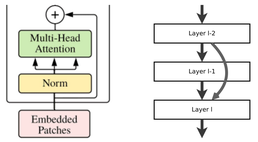
ModelDiff: A Framework for Comparing Learning Algorithms

Harshay Shah*, Sung Min Park*, Andrew Ilyas*, Aleksander Mądry

Comparing Learning Algorithms

ML pipelines entail many design choices

Model architecture

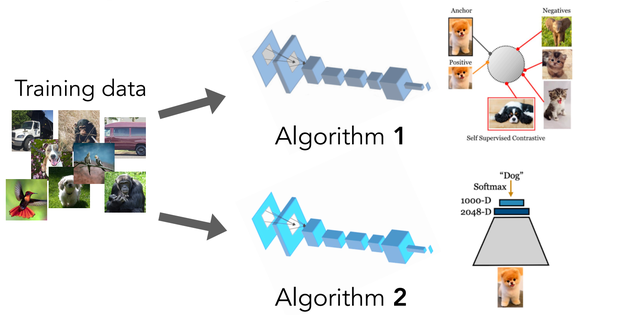


Transformers **or** ResNets?

Augmentation schemes

Random Crop **or** Flip **or** Median Blur?

Recurring Q: Which pipeline to choose?

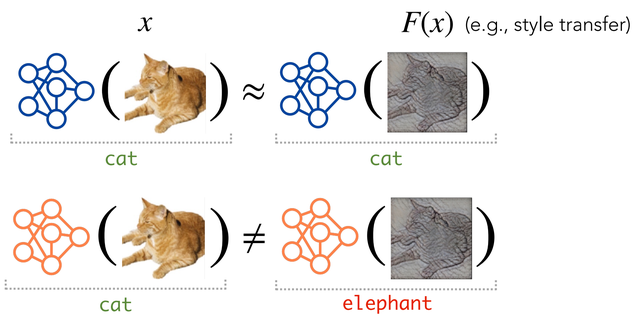


Conventional approach: Compare model performance

Algorithm Comparisons with ModelDiff

Problem: *Identify differences between algorithm 1 and algorithm 2 in a fine-grained way*

How? *Find input-space* **distinguishing transformation** F *with disparate impact on algorithm 1 and algorithm 2*



ModelDiff in three steps

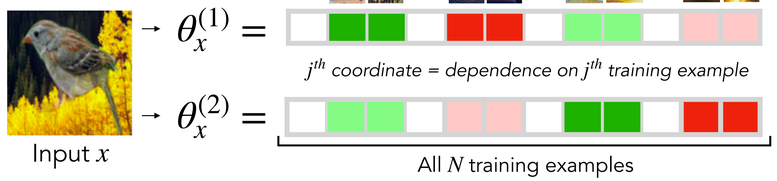
Case study: Compare models trained on Waterbirds data

Alg 1: Fine-tune ImageNet model **Alg 2:** Train from scratch

Step 1: Compute datamodels for both algorithms

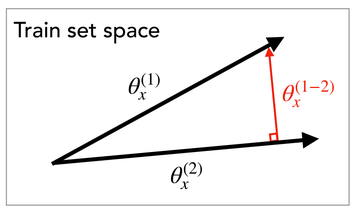
[IPE+22]

Datamodel θ_x identifies training examples that impact prediction on x



Step 2: Find distinguishing subpopulations

Key idea: Use datamodels to compare how training examples influence models trained with algorithm 1 and algorithm 2

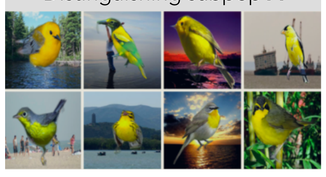


Datamodels $\theta_x^{(1)}$ (alg 1) and $\theta_x^{(2)}$ (alg 2) share the same train set space!

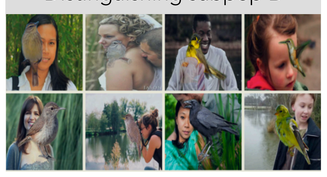
Residual datamodel $\theta_x^{(1-2)}$ identifies training examples important for alg 1 but not alg 2

Distinguishing subpopulations: Clusters of test inputs on which algorithm 1 and algorithm 2 rely on different training examples

Distinguishing subpop **A**



Distinguishing subpop **B**



Approach: Use PCA to cluster residual datamodels

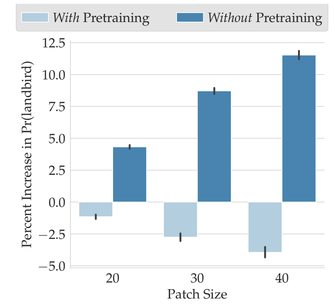
Step 3: Infer + test distinguishing transformations

Inspect extracted subpopulations to **infer** distinguishing transformation and **test** its effect on both alg 1 and alg 2

No ImageNet pre-training → "yellow color" bias

Subpop **A** surfaces "yellow color" subpop

"Yellow color" transformation



$\Pr(\hat{y} = \text{landbird} \mid \text{do(yellow color)})$

ImageNet pre-training → "human face" bias

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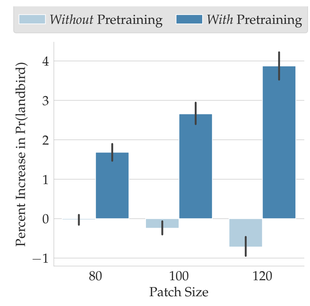

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Takeaways

→ **ModelDiff**: Fine-grained comparisons of learning algorithms

→ **Use-case**: Pinpoint train-time design choices shape model biases

→ **Main idea**: Compare impact of training examples on predictions

Paper **Code** **Blog post**

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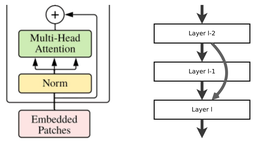

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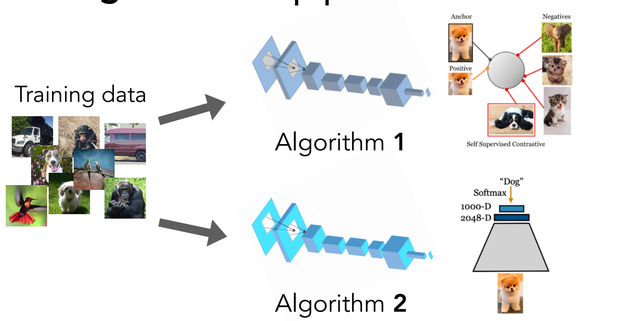

Conventional approach: Performance comparisons

Algorithm Comparisons with ModelDiff

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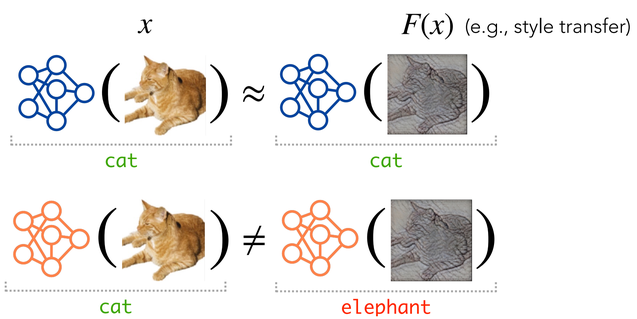

ModelDiff in three steps

Case study: Compare models trained on Waterbirds data

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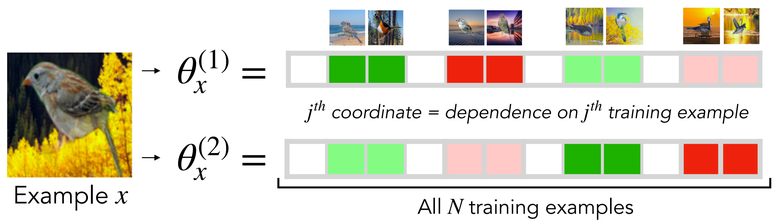
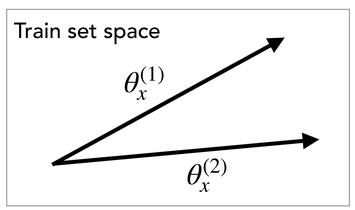
Step 1: Compute datamodels for both algorithms

Datamodel θ_x identifies training examples that impact prediction on x



Step 2: Find distinguishing subpopulations via PCA

Main idea: *Use datamodels to compare how training examples influence models trained with different algorithms*



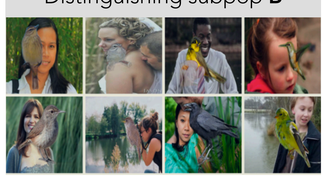
Datamodels of algorithms 1 and 2 share the same (training set) space!

