Bot-or-Not:

Temporal Graph-Based Bot Detection on Twitter

Team 03

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Image source: Freepik

Motivation

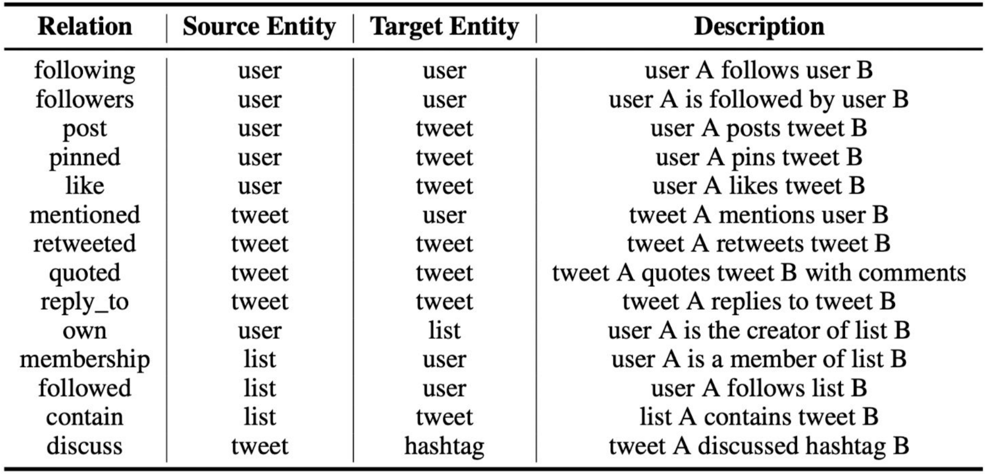
- Our task is to **classify user nodes** as humans or bots
- Bot behaviour is **dynamic**, not static
- Most graph-based bot detectors ignore time
- Twitter graph is inherently **temporal**

Project goal

Construct a discrete-time dynamic graph (**DTDG**) from TwiBot-22 and apply RGCN over temporal snapshots, to capture evolving relational patterns and improve robustness to distribution shift in bot detection.

Twibot 22

- Largest Bot Detection benchmark dataset to date
- Contains **1 million users** and **88 million tweets** collected from Jan 2022 - Feb 2022
- 4 entity types: User, Tweet, Lists and Hashtags
- 14 relation types:



Relation	Source Entity	Target Entity	Description
following	user	user	user A follows user B
followers	user	user	user A is followed by user B
post	user	tweet	user A posts tweet B
pinned	user	tweet	user A pins tweet B
like	user	tweet	user A likes tweet B
mentioned	tweet	user	tweet A mentions user B
retweeted	tweet	tweet	tweet A retweets tweet B
quoted	tweet	tweet	tweet A quotes tweet B with comments
reply_to	tweet	tweet	tweet A replies to tweet B
own	user	list	user A is the creator of list B
membership	list	user	user A is a member of list B
followed	list	user	user A follows list B
contain	list	tweet	list A contains tweet B
discuss	tweet	hashtag	tweet A discussed hashtag B

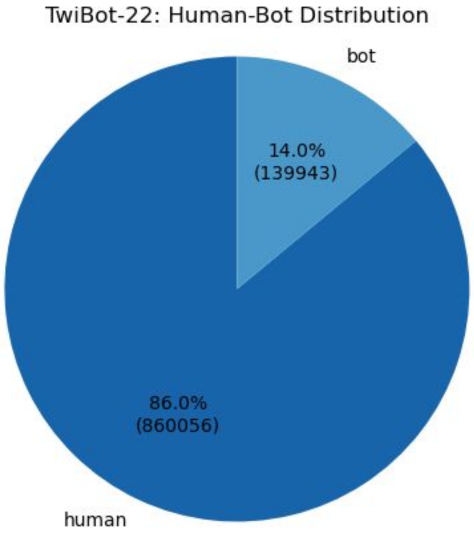
# Nodes	21,359
#Edges	795,397
# Entity Types	1 (user)
# Relation Types	2 (*follower* and *following*)

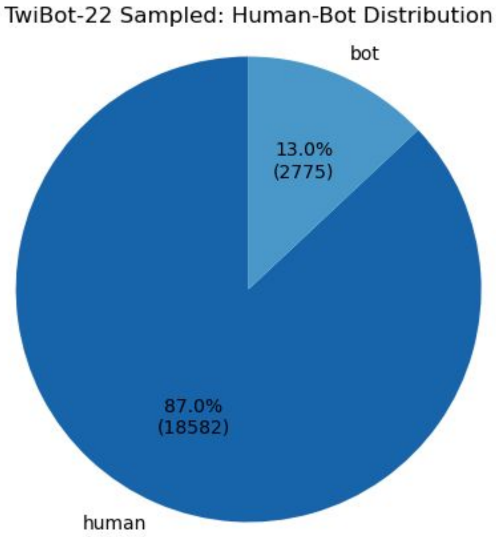
Summary Statistics of the Subsampled Graph

