

EEP 596: LLMs: From Transformers to GPT || Lecture 7

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Univ. of Washington, Seattle

January 29, 2025

Deep Learning References

Deep Learning

Great reference for the theory and fundamentals of deep learning: Book by Goodfellow and Bengio et al [Bengio et al](#)

[Deep Learning History](#)

Embeddings

[SBERT and its usefulness](#) [SBert Details](#)

Last lecture

- Recap of Embeddings and Cosine Similarity
- Glove Embeddings
- Sentence Embeddings with Glove and Sentence Transformer
- Product2Vec






Today's Lecture

- Product2Vec Recap
- Embedding Theory
- Sentence Transformers
- Vector Databases

Product2Vec



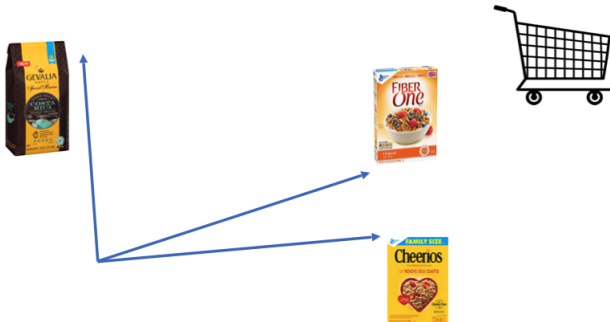
Represent products in product space with a large matrix of embedding coordinate vectors " L "

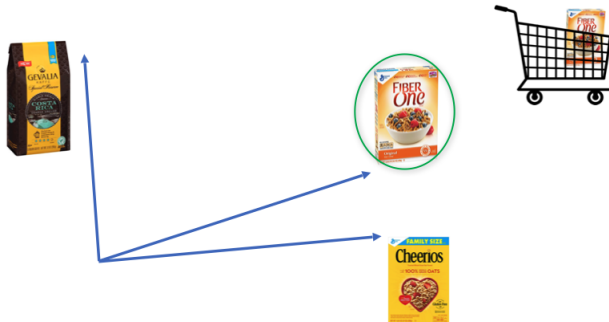
$$L = \begin{pmatrix} 1.5 & 1.9 & 1.8 & 1.4 & \cdots & 0.4 \\ 0.6 & 0.1 & 1.0 & 1.6 & \cdots & 1.9 \\ 0.6 & 1.6 & 1.6 & 1.6 & \cdots & 1.8 \\ 0.6 & 1.0 & 0.1 & 1.6 & \cdots & 0.6 \\ 0.8 & 1.4 & 1.9 & 0.8 & \cdots & 0.7 \end{pmatrix}$$

We obtain these embedding vectors from the Product2Vec service [London et al, 2017]

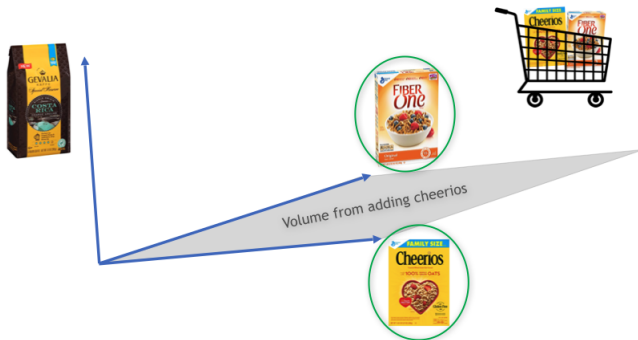
Product2Vec application



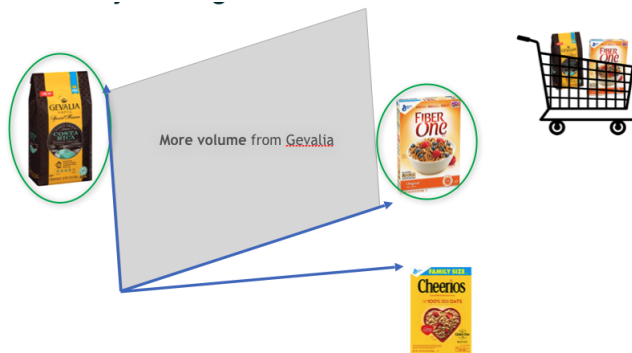
Product2Vec application



Product2Vec application



Product2Vec application




ICE #1

View Similarity or Purchase Similarity

Consider a company that sells products online. As we know, embedding representations for words or products in this case are learned from data. The question is which data to use? These are referred to as signals sometimes. So the question is, does **view similarity** of products represent a better signal for learning embeddings or **purchase similarity**? Remember: Good embeddings embed similar products close to each other dis-similar products away from each other.

