6.863J Natural Language Processing Lecture 16: the boundaries of syntax & semantics – towards constraint-based systems

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#### The Menu Bar

- Administrivia:
- Lab 4 due April 9? (what about Friday)
  - Start w/ final projects, unless there are objections
- Agenda:
  - Shallow instead of 'deep' semantics: MUC
  - Stochastic language use? Some examples
  - How to accommodate: towards constraintbased grammar

# How to integrate all this stuff?

- We saw that we might want to partition syntactic knowledge from semantic...
- But we have to go farther because both of these might be probabilistic in nature
- How to integrate?

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### Integration

- One way: semantic grammar (see below)
- The way we'll explore though:
  - Define linguistic structure
  - Place pr distributions on that structure

## Example

- Syntactic rule = NP → Det N
- Semantic extension = NP:

Apply(lambda (x) (DEF/SING x), N)

- Lexicon:
  - Art:the: DEF/SINGN:guy: Person
- Parse of the NP the guy:
  - NP → Det N ⇒ OK, NP contains article & noun
  - Apply (lambda (x) (DEF/SING x), N) ⇒ OK, NP contains DEF/SING article
  - Apply (lambda (x) (DEF/SING x), Person)  $\Rightarrow$  the N in the NP is Person
  - (DEF/SING Person) ⇒ result of applying lambda calculus ⇒ textual replacement of variable x with argument Person

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Another Example

Syntax:

 $S \rightarrow NP VP$  $VP \rightarrow V NP$ 

NP → Det N

Semantics:

S: Apply(VP, NP) VP: Apply(V, NP)

NP → ART N

NP : Apply(lambda (x) (DFF/SING x), N)

<u>Lexicon</u>:

V:kissed = lambda(o) lambda(x) (kiss past

[agent x] [theme o]) N:guy = person

N:dog = DOG

Det:the = DEF/SING

Top-down parse sentence:

 $S \rightarrow NP VP$  Apply(VP, NP)

 $VP \rightarrow V NP$  Apply(Apply(V, NP), NP)

Lexicon look-up Apply(Apply(lambda(o) lambda(x) (kiss past [agent x] [theme o]), NP), NP)

Apply(Apply(lambda(o) lambda(x) (kiss past [agent x] [theme o]),

Apply(lambda (x) DEF/SING x), N)), NP)

Lexicon look-up Apply(Apply(lambda(o) lambda(x) (kiss past [agent x] [theme o]),

Apply(lambda (x) (DEF/SING x), DOG)), NP)

Apply -operator Apply(Apply(lambda(o) lambda(x) (kiss past [agent x] [theme o]), (DEF/SING DOG),

NP)

Apply -operator Apply(lambda(x) (kiss past [agent x] [theme DEF/SING DOG]), NP)
 NP → ART N Apply(lambda(x) (kiss past [agent x] [theme DEF/SING DOG]), Apply(lambda(x) (kiss past [agent x] [theme DEF/SING DOG]).

Apply(lambda(x) (kiss past [agent x] [theme DEF/SING DOG]), Apply(lambda(x) (DEF/SING \* x), N))

Lexicon look-up Apply(lambda(x) (kiss past [agent x] [theme DEF/SING DOG]), Apply(lambda(x) (DEF/SING \* x), Person))

Apply -operator Apply(lambda(x) (kiss past [agent x] [theme DEF/SING DOG]), (DEF/SING Person))

Apply -operator (kiss past [agent DEF/SING Person] [theme DEF/SING DOG])

#### Semantic Grammar: Definition

- · Syntactic and semantic processing is collapsed in a single framework
- Like a regular grammar but terminal symbols are replaced by semantic categories
- Example:
  - [VP read [NP a book]] or [write [a book]]

VP V NP

READ-VP → READ-VERB READ-STUFF WRITE-VP → WRITE-VERB WRITE-STUFF

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#### Example of a Grammar

- RES-VP  $\rightarrow$  RESERVING RES-MOD
- RES-VP → RESERVING
- DEP-VP → DEPARTING DEP-MODS
- RESERVING → RESERVE-VERB FLIGHT
- RES-MOD → for PERSON
- DEPARTING → DFPART-VFRB
- DEPARTING → DEPART-VERB SOURCE-LOCATION
- DEP-MODS→ DEP-MOD DEP-MODS
- DEP-MODS→ DEP-MOD
- DEP-MOD → to DEST-LOCATION
- DEP-MOD → from SOURCE-LOCATION

