# Our Quest for Interpretable Natural Language Processing

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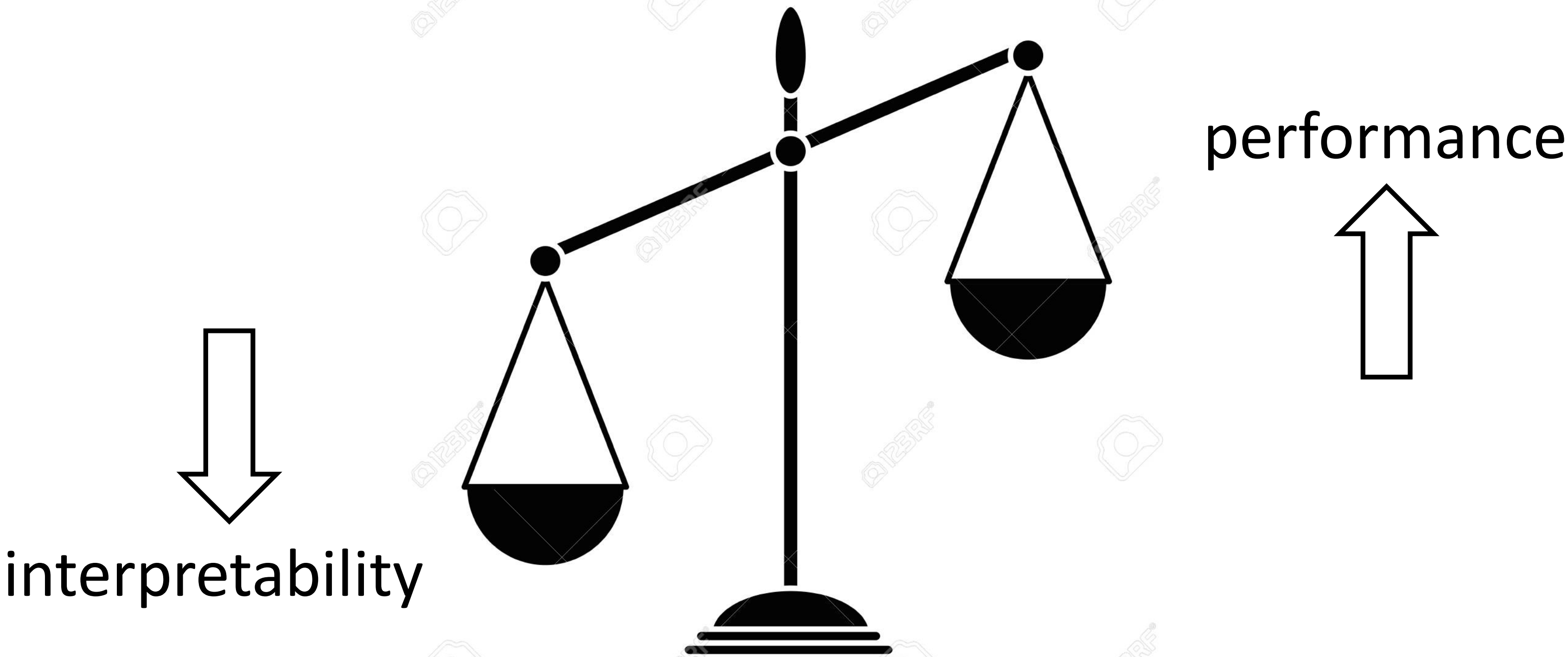
Computational Language Understanding

# Recent ML developments: a deal with the devil



# Interpretability

- Interpretability is an overloaded term in machine learning (ML)
- But we can classify it roughly in two classes

# 1. Post hoc interpretability (Ribeiro et al., 2016)

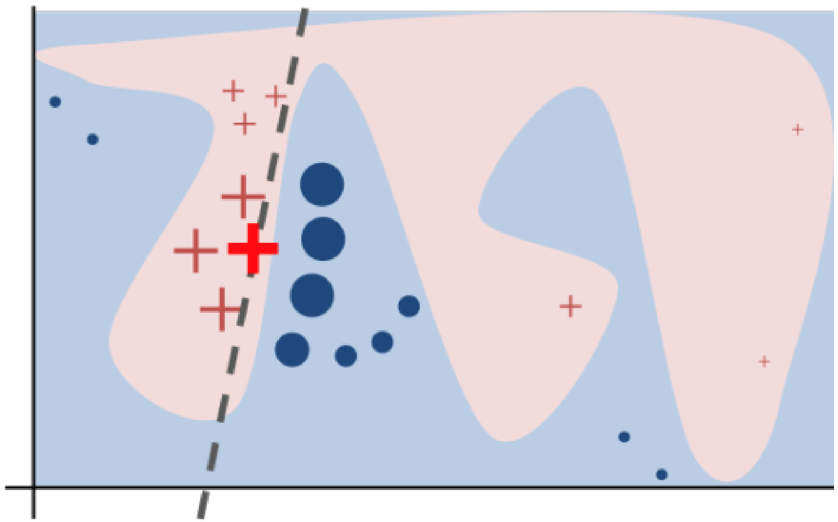
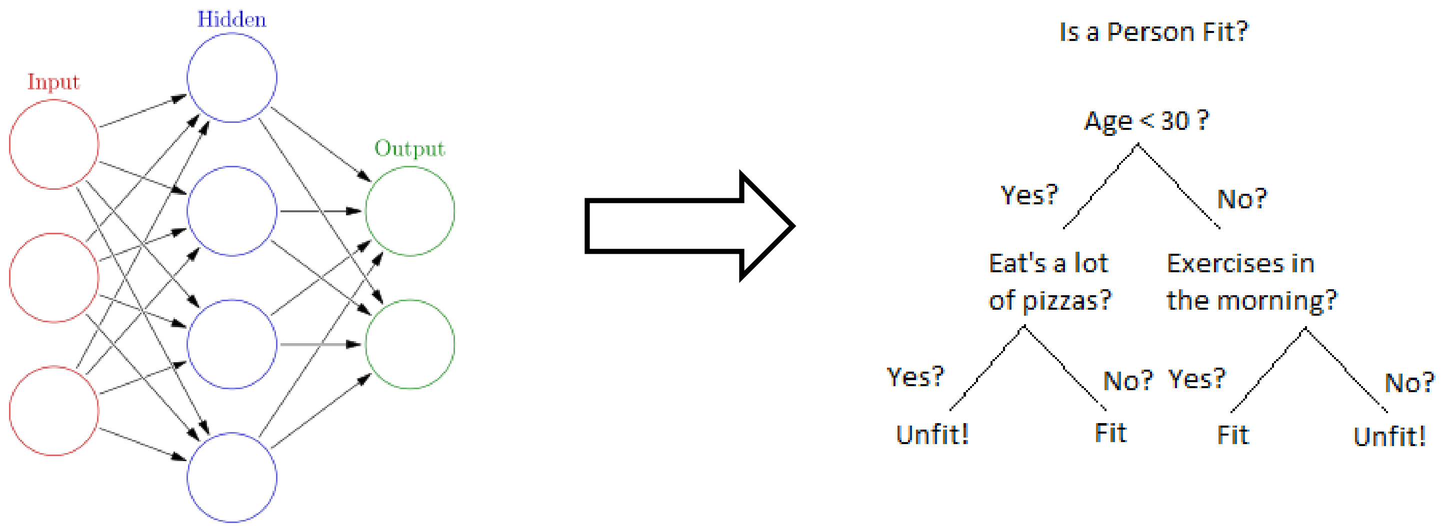


**Figure 3: Toy example to present intuition for LIME. The black-box model's complex decision function $f$ (unknown to LIME) is represented by the blue/pink background, which cannot be approximated well by a linear model. The bold red cross is the instance being explained. LIME samples instances, gets predictions using $f$, and weighs them by the proximity to the instance being explained (represented here by size). The dashed line is the learned explanation that is locally (but not globally) faithful.**

# 2. Global interpretability: Converting the statistical model into something interpretable (aka ”knowledge distillation”)




(Craven and Shavlik, 1996) (Hinton et al., 2015)

# Comparison

- Post hoc interpretability
  - May provide only an approximate explanation (Netflix lies to you ☺)
  - You can’t fix a problem with the original model when identified
- Global interpretability
  - May lose some performance in the conversion
  - Allows corrections to the model when problems are discovered

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# Comparison

- Post hoc interpretability
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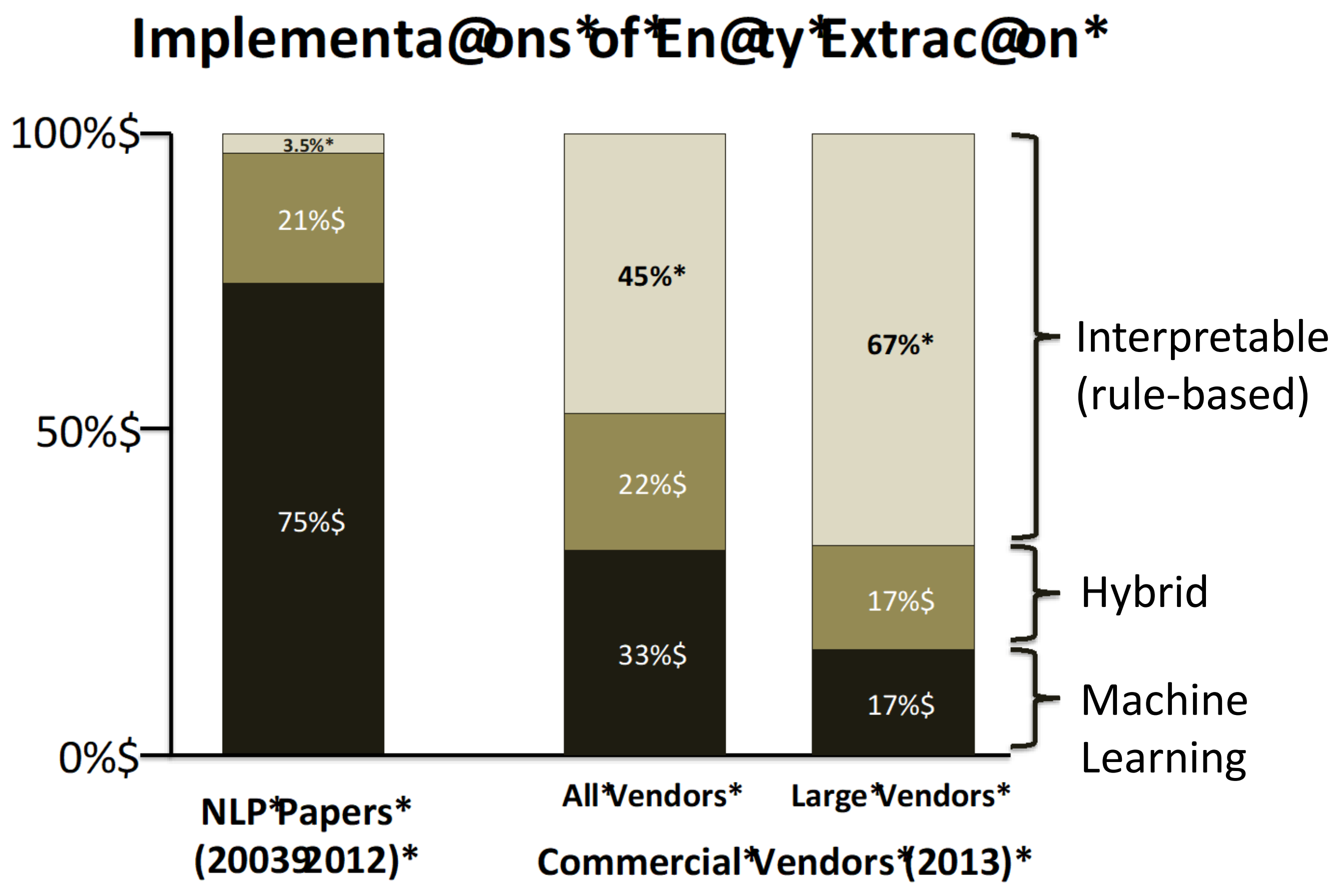
This is our focus!

- **Global interpretability**
  - May lose some performance in the conversion
  - **Allows corrections to the model when problems discovered**

# **Globally interpretable** models for natural language processing

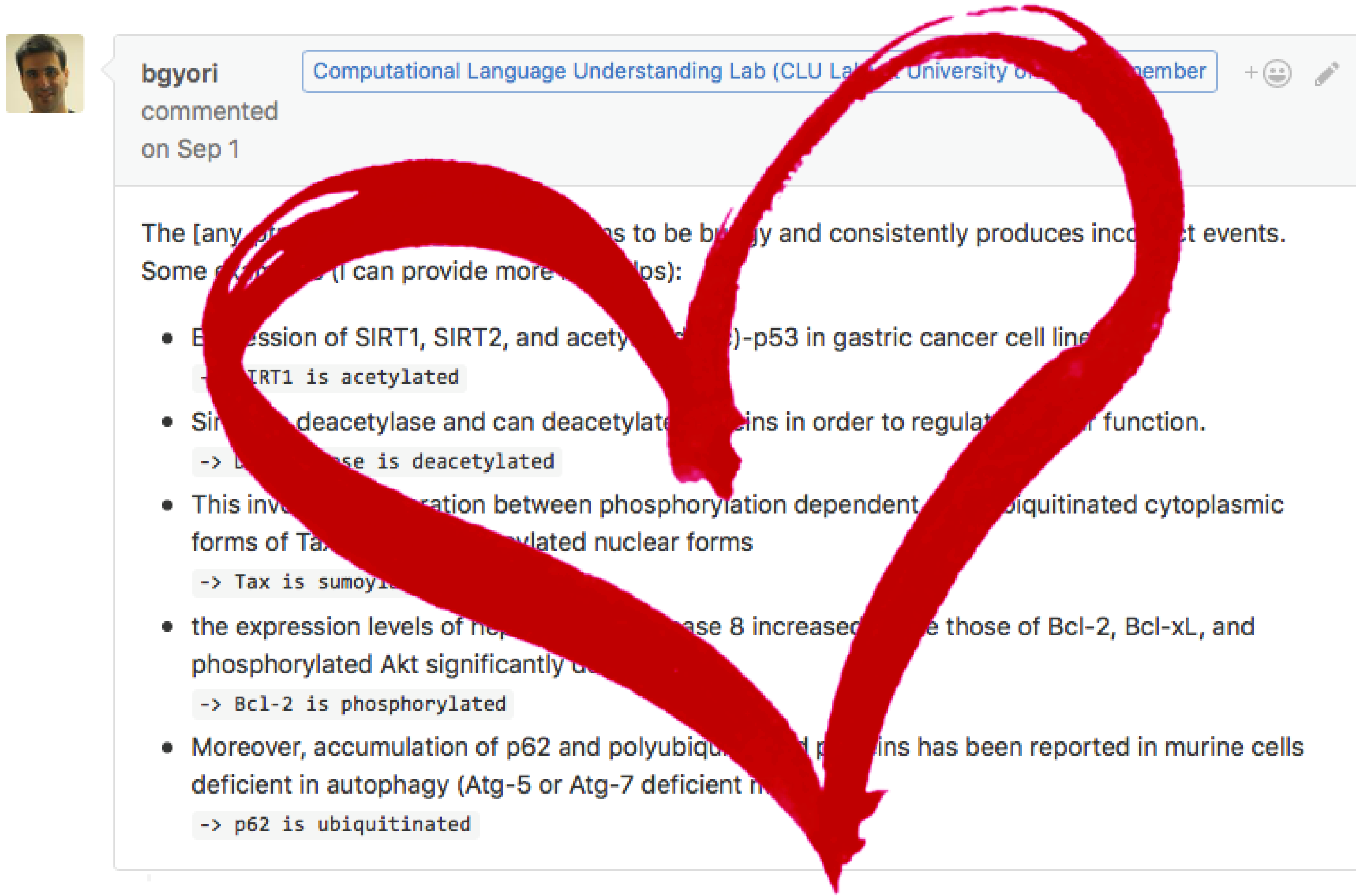
1. Humans can understand the model
2. Humans can change the model

# Academia vs. industry



# Why do we care about global interpretability?

- Most of today's meaningful projects are inter-disciplinary, e.g., ML + medicine
- We can't expect an expert in another domain to understand (and fix!) our statistical classifiers
- But we need to iterate quickly…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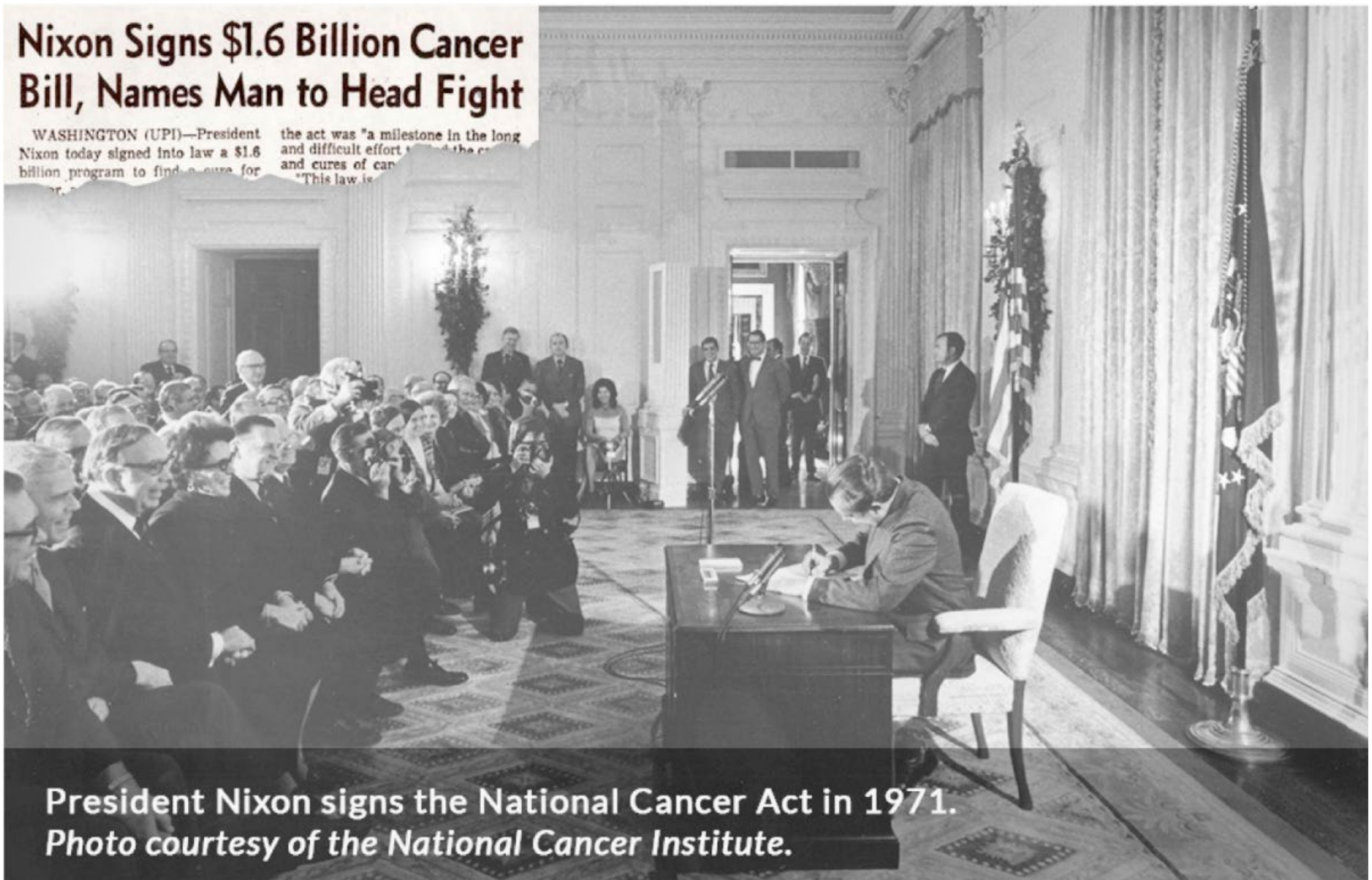
Some
(I can provide more
ps):
ession of SIRT1, SIRT2, and acety
)-p53 in gastric cancer cell line
IRT1 is acetylated
deacetylase and can deacetylat
ins in order to regula
function.
-> 
se is deacetylated
This inv
ation between phosphorylation dependent
iquitinated cytoplasmic
forms of Ta
ylated nuclear forms
-> Tax is sumoyl
the expression levels of
ase 8 increase
e those of Bcl-2, Bcl-xL, and
phosphorylated Akt significantly
-> Bcl-2 is phosphorylated
Moreover, accumulation of p62 and polyubiqu
ins has been reported in murine cells
deficient in autophagy (Atg-5 or Atg-7 deficient
-> p62 is ubiquitinated

# USE CASE: MACHINE READING FOR CANCER RESEARCH

# Why cancer?

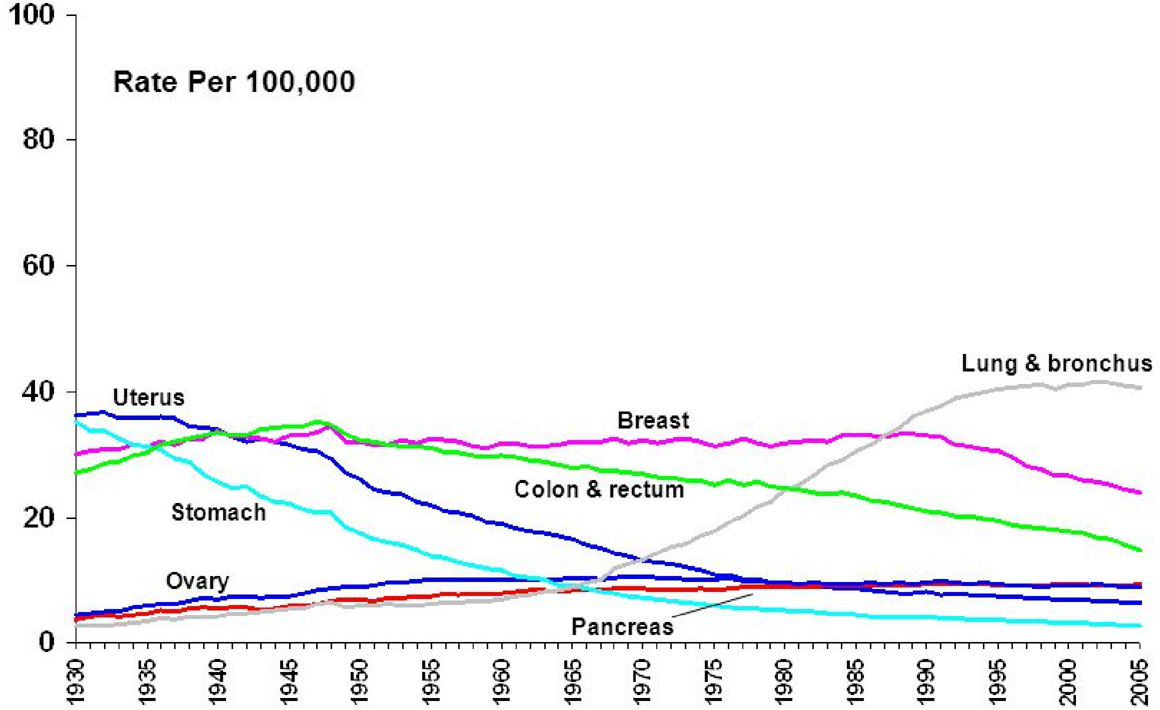


President Nixon signs the National Cancer Act in 1971.
*Photo courtesy of the National Cancer Institute.*

$200 billion have been invested in cancer research since (R. Barzilay, NAACL 2016)

# Why cancer?

Cancer Death Rates* Among Women, US, 1930 – 2005




*Age-adjusted to the 2000 US standard population.
Source: US Mortality Data 1960-2005, US Mortality Volumes 1930-1959,
National Center for Health Statistics, Centers for Disease Control and Prevention, 2008.

# Why cancer?

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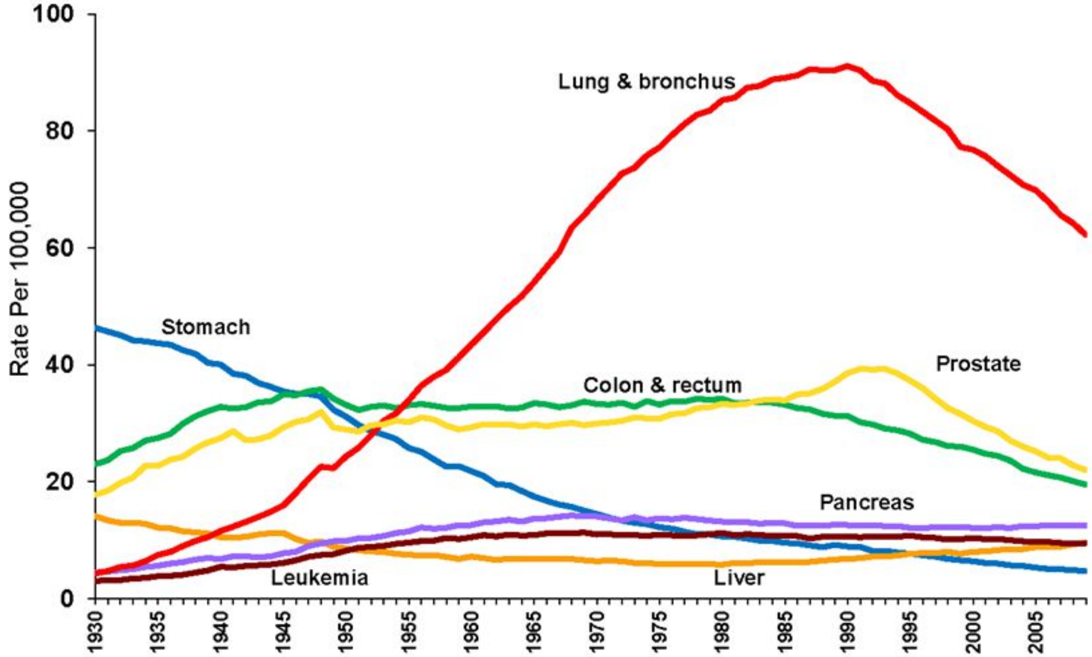


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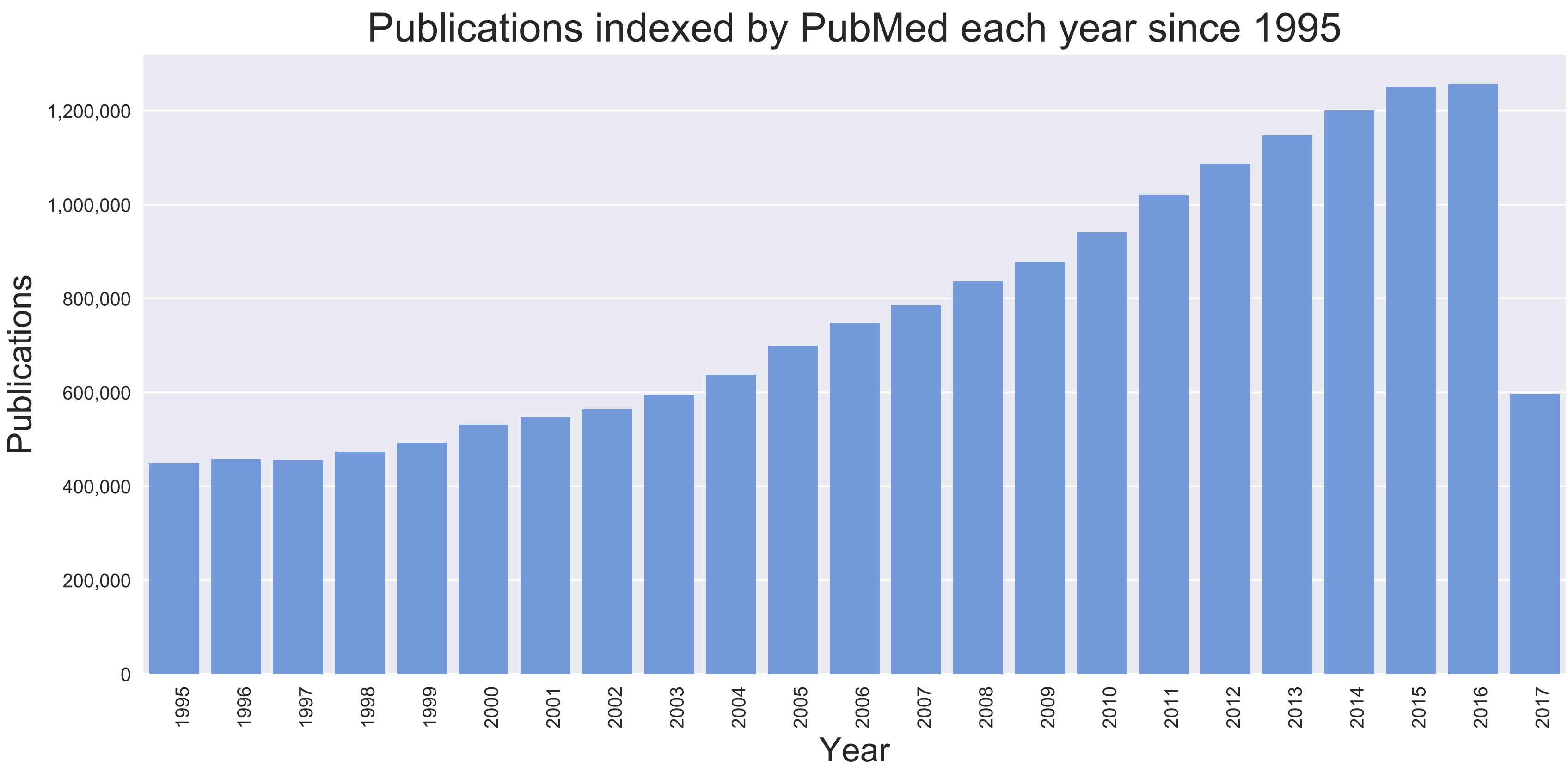
# Why the slow progress?



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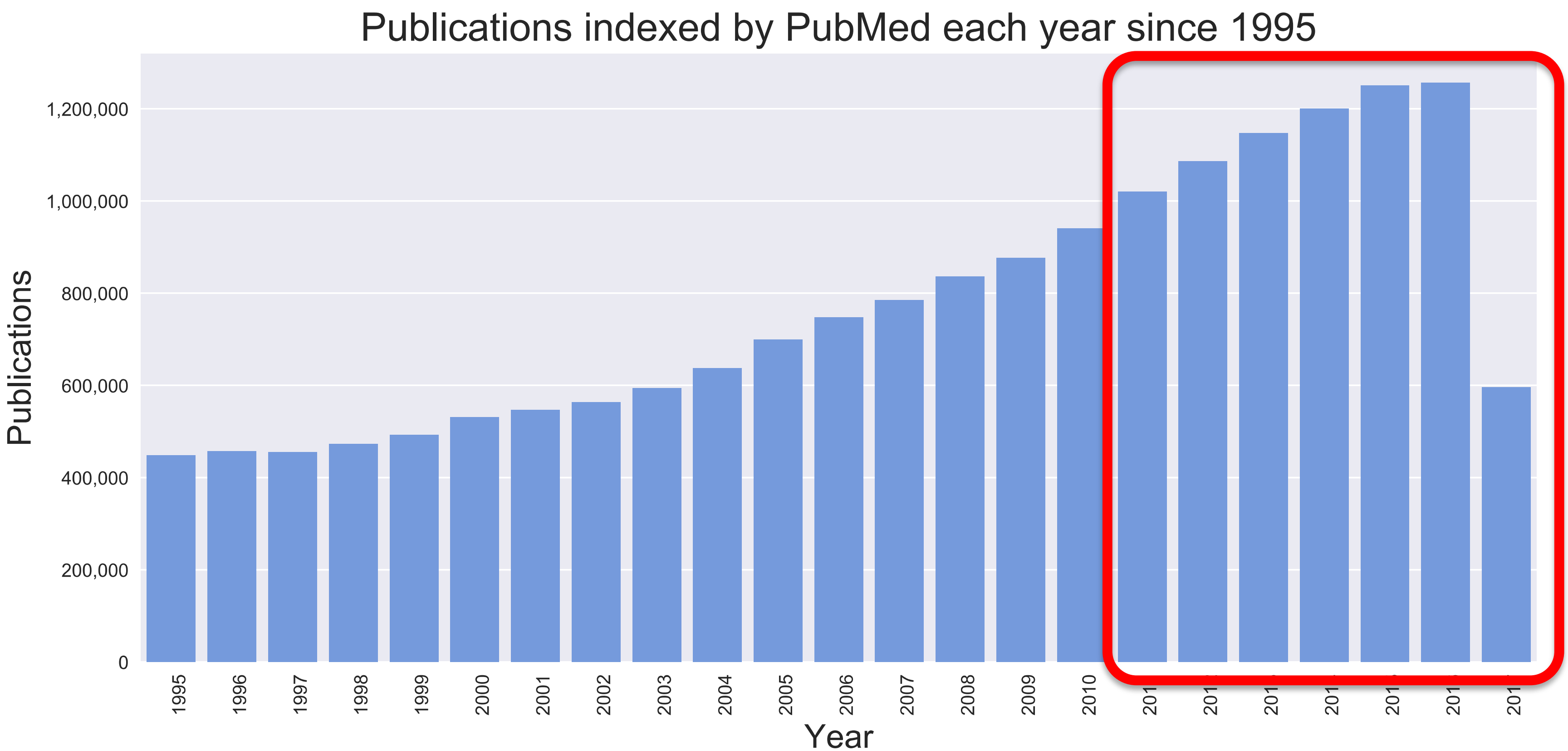



90% are never cited![1]

[1] http://www.smithsonianmag.com/smart-news/half-academic-studies-are-never-read-more-three-people-180950222/?no-ist

The problem of “undiscovered public knowledge”
(Swanson, 1986)

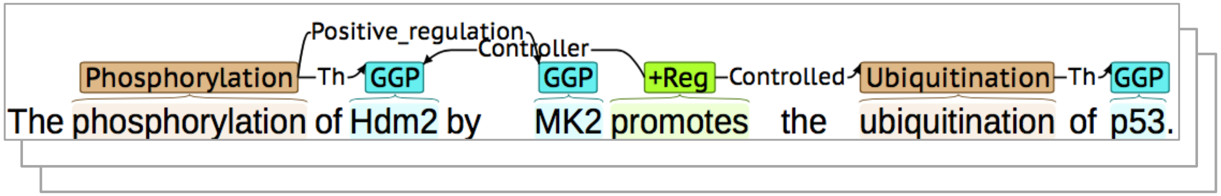
“A knotty puzzle may hold a scientist up for a century, when it may be that a colleague has the solution already and is not even aware of the puzzle that it might solve.”

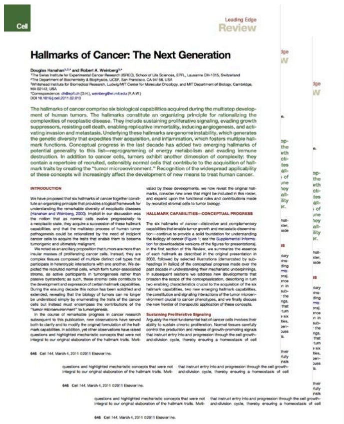
– Isaac Asimov, *The Robots of Dawn*

# We need machine reading

- If humans can’t process this much information, then machines must help!

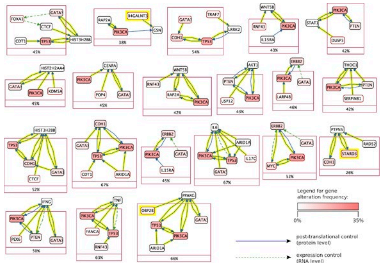
# Machine reading for biomedical literature




**Reading**

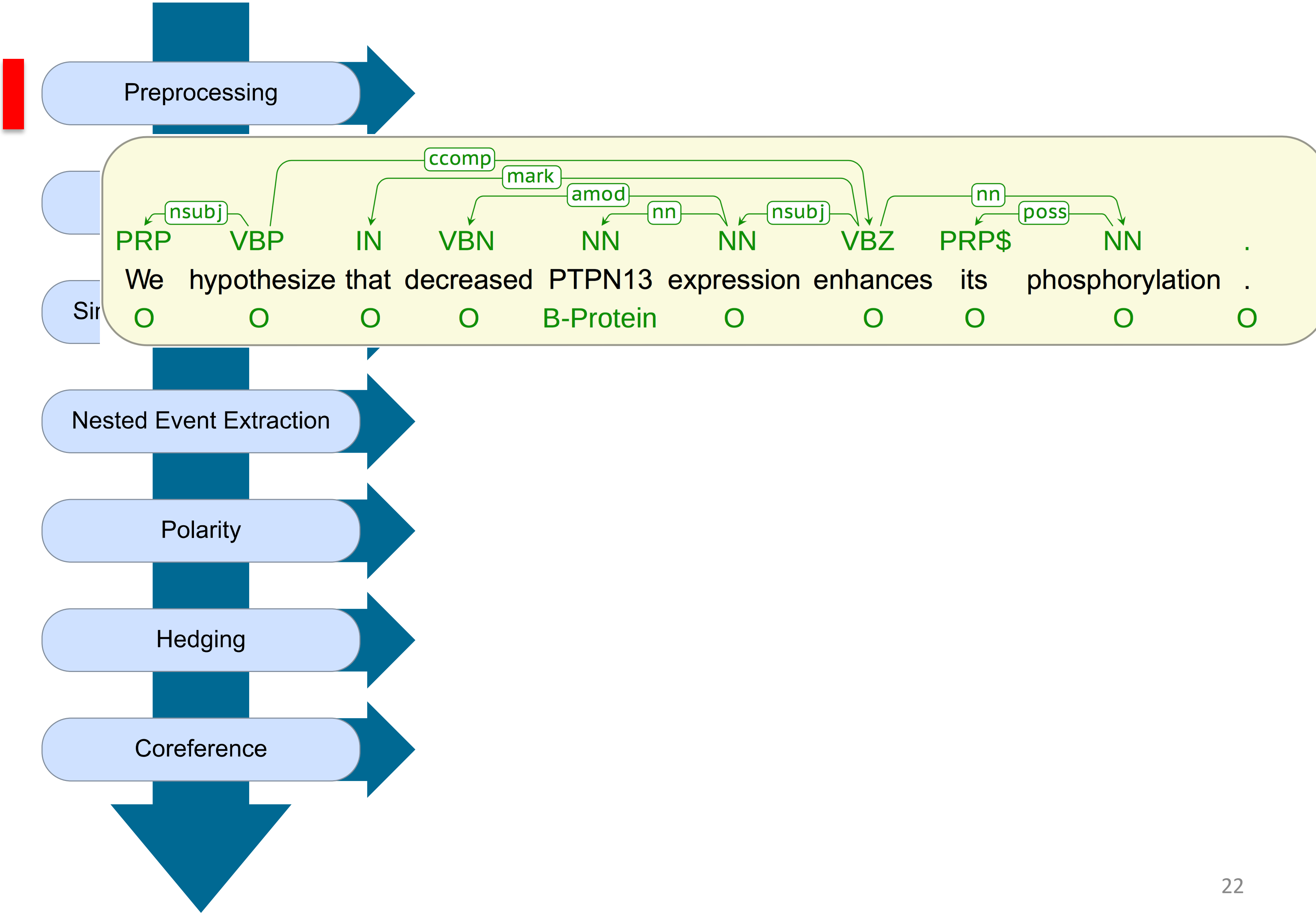
**Assembly**



**Reasoning**

Predict, explain, test, curate, etc.

# REACH (**RE**ading and **A**ssembling **C**ontextual and **H**olistic mechanisms)



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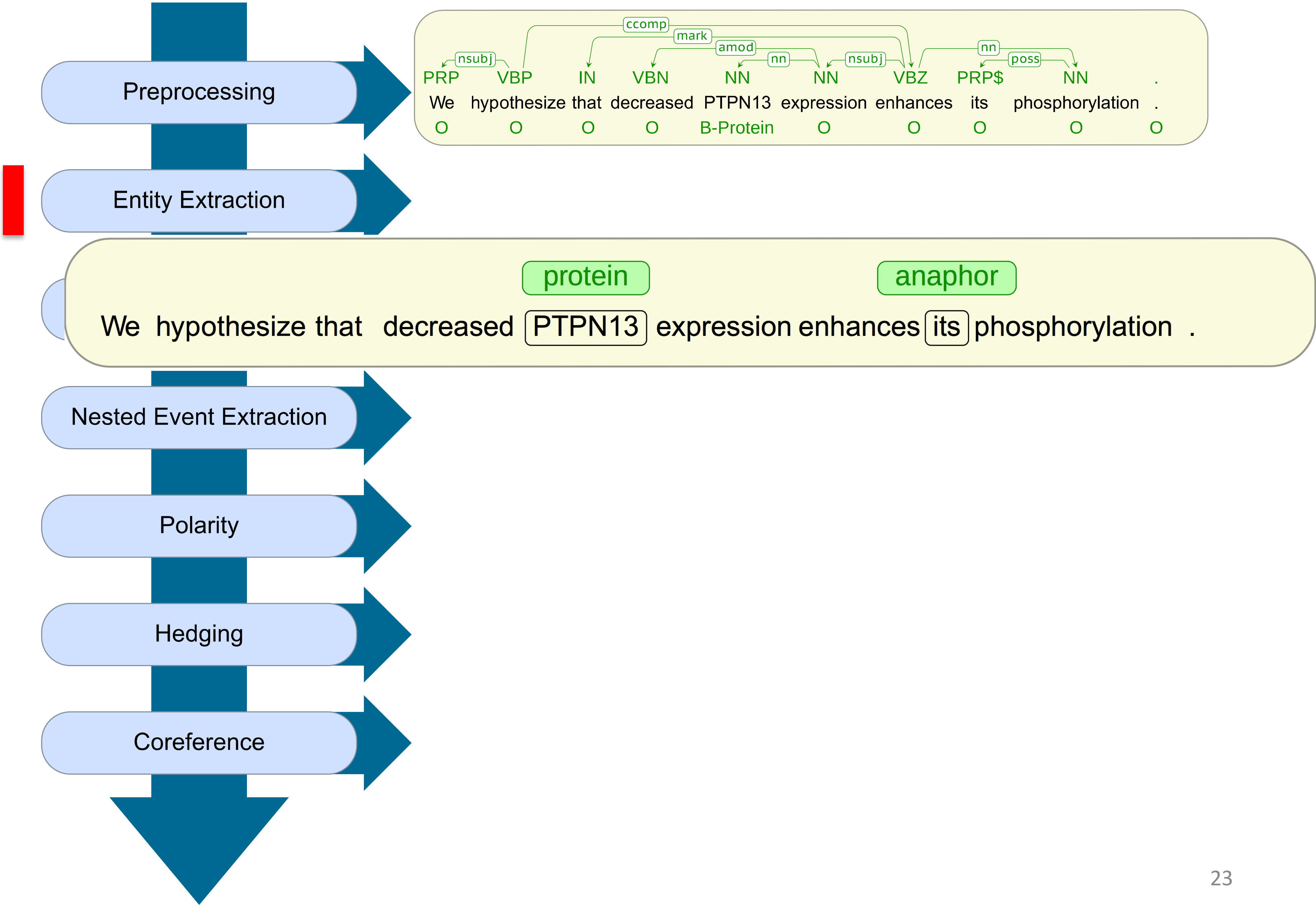

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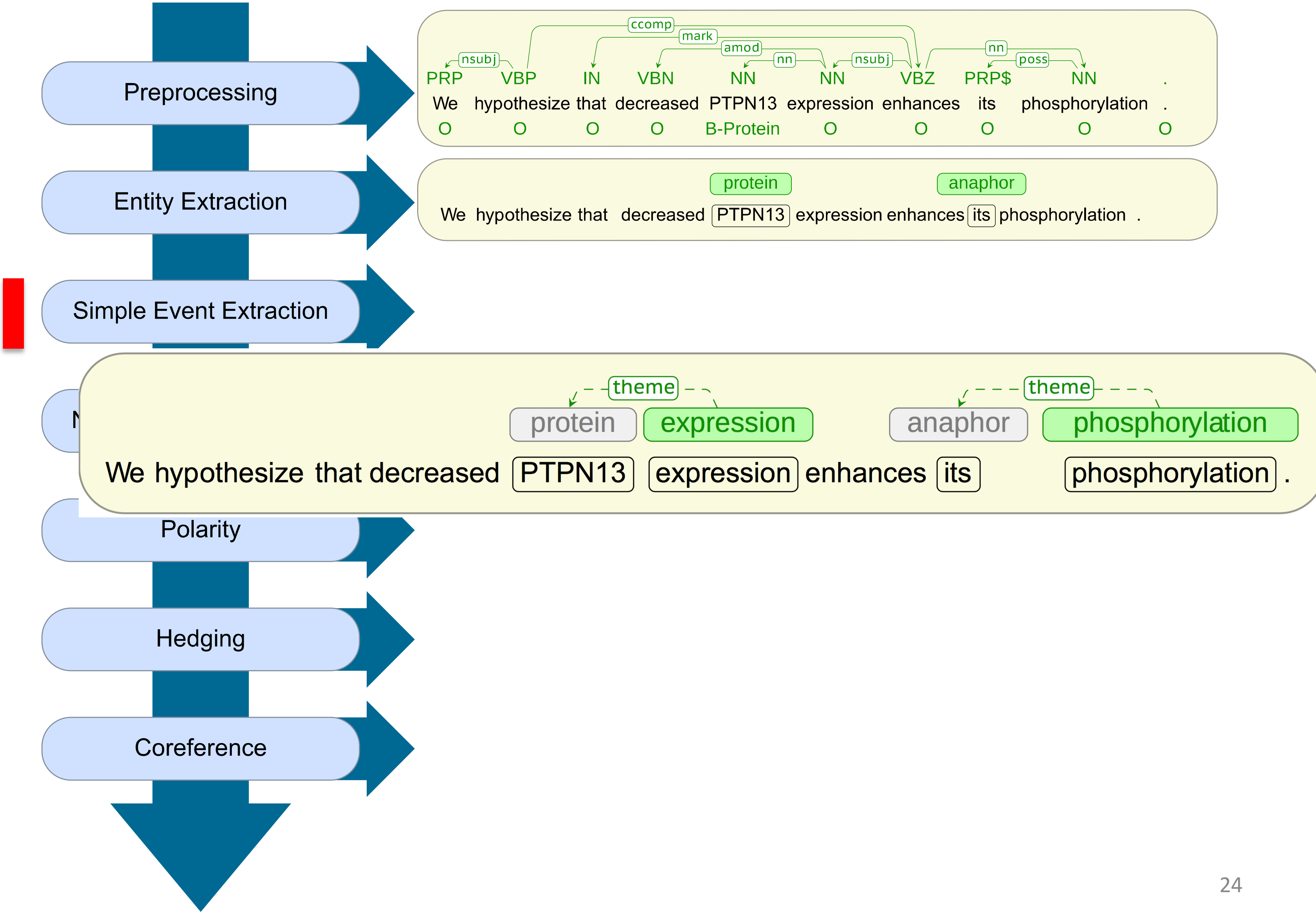

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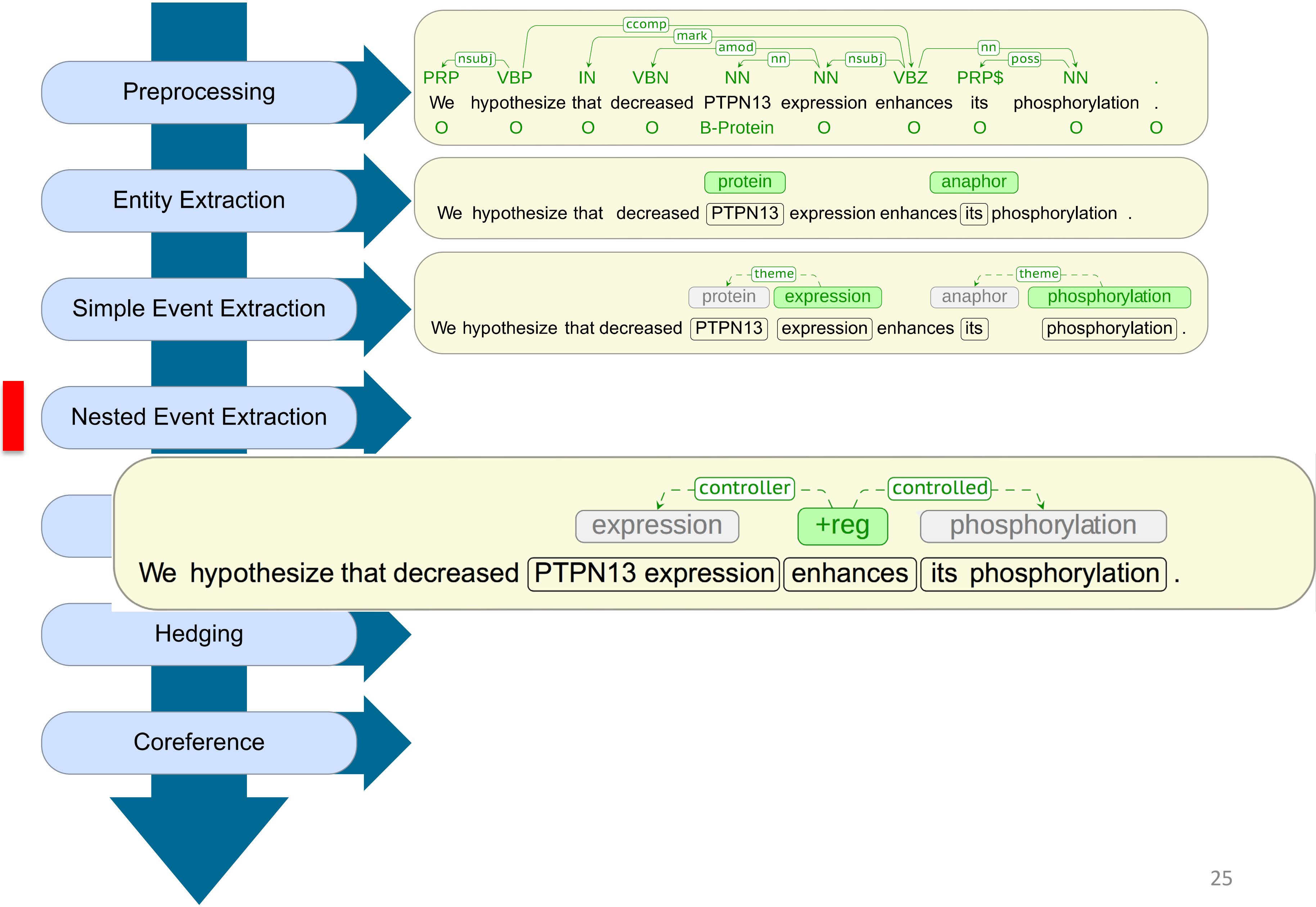

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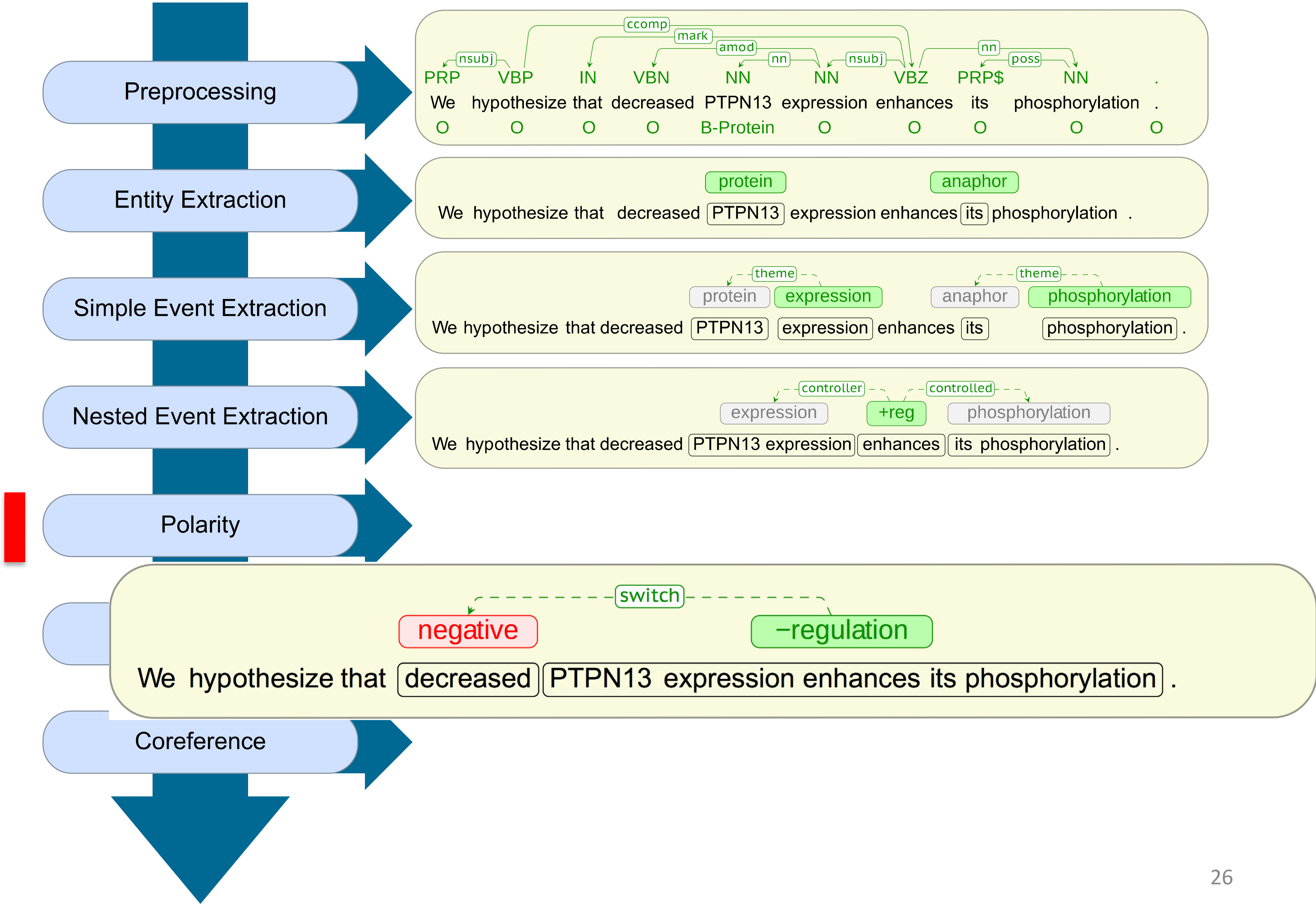

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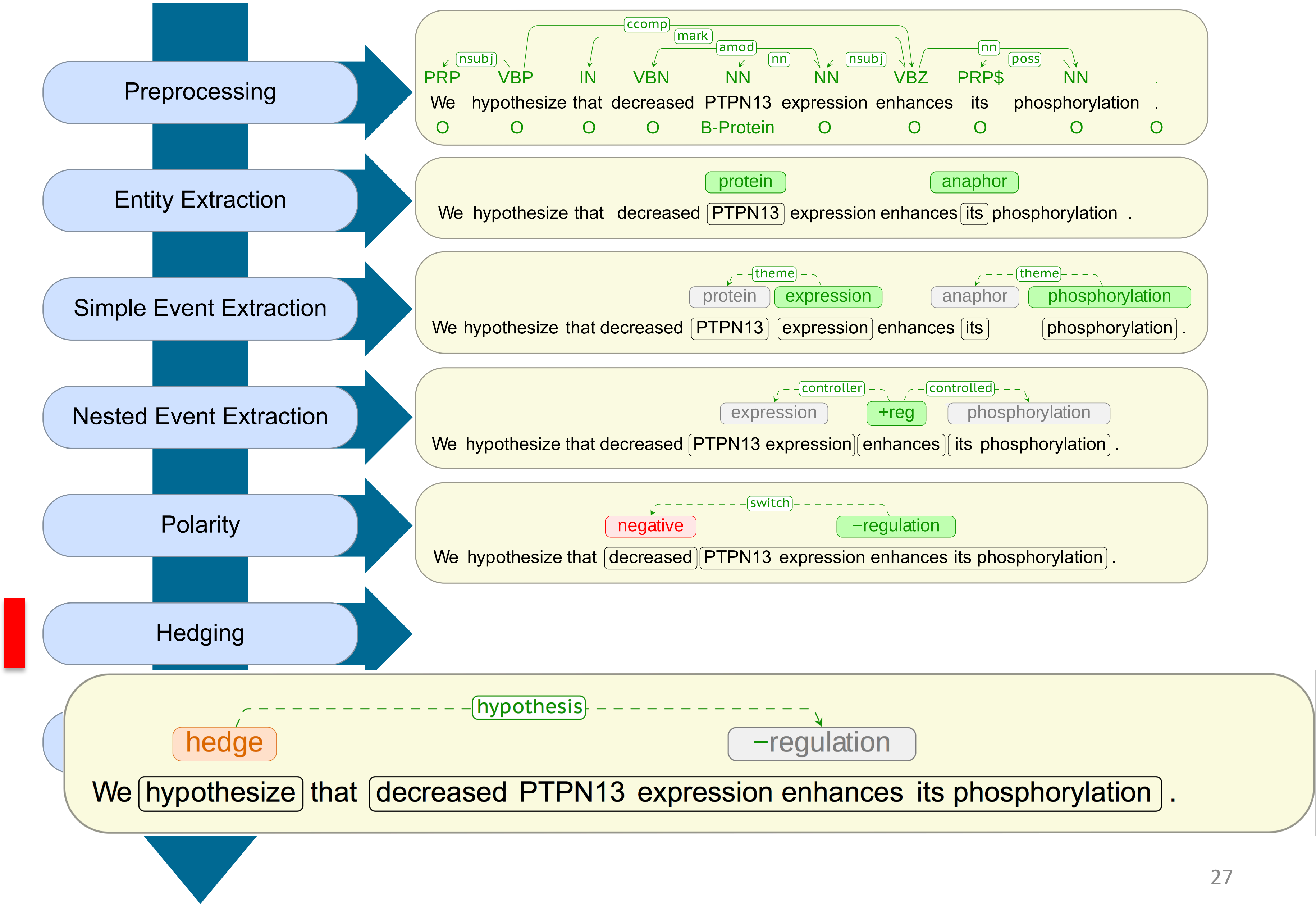

