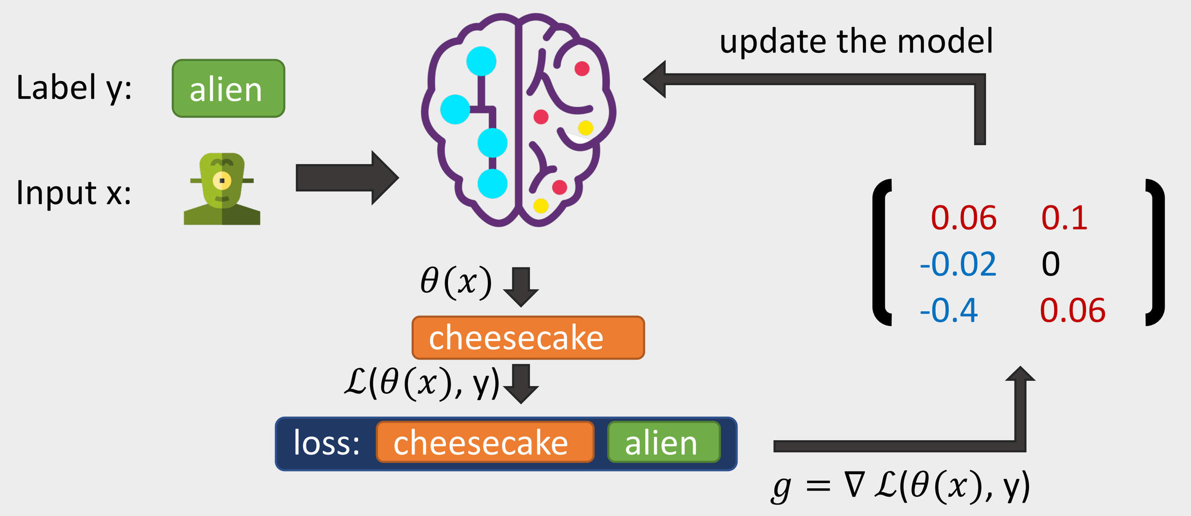
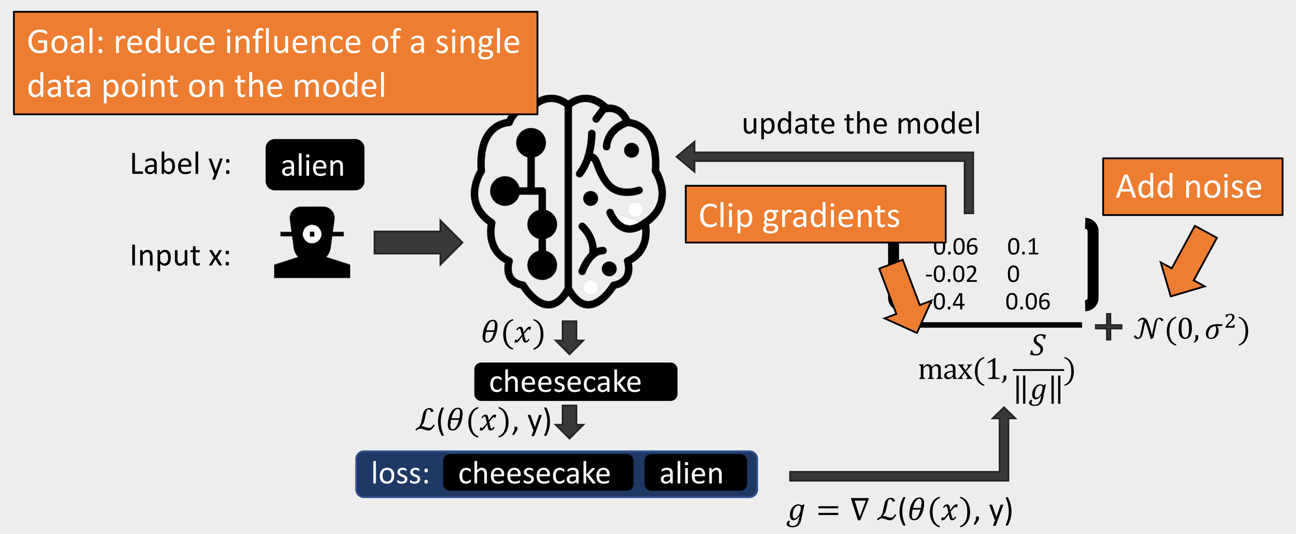