Sampling

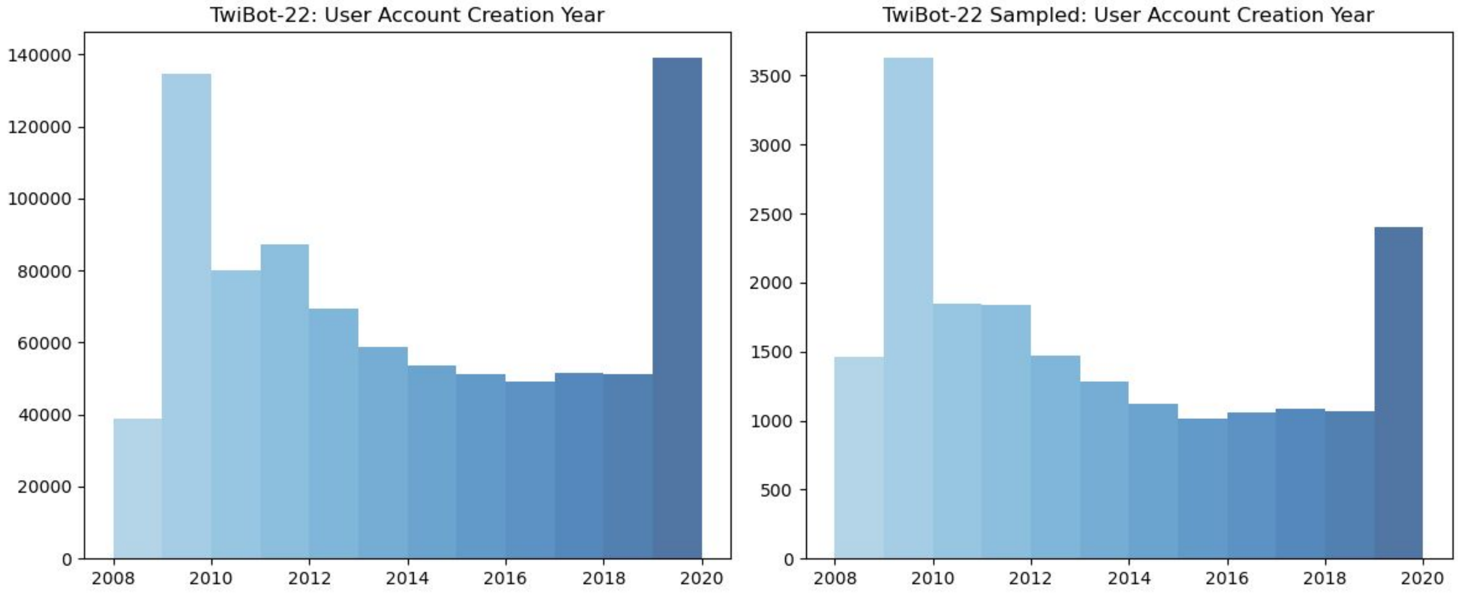
- Dataset subsampled in 3 stages:
  - Stage 1: Seed Selection
  - Stage 2: Graph Expansion
  - Stage 3: Entity Extraction

The sampling pipeline ensures that we maintain:
Human-Bot label distribution





The sampling pipeline ensures that we maintain:
User Account Creation Temporal Distribution



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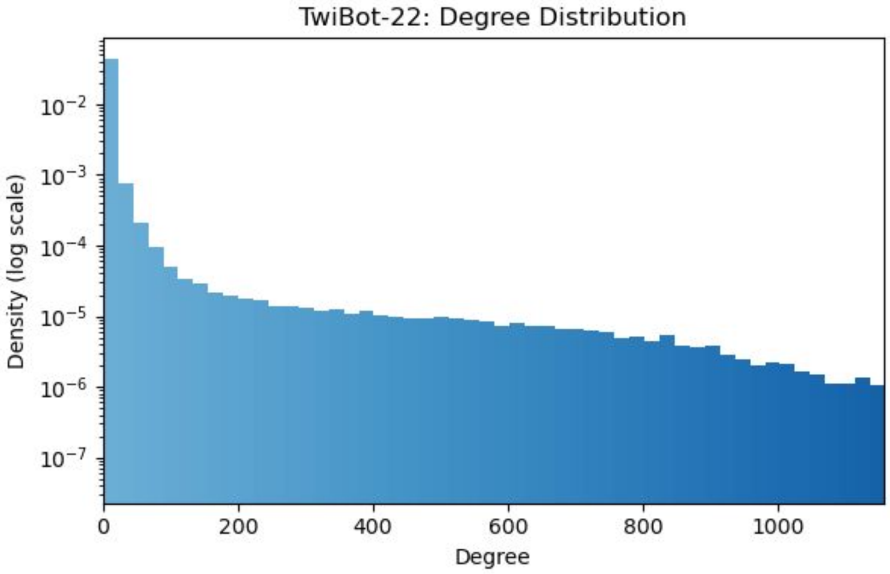
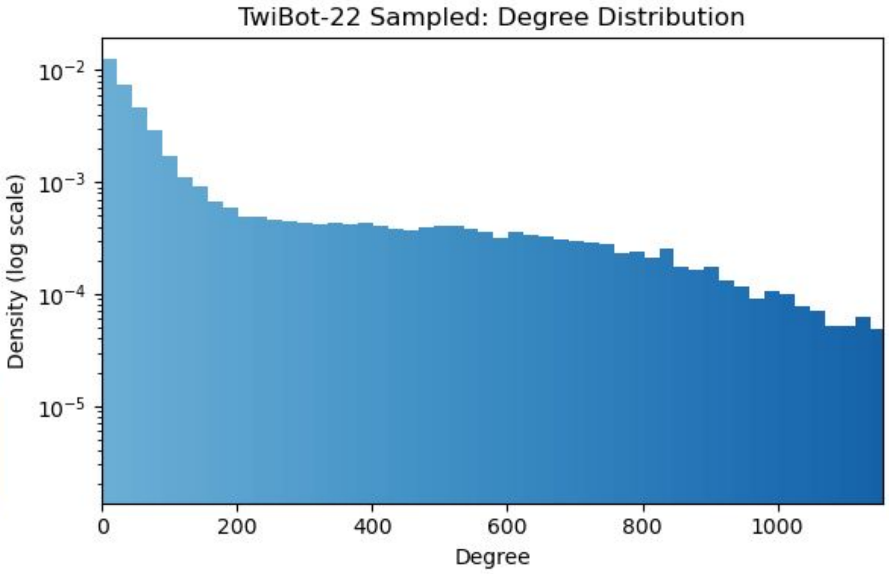
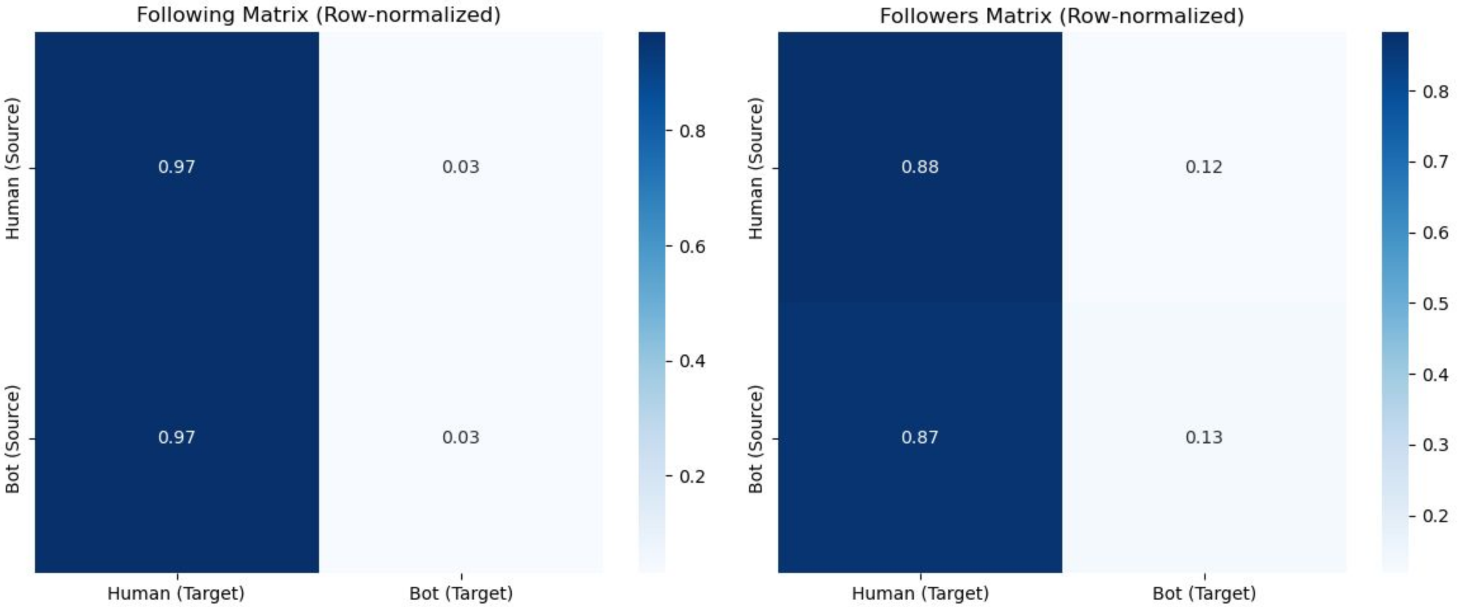
Degree Distribution

