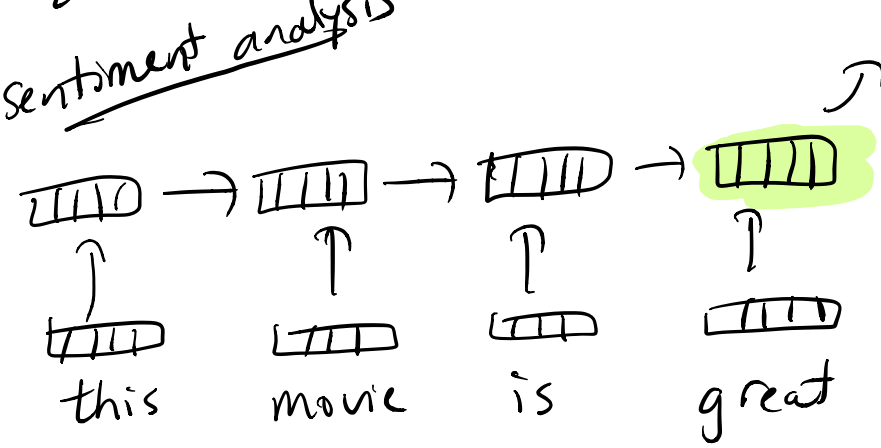
how we used to solve NLP tasks:

~2013

sentiment analysis



1. randomly initialize the model params

$W_h, W_e, e_{1...|V|}, W_o$ all trained from scratch

2. Update all parameters by backprop using cross entropy loss from labeled training set

model has to learn how language works from only a small labeled dataset

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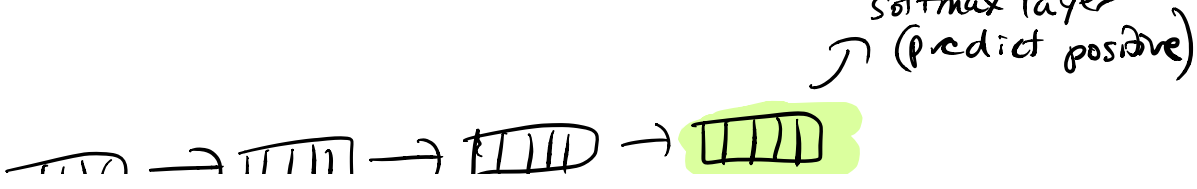
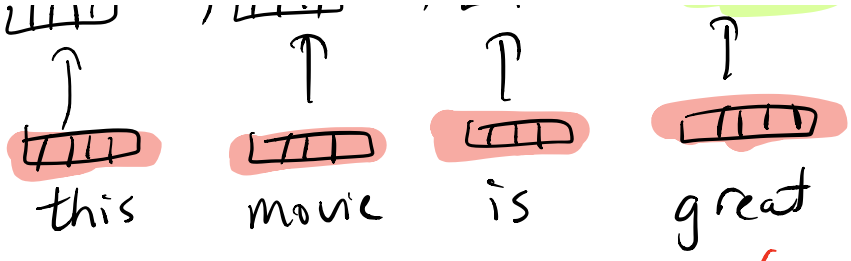
~2014-2017

why train everything from scratch?

how can we leverage lots of unlabeled data?





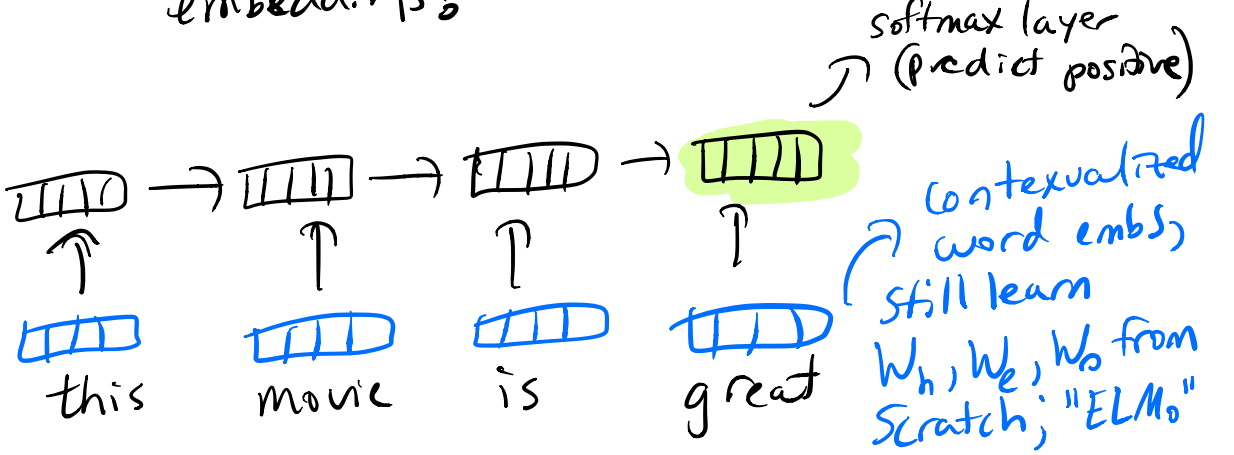
we can pretrain the c_i's (word embs) using another objective fn that takes adv. of unlabeled data (self-supervised)

