CSE 517: Winter 2015
Textual Entailment

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Slides adapted from Ido Dagan, Dan Roth, Fabio Massimo Zanzotto, Jonathan Berant

The Holy grail of NLP….

- Understanding Natural Language Text

British left waffles on nukes

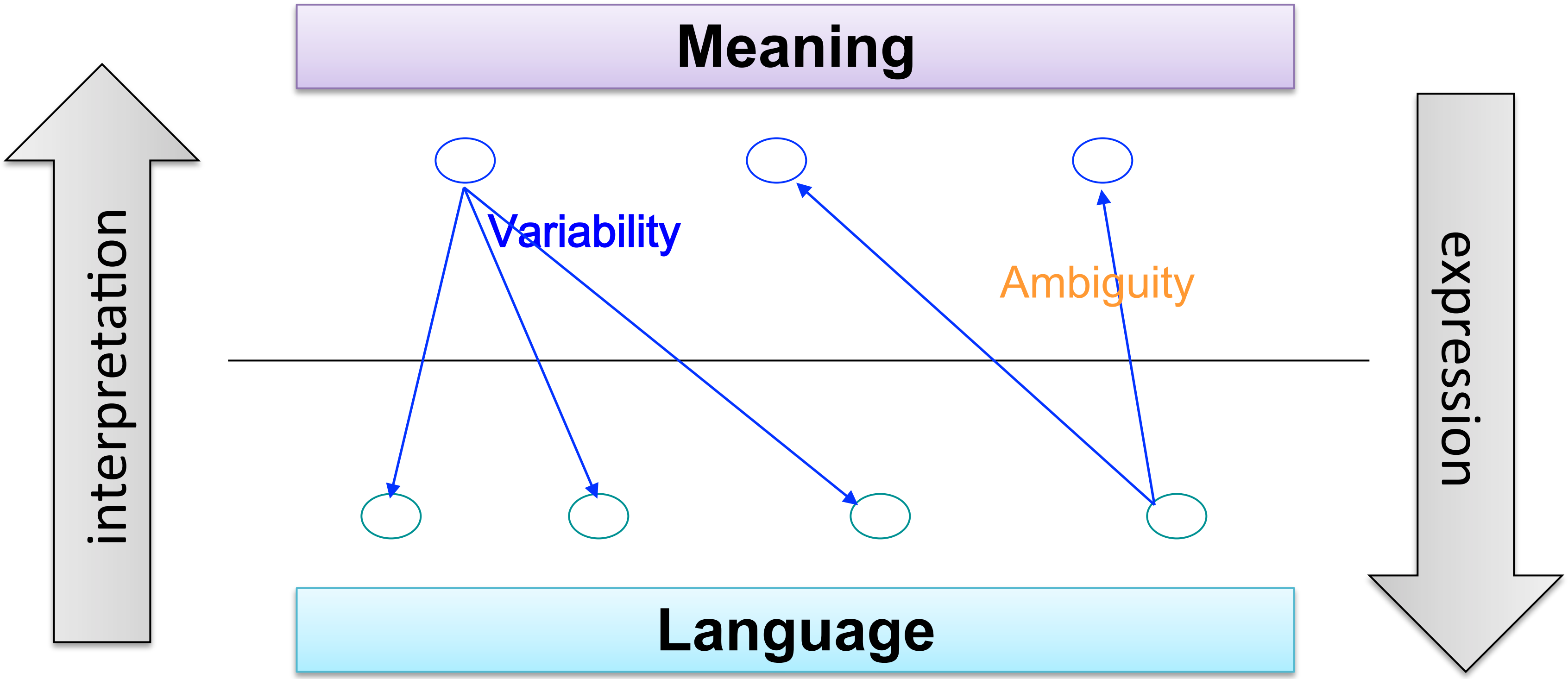
  - Traditional approach: map it to a canonical form
  - Can then (in theory) integrate multiple statements from diverse sources to derive “new” facts
  - Question #1: How to represent its meaning?

$$\exists_x \exists_y \exists_z British(x) \wedge Waffles(y) \wedge Nukes(z) \wedge leave\_on(x, y, z)$$

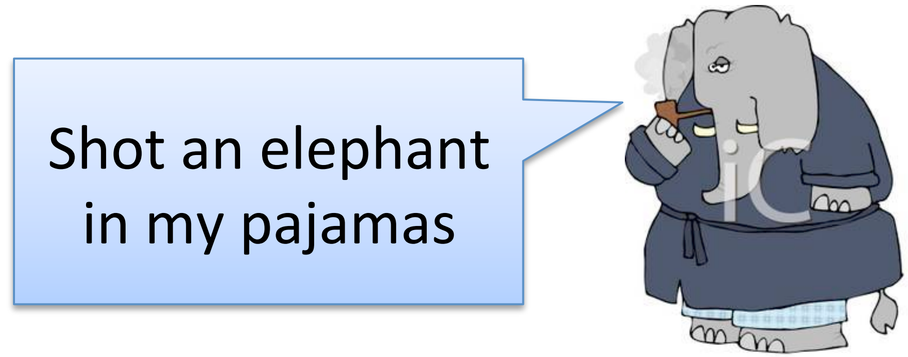
  - Question #0.5: What *is* its meaning?
  - Question #0.1: What does *understand* mean?

Natural Language and Meaning

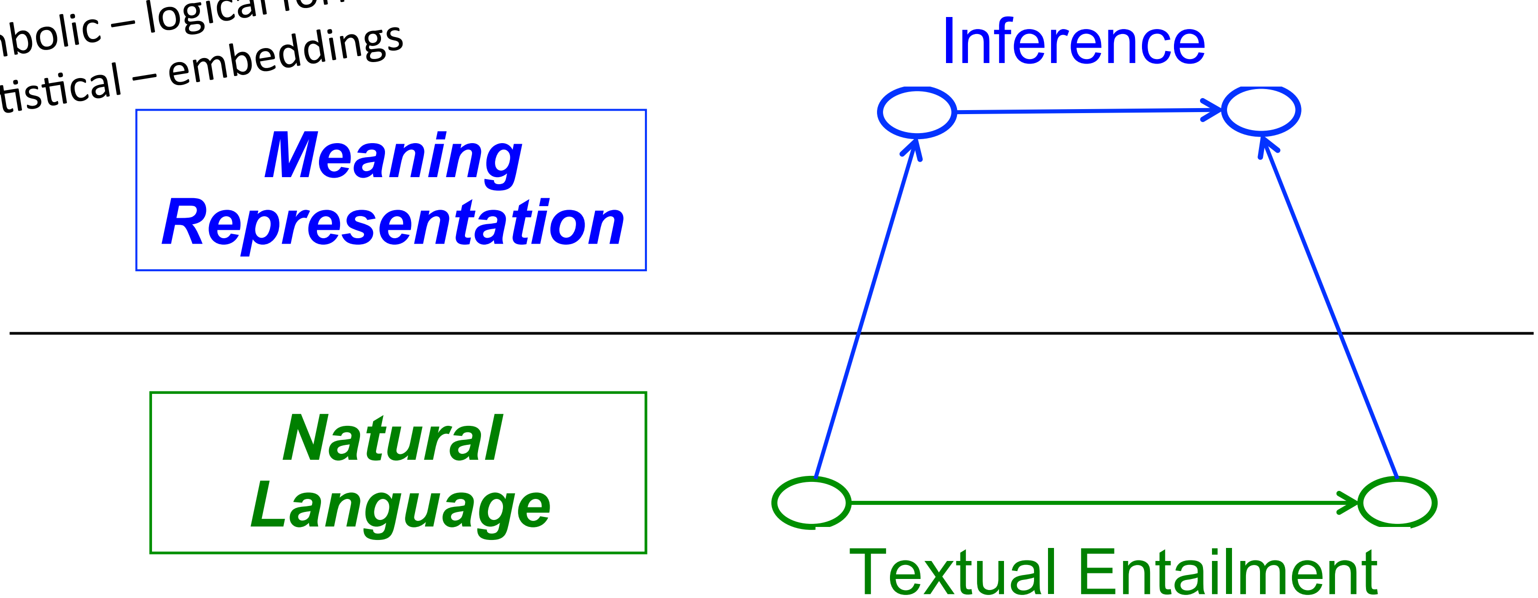
Shot an elephant in my pajamas



Logical Inference VS Textual Entailment



- symbolic – logical forms
- statistical – embeddings



Entailment VS Paraphrasing

The Dow Jones Industrial Average closed up 255

Dow ends up 255

Dow climbs 255

Dow gains 255 points

Stock market hits a record high

Equivalence: *text1* $\Leftrightarrow$ *text2* (paraphrasing)

Entailment: *text1* $\Rightarrow$ *text2*

Textual Entailment: Definition

- A directional relation between two text fragments: *Text (t)* and *Hypothesis (h):*

t entails h $(t \Rightarrow h)$ **if**
humans reading *t* will infer that *h* is most likely true

- Assuming "common background knowledge" – which is indeed expected from applications

Some Examples

[Braz et. al. IJCAI workshop' 05;PARC Corpus]

- T: Legally, John could drive.
- H: John drove.

.

- S: Bush said that Khan sold centrifuges to North Korea.
- H: Centrifuges were sold to North Korea.

.

- S: No US congressman visited Iraq until the war.
- H: Some US congressmen visited Iraq before the war.

- S: The room was full of men.
- H: The room was full of intelligent men.

- S: The New York Times reported that Hanssen sold FBI secrets to the Russians and could face the death penalty.
- H: Hanssen sold FBI secrets to the Russians.

- S: All soldiers were killed in the ambush.
- H: Many soldiers were killed in the ambush.

Textual Entailment with ***Knowledge***

***t* entails *h* (*t* $\Rightarrow$ *h*) if**
humans reading *t* will infer that *h* is most likely true

- For textual entailment to hold we require:
  - *text* AND *knowledge* $\Rightarrow$ *h*

  but
  - *knowledge* should not entail *h* alone
  - Justification: consider time-dependent information, e.g. PresidentOf(US, X)
- Systems are not supposed to validate *h*'s truth regardless of *t* (e.g. by searching *h* on the web)

[id: 5T-39 entail]

TEXT: …While no one accuses Madonna of doing anything illegal in adopting the 4-year-old girl, reportedly named Mercy, there are questions nonetheless about how Madonna is able to navigate Malawi's 18-to-24 month vetting period in just a matter of days or weeks…

HYPOTHESIS:

Madonna is 50 years old.

Contradiction: Definition

- Definition:

  The Hypothesis H of an entailment pair
  contradicts the Text T if
  the relations/events described by H
  are highly unlikely to be true
  given the relations/events described by T.

- Justification: filtering facts from diverse/noisy sources, detecting state changes

Entailment / Contradiction / Unknown?

- Text:

  The purchase of Houston-based LexCorp by BMI for $2Bn prompted widespread sell-offs by traders as they sought to minimize exposure. LexCorp had been an employee-owned concern since 2008.

- Hyp 1: BMI acquired an American company.

Entailment / Contradiction / Unknown?

- Text:

  The purchase of Houston-based LexCorp by BMI for $2Bn prompted widespread sell-offs by traders as they sought to minimize exposure. LexCorp had been an employee-owned concern since 2008.

- Hyp 2: BMI bought employee-owned LexCorp for $3.4Bn.

Entailment / Contradiction / Unknown?

- Text:

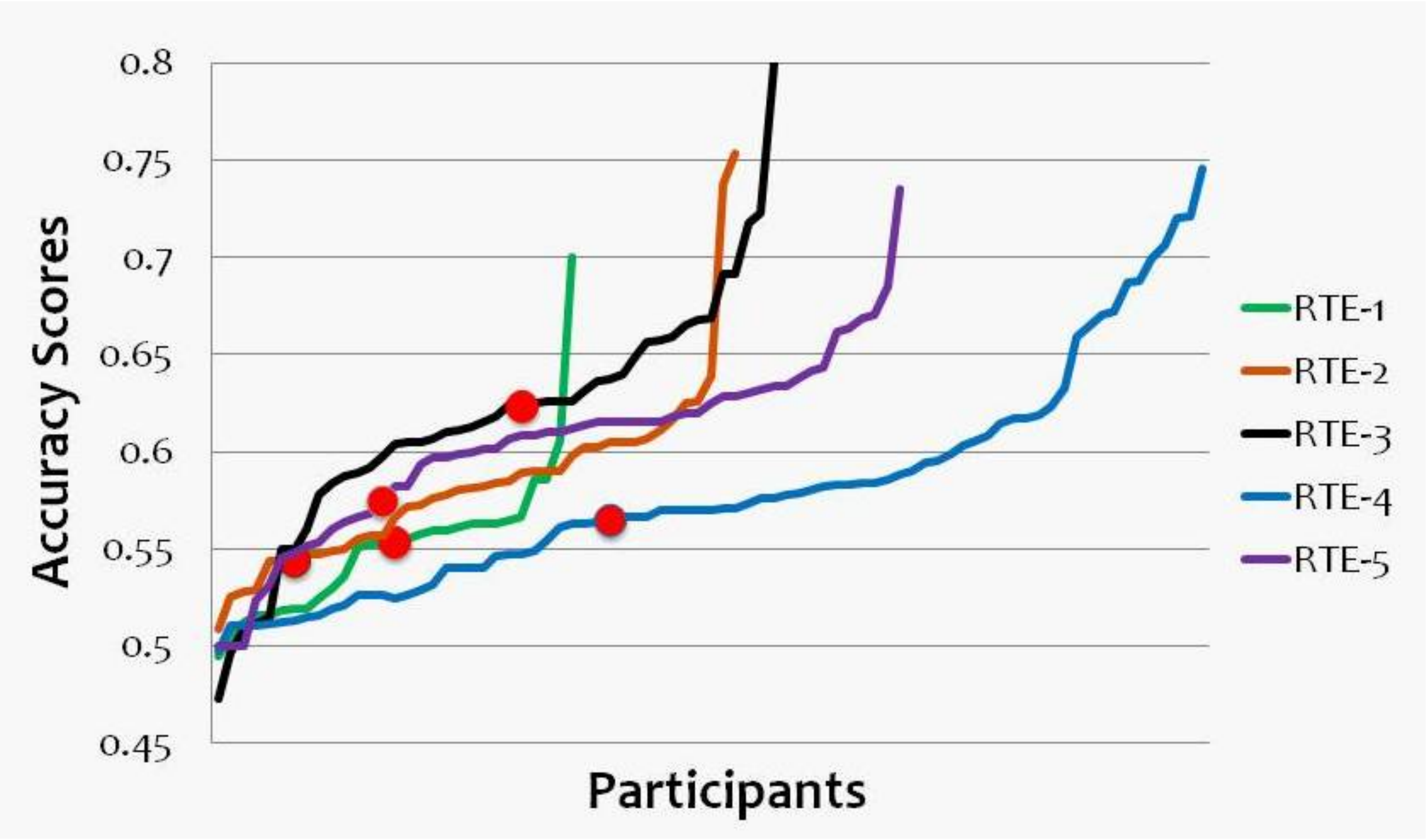
  The purchase of Houston-based LexCorp by BMI for $2Bn prompted widespread sell-offs by traders as they sought to minimize exposure. LexCorp had been an employee-owned concern since 2008.

