DEEP SEMANTIC ANALYSIS OF TEXT

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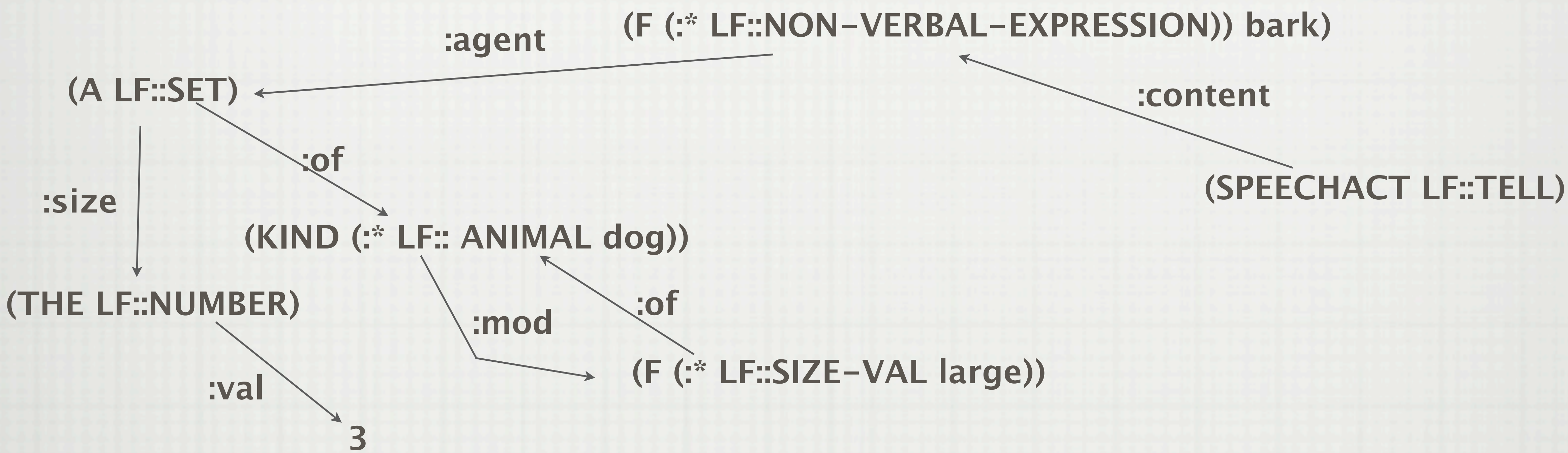
WHAT WE MEAN BY DEEP REPRESENTATION

- WORD SENSE DISAMBIGUATION*
- SEMANTIC ROLES*
- ENTITY IDENTIFICATION, MODIFIER DEPENDENCIES
- QUANTIFICATION & OPERATOR SCOPING
- CO-REFERENCE

*all with respect to some defined ontology

TOWARDS A UNIVERSAL SEMANTIC REPRESENTATION

THE TRIPS LOGICAL FORM



Three large dogs bark

(SPEECHACT v1 LF::TELL :content v2)
(F v2 (:* LF::NON-VERBAL-EXPRESSION bark)
    :agent v3)
(A v3 LF::SET :of V4 :size v6)
(KIND v4 (:* LF::ANIMAL dog) :mod v5)
(F v5 (:* LF::SIZE-VAL large) :of v4)
(THE v6 LF::NUMBER :val 3)

TOWARDS A UNIVERSAL SEMANTIC REPRESENTATION

MAPPING TO MRS-STYLE REPRESENTATION

(LF::F v2 (:* LF::NONVERBAL-EXPRESSION bark) :agent v3 :mods
(v4 v5 v6) :tma ((W::TENSE W::PRES)))

h1: Bark(v2) & agent(v2,v3)

(LF::SOME v3 LF::SET :of v6)

h2: Set(v3) & MemberType(v3, v6)
h2.1:Some(v3,h3, h4)   h3=q h2

(LF::KIND v6 (:* LF::ANIMAL dog))

h2: Dog(v6)

