Continual Zero-Shot Learning

Ivan Skorokhodov

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  - Example 2: a classification model is learning datasets one by one: we do not want its performance on previously learned datasets to decrease.

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- Component-based ([5], [3], etc): divide your network into components, and let future tasks not to break components which are important for previous tasks.

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- Using the knowledge about how inputs and attributes correspond to each other we can detect birds that we have not seen before just based on their class description a_c.

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  - Currently performs better than embedding-based approaches

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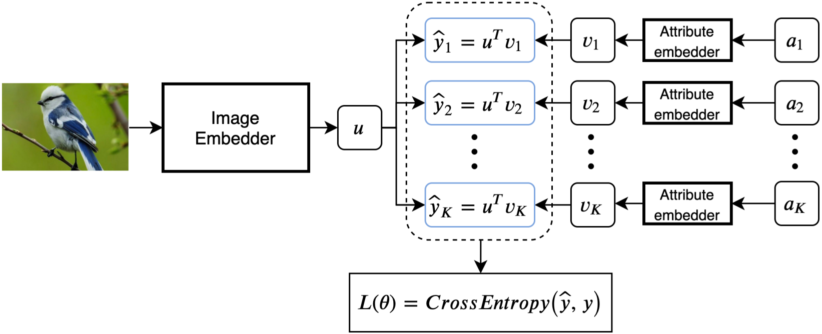
- I.e. build a *zero-shot* model that is trained in a *continual learning* fashion
- Semantic guidance should help to alleviate forgetting without additional regularization and tricks

Model overview



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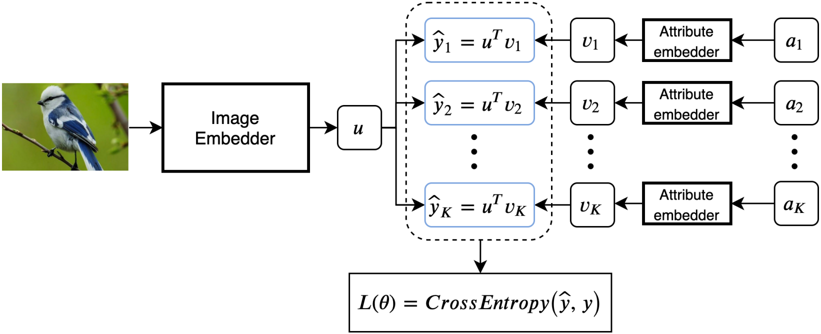

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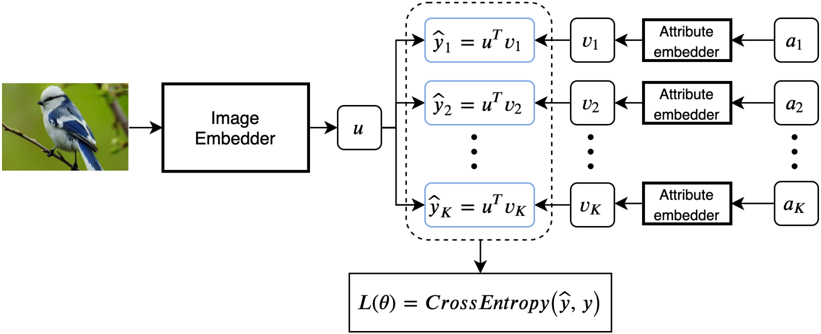

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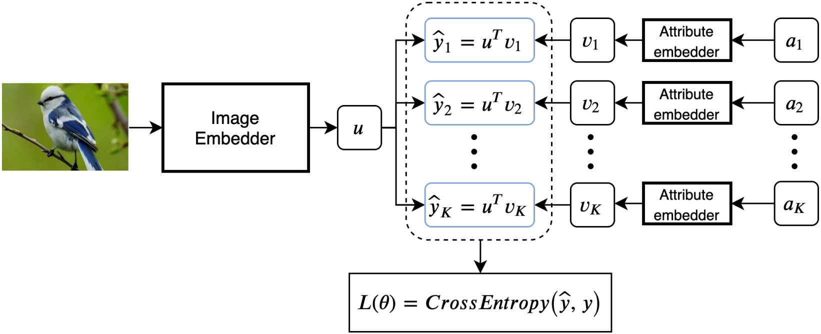

