

DP-Mix: Mixup-based Data Augmentation for Differentially Private Learning

Wenxuan Bao¹, Francesco Pittaluga², Vijay Kumar B G², Vincent Bindschaedler¹

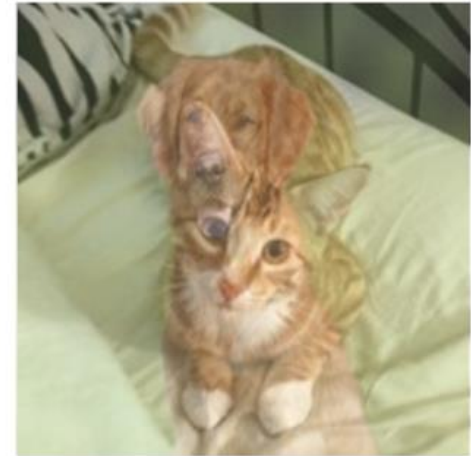
¹University of Florida, ²NEC Labs America

Background | Mixup Data Augmentation

$$\begin{aligned}\hat{x} &= \lambda x_i + (1 - \lambda)x_j, \\ \hat{y} &= \lambda y_i + (1 - \lambda)y_j,\end{aligned}$$

where $\lambda \in [0, 1]$ is a random number

Image



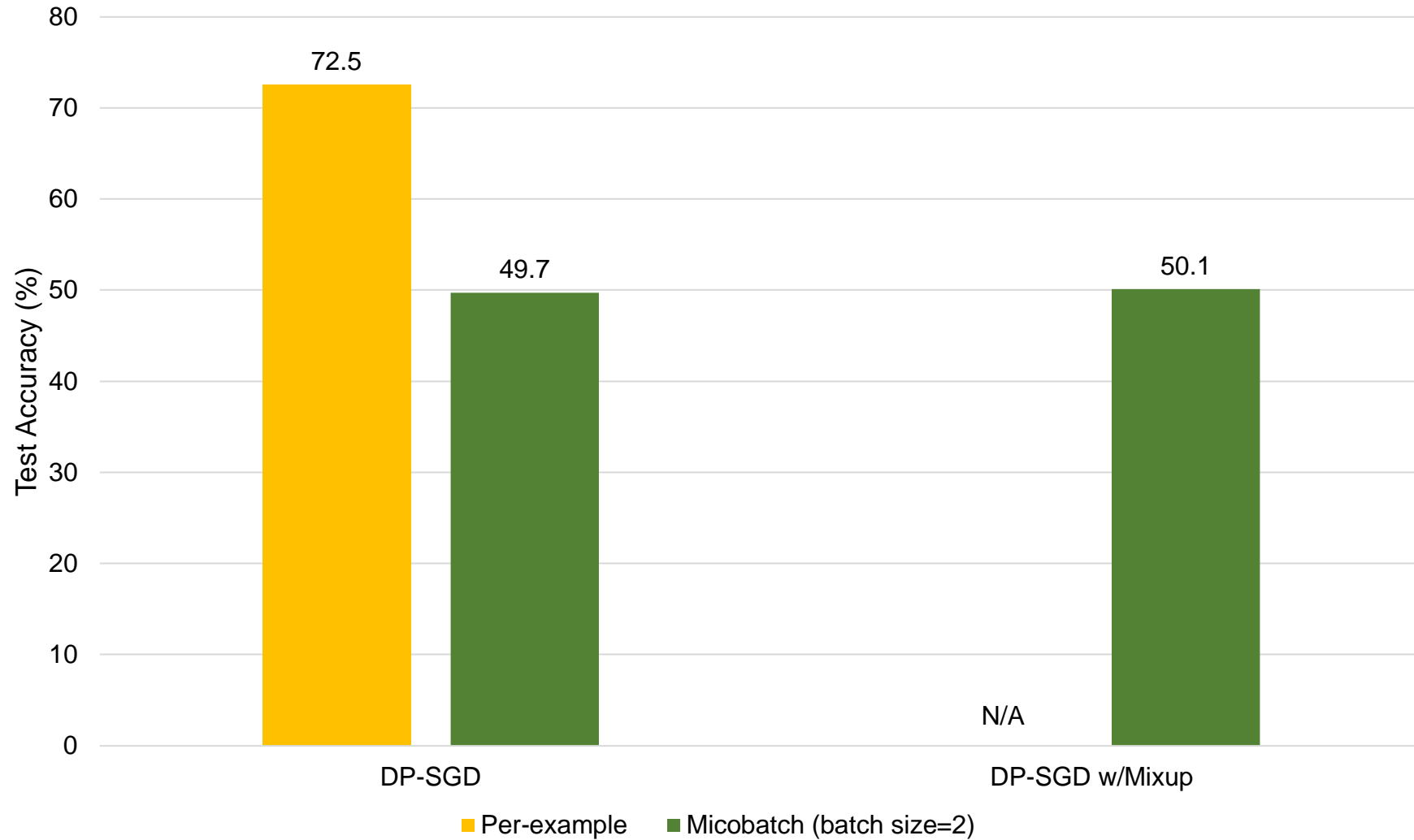
Label

[1.0, 0.0]
cat dog

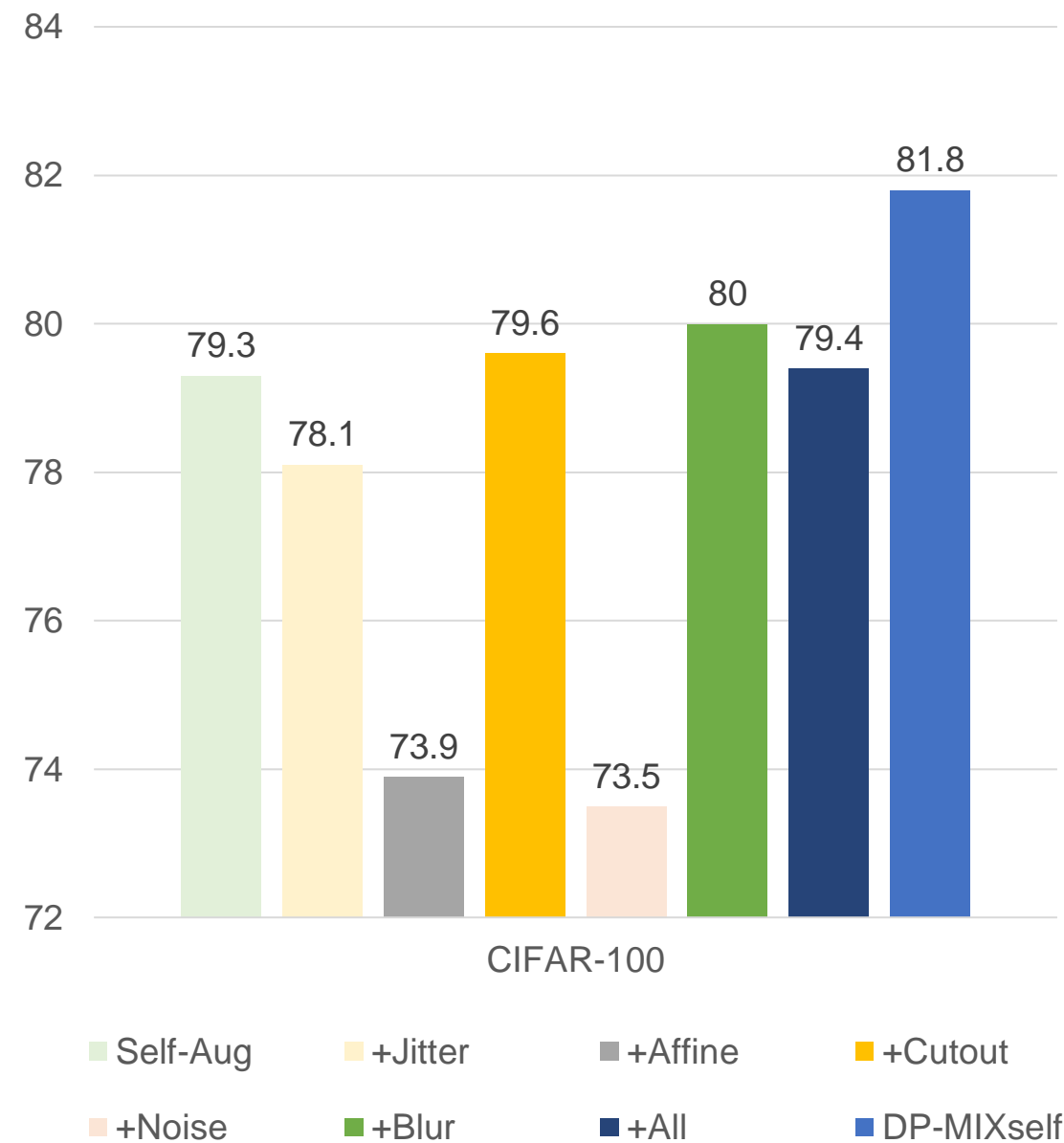
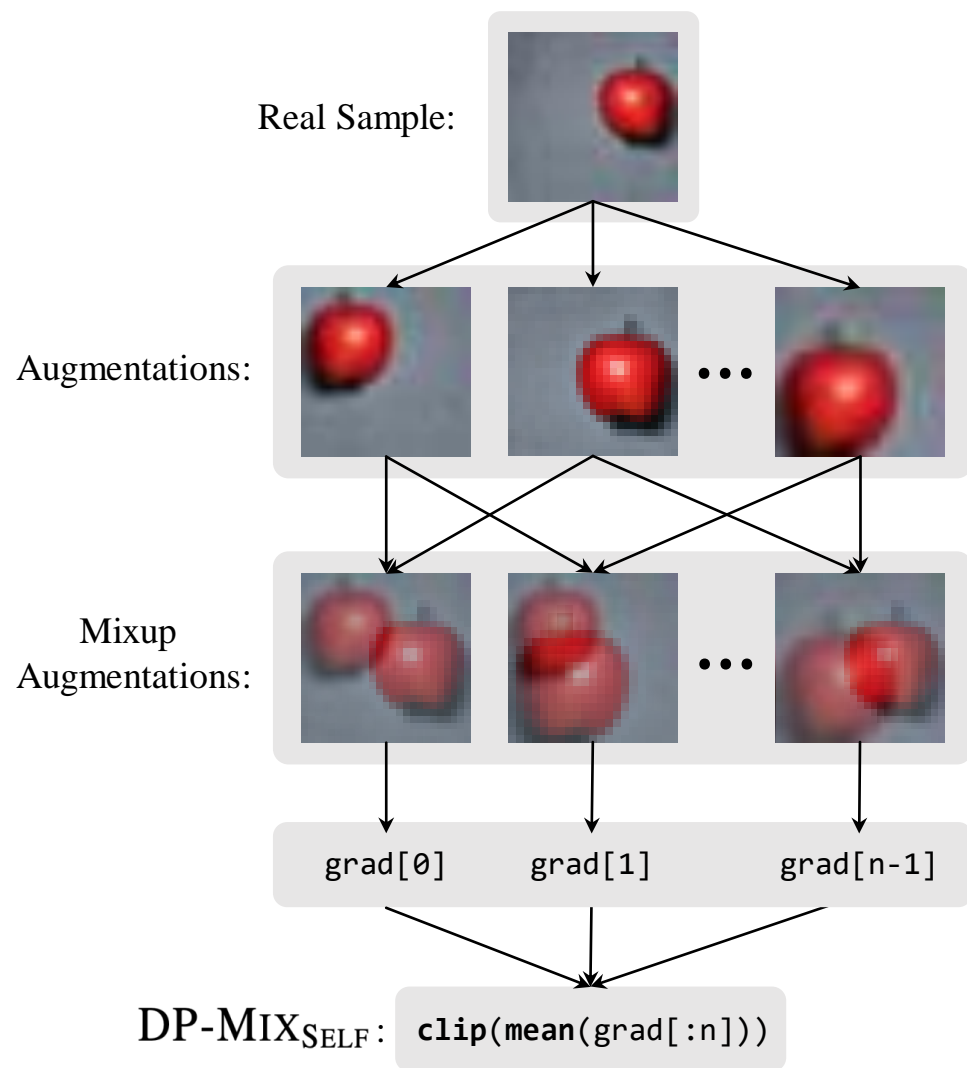
[0.0, 1.0]
cat dog