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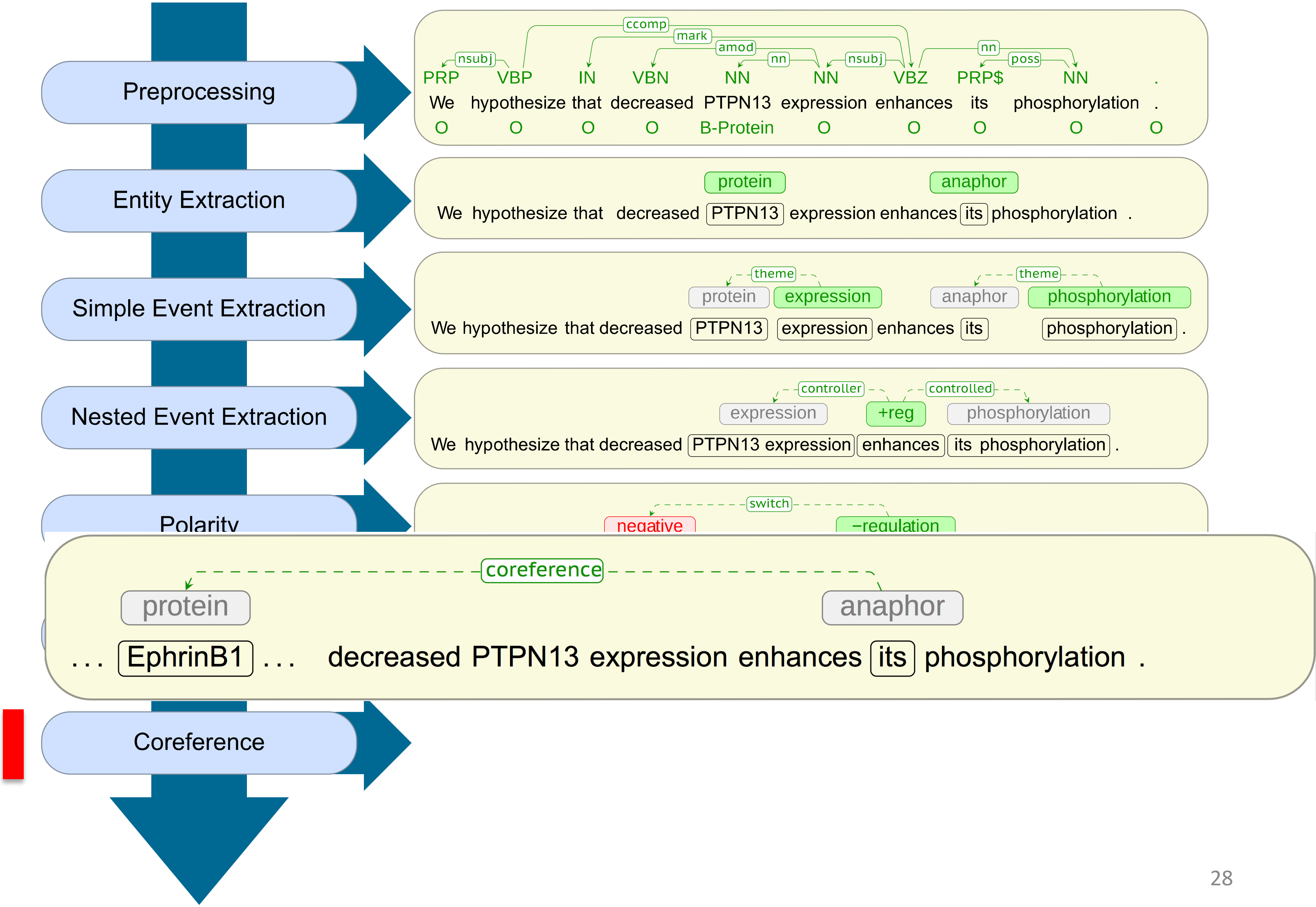

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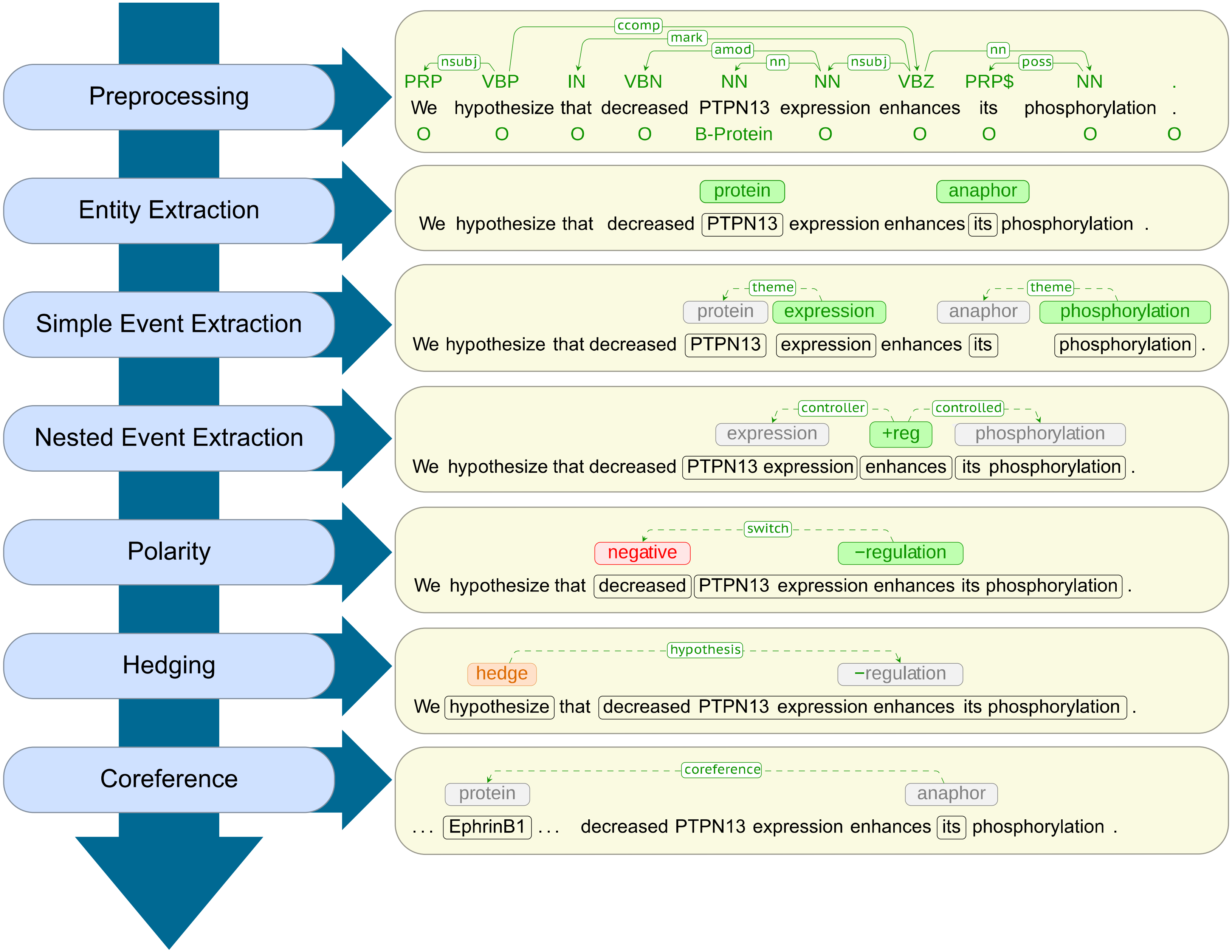


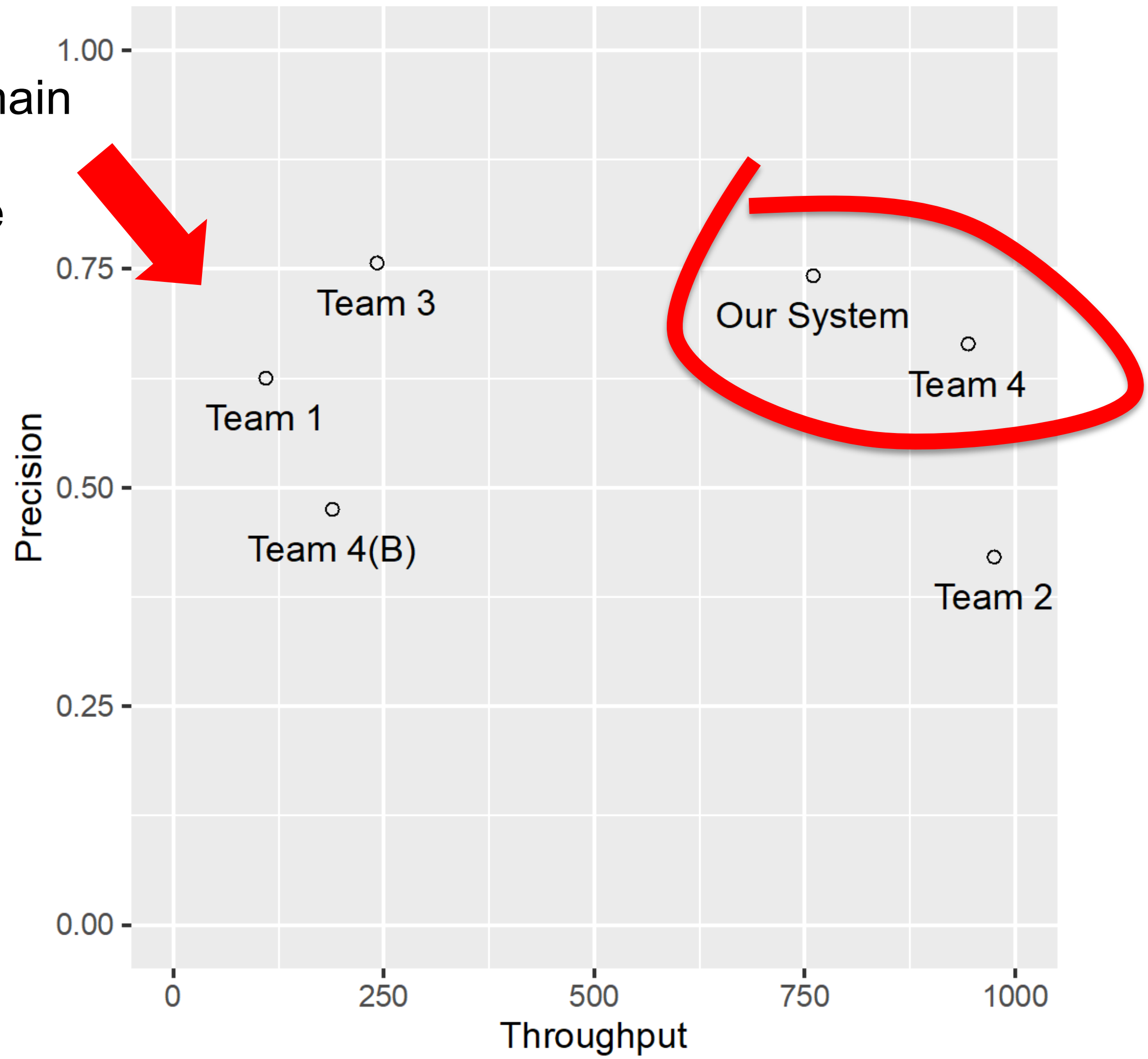
# Few grammar rules

| Type | Syntax | Surface | Total |
|---|---|---|---|
| Entities | 0 | 15 | 15 |
| Generic entities | 0 | 2 | 2 |
| Modifications | 0 | 6 | 6 |
| Mutants | 0 | 9 | 9 |
| Total entities | 0 | 32 | 32 |
| Simple event | [illegible] | [illegible] | 26 |
| Binding | [illegible] | [illegible] | 37 |
| Hydrolysis | [illegible] | [illegible] | 10 |
| Translocatio | [illegible] | [illegible] | 12 |
| Positive regu | [illegible] | [illegible] | 20 |
| Negative regu | [illegible] | [illegible] | 17 |
| Total events | 95 | 27 | 122 |
| Total | 95 | 59 | 154 |

These rules were manually written.
Later I will discuss our work on
using learn such rules using
representation learning.

# How well does machine reading work for a complete reading task?

Human domain experts are around here

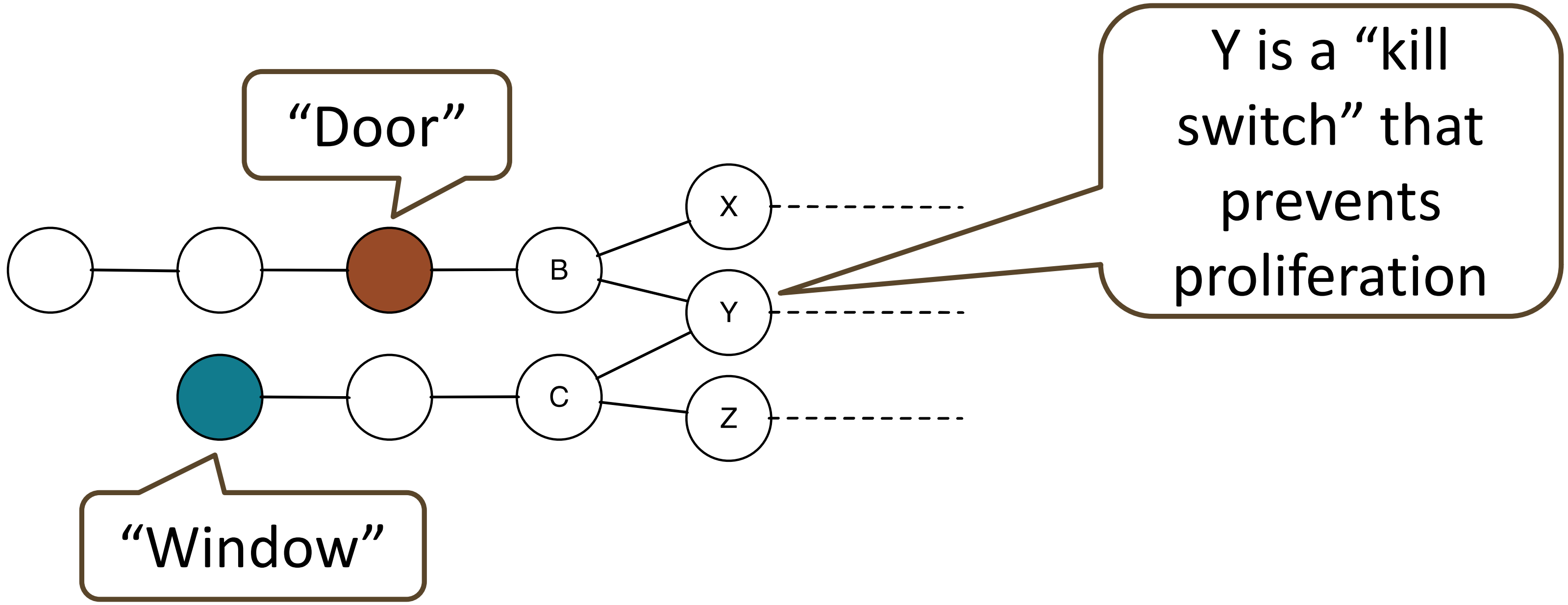


But is machine reading *actually* useful?

# Mutual exclusivity intuition

# The Mutex algorithm (by Emek Demir and colleagues)

Mutex insight: If a tumor "wants" to disable a mechanism, it will mutate something upstream, but it generally won't "pay" for two mutations that do the same thing. So mutually exclusive mutations plus a good model can tell us which mechanisms the tumor disables.






Slide courtesy of: Emek Demir, OHSU

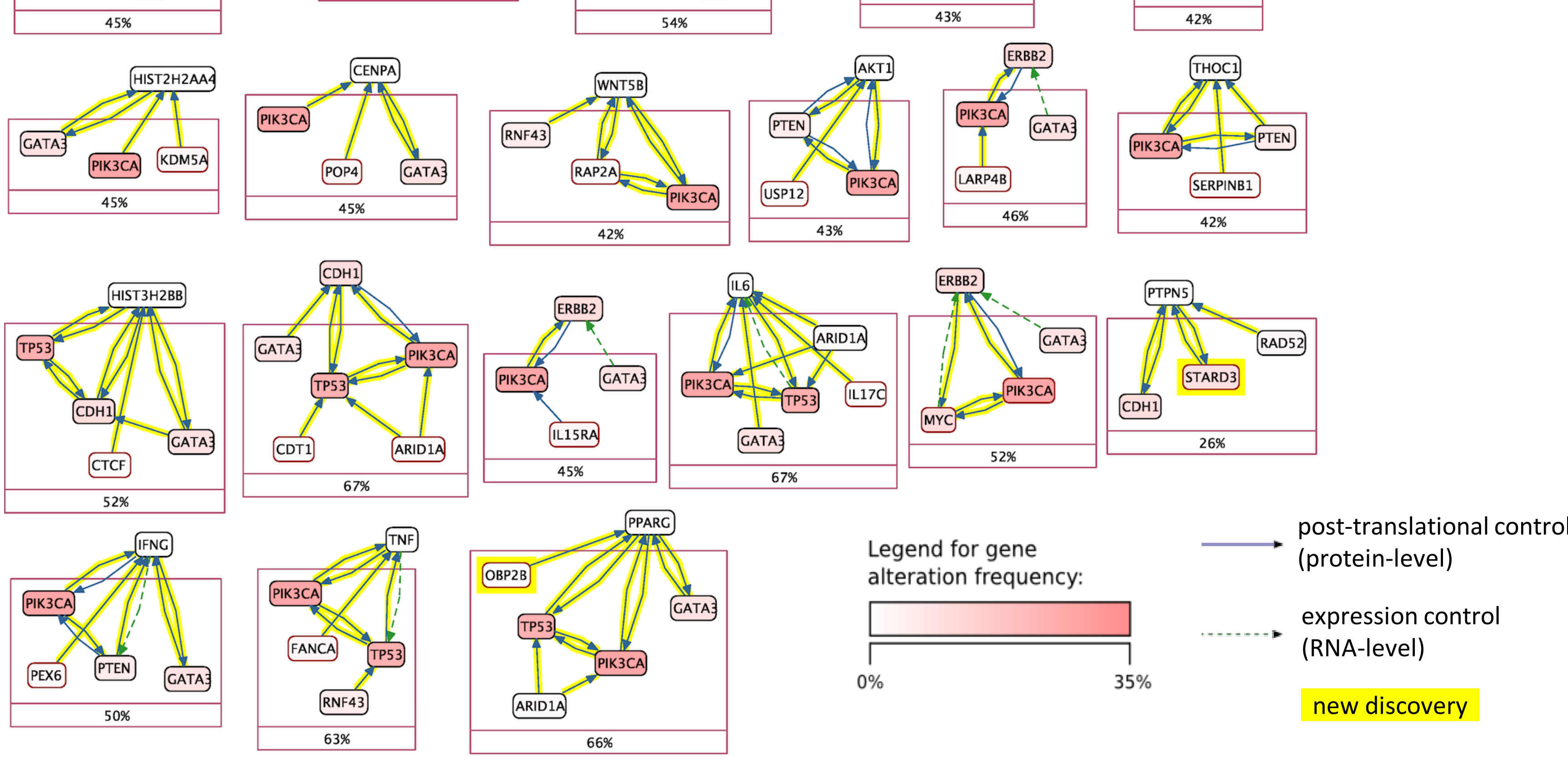
# How Mutex works

Patient data

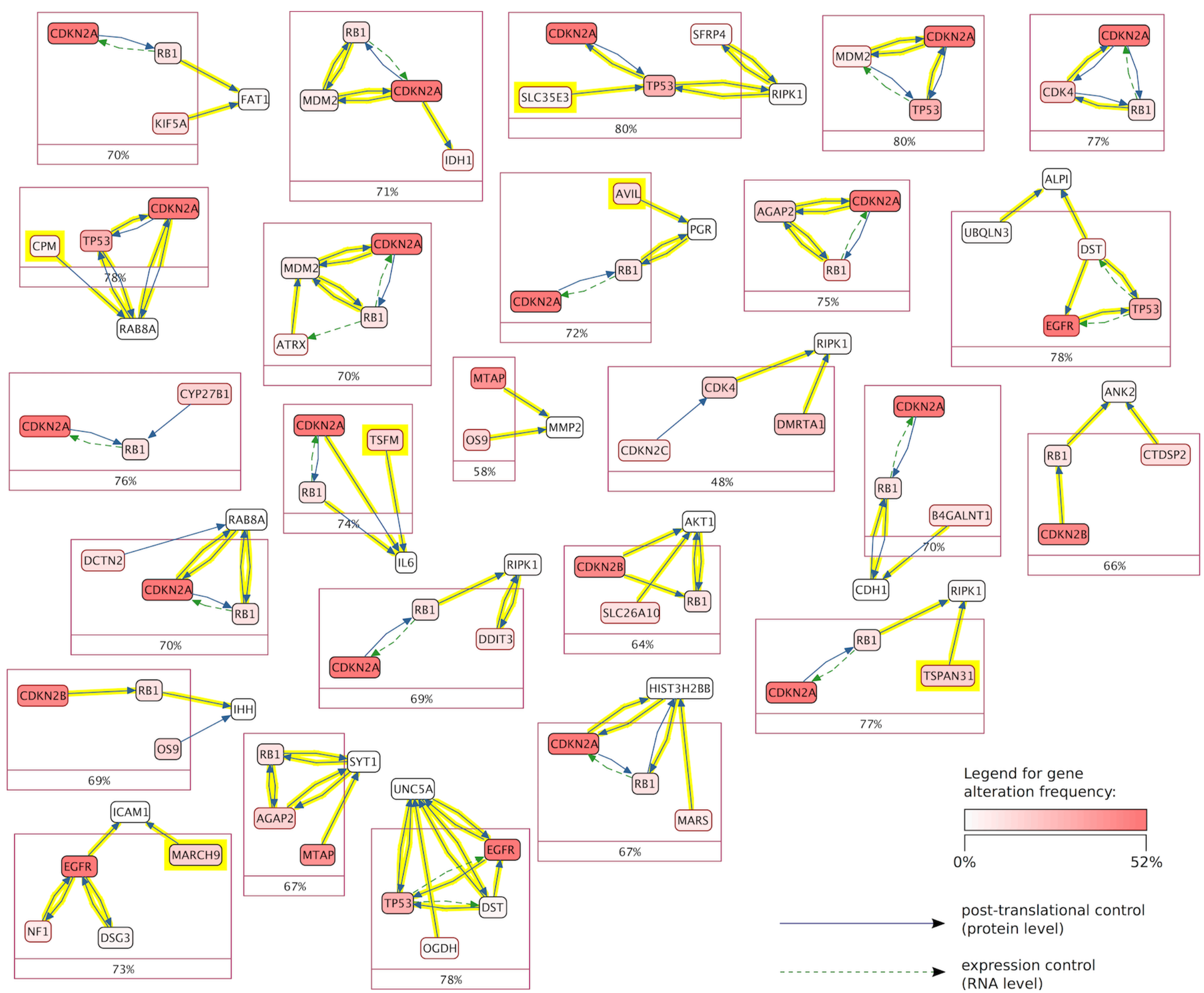
- Mutex does a graph search on the signaling network to find subgraphs of genes that
  - are altered in mutually exclusive manner, and
  - have a common downstream signaling target.

Machine reading contributes here!

# Breast (BRCA)


FOXA1
GATA3
CTCF
CDT1
TP53
HIST3H2BB
45%
RAP2A
B4GALNT3
PIK3CA
GSN
38%
GATA3
TRAF7
LRRK2
CDH1
TP53
54%
WNT5B
RNF43
PIK3CA
IL15RA
43%
PIK3CA
STAT1
PTEN
DUSP3
42%
HIST2H2AA4
GATA3
PIK3CA
KDM5A
45%
CENPA
PIK3CA
POP4
GATA3
45%
WNT5B
RNF43
RAP2A
PIK3CA
42%
AKT1
PTEN
USP12
PIK3CA
43%
ERBB2
PIK3CA
GATA3
LARP4B
46%
THOC1
PIK3CA
PTEN
SERPINB1
42%
HIST3H2BB
TP53
CDH1
GATA3
CTCF
52%
CDH1
GATA3
PIK3CA
TP53
CDT1
ARID1A
67%
ERBB2
PIK3CA
GATA3
IL15RA
45%
IL6
ARID1A
PIK3CA
TP53
IL17C
GATA3
67%
ERBB2
GATA3
PIK3CA
MYC
52%
PTPN5
RAD52
STARD3
CDH1
26%
IFNG
PIK3CA
PEX6
PTEN
GATA3
50%
TNF
PIK3CA
FANCA
TP53
RNF43
63%
PPARG
OBP2B
GATA3
TP53
PIK3CA
ARID1A
66%
Legend for gene alteration frequency:
0%
35%
post-translational control (protein-level)
expression control (RNA-level)
new discovery

# Brain (GBM)



CDKN2A
RB1
FAT1
KIF5A
70%
RB1
MDM2
CDKN2A
IDH1
71%
CDKN2A
SFRP4
TP53
SLC35E3
RIPK1
80%
MDM2
CDKN2A
TP53
80%
CDKN2A
CDK4
RB1
77%
CDKN2A
CPM
TP53
78%
RAB8A
CDKN2A
MDM2
RB1
ATRX
70%
AVIL
PGR
RB1
CDKN2A
72%
AGAP2
CDKN2A
RB1
75%
ALPI
UBQLN3
DST
TP53
EGFR
78%
CYP27B1
CDKN2A
RB1
76%
CDKN2A
TSFM
RB1
74%
IL6
MTAP
OS9
MMP2
58%
RIPK1
CDK4
DMRTA1
CDKN2C
48%
CDKN2A
RB1
B4GALNT1
70%
CDH1
ANK2
RB1
CTDSP2
CDKN2B
66%
RAB8A
DCTN2
CDKN2A
RB1
70%
RIPK1
RB1
DDIT3
CDKN2A
69%
AKT1
CDKN2B
RB1
SLC26A10
64%
RIPK1
RB1
TSPAN31
CDKN2A
77%
CDKN2B
RB1
IHH
OS9
69%
RB1
SYT1
AGAP2
MTAP
67%
HIST3H2BB
CDKN2A
RB1
MARS
67%
ICAM1
MARCH9
EGFR
NF1
DSG3
73%
UNC5A
EGFR
TP53
DST
OGDH
78%
Legend for gene alteration frequency:
0%
52%
post-translational control (protein level)
expression control (RNA level)

Machine reading suggests novel hypotheses that are missed by the authors of the individual publications.

