CoEA: A Cooperative–Competitive Evolutionary Algorithm for Bidirectional Recommendations

Hongke Zhao, Xinpeng Wu, Chuang Zhao, Lei Zhang, *Member, IEEE*, Haiping Ma, and Fan Cheng

***Abstract*—In recent decades, recommender systems have been well studied and widely applied. However, most recommenders unilaterally optimize the results from the buying customers' views without considering expectations of other participants, e.g., merchants. Unfortunately, the expectations of customers and merchants in recommendation are different or even conflicted. Especially for popular group-trading markets, customers and merchants are competing in trading, i.e., customers want to meet their preferences or obtain gains with personal favorite items, while merchants want to recommend wholesale items with setting group-trading terms or conditions. In addition, some practical constraints are not fully considered by prior systems. In this article, we propose a cooperative–competitive evolutionary algorithm (i.e., CoEA) for the bidirectional recommendations in group-trading markets. Specifically, we, respectively, formalize two subproblems with designed objectives for two-sided participants in markets, and integrate the cooperative–competitive optimizations into one framework. Second, CoEA designs a *binary encoding matrix* for individual representation to integrate the two subproblems. Furthermore, by assembling game evolution process, CoEA designs cooperative–competitive evolution operators, i.e., the *cooperative crossover* and *competitive mutation*, which guide the solutions to equilibrium by, respectively, bridging communication between two populations of subproblems and optimizing distinctive objective in each population. Finally, we construct two real applications involving bidirectional recommendations, i.e., the group buying and P2P lending, and conduct extensive experiments with the real-world datasets. By comparing CoEA with several representative recommendation algorithms and evolutionary algorithms, the experimental results clearly demonstrate the effectiveness of CoEA.**

***Index Terms*—Cooperative–competitive evolutionary algorithm (CoEA), equilibrium solution, group-trading markets, recommender systems.**

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I. Introduction

RECOMMENDER systems are tools and techniques providing suggestions for items to each user [1]–[3]. In recent decades, recommender systems have been widely studied in academia and also successfully applied in many practical fields, e.g., electronic commerce [3]–[5], multimedia [6], and social networks [7]. In these areas, the traditional recommendation techniques, i.e., collaborative filterings [8]–[10], content-based methods [11], and hybrid methods [12] are usually pursuing recommendation accuracy [13]. Some other intelligent techniques or algorithms have also been well exploited, where deep learning-based models [3], [9], [10] and evolutionary algorithms [14]–[18] are the representative ones. In the literature, most evolutionary algorithm-based recommenders are designed for exploring and optimizing one or multiple objectives in recommending results, such as accuracy, diversity, and novelty [14], [19]–[21]. For example, Wei *et al.* [20] designed a multiobjective recommender system by considering item profit and novelty besides accuracy. However, no matter the traditional recommenders with pursuing recommendation accuracy or evolutionary algorithms with optimizing other multiple objectives, they mainly consider the preferences from the views of users or customers [1], [2], [14]–[19]. To the best of all knowledge, there is not even research work explicitly exploring the objectives from the merchants' views. Unfortunately, this starting point in research may be quite different from the scenarios in reality and also narrow the application of recommendation algorithms since most markets have more than one types of participants, such as customers and merchants. Actually, in reality, some markets, especially for these burgeoning platform-economy ones [22], we served with recommendations that are complicated and there are still many views or market rules that have not been considered in previous studies.

Especially for the example shown in Fig. 1, group-trading markets, such as group buying [23], [24] and P2P lending [25]–[28], have distinct two different participating users: 1) buying customers and 2) merchants. Furthermore, these markets are often set with group-trading terms or conditions by merchants. Usually, the trading is valid, i.e., offering products and services in group buying or lending in P2P lending, on the condition that a minimum number of buyers or lenders would participate or a minimum amount transaction volume could reach. Otherwise, all the transactions are invalid and will be cancelled. These group-trading conditions definitely reflect

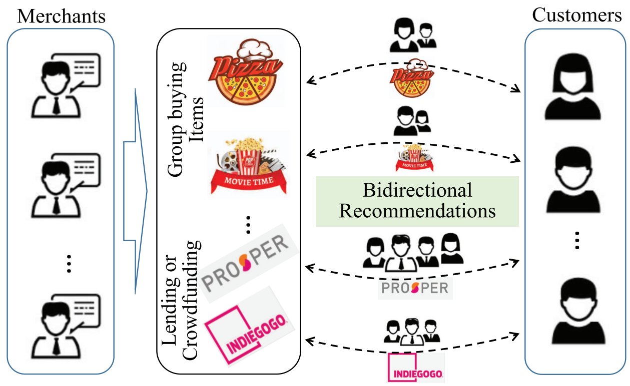


Fig. 1. Bidirectional recommendations in group-trading markets.

the preferences from merchants rather than customers. It is obvious that conventional recommenders are with challenges and not workable enough when facing with both customers and merchants.

Specific to group-trading markets, there are following challenges. First, customers and merchants are competing in trading. Specifically, for buying customers, they want to meet their preferences or obtain gains with personal favorite items, while merchants want to recommend wholesale items with large profits by setting the above group-trading terms or conditions. Thus, from the point of buying customers, recommending should select the items that customers are most like or accept, which is consistent with setting in most prior recommenders [1], [2], [29]. However, from the point of merchants, they may prefer to recommend high-price or well-stocked items for group trading. Unfortunately, these two points are often conflict and there are rarely relevant studies on recommendation systems, which have definitely formalized these different perspectives from two sides of markets. Second, markets also face some constraints. For example, recommending service in an arbitrary manner may result in low user satisfaction. Thus, the recommending volume to each customer should be not very large.

In this article, different from the typical setting in conventional recommenders, we focus on the group-trading markets and formalize recommendation as a bidirectional item-user matching problem. That is, in the recommendation, both the customers' preferences and the merchants' expectations such as the group-trading conditions set by them should be simultaneously considered. Intuitively, the multiobjective evolutionary algorithms (MOEAs) [30]–[34] can be applied to this formalization. However, most of the typical MOEAs optimize the Pareto front. But, these algorithms cannot determine the equilibrium solutions from Pareto front, i.e., the best recommended items accepted by both customers and merchants, i.e., different participants. In addition, though there are many excellent multiobjective optimization algorithms [30], [31], [35]–[37], they cannot be applied to this study effectively because the solution space is much larger, which needs more efficient design.

To this end, for the formalized bidirectional recommendation problem in group-trading markets, we propose a new cooperative–competitive evolutionary algorithm (i.e., CoEA). Specifically, we, respectively, formalize two subproblems with designed objectives and individual populations for the two participants in markets, i.e., one is optimized for the customers' objective, and the other is for the merchants' objective. CoEA integrates the cooperative–competitive optimizations into one framework through population separation, interpopulation interaction, and population integration. Second, for accompanying the proposed new framework, we design a *binary encoding matrix* for individual representation in CoEA. More specifically, by assembling the game process in evolution, CoEA designs cooperative–competitive evolutionary operators, i.e., the *cooperative crossover* and *competitive mutation* to guide the solutions to equilibrium. The cooperative crossover bridges communication between two populations of subproblems while the competitive mutation optimizes distinctive objective in each population. What is more, cooperative crossover could accelerate the convergence greatly through the communication between two populations. Finally, repair and selection operations are conducted for satisfying constraints in specific applications.

For specifying the mechanism of CoEA and evaluating its effectiveness on bidirectional recommendations, we construct two real applications, i.e., the group buying and P2P lending. Specific to these two applications, we define the two-sided objectives by mining their trading rules. In experiments, we conduct extensive experiments with the real-world datasets from group buying and P2P lending. By comparing CoEA with representative recommendation algorithms and single/MOEAs, the experimental results clearly demonstrate the effectiveness of CoEA.

Specifically, the contribution of this study can be summarized as follows.

1) *Problem View:* We formalize the bidirectional recommendations problem in group-trading markets with explicitly modeling the preferences of two-sided participants, i.e., customers and merchants. The study view may bring new insights to relevant research on recommendations.
2) *Algorithm View:* We propose a new cooperative–competitive evolutionary algorithm with creative designs on chromosome coding, crossover, and mutation. The proposed algorithm is instructive to the area of evolutionary computation.
3) *Application View:* We construct two representative applications with collecting real-world datasets and conducting extensive experiments.

We systematically compare and discuss our CoEA and other relevant methods, mainly including recommenders and multiobjective optimization algorithms in Table I. We can see that to the best of all knowledge, our study is the first to explicitly explore the multiple objectives from both customers and merchants. Of course, on the other hand, comparing with other typical recommenders, accuracy is not fully considered and obtained in CoEA though it is also personalized, which is a limitation of this study. Comparing with the representative multiobjective optimization algorithms, the problem scale and solution space of the formalized

TABLE I
COMPARISON BETWEEN CoEA AND OTHER RELEVANT ALGORITHMS. √(◯) INDICATES WHETHER OR NOT IT IS AIMED AT THE CORRESPONDING CONTEXT, AND THE NUMBER OF ★ INDICATES THE RELATIVE DEGREE OF CORRESPONDING DIMENSIONS

Algorithms\Dimensions	Recommendation			Optimization				**Applicability**
	Single-objective (Accuracy)	*Customer-only multi-objective*	*Customer & merchant's multi-objective*	*Problem scale*	*Solution space*	*Solution distribution*	*Convergence efficiency*	
Typical Recommenders [38], [39] [8], [40] [9]	√	◯	◯	\	\	\	\	√(★)
DMT [41]	◯	√	◯	\	\	\	\	√(★★)
Multi-objective Evolutionary Recommenders [19]–[21]	◯	√	\	★★	★★	★★★	★★	√(★★)
Multi-objective Evolutionary Algorithms [30], [36], [37]	\	\	\	★★	★★	★★★	★★	√(★★)
CoEA	◯	◯	√	★★★	★★★	★★	★★★	√(★★★)

bidirectional recommendations in this study are much larger than those benchmark problems. Because CoEA designs a cooperative crossover bridging the two different populations, the population will lose a certain diversity resulting in solution distribution that will be worse under the same convergence. However, the bidirectional recommendations make the traditional MOEAs difficult to converge. In addition, these algorithms are searching solutions with optimizing different objectives independently. In other words, these algorithms fail in finding final equilibrium between different objectives for agreed trading. This characteristic will cause the evolutionary algorithm to be greatly compromised in some real recommendation scenarios, especially our bidirectional recommendations. Thus, on the whole, CoEA has the best applicability to the problems in this study.

The remainder of this article is organized as follows. Section II reviews the relevant work of this study. In Section III, we give the problem formalization about bidirectional recommendations in group-trading markets. Section IV details the proposed cooperative–competitive evolutionary algorithm. Then, we conduct applications in Section V and experiments in Section VI to, respectively, implement and evaluate our algorithm. Finally, Section VII concludes this study.

II. RELATED WORK

In this section, we review the related work of this study from the aspects of recommender systems and evolutionary algorithms, respectively.

A. Recommender Systems

The aim of recommender systems [1] is to obtain a utility function that seeks to predict the "rating" or "preference" of a user toward an item. Traditional recommendation systems can be classified into three categories, that is, content-based methods [42], collaborative filtering methods [43], and hybrid methods [44]. Specifically, content-based recommendation methods [42] match the user's personal profile with a representation of the item. Another common approaches when designing recommender systems are collaborative filtering methods [43], which are based on the assumption that people who preferred similar items in the past will prefer similarly in the future. In order to overcome the cold start and sparsity problems of the recommendation system, hybrid methods [44] were proposed, combining the advantages of content-based methods and collaborative filtering methods. With the development of deep learning, exploiting neural network for recommendation has become a hot topic [3], [9], [10], [45]. Most of these methods are good at representing multisource heterogeneous features for better results. Some of these methods modeled the collaborative filtering with the structures of deep learning models using only the item-user interaction matrix, which are more general and typical [3], [9]. Gu *et al.* [41] proposed to model click-trough rate and conversion rate objectives using a deep multitask leaning for recommendations.

Recently, with the complexity of recommending products and services, the constraint-based recommendation methods [46], [47] have attracted the attention of a wide range of scholars. For example, the search space of recommending algorithms is narrowed by adding time constraints [47]–[49] and context constraints [50]–[52], so as to achieve the constraint-aware recommendations.

With the rise of group buying and lending markets, some preliminary studies on recommendations in these areas have also been conducted [17], [53], [54]. However, for group buying, studies mainly focus on special markets without explicit group-trading conditions or constraints, such as restaurant recommendation [55] or travel package recommendation [56]. Thus, these works have not explicitly modeled the group-trading constraints or objectives. On the other hand, in P2P lending, most of the existing recommendation works only consider the needs of one type of users (such as lenders or borrows in P2P lending), i.e., recommending suitable loans to lenders through investment behavior analysis [26], [57], [58] and risk assessment of loans, or recommending lenders to loans released by borrowers through fundraising analysis [59]–[61]. In general, there are very limited research on recommendation systems that explicitly consider both two types of participants, e.g., customers and merchants in group buying or lenders and borrowers in P2P lending.

B. Relevant Evolutionary Algorithms

With better understanding users' preferences, the recommender system needs to consider many factors, including coverage, diversity, novelty, and so on. It is hard for traditional recommendation systems to meet these demands. Recently, the academic community has begun to consider modeling the recommendation process as a mathematical optimization problem, and made attempts to use evolutionary algorithms to solve this problem [14], [19], [62]. Among the evolutionary algorithms, multiobjective evolutionary algorithms (i.e., MOEAs) [31], [37], [63] were mostly used in previous studies and relevant to the algorithm design in this study.

MOEAs are used to optimize multiple objective functions with the same decision variables, which are getting popular in the recent past decade, mainly because of their ability to find a wide spread of Pareto-optimal solutions in a single simulation run. There were many MOEAs proposed to solve different problems in data mining, e.g., community detection [32], [64], feature selection [65], association rule mining [66], task-oriented pattern mining [67], network vulnerability [68], and image classification [69].

Specific to recommendations, most evolutionary algorithm-based recommenders were designed for exploring and optimizing one or multiple objectives in recommending results, such as accuracy, diversity, and novelty [14], [19]–[21]. For example, Wei *et al.* [20] designed a multiobjective recommender system by considering item profit and novelty besides accuracy. Oliveira *et al.* [70] proposed multiobjective evolutionary rank aggregation following the concepts of SPEA2 that considered three measures when making recommendation, i.e., mean average precision, diversity, and novelty.

However, these evolutionary algorithms optimize multiple objectives in recommending, and they mainly consider the objectives/preferences from the views of users or customers [1], [2], [14]–[19]. To the best of all knowledge, there is not even research work explicitly exploring the objectives from the merchants' views. The comparison and discussion of our study and the relevant works have been shown in Table I.

III. Problem Formalization

In this section, we formalize the definition of bidirectional recommendations in group-trading markets.

Bidirectional Recommendations: In markets (refer to Fig. 1), there are two kinds of users, i.e., customers and merchants, where $U^c = \{u_1^c, u_2^c, \ldots, u_M^c\}$ denotes all (M) customers and $U^m = \{u_1^m, u_2^m, \ldots, u_{M'}^m\}$ denotes all (M') merchants. In addition to users, there are also a number of (N) items, i.e., $V = \{v_1, v_2, \ldots, v_N\}$, which serves as the trading carriers between customers and merchants. From trading, customers and merchants have their own distinctive objectives or goals, which are, respectively, denoted as $\boldsymbol{F_c}$ and $\boldsymbol{F_m}$. Specifically, $\boldsymbol{F_c}$ is usually measured by modeling or optimizing the preferences of customers, while specific to the group-trading markets, $\boldsymbol{F_m}$ can be formalized by optimizing the group-trading conditions set by merchants.

What is more, there may be often some other specific rules for trading constraints, which can be denoted as $\boldsymbol{f(.)}$. The trading constraints may be a Boolean function. Specifically, bidirectional recommendation is to match up the items and customers to satisfy the preferences of served customers (i.e., $\boldsymbol{F_c}$) and the expectations of merchants who provide the items (i.e., $\boldsymbol{F_m}$) under constraints $\boldsymbol{f(.)}$.

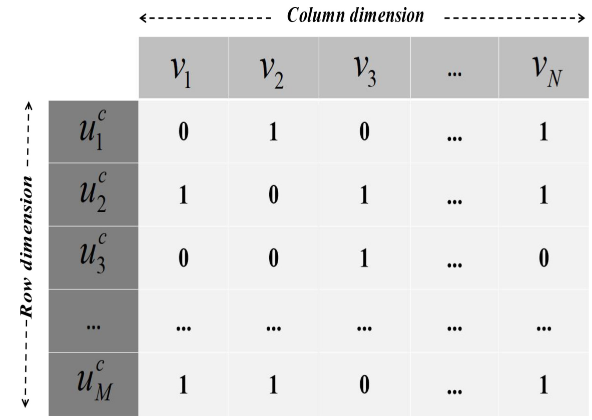


Fig. 2. Example of binary encoding matrix $\boldsymbol{I}$.

