

Co-Promotion Predictions of Financing Market and Sales Market: A Cooperative-Competitive Attention Approach

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Abstract

Market popularity prediction has always been a hot research topic, such as sales prediction and crowdfunding prediction. Most of these studies put the perspective on isolated markets, relying on the knowledge of certain market to maximize the prediction performance. However, these market-specific approaches are restricted by the knowledge limitation of isolated markets and incapable of the complicated and potential relations among different markets, especially some with strong dependence such as the financing market and sales market. Fortunately, we discover potentially symbiotic relations between the financing market and the sales market, which provides us with an opportunity to co-promote the popularity predictions of both markets. Thus, for bridgily learning the knowledge interactions between financing market and sales market, we propose a cross-market approach, namely *CATN: Cooperative-competitive Attention Transfer Network*, which could effectively transfer knowledge of *financing capability* from the crowdfunding market and *sales prospect* from the E-commerce market. Specifically, for capturing the complicated relations especially the cooperation or complement of items and enhancing the knowledge transfer between the two heterogeneous markets, we design a novel *Cooperative Attention*; meanwhile, for finely computing the relations of items especially the competition in specific same market, we further design *Competitive Attentions* for the two markets respectively. Besides, we also distinguish aligned features and unique features to adapt the cross-market predictions. With the real-world datasets collected from *Indiegogo* and *Amazon*, we construct extensive experiments on three types of datasets from the two markets and the results demonstrate the effectiveness and generalization of our CATN model.

Introduction

With the popularity of the E-commerce market, predictions on market popularity have attracted widespread attention (Chatfield 2016; Mills and Mills 2016; Chen et al. 2019). Recently, some scholars are moving to some emerging financing markets such as the crowdfunding (Xu and Cai 2021; Du, Wang, and Li 2020; Li, Rakesh, and Reddy 2016). Studies on the area of E-commerce market pay more attention to the public praise and transaction results, while the studies on crowdfunding emphasize the process of funding and interacting with investors.

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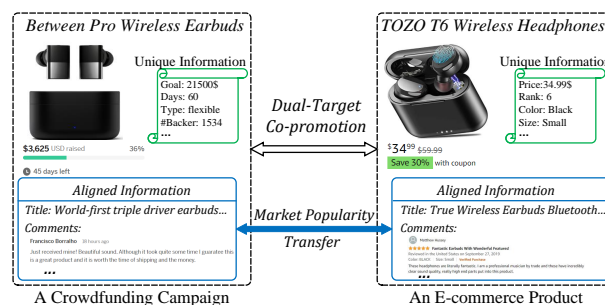


Figure 1: An illustration of crowdfunding and E-commerce.

However, most of these studies put the perspective only on isolated markets. Although they have achieved some excellent results, these market-specific approaches have brought a limit or border to their effectiveness. Firstly, the knowledge limitation of isolated markets leads to the lack of external knowledge of items. As shown in Figure 1, the dotted rectangle on the left represents a crowdfunding campaign of producing headphone in Indiegogo¹, and the right dotted rectangle is a relevant headphone selling in Amazon². Obviously, for newly released campaigns in the crowdfunding market, the sales prospects of ventures are unknown. But it can be inferred from the performance (e.g., the *rating*, *reviews*) of similar products in the sales market. Similarly, the financing performance (e.g. *funding amount*) of campaigns in the crowdfunding market is also valuable for estimating the popularity of E-commerce market. Secondly, the complicated knowledge interactions of items between different markets have not been well exploited. Specifically, the resonant items of financing and sales markets may have a co-promoting cooperative relation in predicting popularity considering the market dependence, while there may be a competitive relations between similar items in specific one market with competing for users. Unfortunately, typical transfer learning approaches may suffer from the low performance when facing the heterogeneous markets, i.e., the financing and sales markets in this study. Besides, traditional methods are also incapable of capturing these above important market relations in prediction.

¹<https://www.Indiegogo.com/>

²<https://www.Amazon.com/>

To address these challenges, we propose a novel approach focusing on a typical financing market and sales market, i.e., crowdfunding and E-commerce, namely *CATN: Cooperative-competitive Attention Transfer Network*. By this way, knowledge could be effectively transferred from heterogeneous markets to co-promote the prediction performance. Specifically, as shown in Figure 2, CATN is equipped with two collaborative prediction tasks, one is designed for predicting sales volume in E-commerce and the other is for predicting funding amount in crowdfunding. For a newly-posted campaign, we can transfer the sales prospect knowledge of relevant products in the E-commerce market to enhance campaigns’ funding performance prediction. Conversely, for selling products in the E-commerce market, we can also transfer the financing capability from crowdfunding market to the E-commerce for popularity prediction. For capturing the complicated relations especially the cooperation or complement of items and also enhancing the knowledge transfer between the two heterogeneous markets, a novel *Cooperative Attention* is designed; meanwhile, for finely computing the relations of items especially the competition in specific same market, two *Competitive Attentions* for the two markets are further suggested respectively. In addition, for alleviating the impacts of negative transfer caused by market peculiarities, we distinguish aligned features and unique features in feature design. The contributions of this paper are threefold.

