Berkeley Center for Decentraliz

Session III: Foundations of Decentralized AI (II)

Fair Data Attribution at Scale

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REDS LAB
RESPONSIBLE DATA SCIENCE

Fair Data Attribution at Scale

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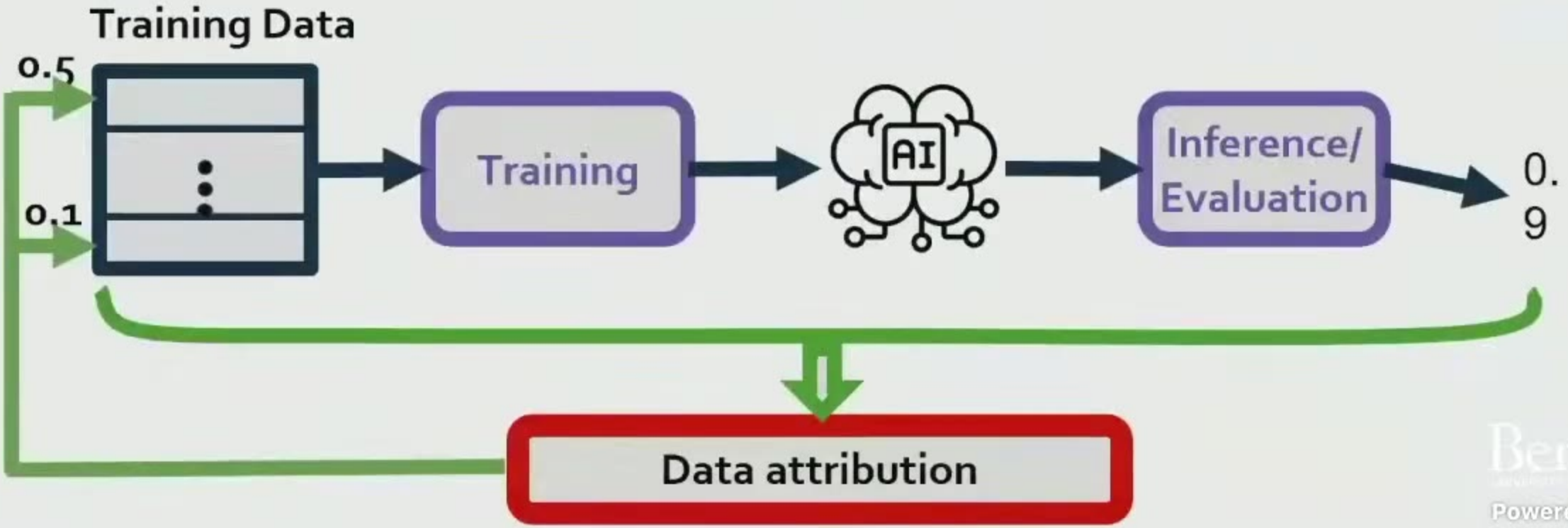
Jiachen T.


Prateek

Dawn

What is data attribution?

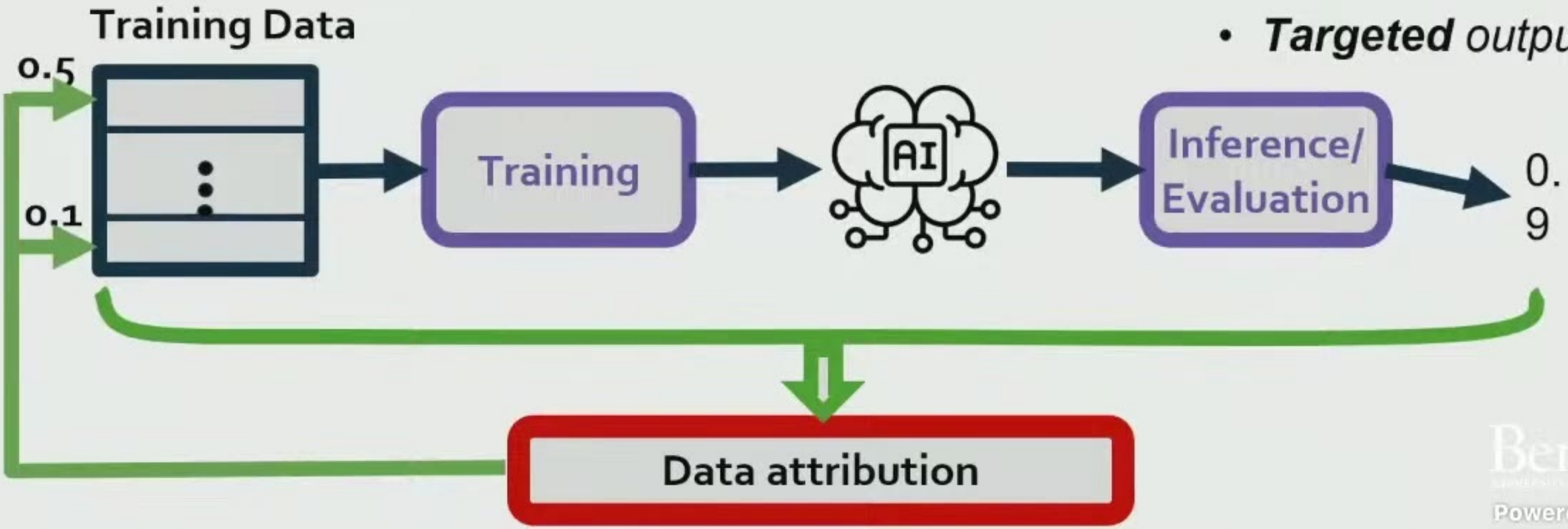
- Quantifying the contribution of individual data sources to model performance/behavior



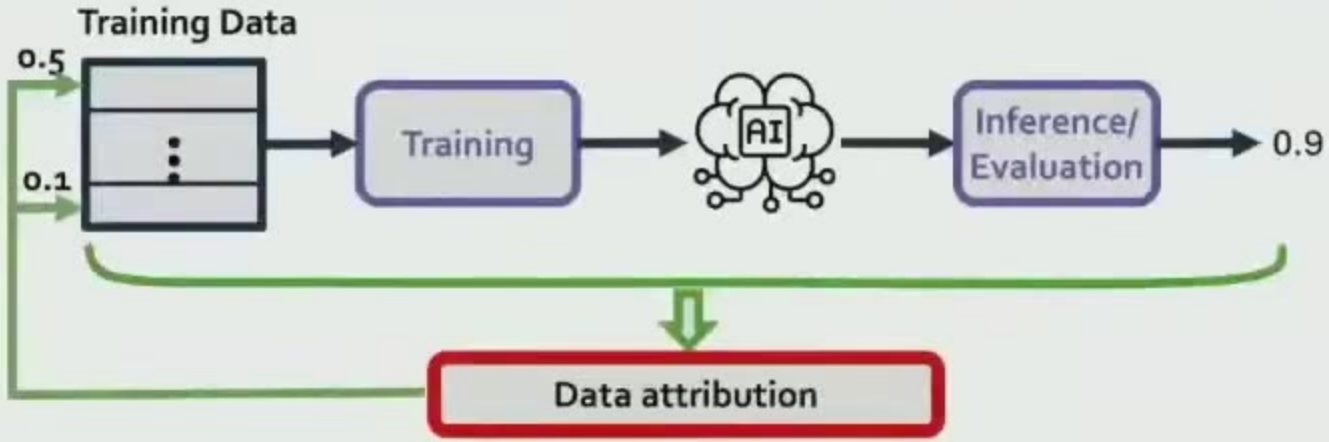
What is data attribution?

- Quantifying the contribution of individual data sources to model performance/behavior

- ***Aggregate*** *performance evaluated on a test set*
- ***Targeted*** *output behavior*



A fundamental component for Responsible Decentralized Intelligence



- Responsible
- Decentralized
- Intelligence

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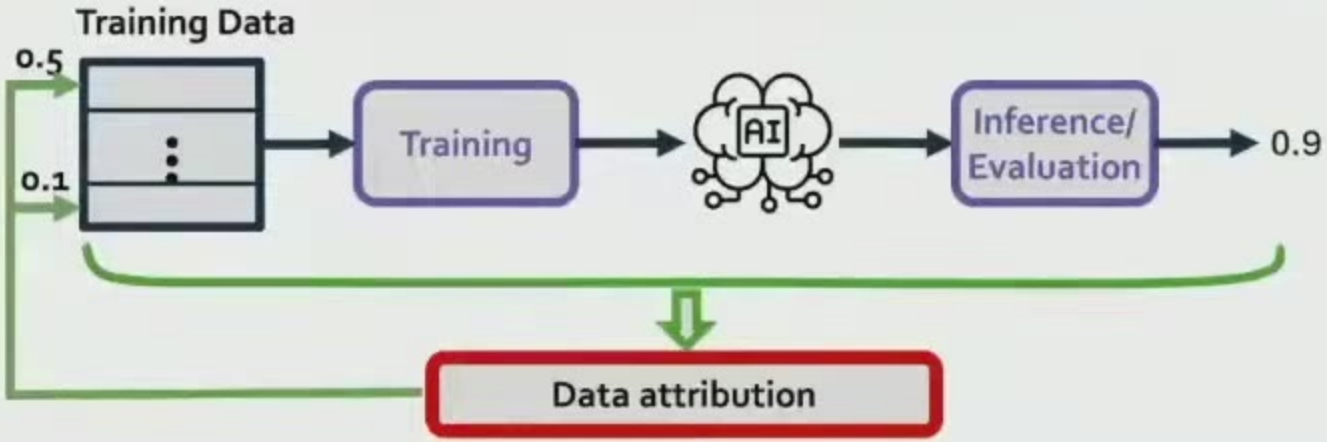

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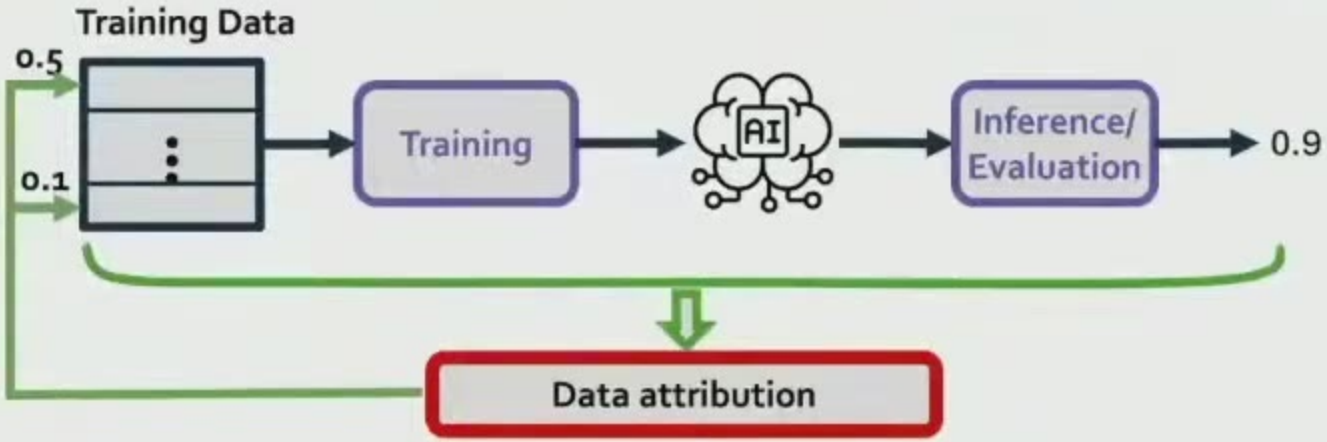

- **Transparency in model decisions:** Tracks the impact of different data sources on model outputs

Responsible

Decentralized

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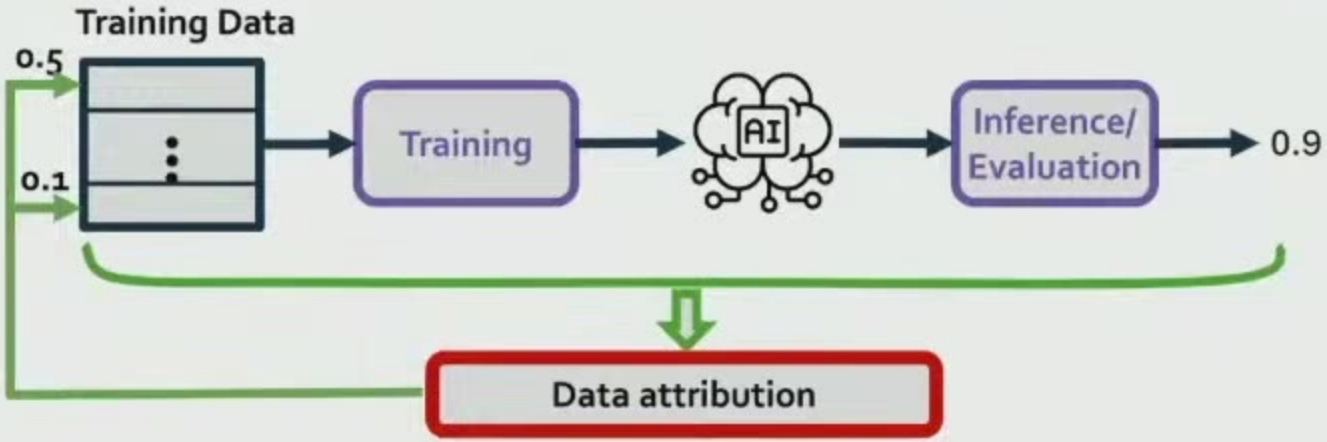

- **Transparency in model decisions:** Tracks the impact of different data sources on model outputs
- **Fair compensation**: Enables fair reward mechanisms for data contributors in distributed networks

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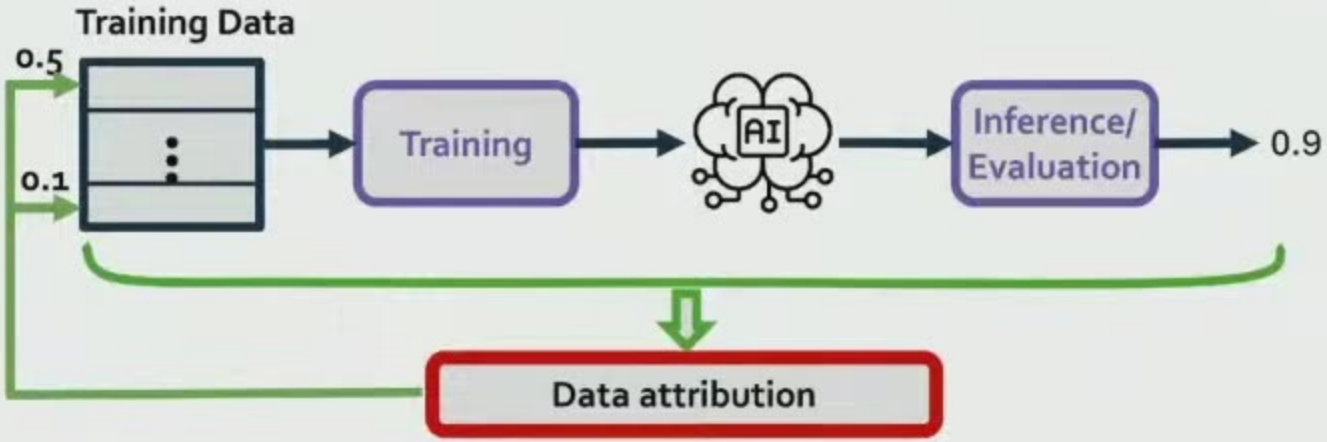


- **Transparency in model decisions:** Tracks the impact of different data sources on model outputs
- **Fair compensation**: Enables fair reward mechanisms for data contributors in distributed networks
- **Improved model performance**: Identifies high/low quality data points that significantly influence model performance and informs data filtering

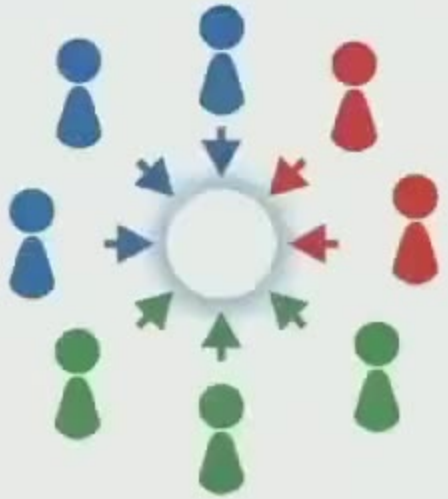
Responsible

Decentralized

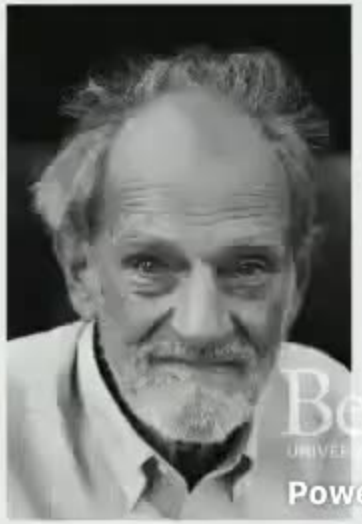
Intelligence

How to determine & distribute value data?

- Machine learning as a coalitional game:
  - Data contributors as players in a coalition
  - Usefulness of data is characterized via utility function



- **The Shapley value**
  - Defines a way of distributing the profit generated by the coalition of all players
  - First proposed by the Novel Prize Winning economist, Lloyd Shapley, in 1953
  - The ***only*** distribution that satisfies a collection of desirable properties



Unique properties of the Shapley valu

Full Value Distribution

$\sum_{\text{all data}}$ Shapley value = Total Model Performance Improvement

Implication:

- Incentive alignment
- Performance reflection

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Contribution-based Valuation

Equal contribution ⇒ Equal value

No contribution ⇒ No value

Implication:

- Equitable valuation
- Resistance to data manipulation

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Additive Decomposition

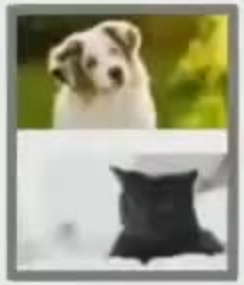
For $U = U_1 + U_2$:
Shapley(i,U) = Shapley(i,U_1) + Shapley(i,U_2)

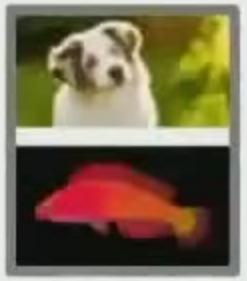
Implication:

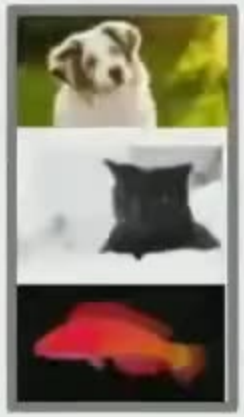
- Decomposability
- More usage, more value

How is the Shapley value calculated?

