Loss Cost Modeling
vs.
Frequency and Severity Modeling

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Description of Frequency-Severity Modeling

- Claim Frequency = Claim Count / Exposure

  Claim Severity = Loss / Claim Count

- It is a common actuarial assumption that:
  - Claim Frequency has an over-dispersed Poisson distribution
  - Claim Severity has a Gamma distribution

- Loss Cost = Claim Frequency **x** Claim Severity
- Can be much more complex

Description of Frequency-Severity Modeling

- A more sophisticated Frequency/Severity model design
  - Frequency – Over-dispersed Poisson
  - Capped Severity – Gamma
  - Propensity of excess claim – Binomial
  - Excess Severity – Gamma
  - Expected Loss Cost = Frequency x Capped Severity

    + Propensity of excess claim + Excess Severity
  - Fit a model to expected loss cost to produce loss cost indications by rating variable

Description of Loss Cost Modeling
Tweedie Distribution

- It is a common actuarial assumption that:
  - Claim count is Poisson distributed
  - Size-of-Loss is Gamma distributed
- Therefore the loss cost (LC) distribution is Gamma-Poisson **Compound** distribution, called Tweedie distribution
  - LC = X1 + X2 + … + XN
  - Xi ~ Gamma for i $\in$ {1, 2,…, N}
  - N ~ Poisson

Description of Loss Cost Modeling
Tweedie Distribution (Cont.)

- Tweedie distribution is belong to exponential family
  - o $\mathrm{Var}(LC) = \phi\mu^{p}$
    - ϕ is a scale parameter
    - μ is the expected value of LC
    - p ϵ (1,2)
      - p is a free parameter – must be supplied by the modeler
      - As p → 1: LC approaches the Over-Dispersed Poisson
      - As p → 2: LC approaches the Gamma

Data Description

- Structure – On a vehicle-policy term level
- Total 100,000 vehicle records
- Separated to Training and Testing Subsets:
  - Training Dataset: 70,000 vehicle records
  - Testing Dataset: 30,000 Vehicle Records
- Coverage: Comprehensive

Numerical Example 1
GLM Setup – In Total Dataset

- Frequency Model
  - Target
    = Frequency
    = Claim Count /Exposure
  - Link = Log
  - Distribution = Poison
  - Weight = Exposure
  - Variable =
    - Territory
    - Agegrp
    - Type
    - Vehicle_use
    - Vehage_group
    - Credit_Score
    - AFA
- Severity Model
  - Target
    = Severity
    = Loss/Claim Count
  - Link = Log
  - Distribution = Gamma
  - Weight = Claim Count
  - Variable =
    - Territory
    - Agegrp
    - Type
    - Vehicle_use
    - Vehage_group
    - Credit_Score
    - AFA
- Loss Cost Model
  - Target
    = loss Cost
    = Loss/Exposure
  - Link = Log
  - Distribution = Tweedie
  - Weight = Exposure
  - P=1.30
  - Variable =
    - Territory
    - Agegrp
    - Type
    - Vehicle_use
    - Vehage_group
    - Credit_Score
    - AFA

Numerical Example 1
How to select "*p*" for the Tweedie model?

- Treat "p" as a parameter for estimation
- Test a sequence of "p" in the Tweedie model
- The Log-likelihood shows a smooth inverse "U" shape
- Select the "p" that corresponding to the "maximum" log-likelihood

Value p Optimization

Log-likelihood	Value p
-12192.25	1.20
-12106.55	1.25
-12103.24	**1.30**
-12189.34	1.35
-12375.87	1.40
-12679.50	1.45
-13125.05	1.50
-13749.81	1.55
-14611.13	1.60

Numerical Example 1
GLM Output (Models Built in Total Data)

		Frequency Model		Severity Model		Frq * Sev	Loss Cost Model (p=1.3)	
		Estimate	Rating Factor	Estimate	Rating Factor	Rating Factor	Estimate	Rating Factor
Intercept		-3.19	0.04	7.32	1510.35	**62.37**	4.10	**60.43**
Territory	T1	0.04	1.04	-0.17	0.84	**0.87**	-0.13	**0.88**
Territory	T2	0.01	1.01	-0.11	0.90	**0.91**	-0.09	**0.91**
Territory	T3	0.00	1.00	0.00	1.00	**1.00**	0.00	**1.00**
………..	……	……..	……..	……..	……..	**……..**	……..	**……..**
agegrp	Yng	0.19	1.21	0.06	1.06	**1.28**	0.25	**1.29**
agegrp	Old	0.04	1.04	0.11	1.11	**1.16**	0.15	**1.17**
agegrp	Mid	0.00	1.00	0.00	1.00	**1.00**	0.00	**1.00**
Type	M	-0.13	***0.88***	0.05	***1.06***	**0.93**	-0.07	**0.93**
Type	S	0.00	***1.00***	0.00	***1.00***	**1.00**	0.00	**1.00**
Vehicle_Use	PL	0.05	***1.05***	-0.09	***0.92***	**0.96**	-0.04	**0.96**
Vehicle_Use	WK	0.00	***1.00***	0.00	***1.00***	**1.00**	0.00	**1.00**

