Abstract KR: Using WordNet and VerbNet for Question Answering

Valeria de Paiva

speaking for the PARC Aquaint team

Dick Crouch, Tracy King, Danny Bobrow,
Cleo Condoravdi, Ron Kaplan,
Annie Zaenen, Lauri Karttunen

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Outline

- Motivation: why use deep linguistic analysis for question answering
- Basic architecture and example structures
- Abstract Knowledge Representation
- The experiment: WordNet/VerbNet
- Discussion

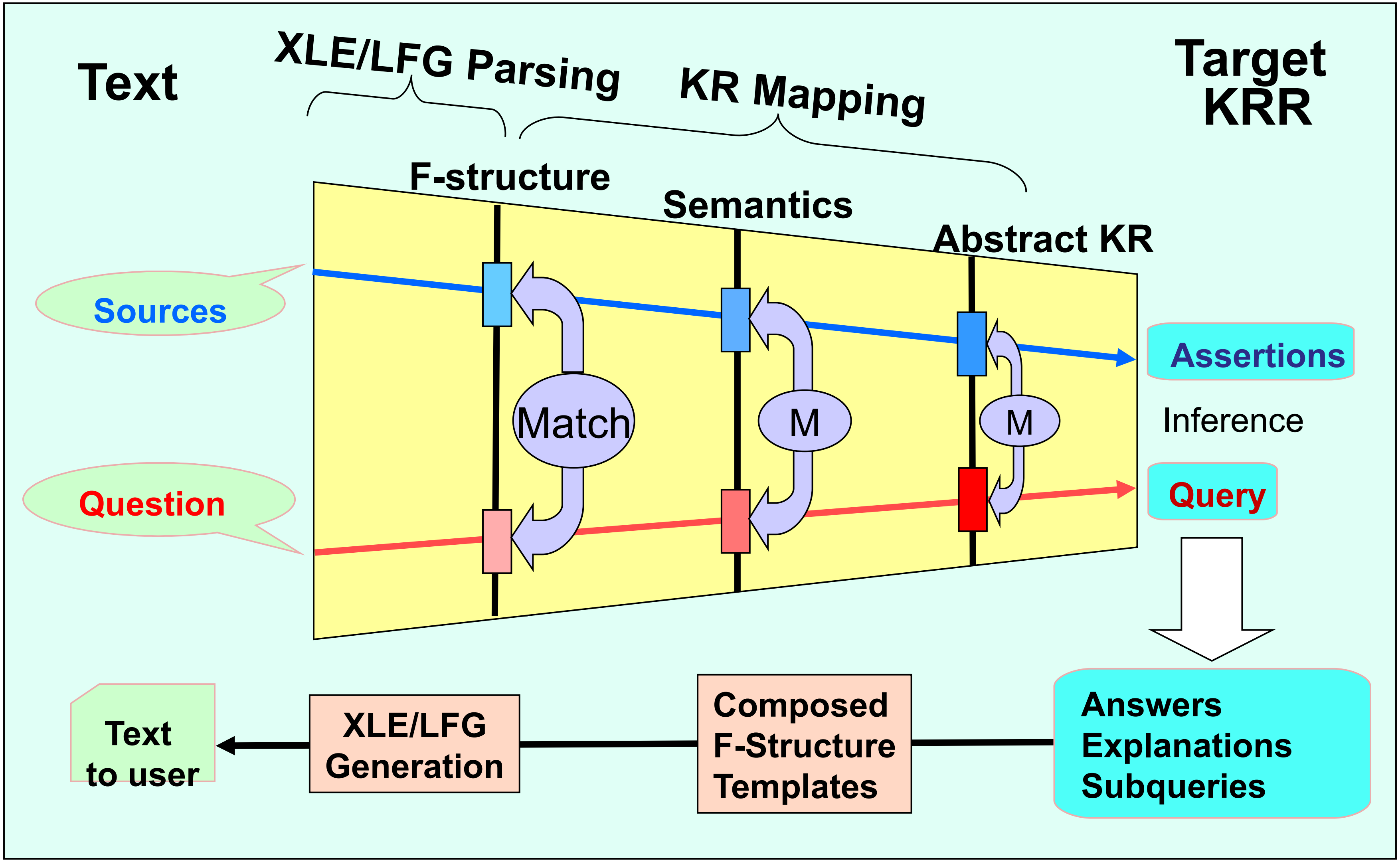
Motivation

- Knowledge-based question answering
  - Deep representations allow high precision and recall, but
  - Typically on restricted domains
  - Hard for users to pose KR questions and interpret KR answers
  - very hard for system to build up knowledge

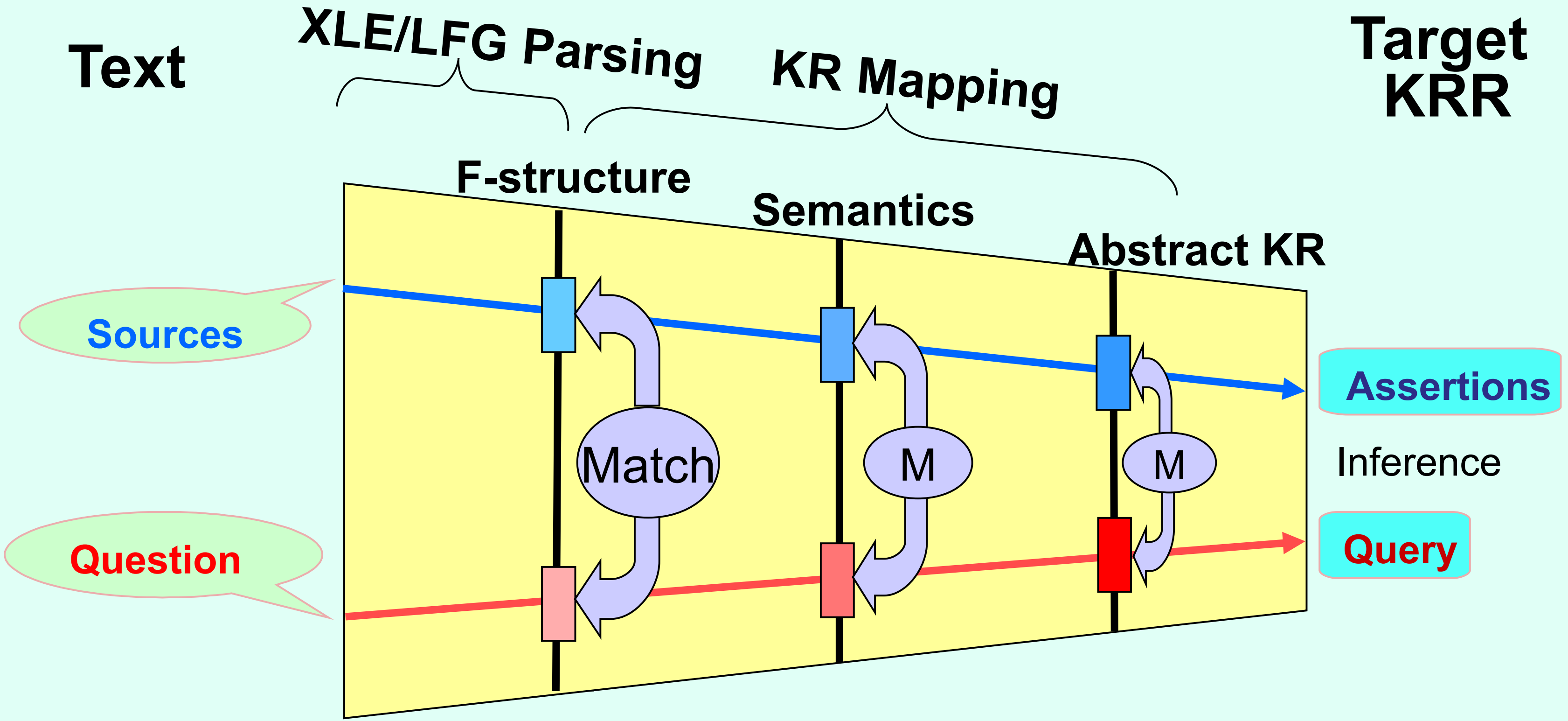
- Shallow, open-domain question answering
  - Broad-coverage
  - Lower precision and recall
  - Easy to pose questions but sensitive to question form

- Question answering at PARC
  - Layered mapping from language to deeper semantic representations
  - Broad-coverage: Matching for answers as light reasoning
  - Expresses KRR answers in real English -- eventually

2-way bridge between language & KR



2-way bridge between language & KR



Theories
Lexical Functional Grammar
Ambiguity management

Infrastructure
XLE
Term rewriting
MaxEnt models

Resources
English Grammar
KR mapping rules
Unified Lexicon

Key Process: Canonicalize representations

- F-structures are semantic representations to some – e.g. logic forms (Rus/Moldovan'01)
- Transformed into (flat and contexted) semantic structures, inspired by Glue, born out of the need to 'pack' semantics (talk to Dick about it..)
- Transformed into (flat and contexted) AKR structures
- Want to discuss semantics to AKR
- but, what does canonicalization buy you?

