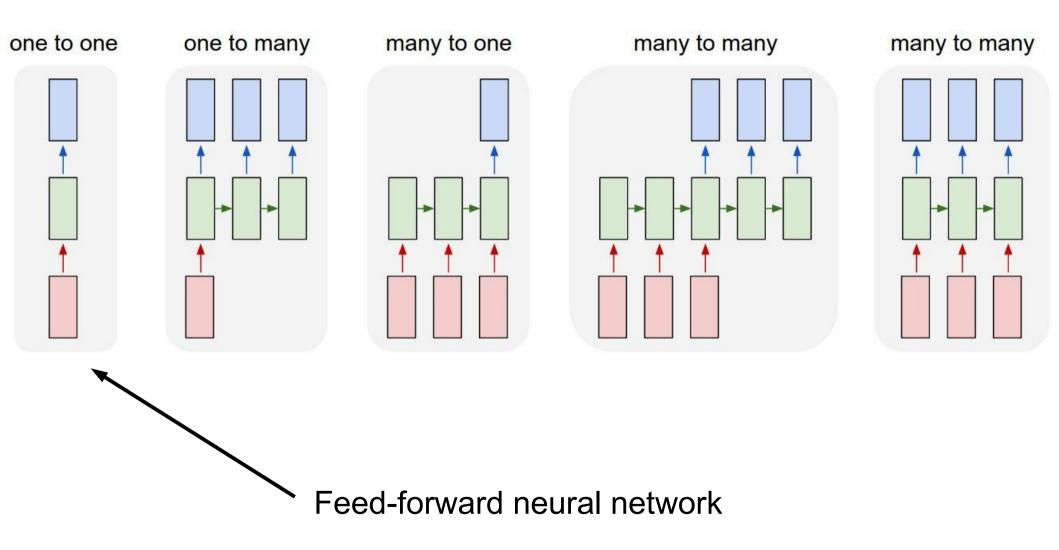
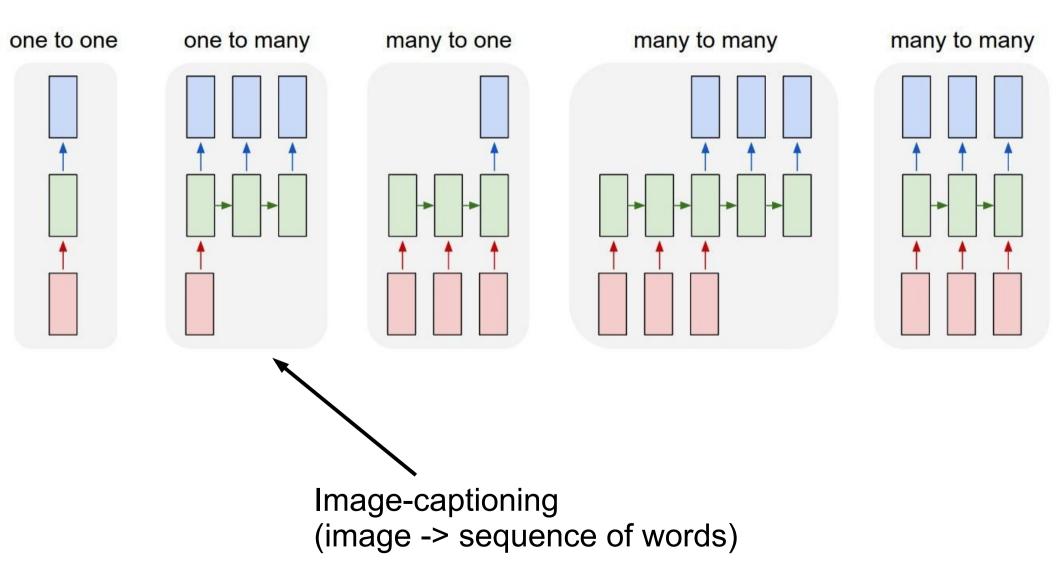
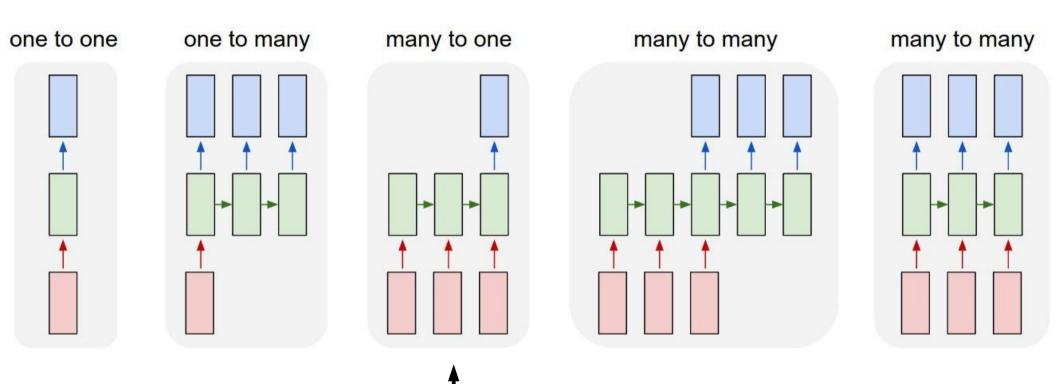
Recurrent Neural Networks + Multimodal Deep Learning (Vision+Language)

Jamie Ryan Kiros University of Toronto

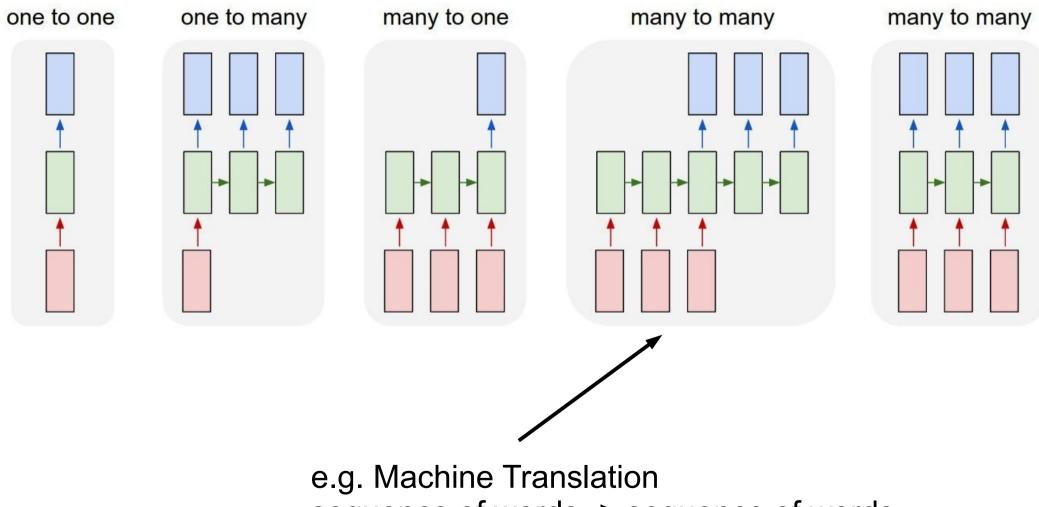




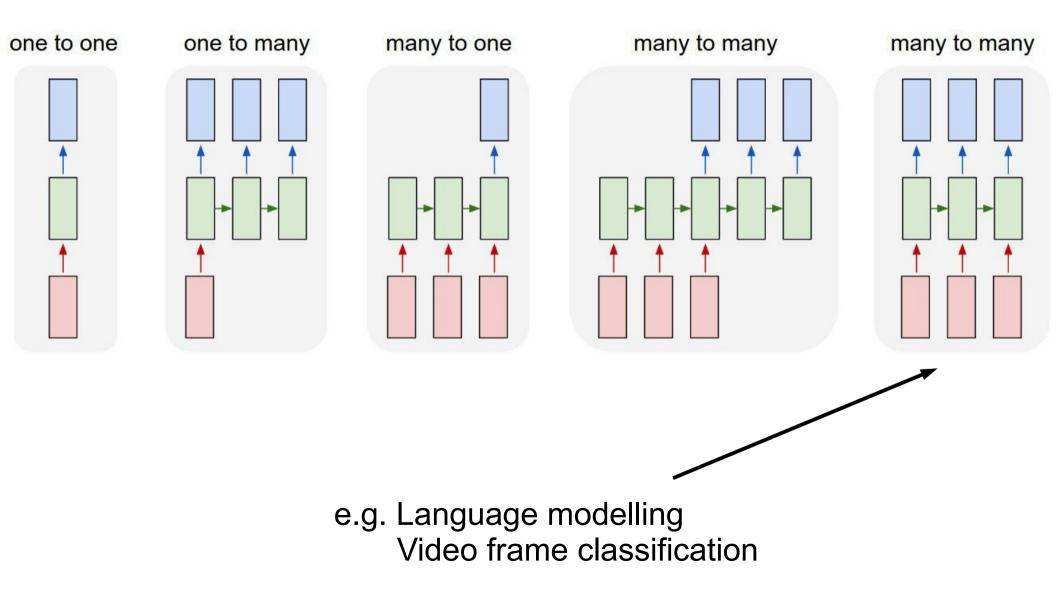




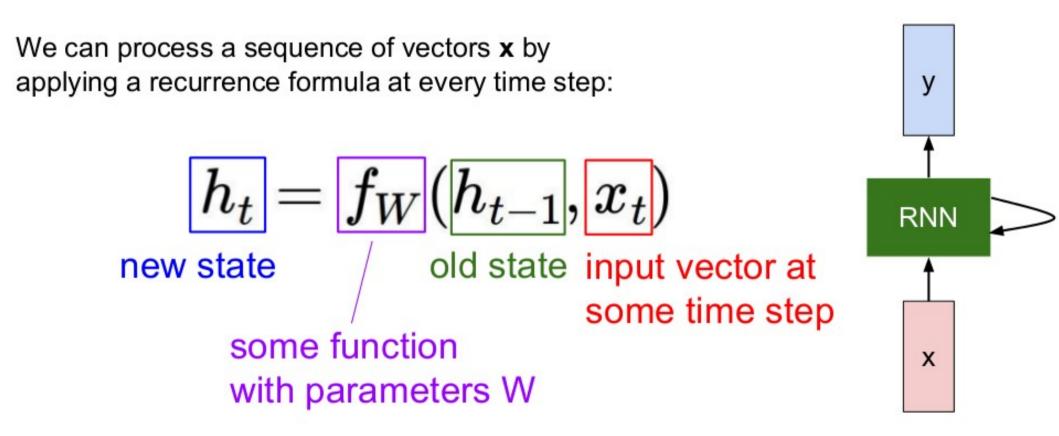
e.g. Sentiment classification sequence of words ->sentiment



sequence of words -> sequence of words

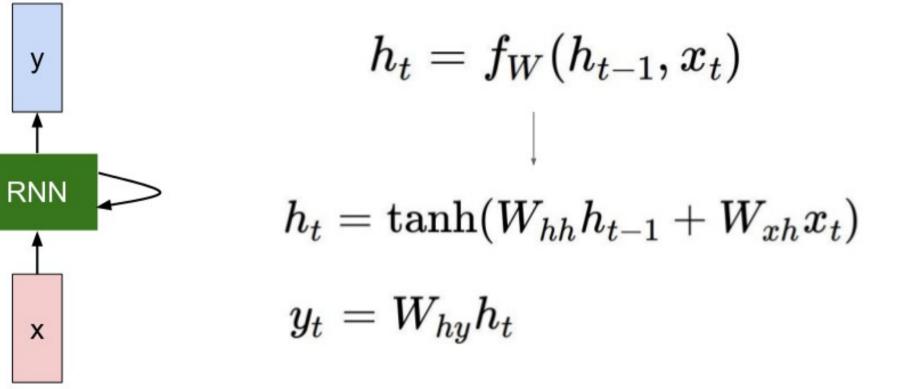


Recurrent Neural Network

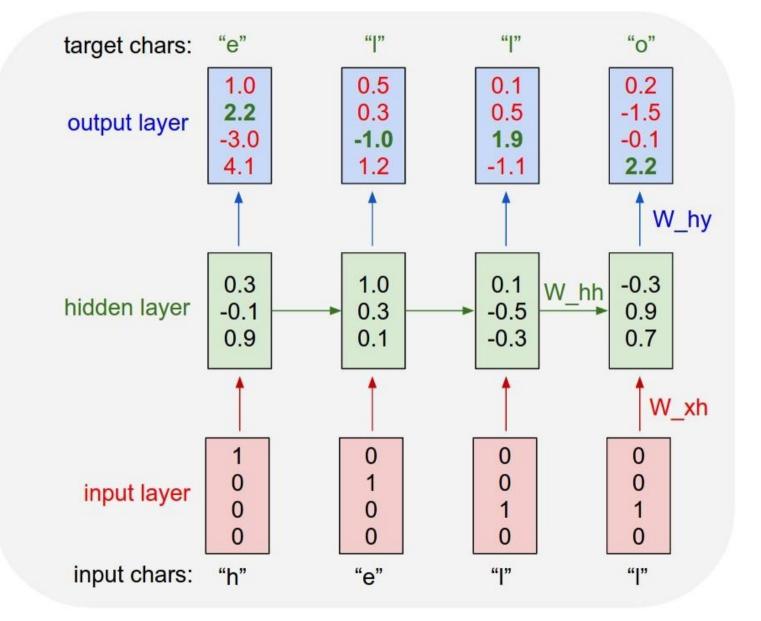


(Vanilla) Recurrent Neural Network

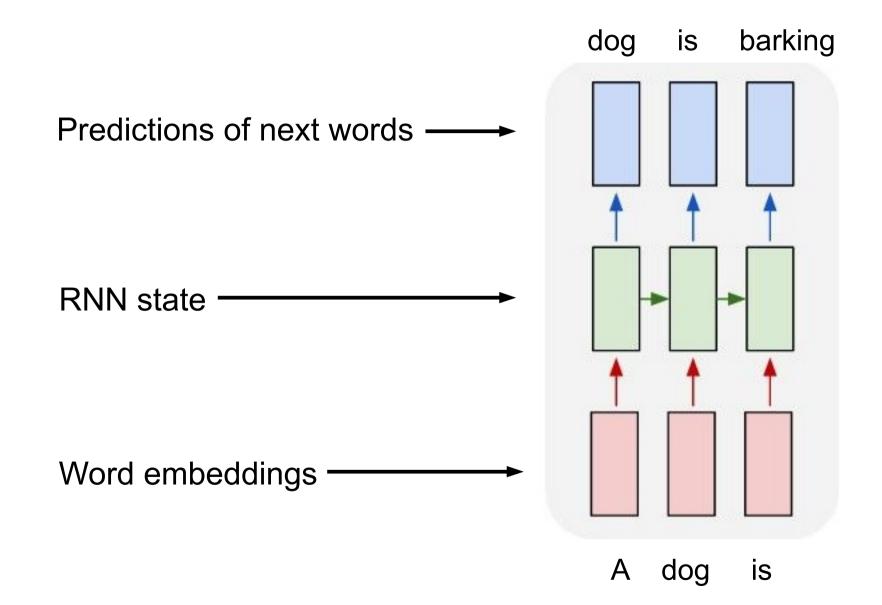
The state consists of a single "hidden" vector h:



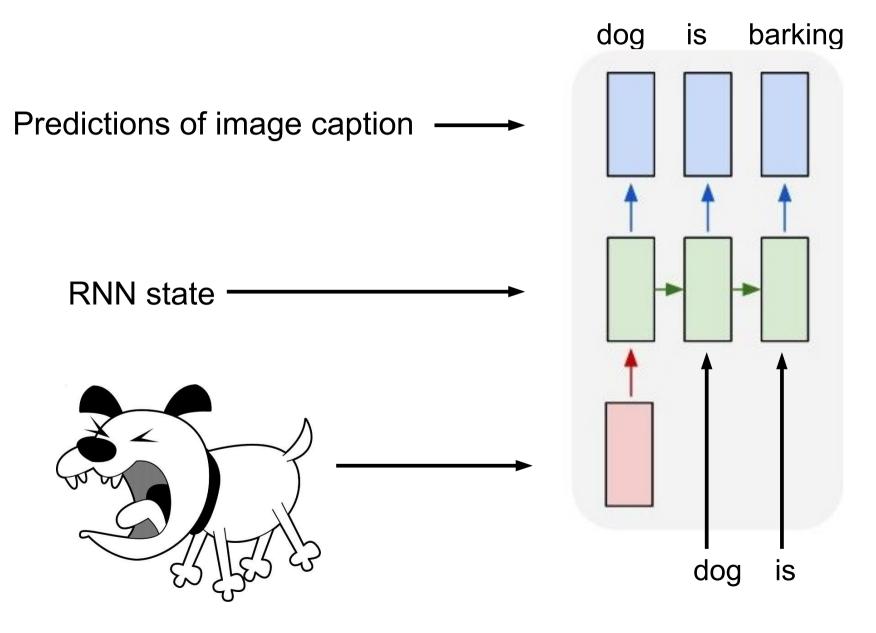
Example: character-level language models



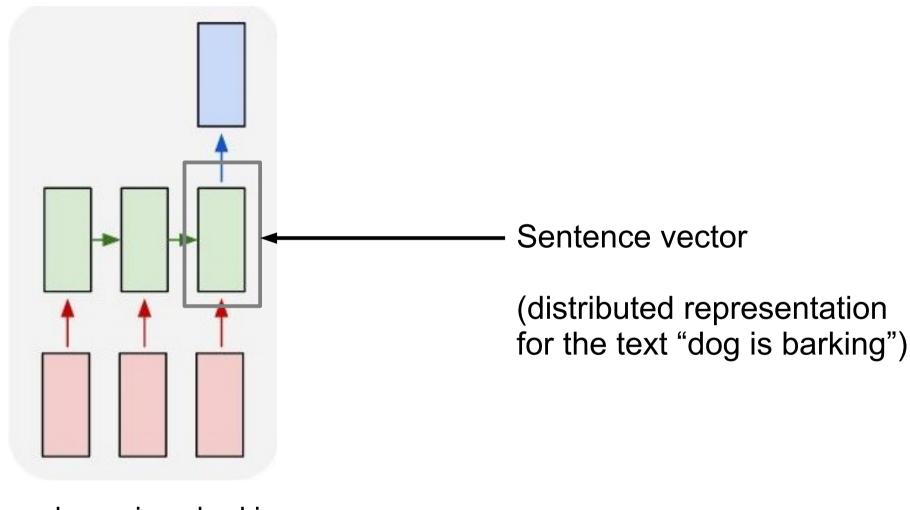
RNNs for language: language models



RNNs for language: decoders (conditional language models)



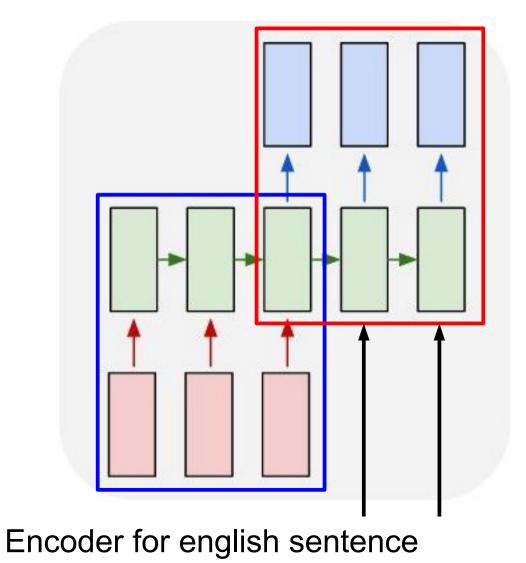
RNNs for language: encoders



dog is barking

RNNs for language: encoder-decoders

Decoder for french sentence



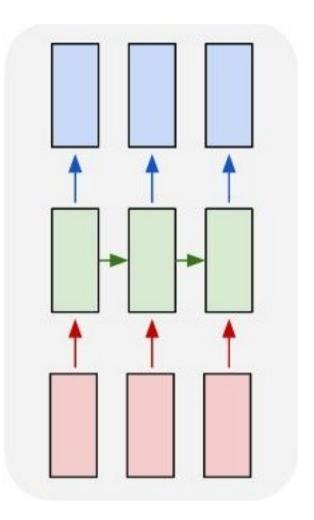
Problems with vanilla RNNs

Vanishing gradient problem

-> use LSTM

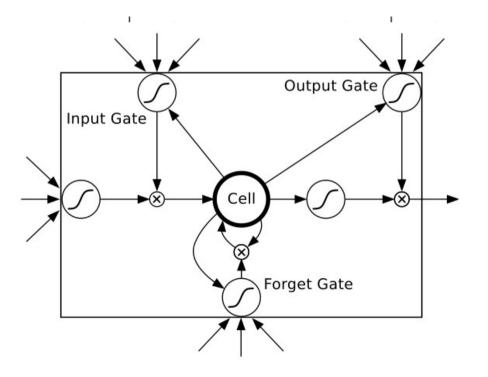
Exploding gradient problem

-> use gradient clipping



Long short-term memory (LSTM) (slide from Alex Graves)

 LSTM is an RNN architecture designed to have a better memory. It uses linear memory cells surrounded by multiplicative gate units to store read, write and reset information



Input gate: scales input to cell (write)

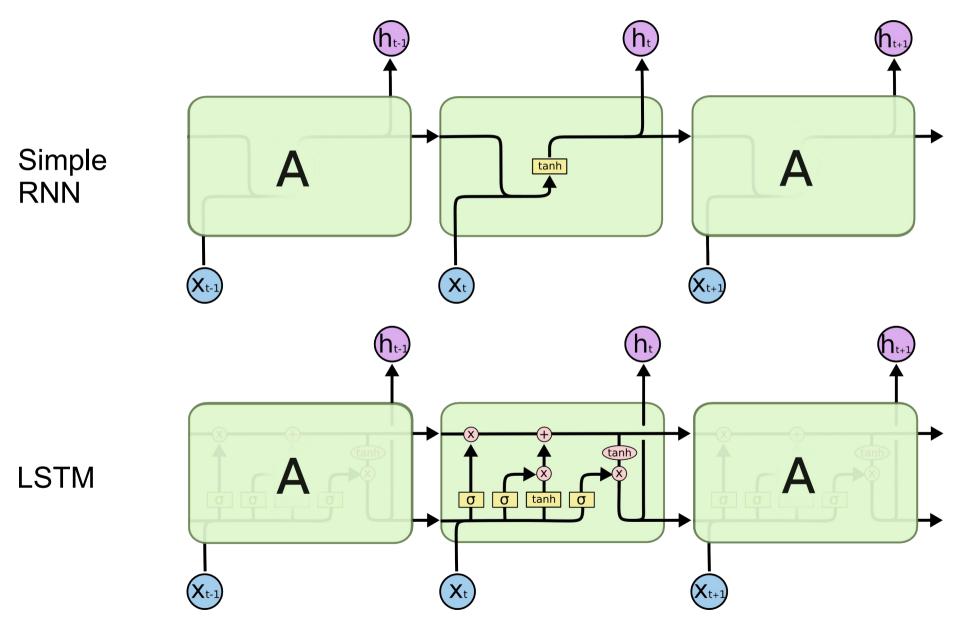
Output gate: scales output from cell (read)

Forget gate: scales old cell value (reset)

• S. Hochreiter and J. Schmidhuber, "Long Short-term Memory" Neural Computation 1997

LSTM vs simple RNN

(images from Chris Olah)



Some successes of the LSTM from 2013-2014 (many more since then!) (list from Schmidhuber)

- 1. Text-to-speech synthesis (Fan et al., Microsoft, Interspeech 2014)
- 2. Language identification (Gonzalez-Dominguez et al., Google, Interspeech 2014)
- 3. Large vocabulary speech recognition (Sak et al., Google, Interspeech 2014)
- 4. Prosody contour prediction (Fernandez et al., IBM, Interspeech 2014)
- 5. Medium vocabulary speech recognition (Geiger et al., Interspeech 2014)
- 6. English to French translation (Sutskever et al., Google, NIPS 2014)
- 7. Audio onset detection (Marchi et al., ICASSP 2014)
- 8. Social signal classification (Brueckner & Schulter, ICASSP 2014)
- 9. Arabic handwriting recognition (Bluche et al., DAS 2014)
- 10. TIMIT phoneme recognition (Graves et al., ICASSP 2013)
- 11. Optical character recognition (Breuel et al., ICDAR 2013)
- 12. Image caption generation (Vinyals et al., Google, 2014)
- 13. Video to textual description (Donahue et al., 2014)
- 14. Syntactic parsing for Natural Language Processing (Vinyals et al., Google, 2014)
- 15. Photo-real talking heads (Soong and Wang, Microsoft, 2014).

Applications to Multimodal tasks (Language+Vision)

(#1): Multimodal image-sentence embeddings

(#2): Image caption generation

(#3): Skip-thought vectors

(#4): Aligning books and movies

(#5): Style analogies + Neural storyteller

Applications to Multimodal tasks (Language+Vision)

(#1): Multimodal image-sentence embeddings

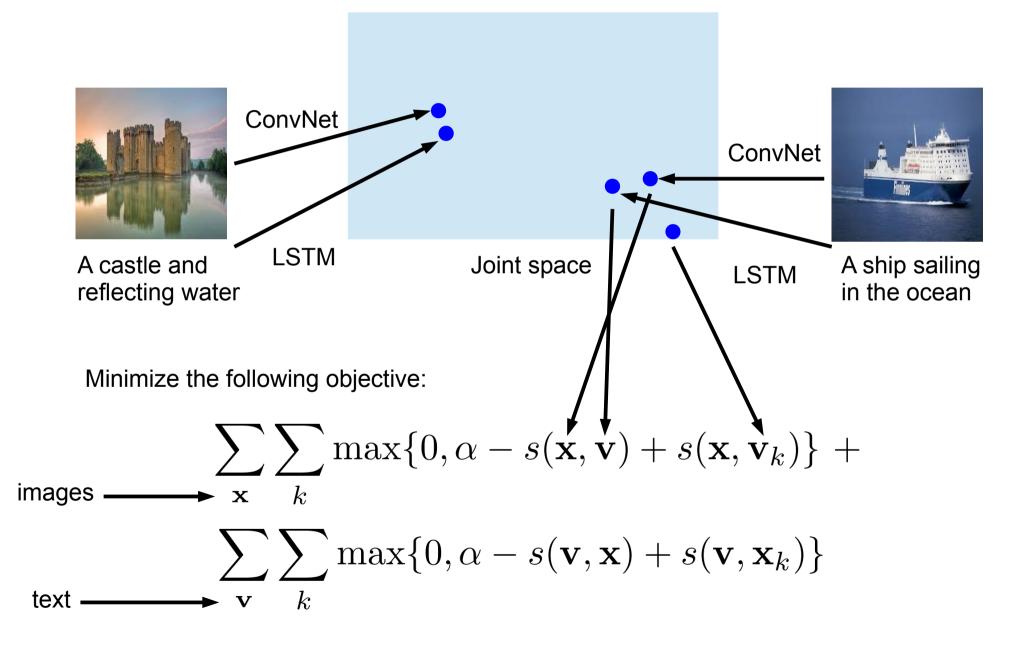
(#2): Image caption generation

(#3): Skip-thought vectors

(#4): Aligning books and movies

(#5): Style analogies + Neural storyteller

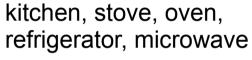
A joint image-text embedding (ConvNet - LSTM)



Train globally, retrieve locally



tower, building, cathedral, dome, castle





bowl, cup, soup, cups, coffee

ski, skiing, skiers, skiiers, snowmobile

beach





Adjectives

Nearest images

fluffy

delicious

adorable





Good retrieval results (sentences)



The dogs are in the snow in front of a fence .



