LT2318 H21 AICS: Tutorial on Image Captioning

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Outline I: Task

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The simplest language-and-vision task that we are going to look at in this course is **image captioning**: describing an image with a single sentence.

- What is included in a standard image captioning model (ICM)?
- How to build an ICM in terms of coding?
- The design tricks for building better ICMs
- How do we *evaluate* ICMs?
- Closer to state-of-the-art ICM: attention and transformers
- A teaser about other language-and-vision tasks we will look in this course

Outline II: Models

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We are going to work mostly with **sequence-to-sequence** models (RNNs, LSTMs) for natural language generation (NLG) in multi-modal setting.

- What does *seq-to-seq* mean and what type of models and/or problems can be solved with such models?
- We will focus a lot on recurrent neural networks, the key concepts and mechanisms behind such networks
- Example RNN: character-level seq-to-seq model

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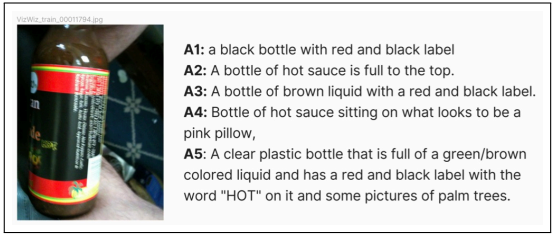
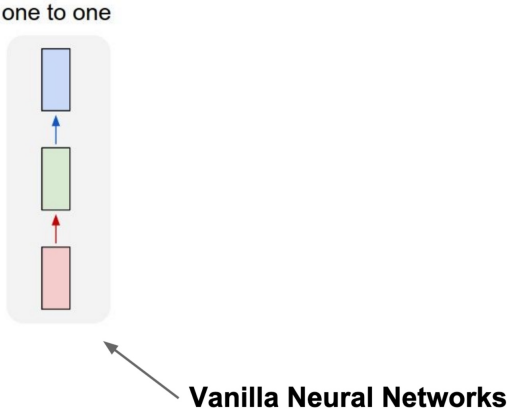
Example of the Project on Image Captioning



The key parts of the projects include:

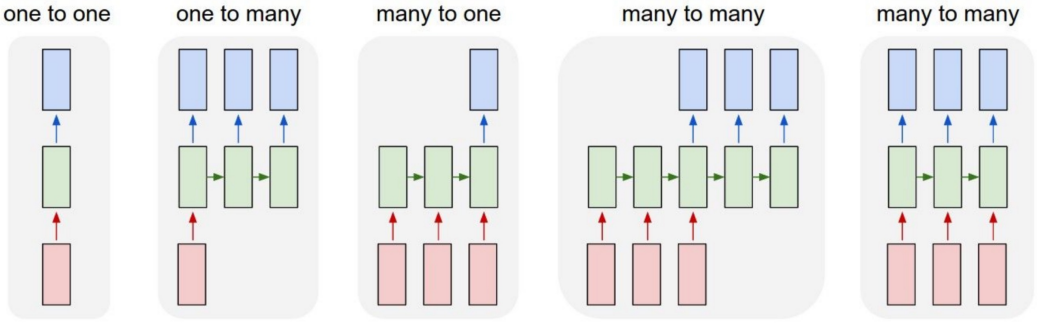
- **VizWiz** (Gurari et al., 2020): the dataset of images taken by people who are either blind or visually impared
- **Image Captioning model with Attention** (Xu et al., 2015)
- Evaluation: report **accuracy, loss, NLG evaluation metrics** (e.g., BLEU (Papineni et al., 2002)), analyse attention on the image

Basics of Sequence Networks[1]

