Using Bifurcations for Diversity in Differentiable Games

Beyond First-order Methods in ML Workshop, ICML 2021

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Introduction

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- Differentiable games generalize single-objective minimization:

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- Games are increasingly important in ML ex., GANs, hyperparam opt., self-play, meta-learning, adversarial examples, numerous others.
- **Goal:** Want to find diverse solutions in differentiable games ex., where players work together or battle each-other.

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- Bifurcations are areas where small changes cause solution differences. Saddles are a key bifurcation in conservative systems from following gradients.
- Following gradients in games is a non-conservative system, so more solution and bifurcation types.
- Because, Hessian's generalization for games i.e., the Game Hessian – may have complex EVals from lack of symmetry.

$$\widehat{\mathcal{H}} = \begin{bmatrix} \mathsf{Player} \ A \ \mathsf{Hessian} \nabla^2_{\theta_A} \mathcal{L}_A & \nabla_{\theta_A} \nabla_{\theta_B} \mathcal{L}_A \\ \nabla_{\theta_B} \nabla_{\theta_A} \mathcal{L}_B^\top & \mathsf{Player} \ B \ \mathsf{Hessian} \nabla^2_{\theta_B} \mathcal{L}_B \end{bmatrix}$$

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- Complex EVals may have EVecs with complex entries. We use an EVec selection for conjugate pairs that has all real entries, so we can follow it.
- We detect and allow for branching at new types of bifurcations ex., Hopf where $\approx \Re$ EVal crosses 0.
- We apply an arbitrary optimization algorithm after branching.



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New Toy Problems



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- Matching Pennies is a 2 param. rock-paper-scissors with imaginary EVals, but only 1 solution.
- Mixing these gives a 2 param. problem like the full IPD with multiple solutions, complex EVals, and a Hopf bifurcation.

Applying our Method on Toy Problems



 For both the small IPD (left) and mixed objective (right) our method – Game Ridge Rider (GRR) – finds all solutions.

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Search Strategy	Cooperate	Defect
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• Randomly initializing then applying a training method only finds 1 solution mode.

Finding Diverse Solutions in the Iterated Prisoners Dilemma

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- Randomly initializing then applying a training method only finds 1 solution mode.
- Our method finds both solution modes.
- If we don't start at a saddle, then branching doesn't affect the solution.

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- We can view methods for diverse solutions in single-objective minimization – i.e., Ridge Rider (RR) – as finding bifurcations in conservative systems and branching.
- This viewpoint allows usage of tools from dynamical systems to generalize RR to non-conservative systems.

Thanks!

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Luke Metz





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References

[1] Jack Parker-Holder, Luke Metz, Cinjon Resnick, Hengyuan Hu, Adam Lerer, Alistair Letcher, Alexander Peysakhovich, Aldo Pacchiano, and Jakob Foerster. Ridge rider: Finding diverse solutions by following eigenvectors of the hessian. In Advances in Neural Information Processing Systems, volume 33, pages 753–765, 2020.

[2] Jakob Foerster, Richard Y Chen, Maruan Al-Shedivat, Shimon Whiteson, Pieter Abbeel, and Igor Mordatch. Learning with opponent-learning awareness. In *International Conference on Autonomous Agents and MultiAgent Systems*, pages 122–130, 2018.



Proposed Algorithm

• Check out the paper for more details.

Algorithm 1 Game Ridge Rider (GRR)-red modifications

- 1: Input: ω^{Saddle} , α , ChooseFromArchive, GetRidges,
- 2: EndRide, Optimize, UpdateRidge
- 3: $\mathcal{A} = \text{GetRidges}(\boldsymbol{\omega}^{\mathsf{Saddle}}) \quad \# \mathsf{Init. Archive}$
- 4: while Archive \mathcal{A} non-empty do
- 5: $j, \mathcal{A} = \text{ChooseFromArchive}(\mathcal{A})$

6:
$$(\boldsymbol{\omega}^j, \boldsymbol{e}_j, \lambda_j) = \mathcal{A}_j$$

- 7: while $\operatorname{EndRide}(\omega^j, e_j, \lambda_j)$ not True do
- 8: $\omega^i \leftarrow \omega^j \alpha e_j$ # Step along the ridge e_j

9:
$$e_j, \lambda_j = \text{UpdateRidge}(\omega^j, e_j, \lambda_j)$$

- 10: $\omega^j = \text{Optimize}(\omega^j)$
- 11: $\mathcal{A} = \mathcal{A} \cup \operatorname{GetRidges}(\omega^j) \# \operatorname{Add} \operatorname{new} \operatorname{ridges}$