CS11-711 Advanced NLP

Conditioned Generation

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Site
https://phontron.com/class/anlp2022/

Language Models

- Language models are generative models of text

$$s \sim P(x)$$

↓

"The Malfoys!" said Hermione.

Harry was watching him. He looked like Madame Maxime. When she strode up the wrong staircase to visit himself.

"I'm afraid I've definitely been suspended from power, no chance—indeed?" said Snape. He put his head back behind them and read groups as they crossed a corner and fluttered down onto their ink lamp, and picked up his spoon. The doorbell rang. It was a lot cleaner down in London.

Text Credit: Max Deutsch (https://medium.com/deep-writing/)

Conditioned Language Models

- Not just generate text, generate text according to some specification

Input *X*	Output *Y* (**Text**)	Task
Structured Data	NL Description	NL Generation
English	Japanese	Translation
Document	Short Description	Summarization
Utterance	Response	Response Generation
Image	Text	Image Captioning
Speech	Transcript	Speech Recognition

Formulation and Modeling

Calculating the Probability of a Sentence

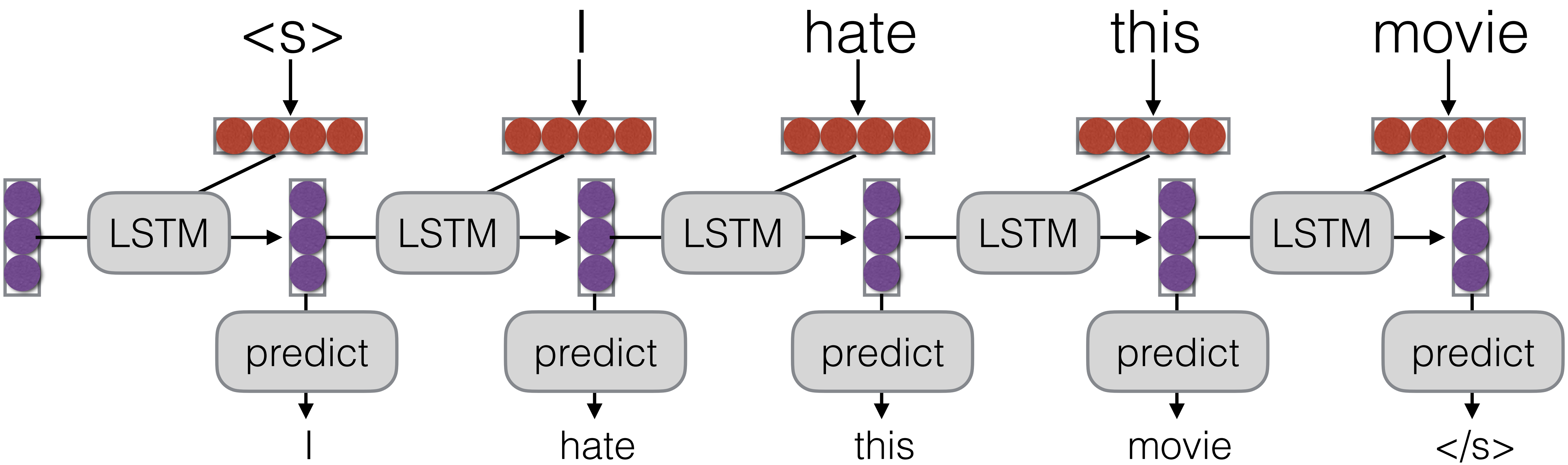
$$P(X) = \prod_{i=1}^{I} P(\underbrace{x_i}_{\text{Next Word}} \mid \underbrace{x_1, \ldots, x_{i-1}}_{\text{Context}})$$

Conditional Language Models

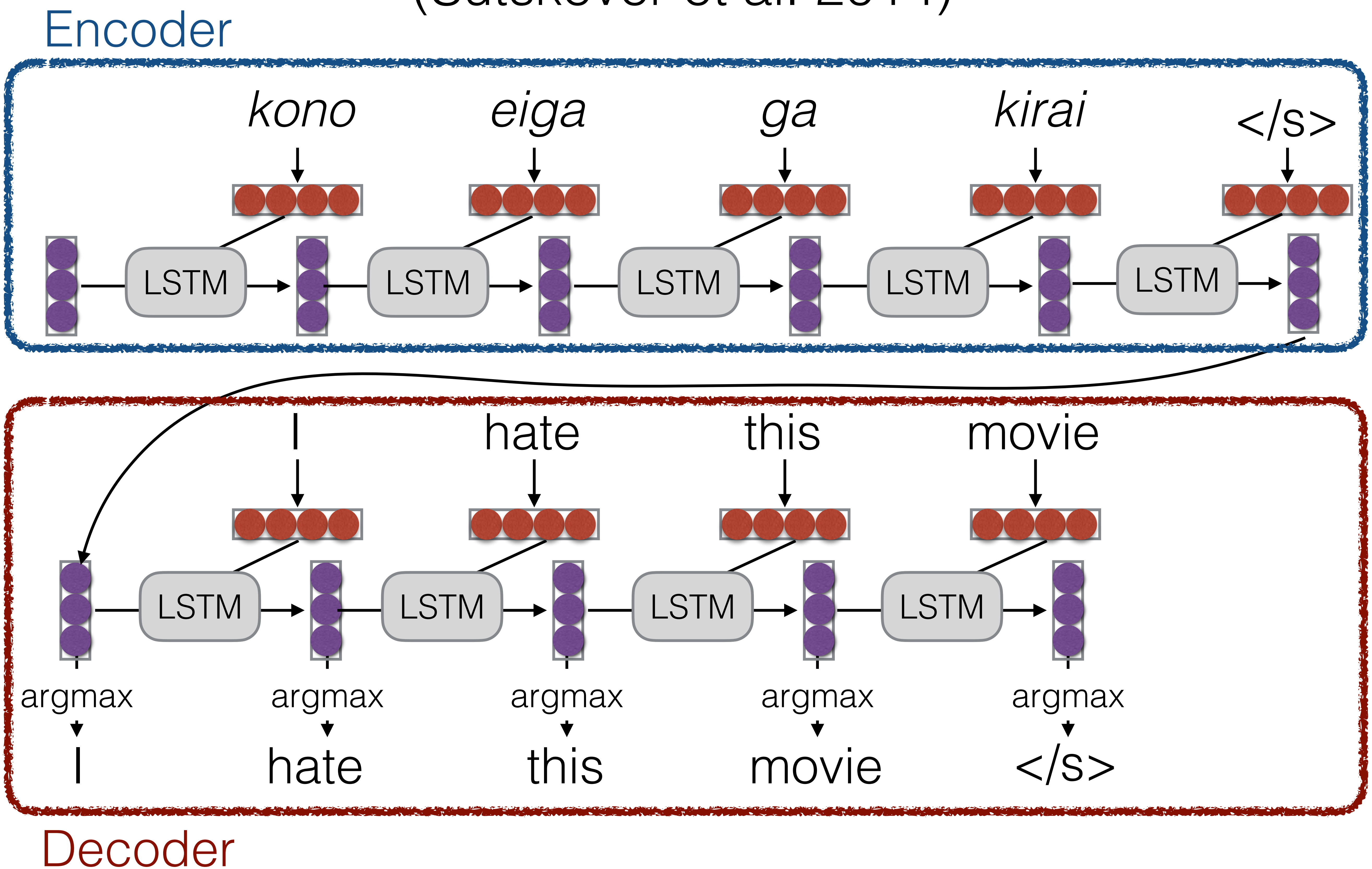
$$P(Y|X) = \prod_{j=1}^{J} P(y_j \mid \underline{X}, y_1, \ldots, y_{j-1})$$

Added Context!

(One Type of) Language Model (Mikolov et al. 2011)



(One Type of) Conditional Language Model
(Sutskever et al. 2014)



Methods of Generation

The Generation Problem

- We have a model of P(Y|X), how do we use it to generate a sentence?

- Two methods:

    - **Sampling:** Try to generate a *random* sentence according to the probability distribution.

    - **Argmax:** Try to generate the sentence with the *highest* score.

Ancestral Sampling

- **Randomly generate** words one-by-one.

$$\boxed{\begin{array}{l}\text{while } y_{j-1} \mathrel{!}= \text{“</s>”:} \\ \quad y_j \sim P(y_j \mid X, y_1, \ldots, y_{j-1})\end{array}}$$

- An **exact method** for sampling from P(X), no further work needed.

