CS11-747 Neural Networks for NLP

Risk,
Minimum Risk Training,
Reinforcement Learning

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Site
https://phontron.com/class/nn4nlp2020/

Maximum Likelihood Training

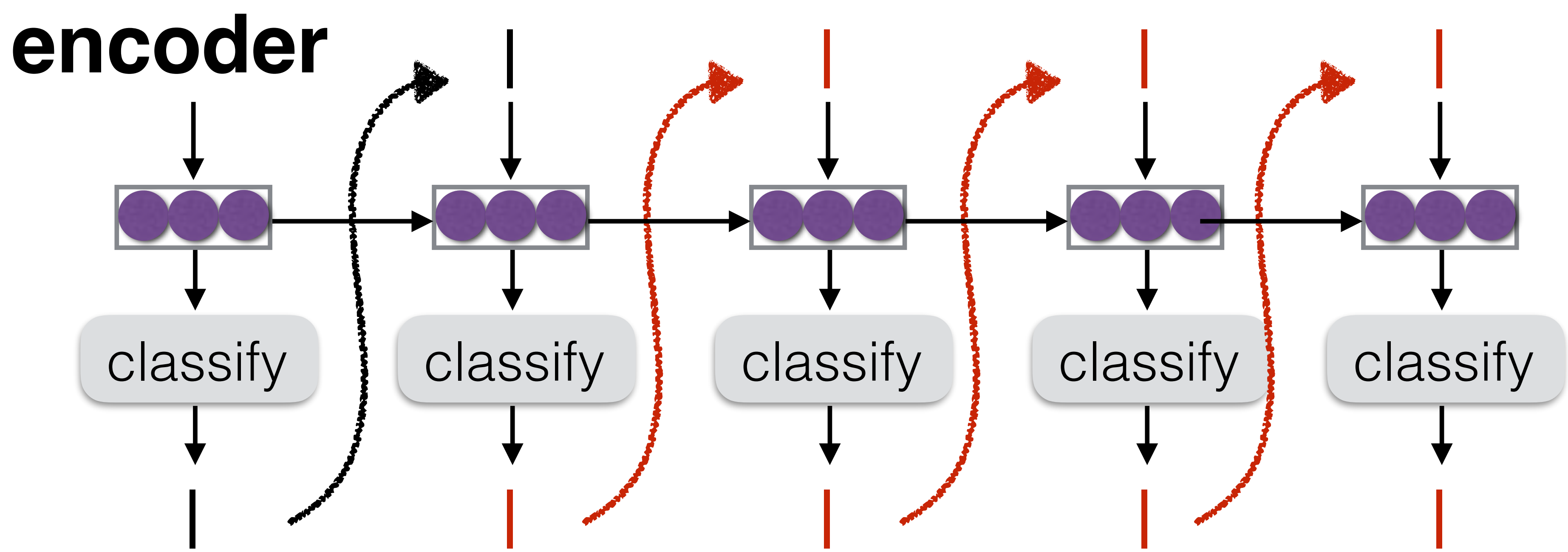
- Maximum the likelihood of predicting the next word in the reference given the previous words

$$\ell(E \mid F) = -\log P(E \mid F)$$
$$= -\sum_{t=1}^{T} \log P(e_t \mid F, e_1, \ldots, e_{t-1})$$

- Also called "teacher forcing"

Problem 1: Exposure Bias

- Teacher forcing assumes feeding correct previous input, but at test time we may make mistakes that propagate



- **Exposure bias:** The model is not exposed to mistakes during training, and cannot deal with them at test

Problem 2: Disregard to Evaluation Metrics

- In the end, we want good outputs
- Good translations can be measured with metrics, e.g. BLEU or METEOR
- Some mistaken predictions hurt more than others, so we'd like to penalize them appropriately

