CS 2731
Introduction to Natural Language Processing

Session 14: Transformers part 2, introduction to LLMs

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University of Pittsburgh | School of Computing and Information

Course logistics: project

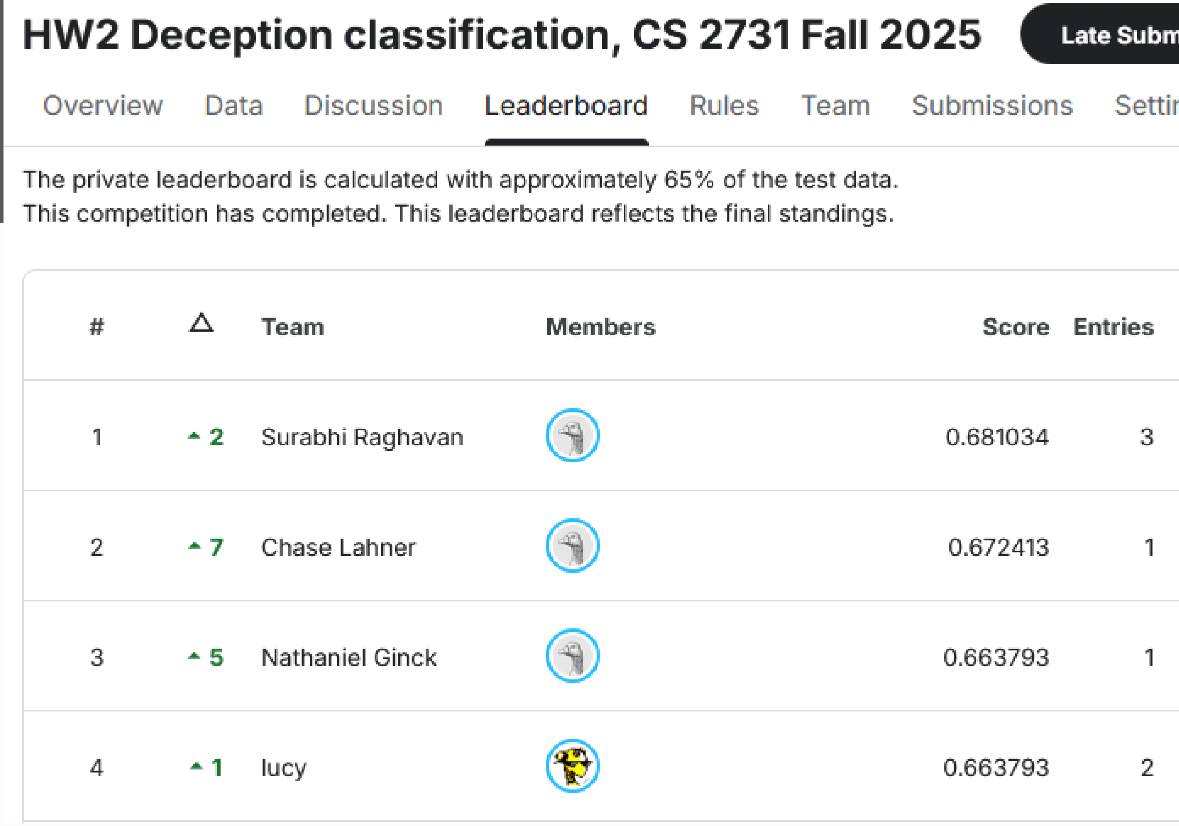
- This **Wed Oct 15**: project peer group feedback
  - Michael has not completely planned this yet, but come with ideas for your proposal and lingering questions you have that classmates may be able to help with
- Next project deliverable: project proposal due **this Thu Oct 16**
  - Will include plans for **task, data, methods, evaluation**
  - Compare multiple approaches, including an LLM-based approach
  - Literature review of at least 3 related papers
    - Baselines to compare your approach to
  - Feel free to email or book office hours with Michael to discuss

Course logistics: project

- Project proposal presentations in-class **next Mon Oct 20**
    - Michael will start a shared PowerPoint that you will add slides to, along with instructions
    - Ungraded
- LLM access
    - We have $150 total as a class to use on OpenAI LLM credits
    - Access to open-source LLM set up on School of Computing and Information servers for API access is coming soon
        - Gemma, LLaMa, Deepseek

Course logistics: Homework 2

- Congrats to Surabhi, Chase, Nate and Lucy!
- Michael is planning on grading HW2 this week



HW2 Deception classification, CS 2731 Fall 2025

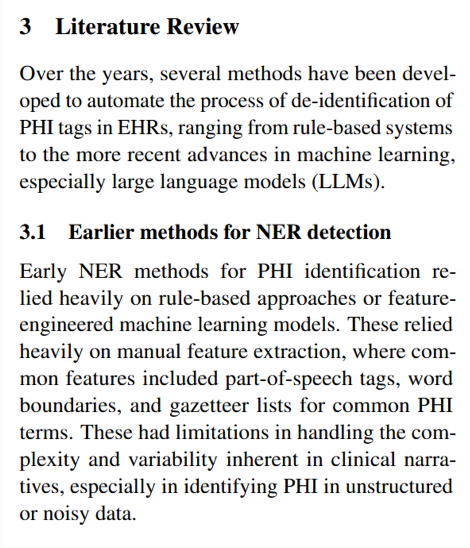
The private leaderboard is calculated with approximately 65% of the test data.
This competition has completed. This leaderboard reflects the final standings.

