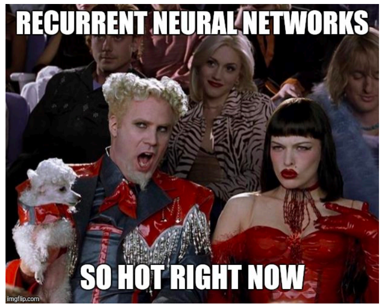
CS388: Natural Language Processing

Lecture 8: RNNs



Credit: Chelsea Voss csvoss.com

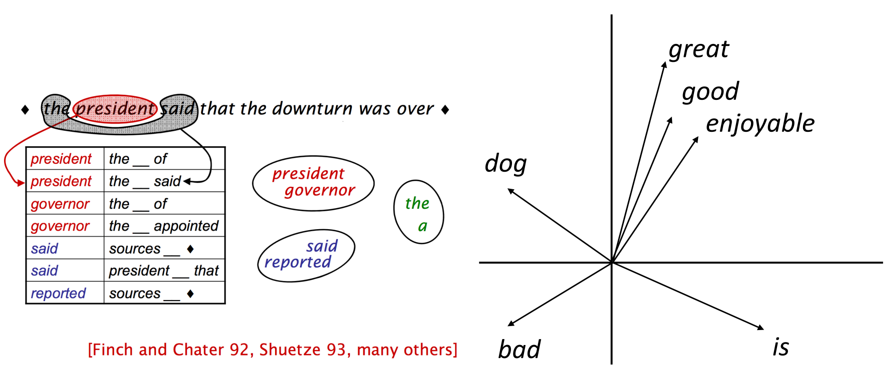
Greg Durrett

TEXAS
The University of Texas at Austin

Administrivia

- Mini 1 back today
- Project 1 due tonight
- Mini 2 out tonight

Recall: Word Vectors

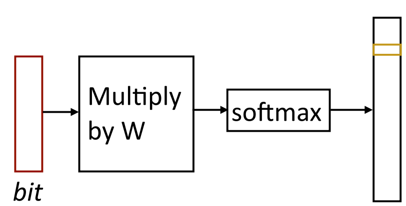


[Finch and Chater 92, Shuetze 93, many others]

Recall: Skip-Gram

- Predict one word of context from word

the dog bit the man



gold = *dog*

$$P(w'|w) = \text{softmax}(We(w))$$

- Another training example: *bit* -> *the*
- Parameters: *d* x |V| vectors, |V| x *d* output parameters (W) (also usable as vectors!)

Mikolov et al. (2013)

This Lecture

- Evaluating word embeddings
- Recurrent neural networks: basics, issues
- LSTMs / GRUs
- Applications / visualizations

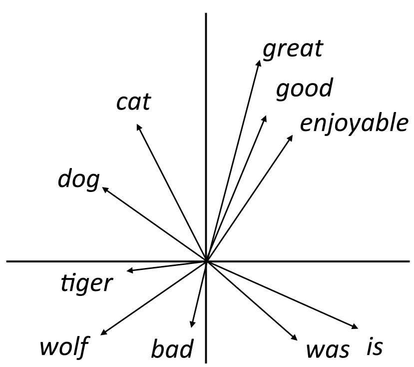
Evaluating Word Embeddings

Evaluating Word Embeddings

- What properties of language should word embeddings capture?
- Similarity: similar words are close to each other
- Analogy:

  good is to best as smart is to ???

  Paris is to France as Tokyo is to ???



Similarity

Method	WordSim Similarity	WordSim Relatedness	Bruni et al. MEN	Radinsky et al. M. Turk	Luong et al. Rare Words	Hill et al. SimLex
PPMI	.755	**.697**	.745	.686	.462	.393
SVD	**.793**	.691	**.778**	.666	**.514**	.432
SGNS	**.793**	.685	.774	**.693**	.470	**.438**
GloVe	.725	.604	.729	.632	.403	.398

- SVD = singular value decomposition on PMI matrix
- GloVe does not appear to be the best when experiments are carefully controlled, but it depends on hyperparameters + these distinctions don't matter in practice

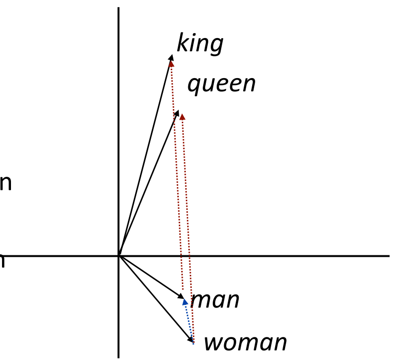
Levy et al. (2015)

Analogies

(king - man) + woman = queen

king + (woman - man) = queen

- Why would this be?
- woman - man captures the difference in the contexts that these occur in
- Dominant change: more "he" with man and "she" with woman — similar to difference between king and queen
- Can evaluate on this as well



What can go wrong with word embeddings?

