Outline of today's lecture

Overview of Natural Language Generation

Components of Natural Language Generation systems

Data for NNs via classical realization

Referring expressions

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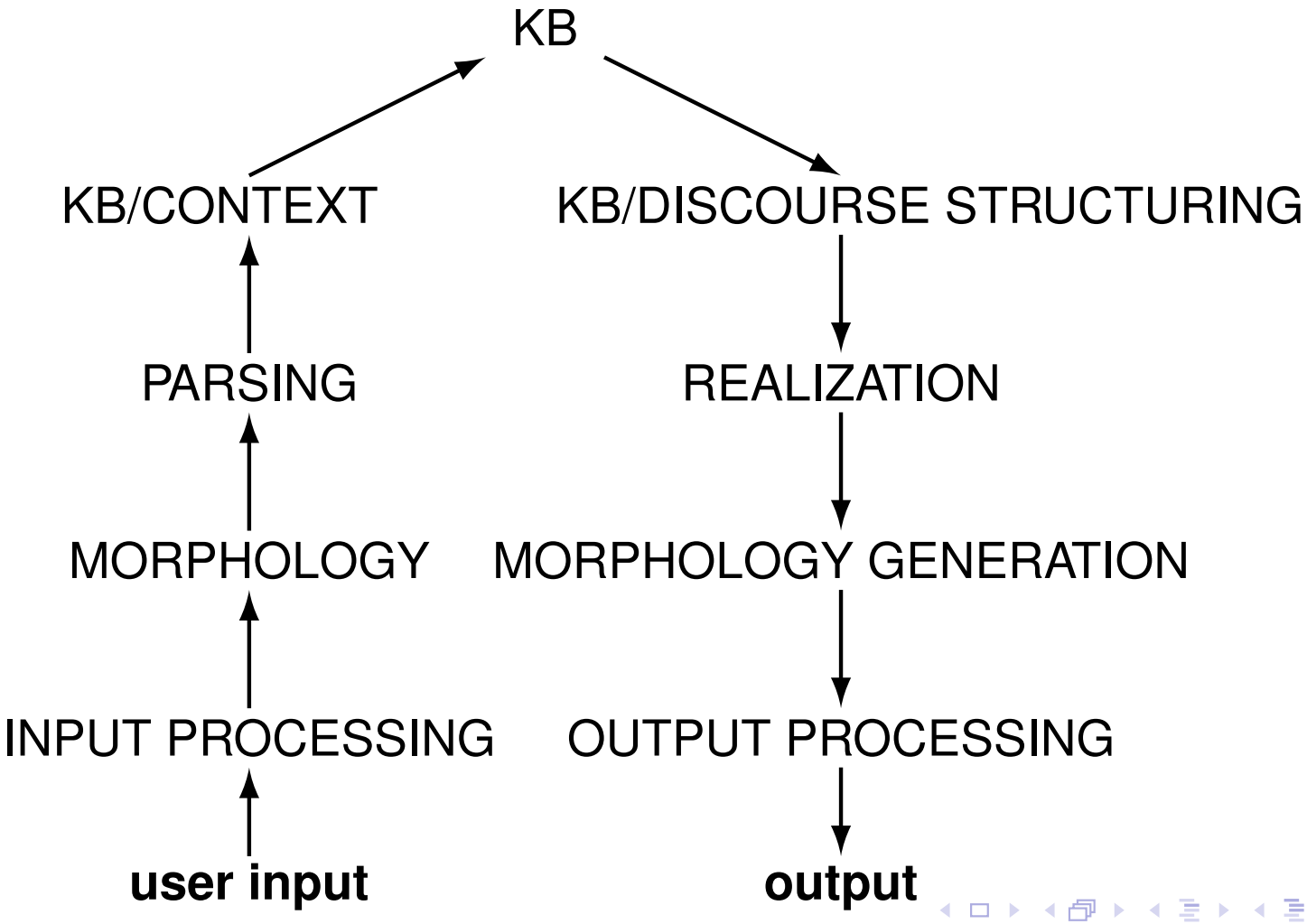
Components of Natural Language Generation systems

Data for NNs via classical realization

Referring expressions

Subtasks in natural language interface to a knowledge base: classic view



Generation from what?!

