Natural language generation

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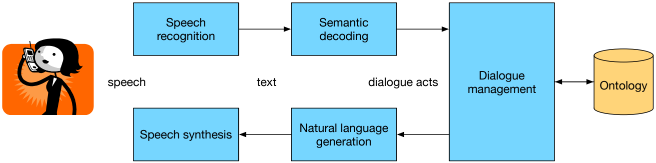
Speech synthesis in dialogue

Natural language generation



Role of natural language generation

- Converts dialogue act (semantics) into natural language
- Gives a persona to dialogue system
- Directly influences how the user perceives a dialogue system

Evaluating natural language generation

What makes a natural language generator good? [Stent et al., 2005]

adequacy correct meaning

fluency linguistic fluency

readabilty fluency in dialogue context

variation multiple realisations for the same concept

BLEU Score [Papineni et al., 2002]

- Evaluating similarity between paired sentences (n-gram match).
- There is a gap between human perception and automated measures.

Correlation coefficent	Adequacy	Fluency
BLEU	0.388	-0.492

- Human evaluation is always the best way to evaluate language generation.

Template-based natural language generator

Define a set of templates which maps dialogue acts into utterances.

Dialogue act	Delexicalised utterance
confirm(area=$V)	Would you like a restaurant in the $V?
confirm(food=$V)	Would you like a $V restaurant?
confirm(food=$V,area=$W)	Would you like a $V restaurant in the $W ?

Template-based natural language generator

Pros simple, usually error free, controllable

Cons time consuming, rigid, not scalable

Trainable generator [Walker et al., 2002]

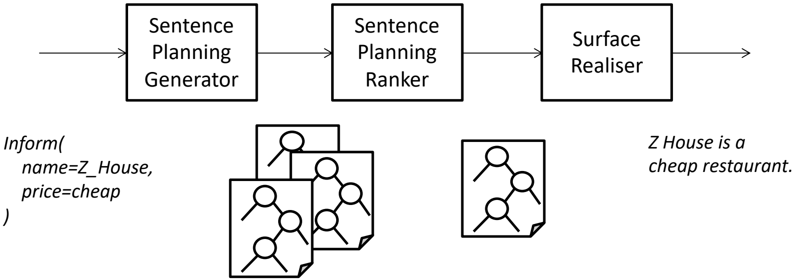
- Divide the problem into a pipeline

  Sentence plan generator Produces multiple sentence plans for a given dialogue act (or set of dialogue acts).

  Sentence plan reranker Ranks possible candidates.

  Surface realiser Turns the top candidate into an utterance.

Trainable generator overview



Sentence plan generator

- Utilise machine learning to do reranking (RankBoost)
- Extract features from sentence plan trees: indicator function f_i relating to traversal features, ancestor features, leaf features, etc. size 3291.

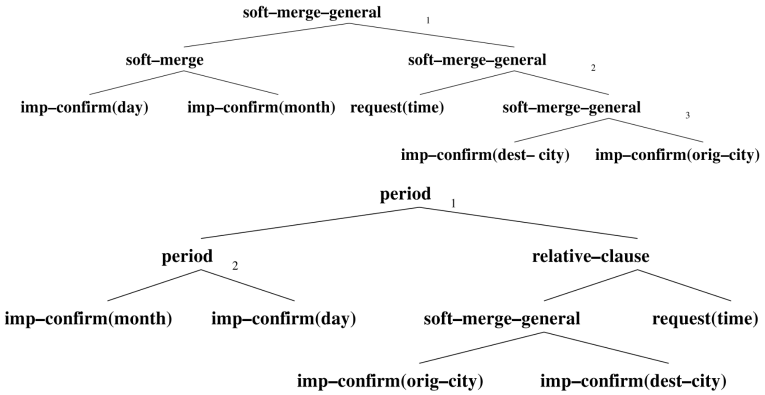
$$F(x) = \sum_i \alpha_i f_i(x)$$

$$Loss = \sum_{x,y \in \mathcal{D}} \exp(-(F(x) - F(y))),$$

where x and y are sentence plans, x is preferred to y, α_i are learnable parameters, and $\mathcal{D}$ are sentence plans referring to a given dialogue act.

Sentence plan generator - example

implicit-confirm(orig-city:NEWARK)
implicit-confirm(dest-city:DALLAS)
implicit-confirm(month:9)
implicit-confirm(day-number:1)
request(depart-time)



Other similar approaches

- Learning sentence plan generation rules.
- Statistical surface realisers.

Properties

Pros Can generate sentences with complex linguistic structure.

Cons Many rules, heavily engineered.

Class-based language modelling for NLG [Oh and Rudnicky, 2000]

- Language modelling

$$p(W) = \prod_t p(w_t | w_0, \cdots, w_{t-1})$$

- Class-based language modelling

$$p(W|u) = \prod_t p(w_t | w_0, \cdots, w_{t-1}, u)$$

- Decoding

$$W^* = \arg\max_W p(W|u)$$

Class-based language modelling for NLG

- Classes:
  inform_area
  inform_address
  inform_phone
  request_area
  ...
- Generation process:
  - Generate utterances by sampling words from a particular class language model in which the dialogue act belongs to.
  - Re-rank utterances according to scores.

Properties

Pros no complicated rules, easy to implement, easy to understand

Cons error-prone

Can we do better?

- RNN as language generator: natural model for modeling sequences
- Long-term dependencies?
- Flexible to condition on auxiliary inputs

Long-term dependencies in NLG:
Example: The restaurant (in the north) is a nice Chinese place.

RNN & Vanishing gradient [Pascanu et al., 2013]

$$
\begin{aligned}
\mathbf{h}_j &= \sigma(W_r \mathbf{h}_{j-1} + W_i \mathbf{w}_j + \mathbf{b}_h) \\
\mathbf{y}_j &= softmax(W_o \mathbf{h}_j + \mathbf{b}_o) \\
\frac{\partial E_3}{\partial W_r} &= \sum_{k=0}^{3} \frac{\partial E_3}{\partial \mathbf{y}_3} \frac{\partial \mathbf{y}_3}{\partial \mathbf{h}_3} \frac{\partial \mathbf{h}_3}{\partial \mathbf{h}_k} \frac{\partial \mathbf{h}_k}{\partial W_r} \\
&= \sum_{k=0}^{3} \frac{\partial E_3}{\partial \mathbf{y}_3} \frac{\partial \mathbf{y}_3}{\partial \mathbf{h}_3} \left(\prod_{j=k+1}^{3} \frac{\partial \mathbf{h}_j}{\partial \mathbf{h}_{j-1}} \right) \frac{\partial \mathbf{h}_k}{\partial W_r} \\
\frac{\partial \mathbf{h}_j}{\partial \mathbf{h}_{j-1}} &= W_r^{\mathrm{T}} diag(\sigma'(W_r \mathbf{h}_{j-1} + W_i \mathbf{w}_j + \mathbf{b}_h)),
\end{aligned}
$$

where $'$ is elementwise derivative. The norm of the last term is smaller than 1 causing vanishing gradient.

LSTM [Hochreiter and Schmidhuber, 1997]

- Sigmoid gates

$$
\begin{aligned}
\mathbf{i}_t &= \sigma(W_{wi}\mathbf{w}_t + W_{hi}\mathbf{h}_{t-1}) \\
\mathbf{f}_t &= \sigma(W_{wf}\mathbf{w}_t + W_{hf}\mathbf{h}_{t-1}) \\
\mathbf{o}_t &= \sigma(W_{wo}\mathbf{w}_t + W_{ho}\mathbf{h}_{t-1})
\end{aligned}
$$

- Proposed cell value

$$
\hat{C}_t = tanh(W_{wc}\mathbf{w}_t + W_{hc}\mathbf{h}_{t-1})
$$

- Update cell and hidden layer

$$
\begin{aligned}
C_t &= \mathbf{i}_t \odot \hat{C}_t + \mathbf{f}_t \odot C_{t-1} \\
\mathbf{h}_t &= \mathbf{o}_t \odot tanh(C_t)
\end{aligned}
$$

LSTM

How it prevents vanishing gradient problem?

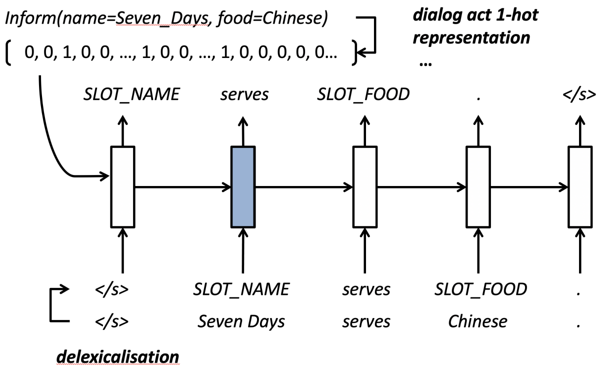
- Consider memory cell, where recurrence actually happens

