COMS W4701: Artificial Intelligence

Lecture 11b: Neural Language Models

Some images adapted from [Jurafsky and Martin]

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Topics

- Natural language processing
- Word embeddings
- Self-attention and transformers
- Large language models

Natural Language Processing

- Language can be used to describe intelligent behavior, including knowledge representation, planning, perceiving and acting

- **Natural language processing** allow computers to *communicate* (with us and each other) and *learn* new knowledge

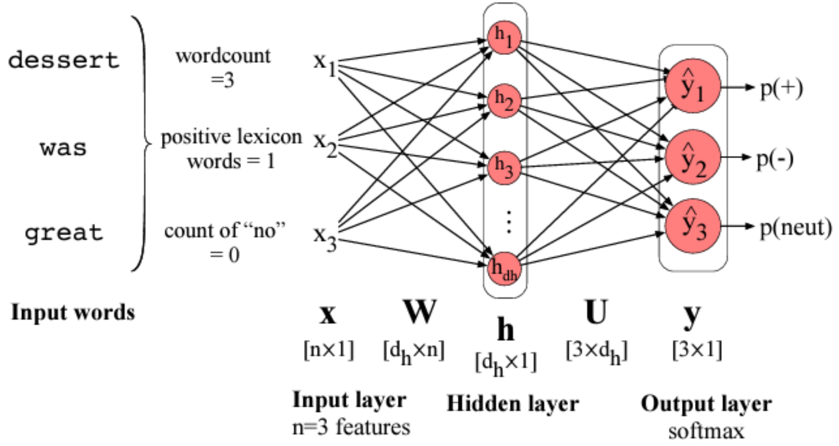
- A **language model** is a probability distribution over possible strings, which can be used for text prediction and translation

NLP Tasks

- Speech recognition (sound to text)
- Text-to-speech, including synthesis of different voices, intonations, dialects, imitations of specific people
- Machine translation between different languages
- Information extraction (summarization, feature extraction), information retrieval (finding documents), question answering

Sentiment Analysis

- **Sentiment analysis**: *Classify* input text by positive or negative orientation
- Applications from marketing (e.g., consumer reviews) to politics
- One idea: We can *associate* different words with positive or negative lexicons and combine them with other *features*

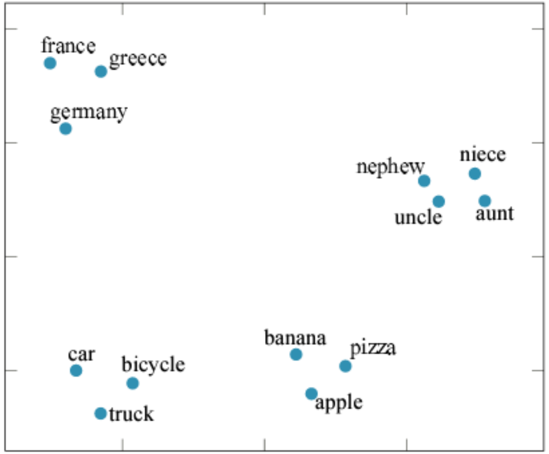


- Given training data, we can then learn a neural network for this task
- Similar issues as in computer vision: Hand-designing good features is hard!

Word Embeddings

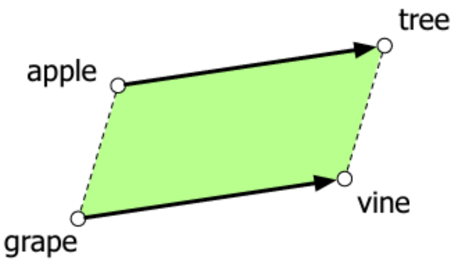
- We need a word representation that captures *context* and *relationships*
- Words may be related by sentiment, syntactically, and/or semantically

- **Word embedding**: A dense, low-dimensional vector representation of a word
- Number of components in the hundreds, much fewer than a vocabulary size or number of documents
- Algorithms like **Word2vec** automatically *learn* embeddings, e.g. by considering how often words appear near each other in a training corpus