It is obvious that $\boldsymbol{F_c}$, $\boldsymbol{F_m}$, and $\boldsymbol{f(.)}$ may have different forms on different markets. Specific to this article, we take the group buying and P2P lending as our research targets, and the preliminaries of these platforms and specific forms of $\boldsymbol{F_c}$, $\boldsymbol{F_m}$, and $\boldsymbol{f(.)}$ will be detailed in Section V.

IV. CoEA: Cooperative–Competitive Evolutionary Algorithm

In this section, we present the cooperative–competitive evolutionary algorithm in detail, which includes a *binary encoding matrix*, *evolutionary framework*, *cooperative crossover*, and *competitive mutation*.

A. Binary Encoding Matrix

Conventionally, in most existing evolutionary algorithms, encoding methods in different forms are proposed, such as the discrete or continuous encodings [71]–[74]. However, in most cases, the genome or chromosome is represented by a D-dimensional vector. In this study, we design a binary encoding matrix for individual representation, which is adaptive to bidirectional recommendations. Similar encoding has been proposed in prior work [75]. However, that work also considers the customer-only multiple objectives, i.e., accuracy and diversity. In addition, that work has not fully considered specialized operator designs for matrix encoding.

Specifically, a binary encoding matrix $\boldsymbol{I}_{M\times N}$ can be represented as a feasible recommending solution for M customer and N items. Fig. 2 shows an example for $\boldsymbol{I}$, where the row dimension could measure the objective of customers, i.e., $\boldsymbol{F_c}$, and the column dimension could describe the objective of merchants (equivalent to items' view in our study), i.e., $\boldsymbol{F_m}$. Each element $e_{i,j} \in \boldsymbol{I}$ is 1 or 0. That is, to say, $e_{i,j} = 1$ represents customer u_i^c and item v_j are currently matched, i.e., item v_j is recommended to customer u_i^c, and it can be also said that the potential customer u_i^c is recommended to item v_j for trading, and vice versa.

Intuitively, the problem definition of bidirectional recommendation is coupled together by two subproblems each of which serves for one type of users (which will be detailed in

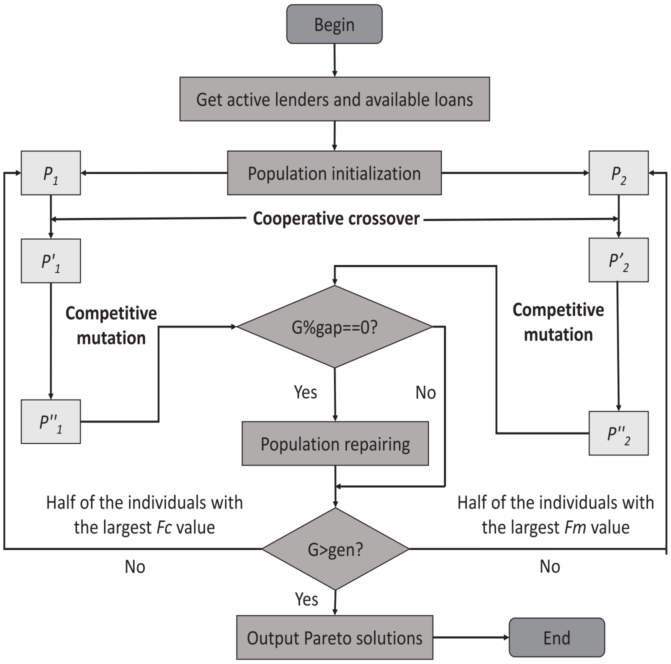


Fig. 3. General evolutionary framework of CoEA.

Algorithm 1: General Evolutionary Framework of CoEA

Input:
psize: the size of population,
gen: the number of generations,
cp: the crossover probability,
mp: the mutation probability,
gap: the generation radix for repairing population;
Output:
$\boldsymbol{PS} \leftarrow$ the final set of optimal solutions;
Step1: Population initialization
$P \leftarrow$ Randomly initialize a population;
for $i = 1$ to *gen* **do**
  Step2: Population evolution
  $P_1 \leftarrow$ Extract the first $psize/2$ individuals from P ranked by objective function $\boldsymbol{F_c}$;
  $P_2 \leftarrow$ Extract the first $psize/2$ individuals from P ranked by objective function $\boldsymbol{F_m}$;
  $P'_1, P'_2 \leftarrow$ Cooperative Crossover(P_1, P_2, $psize/2$, cp);
  $P''_1, P''_2 \leftarrow$ Competitive Mutation(P'_1, P'_2, $psize/2$, mp);
  FP $\leftarrow P \cup P''_1 \cup P''_2$;
  Step3: Population repairing
  if i % $gap == 0$ **then**
    FP $\leftarrow$ Repair the population FP under constraints $\boldsymbol{f(.)}$;
  end if
  Step4: Population choosing
  NonDominatedSorting(FP);
  NewPopulation=[], N=1;
  while (size(NewPopulation)< *psize*) **do**
    NewPopulation = NewPopulation ∪ N-th Front of FP, N++;
  end while
  if (size(NewPopulation)> *psize*) **then**
    Calculate the crowd distance of the solutions in (N-1)-th Front of FP;
    Remove the first size(NewPopulation)- *psize* solutions with smallest crowd distance in (N-1)-th Front from NewPopulation;
  end if
  P = NewPopulation;
end for
$\boldsymbol{PS} \leftarrow$ The solutions on the final Pareto front.

Section IV-B). By designing this binary encoding matrix, the two subproblems can be cleverly unified into one problem. Each dimension of solutions describes one objective from either customers or merchants and every individual solution can simultaneously represent both the customers' and the merchants' objectives in this way. Furthermore, through optimization in evolution, CoEA could get the equilibrium solutions for both customers and merchants rather than the traditional Pareto solution set, which is very different from those in MOEAs.

B. Evolutionary Framework

With the design of the binary encoding matrix, in this section, we introduce the framework of CoEA for population evolution.

Specifically, Fig. 3 shows the evolutionary framework of CoEA. The main idea of CoEA is to divide the bidirectional recommendation problem into two subproblems each of which is assembled with one population. One population evolves toward the preferences of customers, i.e., the objective function $\boldsymbol{F_c}$, and the other population evolves toward the expectations of merchants, i.e., the objective function $\boldsymbol{F_m}$. We can see that CoEA has both individual evolutionary flows for two subpopulations and also allows communication between two subpopulations. In the evolution, the population communication through the proposed cooperative–competitive operators (cooperative crossover in Section IV-C and competitive mutation in Section IV-D) guarantees that the solution converges to equilibrium, i.e., accepted by both customers and merchants. Algorithm 1 details the evolution process, including *population initialization*, *population evolution*, and *population repairing*.

Specifically, in the first step, the traditional random initialization strategy is adopted to generate an initial population P. The population size is *psize*, that is, *psize* binary matrices with M rows and N columns are randomly generated. In the second step, for the two subproblems, two subpopulations P_1 and P_2 are, respectively, extracted from P. In this way, P_1 selects the top $psize/2$ individuals from P according to objective function calculation of customers' preference $\boldsymbol{F_c}$, and P_2 selects the top $psize/2$ individuals from P according to the objection function of merchants' expectations $\boldsymbol{F_m}$. Furthermore, with populations P_1 and P_2, the cooperative crossover operator proposed in Section IV-C is used to produce two new populations P'_1 and P'_2. Then, with the populations P'_1 and P'_2, the competitive mutation operation proposed in Section IV-D is used to obtain two new child populations P''_1 and P''_2, respectively. In each round of evolution, populations P, P''_1, and P''_2 are combined to obtain the final population FP.

Considering the constraints in specific markets and the dominant relationship of solutions, we need to repair the solutions. Specifically, in the third step, when the criterion of repairing population is met, FP is repaired to satisfy the constraints of $\boldsymbol{f}(.)$. $\boldsymbol{f}(.)$ has different forms in different application markets. For example, the number of recommended items for each customer in solutions should be within a reasonable budget of customers or less than a certain number. From FP, *psize* individuals are selected by nondominated sorting and crowded distance sorting [31], [76], [77] for further evolution. Finally, if the maximum generation of iterations is reached, the algorithm terminates and outputs the final Pareto solutions *PS*; otherwise, go back to the second step and repeat these processes in evolution until the stopping criterion is met.

For guaranteeing that the searched solutions will be more probably accepted by both two participants in markets, in the evolution, we design a cooperative crossover operator and a competitive mutation operator. That is, one of the main differences between our study and conventional MOEAs, which do not explicitly model cooperative–competitive communication between different objectives when searching. Specifically, the cooperative crossover operator is used to find the equilibrium between the communication of two subpopulations with defined equilibrium measure, which simultaneously considers objective functions of both customers and merchants, and the competitive mutation operator is further used to search optimal solution in their own searching flow of each type of participants.

