CZSL project overview

February 28, 2020

What was done in October

1. Continual learning pipeline for CUB/AwA
2. Sequential/EWC/MAS/A-GEM baselines for classification with attributes on CUB/AwA datasets
3. Some metrics to measure performance for continual zero-shot learning

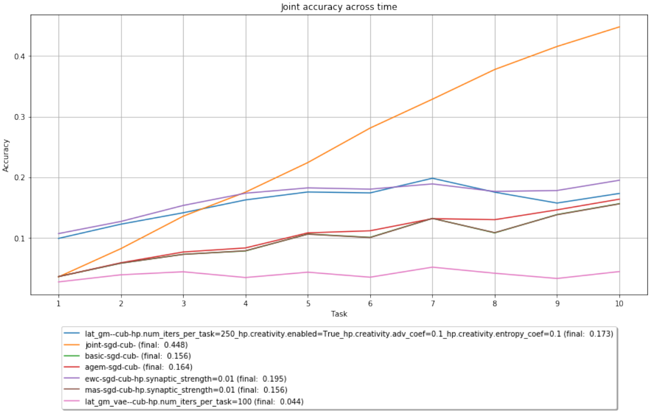

Figure: Joint accuracy on all the remaining unseen classes for CUB

What was done in November

- LGM-GAN on CUB dataset with the *pretrained and fixed* embedder
- LGM-VAE on CUB dataset with the *pretrained and fixed* embedder
  - with/without the learned prior
  - with/without class attributes in VAE/in Classifier
- CL “validation” pipeline from A-GEM paper, trying different optimizers, trying model reinits, tweaking architectures, moving workflow into slurm, some metrics (LCA, forgetting speed) from A-GEM paper, fixing several bugs

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- It feels hard to manipulate images to generate sensible unseen images
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Idea #2: let's just use features from Classifier

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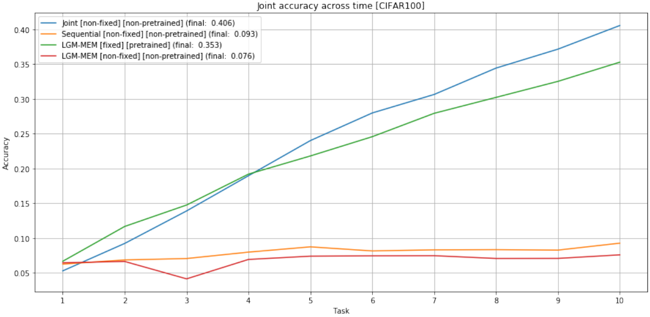

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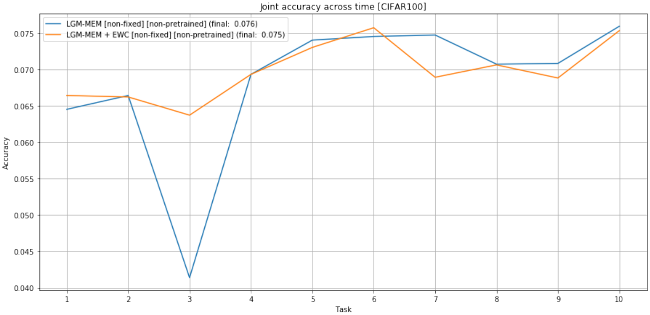

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  - because of that it will not be possible to use it in modern CL setups without task identity or task bounds
- Its performance will depend a lot on EWC performance

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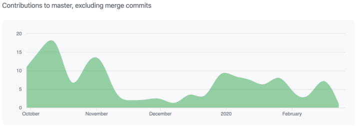