#	△	Team	Members	Score	Entries
1	▲ 2	Surabhi Raghavan		0.681034	3
2	▲ 7	Chase Lahner		0.672413	1
3	▲ 5	Nathaniel Ginck		0.663793	1
4	▲ 1	lucy		0.663793	2

How to do a literature review

- Look for NLP papers related to your topic in ACL Anthology, Semantic Scholar, and Google Scholar
- How have others approached your task or similar tasks? What are other NLP papers that use the same dataset or domain as your project?
- For each paper, note:
    - What they cite in their related work sections (find those papers, iterate)
    - Data
    - Methods
    - Findings
- For at least 3 papers, **organize them into themes of approaches, datasets, findings**
- Ok: X paper did this, Y paper did this, Z paper did that
- Good: X and Y papers did this, while Z improved with that
- Best: X and Y papers did this, Z improved, nobody has yet to do…

Example literature review: removing private health information (PHI)

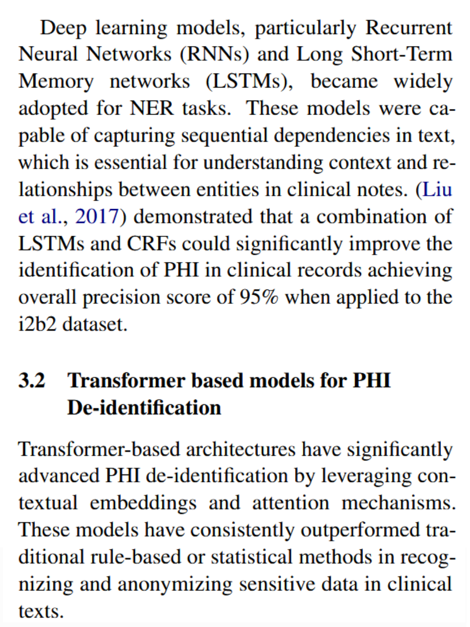


3 Literature Review

Over the years, several methods have been developed to automate the process of de-identification of PHI tags in EHRs, ranging from rule-based systems to the more recent advances in machine learning, especially large language models (LLMs).

3.1 Earlier methods for NER detection

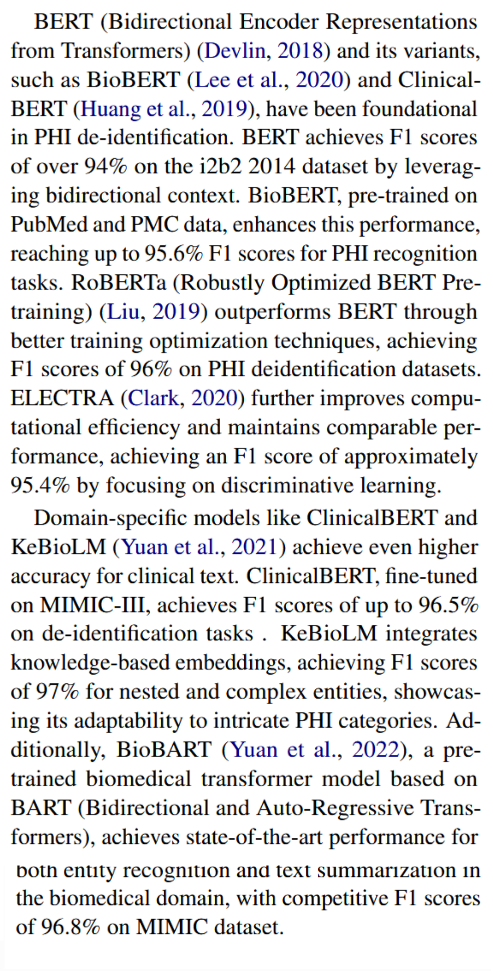
Early NER methods for PHI identification relied heavily on rule-based approaches or feature-engineered machine learning models. These relied heavily on manual feature extraction, where common features included part-of-speech tags, word boundaries, and gazetteer lists for common PHI terms. These had limitations in handling the complexity and variability inherent in clinical narratives, especially in identifying PHI in unstructured or noisy data.



Deep learning models, particularly Recurrent Neural Networks (RNNs) and Long Short-Term Memory networks (LSTMs), became widely adopted for NER tasks. These models were capable of capturing sequential dependencies in text, which is essential for understanding context and relationships between entities in clinical notes. (Liu et al., 2017) demonstrated that a combination of LSTMs and CRFs could significantly improve the identification of PHI in clinical records achieving overall precision score of 95% when applied to the i2b2 dataset.

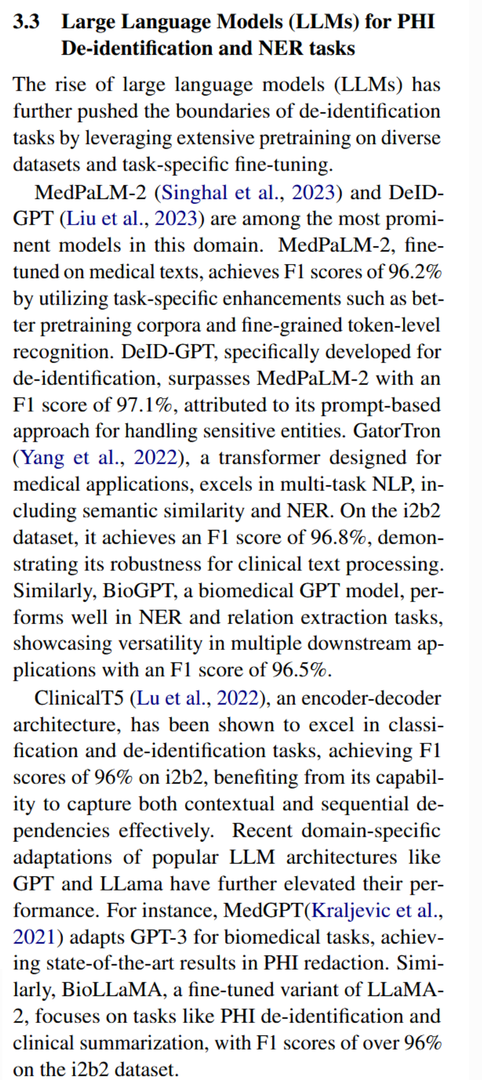
3.2 Transformer based models for PHI De-identification

Transformer-based architectures have significantly advanced PHI de-identification by leveraging contextual embeddings and attention mechanisms. These models have consistently outperformed traditional rule-based or statistical methods in recognizing and anonymizing sensitive data in clinical texts.