- Hyp 3: BMI is an employee-owned concern.

RTE Evaluation

- Examples drawn from NLP tasks/domains
- **~90% pairwise inter-annotator agreement**
- RTE 1-3: ~800 dev, 800 test RTE pairs each ('05- '07)
  - Boolean label: "entailed" vs. "not entailed"
  - BALANCED data set
- RTE 4-5: Ave. text length = 40,100 words ('08, '09) respectively, 2-way and 3-way tasks
  - "entailed", "contradicted", and "unknown"
- Some pilot RTE task data sets as well
- RTE 6 (2010): shift to application focus: IR-like setting

How well are we doing?



Why Textual Entailment?

Question — *Expected answer form*

Who bought Overture? >> X bought Overture

Overture's acquisition by Yahoo — *entails* → Yahoo bought Overture

text — *hypothesized answer*

- IE
- IR
- Summarization
- MT

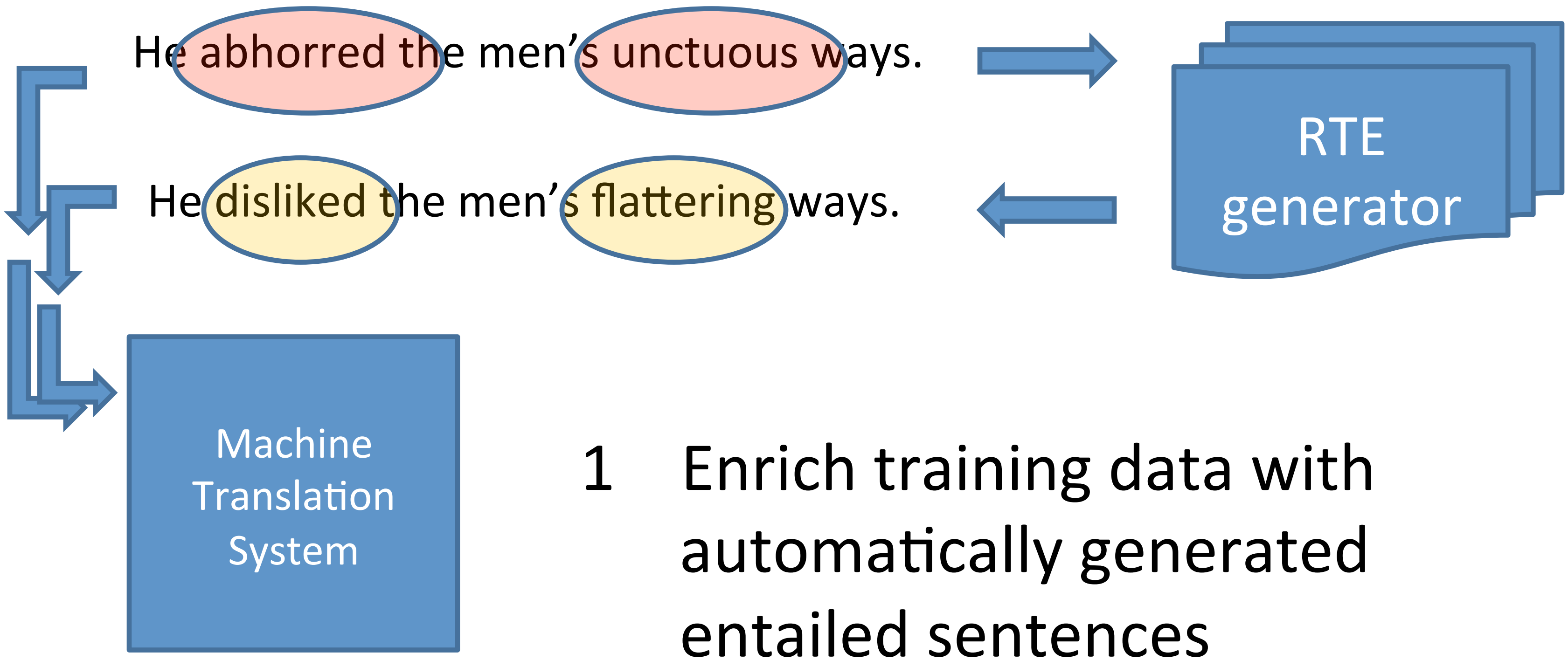
Scalable RTE for exhaustive search

(Roth et al., 2009)

- Target applications like document downgrading (detect classified information): must retrieve ALL instances of specified query
- Two-stage architecture:
  - Push some RTE capabilities into Retrieval step; index shallow semantic markup (NE, NQ, MWE), use similarity metrics in retrieval
  - Post-retrieval RTE step filters results using deeper structure

Textual Entailment for MT

(Mirkin et al., 2009)



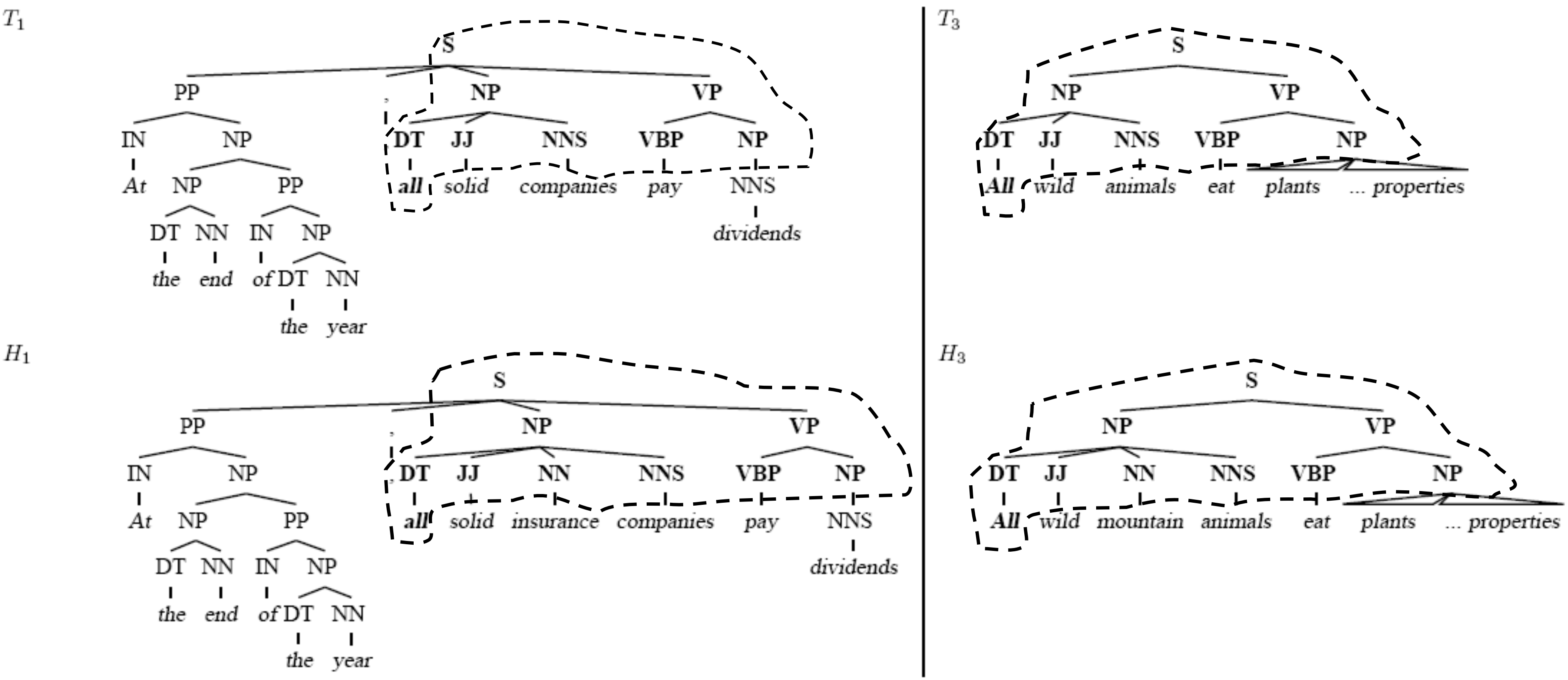
1. Enrich training data with automatically generated entailed sentences
2. Improve MT evaluation

Tree Rewrite Rules for RTE

Learning Rewrite Rules for TE

(Zanzotto, Moschitti, 2006)

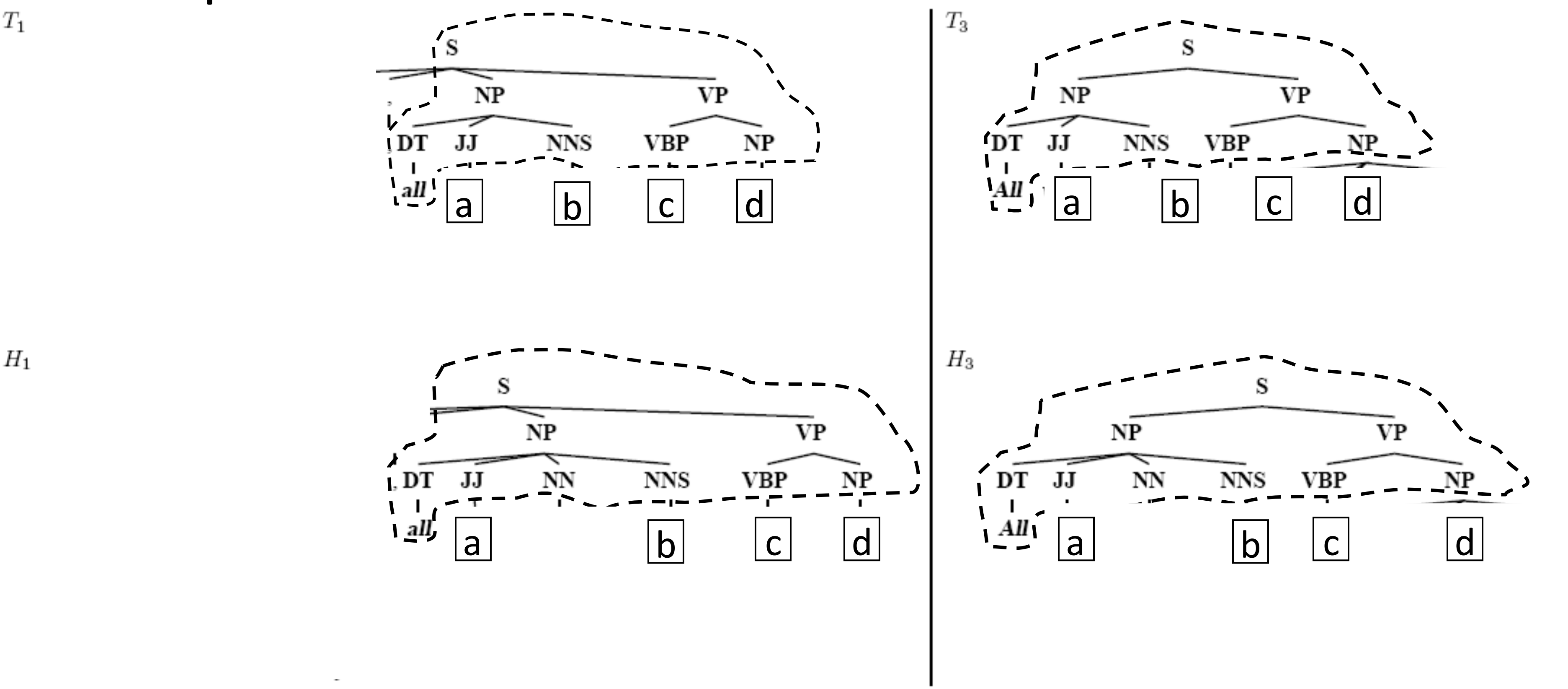
Can we use syntactic tree similarity?



Learning Rewrite Rules for TE

Can we use syntactic tree similarity? YES!

Implied structures can lead to *rewrite rules*

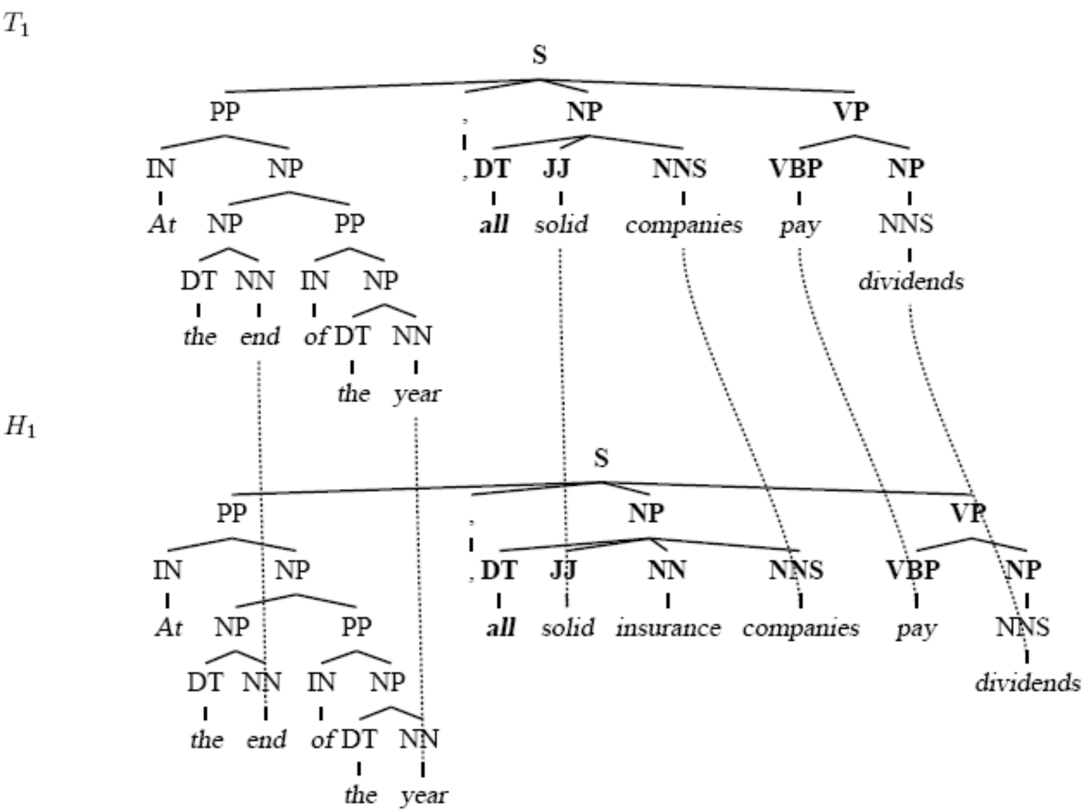


Learning Rewrite Rules for TE

Intra-pair operations

(Zanzotto, Moschitti, 2006)

