BLUE-Lite:
A Knowledge-Based
Lexical Entailment System for RTE6

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Overview

- System Description (BLUE-Lite)
- Results
- Analysis
- Discussion and Ways Forward

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- **System Description (BLUE-Lite)**
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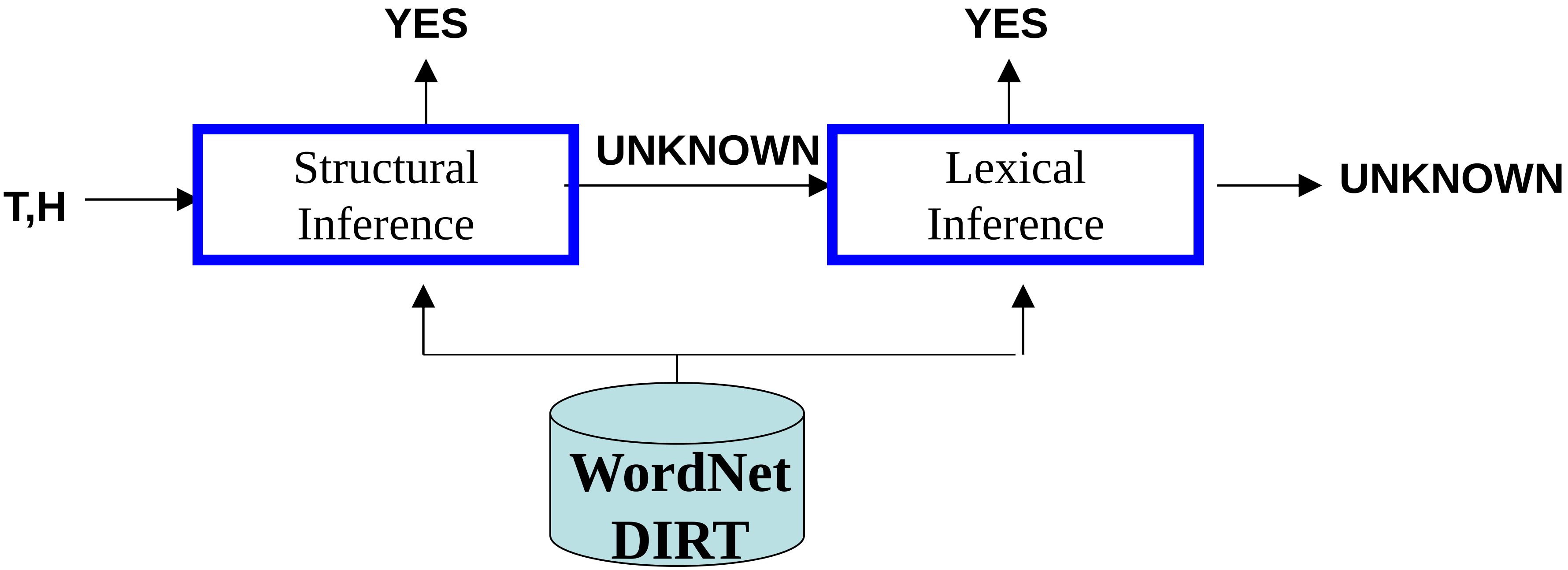
BLUE – from RTE5