BERT (Bidirectional Encoder Representations from Transformers) (Devlin, 2018) and its variants, such as BioBERT (Lee et al., 2020) and ClinicalBERT (Huang et al., 2019), have been foundational in PHI de-identification. BERT achieves F1 scores of over 94% on the i2b2 2014 dataset by leveraging bidirectional context. BioBERT, pre-trained on PubMed and PMC data, enhances this performance, reaching up to 95.6% F1 scores for PHI recognition tasks. RoBERTa (Robustly Optimized BERT Pretraining) (Liu, 2019) outperforms BERT through better training optimization techniques, achieving F1 scores of 96% on PHI deidentification datasets. ELECTRA (Clark, 2020) further improves computational efficiency and maintains comparable performance, achieving an F1 score of approximately 95.4% by focusing on discriminative learning.

Domain-specific models like ClinicalBERT and KeBioLM (Yuan et al., 2021) achieve even higher accuracy for clinical text. ClinicalBERT, fine-tuned on MIMIC-III, achieves F1 scores of up to 96.5% on de-identification tasks . KeBioLM integrates knowledge-based embeddings, achieving F1 scores of 97% for nested and complex entities, showcasing its adaptability to intricate PHI categories. Additionally, BioBART (Yuan et al., 2022), a pre-trained biomedical transformer model based on BART (Bidirectional and Auto-Regressive Transformers), achieves state-of-the-art performance for both entity recognition and text summarization in the biomedical domain, with competitive F1 scores of 96.8% on MIMIC dataset.



3.3 Large Language Models (LLMs) for PHI De-identification and NER tasks

The rise of large language models (LLMs) has further pushed the boundaries of de-identification tasks by leveraging extensive pretraining on diverse datasets and task-specific fine-tuning.

MedPaLM-2 (Singhal et al., 2023) and DeID-GPT (Liu et al., 2023) are among the most prominent models in this domain. MedPaLM-2, fine-tuned on medical texts, achieves F1 scores of 96.2% by utilizing task-specific enhancements such as better pretraining corpora and fine-grained token-level recognition. DeID-GPT, specifically developed for de-identification, surpasses MedPaLM-2 with an F1 score of 97.1%, attributed to its prompt-based approach for handling sensitive entities. GatorTron (Yang et al., 2022), a transformer designed for medical applications, excels in multi-task NLP, including semantic similarity and NER. On the i2b2 dataset, it achieves an F1 score of 96.8%, demonstrating its robustness for clinical text processing. Similarly, BioGPT, a biomedical GPT model, performs well in NER and relation extraction tasks, showcasing versatility in multiple downstream applications with an F1 score of 96.5%.

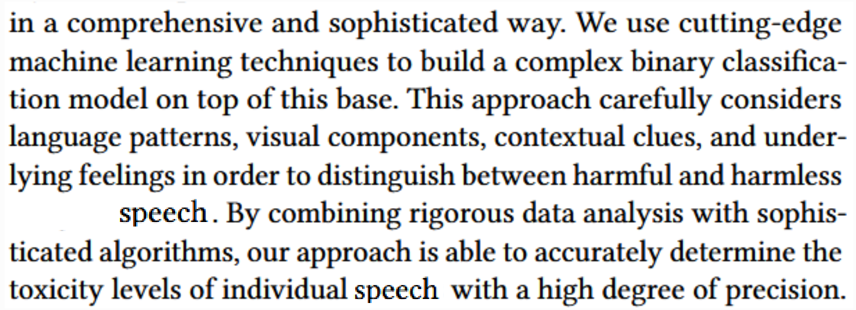
ClinicalT5 (Lu et al., 2022), an encoder-decoder architecture, has been shown to excel in classification and de-identification tasks, achieving F1 scores of 96% on i2b2, benefiting from its capability to capture both contextual and sequential dependencies effectively. Recent domain-specific adaptations of popular LLM architectures like GPT and LLama have further elevated their performance. For instance, MedGPT(Kraljevic et al., 2021) adapts GPT-3 for biomedical tasks, achieving state-of-the-art results in PHI redaction. Similarly, BioLLaMA, a fine-tuned variant of LLaMA-2, focuses on tasks like PHI de-identification and clinical summarization, with F1 scores of over 96% on the i2b2 dataset.

Clarity and using generative AI tools for writing

- Writing **clarity is what I grade** on homework and project reports, not grammar and spelling
  - Computer science writing values clarity and conciseness
- Writing from generative AI is often vague, abstract, wordy, and non-specific to what you did in your project. It isn't recommended
- Generative AI can generate claims that aren't backed up by your project
- ChatGPT and other LLMs don't know what you specifically did or are planning on doing in your project or homework. You could tell them, but at that point just write that down directly in your report!

