Describing Images Using Natural Language

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Motivation

Why image captioning?

- connects NLP and CV
- more than object detection
- image search
- visually impaired

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Objectives

- caption unseen images
- extend existing implementation
- semantic information
- improvement?

a man in a white shirt

construction workers working on a railroad tracks

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Background

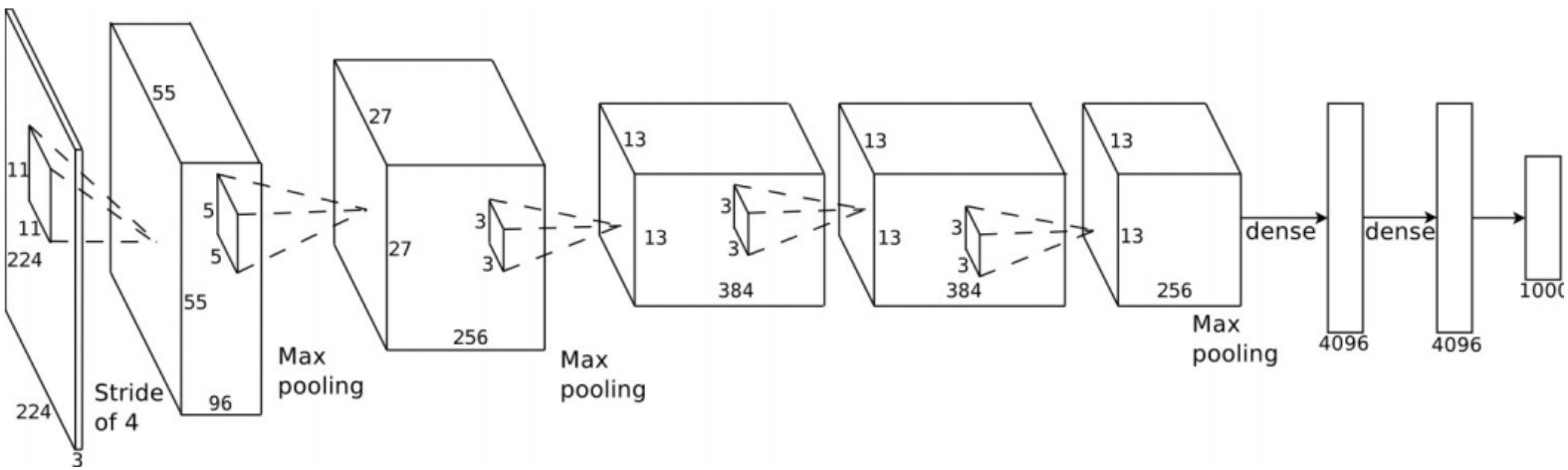
- CNN
- RNN
- LSTM
- LDA
- Stacked CCA

Convolutional Neural Networks (CNN)

- trainable multistage architectures
- each stage outputs set of arrays called feature map
- different types of layers
- faster to train than feed forward
- unsupervised learning
- breakthrough in object recognition

Convolutional Neural Networks (CNN)

