Dynamic Community Detection with Normal Distribution in Temporal Social Networks

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We wanna measure the dynamic connections between people and communities.

Outline

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- Background of Community Detection

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- Motivation of Dynamic Community Detection

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- Observation and Intuition

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- Challenges

Background

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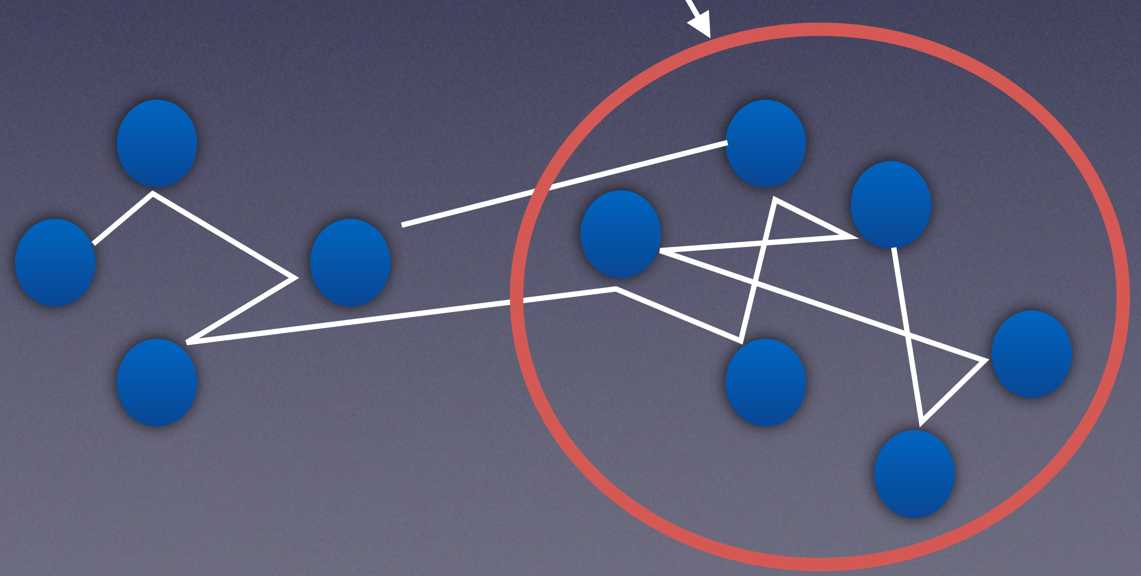
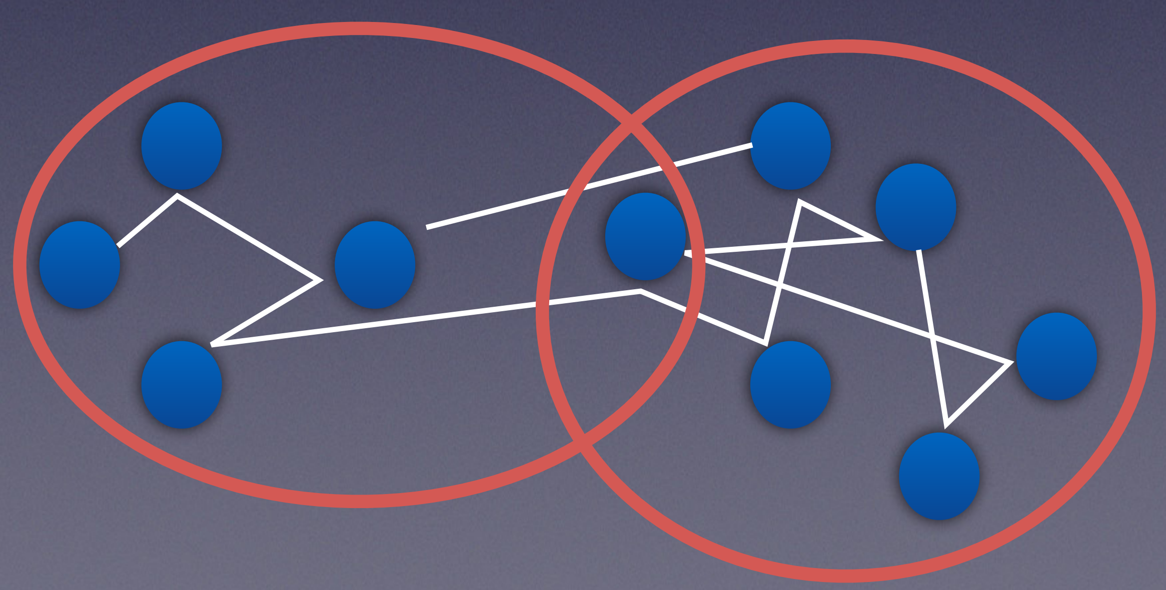


