EEP 596: LLMs: From Transformers to GPT || Lecture 6

Dr. Karthik Mohan

Univ. of Washington, Seattle

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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 Instacart Search Relevance
Instacart Auto-Complete

Attention

Illustration of attention mechanism

Last Lecture

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

Today's Lecture

- Sentence Transformers and BERT
- Loss functions for BERT
- Multi-Head Attention
- SBERT
- Application of Embeddings to Autocomplete and Search Relevance

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

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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"
Should they have the exact same sentence embeddings?

Example 2

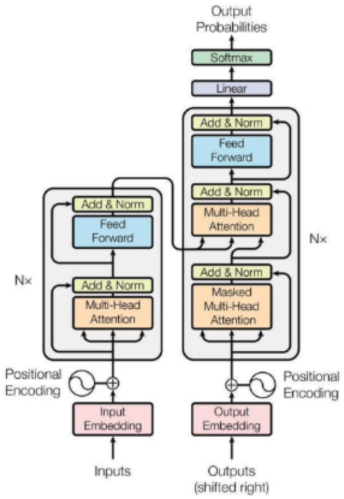
Sentence 1: "I like chocolate milk"
Sentence 2: "I like milk chocolate"
Should they have the same sentence embeddings?

Next Topic: Transformers, BERT and connections to Embeddings

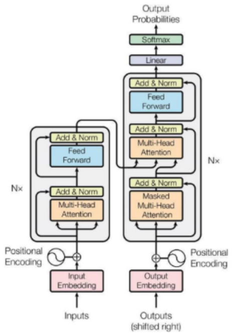
Capturing Sequence of information

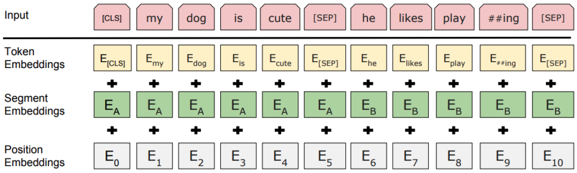
As we discussed in the history of Deep Learning - RNNs and LSTMs are DL archs that are able to capture sequence information in a sentence to some extent (the **chocolate milk** vs **milk chocolate** example). On the other hand, they weren't robust to larger context or multiple sentences and could only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



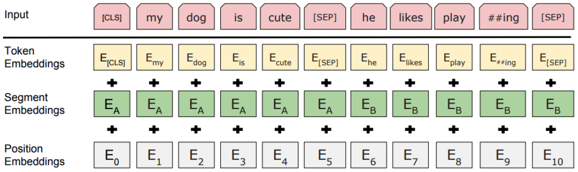
Encoder and Encoder Embeddings



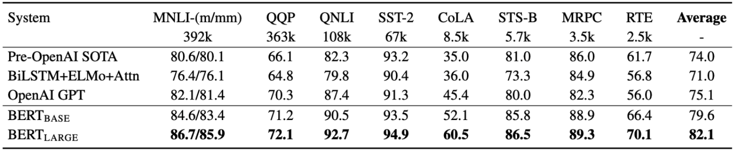


Input
[CLS] my dog is cute [SEP] he likes play ##ing [SEP]
Token Embeddings
$E_{[CLS]}$ E_{my} E_{dog} E_{is} E_{cute} $E_{[SEP]}$ E_{he} E_{likes} E_{play} $E_{\#\#ing}$ $E_{[SEP]}$
Segment Embeddings
E_A E_A E_A E_A E_A E_A E_B E_B E_B E_B E_B
Position Embeddings
E_0 E_1 E_2 E_3 E_4 E_5 E_6 E_7 E_8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

Understanding Encoder/BERT at high-level



BERT - Bi-directional Encoders from Transformers



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BERT$_{\text{BASE}}$	84.6/83.4	71.2	90.5	93.5	52.1	85.8	88.9	66.4	79.6
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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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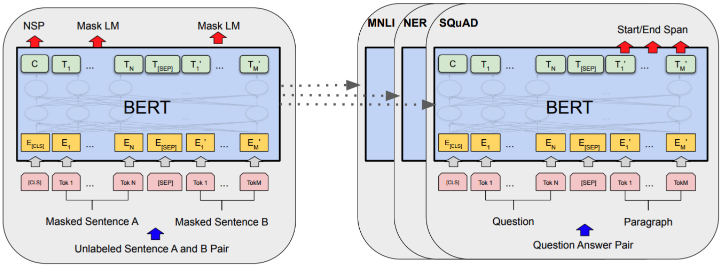
4. **Sentence BERT (sBERT) Embedding:** This is the embedding that you are using in Mini-Project 1, an **encoding** into a vector that's optimized for sentence similarity! (More on this in a bit)

