Instruction Tuning Large Language Models to Understand Electronic Health Records

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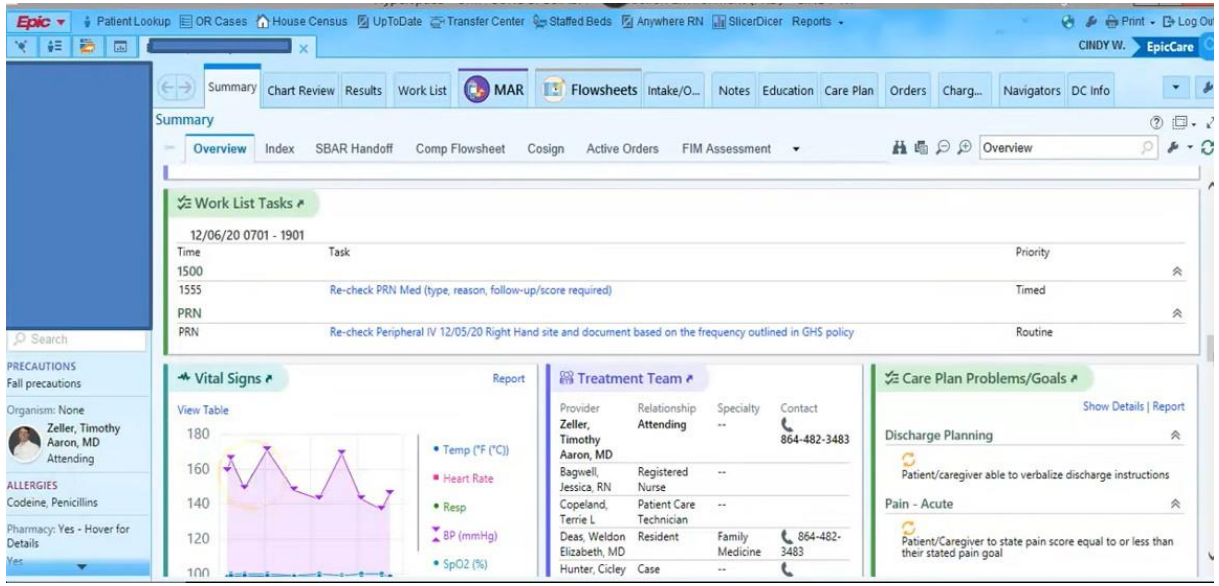
Background: EHR System

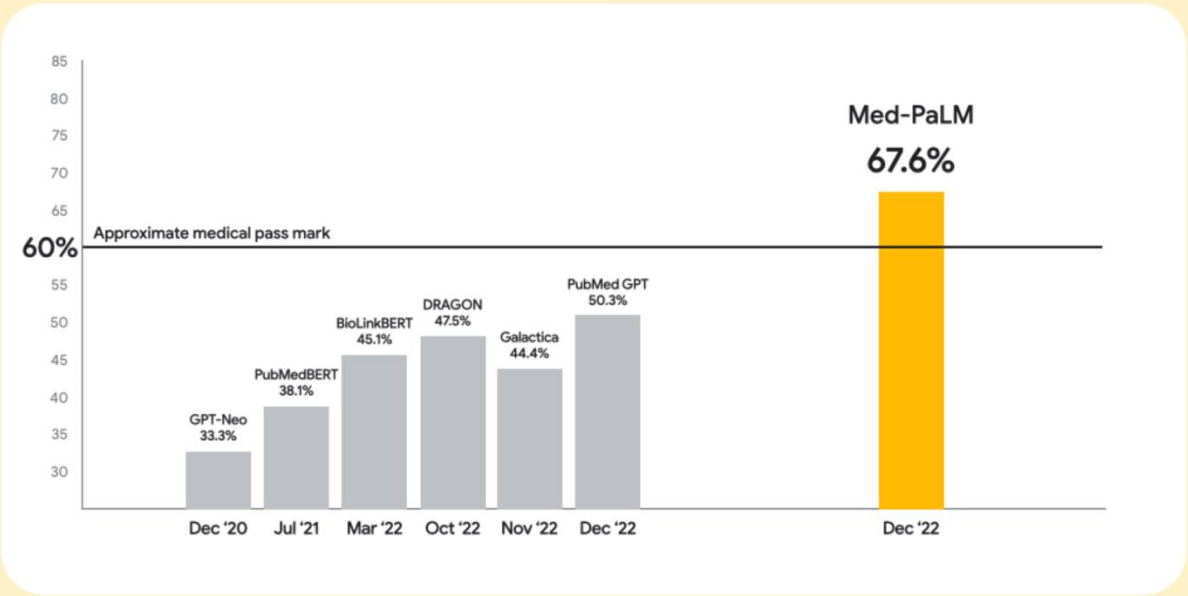
- EHR documents a patient's medical history and care
- Challenges of existing EHR systems:
  - navigating the user interface
  - vast amount of data that needs to be reviewed
  - extra clerical tasks directed to physicians
- There were 165.3 alerts/patient per day, but only 4.5% were important
- Physicians spent an average of 3.17 hours on EHR systems each day



