A Cox model for component lifetimes with spatial interactions

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4th Workshop AMMSI, January 20-21, 2016, Grenoble A Cox model with spatial interactions



- n components displayed on a structure, e.g. a set of crews on a steel plates.
- Components are located on a regular $\sqrt{n} \times \sqrt{n}$ grid.
- The failure of a component may lead to a higher stress on the components in its neighborhood.
- State of components are observed at some inspection times.

Model and Notation

- T_i : the lifetime of component *i*.
- *n* binary stochastic processes: $\forall i \in \{1, ..., n\}, \forall t \ge 0, Y_i(t) = \mathbf{1}_{T_i \le t}$
- A failure of a component leads to an increase of the hazard function of this component.
- Let *B_i* denote the neighborhood of the *i*-th component.

Illustrations of neighborhood (4 neighbors)



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Illustrations of neighborhood (8 neighbors)



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Lifetime distribution

- Hazard function conditionnally to the past (the state of *n* components).
- Let H_t- be the σ-field generated by the *n* binary stochatic processes defined above up to time t⁻
- The hazard function of the *i*-th component, denoted λ_i:

$$orall t \geq \mathbf{0}, \quad \lambda_i(t|\mathcal{H}_{t^-}) = \lambda(t) \exp\left(lpha \sum_{j \in \mathcal{B}_i} \mathcal{C}_j(t) Y_j(t) + eta' Z_i(t)
ight),$$

where $\lambda(\cdot)$ is the baseline hazard function, $\alpha \in \mathbb{R}$, $\beta \in \mathbb{R}^{p}$ and where, for the *i*-th component, $C_{i}(\cdot)$ is a time-dependent covariate and $Z_{i}(\cdot)$ is a vector of ptime-dependent covariates (temperature, constraints, etc.).

Survival function

The survival function of the component *i* is given by:

$$\forall t \geq 0, \quad S_i(t|\mathcal{H}_{t^-}) = \exp\left(-\int_0^t \lambda_i(u|\mathcal{H}_{u^-}) \mathrm{d}u\right).$$

Assume λ is the hazard function of the Weibull distribution with scale parameter a > 0 and shape parameter b > 0:

$$\forall t \ge 0, \quad \lambda(t) = \frac{b}{a} \left(\frac{t}{a}\right)^{b-1}$$

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Simulation in independent case (without covariates)

- Weibull parameters: a = 2 and b = 2.
- square grid of 50×50 components.
- failed component are displayed in red.
- $\alpha = 0$ (no interaction)
- $\beta = 0$ (no covariates)

Plot of failed components (Independent case)



Figure: No interaction ($\alpha = 0$)

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Simulation in dependent case

- Weibull parameters: a = 2 and b = 2.
- square grid of 50×50 components.
- failed component are displayed in red.

• $\beta = 0$ (no covariates)

Plot of failed components (Dependent case)





Time = 0.21 Number of failures: 677



Figure: with interaction ($\alpha > 0$)

Simulation Algorithm

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Simulation Algorithm

Require: $n, a, b, \alpha, \beta, Z_1(\cdot), \ldots, Z_n(\cdot)$

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3: draw U_1, \ldots, U_n i.i.d. from the uniform distribution over [0, 1]
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9: for r \in \{2, \ldots, n\} do
17: end for
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Simulation Algorithm

Require: n. a. b. α , β , $Z_1(\cdot)$, ..., $Z_n(\cdot)$ **1**: $T \leftarrow \text{Vector(length} = n)$ 2: $\tilde{T} \leftarrow \text{Vector(length} = n)$ **3:** draw U_1, \ldots, U_n i.i.d. from the uniform distribution over [0, 1] 4: { Step 1 } 5: set $R \leftarrow \{1, \ldots, n\}$ {set of unfailed components} **6:** draw $\tilde{T}_1, \ldots, \tilde{T}_n: \log(U_i) + \int_0^{t_i} \lambda(s) \exp(\beta' Z_i(s)) ds = 0$ 7: $i_1 \leftarrow \operatorname{argmin}_{i \in B} \tilde{T}_i$ {select the next comp. to fail} 8: $T_{i_1} \leftarrow \tilde{T}_{i_1}$ {store the next failure times} **9:** for $r \in \{2, \ldots, n\}$ do 10: {Step r} 17: end for

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10: {Step r}
11: R \leftarrow R \setminus \{i_{r-1}\} {update the set of non-failed components}
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Available data

- Inspection times, τ₁ < · · · < τ_m, are the same for all components.
- The available data at each inspection time is a binary information on whether the component is failed or not $(Y_i = 0 \text{ or } Y_i = 1).$
- data are interval-censored.
- covariates C_1, \ldots, C_n and Z_1, \ldots, Z_n are observed continuously.