Greedy Search

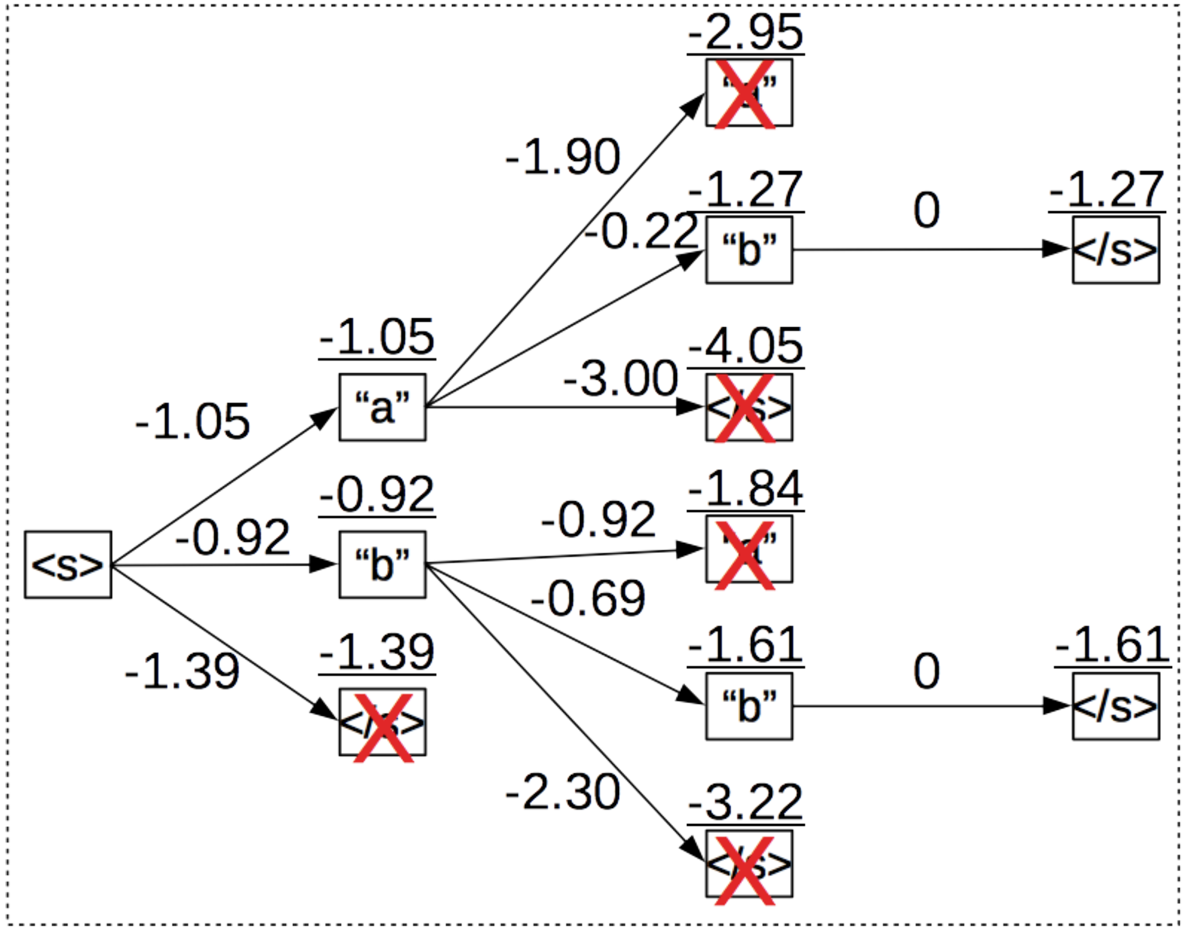
- One by one, pick the single highest-probability word

```
while y_{j-1} != "</s>":
  y_j = argmax P(y_j | X, y_1, …, y_{j-1})
```

- **Not exact, real problems:**
  - Will often generate the "easy" words first
  - Will prefer multiple common words to one rare word

Beam Search

- Instead of picking one high-probability word, maintain several paths



- Adjust the "beam size" *b* to spend more time on searching, find a better scoring hypothesis

Case Studies in Conditional Language Modeling

Translation

- Most widely used example of generation?
- e.g. Translation from **WMT shared tasks** (http://statmt.org/wmt21/)
  - News translation
  - Similar language translation
  - Biomedical translation
  - Low-resource multilingual translation
  - Translation efficiency
  - Terminology-aware translation
  - Lifelong learning

