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Redefining the deviance objective for generalised linear models
Tony Lovick, Pete Lee

Relieving the pressure from tight fitting models

October 2011

Agenda

- Motivation for method
- Concepts behind Case Deleted Deviance
- Simple Example
- Concepts behind Noise Reduction Method
- Real Examples
- Other applications

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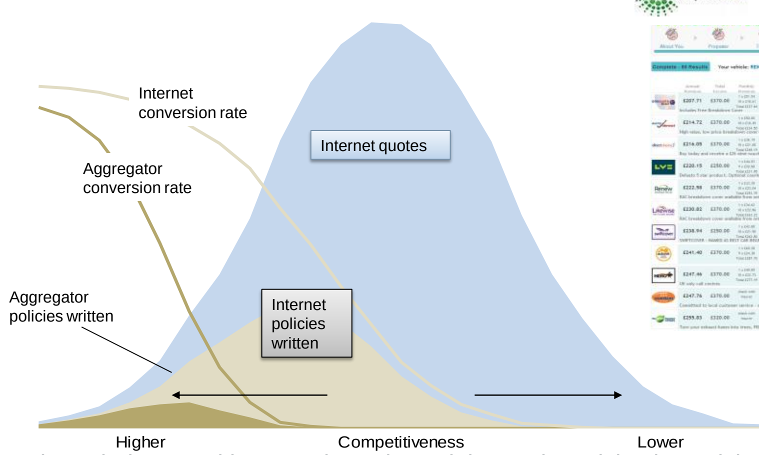
Redefining the deviance objective for generalised linear models

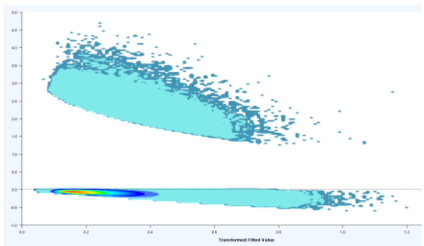
Motivation for method

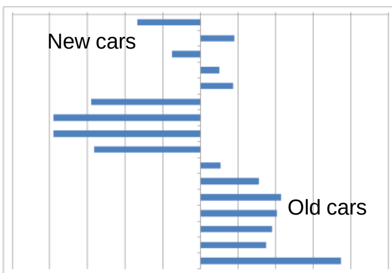
Motivation for method



– Unintended competitiveness through unwitting under-pricing is punished severely

Motivation for methods





- 100+ candidate variables
- ~25 factors – more when looking at e.g. external data for postcoding
- Up to ~12 interactions
- Multi-dimension effects via “scores”
- Reduced scope for competitor benchmarking
- Dilemma of over-fitting vs. danger of anti-selection

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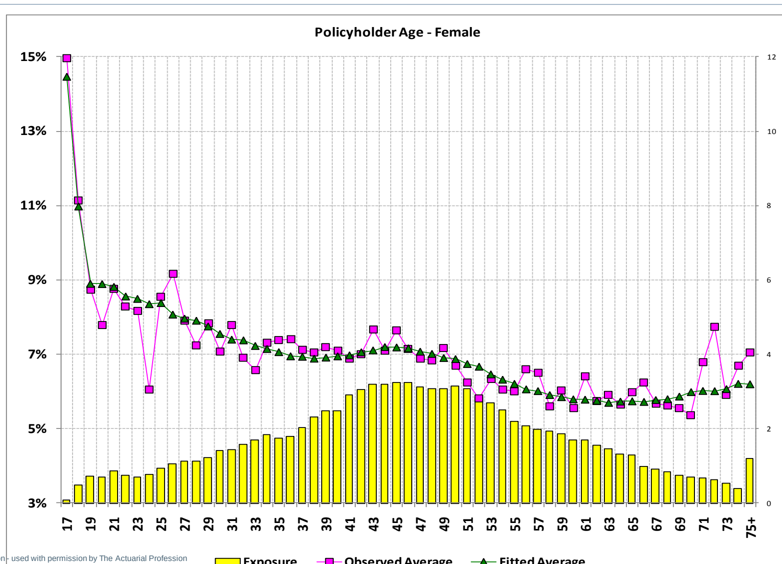
Motivation for methods



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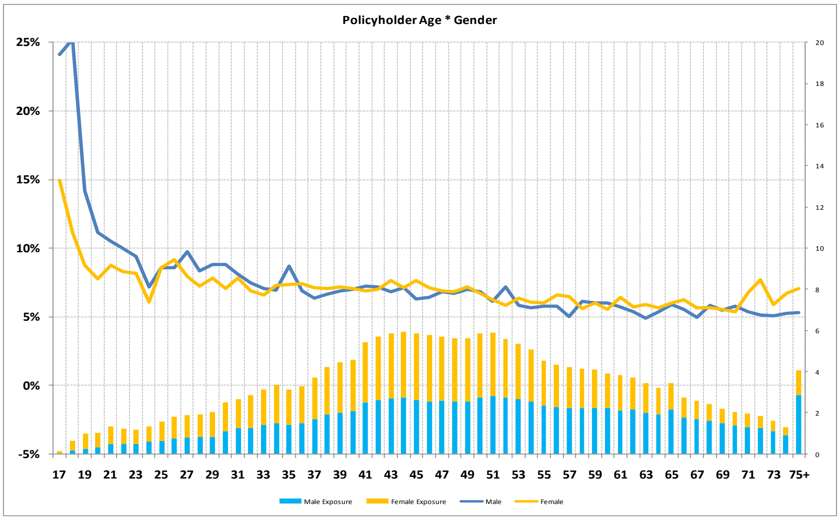
Motivation for methods



