SLLIM: System Log Local Intelligent Model

Authors: Carlos Cruzportillo, Nassos Galiopoulos, Jason Gillette

Affiliation: University of Texas at San Antonio

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Introduction

Problem Statement

The increasing volume of system logs generated by interconnected devices and enterprise systems creates a challenge for IT professionals in efficiently detecting threats and diagnosing issues, necessitating the development of lightweight, intelligent tools for real-time log analysis and query.

Do more with less!

Introduction

Specific Objectives

1. Fine-tune at least two lightweight LLMs for comparative analysis. ✗
2. Evaluate question answering performance of lightweight LLMs versus resource-intensive models in the cybersecurity domain. ✗

Introduction

Research Questions

1. How well can lightweight LLMs detect system issues and security threats from system logs? ✅
2. How effectively can lightweight LLMs perform question answering compared to larger, more resource-intensive models? ✅

Methods

Models

- **meta-llama/Llama-3.1-8B** as a **Large** Subject
- **meta-llama/Llama-3.2-1B** as a *small* Subject

Access to both models was granted through *Meta AI* via *HuggingFace* 😊

Model

Llama-3.1-8B

- Multi-lingual text LLM
- Released July 2024
- 8 billion parameters
- ~32 GB in size at FP32 *(4 bytes per param)*

Model

Llama-3.2-1B

- Multi-lingual text LLM
- Released September 2024
- 1 billion parameters
- ~4 GB in size at FP32 *(4 bytes per param)*

Dataset

- **Source**: LogQA, a question-answering dataset derived from three public log datasets: HDFS, OpenSSH, and Spark.
- **Composition**:
  - **Raw Logs**: 2,000 log entries selected per dataset.
  - **Question Generation**: Utilized a question generation model to create reading comprehension-style questions with answers extracted from the logs.
- **Example**:

```json
{
  "Question": "What is the status of the block blk_-6369730481066968769?",
  "Answer": "terminating",
  "RawLog": "PacketResponder 1 for block blk_-6369730481066968769 terminating"
}
```

Methods

Evaluation Framework

1. Evaluation Metrics

- **Exact Match (EM)**: Binary match between the generated answer and ground truth.
- **Contains Match (CM)**: Evaluates if the generated answer contains the ground truth.
- **Token-based F1**: Precision and recall on aligned tokens.
- **BERTScore**: Semantic similarity using embeddings.

Methods

Experiment Setup

Few-Shot vs Zero-Shot

- **Few-Shot Prompting**:
  - Incorporates 2 examples from the training set as context.
  - Example: "*Context: [Log 1] Question: [Q1] Answer: [A1]*".
- **Zero-Shot Prompting**:
  - Provides no additional examples.
  - Question directly follows the context.

Methods

Inference Workflow

1. **Model Loading**:
   - HuggingFace pipelines with `transformers`.
   - Quantized models using `BitsAndBytesConfig` for memory optimization.
2. **Batch Processing**:
   - Test data processed in batches of 2 for GPU efficiency.
   - Token truncation managed dynamically (`max_new_tokens`).
3. **Data Storage**:
   - Results saved as structured JSON for easy evaluation.
   - Includes metadata: context, question, generated answer.

Why GPU efficiency matters

```
+-----------------------------------------------------------------------------------------+
| NVIDIA-SMI 565.72                 Driver Version: 566.14         CUDA Version: 12.7     |
|-----------------------------------------+------------------------+----------------------+
| GPU  Name                 Persistence-M | Bus-Id          Disp.A | Volatile Uncorr. ECC |
| Fan  Temp   Perf          Pwr:Usage/Cap |           Memory-Usage | GPU-Util  Compute M. |
|                                         |                        |               MIG M. |
|=========================================+========================+======================|
|   0  NVIDIA GeForce RTX 2060        On  |   00000000:01:00.0  On |                  N/A |
| N/A   74C    P0             69W /   80W |    5849MiB /   6144MiB |    100%      Default |
|                                         |                        |                  N/A |
+-----------------------------------------+------------------------+----------------------+
```