ICE #1: View or Purchase Similarity?



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BIOTIN

Extra Strength®

5000mcg PER SERVING

SUPPORTS HEALTHY SKIN & HAIR*

VEGAN | NON-GMO | WITH COCONUT OIL


120 Veggie Softgels | Dietary Supplement

Roll over image to zoom in

- PREMIUM, POTENT FORMULAS:** Take your pick between our High Potency Biotin 2,500 mcg, Extra Strength Biotin 5,000 mcg, and Max Strength Biotin 10,000 mcg—all gluten-free, soy-free, and made with cold-pressed 100% organic coconut oil.
- THE SPORTS RESEARCH DIFFERENCE:** Founded in Southern California in 1980, Sports Research is a family-owned business born from a passion for fitness and wellness. Our goal is to embrace the sport of life through research-backed products created for every body—inside and out.

[Report an issue with this product or seller](#)

Consider a similar item




Amazon Elements Vegan Biotin 5000 mcg - Hair, Skin, Nails, 130 Capsules (4 month supply) (Packaging may vary)

130 Count (Pack of 1)

★★★★★ (32081)

\$5.46 (\$0.07/Count) [prime](#)

[prime](#) Climate Pledge Friendly




Sports Research Vitamin K2 as MK-7 100mcg with Coconut MCT Oil - 120 Veggie Softgels (4 Month Supply)...

★★★★★ 11

\$33.95 [prime](#)

Frequently bought together




BIOTIN

5000mcg with Organic Coconut Oil - Extra Strength...

117th (\$0.15/Count) [prime](#)

+




TRIPLE STRENGTH

Omega-3 Fish Oil - Burgeless Fish Oil Supplement w/EPA & DHA...

124th (\$0.23/Count) [prime](#)

+



D3 + K2


with 5000iu of Vegan D3 & 100mcg of Vitamin K2 as MK7...

125th (\$0.40/Count) [prime](#)

Total price: **\$66.16**

Add all 3 to Cart

Products related to this item



BIOTIN & COLLAGEN

Keratin | Hyaluronic Acid | Hair Growth Support


Pills, 25000 mcg...

★★★★★ 5,705

Amazon's Choice in Hyaluronic Acid Nutritional Supplements

\$27.89 (\$0.44/Count)

[prime](#) [prime](#) Climate Pledge Friendly



BIOTIN


PURE RESEARCH Liquid Biotin & Collagen Hair Growth Drops

60.000mcg - Biotin...

★★★★★ 28,024

\$21.89 (\$0.36/FL OZ)

[prime](#)




D3 + K2

Sports Research Vitamin D3 K2 with 5000iu of Vegan D3 & 100mcg of Vitamin K2 as MK7...

★★★★★ 35,526

\$23.95 (\$0.43/Count)

[prime](#)




BIOTIN & COLLAGEN

Gorvus Biotin & Collagen Hair Growth Support Drops - Hair Supplement - Healthy Skin...

★★★★★ 3,445

\$19.99 (\$10.00/FL OZ)

[prime](#)



BIOTIN & COLLAGEN


Biotin Vitamins For Hair, Skin & Nails - Biotin 5000mcg, Keratin & Collagen...

★★★★★ 957

Amazon's Choice in Biotin Supplements

\$22.97 (\$0.58/Count)

[prime](#)




BIOTIN & COLLAGEN

Superhair Hair Vitamins Extra Strength Biotin 6000mcg, Vitamin C, E, Coconut Oil, Z...

