Continual learning with Hypernetworks

January 9, 2020

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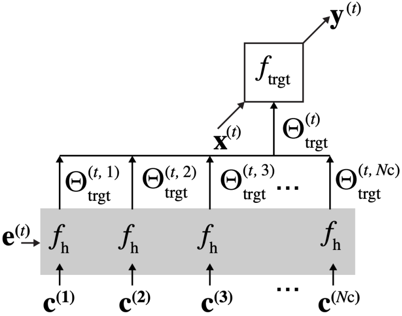
- A meta-model can have less parameters than a target model!
- A good way to reduce number of parameters for a meta-model is to condition it on a layer embedding.



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- θ_{old} — parameters snapshot before starting to learn the current task.

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- Check which task embedding gives the lowest entropy;
- Train a generative memory model and be ready to classify without task identity (in a multi-headed variant);
- Train a generative memory and a model that predicts task identity by an input (in a single-headed variant).

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- They compare the approach to EWC, SI and DGR (these are from 2017), beat them and claim SotA.
- A drawback of the approach is the necessity to recompute parameters for all the previous target models on each iteration.