TensorOpera Router: A Multi-Model Router for Efficient LLM Inference

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TensorOpera AI

Motivation

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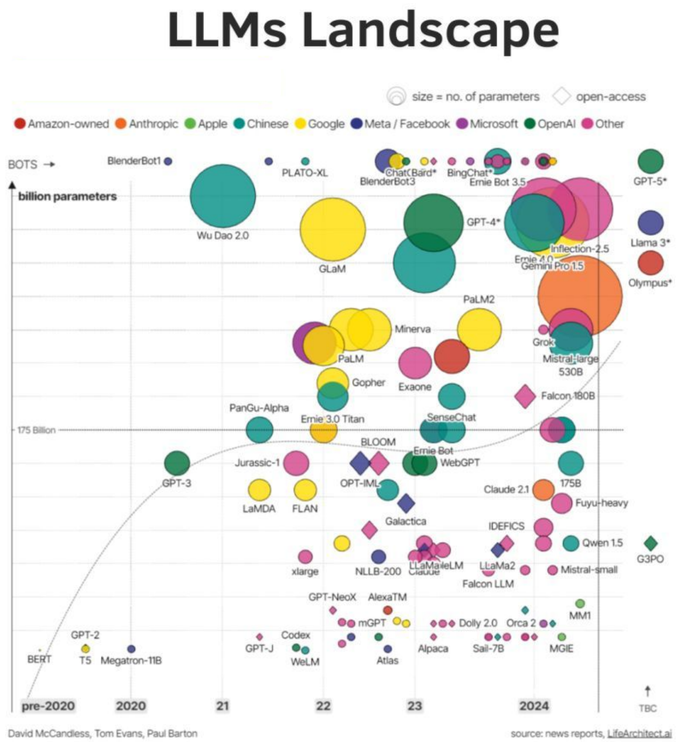
- Different tasks require different expertise.
- Various and diverse LLMs have emerged.
- No LLM fits all purposes.



Problem Statement

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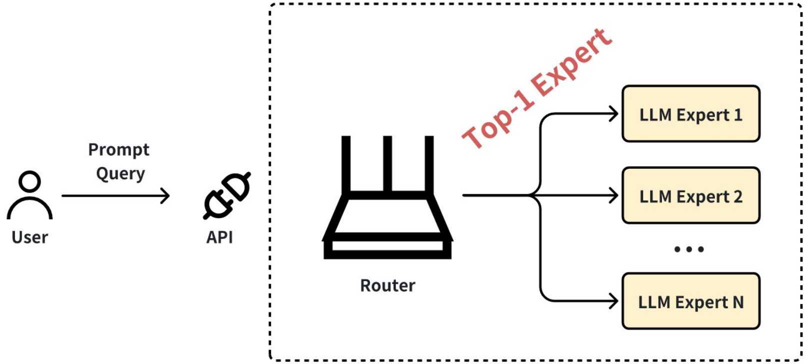
Given the increasing number and diversity of large language models available, there is a need for efficient and intelligent routing systems that:

- Dynamically route queries/tasks to the most suitable LLM expert.
- Optimize resource utilization and costs by balancing workload across models.
- Single API interface for multiple models.
- Seamless selection of expert models while abstracting complexity.



Challenges

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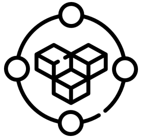
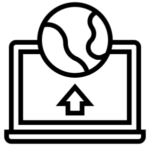
- **Router model training and testing data preparation.**
  - Router's training and testing data need to be representative of the domain queries the router is expected to handle during deployment.

- **Router model selection.**
  - Router model needs to be lightweight to be easily deployable both on the edge and cloud, and quickly parse and assign queries to the most suitable expert.



- **End-to-end routing service deployment.**
  - Automating the training and testing data generation, routing model selection and deployment in real-world setting is an extremely challenging engineering effort.



