Analysing Ego-Networks via Typed-Edge Graphlets: A case study of Chronic Pain Patients

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Abstract. Graphlets, being the fundamental building blocks, are essential for understanding and analysing complex networks. The original notion of graphlets, however, is unable to encode edge attributes in many types of networks, especially in egocentric social networks. In this paper, we introduce a framework to embed edge type information in graphlets and generate a Typed-Edge Graphlets Degree Vector (TyE-GDV). Through applying the proposed method to a case study of chronic pain patients, we find that not only a patient's social network structure could inform his/her perceived pain grade, but also particular types of social relationships, such as friends, colleagues and healthcare workers, are more important in understanding the effect of chronic pain. Further, we demonstrate that including TyE-GDV as additional features leads to significant improvement in a typical machine learning task.

Keywords: edge-labelled graphs, heterogeneous networks, attributed graphs, graphlets, egocentric networks, chronic pain study

1 Introduction

Underlying the formation of complex networks, topological structure has always been a primary focus in network science. Among numerous analytical approaches, graphlets [1] have gained considerable ground in a variety of domains. In biology, it is revealed that proteins performing similar biological functions have similar local structures depicted by the graphlet degree vector [2]. In social science, egocentric graphlets are used to represent the patterns of people's social interactions [3]. More broadly, the notion of graphlets is introduced in computer vision to capture the spatial structure of superpixels [4], or in neuroscience to identify structural and functional abnormalities [5].

However, the original graphlets concept is unable to capture the richer information in networks that contain different types and characteristics of nodes or edges. Specifically, there are situations in which we are more interested in edge-labelled networks. For example, in a routing network where edges represent communication links, the label of each edge indicates the cost of traffic over that edge and is used to calculate the routing strategy. Or in an egocentric social network, the different types of social relationships between the ego and the alters are essential in analysing ego's behaviour and characteristics. Some studies have extended graphlets to attributed networks (also called heterogeneous networks). Still, they either only deal with different types of nodes [6] or they categorise each graphlet into a number of "colored-graphlets" according to the exhaustive combinations of different node types and/or edge types [7, 8].

In this work, we introduce an approach to embedding edge type information in graphlets, named Typed-Edge Graphlets Degree Vector, or TyE-GDV for short. We employ both the classic graphlets degree vector [2] (GDV) and the proposed TyE-GDV to represent and analyse 303 egocentric social networks of chronic pain patients. The real-life data is collected from three chronic pain leagues in Belgium. Each patient selects up to ten connections and each edge is labelled with one social relationship type. After grouping the patients into four groups according to their self-perceived pain grades, we find that patients with higher grades of pain have more star-like structures (3-star graphlets) in their social networks, while patients in lower pain grades groups form more 3-cliques, tailed-triangles, 4-chordal-cycles and 4-cliques. With the additional edge type information provided by TyE-GDV, we further discover that the outnumbered 3-star graphlet in higher pain grade patients is mainly formed of friends or healthcare workers; and that in 3-cliques and 4-cliques, friends and colleagues appear more frequently among patients with lower pain grades.

We further apply TyE-GDV into a node classification task. The dataset contains demographic attributes, detailed information about chronic pain (duration, diagnosis, pain intensity, etc.), and other related data such as the physical functioning score, depression score, social isolation score, etc. We show that the edge-type encoded graphlet features depicted by TyE-GDV are more distinctive than the classic non-typed graphlet features given by GDV in telling apart patients of different pain grades.

The remainder of this paper is organised as follows. Preliminary knowledge is provided in Section 2. Our proposed approach is introduced in Section 3. Experiments, results and analysis are presented in Section 4. And finally we conclude in Section 5 and discuss future directions.

2 Background and Preliminaries

In this section, we introduce the concepts of graphlets and graphlets in the context of egocentric networks.

