

DEEP LEARNING FOR COMPUTER VISION

Summer Seminar UPC TelecomBCN, 4 - 8 July 2016



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Day 4 Lecture 3

Language and Vision



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Acknowledgments

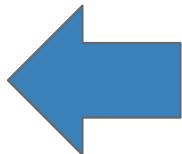


Santi Pascual

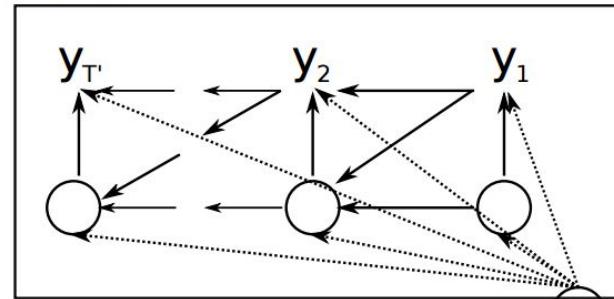


In lecture D2L6 RNNs...

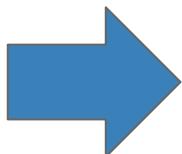
Language OUT



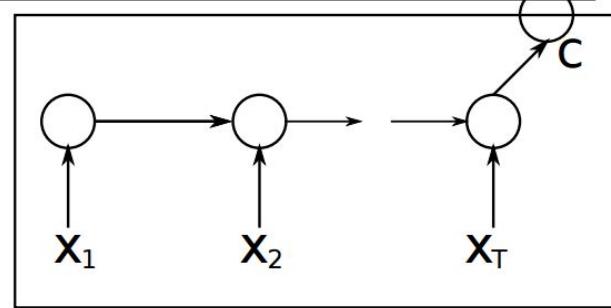
Decoder



Language IN

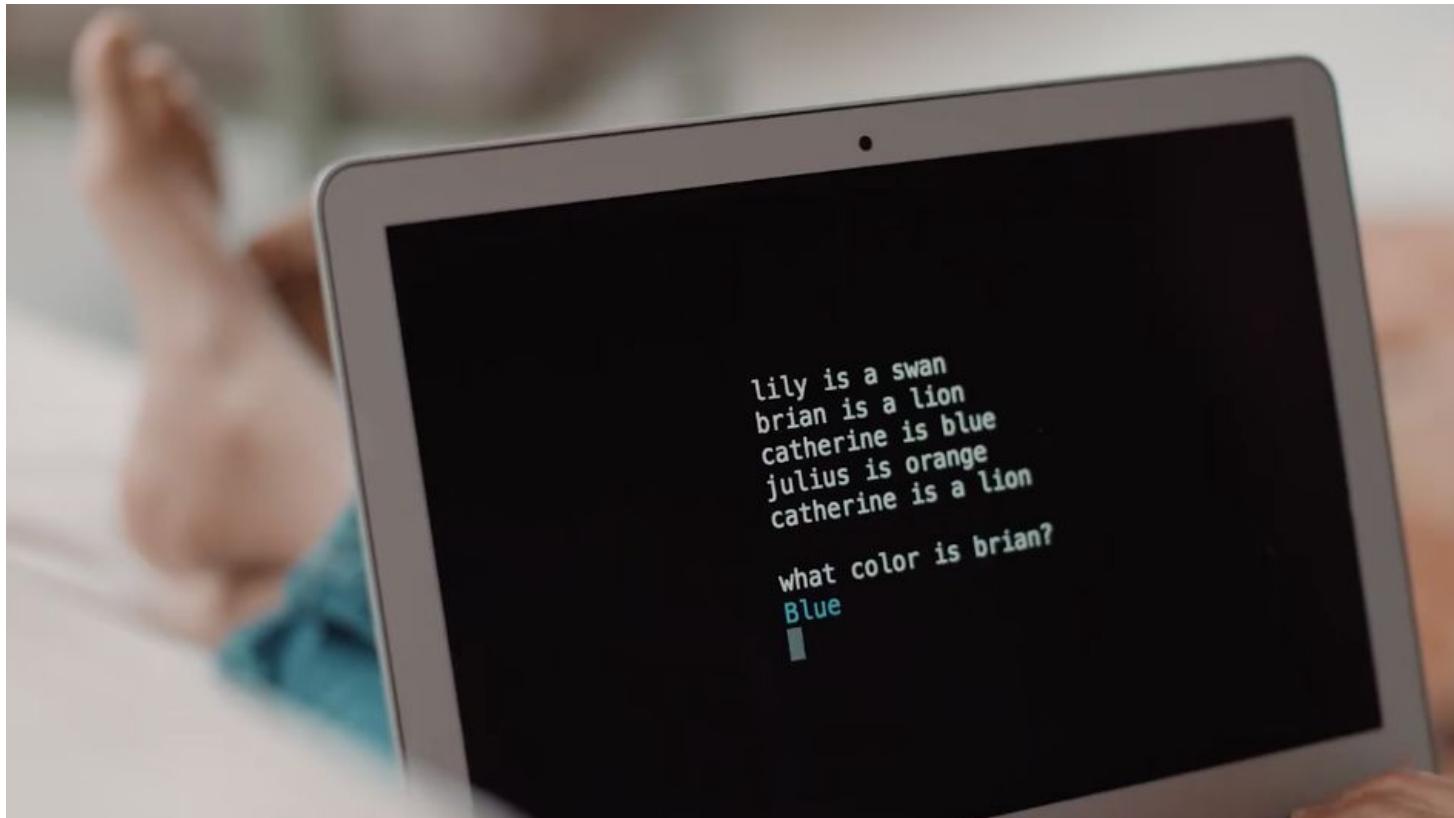
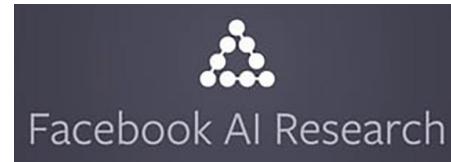


Encoder



Cho, Kyunghyun, Bart Van Merriënboer, Caglar Gulcehre, Dzmitry Bahdanau, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. "[Learning phrase representations using RNN encoder-decoder for statistical machine translation.](#)" arXiv preprint arXiv:1406.1078 (2014).

Motivation



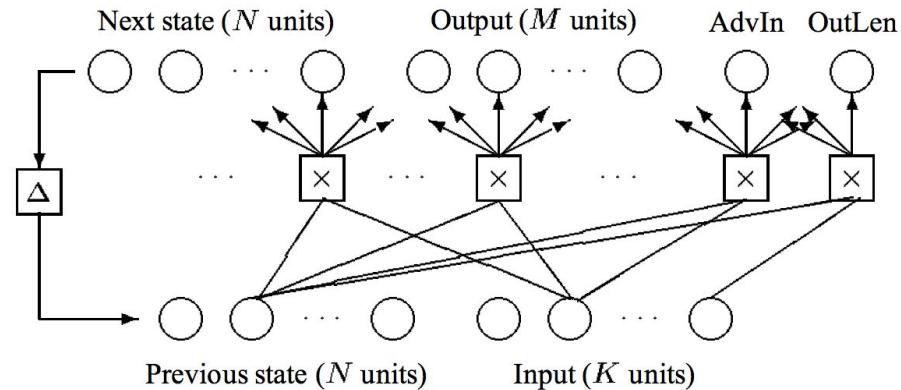
Much earlier than lecture D2L6 RNNs...

Asynchronous translations with recurrent neural nets

Ramón P. Neco, Mikel L. Forcada

Departament de Llenguatges i Sistemes Informàtics,
Universitat d'Alacant, E-03071 Alacant, Spain.

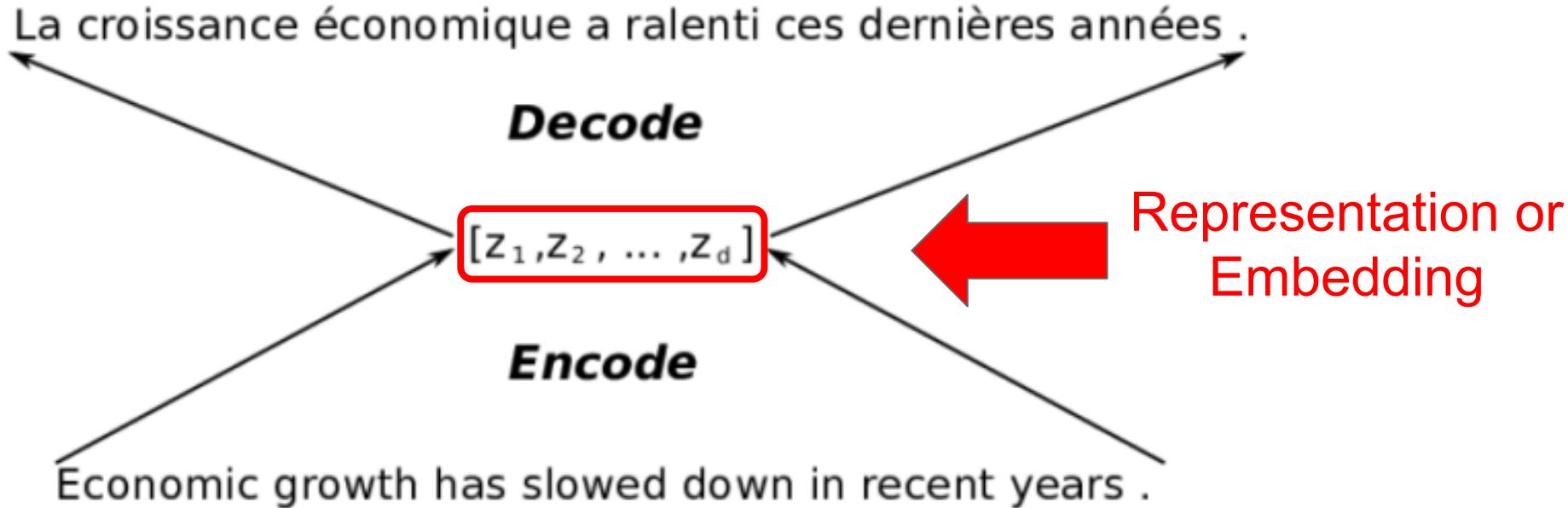
E-mail: {neco, mlf}@dlsi.ua.es



Neco, R.P. and Forcada, M.L., 1997, June. [Asynchronous translations with recurrent neural nets](#). In Neural Networks, 1997., International Conference on (Vol. 4, pp. 2535-2540). IEEE.

Encoder-Decoder

For clarity, let's study a Neural Machine Translation (NMT) case:



Encoder: One-hot encoding

One-hot encoding: Binary representation of the words in a vocabulary, where the only combinations with a single hot (1) bit and all other cold (0) bits are allowed.

Word	Binary	One-hot encoding
zero	00	0000
one	01	0010
two	10	0100
three	11	1000

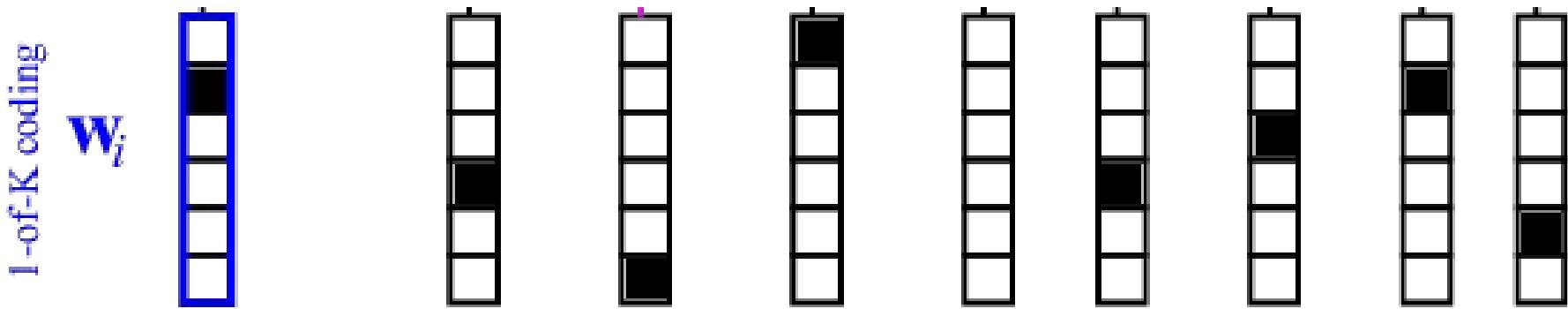
Encoder: One-hot encoding

Natural language words can also be one-hot encoded on a vector of dimensionality equal to the size of the dictionary (K).

Word	One-hot encoding
economic	000010...
growth	001000...
has	100000...
slowed	000001...

Encoder: One-hot encoding

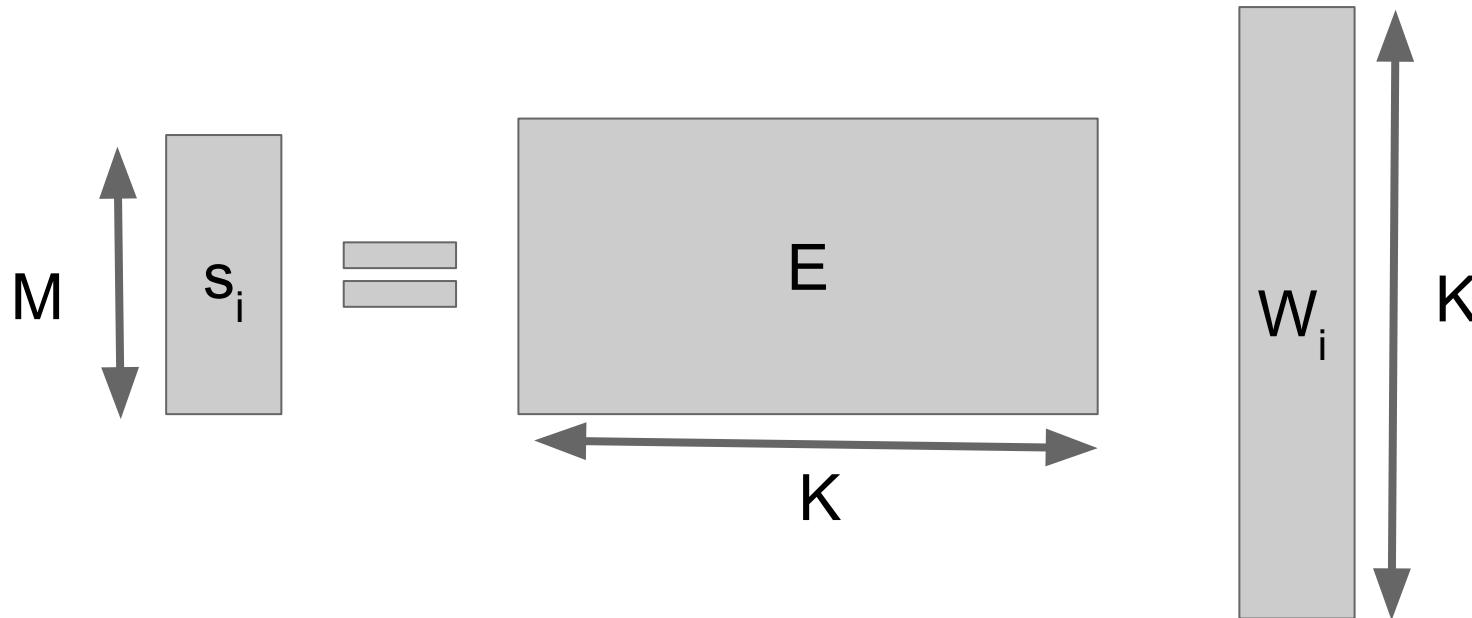
One-hot is a very simple representation: every word is equidistant from every other word.



$e = (\text{Economic}, \text{growth}, \text{has}, \text{slowed}, \text{down}, \text{in}, \text{recent}, \text{years}, \cdot)$

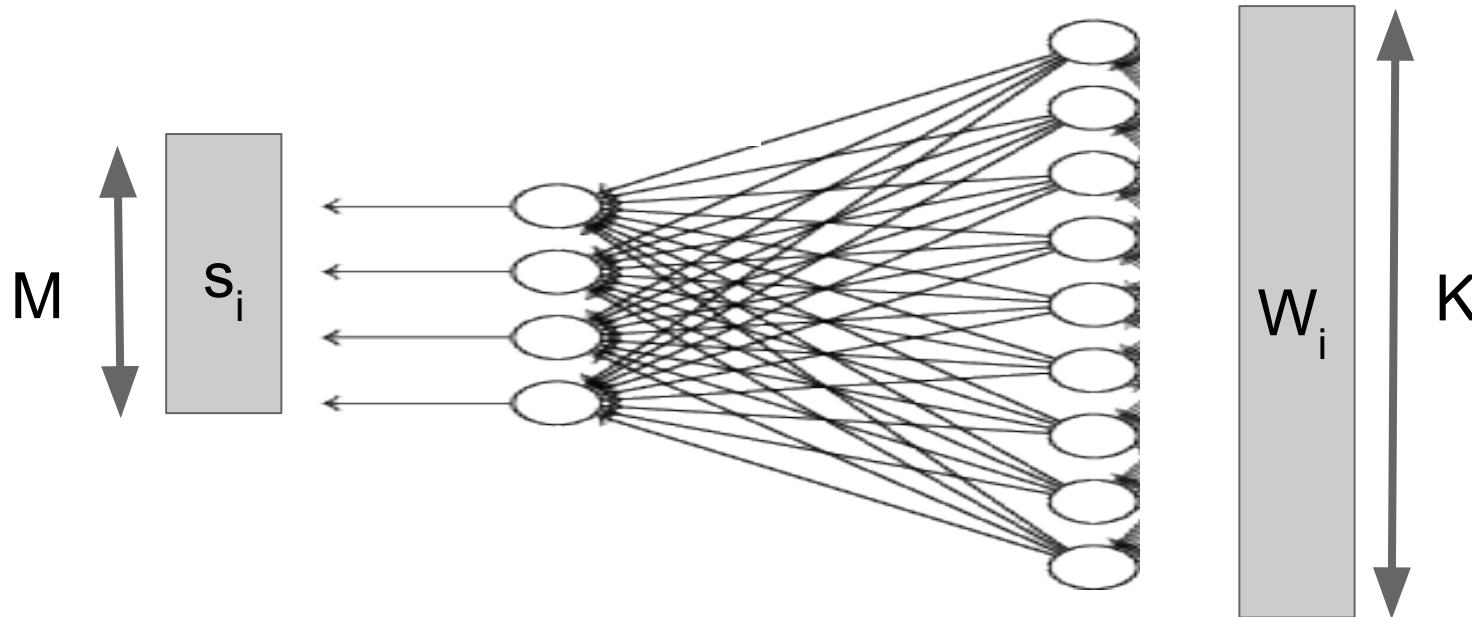
Encoder: Projection to continuous space

The one-hot is linearly projected to a space of lower dimension (typically 100-500) with matrix E for learned weights.



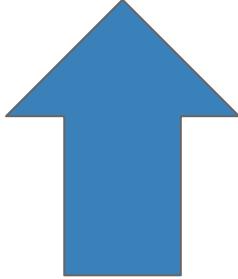
Encoder: Projection to continuous space

Projection matrix E corresponds to a fully connected layer, so its parameters will be learned with a training process.

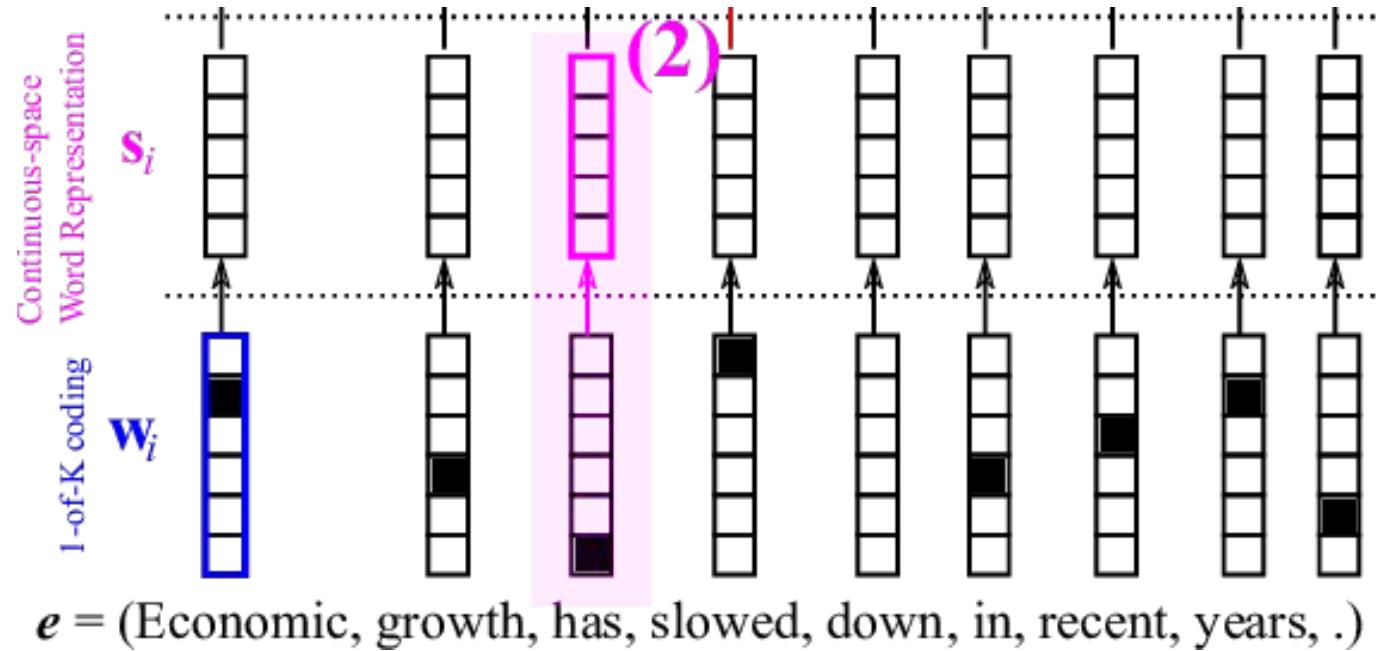


Encoder: Projection to continuous space

Sequence of
continuous-space
word representations



Sequence of words



Encoder: Recurrence

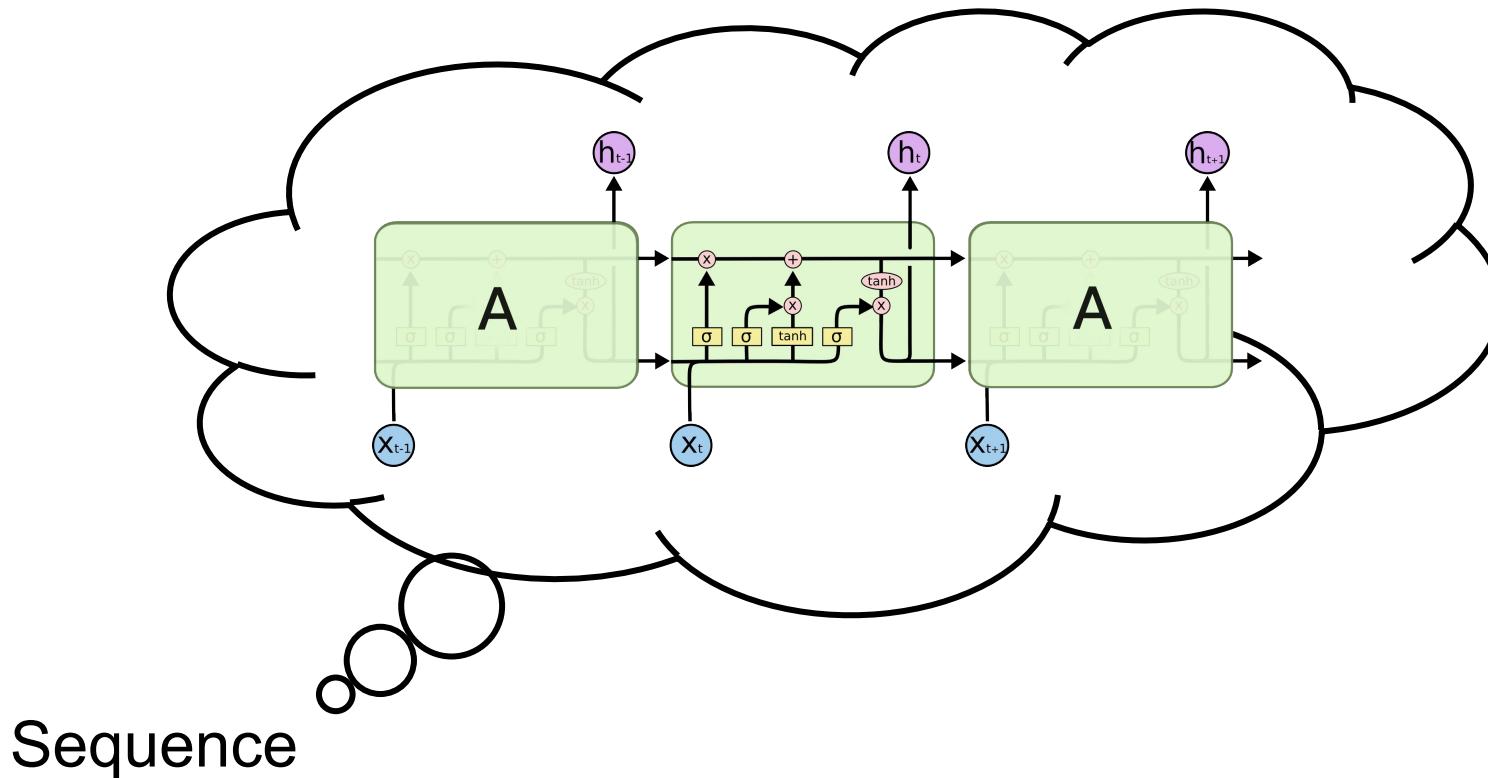
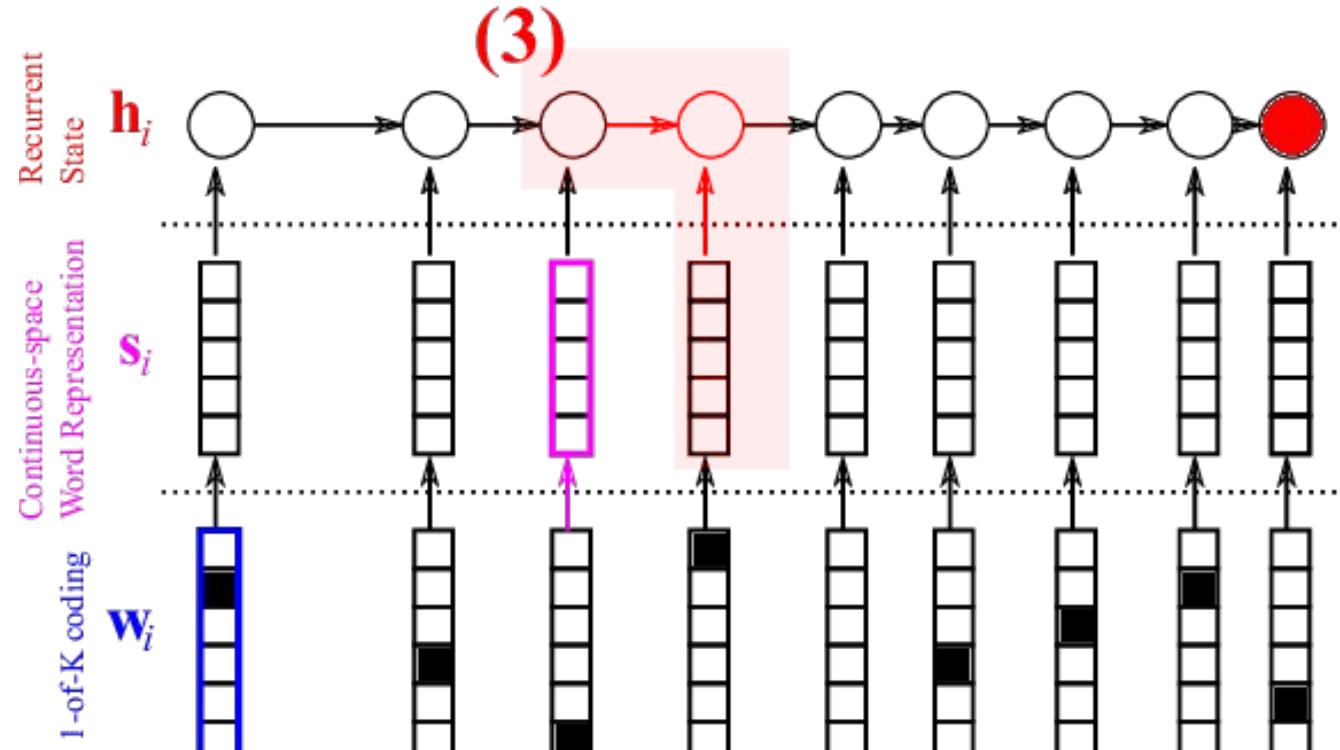