First case: Failure

- N_1 : the set of all failed components at the last inspection time τ_m
- For component *i*, let *j_i* = min{*j*; *Y_i*(τ_j) = 1} be the inspection time s.t. the failure is observed for the first time on the *i*-th component

•
$$\mathcal{N}_{1,r} = \{i \in \mathcal{N}_1; j_i = r\}.$$

- Failure appears between τ_{j_i-1} and τ_{j_i} .
- The probability of this event is given by:

$$\mathbb{P}\left[\tau_{j_i-1} < T_i \leq \tau_{j_i} | \mathcal{H}_{\tau_{j_i}^-}\right] = S_i\left(\tau_{j_i-1} | \mathcal{H}_{\tau_{j_i-1}^-}\right) - S_i\left(\tau_{j_i} | \mathcal{H}_{\tau_{j_i}^-}\right)$$

Second case: No failure

- *N*₀: the set of all unfailed components at the last inspection time *τ_m*.
- We have $\mathbb{P}\left[T_i > \tau_m | \mathcal{H}_{\tau_m^-}\right] = S_i\left(\tau_m | \mathcal{H}_{\tau_m^-}\right)$.
- Notice that the subset \mathcal{N}_0 can be empty, but it cannot be the case for \mathcal{N}_1 .

Pseudo-likelihood

- If $\alpha \neq$ 0, the likelihood function can be difficulty written
- The pseudo-likelihood function (ignoring the dependency), pL is given by:

$$pL\left(\alpha,\beta,\mathbf{a},\mathbf{b}|\mathcal{H}_{\tau_{m}^{-}}\right) = \prod_{i\in\mathcal{N}_{0}} S_{i}\left(\tau_{m}|\mathcal{H}_{\tau_{m}^{-}}\right) \prod_{i\in\mathcal{N}_{1}} \left[S_{i}\left(\tau_{l_{i}-1}|\mathcal{H}_{\tau_{l}^{-}}\right) - S_{i}\left(\tau_{l_{i}}|\mathcal{H}_{\tau_{l_{i}^{-}}}\right)\right] \\ = \prod_{i\in\mathcal{N}_{0}} S_{i}\left(\tau_{m}|\mathcal{H}_{\tau_{m}^{-}}\right) \prod_{r=1}^{m} \prod_{i\in\mathcal{N}_{1,r}} \left[S_{i}\left(\tau_{r-1}|\mathcal{H}_{\tau_{r-1}^{-}}\right) - S_{i}\left(\tau_{r}|\mathcal{H}_{\tau_{r}^{-}}\right)\right],$$

 It could rather be useful to consider the pseudo-log-likelihood function pℓ which is given by:

$$p\ell\left(\alpha,\beta,a,b|\mathcal{H}_{\tau_{m}^{-}}\right) = \sum_{i\in\mathcal{N}_{0}}\log\left[S_{i}\left(\tau_{m}|\mathcal{H}_{\tau_{m}^{-}}\right)\right] + \sum_{r=1}^{m}\sum_{i\in\mathcal{N}_{1,r}}\log\left[S_{i}\left(\tau_{r-1}|\mathcal{H}_{\tau_{r-1}^{-}}\right) - S_{i}\left(\tau_{r}|\mathcal{H}_{\tau_{r}^{-}}\right)\right]$$

Maximum Pseudo-Likelihood Estimator

- Maximum Pseudo-Likelihood Estimator of the parameters cannot be computed neither in a closed-form, nor numerically.
- hazard functions depend on binary stochastic processes Y_1, \ldots, Y_n which are only known at inspection times.
- to compute the survival at time *t*, it is required to the value of the hazard function at any time between 0 and *t*.
- \Rightarrow use of SEM algorithm

SEM Algorithm: Step 0

Step 0: parameter initialization.

For the covariates, set $\hat{\alpha}^{(0)} = 0$ and $\hat{\beta}^{(0)} = 0$ (no effect).

Parameters *a* and *b* can be thus estimated by maximizing the log-likelihood (since components are independent): $\hat{a}^{(0)}$ and $\hat{b}^{(0)}$.

SEM Algorithm: Step k

Step *k*: time-to-failures simulation and updating estimation.

