Classification of Actors in Social Networks Using RLVECO

Bonaventure C. Molokwu¹(✉), Shaon Bhatta Shuvo¹(✉), Narayan C. Kar²(✉), and Ziad Kobti¹(✉)

¹ School of Computer Science, University of Windsor, 401 Sunset Avenue, Windsor, ON N9B-3P4, Canada
{molokwub,shuvos,kobt}@uwindsor.ca
² Centre for Hybrid Automotive Research and Green Energy (CHARGE), University of Windsor, 401 Sunset Avenue, Windsor, ON N9B-3P4, Canada
nkar@uwindsor.ca

Abstract. Several activities, comprising animate and inanimate entities, can be examined by means of Social Network Analysis (SNA). Classification tasks within social network structures remain crucial research problems in SNA. Inherent and latent facts about social graphs can be effectively exploited for training Artificial Intelligence (AI) models in a bid to categorize actors/nodes as well as identify clusters with respect to a given social network. Thus, important factors such as the individual attributes of spatial social actors and the underlying patterns of relationship binding these social actors must be taken into consideration. These factors are relevant to understanding the nature and dynamics of a given social graph. In this paper, we have proposed a hybrid model: Representation Learning via Knowledge-Graph Embeddings and Convolution Operations (RLVECO) which has been modelled for studying and extracting meaningful facts from social network structures to aid in node classification and community detection problems. RLVECO utilizes an edge sampling approach for exploiting features of a social graph, via learning the context of each actor with respect to its neighboring actors, with the aim of generating vector-space embeddings per actor which are further exploited for unexpressed representations via a sequence of convolution operations. Successively, these relatively low-dimensional representations are fed as input features to a downstream classifier for solving community detection and node classification problems about a given social network.

Keywords: Node classification · Feature learning · Feature extraction · Dimensionality reduction · Semi-supervised learning

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1 Introduction and Related Literature

Humans are inhabited in a planet comprised of several systems and ecosystems; and interaction is a natural phenomenon and characteristic obtainable in any given system or ecosystem. Thus, relationship between constituent entities in a given system/ecosystem is a strategy for survival, and essential for the sustenance of the system/ecosystem. Owing to recent AI advances, these real-world (complex) systems and ecosystems can be effectively represented as social network structures. Social (network) graphs [24] are non-static structures which pose analytical challenges to Machine Learning (ML) and Deep Learning (DL) models because of their complex links, random nature, and occasionally massive size. In this regard, we propose RLVECO which is a hybrid DL-based model for classification and clustering problems in social networks.

Node classification and community detection remain open research problems in SNA. The classification of nodes induces the formation of cluster(s). Consequently, clusters give rise to homophily in social networks. Herein our proposed methodology is based on an iterative learning approach [1] which is targeted at solving the problems of node classification and community detection using an edge sampling strategy. Basically, learning in RLVECO is induced via semi-supervised training. The architecture of RLVECO comprises two (2) distinct representation-learning layers, viz: a Knowledge-Graph Embeddings (VE) layer and a Convolution Operations (CO) layer [15]; which are both trained by means of unsupervised training. These layers are essentially feature-extraction and dimensionality-reduction layers where underlying knowledge and viable facts are automatically extracted from the social network structure [17]. The VE layer is responsible for projecting the feature representation of the social graph to a q-dimensional real-number space, \( \mathbb{R}^q \). This is done by associating a real-number vector to every unique actor/node in the social network such that the (cosine) distance of any given tie or edge would capture a significant degree of correlation between its pair of associated actors. Furthermore, the Convolution Operations layer feeds on the Knowledge-Graph Embeddings layer; and it is responsible for further extraction of apparent features and/or representations from the social graph. Finally, a classification layer succeeds the representation-learning layers; and it is trained by means of supervised training. The classifier is based on a Neural Network (NN) architecture assembled using deep (multi) layers of stacked perceptrons (NN units) [6]. Every low-dimensional feature \((X)\), extracted by the representation-learning layers, is mapped to a corresponding output label \((Y)\). These \((X,Y)\) pairs are used to supervise the training of the classifier such that it can effectively/efficiently learn how to identify clusters and classify actors within a given social graph.

RLVECO is capable of learning the non-linear distributed features enmeshed in a social network [9]. Hence, the novelty of our research contribution are as highlighted below:

1. Proposition of a DL-based and hybrid model, RLVECO, designed for resolving tie or link prediction problems in social network structures.
(2) Comprehensive benchmarking results which are based on classic objective functions used for standard classifiers.

(3) Comparative analyses, between RLVECO and state-of-the-art methodologies, against standard real-world social networks.

Also, we have evaluated RLVECO against an array of state-of-the-art models and Representation Learning (RL) approaches which serve as our baselines, viz:

(i) DeepWalk: Online Learning of Social Representations [21].
(ii) GCN: Semi-Supervised Classification with Graph Convolutional Networks [11].
(iii) LINE: Large-scale Information Network Embedding [27].
(iv) Node2Vec: Scalable Feature Learning for Networks [8].
(v) SDNE: Structural Deep Network Embedding [28].

2 Proposed Methodology and Framework

2.1 Definition of Problem

Definition 1. Social Network, SN: As expressed via Eq. 1 such that SN is a tuple comprising a set of actors/vertices, V; a set of ties/edges, E; a metadata function, \( f_V \), which extends the definition of the vertices’ set by mapping it to a given set of attributes, \( V' \); and a metadata function, \( f_E \), which extends the definition of the edges’ set by mapping it to a given set of attributes, \( E' \). Thus, a graph function, \( G(V, E) \subset SN \).

\[
SN = (V, E, f_V, f_E) \equiv (G, f_V, f_E)
\]

\[
\begin{align*}
V & : |\{V\}| = M & \text{set of actors/vertices with size, } M \\
E & : E \subset \{U \times V\} \subset \{V \times V\} \text{ set of ties/edges between } V \\
f_V & : V \to V' & \text{vertices' metadata function} \\
f_E & : E \to E' & \text{edges' metadata function}
\end{align*}
\]  

(1)

Definition 2. Knowledge Graph, KG: \((E, \mathbb{R})\) is a set comprising entities, \( E \), and relations, \( \mathbb{R} \), between the entities. Thus, a KG \([26,31]\) is defined via a set of triples, \( t : (u, p, v) \), where \( u, v \in E \) and \( p \in \mathbb{R} \). Also, a KG \([29]\) can be modelled as a social network, \( SN \), such that: \( E \to V \) and \( \mathbb{R} \to E \) and \((E, \mathbb{R}) \vdash f_V, f_E\).

Definition 3. Knowledge-Graph (Vector) Embeddings, \( X \): The vector-space embeddings, \( X \), generated by the VE layer are based on a mapping function, \( f \), expressed via Eq. 2. \( f \) projects the representation of the graph’s actors to a \( q \)-dimensional real space, \( \mathbb{R}^q \), such that the existent ties between any given pair of actors, \((u_i, v_j)\), remain preserved via the homomorphism from \( V \) to \( X \).

\[
\begin{align*}
f & : V \to X \in \mathbb{R}^q \\
f & : (u, p, v) \to X \in \mathbb{R}^q & \text{Knowledge-Graph Embeddings}
\end{align*}
\]  

(2)
Definition 4. Node Classification: Considering, $SN$, comprising partially labelled actors (or vertices), $V_{lbl} \subset V : V_{lbl} \rightarrow Y_{lbl}$; and unlabelled vertices defined such that: $V_{ulb} = V - V_{lbl}$. A node-classification model aims at training a predictive function, $f : V \rightarrow Y$, that learns to predict the labels, $Y$, for all actors or vertices, $V \subset SN$, via knowledge harnessed from the mapping: $V_{lbl} \rightarrow Y_{lbl}$ (Fig. 1).

Fig. 1. Node classification task in social graphs

2.2 Proposed Methodology

Our proposition, RLVECO, is comprised of two (2) distinct Feature Learning (FL) layers, and one (1) classification layer.

Representation Learning - Knowledge-Graph Embeddings Layer: Given a social network, $SN$, defined by a set of actors/vertices, $V : U \subset V \forall \{u_m, v_m\} \in V$, and $M : m \in M$ denotes the number of unique actors in $SN$. Additionally, let the ties/edges in $SN$ be defined such that: $E \subset \{U \times V\}$; where $u_i \in V$ and $v_j \in V$ represent a source.vertex and a target.vertex in $E$, respectively.

The objective function of the Knowledge-Graph Embeddings layer aims at maximizing the average logarithmic probability of the source.vertex, $u_i$, being
predicted as a neighboring actor to the target vertex, \(v_j\), with respect to all training pairs, \(\forall (u_i, v_j) \in E\). Formally, the function is expressed as in Eq. 3:

\[
\mu = \frac{1}{M} \sum_{m=1}^{M} \left( \sum_{(u_i, v_j) \in E} \log Pr(u_i|v_j) \right)
\]  

(3)

Consequently, in order to compute \(Pr(u_i|v_j)\), we have to quantify the proximity of each target vertex, \(v_j\), with respect to its source vertex, \(u_i\). The vector-embedding model measures this adjacency/proximity as the cosine similarity between \(v_j\) and its corresponding \(u_i\). Thus, the cosine distance is calculated as the dot product between the target vertex and the source vertex. Mathematically, \(Pr(u_i|v_j)\) is computed via a softmax function as defined in Eq. 4:

\[
Pr(u_i|v_j) = \frac{\exp(u_i \cdot v_j)}{\sum_{m=1}^{M} \exp(u_m \cdot v_j)}
\]

(4)

Hence, the objective function of our vector-embedding (VE) model with respect to the SN is as expressed by Eq. 5:

\[
\sum_{(u_i, v_j) \in E} \log Pr(u_i|v_j) = \sum_{(u_i, v_j) \in E} \log \frac{\exp(u_i \cdot v_j)}{\sum_{m=1}^{M} \exp(u_m \cdot v_j)}
\]

(5)

**Representation Learning - Convolution Operations Layer:** This layer comprises three (3) RL or FL operations, namely: convolution, non-linearity, and pooling operations. RLVECO utilizes a one-dimensional (1D) convolution layer \([16]\) which is sandwiched between the vector-embedding and classification layers. Equation 6 expresses the 1D-convolution operation:

\[
\text{FeatureMap}(F) = 1D\_InputMatrix(X) \ast Kernel(K)
\]

\[
f_i = (X \ast K)_i = (K \ast X)_i = \sum_{j=0}^{J-1} x_j \cdot k_{i-j} = \sum_{j=0}^{J-1} k_j \cdot x_{i-j}
\]

(6)

where \(f_i\) represents a cell/matrix position in the Feature Map; \(k_j\) denotes a cell position in the Kernel; and \(x_{i-j}\) denotes a cell/matrix position in the 1D-Input (data) matrix.

The non-linearity operation is a rectified linear unit (ReLU) function which introduces non-linearity after the convolution operation since real-world problems usually exist in non-linear form(s). As a result, the rectified feature/activation map is computed via: \(r_i \in R = g(f_i \in F) = \max(0, F)\).

The pooling operation is responsible for reducing the input width of each rectified activation map while retaining its vital properties. In this regard, the Max Pooling function is defined such that the resultant pooled (or downsampled) feature map is generated via: \(p_i \in P = h(r_i \in R) = \maxPool(R)\).
**Classification - Multi-Layer Perceptron (MLP) Classifier Layer:** This is the last layer of RLVECO's architecture, and it succeeds the representation-learning layers. The pooled feature maps, generated by the representation-learning layers, contain low-level features extracted from the constituent actors in the social graph. Hence, the classification layer utilizes these extracted “low-level features” for classifying actors in a bid to identify clusters contained in the social graph. The objective of the MLP [5] classifier function, \( f_c \), is to map a given set of input values, \( P \), to their respective output labels, \( Y \), viz:

\[
Y = f_c(P, \Theta)
\]

(7)

In Eq. 7, \( \Theta \) denotes a set of parameters. The MLP [4] function learns the values of \( \Theta \) that will result in the best decision (\( Y \)) approximation for the input set, \( P \). The MLP classifier output is a probability distribution which indicates the likelihood of a representation belonging to a particular output class. Our MLP [10] classifier is modelled such that sequential layers of NN units are stacked against each other to form a Deep Neural Network (DNN) structure [3,18].

**Node Classification Algorithm:** Defined via Algorithm 1.

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**Algorithm 1. Proposed Algorithm for Node Classification**

**Input:** \( \{V, E, Y_{lb}l\} = \{\text{Actors, Ties, Ground-Truth Labels}\} \)

**Output:** \( \{Y_{ulb}\} = \{\text{Predicted Labels}\} \)

---

**Preprocessing:**

\( V_{lb}, V_{ulb} \subset V = V_{lb} \cup V_{ulb} \) // \( V_{lb} \): Labelled actors  // \( V_{ulb} \): Unlabelled actors

\( E : (u_i, v_j) \in (U \times V) \) // \( (u_i, v_j) \equiv \text{(source, target)} \)

\( E_{train} = E_t : u_i, v_j \in V_{lb} \)  // \( |E_{train}| = \sum \text{indegree}(V_{lb}) + \sum \text{outdegree}(V_{lb}) \)

\( E_{pred} = E_p : u_i, v_j \in V_{ulb} \)

\( f_c \leftarrow \text{Initialize} \) // Construct classifier model

**Training:**

for \( t = 0 \) to \( |E_{train}| \) do

\( f : E_t \rightarrow [X \in \mathbb{R}^q] \) // Embedding operation

\( f_t \in F = (K \ast X)_t \) // Convolution operation

\( r_t \in R = g(F) = \max(0, f_t) \)

\( p_t \in P = h(R) = \maxPool(r_t) \)

\( f_c|\Theta : p_t \rightarrow Y_{lb} \) // MLP classification operation

end for

**return** \( Y_{ulb} = f_c(E_{pred}, \Theta) \)
2.3 Proposed Architecture/Framework

Figure 2 illustrates the architecture of our proposition, RLVECO.

![Proposed system architecture](image)

Fig. 2. Proposed system architecture

3 Datasets and Materials

3.1 Datasets

With regard to Table 1 herein, seven (7) real-world and benchmark social-graph datasets were utilized for experimentation and evaluation, viz: Cora [22, 25], CiteSeer [22, 25], Facebook Page-Page webgraph [23], Internet-Industry partnerships [2, 12, 13], PubMed-Diabetes [19], Terrorists-Relationship [32], and Zachary-Karate [14, 30].
Table 1. Benchmark datasets

| Dataset               | Nodes  | Edges   | Classes | Description                                                                 |
|-----------------------|--------|---------|---------|-----------------------------------------------------------------------------|
| Cora                  | 2,708  | 5,429   |         | {C1: ‘Case_Based’, C2: ‘Genetic_Algorithms’, C3: ‘Neural_Networks’, C4:     |
|                       |        |         |         | ‘Probabilistic_Methods’, C5: ‘Reinforcement_Learning’, C6: ‘Rule_Learning’,  |
|                       |        |         |         | C7: ‘Theory’}                                                               |
| CiteSeer              | 3,312  | 4,732   |         | {C1: ‘Agents’, C2: ‘Artificial Intelligence’, C3: ‘Databases’, C4: ‘Information |
|                       |        |         |         | Retrieval’, C5: ‘Machine Learning’, C6: ‘Human-Computer Interaction’}      |
| Facebook-Page2Page    | 22,470 | 171,002 |         | {C1: ‘Companies’, C2: ‘Governmental Organizations’, C3: ‘Politicians’, C4: |
|                       |        |         |         | ‘Television Shows’}                                                         |
| PubMed-Diabetes       | 19,717 | 44,338  |         | {C1: ‘Diabetes Mellitus - Experimental’, C2: ‘Diabetes Mellitus - Type 1’,  |
|                       |        |         |         | C3: ‘Diabetes Mellitus - Type 2’}                                          |
| Terrorists-Relation   | 851    | 8,592   |         | {C1: ‘Colleague’, C2: ‘Congregate’, C3: ‘Contact’, C4: ‘Family’}            |
| Zachary-Karate        | 34     | 78      |         | {C1: ‘Community 1’, C2: ‘Community 2’, C3: ‘Community 3’, C4: ‘Community 4’} |
| Internet-Industry     | 219    | 631     |         | {C1: ‘Content Sector’, C2: ‘Infrastructure Sector’, C3: ‘Commerce Sector’}  |

3.2 Data Preprocessing

All benchmark datasets ought to be comprised of actors and ties already encoded as discrete data (natural-number format). However, Cora, CiteSeer, Facebook-Page2Page, PubMed-Diabetes, and Terrorists-Relation datasets are made up of nodes and/or edges encoded in mixed formats (categorical and numerical formats). Thus, preprocessing is necessary to transcode these non-numeric (categorical) entities to their respective discrete (numeric) data representation without semantic loss. Thereafter, the numeric representation of all benchmark datasets are normalized prior to training against RLVECO and the benchmark models.

Table 2. Configuration of RLVECO’s hyperparameters

| Parameter                | Value                   |
|--------------------------|-------------------------|
| Training set:            | 80%                     |
| Test set:                | 20%                     |
| Network width:           | 640                     |
| Batch size:              | 256                     |
| Optimizer:               | AdaMax                  |
| Network depth:           | 6                       |
| Epochs:                  | 1.8 * 10^2              |
| Activation:              | ReLU                    |
| Dropout:                 | 4.0 * 10^{-1}           |
| Learning rate:           | 1.0 * 10^{-3}           |
| Learning decay:          | 0.0                     |
| Embed dimension:         | 100                     |
Fig. 3. Learning curves of RLVECO during training against Cora, CiteSeer, Facebook-Webgraph, PubMed-Diabetes, Terrorists-Relationship, Zachary-Karate, and Internet-Industry-Partnership datasets - loss function vs training epochs.

4 Experiment, Results, and Discussions

RLVECO has been tuned in accordance with the hyperparameters shown in Table 2. Our evaluations herein were recorded with reference to a range of objective functions. Thus, Categorical Cross Entropy was employed as the cost/loss function; while the fitness/utility was measured based on the following metrics: Precision (PC), Recall (RC), F-measure or F1-score (F1), Accuracy (AC), and Area Under the Receiver Operating Characteristic Curve (RO). Moreover, the objective functions have been computed against each benchmark dataset with
regard to the constituent classes (or categories) present in each dataset. The Support (SP) represents the number of ground-truth samples per class/category contained in each dataset.

So as to avoid any bias across-the-board, we have used exactly the same SP for all models inclusive of RLVECO model. However, since RLVECO is based on an edge-sampling technique; the SP recorded against RLVECO model represents the number of edges/ties used for computation as explained in Algorithm 1. Furthermore, the performance of RLVECO during comparative analyses with respect to five (5) popular baselines (DeepWalk, GCN, LINE, Node2Vec, SDNE) when evaluated against the validation/test samples of the benchmark datasets are as documented in Table 3, Table 4, Table 5, Table 6, Table 7, and Table 8 respectively. Consequently, Fig. 3 graphically shows the learning-progress curves of our proposed model, RLVECO, during training over the benchmark datasets. Hence, the dotted-black lines represent learning progress over the training set; and the dotted-blue lines represent learning progress over the test set.

Tables 3, 4, 5, 6, 7, and 8 have clearly tabulated our results as a multi-classification task over the benchmark datasets. For each class per dataset, we have laid emphasis on the F1 (weighted average of the PC and RC metrics) and RO; and we have highlighted the model which performed best (based on F1 and RO metrics) for each classification job using a bold font. Additionally, we have employed a point-based ranking standard to ascertain the fittest model per node classification task. The model with the highest aggregate points signifies the fittest model for the specified task, and so on in descending order of aggregate points. Accordingly, as can be seen from our tabular results herein, our hybrid proposition (RLVECO) is at the top with the highest fitness points. RLVECO’s superior performance, with reference to the results of the comparative analyses herein, is primarily attributed to its dual RL layers which enable it to extract and learn sufficient features of the social network structures. Its biform RL kernel places it at an edge above the state-of-the-art baselines evaluated herein.

The application of dropout regularization was targeted at the hidden layers of RLVECO. $L_2$ regularization ($L_2 = 0.04$) [7] and early stopping [20] were employed herein as add-on regularization techniques to overcome overfitting incurred during the training of RLVECO. Therefore, the application of early stopping with regard to the training of RLVECO over the benchmark datasets were, viz: Cora (after 50 epochs), CiteSeer (after 50 epochs), Facebook-Page2Page (after 50 epochs), PubMed-Diabetes (after 50 epochs), Terrorists-Relation (after 50 epochs), Zachary-Karate (after 50 epochs), and Internet-Industry-Partnership (after 180 epochs). We have used a mini-batch size of 256 for training, testing, and validating because we want to ensure that sufficient patterns are extracted by RLVECO during training before its network weights are updated.
Table 3. Node-classification over Cora dataset. Results are based on the set apart validation sample - dataset vs models.

