# EEP 596: LLMs: From Transformers to GPT || Lecture 8

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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

# Previous Lecture

- Multi-Head Attention
- Triplet Loss vs Classification Loss
- Fine-tuning BERT and SBERT
- Application of Embeddings to Autocomplete and Search Relevance

# Today's lecture

- Application of SBERT and tranformers to Instacart business use-case
- Design of Recommender Systems

# Recap on Instacart Recommendations

# Instacart Recommendations

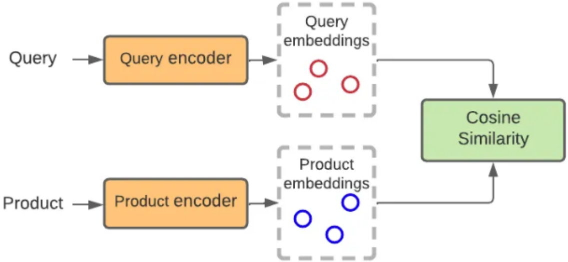


Figure 1. Conceptual diagram of a two-tower model

# Two Tower Architecture

### Two Towers

Self-explanatory, but there are two towers that represent two distinct objects (e.g. sentence A and sentence B or query and product or customer and product, etc).

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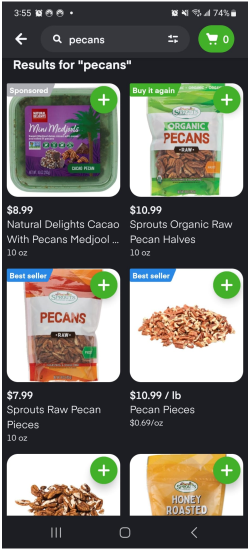
## Instacart/Recommendations Two Tower

In this example, the two towers don't refer to the same kind of object (e.g. sentence) but refer to a product and query. Hence the two towers have distinct weights learned from the data.

# Positive Examples



# High-quality Positive Examples

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

# Negative Examples

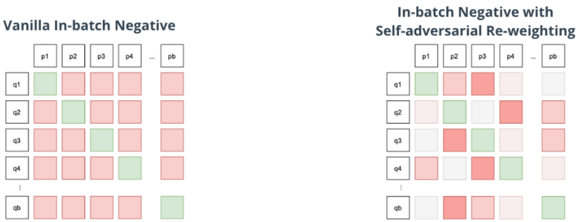



Figure 3. (Left) In the vanilla implementation of in-batch negative, all off-diagonal negative samples are given the same weight. (Right) In our implementation with self-adversarial re-weighting, harder examples are given more weight (darker color), making the task more challenging for the model.

# Negative Examples

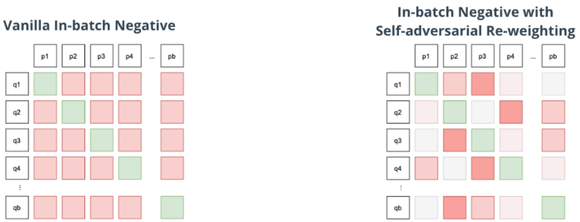



Figure 3. (Left) In the vanilla implementation of in-batch negative, all off-diagonal negative samples are given the same weight. (Right) In our implementation with self-adversarial re-weighting, harder examples are given more weight (darker color), making the task more challenging for the model.

## Self-adverserial data annotation

**Easy Negative examples:** Tortilla → Coffee mug
**Hard Negative examples:** Tortilla → Tostitos Tortilla Chips

# Data Augmentation for Data Set expansion

**Two kinds of Data Augmentation/Data Expansion**

1. **Expanding Product Signals:** This refers to not just using product titles but also product description or even images (multi-modal signals) for bettery *Product Embedding*
2. **Expanding Cold Start Data:** Products that just got launched or are new to the Instacart ecosystem get surfaced through data augmentation. Here - (Query, Product) examples are **synthetically** created as training data for the model so it can learn to recognize and recommend new products.

# Data Augmentation for Data Set exapansion

## Data Augmentation in LLM context

This is a fairly common strategy that gets used in NLP tasks and in the use of LLMs. For instance - Microsoft's **Phi** model, which is a **Small Language Model**(SLM) was trained in part with high-quality *textbook data*, where the textbooks themselves got generated using a more powerful GPT model!