Error and Risk

Error

- Generate an output

$$\hat{E} = \text{argmax}_{\tilde{E}} P(\tilde{E} \mid F)$$

- Calculate its "badness" (e.g. 1-BLEU, 1-METEOR)

$$\text{error}(E, \hat{E}) = 1 - \text{BLEU}(E, \hat{E})$$

- We would like to minimize error

Problem: Argmax is Non-differentiable

- The argmax function makes discrete zero-one decisions
- The gradient of this function is zero almost everywhere, not-conducive to gradient-based training

Risk

- Risk is defined as the expected error

$$\mathrm{risk}(F, E, \theta) = \sum_{\tilde{E}} P(\tilde{E} \mid F; \theta)\mathrm{error}(E, \tilde{E}).$$

- This is includes the probability in the objective function!
- Differentiable, but the sum is intractable
- Minimum risk training minimizes risk, Shen et al. (2016) do so for NMT

Sampling for Risk

- Create a small sample of sentences (5-50), and calculate risk over that

$$\mathrm{risk}(F, E, S) = \sum_{\tilde{E} \in S} \frac{P(\tilde{E} \mid F)}{Z} \mathrm{error}(E, \hat{E})$$

- Samples can be created using random sampling or n-best search

- If random sampling, make sure to deduplicate

Adding Temperature

$$\mathrm{risk}(F, E, \theta, \tau, S) = \sum_{\tilde{E} \in S} \frac{P(\tilde{E} \mid F; \theta)^{1/\tau}}{Z} \mathrm{error}(E, \hat{E})$$

- Temperature helps adjust for the fact that we're only getting a small sample

Reinforcment Learning Basics: Policy Gradient

(Review of Karpathy 2016)

What is Reinforcement Learning?

- Learning where we have an
  - environment X
  - ability to make actions A
  - get a delayed reward R
- **Example of pong:** X is our observed image, A is up or down, and R is the win/loss at the end of the game

Why Reinforcement Learning in NLP?

- We may have a **typical reinforcement learning scenario**: e.g. a dialog where we can make responses and will get a reward at the end.

- We may have **latent variables**, where we decide the latent variable, then get a reward based on their configuration.

- We may have a **sequence-level error function** such as BLEU score that we cannot optimize without first generating a whole sentence.

Supervised MLE

- We are given the correct decisions

$$\ell_{\text{super}}(Y, X) = -\log P(Y \mid X)$$

- In the context of reinforcement learning, this is also called "imitation learning," imitating a teacher (although imitation learning is more general)

Self Training

- Sample or argmax according to the current model

$$\hat{Y} \sim P(Y \mid X) \quad \text{or} \quad \hat{Y} = \text{argmax}_Y P(Y \mid X)$$

- Use this sample (or samples) to maximize likelihood

$$\ell_{\text{self}}(X) = -\log P(\hat{Y} \mid X)$$

- No correct answer needed! But is this a good idea?
- *One successful alternative:* co-training, only use sentences where multiple models agree (Blum and Mitchell 1998)
- *Another successful alternative:* noising the input, to match output (He et al. 2020)

Policy Gradient/REINFORCE

- Add a term that scales the loss by the reward

$$\ell_{\text{self}}(X) = -R(\hat{Y}, Y) \log P(\hat{Y} \mid X)$$

- Outputs that get a bigger reward will get a higher weight

- Quiz: Under what conditions is this equal to MLE?

Credit Assignment for Rewards

- How do we know which action led to the reward?

- Best scenario, immediate reward:

a_1	a_2	a_3	a_4	a_5	a_6
0	+1	0	-0.5	+1	+1.5

- Worst scenario, only at end of roll-out:

a_1	a_2	a_3	a_4	a_5	a_6	
						+3

- Often assign decaying rewards for future events to take into account the time delay between action and reward

Stabilizing Reinforcement Learning

Problems w/ Reinforcement Learning

- Like other sampling-based methods, reinforcement learning is unstable
- It is particularly unstable when using bigger output spaces (e.g. words of a vocabulary)
- A number of strategies can be used to stabilize

