ENGINEERING
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Computational Natural Language Processing

Conditioned Generation

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Language Models

- Language models are generative models of text

$$s \sim P(x)$$

$$\downarrow$$

"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

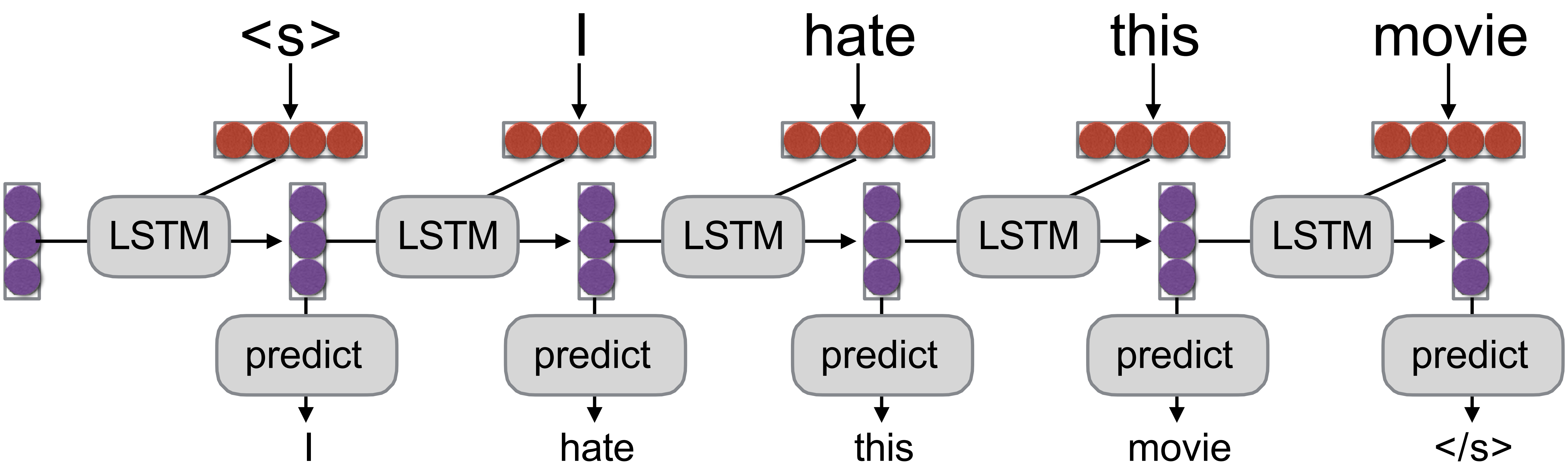
$$P(X) = \prod_{i=1}^{I} P(\underbrace{x_i}_{\text{Next Word}} \mid \underbrace{x_1, \ldots, x_{i-1}}_{\text{Context}})$$

