Semantic Role Labeling Tutorial
NAACL, June 9, 2013

Part 1: Martha Palmer, University of Colorado

Part 2: Shumin Wu, University of Colorado

Part 3: Ivan Titov, Universität des Saarlandes

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Outline

- ## Part 1
  Linguistic Background, Resources, Annotation

  Martha Palmer, University of Colorado

- ## Part 2
  Supervised Semantic Role Labeling and Leveraging Parallel PropBanks

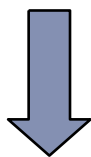 Shumin Wu, University of Colorado

- ## Part 3
  Semi- , unsupervised and cross-lingual approaches

  Ivan Titov, Universität des Saarlandes, Universteit van Amsterdam

Motivation: From Sentences to Propositions
Who did what to whom, when, where and how?

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))

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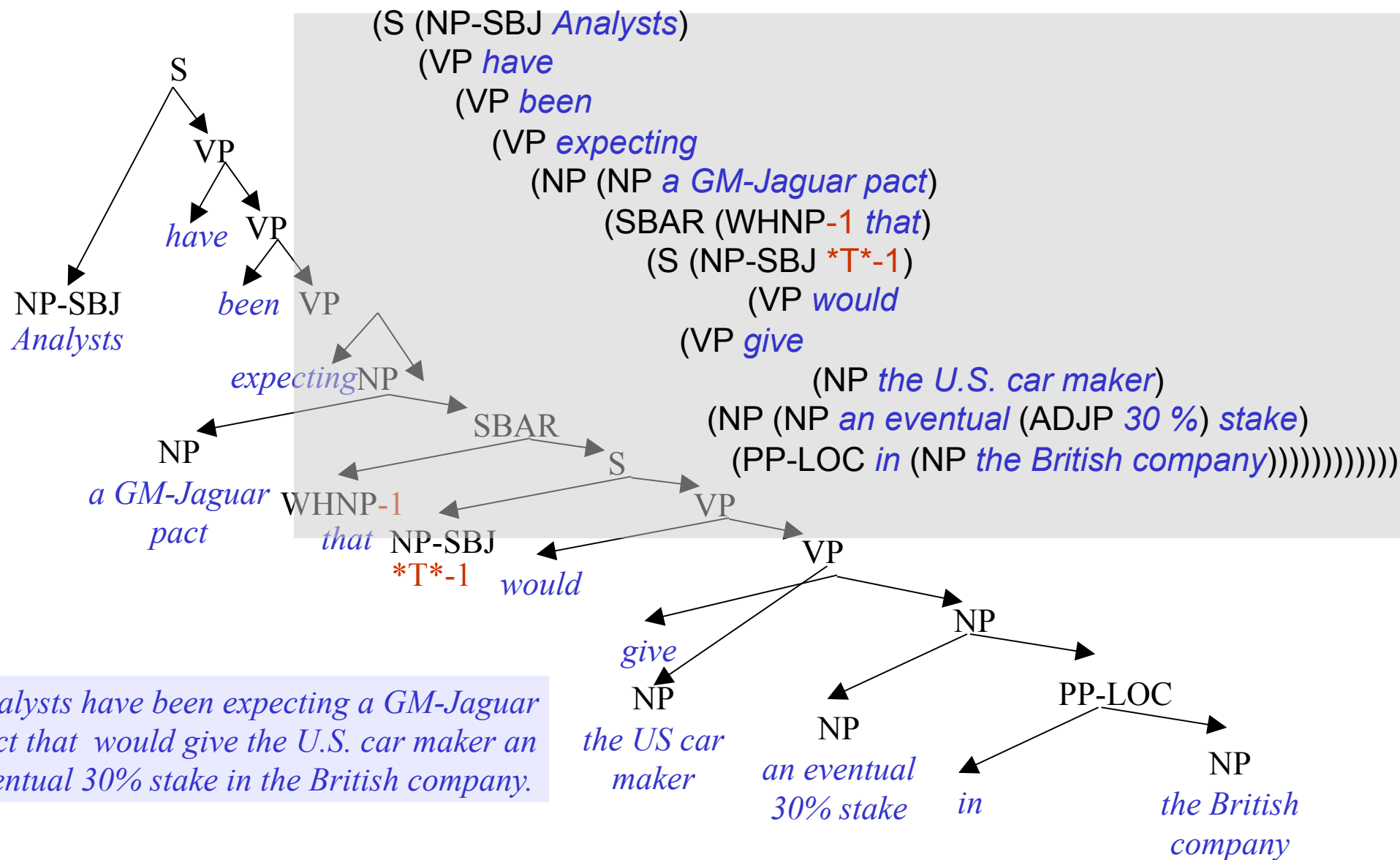C L E A R

Capturing semantic roles

SUBJ
- Dan broke [the laser pointer.]

SUBJ
- [The windows] were broken by the hurricane.

SUBJ
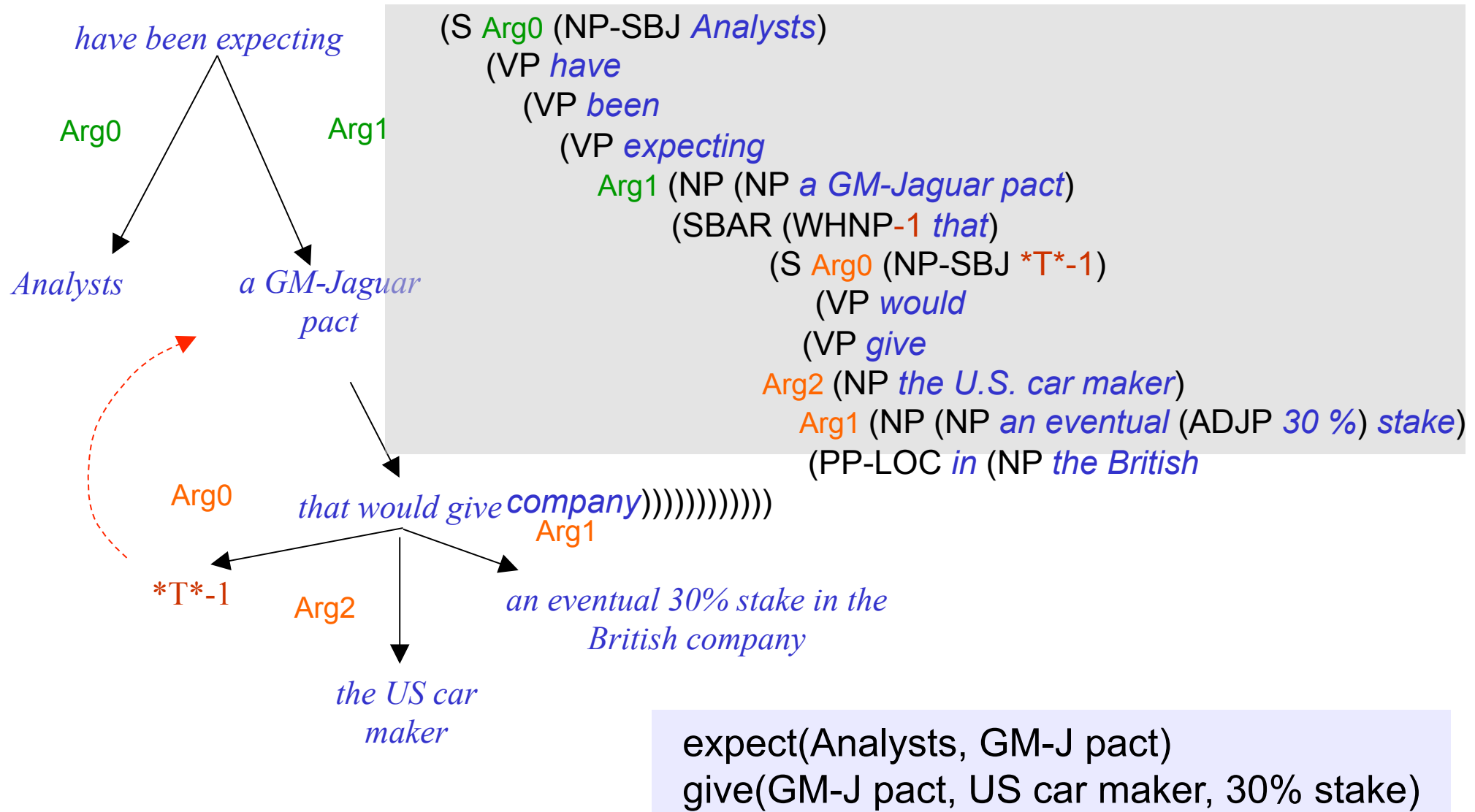- [The vase] broke into pieces when it toppled over.

