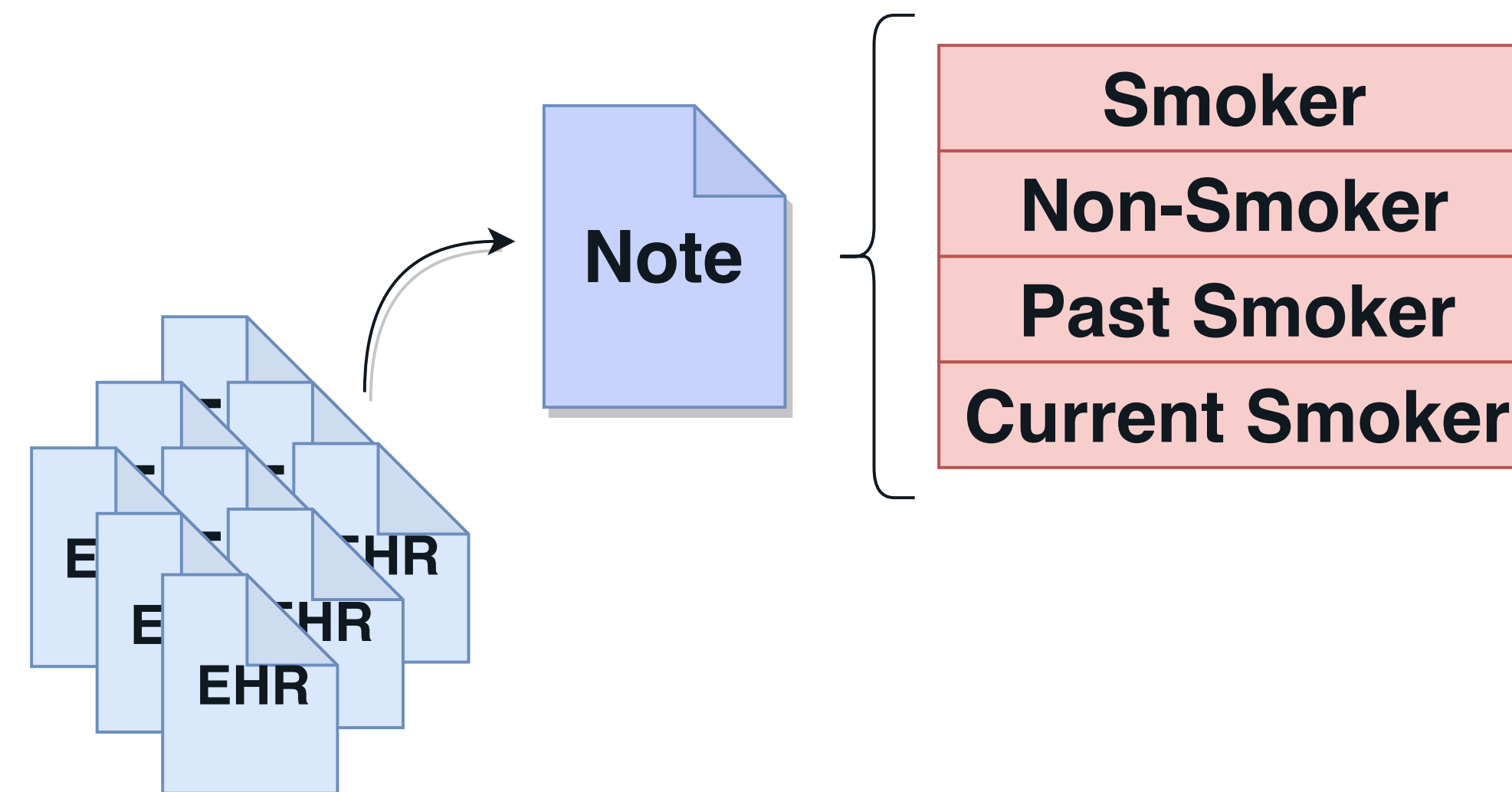


# PHENOTYPING OF CLINICAL NOTES WITH CONTEXTUALIZED NEURAL LANGUAGE MODELS

Andriy Mulyar<sup>1</sup>, Elliot Schumacher<sup>2</sup>, Masoud Rouhizadeh<sup>2</sup>, and Mark Dredze<sup>2</sup>

Virginia Commonwealth University<sup>1</sup>, Johns Hopkins University<sup>2</sup>

## What is Clinical Note Phenotyping?



- **Clinical phenotyping:** extract patient conditions or traits from unstructured clinical text.
- Automated phenotyping of clinical notes:
  - Adds structured information to electronic health records.
  - Enhances the productivity and accuracy of medical coders.
  - Provides information for downstream clinical decision support tasks.