T,H

YES

Structural Inference

UNKNOWN

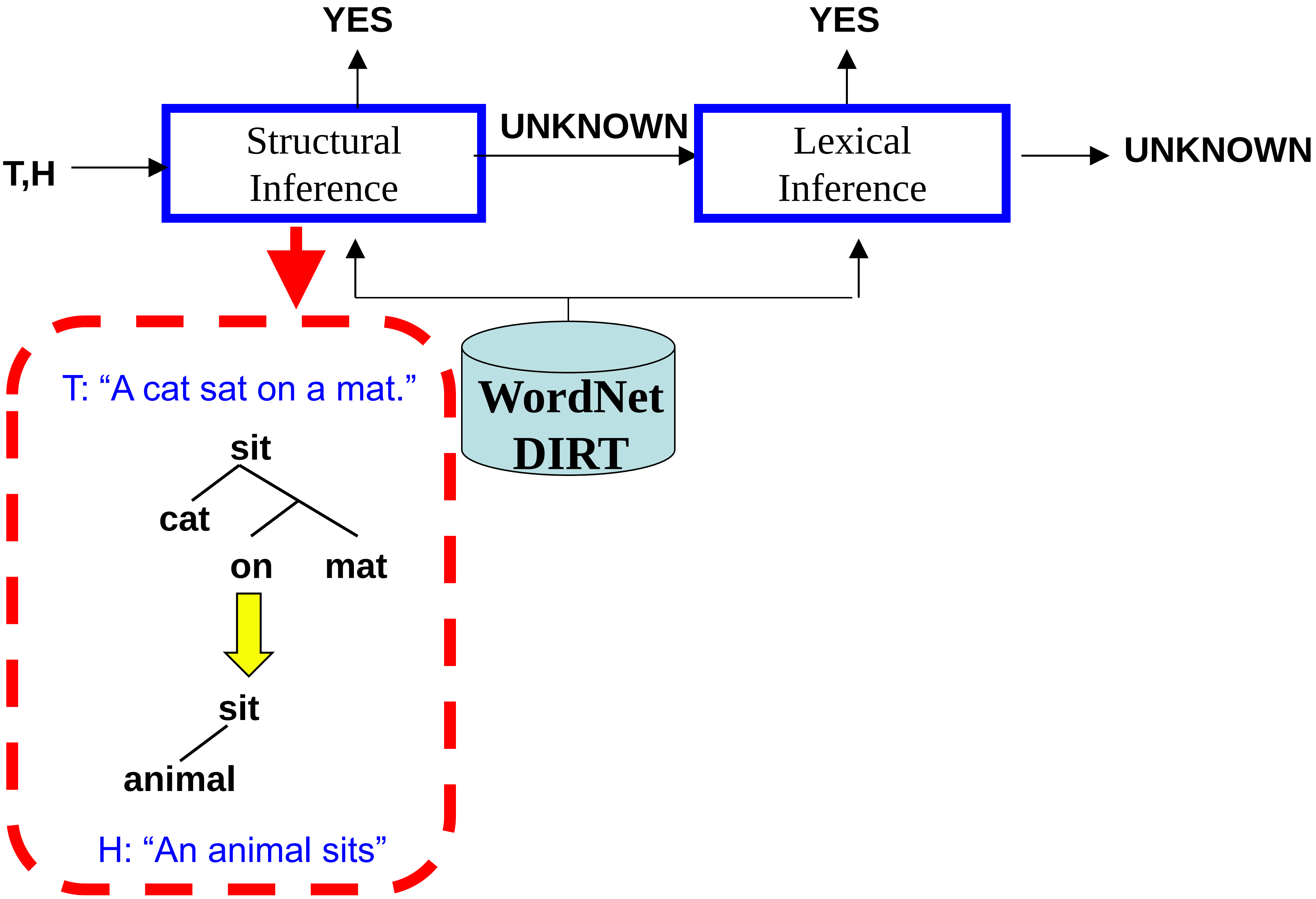
YES

Lexical Inference

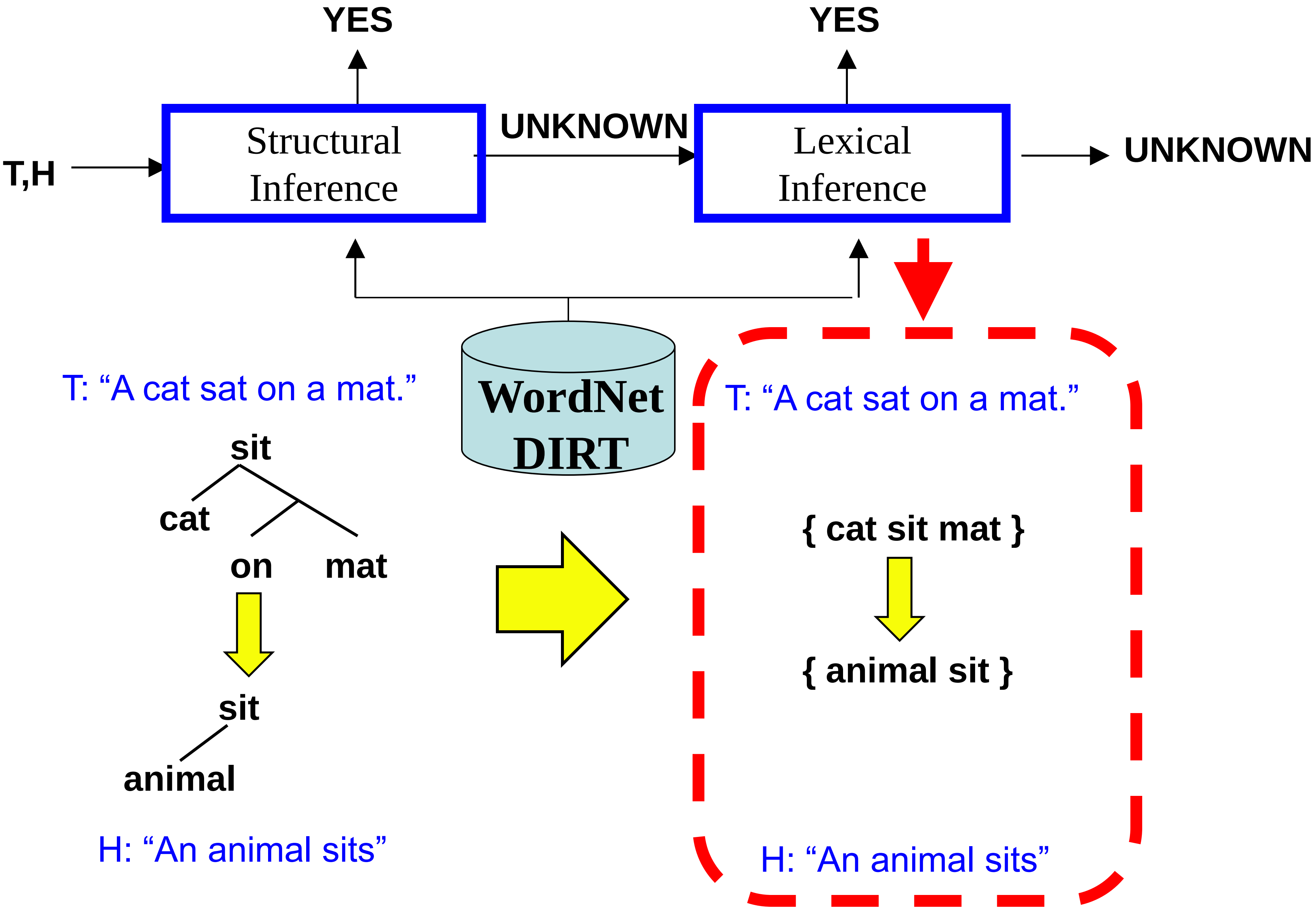
UNKNOWN

WordNet DIRT

BLUE – from RTE5



BLUE – from RTE5



T: “A cat sat on a mat.”

H: “An animal sits”

