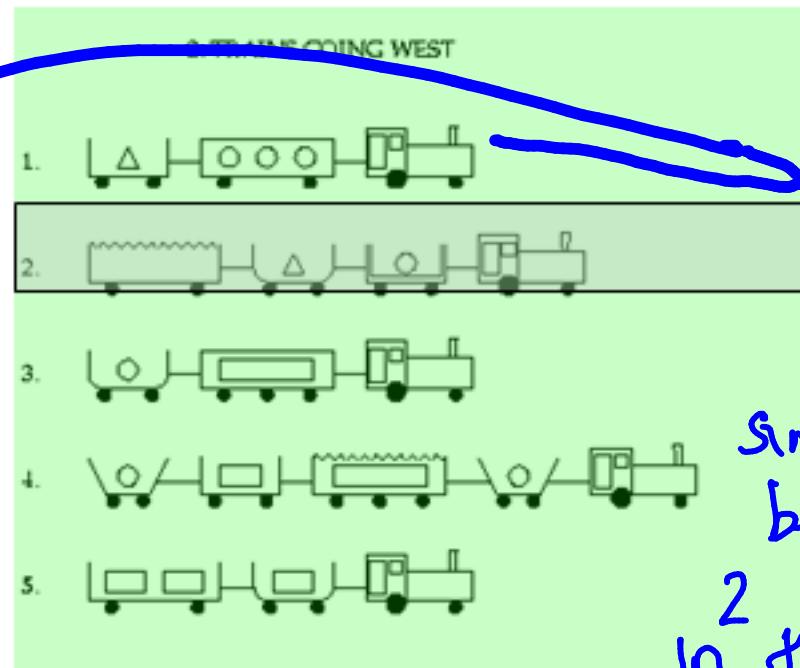
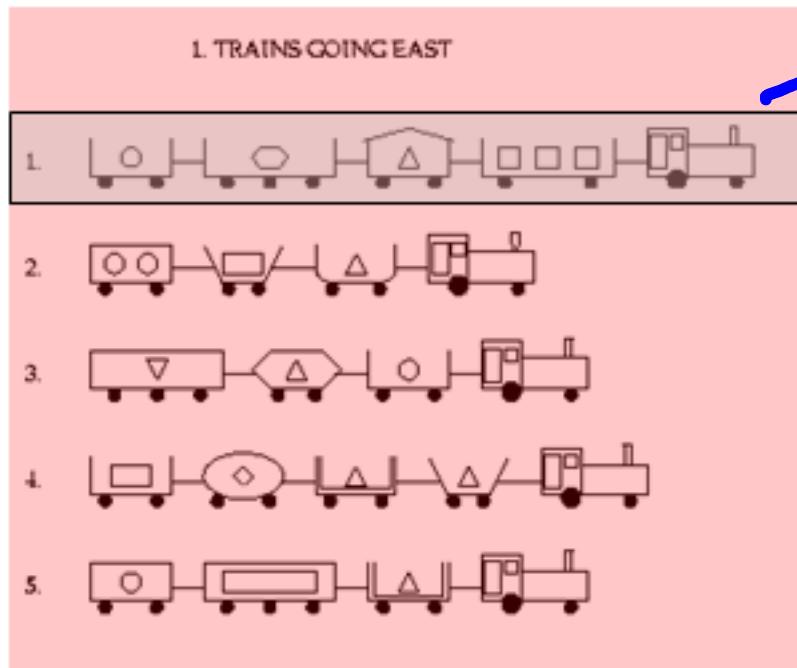