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|                                         |                        |               MIG M. |
|=========================================+========================+======================|
|   0  NVIDIA GeForce RTX 2060        On  |   00000000:01:00.0  On |                  N/A |
| N/A   73C    P0             73W /   80W |    1334MiB /   6144MiB |     41%      Default |
|                                         |                        |                  N/A |
+-----------------------------------------+------------------------+----------------------+
```

Results

Aggregated Metrics

Metric	Llama-3.1-8B ZS	Llama-3.2-1B ZS	Llama-3.1-8B FS	Llama-3.2-1B FS
Exact Match	**0.00**	**0.02**	**0.01**	**0.02**
Contains Match	**0.71**	**0.58**	**0.51**	**0.62**
Token F1	**0.16**	**0.22**	**0.16**	**0.20**
BERTScore	**0.83**	**0.82**	**0.77**	**0.79**

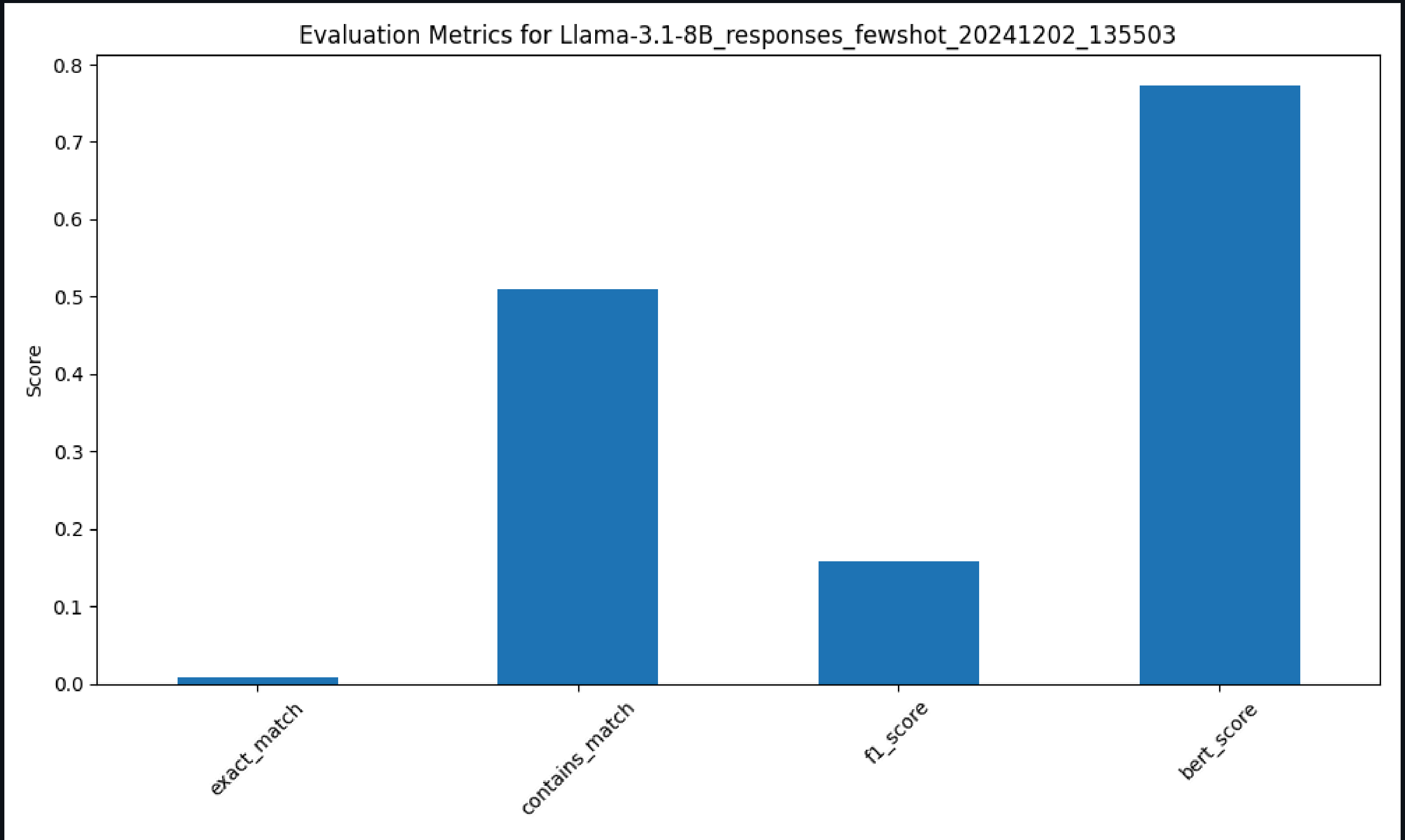
Results (cont.)

Observations

- Larger models exhibited only marginally better performance.
- Few-shot prompting degraded performance.
- Tokenization likely skewed matches and underrepresented performance.

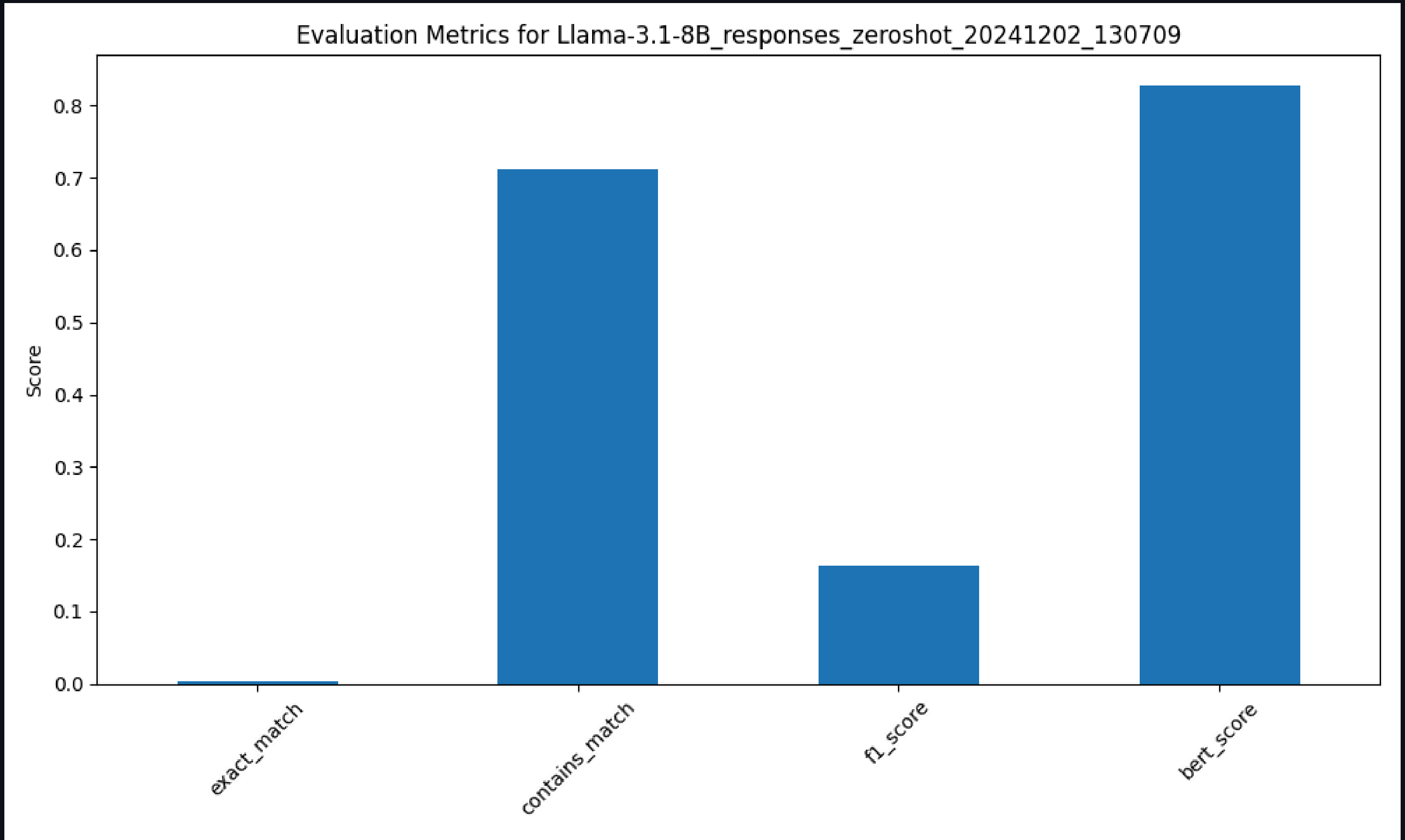
