CS769 Advanced NLP

Structure Prediction

Junjie Hu

WISCONSIN
UNIVERSITY OF WISCONSIN–MADISON

Slides adapted from Graham

https://junjiehu.github.io/cs769-fall23/

Goals for Today

- Problems of structure predictions w.r.t. sentence classification
- Locally (MLE) v.s. Globally normalized likelihood methods
- **Structure perceptron** (hinge loss with margin)
- **Policy Gradient** (**REINFORCE**)
- **Other simpler solutions**

Types of Prediction

- Two classes (**binary classification**)

I hate this movie → positive / negative

- Multiple classes (**multi-class classification**)

I hate this movie → very good / good / neutral / bad / very bad

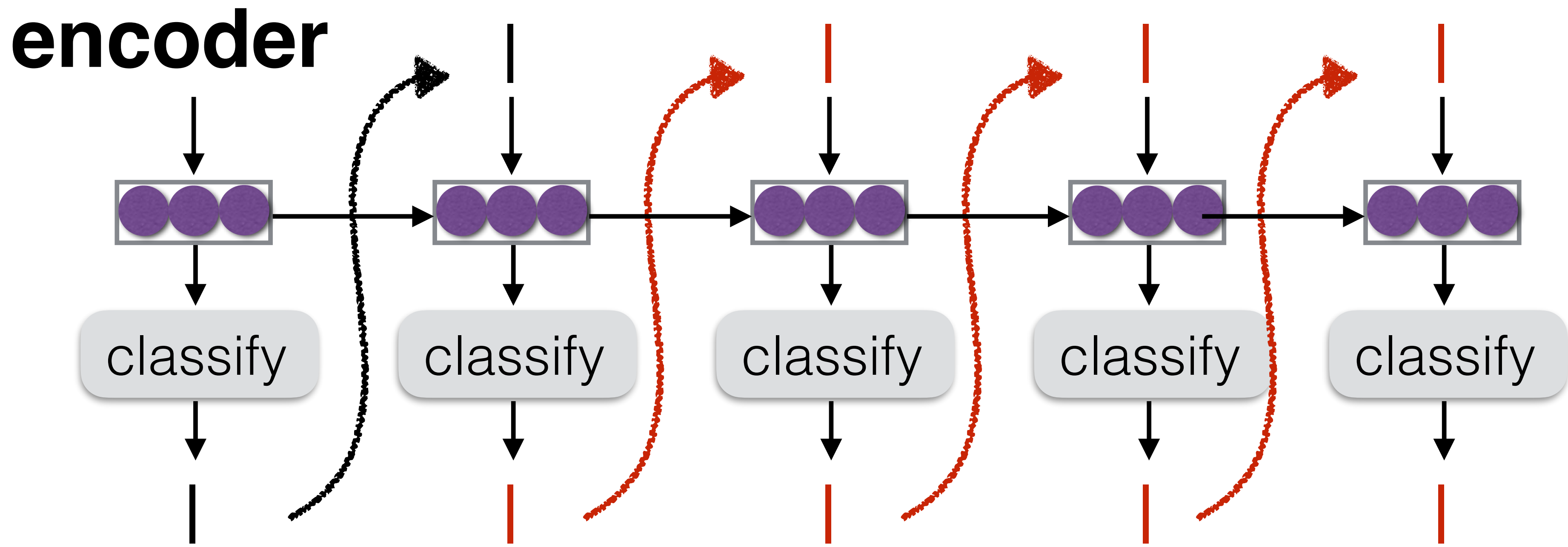
- Exponential/infinite labels (**structured prediction**)

I hate this movie → PRP VBP DT NN

I hate this movie → *kono eiga ga kirai*

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

- Similarly, good responses to a query can be measured by human preference

- Some mistaken predictions hurt more than others, so we'd like to penalize them appropriately

Many Varieties of Structured Prediction!

- **Models:**
  - RNN-based decoders
  - Convolution/self attentional decoders
  - CRFs w/ local factors
- **Training algorithms:**
  - Maximum likelihood w/ teacher forcing
  - Sequence level likelihood
  - Structured perceptron, structured large margin
  - Reinforcement learning/minimum risk training
  - Sampling corruptions of data

Covered already

Covered today

Reminder: Globally Normalized Models

- **Locally normalized models:** each decision made by the model has a probability that adds to one

$$P(Y \mid X) = \prod_{j=1}^{|Y|} \frac{e^{S(y_j|X, y_1, \ldots, y_{j-1})}}{\sum_{\tilde{y}_j \in V} e^{S(\tilde{y}_j|X, y_1, \ldots, y_{j-1})}}$$

- **Globally normalized models (a.k.a. energy-based models):** each sentence has a score, which is not normalized over a particular decision

$$P(Y|X) = \frac{e^{S(Y|X)}}{\sum_{\tilde{Y} \in V*} e^{S(\tilde{Y}|X)}}$$

Globally Normalized Likelihood

Difficulties Training Globally Normalized Models

- Partition function problematic

$$P(Y|X) = \frac{e^{S(Y|X)}}{\boxed{\sum_{\tilde{Y} \in V*} e^{S(\tilde{Y}|X)}}}$$

- Two options for calculating partition function
  - Structure model to allow enumeration via dynamic programming, e.g. linear chain CRF, CFG
  - Estimate partition function through **sub-sampling** hypothesis space

Two Methods for Approximation

- **Sampling:**
  - Sample *k* samples according to the probability distribution
  - *+ Unbiased estimator:* as *k* gets large will approach true distribution
  - *- High variance:* what if we get low-probability samples?
- **Beam search:**
  - Search for *k* best hypotheses
  - *- Biased estimator:* may result in systematic differences from true distribution
  - *+ Lower variance:* more likely to get high-probability outputs

Un-normalized Models: Structured Perceptron

Normalization often Not Necessary for Inference!

