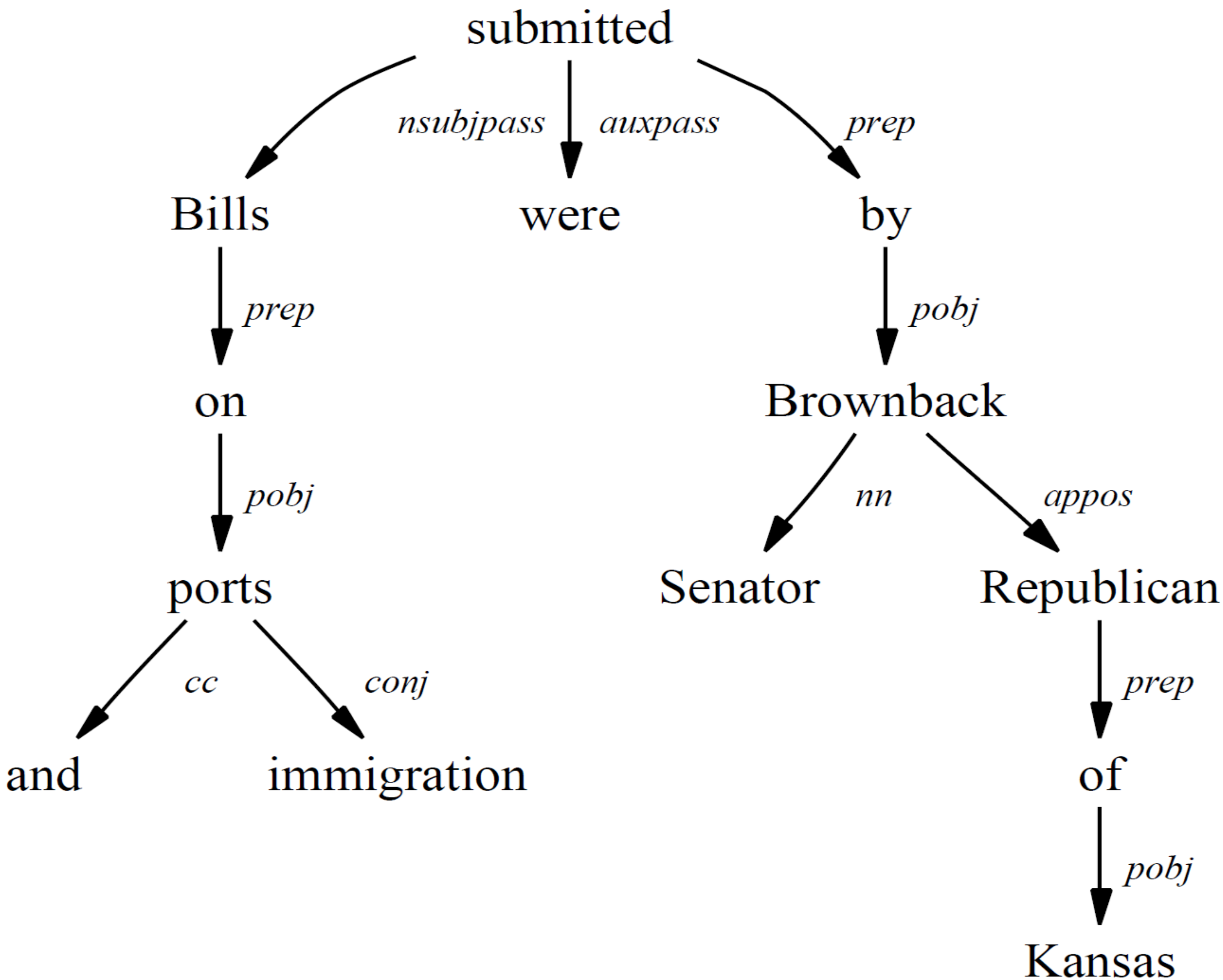
Dependency Parse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and
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of
pobj
Kansas

Dependency Tags

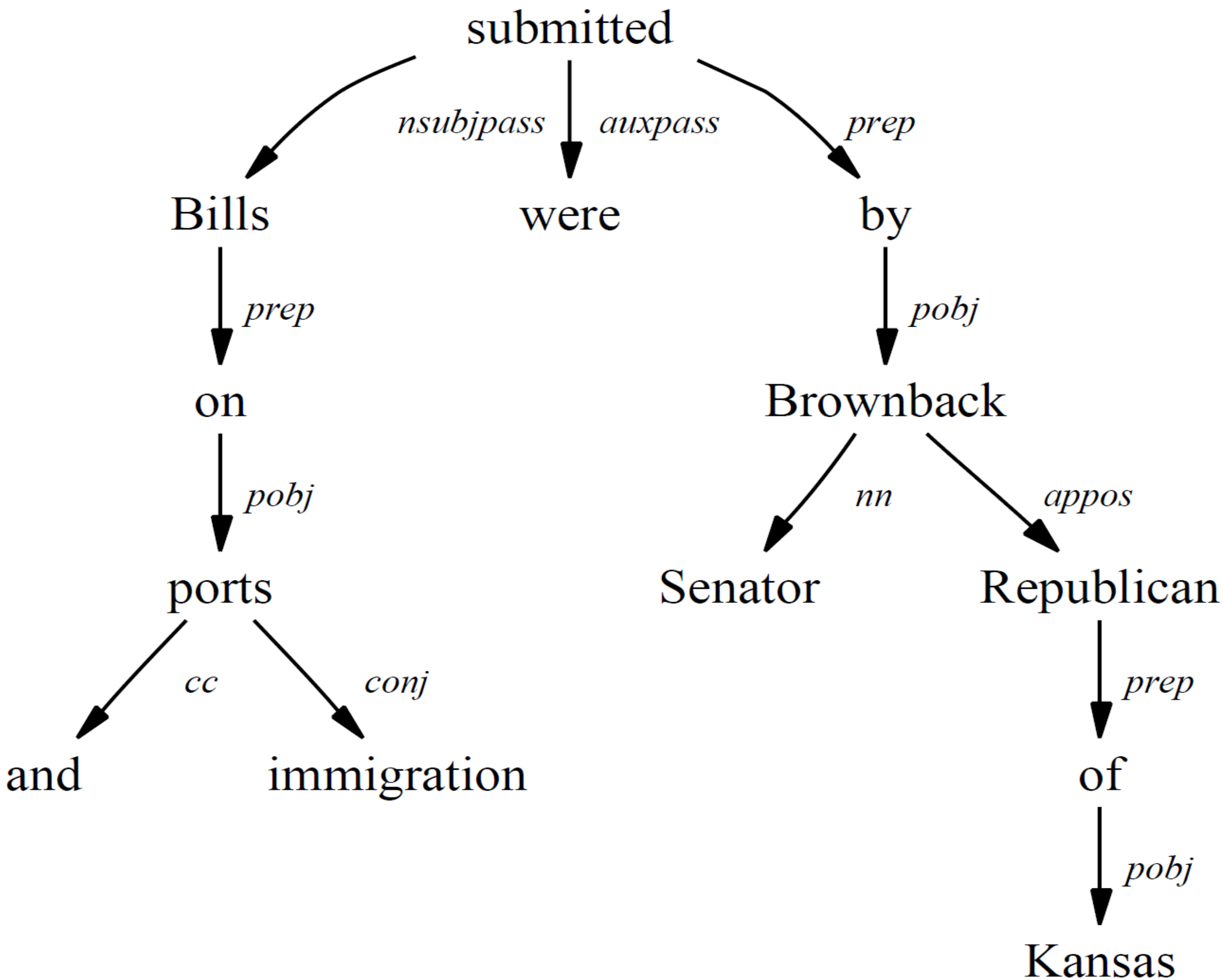
- **aux – auxiliary**
  - **auxpass – passive auxiliary**
  - **cop -- copula**
- **conj – conjunct**
- **cc – coordination**
- ref -- referent
- **subj – subject**
  - **nsubj – nominal subject**
    - **nsubjpass – passive nominal subject**
  - csubj – clausal subject
- **det – determiner**
- **prep – prepositional modifier**

Dependency Tags

- comp – complement
- **mod -- modifier**
- **obj – object**
  - **dobj – direct object**
  - iobj – indirect object
  - **pobj – object of preposition**
- attr – attribute
- ccomp – clausal complement with internal subject
- xcomp – clausal complement with external subject
- acomp – adjectival complement
- compl -- complementizer

Dependency Tags

- **mod – modifier**
- advcl – adverbial clause modifier
- tmod – temporal modifier
- rcmod – relative clause modifier
- **amod – adjectival modifier**
- infmod – infinitival modifier
- partmod – participial modifier
- **appos – appositional modifier**
- **nn – noun compound modifier**
- **poss – possession modifier**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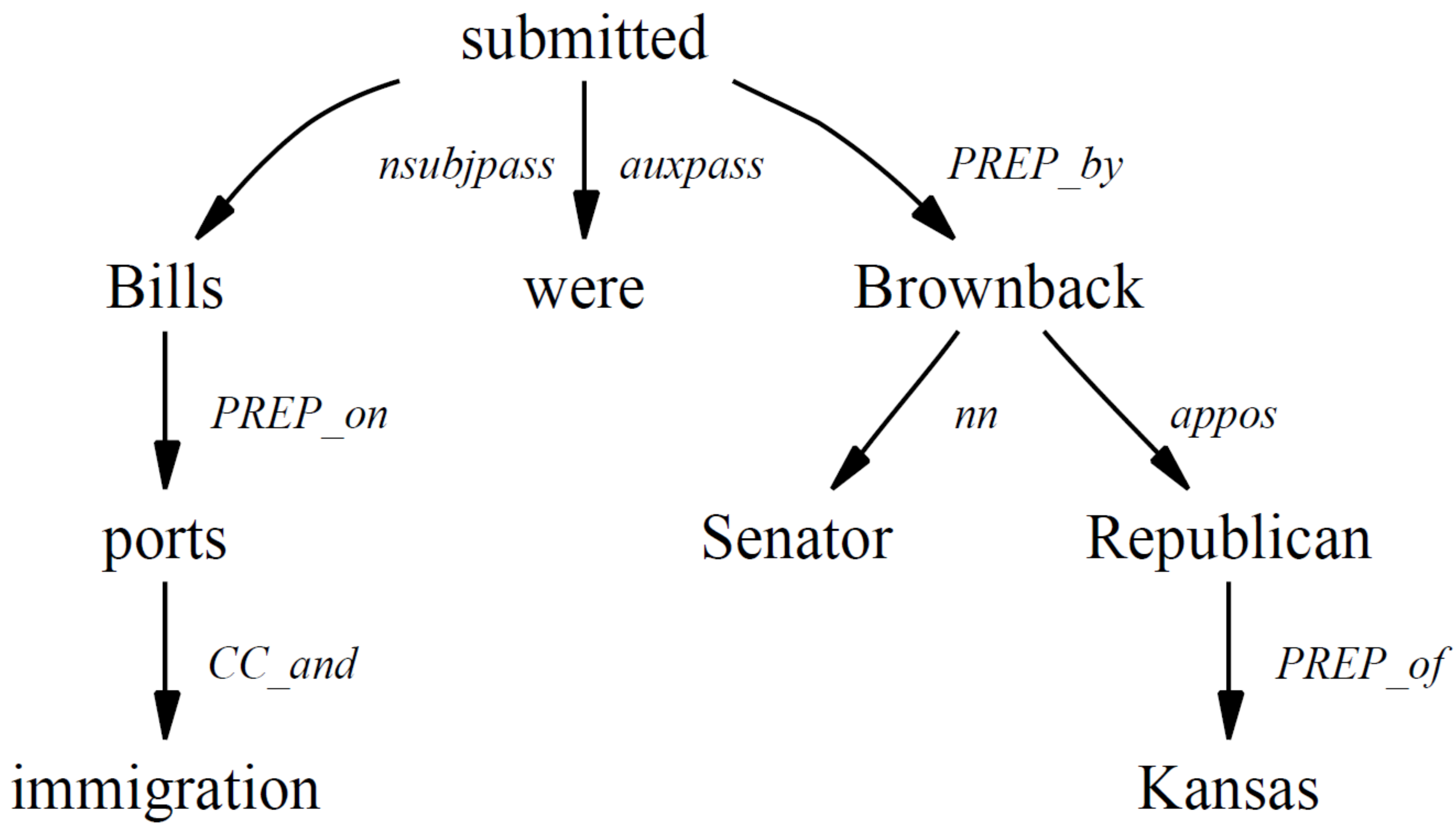
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Kansas