TensorOpera Router Approach

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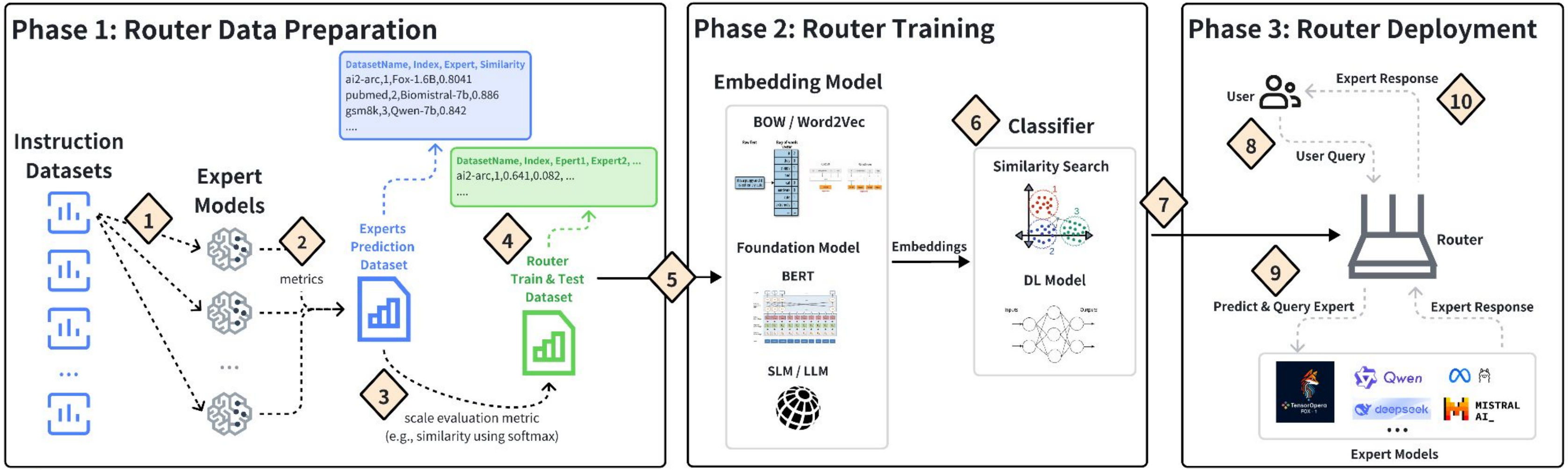

1 Prompt expert models using instruction datasets.

2 Collect performance metrics and create expert dataset with all metrics.

3 Select metric for router training and testing and scale it to probabilities.

4 Prepare router's final training and testing datasets.

5 Pass instruction data through embedding model.

6 Fine-Tune / Train router's classifier on the embeddings.

7 Deploy trained router model.

8 Submit user query to router.

9 Router predicts expert to execute query.

10 Router replies expert's response to user.

Phase 1: Router Data Preparation

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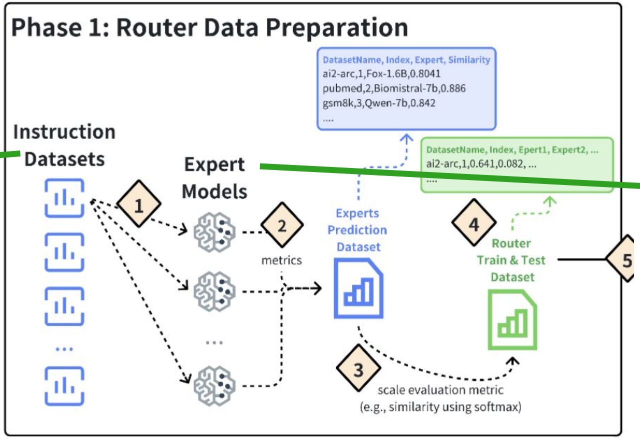
Instruction Datasets

Ai2-ARC (natural sciences)

GSM8k (math)

MBPP (code)

PubMedQA (medical)



Standalone LLM Experts

BioLlama-7B (medical)

BioMistral-7B (medical)

CodeLlama-7B (code)

Fox-1.6B (general)

Mistral-7B (general)

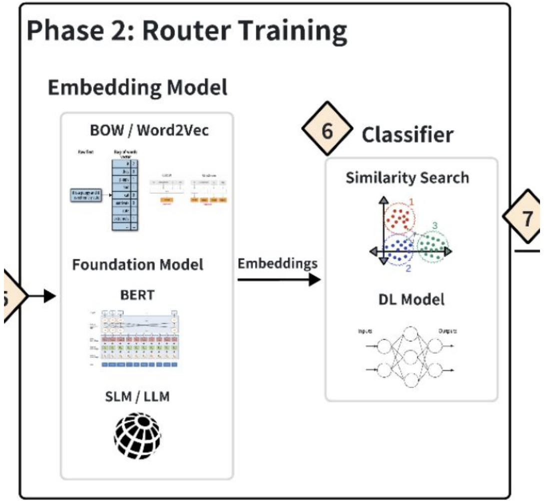
Qwen-7B (general)

MathDeepSeek-7B (math)

