


GLM I
**Introduction to Linear &
Generalized Linear Models**

Casualty Actuarial Society
Ratemaking and Product Management Seminar
March 21, 2011
New Orleans, LA

Ashley Lambeth, FCAS
Safeco Insurance, Liberty Mutual Group

1



Antitrust Notice

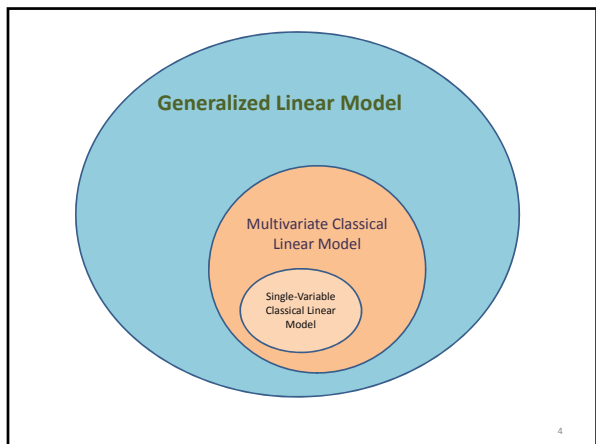
- The Casualty Actuarial Society is committed to adhering strictly to the letter and spirit of the antitrust laws. Seminars conducted under the auspices of the CAS are designed solely to provide a forum for the expression of various points of view on topics described in the programs or agendas for such meetings.
- Under no circumstances shall CAS seminars be used as a means for competing companies or firms to reach any understanding – expressed or implied – that restricts competition or in any way impairs the ability of members to exercise independent business judgment regarding matters affecting competition.
- It is the responsibility of all seminar participants to be aware of antitrust regulations, to prevent any written or verbal discussions that appear to violate these laws, and to adhere in every respect to the CAS antitrust compliance policy.

2

Outline

- I. Introduce our Data
- II. Classical Linear Modeling
- III. Generalized Linear Modeling

3



Outline

- I. Introduce our Data
- II. Classical Linear Modeling
- III. Generalized Linear Modeling

Cracking open the data

veh_value	exposure	lim	numclaims	claimcost	veh_body	veh_age	gender	area	agecat
1.04	0.30300437	0	0	0	CHBACK	3F	E	2	
1.01	0.64887637	0	0	0	CHBACK	2F	A	4	
1.34	0.56947294	0	0	0	CUPE	2F	I	2	
4.14	0.11750093	0	0	0	OSTNWS	2F	D	2	
0.72	0.48280637	0	0	0	CHBACK	4F	E	2	
2.03	0.85420946	0	0	0	PHOTOP	3M	E	4	
1.6	0.85420946	0	0	0	OPANVN	3M	A	4	
1.47	0.52029363	0	0	0	CHBACK	2M	B	4	
0.52	0.38199394	0	0	0	CHBACK	4F	A	3	
0.38	0.52029363	0	0	0	CHBACK	4F	B	4	
1.38	0.85420946	0	0	0	CHBACK	2M	A	2	
1.22	0.85420946	0	0	0	CHBACK	3M	E	4	
1	0.492813142	0	0	0	CHBACK	2F	E	4	
2.04	0.31480241	0	0	0	STTWNG	1M	A	5	
1.66	0.48499928	1	669	509999	SEDAN	1M	B	4	
2.83	0.391512663	0	0	0	SEDAN	2M	E	4	
1.53	0.99303838	1	303	60993	SEDAN	1F	E	4	
0.74	0.51935605	1	401	80541	CHBACK	1M	E	4	
0.27	0.41174038	0	0	0	CHBACK	4F	D	2	
0.89	0.594113023	0	0	0	CHBACK	1F	E	3	
1.95	0.594113023	0	0	0	CHBACK	1M	A	1	
0.39	0.536618754	0	0	0	ISEDAN	4M	E	5	
0.68	0.594113023	0	0	0	STTWNG	2F	E	2	
1.37	0.53137277	0	0	0	CHBACK	2F	B	1	
1.3	0.999315137	0	0	0	CHBACK	2F	A	2	
1.44	0.00010000	0	0	0	CHBACK	1M	E	2	
1.345	0.46388293	0	0	0	CHBACK	2F	E	5	
1.89	0.11750093	0	0	0	CHBACK	3F	E	2	
1	0.28424433	0	0	0	STTWNG	4M	E	2	
1.51	0.0684627	0	0	0	CHBACK	2F	E	2	
4.45	0.594113023	0	0	0	OSTNWS	1F	E	3	
1.73	0.536618754	0	0	0	ISEDAN	2F	A	4	
0.87	0.85420946	0	0	0	CHBACK	1M	D	1	
4.09	0.848731744	0	0	0	CUPE	1M	A	2	
1.51	0.48020101	0	0	0	CHBACK	2M	E	1	