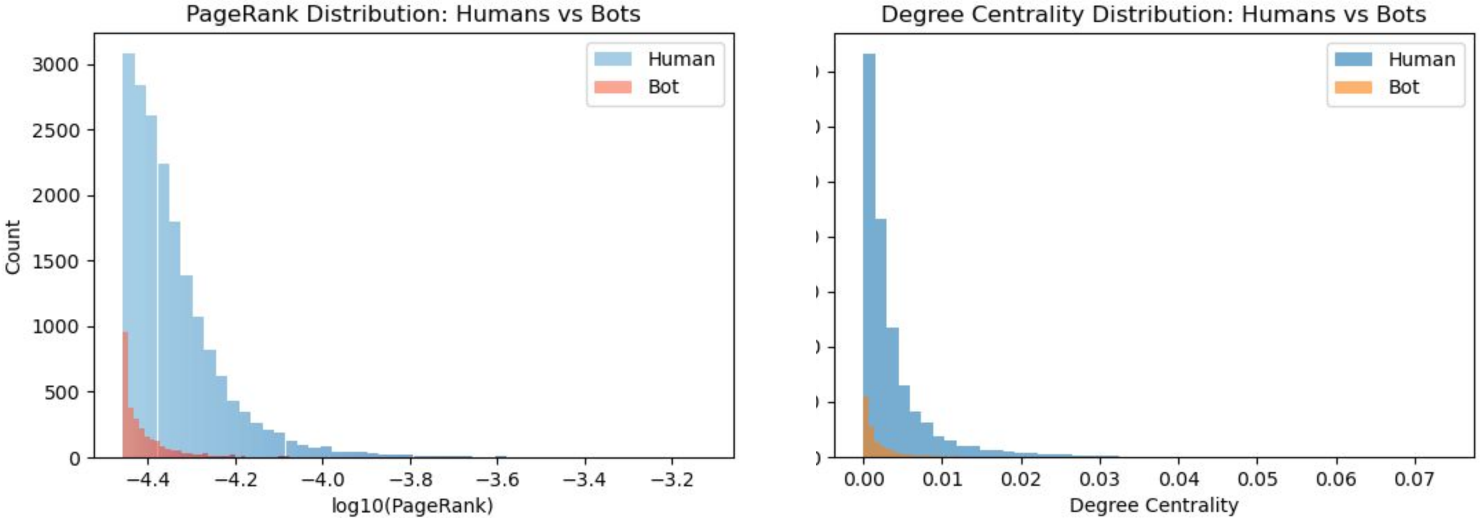




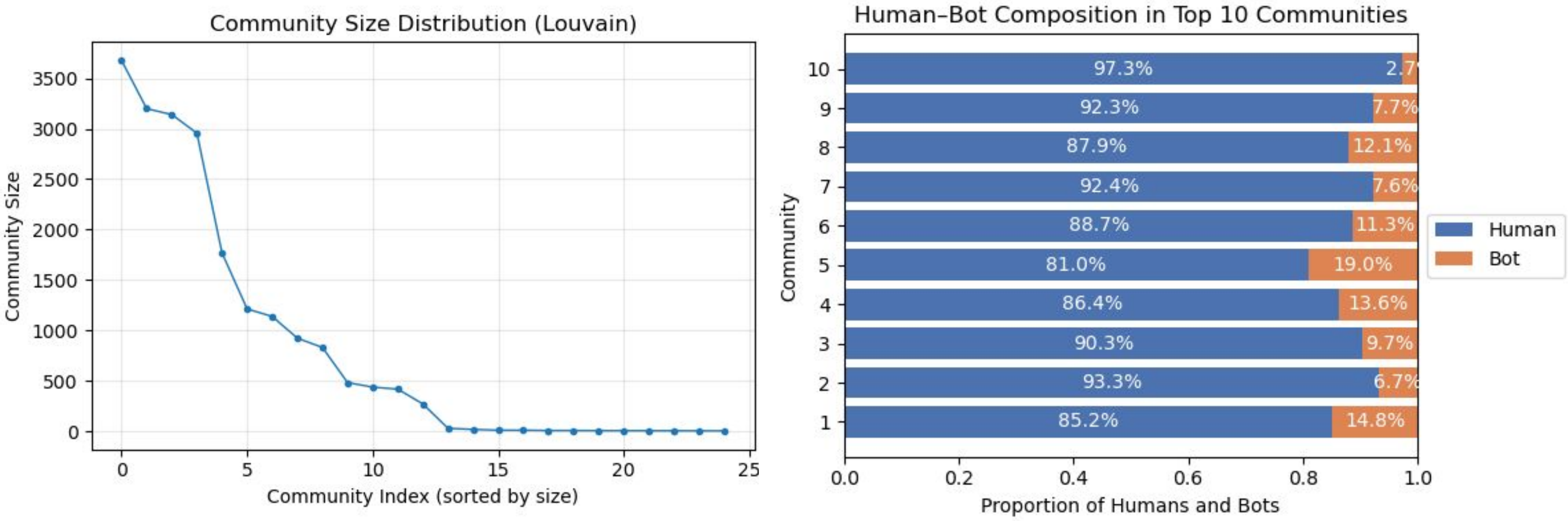
Exploratory Data Analysis



Human - Bot Interaction Confusion Matrix



Centrality Measures Comparison between Humans and Bots



Community Size and Human-Bot Distribution

Discrete Time Dynamic Graph

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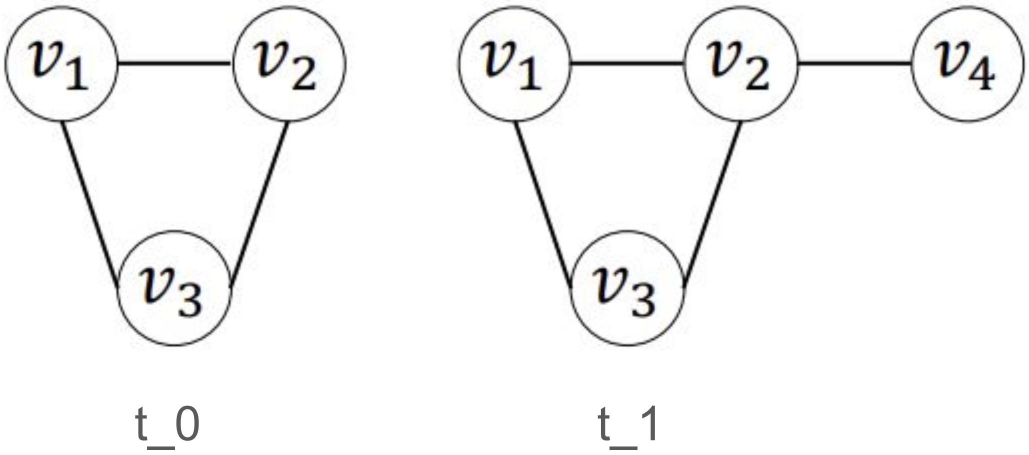

Source: Kazemi et al. (2020), JMLR, Fig. 1

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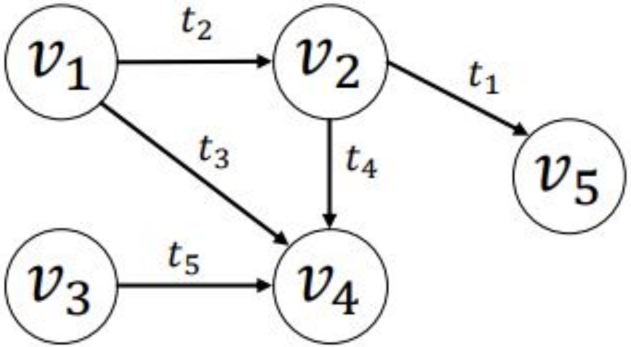

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  - Define weekly time grid from earliest to latest timestamp and build cumulative snapshots: users → tweets → edges progressively added to each week

Feature Engineering

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- Bot detection depends heavily on user behaviour
- Need expressive node embeddings
- Inspired by the **BotRGCN** work, we build similar lightweight features.

Feng, S., Wan, H., Wang, N., & Luo, M. (2021, November). BotRGCN: Twitter bot detection with relational graph convolutional networks. In Proceedings of the 2021 IEEE/ACM international conference on advances in social networks analysis and mining (pp. 236-239).

Static Graph Features

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Numeric Activity Attributes

Categorical Profile Flags

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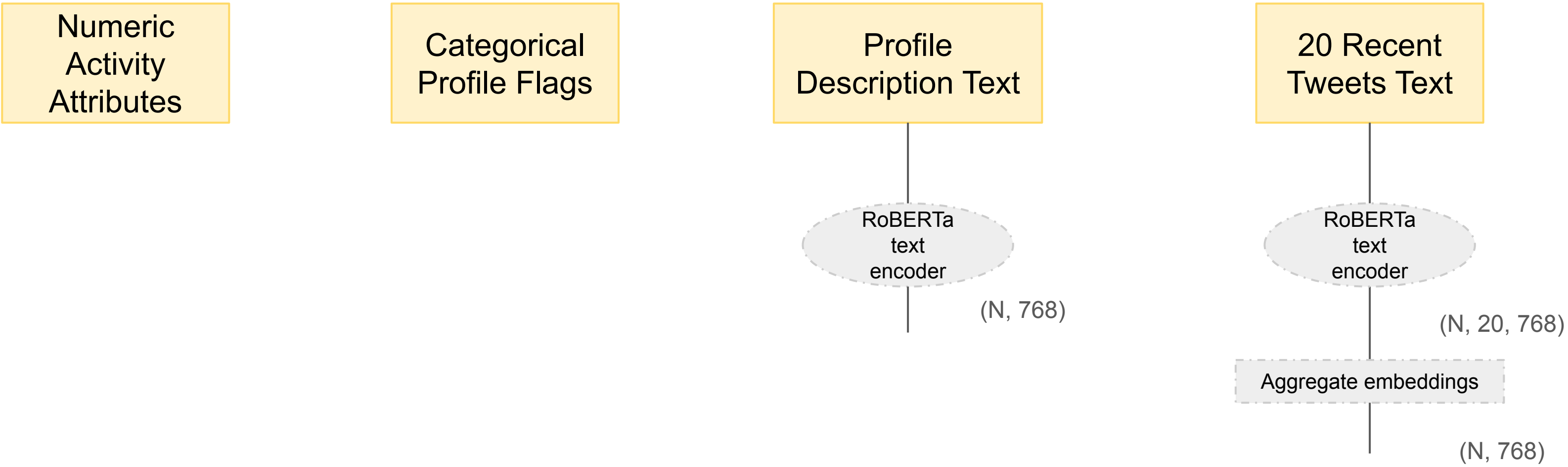

