Key Issues in Building Dialog System and Chatbot

Head First Theory and Practice

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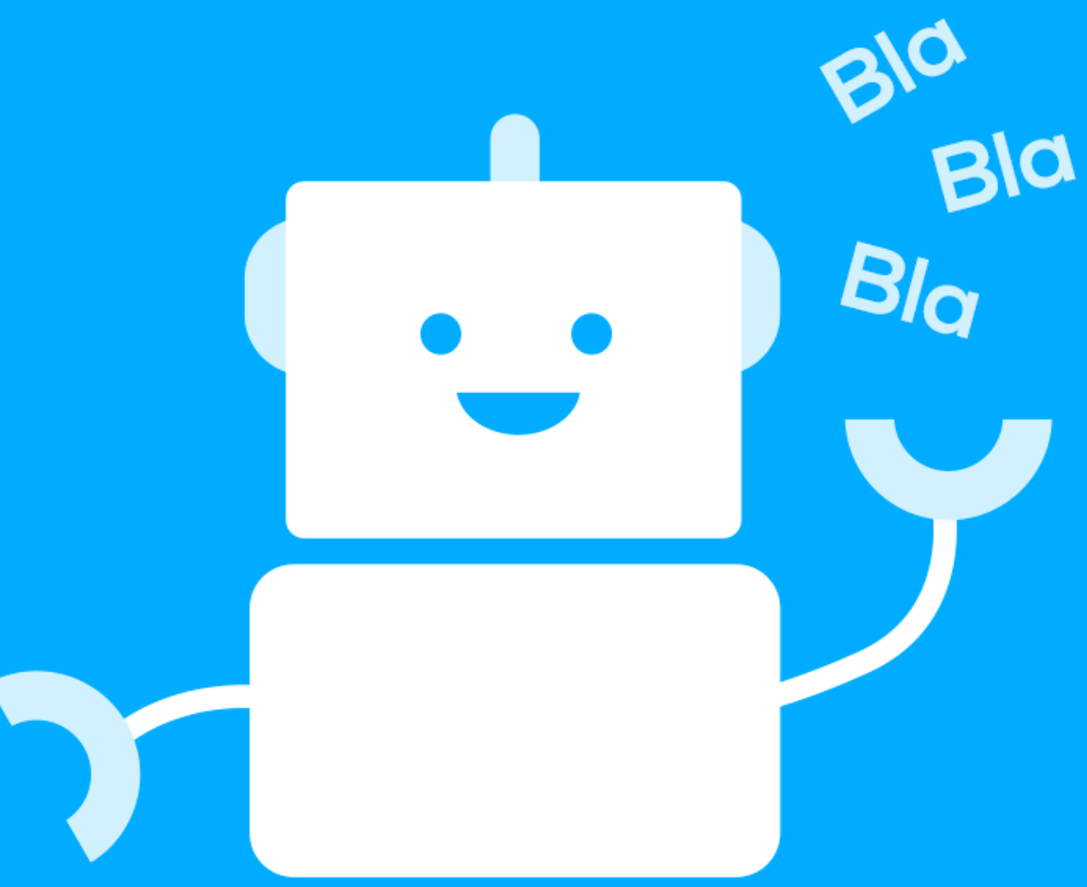


VS.

Mainstream Approaches

Two Paradigms

Two Paradigms

M: Hello, welcome to the Cambridge dialogue system, What kind of food would you like?
H: Yeah I want to find a restaurant that serves European food.
M: Hotel du Vin and Bistro is a nice place. It serves European food.
H: Uh what is the address and phone number?
M: Hotel du Vin and Bistro is a nice place. Their address is XXX and their phone is YYY.
H: Thank you goodbye.
M: Thank you for using this system

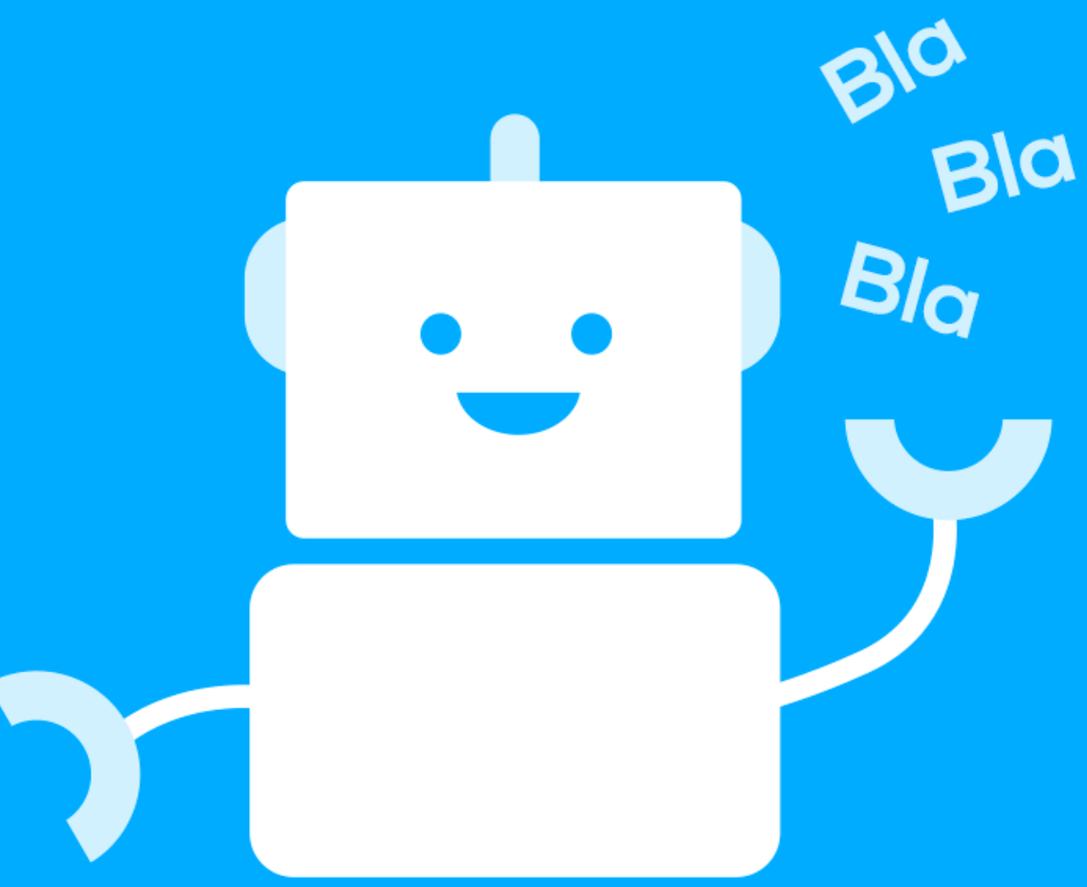
Task-oriented Domain-specific Dialog System

A: How old are you ?
B: I'm 16. Why are you asking ?
A: I thought you were 12.
B: What made you think so ?
A: I don't know what you are talking about.
B: You don't know what you are saying.

Chit-chat Open Domain Conversational Agent

Two Paradigms

- Task-oriented Dialog System
  - Task (*Goal)-oriented, complete a task, e.g. book a hotel
  - Require precise understanding, hard to collect data
  - Modular, highly handcrafted (API), restricted ability, easy to evaluate
- Chit-chat Conversational Agent
  - Chit-chat (non-*goal), auxiliary topics
  - Vast amount of data (but probably not helpful), e.g. movie lines, Weibo posts
  - End-to-end, highly data-driven, hard to evaluate

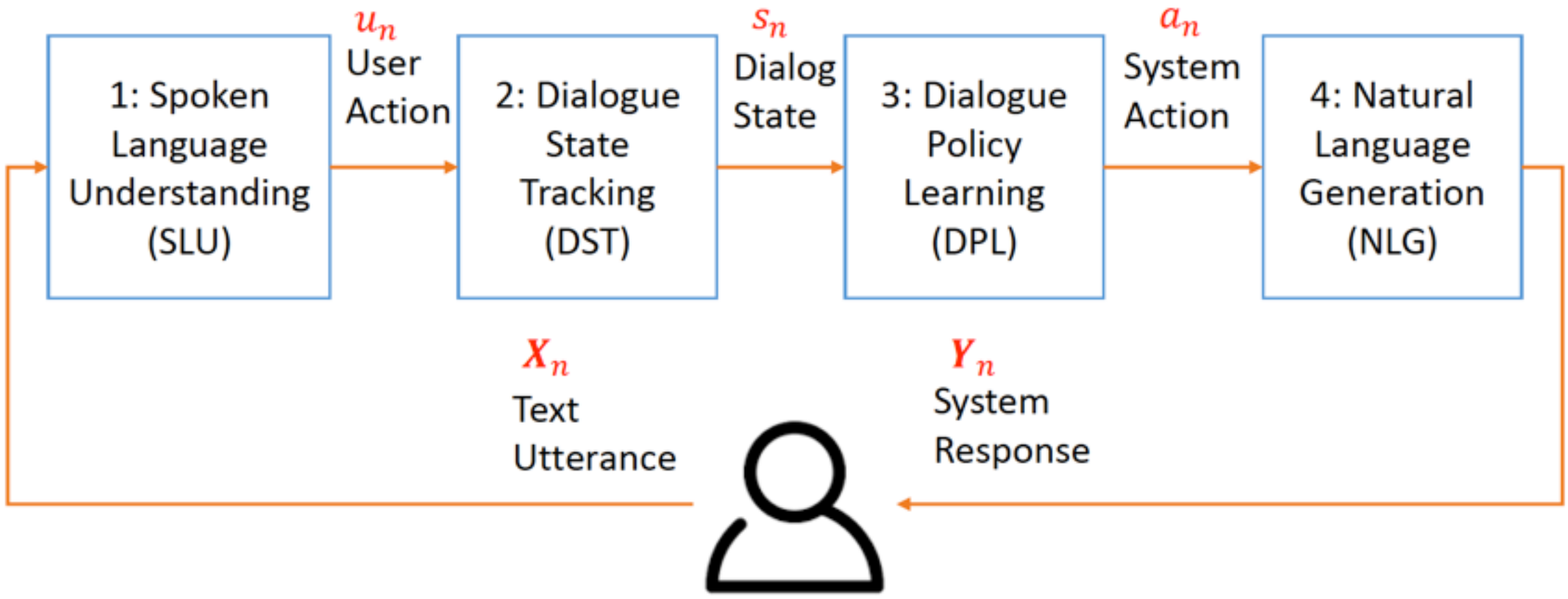


VS.

Task-oriented | Dialog System

Task-oriented Dialog System

- Modular: often 4 modules

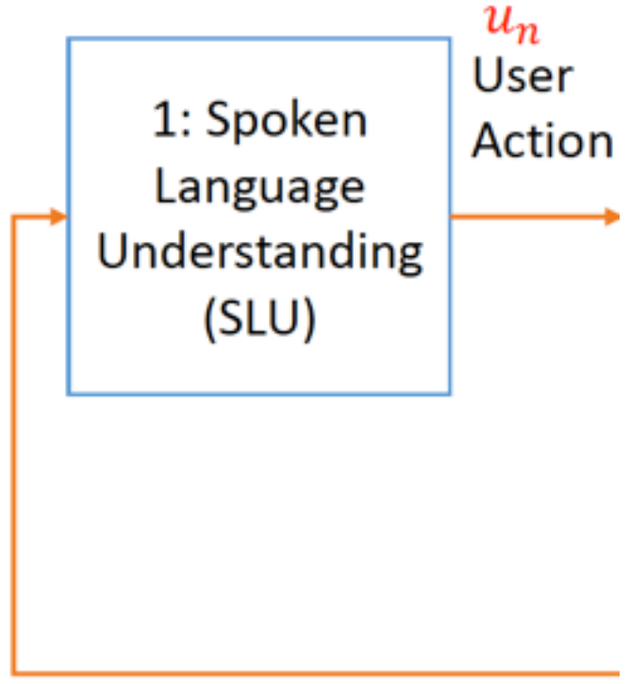


Task-oriented Dialog System

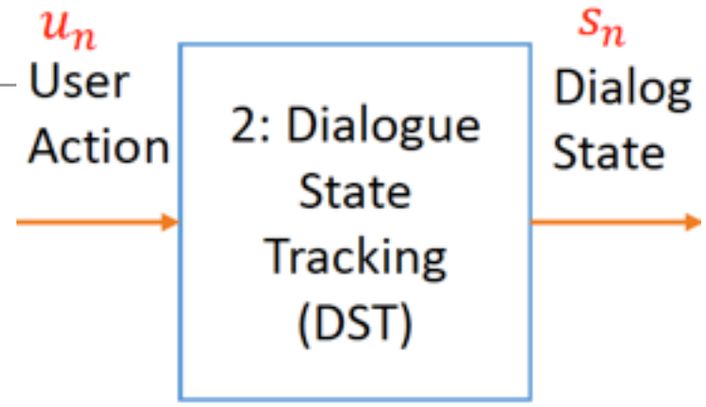
- Modular: often 4 modules
- Sub-modules, sub-tasks:
  - Spoken Language Understanding (SLU)
  - Dialogue State Tracking (DST)
  - Dialogue Policy Learning (DPL)
  - Natural Language Generation (NLG)

Task-oriented Dialog System

- Modular: often 4 modules
- Sub-modules, sub-tasks:
  - Spoken Language Understanding (SLU)
    - SLU turns natural language into user intention and slot-values, and it takes input and outputs structured user action
- Dialogue State Tracking (DST)
- Dialogue Policy Learning (DPL)
- Natural Language Generation (NLG)

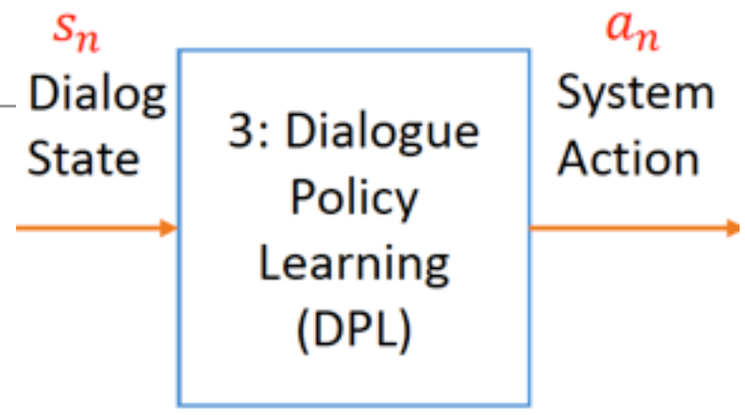


Task-oriented Dialog System



- Modular: often 4 modules
- Sub-modules, sub-tasks:
  - Spoken Language Understanding (SLU)
  - Dialogue State Tracking (DST)
    - DST tracks the current dialogue state, and outputs dialogue state
  - Dialogue Policy Learning (DPL)
  - Natural Language Generation (NLG)

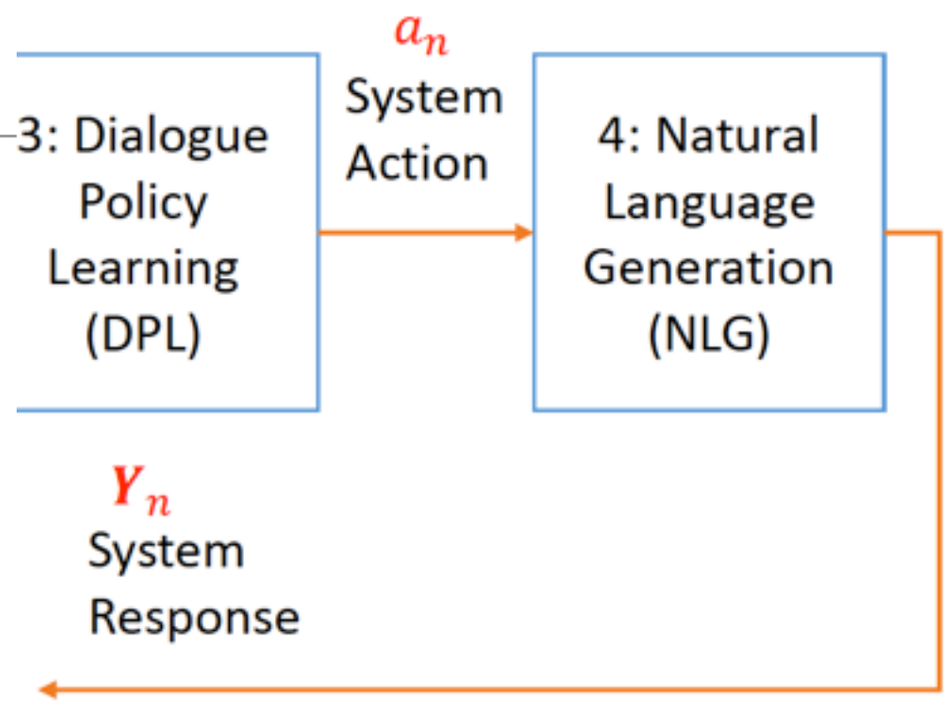
Task-oriented Dialog System



- Modular: often 4 modules
- Sub-modules, sub-tasks:
  - Spoken Language Understanding (SLU)
  - Dialogue State Tracking (DST)
  - Dialogue Policy Learning (DPL)
    - Policy decides which system action to take based on the dialogue state, and it takes dialogue state as input and outputs system action
  - Natural Language Generation (NLG)

Task-oriented Dialog System

- Modular: often 4 modules
- Sub-modules, sub-tasks:
  - Spoken Language Understanding (SLU)
  - Dialogue State Tracking (DST)
  - Dialogue Policy Learning (DPL)
  - Natural Language Generation (NLG)
    - NLG turns a system action into natural language, and it takes the system action as input and outputs the system response



Task-oriented Neural Dialog System [7]

Can I have Korean

Little Seoul serves great Korean .