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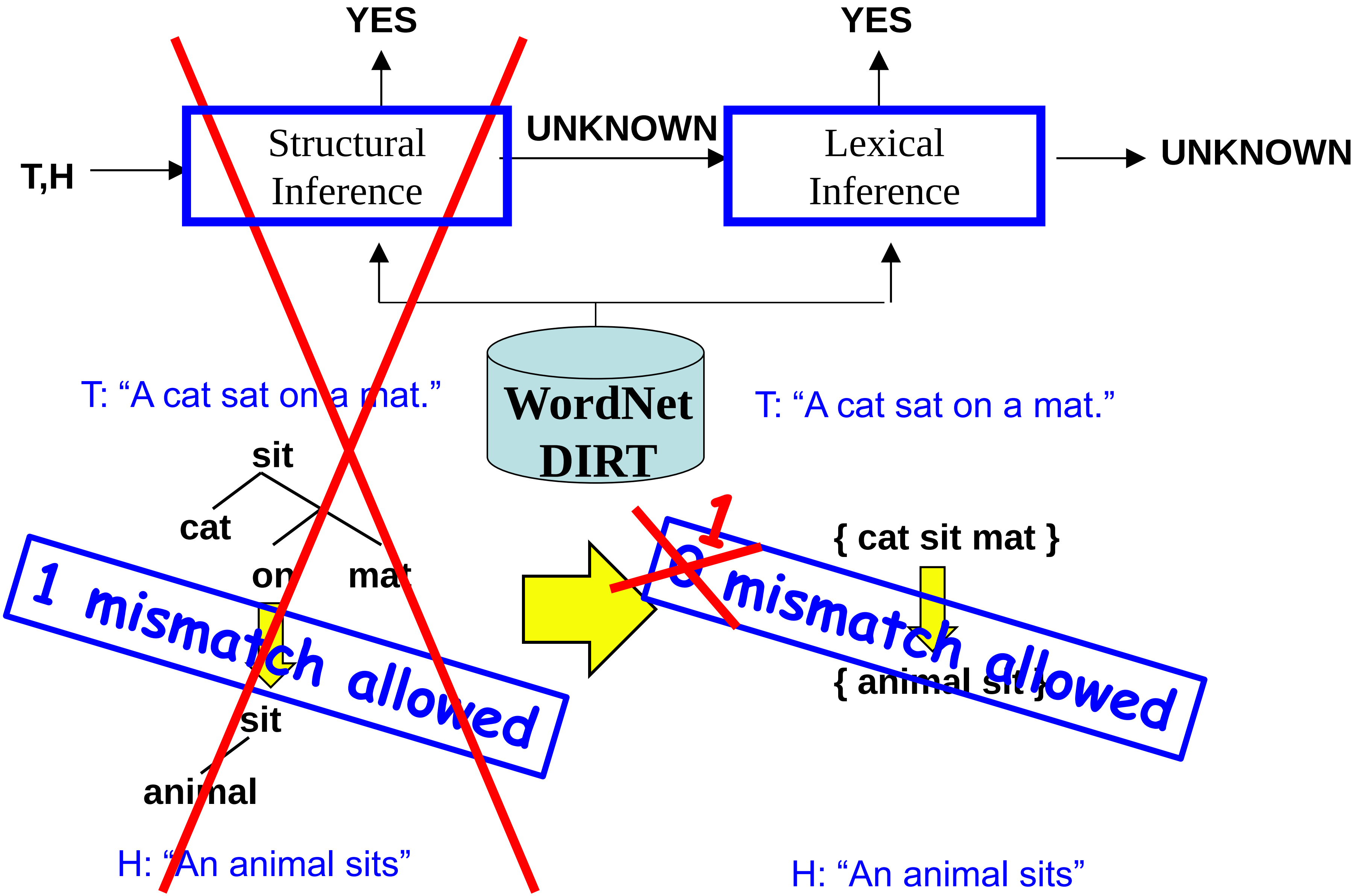
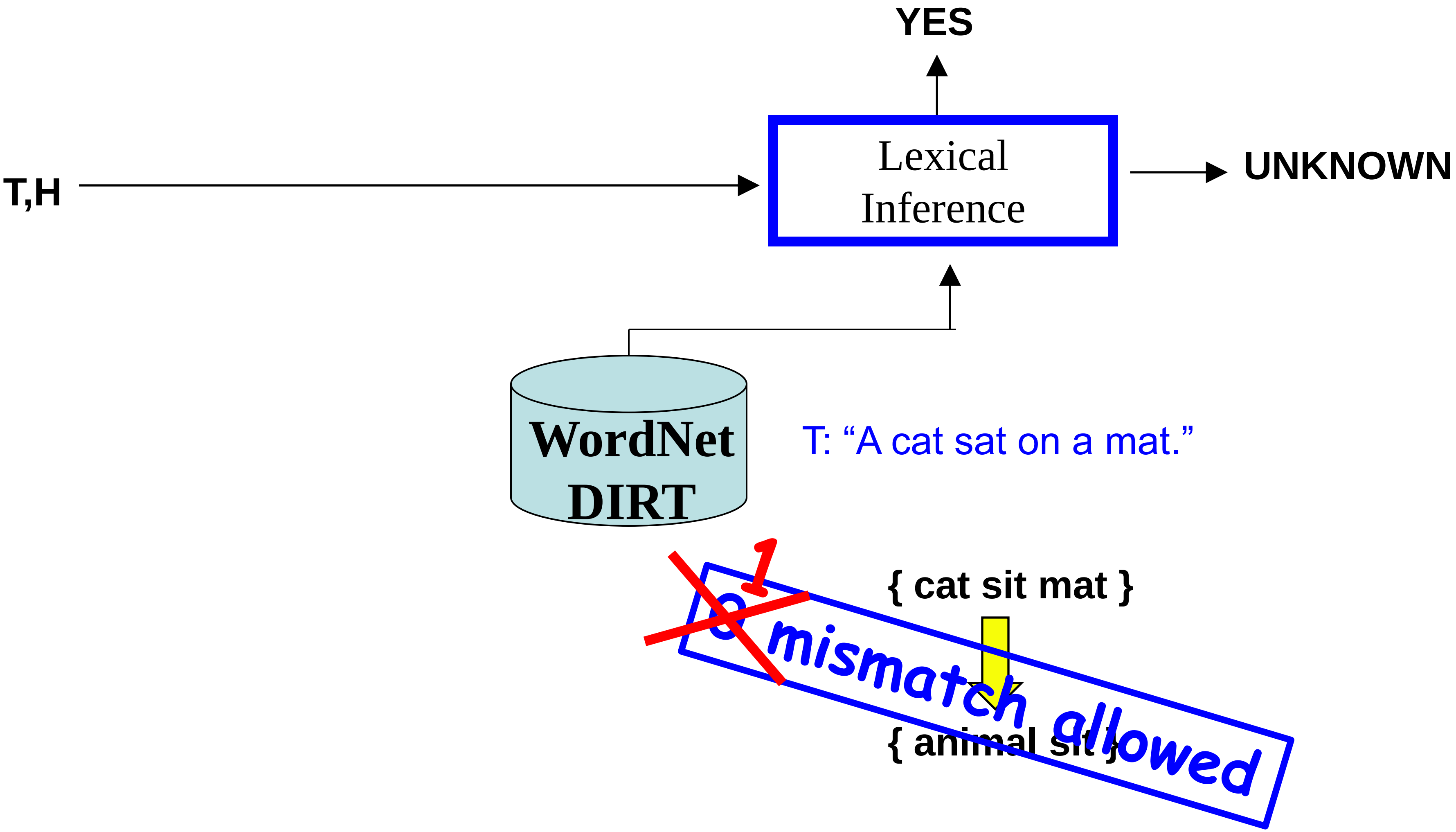
BLUE – from RTE5



BLUE-Lite



YES

T,H

Lexical Inference

UNKNOWN

WordNet DIRT

T: “A cat sat on a mat.”

