Paper Review

**Summary:**

In this paper, the authors bring together a series of simple and efficient machine learning techniques to enable better performance while continually learning robotic manipulation tasks. They show that factors such as low dimensional representation of skill policies, careful pertaining, and optimal curriculum earning can contribute to more efficient skill-skill transfers. They use a hierarchical skill representation that is robust to catastrophic forgetting and learns new skills based on prior knowledge. To further improve the transfer of prior skills they use a minimum spanning tree formulation and obtain the optimal path for acquiring all skills sequentially.

**Strengths:**

This approach has potential within the meta-learning subcategory of few-shot learning by offering fewer training steps to learn policies in the real-world. The paper is easy to follow, and it is well-written and provides sufficient related work and citations. Leveraging the relatability of tasks to improve the speed of multi-task learning (especially in hierarchical or sequential tasks) is a great way to optimize the learning in similar problems. The suggested insight on learning the hardest task first in the given specific setting seems valuable.

**Weaknesses:**

It looks like the first DMST in Figure 3 does not always learn the hardest tasks first. More evidence is needed to strengthen the argument that skill libraries should be initialized by learning the hardest tasks first. This should at least be mentioned on top of the given hypothesis. The setting seems too simple to consider catastrophic forgetting a challenge. There does not appear to be a reference for Meta-World. It would be nice to see how this model can be applied to more complicated situations such as tasks which can be performed in parallel (2 arms for instance in context of this research paper). More research can be done on this to explore this possibility.