Discussion on Murali Haran's talk

- Dear Murali, thanks for the excellent talk !

- Dear Murali, thanks for the excellent talk !
- not a lot of “clever” comments on the method itself and how it is to be compared to other Bayesian reduction techniques ; more a series of questions.

- Dear Murali, thanks for the excellent talk !
- not a lot of "clever" comments on the method itself and how it is to be compared to other Bayesian reduction techniques ; more a series of questions.
- Would have expected more numerical comparisons with existing ones. Any conclusion from your experience ?

- Dear Murali, thanks for the excellent talk !
- not a lot of “clever” comments on the method itself and how it is to be compared to other Bayesian reduction techniques ; more a series of questions.
- Would have expected more numerical comparisons with existing ones. Any conclusion from your experience ?
- Computational cost : any gain when the grid of observations is regular ? when the link function is the canonical ;

- Dear Murali, thanks for the excellent talk !
- not a lot of “clever” comments on the method itself and how it is to be compared to other Bayesian reduction techniques ; more a series of questions.
- Would have expected more numerical comparisons with existing ones. Any conclusion from your experience ?
- Computational cost : any gain when the grid of observations is regular ? when the link function is the canonical ;
- Large-scale $n \approx 10,000$; many details on computational cost/details in terms of n and m. Behaviour in terms of p ? when p increases ?

- Dear Murali, thanks for the excellent talk !
- not a lot of "clever" comments on the method itself and how it is to be compared to other Bayesian reduction techniques ; more a series of questions.
- Would have expected more numerical comparisons with existing ones. Any conclusion from your experience ?
- Computational cost : any gain when the grid of observations is regular ? when the link function is the canonical ;
- Large-scale $n \approx 10,000$; many details on computational cost/details in terms of n and m. Behaviour in terms of p ? when p increases ?
- On a more philosophical side, how is the random projection robust to a wrong covariate ? (select covariates)

“Point process corner”

- **Random Projection** :
  - now quite a well-established technique ; randomizing rows or columns by subsampling, random projection matrix with iid elements (any reason for your choice ?)

"Point process corner"

- **Random Projection** :
  - now quite a well-established technique ; randomizing rows or columns by subsampling, random projection matrix with iid elements (any reason for your choice ?)
  - Link with point processes : to generate diversity/regularity : determinantal point processes ; discrete case has known some success in machine learning ;

“Point process corner”

- **Random Projection** :
  - now quite a well-established technique ; randomizing rows or columns by subsampling, random projection matrix with iid elements (any reason for your choice ?)
  - Link with point processes : to generate diversity/regularity : determinantal point processes ; discrete case has known some success in machine learning ;

- Clear possible **extension** : mixed models for spatial point processes.

“Point process corner”

- **Random Projection** :
  - now quite a well-established technique ; randomizing rows or columns by subsampling, random projection matrix with iid elements (any reason for your choice ?)
  - Link with point processes : to generate diversity/regularity : determinantal point processes ; discrete case has known some success in machine learning ;

- Clear possible **extension** : mixed models for spatial point processes.
  - Given $\mathbf{W}$, $\log \rho(u; \beta, \mathbf{W}) = X\beta + \mathbf{W}$ ($\approx$ intensity of a LGCP)

“Point process corner”

- **Random Projection** :
  - now quite a well-established technique ; randomizing rows or columns by subsampling, random projection matrix with iid elements (any reason for your choice ?)
  - Link with point processes : to generate diversity/regularity : determinantal point processes ; discrete case has known some success in machine learning ;

- Clear possible **extension** : mixed models for spatial point processes.
  - Given $\mathbf{W}$, $\log \rho(u; \beta, \mathbf{W}) = X\beta + \mathbf{W}$ ($\approx$ intensity of a LGCP)
  - Given $\mathbf{W}$, Bermann-Turner approximation ($\int_D \approx \sum_{G \cup \mathrm{data}}$) brings the problem to a (weighted Poisson regression) ;