Frequency & Severity Component Modeling

veh_value	exposure	dim	numclaims	claimcost	veh_body	veh_age	gender	area	agecat
1.06	0.307901437	0	0	0	HBACK	3F	F	C	2
1.06	0.564870537	0	0	0	HBACK	2F	F	A	4
1.26	0.56497264	0	0	0	LITE	2F	F	E	2
4.14	0.317282691	0	0	0	STNWGS	2F	F	D	2
0.72	0.648876537	0	0	0	HBACK	4F	F	C	2
2.03	0.854209446	0	0	0	CHOTOP	3M	F	C	4
1.4	0.854209446	0	0	0	PANVN	3M	A	A	4
1.47	0.953767171	0	0	0	HBACK	2M	B	B	4
0.52	0.361396364	0	0	0	HBACK	4F	F	L	1
0.98	0.52020265	0	0	0	HBACK	4F	F	B	4
1.38	0.854209446	0	0	0	HBACK	2M	A	A	2
1.22	0.854209446	0	0	0	HBACK	3M	F	C	4
1	0.492811342	0	0	0	HBACK	2F	F	A	4
7.04	0.314828811	0	0	0	STNWGS	3M	A	A	4
1.66	0.484595989	1	1	669.509993	SEDAN	3M	B	B	4
2.93	0.391512663	0	0	0	SEDAN	2M	F	C	4
1.53	0.99389876	1	1	826.429994	SEDAN	3F	F	A	4
0.76	0.53856605	1	1	379.895414	HBACK	3M	F	C	4
0.27	0.46174638	0	0	0	HBACK	4F	F	D	2
0.88	0.994118211	0	0	0	HBACK	3F	F	C	3
1.95	0.594118211	0	0	0	HBACK	3M	A	L	1
0.89	0.536816724	0	0	0	SEDAN	2M	F	C	2
1.86	0.594118211	0	0	0	STNWGS	2F	B	B	2
1.37	0.59170777	0	0	0	HBACK	1F	B	L	1
1.3	0.9981037	0	0	0	HBACK	2F	F	A	2
1.44	0.050161019	0	0	0	HBACK	2F	F	A	1
1.849	0.462096763	0	0	0	HBACK	1F	F	C	5
1.3	0.31700691	0	0	0	HBACK	2F	F	C	2
1	0.227474311	0	0	0	STNWGS	4M	F	C	1
1.53	0.08484827	0	0	0	HBACK	2F	F	C	2
4.48	0.984118211	0	0	0	STNWGS	3M	F	C	1
2.17	0.536616374	0	0	0	SEDAN	2F	F	L	4
0.87	0.854209446	0	0	0	HBACK	3M	F	D	3
4.08	0.84872344	0	0	0	LITE	4M	A	A	2
1.31	0.405201817	0	0	0	HBACK	2M	F	C	1

Frequency Model:
Predicts Likelihood to file a claim.

Severity Model:
Predicts size of claim given a claim is filed

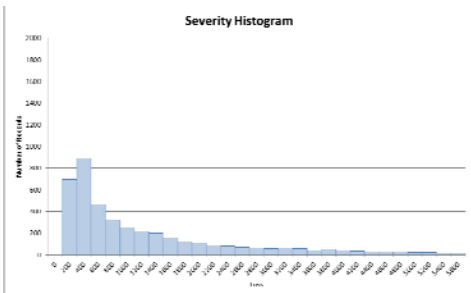
10

Our New Severity Dataset:

veh_value	exposure	dim	numclaims	claimcost	veh_body	veh_age	gender	area	agecat
1.66	0.484595989	1	1	669.509993	SEDAN	3M	B	B	4
1.53	0.99389876	1	1	826.429994	SEDAN	3F	F	A	4
0.76	0.53856605	1	1	379.895414	HBACK	3M	F	C	4
1.89	0.65434138	1	1	151.709997	STNWGS	3M	F	C	2
4.04	0.851471196	1	1	5414.439987	STNWGS	2M	F	C	1
1.38	0.31700691	0	0	0	HBACK	2M	A	A	4
2.62	0.31700691	1	1	1105.769999	STNWGS	1F	F	C	6
0.15	0.071184131	1	1	200	HBACK	2F	F	A	5
1.16	0.9981037	1	1	738.229995	STNWGS	2F	F	B	2
1.56	0.908238611	1	1	3236.599999	MCABA	3M	F	C	4
2.13	0.65434138	1	1	200	SEDAN	3F	F	A	5
0.28	0.90849076	1	1	200	TRUCK	1M	F	C	1
2.41	0.39389888	1	1	407.899997	STNWGS	3M	F	L	1
1.72	0.616016427	1	1	3018.829998	STNWGS	2M	F	A	6
1.95	0.616016427	1	1	1019.899988	STNWGS	2M	F	A	6
2.648	0.257357934	1	1	942.439978	TRUCK	1M	A	L	1
1.56	0.616016427	1	1	738.640003	SEDAN	3F	F	C	5
1.54	0.616016427	1	1	200	STNWGS	2F	F	B	1
1.89	0.760271136	1	1	369.179999	PANVN	3M	D	C	3
0.89	0.64862007	1	1	83.77	SEDAN	2F	F	D	1
4.48	0.91649505	1	1	989.919982	COUPE	2M	B	B	2
4.12	0.646132786	1	1	736.849988	STNWGS	2M	A	A	5
1.58	0.851471196	1	1	369.849996	STNWGS	1M	F	C	3
1.44	0.662977441	1	1	900	LITE	4M	F	C	2
2.83	0.851471196	1	1	851.77	STNWGS	2M	F	C	5
3	0.61627876	1	1	6372.029998	STNWGS	1F	F	C	2
2.29	0.353182762	1	1	900	STNWGS	2F	F	C	4
0.28	0.90849076	1	1	1378.039997	SEDAN	2F	F	C	2
1.29	0.025391566	1	1	200	SEDAN	3M	D	C	3
1.18	0.378284409	1	1	837.859995	SEDAN	2F	F	B	1
4	0.989218117	1	1	2724.209998	STNWGS	3M	F	A	4
2.43	0.760174146	1	1	12876.659974	HBACK	1F	F	B	3
1.47	0.246492571	1	1	937.279988	SEDAN	1M	B	C	3
1.14	0.851471196	1	1	12142.1326	TRUCK	1M	F	C	1
1.48	0.914304311	1	1	2626.349995	STNWGS	3M	F	C	4

