# Squeezing Your Fine-Tuning Data to the Last Drop

From Selection to Rebalancing

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## About Me

- Final-year Ph.D. candidate at Monash University
- Research focus: Large Language Models, Multilinguality, Machine Translation
- 20+ papers in top-tier venues (ICML, ACL, EMNLP, COLING, TACL, etc.)
- Outstanding Paper Award at ACL 2025
- Best Paper Nomination at ACM Multimedia 2024
- Visit/Intern experience: Huawei, Tencent, Alibaba, MBZUAI
- `https://minghao-wu.github.io/`

## Overview

## The Data Challenge in LLM Fine-Tuning

**Why does data matter in LLM fine-tuning?**

- Training data directly shapes model capabilities
- Quality determines how well the model learns
- Diversity ensures comprehensive skill coverage
- Optimization affects learning effectiveness

**Key Challenges:**

- Selection: What data to train on?
- Composition: How to mix datasets?
- Optimization: When to use what data?

**The Pipeline**

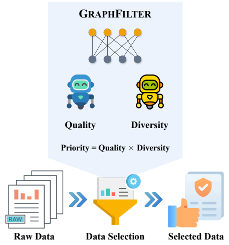
$$\begin{tikzcd}
\text{Large Dataset} \arrow[d] \\
\text{Static Selection} \arrow[d] \\
\text{Selected Subset} \arrow[d] \\
\text{Dynamic Rebalancing} \arrow[d] \\
\text{Optimized Training}
\end{tikzcd}$$

*Two complementary approaches*

## Two Complementary Approaches

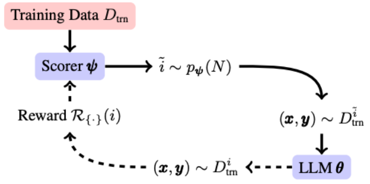
**Study 1: GraphFilter**

- Static Data Selection
- Bipartite graph representation
- Set cover optimization
- Quality × Diversity priority



**Study 2: Mixture-of-Skills**

- Dynamic Rebalancing
- Reinforcement learning framework
- Adaptive data rebalancing
- Skill-aware training


Training Data $D_{\text{trn}}$
Scorer $\boldsymbol{\psi}$
$\tilde{i} \sim p_{\boldsymbol{\psi}}(N)$
Reward $\mathcal{R}_{\{\cdot\}}(i)$
$(\boldsymbol{x}, \boldsymbol{y}) \sim D_{\text{trn}}^{\tilde{i}}$
LLM $\boldsymbol{\theta}$
$(\boldsymbol{x}, \boldsymbol{y}) \sim D_{\text{trn}}^{i}$

## Study 1: GraphFilter

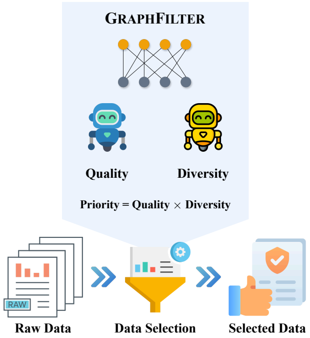
# The Best of Both Worlds: Bridging Quality and Diversity in Data Selection with Bipartite Graph

**Minghao Wu**, Thuy-Trang Vu, Lizhen Qu, Gholamreza Haffari

2025 Forty-Second International Conference on Machine Learning

**Key Contributions:**

- Novel formulation as set cover problem
- Bipartite graph representation
- Multiplicative priority function
- Outperforms 9 baselines on 6 benchmarks



## The Quality-Diversity Dilemma

**Existing Methods Fall Short:**

- Quality-focused: Select high-scoring examples
- Diversity-focused: Maximize coverage
- Problem: One aspect sacrificed for the other

**Real-world Analogy:**

- Curating a library collection
- Want both high-quality books *and* diverse topics
- Balance is key for comprehensive learning