Adding a Baseline

- Basic idea: we have expectations about our reward for a particular sentence

	Reward	Baseline	B-R
"This is an easy sentence"	0.8	0.95	-0.15
"Buffalo Buffalo Buffalo"	0.3	0.1	0.2

- We can instead weight our likelihood by B-R to reflect when we did **better or worse than expected**

$$\ell_{\text{baseline}}(X) = -(R(\hat{Y}, Y) - B(\hat{Y})) \log P(\hat{Y} \mid X)$$

- (Be careful to not backprop through the baseline)

Calculating Baselines

- Choice of a baseline is arbitrary
- Option 1: predict final reward using linear from current state (e.g. Ranzato et al. 2016)
  - **Sentence-level:** one baseline per sentence
  - **Decoder state level:** one baseline per output action
- Option 2: use the mean of the rewards in the batch as the baseline (e.g. Dayan 1990)

Increasing Batch Size

- Because each sample will be high variance, we can sample many different examples before performing update
- We can increase the number of examples (roll-outs) done before an update to stabilize
- We can also save previous roll-outs and re-use them when we update parameters (experience replay, Lin 1993)

Warm-start

- Start training with maximum likelihood, then switch over to REINFORCE
- Works only in the scenarios where we can run MLE (not latent variables or standard RL settings)
- MIXER (Ranzato et al. 2016) gradually transitions from MLE to the full objective

When to Use Reinforcement Learning?

- If you are in a setting where the **correct actions are not given, and the structure of the computation depends on the choices** you make:
  - Yes, you have no other obvious choice.
- If you are in a setting where **correct actions are not given but computation structure doesn't change**.
  - A differentiable approximation (e.g. Gumbel Softmax) may be more stable.
- If you **can train using MLE, but want to use a non-decomposable loss function**.
  - Maybe yes, but many other methods (max margin, min risk) also exist.

An Alternative: Value-based Reinforcement Learning

Policy-based vs. Value-based

- **Policy-based learning:** try to learn a good probabilistic policy that maximizes the expectation of reward

- **Value-based learning:** try to guess the “value” of the result of taking a particular action, and take the action with the highest expected value

Action-Value Function

- Given a state **s**, we try to estimate the "value" of each action *a*
  - Value is the expected reward given that we take that action

$$Q(\boldsymbol{s}_t, a_t) = \mathbb{E}[\sum_t^T R(a_t)]$$

  - e.g. in a sequence-to-sequence model, our state will be the input and previously generated words, action will be the next word to generate
- We then take the action that maximizes the reward

$$\hat{a}_t = \mathrm{argmax}_{a_t} Q(\boldsymbol{s}_t, a_t)$$

  - Note: this is not a probabilistic model!

Estimating Value Functions

- Tabular Q Learning: Simply remember the Q function for every state and update

$$Q(\boldsymbol{s}_t, a_t) \leftarrow (1-\alpha)Q(\boldsymbol{s}_t, a_t) + \alpha R(a_t)$$

- Neural Q Function Approximation: Perform regression with neural networks (e.g. Tesauro 1995)

Exploration vs. Exploitation

- Problem: if we always take the best option, we might get stuck in a local minimum
  - Note: this is less of a problem with stochastic policy-based methods, as we randomly sample actions
- Solution: every once in a while randomly pick an action with a certain probability ε
  - This is called the ε-greedy strategy
- **Intrinsic reward:** give reward to models that discover new states (Schmidhuber 1991, Bellemare et al. 2016)

Examples of Reinforcement Learning in NLP

RL in Dialog

- Dialog was one of the first major successes in reinforcement learning in NLP (Survey: Young et al. 2013)
  - Standard tools: Markov decision processes, partially observed MDPs (to handle uncertainty)
- Now, neural network models for both task-based (Williams and Zweig 2017) and chatbot dialog (Li et al. 2017)