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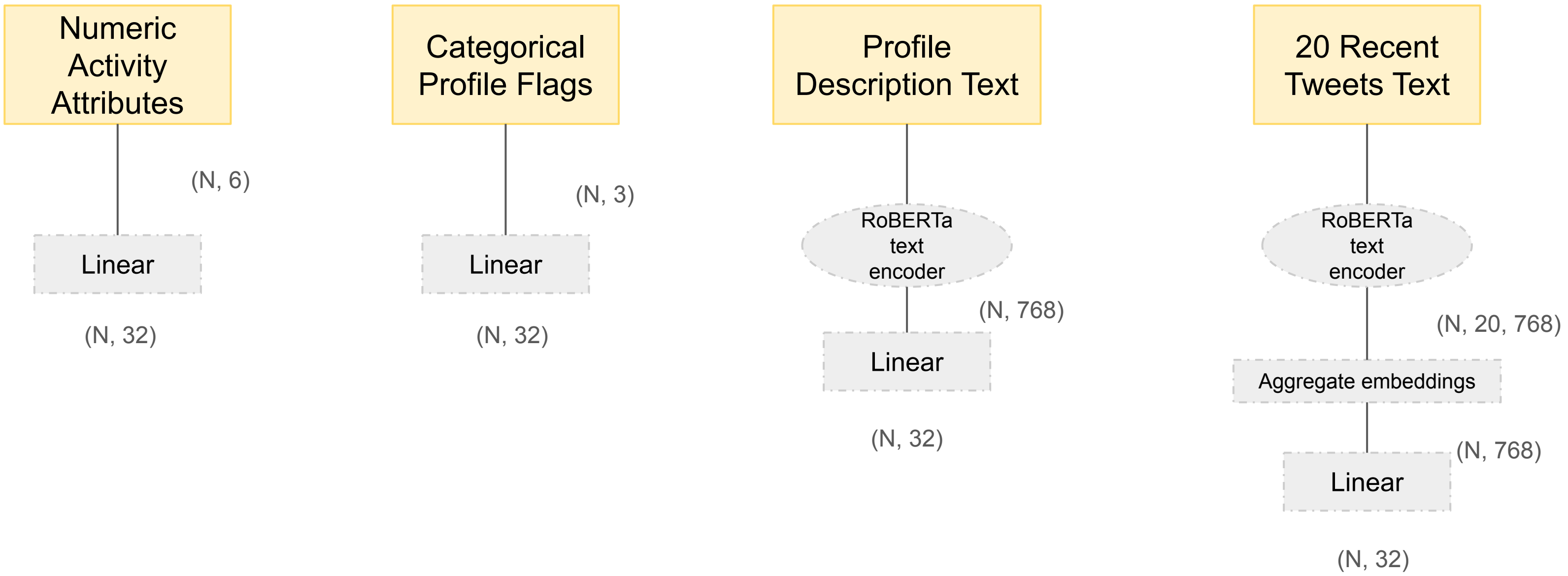

