

**TRAVELERS**

## Finite Mixtures for Insurance Modeling

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Palm Beach, Florida  
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2011 Spring Meeting

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### Outline - Finite Mixture Models (FMM)

- JMP 9 Distribution Platform – finite mixtures
- Interactive JMP Two-Component Normal mixture
- R – two packages - flexmix, gamlss
- SAS – Proc NL MIXED
- JMP's Nonlinear Platform
- STATA FMM module
- More Examples – Poisson counts, WC Losses

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### Outline - Finite Mixture Models (FMM)

- FMM Background

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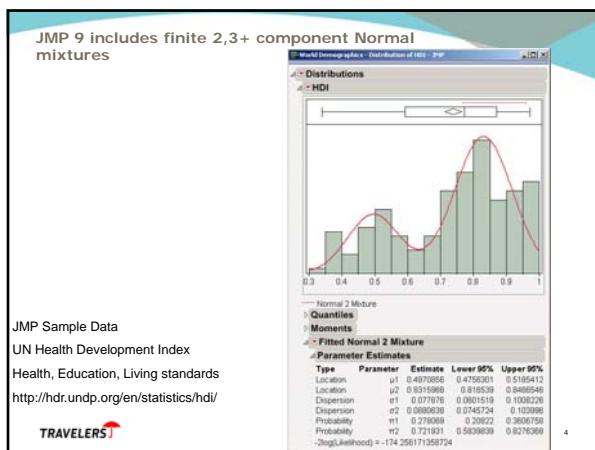
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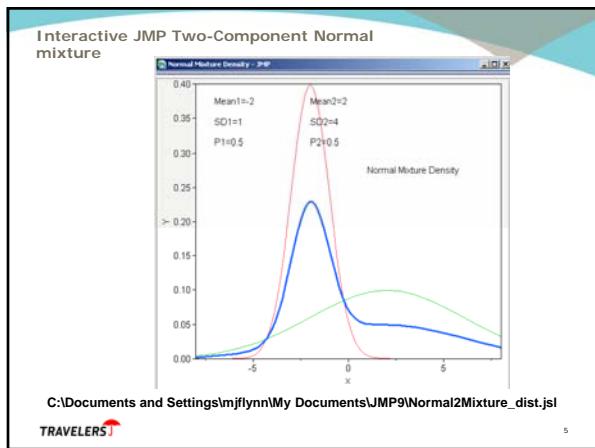
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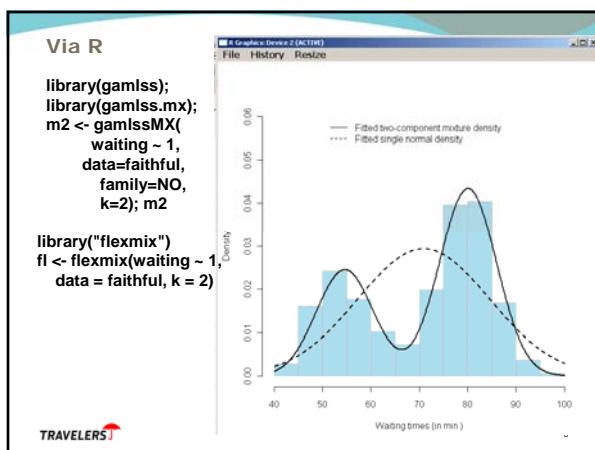
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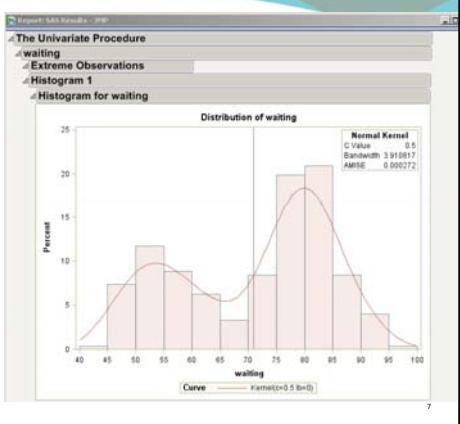


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Via SAS  
Proc  
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Via SAS – obtain starting values

```
/* two-component normal mixture */  
proc sql;  
select log(mean(waiting)-0.5*var(waiting)**0.5) as mu1start,  
       log(mean(waiting)+0.5*var(waiting)**0.5) as mu2start  
  into :mu1start, :mu2start  
     from faithful;  
quit;
```