→ Finding ***anchors***

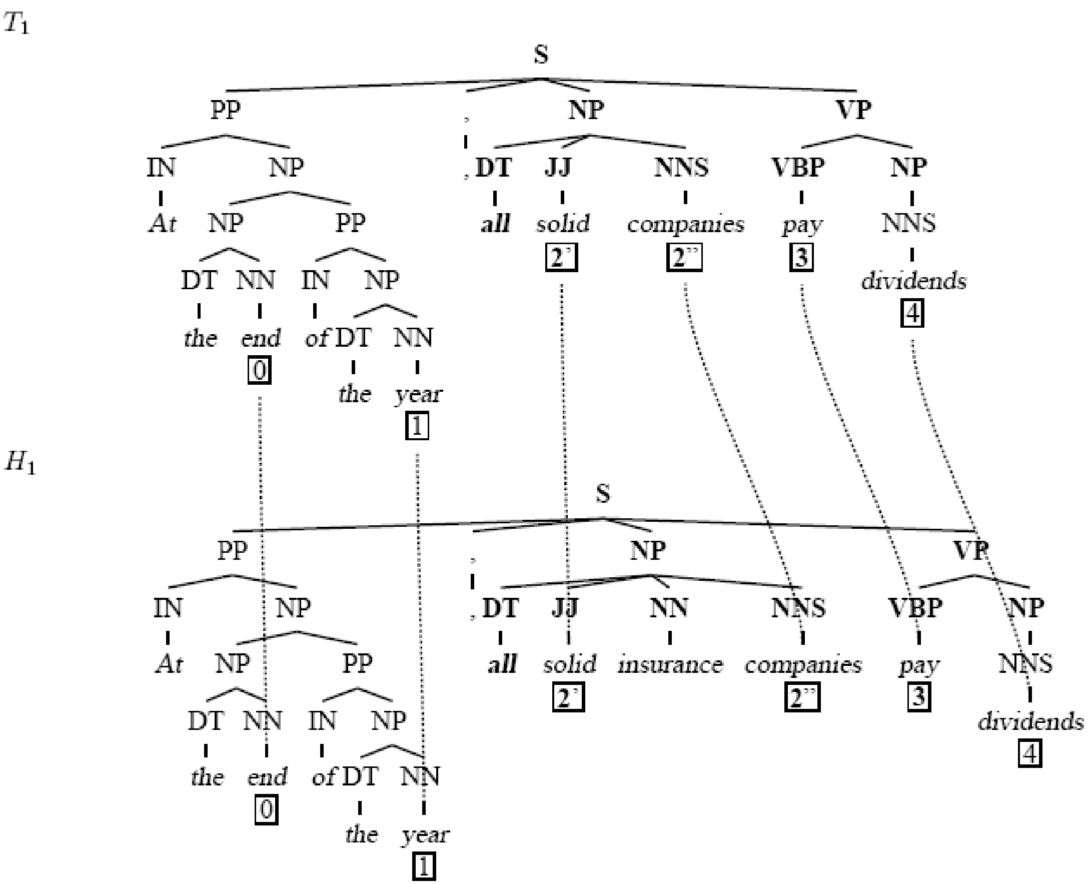


Learning Rewrite Rules for TE

Intra-pair operations

→Finding ***anchors***

→Naming anchors with ***placeholders***



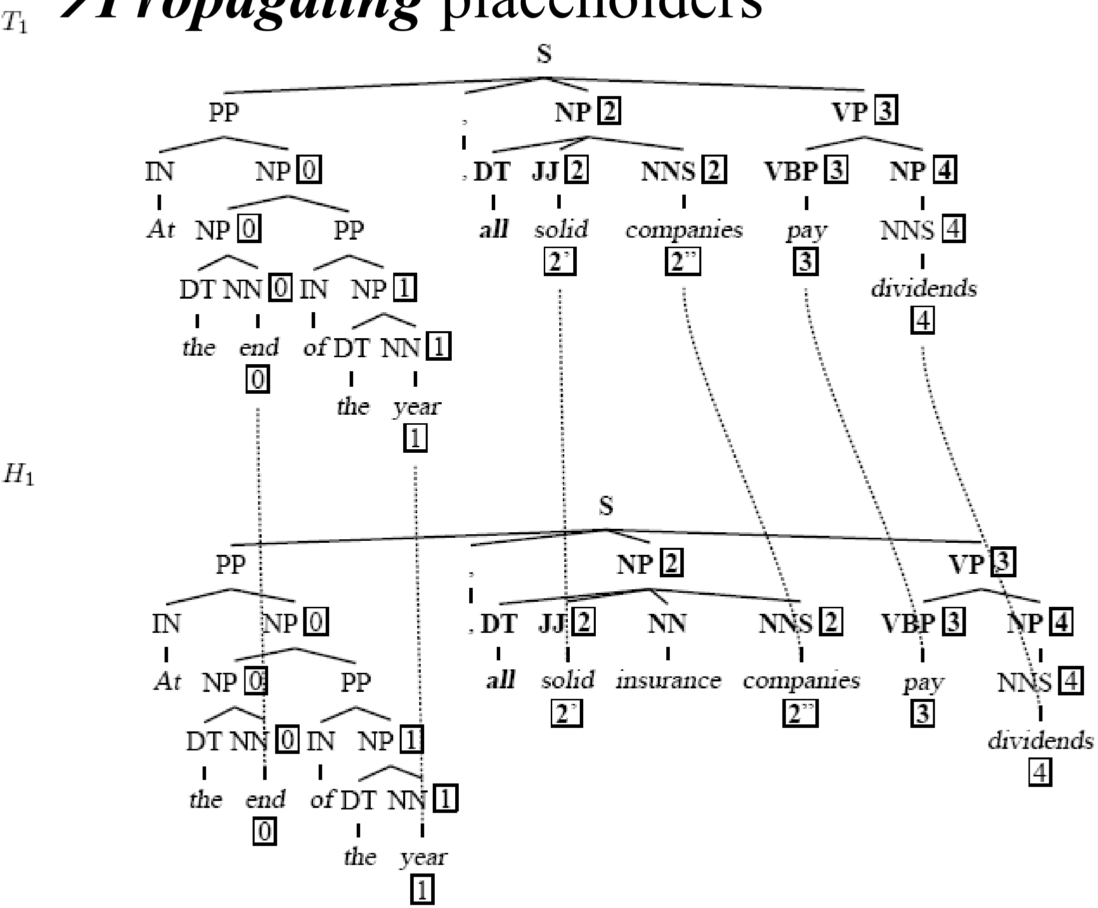
Learning Rewrite Rules for TE

Intra-pair operations

→Finding ***anchors***

→Naming anchors with ***placeholders***

→***Propagating*** placeholders



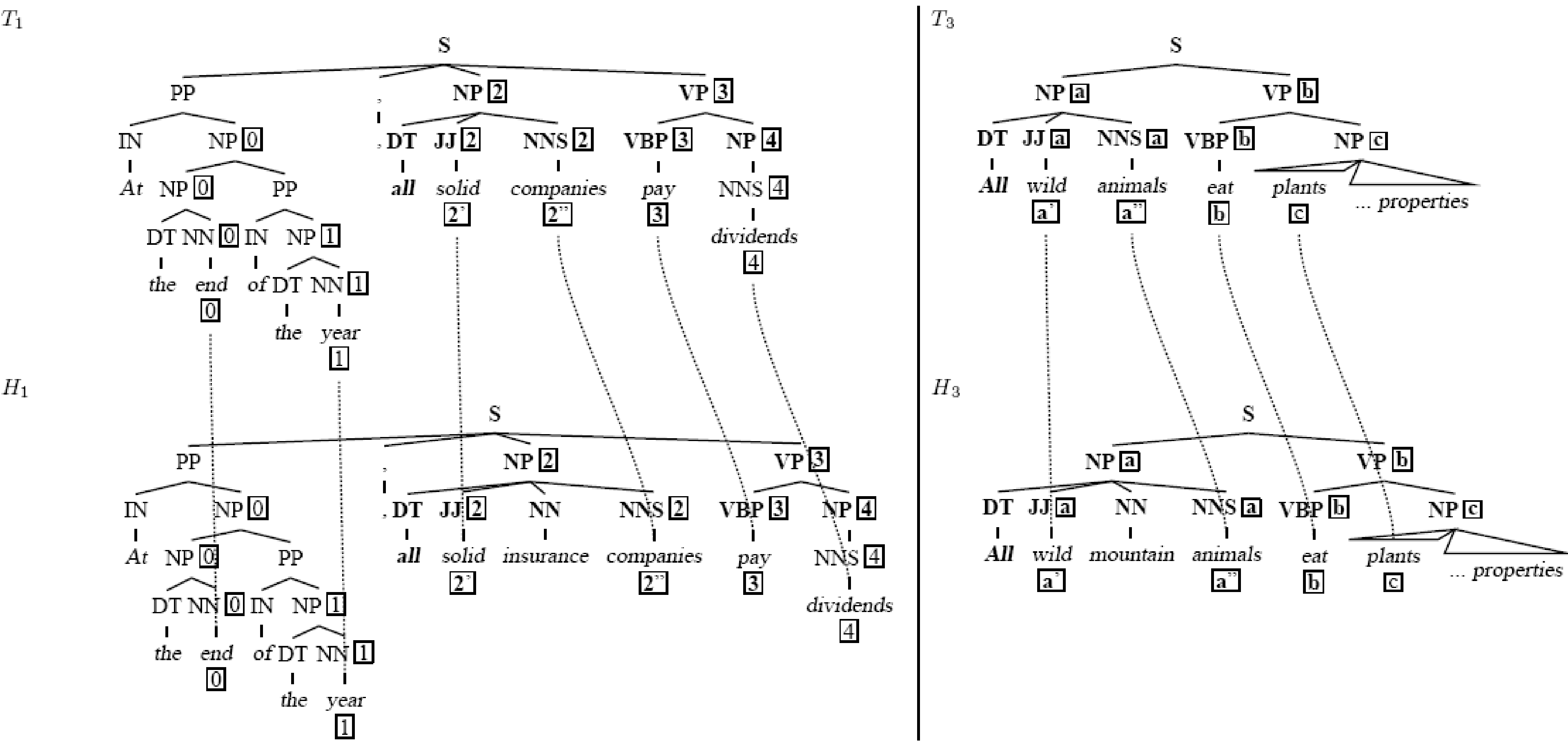
Learning Rewrite Rules for TE

Intra-pair operations ***Cross-pair operations*** (Zanzotto, Moschitti, 2006)

→Finding ***anchors***

→Naming anchors with ***placeholders***

→***Propagating*** placeholders



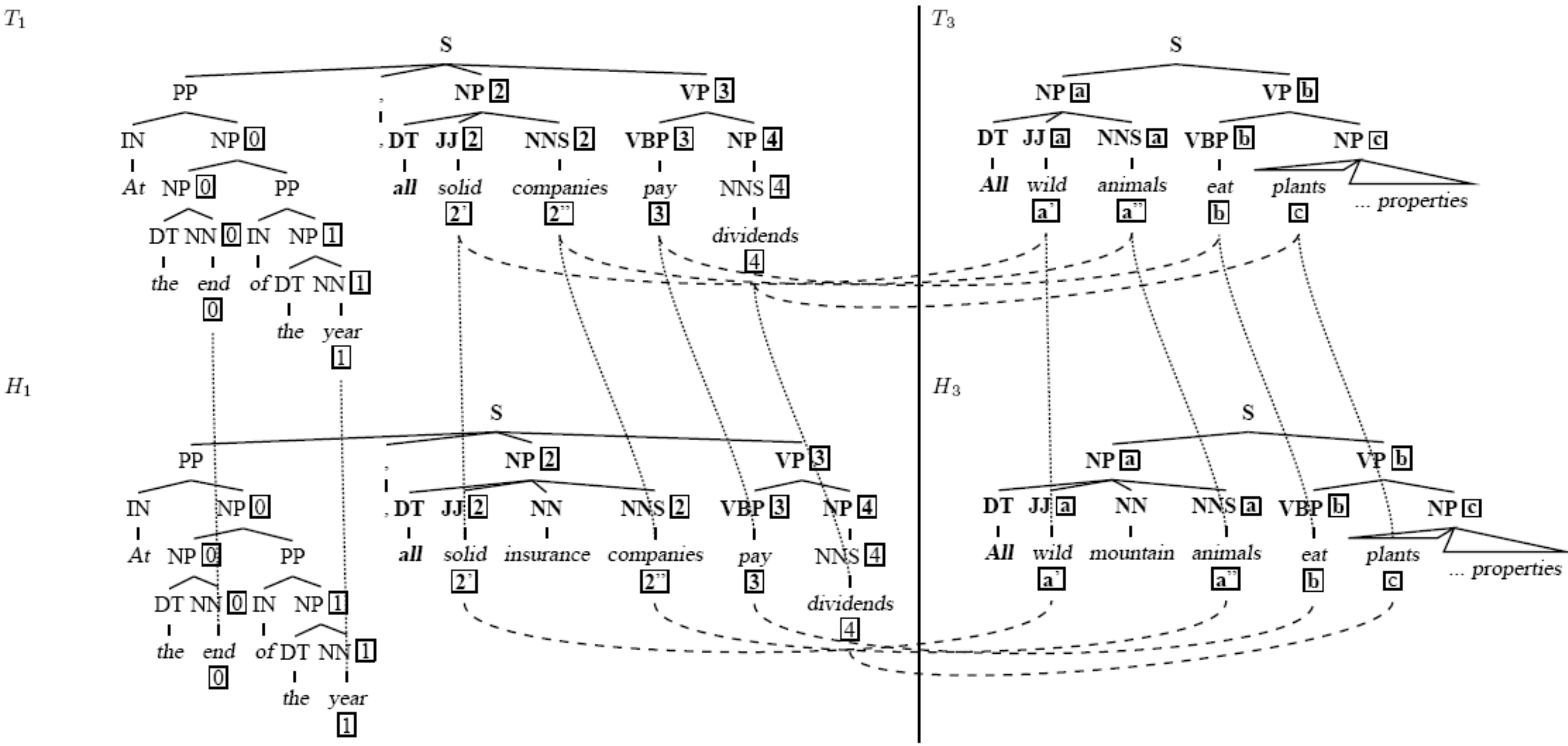
Learning Rewrite Rules for TE

Intra-pair operations

→Finding ***anchors***
→Naming anchors with ***placeholders***
→***Propagating*** placeholders