2.1 Graphlets

Graphlets are small non-isomorphic induced subgraphs of a network [1]. Non-isomorphic means that two subgraphs need to be structurally different, and induced means that all edges between the nodes of a subgraph must be included. At the size of 2 to 5 nodes, there are 30 different graphlets in total. And, when the non-symmetry of node position is taken into consideration, there are 73

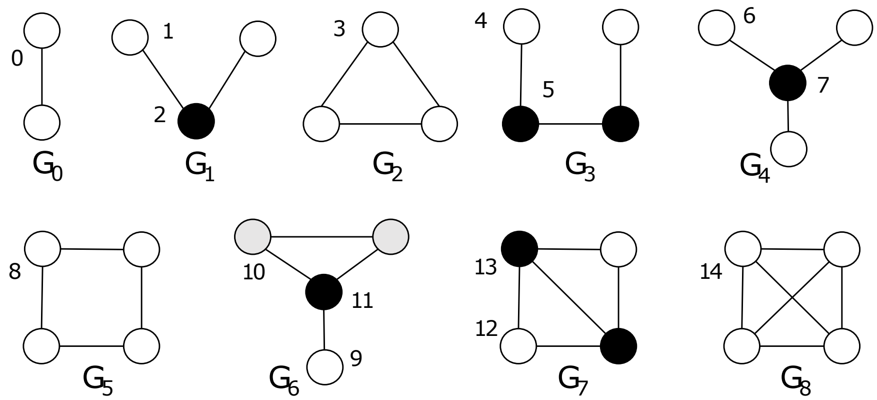

Fig. 1. 9 graphlets and 15 orbits of 2 to 4 nodes.

different local structures, which are also called automorphism orbits [2]. Simply put, orbits are all the unique positions of a subgraph. For any given node, a vector of the frequencies of all 73 orbits is then defined as the Graphlet Degree Vector (GDV). GDV or normalised GDV is often used as node feature to measure the similarities or differences among all nodes.

We summarise graphlets together with their orbits of 2 to 4 nodes in Figure 1. Take G_6 for example, the node at orbit-11 touches orbit-0 three times, orbit-2 twice, orbit-3 once and orbit-11 itself once. Thus, its GDV has 3 at the 0th coordinate, 2 at the 2nd coordinate, 1s at the 3rd and 11th coordinates, and 0 at the remaining coordinates.

2.2 Egocentric graphlets

In social network analysis, egocentric networks are sometimes of particular interest when we care more about the immediate environment around each individual than the entire world [9]. We may want to learn why some people behave the way they do, or why some people develop certain health problems. Since the notion of graphlets is defined at node-level, it is naturally suitable to be applied in egocentric networks, with two modifications. First, some graphlets that do not meet the requirement of being an egocentric network are excluded. For example, in graphlets of size up to 4 nodes (Figure 1), G_3 and G_5 are eliminated because any node in them serving as an ego cannot reach all other nodes with 1-hop. Second, there is no need to distinguish different orbits in egocentric graphlets because only one orbit can act as an ego. Therefore, there are in total 7 egocentric graphlets of size 2 to 4 nodes, which are 2-clique, 2-path, 3-clique, 3-star, tailed-triangle, 4-chordal-cycle and 4-clique (Figure 2).

3 Typed-Edge Graphlet Degree Vector

This section describes the framework for generating edge-type embedded graphlet degree vector.

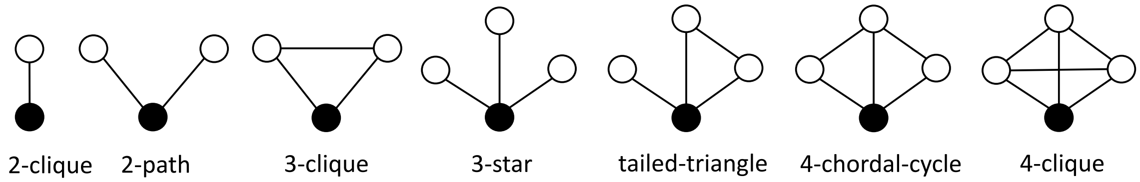

Fig. 2. 7 egocentric graphlets of 2 to 4 nodes. Ego node is painted in black.

The original concept of graphlets manages to capture rich connectivity patterns in homogeneous networks. However, many real-world networks are more complex by containing different types of nodes and edges, making them heterogeneous networks. Specifically, edge type information is crucial in that it indicates the specific relationship between the nodes. For example, in the dataset of this study, each chronic pain patient describes their egocentric social network, including up to ten actors, and each edge is labelled with 1 of 13 types of social relationships. In order to analyse edge-labelled networks at a finer granularity, we propose to embed edge-type information in graphlets. The original graphlet degree vector counts the occurrences of each type of graphlet, and as a result, a one-dimensional vector is created. Here, we propose to construct a two-dimensional vector by counting each type of edge touched by each type of graphlet.