Canonicalization helps matching

- Argument structure:
  - Mary bought an apple./An apple was bought by Mary.
- Synonyms and hypernyms:
  - Mary bought/purchased/acquired an apple.
- Factivity and contexts:
  - Mary bought an apple./Mary did not buy an apple.
  - Mary managed/failed to buy an apple.
  - Ed prevented Mary from buying an apple.
  - We know/said/believe that Mary bought an apple.
  - Mary didn’t wait to buy an apple. (talk to Lauri..)

Canonicalization helps matching

- basic argument structure

Did Mary buy an apple?

“Mary bought an apple.” Yes

“An apple was bought by Mary.” Yes

Semantics gives us:

```
in_context(t, cardinality('Mary':9,sg)),
in_context(t, cardinality(apple:1,sg)),
in_context(t, specifier(apple:1,a)),
in_context(t, tense(buy:3,past)),
in_context(t, buy(buy:3,'Mary':9,apple:1)),
in_context(t, proper_name('Mary':9,name,'Mary'))
```

Canonicalization helps matching

- basic synonyms/hypernyms

Did Mary buy an apple?

“Mary bought an apple.” Yes

“Mary purchased an apple.” Yes

Using Entailment detection:

“Mary bought an apple.” IMPLIES

“Mary purchased an apple.” ?

System Answer is YES

it aligns skolems in the appropriate way:

[purchase##1-buy##1,Mary##0-Mary##0,apple##3-apple##3,t-t]

Canonicalization helps matching

- basic context structure

Negation dealt with by context.

Does

“Mary did not buy an apple.”   imply

“Mary bought an apple” ? No

System Answer is   NO:

Skolems are aligned, respecting contexts

[buy##1-buy##4,Ed##0-Ed##0,apple##3-apple##6,t-t]

we get a conflict:

conflict(uninstantiable(passage,buy##4,t),
                instantiable(question,buy##4,t)))

Canonicalization helps matching

- For negation you may think contexts are an overkill, but for implicative context structure:

Does

“Mary failed to buy an apple.” imply

“Mary bought an apple” ?

System Answer is NO:

under the right skolem alignment

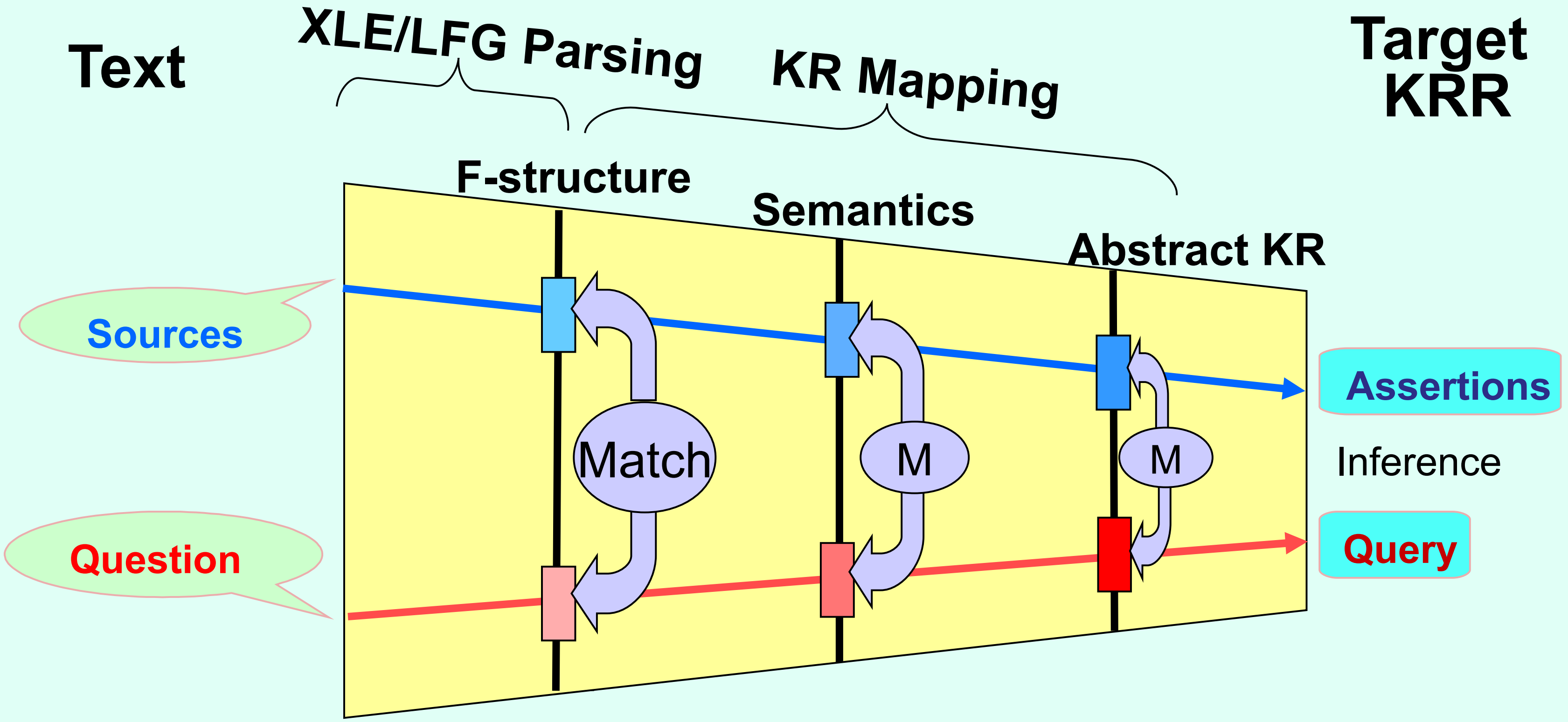
[buy##1-buy##7,Mary##0-Mary##0,apple##3-apple##9,t-t]

That is entailment detection knows about contexts

Overcoming language/KR misalignments: A principled approach

- Language
  - Generalizations come from the structure of the language
  - Representations compositionally derived from sentence structure
- Knowledge representation and reasoning
  - Generalizations come from the structure of the world
  - Representations to support reasoning
- Layered architecture helps with different constraints
- But boundaries are not fixed (like beads in a string?)

This talk: Semantics To AKR only…



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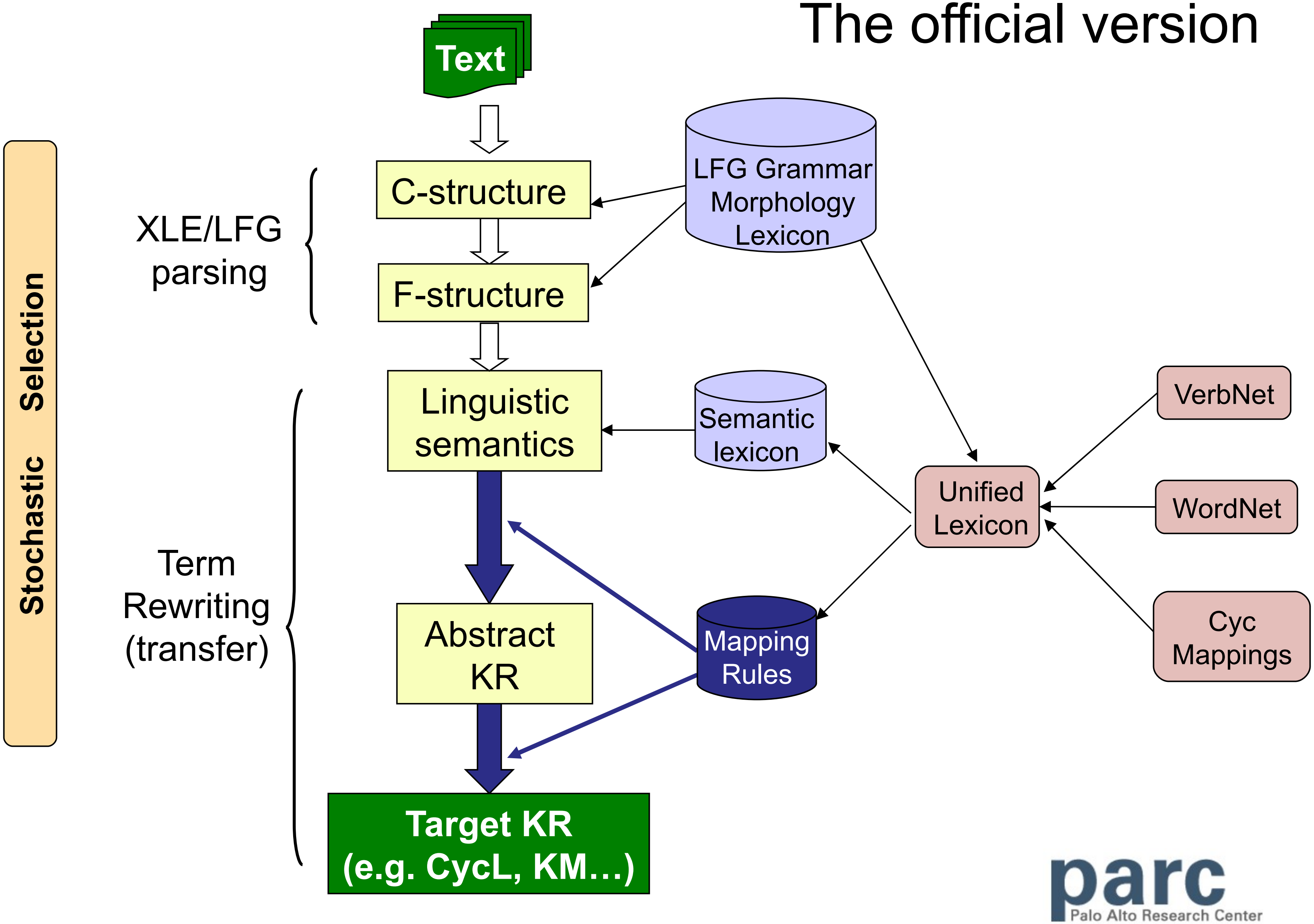
Ambiguity-enabled Text Analysis Pipeline

The official version



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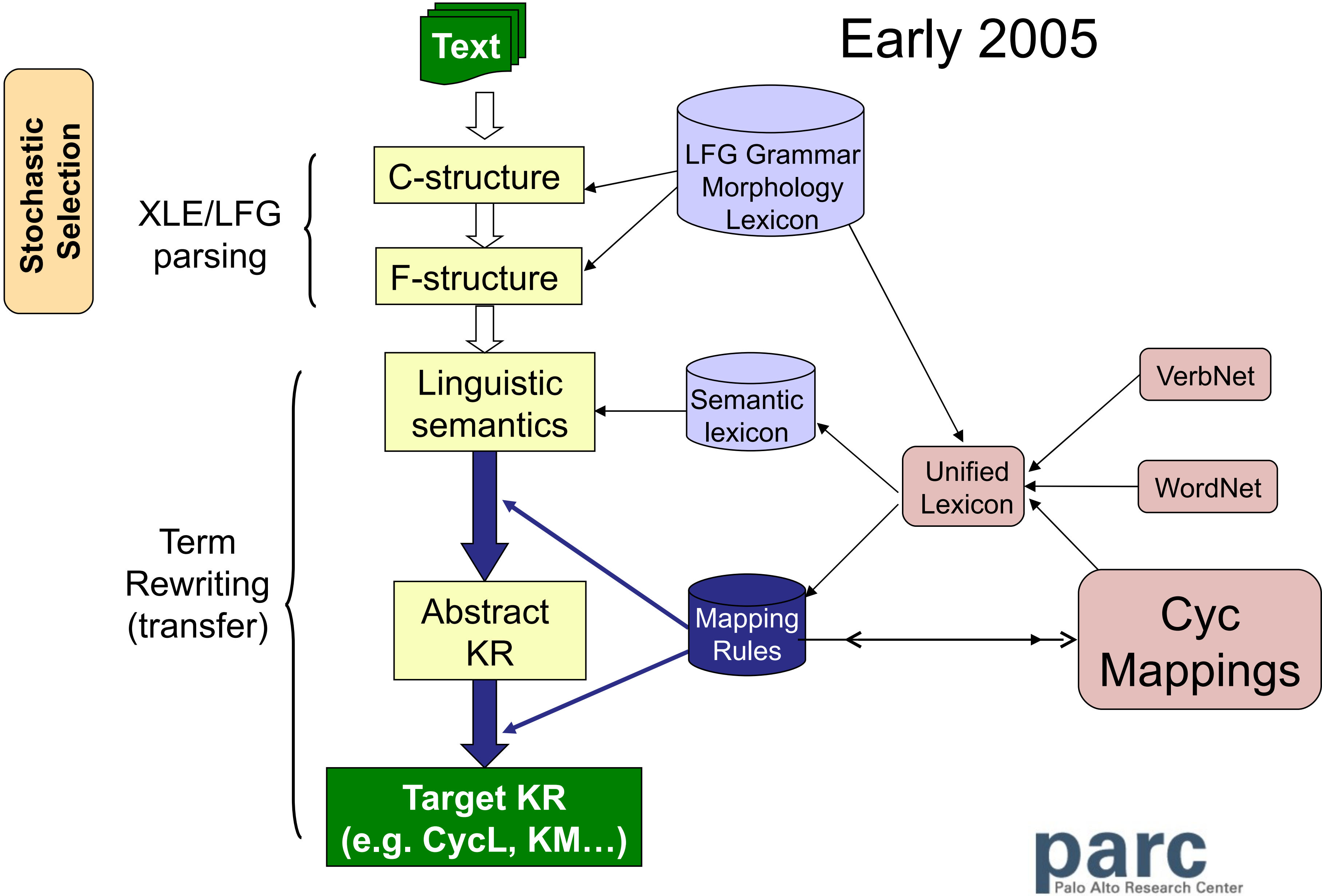
Ambiguity-enabled Text Analysis pipeline



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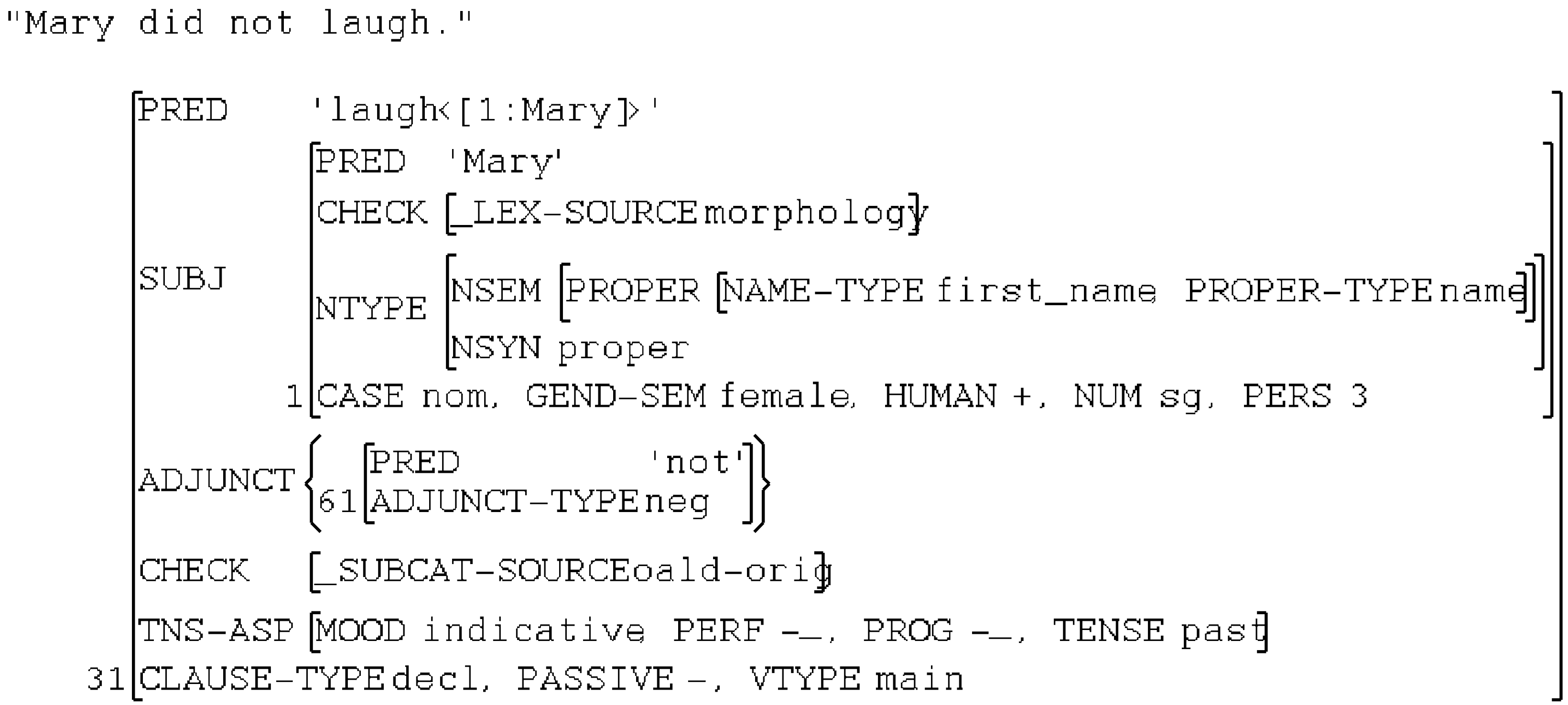
Example structures

String: Mary did not laugh.

Syntax: Functional/dependency structure



```
"Mary did not laugh."

   [PRED       'laugh<[1:Mary]>'                                                          ]
   [           [PRED   'Mary'                                                          ]  ]
   [           [CHECK  [_LEX-SOURCE morphology]                                        ]  ]
   [SUBJ       [       [NSEM [PROPER [NAME-TYPE first_name  PROPER-TYPE name]]]        ]  ]
   [           [NTYPE  [NSYN proper                                           ]        ]  ]
   [          1[CASE nom, GEND-SEM female, HUMAN +, NUM sg, PERS 3                     ]  ]
   [ADJUNCT    {   [PRED           'not']}                                                ]
   [           {61 [ADJUNCT-TYPE neg    ]}                                                ]
   [CHECK      [_SUBCAT-SOURCE oald-orig]                                                 ]
   [TNS-ASP    [MOOD indicative, PERF -_, PROG -_, TENSE past]                            ]
 31[CLAUSE-TYPE decl, PASSIVE -, VTYPE main                                               ]
```

Example structures cont.

Semantics

```
in_context(t,not(ctx(laugh:2))),
in_context(ctx(laugh:2),cardinality('Mary':0,sg)),
in_context(ctx(laugh:2),laugh(laugh:2,'Mary':0)),
in_context(ctx(laugh:2),tense(laugh:2,past)),
in_context(ctx(laugh:2),proper_name('Mary':0,name,'Mary'))
```

Abstract Knowledge Representation

```
 context(t),
context('cx_laugh##4'),
instantiable('Mary##0','cx_laugh##4'),
instantiable('Mary##0',t),
instantiable('laugh_ev##4','cx_laugh##4'),
uninstantiable('laugh_ev##4',t)
role(cardinality_restriction,'Mary##0',sg),
role(bodilyDoer,'laugh_ev##4','Mary##0'),
subconcept('Mary##0','Person'),
subconcept('laugh_ev##4','Laughing'),
temporalRel(startsAfterEndingOf,'Now','laugh_ev##4'),
```

Resources in a Unified Lexicon

- Mapping to abstract KR requires
  - Coverage of most words and constructions
  - Detailed lexical entailments
- Results of merging XLE, VerbNet, Cyc, WordNet
  - 9,835 different verb stems
  - 46,000 verb entries (indexed by subcat/sense)
  - 24,000 with VerbNet information
  - 2,800 with Cyc information
- Triangulation to extend mappings to Cyc concepts
  - 21,000 Verbs with Cyc data
  - 50,000 noun entries, including N-N compounds
  - 2,000 adjectives & adverbs

    (Quality of data not evaluated)

Abstract KR: “Ed fired the boy.”

```
PRED    fire<Ed, boy>
TENSE   past
SUBJ    [ PRED Ed ]
OBJ     [ PRED  boy ]
        [ DEF   +   ]
```

```
(subconcept Ed3 Person)
(subconcept boy2 MaleChild)
(subconcept fire_ev1 DischargeWithPrejudice)
(role fire_ev1 performedBy Ed3)
(role fire_ev1 objectActedOn boy2)
```

Conceptual

```
(context t)
(instantiable Ed3 t)
(instantiable boy2 t)
(instantiable fire_ev1 t)
```

Contextual

```
(temporalRel startsAfterEndingOf Now
   fire_ev1)
```

Temporal

Abstract KR: “Ed fired the gun.”

$$\left[\begin{array}{ll} \text{PRED} & \text{fire<Ed, hun>} \\ \text{TENSE} & \text{past} \\ \text{SUBJ} & \left[\ \text{PRED Ed}\ \right] \\ \text{OBJ} & \left[\begin{array}{ll} \text{PRED} & \text{gun} \\ \text{DEF} & + \end{array}\right] \end{array}\right]$$

```
(subconcept Ed0 Person)
(subconcept gun3 Gun)
(subconcept fire_ev1 ShootingAGun)
(role fire_ev1 performedBy Ed0)
(role fire_ev1 deviceUsed gun3)
```

Conceptual

```
(context t)
(instantiable Ed0 t)
(instantiable gun3 t)
(instantiable fire_ev1 t)
```

Contextual

```
(temporalRel startsAfterEndingOf Now
   fire_ev1)
```

Temporal

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Abstract Knowledge Representation

- Encode different aspects of meaning
  - Asserted content
    - **concepts and arguments, relations among objects**
  - Contexts
    - **author commitment, belief, report, denial, prevent, …**
  - Temporal relations
    - **qualitative relations among time intervals, events**
- Translate to various target KR's

  e.g. CycL,Knowledge Machine, Description Logic, AnsProlog
- Capture meaning ambiguity
  - Mapping to KR can introduce and reduce ambiguity
  - Need to handle ambiguity efficiently
- A Basic Logic for Textual Inference (Bobrow et al, July 05)

Cyc oriented version of AKR

- Cyc concepts: Person, Laughing, DischargeWithPrejudice, etc..
- Cyc Roles: bodilyDoer, performedBy, infoTransferred, etc
- WordNet/VerbNet as fallback mechanisms
- Sortal restrictions from Cyc disambiguate

  e.g, Ed fired the boy/Ed fired the gun.
- Limitation: raggedness of Cyc

How do we know? Can we do better ?

Raggedness?

- It’s clear that Cyc misses many senses of words, particularly more abstract ones.
- “Ed admitted the mistake” gives only:

  (A1, subconcept('admit_ev##1','AdmitToMembership')),

  (A2, subconcept('admit_ev##1','PermittingEntrance'))
- Nothing about “Ed admitted that [Mary had arrived]”.
- Also nothing about “hesitate”, “surprise”, “please”.
- Nothing about “forget” (compare: Ed forgot that Mary left -> Mary left but Ed forgot to leave -> Ed did not leave)

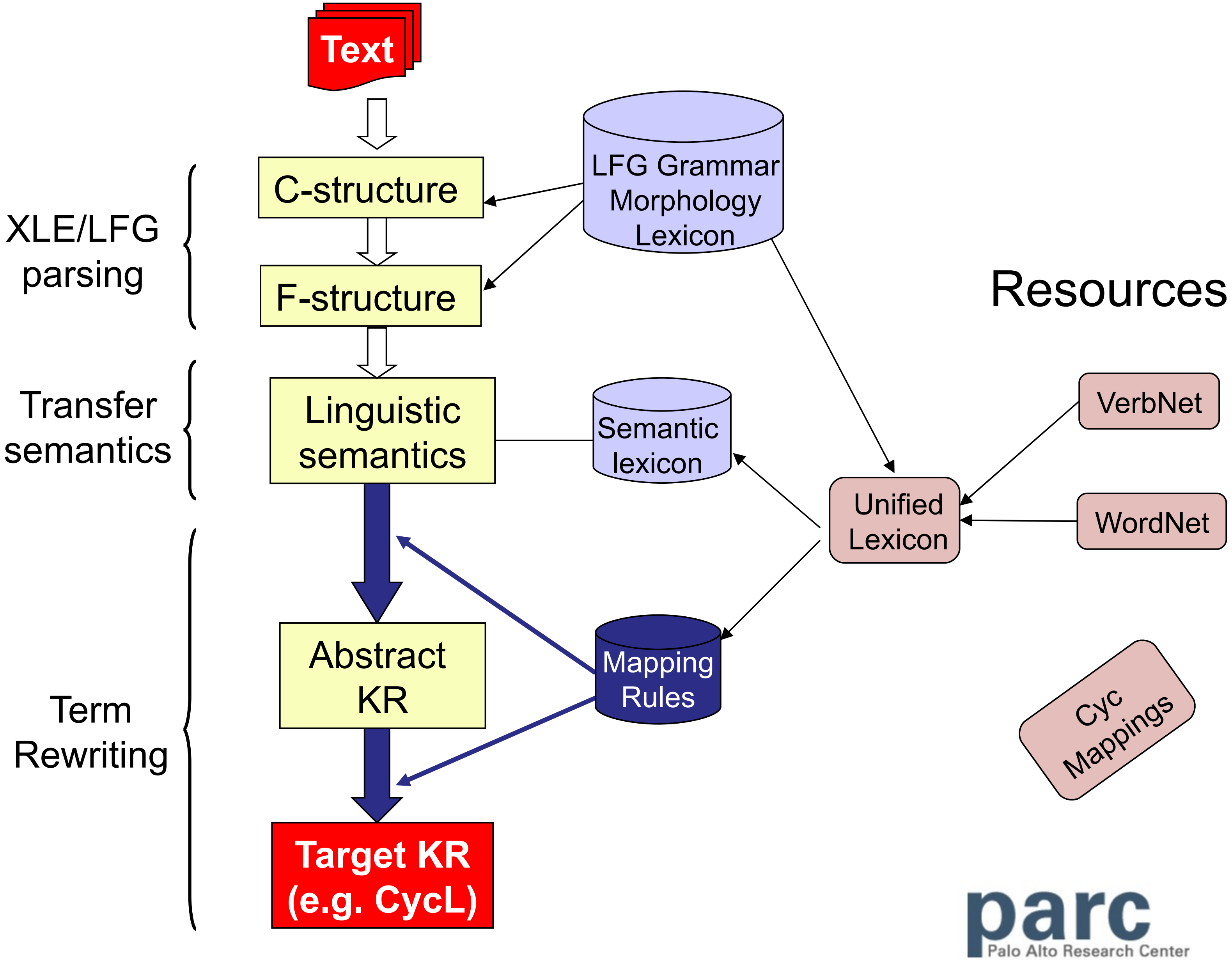
Cyc KR: ambiguating too much?

The school bought the store

3 schools, 2 stores, 3 buy in UL

```
  choice([A1, A2], 1),
  choice([B1, B2], A1),
  choice([C1, C2], A2),
  choice([D1], or(B2,C2)),
  choice([E1, E2], B1),
  choice([F1, F2], C1),
  choice([G1], or(E1,F2)),
  choice([H1], or(E2,F1)),
  choice([I1], or(G1,B2,C2))
….
cf(or(B2,or(C2,E1,F2)), role(buyer,'buy_ev##2','school##1')),
cf(or(B2,or(C2,E1,F2)), role(objectPaidFor,'buy_ev##2','store##4')),
…..
  cf(or(B2,or(C2,E1,F2)), subconcept('buy_ev##2','Buying')),
  cf(or(E2,F1), subconcept('buy_ev##2',buy)),
  cf(D1, subconcept('school##1','SchoolInstitution')),
  cf(G1, subconcept('school##1','SchoolInstitution-KThrough12')),
  cf(H1, subconcept('school##1','GroupFn'('Fish'))),
  cf(A2, subconcept('store##4','RetailStore')),
  cf(A1, subconcept('store##4','RetailStoreSpace'))
```

The Experiment:



Experiment: UL oriented version of AKR

- Cyc only one of the lexical resources
- VerbNet/WordNet "concepts" are synsets
- Roles: very coarse ones from VerbNet
- Goal roles: less refined than Cyc (800+)

  more refined than VerbNet (<20)
- Have infrastructure to experiment:

Can we do knowledge representation with VerbNet/WordNet?

Example “Mary didn’t laugh” AGAIN

Semantics

```
in_context(t,not(ctx(laugh:2))),
in_context(ctx(laugh:2),cardinality('Mary':0,sg)),
in_context(ctx(laugh:2),laugh(laugh:2,'Mary':0)),
in_context(ctx(laugh:2),tense(laugh:2,past)),
in_context(ctx(laugh:2),proper_name('Mary':0,name,'Mary'))
```

Abstract Knowledge Representation

```
context(t),
context('cx_laugh##4'),
instantiable('Mary##0','cx_laugh##4'),
instantiable('Mary##0',t),
instantiable('laugh_ev##4','cx_laugh##4'),
uninstantiable('laugh_ev##4',t)
role(cardinality_restriction,'Mary##0',sg),
role('Agent','laugh##2','Mary##0')
subconcept('Mary##0',[[7626,4576,4359,3122,7127,1930,1740]]),
subconcept('laugh##2',[[31311]])
temporalRel(startsAfterEndingOf,'Now','laugh_ev##4'),
```

Example: The school bought the store

```
KR:
  choice([A1, A2], 1)

Packed Clauses:
  cf(1, context(t)),
  cf(1, instantiable('buy##2',t)),
  cf(1, instantiable('school##1',t)),
  cf(1, instantiable('store##4',t)),
  cf(A1, role('Agent','buy##2','school##1')),
  cf(A2, role('Asset','buy##2','school##1')),
  cf(1, role('Theme','buy##2','store##4')),
cf(1,subconcept('buy##2',[[2186766]])),
cf(1,subconcept('school##1',
      [[8162936,8162558,7943952,7899136,7842951,29714,2236,2119,1740],
      [4099321,2884748,4290445,20846,3991,3122,1930,1740],
      [5686799,5682845,5681825,5631]])),
cf(1,subconcept('store##4',
      [[4153847,3706735,3908195,3262760,4290445,20846,3991,3122,1930,1740],
      [13194813,13194436,13087849,13084632,13084472,13084292,131597020]])),
  cf(1, temporalRel(startsAfterEndingOf,'Now','buy##2'))
```

First thoughts

- Surprisingly easy to change the base ontology
- Modular architecture does help
- Do we have as good results as before?
- Well, no…

Improvements can be made…

- Some WordNet senses of buying should only go with A1, some with A2
- Sortal restrictions/preferences should come in
- But ambiguity is managed without losing meanings

Discussion

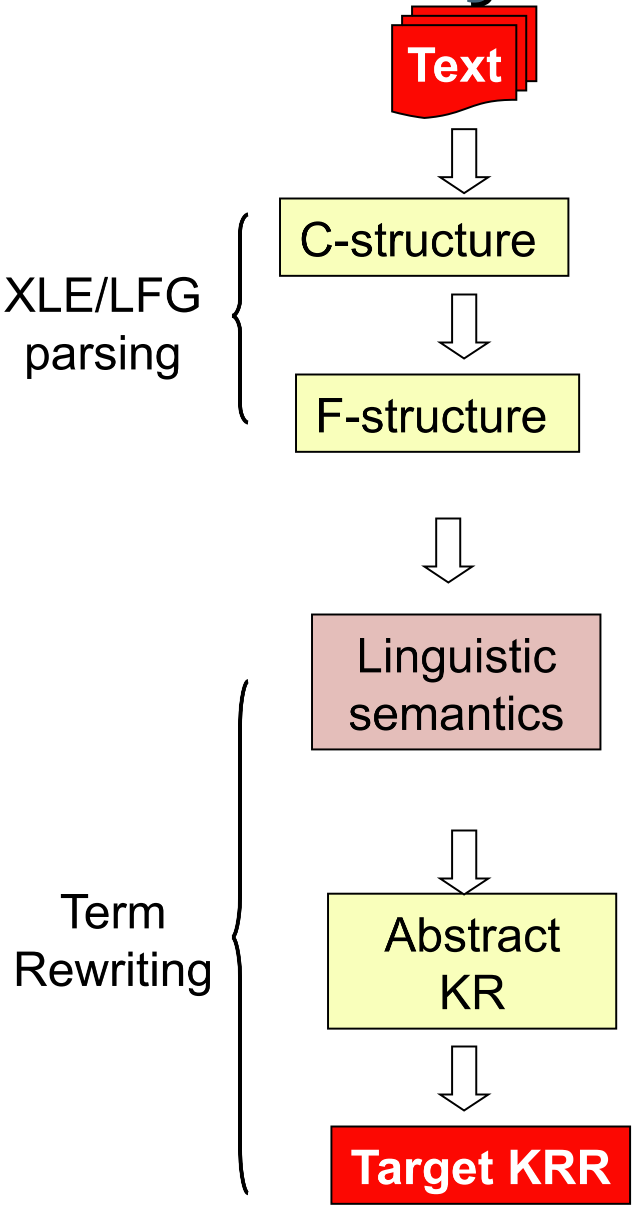
- Experiment ongoing
- Not “serious” report, yet. Gut feelings
- UL marking of factives/implicatives/etc very useful, (much) more needs to be done
- Matching can do more inference than first thought.
- Ambiguity enabling technology on concepts means no need to cluster WN senses ?
- Sortal restrictions/preferences a must ?

Thanks!

Mary fired the boy.

```
 cf(1, context(t)),
 cf(1, instantiable('Mary##0',t)),
 cf(1, instantiable('boy##3',t)),
 cf(1, instantiable('fire##1',t)),
 cf(1, role('Agent','fire##1','Mary##0')),
 cf(1, role('Theme','fire##1','boy##3')),
cf(1,subconcept('Mary##0',[[7626,4576,4359,3122,,1930,1740]])),
cf(1,subconcept('boy##3',
    [[10131706,9487097,7626,4576,4359,3122,7127,1930,1740],
    [9725282,10133569,9487097,7626,4576,4359,31]])),
  cf(A1, subconcept('fire##1',[[1124984],[1123061],[1123474]])),
  cf(A2, subconcept('fire##1',[[2379472]])),
  cf(1, temporalRel(startsAfterEndingOf,'Now','fire##1'))
```

Layered mapping



Text

C-structure

F-structure

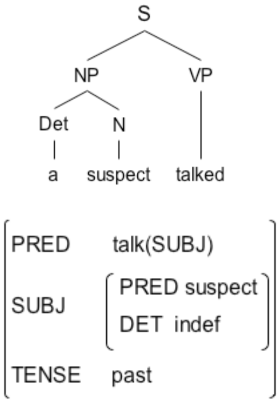
Linguistic semantics

Abstract KR

Target KRR

XLE/LFG parsing

Term Rewriting

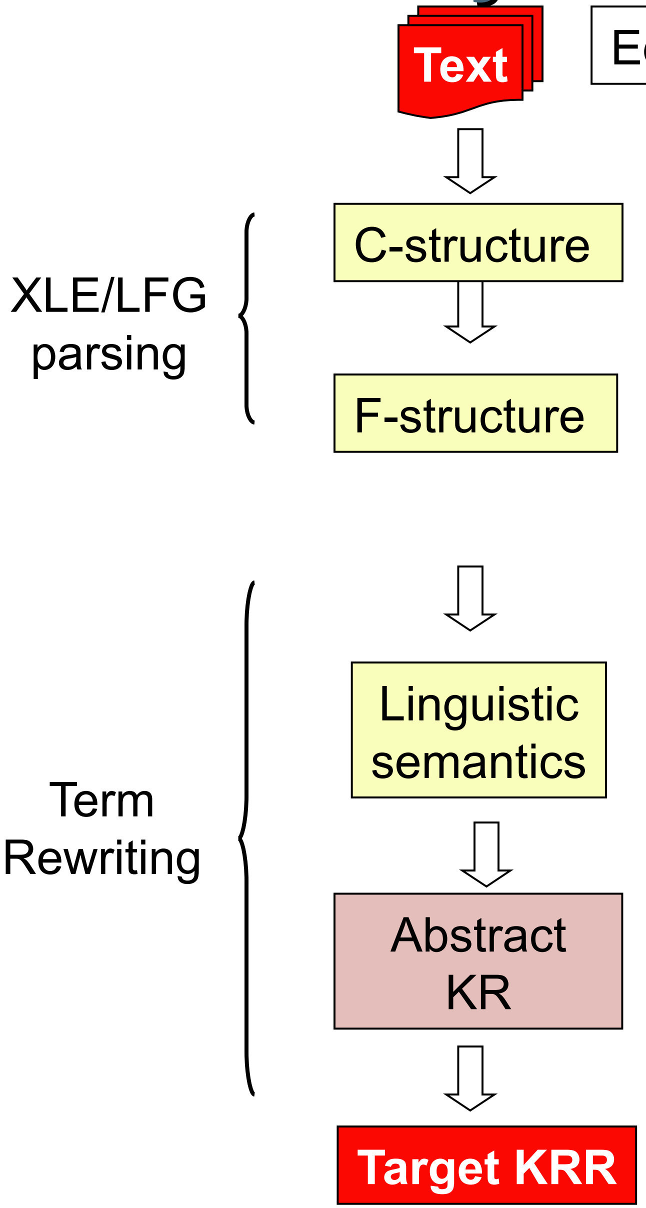


in_context(t,arrive(arrive:2,boy:1)),
in_context(t,cardinality(boy:1,sg)),
in_context(t,specifier(boy:1,a)),
in_context(t,tense(arrive:2,past))

Introduces contexts, cardinality restrictions, etc

Layered mapping

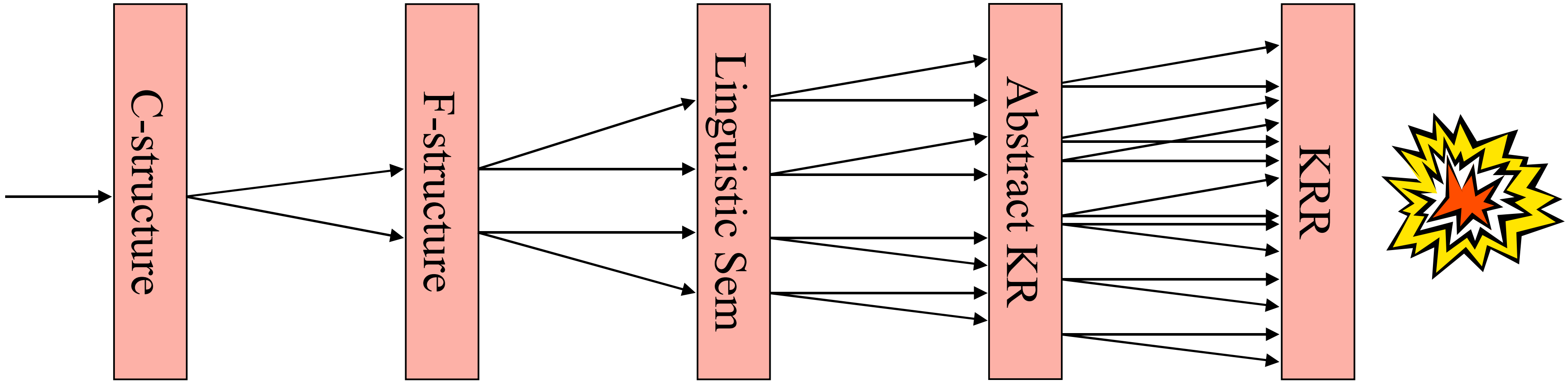
Ed knows that Mary arrived.



```
cf(1, context('cx_arrive##6')),
cf(1, context(t)),
cf(1, context_head('cx_arrive##6','arrive##6')),
cf(1, context_head(t,'know##1')),
cf(1, context_lifting_relation(veridical,t,'cx_arrive##6')),
cf(1, instantiable('Ed##0',t)),
cf(1, instantiable('Mary##4','cx_arrive##6')),
cf(1, instantiable('Mary##4',t)),
cf(1, instantiable('arrive##6','cx_arrive##6')),
cf(1, instantiable('arrive##6',t)),
cf(1, instantiable('know##1',t)),
cf(1, role('Agent','know##1','Ed##0')),
cf(1, role('Theme','arrive##6','Mary##4')),
cf(1, role('Theme','know##1','cx_arrive##6')),
cf(1, subconcept('Ed##0',[[7626,4576,4359,3122,7127,1930,1740]])),
cf(1, subconcept('Mary##4',[[7626,4576,4359,3122,7127,1930,1740]])
cf(1, subconcept('arrive##6',[[1987643]])),
cf(1, subconcept('know##1',[[585692],[587146],[587430],[588050]])),
cf(1, temporalRel(startsAfterEndingOf,'Now','arrive##6')),
cf(1, temporalRel(temporallyContains,'know##1','Now'))
```

Ambiguity is rampant in language

Alternatives multiply within and across layers…



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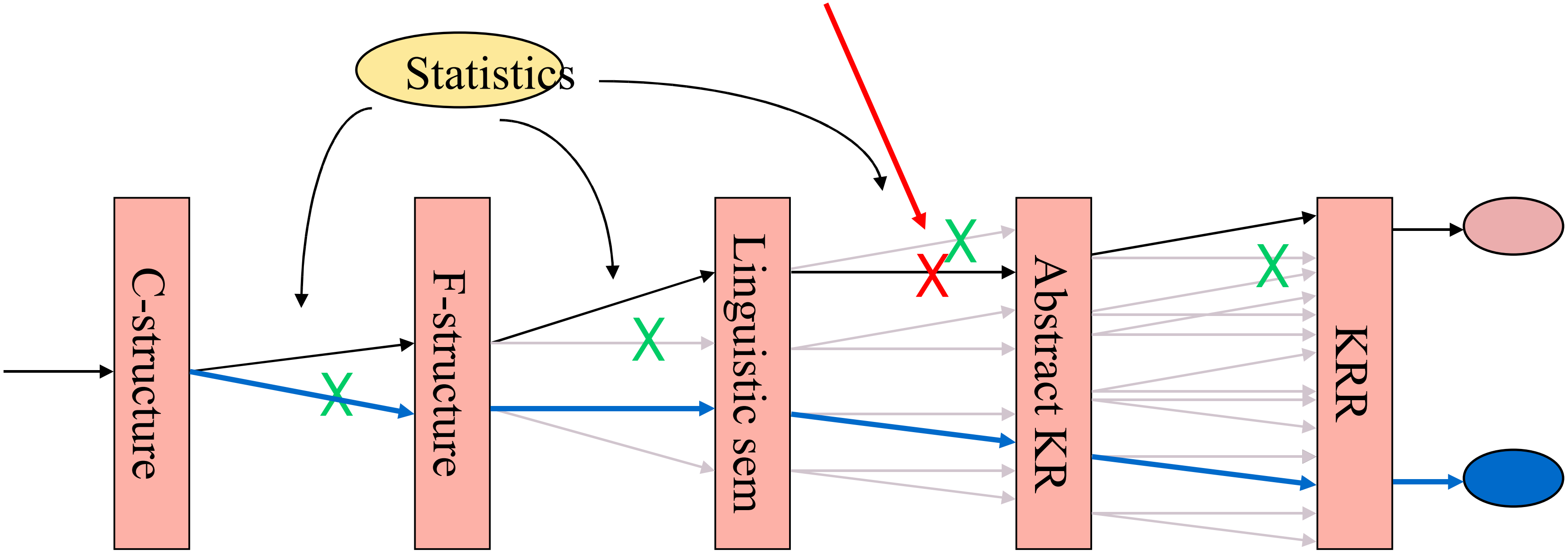
What not to do

- Use heuristics to prune as soon as possible
- Oops: Strong constraints may reject the so-far-best (= only) option



Fast computation, wrong result

Manage ambiguity instead

The sheep liked the fish.