Four men playing basketball, two from each team.



A boy skateboarding



Two men and a woman smile at the camera .



Women participate in a skit onstage .



A man is doing tricks on a bicycle on ramps in front of a crowd .

Not so good retrieval results

(these have ground truth ranked > 100)



two people wearing white shirts and jeans each carrying a skateboard



a dog jumps over a bar with a ball in its mouth .



White medium sized dog is running through the ocean .



A lady holds a little boy While another little boy smiles at them .



A man and a woman walking down a street , carrying luggage .



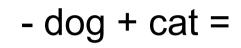
Woman in white dribbling basketball .

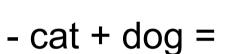
Multimodal linguistic regularities

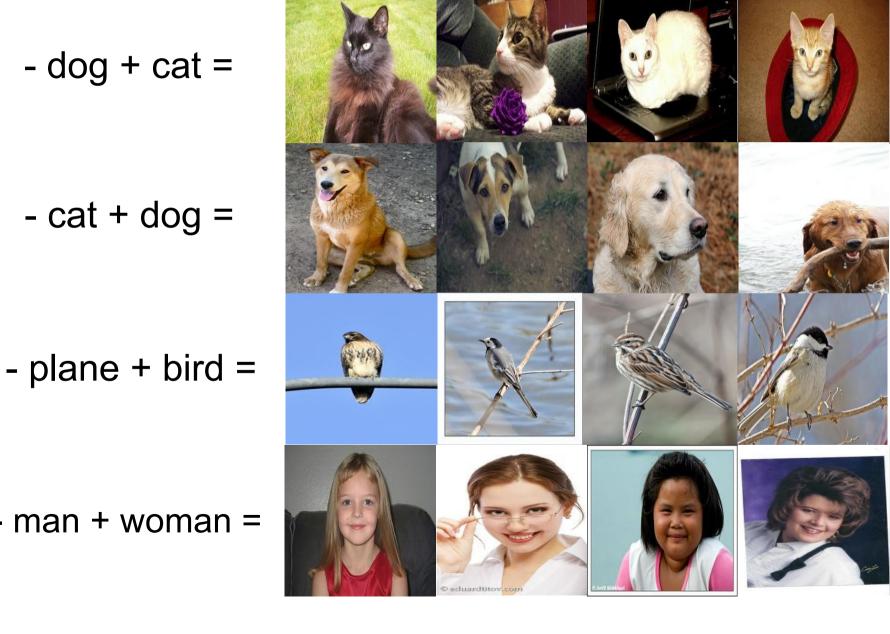
Nearest images



-

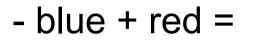






colours





- blue + yellow =

- yellow + red =

- white + red =

Nearest images



Some interesting examples

Nearest images

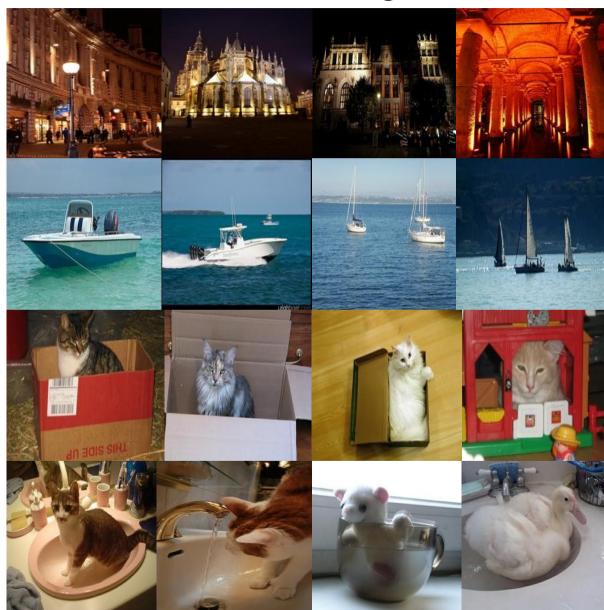


- day + night =

- flying + sailing =

-bowl + box =

-box + bowl =



Sanity check

Nearest images



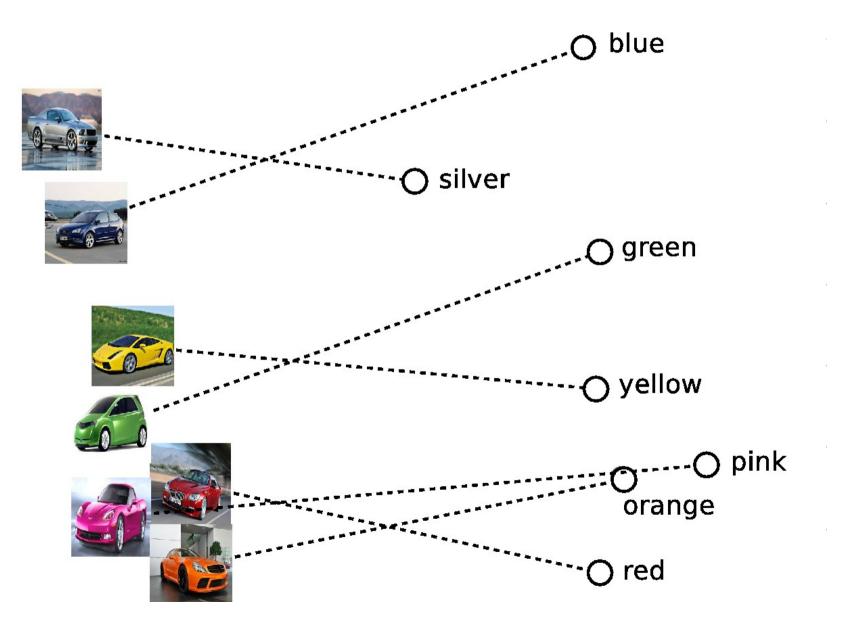
night

sailing

box

bowl

PCA embedding



Why does this work?

 $\begin{array}{l} \mathbf{V}_{car} \ \mathbf{V}_{red} \ \mathbf{V}_{blue} & : \text{word vectors for 'car', 'red', 'blue'} \\ \mathbf{I}_{bcar} \ \mathbf{I}_{rcar} & : \text{embeddings of a blue car and a red car} \end{array}$

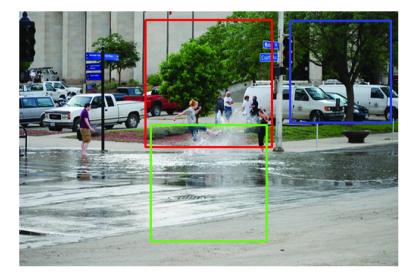
After training a linear encoder, the model has the property that:

$$\mathbf{v}_{blue} + \mathbf{v}_{car} \approx \mathbf{I}_{bcar}$$
 and $\mathbf{v}_{red} + \mathbf{v}_{car} \approx \mathbf{I}_{rcar}$

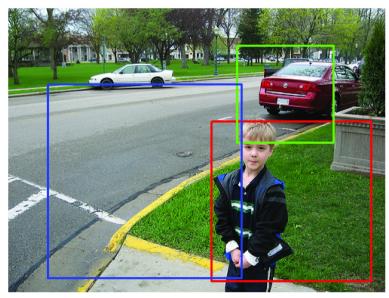
It follows that:

$$\mathbf{v}_{car} \approx \mathbf{I}_{bcar} - \mathbf{v}_{blue}$$
(1)
$$\mathbf{v}_{red} + \mathbf{v}_{car} \approx \mathbf{I}_{bcar} - \mathbf{v}_{blue} + \mathbf{v}_{red}$$
(2)
$$\mathbf{I}_{rcar} \approx \mathbf{I}_{bcar} - \mathbf{v}_{blue} + \mathbf{v}_{red}$$
(3)

