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### A Base for Any Order Gradient Estimation in Stochastic Computation Graphs

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#### Applications of higher order gradients in reinforcement learning and meta-learning

Estimating higher order gradients accurately and efficiently

**Computer Science > Artificial Intelligence** 

#### Learning with Opponent-Learning Awareness

Jakob N. Foerster, Richard Y. Chen, Maruan Al-Shedivat, Shimon Whiteson, Pieter Abbeel, Igor Mordatch (Submitted on 13 Sep 2017 (v1), last revised 19 Sep 2018 (this version, v4))

Computer Science > Machine Learning

#### Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks

Chelsea Finn, Pieter Abbeel, Sergey Levine

(Submitted on 9 Mar 2017 (v1), last revised 18 Jul 2017 (this version, v3))

Computer Science > Machine Learning

DiCE: The Infinitely Differentiable Monte-Carlo Estimator

Jakob Foerster, Gregory Farquhar, Maruan Al-Shedivat, Tim Rocktäschel, Eric P. Xing, Shimon Whiteson

(Submitted on 14 Feb 2018 (v1), last revised 19 Sep 2018 (this version, v3))

Computer Science > Machine Learning

## Continuous Adaptation via Meta-Learning in Nonstationary and Competitive Environments

Maruan Al-Shedivat, Trapit Bansal, Yuri Burda, Ilya Sutskever, Igor Mordatch, Pieter Abbeel

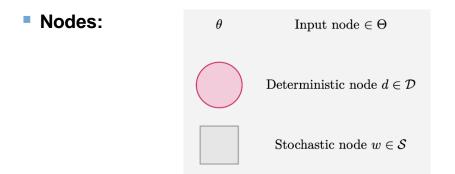
(Submitted on 10 Oct 2017 (v1), last revised 23 Feb 2018 (this version, v2))

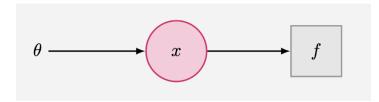


2



#### Stochastic Computation Graphs (Schulman et al., 2015)





Objective function:

$$\mathcal{L} = \mathbb{E}\left[\sum_{c \in \mathcal{C}} c\right]$$

- First Order Gradient
  - Score function estimator
- Higher Order Gradient?



#### DiCE: The Infinitely Differentiable Monte Carlo Estimator (Foerster et al., 2018b)

- The magic box operator: for a set of stochastic nodes
  - 1.  $\Box(\mathcal{W}) \rightarrow 1$ ,
  - 2.  $\nabla_{\theta} \square(\mathcal{W}) = \square(\mathcal{W}) \sum_{w \in \mathcal{W}} \nabla_{\theta} \log p(w; \theta).$
- DiCE objective function



$$\mathcal{L} = \mathbb{E}\left[\sum_{c \in \mathcal{C}} c\right] \qquad \qquad \mathcal{L} = \sum_{c \in \mathcal{C}} \mathbb{C}(\mathcal{S}_c) c \qquad \qquad \mathbb{E}\left[\nabla_{\theta}^n \mathcal{L} \right] \rightarrowtail \nabla_{\theta}^n \mathcal{L}$$
$$\mathcal{S}_c = \{s | s \in \mathcal{S}, s \prec c, \theta \prec s\}$$

• Variance Reduction: baseline term  $\mathcal{B}_{:}$ 

$$\mathcal{L}^b_{:} = \mathcal{L}_{:} + \mathcal{B}_{:} \qquad \qquad \nabla^n_{\theta} \mathcal{L}^b ?$$





First Order Baseline (from original DiCE)

$$\mathcal{B}^{(1)}_{:} = \sum_{w \in \mathcal{S}} (1 - \boxdot(\{w\})) b_w$$

Second Order Baseline

$$\mathcal{B}^{(2)}_{:} = -\sum_{w \in \mathcal{S}} \left( 1 - \mathbb{C}(\{w\}) \right) \left( 1 - \mathbb{C}(\mathcal{S}_w) \right) b_w$$