- What's wrong with learning a word's "meaning" from its usage?
- What data are we learning from?
- What are we going to learn from this data?

What do we mean by bias?

- Identify *she* - *he* axis in word vector space, project words onto this axis
- Nearest neighbor of (b - a + c)

Extreme *she* occupations

1. homemaker	2. nurse	3. receptionist
4. librarian	5. socialite	6. hairdresser
7. nanny	8. bookkeeper	9. stylist
10. housekeeper	11. interior designer	12. guidance counselor

Extreme *he* occupations

1. maestro	2. skipper	3. protege
4. philosopher	5. captain	6. architect
7. financier	8. warrior	9. broadcaster
10. magician	11. figher pilot	12. boss

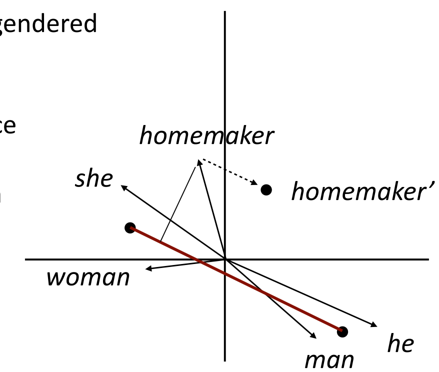
Bolukbasi et al. (2016)

Racial Analogies	
black → homeless	caucasian → servicemen
caucasian → hillbilly	asian → suburban
asian → laborer	black → landowner
Religious Analogies	
jew → greedy	muslim → powerless
christian → familial	muslim → warzone
muslim → uneducated	christian → intellectually

Manzini et al. (2019)

Debiasing

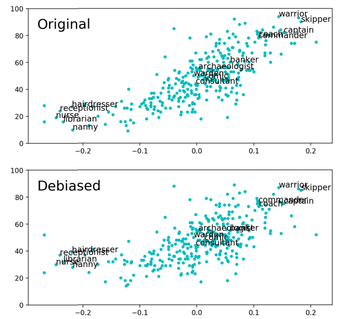
- Identify gender subspace with gendered words
- Project words onto this subspace
- Subtract those projections from the original word



Bolukbasi et al. (2016)

Hardness of Debiasing

- Not that effective…and the male and female words are still clustered together
- Bias pervades the word embedding space and isn't just a local property of a few words



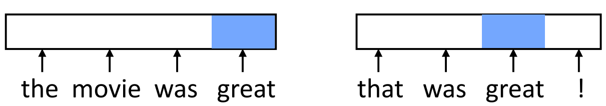
(a) The plots for HARD-DEBIASED embedding, before (top) and after (bottom) debiasing.

Gonen and Goldberg (2019)

RNN Basics

RNN Motivation

- Feedforward NNs can't handle variable length input: each position in the feature vector has fixed semantics



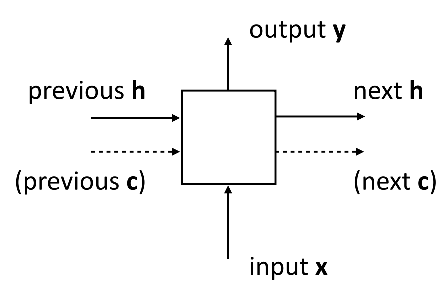
- These don't look related (*great* is in two different orthogonal subspaces)
- Instead, we need to:

1) Process each word in a uniform way

2) …while still exploiting the context that that token occurs in

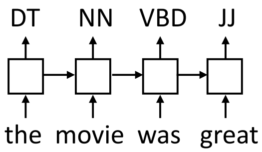
RNN Abstraction

- Cell that takes some input **x**, has some hidden state **h**, and updates that hidden state and produces output **y** (all vector-valued)