C. Cooperative Crossover

Intuitively, the cooperative crossover lets the two populations reconsider the objective from the other-side population's objective in evolution. Specifically, the cooperative crossover operator works as follows. In individual $\boldsymbol{I}$, the ith row represents a set of all items recommended to customer u_i^c, directly determining whether the recommendation satisfies the preference of lender u_i^c. The jth column represents a set of all customers recommended for item v_j, directly determining whether the recommendation can make the trading on v_j successful under the rule set by its corresponding merchant. Algorithm 2 shows the main steps of the cooperative crossover operator, where $P_1[i]$ or $P_2[i]$ represents the ith individual in population P_1 or P_2.

First, we define an indicator for selecting individuals to crossover, and the equilibrium measure Em_k of individual $\boldsymbol{I}_k$ is defined as

$$Em_k = \sum_{i=1}^{m} NV_{ik} \tag{1}$$

where m is the total number of participants (i.e., the size of objective functions $m = 2$), and NV_{ik} represents the normalized importance of individual I_k among all individuals on the ith objective function (F^c or F^m). NV_{ik} can be defined

$$NV_{ik} = \frac{MO_i - CO_{ik}}{MO_i} \tag{2}$$

where MO_i is the maximum value on the ith objective function among all individuals, and CO_{ik} is the ith objective function value of individual I_k. The measure of individual $\boldsymbol{I}_k$ can reach the largest value (i.e., m), if all objectives of $\boldsymbol{I}_k$ can get the largest values. Understandably, the equilibrium measure prefers to select the individuals, which are better on evaluations of both two participants.

Algorithm 2: Cooperative Crossover

Input:
P_1, P_2: the two sub-populations to be crossed,
pop_size: the size of sub-population,
cp: the crossover probability;
Output:
$P_1', P_2' \leftarrow$ new populations generated by crossover operator;
$P_1 \leftarrow$ Sort individuals within P_1 in descending order by equilibrium measure *Em*;
$P_2 \leftarrow$ Sort individuals within P_2 in descending order by equilibrium measure *Em*;
for $i = 1$ to *pop_size* **do**
  $P_1[i] \leftarrow$ Generate a new individual to replace the original individual by column crossover;
  $P_2[i] \leftarrow$ Generate a new individual to replace the original individual by row crossover;
end for
$P_1' \leftarrow P_1$, $P_2' \leftarrow P_2$.

Base on this equilibrium indicator, for each subpopulation P_i ($i = 1$ or 2), individuals within P_i are sorted in descending order by *Em*. Then, two individuals at the same equilibrium rank in P_1 and P_2 are, respectively, selected for crossover to produce individuals for two new subpopulations P_1' and P_2'. For example, the individual with the largest *Em* value in population P_1 will cross with the individual with the largest *Em* value in population P_2, and the individuals with the second ranks on *Em* in population P_1 and P_2 will cross with each other and so on. Specifically, the crossover operator for any two individuals is implemented with our proposed *column crossover* and *row crossover* on binary encoding matrices of chromosomes, which are described as follows.

Let X and Y be the two individuals selected from P_1 and P_2, respectively, and *cp* be the preset crossover probability. First, the first child X' is generated by column crossover. To be specific, we generate N (the number of items) random numbers in [0, 1] corresponding to each column in the individual. If the ith random number is smaller than *cp*, the jth column of X is replaced by the jth column of Y. The column crossover ends until all random numbers have been compared. Finally, we get $X' = X$. In addition, we generate the second child Y' by row crossover. To be specific, we generate M (the number of customers) random numbers in [0, 1] corresponding to each row in the individual. If the ith random number is smaller than *cp*, the ith row of Y is replaced by that of X. Similarly, all random numbers are compared, and the row crossover ends. Finally, we also get the second child $Y' = Y$.

Fig. 4 shows a tiny example for illustrating the operators of cooperative crossover and competitive mutation. As shown in this figure, there are two individuals X and Y with three customers and three items. After the crossover operator, the second column of X is replaced by that of Y with the column crossover, and the second row of Y is replaced by that of X with the row crossover. Then, we can get two new individuals X' and Y'. After the mutation operator (refer to the

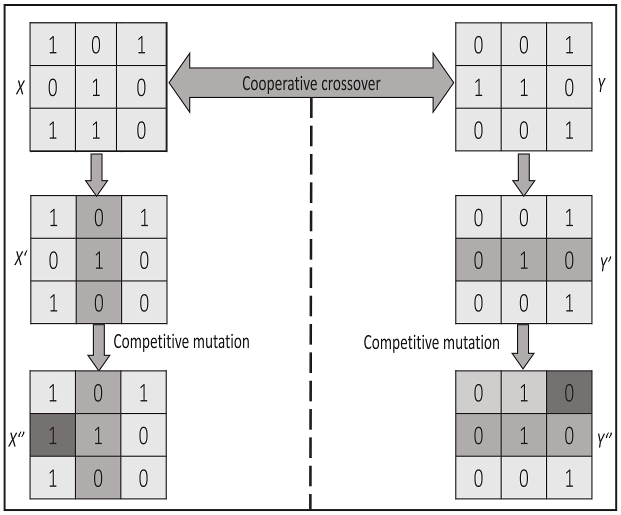


Fig. 4. Illustration of cooperative crossover and competitive mutation.

next section), $X'(2,1)$ is flipped from 0 to 1 and $Y'(1,3)$ is flipped from 1 to 0. Finally, we can get two new individuals X'' and Y''.

We can know that through the cooperative crossover, the superior chromosome in P_2 is shared to the individual in P_1 by column crossover, and the superior chromosome in P_1 is also shared to the individual in P_2 by row crossover. Thus, the crossover operator indeed plays an important role in the communication between P_1 and P_2 and achieves the cooperation optimization for two participants. Actually, cooperative crossover could significantly speed up convergence of CoEA by focusing the searching scope. Of course, it will affect the population diversity to a certain extent, but in our problems, the tradeoff of solutions on multiple objectives is also meaningful and more practical. What is more, the problem scale and solution space are too large to make the traditional evolutionary algorithms difficult to converge. Thus, the cooperative crossover is one core design and contribution in CoEA.

D. Competitive Mutation

The populations P_1 and P_2 are, respectively, selected as the ranking on objective functions $\boldsymbol{F_c}$ and $\boldsymbol{F_m}$. Through the cooperative crossover operator, CoEA reserves individuals or chromosomes in two populations, which are with better equilibrium indicators and perform better on both two objective functions $\boldsymbol{F_c}$ and $\boldsymbol{F_m}$. Then, specific to each subpopulation of subproblem, we propose a competitive mutation operator to guarantee the convergence in each individual evolutionary flow of the algorithm, i.e., respectively, guide two populations toward to their objective $\boldsymbol{F_c}$ or $\boldsymbol{F_m}$.

Algorithm 3 shows the main steps of the competitive mutation operator. First, we generate two random matrices RM_1 and RM_2 of M rows and N columns with elements in the range of [0, 1]. Then, for each individual $P'_1[i]$ in subpopulation P'_1, we compare $RM_1(j,k)$ with the preset mutation probability mp, if $RM_1(j,k) \leq mp$, then flip the corresponding element (j,k) in individual $P'_1[i]$ if it can get better $\boldsymbol{F_c}$ value. Similarly, for each individual $P'_2[i]$ in subpopulation P'_2, we compare $RM_2(j,k)$ with the mutation probability mp, if $RM_2(j,k) \leq mp$, then flip the corresponding element (j,k) in individual $P'_2[i]$ if it can get better $\boldsymbol{F_m}$ value. Through the above process, we can get two new subpopulations P''_1 and P''_2 each of which converges to the corresponding objective in one subproblem.

Algorithm 3: Competitive Mutation

Input:
P'_1, P'_2: two sub-populations to be mutated,
pop_size: the size of sub-population,
mp: mutation probability;
Output:
$P''_1, P''_2 \leftarrow$ two new populations after mutation;

```
for i = 1 to pop_size do
    RM_1, RM_2 ← generate two random matrices of M rows and
        N columns with elements in range of [0, 1];
    for j = 1 to M do
        for k = 1 to N do
            if RM_1[j][k] ≤ mp then
                Flip the corresponding element (j, k) in individual
                    P'_1[i] if it can get better F_c value;
            end if
            if RM_2[j][k] ≤ mp then
                Flip the corresponding element (j, k) in individual
                    P'_2[i] if it can get better F_m value;
            end if
        end for
    end for
end for
P''_1 ← P'_1, P''_2 ← P'_2.
```

We can find that the competitive mutation can be used to improve the convergence degree of the two subpopulations in their respective optimization fields. Note that the individual is not evaluated twice in one evolutionary process, and the individual is evaluated as a whole only when the final solution is selected. Of course, it will increase some additional costs through the local evaluation to determine whether the position is mutated, but the benefits (convergence degree is significantly higher than the general mutation) are also obvious (refer to Figs. 5 and 6).