- **Problem view.** We discover potentially symbiotic relations between the financing market and sales market, which inspires us to construct an interesting study between the E-commerce market and crowdfunding market. Through cross-market transfer learning, we can co-promote the popularity predictions of the two markets.
- **Technical view.** We propose a knowledge-transfer framework, namely CATN, to co-promote the popularity predictions of heterogeneous markets. Second, we innovatively design cooperative attention and competitive attention to model the complicated relations between heterogeneous markets.
- **Experimental view.** With the real-world datasets collected from *Indiegogo* and *Amazon*, we construct extensive experiments on three types of items in the two markets. Experimental results on both markets verify the generalization and effectiveness of CATN.

Related Work

Market analysis has been broadly studied, represented by the sales of products in E-commerce. For traditional E-commerce market, some works treated sales prediction as a typical application of time series analysis, thus, several statistical regression models were developed (Chatfield 2016; Tsoku, Phukunsi, and Metsileng 2017). However, these models predicted the value changes from the sequence itself without considering the impacts from other factors. Therefore, some deep learning methods were proposed to incorporate auxiliary information to enhance sales prediction effects. Zhao and Wang (2017) and Qi et al. (2019) proposed

methods based on CNN and Seq2Seq to predict sales respectively. But these single-domain approaches have the defect of knowledge sparse. For solving this problem, many transfer learning (Long et al. 2015; Pan and Yang 2009; Sun and Saenko 2016) based methods have emerged. These works treated different congeneric products or E-commerce platforms as different domains, and extracted the knowledge from the auxiliary domain to apply it to the target domain. For example, Yuan, Yao, and Benatallah (2019) proposed the DAREc model to extract shared user rating patterns from two types of products, and then performed rating predictions. Fu et al. (2019) proposed a review and content based deep fusion model to make recommendations for cold start users. Unfortunately, these cross-domain approaches still cannot solve the problem of attributes lacking.

In addition to the typical focus on E-commerce, specific to funding market, for both funders and investors, entrepreneurial project evaluation is a significant and concerned problem. Extensive works have been done to study project evaluation and selection on investment decision (Hall and Hofer 1993; Hsu 2007). In these works, various determinants on funding evaluation have been well studied, e.g., informational asymmetry between funders and investors (Gompers 1995; Shane and Cable 2002), experience of founding teams (Delmar and Shane 2006), patents of enterprises (Bertoni, Croce, and D’Adda 2010). Different from the traditional venture capital, crowdfunding which is a new practice of funding a project or venture via the Internet, narrows the gap between funding market and sales market since the similarity of their operation mechanisms. In crowdfunding, tracking funding dynamics (Burtch, Ghose, and Wattal 2016; Mollick 2014) and predicting funding performance (Lu et al. 2014) are the most concerned issues. Specifically, Zhao et al. (2017) developed a novel two-layer framework that could capture the intrinsic relations between campaign-level dynamics and perk-level dynamics. Jin et al. (2019) proposed a Seq2seq based method to model the backing distribution and success time of crowdfunding campaigns. Zhao et al. (2020) proposed a Joint Deep Survival mode to jointly model the donation recurrence and donor retention in crowdfunding.

From the technical view of transfer learning, most traditional transfer learners are derived from items in the homogeneous market, and they are not good at solving the complex research scenarios of heterogeneous markets. Although the above-mentioned advanced approaches have achieved certain effects in their respective market prediction tasks, singularity of information sources and knowledge sparse still are their limitations. In this paper, we discover potentially symbiotic relations between the E-commerce market and crowdfunding market, and propose a cross-market transfer approach. Especially, this approach can co-promote the predictions of items in both markets. Besides, the complex interactions and large heterogeneity between markets that are not considered in the above-mentioned research, we adopt the attention mechanism (Bahdanau, Cho, and Bengio 2014) to enhance transfer and also propose to explore the cooperation and competition relations between items in different markets.

The Proposed Model

In this section, we first briefly introduce the mechanisms of *Indiegogo* and *Amazon*. Then, we formally define the problem and introduce technical details of our proposed model.

The Mechanisms of *Indiegogo* and *Amazon*

This study focuses on both financing markets and sales markets. As illustrated above, for narrowing the gap between the two types of markets, we select the emerging crowdfunding and E-commerce platforms considering their similar mechanisms. Specifically, *Indiegogo* and *Amazon* are respectively the representative ones.

Amazon is a famous E-commerce website with a huge number of users and a rich variety of products. The merchant publishes the title, price and other important parameters of products, and there are an abundant of comments, ratings for users to refer to. Users tend to buy their favorite products with a good reputation. Different from E-commerce, *Indiegogo* is a global website which crowdfunds innovations in technology and design before they go mainstream, and supports entrepreneurs that are working to bring their dreams to life. If entrepreneurs or individuals want to solicit money for their creative campaigns, a crowdfunding campaign posted by describing the title, story, fundraising information including the funding amount, funding period, fundraising progress and so on. In each campaign, *Indiegogo* allows coming visitors to post their comments and start discussion about this project. The discussion continues along with the fundraising process and the comments are gradually accumulated. The potential investors may decide whether to back this project based on comprehensively considering the campaign properties and comments. Combine the above introduction and the example shown in Figure 1, we can see that the two markets have some aligned features, i.e., features with similar functions, such as describing contents (*titles* and *descriptions*), user feedbacks (*comments* or *discussions*); they also have their own unique features, such as the price and ratings of products in *Amazon*, the goal and funding days of campaigns in *Indiegogo*.

Problem Formulation

Suppose the campaigns in crowdfunding market is $E = \{e_1, \dots, e_N\}$, and the products in E-commerce market is $P = \{p_1, \dots, p_M\}$. For each crowdfunding campaign e_i , we know the amount of raised funds $A_i \in \mathbb{R}$ and features including aligned ones a_i^e and unique ones u_i^e . For each E-commerce product p_i , its aligned features are a_i^p and the unique ones are u_i^p . We also know its product rating r_i and comments count rc_i , so we use $R_i = r_i \cdot \ln(rc_i)$ as the market popularity of E-commerce market products, $R_i \in \mathbb{R}$. Our goal is to learn a model \mathcal{M} with these given data and further apply \mathcal{M} to predict the funding performance A_j for the new-posted crowdfunding campaign $e_j \in E'$ when giving its aligned features a_j^e and unique features u_j^e , i.e. $\mathcal{M}(a_j^e, u_j^e) \rightarrow A_j$. For the newly launched product $p_j \in P'$ on the E-commerce market, we apply our proposed model \mathcal{M} to predict its popularity R_j when giving its a_j^p and u_j^p , i.e. $\mathcal{M}(a_j^p, u_j^p) \rightarrow R_j$.

In the following, we will give the details of the proposed model CATN for the co-promotion predictions problem, the framework of which is shown in Figure 2.

Feature Classification and Representation

For alleviating the impacts of negative transfer due to market peculiarities, we classify the features of each market. The first category is the aligned features of both markets, and the second category is the unique features of their corresponding markets, which are heterogeneous in form. For consistency, we carefully preprocess them. Especially, besides usual techniques such as one-hot encoding and Z-score transformation, for the text features like comments, we preliminarily conducted word segment using the National Language Toolkit (*nltk*)³ tool, and take *doc2vec* (Le and Mikolov 2014) to process different text features into vectorial representations. In particular, for better training on regression task, we scale the dependent variables of crowdfunding market, i.e., final funding amount A_i using $\ln(\cdot)$ function (Zhao et al. 2017). Then, we concatenate all the aligned features of E-commerce product p_i to form $a_i^p \in \mathbb{R}^{d_a^p}$, concatenate all the unique features of p_i to form $u_i^p \in \mathbb{R}^{d_u^p}$. Similarly, we get the aligned features $a_i^e \in \mathbb{R}^{d_a^e}$ and unique features $u_i^e \in \mathbb{R}^{d_u^e}$ of the crowdfunding campaign e_i . Specifically, $d_a^p, d_u^p, d_a^e, d_u^e$ are respectively the vectorial dimensions for $a_i^p, u_i^p, a_i^e, u_i^e$. Note that, the features of a_i^p and a_i^e are aligned, they have the same dimension, i.e., $d_a^p = d_a^e$. In the following, for the convenience of representation, we only use one symbol d_a for them indiscriminately.

Cooperative Attention

For capturing the cooperation or complement relations of resonant items and enhancing the transfer effectiveness between the two heterogeneous markets, we propose cooperative attention. Since it is necessary to obtain the transferring knowledge between markets through domain adaptation later, this component only acts on the aligned features, as shown in Figure 2. Moreover, the title and comments in the common knowledge contain a high degree of semantic richness. We hope to find reliable guidance for the target item from related items in the auxiliary market.

Specifically, for the target item, we first calculate the attention score of all items in the auxiliary market, and then assign a weight to all items in the auxiliary market as a guide intensity for the target item. Finally, we integrate the guidance of each item in the auxiliary market into the vector representation of the target item to improve the effect of predicting the market popularity of the target item.