- At inference time, we often just want the **best hypothesis**

$$\hat{Y} = \underset{Y}{\operatorname{argmax}}\ P(Y \mid X)$$

- If that's all we need, no need for normalization!

$$P(Y|X) = \frac{e^{S(Y|X)}}{\sum_{\tilde{Y} \in V*} e^{S(\tilde{Y}|X)}}$$

$$\hat{Y} = \arg\max_{Y} S(Y|X)$$

Structured Perceptron Algorithm

- An extremely simple way of training (non-probabilistic) global models
- Find the **one-best output** according to the model score, and if its score is better than **the correct answer**, update parameters to fix this
- The one-best output may not be as good as the correct answer, but scores higher! We should update models to either decrease its score or increase the correct answer's score.

$$\hat{Y} = \text{argmax}_{\tilde{Y} \neq Y} S(\tilde{Y} \mid X; \theta)$$

Find one best

$$\textbf{if } S(\hat{Y} \mid X; \theta) \geq S(Y \mid X; \theta) \textbf{ then}$$

If score better than reference

$$\theta \leftarrow \theta + \alpha\left(\frac{\partial S(Y|X;\theta)}{\partial \theta} - \frac{\partial S(\hat{Y}|X;\theta)}{\partial \theta}\right)$$

Increase score of ref, decrease score of one-best (here, SGD update)

$$\textbf{end if}$$

Structured Perceptron Loss

- Structured perceptron can also be expressed as a loss function!

$$\ell_{\text{percept}}(X, Y) = \max(0, S(\hat{Y} \mid X; \theta) - S(Y \mid X; \theta))$$

- Resulting **gradient looks like perceptron algorithm**

$$\frac{\partial \ell_{\text{percept}}(X, Y; \theta)}{\partial \theta} = \begin{cases} \frac{\partial S(Y \mid X; \theta)}{\partial \theta} - \frac{\partial S(\hat{Y} \mid X; \theta)}{\partial \theta} & \text{if } S(\hat{Y} \mid X; \theta) \geq S(Y \mid X; \theta) \\ 0 & \text{otherwise} \end{cases}$$

- This is a normal loss function, **can be used in NNs**

- But! Requires **finding the one-best by argmax** in addition to the true candidate: must **do prediction during training**

Contrasting Perceptron and Global Normalization

- **Globally normalized probabilistic model**

$$\ell_{\text{global}}(X, Y; \theta) = -\log \frac{e^{S(Y|X)}}{\sum_{\tilde{Y}} e^{S(\tilde{Y}|X)}}$$

- **Structured perceptron**

$$\ell_{\text{percept}}(X, Y) = \max(0, S(\hat{Y} \mid X; \theta) - S(Y \mid X; \theta))$$

- **Global structured perceptron?**

$$\ell_{\text{global-percept}}(X, Y) = \sum_{\tilde{Y}} \max(0, S(\tilde{Y} \mid X; \theta) - S(Y \mid X; \theta))$$