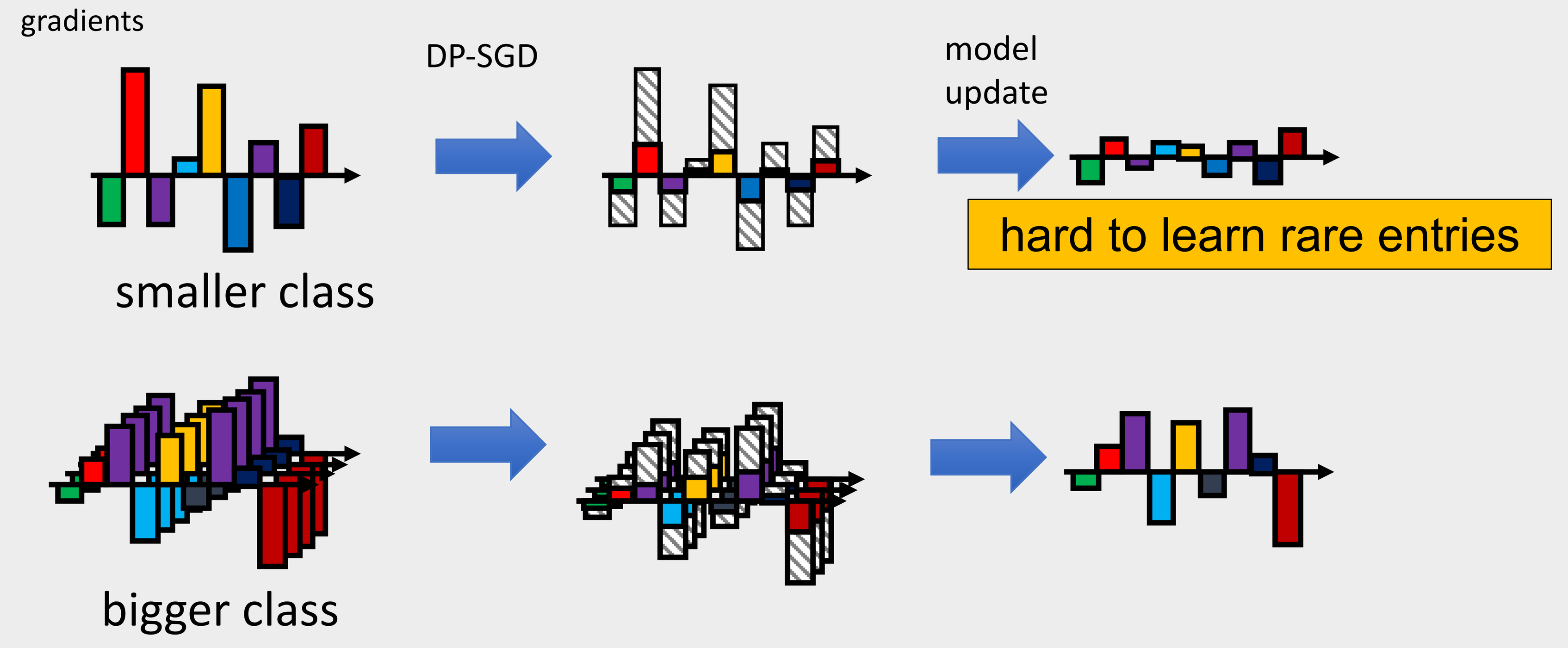
## Background