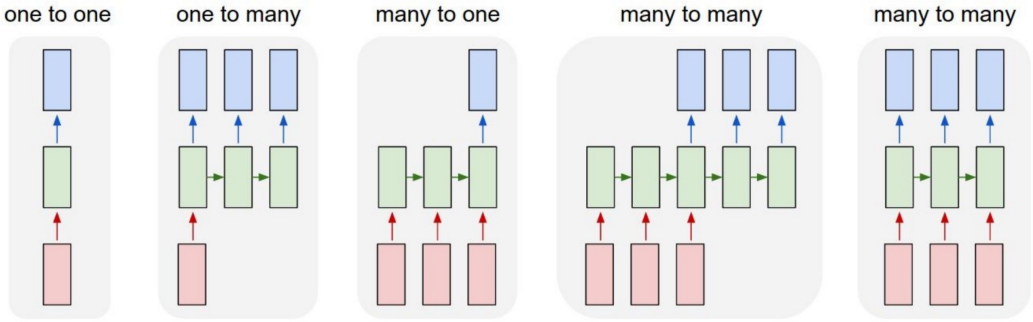


[1] http://karpathy.github.io/2015/05/21/rnn-effectiveness/

Basics of Sequence Networks



Basics of Sequence Networks



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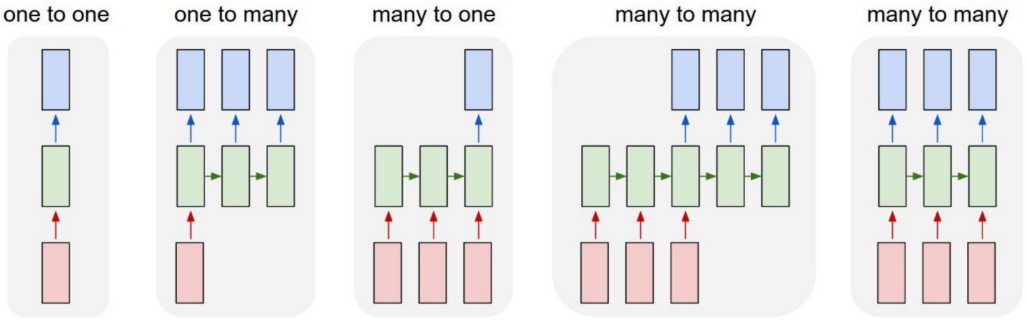
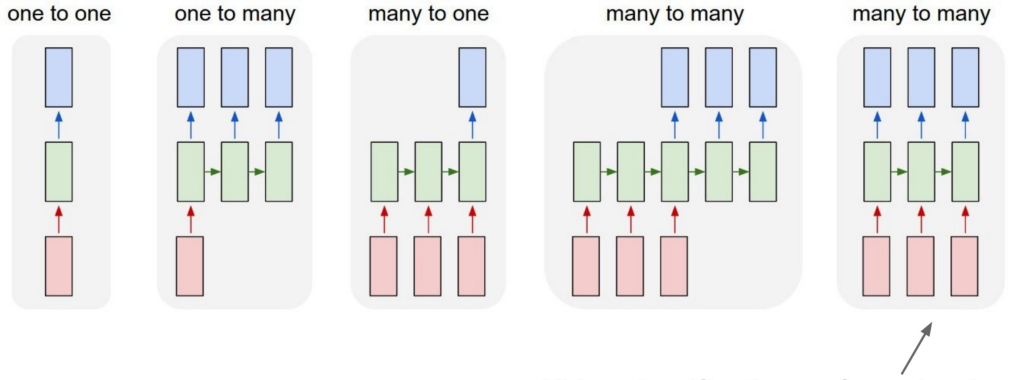
Basics of Sequence Networks

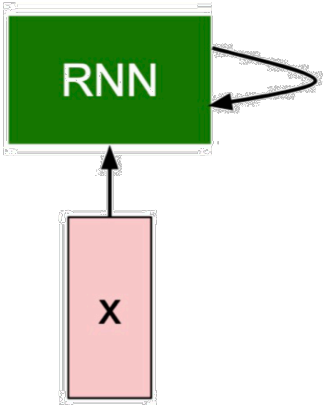


e.g. **Machine Translation**
seq of words -> seq of words

Basics of Sequence Networks

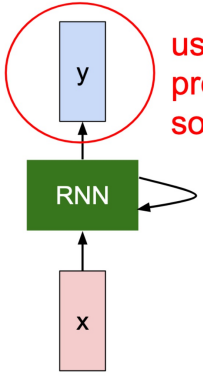


Recurrent Neural Network[2]



[2] http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture10.pdf

Recurrent Neural Network



usually want to predict a vector at some time steps

We can process a sequence of vectors **x** by applying a **recurrence formula** at every time step:

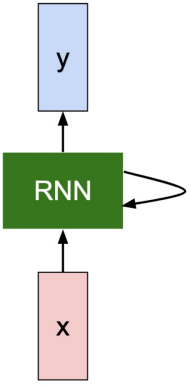
$$h_t = f_W(h_{t-1}, x_t)$$

new state

old state

input vector at some time step

some function with parameters W



Recurrent Neural Network: inner workings

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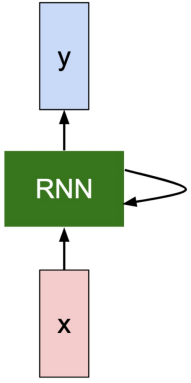
- You can think of hidden state as the memory of the RNN: it encapsulates information from all previous states into one single representations; during training, the model learns this state
- Intuition: in order to predict the next word, we need to take into account what has been stored in the "memory" of the model, e.g., in its hidden state
- Why do we need hidden state and why don't we use the model's output? The output state is a concatenation of all hidden states up to the step t, but to predict the output for the particular current state we use hidden state

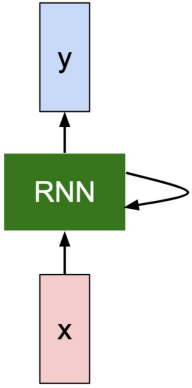
We can process a sequence of vectors **x** by applying a **recurrence formula** at every time step:

$$h_t = f_W(h_{t-1}, x_t)$$

Notice: the same function and the same set of parameters are used at every time step.



The state consists of a single *"hidden"* vector **h**:



$$h_t = f_W(h_{t-1}, x_t)$$

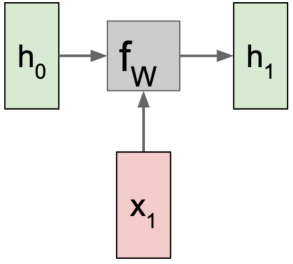
$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t)$$

$$y_t = W_{hy}h_t$$

Why non-linearity?[3]

[3] https://stackoverflow.com/questions/9782071/why-must-a-nonlinear-activation-function-be-used-in-a-backpropagation-neural-net

Recurrent Neural Network: Computational Graph



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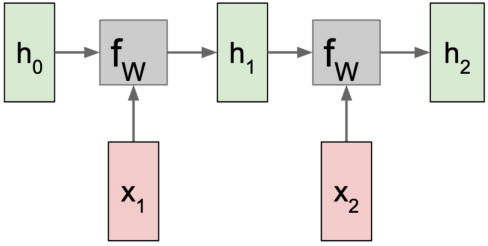

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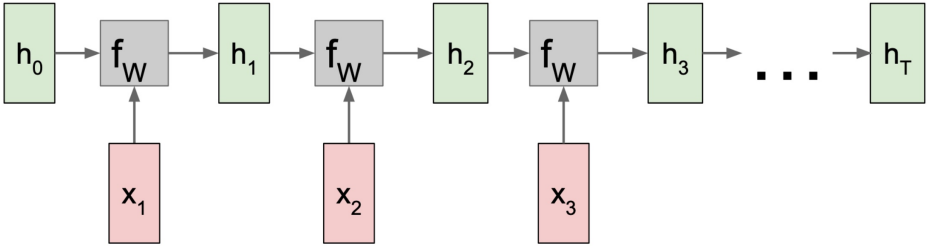