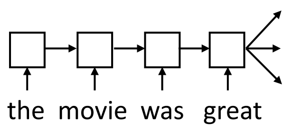
RNN Uses

- Transducer: make some prediction for each element in a sequence



output **y** = score for each tag, then softmax

- Acceptor/encoder: encode a sequence into a fixed-sized vector and use that for some purpose

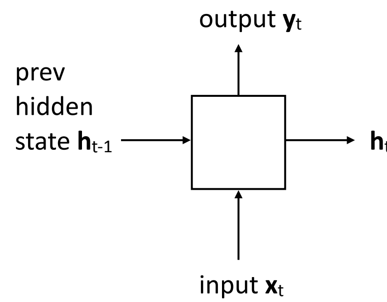


predict sentiment (matmul + softmax)

translate

paraphrase/compress

Elman Networks



$$\mathbf{h}_t = \tanh(W\mathbf{x}_t + V\mathbf{h}_{t-1} + \mathbf{b}_h)$$

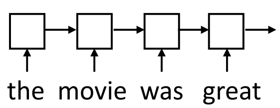
- Updates hidden state based on input and current hidden state

$$\mathbf{y}_t = \tanh(U\mathbf{h_t} + \mathbf{b}_y)$$

- Computes output from hidden state

Elman (1990)

Training Elman Networks



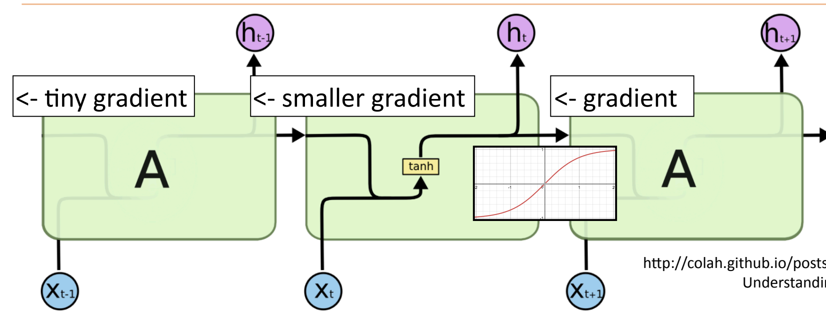
predict sentiment

- "Backpropagation through time": build the network as one big computation graph, some parameters are shared
- RNN potentially needs to learn how to "remember" information for a long time!

it was my favorite movie of 2016, though it wasn't without problems -> +

- "Correct" parameter update is to do a better job of remembering the sentiment of *favorite*

Vanishing Gradient



http://colah.github.io/posts/2015-08-Understanding-LSTMs/

- Gradient diminishes going through tanh; if not in [-2, 2], gradient is almost 0
- Repeated multiplication by V causes problems $\mathbf{h}_t = \tanh(W\mathbf{x}_t + V\mathbf{h}_{t-1} + \mathbf{b}_h)$

LSTMs/GRUs

Gated Connections

- Designed to fix "vanishing gradient" problem using *gates*

$$\mathbf{h}_t = \mathbf{h}_{t-1} \odot \mathbf{f} + \mathrm{func}(\mathbf{x}_t)$$

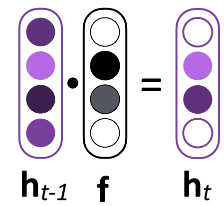
gated

$$\mathbf{h}_t = \tanh(W\mathbf{x}_t + V\mathbf{h}_{t-1} + \mathbf{b}_h)$$

Elman

- Vector-valued "forget gate" **f** computed based on input and previous hidden state

$$\mathbf{f} = \sigma(W^{xf}\mathbf{x}_t + W^{hf}\mathbf{h}_{t-1})$$



- Sigmoid: elements of **f** are in (0, 1)
- If **f** ≈ **1**, we simply sum up a function of all inputs — gradient doesn't vanish! More stable without matrix multiply (*V*) as well

LSTMs

- "Long short-term memory" network: hidden state is a "short-term" memory
- "Cell" **c** in addition to hidden state **h**

