Understanding and Promoting Teacher Connections in Online Social Media: A Case Study on Pinterest

Hamid Karimi[1], Kaitlin T. Torphy[2], Tyler Derr[3], Kenneth A. Frank[2], Jiliang Tang[1]
[1]*Computer Science and Engineering, Michigan State University*, {karimiha,tangjili}@msu.edu
[2]*Counseling, Educational Psychology and Special Education, Michigan State University*, {torphyka,kenfrank}@msu.edu
[3]*Electrical Engineering and Computer Science, Vanderbilt University*, Tyler.Derr@vanderbilt.edu

***Abstract*—In this work, we perform a large-scale investigation of teacher connections in online social media. To this end, we first construct a large dataset of teachers on Pinterest, an image-based popular online social media. Our dataset includes 540 teachers across 5 states and 48 districts, as well as thousands of connections they have established. Then, considering some crucial teacher-related attributes (e.g., their states and grade levels), we characterize direct and indirect teacher connections. Through this characterization, we discover that teachers are predominately connected to their peers in the same district or at least within the same state, and seldom there exist links between teachers outside their districts and states. This hinders the proper diffusion of information and many other advantages that a teacher-teacher connection in an online social media can bring about, e.g., getting advice from their peers. To alleviate this problem, we utilize advances in machine learning and propose a link recommendation system suggesting teachers connect with their similar peers on Pinterest. Our system's evaluation reveals that many new teacher-teacher connections are suggested, which leads to a more cohesive network among teachers rather than the existing localized ego networks.**

Keywords*— *teachers, social media, Pinterest, link recommendation, network analysis

I. Introduction

Online social media platforms have connected billions of people across the globe. Thanks to their free, fast, easy-to-use nature and network across geography, information across online social media is diffused almost instantaneously. In addition to personal purposes, many individuals utilize online social media to improve their professional activities. Within education, many teachers utilize online social media to enhance their educational activities [1], [2], [3], [4], [5]. One of the primary drivers of teachers to turn to online social media is to supplement their instructional and educational resources. In the classroom, many teachers encounter needing additional pedagogical resources to improve their students' learning. Traditional means of educational resource curation (e.g., asking a colleague) is time-consuming and not scalable. In contrast, seeking out educational resources from other teachers in online social media is easily accessible. Additionally, teachers may access resources from those teachers they most admire or perceived expert teachers. The diffusion of resources can be rapid, within the same day, and teachers may integrate resources into their classroom practice quickly and efficiently. In addition to resource supplements, some teachers utilize online social media to seek advice from their peers, share ideas, interact with each other via various online interactions, and so on [6].

Although there is a substantial amount of evidence showing the usefulness of online social media for teachers seeking additional resources [1], [7], social media services (e.g., Pinterest or Twitter) have millions of users and billions of posts. Teachers and their educational resources are likely buried. Therefore, it is unclear how teachers who use online social media for professional career development are connected. Thus, it is essential to understand and consequently facilitate teacher-teacher connections, which can have numerous benefits, including quicker and more efficient diffusion of resources. Aiming to understand teacher connections and subsequently devising a system to encourage teacher-teacher connections in online social media, we take three crucial steps in this paper. First, we construct a large dataset of teachers on Pinterest. Second, we thoroughly explore and analyze the data to characterize teachers' connections on Pinterest. Notably, we compute likelihoods for a social tie while considering a set of teacher-related attributes that might relate to the connection a teacher establishes with another one. Third, we propose an effective and scalable method to recommend teachers in online social media. This system utilizes advances in machine learning and social network analysis and automatically learns salient features from Pinterest's network. To the best of our knowledge, this is the first attempt to promote teacher connections that have the great potential to boost teachers' activities and the diffusion of educational resources. In summary, our contributions are as follows.

- We construct the first known large-scale dataset of teachers on Pinterest.
- We thoroughly analyze the connections that teachers establish with other users on social media and provide new insights.
- We propose a link recommendation method harnessing the advances in social network analysis and machine learning.

II. Related Work

Teachers in social media. Steinbrecher and Hart [8] investigated how teachers use Facebook for personal and professional purposes. They found that pre-service educators use Facebook mostly for personal purposes and seldom professionally. Several studies have shown evidence that teachers increasingly use Twitter for professional purposes, e.g., resource sharing [9], [10], [11]. Carpenter et al. [12] studied how Pinterest is used for educational purposes. They indicated that teachers use Pinterest to promote educational materials. In particular, they discovered that many individuals were sharing resources curated in TeachersPayTeachers.com, a crucial virtual resource pool where teachers may sell/buy various educational resources. Frank et al. [7] thoroughly analyzed the role of social networks and, in particular, showed that Pinterest is providing emerging beneficial opportunities for education. The authors pointed out that teachers in online social networks can act as valuable sources for one another. More specifically, they can spread their expertise, which can aid in reduced teacher differences in education. Another study focusing on teachers' usage of Pinterest [13], conducted for 117 teachers, showed that teachers mostly utilize Pinterest to look for educational resources according to their classroom needs. Torphy et al. [14] examined the diffusion of educational resources on Pinterest. Their results indicated that direct connection between teachers spurs resource curation. Moreover, they showed that Pinterest acts as a promising bridge between teachers helping to diffuse educational resources.

Link recommendation for social networks is an active research area in machine learning. There are two families of link recommendation approaches: learning-based and proximity-based. In the former, a model is trained from the previously observed link establishments, while in the latter, a surrogate is used to proximate the connection establishment between two nodes [15]. Our link recommendation method (Section V) belong to proximity-based method. More specifically, similar to [16], we determine the proximity between two nodes (teachers) based on their structural attributes in the Pinterest network. Interested readers can refer to [15] for a review of link recommendations for social networks.

III. Data

We surveyed 540 teachers across 5 states (Michigan, Illinois, Texas, Indiana, and Ohio), 48 districts, and 99 schools. 428 teachers are females, 13 males, and 99 unspecified. For all surveyed teachers, we acquired their Pinterest handles (usernames), and then through the API (application programming interface) provided by Pinterest, we collected their data from Pinterest. We downloaded 1,205,631 pins shared by the end of Feb 2019. For each teacher, we obtained the list of their followers and followees. A follower is someone who follows that specific teacher, while a followee is someone who is followed by that teacher. For all followees and followers, we retrieved their pins and the list of their connections (i.e., their own followers/followees). Once all connections are identified, we constructed the entire network of our Pinterest users, including the surveyed teachers and their followers/followees. Figure 1 demonstrates the degree distribution where the number of followers and followees are combined. Similar to other (online) social networks, the distributions follow the power-law distribution [17], where most of the nodes have a smaller number of connections and a very small percentage have high degrees. The average degree (i.e., the mean number of connections) is 269.

TABLE I
Statistics of the Pinterest network

# Teachers	540	# links between teachers	1,059
# Other users	98,667	# Links between teachers and others	117,169
# Total users	99,207	# Total links	6,119,338

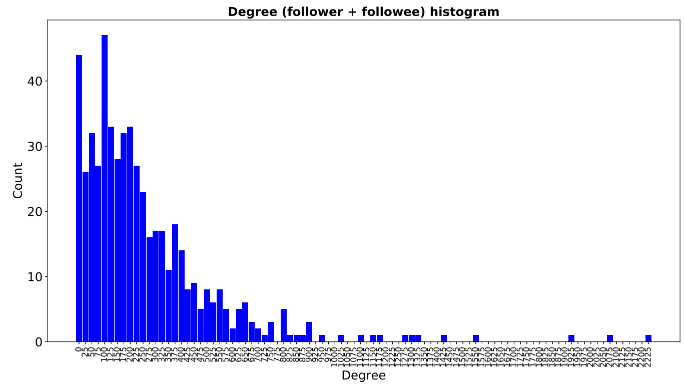

Fig. 1. Degree distribution of teachers on Pinterest network

IV. Teacher Connections Characterization

To deepen our understanding of teacher connections on Pinterest, we characterize their connections while considering some teacher-related attributes. For these attributes, we characterize direct and indirect teacher connections explained in Section IV-A and IV-B, respectively.[1]

A. Direct connection characterization

Given the network of teachers on Pinterest, we evaluate several conditional probabilities in the following format.

$$\mathrm{P}\ (\mathrm{T_i}\ \textbf{attribute}\ \mathrm{T_j} \mid \mathrm{T_i} — \mathrm{T_j}) \tag{1}$$

where $\mathrm{T_i}$ and $\mathrm{T_j}$ are two sample teachers, **attribute** denotes an attribute we consider to investigate teacher-teacher connections, and $\mathrm{T_i} — \mathrm{T_j}$ denotes a connection between teachers $\mathrm{T_i}$ and $\mathrm{T_j}$ on our constructed Pinterest network. Through Eq. (1), we attempt to evaluate how likely two teachers have a specific attribute (i.e., $\mathrm{T_i}$ **attribute** $\mathrm{T_j}$) given that the two teachers are directly connected on Pinterest (i.e., $\mathrm{T_i} — \mathrm{T_j}$).

B. Indirect connection characterization

Teachers on Pinterest can be connected indirectly through a common Pinterest user. Hence, to better characterize teacher connections on Pinterest, we extend the characterization formulated in Eq (1) beyond a direct connection between two teachers and consider the case when two teachers are indirectly connected by an intermediate user who can be another teacher or a Pinterest user unknown to us. One reason to consider the indirect connection is that a teacher may acquire a resource that does not necessarily come from his/her direct connections and may have been curated by other teachers connected indirectly to her/his. Moreover, to enhance information diffusion and mutual collaboration, we might spur a direct connection between two teachers having a common attribute (e.g., teaching at the same deistic or the same grade level) while they are connected indirectly. Given the above discussion, we evaluate a conditional probability for some attributes between two teachers who are connected indirectly:

$$\mathrm{P}\ (\mathrm{T_i}\ \textbf{attribute}\ \mathrm{T_j} \mid \mathrm{T_i} — \mathrm{U} — \mathrm{T_j}\ \mathrm{AND}\ \ \mathrm{T_i} - \times - \mathrm{T_j}) \tag{2}$$

[1]The content of this section has been previously published in our work-in-progress paper [4].

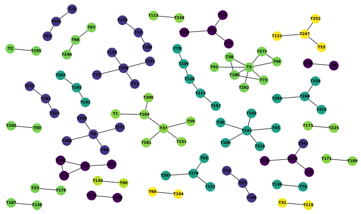

Fig. 2. The physical network

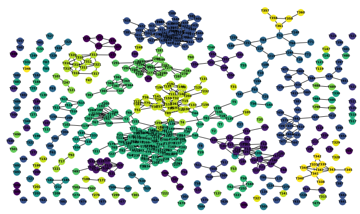

Fig. 3. The virtual network (Pinterest)

where U denotes a Pinterest user bridging teachers T_i and T_j and $T_i - \times - T_j$ signifies that there is no direct connection between T_i and T_j.

C. Teacher-related Attributes

We evaluate teacher connections (either direct or indirect) by considering two sets of teacher-related attributes, i.e., geographical and professional attributes. For geographic attributes, we consider *school*, *district*, *state*, and *physical link*. The reason for including the latter is that physical connections are manifested in a face to face social network among teachers, which is obviously bound to geographic constraints. For professional attributes, we consider *grade level* and number of *shared resource(s)* between two teachers. A shared resource is defined as a pin that is saved (pinned) by both teachers. We consider a binary case whether any number of resources has been shared or none.

D. Physical versus Virtual Network

To further help characterize teacher connections on Pinterest better, we compare physical and Pinterest (virtual) networks of teachers. Figure 2 and Figure 3 illustrate these two networks, respectively. A link is established between two teachers in the physical network if one has sought teaching advice from the other. Moreover, we de-identify teachers and denote them a **T***N*, where *N* is a random number in the range [1, 540] assigned to each teacher. Note that physical edges are only available for a subset of teachers, namely 104 out of the 540 total teachers.

E. Results

In this section, we present the results for teacher connections characterization. Table II shows the results for the characterization of direct teacher-teacher connections (i.e, Eq. (1)) while Table III demonstrates the results for indirect connections between teachers (i.e., Eq. (2)). Note that, for each attribute, we have included the conditional probability of its negation as well.

Q1: Do geographical attributes affect teacher connections on Pinterest?

TABLE II
RESULTS OF DIRECT TEACHER CONNECTIONS CHARACTERIZATION ACCORDING TO EQ. 1

	Attribute	Probability
Geographic	P (T_i ***the same school*** T_j $\mid$ T_i — T_j)	557/1059 = 52.13%
	P (T_i ***different school*** T_j $\mid$ T_i — T_j)	507/1059 = 47.87%
	P (T_i ***the same district*** T_j $\mid$ T_i — T_j)	1016/1059 = 95.94%
	P (T_i ***different district*** T_j $\mid$ T_i — T_j)	557/1059 = 4.06%
	P (T_i ***the same state*** T_j $\mid$ T_i — T_j)	1056/1059 = 99.71%
	P (T_i ***different state*** T_j $\mid$ T_i — T_j)	3/1059 = 0.29%
	P (T_i ***physical link*** T_j $\mid$ T_i — T_j)	31/81 = 38.27%
	P (T_i ***no physical link*** T_j $\mid$ T_i — T_j)	50/81 = 61.73%
Professional	P (T_i ***the same grade level*** T_j $\mid$ T_i — T_j)	230/895 = 25.69%
	P (T_i ***different grade level*** T_j $\mid$ T_i — T_j)	665/895 = 74.31%
	P (T_i ***shared resource*** T_j $\mid$ T_i — T_j)	1059/1059 = 100%
	P (T_i ***no shared resources*** T_j $\mid$ T_i — T_j)	0/1059 = 0%

TABLE III
THE RESULTS OF INDIRECT TEACHER CONNECTIONS CHARACTERIZATION ACCORDING TO EQ. 2

	Attribute	Probability
Geographic	P (T_i ***the same school*** T_j $\mid$ T_i – U – T_j)	878/28040 = 3.13%
	P (T_i ***different school*** T_j $\mid$ T_i – U – T_j)	27162/28040 = 96.87%
	P (T_i ***the same district*** T_j $\mid$ T_i – U – T_j)	5005/28040 = 17.84%
	P (T_i ***different district*** T_j $\mid$ T_i – U – T_j)	23035/28040 = 82.16%
	P (T_i ***the same state*** T_j $\mid$ T_i – U – T_j)	10210/28040 = 36.41%
	P (T_i ***different state*** T_j $\mid$ T_i – U – T_j)	17830/28040 = 63.59%
	P (T_i ***physical link*** T_j $\mid$ T_i – U – T_j)	25/1251 = 2.00%
	P (T_i ***no physical link*** T_j $\mid$ T_i – U – T_j)	1226/1251 = 98.00%
Professional	P (T_i ***the same grade level*** T_j $\mid$ T_i – U – T_j)	3473/24296 = 14.29%
	P (T_i ***different grade level*** T_j $\mid$ T_i – U – T_j)	20823/24296 = 85.71%
	P (T_i ***shared resource*** T_j $\mid$ T_i – U – T_j)	28040/28040 = 100%
	P (T_i ***no shared resources*** T_j $\mid$ T_i – U – T_j)	0/28040 = 0%

The results in Table II show that being at the same school does not have much bearing on two teachers being connected on Pinterest, where a noticeable number of teachers from different schools are connected. It is promising that teachers are being connected to their peers outside their schools. However, the results are opposite for attributes state and district where we can observe that a large majority of connections are between teachers who are coming from the same state and even the same district. In other words, this shows that whether two teachers are connected is predominately based on whether they are coming from the same district/state. Thus, the likelihood of teachers being connected outside their states and districts is minimal. Interestingly, the results are opposite for intermediate connections where, according to Table III, we can observe that the likelihood of two teachers from different schools, districts, and states being bridged by a third person/user (conditioned on that they are not directly connected) is significantly high. Hence, this analysis provides an affirmative answer to the crucial question that *are teachers mostly connected to their peers in the same district/state?* Also, Figure 3 demonstrates the localized nature of teacher-teacher connections on Pinterest, where nodes within a component tend to have the same color (the same district). Another noticeable phenomenon is the effect of attribute *physical link*. According to results presented in Tables II and III, the physical connections have a low likelihood to be reflected on Pinterest. We speculate this is because the teachers might not feel to seek further advice from their colleagues online, and mostly physical interactions suffice them. We believe following up on this topic deserves further investigation and will leave it for the future.

Q2: Are professional attributes of teachers related to their connections on Pinterest?

As for the grade level, we can observe from Tables II and III that not necessarily teaching at the same grade drives teacher connections. This is promising as teachers are not confined to their peers at the same grade level, and connections are driven by the broader notion of *teacher* rather than a specific grade level. Note that we removed teachers with *unspecified* grade level from this analysis. Moreover, we can observe that for both direct teacher and indirect connections, the presence of a shared resource is strongly related to the connection. For a direct teacher-teacher connection, this is not very surprising since, after all, teachers connect to their peers to acquire resources. For indirect connections, nevertheless, this is quite interesting and asks for further explanation. First, note that such a resource does not necessarily need to be curated by either of the two teachers, and it is possible that they both acquired it from the same source. Second, regardless of the producer or the source of the resource(s), the value of 100% for the shared resource(s) attribute in Table III signifies that the resources are in the interest of both teachers while they have likely been diffused to them via some third party.

V. Proposed Method for Link Recommendation

On the one hand, we analyzed our Pinterest network of teachers and discovered that many teacher-teacher connections are confined to the geological constraints –in particular district and state. On the other hand, we would expect online social media to break physical limitations and connect teachers anywhere. We propose a link recommendation system attempting to connect teachers beyond their physical realm to address this issue. First, we present motivations for this system, followed by describing it and evaluating the proposed method.

A. Motivation

One might first wonder that since we identified a sample of teachers on Pinterest, why not just connect them all together. In other words, instead of designing a link recommendation system, we can simply recommend every teacher to every other teacher. This has an undesirable consequence. Human's attention and the extent to which they can consume information on online social media are very limited [18], [19] and by trivially connecting everyone to everyone (here all teachers), we overwhelm users with an excessive amount of information and discourage them from using the social media. Although Pinterest already has a link recommendation method established in the social media platform, it will contain both teachers and non-teachers (which is by far the larger portion of the social network compared

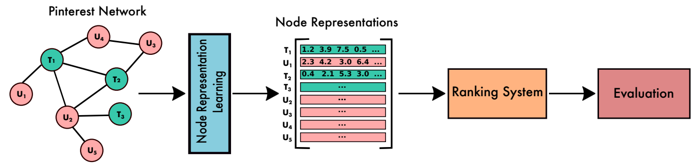

Fig. 4. An illustration of the link recommendation system

to the number of teachers). Thus, if their recommendation list contains both, then it would require a time-consuming process for a teacher to sort through to determine which are indeed teachers. Essentially, this would put the burden on the teachers to investigate the "why" they are being recommended a given user (e.g., for personal or perhaps professional reasons). Hence, we need an enhanced ranking system prioritizing the recommended links, which is the subject of this section.

B. Teacher Link Recommendation

Our proposed method for link recommendation is illustrated in Figure 4. It consists of two important components, including a node representation learning and a ranking system, described as follows.

Node representation learning. We are tasked to identify new teacher-teacher links on Pinterest. To accomplish this, first, we need to extract features from our dataset. Feature extraction from the Pinterest network is carried out using an advanced social network analysis method known as *node representation learning* [20], [21], [22]. In this approach, we automatically learn a numerical representation that encodes structural information embedded in the network for every node in a given network. We adopt the method proposed by Tang et al. [23] known as LINE (Large-scale information network embedding). Here the general idea is that representations are learned such that if two nodes have a link between them, then their representations will be more similar. As illustrated in Figure 4, the system takes as the input the Pinterest network and outputs a numerical representation for each node, including teachers. The size of the representation for each node is 64.

Ranking system. Once we obtain the representation for each user, we start the ranking process described as follows. The core of the ranking system is determining similarity between a teacher (i.e., its learned representation) and other nodes on the Pinterest network. To this end, we use cosine similarity formulated in the following:

$$C(X,Y) = \frac{< X,Y >}{||X|| \times ||Y||} \tag{3}$$

where X and Y are learned node representations, <.,.> denotes the dot product operator, and ||.|| is the ℓ_2 norm of a vector. The cosine similarity is between 0 and 1 where higher values indicate higher similarities. Further, for each teacher, we acquire its cosine similarity against all other nodes in the network. Since the network has many nodes, we sort the similarities and consider only the top K ranked nodes, where K is a pre-defined cut-off threshold. Finally, for the ranked list of K nodes, we start evaluating the performance of the method described next.

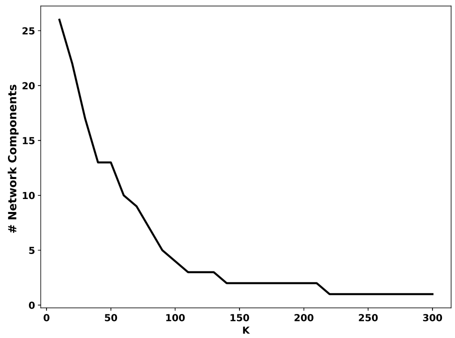

Fig. 5. Number of connected components of the Pinterest network of teachers for different cut-off thresholds

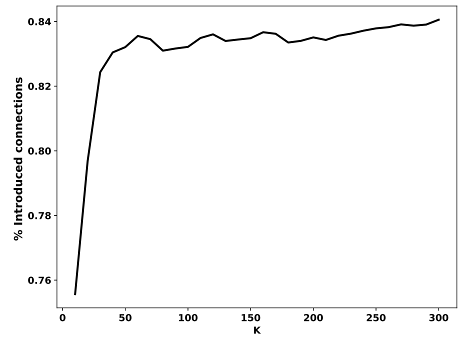

Fig. 8. Ratio of introduced connections to all recommended connections

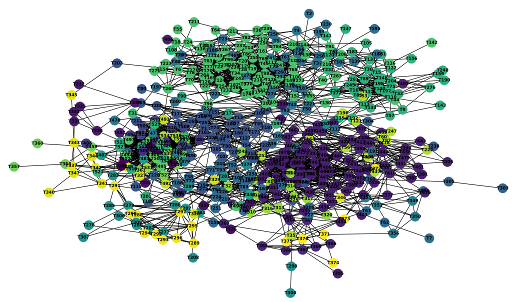

Fig. 6. The promoted network having the recommended connections been established (K=220)

C. Evaluation

In this part, we present the experimental results and evaluate the performance of our method. Recall that the primary motivation of this paper is promoting teacher-teacher connections on Pinterest. More specifically, we attempt to increase connectivity among teachers so they can exchange resources and ideas. Consequently, our evaluations are aligned with this direction.

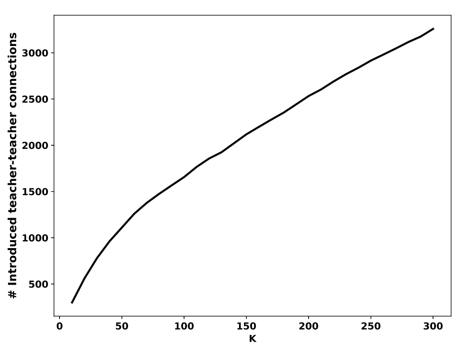

Fig. 7. The absolute number of introduced connections

Number of introduced connections

We expect our link recommendation system to introduce new teacher-teacher connections. Now we evaluate how effective our system is in this regard. To this end, for a given K and a teacher, we identify the number of new teacher-teacher connections in the top K ranked list. Then we sum up all of the new connections for all teachers. Figure 7 shows the number of new recommended teacher-teacher connections while Figure 8 shows the ratio of the new connections to the total number of recommended teacher-teacher connections. As can be observed from these figures, even for small values of K (e.g., K=10), the method successfully recommends new teacher-teacher connections.

The network of teachers

As we explained in Section IV and demonstrated in Figure 3, the Pinterest network for our surveyed teachers is a disconnected network and consists of many sub-networks (i.e., components). Now we investigate the network of our teachers on Pinterest once new connections are established. To this end, we compute the number of components of the network. Figure 5 demonstrates the number of components of the new network versus the threshold K. We can observe that compared to the existing current network, the promoted network enjoys a higher degree of connectivity. As K increases, the network becomes more connected. . We also provide a visualization of the new network in Figure 6. Compared to the existing network – see Figure 3 – we have a more dense network while teachers from distinct districts are connected as well.

Geographic factors on teacher-teacher connections

In Section IV, we showed that teachers are predominantly connected to their peers in the same district or state. Now it would be interesting to see if geographical factors are still related to the teacher-teacher connections. To this end, we again compute the conditional probabilities developed to characterize teacher-teacher connections for the new network. Table IV shows the results for both the existing Pinterest network and the promoted one. We can observe that new connections beyond geographic constraints have been formed. Hence, our proposed link recommendation system can effectively overcome the shortcoming of the Pinterest network regarding teacher-teacher connections.

