Outline

- Linguistic Theories of semantic representation
  - Case Frames – *Fillmore* – FrameNet
  - Lexical Conceptual Structure – *Jackendoff* – LCS
  - Proto-Roles – *Dowty* – PropBank
  - English verb classes (diathesis alternations) - *Levin* - VerbNet
- Manual Semantic Annotation
- Automatic Semantic annotation
- Parallel PropBanks and Event Relations

Thematic Proto-Roles and Argument Selection, David Dowty, *Language 67*: 547-619, 1991

Thanks to Michael Mulyar

Context: Thematic Roles

- Thematic relations (Gruber 1965, Jackendoff 1972)
- Traditional thematic roles types include:

  Agent, Patient, Goal, Source, Theme, Experiencer, Instrument (p. 548).
- “Argument-Indexing View”: thematic roles objects at syntax-semantics interface, determining a syntactic derivation or the linking relations.
- Θ-Criterion (GB Theory): each NP of predicate in lexicon assigned unique θ-role (Chomsky 1981).

Problems with Thematic Role Types

- Thematic role types used in many syntactic generalizations, e.g. involving empirical thematic role hierarchies. Are thematic roles syntactic universals (or e.g. constructionally defined)?
- Relevance of role types to syntactic description needs motivation, e.g. in describing transitivity.
- Thematic roles lack independent semantic motivation.
- Apparent counter-examples to θ-criterion (Jackendoff 1987).
- Encoding semantic features (Cruse 1973) may not be relevant to syntax.

Problems with Thematic Role Types

- Fragmentation: Cruse (1973) subdivides Agent into four types.
- Ambiguity: Andrews (1985) is Extent, an adjunct or a core argument?
- Symmetric stative predicates: e.g. “This is similar to that” Distinct roles or not?
- Searching for a Generalization: What is a Thematic Role?

Proto-Roles

- Event-dependent Proto-roles introduced
- Prototypes based on shared entailments
- Grammatical relations such as subject related to observed (empirical) classification of participants
- Typology of grammatical relations
- Proto-Agent
- Proto-Patient

Proto-Agent

- Properties
  - Volitional involvement in event or state
  - Sentience (and/or perception)
  - Causing an event or change of state in another participant
  - Movement (relative to position of another participant)
  - (exists independently of event named)

  *may be discourse pragmatic

Proto-Patient

- Properties:
  - Undergoes change of state
  - Incremental theme
  - Causally affected by another participant
  - Stationary relative to movement of another participant
  - (does not exist independently of the event, or at all) *may be discourse pragmatic

Argument Selection Principle

- For 2 or 3 place predicates
- Based on empirical count (total of entailments for each role).
- Greatest number of Proto-Agent entailments → Subject; greatest number of Proto-Patient entailments → Direct Object.
- Alternation predicted if number of entailments for each role similar (nondiscreteness).

Worked Example: Psychological Predicates

Examples:

Experiencer Subject	Stimulus Subject
x likes y	y pleases x
x fears y	y frightens x

Describes “almost the same” relation

Experiencer: sentient (P-Agent)

Stimulus: causes emotional reaction (P-Agent)

Number of proto-entailments same; but for stimulus subject verbs, experiencer also undergoes change of state (P-Patient) and is therefore lexicalized as the patient.

Symmetric Stative Predicates

Examples:

This one and that one rhyme / intersect / are similar.

This rhymes with / intersects with / is similar to that.

(cf. *The drunk embraced the lamppost. / *The drunk and the lamppost embraced*.)

Symmetric Predicates: Generalizing via Proto-Roles

- Conjoined predicate subject has Proto-Agent entailments which two-place predicate relation lacks (i.e. for object of two-place predicate).
- Generalization entirely reducible to proto-roles.
- Strong cognitive evidence for proto-roles: would be difficult to deduce lexically, but easy via knowledge of proto-roles.

Diathesis Alternations

Alternations:

- Spray / Load
- Hit / Break

Non-alternating:

- Swat / Dash
- Fill / Cover

Spray / Load Alternation

Example:

Mary loaded the hay onto the truck.
Mary loaded the truck with hay.

Mary sprayed the paint onto the wall.
Mary sprayed the wall with paint.

- Analyzed via proto-roles, not e.g. as a theme / location alternation.
- Direct object analyzed as an Incremental Theme, i.e. either of two non-subject arguments qualifies as incremental theme. This accounts for alternating behavior.

Hit / Break Alternation

John hit the fence with a stick.

John hit the stick against a fence.

John broke the fence with a stick.

John broke the stick against the fence.

- Radical change in meaning associated with *break* but not *hit*.
- Explained via proto-roles (change of state for direct object with break class).

Swat doesn't alternate…

swat the boy with a stick

**swat the stick at / against the boy*

Fill / Cover

Fill / Cover are non-alternating:

Bill filled the tank (with water).

**Bill filled water (into the tank).*

Bill covered the ground (with a tarpaulin).

**Bill covered a tarpaulin (over the ground).*

- Only goal lexicalizes as incremental theme (direct object).

Conclusion

- Dowty argues for Proto-Roles based on linguistic and cognitive observations.
- Objections: Are P-roles empirical (extending arguments about hit class)?

