Thomas W. Yee

*Figures from “Vector Generalized Linear and Additive Models: With an Implementation in R”

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Thomas Yee
Auckland, New Zealand
November 2015

Some, imagining they can best commend themselves to the Eternal by means of statues, are eagerly desirous of them, as if they were certain to obtain more reward from brazen figures unendowed with sense, than from the consciousness of duties honourably and uprightly performed.
—Ammianus Marcellinus
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<.plot>

Fig. 10.2 Expansion of Fig. 10.1(b) with a least squares line added to each subset.

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250 random vectors generated from a standard bivariate normal distribution, with various values of $\rho$. 

Fig. 13.1 250 random vectors generated from a standard bivariate normal distribution, with various values of $\rho$. 

$\rho = 0.9$
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(a) Fitted functions $\hat{f}(x_2)_{12}$ in (15.20) overlaid, with pointwise ±2 SE bands.
(b) Same as Fig. 15.7(b) except the quantiles (purple curves) are constrained to be parallel on the $\eta$-scale (log scale here). The actual sample proportion lying below the curves are 36.4 and 78.4 percent.

Fig. 15.8
The quantiles are positive, nonparallel and noncrossing. Here, $\tau$ has values $0.2(0.1)0.9$. (b) A zoom-in view of the LHS of (a).

Then Fig. 15.9(a) was produced by
Fig. 15.10 (a)–(c) Density plots of expectile derived $g$ (orange solid lines; (15.30)) for the original $f$ of standard normal, standard uniform and standard exponential distributions (blue dashed lines). (d) Illustration of the interpretation of expectiles in terms of centres of balance, the hollow triangles at positions $c_1$ and $c_2$. Here, the vertical dashed line is at the 0.1-expectile, the solid triangle at $\mu(\omega = 0.1)$, which means that (15.33) is satisfied with $\omega = 0.1$. 

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Fig. 15.11 ‘Quantile’ plot from `amlnormal()` applied to `women.eth0`: 5, 25, 50, 75, 95 ‘percentile’ curves. Each regression curve is a regression spline with 3 degrees of freedom (1 = linear fit).
Fig. 15.12  Quantile plot from an \texttt{amlpoisson()} fit using simulated data. The dashed step functions are the \texttt{qpois()} quantiles calibrated with the true mean function and the proportion under the expectile curves. The response has been jitted to aid clarity.
Fig. 15.13 (a) Melbourne maximum temperature data, called `melbmaxtemp`, in °C. (b) Onion method using `qalnormal()` expectiles applied to the data with an assortment of \( w_j \) values. The sample proportions below the curves are 1, 4.8, 20.2, 54.9, 65.2, 74.8, 82.7, 88.2, 91.7, 94.8 percent.
Chapter 16
Figures from Vector Generalized Linear and Additive Models: With an Implementation in R
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Fig. 16.1 GEV densities for values $\mu = 0$, $\sigma = 1$, and $\xi = -\frac{1}{3}, 0, \frac{1}{3}$ (Weibull-, Gumbel- and Fréchet-types respectively). The orange curve is the CDF, the dashed purple segments divide the density into areas of $\frac{1}{10}$. The bottom RHS plot has the densities overlaid.
Fig. 16.2  GPD densities for values $\mu = 0$, $\sigma = 1$, and $\xi = -\frac{1}{3}$, 0, $\frac{1}{3}$ (beta-, exponential- and Pareto-types, respectively). The orange curve is the CDF, the dashed purple segments divide the density into areas of $\frac{1}{10}$. The bottom RHS plot has the densities overlaid.
Fig. 16.3 Gumbel plot of the two highest annual sea levels of the Venice data (*venice*).
Fig. 16.4 Intercept-only GEV model fitted to the \textit{portpirie} annual maximum sea levels data. (a) Scatter plot, and the dashed horizontal lines are the resulting 95\% and 99\% quantiles. (b) Probability plot. (c) Quantile plot. (d) Density plot. (e)–(f) Return level plots, with slight changes in the $x$-axis labelling.
Fig. 16.5 VGAM fitted to the Venice sea level data (fit1).
Fig. 16.6  (a) Quantile plot of the Venice sea level data (fit2). (b) Venice data overlaid with the fitted values of fit3. This model underfits.
Fig. 16.7  (a) The fitted 99 percentile of fit2 and the 99 percentile data values (4th highest sea level each year). (b) Fitted median predicted value (MPV) of the Venice sea level data from fit2. The points are the highest sea levels for each year.
Fig. 16.8  The rain daily rainfall data. (a) Scatter plot. (b) Mean excess plot.
Fig. 16.9 Intercept-only GPD model fitted to the rain daily rainfall data. (a) Scatter plot, with the solid black horizontal line denoting the threshold at 30. The dashed horizontal lines are the resulting 90% and 99% quantiles. (b) Probability plot. (c) Quantile plot. (d) Density plot.
Fig. 17.1 Decision tree diagram for (a) zero-alteration versus (b) zero-inflation. They depict (17.4) and (17.7) respectively. Here, $Y^*$ corresponds to a parent distribution such as the binomial or Poisson, and $Y$ is the response of interest. The probabilities $\omega$ and $\phi$ dictate the decisions.
Fig. 17.2  Probability functions of a (a) zero-inflated Poisson with $\phi = 0.2$, (b) zero-deflated Poisson with $\omega = -0.035$. Both are compared to their parent distribution which is a Poisson($\mu = 3$) in orange.
Fig. 17.3 Estimated component functions for the `deernice` VGAM.
Capture probability estimates with approximate ±2 pointwise SEs, versus wing length with (blue) and without (orange) fat content present fitting a $\mathcal{M}_b$-VGAM, using the prinia data.
Appendix A

Figures from Vector Generalized Linear and Additive Models: With an Implementation in R

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Fig. A.1  The first few Newton-like iterations for a Poisson regression fitted to the V1 data set. The solid orange curve is $\ell(\theta)$ with $\theta = \mu$. The initial value is $\theta^{(1)} = 0.2$. Each iteration $\theta^{(a)}$ corresponds to the maximum of the quadratic (dashed curves) from the previous iteration.
Fig. A.2 Negative binomial $\text{NB}(\mu, k)$ distribution fitted to the machinists data set. The $y$-axis is $\ell$. Let $\theta = k$ and $\theta^* = \log k$. (a) $\ell(\theta)$ is the solid blue curve. (b) $\ell(\theta^*)$ is the solid blue curve. Note: for $H_0 : \theta = \theta_0$ (where $\theta_0 = \frac{1}{3}$), the likelihood-ratio test, score test and Wald test statistics are based on quantities highlighted with respect to $\ell$. In particular, the score statistic is based on the tangent $\ell'(\theta_0)$. 
References