Clarity and using generative AI tools for writing

- If you use generative AI tools for writing, aim for **machine-in-the-loop** writing where you as the human bear most of the rhetorical load (Knowles 2024)
  - AI is more like an assistant than a co-author
- Example of unclear project writing



in a comprehensive and sophisticated way. We use cutting-edge machine learning techniques to build a complex binary classification model on top of this base. This approach carefully considers language patterns, visual components, contextual clues, and underlying feelings in order to distinguish between harmful and harmless speech. By combining rigorous data analysis with sophisticated algorithms, our approach is able to accurately determine the toxicity levels of individual speech with a high degree of precision.

Overview: Transformers part 2, intro to LLMs

- Activity: work through self-attention
- Transformer input and output details
  - Position embeddings
  - Language modeling head
- Intro to LLMs
  - Pretraining LLMs

Activity: work through self-attention

Review: Describe self-attention in transformers

Calculate transformed output for one input word

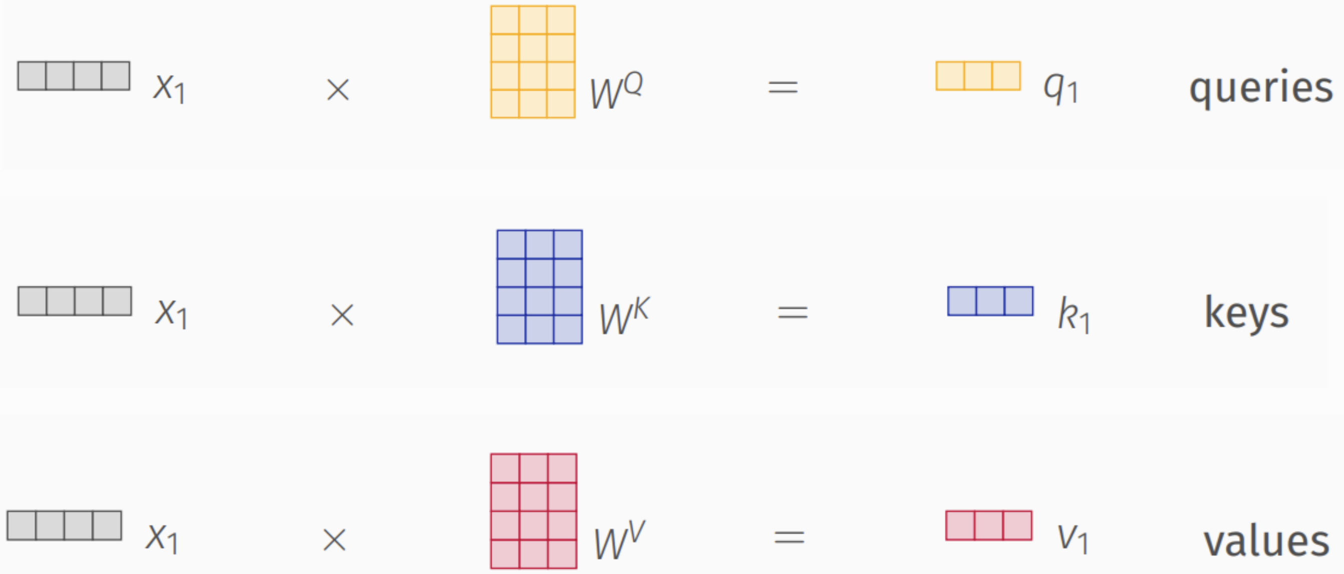
- Example sentence: “we wash our cats” (don’t ask)
- Let’s just calculate the vector output, for one input word: “we”
- High-level points to remember before you get buried in the math:
  - Each token will have an output vector that integrates contextual information from other tokens in the sentence
  - Each token can play a role as a query, key, and value
- Parameters (learned through backpropagation) are assumed given:
  - W^Q, W^K, W^V

Computing Self-Attention, Step One: Compute Key, Query, and Value Vectors

d_x-dimensional embeddings

$d_k \times d_x$-dimensional Weight Matrices

d_k-dimensional vectors



Slide credit: David Mortensen

Dot product: vector · matrix

$$\begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} ax + by + cz \\ dx + ey + fz \\ gx + hy + iz \end{bmatrix}$$

Computing Self-Attention, Step One: Compute Key, Query, and Value Vectors

d_x-dimensional embeddings

$d_k \times d_x$-dimensional Weight Matrices

d_k-dimensional vectors

x_1 = [3, 0, 1, -0.5]

$$x_1 \times W^Q = \begin{bmatrix} 1.5 & 1 & 2 \\ 3 & -2 & 5 \\ 1 & 2 & -2 \\ 9 & 4 & 2 \end{bmatrix} = q_1$$

queries

Find q_1 and k_1

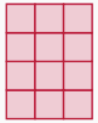
x_1 = [3, 0, 1, -0.5]

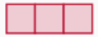
$$x_1 \times W^K = \begin{bmatrix} 1 & 0.5 & 2 \\ -2 & 0.5 & 3 \\ 0.5 & 2 & -3 \\ 5 & 3 & 2 \end{bmatrix} = k_1$$

keys

x_1 = [3, 0, 1, -0.5]

$$x_1 \times W^V = v_1$$





values

Slide credit: David Mortensen

Computing Self-Attention, Step Two: Weighted Sum of Value Vectors

	We	wash	our	cats
	x_1	x_2	x_3	x_4
query-key dot product	$q_1 \cdot k_1 =$	$q_1 \cdot k_2 =$	$q_1 \cdot k_3 =$	$q_1 \cdot k_4 =$
divide by $\sqrt{d_k}$ Assume $d_k = 64$				
softmax				
$\times$ value	$\times\ v_1$	$\times\ v_2$	$\times\ v_3$	$\times\ v_4$
sum	z_1			