To begin with, we give the formal definition of an edge-labelled network.

Definition 1. *An edge-labelled network G is a triple $\langle V, E, \mathcal{T}_e \rangle$, where $V = \{v_1, v_2, ..., v_n\}$ is the set of nodes, $E = \{e_{ij}\} \subset V \times V$ is the set of edges where e_{ij} indicates an edge between nodes v_i and v_j, and $\mathcal{T}_e$ is the set of edge types, where $\tau_{e_{ij}}$ denotes the type of edge e_{ij}.*

The first step of the framework is graph preprocessing, in which the set of edge types is mapped to integers ranging from 0 to $|\mathcal{T}_e|$. For instance, the 13 types of social relationships in the targeted dataset are denoted from 0 to 12 ($\tau_e \in [0, 12]$). Also, the set of types of graphlets $\mathcal{T}_g$ is mapped to integers ranging from 0 to $|\mathcal{T}_g|$. In this work, we consider all possible egocentric graphlets up to 4 nodes (Figure 2). Therefore the seven types of graphlets are coded from 0 to 6 ($\tau_g \in$ [0, 6]).

Algorithm 1 shows the approach of generating a two-dimensional vector of size $|\mathcal{T}_g| \times |\mathcal{T}_e|$, i.e., the Typed-Edge Graphlet Degree Vector (TyE-GDV) for any nodes of interest. Specifically, after initialisation, for each node in a given node set V' and for each type of the seven egocentric graphlets, the vector is updated through the Update function (Algorithm 2). $C(N_i, 2)$ and $C(N_i, 3)$ denotes all possible 2-combinations and 3-combinations of the set of neighbours of node i. Due to the preprocessing step, τ_g and τ_e are conveniently used as indices when updating the vector. For example, if a type '2' graphlet (3-clique) is detected and its three edges are of type '0', '1' and '2', vector elements at coordinates $(2, 0)$, $(2, 1)$ and $(2, 2)$ will increase by 1. In the end, a dictionary of nodes as keys and their corresponding TyE-GDV as values is returned.

Algorithm 1: Typed-Edge Graphlet Degree Vector.

input : preprocessed graph $G = \langle V, E, \mathcal{T}_e \rangle$, set of graphlet types $\mathcal{T}_g$, node set V'.
output: dictionary dic of vectors for all nodes $\in V'$.

initialise: $dic = \{\}$;
foreach $i \in V'$ **do**
  initialise a 2d-vector vec of size $|\mathcal{T}_g| \times |\mathcal{T}_e|$ with zeros;
  foreach $u \in N_i$ **do**
    Update(vec, g_0, e_{iu}); ▷ 2-clique
  foreach $u, v \in C(N_i, 2)$ **do**
    if $v \notin N_u$ **then**
      Update($vec, g_1, [e_{iu}, e_{iv}]$); ▷ 2-path
    else
      Update($vec, g_2, [e_{iu}, e_{iv}, e_{uv}]$); ▷ 3-clique
  foreach $u, v, w \in C(N_i, 3)$ **do**
    if $u \notin N_v \wedge u \notin N_w \wedge v \notin N_w$ **then**
      Update($vec, g_3, [e_{iu}, e_{iv}, e_{iw}]$); ▷ 3-star
    else if $v \in N_u \wedge w \notin N_u \wedge w \notin N_v$ **then**
      Update($vec, g_4, [e_{iu}, e_{iv}, e_{iw}, e_{uv}]$);
    else if $w \in N_u \wedge v \notin N_u \wedge v \notin N_w$ **then**
      Update($vec, g_4, [e_{iu}, e_{iv}, e_{iw}, e_{uw}]$); ▷ tailed-tri
    else if $w \in N_v \wedge u \notin N_v \wedge u \notin N_w$ **then**
      Update($vec, g_4, [e_{iu}, e_{iv}, e_{iw}, e_{vw}]$);
    else if $u \in (N_v \cap N_w) \wedge w \notin N_v$ **then**
      Update($vec, g_5, [e_{iu}, e_{iv}, e_{iw}, e_{uv}, e_{uw}]$);
    else if $v \in (N_u \cap N_w) \wedge w \notin N_u$ **then**
      Update($vec, g_5, [e_{iu}, e_{iv}, e_{iw}, e_{uv}, e_{vw}]$); ▷ 4-chord-cyc
    else if $w \in (N_u \cap N_v) \wedge v \notin N_u$ **then**
      Update($vec, g_5, [e_{iu}, e_{iv}, e_{iw}, e_{uw}, e_{vw}]$);
    else
      Update($vec, g_6, [e_{iu}, e_{iv}, e_{iw}, e_{uw}, e_{vw}, e_{uv}]$); ▷ 4-clique
    $dic[i] = vec$;

