



# MEDVOC: Vocabulary Adaptation for Fine-tuning Pre-trained Language Models on Medical Text Summarization

**Gunjan Balde**\*, Soumyadeep Roy\*, Mainack Mondal, and Niloy Ganguly

Indian Institute of Technology Kharagpur  
L3S Research Center, Germany

\*Equal Contribution



**IJCAI**  
JEJU 2024

# Summarization in Medical Domain

- Summarization in medical domain useful for variety of tasks:
  - Patient Health Query
  - Radiology Report
  - Patient Notes and many more...
- BART and PEGASUS are state of the art open-domain models

But PLMs generalizes poorly to medical domain

# Medical Summarization Example

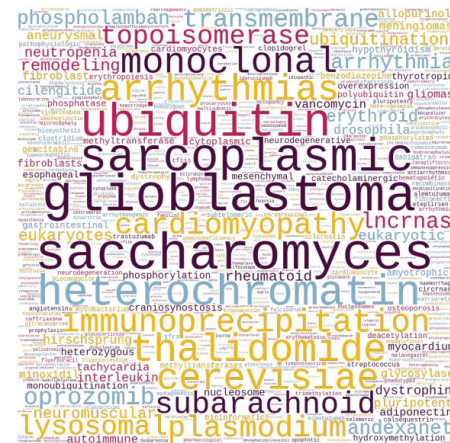
**Source Document:** KNEE OSTEOARTHRITIS ... ruptured anterior cruciate ligament ... meniscus... my question is can you treat me, or turn me can recommend doctors or hospitals to treat in the U.S.

**Reference Summary:** How can I find physician(s) or hospital(s) who specialize in knee osteoarthritis?

**Generated Summary (PLM):** What are the treatments for ruptured anterior cruciate ligament and meniscus?

# Issue: PLM Poorly Tokenizes Medical Words

- Medical Out-of-vocabulary (OOV) words  
glioblastoma: g ##lio ##bla ##sto ##ma
- Affects both encoder and decoder:
  - **Encoder:** Poor tokenization blurs the meaning<sup>[1]</sup>
  - **Decoder:** Generate more tokens per word<sup>[2]</sup>



[1] Hofmann, Valentin et al. "An embarrassingly simple method to mitigate undesirable properties of pretrained language model tokenizers." ACL 2022.

[2] Rust, Phillip, et al. "How Good is Your Tokenizer? On the Monolingual Performance of Multilingual Language Models." ACL IJCNLP 2021.

# Vocabulary Adaptation tackles OOV Words

- Vocabulary Adaptation strategies extends PLM vocabulary
  - Append domain-specific vocabulary **during fine-tuning**
- Existing works (AVocaDo<sup>[1]</sup>, exBERT<sup>[2]</sup>)
  - **Limited to only classification tasks** using **encoder-only** architecture

[1] Hong, Jimin, et al. "AVocaDo: Strategy for Adapting Vocabulary to Downstream Domain." EMNLP 2021.

[2] Tai, Wen, et al. "exBERT: Extending pre-trained models with domain-specific vocabulary under constrained training resources." EMNLP Findings. 2020.

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It requires tackling encoder-decoder / decoder-only architecture

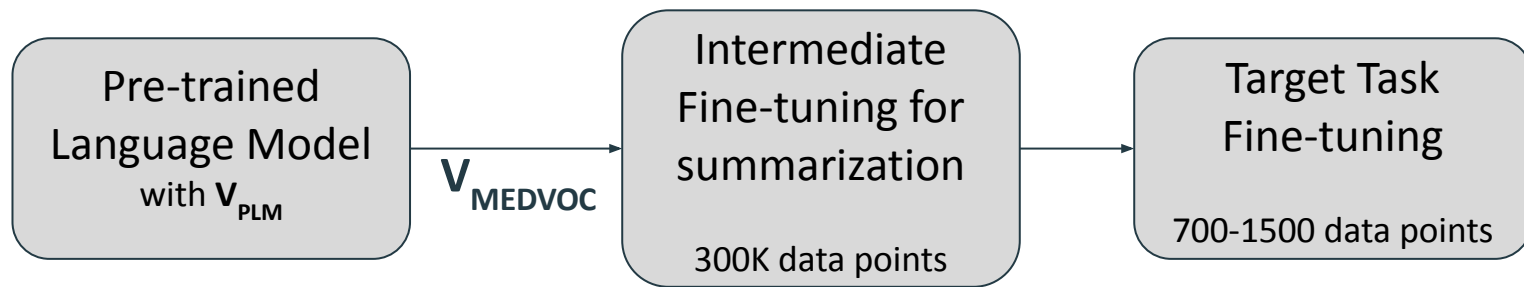
**Can we adapt PLM vocabulary during fine-tuning  
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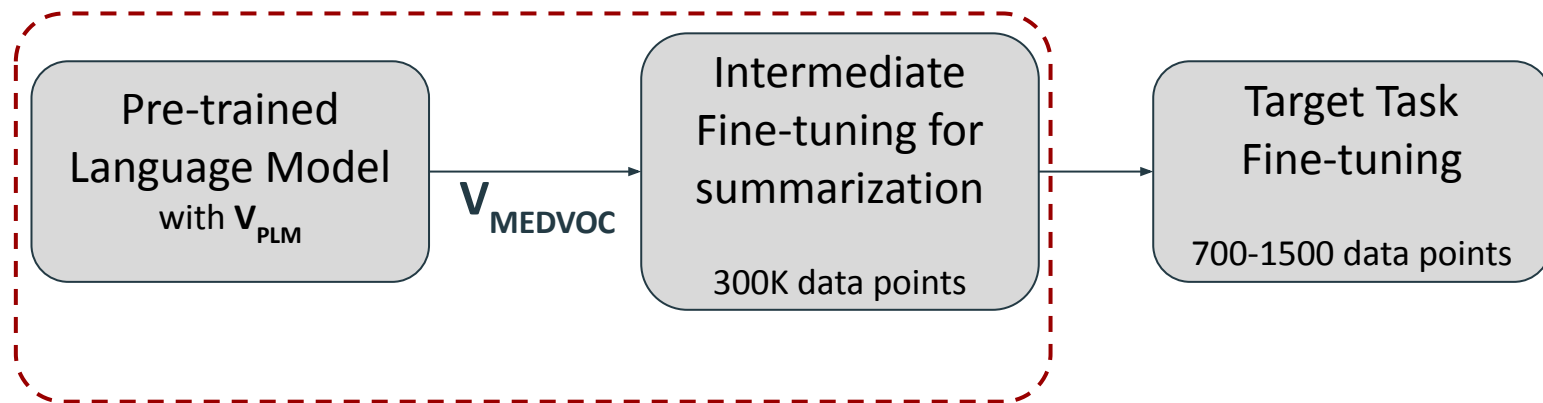
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**MEDVOC: Vocabulary adaptation strategy for domain-specific summarization**

