

Multivariate Analysis의 확장: 상호작용 그리고 곡선형 모형



이 정 보

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Fundamental Concepts

(Included 2013 Spring Talks Slides)


2

Risk Factor (as well prognostic, predictive)

- ◆ Definition: A **risk factor** is a variable associated with an increased risk of disease or infection. Sometimes, **determinant** is also used, being a variable associated with either increased or decreased risk(Wikipedia).
- ◆ **Independent Risk Factor:**
Outcome ← Candidate Risk Factors(A & B) : correlated or causal
Risk Factor A ⊥ Risk Factor B
- ◆ Interpretation: If factor A is an independent risk factor of an outcome, factor A should be associated with the outcome regardless of low & high level of factor B.



Univariate & Multivariate Analysis

- ◆ **Univariate analysis** is the simplest form of quantitative (statistical) analysis. The analysis is carried out with the description of a single variable in terms of the applicable unit of analysis.
- ◆ Univariate analysis contrasts with bivariate analysis – the analysis of two variables simultaneously – or multivariate analysis – the analysis of multiple variables simultaneously. Univariate analysis is commonly used in the first, descriptive stages of research, before being supplemented by more advanced, inferential bivariate or multivariate analysis.
- ◆ **Multivariate analysis (MVA)** is based on the statistical principle of **multivariate statistics**, which involves observation and analysis of more than one statistical outcome variable at a time. In design and analysis, the technique is used to perform trade studies across multiple dimensions while taking into account the effects of all variables on the responses of interest.



이론적수렴의 특징과 개인화적수렴간의 연관성

홍남대학교 의과대학 신경과, 서울대학교 의과대학 신경과
이경재 박인철 이주연 김성복 박상민 임종길 이재영 손은혜

Characteristics of Atopic Myelitis and its Relationship With *Toxocara Canis* Myelitis

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Background: It has recently been reported that atopic disorders are associated with neuroimmunological diseases. Atopic myelitis (AM) has been defined as an idiopathic myelitis with either (1) an atopic disease such as atopic dermatitis, allergic rhinitis, or bronchial asthma, or (2) positive anti-toxin-specific immunoglobulin E (IgE) with hyper-IgE-emia. The aim of this study was to characterize the clinical, radiological, and laboratory profile of AM.

Methods: The characteristics of a group of patients with AM (n=10) were compared with those of a group of non-AM patients (n=10). The history, clinical symptoms, serologic, and cerebrospinal fluid (CSF) findings, and brain and spinal-cord magnetic resonance imaging (MRI) scans of all of the subjects were reviewed.

Results: Clinically, remittent onset occurred more frequently in the AM group than in the non-AM group (72.7% vs. 30.0%, p=0.03). The positivity of specific IgE antibody to *Toxocara canis* was greater in the AM group than in the non-AM group (p=0.03). Swelling (p=0.01) and gadolinium enhancement (p=0.04) on MRI scan also were more frequent in the AM group than in the non-AM group.

Conclusions: These findings suggest that AM is responsible for a considerable proportion of atopic myelitis. It appears that the progression of symptoms onset in atopic patients shows the positivity of specific anti-IgE and the occurrence of swelling and enhancement of the lesion on spinal-cord MRI.

Key Words: Myelitis, Atopy, *Toxocara*, Neurocysticercosis

본 연구는 SPSS 19 통계 프로그램을 이용하였다. 아토피적수렴군과 비아토피적수렴군 간의 차이를 보기 위해 카이제곱, 피셔(Fisher)의 정확검정법과 Mann-Whitney U 검정을 이용하여 비교 분석하였고 아토피적수렴에 영향을 미치는 인자를 알아 보기 위해 로지스틱 회귀분석을 사용하였다. 통계 유의수준은 p<0.05로 하였다.



Table 2. Comparison of clinicolaboratory features between patients with and without atopic myelitis

	AM (n=19)	Non-AM (n=13)	p value
Mean age of onset (yr)	48.3±11.3	47.8±17.3	ns
Sex (male/female)	17/2	8/5	ns
Known history of atopy (%)	2 (11.1)	0 (0)	ns
Mode of onset			0.033
Acute (%)	5 (27.8)	9 (69.2)	
Non-acute (%)	13 (72.2)	4 (30.8)	
Mean duration of initial symptoms to maximal deficit (d)	37.8±27.7	24.8±10.4	ns
Classical symptoms			
Asymmetry (%)	13 (72.2)	7 (53.8)	ns
Only sensory symptoms (%)	15 (83.3)	7 (53.8)	ns
Mean MRC	4.5±6.7	4.5±11.2	ns
Mean MRC extension	58.8±2.9	57.5±4.5	ns
Mean maximal EDSS	3.3±1.0	3.3±2.9	ns
Sphincter symptoms (%)	10 (52.6)	1 (7.7)	ns
Recovery (%)	6 (31.6)	2 (15.4)	ns
Duration of follow-up (month)	36.8±18.2	38.2±24.7	ns
(range: 12-83)		(range: 12-67)	
Imaging findings			
Mean extension (cm)	4.0±4.8	2.2±2.3	ns
Specific IgG in CSF (n=10) (%)	10 (100)	27 (23.6)	0.045
Mean IgG index ratio	0.55±0.11	0.15±0.11	0.002

