Continual Zero-Shot Learning

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  - Example 1: a robot that travels the world and learn new skills. We want it not to forget previous skills while he is acquiring new ones.
  - 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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- Rehearsal-based ([2], [6], etc): store a part of previous data to replay it in the future.
- 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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- At test time we evaluate model performance on unseen dataset D^u
- 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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  - Challenges: how to train a good conditional generative model?
  - Currently performs better than embedding-based approaches

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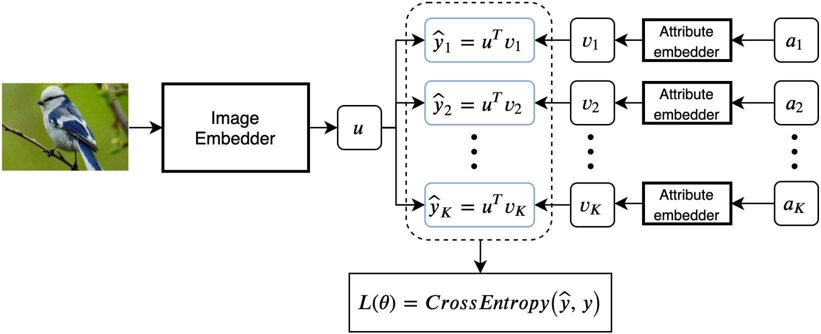
- I.e. build a *zero-shot* model that is trained in a *continual learning* fashion
- Semantic guidance should help to alleviate forgetting without additional regularization and tricks

Baseline model



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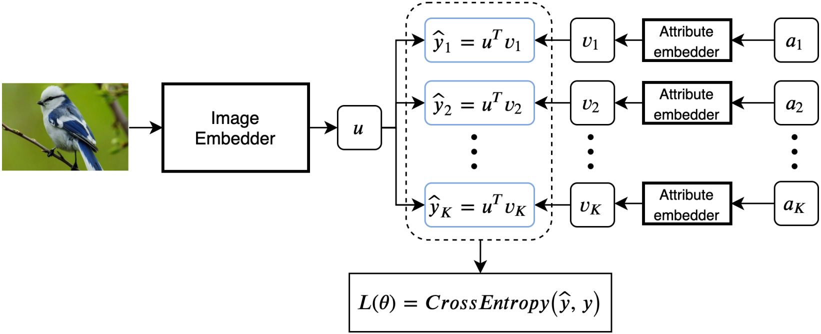

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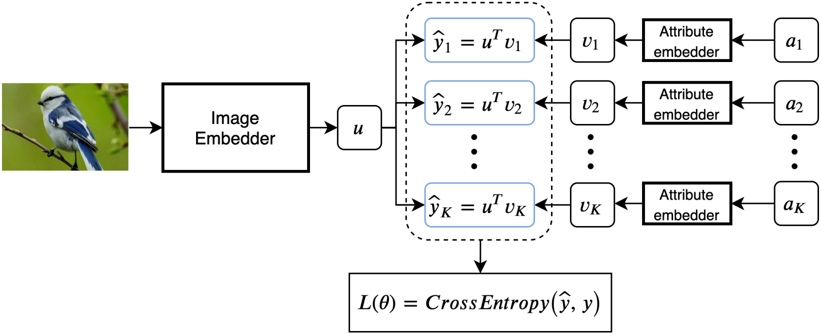

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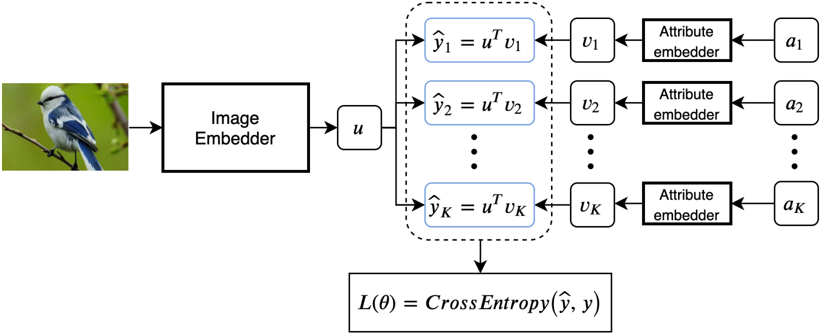