Figure: Cristopher Olah, [“Understanding LSTM Networks”](#) (2015)

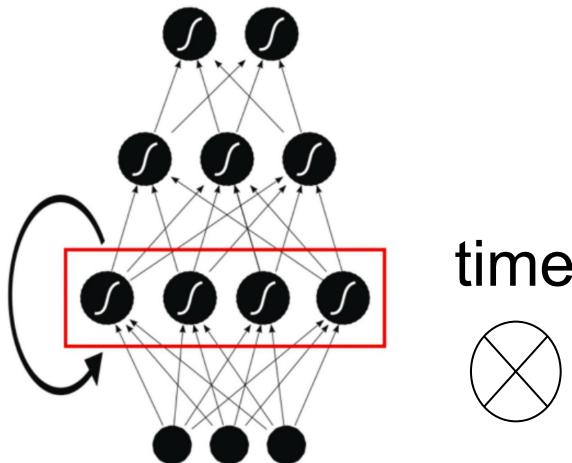
Encoder: Recurrence



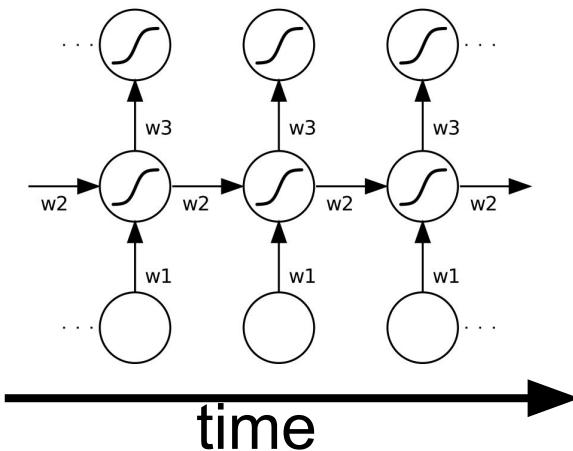
$e = (\text{Economic, growth, has, slowed, down, in, recent, years, .})$

Encoder: Recurrence

Front View



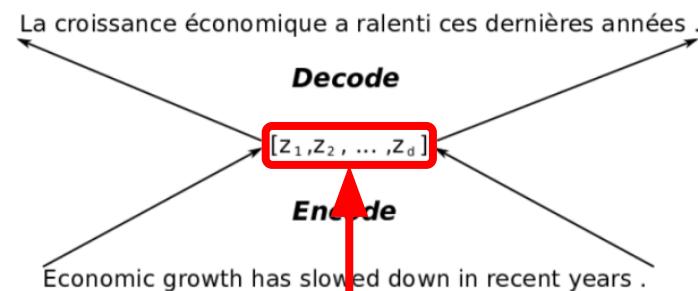
Side View



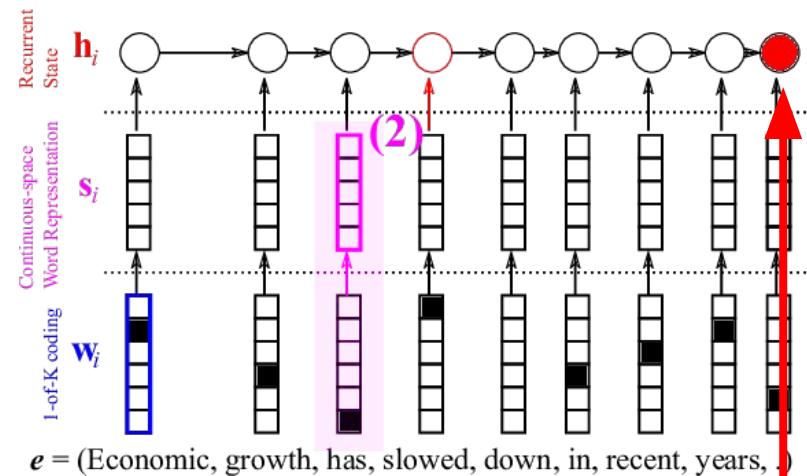
Rotation
90°

Encoder: Recurrence

Front View



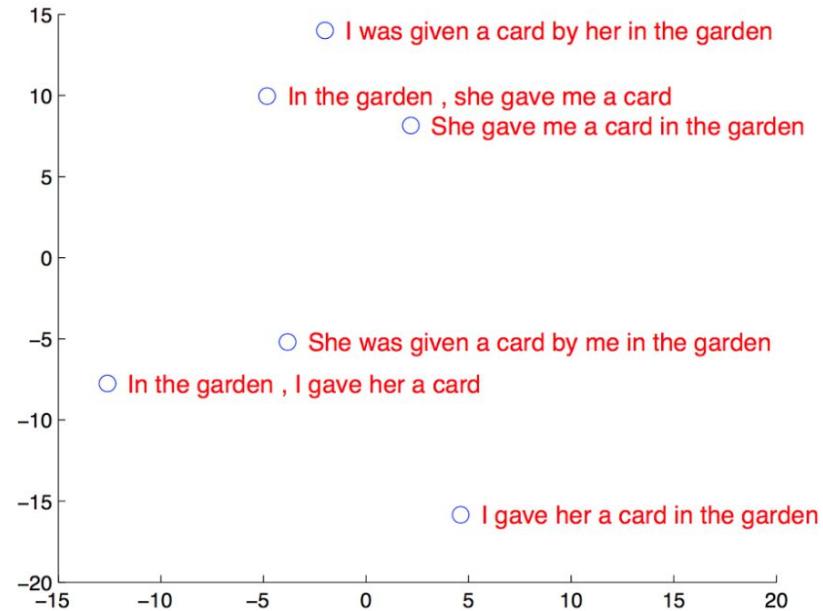
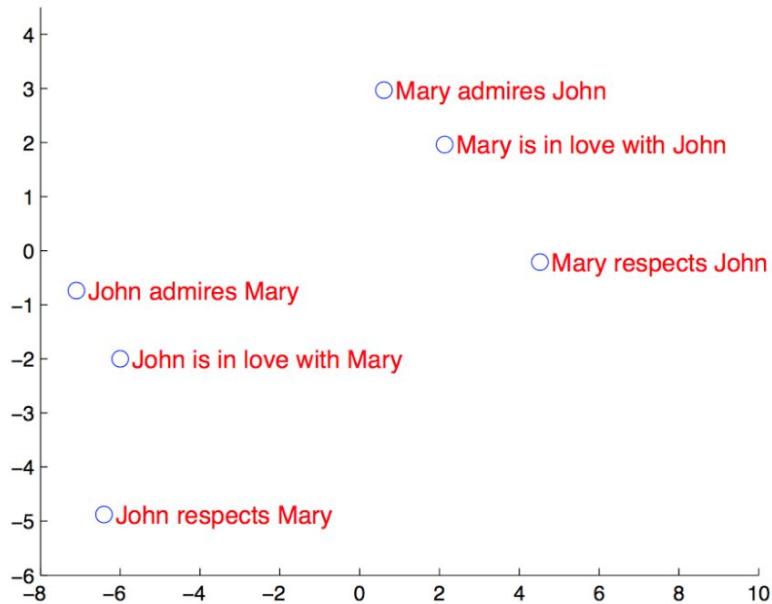
Side View



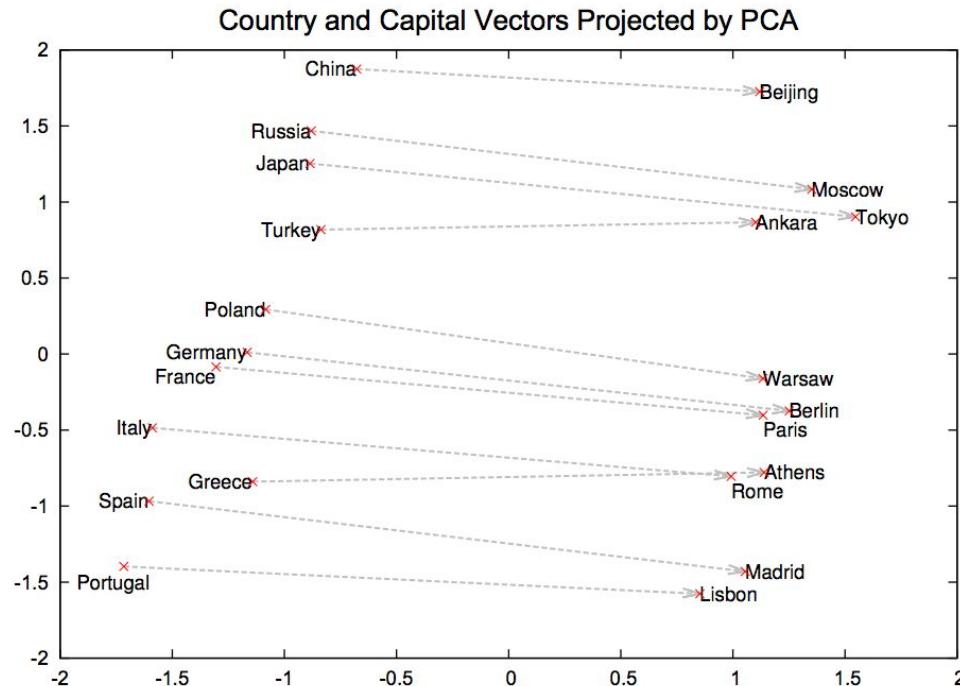
Representation or
embedding of the sentence

Sentence Embedding

Clusters by meaning appear on 2-dimensional PCA of LSTM hidden states



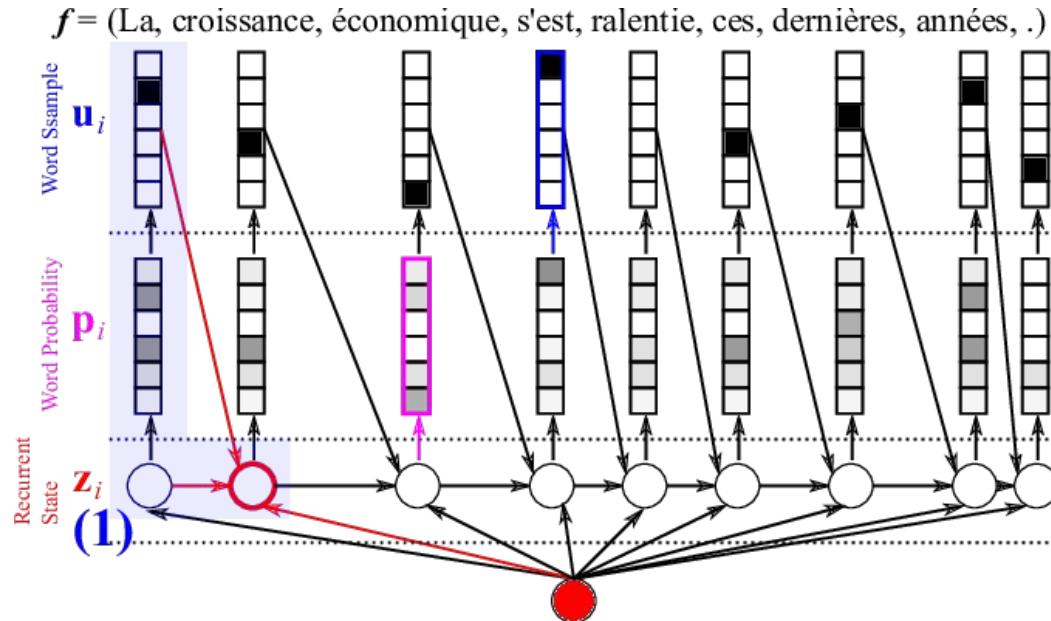
(Word Embeddings)



Mikolov, Tomas, Ilya Sutskever, Kai Chen, Greg S. Corrado, and Jeff Dean. ["Distributed representations of words and phrases and their compositionality."](#) In *Advances in neural information processing systems*, pp. 3111-3119. 2013.

Decoder

RNN's internal state z_i depends on: sentence embedding h_t , previous word u_{i-1} and previous internal state z_{i-1} .



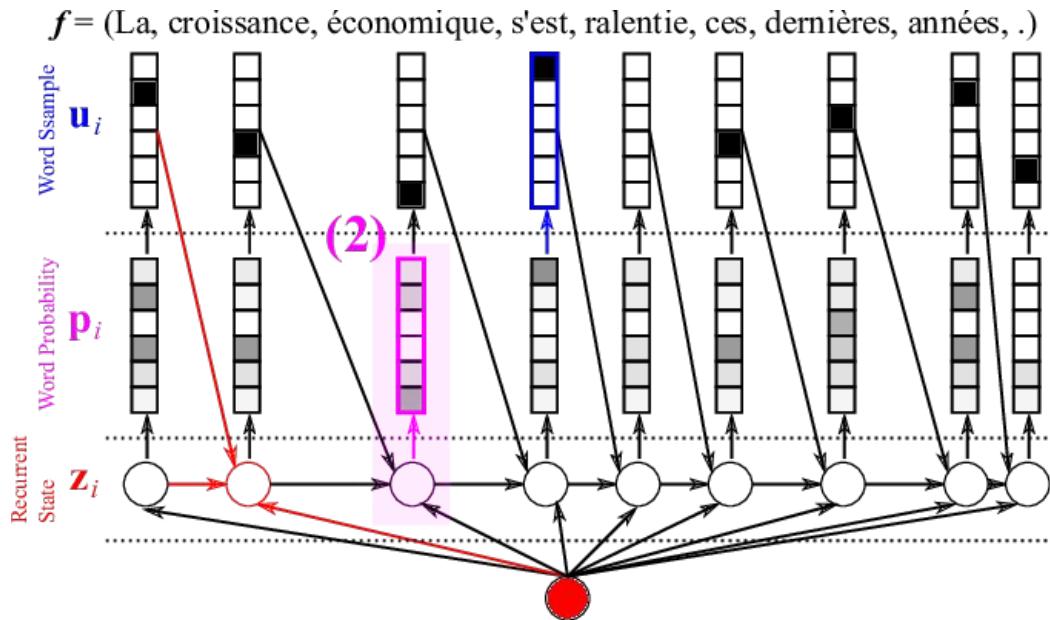
Decoder

With z_i ready, we can score each word k in the vocabulary with a dot product...

$$e(k) = w_k^\top z_i + b_k,$$

Neuron weights for word k

RNN internal state



Decoder

...and finally normalize to word probabilities with a softmax.

Score for word k

$$e(k) = w_k^\top z_i + b_k,$$

Probability that the ith word is word k

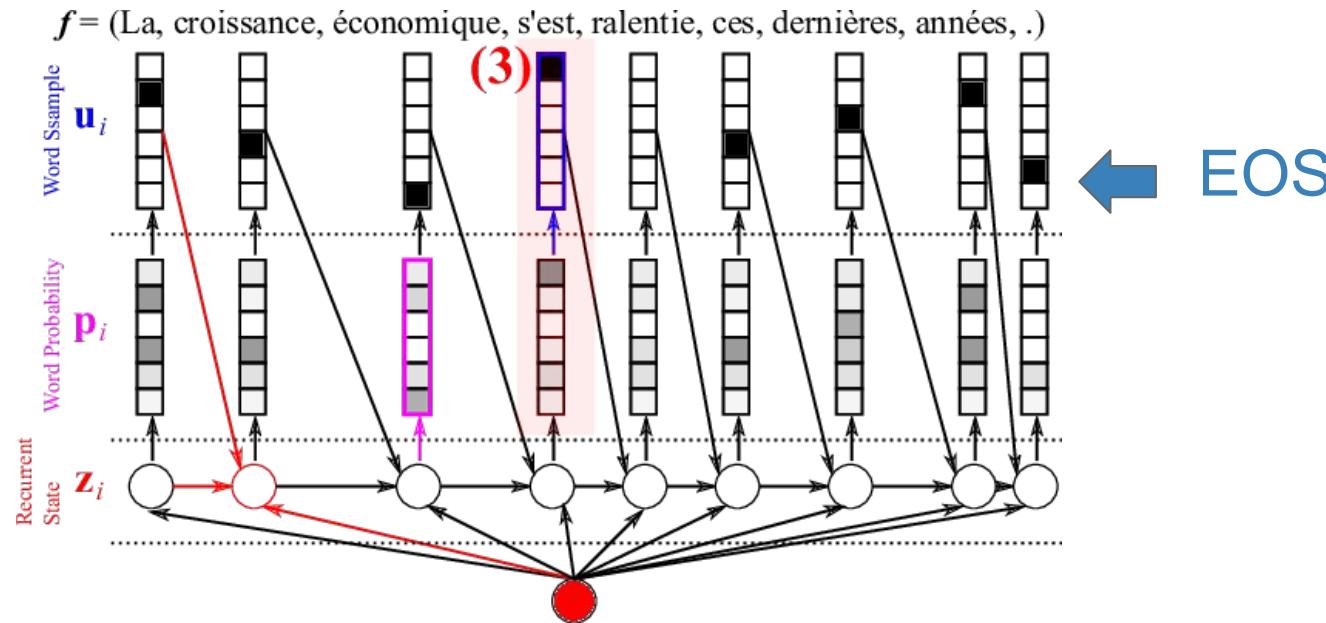
$$p(w_i = k | w_1, w_2, \dots, w_{i-1}, h_T) = \frac{\exp(e(k))}{\sum_j \exp(e(j))}.$$


Previous words Hidden state

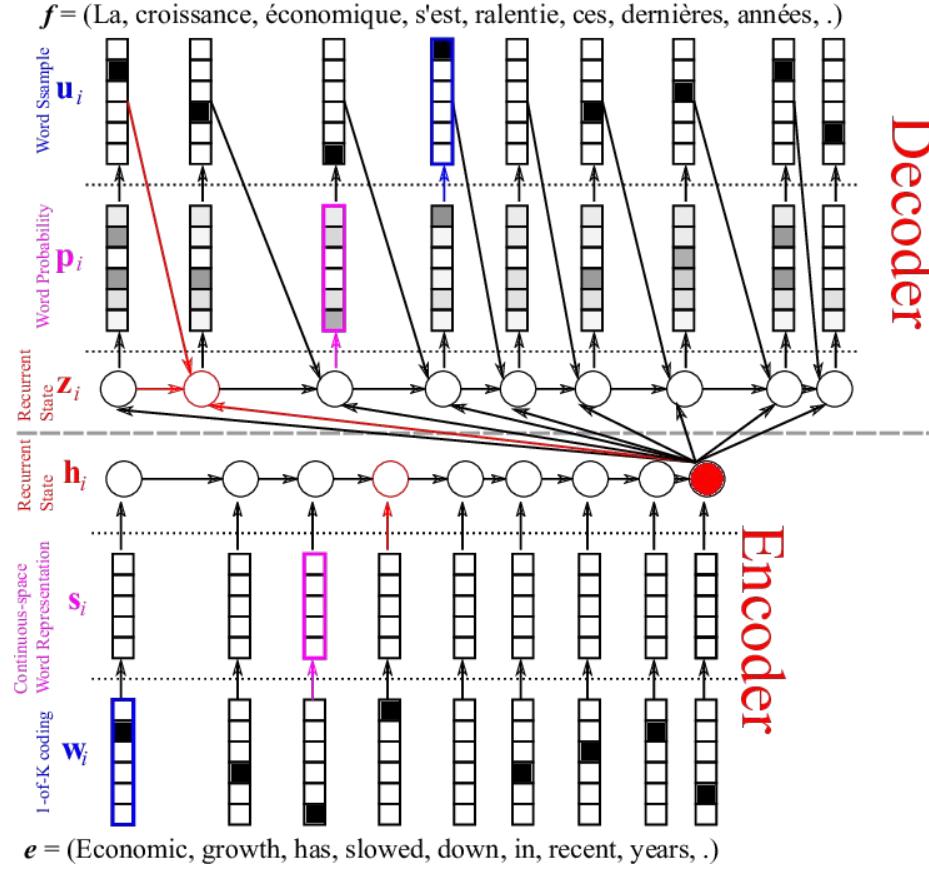
Bridle, John S. "[Training Stochastic Model Recognition Algorithms as Networks can Lead to Maximum Mutual Information Estimation of Parameters.](#)" NIPS 1989

Decoder

More words for the decoded sentence are generated until a <EOS> (End Of Sentence) “word” is predicted.



Encoder-Decoder



Encoder-Decoder: Training

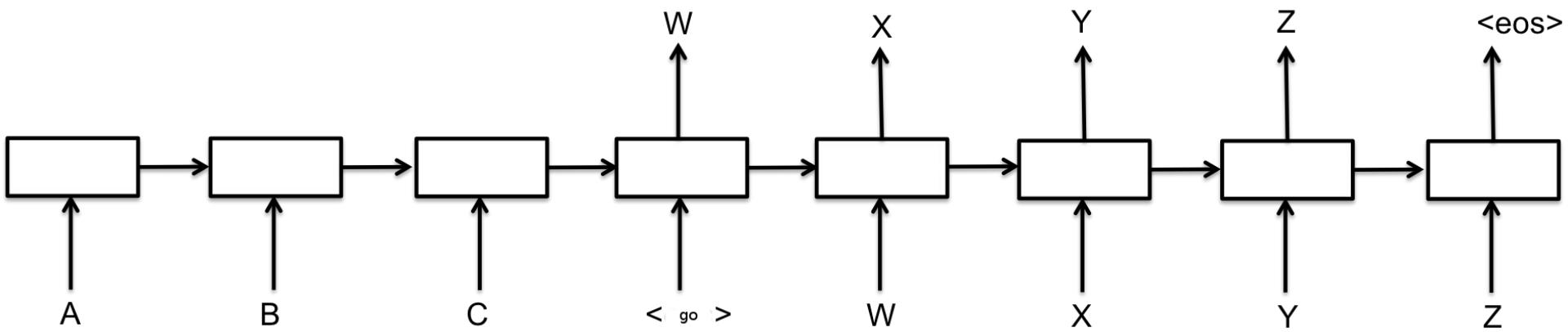
Dataset of pairs of sentences in the two languages to translate.



Source	Translation Model
at the end of the	[a la fin de la] [à la fin des années] [être supprimés à la fin de la]
for the first time	[r © pour la première fois] [été donnés pour la première fois] [été commémorée pour la première fois]
in the United States and	[? aux États-Unis et] [été ouvertes aux États-Unis et] [été constatées aux États-Unis et]
, as well as	[?s , qu'] [?s , ainsi que] [?re aussi bien que]
one of the most	[?t ?l' un des plus] [?l' un des plus] [être retenue comme un de ses plus]

Cho, Kyunghyun, Bart Van Merriënboer, Caglar Gulcehre, Dzmitry Bahdanau, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. "[Learning phrase representations using RNN encoder-decoder for statistical machine translation.](#)" AMNLP 2014.

Encoder-Decoder: Seq2Seq



Sutskever, Ilya, Oriol Vinyals, and Quoc V. Le. ["Sequence to sequence learning with neural networks."](#)
NIPS 2014.

Encoder-Decoder: Beyond text

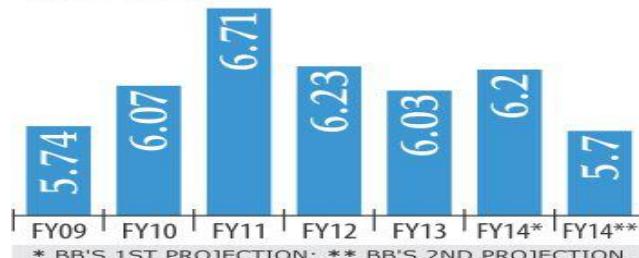
La croissance économique a ralenti ces dernières années .

Decode

$[z_1, z_2, \dots, z_d]$

Encode

ECONOMIC GROWTH
IN PERCENTAGE



Captioning: DeeplImageSent



man in black shirt is playing guitar.



construction worker in orange safety vest is working on road.



two young girls are playing with lego toy.