Background

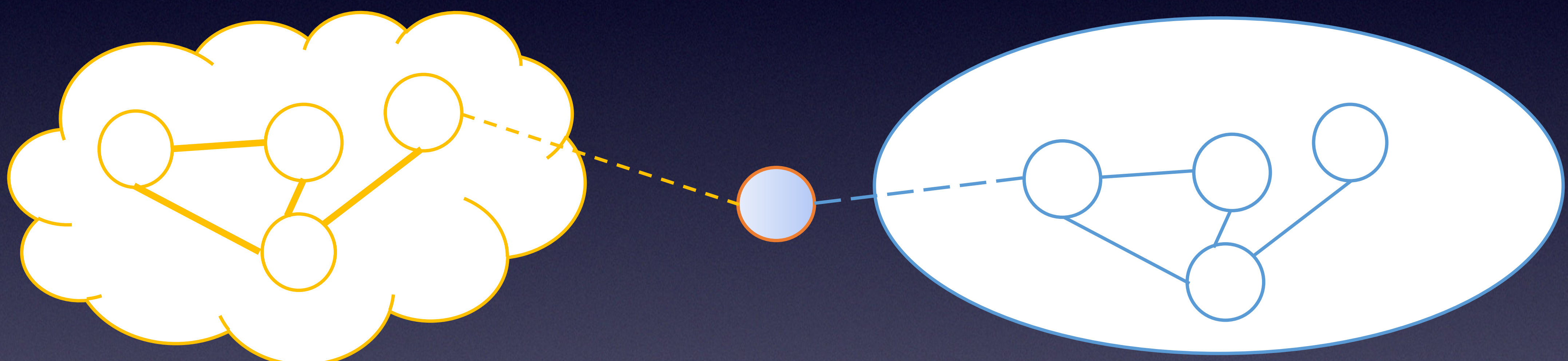
Definition: An **overlapping community** allows some nodes belong to multiple communities.



Static community

Static community

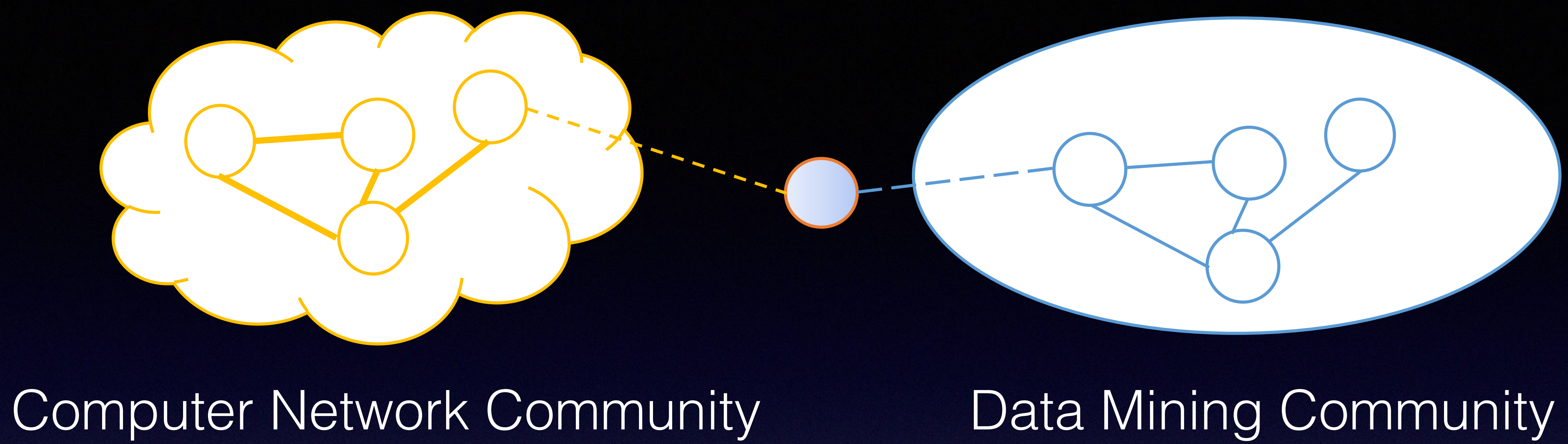
An edge **(u,v)** denotes an interaction between nodes