[0.7, 0.3]
cat dog

Microbatch



Our Method | DP-Mix_{self}



Background | Stable Diffusion



```
{  
  "prompt:" "Futuristic architectures  
            with planets in the  
            background."  
}
```

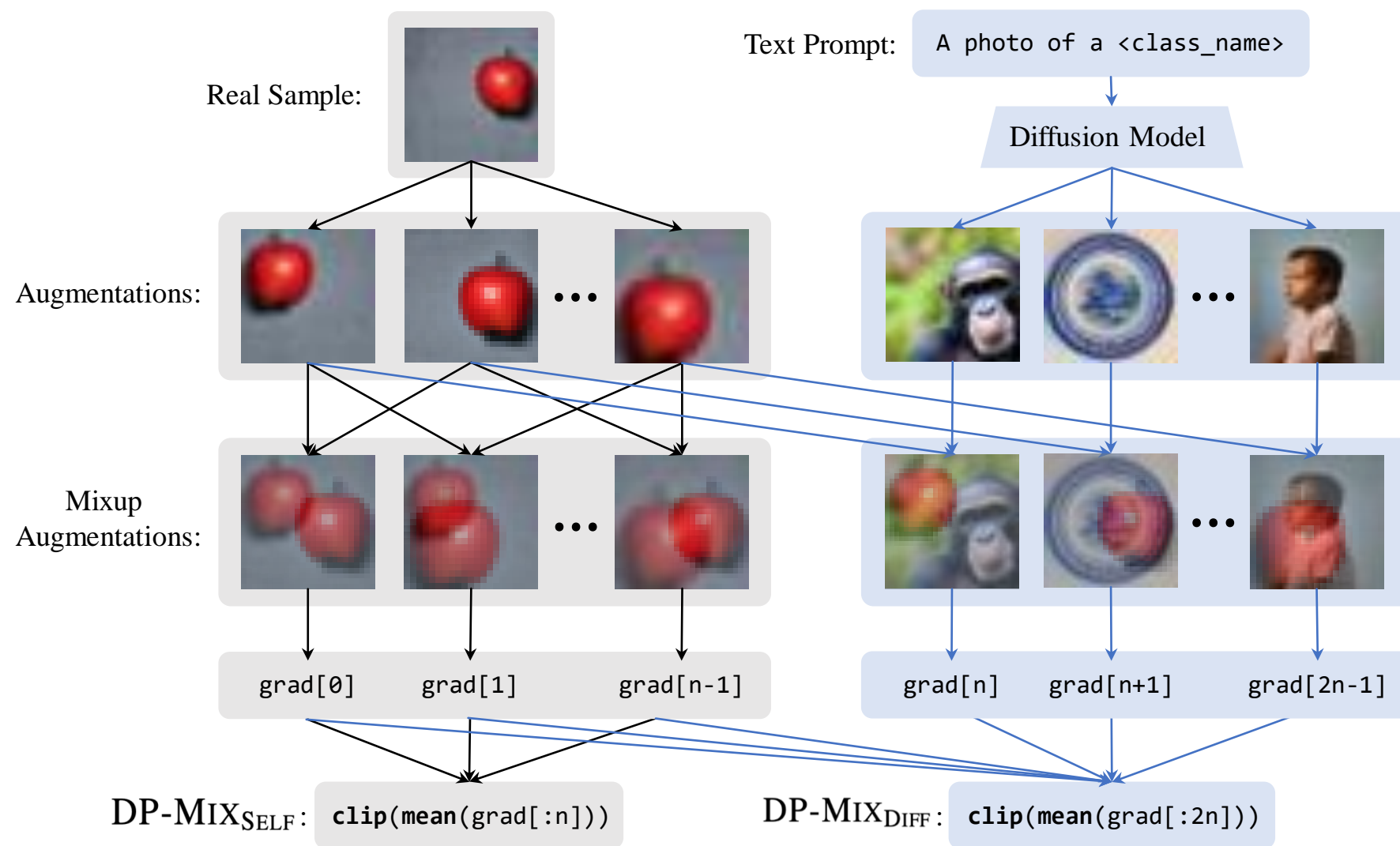


```
{  
  "prompt:" "View of a cyberpunk  
            city."  
}
```



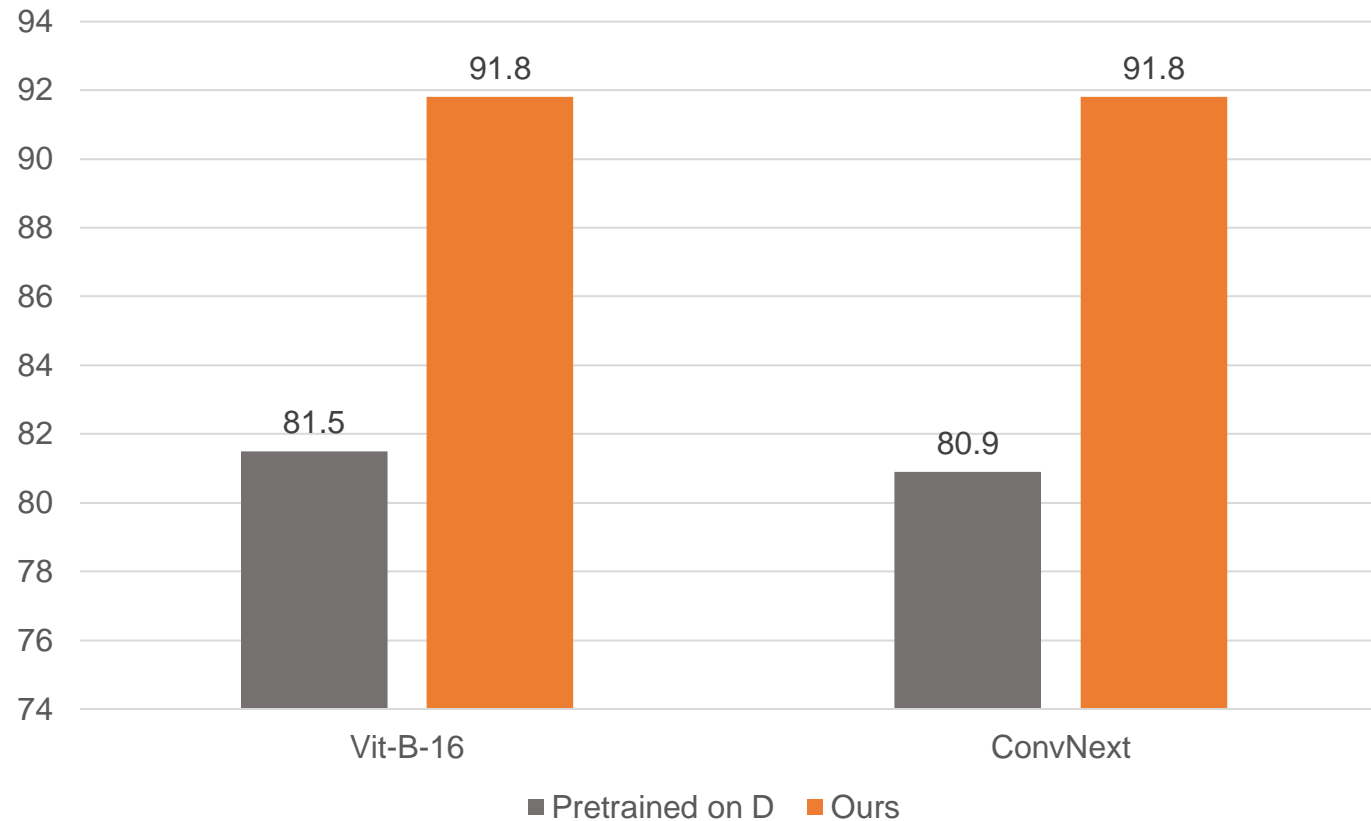
```
{  
  "prompt:" "cyberpunk city at night  
            with transparent neon  
            billboards."  
}
```