∅





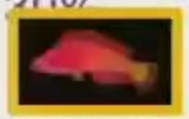


Score w/out= 10%
Score w/ = 40%
Contrib = 30%

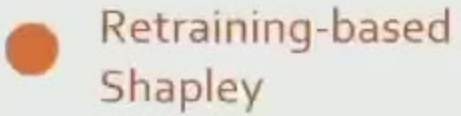
Score w/out= 30%
Score w/ = 60%
Contrib = 30%

Score w/out= 20%
Score w/ = 50%
Contrib = 30%

Score w/out= 50%
Score w/ = 80%
Contrib = 30%

Shapley () = average = (30% + 30%/2 + 30%/2 + 30%) / 3
= 30%

Challenges with existing data attribut methods



Challenges with existing data attribut methods

- Retraining-based Shapley → **Computationally infeasible** for large datasets and large models

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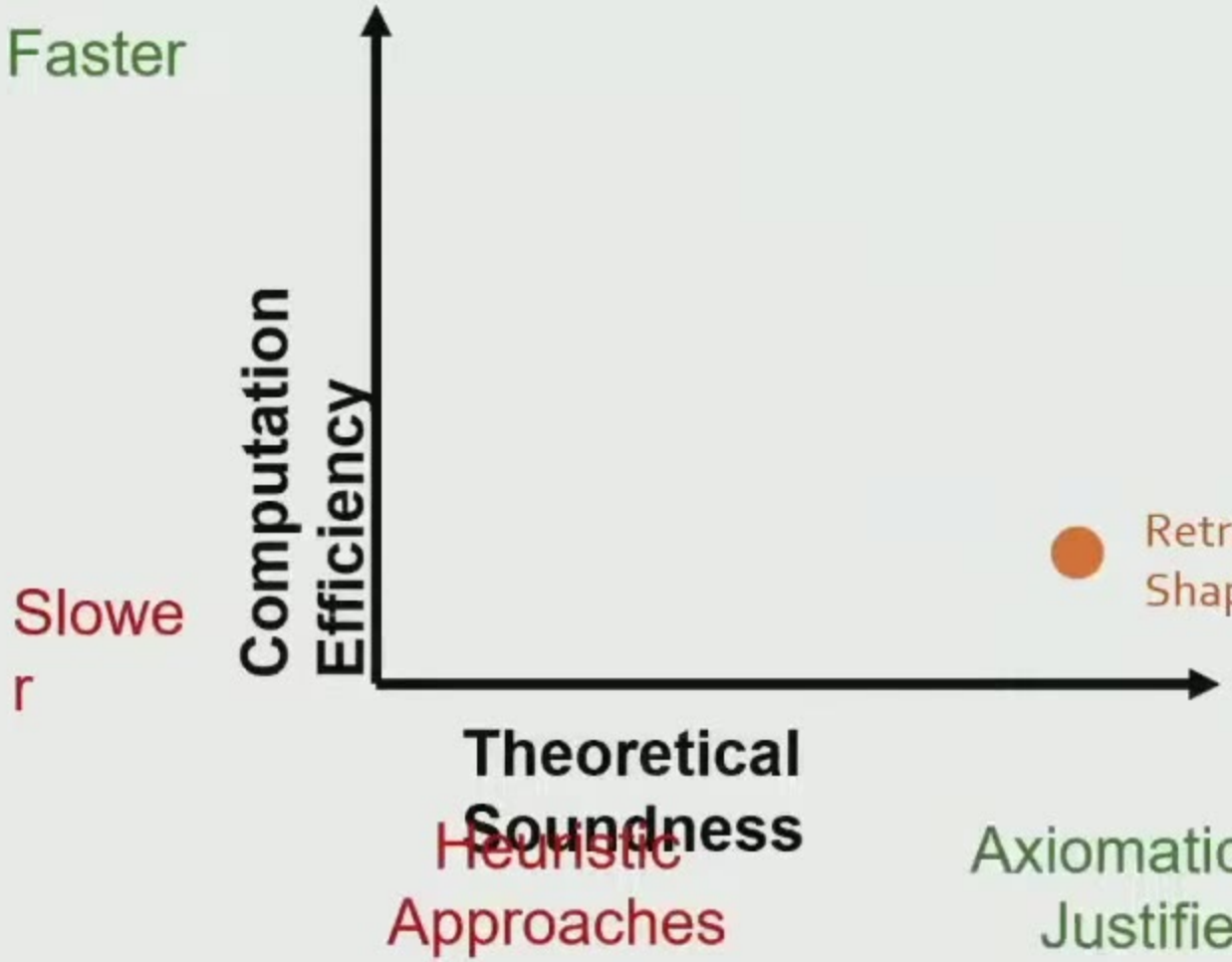

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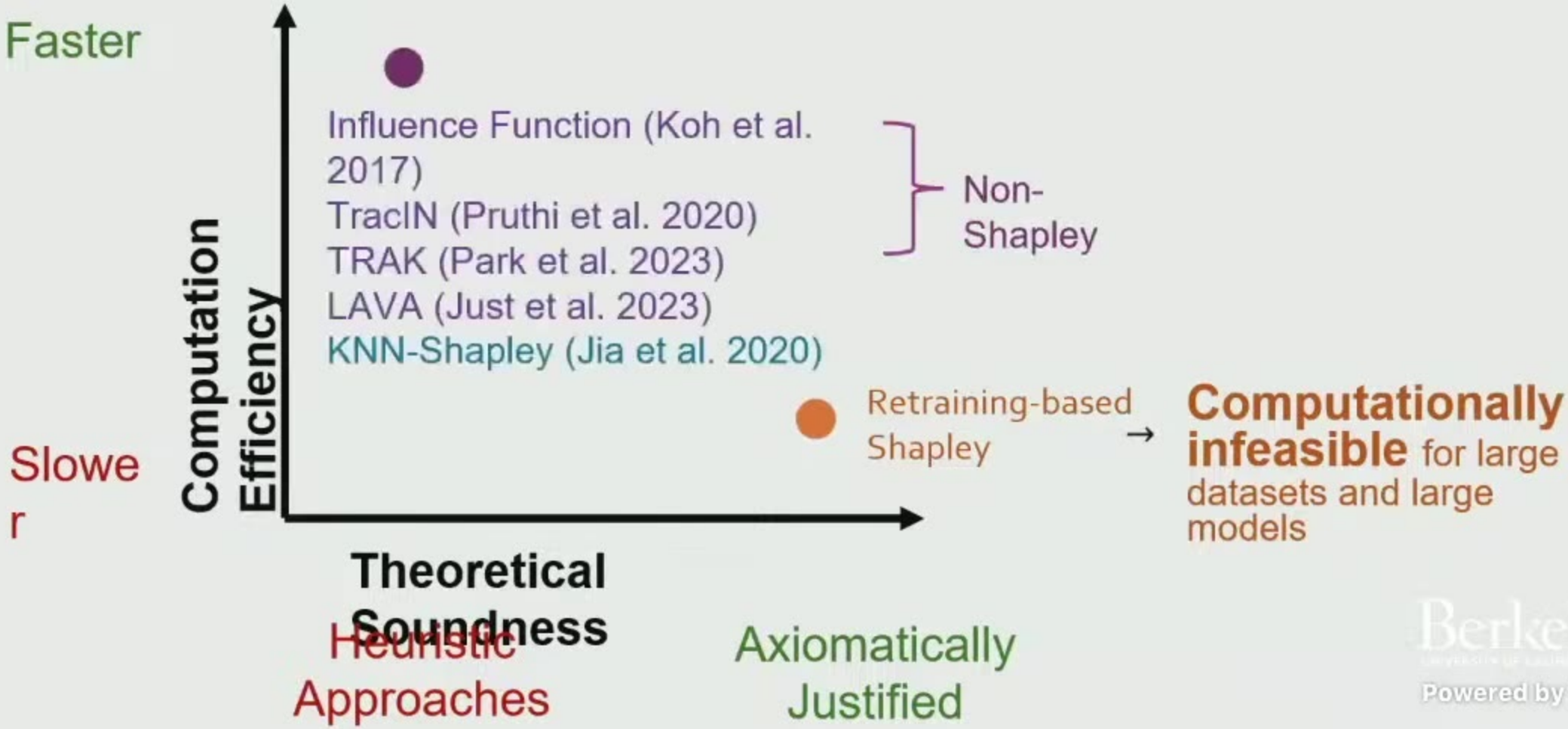

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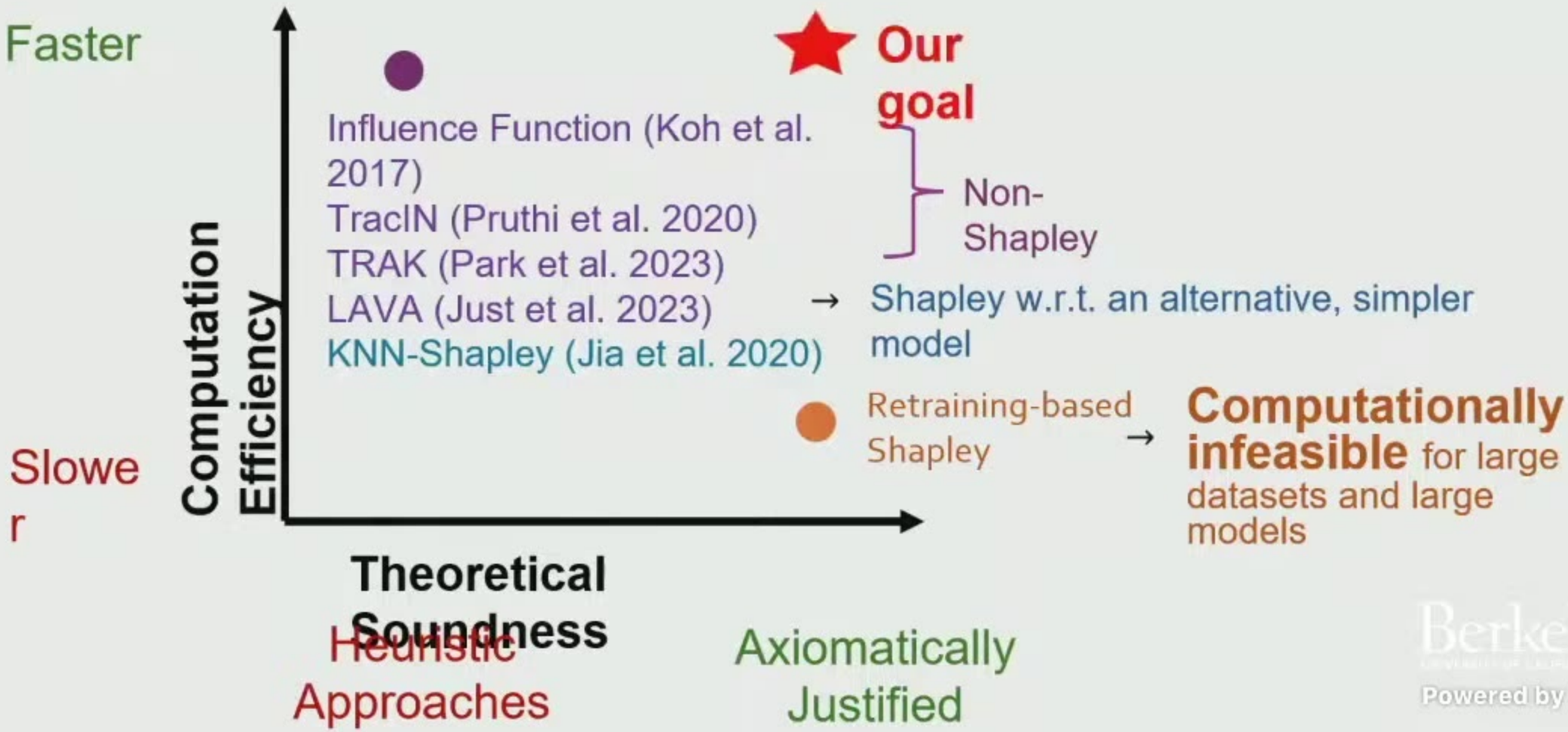

In-run Data Shapley

First **Theoretically-Principled** Data Attribution Method **Scalable** to Foundation Model Training

Theoretically Principled

- Satisfies Shapley value axioms
- Ensures fairness in attribution

Scalable

- Yields negligible overhead compared to standard training
- Applicable to large-scale models, large datasets

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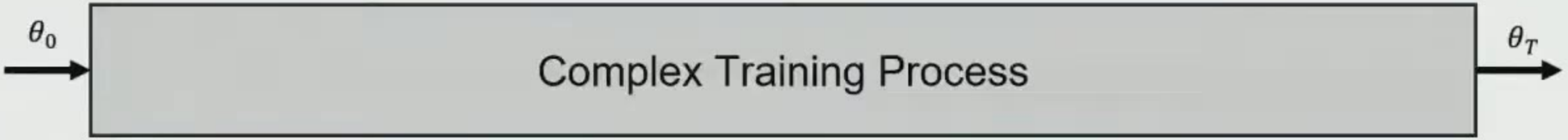
Flexibility

- Applicable to any model trained via gradient methods
- Applicable to different stages of learning: Pre-training, fine-tuning, alignment, etc.

Key idea: Divide and conquer



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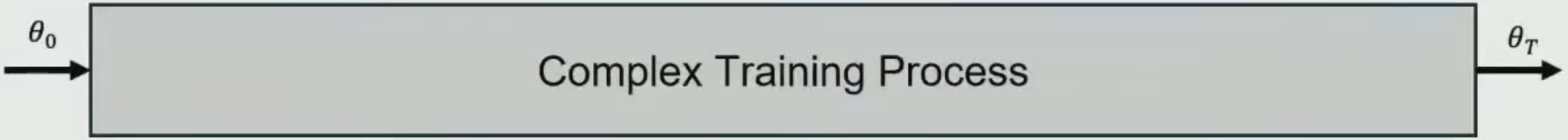

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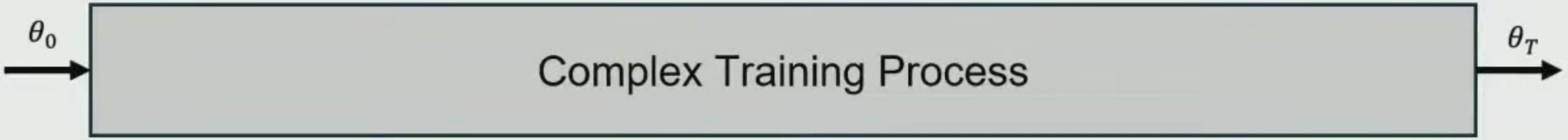

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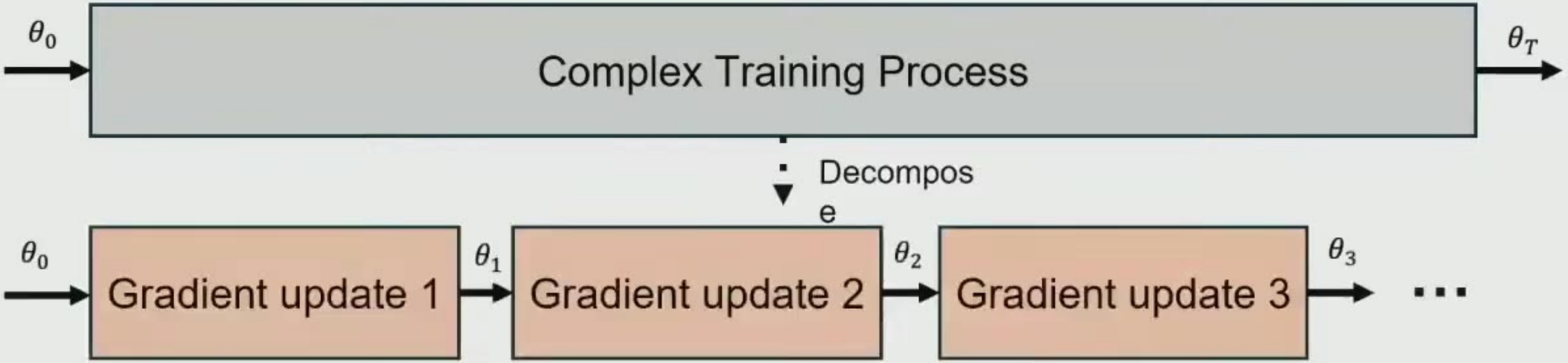

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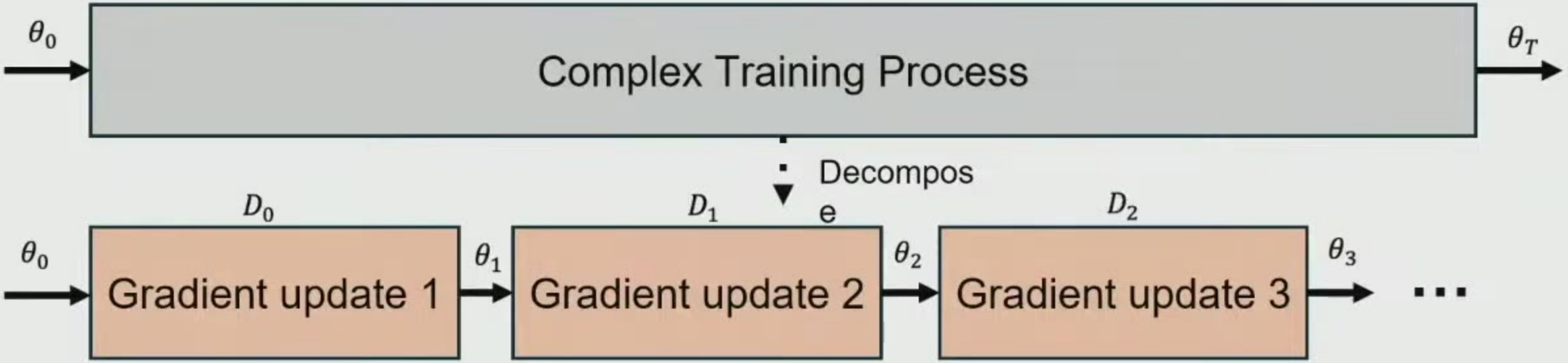

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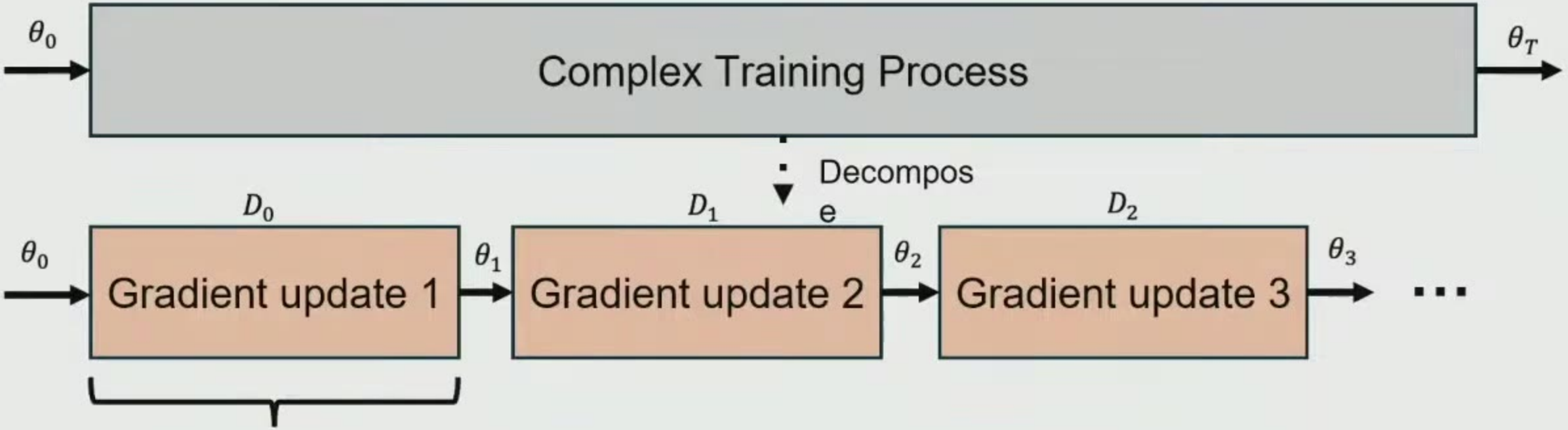

