Multi-Task Optimization over Networks of Tasks (MONET)

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How to Optimize a Large Number of Tasks Simultaneously in Parallel?

Multi-task optimization [1]: find the best solution for *every* task $\boldsymbol{\tau} \in \mathcal{T}$ *simultaneously*:

$$\boldsymbol{\theta}^{\star}_{\boldsymbol{\tau}} = \arg\max_{\boldsymbol{\theta} \in \Theta} f(\boldsymbol{\theta}, \boldsymbol{\tau})$$

- Knowledge transfer between related tasks can **improve** optimization (**positive transfer**), and unrelated tasks can **degrade** optimization (**negative transfer**).
- Baselines (MT-ME [2], PT-ME [3]) are *topologically flat*: task similarity is not structurally modelled for knowledge transfer.

Goal: enhance **positive transfer** by explicitly modelling connectivity between tasks.

Introducing the MONET Algorithm

MONET models the task space as a **graph**: nodes are tasks, edges define who may exchange solutions.

a) MONET Network with Evolutionary Operators b) MONET Task Network on Hexapod (morphological variations)

Figure 1. (a) Each node holds its best solution. (b) Hexapod task network: 2000 morphologies.

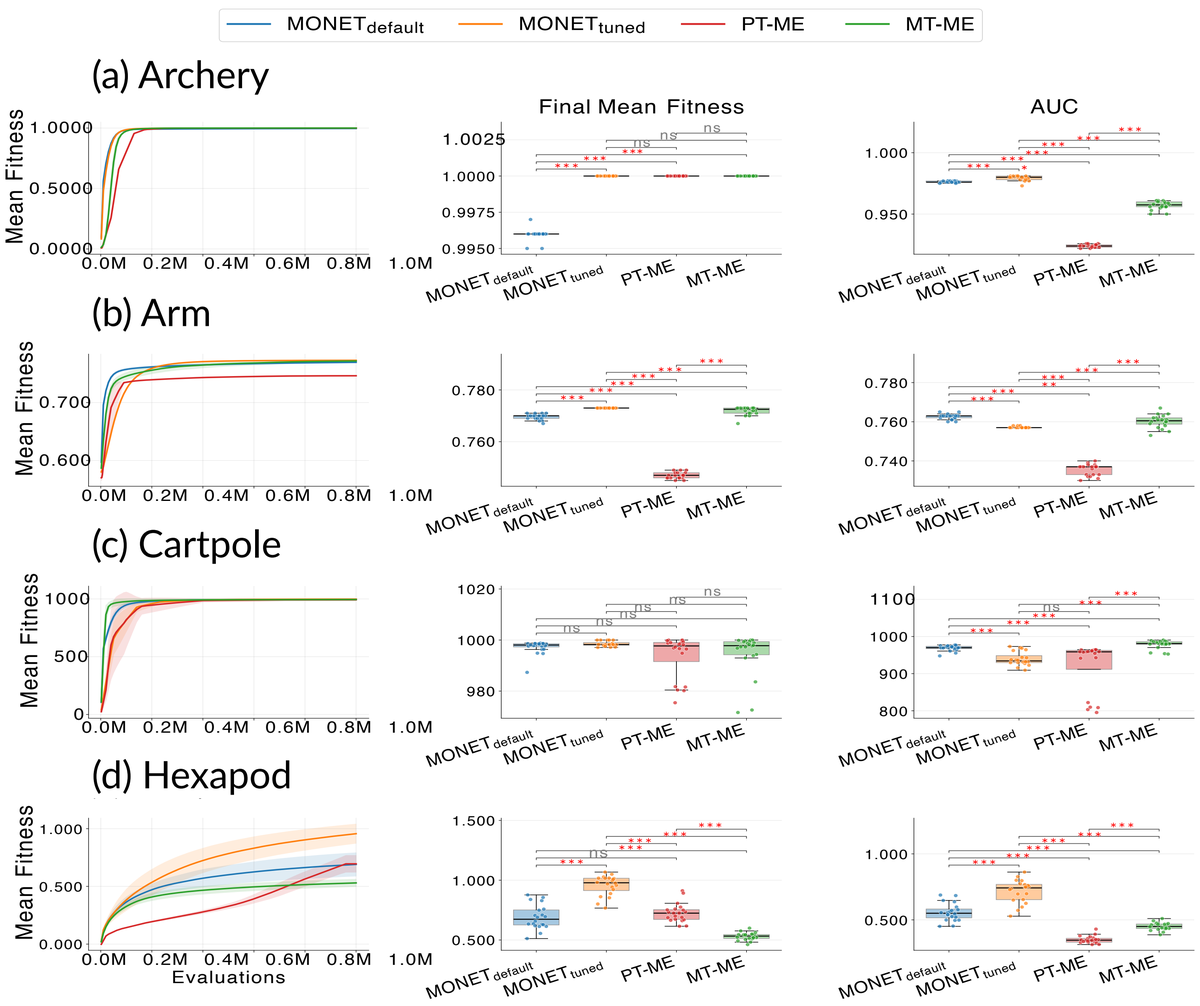
Two mechanisms:

- **Individual learning**: local mutation explores each task.
- **Social learning**: SBX [4] transfers solutions between neighbors.

Two properties:

- **Connectivity**: explicitly defined based on task similarity in the task parameter space.
- **Scalable**: the graph grows with the task set, not task-space dimensionality.

Results



Mann-Whitney U test with Holm-Bonferroni correction: $*p<0.05$, $**p<0.01$, $***p<0.001$, ns = not significant

Figure 2. MONET vs. PT-ME / MT-ME on four benchmark problems.

- Best or tied final fitness on all four domains.
- Hexapod: tuned MONET doubles MT-ME (0.96 vs 0.53).
- Fastest convergence (best AUC) on archery and arm.

Task Domains

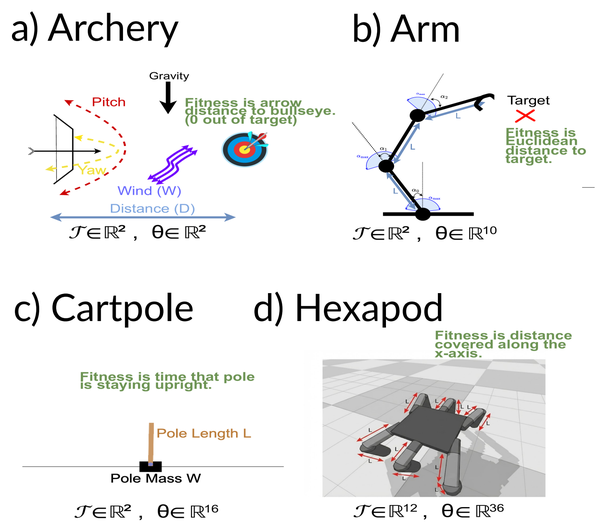


Figure 3. The four benchmark problems.

Main Takeaways

- Task network connectivity enhances optimization at scale.
- The graph controls where transfer happens.
- Largest gains on the highest-dimensional domain.

Next Steps

- What kinds of connectivity to use?
- Can we learn the connectivity?
- Can we have generalized solutions?

References

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