(LF::OP v5 (:* LF::FREQUENCY usually) :core v2)

h3: Usually(h4)   h4 =q h1

(LF::F v6 LF::FREQUENCY :val v9 :of v2)

h5: Frequency(v2, v9)

(LF::EVERY v9 (:* LF::TIME-OBJECT morning))

h6: Morning(v9)
h6.1: Every(v9, h8, h9)   h8 =q h6

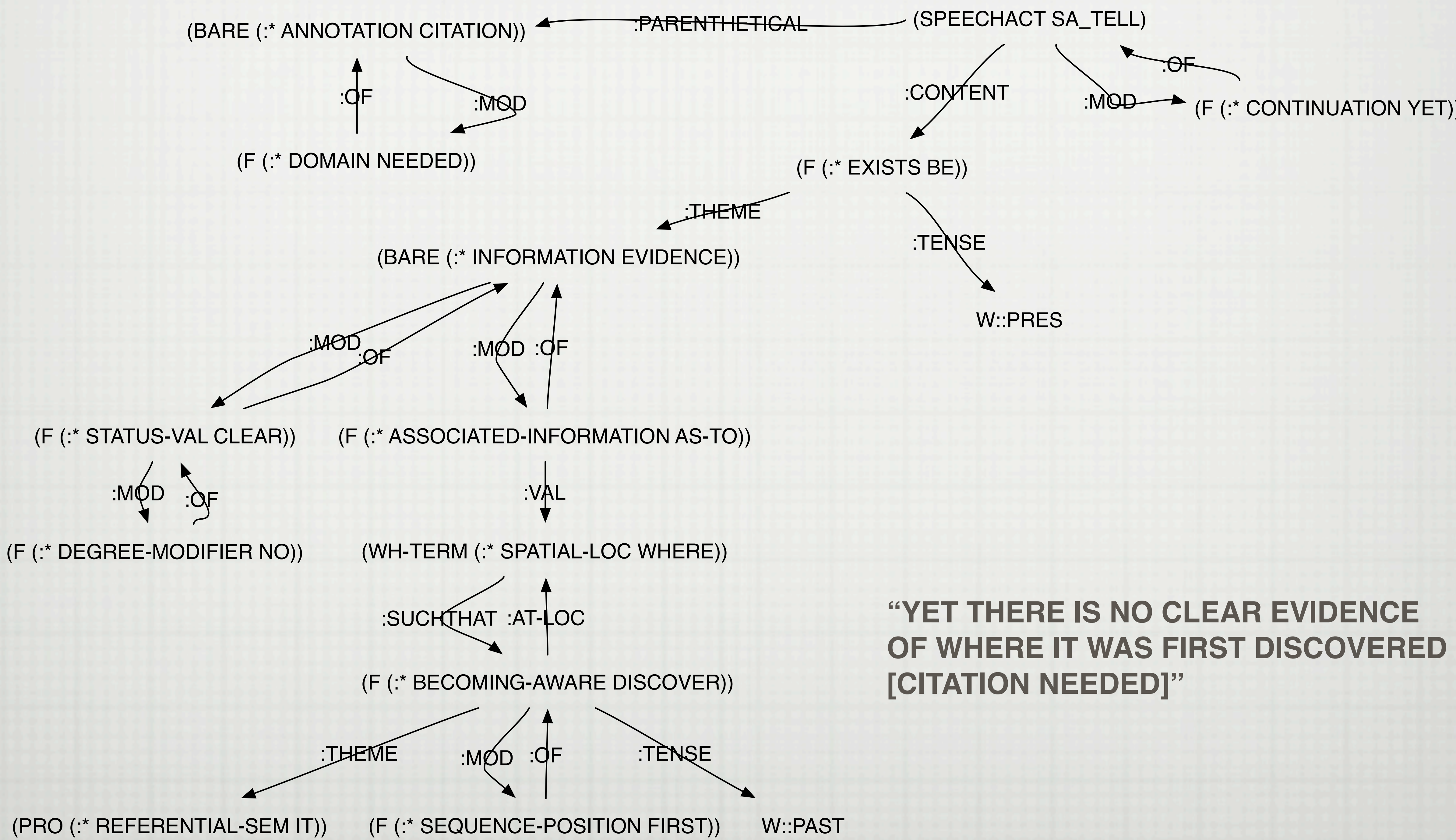
Some dogs usually bark every morning

TOWARDS A UNIVERSAL SEMANTIC REPRESENTATION

CAN WE MAP ANY MRS REPRESENTATION TO AN LF-GRAPH?