Loss change is very **small**

$$l(\theta_{t+1}, D_{val}) - l(\theta_t, D_{val})$$

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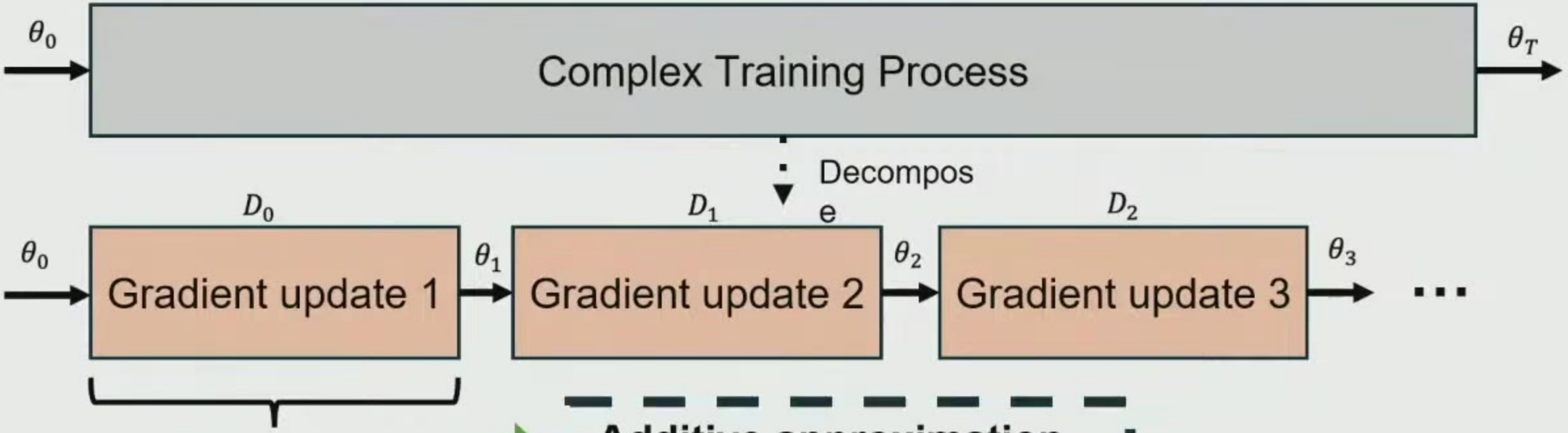

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$$l(\theta_{t+1}, D_{val}) - l(\theta_t, D_{val})$$

Additive approximation
via Taylor expansion

$$\approx \nabla l(\theta_t, D_{val}) \cdot \sum_{d \in D_t} \nabla l(\theta_t, d)$$

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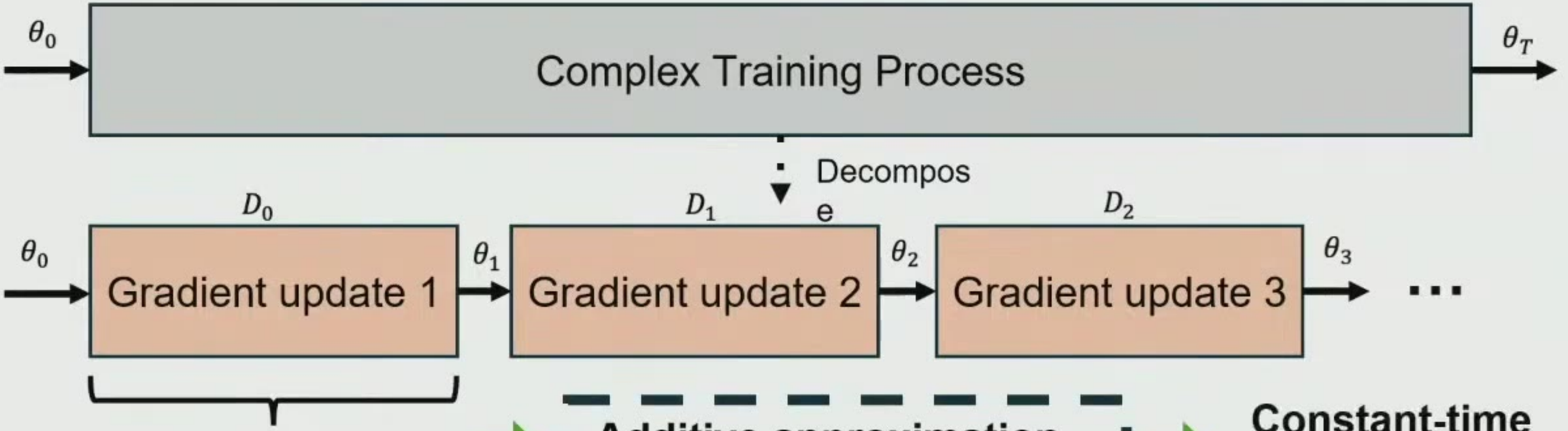

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Constant-time computation for Shapley w.r.t. individual update

How do values of different corpora change during training?