11

Exploring our new dataset



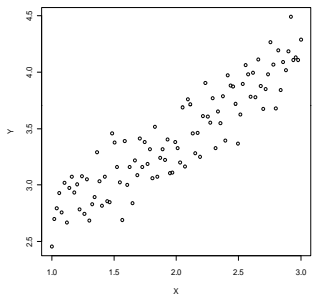
12

Outline

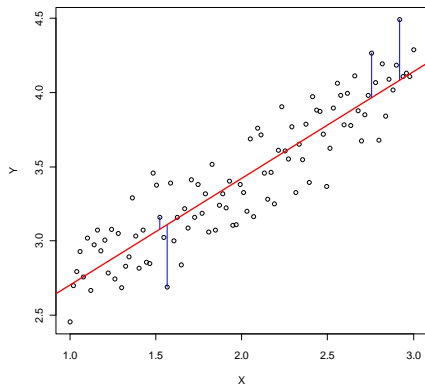
- I. Introduce our Data
- II. Classical Linear Modeling**
- III. Generalized Linear Modeling

16

What is Linear Modeling?



17



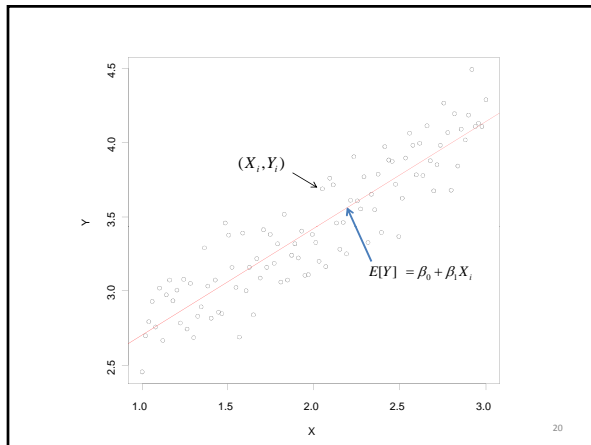
18

Classical Linear Model; Moving Parts

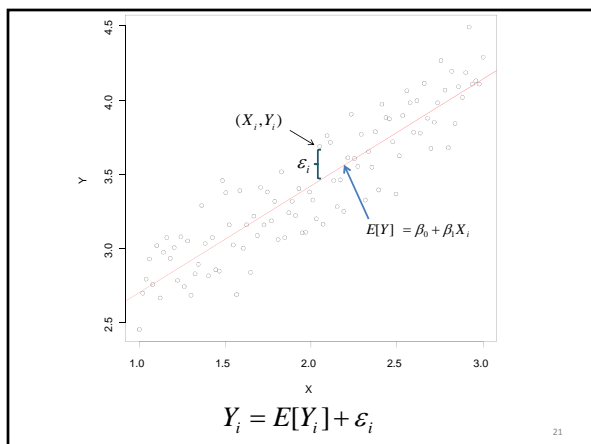
$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i$$

1. Y_i is the (observed) value of response variable in the i^{th} trial
2. β_0 and β_1 are parameters
3. X_i is the (observed) value of the predictor variable in the i^{th} trial
4. ε_i is a random error term with mean 0 and variance σ^2
5. $i = 1, 2, \dots, n$

19 29



20



$$Y_i = E[Y_i] + \varepsilon_i$$

21

Multivariate Classical Linear Model

$$E[Y_i] = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i3} \dots$$

Or, in matrix notation:

$$E[Y] = \beta X$$

22

How does this pertain to insurance modeling?

Gender	Weight	Avg Severity
M	2105	\$ 2,093
F	2832	\$ 1,733

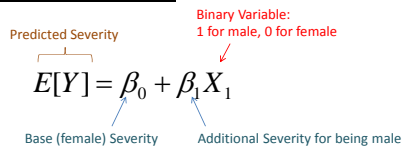
This categorical variable requires a two-parameter model.

23

How does this pertain to insurance modeling?

Gender	Weight	Avg Severity
M	2105	\$ 2,093
F	2832	\$ 1,733

This categorical variable requires a two-parameter model.