For every instruction prompt we collect:

- Negative Log Likelihood
- BERT embeddings similarity score (BERTSim)
- Inference Time (in seconds)
- Total Input Tokens
- Total Output Tokens

Phase 2: Router Training



5 Pass instruction data through embedding model.

6 Fine-Tune / Train router's classifier on the embeddings.

Original Data: (Instruction, BERTSim1, …, BERTSimN)

Scaled Data w/ Softmax Labels:
(Instruction, softmax1(BERTSims, …, BERTSimN), …, softmaxN(BERTSim1, …, BERTSimN))

- **MLP-Router**
  - convert all training queries into their vector representation by fitting a Bag-of-Words model, use cross-entropy loss on the scaled BERTSim scores.
- **BERT-Router**
  - add a classifier head on base BERT and fine-tune BERT by training on the BERT embeddings of all training queries, using cross-entropy loss on the scaled BERTSim scores.

Phase 3: Deployment

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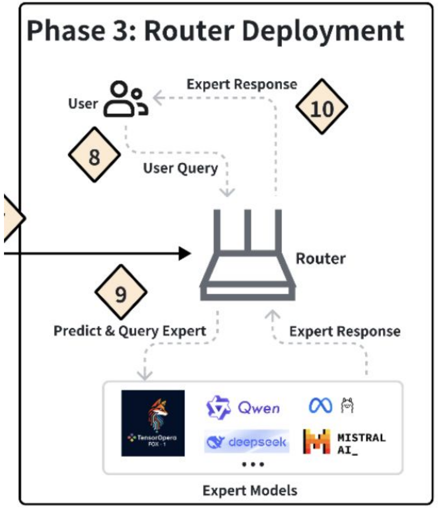

7 Deploy trained router model.

8 Submit user query to router.

9 Router predicts expert to execute query.

10 Router replies expert's response to user.

Router Endpoint Query

```
curl -XPOST http://0.0.0.0:2345/predict -H 'Accept: application/json' -H 'Content-Type:
application/json' -d '{ "messages": [{ "role": "user", "content": "Test" }] }'
```

PolyRouter Service

docker

Router Endpoint Reply


```
{"id":"d4961180721145b1916c7c18e935db6f","object":"chat.completion","created":4318860,"
choices":[{"index":0,"message":{"role":"assistant","content":"It looks like you're
testing me! Is there something specific you'd like to know or discuss? I'm here to
help!"},"finish_reason":"stop"}],"usage":{"prompt_tokens":29,"total_tokens":56,"complet
ion_tokens":27},"expert":"llama3-8b-cloud"}
```

Evaluation Criteria & Baseline Methods

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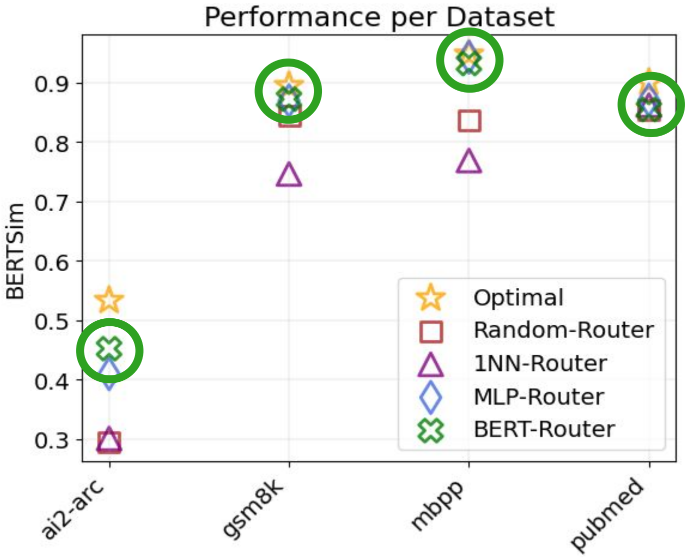
Criteria

- Inference Price Cost ($$/1M tokens)
- Throughput (#tokens/sec)
- BERT Similarity (cosine similarity on BERT embeddings)
- Negative Log-Likelihood (NLL)