Cross-pair operations

→Matching placeholders across pairs



Learning Rewrite Rules for TE

Intra-pair operations

→Finding ***anchors***

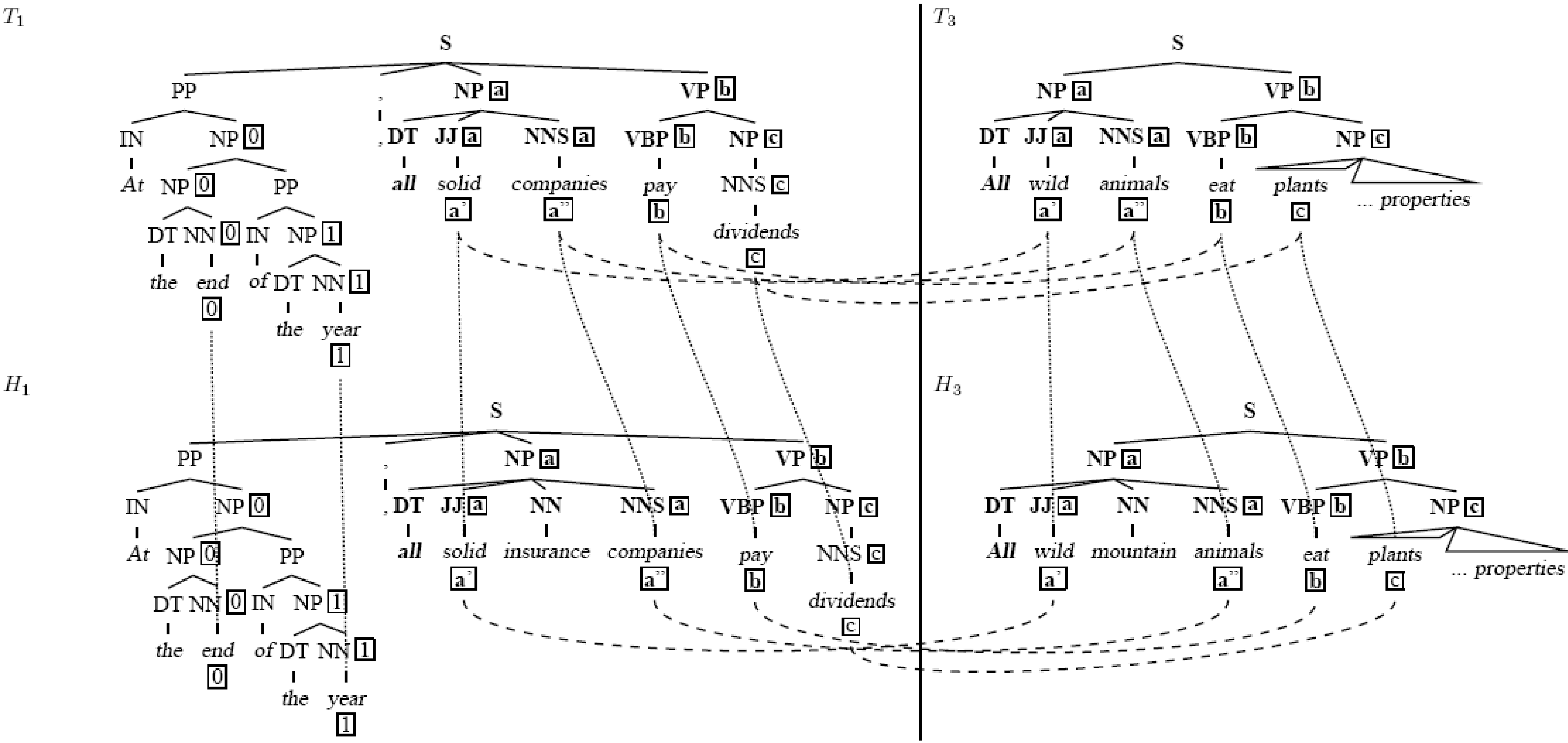
→Naming anchors with ***placeholders***

→***Propagating*** placeholders

Cross-pair operations

→Matching placeholders across pairs

→Renaming placeholders



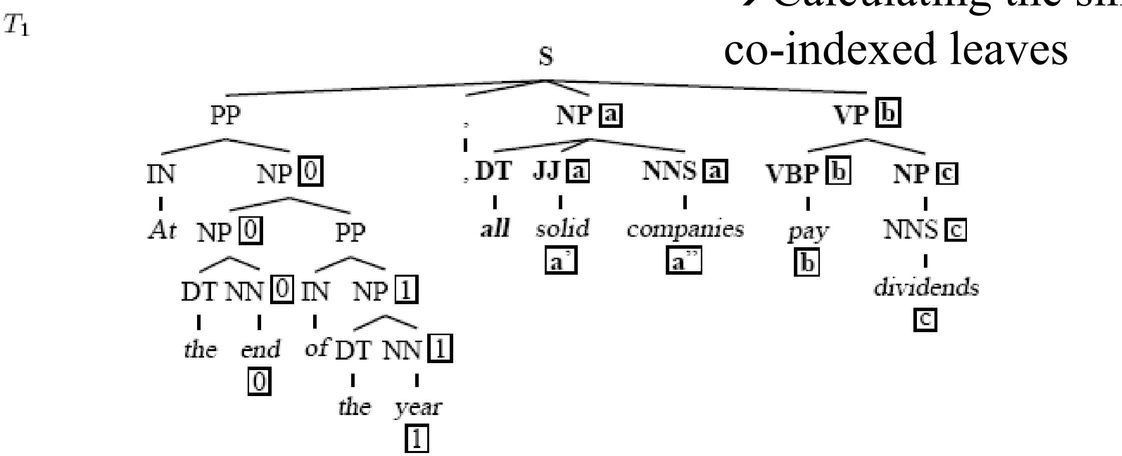
Learning Rewrite Rules for TE

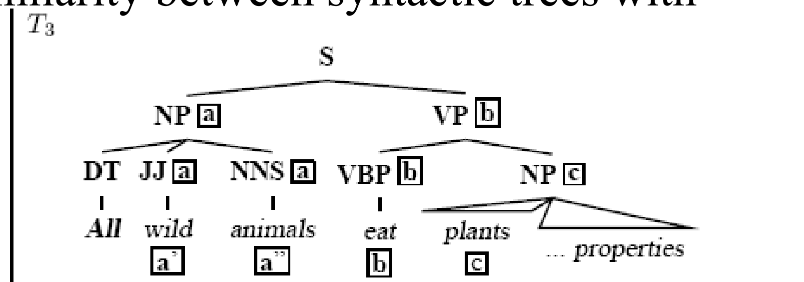
Intra-pair operations

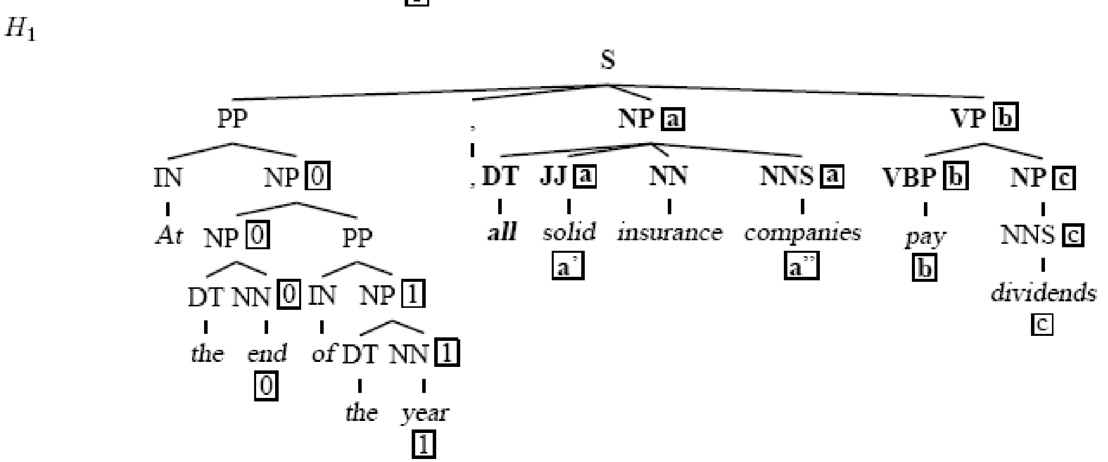
→Finding ***anchors***
→Naming anchors with ***placeholders***
→***Propagating*** placeholders

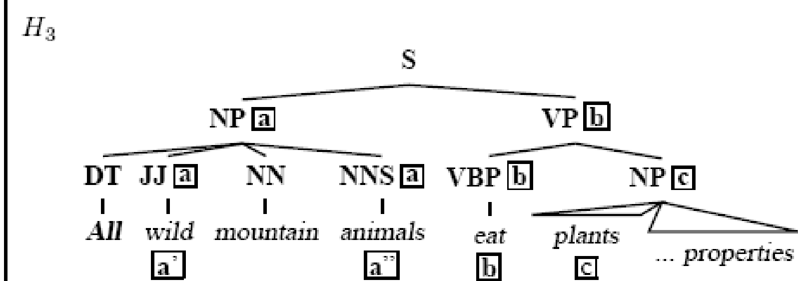
Cross-pair operations

→Matching placeholders across pairs
→Renaming placeholders
→Calculating the similarity between syntactic trees with co-indexed leaves









Learning Rewrite Rules for TE

Intra-pair operations

→Finding ***anchors***
→Naming anchors with ***placeholders***
→***Propagating*** placeholders

Cross-pair operations

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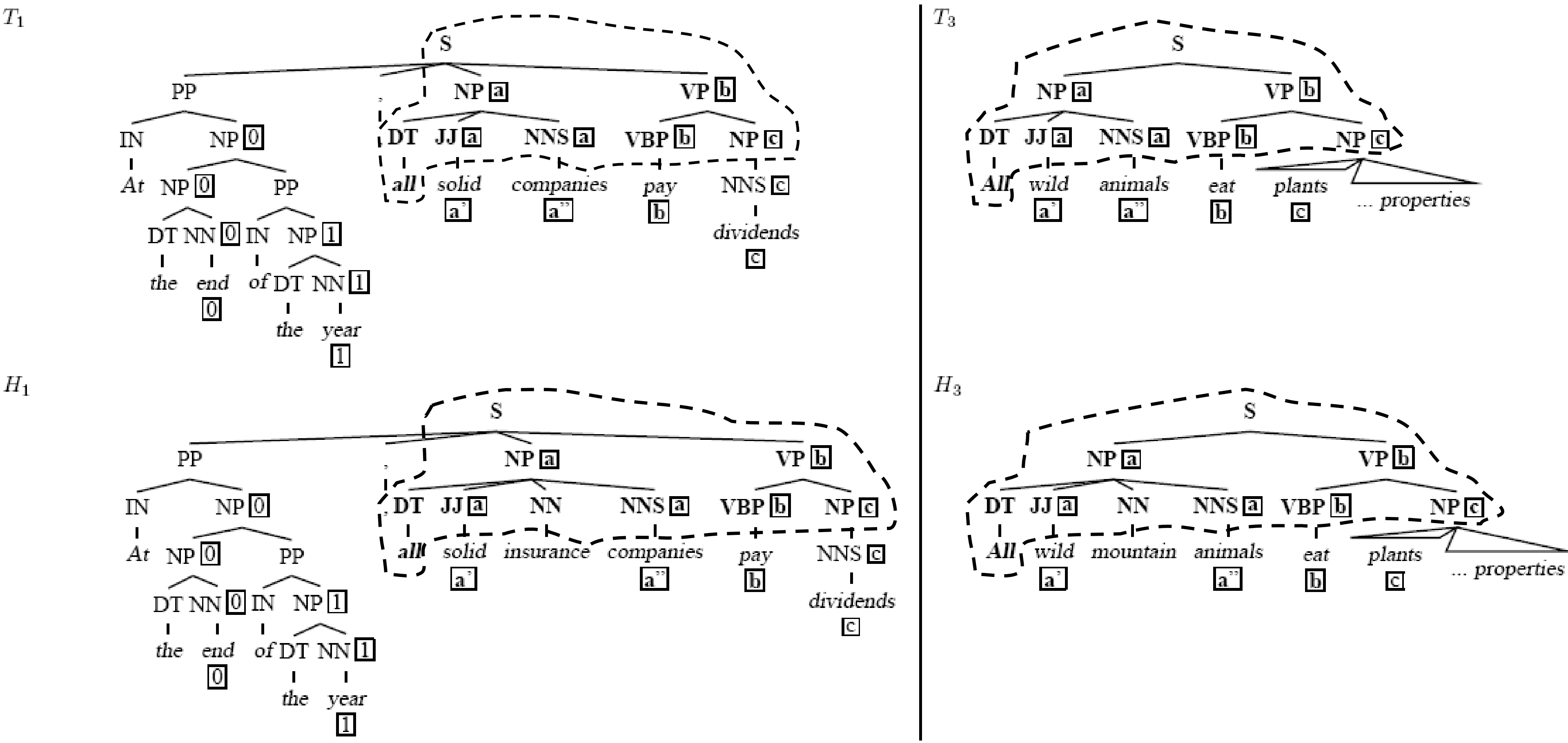


Alignment for Entailment

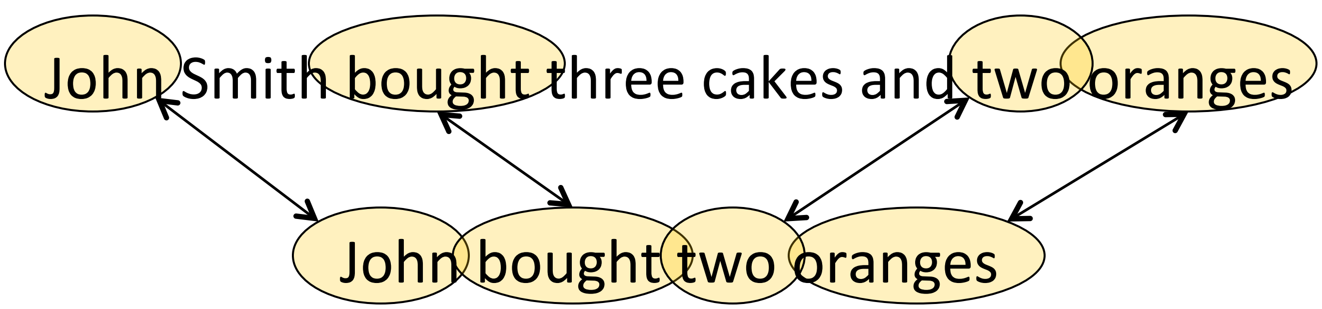
Alignment for RTE

- Idea: break entailment into smaller decisions
- Alignment as a way to recognize relevant Text portions
- Portions of text compared using closed set of operations
  - Operations include lexical similarity, structural similarity
  - Possible to define concepts such as semantic containment and semantic exclusion
  - May be extended using Knowledge bases