**The Challenge**

Quality $\uparrow$

$\downarrow$

Diversity $\downarrow$

**GraphFilter: Best of Both Worlds**

## What is the Set Cover Problem?

**Classic Computer Science Problem:**

- Given a universe of elements $\mathcal{V}$
- Given a collection of sets $\mathcal{U} = \{u_1, u_2, ..., u_m\}$
- Each set $u_i \subseteq \mathcal{V}$
- **Goal**: Find minimum number of sets that cover all elements in $\mathcal{V}$

**NP-Hard Problem:**

- No polynomial-time exact solution
- Greedy approximation works well
- Widely applicable in real-world scenarios

**Mathematical Formulation**

$$\min \textstyle\sum_{i=1}^{m} x_i$$
subject to:
$$\textstyle\sum_{i:e\in u_i} x_i \geq 1, \forall e \in \mathcal{V}$$
$$x_i \in \{0, 1\}$$

where $x_i = 1$ if set $u_i$ is selected

## From Set Cover to Data Selection

**The Connection:**

- Universe $\mathcal{V}$: All possible n-grams
- Sets $\mathcal{U}$: Training sentences
- Coverage: Each sentence covers its n-grams
- Goal: Select sentences that cover diverse n-grams

**Why This Makes Sense:**

- N-grams represent linguistic patterns
- Diverse n-gram coverage = diverse training data
- Natural formulation for diversity

**Data Selection as Set Cover**

**Sentence 1**: "How to cook pasta"

**N-grams**: {how, to, cook, pasta, how_to, to_cook, ...}

**Sentence 2**: "How to bake bread"

**N-grams**: {how, to, bake, bread, how_to, to_bake, ...}

## Bipartite Graph Representation

**Graph Components:**

- Left nodes: Sentences $u_1, u_2, \ldots, u_5$
- Right nodes: N-grams $v_1, v_2, \ldots, v_5$
- Edges: Connect sentences to their n-grams

**Selection Process:**

- Select sentence with highest priority
- Remove covered n-grams from graph
- Update priorities dynamically
- Repeat until budget exhausted

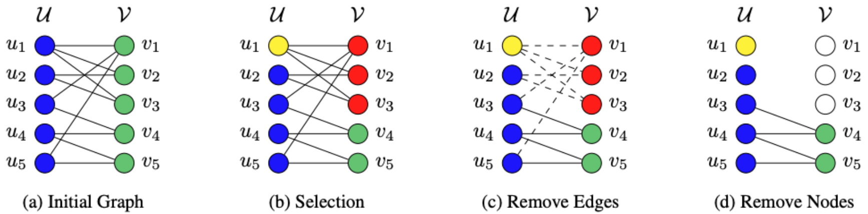


Figure: Example: Selecting $u_1$ covers n-grams $\{v_1, v_2, v_3\}$, then selecting $u_4$ covers remaining n-grams

But wait... This only considers diversity, not quality!

## Incorporating Quality: The Priority Function

**Priority Function Design:**

$$\phi(u) = \text{Quality}(u) \times \max(1, \text{Diversity}(u))$$

**Quality Metric - IFD Score:**

$$\text{Quality}(u) = \text{PPL}(y|x)/\text{PPL}(y)$$

**Diversity Metric - TF-IDF:**

$$\text{Diversity}(u) = \sum_{v \in \mathcal{V}_u} \text{TF-IDF}(v)$$

**Why Multiplicative?**

High Quality + Low Diversity
⇒ Low Priority

Low Quality + High Diversity
⇒ Low Priority

High Quality + High Diversity
⇒ **High Priority**

*Both aspects must be strong for selection!*

We compute quality on instruction-response pairs, diversity on instructions only.

## GraphFilter Algorithm in Action

**Iterative Selection Process:**

1. **Initialize**: Empty selection $\mathcal{S} = \emptyset$
2. **Compute**: Priority $\phi(u)$
3. **Select**: $u^*$ with highest priority
4. **Update**: Remove $u^*$ and n-grams
5. **Repeat**: Until budget $k$ is reached

**Dynamic Priority Updates:**

- Priorities change as n-grams are covered
- Encourages selection of complementary sentences
- Balances quality and remaining diversity

**Computational Efficiency**

- Max-heap $\mathcal{O}(\log N)$ per iteration
- Localized priority updates
- Scalable to large datasets