24

Gender		
	Weight	Av Severity
M	2105	\$ 2,093
F	2832	\$ 1,733

This categorical variable requires a two-parameter model.

$$E[Y] = \beta_0 + \beta_1 X_1$$

Parameter Estimates

$\beta_0 = 1733$
 $\beta_1 = 360$

25

Let's add another variable

Gender		
	Weight	Av Severity
M	2105	\$ 2,093
F	2832	\$ 1,733

Area		
	Weight	Av Severity
A	1181	\$ 1,754
B	1021	\$ 1,758
C	1493	\$ 1,919
D	524	\$ 1,739
E	413	\$ 2,104
F	305	\$ 2,629

26

Let's add another variable

Gender		
	Weight	Av Severity
M	2105	\$ 2,093
F	2832	\$ 1,733

Area		
	Weight	Av Severity
A	1181	\$ 1,754
B	1021	\$ 1,758
C	1493	\$ 1,919
D	524	\$ 1,739
E	413	\$ 2,104
F	305	\$ 2,629

$$E[Y] = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6$$

X1: Binary variable (Male = 1, Female = 0)
 X2: Binary variable (Area A = 1, else = 0)
 X3: Binary variable (Area B = 1, else = 0)
 X4: Binary variable (Area D = 1, else = 0)
 X5: Binary variable (Area E = 1, else = 0)
 X6: Binary variable (Area F = 1, else = 0)

β_0 : Base severity (female from Area C)
 β_1 : Add'l severity from being male
 β_2 : Add'l severity from Area A
 β_3 : Add'l severity from Area B
 β_4 : Add'l severity from Area D
 β_5 : Add'l severity from Area E
 β_6 : Add'l severity from Area F

Example: Female from Area F $E[Y] = \beta_0 + \beta_6$

27

Modeling Software Output

[GLM fit: Identity Link Function, Normal Error Structure]

Parameter Number	Name	Value	Standard Error	Standard Error (%)	Weight	Weight (%)
1	Mean	1,769.64	99.14477	5.6	4,937	100
-	gender (F)				2,832	57.4
2	gender (M)	361.864	100.18706	27.7	2,105	42.6
3	area (A)	-174.419	135.53147	77.7	1,181	23.9
4	area (B)	-170.408	141.33498	82.9	1,021	20.7
-	area (C)				1,493	30.2
5	area (D)	-174.622	176.69103	101.2	524	10.6
6	area (E)	173.704	193.48309	111.4	413	8.4
7	area (F)	707.8558	218.65201	30.9	305	6.2

28

How good is our fit?

Claims	Gender		Area	Gender		Area	Gender	
	M	F		M	F		M	F
A	519	662		\$ 1,899	\$ 1,641		\$ 1,957	\$ 1,595
B	449	572		\$ 1,939	\$ 1,616		\$ 1,961	\$ 1,599
C	618	875		\$ 2,100	\$ 1,792		\$ 2,132	\$ 1,770
D	208	316		\$ 1,666	\$ 1,787		\$ 1,957	\$ 1,595
E	183	230		\$ 2,579	\$ 1,726		\$ 2,365	\$ 1,943
F	128	177		\$ 3,386	\$ 2,083		\$ 2,889	\$ 2,477

29

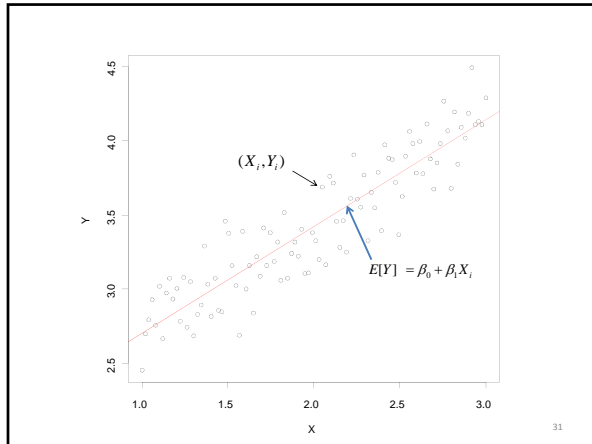
Classical Linear Model; Assumptions

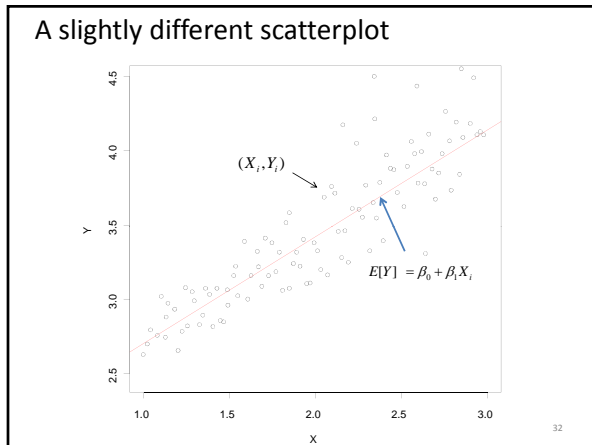
$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i$$

$$Y_i = \mu_{Y_i} + \varepsilon_i$$

1. Y_i is the sum of a constant term and a random term
2. $E\{Y_i\} = \beta_0 + \beta_1 X_i =$ "Linear Predictor"
 1. This implies a linear relationship between X_i and Y_i
3. The error terms ε_i are random variables which;
 1. Are independent
 2. Are normally distributed
 3. Have constant variance, σ^2 .
4. Therefore, the responses, Y_i are also independent normally distributed random variables with constant variance, σ^2 .