$$C_t = \mathbf{i}_t \odot \hat{C}_t + \mathbf{f}_t \odot C_{t-1}$$

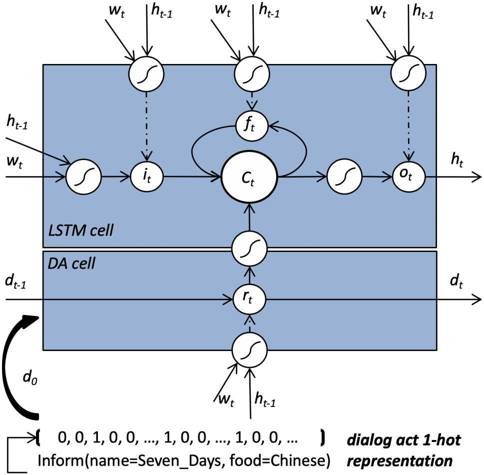
- We can back-propagate the gradient by chain rule

$$\frac{\partial E_t}{\partial C_{t-1}} = \frac{\partial E_t}{\partial C_t}\frac{\partial C_t}{\partial C_{t-1}} = \frac{\partial E_t}{\partial C_t}\mathbf{f}_t$$

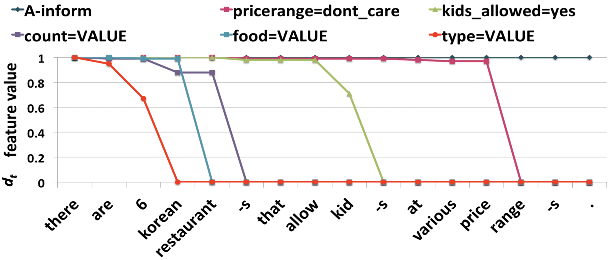
RNN for NLG [Wen et al., 2015a]



Semantically conditioned LSTM [Wen et al., 2015b]



Learned alignemnts



Human evaluation

Method	Informativeness	Naturalness
SC-LSTM	**2.59**	2.50
Class LM	2.46	2.45

Exampes

inform_no_match(area=tenderloin)
there are no restaurants in the tenderloin area.
there are 0 restaurants in the tenderloin area.
unfortunately there are 0 restaurants in the tenderloin area.
i could not find any restaurants in tenderloin.

Properties

Pros
: more accurate, does not require intermediate alignments

Cons
: does not utilise pre-trained word-vector embeddings

Generative pre-training (GPT)

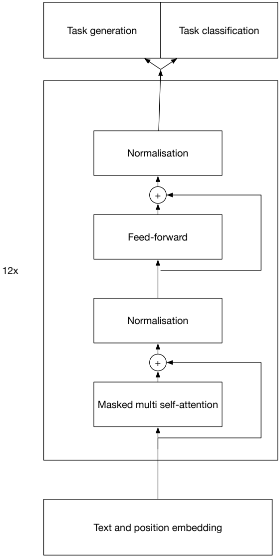
- Autoregressive language model that utilises transformer architecture
- Pretrained on large amounts of crawled text
- Predicts the next token u given context $U = [u_{-k}, \cdots, u_{-1}]$

$$\begin{aligned} \mathbf{h}_0 &= UW_e + W_p \\ \mathbf{h}_l &= transformer(\mathbf{h}_{l-1}), l \in [1, n] \\ p(u) &= softmax(\mathbf{h}_n W_e^T) \end{aligned}$$

- GPT-2 and GPT-3 have effectively the same model structure with substantially more parameters

	GPT	GPT-2	GPT-3
Parameters	117M	1.5B	175B
Data	12GB	40GB	570GB

Generative pre-training (GPT)



Semantically conditioned GPT

- Pre-trains the GPT-2 model with a large corpus of dialogue act and utterance pairs.
- Fine-tuned with only a few domain-specific labels to adapt to new domains.
- Operates on lexicalised inputs.

Human evaluation

Models trained on FewshotWOZ with only 50 dialogue acts in the training set and 500K in test set.

Method	Informativeness	Naturalness
SC-GPT	2.64	2.47
SC-LSTM	2.29	2.13
Human	2.92	2.72

Summary of NLG

- Evaluating NLG is hard. The best way is human evaluation.
- Tree-based NLG is a linguistically motivated approach. By introducing machine learning in the pipeline enables the model to learn from data.
- Language Modeling casts NLG as a sequential prediction problem.
- LSTM overcomes vanishing gradient by sophisticated gating mechanism. The same idea was applied to NLG resulting in semantically conditioned-LSTM, a generator that can learn realisation and semantic alignments jointly.
- Pre-trained transformer models perform particularly well on few shot learning tasks.

Role of a speech synthesiser in a dialogue system

- In a dialogue system the context is available from the dialogue manager.
- Text-to-speech system can make use of the context to produce more natural and expressive speech [Yu et al., 2010].

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Credits

We thank Tsung-Hsien Wen for sharing his slides on Stistical Natual Language Generation.