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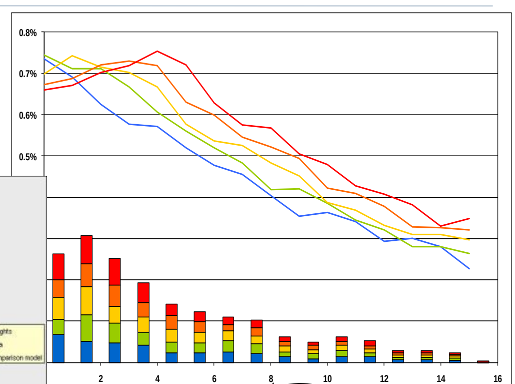
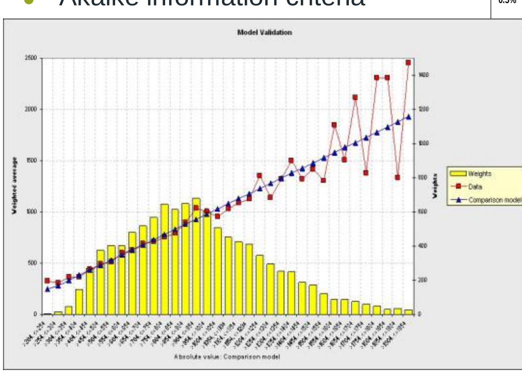
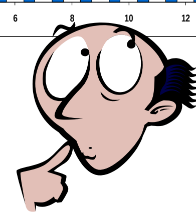
Motivation for methods

- Chi-squared & F-tests
- Wald p-values
- Akaike information criteria







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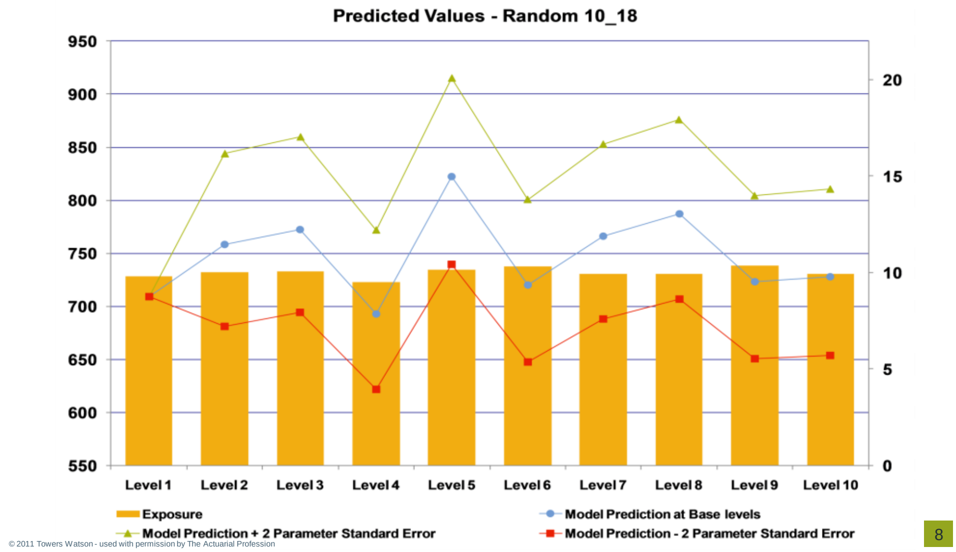
Motivation for methods



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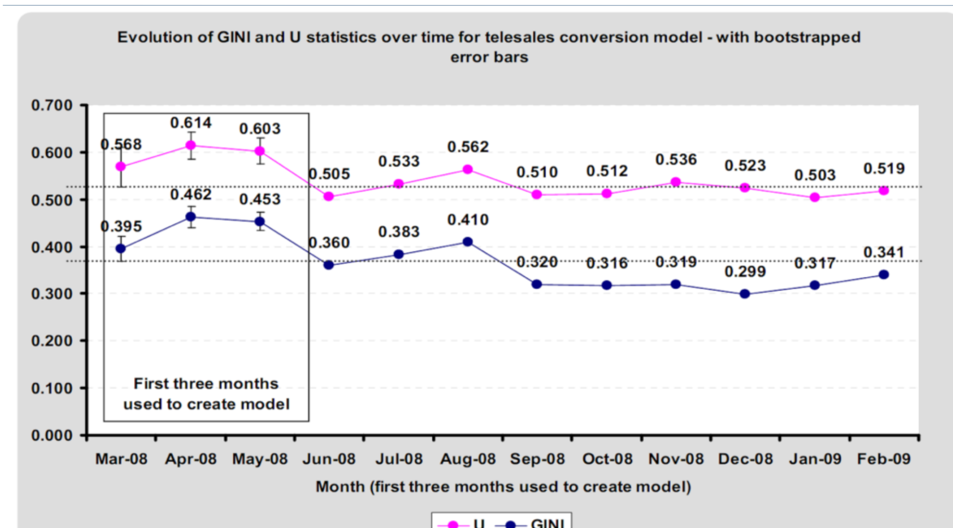
Motivation for methods