More in kLog



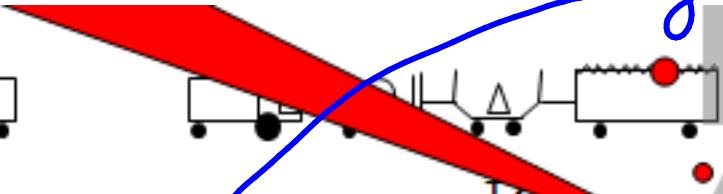
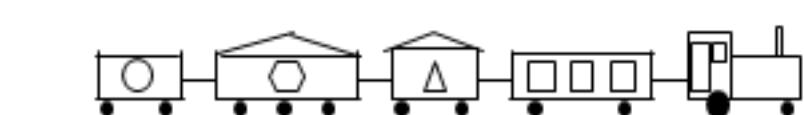
kLog
tries to

compute
similarities
between

2 trains

In the space
of these tables

Has good
support and
confidence



TRAIN	DIR
T1	East
T2	West

HAS_CAR		
	CarID	CarName
T1	C1_1	first
T1	C1_2	second
T1	C1_3	third
T1	C1_4	fourth
T2	C2_1	first
T2	C2_2	second
T2	C2_3	third

SHORT
CarID
C1_2
C1_4
C2_1
C2_3

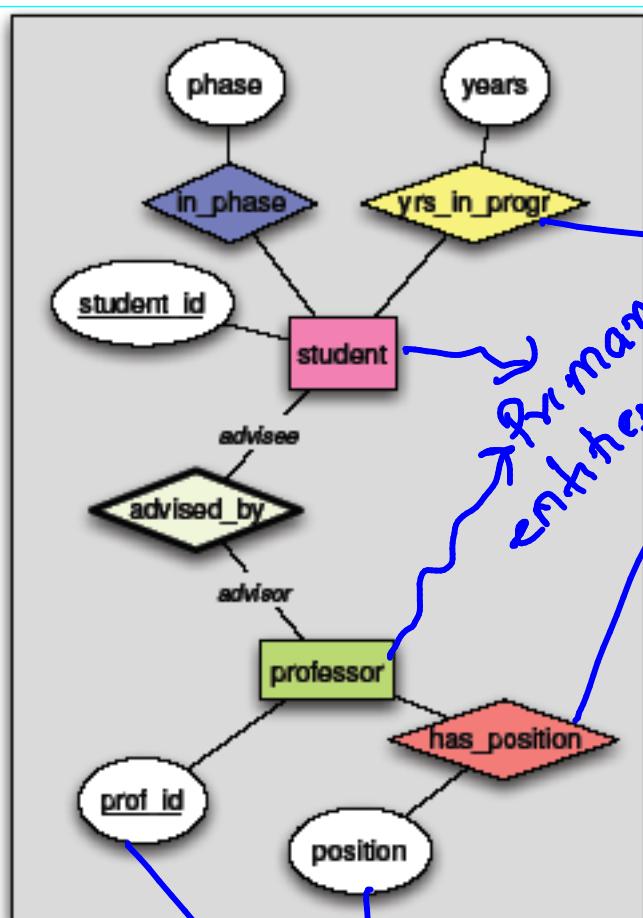
CLOSED
CarID
C1_1
C1_2
C1_3
C1_4
C2_3

LOADS		
	shape	Qty
C1_3	square	3
C1_3	triangle	1
C1_4	Hexagon	1
C1_4	Circle	1
C2_1	Circle	1
C2_2	Triangle	1
C2_3	-	-

Eastbound trains have:
a long car C1, and
C1 is closed -roofed, and
C1 has 3 square loads, and
a short car C2, and
C2 is closed, and
C2 has 1 triangular load, and
a long car C3,
etc.

Goal of klog: Compute similarity

between examples that "efficiently" & "nicely" captures the effect of enumerating all "descriptions" (in First Order Logic) of the example(s)



values in table of cells

name of table (in
above example of
trains)

If we had info on
which trains run after
which trains, we would
have had multiple rectangular
boxes & edges between them

```

signature on_same_paper(
    student_id::student,
    prof_id::professor
)::intensional.

```

```

on_same_paper(S, P) :-
    student(S), professor(P),
    publication(Pub, S),
    publication(Pub, P).

```

```

signature on_same_course(
    student_id::student,
    prof_id::professor
)::intensional.

