

STATA NASUG 2001

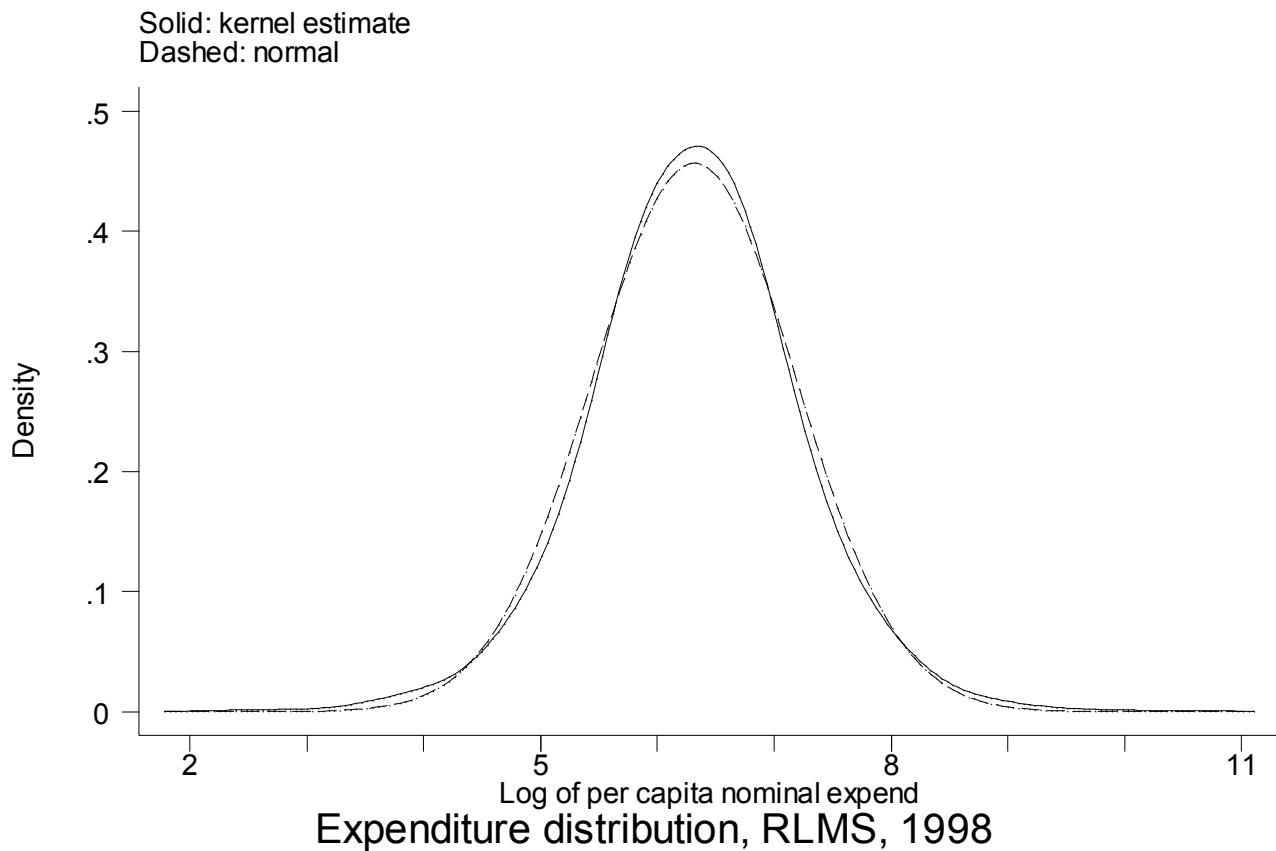
Decomposition of normal mixture by maximum likelihood: denormix package

Stanislav Kolenikov

*University of North Carolina at Chapel Hill
Center for Economic and Financial Research, Moscow,
Russia*

Financial support from EERC (Eurasia Foundation)
and EPA is gratefully acknowledged.