**N-gram Selection**

- Use n-grams up to length 3
- Balances granularity and efficiency
- Captures meaningful linguistic patterns
- Empirically effective

## Experimental Setup

**Training Dataset:**

- **Magpie** dataset (300K instances)
- High-quality instruction-response pairs
- Select 10K subset

**Model Backbones:**

- Gemma-2-2B
- Mistral-7B-v0.3
- Llama-3-8B

**Baseline Methods (9 total):**

- **Heuristic**: Random, Longest
- **Quality-based**: PPL, ArmoRM, AlpaGasus, DEITA, IFD
- **Diversity-based**: K-means, InsTag

**Evaluation Benchmarks (6 total):**

- MMLU, ARC, HellaSwag, GSM8K
- AlpacaEval-2.0, MT-Bench using GPT-4o

## Main Results: GraphFilter Outperforms All Baselines

**Consistent Improvements Against Random:**

- **Gemma-2-2B**: Up to +2.03
- **Mistral-7B**: Up to +2.83
- **Llama-3-8B**: Up to +2.46

**Key Findings:**

- GraphFilter achieves best/second-best on most benchmarks
- Quality-only methods show benchmark bias (e.g., ArmoRM good on AlpacaEval, poor elsewhere)

| | Standard | LLM | ALL |
|---|---|---|---|
| Random | 47.75 | 41.04 | 45.51 |
| Longest | 46.91 | 39.96 | 44.59 |
| Perplexity | 48.27 | 40.28 | 45.61 |
| ArmoRM | 48.21 | <u>42.66</u> | 46.36 |
| AlpaGasus | 48.96 | 41.90 | 46.60 |
| DEITA | 48.78 | 41.70 | 46.42 |
| SuperFilter | 49.10 | 41.91 | 46.70 |
| Kmeans | 48.90 | 41.72 | 46.51 |
| InsTag | <u>49.93</u> | 41.72 | <u>47.19</u> |
| GraphFilter (Ours) | **50.55** | **42.79** | **47.97** |

Table: Main results given by Llama-3-8B on the standardized benchmarks and LLM-as-a-Judge benchmarks. The best results are highlighted in **bold**, and the second-best results are highlighted in <u>underline</u>.

## Main Results: GraphFilter is Computationally Efficient

**Computational Efficiency**

- Max-heap $\mathcal{O}(\log N)$ per iteration
- Localized priority updates
- Scalable to large datasets

| | Runtime (hrs) |
|---|---|
| Perplexity | 0.92 |
| ArmoRM | 5.93 |
| AlpaGasus | 32.34 |
| DEITA | 22.65 |
| SuperFilter | 1.95 |
| Kmeans | 2.26 |
| InsTag | 25.48 |
| GraphFilter (Ours) | 2.48 |
| w/o priority $\phi(u)$ | $0.53^{\dagger}$ |

Table: Runtime (in hours) for selecting 10K training instances. † indicate the CPU-only method.

## Analysis: GraphFilter Balances Quality and Diversity

**Visualization Analysis:**

- **Lexical Diversity**: Measured by MTLD metric
- **Data Quality**: Assessed by SkyworkRM

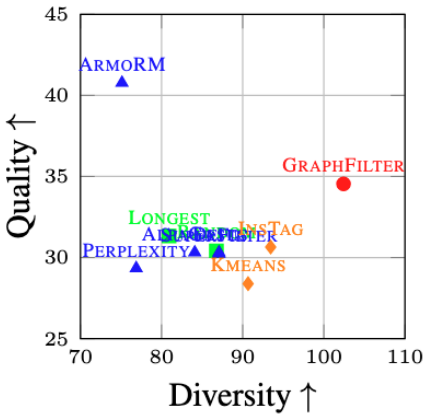
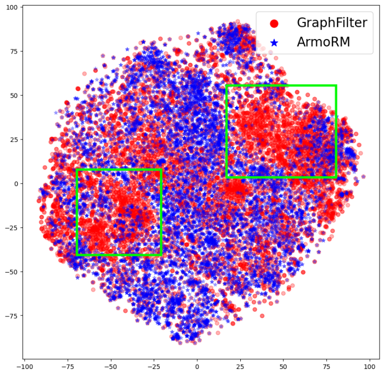


Figure: GraphFilter achieves **highest lexical diversity** and **second-best data quality** among all methods.