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### LLMs as annotators and paraphrasers

Also used often, analogous to the previous Phi model example is annotating inputs with targets using an accurate GPT model or generating more training data through paraphrase of the input.

# Breakouts Time #1: Product Review Classification (12 mins)

## Classifying product reviews

Let's say that you are a data scientist at Sambazon! Sambazon is an online retailer selling millions of products under tens of thousands of product categories. You work in the **Review Moderation and Insights** team that is responsible for deriving actionable insights from customer reviews data. Your team's charter includes understanding the **intent** of the reviews - esp. if its useful or obnoxious. Your team's product manager (PM) suggests that as part of this years roadmap, the product team would like to understand reviews from the lens of the following categories: highly useful, highly passionate, obnoxious and balanced. How would you as a scientist a) approach this problem b) What would be your sources of data? c) What would be the ML approach you would use? d) How would you train the model? e) What if you didn't have labels in the data as your PM suggested? f) What if you had labels for training but not enough data?

# Model Training Architecture

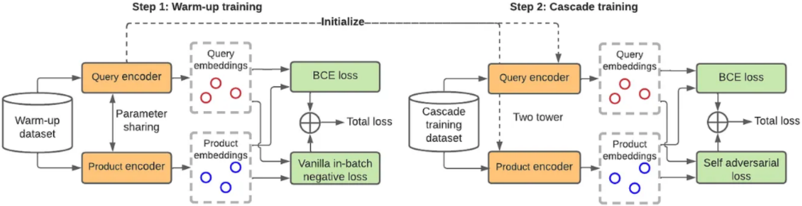



Figure 4. Two-step cascade training for ITEMS.

# System Design

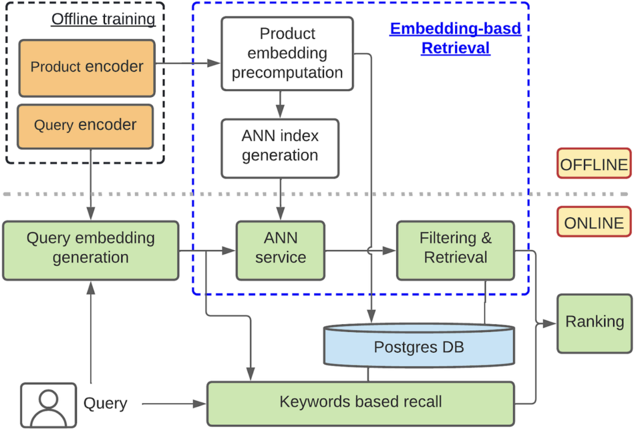


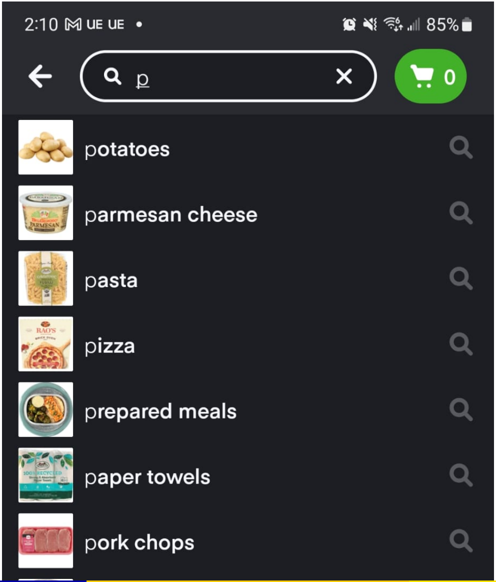

Figure 7. ITEMS system architecture.

