# ANTI-MONEY LAUNDERING IN BITCOIN USING MACHINE LEARNING

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## Anti-Money Laundering in Bitcoin

- Existing systems prove inefficient in tackling the issue of money laundering in Bitcoin.
- The pseudonymity of Bitcoin is an advantage for criminals but the public availability of data is a key advantage for the investigators.

## Objective

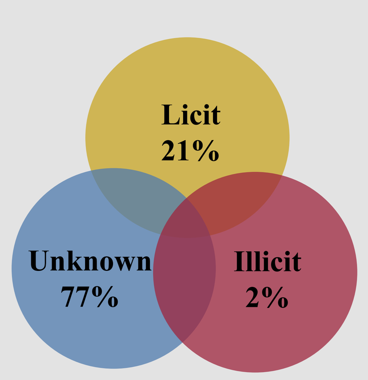
- Our work aims to exploit the publicly available data to develop useful insights that might help in curbing illegal activities.
- In this work, we experiment with various emerging methods that leverage graph information to model the problem and combine the potentialities of these methods to build a better performing system.
- We also aim to further improve our system using Knowledge Distillation (KD)

## Problem Statement

To design an efficient system to classify the unknown transactions as licit or illicit in the Elliptic dataset to tackle the issue of money laundering in Bitcoin.

## Elliptic Dataset

- 2,03,769 transactions/graph nodes and 2,34,355 edges representing the Bitcoin flow.
- 94 local features and 72 aggregate features.



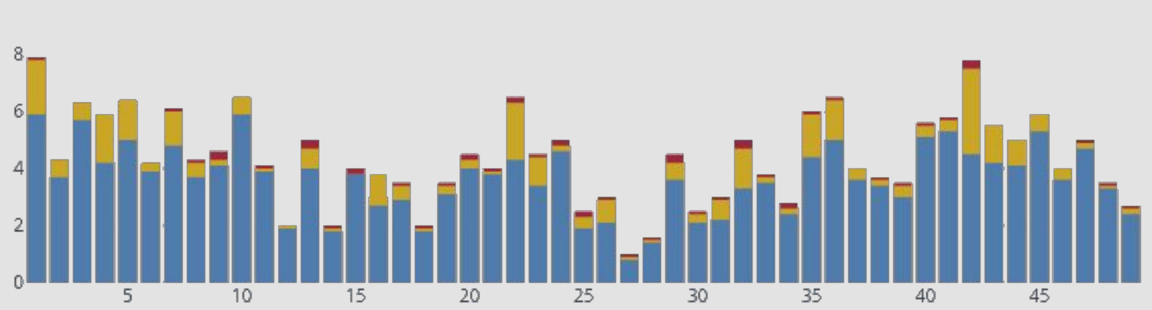




Fig. 1 Number of nodes vs. Timestep

## Methodology - GCDF

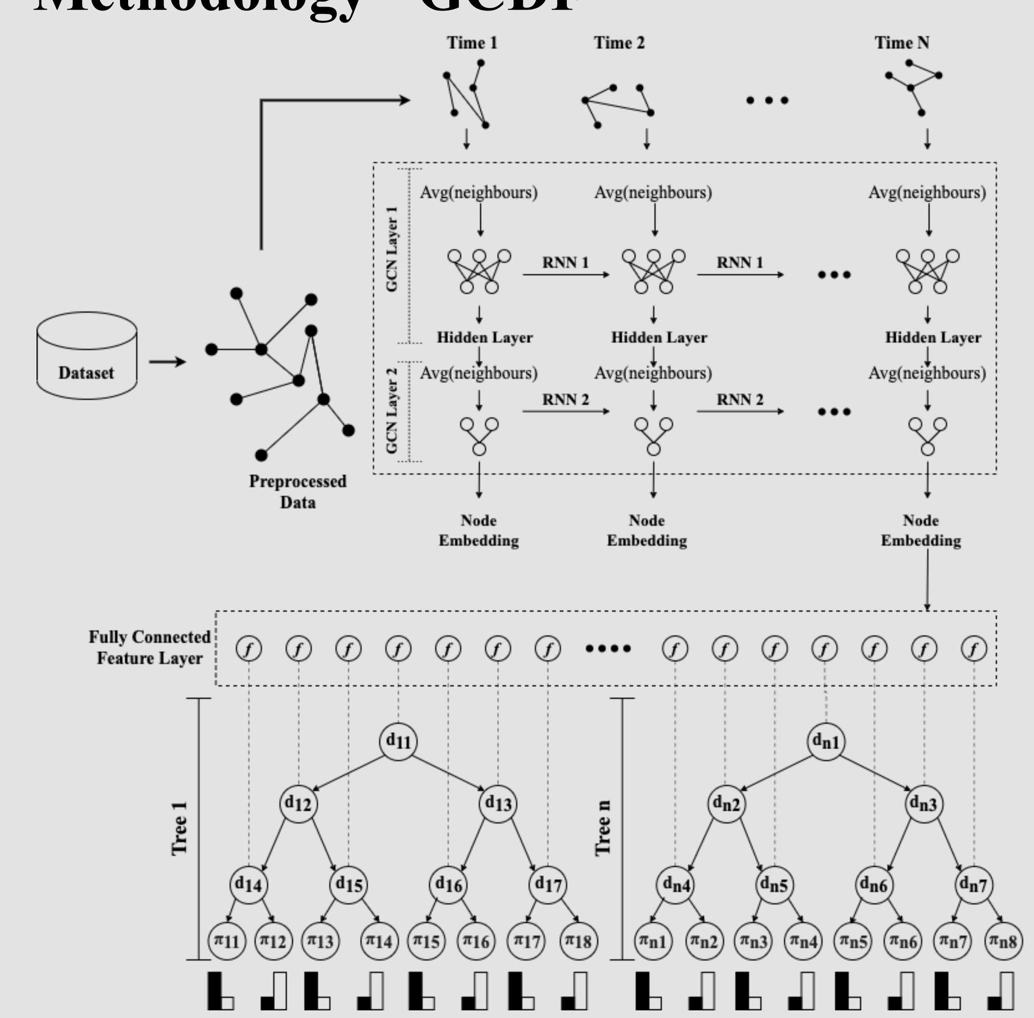



Fig 2. Proposed System - GCDF

Various steps involved in Graph Convolutional Decision Forest (GCDF) :

- Pre-process the dataset
- Feed each timestep to EvolveGCN module
- Feed the node embeddings obtained from EvolveGCN to Deep Neural Decision Forest (DNDF) Module
- Obtain the final prediction

## Fine Tuning using KD

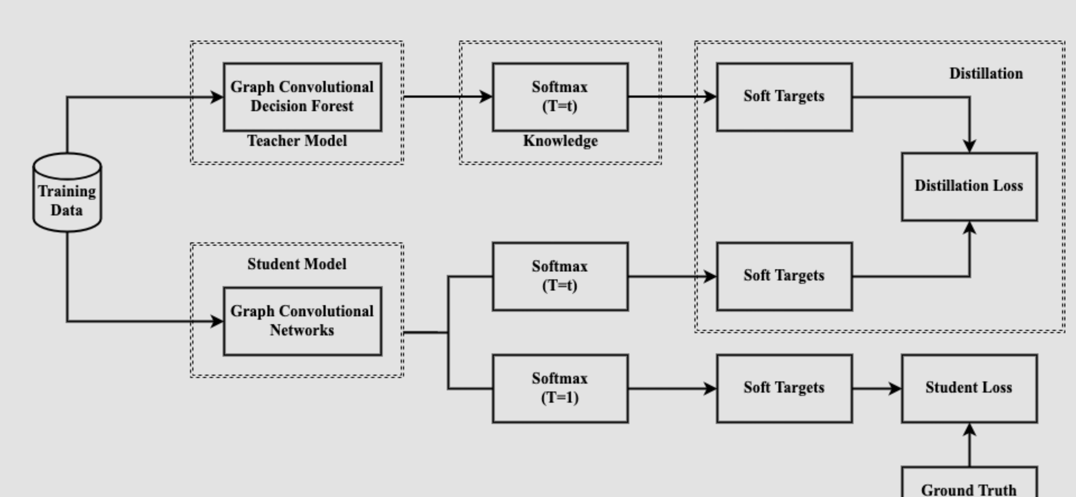



Fig 3. Fine tuning using KD

Various steps involved in fine tuning :