Proposition Bank:
From Sentences to Propositions

Powell met Zhu Rongji

Powell and Zhu Rongji met

Powell met with Zhu Rongji

Powell and Zhu Rongji had a meeting

. . .

battle

wrestle

join

debate

consult

Proposition: **meet**(Powell, Zhu Rongji)

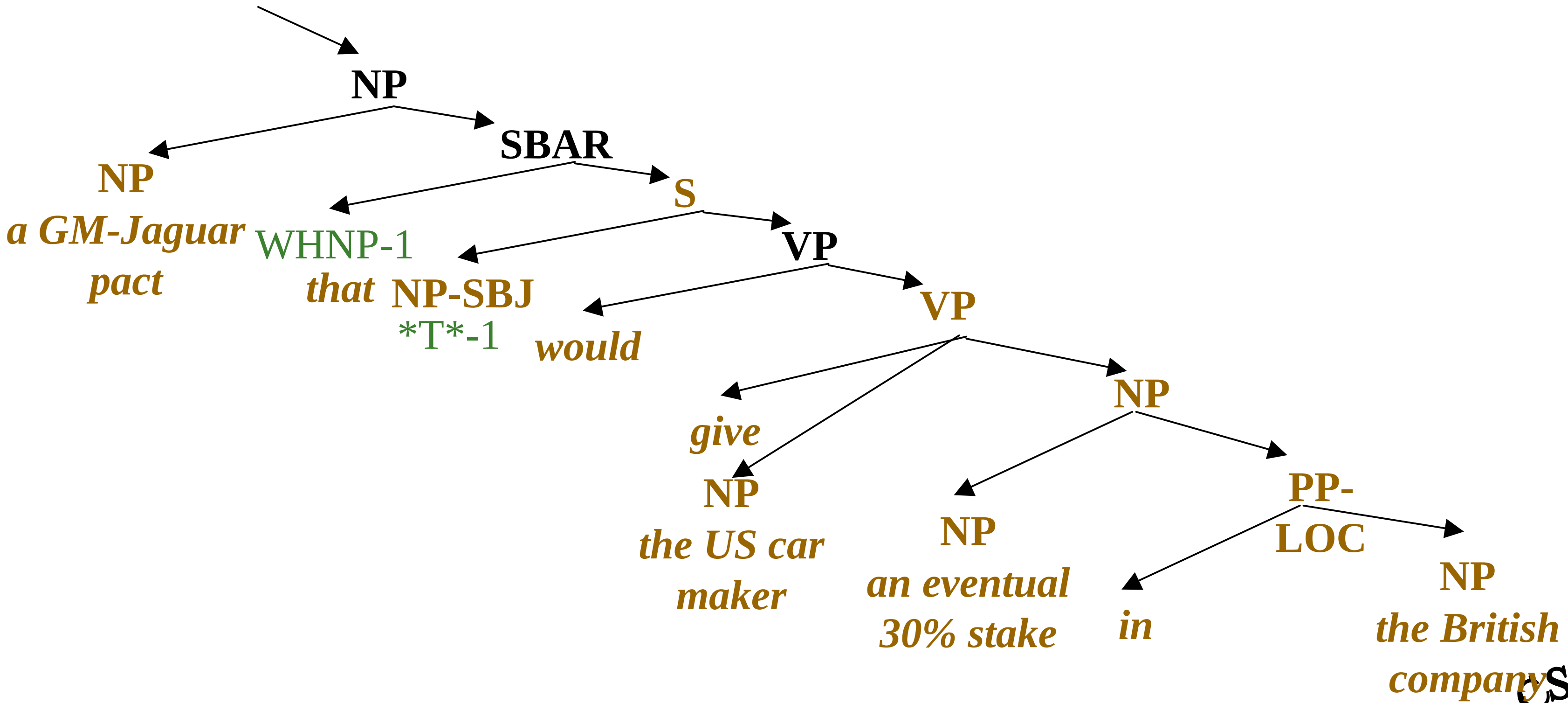
meet(Somebody1, Somebody2)

When Powell met Zhu Rongji on Thursday they discussed the return of the spy plane.