Tai-Seale M, Olson CW, Li J, et al. Electronic Health Record Logs Indicate That Physicians Split Time Evenly Between Seeing Patients And Desktop Medicine. Health Aff (Millwood). 2017;36(4):655-662. doi:10.1377/hlthaff.2016.0811

Opportunity: Streamline EHR with LLM

- LLMs can understand complex inputs and follow human instructions to solve diverse tasks.
- LLMs also encode clinical knowledge



Example of USMLE-style question

A 32-year-old woman comes to the physician because of fatigue, breast tenderness, increased urinary frequency, and intermittent nausea for 2 weeks. Her last menstrual period was 7 weeks ago. She has a history of a seizure disorder treated with carbamazepine. Physical examination shows no abnormalities. A urine pregnancy test is positive. The child is at greatest risk of developing which of the following complications?

A. Renal dysplasia

B. Meningocele

C. Sensorineural hearing loss

D. Vaginal clear cell carcinoma

Goal & Challenges

Goal:

- Develop a conversational AI assistant for EHR data

Capabilities:

- Information extraction:

E.g., “What was the recorded Blood Oxygen level on admission?”

- Clinical reasoning:

E.g., “What is the recommended follow-up plan for the patient’s abdominal pain and gastrointestinal symptoms?”

Challenge 1: Lack of Large-Scale Instruction-Following Data

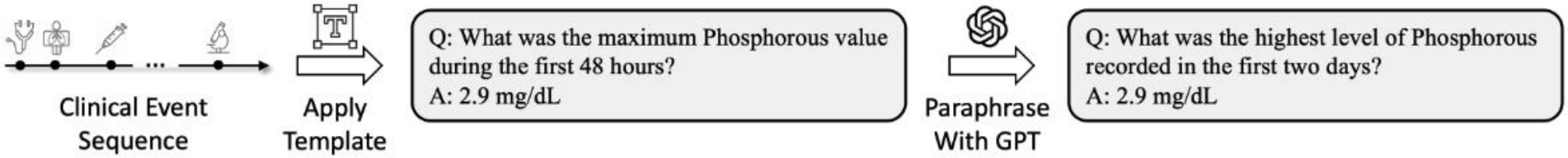
Dataset	Size	Source	Format	Answer Type
MedQA [Jin et al., 2020]	13K	US medical licensing exam	Question + Answer	Multi Choice
MedMCQA [Pal et al., 2022]	6K	AIIMS and NEET PG entrance exams	Question + Answer	Multi Choice
PubMedQA [Jin et al., 2019]	0.5K	PubMed literature	Question + Context + Answer	Multi Choice
MMLU clinical [Hendrycks et al., 2021]	1K	US Medical Licensing Examination	Question + Answer	Multi Choice
EHRSQL [Lee et al., 2023]	24K	MIMIC-III	Question + Answer	SQL
EHRNoteQA [Kweon et al., 2024]	0.9K	MIMIC-IV	Question + Note + Answer	Free Text
MedAlign [Fleming et al., 2024]	0.9K	EHRs (Stanford University)	Question + EHR + Answer	Free Text