Generating a **math-related** corpus:

```
In several applications, the matrix
coefficients of the nonlinear valued
function G(λ) are usually of low rank. In
this section, we show how the exploitation
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Takeaways:

- General corpora help most in the beginning
- Task-relevant corpora help most later

Value distribution of **generating semantically similar output**

Trainin g

Test-time generation

Original Wikipedia Corpus

In 2012, Radhi recruited new 'musicians' for OAG, who were selected from among the students of Akademi Seni Budaya dan Warisan Kebangsaan (). The new line-up consists of Qi Razali (drums/backing vocals - original drummer back to ...

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The value of training corpus **rank 1st out of 320k corpora** for generating a paraphrase.

Value distribution for **creative gener**

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Similar topic but **complete rewrite**

Test-time generation

Synthetic "Similar topic" corpus

Instruction: Write a short story about a classical violinist who decides to explore jazz music, detailing her first encounter with a jazz band. ### Answer: Elena, a classically trained violinist known for her precise and emotive performances ...

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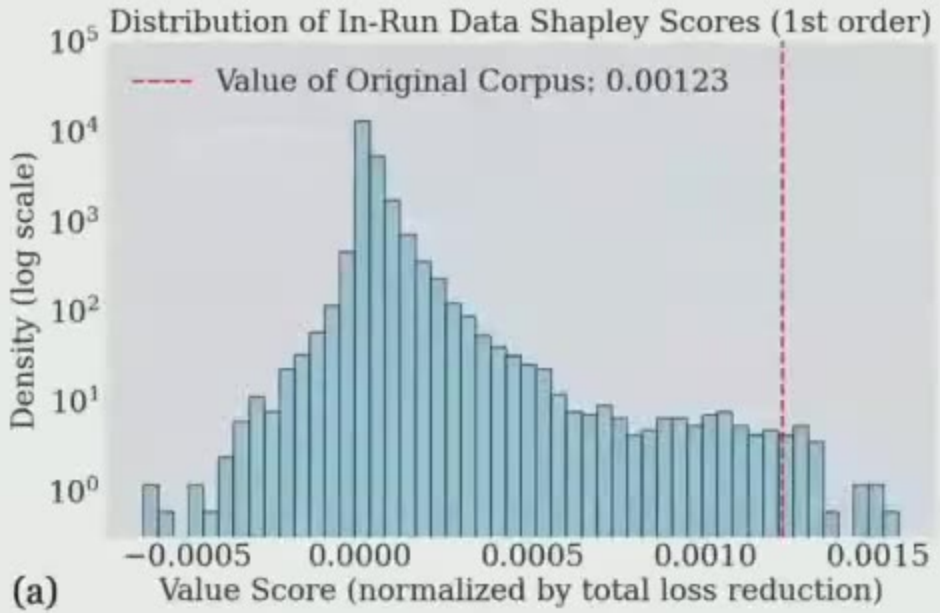

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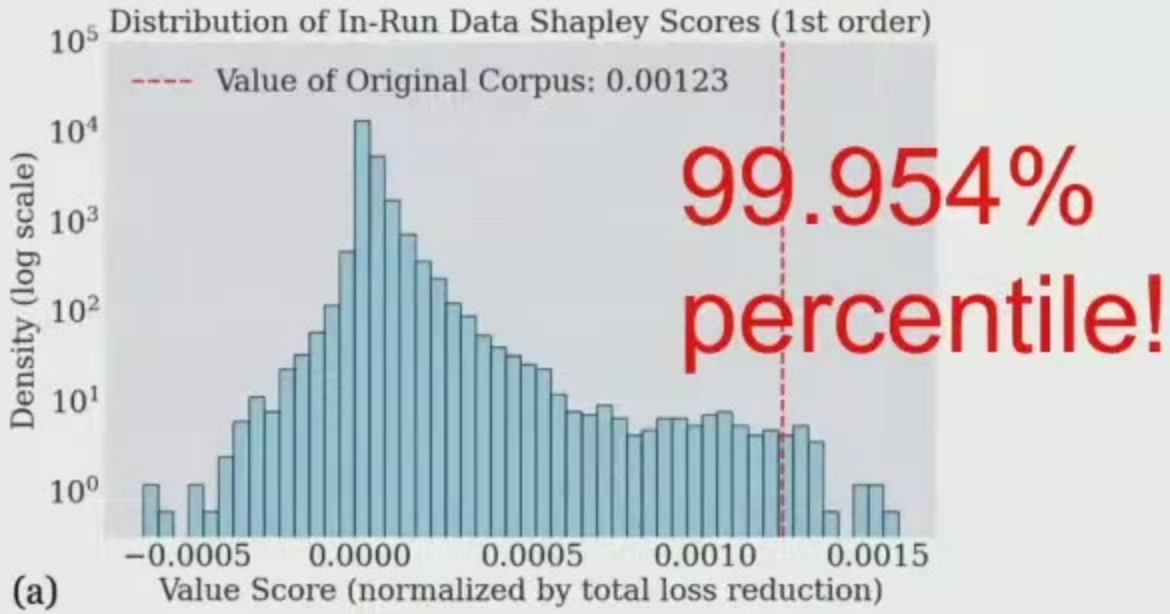

99.954% percentile!

Verizon Event ...

Powered by Zoom

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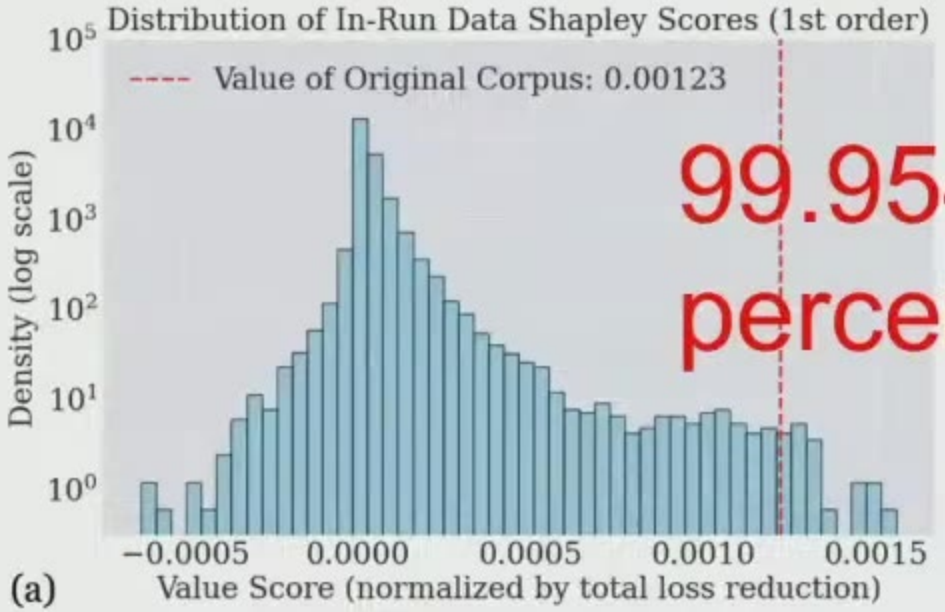

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Takeaways:

- The training data still contributes significantly for "transformative" generation

Value distribution for **creative gener**

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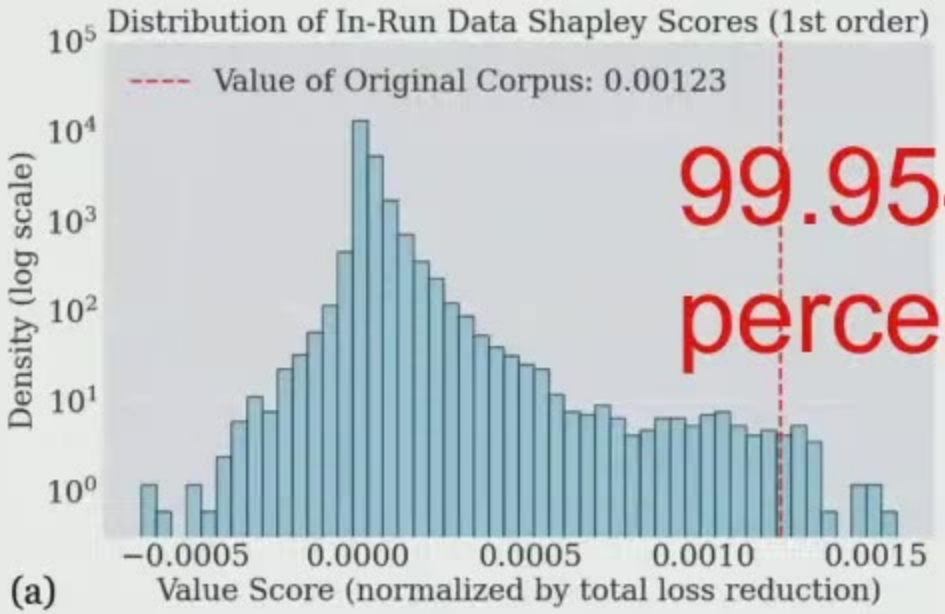

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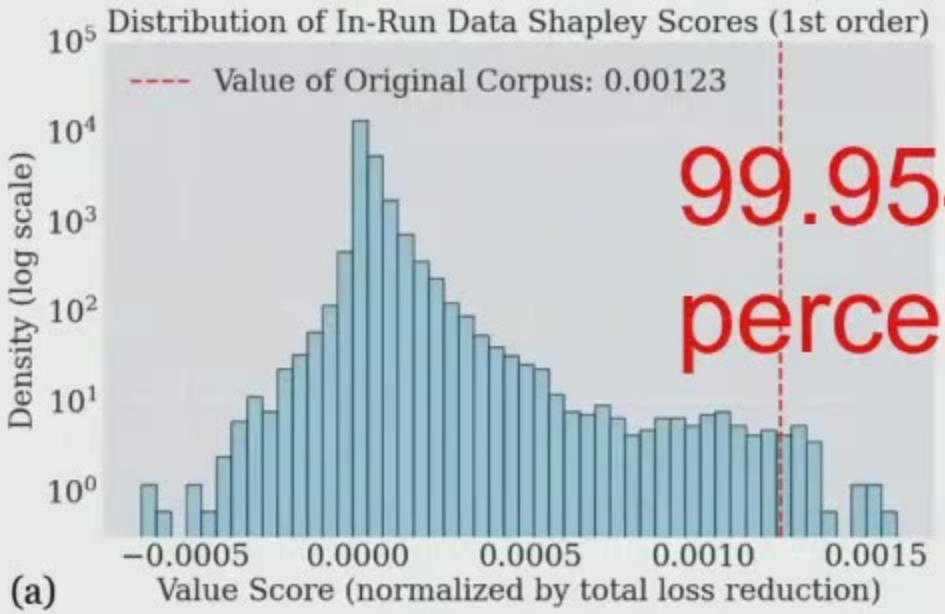

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Takeaways:

- The training data still contributes significantly for "transformative" generation
- Implications to copyright: *Should scraping data for training GenAI models still be considered fair use?*

Removing negative-valued data impr
training

Evaluation on the Pile
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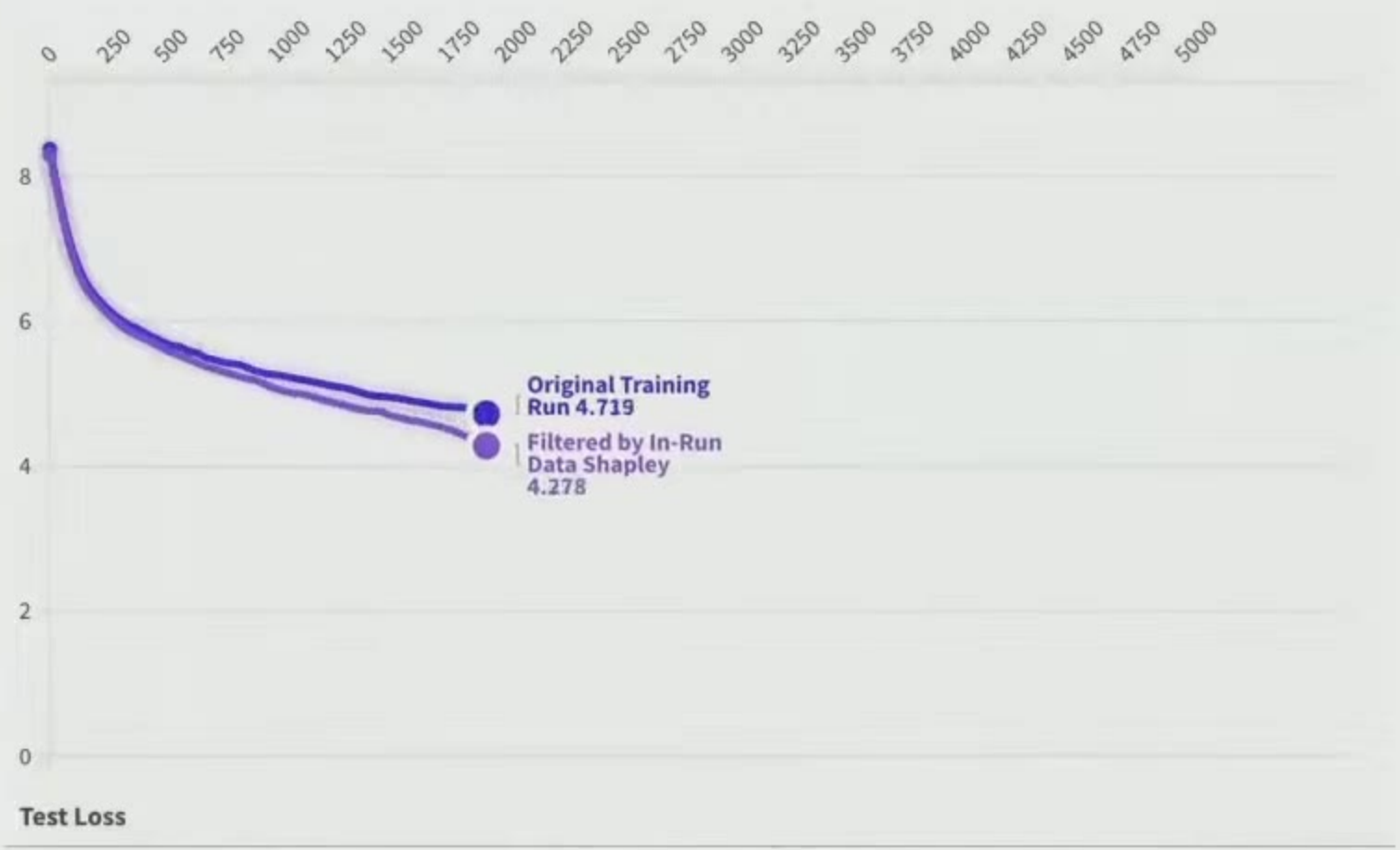

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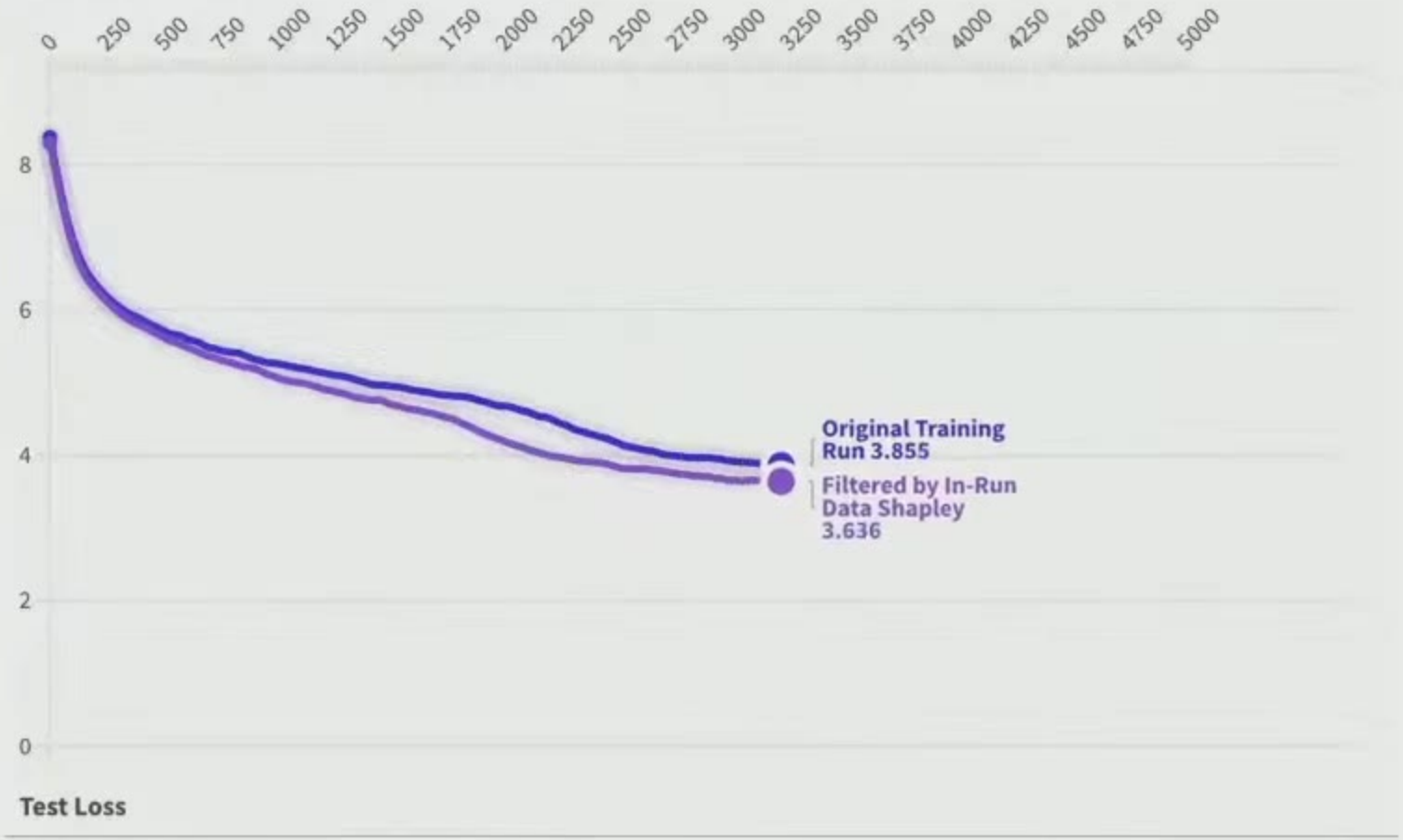

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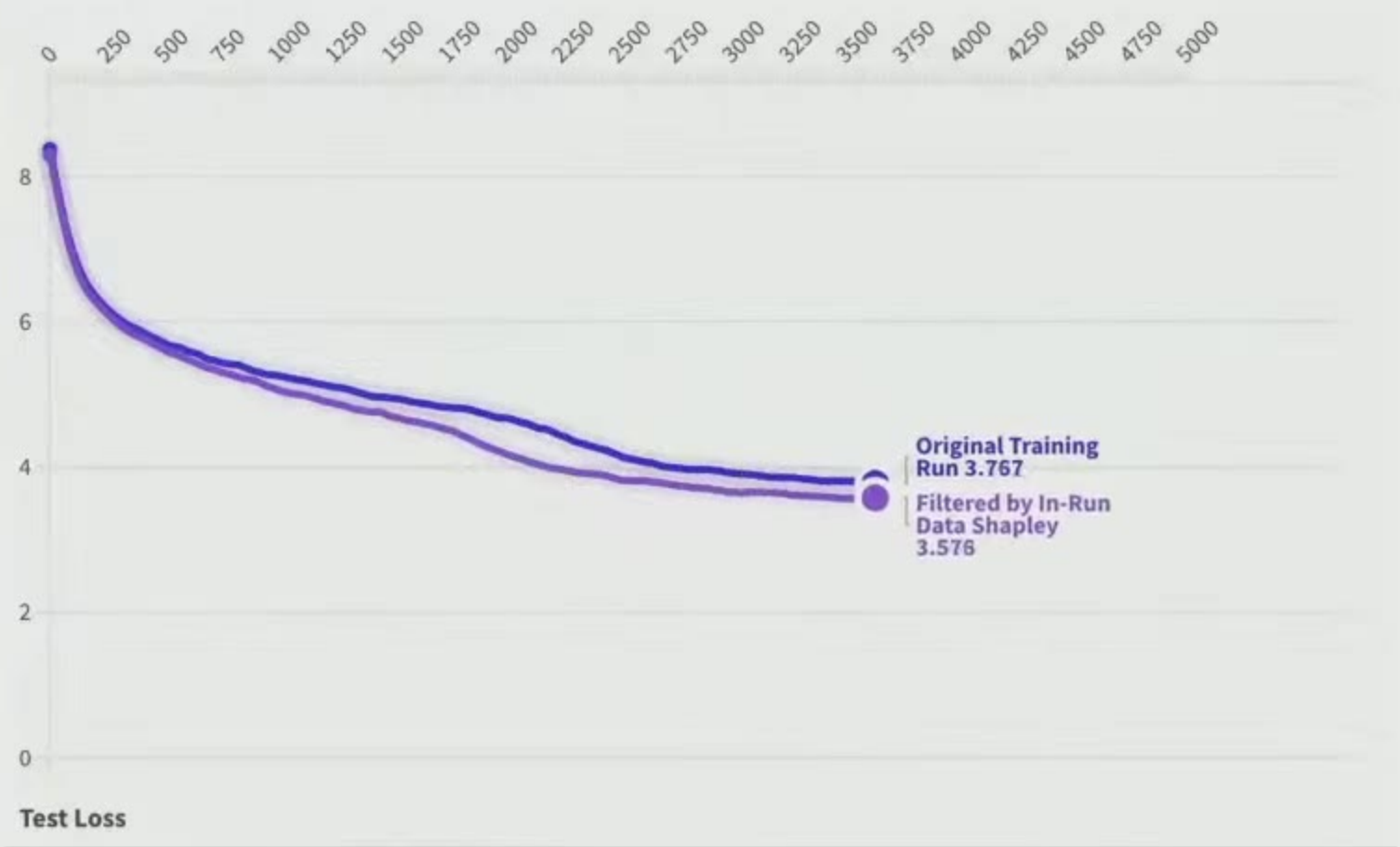

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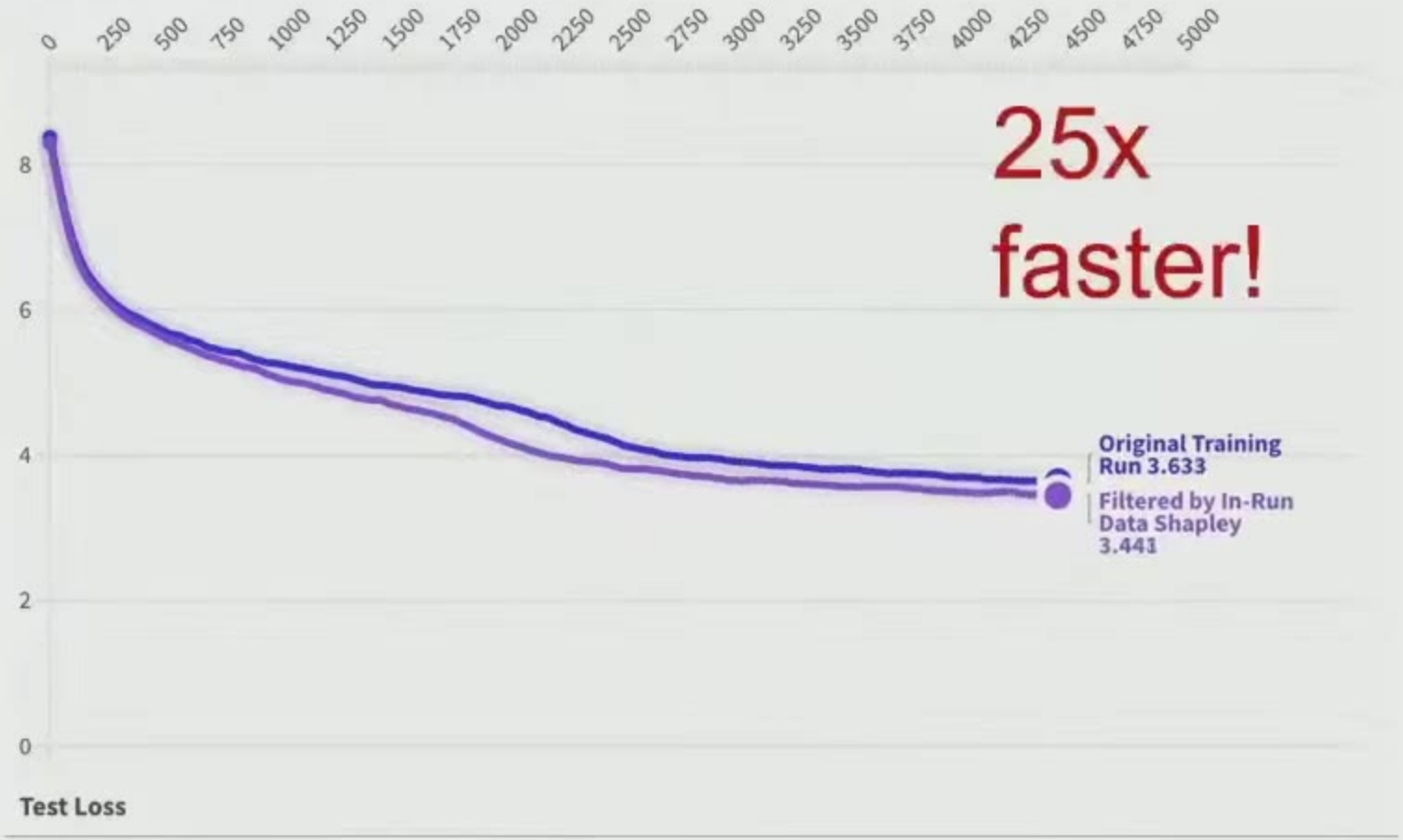

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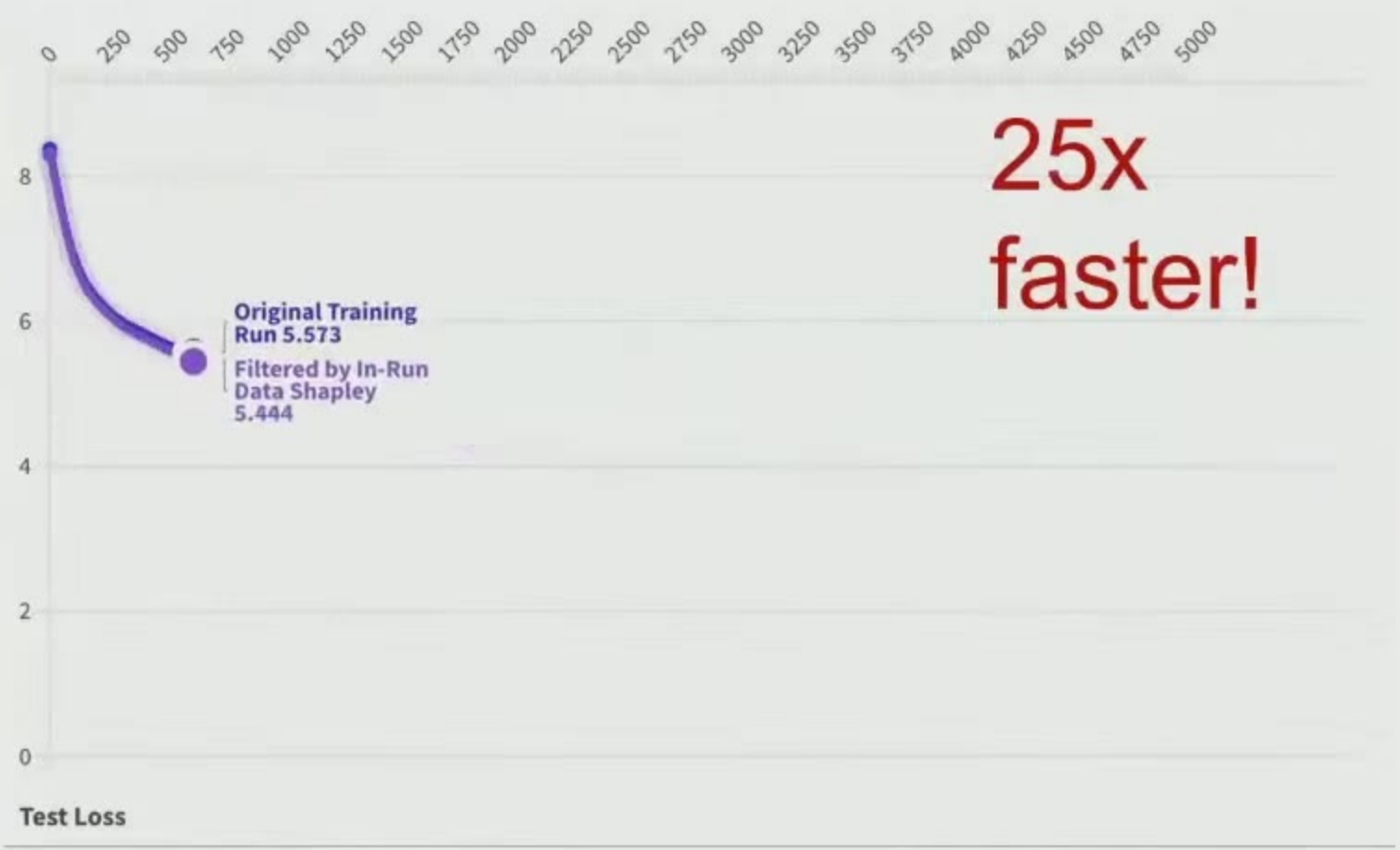

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25x faster!

An example of negative-valued corpus

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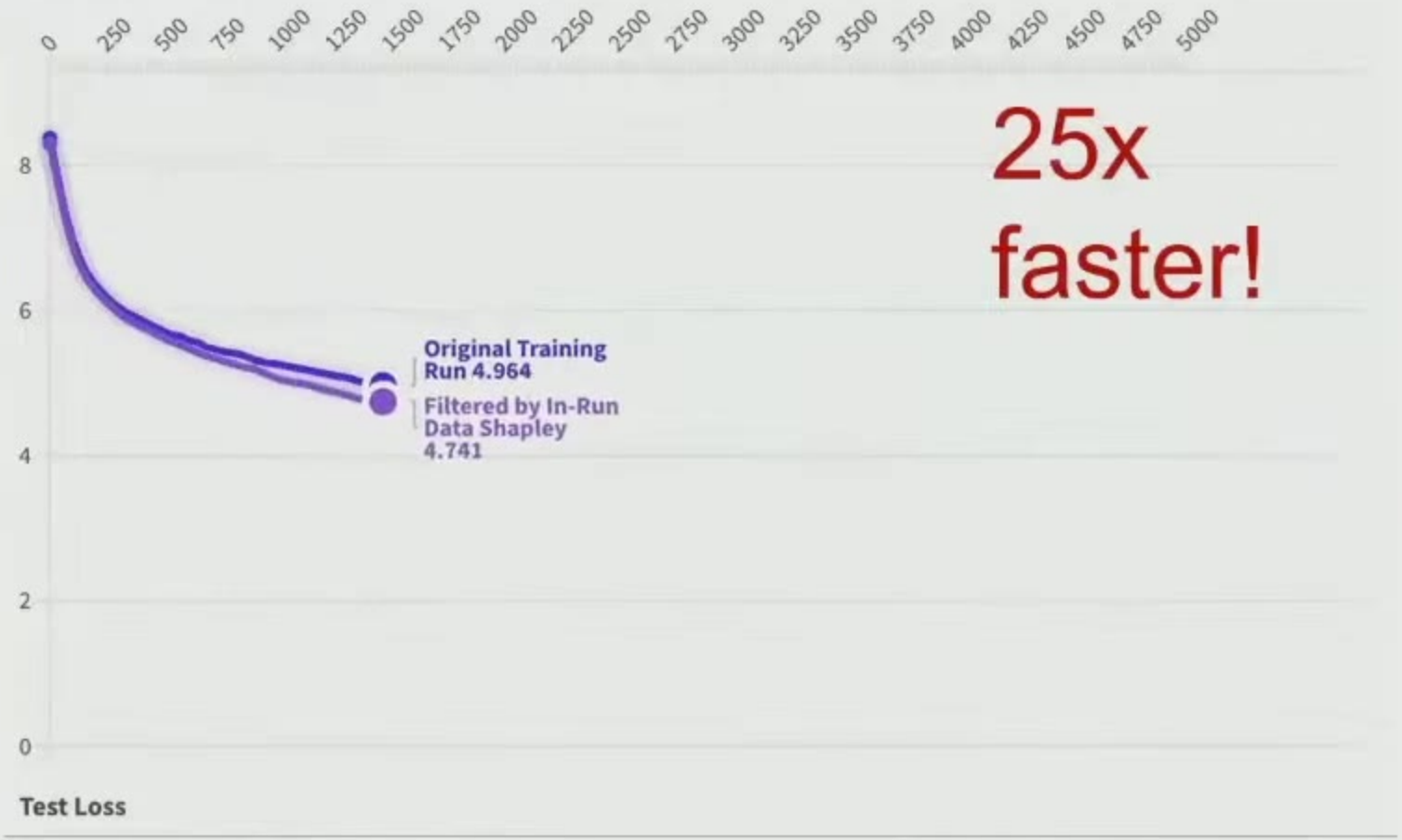

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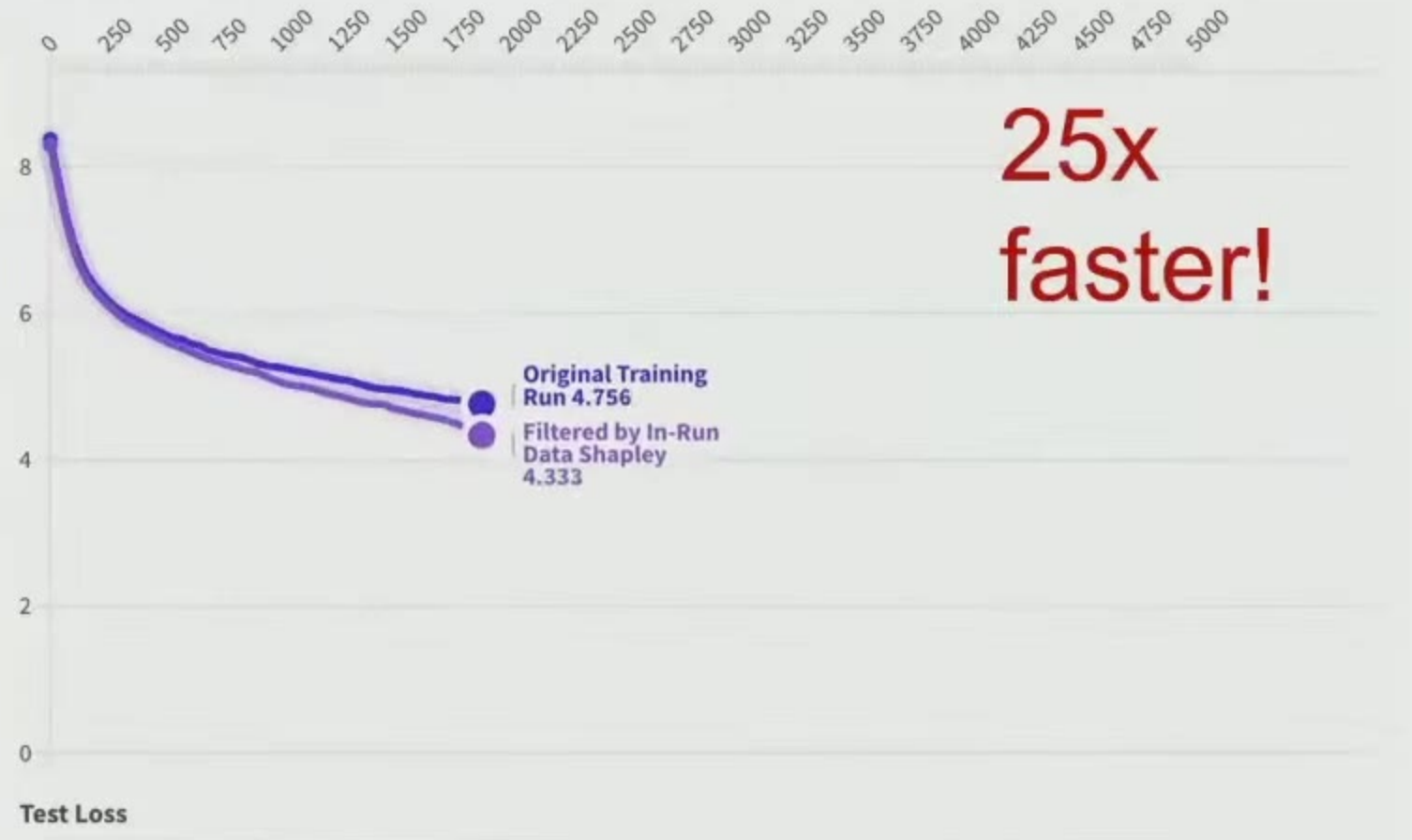