Conditional Language Models

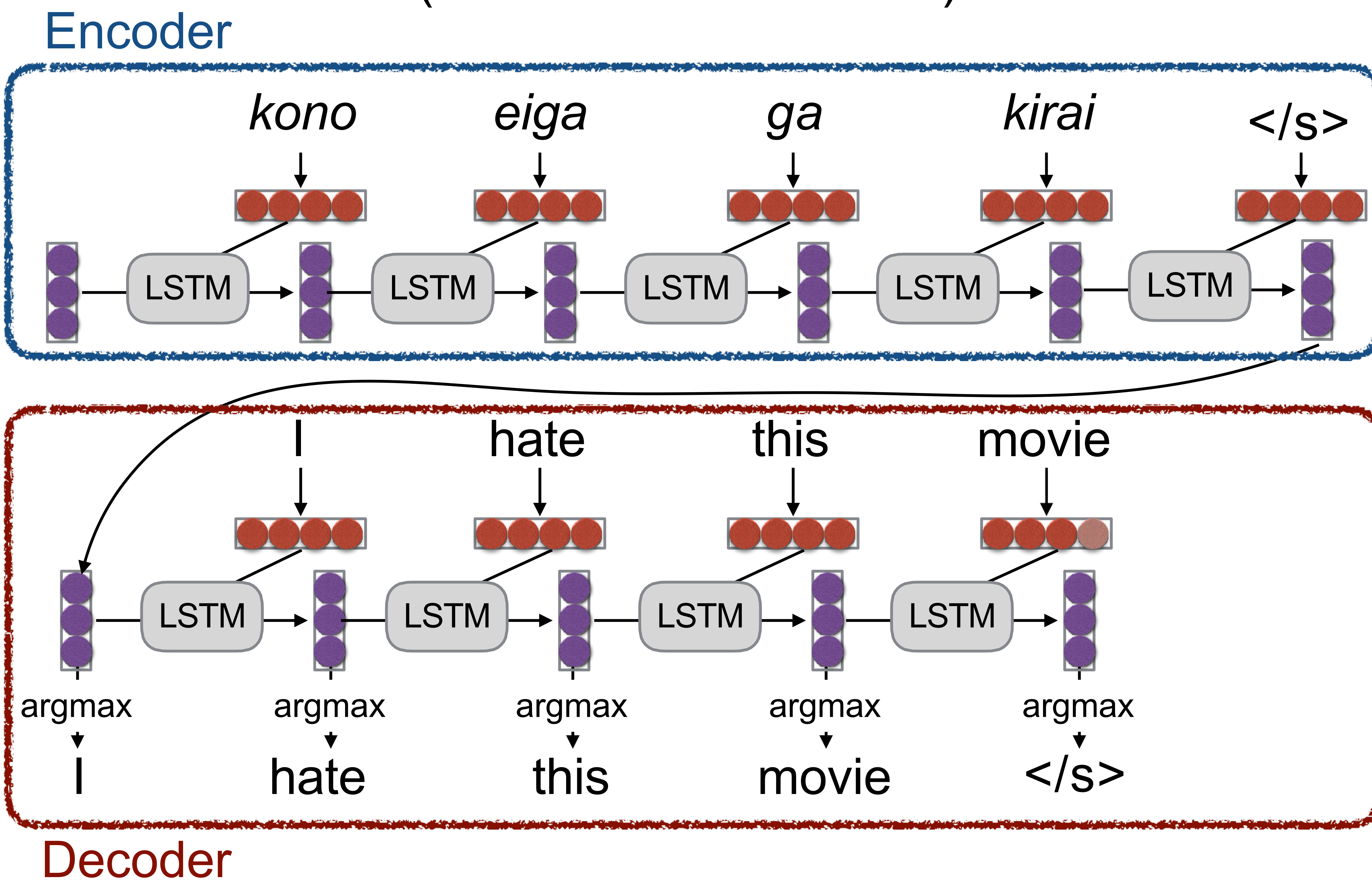
$$P(Y|X) = \prod_{j=1}^{J} P(y_j \mid \underline{X}, y_1, \ldots, y_{j-1})$$

Added Context!

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

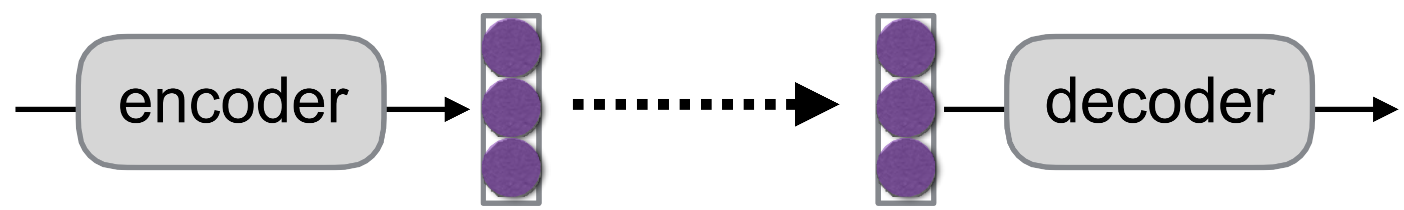


(One Type of) Conditional Language Model
(Sutskever et al. 2014)