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PropBank - A TreeBanked Sentence

(S (NP-SBJ *Analysts*)
    (VP *have*
        (VP *been*
            (VP *expecting*
                (NP (NP *a GM-Jaguar pact*)
                    (SBAR (WHNP-1 *that*)
                        (S (NP-SBJ *T*-1)
                            (VP *would*
                                (VP *give*
                                    (NP *the U.S. car maker*)
                                    (NP (NP *an eventual* (ADJP *30 %*) *stake*)
                                        (PP-LOC *in* (NP *the British company*)))))))))))))

S
├── NP-SBJ *Analysts*
└── VP
    ├── *have*
    └── VP
        ├── *been*
        └── VP
            ├── *expecting*
            └── NP
                ├── NP *a GM-Jaguar pact*
                └── SBAR
                    ├── WHNP-1 *that*
                    └── S
                        ├── NP-SBJ *T*-1
                        └── VP
                            ├── *would*
                            └── VP
                                ├── *give*
                                ├── NP *the US car maker*
                                └── NP
                                    ├── NP *an eventual 30% stake*
                                    └── PP-LOC
                                        ├── *in*
                                        └── NP *the British company*

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

The same sentence, PropBanked

have been expecting

Arg0   Arg1

Analysts   *a GM-Jaguar pact*

Arg0

that would give company

T-1

Arg2

the US car maker

Arg1

an eventual 30% stake in the British company

(S Arg0 (NP-SBJ *Analysts*)
   (VP *have*
      (VP *been*
         (VP *expecting*
            Arg1 (NP (NP *a GM-Jaguar pact*)
               (SBAR (WHNP-1 *that*)
                  (S Arg0 (NP-SBJ **T*-1*)
                     (VP *would*
                        (VP *give*
                           Arg2 (NP *the U.S. car maker*)
                           Arg1 (NP (NP *an eventual* (ADJP *30 %*) *stake*)
                              (PP-LOC *in* (NP *the British*
                                 company)))))))))))))))

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

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SRL Questions

▸ Why Arg0 and Arg1?

▸ What about nouns and adjectives?

▸ What about other languages?

▸ How does PropBank relate to VerbNet and FrameNet?

▸ Will we ever get past the WSJ?

▸ How do SRL systems get trained?

▸ Can this be done without training data?

▸ …..

Why Arg0? Linguistic Background and Resources

- Fillmore – Cases
  - Useful generalizations, fewer sense distinctions,
- Dowty – Proto-typical Agents and Patients
  - A bag of "agentive" entailments
  - **PropBank**
- Levin – Verb classes based on syntax
  - Syntactic behavior is a reflection of the underlying semantics
  - **VerbNet**
- Back to Fillmore and FrameNet
- SemLink
- PropBank ➔ AMR

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Linguistic Background: Case Theory,
The Case for Case, Charles J. Fillmore

‣ **Case relations occur in deep-structure**

  ‣ Surface-structure cases are derived

‣ **A sentence is a verb + one or more NPs**

  ‣ Each NP has a deep-structure case

    ‣ *A(gentive)*

    ‣ *I(nstrumental)*

    ‣ *D(ative) - recipient*

    ‣ *F(actitive) – result*

    ‣ *L(ocative)*

    ‣ *O(bjective) – affected object, theme*

  ‣ Subject is no more important than Object

    ‣ Subject/Object are surface structure

Case Theory Benefits - Generalizations

▸ **Fewer tokens**
  ▸ Fewer verb senses
  ▸ E.g. *cook/bake* [__O(A)] covers
    ▸ Mother is cooking/baking the potatoes
    ▸ The potatoes are cooking/baking.
    ▸ Mother is cooking/baking.

▸ **Fewer types**
  ▸ "Different" verbs may be the same semantically, but with different subject selection preferences
  ▸ E.g. *like* and *please* are both [__O+D]

▸ **Great, let's do it!**

Oops, problems with Cases/Thematic Roles

▸ How many and what are they?
▸ Fragmentation: 4 Agent subtypes? (Cruse, 1973)
  ▸ *The <u>sun</u> melted the ice./<u>This clothes dryer</u> doesn't dry clothes well*
▸ Ambiguity: Andrews (1985)
  ▸ Argument/adjunct distinctions – Extent?
  ▸ *The kitten licked my <u>fingers</u>.* – Patient or Theme?

▸ Θ-Criterion (GB Theory): each NP of predicate in lexicon assigned unique θ-role (Chomsky 1981).

[Agent (or Source) Esau] sold [Theme his birthright]
[Goal to Jacob] for a <u>bowl of porridge</u>.

[Goal Esau] sold <u>his birthright</u>
[Source to Jacob] for a [Theme bowl of porridge].
Jackendoff

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Thematic Proto-Roles and Argument Selection,
David Dowty, 1991

Role definitions have to be determined verb by verb, and with respect to the other roles

- Event-dependent Proto-roles introduced
  - Proto-Agent
  - Proto-Patient
- Prototypes based on shared entailments

Proto-Agent- the *mother*

▸ Properties

    ▸ Volitional involvement in event or state

    ▸ Sentience (and/or perception)

    ▸ Causes 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 – the *cake*

▸ **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 (non-discreteness).

[Mother AGENT] baked a cake.
[The cake PATIENT] baked.

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PropBank Semantic Role Labels – based on Dowty's Proto-roles

- ## PropBank Frame for *break*:

    Frameset **break.01** "break, cause to not be whole":
    Arg0: breaker
    Arg1: thing broken
    Arg2: instrument
    Arg3: pieces

- ## Why numbered arguments?
    - Lack of consensus concerning semantic role labels
    - Numbers correspond to verb-specific labels
    - Arg0 – Proto-Agent, and Arg1 – Proto-Patient, (Dowty, 1991)
    - Args 2-5 are highly variable and overloaded – poor performance

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PropBank seeks to provide consistent argument labels across different syntactic realizations

- Uuuuuuusually…
  - Arg0 = agent, experiencer
  - Arg1 = patient, theme
  - Arg2 = benefactive / instrument / attribute / end state
  - Arg3 = start point / benefactive / instrument / attribute
  - Arg4 = end point

PropBank seeks to assign functional tags to all modifiers or adjuncts to the verb

- ## Variety of ArgM's:
  - TMP - when?   *yesterday, 5pm on Saturday, recently*

  - LOC - where? *in the living room, on the newspaper*

  - DIR - where to/from? *down, from Antartica*

  - MNR - how? *quickly, with much enthusiasm*

  - PRP/CAU -why? *because … , so that …*

  - REC - himself, themselves, each other

  - GOL - end point of motion, transfer verbs? *To the floor, to Judy*

  - ADV - hodge-podge, miscellaneous, "nothing-fits!"