ε-differential privacy (DP) bounds the influence of any single input on the output of a computation. DP machine learning bounds the leakage of training data from a trained model. The ε-parameter controls this bound and thus the tradeoff between "privacy" and accuracy of the model.



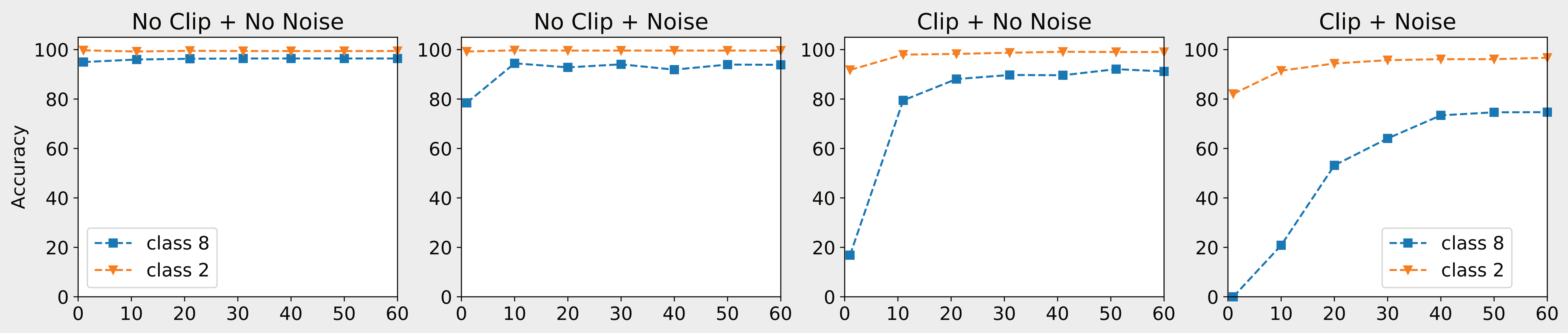




- But the drop in accuracy is not equal across different groups.



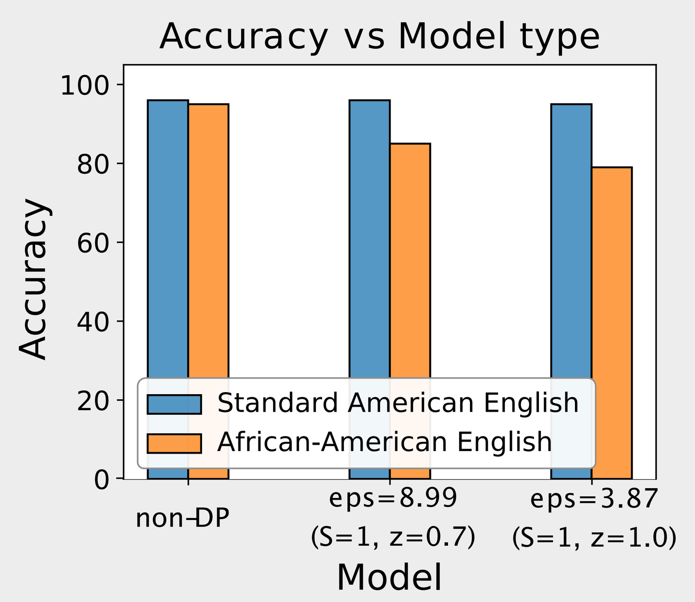

## Experiments

- *MNIST*: combining common regularizers clipping and noise together significantly reduces accuracy on smaller classes.