Table 3. Comparison of radiologic findings between patients with and without atopic myelitis

	AM (n=19)	Non-AM (n=13)	p value
Optical chiasm MRI findings			
Mean brain length (normal body count)	23±4.8	23±8.8	ns
Findings (%)	23 (100)	4 (30.8)	0.004
Gd enhancement (%)	23 (100)	7 (53.8)	
Location (%)			
Central (%)	2 (10.5)	2 (15.4)	ns
Central to basilar (%)	21 (110)	4 (30.8)	ns
Basilar (%)	0 (0)	1 (7.7)	ns
Central to basilar (%)	0 (0)	0 (0)	ns
Brain MRI findings			
Atypical lesions (%)	4 (21.1)	7 (53.8)	ns
White matter lesion (%)	11 (57.9)	4 (30.8)	ns

Table 4. Logistic regression results for clinicoradiologic factors affecting atopic myelitis

	B	SE	Wald	Df	Sig.	Exp (B)	95% CI for Exp (B)	
							Lower	Upper
Male	2.363	1.176	4.036	1	0.045	10.625	1.059	106.573
Non-acute onset	1.766	0.799	4.891	1	0.027	5.850	1.222	27.904
Zonocarpa center (+)	2.526	1.149	4.907	1	0.027	12.500	1.338	116.796
Swelling (MRZ)	2.809	0.961	9.045	1	0.003	18.000	2.737	118.391
Enhancement (MRZ)	1.046	0.951	4.185	1	0.041	7.000	1.085	45.160

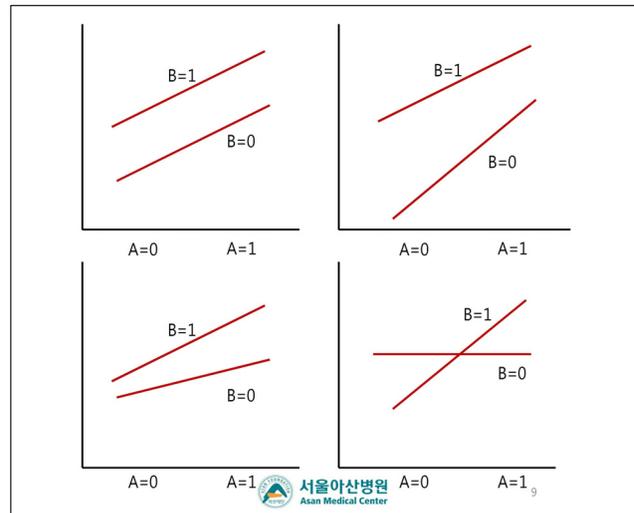
AM, Atopic myelitis; MRI, Magnetic resonance imaging; Gd, Gadolinium; ns, Not significant.

Interaction-1 (Wikipedia)

- In general, **Interaction** is a kind of action that occurs as two or more objects have an effect upon one another. The idea of a two-way effect is essential in the concept of interaction, as opposed to a one-way causal effect. A closely related term is interconnectivity, which deals with the interactions of interactions within systems; combinations of many simple interactions can lead to surprising emergent phenomena.
- In statistics, an **interaction** may arise when considering the relationship among three or more variables, and describes a situation in which the simultaneous influence of two variables on a third is not **additive**. Most commonly, interactions are considered in the context of regression analyses.

Interaction-2 (Wikipedia)

- The presence of interactions can have important implications for the interpretation of statistical models. If two variables of interest interact, the relationship between each of the interacting variables and a third "dependent variable" depends on the value of the other interacting variable. In practice, this makes it more difficult to predict the consequences of changing the value of a variable, particularly if the variables it interacts with are hard to measure or difficult to control.
- The notion of "interaction" is closely related to that of "moderation" that is common in social and health science research:
- The interaction between an explanatory variable and an environmental variable suggests that the effect of the explanatory variable has been moderated or modified by the environmental variable.



