CS11-747 Neural Networks for NLP

Structured Perceptron/ Margin Methods

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

Types of Prediction

- Two classes (**binary classification**)

I hate this movie → negative

positive
negative

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

I hate this movie → very bad

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*

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

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

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

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

Globally Normalized Likelihood

Difficulties Training Globally Normalized Models

- Partition function problematic

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

- 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!

$$P(Y \mid X) = \frac{e^{S(X,Y)}}{\sum_{\tilde{Y} \in V*} e^{S(X,\tilde{Y})}} \qquad \hat{Y} = \underset{Y}{\operatorname{argmax}}\ S(X,Y)$$

The Structured Perceptron Algorithm

- An extremely simple way of training (non-probabilistic) global models
- Find the one-best, and if it's score is better than the correct answer, adjust parameters to fix this

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

Find one best

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

If score better than reference

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

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 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

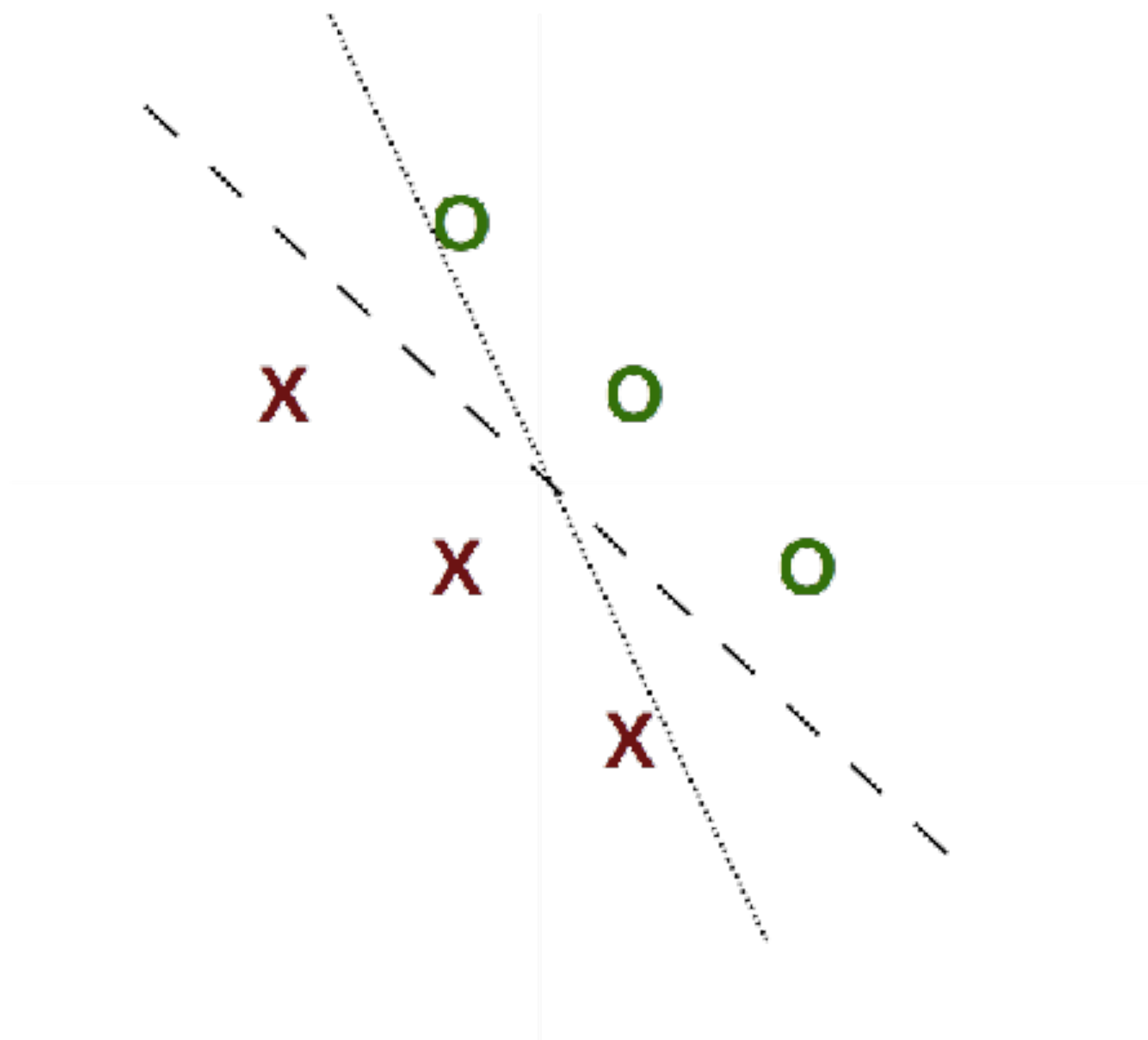
Structured Training and Pre-training

- 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

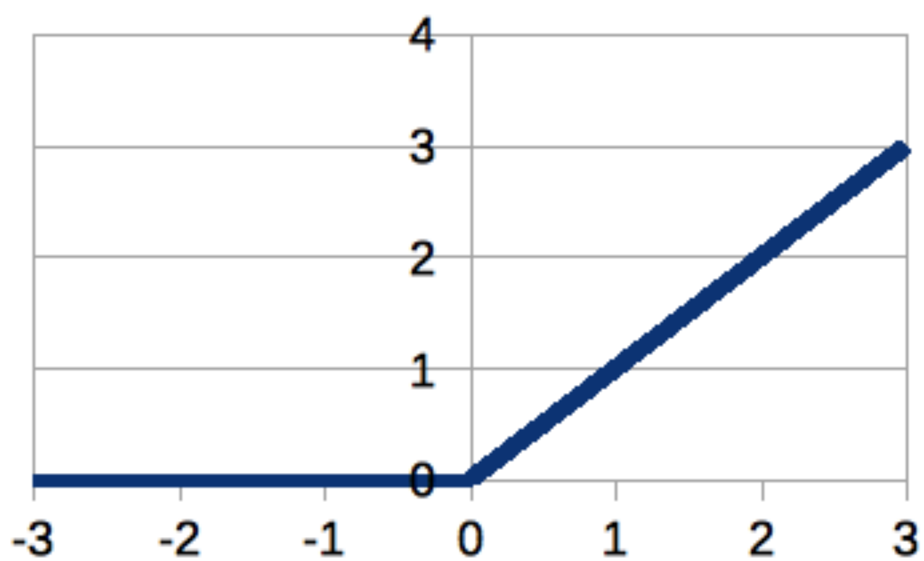
- Which is better, dotted or dashed?



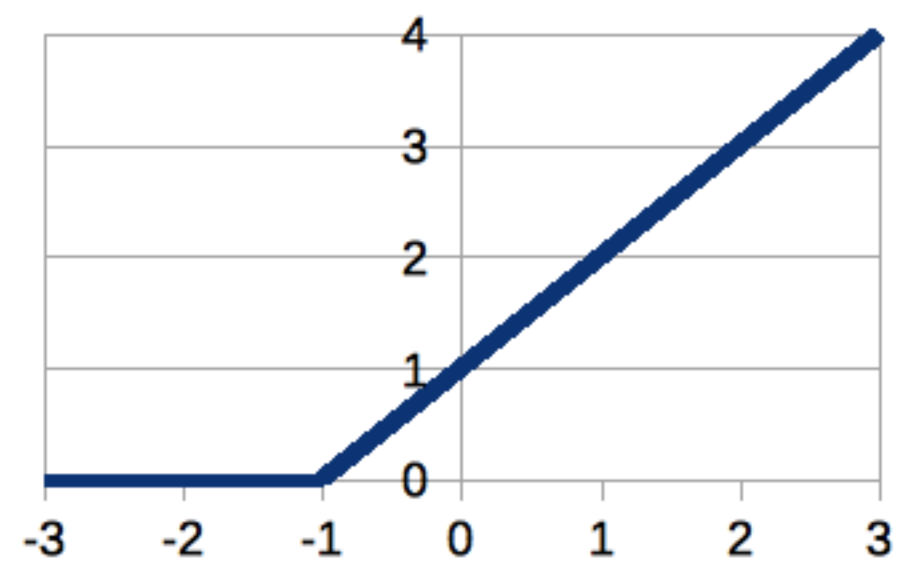
- Both have zero perceptron loss!