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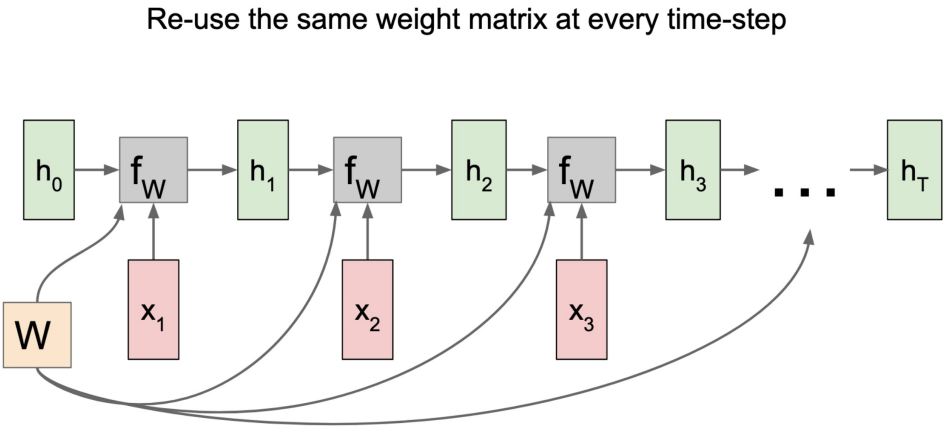

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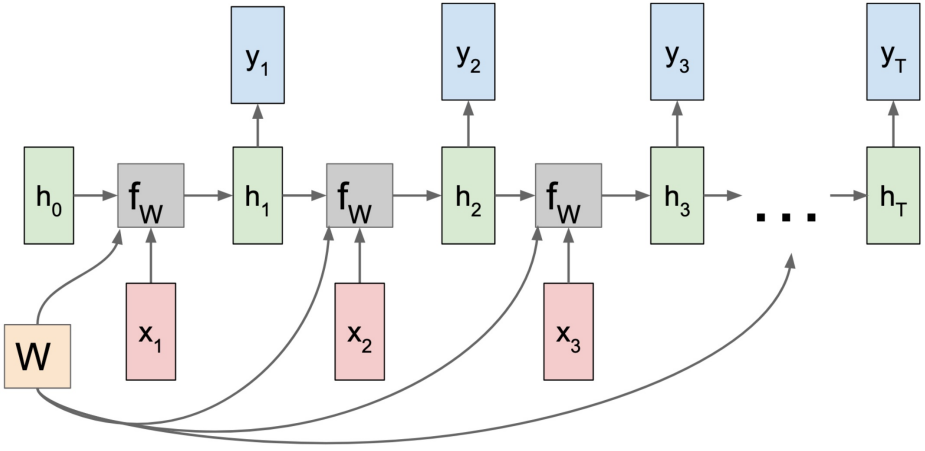

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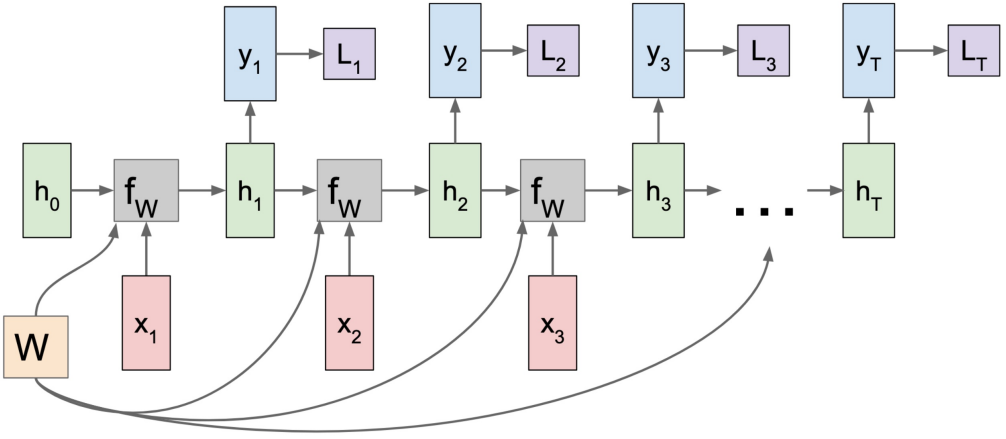