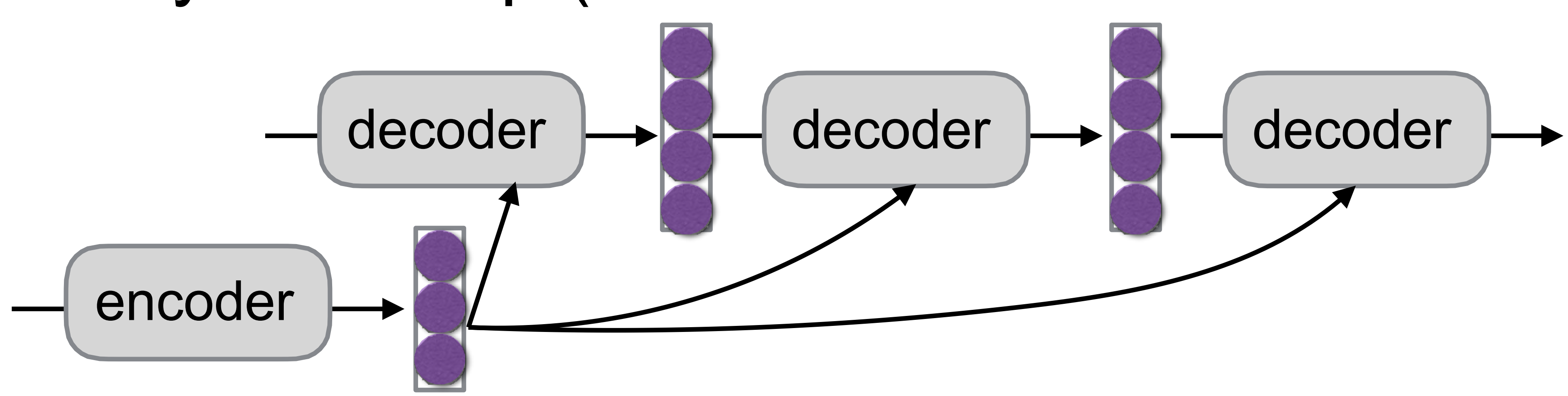
How to Pass Hidden State?

- Initialize decoder w/ encoder (Sutskever et al. 2014)



- Transform (can be different dimensions)

- Input at every time step (Kalchbrenner & Blunsom 2013)



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* probability.