Computer Network Community

Data Mining Community

Example: A static collaboration network within a long period of time (from being Master student to PhD student)



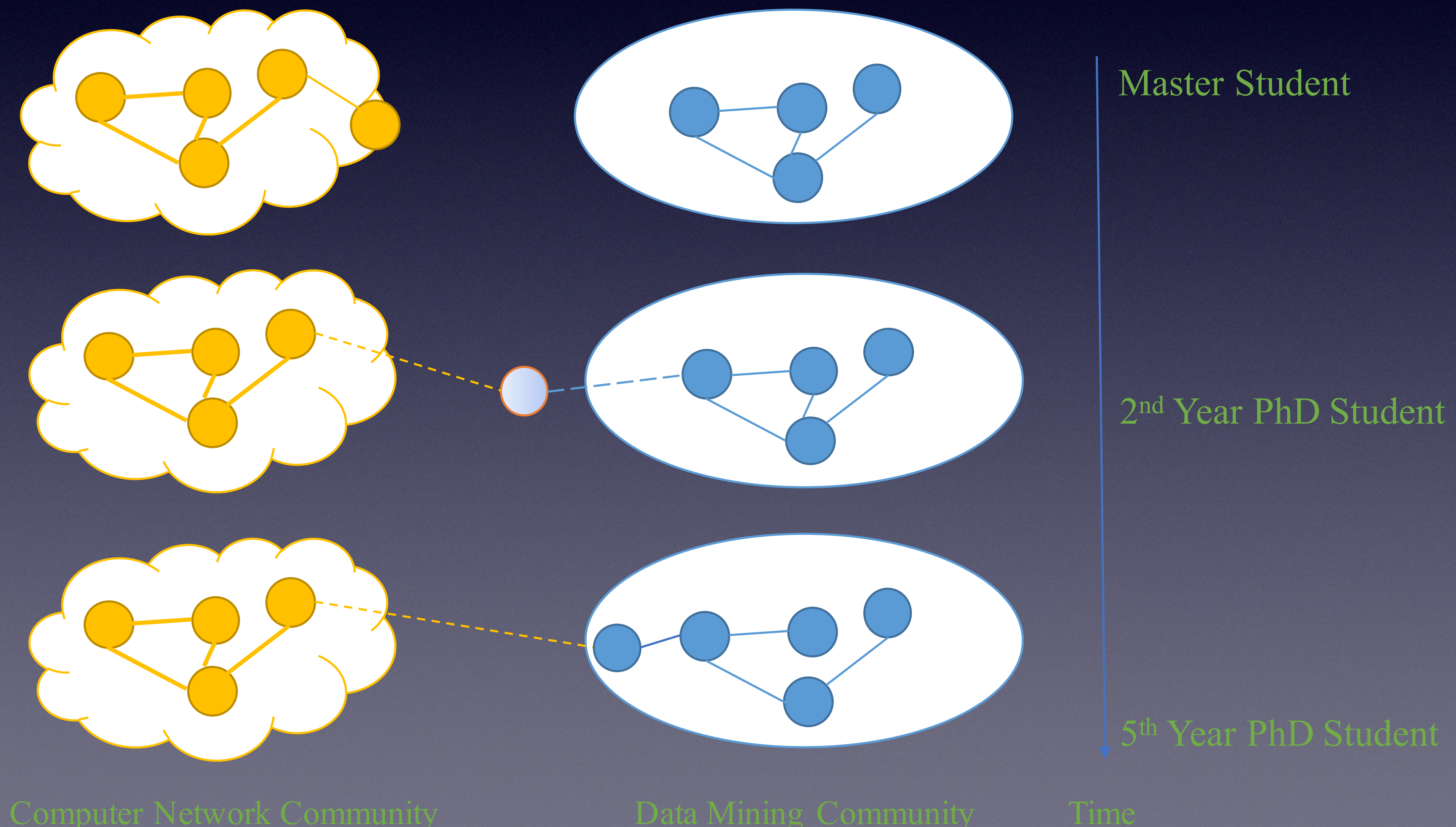
Three Possibilities from This Figure:

- this guy shifted from Computer Network to Data Mining
- this guy shifted from Data Mining to Computer Network
- this guy always did research both of them

What’s the truth?

