Learning from partly observable time-dependent graphs

Jan Ramon

TDLSG workshop @ ECML/PKDD 2017

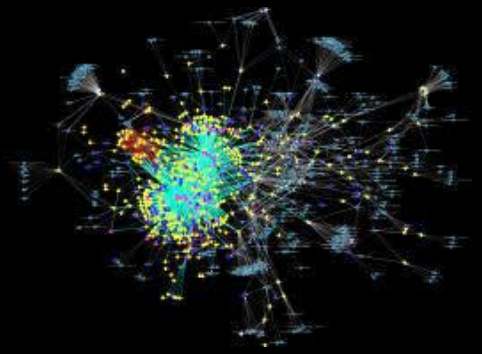
Skopje, September 18th, 2017

Contents

- Introduction
  - Types of time-dependent graphs
  - Unobservable data
- Case studies
  - Traffic
  - homophilic preferential attachment
  - biological networks
- Discussion & conclusions

Types of time-dependent graphs

- Fixed structure, evolving attributes
  - E.g. Gene regulatory network
    - Node: gene
    - Arc: regulation
    - Attribute: expression level
- Fixed attributes, evolving structure
  - E.g. Citation network
    - Node: article
    - Arc: citation
- Evolving attributes, evolving structure
  - E.g. Social network

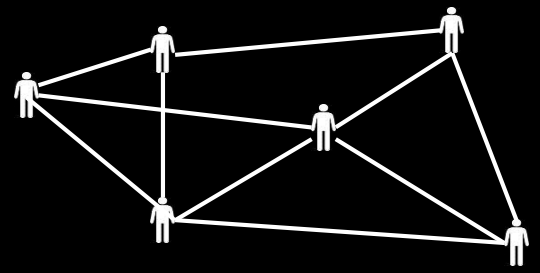


Observability

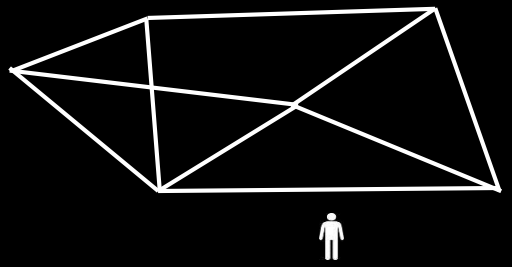
- Collecting actual information
  - is expensive
    - Communication costs
    - Bothering people to record everything
  - Isn’t privacy-friendly
  - May be technically infeasible
    - If observations require destructive measurements

Some observation settings

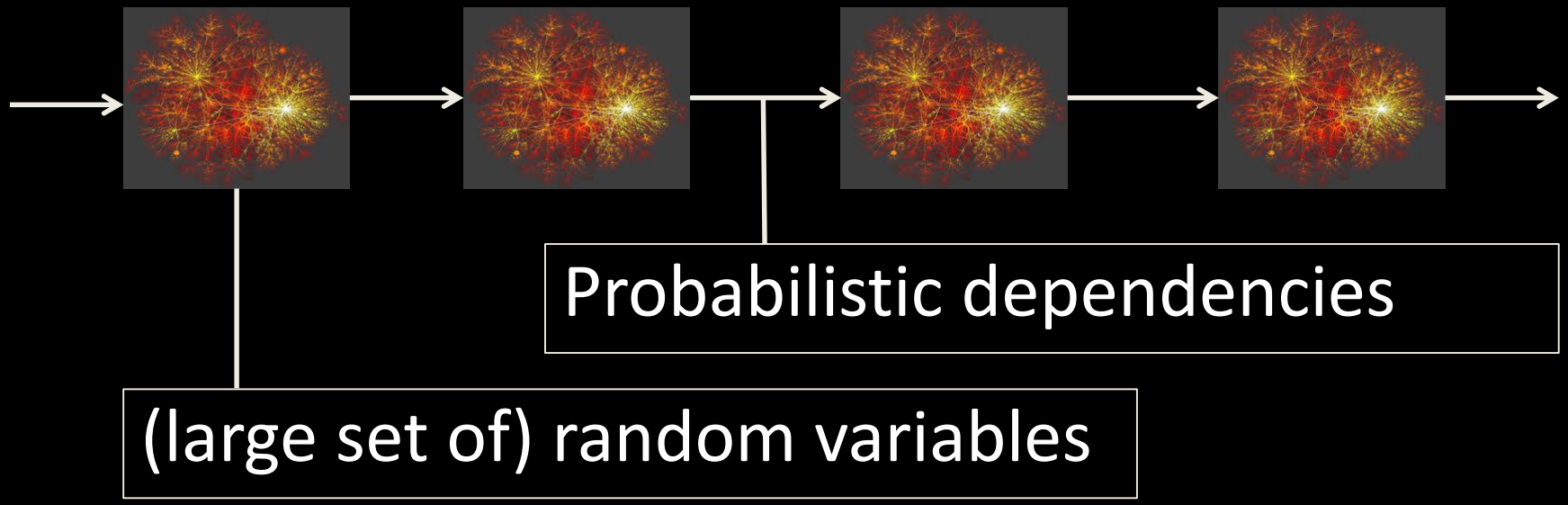
- Nodes as observers
  - Observe/query/inform neighborhood
  - Limited information about distant nodes
  - E.g. Node in communication network
  - E.g. Car in road network



- External observer
  - Overview of graph structure
  - Only limited observation of local details
  - E.g. Service provider in communication network
  - E.g. Government/maintainer monitoring road network



Dynamic probabilistic models



- TD-graph can be modeled with probabilistic relational model (MLN, ProbLog, PRM, RBN, ...)
- But existing inference techniques can’t exploit all structure easily

Exploitable structure

- Uniformity of network
  - closeby vertices are/behave similar(ly)
- Continuity
  - Values don’t change
- Information flow
  - Also: causality
  - (but not easily conditional independence)

Case studies

- Case study 1: Local observation
- Case study 2: Unobservable history
- Case study 3: Destructive measurement

Case study: Traversal time learning in connected cars

- Networks:
  - Traffic
    - Static structure: Road network
    - Time-dependent attribute: traffic load
  - Communication
    - Time-dependent structure: cars communicate if they are close together (sufficiently close to exchange useful traffic experience)

ADEME-Must

Traffic data

- Car collects data:
  - Car sensors (windows, seats, fuel, ...)
  - Real-time data: acceleration, ...
  - GPS localisation
  - Video data
- Infrastructure collects data:
  - Is parking space used?
  - Speed of traffic
- Databases:
  - Maps, navigation data
  - Ride organization (agenda, ride sharing, ...)

Case study: Traversal time learning in connected cars

- Tasks:
  - Understand behavior of other traffic users
  - Understand & maintain car
  - Determine best route (possibly avoiding congestions)
  - Find free parking slots
  - Learn about unusual traffic situations
  - Update world map
  - ...

Case study: Traversal time learning in connected cars

- Two main problems:
  - Learn regularities in the system
  - Collect real-time information sufficiently quickly
    - Learn to commnicate, prioritize, ...
- Here:
  - Learn traversal time of road segments
  - Privacy-friendly

Centralized vs. decentralized

- Privacy
  - Central server can track location of users
- Risk of failure of central service
- Communication & computation cost
  - Amount of applications increases
  - Data volume increases

Constraints

- Each car has a local model of the traffic in its neighborhood
- Cars can only communicate with nearby cars
- Need to respect privacy
- Semi-stream: the car memory is large, but cars hear all broadcasts at most once

Model

- Road segments $e \in E$
  - have average traversal time $\bar{d}_{e,\tau}$ in time-of-days τ.
- Users (cars) $u \in U$
  - prefer to take $\mathrm{w}_{\mathrm{z}}^{\mathrm{u}} \bar{d}_{e,\tau}$ time for a unit distance on roads of type z (highway, local road, ...)
- Actual traversal i of $\mathrm{x}_{\mathrm{i}}^{e} \in E$ by $\mathrm{x}_{\mathrm{i}}^{u} \in U$ at time x_i^t takes time $\mathrm{x}_{\mathrm{i}}^{\mathrm{d}}$, assumed close to $\mathrm{w}_{\mathrm{z}}^{\mathrm{u}} \bar{d}_{e,\tau} + c_i$, where c_i is the additional time due to congestion

Objective function

$$L(w,c) = \sum_i \left(x_i^u - \mathrm{w}_{\mathrm{z}}^{\mathrm{u}} \bar{d}_{e,\tau} - c_i\right)^2$$
$$+\lambda_1 \sum_{i,j} \left(c_i - c_j\right)^2 \exp\left(-\left(x_i^t - x_j^t\right)^2 - d\left(x_i^e, x_j^e\right)\right)$$
$$+ \lambda_2 \sum_i c_i^2$$

Accurate predictions

Traffic situation is often similar in nearby places and at nearby times

Try to explain things with few congestions

Algorithm

- Keep knowledge alive:
  - Broadcast learned average traversal times and current congestions, newcomers in area will learn it, those leaving can forget.
- Decentralized: Not just any optimization algorithm
- EM strategy:
  - Estimate c_i from difference between predicted and observed traversal time and from neighborhood
  - Estimate w_z^u by averaging difference between broadcasted average and personal average.
  - Improve $\bar{d}_{e,\tau}$ incrementally from new observations

Learnability

- Static: Converges rather quickly
  - Quadratic program
  - Each step decreases loss
  - (Wider broadcast is helpful)
- Time-dependent:
  - Target may drift
  - Can converge (and predict well) if target moves sufficiently slowly

Privacy

- Broadcast only
  - Congestion c_i
  - Road traveral time average $\bar{d}_{e,\tau}$
- But not
  - Personal deviation in speed w_z^u
- Apply protocol to broadcast training example (x_i^e, x_i^t, x_i^d) without revealing identity x_i^u
  - Challenge: ensure trust in broadcasted messages (e.g., making traceable in case of misinformation)