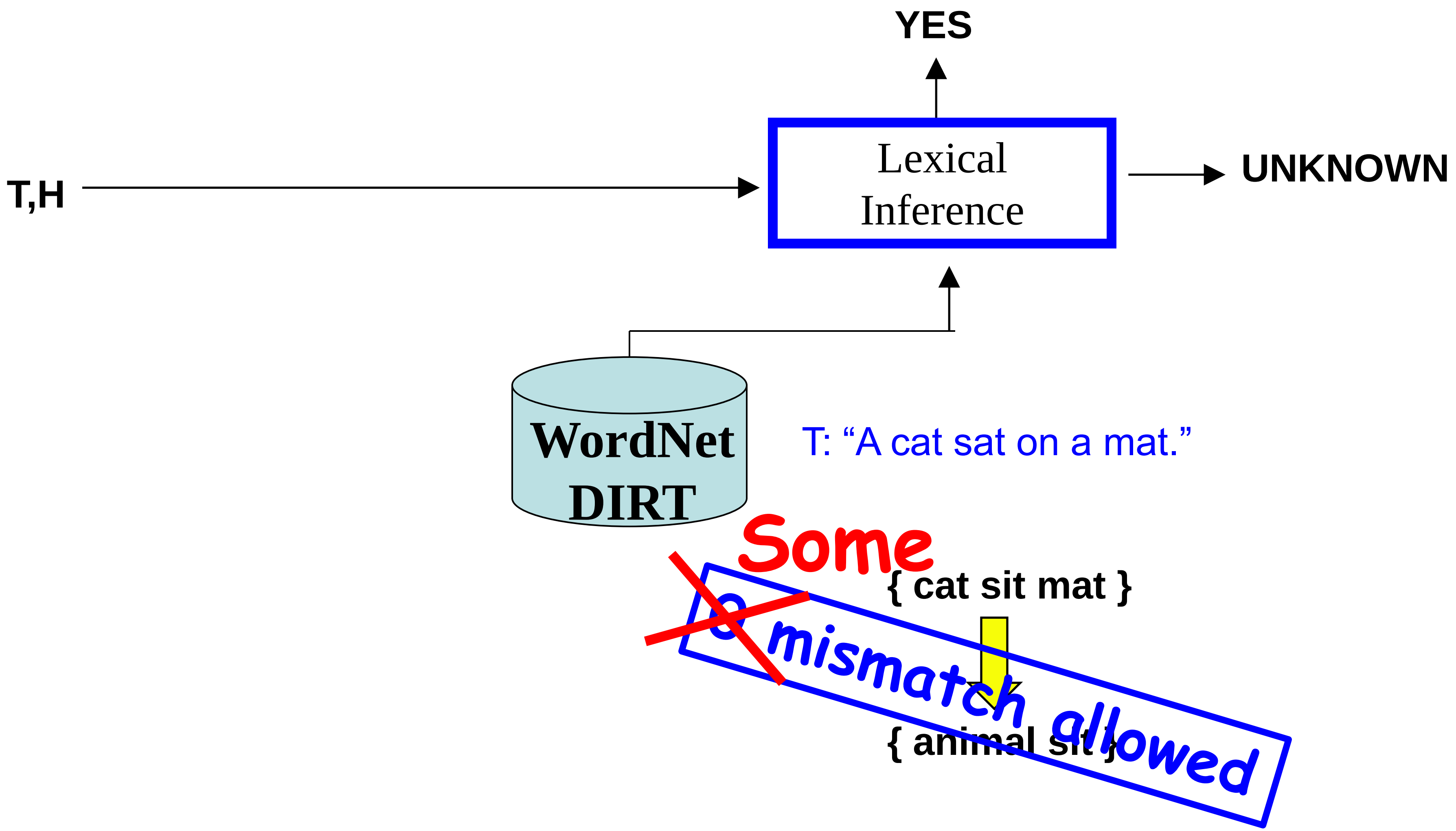
{ cat sit mat }

{ animal sit }

~~0~~ 1 mismatch allowed

H: “An animal sits”

BLUE-Lite



YES

T,H

Lexical Inference

UNKNOWN

WordNet DIRT

T: “A cat sat on a mat.”

Some ~~0~~ mismatch allowed

{ cat sit mat }

{ animal sit }

H: “An animal sits”

BLUE-Lite: “Knowledge-Based Lexical Entailment”

1. Lexical comparison
2. Knowledge-driven (WordNet and DIRT)
3. Context: Use of previous sentence
4. Variable entailment threshold

BLUE-Lite: “Knowledge-Based Lexical Entailment”

1. Lexical comparison

T: The Christian Science Monitor newspaper on Monday pleaded for the release of American reporter Jill Carroll...
H: Jill Carroll was abducted in Iraq.

T: "Christian Science" "Monitor" "newspaper" "Monday" "plead" "release" "American" "reporter" "Jill" "Carroll" …
H: "Jill" "Carroll" "abduct" "Iraq"

Main features:

- Normalize words
- Ignore stop words
- Use multiwords from WordNet
- Names are compared in a special way

BLUE-Lite: “Knowledge-Based Lexical Entailment”

1. Lexical comparison
2. **Knowledge-driven** (WordNet and DIRT)
   - Exploit multiple WordNet relations

WordNet Equivalences:

“speedily” - -> rapidly#r1 ←**pertains-to**→ quick#a1 - - - -> “quick”

nice#a1 ←**similar-to**→ pleasant#s2

build#v1 -**equal**→ construction#n1

WordNet Implications:

car#n1 −**WN−isa**→ vehicle#n1

Baghdad#n1 –**WN-part-of**→ Iraq#n1

DIRT Equivalences:

“loves” ↔ “adores” <- - -

“mark” ↔ “symbolize”

“shoot” ↔ “get” ☹

Derived from DIRT rule:
X loves Y ↔ X adores Y

BLUE-Lite: “Knowledge-Based Lexical Entailment”

1. Lexical comparison
2. Knowledge-driven (WordNet and DIRT)
3. **Context:** Use of previous sentence
   - If an H word is not entailed by T, look in T-1

T: Merck...pulled the...pain drug...
H: Vioxx is a pain drug.

BLUE-Lite: “Knowledge-Based Lexical Entailment”

1. Lexical comparison
2. Knowledge-driven (WordNet and DIRT)
3. **Context:** Use of previous sentence
   - If an H word is not entailed by T, look in T-1

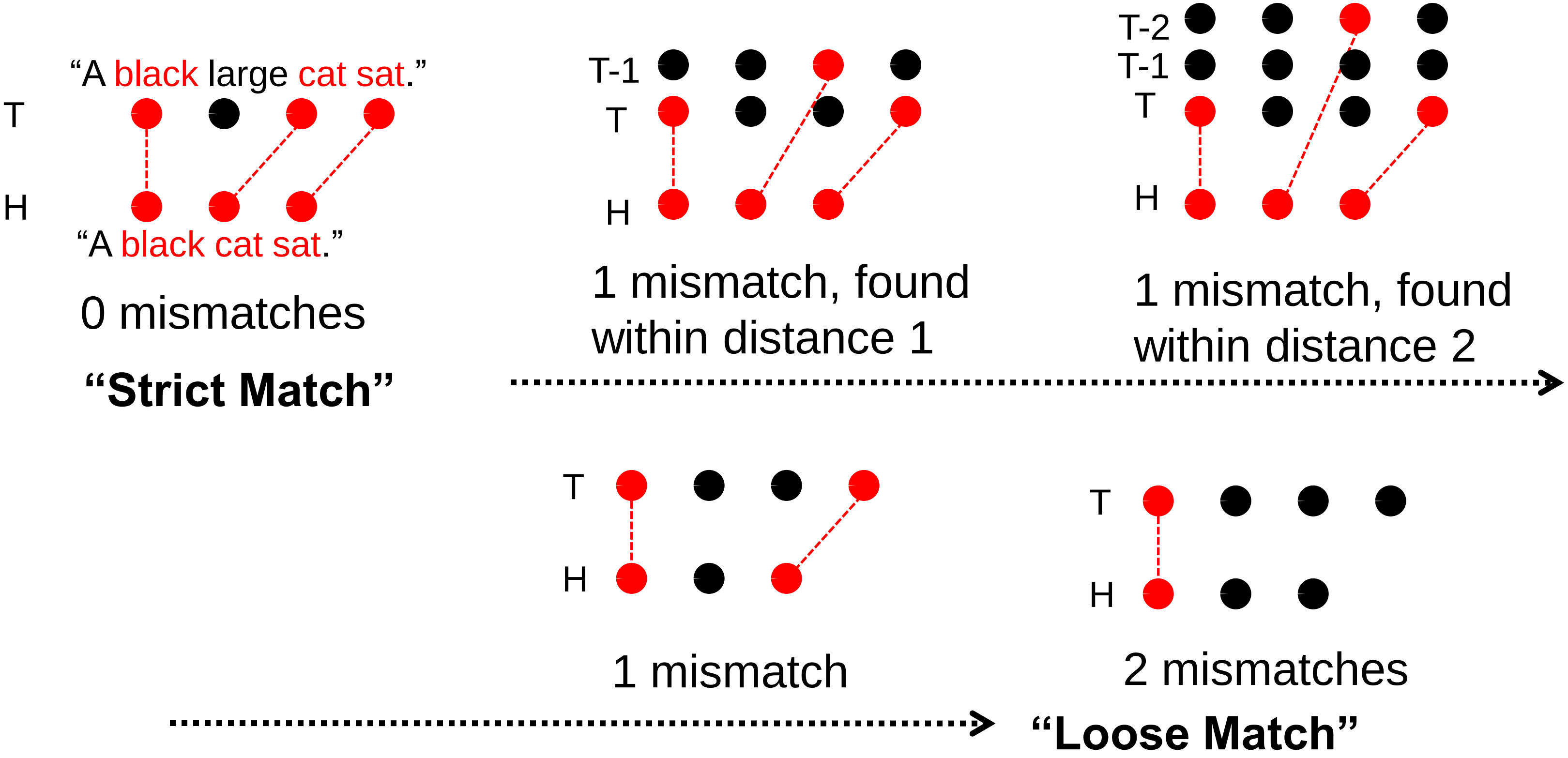
T-1: ...the drug **Vioxx**...