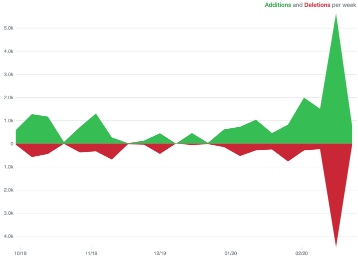

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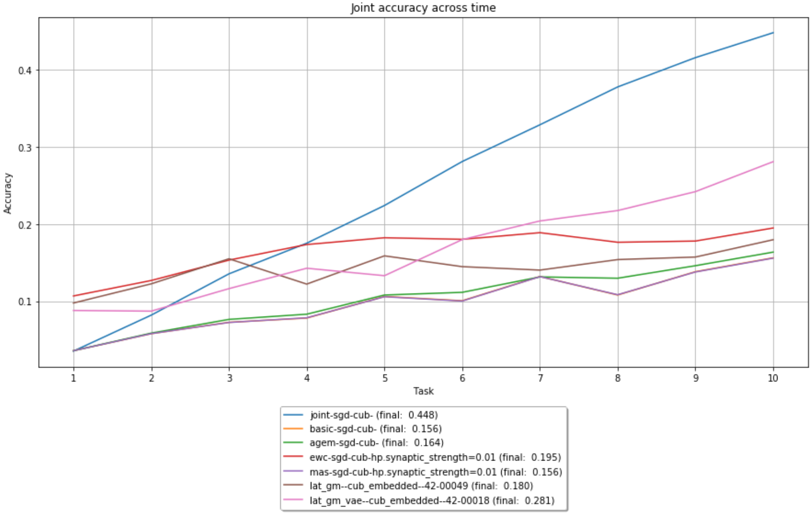
- Some small things: CL setup from ICCV19 paper (i.e. a large first task and small subsequent tasks), task transfer metric, etc.
  - Result: 37% final joint accuracy on CUB (ICCV19 paper has 53%, but they do a lot of "cheating")

LGM-GAN vs LGM-VAE



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Justification 2: Joint classification score was only 31% for CIFAR100 in Deep InfoMax paper (but their latent code size was smaller (64 dim), which improves classification).

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    - Result: described on the previous slide.
  - Training AutoEncoder continually to check its LLL properties
    - Result: it does not forget previous data (it is interesting)

AutoEncoder does not forget previous data

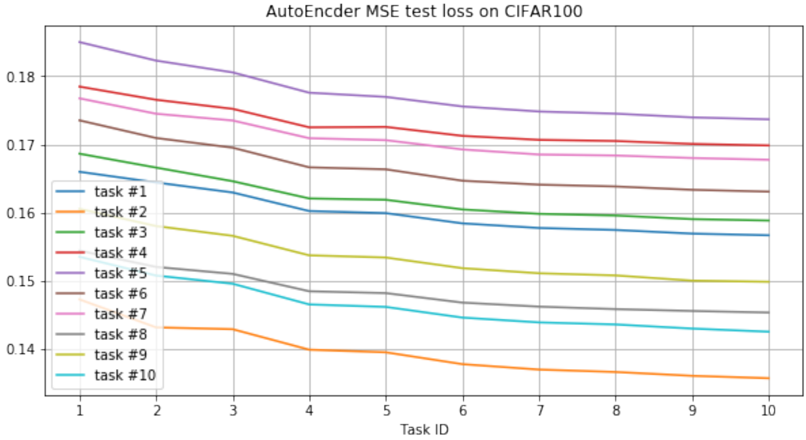

Figure: MSE loss on different tasks for AutoEncoder trained sequentially

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Honestly, there were problems in the paper and how the authors behaved:

- Their approach is cumbersome
- They are not clear about some important details
- They try to conceal their research (do not provide the code, do not respond to emails)

That's why I was unconsciously looking for reasons to drop their baseline:

- I think the way the authors do the research is not the way research should be done
- That's why I didn't want to build upon their work (why should we build upon it and spread it if the authors are hiding it?)

Conclusion

To build a good LGM one needs to solve 2 big problems:

- How to build a good feature extractor, i.e. a feature extractor that provides good features for a classifier.
- How to make its features not to drift away

And currently I do not have any concrete ideas to any of these problems.

Some thoughts:

- I do not want to drop the project because it feels like throwing away a 5-month work.
- But I do not see a concrete and principled idea of how to build LGM.
- Current LGM is already too cumbersome and I believe that cumbersome ideas do not survive unless they have outstanding results (like Mask R-CNN)