4 Experiments and Analysis

In this section, we apply the proposed method to analyse egocentric social networks of chronic pain patients. Our code is available at https://github.com/MingshanJia/explore-local-structure.

4.1 Dataset

The dataset is collected from chronic pain patients of the Flemish Pain League, the League for Rheumatoid Arthritis and the League for Fibromyalgia [10]. Each patient uses the graphical tool GENSI [11] to generate their egocentric social networks containing up to 10 alters. The types of relationship between the ego and the alters are explicitly given (all 13 types of social relationships are listed in Table 1). Participants were also asked to fill out a sociodemographic/pain

Algorithm 2: Update Vector.

Function UPDATE
  input : 2d-vector vec, type of graphlet τ_g, edge list L_e.
  foreach $e \in L_e$ **do**
    $\tau_e = \text{GetType}(e)$;
    `/*` τ_g `and` τ_e `are used as indices in` vec. `*/`
    $vec[\tau_g][\tau_e]$ increase by 1;

questionnaire. After excluding inconsistent and incomplete entries, 303 patients' egocentric social networks and their sociodemographic/pain characteristics constitute the final dataset. The average age of all patients is 53.5 ± 12 years (248 females and 55 males).

Relationship	Type	Total number of occurs.
Partner	T-1	222
Father/Mother	T-2	209
Brother/Sister	T-3	293
Children/Grandchildren	T-4	493
Friend	T-5	506
Family-in-law	T-6	207
Other family	T-7	142
Neighbour	T-8	69
Colleague	T-9	57
Healthcare worker	T-10	233
Member of organisations	T-11	74
Acquaintance	T-12	15
Other	T-13	17

Table 1. Edge type and total number of occurrences of each type in all networks.

Figure 3 gives some basic information about these egocentric networks, including the ego nodes' degree distribution and their edge-type distribution. The edge-type distribution is calculated by summing over all ego nodes on each type of the edges, which is also shown in the third column of Table 1. From the degree distribution (Figure 3a), we know that most patients (62%) have 10 social contacts in their networks. However, we don't expect degree being a discriminative feature in the following analysis because 10 alters is the upper limit in the dataset. The edge-type distribution (Figure 3b) informs us that "friend" and "children" are the most frequent types appearing in these networks. In contrast, edges of types "neighbour", "colleague" and "member of organisations" are underrepresented; "acquaintance" and "other" are almost negligible simply because if somebody is asked to name 10 contacts, they will name strongest contacts and there is no space for "acquaintance" or "other" relationships.

Furthermore, pain grades are calculated by means of the Graded Chronic Pain Scale (GCPS), which assesses both pain intensity and pain disability [12].

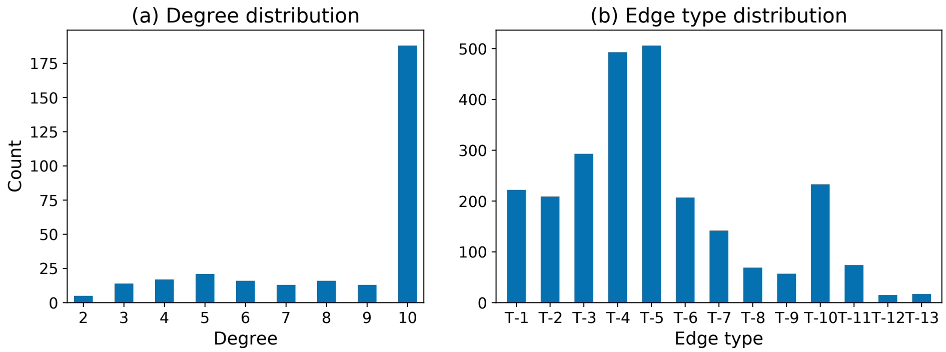

Fig. 3. Degree distribution and edge type distribution of all patients.

