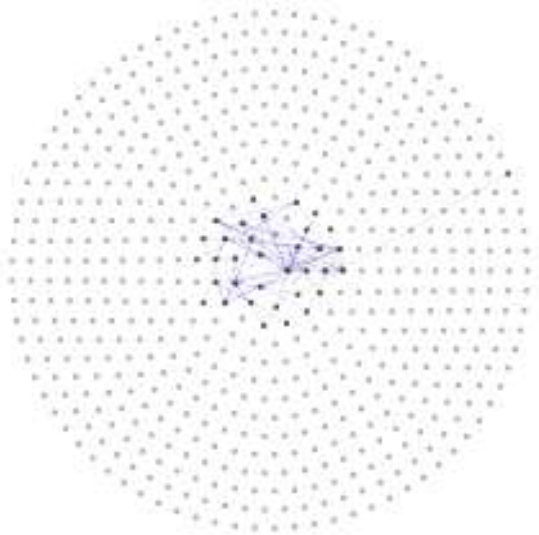


# ESSEN: Improving Evolution State Estimation for Temporal Networks using Von Neumann Entropy

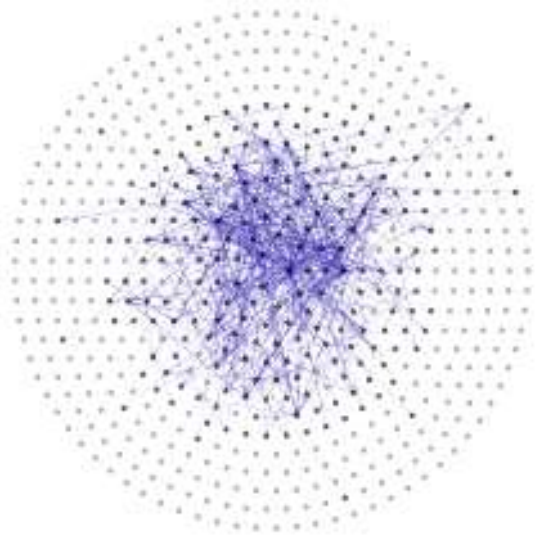
*Qiyao Huang<sup>1</sup>, Yingyue Zhang<sup>1</sup>, Zhihong Zhang<sup>1</sup>, Edwin Hancock<sup>2</sup>*

*<sup>1</sup>Xiamen University, <sup>2</sup>York University*

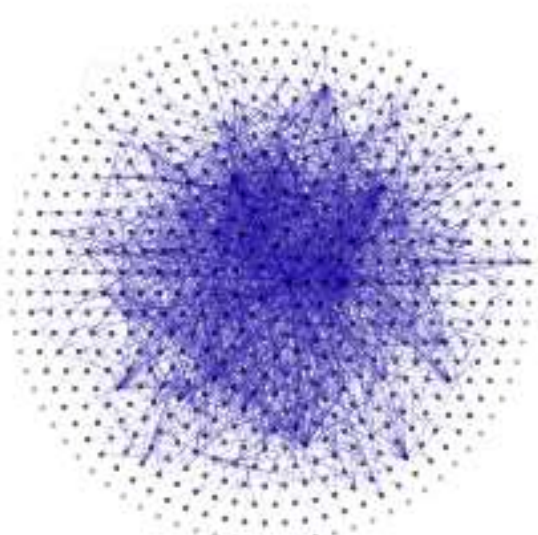
# Temporal Network in MathOverflow website