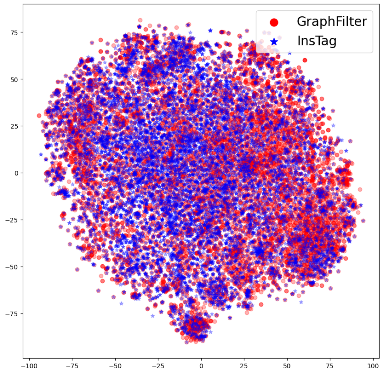
## Analysis: GraphFilter Balances Quality and Diversity

**Semantic Visualization**: t-SNE plots using BGE embeddings

- Selects instructions not chosen by quality-only methods
- Similar semantic diversity to diversity-focused methods



(a) GraphFilter vs. ArmoRM (Quality only)



(b) GraphFilter vs. InsTag (Diversity only)

## Analysis: N-gram Combinations Capture Multi-Level Features

**Different N-grams Capture Different Patterns:**

- **Unigrams (n=1)**: Individual words, basic vocabulary
- **Bigrams (n=2)**: Local word relationships
- **Trigrams (n=3)**: Phrasal patterns, syntax

**Key Finding:**

- Combining 1-grams + 2-grams + 3-grams significantly outperforms individual n-gram types
- Each level provides complementary information
- Integration consolidates features effectively

**Performance by N-gram Type**

| N-gram | ALL |
|---|---|
| 1-gram only | 46.48 |
| 2-gram only | 46.63 |
| 3-gram only | 47.15 |
| 1+2+3-grams | **47.97** |

**Multi-level features are essential!**

## Analysis: Trigrams Provide Optimal Balance

**N-gram Size Analysis ($n_{max}$=1 to 5):**

- **Performance**: Peaks at trigrams ($n_{max}=3$)
- **Efficiency**: Decreases with larger $n_{max}$
- **Diminishing returns**: Beyond $n_{max}=3$

**Why Trigrams Work Best:**

- Capture meaningful linguistic patterns
- Balance granularity and computational cost
- Avoid over-specification of larger n-grams

**N-gram Size Trade-offs**

| $n_{max}$ | ALL | Time (hrs) |
|---|---|---|
| 1 | 46.48 | 2.12 |
| 2 | 47.31 | 2.30 |
| **3** | **47.97** | **2.48** |
| 4 | 47.43 | 3.38 |
| 5 | 47.85 | 4.58 |

**Sweet spot at n=3**

# N-grams Nodes:
0.1M (1-gram) $\rightarrow$ 7.4M (5-gram)

## Analysis: Instruction Diversity Matters Most

**What to Apply GraphFilter To?**

- Each training instance has instruction + response
- Tested three scenarios:
  - Instructions only
  - Responses only
  - Both instructions and responses

**Surprising Result:**

- **Instructions only performs best**
- Instruction diversity more impactful than response diversity
- Quality remains similar
- Rethinking: Response diversity also matters!

| Type | Benchmarks | | | Lexical Diversity | | Quality |
|---|---|---|---|---|---|---|
| | Standard | LLM | ALL | Instruction | Response | |
| Instruction | **50.55** | **42.79** | **47.97** | **102.43** | 71.74 | **81.54** |
| Response | 47.16 | 39.71 | 44.68 | 90.22 | **73.57** | 81.52 |
| Inst. + Resp. | 48.03 | 41.20 | 45.76 | 90.13 | 72.60 | 81.52 |

## Analysis: Budget Determines Quality vs. Diversity Priority

**When to Prioritize What?**

- **Small budgets (1K, 5K)**: Quality methods (SuperFilter) excel
- **Large budgets (10K+)**: Diversity methods (InsTag) catch up
- **All budgets**: GraphFilter consistently demonstrates performance gains

