Updating ML Models

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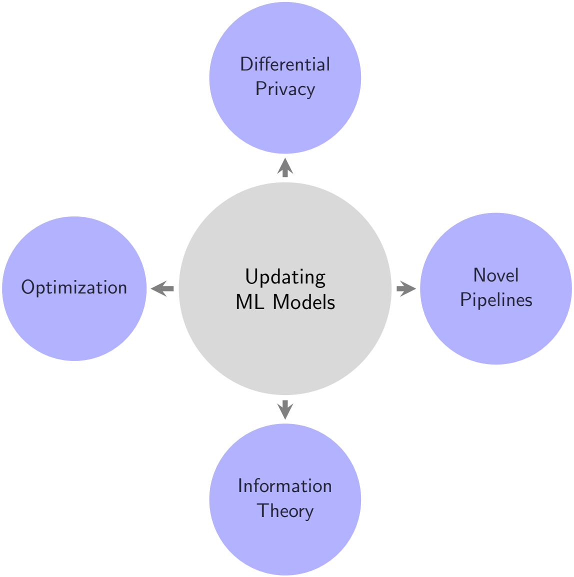
Overview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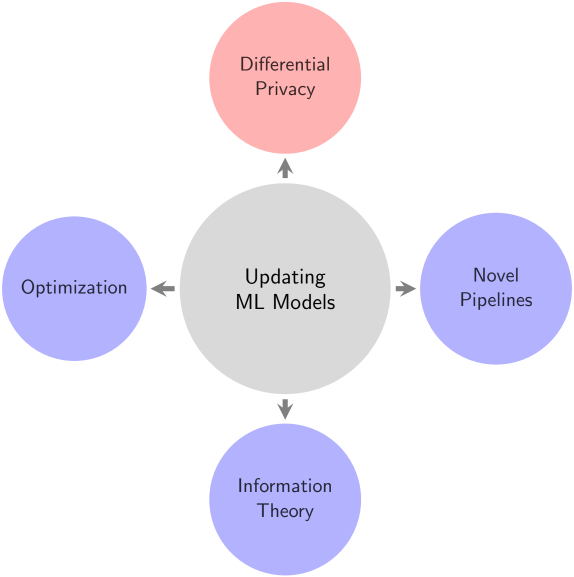
Common Terminology

- Fixed training Dataset $\mathcal{D}$
- Learning Algorithm A (can be randomized)
- Datapoints to be remove $\mathcal{D}_{\mathcal{R}}$, where $|\mathcal{D}_{\mathcal{R}}| = r$, remaining dataset $\mathcal{D}' = \mathcal{D} - \mathcal{D}_{\mathcal{R}}$
- Naive approach is retraining from scratch, i.e, $A(\mathcal{D}')$
- Mechanism M which offers an efficient way to update the model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Certified Data Removal [Guo et al., 2020]

- A outputs a model in hypothesis space $\mathcal{H}$
- Defines ϵ-*certified removal*, $\forall \mathcal{T} \subseteq \mathcal{H}$

$$e^{-\epsilon} \leq \frac{P(M(A(\mathcal{D}), \mathcal{D}_{\mathcal{R}}) \in \mathcal{T})}{P(A(\mathcal{D}') \in \mathcal{T})} \leq e^{\epsilon}$$

- Insufficiency of Parametric indistinguishability
  - Approximate removal processes leaves a gradient residual
  - Residuals can reveal the prior presence of that training sample

Removal Mechanism for Linear Classfiers

- A empirical risk $L(\mathbf{w}; \mathcal{D})$ with a convex loss function $\ell(\mathbf{w}^T\mathbf{x}, y)$
- $\mathbf{w}^* = A(\mathcal{D}) = \text{argmin}_w L(\mathbf{w}; \mathcal{D})$
- To remove a single point $\mathcal{D}_{\mathcal{R}} = \{(\mathbf{x}_n, y_n)\}$
- Newton Update Step: $\mathbf{w}^- = M(\mathbf{w}^*, (\mathbf{x}_n, y_n)) = \mathbf{w}^* - H_{\mathbf{w}^*}^{-1}\nabla$
- Where $H_{\mathbf{w}^*} = \nabla^2 L(\mathbf{w}^*, \mathcal{D}')$ and $\nabla = \lambda\mathbf{w}^* + \nabla\ell((\mathbf{w}^*)^T\mathbf{x}_n, y_n)$
- $H_{\mathbf{w}^*}^{-1}\nabla$ is from *influence function* literature

Influence Function

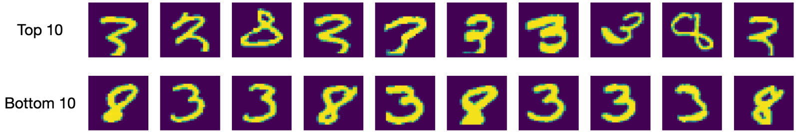


Figure 3. **MNIST training digits sorted by norm of the removal update $\|\mathbf{H}_{\mathbf{w}^*}^{-1}\mathbf{\Delta}\|_2$.** The samples with the highest norm (**top**) appear to be atypical, making it harder to undo their effect on the model. The samples with the lowest norm (**bottom**) are prototypical 3s and 8s, and hence are much easier to remove.