  - PRD - this argument refers to or modifies another: …*ate the meat <u>raw</u>*

SRL Examples
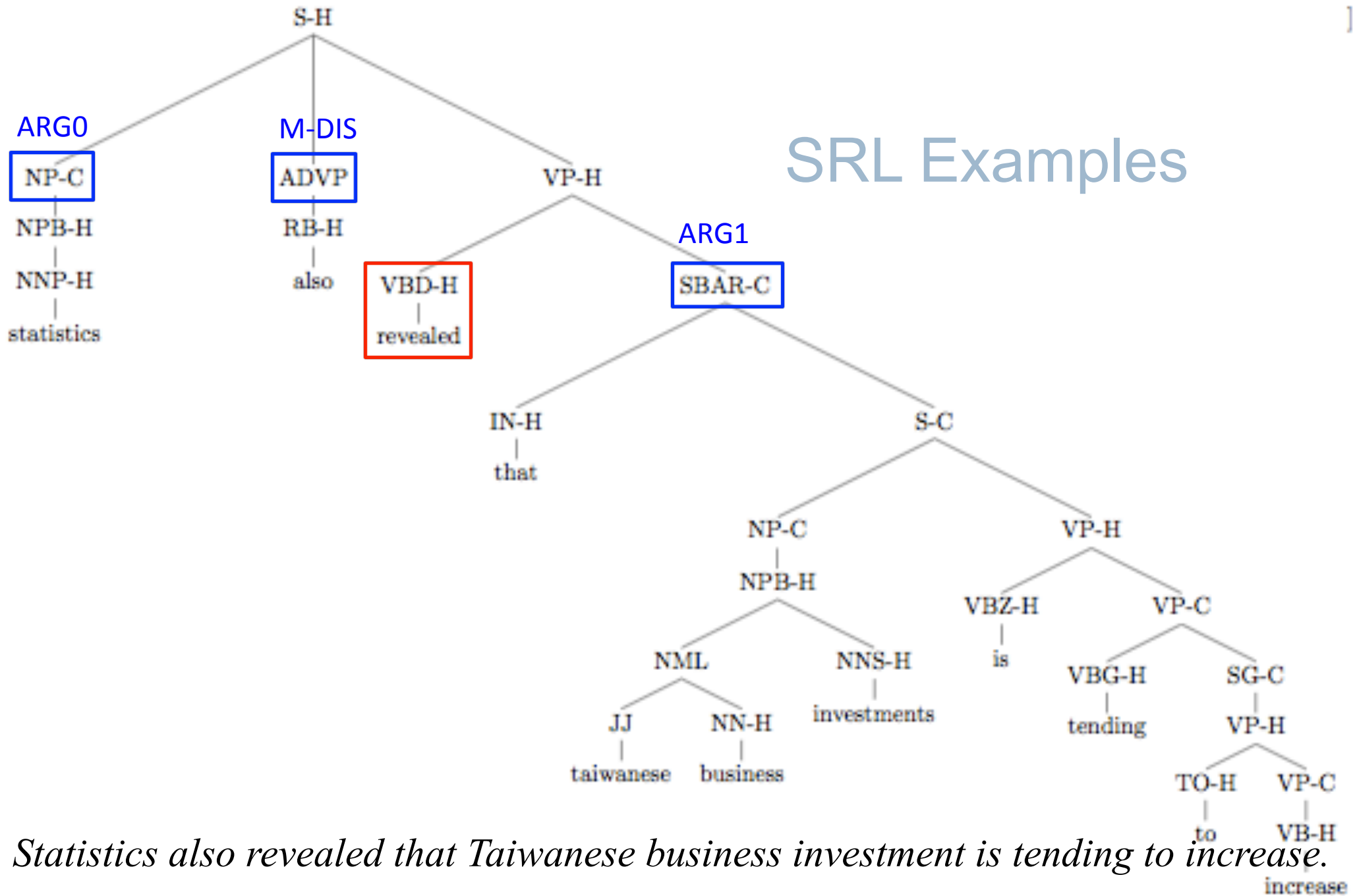
Statistics also revealed that Taiwanese business investment is tending to increase.
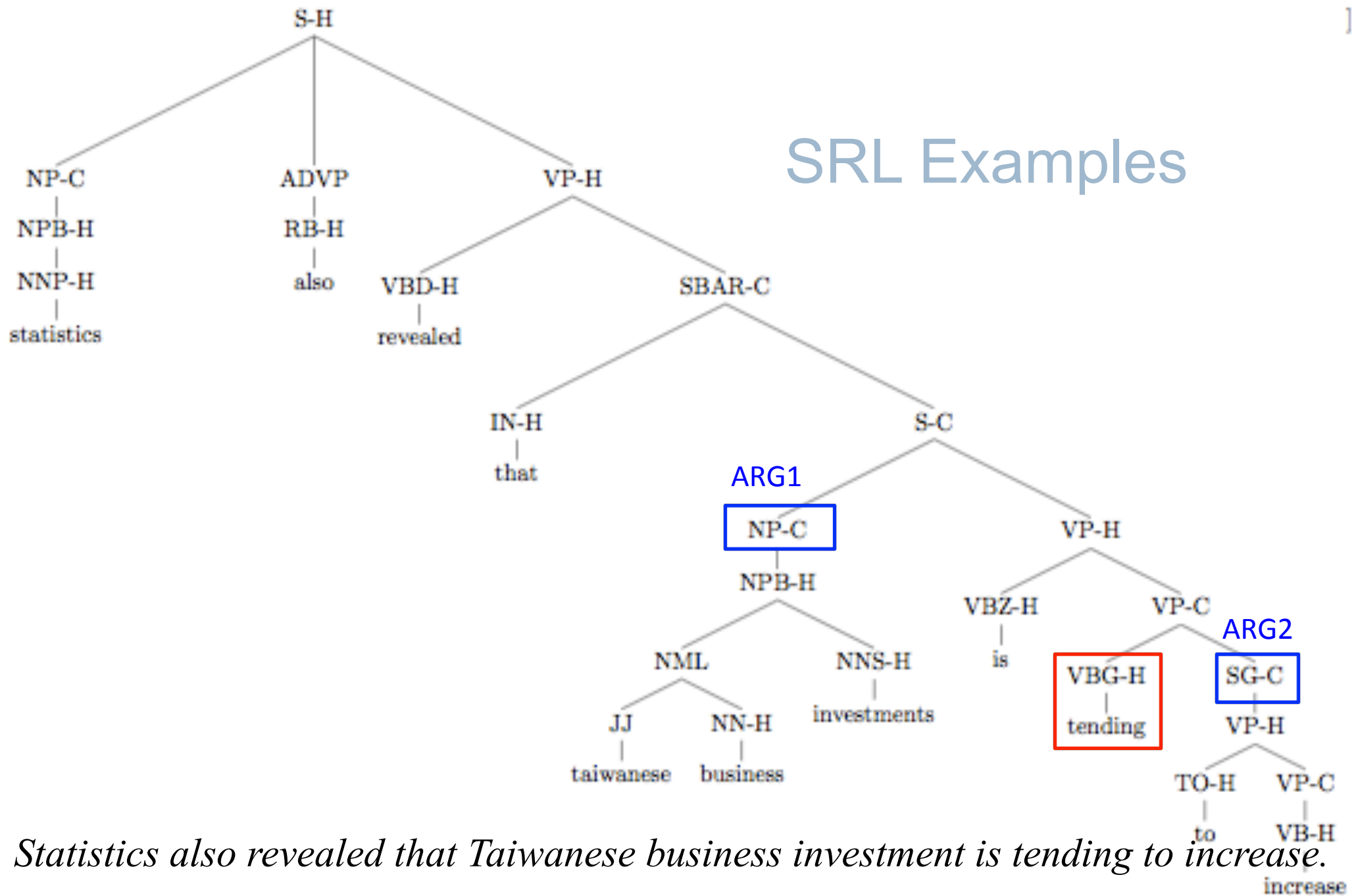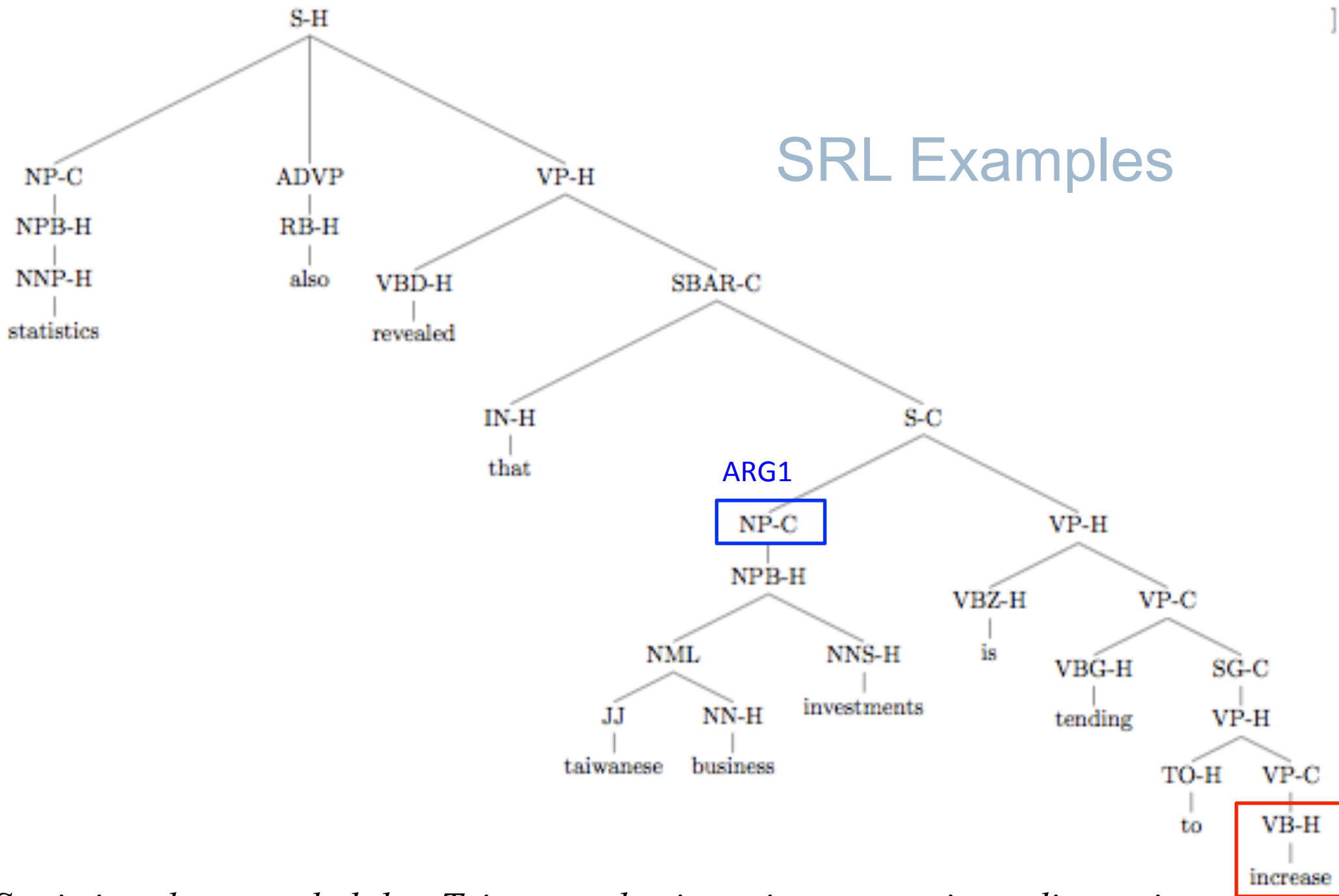
SRL Examples

