

# GUIR: Temporal Information Processing for Clinical Narratives

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■ + Set 2

### Abstract

- We participated in all the subtasks:
- TIMEX3 and EVENT spans (TS, ES)
- TIMEX3 and EVENT attributes (TA, EA)
- Document-time Relations (DR)
- Containment Relations (CR)

Example: "April 23, 2014: The patient did not have any postoperative bleeding so we will resume chemotherapy with a larger bolus on Friday even if there is slight nausea."

- TS: Red, ES: Green
- TA: April 23, 2014 [DATE]; postoperative [PREPOSTEXP]
- EA: chemotherapy [polarity=POS, modality=ACTUAL]
- DR: bleeding BEFORE docTime
- CR [postoperative CONTAINS bleeding]; [Friday CONTAINS resume]
- Our approach is based on **supervised learning**, utilizing various sets **of syntactic**, **lexical**, **and semantic features** with the addition of **manually crafted rules**
- Our system demonstrated substantial improvements over the baselines in all the tasks and consistent above-median results in virtually all sub-tasks.

## Method

## General approach

- Supervised structured learning (CRF) + supervised classification (Logistic Regression)
- Features: Syntactic, lexical, morphological, distributional, domain specific, dependency and semantic roles
- Basic features:
- lowercase; token letter case; if token is title; if token is numeric; if token is stopword; POS tag; brown cluster; prefix; suffix; noun chunk shape of the token; lemma
- CRF + Logistic Regression
- Data
- 293 Train, 147 Dev, 151 Test clinical narratives

#### • TS + ES

- Base features + Domain specific
- UMLS Semantic Types
- Manual rules: For time and also event. E.g. standard patient readings. "Diastolic=55 mm[Hg]"

# Method (Cont'd)

#### TA + EA

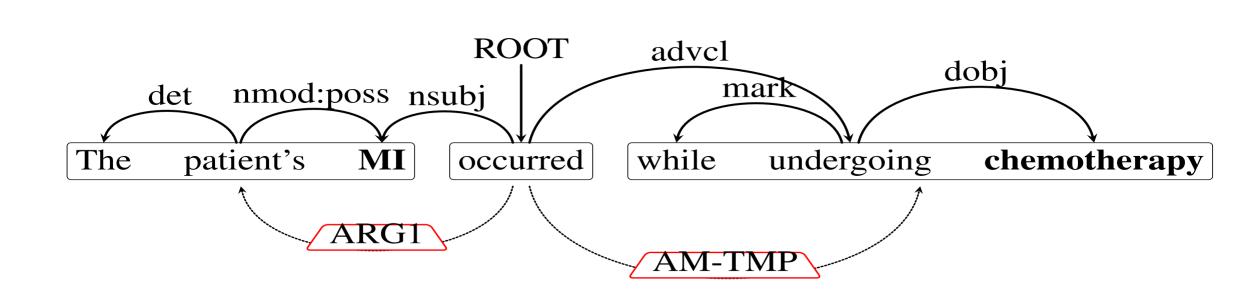
- Base features + Rules
- E.g. "Complete" indicates DEGREE:MOST, "Possibly" indicates MODALITY:HEDGED, and "never" shows POLARITY:NEG

#### • DR

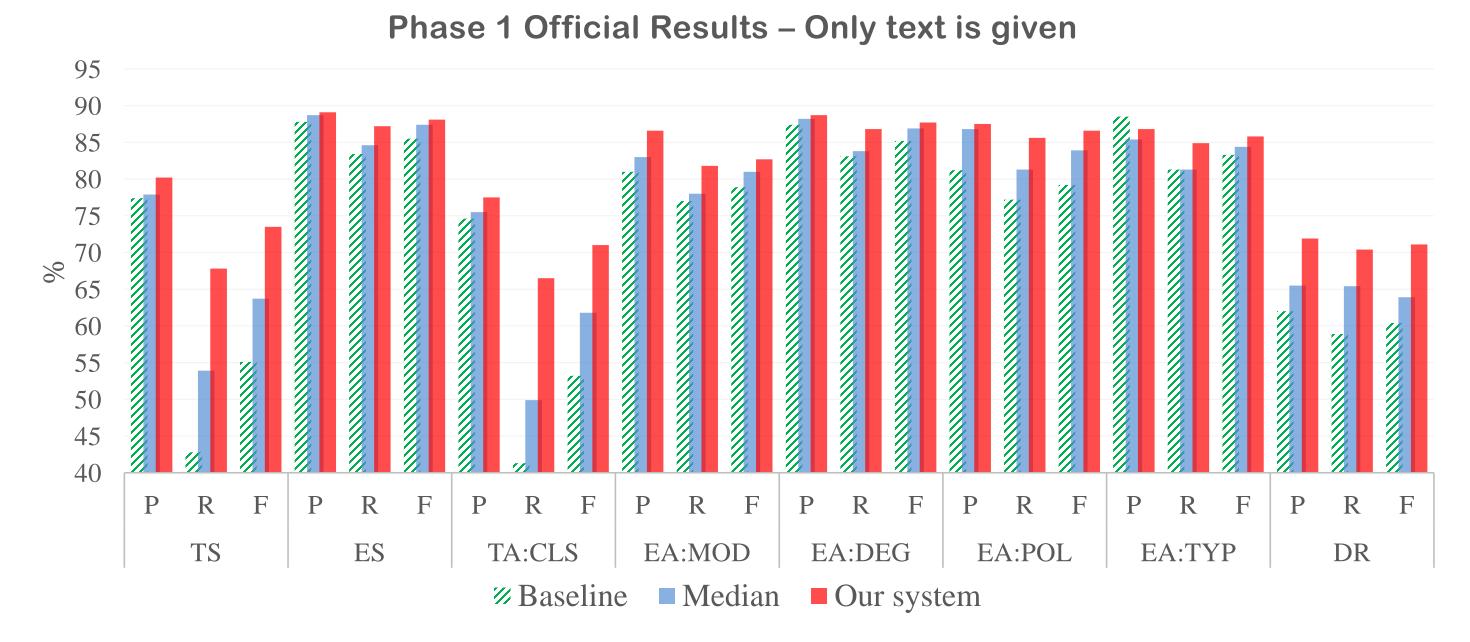
- Base features + two sets of features
- Set 1: UMLS semantic type; tense of the related verb in dependency tree; dependency root of the sentence
- Set 2: class, text and brown cluster of closest TIMEX3 mention; comparison with section time; comparison with document time; sentence tense and modals