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Via SAS – obtain starting values

```
/* two-component normal mixture */  
proc sql;  
select log(mean(waiting)-0.5*var(waiting)**0.5) as mu1start,  
       log(mean(waiting)+0.5*var(waiting)**0.5) as mu2start  
  into :mu1start, :mu2start  
     from faithful;  
quit;
```

Create SAS Macro  
variables – note:  
separation

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Via  
SAS

```

Proc NL MIXED data=faithful;
parms eta_mu1=&mu1start. eta_mu2=&mu2start. eta_sigma1=1.8
eta_sigma2=1.8 eta_p1=0.57 ;
mu1 = exp(eta_mu1);
mu2 = exp(eta_mu2);
sigma1 = exp(eta_sigma1);
sigma2 = exp(eta_sigma2);
p1 = exp(eta_p1)/(1 + exp(eta_p1));
p2 = 1 - p1;
y = waiting;

loglike = logpdf('NORMALMIX', y, 2, p1, p2, mu1, mu2, sigma1, sigma2) ;

model y ~ general(loglike);
estimate 'mu1' mu1; estimate 'mu2' mu2;
estimate 'sigma1' sigma1; estimate 'sigma2' sigma2;
estimate 'p1' p1; estimate 'p2' p2;
run;

```

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Via  
SAS

```

Proc NL MIXED data=faithful;
Starting values (from above)
parms eta_mu1=&mu1start. eta_mu2=&mu2start. eta_sigma1=1.8
eta_sigma2=1.8 eta_p1=0.57 ;
Log link functions
mu1 = exp(eta_mu1);
mu2 = exp(eta_mu2);
sigma1 = exp(eta_sigma1);
sigma2 = exp(eta_sigma2);
p1 = exp(eta_p1)/(1 + exp(eta_p1));
p2 = 1 - p1;
y = waiting;

Normal 2 – Component Finite
Mixture logLikelihood
loglike = logpdf('NORMALMIX', y, 2, p1, p2, mu1, mu2, sigma1, sigma2) ;
*loglike = logpdf('NORMAL', y, mu1, sigma1)*p1 +
(1 - p1)*logpdf('NORMAL', y, mu2, sigma2);

model y ~ general(loglike);
estimate 'mu1' mu1; estimate 'mu2' mu2;
estimate 'sigma1' sigma1; estimate 'sigma2' sigma2;
estimate 'p1' p1; estimate 'p2' p2;
run;

```

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Via SAS  
NL MIXED

The screenshot shows the SAS NL MIXED procedure output. It includes sections for Iteration History, Convergence Status, Fit Statistics, Parameter Estimates, and Additional Estimates. The Convergence Status section notes that the GCONV convergence criterion was satisfied. The Fit Statistics section provides values for -2 Log Likelihood, AIC, AICC, and BIC. The Parameter Estimates section lists estimates for eta\_mu1, eta\_mu2, eta\_sigma1, eta\_sigma2, eta\_p1, mu1, mu2, sigma1, sigma2, p1, and p2, along with their standard errors, DF, t Value, Pr > |t|, Alpha, Lower, and Upper bounds.

Parameter	Estimate	Error	DF	t Value	Pr >  t	Alpha	Lower	Upper	Gradient
eta_mu1	4.00031	0.01249	272	320.309	< .0001*	0.05	3.97572	4.02489	0.00938
eta_mu2	4.38316	0.00624	272	702.298	< .0001*	0.05	4.37088	4.39545	-0.0024
eta_sigma1	1.77008	0.09644	272	20.4776	< .0001*	0.05	1.59989	1.84024	-0.0012
eta_sigma2	1.76945	0.08821	272	25.9409	< .0001*	0.05	1.69517	1.89374	-0.0032
eta_p1	-0.5715	0.03021	272	-6.1314	< .0001*	0.05	-0.755	-0.388	-0.0002
mu1	54.615	0.86208	272	80.0712	< .0001*	0.05	53.2721	55.9676	
mu2	80.0911	0.49988	272	160.228	< .0001*	0.05	79.107	81.0752	
sigma1	5.87121	0.5075	272	11.5688	< .0001*	0.05	4.87208	6.87034	
sigma2	5.88785	0.40024	272	14.6604	< .0001*	0.05	5.07989	6.65581	
p1	0.36099	0.0215	272	16.7863	< .0001*	0.05	0.31850	0.40321	
p2	0.63911	0.0215	272	29.7276	< .0001*	0.05	0.59878	0.68144	

