SignLink: Signed Link Prediction using Contrastive Learning

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Outline

Introduction

- **Signed Graphs:** Graphs that have both positive and negative links.

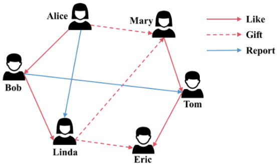

Figure 1: An example of a signed graph in online games, where red lines denote positive links and blue lines denote negative links.

Signed Networks

- **Signed Network:** A network where edges have positive or negative signs.
- **Network Representation on Signed Graphs:**
  - Main idea: constraining nodes closer to "friends" (neighbors connected by positive links) and farther from "enemies" (neighbors connected by negative links).
  - Combining graph neural networks with sociological theories (i.e., balance theory).
- **Structural Balance Theory:** Analyzes stability in signed networks using triad configurations.

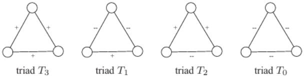

Figure 2: Undirected signed triads. Based on the number of positive edges, triads with an odd number of pluses are balanced (T3,T1), and triads with an even number of pluses (T2,T0) are unbalanced.

Signed Link Prediction

- **What is Signed Link Prediction:** Signed link prediction is a binary classification problem that predicts whether an edge between a pair of nodes is positive or negative.
- **Importance of Signed Link Prediction:**
  - Helps understand user interactions, detect fake news, and identify community polarization.
  - Applications include recommendation systems, fraud detection, and content moderation.
- **Challenges in Signed Link Prediction:**
  - High imbalance in positive and negative edges.
  - Existing theories of homophily do not apply.
  - Need to integrate Structural Balance Theory.

Contrastive Learning in Graphs

- **Graph Contrastive Learning (GCL):** Helps learn more discriminative and robust representations.
- **Positive pairs:** Representations generated from the same node.
- **Negative pairs:** Representations generated from different nodes.
- **Contrastive Objective:** Maximizing agreements between positive pairs while minimizing agreements between negative pairs.

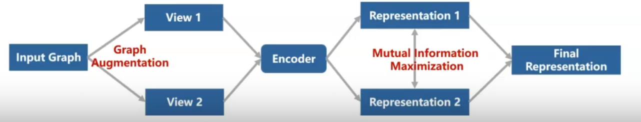

Figure 3: Graph Contrastive Learning Process

Contrastive Learning in Graphs

- Existing Graph Contrastive Learning (GCL) methods are designed for unsigned graphs, making them unsuitable for signed networks.
- Noisy interactions in real-world signed networks lead to misrepresentations in learned embeddings.
- Structural Balance Theory is often overlooked, despite its importance in learning meaningful representations.

Research Objective

- To develop a Graph Contrastive Learning (GCL) framework tailored for signed networks, capturing both positive and negative interactions.
- To design a robust method that effectively handles noisy interactions in signed networks, ensuring reliable link prediction.
- To integrate Structural Balance Theory into the learning process, improving the model's ability to capture meaningful representations in signed graphs.

Existing Signed Network based Contrastive learning

- **SGCL:** Key idea – exploit graph contrastive learning for signed graphs.

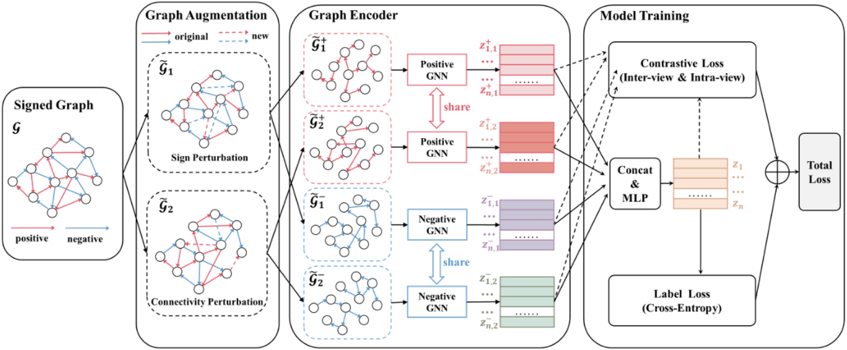

Figure 4: The overall architecture of SGCL, which consists of three major components: (a) Graph Augmentation, (b) Graph Encoder, (c) Model Training.

FRAMEWORK

SGCL - Graph Augmentation

- **Motivation:** Traditional graph augmentations ignore the diverse semantics between positive and negative links in signed graphs.
- **Balance theory:**
    - **Balanced cycles:** Cycles consisting of an even number of negative links.
    - **Unbalanced cycles:** Cycles consisting of an odd number of negative links.
- **Key idea:** Design graph augmentations specific to signed graphs using balance theory.
    - Eliminating spurious balanced cycles and discovering potential balanced cycles.

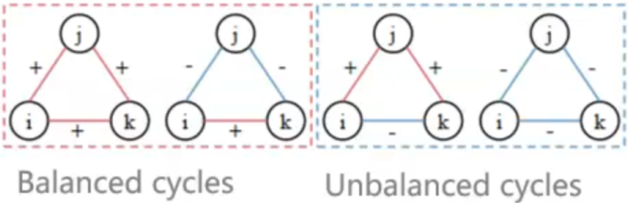

Figure 5: Balanced and Unbalanced Cycles in Signed Graphs

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- **Method:** Perturb existing balanced cycles from different perspectives.
  - **Connectivity Perturbation:** Drop and add links randomly.
  - **Sign Perturbation:** Change the sign of links randomly.
- Apply either the connectivity perturbation or sign perturbation in each iteration.
  - **SGCL-comp:** One graph view by connectivity perturbation and the other by sign perturbation.
  - **SGCL-conn:** Two graph views are both generated by connectivity perturbation.
  - **SGCL-sign:** Two graph views are both generated by sign perturbation.

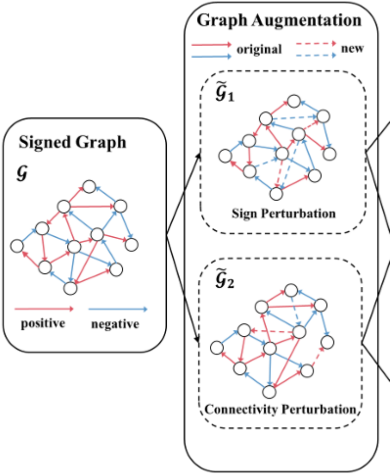


Figure 6: Graph Augmentation Process

FRAMEWORK

SGCL - Graph Encoder

Consistent Representations: $z^+_{i,1}, z^+_{i,2}$

- Learned by positive GNN from positive graphs.
- Imply the information of **“friends”**.

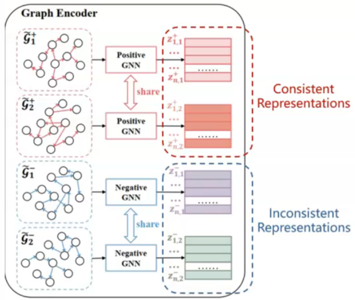
Inconsistent Representations: $z^-_{i,1}, z^-_{i,2}$

- Learned by negative GNN from negative graphs.
- Imply the information of **“enemies”**.

Ultimate Representation: z_i

- Concatenation of four representations of each node.

$$z_i = g(z^+_{i,1} \| z^+_{i,2} \| z^-_{i,1} \| z^-_{i,2}) \qquad (1)$$



SGCL - Graph Encoder: Consistent and Inconsistent Representations

FRAMEWORK

SGCL – Contrastive Objective

Inter-view Contrastive Learning (Inter-view CL)

- **Aim:** Retain the information consistency between different augmented graphs.

Method:

- Maximize the similarities of representations between the same node.
- Minimize the similarities of representations between different nodes.

$$\mathcal{L}_{inter\_pos} = -\frac{1}{I}\sum_{i=1}^{I} \log \frac{\exp(\mathsf{sim}(z_{i,m}^{+}, z_{i,m}^{+})/\tau)}{\sum_{j=1,j\neq i}^{I} \exp(\mathsf{sim}(z_{i,m}^{+}, z_{j,m}^{+})/\tau)}$$

Inter-view CL loss in positive graph

$$\mathcal{L}_{inter\_neg} = -\frac{1}{I}\sum_{i=1}^{I} \log \frac{\exp(\mathsf{sim}(z_{i,m}^{+}, z_{i,m}^{-})/\tau)}{\sum_{j=1,j\neq i}^{I} \exp(\mathsf{sim}(z_{i,m}^{+}, z_{j,m}^{-})/\tau)}$$

Inter-view CL loss in negative graph

$$\mathcal{L}_{inter} = \mathcal{L}_{inter\_pos} + \mathcal{L}_{inter\_neg}$$

Inter-view CL loss

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SGCL – Contrastive Objective
Intra-view Contrastive Learning (Intra-view CL)

- **Aim:** Making nodes close to **"friends"** and far from **"enemies"**.

Method:

- Constraining the ultimate representation of each node close to its consistent representations and far from its inconsistent representations.

$$\mathcal{L}_{\text{intra}} = -\frac{1}{I}\sum_{i=1}^{I}\log\frac{\sum_{m=1}^{M}\exp(\mathsf{sim}(z_i, z_{i,m}^{+})/\tau)}{\sum_{m=1}^{M}\exp(\mathsf{sim}(z_i, z_{i,m}^{-})/\tau)} \tag{2}$$

Intra-view CL loss

Proposed Methodology

- **Research Gap:**
  - Existing contrastive learning (CL) approaches consider perturbations in separate positive and negative graphs.
  - This makes learning immensely challenging due to the interplay between positive and negative edges.
- **Working on a Contrastive Learning-Based Novel Approach:**
  - Effectively integrates both positive and negative edges.
  - Includes Structural Balance Theory.
  - Handles inherent challenges of signed networks, such as high data sparsity and imbalance.

Proposed Framework Overview

- Our framework integrates both classical perturbation-based and structural theory-based augmentations for signed network analysis.
- The goal is to train a model using multi-view contrastive learning that captures richer and more meaningful graph representations.
- Unlike previous approaches that applied uniform or random noise, we introduce a novel structural balance theory-based augmentation.
- By preprocessing unbalanced triads and strategically flipping signs, we embed sociological principles of trust/distrust into the learning process.
- The result is a diverse, semantically consistent set of views that boosts model robustness, generalization, and social awareness.

Key Views

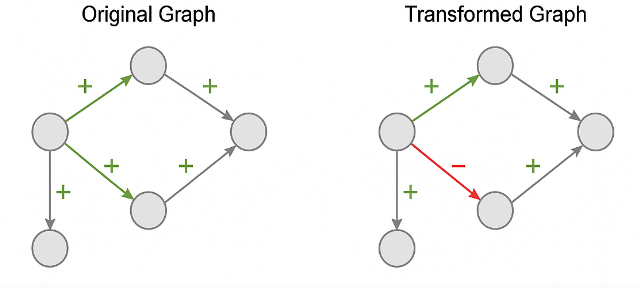
- Our framework leverages four graph views to improve signed link prediction:
  - **Feature Masking:** Each link in the dataset encodes trust via a numerical score (e.g., -10 to +10). In this view, we mask these trust values using a binary mask M and replace the masked entries with Gaussian noise:

$$X' = M \odot X + (1 - M) \odot \mathcal{N}(0, \sigma^2)$$

  - **Sign Flipping:** Randomly inverts edge signs to simulate trust variability.
  - **Structural Perturbation:** Adds/removes edges to promote topological resilience.
  - **Balance Theory Augmentation (Ours):** Strategically flips edges in unbalanced triads to align with social theories.
- These diverse views generate stronger contrastive signals during training, enabling the model to learn representations that are robust, generalizable, and socially informed.

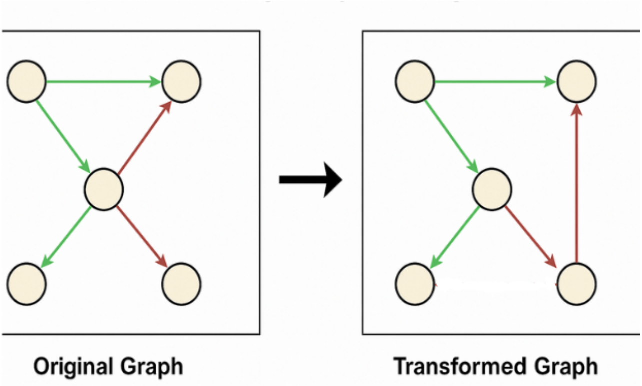
Proposed Methodology

- **View 2: Random Sign-Flipping Augmentation**
  Edge signs are randomly flipped with a global flip ratio γ.