  - Same computational problems as globally normalized probabilistic models

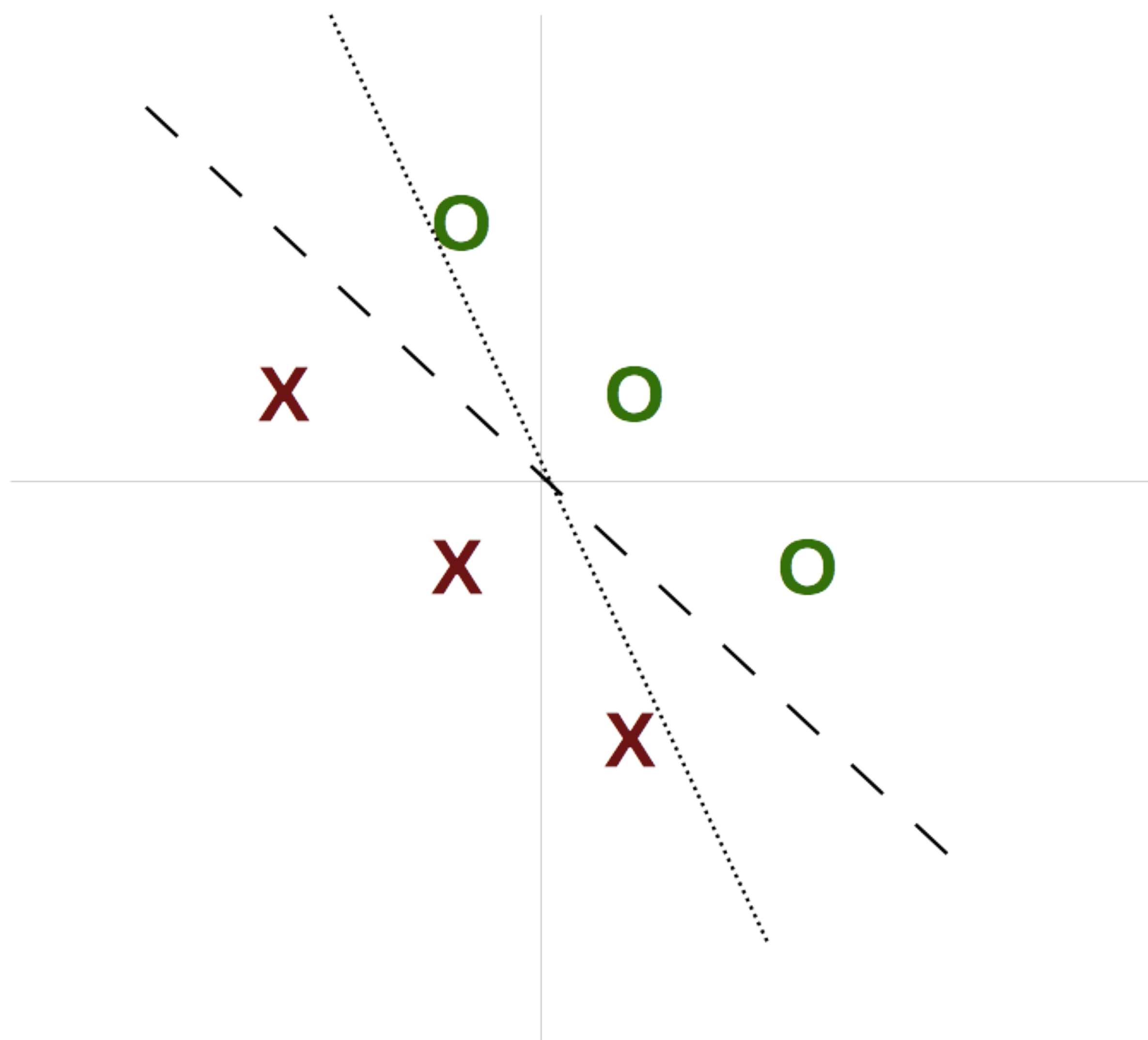
Structured Training and Pre-training

- Neural network models have lots of parameters and a big output space; **training is hard**
- **Tradeoffs** between training algorithms:
  - Selecting just one negative example is inefficient
  - Teacher forcing efficiently updates all parameters, but suffers from exposure bias
- Thus, it is common to **pre-train with teacher forcing, then fine-tune with more complicated algorithm**

Hinge Loss and Cost-sensitive Training

Perceptron and Uncertainty

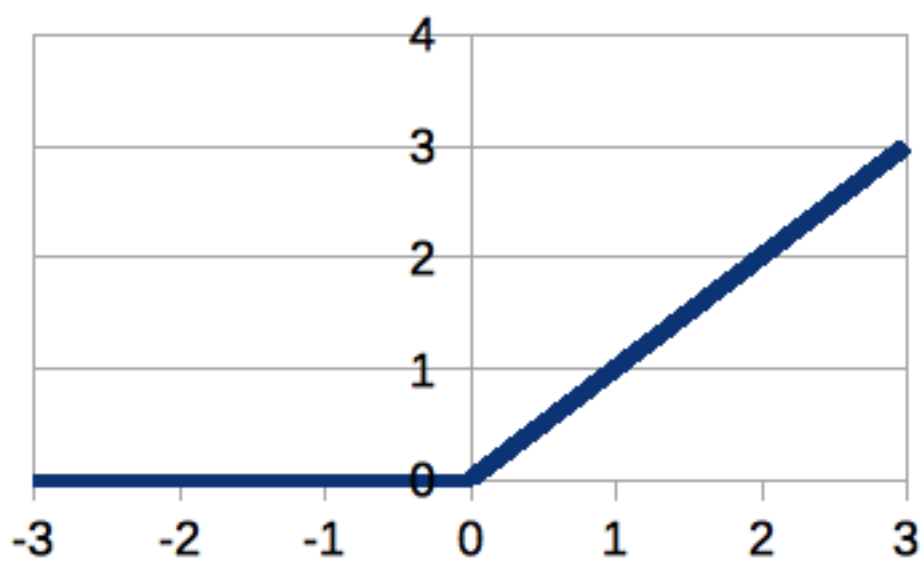
- Which is better, dotted or dashed?



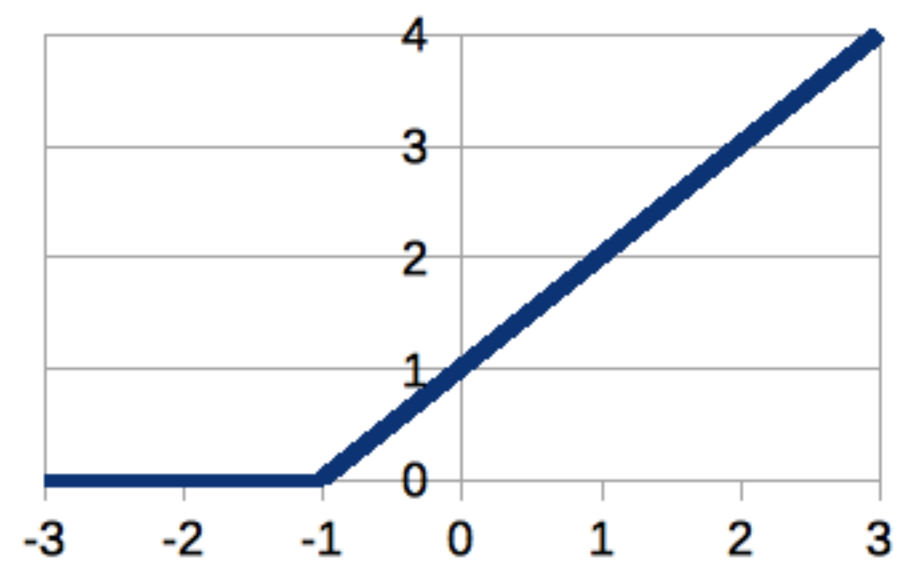
- Both have zero perceptron loss!

Adding a "Margin" with Hinge Loss

- Penalize when incorrect answer is within margin *m*



Perceptron

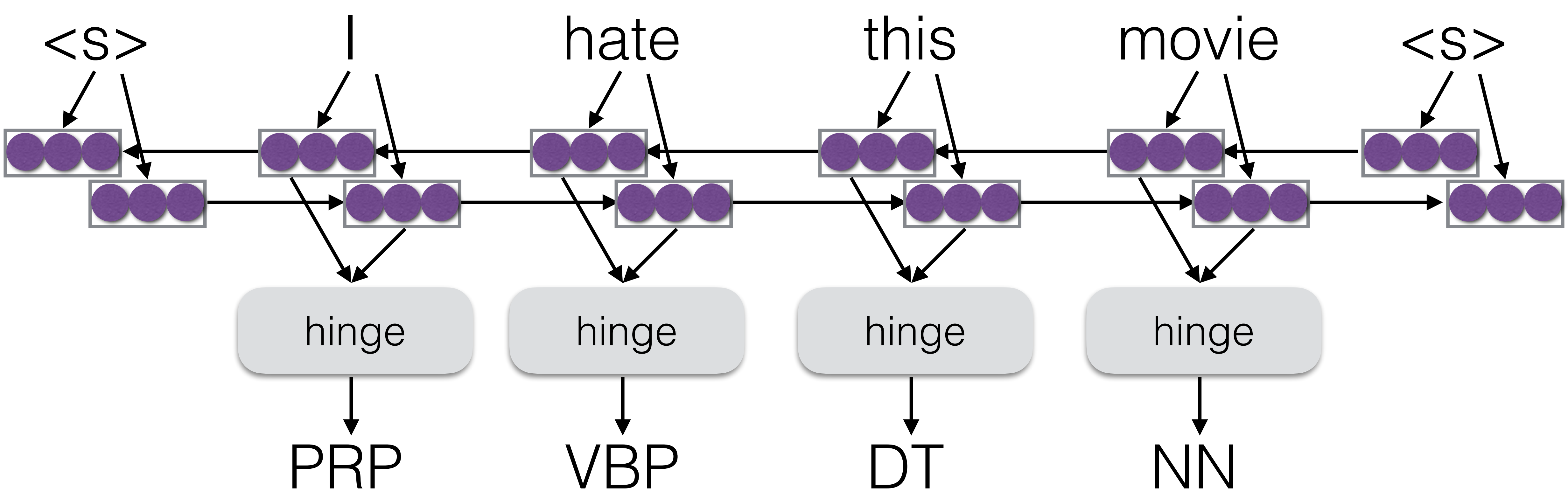


Hinge

$$\ell_{\text{hinge}}(x, y; \theta) = \max(0, m + S(\hat{y} \mid x; \theta) - S(y \mid x; \theta))$$

Hinge Loss for Any Classifier!

- We can swap cross-entropy for hinge loss anytime



e.g.

```
loss = logsoftmax(score, answer)
                ↓
loss = hinge(score, answer, m=1)
```

Cost-augmented Hinge

- Sometimes some decisions are worse than others
  - e.g. VB -> VBP mistake not so bad, VB -> NN mistake much worse for downstream apps
- Cost-augmented hinge defines a cost for each incorrect decision, and sets margin equal to this

$$\ell_{\text{ca-hinge}}(x, y; \theta) = \max(0, \mathrm{cost}(\hat{y}, y) + S(\hat{y} \mid x; \theta) - S(y \mid x; \theta))$$

Costs over Sequences

- **Zero-one loss:** 1 if sentences differ, zero otherwise

$$\text{cost}_{\text{zero-one}}(\hat{Y}, Y) = \delta(\hat{Y} \neq Y)$$

- **Hamming loss:** 1 for every different element (lengths are identical)

$$\text{cost}_{\text{hamming}}(\hat{Y}, Y) = \sum_{j=1}^{|Y|} \delta(\hat{y}_j \neq y_j)$$

- **Other losses:** edit distance, 1-BLEU, etc.

