SemLink - Linking PropBank, VerbNet, FrameNet

Martha Palmer

University of Colorado

September 17, 2009

GL 2009

Computational Language and EducAtion Research

C L E A R

Goals – Ex. Answering Questions

- *Similar concepts*
  - *Where are the grape arbors located?*
  - *Every path from back door to yard was covered by a grape-arbor, and every yard had fruit trees.*

Semlink: Overview

- WordNet, OntoNotes Groupings, PropBank
- VerbNet
  - Verbs grouped in hierarchical classes
  - Explicitly described class properties
- FrameNet
- Links among lexical resources
  - PropBank, FrameNet, WordNet, OntoNotes groupings
- Automatic Semantic Role Labeling with PropBank/Verbnet
- Applications

WordNet – Princeton

(Miller 1985, Fellbaum 1998)

On-line lexical reference (dictionary)

- Nouns, verbs, adjectives, and adverbs grouped into synonym sets
- Other relations include hypernyms (ISA), antonyms, meronyms
- Typical top nodes - 5 out of 25
  - *(act, action, activity)*
  - *(animal, fauna)*
  - *(artifact)*
  - *(attribute, property)*
  - *(body, corpus)*

WordNet – Princeton – *leave, n.4, v.14*

(Miller 1985, Fellbaum 1998)

- Limitations as a computational lexicon
  - Contains little syntactic information
  - No explicit lists of participants
  - Sense distinctions very fine-grained,
  - Definitions often vague
- Causes problems with creating training data for supervised Machine Learning – SENSEVAL2
  - Verbs > 16 senses (including *call*)
  - Inter-annotator Agreement ITA 71%,
  - Automatic Word Sense Disambiguation, WSD 64%

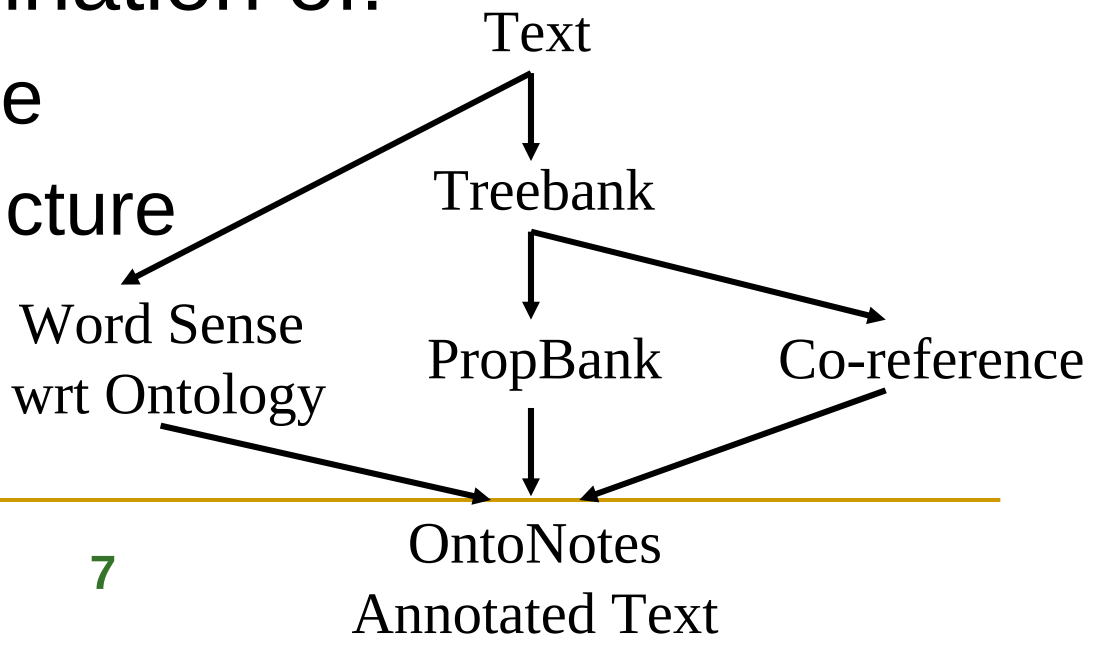
Dang & Palmer, SIGLEX02

Creation of coarse-grained resources

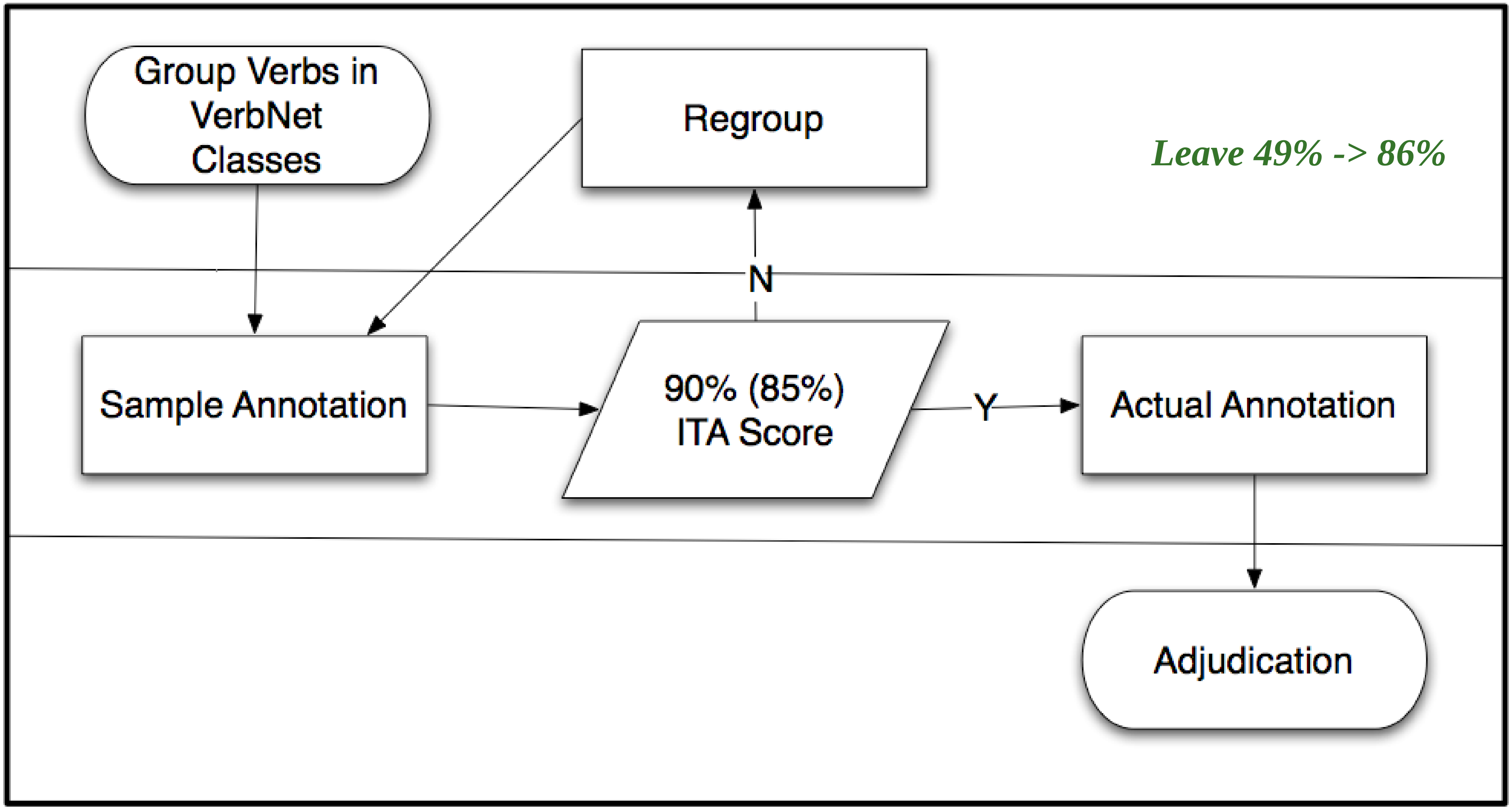
- Unsupervised clustering using rules (Mihalcea & Moldovan, 2001)
- Clustering by mapping WN senses to OED (Navigli, 2006).
- OntoNotes - Manually grouping WN senses and annotating a corpus (Hovy et al., 2006)
- Supervised clustering WN senses using OntoNotes and another set of manually tagged data (Snow et al., 2007) .