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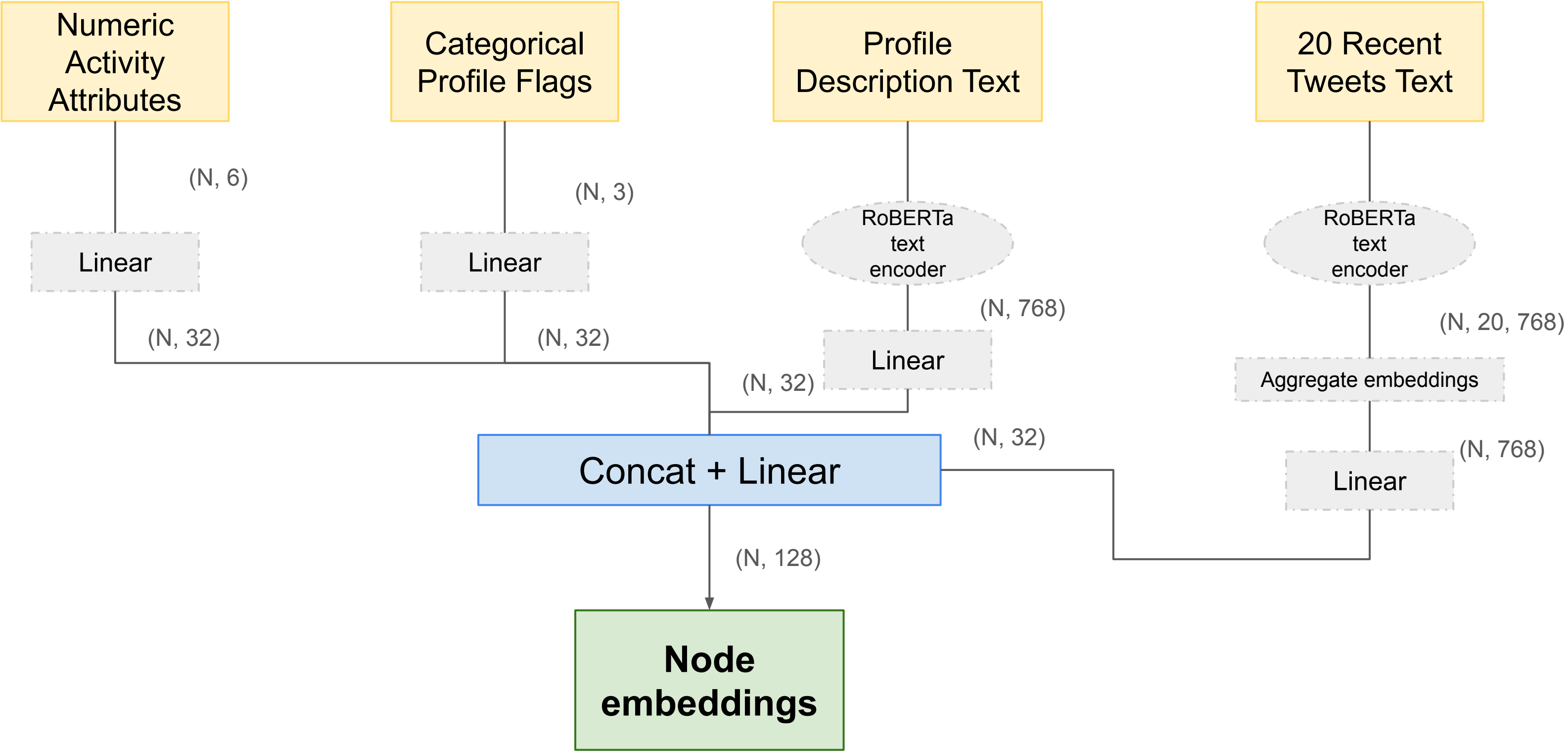
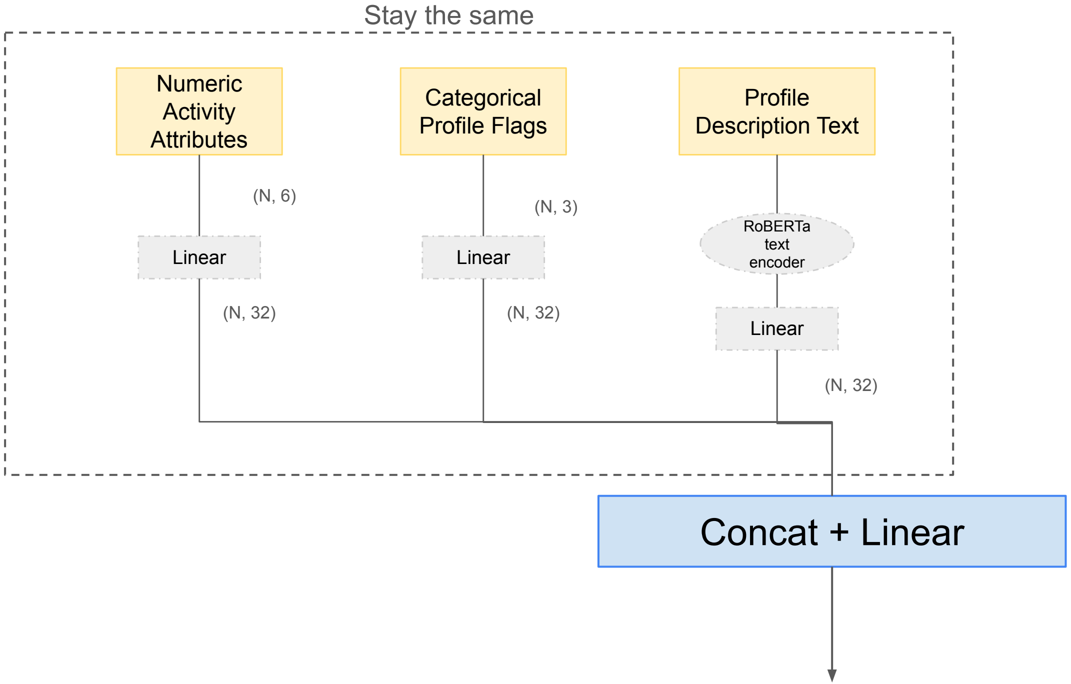