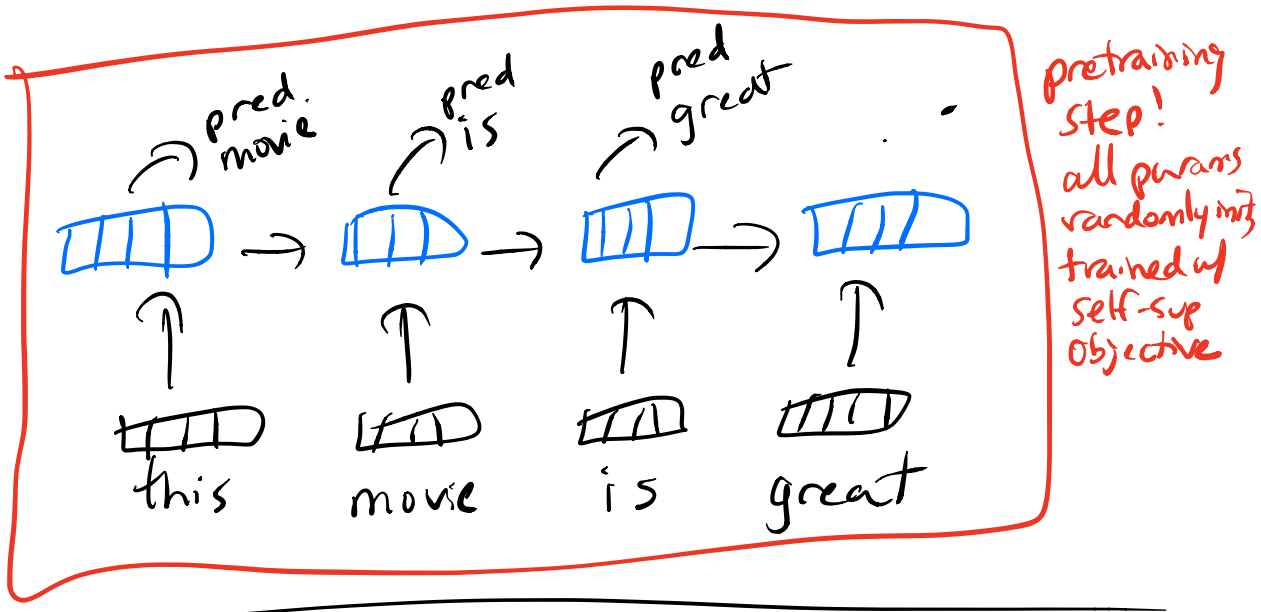
- Word2Vec, GloVe
- instead of starting w/ a random word embedding space, we start from a pretrained space in which word embs. capture some linguistic prop.
- train all other params from scratch (W_h, W_e, W_o)

~2018

- issues w/ ⟩: word embeddings are static, only one vector per word type regardless of context
- the rest of the model (in our case, the RNN) is responsible for learning composition from scratch given just labeled data

– what if we use the hidden states of a NLM instead of static word embeddings?

