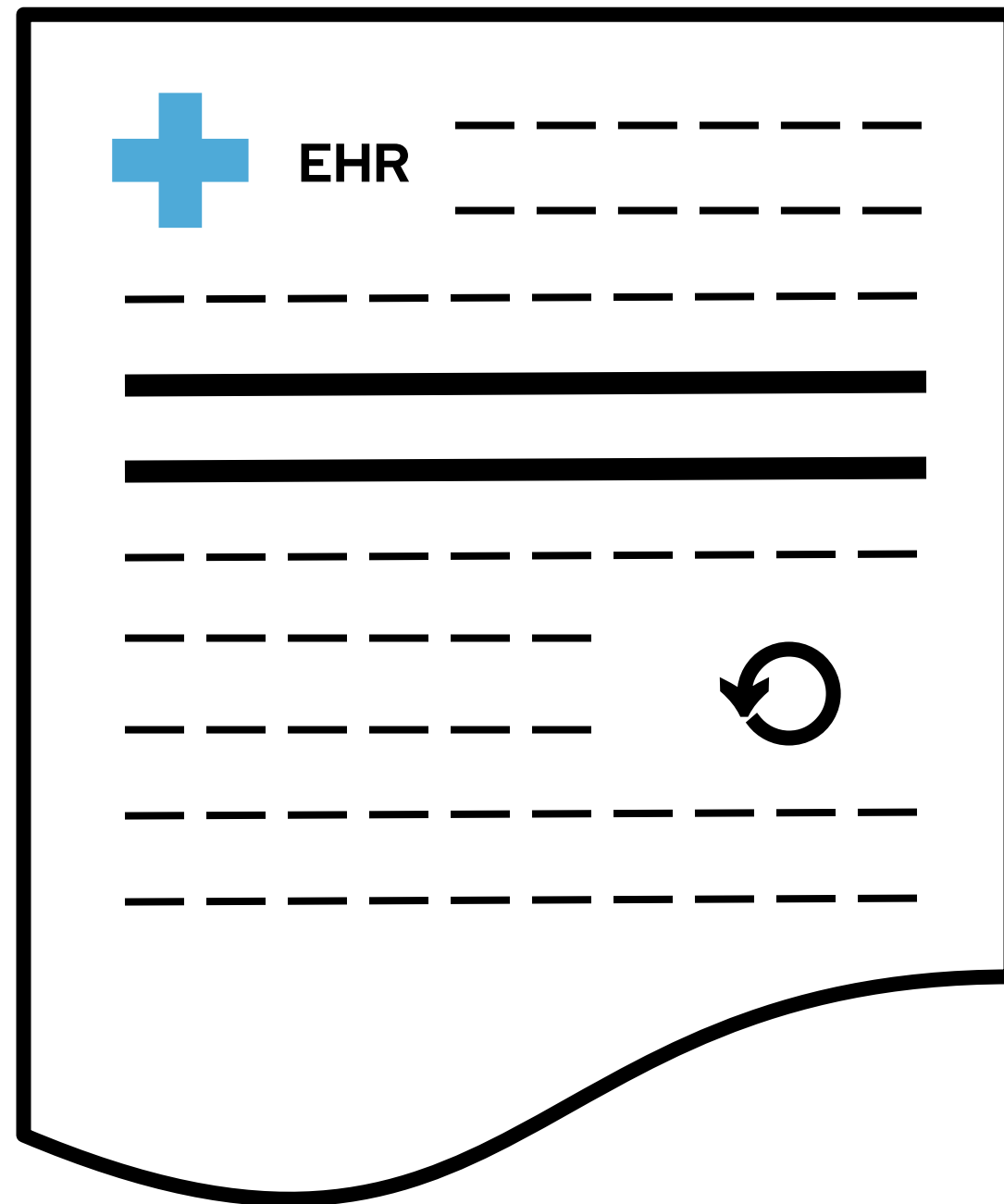


END-TO-END TEMPORAL RELATION EXTRACTION IN THE CLINICAL DOMAIN

Motivation: Problem background ¹



Information overload

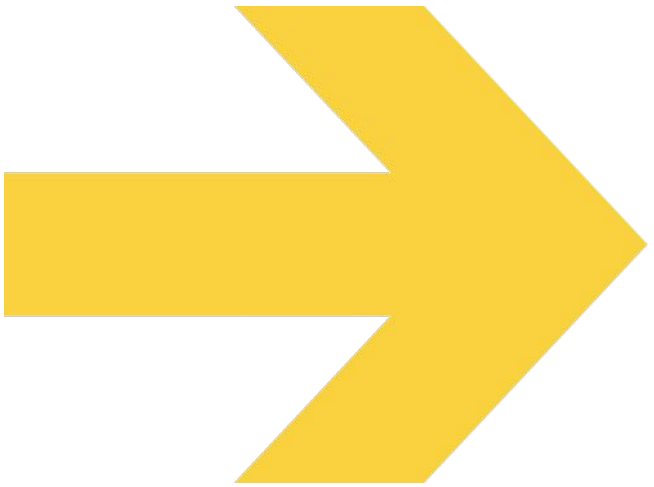
Frequent redundancy

