Improved Temporal Relation Classification

using Dependency Parses and Selective Crowdsourced Annotations

Jun-Ping Ng and Min-Yen Kan

Temporal Relations?

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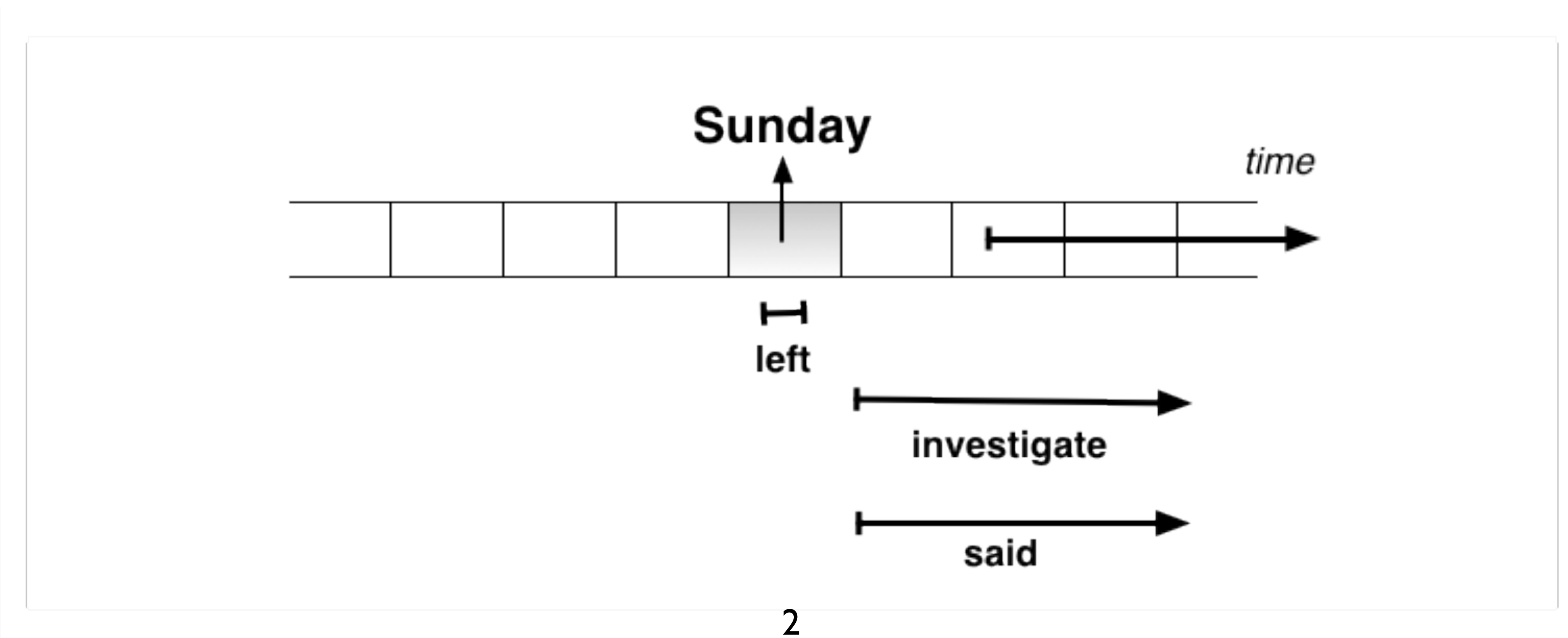

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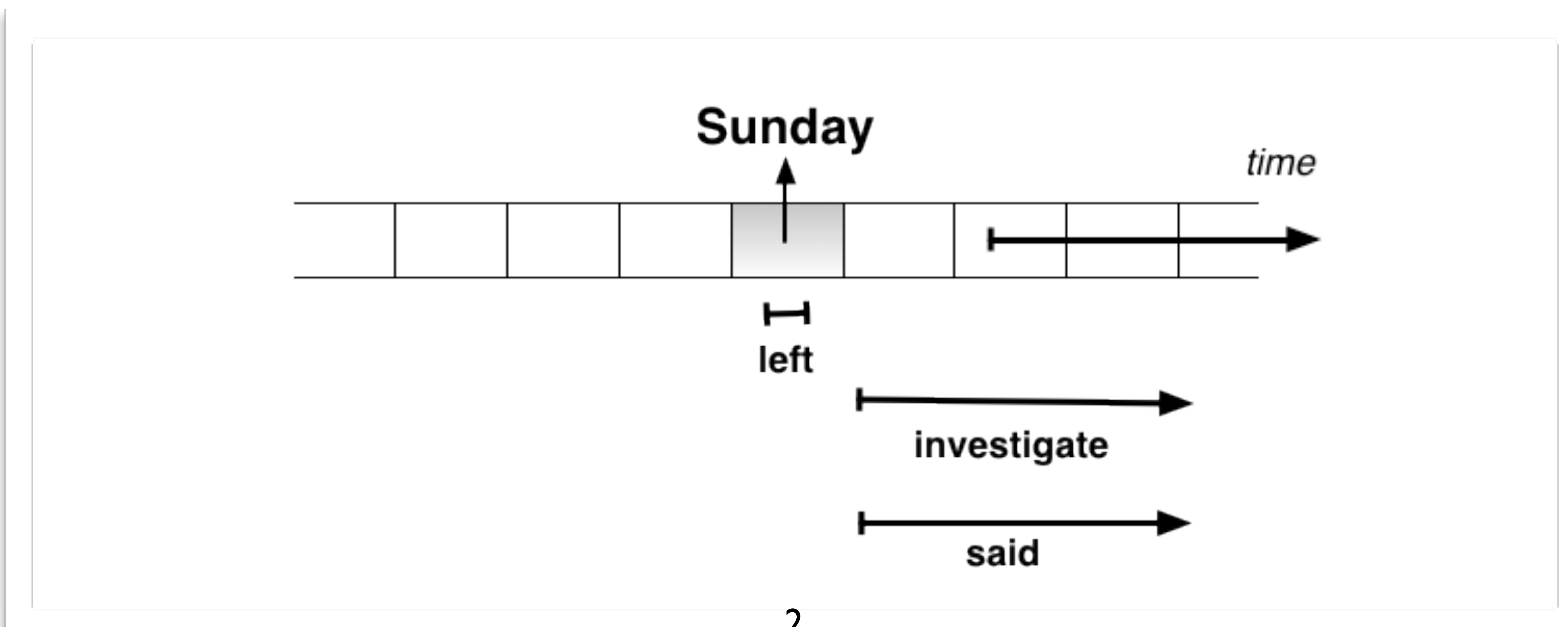

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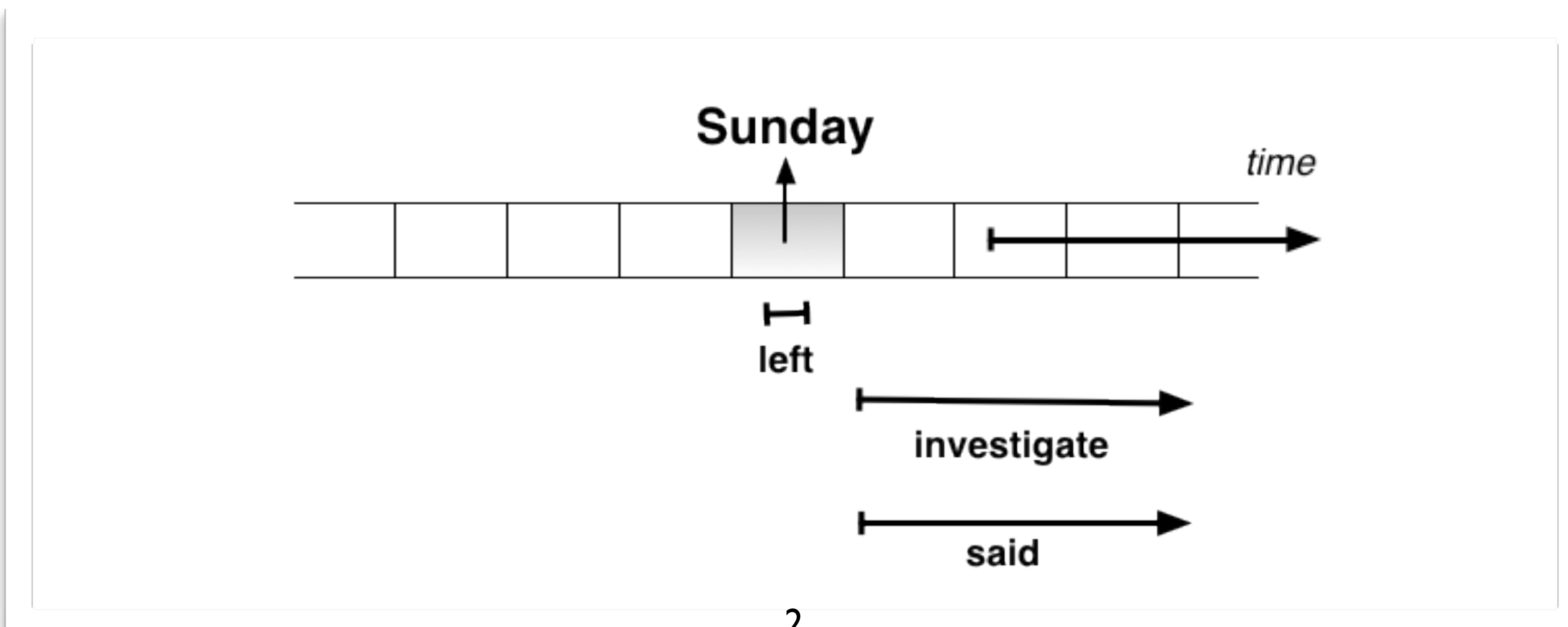
AFTER