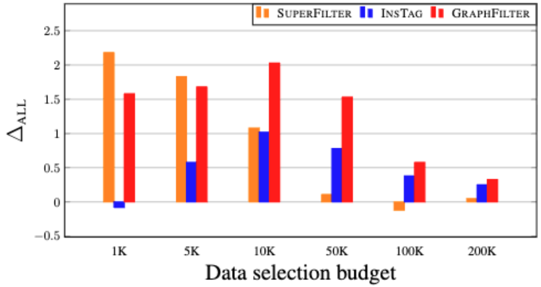


Figure: Relative gains against Random. Budget size affects strategy effectiveness

## From Static Selection to Dynamic Optimization

**GraphFilter Insights:**

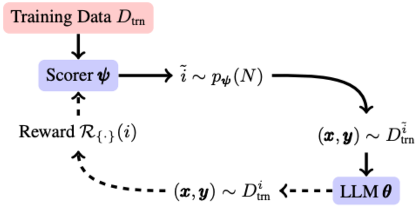
- Quality $\times$ Diversity balance is crucial
- Static selection has limitations
- What about during training?

**New Challenge:**

- Models learn different skills at different rates
- Static data mixing may not be optimal
- Finding the right data mix is expensive

**The Next Question**

*Can we optimize data usage dynamically during fine-tuning?*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$(\boldsymbol{x}, \boldsymbol{y}) \sim D_{\text{trn}}^{\tilde{i}}$
LLM $\boldsymbol{\theta}$
$(\boldsymbol{x}, \boldsymbol{y}) \sim D_{\text{trn}}^{i}$
Reward $\mathcal{R}_{\{\cdot\}}(i)$

**Enter: Mixture-of-Skills**

## Study 2: Mixture-of-Skills

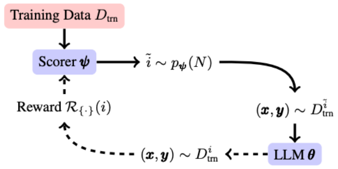
**Mixture-of-Skills: Learning to Optimize Data Usage for Fine-Tuning Large Language Models**

**Minghao Wu**, Thuy-Trang Vu, Lizhen Qu, Gholamreza Haffari

2024 Conference on Empirical Methods in Natural Language Processing

**Key Contributions:**

- Reinforcement learning framework for data rebalancing
- Model-agnostic dynamic optimization
- Adaptive skill development during training
- MoSpec extension for task-specific fine-tuning


Training Data $D_{\text{trn}}$
Scorer $\psi$
$\tilde{i} \sim p_{\psi}(N)$
Reward $\mathcal{R}_{\{\cdot\}}(i)$
$(\boldsymbol{x}, \boldsymbol{y}) \sim D_{\text{trn}}^{\tilde{i}}$
LLM $\boldsymbol{\theta}$
$(\boldsymbol{x}, \boldsymbol{y}) \sim D_{\text{trn}}^{i}$

## The Data Mixing Challenge

**LLMs Need Multiple Skills:**

- Writing, coding, mathematics, chatting, etc.
- Each skill requires different training data
- Datasets are heterogeneous and imbalanced

**Current Problems:**

- **Static mixing**: Ignores learning dynamics
- **Data capping**: Limits large dataset utilization
- **Grid search**: Finding optimal composition is expensive

**Example Challenge**

- Math: 10K samples
- Code: 100K samples
- Chat: 1M samples

**Learning Dynamics:**

- Some skills learned quickly
- Others need more exposure
- Skills can interfere

## Mixture-of-Skills: Bilevel Optimization

**The Framework:**

- Outer level: Optimize LLM parameters $\boldsymbol{\theta}$
- Inner level: Optimize data sampling via scorer network $\boldsymbol{\psi}$
- **Goal**: Learn optimal data usage automatically

**Mathematical Formulation:**

$$\boldsymbol{\psi} = \underset{\boldsymbol{\psi}}{\operatorname{argmin}} \mathcal{J}(D_{\mathrm{trn}}; \boldsymbol{\theta}(\boldsymbol{\psi}))$$

$$\boldsymbol{\theta}(\boldsymbol{\psi}) = \underset{\boldsymbol{\theta}}{\operatorname{argmin}} \mathbb{E}_{i \sim p_{\boldsymbol{\psi}}(N)}[\mathcal{L}(D^{i}_{\mathrm{trn}}; \boldsymbol{\theta})]$$