```

```

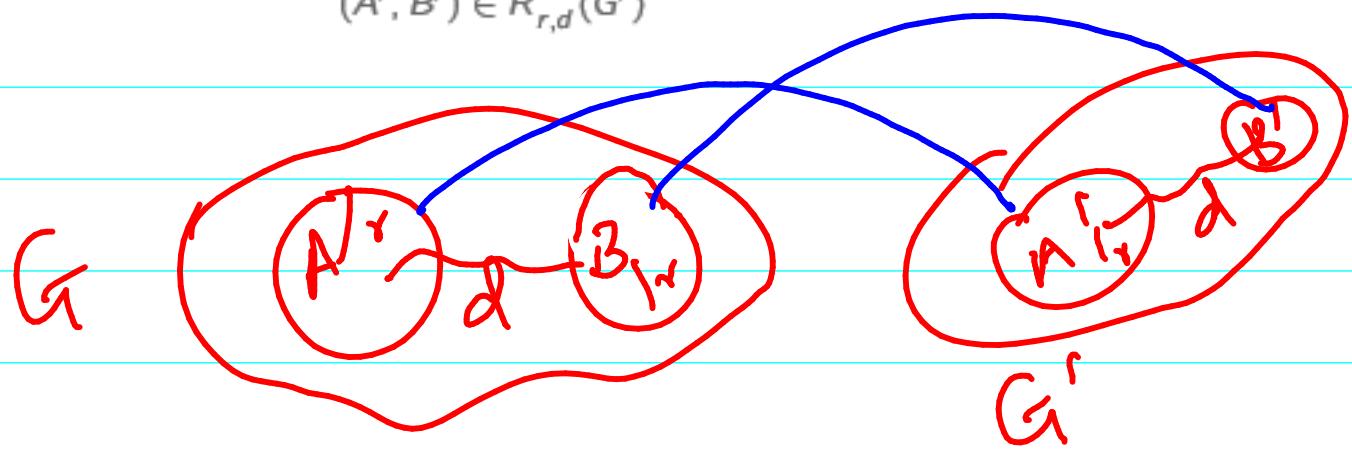
on_same_course(S, P) :-
    professor(P), student(S),
    ta(Course, S, Term),
    taught_by(Course, P, Term).