Exercise

- We learned dependency parsers

Exercise

- We learned dependency parsers

- nsubj(learned-2, I-1)
- amod(parsers-4, dependency-3)
- dobj(learned-2, parsers-4)

Exercise

- I am excited about my project.

Exercise

- I am excited about my project.

dependencies:

- nsubj(excited-3, I-1)
- cop(excited-3, am-2)
- prep(excited-3, about-4)
- poss(project-6, my-5)
- pobj(about-4, project-6)

Exercise

- I am excited about my project.

"collapsed" version of dependencies:

- nsubj(excited-3, I-1)
- cop(excited-3, am-2)
- poss(project-6, my-5)
- prep_about(excited-3, project-6)

Exercise

- Our paper is accepted at ACL

Exercise

- Our paper is accepted at ACL

dependencies:

- poss(paper-2, our-1)
- nsubjpass(accepted-4, paper-2)
- auxpass(accepted-4, is-3)
- prep(accepted-4, at-5)
- pobj(at-5, ACL-6)

Exercise

- Our paper is accepted at ACL

“collapsed” version of dependencies:

- poss(paper-2, our-1)
- nsubjpass(accepted-4, paper-2)
- auxpass(accepted-4, is-3)
- prep_at(accepted-4, ACL-6)

Quiz

- My dog ate yellow bananas at home
- My yellow bananas are eaten by my dog
- I am sad about my bananas

Thematic Roles
PropBank, FrameNet, NomBank
Semantic Role Labeling

Thematic Roles - Definitions

Thematic Role	**Definition**
AGENT	The volitional causer of an event
EXPERIENCER	The experiencer of an event
FORCE	The non-volitional causer of the event
THEME	The participant most directly affected by an event
RESULT	The end product of an event
CONTENT	The proposition or content of a propositional event
INSTRUMENT	An instrument used in an event
BENEFICIARY	The beneficiary of an event
SOURCE	The origin of the object of a transfer event
GOAL	The destination of an object of a transfer event

Thematic Roles - Examples

Thematic Role	**Example**
AGENT	*The waiter* spilled the soup.
EXPERIENCER	*John* has a headache.
FORCE	*The wind* blows debris from the mall into our yards.
THEME	Only after Benjamin Franklin broke *the ice*...
RESULT	The French government has built a *regulation-size baseball diamond*...
CONTENT	Mona asked *"You met Mary Ann at a supermarket?"*
INSTRUMENT	He turned to poaching catfish, stunning them *with a shocking device*...
BENEFICIARY	Whenever Ann Callahan makes hotel reservations *for her boss*...
SOURCE	I flew in *from Boston*.
GOAL	I drove *to Portland*.

Quiz

- Theme – the participant directly affected by an event
- Agent – the volitional causer of an event
- Instrument – an instrument (method) used in an event

- John broke the window.
- John broke the window with a rock.
- The rock broke the window.
- The window broke.
- The window was broken by John.

Why Thematic Roles?

- Shallow meaning representation beyond parse trees
- Question Answering System
  - Data: “Company A acquired Company B”
  - Question: Was company B acquired?
  - ➔ Needs reasoning beyond key word matching

Problems with Thematic Roles

- Need to fragment a role like AGENT or THEME into more specific roles
  - The cook opened the jar with the new gadget.
  - Shelly ate the sliced banana with a fork.

Problems with Thematic Roles

- Need to fragment a role like AGENT or THEME into more specific roles

  - The cook opened the jar with the new gadget.
  - The new gadget opened the jar.

  - Shelly ate the sliced banana with a fork.
  - The fork ate the sliced banana.

Problems with Thematic Roles

- Need to fragment a role like AGENT or THEME into more specific roles
- For instance, there are two kinds of INSTRUMENTS
  - <u>intermediary instruments</u> can appear as subjects
  - <u>enabling instruments</u> cannot appear as subjects

  - The cook opened the jar with the new gadget.
  - The new gadget opened the jar.
  - Shelly ate the sliced banana with a fork.
  - The fork ate the sliced banana.