meet(Powell, Zhu) **discuss([Powell, Zhu], return(X, plane))**

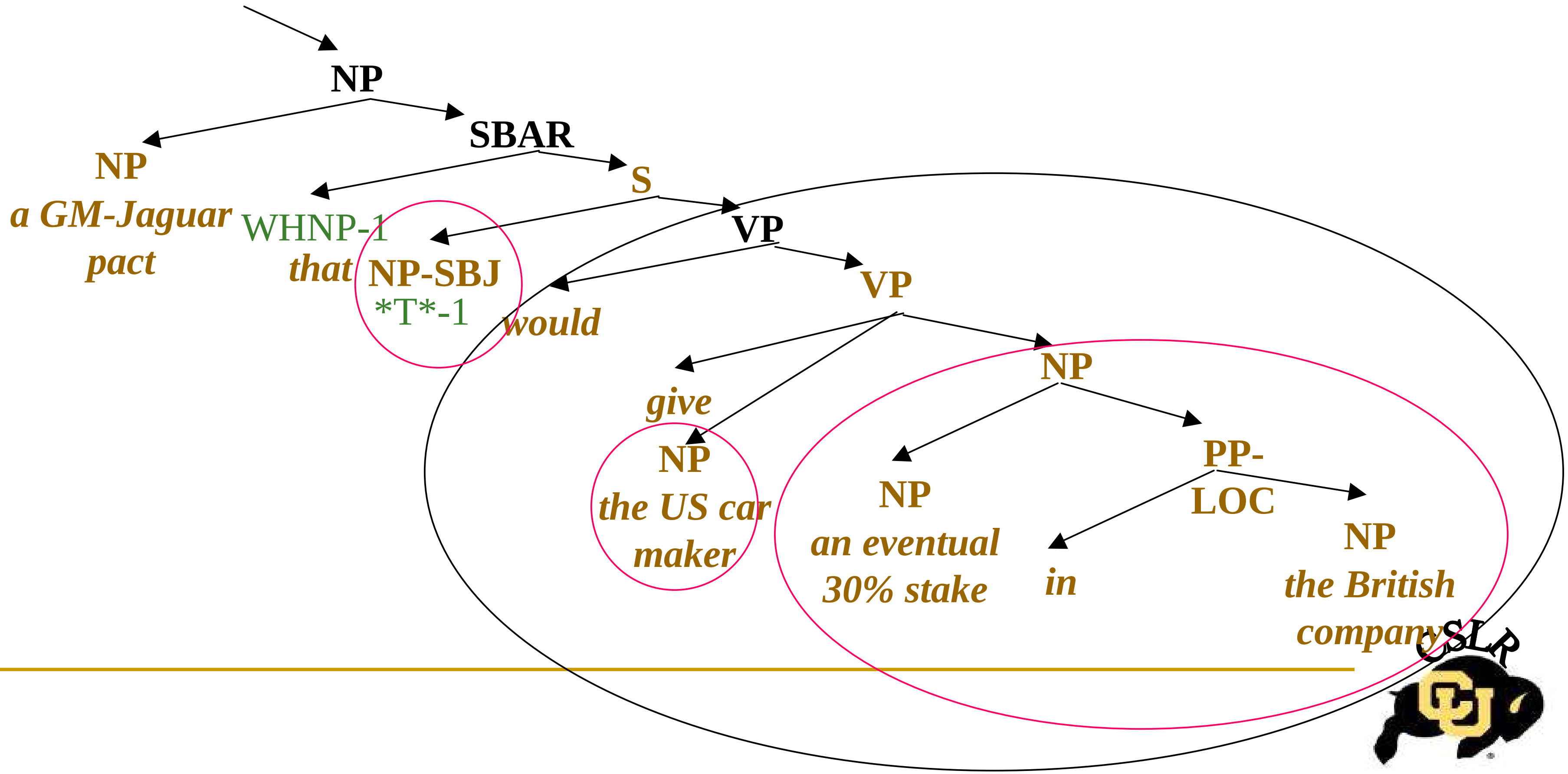
A TreeBanked phrase

a GM-Jaguar pact that would give the U.S. car maker an eventual 30% stake in the British company.



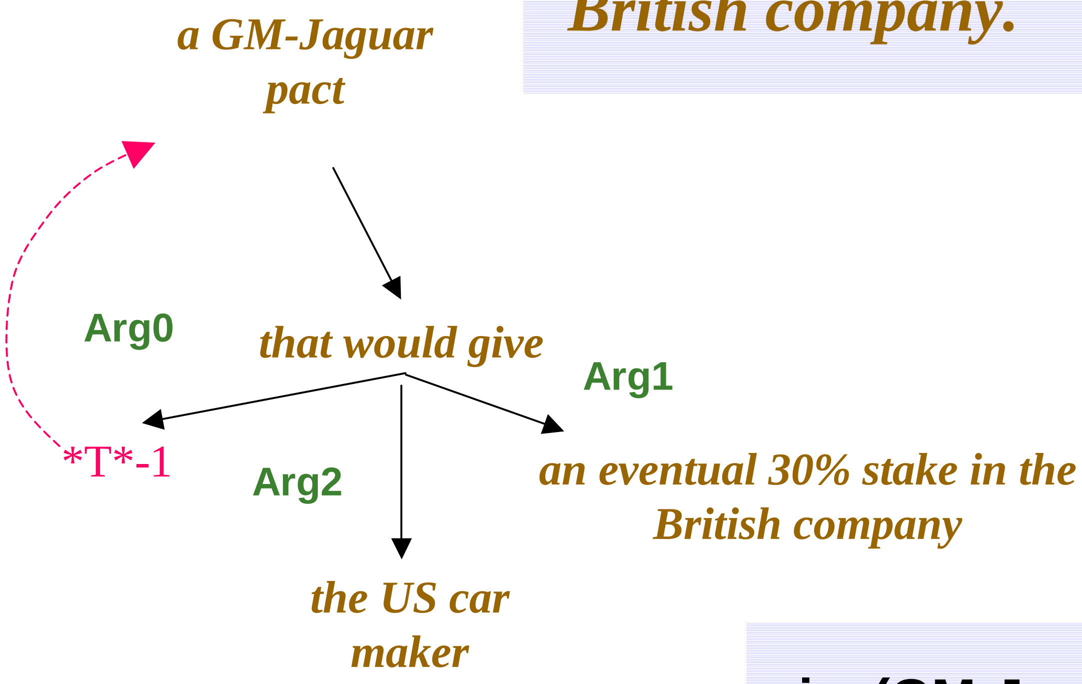
A TreeBanked phrase

a GM-Jaguar pact that would give the U.S. car maker an eventual 30% stake in the British company.