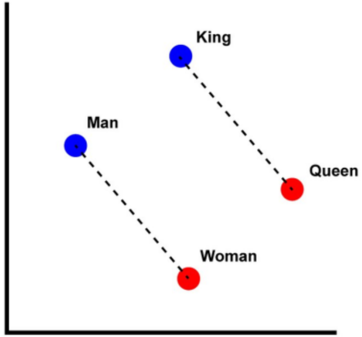
Semantic Relationships

- Embeddings can also learn *analogies* between words, beyond simply noting when they appear near each other



- Vector differences for pairs of words satisfying the same semantic relationships tend to be similar as well

- Word2vec example: “Man” – “woman” ≈ “king” – “queen”
- Embeddings can also be used to map between and translate across different languages



Word Embeddings and Bias

- Bolukbasi et al., “Man is to computer programmer as woman is to homemaker? Debiasing word embeddings”, 2016.

- Authors showed that publicly available word2vec embedding trained on Google News corpus contained significant amounts of gender biases and stereotypes

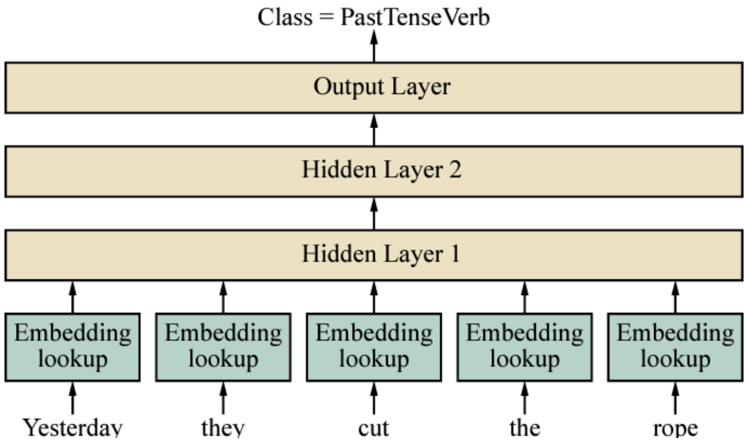
- Proposed methods to reduce bias while preserving clustering and orientation properties

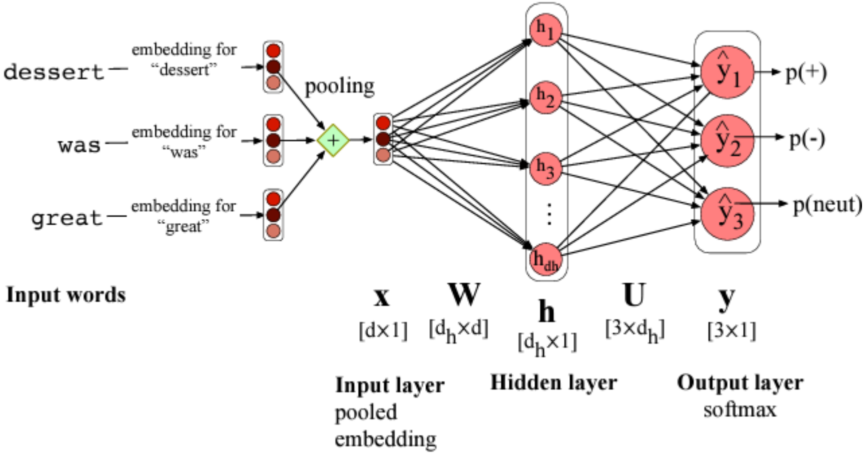
Extreme *she*	Extreme *he*
1. homemaker	1. maestro
2. nurse	2. skipper
3. receptionist	3. protege
4. librarian	4. philosopher
5. socialite	5. captain
6. hairdresser	6. architect
7. nanny	7. financier
8. bookkeeper	8. warrior
9. stylist	9. broadcaster
10. housekeeper	10. magician