Taking an E-commerce market product p_i as an example. The attention weight of all campaigns on the crowdfunding market are as follows,

$$\alpha_{i,j} = \exp\left(a_i^{p\top} \cdot a_j^e\right) / \sum_{k=1}^N \exp\left(a_i^{p\top} \cdot a_k^e\right), \quad (1)$$

where N is the number of crowdfunding market campaigns.

³<https://www.nltk.org>

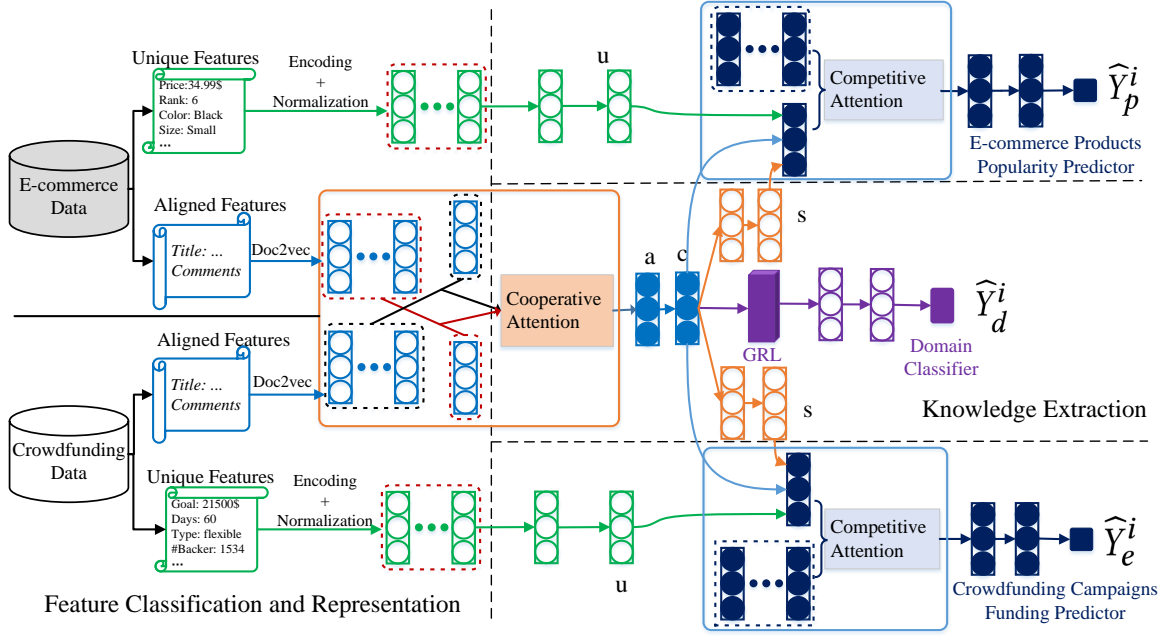


Figure 2: The Framework of CATN.

Then, the new aligned features a_i^p of the E-commerce product p_i that includes crowdfunding market guidance information is transformed into

$$a_i^p = \sum_{k=1}^N \alpha_{i,k} \cdot a_k^e. \quad (2)$$

Knowledge Extraction

In this section, we extract common knowledge c and specific knowledge s from the aligned features a . Besides, we use neural network to extract deeper features of market unique features u . We employ a multi-layer fully-connected network (FCN) to extract common knowledge and unique features' deeper representations of the two markets. Therefore, knowledge of both markets in the output layer of the FCN can be represented as follows,

$$\begin{aligned} c_i^p &= g(FCN(a_i^p)), u_i^p = g(FCN_p(u_i^p)), \\ c_i^e &= g(FCN(a_i^e)), u_i^e = g(FCN_e(u_i^e)), \end{aligned} \quad (3)$$

where the activation function $g(*)$ is *LeakyReLU*. It can be seen that a_i^p and a_i^e share the same FCN, while u_i^p and u_i^e are fitted with different FCN. To extract the common knowledge of a_i^p and a_i^e to achieve domain adaptation, we set up a domain classifier and add a gradient reversal layer as illustrated in (Ganin and Lempitsky 2014). The specific optimization process is in Model Optimization Section.

For c_i^p or c_i^e , two branches are designed to extract the specific knowledge and predict domain label respectively. Take c_i^p as an example, we can get the specific knowledge s_i^p and the domain feature h_d of the E-commerce product p_i , i.e.,

$$s_i^p = g(FCN(c_i^p)), h_d = g(FCN_d(c_i^p)). \quad (4)$$

Similarly, we can get the specific knowledge s_i^e and domain label classification feature h_d of the crowdfunding campaign e_i .