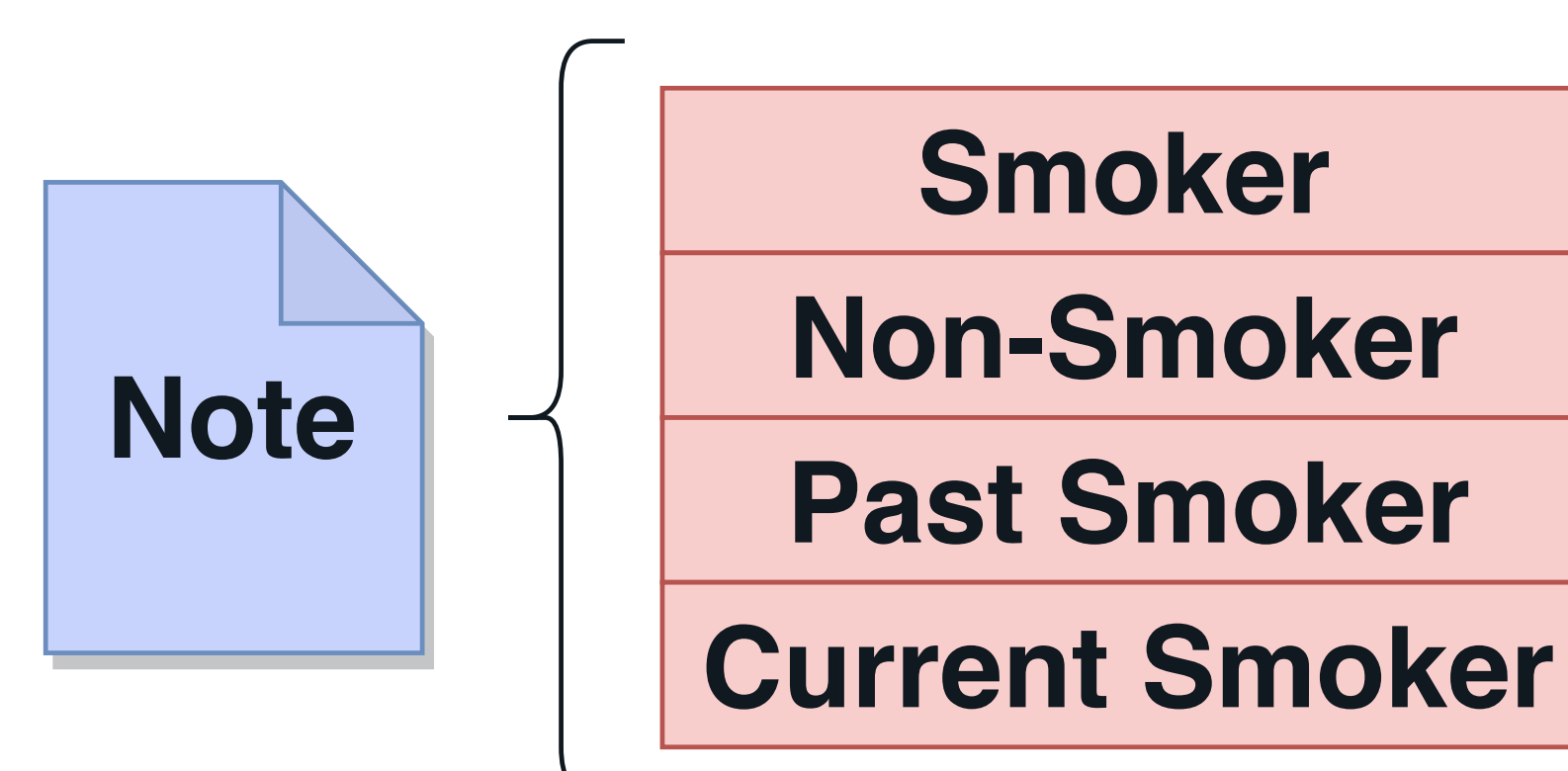
## Why is Phenotyping Difficult?