- Logical form or syntactic structure: inverse of parsing (reversible grammars). Also called realization.
- Formally-defined data: databases, knowledge bases, semantic web ontologies, etc.
- Semi-structured data: tables, graphs etc.
- Unstructured, non-symbolic data: images, videos etc
- Numerical data: e.g., weather reports.

Regeneration: transforming text

Includes:

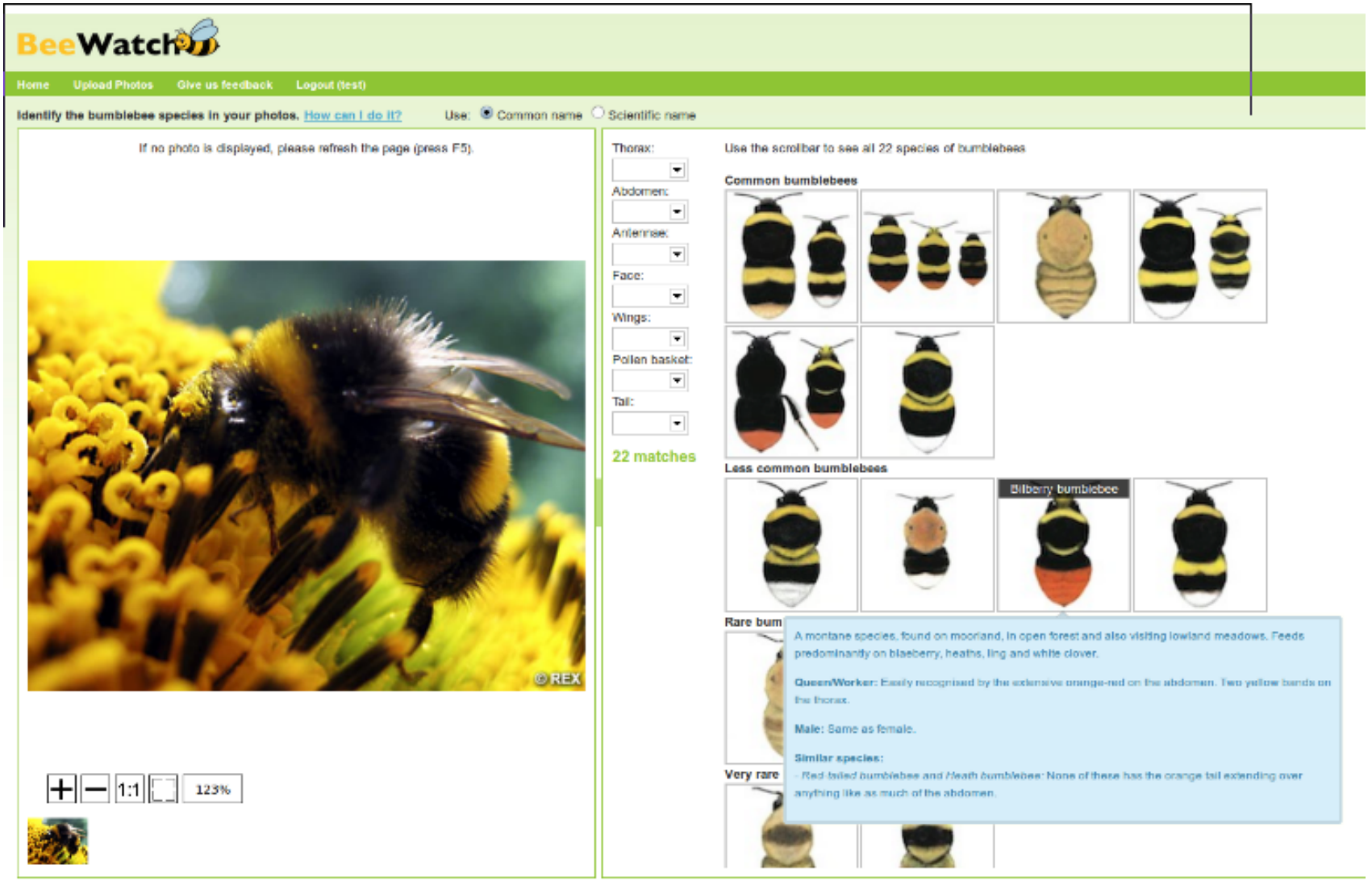
- Text from partially ordered bag of words: statistical MT.
- Paraphrase
- Summarization (single- or multi- document)
- Wikipedia article construction from text fragments
- Text simplification