- NOT IN GENERAL, BUT
- IF WE RESTRICT OURSELVES TO "PRACTICAL MRS": THE MRS STRUCTURES THAT CAN BE GENERATED BY THE GRAMMAR
  - as described in Copestake et al, 2005
- THEN WE CAN PROVE THAT PRACTICAL MRS AND LF GRAPHS ARE EQUIVALENT

EXAMPLE OF LF GRAPH PRODUCED BY PARSER



"YET THERE IS NO CLEAR EVIDENCE OF WHERE IT WAS FIRST DISCOVERED [CITATION NEEDED]"

TRIPS Language Processing

"Let me show you how to find a restaurant"

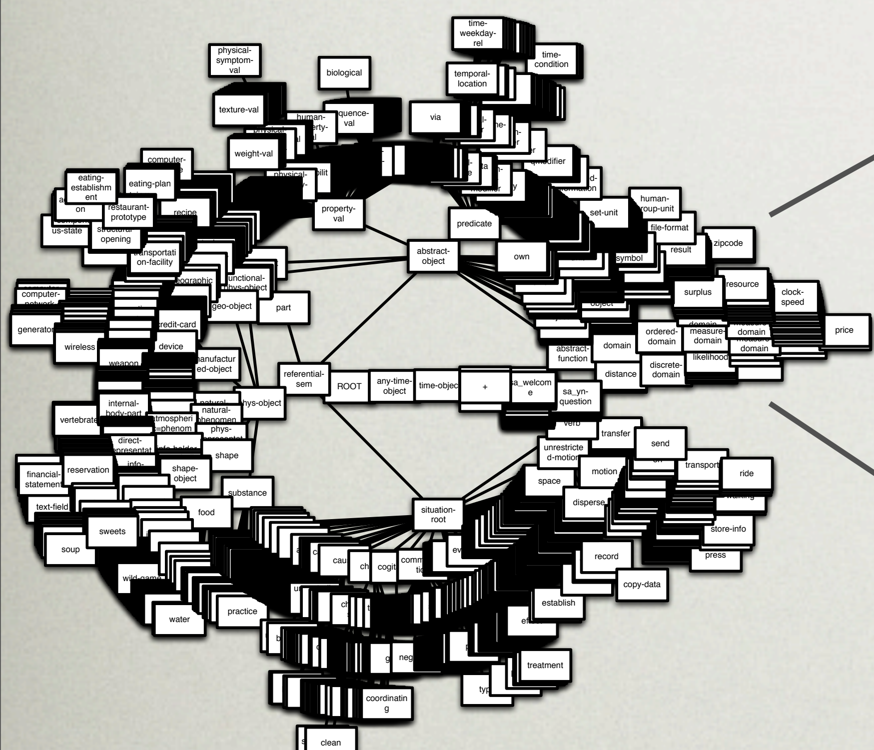
Extensive grammar of Spoken English

14,000 word core semantic lexicon

