

Using Large Language Models to Extract PD-L1 Testing Details from Electronic Health Records

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Background

- The suitability of artificial intelligence (AI) and large language models (LLMs) to assist in curating real-world data (RWD) from electronic health records (EHR) for research has not been extensively evaluated.
- PD-L1 biomarker testing guides cancer treatment decisions. However, results:
 - are hard to access because lab reports are unstructured and require clinical expertise to interpret.
 - vary by cancer type, documentation pattern, and year the test occurred
- This study explored the ability of LLMs to rapidly identify PD-L1 biomarker details in the EHR and the impact of fine-tuning on results.

Methods

- Data source:** The US nationwide Flatiron Health EHR-derived de-identified database, comprising patient-level structured and unstructured data,^{1,2} originating from ~280 cancer clinics (~800 sites of care), majority from community oncology settings.
- Cohort:** Patients diagnosed with one of 15 cancers after 1/1/2011
- Primary Outcome:** PD-L1 biomarker testing details
- Statistical Methods:** Applied open-source LLMs (Llama-2-7B and Mistral-v0.1-7B)^{3,4} to extract seven biomarker details relating to PD-L1 testing:
 - Collection/Receipt/Report Date, Cell type, Percent staining, Combined positive score, and Staining intensity.
 - Two approaches: “zero-shot” experiments (no fine-tuning) exploring a range of prompts and fine-tuning on manually-curated answers from 500/1000/1500 documents.
 - Validation: (1) Used 250 expert human abstracted answers across >15 cancer types; (2) compared performance on percent staining to a deep learning model (LSTM) baseline trained on >10,000 examples.⁵

Results

- LLMs extracted all seven biomarker testing details at once from EHR documents.
- Fine-tuned outputs consistently conformed to desired RWD structure.
- Zero-shot outputs were frequently invalid and exhibited hallucination.
- Fine-tuning performance improved with additional training examples:
 - F1 scores ranged from 0.80–0.95, and date accuracy (within 15 days) ranged from 0.85–0.90.
 - Increasing the number of epochs improved performance with limited training examples, but the effect diminished quickly with moderately more training examples.
- Fine-tuned LLMs exceeded performance of deep learning model baseline ($\Delta F1 = 0.05$) despite significant difference in training data.

Fine-tuned LLMs accurately extracted complex biomarker testing details and results from unstructured clinical documents



Scan for abstract and digital poster

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Limitations

- Results may not translate to other biomarkers, and specifically ones that are not standard of care.
- More work is required to see whether fine-tuning on a range of clinical tasks would lead to improved performance.

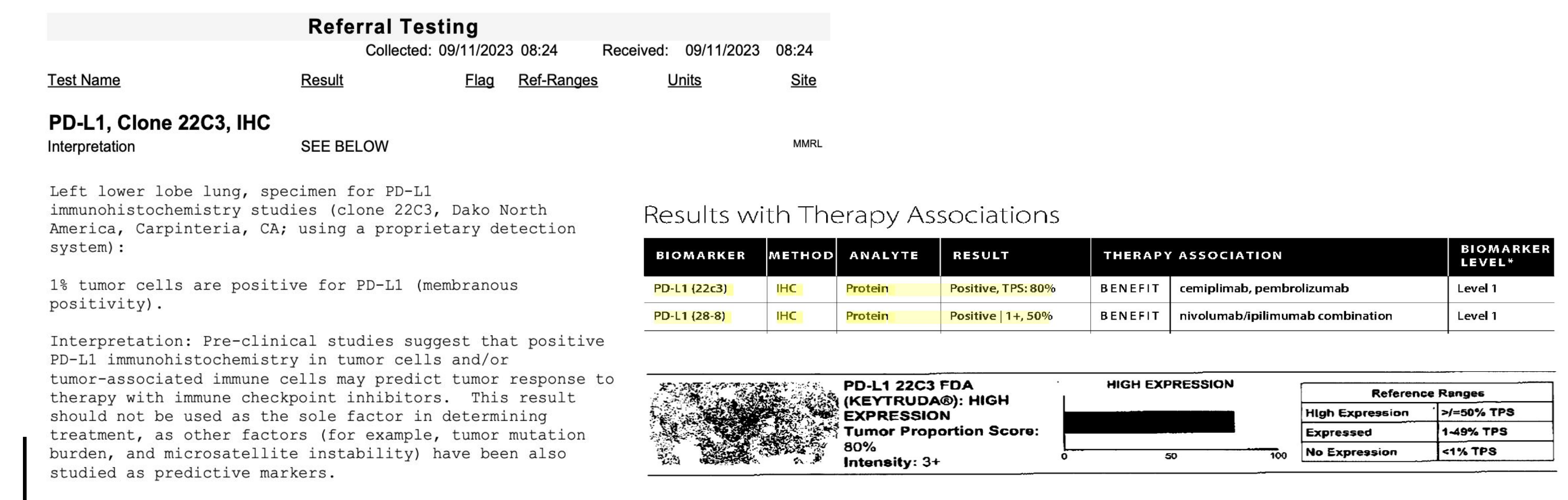
Conclusions

- LLMs, fine-tuned with high-quality labeled data, accurately extracted complex PD-L1 test details from the EHR despite considerable variability in cancer type, documentation, and time.
- Zero-shot prompt extraction not as effective at model scale examined.
- Validation required access to high-quality data labeled by experts with access to the source EHR.