Numerical Example 1
Findings from the Model Comparison

- The LC modeling approach needs less modeling efforts, the FS modeling approach shows more insights.

  - What is the driver of the LC pattern, Frequency or Severity?
  - Frequency and severity could have different patterns.

Numerical Example 1

Findings from the Model Comparison – Cont.

- The loss cost relativities based on the FS approach could be fairly close to the loss cost relativities based on the LC approach, when
  - Same pre-GLM treatments are applied to incurred losses and exposures for both modeling approaches
    - Loss Capping
    - Exposure Adjustments
  - Same predictive variables are selected for all the three models (*Frequency Model, Severity Model and Loss Cost Model*
  - The modeling data is credible enough to support the severity model

Numerical Example 2
GLM Setup – In Training Dataset

- **Frequency Model**
  - Target
    = Frequency
    = Claim Count /Exposure
  - Link = Log
  - Distribution = Poison
  - Weight = Exposure
  - Variable =
    - Territory
    - Agegrp
    - Deductable
    - Vehage_group
    - Credit_Score
    - AFA

Type 3 Statistics

	DF	ChiSq	Pr > Chisq
territory	2	5.9	0.2066
agegrp	2	25.36	<.0001
vehage_group	4	294.49	<.0001
Deductable	2	41.07	<.0001
credit_score	2	64.1	<.0001
AFA	2	15.58	0.0004

- **Severity Model**
  - Target
    = Severity
    = Loss/Claim Count
  - Link = Log
  - Distribution = Gamma
  - Weight=Claim Count
  - Variable =
    - Territory
    - Agegrp
    - Deductable
    - Vehage_group
    - Credit_Score
    - AFA

Type 3 Statistics

	DF	ChiSq	Pr > Chisq
territory	2	15.92	0.0031
agegrp	2	2.31	0.3151
vehage_group	4	36.1	<.0001
Deductable	2	1.64	0.4408
credit_score	2	2.16	0.7059
AFA	2	11.72	0.0028

- **Severity Model (Reduced)**
  - Target
    = Severity
    = Loss/Claim Count
  - Link = Log
  - Distribution = Gamma
  - Weight = Claim Count
  - Variable =
    - Territory
    - Agegrp
    - Vehage_group
    - AFA

Type 3 Statistics

	DF	ChiSq	Pr > Chisq
Territory	2	15.46	0.0038
agegrp	2	2.34	0.3107
vehage_group	4	35.36	<.0001
AFA	2	11.5	0.0032

Numerical Example 2

GLM Output (Models Built in Training Data)

		Frequency Model		Severity Model		Frq * Sev	Loss Cost Model (p=1.3)	
		Estimate	Rating Factor	Estimate	Rating Factor	Rating Factor	Estimate	Rating Factor
Territory	T1	0.03	1.03	-0.17	0.84	0.87	-0.15	0.86
Territory	T2	0.02	1.02	-0.11	0.90	0.92	-0.09	0.91
Territory	T3	0.00	1.00	0.00	1.00	1.00	0.00	1.00
....	...	....						
Deductable	100	0.33	1.38			**1.38**	0.36	1.43
Deductable	250	0.25	1.28			**1.28**	0.24	1.27
Deductable	500	0.00	1.00			**1.00**	0.00	1.00
CREDIT_SCORE	1	0.82	2.28			**2.28**	0.75	2.12
CREDIT_SCORE	2	0.52	1.68			**1.68**	0.56	1.75
CREDIT_SCORE	3	0.00	1.00			**1.00**	0.00	1.00
AFA	0	-0.25	0.78	-0.19	0.83	0.65	-0.42	0.66
AFA	1	-0.03	0.97	-0.19	0.83	0.80	-0.21	0.81
AFA	2+	0.00	1.00	0.00	1.00	1.00	0.00	1.00