(Slides by Marc Bolaños): Karpathy, Andrej, and Li Fei-Fei. "Deep visual-semantic alignments for generating image descriptions." CVPR 2015

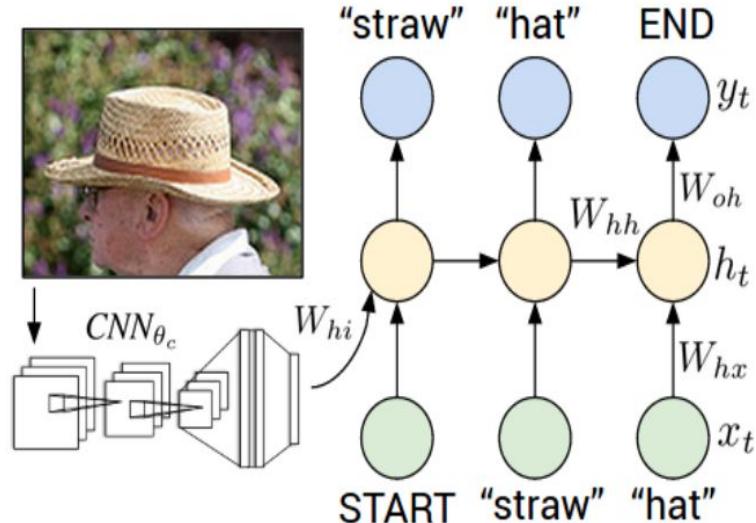
Captioning: DeeplImageSent

only takes into account
image features in the first
hidden state

$$b_v = W_{hi}[CNN_{\theta_c}(I)]$$

$$h_t = f(W_{hx}x_t + W_{hh}h_{t-1} + b_h + \mathbb{1}(t=1) \odot b_v)$$

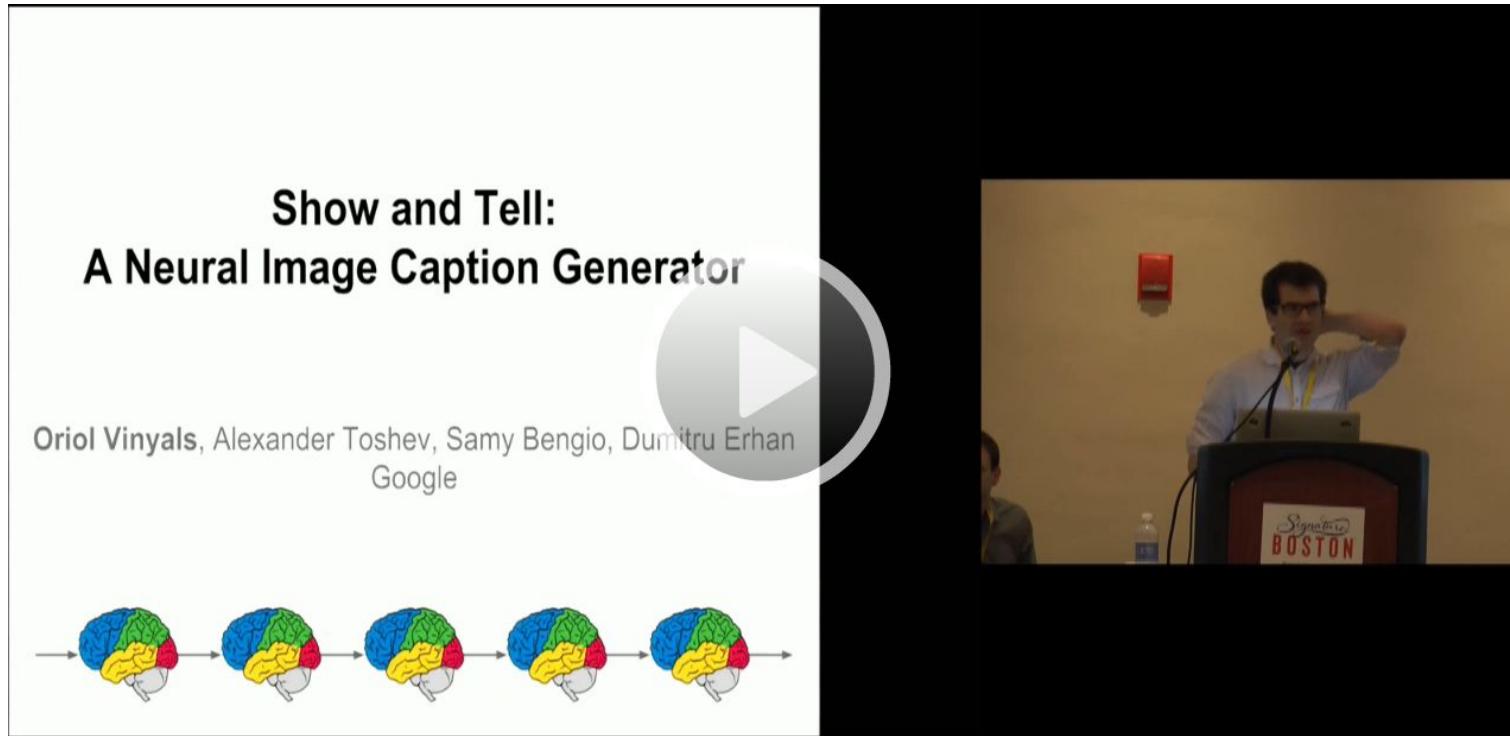
$$y_t = \text{softmax}(W_{oh}h_t + b_o).$$



Multimodal Recurrent
Neural Network

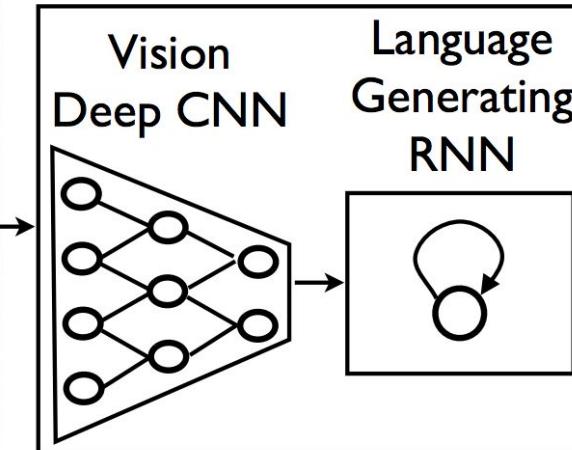
(Slides by Marc Bolaños): Karpathy, Andrej, and Li Fei-Fei. "Deep visual-semantic alignments for generating image descriptions." CVPR 2015

Captioning: Show & Tell



Vinyals, Oriol, Alexander Toshev, Samy Bengio, and Dumitru Erhan. "[Show and tell: A neural image caption generator.](#)" CVPR 2015.

Captioning: Show & Tell

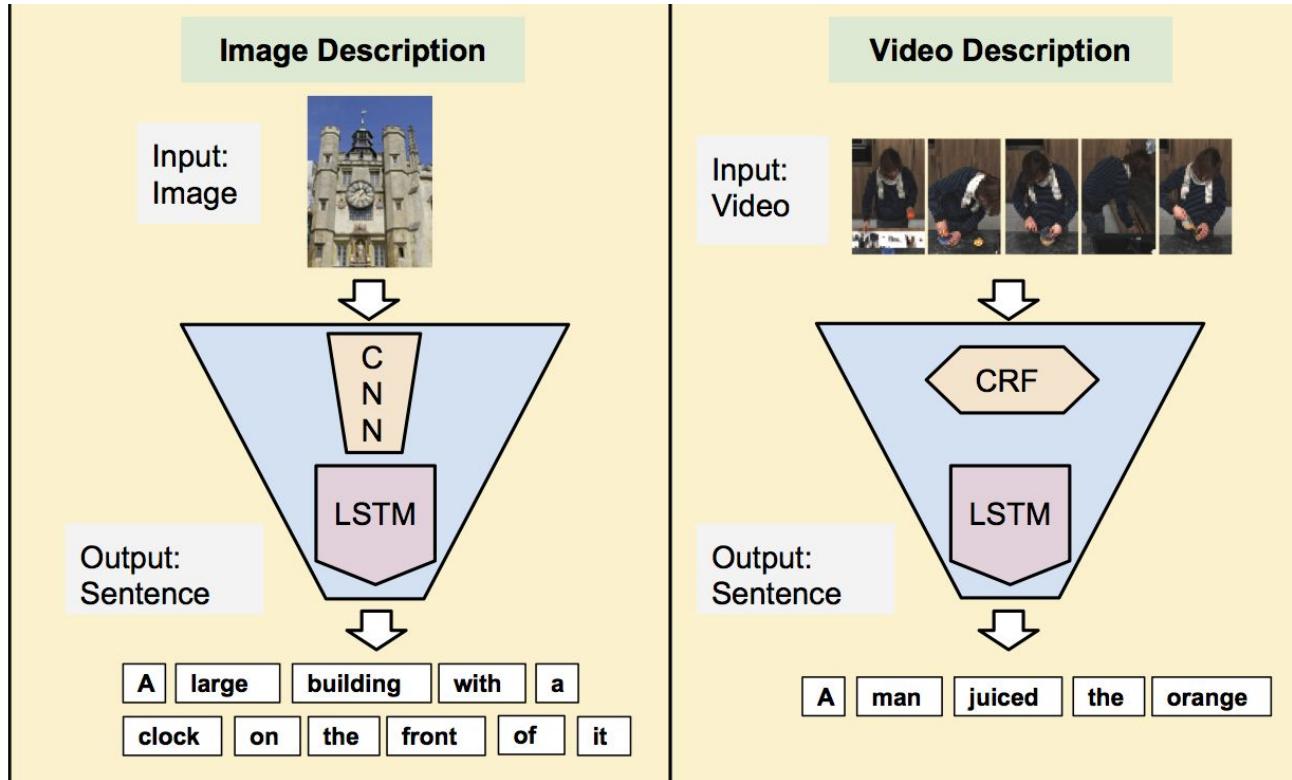


A group of people shopping at an outdoor market.

There are many vegetables at the fruit stand.

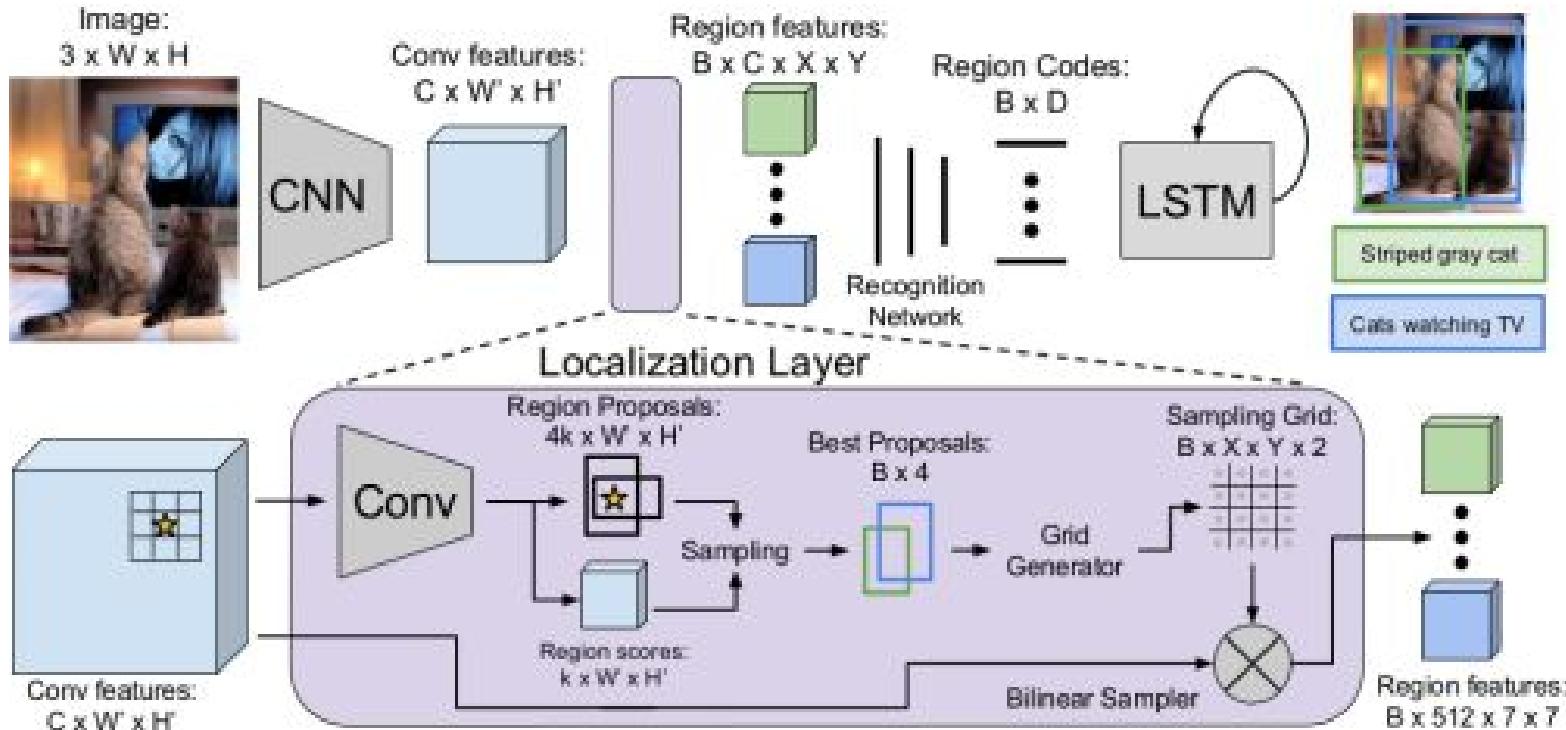
Vinyals, Oriol, Alexander Toshev, Samy Bengio, and Dumitru Erhan. "[Show and tell: A neural image caption generator.](#)" CVPR 2015.