From the above we can see that by assembling the game process in evolution, CoEA designs cooperative–competitive evolutionary operators, i.e., the cooperative crossover and competitive mutation to guide the solutions to equilibrium. The cooperative crossover bridges communication between two populations of subproblems while the competitive mutation optimizes distinctive objective in each population. These cooperative crossover and competitive mutation operators work together to guarantee the equilibrium and Pareto optimality of recommending solutions. Fig. 4 also shows the process of competitive mutation.

V. Implementation on Two Applications

In this section, we introduce two implementation applications of the bidirectional recommendations. The first is group buying and the second is P2P Lending.

A. Group Buying

Group buying [23], [24], also known as collective buying, offers products and services at significantly reduced prices on the condition that a minimum number of buyers would make the purchase or a minimum amount transaction volume could reach. In recent years, many E-commerce platforms launch this business, such as *Taobao*[1] and *Pinduoduo*.[2] The repaid development of group buying has attracted attention from scholars, and extensive studies have been done, which are around topics of marketing strategies [23], [24], [78], behavior analysis [79]–[81], incentive mechanisms [82]–[84], pricing mechanisms [85]–[87], and so on. However, there is rare research on recommendations, which is specifically aimed at group buying.

Different from the common scenarios, recommendations in group buying should consider preferences of two participants, i.e., customers and merchants, and various constraints or factors. For customers, they prefer to select the items whose prices are within the ranges they would accept; while for merchants, they hope that the group-buying trading on specific selling items will be successful, i.e., recommending to enough potential customers for reaching a minimum amount transaction volume.

Specifically, we give the specific expressions of objective functions $\boldsymbol{F_c}$ and $\boldsymbol{F_m}$ in group buying. Note that the objective functions can be flexible based on specific research problems and applications. In this study, without loss of generality, given an individual or solution $\boldsymbol{I}$ in population, the preferences of customers, i.e., the objective function $\boldsymbol{F_c}$, can be defined as

$$\boldsymbol{F_c} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\boldsymbol{I}(i,j)\cdot cfm_{ij}}{\sum_{i=1}^{M}\sum_{j=1}^{N}\boldsymbol{I}(i,j)} \tag{3}$$

where $\boldsymbol{I}(i,j)$ represents the element in the ith row and jth column of the encoding matrix $\boldsymbol{I}$ whose value is 1 or 0, and cfm_{ij} is the degree of conformity between customer u_i^c and item v_j. In this article, we quantify cfm_{ij} by simulating a Gaussian distribution, which is defined as

$$cfm_{ij} = \frac{1}{\sqrt{2\pi}\sigma}e^{-\frac{(P_j/E_i-\mu)^2}{2\sigma^2}} \tag{4}$$

where P_j is the declared price of item v_j, E_i is the average price paid by customer u_i^c in her historical group-buying purchases. Suppose K items customer u_i^c has purchased, then $E_i = 1/K \cdot \sum_{j=1}^{K} P_j$. In addition, σ and μ are tunable parameters, which are set as $\sigma = (1/\sqrt{2\pi})$ and $\mu = 1$ for normalizing $cfm_{i,j}$. The larger value of $\boldsymbol{F_c}$ indicates the better satisfaction of customers from recommending solution $\boldsymbol{I}$.

For the expectations of merchants from the group buying market, the objective function $\boldsymbol{F_m}$ can be defined as

$$\boldsymbol{F_m} = \frac{S}{N}\cdot\frac{VB}{TB} \tag{5}$$

where S represents the number of successful items among all the N selling items in the group buying market, VB is the effective trading amount, and TB is the total amount participating customers pledged. Actually, S/N means the successfully transactional probability of items in the group buying market, while VB/TB reflects the effective utilization rate of payment in the market. The larger value of $\boldsymbol{F_m}$ indicates the better satisfaction of merchants from recommending solution $\boldsymbol{I}$, i.e., more items will be successfully batch sold.

In addition, we define another trading constraints for recommendation, i.e., the number of recommending items to each customers is no larger than a predefined threshold (i.e., Max)

$$f(I_{i,j}) = \prod_{i=1}^{M} g\left(\sum_{j=1}^{N} I_{i,j} \leq \text{Max}\right) \tag{6}$$

where $g(x)$ is an indicator function whose value is 1 when x is true; otherwise, whose value is 0.

B. P2P Lending

We also take P2P lending as another implementation in this study as its similar mechanism with group buying. In the P2P lending market, there are two main kinds of roles: 1) the *borrowers* who want to borrow money from others and 2) the *lenders* who lend money to borrowers. Trading in this market follows the "all-or-nothing" rule [25], [26], [88], which is similar with the trading condition in group buying. Specifically, for borrowing money, the borrower will first create a listing to solicit bids from lenders by describing herself and the reason of borrowing money (e.g., for wedding). Then, if a lender wishes to invest on this listing within its soliciting duration (e.g., one week), a bid is created by her describing how much money she wants to invest (e.g., \$50). Finally, the listings that can receive enough money or a minimum threshold (e.g., 80% of the posted amount by the borrower) in time will turn to loans and begin the repayment periods. Otherwise, all the previous investments on these listings will be canceled.

The mechanism of P2P lending is similar with that in group buying, where the borrowers can be viewed as the merchants who sell the lending contracts for receiving money, and the lenders are the customers who obtain items, i.e., repayment and the loans are the trading items. In addition, the "all-or-nothing" rule is similar with that in group buying. Thus, in P2P lending, we have the similar definition for objective functions of borrowers and lenders.

Specifically, the objective function $\boldsymbol{F_c}$ should be defined by considering the lenders' preferences, i.e.,

$$\boldsymbol{F_c} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\boldsymbol{I}(i,j)\cdot R_j\cdot cfm_{ij}}{\sum_{i=1}^{M}\sum_{j=1}^{N}\boldsymbol{I}(i,j)} \tag{7}$$

where R_j is the declared interest rate of loan v_j. The multiplier of declared interest rate is the only difference in definitions between P2P lending and group buying since the interest rate is the definite and most important benefits for lenders. The other factors are the same with those in group buying. To go along with the context in P2P lending, the degree of conformity between lender u_i^c and loan v_j, i.e., cfm_{ij}, is defined similarly

$$cfm_{ij} = \frac{1}{\sqrt{2\pi}\sigma}e^{-\frac{(R_j/E_i-\mu)^2}{2\sigma^2}} \tag{8}$$

[1] https://www.taobao.com/
[2] https://www.pinduoduo.com/

where E_i is the average expected return rate of lender u_i^c by calculating her historical investment records. Suppose K loans lender u_i^c has invested, then $E_i = 1/K \cdot \sum_{j=1}^{K} R_j$.

The objective function $\boldsymbol{F_m}$ for borrowers is defined in the same way of that in group buying, which is also mainly based on the trading effectiveness, that is

$$\boldsymbol{F_m} = \frac{S}{N} \times \frac{\mathrm{VI}}{\mathrm{TI}} \tag{9}$$

where S represents the number of loans in $\boldsymbol{I}$ those are fully funded during the soliciting-bids period, and N represents the number of all loans in $\boldsymbol{I}$. VI is the sum of valid investments, that is, the sum of the request amounts of all loans those are fully funded during the soliciting-bids period. TI indicates the sum of total investments in $\boldsymbol{I}$. Note that S/N means the fully funded probability of loans in the market, while VI/TI denotes the effective utilization rate of funds in the market. Thus, the multiplication of these two formulas can be used to formalize the borrower's preference. For example, there are five loan requests in the market, suppose their loan amounts are [200, 200, 300, 400, 500] and the investment amounts obtained by these loans are [300, 100, 200, 400, 200]. Thus, only the first and fourth loans have been fully funded, according to the definition, $\boldsymbol{F_m} = (S/N) \times (\mathrm{VI}/\mathrm{TI}) = (2/5) \times ((200 + 400)/(300 + 100 + 200 + 400 + 200)) = 0.2$. The larger value of $\boldsymbol{F_m}$ indicates the better satisfaction of borrowers. In P2P lending, we adopt the same trading constraints with that in group buying shown in (6).

VI. Experiments

In this section, we construct extensive experiments to evaluate our proposed methods. Specifically, by following the representative two applications, i.e., group buying and P2P lending, we, respectively, construct experiments on a real-world group buying dataset and a real-world P2P lending dataset.