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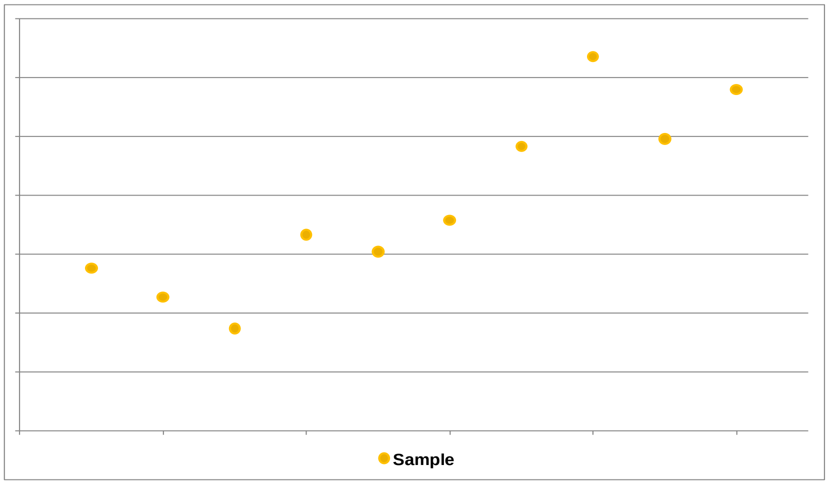
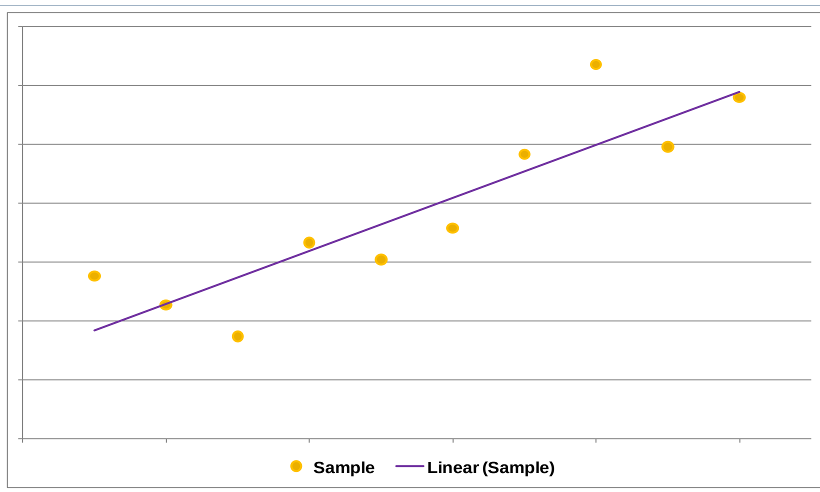
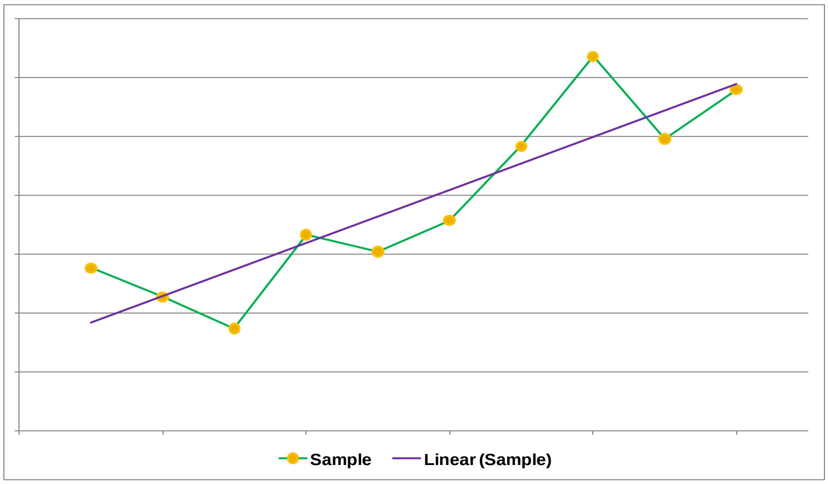
Motivation for methods



Motivation for methods



Motivation for methods



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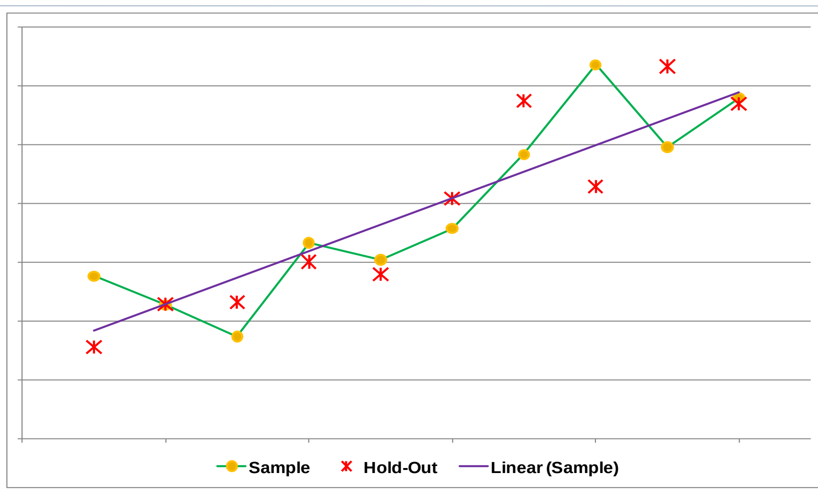
Motivation for methods



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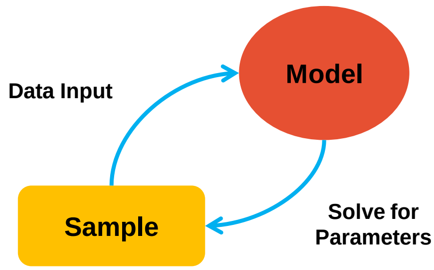
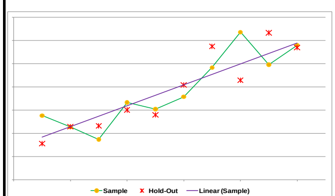
Motivation for methods





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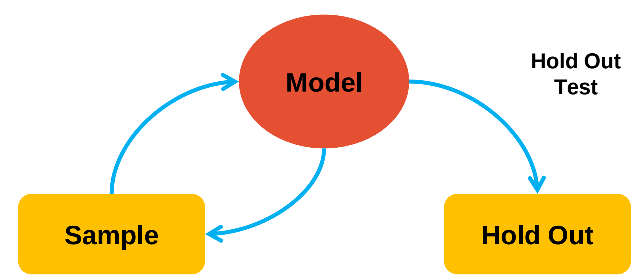
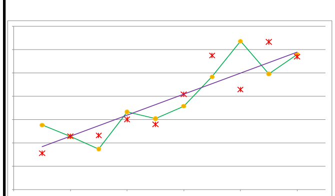
Motivation for methods





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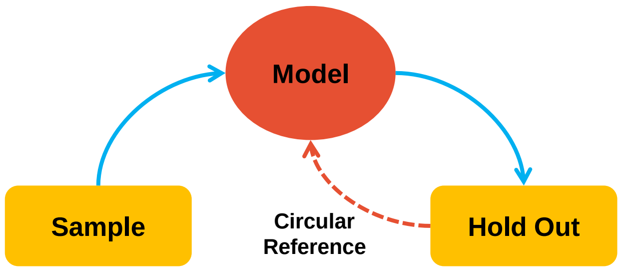
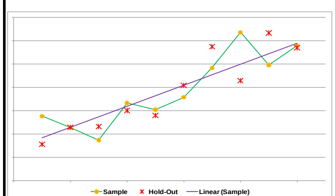
Motivation for methods