- A given phenotype may not be present in a specific clinical note.
  - A phenotype may be present, but not explicitly stated.
- "...The patient currently resides on a friend's couch ..."
- Homeless**
- Signal of a phenomic trait may be present anywhere within a clinical note.

## Phenotyping Benchmarks

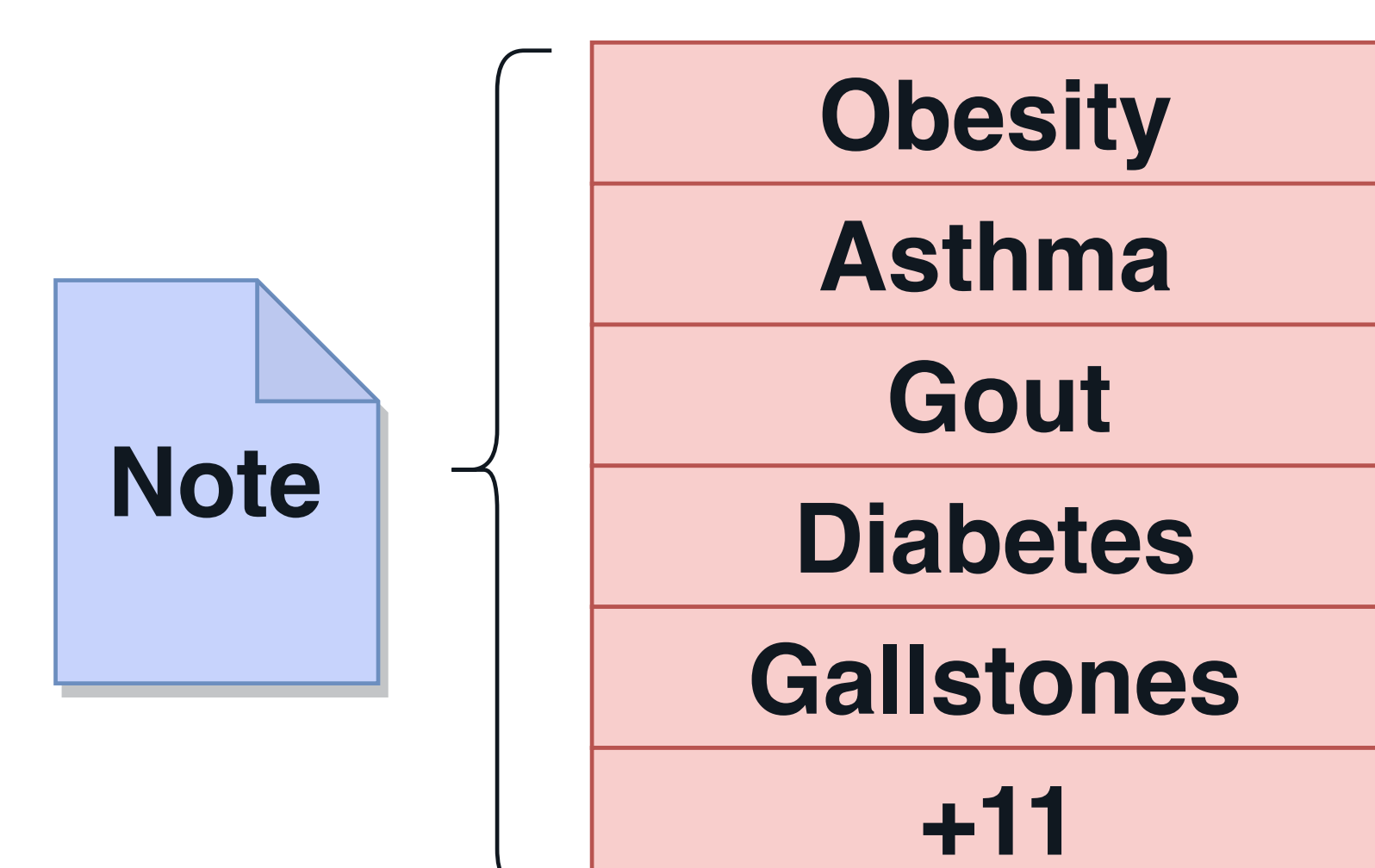
### I2B2 2006: Smoking

Smoking status identification.