Important resources (annotated data) for thematic roles

- Centered around Verbs
  1. Proposition Bank (PropBank)
  2. FrameNet

- Centered around nouns:
  1. NomBank

Proposition Bank (PropBank)

PropBank (Proposition Bank)

- PropBank labels all sentences in the Penn TreeBank.
- Due to the difficulty of defining a universal set of thematic roles, the roles in PropBank are defined w.r.t. each verb sense.
- Numbered roles, rather than named roles
  - e.g. **Arg0, Arg1, Arg2, Arg3**, and so on

PropBank argument numbering

Although numbering differs per **verb sense**, the general pattern of numbering is as follows:

- Arg0 = "Proto-Agent" (agent)
- Arg1 = "Proto-Patient" (direct object / theme / patient)
- Arg2 = indirect object (benefactive / instrument / attribute / end state)
- Arg3 = start point (benefactive / instrument / attribute)
- Arg4 = end point

Different “frameset” for each verb sense

- *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

This page is from Martha Palmer’s.

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.

This page is from Martha Palmer's.

PropBank Framesets

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

This page is from Martha Palmer's.

FrameNet

Grouping “framesets” into “Frame”

Similarity across different framesets:

- [The price of bananas]-arg1 increased [5%]-arg2.
- [The price of bananas]-arg1 rose [5%]-arg2.
- There has been a [5%]-arg2 rise [in the price of bananas]-arg1.

Roles in the PropBank are specific to a verb sense.

Roles in the FrameNet are specific to a frame.

This page is from Martha Palmer’s.

Grouping "framesets" into "Frame"

- Framesets are not necessarily consistent between different senses of the same verb
- Framesets are consistent between different verbs that share similar argument structures
- Out of the 787 most frequent verbs:
  - 1 FrameNet – 521
  - 2 FrameNet – 169
  - 3+ FrameNet - 97

This page is from Martha Palmer's.

Words in “**change_position_on _a_scale**” frame:

VERBS:	dwindle	move	soar	escalation	shift
advance	edge	mushroom	swell	explosion	tumble
climb	explode	plummet	swing	fall	
decline	fall	reach	triple	fluctuation	**ADVERBS:**
decrease	fluctuate	rise	tumble	gain	increasingly
diminish	gain	rocket		growth	
dip	grow	shift	**NOUNS:**	hike	
double	increase	skyrocket	decline	increase	
drop	jump	slide	decrease	rise	

Roles in "**change_position_on _a_scale**" frame:

Core Roles	
ATTRIBUTE	The ATTRIBUTE is a scalar property that the ITEM possesses.
DIFFERENCE	The distance by which an ITEM changes its position on the scale.
FINAL_STATE	A description that presents the ITEM's state after the change in the ATTRIBUTE's value as an independent predication.
FINAL_VALUE	The position on the scale where the ITEM ends up.
INITIAL_STATE	A description that presents the ITEM's state before the change in the ATTRIBUTE's value as an independent predication.
INITIAL_VALUE	The initial position on the scale from which the ITEM moves away.
ITEM	The entity that has a position on the scale.
VALUE_RANGE	A portion of the scale, typically identified by its end points, along which the values of the ATTRIBUTE fluctuate.
Some Non-Core Roles	
DURATION	The length of time over which the change takes place.
SPEED	The rate of change of the VALUE.
GROUP	The GROUP in which an ITEM changes the value of an ATTRIBUTE in a specified way.

Exercise

ATTRIBUTE
DIFFERENCE
FINAL_STATE
FINAL_VALUE
INITIAL_STATE
INITIAL_VALUE
ITEM
VALUE_RANGE
DURATION
SPEED
GROUP

- [Oil] rose [in price] [by 2%].
- [It] has increased [to having them 1 day a month].
- [Microsoft shares] fell [to 7 5/8].
- [cancer incidence] fell [by 50%] [among men].
- a steady increase [from 9.5] [to 14.3] [in dividends].
- a [5%] [dividend] increase…

Exercise

ATTRIBUTE
DIFFERENCE
FINAL_STATE
FINAL_VALUE
INITIAL_STATE
INITIAL_VALUE
ITEM
VALUE_RANGE
DURATION
SPEED
GROUP

- [Oil] rose [in price]-att [by 2%]-diff.
- [It] has increased [to having them 1 day a month]-f-s.
- [Microsoft shares] fell [to 7 5/8]-f-v.
- [cancer incidence] fell [by 50%]-diff [among men]-group.
- a steady increase [from 9.5] –i-v [to 14.3]-f-v [in dividends].
- a [5%]-diff [dividend] increase…

Semantic Role Labeling

(Following slides are modified from Prof. Ray Mooney's slides.)

Semantic Role Labeling (SRL)

- For each clause, determine the semantic role played by each noun phrase that is an argument to the verb.

  agent patient source destination instrument

  - John drove Mary from Austin to Dallas in his Toyota Prius.
  - The hammer broke the window.

- Also referred to a “case role analysis,” “thematic analysis,” and “shallow semantic parsing”

Semantic Roles

- Origins in the linguistic notion of “case” (Fillmore, 1968)
- A variety of semantic role labels have been proposed, common ones are:
  - Agent: Actor of an action
  - Patient: Entity affected by the action
  - Instrument: Tool used in performing action.
  - Beneficiary: Entity for whom action is performed
  - Source: Origin of the affected entity
  - Destination: Destination of the affected entity

Use of Semantic Roles

- Semantic roles are useful for various tasks.
- Question Answering
  - “Who” questions usually use Agents
  - “What” question usually use Patients
  - “How” and “with what” questions usually use Instruments
  - “Where” questions frequently use Sources and Destinations.
  - “For whom” questions usually use Beneficiaries
  - “To whom” questions usually use Destinations
- Machine Translation Generation
  - Semantic roles are usually expressed using particular, distinct syntactic constructions in different languages.

SRL and Syntactic Cues

- Frequently semantic role is indicated by a particular syntactic position (e.g. object of a particular preposition).
  - Agent: subject
  - Patient: direct object
  - Instrument: object of “with” PP
  - Beneficiary: object of “for” PP
  - Source: object of “from” PP
  - Destination: object of “to” PP
- However, these are preferences at best:
  - The hammer hit the window.
  - The book was given to Mary by John.
  - John went to the movie with Mary.
  - John bought the car for $21K.
  - John went to work by bus.

Selectional Restrictions

- Selectional restrictions are constraints that certain verbs place on the filler of certain semantic roles.
  - Agents should be animate
  - Beneficiaries should be animate
  - Instruments should be tools
  - Patients of "eat" should be edible
  - Sources and Destinations of "go" should be places.
  - Sources and Destinations of "give" should be animate.
- Taxanomic abstraction hierarchies or ontologies (e.g. hypernym links in WordNet) can be used to determine if such constraints are met.
  - "John" is a "Human" which is a "Mammal" which is a "Vertebrate" which is an "Animate"

Use of Sectional Restrictions

- Selectional restrictions can help rule in or out certain semantic role assignments.
  - “John bought the car for $21K”
    - Beneficiaries should be Animate
    - Instrument of a “buy” should be Money
  - “John went to the movie with Mary”
    - Instrument should be Inanimate
  - “John drove Mary to school in the van”
    “John drove the van to work with Mary.”
    - Instrument of a “drive” should be a Vehicle

Selectional Restrictions and Syntactic Ambiguity

- Many syntactic ambiguities like PP attachment can be resolved using selectional restrictions.
  - "John ate the spaghetti with meatballs."
    "John ate the spaghetti with chopsticks."
    - Instruments should be tools
    - Patients of "eat" must be edible
  - "John hit the man with a dog."
    "John hit the man with a hammer."
    - Instruments should be tool

Selectional Restrictions and WSD

- Many lexical ambiguities can be resolved using selectional restrictions.
- Ambiguous nouns
  - "John wrote it with a pen."
    - Instruments of "write" should be tools for writing
  - "The bat ate the bug."
    - Agents (particularly of "eat") should be animate
    - Patients of "eat" should be edible
- Ambiguous verbs
  - "John fired the secretary."
    "John fired the rifle."
    - Patients of DischargeWeapon should be Weapons
    - Patients of CeaseEmploment should be Human

Empirical Methods for SRL

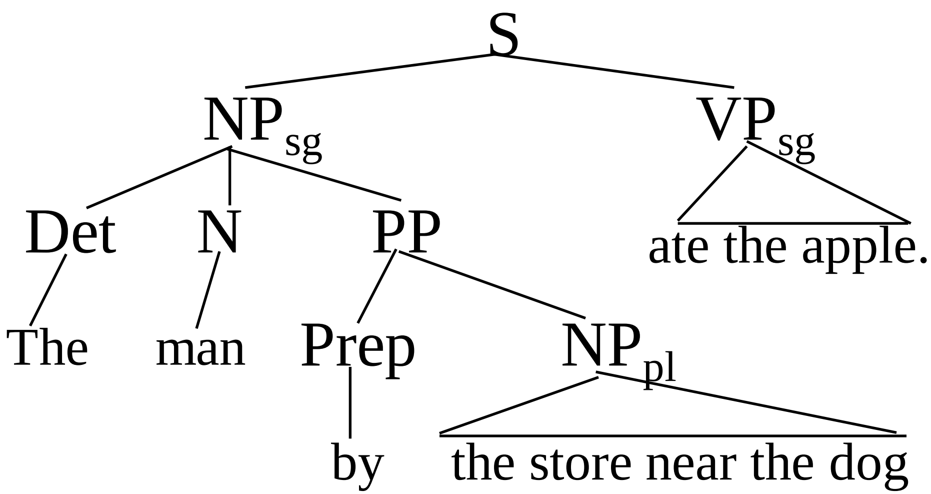
- Difficult to acquire all of the selectional restrictions and taxonomic knowledge needed for SRL.
- Difficult to efficiently and effectively apply knowledge in an integrated fashion to simultaneously determine correct parse trees, word senses, and semantic roles.
- Statistical/empirical methods can be used to automatically acquire and apply the knowledge needed for effective and efficient SRL.

SRL as Sequence Labeling

- SRL can be treated as an sequence labeling problem.
- For each verb, try to extract a value for each of the possible semantic roles for that verb.
- Employ any of the standard sequence labeling methods
  - Token classification
  - HMMs
  - CRFs

SRL with Parse Trees

- Parse trees help identify semantic roles through exploiting syntactic clues like "the agent is usually the subject of the verb".
- Parse tree is needed to identify the true subject.



"The man by the store near the dog ate an apple."

"The man" is the agent of "ate" not "the dog".

SRL with Parse Trees

- Assume that a syntactic parse is available.
- For each predicate (verb), label each node in the parse tree as either not-a-role or one of the possible semantic roles.

Color Code:

not-a-role

agent

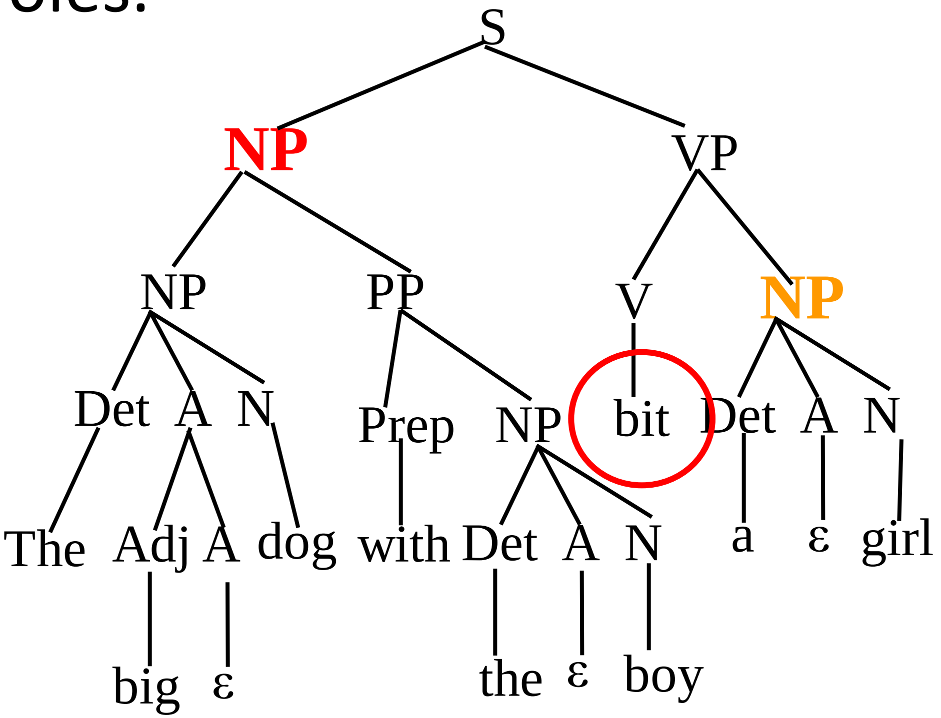
patient

source

destination

instrument

beneficiary



SRL as Parse Node Classification

- Treat problem as classifying parse-tree nodes.
- Can use any machine-learning classification method.
- Critical issue is engineering the right set of features for the classifier to use.

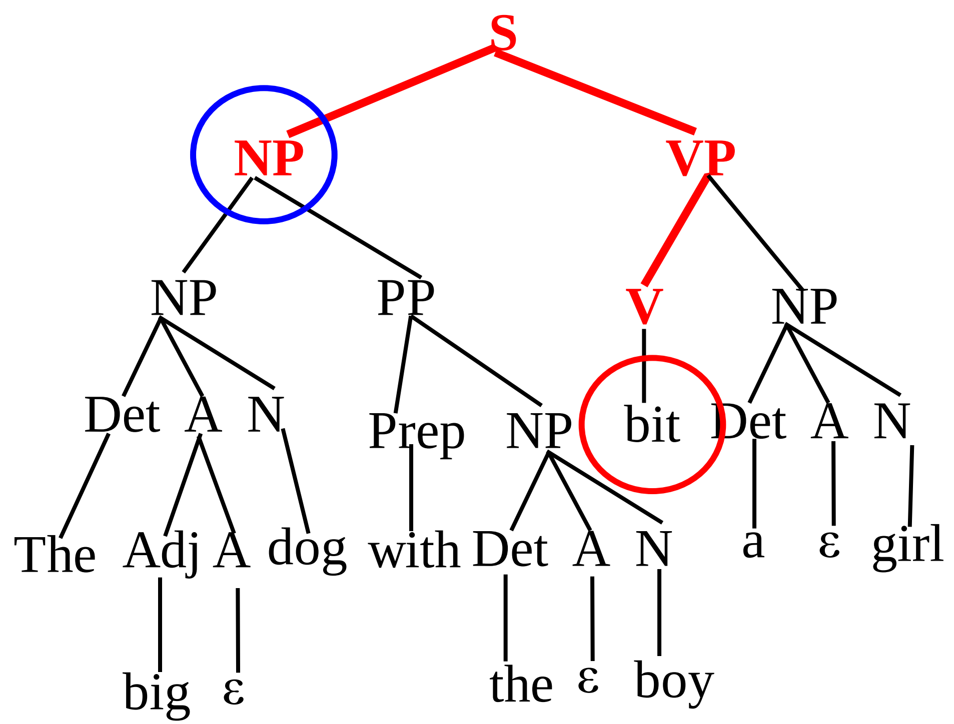
Features for SRL

- **Phrase type**: The syntactic label of the candidate role filler (e.g. NP).
- **Parse tree path**: The path in the parse tree between the predicate and the candidate role filler.