The same phrase, PropBanked

a GM-Jaguar pact that would give the U.S. car maker an eventual 30% stake in the British company.



give(GM-J pact, US car maker, 30% stake)

The full sentence, PropBanked

have been expecting

Arg0

Arg1

Analysts

a GM-Jaguar pact

Arg0

that would give

Arg1

T-1

Arg2

an eventual 30% stake in the British company

the US car maker

Analysts have been expecting a GM-Jaguar pact that would give the U.S. car maker an eventual 30% stake in the British company.

expect(Analysts, GM-J pact)
give(GM-J pact, US car maker, 30% stake)

Frames File Example: *expect*

Roles:

Arg0: expecter
Arg1: thing expected

Example: Transitive, active:

Portfolio managers expect further declines in interest rates.

Arg0: *Portfolio managers*
REL: *expect*
Arg1: *further declines in interest rates*

Frames File example: *give*

Roles:

Arg0: giver

Arg1: thing given

Arg2: entity given to

Example: double object

The executives gave the chefs a standing ovation.

Arg0:	*The executives*
REL:	*gave*
Arg2:	*the chefs*
Arg1:	*a standing ovation*

Word Senses in PropBank

- Orders to ignore word sense not feasible for 700+ verbs
  - *Mary left the room*
  - *Mary left her daughter-in-law her pearls in her will*

Frameset **leave.01** "move away from":
Arg0: entity leaving
Arg1: place left

Frameset **leave.02** "give":
Arg0: giver
Arg1: thing given
Arg2: beneficiary

How do these relate to traditional word senses in VerbNet and WordNet?

Annotation procedure

- PTB II - Extraction of all sentences with given verb
- Create Frame File for that verb *Paul Kingsbury*
  - (3100+ lemmas, 4400 framesets,118K predicates)
  - Over 300 created automatically via VerbNet
- First pass: Automatic tagging *(Joseph Rosenzweig)*
  - http://www.cis.upenn.edu/~josephr/TIDES/index.html#lexicon
- Second pass: Double blind hand correction

  Paul Kingsbury
- Tagging tool highlights discrepancies *Scott Cotton*
- Third pass: *Solomonization* (adjudication)
  - *Betsy Klipple,* ***Olga Babko-Malaya***

Semantic role labels:

Jan broke the LCD projector.

break (agent(Jan), patient(LCD-projector))

Filmore, 68

cause(agent(Jan),
change-of-state(LCD-projector))
(broken(LCD-projector))

Jackendoff, 72

agent(A) -> intentional(A), sentient(A),
causer(A), affector(A)

Dowty, 91

patient(P) -> affected(P), change(P),…

Trends in Argument Numbering

- Arg0 = agent
- Arg1 = direct object / theme / patient
- Arg2 = indirect object / benefactive / instrument / attribute / end state
- Arg3 = start point / benefactive / instrument / attribute
- Arg4 = end point
- Per word vs frame level – more general?

Additional tags (arguments or adjuncts?)

- Variety of ArgM's (Arg#>4):
  - TMP - when?
  - LOC - where at?
  - DIR - where to?
  - MNR - how?
  - PRP -why?
  - REC - himself, themselves, each other
  - PRD -this argument refers to or modifies another
  - ADV –others

Inflection

- Verbs also marked for tense/aspect
  - Passive/Active
  - Perfect/Progressive
  - Third singular (*is has does was*)
  - Present/Past/Future
  - Infinitives/Participles/Gerunds/Finites
- Modals and negations marked as ArgMs

Frames: Multiple Framesets

- Framesets are not necessarily consistent between different senses of the same verb

- Framesets are consistent between different verbs that share similar argument structures, *(like FrameNet)*

- Out of the 787 most frequent verbs:
  - 1 FrameNet – 521
  - 2 FrameNet – 169
  - 3+ FrameNet - 97 (includes light verbs)

Ergative/Unaccusative Verbs

Roles (no ARG0 for unaccusative verbs)

- Arg1 = Logical subject, patient, thing rising
- Arg2 = EXT, amount risen
- Arg3* = start point
- Arg4 = end point

Sales rose 4% to $3.28 billion from $3.16 billion.

The Nasdaq composite index added 1.01 to 456.6 on paltry volume.