Goal

- Be able to classify event-temporal (E-T) relations within a sentence

Outline

- Brief look at state-of-the-art
- Proposed Approach
  - Reducing size of feature space
  - Smart acquisition of data via crowdsourcing
- Error Analysis

State-of-the-art

- Shared tasks TempEval-1 and TempEval-2 held in conjunction with SemEval in 2007 and 2010.
- State-of-the-art systems in TempEval-2 achieve around 65% accuracy
- Work with dataset from TempEval-2 to facilitate benchmarking and comparisons

Data Sparsity

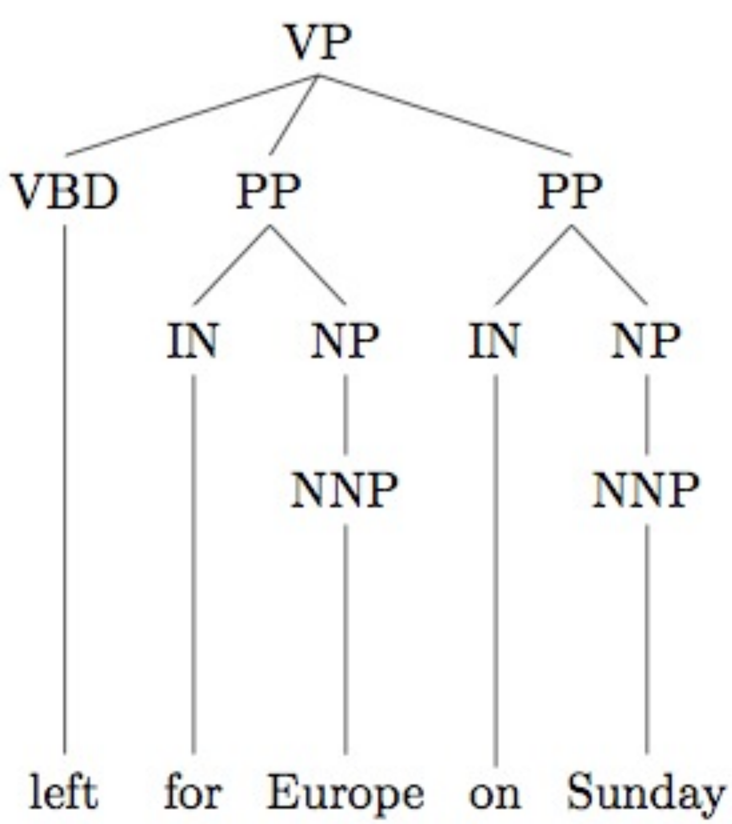
- Features typically employed include
  - lexical cues
  - context
  - sentence structure
- Training set consists of around 959 instances

Proposal

- Reduce dimensionality of feature space
- Increase amount of annotated data available

A Kernel Hypothesis

... **left** for Europe on <u>Sunday</u> ...



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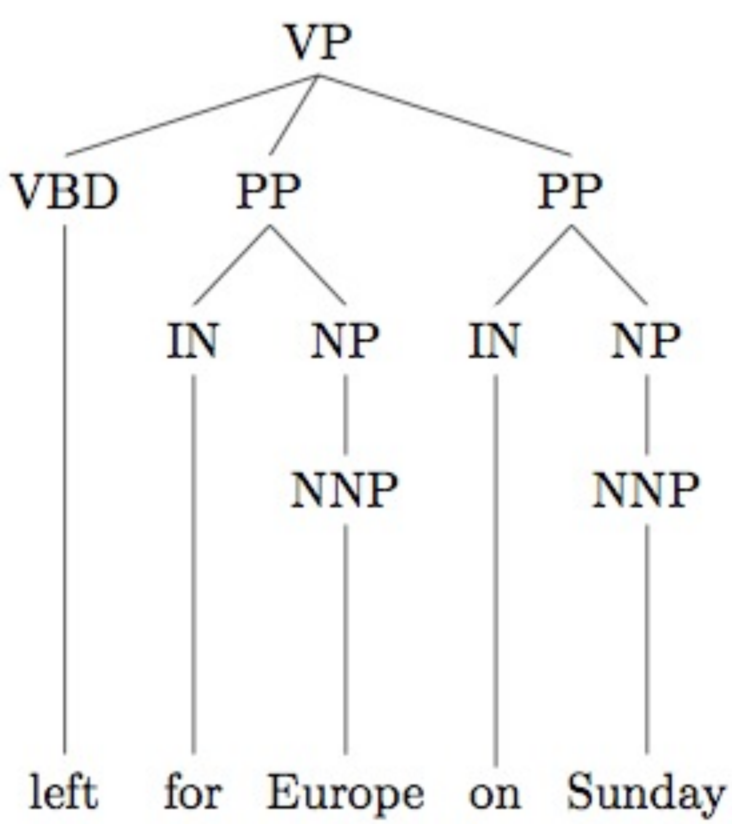

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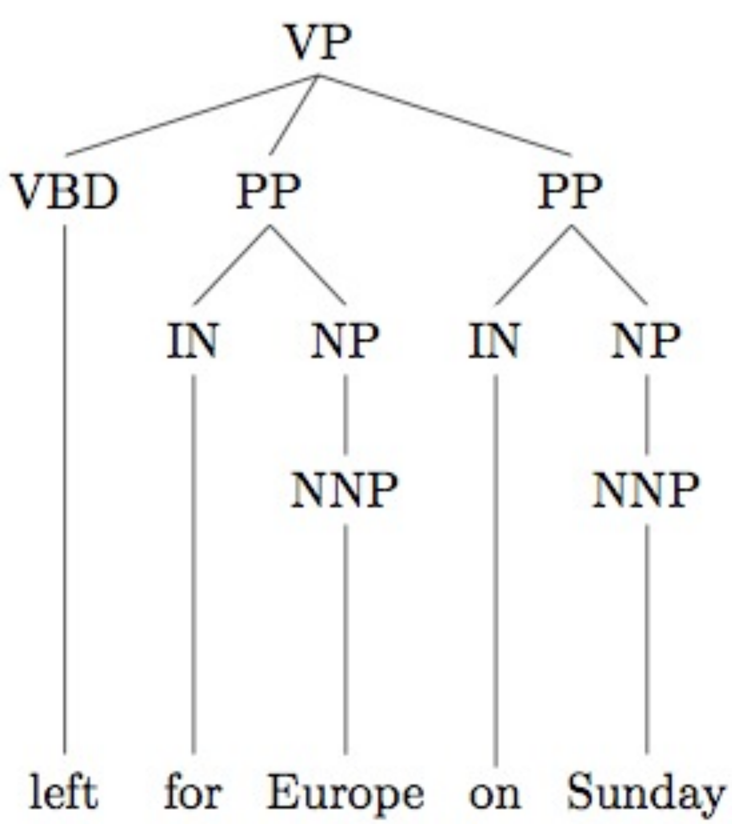

...**went** to America on Monday..

...**partied** at home on Wednesday..

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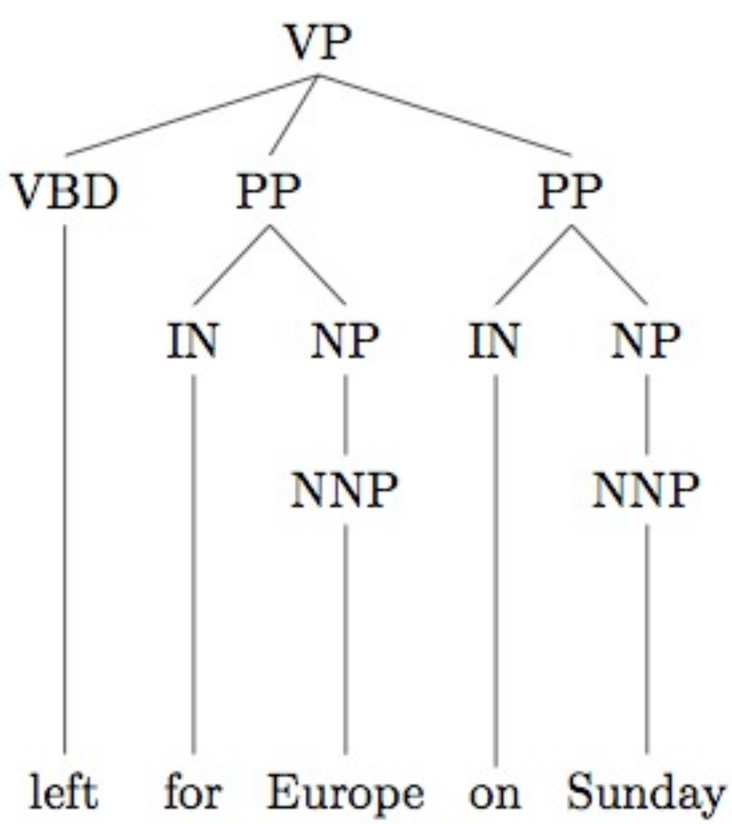