Parse Tree Path Feature: Example 1

Path Feature Value:

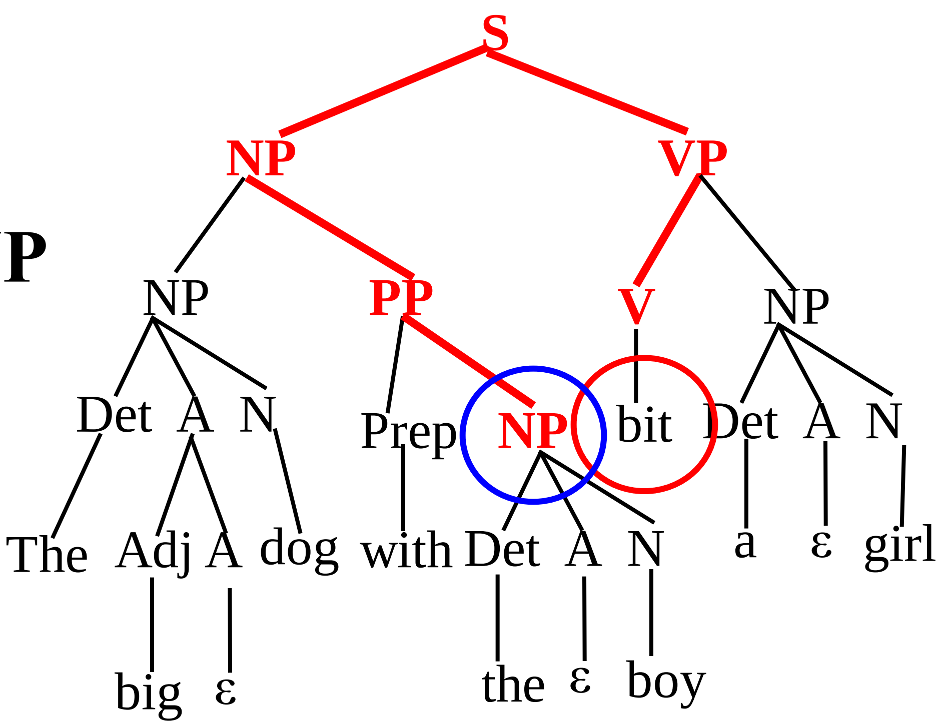
V ↑ VP ↑ S ↓ NP



Parse Tree Path Feature: Example 2

Path Feature Value:

V ↑ VP ↑ S ↓ NP ↓ PP ↓ NP



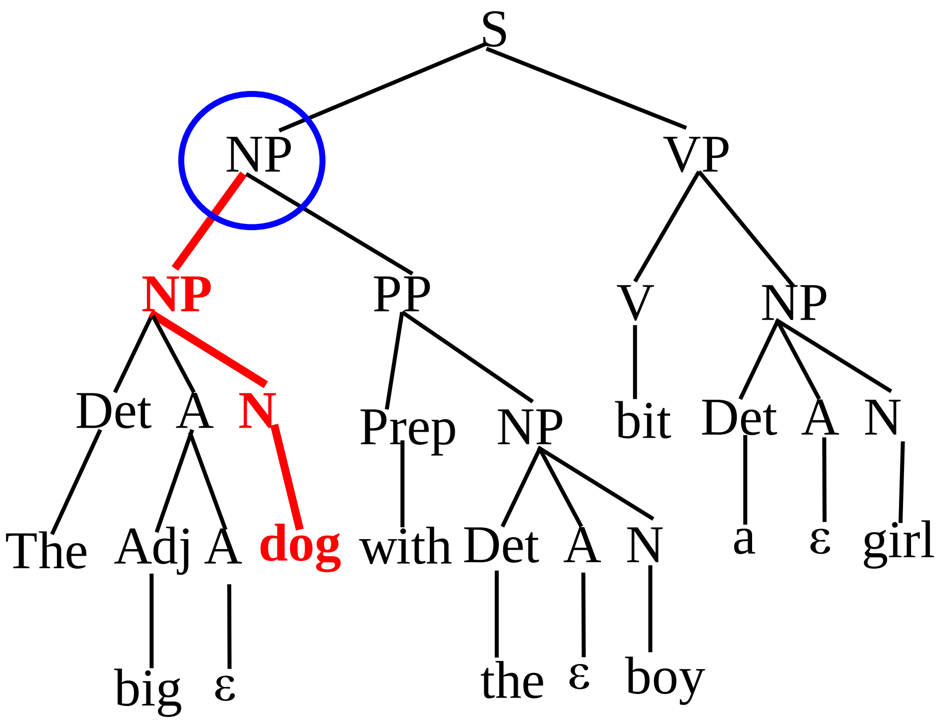
Features for SRL

- **Phrase type**: The syntactic label of the candidate role filler (e.g. NP).
- **Parse tree path**: The path in the parse tree between the predicate and the candidate role filler.
- **Position**: Does candidate role filler ***precede*** or ***follow*** the predicate in the sentence?
- **Voice**: Is the predicate an ***active*** or ***passive*** verb?
- **Head Word**: What is the head word of the candidate role filler?