Motivation



Income distribution analysis:

- The distribution is a mixture of lognormal components (?)
- Transition: changes in labor demand
⇒ discrete mixture

Likelihood function

$$f(x | \theta) = \sum_{k=1}^K \phi_k \frac{1}{\sqrt{2\pi\sigma_k^2}} \exp\left[-\frac{(x - \mu_k)^2}{2\sigma_k^2}\right]$$

$$\theta = (K, \mu_1, \sigma_1^2, \phi_1, \mu_2, \sigma_2^2, \phi_2, \dots), \quad \sum_{k=1}^K \phi_k = 1$$

Constant variance version: $\sigma_1^2 = \sigma_2^2 = \dots$

References

Day, N. E. Estimating the components of a mixture of normal distributions.

Biometrika, **56** (3), 463–474 (1969)

Hathaway, R. A Constrained Formulation of Maximum-Likelihood

Estimation for Normal Mixture Distributions. *Ann. Stat.*, **13** (2), 795–800
(1985)

Basford, K. E., G. J. McLachlan. Likelihood Estimation with Normal
Mixture Models. *Appl. Stat.*, **34**, 282–289 (1985)

Kiefer, J., J. Wolfowitz. Consistency of the Maximum Likelihood Estimator
in the Presence of Infinitely Many Incidental Parameters. *Ann. Math.
Stat.*, **27**, 887–906 (1956)

Difficulties

➤ Homo/heteroskedastic?

Heteroskedastic: ML estimate need not exist

Comparison? Models are non-nested...

➤ Number of components?

Likelihood ratio has an unusual distribution (estimation on the boundary?)

McLachlan, G. J. On bootstrapping the likelihood ratio test statistic for the number of components in a normal mixture. *Appl. Stat.*, **36**, 318–324 (1987)

Feng, Z. D., C. E. McCulloch. Using bootstrap likelihood ratios in finite mixture models. *J. of the Royal Stat. Soc.*, B, **58**, 609–617 (1996)

Information criteria (AIC, SBIC, ICOMP, whatever...)

Goodness of fit (Pearson χ^2 , Kolmogorov-Smirnov?)

Agha, M., D. S. Branker. Algorithm AS 317. Maximum Likelihood Estimation and Goodness-of-fit Tests for Mixtures of Distributions. *Appl. Stat.*, **46** (3), 399–407 (1997).

Syntax

help for **denormix**

Stas Kolenikov, skolenik@unc.edu

Univariate normal mixture decomposition

denormix varname [weight] [**if** exp] [**in** range],
[**level(#)** **noinit** **difficult** **chi2** **icomp** **loglevel(#)**
ncomp(#) **nmax(#)** **restart** **iterate(#)** **gtolerance(#)**
constr(var) **pathto(directory)** **descriptive** **delog**]

Description

denormix performs the decomposition of the varname distribution into the mixture of normals. In other words, it assumes that the true density is the weighted sum of normal densities (with possibly different means and/or variances), and estimates the parameters of such mixture by maximum likelihood.

Tricks

➤ Parameter transformations

To ensure numerical stability and maximization without constraints: $\sigma^2 \rightarrow \log(\sigma^2)$; $\phi \rightarrow \text{multinomial logit}(\phi)$

➤ Convergence

`gtol(1e-4)` recommended option

`error 430`: convergence not achieved

`diag0cnt(e(V))` : singularity of covariance matrix

`symeigen e(V)` : singularity of covariance matrix

Restart if no convergence is diagnosed

➤ Global macros

~10 global macros used: `loglevel`; `ml model statements`; etc.

```
if `loglev' <=1 { global NMDq1 qui }
else { global NMDq1 }
...
global NMD_mod $NMD_mod /m$NMD_n /lnV$NMD_n /lp$NMD_n
...
$NMDq1 ml model lf DeNorMix $NMD_mod ...
```

➤ Dynamic `ml model` definition

Separate `denormdo.do` run from the main `denormix.ado`

```
cap program drop DeNorMix
program define DeNorMix
    version 6
    args lf $NMD_par
    ...