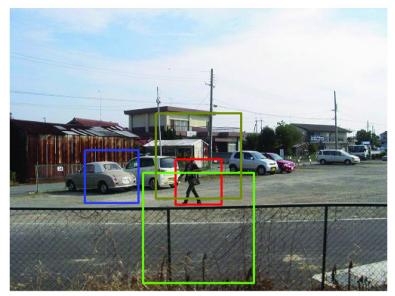
Image-text alignments from scratch



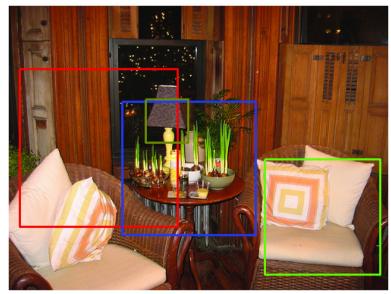
People, water, truck



Boy, car, road

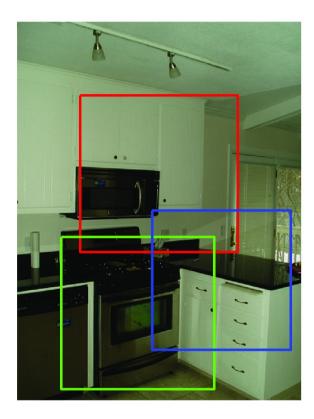


Woman, fence, cars, building

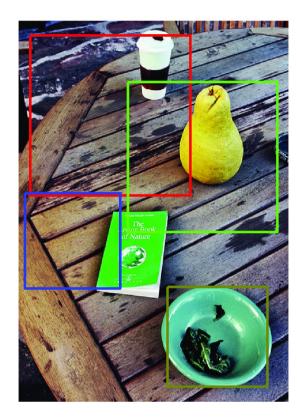


Chair, pillow, table, lamp

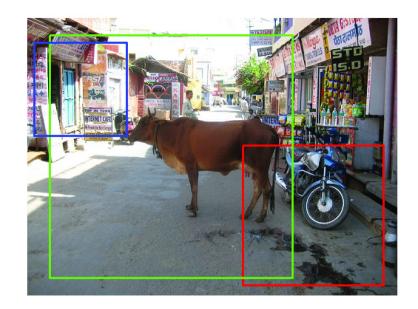
Image-text alignments



Oven, microwave, counter



Cup, pear, book, bowl



Motorcycle, cow, shop

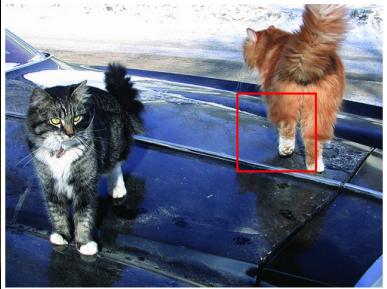


Screen, clock, window, shelf

adjectives



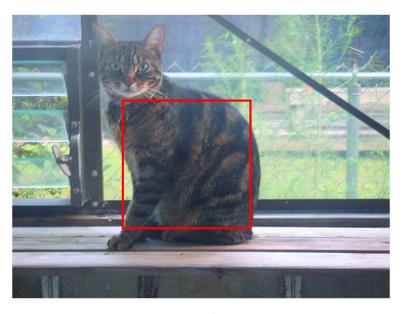
Delicious



fluffy

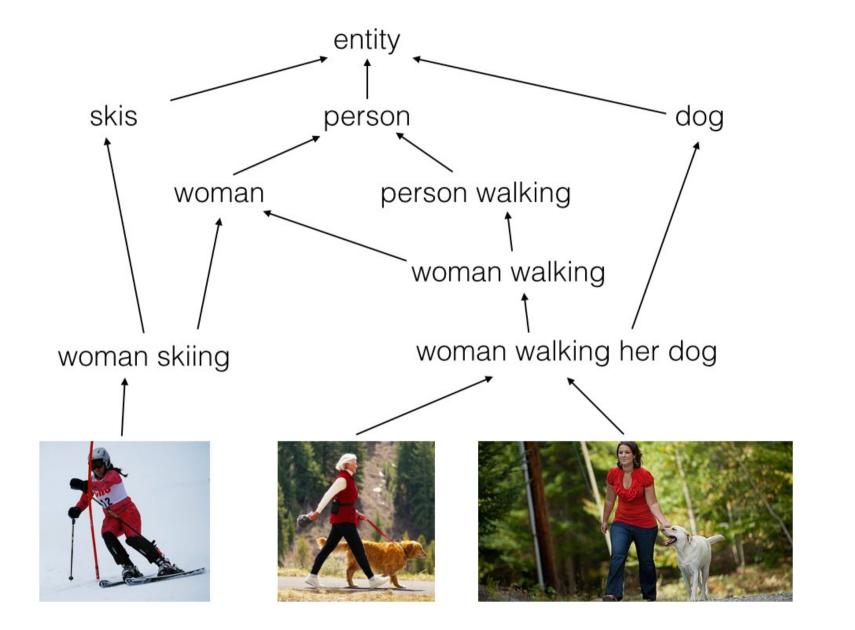


Shiny, round

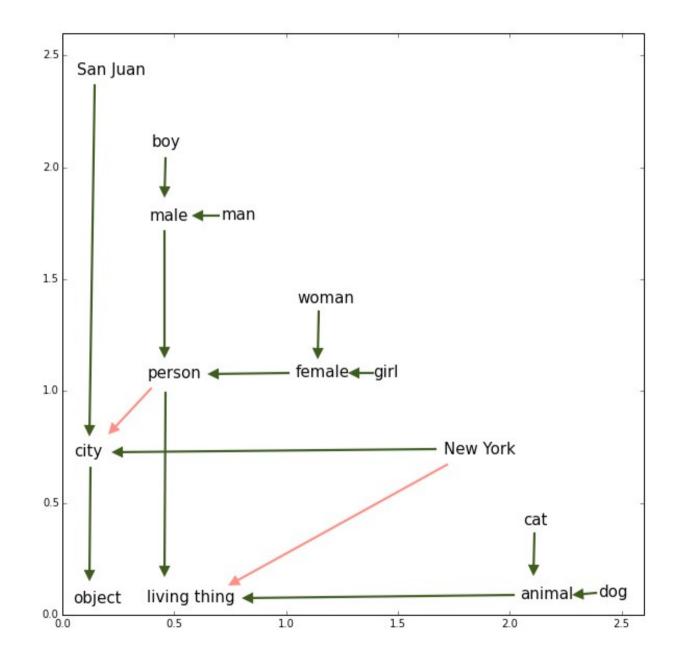


cute

Order-embeddings (Vendrov et al, 2016)



Order-embeddings (Vendrov et al, 2016)





Applications to Multimodal tasks (Language+Vision)

(#1): Multimodal image-sentence embeddings

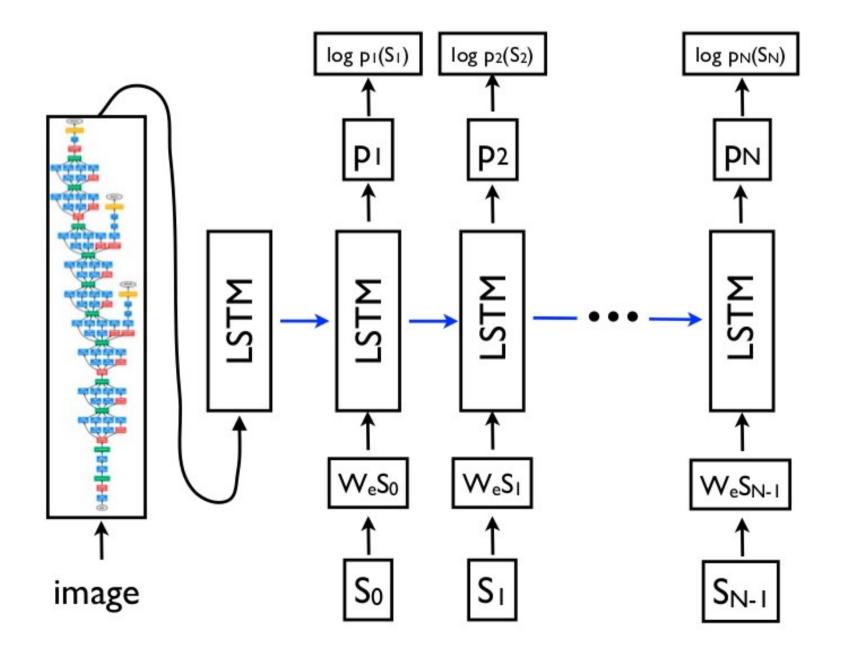
(#2): Image caption generation

(#3): Skip-thought vectors

(#4): Aligning books and movies

(#5): Style analogies + Neural storyteller

Google model: Multimodal LSTM (Vinyals et al, 2015)



Google model: Multimodal LSTM

A person riding a motorcycle on a dirt road.



A group of young people playing a game of frisbee.



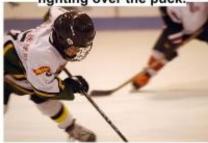
A herd of elephants walking across a dry grass field.



Two dogs play in the grass.



Two hockey players are fighting over the puck.____



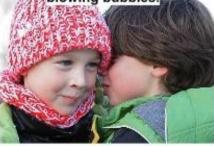
A close up of a cat laying on a couch.



A skateboarder does a trick



A little girl in a pink hat is blowing bubbles.



A red motorcycle parked on the side of the road.



A dog is jumping to catch a frisbee.



A refrigerator filled with lots of food and drinks.



A yellow school bus parked in a parking lot.



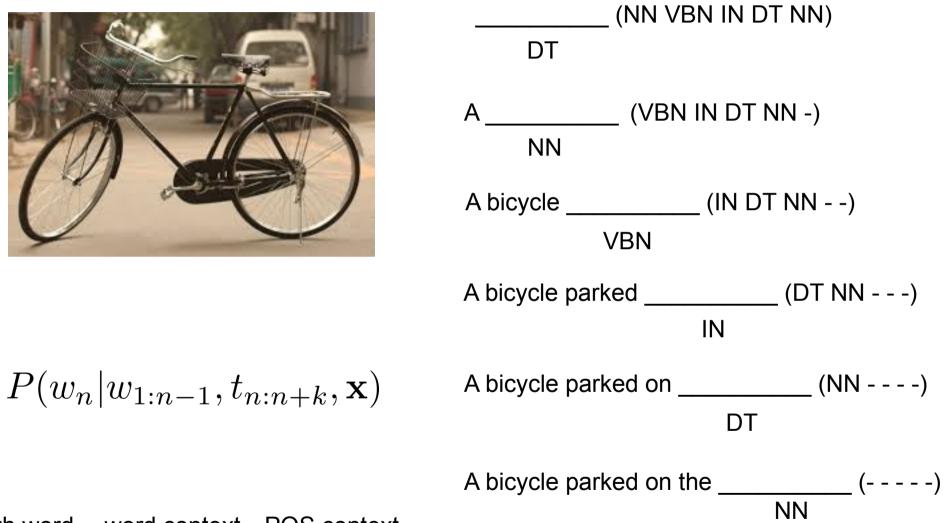
Describes without errors

Describes with minor errors

Somewhat related to the image

Unrelated to the image

Toronto model: Structure-content NLMs



n-th word word context POS context

Some good results - generation



a car is parked in the middle of nowhere .

a ferry boat on a marina with a group of people .



a wooden table and chairs arranged in a room .





there is a cat sitting on a shelf .



a little boy with a bunch of friends on the street .