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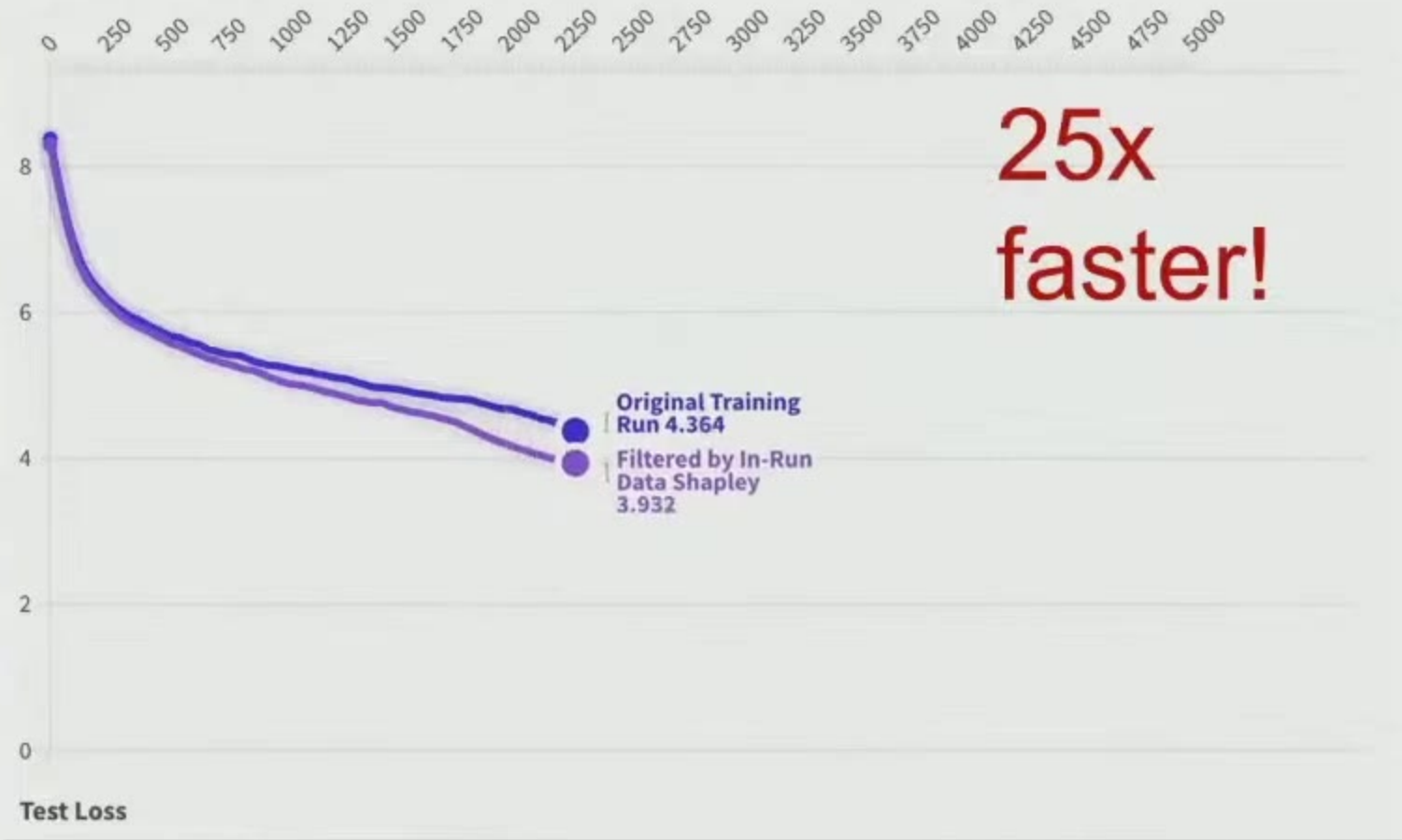

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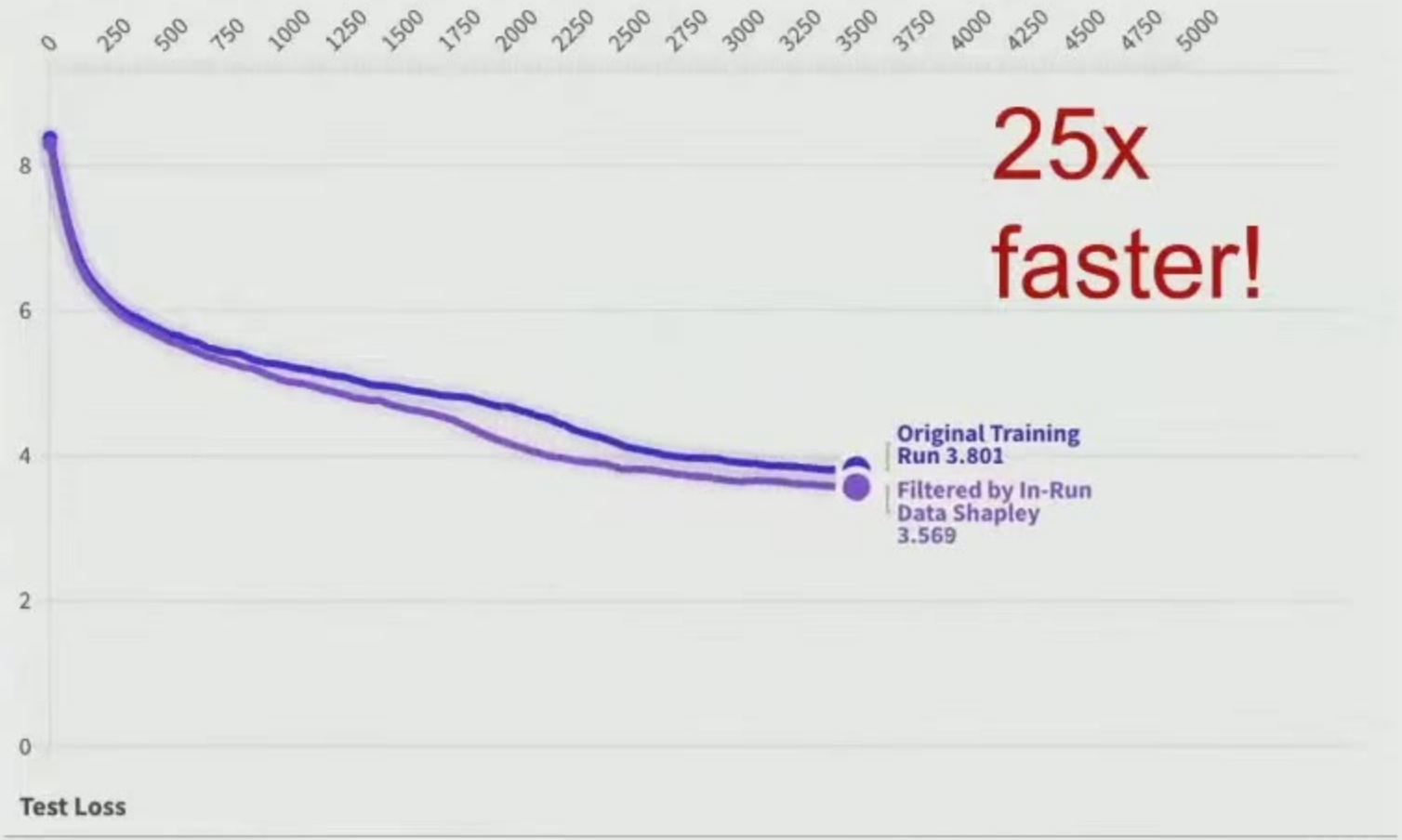

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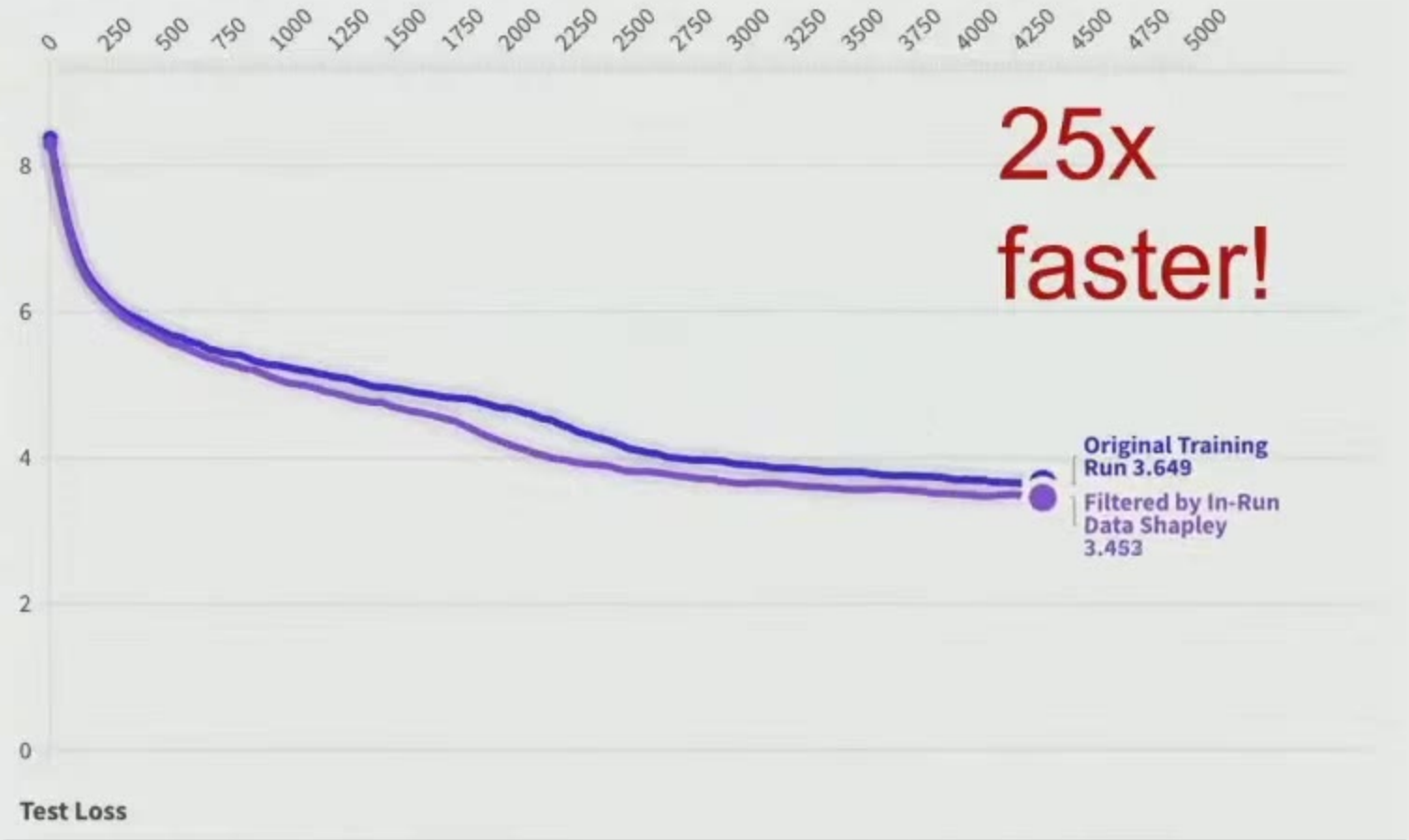

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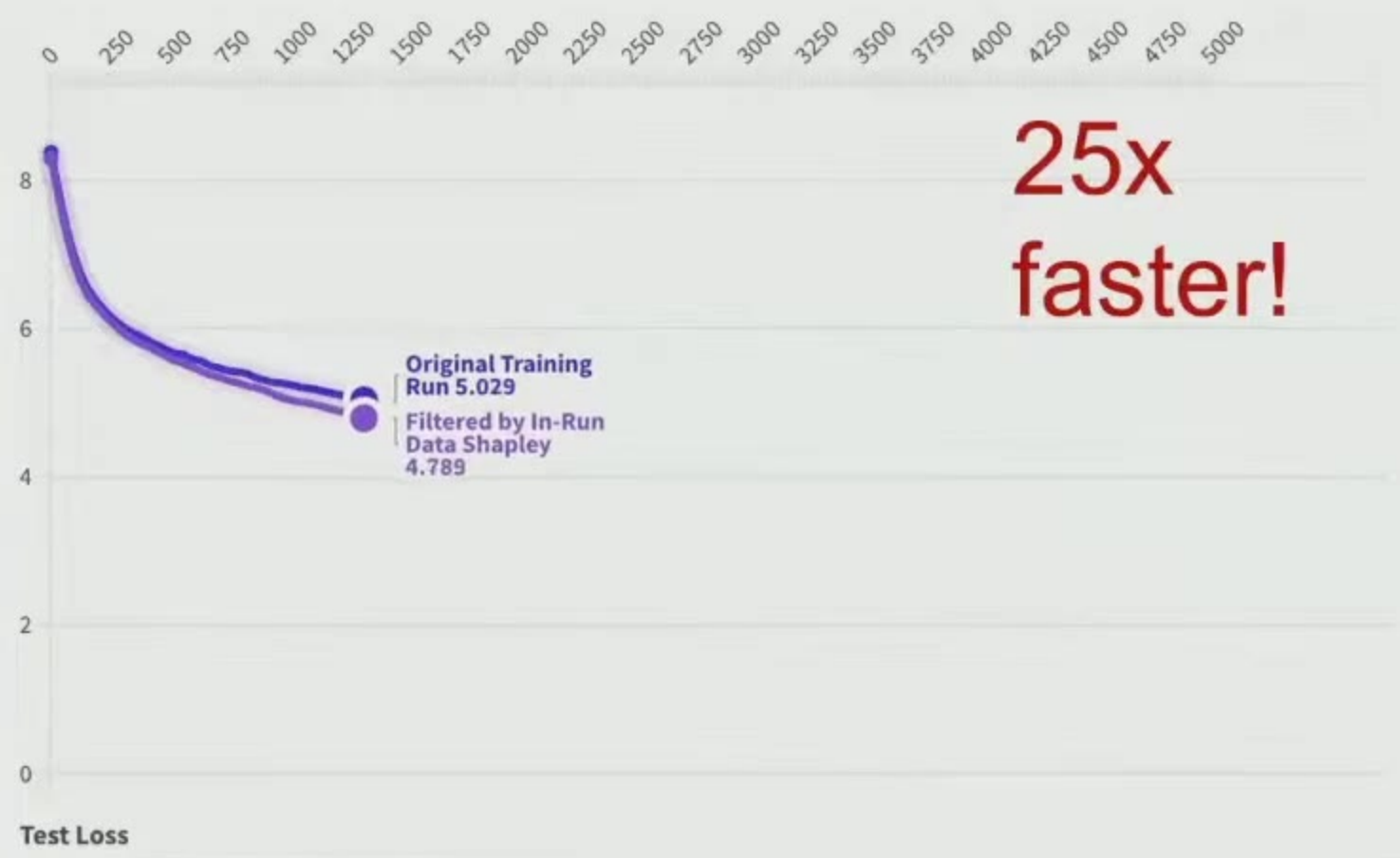

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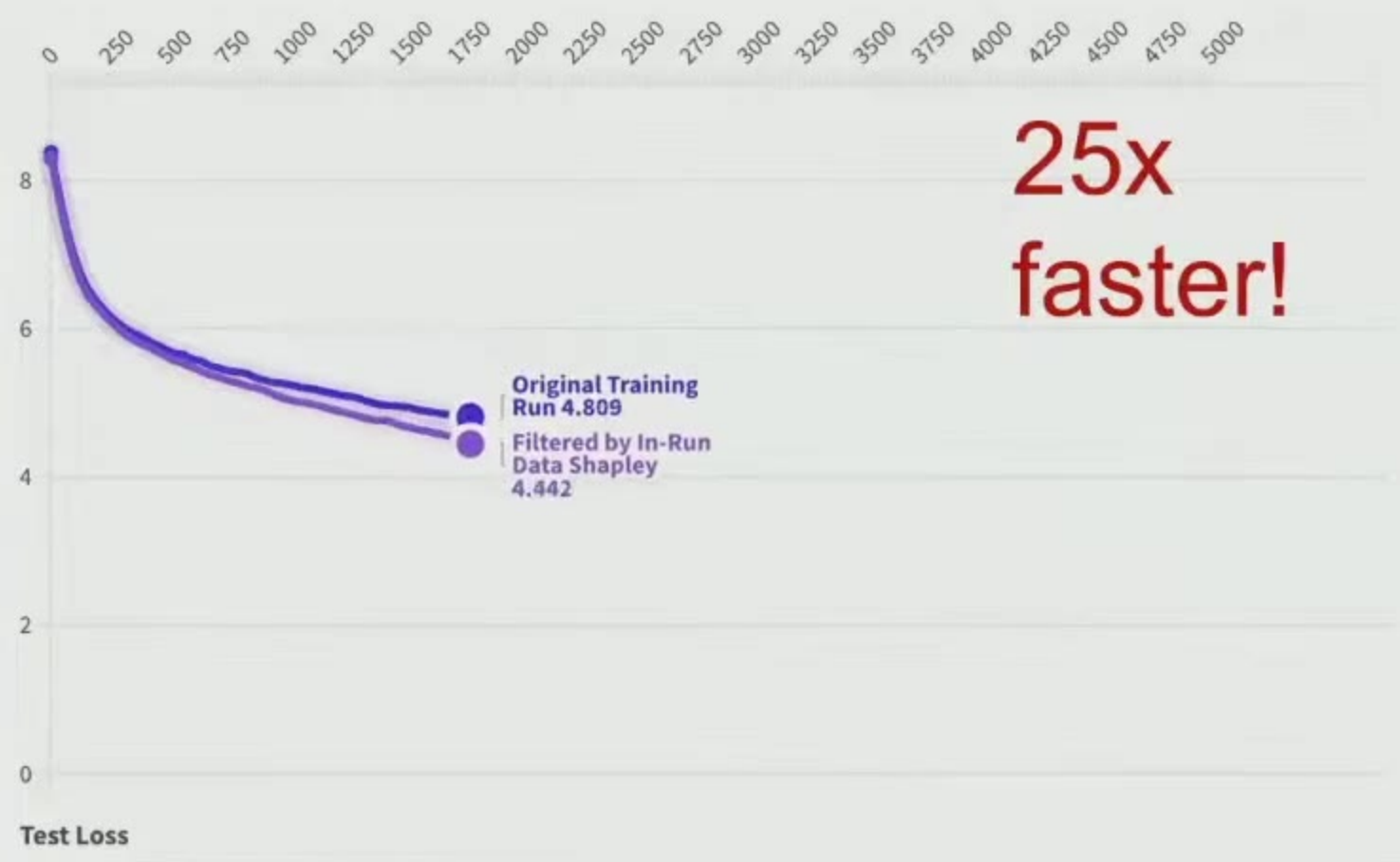

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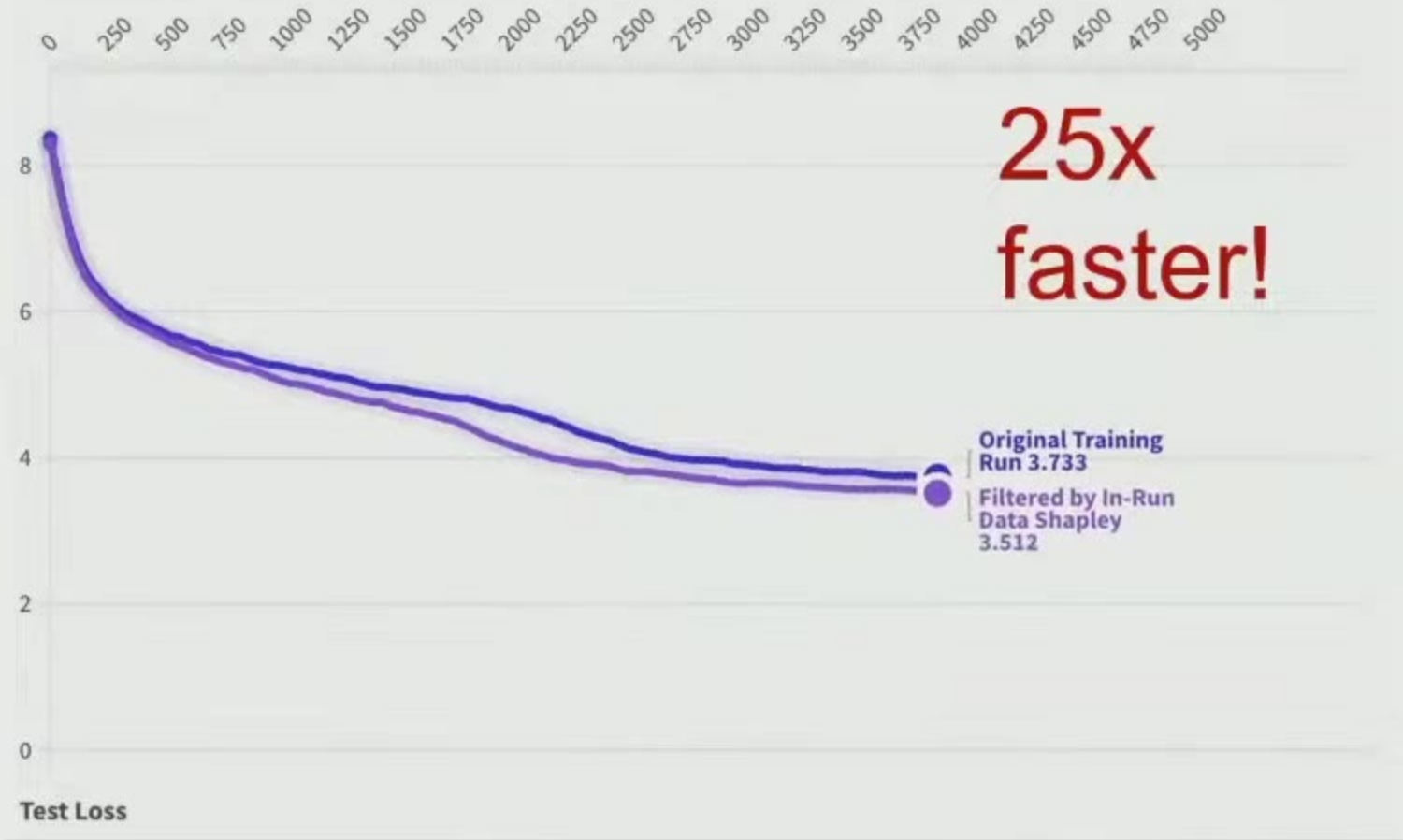

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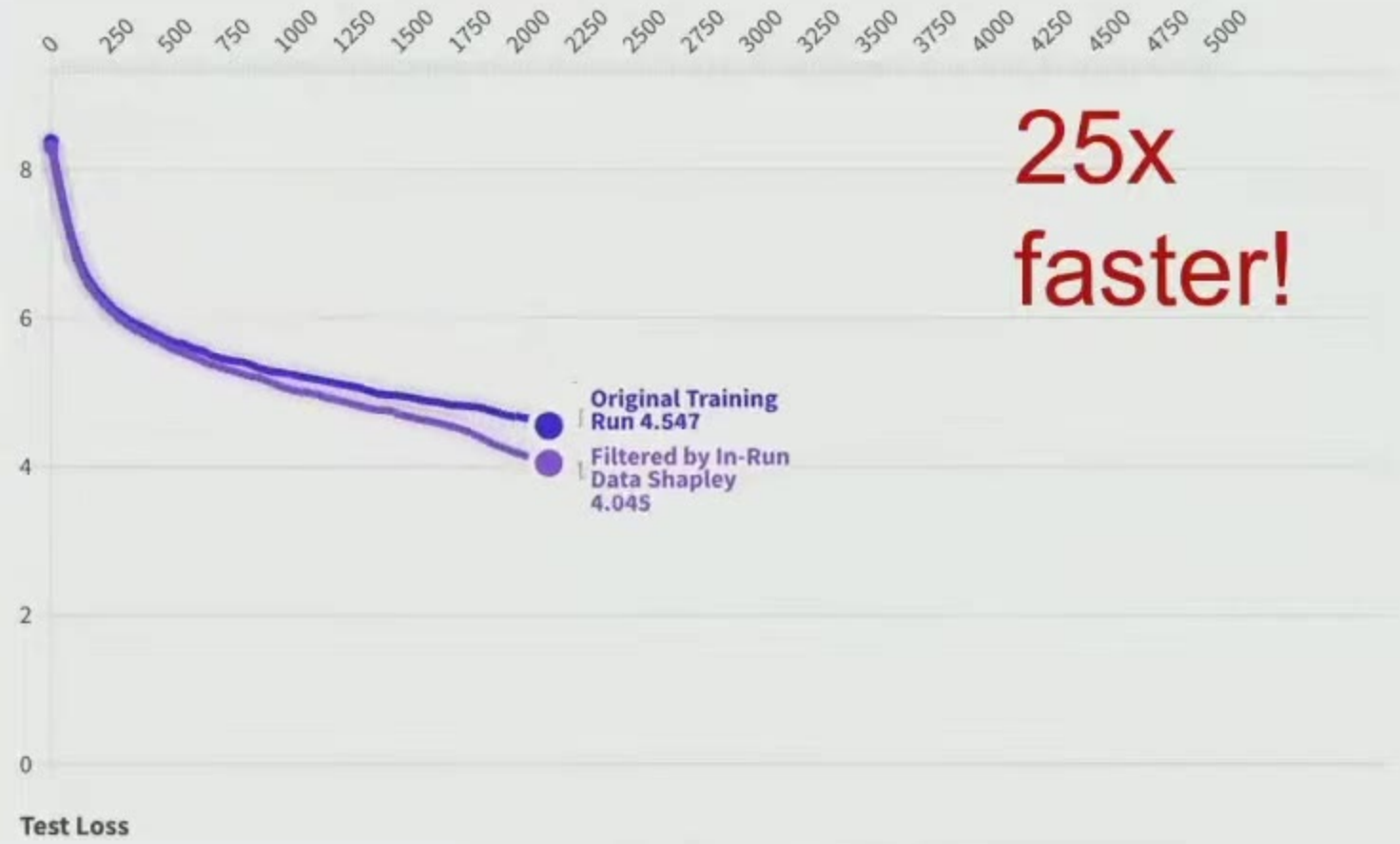

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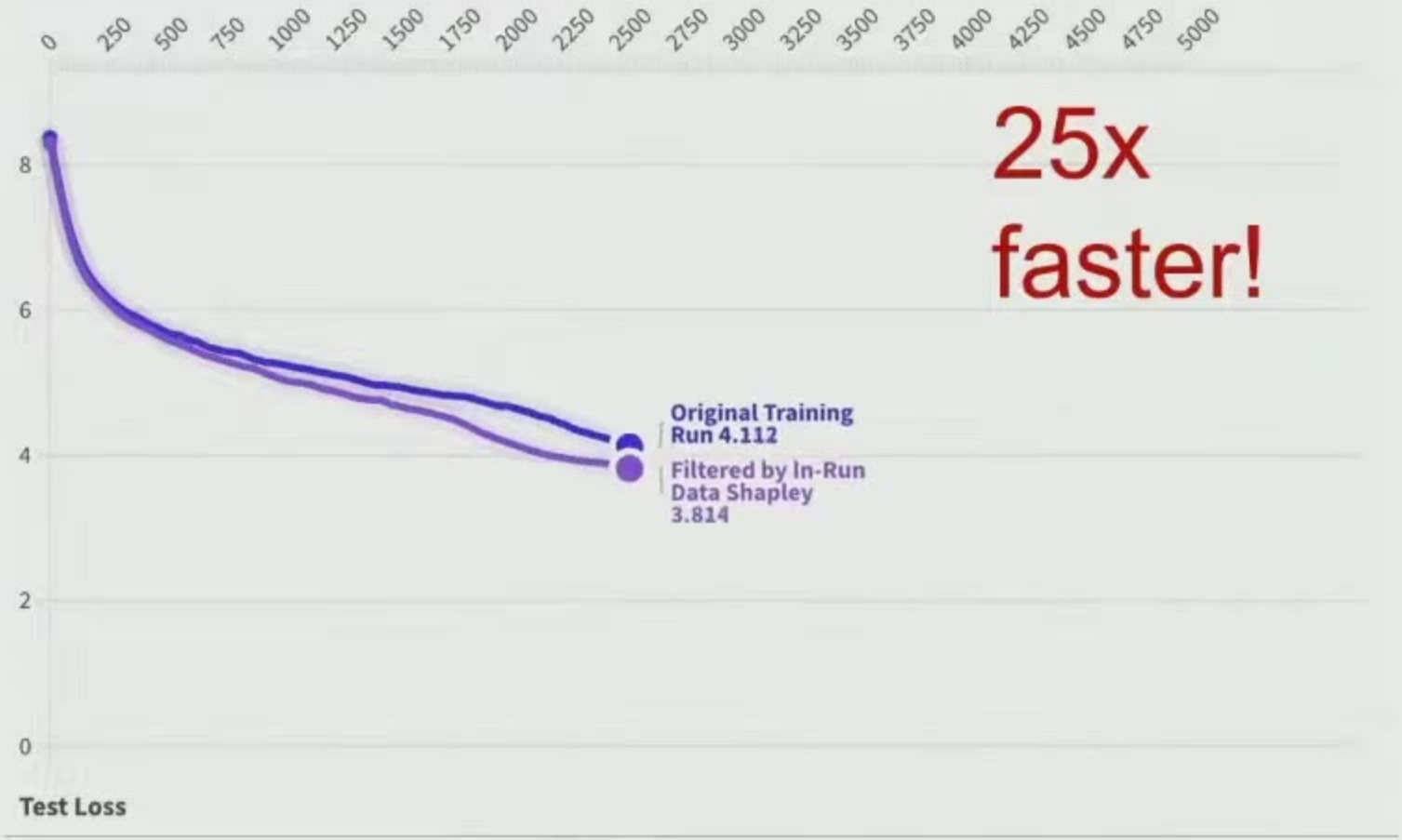

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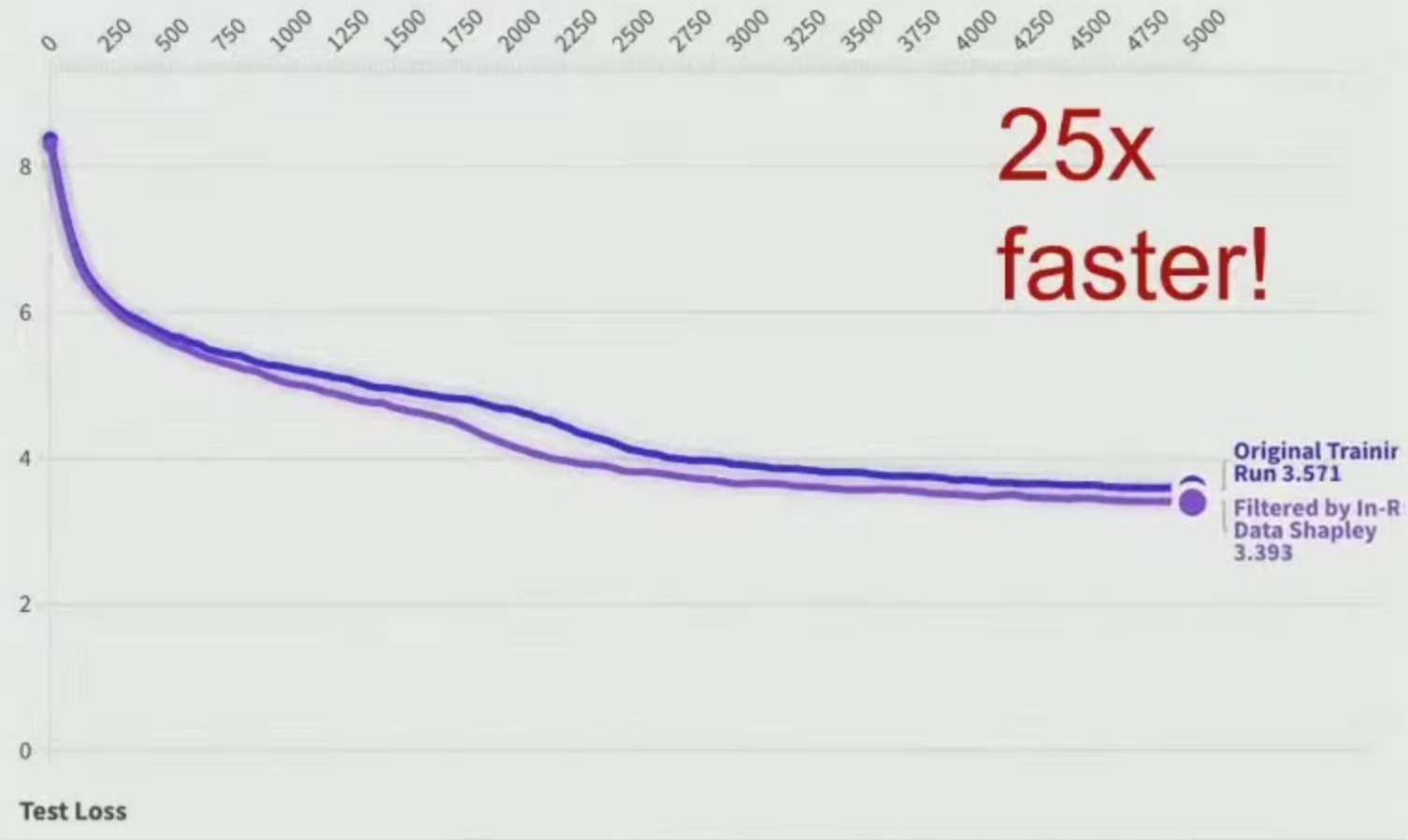

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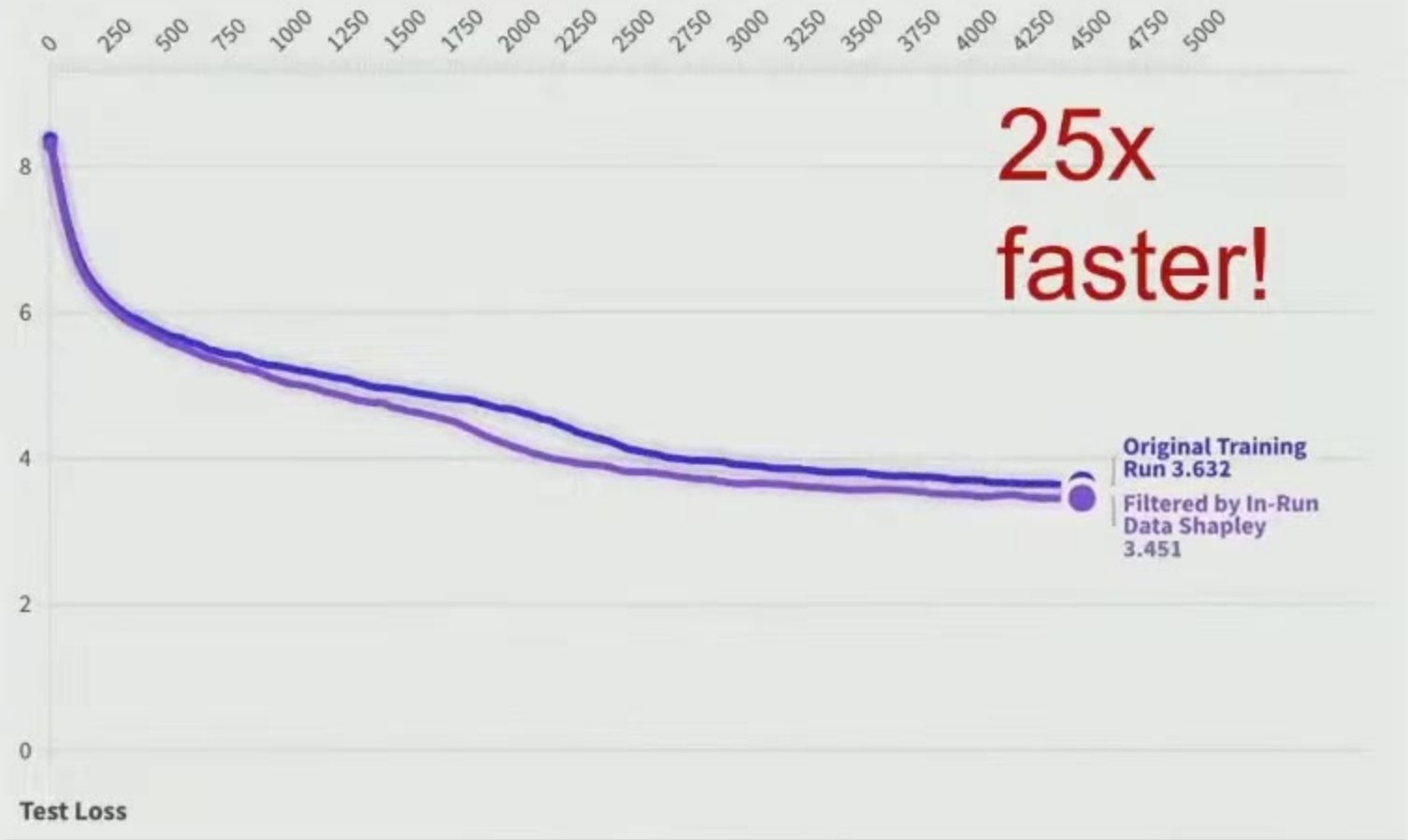

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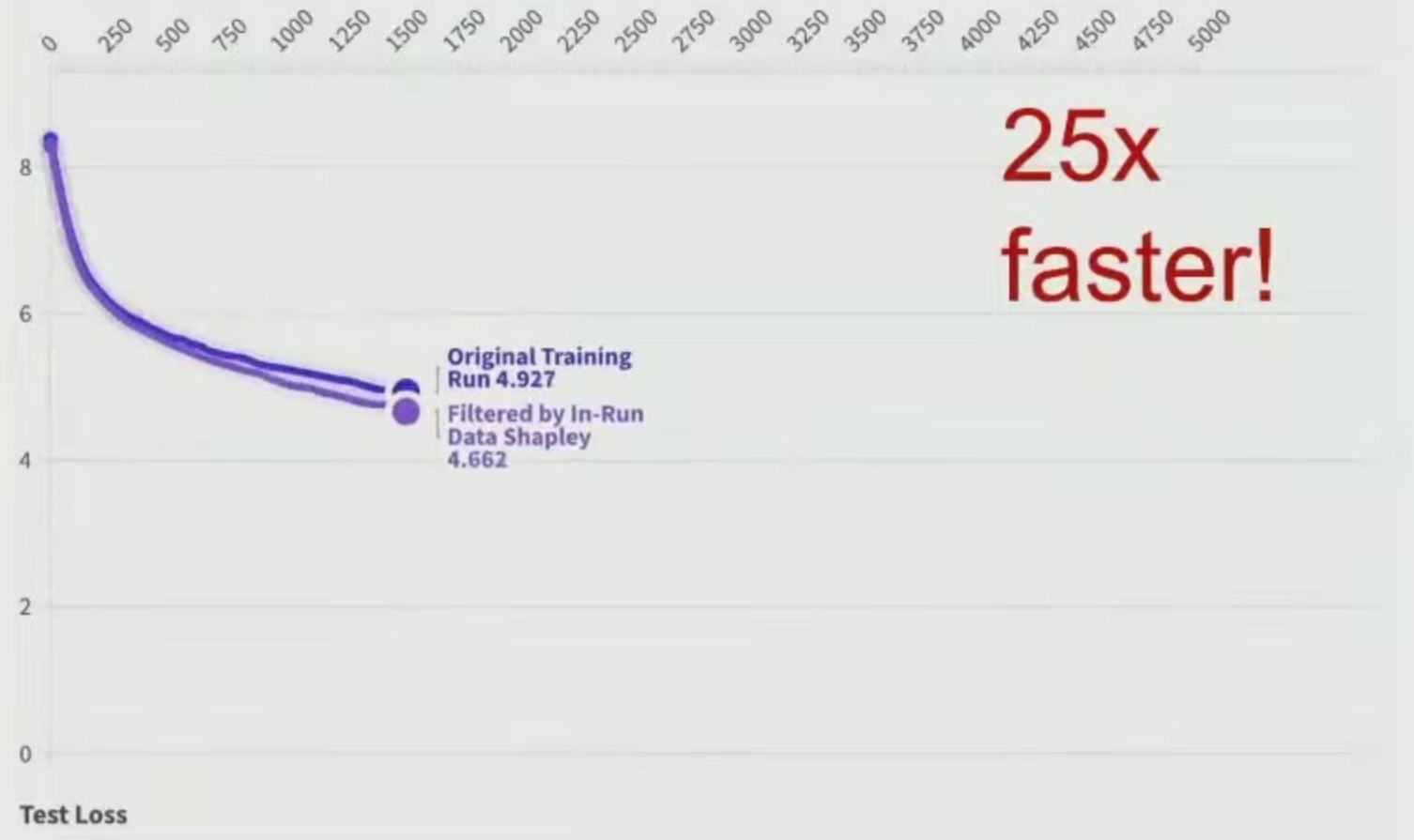

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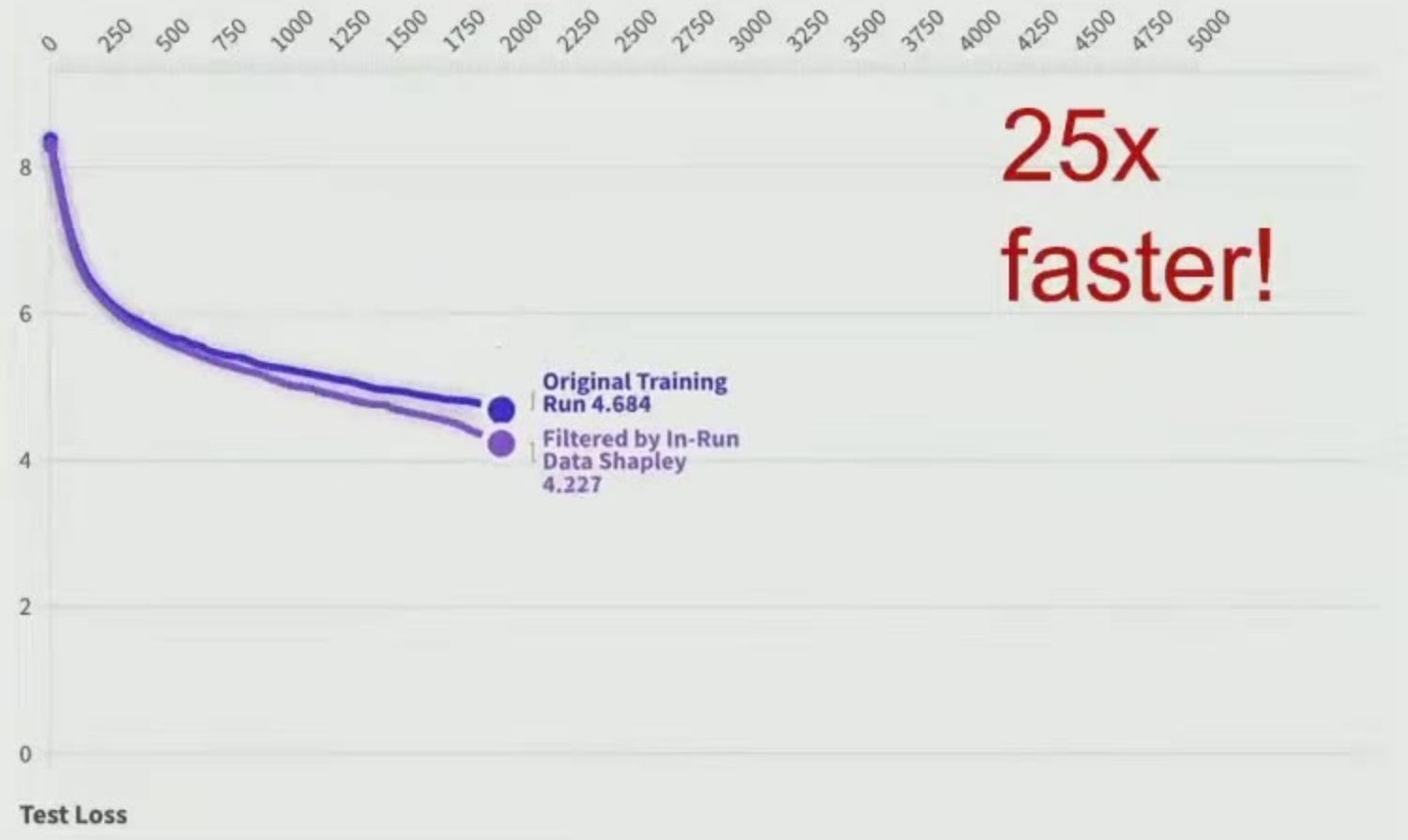

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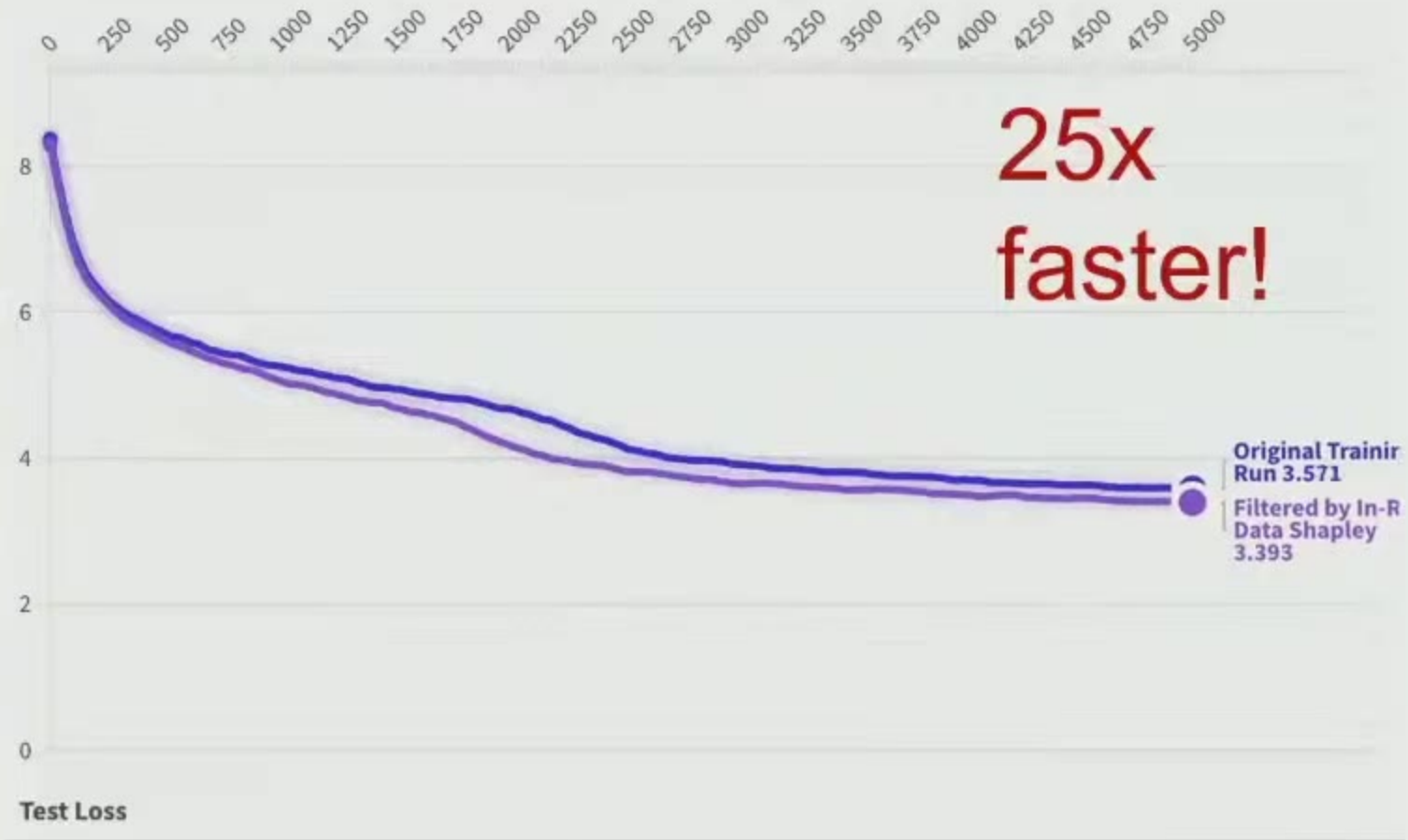

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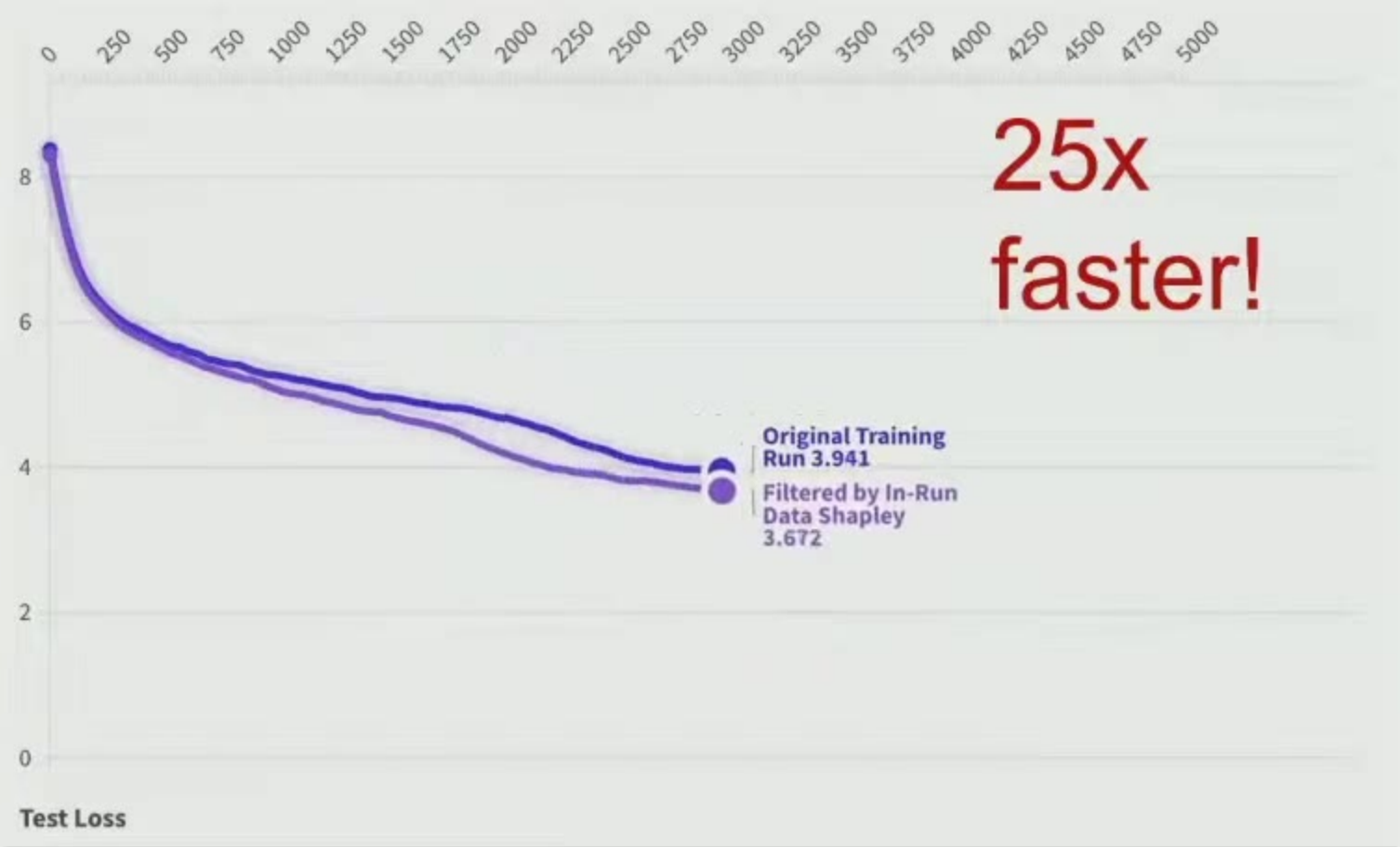

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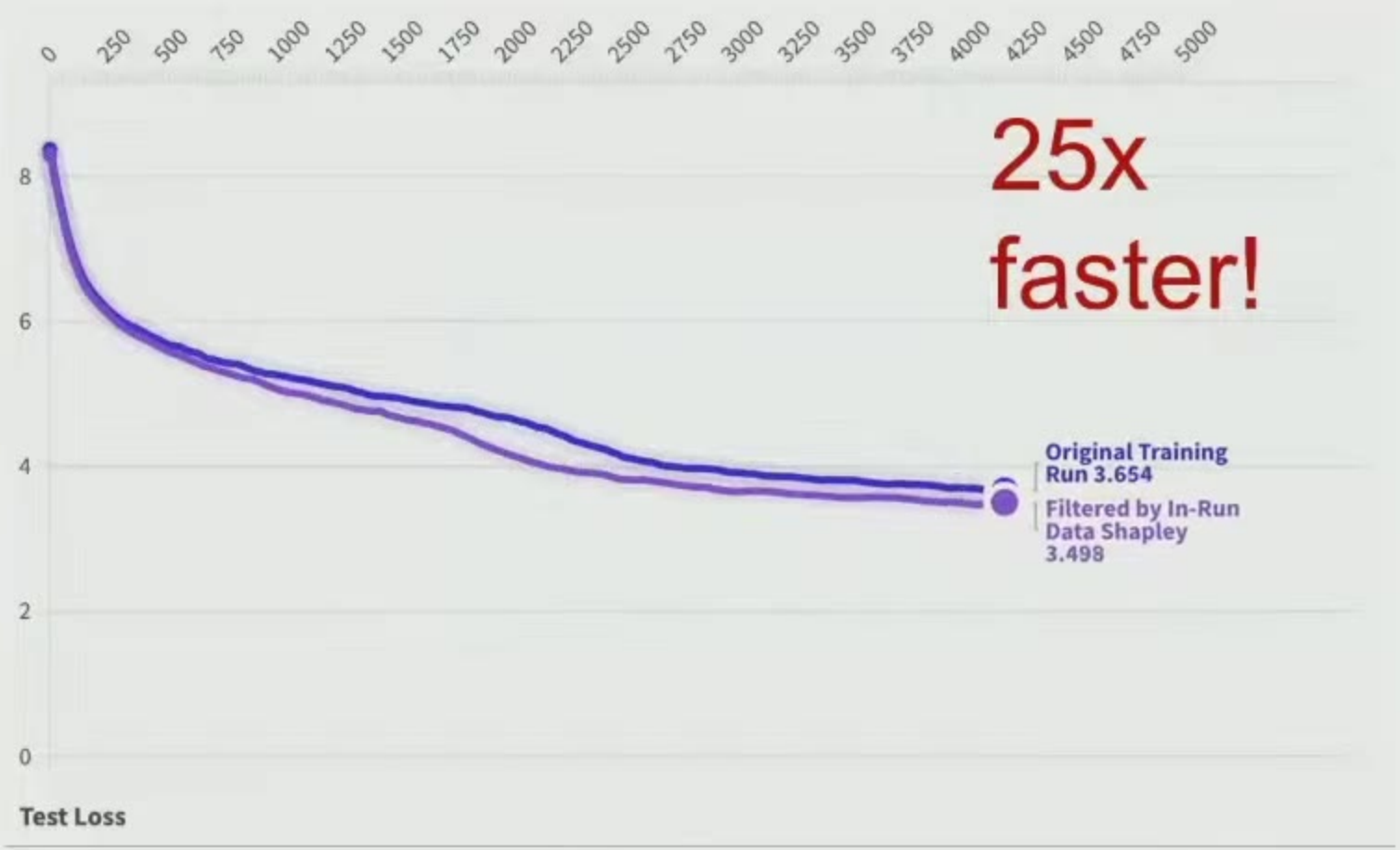

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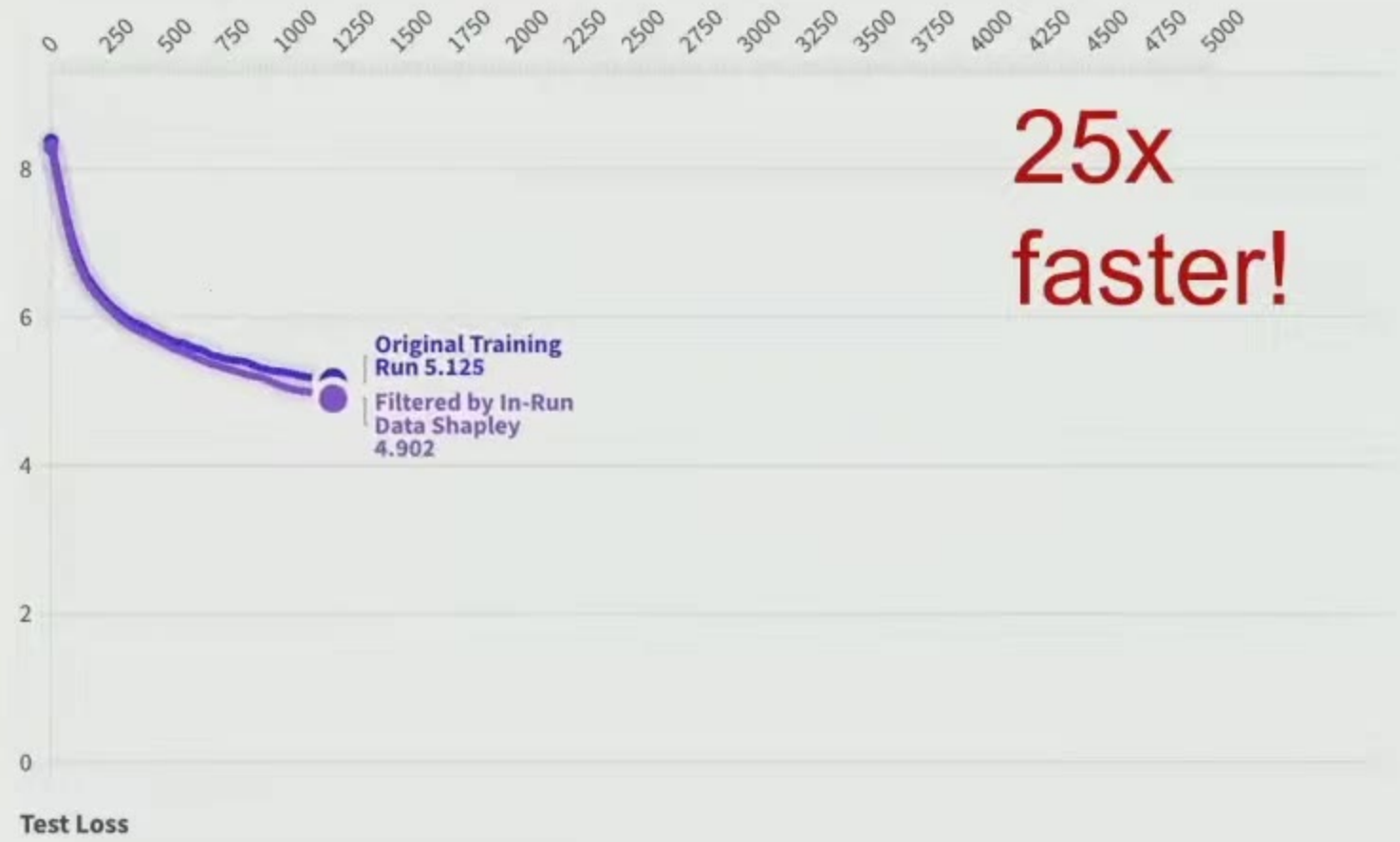

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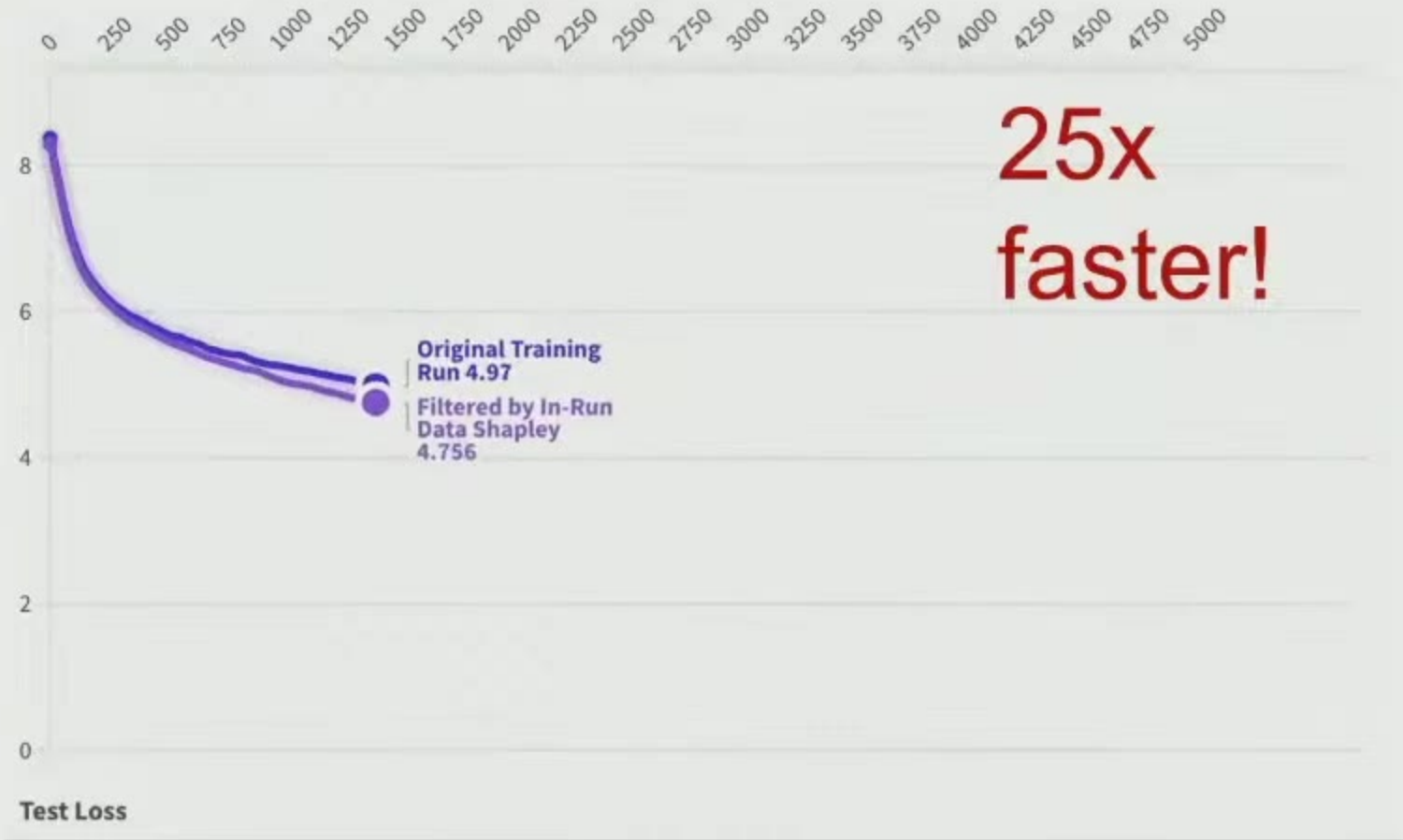

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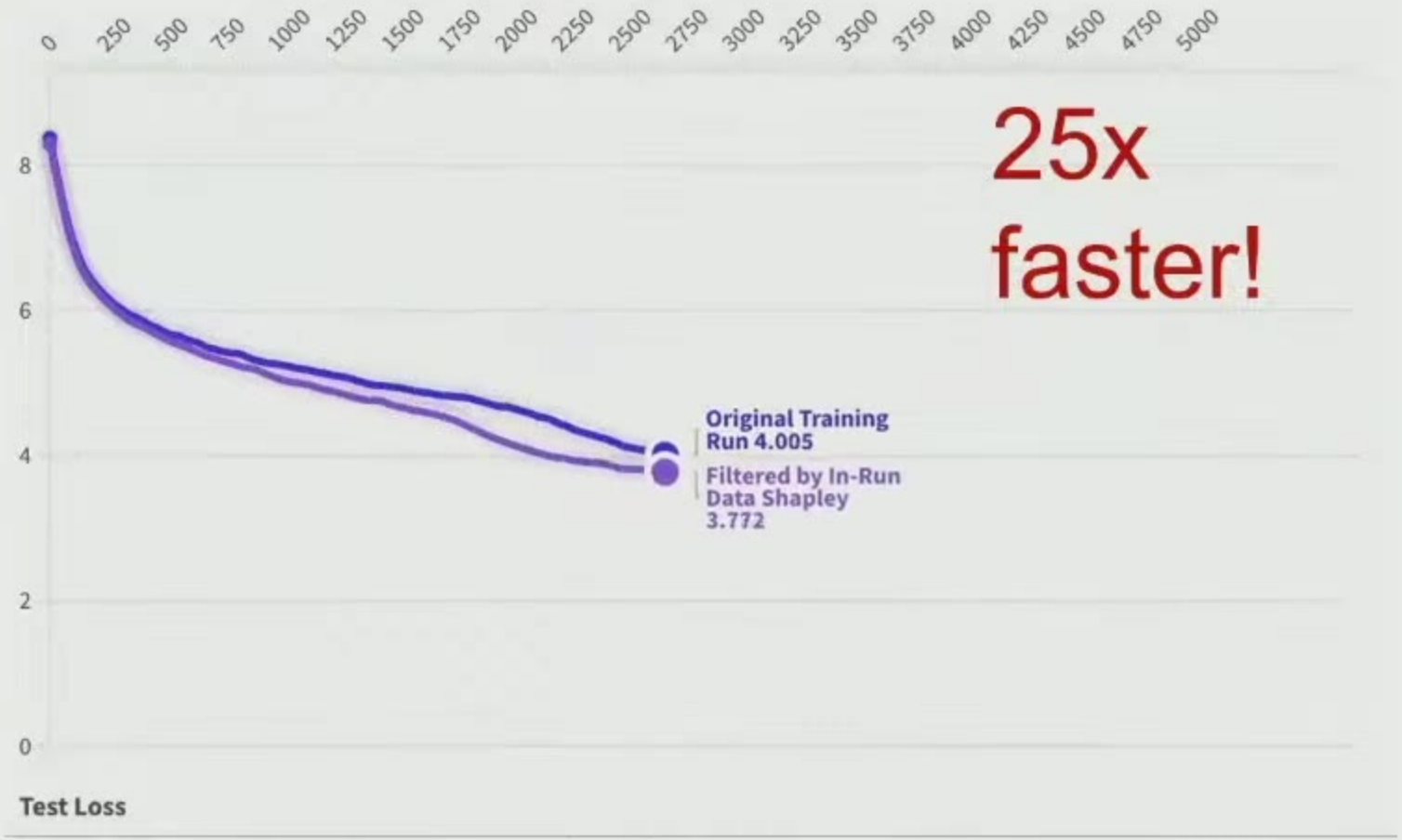

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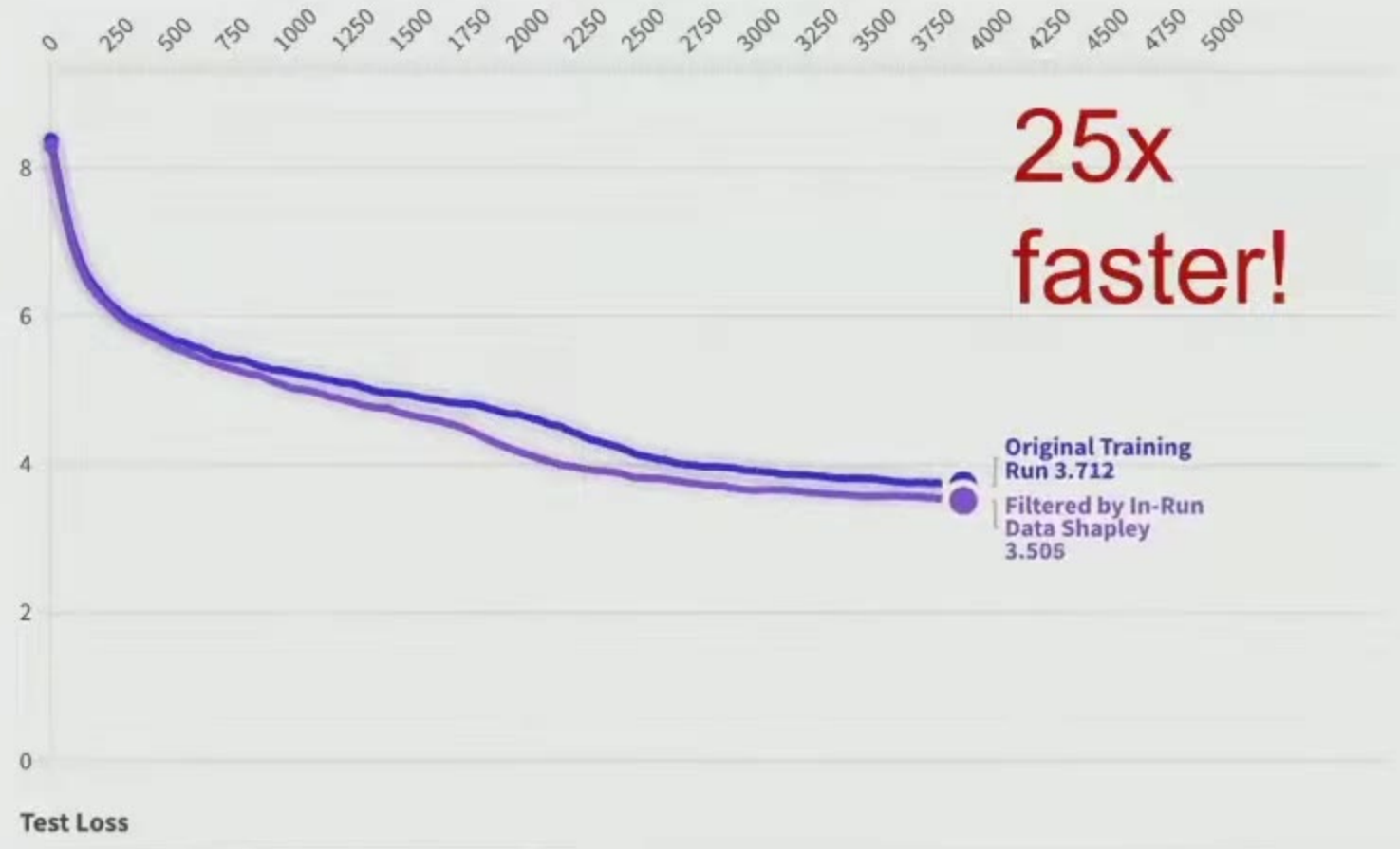

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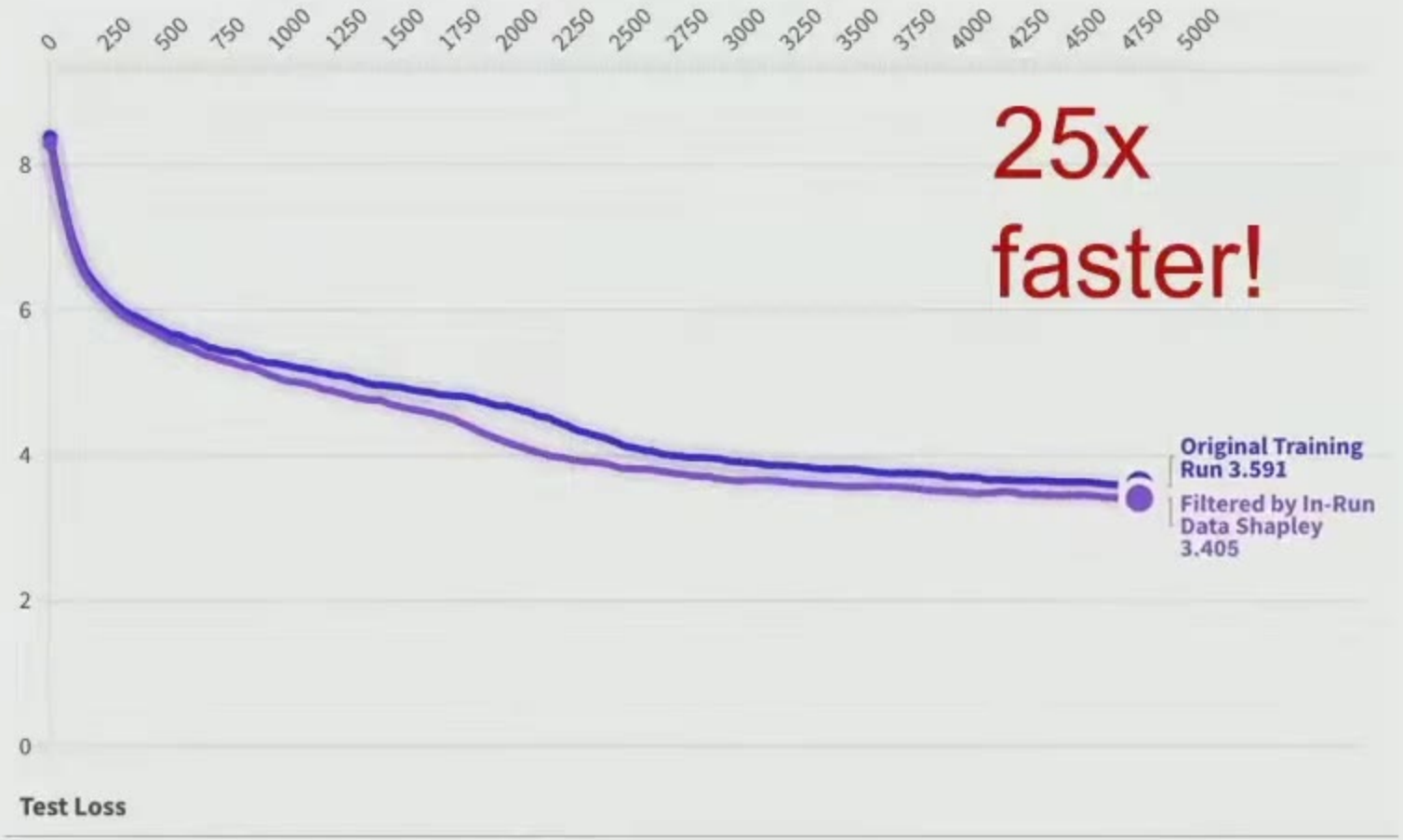

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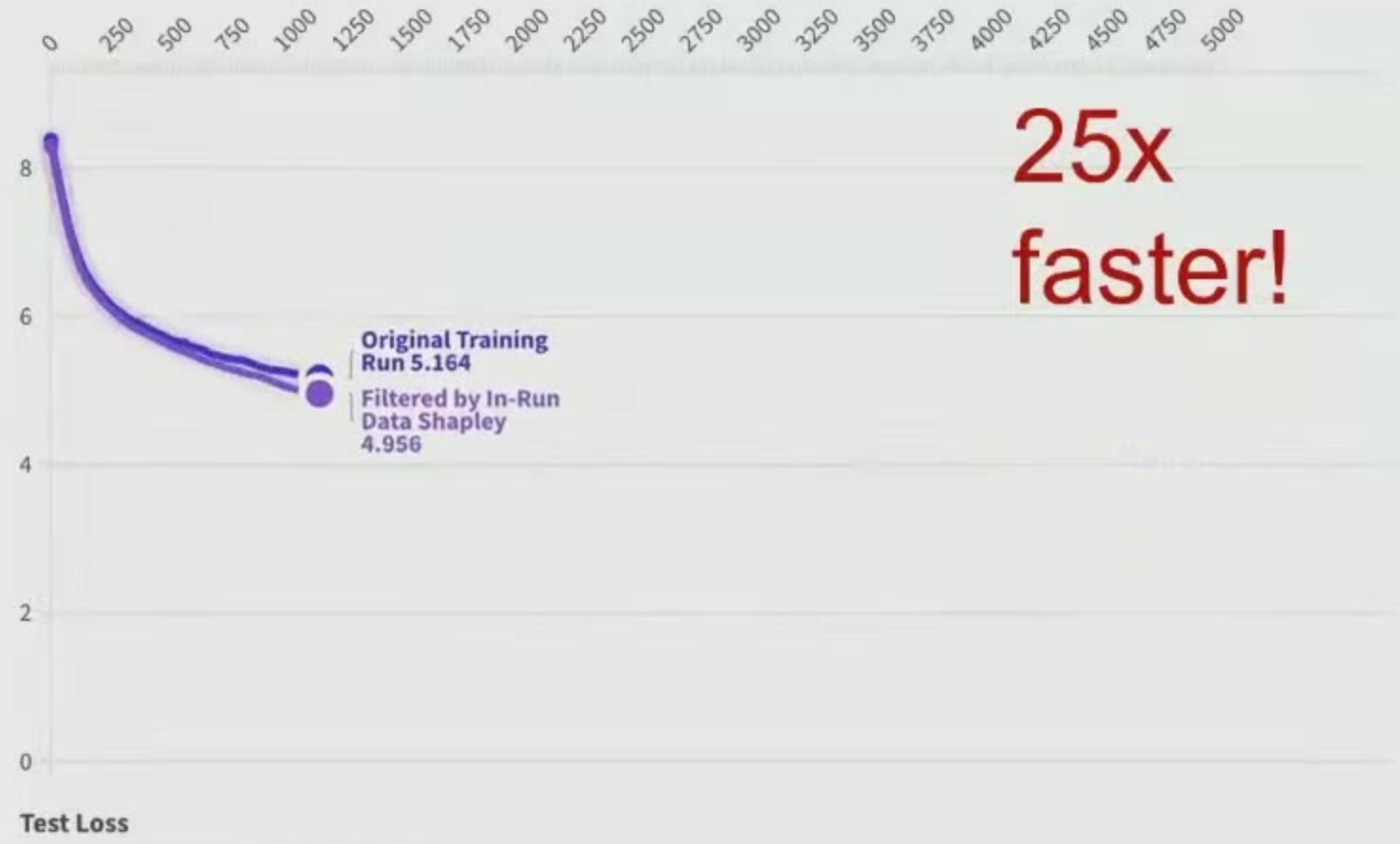

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