30





Outline

- I. Introduce our Data
- II. Classical Linear Modeling
- III. Generalized Linear Modeling**

33

Linear vs. Generalized Linear Model

Assumption	Linear Regression Model	Generalized Linear Model
Relationship between X and Y	Y is a linear combination of X	Y is a function of a linear combination of X
Distribution of Y	Normal	Any distribution from the Exponential family
Variance of Y	Constant	Function of the mean

Flexibility of Relationship between X & Y

- Recall that the Multiple Linear Regression Model can be written as:

$$E[Y_i] = X_i\beta$$
 (Or... $Y_i = \beta_0 + \beta_1X_{i1} + \beta_2X_{i2} + \dots + \beta_nX_{in}$)

Flexibility of Relationship between X & Y

- Recall that the Multiple Linear Regression Model can be written as:

$$E[Y_i] = X_i\beta$$
 (Or... $Y_i = \beta_0 + \beta_1X_{i1} + \beta_2X_{i2} + \dots + \beta_nX_{in}$)
- Generalized Linear Models assume a more general relationship between X and Y:

$$E[Y_i] = h(X_i\beta)$$

Flexibility of Relationship between X & Y

- Generalized Linear Models assume a more general relationship between X and Y:

$$g(Y_i) = X_i\beta$$

Link Function

Examples:

- $Y_i = X_i\beta$ (Identity Link)
- $\ln(Y_i) = X_i\beta$ (Log Link)
- $\ln(Y_i/(1-Y_i)) = X_i\beta$ (Logit Link)
- $1/Y_i = X_i\beta$ (Reciprocal Link)

37

Identity Link vs. Log Link

Identity Link:

- $Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \dots + \beta_n X_{in}$

Log Link:

- $\ln(Y_i) = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \dots + \beta_n X_{in}$
- $Y_i = \exp(\beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \dots + \beta_n X_{in})$
- $Y_i = \exp(\beta_0) \cdot \exp(\beta_1 X_{i1}) \cdot \exp(\beta_2 X_{i2}) \cdot \dots \cdot \exp(\beta_n X_{in})$

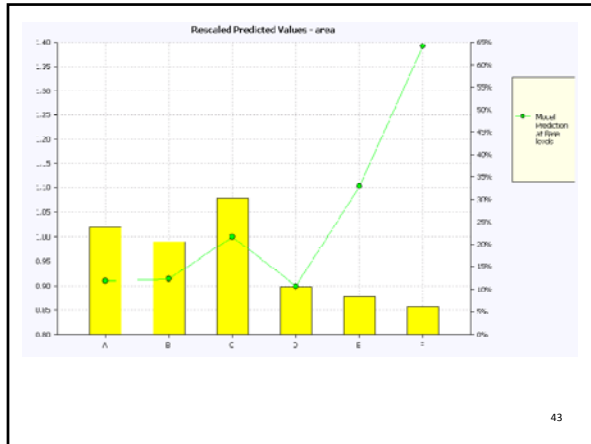
Identity Link produces additive factors; Log Link produces multiplicative factors

38

Why choose log link?

- Convenience: match structure of rating plan/scorecard
- Intuition: Do rating variables have additive or multiplicative effects on severity?
- Evaluation: We can test the appropriateness of the link function

39



Do estimates match the data?

Actual Severity			Predicted Severity (additive)			Predicted Severity (multiplicative)		
Area	Gender		Area	Gender		Area	Gender	
	M	F		M	F		M	F
A	\$ 1,899	\$ 1,641	A	\$ 1,957	\$ 1,595	A	\$ 1,952	\$ 1,590
B	\$ 1,939	\$ 1,616	B	\$ 1,961	\$ 1,599	B	\$ 1,960	\$ 1,596
C	\$ 2,100	\$ 1,792	C	\$ 2,132	\$ 1,770	C	\$ 2,148	\$ 1,750
D	\$ 1,666	\$ 1,787	D	\$ 1,957	\$ 1,595	D	\$ 1,931	\$ 1,573
E	\$ 2,579	\$ 1,726	E	\$ 2,305	\$ 1,943	E	\$ 2,370	\$ 1,930
F	\$ 3,386	\$ 2,082	F	\$ 2,839	\$ 2,477	F	\$ 2,989	\$ 2,435

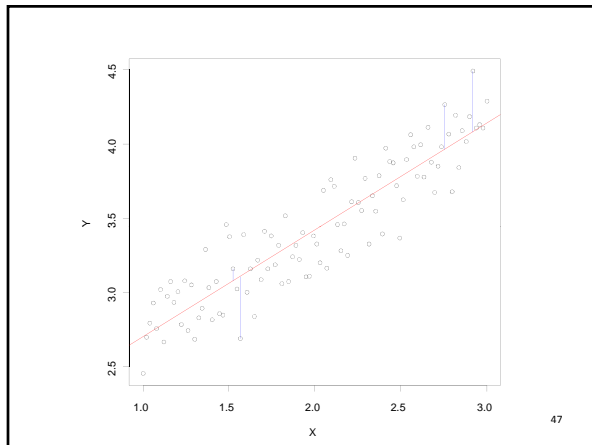
Linear vs. Generalized Linear Model

Assumption	Linear Regression Model	Generalized Linear Model
Relationship between X and Y	Y is a linear combination of X	Y is a function of a linear combination of X
Distribution of Y	Normal	Any distribution from the Exponential family
Variance of Y	Constant	Function of the mean