Challenge 2: Heterogeneous EHR Data

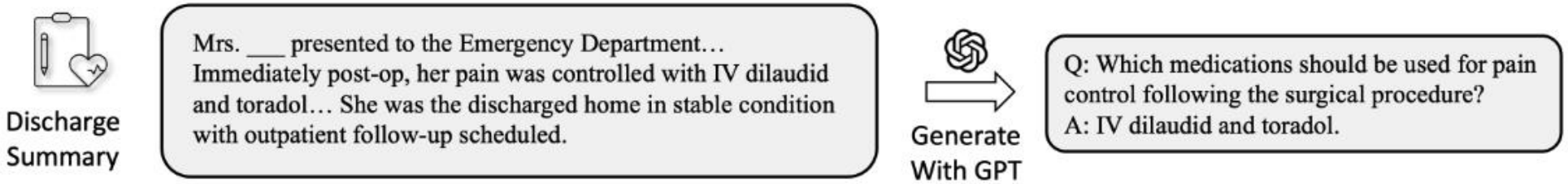
- Complex preprocessing
  - Code mapping
  - Concept standardization
  - Unit normalization

- Feature selection
  - Manually define a subset of features out of hundreds/thousands of events

Solution 1: A dataset of 400K EHR Instruction-Following Data



(a) Generation Pipeline for Schema Alignment Data

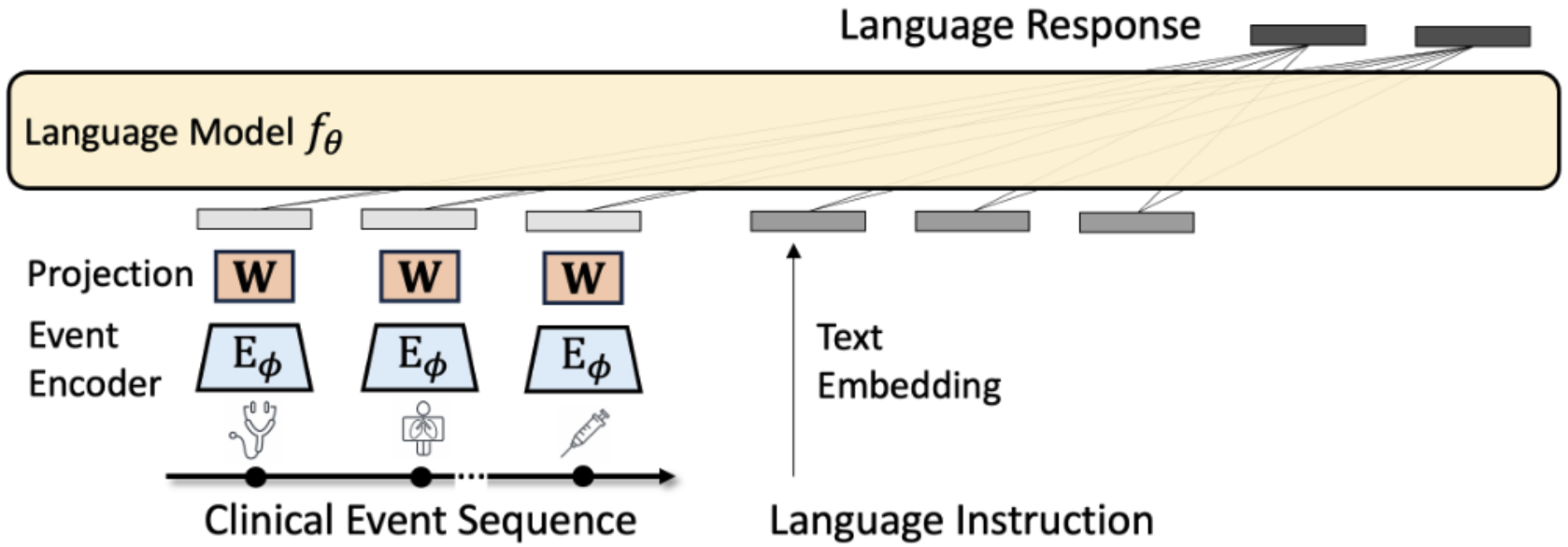


(b) Generation Pipeline for Instruction Following Data

Preliminary: Medical Event Data Standard

- Represent each patient's EHR data as a sequence of event
- Each event consists of a timestamp, a type, and a value
- Convert event to text:
    - 10 min, vital signs for heart rate 75 bpm
    - 20 min, vital signs for blood oxygen 97%
    - 235 min, lab measure for white blood cells, value 3.7 K/uL

