Natural Language Generation

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March 3, 2010
Today’s lecture

1. Demos

2. Basics of NLG
   - NLG concepts
   - Issues in NLG
   - NLG subtasks

3. Architecture of NLG systems
   - Two-step architecture
   - Three-step architecture

4. Hw7
Personals

Fun, loving woman looking to be a seat warmer on occasion this spring and summer. You be over 45, not married, and not a gang type biker. Want someone safe, sane and responsible. I like Harley’s or a decent rice grinder. No crotch rockets. Me: 5’6” HWP 120lb. love to ride, love the sun, love life, love to laugh. I really like men with beards/mustaches/goatees. :o)
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I am educated, stable, employed, 6ft tall, 200 lbs, brown eyes and brown hair. I work long hours at times, im sensitive at times, like good music, food, and conversations. I am a good friend, a good person, and easy to talk to. I’m looking for a slender asian girl who is educated and motivated/passionate. I like a girl who is educated. If you are out there, I would like to get to know you. Your pic gets mine.
Grass pollen levels for Saturday remain at the low levels of recent weeks with values of 1 across the whole country. Therefore only those most sensitive to pollen will be affected.

---

# NLG demo for pollen count

<table>
<thead>
<tr>
<th>Area</th>
<th>Pollen Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>North</td>
<td>1</td>
</tr>
<tr>
<td>North West</td>
<td>1</td>
</tr>
<tr>
<td>Central</td>
<td>1</td>
</tr>
<tr>
<td>North East</td>
<td>1</td>
</tr>
<tr>
<td>South West</td>
<td>1</td>
</tr>
<tr>
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<td>10</td>
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Grass pollen levels for Saturday remain at the low levels of recent weeks with values of 1 across most parts of the country. However, in South Eastern areas, pollen levels will be very high with values of 10.
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What is NLG?

**Definition**

Natural language generation is a CL subfield with the aim of producing meaningful, grammatical utterances in natural language from some *non-linguistic input*.

The NLG process is based on some **communicative goal** (e.g., refute, describe, agree), and according to some larger discourse plan.
Specific Goals

Goal: \textit{describePerson} \textit{SAM}

(subclass Family Collection)
(subclass Human LivingThing)
(subclass MaleHuman Human)
(instance Sam MaleHuman)

(inFamily Sam f1)
(familyName f1 Smith)
(age Sam 32)
(maritalStatus Sam single)
(know Sam Jill)

Sam Smith is 32 years old and is single.
Specific Goals

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Specific Goals

Goal: refute PROP45
given: like(BILL, SALLY)
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given: like(BILL, SALLY)

- It’s not true that Bill likes Sally.
- Bill doesn’t like Sally.
- Bill likes Sally, right!
Specific Goals

Goal: \((\text{compare } WA, \ VA)\)
Given: \(\text{loc}(WA, \text{NORTHWEST}) \land \text{loc}(VA, E\text{ASTCOAST})\)

Washington State is located in the northwest, while Virginia is on the east coast.
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Some generation applications
Some generation applications

- The output component of a machine translation system
Some generation applications

- The output component of a machine translation system
- Interface to a database system
Some generation applications

- The output component of a machine translation system
- Interface to a database system
- Interface to an expert system (math tutor)
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- Autogeneration of help pages for a software system
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- Text summarization
Comparison to NLU

Similarities

- Both utilize a lexicon, grammar, and knowledge representation.
- Both have same “endpoints” (internal computational representation, natural language utterances).
- Both apply symbolic and stochastic (corpus-based) methods.
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Differences

NLU is about hypothesis management, whereas NLG is about choice; when producing NL utterances from non-linguistic material, every bit of information to be encoded in the output has to be chosen along the way. Parsing, or most shallow NLU tasks, ignore certain aspects of meaning; NLG utilizes elaborated meaning representations. Research in NLG has focused more on texts than has NLU.
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- an entire novel
Text coherence

