content2vec

specializing joint representations of product images and text for the task of product recommendation

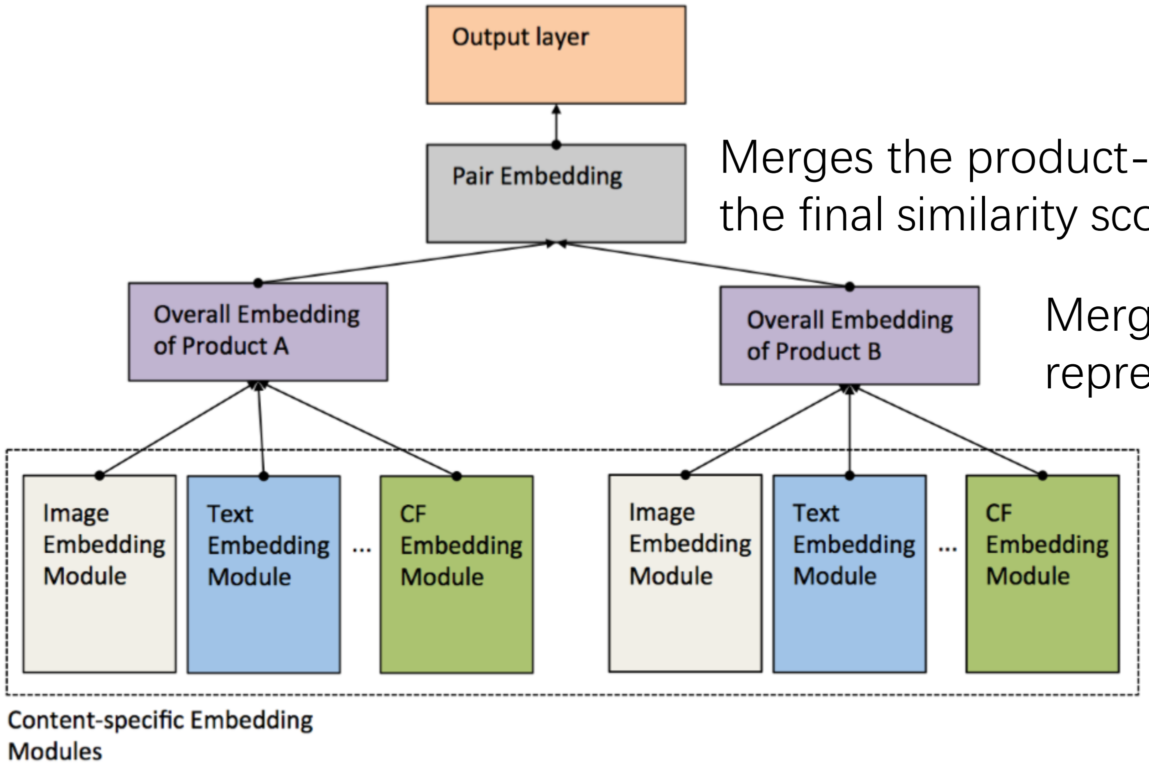
Motivation

- 对电商平台（Amazon，淘宝，Ebay等）中的商品进行向量表示
- 表示学习是基于商品的image, product title , description text和 CF information
- 得到的物品表示向量可以应用在不同任务的推荐系统上，可以解决冷启动和交叉类别的问题

Contribution

- 1. 多模态数据混合的商品推荐的网络结构
- 2. Pairwise Residual Unit –   a new learning component that models the joint product representations.
- 3. 进行了冷启动实验(hard/soft)和交叉类别实验，效果很好

content2vec model architecture



Merges the product-to-product interactions and computes the final similarity score.

Merge all the product information into a unified product representation.

take raw product information and generate the associated vectors.

Content2Vec architecture combines content-specific modules with residual vector to produce embedding vector for each product, then uses these vectors to compute similarities between products.

Function loss

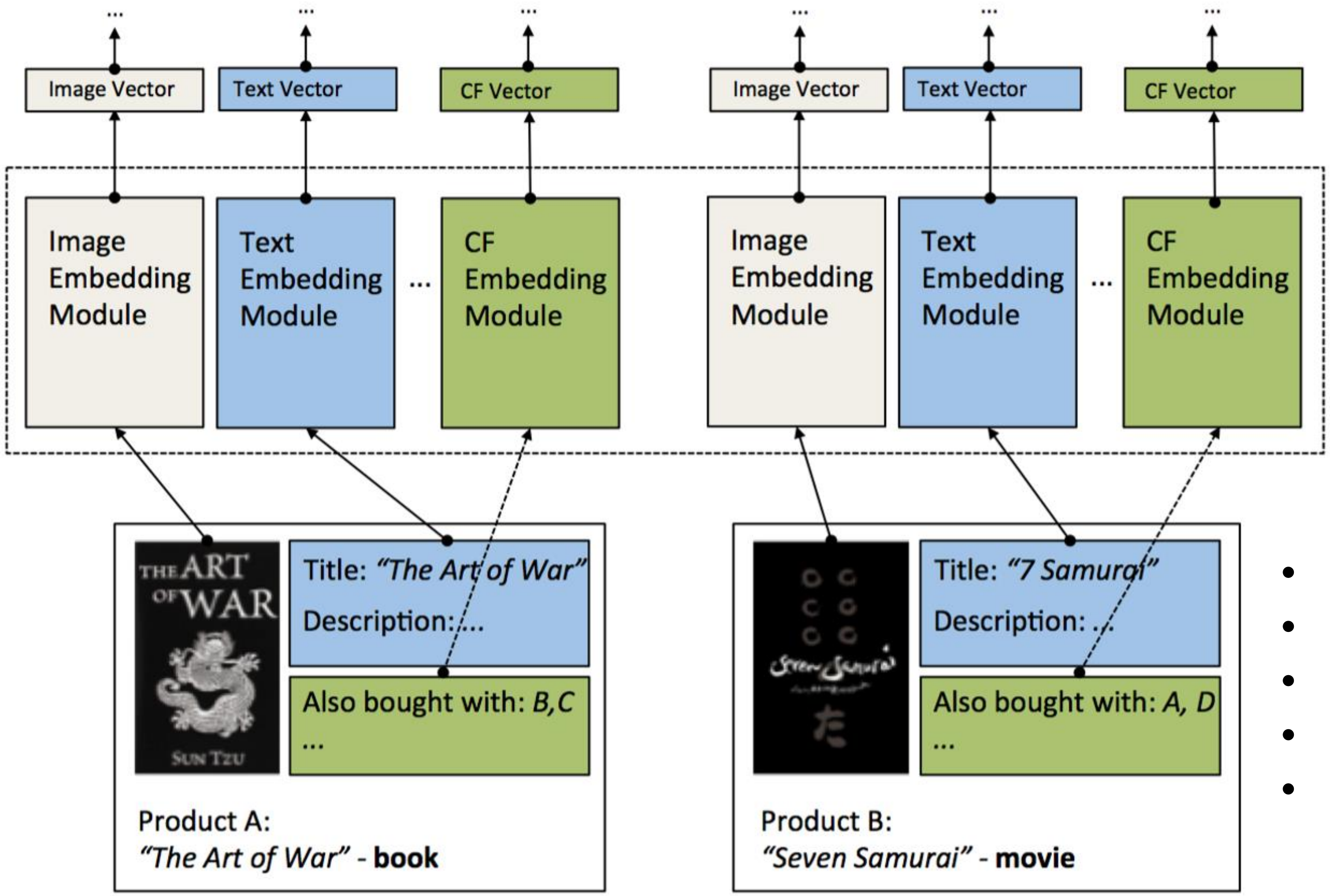
- logistic similarity loss

$$L(\theta) = \sum_{ij} -X_{ij}^{POS} \log \sigma(sim(a_i, b_j)) - X_{ij}^{NEG} \log \sigma(-sim(a_i, b_j)) \tag{1}$$