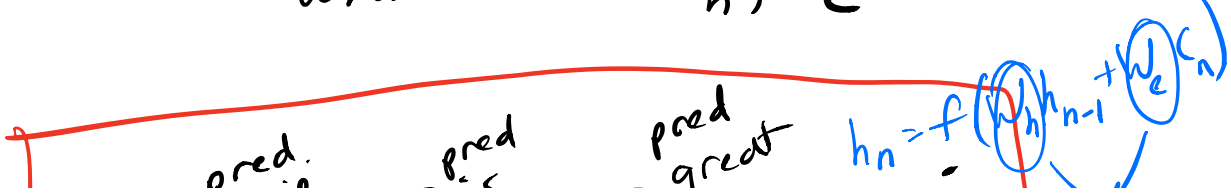


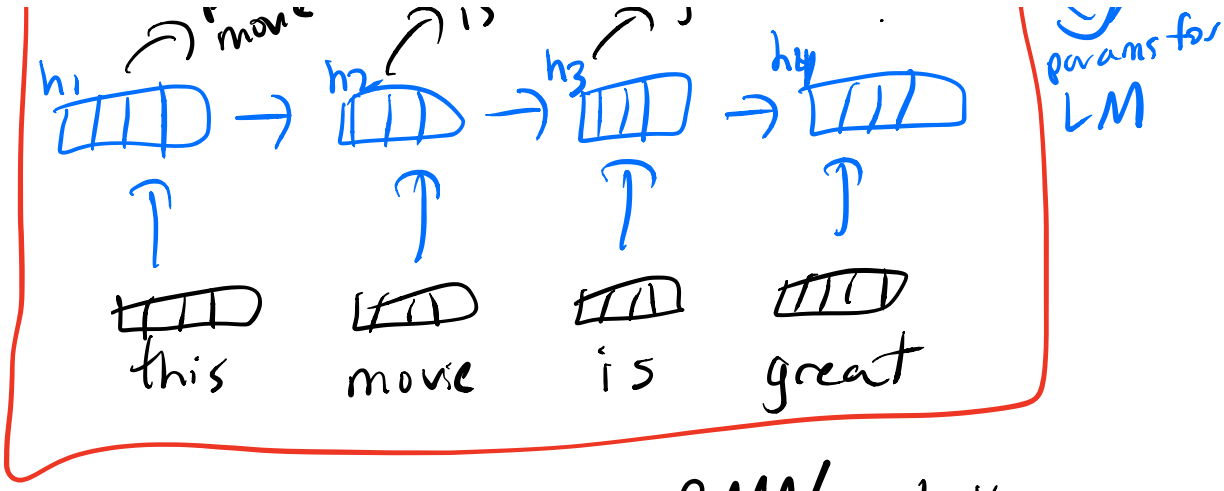


~2019

can we share more params than just the word embeddings?

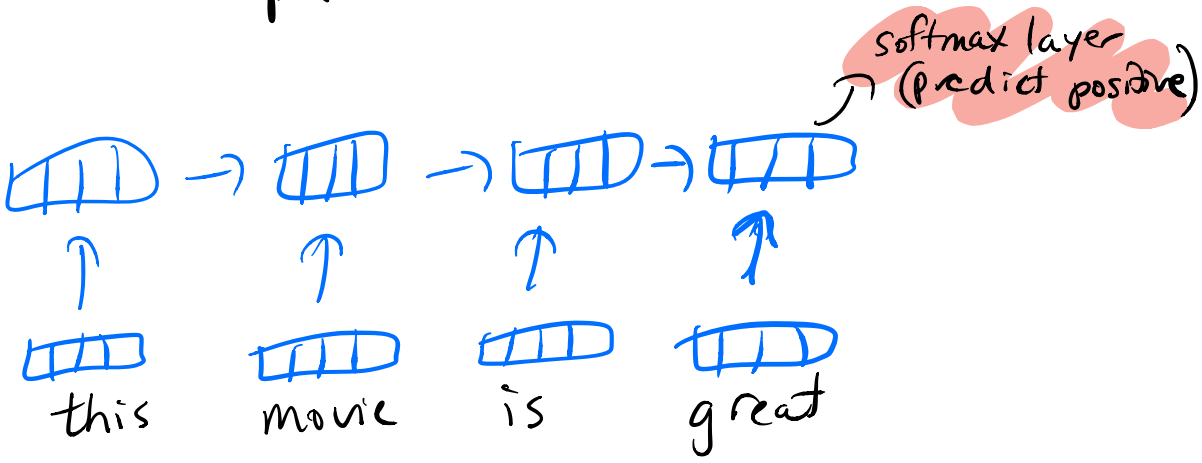
– what about W_h, W_e





initialize my sentiment RNN w/ the LMs $W_h, W_e, C_1 \ldots W_1$

— all we have to do is learn W_o from scratch, all the other params are transferred



this is current paradigm in NLP, popularized by BERT model

— we init our sentiment model w/ a pretrained NLM, and then

backprop the error from a diff. task (downstream task) into these parameters. this is called fine-tuning