How many sheep?

How many fish?

Options multiplied out

$$\left\{\begin{array}{l}\textit{The sheep-sg liked the fish-sg.}\\ \textit{The sheep-pl liked the fish-sg.}\\ \textit{The sheep-sg liked the fish-pl.}\\ \textit{The sheep-pl liked the fish-pl.}\end{array}\right\}$$

Options packed

$$\textit{The sheep}\begin{Bmatrix}\textit{sg}\\ \textit{pl}\end{Bmatrix}\textit{ liked the fish}\begin{Bmatrix}\textit{sg}\\ \textit{pl}\end{Bmatrix}$$

Packed representation:

- Encodes all dependencies without loss of information
- Common items represented, computed once
- Key to practical efficiency with broad-coverage grammars

Embedded contexts:
"The man said that Ed fired a boy."

```
(subconcept say_ev19 Inform-CommunicationAct)
(role say_ev19 senderOfInfo man24)
(role say_ev19 infoTransferred comp21)

(subconcept fire_ev20 DischargeWithPrejudice)
(role fire_ev20 objectActedOn boy22)
(role fire_ev20 performedBy Ed23)
```

```
(context t)
(context comp21)
(context_lifting_rules averidical t comp21)

(instantiable man24 t)
(instantiable say_ev19 t)
(instantiable Ed23 t)

(instantiable boy22 comp21)
(instantiable fire_ev20 comp21)
```

Contexts for negation

"No congressman has gone to Iraq since the war."

- Contextual relations:

  (context t)

  (context not58) *context triggered by negation*

  (context_lifting_rules antiveridical t not58)

  interpretation of negation

- Instantiability claims

  (instantiable go_ev57 not58)

  (uninstantiable go_ev57 t) *entailment of negation*

Local Textual Inference

- Broadening and Narrowing

  Ed went to Boston by bus → Ed went to Boston

  Ed didn't go to Boston → Ed didn't go to Boston by bus

- Positive implicative

  Ed managed to go → Ed went

  Ed didn't manage to go → Ed didn't go

- Negative implicative

  Ed forgot to go → Ed didn't go

  Ed didn't forget to go → Ed went

- Factive

  $$\left.\begin{array}{l}\text{Ed forgot that Bill went}\\ \text{Ed didn't forget that Bill went}\end{array}\right\} \longrightarrow \text{Bill went}$$

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Local Textual Inference

Matching of Abstract KR: Inference by Inclusion

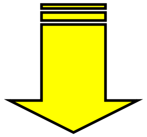
Ed went to Boston by bus. →	Ed went to Boston.
(context t)	(context t)
(instantiable Boston8 t)	(instantiable Boston8 t)
(instantiable Ed9 t)	(instantiable Ed9 t)
(instantiable bus7 t)	
(instantiable go_ev6 t)	(instantiable go_ev6 t)
(role go_ev6 objectMoving Ed9)	(role go_ev6 objectMoving Ed9)
(role go_ev6 toLocation Boston8)	(role go_ev6 toLocation Boston8)
(role go_ev6 vehicle bus7)	
(subconcept Boston8 CityOfBostonMass)	(subconcept Boston8 CityOfBostonMass)
(subconcept Ed9 Person)	(subconcept Ed9 Person)
(subconcept bus7 Bus-RoadVehicle)	
(subconcept go_ev6 Movement-TranslationEvent)	(subconcept go_ev6 Movement-TranslationEvent)
(temporalRel startsAfterEndingOf Now go_ev6)	(temporalRel startsAfterEndingOf Now go_ev6)

NYT 2000: top of the chart

be (un)able to	> 12600
fail to	> 5000
know that	> 4800
acknowledge that	> 2800
be too ADJ to	> 2400
happen to	> 2300
manage to	> 2300
admit/concede that	> 2000
be ADJ enough to	> 1500
have a/the chance to	> 1500
go on/proceed to	> 1000
have time/money to	> 1000

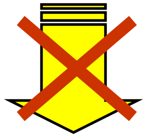
Verbs differ as to speaker commitments

"Bush **realized that** the US Army had to be transformed to meet new threats"



"The US Army had to be transformed to meet new threats"

"Bush **said that** Khan sold centrifuges to North Korea"



"Khan sold centrifuges to North Korea"

Implicative verbs: carry commitments

- Commitment depends on verb context

  Positive (+) or negative (-)

- Speaker commits to truth-value of complement

  True (+) or false (-)

++/- - Implicative

positive context: positive commitment
negative context: negative commitment

“Ed **managed to** leave”

⇒ “Ed left”

“Ed **didn’t manage to** leave”

⇒ “Ed didn’t leave”

+-/-+ Implicative

positive context: negative commitment
negative context: positive commitment

“Ed **forgot to** leave”

⇒ “Ed didn’t leave”

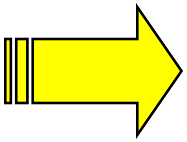
“Ed **didn’t forget to** leave”

⇒ “Ed left”

++ Implicative

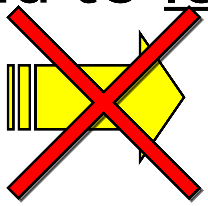
positive context only: positive commitment

“Ann **forced** Ed **to** leave”



“Ed left”

“Ann **didn’t force** Ed **to** leave”



“Ed left / didn’t leave”

+- Implicative

positive context only: negative commitment

“Ed **refused to** leave”

⇒ “Ed didn’t left”

“Ed **didn’t refuse to** leave”

⇏ “Ed left / didn’t leave”

-+ Implicative

negative context only: positive commitment

“Ed **hesitated to** leave”

⇏ “Ed left / didn’t leave”

“Ed **didn’t hesitate to** leave”

⇒ “Ed left”

-- Implicative

negative context only: negative commitment

“Ed **attempted to** leave”

⇏ “Ed left / didn’t leave”

“Ed **didn’t attempt to** leave”

⇒ “Ed didn’t leave”

+Factive

positive commitment no matter what context

“Ann **realized that** Ed left”

“Ann didn’t **realize that** Ed left”

⇒ “Ed left”

Like ++/-+ implicative but additional commitments in questions and conditionals

Did Ann realize that Ed left?

cf. Did Ed manage to leave?

- Factive

negative commitment no matter what context

“Ann **pretended that** Ed left”

“Ann didn’t **pretend that** Ed left”

→ “Ed didn’t leave”

Like +-/-- implicative but with additional commitments

Coding of implicative verbs

- Implicative properties of complement-taking verbs
  - Not available in any external lexical resource
  - No obvious machine-learning strategy
- 1250 embedded-clause verbs in PARC lexicon
- 400 examined on first pass
  - Considered in BNC frequency order
  - Google search when intuitions unclear
- 1/3 are implicative, classified in Unified Lexicon

Matching for implicative entailments

Term rewriting promotes commitments in Abstract KR

"Ed managed to leave."

```
context(cx_leave7)
context(t)
instantiable(leave_ev7 t)
context_lifting_rules(veridical t cx_leave7)
instantiable(Ed0 t)
instantiable(leave_ev7 cx_leave7)
instantiable(manage_ev3 t)
role(objectMoving leave_ev7 Ed0)
role(performedBy manage_ev3 Ed0)
role(whatsSuccessful manage_ev3 cx_leave7)
```

"Ed left."

```
context(t)
instantiable(Ed0 t)
instantiable(leave_ev1 t)
role(objectMoving leave_ev1 Ed0)
```

Embedded examples in real text

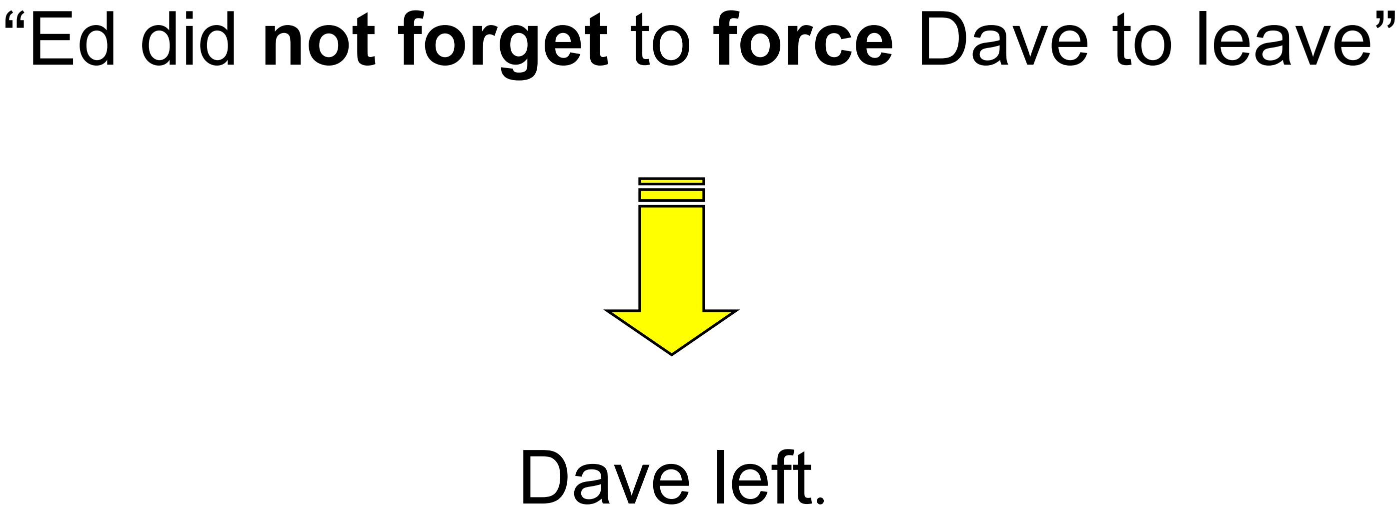
From Google:

Song, Seoul's point man, **did not forget to persuade** the North Koreans to make a “strategic choice” of returning to the bargaining table...