Confounding vs. Interaction

- In clinical trials, confounding and interaction effects are the most common distortions in the evaluation of medication.
- Confounding effects are contributed by various factors such as race & age & gender that **cannot be separated by the design** under the study.
- Interaction effect between factors is a **joint effect** with one or more contributing factors (Chow & Liu, 1995)
- Confounding: impossible to assess the treatment effects
- Interaction: possible

Definition of Confounding

- A confounding variable (also confounding factor, lurking variable, a confound, or confounder) is an **extraneous variable in a statistical model that correlates (positively or negatively) with both the dependent variable and the independent variable.**
- The methodologies of scientific studies therefore need to control for these factors to avoid a false positive (Type I) error; an erroneous conclusion that the dependent variables are in a causal relationship with the independent variable. Such a relation between two observed variables is termed a spurious relationship.
- Thus, confounding is a major threat to the validity of inferences made about cause and effect, i.e. internal validity, as the observed effects should be attributed to the independent variable rather than the confounder.

Introduction By Examples



Hippocampal mean diffusivity and memory in healthy elderly individuals

A cross-sectional study

Background: The relationship between age-related memory decline and hippocampal anatomic changes is a matter of debate.

Objective: To investigate the relationship between age-related memory decline and MRI hippocampal anatomic changes in a cohort of healthy individuals.

Methods: In this cross-sectional study, 76 healthy individuals (44 male and 32 female), ranging in age from 20 to 80 years, were recruited from universities, community recreational centers, hospital personnel, and patients' relatives from 2002 to 2008. These individuals were administered a 3-T MRI protocol with a whole-brain T1-weighted and diffusion-weighted scanning and a neuropsychological assessment. For each subject, we calculated the volumes of the total brain (gray + white matter) and hippocampus. The segmented hippocampus defined the binary masks where mean values of mean diffusivity (MD) evaluation included 1) visuospatial memory (3D).

Results: Hippocampal MD predicted performance of the Rey-Osipkin Complex Figure Test. High mean values predict memory of visuospatial memory. N

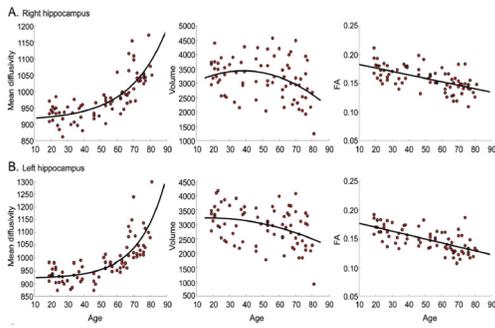
GLOSSARY: AD = Alzheimer disease; DTI = diffusion tensor imaging; TE = echo time; TE =

Figure 1: Age and memory performance in healthy individuals

Regression curves that best fit the relationship in the experimental group between age and performance score on the delayed recall of a 15-word list (A) and age and performance score on the delayed reproduction of Rey figure test (B).

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Figure 2 Age and anatomic variables of interest in healthy individuals



Mood, anxiety, and incomplete seizure control affect quality of life after epilepsy surgery

Objective: We examined the complex relationship between depression, anxiety, and seizure control and quality of life (QOL) outcomes after epilepsy surgery.

Methods: Seven epilepsy centers enrolled 373 patients and completed a comprehensive diagnostic work-up and presurgical and follow-up QOL evaluation. Subjects were evaluated before surgery and then at 3, 12, 24, 36, and 60 months after surgery. Standardized assessments included the Quality of Life in Epilepsy Inventory-89, Beck Depression Inventory (BDI), and Beck Anxiety Inventory (BAI). A novel model (respected measures) analysis was used to assess associations of depression, anxiety, seizure outcome, and seizure history with overall QOL scores and QOL subscore cognitive function.

Results: The groups with excellent and good seizure control and the overall QOL, compared to the group with fair and poor seizure control, were both highly and negatively associated with BDI scores and BAI scores, respectively. In addition, BDI scores were associated with decreased overall QOL scores.

Conclusion: Depression and anxiety are strongly and independently related to quality of life after epilepsy surgery. Interestingly, even partial seizure control, improved QOL. Management of mood and an anxiety state, however, may improve QOL.

GLOSSARY: AED = antiepileptic drug; BM = Beck Anxiety Inventory; BDI = Beck Depression Inventory; QOL = quality of life; Respected measures

Figure 1: QOL stratified by seizure control over time

Least square mean plot based on the modeling results shown in table 2. 20-year seizure control variable demonstrates the relationship between quality of life (QOL) and seizure control over time. The y-axis denotes overall QOL. Scores and color codes the seizure-control status: excellent, good, fair, and poor. The x-axis shows time in months, with the 0 point designating the preoperative evaluation. Six separate comparisons of overall effect of different seizure control groups over QOL. Scores: 1 = excellent vs good; 2 = excellent vs fair; 3 = excellent vs poor; 4 = good vs fair; 5 = good vs poor; 6 = fair vs poor. This p value is represented by: * = not significant; ** = <0.05; *** = <0.001.