# LEARNING INTERPRETABLE MODELS

# Motivation for rule learning

- It took us 1 – 2 person months to build the grammar of 150+ rules for the biomedical domain

- In many cases, one does not have this time
  - Scenario 1: But training data exists
  - Scenario 2: And training data does not exist either…

# Motivation

- It took us 1 – 2 person months to build the grammar of 154 rules for the biomedical domain

- In many cases, one does not have this time
  - **Scenario 1: But training data exists (2 papers)**
  - Scenario 2: And training data does not exist either…

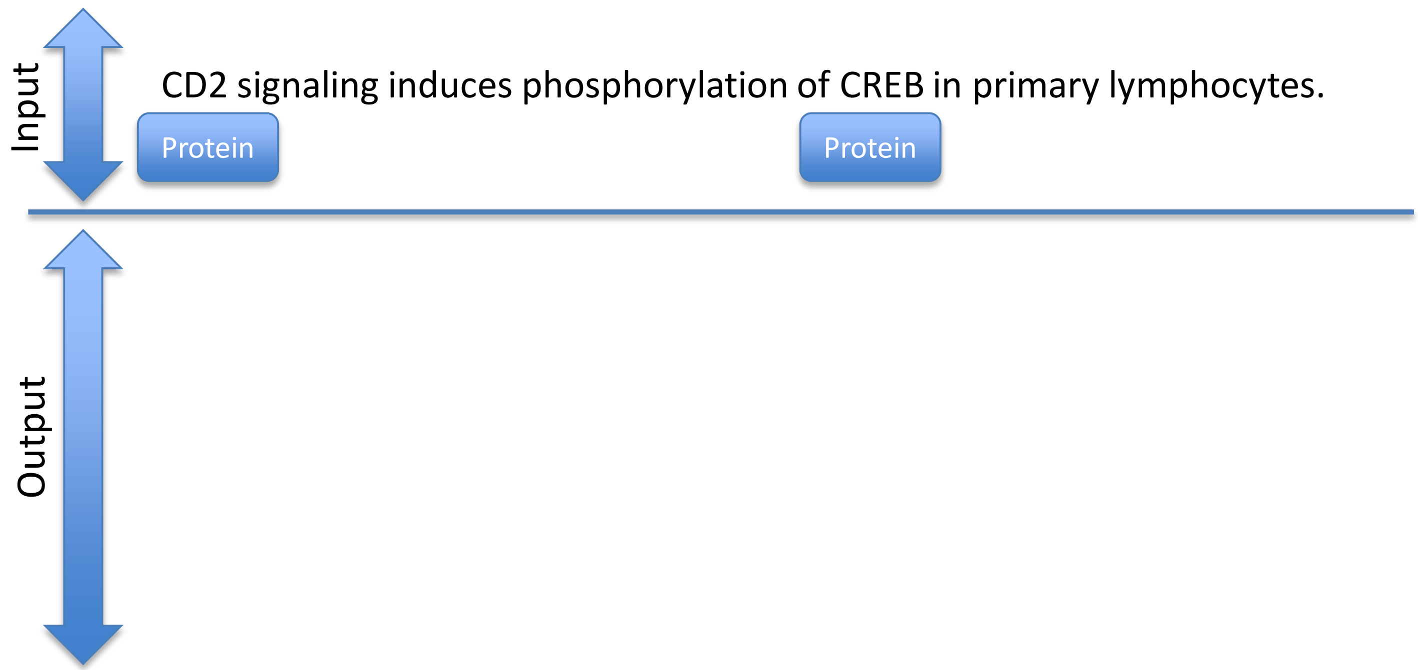
# SnapToGrid: From Statistical to Interpretable Models for Biomedical Information Extraction

**Marco A. Valenzuela-Escárcega, Gus Hahn-Powell, Dane Bell, Mihai Surdeanu**
University of Arizona
Tucson, AZ 85721, USA
{marcov, hahnpowell, dane, msurdeanu}@email.arizona.edu

# A three-step process

1. Train a statistical classifier
   a) Aggressive feature selection using regularization
2. Convert model to rules
   a) Convert features to rules
   b) “Snap to grid”: throw away most statistics by discretizing feature weights
3. Model editing

# BioNLP 2009 Shared Task



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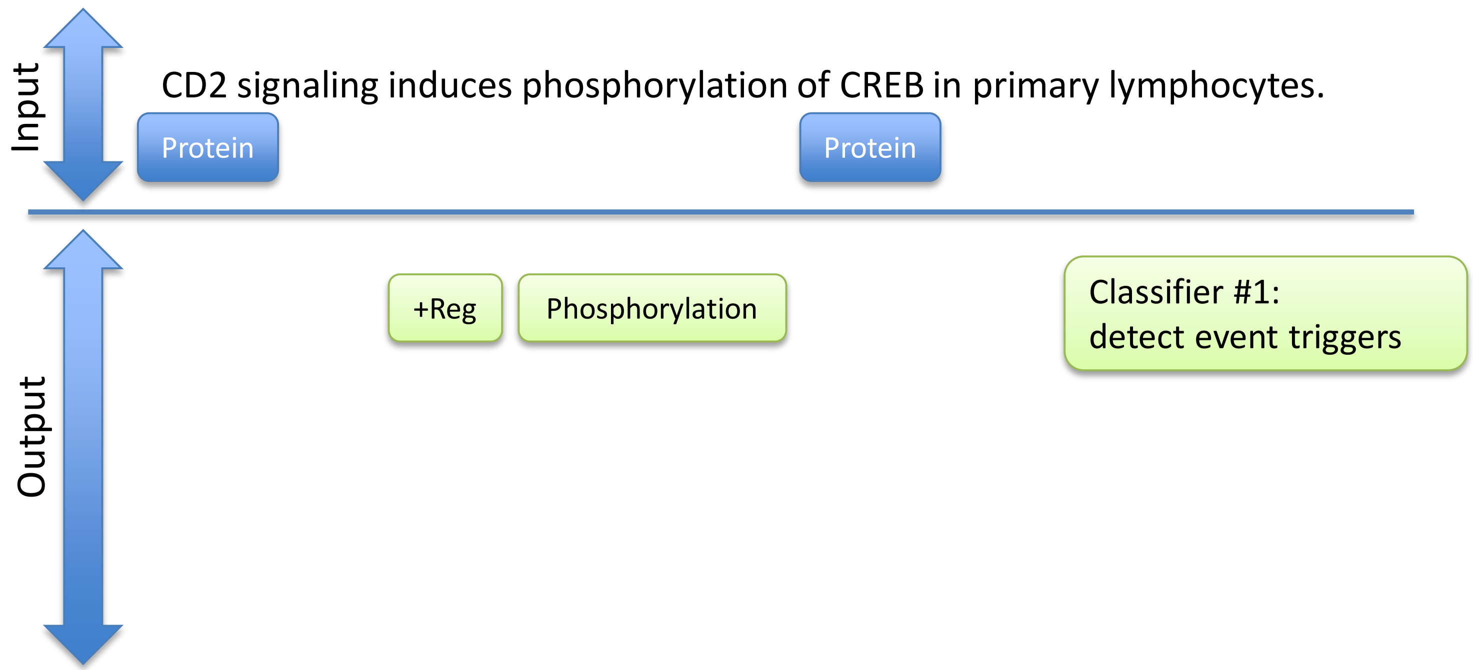

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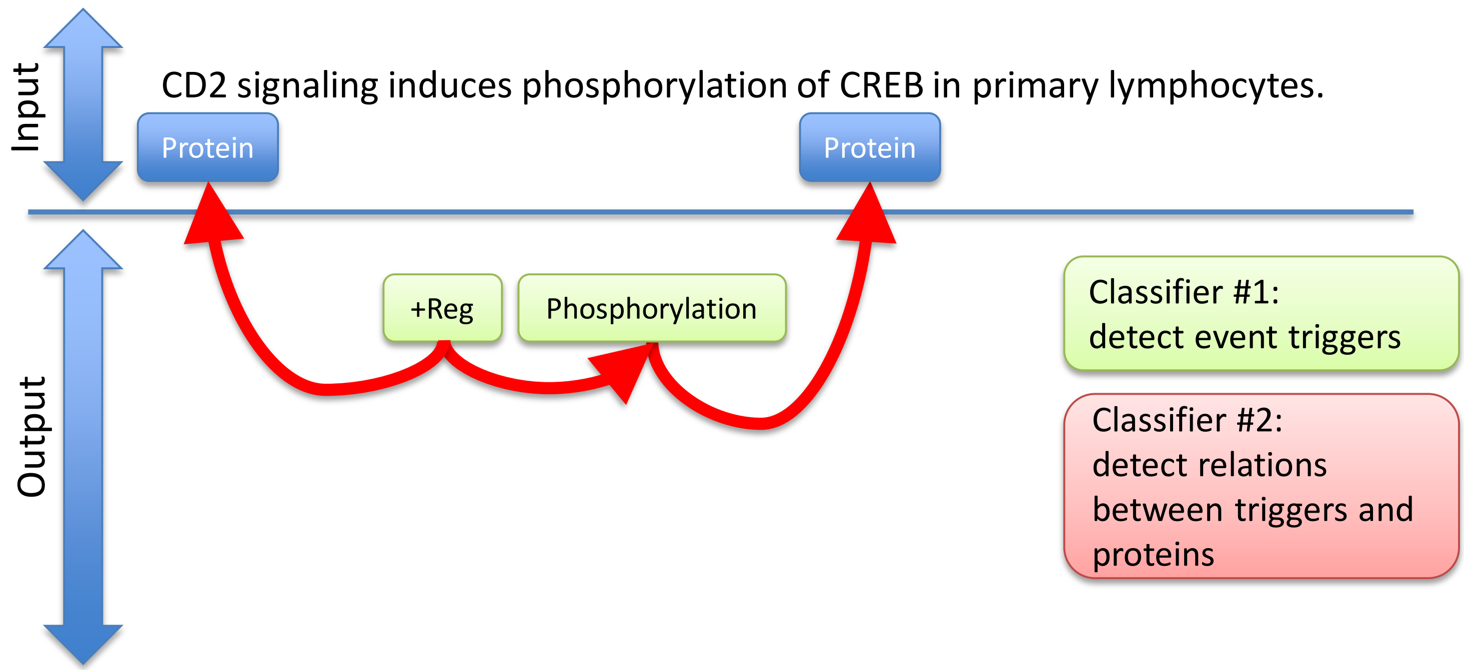


# Step 1: train statistical classifiers

- We use logistic regression for both classifiers
- Feature selection through regularization
  - L1 regularization: aggressive feature selection; slightly lower performance

# Machine learning features

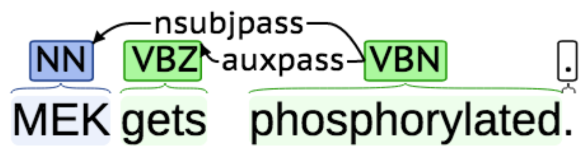
**Triggers**

- Token
  - Word, lemma, gazetteer
- Surface
  - Token features for a window around token of interest
  - Bigrams
- Syntax
  - Dependency paths up to depth 2
  - Token features for token at the end of each path
- Bag-of-words and entity count
  - For whole sentence
  - For window surrounding token of interest

**Relations**

- Path
  - Shortest dependency path between nodes of interest
  - With and without lexicalization
  - Path length
- Surface
  - Words surrounding and between nodes of interest
- Consistency
  - Soft constraints on edges between trigger and arguments (e.g., only regulations have causes)
- N-gram
  - Dependency, token, dependency
  - Token, dependency, token

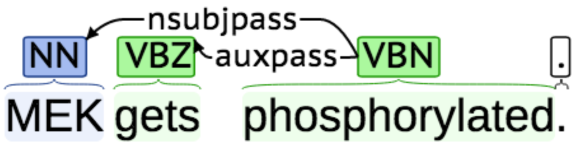
# Step 2: Convert model features to rules




"Passive subject of a phosphorylation trigger that is a protein"

- Features are just patterns
- We simply rewrote them using Odin syntax

# Step 2: Convert model features to rules

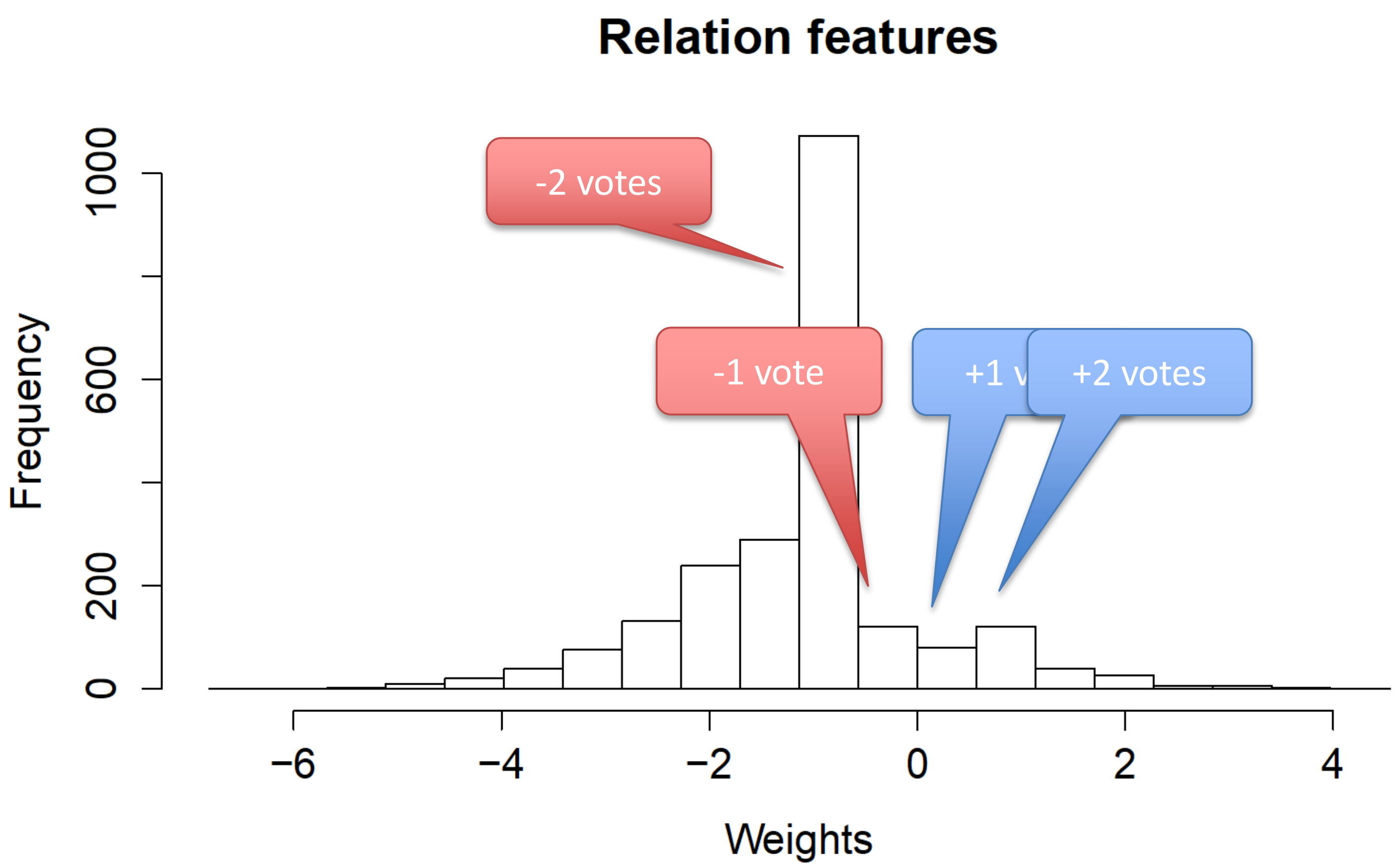



```
-    type : dependency
  label: Phosphorylation
  pattern: |
    trigger:Phosphorylation
    theme:Protein = >nsubjpass
```

# Step 2: Convert model features to rules

- We know have a decision list classifier. But:
- Feature weights are unbounded continuous values
  - Useful for resolving conflicts
  - But nearly impossible to understand/modify
- Rules still need to vote
  - We normalize and discretize weights ("votes") using Scott's rule (used for the generation of bins in histograms)

# Step 2: Convert model features to rules



# Step 2: Convert model features to rules

- Binding
  - PROTEIN recruits PROTEIN
- Localization
  - PROTEIN is recruited to the cytoplasm

```
# vote: +2
- name: Binding_1
  label: Binding
  type: token
  action: countMentions
  pattern: |
    [lemma=recruit & tag=/^(V|N|J)/]
```

```
# vote: +1
- name: Localization_1
  label: Localization
  type: token
  action: countMentions
  pattern: |
    [lemma=recruit & tag=/^(V|N|J)/]
```

# Step 3: Model editing

- Two linguists were given the task of improving the generated rules

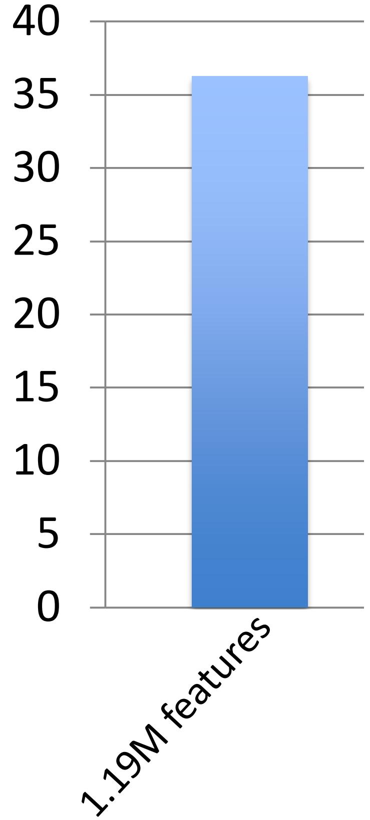
- Constraints:
  - Only have access to the model. No peeking at the training data
  - Approximately one hour to work on the task

# Expert recommendations

- Generalize syntactic patterns, e.g., participants in events may be heads or modifiers of noun phrases
  - E.g.: “K-Ras” or “the K-Ras protein”
- Eliminate trigger rules that were not sufficiently discriminative
- Make rules robust to common parsing mistakes

- (22 total specific recommendations)

# Results on BioNLP 2009



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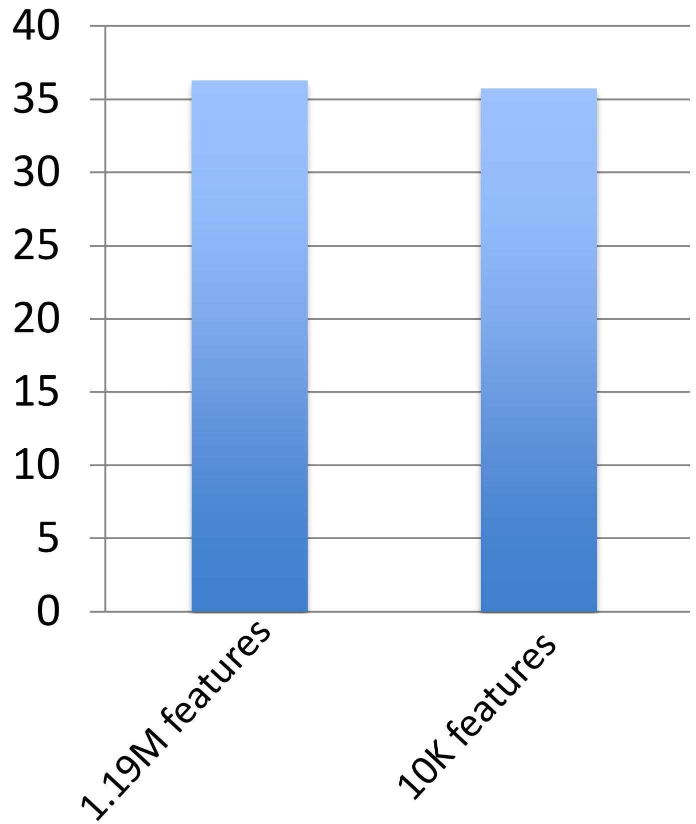

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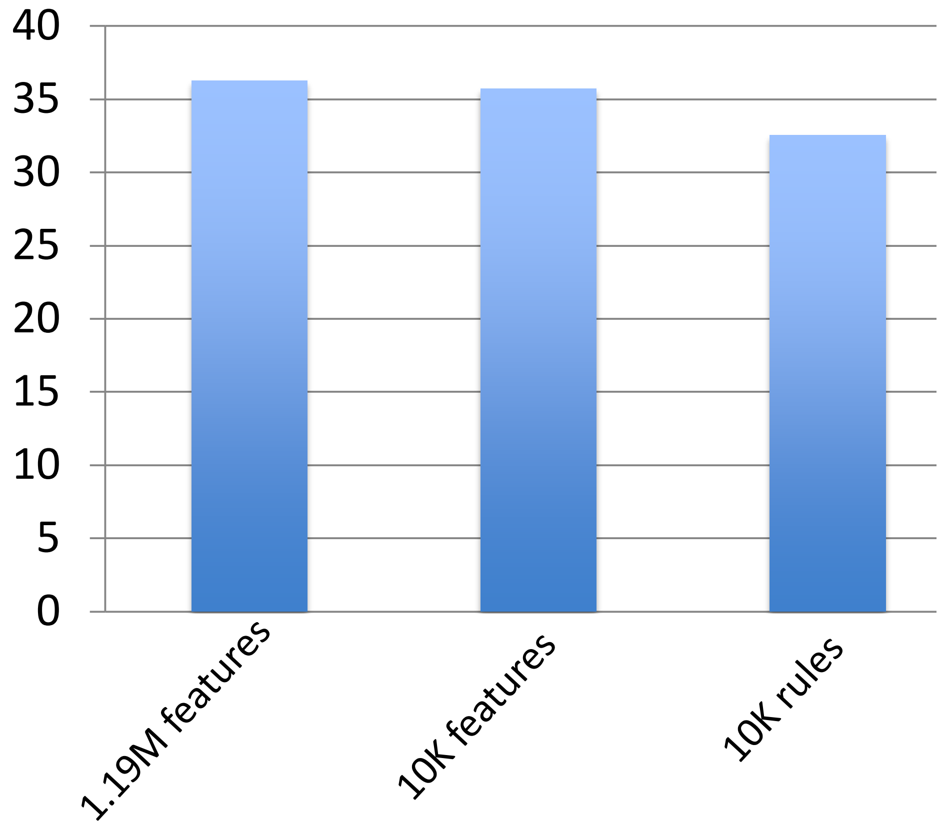
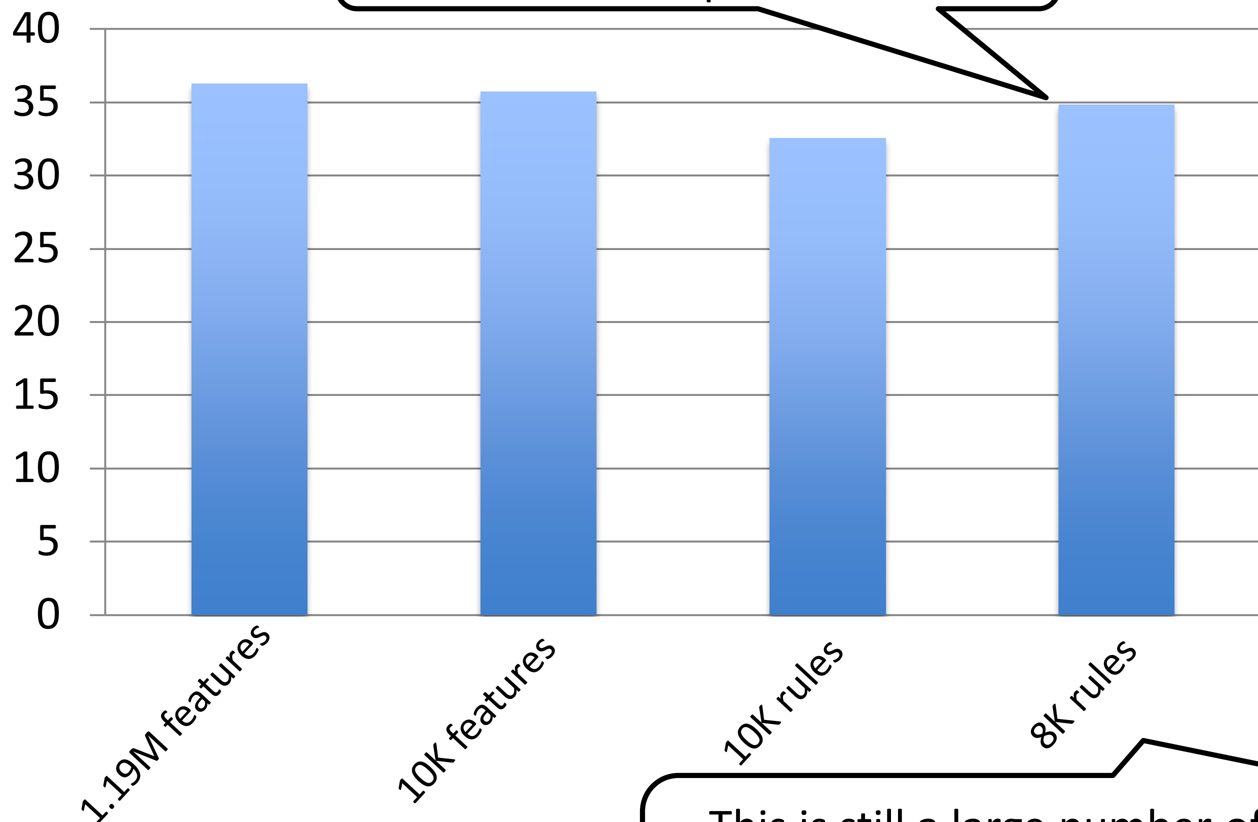


# Results on BioNLP 2009

Nearly the same performance.
But with an interpretable model!




This is still a large number of rules.
We can reduce them by > 1 order of magnitude using automata theory.

# Summary

- Converting statistical models into a deterministic decision list classifier does impact performance negatively
- But keeping the human in the loop allows us to recover almost all the lost performance. And we end up with an interpretable model!

Fine. But how do you do this with neural networks that do not have explicit features?

# Exploring Interpretability in Event Extraction: Multitask Learning of a Neural Event Classifier and an Explanation Decoder

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# Intuition: jointly training for prediction and interpretability!

1. Use neural classifiers instead of the LRs in the previous paper ☺
2. Decode rules from natural language texts (reusing ideas from machine translation)
   – Source language – original texts
   – "Target language" – grammar rule that matches
3. Train them jointly

# Encoder-decoder neural architectures for machine translation

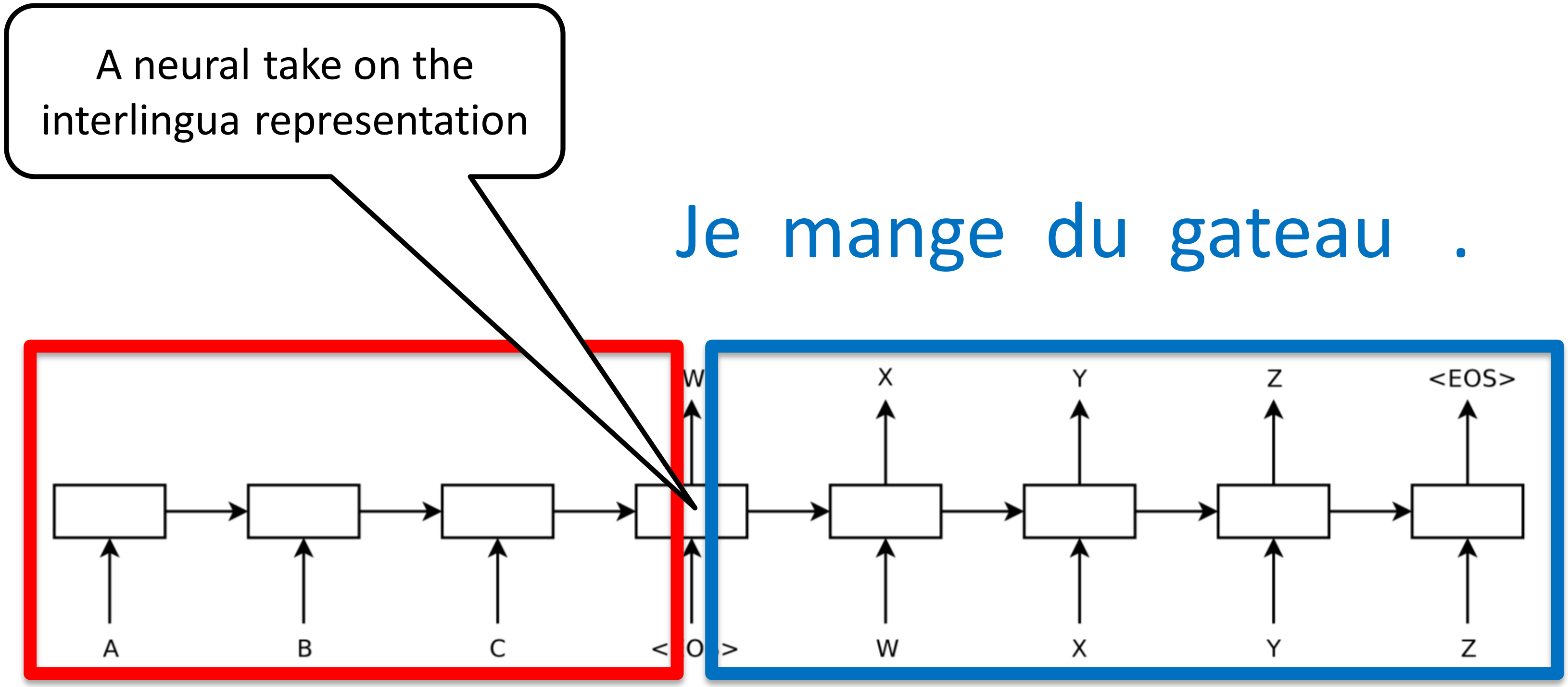



Figure 1: Our model reads an input sentence “ABC” and produces “WXYZ” as the output sentence. The model stops making predictions after outputting the end-of-sentence token. Note that the LSTM reads the input sentence in reverse, because doing so introduces many short term dependencies in the data that make the optimization problem much easier.

I eat cake .