Proposed Methodology

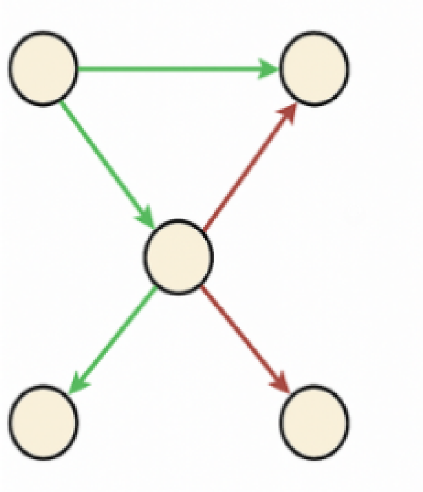
- **View 3: Structural Edge Drop/Add Augmentation**
  for a given signed graph G, edges are dropped with a probability r, suppose if x are +ve and y -ve edges are dropped then x+y new edges are added randomly out of which x are +ve and y are -ve.



Proposed Methodology: View 4 Balance Theory-Based Augmentation

- Leverages social balance theory to identify unstable triads (e.g., $++$) that violate natural trust/distrust patterns.
- Preprocesses the graph to detect edges frequently involved in unbalanced triads and stores them as ‘unstable edges’.
- During training, flips these edges with probability δ to generate a semantically meaningful and socially grounded graph view.

View 4: Balance Theory-Based Augmentation (Visual)



Datasets

- **Bitcoin-Alpha** is a signed directed network where users rate each other's trustworthiness on a scale from -10 to +10.
- Positive and negative edges represent trust and distrust respectively, making it ideal for studying signed link prediction and balance theory.
- The graph has 3,783 nodes, 22,650 positive links, and 1,536 negative links — with 93.65% links being positive, reflecting real-world bias.
- Due to its sparsity and imbalance, it provides a challenging benchmark; our preprocessing pipeline adapts to these traits for effective evaluation.

Experiment Setup and Evaluation Metrics

- We compare combinations of classical augmentations (Feature Masking, Sign Flipping, Structural Perturbation) with our proposed Balance Theory-based augmentation.
- Evaluated combinations include:
  - Pairwise: (1+2), (1+3), (1+4), (2+3), (2+4), (3+4)
  - Full 4-View: (1+2+3+4)
- Evaluation metrics:
  - Micro-F1 Score
  - Binary-F1 Score
  - Macro-F1 Score
  - AUC (Area Under Curve)

Performance Summary on Bitcoin-Alpha Dataset

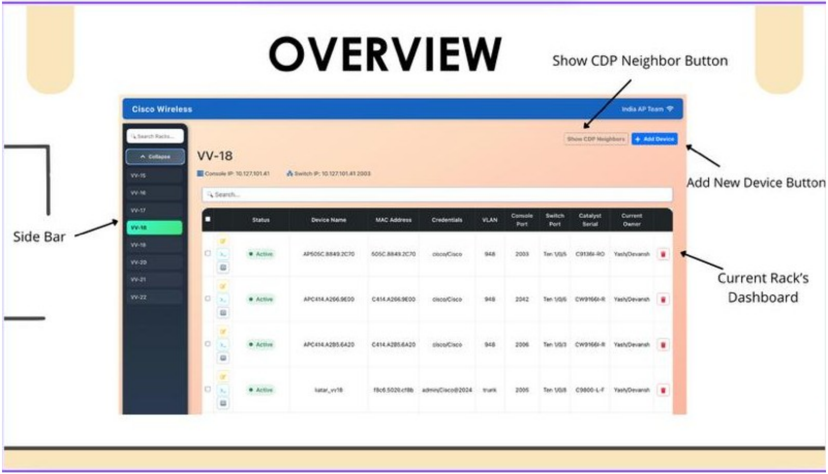
- The combination **(2 + 4): Sign Flipping + Balance Theory** achieves the highest scores across all metrics.
- **View 4 (Balance Theory)** significantly boosts performance — e.g., **+8.83% in Macro-F1** — by embedding social structure into learning.
- The **4-view setup (1+2+3+4)** also performs consistently, showing the effectiveness of diverse augmentations.