Captioning: LSTM for image & video



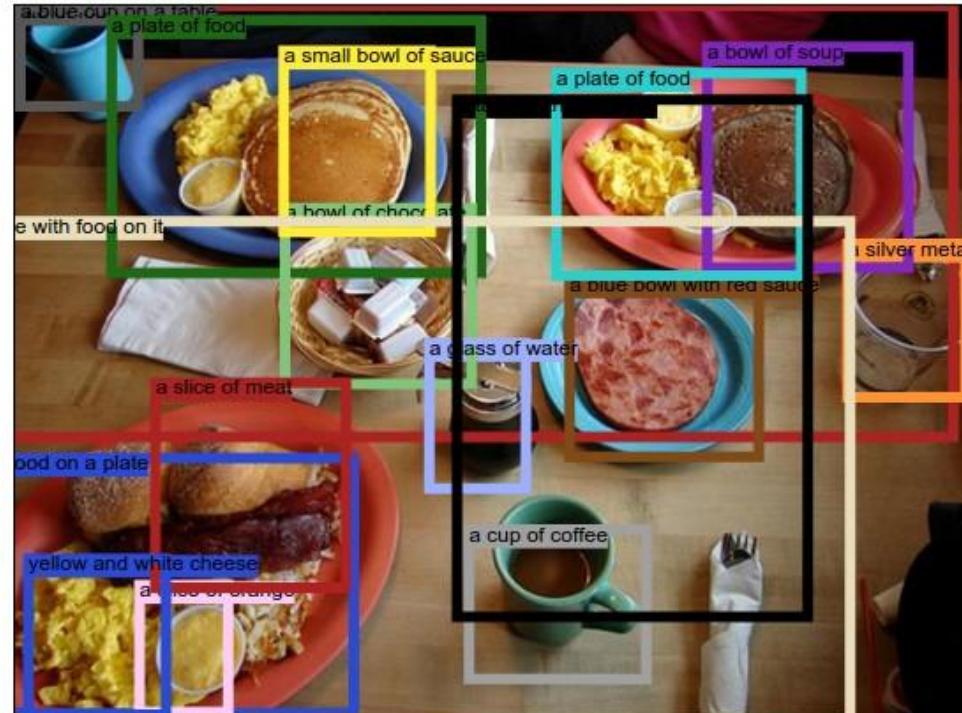
Jeffrey Donahue, Lisa Anne Hendricks, Sergio Guadarrama, Marcus Rohrbach, Subhashini Venugopalan, Kate Saenko, Trevor Darrel. [Long-term Recurrent Convolutional Networks for Visual Recognition and Description](#), CVPR 2015. [code](#)

Captioning (+ Detection): DenseCap



Johnson, Justin, Andrej Karpathy, and Li Fei-Fei. ["Densecap: Fully convolutional localization networks for dense captioning."](#) CVPR 2016

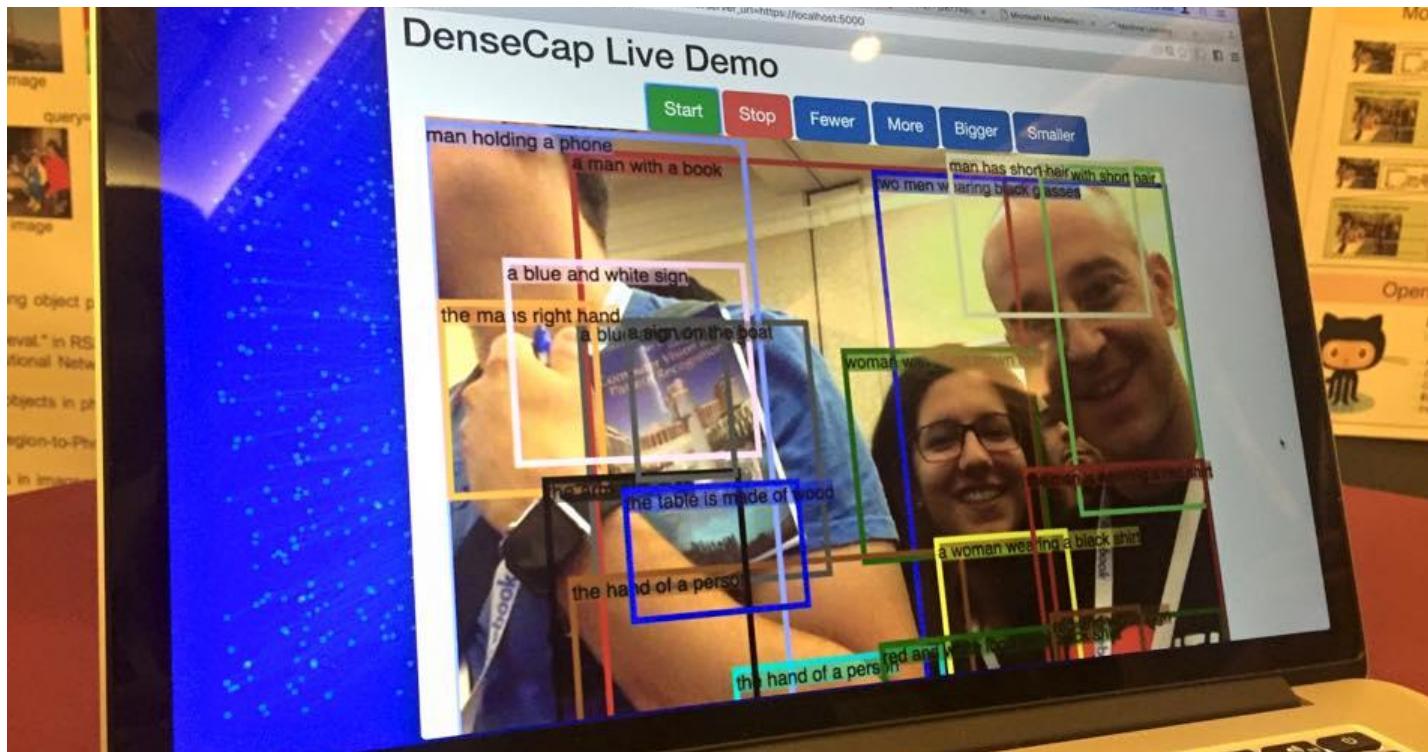
Captioning (+ Detection): DenseCap



a plate of food. food on a plate. a blue cup on a table. a plate of food. a blue bowl with red sauce. a bowl of soup. a cup of coffee. a bowl of chocolate. a glass of water. a plate of food. a silver metal container. a small bowl of sauce. table with food on it. a slice of orange. a table with food on it. a slice of meat. yellow and white cheese.

Johnson, Justin, Andrej Karpathy, and Li Fei-Fei. "[Densecap: Fully convolutional localization networks for dense captioning.](#)" CVPR 2016

Captioning (+ Detection): DenseCap



XAVI: “man has short hair”, “man with short hair”

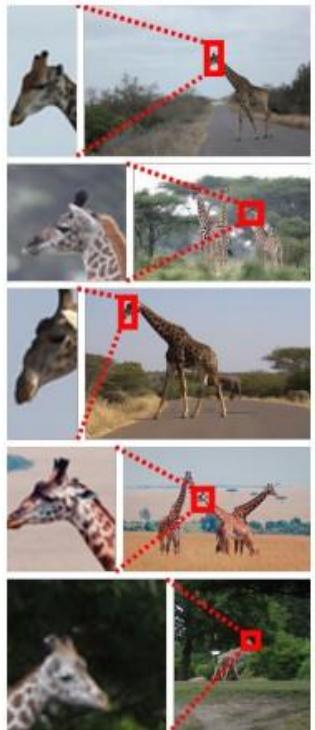
AMAIA: “a woman wearing a black shirt”, “

BOTH: “two men wearing black glasses”

Johnson, Justin, Andrej Karpathy, and Li Fei-Fei. [“Densecap: Fully convolutional localization networks for dense captioning.”](#) CVPR 2016