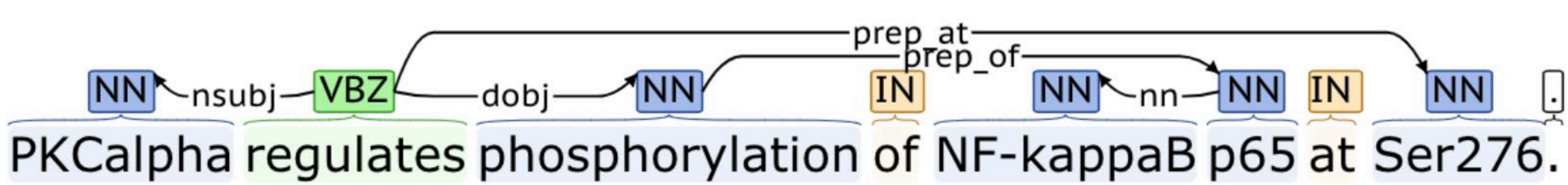
# Our “source” and “target languages”

(target)

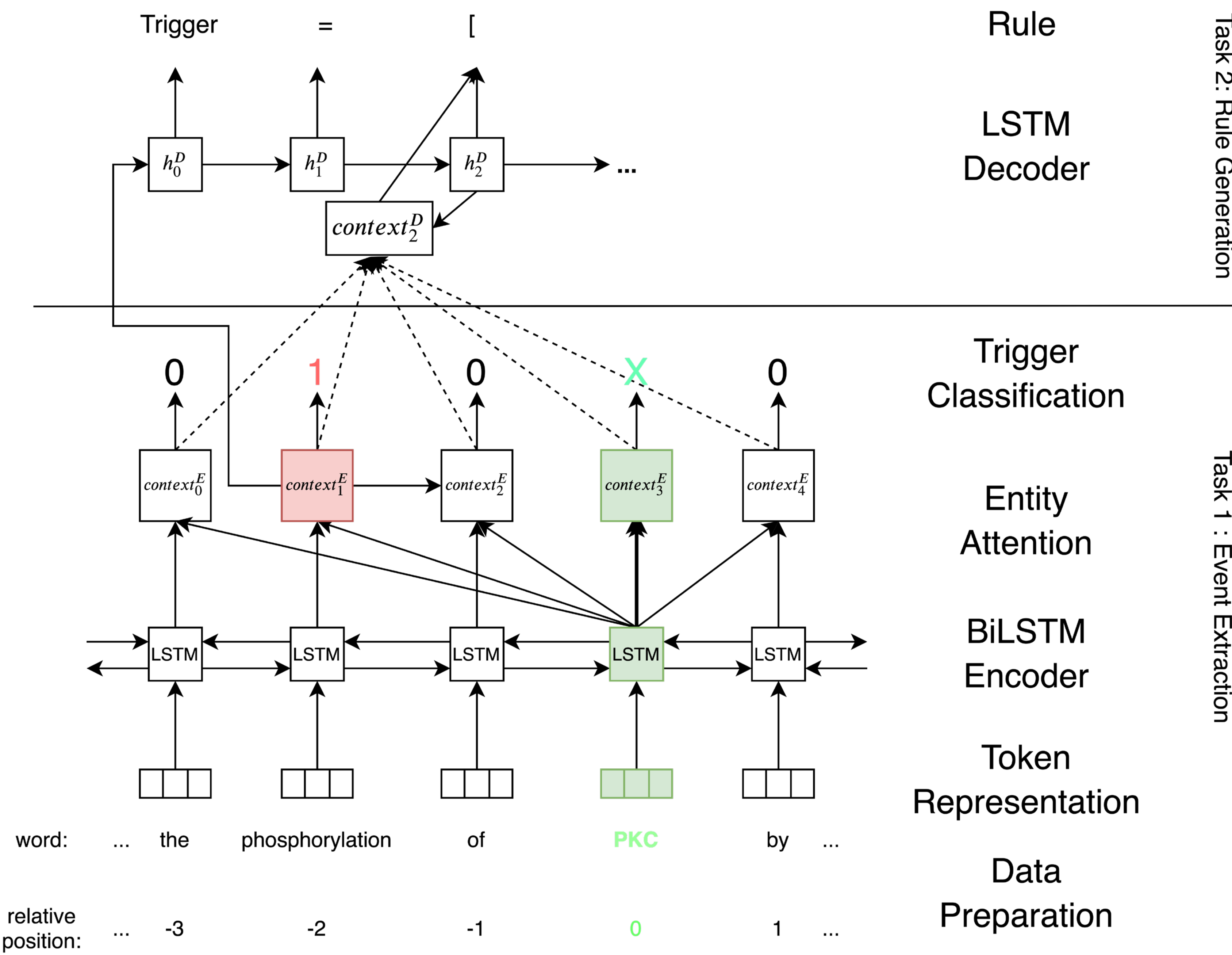
Phosphorylation_syntax_1a_noun:

trigger = [lemma=/phosphorylation/ !word=/(?i)^(de|auto)/]

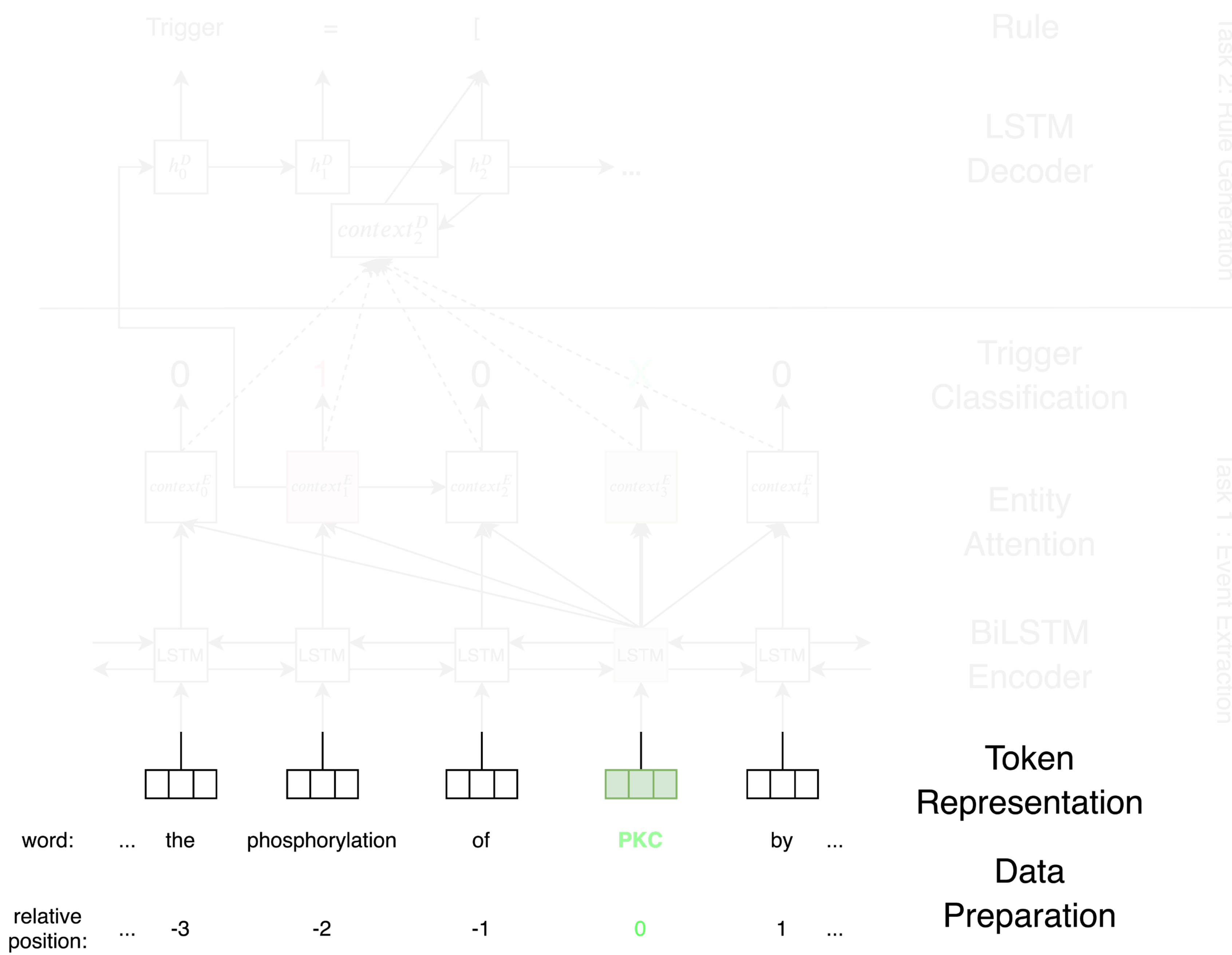
theme:BioChemicalEntity = prep_of appos? /nn|conj_(and|or|nor)|cc/{,2}




(source)



Trigger
=
[
Rule
LSTM Decoder
Task 2: Rule Generation
$h_0^D$
$h_1^D$
$h_2^D$
...
$context_2^D$
0
1
0
X
0
Trigger Classification
$context_0^E$
$context_1^E$
$context_2^E$
$context_3^E$
$context_4^E$
Entity Attention
Task 1 : Event Extraction
LSTM
LSTM
LSTM
LSTM
LSTM
BiLSTM Encoder
Token Representation
word: ... the phosphorylation of PKC by ...
relative position: ... -3 -2 -1 0 1 ...
Data Preparation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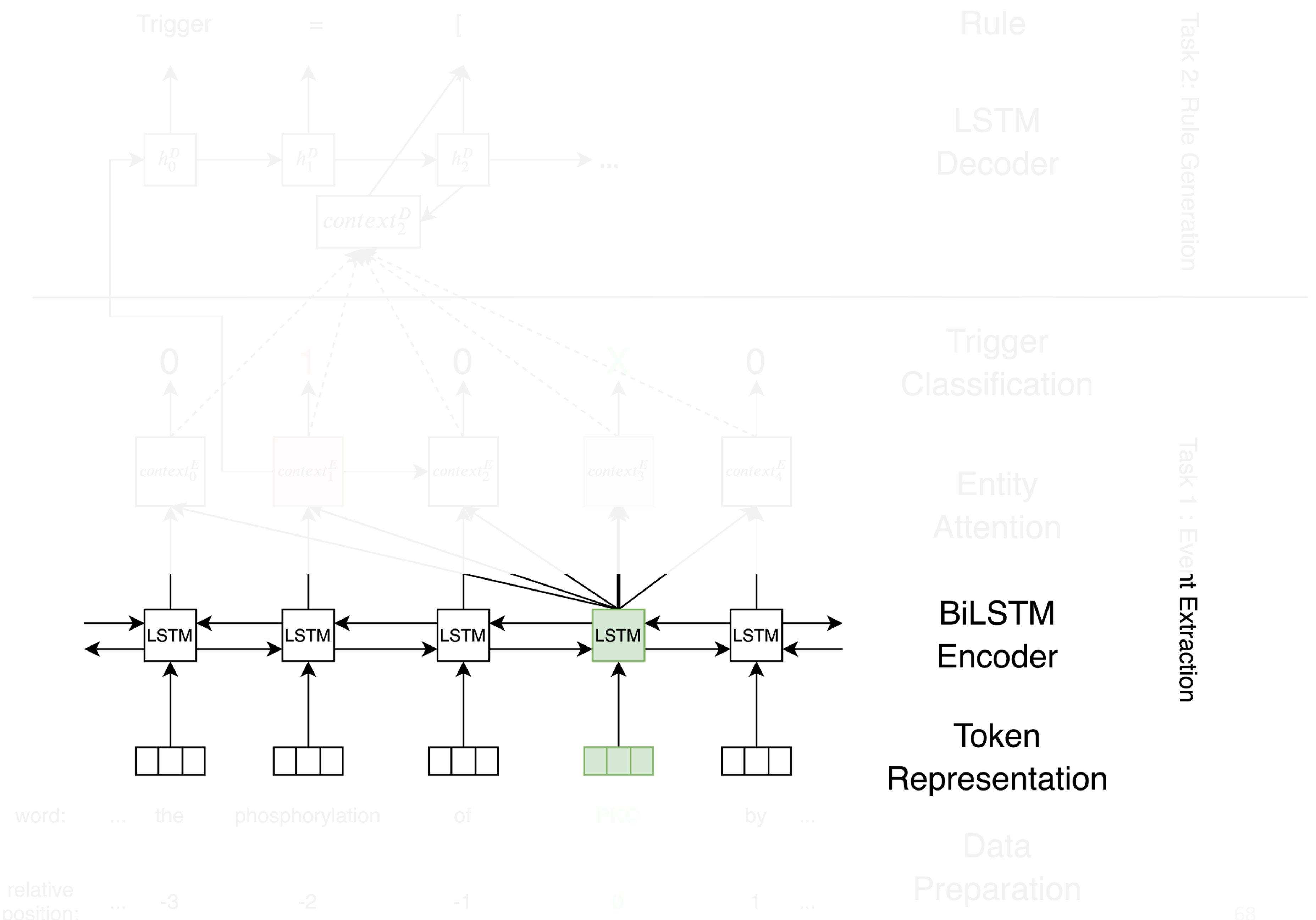

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Task 2: Rule Generation
Trigger
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Encoder
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Representation
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Data
Preparation
relative
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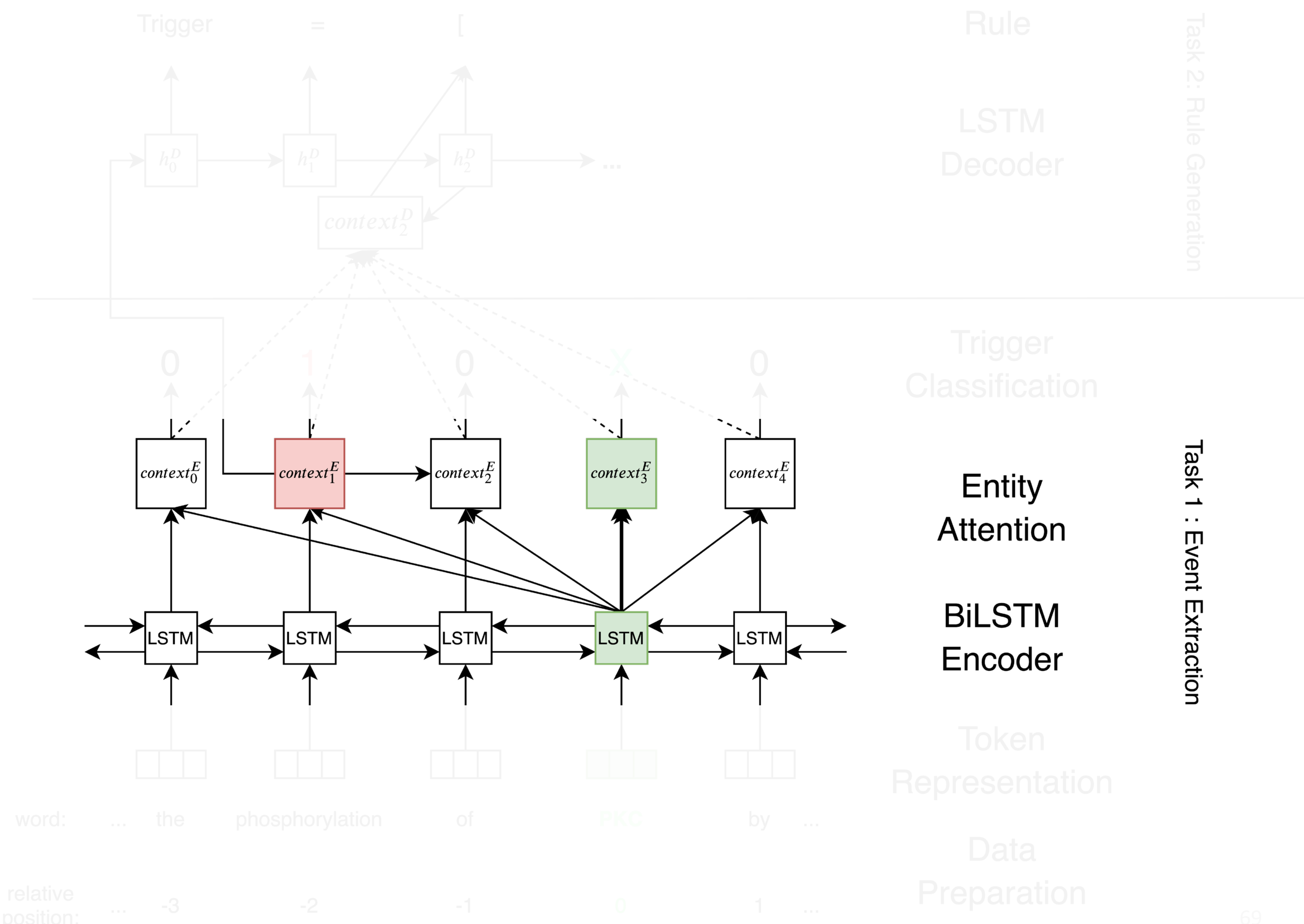
... -3 -2 -1 0 1 ...



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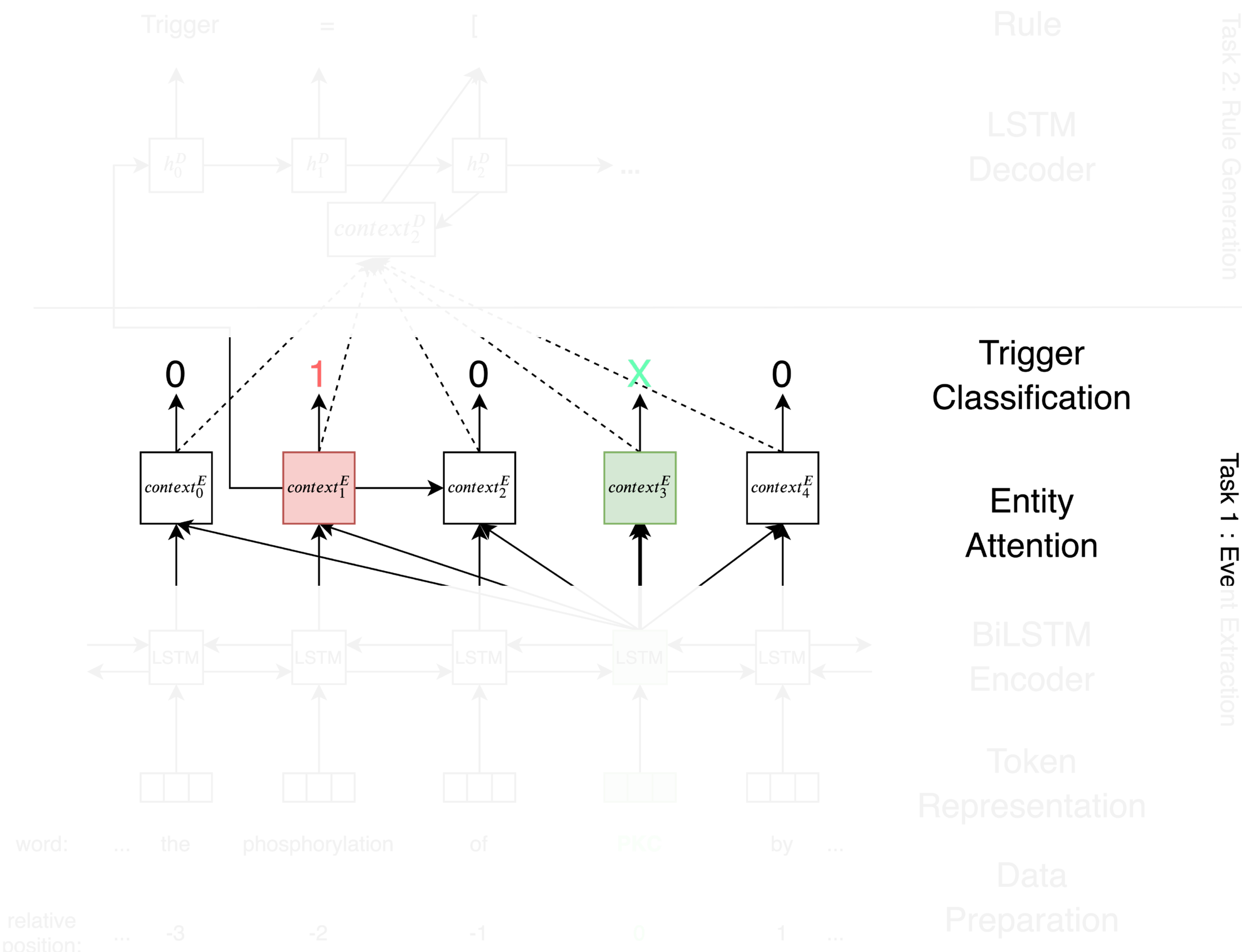
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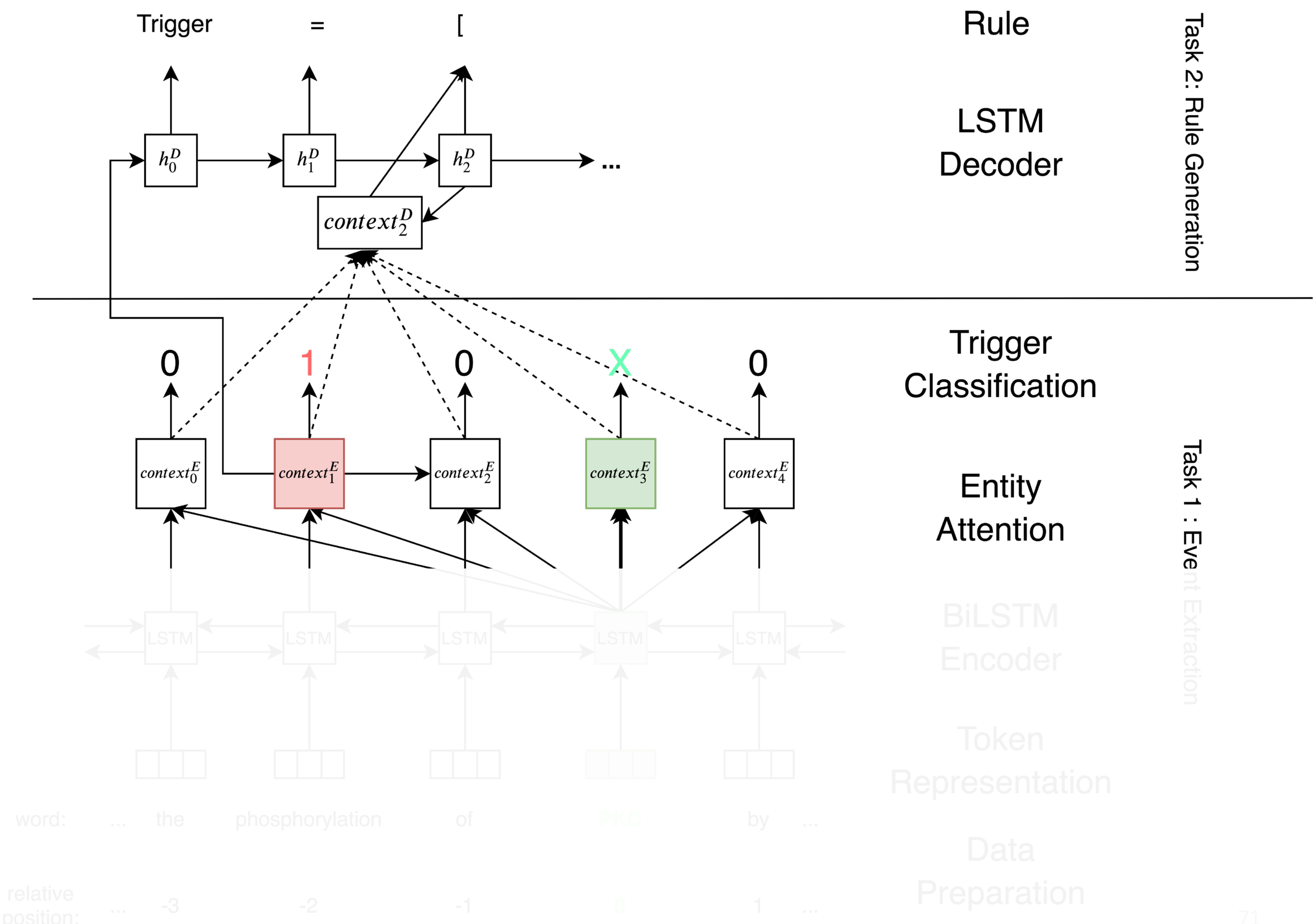

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Task 2: Rule Generation
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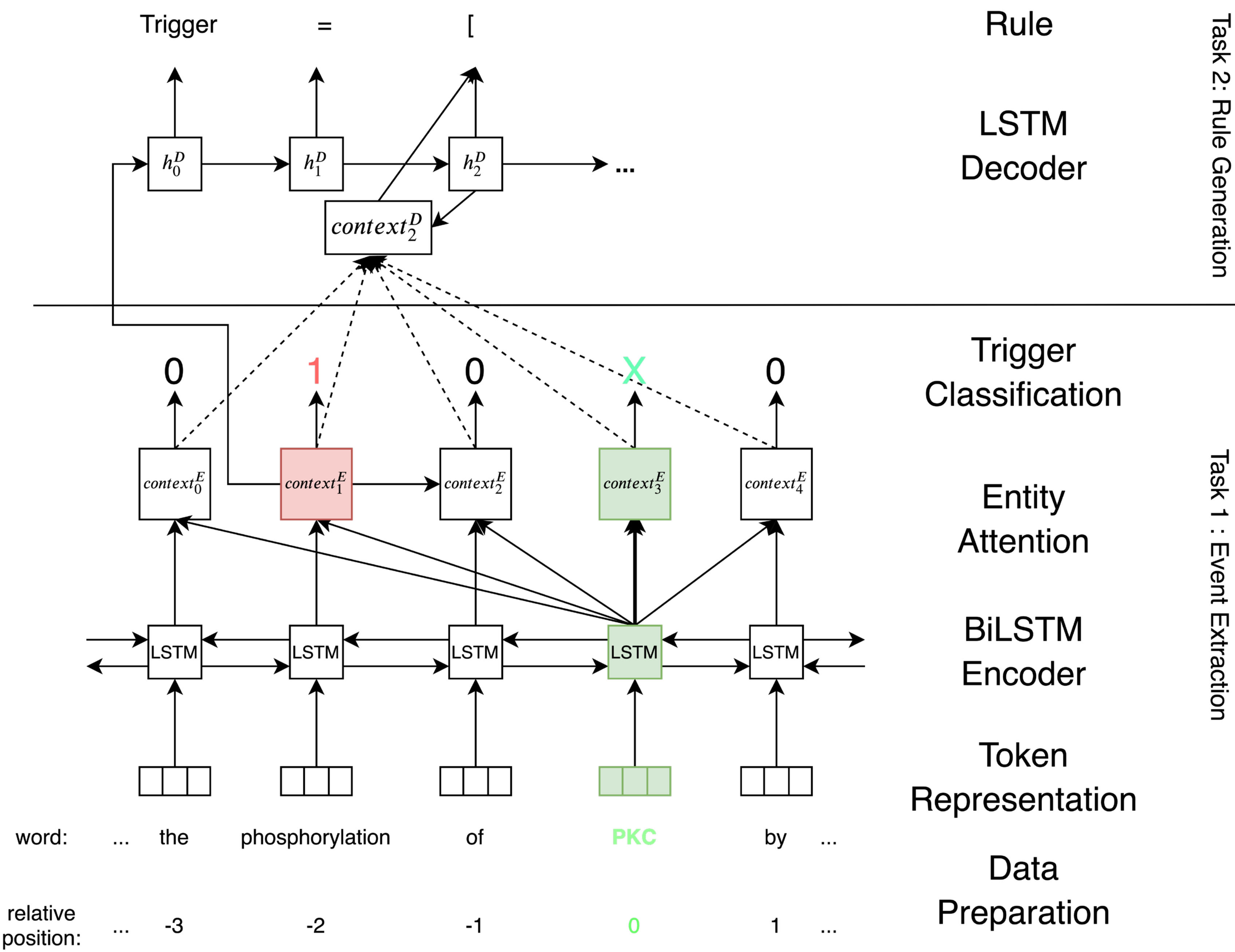

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$context_2^D$
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LSTM
LSTM
LSTM
BiLSTM
Encoder
Task 1 : Event Extraction
Token
Representation
word: ... the phosphorylation of PKC by ...
relative position: ... -3 -2 -1 0 1 ...
Data
Preparation

# Data

- For event classification: BioNLP 2013 (similar to the data used in the previous paper)
- For rule decoding: pairs of (sentence, rule) extracted by our machine reading system with manually written rules
  - Some come from the BioNLP dataset and are aligned with the gold annotations in BioNLP 2013
  - Approximately 15K pairs come from other publications ("silver" data)

# Results for event classification

We extract 3 types of events

| | Phosphorylation (P) | | | Localization (L) | | | Gene Expression (GE) | | |
|---|---|---|---|---|---|---|---|---|---|
| | Precision | Recall | F1 | Precision | Recall | F1 | Precision | Recall | F1 |
| Rule baseline | 92.68 | 48.12 | 63.35 | 66.13 | 44.44 | 53.16 | 51.08 | 69.79 | 58.98 |
| T1 | 87.78 | 49.38 | 63.20 | 100.00 | 4.04 | 7.77 | 89.32 | 64.30 | 74.77 |
| T1 + Silver | 62.75 | 82.50 | 71.28 | 54.55 | 34.34 | 42.15 | 68.43 | 74.31 | 71.25 |
| T1 + Silver + T2 | 84.38 | 68.75 | 75.77 | 76.60 | 39.39 | 52.03 | 69.92 | 71.24 | 70.58 |

- Rule baseline – system with manually written rules
- T1 – supervised neural event classifier
- T1 + Silver – semi-supervised neural event classifier
- T1 + Silver + T2 - semi-supervised neural event classifier trained jointly with the rule decoder

# Results for event classification

| | Phosphorylation (P) | | | Localization (L) | | | Gene Expression (GE) | | |
|---|---|---|---|---|---|---|---|---|---|
| | Precision | Recall | F1 | Precision | Recall | F1 | Precision | Recall | F1 |
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Semi-supervised learning helps!

