FINDR: A Fast Influential Data Selector for NL2Code Pretraining

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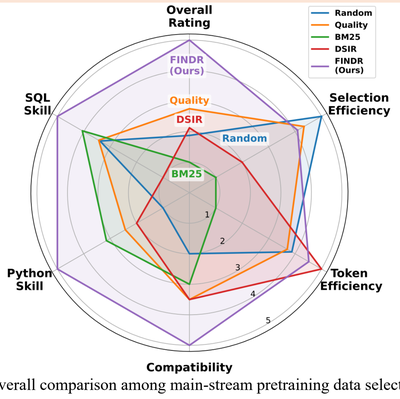
Data Selection for NL2Code

Preamble:

- Large language models (LLMs) have become an exceptionally powerful technology, thanks to the use of enormous pretraining data.
- When moving to downstream tasks (e.g., NL2Code), much of this original pretraining data become a distraction at best or a liability at worst.

Literature Review:

- Existing work solely focus on selecting NL (natural language)-only data. It is unclear and unexplored about its efficacy on NL2Code and programming data.
- Advanced methods face scalability issue, while "fast" methods either fail to select data with characteristics similar to the target domain (e.g., length) or lack diversity.



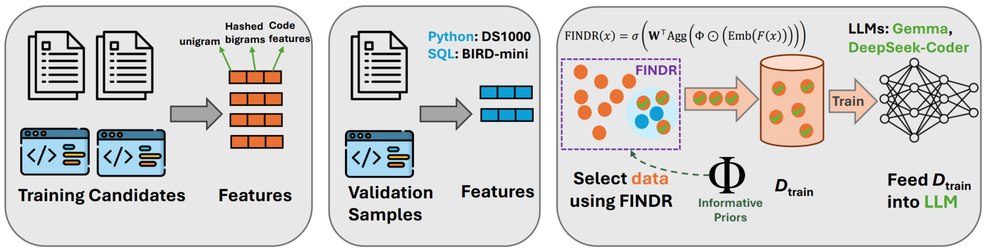
Overall comparison among main-stream pretraining data selectors

Method: FINDR

Training Corpus (D_{raw}): StackV2 47 million Python scripts & 4 million SQL scripts

Validation Set (D_{valid}): 105 Python samples, 50 SQL samples

Data Selection: Logistic regression model with feature-wise importance reweighting



Stage 1a: Feature Extraction on Training Candidates | **Stage 1b: Feature Extraction on Validation Samples** | **Stage 2: Influence Calculation**

Overview of FINDR: **F**ast **IN**fluential **D**ata **R**anker. We first extract code-feature-augmented representations (stage 1), and then leverage informative priors to apply feature importance reweighting to compute influence scores (stage 2).

We use "**influence**" to denote data point-level FINDR score, while "**importance**" means feature-wise importance/weights.

$$\text{FINDR}(x) = \sigma\left(\mathbf{W}^\top \text{Agg}\left(\Phi \odot \left(\text{Emb}\left(F(x)\right)\right)\right)\right)$$

Unigrams + Hash bigrams

Library	Feature Bracket	Expressions/Functions
Matplot	Plotting Functions	`pyplot.plot`, `plot`, `matplotlib.pyplot.hist`, `plt.hist`, `boxplot`, `plt.scatter`, `bar`, `matplotlib.pyplot.boxplot`, `matplotlib.pyplot.plot`, `scatter`, `matplotlib.pyplot.bar`, `plt.bar`, `pyplot.bar`, `plt.plot`, `pyplot.scatter`, `pyplot.hist`, `hist`, `pyplot.boxplot`, `plt.boxplot`, `matplotlib.pyplot.scatter`
Numpy	Array Creation	`np.ones`, `numpy.eye`, `array`, `numpy.zeros`, `numpy.array`, `np.zeros`, `np.array`, `numpy.ones`, `empty`, `zeros`, `np.eye`, `ones`, `eye`, `np.empty`, `numpy.empty`

Code features (capture code-specific constructs, e.g., vectorized function calls)