Competitive Attention

In Cooperative Attention Section, we have elaborated on how to capture cooperation relation between the two heterogeneous markets. For finely computing the competition relations of items in specific one market when predicting the market popularity of crowdfunding campaigns and E-commerce products, we propose a competitive attention which effectively improves the predictions. Through the above components, we have obtained the domain-invariant knowledge (i.e., sharing knowledge) c , specific knowledge s , and unique features u of both markets' items. For E-commerce market product p_i , we first get f_i^p by concatenating these three types of knowledge and features, and then calculate the competitive score of all products in E-commerce market and assign a weight to each product,

$$\begin{aligned} f_i^p &= g(FCN(u_i^p \oplus c_i^p \oplus s_i^p)), \\ \beta_{i,j}^p &= \exp(f_i^{p \top} \cdot f_j^p) / \sum_{k=1}^M \exp(f_i^{p \top} \cdot f_k^p), \end{aligned} \quad (5)$$

where M is the number of products on the E-commerce market. After getting competitive attention of various products in the E-commerce market, a comprehensive representation of the target product that includes the competitive relations can be represented as follows,

$$f_i^p = \theta_1 \cdot f_i^p + (1 - \theta_1) \sum_{k=1}^M \beta_{i,k}^p \cdot f_k^p, \quad (6)$$

where θ_1 is a parameter used to control the market's influence on the products in the prediction. Due to the large differences between different markets, it is necessary for us to introduce such parameters to balance the influence of products in E-commerce on the target product. For the crowdfunding market, it is the same mode of competitive attention.

$$\begin{aligned} f_i^e &= g(FCN(u_i^e \oplus c_i^e \oplus s_i^e)), \\ \beta_{i,j}^e &= \exp(f_i^{e \top} \cdot f_j^e) / \sum_{k=1}^N \exp(f_i^{e \top} \cdot f_k^e), \end{aligned} \quad (7)$$

where N is the number of campaigns on the crowdfunding market. we also use θ_2 to balance the influence of crowdfunding market campaigns on the target campaign. So the ultimate f_i^e of e_i can be represented as follows,

$$f_i^e = \theta_2 \cdot f_i^e + (1 - \theta_2) \sum_{k=1}^N \beta_{i,k}^e \cdot f_k^e. \quad (8)$$

Model Optimization

In this section, f^p and f^e of E-commerce products and crowdfunding campaigns are used to predict their popularity respectively. As shown in Figure 2, the prediction contains two components. One component predicts the popularity of products sold on E-commerce market, and the other predicts the funding performance of campaigns.

$$\hat{Y}_p^i = g(FCN(f_i^p)), \hat{Y}_e^i = g(FCN(f_i^e)). \quad (9)$$

Besides, for the items of both markets, the domain invariance needs to be reflected from their common knowledge, so we set up a domain classifier to predict their respective domain labels according to h_d in Knowledge Extraction Section, i.e.,

$$\hat{Y}_d^i = \text{Sigmoid}(W^d \cdot h_d + b^d), \quad (10)$$

where the W^d, b^d are the weights of network.

For training CATN, we design three loss functions. Specifically, the first loss function is in E-commerce market which is for sales products popularity prediction, the second is in crowdfunding market which is for campaigns funding performance prediction, and the last one is the loss function of the domain classifier shared by both markets. The definitions are as follows,

$$\begin{aligned} \text{Popularity Loss} \quad \mathcal{L}_p(\Theta_p) &= \frac{1}{N_p} \sum_{n=1}^{N_p} (R_i - \hat{Y}_p^i)^2, \\ \text{Funding Loss} \quad \mathcal{L}_e(\Theta_e) &= \frac{1}{N_e} \sum_{n=1}^{N_e} (A_i - \hat{Y}_e^i)^2, \\ \text{Domain Loss} \quad \mathcal{L}_d(\Theta_d, \Theta'_d) &= - \sum_{i=1}^{N_d} Y_d^i \log(\hat{Y}_d^i), \end{aligned} \quad (11)$$

where $\Theta_p, (\Theta_d, \Theta'_d), \Theta_e$ are the optimized parameters in the corresponding routes of CATN. N_p, N_d, N_e are the instance numbers in training sets. We alternately train the data of the E-commerce market and the crowdfunding market to optimize the parameters. When we train E-commerce market products data, $N_d = N_p$; while $N_d = N_e$ when training on crowdfunding market campaigns. Take training process of E-commerce products as an example, the popularity predictor and domain classifier have some common parameters Θ_d (i.e., blue modules in *Knowledge Extraction* component), and Θ'_d are the other parameters in route of domain classifier. For making the feature distribution between markets as similar as possible to extract common knowledge, we seek the parameters Θ_d that maximizes the loss of the domain classifier, while simultaneously seeking the parameters Θ'_d of the domain classifier that minimizes the loss of the domain classifier. Besides, we seek to minimize the loss of the popularity predictor. The total loss function is the combination of the predictor loss and the classifier loss, i.e.,

$$L(\Theta_p, \Theta_d, \Theta'_d) = \mathcal{L}_p(\Theta_p) - \lambda \mathcal{L}_d(\Theta_d, \Theta'_d), \quad (12)$$

where λ controls the trade-off between these two objectives. The optimization objective can be expressed as follows,

$$\begin{aligned} (\hat{\Theta}_p, \hat{\Theta}_d) &= \arg \min_{\Theta_p, \Theta_d} L(\Theta_p, \Theta_d, \Theta'_d), \\ \hat{\Theta}'_d &= \arg \max_{\Theta'_d} L(\Theta_p, \Theta_d, \Theta'_d). \end{aligned} \quad (13)$$

To optimize the objective by stochastic gradient descent (SGD)-like algorithms, the original DANN (Ganin and Lempitsky 2014) introduces the gradient reversal layer (GRL). GRL is a simple structure that has different behaviours for forward and back propagation with no intrinsic parameters. In forward propagation, GRL acts as an identity function to let data pass through, while in back propagation, it calculates the gradient from the subsequent level, multiplies it by $-\lambda$ and then passes it to the preceding layer. Formally, GRL can be treated as a “function”, i.e.,

$$\begin{aligned} \Phi(\mathbf{x}) &= \mathbf{x} \quad (\text{forward propagation}), \\ \frac{d\Phi(\mathbf{x})}{d\mathbf{x}} &= -\lambda \mathbf{I} \quad (\text{back propagation}), \end{aligned} \quad (14)$$

where \mathbf{I} is the identity matrix. GRL is placed immediately after common Knowledge extraction and before the domain classifier. Therefore, the total loss function adapted to SGD-like algorithm is converted as follows,

$$\tilde{L}(\Phi, \Theta_p, \Theta_d, \Theta'_d) = \mathcal{L}_p(\Theta_p) + \lambda \mathcal{L}_d(\Phi, \Theta_d, \Theta'_d). \quad (15)$$

The parameter optimization of crowdfunding-related is the same way. Then, we apply it on popularity prediction for new-start sales products P' and also predict the funding performance of new-start crowdfunding campaigns E' with inputting their aligned features a_j and unique features u_j .

Experiments

In this section, we first introduce the data preprocessing, experimental setup, and then analyze the experimental results from various aspects.

Data Preprocessing

We collect three types of items from *Indiegogo* and *Amazon* as experimental data, i.e., *Fashion, Food, Technology*. After removing some items only with punctuation or special symbols, or without any comments, there is still have 2,402 campaigns and 4,066 products. Table 1 shows the detailed statistics information. In practice, we combine all the comments of one item into a long text, which could represent complete features of this item’s comments. To guarantee training accuracy, we divide these instances into training instances, validation instances, and test instances. Their proportions are 70%, 20%, and 10% respectively.

Table 1: The statistics of the datasets.

Markets datasets	E-commerce			Crowdfunding		
	<i>Fashion</i>	<i>Food</i>	<i>Tech.</i>	<i>Fashion</i>	<i>Food</i>	<i>Tech.</i>
# Instances	1,713	1,151	1,202	725	894	783
# Reviews	119,910	80,570	84,140	4,748	14,214	151,022
# Average reviews	70	70	70	6.5	12.8	192.8

Experimental Setup

Parameter Setting. For fair comparison, we optimize the parameters of CATN and several representative baselines. In the Feature Classification and Representation, items’ comments dimension is set to 400, and the title dimension is set to 100 by doc2vec. For the parameters of all the neural network are initialized as the Gaussian distribution $X \sim \mathcal{N}(0, 0.01)$. According to (Ganin and Lempitsky 2014), we gradually change λ from 0 to 1 using the following schedule, i.e.,

$$\lambda = \frac{2}{1 + \exp(-\gamma \cdot p)} - 1, \quad (16)$$

where γ was set to 10 in all experiments. p is the training progress linearly changing from 0 to 1. Besides, The parameter θ_1 in the competitive attention that is responsible for balancing the competitive influence of the E-commerce market is set to 0.1 on the three datasets of *Fashion*, *Food*, and *Technology*. For the parameter θ_2 , through parameter tuning experiments, we find the best values under different types of datasets. Among them, θ_2 in the *Fashion* and *Technology* category is set to 0.9, and $\theta_2 = 0$ in the *Food* dataset.

Comparison Methods and Metrics. For better evaluating CATN, we conduct extensive experiments on traditional machine learning methods and the variants of CATN.