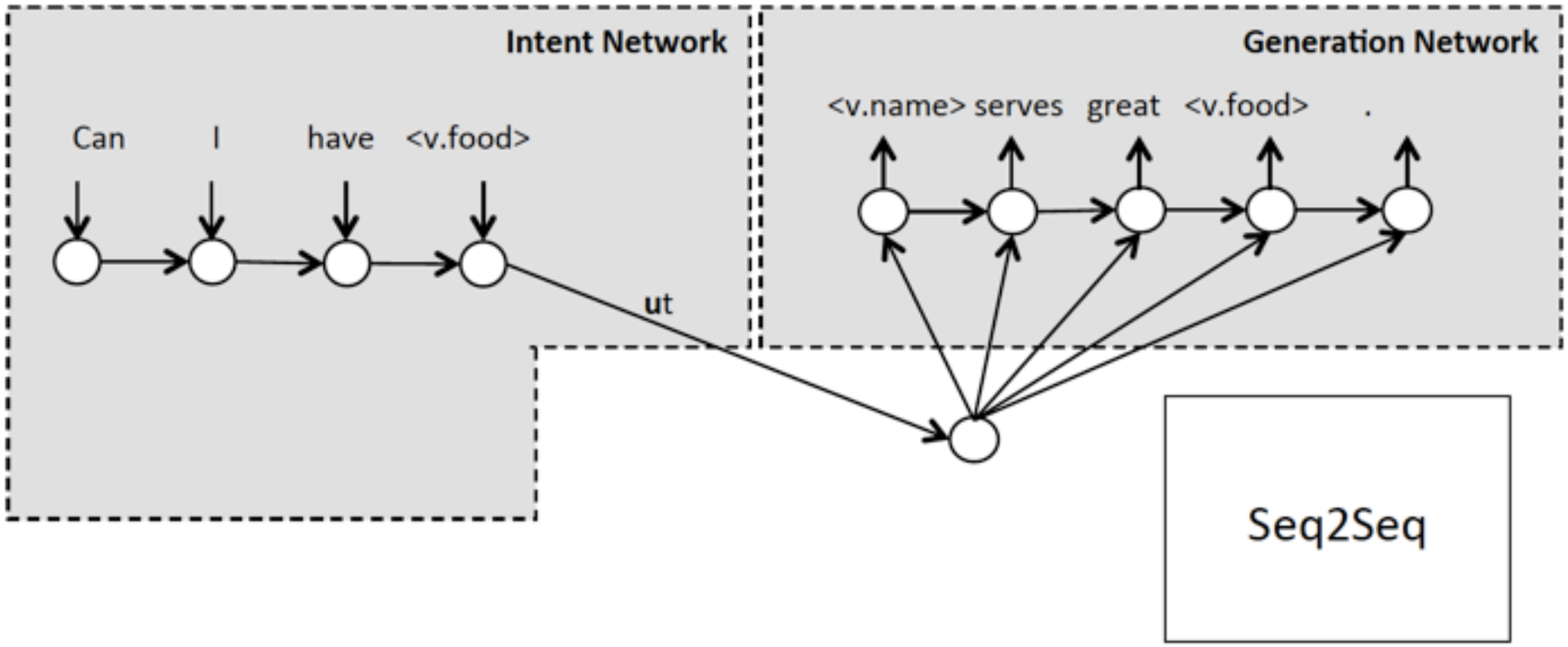
Task-oriented Neural Dialog System

Can I have <v.food>

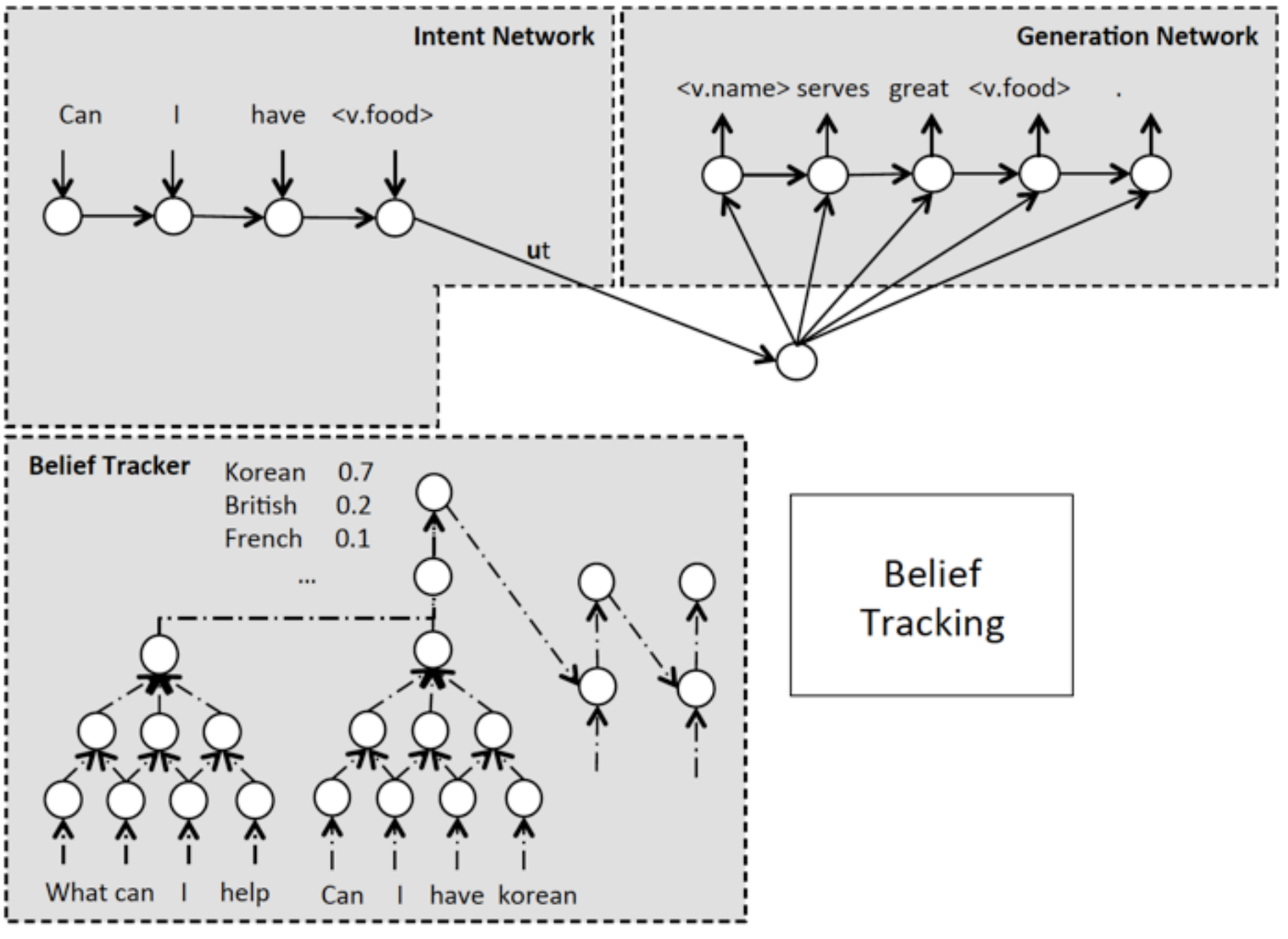
<v.name> serves great <v.food> .

