CS772: Research Project

Zero Shot Unlearning

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Problem Statement

- Survey Paper
- Machine Unlearning
  - Model M, Data D
  - Request:
    - Forget Data $D_f \subset D$
    - Retain Data $D_r = D - D_f$

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- Zero-Shot Machine Unlearning
  - No Access to D_f and D_r

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- Zero-Shot Machine Unlearning
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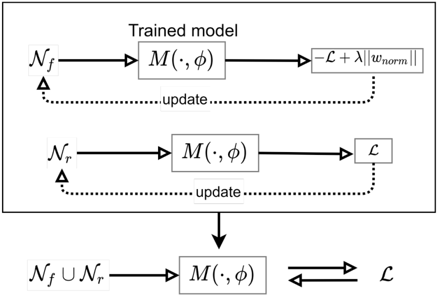
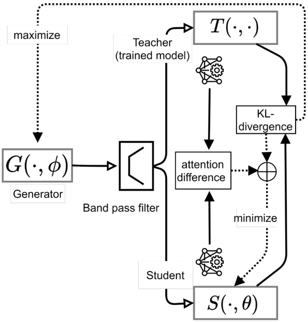
- Approach
  1. Error Minimization-Maximization Noise
  2. Gated Knowledge Transfer

Error Minimization-Maximization Noise



- Inspiration: Fast Yet Effective Machine Unlearning
- Anti-Samples N_f learnt by maximising loss
- Data representatives N_r learnt by minimising loss
- Updates the original model using noise

Gated Knowledge Transfer



- Inspiration: Zero-shot KT via Adversarial Belief Matching
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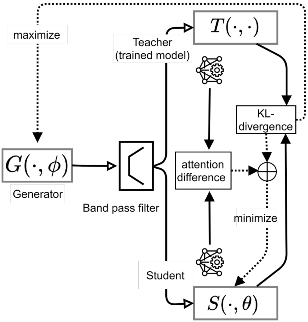

- Inspiration: Zero-shot KT via Adversarial Belief Matching
- Knowledge Distillation to train the student from teacher
- Generator: Max $D_{KL}(T(x_g)||S(x_g)) = \sum_i^{|C|} t_p^{(i)} \log(t_p^{(i)}/s_p^{(i)})$
- Filter images belonging to C_f
- Student - Immitate Teacher's predictions
- Attention - Mimic Inner Layers - Minimise KL

Improvements and Extensions

- Ideas
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  - Positive Samples instead of Anti-Samples
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  - Extending to Regression
  - Positive Samples instead of Anti-Samples
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  - Better Alternatives for generators
- Entropy of predictions
  - Reject if $S(t_p) > \epsilon$
  - Poorer Retain Accuracy
  - Faster Retain Accuracy Restoration
  - Carrying out experimentations

Deep Inversion

- Difference in M^* and M_u
  - Non-zero probability for C_f
  - Due to Attention implicitly learn for C_f
  - Removing Attention: Impacts Performance
  - Reason: Poor Generated Images

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- Difference in M^* and M_u
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  - Reason: Poor Generated Images
- Inspiration: Deep Inversion
  - Idea: To minimise loss on x along with regularisation and matching lower-layer features
  - To determine when to halt in GKT
  - Much Better Images

Generated Images

MNIST Numbers Dataset
Images of Digits from 0-9

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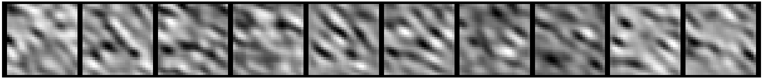
- GKT*



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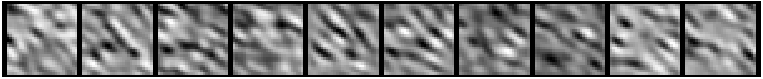
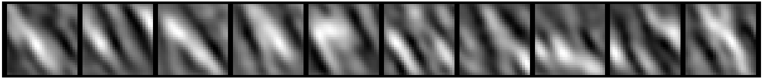


- GKT (with entropy criterion)*



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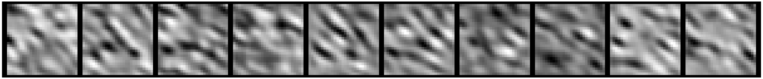

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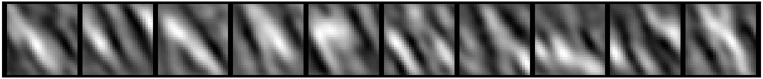

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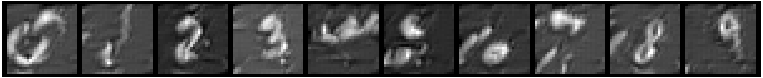

* Images not in order from 0-9. Images generated by the generator before forget accuracy begin to rise

Experimental Results

MNIST Numbers Dataset - `AllCNN` Model
Train: 60,000, Test: 10,000
Retain Accuracy on Test Set:

- Retrain Model: 99.25 %
- GKT: 97.12 %
- M-M: 10.57 %

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If time permits will try to outperform the base paper on some dataset.

Conclusion

- Understand the internals of tackling zero-shot setting
- Determine the source of non-zero forget class accuracy and address it up to certain extent
- Improve upon the quality of images generated
- Decent Results

Learnings

- One of the first research experience
- Ability to read papers
- Exposure to tweaking complex machine learning code
- Repeatedly improving on strategies

Thank You