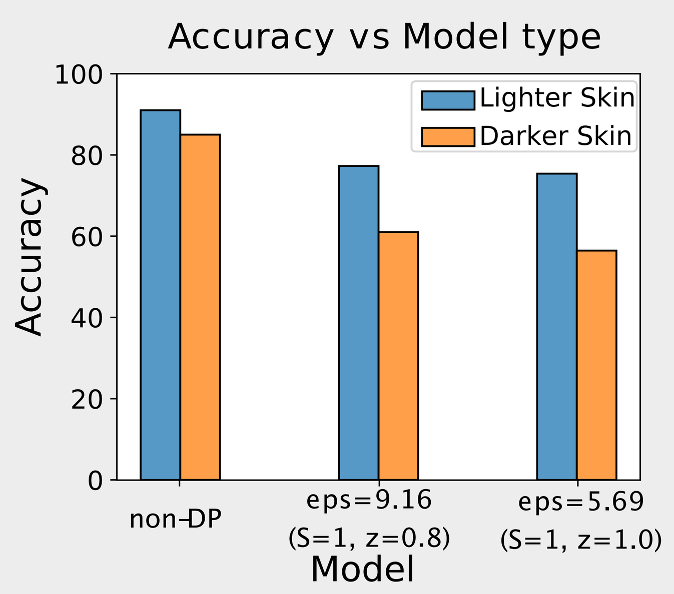



- *Real datasets*: **fair** models turn **unfair**, **unfair** models become **more unfair**.