Alignment for RTE

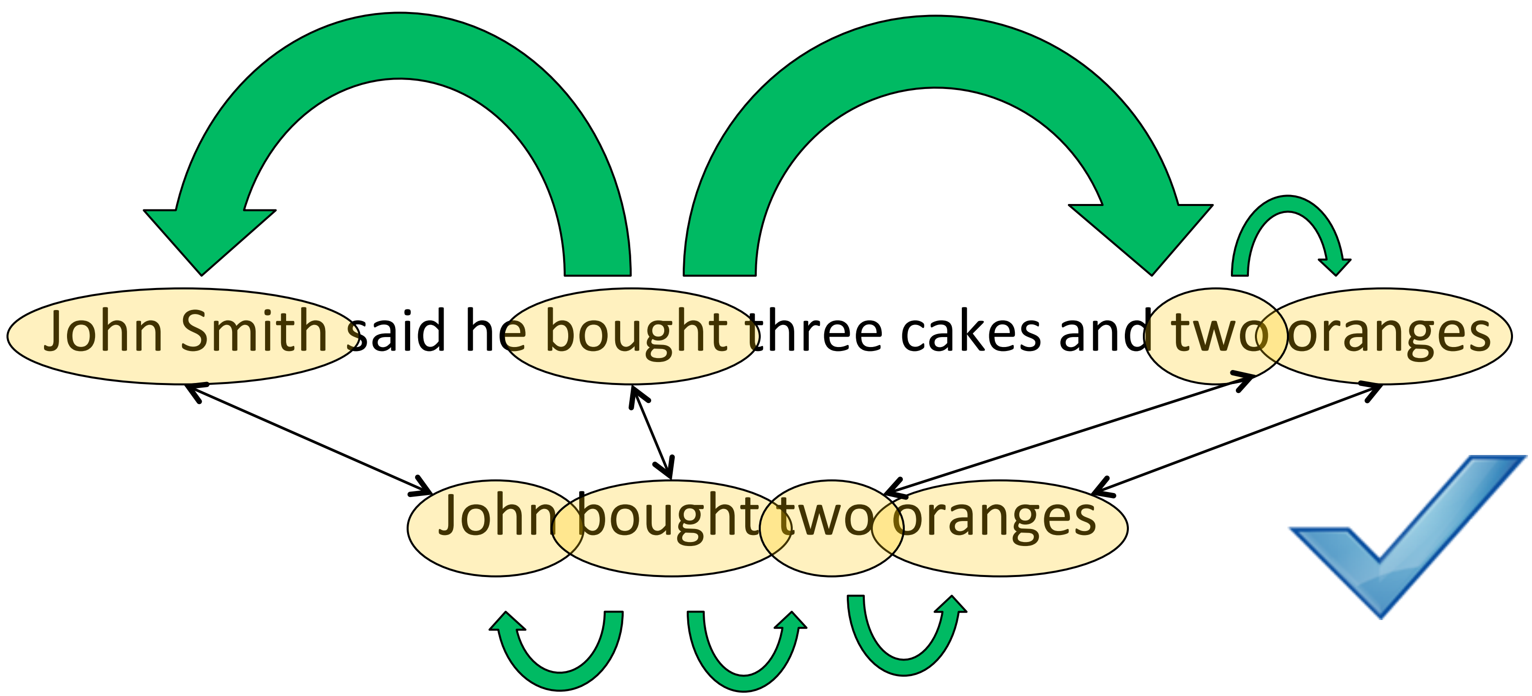
- Impose ***constraints*** on the aggregate set of comparisons we entertain
- E.g. each Hypothesis element can match at most one Text element

Alignment: a mapping from elements in the Hypothesis to elements in the Text under specified constraints



Shallow Alignment as Focus Of Attention

- Pick a "good" shallow alignment
- Use this to query deeper structure/extract features



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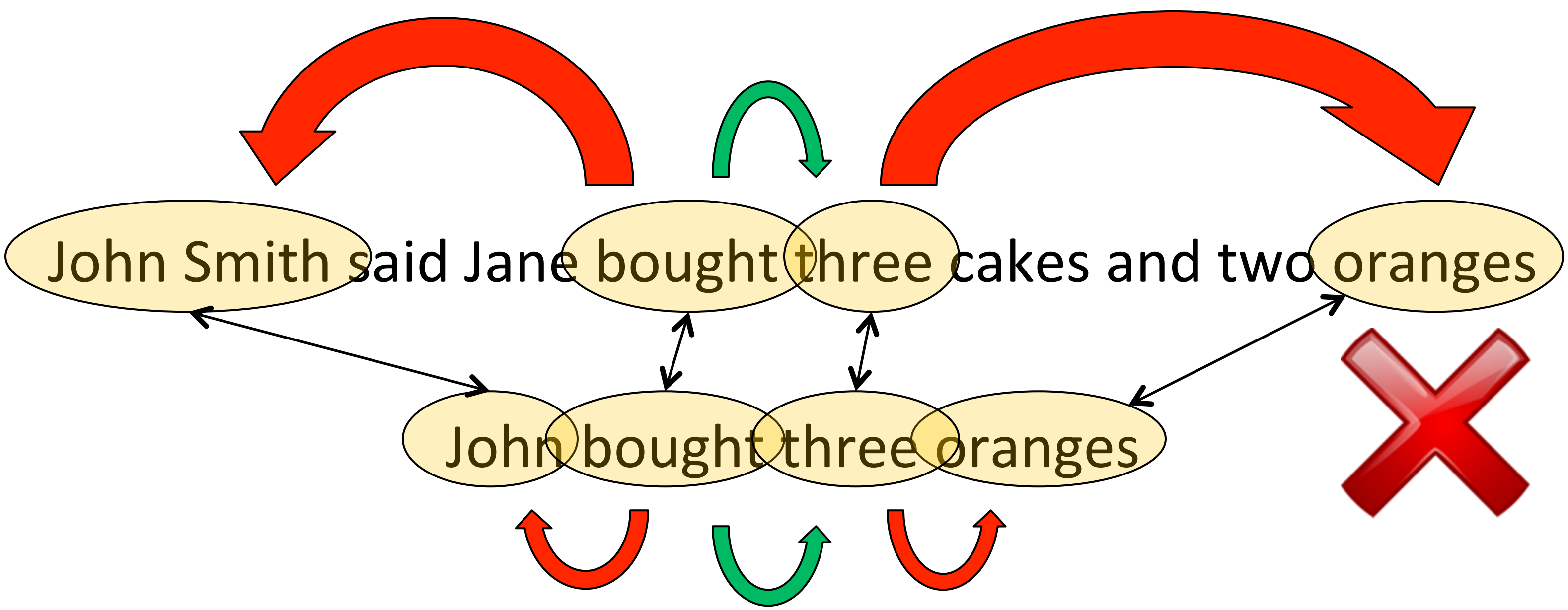
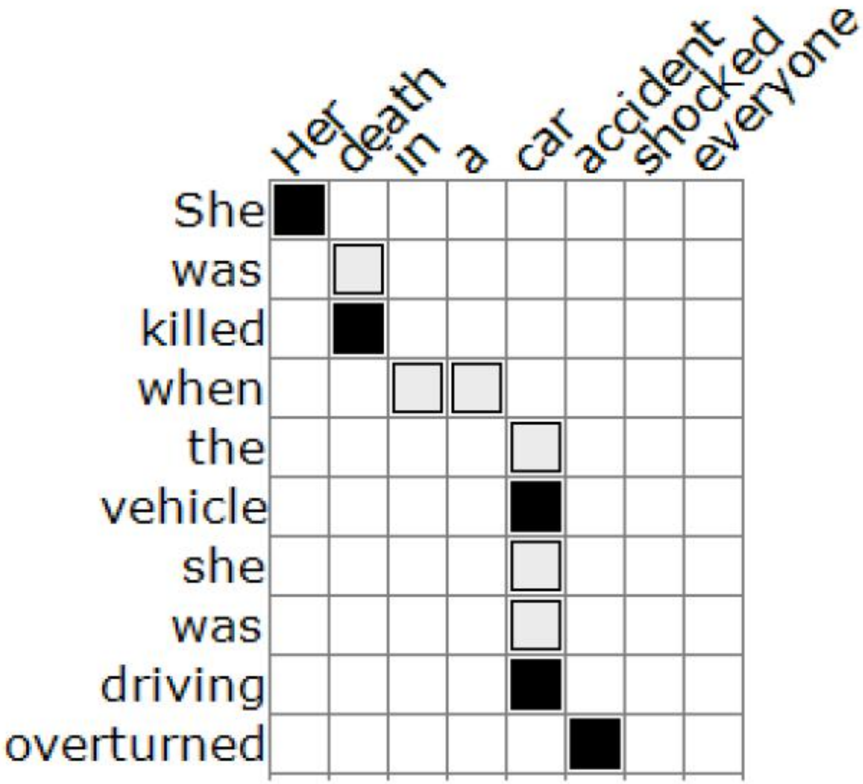


Alignment for RTE

Chambers et al. 2007, deMarneffe et al. 2007

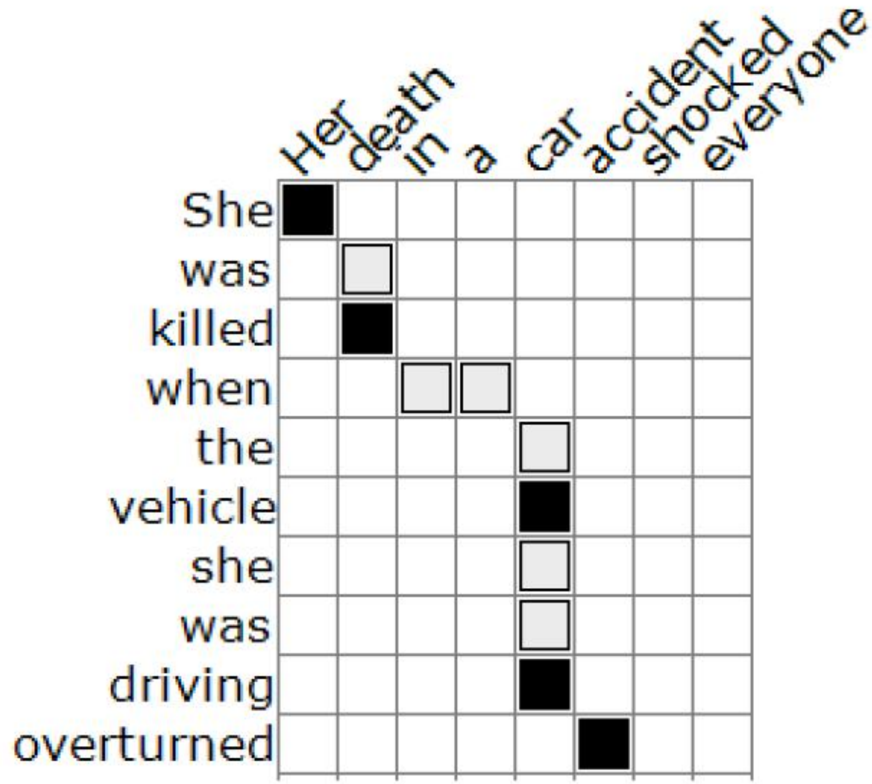
- learn "alignment" from lexical-level labelings
  - Intuition: abstract away some logical structure, irrelevant content
  - Identify the parts of T that "support" H
- Identify "relevant" parts of T via word, edge weight vectors



Alignment for RTE

Chambers et al. 2007, deMarneffe et al. 2007

- Use alignment to extract features for discerning "entailed" from "not entailed", using deeper semantic structure



$$\text{score}(a) = \sum_{i \in h} \text{score}_w(h_i, a(h_i)) + \sum_{(i,j) \in e(h)} \text{score}_e((h_i, h_j), (a(h_i), a(h_j)))$$

Why does alignment work? (when it does...)

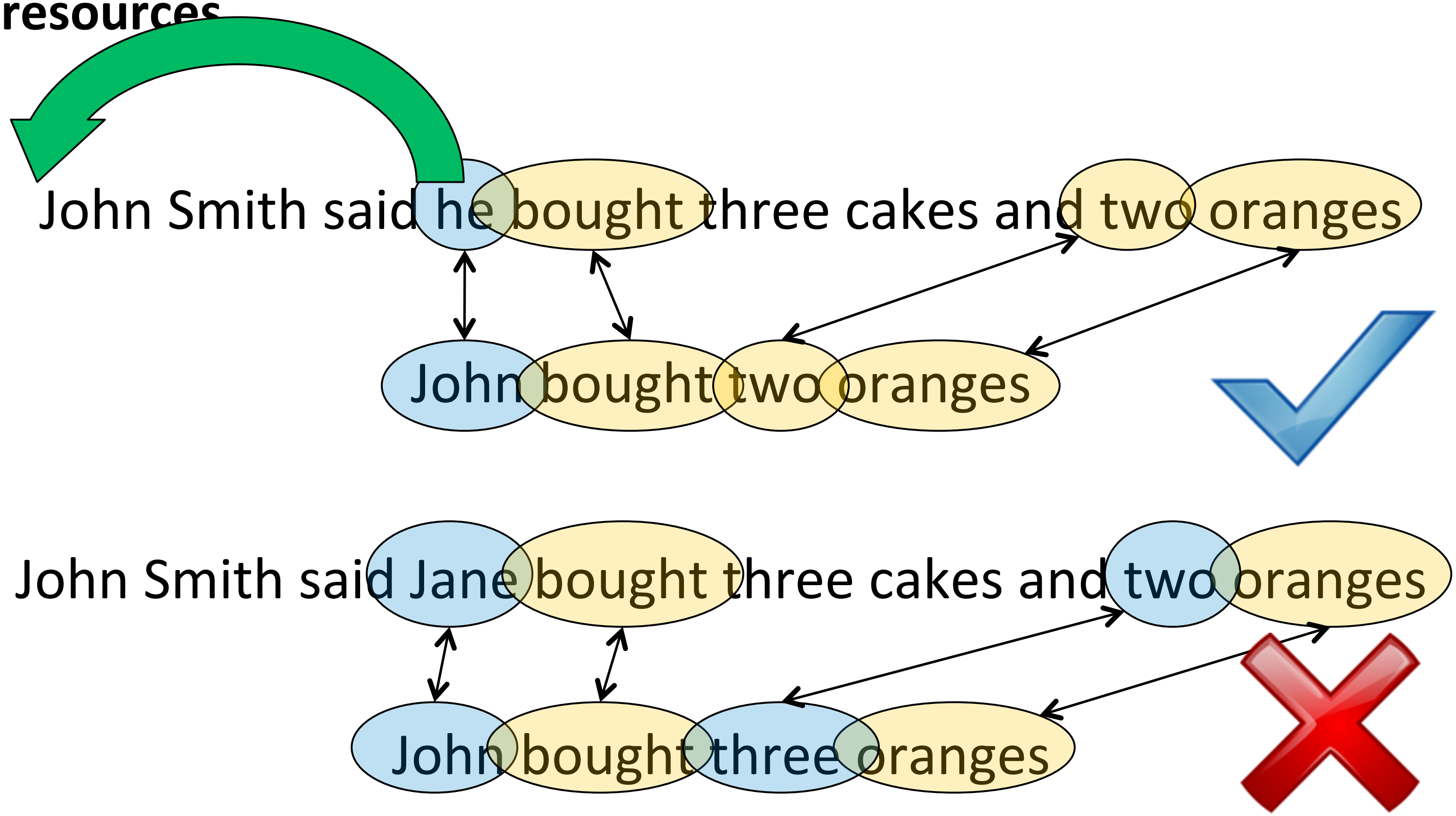
- Comparable to similarity metric approach
  - Trying to capture deeper structure
- Supports discriminative ML by generating sufficiently coarse features
- Works best on cases where content in H is explicit in T
  - But with better deep structure/appropriate representation, expect to do better
- Better inputs => better alignments
  - Problem: pipeline effect for erroneous annotations AND for erroneous alignment

Problems with alignment

- Mapping “relevant” parts may be correct intuition, but “relevant” seems to depend on deep structure
  - Fixed heuristic/learned mapping based on shallow cues is problematic
  - Distance is not a reliable proxy for deep structure
- May be multiple match candidates for many H constituent (i.e., shallow alignment may pick the wrong one)
  - Alignment constraints introduce a problem in fixed two-stage system

Alternative: Using Structure as Focus Of Attention

- **Find best structural match**
- **Base entailment results on results of shallow comparison resources**



Deep-first approach

- Getting correct structure is HARD
  - P(all correct) = 0.9^3 per predicate-argument structure*

  *based on SRL training domain, i.e. optimistic
- Errors in deep structure → problem selecting correct local decision
- Other preprocessing errors – e.g. Coreference – will propagate in same way as shallow-first approach

Insights

Semantic Phenomena

- Conjunctions
  - Jake and Jill ran up the hill — Jake ran up the hill
  - Jake and Jill met on the hill — *Jake met on the hill
- Clausal modifiers

  T: But celebrations were muted as many Iranians observed a Shi'ite mourning month.