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SRL Examples

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Adding a Frameset ID
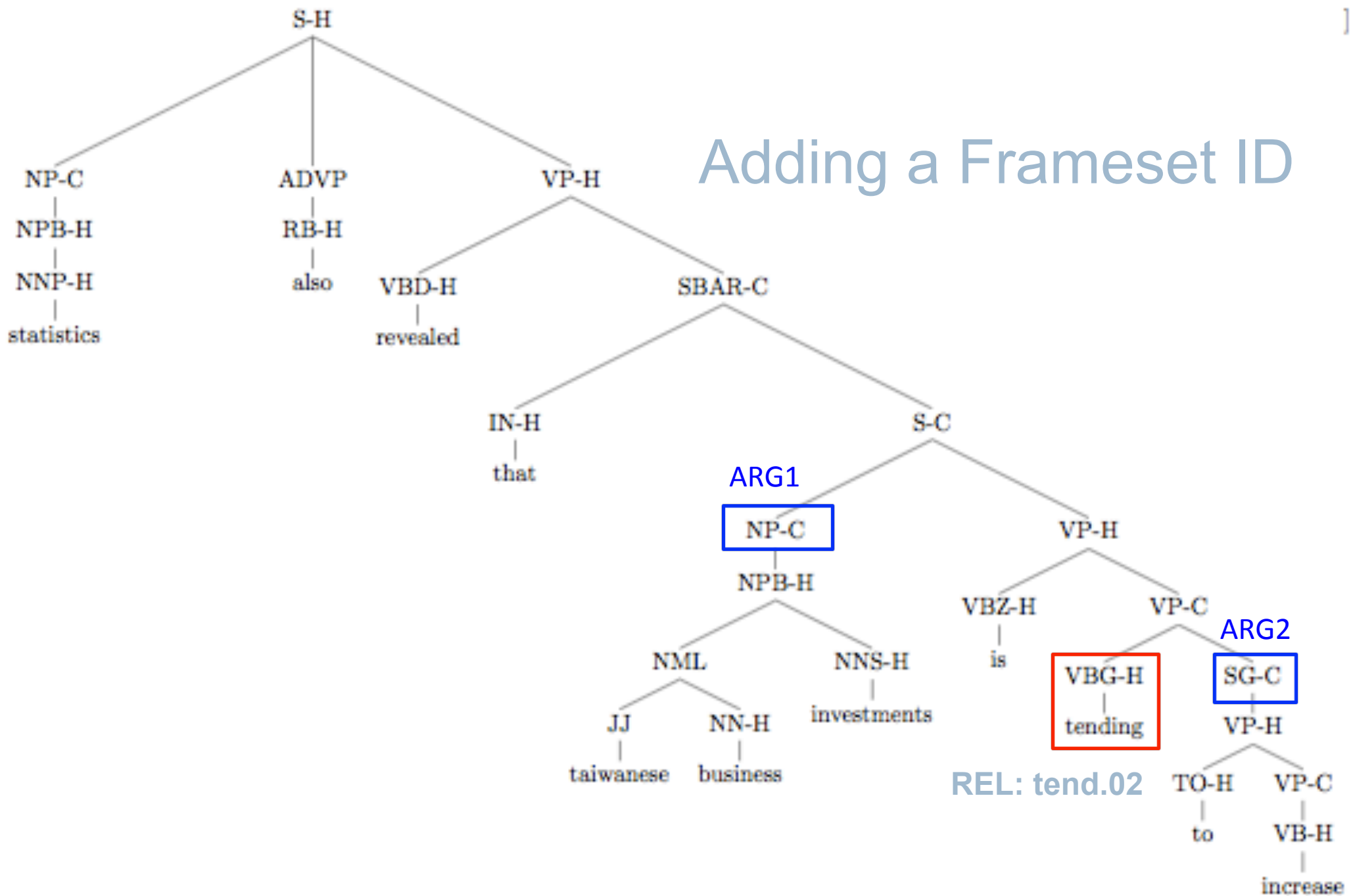
Statistics also revealed that Taiwanese business investment is tending to increase.

Why do we need Frameset ID's?

PropBank Frames Files: tend.01 , *care for*

Roles:

Arg0: tender
Arg1: thing tended (to)

Example: *John* **tends** *to the needs of his patrons.*

Arg0: *John*
REL: *tend*
Arg1: *the needs of his patrons*

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Sense distinctions in PropBank – coarse-grained

PropBank - Frames Files: tend.02, *have a tendency*

Roles:

Arg1: Theme
Arg2: Attribute

Example: *The cost, or premium, **tends** to get fat in times of crisis.*

Arg1: *The cost, or premium*
REL: *tend*
Arg2: *to get fat in times of crisis.*

Visual Example: traces BASED on Jubilee
Choi, et. al., NAACL-10 Demo

```
SBAR
  ⊶ WHNP-1
       WP  What
  ⊶ S
     ⊶ NP-SBJ  2:1-ARG0
          PRP  I
     ⊶ VP
          VBP  have
        ⊶ VP
             VBN  experienced  4:0-rel
           ⊶ NP  5:1-ARG1
                -NONE-  *T*-1
           ⊶ NP-ADV  6:1-ARGM-REC
                PRP  myself
CC  or
```

Adding a Frameset ID

Statistics also revealed that Taiwanese business investment is tending to increase.
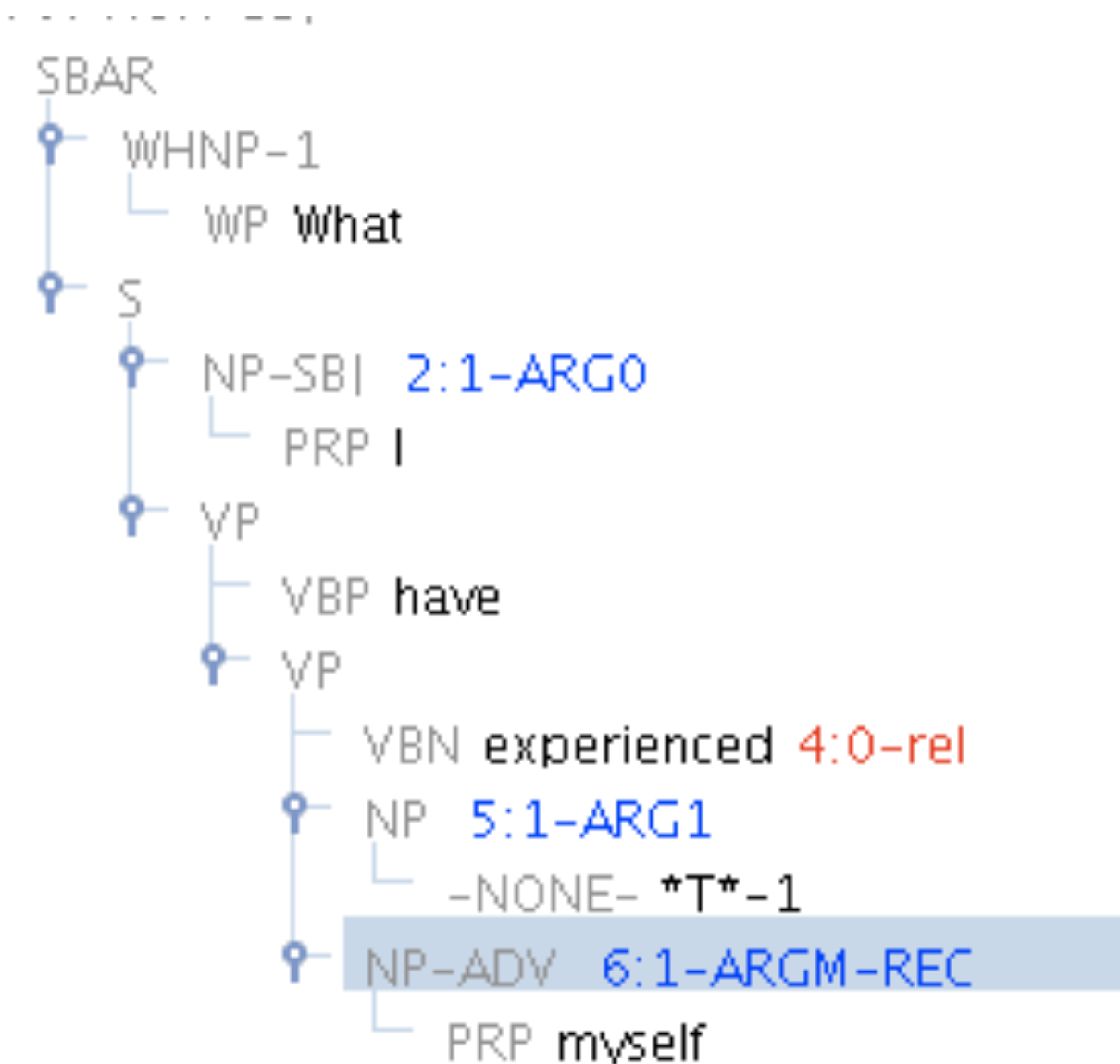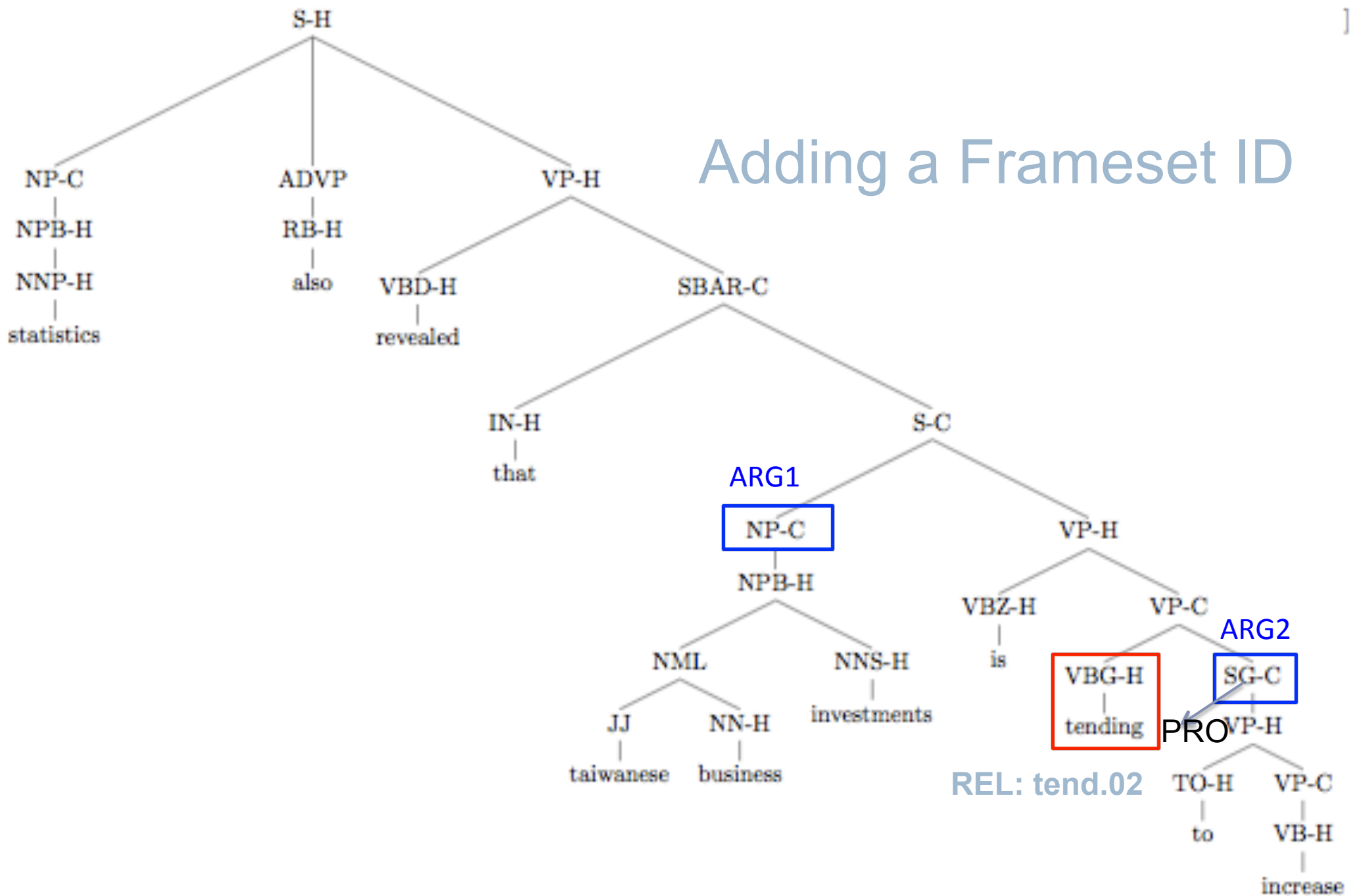
Actual data for *leave*