Also: mixed generation and regeneration systems.

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`


BeeWatch
Home
Upload Photos
Give us feedback
Logout (test)
Identify the bumblebee species in your photos. How can I do it?
Use: Common name Scientific name
If no photo is displayed, please refresh the page (press F5).
© REX
1:1
123%
Thorax:
Abdomen:
Antennae:
Face:
Wings:
Pollen basket:
Tail:
22 matches
Use the scrollbar to see all 22 species of bumblebees
Common bumblebees
Less common bumblebees
Bilberry bumblebee
Rare bum
Very rare
A montane species, found on moorland, in open forest and also visiting lowland meadows. Feeds predominantly on blaeberry, heaths, ling and white clover.
Queen/Worker: Easily recognised by the extensive orange-red on the abdomen. Two yellow bands on the thorax.
Male: Same as female.
Similar species:
- Red-tailed bumblebee and Heath bumblebee: None of these has the orange tail extending over anything like as much of the abdomen.

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.

Approaches to generation

- Classical (limited domain): hand-written rules, 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/neural (still just for limited tasks): machine learning (supervised or non-supervised). May be multiple component (as classical) or end-to-end.

Mixed systems are possible — e.g., some classical systems have template components. Commercial systems in early 1990s: FoG multilingual weather reports.

Generation vs regeneration

- Usable regeneration systems (e.g., for summarization) have been available for a long time.
- Neural sequence-to-sequence models provide state-of-the-art for many regeneration tasks.
- Models are training-data-specific rather than domain-specific.
- Also possible to generate captions or descriptions from images, given sufficient training data.
- These techniques don't (so far?) transfer to the problem of generating from structured data.

Components of a classical 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

Input: cricket scorecard

Result India won by 63 runs						
India innings (50 overs maximum)	R	M	B	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						

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.

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.

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.

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.

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:

with(e,c), _and(c,f,s), card(f,'12'), _four_n(f), card(s,'1'), _six_n(s)

Also: '113 runs' to '113'

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.

Content selection: Learning from aligned scorecards and reports

Result India won by 63 runs						
India innings (50 overs maximum)	R	M	B	4s	6s	SR
SC Ganguly run out (Silva/Sangakarra)	9	37	19	2	0	47.36
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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.

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.*

Write rules to create training set automatically, using numbers and proper names as links. (Parse the reports?)

Statistical content selection and discourse structuring

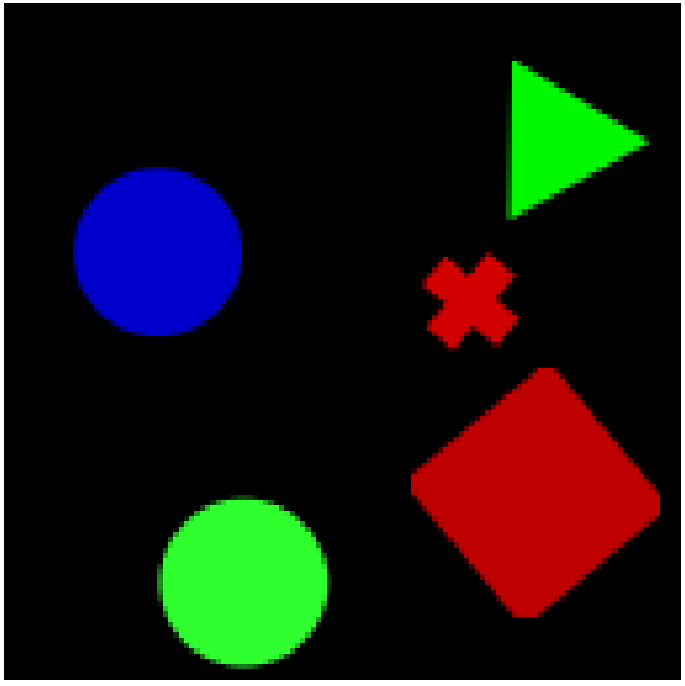
Content selection:

- 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).