Delexicalisation

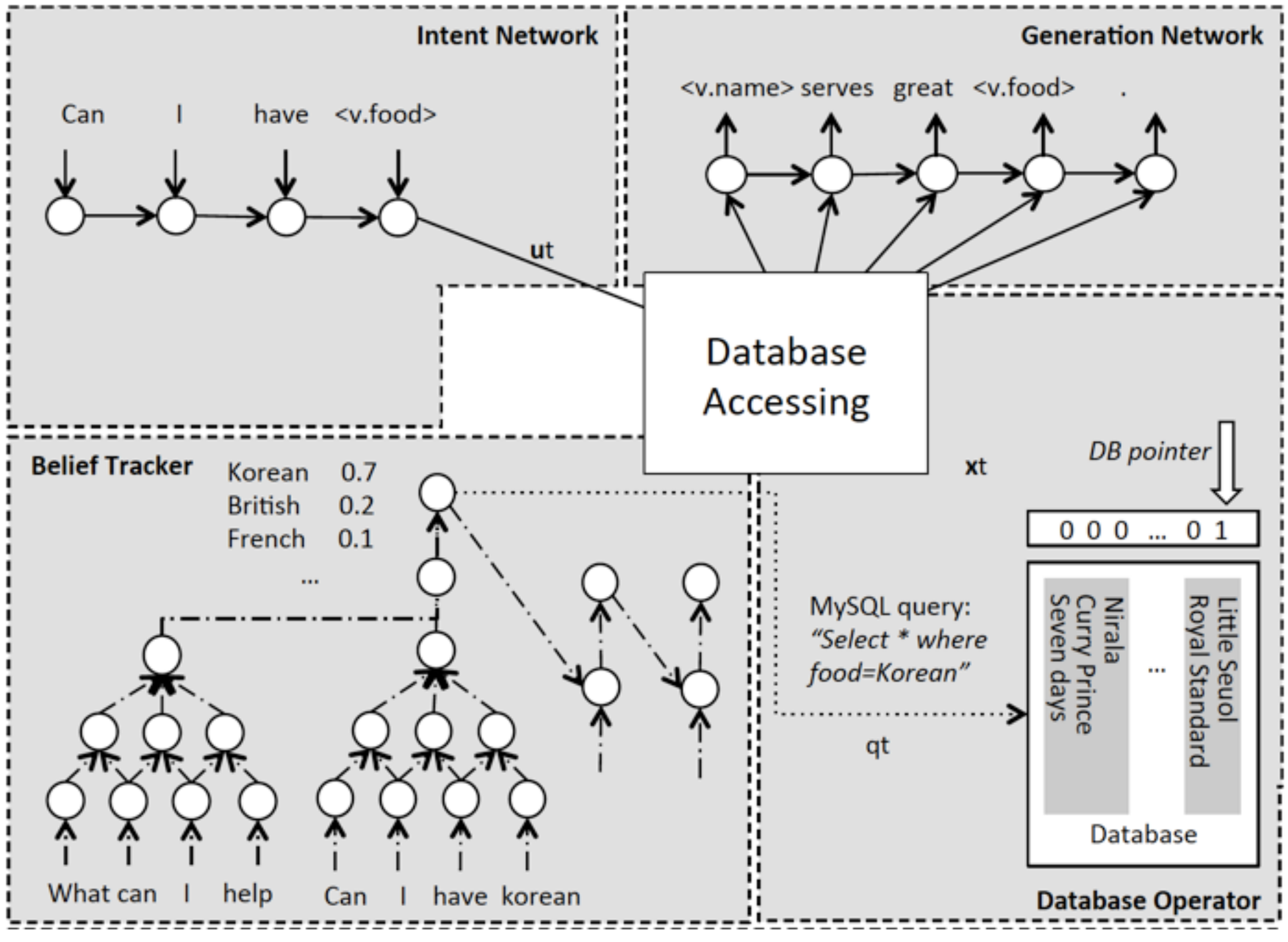
Task-oriented Neural Dialog System



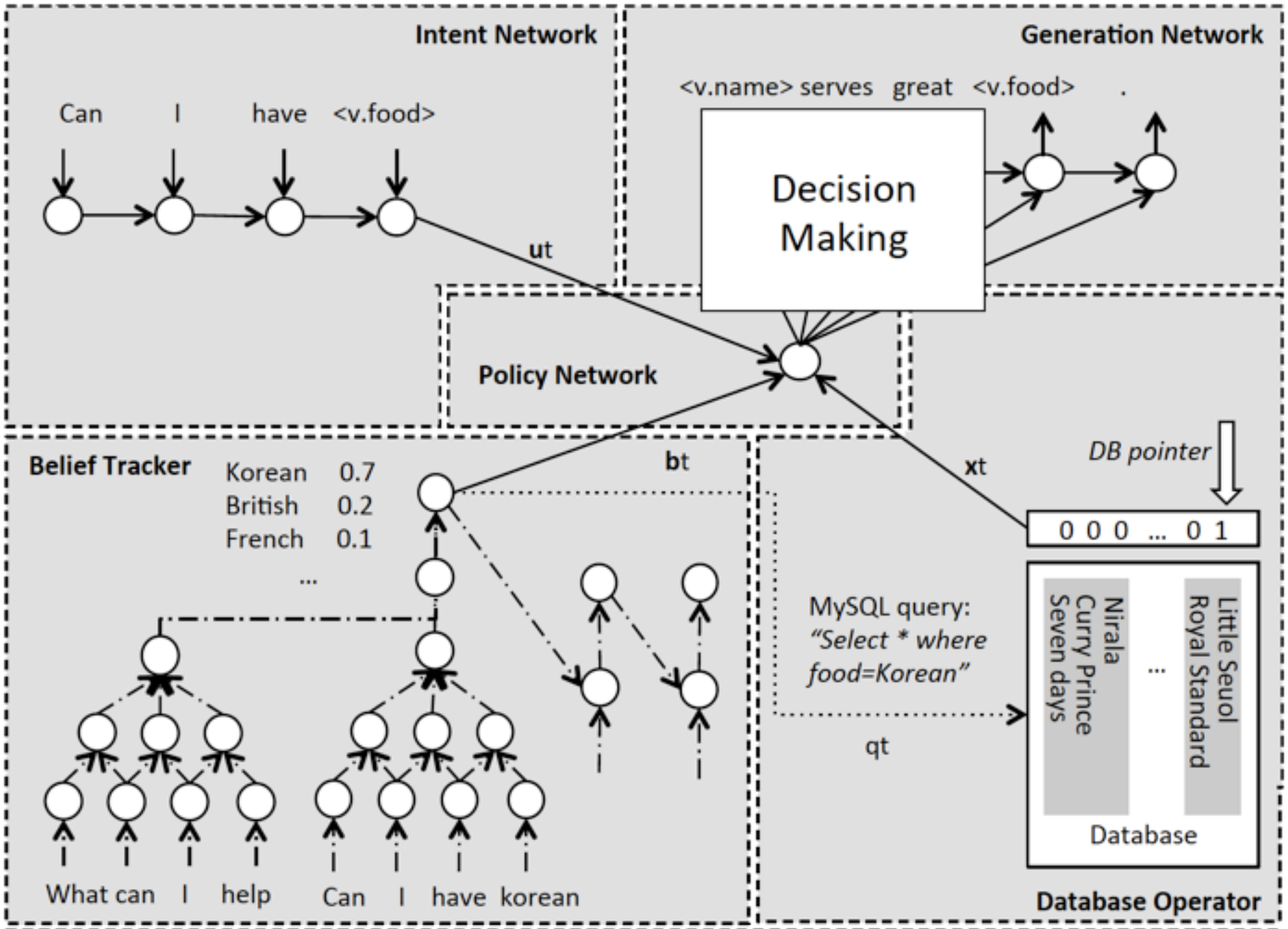
Task-oriented Neural Dialog System



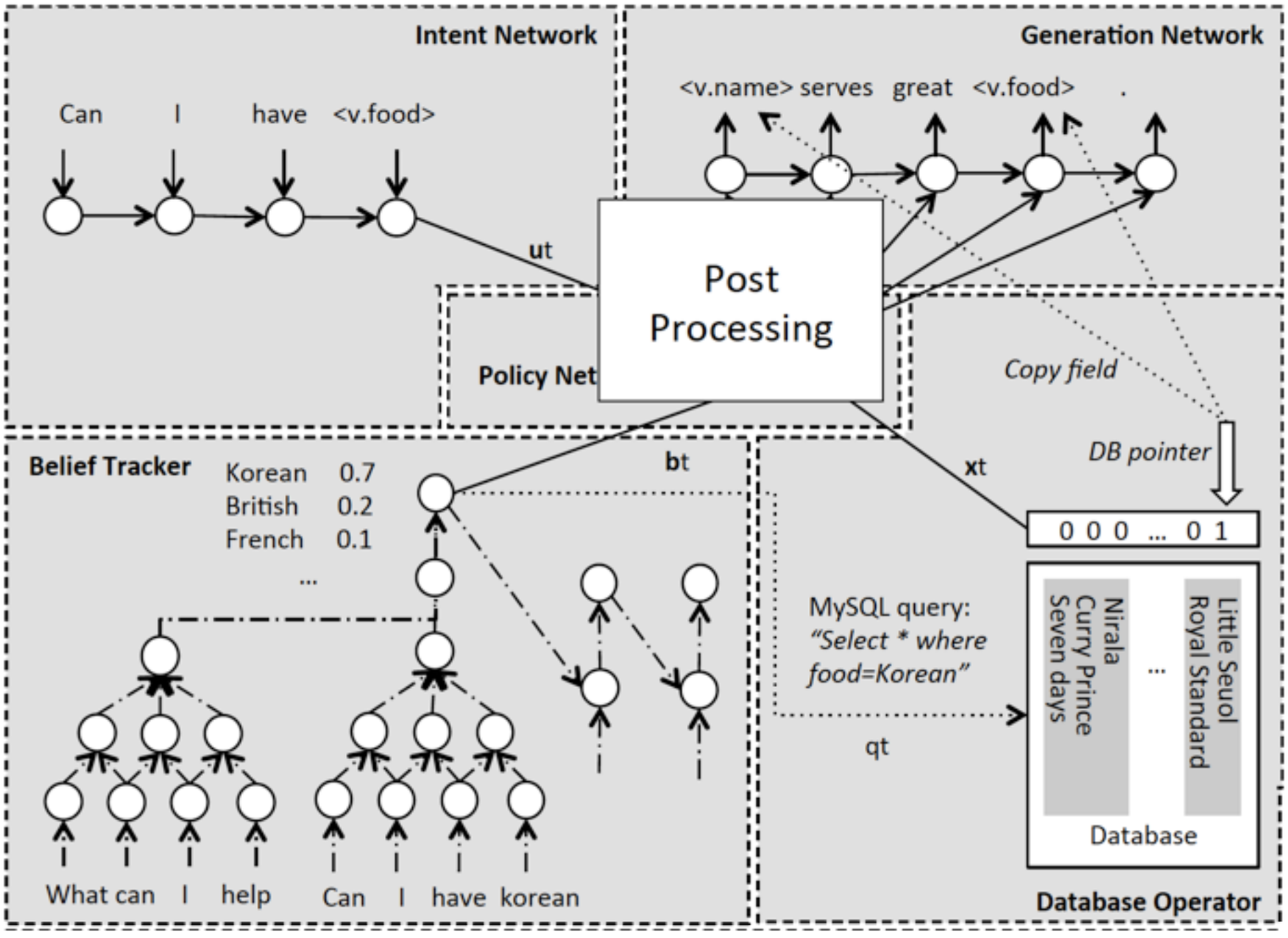
Task-oriented Neural Dialog System

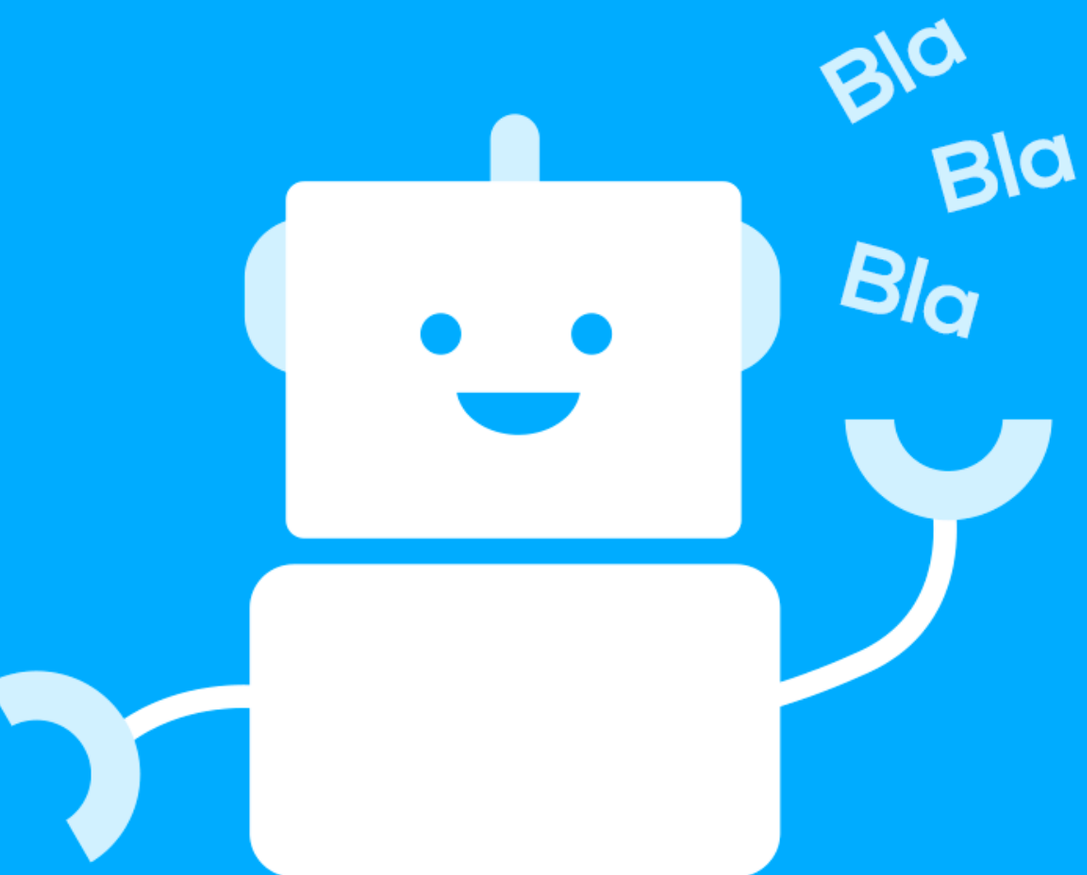


Task-oriented Neural Dialog System



Task-oriented Neural Dialog System





VS.

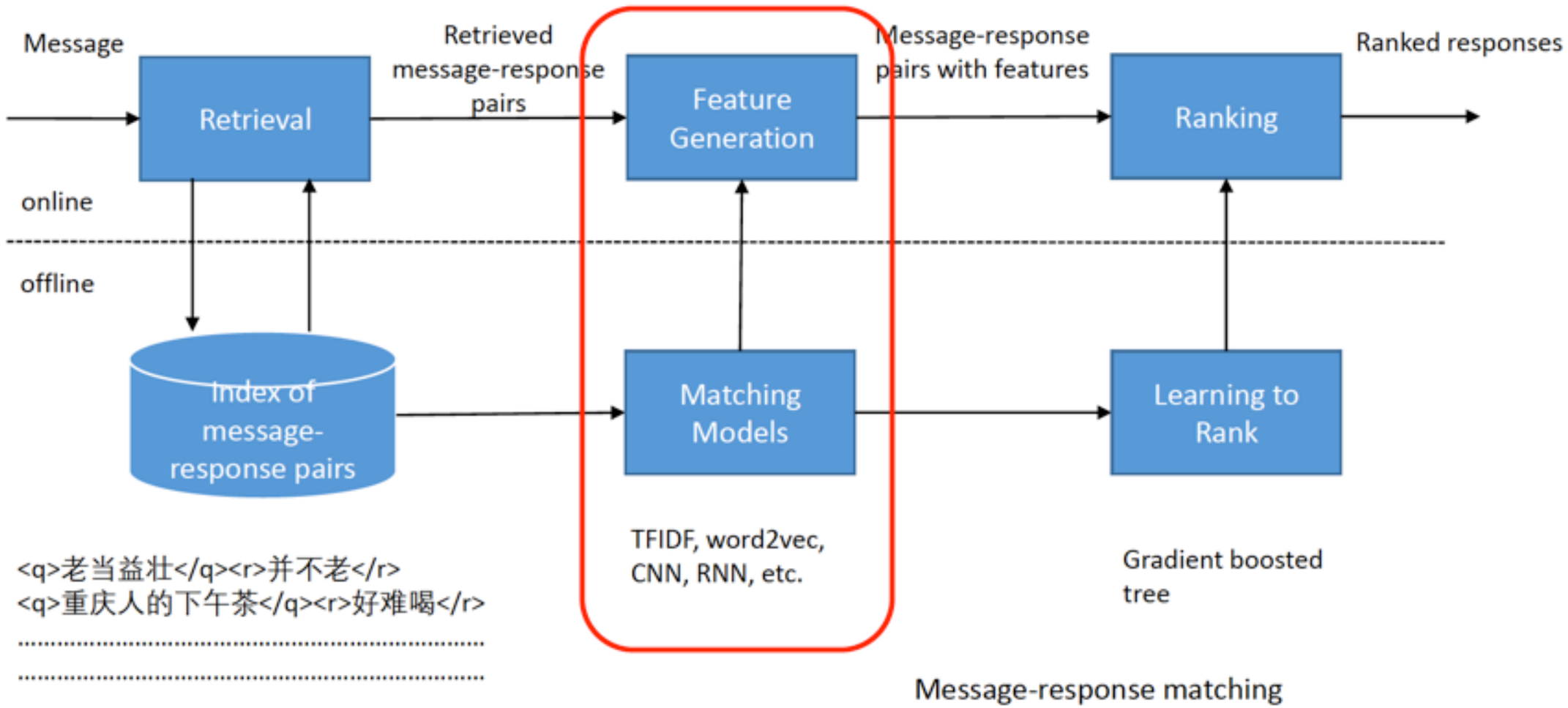
Chit-chat | Conversational Agents

Chit-chat Conversational Agent

- Retrieval-based
- Generation-based

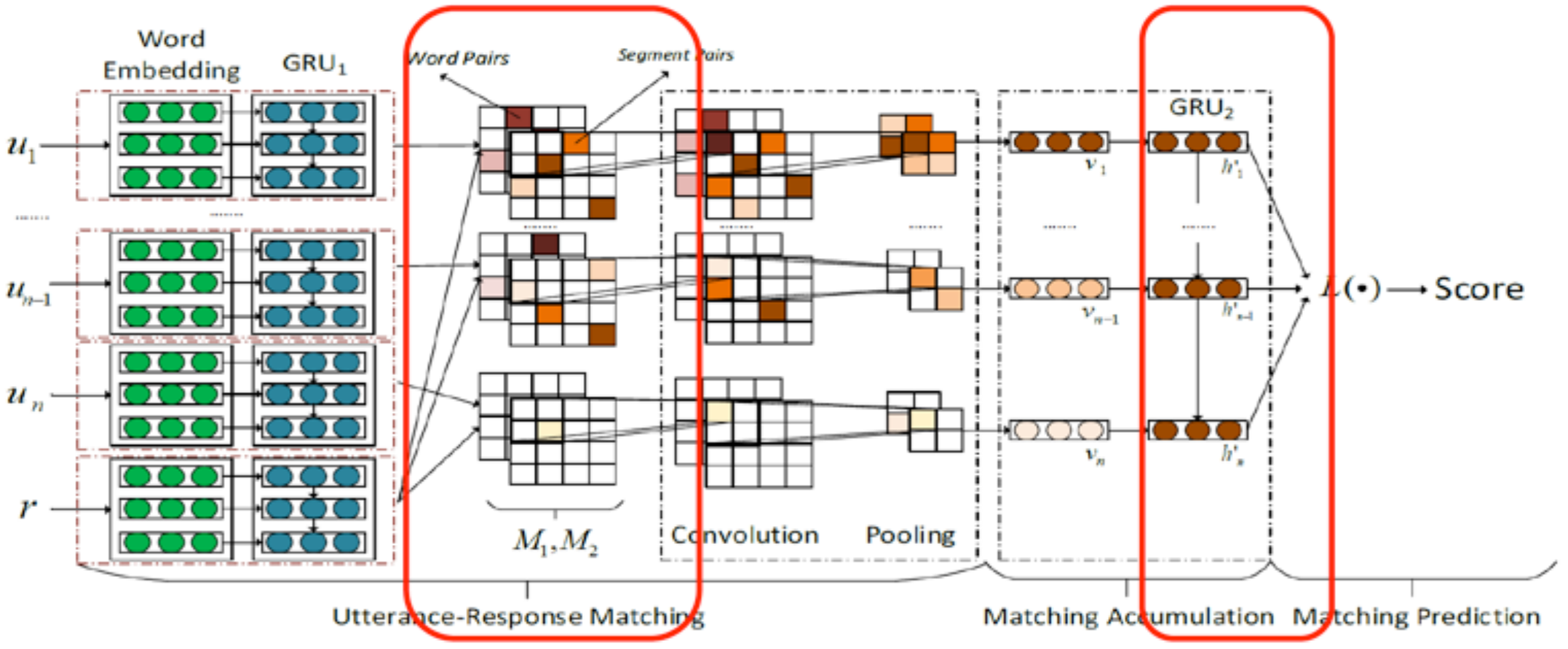
Chit-chat Conversational Agent

- Retrieval-based [9,10]



Chit-chat Conversational Agent

- Retrieval-based [11]

