CONTRIBUTIONS

We propose a scalable structured variational inference algorithm for continuous sigmoidal Cox processes: (STVB).

- Scalable inference in continuous input spaces via a process superposition.
- Efficient structured posterior estimation giving a posterior capturing the complex variable dependencies in the model.
- State-of-the-art performance when compared to alternative inference schemes, link functions, augmentation schemes and representations of the input space.

The Likelihood Function

Discrete likelihood:
\[ p(Y|\lambda) = \prod_{t=1}^{n} \text{Poisson}(y_t; \lambda(t)) \]

Continuous likelihood:
\[ L(N; (x_1, \ldots, x_n); \lambda) = \exp \left( - \int \lambda(x) \, dx \right) \prod_{i=1}^{n} \lambda(x_i) \]

Augmentation via superposition

\[ \lambda(x) = \sum_{k=1}^{K} \lambda_k(x) \]

AUGMENTATION

\[ q(\theta, \lambda) = \sum_{k=1}^{K} q(\theta_k, \lambda_k) \]

We have expressions for \( T_{ij} = 1, \ldots, n \) that avoid sampling from the full posterior and computing the gradient on the stochastic locations.

Time complexity: \( O(N^2) \)

Space complexity: \( O(K^2) \)

KEY REFERENCES


FUTURE RESEARCH

- Test the algorithm in higher dimensional settings.
- Develop a scalable fully structured variational inference scheme by relaxing the factorization assumption in the posterior.

MORE INFORMATION

Python Code: https://github.com/VirgilSTVB

APPLICATION I: NEURAL DATA

STVB
MFVB
VBPP
Neuronal Data
Neuronal data
\[ \mathbb{P}(y|x; \theta) = \prod_{i=1}^{n} \text{Poisson}(y_i; \lambda(x_i)) \]

APPLICATION II: TAXI DATA

STVB
MFVB
VBPP
Taxi Data
Taxi data
\[ \mathbb{P}(y|x; \theta) = \prod_{i=1}^{n} \text{Poisson}(y_i; \lambda(x_i)) \]

APPLICATION III: SPATIO-TEMPORAL TAXI DATA

STVB
MFVB
VBPP
Spatio-temporal Taxi Data
Spatio-temporal data
\[ \mathbb{P}(y|x; \theta) = \prod_{i=1}^{n} \text{Poisson}(y_i; \lambda(x_i)) \]