

Logistic Regression: Basics

Prediction Model: Binary Outcomes

Nemours Stats 101

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General Linear Model

Semiparametric analysis

OUTCOME

Continuous

- Counts Data→
- Survival (Event History Data) →
- Binary/Dichotomous or Binomial →

GM MODEL

- Linear Regression (simple & Multiple)
- Poisson Regression

Cox Regression

Logistic & Binomial

GLM: PURPOSE

- Outcome, response or dependent variable determines model selection
- Estimate the magnitude of association (point estimate) between the outcome variable and the covariates (independent, explanatory or predictor)
- Potentials to control for confounding What is confounding?
- Efficient for model building
- Efficient for prediction of risk or predisposing factors

Case Control Design

- Study population Sampling technique, sample size and power
- Case ascertainment
- Control ascertainment
- Measure of effect / Point estimate
- Statistical analysis
- 2 X 2 table
- Mantel-Haenzel odds ratio
- Logistic Regression Model
 - Conditional versus Unconditional
 - Univariable/Univariate Model
 - Multivariable/multiple model

Logistic Regression

- Models relationship between set of variables or covariates x_i
 - dichotomous such as seizure (yes/no)
 - categorical (Type of cerebral palsy Hemiplegic, Diplegia, etc)
 - continuous (age, systolic blood pressure, weight, height...)

&

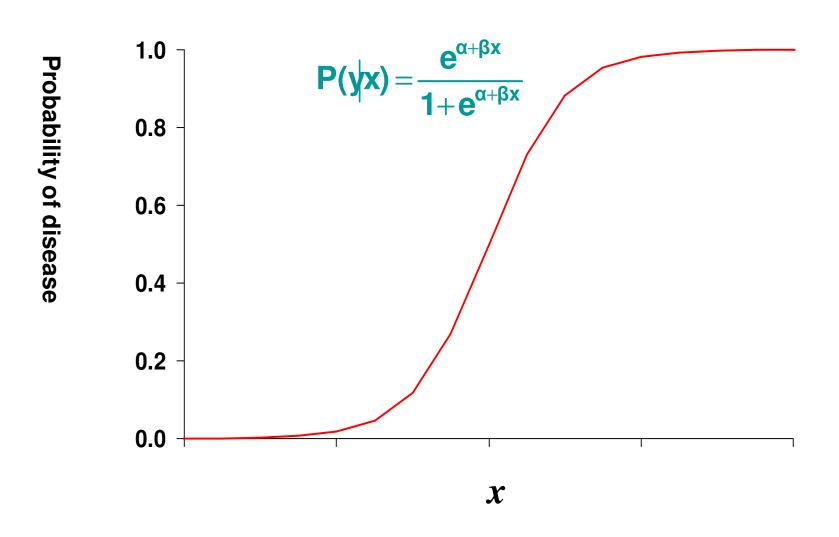
 Binary outcome (Y) variable (deep wound infection, 1= presence or diagnosed case, and 0= absence of deep wound infection)

Probability & Odds

$$\ln \left(\frac{P}{1 - P}\right) = \alpha + \beta x$$

$$\frac{P}{1 - P} = e^{\alpha + \beta x}$$

Logistic Function



Logistic Function

$$P (y | x) = \frac{e^{\alpha + \beta x}}{1 + e^{\alpha + \beta x}}$$

$$\ln \left[\frac{P(y|x)}{1 - P(y|x)} \right] = \alpha + \beta x$$



The logistic function

- Advantages of the logit
 - Simple transformation of P(y|x)
 - Linear relationship with x
 - Can be continuous (Logit between ∞ to + ∞)
 - Known binomial distribution (P between 0 and 1)

$$\ln\left(\frac{P}{1-P}\right) = \alpha + \beta x \qquad \frac{P}{1-P} = e^{\alpha + \beta x}$$

Odds and β

Exposure (x)

Disease (y)	Yes	No
Yes	P(y x=1)	P(y x=0)
No	1-P(y x=1)	1 - P(y x = 0)

$$\frac{P}{1-P} = e^{\alpha + \beta x}$$

$$Odds_{d|e} = e^{\alpha + \beta}$$

$$Odds_{d|\bar{e}} = e^{\alpha}$$

$$OR = \frac{e^{\alpha + \beta}}{e^{\alpha}} = e^{\beta}$$

$$\ln(OR) = \beta$$

OR using 2 X 2 table

- In the Surveillance Epidemiology and End Results data for pediatric (0-19 years) leukemia diagnosed from 1973 through 2007 there were 15,215 cases and 7,459 deaths during the same period. Using the STATA output below, were girls more or less likely to die from leukemia compared to boys.
 - Data instruction on coding: 1=boys and 2= girls.
 - What is the OR?

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Nemours Orthopedic Epidemiology

Notes:

- 1. (/m# option or -set memory-) 50.00 MB allocated to data 2. (/v# option or -set maxvar-) 5000 maximum variables
- . use "C:\Documents and Settings\lholmes\Desktop\leukemiaseer.dta"
- . tab Vitalstatus

cutoff used) 0 1	Freq. 7,756 7,459	Percent 50.98 49.02	⊂um. 50.98 100.00
Vital status recode (study			

. tabodds Vitalstatus Sex

Sex	cases	controls	odds	[95% Conf.	Interval]
1	4183	3828	1.09274	1.04587	1.14171
2	3276	3928	0.83401	0.79622	0.87360

Primary

Label

Age at c

Patient 1 Vital stal

Number Survival Histolog Test of homogeneity (equal odds): chi2(1) = 68.97

Pr>chi2 = 0.0000

Year of | Score test for trend of odds:

chi2(1) =68.97 Pr>chi2 =0.0000

. tabodds Vitalstatus Sex, or

1	1.000000 0.763232	68.97	0.0000	0.715942	0.813645
sex	Odds Ratio	chi2	P>chi2	[95% Conf.	Interval]

diagnosi

Test of homogeneity (equal odds): chi2(1) = 68.97

Pr>chi2 0.0000

Score test for trend of odds: chi2(**1**) 68.97

Pr>chi2 =0.0000

Odds Ratio Computation Using 2 X 2 table

- OR = AD / BC
- Substituting: 16430824 / 1254052 = 1.31
- Interpretation: Boys were 31% more likely to die from leukemia compared to girls.
- Substituting: 1254052 / 16430824 = 0.76
- Interpretation: Compared to boys, girls were 24% (1-0.76) less likely to die.
 - Based on these results, can we conclude that there is a statistically significant difference in mortality by sex of children with leukemia in the SEER data?

β

- β = increase in logodds for a one unit increase in x
- Test of the hypothesis that β=0 (Wald test)

$$\chi 2 = \frac{\beta^2}{\text{Variance}\beta} \qquad \text{(1df)}$$

• Interval testing 95%CI=e^(β±1.96Sξ)

Univariable Logistic Regression Model

One outcome and one independent variable $Y = \beta o + \beta 1X1$, where X1 is the independent variable that can be measured on binary, categorical (discrete) or continuous (cardinal) scale

