# Activity Prediction using Dynamic Graph Embeddings

Jens Petit

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# Outline

# Dynamic Graph Representation Learning

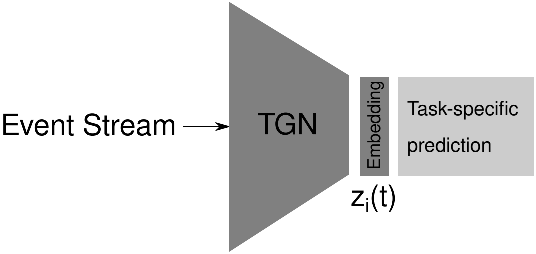
## Discrete-time dynamic graphs (DTDG)

Sequences of static graph snapshots.

## Continuous-time dynamic graphs (CTDG)

Timed list of events, including node addition, deletion and edge addition and deletion.

# Temporal Graph Networks (TGN)




General encoder-decoder framework

Current decoders:

- future edge ('link') prediction
- dynamic node classification

Problem settings:

- Transductive: only nodes which have been used in training
- Inductive: additionally nodes which have *not* been used in training

# Example: TGN for future link prediction[1]

Datasets:

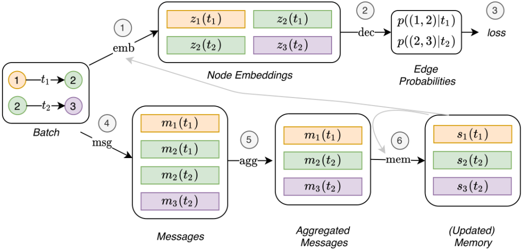
- Reddit, Wikipedia: Bipartite interaction graphs with users and subreddits/pages as nodes.
- Twitter: Users are nodes and retweets are interactions.

All interaction events carry text features (tweets, edits, posts) and 70%-15%-15% (train-valid-test) chronological split is used.

Exemplary decoder: simple MLP decoder mapping from the concatenation of two node embeddings to the probability of the edge

[1] "Temporal Graph Networks For Deep Learning on Dynamic Graphs, *Rossi et al.*"

# Example: TGN encoder

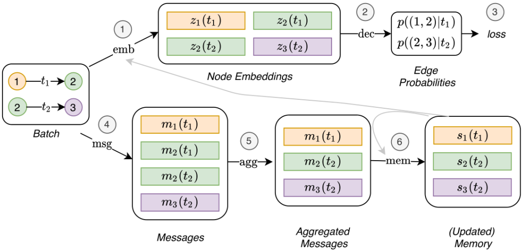



TGN computations on a single batch of time-stamped interactions[2].

Core idea: combining memory module with graph-based operators

[2]Figure taken from "Temporal Graph Networks For Deep Learning on Dynamic Graphs, *Rossi et al.*"

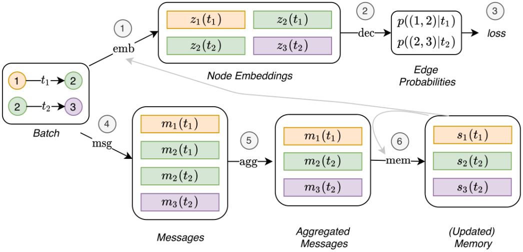
# Message computation




TGN computations on a single batch of time-stamped interactions.

$$\mathbf{m}_i(t) = \mathrm{msg}\left(\mathbf{s}_i(t^-), \mathbf{s}_j(t^-), \Delta t, \mathbf{e}_{ij}(t)\right)$$

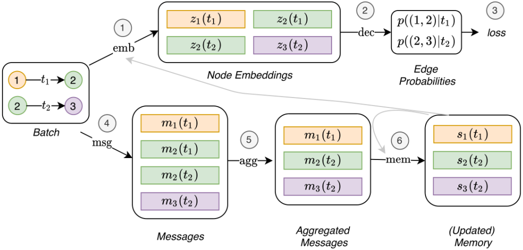
# Message aggregator




Combine all messages in a single batch for a specific node:

$$\bar{\mathbf{m}}_i(t) = \mathrm{agg}\left(\mathbf{m}_i(t_1), \ldots, \mathbf{m}_i(t_b)\right)$$

# Memory update

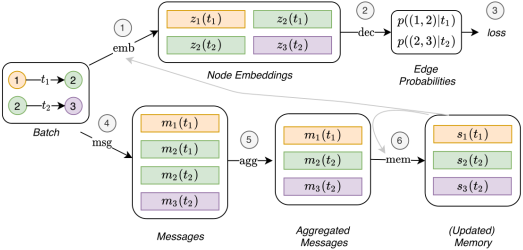



TGN computations on a single batch of time-stamped interactions.

Using a Recurrent Neural Network:

$$\mathbf{s}_i(t) = \mathrm{mem}\left(\bar{\mathbf{m}}_i(t), \mathbf{s}_i(t^-)\right)$$

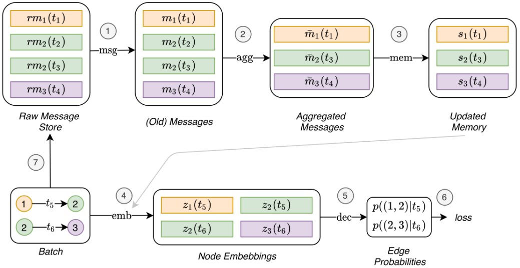
# Embedding computation




$$\mathbf{z}_i(t) = \mathrm{emb}(i, t) = \sum_{j \in \mathcal{N}_i^k([0,t])} h\left(\mathbf{s}_i(t), \mathbf{s}_j(t), \mathbf{e}_{ij}, \mathbf{v}_i(t), \mathbf{v}_j(t)\right),$$