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Table 2 Multivariable regression estimates of the effects of 5-year seizure control, depression, and anxiety on overall QOL and QOL subscores

Characteristics	Overall QOL		Seizure QOL		Physical QOL		Mental health QOL		Cognitive QOL	
	Estimate	p Value	Estimate	p Value	Estimate	p Value	Estimate	p Value	Estimate	p Value
Time	0.45	<0.0001	0.74	<0.0001	0.33	<0.0001	0.25	<0.0001	0.24	<0.0001
Time*time	-0.02	<0.0001	-0.02	<0.0001	-0.01	<0.0001	-0.01	<0.0001	-0.01	<0.0001
Time*time*time	0.0002	<0.0001	0.0002	<0.0001	0.0001	<0.0001	0.0001	<0.0001	0.0001	<0.0001
No. of AEDs (full dose)	-0.30	0.02	-0.63	0.02	-0.23	0.02	-0.23	0.02	-0.23	0.02
Seizure control	0.45	<0.0001	0.74	<0.0001	0.33	<0.0001	0.25	<0.0001	0.24	<0.0001
Excellent	3.78	<0.0001	3.74	<0.0001	3.57	0.0005	2.89	0.0003	2.95	0.01
Good	0.58	0.6	-0.23	0.85	0.73	0.58	-0.33	0.75	1.87	0.22
Fair	2.69	0.002	2.82	0.003	1.48	0.15	1.99	0.01	3.08	0.01
Poor	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Time and seizure control interaction	0.06	<0.0001	-0.0001	<0.0001	0.02	<0.0001	0.52	<0.0001	0.43	<0.0001
Time and excellent	0.05	0.01	0.11	<0.0001	0.05	0.01	-0.01	0.42	0.02	0.33
Time and good	0.02	0.37	0.06	0.009	0.02	0.34	-0.009	0.69	-0.009	0.73
Time and fair	0.04	0.03	0.08	0.001	0.06	0.004	0.007	0.72	-0.004	0.86
Time and poor	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref



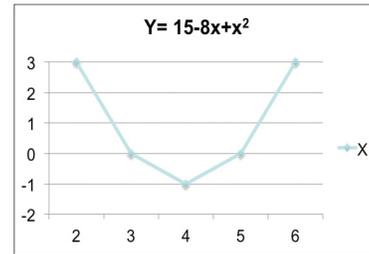
Goals for today

- ◆ A brief refresher of algebra basics
- ◆ Modeling simple curvilinear effects in logistic regression
- ◆ Graphing curvilinear effects
- ◆ Interpreting curvilinear effects
- ◆ Curvilinear effects and data cleaning
- ◆ Advanced Topic: curvilinear interactions



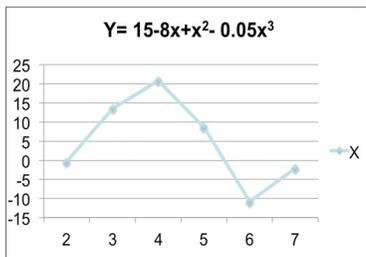
Quick math review

- ◆ A simple quadratic equation:
 - $Y = 15 - 8x + x^2$
 - Use $x = 2, 3, 4, 5, 6$ to sketch out the graph

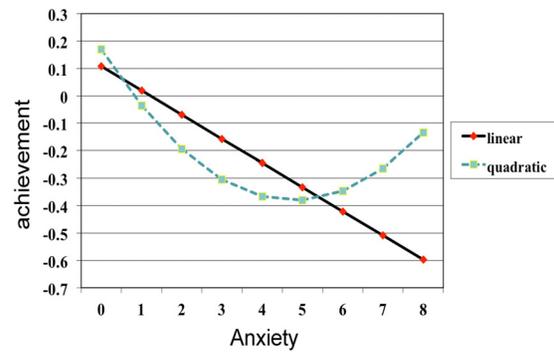


Cubic curves have 2 inflection points

- ◆ A simple cubic equation:
 - $Y = 15 - 8x + x^2 - 0.05x^3$



Why curvilinear regression?



Assumption of linearity

- ◆ Regression Model

$$y = \beta_0 + \beta_1x_1 + \beta_2x_2 + \varepsilon$$
- ◆ In OLS regression we assume that IV is linearly related to DV
- ◆ In logistic regression we assume the IV is "linear on the logit"
 - $\text{Logit}(\hat{Y})$ is linearly related to IV
- ◆ When violated: mis-estimation of model



Causes of curvilinearity

- ◆ True nonlinear relationship
- ◆ Influential data points
- ◆ Violating equal intervals in coding of data



Detection of nonlinear effects

- ◆ Theory
- ◆ Ad hoc testing (quadratic, cubic term)
- ◆ Box-Tidwell transformation