| Model   | Metric | Cora dataset | Points |
|---------|--------|--------------|--------|
|         |        | C1  | C2  | C3  | C4  | C5  | C6  | C7  | μ    |
| RLVECO  | PC     | 0.85| 0.78| 0.80| 0.88| 0.72| 0.90| 0.81| 0.82| 14   |
|         | RC     | 0.86| 0.93| 0.81| 0.87| 0.75| 0.91| 0.78| 0.84|      |
|         | F1     | 0.86| 0.85| 0.81| 0.87| 0.74| 0.91| 0.79| 0.83|      |
|         | AC     | 0.93| 0.98| 0.96| 0.95| 0.93| 0.97| 0.96| 0.95|      |
|         | RO     | 0.90| 0.96| 0.90| 0.92| 0.85| 0.95| 0.88| 0.91|      |
|         | SP     | 541 | 134 | 214 | 405 | 294 | 345 | 237 | 310 |      |
| GCN     | PC     | 0.87| 0.95| 0.89| 0.92| 0.85| 0.89| 0.87| 0.89| 3    |
|         | RC     | 0.85| 0.73| 0.65| 0.82| 0.58| 0.85| 0.73| 0.74|      |
|         | F1     | 0.86| 0.83| 0.75| 0.87| 0.69| 0.87| 0.79| 0.81|      |
|         | AC     | 0.89| 0.93| 0.91| 0.92| 0.88| 0.93| 0.91| 0.91|      |
|         | RO     | 0.88| 0.83| 0.80| 0.89| 0.75| 0.90| 0.83| 0.84|      |
|         | SP     | 164 | 36  | 43  | 85  | 70  | 84  | 60  | 77  |      |
| Node2Vec| PC     | 0.58| 0.78| 0.72| 0.81| 0.80| 0.84| 0.82| 0.76| 0    |
|         | RC     | 0.85| 0.50| 0.53| 0.68| 0.64| 0.74| 0.60| 0.65|      |
|         | F1     | 0.69| 0.61| 0.61| 0.74| 0.71| 0.78| 0.69| 0.69|      |
|         | AC     | 0.77| 0.96| 0.95| 0.92| 0.92| 0.93| 0.94| 0.92|      |
|         | RO     | 0.79| 0.75| 0.76| 0.83| 0.81| 0.86| 0.79| 0.80|      |
|         | SP     | 164 | 36  | 43  | 85  | 70  | 84  | 60  | 77  |      |
| DeepWalk| PC     | 0.57| 0.58| 0.72| 0.58| 0.68| 0.72| 0.63| 0.64| 0    |
|         | RC     | 0.80| 0.42| 0.42| 0.59| 0.39| 0.63| 0.65| 0.56|      |
|         | F1     | 0.67| 0.48| 0.53| 0.58| 0.49| 0.67| 0.64| 0.58|      |
|         | AC     | 0.76| 0.94| 0.94| 0.87| 0.90| 0.90| 0.92| 0.89|      |
|         | RO     | 0.77| 0.70| 0.70| 0.75| 0.68| 0.79| 0.80| 0.74|      |
|         | SP     | 164 | 36  | 43  | 85  | 70  | 84  | 60  | 77  |      |
| LINE    | PC     | 0.35| 0.86| 0.80| 0.65| 0.50| 0.43| 0.61| 0.60| 0    |
|         | RC     | 0.85| 0.17| 0.19| 0.35| 0.20| 0.15| 0.23| 0.31|      |
|         | F1     | 0.50| 0.28| 0.30| 0.46| 0.29| 0.23| 0.34| 0.34|      |
|         | AC     | 0.48| 0.94| 0.93| 0.87| 0.87| 0.84| 0.90| 0.83|      |
|         | RO     | 0.59| 0.58| 0.59| 0.66| 0.59| 0.56| 0.61| 0.60|      |
|         | SP     | 164 | 36  | 43  | 85  | 70  | 84  | 60  | 77  |      |
| SDNE    | PC     | 0.37| 0.83| 0.70| 0.60| 0.54| 0.64| 0.64| 0.62| 0    |
|         | RC     | 0.91| 0.14| 0.16| 0.35| 0.20| 0.27| 0.12| 0.31|      |
|         | F1     | 0.53| 0.24| 0.26| 0.44| 0.29| 0.38| 0.20| 0.33|      |
|         | AC     | 0.50| 0.94| 0.93| 0.86| 0.87| 0.86| 0.89| 0.84|      |
|         | RO     | 0.62| 0.57| 0.58| 0.65| 0.59| 0.62| 0.55| 0.60|      |
|         | SP     | 164 | 36  | 43  | 85  | 70  | 84  | 60  | 77  |      |
Table 4. Node-classification over CiteSeer dataset. Results are based on the set apart test sample - dataset vs models.

| Model    | Metric | CiteSeer dataset | Points |
|----------|--------|-------------------|--------|
|          |        | C1    | C2    | C3    | C4    | C5    | C6    | μ   |        |
| RLVECO   | PC     | 0.76  | 0.81  | 0.78  | 0.43  | 0.88  | 0.60  | 0.71 | 12     |
|          | RC     | 0.84  | 0.83  | 0.79  | 0.60  | 0.79  | 0.65  | 0.75 |        |
|          | F1     | 0.80  | 0.82  | 0.79  | 0.50  | 0.83  | 0.63  | 0.73 |        |
|          | AC     | 0.93  | 0.88  | 0.92  | 0.93  | 0.96  | 0.89  | 0.92 |        |
|          | RO     | 0.90  | 0.87  | 0.87  | 0.78  | 0.89  | 0.79  | 0.85 |        |
|          | SP     | 304   | 609   | 377   | 107   | 225   | 275   | 316 |        |
| GCN      | PC     | 0.80  | 0.78  | 0.86  | 0.95  | 0.91  | 0.75  | 0.84 | 2      |
|          | RC     | 0.76  | 0.76  | 0.73  | 0.08  | 0.67  | 0.54  | 0.59 |        |
|          | F1     | 0.78  | 0.77  | 0.79  | 0.15  | 0.77  | 0.63  | 0.65 |        |
|          | AC     | 0.88  | 0.87  | 0.88  | 0.91  | 0.89  | 0.83  | 0.88 |        |
|          | RO     | 0.84  | 0.83  | 0.83  | 0.53  | 0.81  | 0.72  | 0.76 |        |
|          | SP     | 119   | 134   | 140   | 50    | 102   | 118   | 111 |        |
| Node2Vec | PC     | 0.57  | 0.55  | 0.49  | 0.33  | 0.55  | 0.38  | 0.48 | 0      |
|          | RC     | 0.55  | 0.60  | 0.66  | 0.06  | 0.45  | 0.40  | 0.45 |        |
|          | F1     | 0.56  | 0.58  | 0.56  | 0.10  | 0.50  | 0.39  | 0.45 |        |
|          | AC     | 0.85  | 0.82  | 0.78  | 0.92  | 0.86  | 0.78  | 0.84 |        |
|          | RO     | 0.73  | 0.74  | 0.74  | 0.53  | 0.69  | 0.63  | 0.68 |        |
|          | SP     | 119   | 134   | 140   | 50    | 102   | 118   | 111 |        |
| DeepWalk | PC     | 0.46  | 0.53  | 0.43  | 0.43  | 0.47  | 0.33  | 0.44 | 0      |
|          | RC     | 0.51  | 0.54  | 0.57  | 0.06  | 0.41  | 0.32  | 0.40 |        |
|          | F1     | 0.49  | 0.54  | 0.49  | 0.11  | 0.44  | 0.32  | 0.40 |        |
|          | AC     | 0.81  | 0.81  | 0.75  | 0.92  | 0.84  | 0.76  | 0.82 |        |
|          | RO     | 0.69  | 0.71  | 0.69  | 0.53  | 0.66  | 0.59  | 0.65 |        |
|          | SP     | 119   | 134   | 140   | 50    | 102   | 118   | 111 |        |
| SDNE     | PC     | 0.37  | 0.50  | 0.24  | 0.20  | 0.45  | 0.31  | 0.35 | 0      |
|          | RC     | 0.19  | 0.27  | 0.77  | 0.02  | 0.14  | 0.09  | 0.25 |        |
|          | F1     | 0.25  | 0.35  | 0.36  | 0.04  | 0.21  | 0.14  | 0.23 |        |
|          | AC     | 0.80  | 0.80  | 0.42  | 0.92  | 0.84  | 0.80  | 0.76 |        |
|          | RO     | 0.56  | 0.60  | 0.55  | 0.51  | 0.55  | 0.52  | 0.55 |        |
|          | SP     | 119   | 134   | 140   | 50    | 102   | 118   | 111 |        |
| LINE     | PC     | 0.18  | 0.30  | 0.28  | 0.60  | 0.22  | 0.27  | 0.31 | 0      |
|          | RC     | 0.15  | 0.47  | 0.39  | 0.06  | 0.12  | 0.21  | 0.23 |        |
|          | F1     | 0.16  | 0.36  | 0.32  | 0.11  | 0.15  | 0.24  | 0.22 |        |
|          | AC     | 0.72  | 0.67  | 0.65  | 0.93  | 0.80  | 0.76  | 0.76 |        |
|          | RO     | 0.50  | 0.59  | 0.56  | 0.53  | 0.52  | 0.55  | 0.54 |        |
|          | SP     | 119   | 134   | 140   | 50    | 102   | 118   | 111 |        |
Table 5. Node-classification experiment results over Facebook Page-Page webgraph dataset. Results are based on the reserved validation/test sample - dataset vs models.