Captioning (+ Retrieval): DenseCap

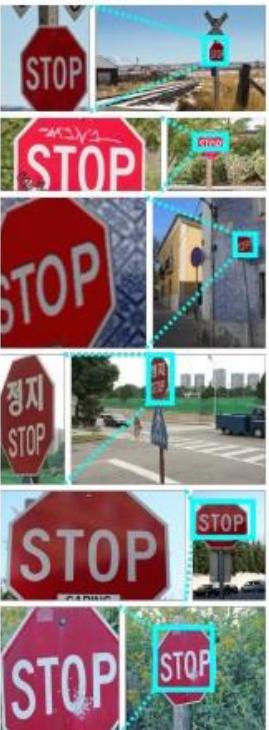
head of a giraffe



legs of a zebra



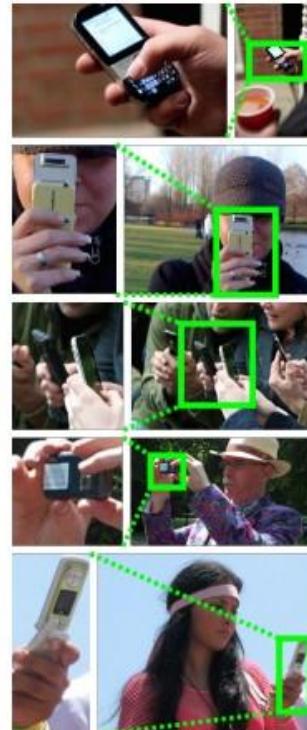
red and white sign



white tennis shoes



hands holding a phone

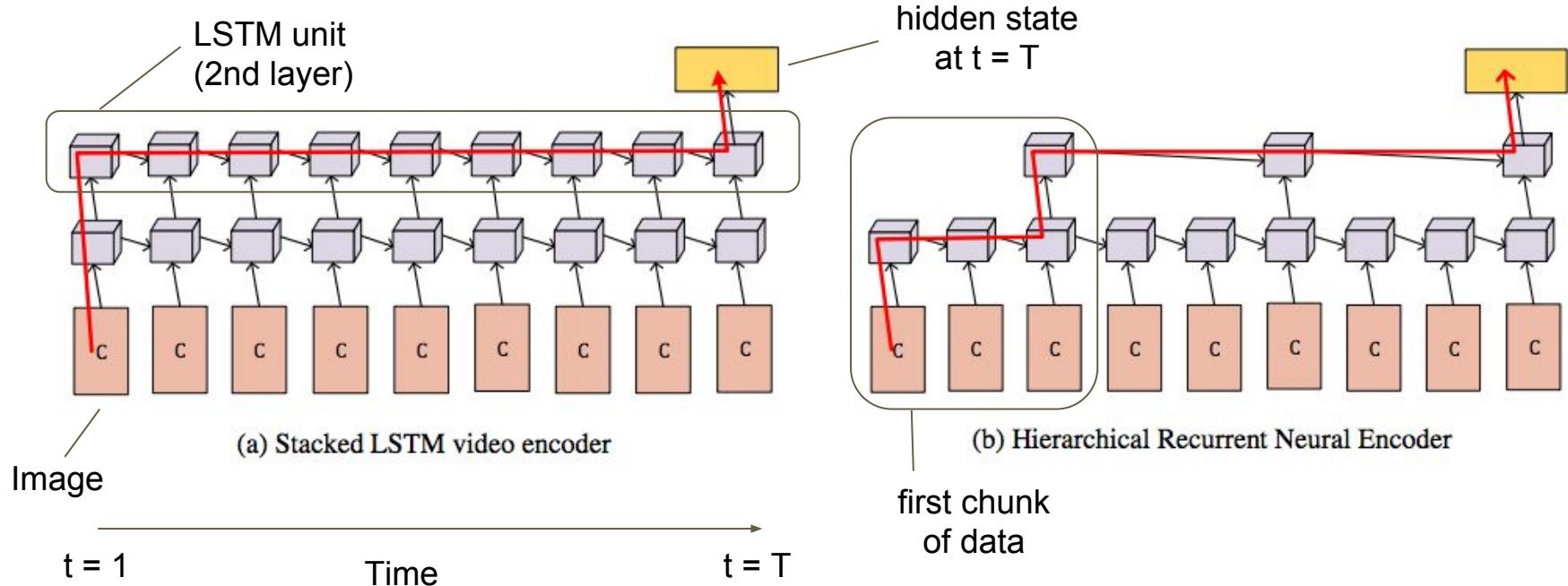


front wheel of a bus



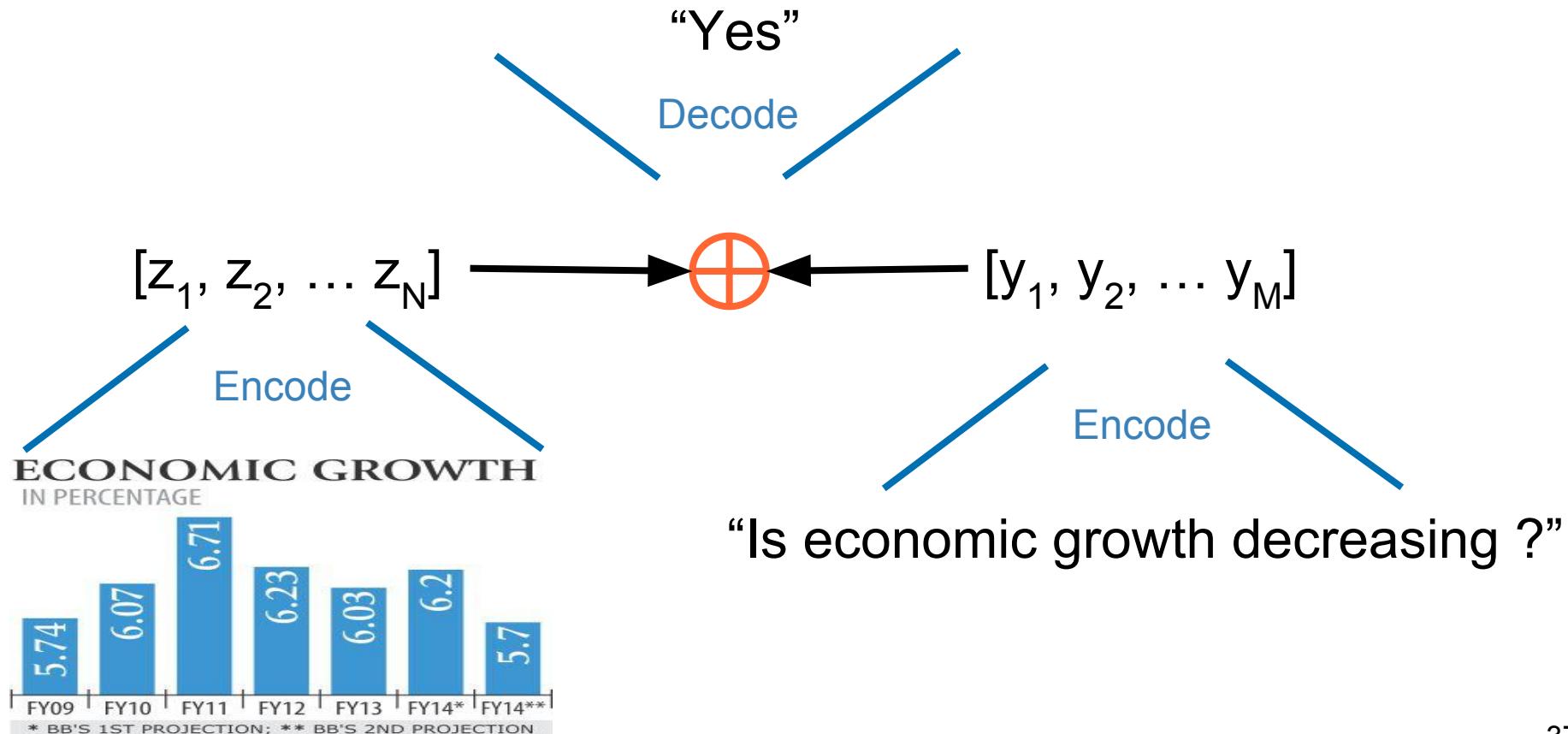
Johnson, Justin, Andrej Karpathy, and Li Fei-Fei. "[Densecap: Fully convolutional localization networks for dense captioning.](#)" CVPR 2016

Captioning: HRNE

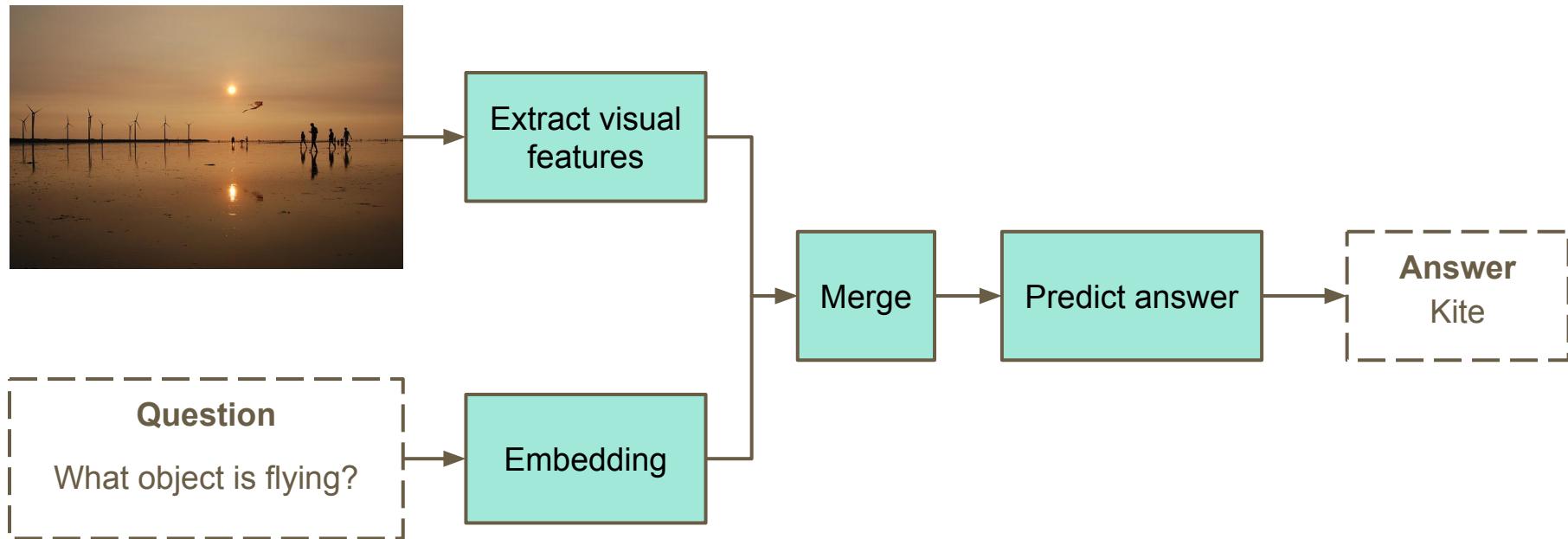


(Slides by Marc Bolaños) Pingbo Pan, Zhongwen Xu, Yi Yang, Fei Wu, Yuetong Zhuang [Hierarchical Recurrent Neural Encoder for Video Representation with Application to Captioning](#), CVPR 2016.

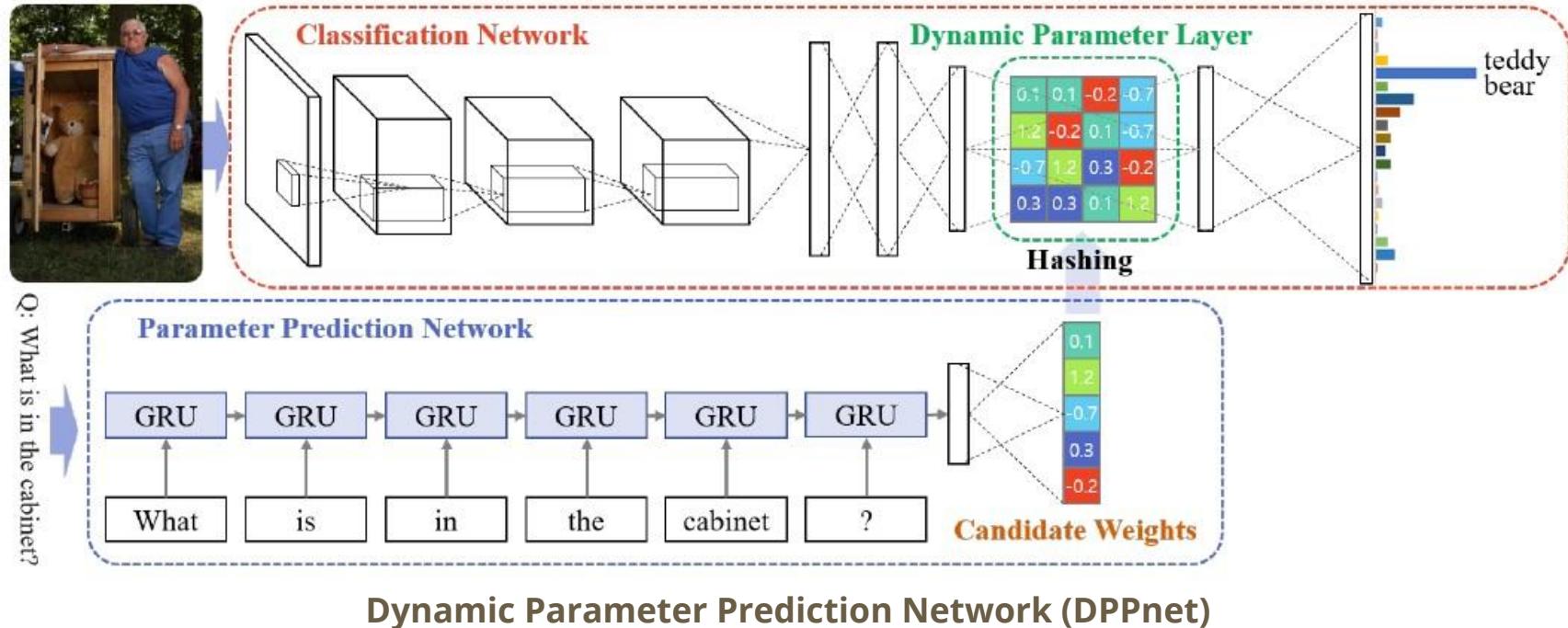
Visual Question Answering



Visual Question Answering

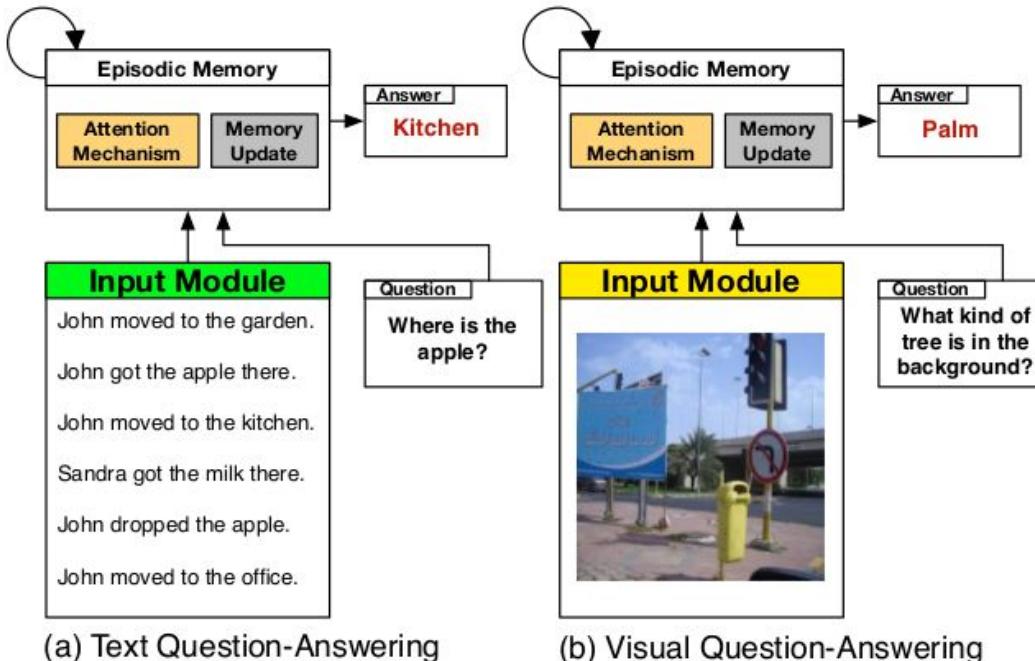


Visual Question Answering



Noh, H., Seo, P. H., & Han, B. [Image question answering using convolutional neural network with dynamic parameter prediction](#). CVPR 2016

Visual Question Answering: Dynamic



(Slides and Slidecast by Santi Pascual): Xiong, Caiming, Stephen Merity, and Richard Socher. "Dynamic Memory Networks for Visual and Textual Question Answering." arXiv preprint arXiv:1603.01417 (2016).

Visual Question Answering: Dynamic

Main idea: split image into local regions.

Consider **each region equivalent to a sentence.**

Local Region Feature Extraction: CNN (VGG-19):

- (1) Rescale input to 448x448.
- (2) Take output from last pooling layer → $D = 512 \times 14 \times 14 \rightarrow 196$ 512-d local region vectors.

Visual feature embedding: W matrix to project image features to “ q ”-textual space.

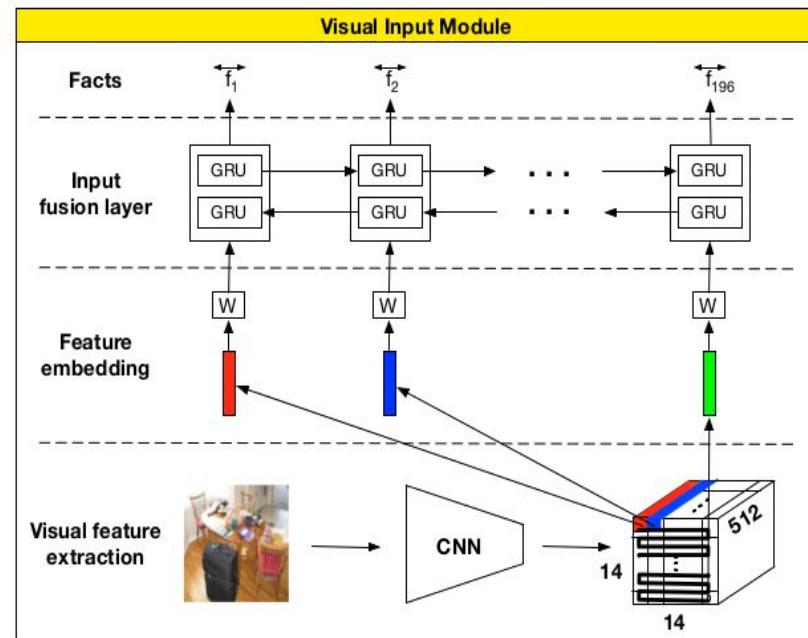


Figure 3. VQA input module to represent images for the DMN.

(Slides and Slidecast by Santi Pascual): Xiong, Caiming, Stephen Merity, and Richard Socher. "Dynamic Memory Networks for Visual and Textual Question Answering." ICML 2016.