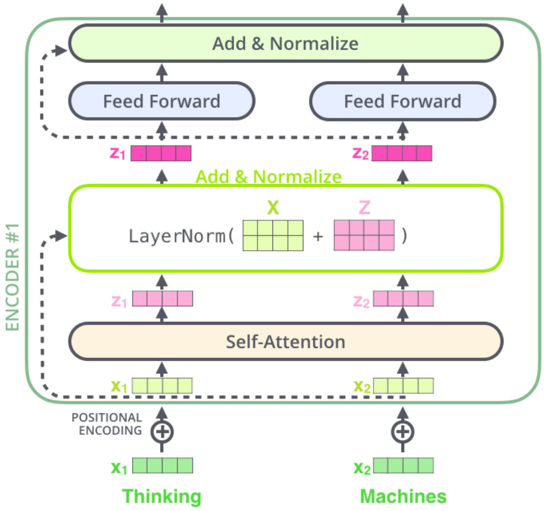
BERT - Bi-directional Encoders from Transformers



Pre-training Fine-Tuning

Parsing Encoding Transformers: Big Picture

Parsing Encoder: Multi-Head Attention and FFN



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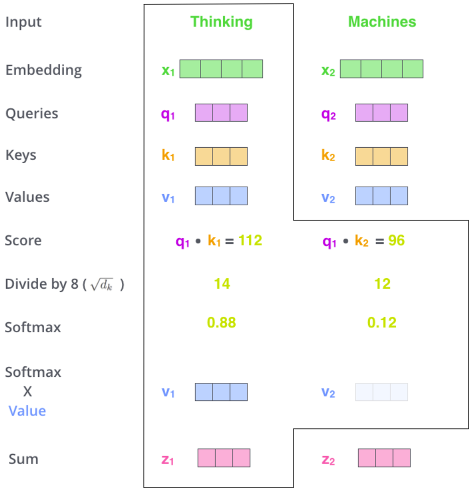

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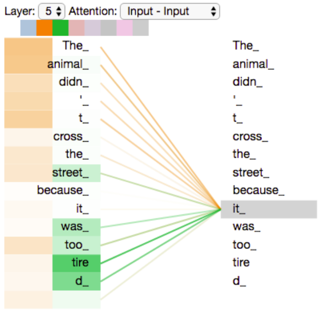
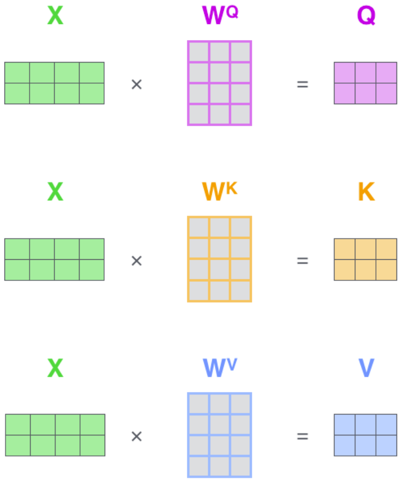


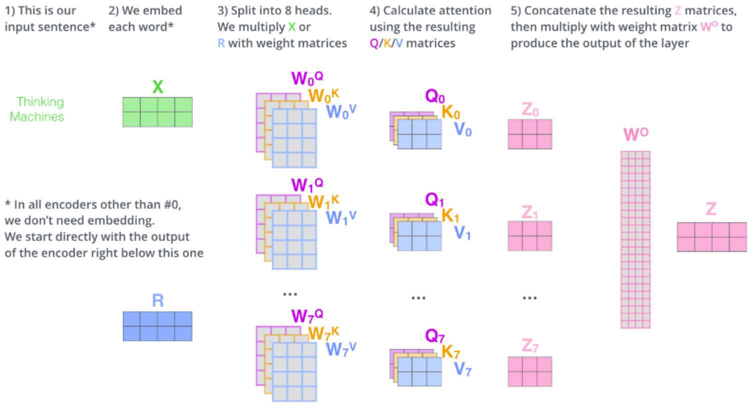
As we encode the word "it", one attention head is focusing most on "the animal", while another is focusing on "tired" -- in a sense, the model's representation of the word "it" bakes in some of the representation of both "animal" and "tired".

