#### Outline of today's lecture

Overview of Natural Language Generation

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An extended example: cricket reports

Learning from existing text

**Referring expressions** 

Overview of Natural Language Generation

#### Overview of Natural Language Generation

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#### Generation

Generation from what?! (Yorick Wilks)

- Logical form: inverse of (deep) parsing. aka realisation (but realisation often from a syntax tree). Special case: in an MT system using semantic transfer.
- Formally-defined data: databases, knowledge bases, semantic web ontologies, etc.
- Semi-structured data: tables, graphs etc.
- Numerical data: e.g., weather reports.
- User input (plus other data sources) in assistive communication.

Generating from data often requires domain experts.

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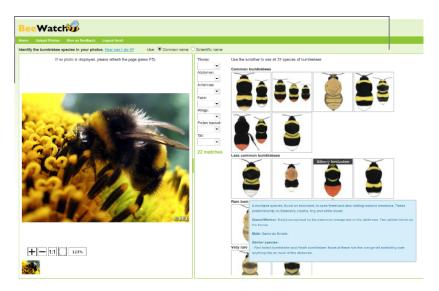
#### Example: Feedback on bumblebee identification

- Citizen scientists send in photos of bumblebees with their attempted identification (based on web interface): expert decides on actual species.
- Problem: expert has insufficient time to explain the errors.
- NLG system input: location data, attempted identification, expert identification, features of both species.
- NLG system output: coherent text explaining error or confirming identification and giving additional information.
  - Better identification training.
  - Expansion from 200 records a year to over 600 a month.
     Blake et al (2012)

homepages.abdn.ac.uk/advaith/pages/Coling2012.pdf

#### Natural Language Processing

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#### Example: Feedback on bumblebee identification

Our expert identified the bee as a Heath bumblebee rather than a Broken-belted bumblebee. ... The Heath bumblebee's thorax is black with two yellow to golden bands whereas the Broken-belted bumblebee's thorax is black with one yellow to golden band. The Heath bumblebee's abdomen is black with one yellow band near the top of it and a white tip whereas the Broken-belted bumblebee's abdomen is black with one yellow band around the middle of it and a white to buff tip. -Overview of Natural Language Generation

### Regeneration: transforming text

- Text from partially ordered bag of words: statistical MT.
- Paraphrase
- Summarization (single- or multi- document)
- Wikipedia article construction from text fragments
- Text simplification

Also: mixed generation and regeneration systems, MT.

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#### Components of a generation system

Content determination deciding what information to convey Discourse structuring overall ordering, sub-headings etc Aggregation deciding how to split information into sentence-sized chunks

Referring expression generation deciding when to use pronouns, which modifiers to use etc

- Lexical choice which lexical items convey a given concept (or predicate choice)
- Realization mapping from a meaning representation (or syntax tree) to a string (or speech)

Fluency ranking

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#### Lexical choice?



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#### Approaches to generation

- Classical (limited domain): hand-written rules for first five steps, grammar for realization, grammar small enough that no need for fluency ranking (or hand-written rules).
- Templates: most practical systems. Fixed text with slots, fixed rules for content determination.
- Statistical (limited domain): components as above, but use machine learning (supervised or non-supervised).
- Regeneration: symbolic or statistical or mixed.

#### Overview of Natural Language Generation

#### An extended example: cricket reports

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### Input: cricket scorecard

Result India won by 63 runs						
India innings (50 overs maximum)	R	М	В	4s	6s	SR
SC Ganguly run out (Silva/Sangakarra)	9	37	19	2	0	47.36
V Sehwag run out (Fernando)	39	61	40	6	0	97.50
D Mongia b Samaraweera	48	91	63	6	0	76.19
SR Tendulkar c Chandana b Vaas	113	141	102	12	1	110.78
Extras (lb 6, w 12, nb 7) 25						
Total (all out; 50 overs; 223 mins) 304						

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#### Output: match report

# India beat Sri Lanka by 63 runs. Tendulkar made 113 off 102 balls with 12 fours and a six. ...

Actual report:

The highlight of a meaningless match was a sublime innings from Tendulkar, ... he drove with elan to make 113 off just 102 balls with 12 fours and a six.

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#### Representing the data

- Granularity: we need to be able to consider individual (minimal?) information chunks (cf factoids in summarisation).
- Abstraction: generalize over instances.
- Faithfulness to source versus closeness to natural language?
- Inferences over data (e.g., amalgamation of scores)?
- Formalism.

e.g., name(team1/player4, Tendulkar), balls-faced(team1/player4, 102)

#### **Content selection**

There are thousands of factoids in each scorecard: we need to select the most important.