**Why RL?**

- Bilevel optimization not directly differentiable
- REINFORCE algorithm handles discrete sampling
- Enables dynamic adaptation

## MoS Algorithm: Step-by-Step Walkthrough

**Algorithm Overview:**

1. **Initialize**: Start with uniform sampling ($\tau = \infty$)
2. **Training Loop**: For each step $t$:
   - Sample dataset $\tilde{i} \sim p_{\boldsymbol{\psi}}(N)$
   - Sample batch from $D^{\tilde{i}}_{\text{trn}}$
   - Update LLM: $\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} - \alpha \nabla_{\boldsymbol{\theta}} \mathcal{L}$
3. **Scorer Update** (every $S$ steps):
   - Sample batch from each dataset
   - Compute rewards $\mathcal{R}(i)$ for each dataset
   - Update scorer: $\boldsymbol{\psi} \leftarrow \boldsymbol{\psi} + \gamma \sum_i \mathcal{R}(i) \nabla_{\boldsymbol{\psi}} \log p_{\boldsymbol{\psi}}(i)$

**Key Components:**

- **Scorer Network $\boldsymbol{\psi}$**: Simple 2-layer MLP
- **Update Frequency $S$**: Computational efficiency
- **Rewards $\mathcal{R}(i)$**: Guide optimization

**Dynamic Adaptation:**

- Sampling probabilities change over time
- Responds to current model state
- Balances different skills automatically

**But how do we design rewards?**

## Reward Design: Three Perspectives

1. **Transferability ($\mathcal{R}_{\textbf{cosine}}$):**
   - Measure similarity between datasets
   - Use mini-batch embeddings from LLM
   - Higher similarity = better transferability

$$\mathcal{R}_{\text{cosine}}(i) = \frac{1}{N} \sum_{n=1}^{N} \frac{\mathbf{z}^i \cdot \mathbf{z}^n}{\|\mathbf{z}^i\| \cdot \|\mathbf{z}^n\|}$$

2. **Difficulty ($\mathcal{R}_{\textbf{diff}}$):**
   - Relative perplexity decrease after fine-tuning
   - Higher values = more difficult datasets need more attention

$$\mathcal{R}_{\text{diff}}(i) = \frac{1}{L} \sum_{j=1}^{L} \frac{\text{PPL}(\mathbf{y}_j^i; \mathbf{x}_j^i, \boldsymbol{\theta})}{\text{PPL}(\mathbf{y}_j^i; \mathbf{x}_j^i, \boldsymbol{\theta}_0)}$$

3. **Learning Trajectory:**
   - Exponential Moving Average (EMA) for stability
   - Smooths reward signals over time
   - Prevents oscillations

$$\mathcal{R}(i) = \beta \mathcal{R}'(i) + (1 - \beta) \mathcal{R}''(i)$$

**Design Principles:**

- **Transferability**: Knowledge sharing
- **Difficulty**: Learning progress
- **Trajectory**: Stability

*Rewards guide the scorer network to make informed sampling decisions*

## Experimental Setup

**Datasets (4 Skills):**

- **Mathematics**: MathInstruct (comprehensive collection)
- **Medicine**: MedInstruct (medical instructions)
- **General**: ShareGPT (diverse, high-quality conversations)
- **NLP**: P3 (660 subsets, diverse NLP tasks)

**Model Backbones (3 total):**

- Qwen1.5-0.5B
- Gemma-2B
- Llama-3-8B

**Baselines:**

- **Heuristic**: Temperature sampling

$$q_\tau(i) = \frac{q(i)^{1/\tau}}{\sum_{n=1}^{N} q(n)^{1/\tau}}$$

  - Proportional ($\tau = 1$), Temperature ($\tau = 10$), Uniform ($\tau = \infty$)
- **Dynamic**: MultiDDS, MultiUAT

**Evaluation:**

- **MMLU**: 57 subjects (Math, Medicine, Others)
- **MT-Bench**: 8 skills (Coding, Writing, etc.)