Summarization

- Take a longer text, and output a shorter text
- Can use *extractive* models that copy input, or *abstractive* models that generate from scratch
- Multiple granularities:
    - Sentence compression (sentence -> shorter sentence)
    - Single document summarization (document -> shorter text)
    - Multi-document summarization (multiple documents -> text)

Dialog Response Generation

- Given an input utterance, generate a response
- e.g. Meena Chatbot (Adiwardana et al. 2020)

Human: Hi!
Meena: Hi there! How's it going?
Human: Pretty well.
Meena: I'm glad to hear it. :D
Human: What is your favorite book?
Meena: Oh, that's a toughie. Right now I'd have to say it's A Dance With Dragons, but Harry Potter is a close second.
Human: Oh I love Harry Potter
Meena: Me too! I've read the series at least five times over.
Human: Haha, same probably. Which one do you like the most
Meena: Probably Chamber of Secrets.
Human: Ah. I like Prisoner of azkaban best
Meena: Yeah, that's a good one too.
Human: Do you like the movies more or the books
Meena: I like the movies more. The books are good, don't get me wrong, but I like the pacing better in the movies.
Human: That is an unpopular opinion
Meena: I know. I'm the only one I know who prefers the movies.

Image Captioning
(e.g. Karpathy et al. 2015)

- Input is image features, output is text

training image

"A Tabby cat is leaning on a wooden table, with one paw on a laser mouse and the other on a black laptop"

- Use standard image encoders (e.g. CNN)

- Often pre-trained on large databases such as ImageNet

From Structured Data
(e.g. Wen et al 2015)

- When you say "Natural Language Generation" to an old-school NLPer, it means this

	SF Restaurant	SF Hotel
act type	inform, inform_only, reject, confirm, select, request, reqmore, goodbye	
shared	name, type, *pricerange, price, phone, address, postcode, *area, *near	
specific	*food *goodformeal ***kids-allowed**	***hasinternet** ***acceptscards** ***dogs-allowed**

bold=binary slots, *=slots can take "don't care" value

Still a Difficult Problem!

- e.g. "Challenges in data-to-document generation" (Wiseman et al. 2017)

TEAM	WIN	LOSS	PTS	FG_PCT	RB	AS ...
Heat	11	12	103	49	47	27
Hawks	7	15	95	43	33	20

PLAYER	AS	RB	PT	FG	FGA	CITY ...
Tyler Johnson	5	2	27	8	16	Miami
Dwight Howard	4	17	23	9	11	Atlanta
Paul Millsap	2	9	21	8	12	Atlanta
Goran Dragic	4	2	21	8	17	Miami
Wayne Ellington	2	3	19	7	15	Miami
Dennis Schroder	7	4	17	8	15	Atlanta
Rodney McGruder	5	5	11	3	8	Miami
Thabo Sefolosha	5	5	10	5	11	Atlanta
Kyle Korver	5	3	9	3	9	Atlanta
...						