#### Exercise

#### • Grammar:

RES-VP → RESERVING
RES-VP → RESERVING RES-MOD
RESERVING → RESERVE-VERB
FLIGHT-NP
RES-MOD → for PERSON
FLIGHT-NP → ART FLIGHT-NOUN
FLIGHT-NP → ART FLIGHT-NOUN
FLIGHT-MODS
FLIGHT-MODS
FLIGHT-MODS
FLIGHT-MODS
FLIGHT-MODS → FLIGHT-MOD
FLIGHT-MOD → from SOURCELOCATION
FLIGHT-MOD → to DEST-LOCATION

#### Lexicon:

FLIGHT-NOUN:flight ART:a PERSON:me LOCATION:Boston LOCATION:Chicago RESERVE-VERB: book

Parse this sentence (bottom-up):

Book a flight from Boston to Chicago for me

## Solution (1)

- FLIGHT-MOD → from SOURCE-LOCATION
   Book a flight [FLIGHT-MOD from SOURCE-LOCATION Boston] to
   Chicago for me
- FLIGHT-MOD → to DEST-LOCATION
   Book a flight [FLIGHT-MOD from SOURCE-LOCATION Boston]
   [FLIGHT-MOD to DEST-LOCATION Chicago] for me
- FLIGHT-MODS → FLIGHT-MOD
   Book a flight [FLIGHT-MOD from SOURCE-LOCATION Boston]
   [FLIGHT-MODS [FLIGHT-MOD to DEST-LOCATION Chicago]] for me
- FLIGHT-MODS → FLIGHT-MOD FLIGHT-MODS
   Book a flight [FLIGHT-MODS [FLIGHT-MOD from SOURCE-LOCATION Boston] [FLIGHT-MODS [FLIGHT-MOD to DEST-LOCATION Chicago]]] for me

# Solution (2)

- FLIGHT-NP → ART FLIGHT-NOUN FLIGHT-MODS
   Book [FLIGHT-NP ART a FLIGHT-NOUN flight [FLIGHT-MODS [FLIGHT-MOD from SOURCE-LOCATION Boston] [FLIGHT-MODS [FLIGHT-MOD to DEST-LOCATION Chicago]]]] for me
- RESERVING → RESERVE-VERB FLIGHT-NP [RESERVING RESERVE-VERB Book [FLIGHT-NP ART a FLIGHT-NOUN flight [FLIGHT-MODS [FLIGHT-MODD from SOURCE-LOCATION Boston] [FLIGHT-MODS [FLIGHT-MOD to DEST-LOCATION Chicago]]]]] for me
- RES-MOD → for PERSON [RESERVING RESERVE-VERB Book [FLIGHT-NP ART a FLIGHT-NOUN flight [FLIGHT-MODS [FLIGHT-MOD from SOURCE-LOCATION Boston] [FLIGHT-MODS [FLIGHT-MOD to DEST-LOCATION Chicago]]]]] [RES-MOD for PERSON me]
- RES-VP → RESERVING RES-MOD
   [RES-VP [RESERVING RESERVE-VERB Book [FLIGHT-NP ART a FLIGHT-NOUN flight
   [FLIGHT-MODS [FLIGHT-MOD from SOURCE-LOCATION Boston] [FLIGHT-MODS
   [FLIGHT-MOD to DEST-LOCATION Chicago]]]]] [RES-MOD for PERSON me]]

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#### Useful?

- Semantic grammars are useful in a limited domain
  - Dialogue system to book flights through the telephone
- For general use → too many rules!

### **Application Continuum**

- Machine Translation
- Unrestricted language comprehension
- Summarization
- Information extraction
  - Find specific information: location, names of terrorists, ...
- Text classification
  - What is the text about (topic detection)?
- Information retrieval

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#### Information Extraction

- Analyzing unrestricted, unstructured text
- Extracting specific structured information
- Enabling technology
  - Converting text to a database (data mining)
  - Summarization

# Example from the terrorism domain

#### Input:

San Salvador, 19 Apr 89. Salvadoran President -elect Alfredo Cristiani condemned the terrorist killing of Attorney general Roberto Garcia Alvarado and accused the Farabundo Marti National Liberation Front (FMLN) of the crime. (...)