Certifing Removal

- $\mathbf{w}^-$ is approximate close to minimizer of $L(\mathbf{w}; \mathcal{D}')$
- $\nabla L(\mathbf{w}^-; \mathcal{D}')$ is gradient residual and if non-zero, reveals Information
- Even a small $\|\nabla L(\mathbf{w}^-; \mathcal{D}')\|_2$ doesn't guarantee certifiable removal
- Therefore, perturb loss at training time

$$L_b(\mathbf{w}; \mathcal{D}) = \sum_{i=1}^{n} \ell(\mathbf{w}^T \mathbf{x}_i, y_i) + \frac{\lambda n}{2} \|\mathbf{w}\|_2^2 + \mathbf{b}^T \mathbf{w}$$

Where $\mathbf{b} \in \mathbb{R}^d$ drawn randomly from some distribution

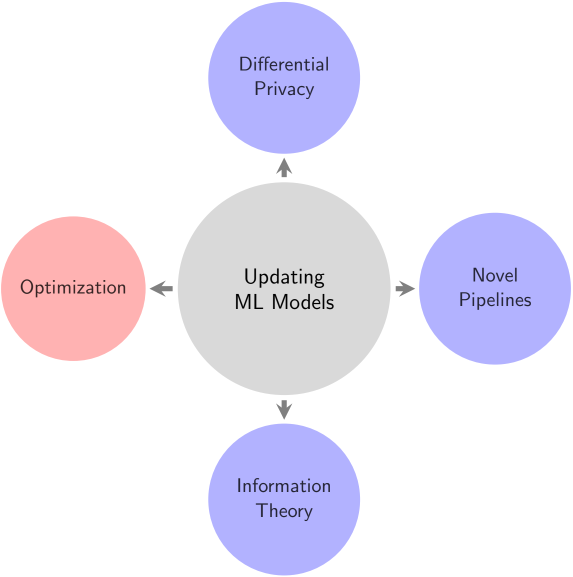
Benefits and Drawbacks

Benefits

- Provides formal guarantee of statistical indistinguishability
- Works well with Differentially Private trained networks
- Uses influence functions to approximate data removal

Limitations

- Requires inverting a Hessian matrix
- Non-convex loss functions not supported
- Adding noise during training hurts model performance
- Very strict notion of removal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DeltaGrad [Wu et al., 2020]

- M targets the Gradient Descent (GD) algorithm
- Naive retraining $A(\mathcal{D}')$ recomputed gradients over all remaining points

$$\mathbf{w}_{t+1}^{U} \leftarrow \mathbf{w}_{t}^{U} - \frac{\eta_t}{n-r} \sum_{i \in \mathcal{D}'} \nabla L_i(\mathbf{w}_t^{U})$$

- Instead rewrite it as a *leave-r-out* formula

$$\mathbf{w}_{t+1}^{I} = \mathbf{w}_{t}^{I} - \frac{\eta_t}{n-r} \left[\sum_{i \in \mathcal{D}} \nabla L_i(\mathbf{w}_t^{I}) - \sum_{i \in \mathcal{D}_{\mathcal{R}}} \nabla L_i(\mathbf{w}_t^{I}) \right]$$

- Much cheaper to compute r gradients, when $r \ll n$

Approximating $\sum_{i \in \mathcal{D}} \nabla L_i(\mathbf{w}_t^I)$

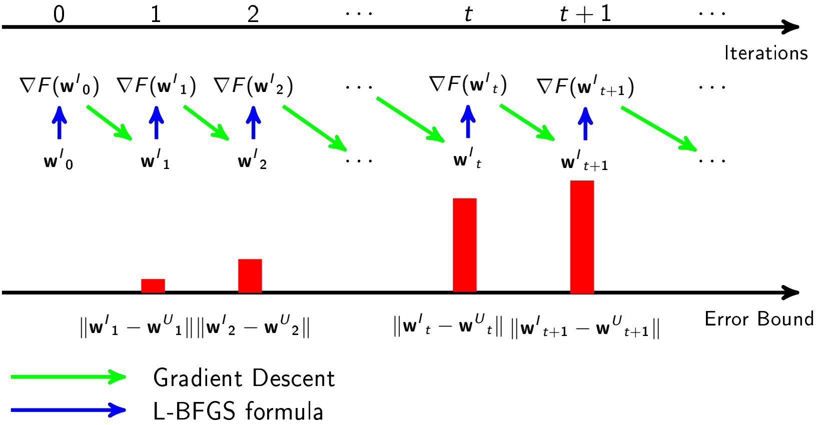
- Need to use historical $\nabla L(\mathbf{w}_t)$ to approximate $\nabla L(\mathbf{w}_t^I)$
- Taylor expansion around $\mathbf{w}_t^I$ gives the following

