

# Can AI Learn to Play like a Pro?: A Case Study on using Transformers for StarCraft II



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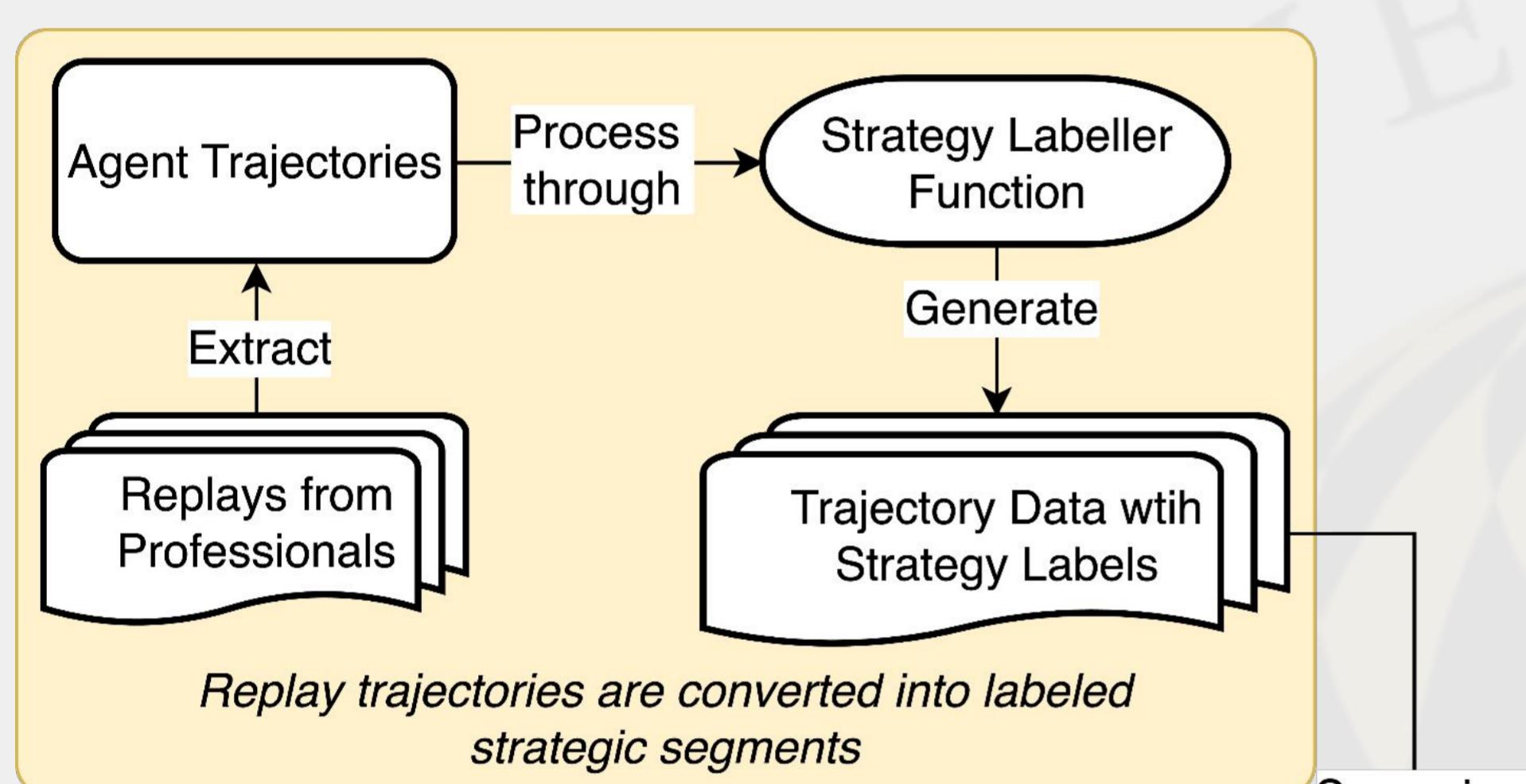
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## MOTIVATION

- **SMAC<sup>[1]</sup>**: Standard benchmark for **MARL**
- Most SMAC approaches relies on **synthetic self-play data**
- Pro SC2Replays → **shows human-led coordination**
- However, data **only contains agent trajectory**
- **Strategy is implicit**
- **No existing approach infers or exploits this strategy from data**

