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Derivation of a scaled binomial as an instance of a general discrete exponential distribution

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The family of discrete distributions having the form

$$f(y) = N p^{by-a} (1-p)^{dy-c} \quad (1)$$

where N is a normalization dependent upon a, b, c, and d.

(1) is a type of general exponential distribution containing several notable cases:

	a	b	c	d	->	f(y)
Bernoulli	0	1	-1	-1		$p^y(1-p)^{1-y}$
Binomial	0	1	-n	-1		$p^y(1-p)^{n-y}$
Geometric	-1	0	0	1		$p(1-p)^y$
Neg. Binomial	-1/k	0	0	1		$p^{1/k}(1-p)^y$

The negative binomial k is taken as the inverse of r (Hilbe 1994)

As a generalized exponential (1) becomes

$$\begin{aligned} f(y) &= \exp\{ (by-a)\ln p + (dy-c)\ln(1-p) + \ln(N) \} \\ &= \exp\{ y(b\ln p + d\ln(1-p)) - (a\ln p + c\ln(1-p)) + \ln(N) \} \\ &= \exp\{ y\theta - g(\theta) + \ln(N) \} \end{aligned}$$

where $\theta = b\ln p + d\ln(1-p)$, and
 $g(\theta) = a\ln p + c\ln(1-p)$

$\mu = g'(\theta) = dp/d(\theta) * d(g)/dp$ using the chain rule

Hence

$$\begin{aligned} 1) \quad d(\theta)/dp &= b/p + d/(1-p) \\ &= \{b(1-p) + dp\} / \{p(1-p)\} \\ &= (b-bp+dp) / \{p(1-p)\} \\ &= \{b-(b+d)p\} / \{p(1-p)\} \end{aligned}$$

$$\text{therefore } dp/d(\theta) = \{p(1-p)\} / \{b-(b+d)p\}$$

$$\begin{aligned} 2) \quad d(g)/dp &= a/p - c/(1-p) \\ &= \{a(1-p) - cp\} / \{p(1-p)\} \\ &= (a-ap-cp) / \{p(1-p)\} \\ &= \{a-(c+a)p\} / \{p(1-p)\} \end{aligned}$$

therefore

$$\begin{aligned} \mu = g'(\theta) &= \{p(1-p)\} / \{b-(b+d)p\} * \{a-(c+a)p\} / \{p(1-p)\} \\ &= \{a-(c+a)p\} / \{b-(b+d)p\} \end{aligned}$$

$$V = g''(\theta) = dp/d(\theta) * d(g')/dp = \{p(1-p)\}/\{b-(b+d)p\} * d(g')/dp$$

$$\text{Solving } d(g')/dp = (ad-bc)/\{b-(b+d)p\}^2$$

therefore

$$\begin{aligned} V &= \{p(1-p)\}/\{b-(b+d)p\} * (ad-bc)/\{b-(b+d)p\}^2 \\ &= \{p(1-p)(ad-bc)\}/\{b-p(b+d)\}^3 \end{aligned}$$

Summarizing, the generalized discrete exponential formulae for μ and V are:

$$\mu = \frac{a-(c+a)p}{b-(b+d)p} \qquad V = \frac{p(1-p)(ad-bc)}{\{b-p(b+d)\}^3}$$

with θ , the canonical link, as $b \ln p + d \ln(1-p)$

Testing these formulae for known members of the family:

i. Bernoulli $a=0; \quad b=1; \quad c=-1; \quad d=-1$

$$\mu = p \qquad V = p(1-p)$$

ii. Binomial $a=0; \quad b=1; \quad c=-n; \quad d=-1$

$$\begin{aligned} \mu &= np/\{1-(0)p\} = np \\ V &= \{p(1-p)n\}/1 = np(1-p) \end{aligned}$$

iii. Geometric $a=-1; \quad b=0; \quad c=0; \quad d=1$

$$\begin{aligned} \mu &= \{-(1-p)\}/-p = (1-p)/p \\ V &= \{p(1-p)(-1)\}/(-p)^3 = (1-p)/p^2 \end{aligned}$$

iv. Negative binomial $a=-1/k; \quad b=0; \quad c=0; \quad d=1$

$$\begin{aligned} \mu &= \{(-1/k)-(-p/k)\}/-p = (-1/k+p/k)/-p = (1-p)/kp \\ V &= \{p(1-p)(-1/k)\}/(-p)^3 = (1-p)/kp^2 \end{aligned}$$

A scaled binomial distribution that is a member of the exponential family can be derived as follows:

$$\text{let } \mu = np \quad \text{and} \quad V = np(1-p)(1+k)$$

Such properties should allow modeling of overdispersed binomial models; eg overdispersed logistic regression.