User Simulators for Reinforcement Learning in Dialog

- Problem: paucity of data!
- Solution, create a user simulator that has an internal state (Schatzmann et al. 2007)
- Dialog system must learn to track user state w/ incomplete information

$$C_0 = \begin{bmatrix} type = bar \\ drinks = beer \\ area = central \end{bmatrix}$$

$$R_0 = \begin{bmatrix} name = \\ addr = \\ phone = \end{bmatrix}$$

Sys 0 Hello, how may I help you?

$$A_1 = \begin{bmatrix} inform(type = bar) \\ inform(drinks = beer) \\ inform(area = central) \\ request(name) \\ request(addr) \\ request(phone) \\ bye() \end{bmatrix}$$

Usr 1 I'm looking for a nice bar serving beer.

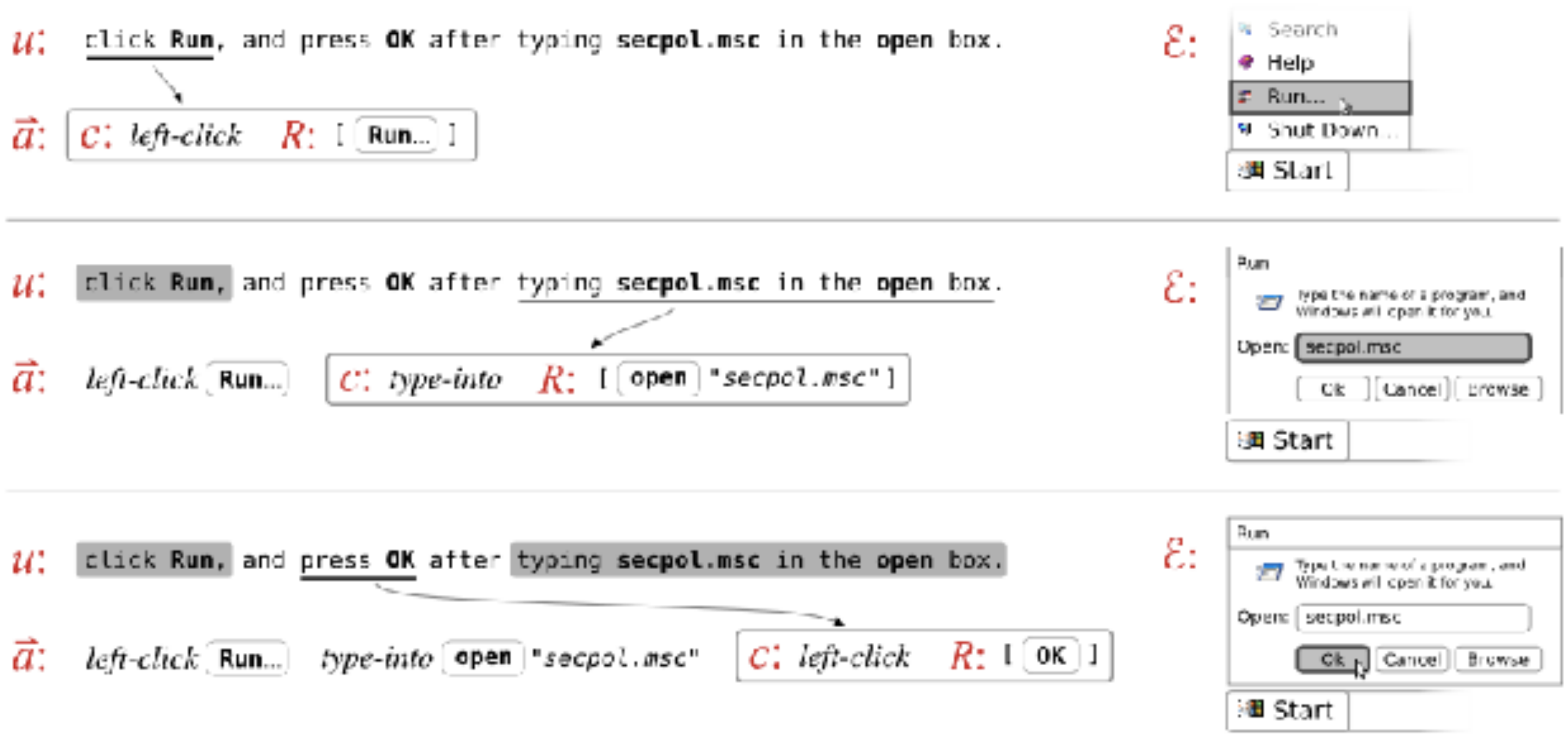
Sys 1 Ok, a wine bar. What pricerange?