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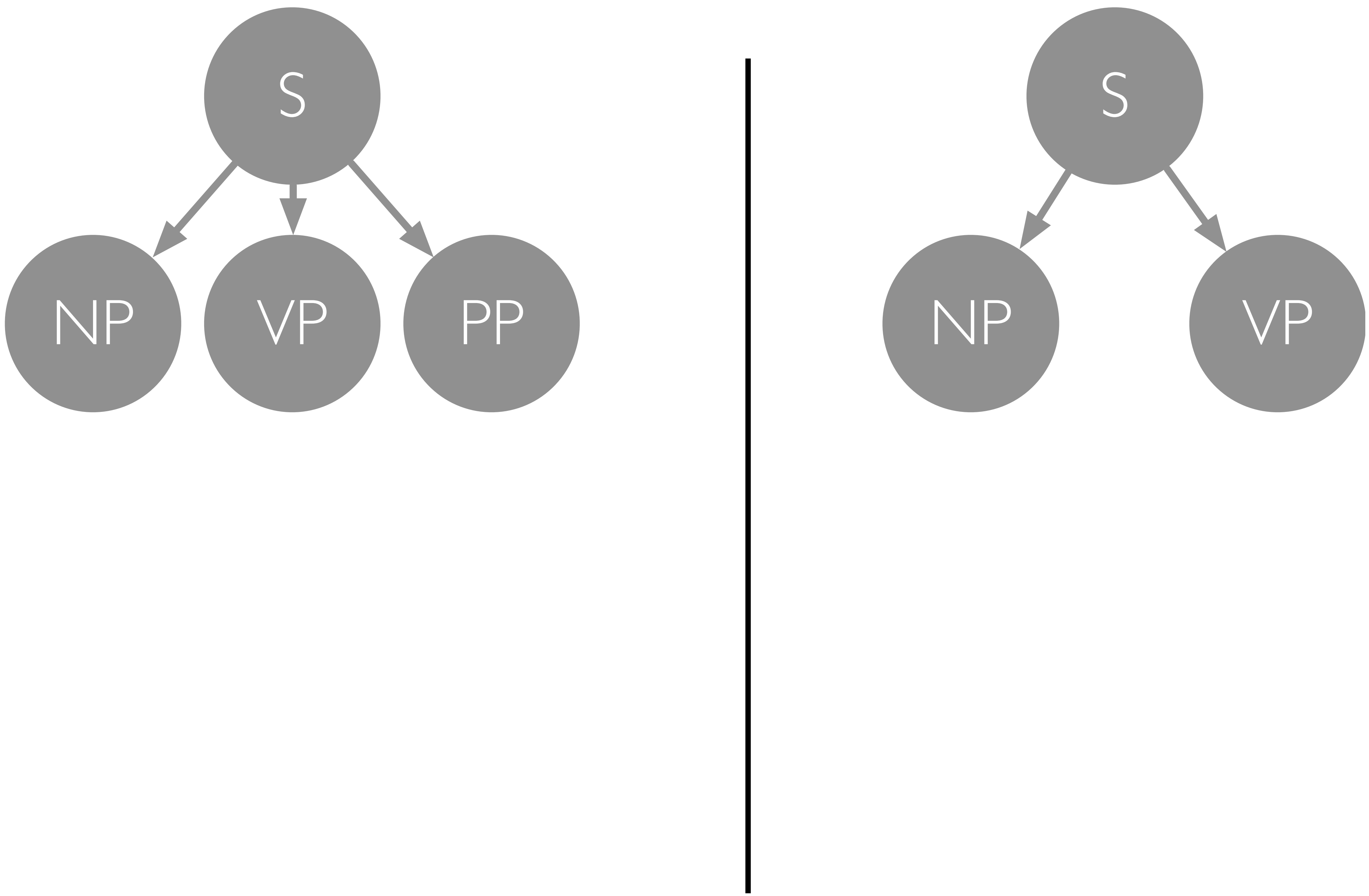
OVERLAP

Convolution Kernels

- Allows us to capture structure similarities easily
- Tree structure used as feature for support vector machines (SVM)
- No need to flatten structure representation into a set of real number features

Structure Similarity



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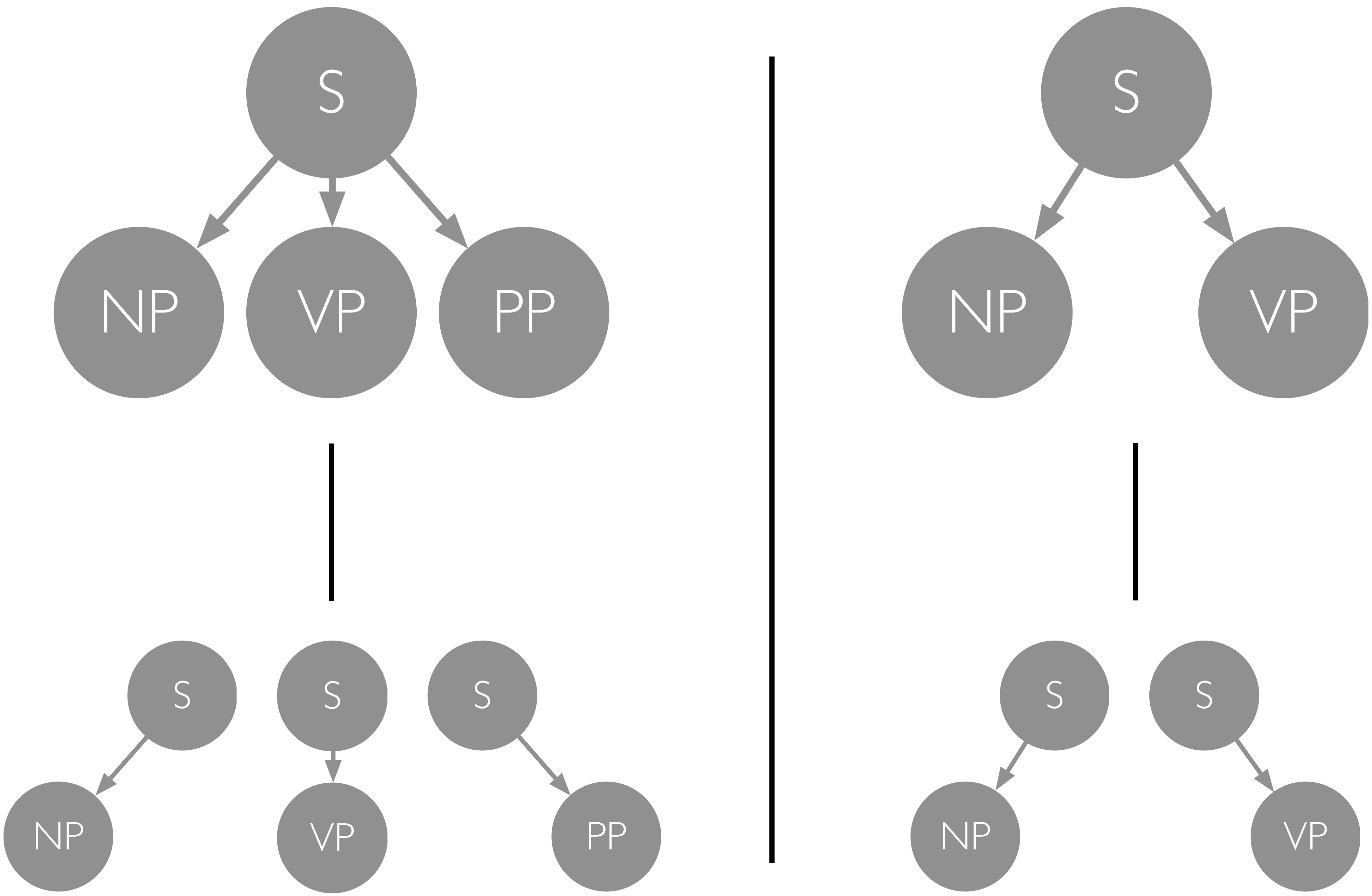
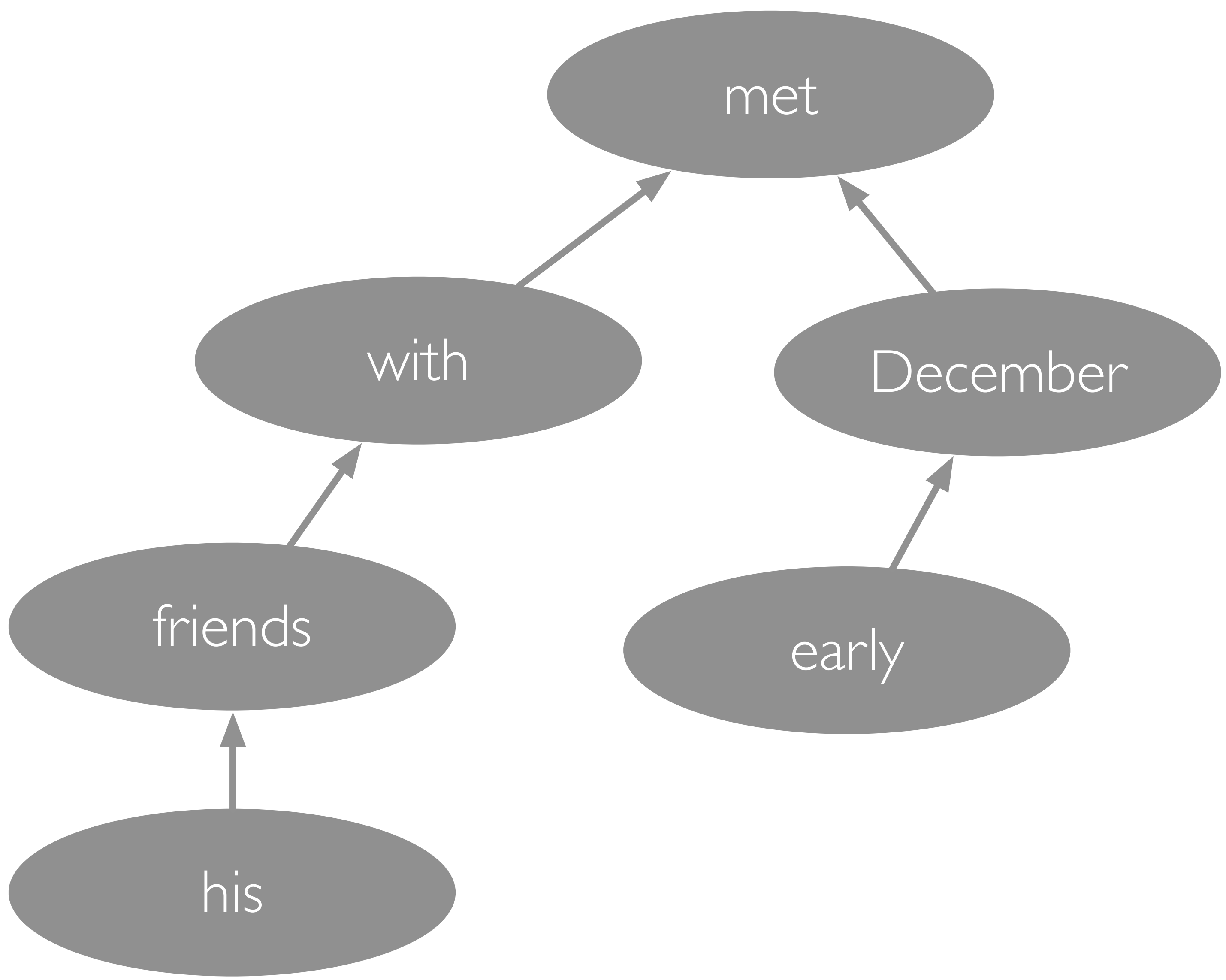