Some failure types



the two birds are trying to be seen in the water . (can't count)



the handlebars are trying to ride a bike rack . (nonsensical)



a giraffe is standing next to a fence in a field . (hallucination)

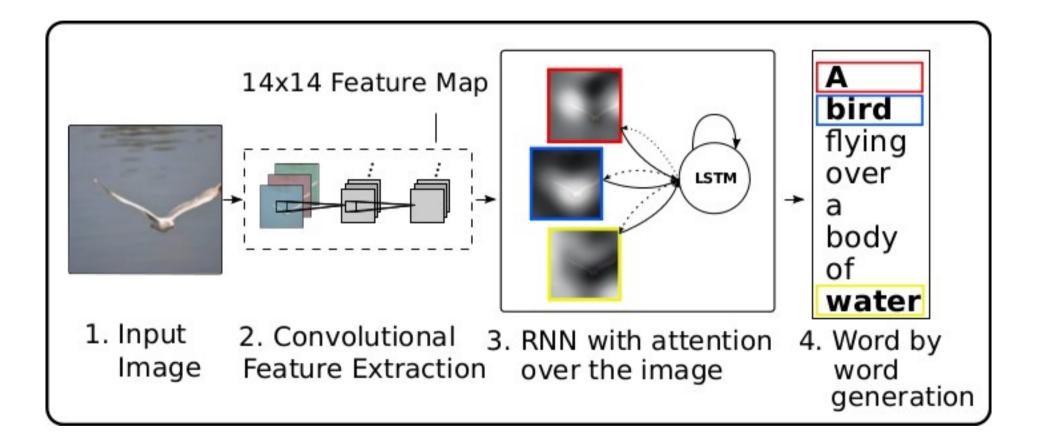




a parked car while driving down the road . (contradiction)

a woman and a bottle of wine in a garden . (gender)

Montreal+Toronto: LSTM with attention (Xu et al, 2015)



Montreal+Toronto: LSTM with attention (Xu et al, 2015)

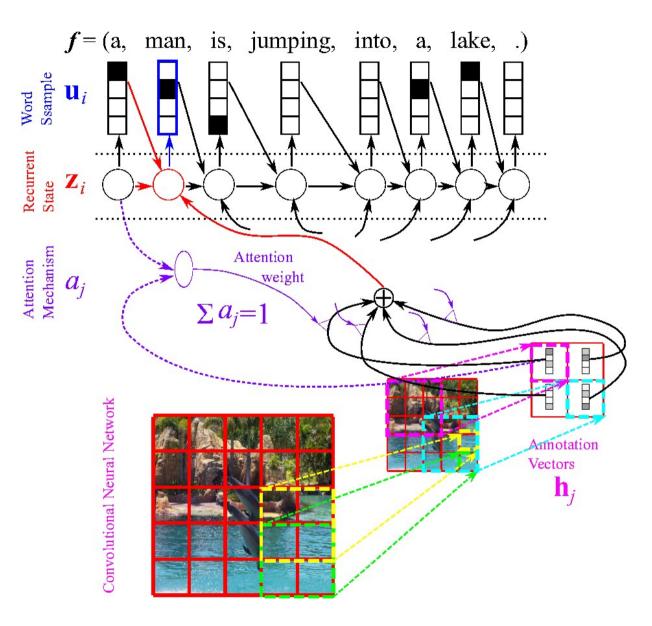


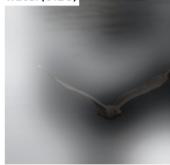
Image caption generation with attention



over(0.25)



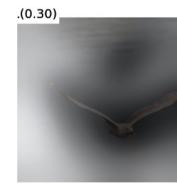
water(0.26)





a(0.24)





bird(0.55)



body(0.36)



flying(0.46)





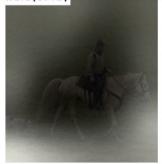
Image caption generation with attention



a(0.17)



field(0.43)





horse(0.24)





man(0.40)



in(0.24)



riding(0.26)





Image caption generation with attention



in(0.39)







the(0.24)



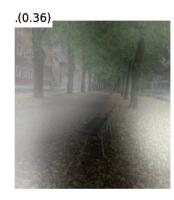


bench(0.60)



middle(0.38)





sitting(0.39)



of(0.29)



Many, many captioning papers...

https://github.com/kjw0612/awesome-rnn#image-captioning

See the above for a full list! (15 papers and counting)

Who is best? Microsoft COCO Competition

Team	M1	M2	Total	Ranking
Google	5	4	9	1st (tie)
MSR	4	5	9	1st (tie)
Montreal- Toronto	3	2	5	3rd (tie)
MSR Captivator	2	3	5	3rd (tie)
Berkeley	1	1	2	5th

M1: Percentage of captions that are evaluated as better or equal to human. M2: Percentage of captions that pass the Turing Test.

Applications to Multimodal tasks (Language+Vision)

(#1): Multimodal image-sentence embeddings

(#2): Image caption generation

(#3): Skip-thought vectors

(#4): Aligning books and movies

(#5): Style analogies + Neural storyteller

Unsupervised Distributed Representations for words and sentences

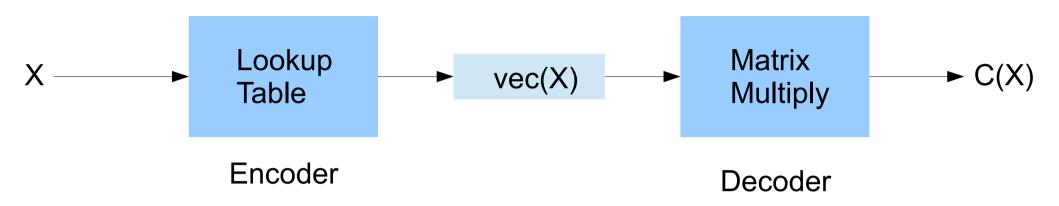
- There is a **massive** amount of available text data
- Good word vectors utilize distributional hypothesis + tons of data Context as a learning signal (implicit or explicit)
- Sentence representations, on the other hand are usually task specific Backprop through the "composition function" using labelled data



Can we abstract how we learn word vectors to construct new objectives for learning sentence vectors?

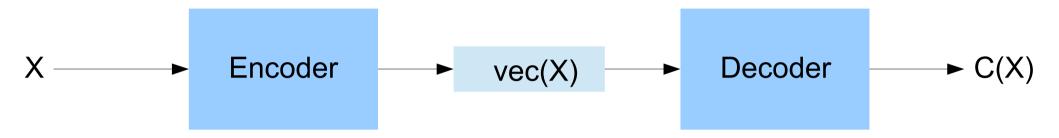
Does the concept of a non-task specific sentence vector even make sense?

Revisiting skip-gram (Mikolov et al. 2013)



- Skip-gram is an encoder-decoder model:
 - Input X: A word
 - Encoder: Lookup table
 - Decoder: Matrix multiply
 - Context C(X): Predictions of surrounding words
- Minimize NLL of context predictions given X

Contextual Encoder-Decoders



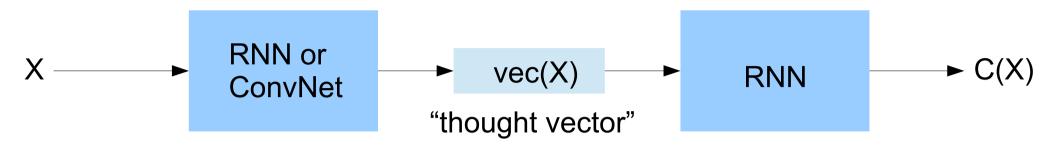
- Skip-gram is just an instance of a more generic family of models!
- If we want to learn a vector for X, we just need to specify:
 - the encoder which maps X to vec(X)
 - the context C(X)
 - the decoder which maps vec(X) to predictions of C(X)
- Does X have to be a word? Why not a sentence? Paragraph? Etc...

From words to sentences

Input	Word	Sentence	
Encoder	Lookup table	RNN or ConvNet	
Context	Surrounding words	Surrounding sentences	
Decoder	Matrix multiply	RNN	

- What is a good context for sentences?
 - We use surrounding words for word context
 - Why not use surrounding sentences for sentence context?

Skip-thought vectors (Kiros et al. 2015)



- Given a sentence X, predict sentences before and after
- Note that we need contiguous text for training!
- BookCorpus dataset: 10K+ books, 70M+ sentences, ~1B words (Zhu+Kiros et al. 2015)



What does it learn? Nearest neighbours:

he ran his hand inside his coat , double-checking that the unopened letter was still there

he slipped his hand between his coat and his shirt , where the folded copies lay in a brown envelope .

im sure youll have a glamorous evening, she said, giving an exaggerated wink.

im really glad you came to the party tonight, he said, turning to her.

although she could tell he had n't been too invested in any of their other chitchat , he seemed genuinely curious about this .

although he had n't been following her career with a microscope , he 'd definitely taken notice of her appearances .