$$A_2 = \begin{bmatrix} negate(drinks = beer) \\ inform(pricerange = cheap) \\ inform(area = central) \\ request(name) \\ request(addr) \\ request(phone) \\ bye() \end{bmatrix}$$

Usr 2 No, beer please!

Mapping Instructions to Actions

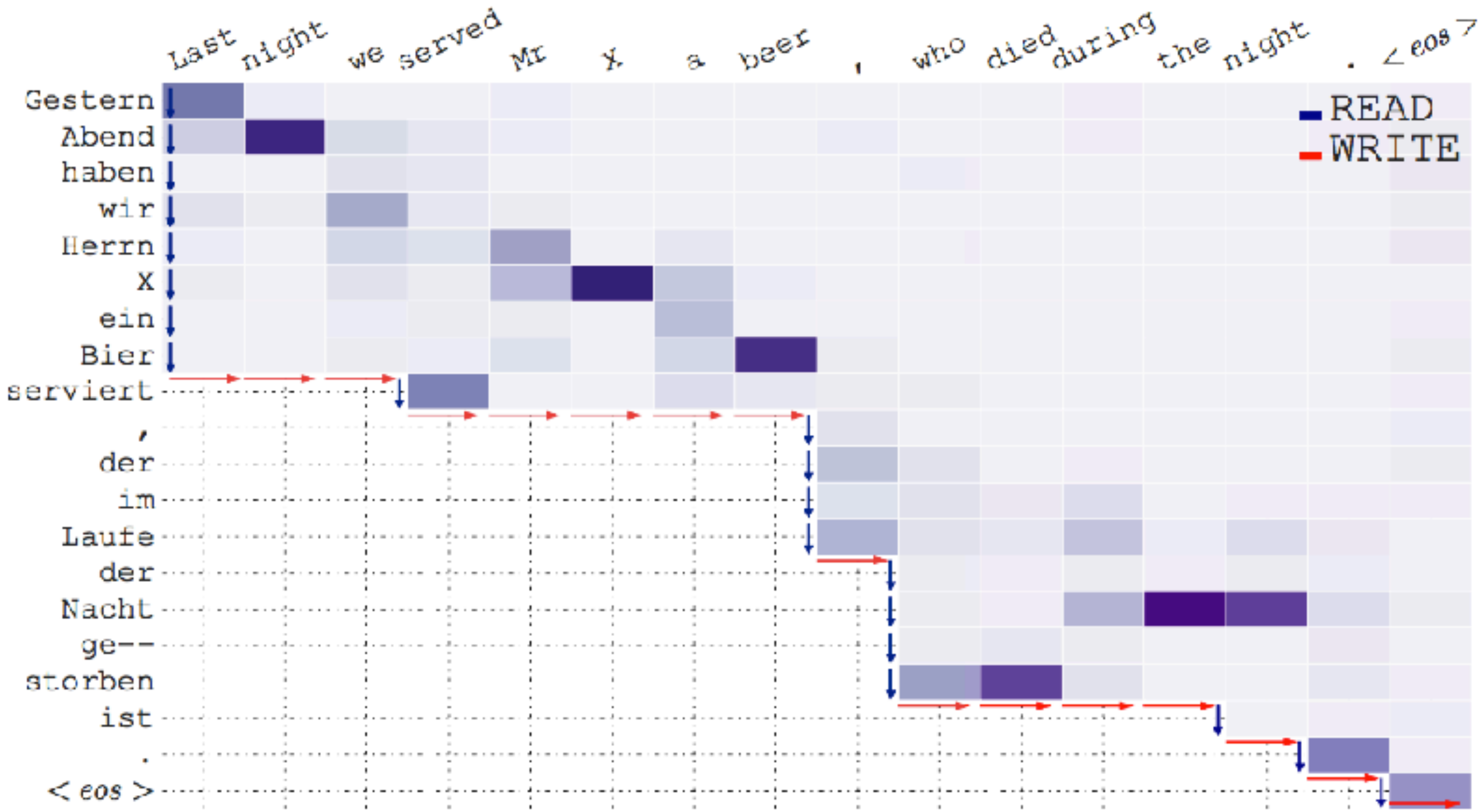
- Following windows commands with weak supervision based on progress (Branavan et al. 2009)