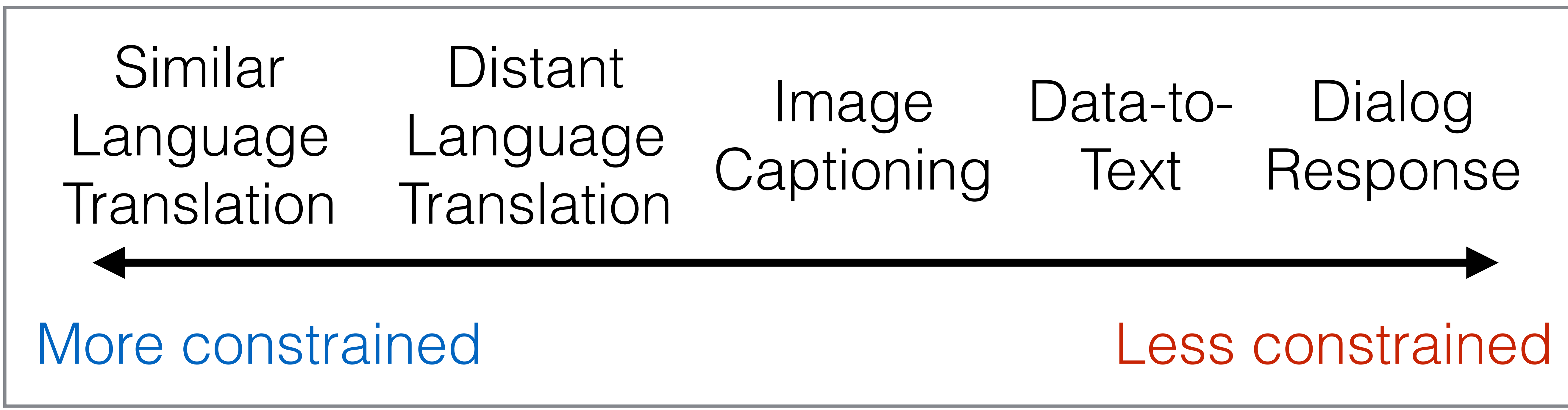
The Utah Jazz (38 - 26) defeated the Houston Rockets (38 - 26) 117 - 91 on Wednesday at Energy Solutions Arena in Salt Lake City . The Jazz got out to a quick start in this one , out - scoring the Rockets 31 - 15 in the first quarter alone . Along with the quick start , the Rockets were the superior shooters in this game , going 54 percent from the field and 43 percent from the three - point line , while the Jazz went 38 percent from the floor and a meager 19 percent from deep . The Rockets were able to out - rebound the Rockets 49 - 49 , giving them just enough of an advantage to secure the victory in front of their home crowd . The Jazz were led by the duo of Derrick Favors and James Harden . Favors went 2 - for - 6 from the field and 0 - for - 1 from the three - point line to score a game - high of 15 points , while also adding four rebounds and four assists ....

Figure 2: Example document generated by the Conditional Copy system with a beam of size 5. Text that accurately reflects a record in the associated box- or line-score is highlighted in blue, and erroneous text is highlighted in red.

- Focused evaluation using, e.g. information extraction

Level of Constraint on Output

- Given the conditioning, the outputs can be more or less constrained, very rough approximation below



- More freedom = more flexibility, but often more difficulty in modeling and evaluation

Controlled Generation

- Add a further constraint in addition to content-based ones
- **Politeness/Style Control:** Take an input *X* and a label indicating style, etc. (e.g. Sennrich et al. 2016)

source	Give me the telephone!
reference	Gib mir das Telefon! [T]
none	Gib mir das Telefon! [T]
polite	Geben Sie mir das Telefon! [V]
informal	Gib mir das Telefon! [T]

- **Personalization:** Take an input *X* and a side information about the speaker (e.g. Hoang et al. 2016)
- etc. etc.

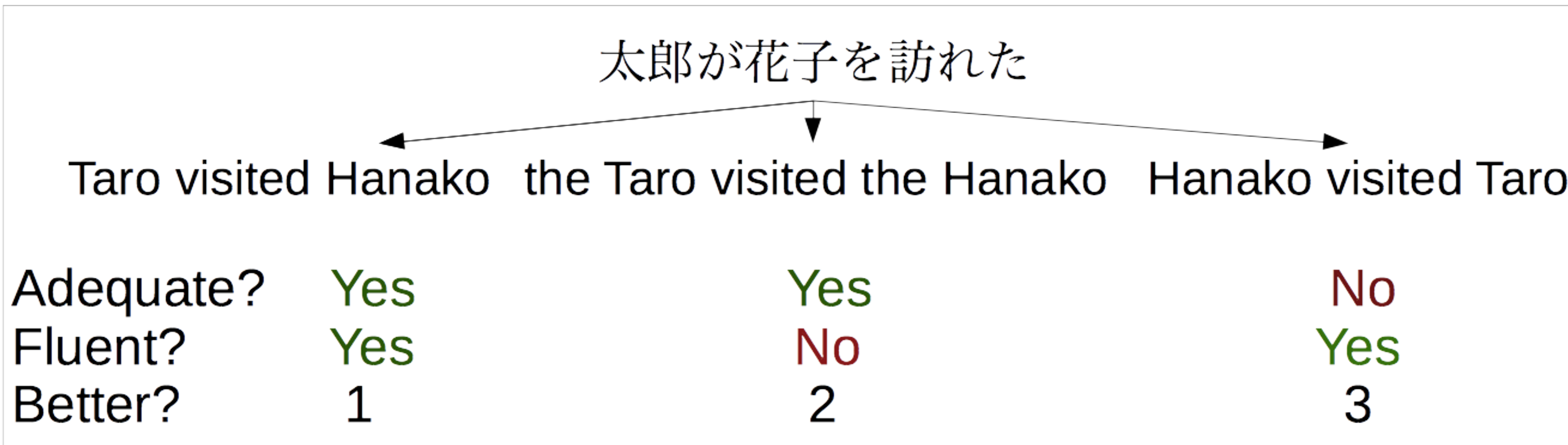
How do we Evaluate?