Setting $a=0$; $b=1$; $c=-n$; $d=-1$, we have, as in the standard binomial,

$$\mu = np = a - (c+a)p$$

and given that, for the binomial, $d=-b$

Since $d = -b$, $c/b=-n$, and $c=-nb$, we can formulate the desired distribution as:

which is simply the binomial with b as a multiplicative factor,

$$\begin{aligned} f(y)_{sb} &= N p^{by-a} (1-p)^{dy-c} \\ &= N p^{by} (1-p)^{-by-c} \\ &= N p^{by} (1-p)^{-by+nb} \\ &= N p^{by} (1-p)^{bn-by} \\ &= N p^{by} (1-p)^{b(n-y)} \end{aligned}$$

Depending on the choice of b , there is a different variance:

$$V = \frac{p(1-p)(-bc)}{(b)^3} = \frac{p(1-p)(-b*-nb)}{b^3} = \frac{p(1-p)(nb^2)}{b^3} = \frac{np(1-p)}{b}$$

Since we wanted $V = np(1-p)(1+k)$ then $b=1/(1+k)$, giving

$$f(y) = N p^{y/(1+k)} (1-p)^{(n-y)/(1+k)}$$

Multiplying p by n gives p . Hence, the inverse link has n as a numerator for grouped data models.

The correct normalization may be found by scaling the variable terms of the binomial normalization by $1/(1+k)$. We do this since we want the binomial if $k=0$. Given

$$\text{Binomial } N = \frac{\Gamma(n+1)}{\Gamma(n-y+1)\Gamma(y+1)}$$

the scaled binomial normalization will appear as

Logistic overdispersion caused by heterogeneity may be accommodated by using a scaled binomial regression model. It is assumed that the ratio of observed to expected counts is a random variable with a mean of 1.0. The scaled binomial family, allows a meaningful interpretation of the parameters.

$$\text{Scaled Binomial} = \frac{1}{1+k} \frac{\Gamma\{n/(1+k) + 1\}}{\Gamma\{(n-y)/(1+k)+1\}\Gamma\{y/(1+k)+1\}}$$

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The full scaled binomial probability density function is then

$$f(y)_{sb} = \frac{1}{1+k} \frac{\Gamma\{n/(1+k) + 1\}}{\Gamma\{(n-y)/(1+k)+1\}\Gamma\{y/(1+k)+1\}} p^{y/(1+k)} (1-p)^{(n-y)/(1+k)}$$

Recalling the general form canonical link

$$\theta = b \ln p + d \ln(1-p)$$

and given that, for the scaled binomial, $d = -b$

$$\begin{aligned}\theta &= b \ln p - b \ln(1-p) \\ &= b \ln(p/(1-p))\end{aligned}$$

which is simply the binomial link with b as a multiplicative factor.

It follows that the inverse link, in terms of p , can be derived as:

$$\begin{aligned}\theta &= b \ln(p/(1-p)) \\ \theta/b &= \ln(p/(1-p)) \\ \theta(1+k) &= \ln(p/(1-p)) \\ e^{\theta(1+k)} &= p/(1-p) \\ e^{-\theta(1+k)} &= (1-p)/p \\ e^{-\theta(1+k)} &= 1/p - 1 \\ 1 + e^{-\theta(1+k)} &= 1/p \\ 1/(1 + e^{-\theta(1+k)}) &= p\end{aligned}$$

Hence

$$p = \frac{1}{1 + e^{-\theta(1+k)}} \quad \text{or} \quad \frac{1}{1 + e^{-\eta(1+k)}}$$

Multiplying p by n gives μ . Hence, the inverse link has n as a numerator for grouped data models.

In terms of the table on the first page, the exponential properties of p in the pdf may be summarized as:

	a	b	c	d	f(y)
Scaled Binomial	0	$1/(1+k)$	$-n$	-1	$p^{y/(1+k)} (1-p)^{(n-y)/(1+k)}$

Logistic overdispersion caused by heterogeneity may be accommodated by using a scaled binomial regression model. k is adjusted such that the χ^2 dispersion approximates 1.0. Unlike many quasiliikelihood models, the scaled binomial, as a full member of the exponential family, allows meaningful interpretation and full use of related diagnostics.

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