Combining Diverse Feature Priors

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Dimitris Tsipras

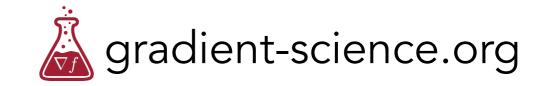


Aleksander Mądry





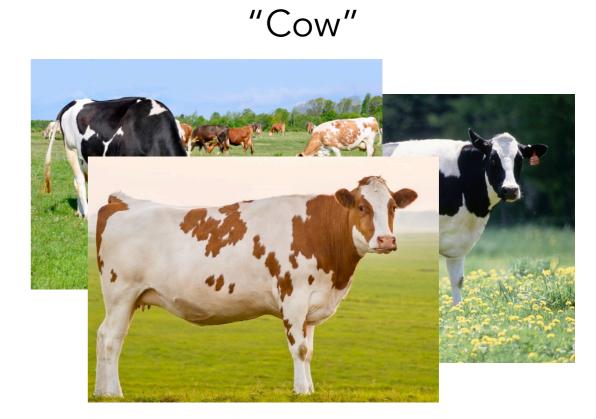




"Camel"



VS.





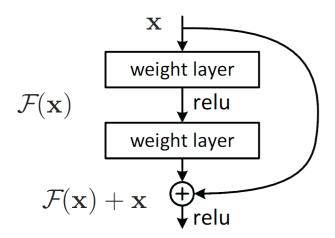
Can it recognize a cow on the beach?



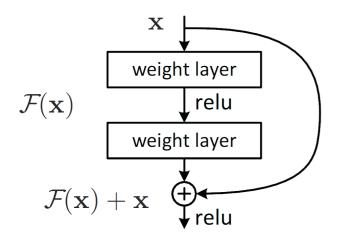
Can it recognize a cow on the beach?

Generalization is driven by feature priors

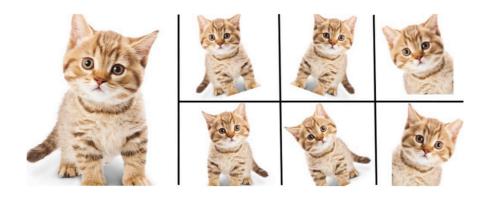
Architecture



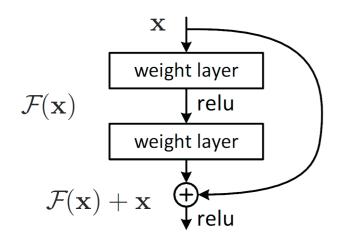
Architecture



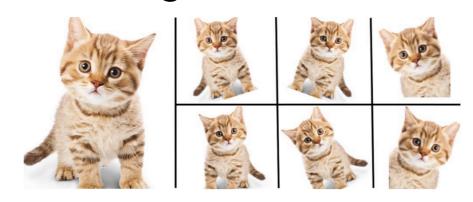
Augmentations



Architecture



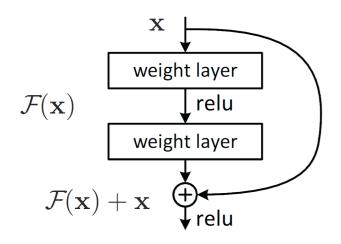
Augmentations



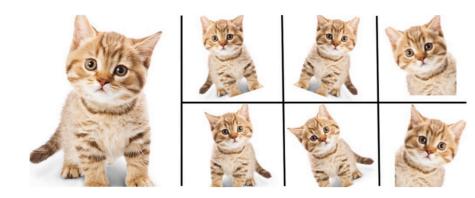
Stylized training



Architecture



Augmentations



Stylized training

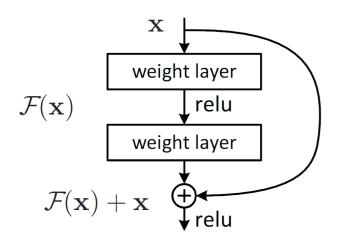


Limited receptive field

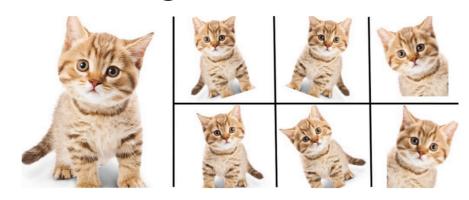


[Brendel Bethge 2019]

