EEP 596: LLMs: From Transformers to GPT || Lecture 5

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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

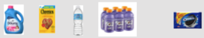
- Recap of Embeddings and Cosine Similarity
- Glove Embeddings
- Sentence Embeddings with Glove and Sentence Transformer
- In-Class Coding Exercise (second half)

Today's Lecture

- Product2Vec and X2Vec - Industry use-cases
- Embedding Theory
- Sentence Transformers
- Vector Databses

Product2Vec

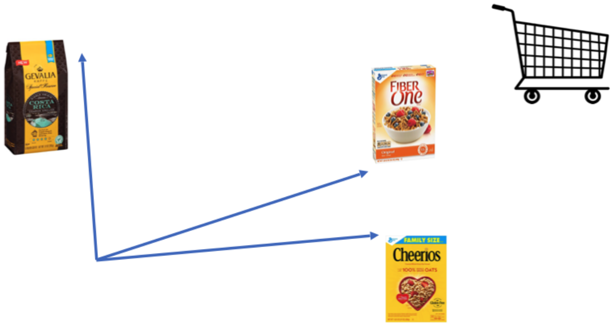
Represent products in product space with a large matrix of embedding coordinate vectors ***“L”***



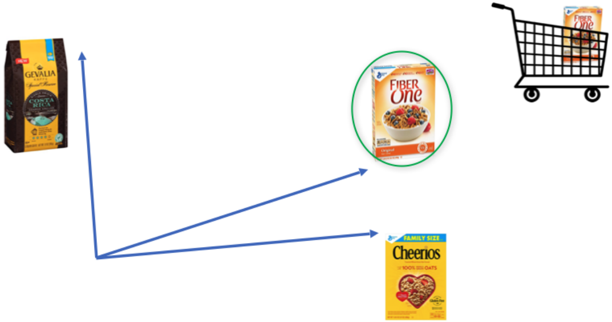
$$L = \begin{pmatrix} 1.5 & 1.9 & 1.8 & 1.4 & \cdots & 0.4 \\ 0.6 & 0.1 & 1.0 & 1.6 & \cdots & 1.9 \\ 0.6 & 1.6 & 1.6 & 1.6 & \cdots & 1.8 \\ 0.6 & 1.0 & 0.1 & 1.6 & \cdots & 0.6 \\ 0.8 & 1.4 & 1.9 & 0.8 & \cdots & 0.7 \end{pmatrix}$$

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

Product2Vec application



Product2Vec application



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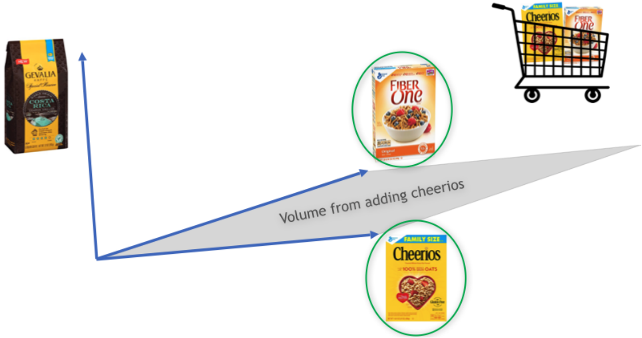


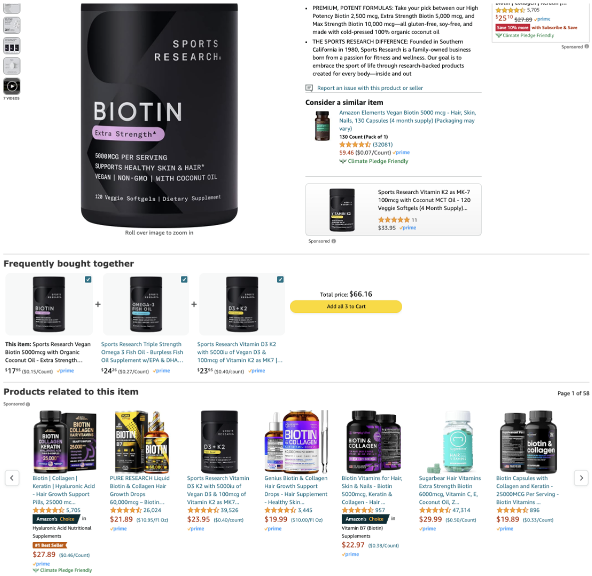
Product2Vec application

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?



Breakout 1: Discuss your favorite X2Vec!