OntoNotes Goal: Modeling Shallow Semantics DARPA-GALE

- AGILE Team: BBN, Colorado, ISI, Penn
- Skeletal representation of literal meaning
- Synergistic combination of:
  - Syntactic structure
  - Propositional structure
  - Word sense
  - Coreference



Empirical Validation – Human Judges the 90% solution (1700 verbs)



Groupings Methodology – Human Judges (w/ Dang and Fellbaum)

- Double blind groupings, adjudication
- Syntactic Criteria (VerbNet was useful)
  - Distinct subcategorization frames
    - *call him an idiot*
    - *call him a taxi*
  - Recognizable alternations – regular sense extensions:
    - *play an instrument*
    - *play a song*
    - *play a melody on an instrument*

SIGLEX01, SIGLEX02, JNLE07, Duffield, et. al., CogSci 2007

Groupings Methodology (cont.)

- Semantic Criteria
  - Differences in semantic classes of arguments
    - Abstract/concrete, human/animal, animate/inanimate, different instrument types,…
  - Differences in the number and type of arguments
    - Often reflected in subcategorization frames
    - *John left the room.*
    - *I left my pearls to my daughter-in-law in my will.*
  - Differences in entailments
    - Change of prior entity or creation of a new entity?
  - Differences in types of events
    - Abstract/concrete/mental/emotional/….
  - Specialized subject domains

OntoNotes Status

- More than 2,000 verbs grouped
- Average ITA per verbs = 89%
- http://verbs.colorado.edu/html_groupings/
- More than 150,000 instances annotated for 1700 verbs
- WSJ, Brown, ECTB, EBN, EBC
- Training and Testing
- *How do the groupings connect to PropBank?*

PropBank – WSJ Penn Treebank

Palmer, Gildea, Kingsbury., CLJ 2005

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)

Lexical Resource - Frames Files: *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 word senses in other resources?

Sense Hierarchy

(Palmer, et al, SNLU04 - NAACL04, NLE07, Chen, et. al, NAACL06)

- PropBank Framesets – ITA >90%
  coarse grained distinctions
  20 Senseval2 verbs w/ > 1 Frameset
  Maxent WSD system, 73.5% baseline, 90%
  - Sense Groups (Senseval-2) - ITA 82%
    Intermediate level
    (includes Levin classes) – 71.7%
    - WordNet – ITA 73%
      fine grained distinctions, 64%

Tagging w/groups,
ITA 90%, 200@hr,
Taggers - 86.9%
Semeval07

Chen, Dligach & Palmer, ICSC 2007

Limitations to PropBank

- WSJ too domain specific,
  - Additional Brown corpus annotation & GALE data
  - FrameNet has selected instances from BNC
- Args2-4 seriously overloaded, poor performance
  - VerbNet and FrameNet both provide more fine-grained role labels

VerbNet: Basis in Theory

- Beth Levin, *English Verb Classes and Alternations* (1993)
- Verb class hierarchy: 3100 verbs, 47 top level classes, 193
- *"Behavior of a verb . . . is to a large extent determined by its meaning"* (p. 1)

  Amanda hacked the wood with an ax.

  Amanda hacked at the wood with an ax.

  Craig notched the wood with an ax.

  *Craig notched at the wood with an ax.
- Can we move from syntactic behavior back to semantics?

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

VerbNet – *Karin Kipper Schuler*

- 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) and FrameNet frames

Hacking and *Notching*

- Same thematic roles:
  - Agent, Patient, Instrument

- Some shared syntactic frames,
  - e.g. Basic Transitive (Agent V Patient)

- Different Semantic predicates

VerbNet Semantic Predicates

- *Hack: cut-21.1*

    cause(Agent, E)

    manner(during(E), Motion, Agent)

    contact(during(E), ?Instrument, Patient)

    degradation_material_integrity(result(E), Patient)

- *Notch: carve-21.2*

    cause(Agent, E)