## Main Results: MoS Consistently Outperforms Baselines

**Consistent Improvements:**

- **Qwen1.5-0.5B**: +0.96 improvement
- **Gemma-2B**: +1.15 improvement
- **Llama-3-8B**: +2.45 improvement

**Key Findings:**

- Larger models benefit more from MoS
- No universally optimal temperature $\tau$
- Different rewards work better for different models
- EMA consistently helps performance

| | MMLU | MT | ALL |
|---|---|---|---|
| Prop. ($\tau = 1$) | 56.78 | 6.52 | 60.97 |
| Temp. ($\tau = 10$) | 56.17 | 6.66 | 61.40 |
| Uni. ($\tau = \infty$) | 55.72 | 6.63 | 60.99 |
| MultiDDS | 56.65 | 6.69 | 61.77 |
| MultiUAT | 55.66 | 6.67 | 61.18 |
| MoS + cos | 56.95 | 6.80 | 62.49 |
| MoS + cos + EMA | <u>58.08</u> | **6.96** | **63.85** |
| MoS + diff | 57.93 | 6.81 | 63.00 |
| MoS + diff + EMA | **58.34** | <u>6.82</u> | <u>63.26</u> |

Table: Results on MMLU and MT-Bench given by Llama-3-8B. Best results in **bold**, second-best <u>underlined</u>.

## Analysis: MoS Adapts Data Usage Dynamically

**Dynamic Sampling Behavior:**

- Sampling probabilities evolve over training
- Reflects changing model needs
- Balances skill development

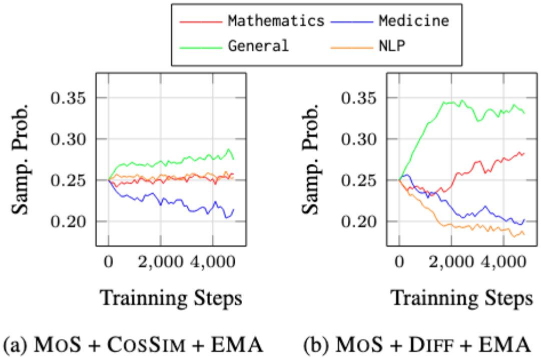


Figure: Sampling probabilities for each dataset over training steps. MoS adjusts focus dynamically.

## Analysis: MoS is Robust to Sampling Priors

**Initialization Sensitivity:**

- MoS starts with uniform sampling ($\tau = \infty$)
- What if we start with different priors?
- **Key Finding**: MoS consistently outperforms best heuristic baseline regardless of initialization

**Robustness Analysis:**

- All MoS variants beat Temperature ($\tau = 10$) baseline
- Proper prior selection can further enhance performance
- **MoS is robust and effective**

| | Prior $\tau$ | MMLU | MT | ALL |
|---|---|---|---|---|
| Heuristic | 10 | 56.17 | 6.66 | 61.40 |
| MultiDDS | 1 | 56.65 | 6.69 | 61.77 |
| | 10 | 56.88 | 6.58 | 61.34 |
| | $\infty$ | 55.66 | 6.67 | 61.18 |
| MoS | 1 | 56.51 | 6.81 | 62.29 |
| | 10 | 58.22 | **6.91** | **63.66** |
| | $\infty$ | **58.34** | 6.82 | 63.26 |

Table: MoS performance with different sampling priors using Llama-3-8B. All variants outperform the best heuristic baseline.

**Takeaway**: MoS learns to adapt regardless of how you start!

## Analysis: MoS is Compatible with Data Selection Methods

**Combining MoS with Instance Selection:**

- Use Instruction-Following Difficulty (IFD) to select top 10% instances
- Apply MoS dynamic rebalancing on selected data
- **Best of both worlds**: Quality selection + dynamic optimization

**Complementary Effects:**

- Static selection improves data quality
- MoS optimizes usage of selected data
- **Complementary approaches** enhance final performance

| | MMLU | MT | ALL |
|---|---|---|---|
| Random | | | |
| Temp. ($\tau = 10$) | 54.89 | 6.63 | 60.62 |
| MoS | 55.21 | 6.72 | 61.15 |
| IFD Selection | | | |
| Temp. ($\tau = 10$) | 55.13 | 6.69 | 61.02 |
| MoS | **56.43** | **6.77** | **62.05** |

Table: Combining MoS with instance selection (IFD) further improves performance using Llama-3-8B.