Results (cont.)

Metric Comparison



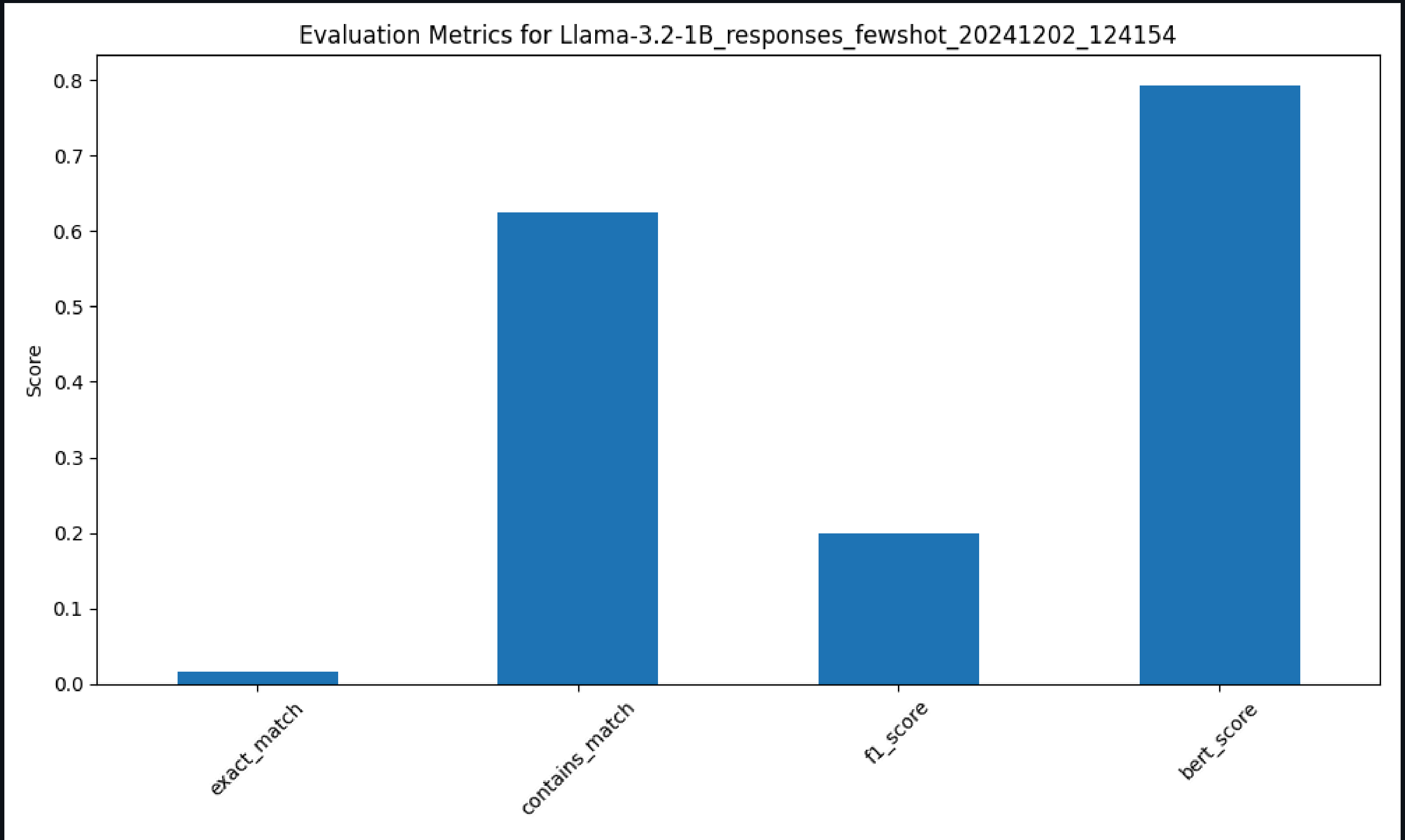
Results (cont.)

Metric Comparison



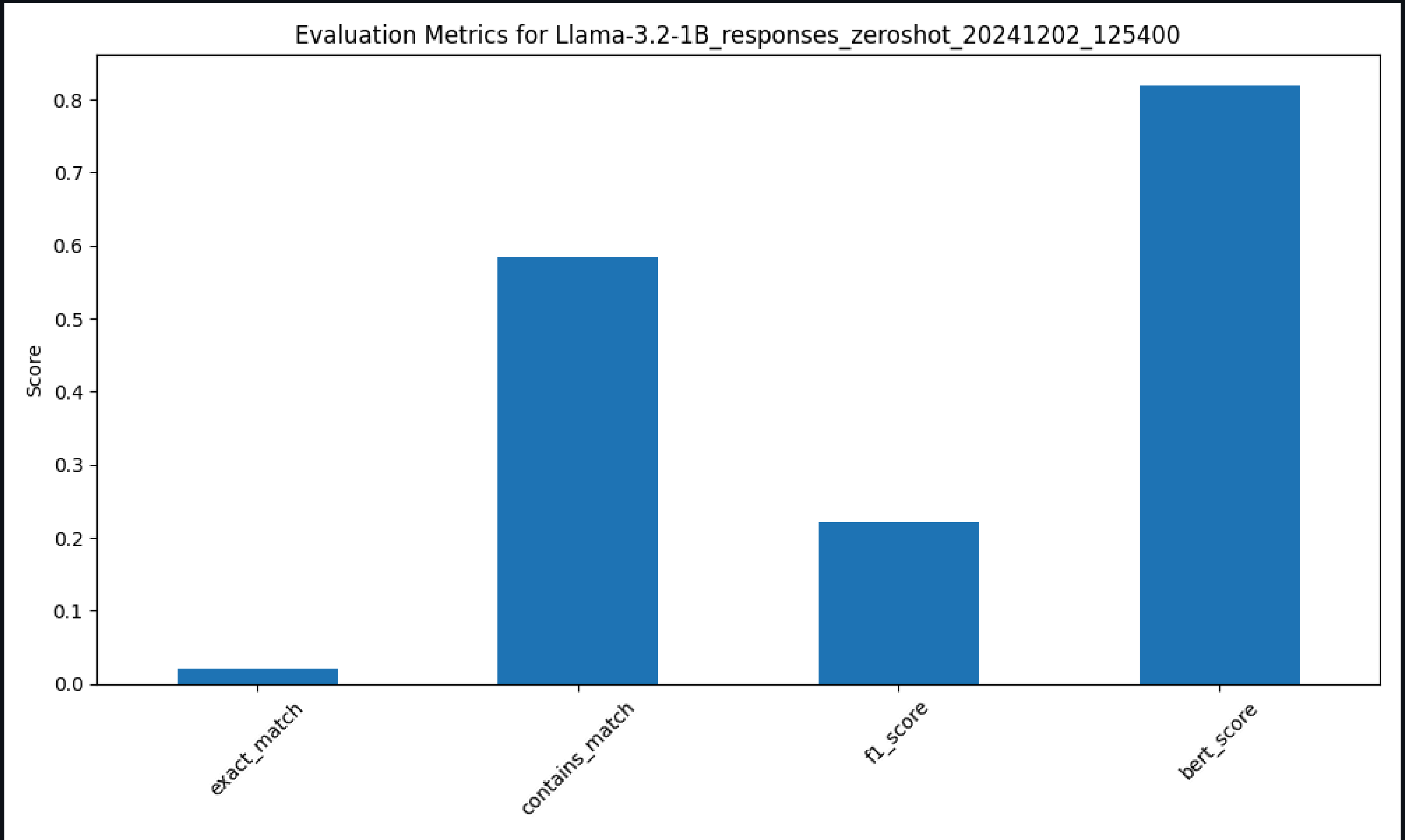
Results (cont.)

Metric Comparison



Results (cont.)

Metric Comparison



Key Findings

1. **Model Efficiency**:
    - Llama-3.2-1B successfully handles domain-specific tasks with minimal resources.
    - Llama-3.1-8B demonstrates no significant performance gain.
2. **Few-Shot Effectiveness**:
    - Few-shot prompting introduces noise and complexity, for no performance gain.
3. **Challenges**:
    - Token alignment in noisy log contexts affects EM and F1 scores.
    - BERTScore highlights semantic drift in generated answers.
    - BERTScore does not tell the full story as wrong answers can be

Conclusion

Contributions

1. A comparative analysis of **lightweight** and **large-scale** LLMs in log-based QA tasks.
2. A novel application of lightweight LLMs on Log analysis tasks.

Next Steps

1. Fine-tuning vs. in-context learning.
2. Improving / validating evaluation.
3. Exploring other evaluation metrics for log anomaly detection.
4. Expand scope of log analysis to threat detection.

Questions?