DTDG Features



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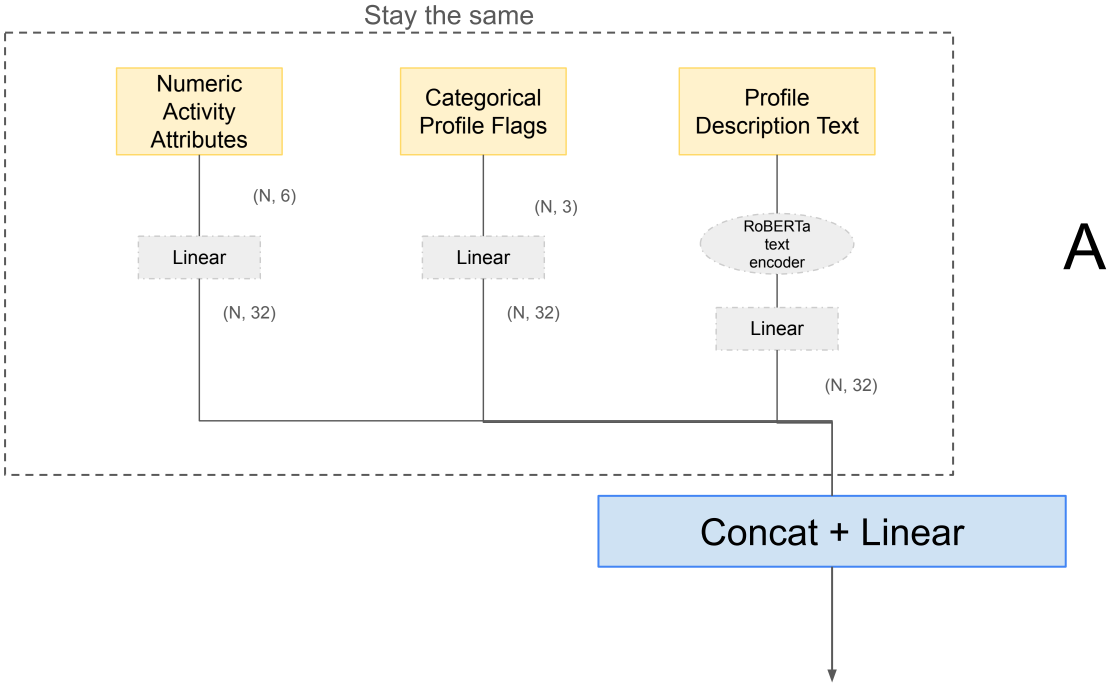
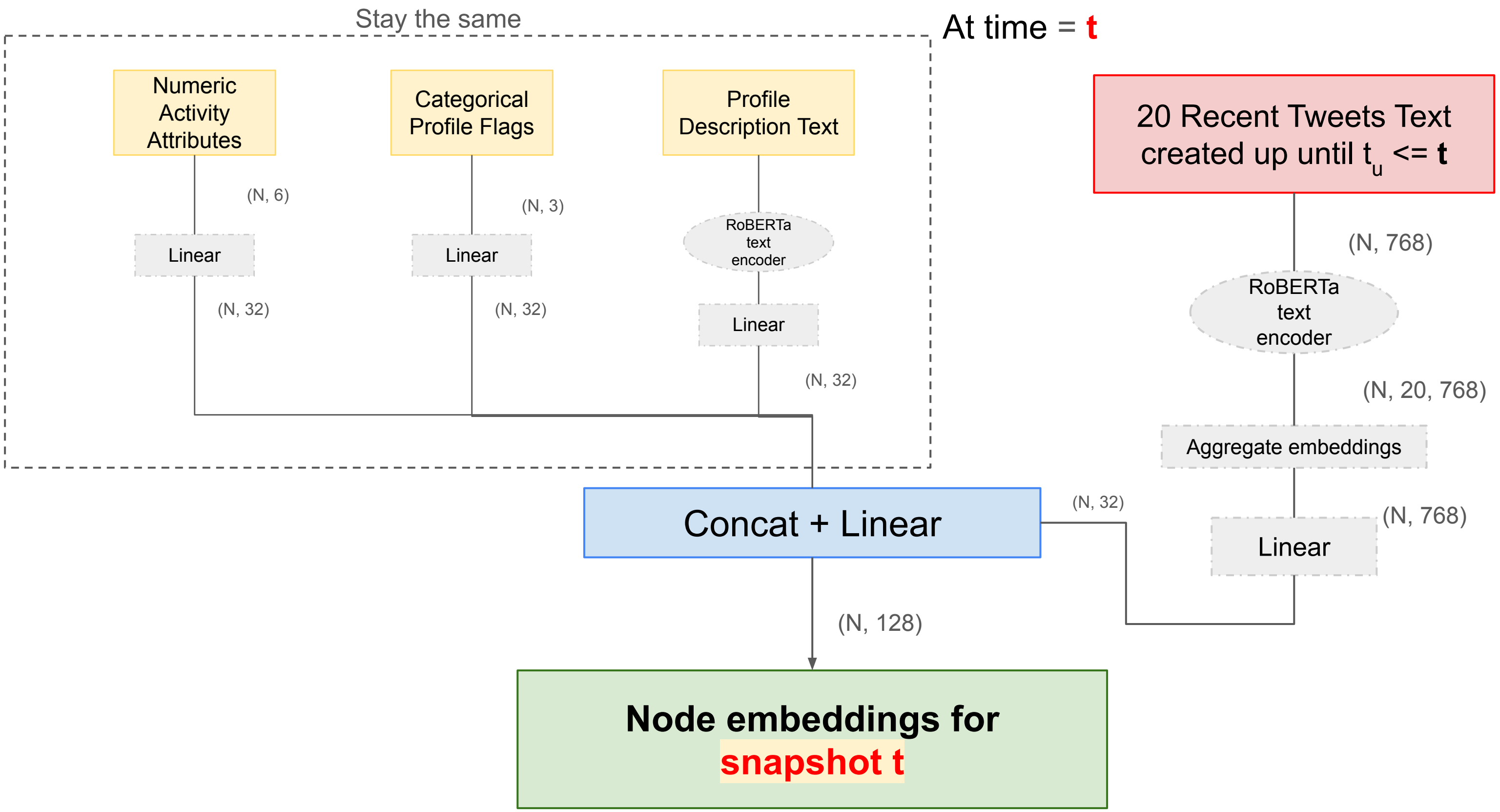


At time = t

DTDG Features



Stay the same

At time = **t**

Numeric Activity Attributes

(N, 6)

Linear

(N, 32)

Categorical Profile Flags

(N, 3)

Linear

(N, 32)

Profile Description Text

RoBERTa text encoder

Linear

(N, 32)

20 Recent Tweets Text created up until t_u <= **t**

(N, 768)

RoBERTa text encoder

(N, 20, 768)

Aggregate embeddings

(N, 768)

Linear

(N, 32)

Concat + Linear

(N, 128)

Node embeddings for snapshot t

BotRGCN

- Graph edges encode two **asymmetric** relations:
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  - user follows another (*following*)
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- Vanilla GCN treats edges as homogeneous, loses **social network semantics**.
- BotRGCN assigns relation-specific transformations for the 2 relations
- Since each relation has its **own weight matrix**
  - the model can learn patterns like ‘follows many people but followed by few’

BotRGCN

Architecture

1. 2-layer R-GCN
   - 128 → 128 (LeakyReLU, dropout)
   - 128 → 128 (LeakyReLU)
2. MLP classifier
   - 128 → 128 → 2 (logits)
3. Trained on static graph with node embeddings.

Static embeddings ignore evolution of user behaviour.