Adding a "Margin" with Hinge Loss

- Penalize when incorrect answer is within margin *m*



Perceptron

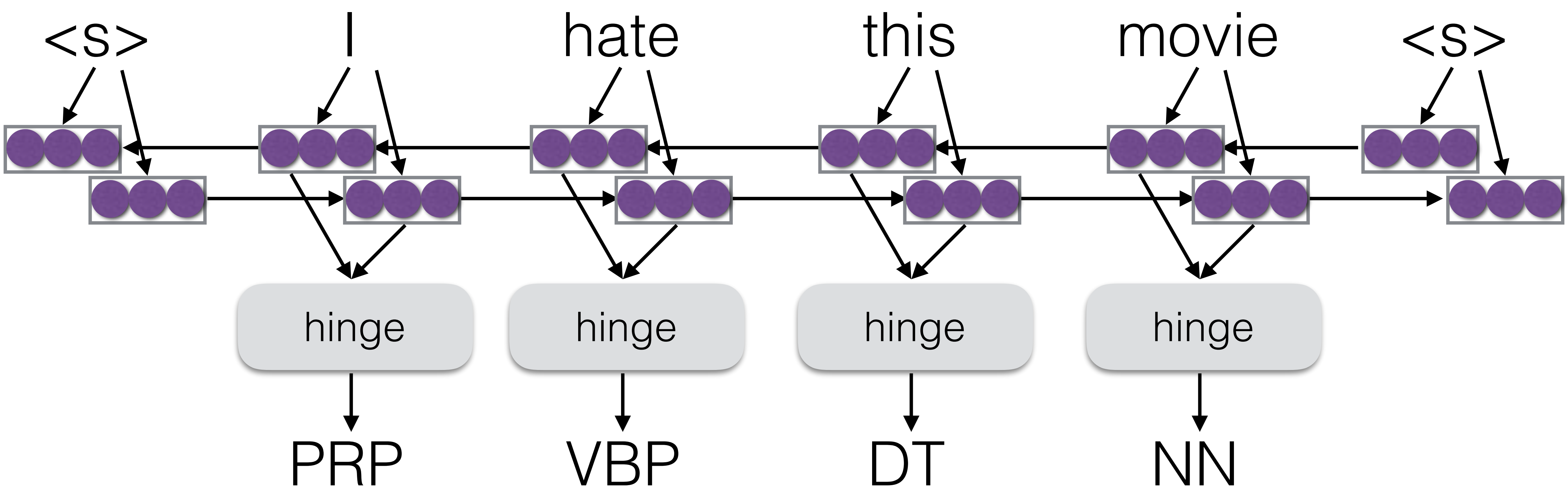


Hinge

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

Hinge Loss for Any Classifier!