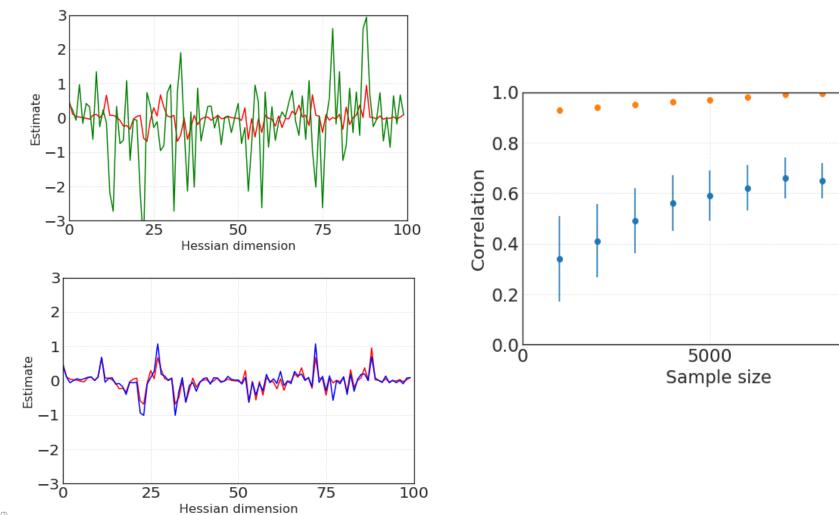
Higher Order Baseline

$$\mathcal{B}_{:} = \mathcal{B}_{:}^{(1)} + \mathcal{B}_{:}^{(2)}$$

$$= \sum_{w \in \mathcal{S}} b_w \left( 1 - \mathbb{C}(\{w\}) \right) \cdot \mathbb{C}(\mathcal{S}_w) \qquad \mathbb{E} \left[ \nabla_{\theta}^2 \mathcal{L}_{:}^b \right] \rightarrow \nabla_{\theta}^2 \mathbb{E} \left[ \mathcal{L} \right]$$



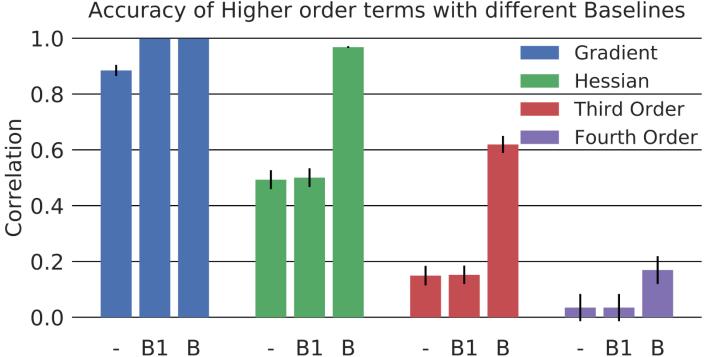
#### **First and Second Order Baselines**



10000



#### **Higher Order Baselines**



#### Accuracy of Higher order terms with different Baselines



#### Learning with Opponent Learning Awareness – DiCE (Foerster et al., 2018b)

$$\mathcal{L}^{1}(\theta_{1},\theta_{2})_{\text{LOLA}} = \mathbb{E}_{\pi_{\theta_{1}},\pi_{\theta_{2}}+\Delta\theta_{2}(\theta_{1},\theta_{2})} [\sum_{t=0}^{T} \gamma^{t} r_{t}^{1}]$$

$$\Delta\theta_{2}(\theta_{1},\theta_{2}) = \alpha_{2} \nabla_{\theta_{2}} \mathbb{E}_{\pi_{\theta_{1}},\pi_{\theta_{2}}} [\sum_{t=0}^{T} \gamma^{t} r_{t}^{2}]$$

