SearchGCN: Powering Embedding Retrieval by Graph Convolution Networks for E-Commerce Search

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Abstract

Graph convolution networks (GCN), which recently becomes new state-of-the-art method for graph node classification, recommendation and other applications, has not been successfully applied to industrial-scale search engine yet. In this proposal, we introduce our approach, namely SearchGCN, for embedding-based candidate retrieval in one of the largest e-commerce search engine in the world. Empirical studies demonstrate that SearchGCN learns better embedding representations than existing methods, especially for long tail queries and items. Thus, SearchGCN has been deployed into JD.com’s search production since July 2020.

CCS Concepts

• Computing methodologies → Neural networks; • Information systems → Information retrieval.

Keywords

Search; Neural networks; Graph convolution networks; Representation learning

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1 Introduction

E-commerce search, which serves as an essential part of online shopping platforms, typically consists of three steps: query processing, candidate retrieval and ranking. In this paper, we focus solely on the candidate retrieval step which aims to retrieve thousands of candidates from billions of items.

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Figure 1: Illustration of e-commerce search graph.

Despite the recent advance of embedding based retrieval methods [3] and their successful applications in candidate retrieval stage, in practice we still notice a few drawbacks: 1) representations of low-frequency items are not well learned due to their rare occurrences; 2) Query embeddings are computed purely from a handful of query tokens, which sometimes can not capture the query semantic meanings well; 3) The training efficiency is low, mainly because that each training example consists of only one pair of query and clicked item.

In this paper, we explore Graph Convolution Networks (GCN) to enrich entity representations by aggregating related neighbor’s information. In our case of e-commerce search, it is very likely that we can learn a better embedding representation for a user query, if we can aggregate information from the most clicked or bought items for the query to alleviate the shortage of query tokens. Likewise, we can learn a better item embedding representation, if we can aggregate information from the most frequent queries that lead to the item clicks or orders. Figure 1 shows a quick glance of typical e-commerce graph which illustrates how a query aggregates information from related items. Moreover, we explore how to improve the training efficiency by neighbor sampling.

2 Method

Given a graph $G = (\mathcal{V}, \mathcal{E})$ where each $v \in \mathcal{V}$ stands for an entity node, and each $e \in \mathcal{E}$ stands for an edge between two entities, let’s denote the set of all the neighbors for a node $v$ as $\mathcal{N}_v$, the set of queries as $\mathcal{Q}$, and the set of items as $\mathcal{I}$, where $\mathcal{Q} \subseteq \mathcal{V}$ and $\mathcal{I} \subseteq \mathcal{V}$.

 Neighbor Aggregation. The core of GCN is to compute the $l$-th layer’s representation of a target node by all its neighbors and itself in $(l-1)$-th layer. Formally, we can define the aggregation operation as follows

$$h_v^l = \text{AGGREGATE}(h_{u}^{l-1}, h_{u}^{l-1}, v \in \mathcal{N}_v),$$

where $h_u^{l-1}$ denotes the $(l-1)$-th layer’s representation of node $u$. The aggregation results from the neighbors and itself are then combined through a feed-forward layer to get the final $l$-th layer embedding of node $v$.

$h_v^l = \text{ff}(\text{AGGREGATE}(h_{u}^{l-1}, h_{u}^{l-1}, v \in \mathcal{N}_v), h_v^{l-1}, w_v^l),$
where $h^l_v \in \mathbb{R}^d$ denotes the $d$-dimensional embedding representation of a node $v$ at $l$-th layer, the AGGREGATE function is a pooling function that takes the target node and all its neighbor nodes as inputs.

In SearchGCN, we use the following neighbor aggregation function that can be explained as a weighted sum of all its neighbors,

$$h^l_v = \sum_{u \in \mathcal{N}_v} d^{l-1}_u h^{l-1}_u,$$  

where $\mathcal{N}_v$ is the set of neighbors of node $v$. $d^{l-1}_u$ is the weight of edge $(u, v)$.

### Neighbors Sampling
Since our e-commerce graph has hundreds of millions of nodes and billions of edges, which is too large to be fully loaded into computer memory, and the e-commerce graph appears to be significant imbalance, which makes the neighbor aggregation expensive. Therefore, to be practical in an industrial system, we need to develop a neighbor sampling approach that is efficient in both memory and computation.

First, we prune the neighborhood size for each node to at most 50, by the weights of the edges between each neighbor and the target node, to allow us to load all edges into memory during the training. Second, we introduce randomness to neighbor sampling, by sampling some fixed number (e.g., 10) of neighbors according to edge weights, to reduce the computational cost to aggregate neighbors and increase model generalization ability.

### Experiments
We conduct experiments on a data set of 60 days’ user click logs and we can assume that if an item is clicked for a query, the item is relevant to the query.

#### Offline Evaluation
We compare SearchGCN with a few baseline methods and report the evaluation results in Table 1. SearchGCN-mean adopts mean aggregator that gives equal weight to all neighbors. SearchGCN-attention adopts attention mechanism in aggregation function as shown in Eqs. (1) and (2). SearchGCN-mask adopts neighbor masking on both query and item side to mask the target query and item.

#### Online A/B Tests
We conducted live experiments over 10% of the entire site traffic during a period of one week using a standard A/B testing configuration. To protect confidential business information, only relative improvements are reported. Table 2 shows that the proposed SearchGCN retrieval improves the production system for core business metrics in e-commerce search, including user conversation rate (UCVR), revenue per mille (RPM) and gross merchandise value (GMV). As a result, the proposed SearchGCN has been deployed into JD.com’s search production since July 2020.

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