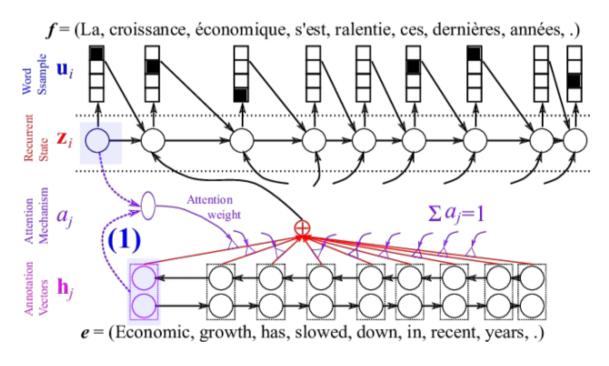
Related models and ideas

- Paragraph Vector (Le & Mikolov, 2014)
 - Encoder: Lookup table
 - Decode: Words in the sentence/paragraph
- Sequence Autoencoders (Dai & Le, 2015)
 - Encoder: LSTM
 - Decode: Words in the sentence
- C-PHRASE (Pham et al., 2015)
 - Encoder: Sum of word vectors
 - Decode: Syntactic context each each level of hierarchy

Main weakness: These models only look at the current sentence! Ignores the context of which the sentence occurs

Cramming everything into a vector

- For some tasks (MT, QA, reading comprehension), this doesn't make a whole lot of sense
 - Instead, dynamically update the representation of a sentence
 - "Zone in" on the relevant parts at any given time
 - Attention mechanisms, memory networks, etc



(Bahdanau et al., 2014)



Can we still make use of unsupervised sentence vectors for these tasks? How can we utilize skip-thought vectors for multimodal tasks?

Applications to Multimodal tasks (Language+Vision)

(#1): Multimodal image-sentence embeddings

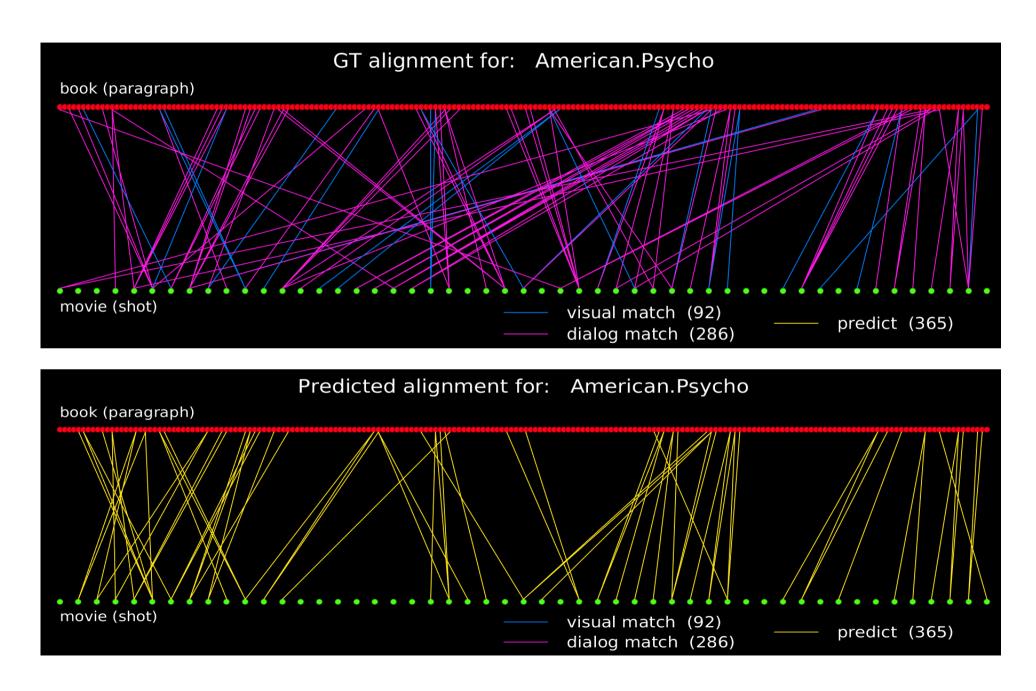
(#2): Image caption generation

(#3): Skip-thought vectors

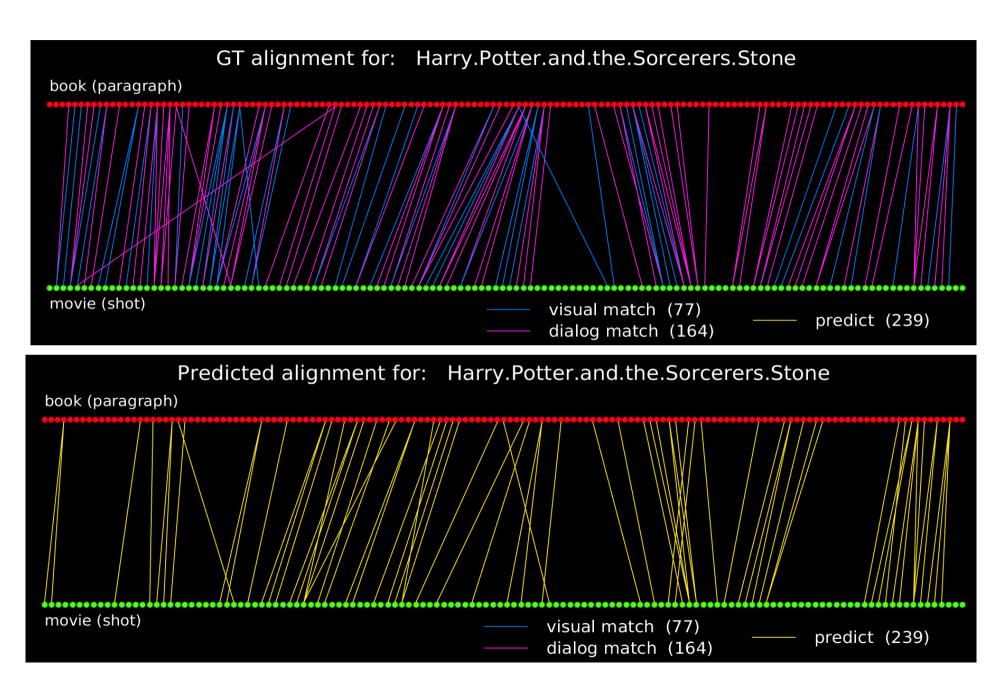
(#4): Aligning books and movies

(#5): Style analogies + Neural storyteller

Aligning books and movies (Zhu+Kiros et al., 2015)

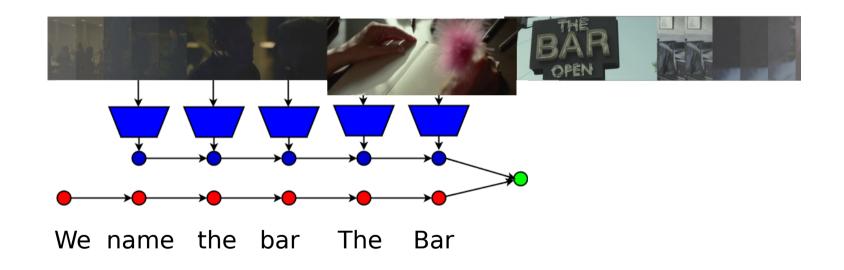


Aligning books and movies (Zhu+Kiros et al., 2015)



How it works

- Context-aware CNN that combines:
 - Text-to-text similarity: Skip-thoughts + tf-idf + BLEU(1-5)
 - Video-to-text similarity: Visual-semantic embedding of clips and DVS



 Chain CRF: Unaries are CNN outputs Pairwise terms for consistency between nearby alignments

Alignment results



[02:14:29:02:14:32] Good afternoon, Harry.

. . .

... He realized he must be in the hospital wing. He was lying in a bed with white linen sheets, and next to him was a table piled high with what looked like half the candy shop.

"Tokens from your friends and admirers," said Dumbledore, beaming. "What happened down in the dungeons between you and Professor Quirrell is a complete secret, so, naturally, the whole school knows. I believe your friends Misters Fred and George Weasley were responsible for trying to send you a toilet seat. No doubt they thought it would amuse you. Madam Pomfrey, however, felt it might not be very hygienic, and confiscated it."

Alignment results (X movie/book)

Batman.Begins



[01:38:41:01:38:44] I'm gonna give you a sedative. You'll wake up back at home.

A Captive s Submission

"I believe you will enjoy your time here. I am not a harsh master but I am strict. When we are with others, I expect you to present yourself properly. What we do here in your room and in the dungeon is between you and I. It is a testament to the trust and respect we have for each other and no one else needs to know about our arrangement. I'm sure the past few days have been overwhelming thus far but I have tried to give you as much information as possible. Do you have any questions?"