★★★★★ 47,314

\$29.99 (\$0.30/Count)

[prime](#)



BIOTIN & COLLAGEN

Biotin Capsules with Collagen and Keratin - 25000mcg Per Serving - Biotin Vitamins...

★★★★★ 896

\$19.89 (\$0.33/Count)

[prime](#)

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Generating Sentence Embeddings from Glove

Averaging embeddings of words: If we have a word embedding, how do we generate the sentence embedding?

Generating Sentence Embeddings from Glove

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Simple Solution: Just average the word embeddings

How do we improve Sentence Embeddings?

Sentence Embeddings

As you are probably observing in your Mini-Project 1 assignment - Averaging word embeddings doesn't "perform" as well. So we need sentence embeddings that do better than just averaging word embeddings

- Perhaps, capture the sequence of information flow in a sentence.

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Example 1

Sentence 1: "Me loves my friend"

Sentence 2: "My friend loves me"

Should they have the exact same sentence embeddings?

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Example 1

Sentence 1: "Me loves my friend"

Sentence 2: "My friend loves me"

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Example 2

Sentence 1: "I like chocolate milk"

Sentence 2: "I like milk chocolate"

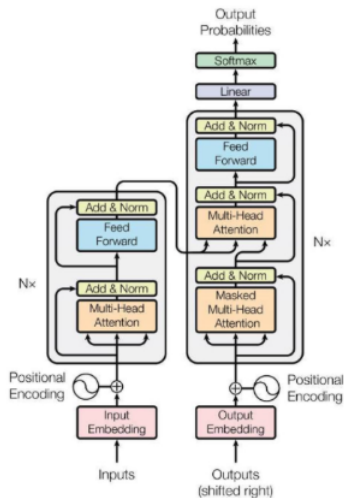
Should they have the same sentence embeddings?

Next Topic: Transformers, BERT and connections to Embeddings

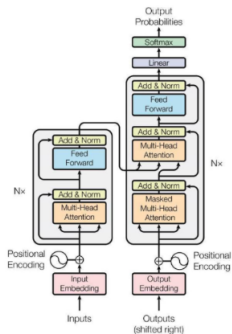
Capturing Sequence of information

As we discussed in the history of Deep Learning - RNNs and LSTMs are DL archs that are able to capture sequence information in a sentence to some extent (the **chocolate milk** vs **milk chocolate** example). On the other hand, they weren't robust to larger context or multiple sentences and could only operate with smaller sentence lengths. This is where the advent of Transformers was a breakthrough for ML/DL and AI in general - They could do much better in capturing context, sequential information, supported multiple sentences and paragraphs, etc.

Transformers - Encoder and Decoder Architecture

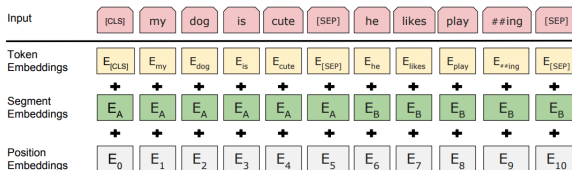


Encoder and Encoder Embeddings



Input	[CLS]	my	dog	is	cute	[SEP]	he	likes	play	#ing	[SEP]
Token Embeddings	$E_{[CLS]}$	E_{my}	E_{dog}	E_{is}	E_{cute}	$E_{[SEP]}$	E_{he}	E_{likes}	E_{play}	$E_{\#ing}$	$E_{[SEP]}$
	+	+	+	+	+	+	+	+	+	+	+
Segment Embeddings	E_A	E_A	E_A	E_A	E_A	E_A	E_B	E_B	E_B	E_B	E_B
	+	+	+	+	+	+	+	+	+	+	+
Position Embeddings	E_0	E_1	E_2	E_3	E_4	E_5	E_6	E_7	E_8	E_9	E_{10}