Parsing Encoder: Multi-Head Attention and FFN



Every row in the X matrix corresponds to a word in the input sentence. We again see the difference in size of the embedding vector (512, or 4 boxes in the figure), and the q/k/v vectors (64, or 3 boxes in the figure)

Parsing Encoder: Multi-Head Attention and FFN



1) This is our input sentence*
2) We embed each word*
3) Split into 8 heads. We multiply X or R with weight matrices
4) Calculate attention using the resulting Q/K/V matrices
5) Concatenate the resulting Z matrices, then multiply with weight matrix W^O to produce the output of the layer
Thinking Machines
X
R
* In all encoders other than #0, we don't need embedding. We start directly with the output of the encoder right below this one
W0Q W0K W0V
W1Q W1K W1V
W7Q W7K W7V
Q0 K0 V0
Q1 K1 V1
Q7 K7 V7
Z0
Z1
Z7
WO
Z

ICE #0: Self-attention Exercise

Let's go through a self-attention python calculation exercise to understand it better. Let $x = [[1, 2, 3, -1], [3, -4, -7, 5]]$ be the input token embeddings. In the first layer of the encoder of the transformer, the weight matrices are given by $W^Q = [[-1, 2, 0], [2, 3, -5], [1, 0, 0], [-3, 1, 2]]$, $W^K = [[1, 2, 3], [2, 4, 3], [3, 0, 3], [-1, 5, 2]]$, $W^V = [[-1, -2, 3], [2, -4, 0], [0, 0, 1], [1, 0, -7]]$. Compute the soft-max similar to what we did in the previous walk-through. You can use python matrix multiplication (e.g. numpy) to arrive at the solution. Question is which token (token 1 or token 2) does token 2 place more attention on?

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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ICE: What is the loss function for Binary Classification?

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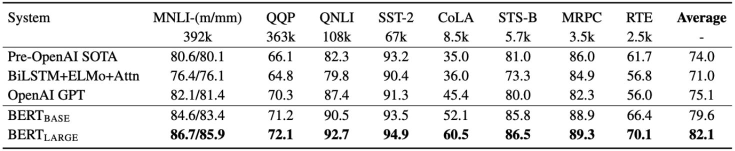

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Sentence BERT a.k.a sBERT

Uses Siamese Twins architecture

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Advantages of sBERT

More optimized for Sentence Similarity Search.

Sentence BERT - Siamese BERT architecture

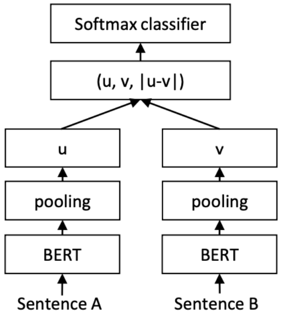


Figure 1: SBERT architecture with classification objective function, e.g., for fine-tuning on SNLI dataset. The two BERT networks have tied weights (siamese network structure).

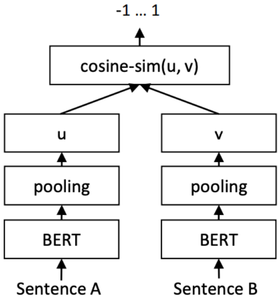
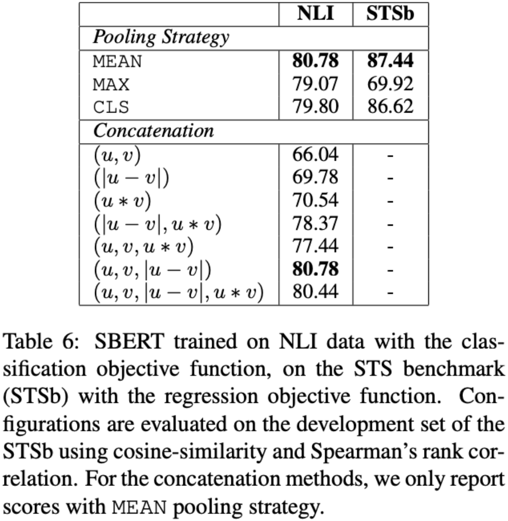


Figure 2: SBERT architecture at inference, for example, to compute similarity scores. This architecture is also used with the regression objective function.