Augmentation Views	Micro-F1	Binary-F1	Macro-F1	AUC
SGCL Paper (Baseline)	0.9523	0.9748	0.7622	0.9104
1 + 2	0.9551 (+0.29%)	0.9762 (+0.14%)	0.7889 (+3.51%)	0.9576 (+5.19%)
1 + 3	0.9551 (+0.29%)	0.9764 (+0.16%)	0.7558 (-0.84%)	0.9557 (+4.98%)
1 + 4	0.9533 (+0.10%)	0.9754 (+0.06%)	0.7631 (+0.12%)	0.9605 (+5.50%)
2 + 4	**0.9647 (+1.30%)**	**0.9813 (+0.67%)**	**0.8295 (+8.83%)**	**0.9700 (+6.55%)**
3 + 4	0.9528 (+0.05%)	0.9751 (+0.03%)	0.7653 (+0.41%)	0.9593 (+5.38%)
All Views (1+2+3+4)	0.9542 (+0.20%)	0.9760 (+0.12%)	0.7464 (-2.07%)	0.9571 (+5.13%)

Internship Project: Cisco (Wireless AP Division)

- **Team Role:** Worked in the Wireless Access Point (AP) team focusing on firmware development, diagnostics, and tooling for AP models.
- **Key Projects:**
    - **Code Quality Improvement:** Resolved compiler/static warnings in AP image builds to improve maintainability and build reliability.
    - **Rack UI Portal:** Built a full-stack web interface (React + Flask) for managing networking racks and devices in Cisco labs.
    - **MiniDump Enablement:** Modified bootloader logic to persist crash diagnostics locally on APs, ensuring recovery even under poor network conditions.
- **Tech Stack:** C, React.js, Flask, Bootstrap, Python, embedded systems.
- **Impact:** Improved firmware quality, streamlined device management workflows, and enhanced fault recovery capabilities for production APs.

Rack UI Device Management Portal (Cisco Internship)



References I

[1] Lin Shu, Erxin Du, Yaomin Chang, Chuan Chen, Zibin Zheng, Xingxing Xing, and Shaofeng Shen. SGCL: Contrastive Representation Learning for Signed Graphs. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management*, pages 1671–1680, 2021. DOI: 10.1145/3459637.3482478

[2] Jure Leskovec, Daniel Huttenlocher, and Jon Kleinberg. Signed Networks in Social Media. In *CHI 2010: 28th ACM Conference on Human Factors in Computing Systems*, 2010. DOI: 10.48550/arXiv.1003.2424

Thank you!

FRAMEWORK

Motivation: Positive and negative links have distinct semantic properties.

- **Positive Links:** Closeness to friends.
- **Negative Links:** Hatred to enemies.

Design: Two separate GNNs to aggregate positive and negative links.

- **Positive GNN:** Learns node representations from positive graphs.
- **Negative GNN:** Learns node representations from negative graphs.

$$\alpha_{ij}^{+} = \frac{\exp(\text{LeakyReLU}(a^{+}[h_i^{+}W_t^{+} \parallel h_j^{+}W_a^{+}]^T))}{\sum_{t \in \mathcal{N}_i^{+}} \exp(\text{LeakyReLU}(a^{+}[h_i^{+}W_t^{+} \parallel h_t^{+}W_a^{+}]^T))} \tag{3}$$

$$\alpha_{ij}^{-} = \frac{\exp(\text{LeakyReLU}(a^{-}[h_i^{-}W_t^{-} \parallel h_j^{-}W_a^{-}]^T))}{\sum_{t \in \mathcal{N}_i^{-}} \exp(\text{LeakyReLU}(a^{-}[h_i^{-}W_t^{-} \parallel h_t^{-}W_a^{-}]^T))} \tag{4}$$

Attention Coefficient

FRAMEWORK

$$h_i^{+\prime} = \Big\Vert_{k=1}^{K} \sigma \left(\sum_{j \in \mathcal{N}_i^+} \alpha_{ij}^{k,+} h_j^+ W_b^+ \right) \tag{5}$$

$$h_i^{-\prime} = \Big\Vert_{k=1}^{K} \sigma \left(\sum_{j \in \mathcal{N}_i^-} \alpha_{ij}^{k,-} h_j^- W_b^- \right) \tag{6}$$

Aggregation

$$z_i^+ = \left[h_i^{(0),+} \Vert h_i^{(1),+} \Vert \ldots \Vert h_i^{(L),+} \right] W_c^+ \tag{7}$$

$$z_i^- = \left[h_i^{(0),-} \Vert h_i^{(1),-} \Vert \ldots \Vert h_i^{(L),-} \right] W_c^- \tag{8}$$

Concatenation