Leave .01 "move away from" Arg0 rel Arg1 Arg3
Leave .02 "give" Arg0 rel Arg1 Arg2

sub-ARG0 obj-ARG1 44

sub-ARG0 20

sub-ARG0 NP-ARG1-with obj-ARG2 17

sub-ARG0 sub-ARG2 ADJP-ARG3-PRD 10

sub-ARG0 sub-ARG1 ADJP-ARG3-PRD 6

sub-ARG0 sub-ARG1 VP-ARG3-PRD 5

NP-ARG1-with obj-ARG2 4

obj-ARG1 3

sub-ARG0 sub-ARG2 VP-ARG3-PRD 3

Annotation procedure, WSJ PropBank

Palmer, et. al., 2005

▸ 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**

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Annotator accuracy – ITA 84%

Annotator Accuracy-primary labels only
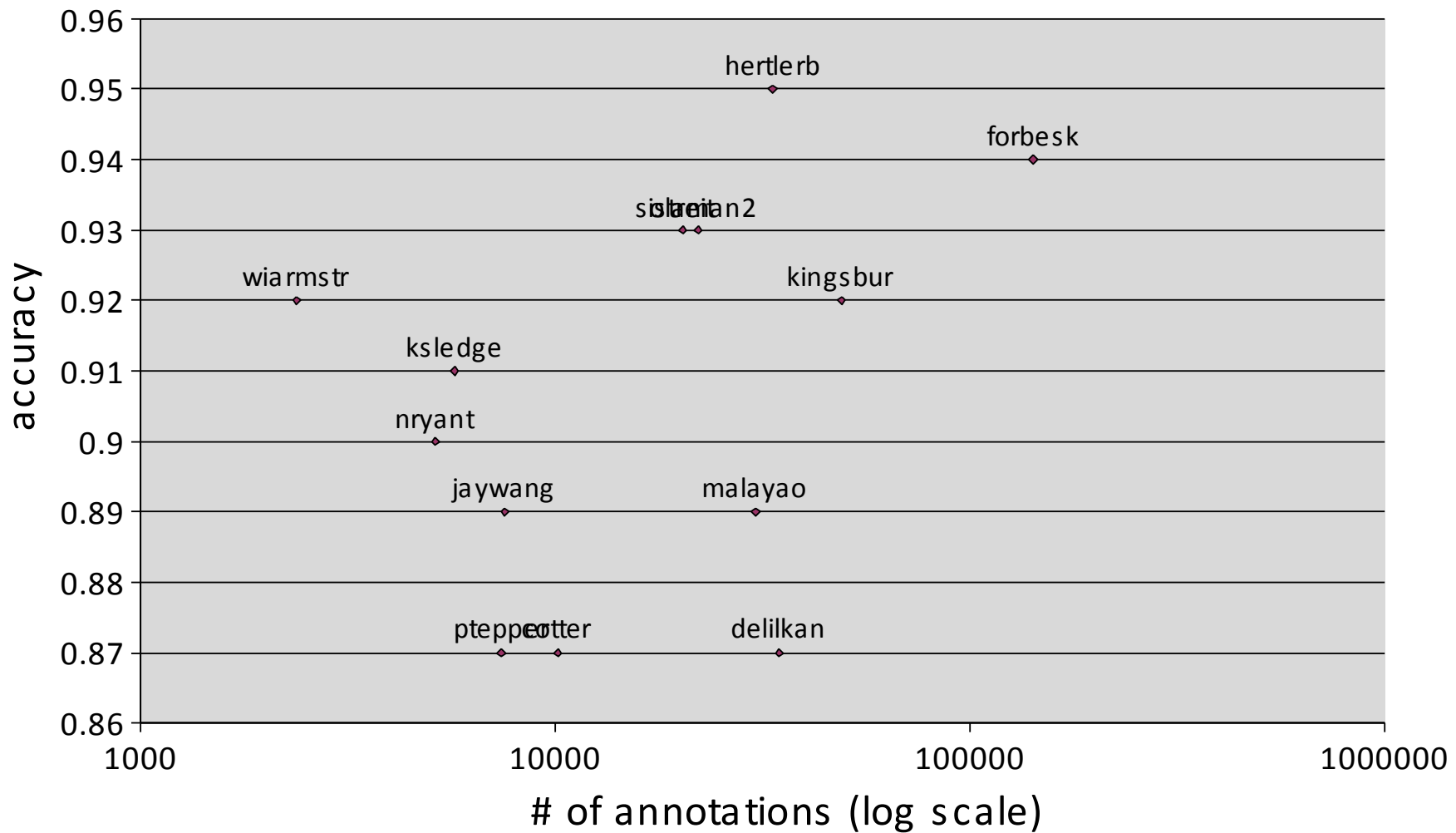
SRL Questions

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A Preliminary Classification of English Verbs, *Beth Levin*

▸ **Based on diathesis alternations**

   ▸ The range of syntactic variations for a class of verbs is a reflection of the underlying semantics

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

▸ **Based on pairs of syntactic frames.**
  John broke the jar. /   Jars break easily. /   The jar broke. /*John broke at the jar.
  John cut the bread. / Bread cuts easily. / *The bread cut/John cut at the bread..

▸ Reflect underlying semantic components
   contact, directed motion,
   exertion of force, change of state

▸ Synonyms, syntactic patterns (*conative*), relations

Break Levin class - *Change-of-state*

break

chip

crack

crash

crush

fracture

rip

shatter

smash

snap

splinter

split

tear
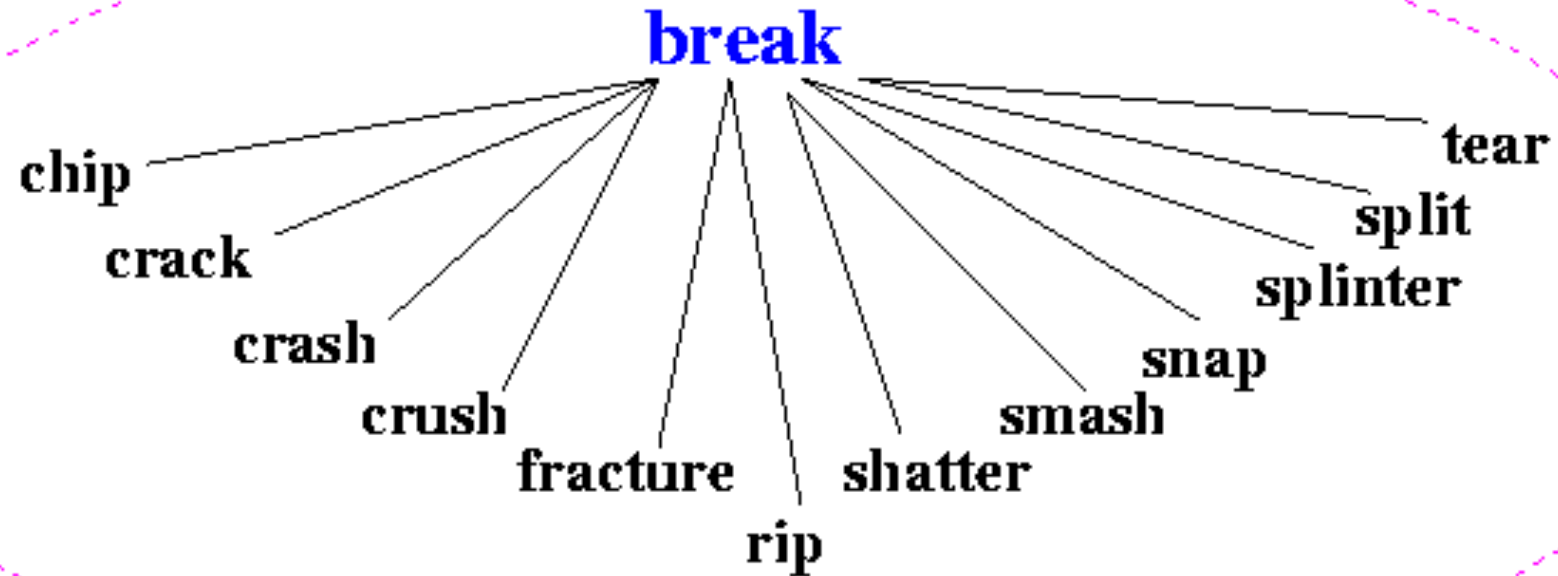
Confusions in Levin classes?