Understanding Encoder/BERT at high-level



BERT - Bi-directional Encoders from Transformers

System	MNLI-(m/mm)	QQP	QNLI	SST-2	CoLA	STS-B	MRPC	RTE	Average
	392k	363k	108k	67k	8.5k	5.7k	3.5k	2.5k	-
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.8	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	87.4	91.3	45.4	80.0	82.3	56.0	75.1
BERT _{BASE}	84.6/83.4	71.2	90.5	93.5	52.1	85.8	88.9	66.4	79.6
BERT _{LARGE}	86.7/85.9	72.1	92.7	94.9	60.5	86.5	89.3	70.1	82.1

Parsing the Embeddings and Encoder/Decoder Terminology

- 1 **Encoder:** The **architecture component** of the transformer that transforms inputs through a series of Neural layers into a vector (embedding). This vector can then be useful for downstream tasks: Emotion detection, Classification, etc

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- ② **Decoder:** The **architecture component** of the transformer that transforms inputs one at a time to generate words in sequence. Example: You ask a question of ChatGPT and it starts generating words, one at a time - Just like it were typing. That's decoder in action.

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- 3 **Input Embedding:** How an input gets embedded as a vector. What would be the starting point to embed "chocolate milk" as a vector?

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- ❶ **Encoder:** The **architecture component** of the transformer that transforms inputs through a series of Neural layers into a vector (embedding). This vector can then be useful for downstream tasks: Emotion detection, Classification, etc
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- ❸ **Input Embedding:** How an input gets embedded as a vector. What would be the starting point to embed “chocolate milk” as a vector?
- ❹ **Token Embedding:** This refers to the individual token embeddings or word embeddings (or sub-word embeddings)

Parsing the Embeddings and Encoder/Decoder Terminology

- ① **Segment Embedding:** This refers to a generic embedding that says this was segment 1 or segment 2 of the input

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- ③ **BERT Embedding:** This is the embedding or the vector used after having gone through the Encoder Architecture

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- ❹ **Sentence BERT (sBERT) Embedding:** This is the embedding that you are using in Mini-Project 1, an **encoding** into a vector that's optimized for sentence similarity! (More on this in a bit)

Linear Transformations and Projections

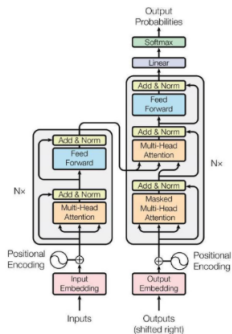
Path of a sentence through transformer layers

Llama3 High-level Numbers

Llama 3 70B Model

- Parameters: Approximately 70 billion.
- Vocabulary Size: 128,000 tokens.
- Total tokens seen: 15 trillion
- Context Window: Supports sequences up to 8,192 tokens.
- Architecture:
- Layers: 80 transformer blocks.
- Attention Heads: 64 heads per layer.
- Feature Dimension: 8,192.
- Hidden Dimension: 10,649.

Encoder and Encoder Embeddings



Input	[CLS] my dog is cute [SEP] he likes play #ing [SEP]										
Token Embeddings	$E_{[CLS]}$	E_{my}	E_{dog}	E_{is}	E_{cute}	$E_{[SEP]}$	E_{he}	E_{likes}	E_{play}	$E_{\#ing}$	$E_{[SEP]}$
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Position Embeddings	E_0	E_1	E_2	E_3	E_4	E_5	E_6	E_7	E_8	E_9	E_{10}

In-class Coding exercise - Carries Bonus points for grade

Compute Sentence Embedding (15 mins)

Instructions: Write a python module to compute sentence embeddings given words and their embeddings.

Encapsulate your code in a class structure. With one method for each of the sentence embedding computations asked below. Each method takes in as input a sentence and outputs a sentence embedding. Also have class variables to store vocab embeddings, filler words and attention weights (part 3).

Submit: Your code on canvas link that will be opened up shortly for bonus points that can be used towards your grade.

Vocabulary: Assume the vocabulary consists of 5 words:
I, lot, love, chocolate, milk.