Loss Function for SBERT

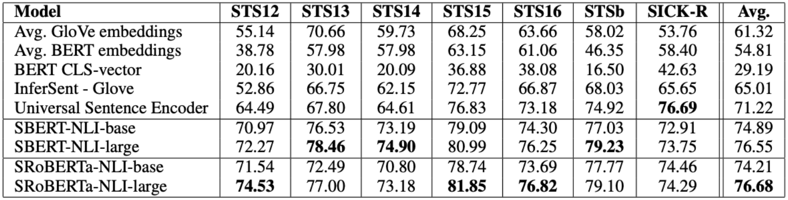
Pooling Strategy for SBERT



	NLI	**STSb**
Pooling Strategy		
MEAN	**80.78**	**87.44**
MAX	79.07	69.92
CLS	79.80	86.62
Concatenation		
(u, v)	66.04	-
$(\|u - v\|)$	69.78	-
$(u * v)$	70.54	-
$(\|u - v\|, u * v)$	78.37	-
$(u, v, u * v)$	77.44	-
$(u, v, \|u - v\|)$	**80.78**	-
$(u, v, \|u - v\|, u * v)$	80.44	-

Table 6: SBERT trained on NLI data with the classification objective function, on the STS benchmark (STSb) with the regression objective function. Configurations are evaluated on the development set of the STSb using cosine-similarity and Spearman's rank correlation. For the concatenation methods, we only report scores with MEAN pooling strategy.

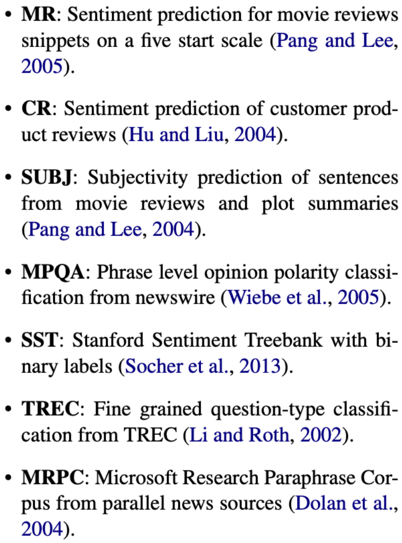
Sentence BERT Cosine Similarity Results



Model	STS12	STS13	STS14	STS15	STS16	STSb	SICK-R	Avg.
Avg. GloVe embeddings	55.14	70.66	59.73	68.25	63.66	58.02	53.76	61.32
Avg. BERT embeddings	38.78	57.98	57.98	63.15	61.06	46.35	58.40	54.81
BERT CLS-vector	20.16	30.01	20.09	36.88	38.08	16.50	42.63	29.19
InferSent - Glove	52.86	66.75	62.15	72.77	66.87	68.03	65.65	65.01
Universal Sentence Encoder	64.49	67.80	64.61	76.83	73.18	74.92	**76.69**	71.22
SBERT-NLI-base	70.97	76.53	73.19	79.09	74.30	77.03	72.91	74.89
SBERT-NLI-large	72.27	**78.46**	**74.90**	80.99	76.25	**79.23**	73.75	76.55
SRoBERTa-NLI-base	71.54	72.49	70.80	78.74	73.69	77.77	74.46	74.21
SRoBERTa-NLI-large	**74.53**	77.00	73.18	**81.85**	**76.82**	79.10	74.29	**76.68**

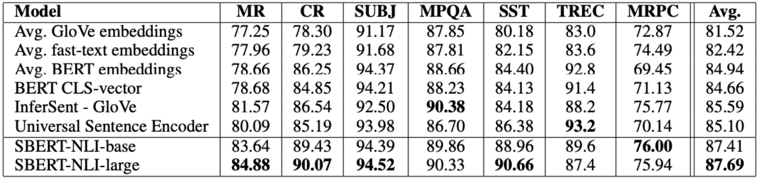
Table 1: Spearman rank correlation ρ between the cosine similarity of sentence representations and the gold labels for various Textual Similarity (STS) tasks. Performance is reported by convention as $\rho \times 100$. STS12-STS16: SemEval 2012-2016, STSb: STSbenchmark, SICK-R: SICK relatedness dataset.