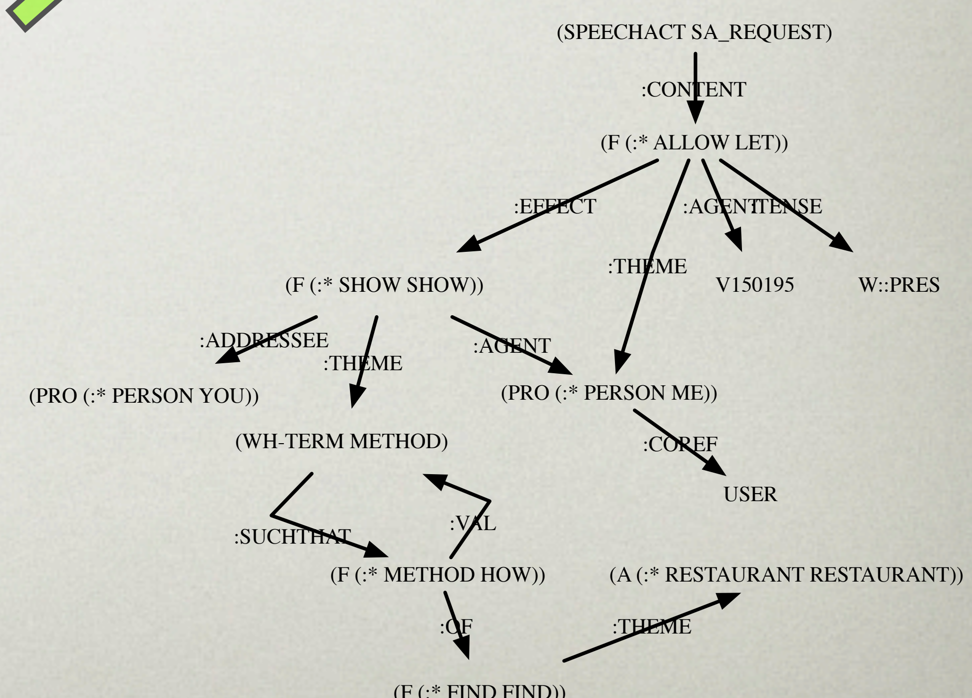
100,000+ word Dynamically-constructed semantic Lexicon

Wordnet, Comlex

Robust Chart Parser



Generic 2000+ Concept Ontology



LF graph

SEMANTIC LEXICON

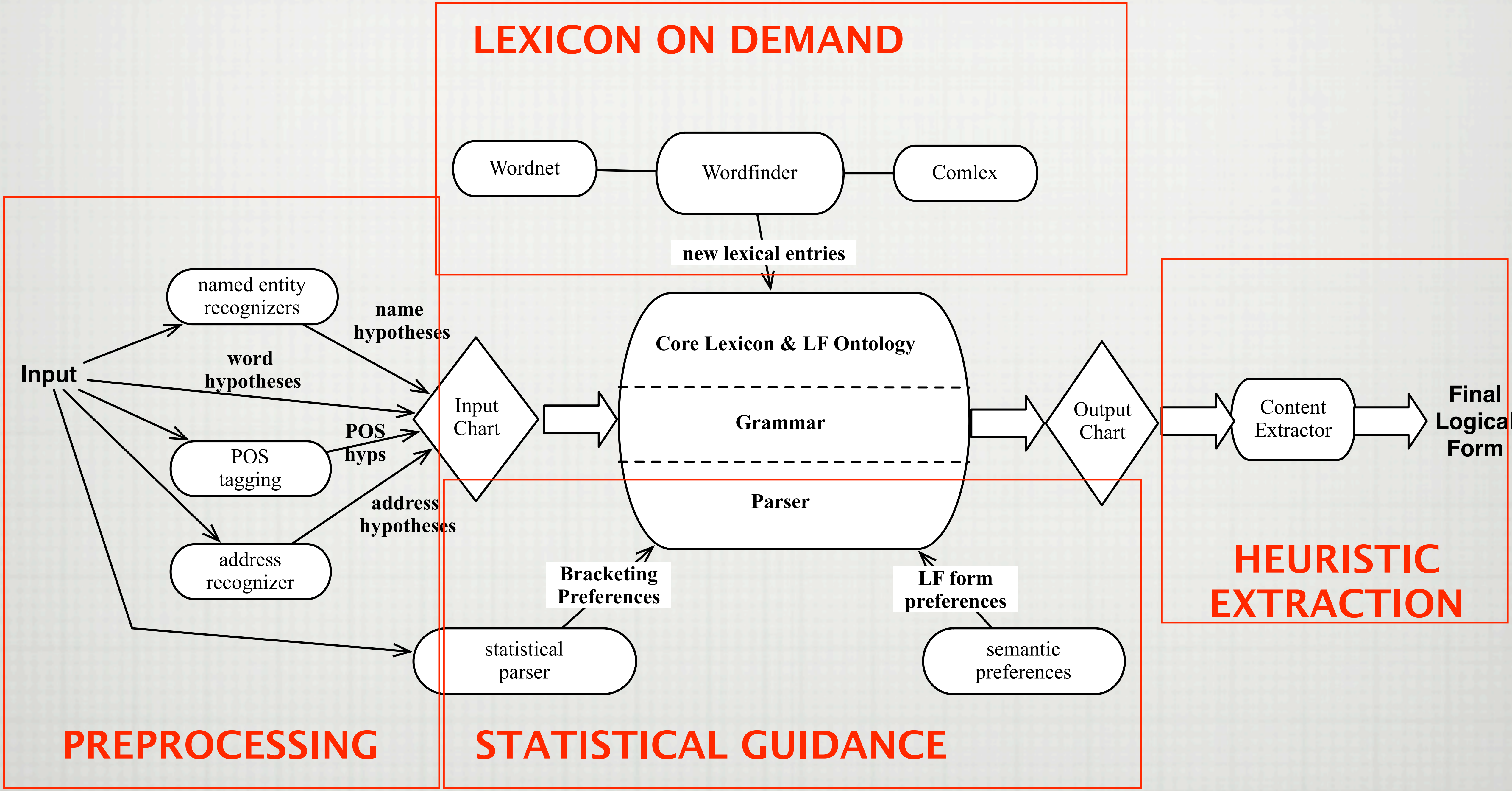
- DOMAIN GENERAL LINGUISTIC ONTOLOGY
  - "DEEPER" THAN ARGUMENT STRUCTURE
  - LESS FINE-GRAINED THAN WORDNET
  - STRONGLY INFLUENCED BY FRAMENET AND EUROWORDNET
  - REFINE SENSES ONLY TO THE LEVEL OF LINGUISTIC RELEVANCE BASED ON EXPERIENCE BUILDING SYSTEMS TO SUPPORT REASONING

Sense	Example	# wordnet senses	Type Specific Semantic Roles
CONSUME	Take an aspirin	1	:agent :theme
MOVE	Take it to the store	7	:agent :theme :to-loc
ACQUIRE	Take a picture	16	:theme :recipient :cost
SELECT	I'll take that one	4	:agent :theme
COMPATIBLE-WITH	The projector takes 100 volts	2	:affected :theme
TAKE-TIME	It took three hours	1	:theme :duration

GRAMMAR & PARSING

- **AUGMENTED CONTEXT FREE GRAMMAR WITH FEATURE UNIFICATION**
  - **SIMULTANEOUS SYNTACTIC AND SEMANTIC PROCESSING**
  - **SUBCATEGORIZATION IS LEXICALIZED**
  - **PASSIVES, DATIVE SHIFTS, GERUNDS, GAPS, ETC. HANDLED EXPLICITLY IN GRAMMAR**
- **SEARCH IS PREFERENCE-BASED**
  - **BEST-FIRST SEARCH USING RULE AND LEXICAL PREFERENCES BASED ON A DECADE OF EXPERIENCE**
- **PRODUCES CHART OF SEMANTIC HYPOTHESES**
  - **BEST FIRST, STOPS WHEN DESIRED # INTERPRETATIONS FOUND**
    - **(OR TIMES OUT ON UPPER LIMIT ON # CONSTITUENTS)**
- **MEANING EXTRACTION**
  - **SEARCH CHART FOR “BEST” SEQUENCE OF SEMANTIC UNITS**

