**Dynamic modeling of spike count data with non-Poisson variability**

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# Abstract

# Introduction

Drift…

(Rokni et al. 2007)

(Chestek et al. 2007)

(Stevenson et al. 2011)

(Tomko and Crapper 1974)

Stability…

(Dickey et al. 2009)

(Steinmetz et al. 2021) [shows that correcting for electrode drift reduces some instability]

[some amount of drift is functional] adaptation/plasticity…

(Lesica et al. 2007)

Variability…

(Ghanbari et al. 2019)

(Stevenson 2016)

(Fenton and Muller 1998)

(Barbieri et al. 2001)

(Maimon and Assad 2009)

(Churchland et al. 2010)

(Churchland et al. 2011)

(Eden et al. 2004)

(Brown et al. 2001)

(DeWeese and Zador 1998)

# Methods

[It’s helpful to add a couple sentences at the beginning here to explain/remind readers of the goal… e.g. Here we consider a dynamic GLM with Conway-Maxwell Poisson observations to describe time-varying spike counts. We first introduce the model, then inference…]

## Dynamic Conway-Maxwell Poisson Model

Denote the spike counts of neuron at time bin as , for The spikes follow Conway-Maxwell Poisson (CMP) distributions component-wise, with parameters and . The probability mass function (pmf) of CMP is

, where is the normalizing constant. The parameter controls different dispersion patterns, i.e. equi- (), over- () or under-dispersion (). Three common distributions occur as special cases: (1) the Poisson (), (2) geometric () and (3) Bernoulli ().

The CMP parameters at are modeled by two log-linear models, and , with and .The state vector is assumed to progress linearly with a Gaussian noise, .

In summary, the neurons follow CMP distributions independently, conditioning on state vector .

The state vector evolves linearly:

In this paper, we set for convenience.

## Inference by Gaussian approximation

To fit the model to data we need to estimate the time-varying state vector In this section, we first assume **F** and **Q** are known. Since the observations are CMP distributed, we cannot estimate in closed form. Instead, here we approximate it by a multivariate Gaussian distribution, , with . The parameters of this Gaussian are found by a global Laplace approximation, i.e., and . The log-posterior is given by:

, where is the log-likelihood. The log-posterior is concave (Gupta et al. 2014), and the Markovian structure of the state vector dynamics makes it possible to optimize by Newton-Raphson (NR) in time (Paninski et al. 2010). After the Newton update, we can further quantify the uncertainty for the CMP parameters and the underlying rates (see Appendix).

There are several technical challenges involved with performing the Newton update with CMP observations. Firstly, in order to find the gradient and Hessian we need to calculate moments of and , which have no closed forms (cite Minka/Shmueli?). These moments are generally calculated by truncated summation, and when and , truncated summation is computationally costly, since we need many steps for accurate approximation. However, these moments can be efficiently approximated using previous [cite approximations] asymptotic results (see Appendix). A second challenge is that the Hessian is not robust to outliers (see Appendix). However, using Fisher scoring where we replace the observed information by the expected information, we can ensure robustness. This modification sacrifices some efficiency, but results in…. Finally, a third challenge is that the Newton updates take a long time to converge if the initial state estimate is far from the maximum of the posterior, especially when is large. To resolve this issue, we use a smoothing estimate with local Gaussian approximation as a “warm start”. The forward filtering stage for Poisson case is derived in the appendix of (Eden et al. 2004), and we can implement CMP filtering following the same rationale.

[add equations for updates here?]

Although doing smoothing is fast, the estimations will be biased too much for large dynamics. In the forward filtering stage, the Gaussian approximation at each step is conducted locally at the recursive prior . This will be statistically inefficient when recursive prior is too far away from the posterior mode, or when there is a huge “jump” in the state vector. Moreover, using Fisher scoring for robustness makes the algorithm even less efficient. In this case, it is essential to do global Laplace approximation by NR.T

## Robust and quick estimation

For the applications to neural data examined here, we assume that . However, we still need to estimate the process noise . When is small, especially when , different values will have a substantial influence on estimation. One possible way to estimate is to use Expectation Maximization (cite). However, using the Laplace approximation for at E-step breaks the usual guarantee of non-decreasing likelihoods in EM, and, hence, may lead to divergence. This problem is even exacerbated for CMP distribution. To avoid that, we can sample posteriors directly by MCMC. However, the lack of closed-form moments for the CMP distribution makes sampling computationally intensive. Here, to estimate the robustly and quickly, we assume is diagonal and estimate it by maximizing the prediction likelihood in the filtering stage, as in (Wei and Stevenson 2021).