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Via JMP – nonlinear platform - setup

```

dt = Current Data Table();
// set up the negative log likelihood with
// starting values
ll <- new column("Normmix");
Exform = expr(
ll <- set formula(Parameter(
{ eta_mu1=4.160438,
eta_mu2=4.352785, eta_sigma1=1.8,
eta_sigma2=1.8, eta_p1=-0.57 },
mu1 = exp(eta_mu1);
mu2 = exp(eta_mu2);
sigma1 = exp(eta_sigma1);
sigma2 = exp(eta_sigma2);

p1 = exp(eta_p1)/(1 + exp(eta_p1));
p2 = 1 - p1;

-log(Normal Mixture Density( :waiting,
mu1 / mu2, sigma1 / sigma2, p1 / p2 ))
));
:TRAVELERS eval(eval Expr(exform));

```

Via JMP  
Nonlinear Platform

```

nl = Nonlinear(
Loss( :Normmix ),
Numeric Derivatives Only( 1 ),
Loss is Neg LogLikelihood( 1 ),
QuasiNewton BFGS,
Finish,
Custom Estimate( exp(eta_mu1) ),
Custom Estimate( exp(eta_mu2) ),
Custom Estimate( exp(eta_sigma1) ),
Custom Estimate( exp(eta_sigma2) ),
Custom Estimate(
exp(eta_p1)/(1 + exp(eta_p1) ) ,
Custom Estimate(
1 - exp(eta_p1)/(1 + exp(eta_p1)) ,
);

```

Via JMP  
Nonlinear Platform  
output

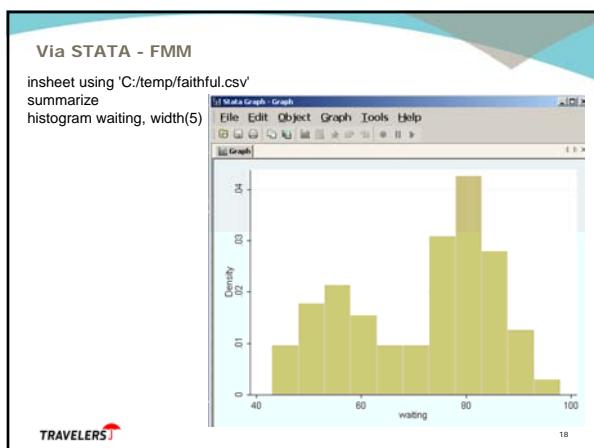
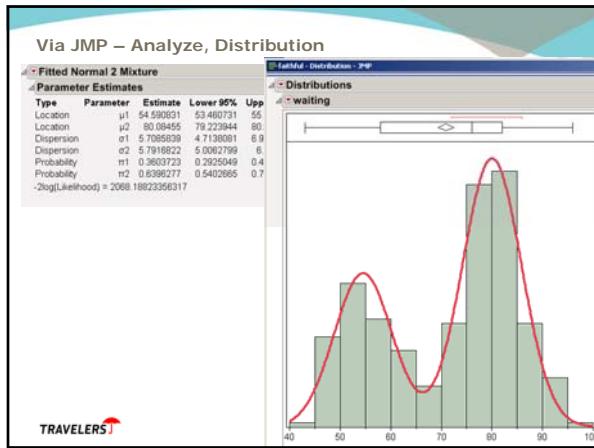
Parameter	Estimate	AproxStdErr
eta_mu1	4.000305937	0.01281147
eta_mu2	4.383164351	0.00629975
eta_sigma1	1.7700623482	0.09153827
eta_sigma2	1.7694686025	0.06832852
eta_p1	-0.571520402	0.13515025

Solved By: Numerical BFGS

Correlation of Estimates

	Exp(eta_mu1)	Exp(eta_mu2)	Exp(eta_sigma1)	Exp(eta_sigma2)
Exp(eta_mu1)	1			
Exp(eta_mu2)		1		
Exp(eta_sigma1)			1	
Exp(eta_sigma2)				1