T: Merck...pulled **the...pain drug**...

H: Vioxx is a pain drug.

BLUE-Lite: “Knowledge-Based Lexical Entailment”

1. Lexical comparison
2. Knowledge-driven (WordNet and DIRT)
3. Context: Use of previous sentence
4. **Variable entailment threshold**
   - How good a match implies entailment?



0 mismatches

“Strict Match”

1 mismatch, found within distance 1

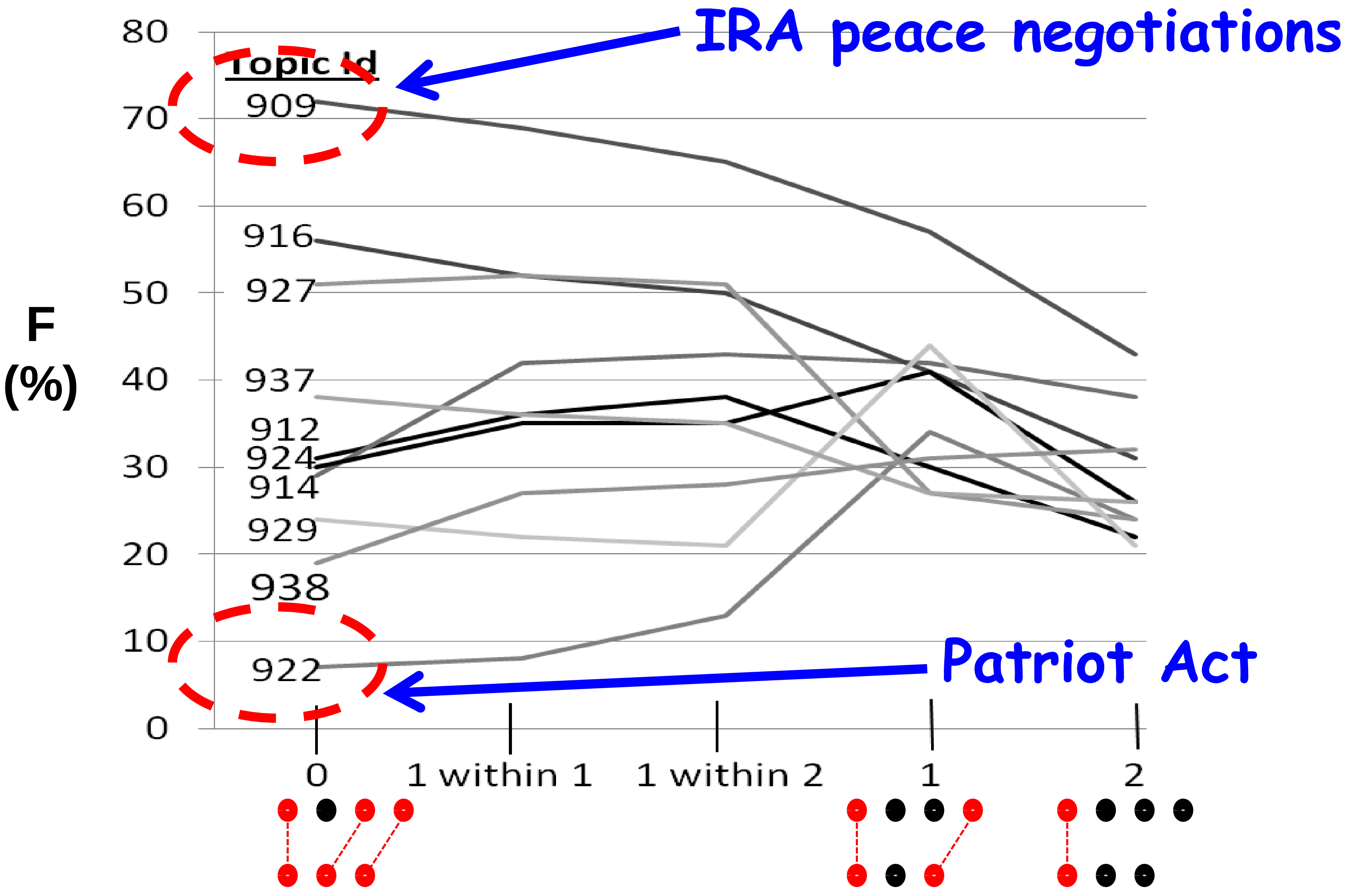
1 mismatch, found within distance 2

1 mismatch

2 mismatches

“Loose Match”

Some topics are more difficult than others…



IRA peace negotiations

Patriot Act

Strict Match ⇢ **Loose Match**

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Results (F-Measure)

	Knowledge Sources ↓	**Entailment Threshold** (number of mismatches allowed)			
		0	1 within 1	1	Variable
Training Data	none	21.81	26.24	39.72	39.72
	DIRT	25.07	31.06	39.72	40.45
	WN	31.81	36.36	39.69	43.27
	WN+DIRT	37.59	40.30	35.29	42.68
Test Data	none	23.35	27.66	40.35	40.56
	DIRT	25.47	30.72	40.55	39.57
	WN	35.44	39.41	38.68	40.02
	WN+DIRT	37.20	41.56	38.74	43.99

Simple strategy (all but one H words in T) does well, even with no knowledge!