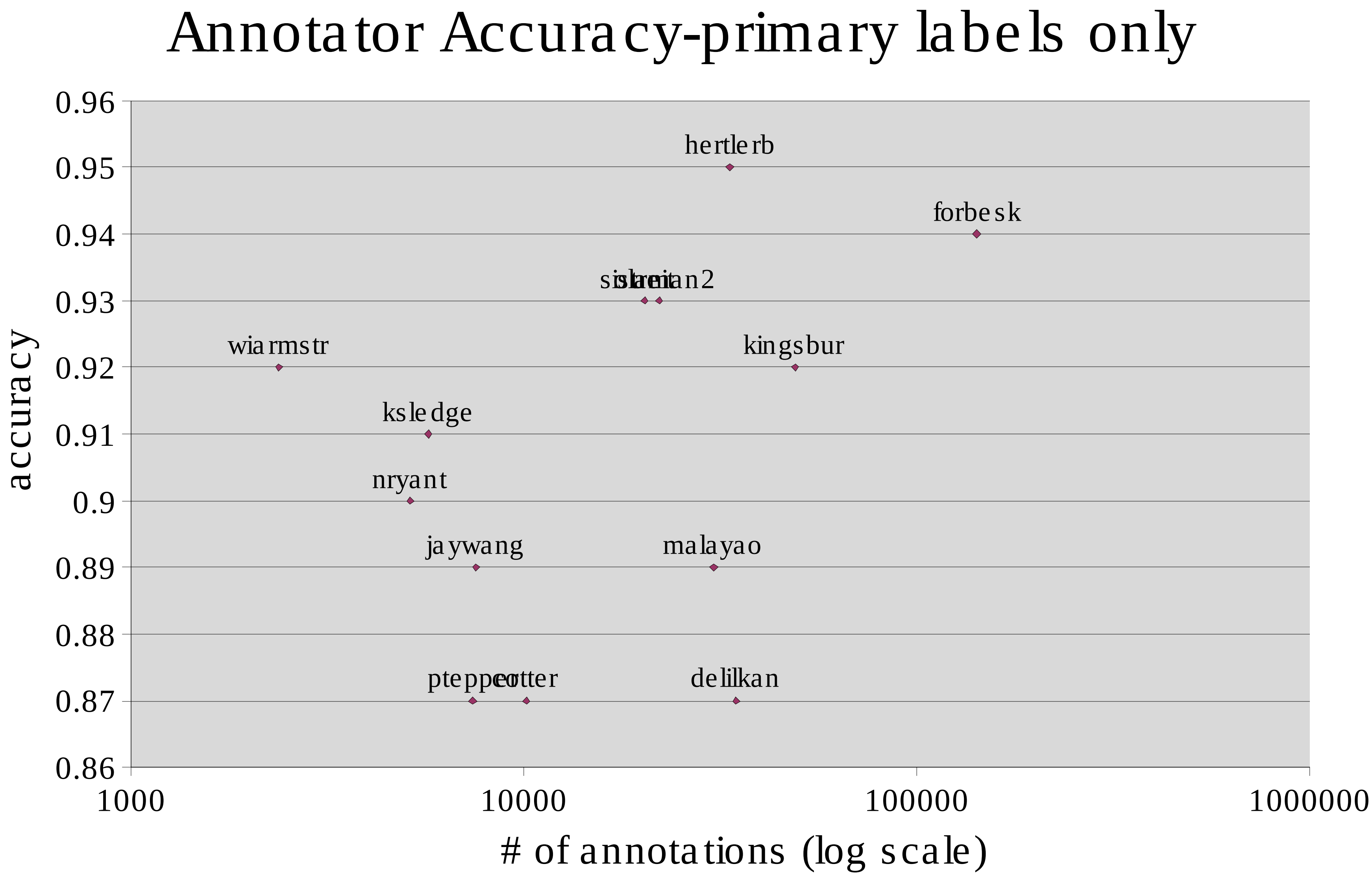
PropBank/FrameNet

Buy	Sell
Arg0: buyer	Arg0: seller
Arg1: goods	Arg1: goods
Arg2: seller	Arg2: buyer
Arg3: rate	Arg3: rate
Arg4: payment	Arg4: payment

More generic, more neutral – maps readily to VN,TR

Rambow, et al, PMLB03

Annotator accuracy – ITA 84%



Limitations to PropBank

- Args2-4 seriously overloaded, poor performance
  - VerbNet and FrameNet both provide more fine-grained role labels
- WSJ too domain specific, too financial, need broader coverage genres for more general annotation
  - Additional Brown corpus annotation, also GALE data
  - FrameNet has selected instances from BNC

Levin – English Verb Classes and Alternations: A Preliminary Investigation, 1993.

Levin classes *(Levin, 1993)*

- 3100 verbs, 47 top level classes, 193 second and third level

- Each class has a syntactic signature based on alternations.
  John broke the jar. / The jar broke. / Jars break easily.

  *John cut the bread. / *The bread cut. / Bread cuts easily.*

  *John hit the wall. / *The wall hit. / *Walls hit easily.*

Levin classes *(Levin, 1993)*

- Verb class hierarchy: 3100 verbs, 47 top level classes, 193
- Each class has a syntactic signature based on alternations.

  John broke the jar. / The jar broke. / Jars break easily.