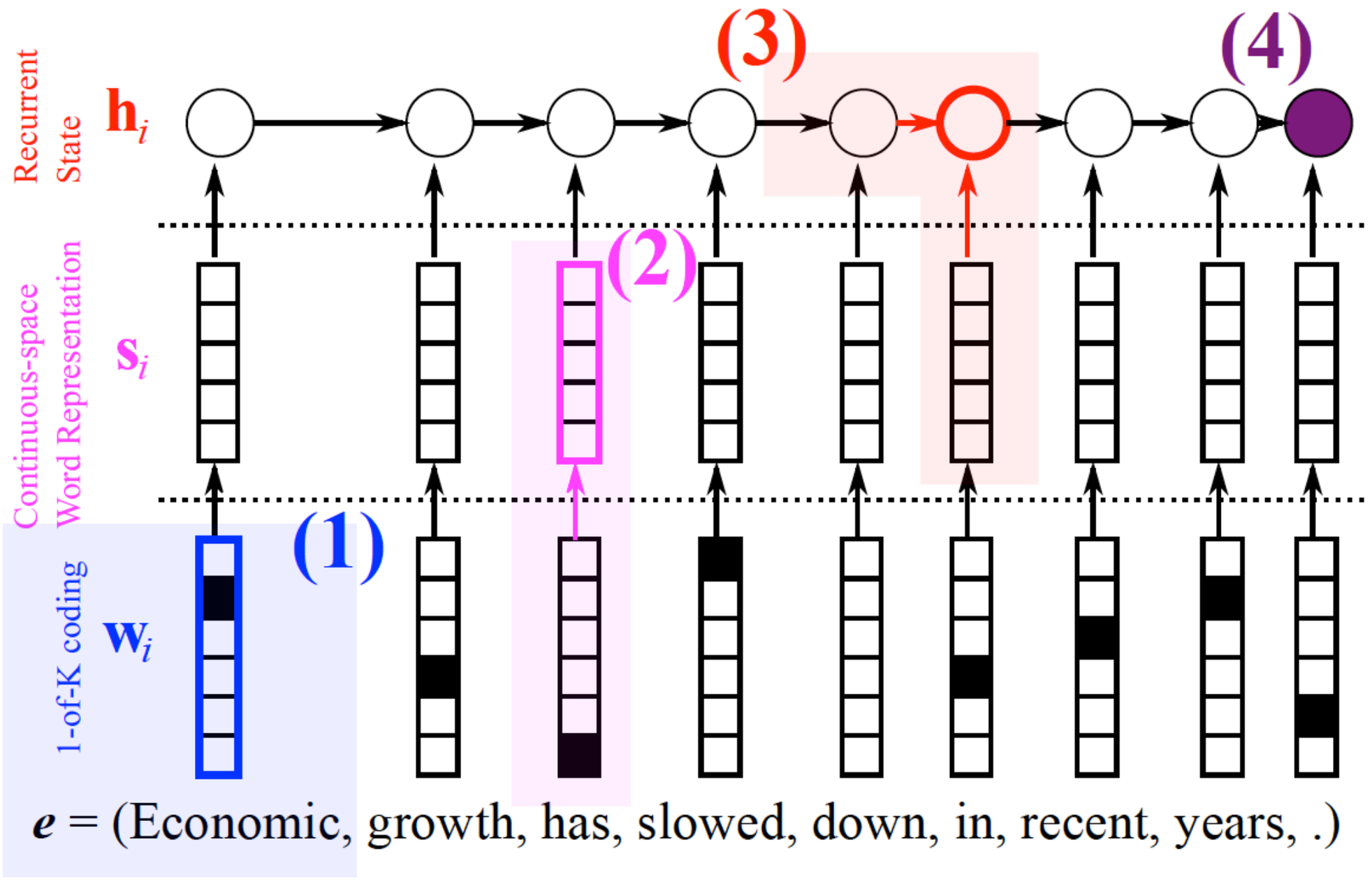


Matching each utterance with response at the beginning

Modeling utterance relationship

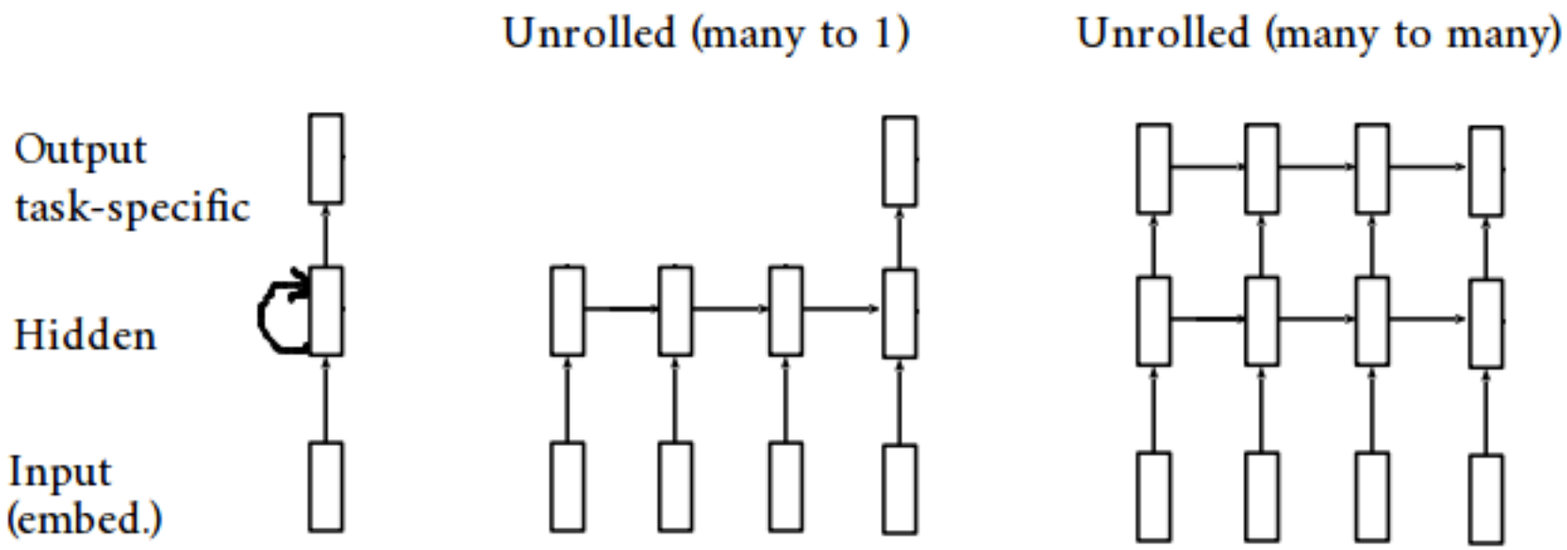
Chit-chat Conversational Agent

- Generation-based



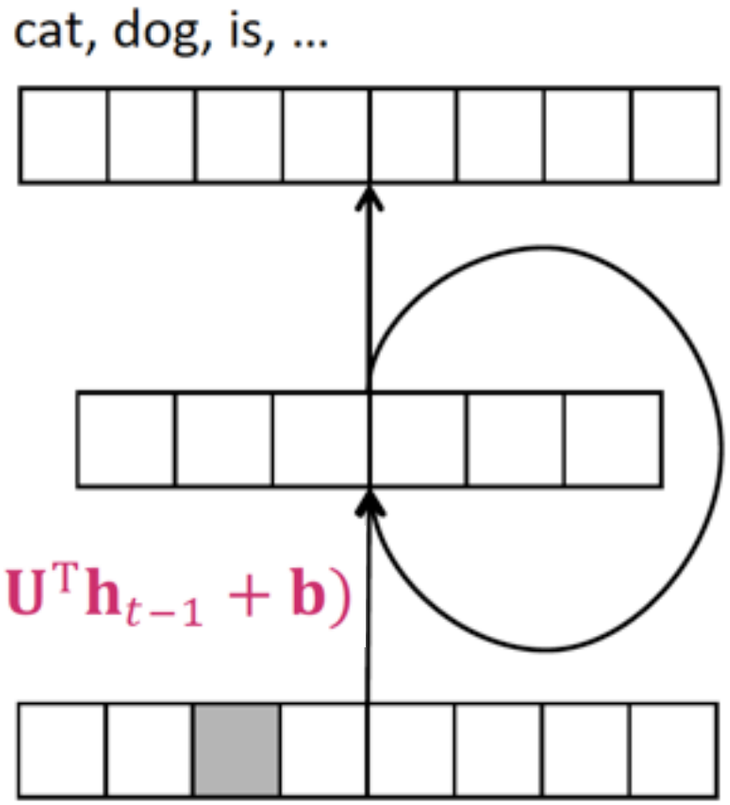
Recurrent Neural Networks (RNN)

- Sentence as sequence of words
- Recursively

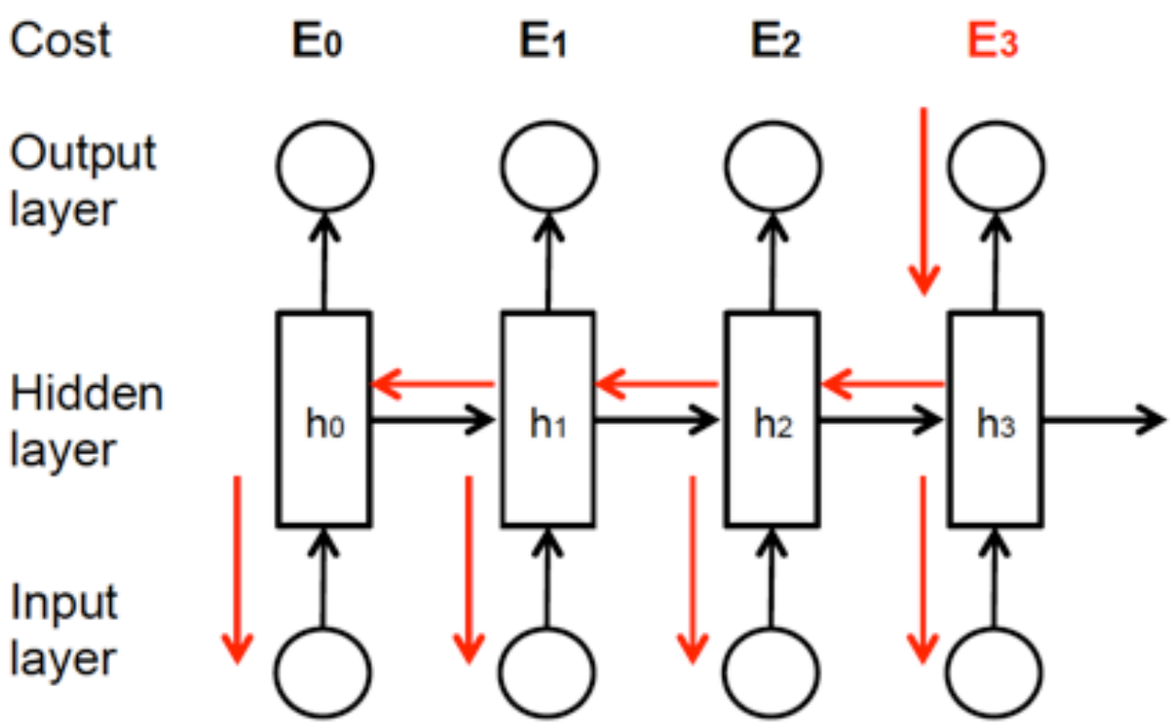


RNN Language Model (RNNLM) [2]

- Non Markovian assumption
- RNNLM
  - 1-of-V encoding for each word x_t
  - Recurrent transition function $\mathbf{h}_t = \tanh(\mathbf{W}^{\mathrm{T}}\mathbf{x}_t + \mathbf{U}^{\mathrm{T}}\mathbf{h}_{t-1} + \mathbf{b})$
  - Softmax output $\mathbf{p}_t = \mathrm{softmax}(\mathbf{V}^{\mathrm{T}}\mathbf{h}_t + \mathbf{c})$
  - Read, update, predict!
  - Can model dependency of arbitrary length



RNN Optimization & Problem



$$\mathbf{h}_t = \tanh(\mathbf{W}^{\mathrm{T}}\mathbf{x}_t + \mathbf{U}^{\mathrm{T}}\mathbf{h}_{t-1} + \mathbf{b})$$

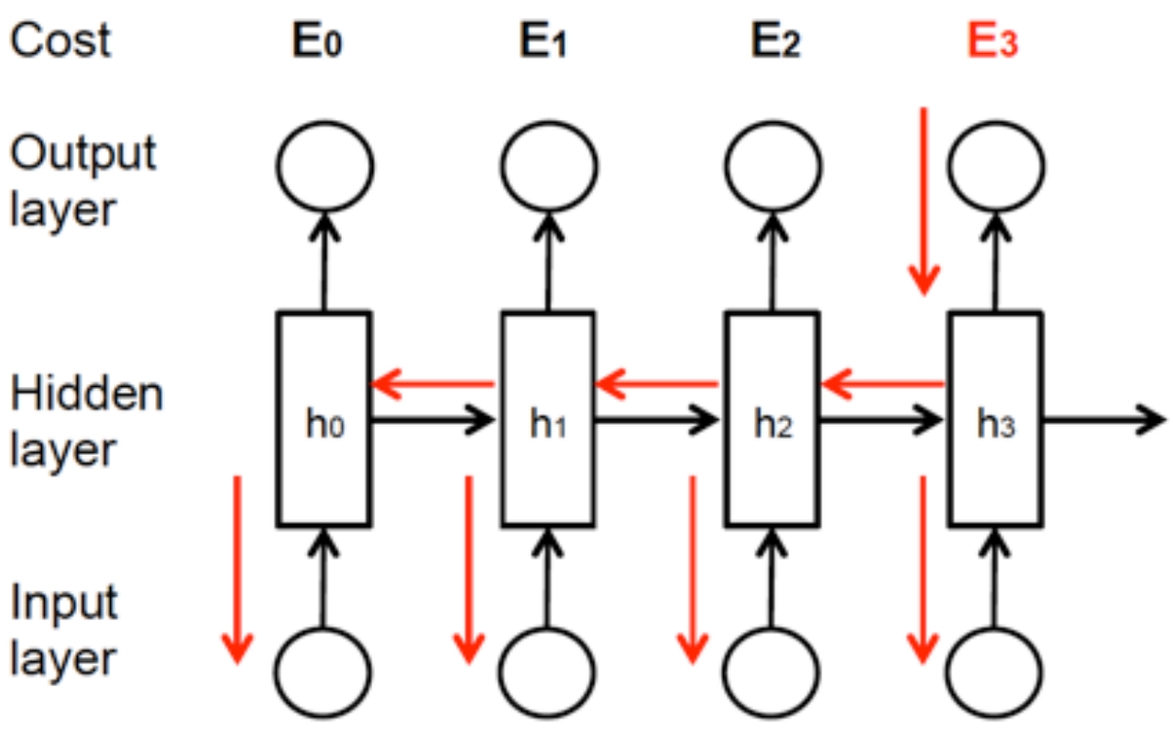
$$\mathbf{p}_t = \mathrm{softmax}(\mathbf{V}^{\mathrm{T}}\mathbf{h}_t + \mathbf{c})$$

$$E_3 = -\mathbf{y}_3^{\mathrm{T}} \log_{10} \mathbf{p}_3$$

$$\frac{\partial E_3}{\partial \mathbf{W}} = \sum_{k=0}^{3} \frac{\partial E_3}{\partial \mathbf{p}_3} \frac{\partial \mathbf{p}_3}{\partial \mathbf{h}_3} \frac{\partial \mathbf{h}_3}{\partial \mathbf{h}_k} \frac{\partial \mathbf{h}_k}{\partial \mathbf{W}}$$

$$= \sum_{k=0}^{3} \frac{\partial E_3}{\partial \mathbf{p}_3} \frac{\partial \mathbf{p}_3}{\partial \mathbf{h}_3} \left(\prod_{j=k+1}^{3} \frac{\partial \mathbf{h}_j}{\partial \mathbf{h}_{j-1}} \right) \frac{\partial \mathbf{h}_k}{\partial \mathbf{W}}$$

RNN Optimization & Problem



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$$= \sum_{k=0}^{3} \frac{\partial E_3}{\partial \mathbf{p}_3} \frac{\partial \mathbf{p}_3}{\partial \mathbf{h}_3} \left(\prod_{j=k+1}^{3} \frac{\partial \mathbf{h}_j}{\partial \mathbf{h}_{j-1}} \right) \frac{\partial \mathbf{h}_k}{\partial \mathbf{W}}$$

$$\frac{\partial \mathbf{h}_j}{\partial \mathbf{h}_{j-1}} = \mathbf{U}^{\mathrm{T}} \cdot \mathrm{diag}(\tanh'(\mathbf{m}_j))$$ ← Jacobian Matrix

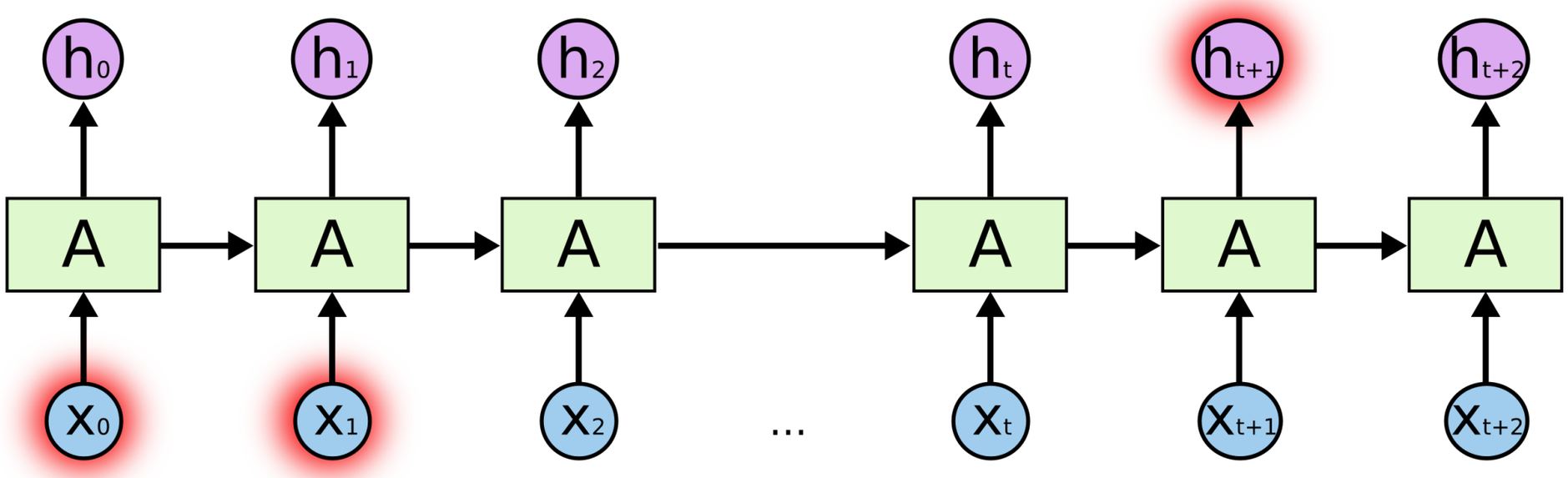
$$\mathbf{m}_j = \mathbf{W}^{\mathrm{T}}\mathbf{x}_j + \mathbf{U}^{\mathrm{T}}\mathbf{h}_{j-1} + \mathbf{b}$$

$$\|\mathbf{U}\| \cdot \left\|\mathrm{diag}\left(\tanh'(\mathbf{m}_j)\right)\right\| < 1$$