$$\nabla L(\mathbf{w}_t^I) = \nabla L(\mathbf{w}_t) + \mathbf{H}_t \cdot (\mathbf{w}_t^I - \mathbf{w}_t)$$

Where $\mathbf{H}_t = \int_0^1 \mathbf{H}(\mathbf{w}_t + x(\mathbf{w}_t^I - \mathbf{w}))dx$

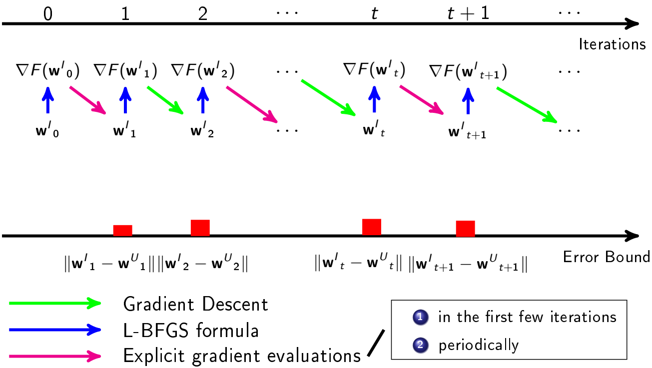
- Maintaining a Hessian matrix is expensive, so leverage the L-BFGS algorithm to compute a Hessian-vector product
- This leads to issues in error bounds of the approximation

Problem with Error Bound



Controlling the Errors

- Do explicit evaluations for j_0 "burn-in" iterations and then periodically every T_0 iterations



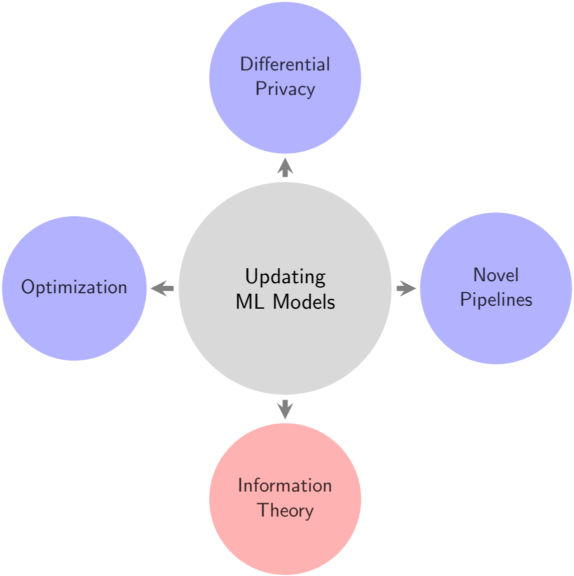
Benefits and Limitations

Benefits

- Handles both additions nad deletions of datapoints
- Can be applied to any ML model trained using Stochastic Gradient Descent
- Approximation guarantees and empirical results on

Limitaitons

- Needs to cache all weights $\mathbf{w}_t$ and gradients $\nabla L(\mathbf{w}_t)$ during training
- Requires tuning of T_0 and j_0 based on dataset
- For SGD, only works with large batch sizes (> 10000), which hurts model performance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Eternal Sunshine of the Spotless Net [Golatkar et al., 2020]

- $P(\mathbf{w}|\mathcal{D})$ distribution of algorithm A
- M is called *scrubbing function* applied to $\mathbf{w}$
- $P(M(\mathbf{w})|\mathcal{D})$ is distribution of possible weights after scrubbing
- Motivation: disallow attacker to use *read-out function* $f(\mathbf{w})$ to gain information about $\mathcal{D}_{\mathcal{R}}$
- Therefore, optimal scrubbing function must have

$$\mathrm{KL}(P(f(M(\mathbf{w}))|\mathcal{D}) \parallel P(f(S_0(\mathbf{w}))|\mathcal{D}')) = 0$$

  Where S_0 is a *certificate* of forgetting
- To be agnostic of $f(\cdot)$, minimize

$$\mathrm{KL}(P(M(\mathbf{w})|\mathcal{D}) \parallel P(S_0(\mathbf{w})|\mathcal{D}'))$$

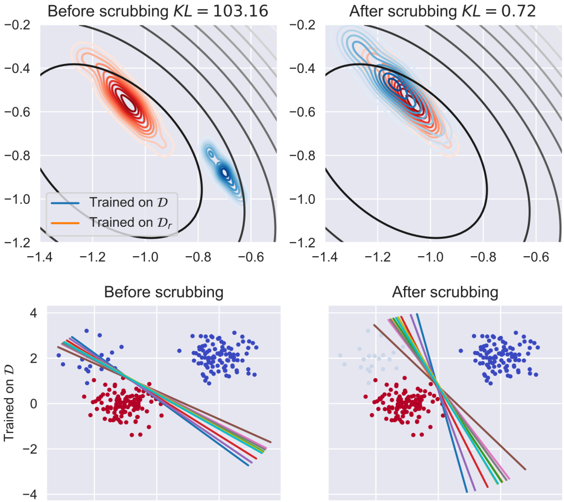
Forgetting Lagrangian

- A trivial noise scrubbing is $M(\mathbf{w}) = S_0(\mathbf{w}) = w + \sigma n$, where $n \sim \mathcal{N}(0, I)$
- As $\sigma \to \infty$, $\mathrm{KL}(p \| q) \to 0$, which invalidates the model
- Define the *Forgetting Lagrangian*:

$$\mathcal{L} = \mathbb{E}_{M(\mathbf{w})}[L_{\mathcal{D}'}(\mathbf{w})] + \lambda \mathrm{KL}(P(M(\mathbf{w})|\mathcal{D}) \parallel P(S_0(\mathbf{w})|\mathcal{D}'))$$

- Use quadratic approximation and noise to scrub weights
- $M(\mathbf{w}) = h(\mathbf{w}) + n$ and $S_0 = w + n'$ where $h(\mathbf{w})$ is deterministic and $n, n' \sim \mathcal{N}(, \Sigma)$

Scrubbing Example



Robust Quadratic Scrubbing

- Noisy Newton update, as $t \to \infty$ is defined as

$$M_t(\mathbf{w}) = \mathbf{w} - \mathbf{H}^{-1}\nabla L_{\mathcal{D}'}(\mathbf{w}) + (\lambda\sigma_h^2)^{1/4}\mathbf{H}^{-1/4}$$

  Where $\mathbf{H} = \nabla^2(L_{\mathcal{D}'}(\mathbf{w}))$, σ_h represents error in approximating SGD with a continuous gradient flow and λ hyperparameter
- For Deep Neural Networks, Hessian matrix is expensive to compute and store
- Simplified scrubbing to only adding noise

$$M(\mathbf{w}) = \mathbf{w} + (\lambda\sigma_h^2)^{1/4}F^{-1/4}$$

- F is the Fisher Information Matrix, computed using the Levenberg- Marquardt semi-positive-definite approximation of $\nabla^2 L_{\mathcal{D}}(\mathbf{w})$

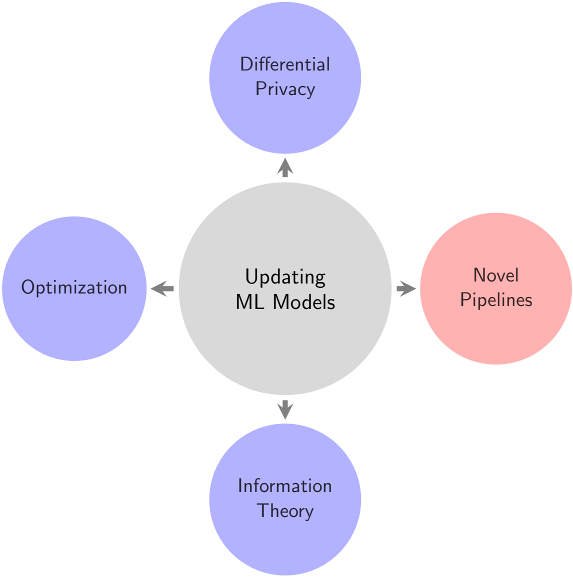
Benefits and Limitations

Benefits

- Works for Deep Neural Networks
- Allows to remove a entire class, multiple classes, or a subset of a class of the training dataset
- Process is optimal if quadratic assumptions hold true

Limitations

- Space and time complexity of approach unknown
- Considers worst case of attacker using any read-out function $f(\cdot)$
- Results based on stability of SGD after pre-training networks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Machine Unlearning: SISA [Bourtoule et al., 2020]

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