Case study: Homophillic preferential attachment

- Preferential attachment → powerlaw graphs
  - Very simple
  - Very popular
  - No data

- E.g. Social networks
- Can we parameterize the generative process to understand better?
  - Parameterized preferential attachment PA_θ
  - Newly arrived node selects neighbors v with probability $PA_\theta(v)$

Homophilic preferential attachment
Problem statement

- We only see the end-result, nobody kept a log
- Can we still estimate θ ?
- Simple case: homophily
  - Each vertex v has feature vector $x^v \in F$ with distribution $p_f(.)$
  - Probability of selecting neighbor v for u is proportional to $\sum_i \theta_i x_i^u x_i^v$.

Learning homophillic weights

- Known history (order in which nodes arrive):
  - Regression
  - Given newcomer features, existing node features and edge (1) / no-edge (0)
- Undirected graph:
  - Can’t reconstruct attachment examples directly
  - Probabilistic approach
  - Assume order of node arrivals is random

Homophilic preferential attachment
Solution by minimizing loss

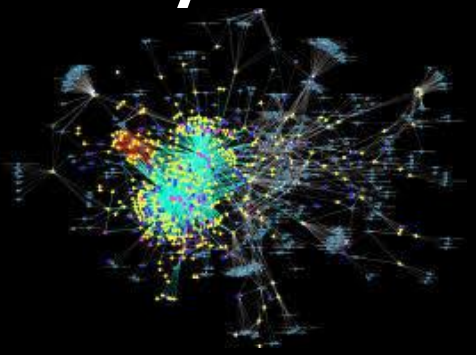
$$L(w)$$
$$= \sum_{x \in F} \sum_{y \in F} \left(E_{x,y} - \frac{p_f(x) p_f(y) \sum_i w_i x_i y_i}{\sum_{z \in F} p_f(z) \sum_i w_i x_i z_i} \right.$$

Learnability

- Yes, one can learn from a snapshot
  - Need $O(\epsilon^{-2} p_{min}^{2})$ examples

- Extensions:
  - Including degree, patterns, ...
  - Becomes quickly more complex

Case study: biological regulatory networks



- Network:
  - Nodes: genes
  - Arcs: regulations
- More activated genes (high expression level) generate more transcription factors that (up or down) regulate other genes.

$$v_{g,t} = f(v_{pa(g,1),t-1}, v_{pa(g,2),t-1}, \dots)$$

where $pa(g,i)$ is i-th parent of gene g and $v_{g,t}$ is expression level of gene g at time t.

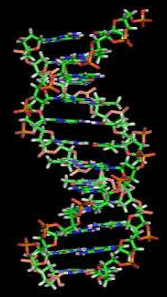
chist-era Adalab

Learning task

- Given:
  - Input (experimental setup), output (measurement) pairs
- Learn:
  - The network
    - structure pa
    - combination functions f
- Active learning operators:
  - Can choose experiment

Biological regulatory networks

- Hardness:
  - In principle turing complete (see also DNA computing)
  - Hence, learning network from (only) input and output is hard.
- Experiments:
  - Destructive
  - May measure output at selected point in time
  - May modify the network (gene knock out)



Biological regulatory networks

- Program induction?
  - Learning programs from input-output pairs is hard
  - But what if we can also get input-output pairs of programs obtained by deleting lines in the original program?
- Approach:
  - Hill climbing through model space
    - In each iteration evaluate minor changes to model
  - Exploit domain knowledge
- Results:
  - Can’t expect to learn exactly the same network
  - With sufficient domain knowledge, improvements on prior models can be made

Case studies

Setting	Observation	Exploit	
Traffic	Neighborhood Semi-stream Multi-agent	Continuity Collaboration (info flow) (regularity of network)	Stochastic gradient
Preferential attachment	Global Only present Single world	Regularity of network (and Large Scale)	Analysis & optimization
Regulatory network	Selected variable Selected time Repeatable	Experimental options (info flow)	Hill climbing

Discussion – Generic approaches?

- Several types of settings for time-dependent networks.
  - Wide range in learnability
- generic probabilistic model solvers can’t (yet) exploit the various structures. How does this map to lifted inference?
- Meta-learning from 3 case studies:
  - Network regularity (i.e. High network entropy) is important in determining learnability

Discussion - Complexity

- What makes learning from time-dependent large-scale partially-observed graphs hard?
  - No network regularity
  - Long sequences without good observations (as in (PO)MDPs) (making information flow harder to exploit)
  - Discrete / non-continuous / combinatorial evolution

Conclusions

- TD graph is often not fully observable
- LS can help to collect sufficient information
- Often domain-specific solutions needed

Future directions

- More in-depth study of learnability
  - Exploit network regularity?
- More generic approach?
  - Can we automatically understand structure, information flow, ...?
- Tagging: only “TDG” may not be sufficient
  - Can we isolate frequently recurring (sub)problems?

Questions?