The rules

- ◆ test quadratic curve via squaring independent variable
 - $\text{Logit}(\hat{Y}) = a + b_1x + b_2x^2$
- ◆ test cubic curve via cubing IV
 - $\text{Logit}(\hat{Y}) = a + b_1x + b_2x^2 + b_3x^3$
- ◆ Can only test squared term with X in equation
- ◆ Can only test cubed term with X and X² in equation



Fitting Curvilinear Model



Curvilinear logistic regression in practice

Table 7.x

Relationship of Age and Benign forgetfulness –linear model only

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
AGE	.045	.001	1381.895	1	.000	1.046	1.044	1.048
Step 1 ^a								
Constant	-4.631	.074	3890.651	1	.000	.010		

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



Add quadratic term

- ◆ Significant Δ -2LL ($\chi^2_{(2)} = 298.45, p < .0001$)

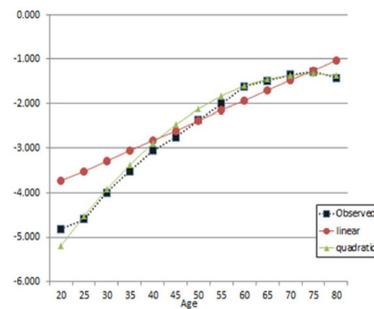
Table 7.x

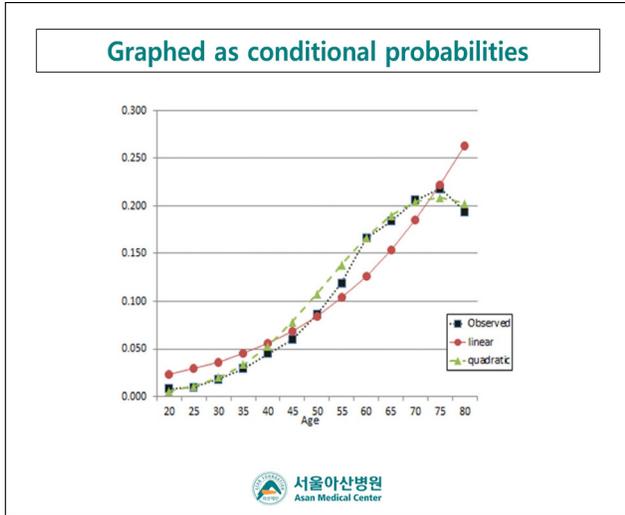
Predicting benign forgetfulness from Age and Age²

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
AGE	.19402	.010	405.285	1	.000	1.214	1.191	1.237
Step 1 ^a								
AGE ²	-.001301	.000	253.400	1	.000	.999	.999	.999
Constant	-8.56625	.275	971.730	1	.000	.000		



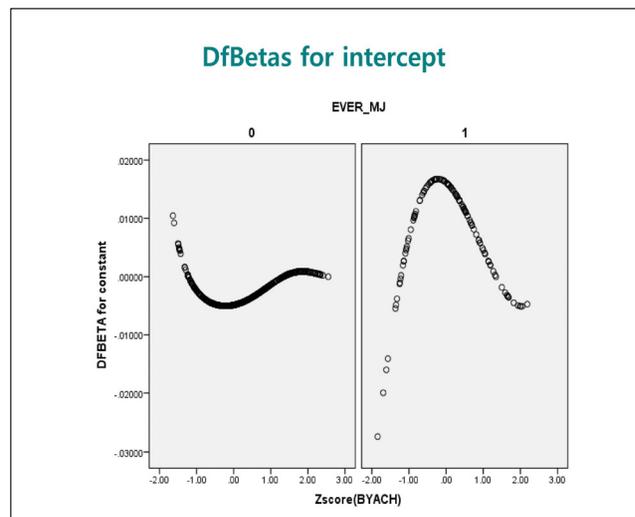
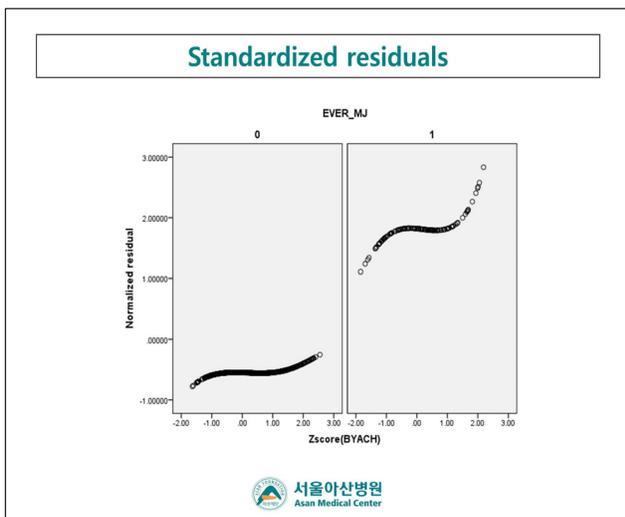
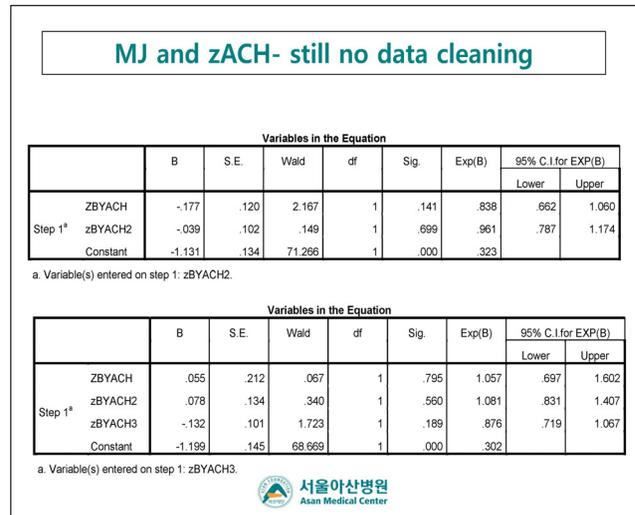
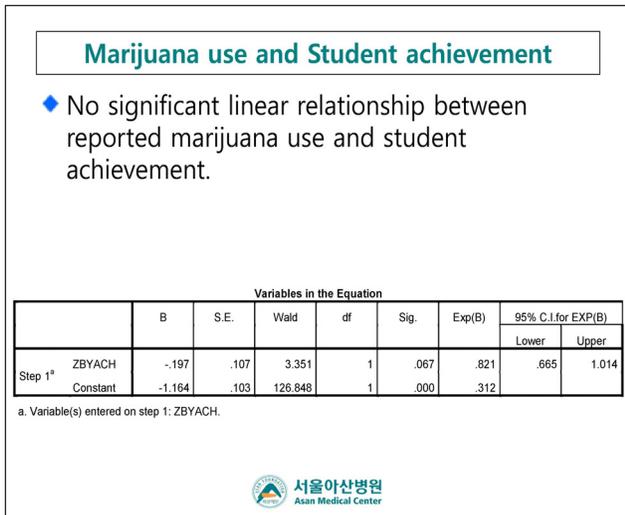
Cubic term significant but very small Δ -2LL