Features

... met with his friends early December ...



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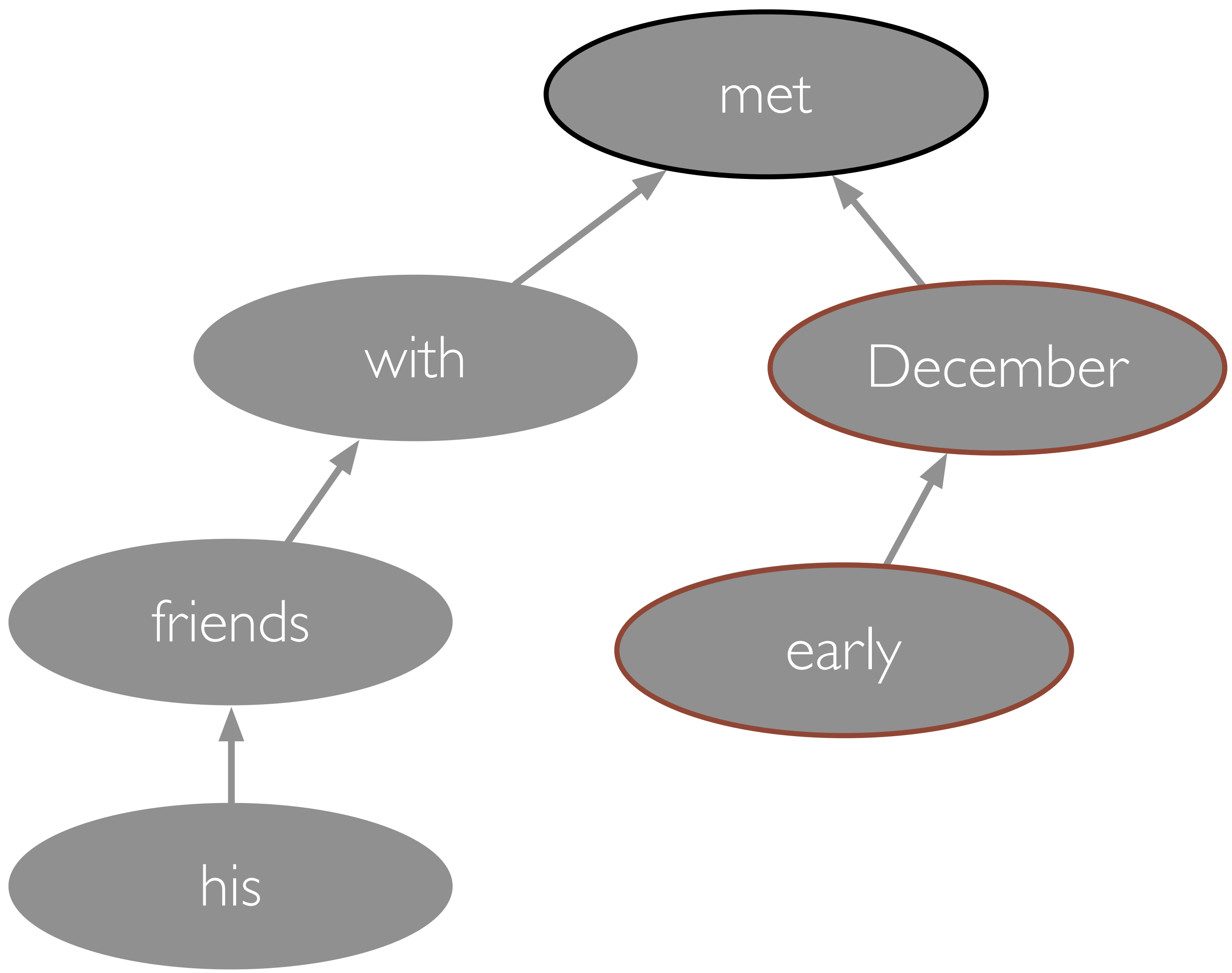

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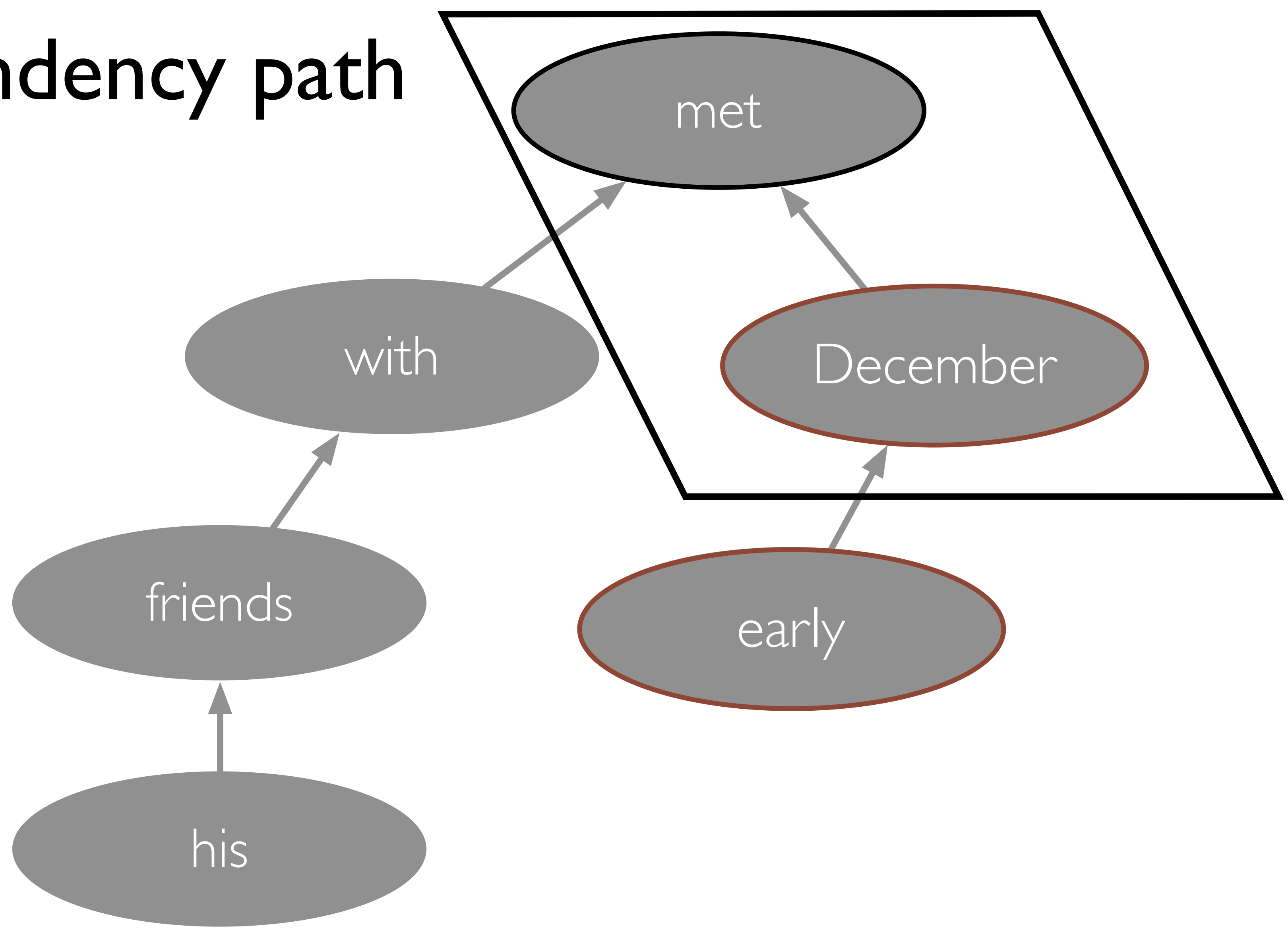
(1) dependency path