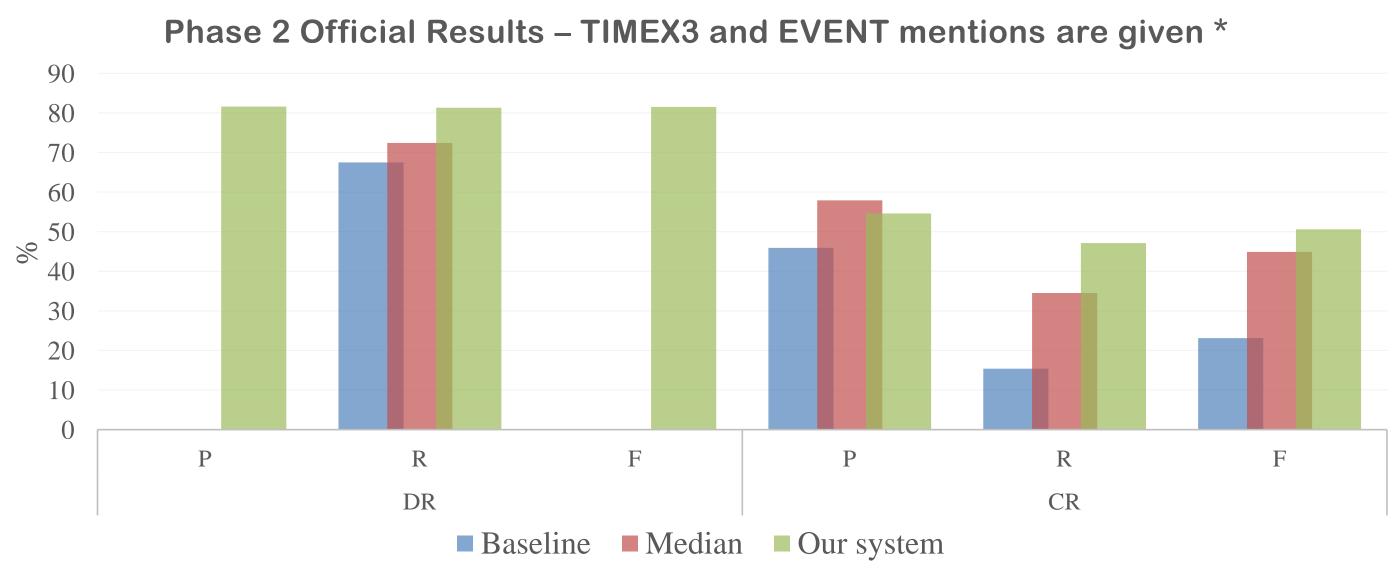
#### • CR

Base features + Semantic frames, dependency features,
UMLS semantic types, verb tense and sentence root