Results (F-Measure)

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WordNet + DIRT + Variable thresholding together adds 3%-4% improvement

(Close to overall best system 48%)

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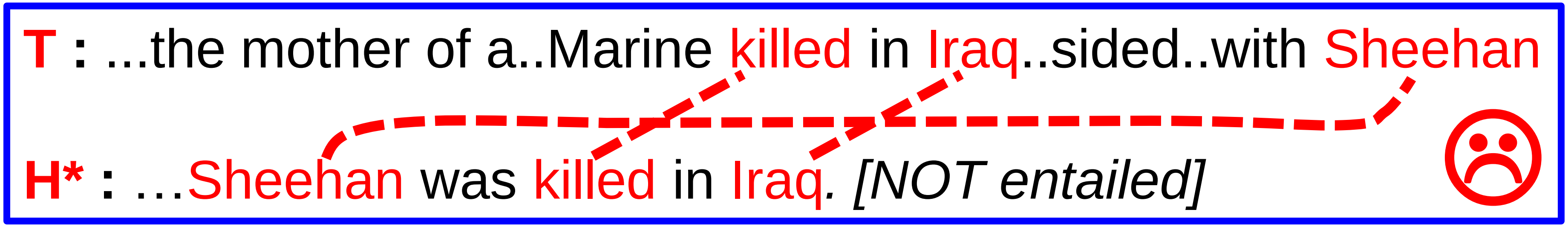
Analysis: 1. Ignoring structure

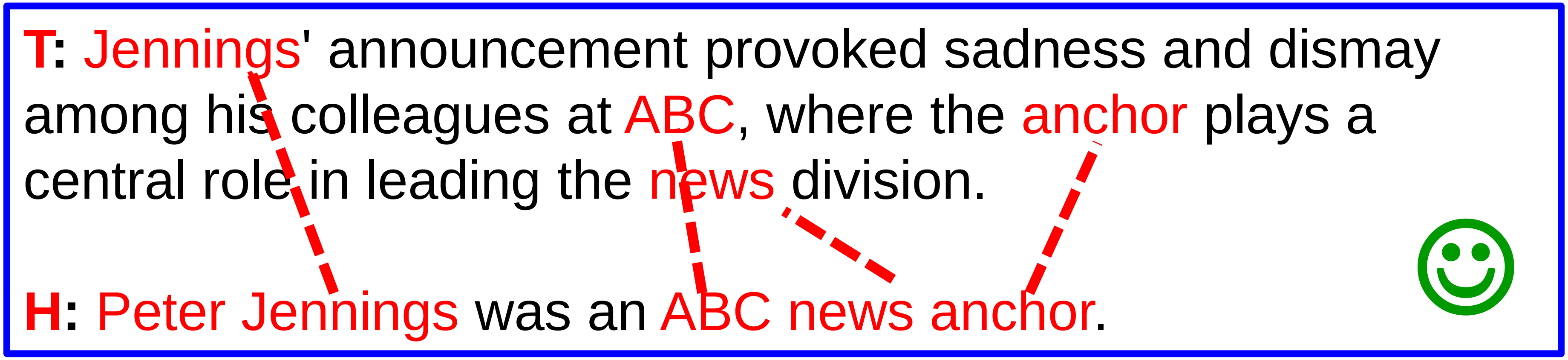
- Surprising that ignoring structure works at all…



T : ...the mother of a..Marine killed in Iraq..sided..with Sheehan

H* : …Sheehan was killed in Iraq. *[NOT entailed]* ☹

- …but this kind of example is common…

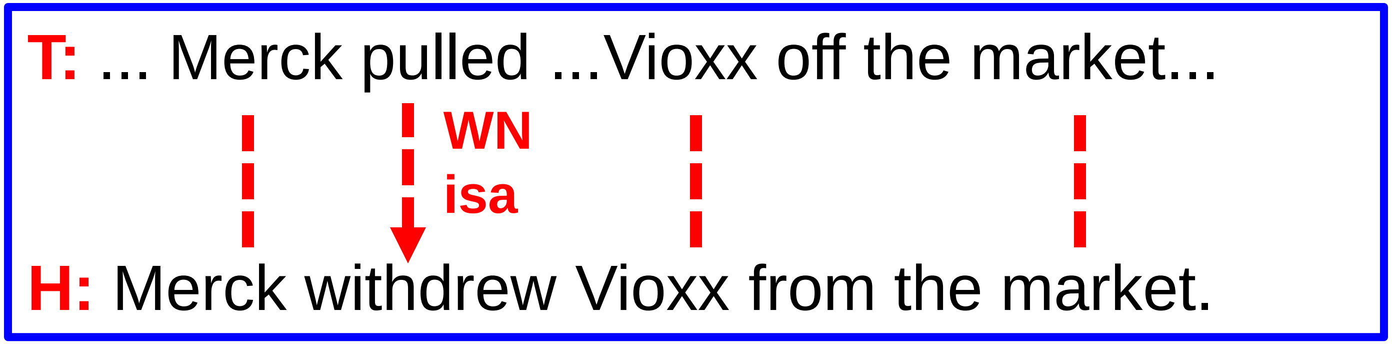


T: Jennings' announcement provoked sadness and dismay among his colleagues at ABC, where the anchor plays a central role in leading the news division.

H: Peter Jennings was an ABC news anchor. ☺

Analysis: 2. WordNet

- WordNet gives us a small overall advantage (3%-4%)…

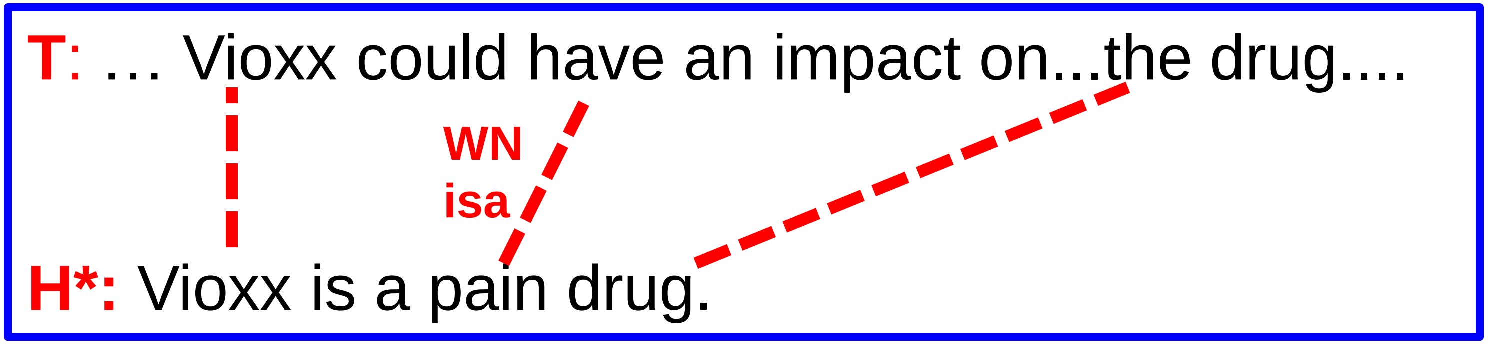


T: ... Merck pulled ...Vioxx off the market...

H: Merck withdrew Vioxx from the market.

☺

- …but can go wrong…



T: … Vioxx could have an impact on...the drug....

H*: Vioxx is a pain drug.

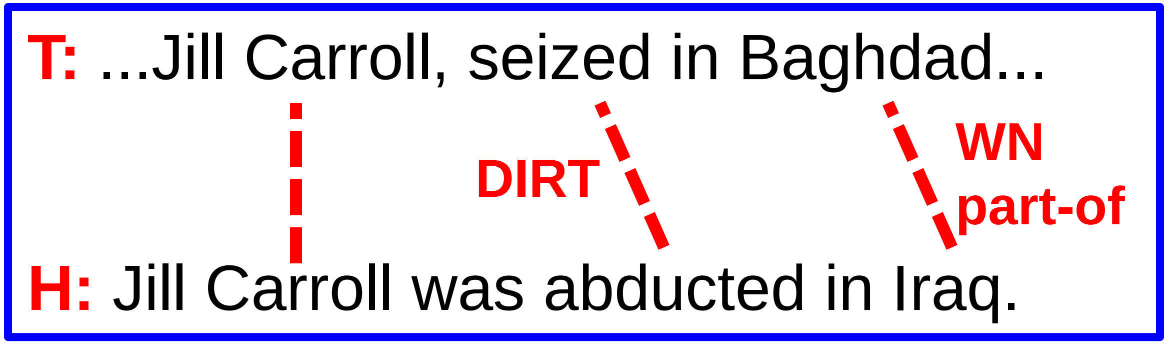
☹

have#v12 [isa suffer#v6 = pain#n1]: "have": suffer from; be ill with; as in "She has arthritis".