Vanishing Gradient Problem! [1]

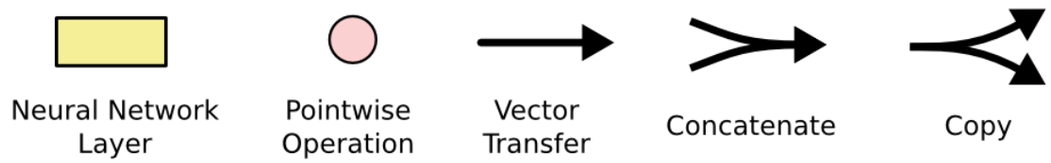
Long-Short Term Memory (LSTM)

- RNN has difficulty in long dependancies [3]

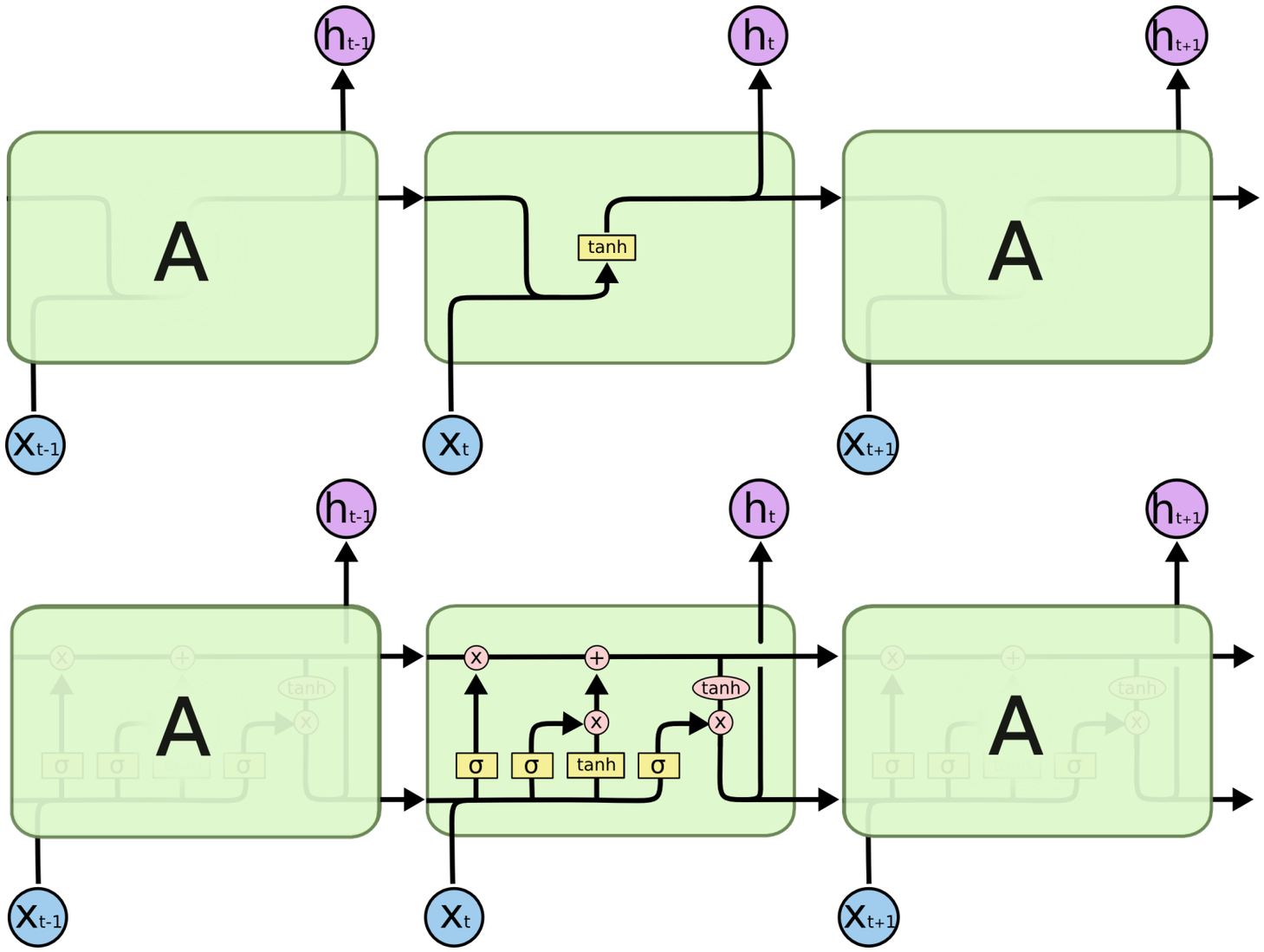


Long-Short Term Memory (LSTM)

- Four interacting layers [3]



- RNN



- LSTM

Long-Short Term Memory (LSTM)

- Three sigmoid gates and One cell

$$\mathbf{i}_t = \sigma(\mathbf{W}_{wi}\mathbf{x}_t + \mathbf{W}_{hi}\mathbf{h}_{t-1})$$

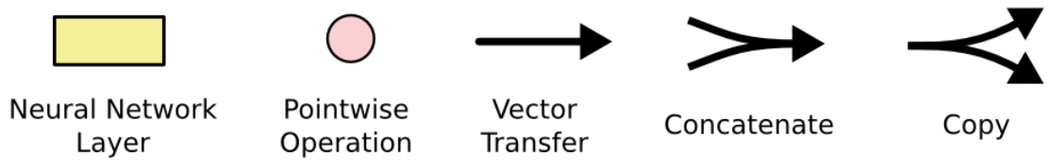
$$\mathbf{f}_t = \sigma(\mathbf{W}_{wf}\mathbf{x}_t + \mathbf{W}_{hf}\mathbf{h}_{t-1})$$

$$\mathbf{o}_t = \sigma(\mathbf{W}_{wo}\mathbf{x}_t + \mathbf{W}_{ho}\mathbf{h}_{t-1})$$

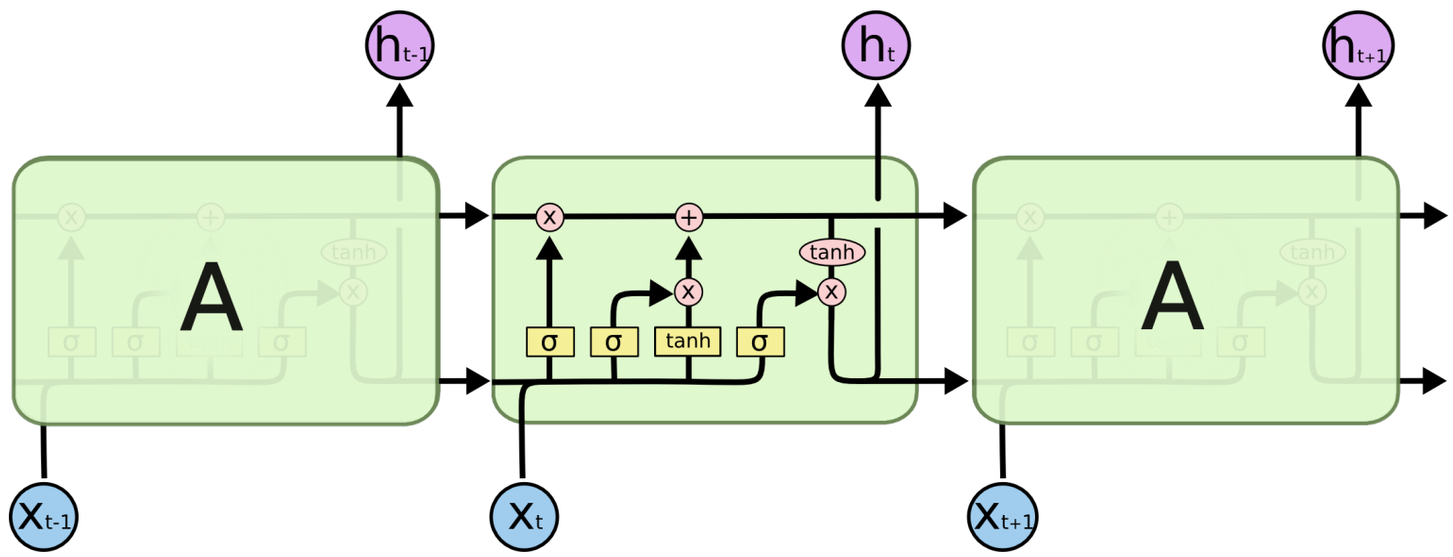
$$\hat{\boldsymbol{c}}_t = \tanh(\mathbf{W}_{wc}\mathbf{x}_t + \mathbf{W}_{hc}\mathbf{h}_{t-1})$$

$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \hat{\boldsymbol{c}}_t$$

$$\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t)$$



- LSTM



Sigmoid gates - forget

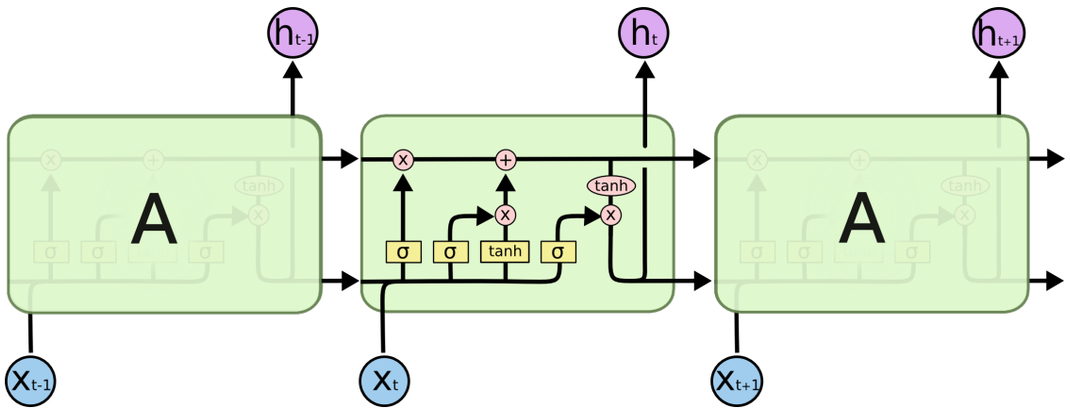
- Three sigmoid gates and One cell

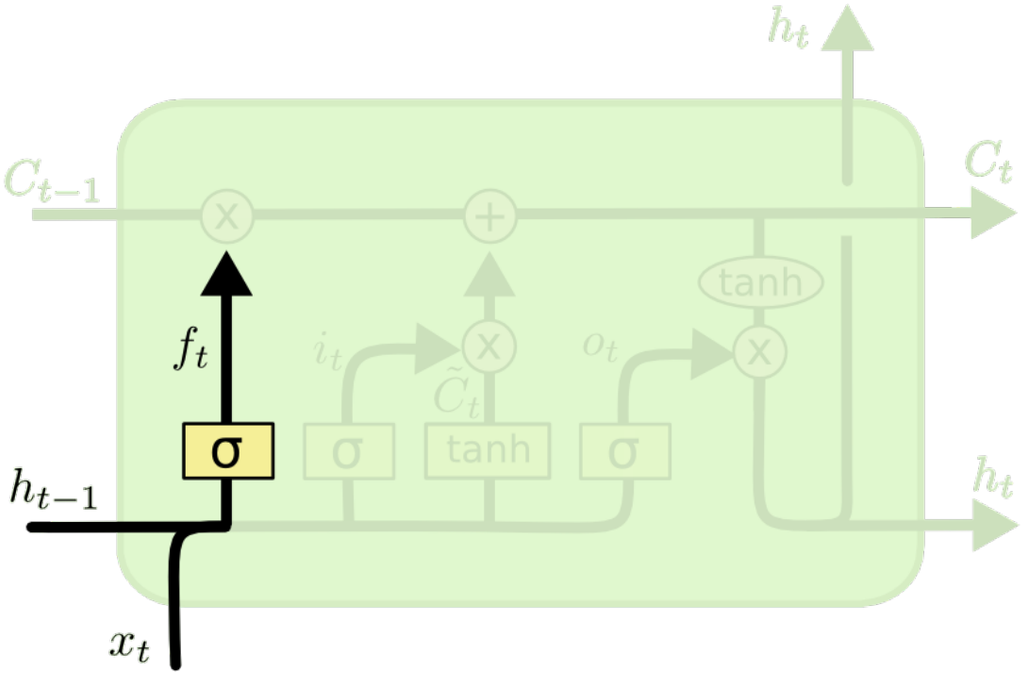
$$\mathbf{i}_t = \sigma(\mathbf{W}_{wi}\mathbf{x}_t + \mathbf{W}_{hi}\mathbf{h}_{t-1})$$

$$\mathbf{f}_t = \sigma(\mathbf{W}_{wf}\mathbf{x}_t + \mathbf{W}_{hf}\mathbf{h}_{t-1})$$

$$\mathbf{o}_t = \sigma(\mathbf{W}_{wo}\mathbf{x}_t + \mathbf{W}_{ho}\mathbf{h}_{t-1})$$

$$\hat{\boldsymbol{c}}_t = \tanh(\mathbf{W}_{wc}\mathbf{x}_t + \mathbf{W}_{hc}\mathbf{h}_{t-1})$$





$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \; + \; b_f\right)$$

Sigmoid gates - new information

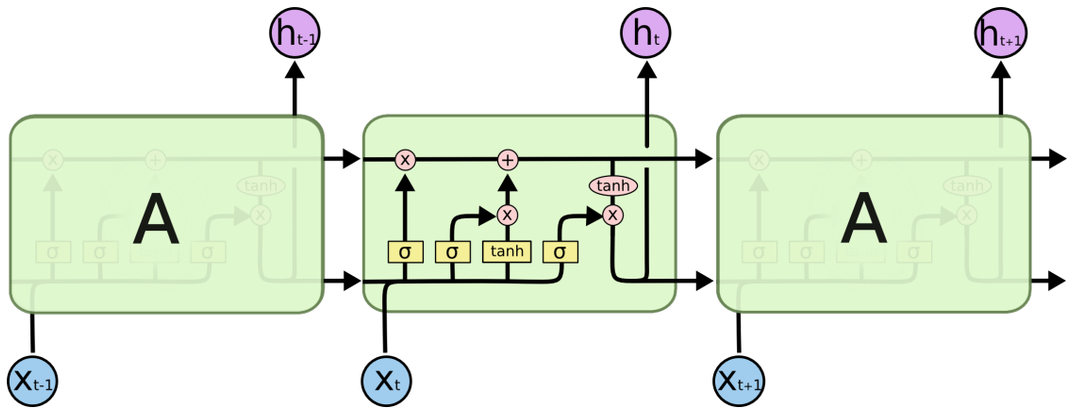
- Three sigmoid gates and One cell

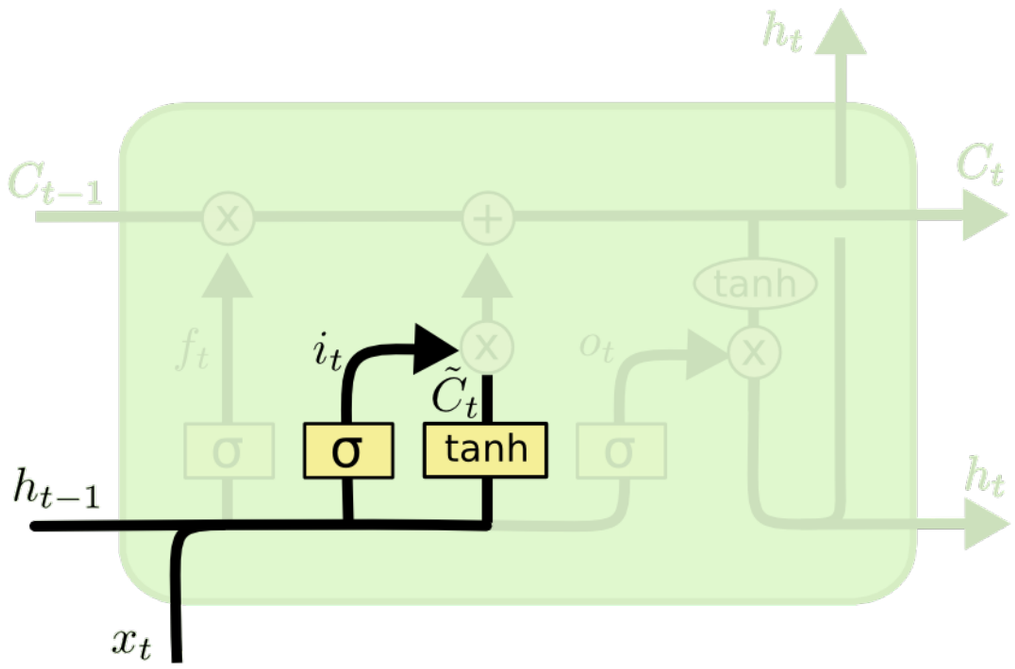
$$\mathbf{i}_t = \sigma(\mathbf{W}_{wi}\mathbf{x}_t + \mathbf{W}_{hi}\mathbf{h}_{t-1})$$

$$\mathbf{f}_t = \sigma(\mathbf{W}_{wf}\mathbf{x}_t + \mathbf{W}_{hf}\mathbf{h}_{t-1})$$

$$\mathbf{o}_t = \sigma(\mathbf{W}_{wo}\mathbf{x}_t + \mathbf{W}_{ho}\mathbf{h}_{t-1})$$

$$\hat{\boldsymbol{c}}_t = \tanh(\mathbf{W}_{wc}\mathbf{x}_t + \mathbf{W}_{hc}\mathbf{h}_{t-1})$$





$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \; + \; b_i\right)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \; + \; b_C)$$

Sigmoid gates - Cell Value

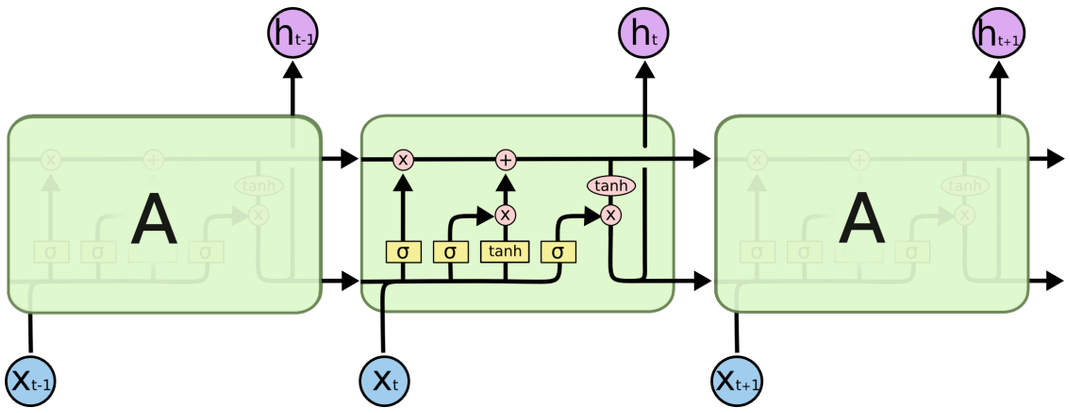
- Three sigmoid gates and One cell

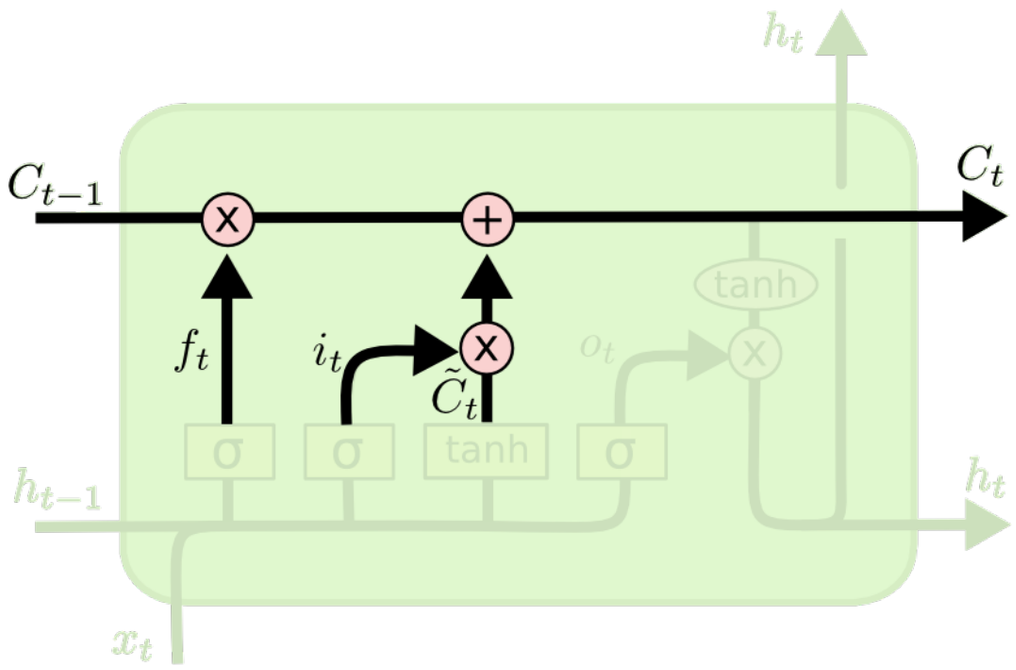
$$\mathbf{i}_t = \sigma(\mathbf{W}_{wi}\mathbf{x}_t + \mathbf{W}_{hi}\mathbf{h}_{t-1})$$

$$\mathbf{f}_t = \sigma(\mathbf{W}_{wf}\mathbf{x}_t + \mathbf{W}_{hf}\mathbf{h}_{t-1})$$

$$\mathbf{o}_t = \sigma(\mathbf{W}_{wo}\mathbf{x}_t + \mathbf{W}_{ho}\mathbf{h}_{t-1})$$

$$\hat{\boldsymbol{c}}_t = \tanh(\mathbf{W}_{wc}\mathbf{x}_t + \mathbf{W}_{hc}\mathbf{h}_{t-1})$$





$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

Sigmoid gates - Output

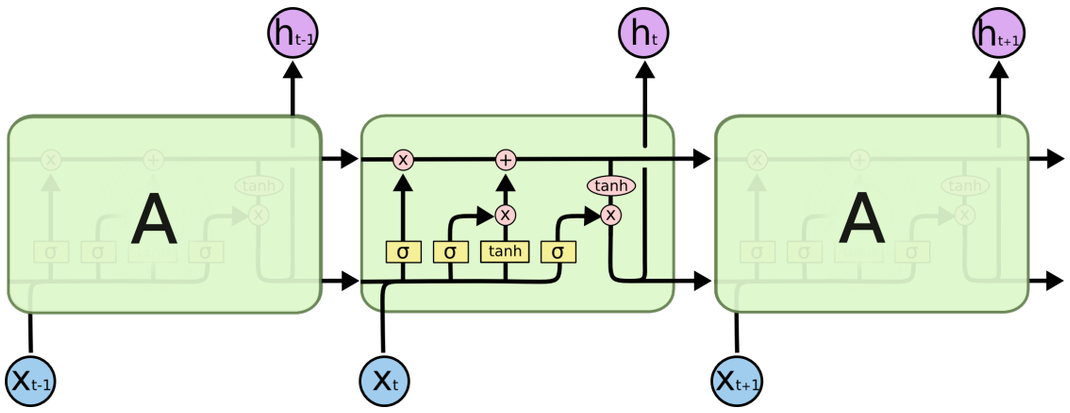
- Three sigmoid gates and One cell

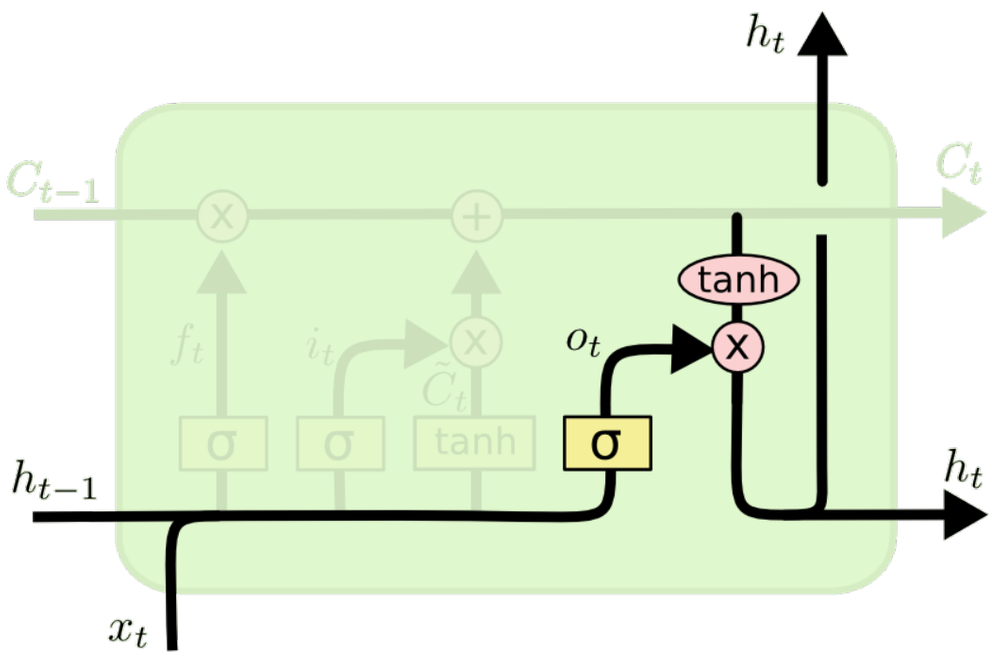
$$\mathbf{i}_t = \sigma(\mathbf{W}_{wi}\mathbf{x}_t + \mathbf{W}_{hi}\mathbf{h}_{t-1})$$

$$\mathbf{f}_t = \sigma(\mathbf{W}_{wf}\mathbf{x}_t + \mathbf{W}_{hf}\mathbf{h}_{t-1})$$

$$\mathbf{o}_t = \sigma(\mathbf{W}_{wo}\mathbf{x}_t + \mathbf{W}_{ho}\mathbf{h}_{t-1})$$

$$\hat{\boldsymbol{c}}_t = \tanh(\mathbf{W}_{wc}\mathbf{x}_t + \mathbf{W}_{hc}\mathbf{h}_{t-1})$$





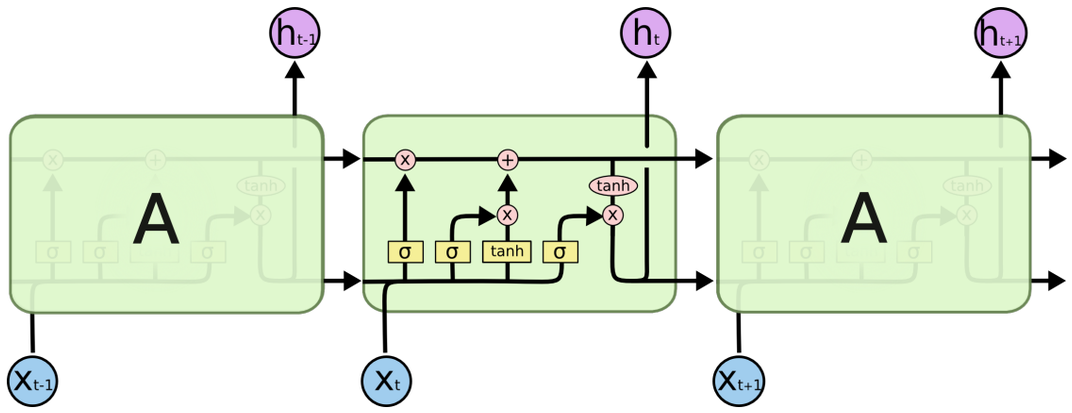
$$o_t = \sigma\left(W_o\left[h_{t-1}, x_t\right] + b_o\right)$$

$$h_t = o_t * \tanh\left(C_t\right)$$

LSTM theoretically prevent gradient vanishing

- Consider memory cell update

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



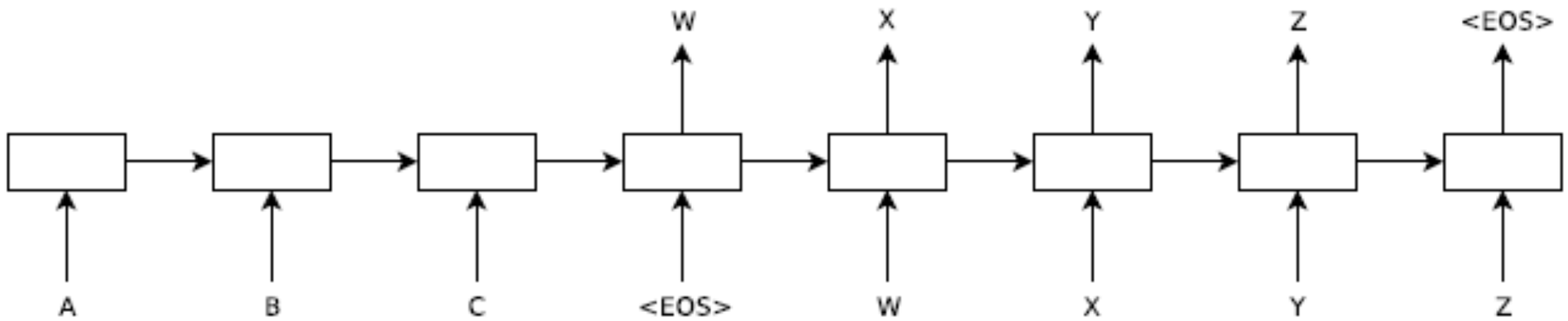
- We can back-prop the gradient by chain rule

$$\frac{\partial E_t}{\partial C_{t-1}} = \frac{\partial E_t}{\partial C_t}\frac{\partial C_t}{\partial C_{t-1}} = \frac{\partial E_t}{\partial C_t} f_t$$

- If ft maintains a value of 1, gradient is perfectly propagated.

