# 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 .

Then the likelihood is:

, where

And the log-likelihood is:

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

Take log on 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 , . **(I just noticed that , and this will give a more intuitive expression. Will do later.)** Then,

Plug these in:

**(Just notice that this can rewrite as:**

**Actually, we can write it in a more compact way. For n i.i.d. general COM-Poisson, If we define .**

**And**

**Will give a more compact expression later…**

**)**

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

OK, now we need to deal with , , , and .

From Wikipedia: , and

To save notations when doing derivation, temporarily denote and

To further simplify notations, let

, , , and .

Then,

, ,

, and

To summarize:

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

# In Context of Linear Regression

Let

Then , , and

That makes the filter looks cleaner…

To summarize: