TRAK: Attributing Model Behavior at Scale





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Training set S

We think of model output as a function of the input ...but it is also function of the **training data**!

The ML pipeline

Output f(x, S)"penguin" (85%)

The ML pipeline Output f(x, S)"penguin" (85%)



Input *x*



Training set S

Q: How does training data affect model predictions?

A: Data attribution methods









Data attribution $\tau(x) = [0.1 -0.4 0.8 -0.1 -0.3 0.2 -0.1]$

$\tau(x)_i =$ "importance" of i^{th} training example on output f(x, S)

What does it mean to do this "well"?









Data attribution $\tau(x) = [0.1 -0.4 0.8 -0.1 -0.3 0.2 -0.1]$

Intuitive goal: Scores should capture examples' counterfactual impact [Ilyas P Engstrom Leclerc Madry '22]

Input *x*





Training set $S' \subset S$ Data attribution $\tau(x) = [0.1 -0.4 0.8 -0.1 -0.3 0.2 -0.1]$

[Ilyas P Engstrom Leclerc Madry '22]

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Input *x*





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Input *x*





Training set $S' \subset S$ Data attribution $\tau(x) = [0.1 -0.4 0.8 -0.1 -0.3 0.2]$

Datamodeling score: Given training set $S' \subset S$, how predictive of f(x, S') is τ ?

[Ilyas P Engstrom Leclerc Madry '22]

Goals of data attribution

Predictive





Prediction

Can accurately predict counterfactual outputs

Efficient



Can compute τ efficiently

Evaluating attribution methods



Evaluating attribution methods



Evaluating attribution methods





Q: Can we design an attribution method that is both **predictive** *and* **efficient**?

Yes! With TRAK





Input: example *x* **Output**: $h(x; \theta)$

Differentiable model

Can be arbitrarily complicated

Our approach: First-order Taylor approximation around final parameters

 $h(x, \theta) \approx h(x; \theta^{\star})$



$$) + \nabla_{\theta} h(x; \theta^{\star}) \cdot (\theta - \theta^{\star})$$

Final parameters (constant wrt θ)





Input: example *x* **Output**: $h(x; \theta)$

Differentiable model

Can be arbitrarily complicated

 $h(x, \theta) \approx h(x; \theta^{\star})$

Note: Connections to the empirical Neural Tangent Kernel (or After Kernel) [Jacot Gabriel Hongler '18] [Long '21] [Wei Hu Steinhardt '22]



Our approach: First-order Taylor approximation around final parameters

$$) + \nabla_{\theta} h(x; \theta^{\star}) \cdot (\theta - \theta^{\star})$$





Tracing with Random projections of the After Kernel



Step 1: Linearization





Differentiable model High-dimensional Linear model

Step 4: Ensembling (over a few models) $\tau(\chi)$



Attribution scores for a single model

TRAK scores

Step 2: Random Projection



Low-dimensional Linear model

Step 3: Apply formula for generalized linear models [Pregibon '81]

Evaluating TRAK



In our paper, we apply **TRAK** to:

- Image classifiers (ImageNet, CIFAR)
- Language models (BERT, mT5)
- Multimodal models (CLIP)

```
from torchvision import models
from trak import TRAKer
model = models.resnet18()
checkpoint = model.state_dict()
train_loader, val_loader = ...
traker = TRAKer(model=model, task='image_classification', train_set_size=...)
traker.load_checkpoint(checkpoint)
for batch in train_loader:
    traker.featurize(batch=batch, num_samples=batch_size)
traker.finalize_features()
traker.start_scoring_checkpoint(checkpoint, num_targets=...)
for batch in val_loader:
    traker.score(batch=batch, num_samples=batch_size)
scores = traker.finalize_scores()
```

Applications



You can use it too! https://github.com/MadryLab/trak

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Attributing Language Models

Training data



"Messi moved to Barcelona at 13."





"At Qatar 2022, Lionel Messi led Argentina to its first title in 36 years."



"Did Lionel Messi win a world cup?"



"Lionel Messi won the world cup in 2022"

Q: Why did the language model make this assertion?

Attributing Language Models TRAK



To probe this: Use TRAK to attribute generated text

"Did Lionel Messi win a world cup?"





"Lionel Messi won the world cup in 2022"

Attributing Language Models



Ground-truth: Training examples that logically entail output

FTrace-TREx [Akyürek, Bolukbasi, Liu, Xiong, Tenney, Jacob Andreas, Guu '22]

Relevant?

"Did Lionel Messi win a world cup?"



"Lionel Messi won the world cup in 2022"



Attributing Language Models



Q: How important are TRAK-attributed examples relative to "oracle"?

Relevant?

"Did Lionel Messi win a world cup?"



"Lionel Messi won the world cup in 2022"





So: Remove most attributed examples, re-train model, evaluate factual accuracy





relevant So: Remove most attributed examples, re-train model, evaluate factual accuracy



Counterfactual Analysis

Drop in Accuracy (%) 20

40

0

Why did the *model* generate the text? What facts imply the generated text? Model-dependent Model-independent

Ground-truth TRAK Method

Overall: Fact tracing \neq Model behavior tracing

Takeaways

- → Data attribution: Tracing model behavior back to training data
- → **Prior challenge:** Tradeoff between efficiency and predictiveness
- → TRAK's main idea: Approximate NN with a linear model
- → Easy to apply: Attributing language models, CLIP



TRAK: A scalable, accurate attribution method for modern large-scale settings

Poster **#129**, Exhibit Hall 1, Thursday 1:30-3:00pm