  change-of-state

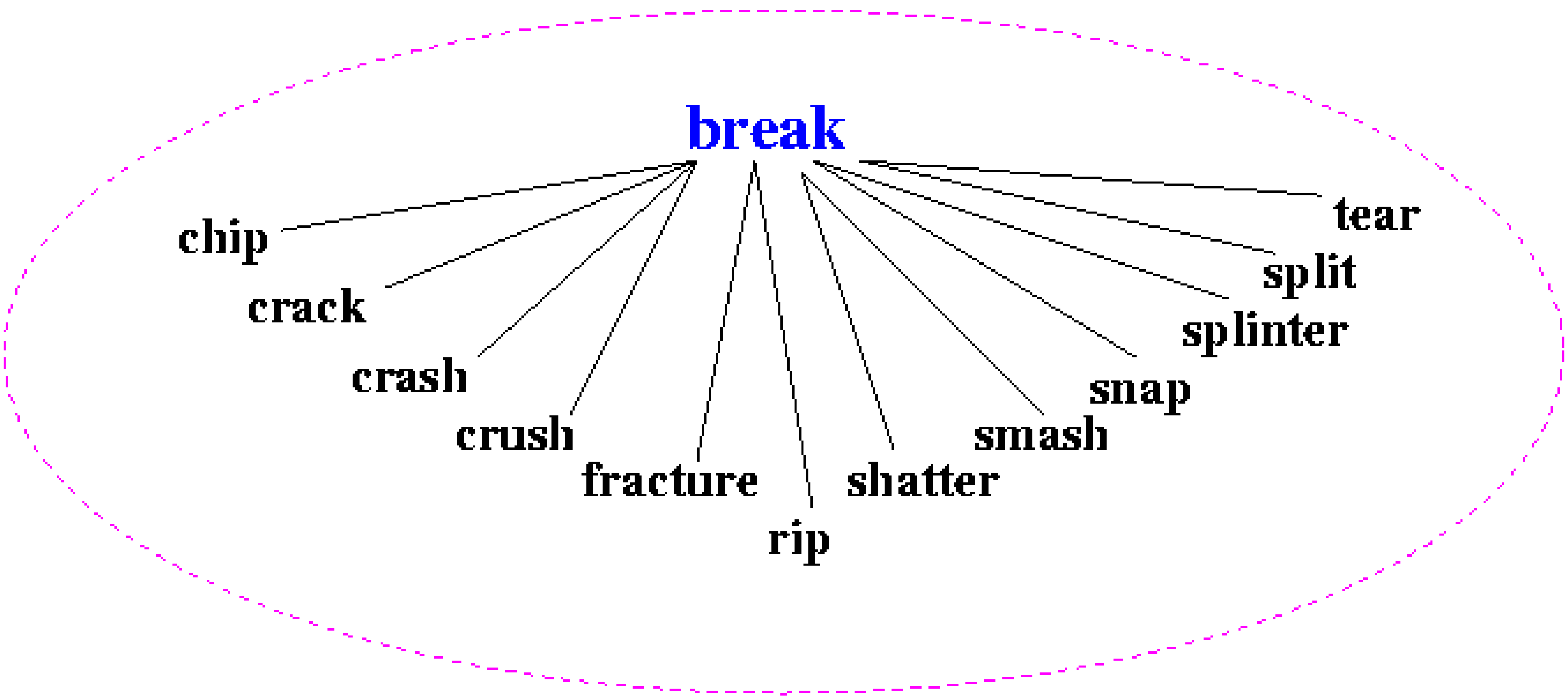
  *John cut the bread. / *The bread cut. / Bread cuts easily.*

  change-of-state, recognizable action,
  sharp instrument

  *John hit the wall. / *The wall hit. / *Walls hit easily.*

  contact, exertion of force

Break Levin class - *Change-of-state*



Limitations to Levin Classes

Dang, Kipper & Palmer, ACL98

- Coverage of only half of the verbs (types) in the Penn Treebank (1M words,WSJ)
- Usually only one or two basic senses are covered for each verb
- Confusing sets of alternations
  - Different classes have almost identical "syntactic signatures"
  - or worse, contradictory signatures

Multiple class listings

- Homonymy or polysemy?
  - *draw a picture, draw water from the well*
- Conflicting alternations?
  - *Carry* verbs disallow the Conative,

    *(*she carried at the ball),* but include

    {push,pull,shove,kick,yank,tug}
  - also in *Push/pull* class, does take the Conative *(she kicked at the ball)*