10<sup>th</sup> Day

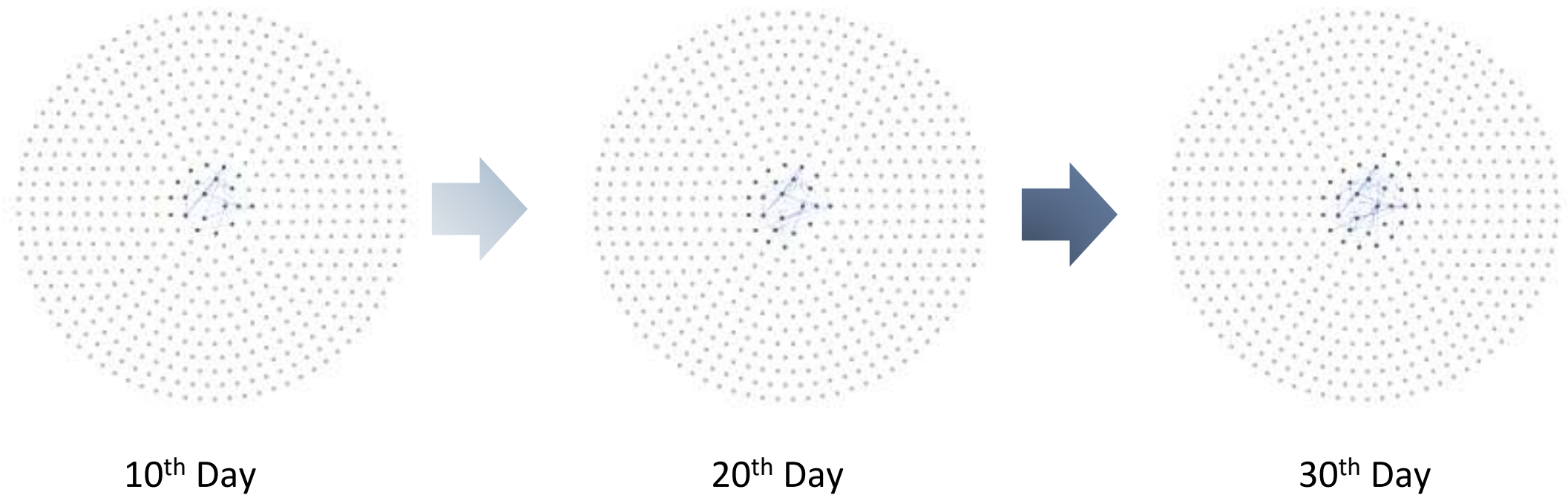


20<sup>th</sup> Day

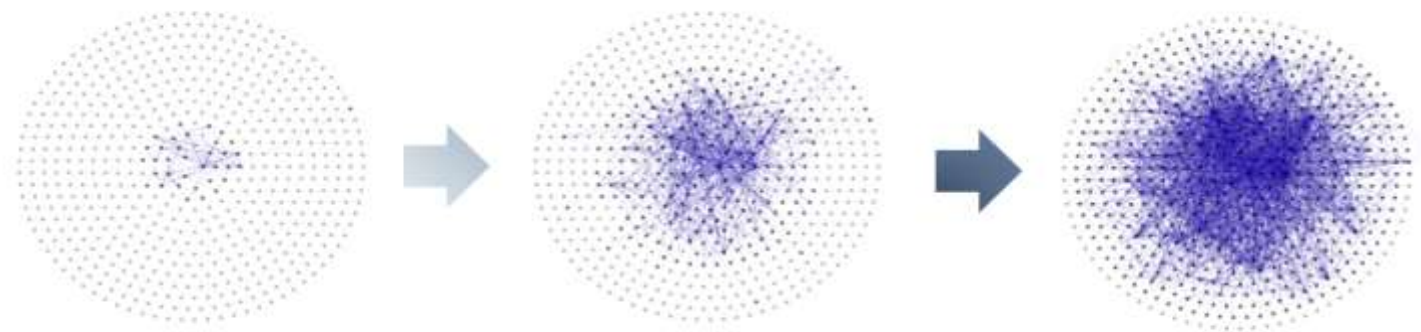


30<sup>th</sup> Day

# Temporal Network in BitcoinOTC platform



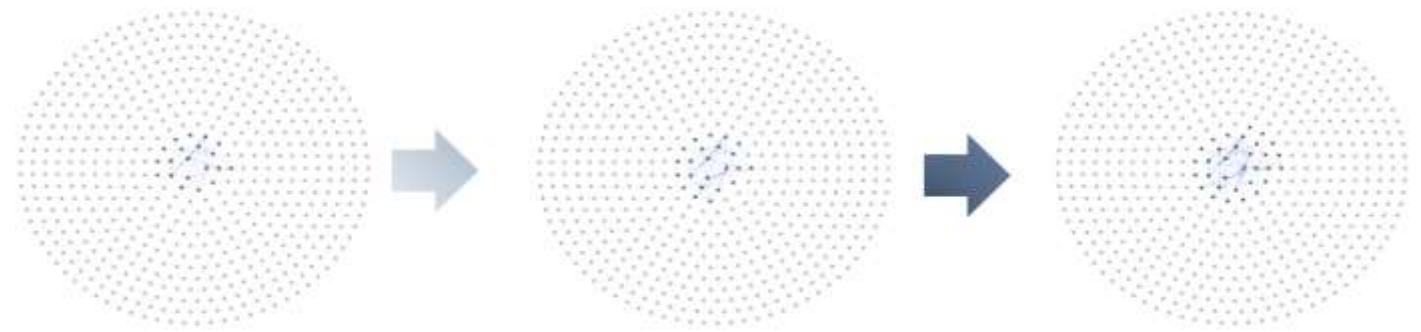
# Evolution State Estimation



10<sup>th</sup> Day

20<sup>th</sup> Day

30<sup>th</sup> Day

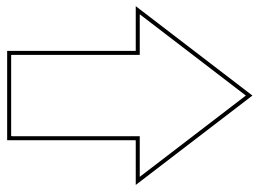
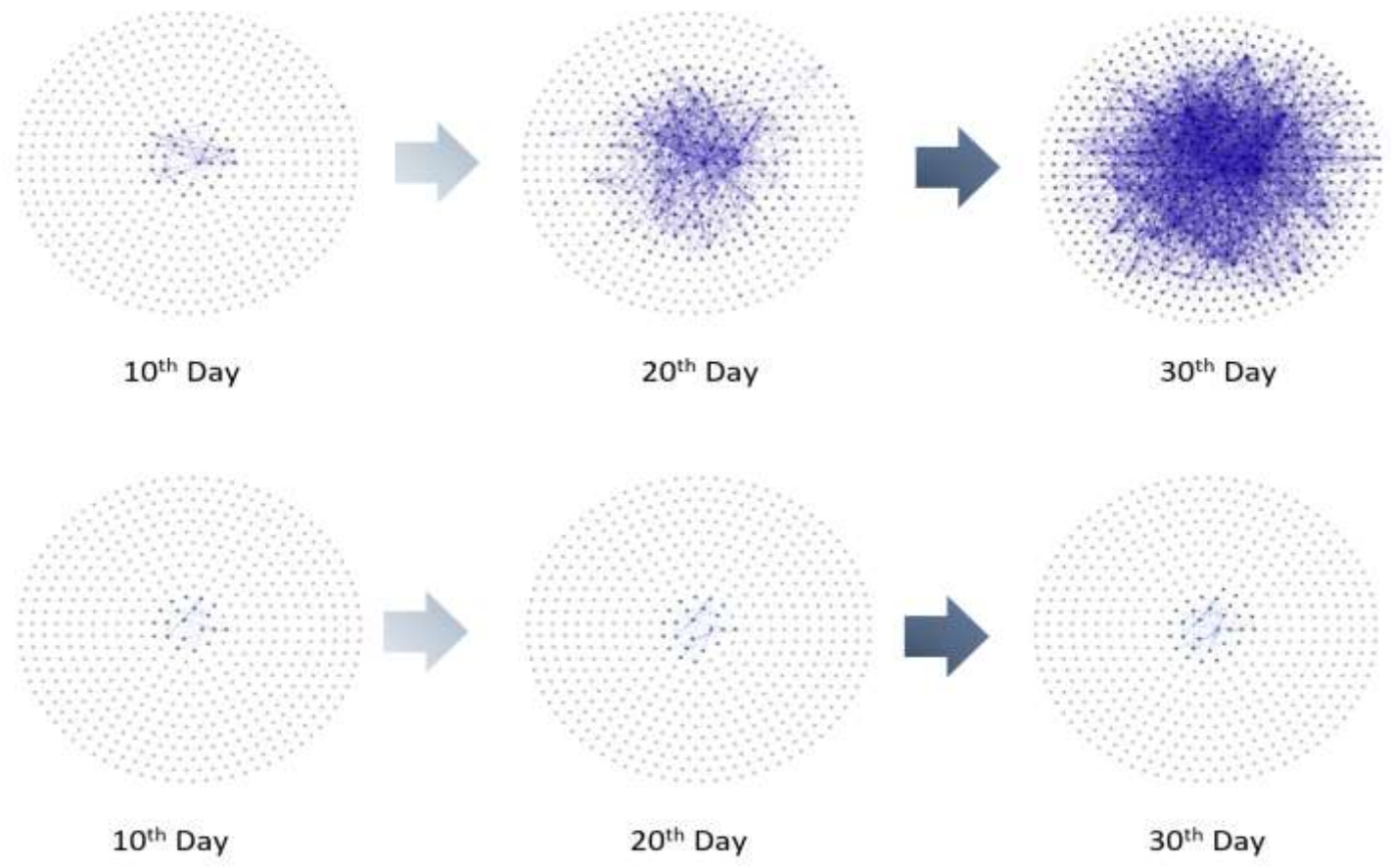