A. Experimental Datasets

Specifically, the dataset of group buying is collected from Tmall,[3] which is one of the largest e-commerce website in China, and the dataset of P2P lending is download from Prosper,[4] which is the first P2P lending platform in the U.S. when it has launched since 2006.

1) Tmall Dataset: This dataset contains all the behaviors of approximately one million random users with behaviors between November 25, 2017 and December 3, 2017, including 987 994 users, 4 162 024 items, 9439 item categories, and 100 150 807 interactions. Specifically, we extracted two copies of data by selecting items those were set for different-size groups for group buying. In this data, we have the price and agreed group-trading size for each item. Through the buying interactions, we also know the successful participation behaviors rather than all the participation behaviors in group-buying activeness that is different from that in the other application, i.e., P2P lending, we know all the bidding of lenders no matter each bidding is successful or not. Accordingly, for the items in two copies of data extracted from Tmall, the average price is *RMB* 291.44 and average preset group-trading size is 28.88 of the extracted data with smaller groups, and the average price is *RMB* 213.48 and average preset group-trading size is 70.01 of the other data with larger groups.

2) Prosper Dataset: This dataset collects all transaction records in Prosper platform of more than five years, including 62 782 lenders, 175 945 borrowers, and 387 848 loans. Because the collecting time of this dataset is quite long especially comparing with the periods of loans. In order to obtain active lenders and available loans, we set a time point CT to get all active lenders and available loans. Specifically, lenders who have invested within seven days before CT are considered as the active lenders in that time, while all loans in the soliciting-bids period at CT time are considered as available loans. These settings are the same with those in relevant work [17]. In our experiments, the start time of the data set is set to the first day (i.e., $CT = 0$), and we randomly select two time points from the dataset, i.e., $CT = 1700$ and $CT = 1800$. We also make the statistics on average participated lenders on each loan and their average pledging bidding amount, which are equivalent to the group-trading size and price of item. The data information is summarized in Table II.

B. Evaluation Metrics

We, respectively, adopt multiple metrics for evaluating the recommending performance in group buying and P2P lending. In the two markets, the metrics are defined in a similar way with subtle differences.

1) Metrics in Group Buying: For comparing the performance of algorithms in the group buying scenario, we adopted three evaluation metrics, i.e., group purchase success rate (denoted as GPSR), capital utilization rate (denoted as CUR), and customer/user's preference (denoted as UP). Formally, the GPSR is defined

$$\mathrm{GPSR} = \mathrm{GPS}/N \tag{10}$$

where GPS indicates the number of successfully trading items whose purchase volume has reached the appointed amount, and N represents the number of all items selling in platform. This metric is to measure the effectiveness of market or the satisfaction of merchants. In other words, this metric evaluates the efficiency of algorithm in finding the potential participated customers for group-buying items.

The second metric CUR is to measure the utilization of funds on the platform. Regardless of buyers, merchants, or platform, they hope that buyers can successfully purchase the products they want. Only in this way can the pledged money is effective and the trading can be beneficial to both two parties. Formally, the CUR is defined as

$$\mathrm{CUR} = \mathrm{VP}/\mathrm{TP} \tag{11}$$

where VP is the sum of all items those are validly purchased. TP indicates the sum of all the products recommended to customers or buyers.

The third metric *UP* directly adopts the objective function shown in (3) to measure whether the items recommended to

[3]https://www.tmall.com/

[4]https://www.prosper.com/

TABLE II
DATA INFORMATION

Data	Data Partitioning	#Customers/Lenders	#Items/Loans	Average group size	Average price
Tmall	smaller groups	987,994	4,162,024	28.88	*RMB* 291.44
	larger groups			70.01	*RMB* 213.48
Prosper	1,700-th day	3,607	544	144.32	\$ 49.59
	1,800-th day	3,196	645	128.19	\$ 50.59

buyers meet their preferences on price. In fact, the metric *UP* directly adopts the objective function $\boldsymbol{F_c}$ while GPSR and CUR partially reflect the objective function $\boldsymbol{F_m}$.

2) Metrics in P2P Lending: Similarly, for comparing the performance of algorithms in the P2P lending scenario, we adopted four evaluation metrics, i.e., loan success rate (denoted as LSR), CUR, investment income ratio (denoted as IIR), and lender's preference (LP). Formally, the LSR is defined

$$\mathrm{LSR} = \mathrm{LS}/N \tag{12}$$

where LS represents the number of loans in the recommendation candidates that were fully funded during their soliciting-bids period, and N represents the number of all available loans at CT. This metric reflects the satisfaction of borrowers, i.e., the efficiency of algorithm in finding the potential participated lenders for loans.

The second metric CUR is to measure the utilization of funds on the platform. Regardless of lenders, borrowers, or platform, they hope that the funds invested in the platform can be used in the projects. Only in this way can the funds be beneficial to both two parties. Formally, the CUR is defined as

$$\mathrm{CUR} = \mathrm{VI}/\mathrm{TI} \tag{13}$$

where VI is the sum of all effective investments, that is, the sum of the request amounts of all loans that were fully funded. TI indicates the sum of all loans recommended to lenders.

Different from the group buying, we also adopt another important measure in P2P lending, i.e., the third metric IIR is to evaluate the average return of all lenders in the entire market. This is the most concerned issue of lenders in reality and also an important evaluation on recommendation in finance [17]. For loans that have been fully funded, they will eventually have a status of nondefault (repayment) or default. When the loan eventually defaults, the return will be negative. Thus, this indicator also measures the risk of recommending loans. Formally, the IIR is defined as

$$\mathrm{IIR} = \sum_{j=1}^{N} Rt_j/\mathrm{TI} \tag{14}$$

where Rt_j represents the final real return (repayment or default) of the loan v_j. TI indicates the sum of all the loans recommended to lenders. Note that for loans with final status in the dataset, we calculate the return according to their final status. For loans that have not been actually fully funded in the recommendation, we randomly simulate the final state of the loan 20 times according the average default rate in the market, and the average return of 20 simulations is then obtained to approximate the specific return of the loan.

The fourth metric LP directly adopts the objective function shown in (7) to measure whether the loans recommended to lenders meet their preferences on return and risk.

C. Comparison Algorithms

In our experiments, the proposed method is denoted as CoEA. In addition, we test other multiple algorithms for comparison from various aspects. Generally speaking, these comparison algorithms can be classified into four categories, i.e., traditional recommendation algorithms, MOEA, single-objective evolutionary algorithms, and variants of CoEA.

1) *Traditional Recommendation Algorithms:* We implement user-based CF (UCF) [38], [39], item-based CF (ICF) [8], [40], and one advanced deep matrix factorization (DMF) model [9] for the formalized bidirectional recommendations. Specifically, UCF matches users and items by calculating the similarity between users, and ICF matches users and items by calculating the similarity between items. DMF first constructs a user-item matrix with nonpreference implicit feedback/interaction. Then, DMF presents a deep structure learning architecture to learn a common low-dimensional space for the representations of users and items.
2) *Multiobjective Evolutionary Algorithms:* We implement several representative MOEAs, including NSGA-II, SPEA2, MOEA-D, ARMOEA, and ToP. Based on the proposed matrix encoding method and designed specific objectives in this study, the multiobjective evolutionary framework of NSGA-II [31], SPEA2 [35], MOEA-D [30], ARMOEA [36], and ToP [37] is extended for solving the formalized bidirectional recommendation problems. For MOEA-D and ARMOEA algorithms, we adjust the reference points according to the distribution of candidate solutions in the current population at each generation, which is the most commonly adopted settings [36].
3) *Single-Objective Evolutionary Algorithms:* In order to verify the advantages of the proposed algorithm framework in solving the bidirectional recommendation problems, we also compare CoEA with $\boldsymbol{F_m}$-Optimizer and $\boldsymbol{F_c}$-Optimizer. Specifically, $\boldsymbol{F_c}$-Optimizer uses the evolutionary algorithm with our proposed strategies to individually optimize the objective $\boldsymbol{F_c}$ to obtain the optimal solution for customers/lenders without considering merchants/borrowers, and $\boldsymbol{F_m}$-Optimizer optimizes the objective $\boldsymbol{F_m}$ to obtain the optimal solution for merchants/borrowers without considering customers/lenders.
4) *Variants of CoEA:* In order to show the effectiveness of the proposed cooperative crossover and competitive

TABLE III
EXPERIMENTAL PARAMETER SETTING

Datasets	$psize$	gen	Max	gap	cp	mp
Tmall	100	200	30	10	0.25	0.1
Prosper	100	200	50	10	0.25	0.1

mutation, we compare CoEA with its two variants, namely, CoEA(-C) and CoEA(-M). Specifically, CoEA(-C) is the same as CoEA except that it replaces the cooperative crossover operator with the traditional single-point crossover operator. CoEA(-M) only changes the competitive mutation operator of CoEA to the traditional random mutation operator, and the rest is consistent with CoEA.