☹

Analysis: 3. DIRT

- DIRT was sometimes helpful, e.g.,



T: ...Jill Carroll, seized in Baghdad...

H: Jill Carroll was abducted in Iraq.

☺

- …but inconclusive impact (+/- 1%) overall, e.g.,:

run ↔ oversee
mark ↔ symbolize
say ↔ report
shoot ↔ injure

☺

shoot ↔ get
withdraw ↔ back
remember ↔ expect
deliver ↔ make

☹

Analysis: 4. Lack of General Knowledge

- Several examples failed due to lack of general knowledge

T: Local schools have already closed...amid fears the hurricane could strike...
H: Texas braced for Hurricane Rita.

☹

T: Jennings anchored ABC's evening news for two years...
H: Peter Jennings delivered the news to Americans each night.

☹

T: …the foundation will be a fund-raising organization.
H: The …Foundation was created to raise money.

☹

Analysis: 5. Other Challenges

- **Negation, modals**
  - T: …did not need to be withdrawn… H:…withdrew…
- **Arithmetic**
  - T: …after..blast…two..explosions… H: Three blasts…
- **Calendrics**
  - T: …last Thursday… H: …September 30, 2004.
- **Geography**
  - T: …in Shitani and Ras Soltan… H: …in Sinai
- **Idioms**
  - T: …tower outlines… H: …footprints of the towers…
- **Cataphora**

  T: The angry mother of a fallen U.S. soldier...
  T+2: Cindy Sheehan told reporters...
  T+6: Her son, Casey, 24, was killed in…Iraq...

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Coherence and Structure

- Why does ignoring structure work at all?
  - Clearly structure affects entailment:

T: Casey Shehan was in Iraq
H*: Iraq was in Casey Sheehan.

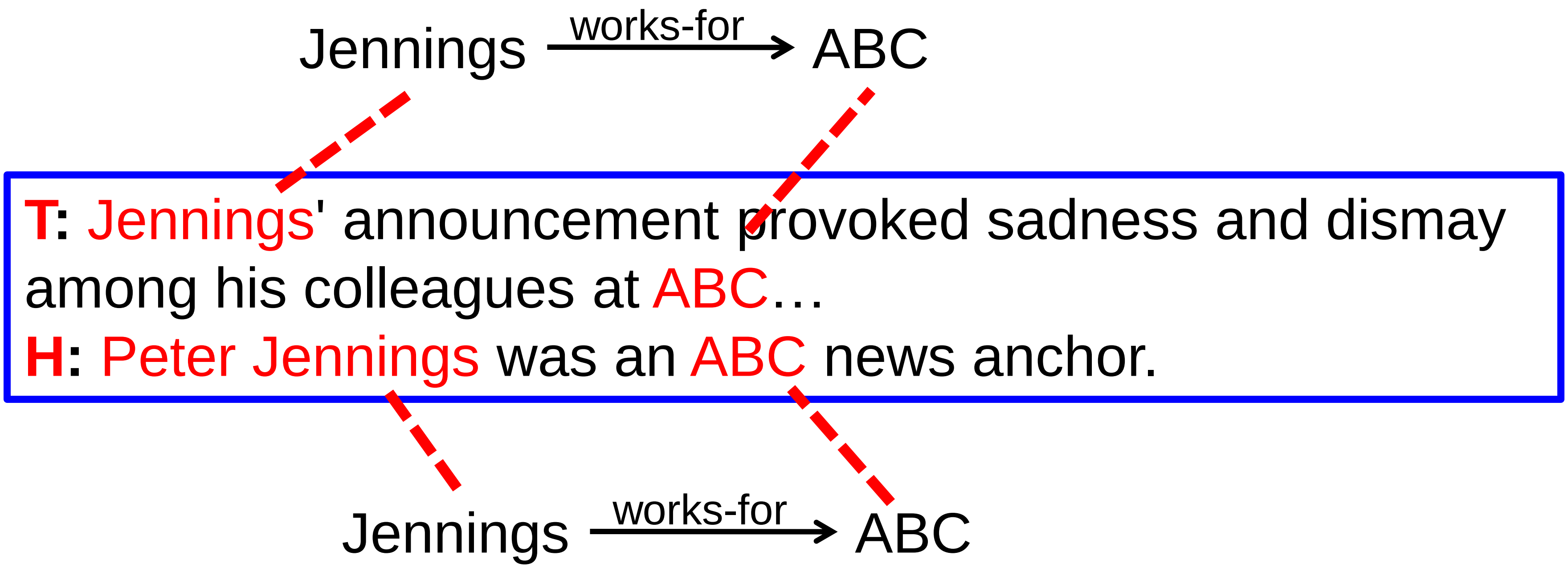
- **BUT:** most restructurings are non-sensical, so will not be seen in “coherent” datasets

A Coherence Conjecture

IF T and H are coherent (not non-sensical)
AND two words in H also occur in T
THEN **it is likely that the semantic relationship between the pair are the same in T and H**

Coherence and Structure

- For example:



T: Jennings' announcement provoked sadness and dismay among his colleagues at ABC…

H: Peter Jennings was an ABC news anchor.

Other Entailment Tasks

- **True/False Question-Answering**
  - Less constrained (query is coherent, but may be false)

H*: Gerry Adams is the prime minister of Ireland? (No)

  - **Structure needed more**

- **Find-a-value Question-Answering**
  - Even less constrained

H: Someone is the prime minister of Ireland?

  - **Structure is critical!**

What are the Ways Forward?

1. Re-introduce use of **structure**
2. **Clean and improve** existing resources

X reviews Y ↔ X approves Y	should be directional
X rejects Y ↔ X approves Y	remove antonyms
X estimates Y ↔ X increases Y	doesn’t “make sense”

3. **Add more rules** (Mechanical Turk?)