Includes specific cases like: memory directly, time projection (JODIE), Temporal Graph Attention (TGAT), Temporal Graph Sum

# TGN training




TGN training [3]

Problem: memory-related modules (Message function, Message aggregator, and Memory updater) do not directly influence the loss and therefore do not receive a gradient -> memory update before predictions

[3] Figure taken from "Temporal Graph Networks For Deep Learning on Dynamic Graphs, *Rossi et al.*"

# GDELT Dataset

## The GDELT Dataset

*"The GDELT Project monitors the world's broadcast, print, and web news from nearly every corner of every country in over 100 languages and identifies the people, locations, organizations, themes, sources, emotions, counts, quotes, images and events driving our global society every second of every day, creating a free open platform for computing on the entire world."*

- Global Knowledge Graph
- Global Event Database
- Global Entity Graph
- Global Frontpage Graph

# The Global Entity Graph

Random sample of news articles every 15 minutes (roughly 100k per day)

Google NLP API extracts entities from each article


```
{
  "url": "https://chicago.suntimes.com/news/washington-state-ends-racially-biase
  "lang": "en",
  "date": "2018-10-12T00:15:00Z",
  "score": -0.2,
  "magnitude": 12.3,
  "entities": [
    {
      "name": "Supreme Court",
      "type": "ORGANIZATION",
      "numMentions": 1,
      "avgSalience": 0.04405
    },
    ...
}
```

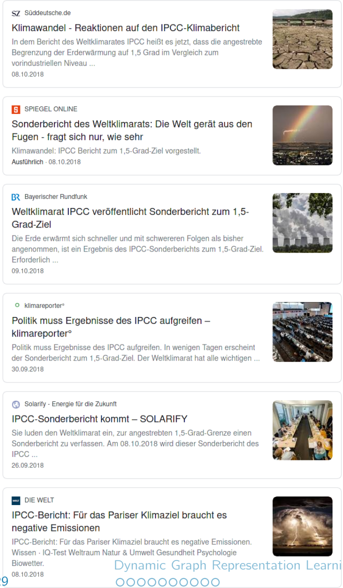
# Creating a Graph

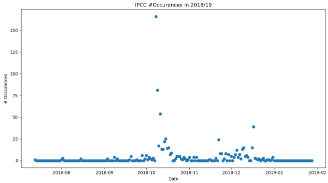
Each pair of entities occurring in a single article correspond to an edge event with timestamp:

```
Nathan Trott          RB Leipzig
Manchester United     RB Leipzig
West Ham              RB Leipzig
Timo Werner           RB Leipzig
Ralf Rangnick         RB Leipzig
Bundesliga            RB Leipzig
Patrick Dempsey       Leipzig
Leipzig               Germany
Patrick Dempsey       Leipzig
Leipzig               Germany
Patrick Dempsey       Leipzig
Leipzig               Germany
...
```

Restricting to the 4 most salient entities gives roughly 200k edges per day

# Data Example: IPCC




# Occurrences IPCC

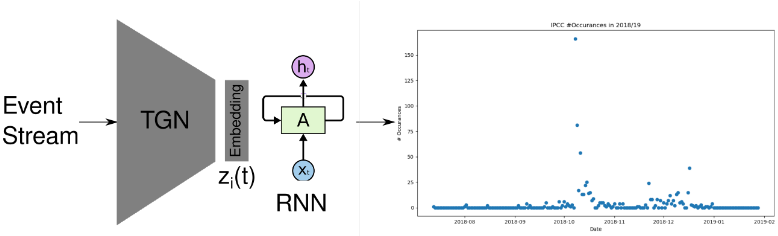
| entity_1 | entity_2 | count |
|---|---|---|
| IPCC | India | 18 |
| Michael McCormack | IPCC | 15 |
| Scott Morrison | IPCC | 15 |
| India | IPCC | 15 |
| Donald Trump | IPCC | 15 |
| United States | IPCC | 14 |
| European Union | IPCC | 14 |
| Hoesung Lee | IPCC | 14 |
| ottish Government | IPCC | 12 |
| IPCC | US | 12 |

# Research Idea

# Motivation

How can we identify entities with similar temporal dynamics, e.g. “hot” topics?

# Approach




Replace decoder with a RNN which predicts the future #Occurrences per day for a given entity and time horizon

# Approach

*Why is the graph information relevant?*

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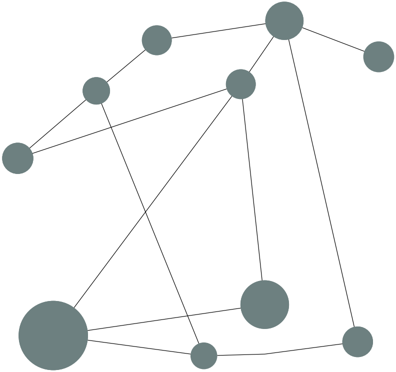
The neighborhood should be strong indicator for future behavior: If all my neighbors are getting popular, then it is very likely that I will too.



# The Embedding Space

- before (link prediction): similarity predicts future link between two entities
- now (activity prediction): embedding space represents temporal dynamics
  - clustering
  - split relative and absolute dynamics
  - duplicate detection

# Details

- Current state:
  - preparing dataset
- Baseline: time series prediction for number of occurrences (no neighborhood info)
- Open questions:
  - What is a single data point?
  - How to batch the data?