Dynamic community in dynamic (temporal) networks

An edge **(u, v, t_u, t_v)** denotes
an interaction and its related times between nodes



Observation

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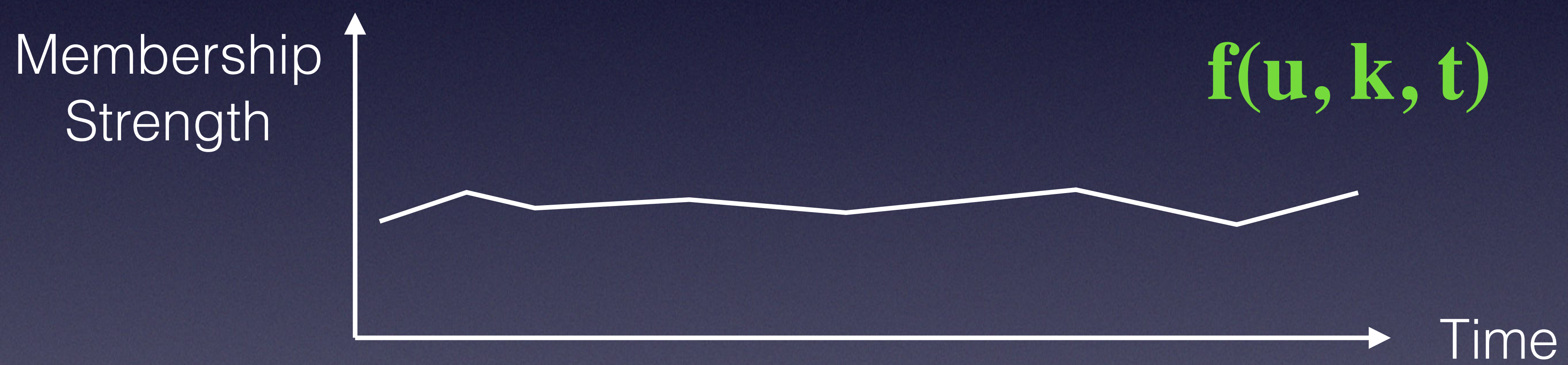
1) stable, not time-varying



