

MLSS 2016 – Practical

Machine Learning for Networks

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MLSS 2016
CADIZ

Getting ready

1. Install CVX for MATLAB / cvxpy for Python

Mathematically

<http://cvxr.com/cvx/download/>

```
minimize  $f_0(x)$   
subject to  $f_i(x) \leq 0, \quad i = 1, \dots, m$   
 $h_i(x) = 0, \quad i = 1, \dots, p$ 
```

In CVX

```
cvx_begin  
    variables x(n)  
    minimize(f0(x))  
    subject to  
        f(x) <= 0  
        A * x - b == 0  
cvx_end
```

```
import cvxpy as CVX  
x = CVX.Variable(n)  
constraints = [  
    f(x) <= 0,  
    A * x - b == 0  
]  
prob = CVX.Problem(  
  
    CVX.Minimize(f0(x)),  
    constraints)  
prob.solve()
```

NB: f_0 and f_i must be convex and h_i must be affine

Outline

Point Processes → Simulation and estimation

Part I

Information Diffusion



NetRate

[Gomez Rodriguez et al., ICML
2011]

Part II

Social Activity



Hawkes Process

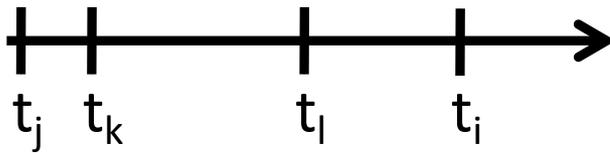
[Aalen et al., Springer 2008]

Task I

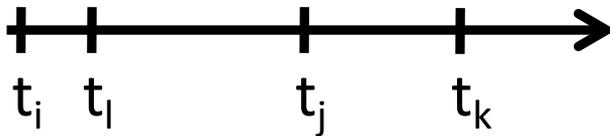
Estimate transmission rates in NetRate model with exponential transmission function.

Data

Cascade 1

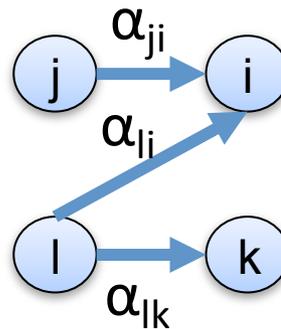


Cascade N



Model

NetRate



Estimation

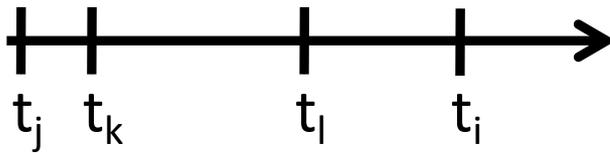
?

Task I

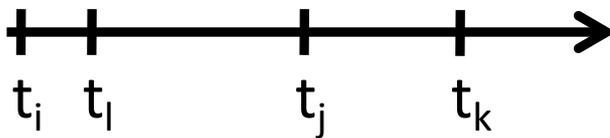
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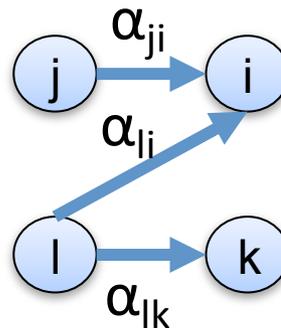


Cascade N



Model

NetRate



Estimation

MLE solution

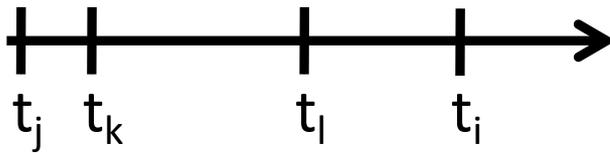
$$\max_{\{\alpha_{ji}\}} \sum_c \log f(\{t_j\}^c; \{\alpha_{ji}\})$$

Task I

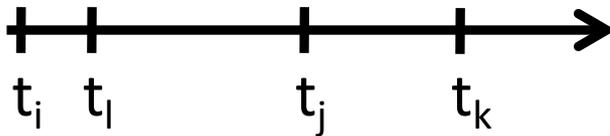
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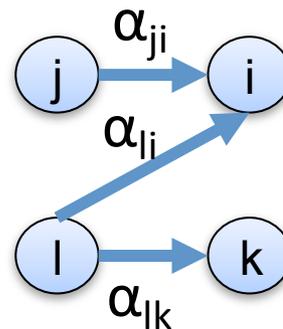


Cascade N



Model

NetRate



Estimation

MLE solution

$$\max_{\{\alpha_{ji}\}} \sum_c \log f(\{t_j\}^c; \{\alpha_{ji}\})$$

Exercise 1

Task I

The **likelihood of a cascade** by time T is:

$$f(\mathbf{t}; \mathbf{A}) = \prod_{i:t_i \leq T} \prod_{m:t_m > T} S(T|t_i; \alpha_{i,m}) \times \prod_{k:t_k < t_i} S(t_i|t_k; \alpha_{k,i}) \left(\sum_{j:t_j < t_i} H(t_i|t_j; \alpha_{j,i}) \right)$$

MLE estimation:

$$\begin{array}{ll} \text{maximize}_{\mathbf{A}} & \sum_{c \in C} \log f(\mathbf{t}^c; \mathbf{A}) \\ \text{subject to} & \alpha_{j,i} \geq 0, \quad i, j = 1, \dots, N, \quad i \neq j \end{array}$$

Task I

<https://github.com/Networks-Learning/mlss-2016>

Networks-Learning / mlss-2016

Watch 3

Star 0

Fork 0

Code

Issues 0

Pull requests 0

Pulse

Graphs

MLSS 2016 material.