Patients are then classified into 5 grades based on their average intensity and disability scores: grade-0 no pain; grade-1 low intensity and low disability; grade-2 high intensity and low disability; grade-3 moderate disability regardless of pain intensity; and grade-4 high disability regardless of pain intensity. Because all participants are chronic pain patients, their GCPS grades range from grade-1 to grade-4. Specifically, we have 21 patients of grade-1, 33 patients of grade-2, 67 patients of grade-3 and 182 patients of grade-4. In this work, we aim to explore whether the graphlets and typed-edge graphlets are beneficial to recognising GCPS grades of chronic pain patients.

4.2 Analysing pain grades via GDV and TyE-GDV

Previous studies have revealed that social interactions play an important role in the perception of pain [13]. For example, a strong association was found between perceived social support and pain inference [14]; and improvements in social isolation lead to significant improvements in patients' emotional and physical functioning [15]. Usually, the social context of a patient is measured by means of the Patient Reported Outcome Measurement Information System (PROMIS®) [16] or the Social Support Satisfaction Scale (ESSS) [17]. These measurements, however, are not based on patients' actual social networks and therefore cannot provide insights on the impact of network structures or specific types of interactions. To cope with this issue, we apply the classic graphlets and the proposed typed-edge graphlets to analyse patients' social networks.

First, we calculate the average Graphlet Degree Vectors of patients from each GCPS grade. A parallel coordinates plot shows the average degrees of all seven egocentric graphlets at each grade (Figure 4). We see that patients of higher-grade pains (grade 3 and grade 4) have more star-like structures (3-star graphlets) in their social networks, and patients of lower pain grades (grade 1 and grade 2) form more 3-cliques, tailed-triangles, 4-chordal-cycles and 4-cliques. A worse connected star-like structure indicates a more isolated social environment, and a better connected structure such as the 3-clique or the 4-clique could be a sign of better social support. These findings are consistent with the previously

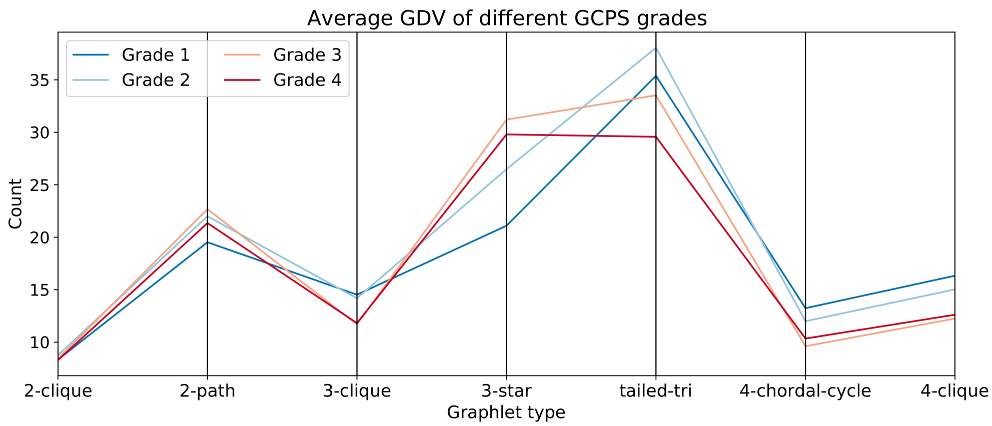

Fig. 4. Parallel coordinates plot of average GDV of different GCPS grades. Each coordinate represents the average number of graphlets belonging to that type.

mentioned studies [13–15] and provide further evidence that a patient's social network could inform the perceived pain grade. In addition, we find that the number of connections (2-cliques) does not help distinguish pain grades. This may result from the limited number of contacts in the dataset. Still nevertheless, another work also found that the size of a patient's egocentric social network is not significantly related to changes in pain [18]. This also explains why more complicated network structures should be considered in the analysis of patients' social networks.

Further, in order to investigate the relationship between the types of interactions and the pain grades, we employ the Typed-Edge Graphlet Degree Vector and focus on two particular graphlets, i.e. the poorly connected 3-star graphlet and the well connected 4-clique graphlet. These two graphlets are chosen because they present distinct differences between patients of lower pain grades and patients of higher pain grades. For each of the graphlets, we calculate the average TyE-GDV of patients from every pain grade and generate a parallel coordinates plot (Figure 5). We find that in the 3-star graphlet (Figure 5a), higher-grade pain patients have significantly more edges of type '5' (friend) and type '10' (healthcare worker) than lower-grade pain patients. In other words, friends and healthcare workers are not well connected in higher-grade pain patients. It thus provides the potential for interventions that increase the social involvements of a patient's friends and healthcare workers to improve the management of chronic pain.

