## FiD-ICL: A Fusion-in-Decoder Approach for Efficient In-Context Learning

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## TL;DR We adapt fusion-in-decoder models (originally designed for open-domain QA) to perform in-context learning. 🕂 Efficiency Performance FiD-ICL outperforms Concat-ICL and Ensemble-ICL. FiD-ICL is *faster* than Concat-ICL and Ensemble-ICL; The gap between FiD-ICL and fine-tuning is <3% on P3 meta-test tasks. More efficient than fine-tuning when considering optimization costs. **Experiment Setting** Motivation: QA vs. ICL Data **Retrieval-Augmented Generation Closed-book QA Fusion-in-Decoder** Public Pool of Prompts (P3) (Roberts et al., 2020) (Lewis et al., 2020) (Izacard et al., 2020) (Sanh et al., 2022; Bach et al., 2022) Passage 1 Passage 2 Passage 3 Question NQ-Open Passage 1 Passage 2 Passage 2 Passage 3 Passa Question NQ-Open **Training Procedure** Encoder Encoder Encoder Encoder Encoder Meta-train on seen tasks: Decoder Decoder +18% +4% Meta-test on unseen tasks Decoder Answer Answer (same LM) (smaller LM) Answer **Compared Methods** Few-shot In-Context Learning Meta-Test Meta-Train T0 ICL Zero-shot Learning **This work: FiD-ICL** Method Fine-tune # shots Initialize from T5-LM Example 1 Example 2 Example 3 Input Input Example 1 Example 2 Example 3 Input Zero-shot × Encoder Concat/FiD/Ensemble-ICL X Encoder Encoder Encoder Encoder Simple/TFew Fine-tune Decoder Ð Decoder Typically Initialize from T0 Output Decoder Output Performance↑ Zero-shot Concat/FiD/Ensemble-ICL × Output Simple/TFew Fine-tune Performance: P3 Meta-Test (11 Held-out Tasks) Zero-shot In-context Learning (gradient-free, 16-shot) Fine-tuning (gradient-based, 16-shot) T-Few FT Simple FT Zero-shot FiD-ICL (Proposed) Concat-ICL Ensemble-ICL 65 % Base Size (220M) Large Size (800M) XL Size (3B) 4