Garcia Alvarado, 56, was killed when a bomb placed by urban guerrillas on his vehicle exploded as it came to a halt at an intersection in downtown San Salvador.

Vice President -elect Francisco Merino said that when the attorney-general's car stopped at a light on a street in downtown San Salvador, an individual placed a bomb on the roof of the armored vehicle. (...)

According to the police and Garcia Alvarado's driver, who escaped unscathed, the attorney general was traveling with two bodyguards. One of them was injured.

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# Example from the terrorism domain

#### Output template:

Incident: Date 19 APR 89

Incident: Location El Salvador: San Salvador

Incident: Type Bombing

Perpetrator: Individual ID urban guerrillas

Perpetrator: Organization ID FMLN

Perpetrator: Organization conf suspected or accused

Physical target: description vehicle Physical target: effect some damage

Human target: name Roberto Garcia Alvarado Human target: description attorney general

Alvarado, driver, bodyguards

Human target: effect death: alvarado, no injury:

driver, injury: bodyguards

### **Example System: FASTUS**

- Finite-State Automaton Text Understanding System (SRI International)
- Cascaded non-deterministic finite-state automaton:
  - · from linguistic to domain-dependent
  - from simple (word level) to complex (phrase level)
- Cascade = series of FS systems
  - Tokenization → Complex Words → Basic Phrases →
     Complex Phrases → Semantic Patterns → Merging
- MUC (Message Understanding Conference)
- Evaluation → recall and precision, F<sub>β</sub>

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#### Evaluation

- Precision = # correct answers# total answers
- Recall = # correct answers
   # possible correct answers

• 
$$F_{\beta} = \frac{((\beta^2 + 1) \times P \times R)}{(\beta^2 \times P \times R)}$$

#### Architecture – Steps 1 to 3

- Tokenization → split words and punctuation
  - He is mr. Jones! → He is mr. Jones!
- Named-entity recognition & multi-word phrases
  - Multi-word phrases: set up, joint venture
  - Named entities: Secretary General Annan, Prof. Dr. L. Steels
- Find basic phrases:
  - · Nominal and verbal phrases
  - · Prepositions
  - Particles

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#### After step 3 ...

Bridgestone Sports Co. [company name] said [VG] Friday [NG] it [NG] had set up [VG] a joint venture [NG] in [Prep]
 Taiwan [location NG] with [Prep] a local concern [NG] and [Conj] a Japanese trading house [NG] to produce [VG] golf clubs [NG] to be shipped [VG] to [Prep] Japan [location NG]

### Architecture – Step 4

- Construction of complex nominal and verbal groups
  - · Apposition
    - the secretary general Koffi Annan
  - PP-attachment
    - · production of spice girl dolls
  - Domain entities

 Relationship: tie-up; jv-company: Bridgestone

• Activity: production; product: spice girl

dolls

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#### Architecture - Step 5 & 6

- Recognition and construction of event structures:
  - <companies> <set-up> <joint-venture> with <companies>
  - <produce> <product>
  - <company> <capitalized> at <currency>
  - <company> <start> <activity> in/on <date>
- Fusion of event structures referring to the same event = (co-)reference resolution

#### **FASTUS – Evaluation**

- MUC-4:
  - 44% recall and 55% precision
- Human-level competence: 65-80% reliability
- Speed:
  - 2500 words per minute
  - · 10 seconds per text
  - 9000 texts per day
- Simple, accurate, 2 x fast → fast in runtime & fast in development time
- · Japanese version:
  - 34% recall
  - · 56% precision

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# How to integrate in general Language & statistics

- "All grammars leak" Sapir, 1921
- Is this true? What do we do?
- An example subcategorization & thematic roles

#### A leak

 "By the time their son was born, though, Honus Whiting was beginning to understand and privately share his wife's opinion, at least as it pertained to Empire Falls"

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# Subcategorization: what we have been doing

- Eat vs. devour:
   John ate the meal/John ate
   Bill devoured the meal/Bill devoured
- Verb selects category of its complements
   at least the syntactic category

# Subcategorization?

- Example:
  - consider: \_\_ NP[acc] {AdjP, NP, VP[inf]}
  - regard: \_\_ NP[acc] as {NP, AdjP}
  - think: \_\_ CP[that], \_\_ NP[acc] NP

There are standard examples for these – cf. Lab 3.

