

IpNTK: Better Generalisation with Less Data via Sample Interaction During Learning

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IpNTK: Sample Relationship through Learning Dynamics

Samples having Similar Learning Effects

Intuition



Samples having Similar Learning Effects

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Question: how to find out the samples having similar learning effects in DL?

Answer: a novel lpNTK derived via first-Order Taylor approximation to sample interaction, i.e. how learning \mathbf{x}_u changes the prediction on \mathbf{x}_o

Formal Definition of IpNTK

labelled pseudo neural tangent kernel (IpNTK)

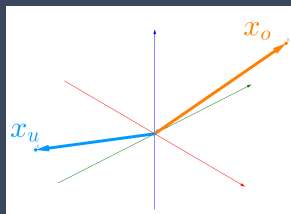
$$\begin{aligned}\kappa((\mathbf{x}_o, y_o), (\mathbf{x}_u, y_u)) &\triangleq \frac{1}{K} \sum \left[\mathbf{s}(y_u) \cdot \mathbf{s}(y_o)^\top \right] \odot \mathbf{K}(\mathbf{x}_o, \mathbf{x}_u) \\ &= \underbrace{\left[\frac{1}{\sqrt{K}} \mathbf{s}(y_o)^\top \nabla_{\mathbf{w}} \mathbf{z}(\mathbf{x}_o) \right]}_{1 \times d} \cdot \underbrace{\left[\nabla_{\mathbf{w}} \mathbf{z}(\mathbf{x}_u)^\top \mathbf{s}(y_u) \frac{1}{\sqrt{K}} \right]}_{d \times 1}\end{aligned}\quad (1)$$

Feature representation of (\mathbf{x}, y) under IpNTK:

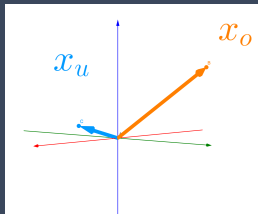
$$\frac{1}{\sqrt{K}} \mathbf{s}(y)^\top \nabla_{\mathbf{w}} \mathbf{z}(\mathbf{x}) \rightarrow \text{a } 1 \times d \text{ vector!}$$

Sample Relationships under IpNTK Feature Representation

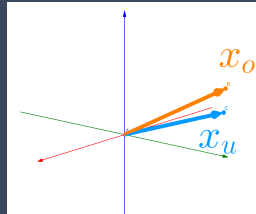
(\mathbf{x}, y) corresponds to a **vector** in the gradient space



(a) Contradictory



(b) Unrelated



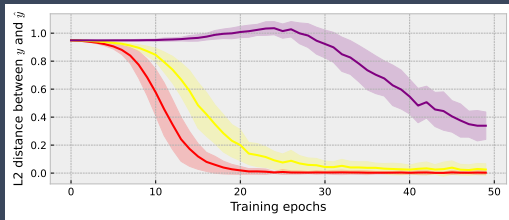
(c) Interchangeable

- Interchangeable: $\mathbf{x}_u \uparrow \vee \mathbf{x}_o \uparrow \Rightarrow \mathbf{x}_u \uparrow \wedge \mathbf{x}_o \uparrow$
- Unrelated: $\mathbf{x}_u \uparrow \Rightarrow \mathbf{x}_o - \quad \wedge \quad \mathbf{x}_o \uparrow \Rightarrow \mathbf{x}_u -$
- Contradictory: $\mathbf{x}_u \uparrow \Rightarrow \mathbf{x}_o \downarrow \quad \wedge \quad \mathbf{x}_o \uparrow \Rightarrow \mathbf{x}_u \downarrow$

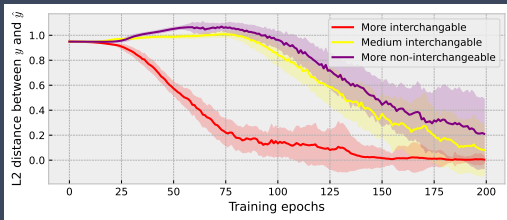
Use Case 1: Control Learning Difficulty

For a given target sample:

- More interchangeable \rightarrow easier to learn
- More contradictory \rightarrow harder to learn
- More unrelated \rightarrow between the above two cases



(a) on MNIST



(b) on CIFAR-10

Use Case 2: Predict Forgetting Events during Learning

Predict forgetting events with **lpNTK**:

Benchmarks	Precision		Recall		F1-score	
	Mean	Std	Mean	Std	Mean	Std
MNIST	42.72%	$\pm 6.55\%$	59.02%	$\pm 7.49\%$	49.54%	$\pm 6.99\%$
CIFAR-10	49.47%	$\pm 7.06\%$	69.50%	$\pm 7.49\%$	57.76%	$\pm 7.36\%$

Predict forgetting events with **eNTK**:

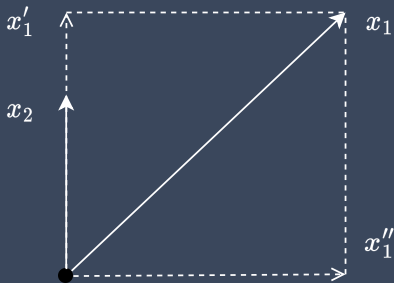
Datasets	Precision		Recall		F1-score	
	Mean	Std	Mean	Std	Mean	Std
MNIST	95.56%	$\pm 8.14\%$	86.67%	$\pm 13.67\%$	89.96%	$\pm 7.10\%$
CIFAR-10	96.99%	$\pm 3.99\%$	98.99%	$\pm 1.61\%$	97.87%	$\pm 2.08\%$

Use Case 3: Improve Generalisation Performance in Image Classification

Outline

- Do we really need all those interchangeable samples for good generalisation?
- Can we improve the generalisation performance by removing the bias in the data towards the numerous interchangeable samples?

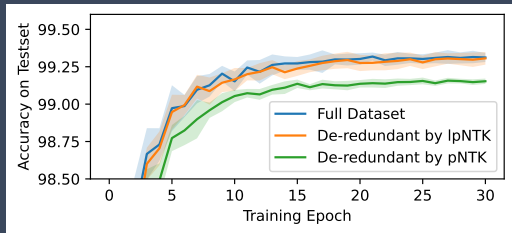
Redundant Samples



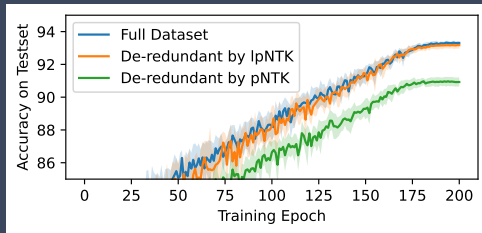
Formal Definition

For a labelled sample (\mathbf{x}, y) , if there exists another labelled sample (\mathbf{x}', y') where $\mathbf{x}' \neq \mathbf{x}$ such that $\kappa((\mathbf{x}, y), (\mathbf{x}', y')) > \kappa((\mathbf{x}, y), (\mathbf{x}, y))$, then (\mathbf{x}, y) is considered as a redundant sample.

Experiments on Removing Redundant Samples



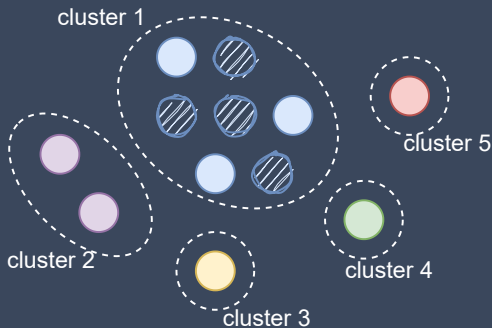
(a) MNIST



(b) CIFAR-10

Poisoning Samples

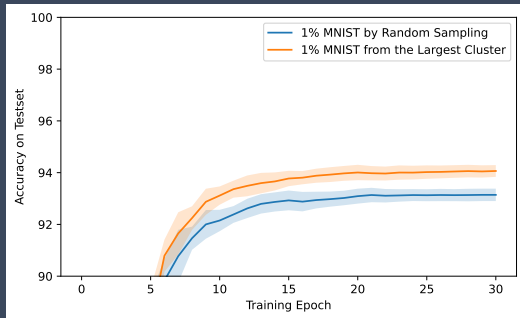
For a given set of samples \mathbb{T} , if performance trained on $\tilde{\mathbb{T}} > \mathbb{T}$ (where $\tilde{\mathbb{T}} \subset \mathbb{T}$), $\mathbb{T} \setminus \tilde{\mathbb{T}}$ are considered as poisoning samples.



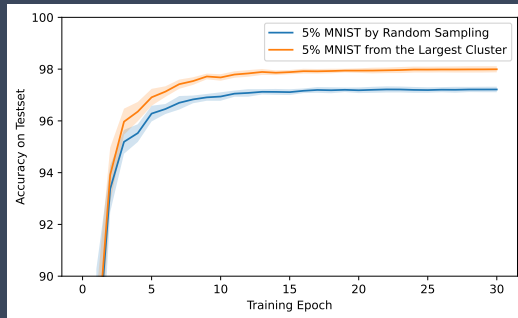
Experiment Results on Pruning Image Training Sets

Benchmarks	Full	lpNTK	EL2N	GraNd	Forgot Score
MNIST	99.31(± 0.03)%	99.37(± 0.04)%	99.33(± 0.06)%	99.28(± 0.05)%	99.26(± 0.06)%
CIFAR10	93.28(± 0.06)%	93.55(± 0.12)%	93.32(± 0.07)%	92.87(± 0.13)%	92.64(± 0.22)%

Side Point: Remove Small Clusters when #Samples is Small



(a) 1%



(b) 5%

Thank You!