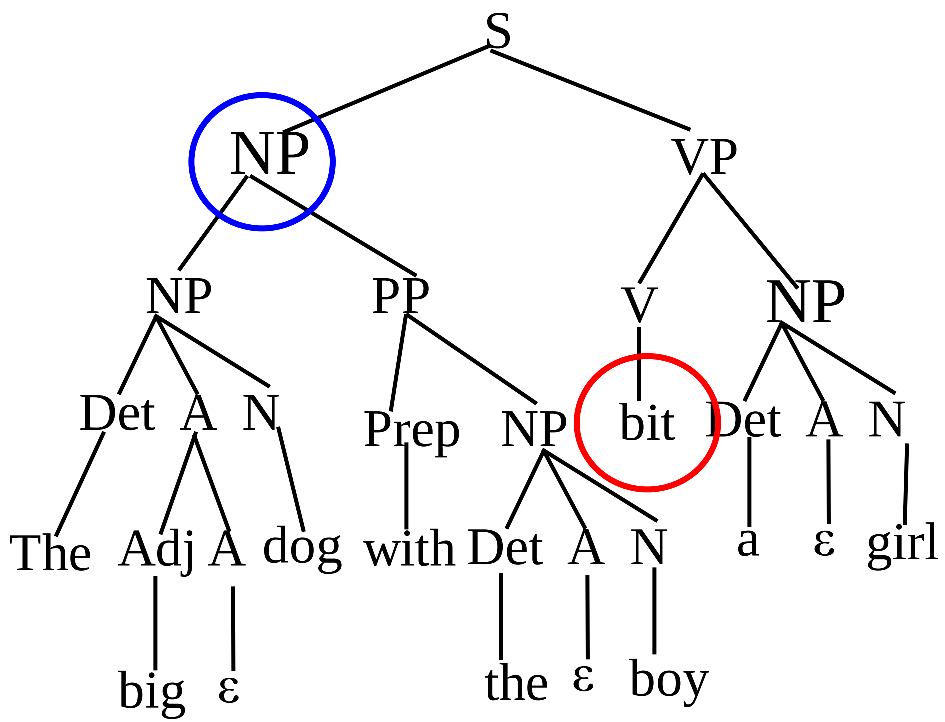
Head Word Feature Example

- There are standard syntactic rules for determining which word in a phrase is the **head**.

Head Word:
dog



Complete SRL Example



Phrase type	**Parse Path**	**Position**	**Voice**	**Head word**
NP	**V↑VP↑S↓NP**	precede	active	dog

Issues in Parse Node Classification

- Many other useful features have been proposed.
  - If the parse-tree path goes through a PP, what is the preposition?
- Results may violate constraints like "an action has at most one agent"?
  - Use some method to enforce constraints when making final decisions. i.e. determine the most likely assignment of roles that also satisfies a set of known constraints.
- Due to errors in syntactic parsing, the parse tree is likely to be incorrect.
  - Try multiple top-ranked parse trees and somehow combine results.
  - Integrate syntactic parsing and SRL.

More Issues in Parse Node Classification

- Break labeling into two steps:
  - First decide if node is an argument or not.
  - If it is an argument, determine the type.

SRL Datasets

- FrameNet:
  - Developed at Univ. of California at Berkeley
  - Based on notion of Frames
- PropBank:
  - Developed at Univ. of Pennsylvania
  - Based on elaborating their Treebank
- Salsa:
  - Developed at Universität des Saarlandes
  - German version of FrameNet

FrameNet

- Project at UC Berkeley led by Chuck Fillmore for developing a database of frames, general semantic concepts with an associated set of roles.
- Roles are specific to frames, which are "invoked" by multiple words, both verbs and nouns.
  - JUDGEMENT frame
    - Invoked by: V: blame, praise, admire; N: fault, admiration
    - Roles: JUDGE, EVALUEE, and REASON
- Specific frames chosen, and then sentences that employed these frames selected from the British National Corpus and annotated by linguists for semantic roles.
- Initial version: 67 frames, 1,462 target words,
  49,013 sentences, 99,232 role fillers

FrameNet Results

- Gildea and Jurafsky (2002) performed SRL experiments with initial FrameNet data.
- Assumed correct frames were identified and the task was to fill their roles.
- Automatically produced syntactic analyses using Collins (1997) statistical parser.
- Used simple Bayesian method with smoothing to classify parse nodes.
- Achieved 80.4% correct role assignment. Increased to 82.1% when frame-specific roles were collapsed to 16 general thematic categories.

PropBank

- Project at U Penn lead by Martha Palmer to add semantic roles to the Penn treebank.
- Roles (Arg0 to ArgN) specific to each individual verb to avoid having to agree on a universal set.
  - Arg0 basically "agent"
  - Arg1 basically "patient"
- Annotated over 1M words of Wall Street Journal text with existing gold-standard parse trees.
- Statistics:
  - 43,594 sentences 99,265 propositions (verbs + roles)
  - 3,324 unique verbs 262,281 role assignments

CONNL SRL Shared Task

- CONLL (Conference on Computational Natural Language Learning) is the annual meeting for the SIGNLL (Special Interest Group on Natural Language Learning) of ACL.
- Each year, CONLL has a "Shared Task" competition.
- PropBank semantic role labeling was used as the Shared Task for CONLL-04 and CONLL-05.
- In CONLL-05, 19 teams participated.

CONLL-05 Learning Approaches

- Maximum entropy (8 teams)
- SVM (7 teams)
- SNoW (1 team) (ensemble of enhanced Perceptrons)
- Decision Trees (1 team)
- AdaBoost (2 teams) (ensemble of decision trees)
- Nearest neighbor (2 teams)
- Tree CRF (1 team)
- Combination of approaches (2 teams)

CONLL Experimental Method

- Trained on 39,832 WSJ sentences
- Tested on 2,416 WSJ sentences
- Also tested on 426 Brown corpus sentences to test generalizing beyond financial news.
- Metrics:
  - **Precision**: (# roles correctly assigned) / (# roles assigned)
  - **Recall**: (# roles correctly assigned) / (total # of roles)
  - **F-measure**: harmonic mean of precision and recall

Best Result from CONLL-05

- Univ. of Illinois system based on SNoW with global constraints enforced using Integer Linear Programming.

WSJ Test			**Brown Test**		
P(%)	**R(%)**	**F(%)**	**P(%)**	**R(%)**	**F(%)**
82.28	76.78	79.44	73.38	62.93	67.75

Issues in SRL

- How to properly integrate syntactic parsing, WSD, and role assignment so they all aid each other.
- How can SRL be used to aid end-use applications:
  - Question answering
  - Machine Translation
  - Text Mining