- Visual instructions with neural nets (Misra et al. 2017)

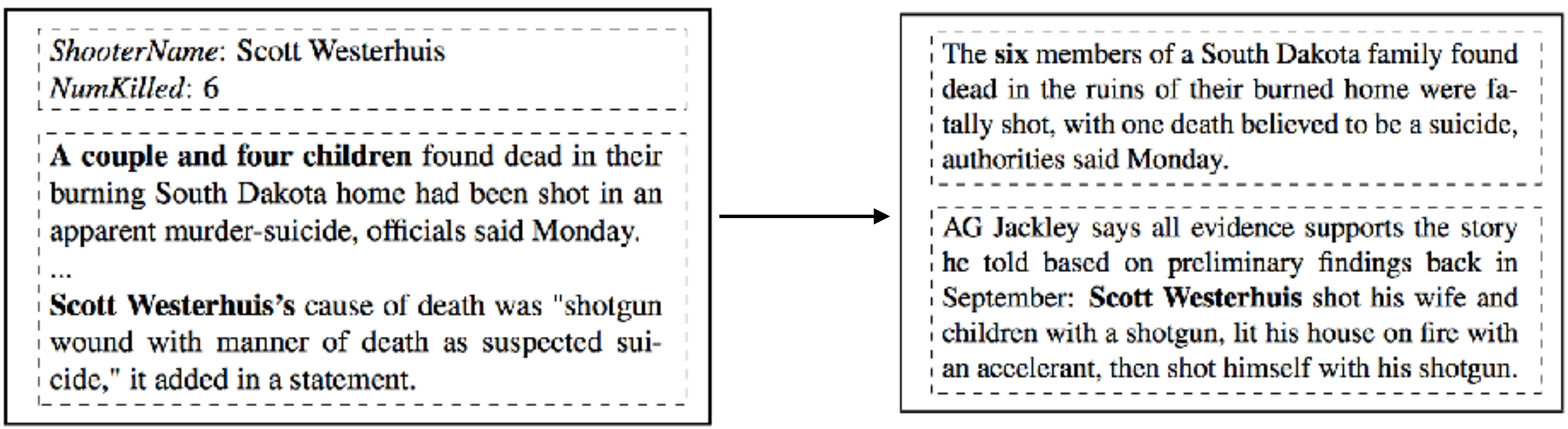
Reinforcement Learning for Making Incremental Decisions in MT

- We want to translate before the end of the sentence for MT, agent decides whether to wait or translate (Grissom et al. 2014, Gu et al. 2017)