Poor accessibility to information ultimately leads to *worse clinical care*.

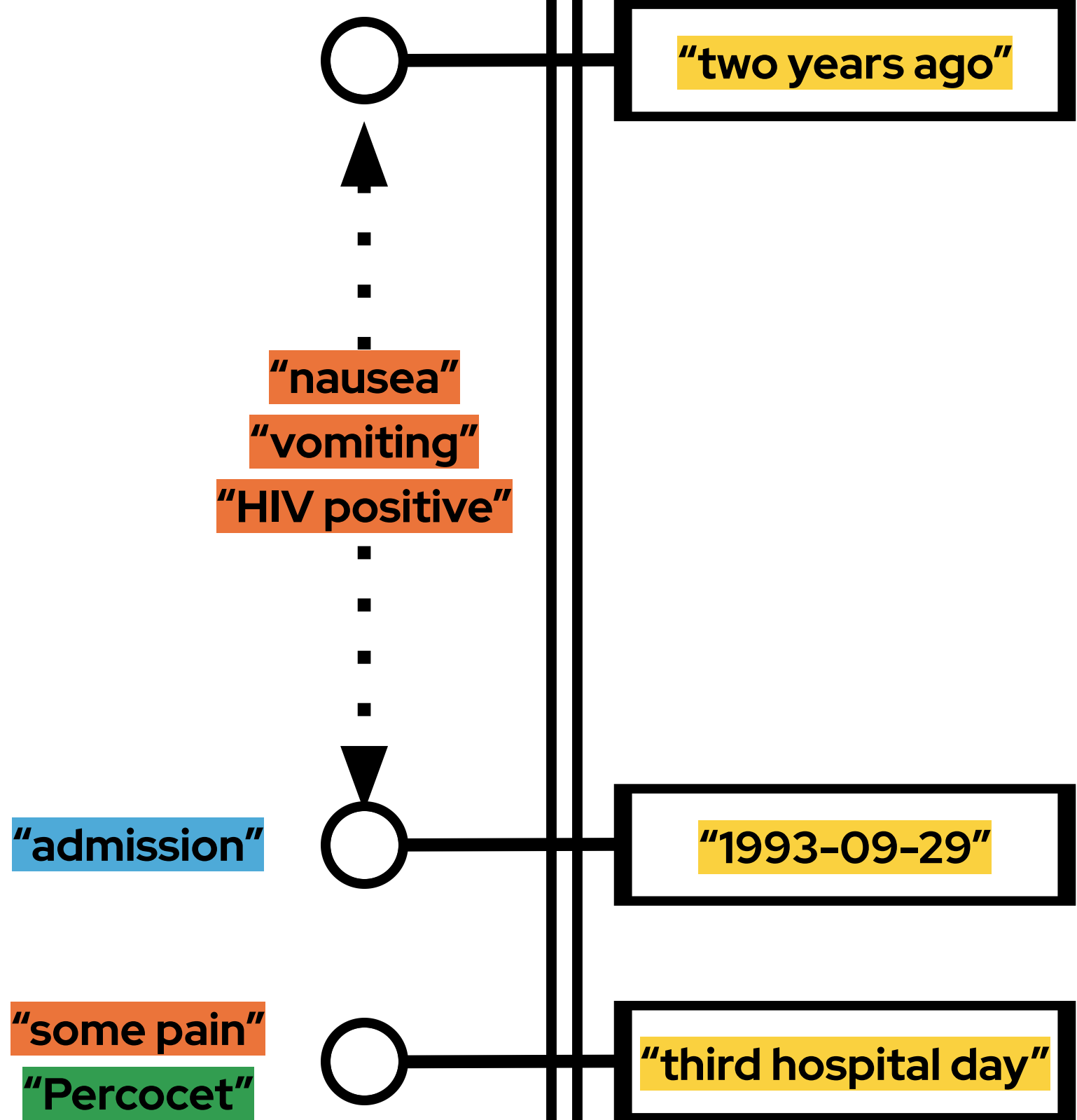
Clinical narratives are the *most reviewed* data in the clinical workflow because they contain *abundant* and *valuable* information.