Structured Hinge Loss

- Hinge loss over sequence with the largest margin violation

$$\hat{Y} = \text{argmax}_{\tilde{Y} \neq Y} \text{cost}(\tilde{Y}, Y) + S(\tilde{Y} \mid X; \theta)$$

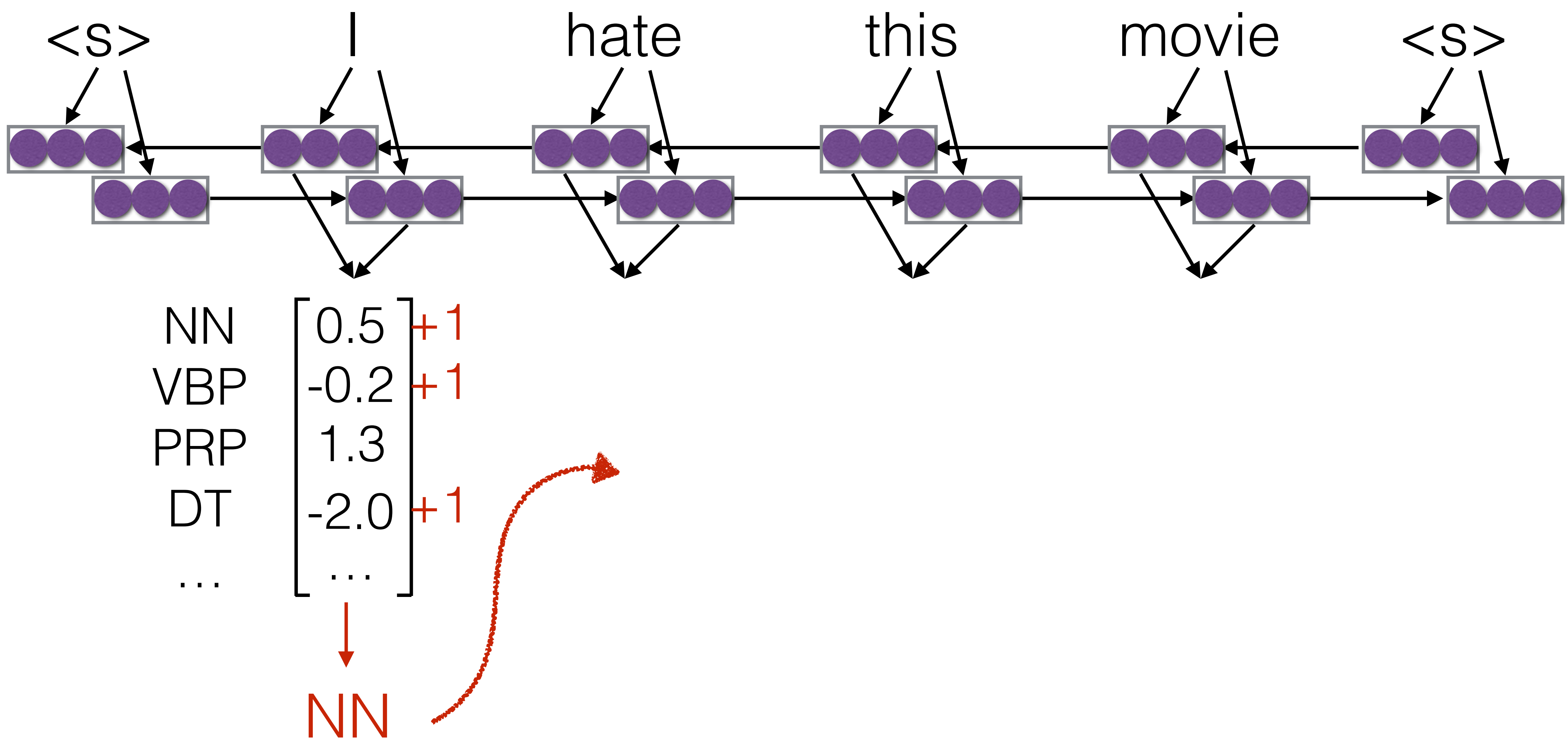
$$\ell_{\text{ca-hinge}}(X, Y; \theta) = \max(0, \text{cost}(\hat{Y}, Y) + S(\hat{Y} \mid X; \theta) - S(Y \mid X; \theta))$$

- **Problem:** How do we find the argmax above?

- **Solution:** In some cases, where the cost can be calculated easily, we can consider cost in search.

Cost-Augmented Decoding for Hamming Loss

- Hamming loss is decomposable over each word
- **Solution:** add a score = cost to each incorrect choice during search



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 (exploration) or argmax (exploitation)** according to the current model