- We can swap cross-entropy for hinge loss anytime



e.g. in DyNet

```
loss = dy.pickneglogsoftmax(score, answer)
                    ↓
loss = dy.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

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

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

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

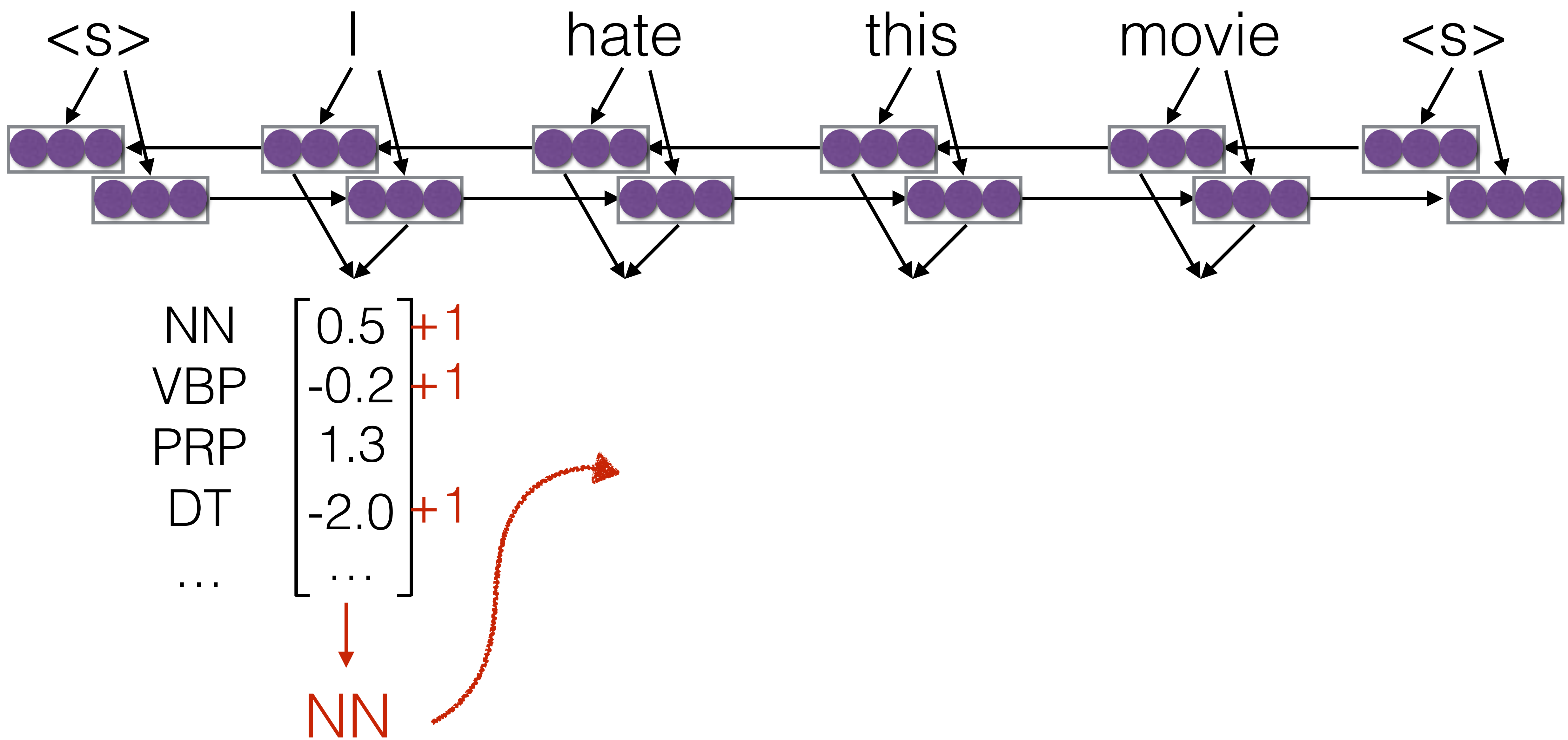
$$\ell_{\text{ca-hinge}}(X, Y; \theta) = \max(0, \text{cost}(\hat{Y}, Y) + S(\hat{Y} \mid X; \theta) - S(Y \mid X; \theta))$$

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

- **Solution:** In some cases, where the loss can be calculated easily, we can consider loss 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