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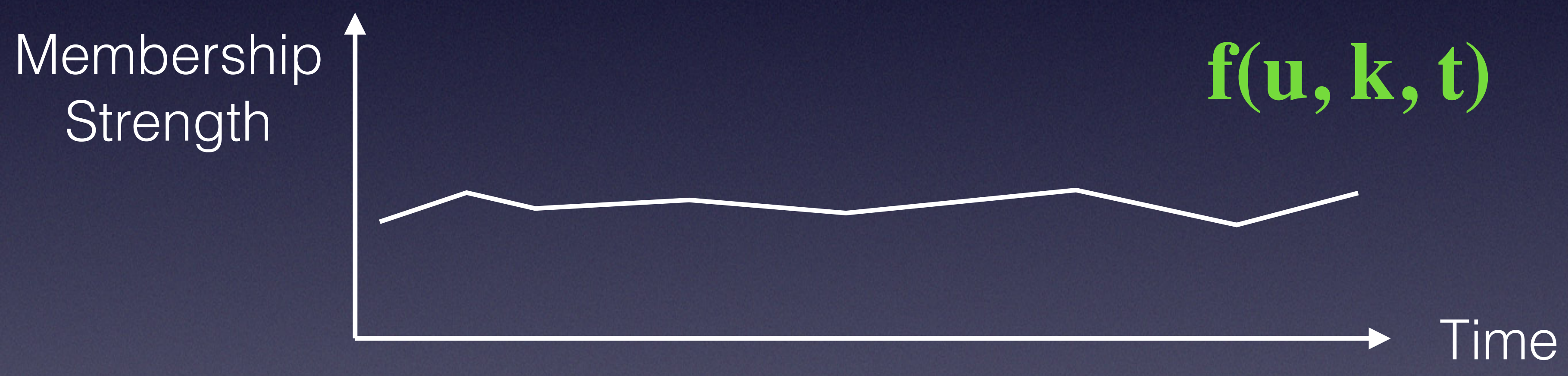
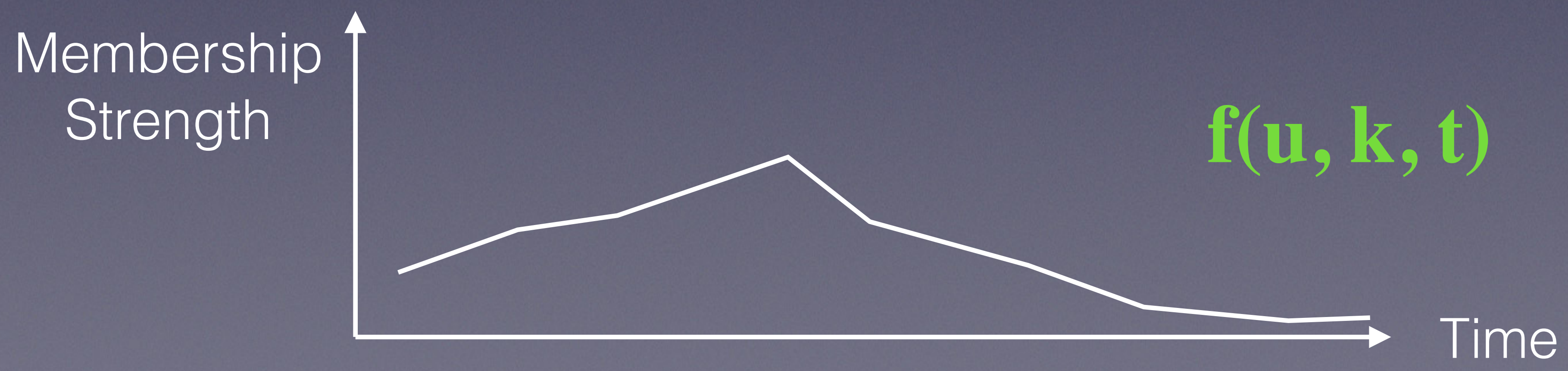
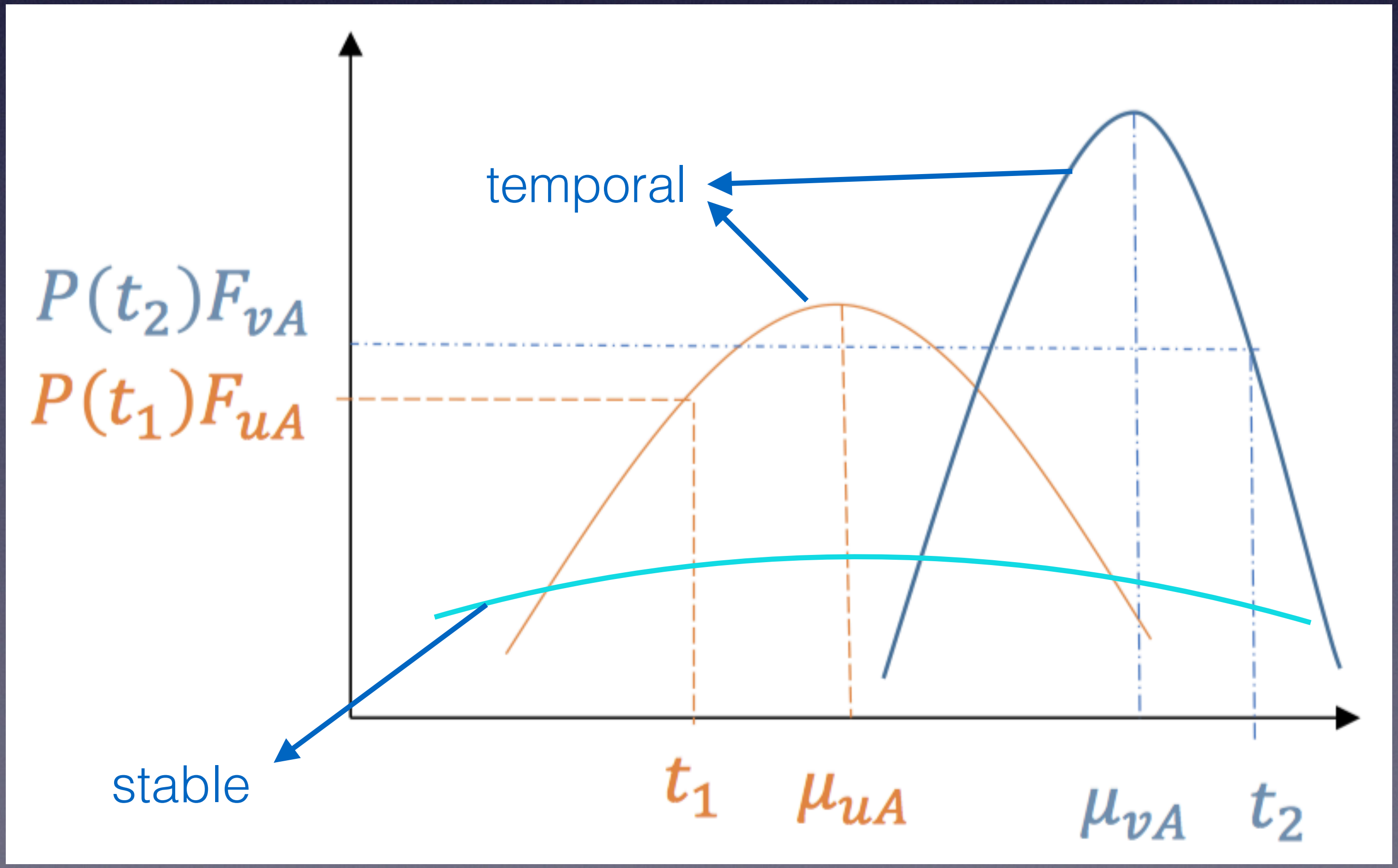