Feature Extraction (Stage 1)

Feature-wise importance is determined by:

$$\Phi[\mathcal{D}_{val}, \mathcal{D}_{raw}] = \min(\text{REG}[\frac{\Phi'_{\mathcal{D}_{val}}[\mathbf{f}]}{\Phi'_{\mathcal{D}'_{raw}}[\mathbf{f}]}], M)$$

Φ' is the frequency-based raw importance for each feature:

$$\Phi'_{\mathcal{D}}[\mathbf{f}] = \frac{\sum_{j=1}^{n} \mathbf{f}_j}{\sum_{i=1}^{n} \mathbf{1}^\top \mathbf{f}_i}$$

REG is a regularization factor balancing priors vs. uniform weights, controlled by hyper-parameter γ:

$$\text{REG}[\phi] = \gamma(1-\phi) + \phi$$

M caps importance to prevent FINDR learning feature-wise shortcuts.

Feature-wise Importance (Φ) Calculation

Results & Analyses

	DeepSeek-Coder						Gemma					
	Origin	Surface	Semantic	Difficult	Perturbation	Overall	Origin	Surface	Semantic	Difficult	Perturbation	Overall
Base Model	19.9	9.2	17.5	6.8	12.0	15.1	13.8	7.2	9.8	4.9	7.6	10.1
Random Selection	20.7	8.6	16.7	4.9	11.0	14.7	15.3	6.6	10.7	**6.2**	8.2	10.9
Quality Classifier	21.2	9.3	15.8	6.2	11.2	15.1	17.0	**10.5**	11.5	**6.2**	9.7	12.5
BM25	22.2	6.6	14.1	5.6	9.5	14.4	**21.0**	7.9	**14.5**	4.9	9.8	**14.2**
DSIR	22.2	9.9	17.5	5.9	12.0	15.9	15.3	5.3	12.4	5.6	8.4	11.1
FINDR (Ours)	**24.2**	**12.2**	**18.4**	**7.1**	**13.3**	**17.5**	19.0	9.2	14.1	**6.2**	**10.4**	13.7

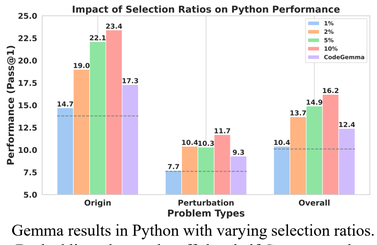
Comparison of FINDR with data selection baselines in the Python domain, measured by Pass@1.

	DeepSeek-Coder				Gemma			
	Easy	Med.	Hard	Overall	Easy	Med.	Hard	Overall
Base	**26.5**	8.8	**2.0**	11.1	12.2	2.8	**3.9**	5.1
Random	18.4	5.7	**2.0**	7.6	11.2	2.8	2.9	4.7
Quality	19.4	3.8	1.0	6.6	**18.9**	2.0	2.9	5.9
BM25	22.5	6.4	**2.0**	8.9	17.9	**3.2**	2.0	6.1
DSIR	4.1	0.0	0.0	0.9	6.6	0.6	0.0	1.8
FINDR	25.5	**11.2**	**2.0**	**12.2**	**18.9**	2.8	**3.9**	**6.6**

Comparison of FINDR with data selection baselines in the SQL domain, measured by Execution (EX).

Take-home Messages:

- Random selection often degrades performance.
- FINDR selects on-target data that consistently boosts base models across domains.
- FINDR generally outperforms strong baselines by non-trivial margins.
- FINDR demonstrates superior robustness on "Difficult" examples.
- NL-targeted selectors do not necessarily excel at NL2Code.



Gemma results in Python with varying selection ratios. Dashed lines denote the off-the-shelf Gemma results.

Further Study on Selection Ratio:

- Continuously trained models exceed the base model once the ratio reaches 2%.
- Performance generally rises further beyond 2%, albeit with diminishing return.
- Gemma trained on 2% FINDR-selected data surpasses CodeGemma despite its extensive pretraining.
- Similar trend observed in the SQL domain.

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