References

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Figure 1.



ZERO SHOT

FINE TUNED

Prompt

Using the provided document, extract the results of the patient's PD-L1 test. Return the results in a JSON structure with the following keys:
 - "percent_staining" # may also be referred to as tumor proportion (TPS)
 - "staining_intensity"
 - "expression_level"
 - "interpretation" # may be positive or negative/not detected
 Only include information that can be found in the document.

Output

```
Sure! Here is the result of the patient's PD-L1 test in a JSON structure:
{
  "PD-L1": {
    "Tumoral Proportion Score (TPS)": 80,
    "Clone 22C3": {
      "Membranous pattern of expression in 80% of tumor cells": true
    }
  }
}
```

Note that the PD-L1 test results are only available for the tumor sample (C23-006350). The other sample (C23-006349) does not have PD-L1 test results.

Output

```
{
  "percent_staining": "80",
  "staining_intensity": "Not Specified",
  "expression_level": "High",
  "interpretation": "Negative",
}
```

Figure 3.

F1 Score for different extracted variables

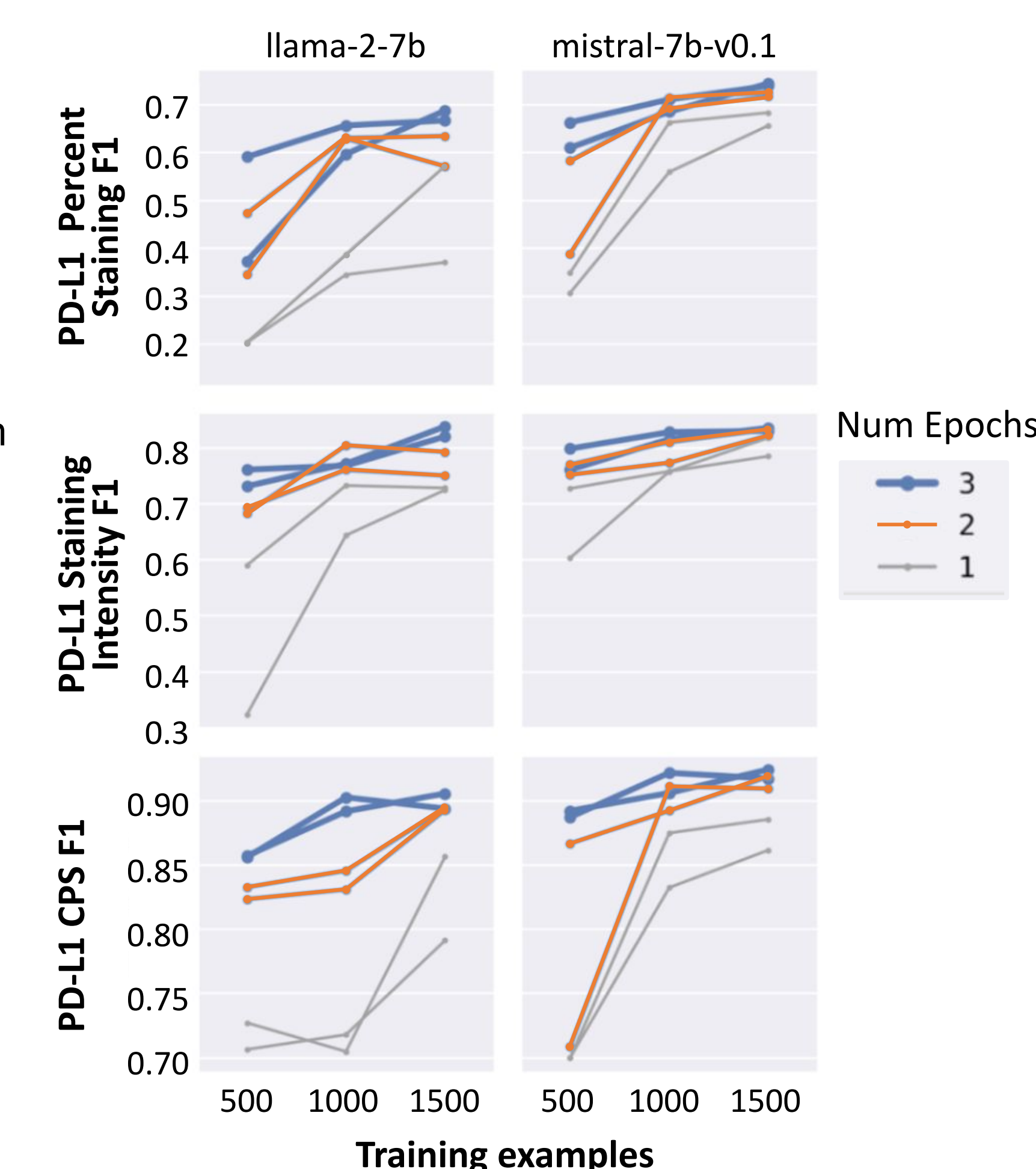


Figure 2.

Ability to parse response into json, and into valid json