Sequence to sequence learning with

- The encoder-decoder framework [4]

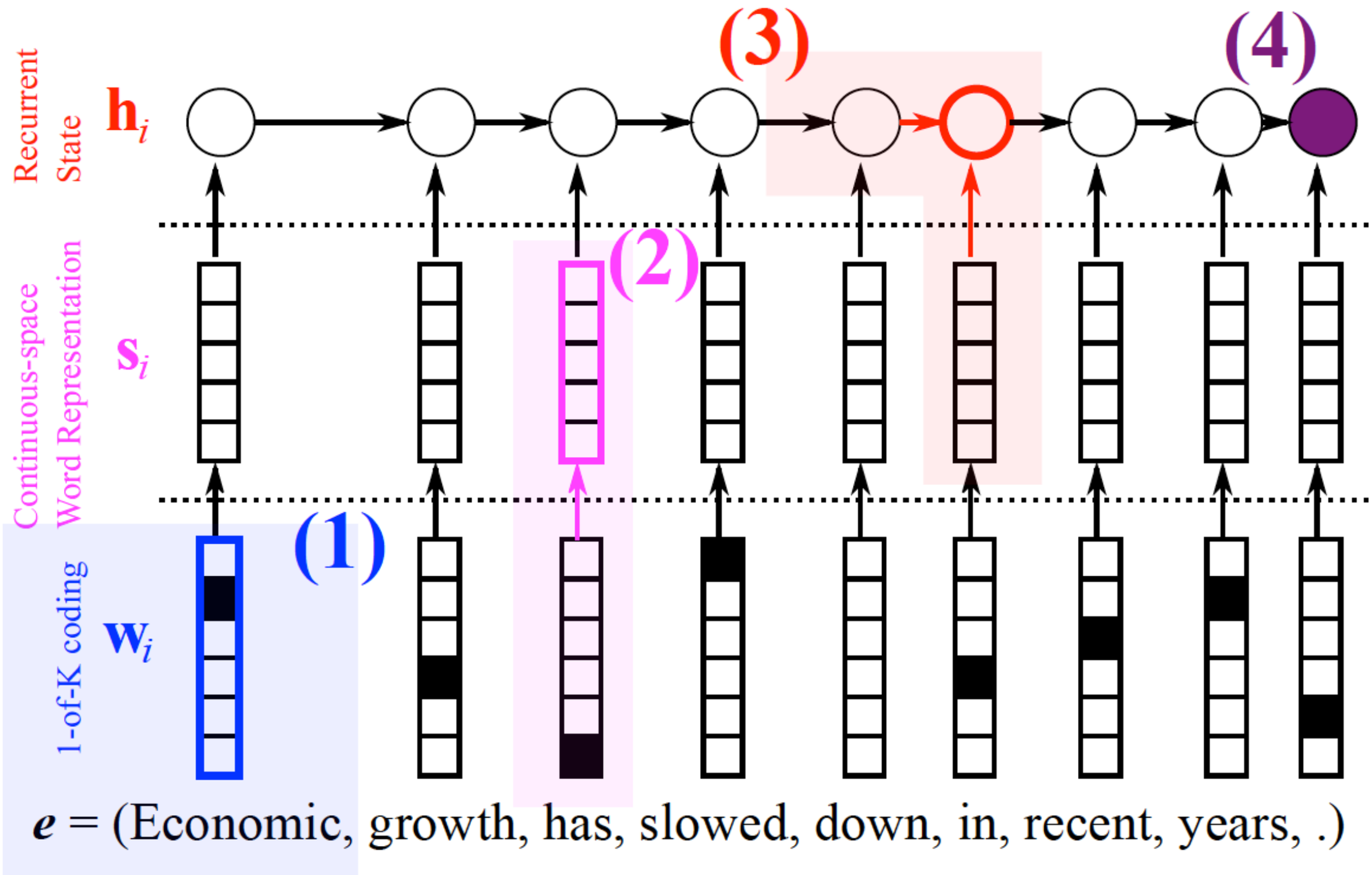


- Encoder reads sentence “A B C” in source language
- Decoder generates sentence “W X Y Z” in target language

The encoder-decoder framework

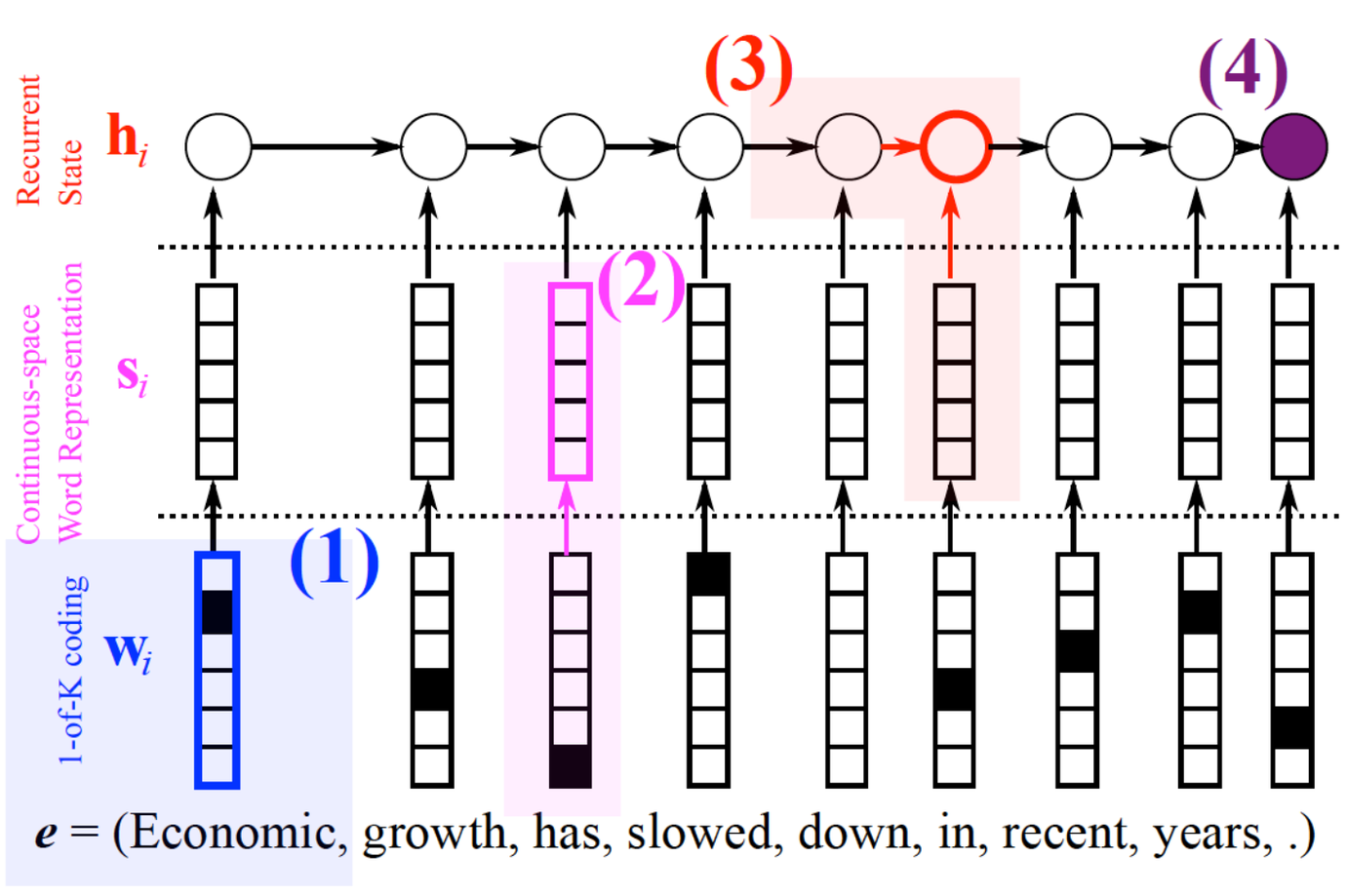
- Comprehensive
  - It unites content understanding and language modelling in a single architecture.
  - Thus, it allows the end-to-end automatic generation.
- Flexible
  - It allows to condition on anything, i.e. images, videos, words, etc.
- Scalable
  - Able to supplement the language model with external corpora.

The encoder-decoder framework — Encoder

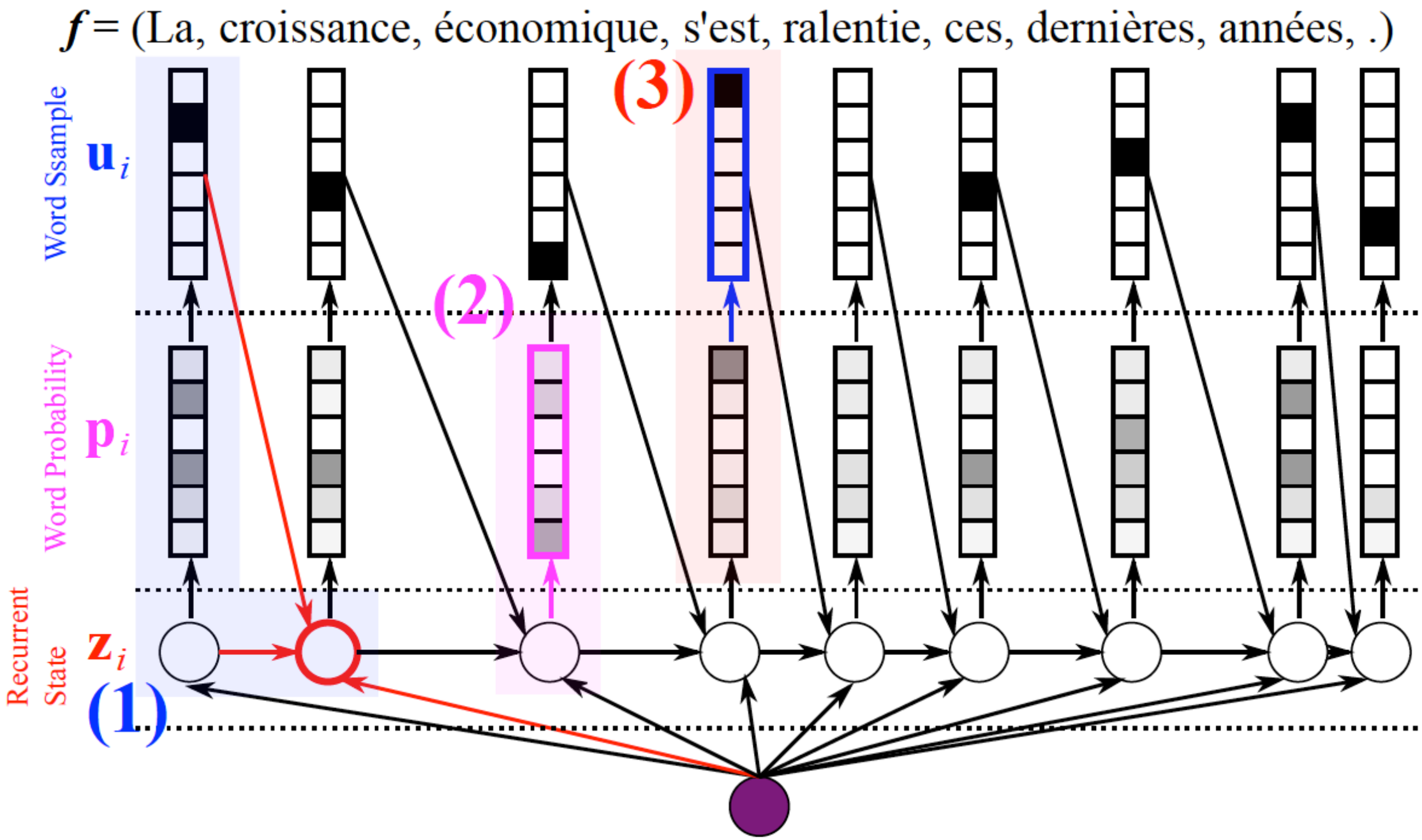


The encoder-decoder framework — Encoder

- 1-of-K coding of source words
- Continuous-space representation
- Recursively read words

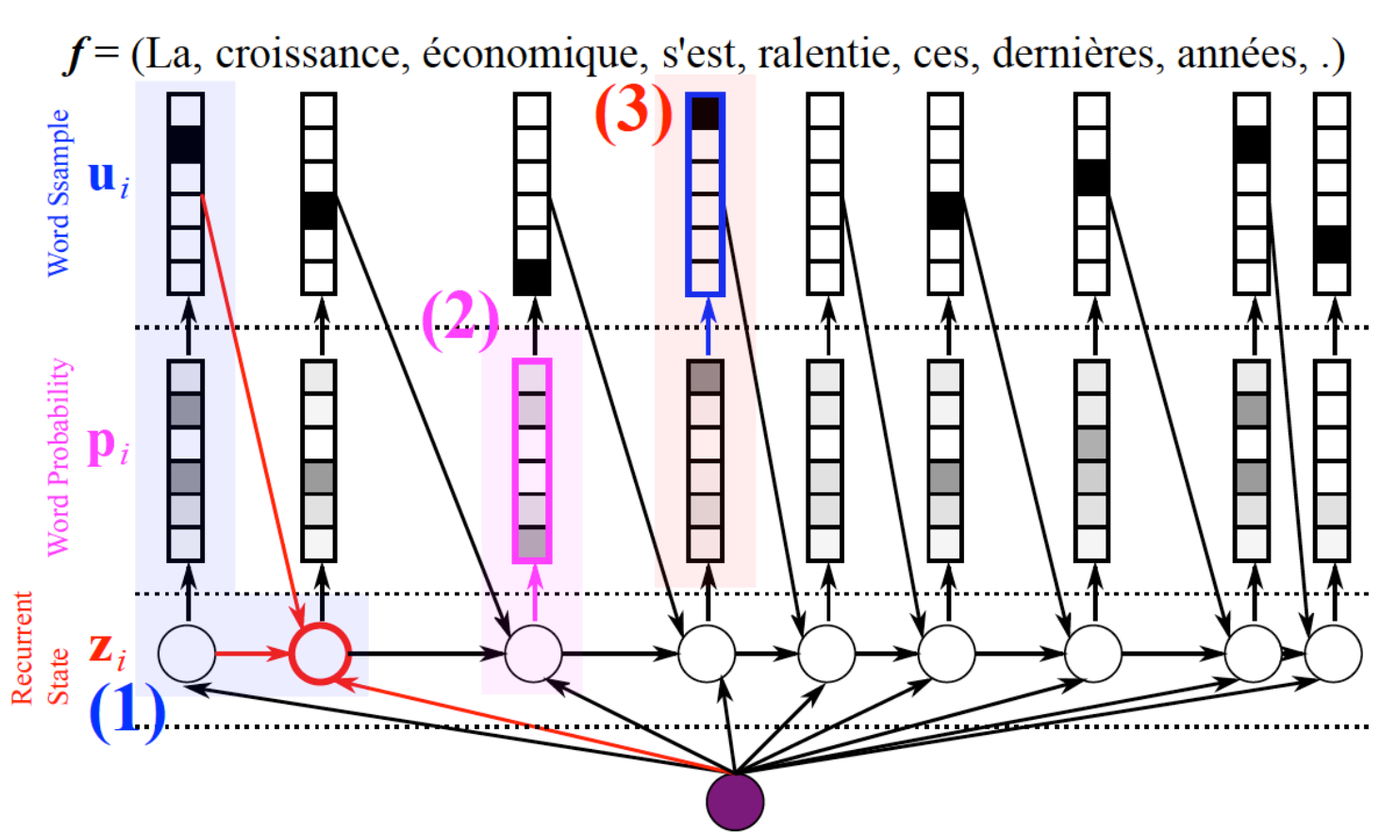


The encoder-decoder framework — Decoder



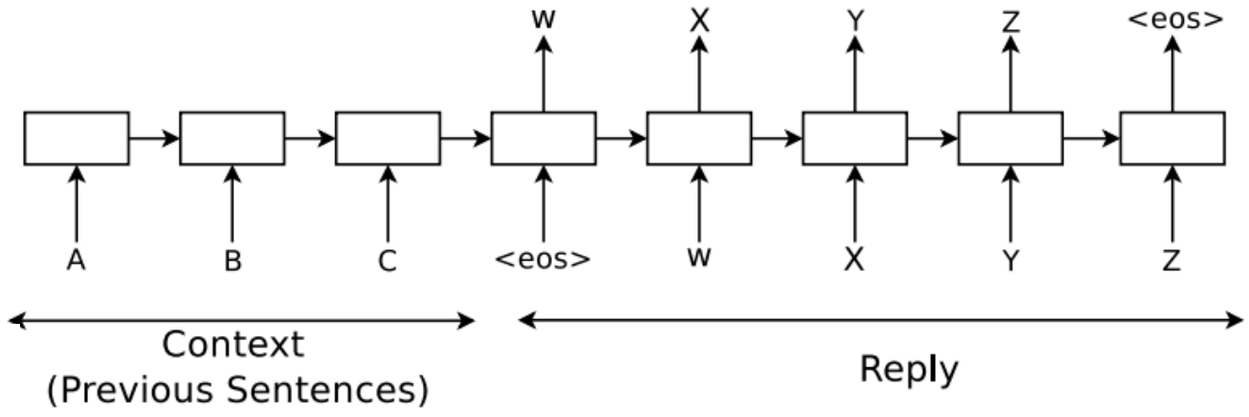
The encoder-decoder framework — Decoder

- Recursively update the memory
- Compute the next word probability
- Sample a next word



A Neural Conversational Model

- The encoder-decoder [6]