▸ Not semantically homogenous
  ▸ {*braid, clip, file, powder, pluck, etc...*}

▸ Multiple class listings
  ▸ homonymy or polysemy?

▸ Alternation contradictions?
  ▸ *Carry* verbs disallow the Conative, but include
  ▸ {*push,pull,shove,kick,draw,yank,tug*}
  ▸ also in *Push/pull* class, does take the Conative

Intersective Levin Classes

"apart" CH-STATE

"across the room"

CH-LOC

"at" ¬CH-LOC
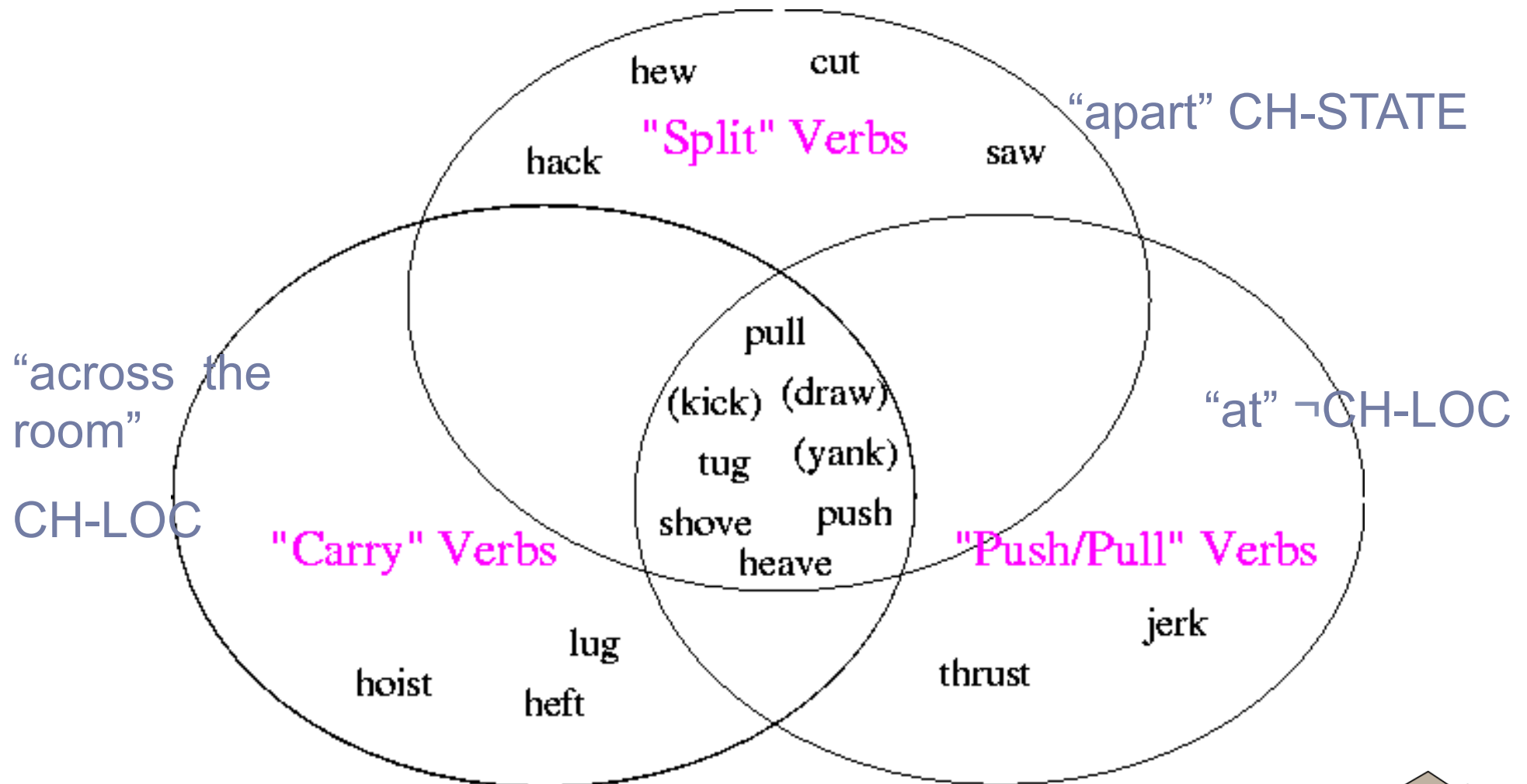
Dang, Kipper & Palmer, ACL98

Intersective Levin Classes

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

$\Longrightarrow$ VERBNET

verbs.colorado.edu/verb-index/
index.php

VerbNet – *Karin Kipper Schuler*

‣ Class entries:
  ‣ Capture generalizations about verb behavior
  ‣ Organized hierarchically
  ‣ Members have common semantic elements, **semantic roles (28**) and syntactic frames

‣ Verb entries:
  ‣ Refer to a set of classes (different senses)
  ‣ each class member linked to WN synset(s) and FrameNet frames

‣ Currently 6300 verbs

‣ Adding Constructions

  Hwang, et.al, NAACL-HLT Construction Workshop, 2010

  Bonial, et. al., ACL RELMS Workshop, 2011

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VerbNet example – *Pour-9.5*

How does VerbNet relate to FrameNet?

FrameNet, Chuck Filmore

➢ The **lexical unit** (Cruse 1986), – <u>a pairing of a word with a sense (or a FrameNet frame.</u>)

➢ In one of its senses, the verb *observe* evokes a frame called **Compliance**: this frame concerns people's responses to norms, rules or practices.

   ▸ *Our family* **observes** *the Jewish dietary laws.*
   ▸ *You have to* **observe** *the rules or you'll be penalized.*

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The FrameNet Product – ADD STATS

The FrameNet database constitutes

▸ a set of **frame descriptions**

   ▸ **Frames, Frame Elements, Valence Possibilities**

▸ a set of **corpus examples** annotated with respect to the frame elements of the frame evoked by each lexical unit

▸ **lexical entries**, including definitions and displays of the combinatory possibilities of each lexical unit, as automatically derived from the annotations

▸ a display of **frame-to-frame relations**, showing how some frames are elaborations of others, or are components of other frames.

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Frame Elements for Compliance

The **Frame Elements** that figure in the Compliance **frame** are called

- ▸ **Norm** (the rule, practice or convention)
- ▸ **Protagonist** (the person[s] reacting to the Norm)
- ▸ **Act** (something done by the Protagonist that is evaluated in terms of the Norm)
- ▸ **State_of_affairs** (a situation evaluated in terms of the Norm)

> - You do a whole frame for just *observe?*
> - No. There are other Compliance words too.

V - *adhere, comply, conform, follow, heed, obey, submit, ...;*

AND NOT ONLY VERBS

N - *adherence, compliance, conformity, obedience, observance, ...;*

A - *compliant, obedient, ...;*
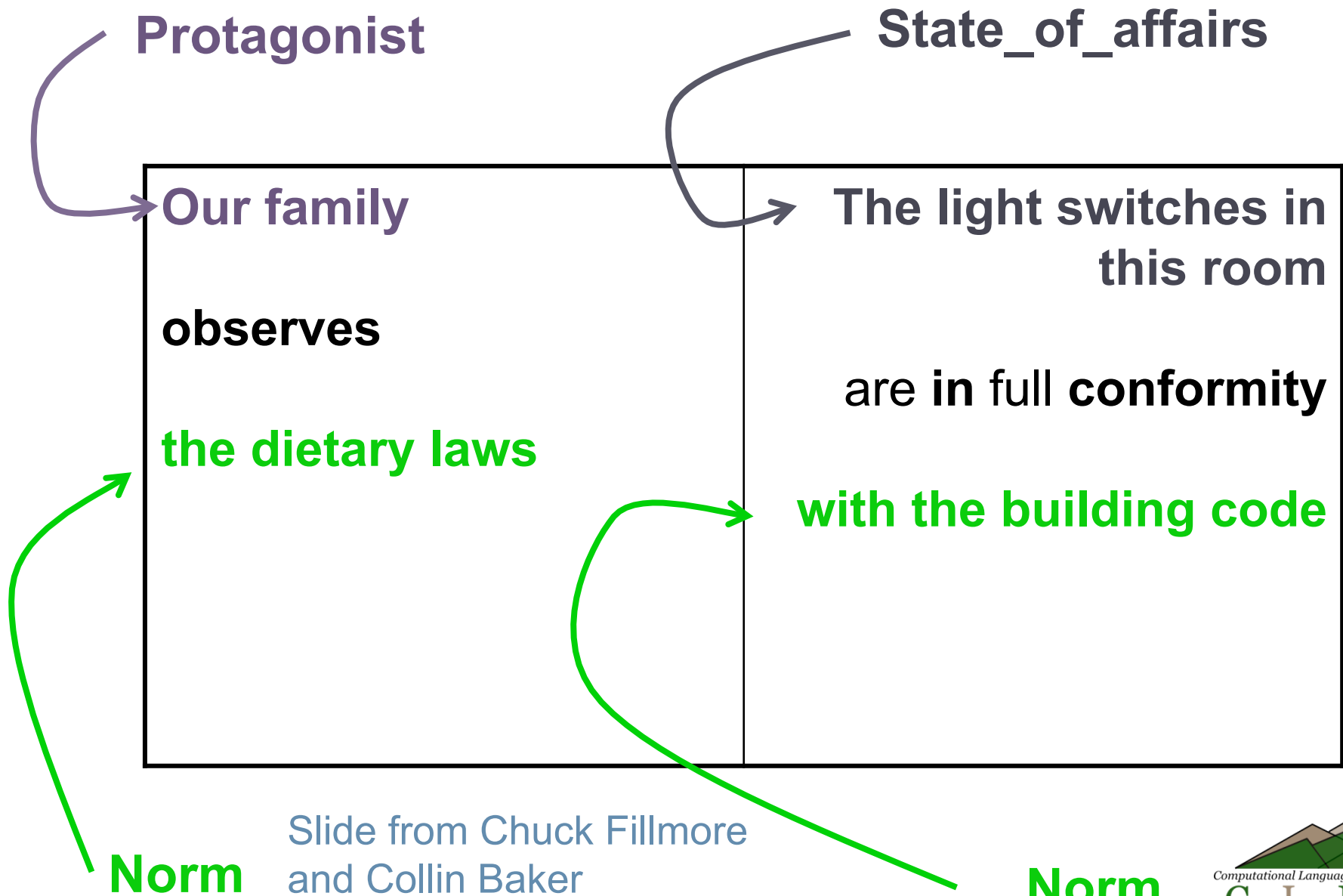
PP - *in compliance with, in conformity to, ...;*