10<sup>th</sup> Day

20<sup>th</sup> Day

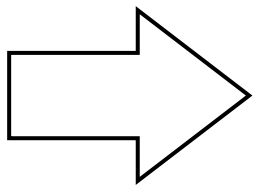
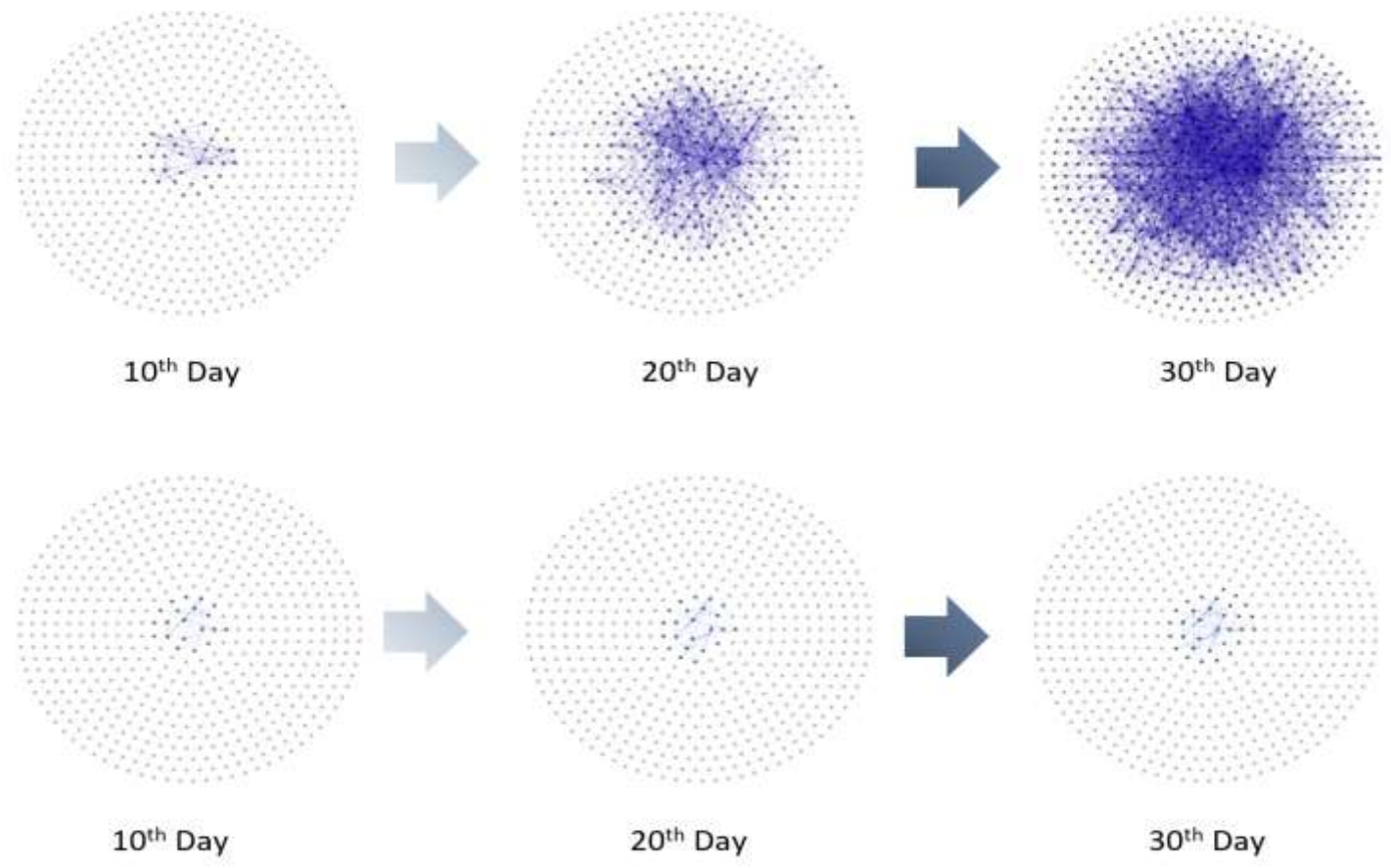
30<sup>th</sup> Day

