Yale

Machine Unlearning

CPSC 471/571: Trustworthy Deep Learning

Rex Ying

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- Machine Unlearning
  - Introduction and Motivation
  - Unlearning Definition
  - Model-agnostic Approach
    - Boundary Unlearning
  - Model-intrinsic Approach
    - **P**rojective **R**esidual **U**pdate for Linear Models
    - Forget-Me-Not for Attention Model
    - SalUn for Diffusion Model
  - Data-driven Approach
    - SISA Training

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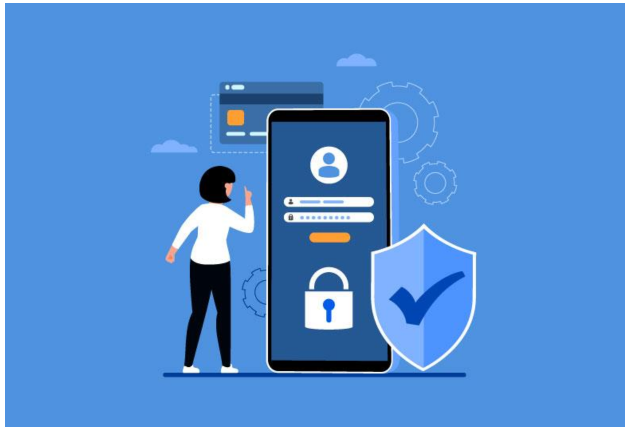
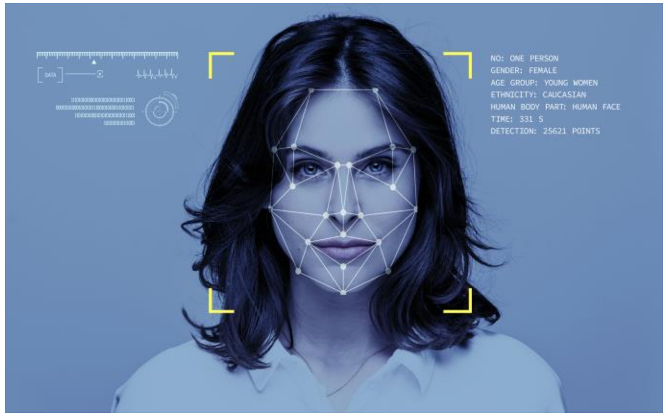
Real-world Use Cases

- There is a need for **information removal** from ML systems e.g., user's request, inappropriate information, sensitive data, outdated or inaccurate information.



Privacy Protection

Healthcare Data Sensitivity



Personal Identity Unlearning

Machine Unlearning Motivation

- **Motivation:** enable the ML system to **delete and unlearn certain information** to address the privacy concerns that arise from the data storage.
- **Naïve Solution:** Remove data point and **retrain the model from scratch** (exact unlearning of the data)
- However, **the cost of retraining is increasingly expensive** as ML models are trained on large datasets.

Focus of this lecture: how to efficiently and effectively unlearn certain information?

Machine unlearning | European Data Protection Supervisor

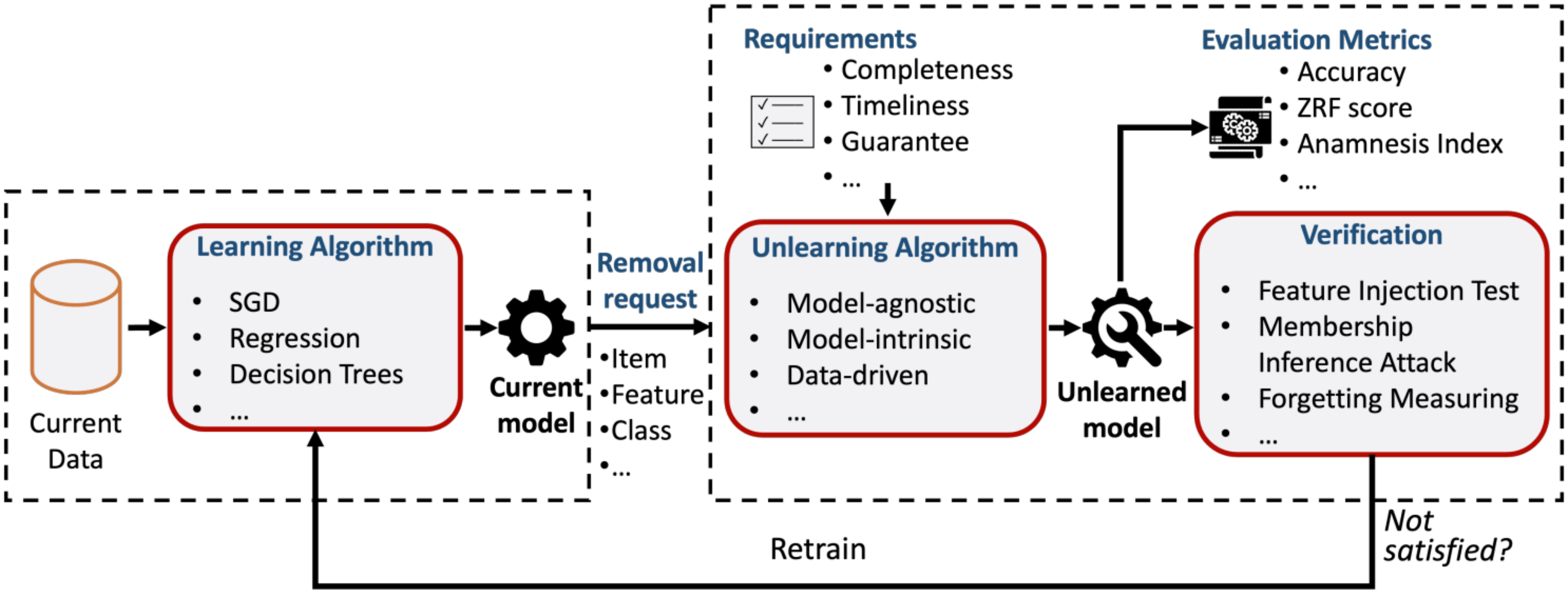
Machine Unlearning – A Potential Option for Remedy?

Leveraging Per-Example Privacy for Machine Unlearning

Deep Forgetting & Unlearning for Safely-Scoped LLMs — AI Alignment Forum

Machine Unlearning Setting

- **Goal of Machine Unlearning:** To design **efficient (low retraining cost)** unlearning protocols that satisfy **guarantees of data removal** and **model performance**



Types of Unlearning Requests

- **Item / data removal**
  - Requests to **remove certain items/data points** from the training set
- **Feature removal**
  - **Malicious or sensitive features** that are present in a set of data
  - Requests to remove certain features in a set of training data
- **Class/label removal**
  - The samples to be forgotten **belong to a single class**
  - Requests to **remove the entire class** and the samples belonging to it.
- **Concept removal**
  - Requests to remove specific **knowledge** or **patterns** learned by a model

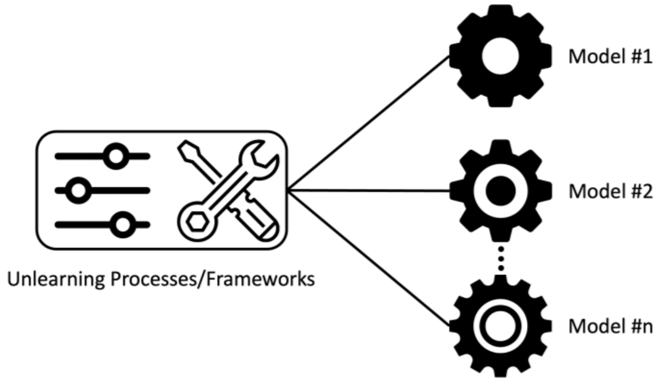
Examples?

Design Requirements

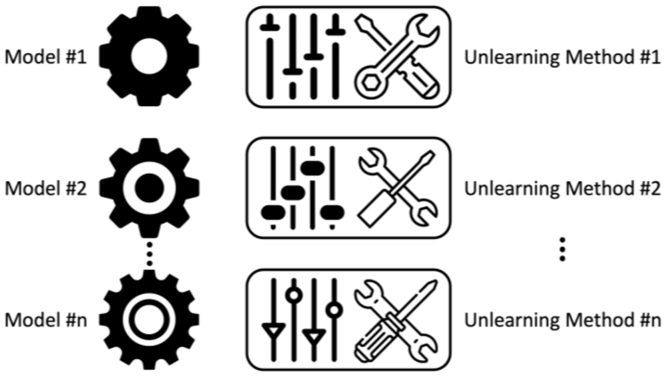
- **Completeness (Consistency):** the unlearned model and the re-trained model should **make the same predictions about training samples**.
  - Usually formulated as *an optimization objective* in an unlearning algorithm
- **Timeliness and light-weight:** the unlearned model should be **more efficient** than retraining and **light-weight**
- **Model-agnostic:** an ideal unlearning algorithm should **be generic for different machine learning models.**
- **Provable guarantees:** the unlearning algorithm should be able to **provide provable guarantees of unlearning**

Machine Unlearning Approaches

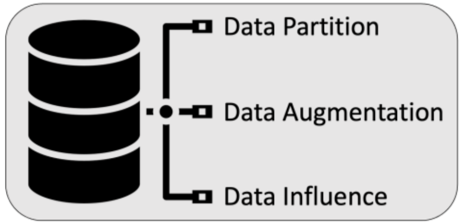
- **Model-agnostic Approaches**
  - Machine unlearning processes or frameworks that are **applicable for different models**, such as linear models, deep neural networks, etc.
- **Model-intrinsic Approaches**
  - Machine unlearning methods **designed for a specific type of models**.
- **Data-driven Approaches**
  - Using **data partition, data augmentation and data influence** to speed up the retraining process.