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Via STATA - FMM

```
insheet using 'C:/temp/faithful.csv'
summarize
histogram waiting, width(5)
fmm waiting, components(2) mixtureof(normal)

component Normal regression
Number of obs = 272
Wald chi2(0) = .
Prob > chi2 = .

waiting      Coef.  Std. Err.      z   P>|z|   [95% Conf. Interval]
component1_cons | 54.61486  .699675   78.06  0.000  53.24352  55.98619
component2_cons | 80.09107  .5045947  158.72  0.000  79.10208  81.08006
/_Imlogitp1    | -.5715204  .1351187  -4.23  0.000  -.8363481  -.3066927
/_Insigm1       | 1.770062   .091518   19.34  0.000  1.59069  1.949434
/_Insigm2       | 1.769469   .0683333  25.89  0.000  1.635538  1.903399
sigma1          | 5.871219   .5373224
sigma2          | 5.867734   .4009615
p11             | .3608861  .0311648
p12             | .6391139  .0311648
```

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Time Permitting – Additional Examples

Proc FMM.sas – FMM(2) Poisson – Counts - regressors  
 Exp\_mix.sas – FMM Exponential, Gamma dists  
 WC\_Loss.sas – FMM Gamma with regressors

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SAS recently announced experimental Proc FMM coming in SAS/STAT 9.3

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 Research Statistician Developer - Finite Mixture Models job at SAS In Cary, NC  
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 Location: Cary, NC  
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 Join the world's leading statistical software company and make a difference in the way that statistics is practiced. SAS is looking for a developer with a strong statistical background and excellent programming skills to develop statistical software for analysis of finite mixture models. In this position, you will implement specialized methods in new and existing SAS procedures. You will keep up with the forefront of statistical methodology and work closely with statisticians throughout the process. You will program in SAS, and program these methods in C. You will also test and document the software and present it to professional statistical audiences. Qualifications: Essential - Ph.D. in biostatistics, statistics, or a related field - Experience in statistical modeling - Graduate-level research in

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**Further reading:**

Deb, Partha and J. F. Burgess Jr., A quasi-experimental comparison of statistical models for health care expenditures, 2003, wp, <http://urban.hunter.cuny.edu/RePEc/ht/papers/debburgess10.pdf>

Grun, Bettina and Friedrich Leisch, Fitting Finite Mixtures of Generalized Linear Regressions in R, Computational Statistics and Data Analysis, 2006, <http://statmath.wu.ac.at/projects/AASC/mixtures/Gruen+Leisch-2007b.pdf>

Klugman, Stuart and Jacques Rioux, Toward a unified approach to fitting loss models, North American Actuarial Journal, Jan-06, 10, 1, 63-83, <http://www.iowactuariesclub.org/library/lossmodels.pdf>

Lee, Andy H., Kui Wang, Kelvin K.W. Yau, Geoffrey J. McLachlan and S.K. Ng  
Maternity length of stay modeling by gamma mixture regression with random effects  
Biometrical Journal, Aug-2007, v49, n5, p750-764  
[http://www.maths.uq.edu.au/~qm/wynn\\_biom07.doc](http://www.maths.uq.edu.au/~qm/wynn_biom07.doc)

Leisch, Friedrich and Bettina Gruen, "FlexMix Version 2: Finite mixtures with concomitant variables and varying and constant parameters", Journal of Statistical Software, 2007, 28(4), 1-35, <http://cran.r-project.org/web/packages/flexmix/vignettes/mixture-regressions.pdf>

Park, Byung-Jung and Dominique Lord, Application of Finite Mixture Models for Vehicle Crash Data Analysis, wp, Feb-2009, [https://ceprofs.civil.tamu.edu/dlord/papers/park\\_lord\\_%20finite\\_mixture\\_model.pdf](https://ceprofs.civil.tamu.edu/dlord/papers/park_lord_%20finite_mixture_model.pdf)

Rempala, Grzegorz A. and Richard A. Derrig, Modeling Hidden Exposures in Claim Severity via the EM Algorithm, ASTIN Colloquium - Bergen, Norway Jun-2004, [http://www.actuaries.org/ASTIN/Colloquia/Bergen/Rempala\\_Derrig.pdf](http://www.actuaries.org/ASTIN/Colloquia/Bergen/Rempala_Derrig.pdf)

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**Further reading:**

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Teodorescu, Sandra, Different approaches to model the loss distribution of a real data set from motor third party liability insurance, Romanian Journal of Insurance, Apr-2010, 93-104, [http://www.ima-imr.ro/en/publications/assets/pdf/Romanian%20Journal%20of%20Insurance%20Year%202010%20No\\_4.pdf#page=94](http://www.ima-imr.ro/en/publications/assets/pdf/Romanian%20Journal%20of%20Insurance%20Year%202010%20No_4.pdf#page=94)

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**Thank you — Questions?**

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 860.954.0894

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