SentEval DataSets



- **MR**: Sentiment prediction for movie reviews snippets on a five start scale (Pang and Lee, 2005).
- **CR**: Sentiment prediction of customer product reviews (Hu and Liu, 2004).
- **SUBJ**: Subjectivity prediction of sentences from movie reviews and plot summaries (Pang and Lee, 2004).
- **MPQA**: Phrase level opinion polarity classification from newswire (Wiebe et al., 2005).
- **SST**: Stanford Sentiment Treebank with binary labels (Socher et al., 2013).
- **TREC**: Fine grained question-type classification from TREC (Li and Roth, 2002).
- **MRPC**: Microsoft Research Paraphrase Corpus from parallel news sources (Dolan et al., 2004).

Sentence BERT on SentEval Results



Model	**MR**	**CR**	**SUBJ**	**MPQA**	**SST**	**TREC**	**MRPC**	**Avg.**
Avg. GloVe embeddings	77.25	78.30	91.17	87.85	80.18	83.0	72.87	81.52
Avg. fast-text embeddings	77.96	79.23	91.68	87.81	82.15	83.6	74.49	82.42
Avg. BERT embeddings	78.66	86.25	94.37	88.66	84.40	92.8	69.45	84.94
BERT CLS-vector	78.68	84.85	94.21	88.23	84.13	91.4	71.13	84.66
InferSent - GloVe	81.57	86.54	92.50	**90.38**	84.18	88.2	75.77	85.59
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SBERT-NLI-base	83.64	89.43	94.39	89.86	88.96	89.6	**76.00**	87.41
SBERT-NLI-large	**84.88**	**90.07**	**94.52**	90.33	**90.66**	87.4	75.94	**87.69**

Table 5: Evaluation of SBERT sentence embeddings using the SentEval toolkit. SentEval evaluates sentence embeddings on different sentence classification tasks by training a logistic regression classifier using the sentence embeddings as features. Scores are based on a 10-fold cross-validation.

ICE #1

Let's say we want to automatically convert a **Natural Language Query** to a **SQL** query. E.g. "Which quarter in the past 5 years had the most amount of sales for fashion products" to "SELECT ... FROM ... WHERE ..." What kind of deep learning architecture would support this problem?

1. SBERT
2. LSTM to LSTM sequence model
3. GPT-2
4. Feed Forward Neural Network

Fine-Tuning Transformers for down-stream tasks

A methodology for fine-tuning transformers for classification tasks

1. **Pick Base pre-trained Architecture:** Pick a base pre-trained architecture as a starting point for your fine-tuning. Example: `bert-base-uncased` is one such pre-trained model that can be loaded through `Hugging Face Transformers Library`

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4. **Set training schedule, hyper-parameters, etc:** Set up optimizer (e.g. ADAM), hyper-parameters, training schedule, etc for training.

ICE #2

BERT Embeddings and Emotion Detection

Let's say you want to do emotion detection by fine-tuning BERT (Encoding Transformer) on a data set. One of the outputs of the *BERT pre-trained model* for a given input is the *last-hidden-state*. This includes an embedding for every token that was passed into BERT.
Let's say you are going to start with the last hidden layer and use that as input for your *fine-tuned* model. This ICE is about the dimensionality of the inputs and outputs. Let's say you have sentences of the kind: "I am looking forward to today! It's going to be a big day" This sentence conveys excitement. There are 13 words in this input and using *word-piece tokenization*, you arrive at 20 sub-tokens as input into the BERT model. The last hidden layer includes an embedding for every single token. Let's say the embedding dimension for a token is 768.

ICE #2 continued

BERT Embeddings and Emotion Detection

There are 13 words in this input and using *word-piece tokenization*, you arrive at 20 sub-tokens as input into the BERT model. The last hidden layer includes an embedding for every single token. Let's say the embedding dimension for a token is 768. For the purpose of emotion detection - You can either use the *CLS* token (Start token) embedding (also called the pooled embedding) or you can take the average of the embeddings of the tokens in the last hidden layer of BERT. a) What's the dimension of the pooled BERT embedding of this particular input example b) What's the dimension of the CLS/Start token embedding in this example? c) what's the total dimension of the last hidden layer?