Model-agnostic Approaches



Model-intrinsic Approaches

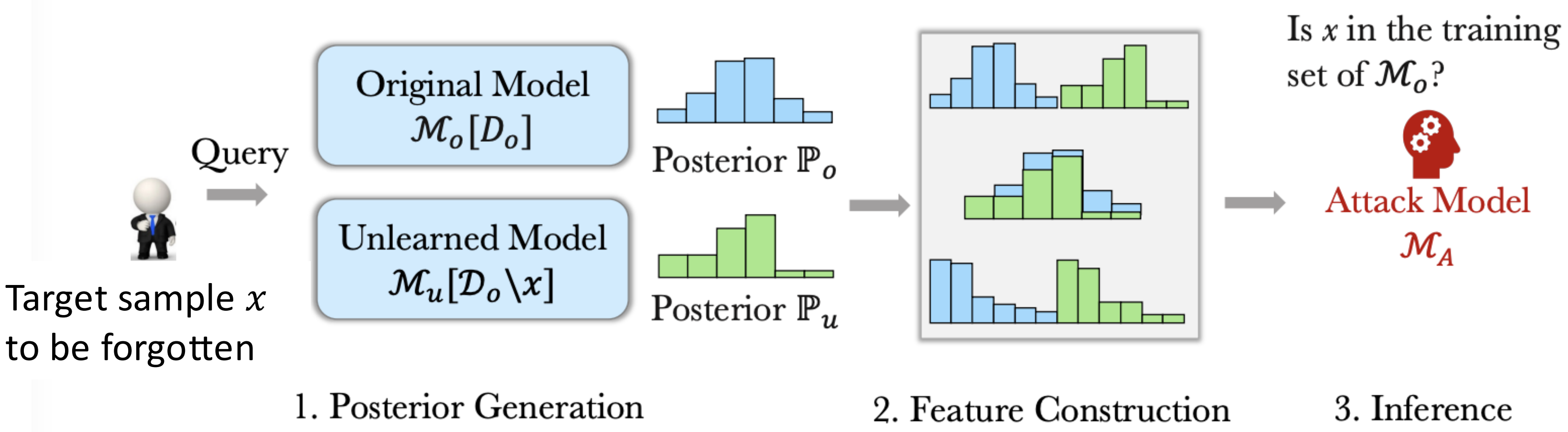


Data-driven Approaches

Figure source

Unlearning Verification

- **Goal: verify the effectiveness of the machine unlearning by detecting information leaks**
- Methods: membership inference, feature injection test, backdoor attacks, etc.
- Recall the threats to information exposure:
  - e.g., **membership inference attack** is trained to predict *whether a data item belongs to the training set*. Hence, it can be used in **unlearning verification**



Chen, Min, et al. "When machine unlearning jeopardizes privacy."

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Definition of Unlearning (1)

- **Train a model A: $\mathcal{Z}^* \to \mathcal{H}$,** where $\mathcal{Z}^*$**: all possible training datasets**; $\mathcal{H}$**: a hypothesis space** of all possible machine learning models
- $D_f \subset D$ denotes the forgetting dataset, D is the original dataset
- $U(D, D_f, A(D))$ **: the unlearned model**;
- $A(D \backslash D_f)$ **: the retrained model from scratch**.
- **Exact Unlearning:** the $\boxed{\text{distributions}}$ of $U(D, D_f, A(D))$ and $A(D \backslash D_f)$ are exactly the same.
  distribution of the parameters / outputs
- **Approximate Unlearning:** the distance between distributions of $U(D, D_f, A(D))$ and $A(D \backslash D_f)$ is bounded.

Definition of Unlearning (2)

- **Definition [Exact Unlearning]** Given a learning algorithm $A(\cdot)$, the unlearning algorithm $U(\cdot)$ is *an exact unlearning process* iff $\forall \mathcal{T} \subseteq \mathcal{H}, D \in \mathcal{Z}^*, D_f \subset D$:

$$\Pr\left(A\left(D \backslash D_f\right) \in \mathcal{T}\right) = \Pr\left(U\left(D, D_f, A(D)\right) \in \mathcal{T}\right)$$

where $\Pr(\cdot)$ is the **distribution of the parameters / outputs** of the model over a function space $\mathcal{T}$.

- **Definition [ε-Approximate Unlearning]** Given a learning algorithm $A(\cdot)$, the unlearning algorithm $U(\cdot)$ is *an ε-approximate unlearning process* iff $\forall \mathcal{T} \subseteq \mathcal{H}, D \in \mathcal{Z}^*, z \in D$:

$$e^{-\varepsilon} \leq \frac{\Pr(U(D, z, A(D)) \in \mathcal{T})}{\Pr(A(D \backslash \mathrm{z}) \in \mathcal{T})} \leq e^{\varepsilon}$$

where z is the single removed sample

Relationship to DP

- Recall differential privacy:

$$\forall \mathcal{T} \subseteq \mathcal{H}, D \text{ and } z \in D,\ e^{-\varepsilon} \leq \frac{\Pr(A(D) \in \mathcal{T})}{\Pr(A(D \backslash z) \in \mathcal{T})} \leq e^{\varepsilon}$$

where z is the single removed sample.

- **ε-Differential Privacy implies ε-approximate unlearning.**

Note: ε-differential privacy is a very strong condition. If $A(\cdot)$ is differentially private for any data, then it will **suffer significant accuracy loss**!

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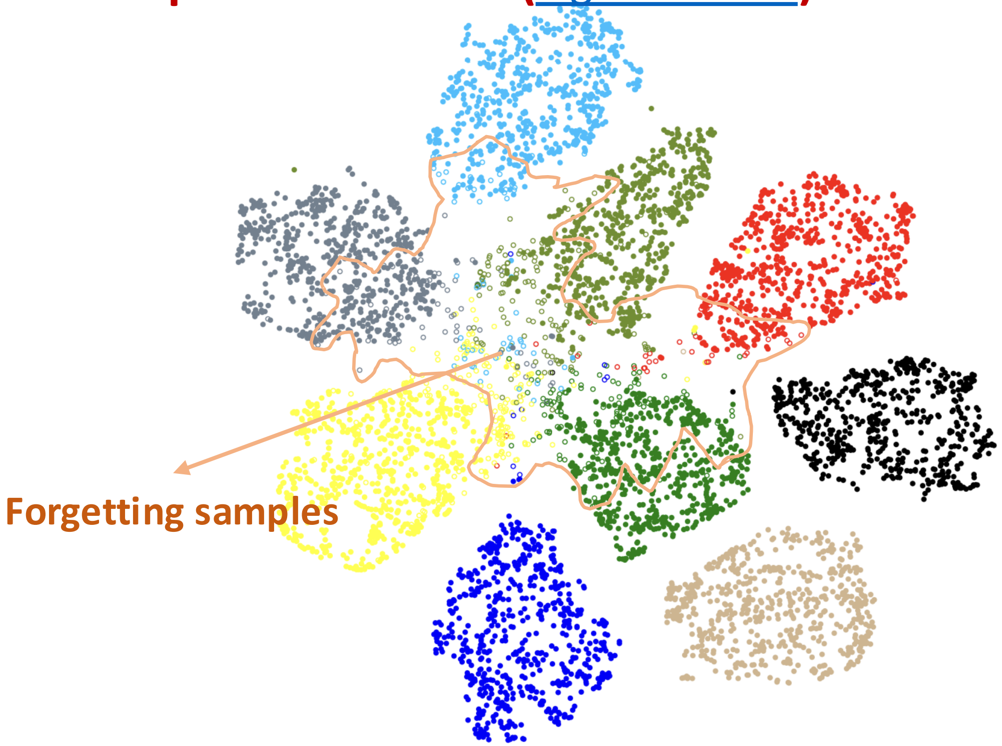
Decision Space of an Unlearned Model

Colors represent Classes (Figure source)



The decision space of the **model retrained on the remaining dataset from scratch**

- The **solid dots** are remaining samples.
- The **hollow circles** are the forgotten samples

Observation:

- the forgetting samples **spread around** the decision space of the retrained model

  => the decision boundary of the forgetting samples has been broken after unlearning

- most of the forgetting samples **move to the borders of other clusters**

  => samples at the cluster borders in the decision space will be predicted with large uncertainty.

Boundary Unlearning (1)

- **Motivation:** Boundary unlearning **shifts the decision boundary** of the original model to **imitate** the decision behavior of the retrained model
- **Guideline**:
  - Destroy the boundary of the forgetting class
  - Maintain the boundary of the remain classes
  - Push the forgetting data to the border of other clusters
- Boundary Unlearning is a **model-agnostic** method with two approaches:
  - **Boundary Shrink:** breaks the decision boundary of the forgetting class
  - **Boundary Expanding:** disperse the forgetting class

Boundary Unlearning (2)

- $\mathcal{D} = \{\boldsymbol{x}_i, y_i\}_{i=1}^N$ is the training dataset. $\mathcal{Y} = \{1, \ldots, K\}$ denotes the label space where K is the total number of classes. $\mathcal{D}_f$ is the forgetting dataset.
- Parameters of the original model and the unlearned model are $\boldsymbol{\theta_o}$ and $\boldsymbol{\theta_u}$
- Boundary unlearning is designed for the case where $\mathcal{D}_f$ consists of the samples of **an entire class**, e.g., class y *(a limitation of the work)*
- **Unlearning Objective:**

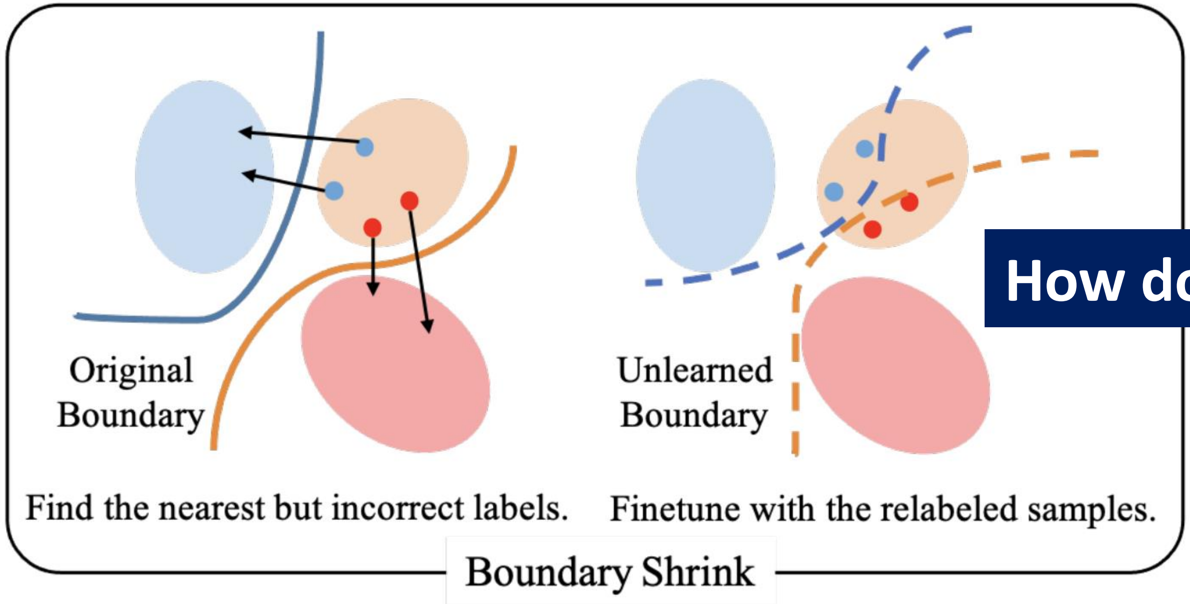
The predicted label on the forgetting samples is different from the unlearning label y

$$\underset{k}{\operatorname{argmax}} f_{\boldsymbol{\theta_u}}^k(\boldsymbol{x}_f) \neq y \text{ for } \forall \boldsymbol{x}_f \in \mathcal{D}_f,$$

where f^k indicates the logit output on the k-th class

Boundary Shrink (1)

- Finetuning with random labels on forgetting samples will make them too conspicuous, since they are predicted with **excessive uncertainty**.
- Instead, **Boundary Shrink** pushes the forgetting samples close to the new decision boundary, making the predictions on these forgetting samples with **low certainty**.



How do we push the samples?

Boundary Shrink (2)

- (a) Given an initial forgetting sample $\boldsymbol{x}_f$, update its corrupted example by neighbor searching with a noise bound ϵ:

$$\boldsymbol{x'}_f = \boldsymbol{x}_f + \epsilon \cdot \text{sign}\left(\nabla_{\boldsymbol{x}_f}\mathcal{L}(\boldsymbol{x}_f, y, \boldsymbol{\theta_o})\right)$$

$$\text{sign}(x) := \begin{cases} -1 & \text{if } x < 0, \\ 0 & \text{if } x = 0, \\ 1 & \text{if } x > 0. \end{cases}$$

- (b) Get ***nearest but incorrect (nbi)*** labels $\boldsymbol{y^f_{nbi}}$:

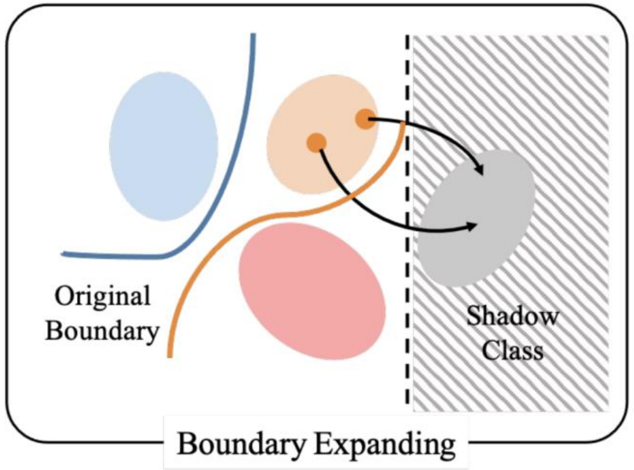
$$\boldsymbol{y^f_{nbi}} \leftarrow \text{softmax}(f_{\boldsymbol{\theta_o}}(\boldsymbol{x'}_f))$$

- (c) Finetune the original model with $\boldsymbol{y^f_{nbi}}$ for forgetting samples $\boldsymbol{x}_f$:

$$\boldsymbol{\theta_u} = \text{argmin}_{\boldsymbol{\theta}}(\sum_{(\boldsymbol{x}_f, \boldsymbol{y^f_{nbi}}) \in \mathcal{D}_f} \mathcal{L}\left(\boldsymbol{x}_f, \boldsymbol{y^f_{nbi}}, \boldsymbol{\theta}\right))$$

High-level Intuition of Boundary Expanding

- Recall: in the previous observation, most forgetting samples move to the border of other clusters on the retrained model. Therefore, they are predicted as other classes with **low certainty.**
- Lower certainty means that the output probabilities (from logits) are more evenly **distributed**.
- **Boundary Expanding** assigns all forgetting samples to **an extra shadow class** of the original model, which will exploit a new area in the decision space.



Boundary Expanding

- The model is finetuned with the forgetting samples $\boldsymbol{x}_f$ and the shadow class label y_{shadow}:

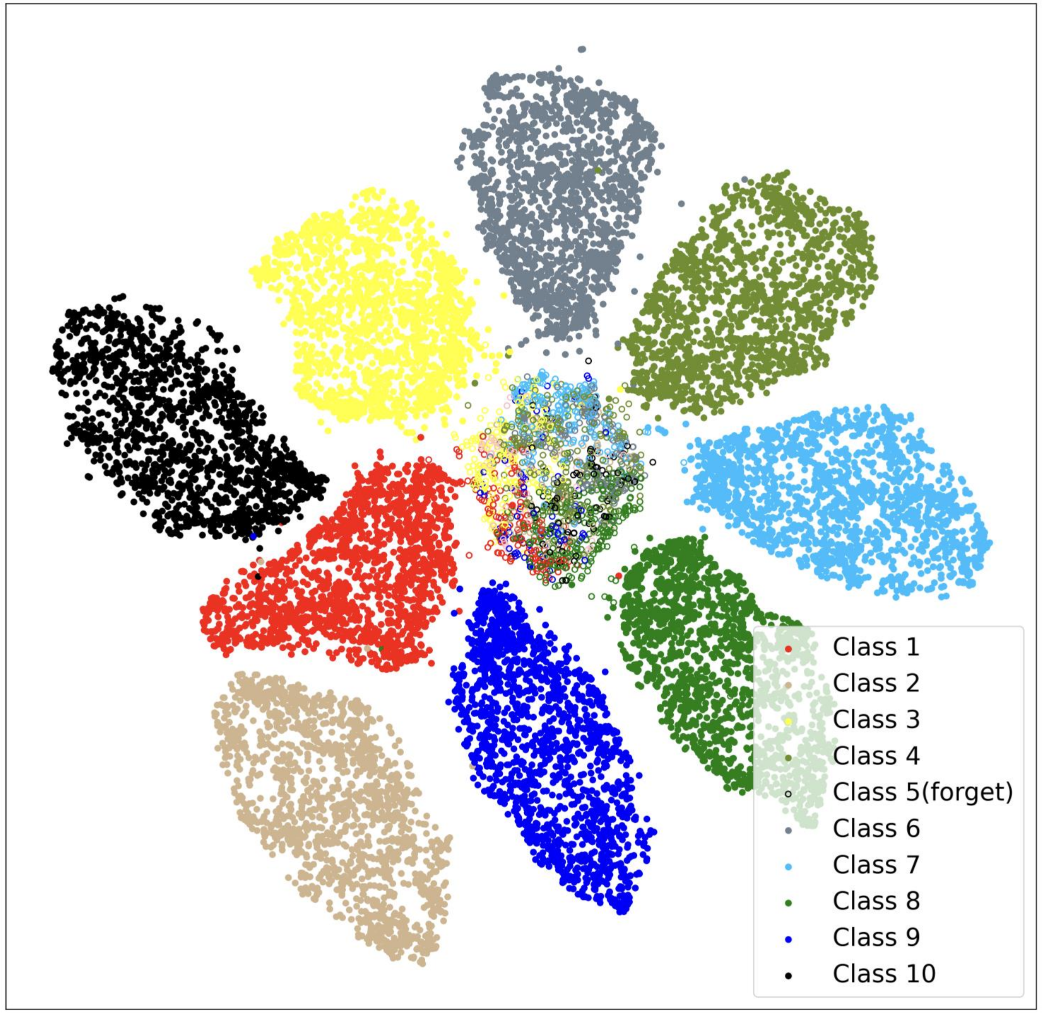
$$\theta_u = \underset{\theta}{\operatorname{argmin}} \sum_{(\boldsymbol{x}_f, y_{shadow}) \in \mathcal{D}_f} \mathcal{L}(\boldsymbol{x}_f, y_{shadow}, \theta)$$

an additional neuron is added at the last layer of the original model for y_{shadow}

- The logit output $f_{\theta_u}(\boldsymbol{x}_f)$ for forgetting sample $\boldsymbol{x}_f \in \mathcal{D}_f$ tends to be **low** and **even** on the original classes => disperse in the decision space of the retrained model.

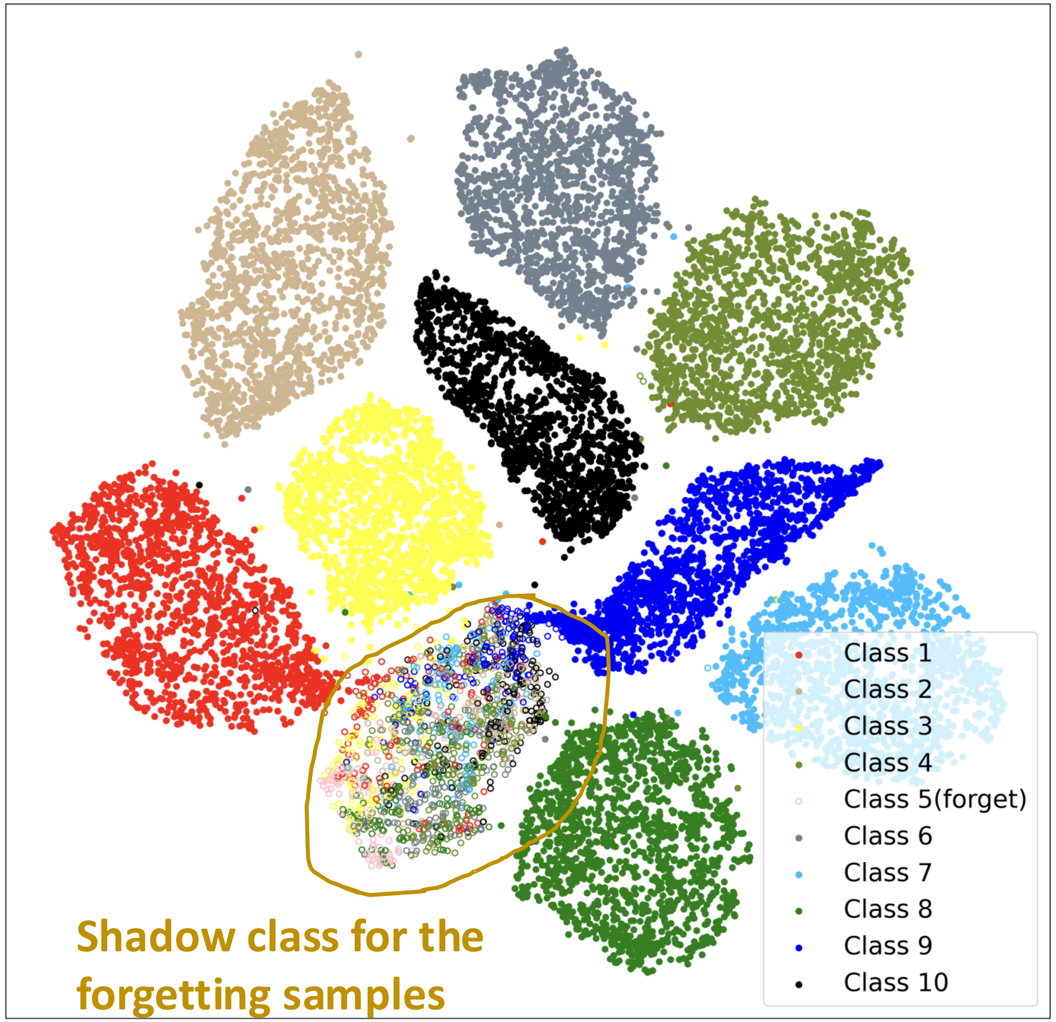
Use the logit output on the original classes during inference stage.

Decision Space (After Boundary Shrink)



1. the forgetting data (hollow circles) are predicted **as the nearest classes** after applying Boundary Shrink.
2. Some hollow circles move to other clusters, indicating that **the decision space of the forgetting class is split** by its near classes.
3. The clusters of remaining classes still keep compact.

Decision Space (After Boundary Expanding)



1. The cluster of the forgetting samples is pushed away from the center, creating **a shadow class.**
2. The clusters of remaining classes are maintained.

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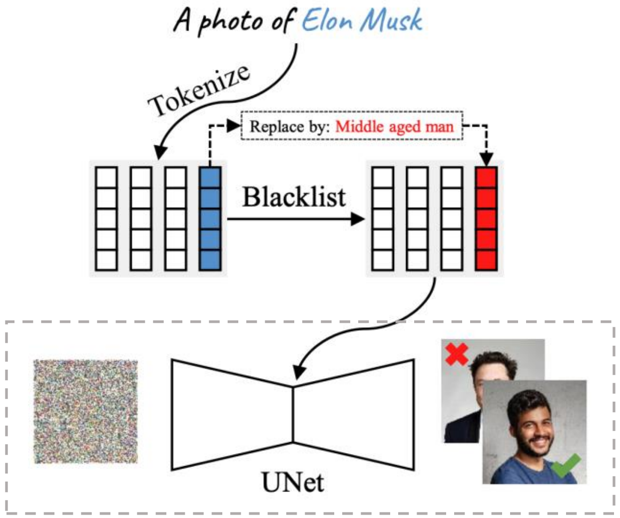
Forget-Me-Not: Concept Forgetting

- A **concept** is an abstract term representing an intuited object of thought, which also serves as the foundation for people's perceptions.
- **Forget-Me-Not** is an efficient, plug-and-play method for concept forgetting and correction.

Concept Forgetting: target concepts are removed and forgotten without compromising the output quality (*Van Gogh* in this case)

Concept Correction & Disentangle: correct a dominant or undesired concept in a prompt

Naïve Forgetting

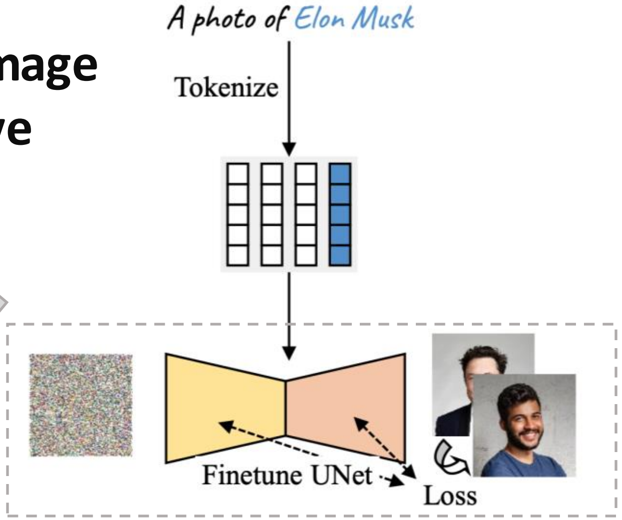


Target concept to forget: Elon Musk

(a) Token Blacklist: simply replace the target tokens with a different one.

