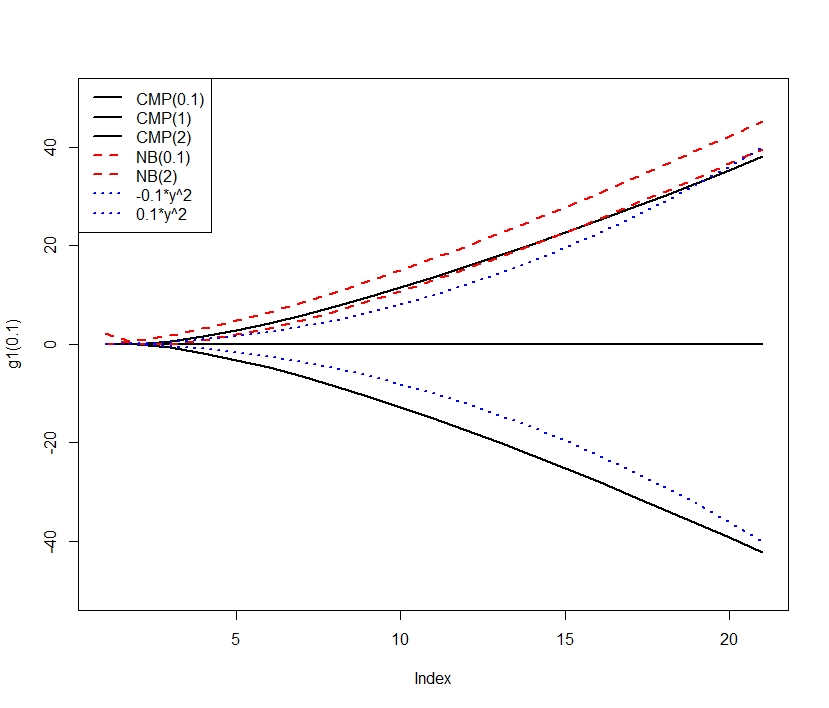
Generalized count distribution

Different from Gao et el., I don’t include intercept into . Actually, I firstly consider things more general than linear regression form, i.e. is not necessarily .

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Support | pdf |  |  |
| Binomial |  |  |  |  |
| Negative Binomial |  |  |  |  |
| Poisson |  |  |  |  |
| COM-Poisson |  |  |  |  |

Plot against y:



It seems that can approximate well (capture different convexity for ). Will discuss it later.

OK, general derivation:

Denote and define dispersion parameter as . Therefore and denote .

So the general filtering:

Further, denote . is a function that only depends on .

OK, let’s deal with and . As previous

Let’s do it piece by piece:

1.

Generally, for nearly any real-valued () function . Denote , then and

Then,

Since,

and ,

Therefore,

2.

Generally, for nearly any real-valued () functions and .

Since are independent on each other.

In our case, all are first order,

OK, let’s plug in and

By

We can get:

OK, finally,

And for each special case:

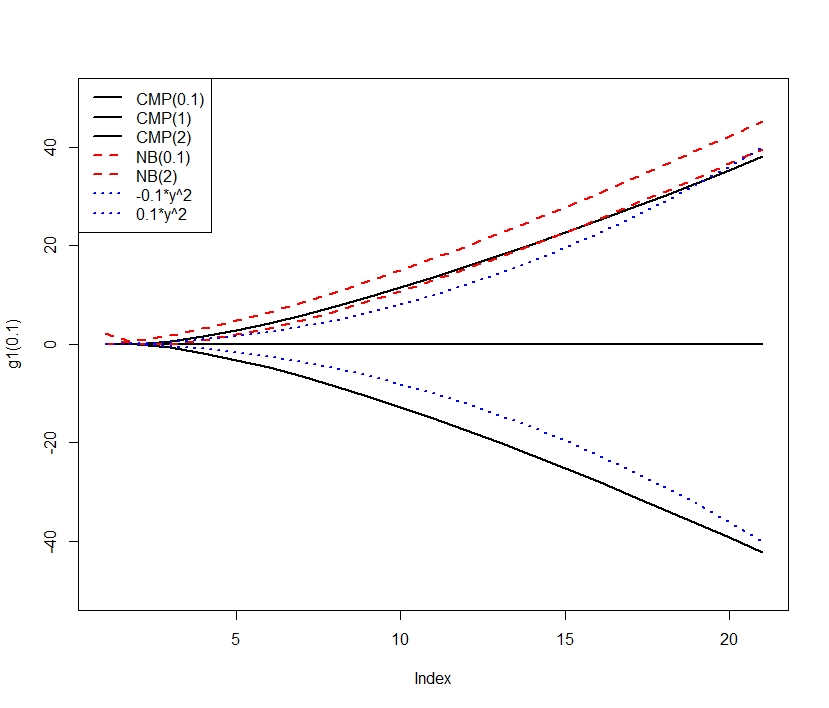
|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  |  |  |  |  |  |
| Binomial |  |  | 0 | 0 | 0 |
| Negative Binomial |  |  |  |  |  |
| Poisson |  |  | 0 | 0 | 0 |
| COM-Poisson |  |  |  |  |  |

Fisher scoring version:

The moment may be evaluated numerically, if there’s no closed form.

Approximation by 2nd order polynomial:

Motivated by this:



Let and , then .

Then the Fisher-scoring filter is:

In the context of linear regression: