Optimized Social Explanation for Educational Platforms

Italo Zoppis[1], Riccardo Dondi[2], Sara Manzoni[1], Giancarlo Mauri[1], Luca Marconi[3] and Francesco Epifania[3]

[1]*Department of Computer Science, University of Milano Bicocca, Milano, Italy*

[2]*Department of Letters, Philosophy, Communication, University of Bergamo, Bergamo, Italy*

[3]*Social Things srl, Milano, Italy*

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Abstract: Recommender Systems have became extremely appealing for all technology enhanced learning researches aimed to design, develop and test technical innovations which support and enhance learning and teaching practices of both individuals and organizations. In this scenario a new emerging paradigm of explainable Recommander Systems leverages social friend information to provide (social) explanations in order to supply users with his/her friends' public interests as explained recommendation.

In this paper we introduce our educational platform called "WhoTeach", an innovative and original system to integrate knowledge discovery, social networks analysis, and educational services. In particular, we report here our work in progress for providing "WhoTeach" environment with optimized Social Explainable Recommandations oriented to design new teachers' programmes and courses.

1 INTRODUCTION

Recent approaches in explainable Recommander Systems (RS) leverage social friend information to supply users with explanations, concerning his/her social friends' public interests as recommended explanations. In fact, user-based RS has shown critical aspects, mainly due to the lack of important information (regulated by privacy) and the difficulty of recognizing the generated opinions (i.e, explanations) as valid or correct. In this regard, it is generally more acceptable to inform the users about social friends' public interests on the recommended items. As a result, part of current literature of recommender systems is focused on generating social explanations with the help of social information. For example, in (Papadimitriou et al., 2012) human-style, item-style, feature style and hybrid-style explanations in social recommender systems are considered by reporting geo-social explanations that combine geographical with social data. Sharma and Cosley (Sharma and Cosley, 2013) studied the effects of social explanations in music recommendation context by providing the target user with the number of friends that liked the recommended items. Chaney et al. (Chaney et al., 2015) presented social Poisson factorization, a Bayesian model that incorporates a user's latent preferences for items with the latent influences of her friends, which provides a source of explainable serendipity (i.e., pleasant surprise due to novelty) to users.

Based on a similar relational context, in (Quijano-Sanchez et al., 2017) recommendations are explained on similar users that are friends with the target user. In this case, social explanation is introduced in a system as group recommendation, which significantly increase the user intent to follow the recommendations, the user satisfaction, and the system efficiency to help users make decisions.

By following these ideas, we focus on the problem of modeling an optimized space of users (teachers) and items (resources), where social interaction is promoted, and Explainable Recommander Systems (ERS) can benefit from social information to supply recommended explanations. This perspective follows an interesting research area where graphs are taken as models for explainable recommendations (He et al., 2015; Heckel et al., 2017; Wang et al., 2018). In particular, we consider the case where new teachers, (Target Teachers, T), could be interested to meet some other colleagues (experienced teachers, X) for sharing information on recommended items (R). In this situation, the platform could encourage, for example, new

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teachers to socialize, and confront with the experience of specific collegues, who have already held similar (or alternative) programmes and courses. Similarly, the Recommender System can supply Target Teachers with clarifications concerning experienced teachers' public experiences as recommended explanations.

In this paper, we first introduce our educational platform called "WhoTeach"; an innovative platform to integrate knowledge discovery, social networks and educational services. Then, we report our work in progress to enhance "WhoTeach" with the capability described above for the design of new teachers' programme and course material. It is clear that, in such general situation, a proper handling of procedures and data is fundamental in order to convert available information into useful formulation that leads to particular (induced) communities. Please notice that the intent here is to develop the fundamentals for the considered social optimization problem (future implementation will be discussed in the conclusion section).

From a theoretical perspective our consideration can be expressed as the problem of finding cohesive subgraphs (with particular properties), inside a network. Unfortunately, as we report in this paper, the intrinsic complexity of the considered computational problem make optimization potentially impracticable. For this reason, we designed a specific heuristic (i.e., Genetic Algorithms, GAs) to seek faster approximation solutions.

More in details, we introduce the "WhoTeach" platform in Section 2. In Section 3.1 we consider the main theoretical aspects. Then, in Section 4, we discuss the GA-based approach to seek approximated results for our formulation. Finally, after reporting numerical experiments on simulated data (Section 5), we conclude the paper (Section 6) by discussing our results and describing future directions of this research.

2 WhoTeach

WhoTeach is an innovative and original system, conceived to promote the development of professional or academic competences of self-employed, managers or students by aggregating and disseminating knowledge created by experts. Hereinafter the experts will be called *teachers*, while learners will be also called *students*, regardless their professional or academic role in the organization in which they belong.

WhoTeach can be described as a Social Intelligent Learning Management System (SILMS). In fact, WhoTeach is distinguished from many traditional e-learning platforms thanks to the presence of two main components:

1. a recommender system, aimed at suggesting both teachers the right resources, in any format, to create their courses and students the right courses according to their educational background, their profile and their target;
2. a social network, aimed at allowing experience and knowledge exchange among peers, learners and teachers, so as to create communities of practice and of interest to empower the learning process. The platform is designed for demanding users, who want to teach or to learn in highly-dynamic disciplinary environments. Specifically it is the result of the exploitation of the European project NETT, with the aim of gathering a Social Network for improving and promoting the diffusion of the entrepreneurship knowledge and mind-set.

Teaching requires the organization of effective ad hoc courses, thus teachers need to get adequate didactic resources to avoid frustration and waste of time and to create high-quality courses and materials: thus WhoTeach provides them with suggestions to support and guide them in the organization of their courses. In order to obtain the creation of an effective and high-level course, the recommender system helps by reducing the high number of available resources, thus time and exhausting attempts to search teaching material. Moreover, it provides learners with a suggested path to improve specific skills, according to their profile, personal interests, usage history and evaluation check-lists.

A distinguishing approach in the SILMS is the use of learning algorithms to identify relations between the features of the platform contents that may prove suitable to the inquirer. Thanks to the massive use of metadata, the contents may be homogeneously identified through a vector of parameters (the metadata representation). In addition, thanks to the feedback of the previous users and the expertise of the system administrators, each composition of vectors in courses may be associated to a score. This enables a dynamical decision tree procedure where, depending on the current choice of the user, the system proposes branches of decision trees that may lead to satisfactory completion of the course, possibly listed in a monotone ranking.

The learning material is organised in different knowledge areas and contents are divided in resources, modules and courses. In particular, the resources can be different in their structure(wiki, discussion forum, eBook, etc) and format (word, pdf,etc). Classification through metadata allows reuse of learning materials. Every user can rate materials and courses found in SILMS; the evaluations are stored in a table ad-hoc (created by SILMS Developers) and used to implement the recommender system.

Learning and training are social activities, especially when the learning objects are relatively new, hence not yet assessed in well established disciplines. Thus, the second pillar of the platform structure is a social network where communities of teachers are fostered around each disciplinary sector. The objective is to transform a personal learning experience in a more collaborative and amazing one, obtaining better results. To this aim, SILMS platform is equipped with standard social network tools (like blogs, chat, forum, messaging), plus the following advanced functionalities tailored for NETT project:

- Definition of Community. Around each disciplinary sector it is possible to define specific communities of teachers. These communities are moderated by the master of the knowledge area associated to each discipline sector. The objective of these communities is to transform a personal learning experience in a more collaborative and amazing one, obtaining better results. Moreover, thematic communities can be freely created by teachers.
- Sharing of Didactical Materials. Beside the official version of didactic materials published within the SILMS platform, there is the possibility to share non official material, without waiting experts' or masters' approvals.
- Informal Communication Among Users. While sharing, teachers should receive private or public feedbacks that can help him/her in improving his/her materials. Moreover, communications among contributors/experts and experts/ masters can be conducted through social network facilities.
- Teacher's Profile. Teachers are called to create and edit their own profile, where personal experience or school education can be reported. This enables masters to promote contributors in experts relying on competence and credits. It also fosters social activities of users, who can get in touch with other teachers beyond the SILMS platform through either internal tools or external tools, e.g. Skype.
- Followers. Teachers can create a network composed by people with the same interests or experiences. Among them, people can follow a particular content of a user and consequently receive updates and news, keeping in touch with teachers with either the same skills or working, anyway, in the same field.

Therefore, the idea is that this kind of social network can give rise to rich, efficient and fruitful communities of practice rooted on the common goal of favoring course design activities.

From a technical perspective, the system consists of a PHP shell piloting and empowering the customization of the Moodle platform, as for a Content Management System and Mahara as for a nested Social Network. Mahara is a fully-featured web application to build an electronic portfolio. A user can create journals, upload files, embed social media resources from the web and collaborate with other users in groups. What makes Mahara different from other ePortfolio systems is that the user can control which items and what information other users see within their portfolio.

