

Refactoring Policy for Compositional Generalizability using Self-Supervised Object Proposals

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Compositional Generalization

Generalize?



Challenges of Classical RL



Optimization Challenge

Training environments

Neural Network

Challenges of Classical RL



Generalization Challenge

Neural Network Test environments

Refactorization



Demonstration Acquisition without Generalizability Concerns

Refactorization



Strong inductive bias for generalization

Refactorize Demonstration into Compositional Generalizable Policy

Object-centric Policy



Strong inductive bias: Object-centric Scene Graph

Experiments

- Flexible number of objects
- Random object arrangement
- Composition of foreground/background



Multi-MNIST



FallingDigit



BigFish

Multi-MNIST

Object-centric graph can be a strong inductive bias for compositional generalizability



Training Set

Test Set

Method	Train Acc	Test Acc
CNN	90.5(2.9)	12.0(2.1)
Relation Net	96.4(0.8)	8.4(4.7)
Ours	80.2(0.2)	51.2(1.2)

FallingDigit

The student network with object-centric graph inductive bias can refactorize the teacher policy into a compositional generalizable policy



Train on 3 digits





CNN-based RL policy fails to generalize to 9 digits

GNN-based refactorized policy generalizes to 9 digits

BigFish

More robust to different composition of foreground and background





Training Environments

Test Environments

Conclusion

- Refactorization through a proper student network with strong inductive bias can ease optimization and achieve compositional generalizability.
- In difficult environments with sophisticated reasoning, long-range interaction, or unfamiliar background, GNN-based student policy shows stronger performance and robustness.
- We implement an effective object-centric policy learning framework with an improved self-supervised object detector.

Thank you!