

## Safety Fine-Tuning

In this section, we describe our approach to safety fine-tuning, including safety categories, annotation guidelines, and the techniques we use to mitigate safety risks. We employ a process similar to the general

fine-tuning methods as described in Section 3, with some notable differences related to safety concerns. Specifically, we use the following techniques in safety fine-tuning:

1. **Supervised Safety Fine-Tuning:** We initialize by gathering adversarial prompts and safe demonstrations that are then included in the general supervised fine-tuning process (Section 3.1). This teaches

the model to align with our safety guidelines even before RLHF, and thus lays the foundation for high-quality human preference data annotation.

2. **Safety RLHF:** Subsequently, we integrate safety in the general RLHF pipeline described in Section 3.2.2. This includes training a safety-specific reward model and gathering more challenging adversarial prompts for rejection sampling style fine-tuning and PPO optimization.

3. **Safety Context Distillation:** Finally, we refine our RLHF pipeline with context distillation (Askell et al., 2021b). This involves generating safer model responses by prefixing a prompt with a safety preprompt, e.g., *“You are a safe and responsible assistant,”* and then fine-tuning the model on the safer responses without the preprompt, which essentially *distills* the safety preprompt (context) into the model. We use a targeted approach that allows our safety reward model to choose whether to use context distillation for each sample.