Motivation: Problem background



With **Temporal Relation Extraction (TRE)**, we can retrieve useful timelines that require *less effort* and *time* to assimilate the information.



Motivation: Previous approaches

	Other clinical TRE approaches	Our clinical TRE approach
Task	Focus on Relation extraction (Haq et al. 2021, Lin et al. 2020, Zhou et al. 2020)	End-to-End: Entity extraction + Relation extraction
Relation types	Explicit, intra-sentence temporal relations (Alfattni et al. 2021, Guan et al. 2020)	Explicit and implicit + Intra-sentence and cross-sentence temporal relations

Motivation: Our proposal



- Since we use shared model weights from the pre-training phase, fine-tuning allows to adapt a general-domain model with very *low resources and time*.

*Relation Extraction By End-to-end Language generation (Cabot et al. 2021)

Methodology: Dataset

EVENT types

PROBLEM

TEST

TREATMENT

DEPARTMENT

OCCURRENCE

EVIDENTIAL

TIMEX3 types

DATE

TIME

DURATION

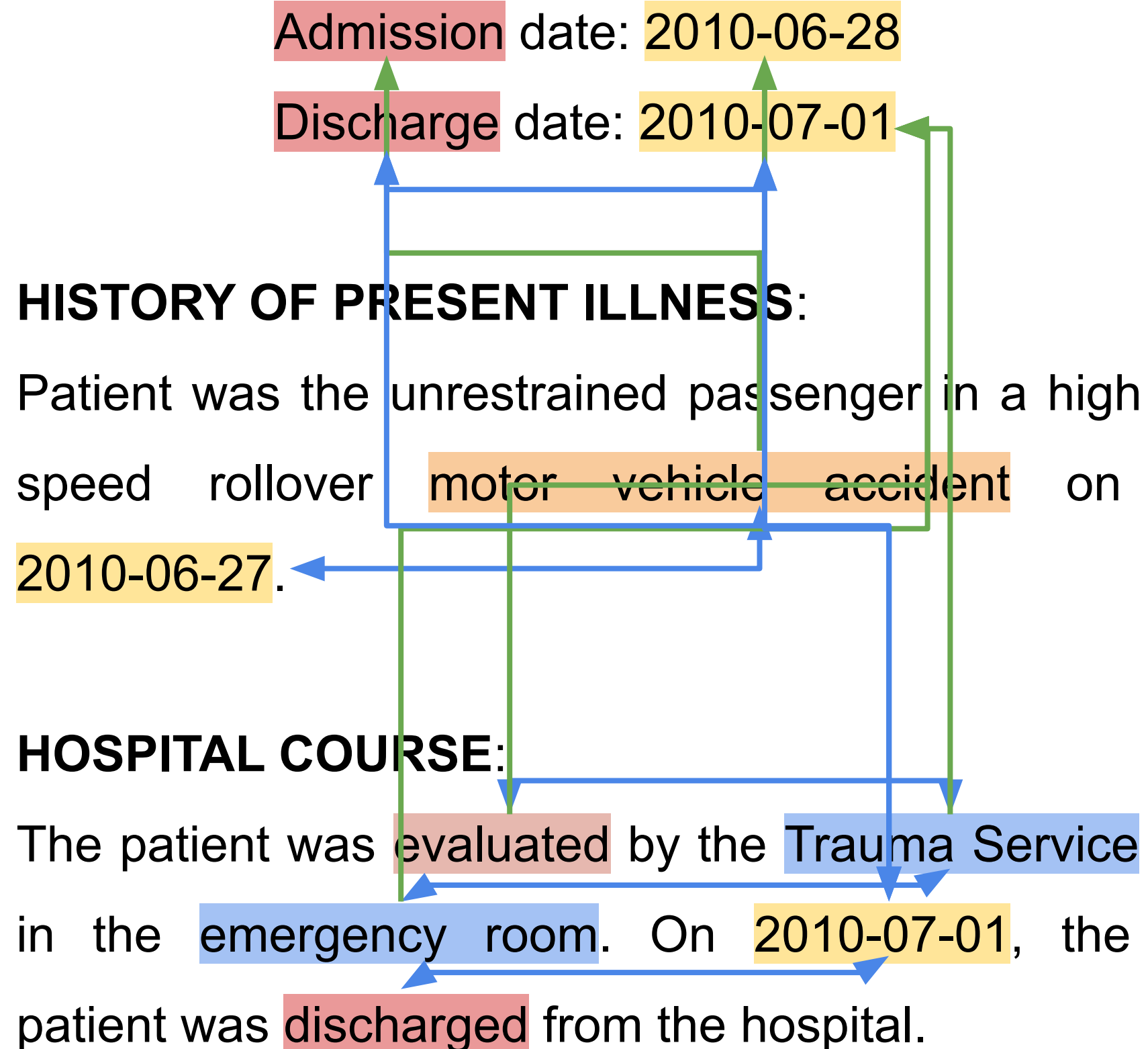
FRQUENCY

TLINK types

BEFORE

AFTER

OVERLAP



The i2b2 2012 corpus contains 310 discharge summaries annotated with *clinical events*, *temporal relations*, and *time expressions*.

Methodology: Problem formulation

Given a clinical document x containing a set of n temporal relations, we want to maximize the probability of generating the desired sequence of relations y autoregressively.

$$\hat{y} = \arg \max_y p(y | x) = \arg \max_y \prod_{i=1}^n p(y_i | y_{<i}, x)$$