- CNN is a standard convolutional neural network (Santos and Gatti 2014; Kim 2014) with inputting the campaign(product) properties and comments.
- RR is the Ridge Regression algorithm (Hoerl, Kannard, and Baldwin 1975) which is applied to the formalized regression task.
- MLP (Multilayer Perceptron (Bengio 2009)) is also called Artificial Neural Network. Besides the input and output layers, it can have multiple hidden layers.
- CATN-Coo is a variant without cooperative attention, i.e., we do not consider the cooperation relation between crowdfunding market and E-commerce market.
- CATN-ComE is a variant without competitive attention in E-commerce market. In this variant, we give up exploring the competitive relations of E-commerce market.
- CATN-ComC is a variant without competitive attention in crowdfunding market, i.e., we give up exploring the competitive relations of crowdfunding market.
- CATN-Trans is the last variant of CATN, which is exclude the knowledge extraction part. We separately predict the item popularity of the two markets.

Since the problem to be solved is a regression problem, we adopt widely-used valuation metrics, i.e., *Root Mean Square Error (RMSE)* and *Mean Absolute Error (MAE)* to evaluate the prediction performances.

Experimental Results and Analysis

Performance Evaluation. The experimental results of *RMSE* and *MAE* on crowdfunding campaigns’ funding performance prediction are shown in Table 2, and the results on

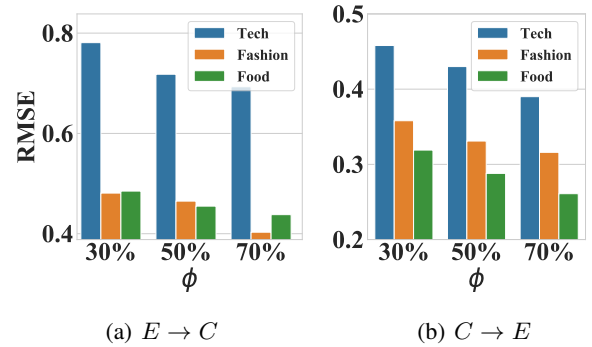


Figure 3: Impact of different levels of data.

E-commerce products popularity prediction are presented in Table 3. The best performance of these models is shown in boldface. First, we discuss the experimental results of the crowdfunding. From Table 2, we can see that all the best results are from the CATN-series. The overall performance of CATN-Trans which discards common knowledge but retains the attention of competition and cooperation, ranks second only to CATN. These two best models also reflect the important role of cooperative attention and cooperative attention. Besides, since CATN-ComE abandons the competitive attention of the E-commerce and does not have much impact on the funding performance prediction, CATN-ComE also achieve good results. By comparing the results of CATN and CATN-Coo in Table 2 and Table 3, we can see that the cooperative attention has a relatively greater effect on the crowdfunding market. Compared with the crowdfunding market, the E-commerce market has more items and richer semantic features, so cooperative attention is more important in predicting the funding performance of crowdfunding campaigns. We will analyze the impact of different levels of auxiliary market data on the target market prediction in the next subsection.

On the other hand, from the experimental results of E-commerce market shown in Table 3, all the best results are from the complete model. Similarly, since CATN-ComC abandons the competitive attention of the crowdfunding market, it does not have much impact on the prediction of products popularity, so CATN-ComC also achieve good results. By comparing CATN and CATN-ComE, we can see that the role of cooperative attention in the E-commerce market is higher than that in the crowdfunding market. This is also because the richer items and semantics of E-commerce market. And from the overall experimental results of both markets, CATN-series are basically far better than traditional deep learning methods.

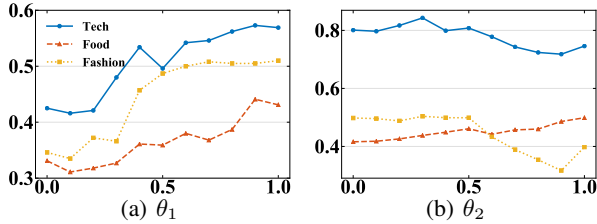
Impact of Different Levels of Data. Apart from the overall performance compared with the baselines, we also study the impact of different ϕ on the target market prediction, where ϕ is the proportion of auxiliary market data participating in the training. We set ϕ to “30%”, “50%”, and “70%”, and view the prediction results on the three types of datasets. Figure 3(a) shows the impact of different proportions of E-commerce products on the performance of crowdfund-

Table 2: Funding performance prediction on crowdfunding.