X2Vec (10 mins)

In your breakout group - Discuss an application from your company or pet project that you think would benefit from **Vector Similarity Search**. Be specific about it - What's the product? data, features, etc. What's your X here? Can you see how X2Vec representation and similarity search would benefit your application. How would you learn X2vec for your application? And how would you use it?

Let's list out some X's in X2Vec!

Generating Sentence Embeddings from Glove

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

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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

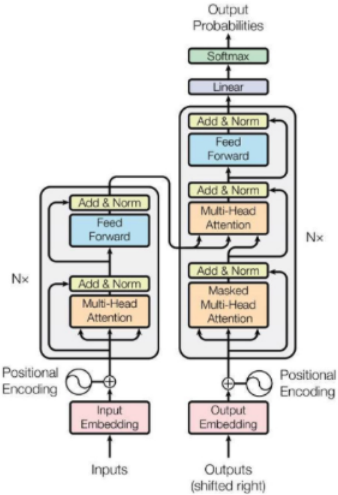
Sentence 1: "I like chocolate milk"
Sentence 2: "I like milk chocolate"
Should they have the same sentence embeddings?

Next Topic: Transformers, BERT and connections to Embeddings

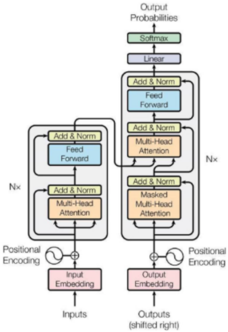
Capturing Sequence of information

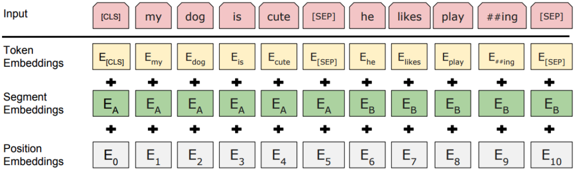
As we discussed in the history of Deep Learning - RNNs and LSTMs are DL archs that are able to capture sequence information in a sentence to some extent (the **chocolate milk** vs **milk chocolate** example). On the other hand, they weren't robust to larger context or multiple sentences and could only 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

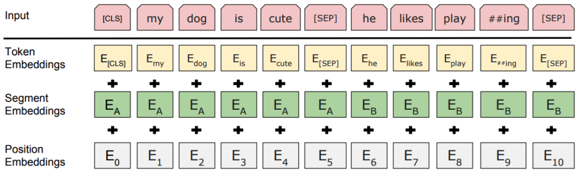


Encoder and Encoder Embeddings





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
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.5	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**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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4. **Token Embedding:** This refers to the individual token embeddings or word embedddings (or sub-word embeddings)

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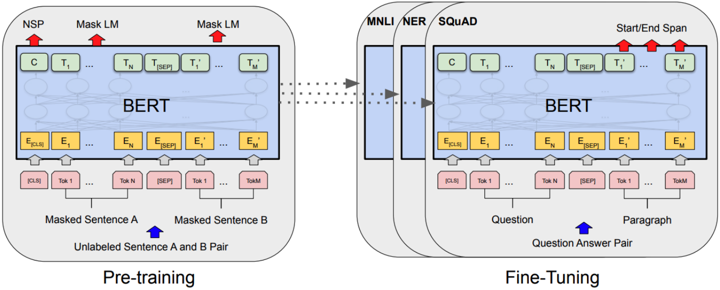
4. **Sentence BERT (sBERT) Embedding:** This is the embedding that you are using in Mini-Project 1, an **encoding** into a vector that's optimized for sentence similarity! (More on this in a bit)

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

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Data set!

English Wikipedia and book corpus documents!

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

ICE: What is the loss function for Binary Classification?

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Sentence BERT a.k.a sBERT

Uses Siamese Twins architecture

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Advantages of sBERT

More optimized for Sentence Similarity Search.

SBERT - Siamese BERT architecture

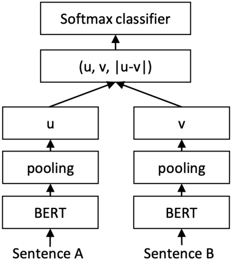

Figure 1: SBERT architecture with classification objective function, e.g., for fine-tuning on SNLI dataset. The two BERT networks have tied weights (siamese network structure).

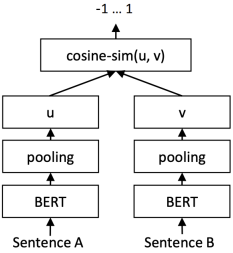

Figure 2: SBERT architecture at inference, for example, to compute similarity scores. This architecture is also used with the regression objective function.

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?