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```
name(team1, India), total(team1, 304),
name(team2, Sri Lanka), result(win, team1, 63),
name(team1/player4, Tendulkar),
runs(team1/player4, 113),
balls-faced(team1/player4, 102),
fours(team1/player4, 12),
sixes(team1/player4, 1)
```

#### Discourse structure and (first stage) aggregation

Distribute data into sections and decide on overall ordering:

*Title: name(team1, India), name(team2, Sri Lanka), result(win,team1,63)* 

First sentence: name(team1/player4, Tendulkar), runs(team1/player4, 113), fours(team1/player4, 12), sixes(team1/player4, 1), balls-faced(team1/player4, 102)

Reports often state the highlights and then describe events in chronological order.

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#### Predicate choice (lexical selection)

Mapping rules from the initial scorecard predicates:  $result(win,t1,n) \mapsto \_beat\_v(e,t1,t2), \_by\_p(e,r),$   $\_run\_n(r), card(r,n)$  $name(t,C) \mapsto named(t,C)$ 

This gives:

name(team1, India), name(team2, Sri Lanka), result(win,team1,63)  $\mapsto$ named(t1,'India'), named(t2, 'Sri Lanka'), \_beat\_v(e,t1,t2), \_by\_p(e,r), \_run\_n(r), card(r,'63')

Realistic systems would have multiple mapping rules. This process may require refinement of aggregation.

#### Generating referring expressions

named(t1p4, 'Tendulkar'), \_made\_v(e,t1p4,r), card(r,'113'), run(r), \_off\_p(e,b), ball(b), card(b,'102'), \_with\_(e,f), card(f,'12'), \_four\_n(f), \_with\_(e,s), card(s,'1'), \_six\_n(s)  $\rightarrow$  Tendulkar made 113 runs off 102 balls with 12 fours with 1 six.

This is not grammatical. So convert:

\_with\_(e,f), card(f, '12'), \_four\_n(f), \_with\_(e,s), card(s, '1'), \_six\_n(s)

into:

Also: '113 runs' to '113'

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An extended example: cricket reports

#### Realisation

Produce grammatical strings in ranked order:

Tendulkar made 113 off 102 balls with 12 fours and one six.

Tendulkar made 113 with 12 fours and one six off 102 balls.

. . .

113 off 102 balls was made by Tendulkar with 12 fours and one six.

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Learning from existing text

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An extended example: cricket reports

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Referring expressions

Learning from existing text

## Learning from aligned scorecards and reports

Result India won by 63 runs						
India innings (50 overs maximum)	R	М	В	4s	6s	SR
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### Learning from aligned scorecards and reports

Annotate reports with corresponding data structures:

The highlight of a meaningless match was a sublime innings from Tendulkar (team1 player4), ... and this time he drove with elan to make 113 (team1 player4 R) off just 102 (team1 player4 B) balls with 12 (team1 player4 4s) fours and a (team1 player4 6s) six.

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Learning from existing text

## Learning from aligned scorecards and reports

Produce a dataset with large numbers of annotated reports:

- Either: annotate training set by hand (boring!)
- Or: write rules to create training set automatically, using numbers and proper names as links. (Parse the reports?)

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Learning from existing text

## Statistical content selection and discourse structuring

Content selection:

- Treat as a classification problem: derive all possible factoids from the data source and decide whether each is in or out, based on training data. Kelly et al (2009) using cricket data.
- Categorise factoids into classes, group factoids.
- Problem: avoiding 'meaningless' factoids, e.g. player names with no additional information about their performance.

Discourse structuring: generalising over reports to see where particular information types are presented (cf Wikipedia article generation).

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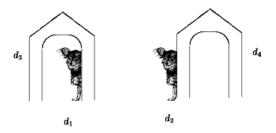


### **Referring expressions**

Given some information about an entity, how do we choose to refer to it?

- Pronouns/proper names/definite expressions etc (generate and test using anaphora resolution).
- Ellipsis and coordination (as in cricket example)
- Attribute selection: need to include enough modifiers to distinguish the expression from possible distractors. e.g., the dog, the big dog, the big dog in the basket.

#### Entities and referring expressions





Another scene: Two dogs and two doghouses (from Krahmer and Theune [2002]).

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#### A meta-algorithm for generating referring expressions

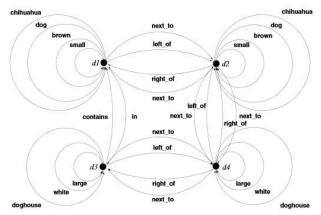


Figure 3 A graph representation of the scene in Figure 2.

## A meta-algorithm for generating referring expressions

- Predicates in the KB are arcs on a graph, with nodes corresponding to entities.
- A description is a graph with unlabelled nodes: it matches the KB graph if it can be 'placed over' it (subgraph isomorphism).
- A distinguishing graph is one that refers to only one entity (i.e., it can only be placed over the KB graph in one way).
- If description refers to entities other than the one we want, the others are distractors.
- Aim: lowest cost distinguishing graph.

## Algorithm

- 1. Start from node we want to describe (e.g., d2)
- 2. Expand graph by adding adjacent edges.
- Cost function associated with each edge: e.g., full brevity — edge cost is 1.
- 4. Explore search space, only retaining graphs cheaper than best solution.

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5.  $n^{K}$  where K is upper bound on number of edges.

#### Some issues

- Humans often use redundant expressions.
- Verbosity may be politer, easier to understand, convey emphasis etc
- Require knowledge of syntax: not just predicates. e.g., earlier and before.
- Limited domain: corpus-based method may be preferable.

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