Flexibility of Distribution of Y

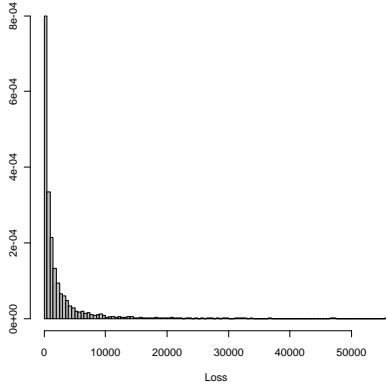
- Least-squares estimation implicitly assumes observations come from normal distribution

46

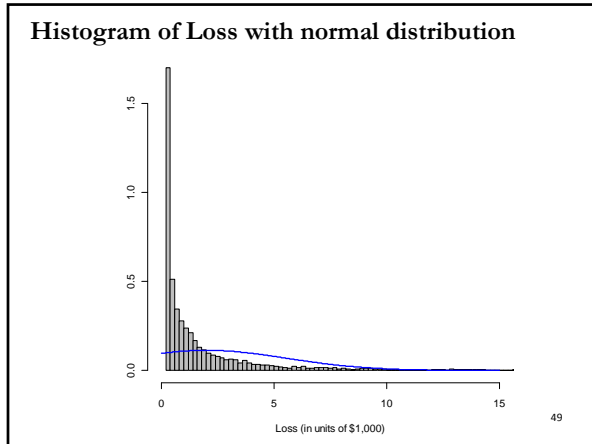


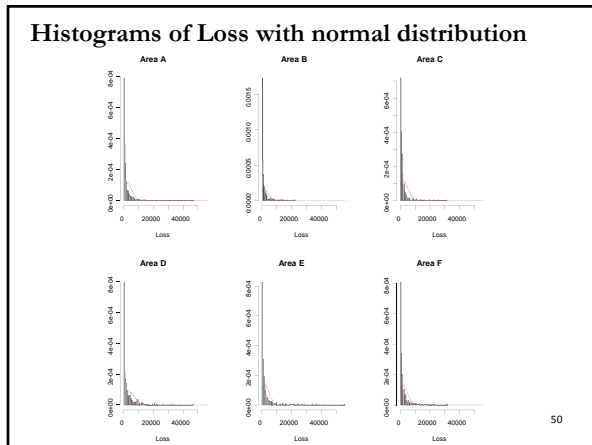
47

Histogram of loss



48





Flexibility of Distribution of Y

- Least-squares estimation implicitly assumes observations come from normal distribution
- Problems with normal distribution assumption
 - Severity distributions usually skewed to right
 - Higher mean of Y associated with higher variance
 - Values of response may be restricted to positive

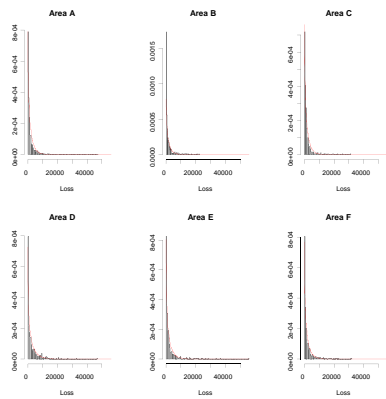
51

Exponential Family of Distributions

- In a GLM, Y_i may be distributed according to any member of the Exponential family of distributions
- Two Key Features of the Exponential Family:
 - The distribution is completely specified in terms of its mean and variance
 - The variance of Y_i is a function of the mean
- Familiar Examples: Normal, Poisson, Gamma, Inverse Gaussian

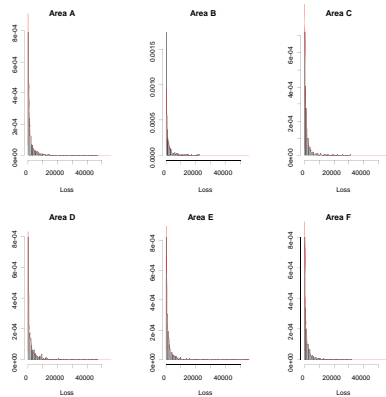
52

Histograms of Loss with gamma distribution

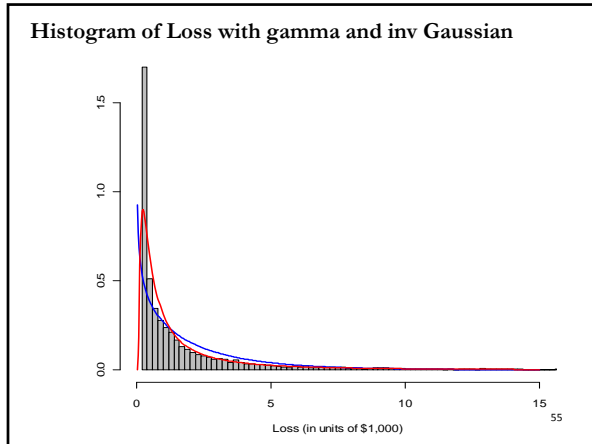


53

Histograms of Loss with inv. Gaussian distributions



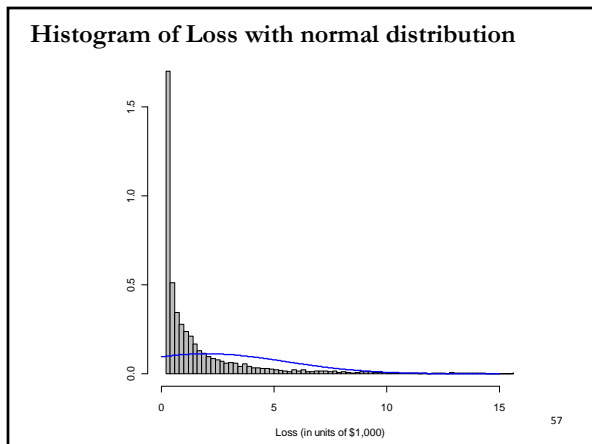
54



Least Squares vs. Maximum Likelihood

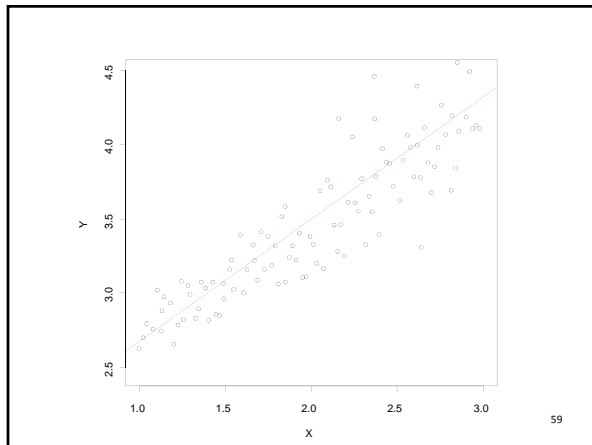
- For each observation (X_i, Y_i) , consider the probability of Y_i based on assumed distribution.
- Further, consider the product of the n probabilities.
- The estimators (β) are those values that maximize the product of the n probabilities.
- (If a normal distribution is assumed, maximum likelihood is equivalent to minimizing sum of squared errors.)

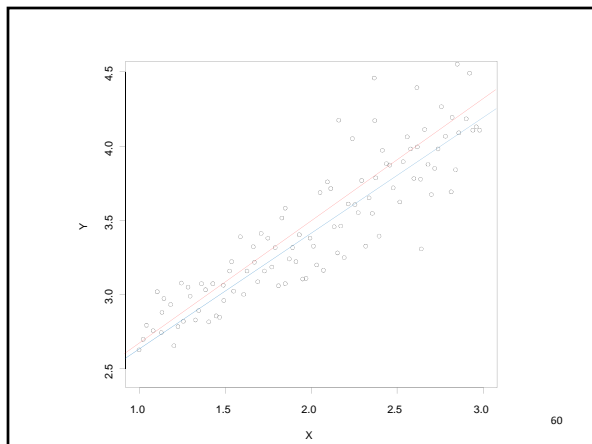
56



Linear vs. Generalized Linear Model

Assumption	Linear Regression Model	Generalized Linear Model
Relationship between X and Y	Y is a linear combination of X	Y is a function of a linear combination of X
Distribution of Y	Normal	Any distribution from the Exponential family
Variance of Y	Constant	Function of the mean





Flexibility of Variance of Y

- The variance of Y_i is allowed to vary with the expected value of Y_i (μ)
- Variance functions link the variability of Y_i to the expected value of Y_i (μ)

Distribution of Y	Variance Function
Normal	1 (variance is constant across cells)
Poisson	μ (variance is proportional to mean)
Gamma	μ^2 (CV is constant across cells)
Inverse Gaussian (Normal)	μ^3
Binomial	$\mu(1 - \mu)$
More General Case	μ^p (Tweedie if $p < 0$, $1 < p < 2$, $p > 2$)

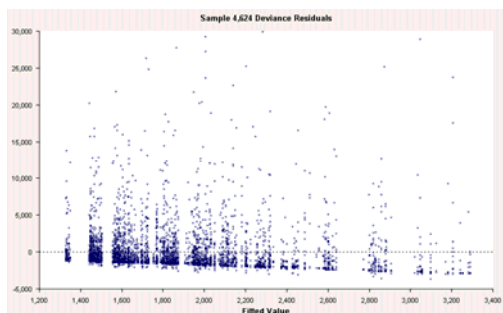
61

Error structure Diagnostics

- Deviance residuals against fitted value
 - *Deviance*: in a GLM, more weight given to differences in fitted vs. actual when variance function is small
 - *Deviance residual*: square root of an observation's contribution to total deviance
 - Plotting *deviance residual* against fitted value can highlight problems with error structure assumption
- Histogram of deviance residuals