↓

Song persuaded the North Koreans…

Promotion for a (simple) embedding



“Ed did **not forget** to **force** Dave to leave”

Dave left.

Conclusions

- Broad coverage, efficient language to KR system
- Need extensive resources (ontologies, argument mappings)
  - Much work to incorporate
- Use layered architecture
  - Matching as well as reasoning
- KR mapping both increases and decreases ambiguity

Term-Rewriting for KR Mapping

- Rule form

  <Input terms> ==> <Output terms> (obligatory)
  <Input terms> ?=> <Output terms> (optional)
  (optional rules introduces new choices)

- Input patterns allow
  - **Consume term if matched: Term**
  - **Test on term without consumption: +Term**
  - **Test that term is missing: -Term**
  - **Procedural attachment: {ProcedureCall}**

- Ordered rule application
  - **Rule1 applied in all possible ways to Input to produce Output1**
  - **Rule2 applied in all possible ways to Output1 to produce Output2**

Example rules: depassivisation

```
+VTYPE(%V, %%), +PASSIVE(%V,+),
 SUBJ(%V, %LogicalOBJ)
==>
 OBJ(%V, %LogicalOBJ).

 +VTYPE(%V, %%), +PASSIVE(%V,+),
 OBL-AG(%V,%LogicalSUBJ), PFORM(%LogicalSUBJ, %%)
==>
 SUBJ(%V, %LogicalSUBJ).

 +VTYPE(%V, %%), +PASSIVE(%V,+),
 -SUBJ(%V,%%)
==>
 SUBJ(%V, %AgtPro),
 PRED(%AgtPro, agent_pro), PRON-TYPE(%AgtPro, null_agent).
```

Term-rewriting can introduce ambiguity

- Alternative lexical mappings

```
/- cyc_concept_map(bank, FinancialInstitution).
 /- cyc_concept_map(bank, SideOfRiver).
```

Permanent Background Facts

```
 ist(%%, %P( %Arg)),
cyc_concept_map(%P, %Concept)
  ==> sub_concept(%Arg, %Concept).
```

Mapping from Predicate to Cyc concept

- Input term

```
ist(ctx0, bank(bank##1))
```

- Alternative rule applications produce different outputs

  Rewrite system represents this ambiguity by a new choice

- Output
  - C1: sub_concept(bank##1, FinancialInstitution)
    C2: sub_concept(bank##1, SideOfRiver)
  - (C1 xor C2) ↔ 1

Rules can prune ill-formed mappings

- The bank hired Ed

```
hire(%E),  subj(%E, %Subj), obj(%E, %Obj),
+sub_concept(%Subj, %CSubj), +sub_concept( %Obj, %CObj),
{genls( %CSubj, Organization), genls( %CObj, Person)}
 ==> sub_concept(%E, EmployingEvent),
        performedBy(%E, %Subj),  personEmployed(%E, %Obj).
```

Rule for mapping *hire*

- From Cyc: genls(FinancialInstitution, Organization)   true
  genls(SideOfRiver, Organization)   false

- If bank is mapped to SideOfRiver, the rule will not fire.
  This leads to a failure to consume the subject.

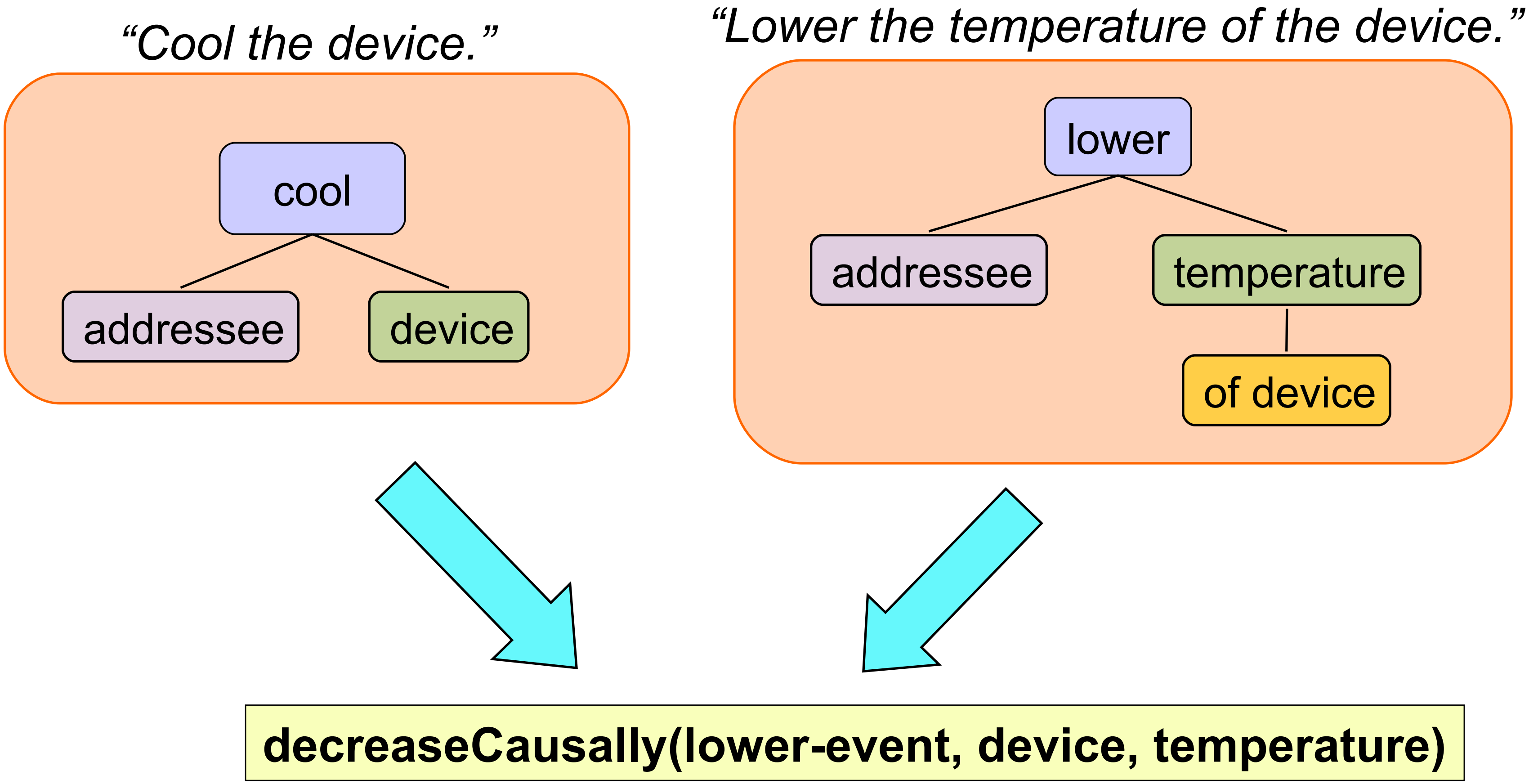
```
subj(%%,%%) ==> stop.
```

  prunes this analysis from the choice space.
- In general, later rewrites prune analyses that don’t consume grammatical roles.

The NLP-KR Gap

- There have been parallel efforts on text-based and knowledge-based question answering
  - Benefits of knowledge-based approaches inaccessible without some bridge from text to KR.
- Prime Goal
  - Robust, broad coverage mapping from texts and questions to KR
  - Allow KRR systems with lots of world knowledge to answer questions
- Second-thoughts Goal
  - Robust, broad coverage mapping from texts and questions to KR
  - Allow system with basic knowledge of English to answer questions

Canonical conceptual semantics



“Cool the device.”

cool

addressee

device

“Lower the temperature of the device.”

lower

addressee

temperature

of device

decreaseCausally(lower-event, device, temperature)