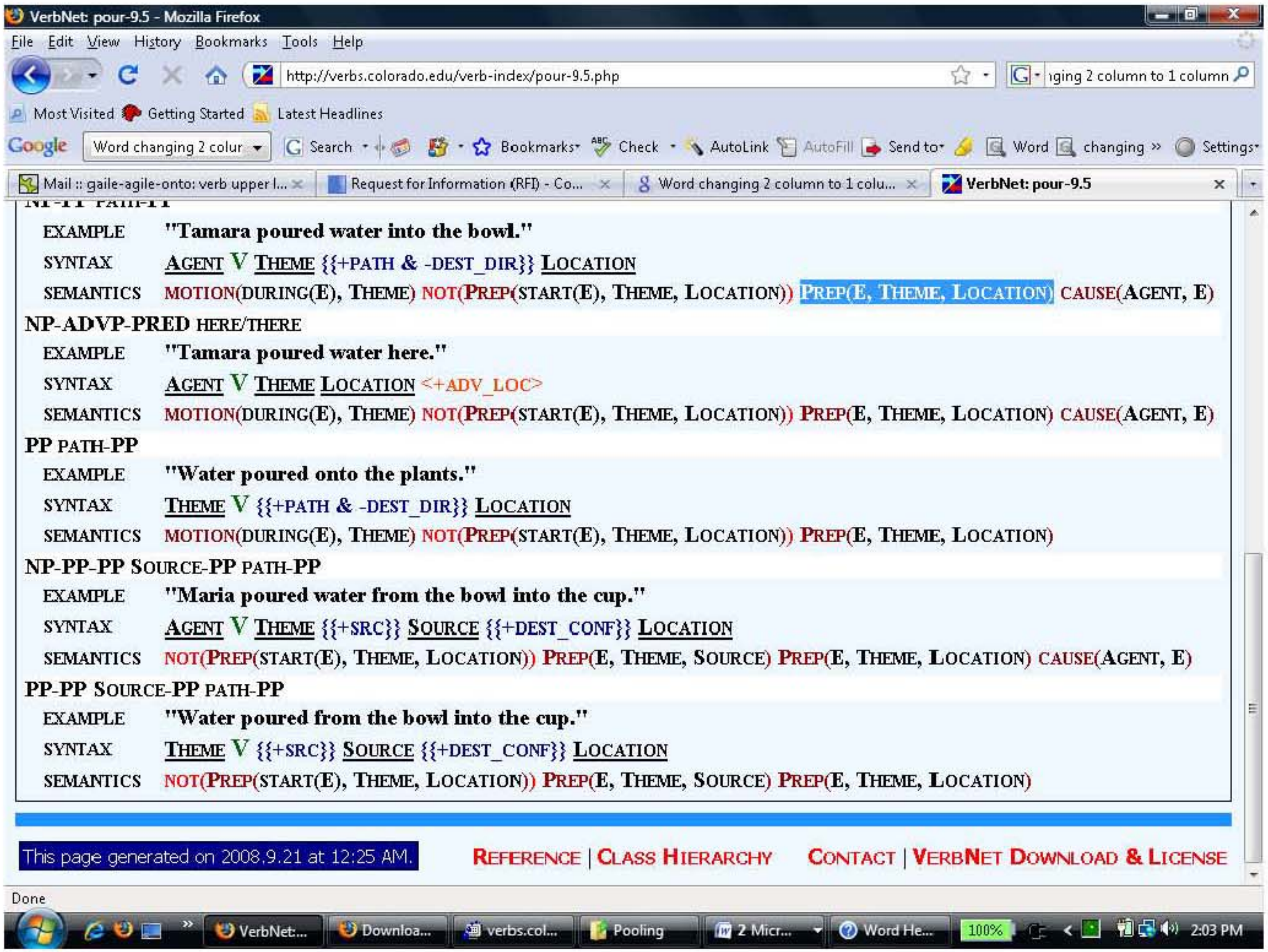
    contact(during(E), ?Instrument, Patient)

    degradation_material_integrity(result(E), Patient)

    physical_form(result(E), Form, Patient)

VerbNet example – *Pour-9.5*

VerbNet *Pour-9.5* (cont.)



Hidden Axioms

- EXAMPLE: *Tamara poured water into the bowl.*
- SYNTAX: AGENT V THEME LOCATION
- SEMANTICS
  - CAUSE(AGENT,E)
  - MOTION(DURING(E), THEME),
  - NOT(PREP(START(E), THEME, LOCATION)),
  - PREP(E, THEME, LOCATION)

Hidden Axioms **REVEALED!**

- EXAMPLE: *Tamara poured water into the bowl.*
- SYNTAX: AGENT V THEME LOCATION
- SEMANTICS
- POUR.*pour9.5* (AGENT, THEME LOCATION) →

  CAUSE(AGENT,E),

  MOTION(DURING(E), THEME),

  NOT(PREP(START(E), THEME, LOCATION)),

  PREP(E, THEME, LOCATION).

VerbNet – *cover fill-9.8*

- **WordNet Senses: …,** cover(1,2, 22, 26),…, staff(1),

- **Thematic Roles:** Agent [+animate]
  Theme [+concrete],
  Destination [+location, +region]

- **Frames with Semantic Roles**

  "The employees staffed the store"

  " The grape arbors covered every path"

  Theme V Destination

  location(E,Theme,Destination)
  location(E,grape_arbor,path)

VerbNet as a useful NLP resource

- Semantic role labeling
- Inferences

*While many of the weapons used by the insurgency are leftovers from the Iran-Iraq war, Iran is still **providing** deadly weapons such as EFPs -LRB- or Explosively Formed Projectiles -RRB-.*

provide(Agent, Theme, Recipient)

VerbNet as a useful NLP resource

- Semantic role labeling
- Inferences

*While many of the weapons used by the insurgency are leftovers from the Iran-Iraq war, Iran is still **providing** deadly weapons such as EFPs -LRB- or Explosively Formed Projectiles -RRB-.*