## Neural Data

[need to add section here with description and citations for V1 and HC data, similar to Neural Comp paper or can also look at the J Comp Neuro CMP paper. This should also include details on and ]

# Results

## Figure 1

Code: [figure1\_singleNu\_dirShift.m](https://github.com/weigcdsb/COM_POISSON/blob/main/demo/figure1/figure1_singleNu_dirShift.m)



Simulation settings: 100 directions from 0 to 1 rad. 100 trials. is modeled by with 10 knots, , i.e., over- to under- dispersion.



## Simulation

TBD…

Q optimization (Do we need this? It has been illustrated in SMOOTH-GBLM, and it’s shouldn’t be the focus of this paper)

|  |  |  |  |
| --- | --- | --- | --- |
| Heatmap | Q\_lam  Y = estimated log10(Q\_lam)  X = true log10(Q\_lam)  Color: yellow = small Q\_nu; black = large Q\_nu | Q\_nu  Y = estimated log10(Q\_nu)  X = true log10(Q\_nu)  Color: purple = small Q\_lam; black = large Q\_lam | fitting |
| Chart  Description automatically generated | Chart, scatter chart  Description automatically generated | Chart, scatter chart  Description automatically generated | Graphical user interface  Description automatically generated with low confidence |

## Application

V1 data

Code: [v1\_comparison\_nan.m](https://github.com/weigcdsb/COM_POISSON/blob/main/demo/v1/v1_comparison_nan.m); [compare\_all\_na.m](https://github.com/weigcdsb/COM_POISSON/blob/main/demo/v1/compare_all_na.m); [demo\_v1\_pd.m](https://github.com/weigcdsb/COM_POISSON/blob/main/demo/v1/demo_v1_pd.m)



Hippocampus data

Code: [hc\_comparison\_v2.m](https://github.com/weigcdsb/COM_POISSON/blob/main/demo/hc/hc_comparison_v2.m);



Should we separate the direction (-200 ~ 200) or ignore the direction (0 ~ 200)? I prefer to use -200 ~ 200 (left plot) rather than the right one. Since the direction is different, the (empirical) mean and FF should be separated.

# Discussion

Omitted variables can increase the apparent variability of observations via the law of total variance. For example, in the hippocampus, place cell firing is highly variable on different passes through the field (cite Fenton). This may be partially due to joint selectivity to position, speed, and head direction, as well as the influence of theta phase. Here, rather than model these distinct covariates assuming Poisson observations, we allow the variability to be non-Poisson.

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# Appendix

## Approximation of moments for Conway-Maxwell Poisson distribution

In order to efficiently estimate the state-vector for the dynamical CMP model, we make use of a previous for the pmf . Assume and , let , and

Then the moments are (The highlights can be found in the reference, the covariance is calculated by myself):

Here we use this approximation when … and use a truncated summation otherwise.

## Gradient and Hessian of the log-posterior

We estimate the state vector by maximizing the log-posterior with Newton-Raphson updates. Denote and .

[add basic equation for NR updates?]

The gradient:

, where , and .

The Hessian:

, where

When , the Hessian may be ill-conditioned or even positive-definite. Because of the factorial, the “outliers” are common. To ensure the robustness, do Fisher scoring, i.e. replace the observed information by the expected information , so that .

## Quantifying Uncertainties

After convergence, we have an approximation of the log-posterior , and we can use this approximation to quantify the state uncertainty as well as uncertainty about the mean rate at each time.

To find the state uncertainty, let , then .

Then to find the uncertainty in the conditional mean rate , we need the covariance matrix of the CMP parameters at time can be calculated by property of multivariate log-normal distribution. The conditional mean firing rate, is , whose variance can be calculated by the Delta method:

We can calculate the moments as in the first section of the appendix, or we can use a simpler approximation when or . Then and .