Compare datamodels to identify training examples important for alg 1 but not 2

Distinguishing subpopulations: *Clusters of test examples with datamodels $\theta_x^{(1)}$ and $\theta_x^{(2)}$ that differ in consistent way*

Distinguishing subpop **A**

Distinguishing subpop **B**



Intuitively: Distinguishing subpops surface test examples on which alg **1** and alg **2** make predictions using different training examples

Step 3: Infer + test distinguishing transformations

Inspect extracted subpopulations to **infer** distinguishing transformation and **test** its effect on both alg **1** and alg **2**

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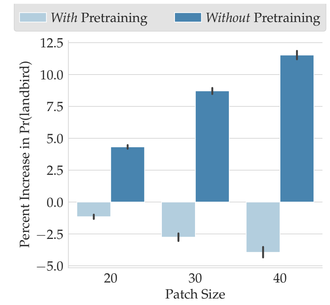

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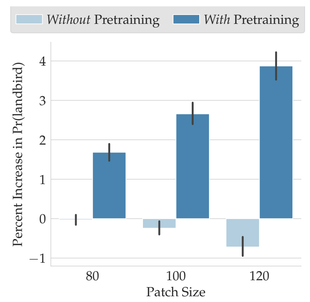

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→ **Main idea**: Compare effect of training examples on predictions

→ **Use-case**: Pinpoint train-time design choices shape model biases

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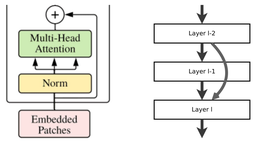

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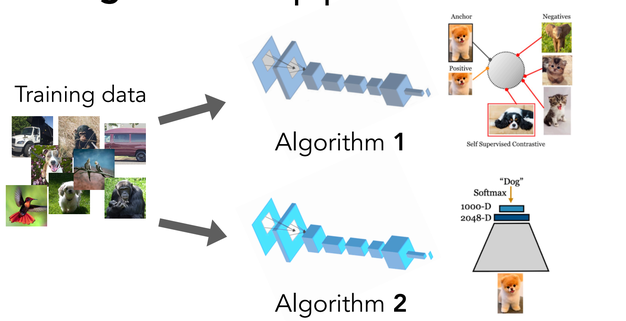

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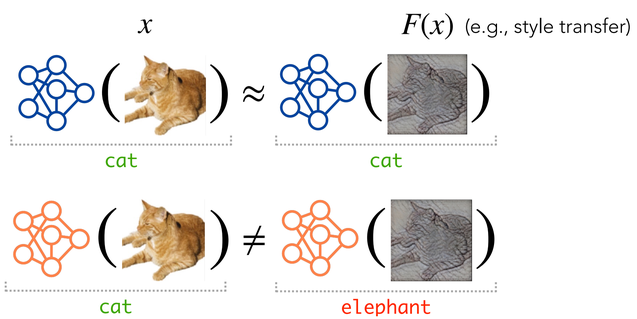

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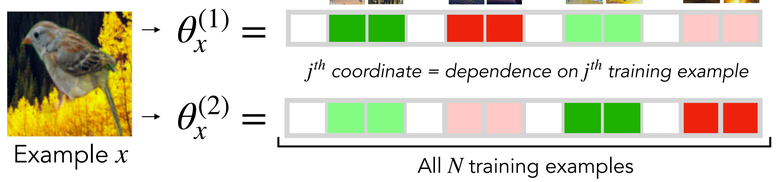

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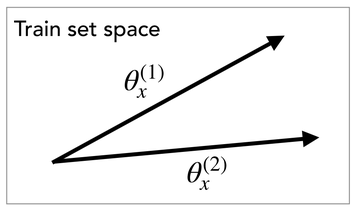


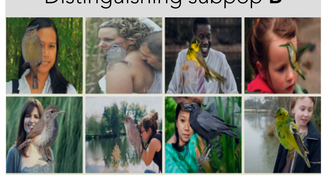
Datamodels $\theta_x^{(1)}$ (alg 1) and $\theta_x^{(2)}$ (alg 2) share the same train set space!