2) temporal and always with mono peak



Our Intuition

Use Normal Distribution to model the strength of membership — adding a pair of (μ , σ) as temporal factors to describe strength of membership



Problem Definition: Community Detection

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- **Given n nodes (people) and m edges (interaction) -> G(V,E)**
- **To find number of k communities where people belong to**
- **TWO observation:**
  - If two people interact often -> P (same community)
  - If two people belong to same community -> P (Interact)

Modeling for static community detection in BigClam

- Define:
  - F_{uc} -> weight between user u and community c
  - P(u, v) -> The possibility of interaction between users u and v
- Assume one community c connects users u and v with

$$P(u,v|c) = 1-\exp(-F_{uc} \cdot F_{vc})$$

- We have

$$P(u,v) = 1-\exp(-\sum_{C} F_{\mathrm{uc}} \cdot F_{vc})$$

Learning for static community detection in BigClam

How can we get F:

- **Maximizing the log likelihood of:**

$$\boldsymbol{l(F) = log\ P(G|F)}$$

$$\hat{\mathrm{F}} = \underset{\boldsymbol{F \geq 0}}{\boldsymbol{arg}\max}\, \boldsymbol{l(F)}$$

- **where**

$$l(F) = \sum_{(u,v)\in E} \log(1 - \exp(-F_u F_v^T)) - \sum_{(u,v)\notin E} F_u F_v^T$$

Learning for static community detection in BigClam

Block coordinate gradient ascent algorithm

$$l(F) = \sum_{(u,v)\in E} \log(1-\exp(-F_u F_v^T)) - \sum_{(u,v)\notin E} F_u F_v^T$$

We can solve subproblem for each u,

- **Update F_u for each u with the other F_v fixed**
- **Became a convex optimization problem**

$$l(F_u) = \sum_{v\in\mathcal{N}(u)} \log(1-\exp(-F_u F_v^T)) - \sum_{v\notin\mathcal{N}(u)} F_u F_v^T$$

$$\nabla l(F_u) = \sum_{v\in\mathcal{N}(u)} F_v \frac{\exp(-F_u F_v^T)}{1-\exp(-F_u F_v^T)} - \sum_{v\notin\mathcal{N}(u)} F_v$$

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Our Modeling for Dynamic Community Detection

Assume every user has a time distribution between community c

- $\text{Gaussian}_{uc} \sim (\mu_{uc}, \sigma^2_{uc})$
- $P(u,v) = 1-\exp(-\sum_C F_{uc} \cdot F_{vc})$ ->

$$P(u,t_1,v,t_2) = 1-\exp(-\sum_C F_{uc} \cdot \text{Gau}_{uc}(t_1) \cdot F_{vc} \cdot \text{Gau}_{vc}(t_2))$$

Parameter Learning for Dynamic Community Detection

Maximizing the log likelihood of:

- $\boldsymbol{l(F, Gau) = log\ P(G|F, Gau)}$ **Gau -> f**

$$\hat{F}, \hat{f} = \underset{F \geq 0, f \geq 0}{arg\max}\, l(F, f) \qquad f(t_1|u,k) = \frac{1}{\sqrt{2\pi}\sigma_{uk}} \exp(-\frac{(t_1 - t_{uk})^2}{2\sigma_{uk}^2})$$

$$l(F, f) = \sum_{(u,v,t_1,t_2) \in E} log(1 - \exp(-\sum_{k=0}^{C} F_{uk} f(t_1|u,k) F_{vk} f(t_2|v,k)))$$
$$- \sum_{(u,v,t_1,t_2) \notin E} \sum_{k=0}^{C} F_{uk} f(t_1|u,k) F_{vk} f(t_2|v,k))$$

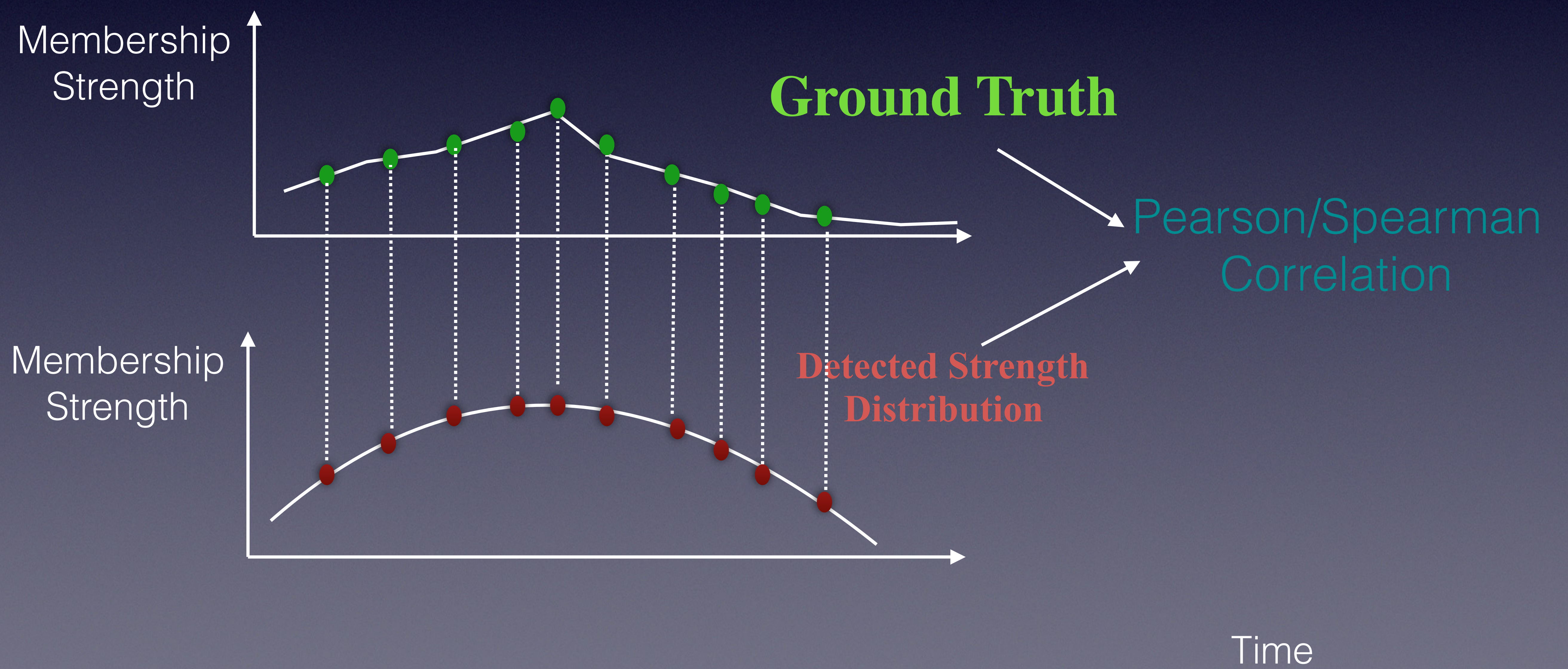
Random Sampling of Negative Samples

Evaluation on the membership strength matrix F

- Relative Accuracy
- Average F1 Score
- Omega Index
- Normalized Mutual Information

Evaluation on the estimated temporal factors (μ , σ)

- Pearson/Spearman Correlation



Thank You!