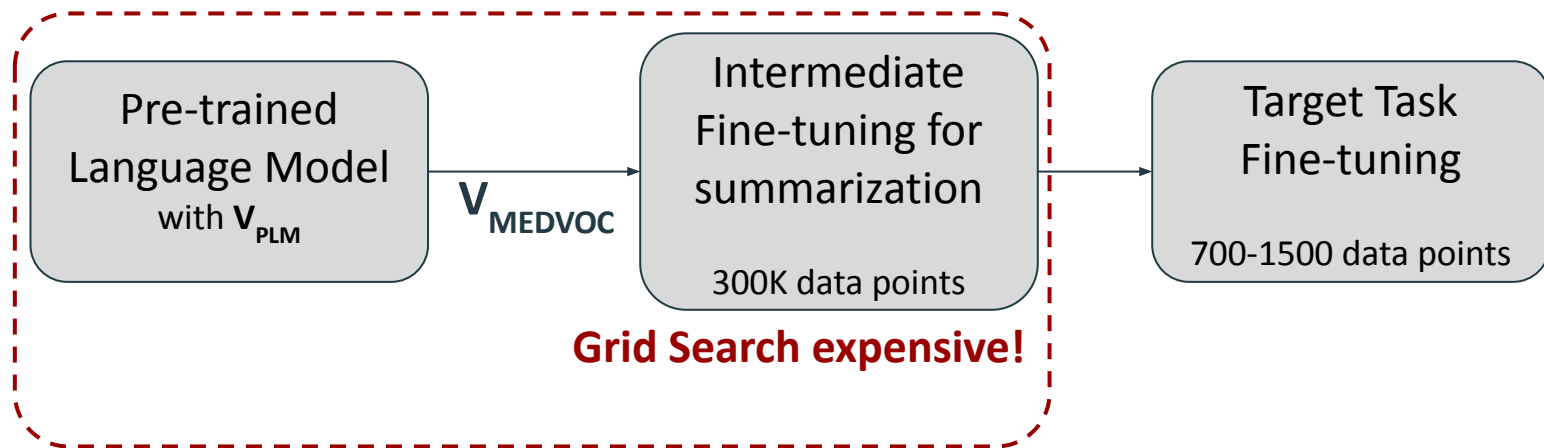
# MEDVOC at a glance



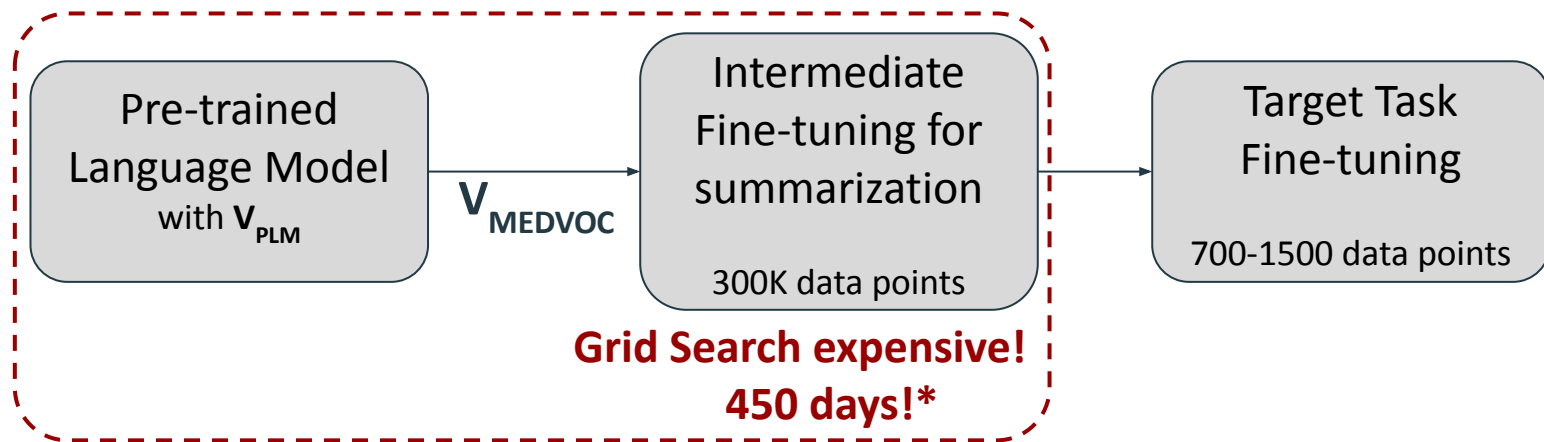
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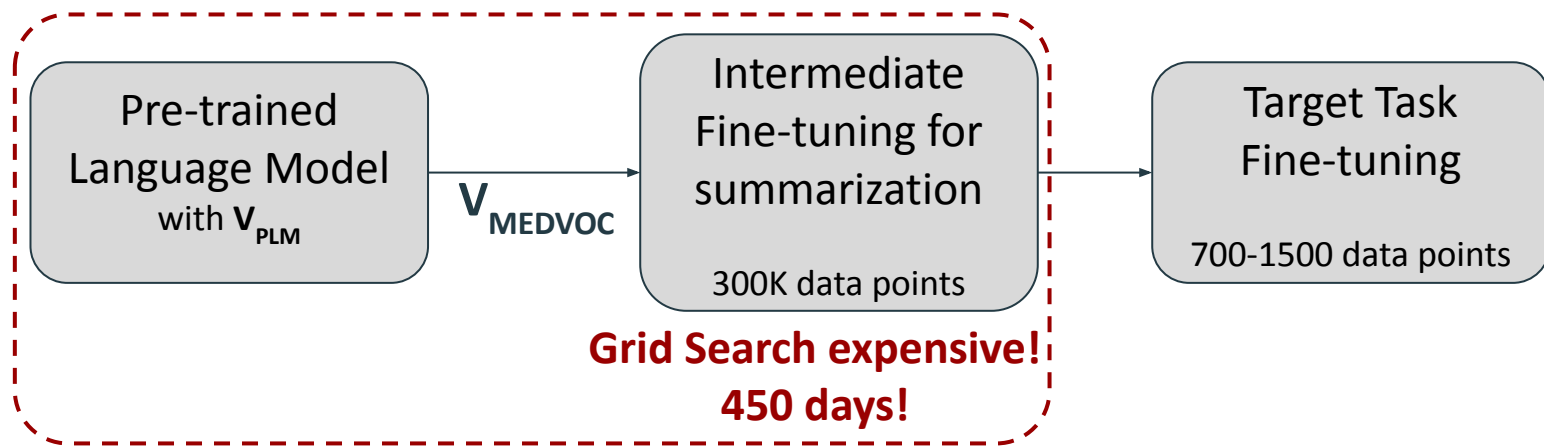
# MEDVOC at a glance



