# General Form

Since we are now interested in dispersion, we need our time bin be large enough to allow multiple spikes. And we also need independent observations. Denote the number of spikes at step in neuron be and all observations at step as

If we only allow be 1 or 0, then the distribution is forced to be Bernoulli or approximately Poisson because of small intervals.

Denote and . Similarly, for , , and .

Then the likelihood is:

, where

And the log-likelihood is:

Then follow the same rationale as (A.3) in Eden’s paper:

Take log in both sides:

Differentiate once and twice with respect to (notice ):

Evaluating these 2 derivatives at yields:

OK, let’s deal with and

Denote the common expectation and variance at step as and .

As known from COM-Poisson: and . Notice that . Then,

Plug these in:

When and , then this is exactly as derived in Eden’s paper.

OK, the final piece is to deal with and . Just from Wikipedia, and

To summarize:

Well, it looks daunting… But if we implement it in the context of linear regression, things will be better

# In Context of Linear Regression

Let

Then , , and

That makes the filter looks cleaner…

To summarize:

# Numerical Summation

Since is generally small, numerical approximation of , and should be done in the first few terms. For example, we can calculate as follows:

function sum1 = Z\_calc(lam, nu, n)

termlim = 1e-6;

sum1 = 0;

for js = 1:n

term = exp(log(lam^(js-1)) - nu\*gammaln(js));

if(js > 3)

if((term/sum1) < termlim)

break

end

end

sum1 = sum1 + term;

end

end