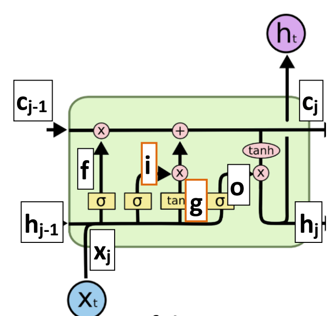
$$\mathbf{c}_t = \mathbf{c}_{t-1} \odot \mathbf{f} + \boxed{\mathrm{func}(\mathbf{x}_t, \mathbf{h}_{t-1})}$$

- Vector-valued forget gate **f** depends on the **h** hidden state

$$\mathbf{f} = \sigma(W^{xf}\mathbf{x}_t + W^{hf}\mathbf{h}_{t-1})$$

- Basic communication flow: **x** -> **c** -> **h** -> output, each step of this process is gated in addition to gates from previous timesteps

LSTMs



$$\mathbf{c_j} = \mathbf{c_{j-1}} \odot \mathbf{f} + \boxed{\mathbf{g} \odot \mathbf{i}}$$

$$\mathbf{f} = \sigma(\mathbf{x_j W^{xf}} + \mathbf{h_{j-1} W^{hf}})$$

$$\mathbf{g} = \tanh(\mathbf{x_j W^{xg}} + \mathbf{h_{j-1} W^{hg}})$$

$$\mathbf{i} = \sigma(\mathbf{x_j W^{xi}} + \mathbf{h_{j-1} W^{hi}})$$

$$\mathbf{h_j} = \tanh(\mathbf{c_j}) \odot \mathbf{o}$$

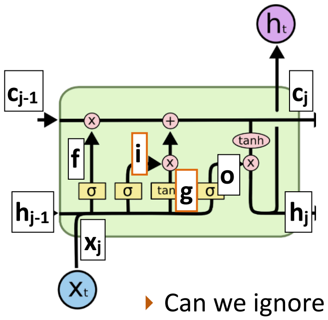
$$\mathbf{o} = \sigma(\mathbf{x_j W^{xo}} + \mathbf{h_{j-1} W^{ho}})$$

- **f**, **i**, **o** are gates that control information flow
- **g** reflects the main computation of the cell

Goldberg lecture notes

http://colah.github.io/posts/2015-08-Understanding-LSTMs/

LSTMs



$$\mathbf{c_j} = \mathbf{c_{j-1}} \odot \mathbf{f} + \boxed{\mathbf{g} \odot \mathbf{i}}$$

$$\mathbf{f} = \sigma(\mathbf{x_j}\mathbf{W^{xf}} + \mathbf{h_{j-1}}\mathbf{W^{hf}})$$

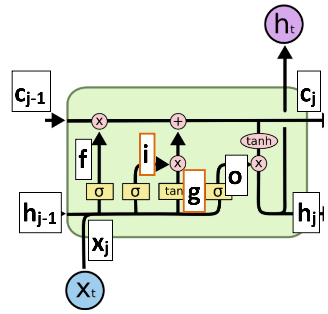
$$\boxed{\begin{aligned} \mathbf{g} &= \tanh(\mathbf{x_j}\mathbf{W^{xg}} + \mathbf{h_{j-1}}\mathbf{W^{hg}}) \\ \mathbf{i} &= \sigma(\mathbf{x_j}\mathbf{W^{xi}} + \mathbf{h_{j-1}}\mathbf{W^{hi}}) \end{aligned}}$$

$$\mathbf{h_j} = \tanh(\mathbf{c_j}) \odot \mathbf{o}$$

$$\mathbf{o} = \sigma(\mathbf{x_j}\mathbf{W^{xo}} + \mathbf{h_{j-1}}\mathbf{W^{ho}})$$

- Can we ignore the old value of **c** for this timestep?
- Can an LSTM sum up its inputs **x**?
- Can we ignore a particular input **x**?
- Can we output something without changing **c**?