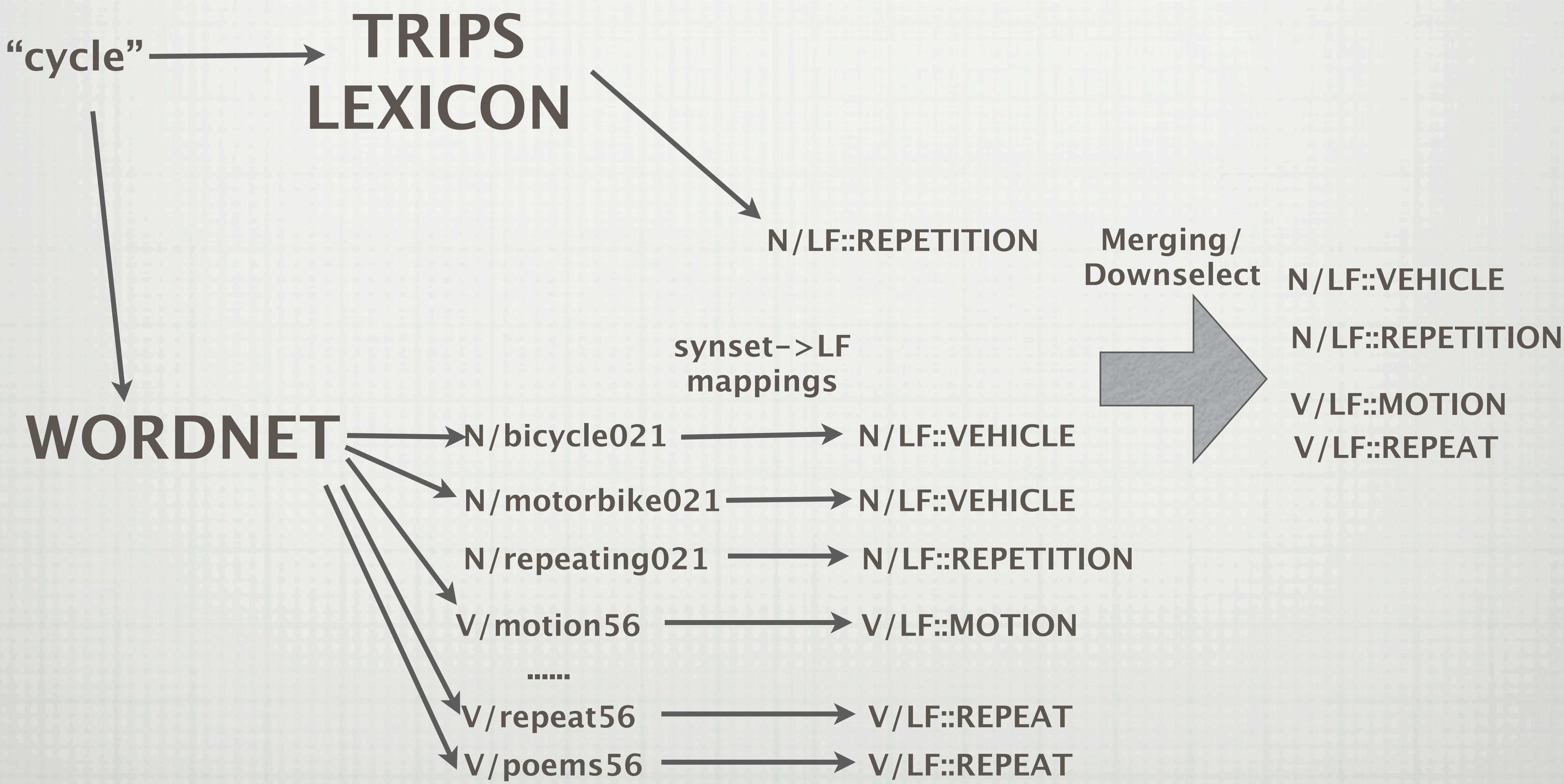
ATTAINING BROAD-COVERAGE "DEEP" PARSING



PREPROCESSING

<table>
<tr><th></th><th>The</th><th>New</th><th>York</th><th>Times</th><th>is</th><th>at</th><th>125</th><th>Main</th></tr>
<tr><td>regular input to lexicon</td><td>word/the</td><td>word/new</td><td>word/york</td><td>word/times</td><td>word/is</td><td>word/at</td><td>word/125</td><td>word/main</td></tr>
<tr><td>POS preference</td><td>ART/the</td><td>ADJ/new</td><td>N/york</td><td>N/times</td><td>V/is</td><td>P/at</td><td>N/125</td><td>ADJ/main</td></tr>
<tr><td rowspan="2">NER</td><td colspan="4">NAME/The New York Time/LF::ORGANIZATION</td><td rowspan="2"></td><td rowspan="2"></td><td rowspan="2"></td><td rowspan="2">NAME/Main/ LF::GEO-REGION</td></tr>
<tr><td></td><td colspan="2">NAME/New York/ LF::GEO-REGION</td><td></td></tr>
<tr><td>Address Recognizer</td><td></td><td></td><td></td><td></td><td></td><td></td><td colspan="2">NAME/125 Main/ LF::ADDRESS</td></tr>