ShapeWorld (Alex Kuhnle)

Training and testing NNs with grounded language:



All circles are to the left of a red cross.

$$\forall s_1 \in W : \text{circle}(s_1.\text{shape}) \Rightarrow$$
$$\Big(\exists s_2 \in W : \text{cross}(s_2.\text{shape}) \wedge \text{red}(s_2.\text{colour}) \wedge s_1.\text{x} < s_2.\text{x}\Big)$$

ShapeWorld (cont.)

- Automatically generate huge number of models in various classes: generate diagrams and meaning representation (DMRS) from models.
- Generate English captions from DMRS using English Resource Grammar (both true and false captions).
- Use pictures and captions to train NNs for VQA: evaluate including unseen combinations (e.g., red triangle).
- Finding: performance of some standard VQA approaches (CNN/LSTM) surprisingly bad on unseen combinations.
- Now finally getting close to 100% with FiLM (except with very simple classes, where it overfits).

Why use artificial data?

Investigate NN models very precisely, including checking whether they learn different linguistic phenomena.

- For instance, quantifiers like most require more structure to learn properly than adjectives.
- most white cats are deaf vs most deaf cats are white
  most(x, white(x) and cat(x), deaf(x))
  most(x, deaf(x) and cat(x), white(x))

Avoids some methodological problems:

- Balance the data: avoid bias problems.
- Automatic evaluation.

Addition rather than replacement for more natural datasets.
ShapeWorld supports multiple types of experiments: generating descriptions, generation from structured data.

Caption generation

Figure 5. A selection of evaluation results, grouped by human rating.

from Vinyals et al 2015

`https://arxiv.org/pdf/1411.4555.pdf`

Caption generation

Usual caption generation approach:

- Train models with parallel captions and images and evaluate using BLEU (as in MT).
- BLEU: metric that is based on closeness to a reference phrase or sentence.
- Problem: good captions may be nothing like the reference but terrible captions may be similar (cf MT).

Our findings: the language model does a lot of work (data biases, cf VQA).

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

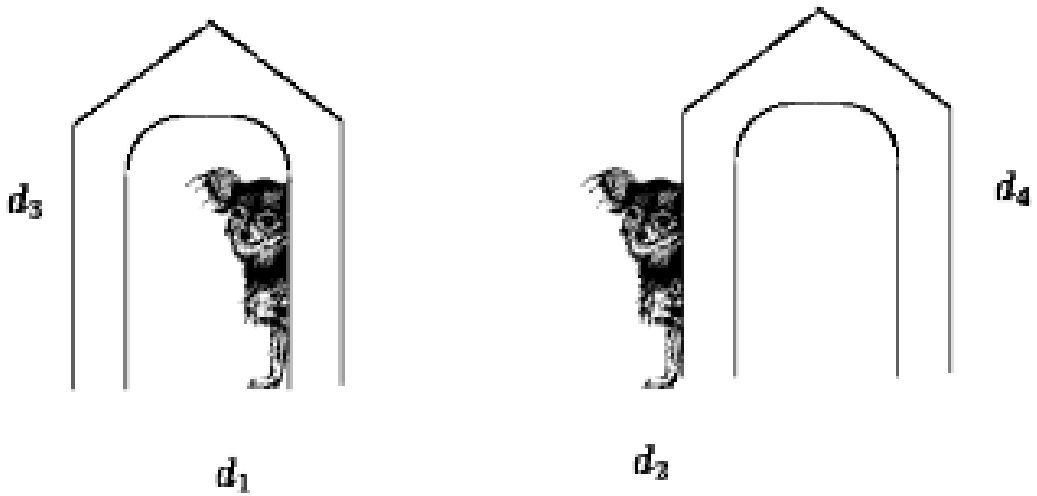


Figure 2
Another scene: Two dogs and two doghouses (from Krahmer and Theune [2002]).

A meta-algorithm for generating referring expressions

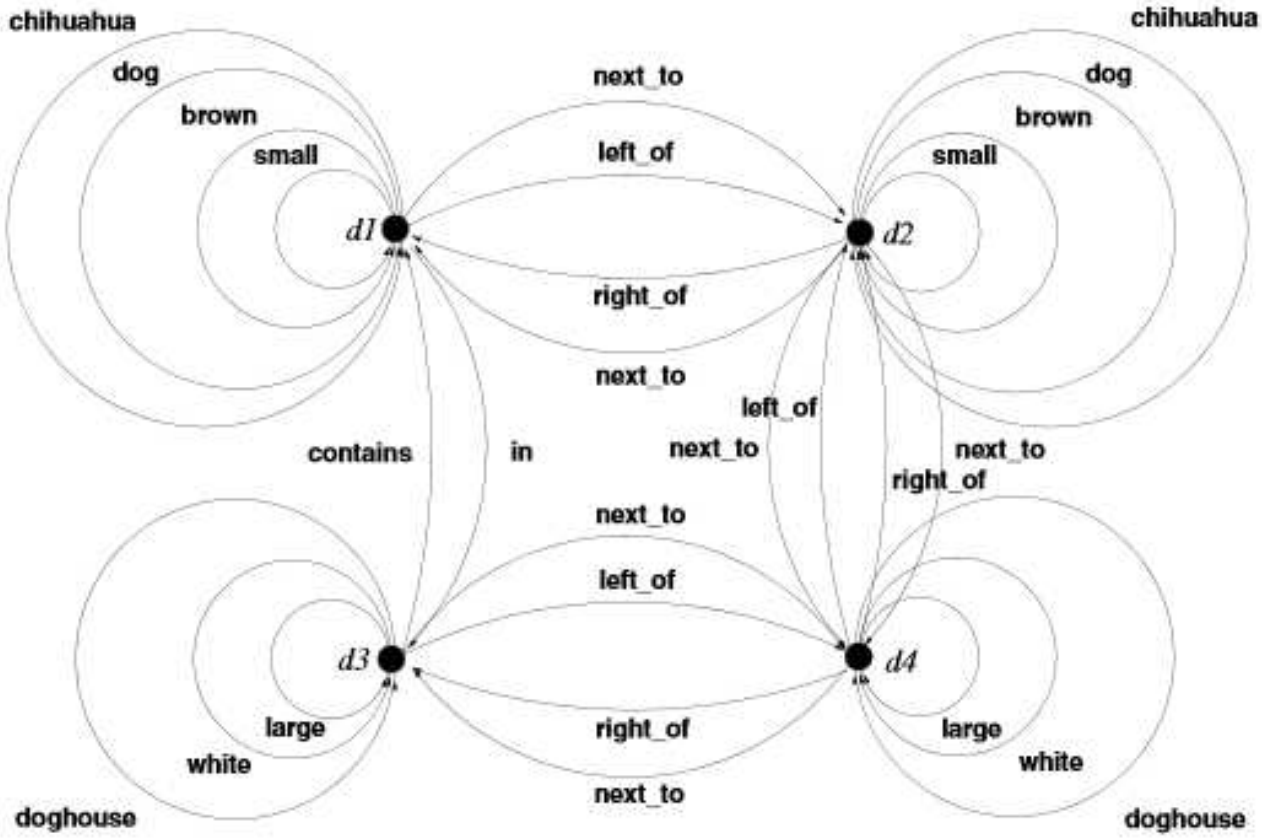


Figure 3
A graph representation of the scene in Figure 2.

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.
3. 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.
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: sensible if generating from a knowledge-base, otherwise corpus-based methods are needed.