Then from the average TyE-GDV of the 4-clique graphlet (Figure 5b), we observe that lower-grade pain patients have more edges of type '5' (friend) than higher-grade pain patients (5.2 compared to 3.2). That is to say, friends appear more often in these tightly connected groups among patients of lower-grade pain. The importance of the friend relationship is revealed in both 3-star and 4-clique graphlets. As pointed out by other studies [19, 20], patients with severe chronic pain may be at risk of deterioration in their friendships and are in need of sup-

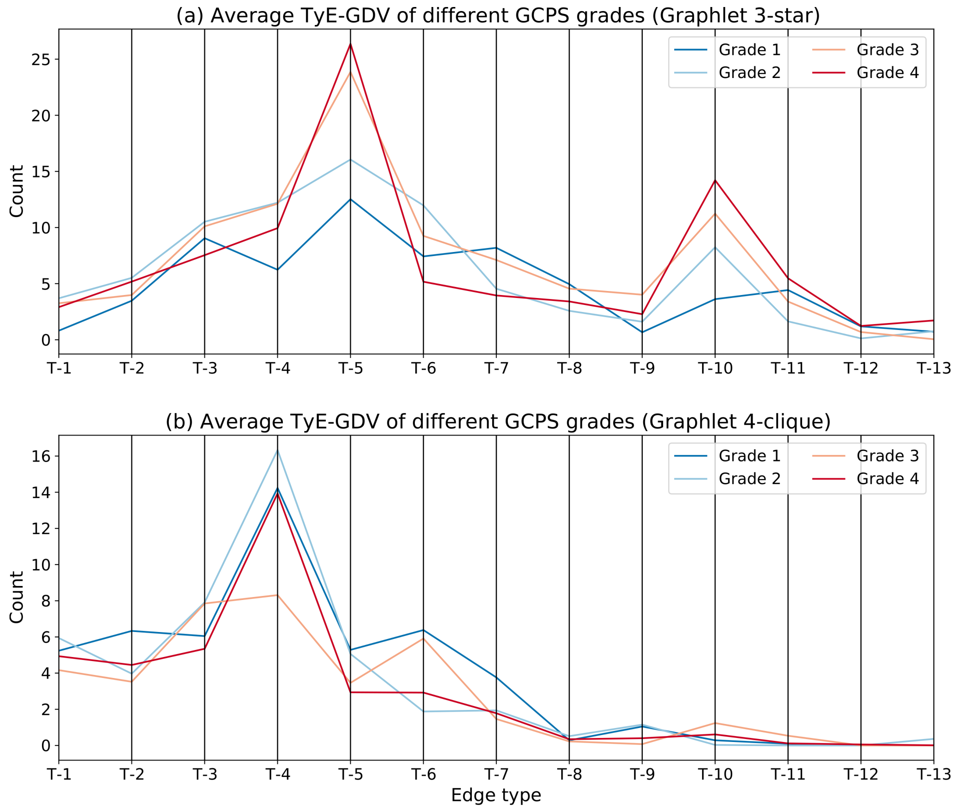

Fig. 5. Parallel coordinates plot of average TyE-GDV of different GCPS grades for two graphlets. Each coordinate represents the average number of edges belonging to that type.

portive behaviours from friends. Another marked contrast between the higher-grade and lower-grade pain patients is in edge type '9' (colleague). Colleagues hardly appear (0.24 on average) in these closely connected structures among the former group, whereas more than one colleague (1.1 on average) emerges among the latter group. It may reflect the adverse effects of severe chronic pain on patients' professional activities [21]. To give an intuitive understanding of the structural differences, we give two actual examples from the dataset as the social network prototypes of pain grade-1 and pain grade-4, respectively (Figure 6).

This experiment shows that the extra information brought by TyE-GDV provides us with more insights into the relationship between patients' social link types and their pain grades. Therefore, it has implications for how therapeutic interventions could be improved by increasing particular types of social connections.