LSTMs



- Ignoring recurrent state entirely:
  - Lets us get feedforward layer over token
- Ignoring input:
  - Lets us discard stopwords
- Summing inputs:
  - Lets us compute a bag-of-words representation

Goldberg lecture notes

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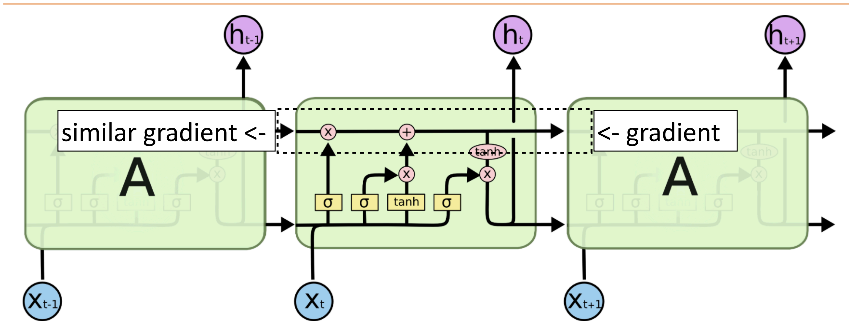
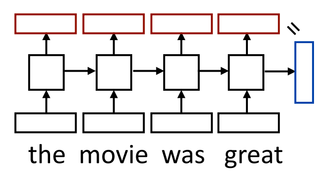
LSTMs



- Gradient still diminishes, but in a controlled way and generally by less — sometimes initialize forget gate = 1 to remember everything to start

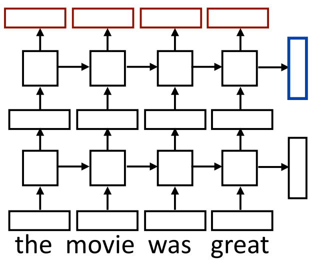
http://colah.github.io/posts/2015-08-Understanding-LSTMs/

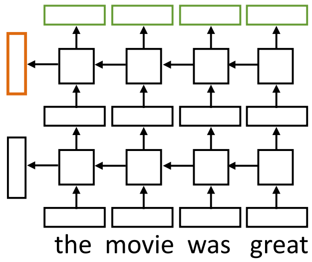
What do RNNs produce?



- Encoding of the sentence — can pass this a decoder or make a classification decision about the sentence
- Encoding of each word — can pass this to another layer to make a prediction (can also pool these to get a different sentence encoding)
- RNN can be viewed as a transformation of a sequence of vectors into a sequence of context-dependent vectors

Multilayer Bidirectional RNN

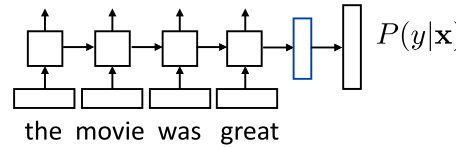




- Sentence classification based on concatenation of both final outputs

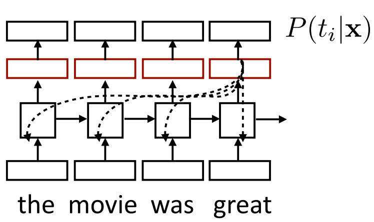
- Token classification based on concatenation of both directions' token representations

Training RNNs



- Loss = negative log likelihood of probability of gold label (or use SVM or other loss)
- Backpropagate through entire network
- Example: sentiment analysis

Training RNNs



- Loss = negative log likelihood of probability of gold predictions, summed over the tags
- Loss terms filter back through network
- Example: language modeling (predict next word given context) or POS tagging

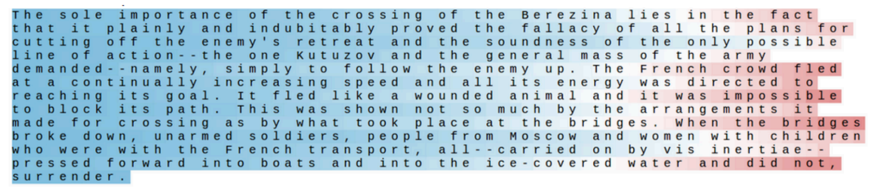
Applications

What can LSTMs model?