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

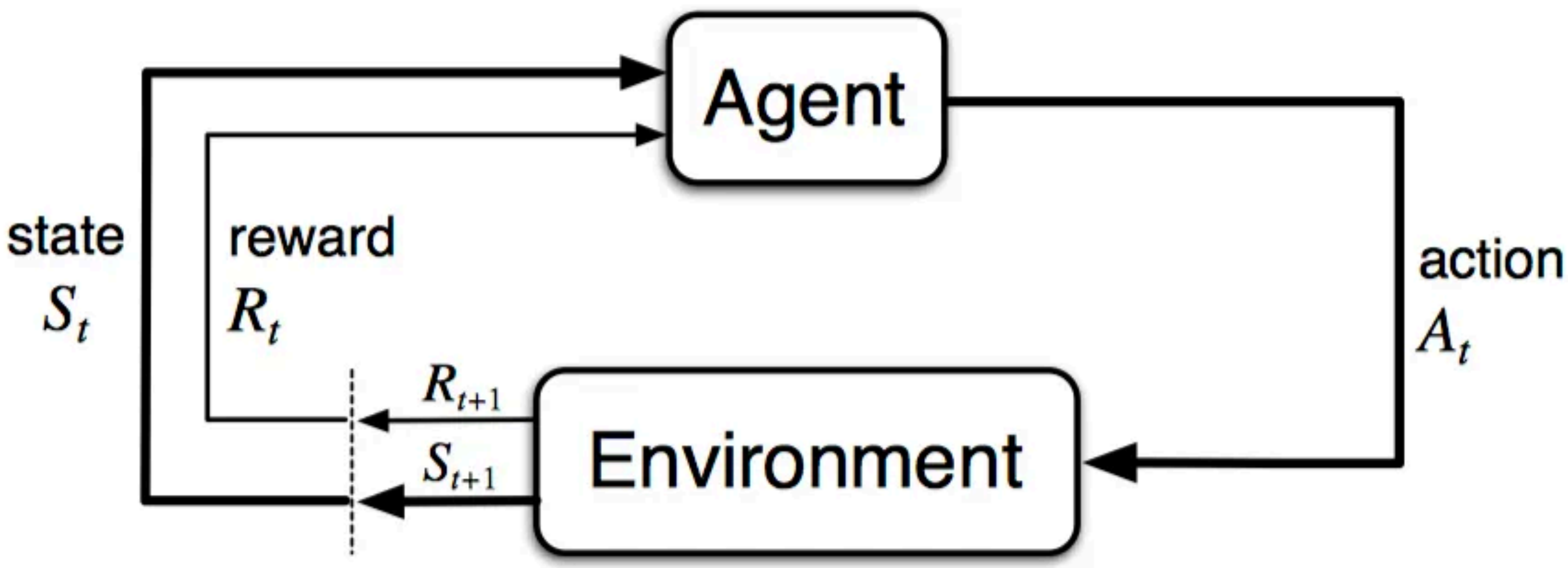
- Use this sample (or samples) to maximize likelihood

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

- 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

- Markov decision process (MDP): defines the probability of transitioning into a new state, getting a reward given the current state and the execution of an action.



s given a state in a

  - Example, LLM is a policy over next tokens (actions) given a prefix (state)

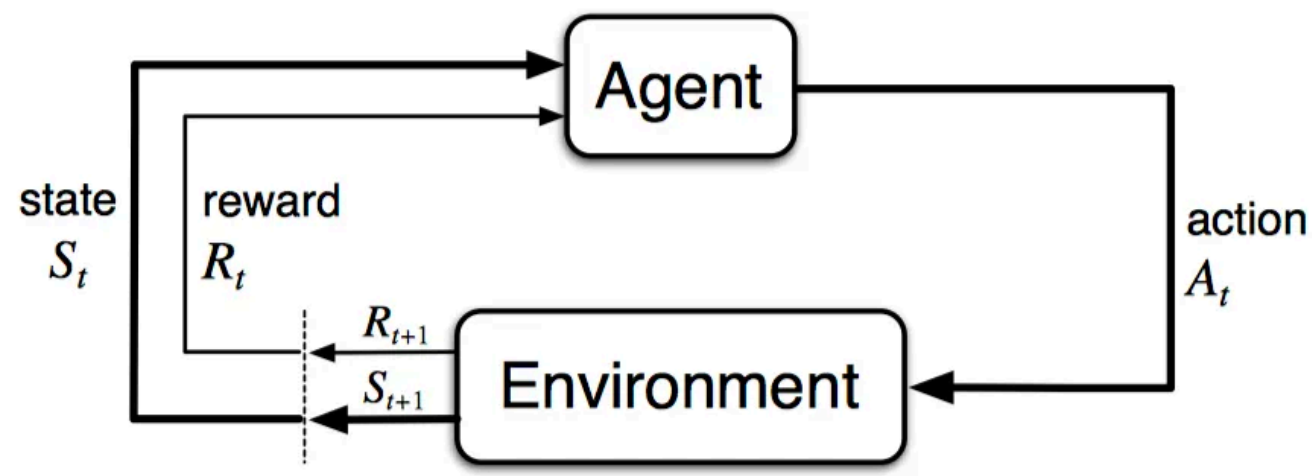
- RL objective: maximize the “expected” reward following a parametrized policy (e.g., text generative models)

Policy Gradient/REINFORCE

- Markov decision process (MDP): defines the probability of transitioning into a new state, getting a reward given the current state and the execution of an action.