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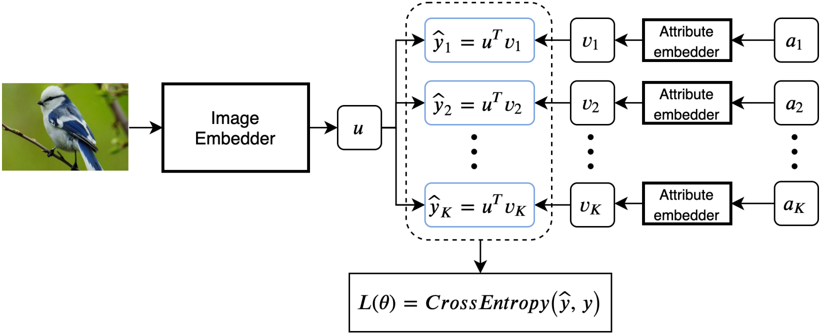

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- Image embedder produces $u = f_\theta(x)$
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- We want the distance $d(u, v)$ to be low for proper pairs x, a and large for improper ones.

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3. (2) is a special case of $(u - \mu_c)^\top V_c (u - \mu_c)$ (Maholonobis distance squared)
4. (3) is a part of gaussian log-density $\mathcal{N}(u|\mu_c, \Sigma_c)$

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- This gives us a way to do log-likelihood maximization for $P(y_c|u)$
- The only change is that we now compute logits as $\log \mathcal{N}(u|\mu_c, \Sigma_c)$:

$$\log p(u|y_c) = \log \left[(2\pi)^{-\frac{k}{2}} \det(\Sigma_c)^{-\frac{1}{2}} e^{-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu}_c)^\top \boldsymbol{\Sigma}_c^{-1}(\mathbf{x}-\boldsymbol{\mu}_c)} \right]$$

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[1]Values taken from tqdm measurements on a single preliminary experiment

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- Solution: let's output Σ_c^{-1} directly as LL^T (Cholesky decomposition) and use the identity $\det \Sigma_c = 1/\det(\Sigma_c^{-1})$.

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- A problem: in density computation for $\mathcal{N}(u|\mu_c, \Sigma_c)$ we need to compute $\det \Sigma_c$ and Σ_c^{-1}.
- Solution: let's output Σ_c^{-1} directly as LL^T (Cholesky decomposition) and use the identity $\det \Sigma_c = 1/\det(\Sigma_c^{-1})$.
- In clock-wall time, GMM vs baseline works 15% slower on CUB and 0% slower on AwA[1].

[1]Values taken from tqdm measurements on a single preliminary experiment

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Additional benefit: we now have a principled generative model since our loss encourages discriminative training for $f(x)$ and generative training for $g(a)$ at the same time.

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For each attribute a_c predict 4 things:

- mean vector $\mu_c = W_\mu a_c$ of size n
- covariance diagonal $\sigma_c = W_\sigma a_c$ of size n
- covariance left matrix $A_c = \mathbb{W}_A a_c$ of size $n \times r$ (we set $r = 5$)
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Now we can compute inverse covariance:

$$L_c^{-1} = \text{tril}(A_c \times B_c) + \text{Diag}(\sigma_c),$$

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Using μ_c and Σ^{-1} we can now compute $\mathcal{N}(u|\mu_c, \Sigma_c)$ in a fast way.

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  - Use the same hyperparameters grid for both models
- Metrics: accuracy on seen, accuracy on unseen, harmonic mean, AUSUC, forgetting, etc.

The problem

The problem is that it does not quite work in practice...

- Baseline model has normalize+scale trick which is *crucial* to achieve good performance
- However, for the GMM this trick is not applicable
- How can we do normalize+scale for the GMM?

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