- Sentiment
  - Encode one sentence, predict
- Language models
  - Move left-to-right, per-token prediction
- Translation
  - Encode sentence + then decode, use token predictions for attention weights (later in the course)

Visualizing LSTMs

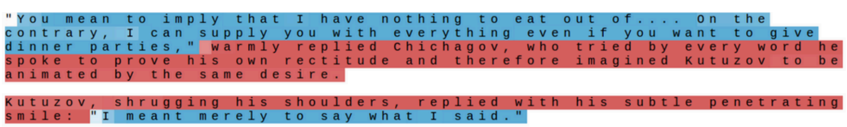
- Train *character* LSTM language model (predict next character based on history) over two datasets: War and Peace and Linux kernel source code
- Visualize activations of specific cells (components of **c**) to understand them
- Counter: know when to generate \n



Karpathy et al. (2015)

Visualizing LSTMs

- Train *character* LSTM language model (predict next character based on history) over two datasets: War and Peace and Linux kernel source code
- Visualize activations of specific cells to see what they track
- Binary switch: tells us if we're in a quote or not



Karpathy et al. (2015)

Visualizing LSTMs

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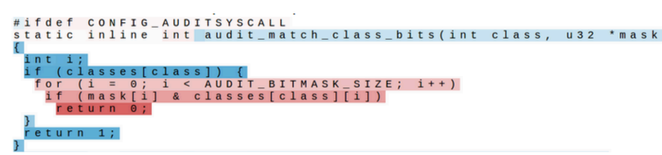
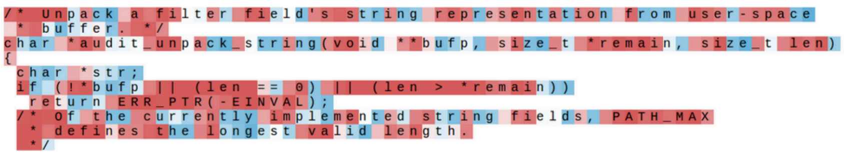
- Visualize activations of specific cells to see what they track
- Stack: activation based on indentation



Karpathy et al. (2015)

Visualizing LSTMs

- Train *character* LSTM language model (predict next character based on history) over two datasets: War and Peace and Linux kernel source code
- Visualize activations of specific cells to see what they track
- Uninterpretable: probably doing double-duty, or only makes sense in the context of another activation



Karpathy et al. (2015)

What can LSTMs model?

- Sentiment
  - Encode one sentence, predict
- Language models
  - Move left-to-right, per-token prediction
- Translation
  - Encode sentence + then decode, use token predictions for attention weights (later in the course)
- Textual entailment
  - Encode two sentences, predict

Sentiment Analysis

- Semi-supervised method: initialize the language model by training to reproduce the document in a seq2seq fashion (a type of pre-training called a sequential autoencoder)

Model	Test error rate
LSTM with tuning and dropout	13.50%
LSTM initialized with word2vec embeddings	10.00%
LM-LSTM (see Section 2)	7.64%
SA-LSTM (see Figure 1)	7.24%
Full+Unlabeled+BoW [21]	11.11%
WRRBM + BoW (bnc) [21]	10.77%
NBSVM-bi (Naïve Bayes SVM with bigrams) [35]	8.78%
seq2-bow*n*-CNN (ConvNet with dynamic pooling) [11]	7.67%
Paragraph Vectors [18]	7.42%

Dai and Le (2015)

Natural Language Inference

Premise		Hypothesis
A boy plays in the snow	*entails*	A boy is outside
A man inspects the uniform of a figure	*contradicts*	The man is sleeping
An older and younger man smiling	*neutral*	Two men are smiling and laughing at cats playing

- Long history of this task: "Recognizing Textual Entailment" challenge in 2006 (Dagan, Glickman, Magnini)
- Early datasets: small (hundreds of pairs), very ambitious (lots of world knowledge, temporal reasoning, etc.)

SNLI Dataset

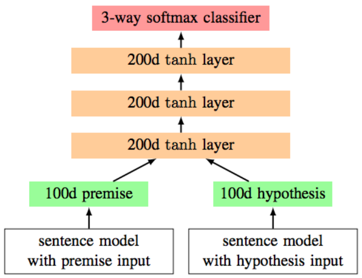
- Show people captions for (unseen) images and solicit entailed / neural / contradictory statements
- >500,000 sentence pairs
- Encode each sentence and process

100D LSTM: 78% accuracy

300D LSTM: 80% accuracy
(Bowman et al., 2016)

300D BiLSTM: 83% accuracy
(Liu et al., 2016)

- Later: better models for this



Bowman et al. (2015)

Takeaways

- RNNs can transduce inputs (produce one output for each input) or compress the whole input into a vector
- Useful for a range of tasks with sequential input: sentiment analysis, language modeling, natural language inference, machine translation