$$L_{NS}(\theta) = \sum_{ij} -X_{ij}^{POS} (\log \sigma(sim(a_i, b_j)) + \sum_{l=1}^{k} \mathbb{E}_{n_l \sim P_D} \log \sigma(-sim(a_i, n_l))) \tag{2}$$

where:
$\theta = (a_i, b_j)$ is the set of model parameters, where a_i and b_j are the embedding vectors for the products A and B,
$sim(a_i, b_j) = \alpha < a_i, b_j > +\beta$ is the similarity function between a_i and b_j, α and β are scalar values,
X_{ij}^{POS} is the frequency of the observed item pair ij (e.g. the frequency of the positive pair ij),
$X_{ij}^{NEG} = X_i - X_{ij}^{POS}$ is the frequency of the unobserved item pair ij (we assume that all unobserved pairs are negatives),
P_D probability distribution used to sample negative context examples n_l,
k is a hyper parameter specifying the number of negative examples per positive example.

content2vec modules



- 图像信息：AlexNet for Image Classification
- 文本信息：Word2vec、Text CNN
- CF信息： prod2vec
- 类别信息： META-prod2vec
- joint product embedding： pairwise residual unit

experiments

- Hard cold start regime : all product pairs used in validation and testing are over products unseen in training. This tests the hardest recommendation setup, where all testing data is new.
- non-cold start regime: the vast majority of the products in the test set are available at training time.
- soft cold start regime: some of the products in the test set are available at training time.

Evaluation

- Task: product link prediction task, similar to (He & McAuley, 2015).
- the observed product pairs as positive examples and all unknown pairs as negatives.
- generate negative pairs according to the popularity of the products in the positive pairs (negative examples between popular products are more likely to be generated) with a positive to negative ratio of 1:2.
- Metrics: AUC(for the link prediction task,)

results

Recommendation Model	Books	Movies	Mixed
Models trained on Books dataset			
Book ImageCNN specialized	81%	78%	64%
Book TextCNN	72%	79%	76%
Book Content2Vec-linear	83%	83%	76%
Book Content2Vec-crossfeat	86%	83%	83%
Book Content2Vec-res	89%	83%	77%
Book Content2Vec-embedpairs	90%	82%	77%
Models trained on Movies dataset			
Movie ImageCNN specialized	59%	92%	60%
Movie TextCNN	63%	90%	65%
Movie Content2Vec-linear	64%	94%	65%
Movie Content2Vec-crossfeat	62%	94%	63%
Movie Content2Vec-res	60%	95%	66%
Movie Content2Vec-embedpairs	64%	94%	65%

Table1: AUC results of image and text-based embeddings on hard cold-start data set on Book, Movie and Mixed category test product pairs.

results

Recommendation Model	Test
Content2Vec-linear	84%
Content2Vec-res	87%
Prod2Vec	96%
Content2Vec-linear+	97%
Content2Vec-res+	97%

Table 2: AUC results on non cold-start dataset.

Recommendation Model	Test
ImageCNN	80%
TextCNN	78%
Content2vec-linear	88%
Content2vec-res	89%
Content2vec-embed_pairs	90%
Prod2vec	86%
Content2vec-linear+	89%
Content2vec-res+	92%
Content2vec-embed_pairs+	92%

Table 3: AUC results on soft cold-start dataset.

extention

- 快手比赛数据训练集和测试集的item完全不同，user完全相同
- 可以假设每个用户点击的item为相似item，在测试集里加入一些训练集里加入训练集中被user点击的item，然后用训练集进行训练。
- 预测混合后的测试集，输出的是两个item之间的相似度，找出与之前被点击的item足够相似的item，判定为点击。
- 参考实验中soft-cold-start部分的结果