# MEDVOC at a glance



# MEDVOC at a glance



- MEDVOC optimizes fragment score to optimize performance
- Brings down search time to **2 hours**

# Evaluation Setup

- Three summarization models — BertSumAbs, BART, and PEGASUS
- Three kinds of baselines:
  - Vocabulary adaptation — AVocaDo<sup>[1]</sup> and PubMedBERT<sup>[2]</sup>
  - Domain-Specific Models — BioBERT and BioBART
  - two ablation baselines — IFT-CNN and IFT-PAC
- Metrics: **Rouge**, BertScore, and Concept-Score

[1] Hong, Jimin, et al. "AVocaDo: Strategy for Adapting Vocabulary to Downstream Domain." EMNLP 2021.

[2] Gu, Yu, et al. "Domain-specific language model pretraining for biomedical natural language processing." ACM Transactions on Computing for Healthcare (HEALTH) 2021.

# Datasets

- Query Focused Summarization
  - EBM, BioASQ
    - SD —Query + PubMed Abstract
    - RS —Answer
- Patient Healthcare Query Summarization
  - MeQSum, CHQSum
    - SD —Patient Query
    - RS —a concise Question



## MEDVOC outperforms baselines across tasks

Dataset	R-L (Domain)	R-L (IFT-CNN)	R-L (IFT-PAC)	R-L (MEDVOC)
EBM	19.19	18.65	<u>19.35</u>	<b>20.03</b>
BioASQ	44.23	42.31	<u>43.60</u>	<b>45.98</b>
MeQSum	51.23	50.51	<u>52.47</u>	<b>53.63</b>
CHQSum	37.56	38.36	<u>38.45</u>	<b>38.75</b>