D. Case study: Teacher identification

In this part, we present a case study that shows how our proposed link recommendation method can help us identify users on Pinterest who are likely to be teachers (but yet unknown to us). To this end, we extract and then merge their top 300 ranked users into a single list for each of our teachers. Then we retrieve the most common user, i.e., the one most frequently recommended to existing teachers under the condition the user is not already among our 540 teacher sample. We carefully verified this user's profile and retrieved some information about them, which is demonstrated in Table V. Several strong indications

TABLE IV
COMPARING THE INFLUENCE OF GEOGRAPHIC CONSTRAINTS BETWEEN THE EXISTING NETWORK AND THE PROMOTED ONE

Attribute	Existing network	Promoted network
P (T_i ***the same school*** T_j | T_i — T_j)	52.13%	15.29%
P (T_i ***different school*** T_j | T_i — T_j)	47.87%	84.71%
P (T_i ***the same district*** T_j | T_i — T_j)	95.94%	44.44%
P (T_i ***different district*** T_j | T_i — T_j)	4.06%	55.56%
P (T_i ***the same state*** T_j | T_i — T_j)	99.71%	67.11%
P (T_i ***different state*** T_j | T_i — T_j)	0.29%	32.25%
P (T_i ***physical link*** T_j | T_i — T_j)	38.27%	25.19%
P (T_i ***no physical link*** T_j | T_i — T_j)	61.73%	74.81%

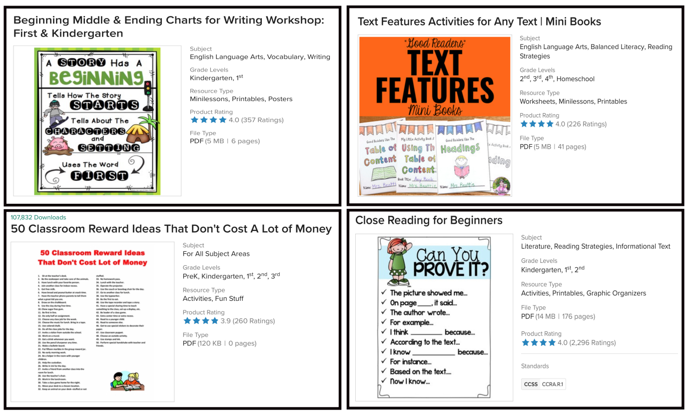

Fig. 9. Several sample resources saved (pinned) by the user identified as teacher

are showing that this person is indeed a teacher. First, more than 40% of their his/her resources have been categorized as 'education' (according to Pinterest). Second, he/she has saved many resources acquired from TeachersPayTeachers.com. More than 60% of his/her resources (pins) are shared among our sampled teachers. Several boards in his/her profile (e.g., *For the Classroom*) particularly created to maintain educational pins –mostly from TeachersPayTeachers.com. Figure 9 illustrates several resources collected (i.e., pinned) by this person. We can observe that resources are related to K-12 education.

Thus, this provides us with a very satisfying result of confidence that our proposed link recommendation method can help discover unidentified teachers on Pinterest. It is worth noting that we have developed a systematic and scalable approach to automatically mark unknown users who are likely to be teachers and thus augment the teacher dataset [5].

VI. CONCLUSION

In this paper, we thoroughly analyzed teachers' connections and discovered that many teacher-teacher connections are confined to geographical factors such as state and district. To address this issue, we proposed a link recommendation method. The method first takes advantage of the structure of the Pinterest network and automatically extracts salient features from the network for each user. We evaluated the performance of the proposed method and showed many new connections would be introduced. More importantly, we showed that the new recommended links are no longer confined to geographic factors.

TABLE V
SOME ATTRIBUTES OF THE USER IDENTIFIED AS A TEACHER.

Attribute	Value
# Resources (pins)	1284
# Educational resources (pins)	555
# Resources from TeachersPayTeachers.com	95
# Connections	55
# Shared resources with our teachers	803
# Connections to our teachers	9
# Boards	26
Sample education-related board names	*For the Classroom* *Crushing Comprehension* *Math Madness* *Letters. Sounds. & Word Work*

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