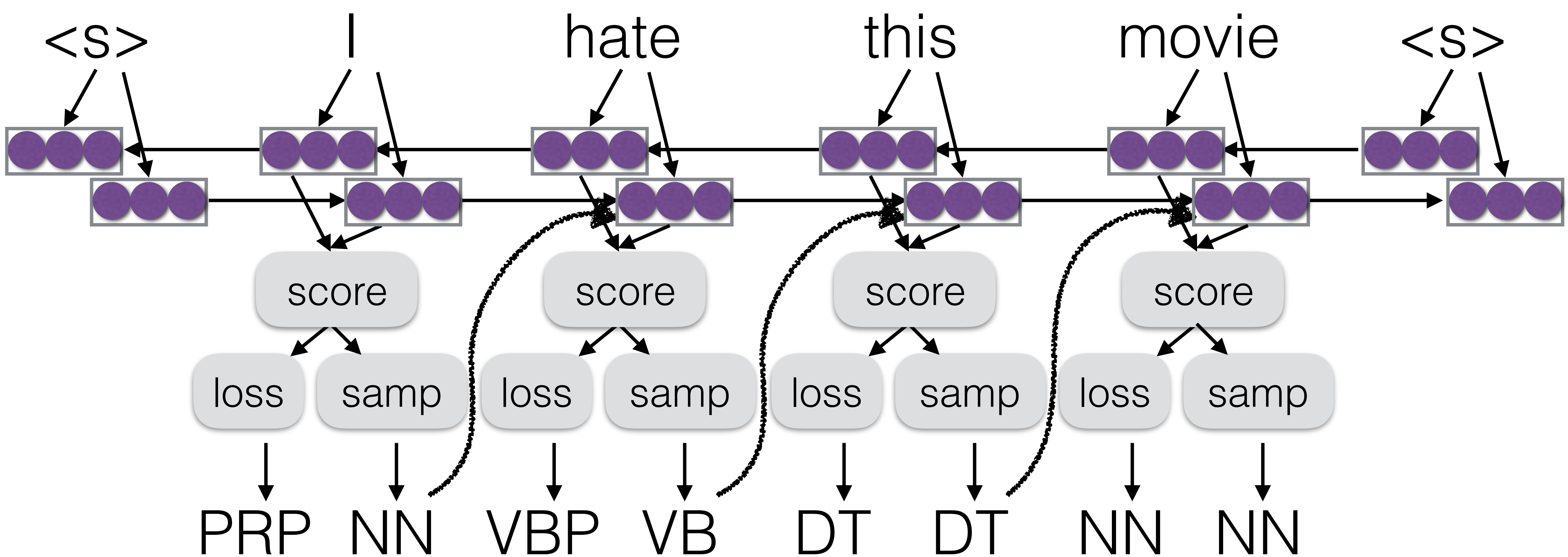
Simpler Remedies to Exposure Bias

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

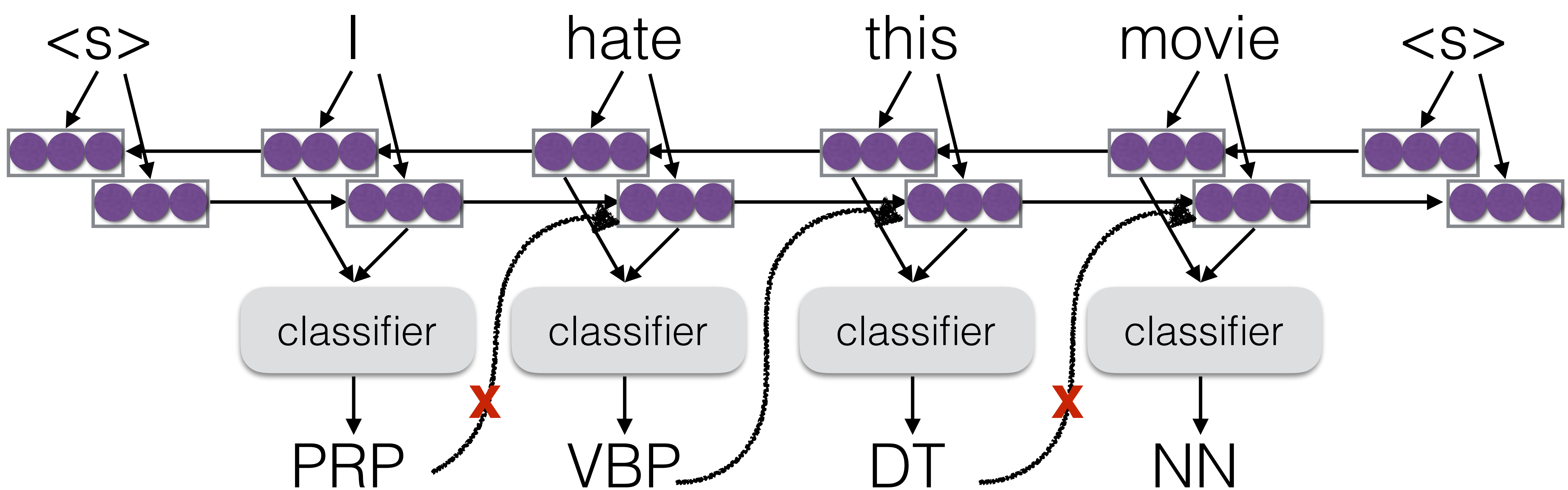


  - Start with no mistakes, and then gradually introduce them using annealing

- How to choose the next tag? Use the gold standard, or create a “dynamic oracle” (e.g. Goldberg and Nivre 2013)

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

I	hate	this	movie
		↕ MLE	
PRP	**NN**	DT	NN
		↑ sample	
PRP	VBP	DT	NN

- Sampling probability proportional to goodness of output
- Can be shown to approximately minimize risk (next class)

Questions?