# Results for event classification

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Jointly training for prediction and interpretability helps prediction!

# Results for rule decoding

| | BLEU | Exact Matches | Non-exact Explainable Matches |
|---|---|---|---|
| P | 93.80 | 86.11 | 2/15 |
| L | 83.78 | 84.33 | 1/9 |
| GE | 78.99 | 76.45 | 10/43 |

# Rule error analysis

<table>
<tr><th>Hand-written Rule<br>Go to page 8</th><th>Decoded Rule</th></tr>
<tr><td>trigger = [ lemma = /phosphorylate/ & ! word = /(?i)^(de|auto)/ & tag = /^(V|JJ)/ & ! mention = ModificationTrigger ]<br><br>theme : BioChemicalEntity = > nsubjpass prep_of ? /conj_(and|or|nor)|nn|cc/ { , 2 }</td><td>trigger = [ lemma = /phosphorylate/ & ! word = /(?i)^(de|auto)/ & tag = /^(V|JJ)/ & ! = ModificationTrigger ]<br><br>theme : BioChemicalEntity = > nsubjpass prep_of ? /conj_(and|or|nor)|nn|cc/ { , 2 }</td></tr>
<tr><td>trigger = [ lemma = /detect|localiz|locat|releas|secret|translocat/ & ! word = /(?i)^de/ ]<br><br>theme : BioChemicalEntity = prep_of ? appos ? /conj_(and|or|nor)|cc|nn/ { , 2 }</td><td>trigger = [ lemma = /detect|localiz|locat|releas|secret|translocat/ & ! word = /(?i)^de/ & ! outgoing = /prep_(by|of)/ ]<br><br>theme : BioChemicalEntity = < /conj_(and|or|nor)/ ? /conj_(and|or|nor)|cc|nn|prep_of/ { , 2 }</td></tr>
<tr><td>trigger = [ lemma = / phosphorylation / & ! word = / ( ? i ) ^ ( de | auto ) / & ! outgoing = / prep_ ( by | of ) / ]<br><br>theme : BioChemicalEntity = < / conj_ ( and | or | nor ) / ? / conj_ ( and | or | nor ) | cc | nn | prep_of / { 2 } site : Site ? = nn | < dobj ? / prep_ ( at | on ) / num ?</td><td>trigger = [ lemma = / phosphorylate / & ! word = / ( ? i ) ^ ( de | auto ) / & tag = / ^ ( V | JJ ) / & ! mention = ModificationTrigger ]<br><br>cause : BioChemicalEntity ? = < xcomp ? ( nsubj | agent | < vmod ) / appos | nn | conj_ ( and | or | nor ) | cc / { 2 }<br><br>theme : BioChemicalEntity = ( dobj | xcomp ) / conj_ ( and | or | nor ) | dep | cc | nn | prep_of / { 2 } ( > > [ word = by ] ) { 2 } site : Site ? = dobj ? / prep_ ( at | on ) | nn | conj_ ( and | or | nor ) | cc / { 2 }</td></tr>
</table>

**Green** – missed text in the decoded rule
**Red** – hallucinated text

# Summary

- A neural approach that jointly trains for prediction and interpretability
- The joint training improves prediction!

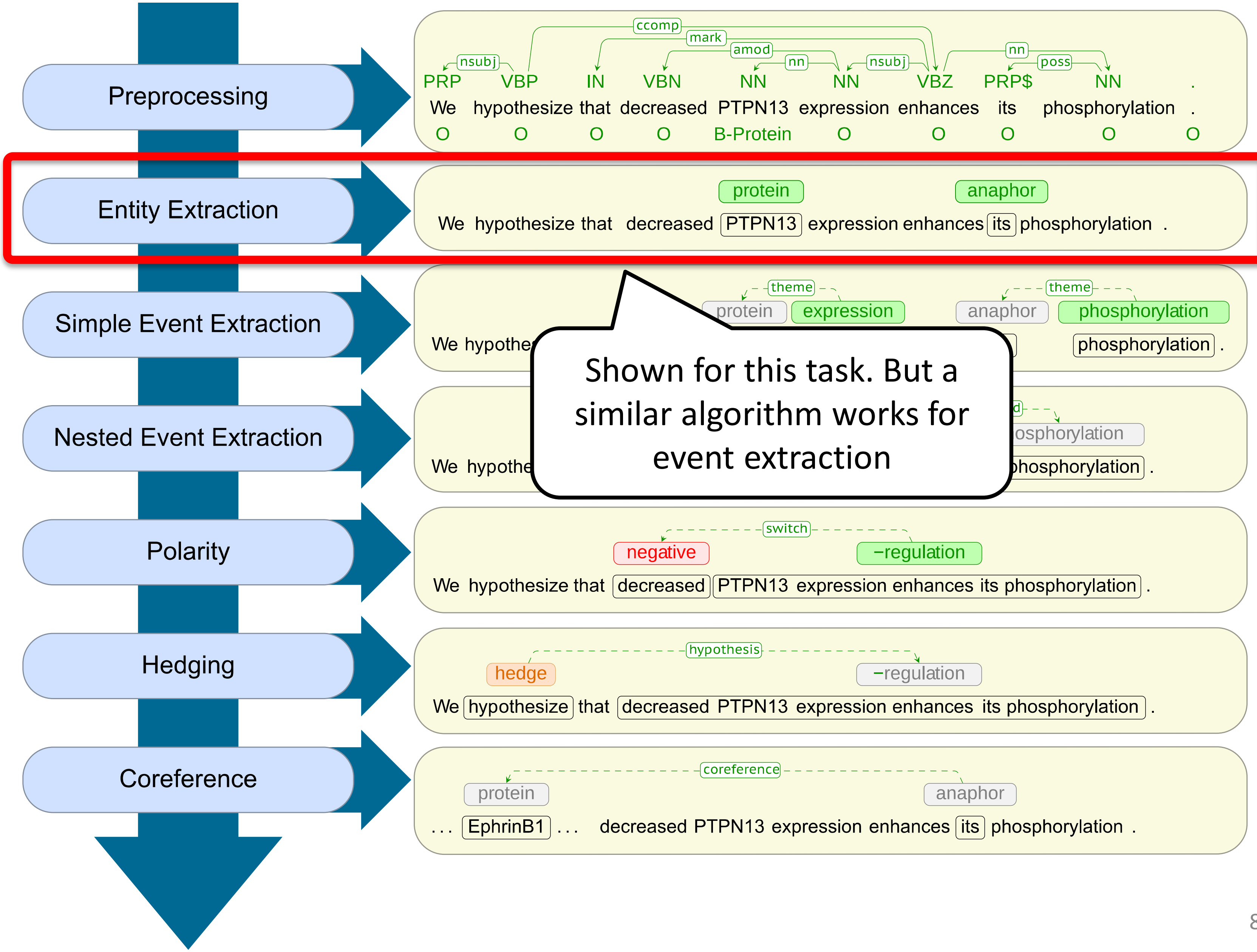
# Motivation

- It took us 1 – 2 person months to build the grammar of 154 rules for the biomedical domain
- In many cases, one does not have this time
  - Scenario 1: But training data exists
  - **Scenario 2: And training data does not exist either…**

# Lightly-supervised Representation Learning with Global Interpretability

**Andrew Zupon, Maria Alexeeva, Marco A. Valenzuela-Escárcega,**
**Ajay Nagesh,** and **Mihai Surdeanu**
University of Arizona, Tucson, AZ, USA
{zupon, alexeeva, marcov, ajaynagesh, msurdeanu}@email.arizona.edu

# Architecture and walkthrough example



# Traditional rule bootstrapping algorithm for entity classification

Problem: brittle statistics, estimated only with respect to known information!

city of San Francisco ✓

**En** **ns**

Seeds → LOC of ___

LOC or of ___

# Learning to read

We want to combine:

- The advantages of representation learning, aka "word embeddings"
  - Neural network language models handle unsupervised data well
- The interpretability of our current approach
  - Produce patterns in the end
- Keep the human in the loop, but minimally
  - Just a few examples

# Starting point: distributional hypothesis

- Distributional hypothesis:
  - By looking at a word's context, one can infer its meaning (Harris, 1954)
  - You shall know a word by the company it keeps (Firth, 1957)

# Example

- tasty *X*
- *X* with butter
- *X* and coffee
- greasy *X*

# Example

- tasty *X*
- *X* with butter
- *X* and coffee
- greasy *X*

# Starting point: word2vec, skip-gram

You shall know a word by the company it keeps.

- Firth, 1957

You shall know the company by the word it keeps.

- Word2vec, skip-gram

# Starting point: word2vec, skip-gram

The city of Tucson is the place to vacation !

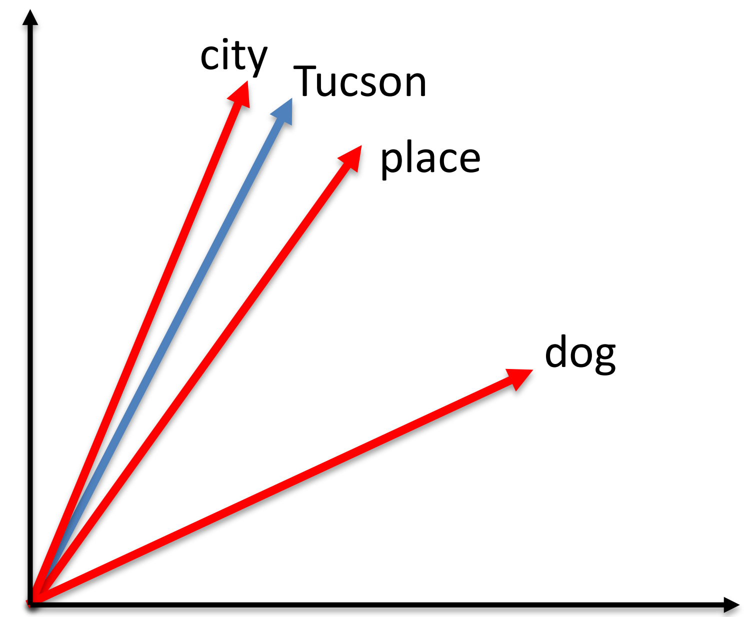
P(city|Tucson) ++

P(place|Tucson) ++

...

P(dog|Tucson) - -

...



# Two important changes

- We will learn embeddings for *both named entities and patterns*
  - An entity's context is defined by the patterns that match it
- Added supervision in the objective function, to incorporate human-provided information
  - We have "seed" names in each category

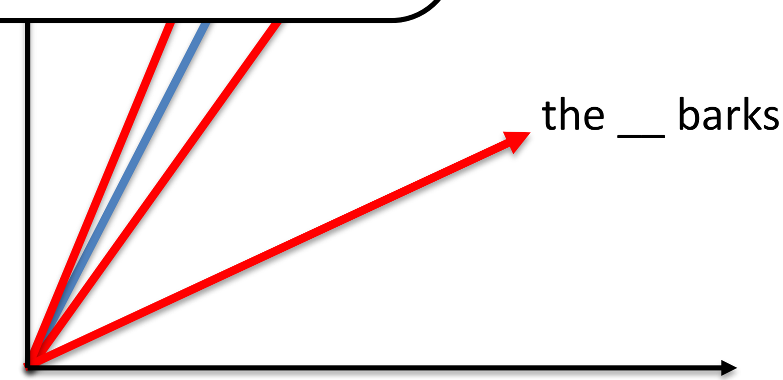
# Context as patterns

The city of Tucson is the place to vacation !

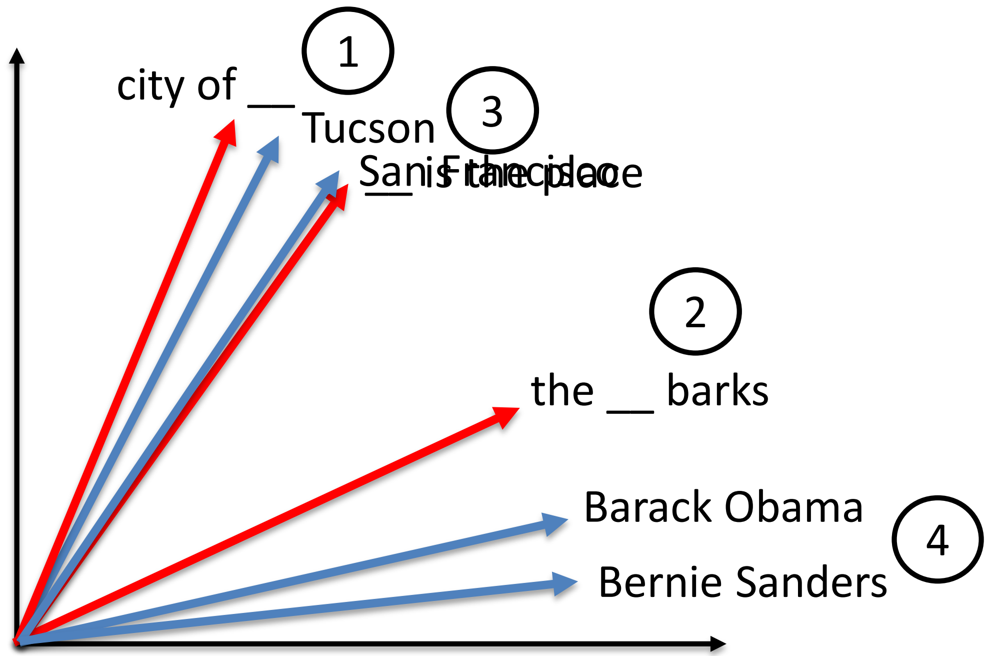
We can export the patterns closest to a category to be used in our grammars!

P(city of __|Tucs
P(__ is the place
…
P(the __ barks|Tucson) - -
…

Just n-grams…



# Objective function




1 2 Unsupervised, directly “inherited” from skip-gram

3 4 Light supervision from a few seed examples, iteratively expanded

# EmBoot

SGD on the previous objective function

**<u>Entities</u>**

Seeds → LOC: San Francisco

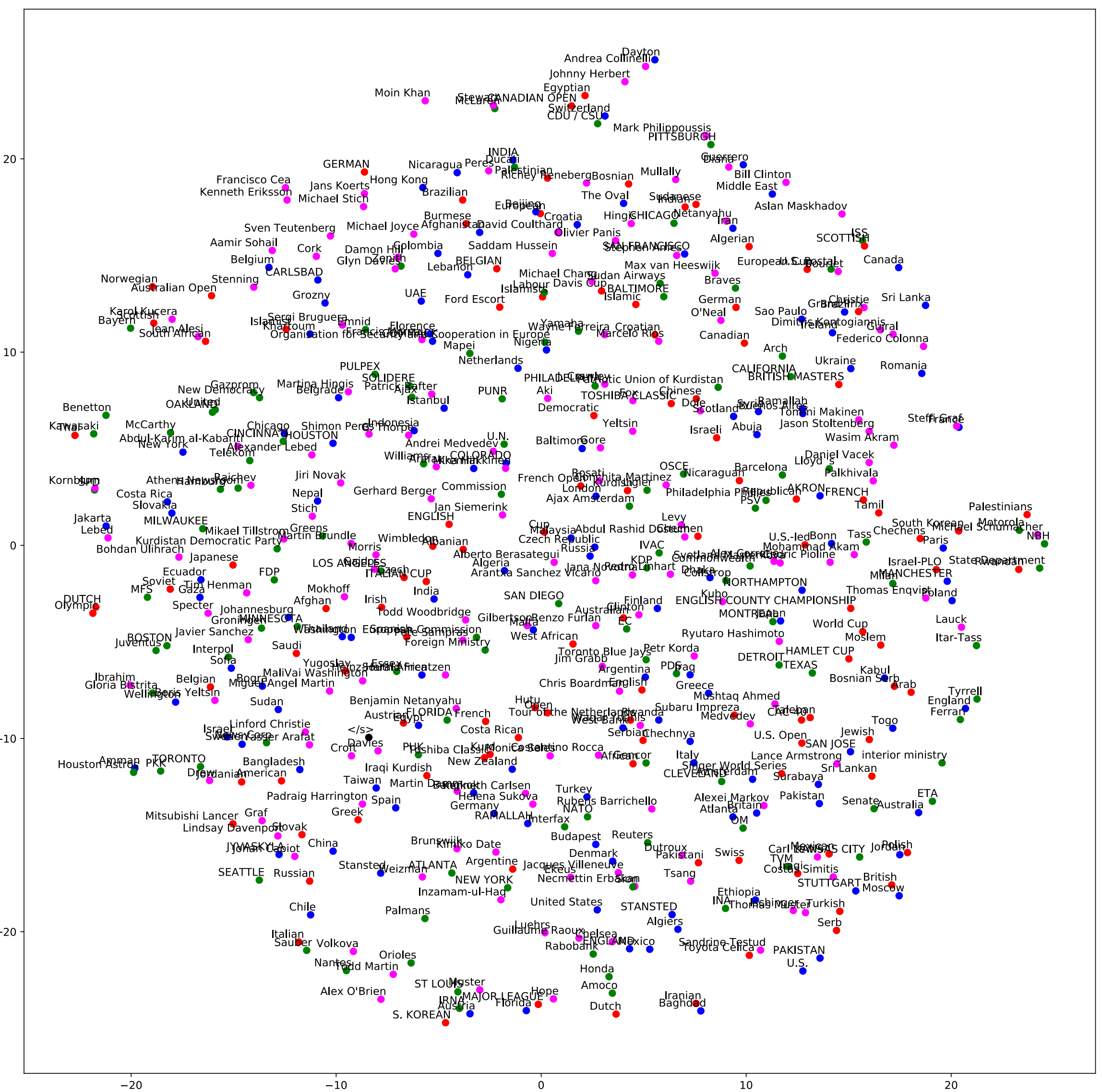
LOC: Los Angeles

**embedding vectors for entities and patterns**

Promote entities closest to the seeds

# Visualization of the training procedure

- On the CoNLL-2003 dataset
  - PER = **purple**
  - LOC = **blue**
  - ORG = **green**
  - MISC = **red**
- Human contribution: seed set with 10 entities in each category
  - PER: Clinton, Dole, …
  - LOC: U.S., Germany, …
  - ORG: Reuters, U.N., …
  - MISC: Russian, German, …



Dayton
Andrea Collinelli
Johnny Herbert
Egyptian
Moin Khan
CANADIAN OPEN
Switzerland
CDU / CSU
Mark Philippoussis
PITTSBURGH
INDIA
GERMAN
Nicaragua
Palestinian
Bosnian
Mullally
Bill Clinton
Middle East
Francisco Cea
Kenneth Eriksson
Jans Koerts
Hong Kong
Michael Stich
Brazilian
The Oval
Sudanese
Aslan Maskhadov
Croatia
CHICAGO
Netanyahu
Iran
Sven Teutenberg
Michael Joyce
David Coulthard
Olivier Panis
Algerian
SCOTTISH
Aamir Sohail
Cork
Damon Hill
Colombia
Saddam Hussein
SAN FRANCISCO
Canada
Belgium
CARLSBAD
Glyn Davies
BELGIUM
Lebanon
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Norwegian
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Australian Open
Michael Chang
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Sri Lanka
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Croatian
Ireland
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Nigeria
Canadian
Federico Colonna
Mapei
Arch
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Ramallah
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Yeltsin
Tommi Makinen
Steffi Graf
Chicago
Shimon Peres
Abuja
Jason Stoltenberg
Abdul-Karim al-Kabariti
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Israeli
Wasim Akram
New York
Alexander Lebed
Andrei Medvedev
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COLORADO
Daniel Vacek
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Jiri Novak
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Gerhard Berger
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Greens
CUP
Abdul Rashid Dostum
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Paris
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Martin Brundle
Wimbledon
Albanian
Czech Republic
Bonn
Tass
Kurdistan Democratic Party
Russia
IVAC
Mohammad Akam
Bohdan Ulihrach
Alberto Berasategui
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ITALIAN CUP
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MANCHESTER
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Milan
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DUTCH
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Olympic
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Irish
SAN DIEGO
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Specter
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Todd Woodbridge
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Clinton
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Javier Sanchez
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Ryutaro Hashimoto
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Toronto Blue Jays
Petr Korda
HAMLET CUP
Sofia
Jim Grabb
DETROIT
TEXAS
Argentina
Ibrahim
Belgian
MaliVai Washington
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Gloria Bistrita
Miguel Angel Martin
Chris Boardman
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Greece
Bosnian Serb
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Wellington
Boris Yeltsin
Mushtaq Ahmed
England
Sudan
Benjamin Netanyahu
Hutu
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Lance Armstrong
interior ministry
Jordanian
American
Iraqi Kurdish
Singer World Series
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Sri Lankan
Taiwan
Martin Dahlin
Magnus Carlsen
Surabaya
Turkey
Padraig Harrington
Spain
Helena Sukova
Alexei Markov
Pakistan
ETA
Germany
Rubens Barrichello
Senate
Australia
Mitsubishi Lancer
Graf
Greek
RAMALLAH
NATO
Atlanta
Britain
Lindsay Davenport
Slovak
Interfax
Budapest
Reuters
China
Brunswijk
Kimiko Date
Dutroux
Denmark
Swiss
Polish
JYVASKYLA
Johan Cabiot
Stansted
Weizman
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Argentine
Jacques Villeneuve
Pakistani
Mexican
Jordan
SEATTLE
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NEW YORK
Necmettin Erbakan
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STUTTGART
British
Moscow
Inzamam-ul-Haq
Ethiopia
Chile
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Palmans
Algiers
Serb
Italian
Sauber
Volkova
Guillaume Raoux
Chelsea
Mexico
Sandrine Testud
Toyota Celica
Rabobank
PAKISTAN
Orioles
ENGLAND
Nantes
Todd Martin
Honda
U.S.
ST LOUIS
Amoco
Alex O'Brien
IRNA
MAJOR LEAGUE
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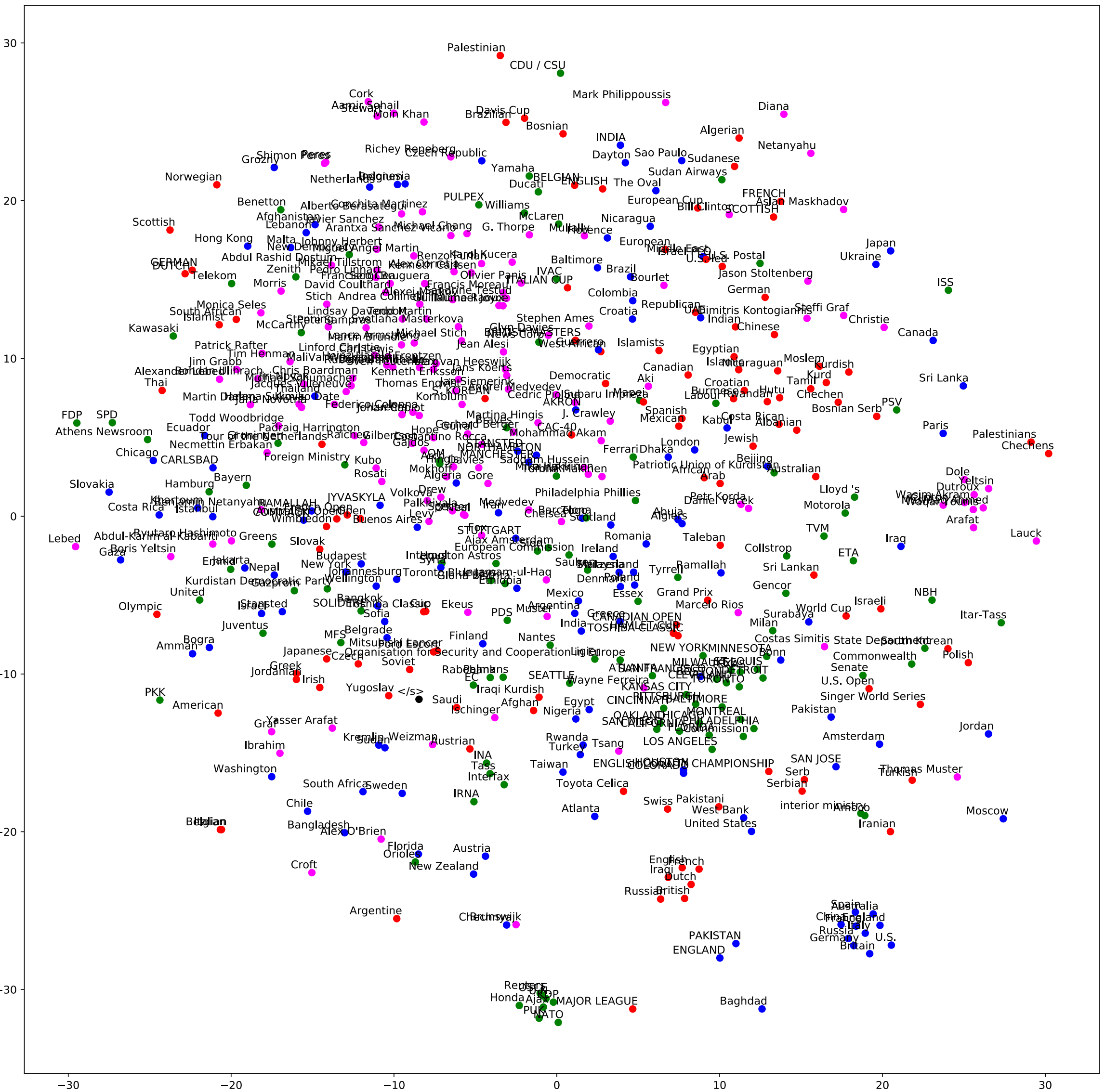
Palestinian
CDU / CSU
Mark Philippoussis
Diana
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Netanyahu
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Jordan
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Baghdad
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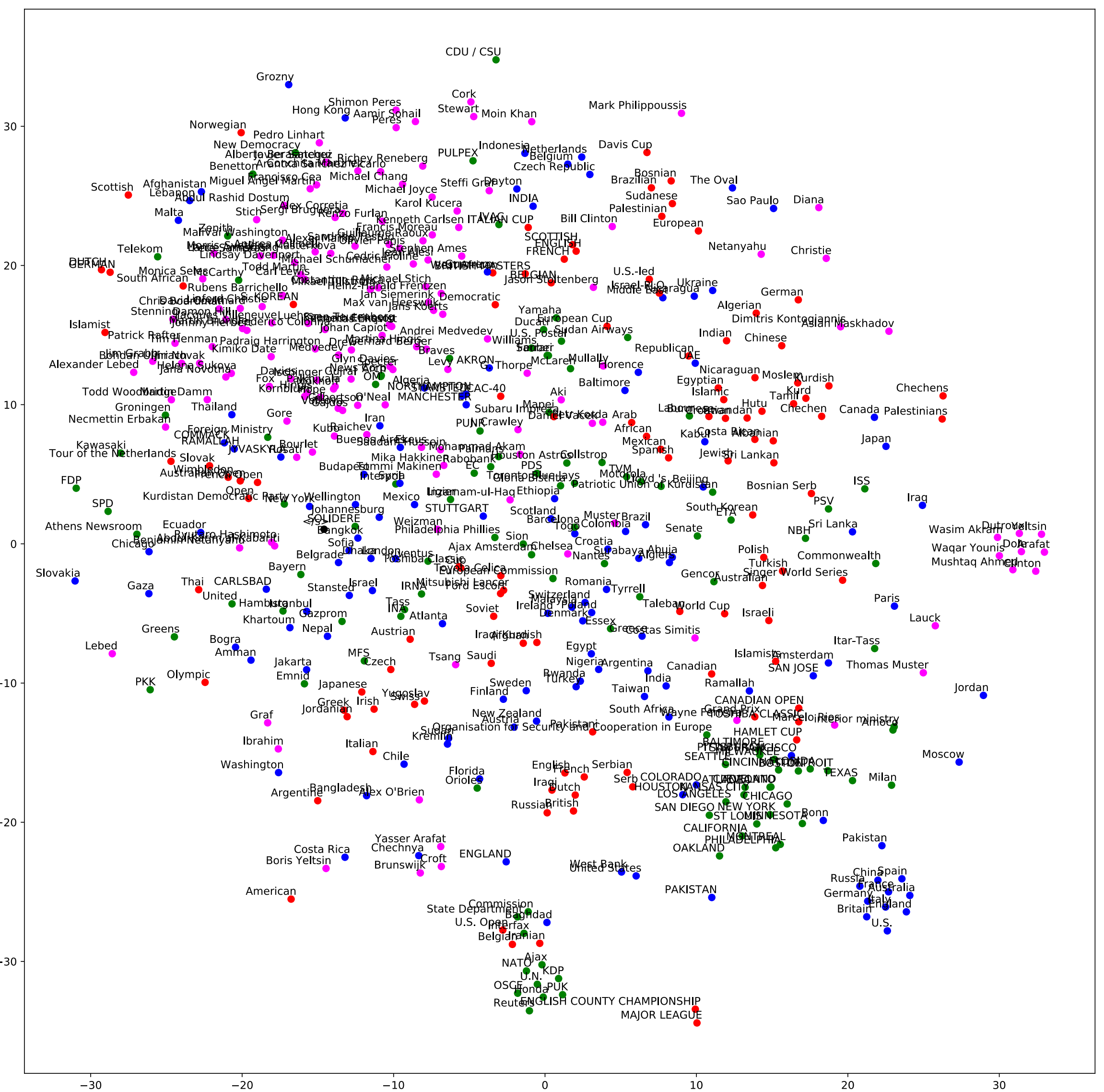