LLM

Feedback



Response

Human

- Policy: is defined as a probability distribution of actions given a state in MDP
  - Example: **LLM** is a policy over **next tokens (actions)** given **a prefix prompt (state)**

Policy Gradient/REINFORCE

- RL objective: maximize expected rewards.

$$J(\theta) = \mathbb{E}_{\pi}[R(Y)]$$
$$\pi = P_{\theta}(Y|X)$$

Here the policy is a parameterized text generative model

- Use stochastic gradient **ascent** to update model parameters (for a **maximization** objective)

$$\theta \leftarrow \theta + \alpha \nabla J(\theta)$$

Policy Gradient/REINFORCE

- Rewrite the gradient of the policy as:

$$\begin{aligned}
\nabla J(\theta) &= \nabla \mathbb{E}_\pi[R(Y)] \\
&= \nabla \frac{1}{N} \sum_{\hat{Y} \sim \pi} P_\theta(\hat{Y}|X) R(\hat{Y}) \qquad \rightarrow \text{sample } N \text{ outputs from } \pi \\
&= \frac{1}{N} \sum_{\hat{Y} \sim \pi} \nabla P_\theta(\hat{Y}|X) R(\hat{Y}) \\
&= \frac{1}{N} \sum_{\hat{Y} \sim \pi} P_\theta(\hat{Y}|X) \nabla \log P_\theta(\hat{Y}|X) R(\hat{Y}) \\
&= \mathbb{E}_\pi \, [\nabla \log P_\theta(Y|X) R(Y)]
\end{aligned}$$

- Hence, the PG problem can also be rewritten as the minimization of the following loss

$$L(\theta) = \mathbb{E}_\pi[-\log P_\theta(Y|X) R(Y)] = \frac{1}{N} \sum_{\hat{Y} \sim \pi} \boxed{-\log P_\theta(\hat{Y}|X) R(\hat{Y})}$$

Define this as a policy loss ℓ_{policy}

$$\theta \leftarrow \theta - \alpha \nabla L(\theta)$$

Policy Gradient/REINFORCE

- Add a term that scales the loss by the reward

$$\ell_{\text{policy}} = -R(\hat{Y}) \log P(\hat{Y}|X)$$

- Reward function: Outputs that get a bigger reward will get a higher weight

    - If we only have labeled data (X, Y^*), we can replace $R(\hat{Y})$ by $R(\hat{Y}, Y^*)$, where we can compare the semantic or lexical distance between the sampled output and the human-reference output. Example: use the **BLEU** score

    - Alternatively, **we can ask for human feedback, and learn a reward model**. Example: **ChatGPT** learn a reward function from ranking of model outputs provided by human.

- Quiz: Under what conditions is the above loss equal to MLE?

- $\hat{Y}$ can be obtained by **sampling or argmax (greedy decoding)**, in the same way as self-training (c.f. exploration-exploitation trade-off).

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

Generic RL Framework for Text Generation

- Pretrain a policy model by self-supervised learning
- For each prefix X:
  - Sample a batch of output sequences $\hat{Y}$
  - Compute the reward of all sampled outputs
  - Compute Policy Gradients $\nabla L(\theta)$, which is the gradient of the negative log-likelihood weighted by the reward
  - Update the model parameters

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	R-B
"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 R-B 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 (often heuristics)
- 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

Proximal Policy Optimization (PPO)

- We do need warm-start (i.e., pre-training), and we also want the updated model to be closed to the pre-trained checkpoint

- In addition to maximizing the reward, we add a regularization term

$$J_{\mathrm{PPO}}(\theta) = \mathbb{E}_{\pi}\left[R(Y) - \beta \log \frac{P_{\theta}(Y|X)}{P_{\theta_{\mathrm{pretrain}}}(Y|X)}\right]$$