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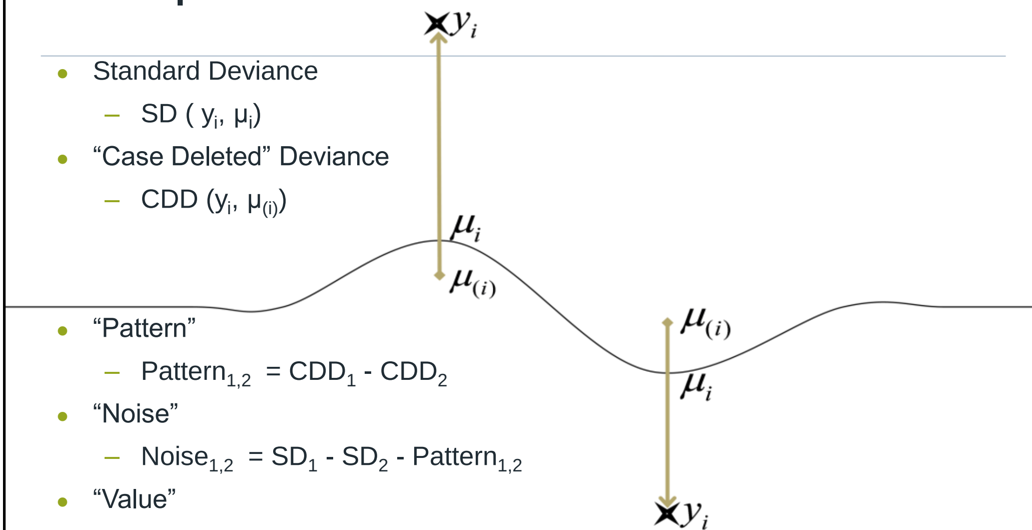
Redefining the deviance objective for generalised linear models

Concepts behind Case Deleted Deviance

Concepts behind the Case Deleted Deviance

- Standard Deviance
  - SD (y_i, μ_i)
- "Case Deleted" Deviance
  - CDD (y_i, $\mu_{(i)}$)



- "Pattern"
  - $\text{Pattern}_{1,2} = \text{CDD}_1 - \text{CDD}_2$
- "Noise"
  - $\text{Noise}_{1,2} = \text{SD}_1 - \text{SD}_2 - \text{Pattern}_{1,2}$
- "Value"
  - $\text{Value}_{1,2} = \text{Pattern}_{1,2} – 5 * \text{Noise}_{1,2}$

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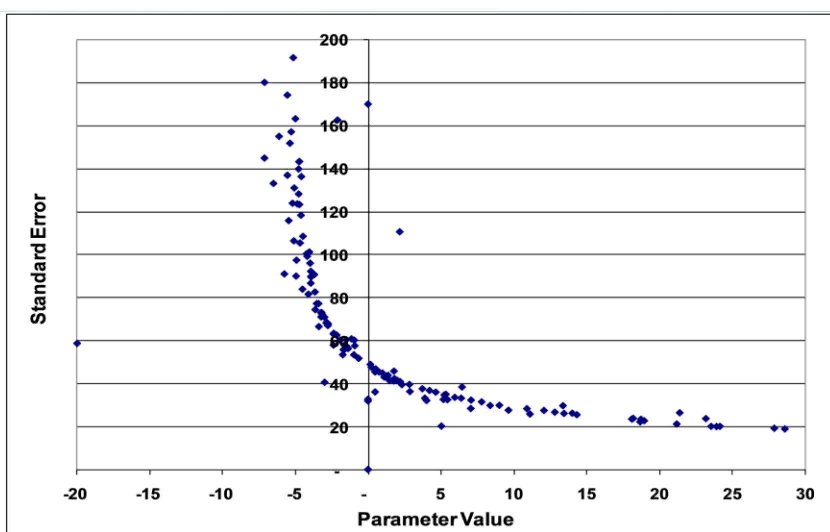
Concepts behind the Case Deleted Deviance



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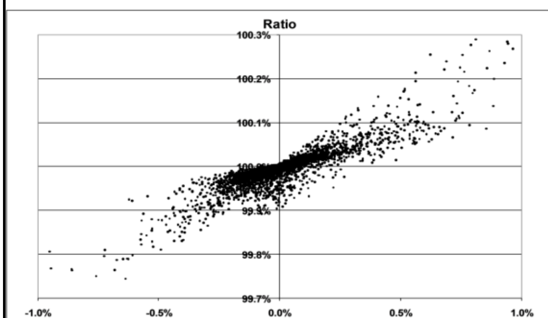
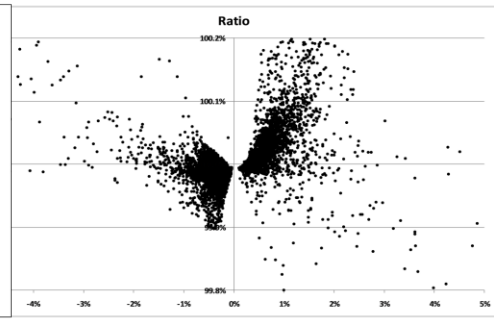
Concepts behind the Case Deleted Deviance

- The approximate method to calculate μ_i is
  - 99.9% accurate
  - "n" times faster