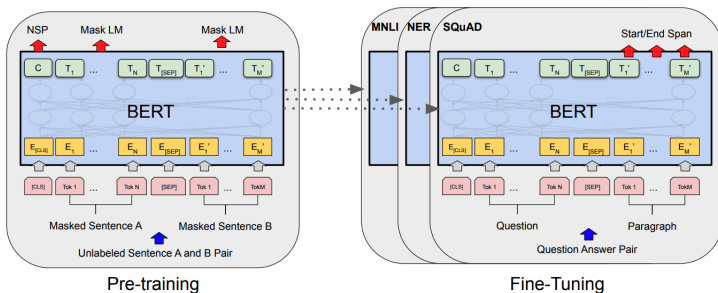
Sentence: Consider the following sentence: I love chocolate milk as well! Assume the embedding(*i*th word) = $[i - 1, i + 1]$ where *i* is 0-indexed.

In-class Coding exercise - Carries Bonus points for grade

Compute Sentence Embedding (15 mins)

- 1. Simple Average Embedding:** Compute the sentence embedding by simple averaging. For any word not in vocabulary, use the embedding as $[-1, -1]$. What's the resulting sentence embedding with this approach?
- 2. Skip filler words embedding:** Let filler words be *[I, and, as, for, it, or, maybe]*. If you encounter any filler words in a sentence, skip the filler word for the embedding computation. What's the sentence embedding with this approach?
- 3. Learned Sentence embedding:** Assume you learned a set of weights that in word embeddings as input and give out sentence embedding as output. This is done by taking a weighted average of the embeddings. For the above sentence, let the weights learned could be from a self-attention layer. Assume the weights for words in the vocabulary are: $[0.5, 1, 0.7, 0.9, 0.3, 0.2, 0.1]$. What would be the resulting embedding?

BERT - Bi-directional Encoders from Transformers



BERT pre-training

Two Tasks

- ① **Masked LM Model:** Mask a word in the middle of a sentence and have BERT predict the masked word
- ② **Next-sentence prediction:** Predict the next sentence - Use both positive and negative labels. How are these generated?

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ICE: Supervised or Un-supervised?

- ① Are the above two tasks supervised or un-supervised?

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ICE: Supervised or Un-supervised?

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Data set!

English Wikipedia and book corpus documents!

Loss Function for Masked Language Model (MLM)

Loss Function for MLM mimicks which type of classic ML model?

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Cross-Entropy

$$L(p, \hat{p}) = - \sum_i [p_i \log(\hat{p}_i) + (1 - p_i) \log(1 - \hat{p}_i)]$$

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$$L(p, \hat{p}) = - \sum_i [p_i \log(\hat{p}_i) + (1 - p_i) \log(1 - \hat{p}_i)]$$

ICE: What is the loss function for Binary Classification?

BERT - Bi-directional Encoders from Transformers

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Sentence BERT a.k.a sBERT

Uses Siamese Twins architecture

Sentence BERT a.k.a sBERT

Uses Siamese Twins architecture

Advantages of sBERT

More optimized for Sentence Similarity Search.

SBERT - Siamese BERT architecture

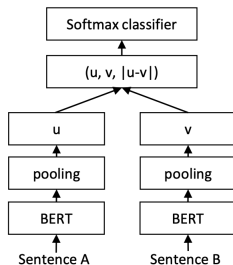


Figure 1: SBERT architecture with classification objective function, e.g., for fine-tuning on SNLI dataset. The two BERT networks have tied weights (siamese network structure).

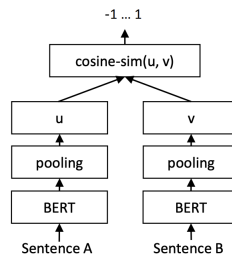


Figure 2: SBERT architecture at inference, for example, to compute similarity scores. This architecture is also used with the regression objective function.

Loss Function for SBERT

Breakouts Time #2

Retrieving Tables with Chat bots — 7 mins

You are building a chat-bot product at your company where queries come in from customers that own data in your company's cloud service. Your chat-bot responds and retrieves the right table or combination of tables (through merge/filter operations) that contains this information or returns back with follow up questions to get more precise information or get back with a "Sorry, I don't have that information" response. How would you go about building a chat-bot like this? What data would you use? What data stores/data bases would be appropriate? What Deep Learning models would you use, would it be supervised or un-supervised learning? What would be your evaluation metric? How would you test if your chat bot is accurate in its responses?