The Moodle system was chosen because of its high diffusion within the school and due to the presence of a wide development community. The platform has been then integrated with social network features coming from Mahara, in order to introduce meta-services as previously described.

3 SOCIAL OPTIMIZATION PROBLEMS

Suppose we wish to model the situation where new users (i.e., target teachers, or T as they will be referred in this paper) are interested to design new courses by applying resources and recommended materials already used by colleagues, who have held similar (or even alternative) courses.

In this case, T could benefit from the social interaction with their colleagues, to confront with their past experience, and to deepen knowledge about their social friends' public interests on the recommended items. As reported above, it should be useful for a social platform to encourage, and optimize the creation of a sub-network of users (teachers) and items (resources) from the available data.

3.1 Problems Formulation

From a theoretical point of view, a network is most commonly modeled using a graph which represents relationships between objects, V (vertices), through a set of edges, E. In this way, our goal can be formulated by maximizing, within a defined graph, a *cohesive* sub-graph (i.e., by seeking the largest cohesive sub-graph) with particular properties (as we will detail in the following). Finding cohesive subgraphs inside a network is a well-known problem that has been applied in several contexts (Bader and Hogue, 2003; Spirin and Mirny, 2003; Sharan and Shamir, 2000).

While a classical approach to compute dense subgraphs is the identification of cliques (i.e., complete sub-graphs induced by a set of vertices which are all pairwise connected by an edge), this definition is often too stringent for particular applications. This is the case, when the knowledge on how an individual (vertex) is embedded in the sub-network (e.g., some vertices could act as "bridges" between groups, as in our case) is a critical issue to take into account. Therefore alternative definitions of cohesive sub-graphs can be introduced, for example by relaxing some constraints, leading to the concept of *relaxed clique* (Komusiewicz, 2016). Here, we follow this approach by relaxing the definition of distance between vertices. In a clique distinct vertices are at distance of 1, in our case, vertices can be at distance of at most $s = 2$. A sub-graph where all the vertices are at distance of at most 2 is called a 2-*club* (or, more in general, *s-club* for different values of s).

3.2 Main Definitions

Let us consider a graph $G = (V,E)$, and a subset $V' \subseteq V$. We denote by $G[V']$ the subgraph of G induced by V'. Formally $G[V'] = (V',E')$, where

$$E' = \{\{u,v\} : u,v \in V' \wedge \{u,v\} \in E\}.$$

Given a set $V' \subseteq V$, we say that V' *induces* the graph $G[V']$[1]. The *distance* $d_G(u,v)$ between two vertices u,v of G, is the length of a shortest path in G which has u and v as endpoints. The *diameter* of a graph $G = (V,E)$ is $\max_{u,v\in V} d_G(u,v)$, i.e., the maximum distance between any two vertices of V. In other words, a 2-club in a graph $G = (V,E)$ is a sub-graph $G[W]$, with $W \subseteq V$, that has diameter of at most 2.
Moreover, given a vertex $v \in V$, we define the set $N(v)$ as follows:

$$N(v) = \{u : \{v,u\} \in E\}$$

$N(v)$ is called the neighborhood of v.

We formulate the "social computational problem" described above, using 2-clubs, in such a way that paths connecting T with items R has to "transit" through $x \in X$.

In this way, we are currently seeking (within the input "social graph") a 2-Club, $G[T \cup X \cup R]$, where T, X and R represent the sets of new users, experienced teachers, and resources, respectively.

Please notice that, if such a structure (i.e., a maximum size 2-clubs) exists, then for any pair of vertices, it must exist at least one simple path of length 2, i.e., a path composed by a triple of vertices. This, in turn, will also be true for any pair, (t,r) where $t \in T, r \in R$. Indeed, our goal will be to find a largest-size 2-clubs which has the further property of providing, the maximum number of pairs (t,r), characterized by the triple of vertices $(t,x,r) \in (T \times X \times R)$. In this case, the following set of fundamentals edges are important to provide a correct optimization procedure.

- Edges between users, E, (i.e.,, between new teachers T and experienced teachers X), expressing e.g., interest to cooperate, similarity etc.
- Edges between users and items, F, expressing that an experienced teacher x, has already applied a course resource, r. In this case the edges in $X \times R$ will be constructed by knowing both the educational history of each (experienced) teacher, x, and the resource r, which x has already applied for its courses.

In this situation, the paths given by the triple of vertices $(t,x,r) \in (T \times X \times R)$ would suggest to teacher $t \in T$ to contact colleagues, $x \in X$, about the recommended resource, $r \in R$. For sake of clarity, before defining computationally the problem, we refer to any vertex, $x \in X$, for which there exists at least one pair $(t,r) \in T \times R$ within its neighborhood $N(x)$ as "feasible vertex". Similarly, a set of "feasible vertices" $\mathcal{C}$ will be referred as "feasible set", and a pair (t,r), for which there exists the feasible vertex $x \in X$, will be named "'feasible pair". Considering the above discussion, we can define the following variant of the 2-clubs maximization problem.

Problem 1. ***Input:*** *a graph* $G = (T \cup X \cup R, E \cup F)$. ***Output:*** *a set* $V' \subseteq T \cup X \cup R$ *such that* $G[V']$ *is a* 2-*club having both maximum size and the largest number of feasible pairs.*

4 A GENETIC ALGORITHM

The complexity of Maximum *s*-club has been extensively studied in literature, and unfortunately it turns to be NP-hard for each $s \geq 1$ (Bourjolly et al., 2002). The same property holds for our variant of Maximum 2-club, thus making optimization potentially impracticable. For this reason, we designed a Genetic Algorithm (GA) to seek faster approximation solutions see, e.g., (Mitchell, 1996) for details.

[1]Notice that all the graphs we consider are undirected.

In particular, given an input graph $G = (V, E)$, the proposed GA represents a solution (a subset $V' \subseteq V$ such that $G[V']$ is a 2-club of G) as a binary chromosome c, of size $n = |V|$, such that for all $v_i \in V'$, $c[i]$ is either 1 or 0. Note that, with a slight abuse of notation, we will denote by $G[c]$ the subgraph of G induced by the representation of chromosome c. Similarly, $V[c]$ and $E[c]$ will denote the set of vertices (V') and edges of $G[c] = G[V']$.

During the offspring generation, chromosomes are interpreted as hypotheses of feasible solutions, undergoing to mutation, crossover and selection. Chromosome evaluation (i.e., hypothesis on a potential 2-club) is then provided, as usually, through the fitness function. For space requirements in the following sections, only 2 relevant issue of this approach are detailed, namely fitness and mutation. Currently, crossover operator does not differ significantly from the standard definition.

4.1 Fitness Definition

In this paper, fitness is designed to promote adaptation in such a way that new candidate chromosomes, able to represent graphs with correct diameter value (i.e., not grater than 2) will "evolve" through specific mutation and standard crossover. In particular, given a chromosome c, and an input graph $G = (V, E)$, the fitness promote such a mechanism using the following quantities.

1. An estimation of the number of feasible vertices v
2. The number of vertices, n_V, of the (sub)graph, $G[c]$, induced by c.

In particular, for any chromosome c, we observed a sample S of vertex $v \in V[c]$ and by considering the induced sub-graph representation $G[c]$, we evaluated the following fitness:

$$f(n_v; \text{diam}) = \begin{cases} (n/|S|)n_v & \text{if } 0 \leq \text{diam} \leq 2 \text{ ;} \\ \frac{1}{n_v} & \text{if } 2 < \text{diam} \text{ ,} \end{cases} \quad (1)$$

where n_v is the cardinality of $G[c]$, i.e., the sub-graph induced (speculated) by c, and n is the frequency of "feasible" vertex observed in S, i.e., $\sum_{k=1}^{n} I(x_k \in \mathcal{C})$, with:

$$I(x)_k = \begin{cases} 1 & \text{if } x_k \in \mathcal{C} \text{ ;} \\ 0 & \text{otherwise.} \end{cases} \quad (2)$$

In this way, by using the proportion, $n/|S|$, the fitness weights (when $0 \leq \text{diam} \leq 2$) the number of vertices n_v in $G[c]$, thus promoting large (sub)graph. On the other hand, when diam > 2 (i.e., unfeasible solutions), we have fitness values which decrease asymptotically for large (sub)graph size, n_v, thus penalizing the corresponding chromosome.

4.2 Mutation

To promote adaptation (with regard to the Maximum 2-club problem), we defined 2 types of mutation, respectively applied with equal probability.

- Mutation Operator 1 has the objective to correct hypotheses (i.e., chromosomes) consistently and parsimoniously. Since any chromosome, by construction, induce a sub-graph $G[V']$ of G, which should reflects feasible solutions, such hypotheses are partially verified using the following principle. Given a selected chromosome c, a vertex v' is (randomly) sampled from the set $V_+ = \{v_i : c[i] = 1\}$ and the minimum length of simple paths connecting every pair $(v_i, v'), v_i \in V_+/v'$ is checked to be consistent with the chromosome "hypothesis", i.e., since each chromosome "speculates" a feasible 2-club, for such hypothesis to be true, there must be, at least, a simple path of size at most equal to 2 connecting any $v_i \in V_+$ with v'. If a negative feedback is observed after this verification, then the sampled vertex v' is flipped to 0.
- Mutation Operator 2. This operator has the objective to (parsimoniously) increment the size of a solution. In this case, given a selected chromosome c a vertex v' is sampled from $V_- = \{v_j : c[j] = 0\}$ and the minimum length of simple paths connecting every pair (v_i, v') ($v_i \in V_+$) is checked to be consistent with the chromosome c's hypothesis. In this case, we consider to extend the solution represented by c, by adding v' to V_+ if the minimum distances from v' to vertices of V_+ are not larger than 2.

5 NUMERICAL EXPERIMENTS

The genetic algorithm described in Sec. 4 was coded in R using the "GA" package (Scrucca, 2013). The main objective was to evaluate the capability of GAs to obtain correct solutions for Problem 1 in a reasonable time.

Results are given for synthetic data, by sampling Erdos-Renyi random graphs $ER(n, p)$ with different values of number of vertices, n, and edge probability $p = 0.4$ (Bollobas, 2001). To provide correctness at "reasonable" cost (Lewis and Papadimitriou, 1997), we followed the standard practice of evolutionary algorithms: keep the tractability of the search operators and the fitness, and promote, at the same time, evaluable chromosomes, which in our case, provide feasible input diameter values. Moreover, a widely applied principle for termination has been applied: we set up

Table 1: Performances: Models (Erdos-Renyi); Fitness (Fit); Input Diameter (InD); Output Diameter (OutD); Output Nodes (OutN), Input Feasible vertices (InFeas); In/out Ratio of Feasible Vertices (IORatio); User (T1) and System Time (T2).

Models	Fit	InD	OutD	OutN	Ratio	IFeas	IORatio	T1	T2
ER(25,0.4)	10.3	3	2	10.3	0.413	8	0.452	55.6	1.11
ER(50,0.4)	28.3	3	2	29.7	0.593	18.7	0.758	289	3.34
ER(100,0.4)	53.7	2.3	2	83.3	0.833	31.3	0.927	645	2.33
ER(150,0.4)	80.4	2	2	145	0.964	47	0.965	792	1.04
ER(300,0.4)	149	2	2	285	0.951	103	0.955	2776	2.98

both the number of re-evaluation of the fitness over new populations (equivalently, the number of the GA iterations), and the number of consecutive generations without improvement of the best fitness value[2]. Note that to check the robustness of the solutions, each ER model has been sampled iteratively 3 times. The results are reported in Tables 1.

The following main considerations emerge from the results.

- In all models, we obtained correct 2-clubs (Diameter value ≤ 2).
- Clearly, due to the complexity of the problem, we cannot compare the optimal solution with the ones given by the GA. Therefore, to give a qualitative idea of the approximated solutions, we reported the output over input ratio of feasible vertices. Evaluable solutions are those for which this ratio is close to 1. In these cases, the environment provides at least one feasible vertex as defined above.
- While the size of the inferred communities does not seem to differ, the (average) number of iterations of the last level site, for the distributed case, is much lower than the iterations reported by the standard, centralized evolution. This is also evident from the decrease in the average execution time per level, reported by the distributed case. Since GA uses the same parameters for the standard and the distributed evolution, this behavior can surely be traced back to the initial suggestions that each lower level site receives from the higher level.
- System time seems to be reasonable ($T2 \leq 4$) on the considered instances.

6 CONCLUSIONS

In this paper we introduced our work in progress to enhance the WhoTeach platform with optimized explanations concerning social users' public interests. We considered this issue from a computational point of view by defining a variant of a well known optimization problem. Due to the hardness of the formulated question, we presented some introductory results on how we apply GAs for obtaining approximated solutions (i.e., see also (Dondi et al., 2017; Dondi et al., 2016)). Our interest for future implementation of this research will be focused on the following items:

- The platform should be able to not only provide the user (target teacher) with an optimized "list" of his social (experienced) friends, but even focusing on the specific (identification) of (target) user's requirement (i.e. items). In this way the systems should provide the (optimized) enumerated list of items in agreement both with the user requests, and the "expert" teacher experiences.
- In a further step of generalization, the platform should be able to provide learners and teachers with optimised suggestions taking into consideration the weighted requirements coming from different communities or sub-communities: e.g teachers enrich their courses through information and insights coming not only from other teachers but also from the dynamics of the context.
- Another important issue is related to the possibility of using WhoTeach as an e-recruitment system: the platform then should be able to provide companies with optimised social recommendations so as to match users' and companies' needs. That would allow learners to adapt their learning path so as to keep it up-to-date and to gain all the necessary professional skills and meta-competencies required by the labour market.