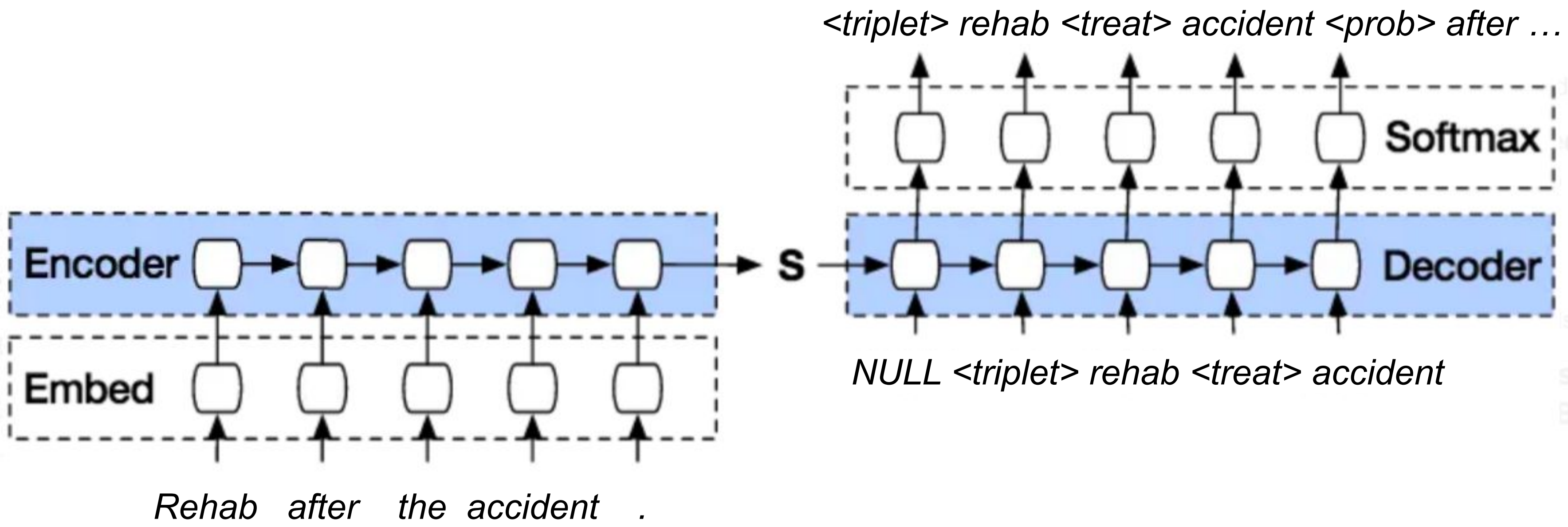
Any relation y_j is represented like a 6-tuple of tokens, such as:

$$y_j = \{ \boxed{y_{j1}}, \boxed{y_{j2}}, \boxed{y_{j3}}, \boxed{y_{j4}}, \boxed{y_{j5}}, \boxed{y_{j6}}, \dots \}$$

$\langle \text{triplet} \rangle$ *accident* $\langle \text{prob} \rangle$ *rehab* $\langle \text{treat} \rangle$ *before* ...

$x =$ "The patient had an *accident* and went to *rehab*."