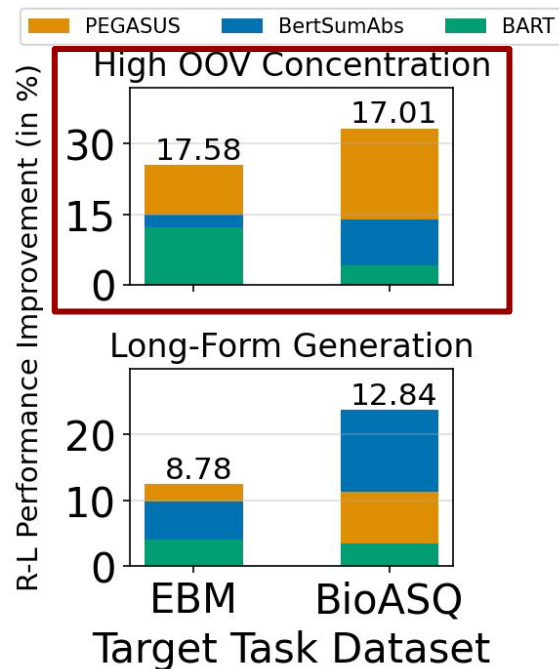
# MEDVOC outperforms existing vocabulary adaptation baselines

- **AVocaDo**- strategy for classification
  - **4%** improvement
- **PubMedBERT** - Domain-specific vocabulary
  - **33%** improvement

	PubMed BERT	AVocaDo	MEDVOC
EBM	17.76	<u>18.43</u>	<b>19.59</b>
BioASQ	26.65	<u>45.86</u>	<b>47.54</b>
MeQSum	39.79	<u>49.30</u>	<b>51.49</b>
CHQSum	30.59	<u>34.49</u>	<b>35.11</b>

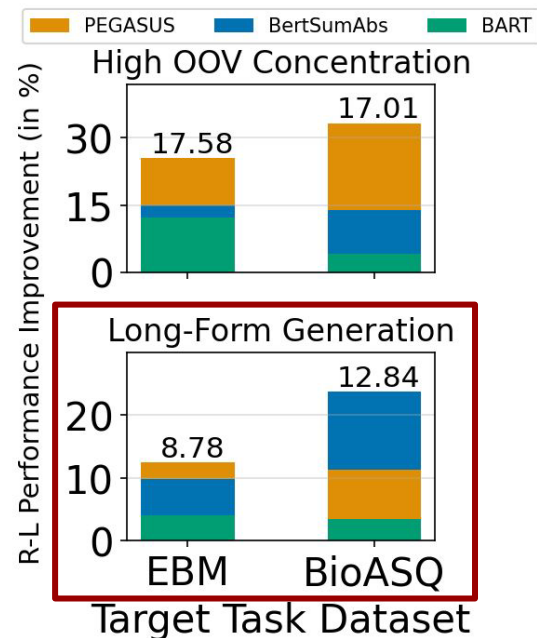
# MEDVOC improves over baselines in challenging scenarios

- High OOV concentration
  - Subset where RS has high unigram OOV
  - **17.29%** improvement



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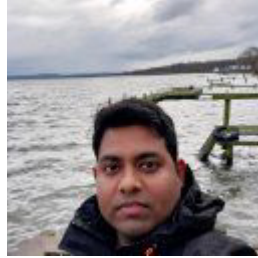
- High OOV concentration
  - Subset where RS has high unigram OOV
  - **17.29%** improvement
- Long-Form Generation
  - Subset where RS was longer in length
  - **10.81%** improvement



# Conclusion and Key Takeaways

- **First vocabulary adaptation work** for domain-specific summarization
- MEDVOC adapts models of **varying parameter and vocabulary sizes**
- Minimal additional parameters upto 1.59% w.r.t. original model size
- Medical experts found MEDVOC summaries to be **more faithful**
- MEDVOC generalizable to other domains with high vocabulary mismatch

# Thank You!



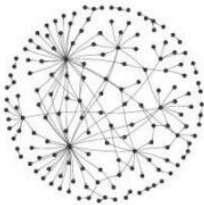
Soumyadeep Roy



Mainack Mondal



Niloy Ganguly



CNeRG



Codebase



Preprint

PMRF  
Prime Minister's Research Fellows