Ancestral Sampling

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

while y_{j-1} != "</s>":
  $y_j \sim P(y_j \mid X, y_1, \ldots, y_{j-1})$

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

Greedy Search

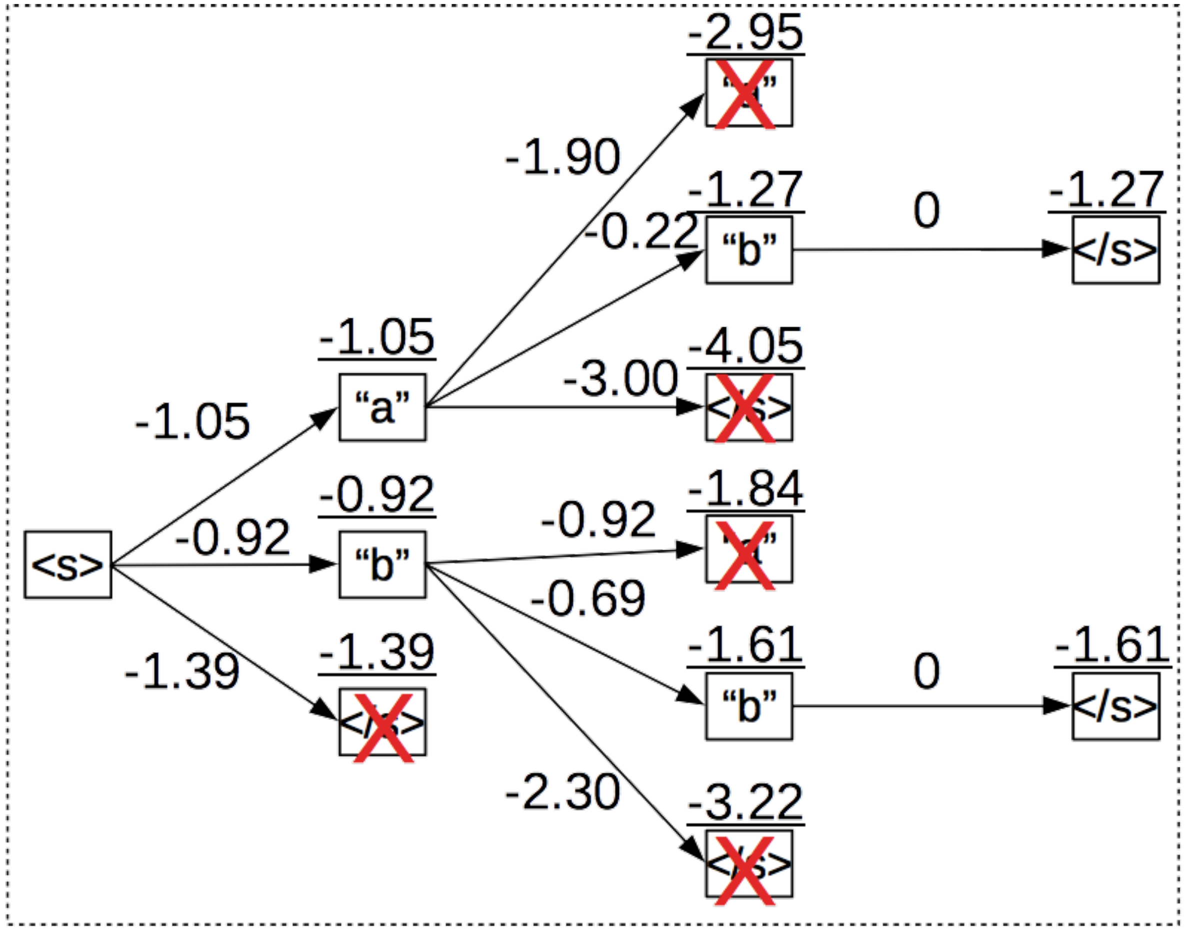
- One by one, pick the single highest-probability word