$k_2 = [3, 4, 3]$
$k_3 = [5, 2, 3]$
$k_4 = [3, 2, 1]$

$v_1 = [1, 0.5, -1]$
$v_2 = [4, 5, -2]$
$v_3 = [-3, 2, 2]$
$v_4 = [1, 1, 6]$

Slide credit: David Mortensen

Transformer input and output

Token and Position Embeddings

- The matrix X (of shape [$N \times d$]) has an embedding for each word in the context.
- This embedding is created by adding two distinct embedding for each input: **token** and **position** embeddings
- Since self-attention doesn't build in order information, we need to encode the order of the sentence in our keys, queries, and values

Slide adapted from Jurafsky & Martin

Token Embeddings

Embedding matrix E has shape $|V| \times d$

- One row for each of the $|V|$ tokens in the vocabulary.
- Each word is a row vector of d dimensions

Given: string "*Thanks for all the*"

1. Tokenize with BPE and convert into vocab indices

   w = [5,4000,10532,2224]

2. Select the corresponding rows from E, each row an embedding

   (row 5, row 4000, row 10532, row 2224).

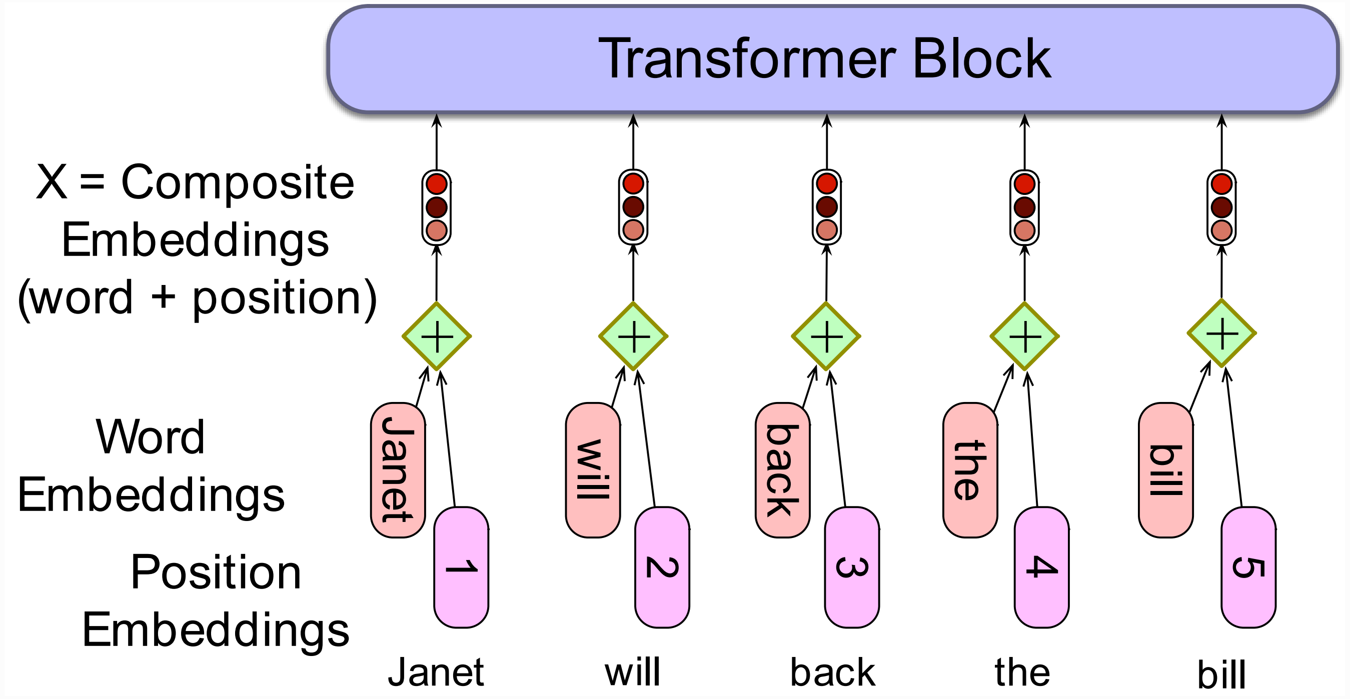
Slide adapted from Jurafsky & Martin

Position Embeddings

- There are many methods, but we'll just describe the simplest: absolute position.
- Goal: learn a position embedding matrix E_{pos} of shape $1 \times N$
- Start with randomly initialized embeddings
  - one for each integer up to some maximum length.
  - i.e., just as we have an embedding for the word *fish*, we’ll have an embedding for position 3 and position 17.
- As with word embeddings, these position embeddings are learned along with other parameters during training.