Architecture



Augmentations



Robust optimization

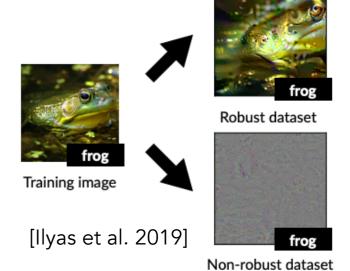
Stylized training

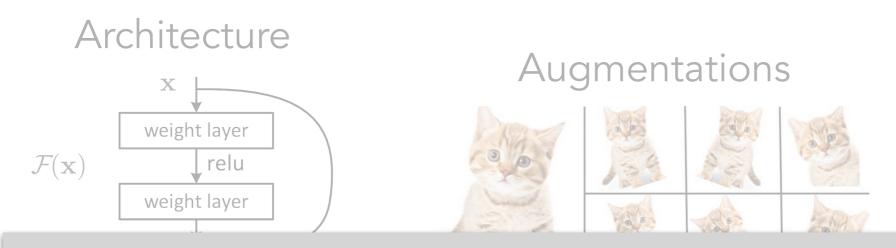


Limited receptive field



[Brendel Bethge 2019]





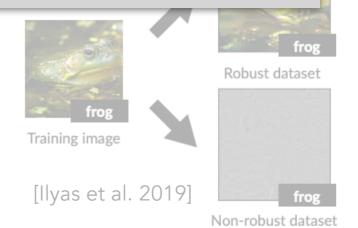
How can we harness this emerging space of **feature priors**?



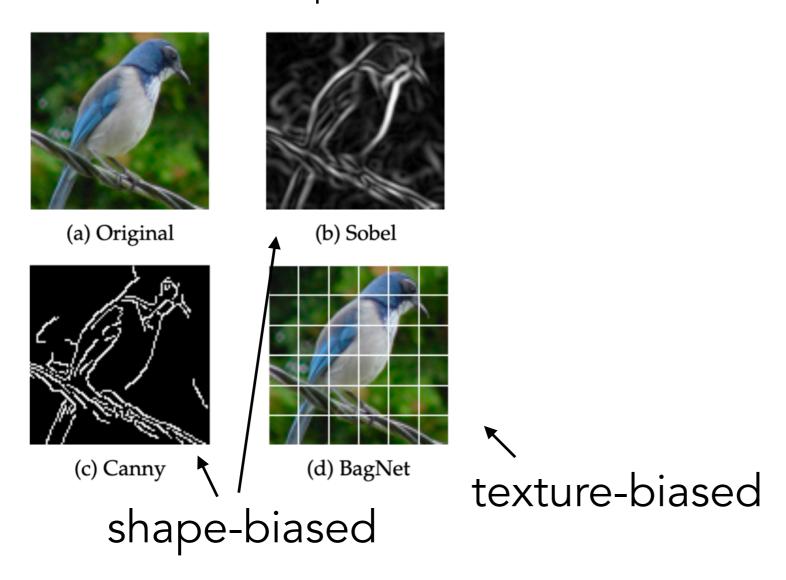
Limited receptive field



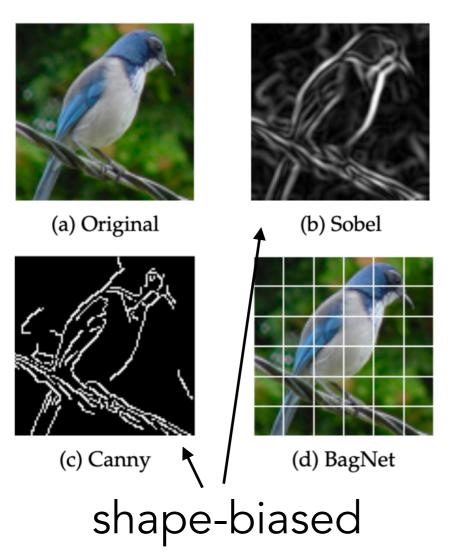
[Brendel Bethge 2019]



Train models with diverse feature priors



Train models with diverse feature priors



Correlation of correct predictions

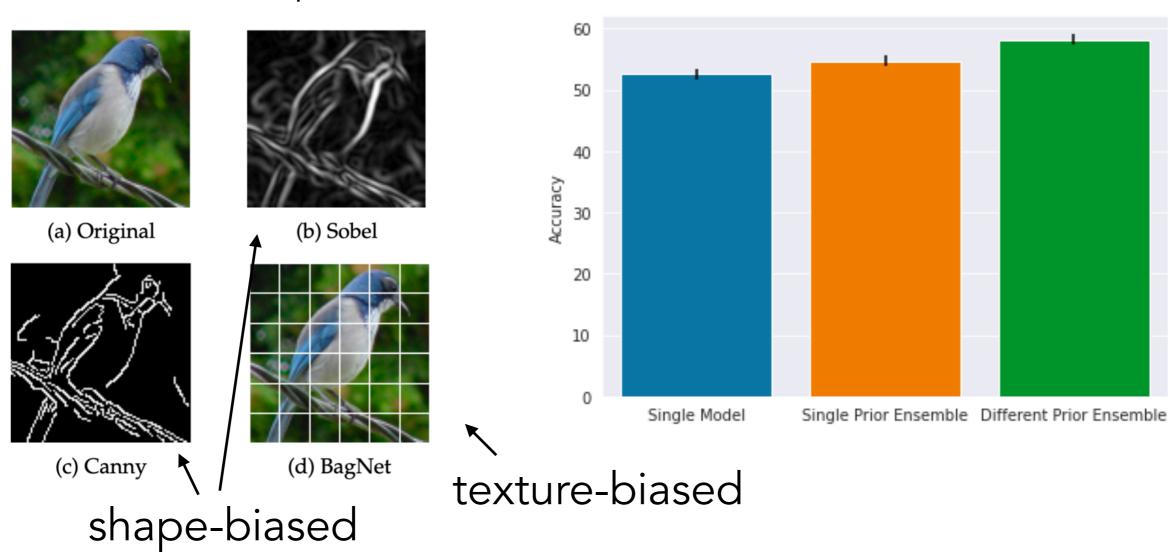
| | CIFAR-10 | | | |
|---------------|----------|-------|-------|--------|
| | Standard | Canny | Sobel | BagNet |
| Standard | 0.598 | 0.237 | 0.259 | 0.38 |
| Canny | | 0.545 | 0.324 | 0.143 |
| Sobel | | | 0.594 | 0.173 |
| BagNet | | | | 0.655 |

texture-biased

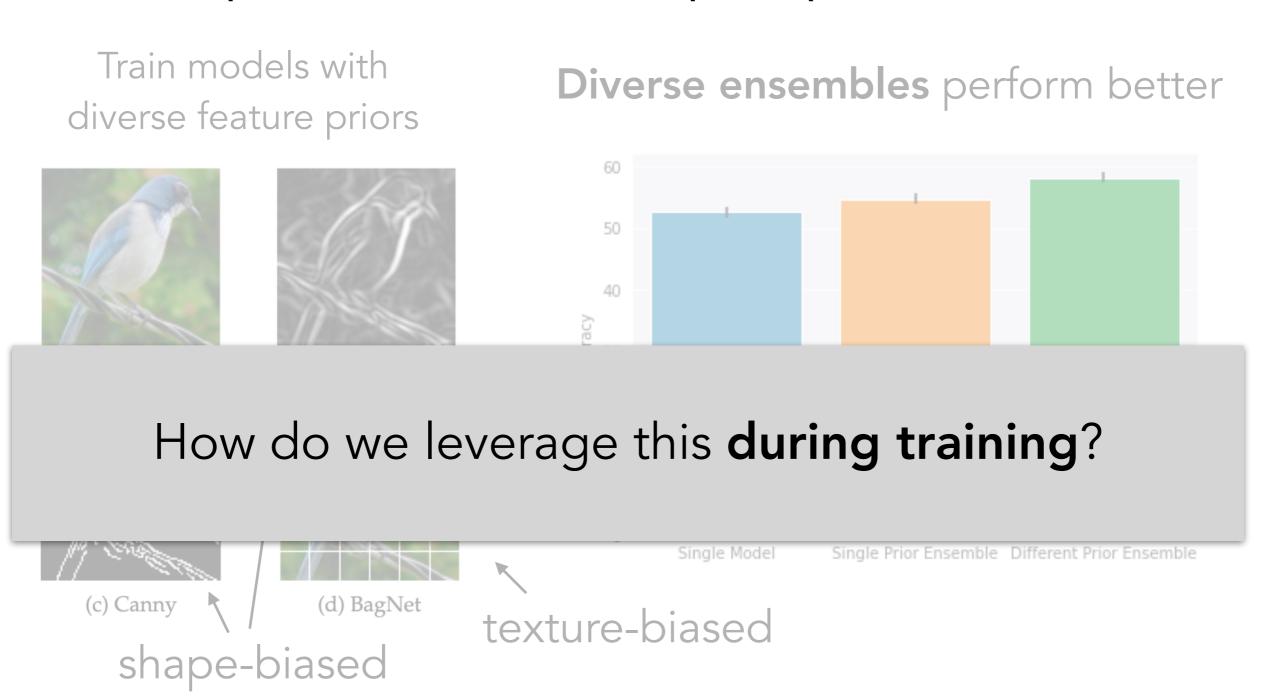
Models with different feature priors make different mistakes

Train models with diverse feature priors

Diverse ensembles perform better



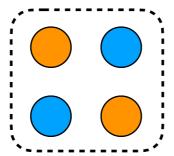
Models with different feature priors make different mistakes



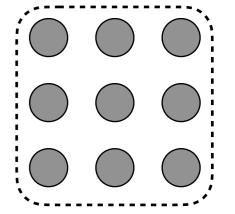
Models with different feature priors make different mistakes

Self-training

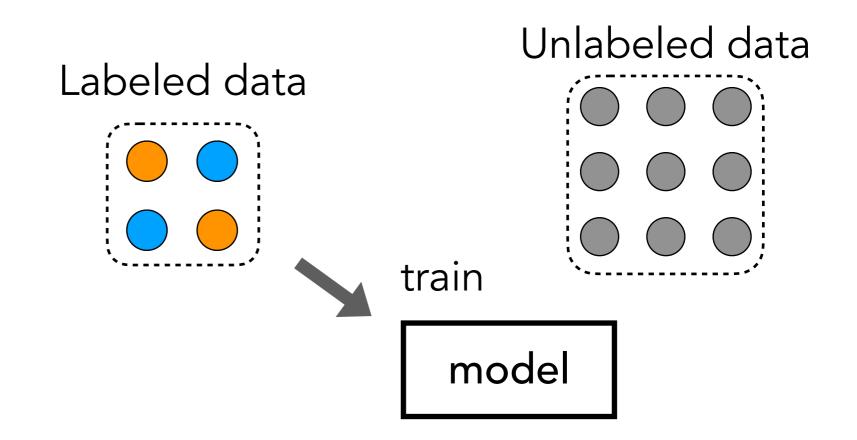
Labeled data



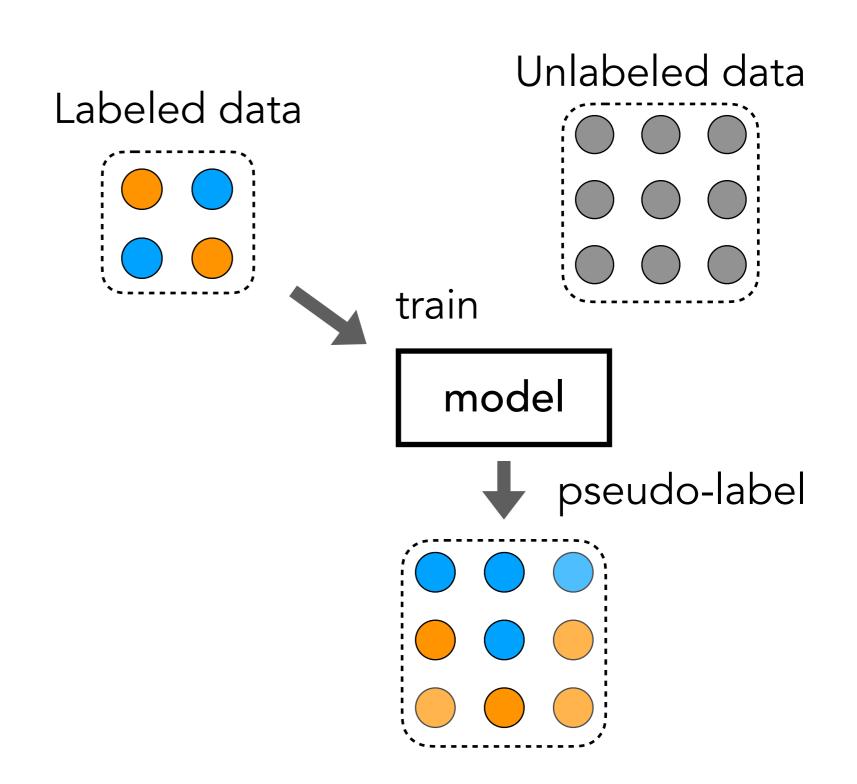
Unlabeled data



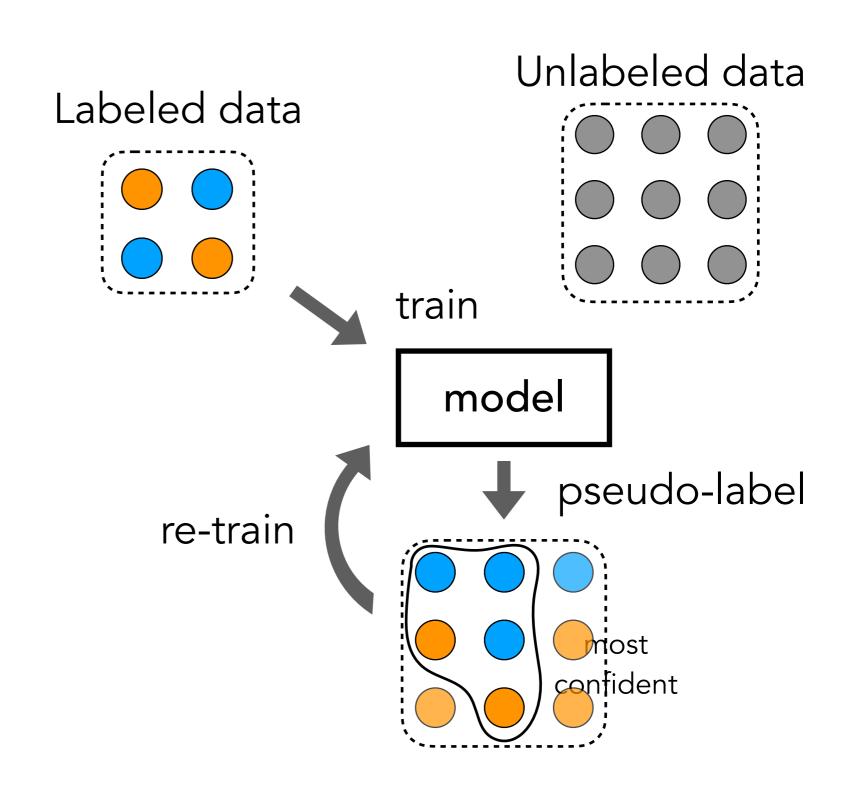
Self-training



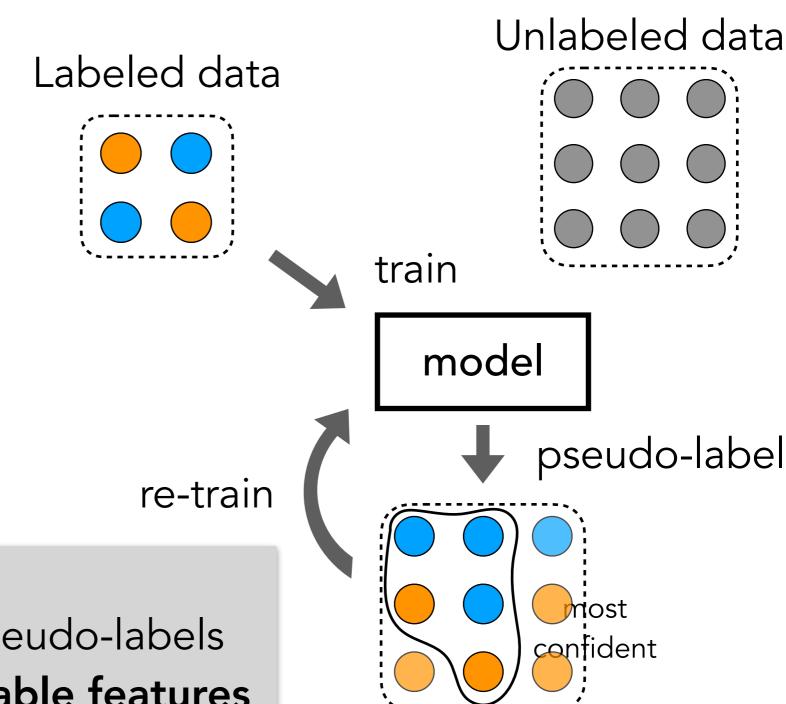
Self-training



Self-training

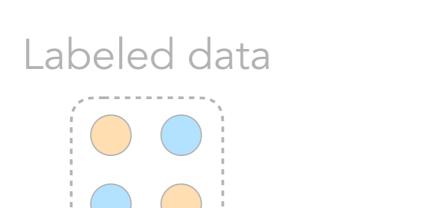


Self-training



Confirmation bias: Pseudo-labels can propagate undesirable features

Self-training



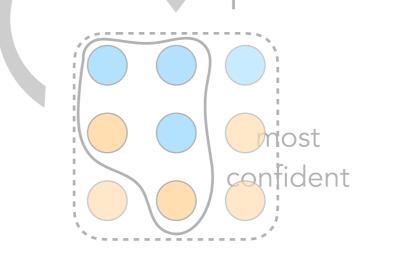
Unlabeled data



Can we mitigate this through leveraging **diverse feature priors**?