Methodology: Model overview

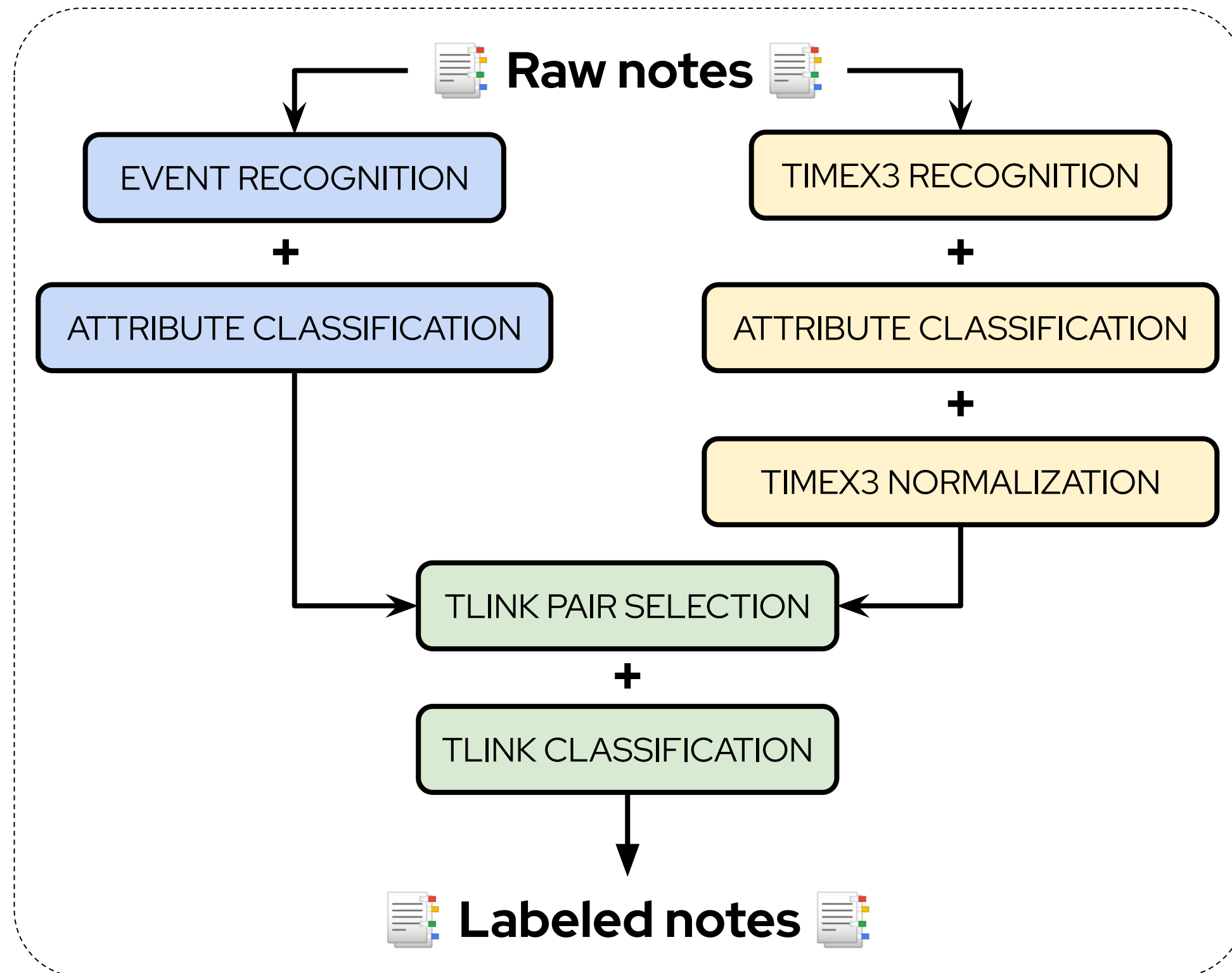


We are able to extract entities, time expressions and relations in one pass.

Experimentation: Evaluation

Baseline: Best systems in the i2b2 2012 challenge (End-To-End Track)

OVERVIEW
OF A **TRE**
PIPELINE
APPROACH



Evaluation method:
TempEval3

F-score, Precision, Recall for *time relations* are the main metrics and are calculated based on *temporal awareness*.

$$Precision = \frac{|Sys_{relation}^- \cap Ref_{relation}^+|}{|Sys_{relation}^-|}$$