# Breakouts Time #2

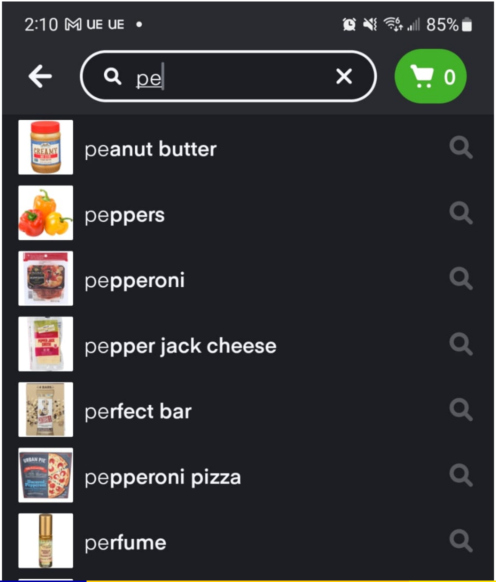
**Auto-complete — 5 mins**

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



# Instacart Auto-Complete



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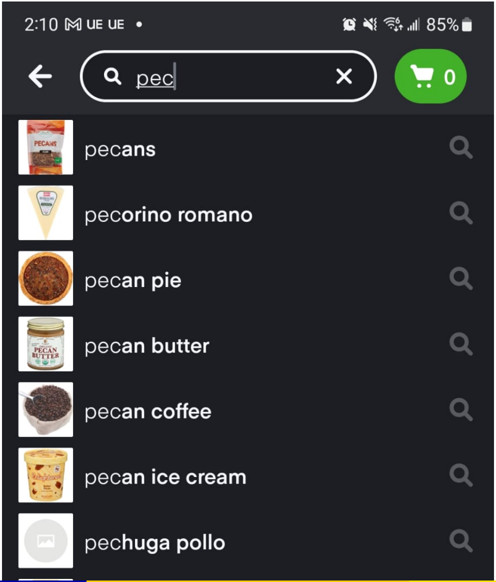

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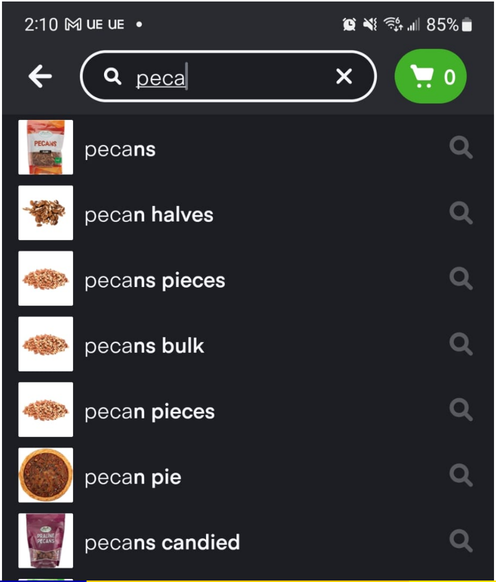
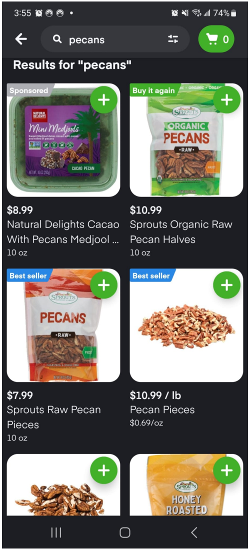


# Instacart Auto-Complete and Search Results



# Instacart Diversifying Auto-Complete

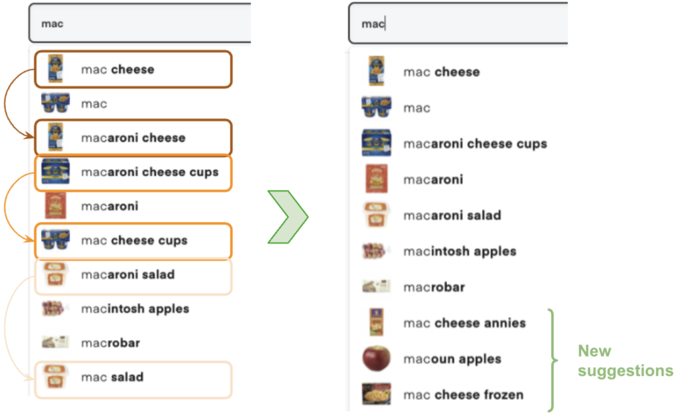



Figure 9. Autocomplete when a customer searches for “mac”, before (left) and after (right) semantic deduplication.