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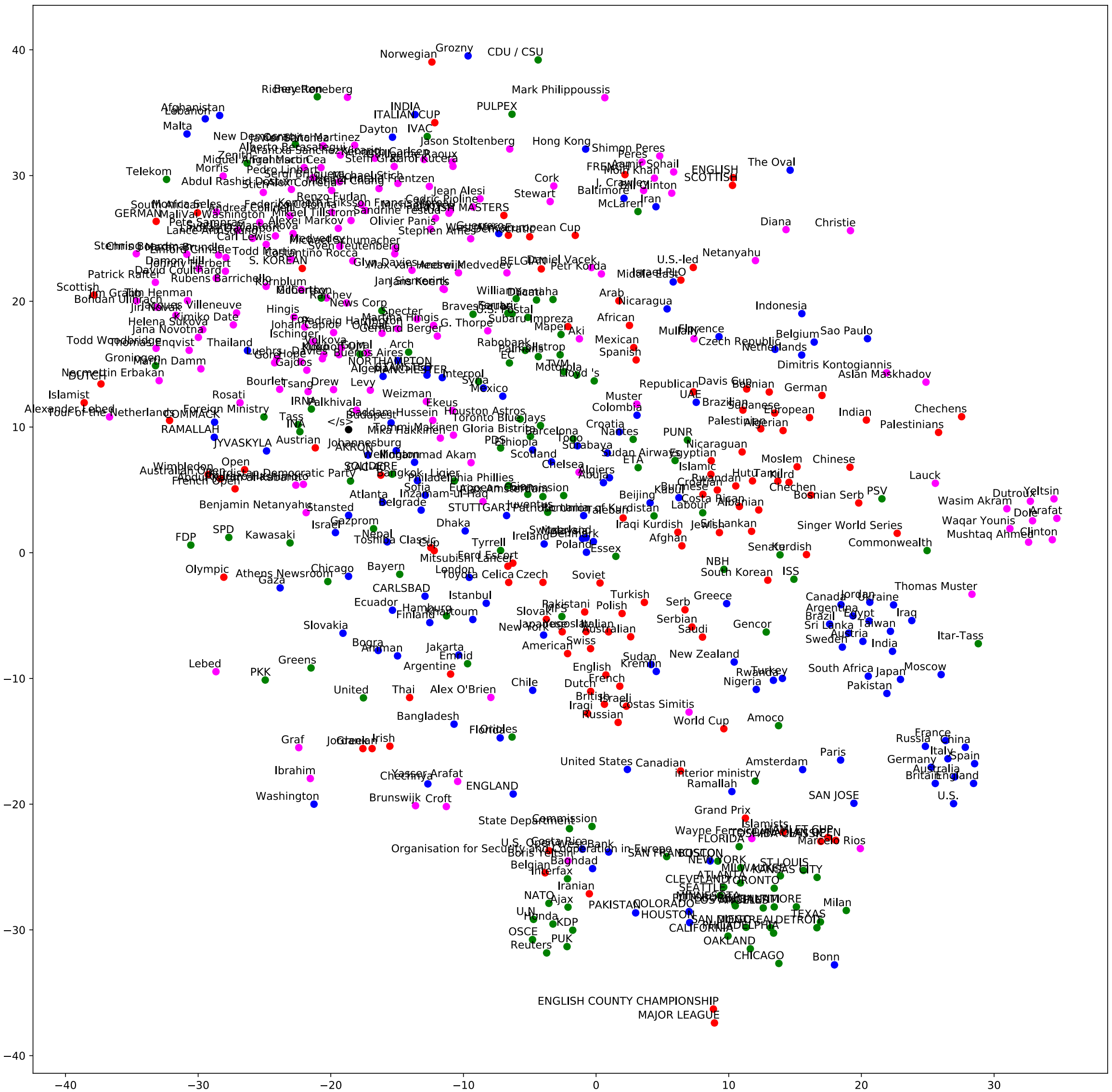

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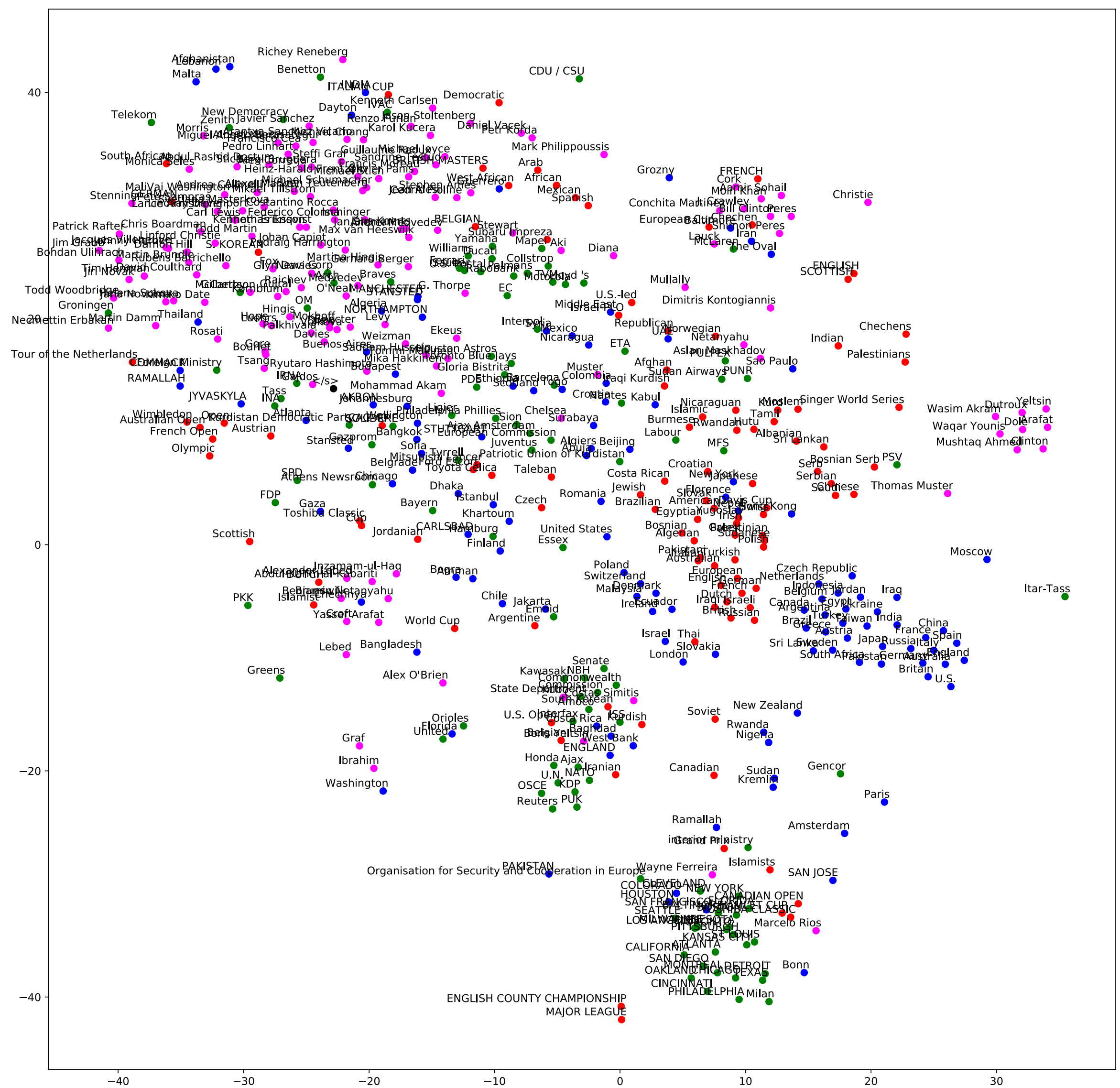
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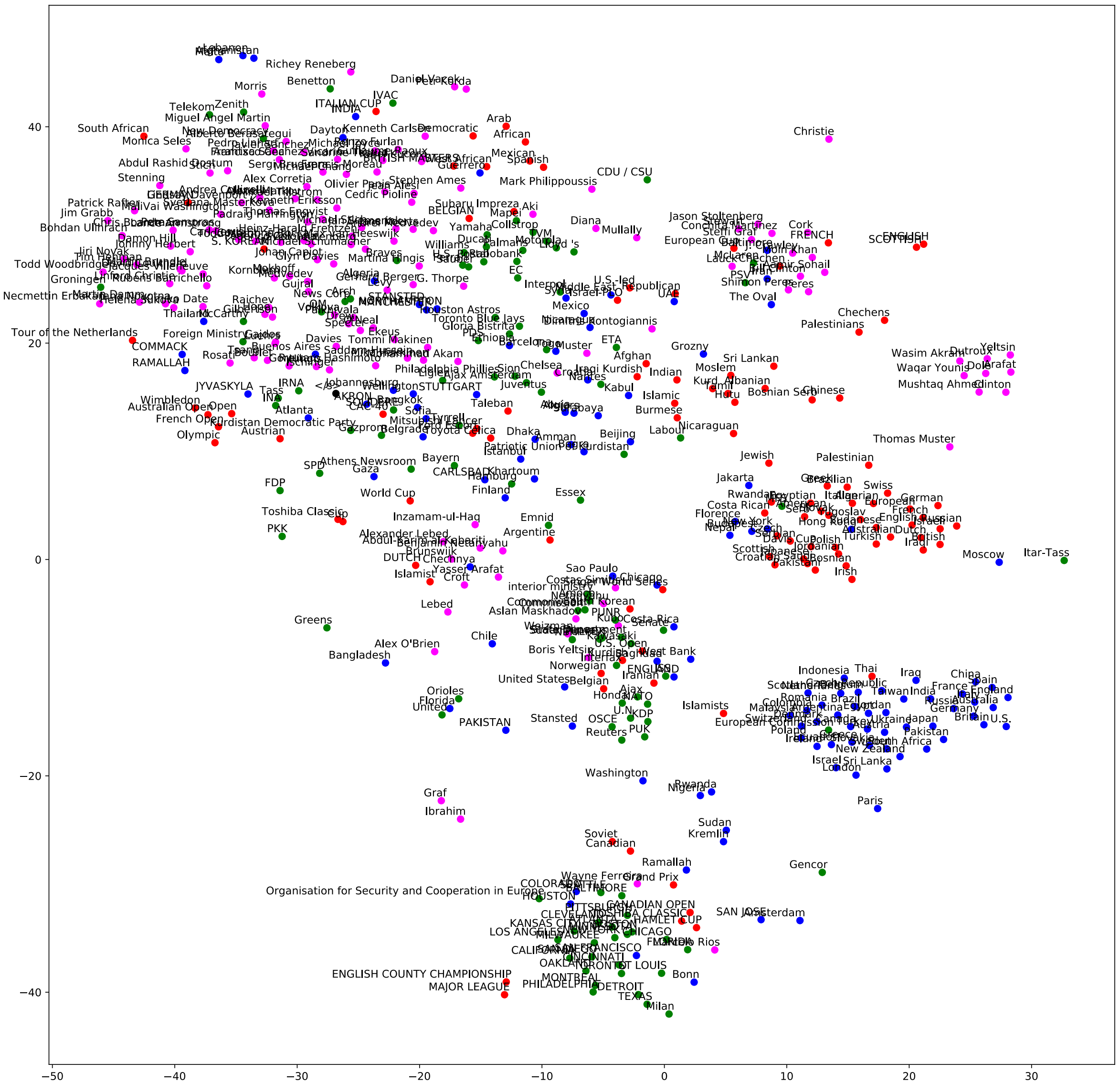
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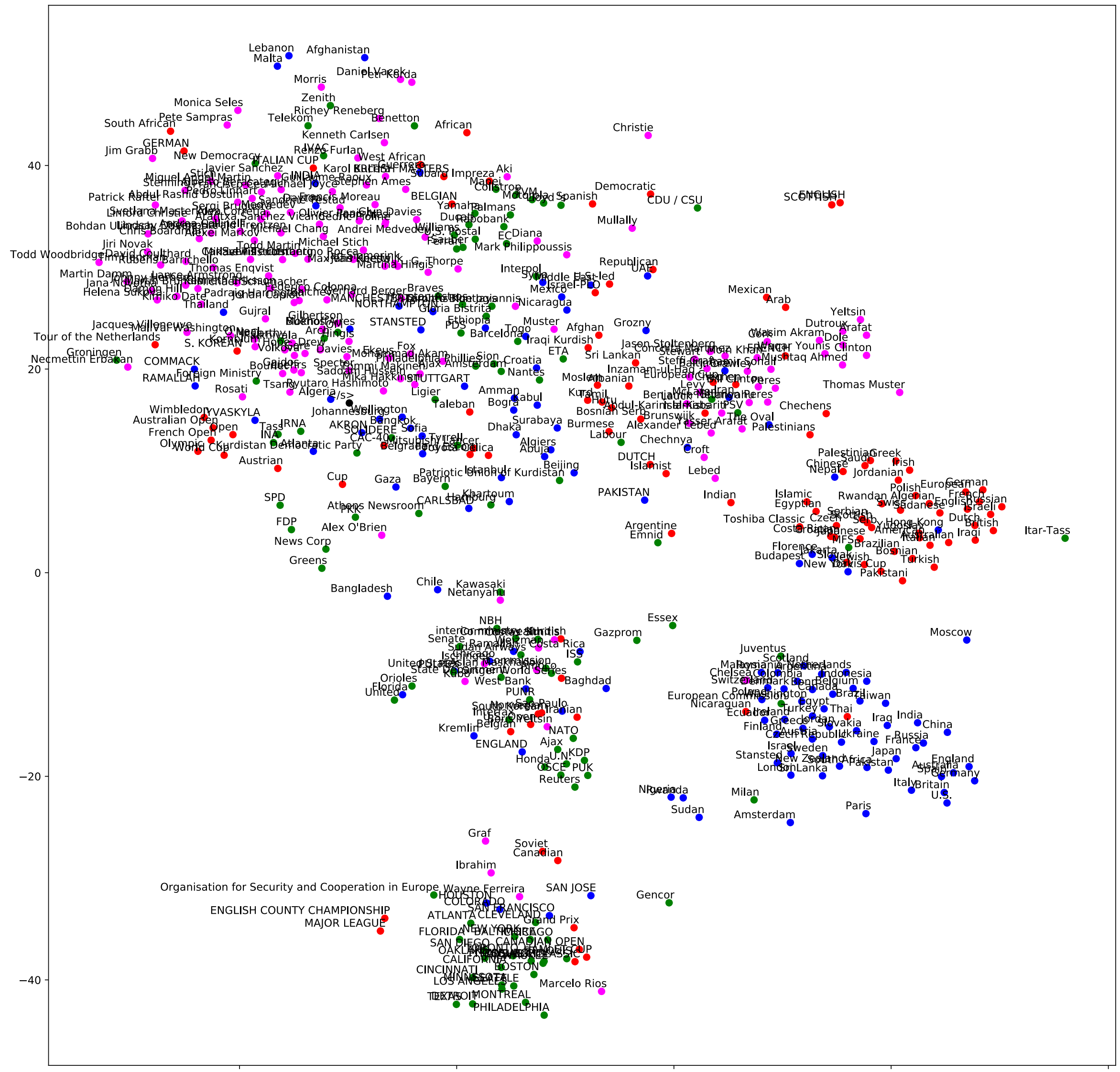

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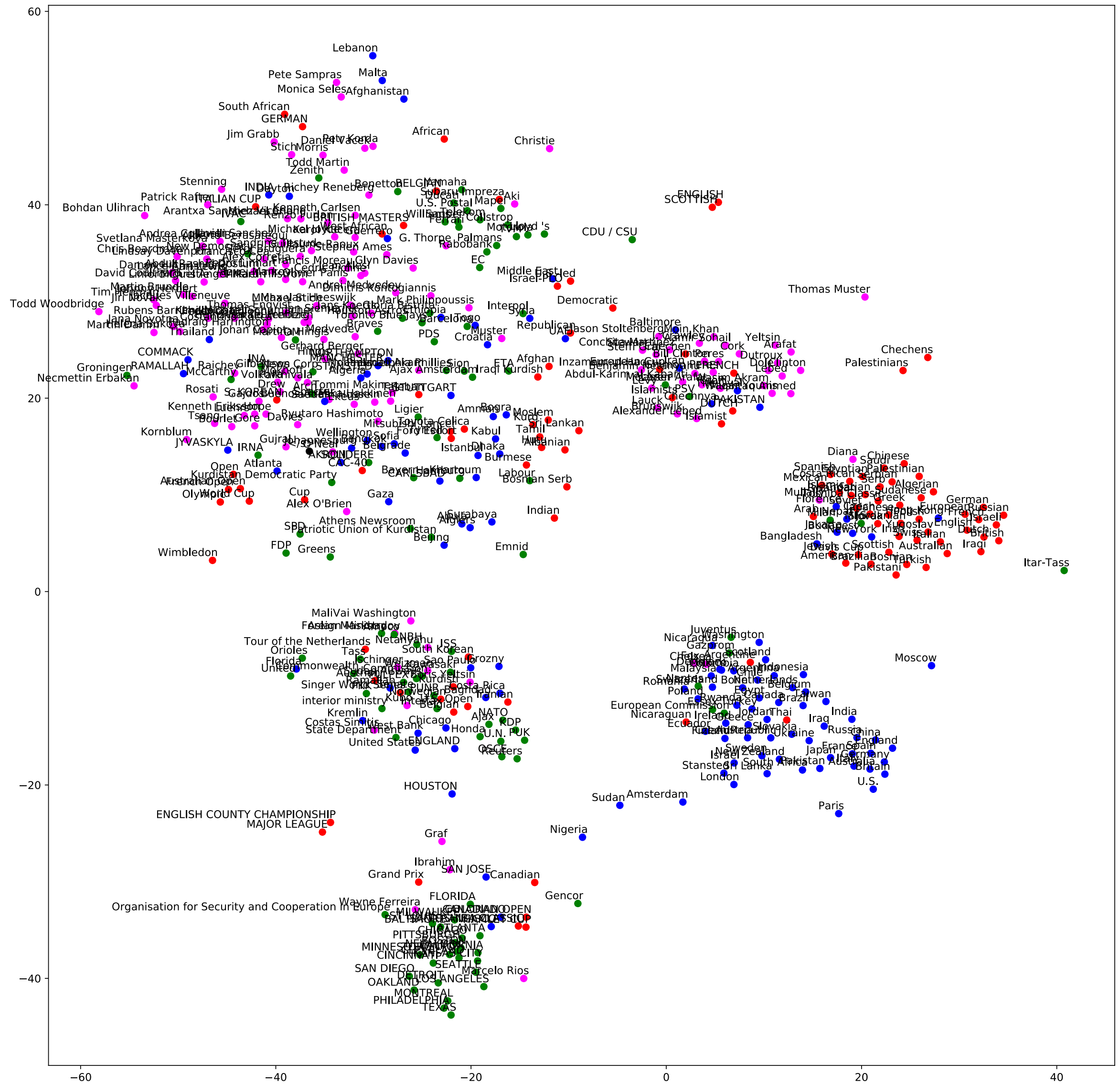
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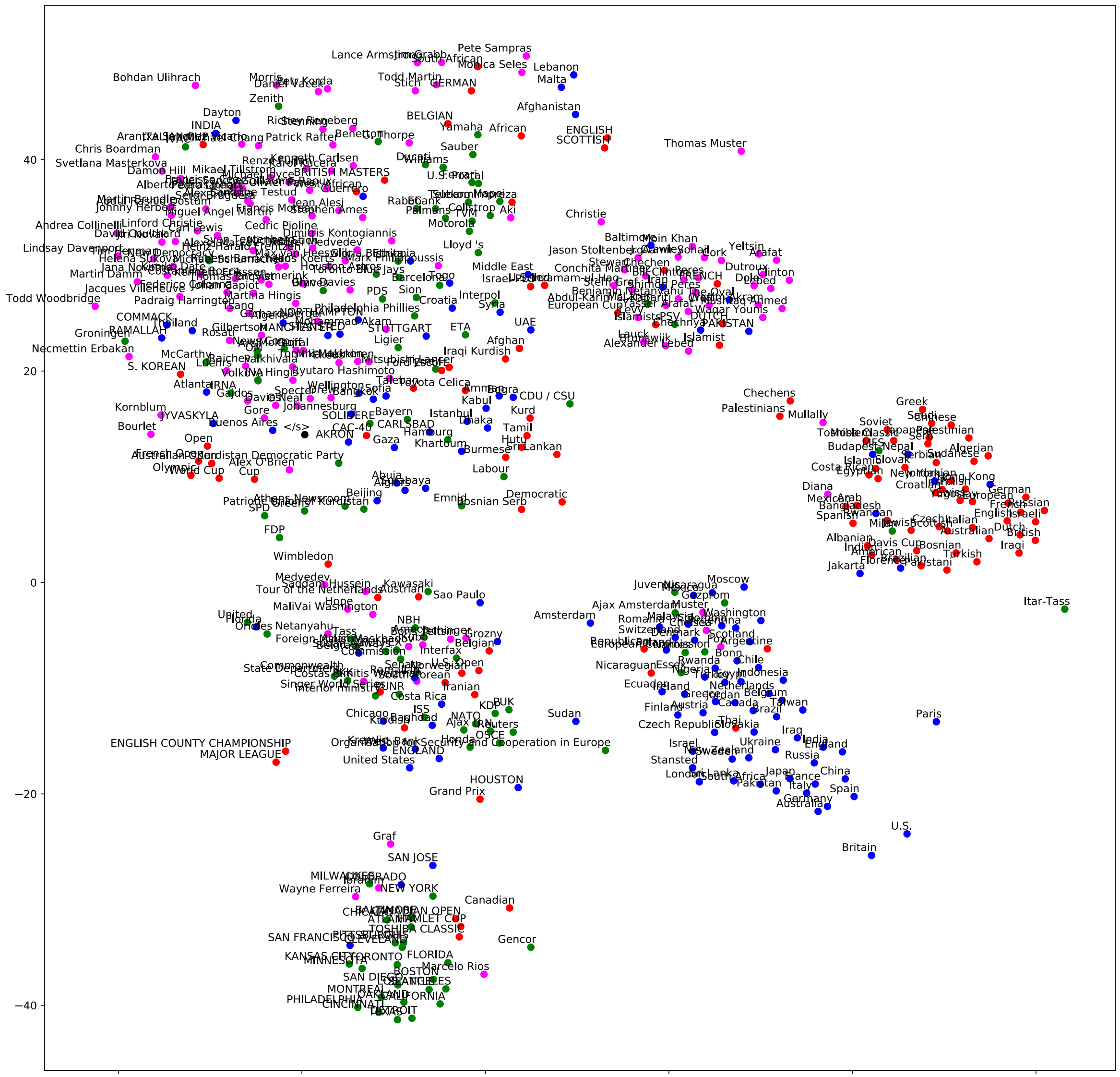

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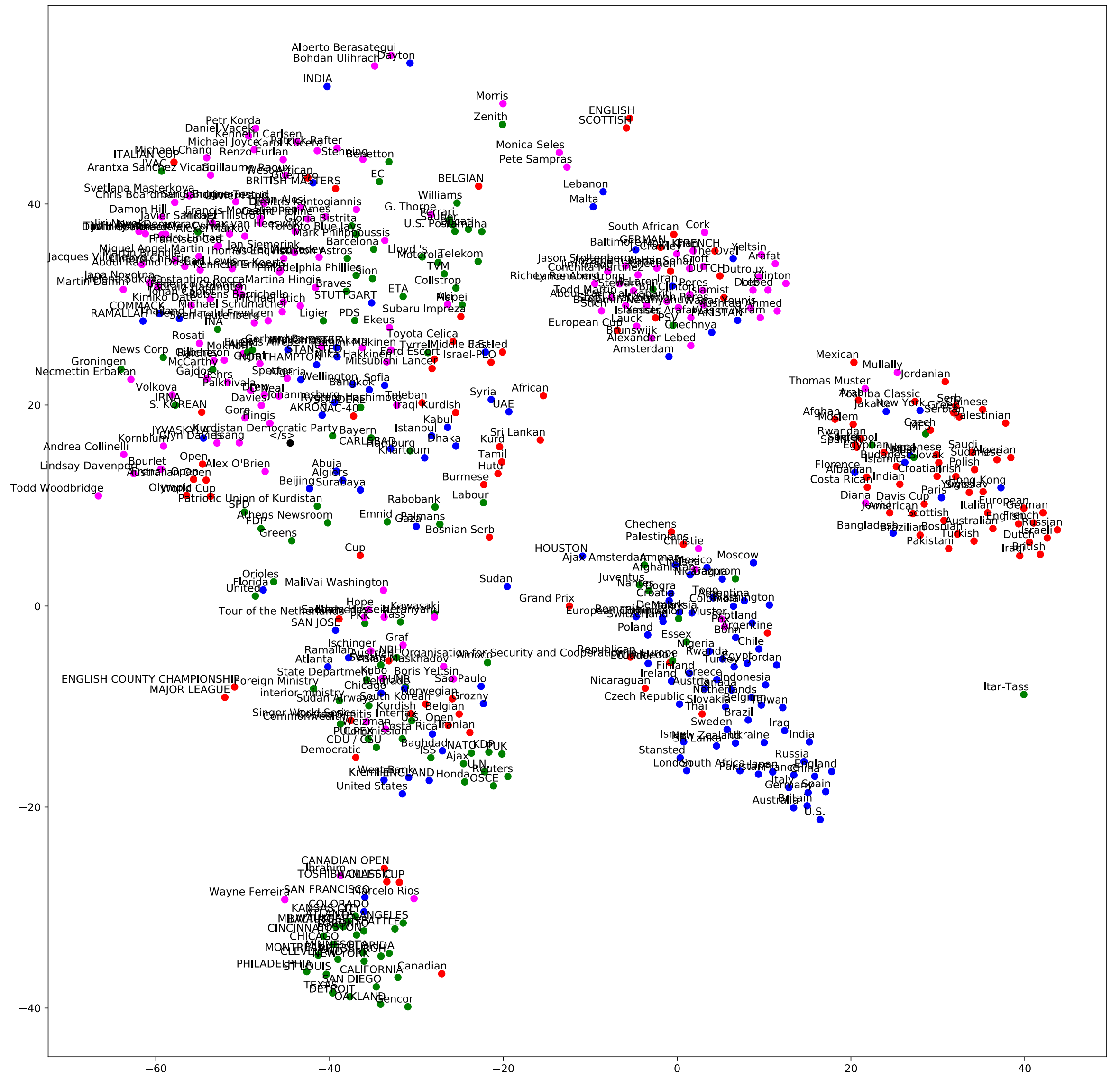
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Tour of the Netherlands
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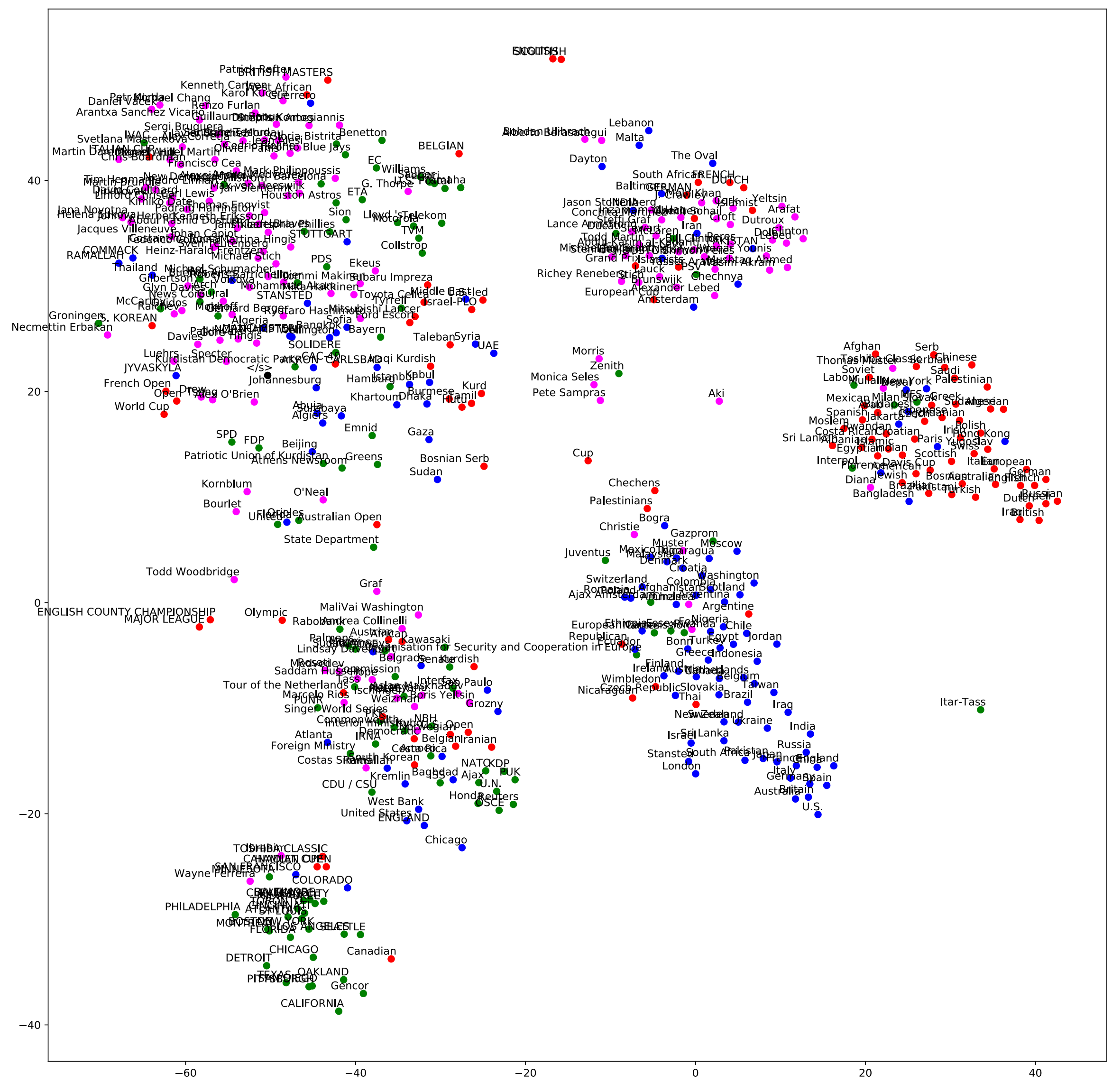