	Gender stereotype *she*-*he* analogies	
sewing-carpentry	registered nurse-physician	housewife-shopkeeper
nurse-surgeon	interior designer-architect	softball-baseball
blond-burly	feminism-conservatism	cosmetics-pharmaceuticals
giggle-chuckle	vocalist-guitarist	petite-lanky
sassy-snappy	diva-superstar	charming-affable
volleyball-football	cupcakes-pizzas	lovely-brilliant
	Gender appropriate *she*-*he* analogies	
queen-king	sister-brother	mother-father
waitress-waiter	ovarian cancer-prostate cancer	convent-monastery

Classification with Embeddings

- Once we have a pretrained set of embeddings, we can convert text into these and feed them as inputs into a neural network classifier
- Can also **pool** embeddings together, e.g. via summation, mean, etc.
- Can perform tasks such as part-of-speech tagging and sentiment analysis



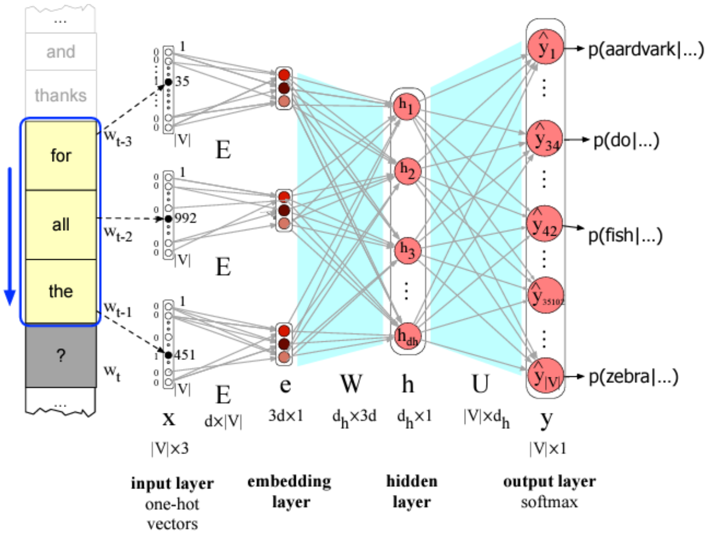


Language Modeling

- **Language modeling** is the task of *predicting* upcoming words from prior words
- A **neural language model** is a neural network that takes in some number of words and outputs a probability distribution over possible next words

- **Forward inference**: Compute the embeddings of a *moving window* and feed them through a network to obtain prediction probabilities

- Embeddings may be pretrained, or trained simultaneously with the network classifier

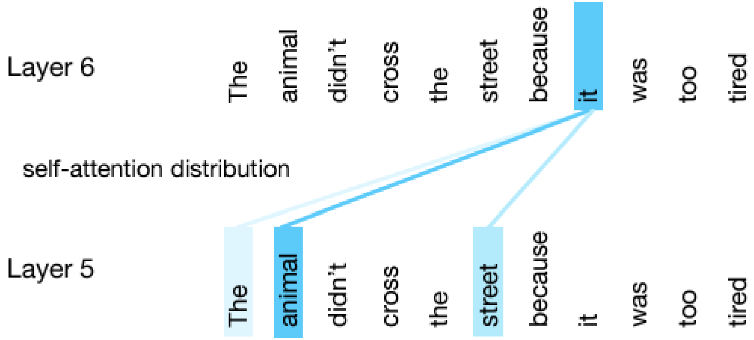


Self-Attention

- In language, words are often related despite *not* being in close proximity
  - Ex: “The *animal* didn’t cross the street because *it* was too tired.”
- Similar “non-proximity” context also appears in machine translation

- **Self-attention** computes, for a **query** word in a given sequence, a *weighted average* over all prior **key** words and their context **values**

- The same embedding may have different *projections* depending on the role that it is playing in a sequence

