generation

Inference and Neural Dialogue Modeling

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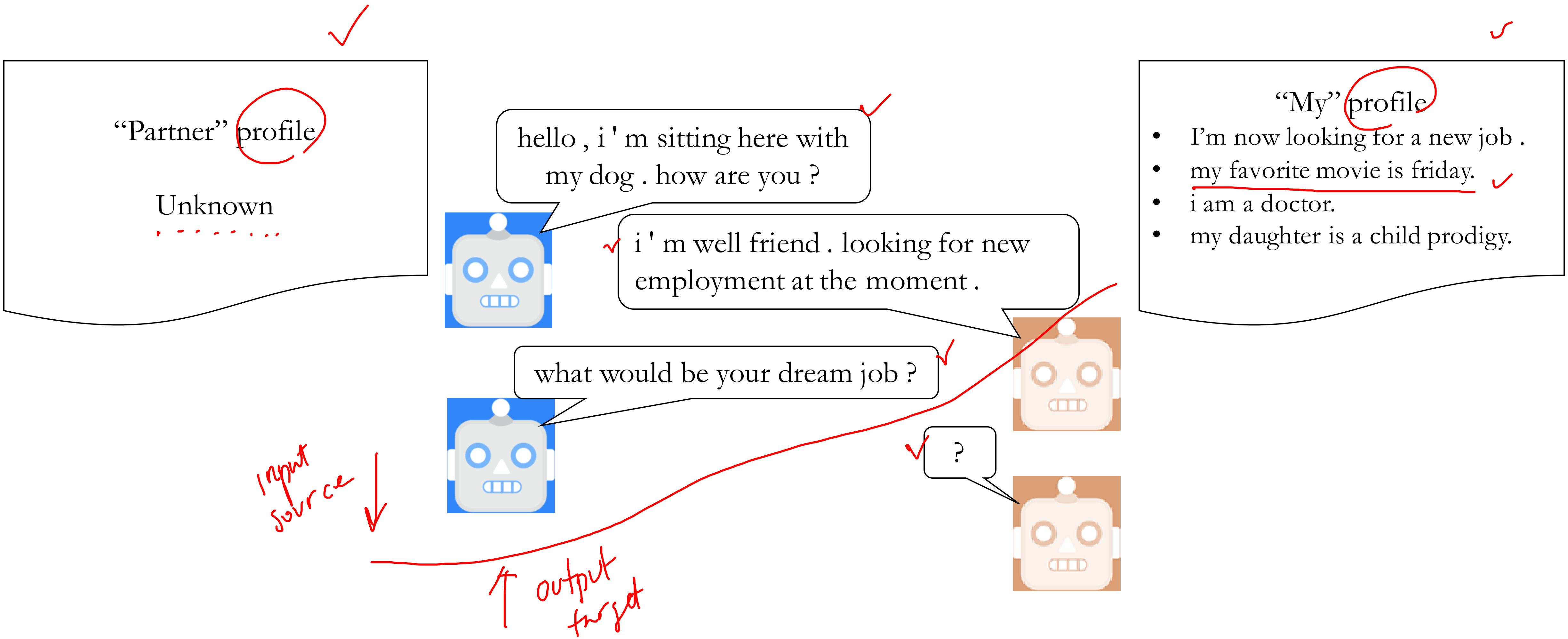
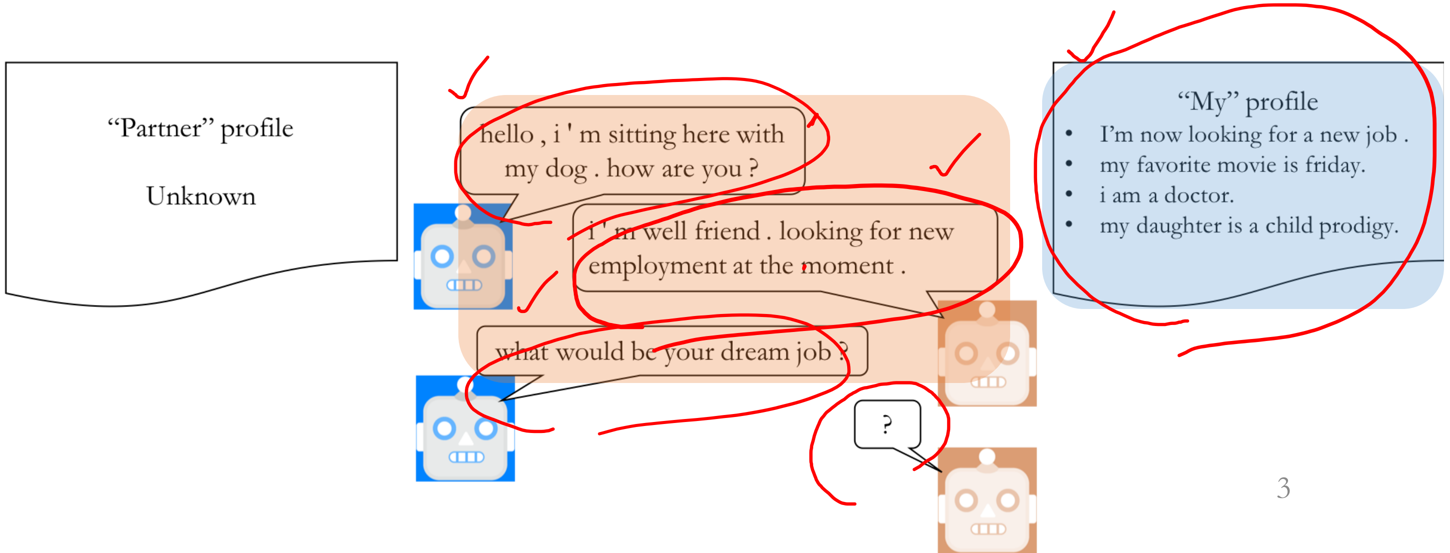
Building a simple neural conversational model