Numerical Example 2
Model Comparison In Testing Dataset

- In the testing dataset, generate two sets of loss cost Scores corresponding to the two sets of loss cost estimates
  - Score_fs (based on the FS modeling parameter estimates)
  - Score_lc (based on the LC modeling parameter estimates)
- Compare goodness of fit (GF) of the two sets of loss cost scores in the testing dataset
  - Log-Likelihood

Numerical Example 2
Model Comparison In Testing Dataset - Cont

GLM to Calculate GF Stat of Score_fs

Data: Testing Dataset

Target: Loss Cost

Predictive Var: Non

Error: tweedie

Link: log

Weight: Exposure

P: 1.15/1.20/1.25/1.30/1.35/1.40

Offset: log(Score_fs)

GLM to Calculate GF Stat of Score_lc

Data: Testing Dataset

Target: Loss Cost

Predictive Var: Non

Error: tweedie

Link: log

Weight: Exposure

P: 1.15/1.20/1.25/1.30/1.35/1.40

Offset: log(Score_lc)

Numerical Example 2
Model Comparison In Testing Dataset - Cont

GLM to Calculate GF Stat
Using Score_fs as offset

Log likelihood from output

P=1.15 log-likelihood=-3749
P=1.20 log-likelihood=-3699
P=1.25 log-likelihood=-3673
P=1.30 log-likelihood=-3672
P=1.35 log-likelihood=-3698
P=1.40 log-likelihood=-3755

GLM to Calculate GF Stat
Using Score_lc as offset

Log likelihood from output

P=1.15 log-likelihood=-3744
P=1.20 log-likelihood=-3694
P=1.25 log-likelihood=-3668
P=1.30 log-likelihood=-3667
P=1.35 log-likelihood=-3692
P=1.40 log-likelihood=-3748

The loss cost model has better goodness of fit.

Numerical Example 2

Findings from the Model Comparison

- In many cases, the frequency model and the severity model will end up with different sets of variables. More than likely, less variables will be selected for the severity model
  - Data credibility for middle size or small size companies
  - For certain low frequency coverage, such as BI…
- As a result
  - F_S approach shows more insights, but needs additional effort to roll up the frequency estimates and severity estimates to LC relativities
  - In these cases, frequently, the LC model shows better goodness of fit

A Frequently Applied Methodology

Loss Cost Refit

- Loss Cost Refit
  - Model frequency and severity separately
  - Generate frequency score and severity score
  - LC Score = (Frequency Score) x (Severity Score)
  - Fit a LC model to the LC score to generate LC Relativities by Rating Variables
  - Originated from European modeling practice

- Considerations and Suggestions
  - Different regulatory environment for European market and US market
  - An essential assumption – The LC score is unbiased.
  - Validation using a LC model

Constrained Rating Plan Study

- Update a rating plan with keeping certain rating tables or certain rating factors unchanged
- One typical example is to create a rating tier variable on top of an existing rating plan
  - Catch up with marketing competitions to avoid adverse selection
  - Manage disruptions

Constrained Rating Plan Study - Cont

- Apply GLM offset techniques
- The offset factor is generated using the unchanged rating factors.
- Typically, for creating a rating tier on top of an existing rating plan, the offset factor is given as the rating factor of the existing rating plan.
- All the rating factors are on loss cost basis. It is natural to apply the LC modeling approach for rating tier development.

How to Select Modeling Approach?

- Data Related Considerations
- Modeling Efficiency Vs. Actuarial Insights
- Quality of Modeling Deliverables
  - ➢ Goodness of Fit (on loss cost basis)
  - ➢ Other model comparison scenarios
- Dynamics on Modeling Applications
  - ➢ Class Plan Development
  - ➢ Rating Tier or Score Card Development
- Post Modeling Considerations
- Run a LC model to double check the parameter estimates generated based on a F-S approach

An Exhibit from a Brazilian Modeler

Exposição > 0	Erro Geral
Tweedie	-2%
Bin. Neg. e Gamma	8%
Poisson e Gamma	7%
Bin. e Gamma	7%
Rosa dos Ventos	23%
Exposição > 50	**Erro Geral**
Tweedie	3%
Bin. Neg. e Gamma	10%
Poisson e Gamma	9%
Bin. e Gamma	9%
Rosa dos Ventos	35%
Exposição > 100	**Erro Geral**
Tweedie	2%
Bin. Neg. e Gamma	8%
Poisson e Gamma	7%
Bin. e Gamma	7%
Rosa dos Ventos	34%
Exposição > 200	**Erro Geral**
Tweedie	0%
Bin. Neg. e Gamma	5%
Poisson e Gamma	4%
Bin. e Gamma	4%
Rosa dos Ventos	32%