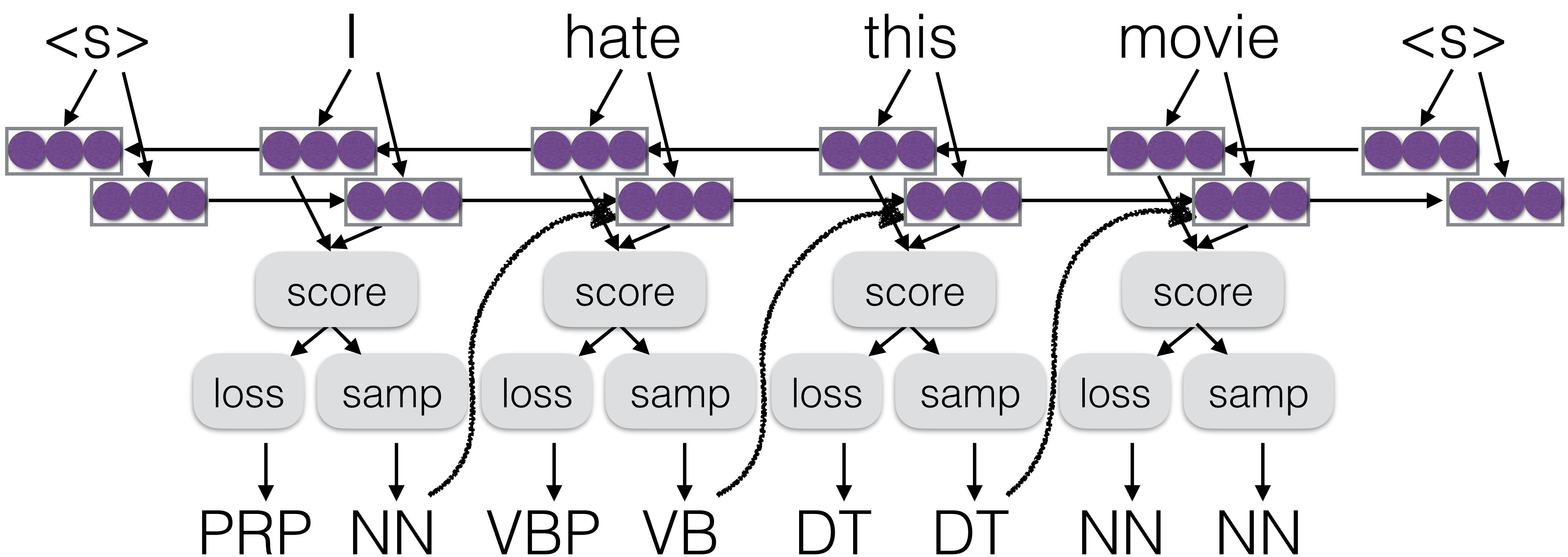
Other Simpler Remedies to Exposure Bias

What’s Wrong w/ Structured Hinge Loss?

- It may work, but…
  - Considers fewer hypotheses, so **unstable**
  - Requires decoding, so **slow**
- Generally must resort to pre-training (and even then, it’s not as stable as teacher forcing w/ MLE)

Solution 1: Sample Mistakes in Training (Ross et al. 2010)

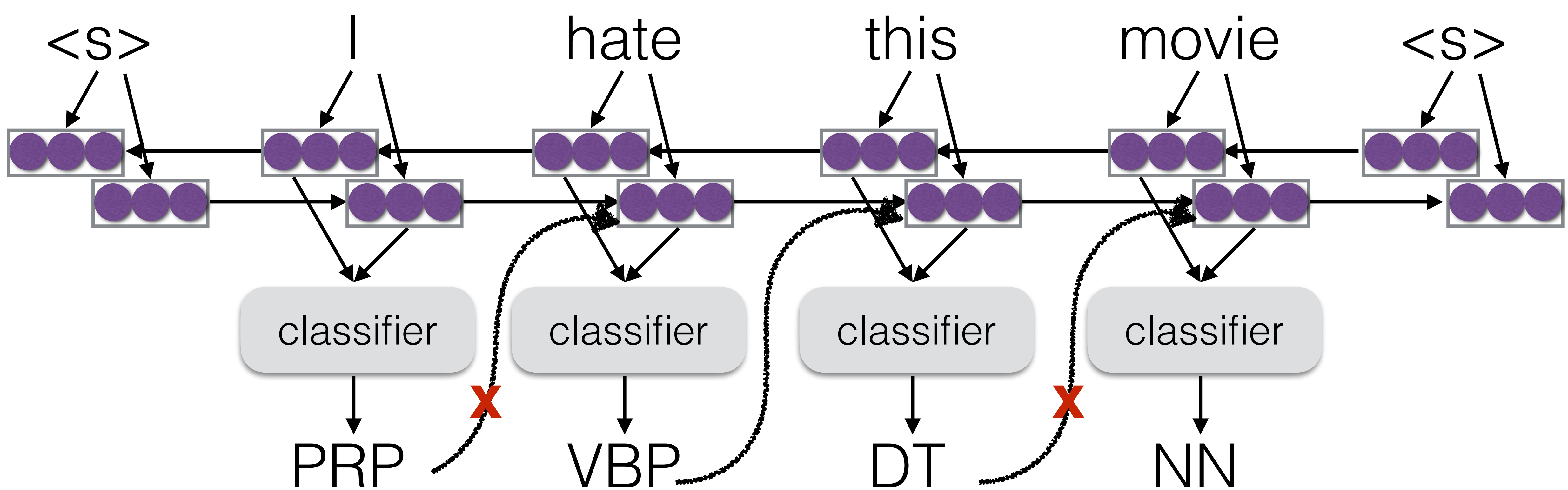
- DAgger, also known as “scheduled sampling”, etc., randomly samples wrong decisions and feeds them in



- Start with no mistakes, and then gradually introduce them using annealing

Solution 2: Drop Out Inputs

- **Basic idea:** Simply don't input the previous decision sometimes during training (Gal and Ghahramani 2015)



- Helps ensure that the model doesn't rely too heavily on predictions, while still using them

Solution 3: Corrupt Training Data

- Reward augmented maximum likelihood (Nourozi et al. 2016)
- **Basic idea:** randomly sample incorrect training data, train w/ maximum likelihood

$$\mathcal{L}_{\mathrm{RAML}}(\boldsymbol{\theta}; \tau, \mathcal{D}) = \sum_{(\mathbf{x}, \mathbf{y}^*) \in \mathcal{D}} \left\{ - \sum_{\mathbf{y} \in \mathcal{Y}} q(\mathbf{y} \mid \mathbf{y}^*; \tau) \log p_{\theta}(\mathbf{y} \mid \mathbf{x}) \right\}$$

I	hate	this	movie
		$\updownarrow$ MLE	
PRP	**NN**	DT	NN
		$\uparrow$ sample	
PRP	VBP	DT	NN

- Sampling probability proportional to goodness of output
- Can be shown to approximately minimize risk

Questions?