provide(Iran, weapons, ?Recipient) →

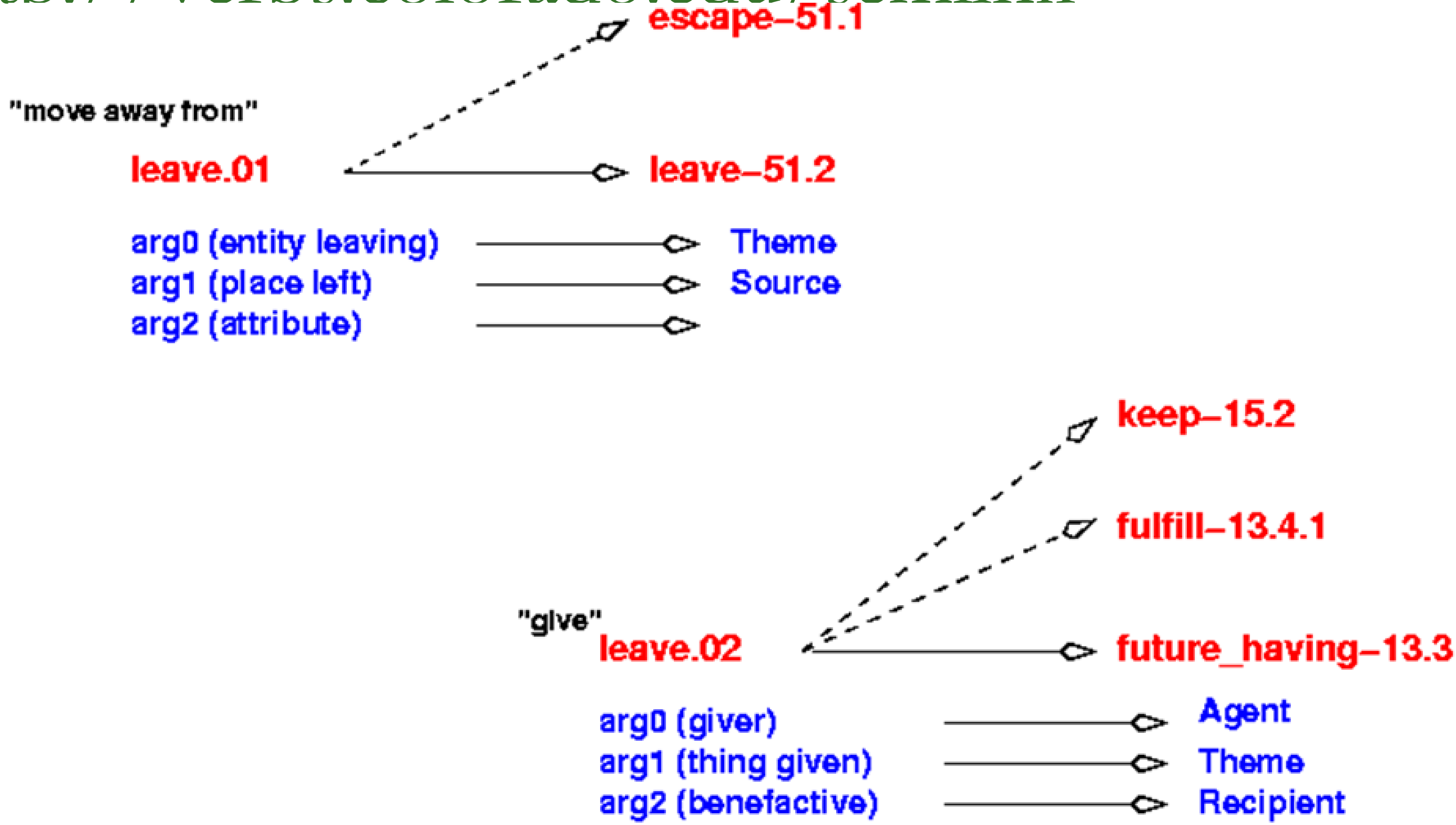
cause(Iran, E)

has_possession(start(E), Iran, weapons)

has_possession(end(E), ?Recipient, weapons)

transfer(during(E), weapons)

Mapping from PB to VerbNet http://verbs.colorado.edu/semlink



FrameNet: Telling.*inform*

Time	In 2002,
Speaker	the U.S. State Department
Target	INFORMED
Addressee	North Korea
Message	that the U.S. was aware of this program , and regards it as a violation of Pyongyang's nonproliferation commitments

PropBank/VerbNet/FrameNet

- Complementary
- 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
- So…. We're also mapping VerbNet to FrameNet

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

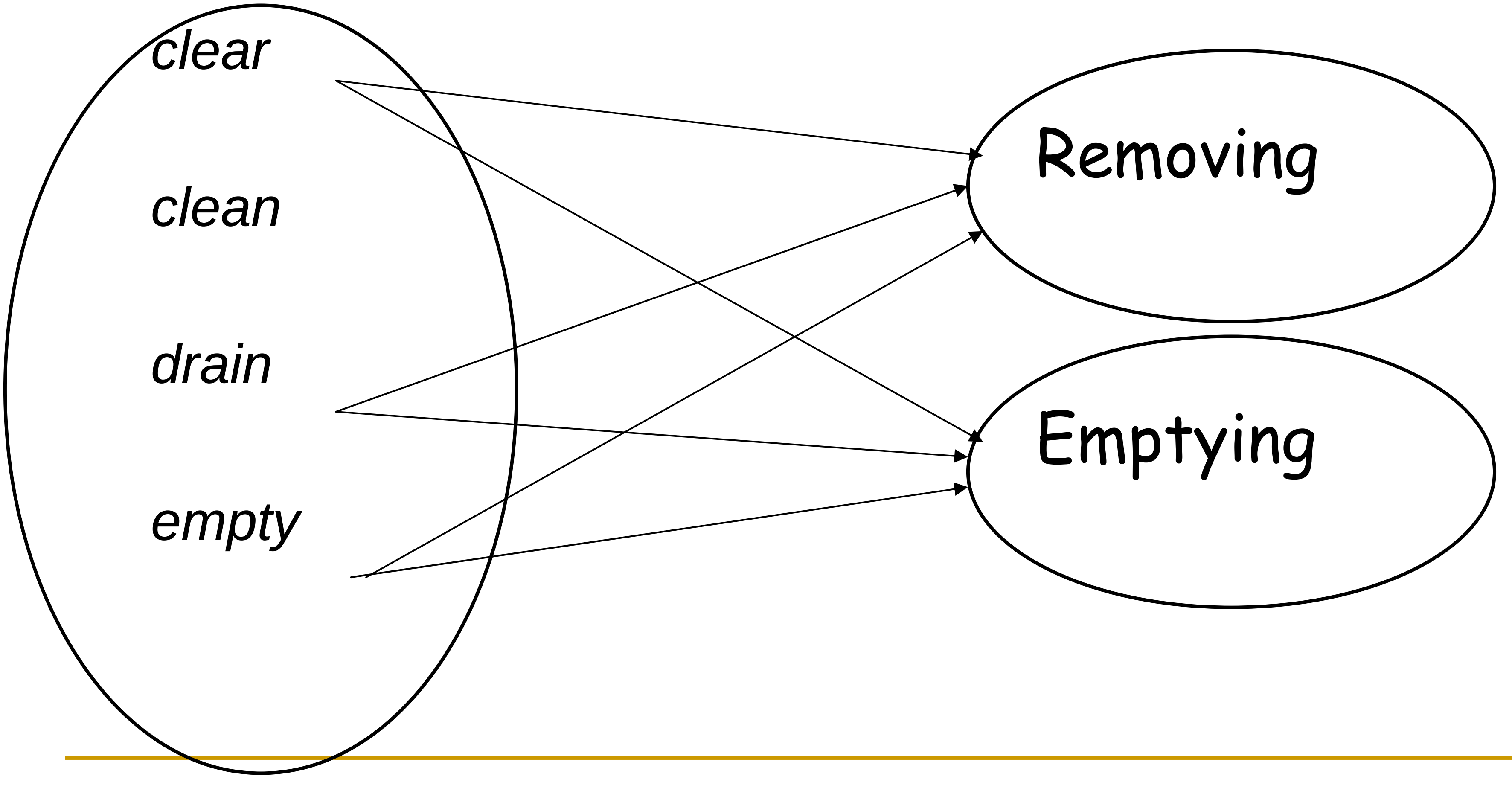
Frameset id = ***leave.02***	Sense = *give*	VerbNet class = ***future-having 13.3***
Arg0	Giver	Agent/Donor*
Arg1	Thing given	Theme
Arg2	Benefactive	Recipient