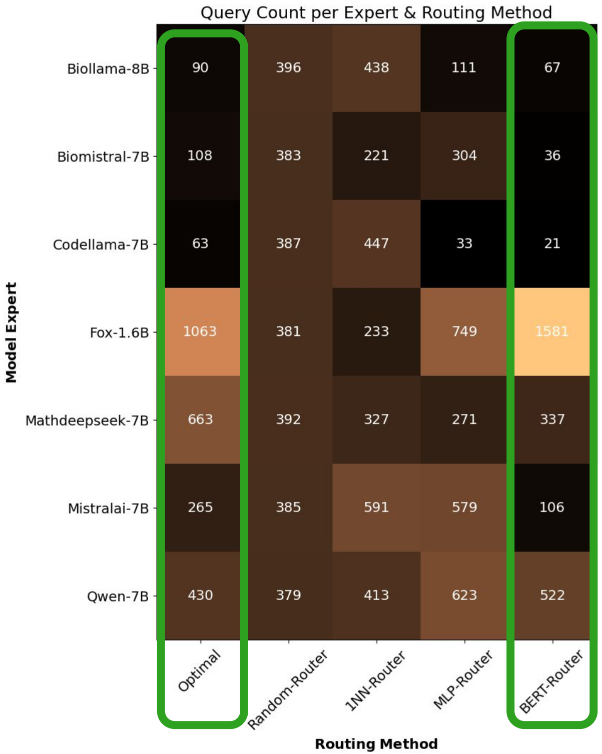
Routing Baselines

- **Zero-Router**
  - average performance of all available experts without any routing logic
- **Optimal-Router**
  - for any given query the optimal set of values is the minimum cost, maximum throughput, maximum BERTSim, minimum NLL recorded by any expert model or routing method.
- **Random-Router**
  - pick a random expert from all available experts.
- **1NN-Router**
  - for every test query find its closest training query (w.r.t. embedding space) and assign the expert that exhibited the best performance for the training query.

Router Performance per Dataset & Query Cardinality per Expert



BERT Router exhibits the best performance



Model Expert	Optimal	Random-Router	1NN-Router	MLP-Router	BERT-Router
Biollama-8B	90	396	438	111	67
Biomistral-7B	108	383	221	304	36
Codellama-7B	63	387	447	33	21
Fox-1.6B	1063	381	233	749	1581
Mathdeepseek-7B	663	392	327	271	337
Mistralai-7B	265	385	591	579	106
Qwen-7B	430	379	413	623	522

BERT Router assigns similar number of queries per expert as Optimal

Trilemma Evaluation (Cost, Throughput, Performance)

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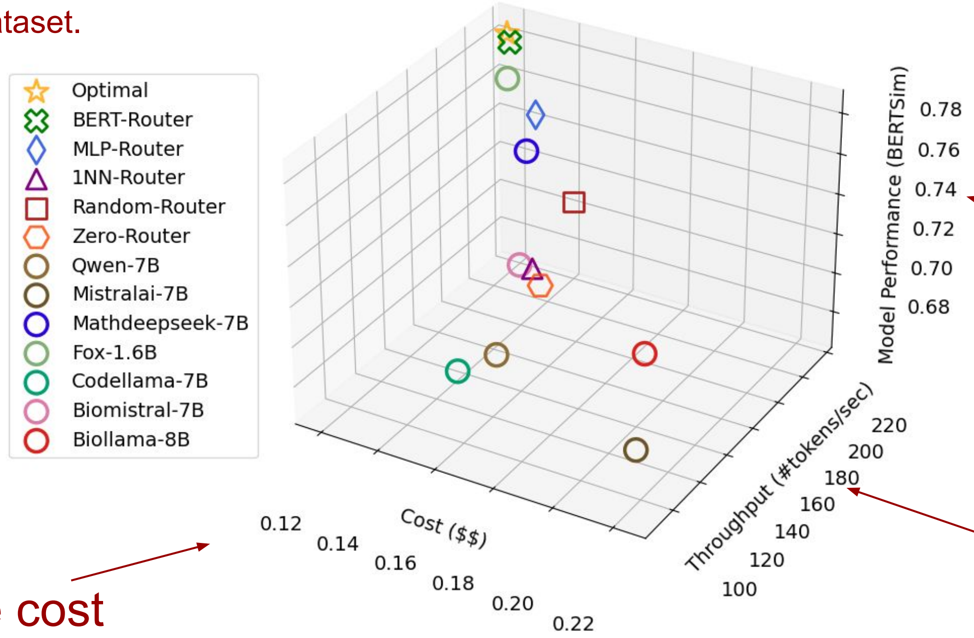
Test Queries: random 20% selection from each benchmark dataset.



avg performance
(across all test queries)

avg throughput
(across all test queries)

avg price cost
(across all test queries)

Future Directions
Hybrid AI
Edge-to-Cloud Collaboration