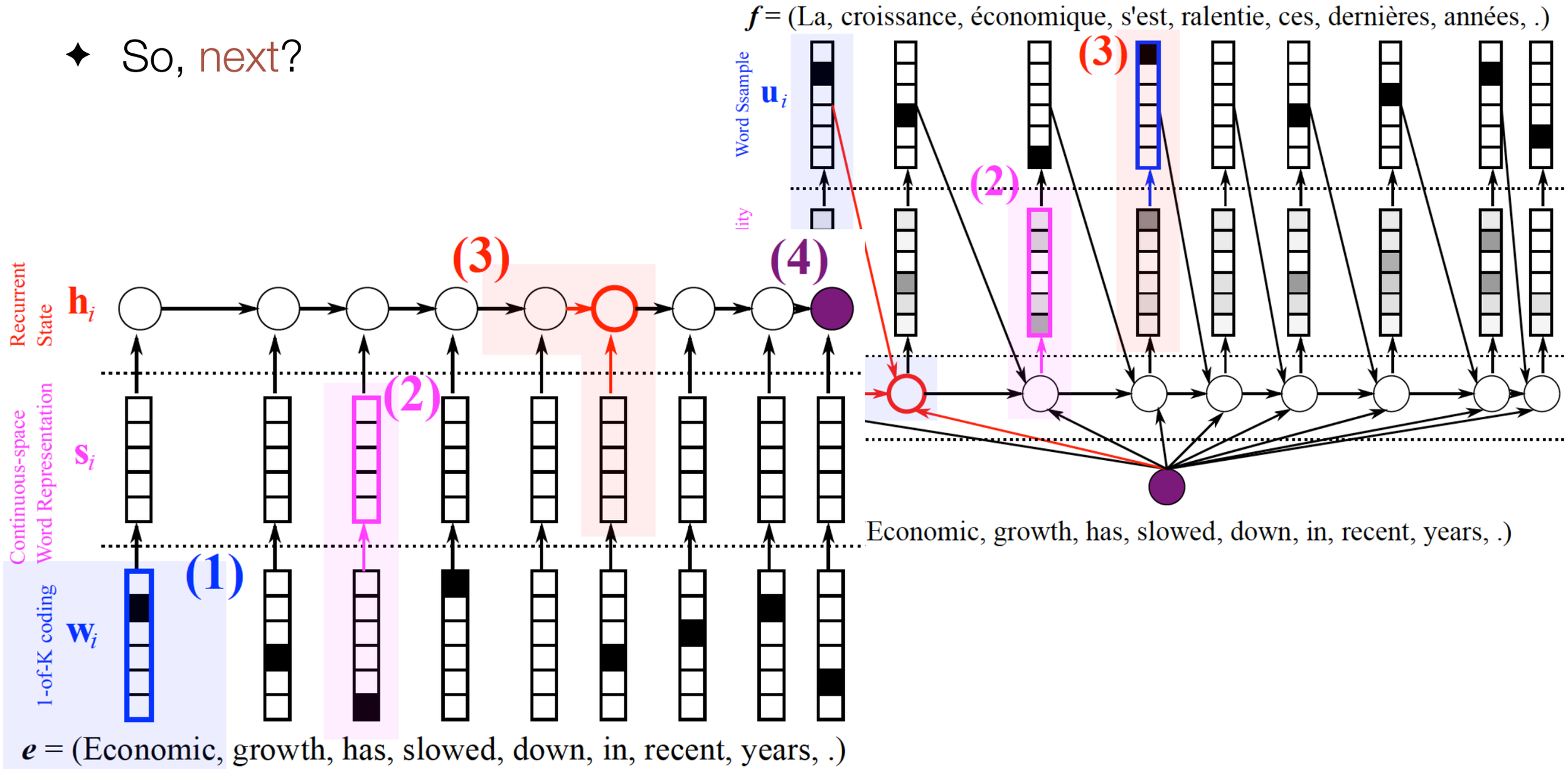


Human: *what is the purpose of life ?*
Machine: *to serve the greater good .*
Human: *what is the purpose of living ?*
Machine: *to live forever .*
Human: *what is the purpose of existence ?*
Machine: *to find out what happens when we get to the planet earth .*
Human: *where are you now ?*
Machine: *i 'm in the middle of nowhere .*
Human: *what is the purpose of dying ?*
Machine: *to have a life .*
Human: *what is the purpose of being intelligent ?*
Machine: *to find out what it is .*
Human: *what is the purpose of emotions ?*
Machine: *i don 't know .*

Human: *what do you think about tesla ?*
Machine: *he 's a good conductor .*
Human: *what do you think about bill gates ?*
Machine: *he 's a good man .*
Human: *What do you think about messi ?*
Machine: *he 's a great player .*
Human: *what do you think about cleopatra ?*
Machine: *oh , she 's very regal .*
Human: *what do you think about england during the reign of elizabeth ?*
Machine: *it was a great place .*

It looks fantastic, but…

- “You can’t cram the meaning of a whole %&!$# sentence into a single $&! #* vector!”
- So, next?



Difficulties for all generation tasks

- RNN/LSTM's problem
  - impotent for too long sentences (semantic drift)
  - grammatically problematic
  - highly frequent pattern domination (less variation)

Difficulties for all generation tasks

- RNN/LSTM's problem[8]

i went to the store to buy some groceries .
i store to buy some groceries .
i were to buy any groceries .
horses are to buy any groceries .
horses are to buy any animal .
horses the favorite any animal .
horses the favorite favorite animal .
horses are my favorite animal .

Table 1: Sentences produced by greedily decoding from points between two sentence encodings with a conventional autoencoder. The intermediate sentences are not plausible English.

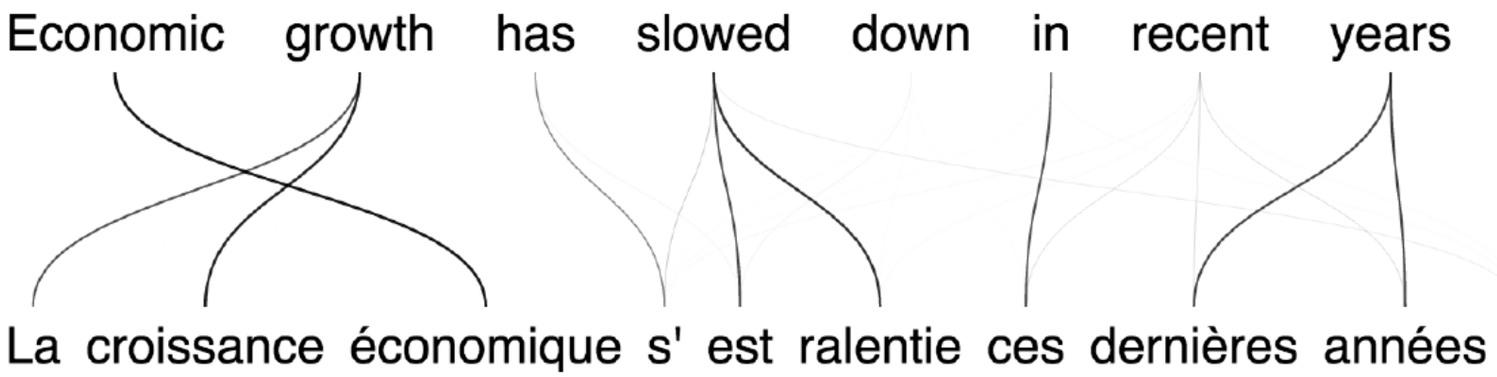
" i want to talk to you . "
"i want to be with you . "
"i do n't want to be with you . "
i do n't want to be with you .
she did n't want to be with him .
he was silent for a long moment .
he was silent for a moment .
it was quiet for a moment .
it was dark and cold .
there was a pause .
it was my turn .

Table 8: Paths between pairs of random points in VAE space: Note that intermediate sentences are grammatical, and that topic and syntactic structure are usually locally consistent.

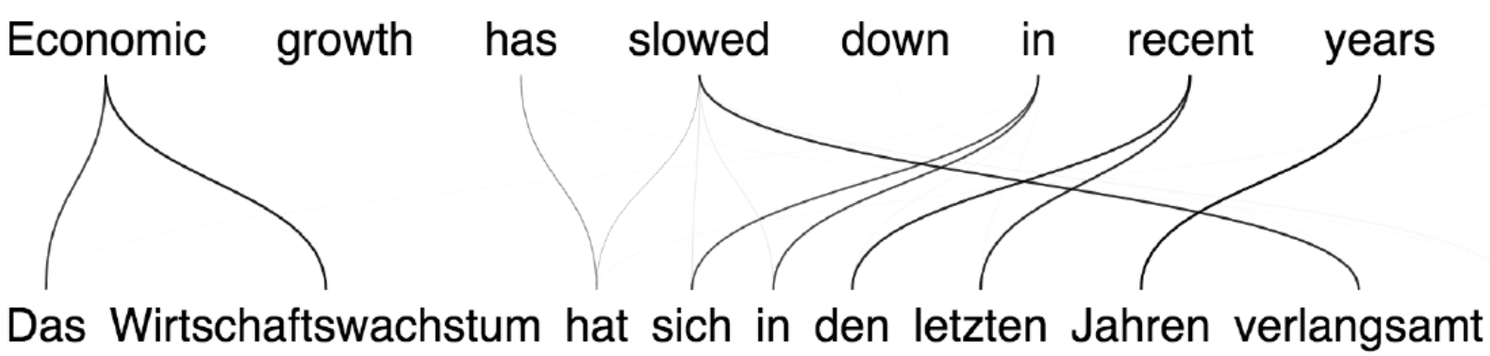
Attention-based Neural Machine Translation

- ✦ fixed representation of source sentence —> soft and dynamic[5]

English-French

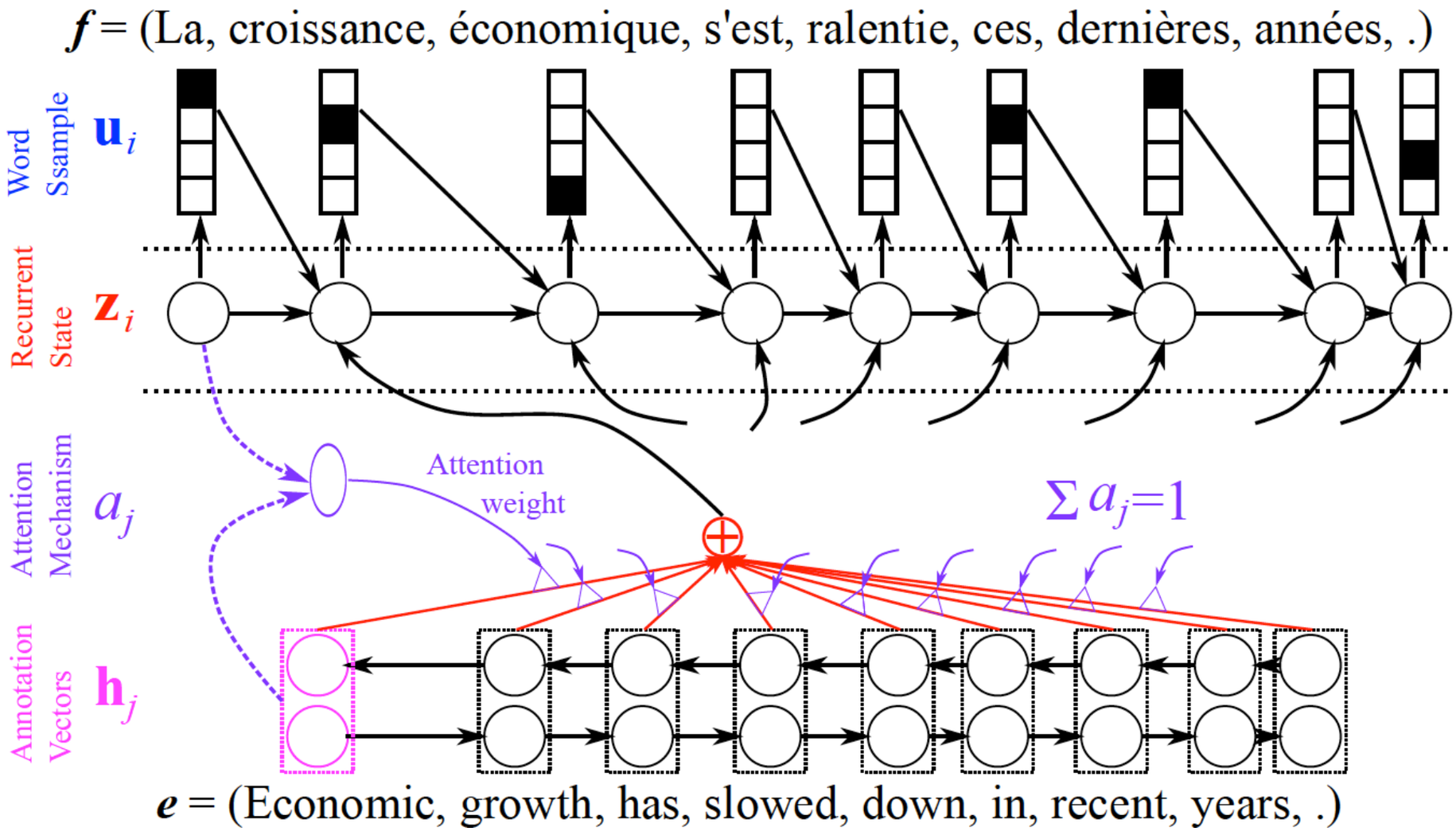


English-German



Attention Mechanism

- fixed representation of source sentence —> soft and dynamic[5]



Attention Mechanism

- At every generation step t [5]
  - Score source h_j by

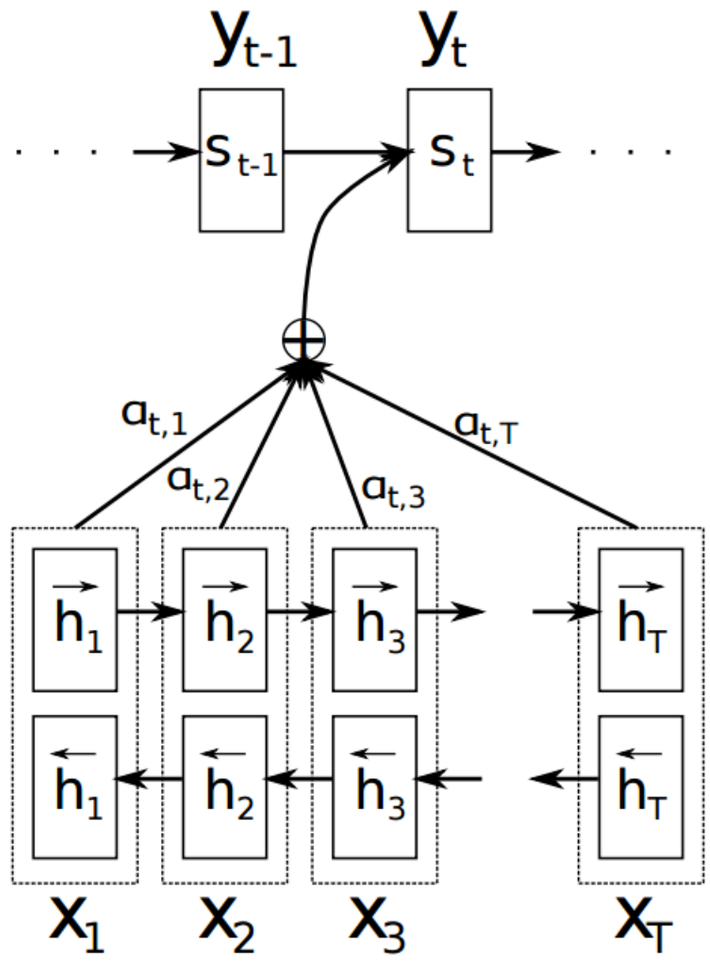
$$e_{tj} = \mathbf{v}^{\mathrm{T}} \tanh(\mathbf{W} \cdot \mathbf{s}_{t-1} + \mathbf{U} \cdot \mathbf{h}_j)$$

$$\alpha_{tj} = \mathrm{softmax}(e_{tj})$$

  - Take an expectation over sources

$$\mathbf{c}_t = \sum_j \alpha_{tj} \, \mathbf{h}_j$$

- Everything is differentiable.
  Back-prop end-to-end!



Homework

- Tutorial Reading:
  - Deep Learning For Chatbots:
    - http://www.wildml.com/2016/04/deep-learning-for-chatbots-part-1-introduction
    - http://www.wildml.com/2016/07/deep-learning-for-chatbots-2-retrieval-based-model-tensorflow/
- Code Reading:
  - Neural Dialog System: https://github.com/shawnwun/NNDIAL
  - A Neural Conversational Model: https://github.com/Conchylicultor/DeepQA
  - Attention-based Conversational Model: https://github.com/pbhatia243/Neural_Conversation_Models

Thanks for your attention!

Q&A

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