# Evolution State Estimation



**Generalizability**

# Evolution State Estimation



**Generalizability**

**Efficiency**

# Summary of Contribution

- Provides a method to **approximate** the von Neumann entropy for temporal networks.
- Introduces a new perspective to encode evolution aware node representations using the **von Neumann entropy aware attention mechanism** and **virtual evolution node representation learning**.
- Proposes a novel **Mixture of Thermodynamic Experts Decoder** which can recognize temporal network evolution states adaptively.



# Von Neumann Entropy

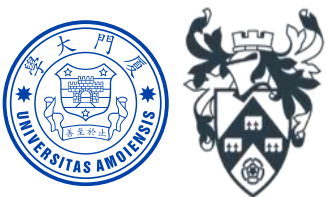
- **VNE** is a representation of structures widely used to characterize the salient features of quantum systems.
- Using quantum analogy, the interpretation of the normalised Laplacian as a density matrix opens up the possibility of computing the von Neumann entropy in networks.

$$S_{VN}(G) = -\text{Tr}(\rho \log \rho) = -\sum_{i=1}^{|\mathcal{V}|} \frac{\lambda_i}{|\mathcal{V}|} \log \frac{\lambda_i}{|\mathcal{V}|}$$



# Approximate Von Neumann Entropy for Temporal Networks

- **The dynamic nature of the temporal network**



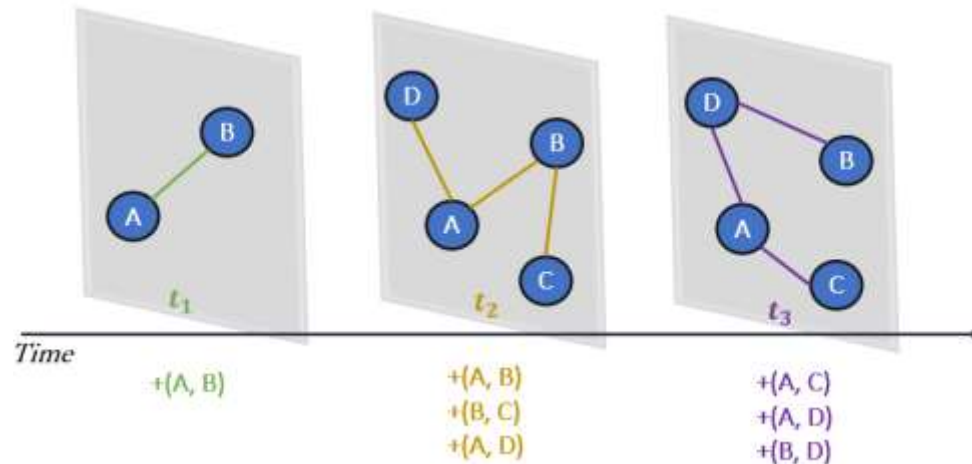
# Approximate Von Neumann Entropy for Temporal Networks

- The dynamic nature of the temporal network

## Solution:

(1) Select a specific time interval for the temporal network and aggregate edge weights or frequencies over this interval.

(2) The number of occurrences within the chosen time frame determines the strength of an edge.



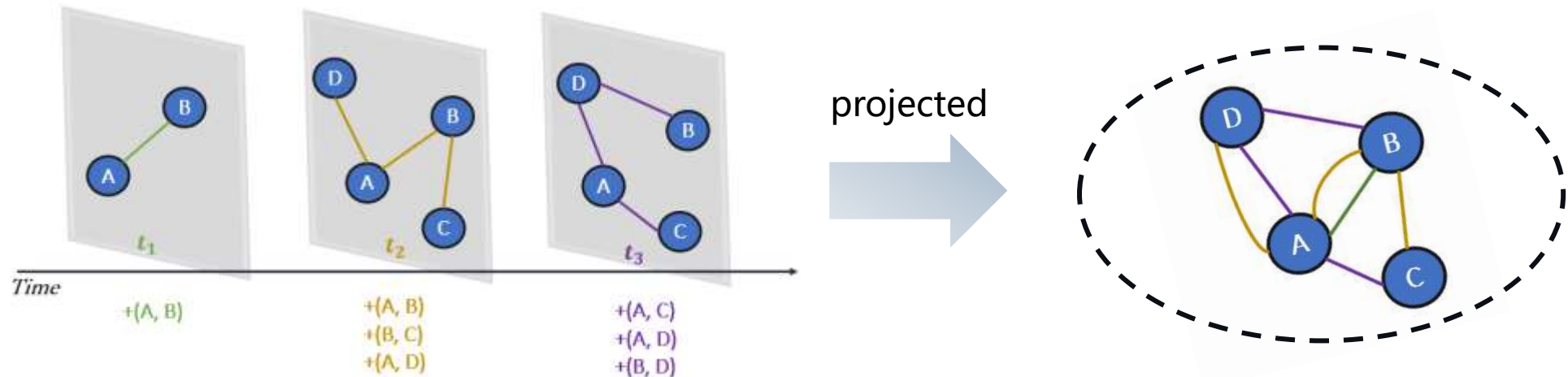
# Approximate Von Neumann Entropy for Temporal Networks

- The dynamic nature of the temporal network

## Solution:

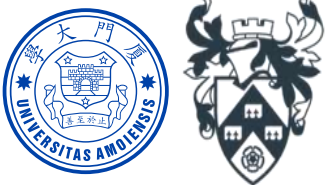
(1) Select a specific time interval for the temporal network and aggregate edge weights or frequencies over this interval.

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# Approximate Von Neumann Entropy for Temporal Networks

- **The computationally expensive time complexity of obtaining the Laplacian eigenvalues.**



# Approximate Von Neumann Entropy for Temporal Networks

- The computationally expensive time complexity of obtaining the Laplacian eigenvalues.

## Solution:

(1) Taylor expansion for  $\ln \frac{\hat{\lambda}_j}{|V|}$  and keep the first item

(2) Using the nature of normalized Laplacian matrix

$$\begin{aligned}
 S_{VN}(G) &= - \sum_j \frac{\hat{\lambda}_j}{|V|} \ln \frac{\hat{\lambda}_j}{|V|} \simeq \sum_j \frac{\hat{\lambda}_j}{|V|} \left( 1 - \frac{\hat{\lambda}_j}{|V|} \right) \\
 &= \frac{1}{|V|} \sum_i \lambda_j - \frac{1}{|V|^2} \sum_j \lambda_j^2 \\
 &= \frac{\text{Tr}[\hat{L}]}{|V|} - \frac{\text{Tr}[\hat{L}^2]}{|V|^2} \\
 &= \frac{|V|}{|V|} - \frac{|V|}{|V|^2} - \sum_{(u,v) \in e} \frac{1}{|V|^2 d_u d_v} \\
 &= 1 - \frac{1}{|V|} - \frac{1}{|V|^2} \sum_{(u,v) \in e} \frac{1}{d_u d_v}
 \end{aligned}$$



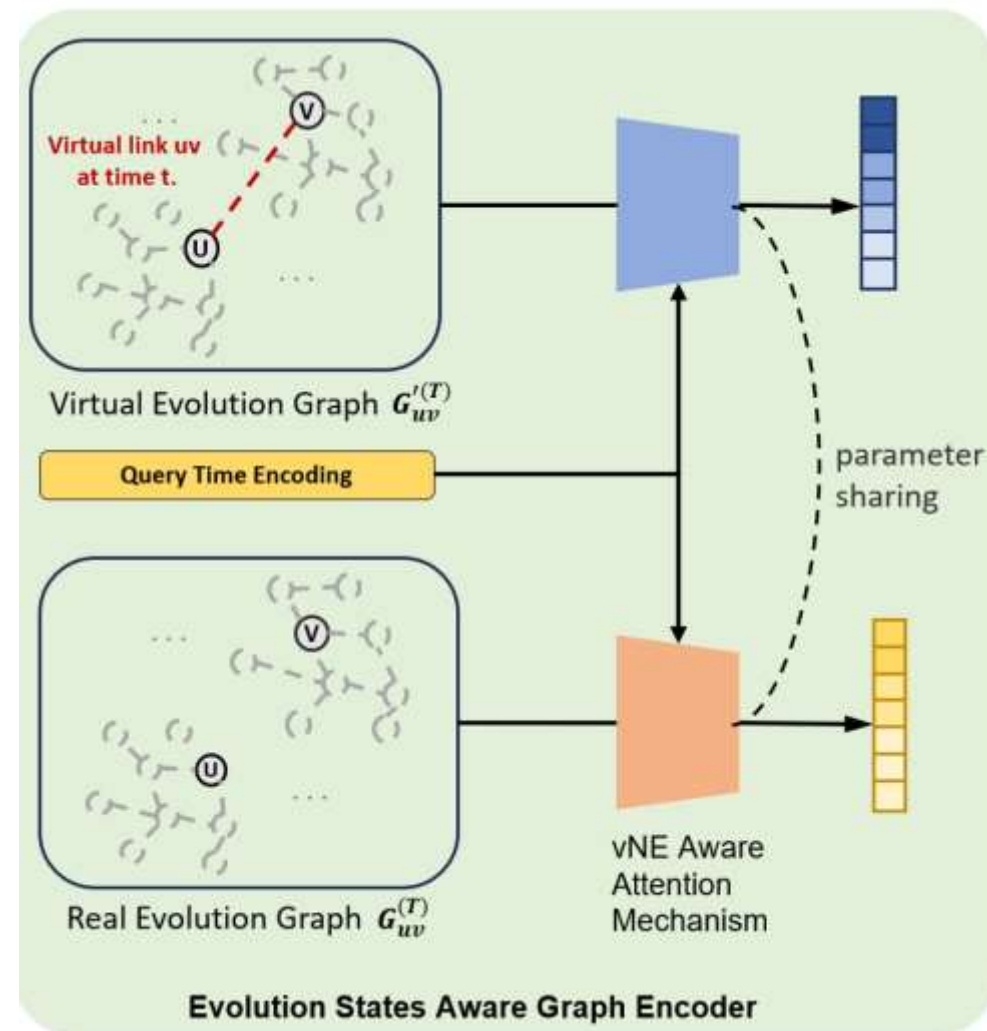
# Evolution States Aware Graph Encoder

## 1) Von Neumann Entropy Aware Attention Mechanism

$$S_{VN}(G) = 1 - \frac{1}{|V|} - \frac{1}{|V|^2} \sum_{(u,v) \in e} \frac{1}{d_u d_v}$$