RL for Information Retrieval

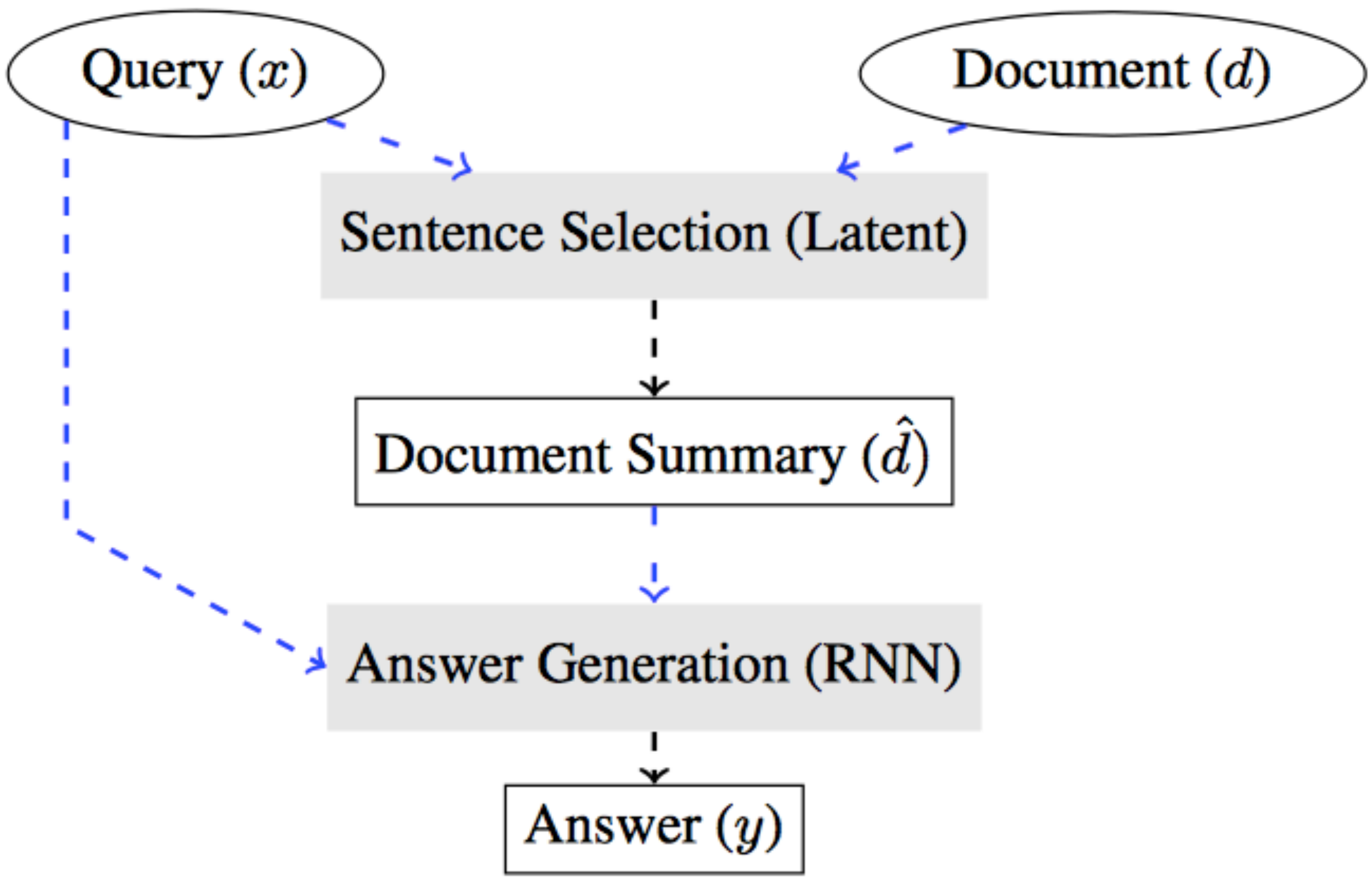
- Find evidence for an information extraction task by searching the web as necessary (Narasimhan et al. 2016)



- Perform query reformulation (Nogueira and Cho 2017)