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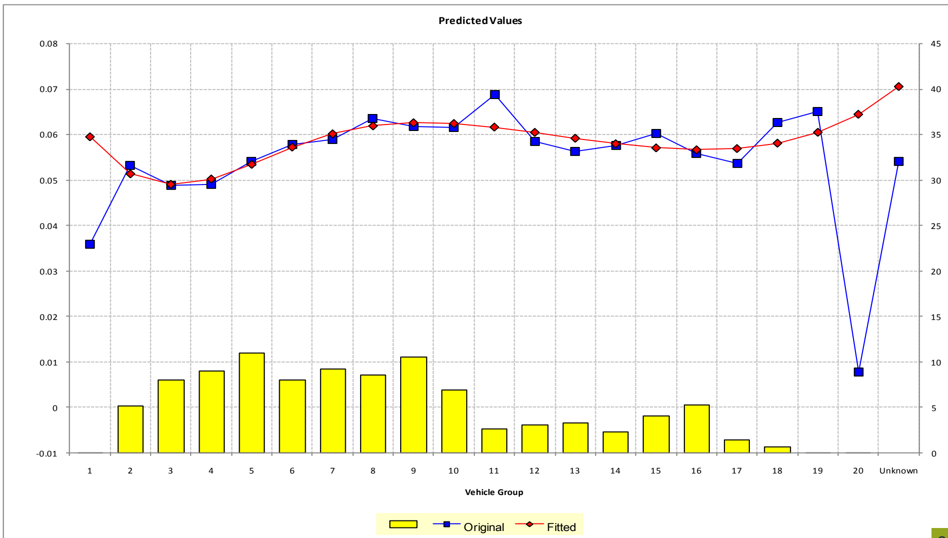
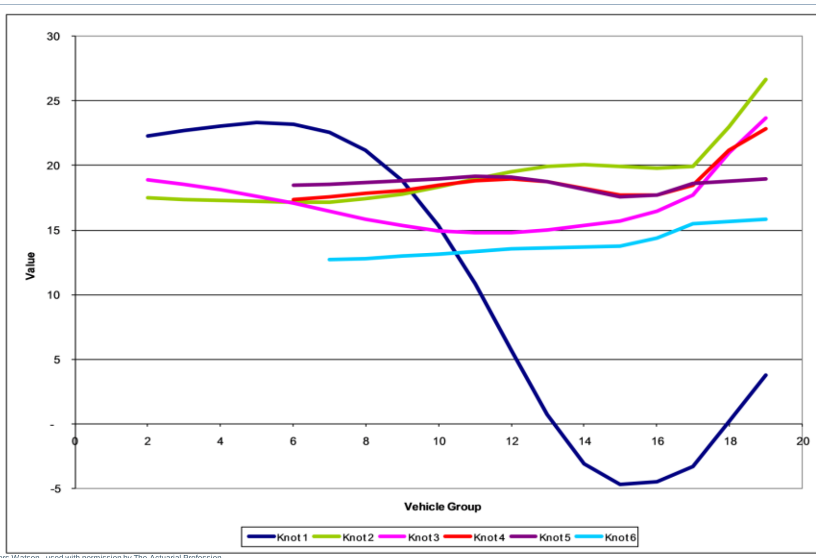
Simple Example

Simple Example



Simple Example



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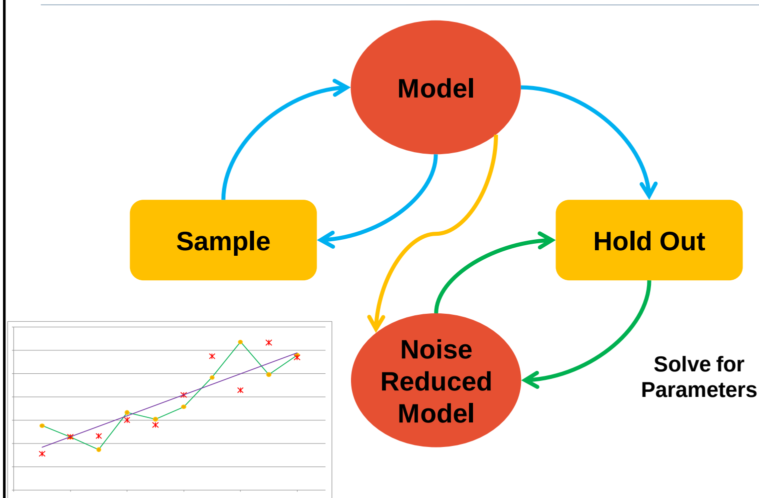
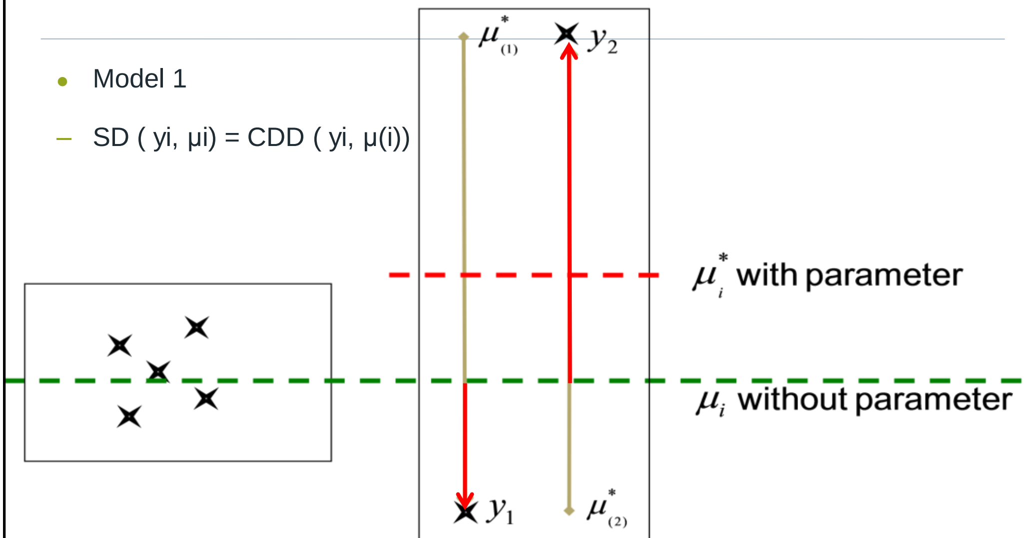
Concepts behind Noise Reduction Method