Basic Evaluation Paradigm

- Use parallel test set
- Use system to generate translations
- Compare target translations w/ reference

Human Evaluation

- Ask a human to do evaluation



- Final goal, but slow, expensive, and sometimes inconsistent

Human Evaluation Shared Tasks

- **Machine Translation**
  - Conference on Machine Translation (WMT) shared tasks http://www.statmt.org/wmt20/
- **Composite Leaderboard**
  - GENIE leadeboard for QA, summarization, MT https://genie.apps.allenai.org/

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BLEU

- Works by comparing n-gram overlap w/ reference

Reference: Taro visited Hanako

System: the Taro visited the Hanako

1-gram: 3/5
2-gram: 1/4

Brevity: min(1, |System|/|Reference|) = min(1, 5/3)

brevity penalty = 1.0

BLEU-2 = $(3/5*1/4)^{1/2} * 1.0$
= 0.387

- **Pros:** Easy to use, good for measuring system improvement
- **Cons:** Often doesn't match human eval, bad for comparing very different systems

Embedding-based Metrics

- Recently, many metrics based on neural models
  - **BertScore:** Find similarity between BERT embeddings (unsupervised) (Zhang et al. 2020)
  - **BLEURT:** Train BERT to predict human evaluation scores (Sellam et al. 2020)
  - **COMET:** Train model to predict human eval, also using source sentence (Rei et al. 2020)
  - **PRISM:** Model based on training paraphrasing model (Thompson and Post 2020)
  - **BARTScore:** Calculate the probability of source, reference, or system output (Yuan et al. 2021)

Perplexity

- Calculate the perplexity of the words in the held-out set *without* doing generation
- **Pros:** Naturally solves multiple-reference problem!
- **Cons:** Doesn’t consider decoding or actually generating output.
- May be reasonable for problems with lots of ambiguity.

Which One to Use?

- **Meta-evaluation** runs human evaluation and automatic evaluation on the same outputs, calculates correlation
- Examples:
  - **WMT Metrics Task** for MT (Mathur et al. 2021)
  - **RealSumm** for summarization (Bhandari et al. 2020)
- Evaluation is hard, especially with good systems! Most metrics had no correlation w/ human eval over best systems at some WMT 2019 tasks

Revisiting Search

Bad Model + Big Beam = Big Trouble!

- If your underlying model is bad, finding a *better scoring hypothesis* can equal *worse generations*!

e.g. in machine translation, leads to short hypotheses (Stahlberg and Byrne 2019)