| Model      | Metric | Facebook-Page2Page dataset | Points |
|------------|--------|-----------------------------|--------|
|            |        | C1  | C2  | C3  | C4  | μ     |
| RLVECO     | PC     | 0.87| 0.95| 0.91| 0.87| 0.90  | 8      |
|            | RC     | 0.84| 0.85| 0.85| 0.86| 0.85  |        |
|            | F1     | **0.85**| **0.90**| **0.88**| **0.86**| 0.87  |        |
|            | AC     | 0.96| 0.90| 0.94| 0.97| 0.94  |        |
|            | RO     | **0.97**| **0.97**| **0.98**| **0.98**| 0.98  |        |
|            | SP     | 9989| 33962| 16214| 6609| 16694 |        |
| Node2Vec   | PC     | 0.81| 0.84| 0.81| 0.84| 0.83  | 0      |
|            | RC     | 0.82| 0.87| 0.85| 0.67| 0.80  |        |
|            | F1     | 0.81| 0.85| 0.83| 0.74| 0.81  |        |
|            | AC     | 0.89| 0.91| 0.91| 0.93| 0.91  |        |
|            | RO     | 0.87| 0.90| 0.89| 0.82| 0.87  |        |
|            | SP     | 1299| 1376| 1154| 665 | 1124  |        |
| DeepWalk   | PC     | 0.75| 0.84| 0.76| 0.75| 0.78  | 0      |
|            | RC     | 0.81| 0.85| 0.82| 0.52| 0.75  |        |
|            | F1     | 0.78| 0.84| 0.79| 0.62| 0.76  |        |
|            | AC     | 0.87| 0.90| 0.89| 0.90| 0.89  |        |
|            | RO     | 0.85| 0.89| 0.87| 0.75| 0.84  |        |
|            | SP     | 1299| 1376| 1154| 665 | 1124  |        |
| LINE       | PC     | 0.53| 0.66| 0.72| 0.66| 0.64  | 0      |
|            | RC     | 0.72| 0.71| 0.59| 0.29| 0.58  |        |
|            | F1     | 0.61| 0.68| 0.65| 0.40| 0.59  |        |
|            | AC     | 0.73| 0.80| 0.83| 0.87| 0.81  |        |
|            | RO     | 0.73| 0.77| 0.75| 0.63| 0.72  |        |
|            | SP     | 1299| 1376| 1154| 665 | 1124  |        |
| SDNE       | PC     | 0.49| 0.80| 0.70| 0.65| 0.66  | 0      |
|            | RC     | 0.90| 0.63| 0.50| 0.19| 0.56  |        |
|            | F1     | 0.64| 0.70| 0.58| 0.29| 0.55  |        |
|            | AC     | 0.70| 0.84| 0.82| 0.86| 0.81  |        |
|            | RO     | 0.76| 0.78| 0.71| 0.58| 0.71  |        |
|            | SP     | 1299| 1376| 1154| 665 | 1124  |        |
Table 6. Node-classification experiment over PubMed-Diabetes dataset. Results are based on the reserved validation/test sample - dataset vs models.

| Model     | Metric | PubMed-Diabetes dataset | Points |
|-----------|--------|-------------------------|--------|
|           |        | C1  | C2  | C3  | μ     |
| RLVECO    | PC     | 0.76| 0.83| 0.84| 0.81  | 6     |
|           | RC     | 0.60| 0.88| 0.91| 0.80  |       |
|           | F1     | 0.67| 0.86| 0.87| 0.80  |       |
|           | AC     | 0.89| 0.88| 0.90| 0.89  |       |
|           | RO     | 0.92| 0.94| 0.95| 0.94  |       |
|           | SP     | 3300| 7715| 7170| 6062  |       |
| DeepWalk  | PC     | 0.65| 0.57| 0.58| 0.60  | 0     |
|           | RC     | 0.15| 0.67| 0.71| 0.51  |       |
|           | F1     | 0.24| 0.62| 0.63| 0.50  |       |
|           | AC     | 0.81| 0.67| 0.68| 0.72  |       |
|           | RO     | 0.56| 0.67| 0.69| 0.64  |       |
|           | SP     | 821 | 1575| 1548| 1315  |       |
| Node2Vec  | PC     | 0.74| 0.47| 0.49| 0.57  | 0     |
|           | RC     | 0.03| 0.65| 0.55| 0.41  |       |
|           | F1     | 0.05| 0.55| 0.52| 0.37  |       |
|           | AC     | 0.80| 0.57| 0.60| 0.66  |       |
|           | RO     | 0.51| 0.58| 0.59| 0.56  |       |
|           | SP     | 821 | 1575| 1548| 1315  |       |
| SDNE      | PC     | 0.65| 0.43| 0.74| 0.61  | 0     |
|           | RC     | 0.05| 0.96| 0.17| 0.39  |       |
|           | F1     | 0.10| 0.59| 0.27| 0.32  |       |
|           | AC     | 0.80| 0.48| 0.65| 0.64  |       |
|           | RO     | 0.52| 0.56| 0.56| 0.55  |       |
|           | SP     | 821 | 1575| 1548| 1315  |       |
| LINE      | PC     | 0.48| 0.42| 0.44| 0.45  | 0     |
|           | RC     | 0.05| 0.60| 0.46| 0.37  |       |
|           | F1     | 0.08| 0.50| 0.45| 0.34  |       |
|           | AC     | 0.79| 0.51| 0.56| 0.62  |       |
|           | RO     | 0.52| 0.53| 0.54| 0.53  |       |
|           | SP     | 821 | 1575| 1548| 1315  |       |

5 Limitations and Conclusion

The benchmark models (baselines) evaluated herein were executed using their default parameters. We were not able to evaluate GCN [11] against Facebook-Page2Page, PubMed-Diabetes, Internet-Industry-Partnership, and Zachary-Karate datasets; because these aforementioned datasets do not possess individual vector-based feature set which is required by the GCN model for input-data
| Model    | Metric | Terrorists-Relation dataset | Points |
|----------|--------|-----------------------------|--------|
|          |        | C1  | C2  | C3  | C4  | μ    |        |
| RLVECO   | PC     | 0.93| 0.91| 0.46| 1.00| 0.83| 6      |
|          | RC     | 0.97| 0.97| 0.42| 0.97| 0.83|        |
|          | F1     | 0.95| 0.94| 0.44| 0.98| 0.83|        |
|          | AC     | 0.95| 0.98| 0.89| 0.99| 0.95|        |
|          | RO     | 0.98| 1.00| 0.85| 1.00| 0.96|        |
|          | SP     | 1706| 491 | 319 | 561 | 769 |        |
| GCN      | PC     | 0.94| 0.74| 0.67| 0.96| 0.83| 5      |
|          | RC     | 0.90| 0.95| 0.60| 1.00| 0.86|        |
|          | F1     | 0.92| 0.83| 0.63| 0.98| 0.84|        |
|          | AC     | 0.92| 0.95| 0.88| 0.99| 0.94|        |
|          | RO     | 0.98| 0.99| 0.91| 1.00| 0.97|        |
|          | SP     | 92  | 21  | 30  | 27  | 43  |        |
| DeepWalk | PC     | 0.88| 0.82| 0.64| 0.86| 0.80| 0      |
|          | RC     | 0.90| 0.86| 0.53| 0.93| 0.81|        |
|          | F1     | 0.89| 0.84| 0.58| 0.89| 0.80|        |
|          | AC     | 0.88| 0.96| 0.86| 0.96| 0.92|        |
|          | RO     | 0.88| 0.92| 0.73| 0.95| 0.87|        |
|          | SP     | 92  | 21  | 30  | 27  | 43  |        |
| Node2Vec | PC     | 0.86| 0.82| 0.60| 0.86| 0.79| 0      |
|          | RC     | 0.88| 0.86| 0.50| 0.93| 0.79|        |
|          | F1     | 0.87| 0.84| 0.55| 0.89| 0.79|        |
|          | AC     | 0.86| 0.96| 0.85| 0.96| 0.91|        |
|          | RO     | 0.86| 0.92| 0.71| 0.95| 0.86|        |
|          | SP     | 92  | 21  | 30  | 27  | 43  |        |
| LINE     | PC     | 0.82| 0.82| 0.58| 0.92| 0.79| 0      |
|          | RC     | 0.92| 0.86| 0.37| 0.85| 0.75|        |
|          | F1     | 0.87| 0.84| 0.45| 0.88| 0.76|        |
|          | AC     | 0.85| 0.96| 0.84| 0.96| 0.90|        |
|          | RO     | 0.84| 0.92| 0.65| 0.92| 0.83|        |
|          | SP     | 92  | 21  | 30  | 27  | 43  |        |
| SDNE     | PC     | 0.77| 0.90| 0.56| 1.00| 0.81| 0      |
|          | RC     | 0.92| 0.86| 0.30| 0.85| 0.73|        |
|          | F1     | 0.84| 0.88| 0.39| 0.92| 0.76|        |
|          | AC     | 0.81| 0.97| 0.84| 0.98| 0.90|        |
|          | RO     | 0.80| 0.92| 0.62| 0.93| 0.82|        |
|          | SP     | 92  | 21  | 30  | 27  | 43  |        |
Table 8. Node-classification experiment over Zachary-Karate and Internet-Industry-Partnership datasets. Results are based on the reserved validation sample - datasets vs models. N.B.: Mtc = Fitness Metric; Pts = Points.