Motivation for methods



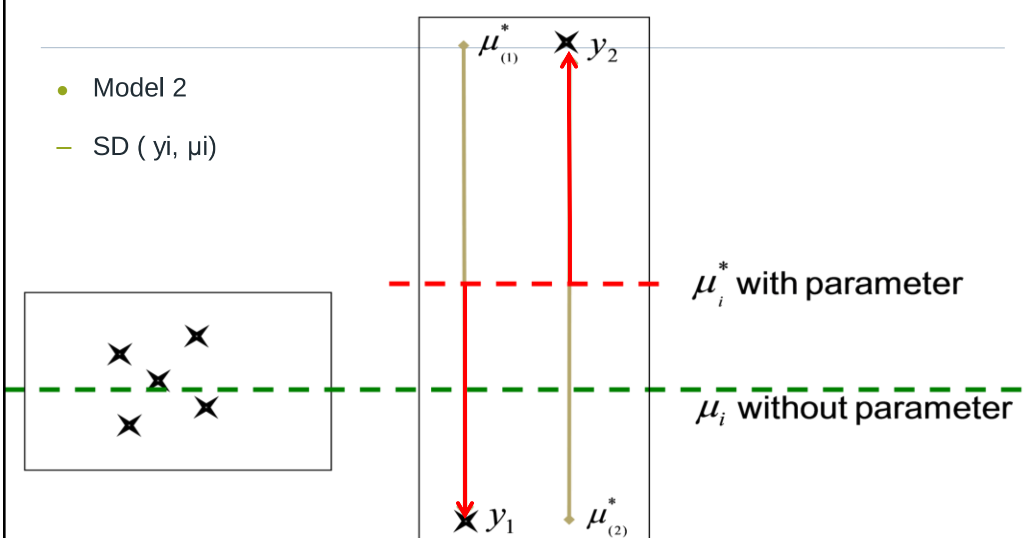
Concepts behind the Noise Reduction Method

- Model 1
  - SD (yi, μi) = CDD (yi, μ(i))



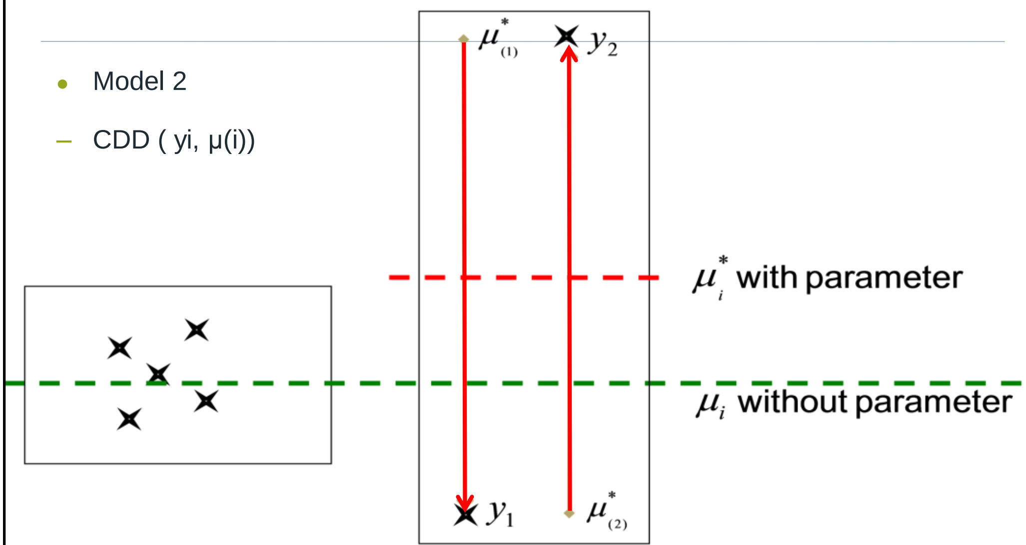
Concepts behind the Noise Reduction Method

- Model 2
  - SD (yi, μi)



Concepts behind the Noise Reduction Method

- Model 2
  – CDD (yi, μ(i))



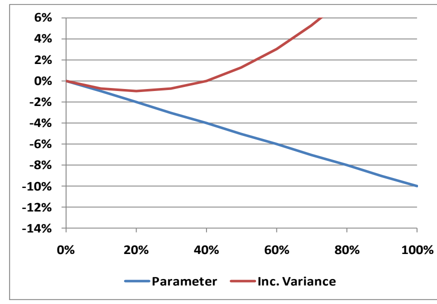
Concepts behind the Noise Reduction Method

- Find the “best” scalars in the “Case Deleted Deviance” sense
- Higher Variance parameters get scaled back most
- Take account of parameter correlations

			ndard Error	Standard Error (%)	Alias Indicator (%)	Weight	Weight (%)	Exp(Value)
			0.031	1.1		236,207	100.0	0.064
			0.020	34.1		100,320	42.5	0.942
						135,888	57.5	
						200,845	85.0	
			0.027	23.6		35,362	15.0	1.120
			0.010	8.9		236,207	100.0	1.124
14	VA Curve 1(OPoly(1))	-0.265	0.016	6.0		219,928	93.1	0.768
15	VA Curve 1(OPoly(2))	-0.076	0.017	22.5		219,928	93.1	0.926
16	PA Curve 1spline 1(OPoly(1))	0.212	0.039	18.5		8,194	3.5	1.236
17	PA Curve 1spline 3 (OPoly(1))	0.041	0.009	23.1		229,373	97.1	1.042
18	PA Curve 1spline 4 (OPoly(1))	-0.064	0.009	13.9		229,373	97.1	0.938
19	YADA Curve 1(OPoly(1))	-0.176	0.014	8.2		236,207	100.0	0.838
20	YADA Curve 1(OPoly(2))	0.062	0.012	19.0		236,207	100.0	1.064
21	VG Curve 1spline 1(OPoly(1))	-0.242	0.119	49.4		203,278	86.1	0.785
22	VG Curve 1spline 2 (OPoly(1))	-0.116	0.070	60.0		235,863	99.9	0.890
23	VG Curve 1spline 3 (OPoly(1))	-0.050	0.055	109.6		235,863	99.9	0.951
24	VG Curve 1spline 4 (OPoly(1))	-0.177	0.092	52.3		235,863	99.9	0.838

Concepts behind the Noise Reduction Method

- Find the "best" scalars in the "Case Deleted Deviance" sense
- Higher Variance parameters get scaled back most
- Take account of parameter correlations