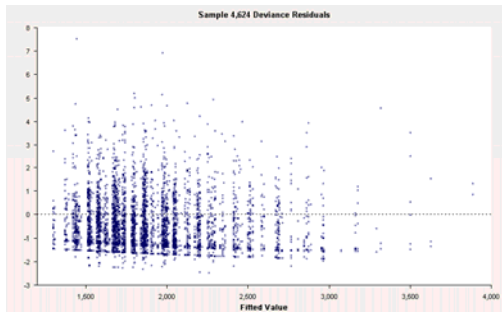
62

Error structure diagnostics: Normal



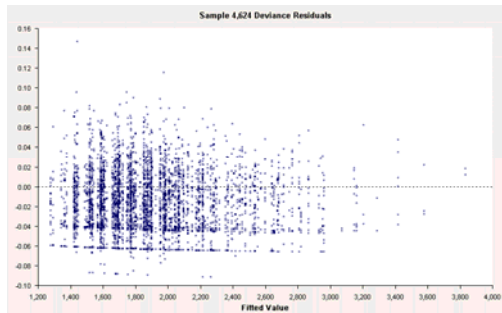
63

Error structure diagnostics: Gamma



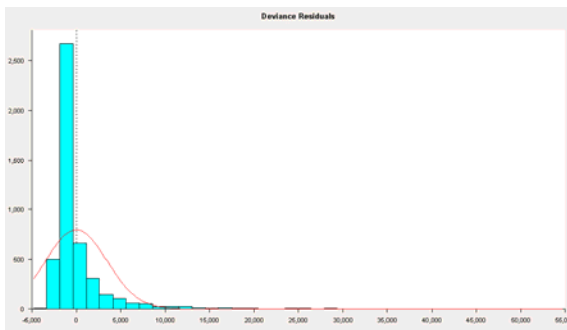
64

Error structure diagnostics: Inv. Gaussian



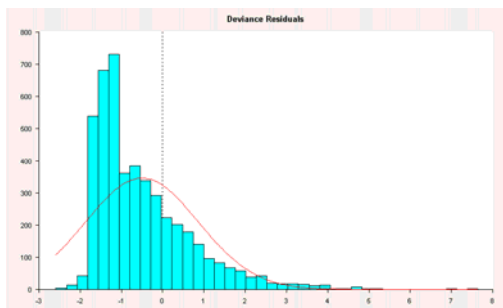
65

Error structure diagnostics: Normal



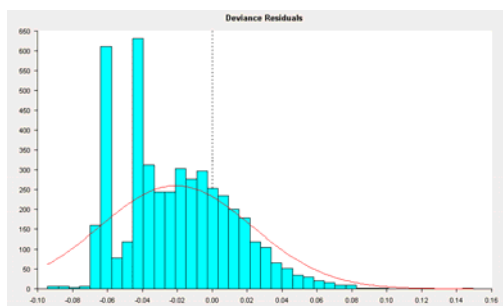
66

Error structure diagnostics: Gamma



67

Error structure diagnostics: Inv. Gaussian

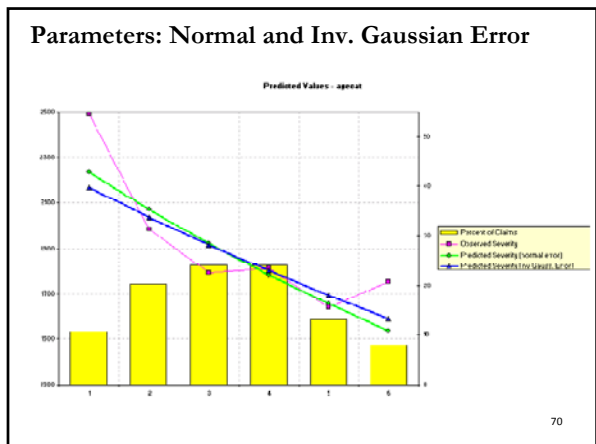


68

Model comparison: normal vs. inverse Gaussian

Parameter	Name	[Log Link, Normal Error Structure]			[Log Link, Inv Gaussian Error Structure]		
		Value	Standard Error	Exp(Value)	Value	Standard Error	Exp(Value)
1	Mean	7.47	0.0539	1,749.90	7.49	0.0507	1,783.61
-	gender (F)						
2	gender (M)	0.2051	0.05196	1.2277	0.1711	0.05212	1.1867
3	area (A)	-0.0959	0.07417	0.9085	-0.0934	0.06874	0.9108
4	area (B)	-0.0918	0.0774	0.9123	-0.0941	0.07155	0.9102
-	area (C)						
5	area (D)	-0.1069	0.09972	0.8986	-0.0783	0.08922	0.9247
6	area (E)	0.098	0.09284	1.103	0.0664	0.10333	1.0687
7	area (F)	0.3303	0.08776	1.3914	0.2866	0.12842	1.3319

69



Common choices for some model types

Target	Link Function	Error
Claim Frequency	log	Poisson
Claim Severity	log	gamma
Loss Costs	log	Tweedie
Probability of Renewal	logit	binomial

71

- ### Further modeling
- Explore significance of other variables
 - Group levels on our chosen variables
 - Add interactions
 - (see GLM II)
- 72

References/Resources

De Jong, P., and Heller, G.Z. 2008. *Generalized Linear Models for Insurance Data*. Cambridge University Press

Anderson, D., Feldblum, S., Modlin, C., Schirmacher, D., Schirmacher, E., Thandi, N. 2007. *A Practitioner's Guide to Generalized Linear Models*. CAS Discussion Paper Program

Hardin, J. and Hilbe, J. 2001. *Generalized Linear Models and Extensions*. College Station, Texas: Stata Press