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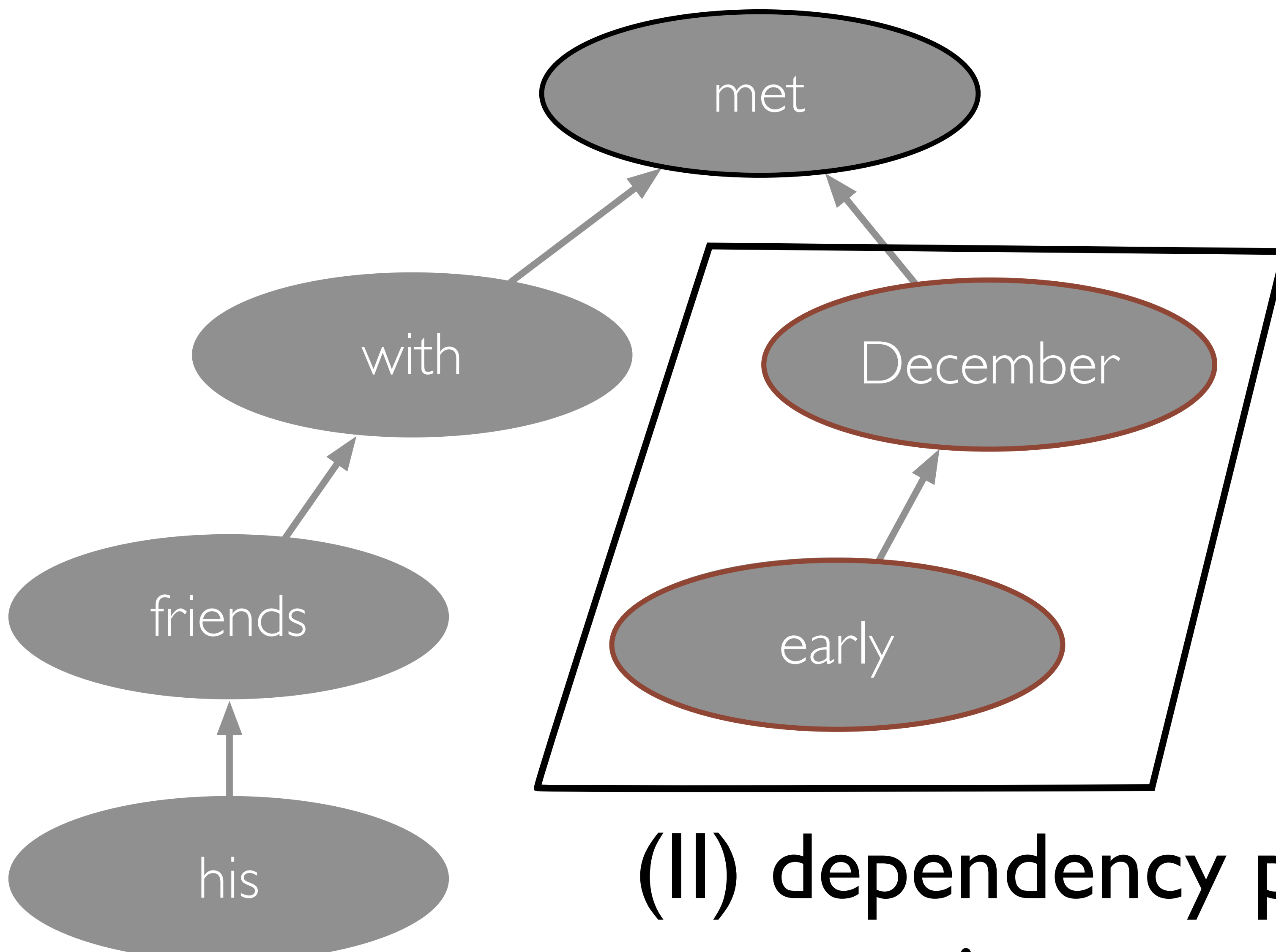

(II) dependency parse of time expression

Comparisons

System	Accuracy
ConvoDep	67.4%
TRIOS	65.0%
JU_CSE	63.0%
NCSU_indi	63.0%
NCSU_joint	63.0%
TRIPS	63.0%
USFD2	63.0%

- Trained on TempEval-2 training set, Tested on TempEval-2 testing set

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Precision	0.828
Recall	0.512
F1	0.523

✦ Trained on TempEval-2 training set, Tested on TempEval-2 testing set

Getting More Data

- Crowdsourcing is a cheap, efficient avenue for large scale data annotation
- But temporal annotations are not trivial
- We want to investigate
  - the quality of crowdsourced temporal annotations
  - effective ways to gather the annotations

Task Setup

- Crowdsourcing via Crowdflower
  - Data validation to improve data quality
- Raw data collected from news articles
  - Event and time expressions extracted during pre-processing

Is It Useful?

- Collected initial dataset of 1000 instances
- Trained SVM classifier with convolution kernels

Is It Useful?

System	Accuracy	F1	Precision	Recall
ConvoDep	67.4%	0.523	0.828	0.512
CF-1000	65.2%	0.525	0.578	0.535
CF-1000 + TE	71.7%	0.615	0.726	0.598

✦ Tested on TempEval-2 testing set

A Smarter Way

- Are we able to collect less data but still remain effective?
- Insight - Instances are not equally hard

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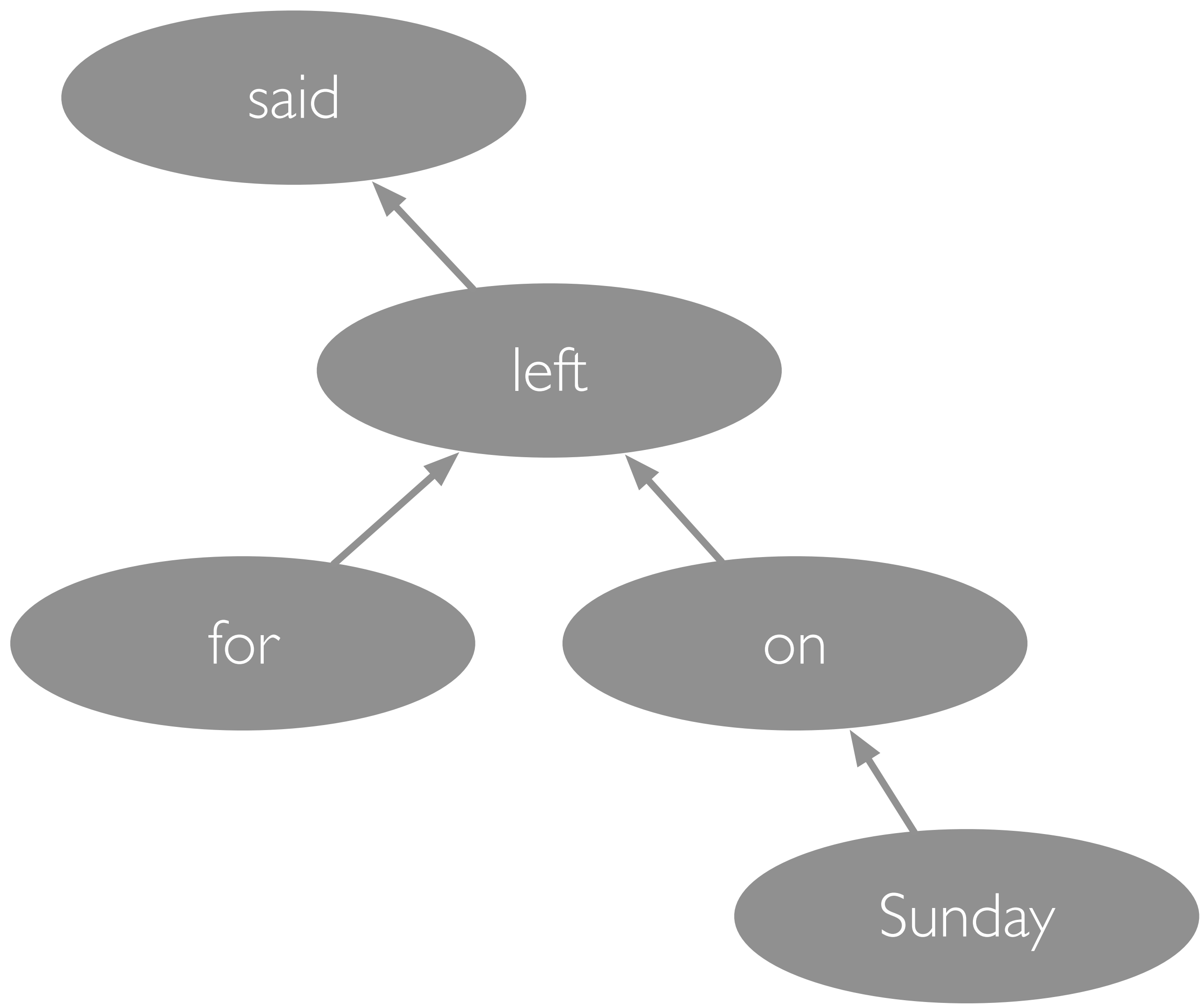
Hard Instances