Data cleaning & curvilinear effects

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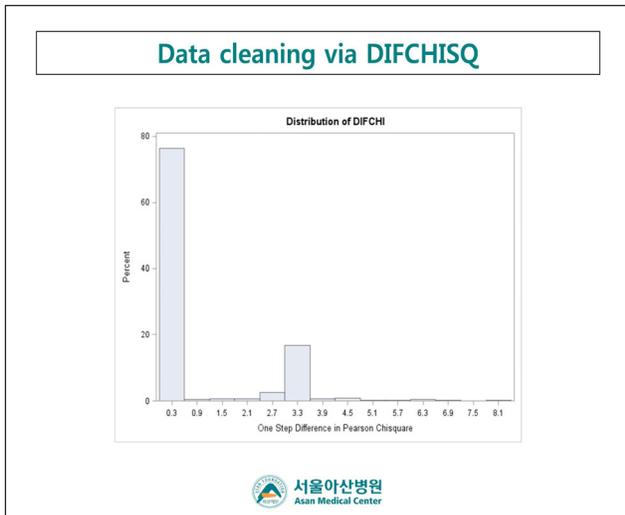
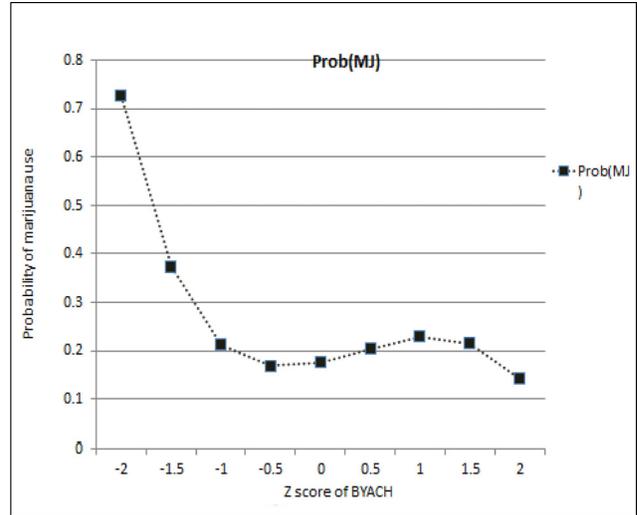
After very conservative data cleaning

Regression line equation:

$$\text{Logit}(\hat{Y}) = -1.546 + 0.296(\text{ZBYACH}) +$$

Variables in the Equation								
	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
ZBYACH	.296	.227	1.695	1	.193	1.344	.861	2.097
zBYACH2	.285	.148	3.682	1	.055	1.329	.994	1.778
zBYACH3	-.247	.110	5.075	1	.024	.781	.630	.968
Constant	-1.546	.166	87.138	1	.000	213		

a. Variable(s) entered on step 1: zBYACH3.