Our Method | DP-Mix_{diff}



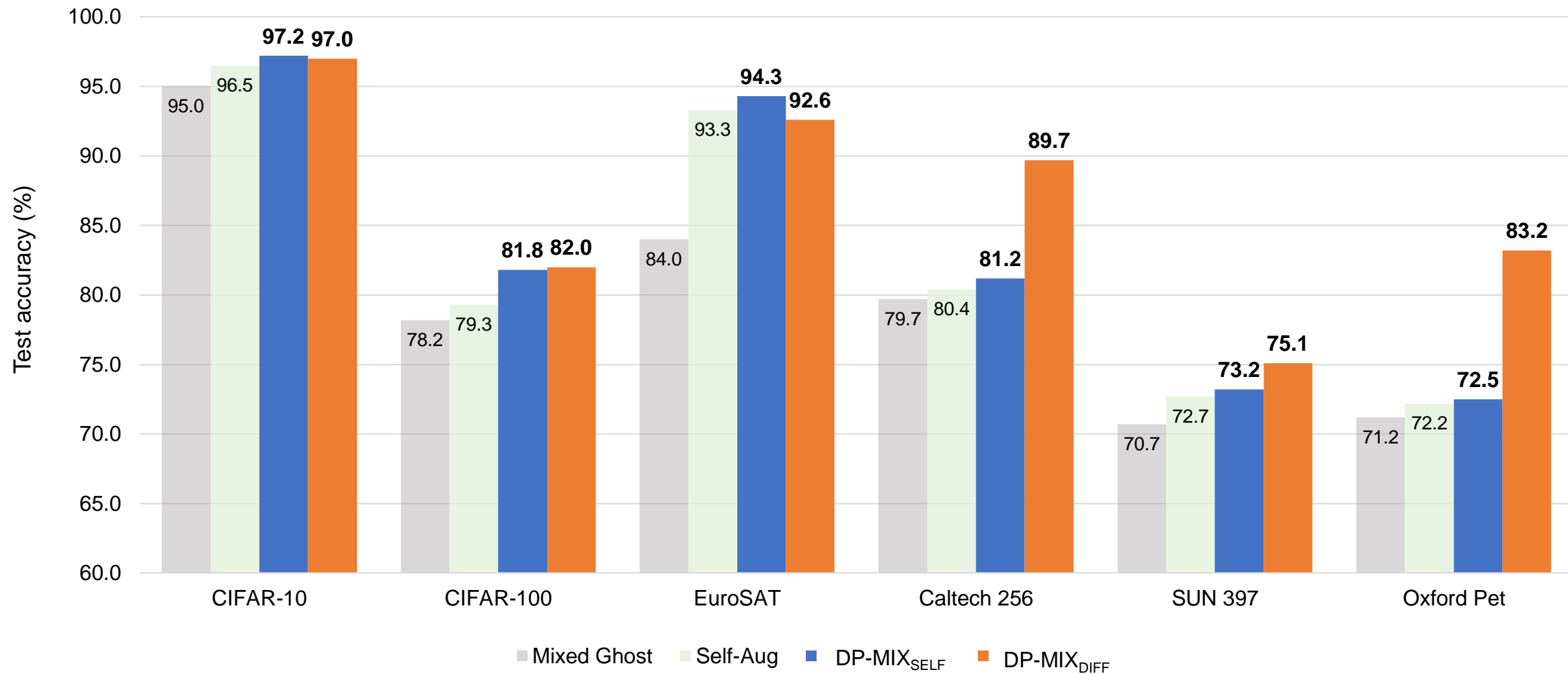
DP-Mix_{diff} vs Pretraining with Diffusion Data