- Order event expressions in increasing order from time expression in dependency parse



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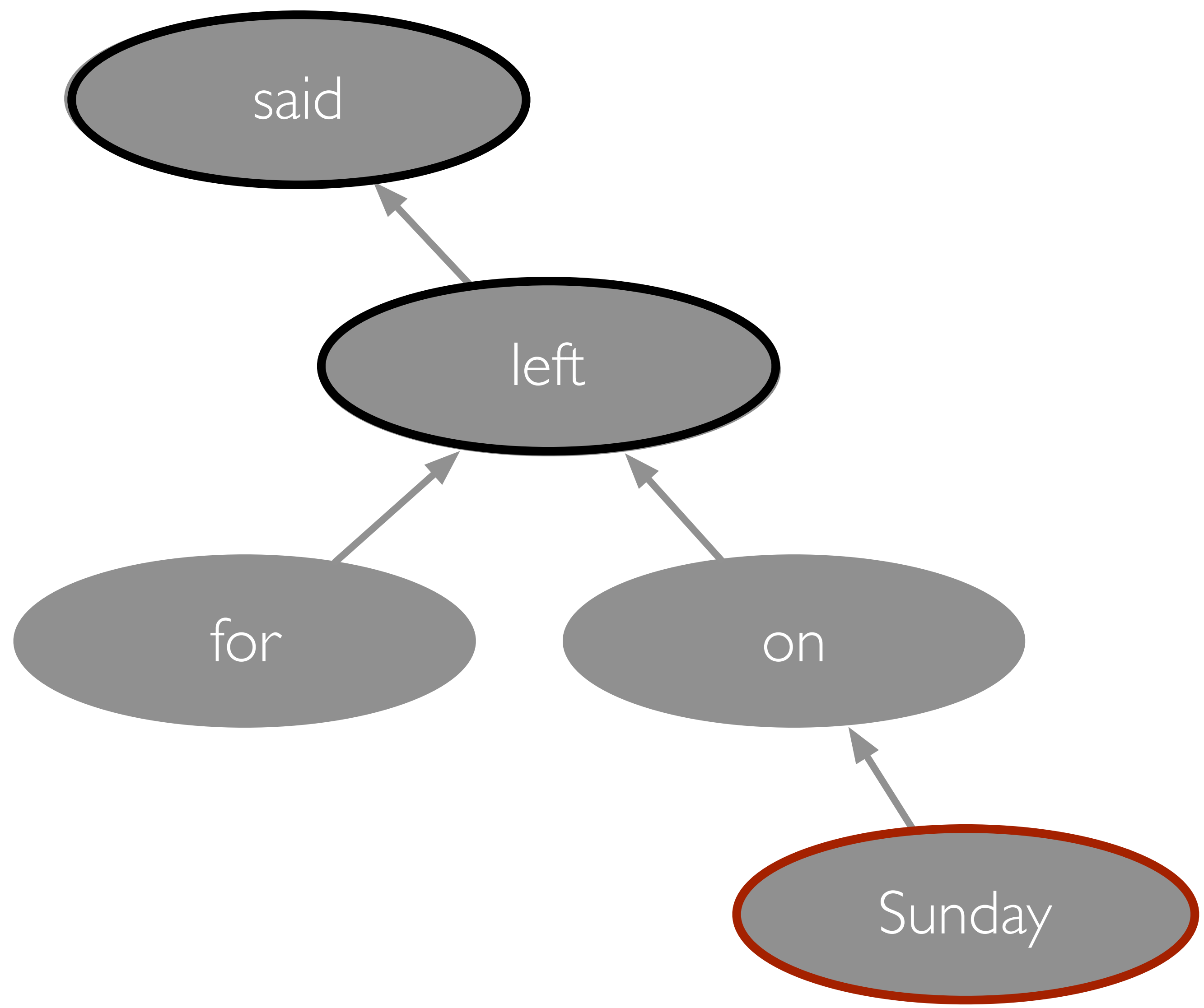

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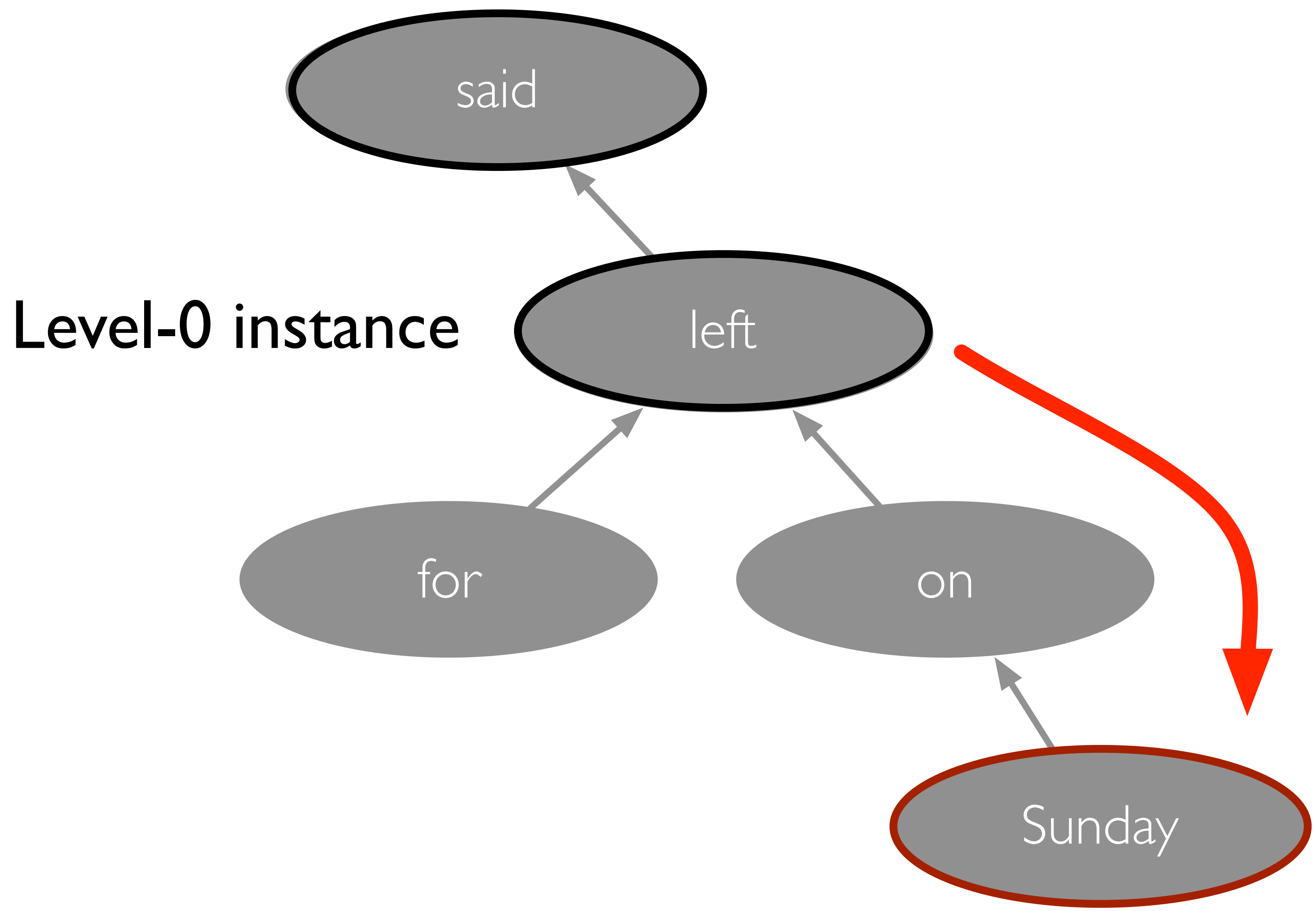