For consistency, the general parameters involved in our experiments for comparison algorithms are set according to Table III. Note that the proposed algorithm CoEA and MOEAs could recommend multiple solutions to each user, i.e., getting solution set on each run. For fair comparison, the results of CoEA and MOEAs on specific metrics are calculated as average values of all solutions. We record the convergence of MOEAs with the *gen* from 1 to 200 and the detailed experimental results and analysis can be found in Section I of the supplementary material. Finally, when comparing recommendation results, *gen* of all the MOEAs is set as 200. It was noted that all compared algorithms use the proposed population repairing operation. All comparison algorithms in experiments are implemented in MATLAB and the experiments are performed on a Windows 10 computer with AMD R7-3700X 4.00 GHZ CPU, 32 GB RAM.[5]

D. Experimental Results

In this section, we, respectively, report the recommending results on group buying and P2P lending.

1) Results on Tmall: Table IV records the performance of all comparison algorithms in terms of three evaluation metrics on the *Tmall* dataset of group buying, respectively, and all values are the average of all solutions obtained by each algorithm. In the table, every resulting value is followed with the rank of the corresponding algorithm among results of all algorithms in the parentheses and the best performance for each metric is marked with bold. Note that the average rank (AveRank) summarizes the overall ranking results of each algorithm on all the metrics.

From Table IV, it can be found that our CoEA can obtain the best AveRank over the three metrics. In other words, CoEA can get best equilibrium solutions that balance the needs of customers and merchants at the same time. We can also find that $\boldsymbol{F_c}$-Optimizer performs best on *UP*, and $\boldsymbol{F_m}$-Optimizer performs best on GPSR, since that they only optimize one objective while neglecting the other objective. In other words, they all only meet the needs of one type of user (customers or merchants). $\boldsymbol{F_m}$-Optimizer also performs better on CUR. In fact, the metric *UP* directly adopts the objective function $\boldsymbol{F_c}$ while GPSR and CUR partially reflect the objective function $\boldsymbol{F_m}$. In addition, we can observe that CoEA outperforms UCF, ICF, DMF, CoEA(-C), CoEA(-M), and other MOEAs, including NSGA-II, SPEA2, MOEA-D, ARMOEA, and ToP. Then, CoEA(-C) outperforms these MOEAs in terms of the four metrics and CoEA(-M) outperforms these MOEAs in terms of the overall metric (*AveRank*) on larger groups, which validates the effectiveness of the proposed evolutionary framework and the designed two evolutionary operators in this article. The results of *UP* on smaller groups are much better than those on larger groups, which implies that customers are more likely not to be satisfied when participating in larger group for buying.

To further illustrate the effectiveness of the proposed framework and operators, Fig. 5 presents the distribution of solutions obtained by UCF, ICF, DMF, NSGA-II, SPEA2, MOEA-D, ARMOEA, ToP, CoEA(-M), CoEA(-C), and CoEA in the objective space (where *x*-axis represents the objective function $\boldsymbol{F_c}$ and *y*-axis represents the objective function $\boldsymbol{F_m}$). As shown in this figure, these MOEAs (NSGA-II, SPEA2, MOEA-D, ARMOEA, and ToP) have almost the same performance (significantly worse than CoEA and these results are quite consistent with those of convergence on HV in Section I in the supplementary material, we zoom-in part with rectangle for better observation) on the bidirectional recommendation problem, because these MOEAs find multiple nondominated solutions on the two objectives without considering the equilibrium between them. Also, because the length of individual coding reaches more than one million, which makes the search efficiency of traditional multiobjective algorithms very poor. By comparing CoEA with CoEA(-M), it can be found that the competitive mutation operator can effectively improve the degree of convergence. By comparing CoEA and CoEA(-C) especially on the data with smaller groups, it can be seen that the cooperative crossover operator can make the obtained solutions more balanced and centralized.

2) Results on Prosper: Table V records the performance of all comparison algorithms at *CT* = 1700 and *CT* = 1800 in terms of four evaluation metrics in P2P lending, respectively.

From Table V, it can be found that our CoEA can obtain the best AveRank over the four metrics on the two Prosper datasets. Compared with the real records ("Real" in Table V lenders select loans by themselves with biddings. We can get these results in Prosper data directly) in the dataset, CoEA can greatly improve the trading efficiency of the platform and make the borrower and lender more satisfied. We can also find that $\boldsymbol{F_c}$-Optimizer performs best on *LP*, and $\boldsymbol{F_m}$-Optimizer performs best on LSR, since that they only optimize one objective while neglecting the other objective. They all only meet the needs of one type of user (lenders or borrowers). In addition, we can observe that CoEA outperforms UCF, ICF, DMF, CoEA(-C), CoEA(-M), and other MOEAs, including NSGA-II, SPEA2, MOEA-D, ARMOEA, and ToP. Then, both CoEA(-C) and CoEA(-M) outperform these MOEAs in terms of the overall metric, i.e., *AveRank*. Actually, the metrics LSR, CUR, and LP in P2P lending are, respectively, equivalent to GPSR, CUR, and UP; thus, their results are similar. On the unique metric CUR, which evaluates the average return of lenders getting from the recommending loans, CoEA, the variants of CoEA [COEA(-M) and COEA(-C)], $\boldsymbol{F_m}$-Optimizer,

[5] We will share all the experimental datasets and source code.

TABLE IV
PERFORMANCE OF ALL ALGORITHMS IN GROUP BUYING (LEFT: SMALLER GROUPS AND RIGHT: LARGER GROUPS)

Algorithms	*GPSR*	*CUR*	*UP*	*AveRank*	*GPSR*	*CUR*	*UP*	*AveRank*
UCF	0.5346(12)	0.1135(13)	0.2491(13)	12.67	0.3134(11)	0.2144(13)	0.0420(13)	12.33
ICF	0.3865(13)	0.3580(6)	0.6015(4)	7.67	0.1337(13)	0.2175(12)	0.0724(6)	10.33
DMF	0.7308(10)	0.3785(5)	0.3785(11)	8.67	0.2971(12)	0.2280(11)	0.5822(2)	8.33
NSGA-II	0.8279(4)	0.2153(11)	0.3813(9)	8.00	0.8394(8)	0.3260(10)	0.0667(9)	9.00
SPEA2	0.8279(4)	0.2163(9)	0.3812(10)	7.67	0.8375(9)	0.3272(8)	0.0659(12)	9.67
MOEA-D	0.8231(7)	0.2162(10)	0.3819(8)	8.33	0.8519(5)	0.3339(6)	0.0662(11)	7.33
ARMOEA	0.8260(6)	0.2165(8)	0.3850(6)	6.67	0.8481(6)	0.3355(5)	0.0663(10)	7.00
ToP	0.8192(8)	0.2145(12)	0.3836(7)	9.00	0.8413(7)	0.3264(9)	0.0669(8)	8.00
$\boldsymbol{F_c}$-Optimizer	0.6394(11)	0.5025(4)	**0.9996**(1)	5.33	0.3394(10)	0.4720(4)	**0.9756**(1)	5.00
$\boldsymbol{F_m}$-Optimizer	**0.9644**(1)	**0.6878**(1)	0.5599(5)	2.33	**1.0000**(1)	0.8728(3)	0.0749(5)	3.00
CoEA(-M)	0.8132(9)	0.2247(7)	0.3660(12)	9.33	0.8694(4)	0.3304(7)	0.0670(7)	6.00
CoEA(-C)	0.9016(3)	0.5744(3)	0.9620(3)	3.00	0.9783(3)	0.8787(2)	0.2455(3)	2.67
CoEA	0.9085(2)	0.5979(2)	0.9661(2)	**2.00**	0.9838(2)	**0.8809**(1)	0.2431(4)	**2.33**