[2]See, e.g. (Safe et al., 2004), for a critical analysis of various aspects associated with the specification of termination conditions in a simple genetic algorithm.

REFERENCES

Bader, G. D. and Hogue, C. W. V. (2003). An automated method for finding molecular complexes in large protein interaction networks. *BMC Bioinformatics*, 4:2.

Bollobas, B. (2001). *Random Graphs*. Cambridge University Press.

Bourjolly, J., Laporte, G., and Pesant, G. (2002). An exact algorithm for the maximum k-club problem in an undirected graph. *European Journal of Operational Research*, 138(1):21–28.

Chaney, A. J., Blei, D. M., and Eliassi-Rad, T. (2015). A probabilistic model for using social networks in personalized item recommendation. In *Proceedings of the 9th ACM Conference on Recommender Systems*, pages 43–50. ACM.

Dondi, R., Mauri, G., and Zoppis, I. (2016). Clique editing to support case versus control discrimination. In *Intelligent Decision Technologies*, pages 27–36. Springer.

Dondi, R., Mauri, G., and Zoppis, I. (2017). Orthology correction for gene tree reconstruction: theoretical and experimental results. *Procedia computer science*, 108:1115–1124.

He, X., Chen, T., Kan, M.-Y., and Chen, X. (2015). Tri-rank: Review-aware explainable recommendation by modeling aspects. In *Proceedings of the 24th ACM International on Conference on Information and Knowledge Management*, pages 1661–1670. ACM.

Heckel, R., Vlachos, M., Parnell, T., and Dünner, C. (2017). Scalable and interpretable product recommendations via overlapping co-clustering. In *Data Engineering (ICDE), 2017 IEEE 33rd International Conference on*, pages 1033–1044. IEEE.

Komusiewicz, C. (2016). Multivariate algorithmics for finding cohesive subnetworks. *Algorithms*, 9(1):21.

Lewis, H. R. and Papadimitriou, C. H. (1997). *Elements of the Theory of Computation*. Prentice Hall PTR.

Mitchell, M. (1996). *An introduction to genetic algorithms*. Complex adaptive systems. MIT press, Cambridge (Mass.).

Papadimitriou, A., Symeonidis, P., and Manolopoulos, Y. (2012). A generalized taxonomy of explanations styles for traditional and social recommender systems. *Data Mining and Knowledge Discovery*, 24(3):555–583.

Quijano-Sanchez, L., Sauer, C., Recio-Garcia, J. A., and Diaz-Agudo, B. (2017). Make it personal: a social explanation system applied to group recommendations. *Expert Systems with Applications*, 76:36–48.

Safe, M., Carballido, J., Ponzoni, I., and Brignole, N. (2004). On stopping criteria for genetic algorithms. *Advances in Artificial Intelligence–SBIA 2004*, pages 405–413.

Scrucca, L. (2013). GA: A package for genetic algorithms in R. *Journal of Statistical Software*, 53(4):1–37.

Sharan, R. and Shamir, R. (2000). Center CLICK: A clustering algorithm with applications to gene expression analysis. In *Proc. of the Eighth Int. Conf. on Intelligent Syst. for Molecular Biol., August 19-23, 2000, La Jolla / San Diego, CA, USA*, pages 307–316.

Sharma, A. and Cosley, D. (2013). Do social explanations work?: studying and modeling the effects of social explanations in recommender systems. In *Proceedings of the 22nd international conference on World Wide Web*, pages 1133–1144. ACM.

Spirin, V. and Mirny, L. A. (2003). Protein complexes and functional modules in molecular networks. *Proceedings of the National Academy of Sciences*, 100:12123–12–128.

Wang, X., He, X., Feng, F., Nie, L., and Chua, T.-S. (2018). Tem: Tree-enhanced embedding model for explainable recommendation. In *Proceedings of the 2018 World Wide Web Conference on World Wide Web*, pages 1543–1552. International World Wide Web Conferences Steering Committee.