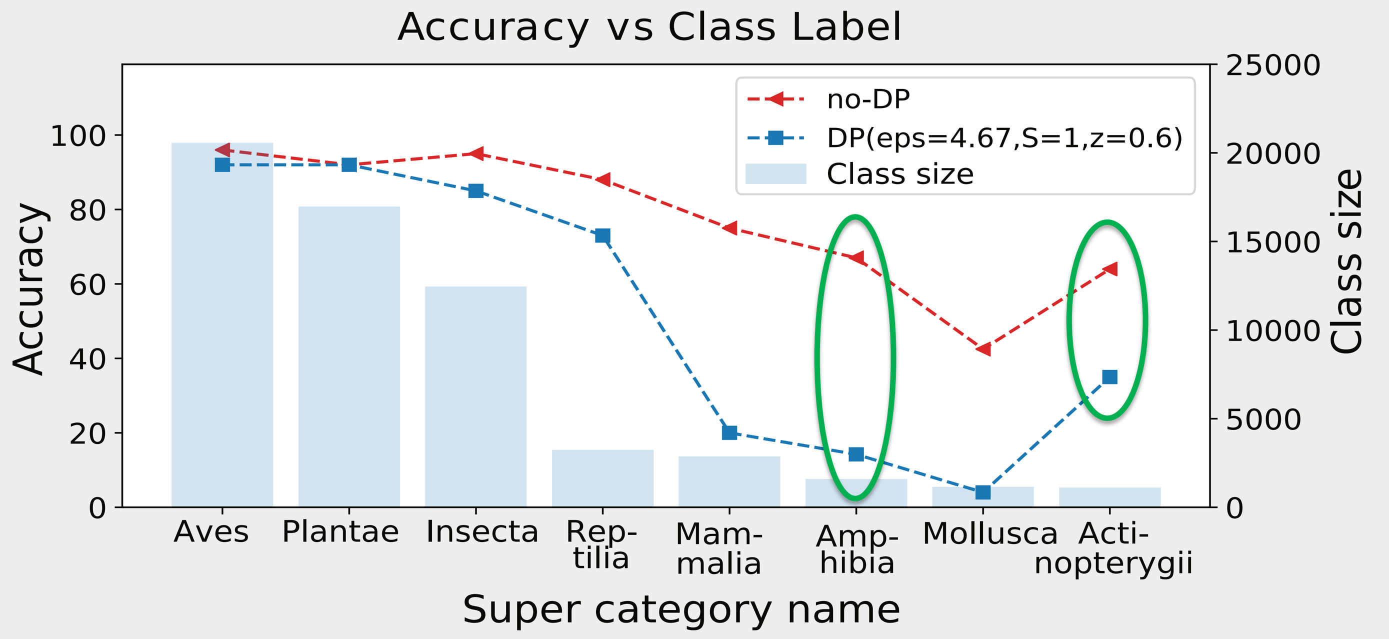
### Twitter African-American English




### IBM Diversity in Faces

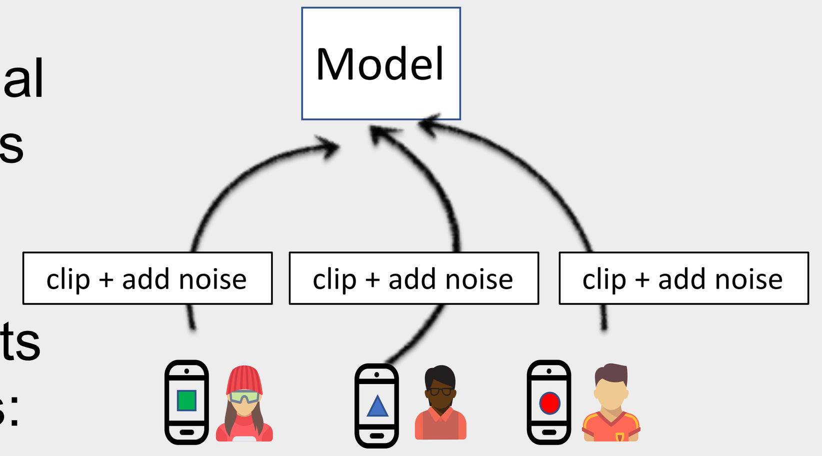


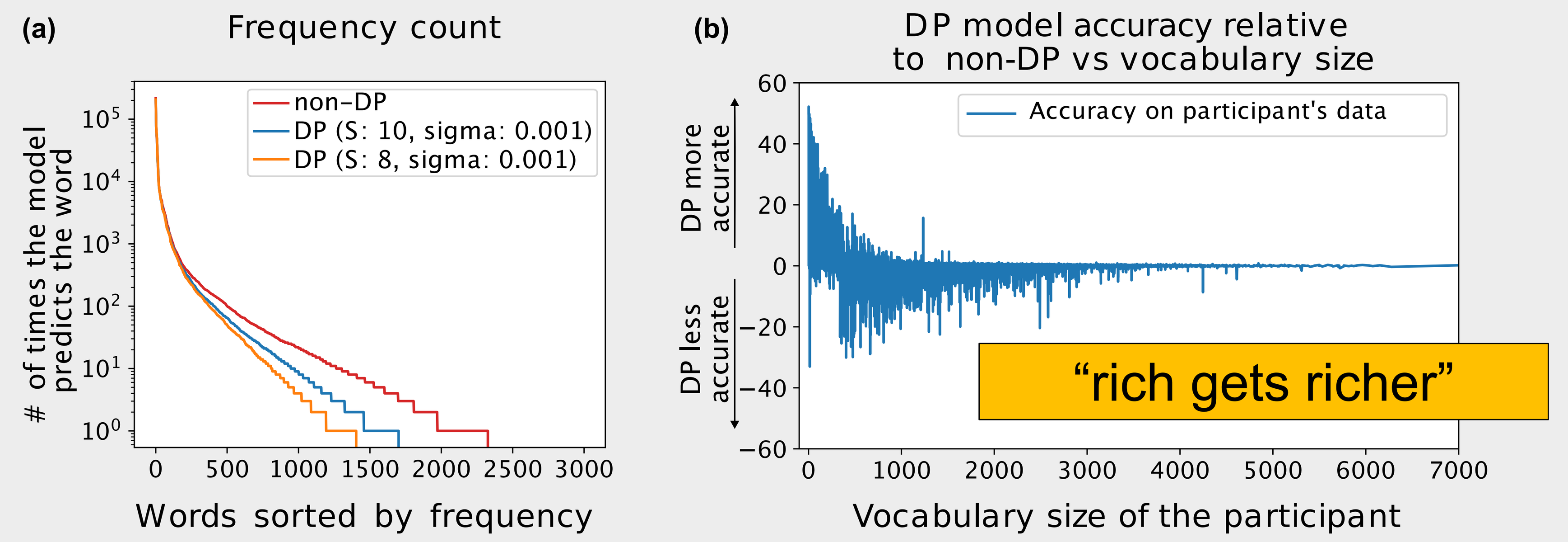

- *iNaturalist dataset*: accuracy for DP model significantly drops on smaller-size classes, ***but it's not only the size that causes this drop.***