```

Experience with real data

RLMS, 3600+ households; ~10 ths. individuals.

Results: “large errors” for heteroskedastic model; three components for homoskedastic model.

- Performance of Stata’s `m1` optimizer

Rescaling is great; `difficult` is also great.

- Computation speed

Might take several hours / several hundred iterations at my Pentium II 333 MHz. Suggestion: specify `iterate(200)` so as not to waste time.

- Multiple maxima

Yes, there are. If the number of components is greater than the “optimal” one, then you are bound to find 3-5-... maxima.

- Bad identification

Two or more components may stick together; most of the time diagnosed by the convergence tracker.

- Large samples curse

Sample sizes $1-3 \cdot 10^3$: χ^2 statistic is U-shaped wrt K .

Sample size 10^4 : χ^2 statistic is ≥ 50 .

Further development (?)

- prediction: densities, cdfs, discriminant analysis
- EM-type algorithm: update means & variances
 - update proportions

Peters, B. C. Jr., H. F. Walker. An Iterative Procedure for Obtaining Maximum-Likelihood Estimates of the Parameters for a Mixture of Normal Distributions. *SIAM J. of Appl. Math.*, **35** (2), 362–378 (1978).

Xu, L., M. I. Jordan. On Convergence Properties of the EM Algorithm for Gaussian Mixtures. *Neural Computation*, **8**, 129–151 (1996)

- graphical output
- penalized likelihood for difference in variances
- `constr(mean)` was thought of initially

VISIT MY STATA SITE

net from <http://www.komkon.org/~tacik/stata>

Large sample

weighted noinit: 9176 observations

Results with strata <1% are discarded (most of the runs with 4-5 components)

Smaller sample

3619 observations (1 outlier)

	initial	improve	Iteration 0	Last iteration	AIC	ICOMP	Chi2()	Prob	Freq	Components
1				(1)	3564.37	3565.68	65.55 (12)	0.000	always	Mode
2	-2727.33	-2093.25	-2000.10	-1730.96 (5/9)	3461.93	3473.32	43.27 (10)	0.000	5	Mode + R hump (<1%)
2	-2727.33	-1896.25	-1896.25	-1761.27 (6/9)	3522.53	3534.15	43.80 (10)	0.000	4	Mode + L hump (1.1%)
2									3	Mode^2
3	-2789.54	-1810.20	-1810.20	-1698.39 (6/7)	3396.78	3410.52	17.40 (8)	0.026	5	Mode + L hump (2.0%) + R hump (0.5%)
3	-2789.54	-1799.46	-1729.60	-1710.85 (8)	3421.71	3439.75	33.88 (8)	0.000	1	Mode + R hump (1.5%)+ outlier
3				-1730.96 -1761.27					4	Mode + hump^2 or Mode^2 + hump
4				-1698.39					6	Mode^2 + L hump (2.0%) + R hump (0.5%)
4	-2814.77	-2482.82	-1830.13	-1669.55 (6/24)	3339.09	3367.64	12.00 (6)	0.062	3	Mode + L hump (2.9%) + R hump (1.4%) + outlier
4	-2826.54	-2043.54	-1777.81	-1698.22 (8)	3396.44	3482.75	17.42 (6)	0.008	1	Mode + L hump (2.1%) + LL hump (<1%) + R hump (1.1%)
5	-2826.54	-2052.48	-1794.78	-1668.41 (7/8)	3336.82	3361.98	11.04 (4)	0.026	3	Mode + L hump (3.6%) + LL hump (0.1%) + R hump (1.4%) + outlier
5	-2826.54	-1912.52	-1900.05	-1667.17 (8/16)	3334.34	3361.70	9.22 (4)	0.056	2	Mode + R hump (3.1%) + L hump (3.2%) + RR hump (0.3%) + outlier
5				-1669.55					4	Mode^2 + L hump (2.9%) + R hump (1.4%) + outlier