re-train

Confirmation bias: Pseudo-labels can propagate undesirable features



Key idea: Different feature priors lead to

models that learn different features

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Shape-biased model



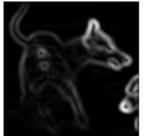






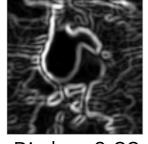
Unlabeled data

Texture-biased model

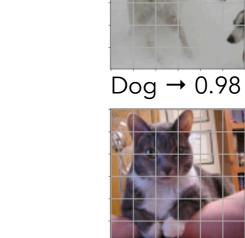








Cat \rightarrow 0.82 Bird → 0.99





 $Car \rightarrow 0.90$

Key idea: Different feature priors lead to models that learn different features











Unlabeled data

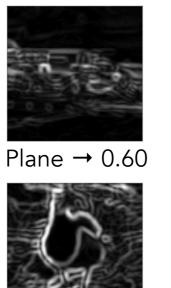
Texture-biased model

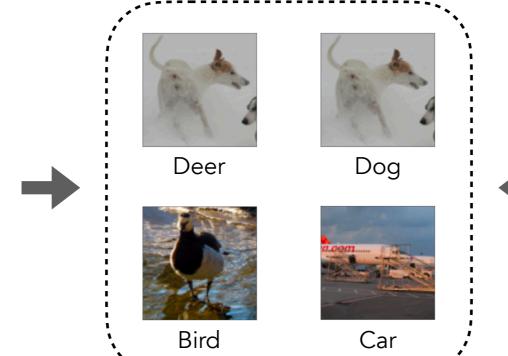


