Improvement 1) Current: DK trained just at the highest fidelity level (~5 samples) → improvement → train on all fidelity levels (~100–625 samples)

Assumption $v = f(p) + \varepsilon$, $\varepsilon \sim \mathcal{N}(0, b^2)$

→ improvement → $v = f(p) + \varepsilon(p)$, $\varepsilon \sim \mathcal{N}(0, b^2(p))$

$$b^2(p) = \frac{\hat{y}(1-\hat{y})}{b}$$

assume $\hat{y} = y$ – unbiased across all fidelity levels

– variance of accuracy of prompt $p \sim Bi(b, y)$

$b$ ← fidelity level of prompt $p$

Practice: Gaussian Likelihood → Fixed Noise Gaussian Likelihood + train on all data right before each SH bucket

$K \to K+D$

$\text{diag}\{b^2(p)\}$

Improvement 2) HyPE = Hyperband Prompt Evolution

- Instructions: $S_I = \frac{\sum_p \text{budget}(p) \cdot \text{acc}(p)}{\sum_p \text{budget}(p)}$ – weighted average of accuracy of the instruction $i$ in prompt $p$

  ↑ consistency metric

  → or Laplace smoothing: $S_I = \frac{\sum_j k_{ij} + \alpha}{\sum_j n_{ij} + \alpha + \beta}$ $\left(\begin{matrix}\alpha=1\\ \beta=1\end{matrix}\right\}$ uniform prior)

  # correct of instruction $i$ and example $j$

  budget of instruction $i$ and example $j$

  - select top $k$ based on $S_I$
  - ProTeGi edit (failed examples → gradients → edits) → new instructions

- Examples: $S_E$ = analogy to $S_I$ or Relative Lift Score 1) $\mu_{I_i}$ = mean acc. of instruction $i$

  2) $\Delta_{ij} = \text{acc}(I_i, E_j) - \mu_{I_i}$

  3) $S_E = \frac{1}{|I_{seen}|} \sum_i \Delta_{ij}$

  - select top $k$ based on $S_I$
  - find failed examples and rework GT output (better reasoning)