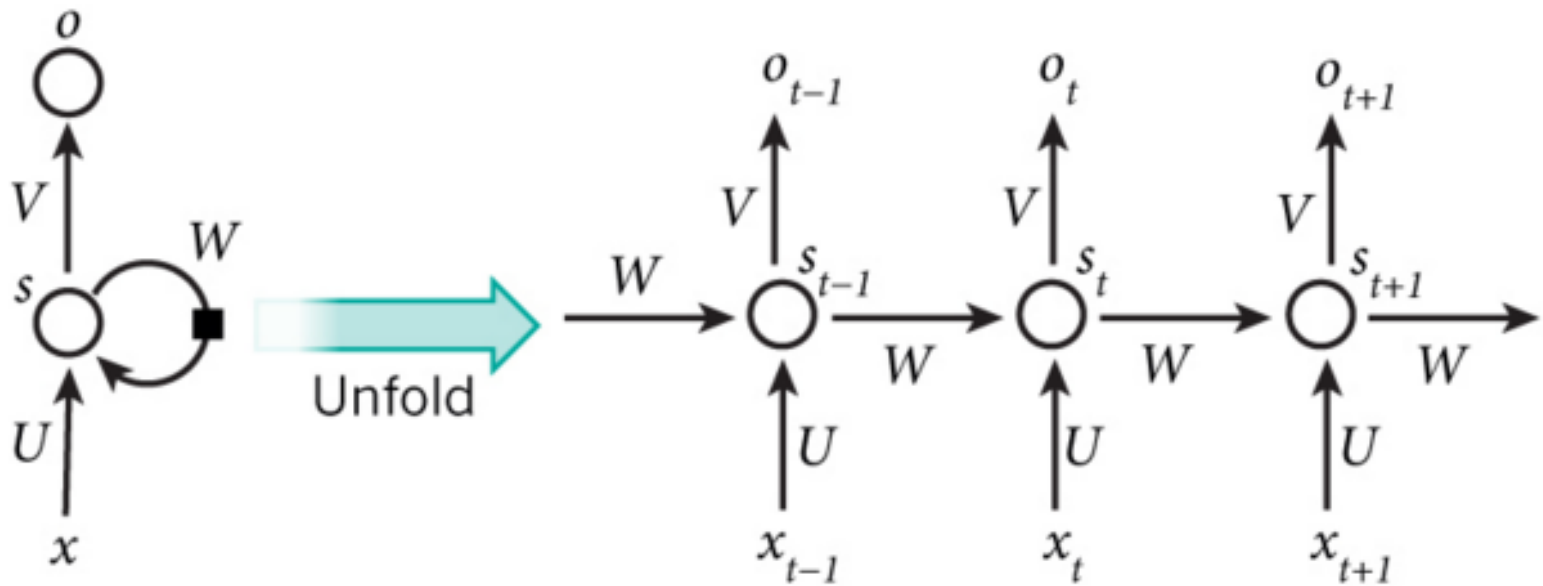
- ImageNet Classification
- deeper Models: VGGNet 16 layers
  [Simonyan and Zisserman, 2015]
- use of layers for other tasks



[Krizhevsky et al., 2012]

Recurrent Neural Networks (RNN)

- predicting sequential data
- encode temporal information
- use as language model
- words represented as word vectors

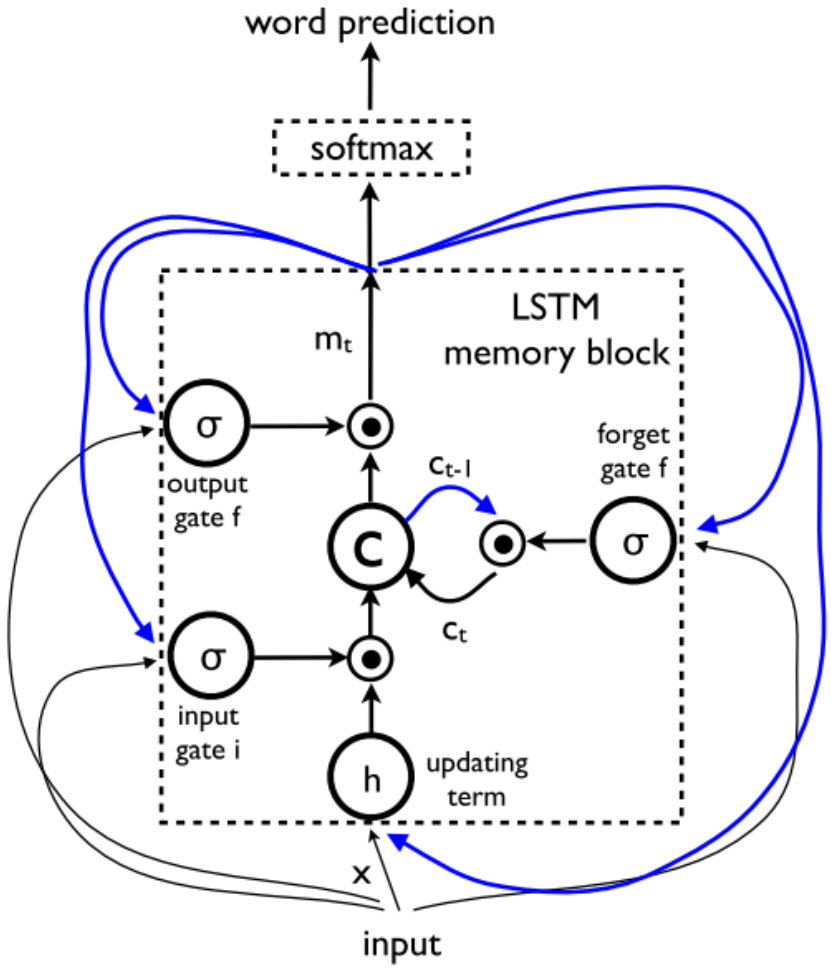


[LeCun et al., 2015]

Long Short-Term Memory (LSTM)

[Hochreiter and Schmidhuber, 1997]

- RNN with memory cells
- capture long-term dependencies



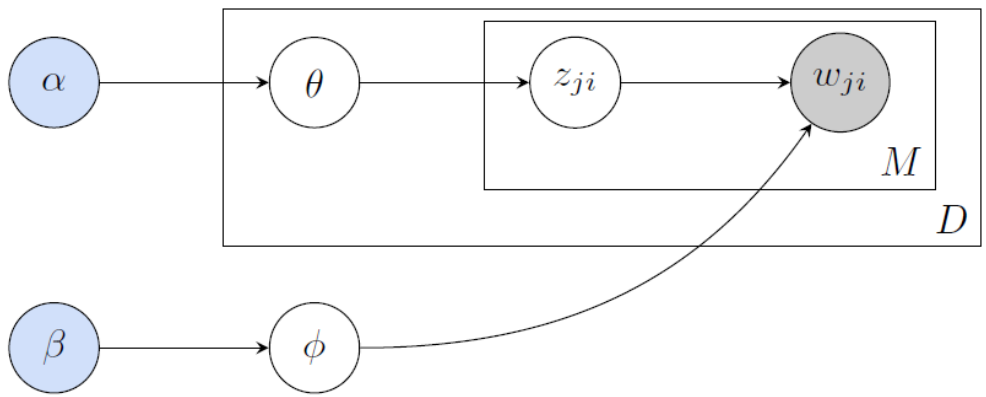
[Vinyals et al., 2015]

LDA [Blei et al., 2012]

- generative probabilistic model for discrete data
- documents generate topics
- topics generate words
- train with e.g. Gibbs sampling

LDA

- θ: per-document topic distribution
- z: topic
- w: word



$$P(player|doc_i) = P(topic_{sport}|doc_i)P(player|topic_{sport})$$

Stacked CCA [Gong et al., 2014]

- CCA
  - canonical correlation analysis
  - maps two matrices (A, B) into intermediate representation
  - maximum correlation between projections of A and B
- improve embeddings with extra information
  - CCA on extra dataset: A, B
  - $\hat{X} = [X, \phi(XA)]$, $\hat{Y} = [Y, \phi(YB)]$
  - another CCA on top

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Related Work

- Deep Visual-Semantic Alignments for Genating Image Descriptions [Karpathy and Fei-Fei, 2015]
- Show and Tell: A Neural Image Caption Generator [Vinyals et al., 2015]
- Guiding Long-Short Term Memory for Image Caption Generation [Jia et al., 2015]

[Karpathy and Fei-Fei, 2015]

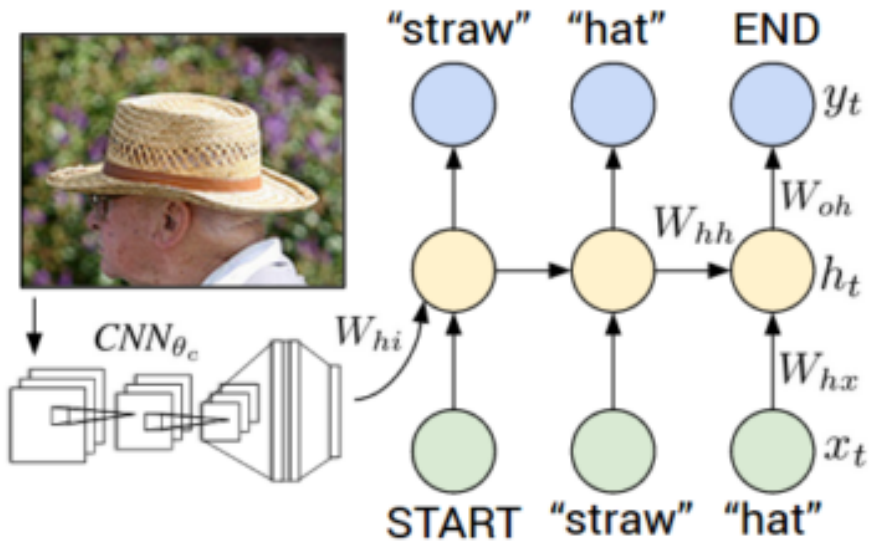
- two goals
  - dense image description based on alignments
  - describing a full image with one sentence

- alignment model
  - Region CNN (RCNN) to detect objects [Girshick et al., 2014]
  - bidirectional RNN to compute word representations
  - alignment objective

[Karpathy and Fei-Fei, 2015]

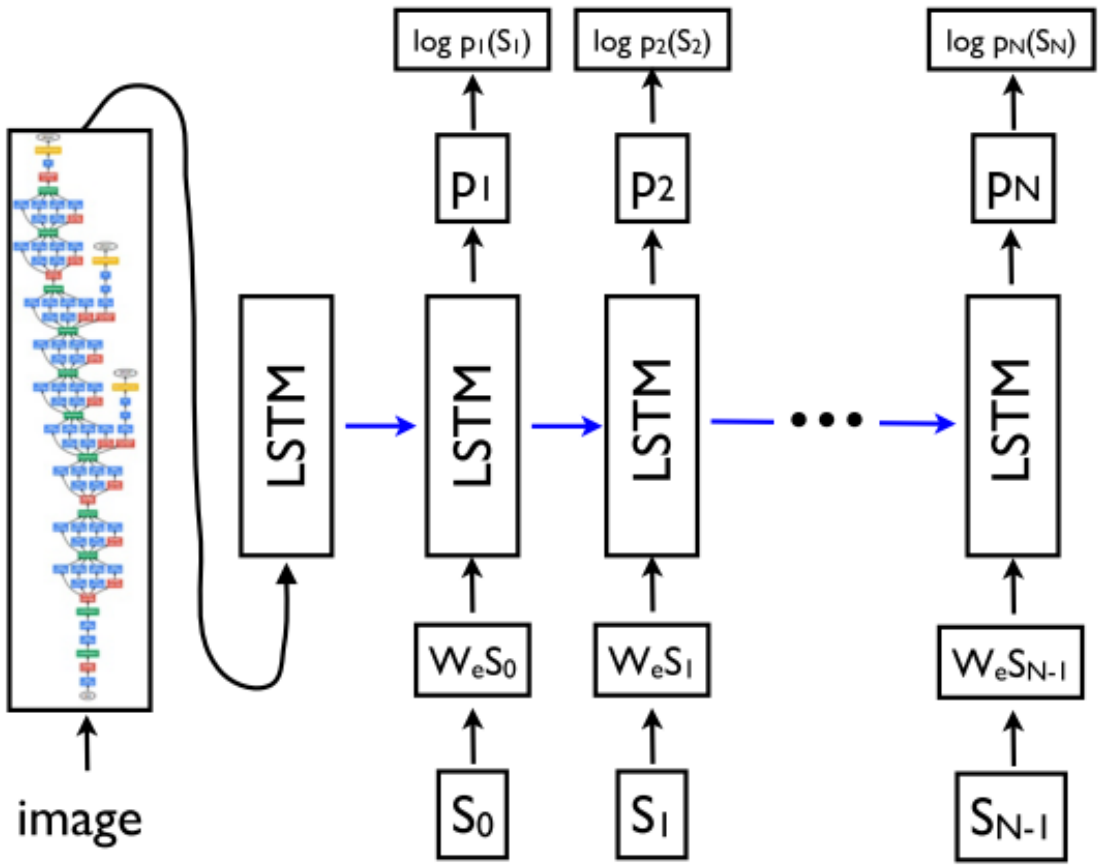
- Multimodal RNN
  - CNN
  - RNN
  - Softmax classifier
  - predicting a sentence with beam search

- Evaluation:
  - ranking image-sentence retrieval (recall)
  - sentence predictions (Bleu,METEOR,CIDEr)