54 commits

3 branches

0 releases

1 contributor

Branch: cascad...

New pull request

New file

Find file

HTTPS

<https://github.com/Netw>



Download ZIP

This branch is 1 commit ahead, 1 commit behind master.

Pull request Compare

musically-ut Add solutions of cascade parts.

Latest commit 567577d 11 hours ago

graph_inference	Add solutions of cascade parts.	11 hours ago
recurrent_events	Remove solutions, provide problems.	11 hours ago
.gitignore	Ignore the default cascade output.	a month ago
README.md	Add basic requirements for the code.	26 days ago
requirements.txt	Make requirements more stringent.	a month ago

OUTLINE

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Hawkes Process

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Task II

Generate samples from a (univariate) Hawkes Process

Model

Simulation

Estimation

Hawkes process

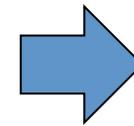
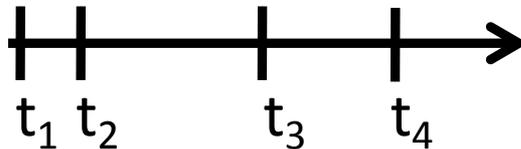
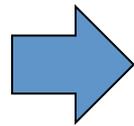
Ogata's algorithm

MLE solution

$\lambda_0 =$ Base intensity

$$k_\alpha(t) = \alpha e^{-w(t-t_i)}$$

$$\lambda(t) = \lambda_0 + \sum_{i:t_i \in \mathcal{H}(t)} k_\alpha(t - t_i)$$



$$\max_{\alpha, \lambda_0} \mathcal{L}(t_1, \dots, t_n)$$

Task II

Generate samples from a (univariate) Hawkes Process

Model

Hawkes process

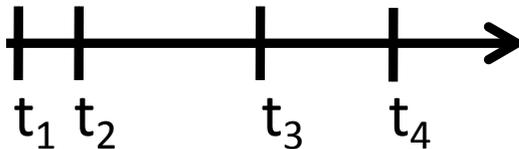
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Simulation

Ogata's algorithm



Exercise 2

Estimation

MLE solution

$$\max_{\alpha, \lambda_0} \mathcal{L}(t_1, \dots, t_n)$$

Task II

Ogata's Algorithm:

1: **Input:** λ_0 , α and T

2: Initialize: $n \leftarrow 1$, $\lambda^* \leftarrow \lambda_0$

Generate first event:

3: Generate $q \sim \mathcal{U}_{[0,1]}$ and $s \leftarrow -\frac{1}{\lambda^*} \ln(q)$

4: **if** $s > T$, **then** go to last step.

5: **else** Set $t_1 \leftarrow s$ and $n \leftarrow n + 1$,

General subroutine:

6: **while** $s < T$ **do**

7: Update $\lambda^* \leftarrow \lambda(t_{n-1}) + \alpha$

8: Generate $q \sim \mathcal{U}_{[0,1]}$ and $s \leftarrow t_{n-1} - \frac{1}{\lambda^*} \ln(q)$

9: **if** $s > T$, **then** go to last step

10: **else Rejection Test:**

 Sample $d \sim \mathcal{U}_{[0,1]}$

if $d \leq \frac{\lambda(s)}{\lambda^*}$, **then** $t_n \leftarrow s$ and $n \leftarrow n + 1$

else update $\lambda^* \leftarrow \lambda(s)$.

end while

11: **Output:** Retrieve the events ($\{t_n\}$) on $[0, T]$

[Ogata, 1981]

Task II

Ogata's Algorithm:

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- 2: Initialize: $n \leftarrow 1$, $\lambda^* \leftarrow \lambda_0$

Generate first event:

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Sample $d \sim \mathcal{U}_{[0,1]}$
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else update $\lambda^* \leftarrow \lambda(s)$.

end while

- 11: **Output:** Retrieve the events ($\{t_n\}$) on $[0, T]$

$$\lambda(t) = \lambda_0 + \sum_{i:t_i \in \mathcal{H}(t)} k_\alpha(t - t_i)$$

History up to but
not including t .

Task II

Conditional intensity rate

$$\lambda_u^*(t)$$



Events likelihood

$$\mathcal{L} = \underbrace{\sum_{i=1}^n \log \lambda^*(t_i) - \int_0^T \lambda^*(\tau) d\tau}$$

Maximum likelihood approach to find model parameters!

$$\max_{\alpha, \lambda_0} \mathcal{L}(t_1, \dots, t_n)$$



Downloads

NetRate:

Paper: <http://www.mpi-sws.org/~manuelgr/pubs/netrate-icml11.pdf>

Code: <https://github.com/Networks-Learning/netrate>

Hawkes Process:

Slides: http://lamp.ecp.fr/MAS/fiQuant/ioane_files/HawkesCourseSlides.pdf

Code: <https://github.com/dunan/MultiVariatePointProcess>

CVX:

Slides: http://web.stanford.edu/class/ee364a/lectures/cvx_tutorial.pdf

Code: <http://cvxr.com/cvx/download/>