*FrameNet Label

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

Mapping Issues (2)
VerbNet verbs mapped to FrameNet

- *VerbNet clear-10.3*
- FrameNet Classes



Mapping Issues (3)

VerbNet verbs mapped to FrameNet

VN Class: *put 9.1*

Members: *arrange*, immerse, lodge, mount, sling***

Thematic roles:

- agent (+animate)
- theme (+concrete)
- destination (+loc, -region)

Frames:

- …

*different sense

** not in FrameNet

FrameNet frame: *place*

Frame Elements:

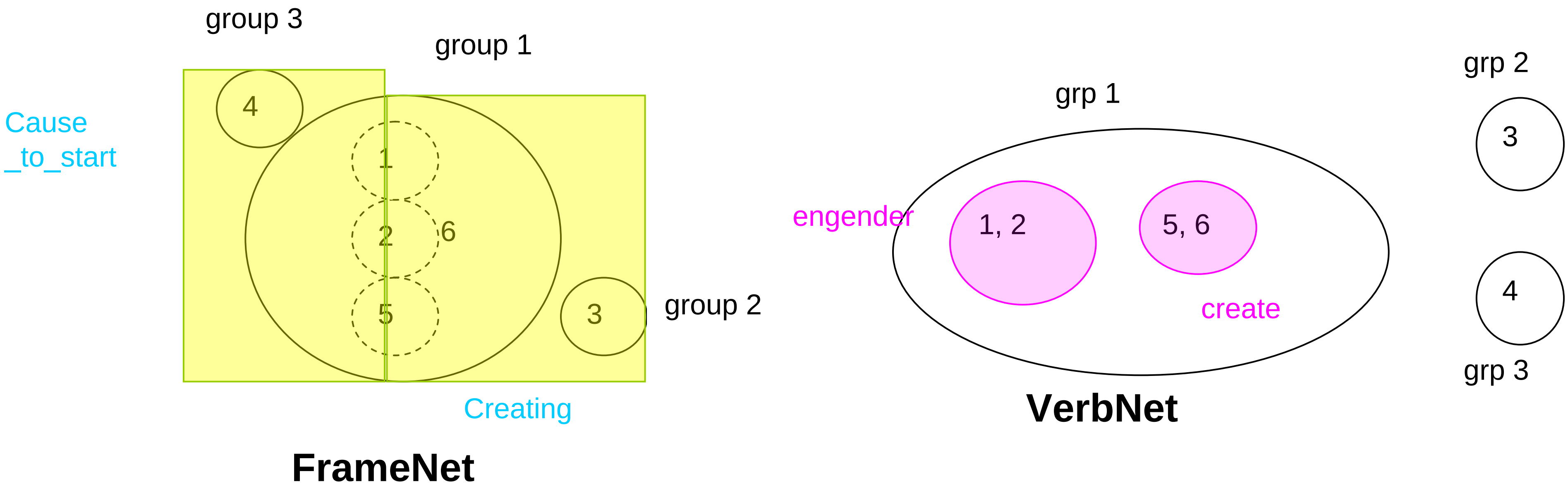
- Agent
- Cause
- Theme
- Goal

Examples:

- …

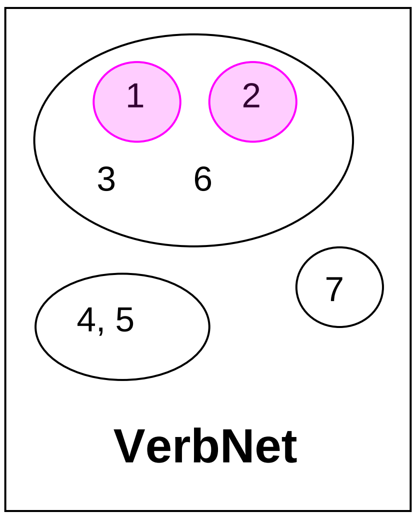
Class formation Issues: *create*

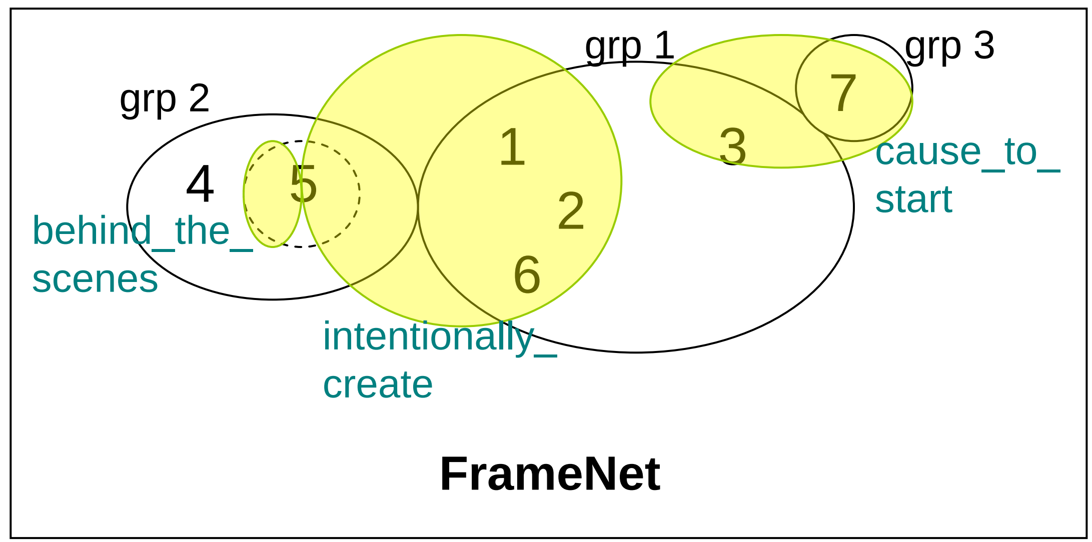
Susan Brown



Class formation Issues: *produce*

Susan Brown

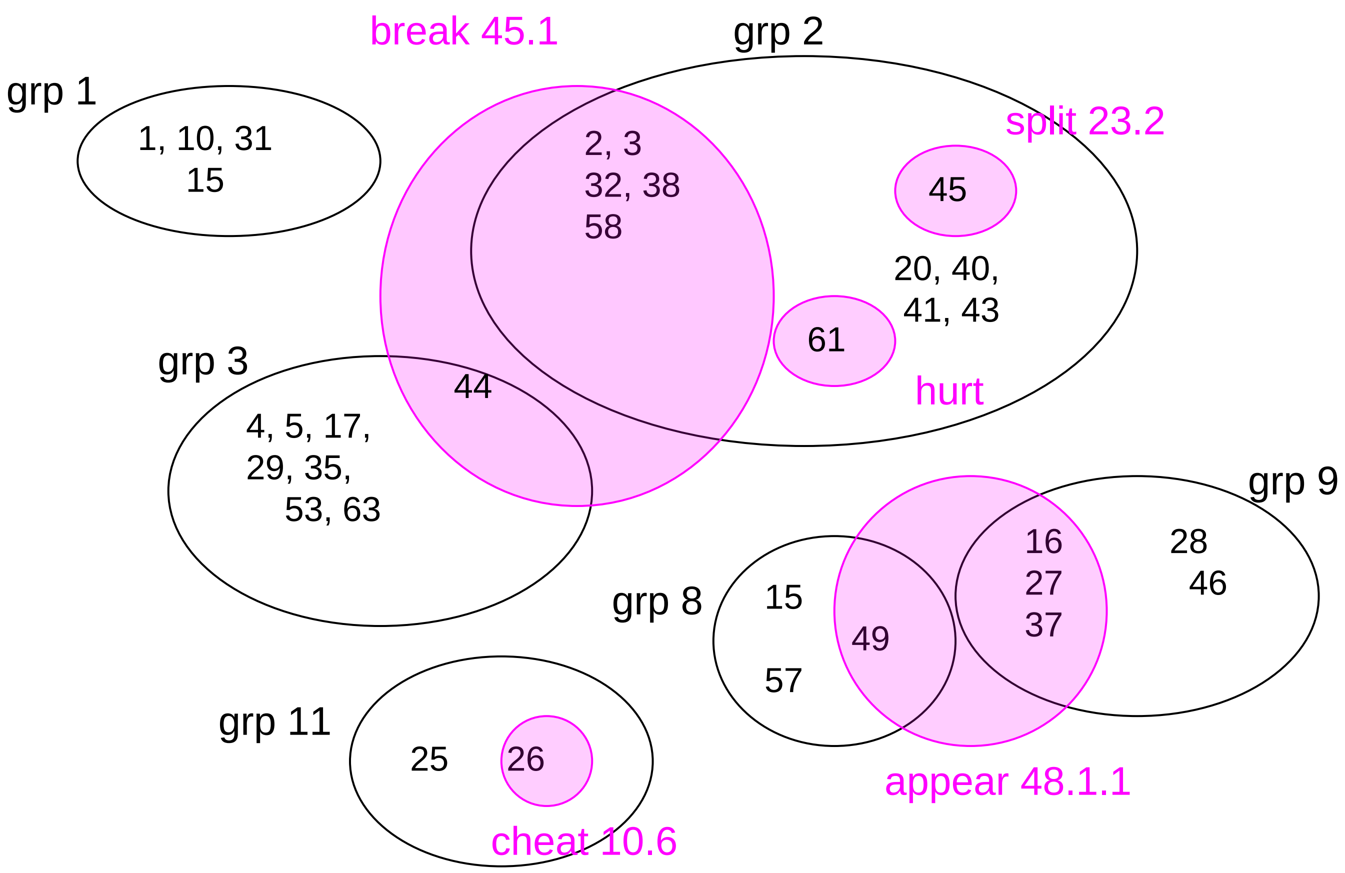




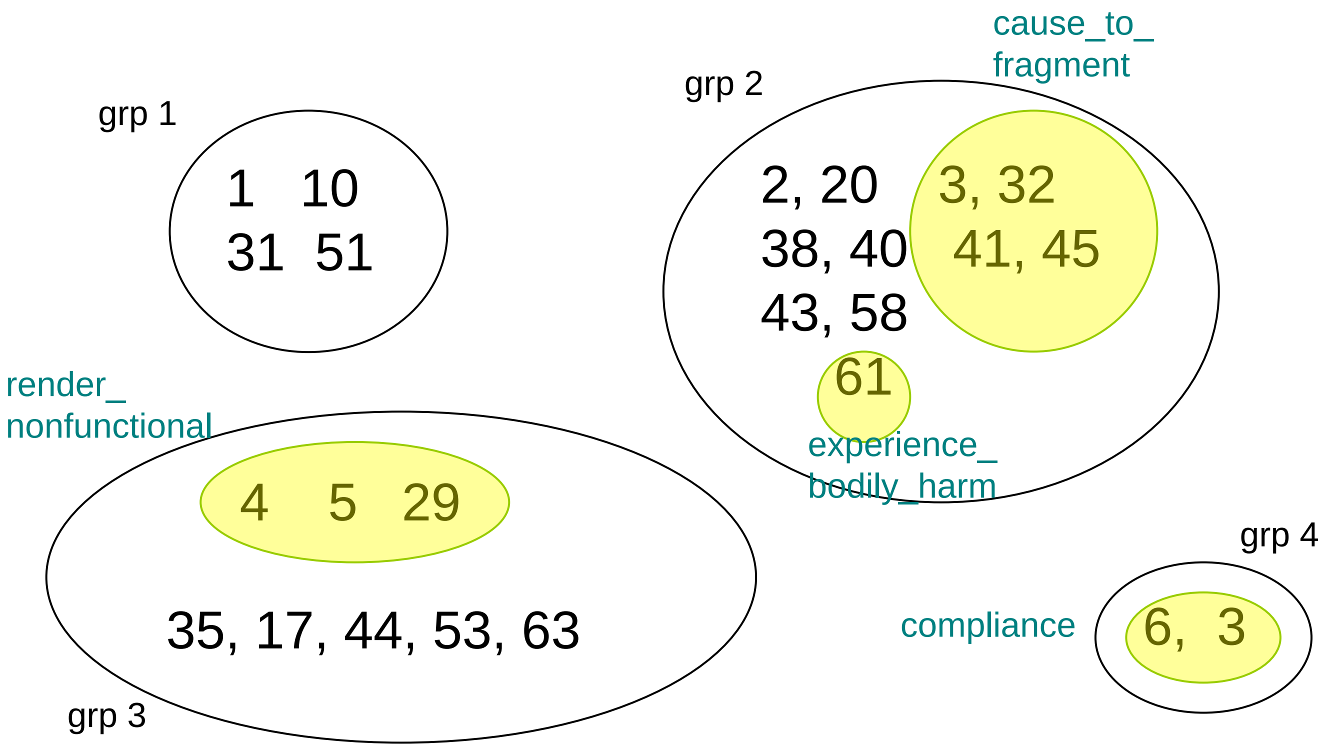
Class formation Issues: *break*/Verbnet

Susan Brown

WN44 – the skin broke
WN49 – the simple vowels broke in many Germanic languages

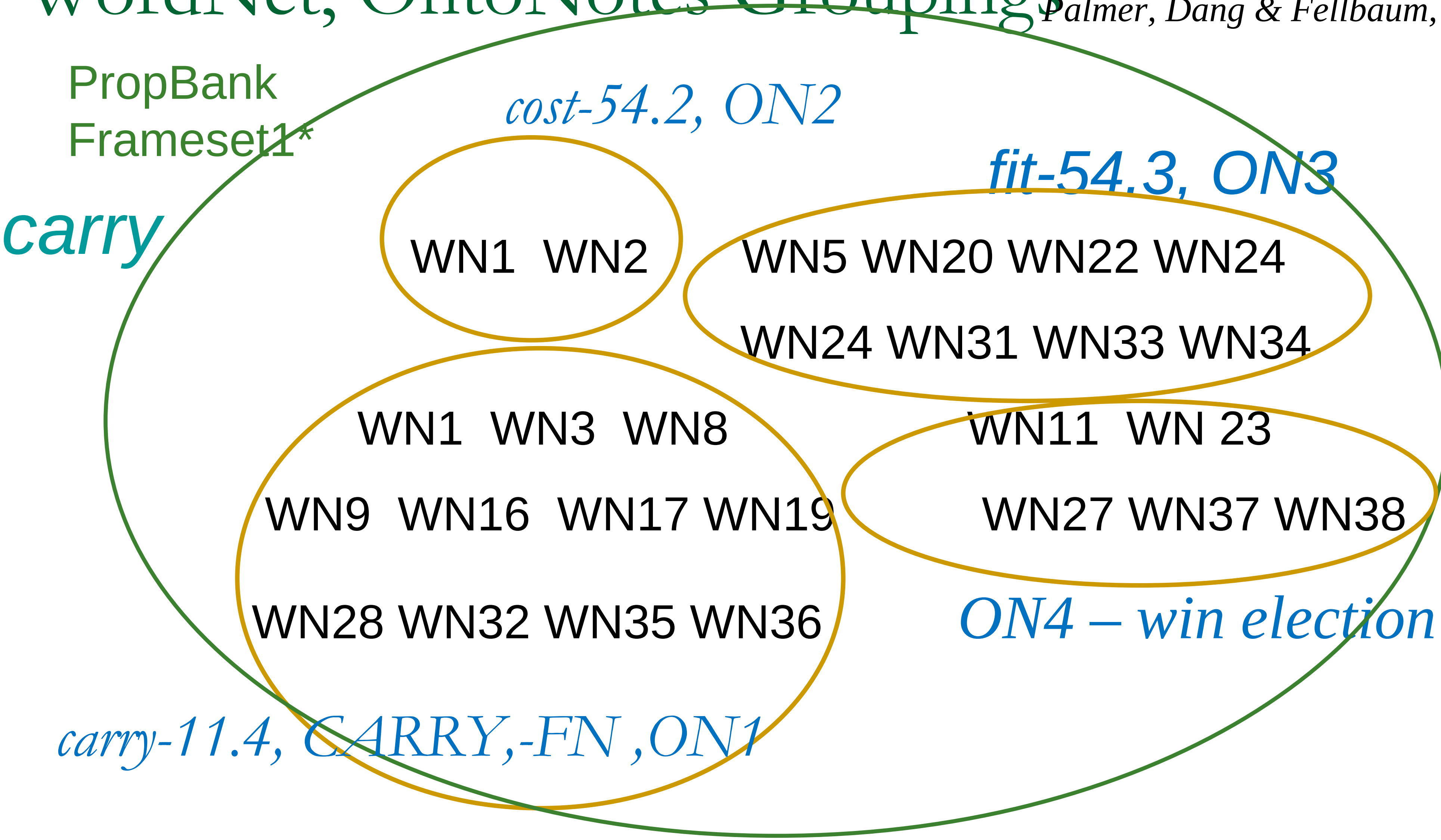


Class Formation Issues: *break*/FrameNet
Susan Brown



SEMLINK-PropBank, VerbNet, FrameNet, WordNet, OntoNotes Groupings

Palmer, Dang & Fellbaum, NLE ...



***ON5-ON11 carry oneself,carried away/out/off, carry to term**

WordNet: - leave, 14 senses, grouped

WN1, WN5,WN8

Depart, a job, a room, a dock, a country

WN6 WN10 WN2 WN 4 WN9 WN11 WN12

WN14 Wnleave_off2,3 WNleave_behind1,2,3

WNleave_alone1 WN13

Leave behind, leave alone

WN3 WN7

Create a State

WNleave_off1

"leave off" stop, terminate

WNleave_out1, Wnleave_out2

exclude

WordNet: - leave, 14 senses, groups, PB

WN1, WN5,WN8

4

Depart, a job, a room, a dock, a country (for X)

1

2

WN6 WN10 WN2 WN 4 WN9 WN11 WN12

WN14 WNleave_off2,3 WNleave_behind1,2,3

Leave behind, leave alone

WNleave_alone1 WN13

5

WN3 WN7

Create a State /cause an effect:
Left us speechless, leave a stain

WNleave_off1

WNleave_out1, WNleave_out2

stop, terminate:
the road leaves off, not leave off your jacket, the results

exclude

3

Leave behind, leave alone…

- ***John left his keys at the restaurant.***

  We left behind all our cares during our vacation.

  They were told to leave off their coats.

  Leave the young fawn alone.

  Leave the nature park just as you found it.

  I left my shoes on when I entered their house.

  When she put away the food she left out the pie.

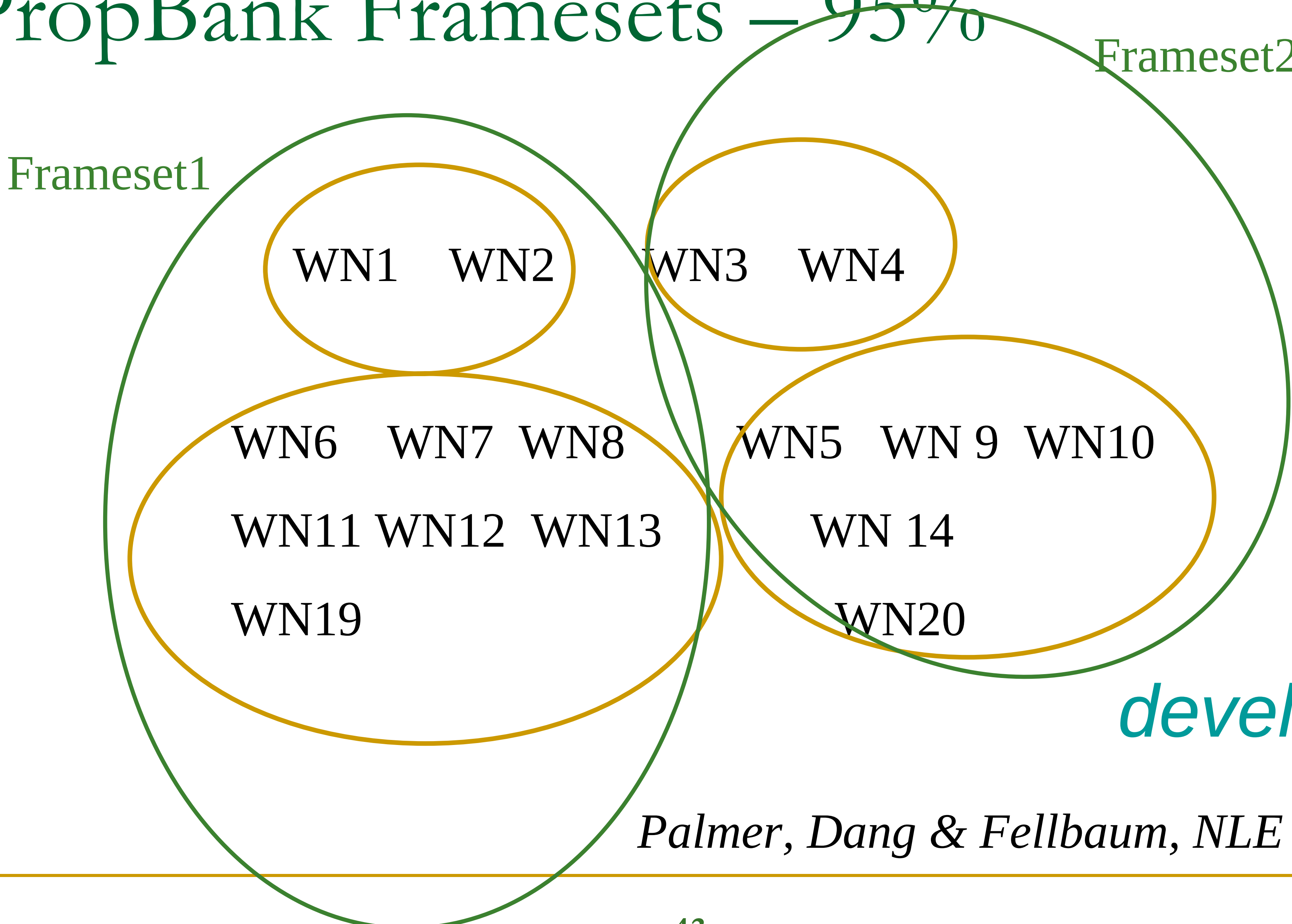
  Let's leave enough time to visit the museum.

  He'll leave the decision to his wife.

  When he died he left the farm to his wife.

  I'm leaving our telephone and address with you.

Overlap between Groups and PropBank Framesets – 95%



develop

Palmer, Dang & Fellbaum, NLE 2007

Sense Hierarchy

(Palmer, et al, SNLU04 - NAACL04, NLE07, Chen, et. al, NAACL06)

- PropBank Framesets – ITA >90%
  coarse grained distinctions
  20 Senseval2 verbs w/ > 1 Frameset
  Maxent WSD system, 73.5% baseline, 90%

  - Sense Groups (Senseval-2) - ITA 82%
    Intermediate level
    (includes Levin classes) – 71.7%

    - WordNet – ITA 73%
      fine grained distinctions, 64%

Tagging w/groups,
ITA 90%, 200@hr,
Taggers - 86.9%
Semeval07

Chen, Dligach & Palmer, ICSC 2007

Broader coverage still needed

- Only 78% of PropBank verbs included in VN
- Most classes focused on verbs with NP and PP complements
- Neglected verbs that take adverbial, adjectival, and sentential complements

MappingPropBank/VerbNet/FrameNet

http://verbs.colorado.edu/~mpalmer/verbnet

- Extended VerbNet 5,391 lexemes
  - (100+ new classes from *(Korhonen and Briscoe, 2004; Korhonen and Ryant, 2005))*
  - now covers 91% of PropBank tokens. *Kipper, et. al., LREC-04, LREC-06, LREJ-08, NAACL09 Tutorial*
- Semi-automatic mapping of PropBank instances to VerbNet classes and thematic roles, hand-corrected. (now FrameNet)
- VerbNet class tagging as automatic WSD
- Run SRL, map Arg2 to VerbNet roles, Brown performance improves

Yi, Loper, Palmer, NAACL07

Can SemLink improve Generalization?

- SRL Performance 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

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, Yi, Loper, Palmer, NAACL07

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

WSJ

BROWN

Summary

- Reviewed available lexical resources
  - WordNet, Groupings, PropBank, VerbNet, FrameNet
- We need a whole that is greater than the sum of the parts – Semlink
- Greater coverage, greater richness, increased training data over more genres, opportunities for generalizations

Need more feedback - and you can give it to us

- On VerbNet classifications
- On FrameNet classifications
- On OntoNotes groupings vs WN vs PB
- On usefulness of the distinctions made by all of the above

Acknowledgments

- We gratefully acknowledge the support of the National Science Foundation Grants for , Consistent Criteria for Word Sense Disambiguation and Robust Semantic Parsing, and DARPA-GALE via a subcontract from BBN.