```

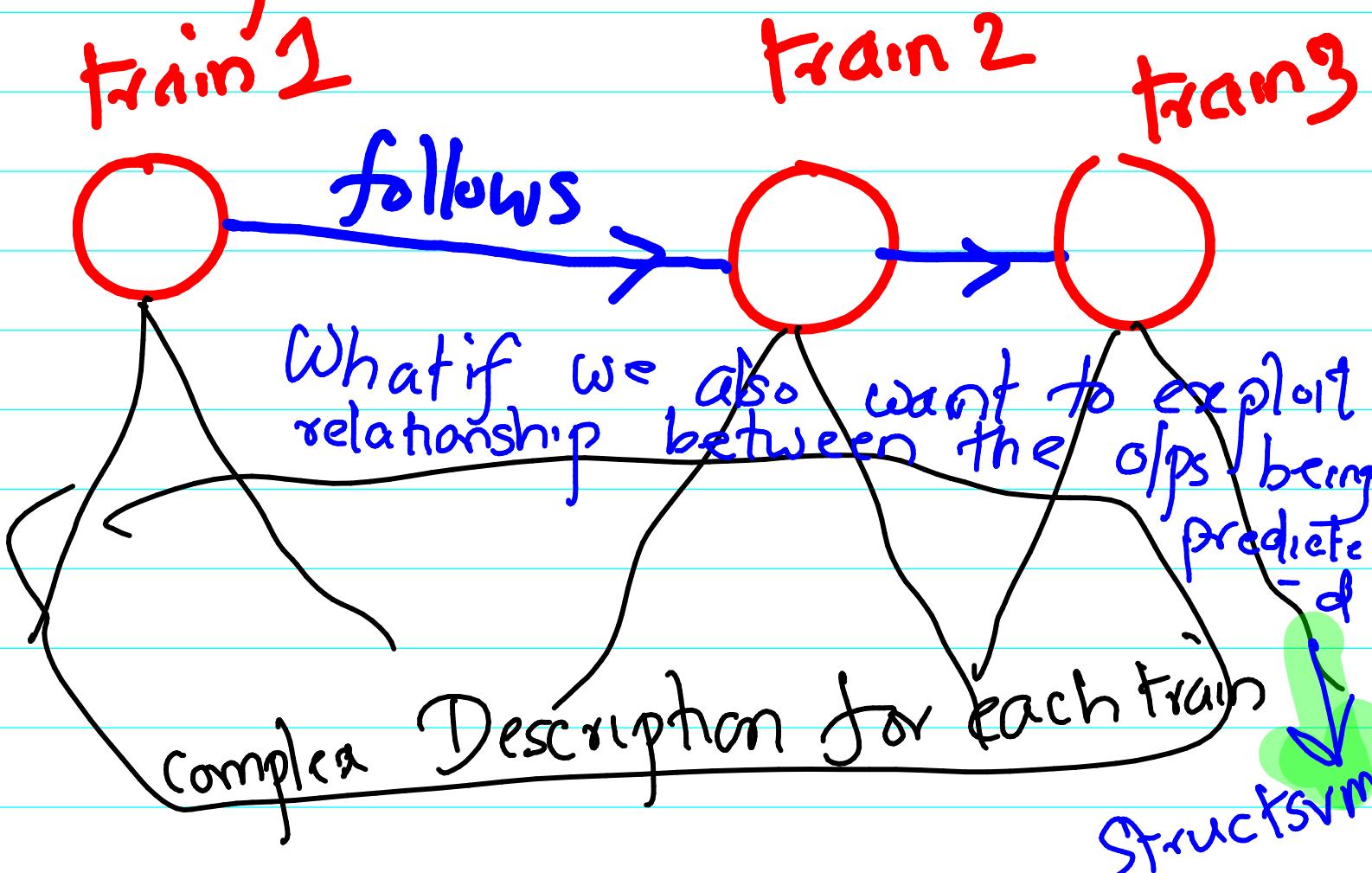
Not specified in
 tables but are
 "views" defined through
 this "join" like query
 Specified as before
 in relational tables

- $\kappa_{r,d}$ counts common NP's between two graphs.

$$\kappa_{r,d}(G, G') = \sum_{\substack{(A, B) \in R_{r,d}^{-1}(G) \\ (A', B') \in R_{r,d}^{-1}(G')}} \delta(A, A') \delta(B, B')$$