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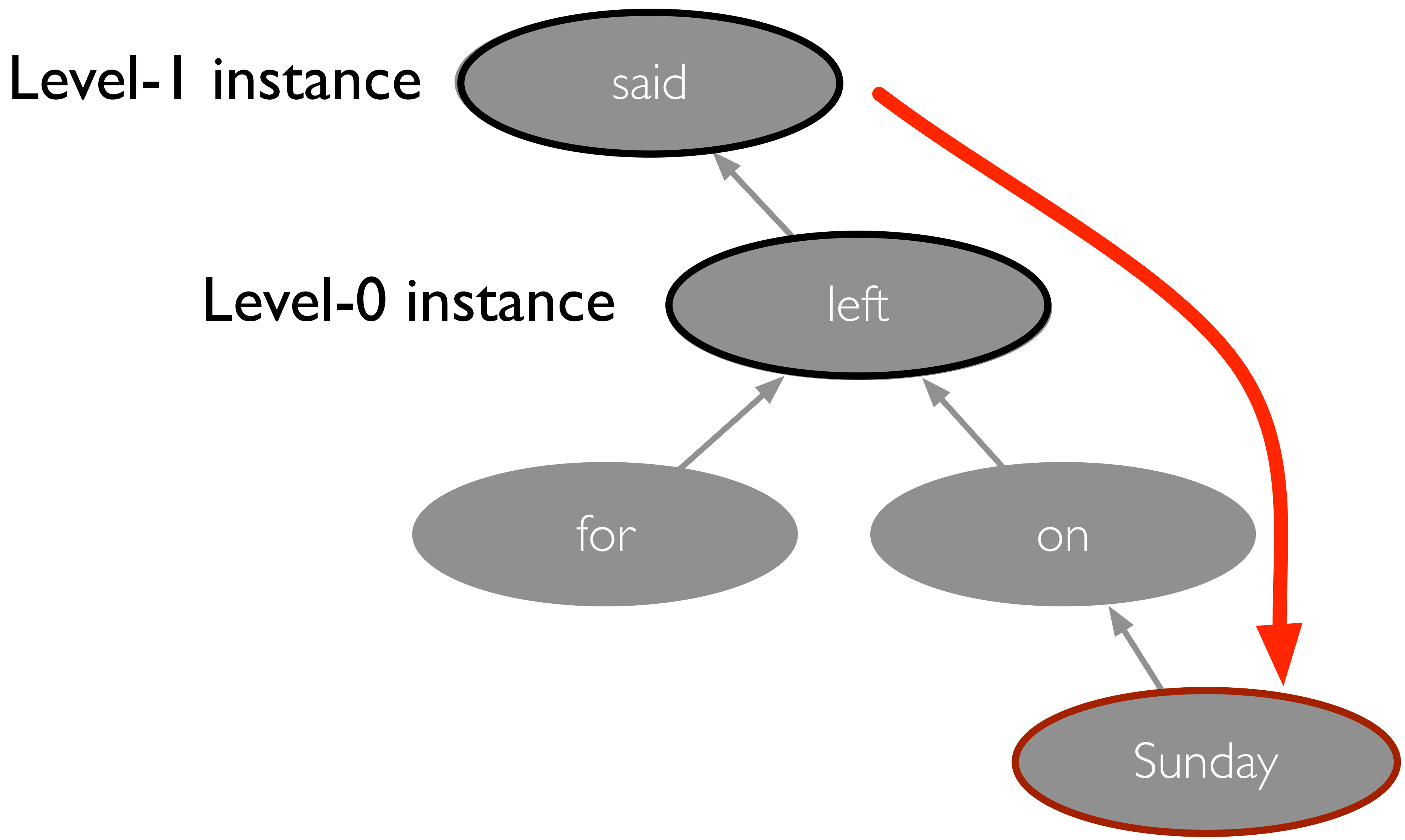


Easy Level-0 Instances

- Level-0 instances are much easier to get correct

Accuracy (%)				
Level-0 (59)	Level-1 (47)	Level-2 (21)	Level-3 (10)	Level-4 (1)
84.5	66.0	42.9	30.0	100.0

✦ Tested on TempEval-2 testing set

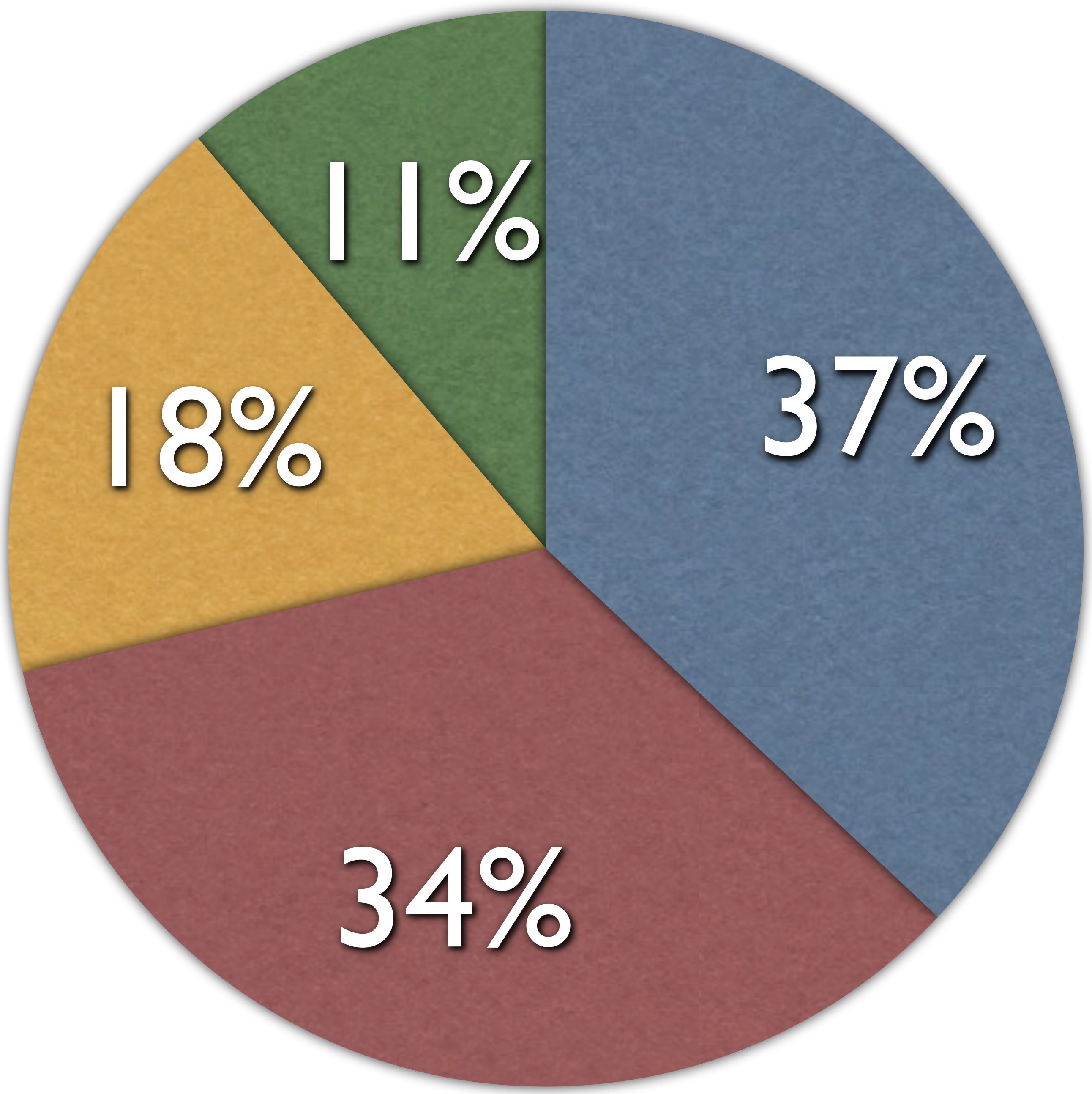
Selective Annotation

- Dropping Level-0 instances does not lead to drop in performance

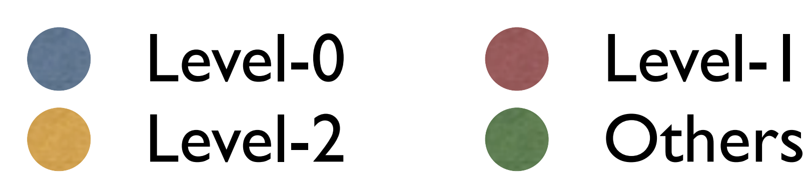
System	Accuracy	F1	Precision	Recall
ConvoDep	67.4%	0.523	0.828	0.512
CF-NoLevel0	73.2%	0.639	0.659	0.643
CF-Full	73.2%	0.641	0.660	0.647

✦ Tested on TempEval-2 testing set

Annotation Savings



- Level-0 instances form up to 37% of the annotated data



Analysis

- Why missing out on 37% of training instances causes no drop in performance?
- How to approach performance upper-bound?