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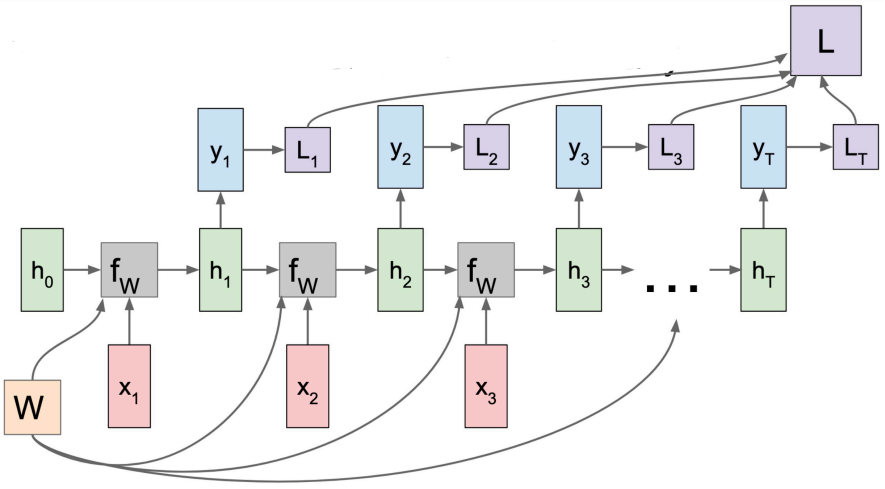
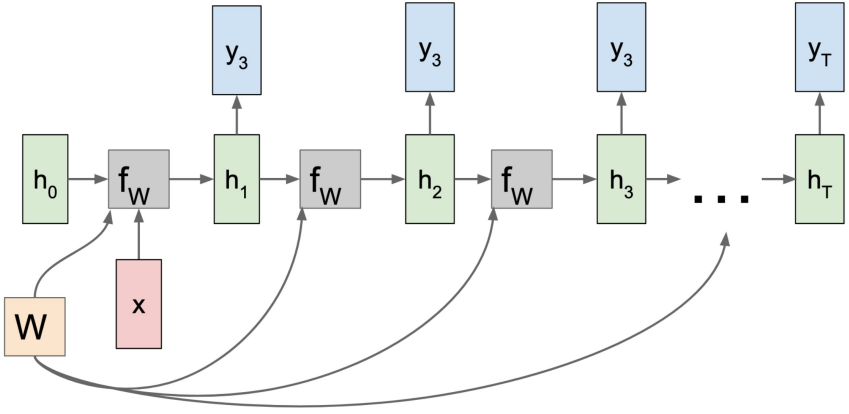


Recurrent Neural Network for Image Captioning

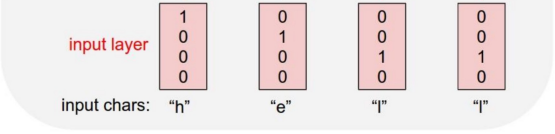


Example RNN: character-level generation

Example:
Character-level
Language Model

Vocabulary:
[h,e,l,o]

Example training sequence:
“hello”



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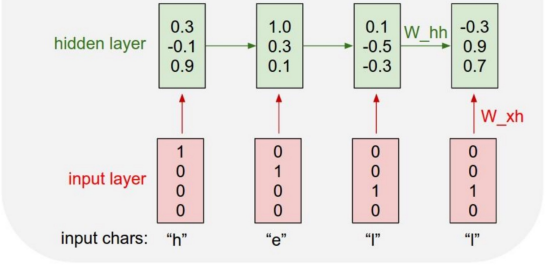

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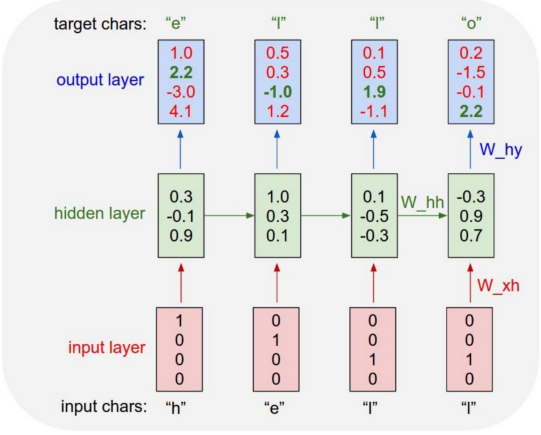

Example RNN: character-level generation

Example: Character-level Language Model Sampling

Vocabulary:
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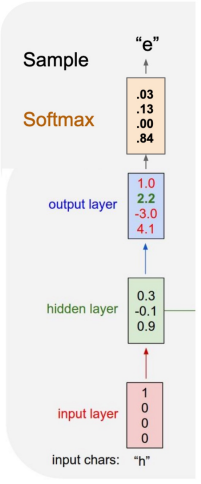
At test-time sample characters one at a time, feed back to model



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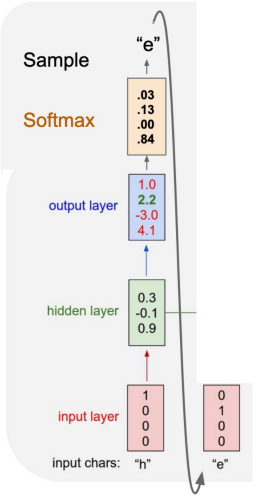

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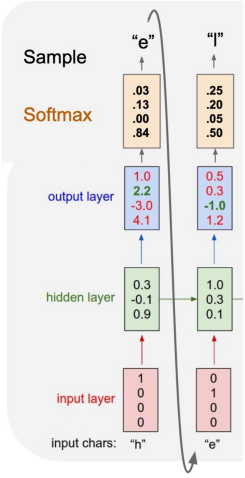

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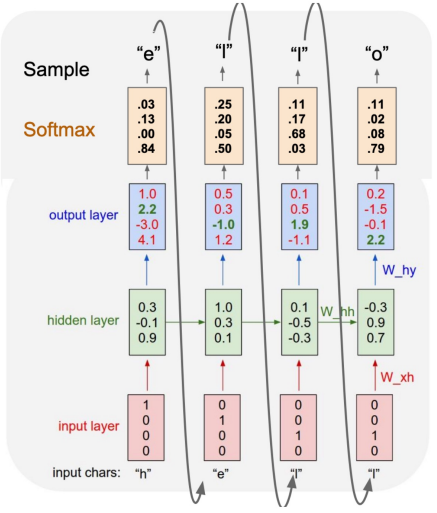

Image Captioning

Classic literature on neural image captioning:
Mao et al. (2014); Karpathy and Fei-Fei (2015); Vinyals et al. (2015); Donahue et al. (2016); Chen and Zitnick (2014)