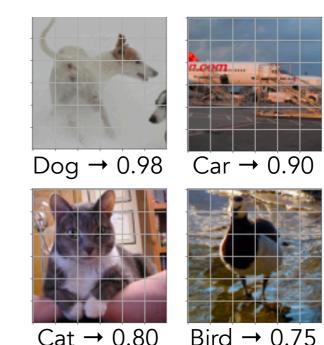










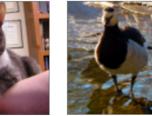


Key idea: Different feature priors lead to models that learn different features



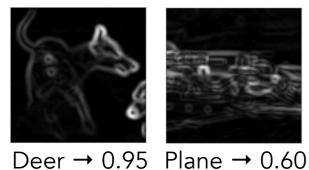


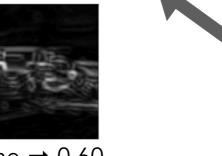




Unlabeled data

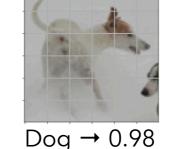
Texture-biased model









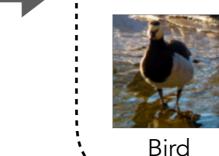




Dog



Cat \rightarrow 0.82 Bird → 0.99

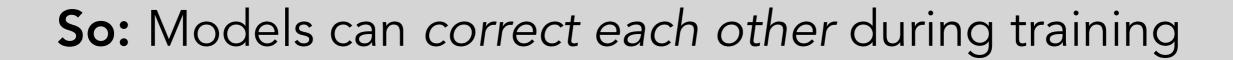


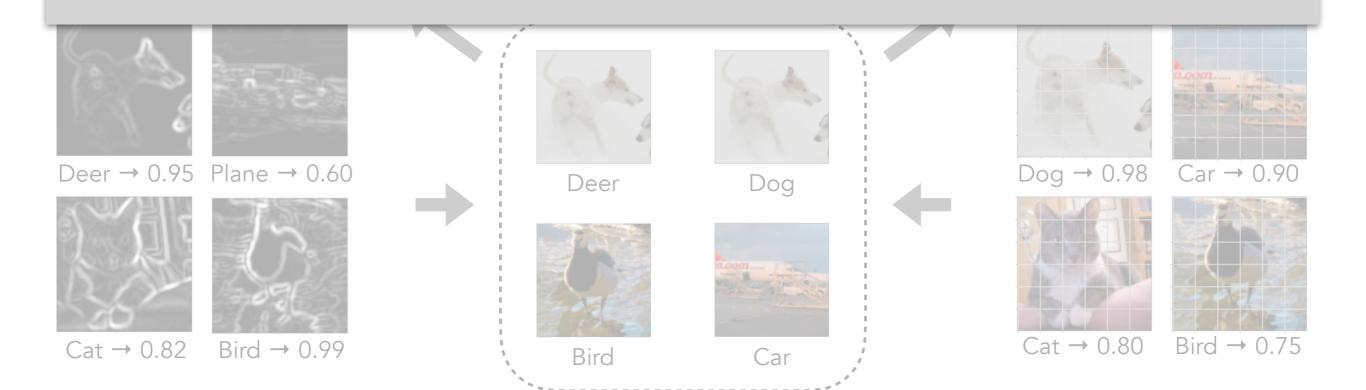
Car

Cat $\rightarrow 0.80$

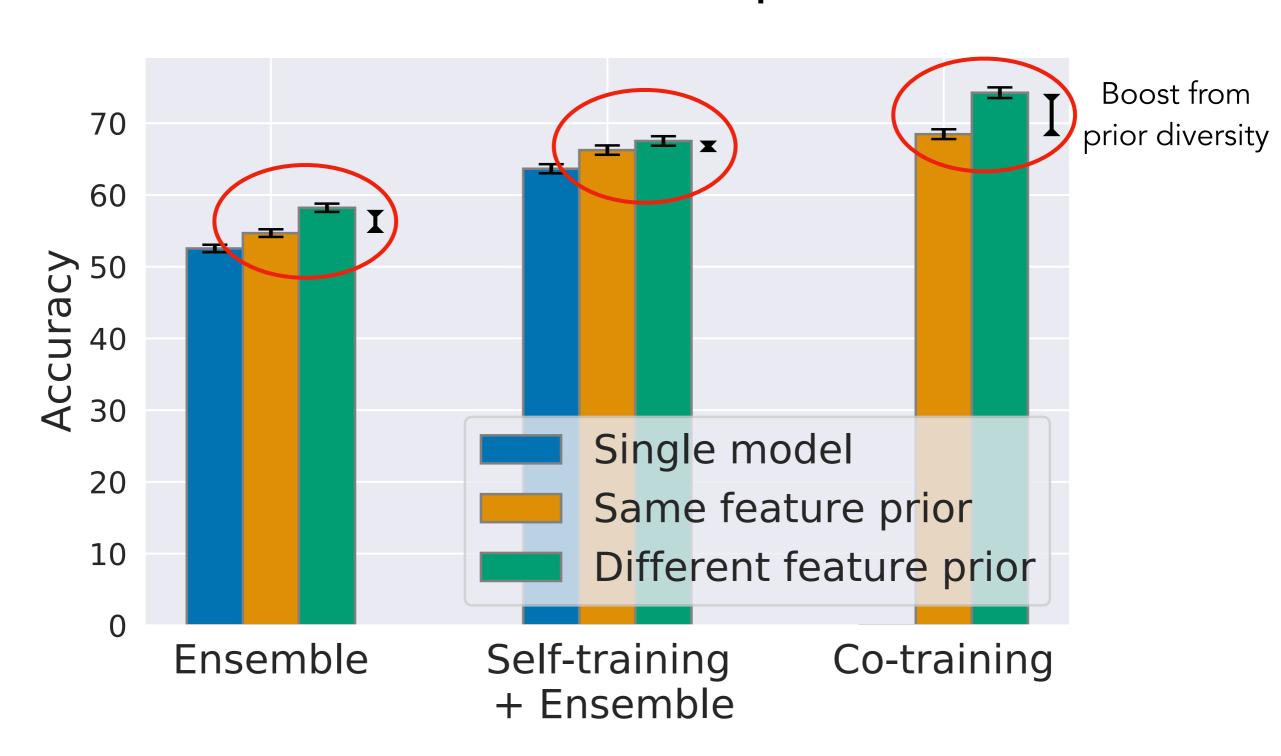
Bird $\rightarrow 0.75$

Key idea: Different feature priors lead to models that learn **different features**