Building a simple neural conversation~~al~~ model

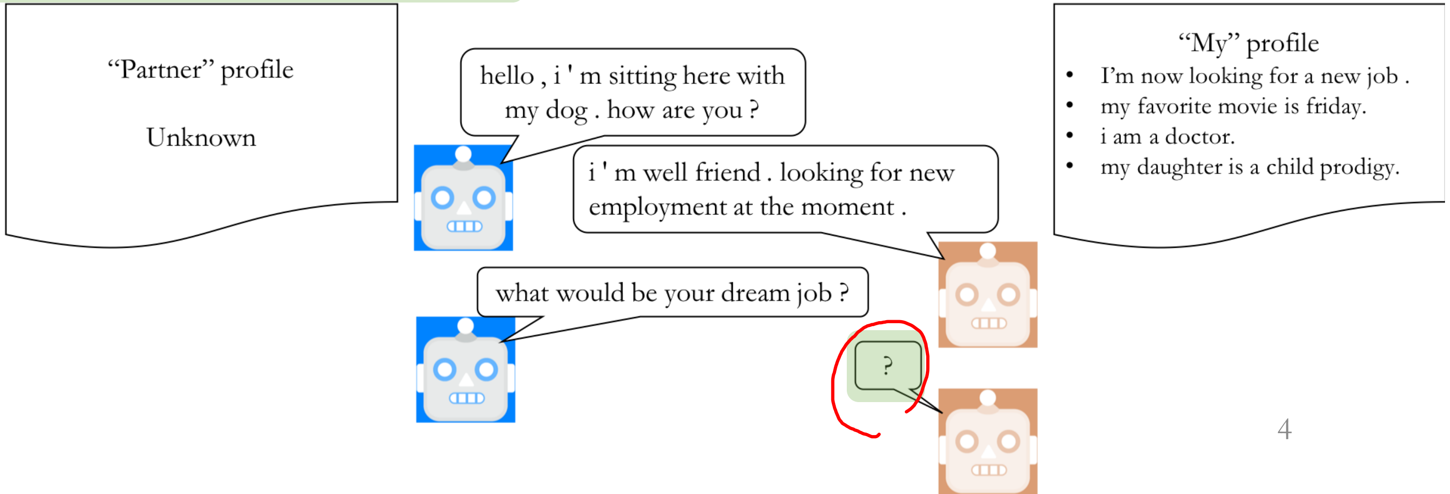
profile

- Input: a flat sequence of personality descriptions and previous utterances
  - <p>I'm now looking for a new job.<\n><p>my favourite movie is friday.<p>I am a doctor<\n><p>my daughter is a child prodigy<\n><u1>hello, I'm sitting here with my dog. How are you?<\n><u2>I'm well friend. Looking for new employment at the moment.<\n><u1>what would be your dream job?<\n>



Building a simple neural conversational model

- Input: a flat sequence of personality descriptions and previous utterances
  - <p>I’m now looking for a new job.<\n><p>my favourite movie is friday.<p>I am a doctor<\n><p>my daughter is a child prodigy<\n><u1>hello, I’m sitting here with my dog. How are you?<\n><u2>I’m well friend. Looking for new employment at the moment.<\n><u1>what would be your dream job?<\n>
- Target: a flat sequence of human/annotator’s reponse
  - My dream job is to teach at a medical school.<\n>*



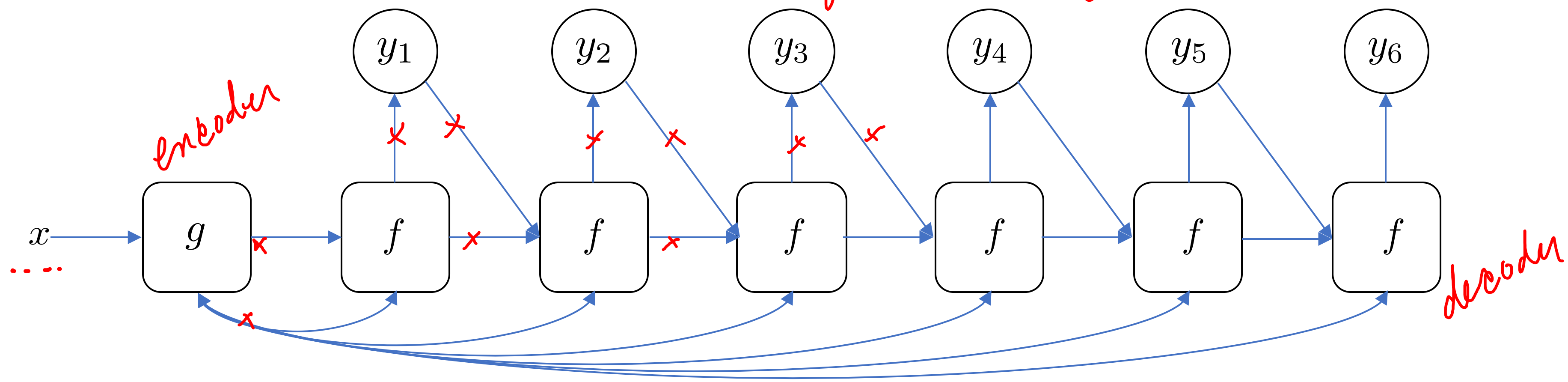
* I just made this up…

Neural conversation as neural machine translation

$$p(Y|x) = \prod_{t=1}^{T} p(y_t|y_1,\ldots,y_{t-1},x)$$

Conditional lang model

autoregressive modelling.

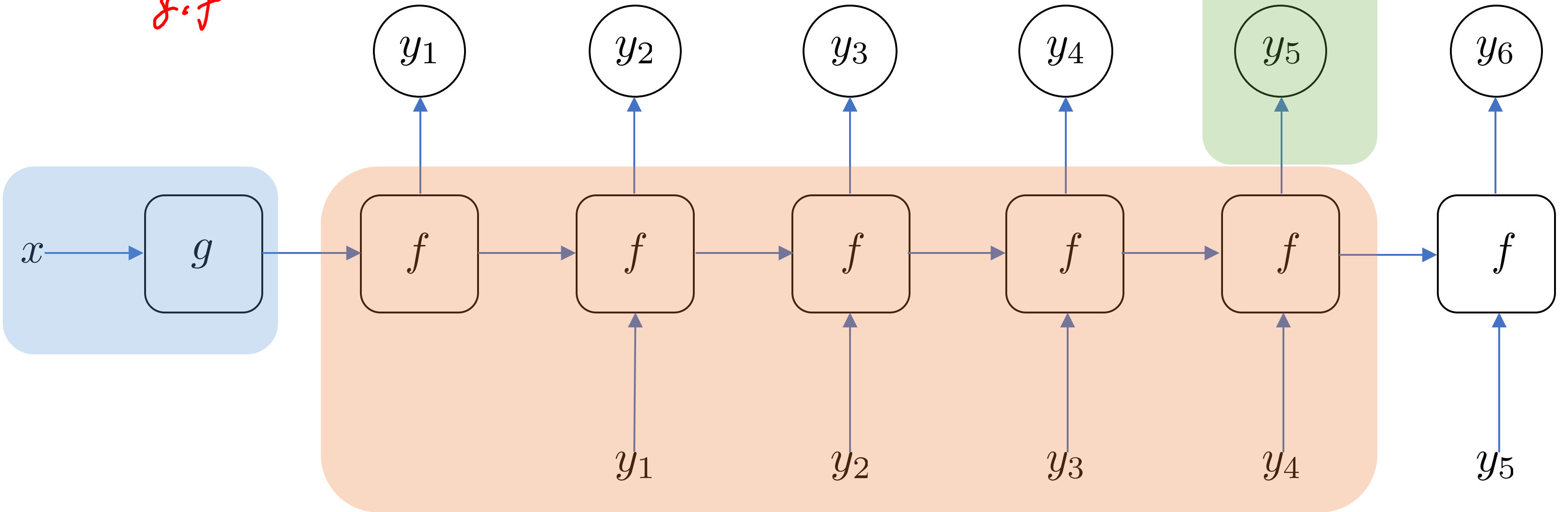


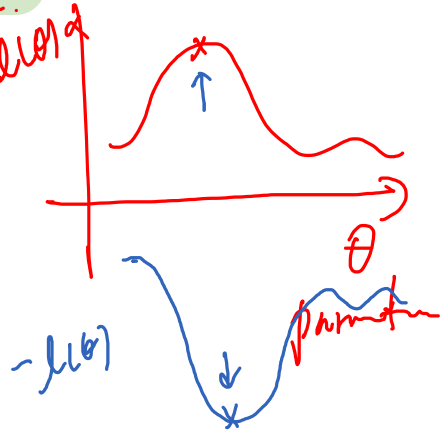
- Input x : personality descriptions + pervious utterances
- Encoder $g : \mathcal{X} \rightarrow \mathbb{R}^{d\times\cdots\times d}$ maps the input to a set of vectors
- Decoder $f : \mathcal{R}^{d'} \times \mathcal{Y} \rightarrow \mathcal{R}^{d'} \times \Delta^{|\mathcal{Y}|}$ predicts the next symbol
- A discrete sequence output $(y_1,\ldots,y_T) \in \{1,2,\ldots,|\mathcal{Y}|\}^T$

Learning – Maximum Log-Likelihood Learning

$$\max_{g,f} \log p(Y^*|x) = \sum_{t=1}^{T} \log p(y_t^*|y_1^*,\dots,y_{t-1}^*,x)$$

$= \min_{g,f} -\log p(Y^*|x)$





- Maximizes the log-probability of a correct next utterance
- Learns to predict the next token: $\log p(y_t^*|y_1^*,\dots,y_{t-1}^*,x)$

Learning – Maximum Log-Likelihood Learning

$$\max_{g,f} \log p(Y^*|x) = \sum_{t=1}^{T} \log p(y_t^*|y_1^*, \ldots, y_{t-1}^*, x)$$

- We know how to train this pretty well (now)
  - Long short-term memory (LSTM, Hochreiter&Schmidhuber, 1999)
  - Gated recurrent units (GRU, Cho et al., 2014)
  - Convolutional networks (Dauphin et al., 2017), Time delay networks (Waibel et al., 1989)
  - Memory networks (Sukhbataar et al., 2016), Self-Attention (Vaswani et al., 2017)

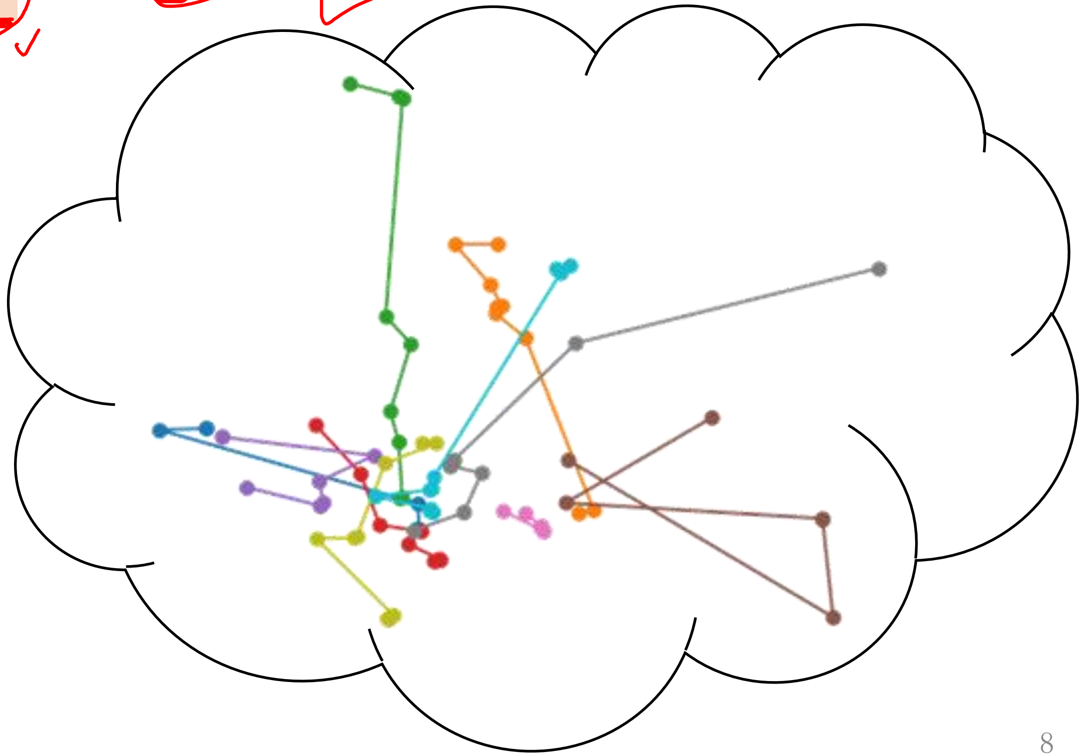
Transformers

Inference / Generation

- Finding a relatively-heavy needle in a exponentially-large haystack

$$\hat{Y} = \arg\max_{Y \in \mathcal{Y}} \log p(Y|x)$$

- Approximate, sequential local search
  - Greedy search
  - Beam search
  - And more…



Inference – Greedy search

big-O

$O(|V| \cdot T)$ ← max length of the response

vocabulary

exhaustive search $O(|V|^T)$

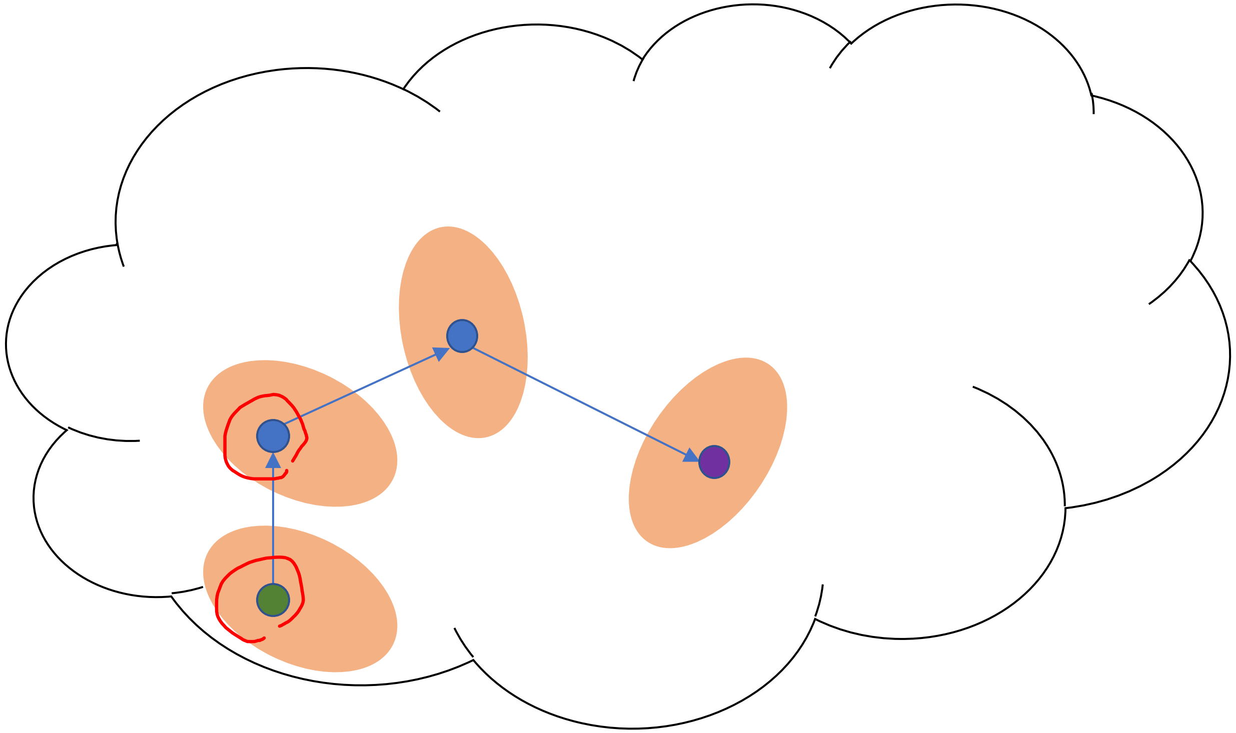
- Choose the best symbol each time step

$$\hat{y}_t = \arg\max_{y_t \in V} \log p(y_t | \hat{y}_1 \cdots \hat{y}_{t-1}, x)$$

$$\boxed{\hat{Y} = \arg\max_{Y} \log p(Y|x)}$$

- Heavily sub-optimal
  - No future consequence considered
  - Early commitment cannot be reverted

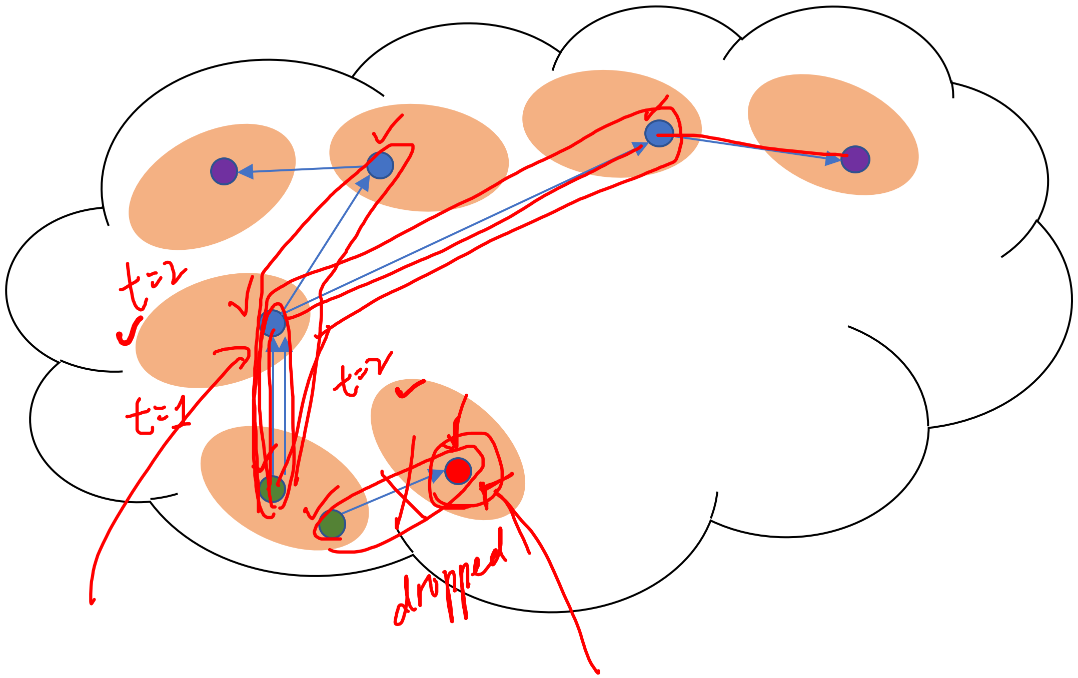
- Somehow, most widely used in neural dialogue generation…



Inference – Beam search

- de facto standard in neural language generation
  - Machine translation
- Better than greedy search, because no early commitment to any token
  - Future consequences are taken into account up to a certain level
- Controlled complexity: beam width

$O(T \cdot |V| \cdot K)$



Beam search in detail

$|V|^t$

discrepancy

- Exact search is intractable because $|\mathcal{H}_t| = \cancel{2^{|V|}}$
- Instead, beam search limits the size of hypothesis set at each time step: $|\mathcal{H}_t| = K$
- By expanding each hypothesis $(a_1, a_2, \ldots, a_{t-1}) \in \mathcal{H}_{t-1}$ with all possible unique words

hypothesis set at time t-1

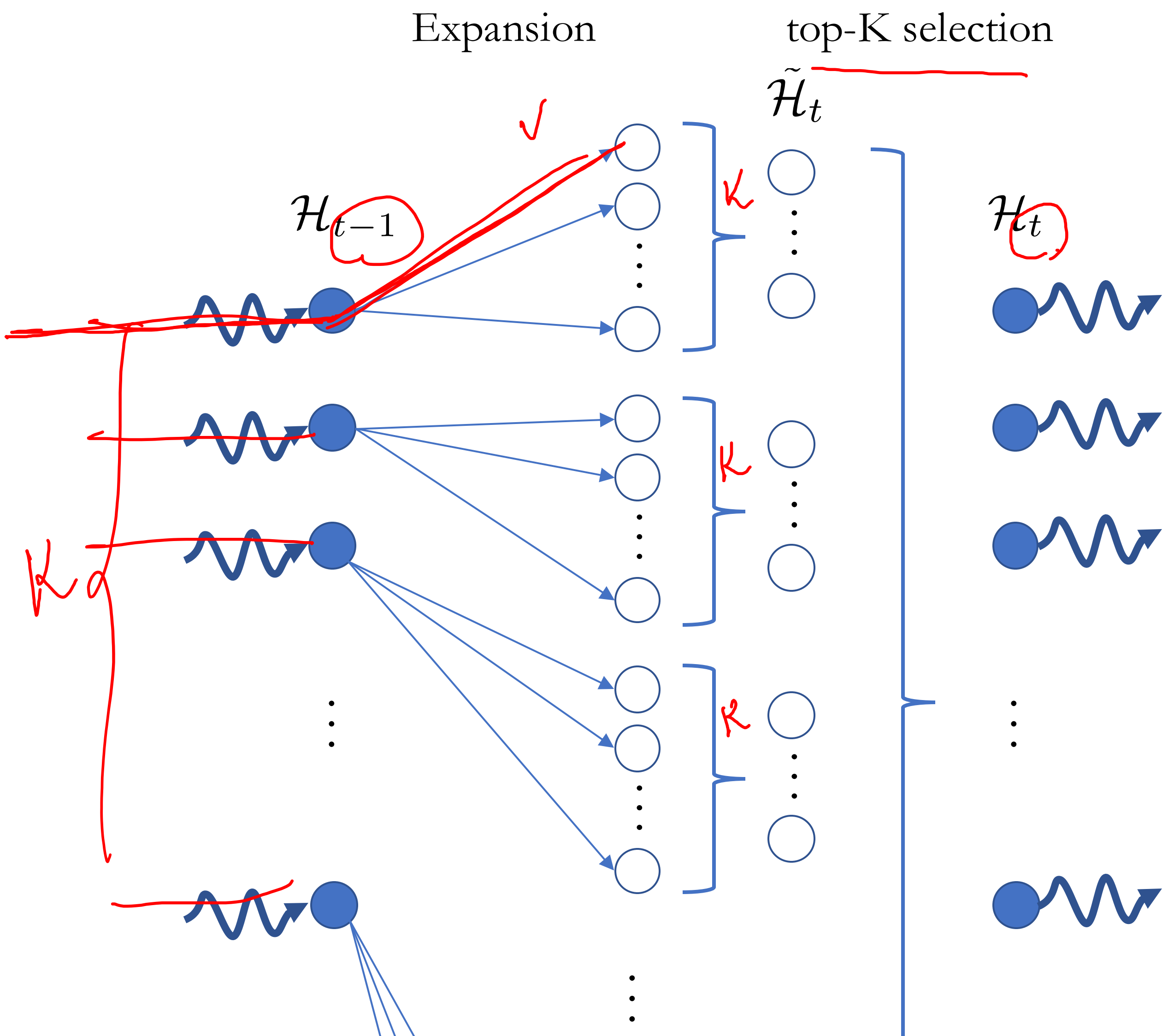
$$\hat{y}^k_{t,a} = \boxed{(a^k_1, a^k_2, \ldots, a^k_{t-1}, a)}, \text{ where } a \in V$$

- We end up with $K \times K$ candidate hypotheses $\tilde{\mathcal{H}}_t$ $K \times |V|$
- Construct the next hypothesis set by

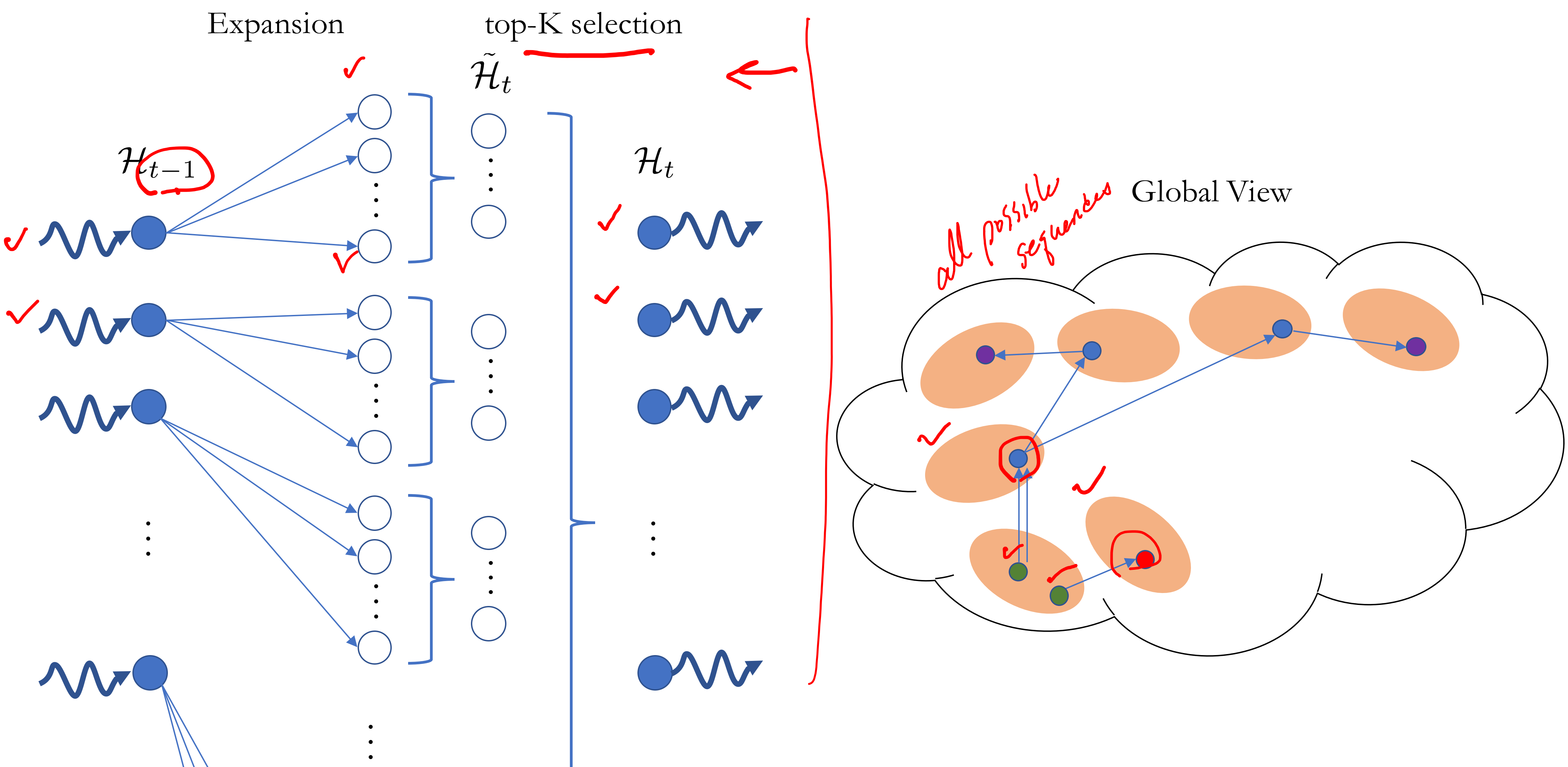
$$\mathcal{H}_t = \arg \underset{\hat{y} \in \tilde{\mathcal{H}}_t}{\text{top-}K} \underbrace{\sum_{t'=1}^{t} \log \pi(\hat{y}_t | \hat{y}_{<t}, X)} + \underbrace{R(\hat{y}, \tilde{\mathcal{H}}, \pi)}$$

- Continue until all the hypotheses terminate (<eos>)

Beam search in autoregressive models

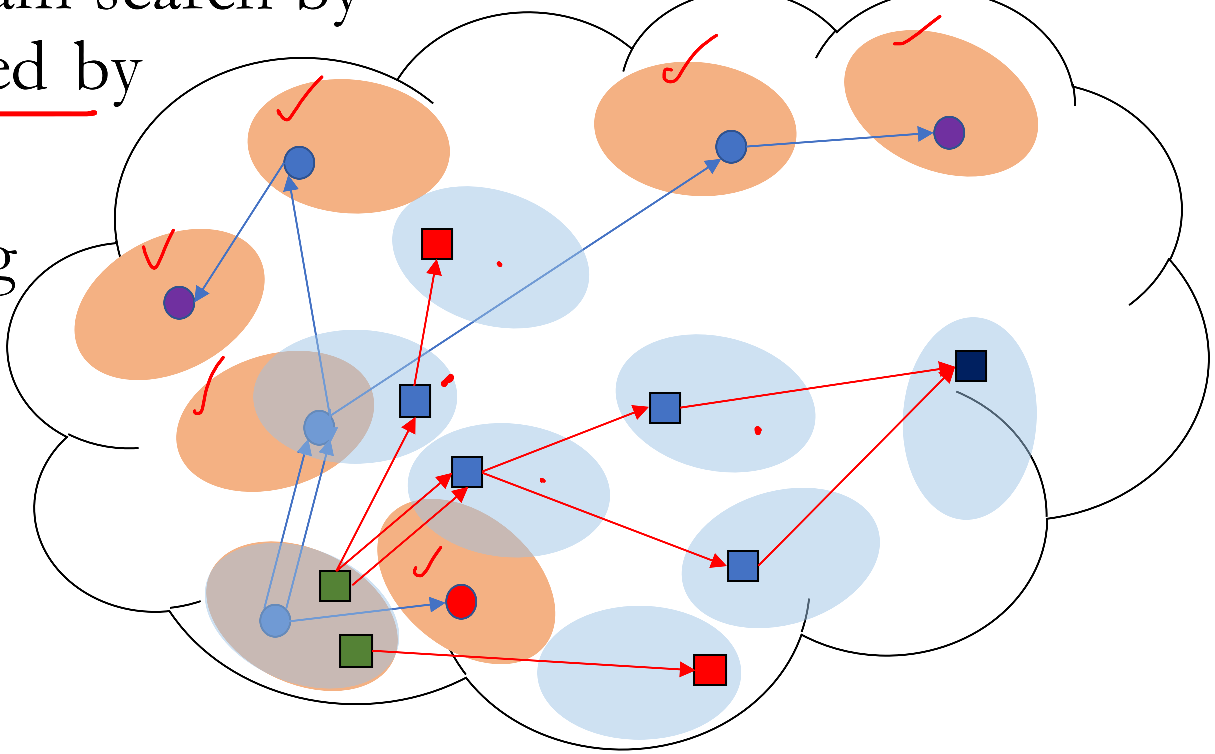


Beam search in autoregressive models



Inference – Iterative Beam search

- Inspired by Batra et al. [2012] and Li&Jurafsky [2016]
- Covers a larger search space than beam search by avoiding any search subspace explored by earlier iterations of beam search
- More effective than simply increasing the beam width: higher diversity
- No additional hyperparameter
    - # of iterations: computational budget



* Efficient semi-parallel implementation is possible and available.

Inference – top-K sampling

- Introduced in, e.g., [Fan et al., 2018]
- Ancestral sampling from

$$\tilde{p}(Y|X) = \prod_{t=1}^{T} \tilde{p}(y_t|y_{<t}, X),$$

where

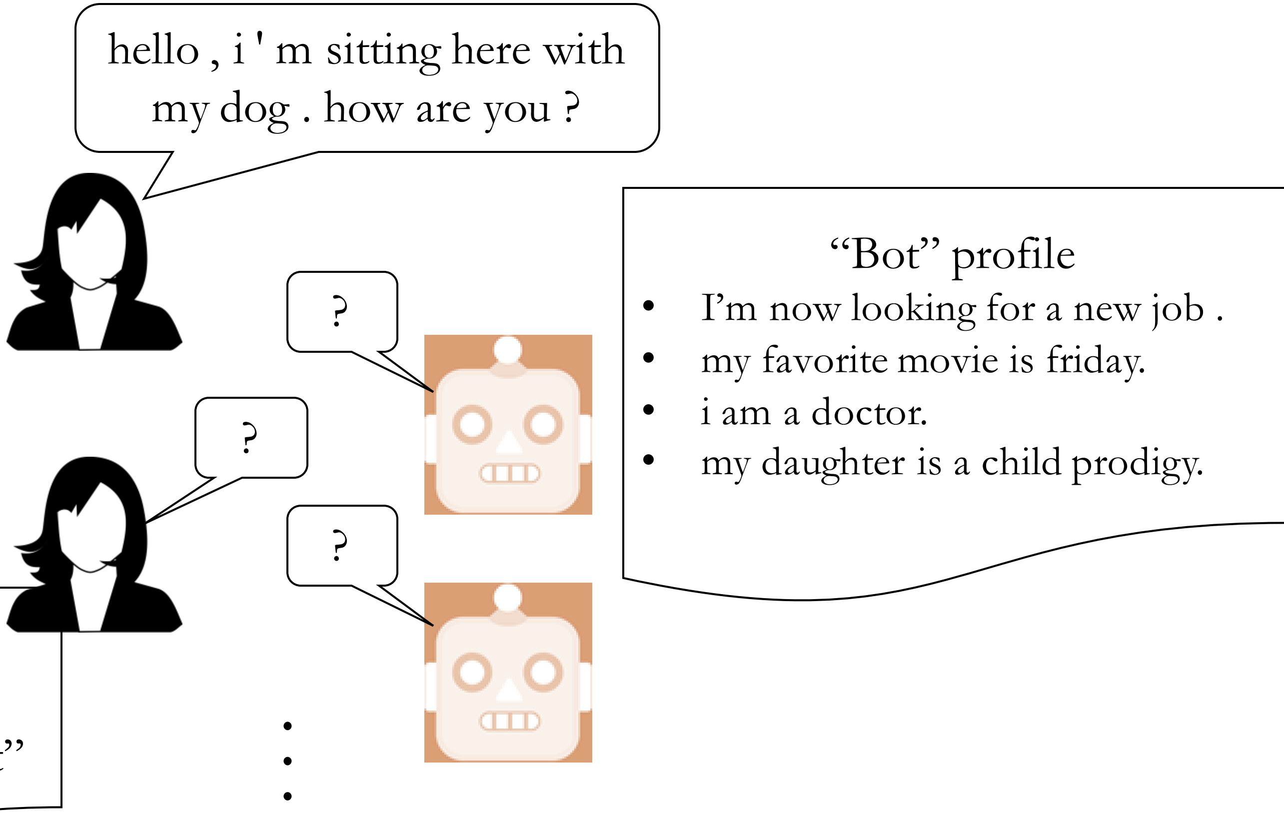
$$\tilde{p}(y_t|y_{<t}, X) \propto \begin{cases} p(y_t|y_{<t}, X), & \text{if } \boxed{\text{rank}(y_t|y_{<t}, X) \geq K} \\ 0, & \text{otherwise} \end{cases}$$

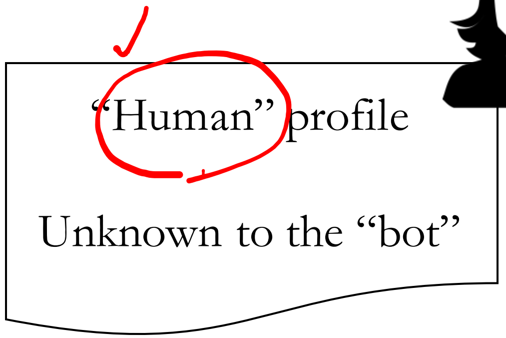
- I have absolutely no idea what this distribution actually looks like
- Stochastic behavior → problematic for evaluation and debugging

Human evaluation

BLEU for MT

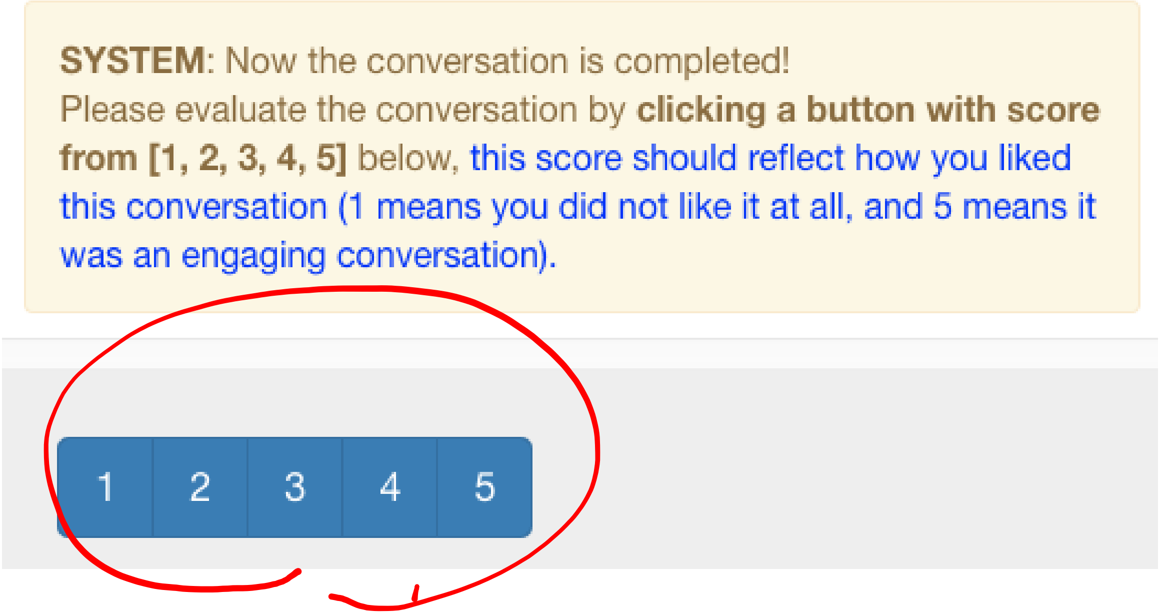
- Single-turn evaluation is not enough
  - Exposure bias
  - Self-consistency
- $\boxed{\text{Multi-turn evaluation}}$ is necessary
  - Multi-turn human-bot conversation
  - Absolute scoring





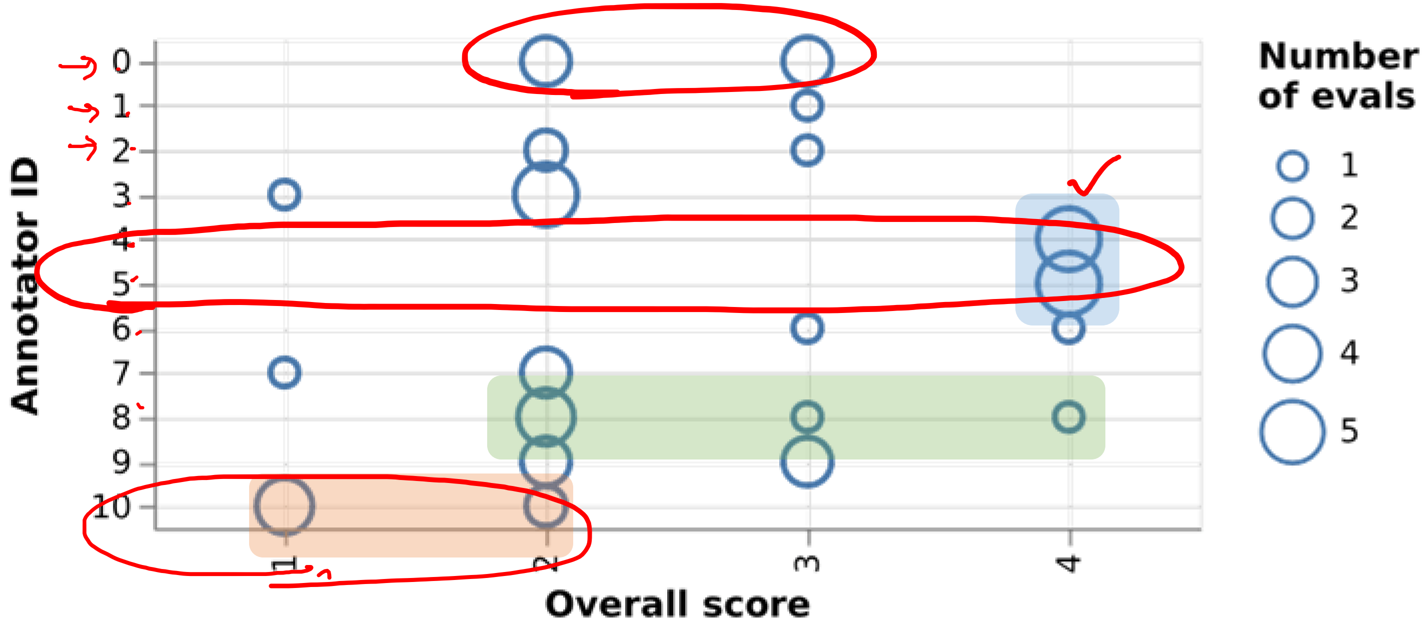
Multi-turn evaluation and absolute scoring

- A human evaluator makes a conversation of at least 5-6 turns with a bot.
- Each conversation is scored from {1, 2, 3, 4}



Multi-turn evaluation and absolute scoring

- Each conversation is scored from {1, 2, 3, 4, 5}
  - The evaluator is also asked to mark each bot utterance as "good" or "bad".
- Unfortunately, human evaluators are not well-calibrated
  - Some are too generous, while others are too harsh, and some are just random…



Model-based

Bayesian calibration of evaluation scores

- Model score (unobserved)

$$\mu_n \sim \mathcal{U}(1,5)$$

$$S_n \sim \mathcal{N}(\mu_n, 1^2)$$

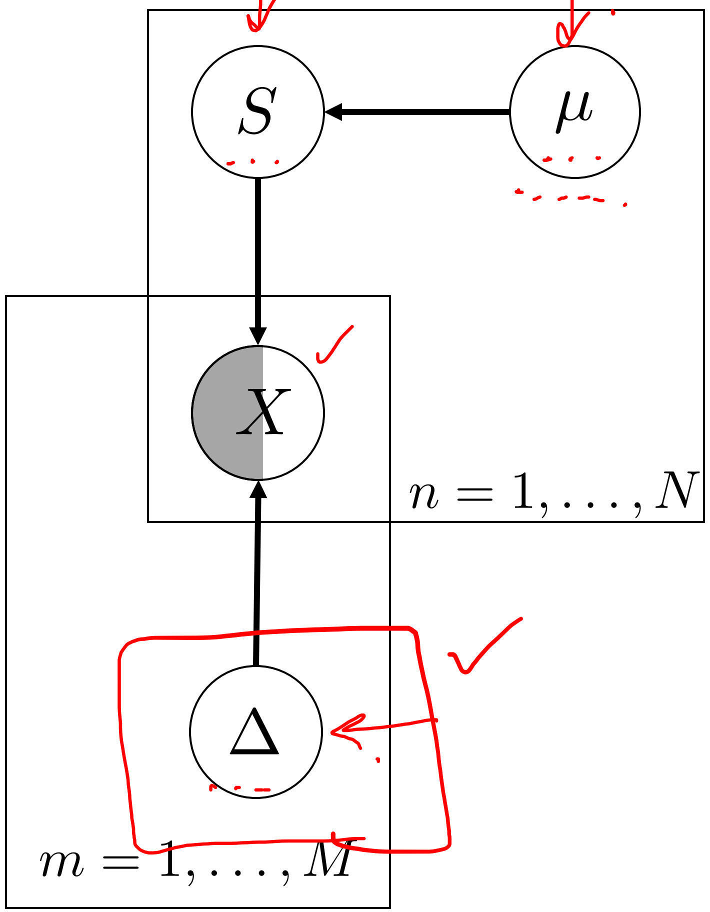
- Evaluator bias (unobserved)

$$\Delta \sim \mathcal{N}(0, 1^2)$$

- Collected scores (partially observed)

$$X_{nm} \sim \mathcal{N}(S_n + \Delta_m, 1^2)$$

- Inference: NUTS [Hoffman&Gelman, 2011]
- Used Pyro* for inference and generality



* https://eng.uber.com/pyro/

Human evaluation [Kulikov et al., arXiv 2018]

Search Algorithm	Raw scores		Calibrated scores	
	Average	**Std. Dev.**	**Average**	**Std. Dev.**
Greedy	2.56	0.98	2.40	0.25
Beam(10)	2.67	0.86	2.66	0.25
Iterative Beam(5,15)	2.80	0.90	2.75	0.26
Human	3.62	0.71	3.46	0.26

- Up to 0.35/4.0 improvement with a better search algorithm
- Without Bayesian calibration, too large a std. dev. due to the evaluator bias
- Search/inference matters.