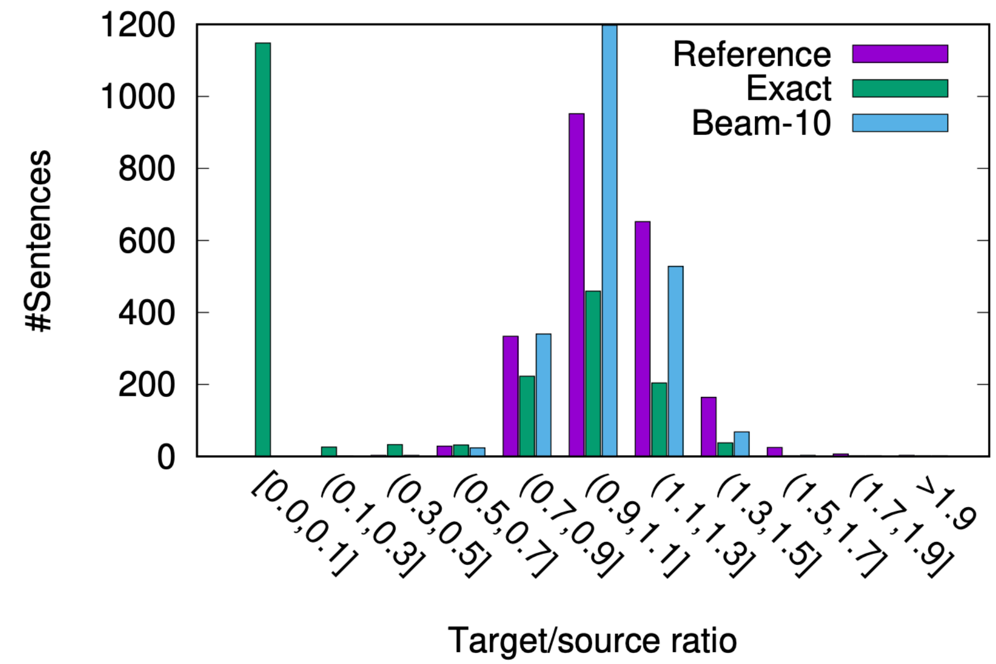


Figure 3: Histogram over target/source length ratios.

e.g. in open-ended generation, leads to repetition (Holtzman et al. 2019)

The number of stranded whales has increased by more than 50 per cent in the past year, with the number of stranded whales on the West Australian coast increasing by more than 50 per cent in the past year. The number of whales stranded on the West Australian coast has increased by more than 50 per cent in the past year, with the number of stranded whales on the West Australian coast increasing by more than 50 per cent in the past year.

Alternative 1: *Worse* Search for *Better* Outputs

- Find lower-scoring hypotheses that are nonetheless better

P(x_6 | "The capital of Pennsylvania is")

Harrisburg	34.3%
Philadelphia	31.1%
Pittsburgh	12.9%
Easton	2.2%
Lancaster	1.8%
Allentown	1.6%
Washington	1.5%

Top-k Sampling
(e.g. k=5)

Nucleus Sampling
(e.g. p=0.8)

Alternative 2: Better Decision Rule

- minimum Bayes risk (e.g. Fernandes et al. 2022)

$$\mathrm{BayesRisk}(y|x) = \sum_{\tilde{y}} P(\tilde{y}|x)\mathrm{Error}(y, \tilde{y}) \qquad \hat{y} = \underset{y}{\mathrm{argmin}}\ \mathrm{BayesRisk}(y|x)$$

P(y | “What is your name”)	I don’t know	20.1%
	My name is Jane	10.4%
	My name is John	9.2%
	My name is Robert	8.3%

- Common method:
  - generate n-best list (using beam search or sampling)
  - rescore n-best list

Toolkit: https://github.com/deep-spin/qaware-decode

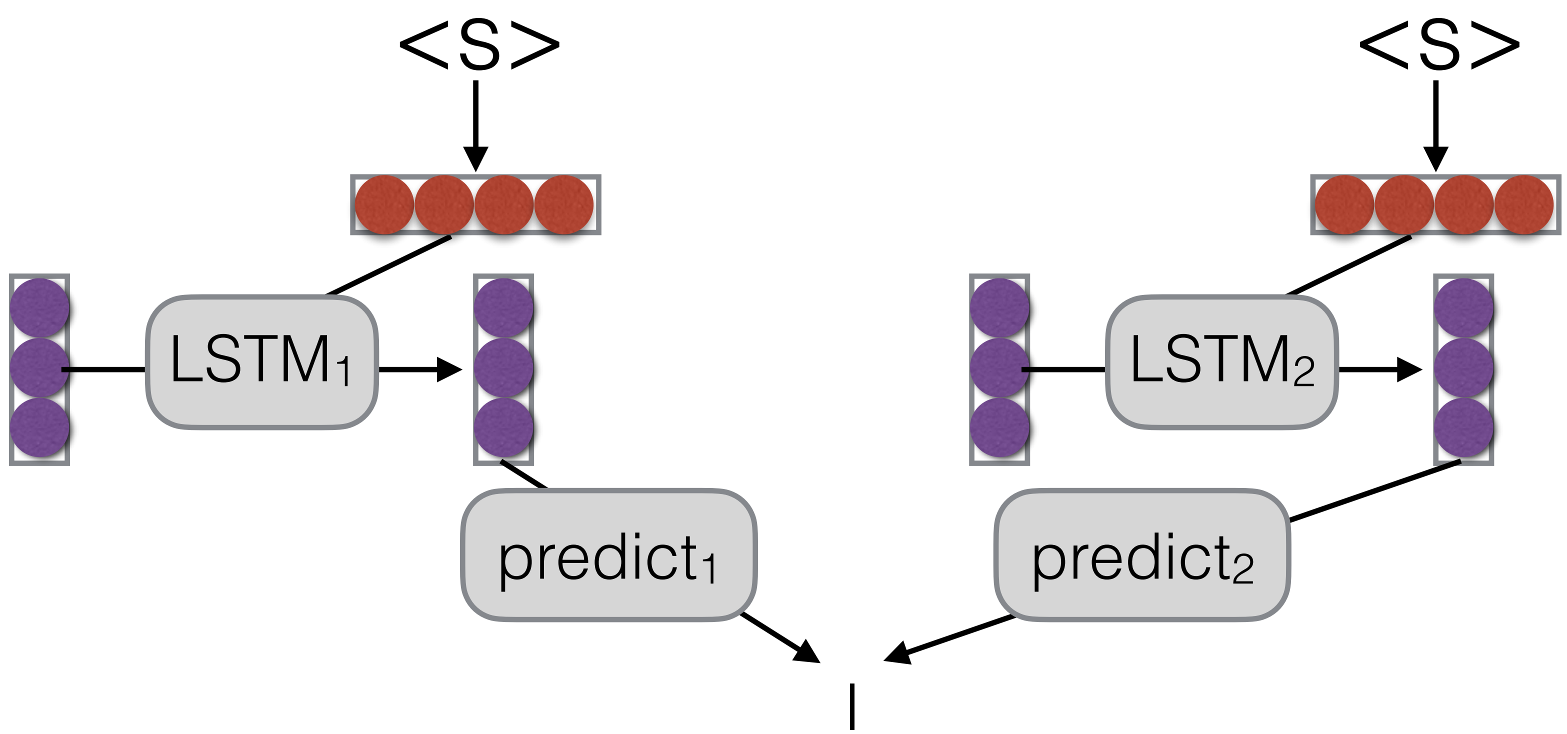
Alternative 3: Train Better Model!