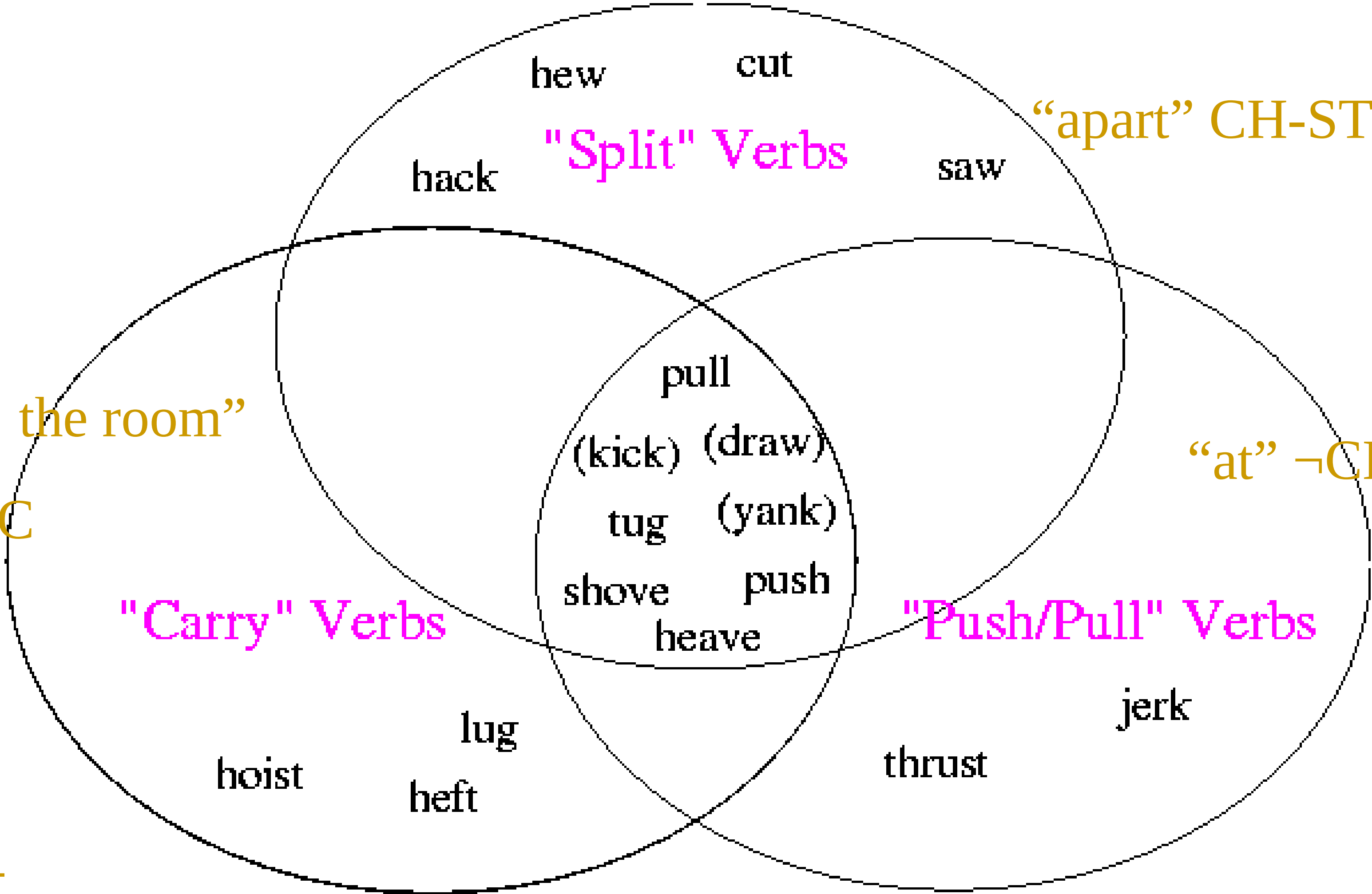
Intersective Levin Classes

“apart” CH-STATE

“across the room”

CH-LOC

“at” ¬CH-LOC



Dang, Kipper & Palmer, ACL98

Intersective Levin Classes

- More syntactically and semantically coherent
  - sets of syntactic patterns
  - explicit semantic components
  - relations between senses

→

VERBNET

verbs.colorado.edu/~mpalmer/verbnet

VerbNet – *Karin Kipper*

- Class entries:
  - Capture generalizations about verb behavior
  - Organized hierarchically
  - Members have common semantic elements, semantic roles and syntactic frames
- Verb entries:
  - Refer to a set of classes (different senses)
  - each class member linked to WN synset(s) (not all WN senses are covered)

Hand built resources vs. Real data

- VerbNet is based on linguistic theory –

  how useful is it?

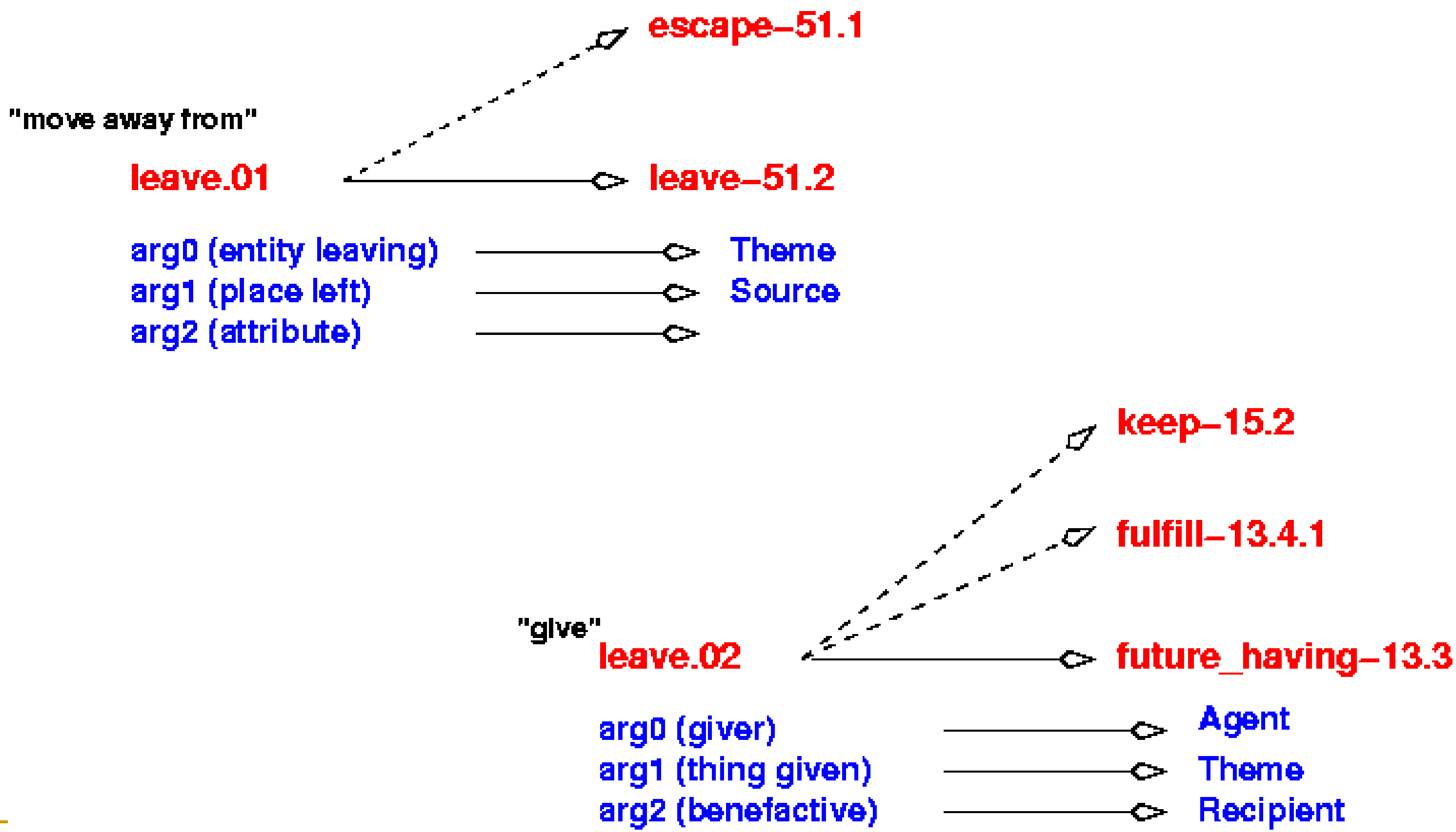
- How well does it correspond to syntactic variations found in naturally occurring text?