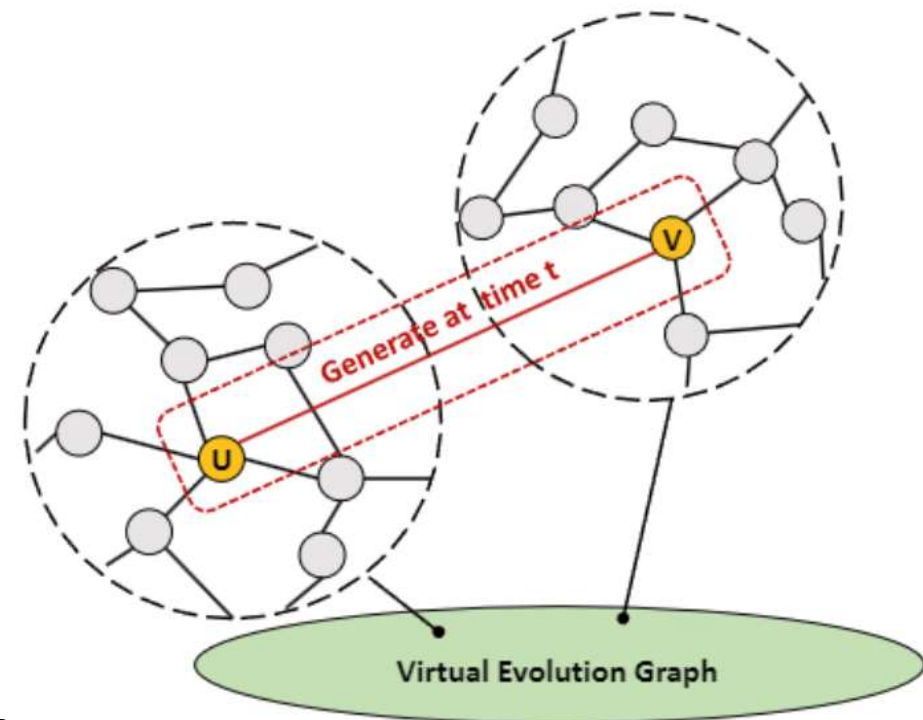
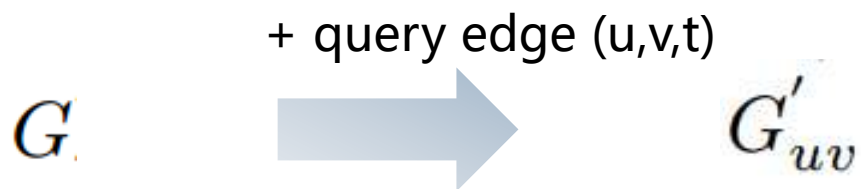
$$S_{VN}^{uv}(G_t) = \frac{1}{|E|} - \frac{1}{|V||E|} - \frac{1}{|E||V|^2} \frac{1}{d_u d_v}$$

$$\alpha_v^{(l)} = \frac{Q_u^{(l)} (K_v^{(l)})^T}{\sqrt{d_n}} + S_{VN}^{uv}(G_t)$$



# Evolution States Aware Graph Encoder

## 2) Virtual Evolution Node Representation Learning



The change of virtual evolution is instantaneous. View the evolution process as an **isochoric process** in the network.

The **thermodynamic temperature** of the virtual evolution path can be computed.

# Mixture of Thermodynamic Experts Decoder

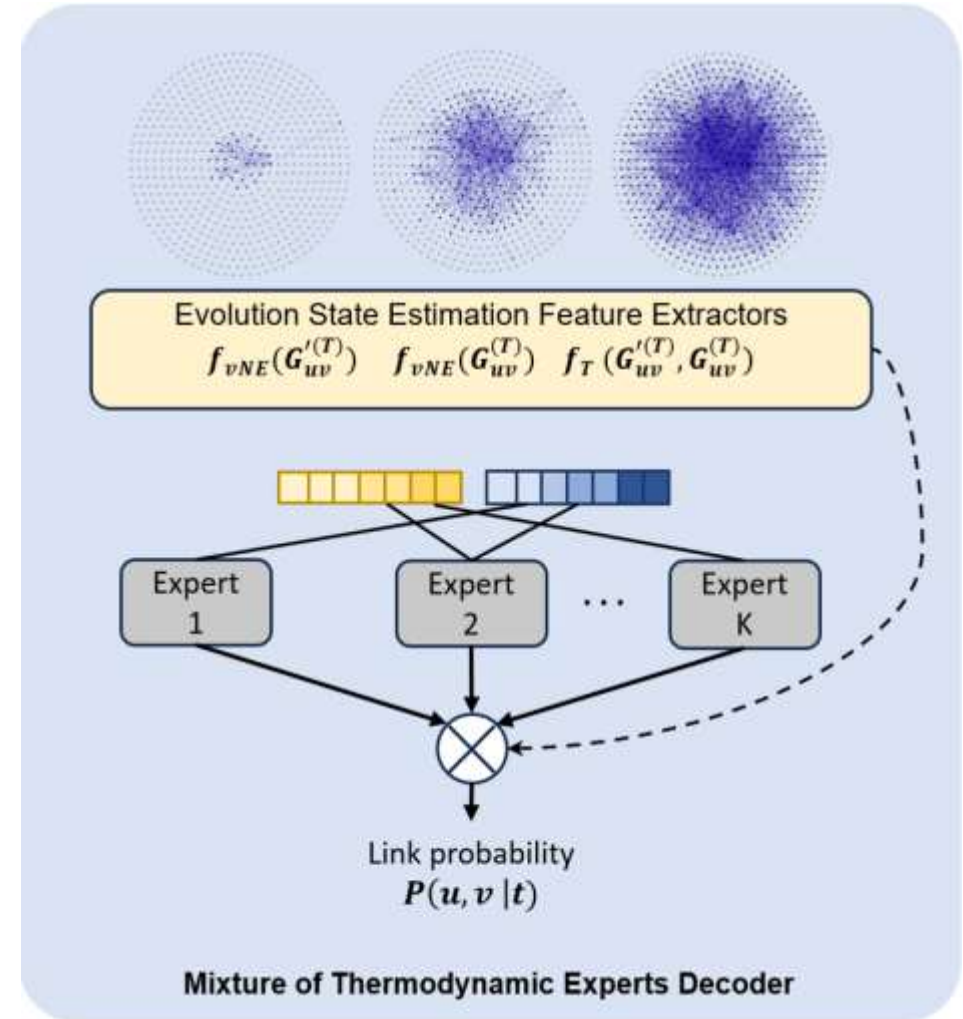
## Evolution State Feature Extractor:

Computing thermodynamic vector that includes **vNE** of original and virtual evolution graphs and **thermodynamic temperature** of the virtual evolution path.

$$score(u, v, t) = \sum_{i=1}^Y \sigma(W_i(h_u, h_v, h'_v - h_v, h'_u - h_u)) \pi_i$$

$$\pi_i = softmax_i((\mathcal{T}(G, G'_{uv}) \| S_{VN}(G)) \| S_{VN}(G'_{uv})) W_{\pi})$$

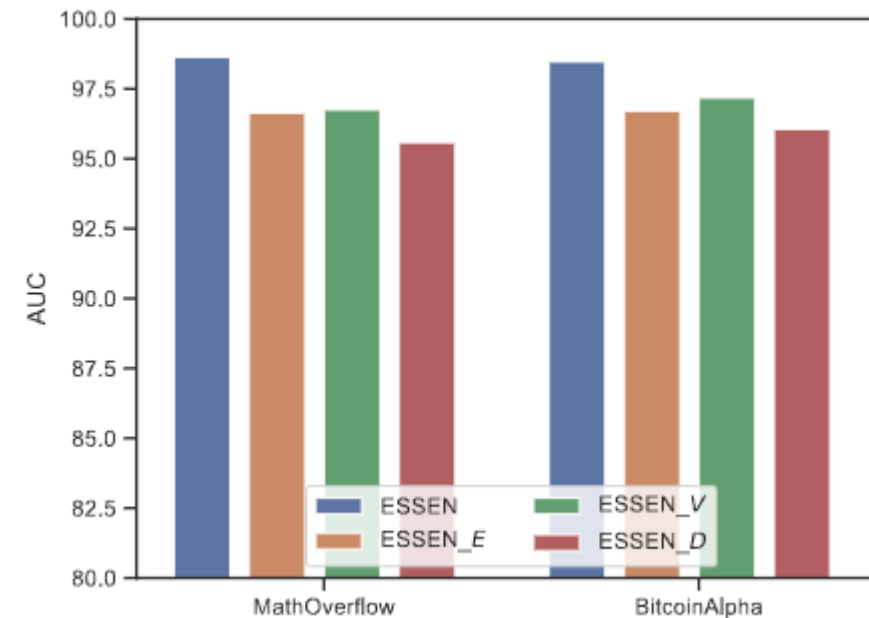
**Time Complexity:**  $O(|V|^2)$ , where  $V$  can be replaced with the neighborhood size under the sampling setting.





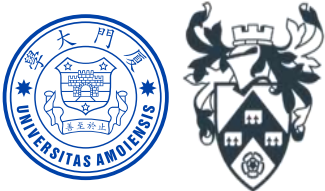
# Performance

Task	Methods	MathOverflow	BitcoinAlpha	BitcoinOTC	Wikipedia
Transductive	JODIE	86.07 $\pm$ 0.48	91.14 $\pm$ 0.18	92.29 $\pm$ 0.11	93.58 $\pm$ 2.00
	DyRep	80.77 $\pm$ 0.65	79.39 $\pm$ 3.17	79.21 $\pm$ 4.10	94.22 $\pm$ 0.27
	TGN	80.47 $\pm$ 3.24	86.71 $\pm$ 1.00	86.78 $\pm$ 2.29	98.46 $\pm$ 0.10
	TGAT	71.80 $\pm$ 0.91	78.99 $\pm$ 0.50	79.53 $\pm$ 0.67	95.34 $\pm$ 0.10
	CAW	53.82 $\pm$ 0.28	64.70 $\pm$ 0.93	73.95 $\pm$ 1.22	<u>98.96 <math>\pm</math>0.10</u>
	TDLG	84.02 $\pm$ 0.16	92.83 $\pm$ 0.22	93.48 $\pm$ 0.22	88.93 $\pm$ 0.09
	NeurTWs	<u>92.56 <math>\pm</math>0.51</u>	<u>93.95 <math>\pm</math>0.41</u>	<u>95.75 <math>\pm</math>0.01</u>	94.54 $\pm$ 0.87
	ESSEN	<b>98.60 <math>\pm</math>0.40</b>	<b>99.10 <math>\pm</math>0.16</b>	<b>98.88 <math>\pm</math>0.42</b>	<b>99.03 <math>\pm</math>0.33</b>
Inductive	JODIE	67.06 $\pm$ 0.42	74.47 $\pm$ 0.16	76.21 $\pm$ 0.47	91.44 $\pm$ 1.99
	DyRep	63.50 $\pm$ 0.66	66.27 $\pm$ 0.73	65.09 $\pm$ 0.86	91.03 $\pm$ 0.34
	TGN	64.50 $\pm$ 1.17	69.36 $\pm$ 0.94	76.52 $\pm$ 1.25	97.70 $\pm$ 0.18
	TGAT	60.02 $\pm$ 0.75	66.42 $\pm$ 1.17	66.62 $\pm$ 1.99	93.99 $\pm$ 0.30
	CAW	57.67 $\pm$ 0.33	64.38 $\pm$ 1.01	72.99 $\pm$ 0.46	<u>98.75 <math>\pm</math>0.14</u>
	TDLG	74.31 $\pm$ 1.58	83.85 $\pm$ 1.65	85.22 $\pm$ 3.89	45.77 $\pm$ 3.06
	NeurTWs	<u>91.83 <math>\pm</math>0.13</u>	<u>94.20 <math>\pm</math>0.26</u>	<u>96.08 <math>\pm</math>0.38</u>	94.63 $\pm$ 0.47
	ESSEN	<b>98.33 <math>\pm</math>0.28</b>	<b>98.07 <math>\pm</math>0.64</b>	<b>98.67 <math>\pm</math>0.31</b>	<b>98.80 <math>\pm</math>0.10</b>