| Model     | Mtc  | Zachary-Karate dataset | Internet-Industry-Partnership |
|-----------|------|-------------------------|-------------------------------|
|           |      | C1 | C2 | C3  | C4 | μ | C1 | C2 | C3  | μ | Pts |
| RLVECO    | PC   | 1.00 | 0.67 | 0.20 | 1.00 | 0.72 | 7   | 0.33 | 0.96 | 0.29 | 0.53 |
|           | RC   | 1.00 | 0.89 | 1.00 | 0.50 | 0.85 | 6.5  | 0.77 | 0.76 | 0.76 | 0.73 |
|           | F1   | 1.00 | **0.76** | **0.33** | 0.67 | 0.69 | **0.44** | **0.86** | 0.42 | 0.57 |
|           | AC   | 1.00 | 0.81 | 0.69 | 0.77 | 0.82 | 0.84 | 0.78 | 0.87 | 0.83 |
|           | RO   | 1.00 | **0.83** | **0.83** | **0.75** | 0.85 | **0.76** | **0.81** | **0.82** | 0.80 |
|           | SP   | 3   | 9   | 2   | 12  | 7   | 26   | 238 | 17  | 94  | 5   |
| SDNE      | PC   | 0.00 | 0.55 | 0.00 | 0.60 | 0.28 | 2   | 0.00 | 0.61 | 0.00 | 0.20 |
|           | RC   | 0.00 | 0.50 | 0.00 | 1.00 | 0.38 | 0.00 | 1.00 | 0.00 | 0.33 |
|           | F1   | 0.00 | 0.50 | 0.00 | **0.75** | 0.31 | 0.00 | 0.76 | 0.00 | 0.25 |
|           | AC   | 0.86 | 0.71 | 0.86 | 0.71 | 0.79 | 0.82 | 0.61 | 0.80 | 0.74 |
|           | RO   | 0.50 | 0.65 | 0.50 | **0.75** | 0.60 | 0.50 | 0.50 | 0.50 | 0.50 |
|           | SP   | 1   | 2   | 1   | 3   | 2   | 8    | 27  | 9   | 15  | 0   |
| LINE      | PC   | 0.00 | 0.50 | 0.00 | 0.60 | 0.28 | 2   | 0.00 | 0.61 | 0.00 | 0.20 |
|           | RC   | 0.00 | 0.50 | 0.00 | 1.00 | 0.38 | 0.00 | 1.00 | 0.00 | 0.33 |
|           | F1   | 0.00 | 0.50 | 0.00 | **0.75** | 0.31 | 0.00 | 0.76 | 0.00 | 0.25 |
|           | AC   | 0.86 | 0.71 | 0.86 | 0.71 | 0.79 | 0.82 | 0.61 | 0.80 | 0.74 |
|           | RO   | 0.50 | 0.65 | 0.50 | **0.75** | 0.60 | 0.50 | 0.50 | 0.50 | 0.50 |
|           | SP   | 1   | 2   | 1   | 3   | 2   | 8    | 27  | 9   | 15  | 0   |
| DeepWalk  | PC   | 0.00 | 0.40 | 0.00 | 0.50 | 0.23 | 0   | 0.50 | 0.81 | 0.36 | 0.56 |
|           | RC   | 0.00 | 1.00 | 0.00 | 0.33 | 0.33 | 0.12 | 0.93 | 0.44 | 0.50 |
|           | F1   | 0.00 | 0.57 | 0.00 | 0.40 | 0.24 | 0.20 | **0.86** | 0.40 | 0.49 |
|           | AC   | 0.86 | 0.57 | 0.86 | 0.57 | 0.72 | 0.82 | 0.82 | 0.73 | 0.79 |
|           | RO   | 0.50 | 0.70 | 0.50 | 0.54 | 0.56 | 0.55 | 0.79 | 0.62 | 0.65 |
|           | SP   | 1   | 2   | 1   | 3   | 2   | 8    | 27  | 9   | 15  | 1   |
| Node2Vec  | PC   | 0.00 | 0.00 | 0.00 | 0.25 | 0.06 | 0   | 0.00 | 0.68 | 0.75 | 0.48 |
|           | RC   | 0.00 | 0.00 | 0.00 | 0.33 | 0.08 | 0.00 | 1.00 | 0.33 | 0.44 |
|           | F1   | 0.00 | 0.00 | 0.00 | 0.29 | 0.07 | 0.00 | 0.81 | **0.46** | 0.42 |
|           | AC   | 0.86 | 0.29 | 0.86 | 0.29 | 0.58 | 0.82 | 0.70 | 0.84 | 0.79 |
|           | RO   | 0.50 | 0.20 | 0.50 | 0.29 | 0.37 | 0.50 | 0.62 | 0.65 | 0.59 |
|           | SP   | 1   | 2   | 1   | 3   | 2   | 8    | 27  | 9   | 14.67 | 1   |

processing. Overall, RLVECO’s remarkable performance with reference to our benchmarking results can be attributed to the following:

(i) The RL kernel of RLVECO is constituted of two (2) distinct layers of FL, viz: Knowledge-Graph Embeddings and Convolution Operations [15].
(ii) The high-quality data preprocessing techniques employed herein with respect to the benchmark datasets. We ensured that all the constituent actors of a given social network were transcoded to their respective discrete...
data representations, without any loss in semantics, and normalized prior to training and/or testing.

6 Future Work and Acknowledgements

We intend to expand RLVECO’s scope such that it can be applied for resolving other open research problems in SNA. Also, we are sourcing for additional baselines (benchmark models) and real-world social network datasets for extensive validation of RLVECO. This research was supported by International Business Machines (IBM) via the provision of computational resources necessary to carry out our experiments. Also, this work was enabled in part via support provided by SHARCNET and Compute Canada (www.computecanada.ca).

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