## Federated Learning

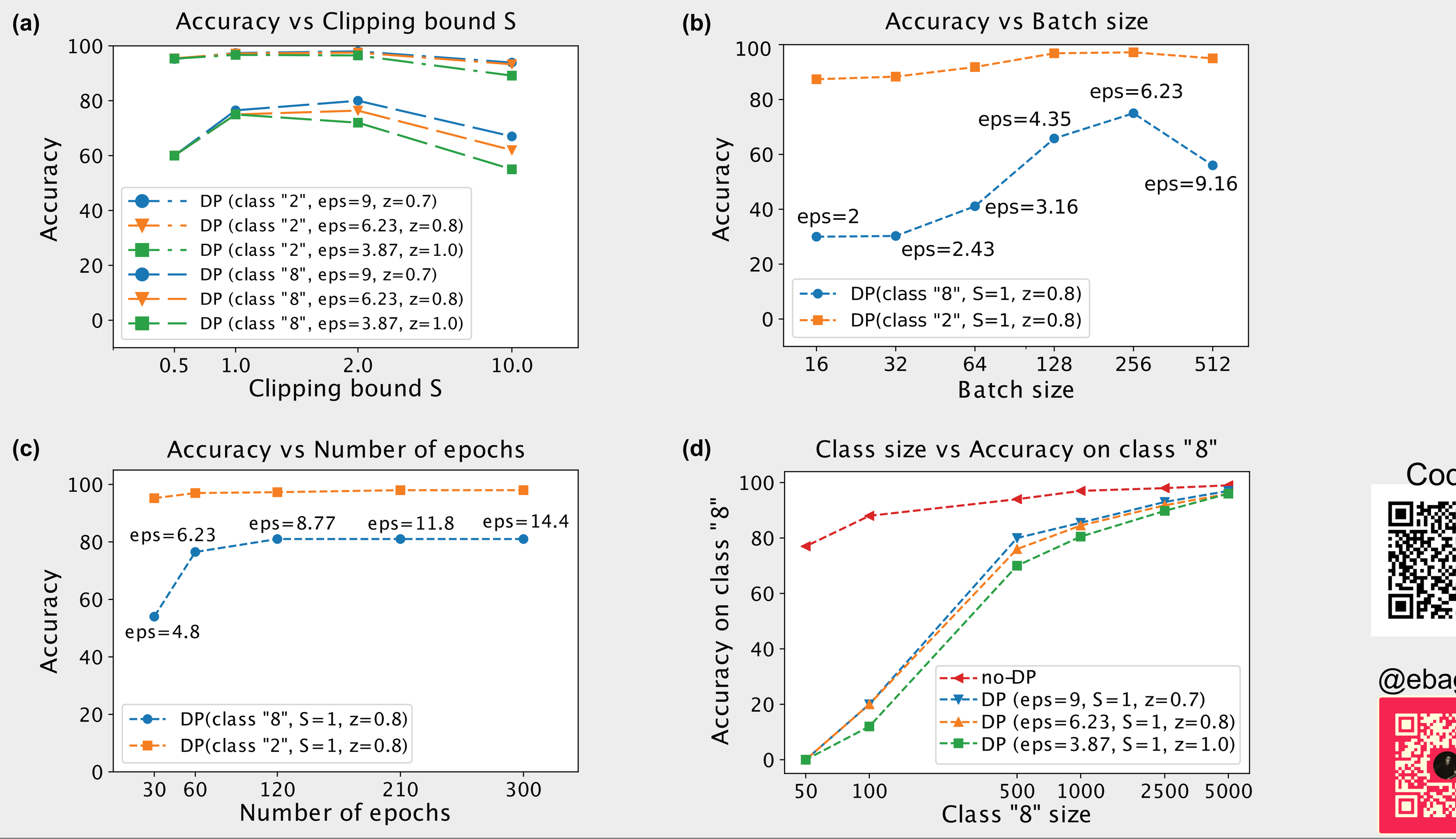
- Federated learning approach trains individual models on participants' data and aggregates produced models into a single global model
- DP preserves **participant-level** privacy
- We use Reddit dataset of 80,000 participants
- DP-models overfit to **simpler vocabularies**:




### Hyperparameters + size effects:

- Accuracy drop depends on (a) clipping and noise values, (b) batch size, (c) number of epochs, and depends the most on (d) class size.




Code:

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