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# Example – consider w/ no 'as'

- John considers vanilla to be an acceptable flavor
- John considers vanilla an acceptable flavor
- John considers vanilla quite an acceptable flavor
- John considers vanilla among the most acceptable flavors

#### But what about these?

- John considers vanilla as an acceptable flavor
- John considers vanilla as quite acceptable
- John considers vanilla as among the most acceptable flavors
- John considers vanilla as being among the most acceptable flavors

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# Compare "regard"

- John regards vanilla as an acceptable flavor
- John regards vanilla to be an acceptable flavor
- (supposed to be the opposite of "consider"!)

#### Or consider "turn out"

- Takes AdjP but not a present participle:
  - John turned out political
  - John turned out doing all the work

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# The 'paper of record' – the NY times – doesn't support the linguists

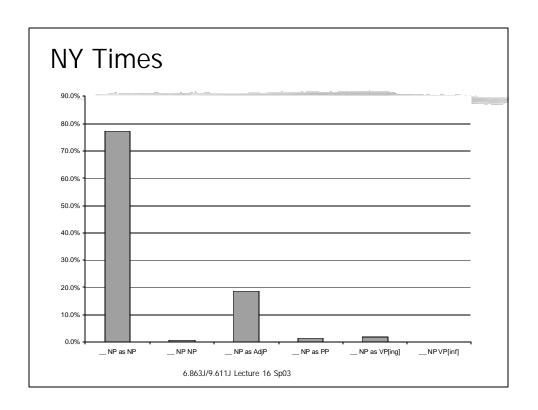
#### Consider as:

- The boys consider her as family and she participates in everything we do.
- Greenspan said, "I don't consider it as something that gives me great concern.
- "We consider that as part of the job," Keep said.
- Although the Raiders missed the playoffs for the second time in the past three seasons, he said he considers them as having championship potential.
- Culturally, the Croats consider themselves as belonging to the "civilized" West, ...

# Regarding the NY Times

- As 70 to 80 percent of the cost of blood tests, like prescriptions, is paid for by the state, neither physicians nor patients regard expense to be a consideration
- Conservatives argue that the Bible regards homosexuality to be a sin
- But it turned out having a greater impact than any of us dreamed
- On the big night, Horatio ended up flattened on the ground like a fried egg with the yolk broken

How to solve this? Use probabilities...!



# And in general

- Instead of using a subset of the data
- Use a superset...and add distributional pr weights

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#### Mutual aid

- Most formal models: no frequency information, and so grammaticality judgments or exploration of a factorial typology cross-linguistically is used
- Most "corpus linguistics": there is frequency information, but an insufficiently developed theory of abstract syntax ("hidden structure") for the frequency information to interact productively with a formal theory
- Goal: to get productive mutual feedback

## Incorporating knowledge

Do density estimation
 P(form | meaning context)

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## Application: retire

- Step 1: look at what dictionary or wordnet has for subcat
  - Result: intrans; transitive NP; PP (to, from)
- Step 2: see whether these examples attested (viz., Wall Street Journal)
  - Mr Riley plans to retire to the 1.5million dollar ranch he is building in Cody, Wyoming
  - Mr Frey, 64, remains chairman but plans to retire from that post in June
  - To all those wishing to retire in Mexico, let me offer these suggestions
  - · Donald Tanselle, 62, will retire as VP of banking
  - A worker contributing 10% of earnings will be able to retire on a peasion equal to 2/3 of their salary

#### What now?

- Step 3: do some statistics
- PP [on] is 'monetary support' so are these real argument or adjuncts?
- Answer: don't decide!
- Calculate conditional statistics
- Look at 1987 WSJ, and we get this:

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#### WSJ conditional pr's

- P(NP[subj]|V=retire) = 1.0
- P(NP[obj]|V=retire) = 0.52
- P(PP[from]|V=retire) = 0.05
- P(PP[as]|V=retire) = 0.06

(Pr of having certain <u>argument</u> adds to 1) (assumes independence between arguments – chance getting PP[as] indep of getting PP[from])

#### We can recalculate entire frame

- $P(NP[subj]_{vertire}) = 0.25$
- $P(NP[subj]_NP[obj]|V=retire) = 0.50$
- P(NP[subj]\_\_\_PP[from]|V=retire) = 0.04
- P(NP[subj]\_\_\_PP[from]PP[after]|V=retire) = 0.003

...