Comparing DfBeta vs. DIFCHISQ

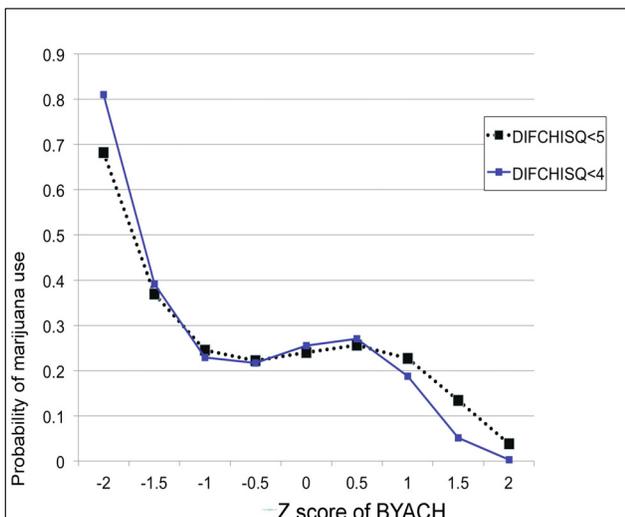
◆ After DfBeta cleaning

Variables in the Equation								
	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
ZBYACH	.296	.227	1.695	1	.193	1.344	.861	2.097
zBYACH2	.285	.148	3.682	1	.055	1.329	.994	1.778
zBYACH3	-.247	.110	5.075	1	.024	.781	.630	.968
Constant	-1.546	.166	87.138	1	.000	213		

a. Variable(s) entered on step 1: zBYACH3.

After
DIFCHISQ
cleaning:

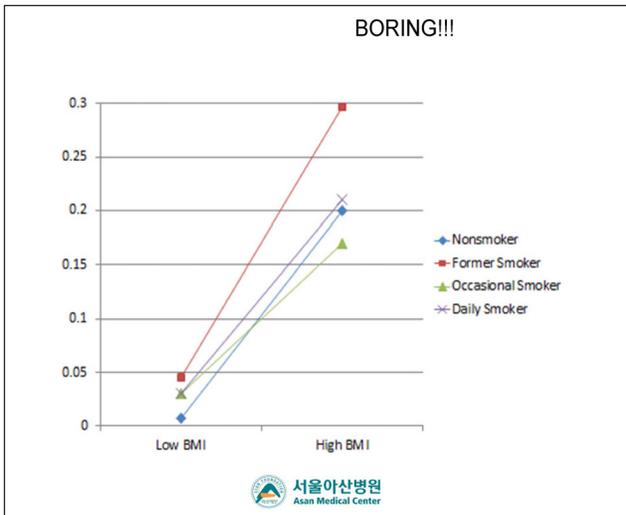
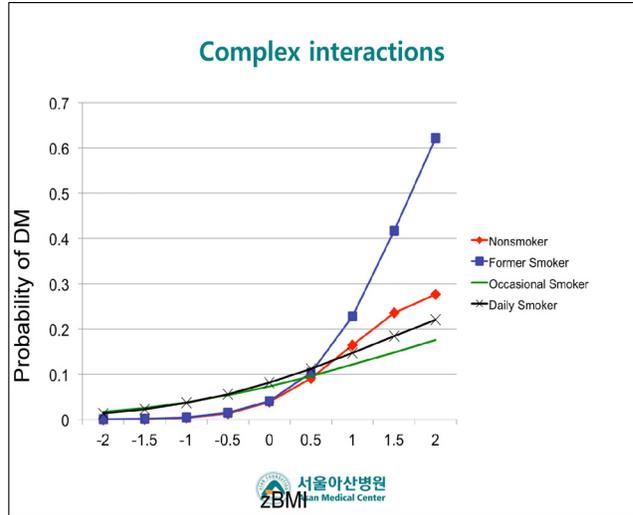
Analysis of Maximum Likelihood Estimates						
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	
Intercept	1	-1.1514	0.1449	63.1217	<.0001	
ZBYACH	1	0.2683	0.2421	1.2283	0.2677	
zBYACH2	1	-0.0214	0.1401	0.0234	0.8784	
zBYACH3	1	-0.3168	0.1314	5.8118	0.0159	



Summary so far...

- ◆ Surprisingly simple to find curvilinear effects
- ◆ Surprisingly challenging to find examples of data cleaning eliminating curvilinear effects
- ◆ This type of analysis is procedurally similar to logistic regression with multiple IVs but all different aspects of SAME IV.