- Pre-training on diffusion samples does **not** improve performance; mixing up training samples with them does



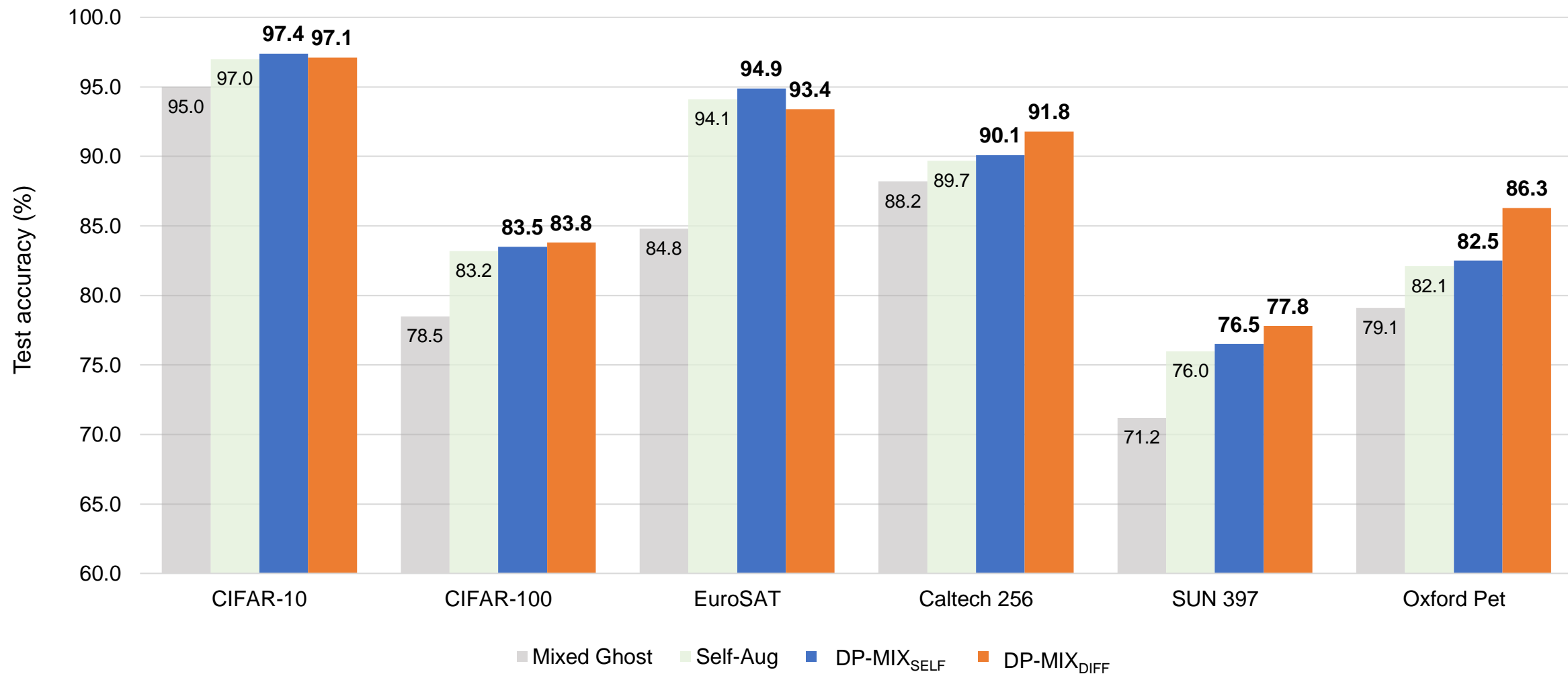
Caltech 256

Main Results



$\epsilon=1$

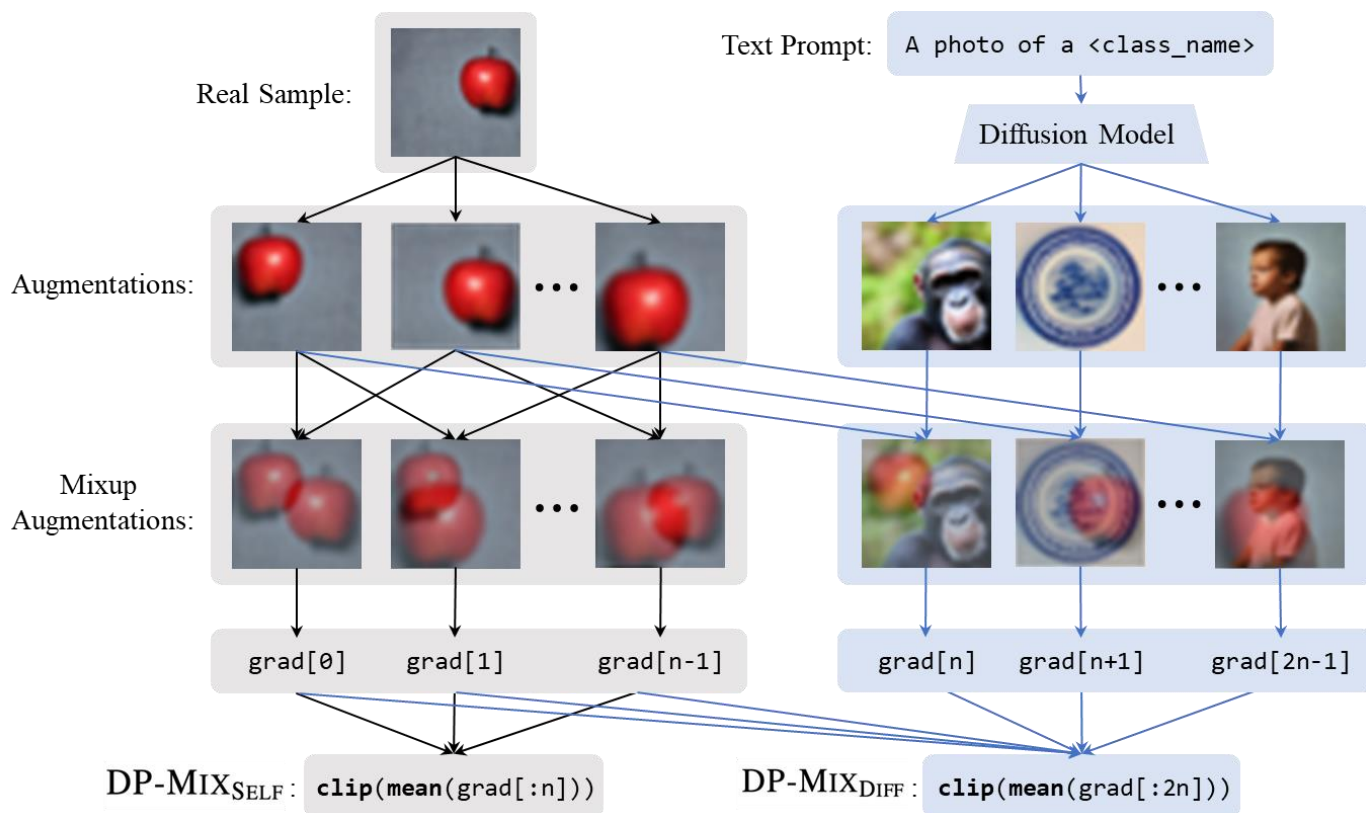
Main Results



$\epsilon=2$

Takeaway

- We show how to apply ***mixup*** for DP training of ML models and demonstrate it surpasses the prior SoTA ***at no extra privacy cost***.



<https://wenxuan-bao.github.io>