- simulate T_1, \ldots, T_n using Sim. Algo. and considering the parameters $\hat{\alpha}^{(k-1)}, \hat{\beta}^{(k-1)}, \hat{a}^{(k-1)}$ and $\hat{b}^{(k-1)};$
- 2 update the estimation by maximizing numerically the pseudo-log-likelihood function: $\hat{\beta}^{(k)}$, $\hat{\alpha}^{(k)}$, $\hat{a}^{(k)}$ and $\hat{b}^{(k)}$

The final estimator is then given by considering the ergodic average of the estimators:

$$\widehat{\alpha} = \frac{1}{K} \sum_{k=1}^{K} \widehat{\alpha}^{(k)}, \quad \widehat{\beta} = \frac{1}{K} \sum_{k=1}^{K} \widehat{\beta}^{(k)}, \quad \widehat{a} = \frac{1}{K} \sum_{k=1}^{K} \widehat{a}^{(k)} \quad \text{and} \quad \widehat{b} = \frac{1}{K} \sum_{k=1}^{K} \widehat{b}^{(k)}.$$

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Simulation Algorithm based on observations 1

```
Require: n, a, b, \alpha, \beta, Z_1(\cdot), \ldots, Z_n(\cdot), \mathbf{D}_{obs}
 1: T \leftarrow \text{Vector(length} = n)
2: \tilde{T} \leftarrow \text{Vector(length} = n)
3: draw U_1, \ldots, U_n i.i.d. from the uniform distribution over [0: 1]
4: {Interval I<sub>1</sub>}
5: R \leftarrow I_1 {set of unfailed components in I_1 }
6: for j \in I_1 do
7: draw \tilde{T}_i: \log(U_i) + \int_0^{t_j} \lambda(s) \exp(\beta' Z_j(s)) ds = 0
8: end for 9: h \leftarrow \operatorname{argmin}_{j \in R} \tilde{T}_j {select the next comp. to fail}
 10: T_h \leftarrow \tilde{T}_h {store the next failure times}
 11: if n_1 > 1 then
 12:
             for r \in \{2, ..., n_1\} do
 13: R \leftarrow R \setminus \{h\} {update the set of non-failed components in I_1}
 14:
          for i \in B_h \cap R do
                         draw \tilde{T}_j: log(U_j) + \int_{T_h}^{t_j} \lambda(s) \exp\left(\beta Z(s) + \alpha \sum_{k \in B_i} C_k(s) Y_k(s)\right) ds = 0
 15:
16:
                   end for
                    h \leftarrow \operatorname{argmin}_{i \in R} \tilde{T}_i {select the next comp. to fail}
 18:
                    T_h \leftarrow \tilde{T}_h { store the next failure times }
19: en
20: end if
              end for
```

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Simulation Algorithm based on observations 2

1: for $i \in \{2, ..., m\}$ do 2: 3: 4: 5: {Interval I;} $R \leftarrow l_i$ if $n_i > 0$ then for $i \in I_1$ do draw \tilde{T}_{j} : log $(U_{j}) + \int_{\tau_{i-1}}^{t_{j}} \lambda(s) \exp\left(\beta Z(s) + \alpha \sum_{k \in B_{i}} C_{k}(s) Y_{k}(s)\right) ds = 0$ 6: 7: 8: end for $h \leftarrow \operatorname{argmin}_{i \in R} \tilde{T}_i$ {select the next comp. to fail} 9: $T_h \leftarrow \tilde{T}_h$ {store the next failure times} 10: if $n_1 > 1$ then 11: for $r \in \{2, ..., n_1\}$ do 12: $R \leftarrow R \setminus \{h\}$ {update the set of non-failed components in I_i } 13: for $i \in B_h \cap R$ do draw \tilde{T}_j : log(U_j) + $\int_{T_h}^{t_j} \lambda(s) \exp\left(\beta Z(s) + \alpha \sum_{k \in B_i} C_k(s) Y_k(s)\right) ds = 0$ 14: 15: 16: end for $h \leftarrow \operatorname{argmin}_{i \in R} \tilde{T}_i$ {select the next comp. to fail} 17: $T_b \leftarrow \tilde{T}_b$ {store the next failure times} 18: 19: 20: 21 end for end if end if end for

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Numerical Illustration

- inspection times are periodic, say $\tau_j = j\delta$ for some $\delta > 0$.
- $n = 20 \times 20$ components.
- simulations with a = 2, b = 3, $\alpha = 1$, K = 100 and $\delta = 0.1$.
- no covariate/no constraint:

$$\forall t \geq \mathbf{0}, \quad \lambda_{i,j}(t|\mathcal{H}_{t^-}) = \lambda(t) \exp\left(\alpha \sum_{(i',j') \in \mathcal{B}_{i,j}} Y_{i',j'}(t)\right).$$



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â	ĥ	$\hat{\alpha}$
2.206064	2.645539	1.019503

Future Work

 Constraint exerced at the center of the grid (e.g. n = 2p + 1) and diffused isotropically from the center as follows:

$$C_{i,j}(t) = \exp\left(-\frac{1}{\sigma^2}\left((i-p-1)^2+(j-p-1)^2\right)\right).$$

Application on real data