(Sum of pr's of all frames adds to 1)

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## Then we can do things like this

- Integrate pr of a 'frame' into the syntactic structure
- Pr that a VP is headed by a certain verb, and arguments surrounding that verb:
- $P(VP \rightarrow V[retire] PP[from]) =$  P(head=retire|VP)  $x P(VP \rightarrow V PP|VP, head=retire)$
- · Actually, it's more than surface subcat info
- Consider:
  - · Martinez will retire next year

#### General model for verb subcat

- Want:  $P(Subcat = f \mid Verb = v)$
- We model subcategorization at the level of the argument structure *a*, which groups data
- Decompose as:
  - P(f | v) = P(a,m | v) = P(a | v)P(m | a,v)
- Mappings m (including deletions, insertions) are few, and fairly consistent for <u>semantic</u> roles
- Verb classes:  $P(a \mid v) = \sum_{vc} P(vc \mid v) P(a \mid vc)$

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#### So...

- Payoff: this knowledge builds parsers that do very, very well – the best
- How can we acquire this info automatically?

## Lerner (Brent 1993)

- Cues
  - A pattern that can be matched against unrestricted text
  - NP NP → (OBJ|SUBJ\_OBJ|CAP) (PUNC|CC)
    - [...] greet Peter, [...]
    - [...] see him. [...]
    - [...] love it, if [...]
    - [...] came Thursday, [...] → error!
- Hypothesis Testing
  - Initial or null hypothesis (H<sub>0</sub>) → frame is not appropriate for verb
  - If cue indicates with high probability that frame is appropriate  $\xrightarrow[6.863]{/9.611J}$  reject  $H_0$  sp03

# Hypothesis Testing

$$p_E = P(v^i(f^j) = 0 | C(v^i, c^j) \ge m) = \sum_{r=m}^n \binom{n}{r} e_j^r (1 - e_j)^{n-r}$$

- Verb  $v^i$  occurs n times, and there are m = n occurrences with a cue  $c^j$  for frame  $f^j$
- $v^{i}(f^{j}) = 0 \rightarrow$  frame  $f^{j}$  is <u>not</u> appropriate for verb  $v^{i}$
- $C(v^i,c^j) \rightarrow$  number of times verb  $v^i$  occurs with cue  $c^j$
- $e_j \rightarrow$  error rate of cue  $c^j \rightarrow$  the probability that the cue matches, but that it is not evidence for a frame
- Determine a threshold a
- $P_E < a \rightarrow \text{reject H}_0$
- $P_E > a \rightarrow H_0$  is correct

### Hypothesis Testing - Example

$$p_E = P(v^i(f^j) = 0 | C(v^i, c^j) \ge m) = \sum_{r=m}^n \binom{n}{r} e_j^r (1 - e_j)^{n-r}$$

- Verb = greet  $\rightarrow$  occurs 80 times (n = 80)
- Cue = (OBJ|SUBJ\_OBJ|CAP) (PUNC|CC)  $\rightarrow$  has e = 0.25
- Frame = NP\_\_ NP
- C(greet,(OBJ|SUBJ\_OBJ|CAP) (PUNC|CC)) = 11 (m = 11 and r = 11)

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#### Hypothesis Testing – Example

$$\begin{aligned} p_E &= P \Big( \text{greet} \big( \text{ NP NP} \big) = 0 \Big| C \Big( \text{greet}, ((\text{OBJ}|\text{SUBJ\_OBJ}|\text{CAP})(\text{PUNC}|\text{CC}))} \big) \ge 11 \Big) \\ p_E &= \sum_{r=11}^{80} \binom{80}{r} 0.25^r \big( 1 - 0.25 \big)^{80-r} \\ p_E &= \binom{80}{11} 0.25^{11} \big( 1 - 0.25 \big)^{80-11} + \ldots + \binom{80}{80} 0.25^{80} \big( 1 - 0.25 \big)^{80-80} \\ p_E &= 0.011 \end{aligned}$$

- Threshold = 0.02
- Do we accept or reject the H<sub>0</sub> (= frame NP\_\_NP is <u>not</u> appropriate for the verb *greet*)?
- Reject  $\rightarrow$  P<sub>F</sub> = 0.011 < 0.02

# **Evaluating Lerner**

- Very high precision → always close to 100%
- Recall is lower → only 60%
- Only for six frames ...

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# We can start adding pr's to everything...

- PP attachment ('eat ice-cream with a spoon')
- Selectional preference (eat→ theme → food)