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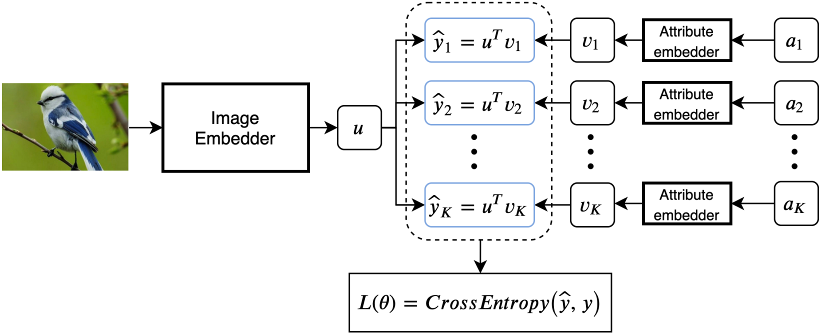

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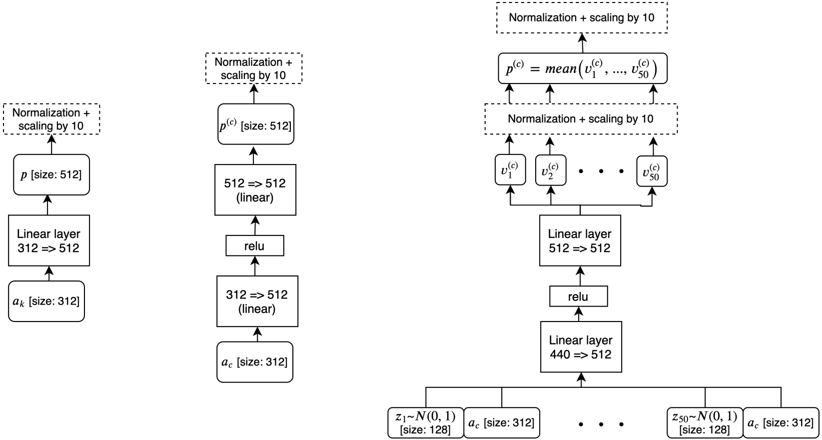
- We want the distance $d(u, v)$ to be low for proper pairs x, a and large for improper ones.

Trying different attribute embedders



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What else to try?

- Initializations?
- Residual connections?

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  - This means that the generator works just by adding a bit of noise to our prototypes.

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  - But then we have

$$p_k = \mathbb{E}_z [G(z, a_k)] = \mathbb{E}_z [W_z z + W_a a_k] = 0 + W_a a_k = W_a a_k$$

  - This means that the generator works just by adding a bit of noise to our prototypes.
- Does it mean that using a linear generator is not sensible?
- If so, can we fix that without introducing new layers (since it works worse)?

Question 3: what is the simplest generative model?

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- Our image embedder outputs feature vectors

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- Our image embedder outputs feature vectors
- We want to fit this distribution, but based on class attributes, so to have
  - We can't store mean/covariances of the past task since our feature extractor is changing over time

References

- Rahaf Aljundi et al. "Memory Aware Synapses: Learning what (not) to forget". In: *CoRR* abs/1711.09601 (2017).
- Arslan Chaudhry et al. "Efficient Lifelong Learning with A-GEM". In: *International Conference on Learning Representations*. 2019.
- Chrisantha Fernando et al. "PathNet: Evolution Channels Gradient Descent in Super Neural Networks". In: *CoRR* abs/1701.08734 (2017).
- James Kirkpatrick et al. "Overcoming catastrophic forgetting in neural networks". In: *Proceedings of the National Academy of Sciences* 114.13 (2017), pp. 3521–3526.
- Joan Serra et al. "Overcoming Catastrophic Forgetting with Hard Attention to the Task". In: *ICML*. Vol. 80. Proceedings of Machine Learning Research. PMLR, Oct. 2018, pp. 4548–4557.
- Chenshen Wu et al. "Memory Replay GANs: Learning to Generate New Categories without Forgetting". In: *Advances in Neural Information Processing Systems 31*. Curran Associates, Inc., 2018, pp. 5962–5972.