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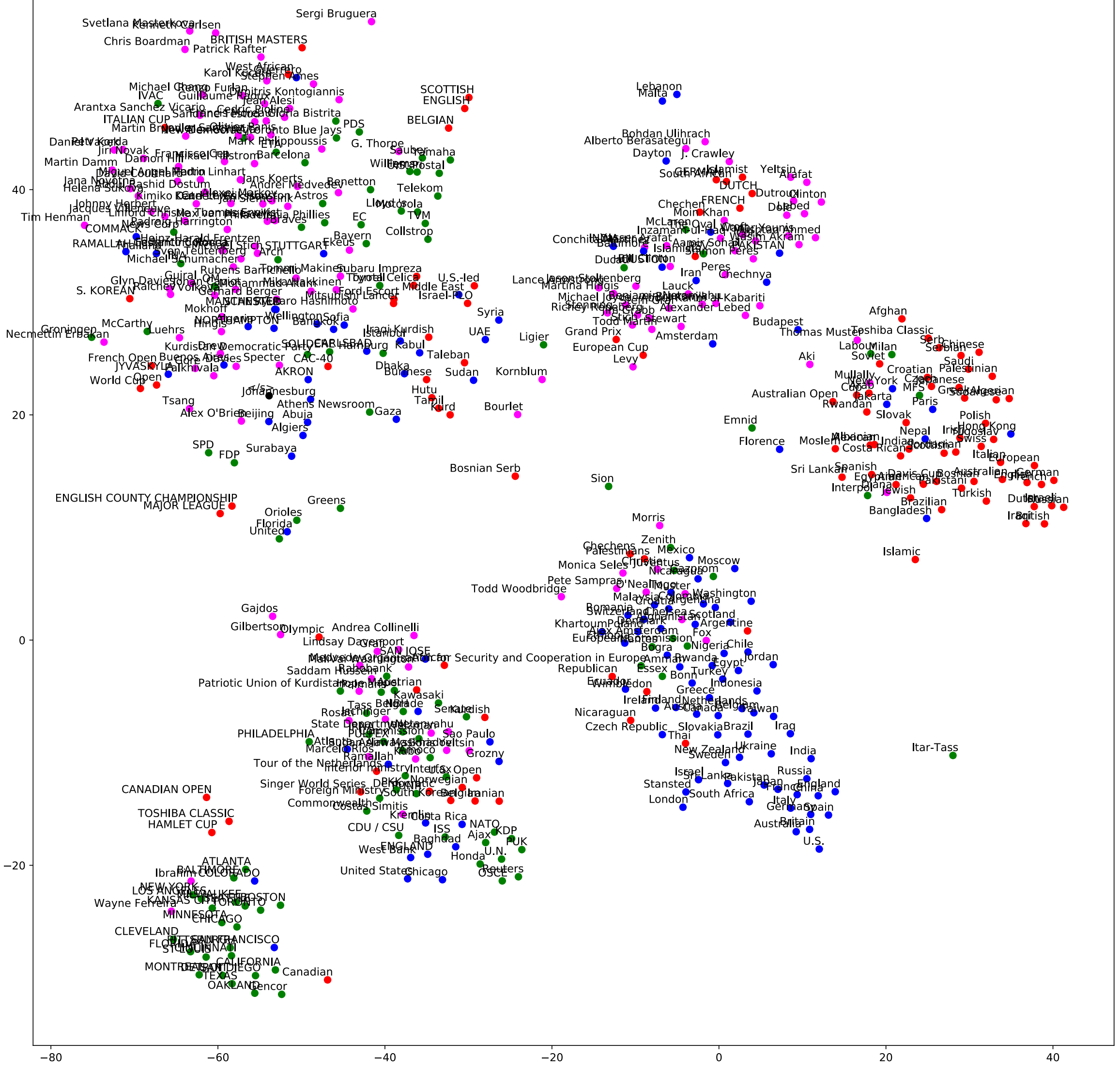

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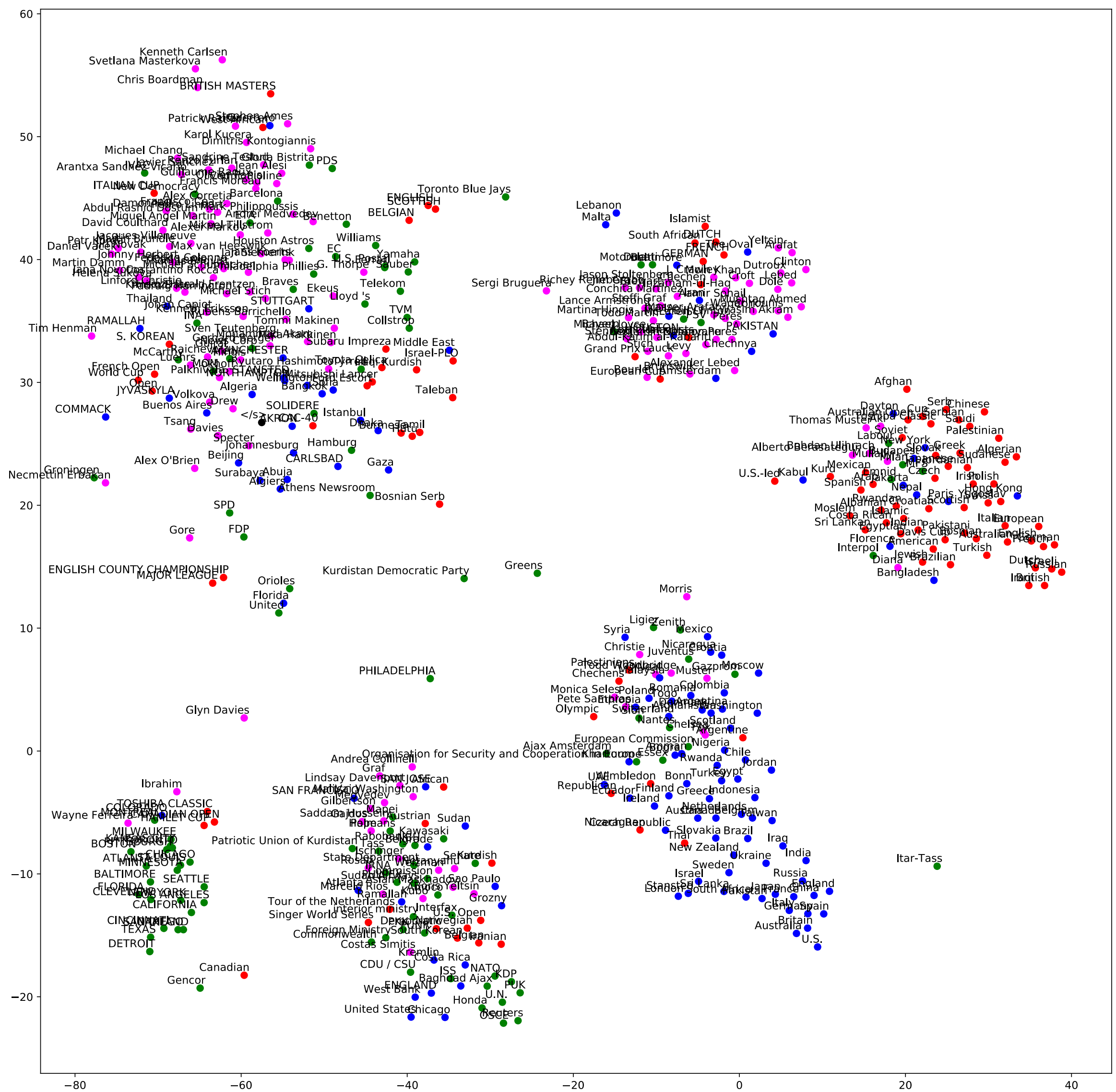

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Benetton
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Lance Armstrong
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Chechnya
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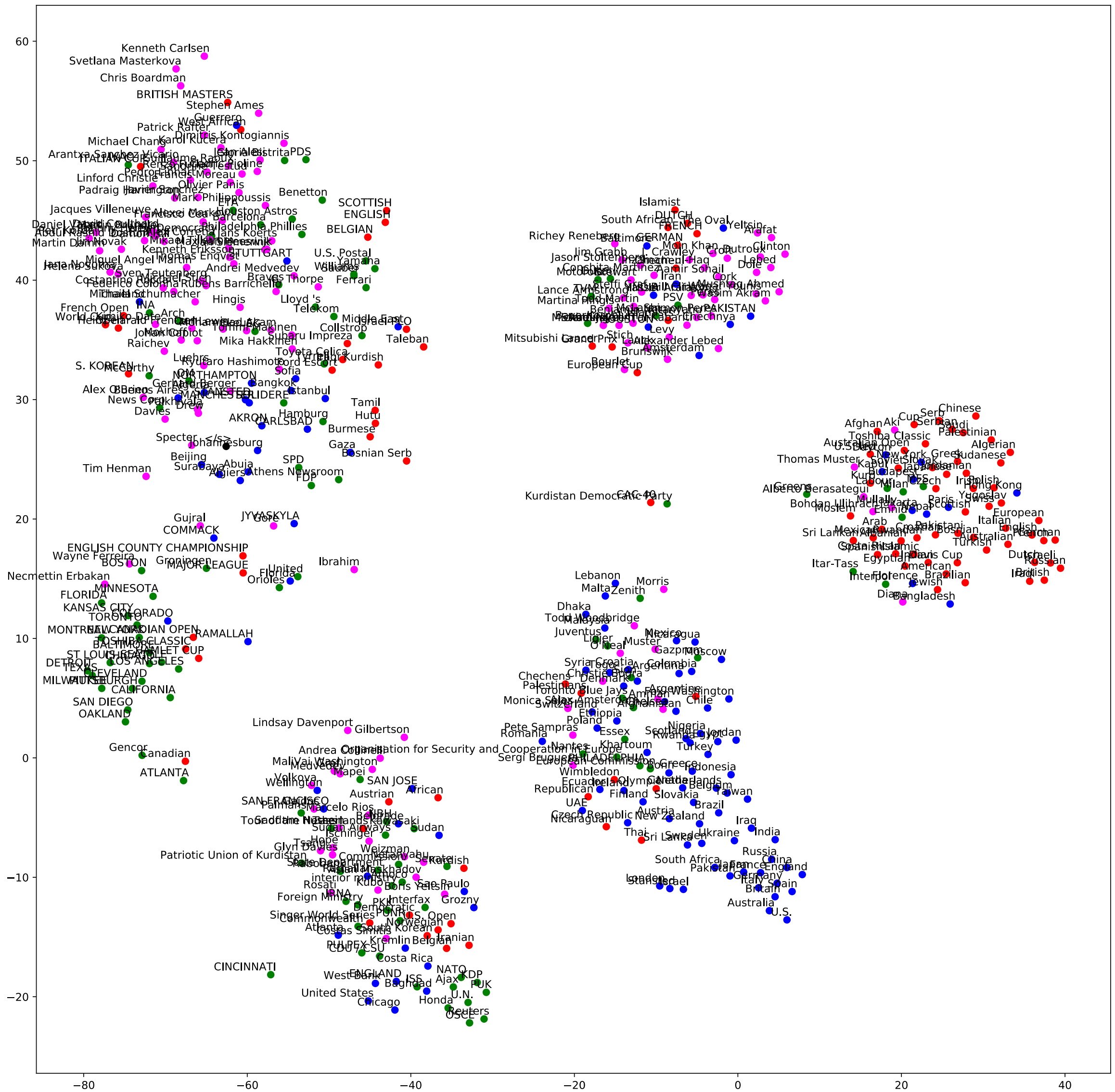

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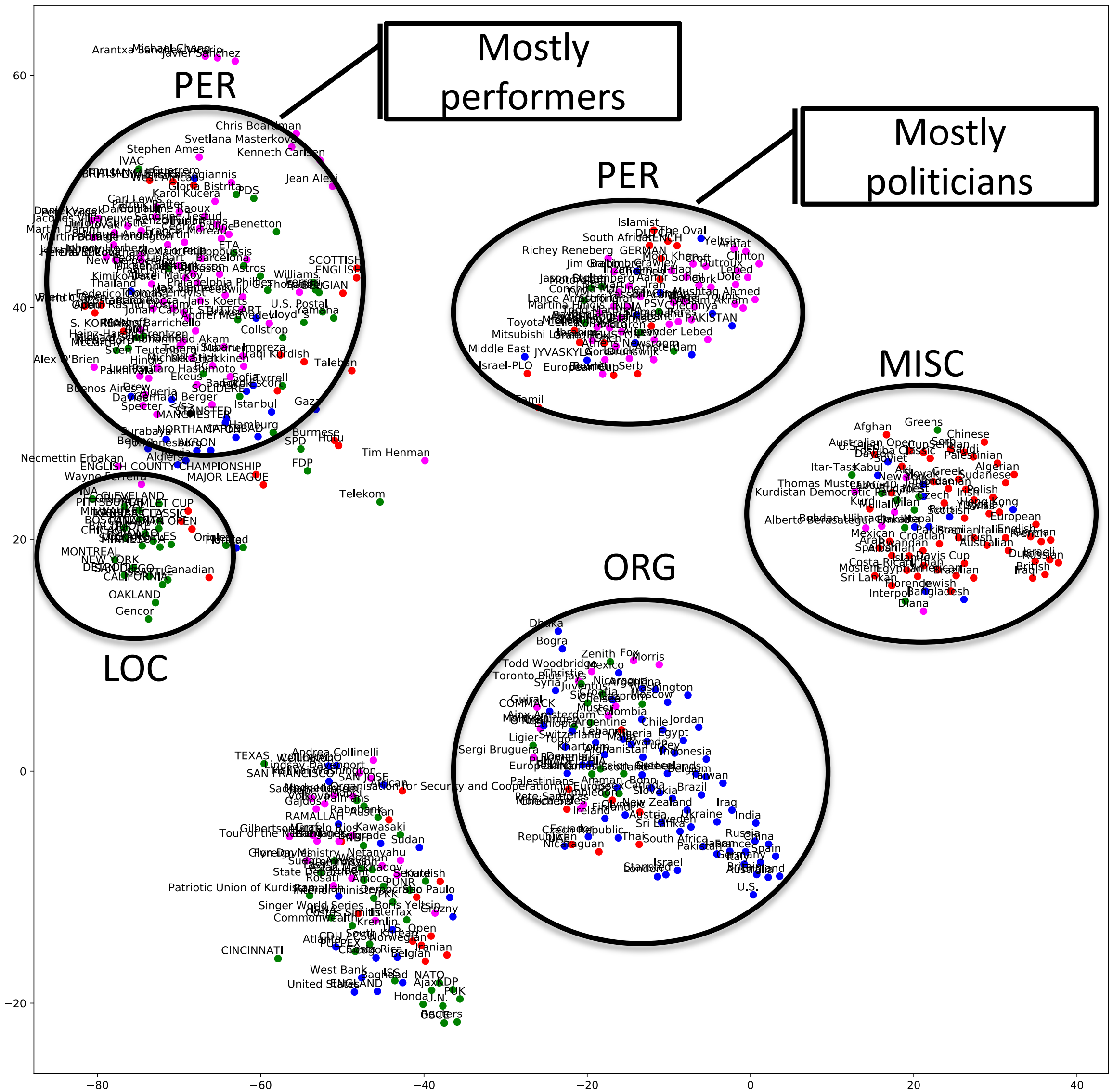

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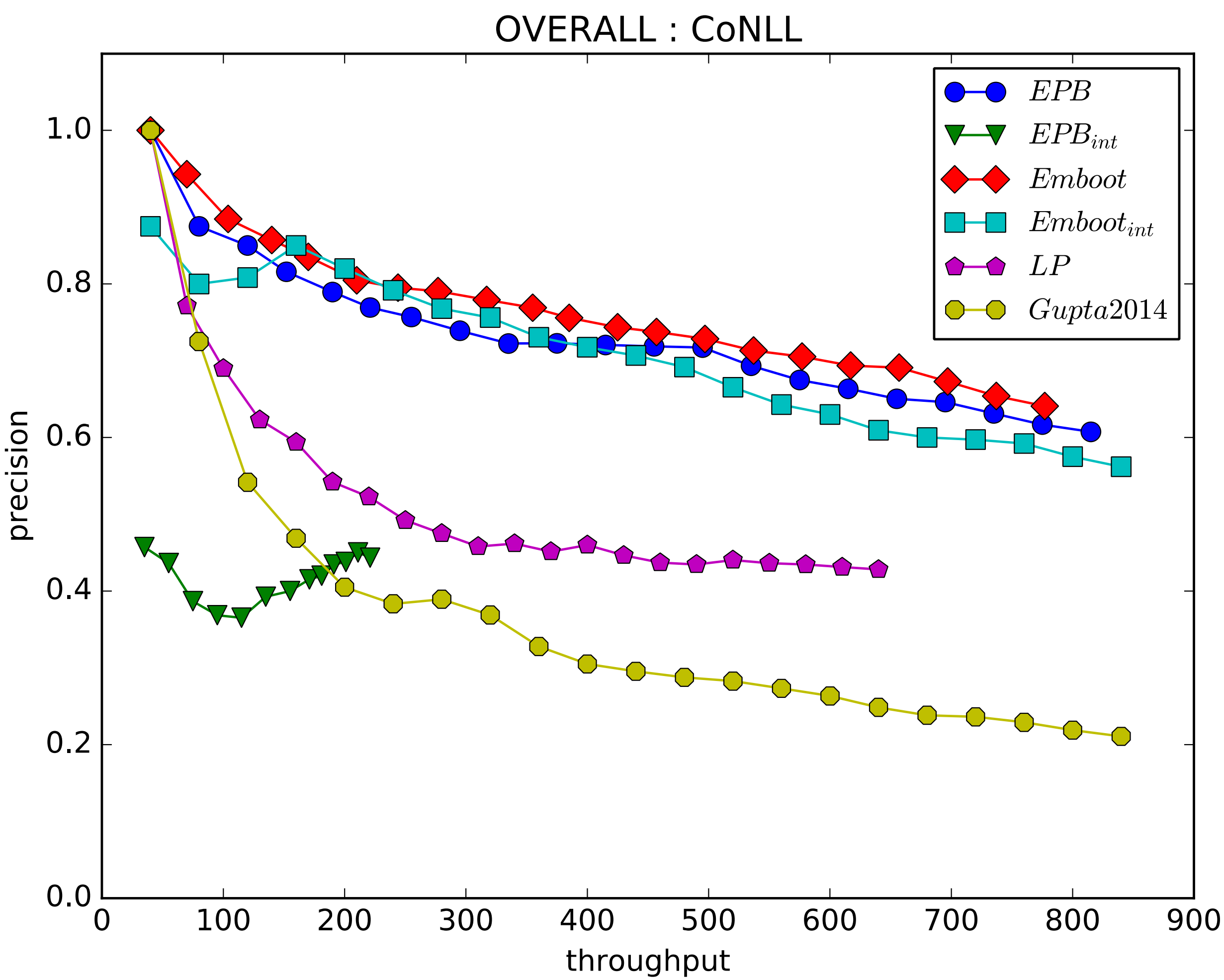
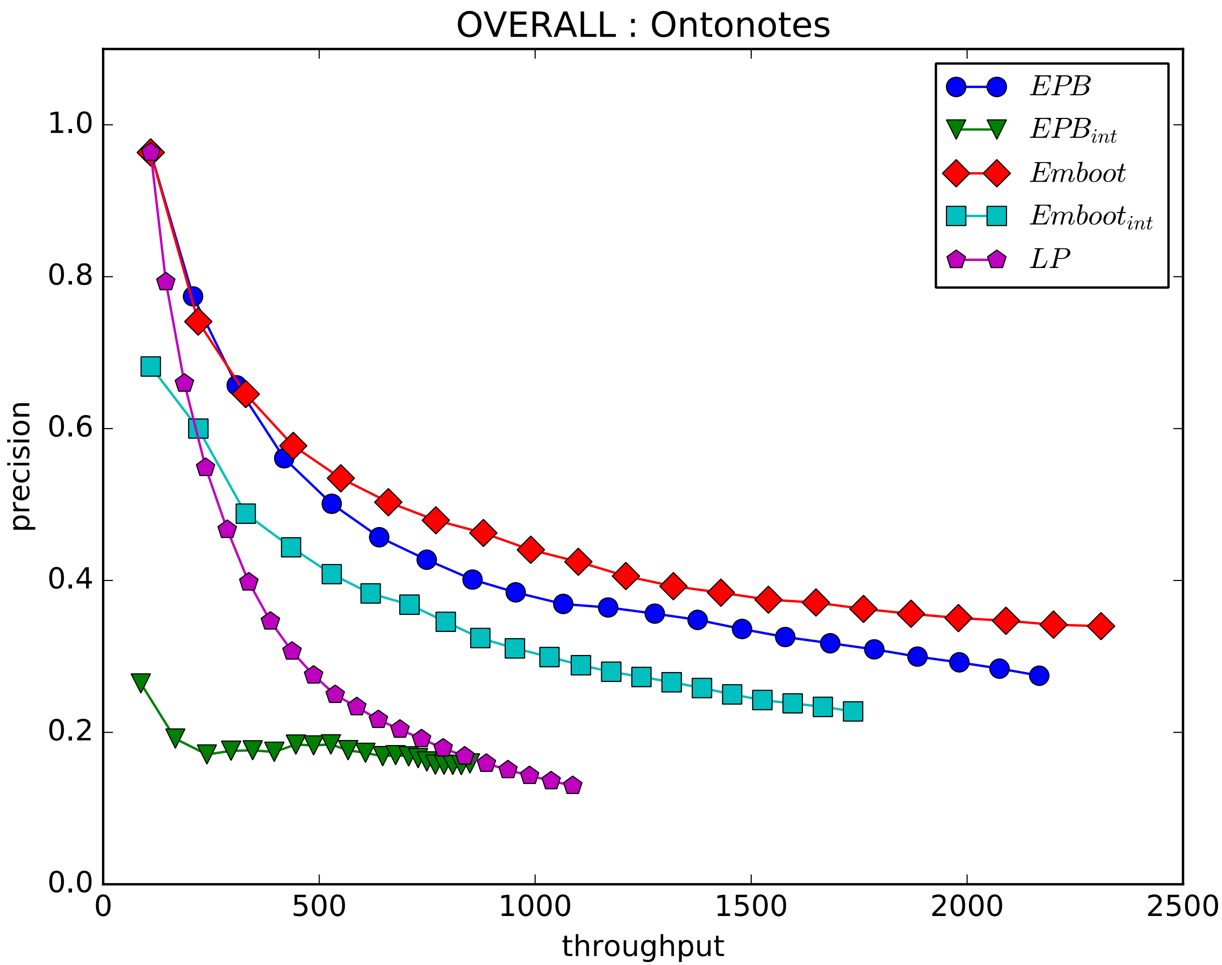
# Results, CoNLL dataset (4 classes)



# Results, OntoNotes (11 classes)



# Summary

- A lightly-supervised approach that jointly learns representations for entities and patterns that extract them
- State-of-the-art results for semi-supervised learning
- The rules can be edited by domain experts, and this leads to further improvements in performance (not shown)

# Take-home message

- For large, inter-disciplinary projects we need to move beyond "black-box" methods to approaches that produce globally interpretable models
- We can produce such interpretable models using deep learning (best of both worlds?)

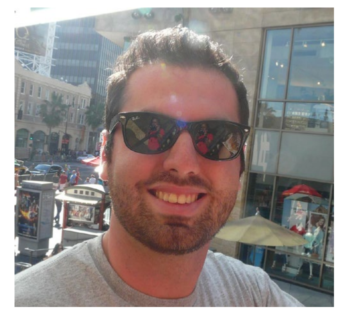
# Bibliography

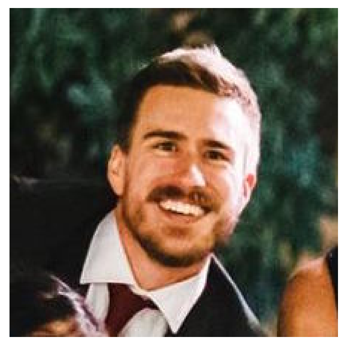
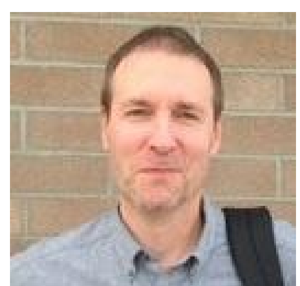

1. M.A. Valenzuela-Escarcega, G. Hahn-Powell, T. Hicks, and M. Surdeanu. *A Domain-independent Rule-based Framework for Event Extraction*. ACL-IJCNLP, 2015.
2. M. A. Valenzuela-Escarcega, G. Hahn-Powell, and M. Surdeanu. *Description of the Odin Event Extraction Framework and Rule Language*. arXiv:1509.07513, 2015.
3. D. Bell, G. Hahn-Powell, M. A. Valenzuela-Escarcega, and M. Surdeanu. *An Investigation of Coreference Phenomena in the Biomedical Domain*. LREC, 2016.
4. M. A. Valenzuela-Escarcega, G. Hahn-Powell, and M. Surdeanu. *Odin's Runes: A Rule Language for Information Extraction*. LREC, 2016.
5. G. Hahn-Powell, D. Bell, M. A. Valenzuela-Escarcega, and M. Surdeanu. *This before That: Causal Precedence in the Biomedical Domain*. BioNLP, 2016.
6. Large-scale Automated Machine Reading Discovers New Cancer Driving Mechanisms. Valenzuela-Escarcega, M. A.; Babur, O.; Hahn-Powell, G.; Bell, D.; Hicks, T.; Noriega-Atala, E.; Wang, X.; Surdeanu, M.; Demir, E.; and Morrison, C. T. Database: The Journal of Biological Databases and Curation. 2018.
7. Lightly Supervised Representation Learning with Global Interpretability. Zupon, A.; Alexeeva, M.; Valenzuela-Escarcega, M. A.; Nagesh, A.; and Surdeanu, M. In Proceedings of the 3rd Workshop on Structured Prediction for Natural Language Processing, 2019.
8. Z. Tang, M.A. Valenzuela-Escarcega, and M. Surdeanu. Exploring Interpretability in Event Extraction: Multitask Learning of a Neural Event Classifier and an Explanation Decoder. In preparation.

# Many thanks to my collaborators!








# THANK YOU!
## QUESTIONS?

# Conflict of interest disclosure

- M. Surdeanu discloses a financial interest in Lum.ai. This interest has been disclosed to the University of Arizona Institutional Review Committee and is being managed in accordance with its conflict of interest policies.