## Results

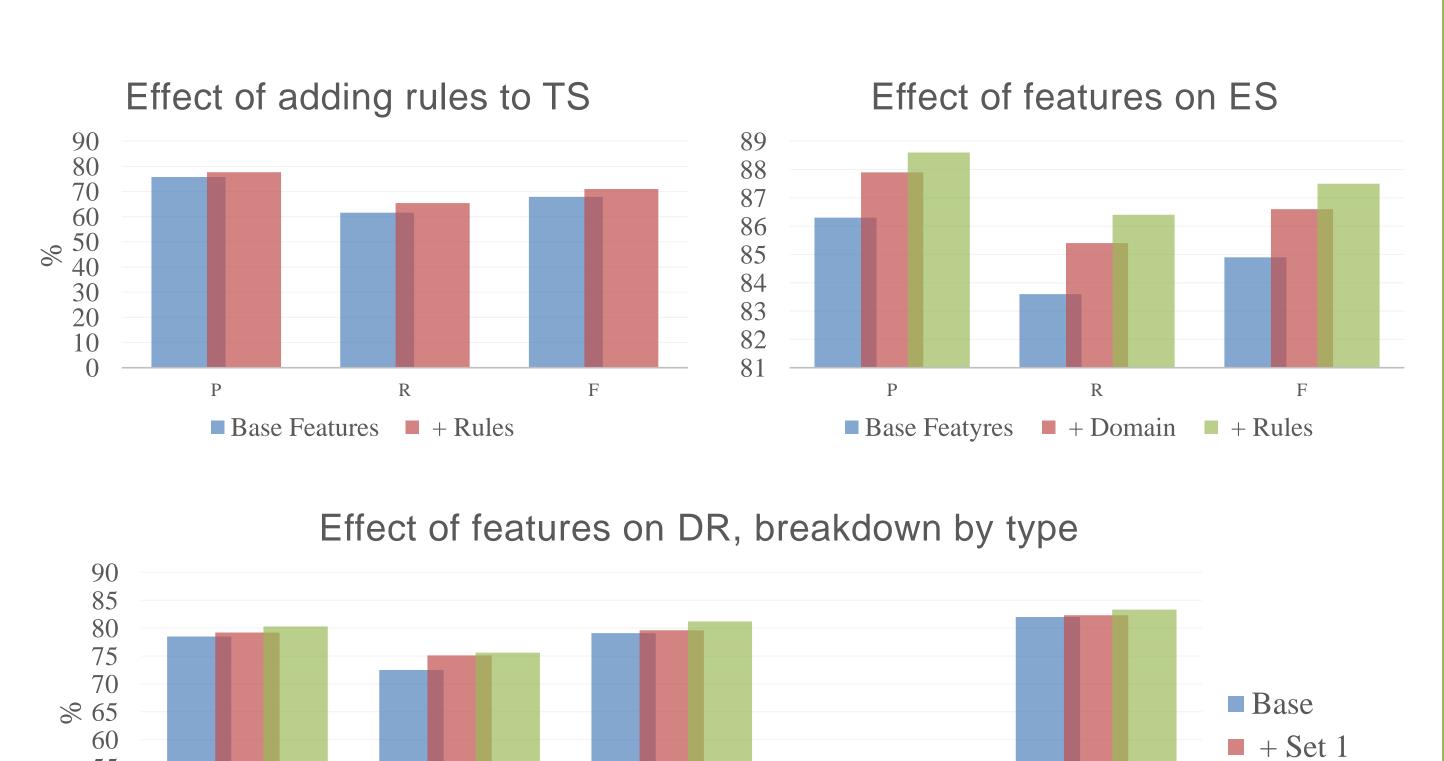


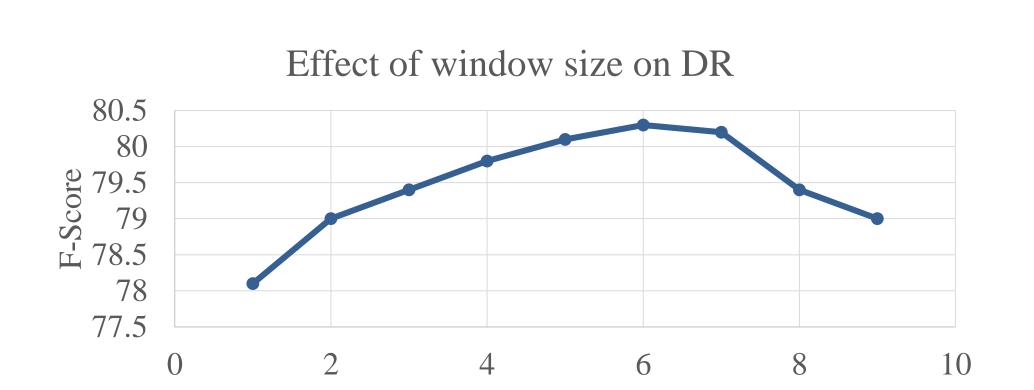


\* Baseline and median for Precision and F1 of DR were not reported

# Results (cont'd)

#### Analysis





## **Discussion and Conclusions**

DR Types

- Our approach was based on a feature-rich supervised classification for all the tasks
- We showed consistent improvement over the median results in virtually all the tasks
- Features like brown clusters, dependency based features, domain specific features and SRL features are helpful in most of the tasks
- We observed improvements by adding manual features. Excessive addition of rules, results in increased recall but much lower precision and should be avoided.
- Our approach for narrative containers was limited to intrasentence relations and many of the missed cases, were due to cross-sentence relations