Retrieving stories for images



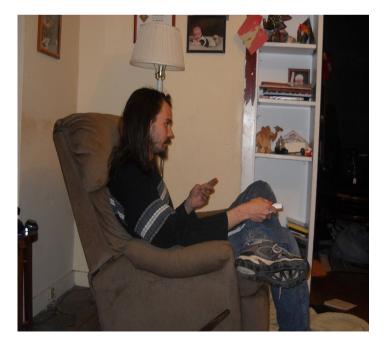
the club was a little emptier than i would have expected for the late afternoon , and the bartender , in red waistcoat and bowtie , was busy wiping down his counter , replacing peanuts and putting out new coasters .

a television with the latest la liga news was hung in an upper corner , and behind him , rows of bottles were reflected in a giant bar mirror .

above the stools , a pergola-type overhead structure held rows of wine glasses .

it was a classy place , with ferns in the corner , and not the kind of bar to which i was accustomed .

my places usually had a more ... relaxed feel .



he felt like an idiot for yelling at the child , but his frustration and trepidation was getting the better of him .

he glanced toward the shadowed hall and quickly nodded toward melissa before making his way forward .

he came across more children sitting upon a couch in the living room .

they watched him , but did n't move and did n't speak . his skin started to feel like hundreds of tiny spiders were running up and down it and he hurried on .

Can we generate stories instead?

Applications to Multimodal tasks (Language+Vision)

(#1): Multimodal image-sentence embeddings

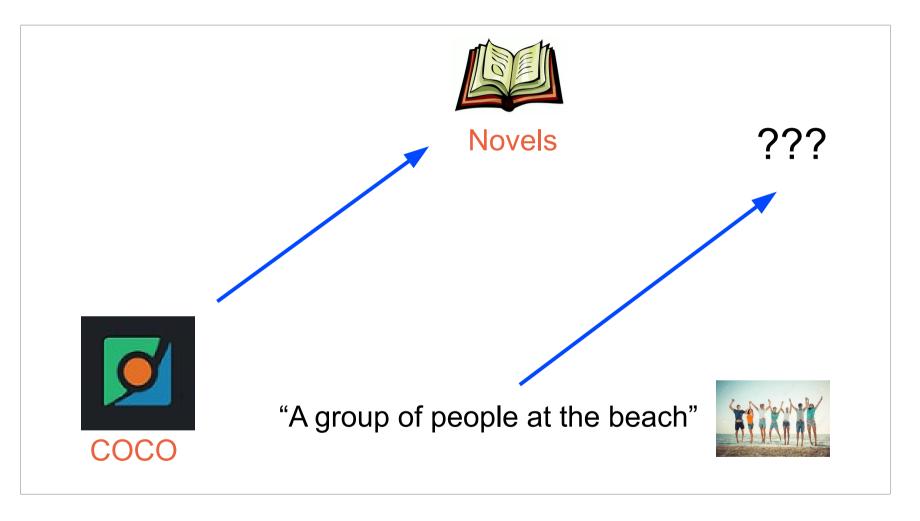
(#2): Image caption generation

(#3): Skip-thought vectors

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(#5): Style analogies + Neural storyteller

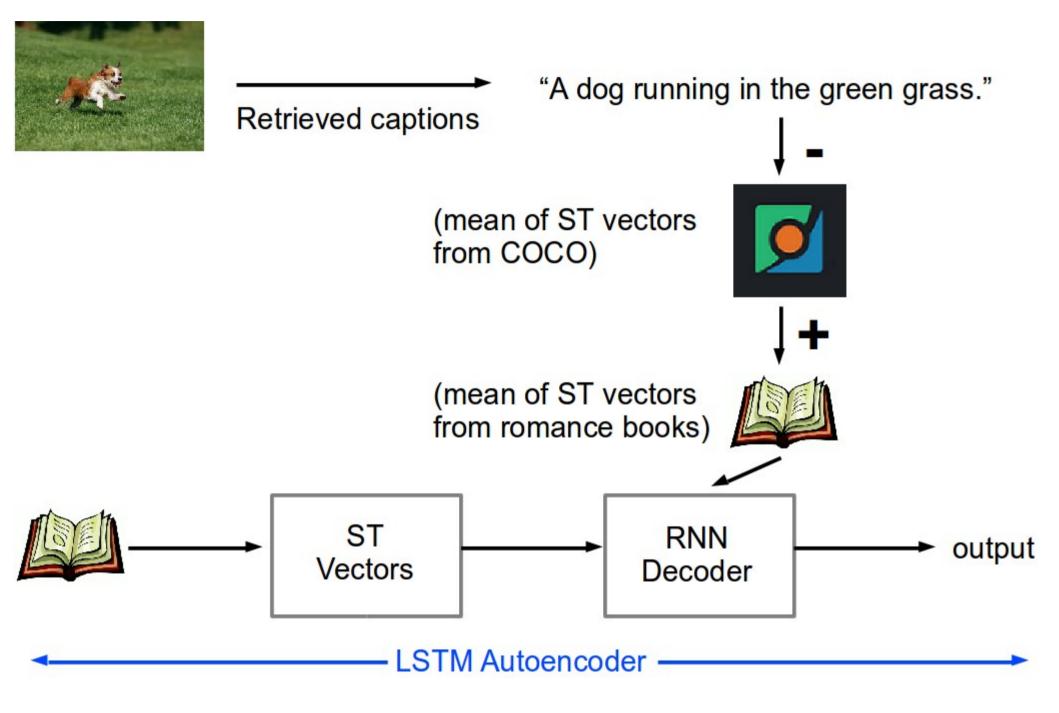
(#3) Style analogies with thought vectors



"A group of people at the beach"



The Neural-Storyteller



Results





We were barely able to catch the breeze at the beach , and it felt as if someone stepped out of my mind . She was in love with him for the first time in months , so she had no intention of escaping . The sun had risen from the ocean , making her feel more alive than normal . She 's beautiful , but the truth is that I do n't know what to do . The sun was just starting to fade away , leaving people scattered around the Atlantic Ocean . I d seen the men in his life , who guided me at the beach once more .

Results (Samim Winiger*)

*"Generating stories about images"



Generated story about image Model: Romantic Novels

"He was a shirtless man in the back of his mind, and I let out a curse as he leaned over to kiss me on the shoulder.

He wanted to strangle me, considering the beatiful boy I'd become wearing his boxers."

Results (Samim Winiger*)

*"Generating stories about images"

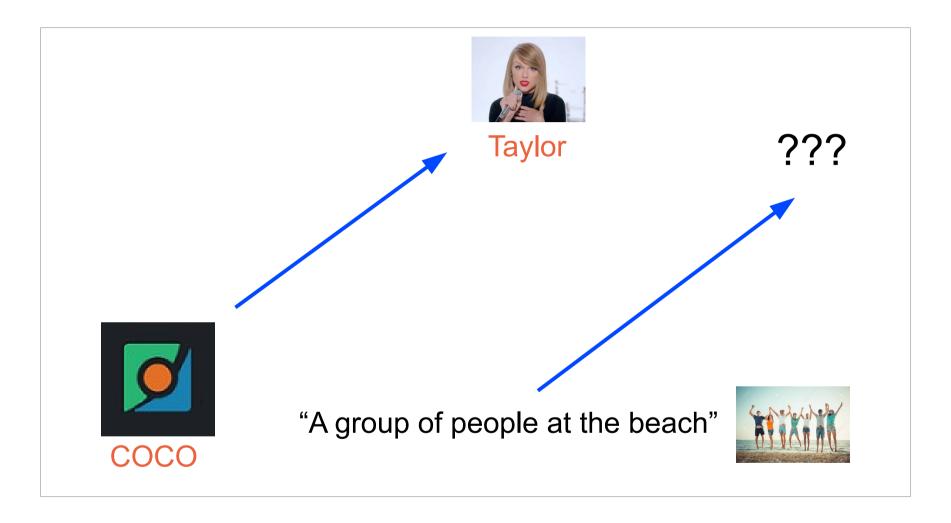


Generated story about image Model: Romantic Novels

"We men were in a tense position at the end of the meeting. And i looked up at my best friend.

Of course, i had no intention of letting him go. I don't know what else to say, but he is also the most beautiful man you ever meet."

What about Taylor Swift?



"A group of people at the beach"







Results





You re the only person on the beach right now you know I do n't think I will ever fall in love with you and when the sea breeze hits me I thought Hey

(#3) Results (Samim Winiger*)

*"Generating stories about images"



Generated story about image Model: Taylor Swift Lyrics

"I give you a man , I don't know what 's happening to me , and when I look back at the stage, I say, God , I love you more than I should."

(#3) Results (Samim Winiger*)

*"Generating stories about images"



Generated story about image Model: Taylor Swift Lyrics

"Like I 'm standing right now , man, it s going to be a sidewalk in the street, I thought, Oh my God, I don't see you walking away."

Resources and Code

Resources and code



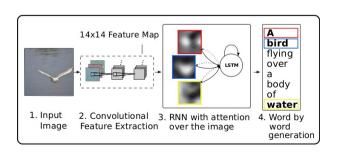
https://github.com/ryankiros

- Skip-thought vectors
- Neural-Storyteller
- Visual Semantic Embeddings



http://www.cs.toronto.edu/~mbweb/

- BookCorpus dataset
- Ground-truth Movie/Book alignments



https://github.com/kelvinxu/arctic-captions

- "Show, attend and Tell" code

Andrej Karpathy

https://github.com/karpathy http://cs231n.stanford.edu/

- char-rnn
- neuraltalk
- neuraltalk2
- randomfun



http://cs231n.stanford.edu/slides/winter1516_lecture10.pdf

Learn more about RNNs

- https://github.com/kjw0612/awesome-rnn

Large collection of lectures, papers and code

My awesome collaborators (for multimodal learning)

Toronto

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