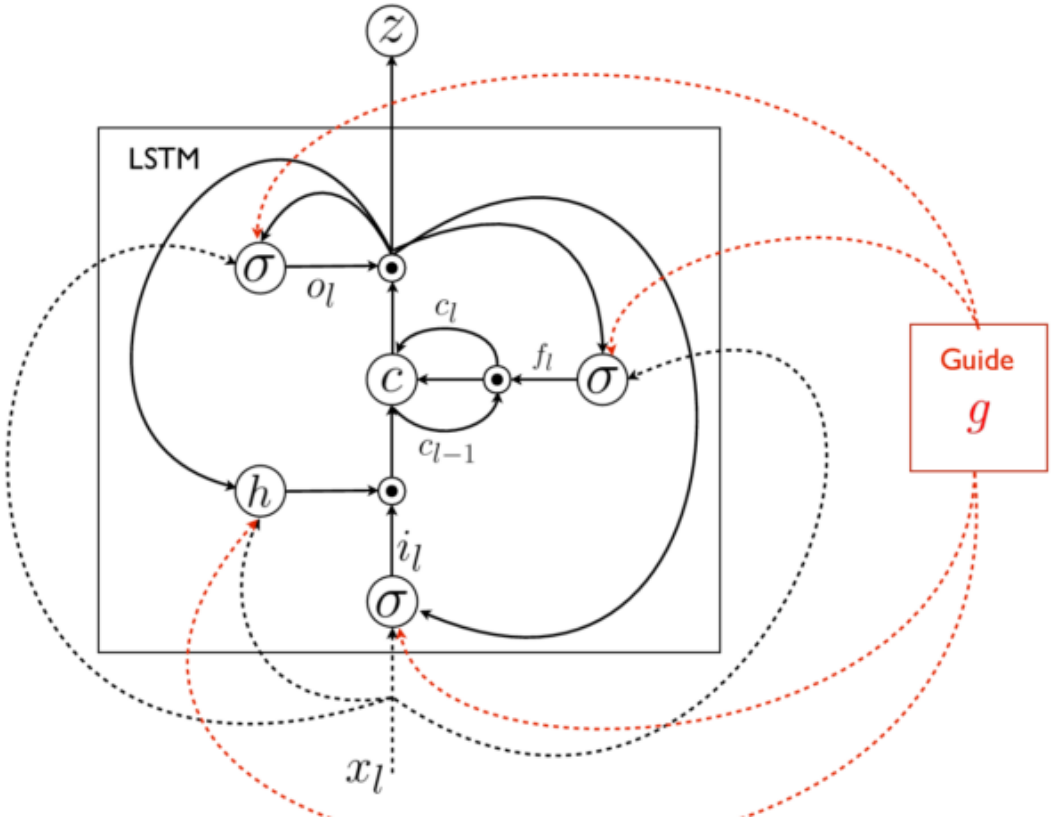
Neural Image Caption (NIC) [Vinyals et al., 2015]

- CNN
- LSTM-based sentence generator
- train: maximize probability of generating the right caption
- inference: beam search or sampling



[Jia et al., 2015]

- extension of NIC implementation by Karpathy
- add semantic information as extra input to LSTM block (guided LSTM)
  - close sentences
  - CCA
  - image
- length normalization strategies for beam search



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Datasets

Manually annotated datasets:

- Flickr30k [Young et al., 2014]
  - 31.783 images
  - 5 captions per image
- MS COCO [Lin et al., 2014]
  - Common Objects in COntext
  - over 330.000 images
  - 5 captions per image
  - non-iconic scenes

(a) Iconic object images (b) Iconic scene images (c) Non-iconic images

Datasets

Flickr30k Entities [Plummer et al., 2015]

- 276.000 annotated bounding boxes
- corresponding fragments of captions

A man with **pierced ears** is wearing **glasses** and **an orange hat**.
A man with **glasses** is wearing **a beer can crotched hat**.
A man with **gauges** and **glasses** is wearing **a Blitz hat**.
A man in **an orange hat** starring at **something**.
A man wears **an orange hat** and **glasses**.

During **a gay pride parade** in **an Asian city**, **some people** hold up **rainbow flags** to show their **support**.
A group of youths march down **a street** waving **flags** showing **a color spectrum**.
Oriental people with **rainbow flags** walking down **a city street**.
A group of people walk down **a street** waving **rainbow flags**.
People are **outside** waving **flags** .

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Methodology

- modify NeuralTalk[1] code which implements both Karpathy and Vinyals
- Feedforward Sequential Memory Neural Networks without Recurrent Feedback [Zhang et al., 2015]
- LDA
  - learn LDA on training set
  - train perceptron to predict topic distribution on given image feature
  - predict topic distribution on unseen images with network
  - use topic distribution as additional input for RNN

[1] `https://github.com/karpathy/neuraltalk`

Methodology

- transform Flickr30kEntities to useful data
  - tf-idf representation for sentence snippets
  - CNN feature vectors for image snippets
- add semantic information with guided LSTM
  - stacked CCA based on Flickr30kEntities data
  - LDA

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Results from literature

	B1	**B2**	**B3**	**B4**
Karpathy	57.3	36.9	24.0	15.7
Vinyals	66.3	42.3	27.7	18.3
Jia	64.4	44.6	30.5	20.6
Human	68			

Experimental Results

	B1	**B2**	**B3**	**B4**
RNN	65.1	43.1	29.0	18.9
RNN + LDA	64.5	43.1	27.9	17.6
LSTM	59.1	37.2	22.8	14.0
Human	68			

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Future Work

- finetune current networks
- finish gLSTM with Flickr30k Entities and LDA
- investigate dense captioning
  - Faster RCNN
  - Flickr30k Entities
- use Torch to make a faster implementation

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Conclusion

- working implementations
- similar/better results are possible
- new ideas to further investigate

Questions?

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