Such texts exhibit a certain structure and we can speak of their well-formedness, just like any other unit of language.
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A **coherent** text is one whose parts are interrelated in meaningful way. An incoherent text is one whose parts do not bind together in a naturalistic manner.
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- Pronominalization
- Temporal expressions
Text coherence: pronominal expressions

James Riddle “Jimmy” Hoffa (born February 14, 1913, disappeared July 30, 1975), was an American labor leader. As the president of the International Brotherhood of Teamsters from the mid-1950s to the mid-1960s, Hoffa wielded considerable influence. After he was convicted of attempted bribery of a grand juror, he served nearly a decade in prison. He is also well-known in popular culture for the mysterious circumstances surrounding his unexplained disappearance and presumed death. His son James P. Hoffa is the current president of the Teamsters.
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During Buck’s time in jail, Clyde had been the driver in a store robbery. The wife of the murder victim, when shown photos, picked Clyde as one of the shooters. On August 5, 1932, while Bonnie was visiting her mother, Clyde and two associates were drinking alcohol at a dance in Stringtown, Oklahoma (illegal under Prohibition). When they were approached by sheriff C.G. Maxwell and his deputy, Clyde opened fire, killing deputy Eugene C. Moore. That was the first killing of a lawman by what was later known as the Barrow Gang, a total which would eventually amount to nine slain officers.
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**Evaluation techniques:**
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Evaluation techniques:

- Turing Test (subjective)
- task-oriented (expensive)
- statistical comparison with real texts (untrustworthy)
Turing Test for evaluation of an NLG system

5 Indistinguishable from human
4 Most likely human
3 Maybe human or machine
2 Most likely machine
1 Definitely machine
Grice’s Conversational Maxims
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- **Quantity**: Make your contribution as informative as is required
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- **Quality**: Do not say what you believe is false. Do not say that for which you lack adequate evidence.
- **Relation**: Be relevant.
- **Manner**: Be perspicuous, avoid obscurity of expression, avoid ambiguity, be brief, be orderly.
Statistical evaluation scenarios

Comparison with humanly produced texts:
Statistical evaluation scenarios

Comparison with humanly produced texts:

- text length, mean length of utterance (MLU)
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- number of long distance dependencies
General evaluation criteria

Despite the challenges, we can posit some fundamental criteria for evaluating NLG systems:
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- **textual flow**: is the language choppy or smooth?
NLG subtask: Non-linguistic

There are several tasks for a full generation system:
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- **content determination**: task of deciding what information is to be communicated
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- **content determination**: task of deciding what information is to be communicated

- **discourse structuring**: deciding how to package the ‘chunks’ of content
NLG subtask: Linguistic
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- **lexicalization**: determine the particular words and construction types to use
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Need to modularize the above tasks appropriately, given the goal of the NLG system and the available resources.
Lexicalization

(1) a. Mary’s car
b. the car owned by Mary
Lexicalization

(3) a. Mary’s car
   b. the car owned by Mary

(4) a. the ship’s cargo hold
   b. the cargo hold which is part of the ship
(5) a. I am Ron Paul. I am a rogue Republican.
    b. My name is Ron Paul and I’m a rogue Republican.
(7)  a. I am Ron Paul. I am a rogue Republican.
    b. My name is Ron Paul and I’m a rogue Republican.

(8)  a. The course number is ling571.
    b. The course is difficult. The course is open to undergraduates.
    c. Ling571 is difficult, but open to undergraduates.
Agrgregation: other examples

John's bicycle is red
Mary's bicycle is yellow
Tom's bicycle is blue
Lisa's bicycle is red
becomes:
John and Lisa have red bicycles.
Tom's and Mary's bicycles are blue and yellow respectively.
Agrregation: other examples

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Agregation: other examples

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All telecom companies in the world except Alcatel made profit in 2004.
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Referring Expressions

(9) a. I know that guy.
    b. I know Noam Chomsky.
Referring Expressions

(11) a. I know that guy.
    b. I know Noam Chomsky.

(12) a. It’s a long-legged, hairy one.
    b. The European wolf spider is a long-legged, hairy spider.
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Ways to generate

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- canned text (easy, brittle)
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- template-based generation (easy, more flexible, ad hoc)
Ways to generate

A generation system can be devised for individual utterances or whole texts.