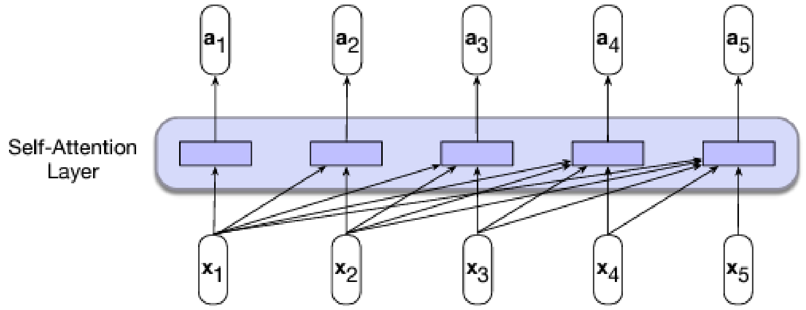


Self-Attention

- We can learn *weight matrices* $\mathbf{W}_q$, $\mathbf{W}_k$, $\mathbf{W}_v$ to project an embedding $\mathbf{x}_i$ into its **query** $\mathbf{q}_i = \mathbf{x}_i\mathbf{W}_q$, **key** $\mathbf{k}_i = \mathbf{x}_i\mathbf{W}_k$, and **value** $\mathbf{v}_i = \mathbf{x}_i\mathbf{W}_v$ representations

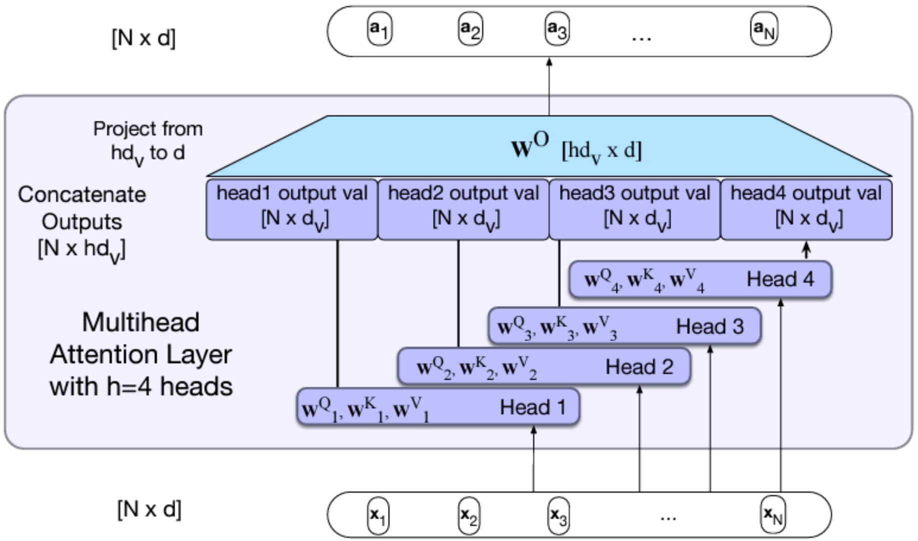
- Compute a normalized score $\alpha_{ij} = \mathrm{softmax}(\mathbf{q}_i \cdot \mathbf{k}_j)$, for all $j \le i$
- The output is the weighted sum of all previous values: $\mathbf{a}_i = \sum_{j \le i} \alpha_{ij} \mathbf{v}_j$

- Self-attention is generally *asymmetric* ($\alpha_{ij} \neq \alpha_{ji}$) since the context of words depends on their roles



Multihead Attention

- One set of projection matrices for each word may not adequately capture all semantic, syntactic, and discourse relationships among them
- **Multihead self-attention** learns distinct sets of parameters for extracting different context information
- Self-attention outputs from each "head" are then concatenated and then projected back into a sequence with the same size as the input

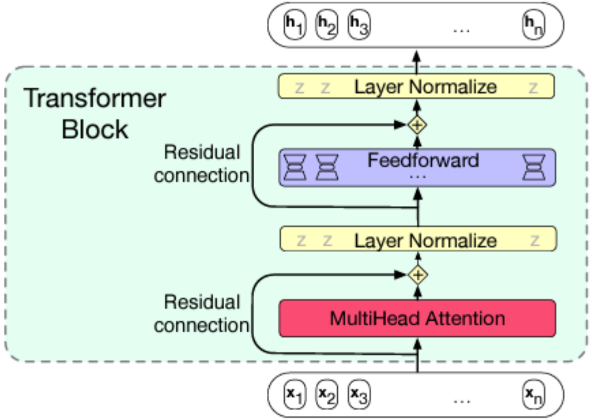


Transformer Blocks

- A **transformer** architecture consists of multiple self-attention layers interleaved with normalization and feedforward (nonlinear) layers