**Key Insight**: Static selection and dynamic rebalancing address different aspects of data optimization!

## MoSpec: Fine-tuning from Generalist to Specialist

**The Specialization Challenge:**

- Large general-purpose models are costly to deploy
- Many applications need only narrow functionalities
- Smaller specialized models often outperform larger generalist ones

**MoSpec Approach:**

- Harnesses diverse datasets to enhance target task performance
- Assigns higher rewards to target domain (e.g., mathematics)
- Learns optimal dataset distribution for specific capabilities

**Example: Math Specialization**

- Target: Mathematics dataset
- Supporting: General, Medicine, NLP datasets
- **MoSpec + cosine**: Compute similarity between Math and other datasets
- **MoSpec + diff**: Double reward for Math dataset

**Key Insight:** *SFT datasets from other domains are beneficial for the target task, especially when target dataset is incomplete*

## MoSpec Results: Math Specialization Performance

**Experimental Setup:**

- **Target**: Math specialization
- **Baselines**:
  - Temp. ($\tau = 10$)
  - MathLlama (trained only on Math)
- **Evaluation**: GSM8K, MATH, MMLU-math (M-math) benchmarks

**Key Findings:**

- **MathLlama performs worst**
- **Other datasets are beneficial**
- **MoSpec learns optimal mixing** for specialization

| | GSM8K | MATH | M-math | ALL |
|---|---|---|---|---|
| *Generalist* | | | | |
| Temp. ($\tau = 10$) | 49.62 | 9.54 | 28.36 | 29.17 |
| MoS + cos + EMA | 50.40 | 9.78 | 27.60 | 29.26 |
| MoS + diff + EMA | 49.58 | 10.26 | **32.81** | 30.88 |
| *Math Specialist* | | | | |
| MathLlama | 41.02 | 9.76 | 30.34 | 27.04 |
| MoSpec + cos + EMA | 51.10 | 10.64 | 30.16 | 30.63 |
| MoSpec + diff + EMA | **52.10** | **11.40** | 32.24 | **31.91** |

Table: Math specialization results. MoSpec outperforms both generalist models and math-only training.

**+4.87 improvement** over math-only training!

## MoSpec Results: Sampling Behavior Analysis

**Dynamic Data Usage:**

- MoSpec adjusts dataset sampling over training
- Increases focus on target domain (Math)
- Leverages supporting datasets effectively

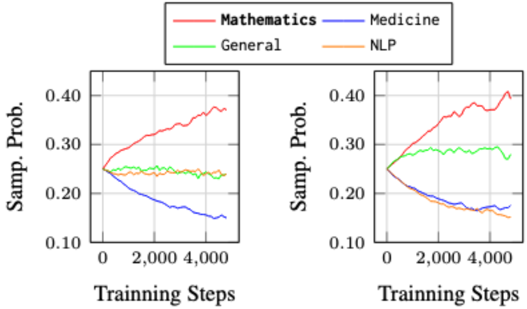


Figure: Sampling probabilities during Math specialization. **Left**: MoSpec + cos + EMA; **Right**: MoSpec + diff + EMA. Both increase focus on Math over time.

## Summary of Contributions

**GraphFilter: Principled Static Selection**

- Novel set cover formulation for data selection
- Bipartite graph representation balancing quality $\times$ diversity
- Consistent improvements across models and benchmarks
- Computationally efficient and scalable

**MoS: Intelligent Dynamic Optimization**

- Model-agnostic RL framework for data rebalancing
- Adaptive skill development during fine-tuning
- Substantial performance improvements
- MoSpec extension for task specialization

**Comprehensive solution covering the entire data optimization pipeline**

## Thank You

**Questions & Discussion**

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