</table>

LEXICON ON DEMAND



STATISTICAL GUIDANCE*

SYNTACTIC PREFERENCES

	The	New	York	Times	is	at	125	Main
Preferred constituent boundary	[NP			]	[VP	[PP	[NP	]]]

Parser boosts constituents that match predicted constituent boundaries (Swift, Allen & Gildea, 2005)

SEMANTIC PREFERENCES

LF::CONSUME :agent LF::PERSON :theme LF::FOOD
LF::CAUSE-TO-MOVE :agent LF::PERSON :theme LF::VEHICLE
LF::PART-OF :theme LF::PHYS-STRUCTURE :affected LF::PHYS-STRUCTURE
...

Parser boosts constituents that match predicted LF forms

* **preferences we not used in the evaluation reported here**

EVALUATION

- COMPUTING PRECISION AND RECALL ON LF GRAPHS

PARSER OUTPUT

(F (:* LF::NON-VERBAL-EXPRESSION)) bark)

:theme

:of (KIND (:* LF:: MOVE dog))

(A LF::SET)

:mod

:of

(BARE (:* LF::SIZE-VAL large))

GOLD GRAPH

(F (:* LF::NON-VERBAL-EXPRESSION)) bark)

:agent

(A LF::SET)

:of

:size

(KIND (:* LF:: ANIMAL dog))

(THE LF::NUMBER)