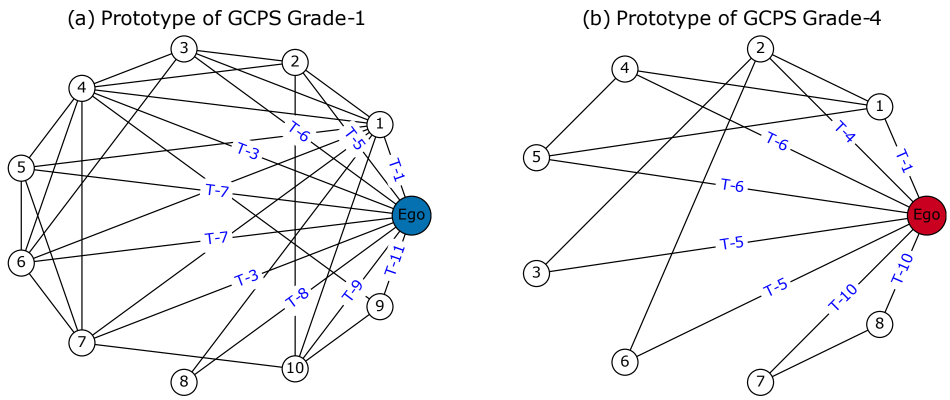

Fig. 6. Prototypes of GCPS grade-1 and GCPS grade-4.

4.3 Predicting pain grades via GDV and TyE-GDV

As a new approach capturing both topological structures and edge attributes, TyE-GDV provides additional information for ego node analyses and inferences. We further exhibit its usage in a node classification task where significant improvement is observed on test set performance.

Node classification is one of the most popular and widely adopted tasks in network science [22], where each node is assigned a ground truth category. Here, we aim to predict the GCPS grade of chronic pain patients. In order to test the utility of TyE-GDV as extra features, we fit three sets of features into a random forest classifier. The first set, the baseline, includes patients' demographic attributes, pain-related descriptions and physical/psychological well-being indicators. Since the baseline contains no structural information, we identify it as raw features. The second set includes the raw features plus the classic GDV. The third set includes the raw features plus the proposed TyE-GDV. As the dataset is not large and the distribution of four grades is not balanced (see Section 4.1), we adopt a stratified 5-fold cross-validation [23] to evaluate the classification performance with different sets of features. Also, because decision tree-based models are inherently stochastic, we repeat the above step 500 times and report the mean metric score.

	Macro F1 (Mean ± Std)	Gain over raw feat. (Mean)	Time (Sum)
Stratified	0.248 ± 0.024	—	3
Raw feat.	0.578 ± 0.005	—	116
Raw feat. + GDV	0.597 ± 0.008	3.3%	138
Raw feat. + TyE-GDV	0.619 ± 0.004	7.1%	252

Table 2. Prediction results in average macro-F1 score (± standard deviation), average gain over raw features, and total running time of 500 repetitions.

We report the average macro-F1 scores of three models in Table 2. The macro-F1 score is chosen because this is a multi-class classification problem and the distribution of the four classes is unbalanced. A naive classifier (Stratified) is also added in the table, which generates predictions by respecting the class distribution in the training set. We observe a significant 7.1% improvement after adding TyE-GDV to the raw features. In comparison, adding GDV leads to an improvement of about 3.3%. As expected, however, the running time of using TyE-GDV also increases with an increased dimension of features (total running time of 500 repetitions is shown in the last column of Table 2). This experiment shows that the structural information captured by GDV and especially the edge attribute information captured by TyE-GDV are useful as additional features to predict a patient's pain grade.

5 Conclusion

In this paper, we proposed to embed edge type information in graphlets, and we introduced the framework for calculating Typed-Edge Graphlets Degree Vector for ego nodes. After applying GDV and TyE-GDV to the chronic pain patients dataset, we found that 1) a patient's social network structure could inform their perceived pain grade; and 2) particular types of social relationships, such as friends, colleagues and healthcare workers, could bear more importance in understanding the effect of chronic pain and therefore lead to more effective therapeutic interventions. We also showed that including GDV or TyE-GDV as additional features results in improvement of a typical machine learning task that predicts patients' pain grades. Future studies will extend TyE-GDV by incorporating all orbits of graphlets and applying them to sociocentric networks or further considering the dynamics of time-varying networks.

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