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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- 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

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  - Problem #2: Attributes do not have optimal “discriminative” power

References

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