Solution 2: A Foundation Model for EHR Data



Two-Stage Training

- Stage 1: Training for Schema Alignment
  - Only train the projection matrix with 350K QA pairs generated from the template and then paraphrased by GPT-3.5

- Stage 2: Training for Clinical Reasoning
  - Train both the LLM and the projection matrix with 50K QA pairs for clinical reasoning

Results 1: Llemr as a Conversational Clinical AI Assistant

Model	Schema Alignment	Clinical Reasoning	Overall
Llama-2-7b-chat-hf [Touvron et al., 2023]	47.66 ± 15.31	47.55 ± 11.73	47.60 ± 9.62
SynthIA-7B-v1.3 [Tissera, 2023]	47.18 ± 5.84	49.16 ± 4.99	48.17 ± 3.83
Mistral-7B-OpenOrca [Lian et al., 2023]	51.75 ± 8.20	51.18 ± 7.67	51.46 ± 5.60
Llama-3-8b-Instruct [Touvron et al., 2023]	56.18 ± 7.08	55.07 ± 7.25	55.62 ± 5.05
MPT-7b-8k-instruct [MosaicML, 2023]	68.13 ± 8.95	53.90 ± 4.92	61.01 ± 5.19
vicuna-7b-v1.5 [Chiang et al., 2023]	66.81 ± 5.61	62.40 ± 4.59	64.60 ± 3.63
dolphin-2.0-mistral-7b [Cognitive, 2023]	63.06 ± 5.36	72.66 ± 7.47	67.86 ± 4.64
`Llemr` + Stage 1	**69.71 ± 6.32**	64.35 ± 7.21	67.03 ± 6.83
`Llemr` + Stage 1&2	**70.42 ± 5.88**	**76.23 ± 4.23**	**73.33 ± 5.30**

Results 2: Llemr on Standard Clinical Predictive Benchmarks

Method	Mortality	Readmission	Length-of-Stay	Diagnosis
RNN [Cho et al., 2014]	0.8002 (0.02)	0.6643 (0.01)	0.6833 (0.03)	0.7735 (0.01)
Transformer [Vaswani et al., 2017]	0.8241 (0.03)	0.7006 (0.01)	0.6990 (0.01)	0.8025 (0.02)
RETAIN [Choi et al., 2016a]	0.8302 (0.02)	0.6994 (0.01)	0.7015 (0.01)	0.8073 (0.02)
GRASP [Zhang et al., 2021]	0.8362 (0.01)	0.7155 (0.01)	0.7100 (0.03)	0.8005 (0.02)
GenHPF [Hur et al., 2024]	0.8258 (0.02)	0.7102 (0.01)	0.6993 (0.02)	0.8103 (0.03)
REMed [Kim et al., 2024]	0.8346 (0.02)	0.7193 (0.02)	0.7018 (0.01)	**0.8128 (0.01)**
`Llemr`	**0.8388 (0.01)**	**0.7251 (0.03)**	**0.7132 (0.01)**	0.8086 (0.01)

Conclusion

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- Goal
  - Develop a conversational AI assistant for EHR data
- Challenges
  - Lack of large-scale instruction-following data
  - Heterogeneous EHR data
- Method
  - MIMIC-Instr, a dataset of over 400K open-ended instruction-tuning data generated by GPT-3.5
  - Llemr, a generic framework designed to empower LLMs to encode EHR data with heterogeneous schema
- Result
  - Outperforms SOTA LLMs in answering diverse inquiries about a patient
  - Performs on par with SOTA baselines when further fine-tuned for clinical predictive tasks