- Your problems are because your model is scoring bad hypotheses highly, so fix it!
- Methods:
  - **Minimum risk training** (e.g. through reinforcement learning, enumeration)
  - **Margin-based training** (e.g. through ranking, "contrastive learning")
- More in later classes

An Aside:
Model Ensembling

Ensembling

- Combine predictions from multiple models



- Why?
  - Multiple models make somewhat uncorrelated errors
  - Models tend to be more uncertain when they are about to make errors
  - Smooths over idiosyncrasies of the model

Linear Interpolation

- Take a weighted average of the M model probabilities

$$P(y_j \mid X, y_1, \ldots, y_{j-1}) = \sum_{m=1}^{M} \underbrace{P_m(y_j \mid X, y_1, \ldots, y_{j-1})}_{\text{Probability according to model } m} \underbrace{P(m \mid X, y_1, \ldots, y_{j-1})}_{\text{Probability of model } m}$$

- Second term often set to uniform distribution 1/M

Log-linear Interpolation

- Weighted combination of log probabilities, normalize

$$P(y_j \mid X, y_1, \ldots, y_{j-1}) =$$
$$\underbrace{\text{softmax}}_{\text{Normalize}} \left(\sum_{m=1}^{M} \underbrace{\lambda_m(X, y_1, \ldots, y_{j-1})}_{\text{Interpolation coefficient for model } m} \underbrace{\log P_m(y_j \mid X, y_1, \ldots, y_{j-1})}_{\text{Log probability of model } m} \right)$$

- Interpolation coefficient often set to uniform distribution 1/M

Linear or Log Linear?

- Think of it in logic!
- **Linear:** “Logical OR”
    - the interpolated model likes any choice that a model gives a high probability
    - use models with models that capture different traits
    - necessary when any model can assign zero probability
- **Log Linear:** “Logical AND”
    - interpolated model only likes choices where all models agree
    - use when you want to restrict possible answers

Parameter Averaging
(e.g. Bahar et al. 2017)

- **Problem:** Ensembling means we have to use *M* models at test time, increasing our time/memory complexity
- Parameter averaging is a cheap way to get some good effects of ensembling
- Basically, write out models several times near the end of training, and take the average of parameters

Ensemble Distillation (e.g. Kim et al. 2016)

- **Problem:** parameter averaging only works for models within the same run
- Knowledge distillation trains a model to **copy the ensemble**
  - Specifically, it tries to match the distribution over predicted words
  - Why? We want the model to make the same mistakes as an ensemble
- Shown to increase accuracy notably

Questions?