  H: Many Iranians observed a Shi'ite mourning month.
- Relative clauses
  - The assailants fired six bullets at the car, which carried Vladimir Skobtsov.
  - The car carried Vladimir Skobtsov.

Semantic Phenomena

- Appositives
  - Frank Robinson, a one-time manager of the Indians, has the distinction for the NL…
  - Frank Robinson is a one-time manager of the Indians.
- Passive/active
  - We have been approached by the investment banker.
  - The investment banker approached us.
- Genitive modifier
  - Malaysia's crude palm oil output has risen.
  - The crude palm oil output of Malaysia has risen.

Logical Structure

- Factivity: Uncovering the context in which a verb phrase is embedded
  - We believe the terrorists entered the building.
- Polarity : negative markers or a negation-denoting verb (e.g. *deny, refuse, fail*)
  - The terrorists failed to enter the building.
  - Terrorists never entered the building.
- Modality/Negation Dealing with modal auxiliary verbs (can, must, should), that modify verbs' meanings
  - The terrorists might not have entered the building.
- Can be hard to identify the scope of the modifier.

Logical structure cont'd

- Superlatives/Comparatives/Monotonicity: inflecting adjectives or adverbs.
  - Examples:

    TEXT: All companies are required to file reports at the end of the fiscal year.

    HYP 1: All tax companies are required to file reports. ✓

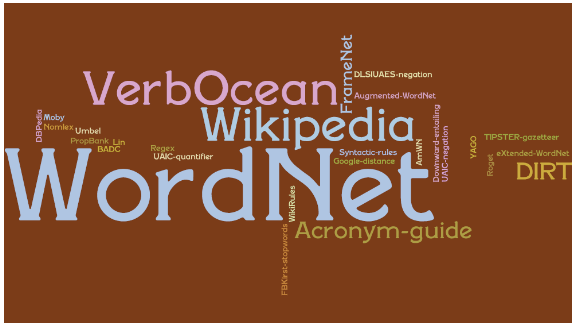
    Hyp 2: All companies are required to file tax reports. ✗

- Quantifiers, determiners and articles

    Hyp 3: Some companies are required to file reports. ✓

    Hyp 4: 300 companies are required to file reports. ✗

Knowledge Acquisition for Entailment



The Knowledge Bottleneck

- Linguistic and world knowledge – integral part of RTE
- Missing knowledge resources – a barrier for further advances in RTE (Bar-Haim et al., 2006, Giampiccolo et al., 2007)

<u>We need</u>:

- Broad-coverage entailment knowledge resources
- Models for applying knowledge selectively in context
  - Even using WordNet effectively is still an open issue (WSD)

Entailment Rules

- Most of the knowledge utilized by TE systems may be represented by entailment rules
- *<u>Entailment rule</u>*: entailment relation between two text fragments, possibly with variables
  - *lhs* → *rhs* (*entailing* → *entailed*)
  - Paraphrases: bidirectional entailment rules

  New York → *city* (lexical rule)

  X buy Y from Z ↔ *Z sell Y to X* (template-based rule)

  Y is V[ed] by X → *X V Y*

- Local inferences – combined to form complex entailments

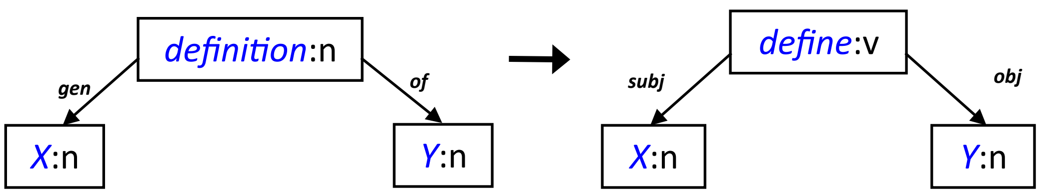
Template-based Rules

- Rules between templates with shared arguments
  - Templates are text fragments with variables
  - Highly generic representation – useful also for syntactic-based rules

X buy Y → *X pay for Y*   *X snore* → *X sleep*

X's definition of Y ↔ *X define Y*   *X's definition by Y* ↔ *Y define X*

- Typically represented as transformations between parse sub-trees



  - Additional syntactic annotation for semantic disambiguation (Macleod et al., 1998; Szpektor and Dagan, 2009)

X broke$_{intransitive}$ → *X was damaged* vs. *X broke*$_{transitive}$ → *X damaged*

Entailment Rule Acquisition

The WordNet Lexicon (Miller, 1995)

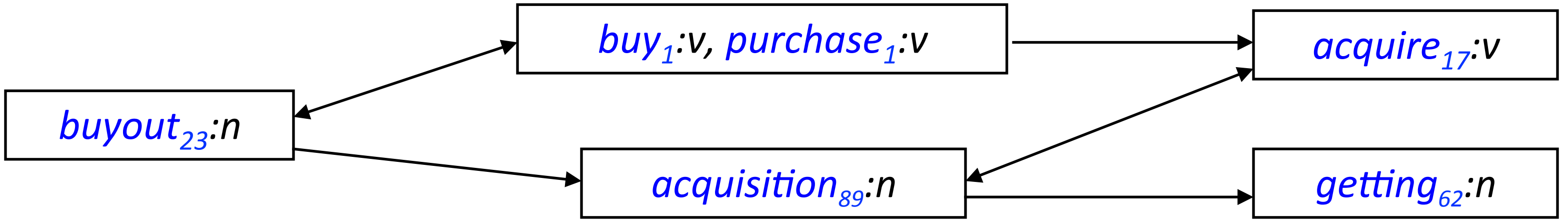
- WordNet – lexical database organized by meanings (*synsets)*

  S1: buy, purchase (obtain by purchase)

  S2: bribe, corrupt, buy, . . . (make illegal payments to in exchange for favors . . .)

- WordNet contains lexical relations – some useful for inference
  - hypernymy (*capital* → *city*), instance-of (*Paris* → *city*), derivationally-related (*acquire* ↔ *acquisition*), meronymy (*car* → *wheel*)

- Relations define a directed "entailment" graph for terms
  - Traverse the graph to generate entailment rules
  - Measure distance between terms on the graph (WordNet similarity)



WordNet Extensions

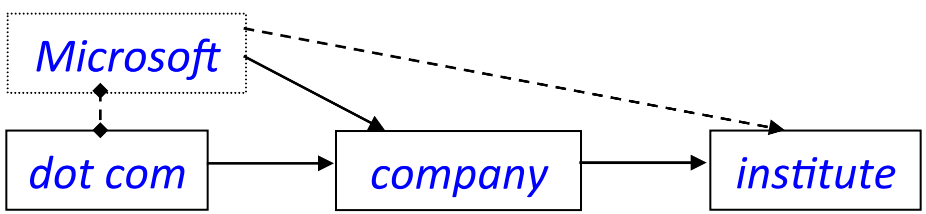
- ***eXtended WordNet*** (Moldovan and Rus, 2001)
  automatically generate rules from WordNet glosses

  S: excellent, first-class (of the highest quality)

  $\Downarrow$

  X is excellent → *X is of the highest quality*

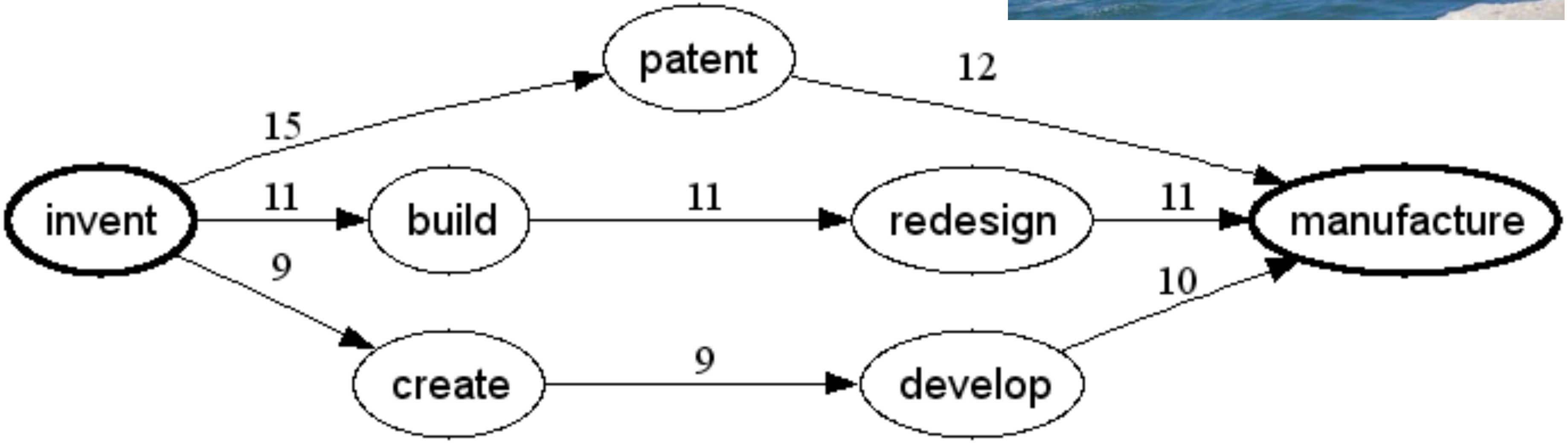
- ***Augmented WordNet*** (Snow et al., 2006)
  automatically add new terms to the WordNet graph
  1. Extract hyponym candidates using a *hypernymy* classifier
  2. Greedily add the candidate that best meets the transitivity constraints in the graph



VerbOcean

(Chklovski and Pantel, 2004)

... Jump Right In!



Example: VerbOcean's temporal precedence chains (the "happens-before" relation) between *invent* and *manufacture* shown with edge weights

VerbOcean (Chklovski and Pantel, 2004)

- Pattern-based approach for broad-coverage semantic network of verbs

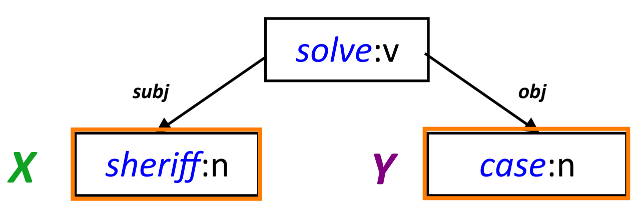
  similarity (*produce* :: *create*)
  strength (*permit* :: *authorize*)
  antonymy (*open* :: *close*)
  happens-before (*buy* :: *own*)
  enablement (*fight* :: *win*)

1. Start with highly associated candidate verb-pair (*fight* :: *win*)
2. Query the Web with manually constructed patterns for each relation
   – *enablement*: *X*ed * by *Y*ing the (*won by fighting the*)
   – *happens-before*: *X*ed and then *Y*ed (*fought and then won*)
3. Score each verb-pair/pattern co-occurrence (PMI)
   – A relation is considered correct if its pattern score exceeds a threshold
4. Prune based on consistency of selected relations with each other
   – "If *happens-before* is not detected, ignore detection of *enablement*"

Distributional Similarity between Frames

- Similar to the lexical case
  - Templates – often paths in dependency parse-trees
  - Features – argument instantiations
- DIRT: (Lin and Pantel, 2001)
  1. Create a word co-occurrence vector for each variable in a binary template
  2. Templates with similar vectors are considered semantically related
     - Lin similarity measure

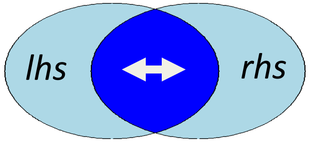
The sheriff solved the case

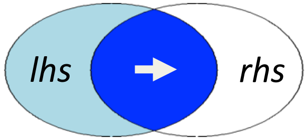


X find a solution to Y		***X solve Y***	
Slot X	**Slot Y**	**Slot X**	**Slot Y**
commission	*strike*	*committee*	*problem*
committee	*crisis*	*clout*	*crisis*
government	*problem*	*government*	*mystery*
legislator	*budget deficit*	*petition*	*woe*
sheriff	*murder*	*sheriff*	*case*

Directional Similarity Measures

- How to find the direction of asymmetric relations?
  - Feature distribution (Lee, 1999)
  - Feature inclusion (Weeds and Weir, 2003; Geffet and Dagan, 2005)

symmetric: 

inclusion: 