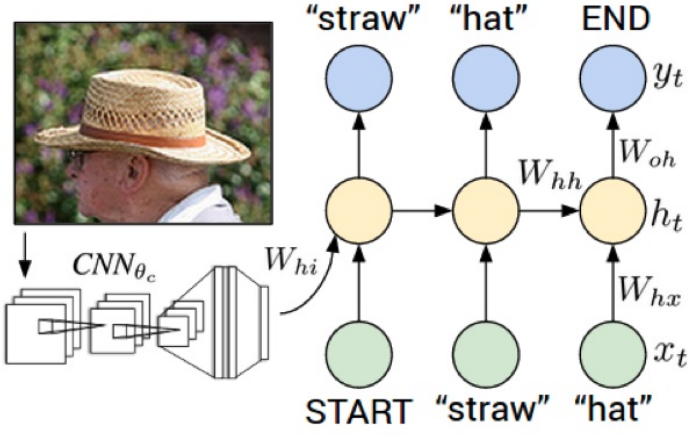

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Image Captioning: how do we do it?

This image is CC0 public domain

test image

Image Captioning: how do we do it?

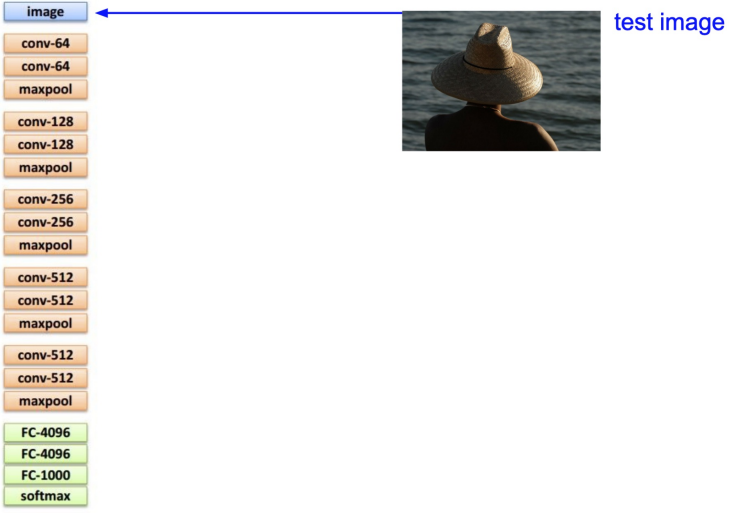

Image Captioning: how do we do it?

test image

CLASP

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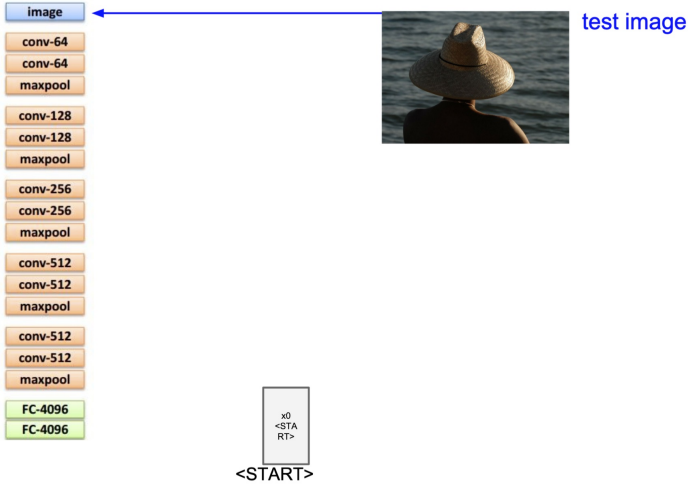

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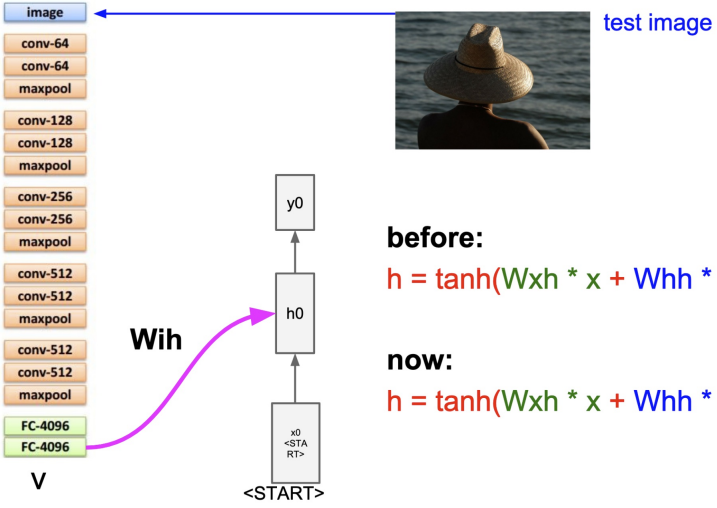

before:

h = tanh(Wxh * x + Whh * h)

now:

h = tanh(Wxh * x + Whh * h + **Wih * v**)

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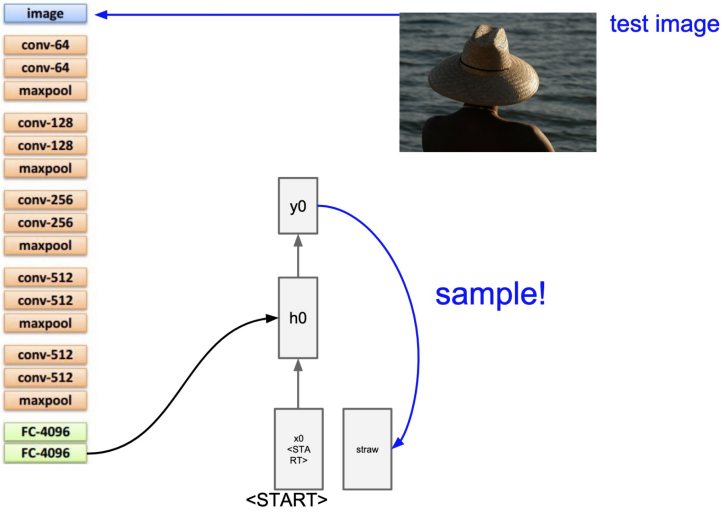
Image Captioning: how do we do it?