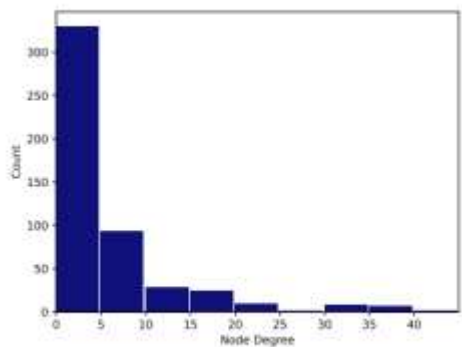


Ablation Study

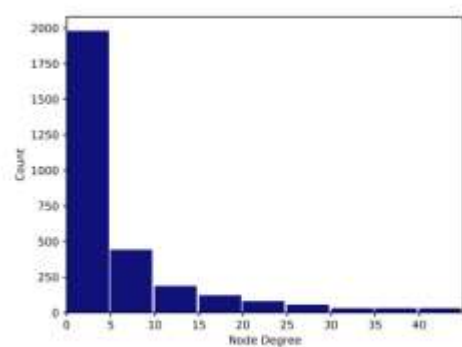
Link Prediction



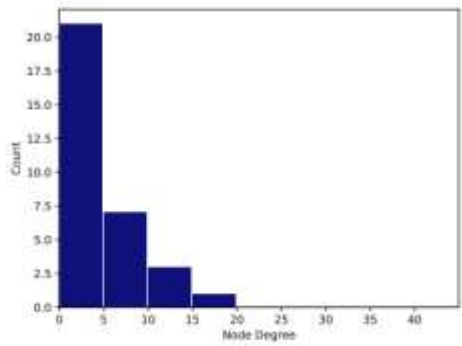
# Qualitative Analysis



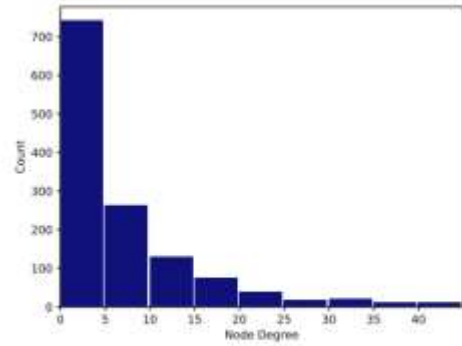
(a) MathOverflow: 30th Day



(b) MathOverflow: 270th Day

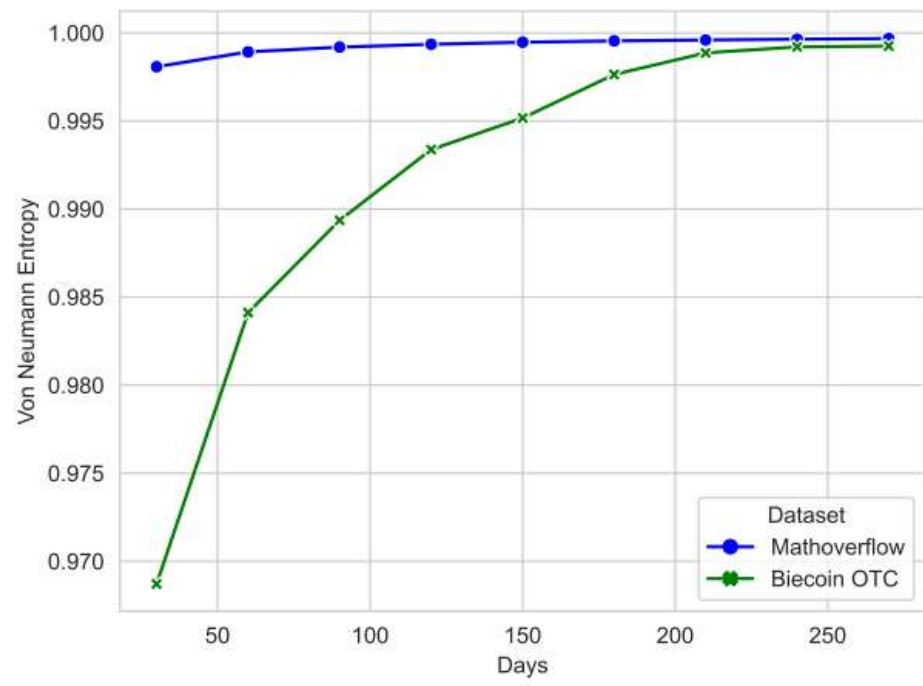


(c) BitcoinOTC: 30th Day



(d) BitcoinOTC: 270th Day

Degree distribution



Approximate von Neumann entropy can help model to understand network evolution structure.





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XIAMEN UNIVERSITY



UNIVERSITY  
*of York*

**ESSEN: Improving Evolution State Estimation for  
Temporal Networks using Von Neumann Entropy**

**Thank You for Listening!**