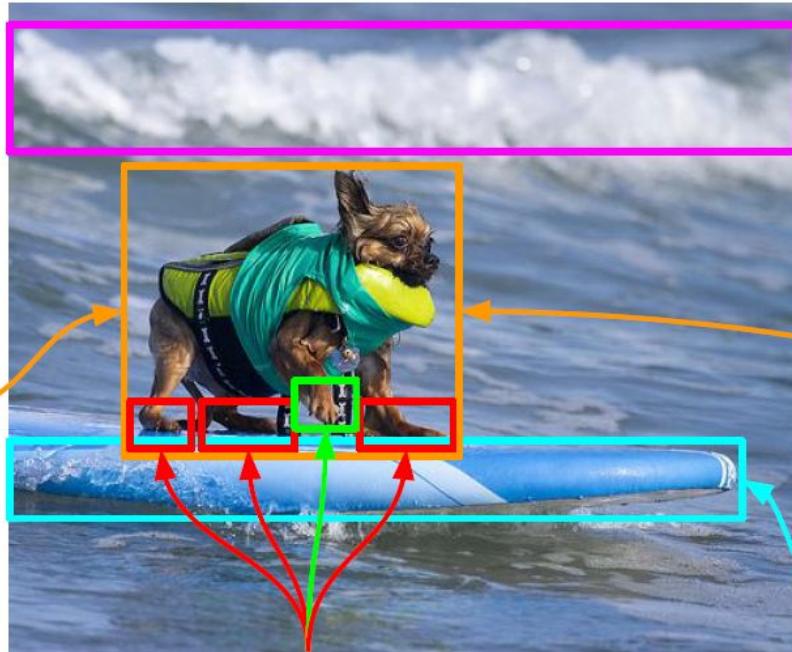
Visual Question Answering: Grounded

Where does this scene take place?

- A) In the sea. ✓
- B) In the desert.
- C) In the forest.
- D) On a lawn.

What is the dog doing?

- A) Surfing. ✓
- B) Sleeping.
- C) Running.
- D) Eating.



Why is there foam?

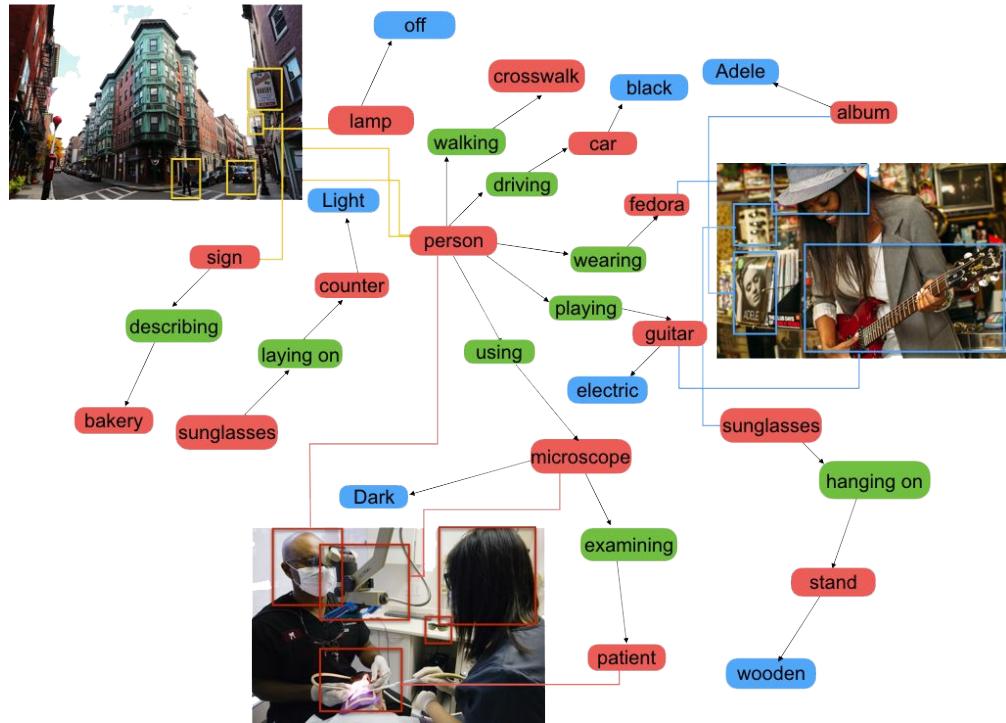
- A) Because of a wave. ✓
- B) Because of a boat.
- C) Because of a fire.
- D) Because of a leak.

What is the dog standing on?

- A) On a surfboard. ✓
- B) On a table.
- C) On a garage.
- D) On a ball.

(Slides and Screencast by Issey Masuda): Zhu, Yuke, Oliver Groth, Michael Bernstein, and Li Fei-Fei. "Visual7W: Grounded Question Answering in Images." CVPR 2016.

Datasets: Visual Genome



Krishna, Ranjay, Yuke Zhu, Oliver Groth, Justin Johnson, Kenji Hata, Joshua Kravitz, Stephanie Chen et al. "[Visual genome: Connecting language and vision using crowdsourced dense image annotations.](#)" *arXiv preprint arXiv:1602.07332* (2016).

Datasets: Microsoft SIND

Example Generated Story

1



2



3



4



5



The dog was ready to go.

He had a great time on the hike.

And was very happy to be in the field.

His mom was so proud of him.

It was a beautiful day for him.

Photos by [kameraschwein](#) / CC BY-NC-ND 2.0

Microsoft SIND

Challenge: Microsoft Coco



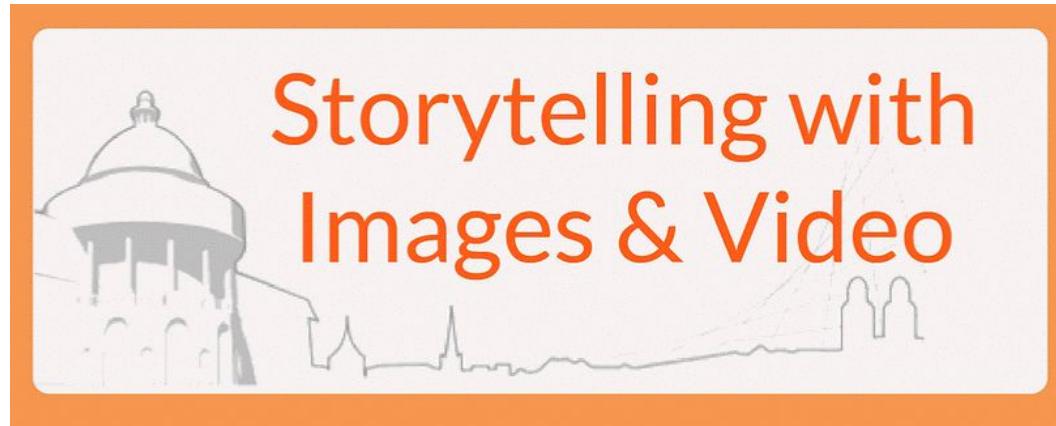
The man at bat readies to swing at the pitch while the umpire looks on.



A large bus sitting next to a very tall building.

Captioning

Challenge: Storytelling



Storytelling

Challenge: Movie Description



Movie Description, Retrieval and Fill-in-the-blank

Challenges: Movie Question Answering

The Lord of the Rings: The Return of the King
Who sees Denethor trying to kill himself and Faramir on a bonfire?
<ul style="list-style-type: none">- Gandalf!- Gandalf!- Denethor has lost his mind!- He's burning Faramir alive!
Pippin
Aragorn
Gandalf
Eowyn
Sam

Movie	E.T. the Extra-Terrestrial
Question	Do aliens leave one of their own on Earth on purpose?
Story	
Correct answer	No, they leave it accidentally
Wrong answer 1	Yes, they leave it on purpose
Wrong answer 2	No, it falls off the spaceship
Wrong answer 3	Yes, they leave it as a spy
Wrong answer 4	They don't leave any of their kind on Earth

Movie Question Answering

Challenges: Visual Question Answering

VQA Visual Question Answering



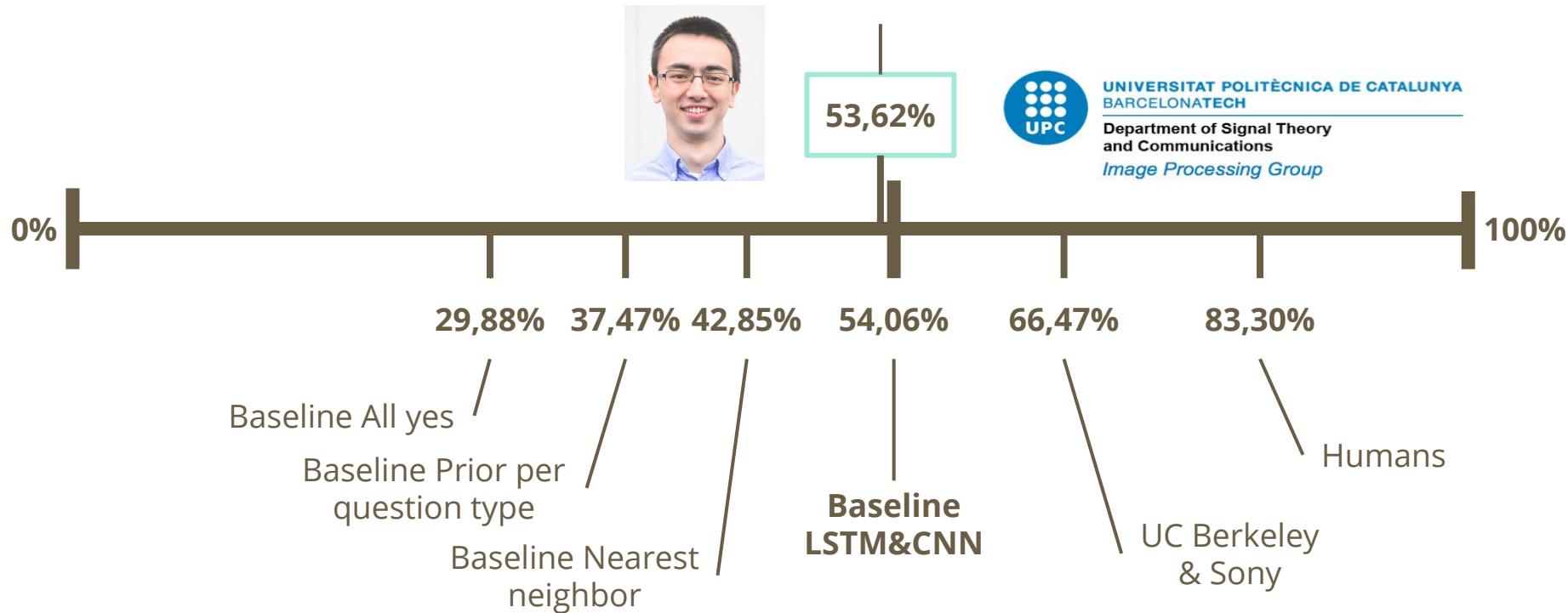
What is the mustache
made of?

AI System

bananas

Visual Question Answering

Challenges: Visual Question Answering



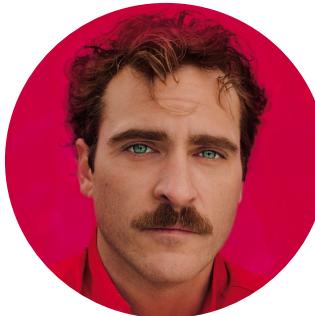
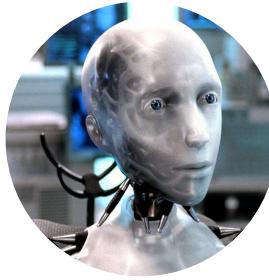
Summary

- Embedding language and vision into semantic embeddings allows fusion learning.
- Very high interest among researchers. Great topic for your thesis.
- Will vision and language (and multimedia) communities be merged with (absorbed by) the machine learning one ?

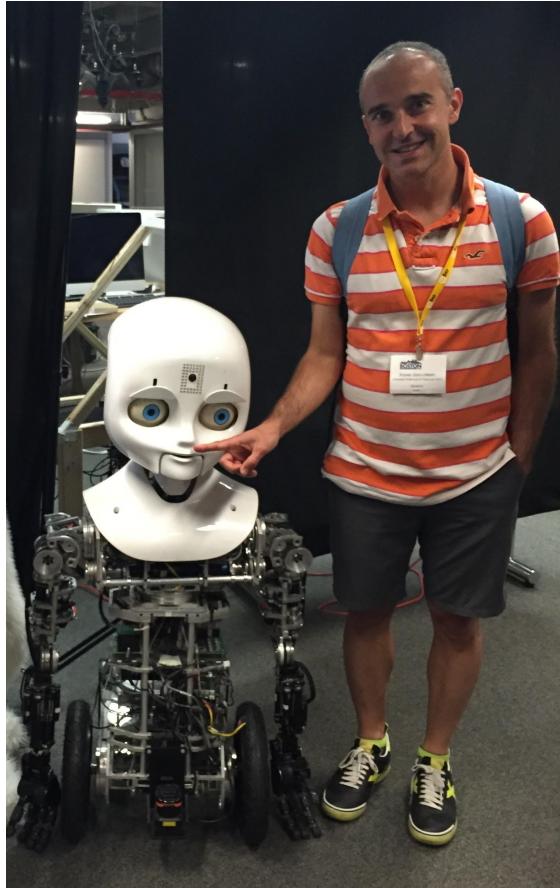
Conclusions



New Turing test? How to evaluate AI's image understanding?



Thanks ! Q&A ?



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