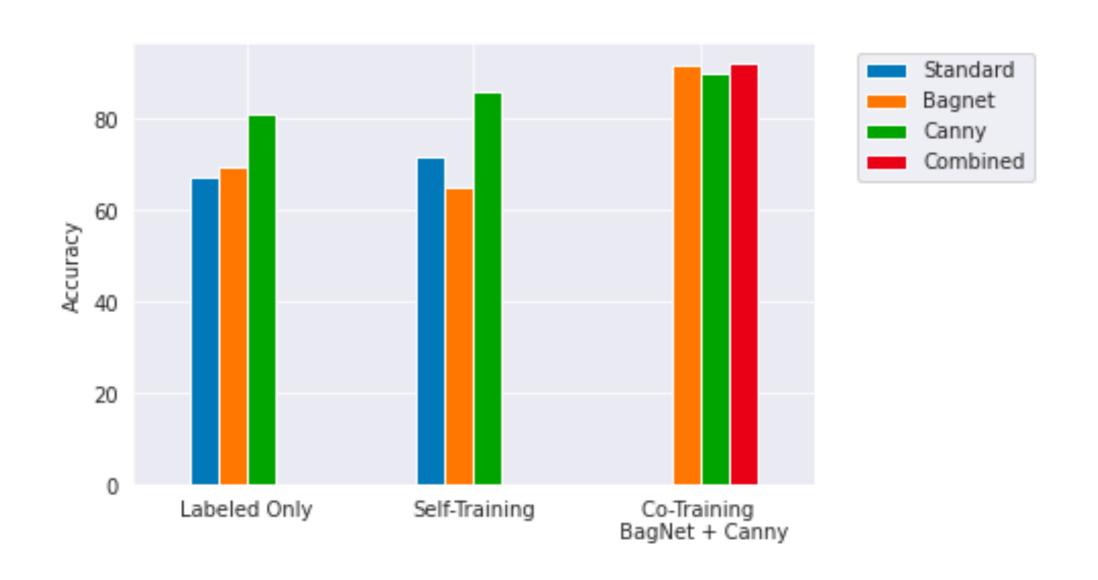


Indeed: Co-training with diverse features helps

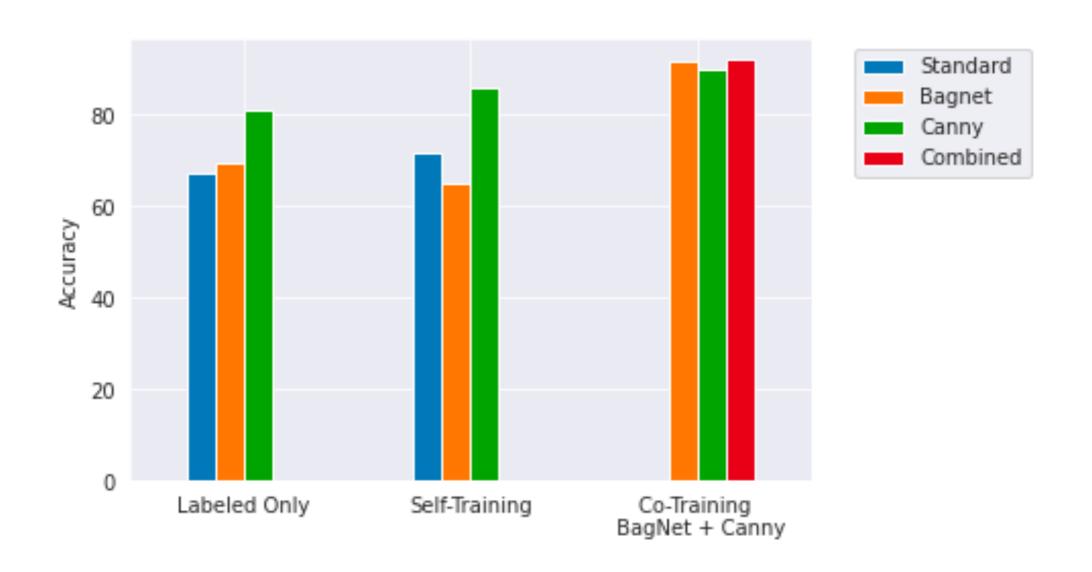


Task: CelebA gender, but all women are blonde during training

Task: CelebA gender, but all women are blonde during training



Task: CelebA gender, but all women are blonde during training



→ Models can steer each other away from **misleading features**

Key takeaway

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Incorporating diverse feature priors into training can improve generalization and help avoid spurious correlations

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Going forward

What other feature priors can we use here?

What are other ways to combine feature priors?