Temporal BotRGCN: EvoRGCN

- **Principle:** Instead of having a sequential model measure the change in node embeddings, we evolve the weight matrices themselves through a matrix-valued GRU.[1]

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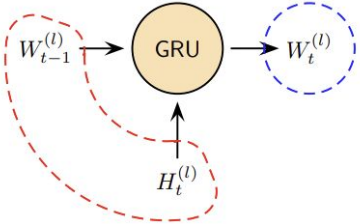
- **Architecture:**
  - **Step 1 - Weight Evolution**:
    - **Input:** Previous weights W^{l}_{t-1} (red dashed) + Current node embeddings H^{l}_{t} (red dashed)
    - **Process:** MatGRU takes both inputs
    - **Output:** Evolved weights W^{l}_{t} (blue dashed)



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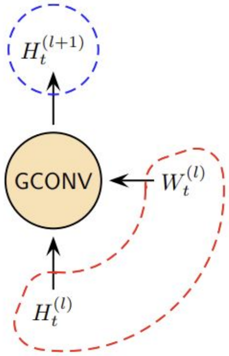
- **Architecture:**
  - **Step 2 - Relational Graph Convolution**:
    - **Input:** Current node embeddings H^l_t + Evolved weights W^l_t
    - **Process:** RGCN operation
    - **Output:** Next layer embeddings H^l_{t+1} (blue dashed)



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Results

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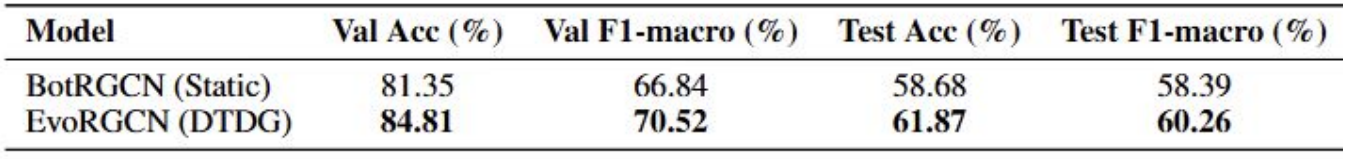

Model	Val Acc (%)	Val F1-macro (%)	Test Acc (%)	Test F1-macro (%)
BotRGCN (Static)	81.35	66.84	58.68	58.39
EvoRGCN (DTDG)	**84.81**	**70.52**	**61.87**	**60.26**

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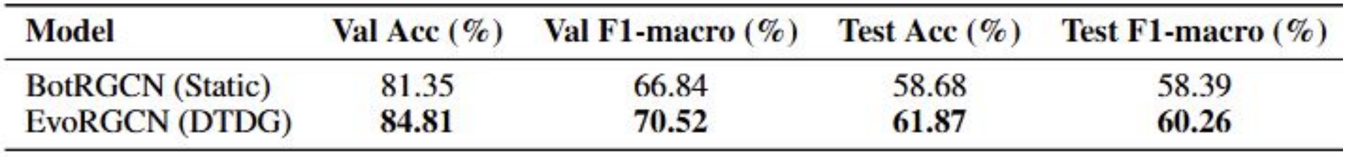

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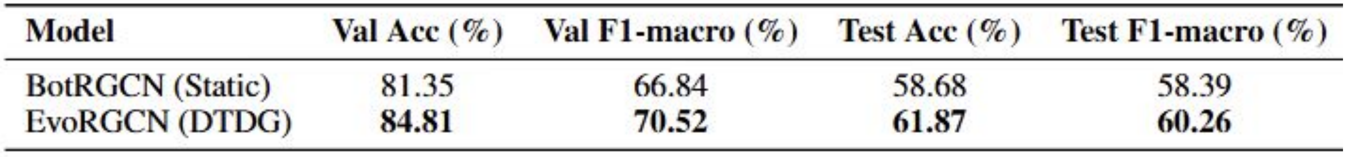

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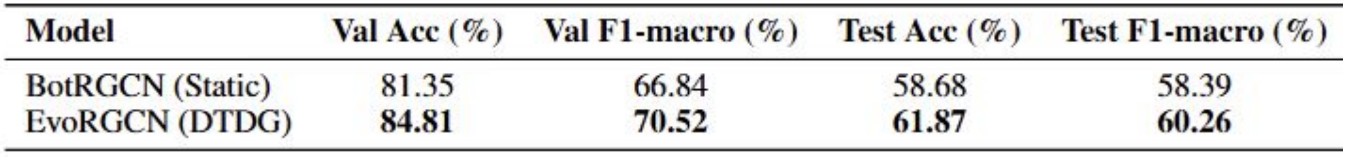

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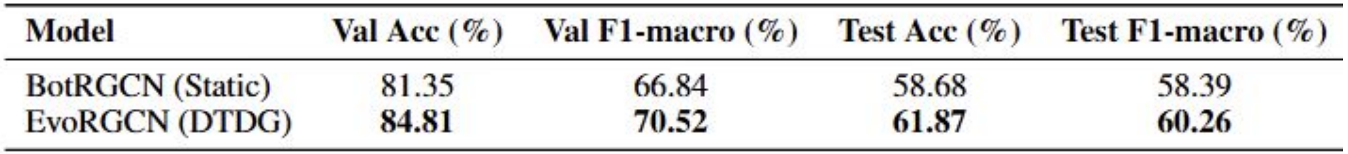

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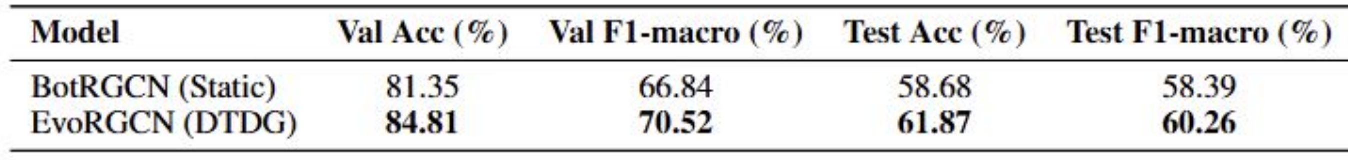

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- Key advantages of temporal modeling:
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  - Models behavioral drift and evolving bot strategies (static models cannot)
  - Better handles distribution shift to future users

Future Work

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- Deploy our model to a sophisticated bot-detection pipeline with simple heuristics before applying our detector.