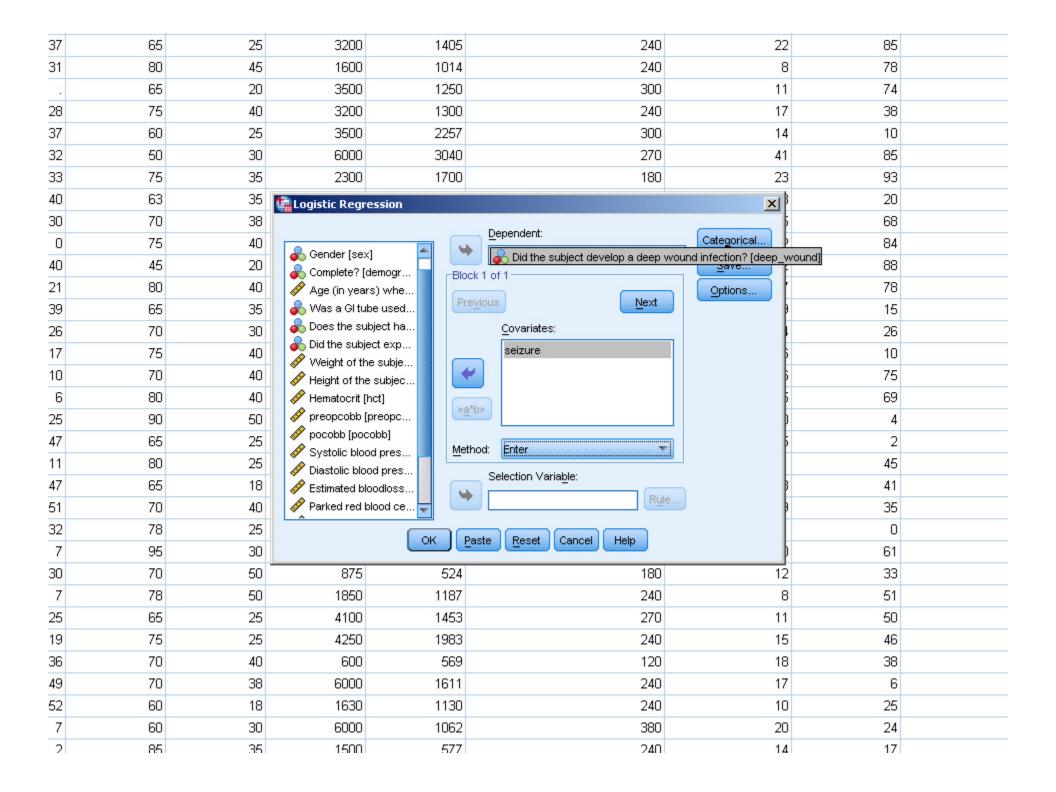
Vignette

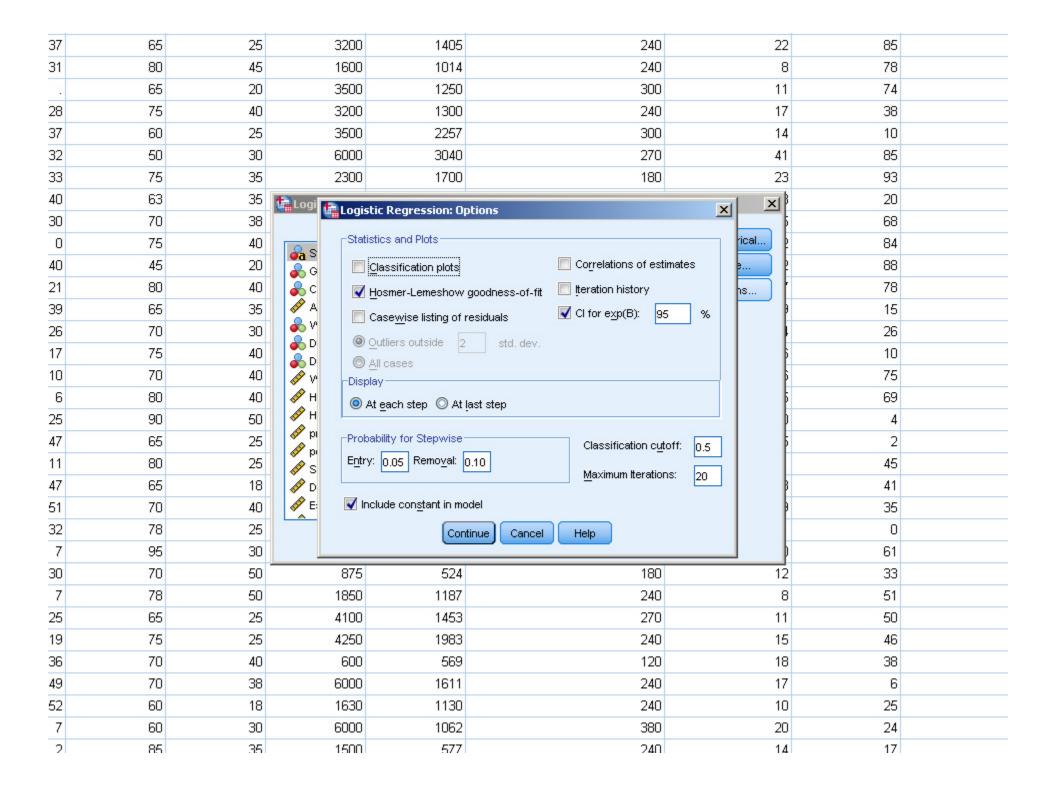
- Suppose there is an association between deep wound infection and weight as well as seizure among CP children who underwent posterior spinal fusion for curve deformities correct.
- Using the sample data and one regression method that fits the suggested hypotheses, examine this relation and draw a meaningful inference from your result.
 - Hints: Deep wound infection is measured on a binary scale, weight on continuous and seizure on a dichotomous scale.