- Like ConvNets, successive transformer blocks extract new and higher levels of context given outputs of previous blocks

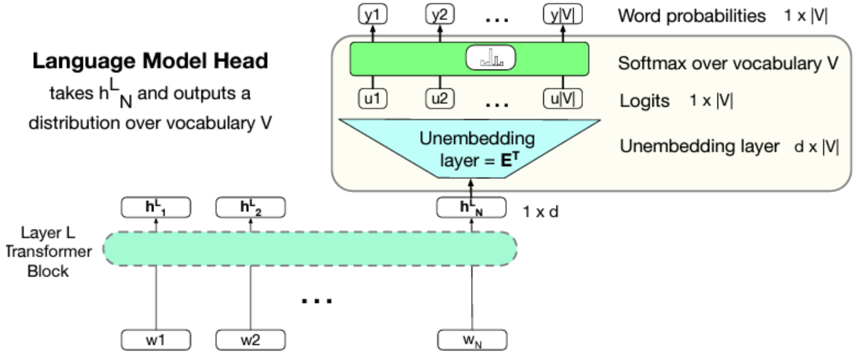
- Each attention layer *contextualizes* a word/token with other tokens to extract linguistic information
- Large language models stack dozens of these blocks together



Input and Output Layers

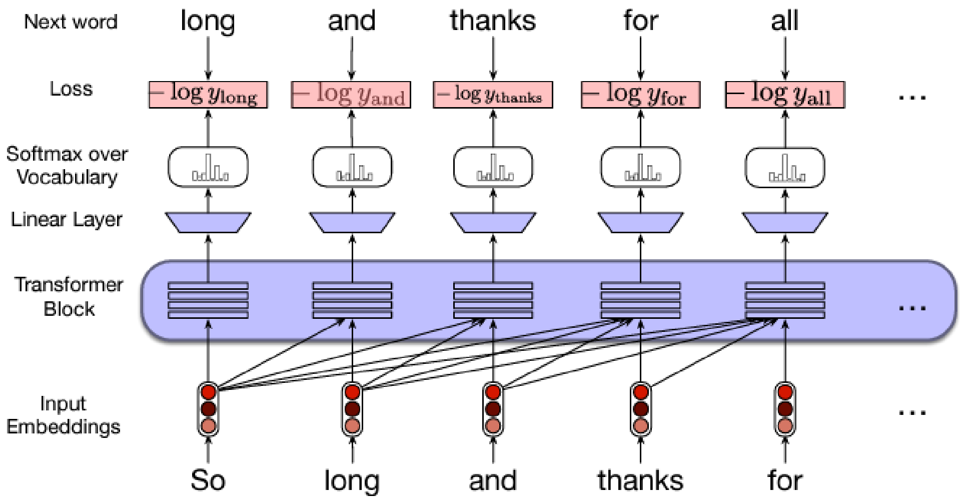
- Self-attention is agnostic to word *order*, which provides important context
- Input embeddings typically consist of a sum of the corresponding *word* embedding with an embedding for the *position* in the sequence

- How to use the output of a transformer for word prediction?
- The **model head** “unembeds” the last token and projects it into a probability distribution over the vocabulary
- A word can then be generated from this distribution