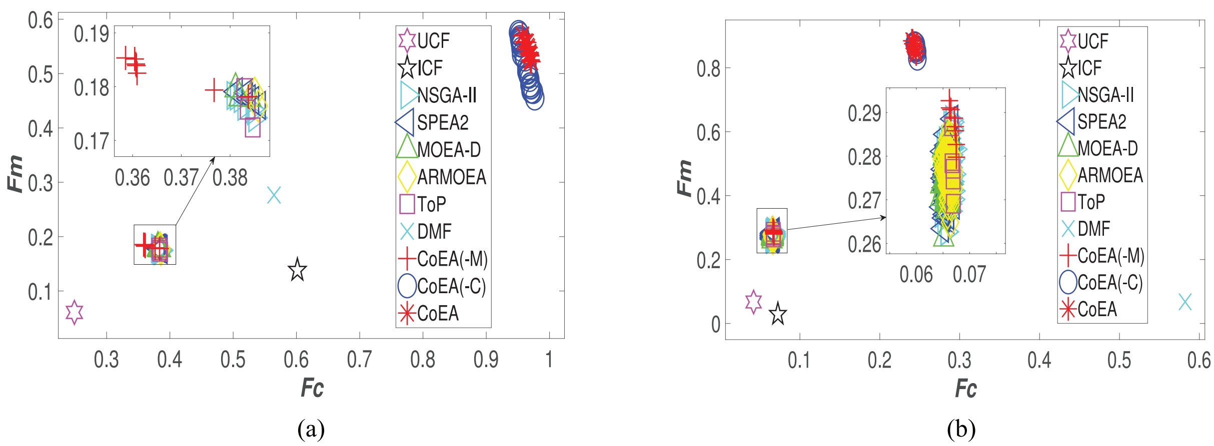


Fig. 5. Solutions in objective space of compared algorithms in group buying. (a) Smaller groups. (b) Larger groups.

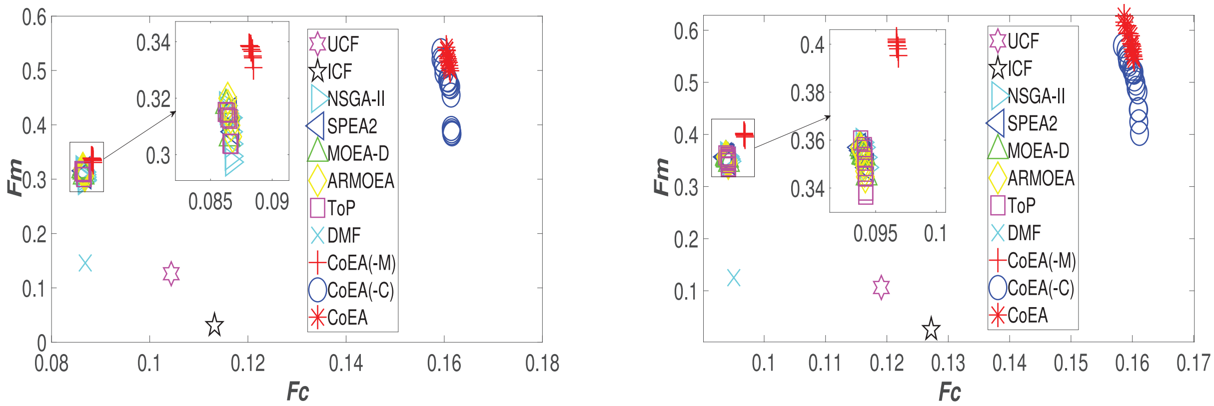
TABLE V
PERFORMANCE OF ALL ALGORITHMS IN PROSPER (LEFT: $CT = 1700$ AND RIGHT: $CT = 1800$)

Algorithms	*LSR*	*CUR*	*IIR*	*LP*	*AveRank*	*LSR*	*CUR*	*IIR*	*LP*	*AveRank*
Real	0.1949(14)	0.3975(5)	0.0094(13)	- (14)	11.50	0.2109(13)	0.4193(6)	0.0061(14)	- (14)	11.75
UCF	0.5404(11)	0.2320(13)	0.0147(11)	0.1044(5)	10.00	0.4000(11)	0.2635(12)	0.0156(12)	0.1191(5)	10.00
ICF	0.2813(13)	0.1093(14)	0.0061(14)	0.1132(4)	11.25	0.1845(14)	0.1409(14)	0.0091(13)	0.1272(4)	11.25
DMF	0.6066(10)	0.5066(2)	0.0137(12)	0.0867(7)	7.75	0.5085(10)	0.2461(13)	0.0161(11)	0.0950(7)	10.25
NSGA-II	0.9234(8)	0.3337(11)	0.0216(7)	0.0865(10)	9.00	0.9004(5)	0.3935(7)	0.0269(6)	0.0941(8)	6.50
SPEA2	0.9256(6)	0.3358(9)	0.0211(9)	0.0867(7)	7.75	0.8997(6)	0.3931(8)	0.0256(10)	0.0940(10)	8.50
MOEA-D	0.9265(5)	0.3365(8)	0.0214(8)	0.0864(13)	8.50	0.8992(7)	0.3928(9)	0.0260(9)	0.0940(10)	8.75
ARMOEA	0.9271(4)	0.3373(7)	0.0208(10)	0.0866(9)	7.50	0.8984(8)	0.3919(10)	0.0266(7)	0.0939(12)	9.25
ToP	0.9246(7)	0.3348(10)	0.0221(6)	0.0865(10)	8.25	0.8961(9)	0.3897(11)	0.0262(8)	0.0941(8)	9.00
$\boldsymbol{F_c}$-Optimizer	0.3143(12)	0.3254(12)	0.0273(4)	**0.2658**(1)	7.25	0.2977(12)	0.4197(5)	0.0343(3)	**0.2731**(1)	5.25
$\boldsymbol{F_m}$-Optimizer	**0.9982**(1)	0.4750(4)	0.0310(3)	0.0865(10)	4.50	**1.0000**(1)	0.5438(3)	0.0287(5)	0.0931(13)	5.50
CoEA(-M)	0.9307(3)	0.3604(6)	0.0230(5)	0.0883(6)	5.00	0.9198(3)	0.4342(4)	0.0290(4)	0.0968(6)	4.25
CoEA(-C)	0.9200(9)	0.5027(3)	0.0318(2)	0.1607(3)	4.25	0.9118(4)	0.5526(2)	0.0355(2)	0.1601(2)	2.50
CoEA	0.9489(2)	**0.5473**(1)	**0.0352**(1)	0.1608(2)	**1.75**	0.9527(2)	**0.6109**(1)	**0.0380**(1)	0.1596(3)	**1.50**

and $\boldsymbol{F_c}$-Optimizer, respectively, obtain the top five ranking results.

Fig. 6 presents the distribution of solutions obtained by UCF, ICF, DMF, NSGA-II, SPEA2, MOEA-D, ARMOEA, ToP, CoEA(-M), CoEA(-C), and CoEA in the objective space. As shown in this figure, the solution distribution of these MOEAs (NSGA-II, SPEA2, MOEA-D, ARMOEA, and ToP) is very close to a small local range. Thus, they have similar performance on the bidirectional recommendation problem, because these MOEAs find multiple nondominated solutions on the two objectives without considering the equilibrium between them.

By comparing the results on Prosper and Tmall, we can find that the performance of CoEA on Prosper is more significant. One possible reason is that CoEA performs much more better when optimizing the large groups. All in all, the results on Prosper and Tmall show consistency, which are clearly demonstrated the effectiveness of CoEA on bidirectional recommendations in group-trading markets, i.e., group buying and P2P lending.



(a) (b)

Fig. 6. Solutions in objective space of compared algorithms at different time points in P2P lending. (a) $CT = 1700$. (b) $CT = 1800$.

VII. Conclusion and Future Work

In this article, we presented a focused study on bidirectional recommendations in group-trading markets. Customers and merchants are competing in trading, i.e., customers want to meet their preferences or obtain gains with personal favorite items, while merchants want to recommend wholesale items with setting trading terms or conditions. Then, we proposed a cooperative–competitive evolutionary algorithm. Specifically, we, respectively, formalized two subproblems with designed objectives for the two participants in markets, and integrated the cooperative–competitive optimizations into one framework. Furthermore, the binary encoding matrix, cooperative crossover, and competitive mutation were designed and assembled in CoEA. In this study, we constructed two real applications, i.e., the group buying and P2P lending, and conducted extensive experiments with real-world datasets. By comparing CoEA with representative recommendation algorithms and single/MOEAs, the experimental results clearly demonstrated the effectiveness of CoEA on bidirectional recommendations in group-trading markets.

In the future, we will improve the equilibrium measure for better selecting individuals and adapt the proposed algorithm framework and operators to other scenarios or solving relevant optimization problems. Although our CoEA is designed for bidirectional recommendations in the group-trading markets, it is general and flexible enough to be applied to other general platforms or markets with accessing available data and investigating the objectives.

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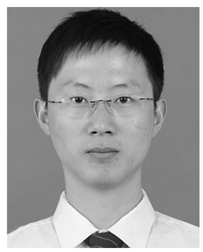

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