Characterizing Data Points via Second-Split Forgetting

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ML Datasets Have Both “Hard” and “Easy” Examples

[Carlini et. al. 2019; Distribution Density, Tails, and Outliers in Machine Learning: Metrics and Applications]
ML Datasets Have Both “Hard” and “Easy” Examples

Some Examples are Hard because they are Mislabeled

[Carlini et. al. 2019; Distribution Density, Tails, and Outliers in Machine Learning: Metrics and Applications]
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Other Examples are Hard because of being Atypical

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ML Datasets Have Both “Hard” and “Easy” Examples

ImageNet: bobsled class

Typical Examples

[Feldman and Zhang 2020; What Neural Networks Memorize and Why?]
ML Datasets Have Both “Hard” and “Easy” Examples

ImageNet: bobsled class

Typical Examples

[Mislabeled Example]

Rare Example

[Feldman and Zhang 2020; What Neural Networks Memorize and Why?]
ML Datasets Have Long Tails of Atypical Examples

[Zhu et. al. 2014; Capturing Long-tail Distributions of Object Subcategories]
Memorizing Rare Examples Improves Generalization

CIFAR-10 truck class

[Fieldman and Zhang 2020; What Neural Networks Memorize and Why?]
ML Datasets Have Many Mislabeled Examples Too

[Northcutt et. al. 2021; Pervasive Label Errors in Test Sets Destabilize Machine Learning Benchmarks]
Memorizing Mislabeled Examples **Hurts** Generalization

![Test Set Performance on CIFAR10](chart.png)

% Uniform Label Noise in Training Set

Accuracy
Can we characterize examples based on different causes of hardness?
Learning and Forgetting Dynamics

1. Split a dataset into two halves
2. Train on the 1st split till convergence (100% train accuracy)

Learning Time: Earliest epoch during 1st split training after which an example is always predicted correctly.
Learning and Forgetting Dynamics

1. Split a dataset into two halves
2. Train on the 1st split till convergence (100% train accuracy)
3. Now continue fine-tuning on the 2nd split (with these weights)
4. Track accuracy of examples from 1st split as we continue training on 2nd

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**Learning Time:** Earliest epoch during 1st split training after which an example is always predicted correctly.

**Second-split Forgetting Time (SSFT):** Earliest epoch during 2nd split fine-tuning after which an example from the 1st split is always predicted incorrectly.
Main Result

- **Mislabeled Examples:** learnt late, forgotten fast
- **Rare Examples:** learnt late, forgotten late
- **Complex Examples:** learnt late, never forgotten
- **Typical Examples:** learnt early, never forgotten
Mislabeled Examples: Learnt Late, Forgotten Early

**Setup:** Randomly flip labels of 10% examples (both 1\textsuperscript{st} and 2\textsuperscript{nd} split)
Mislabeled Examples: Learnt Late, Forgotten Early

Setup: Randomly flip labels of 10% examples (both 1\textsuperscript{st} and 2\textsuperscript{nd} split)

Observation:

1. Mislabeled examples are learnt late
2. A large fraction of clean examples is also learnt late
3. The SSFT histogram visually shows a strong separation between mislabeled and clean examples
Complex Examples: Learnt late, Not Forgotten

**Setup:** Make a dataset with the union of CIFAR10 (complex) and MNIST (simple) images.
Complex Examples: Learnt late, Not Forgotten

Setup: Make a dataset with the union of CIFAR10 (complex) and MNIST (simple) images.

Observation:

1. Complex and Mislabeled Examples are both learnt late
2. SSFT for complex and simple examples is similar
3. Mislabeled Examples are forgotten quickly
Atypical Examples: Learnt Late, Forgotten Late

Desired dataset qualities:
1. Dataset where frequency is the only cause of example hardness
2. All classes must be *equally* complex, or have similar hardness
Atypical Examples: Learnt Late, Forgotten Late

Desired dataset qualities:
1. Dataset where frequency is the only cause of example hardness
2. All classes must be equally complex, or have similar hardness

How can we achieve this?

a. CIFAR100 has 20 super-classes. Each has 5 subgroups
b. Resample a dataset with \{500, 250, 125, 64, 32\} examples per subgroup in a superclass
   c. Randomize all observations over multiple subgroup orderings
Constructing a Long-Tailed Dataset From CIFAR-100

Classes (20)

Aquatic Mammals
- Whale
- Beaver
- Seal
- Otter
- Dolphin

Flowers

Biased sampling of Subpopulations

Long-Tailed Aquatic Mammals
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Aquatic Mammals:
- Whale
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Biased sampling of Subpopulations

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Long-Tailed Aquatic Mammals
Atypical Examples: Learnt Late, Forgotten Late

1. Examples from rare subgroups are learnt slowly
2. SSFT is nearly independent of the subgroup frequency
3. Suggests that learning time can confound rare and mislabeled examples
Learning and Forgetting Dynamics: MNIST Dataset
Earliest Forgotten examples in SST-2 are mislabeled

The phenomenon of second-split forgetting is consistent across modalities.

○ Examples with lowest SSFT when fine-tuning a BERT model on SST-2 are shown below.

| Sentences in SST-2 dataset with smallest forgetting time                                                                 | Label |
|---------------------------------------------------------------------------------------------------------------------------|-------|
| The director explores all three sides of his story with a sensitivity and an inquisitiveness reminiscent of Truffaut       | Neg   |
| Beneath the film’s obvious determination to shock at any cost lies considerable skill and determination, backed by sheer nerve | Neg   |
| This is a fragmented film, once a good idea that was followed by the bad idea to turn it into a movie                      | Pos   |
| The holiday message of the 37-minute Santa vs. the Snowman leaves a lot to be desired.                                     | Pos   |
| Epps has neither the charisma nor the natural affability that has made Tucker a star                                       | Pos   |
| The bottom line is the piece works brilliantly                                                                         | Neg   |
| Alternative medicine obviously has its merits ... but Ayurveda does the field no favors                                 | Pos   |
| What could have easily become a cold, calculated exercise in postmodern pastiche winds up a powerful and deeply moving example of melodramatic moviemaking | Neg   |
| Lacks depth                                                                                                              | Pos   |
| Certain to be distasteful to children and adults alike, Eight Crazy Nights is a total misfire                            | Pos   |
Failure Modes of ML Models

Setup: Create a 2-class classification problem from CIFAR-10 (Horses & Planes)
Failure Modes of ML Models

Setup: Create a 2-class classification problem from CIFAR-10 (Horses & Planes)

Observation: Examples with lowest SSFT are
  a. Horses with Blue Background
  b. Planes with Green Background

Suggests that the classifier may have used background as a (spurious) feature during first split training.
Improving Dataset Utility

1. Removing the earliest forgotten examples helps increase test accuracy.
   - This suggests that SSFT finds pathological examples.

2. Removing the last learnt examples hurts test accuracy more than random removal.
   - This suggests that learning time finds atypical examples that help generalization.
Theoretical Results on a Linear Model

Input: \( x = (\mu + \epsilon) \in \mathbb{R}^d \)
Label: \( y = \pm 1 \)
Model: \( f(x) = w \cdot x; \ w \in \mathbb{R}^d \)

Noise: \( \epsilon \sim N(0,\sigma^2 I_d) \)
Signal: \( \mu_1 = \begin{cases} \mu; & j \in \{1 \ldots k\} \\ 0; & \text{o.w.} \end{cases} \)

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Majority Group 1

\[
\begin{array}{cccccccccccccccc}
\mu + \epsilon & \mu + \epsilon & \mu + \epsilon & \epsilon & \epsilon & \epsilon & \epsilon & \epsilon & \epsilon & \epsilon & \epsilon & \epsilon & \epsilon & \epsilon & \epsilon \\
\end{array}
\]

Majority Group 2

\[
\begin{array}{cccccccccccccccc}
\epsilon & \epsilon & \epsilon & \mu + \epsilon & \mu + \epsilon & \mu + \epsilon & \epsilon & \epsilon & \epsilon & \epsilon & \epsilon & \epsilon & \epsilon & \epsilon & \epsilon \\
\end{array}
\]

Rare Group 1

\[
\begin{array}{cccccccccccccccc}
\epsilon & \epsilon & \epsilon & \epsilon & \epsilon & \epsilon & \mu + \epsilon & \mu + \epsilon & \mu + \epsilon & \epsilon & \epsilon & \epsilon & \epsilon & \epsilon & \epsilon \\
\end{array}
\]

\( k \ll d \)

\( d \)
Asymptotic Forgetting

**Theorem 1** (Asymptotic Forgetting (informal)). *For sufficiently small learning rate, given datasets \( S_A, S_B \sim D^n \). After training for \( T' \to \infty \) epochs, the following hold with high probability:

1. **Mislabeled and Rare examples from** \( S_A \) **are forgotten.**
2. **Complex examples from** \( S_A \) **are not forgotten.**

1. Dataset is separable with high probability.
2. The classifier will converge to min-norm solution for any bounded initialization [Soudry et. al.].
3. Asymptotic Solution should be independent of first-split training.
4. Use Generalization bound from Chatterji and Long.

*Being forgotten for rare examples implies random guessing, whereas it implies incorrect prediction for mislabeled examples.*
Intermediate Time Forgetting

**Theorem 2** (Intermediate-Time Forgetting (informal)). *For sufficiently small learning rate, given two datasets $S_A, S_B \sim D^n$. For a model initialized with weights, $w_B(0) = w_A(T)$ and trained for $T' = f(T)$ epochs, the following hold with high probability:

1. Mislabeled examples from $S_A$ are no longer incorrectly predicted.
2. Rare examples from $S_A$ are not forgotten.

1. *Representer Theorem*: Change in $w$ is a weighted sum of examples from the second split $\sum \beta_i x_i$.
2. Change in prediction is dot product of examples from first split with $\sum \beta_i x_i$.
3. This dot product has zero mean (only noise) for rare examples. (Orthogonal signal directions)
4. But mislabeled examples have a negative mean dot product since they are from majority group.
5. Rare example prediction changes much slower than mislabeled examples.
Conclusions

- **Mislabeled Examples**: learnt late, forgotten fast
- **Rare Examples**: learnt late, forgotten late
- **Complex Examples**: learnt late, never forgotten
- **Typical Examples**: learnt early, never forgotten

Applications

- Finding Mislabeled Examples
- Identifying Spurious Attributes
- Improving Dataset Utility