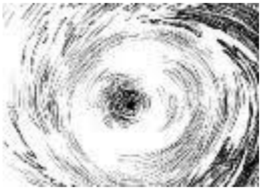
“close school” --suggests⟶ “brace for hurricane”

But: These all seem like small tweaks…

What are the Ways Forward? (cont)

- Each “rule” is a tiny manifestation of deeper knowledge

“close school” --suggests→ “brace for hurricane”



Threat of hurricane →

evacuate people
board up buildings
close schools
assemble supplies
response preparations →

Hurricane hits
Buildings damaged
Trees knocked down
Electricity out →

Clear roads
Repair buildings
People return
Restore power

Danger approaching → Prepair for impact → Danger arrives → Damage caused → Recovery

What are the Ways Forward? (cont)

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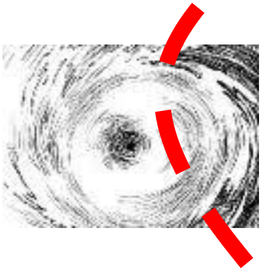

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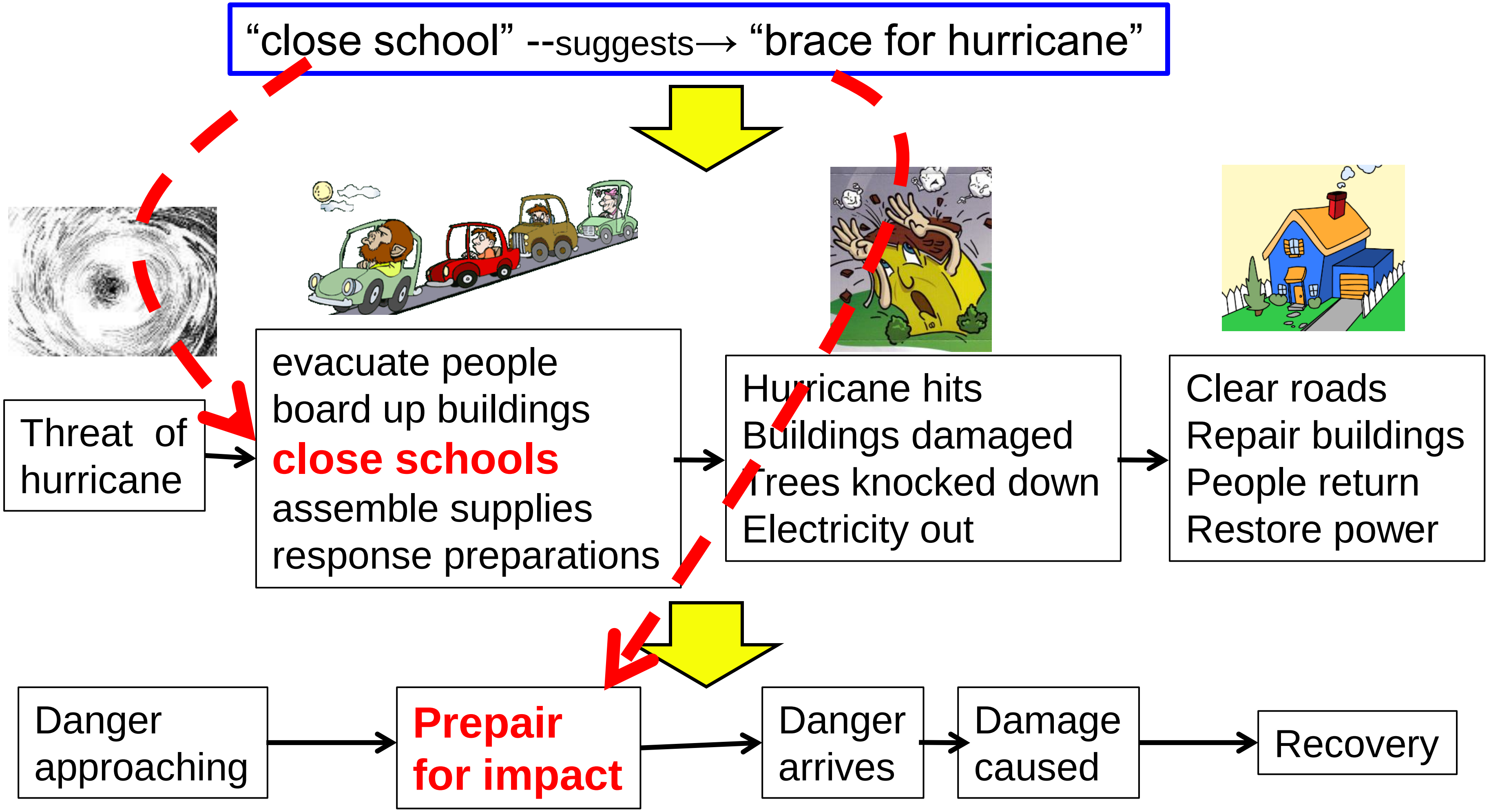

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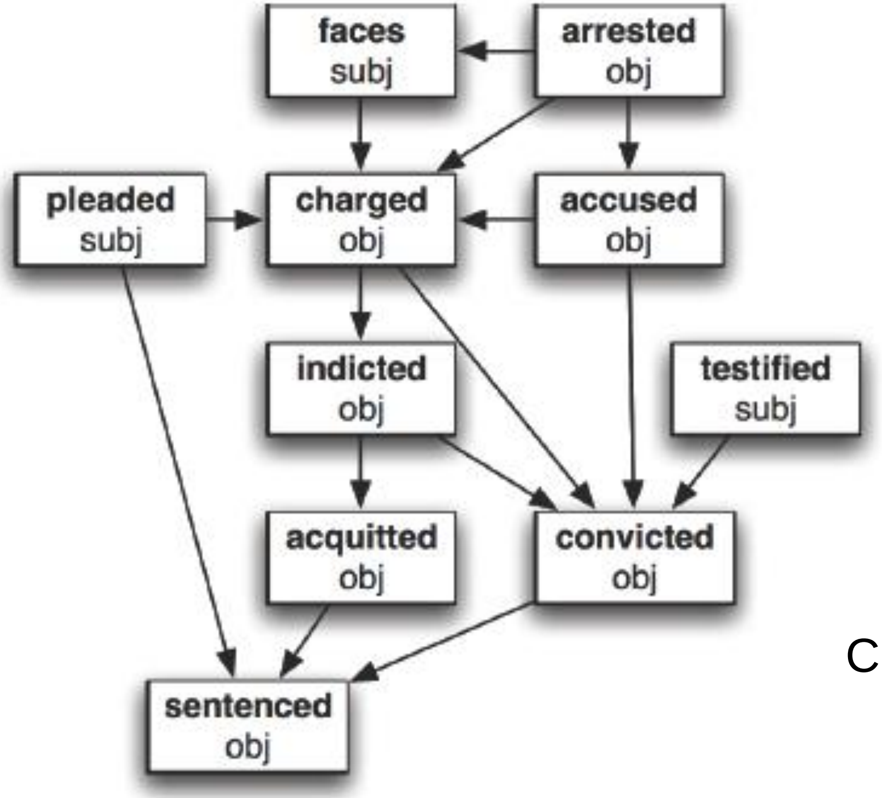
Damage caused

Recovery

What are the Ways Forward? (cont)

- Can we build/mine such things?



Chambers & Jurafsky, 2008

Summary

- **BLUE-Lite:** Knowledge-Based Lexical Entailment
  - Match lexical items
  - WordNet + DIRT for comparison
  - Use of previous sentence for context
  - Topic-specific entailment threshold
- All help (a bit) to **get improved entailment**
- **But** to do really well (F > 0.50) need…
  - Use of structural information
  - Cleaner knowledge
  - (Lots!) more knowledge

Thank you!