$$Recall = \frac{|Ref_{relation}^- \cap Sys_{relation}^+|}{|Ref_{relation}^-|}$$

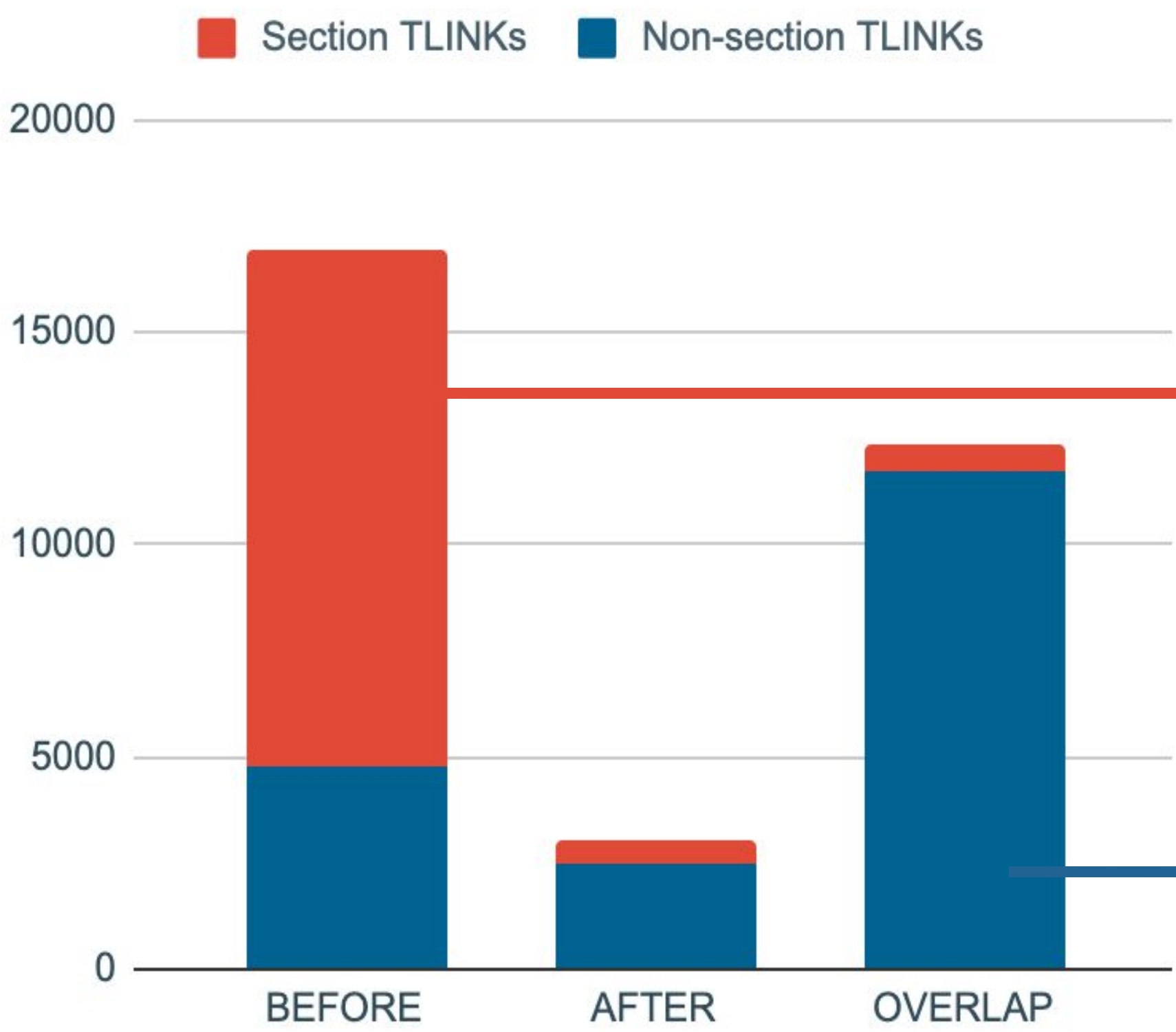
Experimentation: Results

System	TLINK			EVENT		TIMEX3	
	F1	P	R	Span F1	Type P	Span F1	Type P
Tang et al., 2013	0.63	0.7	0.57	0.9	0.84	0.87	0.85
Xu et al., 2013	0.59	0.59	0.59	0.92	0.86	0.91	0.88
Our proposal*	0.58	0.65	0.52	0.78	0.72	0.77	0.65
Roberts et al., 2013	0.53	0.48	0.57	0.89	0.8	0.89	0.78

*Results after 10 epochs of fine-tuning on a single Tesla P100 GPU.