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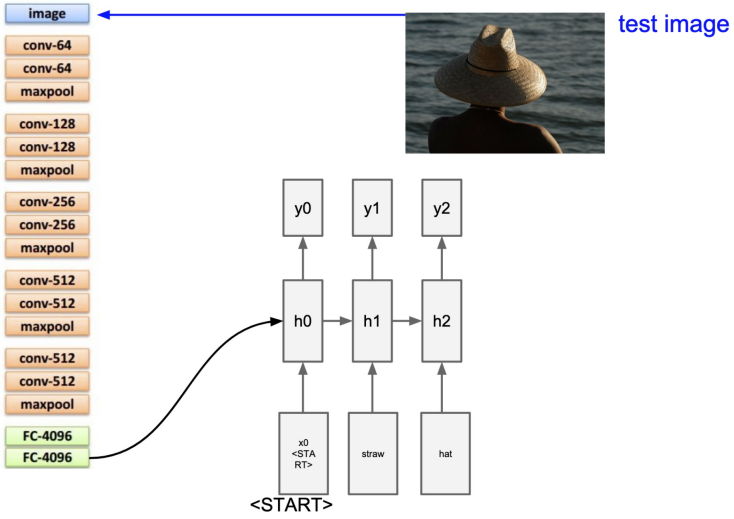

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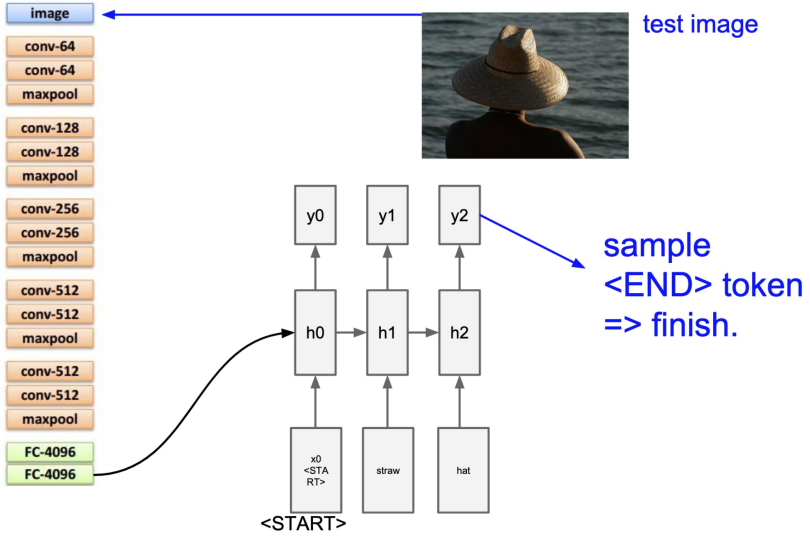

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Image Captioning: good examples

A cat sitting on a suitcase on the floor

A cat is sitting on a tree branch

A dog is running in the grass with a frisbee

A white teddy bear sitting in the grass

Two people walking on the beach with surfboards

A tennis player in action on the court

Two giraffes standing in a grassy field

A man riding a dirt bike on a dirt track

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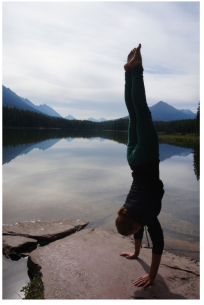
Image Captioning: bad examples

A woman is holding a cat in her hand

A person holding a computer mouse on a desk



A woman standing on a beach holding a surfboard

A bird is perched on a tree branch

A man in a baseball uniform throwing a ball

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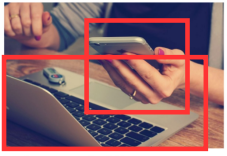
Why would the model make such mistakes?

A woman is holding a cat in her hand



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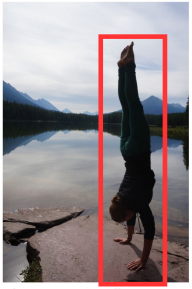


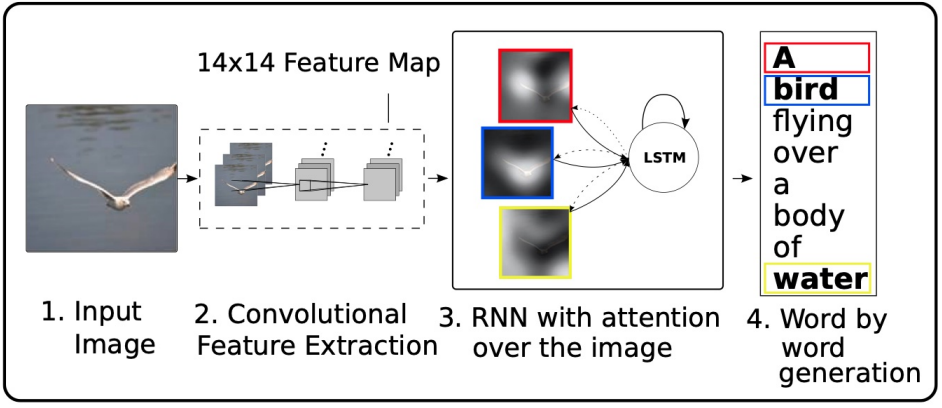
A woman standing on a beach holding a surfboard

A bird is perched on a tree branch

A man in a baseball uniform throwing a ball

- frequency of concepts co-occurring together (e.g., computer mouse - computer desk, tree - bird, cat - woman)
- each image is unique, so **more focus on important parts of the image** might help the model to correctly describe the image

Image Captioning with Attention (Xu et al., 2016)



Why do we need attention and what is so interesting about it?

