Open and Real-World Human-AI Coordination by Heterogeneous Training with Communication

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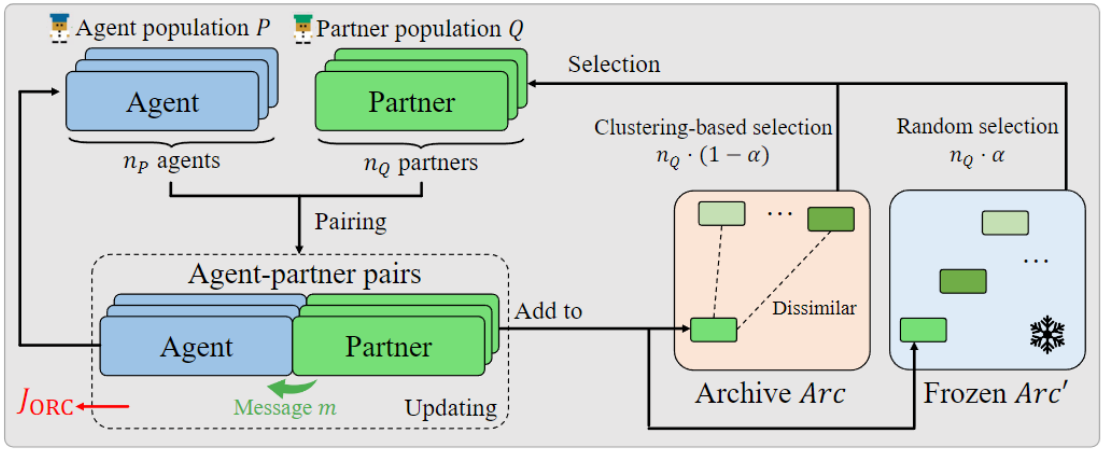
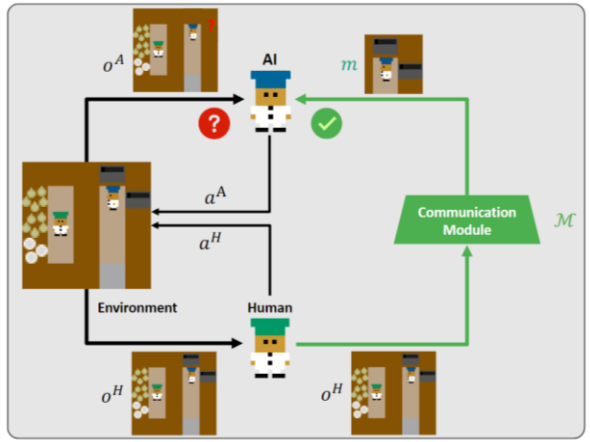
Problems & Ideas

- Human-AI coordination aims to develop AI agents capable of effectively coordinating with human partners.
  - Recent studies have shown promising advancements in open-world settings, but usually assume an overly idealistic scenario by assuming homogeneity between the agent and the partner, which deviates from real-world conditions.





Heterogeneous training with Communication (HeteC) for ORC. HeteC builds upon a heterogeneous training framework and enhances partner population diversity by using mixed partner training and frozen historical partners. Additionally, HeteC incorporates a communication module that enables human partners to communicate with AI agents, mitigating the adverse effects of partially observable environments.

Main Contributions

- Contributions:
  - We formulate the open and real-world human-AI coordination (ORC) problem, which aims is to train an agent that can effectively coordinate with unseen and heterogeneous human partners;
  - We introduce ORCBench, a benchmark specifically designed for ORC. ORCBench includes various environments and algorithms, where the agent and human partner have different abilities;
  - We present an efficient algorithm, HeteC, for solving ORC problems. Experimental results across different environments in ORCBench demonstrate the superior performance of HeteC.

Environment	Partner	Fully Observable		Mask 1		Mask 2		Mask 3	
		MAZE	HeteC	MAZE	HeteC	MAZE	HeteC	MAZE	HeteC
CR	SP	**178.25±17.80**	160.375±16.01	66.5±12.72	**150.5±21.01**	112.5±26.83	**116.625±11.31**	64.5±30.68	**130.5±9.06**
	MEP	**186.75±13.54**	173.125±10.71	80.5±34.47	**182.5±16.37**	76.0±15.02	**156.99±29.68**	42.75±2.11	**170.125±29.03**
	MAZE	**217.0±10.89**	201.5±17.02	78.25±29.66	**205.875±8.45**	88.25±21.27	**206.375±17.63**	71.875±25.59	**196.375±13.24**
H-CR	SP	127.25±16.41	**140.75±17.25**	30.625±21.01	**175.375±41.31**	142.75±58.03	**156.375±23.91**	14.7±7.92	**139.125±35.62**
	MEP	**211.75±8.97**	208.625±9.73	6.0±3.45	**193.6±48.16**	213.625±13.18	**221.75±4.95**	10.275±5.77	**209.25±12.43**
	MAZE	213.925±14.61	**219.875±10.02**	5.5±2.94	**218.75±12.09**	214.375±5.74	**227.5±6.92**	54.23±46.21	**205.5±10.01**
AA	SP	183.375±23.73	**160.375±17.37**	18.675±29.15	**141.5±29.26**	113.51±31.52	**169.5±32.78**	38.0±57.31	**148.625±26.38**
	MEP	**269.625±22.31**	257.5±29.61	31.375±40.05	**248.375±44.05**	144.875±18.23	**271.85±15.55**	76.125±74.53	**235.75±17.94**
	MAZE	334.125±19.29	**365.0±6.09**	26.3±8.01	**360.25±7.89**	169.375±10.62	**356.625±8.83**	157.625±30.29	**347.5±10.07**
AA-2	SP	**128.875±28.83**	117.25±37.81	65.375±41.07	**84.3±53.83**	90.875±6.39	**97.125±57.22**	91.125±32.65	**111.0±16.32**
	MEP	190.5±13.66	**199.75±49.32**	23.5±7.23	**217.0±29.81**	97.375±17.11	**231.625±19.97**	142.25±20.94	**200.6±14.36**
	MAZE	243.75±16.72	**272.0±16.0**	26.375±4.95	**245.625±9.77**	93.5±52.84	**252.375±8.83**	225.625±11.42	**260.0±2.21**
FC	SP	99.0±16.25	**101.625±15.87**	4.625±5.65	**99.5±9.44**	5.2±6.31	**110.4±8.69**	8.025±5.24	**108.5±20.68**
	MEP	116.0±12.54	**129.3±33.01**	5.225±3.43	**108.125±32.265**	5.625±5.28	**110.75±29.97**	3.475±2.19	**107.375±18.18**
	MAZE	173.0±13.62	**185.875±5.45**	3.7±2.31	**120.375±35.85**	5.0±2.59	**185.5±9.15**	24.775±29.38	**181.375±2.21**
Average Ranking		1.6	1.4	2	1	2	1	2	1

Our method (HeteC) outperforms state-of-the-art method (MAZE) in different benchmarks under different settings.