Performance Breakdown

- Classifier does better on OVERLAP relations

System	Overlap			Before			After		
	P	R	F1	P	R	F1	P	R	F1
CF-NoLevel0	0.72	0.96	0.82	0.56	0.45	0.50	0.70	0.52	0.60
CF-Full	0.72	0.95	0.81	0.57	0.40	0.47	0.70	0.60	0.64

Label Distribution

- Level-0 instances contain less AFTER and BEFORE instances

Label	Distribution of Labels (%)		
	Level-0	Level-1	Level-2
AFTER	10.1	21.2	23.6
BEFORE	5.1	13.7	16.1

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Confusion Matrix

- BEFORE mis-classified as AFTER

Actual Label	Predicted Label		
	OVERLAP	BEFORE	AFTER
OVERLAP	78	2	1
BEFORE	7	9	4
AFTER	13	0	14

✦ Confusion matrix for CF-NoLevel0

Confusion Matrix

- BEFORE mis-classified as AFTER

Actual Label	Predicted Label		
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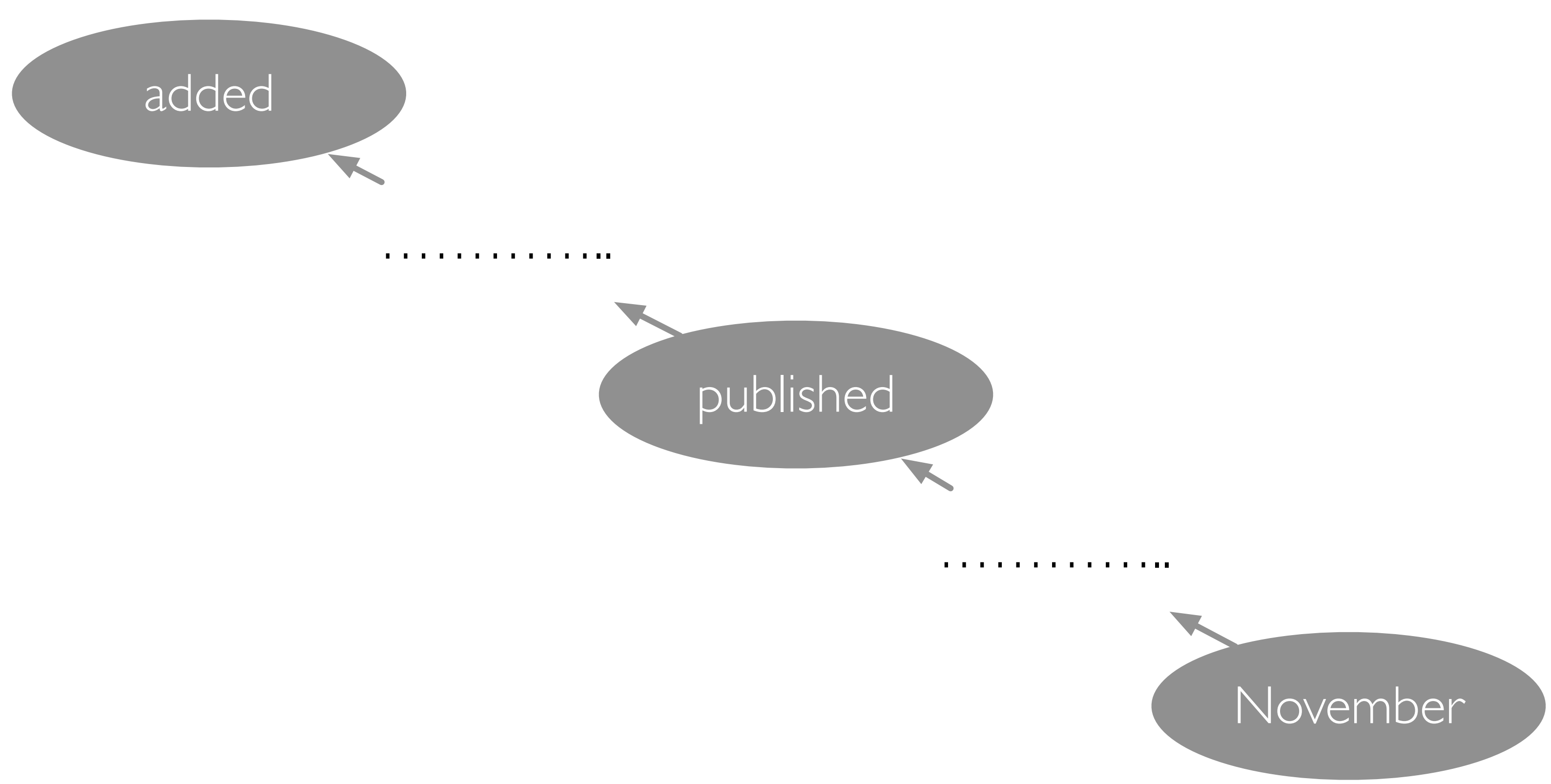
Copula Modifiers

BEFORE

He **added** that final guidelines to be published in early <u>November</u> will determine whether the bank is in compliance.



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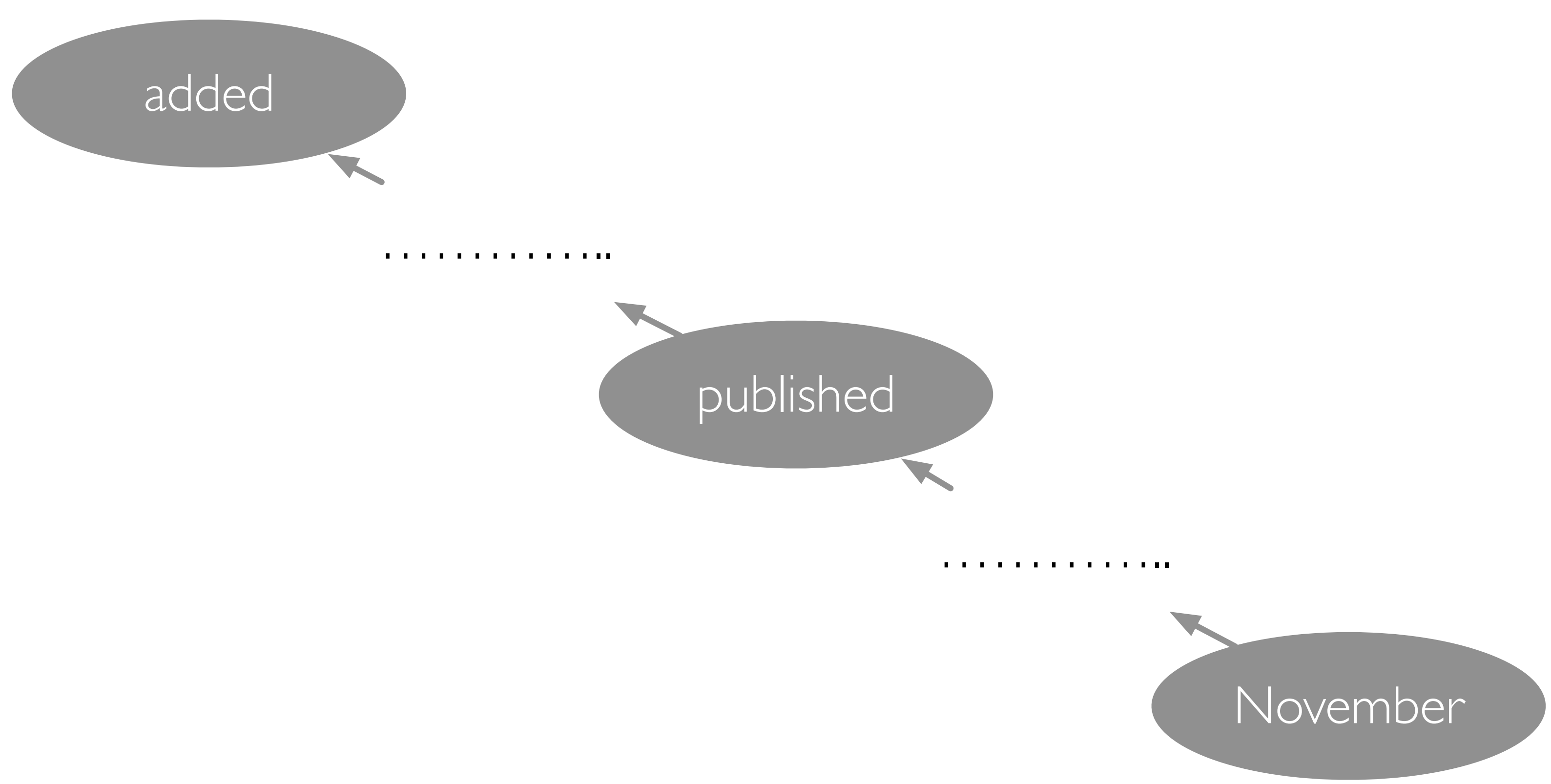

Missing Feature

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Round Up

- Improved event-temporal relation classification
  - By reducing input feature space
  - By increasing amount of annotated data
    - Demonstrated efficacy of crowdsourced annotations
    - Proposed an optimization to reduce the annotation effort required

Thank you!

Questions?

Dataset can be downloaded at

http://wing.comp.nus.edu.sg/~junping/etrcc/page/index.html

Breakdown of Data

Data Set	Relative size of partition (%)			
	Level-0	Level-1	Level-2	Others
TempEval-2 Training	40.9	35.2	15.1	8.8
TempEval-2 Testing	41.4	34.3	15.7	8.6
CF-Full	37.0	34.3	17.5	11.2