  → PropBank

Mapping from PropBank to VerbNet

Frameset id = ***leave.02***	Sense = *give*	VerbNet class = ***future-having 13.3***
Arg0	Giver	Agent
Arg1	Thing given	Theme
Arg2	Benefactive	Recipient

Mapping from PB to VerbNet



Mapping from PropBank to VerbNet

- Overlap with PropBank framesets
  - 50,000 PropBank instances
  - < 50% VN entries, > 85% VN classes
- Results
  - MATCH - 78.63%. (80.90% relaxed)
  - *(VerbNet isn't just linguistic theory!)*
- Benefits
  - Thematic role labels and semantic predicates
  - Can extend PropBank coverage with VerbNet classes
  - WordNet sense tags

Mapping PropBank/VerbNet

- Extended VerbNet now covers 80% of PropBank tokens. *Kipper, et. al., LREC-04, LREC-06*

  (added Korhonen and Briscoe classes)
- Semi-automatic mapping of PropBank instances to VerbNet classes and thematic roles, hand-corrected. (final cleanup stage)
- VerbNet class tagging as automatic WSD
- Run SRL, map Args to VerbNet roles

Can SemLink improve Generalization?

- Overloaded Arg2-Arg5
  - PB: verb-by-verb
  - VerbNet: same thematic roles across verbs
- Example
  - Rudolph Agnew,…, was named [ARG2 {Predicate} a nonexecutive director of this British industrial conglomerate.]
  - ….the latest results appear in today's New England Journal of Medicine, a forum likely to bring new attention [ARG2 {Destination} to the problem.]
- Use VerbNet as a bridge to merge PB and FN and expand the Size and Variety of the Training

Automatic Labelling of Semantic Relations – Gold Standard, 77%

- Given a constituent to be labelled
- Stochastic Model
- Features:
  - Predicate, *(verb)*
  - Phrase Type, *(NP or S-BAR)*
  - Parse Tree Path
  - Position *(Before/after predicate)*
  - Voice *(active/passive)*
  - Head Word of constituent

Gildea & Jurafsky, CL02, Gildea & Palmer, ACL02

Additional Automatic Role Labelers

- Performance improved from 77% to 88%
  Automatic parses, 81% F, Brown corpus, 68%
  - Same features plus
    - Named Entity tags
    - Head word POS
    - For unseen verbs – backoff to automatic verb clusters
  - SVM's
    - Role or not role
    - For each likely role, for each Arg#, Arg# or not
    - No overlapping role labels allowed

Pradhan, et. al., ICDM03, Sardeneau, et. al, ACL03,Chen & Rambow, EMNLP03, Gildea & Hockemaier, EMNLP03, Yi & Palmer, ICON04 CoNLL-04, 05 Shared Task

Arg1 groupings; (Total count 59710)

Group1 (53.11%)	Group2 (23.04%)	Group3 (16%)	Group4 (4.67%)	Group5 (.20%)
Theme; Theme1; Theme2; Predicate; Stimulus; Attribute	**Topic**	**Patient; Product; Patient1; Patient2**	**Agent; Actor2; Cause; Experiencer**	**Asset**

Arg2 groupings; (Total count 11068)

Group1 (43.93%)	Group2 (14.74%)	Group3 (32.13%)	Group4 (6.81%)	Group5 (2.39%)
Recipient; Destination; Location; Source; Material; Beneficiary	**Extent; Asset**	**Predicate; Attribute; Theme; Theme2; Theme1; Topic**	**Patient2; Product**	**Instrument; Actor2; Cause; Experiencer**

Process

- Retrain the SRL tagger
  - Original:
    - Arg[0-5,A,M]
  - ARG1 Grouping: (similar for Arg2)
    - Arg[0,2-5,A,M] Arg1-Group[1-6]
- Evaluation on both WSJ and Brown
- More Coarse-grained or Fine-grained?
  - more specific: data more coherent, but more sparse
  - more general: consistency across verbs even for new domains?

SRL Performance (WSJ/BROWN)

Loper, Yi, Palmer, SIGSEM07

System	Precision	Recall	F-1
Arg1-Original	89.24	77.32	82.85
Arg1-Mapped	90.00	76.35	82.61
Arg2-Original	73.04	57.44	64.31
Arg2-Mapped	84.11	60.55	70.41
Arg1-Original	86.01	71.46	78.07
Arg1-Mapped	88.24	71.15	78.78
Arg2-Original	66.74	52.22	58.59
Arg2-Mapped	81.45	58.45	68.06