AND NOT ONLY WORDS FOR POSITIVE RESPONSES TO NORMS

V - *break, disobey, flout, transgress, violate ,...;*

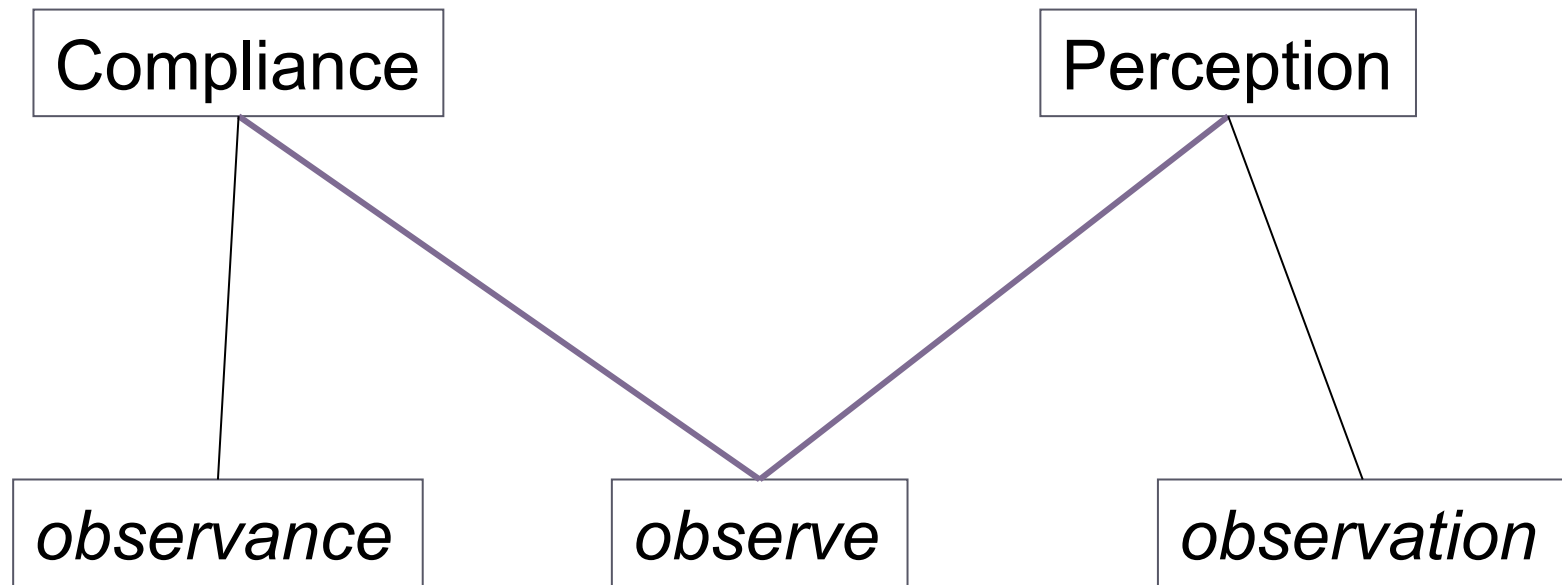N - *breach, disobedience, transgression, violation,...;*

PP - *in violation of, in breach of, ...*

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Tagging Compliance sentences

Protagonist

State_of_affairs

Our family

observes

the dietary laws

The light switches in this room

are **in** full **conformity**

with the building code

Norm

Norm

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words, frames, lexical units

| Compliance | | Perception |

| observance | observe | observation |

2 lexical units sharing same form:
Compliance.*observe*,
Perception.*observe*

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escape–51.1

"move away from"

leave.01 ——→ leave–51.2

arg0 (entity leaving) ——→ Theme
arg1 (place left) ——→ Source
arg2 (attribute) ——→

keep–15.2

fulfill–13.4.1

"give"
leave.02 ——→ future_having–13.3

arg0 (giver) ——→ Agent
arg1 (thing given) ——→ Theme
arg2 (benefactive) ——→ Recipient

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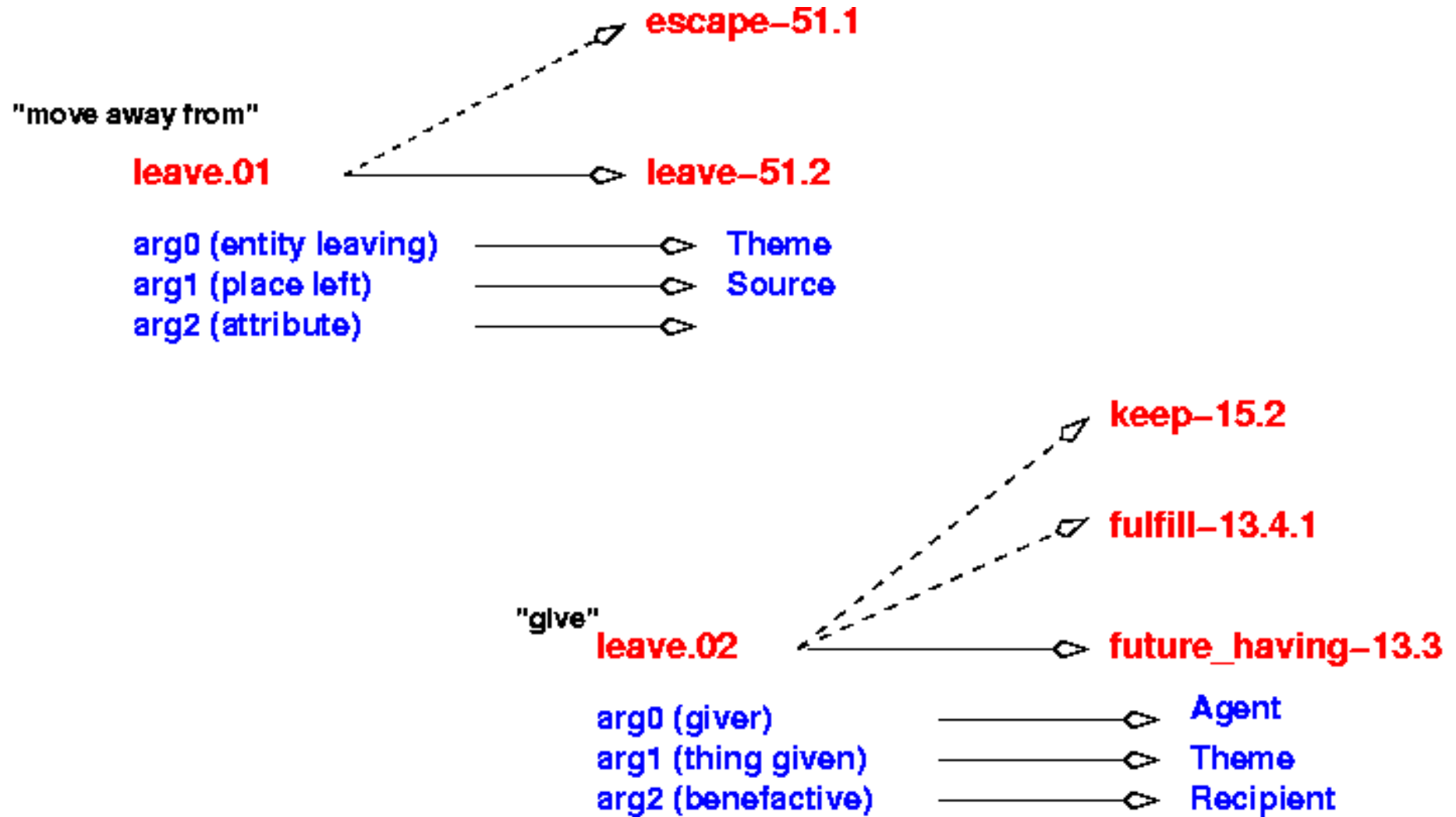
Mapping from PropBank to VerbNet (similar mapping for PB-FrameNet) - SemLink

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

*FrameNet Label

Baker, Fillmore, & Lowe, COLING/ACL-98
Fillmore & Baker, WordNetWKSHP, 2001

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PropBank/FrameNet - SemLink

Buy

Arg0: buyer

Arg1: goods

Arg2: seller

Arg3: rate

Arg4: payment

Sell

Arg0: seller

Arg1: goods

Arg2: buyer

Arg3: rate

Arg4: payment
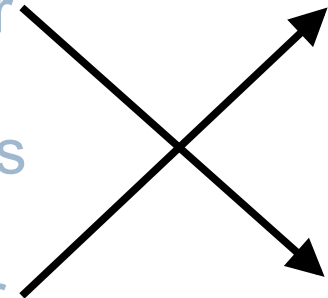
More generic, more neutral – maps readily to VN,TR

Rambow, et al, PMLB03

Can SemLink improve Generalization?