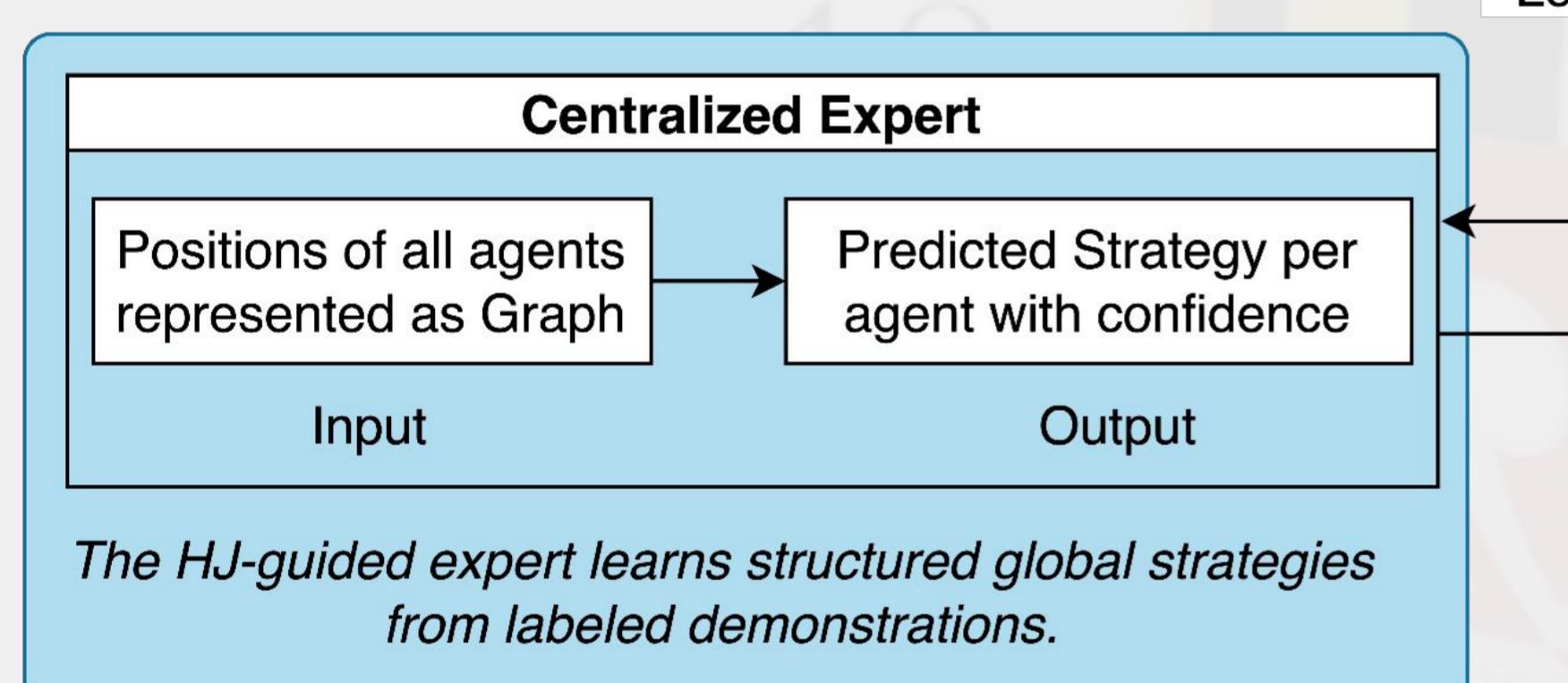


StarCraft II Gameplay



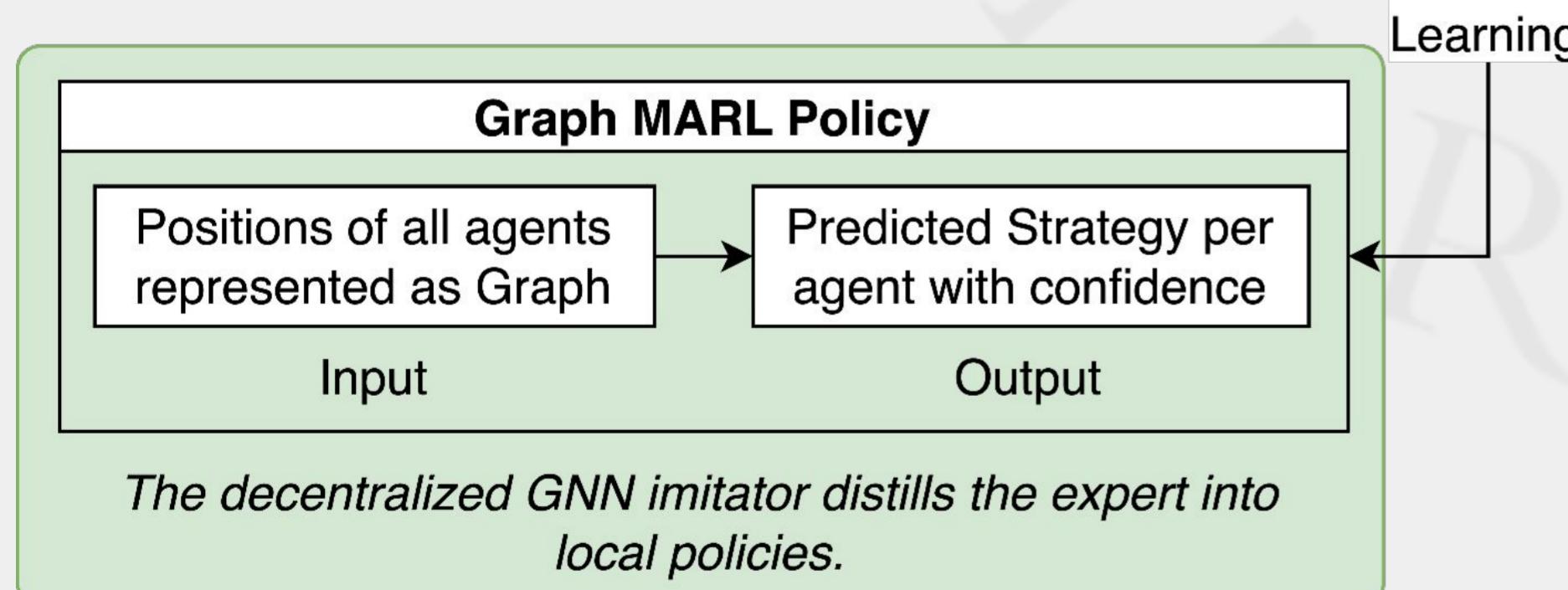
## STRATEGY INFERENCE

- Decomposes global state **local 1v1 and 2v1 subgames**
- Matches observed agent actions against **pre-computed HJ-optimal templates**
- Assigns **strategy label** with **confidence** based on action similarity
- Smooths labels temporally to form consistent strategic segments



## POLICY LEARNING

- Distribution over **strategy modes**, not actions
- **Structured teacher**, not a deployable controller



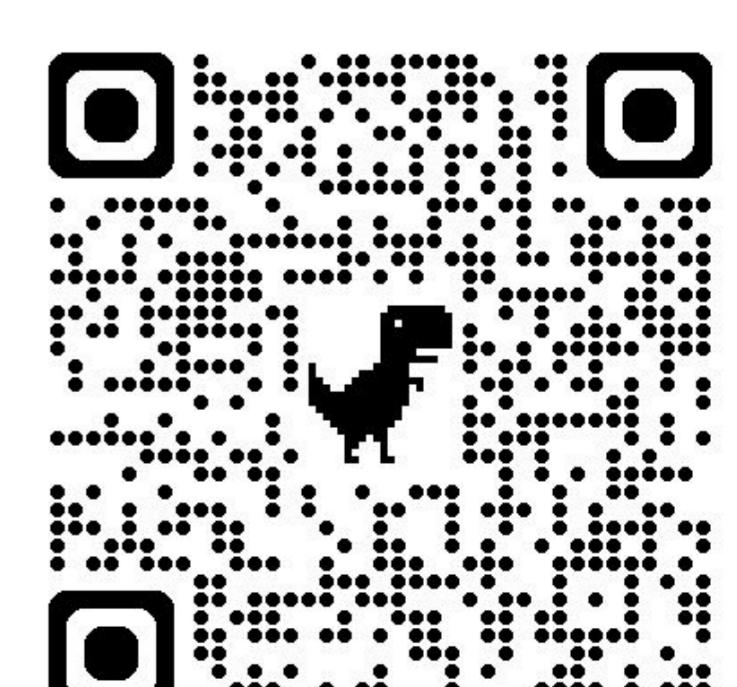
## DECENTRALIZATION

- Agent observes local neighborhood state only
- Learns to predict **strategy-conditioned decisions**
- Preserves coordination through message passing

## EVALUATION PLAN & EXPECTED RESULTS

- Evaluated using representative SMAC scenarios
- Performance metrics:
  - **Win Rate**: Expected to be higher than typical MARL training
  - **Robustness and Generalization**: One model for multiple scenarios
  - **Sample Efficiency and Training Stability**: Benefits of imitation learning

QR FOR CONTACT INFO AND REFERENCES



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