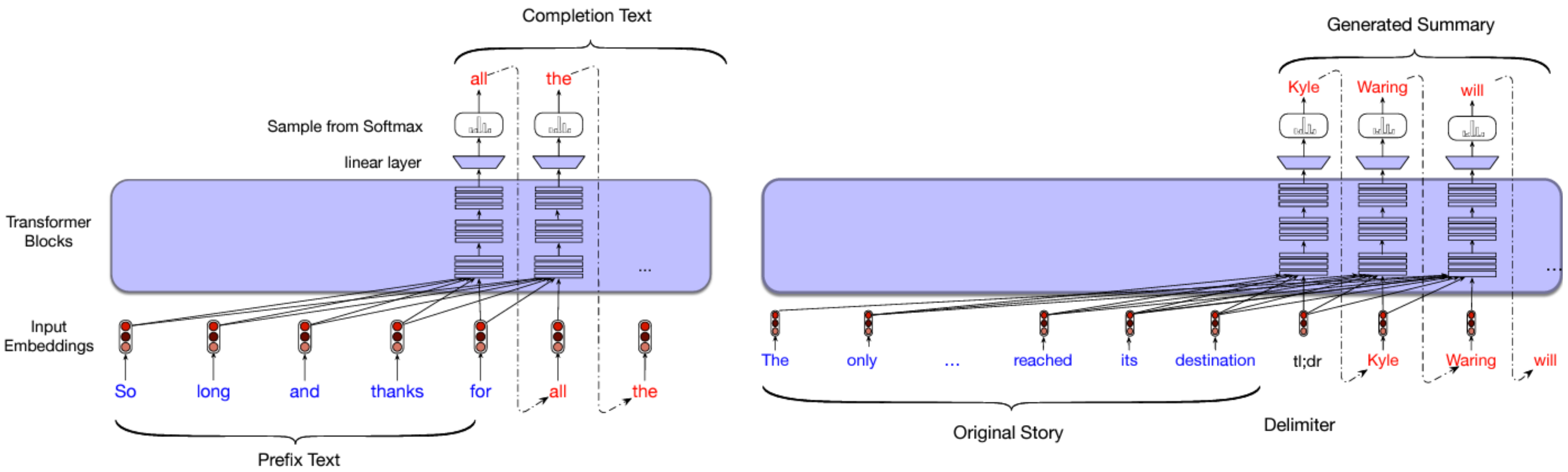
Self-Supervised Training

- To train on a general unlabeled corpus, the *sequence* of words encountered acts as a "ground truth", allowing for **self-supervised training**
- Data can be easily acquired from crawls of web text, including Wikipedia, news sites, patent docs, books
- Same ideas as general neural net training: Predict outputs from batches of data, compute losses and gradients, update weights



NLP with Transformers

- Many NLP tasks can be cast as word prediction given input text
- Transformers can accommodate long contexts (e.g., thousands of tokens)
- Textual answers and summaries can be generated by repeatedly feeding back each new word into the transformer



Large Language Models

- Like ConvNets, transformer architectures have rapidly improved over time (since 2017, “Attention Is All You Need” by Vaswani et al.)

- State-of-the-art models are *huge* and excel in many NLP tasks
- Ex: GPT-3 has 175B parameters, trained with 300B tokens

- Relatively easy to do transfer learning on pretrained embeddings and models
- Training process can also be augmented by prompt engineering
- Performance has been shown to scale up with model size, dataset size, and amount of training computations

Some LLM Considerations

- Like ConvNets, transformer models are *end-to-end*; no reliance on hand-crafted features or classical knowledge of grammars, parsing, semantics, etc.
- Transformers can more easily adapt to new domains and new languages

- Highly debated whether LLMs actually *understand* the knowledge on which they are trained, or whether they are just "stochastic parrots"

- LLMs are prone to **hallucination**, claims that are coherent but false
- Hicks et al., "ChatGPT is bullshit" (published this month)

LLMs and Bias

- Bender et al., “On the danger of stochastic parrots: Can language models be too big?”
- From 2021, outlining bias and other risks of big data and LLMs
- Internet users biased toward younger users, more developed countries, and men

- Toxic viewpoints on the Internet generally exceed prevalence in general population
- Marginalized populations are less welcome due to harassment and abuse
- Automated data cleaning may also further filter out marginalized voices

- Outdated or static training data may also be problematic, especially on rapidly changing social views and movements

Summary

- Natural language processing tasks include speech recognition, machine translation, information extraction, information retrieval, Q&A, and more

- Words (tokens) are usually represented using learned embedding vectors
- The self-attention mechanism computes contextual relationships between tokens in a given sequence

- Transformer models use self-attention to extract multiple levels of context
- Form the basis of large language models, which have shown great performance in many NLP tasks, many based on text generation