1	1 Did the subject experi	ence seizures? 34.00	37.00	115	37	65	25	3200
1	1 30.50	142.00	41.00	90	31	80	45	1600
1	1 34.60	140.00	35.00	64		65	20	3500
1	1 24.60	135.40	40.00	58	28	75	40	3200
1	1 37.00	149.00	39.00	57	37	60	25	3500
1	1 27.40	140.00	43.00	108	32	50	30	6000
1	1 30.60		29.00	88	33	75	35	2300
1	1 15.60		39.00	98	40	63	35	1700
1	1 22.00		36.00	89	30	70	38	2300
1	1 34.30	151.00	41.00	70	0	75	40	5650
1	1 24.10	120.00	42.00	89	40	45	20	600
1	1 33.70	124.00		88	21	80	40	2400
1	1 40.80		34.00	64	39	65	35	2500
1	1 28.70	150.00		50	26	70	30	7770
1	0 52.40	169.00		65	17	75	40	3000
0	1 27.50	142.00		85	10	70	40	2500
1	1 20.50	125.00	36.20	54	6	80	40	931
1	1 27.30	130.00	40.20		25	90	50	1700
1	1 33.00		37.00	93	47	65	25	4600
1	1 25.00		39.50	59	11	80	25	2699
1	0 47.20	140.00	36.30	87	47	65	18	1600
0	0 35.90	144.50			51	70	40	1300
1	1 21.50	119.00		84	32	78	25	3600
0	1 37.20	133.00	30.00	60	7	95	30	2000
1	1 24.70	140.00	47.00		30	70	50	875
0	0 30.00		42.00	55	7	78	50	1850
0	0 28.60	143.50	43.00	88	25	65	25	4100
1	1 28.30	136.00	40.60	96	19	75	25	4250
1	1 17.70	123.00	37.00	76	36	70	40	600
0	1 51.20	154.00	41.50		49	70	38	6000
1	1 14.90		40.00	90	52	60	18	1630
1	1 32.30		41.00	75	7	60	30	6000
Π	1 41.30		43 00	45	2	85	35	1500

55	55	35	4000	1740	210	18	100	
37	65	25	3200	1405	240	22	85	
31	80	45	1600	1014	240	8	78	
	65	20	3500	1250	300	11	74	
28	75	40	3200	1300	240	17	38	
37	60	25	3500	2257	300	14	10	
32	50	30	6000	3040	270	41	85	
33	75	35	2300	1700	180	23	93	
40	63	35	1700	916	120	13	20	
30	70	38	2300	1642	150	15	68	
0	75	40	5650	2614	240	12	84	
40	45	20	600	300	180	12	88	
21	80	40	2400	1600	240	27	78	
39	65	35	2500	1068	240	9	15	
26	70	30	7770	2132	240	14	26	
17	75	40	3000	1181	240	6	10	
10	70	40	2500	1689	240	6	75	
6	80	40	931	874	240	15	69	
25	90	50	1700	933	240	10	4	
47	65	25	4600	1257	270	15	2	
11	80	25	2699	984	240	21	45	
47	65	18	1600	1083	240	28	41	
51	70	40	1300	686	300	9	35	
32	78	25	3600	1314	240	41	0	
7	95	30	2000		270	20	61	
30	70	50	875	524	180	12	33	
7	78	50	1850	1187	240	8	51	
25	65	25	4100	1453	270	11	50	
19	75	25	4250	1983	240	15	46	
36	70	40	600	569	120	18	38	
49	70	38	6000	1611	240	17	6	
52	60	18	1630	1130	240	10	25	
7	60	30	6000	1062	380	20	24	

37	Generali	zed Linear Models	3200	1405	240	22	85	
31	Mi <u>x</u> ed M	odels •	1600	1014	240	8	78	
	<u>C</u> orrelate	e >	3500	1250	300	11	74	
28	<u>R</u> egress		Automatic Linear Modeling		240	17	38	
37	Loglinea		Linear		300	14	10	
32	Classi <u>f</u> y		Curve Estim	ation	270	41	85	
33		on Reduction	Rartial Leas		180	23	93	
40	Sc <u>a</u> le		Binary Logi:		120	13	20	
30	<u>N</u> onpara Forecas	metric Tests			150	15	68	
0			Multinomial I	Logistic	240	12	84	
40		Survival Multiple Response Complex Samples Quality Control			180	12	88	
21					240	27	78	
39	0.000				240	9	15	
26	ROC Cur		<u>₩</u> eight Estir	nation	240	14	26	
17	Amos 19		2-Stage Least Squares		240	6	10	
10	70	40	Optimal Sca	ling (CATREG)	240	6	75	
6	80	40	931	874	240	15	69	
25	90	50	1700	933	240	10	4	
47	65	25	4600	1257	270	15	2	
11	80	25	2699	984	240	21	45	
47	65	18	1600	1083	240	28	41	
51	70	40	1300	686	300	9	35	
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36	70	40	600	569	120	18	38	
49	70	38	6000	1611	240	17	6	
52	60	18	1630	1130	240	10	25	
7	60	30	6000	1062	380	20	24	
2	85	35	1500	577	240	14	17	





SPSS Output β , Exp β , Wald test

Variables in the Equation

								95% C.I.for EXP(B)	
		В	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Step 1ª	seizure	.181	.746	.059	1	.808	1.198	.278	5.166
	Constant	847	.690	1.508	1	.220	.429		

a. Variable(s) entered on step 1: seizure.

OR Interpretation

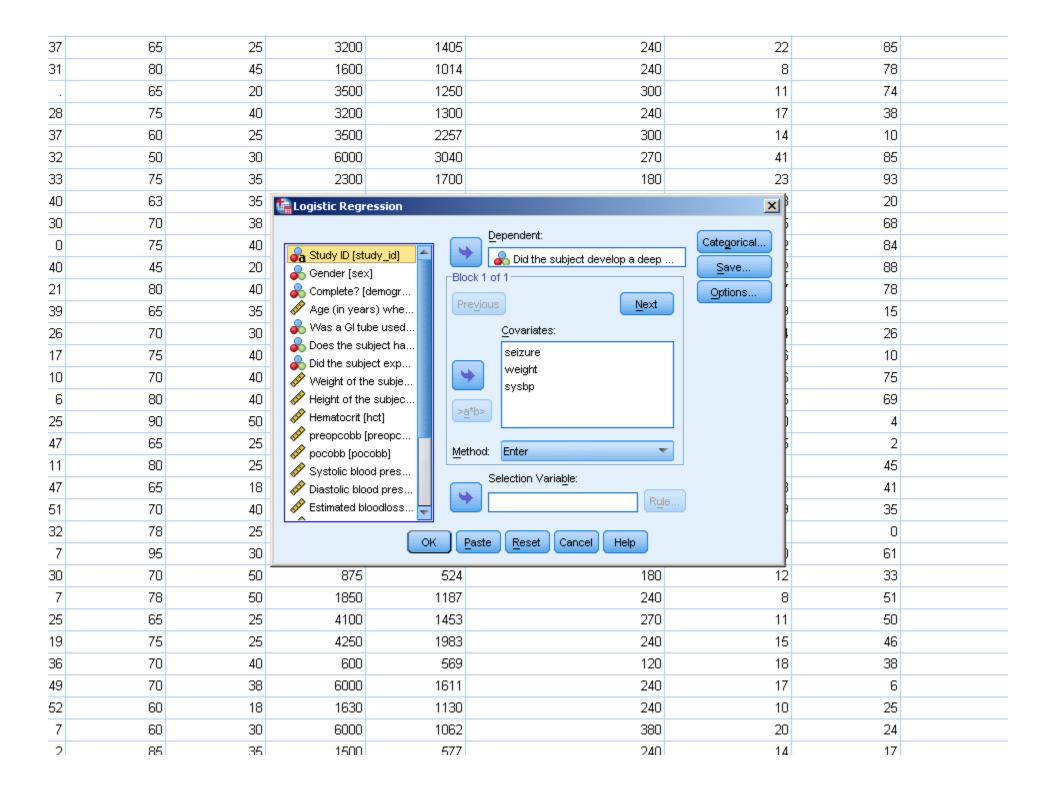
- OR determines the status of the exposure since the disease in a case control study occurred prior to the study conduct.
- Therefore, the investigator's attempt is to retrospectively determine the exposure status comparing cases with the control.
- OR = 1.0 implies no association between the exposure and the disease or outcome of interest
- OR < 1 means that the exposure is protective
- OR > 1 implies that the outcome is associated with exposure, and increases as the exposure increases.
 - In the sample data, though statistically insignificant, among those who had seizure, there was 20% increased odds of having deep wound infection compared to those without.