1. 768, 15630 and 768
2. 768, 768 and 768
3. 15360, 768 and 15630
4. 768, 768 and 15360

ICE #3

Why does pooling of the output need to be done for sequence classification (e.g. emotion detection)?

1. Reduces the dimensionality
2. Averages context from all the tokens
3. Computational concerns for training the fine-tuned model
4. All of the above

Application of SBERT Embeddings to Instacart Recommendations

Instacart Recommendations

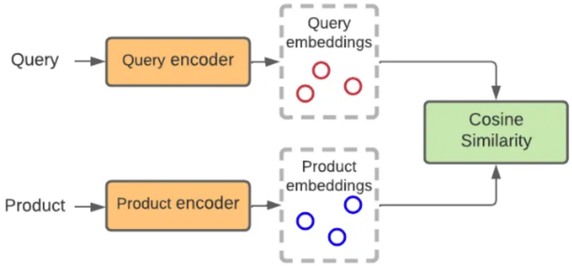
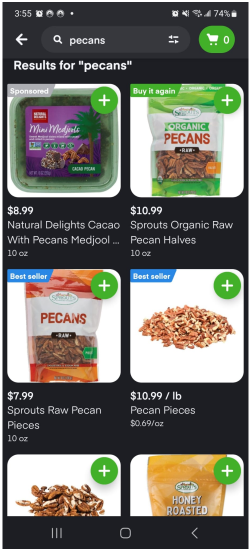


Figure 1. Conceptual diagram of a two-tower model

Positive Examples



3:55 • 74%

pecans

0

Results for "pecans"

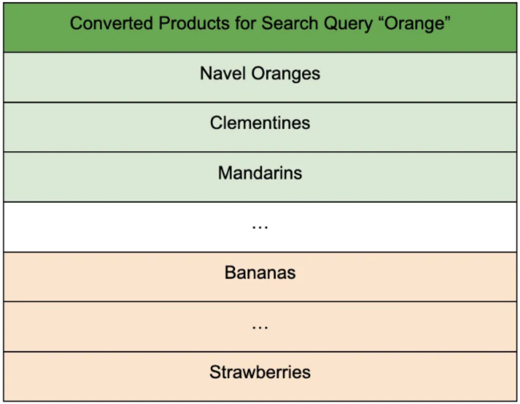
$8.99
Natural Delights Cacao With Pecans Medjool ...
10 oz

$10.99
Sprouts Organic Raw Pecan Halves
10 oz

$7.99
Sprouts Raw Pecan Pieces
10 oz

$10.99 / lb
Pecan Pieces
$0.69/oz

High-quality Positive Examples



Converted Products for Search Query “Orange”
Navel Oranges
Clementines
Mandarins
...
Bananas
...
Strawberries

Negative Examples

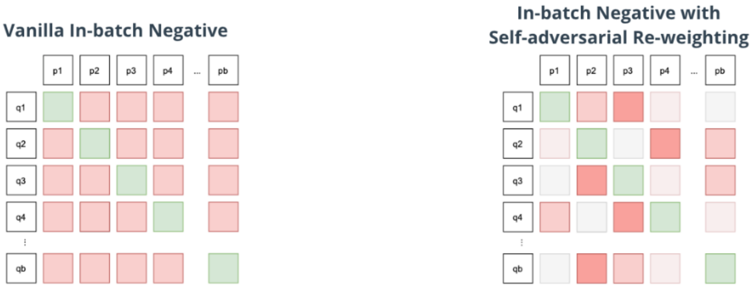

Vanilla In-batch Negative
p1
p2
p3
p4
...
pb
q1
q2
q3
q4
qb
In-batch Negative with Self-adversarial Re-weighting
p1
p2
p3
p4
...
pb
q1
q2
q3
q4
qb

Figure 3. (Left) In the vanilla implementation of in-batch negative, all off-diagonal negative samples are given the same weight. (Right) In our implementation with self-adversarial re-weighting, harder examples are given more weight (darker color), making the task more challenging for the model.