C_{jk} Is the Variance Covariance Matrix

$$C_{jk} = \left(\sum_p X_{pj}{}^m W_p X_{pk} \right)^{-1}$$

$$C^*_{jk} = \begin{cases} Var(\lambda_j \beta_j) = \lambda_j^2 Var(\beta_j) & , j = k \\ Cov(\lambda_j \beta_j, \lambda_k \beta_k) = \lambda_j \lambda_k Cov(\beta_j, \beta_k) & , j \neq k \end{cases}$$

$$h_i = \sum_{jk} X_{ij} C_{jk} X_{ik} W_i$$

$$h^*_i = \sum_{jk} X_{ij} C^*_{jk} X_{ik} W_i$$

$$\eta_{(i)} = \eta_i - \left(\frac{h_i}{1 - h_i} \right) g'(\mu_i)(y_i - \mu_i)$$

$$\eta^*_{(i)} = \eta^*_i - \left(\frac{h^*_i}{1 - h^*_i} \right) g'(\mu_i)(y_i - \mu_i)$$

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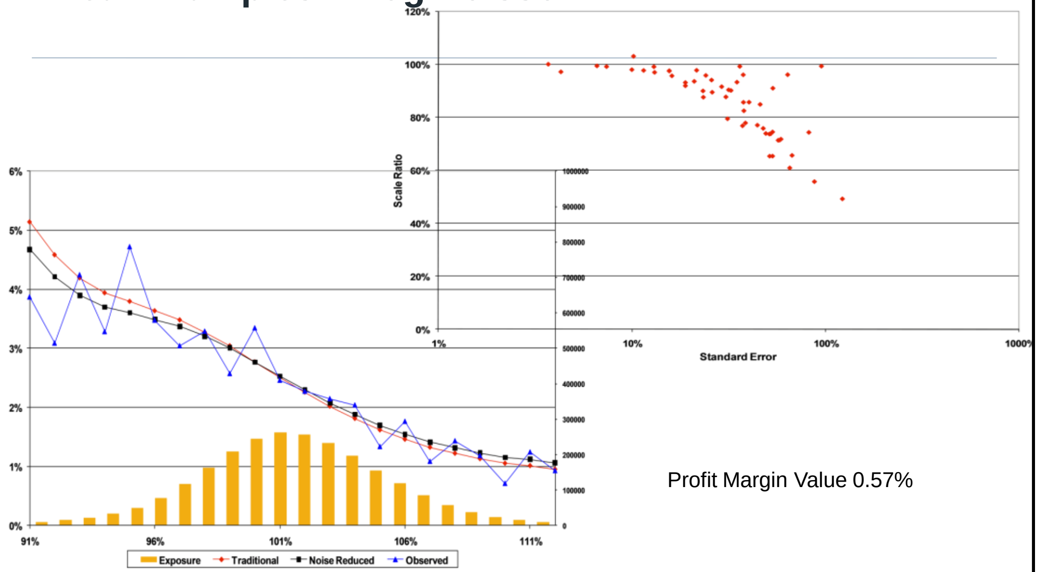
Real Examples

Real Examples – Log Poisson



Profit Margin Value 0.57%

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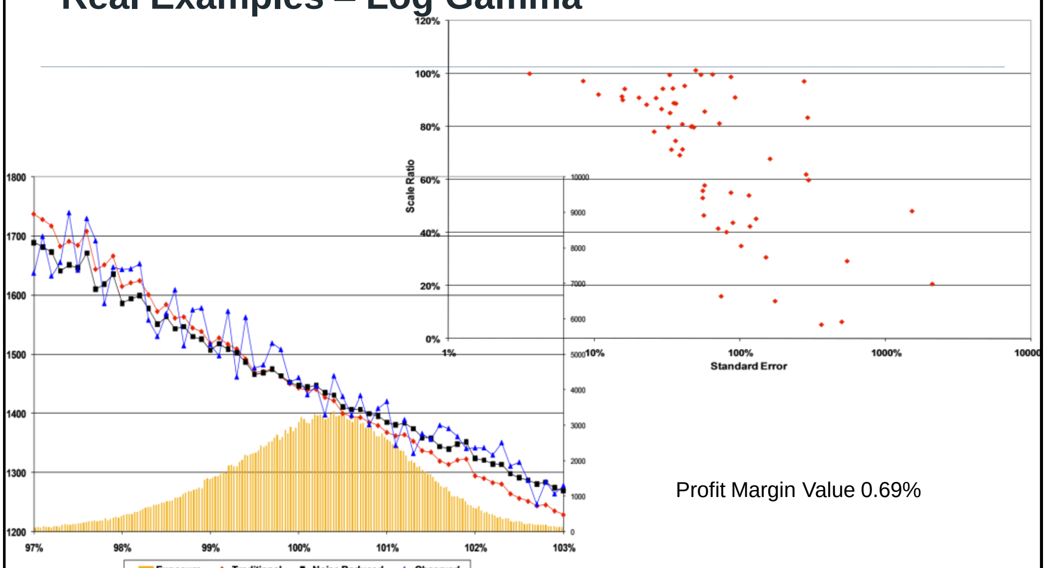
Real Examples – Log Gamma



Profit Margin Value 0.69%

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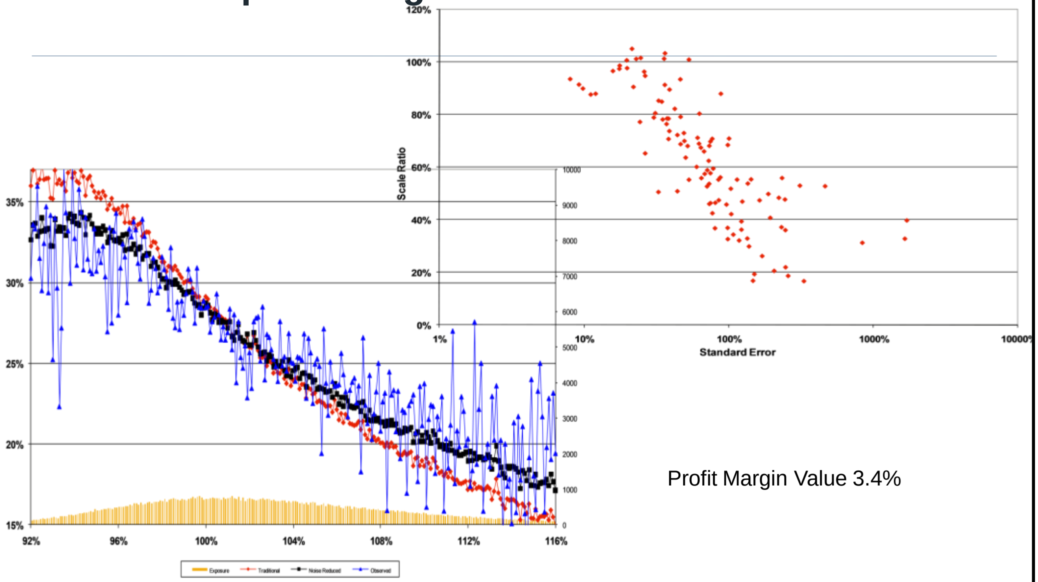
Real Examples – Logit Binomial



Profit Margin Value 3.4%

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Other applications

Other Applications

- "Case Deleted" Deviance
  - Completely generic concept, that can be applied to any model type
  - For models with quadratic parameter convergence, a similar approximation should exist
- "Value" Measure
  - An absolute mechanism to compare disparate model options.
- Noise Reduction Method
  - GLMs are convenient in that they generate the Variance Covariance matrix as part of the solution.
  - But could be applied to any model where this can be estimated.
  - Result is a set of scaled parameters which are "most predictive".

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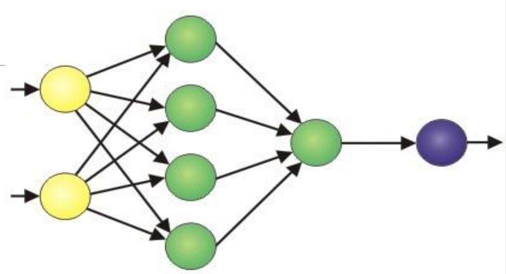
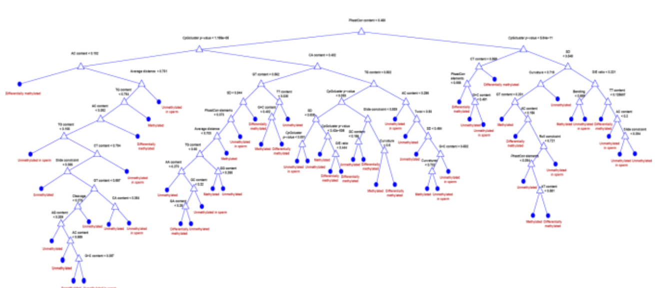
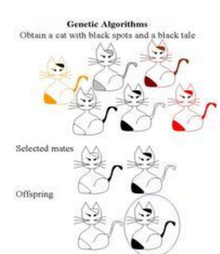
Other Applications

- Can be applied to
  - Neural Networks,
  - Genetic Algorithms,
  - Decision Trees, etc.







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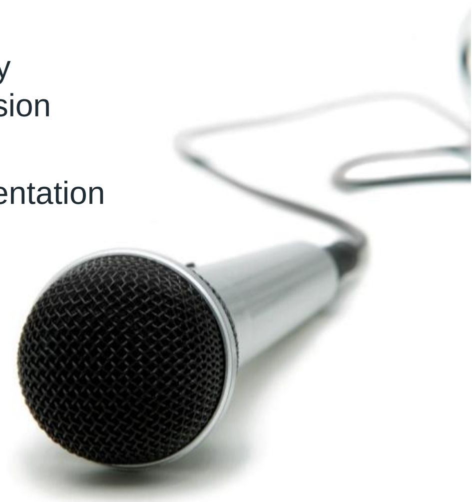
Questions or comments?

Expressions of individual views by members of The Actuarial Profession and its staff are encouraged.

The views expressed in this presentation are those of the presenter.



Tony Lovick, MA FIA
Pricing Actuary

- Tony graduated in Mathematics from Oxford University in 1987, and qualified as a Fellow of the Institute of Actuaries in 1994. He spent twenty one years with Aviva Group, before joining EMB as a Senior Consultant.
- Tony undertook a number of roles within Aviva, most recently as Price Optimisation Actuary, “Pay as you drive” Actuary and Head of Statistics and Development, in the Personal Lines Pricing Division of Norwich Union.*
- Tony is interested in innovative actuarial research and its delivery through pragmatic systems development. As Price Optimisation Actuary he undertook the client side pricing and architecture design, concluding in a successful Motor Renewal pilot.
- As the actuary leading the research for Pay as you drive, he helped inspire the analysis, build of the data warehouse systems**, and launch of the product to market. As part of this project Aviva prepared two patents with Tony listed as the inventor, one of which is now granted***.
- As Head of Statistics he led the implementation of full postcode risk cost models for motor and home insurance, pioneering the introduction of external data to Aviva rating systems.

* http://www.linkedin.com/in/anthonylovick

** http://www.silicon.com/financialservices/0,3800010322,39169285,00.htm

*** http://v3.espacenet.com/textdoc?DB=EPODOC&IDX=GB2436880&F=0

Peter Lee FIA
Director

- Peter Lee is a Director at Towers Watson and global lead in pricing innovation with over twenty years experience in non-life insurance. Prior to joining EMB Peter worked at Allianz UK as the Personal Lines Actuary.
- Whilst at EMB, Peter worked for a large number of insurers throughout the world in different regulatory regimes, advising over a broad spectrum of areas and products ranging from claims reserving to pricing and the design of management information. Throughout his career Peter has been at the forefront of innovation, being one of the pioneers of the application of statistical modelling to personal lines pricing and then extending these techniques to commercial lines.
- More recently Peter developed EMB's price optimisation solution which has now been implemented in many of the largest general insurers in the world. Much of Peter's work involves embedding technical analysis and demand-based pricing into a wider pricing process, allowing these enhanced capabilities to be more effectively leveraged. Peter is now working with clients to link pricing and marketing to provide an enhanced framework for managing customer value.

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