Downsides:
- Does not achieve good forgetting effect.
- May inadvertently affect other concepts that share the same/similar prompt.

text-to-image generative model

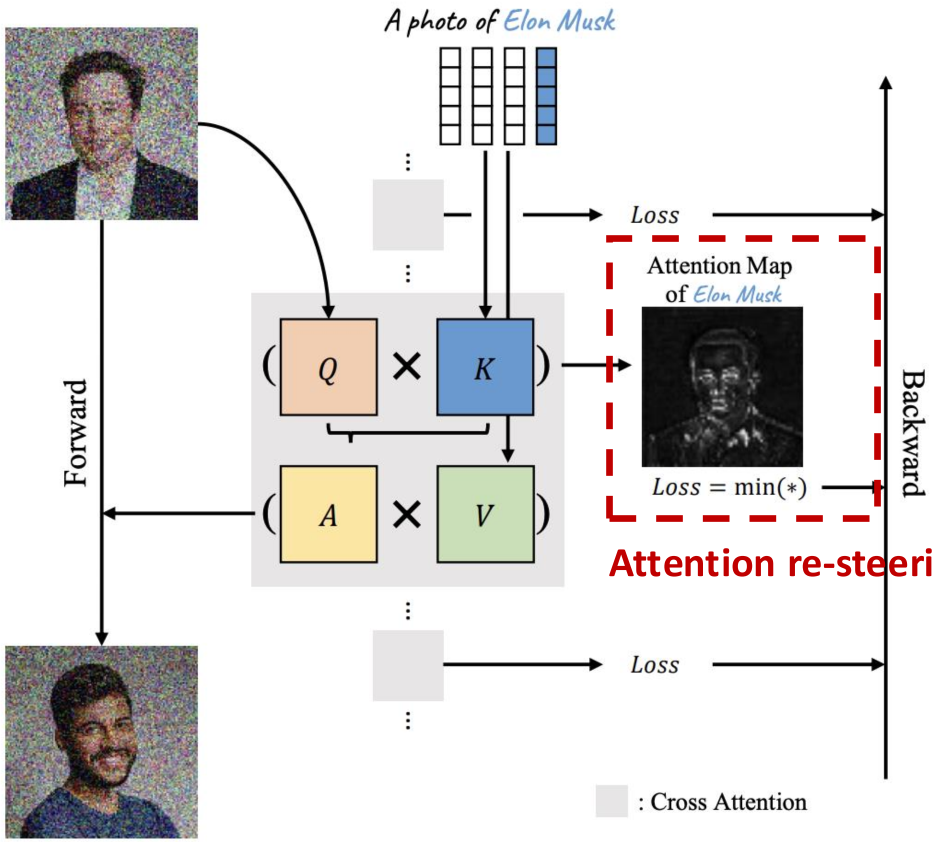


(b) Naïve Finetuning: finetune model weights such that the new weights generate outputs with unrelated concepts

Downside:
- It breaks model integrity by simultaneously corrupting other unrelated concepts during its finetuning process.

FMN: Attention Re-steering

- **Forget-Me-Not (FMN)** is a **model-intrinsic** approach for all **attention-based text-to-image generative models**.
- **Attention Resteering:**
  - **Locate** the part of text embeddings associated with the forgetting concepts.
  - **Compute** the attention maps between input features and these embeddings
  - **Minimize** the attention maps and **backpropagate** the network

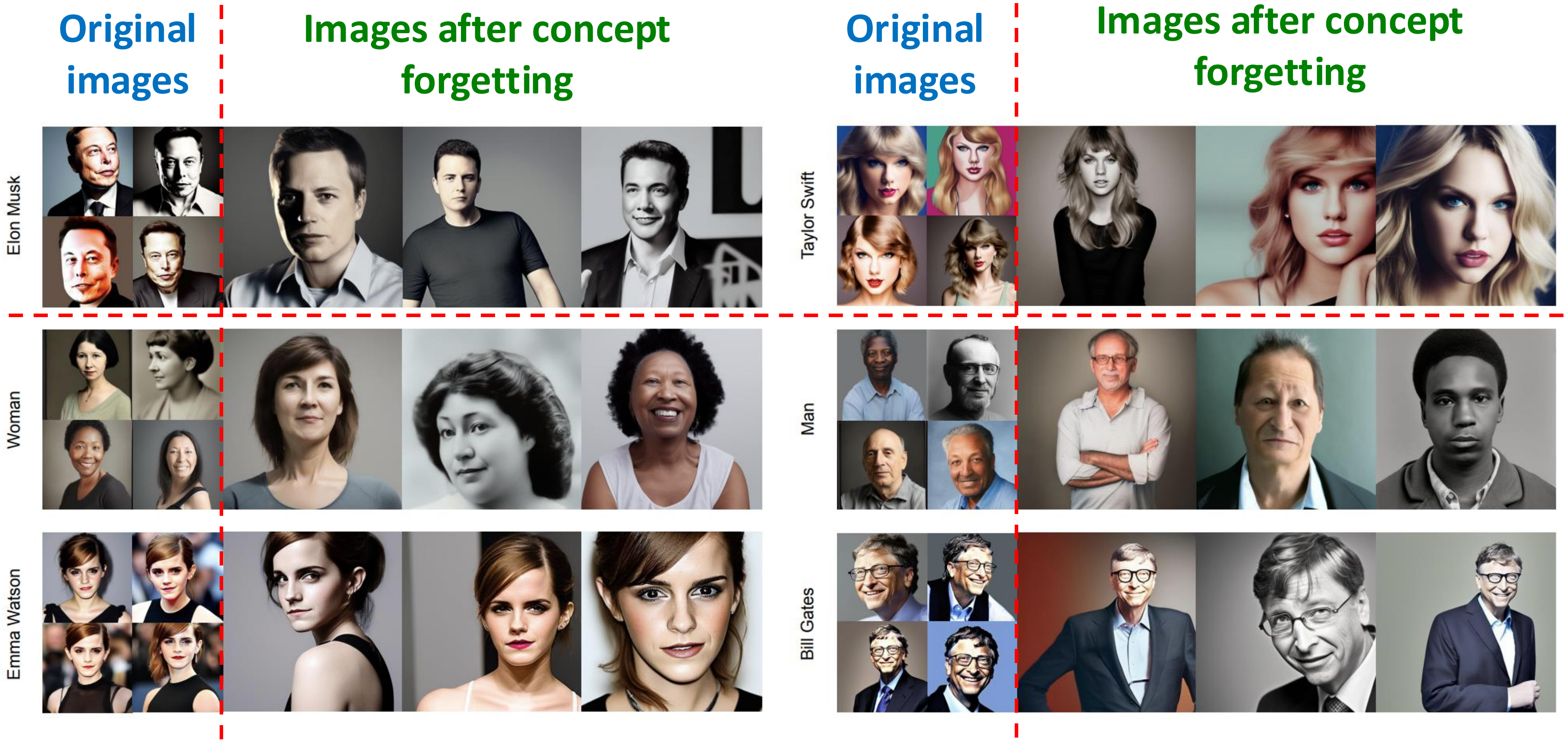


Attention re-steering loss

Results on Multi-Concept Model

Multi-concepts to forget

FMN has minimal impact on other concepts and maintain the image quality



FMN (1) successfully removes the concepts of Elon Musk and Taylor Swift, (2) while maintaining the image quality with unrelated concepts.

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SalUn: Saliency-based Unlearning

- **Motivation of SalUn:** utilize weight saliency to identify model weights that are **sensitive to the forgetting data/class/concept.**
- SalUn is a **model-intrinsic** approach for **diffusion-based models** on image tasks (e.g., image / text / graph / sequence generation).

- recall the notations:

  $\mathcal{D} = \{\boldsymbol{z}_i = (\boldsymbol{x}_i, \boldsymbol{y}_i)\}_{i=1}^{N}$ is the original N data points with data feature $\boldsymbol{x}_i$ and label $\boldsymbol{y}_i$.

  $\mathcal{D}_f \subseteq \mathcal{D}$ denotes the forgetting dataset and $\mathcal{D}_r = \mathcal{D} \backslash \mathcal{D}_f$ is the remaining dataset.

  Original model trained on $\mathcal{D}$ is parameterized as $\boldsymbol{\theta}_o$

  Unlearned model from $\boldsymbol{\theta}_o$ on $\mathcal{D}_f$ or $\mathcal{D}_r$ is parameterized as $\boldsymbol{\theta}_u$

Diffusion Process

- SalUn is specifically designed for diffusion-based model
  - Let $\boldsymbol{\theta}$ denote the parameters of the diffusion generator, conditioned on the text prompt/concept c. $\mathbf{x}_t$ is the latent feature at the diffusion step t.
  - A diffusion model (DM) training uses MSE loss:

$\epsilon_{\boldsymbol{\theta}}$ **: Diffusion generator parameterized by** $\boldsymbol{\theta}$

$$\ell_{\mathrm{MSE}}(\boldsymbol{\theta}; \mathcal{D}) = \mathbb{E}_{\mathcal{D}} \mathbb{E}_{t, \epsilon \sim \mathcal{N}(0,1)} \left[\| \epsilon - \boxed{\epsilon_{\boldsymbol{\theta}}(\mathbf{x}_t \mid c)} \|_2^2 \right]$$

  - Main idea: Decompose the original model weights $\boldsymbol{\theta}_o$ into two distinct components:
    - The **salient** model weights to be updated during machine unlearning process
    - The **intact** model weights that remain unchanged

Question: how to detect the salient model weights?

Forgetting Loss

- SalUn uses the **gradient of a forgetting loss** as the weight saliency map
- Forgetting loss usually follows the training loss on the forgetting dataset $\mathcal{D}_f$, denoted as $\ell_{\mathrm{f}}(\boldsymbol{\theta}; \mathcal{D}_f)$
  - For classification: $\ell_{\mathrm{f}}(\boldsymbol{\theta}; \mathcal{D}_f) = \mathbb{E}_{(\mathbf{x},y)\sim\mathcal{D}_{\mathrm{f}}}[\ell_{\mathrm{CE}}(\boldsymbol{\theta}; \mathbf{x}, y)]$; (CE: cross-entropy)
  - For generation: $\ell_{\mathrm{f}}(\boldsymbol{\theta}; \mathcal{D}_f) = \ell_{\mathrm{MSE}}(\boldsymbol{\theta}; \mathcal{D}_{\mathrm{f}})$

Weight Saliency Map

Weight Saliency Map Calculation:

Reflects the weight sensitivity to the forgetting instance in $\mathcal{D}_f$

$$\mathbf{m}_\mathrm{s} = \mathbf{1}\left(\boxed{\left| \nabla_{\boldsymbol{\theta}} \ell_\mathrm{f}(\boldsymbol{\theta}; \mathcal{D}_\mathrm{f}) \right|_{\boldsymbol{\theta}=\boldsymbol{\theta}_0}} \right| \geqslant \gamma\right)$$

- $\mathbf{1}(g \geq \gamma)$ an element-wise indicator function that yields binary outputs. $\gamma > 0$ is a hard threshold.

The **unlearning model $\boldsymbol{\theta}_{\boldsymbol{u}}$** is then updated as:

Tunable in the unlearning process

Pre-trained, fixed in the unlearning process

$$\boldsymbol{\theta}_{\boldsymbol{u}} = \underbrace{\mathbf{m}_\mathrm{s} \odot \boldsymbol{\theta}}_{\text{Salient weights}} + \underbrace{(\mathbf{1} - \mathbf{m}_\mathrm{s}) \odot \boldsymbol{\theta}_o}_{\text{Original weights}}$$

SalUn Training: classification

- **Assign Random image label** to a forgetting data point and fine-tune the salient weights:

$$\min_{\boldsymbol{\theta}} L^{(1)}_{\mathrm{SalUn}}(\boldsymbol{\theta_u}) := \mathbb{E}_{(\mathbf{x},y)\sim\mathcal{D}_f,\, y'\neq y}[\ell_{\mathrm{CE}}(\boldsymbol{\theta_u}; \mathbf{x}, y')]$$

  - Tune $\boldsymbol{\theta}$ to update $\boldsymbol{\theta_u}$ by $\boldsymbol{\theta_u} = \mathbf{m}_s \odot \boldsymbol{\theta} + (\mathbf{1} - \mathbf{m}_s) \odot \boldsymbol{\theta_o}$
  - y' is the random label of the image $x \in \mathcal{D}_f$, which is different from the original one
  - Random Label Assignment removes the knowledge from $\mathcal{D}_f$ and maintain the model's performance on unrelated samples.

SalUn Training: generation

- In diffusion-based generation task, SalUn associates the forgetting concept c with a misaligned image x' that does not belong to the concept c.

$$\underset{\boldsymbol{\theta}}{\text{minimize}} L_{\text{SalUn}}^{(2)}(\boldsymbol{\theta}_{\boldsymbol{u}}):$$

Remove the concept knowledge from $\mathcal{D}_f$

$$= \mathbb{E}_{(x,c)\sim\mathcal{D}_f, t, \epsilon\sim\mathcal{N}(0,1), c'\neq c} \boxed{\left[\| \epsilon_{\boldsymbol{\theta}_{\boldsymbol{u}}}(\boldsymbol{x}_t \mid c') - \epsilon_{\boldsymbol{\theta}_{\boldsymbol{u}}}(\boldsymbol{x}_t \mid c) \|_2^2 \right]} + \alpha \ell_{\text{MSE}}(\boldsymbol{\theta}_{\boldsymbol{u}}; \mathcal{D}_{\text{r}})$$

  - $c' \neq c$ indicates that c' is different from c.
  - α is a regularization parameter that balances **unlearning quality** and **image generation quality** (preserved by $\ell_{\text{MSE}}(\boldsymbol{\theta}_{\boldsymbol{u}}; \mathcal{D}_{\text{r}})$).

Experiments: Image Generation

Generated Images under I_i: forgotten class (airplane) or C_i: non-forgetting class

- **Random:** apply random weight saliency mask in **SalUn**
- For the given forgetting class, using random weight saliency mask in SalUn generates **noisy and unrecognizable images**
- For the non-forgetting classes, random weight saliency mask **degrades** the generation quality
- SalUn leverages a proper weight saliency map, leading to better forgetting performance

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SISA Training

SISA: **S**harded, **I**solated, **S**liced, and **A**ggregated Training

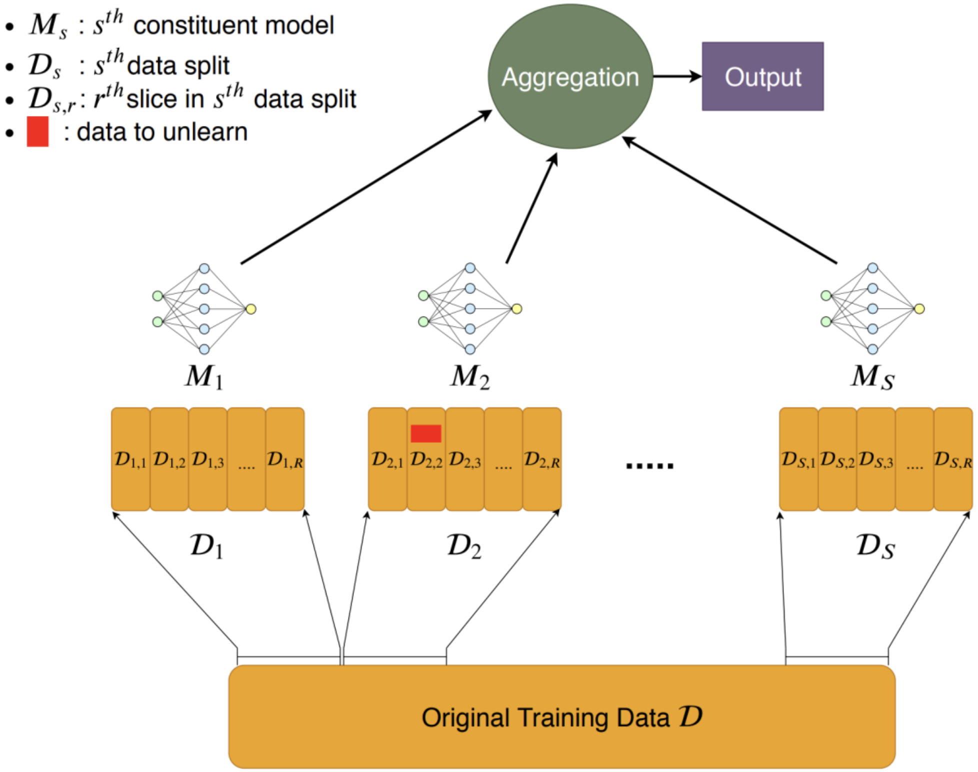
At Training phase:

- Data is divided into **shards D_s**
- Each shard is further split into **slices $D_{s,r}$**
- Incrementally train the constituent model M_s by **saving the parameters of M_s before training it with a new slice.**

At Inference phase:

- aggregate the responses of constituent models

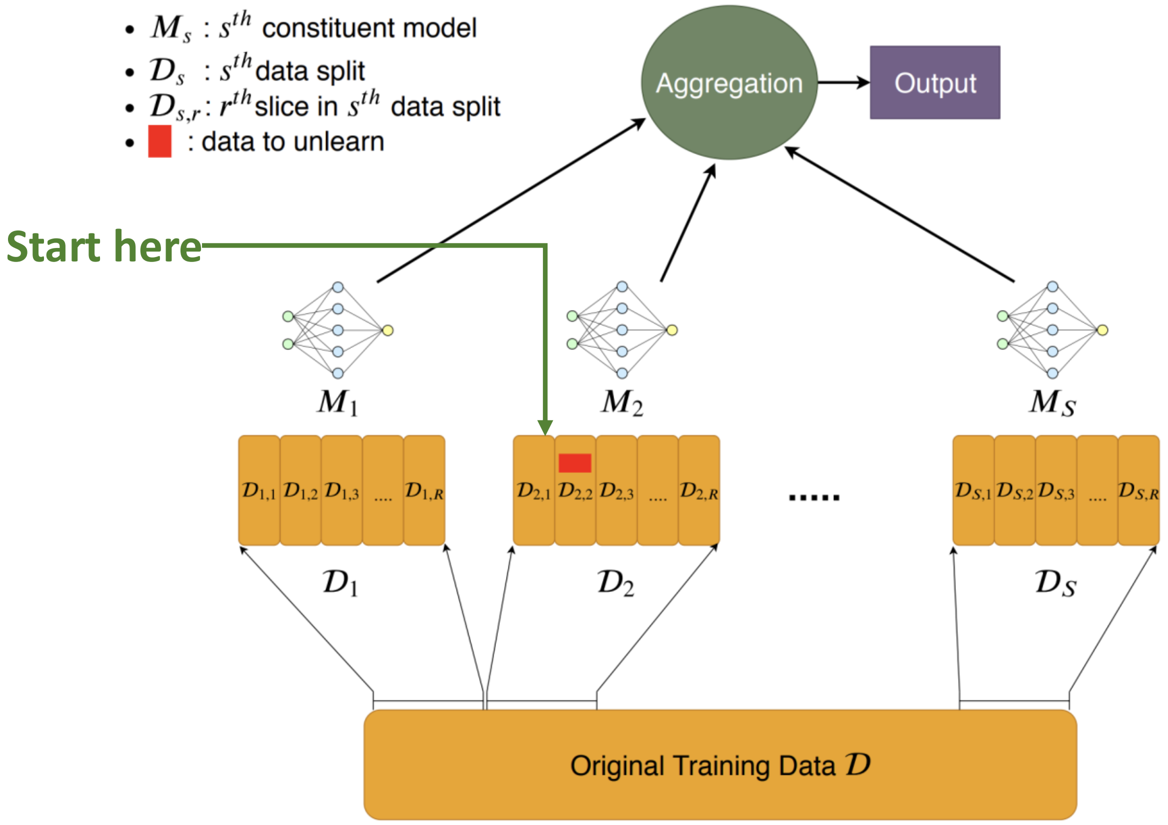
Average constituent models



SISA: Unlearning Guarantee

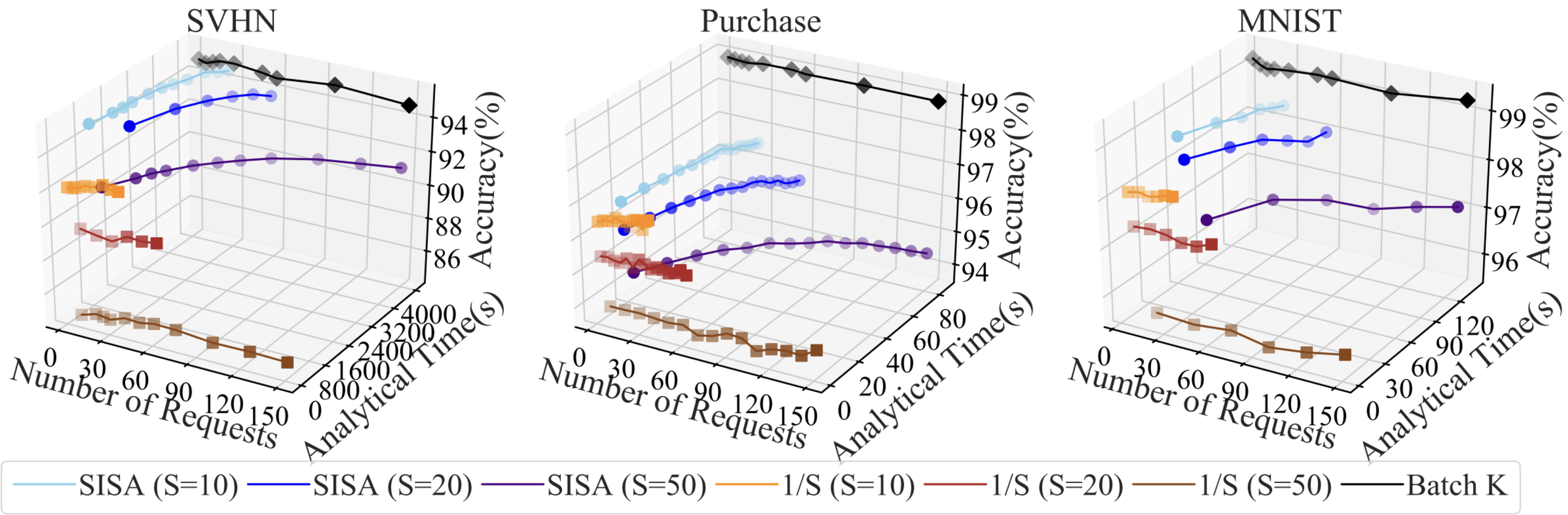
Limited Retraining Cost due to the **incremental training process**:

- only the constituent model whose shard contains the point to be unlearned is affected.
- retraining starts from **the last parameter state / model checkpoint** saved prior to the slice containing this point.
- e.g., $D_{2,2}$ is to be unlearned, only retrain M_2 from the state saved after $D_{2,1}$



Evaluation: Accuracy & Retraining Time (1)

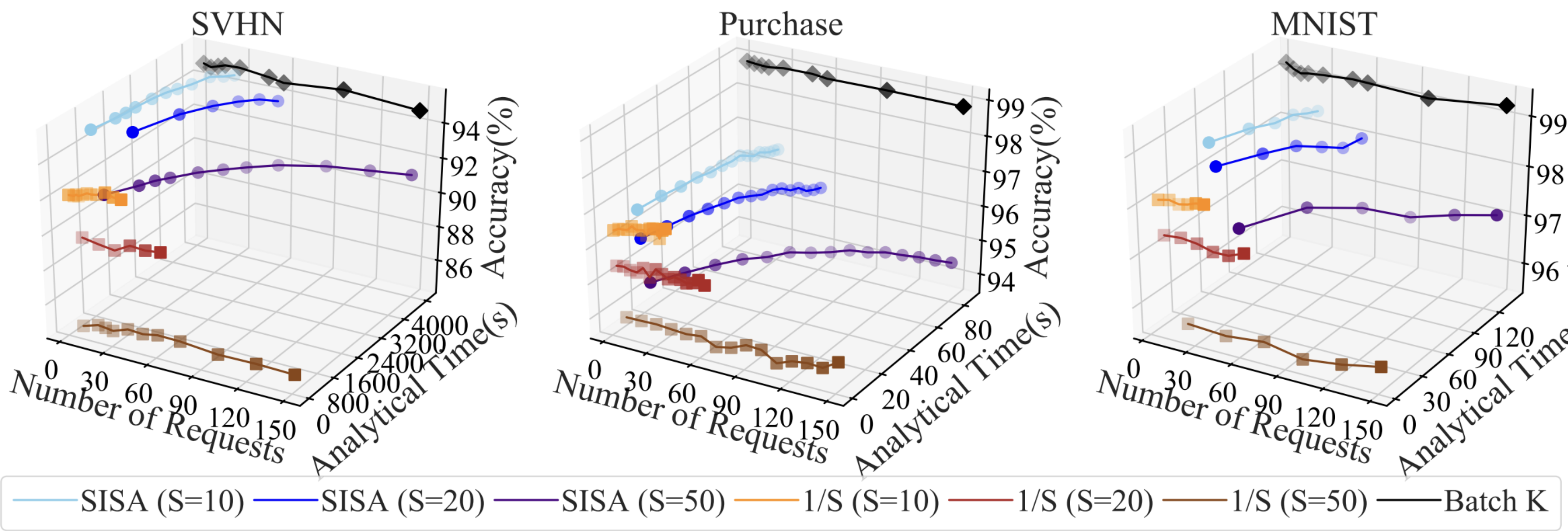
- **Baselines:**
  - Batch K: **retrain the entire model** after every K unlearning requests
  - $\frac{1}{S}$: split the data into S shards and **only retrain the one that contains the point to be unlearned**
- Dataset: SVHN, Purchase, MNIST
- S: number of shards



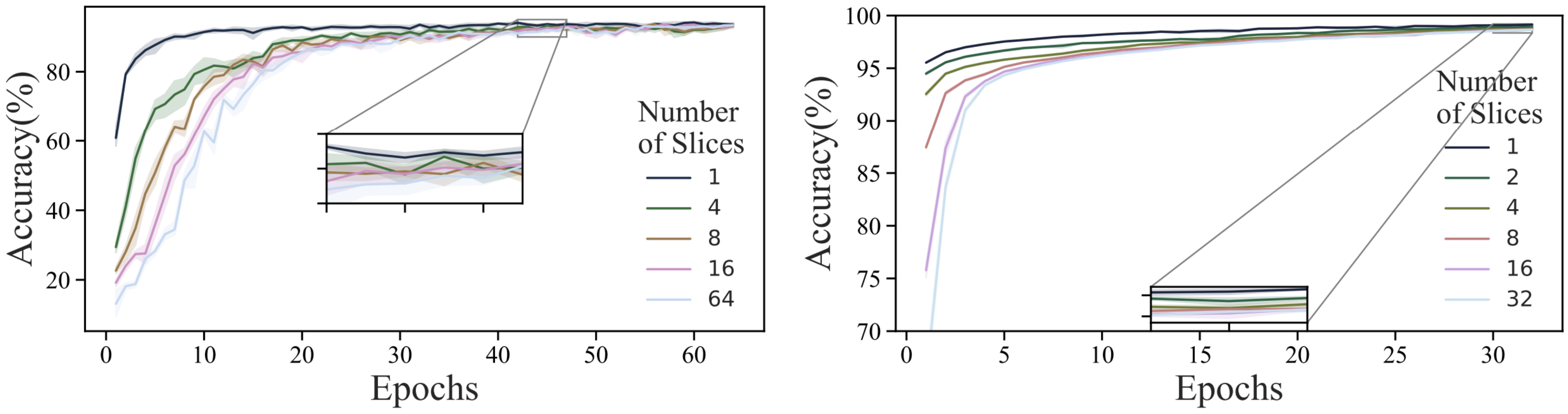
Evaluation: Accuracy & Retraining Time (2)

- Batch K achieves **high accuracy**, but needs a **longer retraining time**
- $\frac{1}{S}$ achieves **low accuracy**, and needs a **shorter retraining time**
- SISA achieves the **best trade-off between accuracy and retraining time**
- **Increasing S will degrade the accuracy**

Ensure each shard has sufficiently many data points to ensure high accuracy for each constituent model!



Evaluation: Impact of Slicing

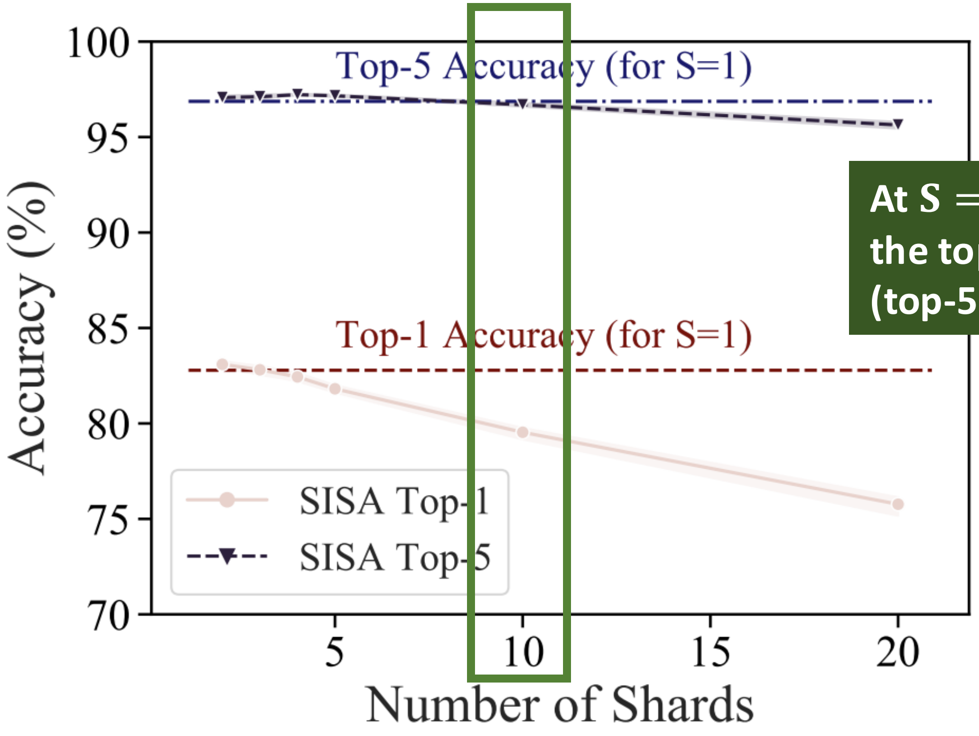


(a) Accuracy vs. Number of epochs for SVHN dataset. (b) Accuracy vs. Number of epochs for Purchase dataset.

1. **Slicing the shard takes more epochs to achieve high accuracies**
2. **For a small number of epochs, models with more slicing have lower accuracy, since they have significantly less amount of data at the beginning.**

Evaluation: Transfer Learning / Pretraining

- Train a base ResNet-50 on Imagenet (relatively complex dataset) and transfer it to CIFAR-100 dataset (simpler dataset)
- Baseline: $S = 1$ (retrain over the entire dataset)

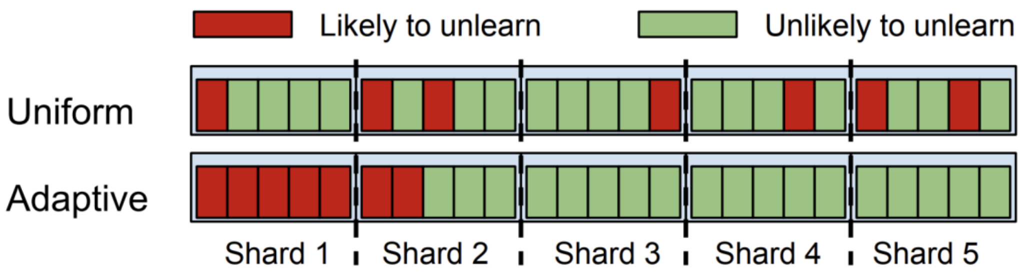


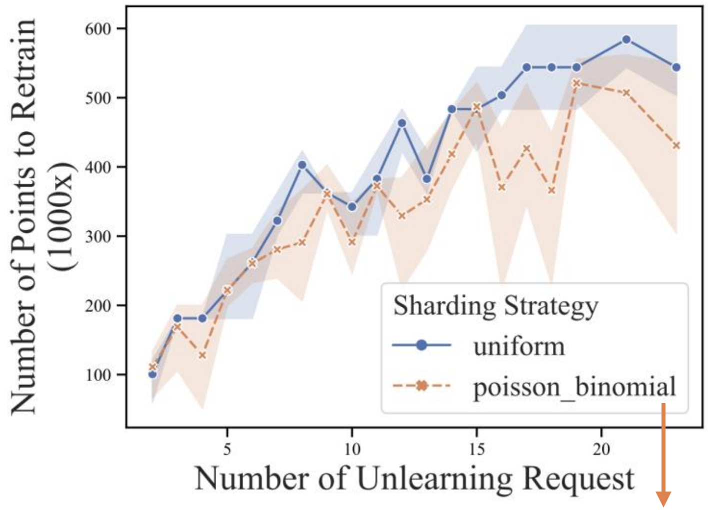
At $\mathbf{S = 10}$,
the top-1 accuracy gap $\approx 4\%$; the top-5 accuracy gap $\leq 1\%$
(top-5 accuracy is more representative metric for complex tasks)

Increasing S introduces an negligible accuracy drop, in comparison to entire retraining.

Adaptive Unlearning

- **A priori knowledge** of users' probability for requesting unlearning can improve SISA unlearning
- **Distribution-aware sharding:** maximize shard size; minimize the chance that a shard has at least one unlearning request





The adaptive sharding can reduce analytical retraining time!

Assume each request is an independent Bernoulli trial, then group of requests follows a Poisson Binomial distribution

Summary of the Lecture

- Machine Unlearning Motivation: the data/user have the *"right to be forgotten"*
- Goal of Machine unlearning: to design **efficient** unlearning algorithms that forget certain data, class, feature, concept, etc.
- Machine unlearning algorithms should **maintain performance on the unchanged data**
- Machine unlearning methods include **model-agnostic** approaches, **model-intrinsic** approaches and data-driven approaches.