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

- **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

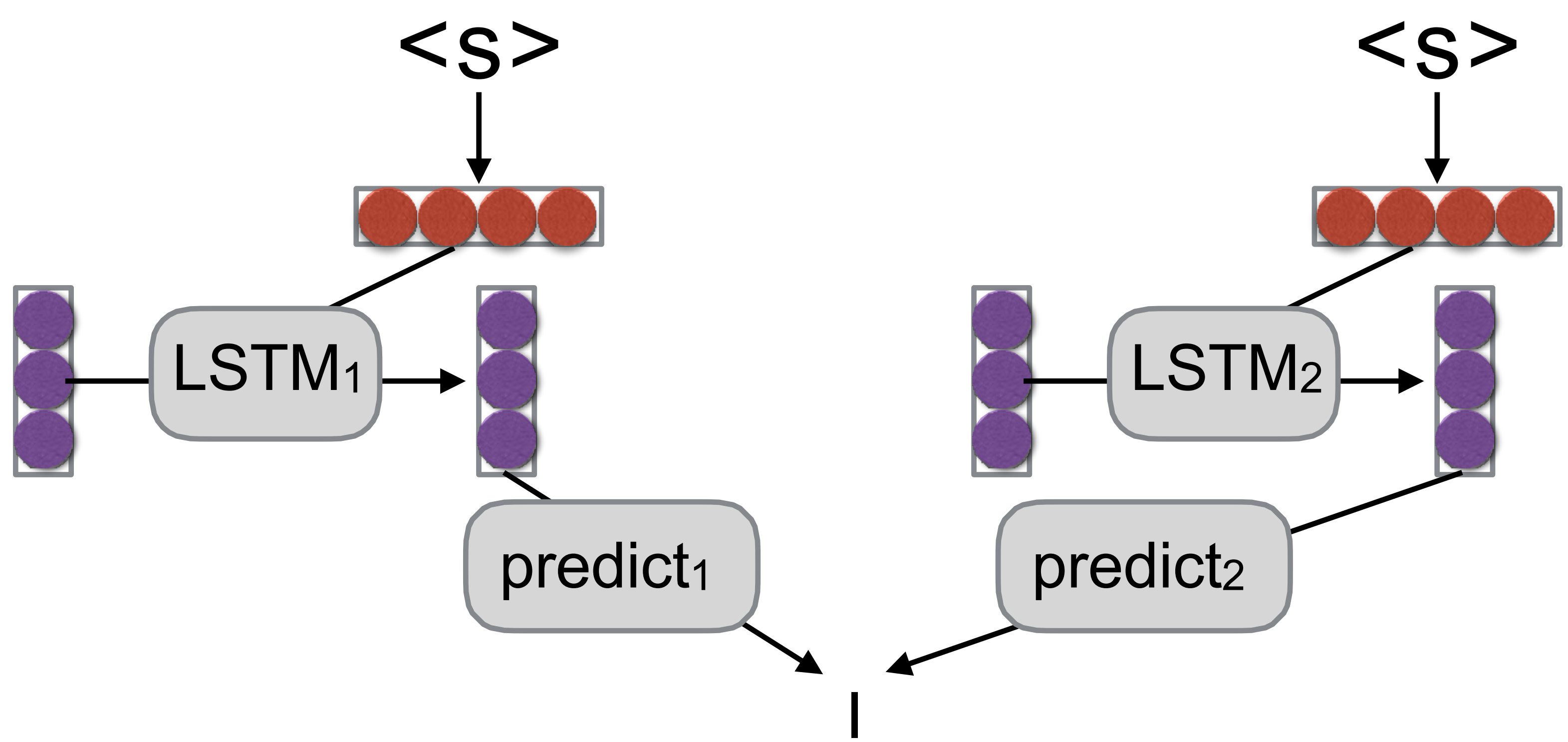


- Some in reading materials, more in a later class

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

- **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 description over predicted words
  - Why? We want the model to make the same mistakes as an ensemble
- Shown to increase accuracy notably

Stacking

- What if we have two very different models where prediction of outputs is done in very different ways?

- e.g. a phrase-based translation model and a neural MT model (Niehues et al. 2017)

- Stacking uses the **output of one system in calculating features for another** system

Case Studies in Conditional Language Modeling

From Images
(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

Check out this review paper:

Deep Learning Approaches on Image Captioning: A Review

TARANEH GHANDI, McMaster University, Canada
HAMIDREZA POURREZA, Ferdowsi University of Mashhad, Iran
HAMIDREZA MAHYAR, McMaster University, Canada

Image captioning is a research area of immense importance, aiming to generate natural language descriptions for visual content in the form of still images. The advent of deep learning and more recently vision-language pre-training techniques has revolutionized the field, leading to more sophisticated methods and improved performance. In this survey article, we provide a structured review of deep learning methods in image captioning by presenting a comprehensive taxonomy and discussing each method category in detail. Additionally, we examine the datasets commonly employed in image captioning research, as well as the evaluation metrics used to assess the performance of different captioning models. We address the challenges faced in this field by emphasizing issues such as object hallucination, missing context, illumination conditions, contextual understanding, and referring expressions. We rank different deep learning methods' performance according to widely used evaluation metrics, giving insight into the current state-of-the-art. Furthermore, we identify several potential future directions for research in this area, which include tackling the information misalignment problem between image and text modalities, mitigating dataset bias, incorporating vision-language pre-training methods to enhance caption generation, and developing improved evaluation tools to accurately measure the quality of image captions.

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

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 penalty = 1.0

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

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

- **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)

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 ()

- Evaluation is hard, especially with good systems! Most metrics had no correlation w/ human eval over best systems at some WMT 2019 tasks

Questions?