Structured output prediction



So far: $K(\text{train 1}, \text{train 2})$ was computed using complex methods

But

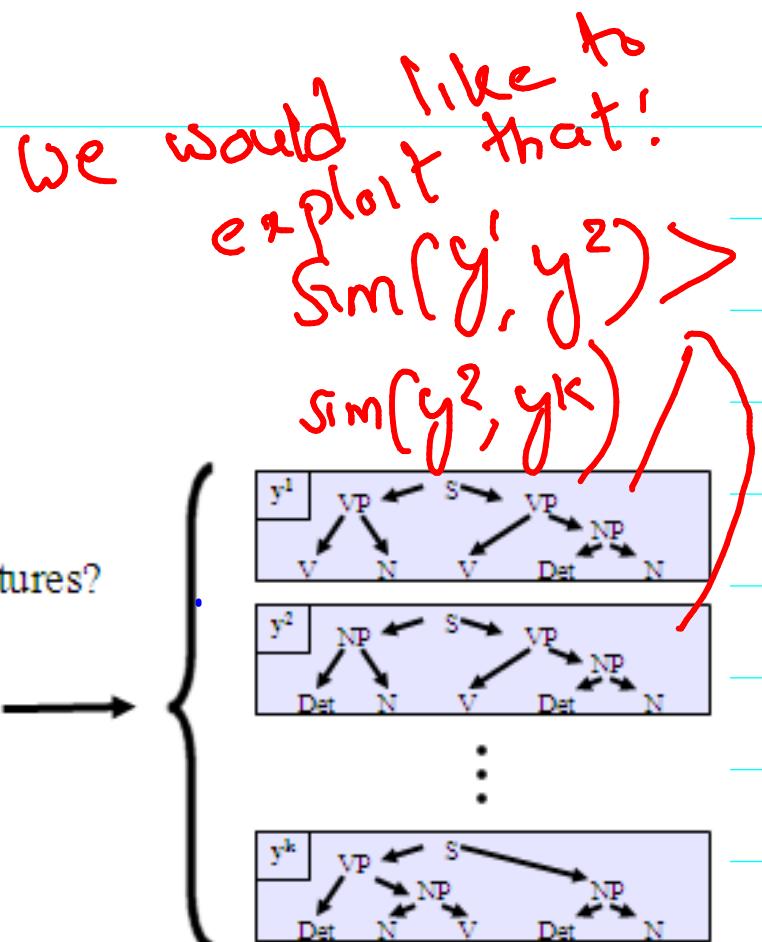
$$f(\text{train}) = \sum_{\text{train}(i) \in \mathcal{D}} \alpha_i y_i K(\text{train}, \text{train}(i))$$

$y_i = 1 \text{ if } -1 \leq \omega^T x_i \leq 1$

- **Problems:**

- Exponentially many classes!
 - How to predict efficiently?
 - How to learn efficiently?
- Potentially huge model!
 - Manageable number of features?

x The dog chased the cat



Soln 1:

$$w_y^\top \phi(x) \rightarrow w^\top \phi(x, y)$$

Standard tradeoff

I.e we need to look at substructures within y the way we looked at substructures within parse trees for x earlier

Joint Feature Map for Trees

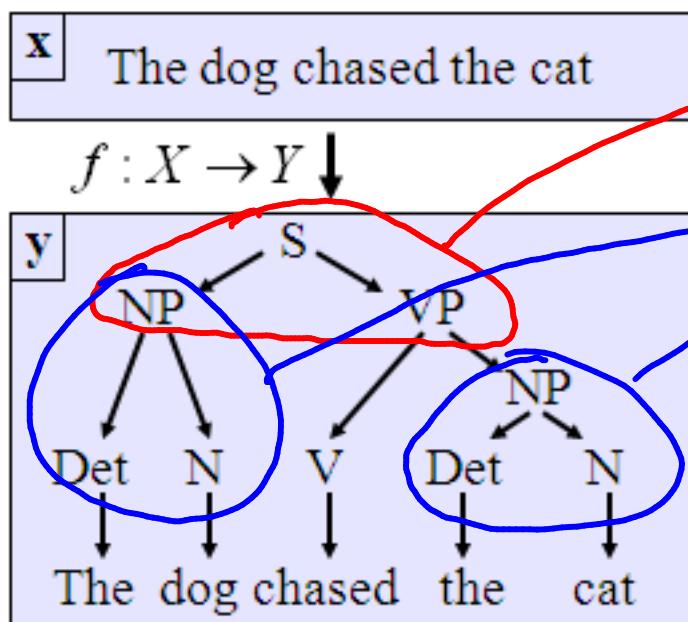
- **Weighted Context Free Grammar**

- Each rule r_i (e.g. $S \rightarrow NP VP$) has a weight w_i

- Score of a tree is the sum of its weights

- Find highest scoring tree $h(\vec{x}) = \text{argmax}_{y \in Y} [\vec{w}^T \Phi(x, y)]$

CKY Parser



1	$S \rightarrow NP VP$
0	$S \rightarrow NP$
2	$NP \rightarrow Det N$
1	$VP \rightarrow V NP$
:	
0	$Det \rightarrow dog$
2	$Det \rightarrow the$
1	$N \rightarrow dog$
1	$V \rightarrow chased$
1	$N \rightarrow cat$