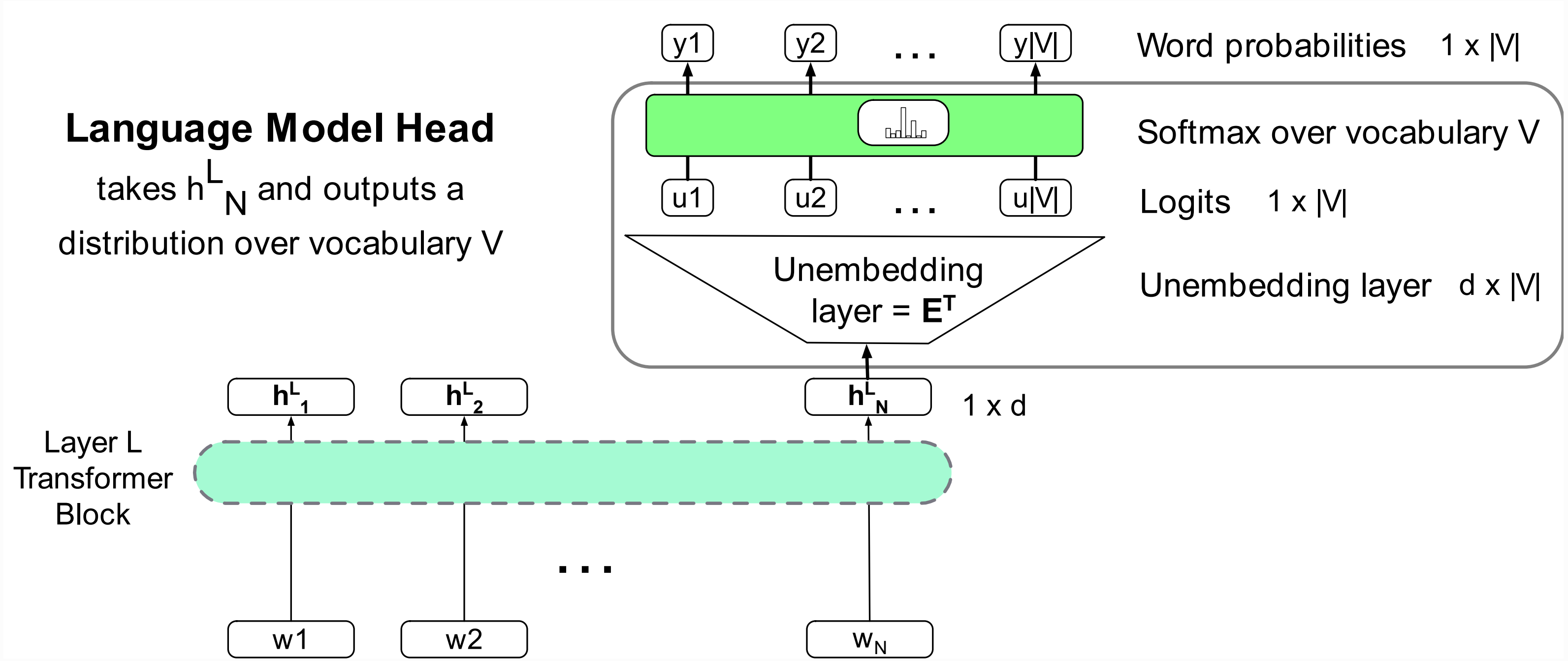
Slide adapted from Jurafsky & Martin

Each **x** is just the sum of word and position embeddings



Slide adapted from Jurafsky & Martin

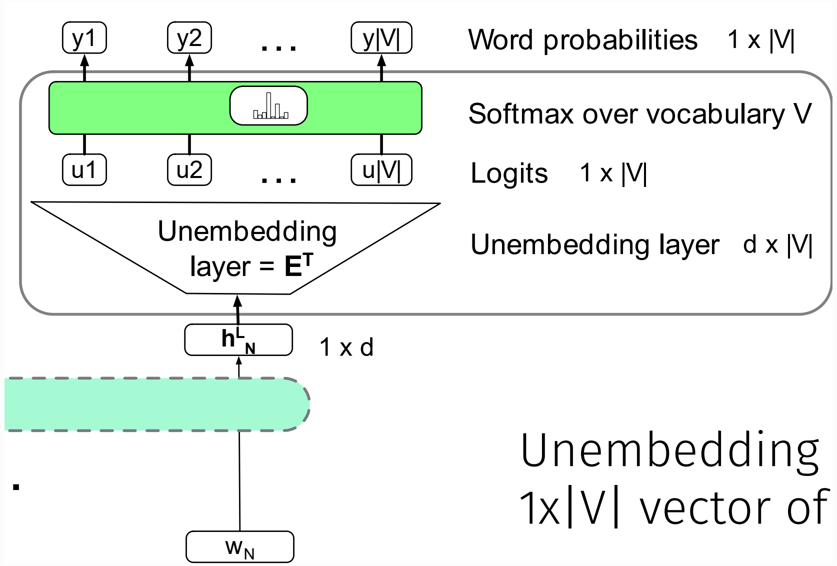
Language modeling head


Language Model Head
takes h^L_N and outputs a distribution over vocabulary V
y1
y2
...
y|V|
Word probabilities 1 x |V|
Softmax over vocabulary V
u1
u2
...
u|V|
Logits 1 x |V|
Unembedding layer = E^T
Unembedding layer d x |V|
h^L_1
h^L_2
h^L_N
1 x d
Layer L Transformer Block
...
w1
w2
w_N

Slide adapted from Jurafsky & Martin

Language modeling head

Unembedding layer: FFN layer projects from h^L_N (shape $1 \times d$) to probability distribution vector over the vocabulary



y1
y2
...
y|V|
Word probabilities 1 x |V|
Softmax over vocabulary V
u1
u2
...
u|V|
Logits 1 x |V|
Unembedding layer = $\mathbf{E}^T$
Unembedding layer d x |V|
$\mathbf{h}^L_N$
1 x d
w_N

