## Discovering Creative Behaviors through **DUPLEX**: **D**iverse **U**niversal Features for **P**olicy **Ex**ploration



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Thirty-Eighth Annual Conference on Neural Information Processing Systems (NeurIPS), 2024 <sup>†</sup>internship project while at Sony AI.

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# Superhuman but FUN?



# Superhuman and FUN

**DUPLEX** contributes to diversity learning in RL by improving on previous work to better **preserve the diversity vs. near-optimality trade-off** in highly-dynamic environments and multi-context settings.

Showing diversity and acting differently in the world is fundamental to create engaging experiences for users

#### **Context-conditioned diversity learning**

Diversity( $\Pi$ ) is a metric of dissimilarity among policies in a set  $\Pi$  with a common goal. Formally, if  $\psi_{\pi_i}$  and  $\psi_{\pi_j}$  are a function of state-occupancy of relevant features of any two policies in  $\Pi$ , then their dissimilarity is given by  $||\psi_{\pi_i} - \psi_{\pi_j}||$ . A non-zero value of this norm indicates dissimilarity, with larger values indicating greater divergence between the policies. Mathematically, diversity is defined as the sum of the minimum L2 dissimilarity norms in

Diversity(\Pi) = 
$$\frac{1}{2 \operatorname{size}(\Pi)} \cdot \sum_{\substack{\forall \pi_i, \pi_j \in \Pi, \\ i!=j}} \min ||\psi_{\pi_i} - \psi_{\pi_j}||_2^2$$

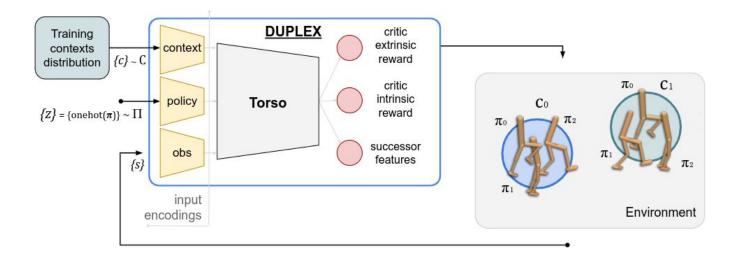
#### **Context-conditioned diversity learning**

Accordingly, we measure  $\psi$  distances to enforce **context-conditioned diversity within**  $\Pi$ . We aim at training an RL agent that, given a context *c*, discovers a set of *n* near-optimal policies by optimizing our objective function

$$\max_{\Pi} \text{ Diversity}(\Pi) \text{ s.t } d_{\pi_c} \cdot r_e \ge \rho \hat{v}_e, \quad \forall \pi_c \in \Pi$$

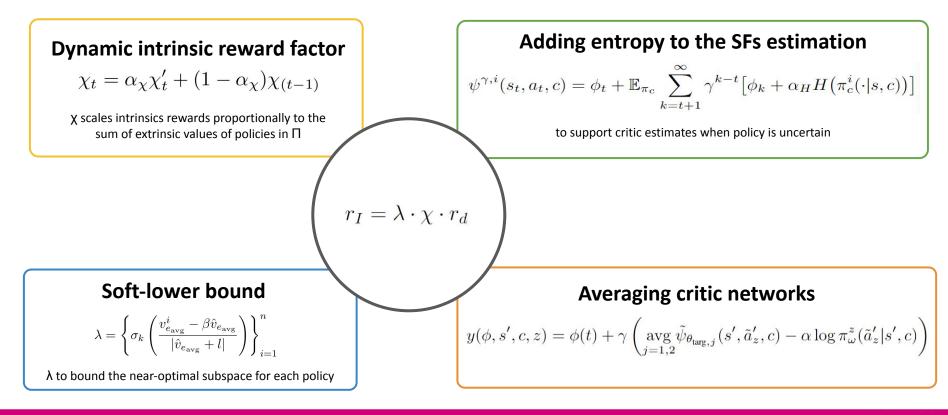
that forces the policies in  $\Pi$  to only **explore for diversity within the near-optimal region of the target value** 

#### **Data flow**



DUPLEX receives three inputs: (i) a context vector describing **task requirements** and environment dynamics; (ii) an **encoding of the policy**; (iii) and the current **state of the environment**. The critic network returns estimates for the **intrinsic and extrinsic rewards and successor features** to drive diverse behavior discovery. Finally, the algorithm samples policies in  $\Pi$  uniformly and rolls them out to collect more experience.

DUPLEX stabilizes training and achieves diverse competitive policies by introducing novel components to modulate the contribution of the intrinsics reward



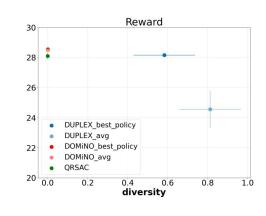
### **Results: GranTurismo<sup>™</sup> 7**

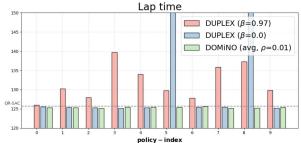
DUPLEX trains diverse competitive policies in hyper-realistic driving simulators





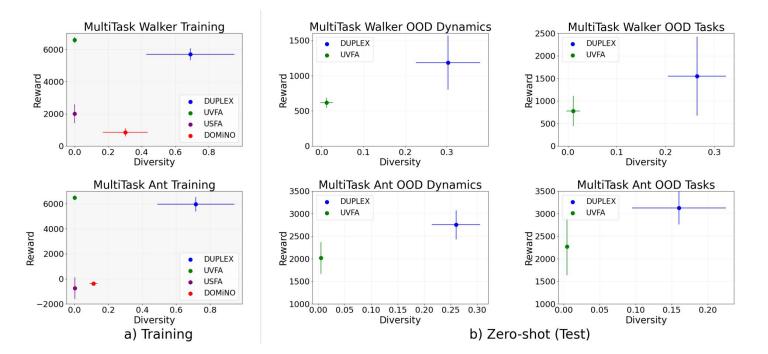
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### **Results: MuJoCo Walker2d and Ant**

DUPLEX improves the diversity vs near-optimality trade-off both within- and out-of- distribution settings



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more videos and results

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