Model Training Architecture

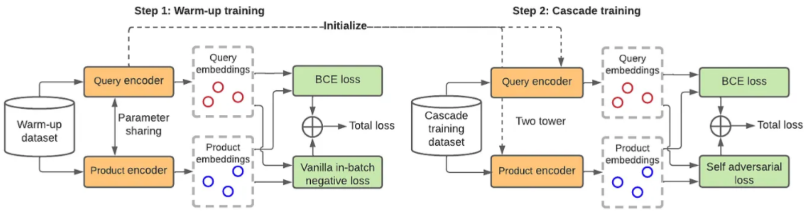


Figure 4. Two-step cascade training for ITEMS.

System Design

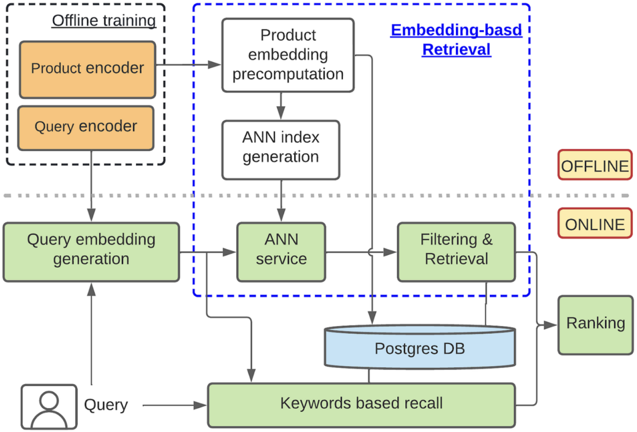


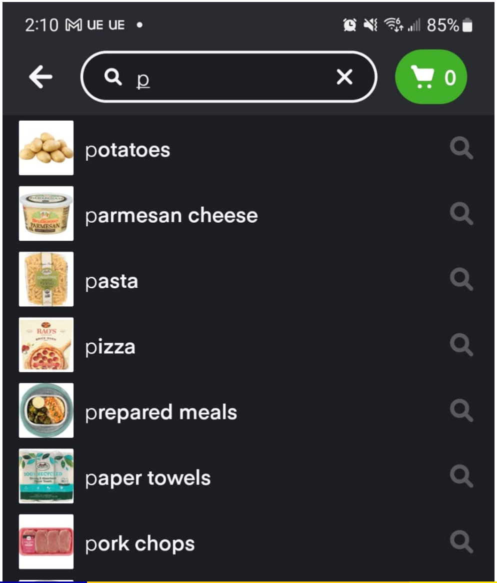
Figure 7. ITEMS system architecture.

Breakouts Time #1

Auto-complete — 5 mins

Let's say you are tasked with building an in-email auto-completion application, which can help complete partial sentences into full sentences through suggestions (auto-complete). How would you use what we have learned so far to model this? What architecture would you use? What would be your data? And what are some pitfalls or painpoints your model should address?