Datesets	Metrics	Method							
		CNN	RR	MLP	CATN-Coo	CATN-ComE	CATN-ComC	CATN-Trans	CATN
Fashion	RMSE	0.5504(5)	0.8984(8)	0.7298(7)	0.5618(6)	0.5034(4)	0.5016(3)	0.4398(2)	0.4026(1)
	MAE	0.4194(5)	0.7136(8)	0.5824(7)	0.4380(6)	0.3314(3)	0.3800(4)	0.2934(2)	0.2912(1)
Food	RMSE	0.6444(5)	0.8444(8)	0.6948(6)	0.7936(7)	0.5140(2)	0.5792(4)	0.5150(3)	0.4384(1)
	MAE	0.4582(5)	0.6174(8)	0.5528(6)	0.5918(7)	0.3668(3)	0.4378(4)	0.3366(2)	0.3250(1)
Technology	RMSE	0.7958(4)	1.3130(8)	0.8362(6)	0.9272(7)	0.7078(2)	0.8028(5)	0.7524(3)	0.6932(1)
	MAE	0.6140(5)	0.6280(6)	0.6714(7)	0.7072(8)	0.5378(3)	0.6052(4)	0.5134(1)	0.5210(2)
AveRank(RMSE)		4.667	8	6.333	6.667	2.667	4	2.667	1
AveRank(MAE)		5	7.333	6.667	7	3	4	1.667	1.333

Table 3: Popularity prediction on E-commerce.

Datesets	Metrics	Method							
		CNN	RR	MLP	CATN-Coo	CATN-ComE	CATN-ComC	CATN-Trans	CATN
Fashion	RMSE	0.4088(6)	0.4718(8)	0.3780(5)	0.3444(3)	0.4192(7)	0.3360(2)	0.3504(4)	0.3162(1)
	MAE	0.2490(3)	0.3660(8)	0.2912(6)	0.2540(4)	0.3094(7)	0.2608(5)	0.2410(2)	0.2404(1)
Food	RMSE	0.4134(6)	0.6950(8)	0.4462(7)	0.3032(3)	0.3680(5)	0.3090(4)	0.2796(2)	0.2608(1)
	MAE	0.2244(3)	0.5544(8)	0.3564(7)	0.2390(5)	0.2766(6)	0.2292(4)	0.2054(2)	0.2002(1)
Technology	RMSE	0.4714(5)	0.6794(8)	0.4786(6)	0.4376(4)	0.5312(7)	0.4092(2)	0.4374(3)	0.3896(1)
	MAE	0.3758(6)	0.5386(8)	0.3620(5)	0.3286(4)	0.4028(7)	0.3164(2)	0.3206(3)	0.3028(1)
AveRank(RMSE)		5.667	8	6	3.333	6.333	2.667	3	1
AveRank(MAE)		4	8	6	4.333	6.667	3.667	2.333	1

Figure 4: Impact of θ_1 in Amazon and θ_2 in Indiegogo.

ing campaigns funding prediction. Figure 3(b) shows the impact of different proportions of crowdfunding campaigns participating in training on the prediction performance of E-commerce products' popularity. From the results, one can draw the conclusion that when ϕ gets increases, *RMSE* will gradually decrease. It can be seen that the predictions results of items popularity in the target market will be more accurate as the data and semantics of auxiliary market become rich. So we believe that if we can get more data in both markets, this model will achieve better results.

Balance Parameter Sensitivity. In this subsection, we test the balance parameter sensitivity of CATN and present the results on the task of regression with different parameter settings. Specifically, we explore how different balance parameters θ_1 and θ_2 influence the experimental results.

The results on *RMSE* are shown in Figure 4. θ_1 balances the influence of other products on the target product in the prediction. The smaller θ_1 is, the greater the influence of the market on the popularity of the target product. Judging from the experimental results of the three datasets in E-commerce market, when θ_1 is about 0.1, the product popularity predic-

tion achieves the best results, which means that the popularity of products has a relatively large degree of mutual influence, the competition between products is relatively strong. θ_2 balances the degree of influence between the crowdfunding market campaigns. From the experiment results of θ_2 , it can be seen that the result is the best when the value of θ_2 is 0.9 on the two datasets of *Fashion* and *Technology*. This means that in these two types of crowdfunding markets, the influence of fundraising competition between campaigns is relatively weak. On the *Food* dataset, the prediction effect is best when $\theta_2=0$, which shows that the competitive influence in *Food* crowdfunding campaigns is particularly strong, and the degree of influence among campaigns is very high.

Conclusion

In this paper, we discovered potentially symbiotic relations between the financing market and the sales market which motives us to propose a framework called CATN to transfer the complementary knowledge between the two isolated markets. CATN effectively co-promote the effect of popularity predictions of newly-posed items on both E-commerce and crowdfunding markets. Besides, for capturing complex interaction between markets, we innovatively designed two important components, i.e., *Cooperative Attention* and *Competitive Attention*. Cooperative attention explores different degrees of knowledge of the items in the auxiliary markets, and competitive attention measures the impact of other items in specific same market. We demonstrated that our proposed model achieved the best results on both tasks of products popularity prediction and campaigns funding prediction on three types of datasets. For future work, we will collect more large-scale datasets to further evaluate and optimize our proposed CATN model.

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