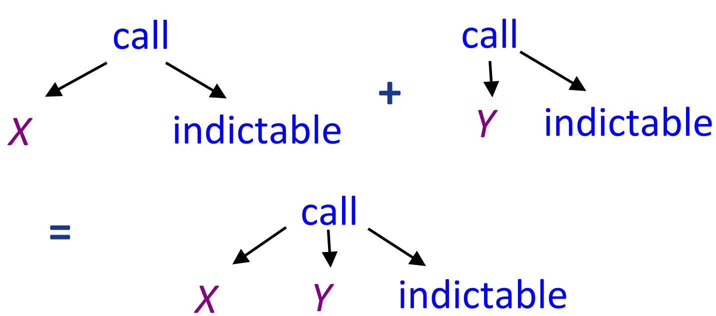
Top-10 entailing words for *food*

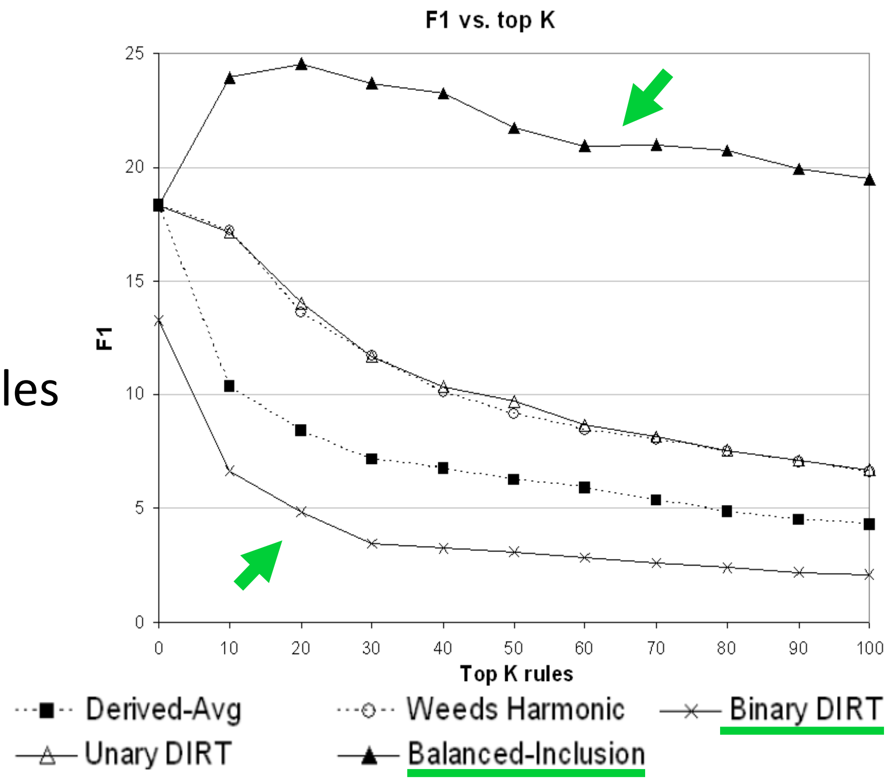
symmetric (Lin 1998)	*meat, beverage, goods, medicine, drink, clothing, food stuff, textile, fruit, feed*
directional (Kotlerman et al. 2009)	*food stuff, food product, food company, noodle, canned food, feed, salad dressing, bread, food aid, drink*

Directional Distributional Similarity

IE experiment

- Directional measure outperformed symmetric measures
- Unary rules outperformed binary rules





Entailment Rule Application

Ambiguity in Rule Application

- A rule is considered correct if it yields correct inferences when applied in valid contexts

  X charge *Y* → *X* bill *Y*

  valid context: *"Telemarketers charged the account"*
  → *Telemarketers billed the account*

  invalid context: *"Prosecutors charged Nichols with bombing"*
  → *Prosecutors billed Nichols*

- Problem: term disambiguation in context
  - Known problem in many NLP apps, e.g. QA, IE, RTE search task
  - Less dominant in classic RTE datasets
    - The T-H pairs were usually chosen within the same context

Unsupervised Context Models

- <u>Task</u>: decide whether a context is valid for rule application

    t: *Children acquire new languages*

    r: *acquire* → *own*

- Typical Word Sense Disambiguation (WSD) is not enough
  - No sense-annotated training data for large-scale resources
  - Inference applicability goes beyond senses

    produce milk vs. *produce eggs* for *produce* → *lay*

- Use unsupervised context models
  - Strategy: detect contexts that are common to *lhs* and *rhs*
  - Unlike WordNet, “senses” are modelled by surface words
    - Not explicit sense-ids

Graph-based Textual Entailment

Predicative Entailment Rules

- Extracting Knowledge from medical text
- NLP for Health Intelligence

Y is a symptom of X ⇒ X cause Y

X cause an increase in Y ⇒ X affect Y

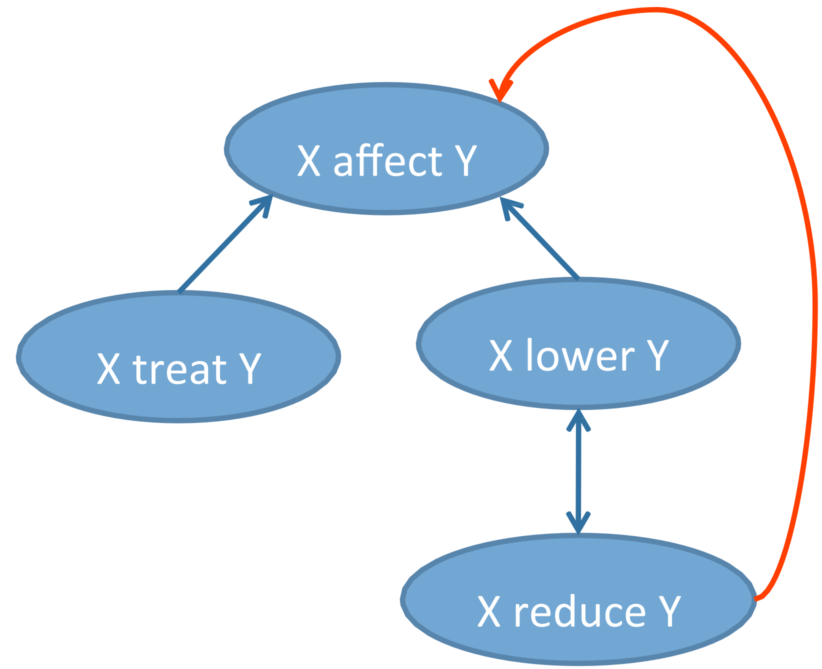
X's treatment of Y ⇒ X treat Y

treat(Norvasc,BP)
affect(Norvasc,BP)
treat(insulin,metab.)
affect(diet,diabetes)
raise(wine,faRgue)
lower(wine,BP)

Entailment Graphs

X affect Y ⇒ X treat Y	✗
X treat Y ⇒ X affect Y	✓
X affect Y ⇒ X lower Y	✗
X lower Y ⇒ X affect Y	✓
…	
…	
X lower Y ⇒ X reduce Y	✓
X reduce Y ⇒ X lower Y	✓

⇨



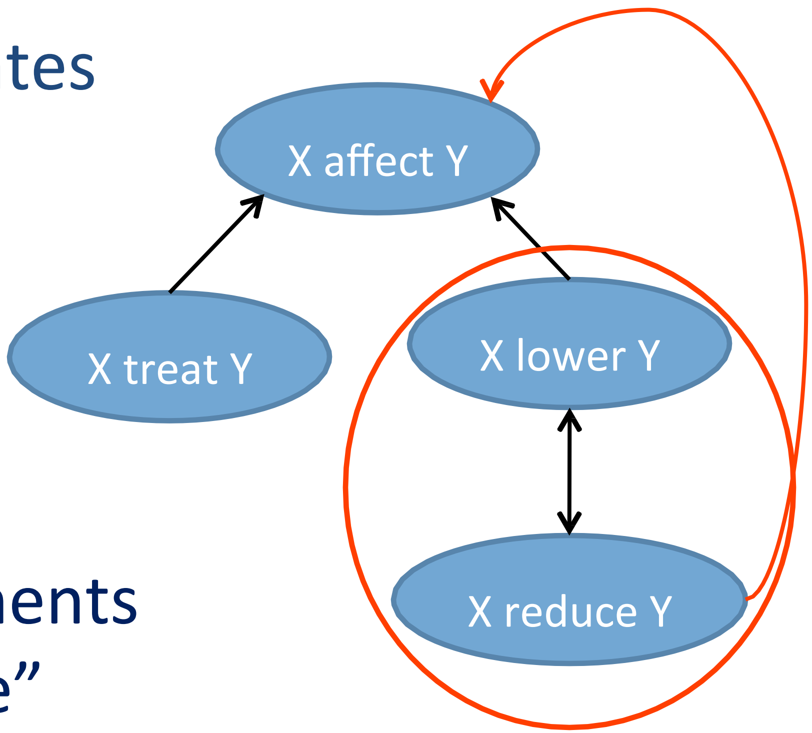
Learning rules automatically from data

Berant et al system learns ~10,000,000 (noisy) rules

Structural constraints help reducing the noise in the learned rules

Entailment Graphs

- Nodes: propositional templates
- Edges: entailment rules



Properties

- Entailment is **transitive**
- Strong connectivity components correspond to "equivalence"
    - Caveat: ambiguity

Learning Entailment Graph Edges

Input: Corpus *C*

Output: Entailment graph $G = (P,E)$

1. Extract propositional templates *P* from *C*
2. Train a **local** entailment classifier: given (p_1,p_2), estimate whether $p_1 \rightarrow\rightarrow p_2$
3. Decoding: Find the edges of the graph using the local probabilities and a transitivity constraint

Constrained Optimization
with
Integer Linear Programming

Graph Objective Function

- Use local classifier probabilities p_{ij} to express the graph probability:

$$\hat{G} = \arg\max_{X} \sum_{i \neq j} w_{ij} \cdot x_{ij} \qquad x_{ij} = \begin{cases} 1 & i \rightarrow j \\ 0 & \text{else} \end{cases}$$

$$w_{ij} = \log \frac{p_{ij} \cdot \theta}{(1 - p_{ij}) \cdot (1 - \theta)}$$

"density" prior

Global Learning of Edges

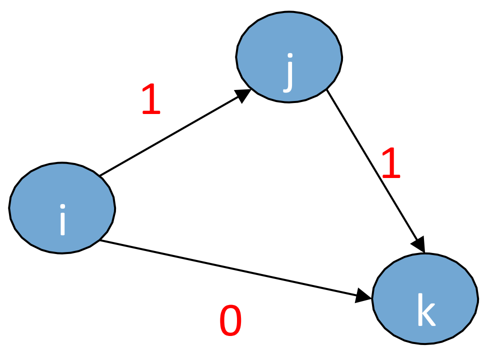
<u>Input</u>: Set of nodes *V*, weighting function $w{:}V\times V \rightarrow R$
<u>Output</u>: Set of directed edges *E* that maximizes the objective function under a **global transitivity constraint**

- Problem is NP-hard:
  - Reduction from "Transitive Subgraph" (Yannakakis, 1978)

<u>Input</u>: Directed graph $G = (V,E)$
<u>Output</u>: Maximal set of edges $A \subseteq E$ such that $G' = (V,A)$ is transitive

- Integer Linear Programming Formulation

Integer Linear Program



$$\hat{G} = \arg\max \sum_{i \neq j} w_{ij} \cdot \boxed{x_{ij}}$$

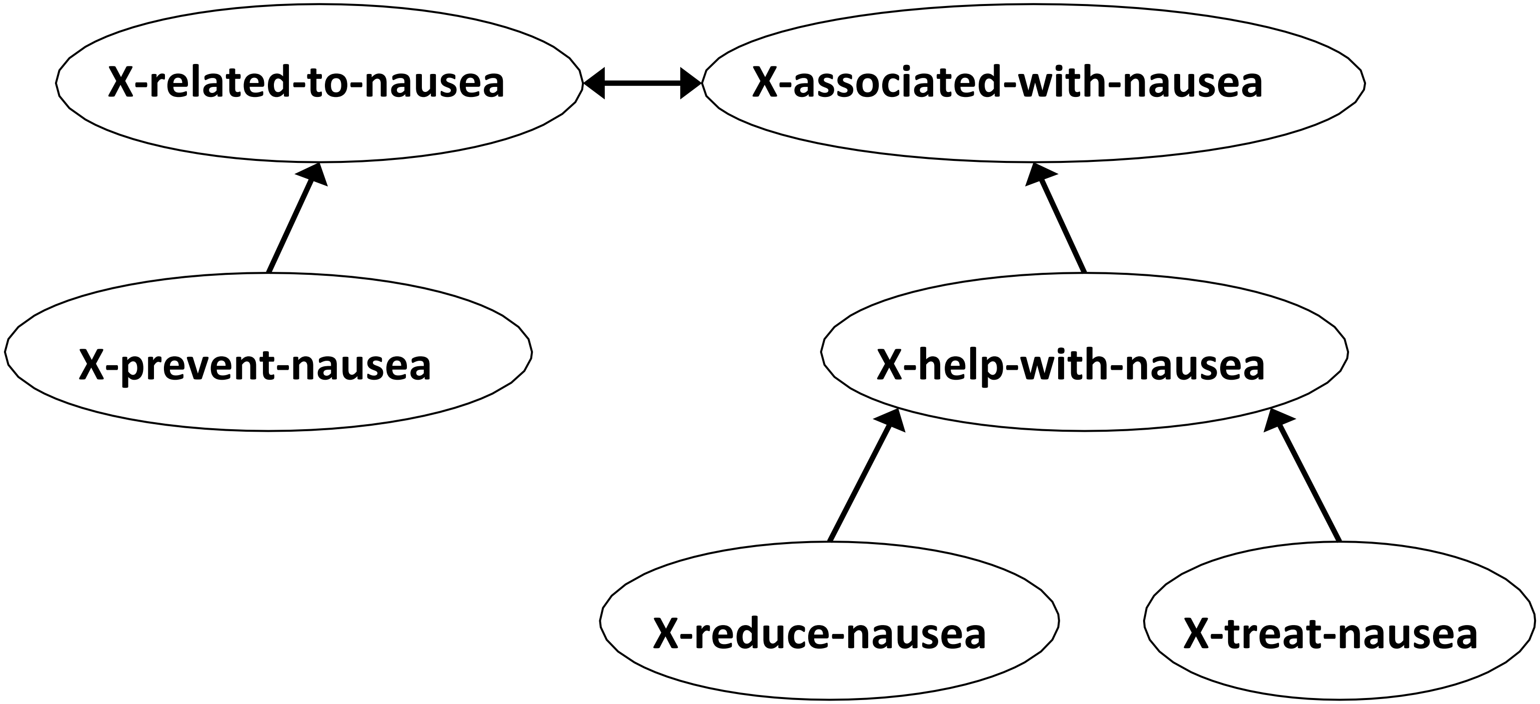
$$\boxed{\forall i, j, k \in V,\ x_{ij} + x_{jk} - x_{ik} \leq 1}$$

1 + 1 - 0 = 2 > 1

$$x_{ij} \in \{0,1\}$$

- Variables: x_{ij}
- Objective function: maximizes P(G)
- Global transitivity constraint: --- $O(|V|^3)$ constraints