$\phi(x, y)$ is a fixed length vector of size $|G|$
i.e # of prod

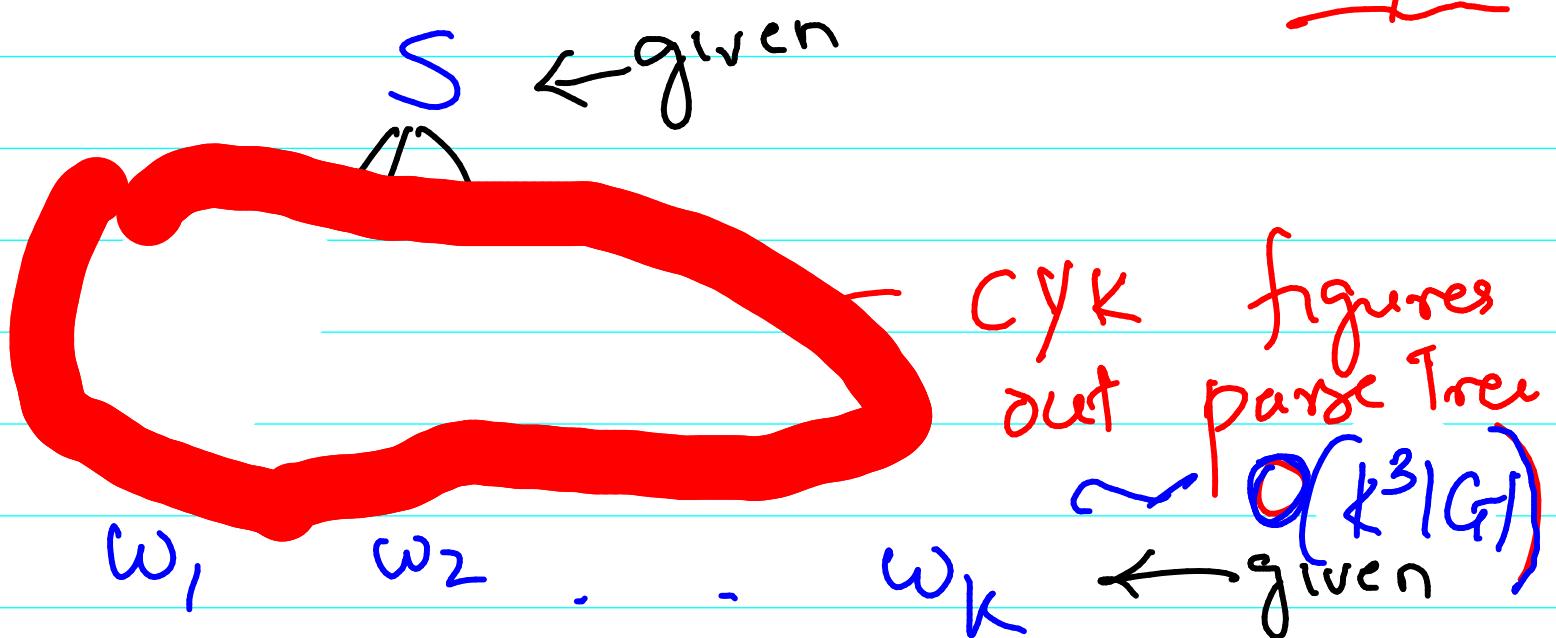
This list of productions is manually created and available

Q1: At the end of training, we have a set of productions along with weight for each. Given a sentence, how to find the "parse tree with highest weight"?

Ans: Modify CYK algo (used for
parsing using context free
grammar) to handle weights

http://en.wikipedia.org/wiki/CYK_algorithm

H/w



Q2: How to allow for slackness in the loss function that accounts for and accommodates "almost similar" parse trees (similar to the correct parse tree)