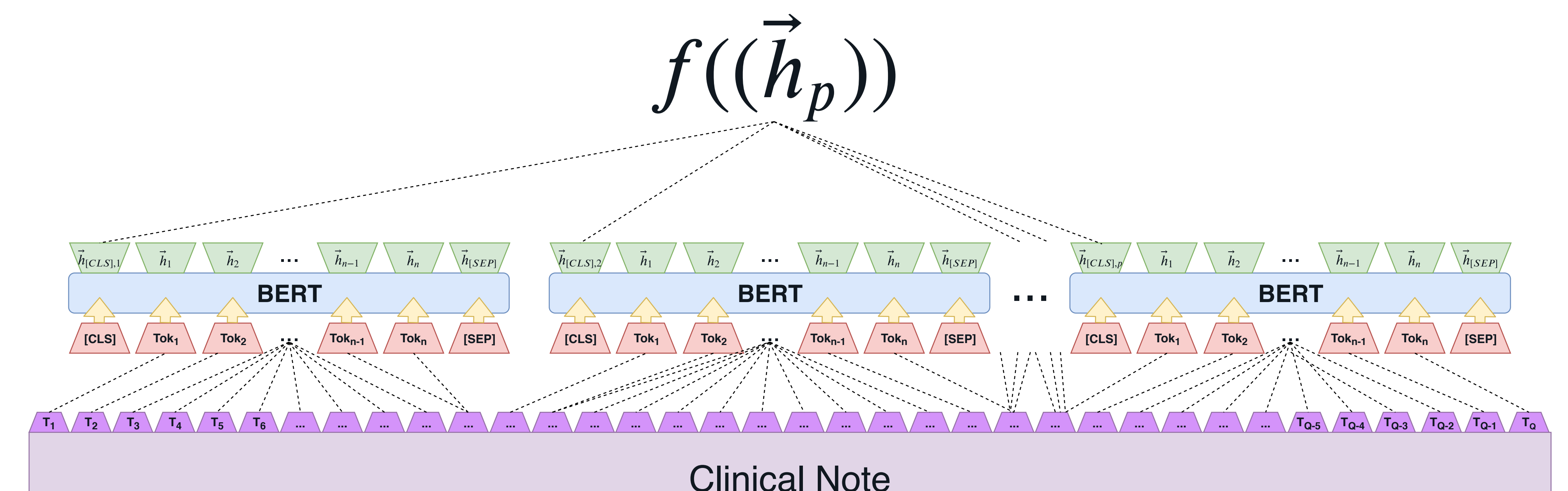
### I2B2 2008: Obesity

Disease presence identification in discharge notes.



## End-to-End Phenotyping with Language Models

- Frame phenotyping as a document classification task.
- Unroll a pre-trained, fixed context window language model (BERT) to generate a sequence of locally contextualized classifier token representations.
- Encode a global document context vector from local classifier token sequences and train with cross-entropy classification head.



## Experiments

- Global Context Heads  
 $f(\vec{h}_p)$ 
  - Dimension-wise max
  - Concatenation (identity)
  - Transformer Encoder
  - LSTM Encoder

	I2B2 2006: Smoking	I2B2 2008: Obesity
$f_{\max}$	50.3	74.7
$f_I$	82.9	76.8
$f_{\text{Transformer}}$	75.9	<b>97.7</b>
$f_{\text{LSTM}}$	<b>98.1</b> (97.1 $\pm$ .48)	<b>99.7</b> (93.9 $\pm$ .59)
Shared Task 1 <sup>st</sup> Place	90.0	95.0
Majority Label Baseline	81.0	74.4
DocBert	80.2	67.6
CNN	77.0	—
CNN + Rules	—	96.2

- **State-of-the-art** performance with LSTM encoder.
- Outperforms rule based techniques with no task specific dictionary searches or rules.
- Sequence of classifier tokens has average length  $\sim 7$  across both tasks.
  - Transformer Encoder and LSTM Encoder treat global context encoding as sequence compression problem.