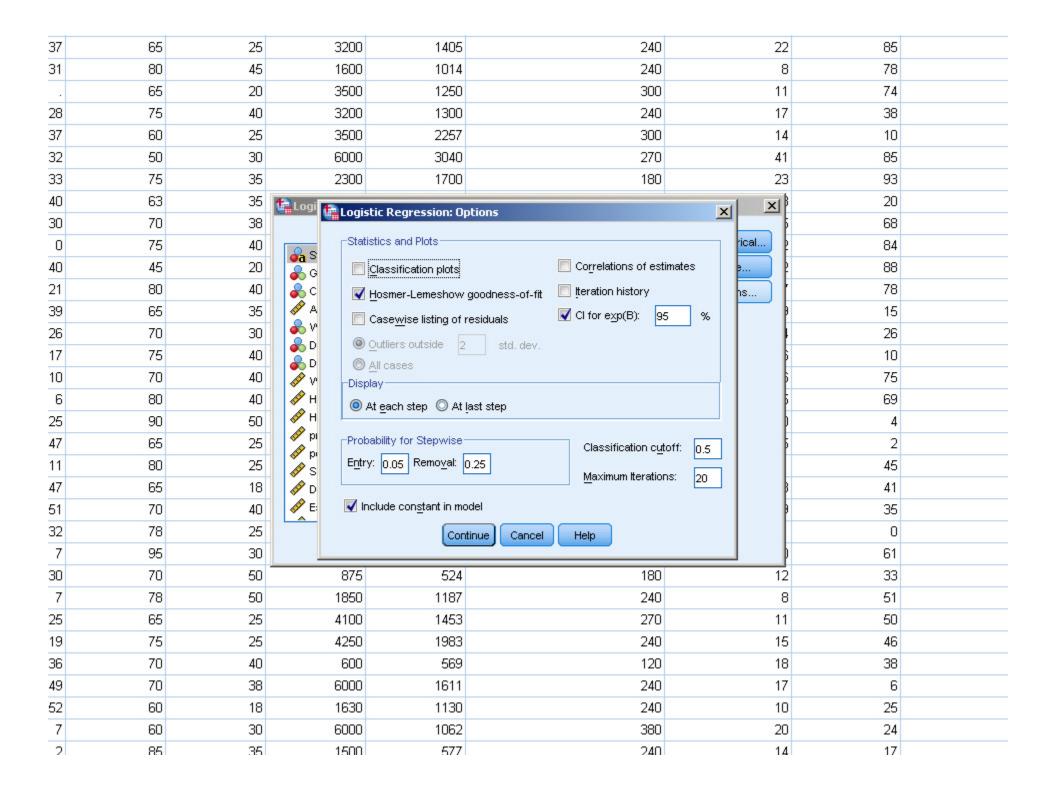
Multivariable Logistic Regression

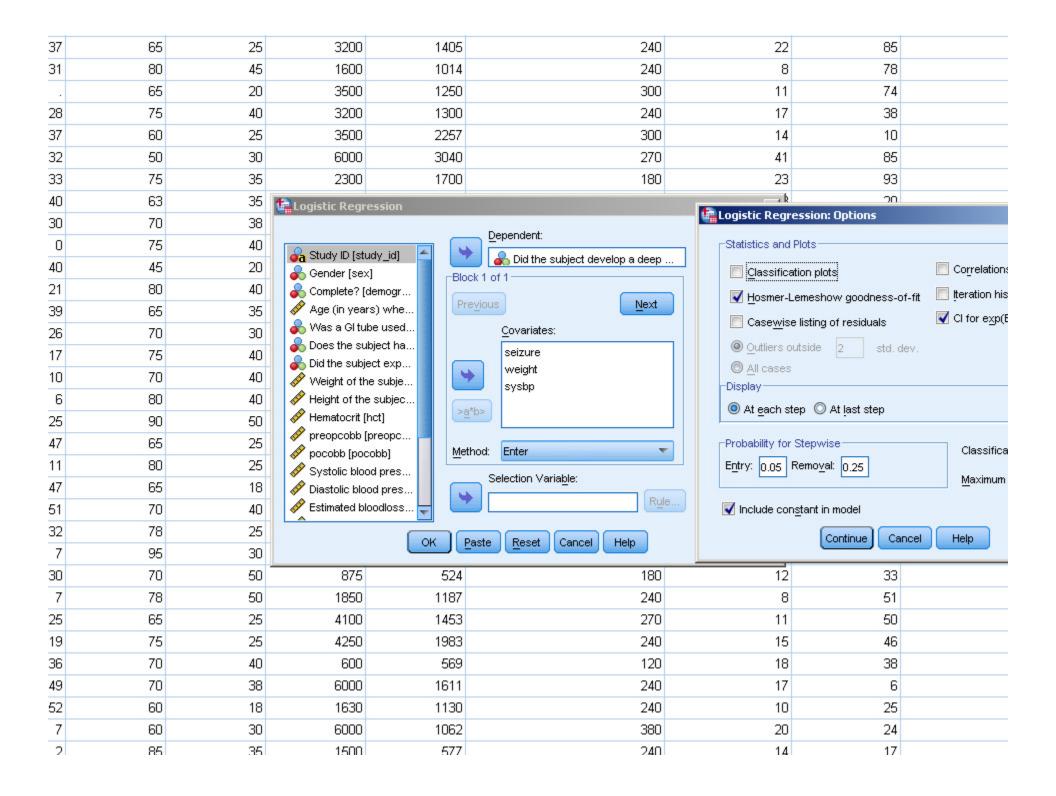
 $Y = \beta o + \beta 1X1 + \beta 2X2 + \beta 3X3 \dots$ βzXz , where the outcome is measured on a binary scale (1,0) and the independent, explanatory or predictor are measured on scales similar to univariable model

Model Building

- Variables selection criteria
- Style Forward & backward
- Model Fitness
- Hosmer-Lemeshow Test
- Model check
 - Interaction as full model
 - Reduced Model







SPSS Output

Variables in the Equation

								95% C.I.for EXP(B)	
		В	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Step 1ª	seizure	.603	.838	.517	1	.472	1.827	.354	9.446
	weight	.054	.028	3.852	1	.050	1.056	1.000	1.114
	sysbp	.095	.034	8.085	1	.004	1.100	1.030	1.175
	Constant	-10.113	2.990	11.437	1	.001	.000		

a. Variable(s) entered on step 1: seizure, weight, sysbp.

OR Interpretation

 After adjustment for patients weight, and systolic blood pressure, there was insignificant 83% odds of developing deep wound infection among patients with seizure compared to those without, OR = 1.83, 95% Confidence Interval, 0.35-9.50, p = 0.47.

Credits

- The preparation of these slides benefited from works done on logistic regression by great minds like D. Hosmer & S. Lemeshow, and Odds Ratio by Mantel & Haenzel.
- And for those not mentioned, thanks for your contributions to the development of this fine technique to evidence discovery in medicine and biomedical sciences.