$$\int_{-1.6}^{-1.2} \frac{W/2 \text{nd order baseline}}{Wo 2 \text{nd order baseline}} \int_{-1.6}^{-1.6} \frac{W/2 \text{nd order baseline}}{W_{0} 2 \text{nd order baseline}} \int_{-1.6}^{-1.6} \frac{W/2 \text{nd order baseline}}{W_{0} 2 \text{nd order baseline}} \int_{-1.6}^{-1.6} \frac{W/2 \text{nd order baseline}}{W_{0} 2 \text{nd order baseline}} \int_{-1.6}^{-1.6} \frac{W/2 \text{nd order baseline}}{W_{0} 2 \text{nd order baseline}} \int_{-1.8}^{-1.2} \frac{W/2 \text{nd order baseline}}{W_{0} 2 \text{nd order baseline}} \int_{-1.6}^{-1.6} \frac{W/2 \text{nd order baseline}}{W_{0} 2 \text{nd order baseline}} \int_{-1.8}^{-1.6} \frac{W/2 \text{nd order baseline}}{W_{0} 2 \text{nd order baseline}} \int_{-1.8}^{-1.6} \frac{W/2 \text{nd order baseline}}{W_{0} 2 \text{nd order baseline}} \int_{-1.8}^{-1.6} \frac{W/2 \text{nd order baseline}}{W_{0} 2 \text{nd order baseline}} \int_{-1.8}^{-1.6} \frac{W/2 \text{nd order baseline}}{W_{0} 2 \text{nd order baseline}} \int_{-1.8}^{-1.6} \frac{W/2 \text{nd order baseline}}{W_{0} 2 \text{nd order baseline}} \int_{-1.8}^{-1.6} \frac{W/2 \text{nd order baseline}}{W_{0} 2 \text{nd order baseline}} \int_{-1.8}^{-1.6} \frac{W/2 \text{nd order baseline}}{W_{0} 2 \text{nd order baseline}} \int_{-1.8}^{-1.6} \frac{W/2 \text{nd order baseline}}{W_{0} 2 \text{nd order baseline}} \int_{-1.8}^{-1.6} \frac{W/2 \text{nd order baseline}}{W_{0} 2 \text{nd order baseline}} \int_{-1.8}^{-1.6} \frac{W/2 \text{nd order baseline}}{W_{0} 2 \text{nd order baseline}} \int_{-1.8}^{-1.6} \frac{W/2 \text{nd order baseline}}{W_{0} 2 \text{nd order baseline}} \int_{-1.8}^{-1.6} \frac{W/2 \text{nd order baseline}}{W_{0} 2 \text{nd order baseline}} \int_{-1.8}^{-1.6} \frac{W/2 \text{nd order baseline}}{W_{0} 2 \text{nd order baseline}} \int_{-1.8}^{-1.6} \frac{W/2 \text{nd order baseline}}{W_{0} 2 \text{nd order baseline}} \int_{-1.8}^{-1.6} \frac{W/2 \text{nd order baseline}}{W_{0} 2 \text{nd order baseline}} \int_{-1.8}^{-1.6} \frac{W/2 \text{nd order baseline}}{W_{0} 2 \text{nd order baseline}} \int_{-1.8}^{-1.6} \frac{W/2 \text{nd order baseline}}{W_{0} 2 \text{nd order baseline}} \int_{-1.8}^{-1.6} \frac{W/2 \text{nd order baseline}}{W_{0} 2 \text{nd orde$$

200

400

Iterations

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600



- A baseline for efficient estimations of higher order gradients using DiCE formalism
- Examples:
  - Gradient estimations up to 4<sup>th</sup> order
  - LOLA-DiCE with 2<sup>nd</sup> order baseline
- Future work
  - Extending the framework to a base-generating term for any order gradient estimators
  - Further applications in RL and meta-learning



- Al-Shedivat, M., Bansal, T., Burda, Y., Sutskever, I., Mordatch, I., and Abbeel, P. Continuous adaptation via metalearning in nonstationary and competitive environments. *CoRR*, abs/1710.03641, 2017.
- Finn, C., Abbeel, P., and Levine, S. Model-agnostic meta-learning for fast adaptation of deep networks. In Proceedings of the 34th International Conference on Machine Learning, ICML 2017, pp. 1126–1135, 2017.
- Foerster, J., Chen, R. Y., Al-Shedivat, M., Whiteson, S., Abbeel, P., and Mordatch, I. Learning with opponentlearning awareness. In *Proceedings of the 17th International Conference on Autonomous Agents and Multi-Agent Systems*, pp. 122–130. International Foundation for Autonomous Agents and Multiagent Systems, 2018a.
- Foerster, J., Farquhar, G., Al-Shedivat, M., Rocktäschel, T., Xing, E., and Whiteson, S. Dice: The infinitely differentiable monte carlo estimator. In *Proceedings of the 35th International Conference on Machine Learning*, volume 80 of *Proceedings of Machine Learning Research*, pp. 1524–1533, Stockholmsmssan, Stockholm Sweden, 10–15 Jul 2018b. PMLR. URL http://proceedings.mlr. press/v80/foerster18a.html.
- Schulman, J., Heess, N., Weber, T., and Abbeel, P. Gradient estimation using stochastic computation graphs. In Advances in Neural Information Processing Systems 28: Annual Conference on Neural Information Processing Systems, pp. 3528–3536, 2015.



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