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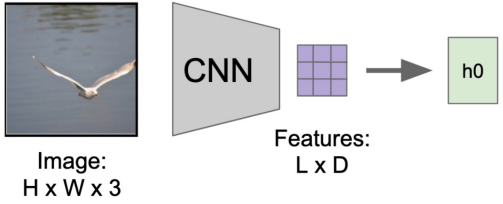
- prior to language-and-vision tasks, attention has been initially introduced in the domain of machine translation (Bahdanau et al., 2016)
- the main idea is that **every word that we say is grounded in the image and we want our model to correctly ground words into objects**
- it is hard to ground relations (e.g., flying) and both language and vision modalities can be more important for grounding of particular word types (Lu et al., 2017; Ghanimifard and Dobnik, 2019; Ilinykh and Dobnik, 2021)
- *project idea sketch*: examine grounding of (spatial) relations in multi-modal set-up

Attention in ICM



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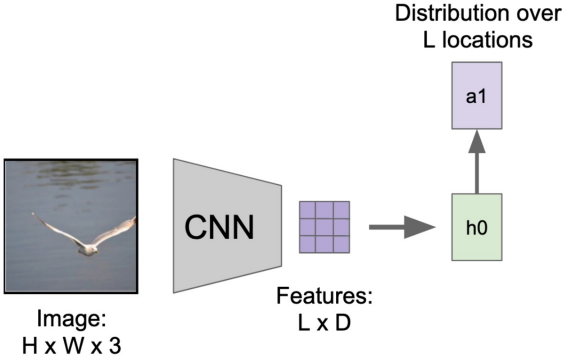
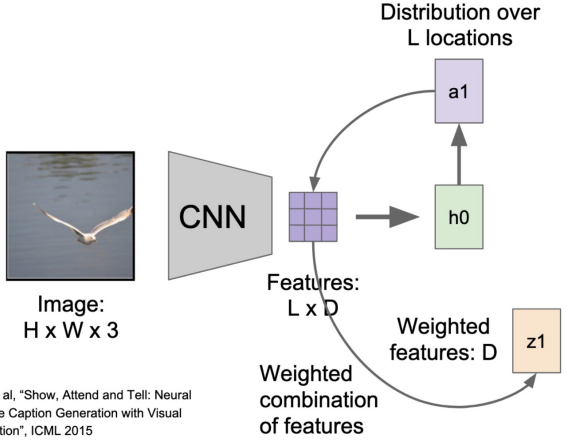


Attention in ICM



Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

$$z = \sum_{i=1}^{L} p_i v_i$$

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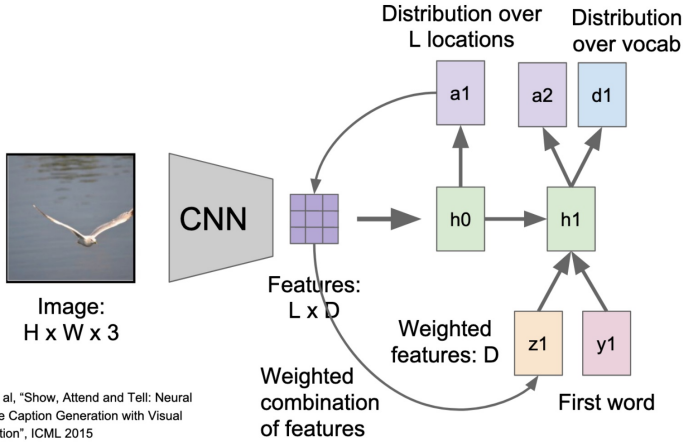
Attention in ICM



:u et al, "Show, Attend and Tell: Neural
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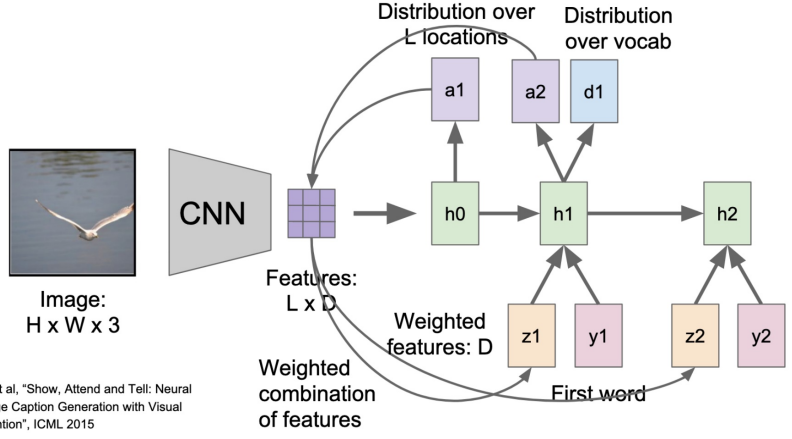
Attention in ICM



Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

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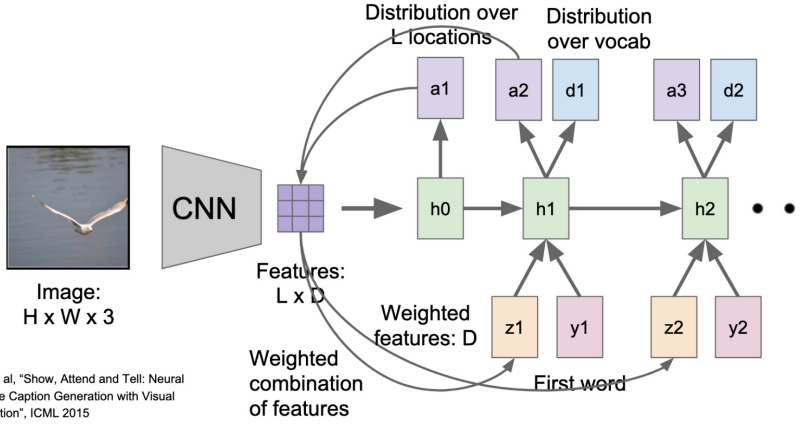
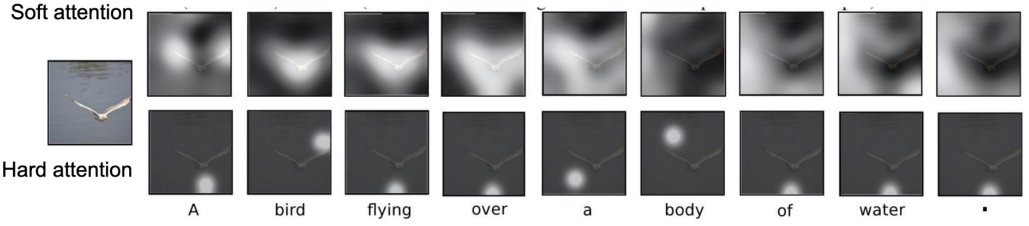
Attention in ICM



Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

Attention in ICM

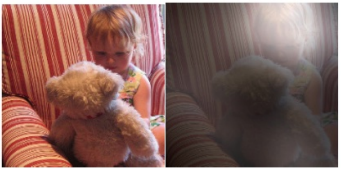


Attention in ICM

A woman is throwing a frisbee in a park.

A dog is standing on a hardwood floor.

A stop sign is on a road with a mountain in the background.



A little girl sitting on a bed with a teddy bear.

A group of people sitting on a boat in the water.

A giraffe standing in a forest with trees in the background.

Attention helps with gender bias in captioning models

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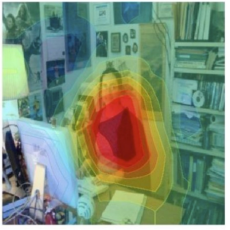
Wrong

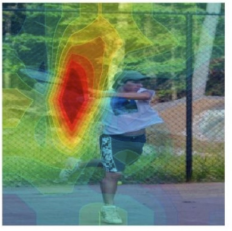
Baseline:
*A **man** sitting at a desk with a laptop computer.*

Right for the Right Reasons



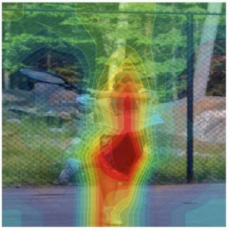
Our Model:
*A **woman** sitting in front of a laptop computer.*

Right for the Wrong Reasons



Baseline:
*A **man** holding a tennis racquet on a tennis court.*

Right for the Right Reasons



Our Model:
*A **man** holding a tennis racquet on a tennis court.*

Burns et al. "Women also Snowboard: Overcoming Bias in Captioning Models" ECCV 2018
Figures from Burns et al, copyright 2018. Reproduced with permission.

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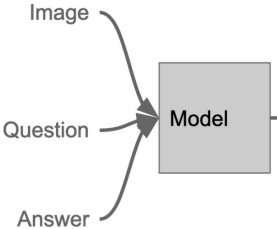
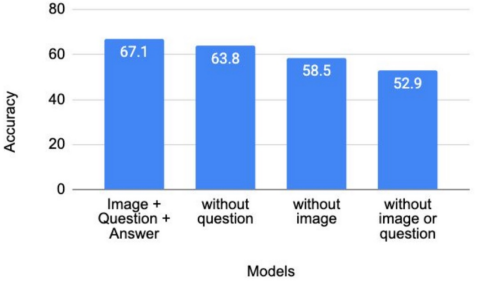
Attention helps with dataset biases

What is the dog playing with?

Frisbee





Jabri et al. "Revisiting Visual Question Answering Baselines" ECCV 2016

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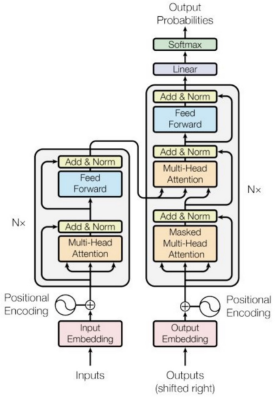
Recently in Natural Language Processing… New paradigms for reasoning over sequences

[“Attention is all you need”, Vaswani et al., 2018]

- New “Transformer” architecture no longer processes inputs sequentially; instead it can operate over inputs in a sequence in parallel through an attention mechanism

- Has led to many state-of-the-art results and pre-training in NLP, for more interest see e.g.
  - “BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding”, Devlin et al., 2018
  - OpenAI GPT-2, Radford et al., 2018



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Conclusions and Future Content

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- image captioning is the core task in language-and-vision field
- standard neural architecture: CNN + LSTM (encoder-decoder, seq-to-seq)
- SOTA: transformers (all inputs are processed simultaneously)
- *Next tutorials*: we will look at decoding, evaluation of captioning models, different modes of image representation, more complex tasks (e.g., visual question answering, visual dialogue, situated interaction)
- **but now**, we are going to code!

Before we start coding...

- An image is worth a thousand words
- How to choose the best way to describe an image? And should we even choose one?

Before we start coding...

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- Each of us describes what we see based on our personal individual background
- How do we account for that?

Before we start coding...

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- What do we want to describe in the image? Which objects are important or not important?
- When do we want to describe objects? Is there some order of objects that we use?
- How to describe objects? Which attributes we want to mention and which relations?

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