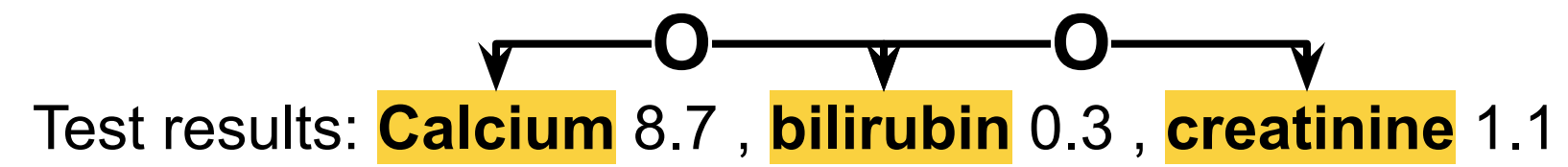
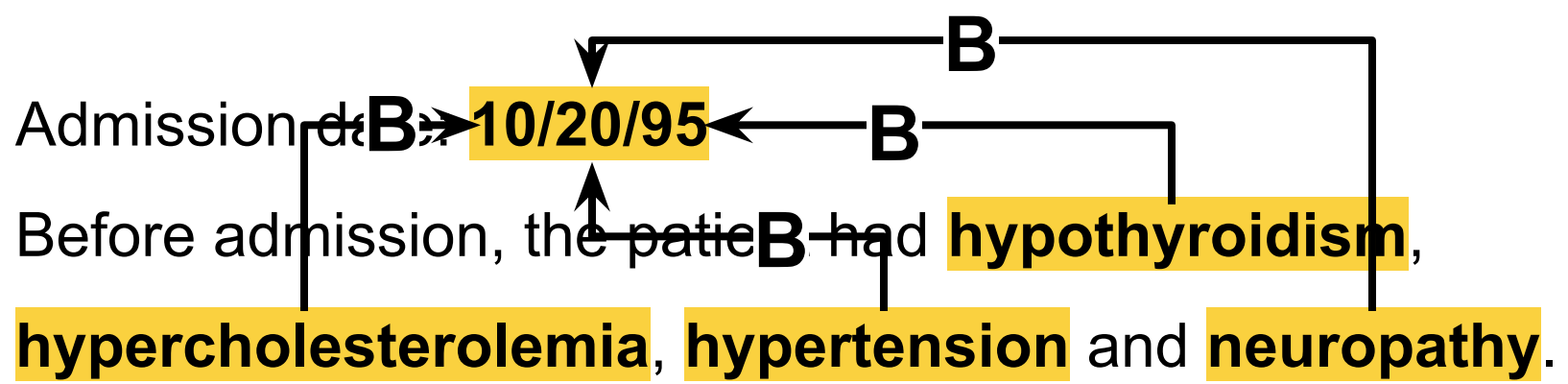
Analysis

Predicted temporal relations by class



Predictions are skewed by the *class imbalance* in the training corpus, where most of the:

- Section TLINKs are of **BEFORE** type
- Non-section TLINKs are of **OVERLAP** type



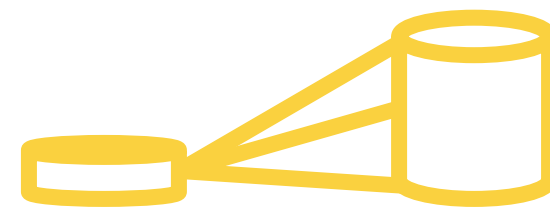
Conclusion & Future work

- Demonstrated that clinical TRE can be performed as a *single task*

in a *resource- and time-limited* environment, but ...

- Calculating the **transitive closure** would allow to:

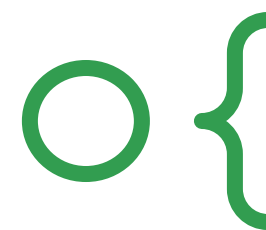
- mitigate the class imbalance.



- take into account a higher number of implicit relations.



- expand the training corpus.



- Use a training corpus with **narrative containers**.