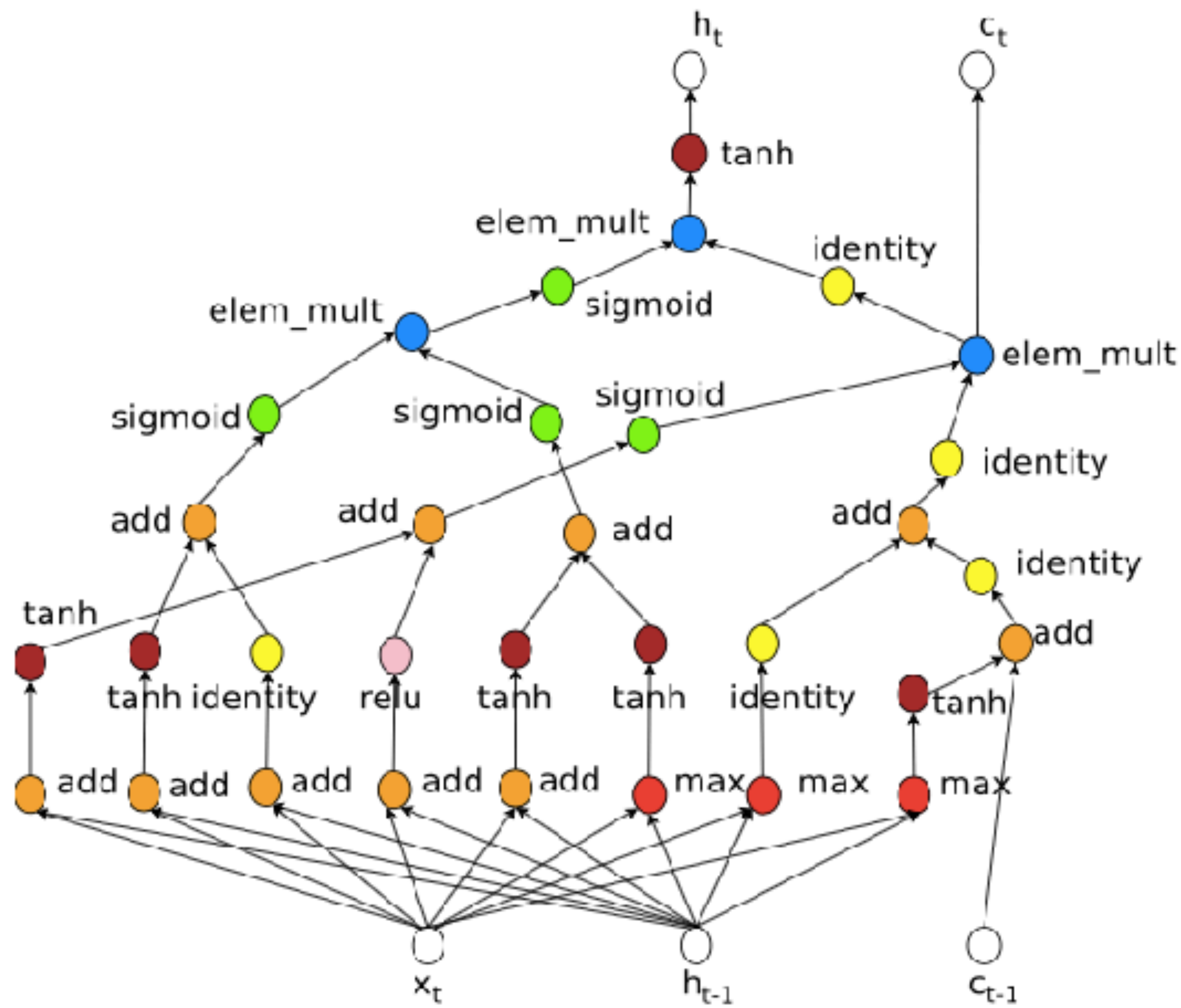
RL for Coarse-to-fine Question Answering (Choi et al. 2017)

- In a long document, it may be useful to first pare down sentences before reading in depth



RL to Learn Neural Network Structure (Zoph and Le 2016)

- Generate a neural network structure, try it, and measure the results as a reward



Questions?