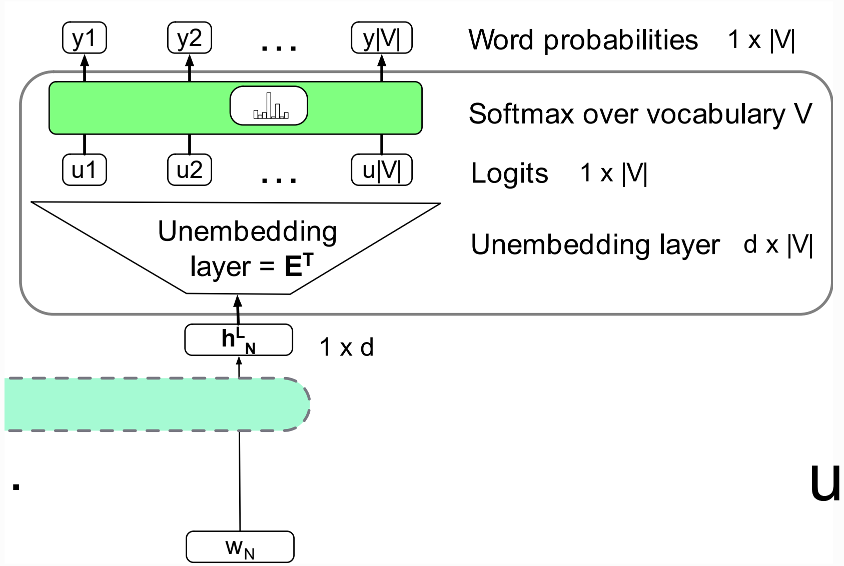
Why "unembedding"? **Tied** to E^T

Weight tying, we use the same weights for two different matrices

Unembedding layer maps from an embedding to a 1x|V| vector of logits

Slide adapted from Jurafsky & Martin

Language modeling head



y1
y2
…
y|V|
Word probabilities 1 x |V|
Softmax over vocabulary V
u1
u2
…
u|V|
Logits 1 x |V|
Unembedding layer = E^T
Unembedding layer d x |V|
h^L_N
1 x d
w_N

Logits, the score vector u

One score for each of the $|V|$ possible words in the vocabulary V. Shape $1 \times |V|$.

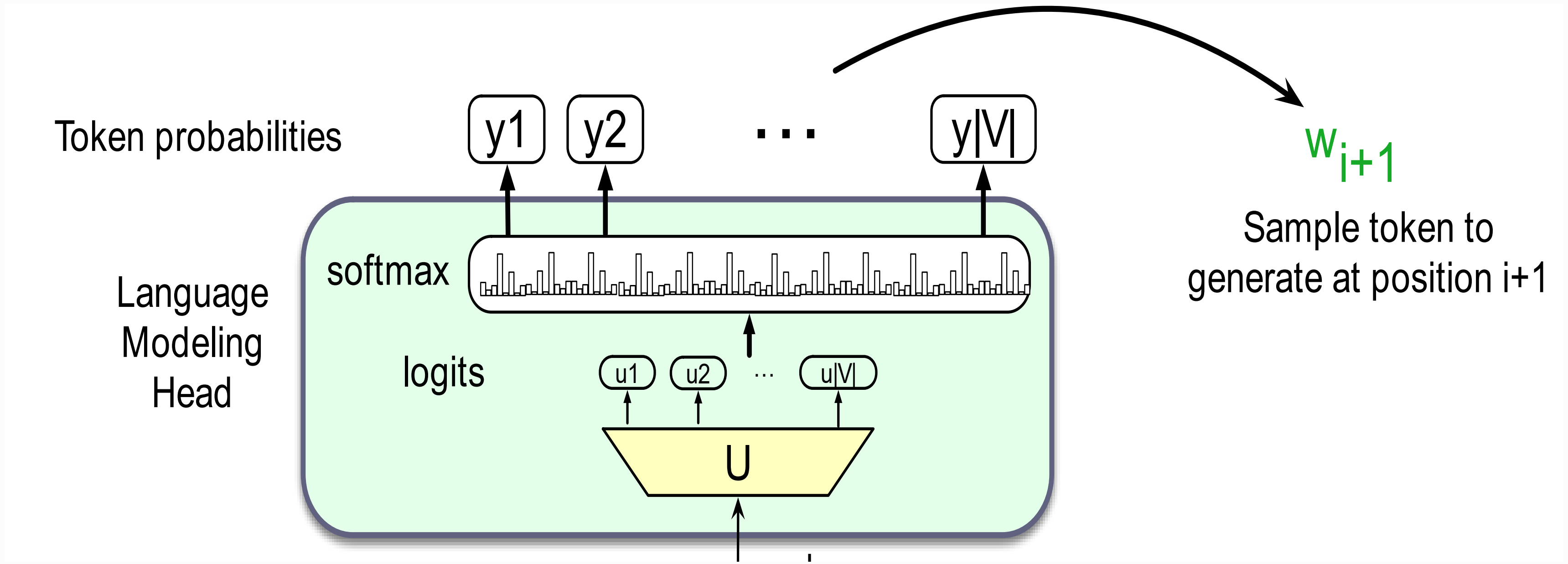
Softmax turns the logits into probabilities over vocabulary. Shape $1 \times |V|$.

$$u = h^L_N \; E^T$$

$$y = \text{softmax}(u)$$

Slide adapted from Jurafsky & Martin

The final transformer language model



Slide adapted from Jurafsky & Martin

Intro to large language models (LLMs): pretraining and finetuning

Language models

- Remember the simple n-gram language model
  - Assigns probabilities to sequences of words
  - Generate text by sampling possible next words
  - Is trained on counts computed from lots of text
- Large language models are similar and different:
  - Assigns probabilities to sequences of words
  - Generate text by sampling possible next words
  - **Are trained by learning to guess the next word**

Slide adapted from Jurafsky & Martin

Large language models

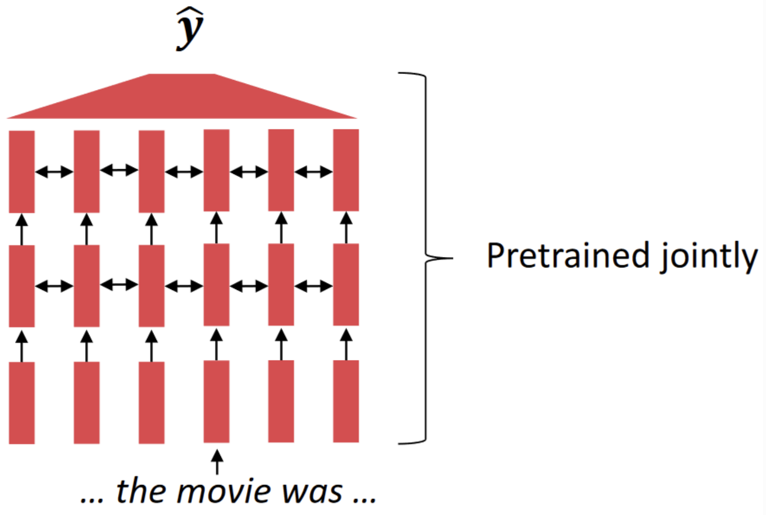
- Even through pretrained only to predict words
- Learn a lot of useful language knowledge
- Since training on a **lot** of text

Slide adapted from Jurafsky and Martin

Pretraining **whole models**

In contemporary NLP:

- All (or almost all) parameters in NLP networks are initialized via **pretraining**.
- Pretraining methods **hide parts of the input** from the model, and train the model to reconstruct those parts.
- This has been exceptionally effective at building strong:
    - representations of language
    - parameter initializations for strong NLP models
    - probability distributions over language that we can sample from



[This model has learned how to represent entire sentences through pretraining]

Slide adapted from John Hewitt

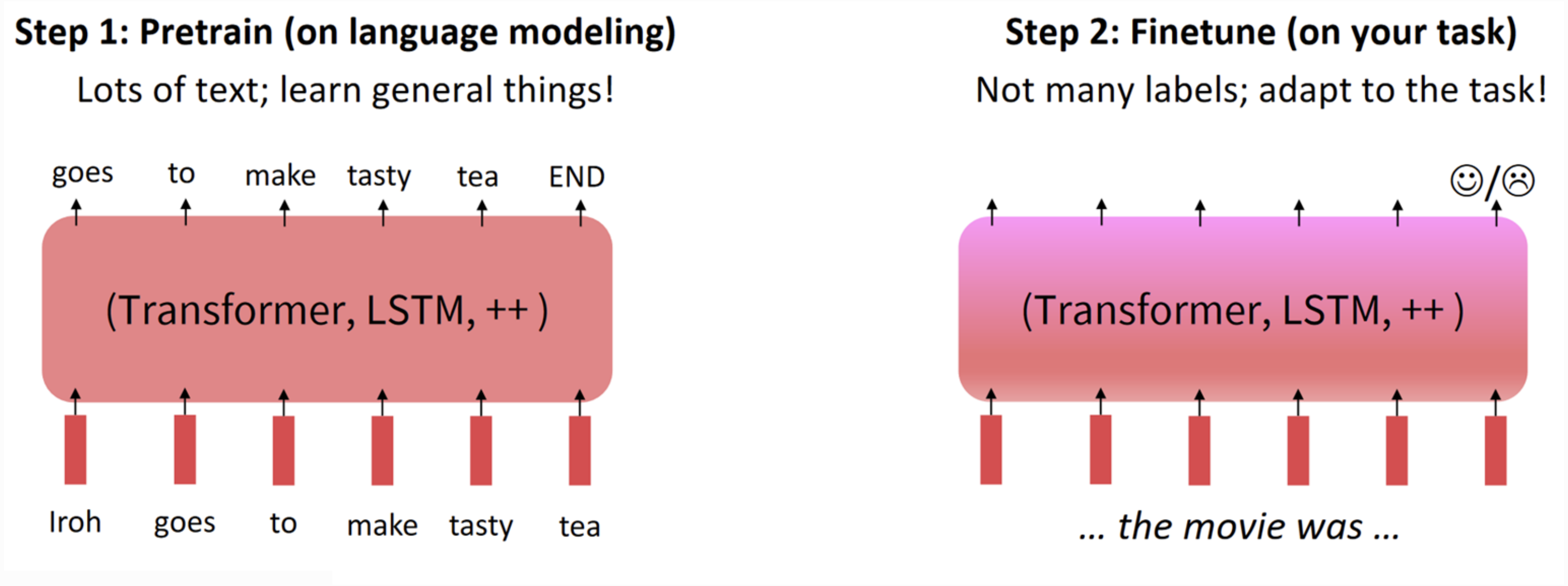
What can we learn from reconstructing the input?

- MIT is located in ___________, Massachusetts.
- I put ___ fork down on the table.
- The woman walked across the street, checking for traffic over ___ shoulder.
- I went to the ocean to see the fish, turtles, seals, and _____.
- Overall, the value I got from the two hours watching it was the sum total of the popcorn and the drink. The movie was ___.
- Iroh went into the kitchen to make some tea. Standing next to Iroh, Zuko pondered his destiny. Zuko left the ______.
- I was thinking about the sequence that goes 1, 1, 2, 3, 5, 8, 13, 21, ____

Slide adapted from John Hewitt

The pretraining + finetuning paradigm

Pretraining can improve NLP applications by serving as parameter initialization.



Step 1: Pretrain (on language modeling)
Lots of text; learn general things!
goes
to
make
tasty
tea
END
(Transformer, LSTM, ++)
Iroh
goes
to
make
tasty
tea
Step 2: Finetune (on your task)
Not many labels; adapt to the task!
☺/☹
(Transformer, LSTM, ++)
… the movie was …

Slide adapted from John Hewitt