- Train GCDF as the teacher model and obtain the distillation loss
- Train GCN as the student model using the distillation loss
- Obtain final predictions from the student model

## Tools

- Python
- NumPy
- Sklearn
- PyTorch

## Evaluation Measures

- Precision
- Recall
- F1-Score
- Micro Average F1-Score

## Results

| Performance Comparison | Illicit | | | Micro Avg F1 |
|---|---|---|---|---|
| | Precision | Recall | F1 | |
| Logistic Regression (AF + NE) | 0.457 | 0.651 | 0.537 | 0.9297 |
| Random Forest (AF + NE) | 0.984 | 0.647 | 0.781 | 0.9772 |
| MLP (AF + NE) | 0.784 | 0.542 | 0.641 | 0.9619 |
| Graph Convolutional Network | 0.8674 | 0.4774 | 0.6158 | 0.9613 |
| GraphSAGE | 0.8534 | 0.8385 | 0.8939 | 0.8278 |
| EvolveGCN | 0.998 | 0.8663 | 0.9249 | 0.8663 |
| GCDF | 0.9953 | 0.8663 | 0.9251 | 0.8663 |

Table. 1 GCDF vs. Other Methods; AF – All Features, NE – Node Embeddings

| Methods | Illicit | | | Micro-avg F1 |
|---|---|---|---|---|
| | F1 score | Precision | Recall | |
| GCDF (Without KD) | 0.9251 | 0.9953 | 0.8663 | 0.8663 |
| GCDF (With KD) - T | 0.9251 | 0.9953 | 0.8663 | 0.8663 |
| GCDF (With KD) - S | 0.9525 | 0.9936 | 0.9166 | 0.9191 |

Table. 2 Effect of KD on GCDF

| Methods | Teacher | | | | Student | | | |
|---|---|---|---|---|---|---|---|---|
| | F1 Score | Precision | Recall | Micro-avg F1 | F1 Score | Precision | Recall | Micro-avg F1 |
| GCN | 0.444 | 0.305 | 0.406 | 0.9946 | 0.8175 | 0.7828 | 0.8751 | 0.708 |
| EvolveGCN | 0.9251 | 0.9931 | 0.8663 | 0.8663 | 0.9252 | 0.9999 | 0.8666 | 0.8666 |
| GCDF | 0.9251 | 0.9953 | 0.8663 | 0.8663 | 0.9525 | 0.9936 | 0.9166 | 0.9191 |

Table. 3 Other Methods in KD

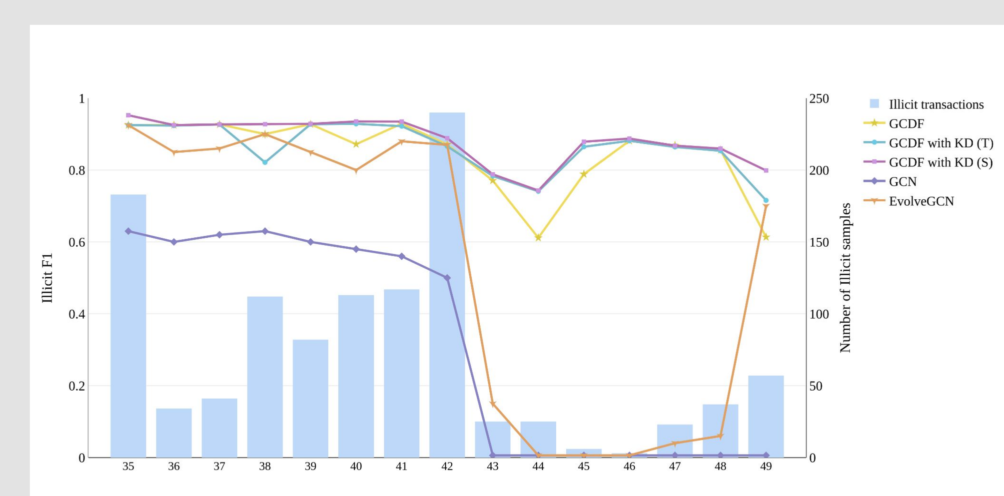
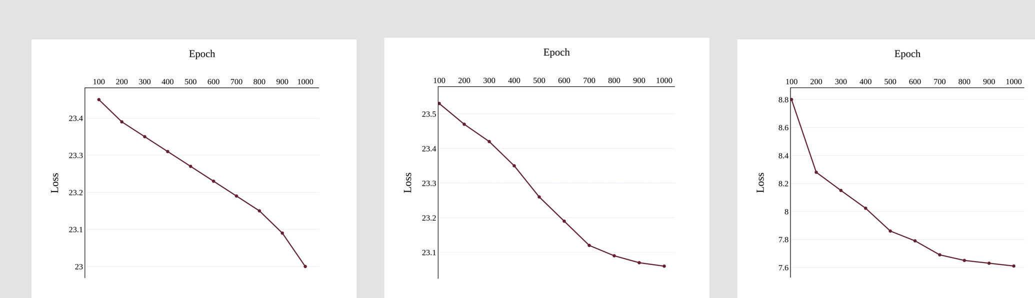



Fig 4. Illicit F1 results over timespan




(a)GCDF (b)GCDF with KD (T) (c)GCDF with KD (S)

Fig 5. Loss vs. Epoch ; T-Teacher S-Student

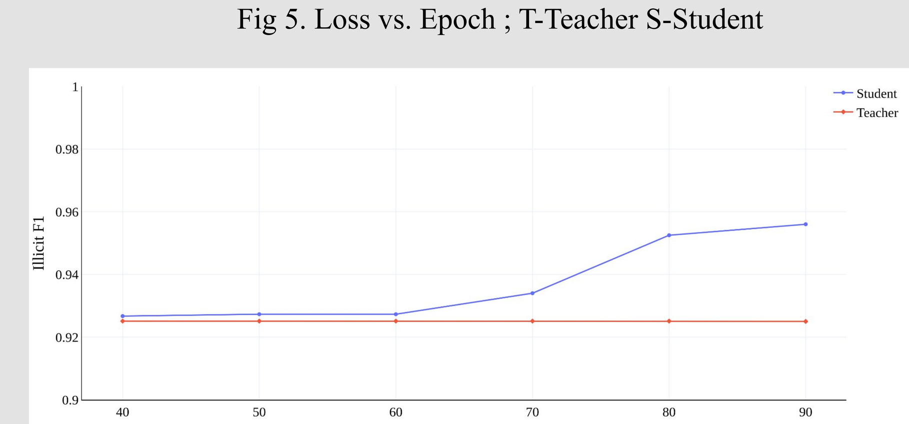



Fig 6. Illicit F1 vs. Tree size in DNDF

## Inferences

- GCDF performs best with a 70:30 temporal split of training and test data respectively.
- 80 trees of depth 8 each in DNDF was able to give satisfactory results both in terms of performance and execution time.
- Loss incurred while training student convincingly reduced with the introduction of KD
- There was an observable performance boost in the student model as compared to the teacher model.

## Conclusion

- Out of the benchmark methods, Random Forest gives the best result. But this does not incorporate any graph information.
- The importance of utilising a concatenation between dynamic graph learning and ensemble feature learning is demonstrated in this work.
- The results show the superiority of the proposed model to classify the illicit transactions in the Elliptic dataset.
- Additionally, the application of KD gave finer results

## Future Works

- Elliptic dataset has the main limitation of having a new node set for each new graph snapshot; this needs to be addressed while considering a dynamic setting.
- Capturing the temporal dynamics by modelling the data as a time-varying graph and using it for detecting illicit activities can be another interesting future work.

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*Accepted for publication in Data Technologies and Applications Journal (SCI), Emerald Publisher.*