:mod

:of

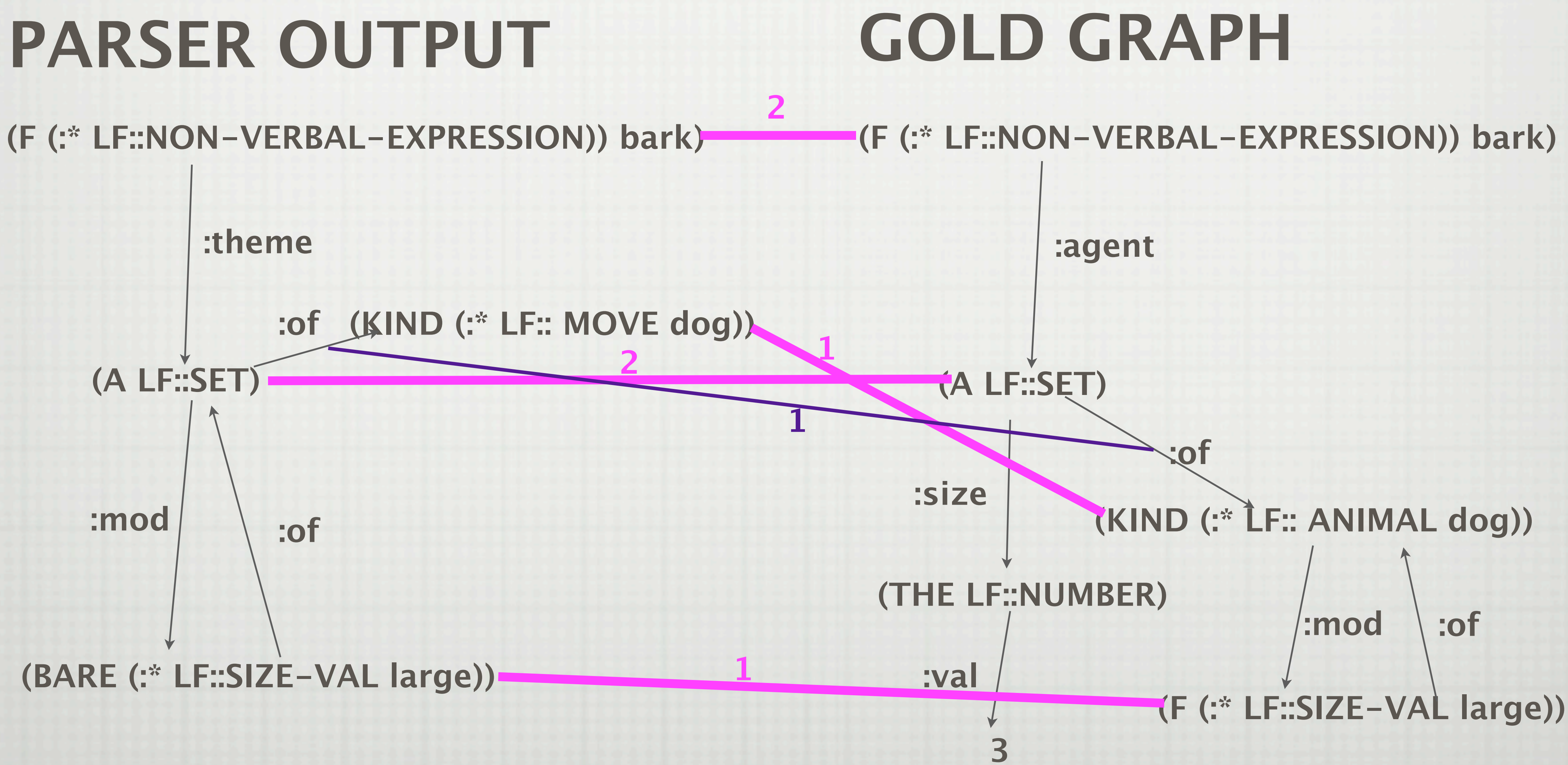
:val

(F (:* LF::SIZE-VAL large))

3

EVALUATION

- NEED SCORING FUNCTION FOR NODE & ARC MATCHING
- FIND THE NODE ALIGNMENT THAT MAXIMIZES THE CUMULATIVE SCORE



CURRENT EVALUATION SCHEME

- **GIVEN AN ALIGNMENT FUNCTION A_G FROM**
  - **NODES IN A TEST GRAPH T --> NODES IN A GOLD GRAPH G**
- **NODE SCORE $SC_{A_G}(N)$**
  - **1 IFF SPECIFIER(N)=SPECIFIER(A_G(N))** PLUS
  - **1 IFF TYPE(N)=TYPE(A_G(N))**
- **EDGE SCORE $SC_{A_G}(E) = 1$**
  - **IFF GOLD GRAPH CONTAINS THE EDGE**
  A_G(START(E))--LABEL(E)--> A_G(END(E))
- **SCORE FOR TEST GRAPH T GIVEN GOLD GRAPH G**
  - **$SCORE(T,G) = MAX_{A_G}(SUM_N\ SC_{A_G}(N) + SUM_E\ SC_{A_G}(E))$**
- **PRECISION = SCORE(T,G)/SCORE(T,T)**
- **RECALL = SCORE(T,G)/SCORE(G,G)**

PERFORMANCE AGAINST GOLD STANDARDS

Text	Base System		Final System	
	Prec	Recall	Prec	Recall
1 “physics”	70.1%	70.1%	70.7%	76.0%
2 “cancer”	62.1%	71.9%	62.8%	72.8%
3 “dining”	86.7%	90.4%	90.8%	94.6%
4 “dogs”	63.0%	68.6%	63.8%	67.7%
5 “guns”	55.0%	64.0%	60.3%	69.5%
6 “gardens”	47.4%	53.6%	56.2%	62.1%
7 “wind”	n/a	n/a	65.8%	76.3%
Average	64.1%	69.7%	67.1%	74.1%