- After PropBank, SRL improved from 77% to 88% Automatic parses, 81% F, Brown corpus, 68%
- 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

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VerbNet - 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]
  ▸ ARG2 Grouping: Arg[0,2-5,A,M] Arg1-Group[1-6]

▸ **Evaluation**
  ▸ WSJ   [+6%]
  ▸ Brown   [+10%]

▸ **More Coarse-grained or Fine-grained?**
  ▸ more specific: data more coherent, but more sparse
  ▸ more general: consistency across verbs even for new domains?

PropBank/VerbNet/FrameNet - SemLink

▸ Complementary resources

▸ Redundancy is harmless, may even be useful

▸ PropBank provides the best training data

▸ VerbNet provides the clearest links between syntax and semantics

▸ FrameNet provides the richest semantics

▸ Together they give us the most comprehensive coverage

▸ SemLink - http://verbs.colorado.edu/semlink/

　　▸ WSJ, sense tags and SRL, mappings to VN and FN

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WSJ instance example from SemLink

Pierre Vinken , 61 years old ,

will join

the board

as a nonexecutive director Nov. 29.

nw/wsj/00/wsj_0001.parse
 0 8 gold join-v 22.1-2-1 Cause_to_amalgamate join.01
0:2-ARG0=Agent;Agent
7:0-ARGM-MOD
8:0-rel
9:1-ARG1=Patient;Part_1
11:1-ARGM-PRD 15:1-ARGM-TMP

Annotated Data – Current PropBank Status

Pradhan, et.al., IJSC 2007, Albright, et. al., JAMIA, 2013, Palmer, et. al., ICON-09

▸ DARPA-GALE, OntoNotes 5.0
  ▸ BBN, Brandeis, **Colorado**, Penn
  ▸ Multilayer structure: NE, TB, **PB, WS**, Coref
  ▸ Three languages: **English, Arabic**, Chinese
  ▸ Several Genres (@ ≥ 200K): NW, BN, BC, WT
    ▸ Close to 2M words @ language (less PB for Arabic)
  ▸ Parallel data, E/C, E/A
  ▸ PropBank frame coverage for rare verbs
  ▸ Recent PropBank extensions

▸ Clinical Notes – 400K available, goal is 700K

▸ Hindi/Urdu PropBank, 400K Hindi, 200K Urdu

▸ BOLT – discussion forums, SMS, email, Egyptian

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PropBank Verb Frames Coverage

- ▸ The set of verbs is open

- ▸ But the distribution is highly skewed

- ▸ For English, the 1000 most frequent lemmas cover 95% of the verbs in running text.

  - ▸ Graphs show counts over English Web data containing 150 M verbs.
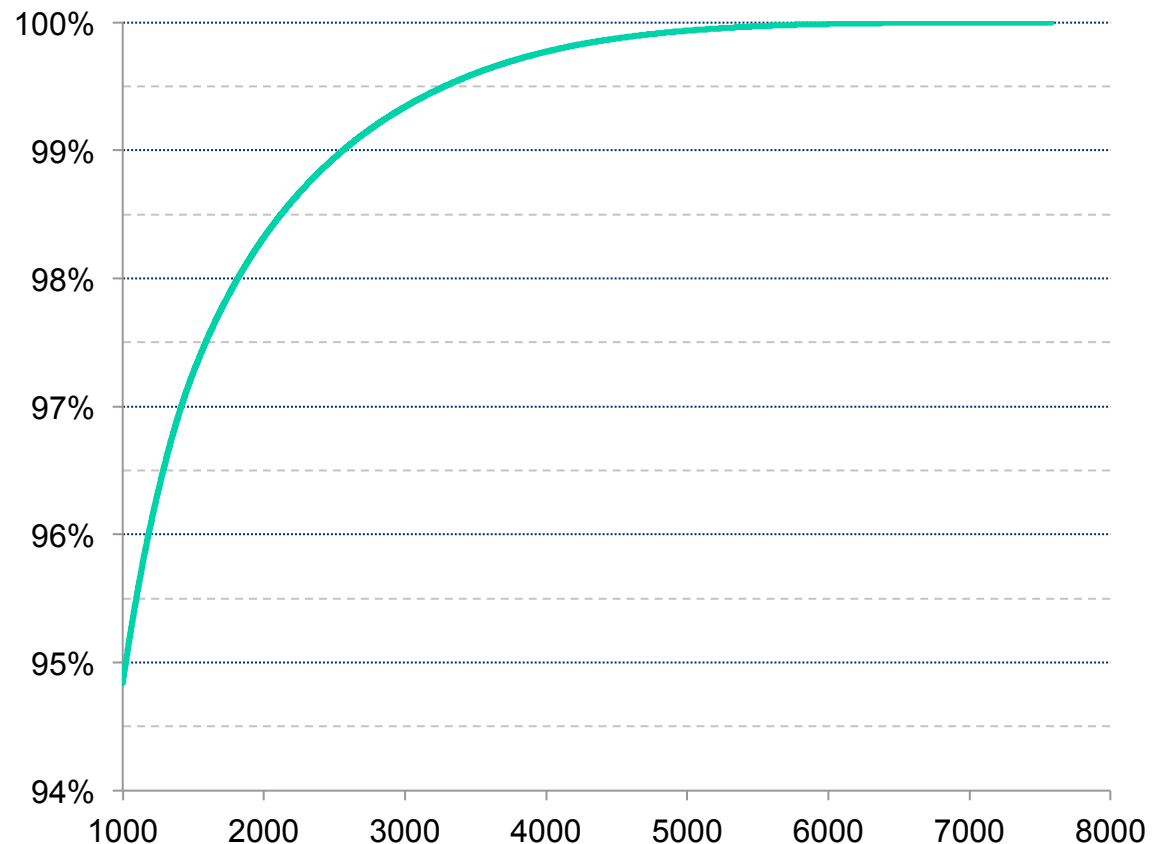
Verb Frames Coverage By Language – Current Count of Senses (lexical units)

Language	Final Count	Estimated Coverage in Running Text
English	10,615*	99%
Chinese	24,642	98%
Arabic	7,015	99%

- Only 111 English adjectives

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Included in OntoNotes 5.1: Extensions to PropBank

- **Original annotation coverage:**
  - PropBank: verbs; past participle adjectival modifiers
  - NomBank: relational and eventive nouns.

- **Substantial gap – now bridging**
  - Uniform treatment of light verbs,
  - Additional predicative adjectives,
  - Eventive nouns

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Gaps in proposition coverage

▸ Event Coreference chains include nominalizations with and without light verbs

  ▸ *"China has threatened to slap sanctions on American companies that sell arms to its rival Taiwan as part of a range of punitive actions Beijing is taking to protest the deal...'China will make further judgments as appropriate,' Xinhua reported."*

  ▸ Light verb/nominalization examples:

    slap sanctions, taking actions, make judgments

▸ PropBank structures for eventive nouns

  ▸ sanction(China, US companies),

  ▸ act(China),

  ▸ judge(China, US companies)

English Noun and LVC annotation

- **Example Noun:** *Decision*
    - Roleset: Arg0: decider, Arg1: decision…

    - "…[your$_{ARG0}$] [decision$_{REL}$]
      [to say look I don't want to go through this anymore$_{ARG1}$]"

- **Example within an LVC:** *Make a decision*
    - "…[the President$_{ARG0}$] [made$_{REL-LVB}$]
      the [fundamentally correct$_{ARGM-ADJ}$]
      [decision$_{REL}$] [to get on offense$_{ARG1}$]"

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2-pass annotation, post-processing

- *China will make further judgments as appropriate.*
- Verb - REL: *[make]*,
  - Arg0: *China,*
  - ArgPRX: *further judgments as appropriate.*
- Noun – RELPRX: *[judgment]*
  - Arg0: *China*
  - ArgM-PRD: *as appropriate*
- *Merged – REL: RELPRX: [make] [judgment]*
  - Arg0: *China*
  - ArgM-PRD: *as appropriate*

Abstract Meaning Representations – AMR,
Maximal Use of PropBank Frame Files,

Knight, et. al., LAW-2013

He was not aware of research on smokers of the Kent cigarettes.

```
(r / realize-01

  :polarity -
 :ARG0 (h / he)

  :ARG1 (r3 / research-01
        :ARG1 (p4 / person
              :ARG0-of (s / smoke-02
                    :ARG1 (c2 / cigarette

                          :name (k / name

                            :op1 "Kent"))))))
```

To get to canonical concept, we stem to English verbs,
  where PropBank arguments are best described.
General direction of stemming:
  adverb → adjective → noun → verb

SRL Questions

‣ Why Arg0 and Arg1?

‣ What about nouns and adjectives?

‣ What about other languages?

‣ How does PropBank relate to VerbNet and FrameNet?

‣ Will we ever get past the WSJ?

‣ How do SRL systems get trained?

‣ Can this be done without training data?

‣ …..

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