Concept-Focused Entailment Graphs

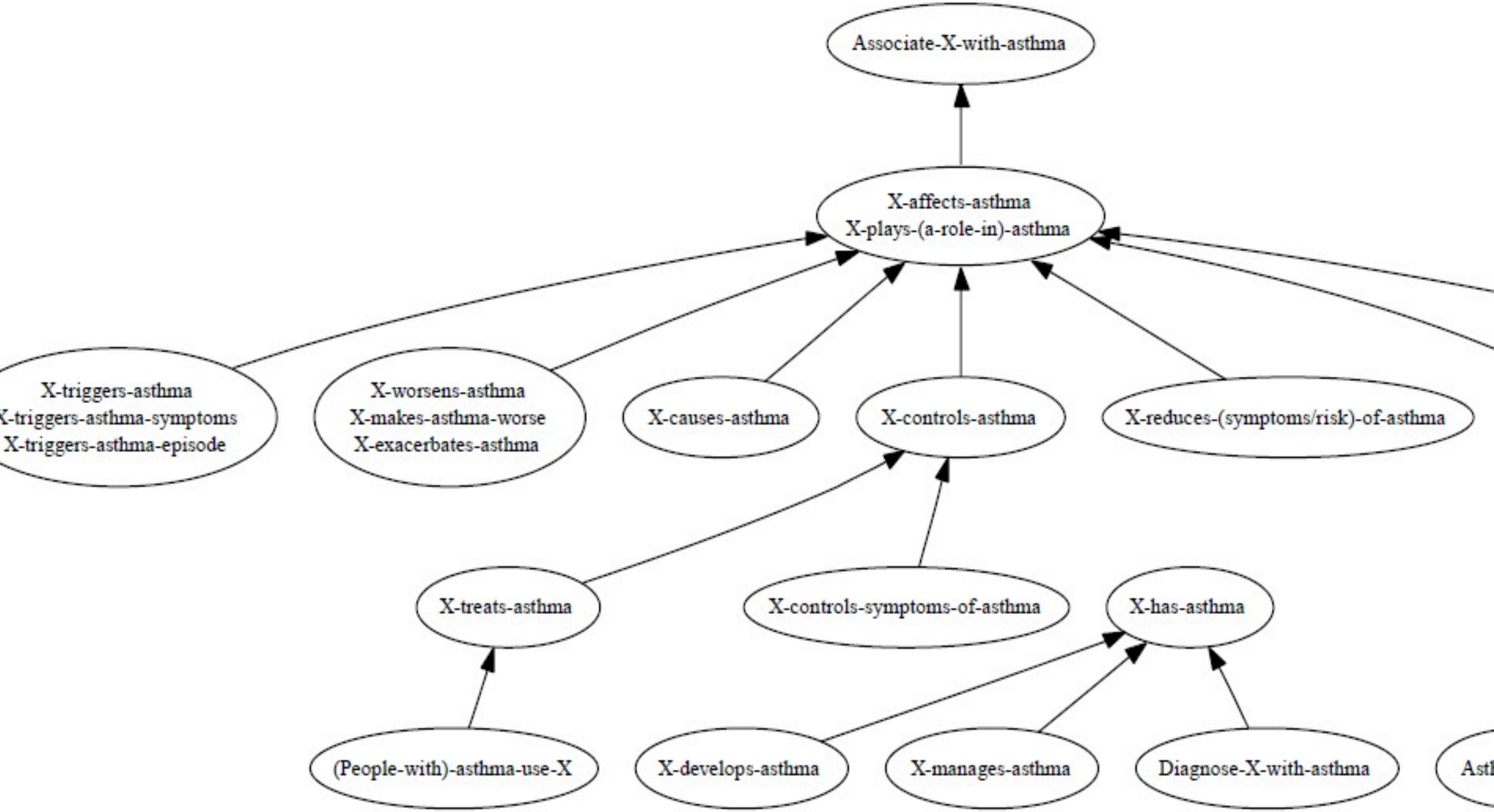


- Argument is instantiated by a target concept *(nausea)*
- Instantiating an argument reduces ambiguity

Evaluation

- 50 million word tokens **healthcare** corpus
- Ten medical students prepared gold standard graphs for 23 medical concepts:
  - Smoking, seizure, headache, lungs, diarrhea, chemotherapy, HPV, Salmonella, Asthma, etc.
- Evaluation:
  - F_1 on set of learned edges vs. gold standard

Gold Standard Graph --- Asthma

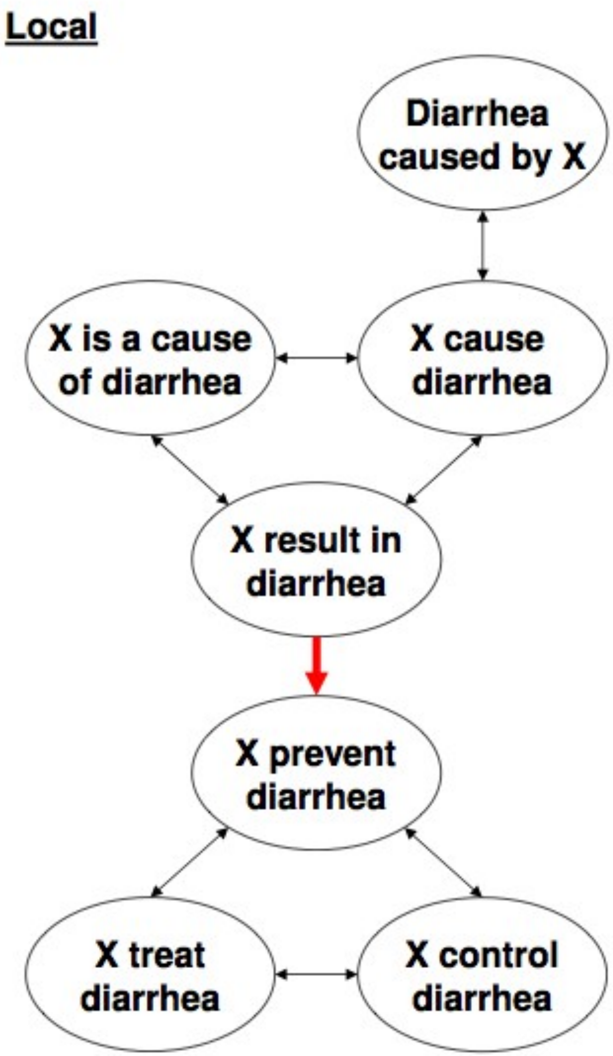


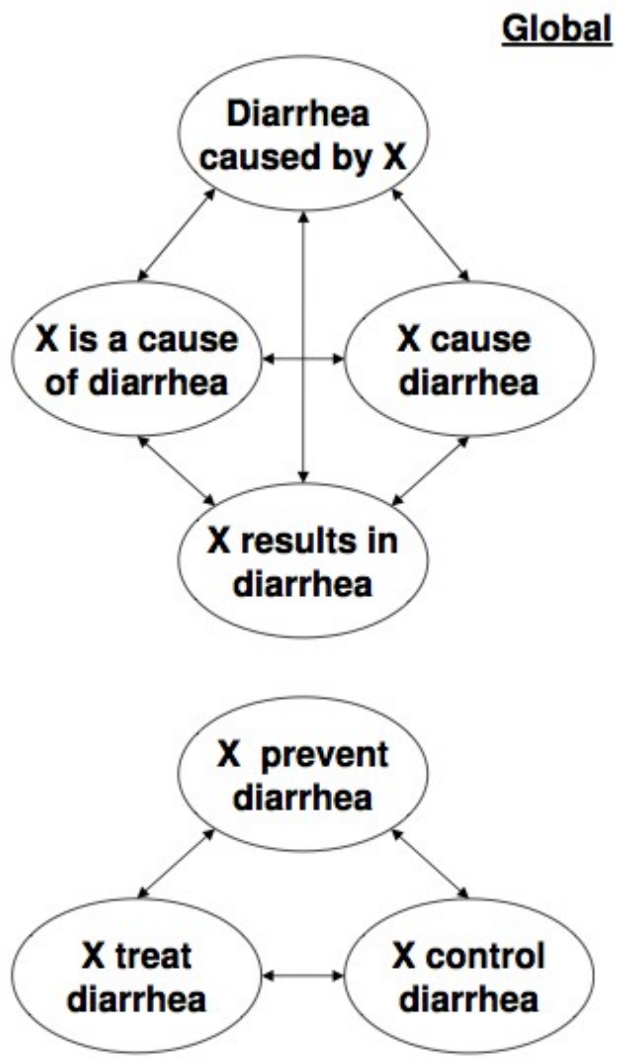
Experimental Results

	recall	**Precision**	**F_1**
ILP---global	46.0	50.1	**43.8***
Greedy	45.7	37.1	36.6
ILP---local	44.5	45.3	38.1
Local_1	53.5	34.9	37.5
Local_2	52.5	31.6	37.7
Local*_1	53.5	38.0	39.8
Local*_2	52.5	32.1	38.1
WordNet	10.8	44.1	13.2

- Local algorithms
  - Distributional similarity
  - WordNet
  - Local classifier
- Global algorithms
  - ILP/Snow et al. (greedy optimization)

	Global=true/Local=false	Global=false/Local=true
Gold standard = true	48	42
Gold standard = false	78	494





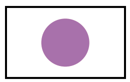
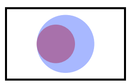
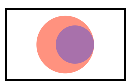
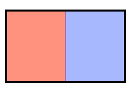
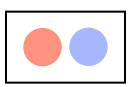
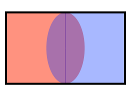
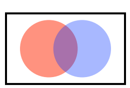
Natural Logic Inference (Natural-LI)

Natural logic (NatLog)

- MacCartney, Manning, Angeli (at Stanford)
- Use natural logic representation for TE
- Initial implementation of alignment based entailment inference
- Inference patterns built over shallow surface forms, instead of full semantic interpretation

7 basic entailment relations

Slides based out of Bill MacCartney and Chris Manning's talk in COLING 2008.

Venn	symbol	name	example
	P = Q	equivalence	*couch* = *sofa*
	P ⊏ Q	forward entailment (strict)	*crow* ⊏ *bird*
	P ⊐ Q	reverse entailment (strict)	*European* ⊐ *French*
	P ^ Q	negation (exhaustive exclusion)	*human* ^ *nonhuman*
	P | Q	alternation (non-exhaustive exclusion)	*cat* | *dog*
	P _ Q	cover (exhaustive non-exclusion)	*animal* _ *nonhuman*
	P # Q	independence	*hungry* # *hippo*

Relations are defined for all semantic types: *tiny* ⊏ *small*, *hover* ⊏ *fly*, *kick* ⊏ *strike*, *this morning* ⊏ *today*, *in Beijing* ⊏ *in China*, *everyone* ⊏ *someone*, *all* ⊏ *most* ⊏ *some*

Entailment & semantic composition

- Ordinarily, semantic composition preserves entailment relations:

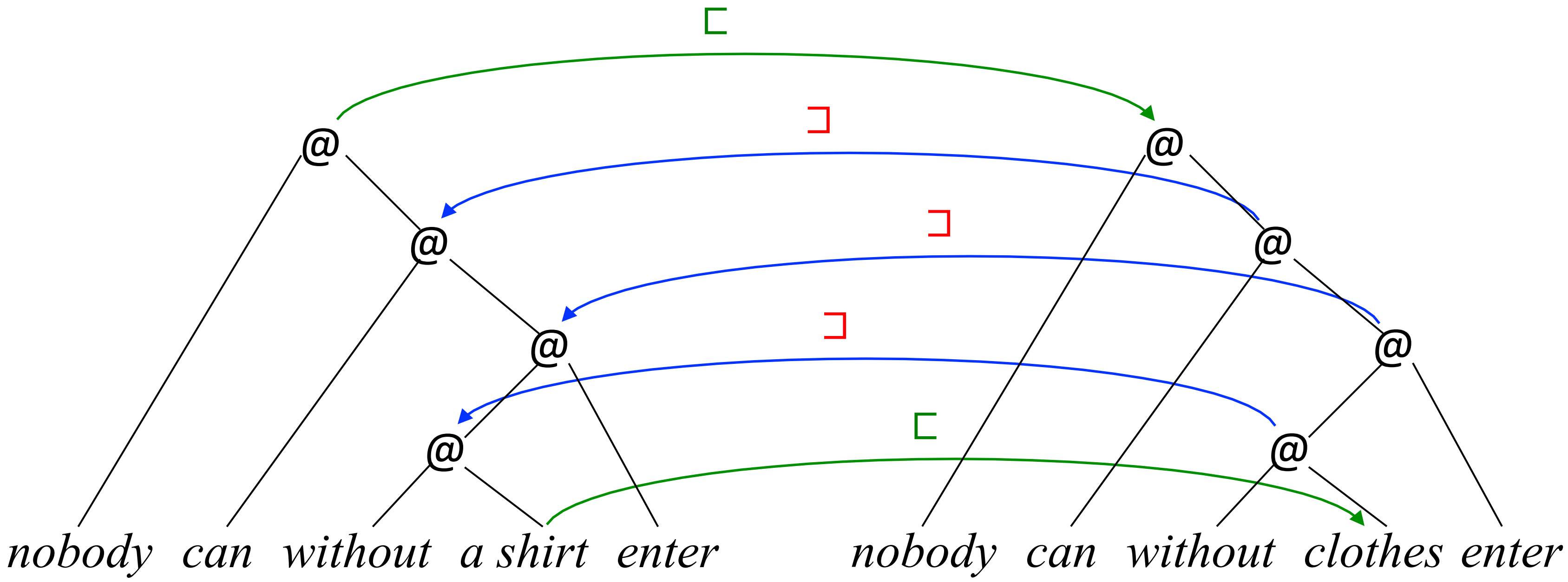
  pork $\sqsubset$ *meat* => *eat pork* $\sqsubset$ *eat meat*

  bird | *fish* => *big bird* | *big fish*

- But many semantic functions behave differently:
  tango $\sqsubset$ *dance* $\Rightarrow$ *refuse to tango* $\sqsupset$ *refuse to dance*
  French | *German* $\Rightarrow$ *not French* _ *not German*

Projecting entailment relations upward

- Assume idealized semantic composition trees
- Propagate entailment relation between atoms upward, according to projectivity class of each node on path to root



A (weak) inference procedure

1. Find sequence of edits connecting *P* and *H*
   - Insertions, deletions, substitutions, …
2. Determine lexical entailment relation for each edit
   - Substitutions: depends on meaning of substituends: *cat* | *dog*
   - Deletions: $\sqsubset$ by default: *red socks* $\sqsubset$ *socks*
   - But some deletions are special: *not ill* ^ *ill, refuse to go* | *go*
   - Insertions are symmetric to deletions: $\sqsupset$ by default
3. Project up to find entailment relation across each edit
4. Compose entailment relations across sequence of edits
   - à la Tarski's relation algebra

Entailment composition

P	*Jimmy Dean*	*refused to*			*move*	*without*	*blue*	*jeans*
H	*James Dean*		*did*	*n't*	*dance*	*without*		*pants*
edit index	1	2	3	4	5	6	7	8
edit type	SUB	DEL	INS	INS	SUB	MAT	DEL	SUB
lex feats	strsim= 0.67	implic: –/o	cat:aux	cat:neg	hypo			hyper
lex entrel	=	|	=	^	⊐	=	⊏	⊏
projec-tivity	↑	↑	↑	↑	↓	↓	↑	↑
atomic entrel	=	|	=	^	⊏	=	⊏	⊏
compo-sition	=	|	|	⊏	⊏	⊏	⊏	⊏

final answer