- canned text (easy, brittle)
- template-based generation (easy, more flexible, ad hoc)
- feature collection and linearization (very hard, flexible, theory driven)
Templates from ELIZA program

( "Perhaps you don’t want to %1."
  "Do you want to be able to %1?"
  "If you could %1, would you?")
...

( "Why do you think I am %1?"
  "Does it please you to think that I’m %1?"
  "Perhaps you would like me to be %1."
  "Perhaps you’re really talking about yourself?")
NLP reference architecture

1. Speech analysis
2. Pronunciation model
3. Speech synthesis

4. Morphological and lexical analysis
5. Morphological rules
6. Morphological realization

7. Parsing
8. Lexicon and grammar
9. Syntactic realization

10. Contextual reasoning
11. Discourse context
12. Utterance planning

13. Domain knowledge
14. Application reasoning and execution
Two common architectures (two- and three- step systems)

Based on splitting up the NLG subtasks (e.g., textplanner, lexical aggregation).

Based on how complex the system needs to be.
NLG architecture:  Two-step

non-linguistic input

Deep generation (discourse planning)

MessageSpecification

Surface generation (sentence planning)

KB

grammar

NL utterance
Two-step: Main components

1. **Deep generation**: determines and structures content of resulting text; insert words (lexicalization); map message to linguistic structure

2. **Surface generation**: fill in grammatical details, some lexicalization
Two-step: Example systems

Used in simpler, early systems:

- FOG System: generates weather reports from numerical weather simulations.
- Peba: generates taxonomic descriptions or comparisons of animals from a knowledge base of animal facts.

Problems in modularization and control over choice. In general, it’s really hard to strictly keep the non-linguistic choices separate from the linguistic choices.
Example from FOG System: weather text

Winds southwest 15 diminishing to light, late this evening.
Winds light Friday. Showers ending late this evening. Fog.
Outlook for Saturday...light winds.
The small spined monotreme belongs to the Echidna Family. Its nose is a long snout. The Echidna lives by itself.
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NLG architecture: Three-step

- Text Planner
  - TextPlan
  - Microplanner
    - TextSpecification
    - Surface Realizer
      - cohesive text

Input: non-linguistic input

Lexicon

Grammar

KB
Three-step: Example systems

Better systems

More flexible, more modular. More control over the output.

- **WEATHERREPORTER**: more complex, cohesive weather reports
- **KNIGHT System**: a biology explanation system, from knowledge base to explanatory paragraphs

More flexible, more modular. More control over the output.
## Three-step: Main components

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<tr>
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<th>Content task</th>
<th>Structure task</th>
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<tbody>
<tr>
<td><em>Text Planner</em></td>
<td>content determination</td>
<td>rhetorical structuring</td>
</tr>
<tr>
<td><em>Microplanner</em></td>
<td>lexicalization; referring expression generation</td>
<td>aggregation</td>
</tr>
<tr>
<td><em>Surface Realizer</em></td>
<td>linguistic realization</td>
<td>structure realization</td>
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</table>
The month was rather dry with only three days of rain in the middle of the month. The total for the year so far is very depleted again.
Embryo sac formation is a kind of female gametophyte formation. During embryo sac formation, the embryo sac is formed from the megaspore mother cell. Embryo sac formation occurs in the ovule.
Today’s lecture

1. Demos

2. Basics of NLG
   - NLG concepts
   - Issues in NLG
   - NLG subtasks

3. Architecture of NLG systems
   - Two-step architecture
   - Three-step architecture

4. Hw7
Hw7, main points

Tasks
Hw7, main points

Tasks

1. Create code to process an input text specification (XML)
Hw7, main points

Tasks

1. Create code to process an input text specification (XML)
2. Build a microplanner (in language of your choice)
Hw7, main points

Tasks

1. Create code to process an input text specification (XML)
2. Build a microplanner (in language of your choice)
3. Use the SimpleNLG (v.4) surface realizer (Java)