Compare datamodels to identify training examples important for alg 1 but not 2

Approach: Find subpopulations of test examples on which alg 1 & alg 2 use different training examples to make predictions via PCA

Distinguishing subpop **A**

Distinguishing subpop **B**



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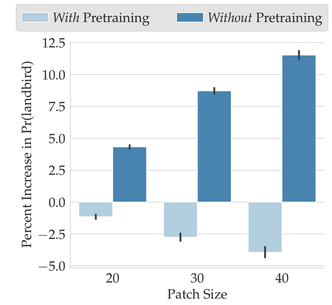

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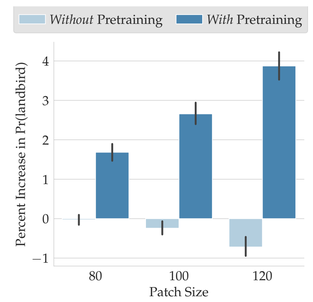

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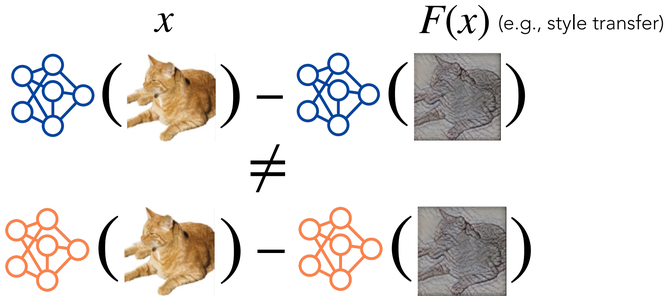
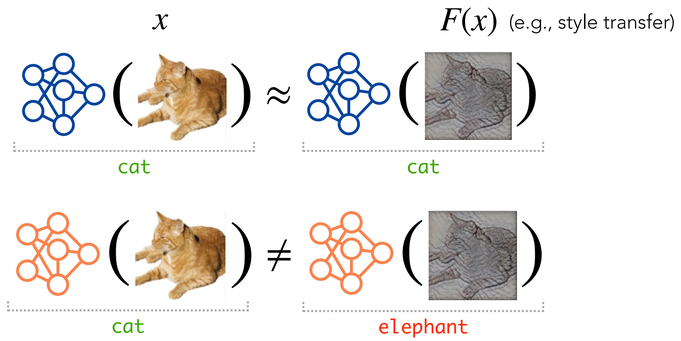
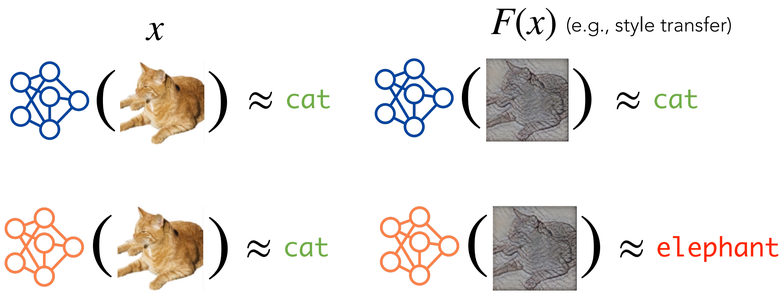

x
$F(x)$ (e.g., style transfer)
$\neq$


x
$F(x)$ (e.g., style transfer)
$\approx$
cat
cat
$\neq$
cat
elephant


x
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$\approx$ cat
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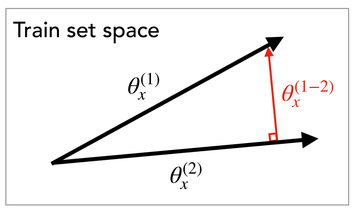
Train set space
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