Instacart Auto-Complete and Search Relevance



2:10 UE UE • 85%

p

0

potatoes

parmesan cheese

pasta

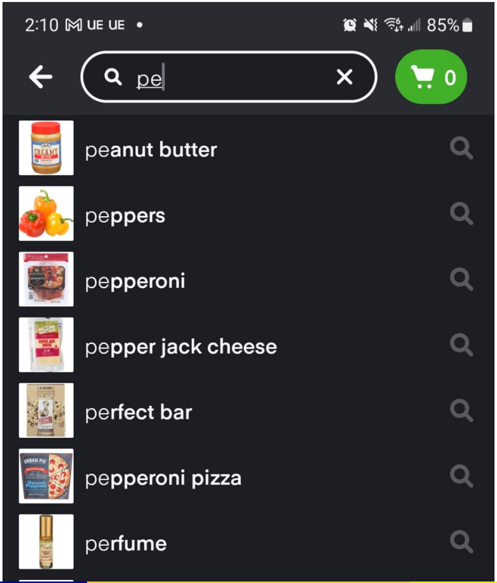
pizza

prepared meals

paper towels

pork chops

Instacart Auto-Complete


2:10 UE UE 85%

pe

0

peanut butter

peppers

pepperoni

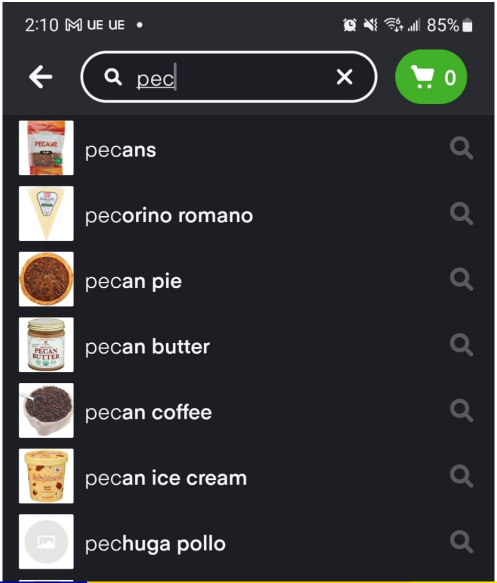
pepper jack cheese

perfect bar

pepperoni pizza

perfume

Instacart Auto-Complete



2:10 UE UE • 85%

pec

0

pecans

pecorino romano

pecan pie

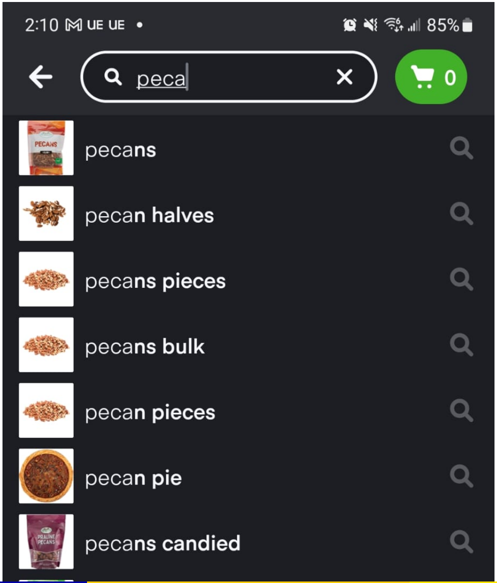
pecan butter

pecan coffee

pecan ice cream

pechuga pollo

Instacart Auto-Complete


2:10 85%

peca

0

pecans

pecan halves

pecans pieces

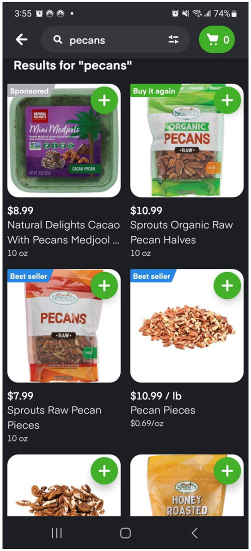
pecans bulk

pecan pieces

pecan pie

pecans candied

Instacart Auto-Complete and Search Results



pecans

Results for "pecans"

Sponsored
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Pecan Pieces
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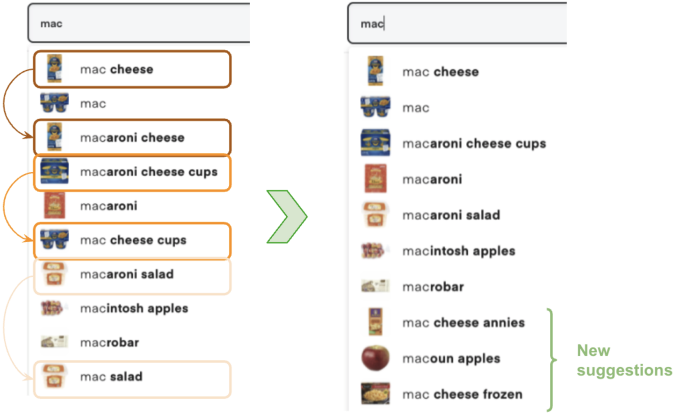
Instacart Diversifying Auto-Complete



mac

- mac cheese
- mac
- macaroni cheese
- macaroni cheese cups
- macaroni
- mac cheese cups
- macaroni salad
- macintosh apples
- macrobar
- mac salad

mac

- mac cheese
- mac
- macaroni cheese cups
- macaroni
- macaroni salad
- macintosh apples
- macrobar
- mac cheese annies
- macoun apples
- mac cheese frozen

Figure 9. Autocomplete when a customer searches for "mac", before (left) and after (right) semantic deduplication.