With Interaction

Linear interactions

- ◆ An interaction allows for effect of X_1 to be non-constant across the range of X_2

$$\text{Logit}(Y) = b_0 + b_1X_1 + b_2X_2 + b_3X_1X_2$$

- ◆ If you as researcher do NOT model interaction, you are explicitly asserting b_3 is 0.
- ◆ Should be tested rather than asserted



"Simple" curvilinear effects

- ◆ A curvilinear effect allows for modeling of nonlinear relationships

$$\text{Logit}(Y) = b_0 + b_1X_1 + b_2X_1^2 + b_3X_1^3 + \dots + b_kX_1^k$$

- ◆ If you as researcher do NOT model a curvilinear effect, you are explicitly asserting that $b_2 \rightarrow b_k$ all 0.
- ◆ Should be tested rather than asserted



Review of procedures

- ◆ Z score continuous variables (or center)
- ◆ Create powered terms by raising X to a power
 - Such as X^2 and X^3
- ◆ Dichotomous and categorical variables cannot have curvilinear effects

- ◆ Enter linear effects on a block
- ◆ Enter all higher-order terms on another block
- ◆ Change in -2LL evaluates whether ANY curvilinear effect is significant



Procedurally...

- ◆ **Curvilinear interaction** means that the nature or shape of a curvilinear effect depends upon another variable.
i.e. different groups have different curves
- ◆ Create the following terms:
 - X and Z are independent variables
 - X² and Z² are quadratic effects of X and Z
- ◆ Create cross-products of these terms
 - XZ
 - X²Z and XZ²
 - X²Z²



Two variables, one curvilinear effect

$$\text{Logit}(Y) = b_0 + b_1X + b_2X^2 + b_3Z + b_4XZ + b_5X^2Z$$

or

$$\text{Logit}(Y) = b_0 + b_1X + b_2X^2 + b_3X^3 + b_4Z + b_5XZ + b_6X^2Z + b_7X^3Z$$



Two curvilinear effects

$$\text{Logit}(Y) = b_0 + b_1X + b_2X^2 + b_3Z + b_4Z^2 + b_5XZ + b_6X^2Z + b_7XZ^2 + b_8X^2Z^2$$

or

$$\text{Logit}(Y) = b_0 + b_1X + b_2X^2 + b_3X^3 + b_4Z + b_5Z^2 + b_6Z^3 + b_7XZ + b_8X^2Z + b_9XZ^2 + b_{10}X^2Z^2 + b_{11}X^3Z + b_{12}X^3Z^2 + b_{13}XZ^3 + b_{14}X^2Z^3 + b_{15}X^3Z^3$$



Prediction

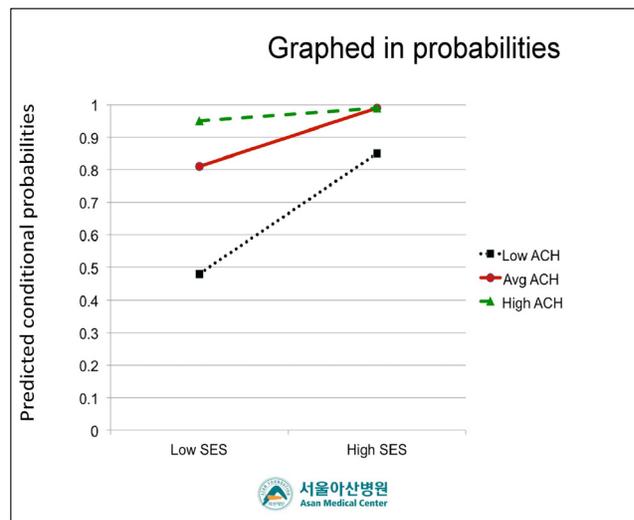
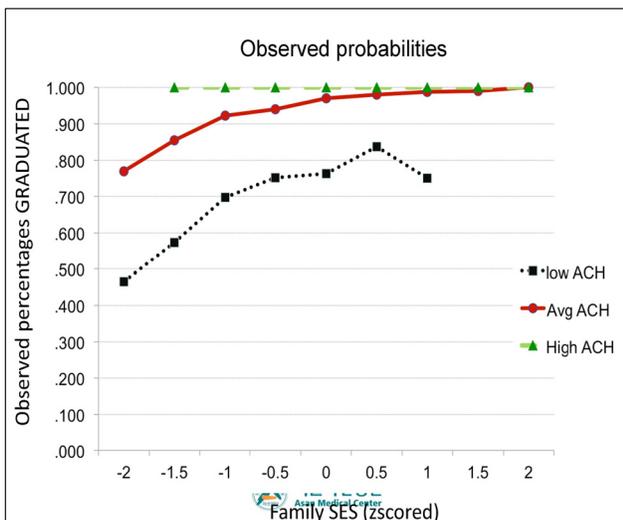


Table 14
Summary of curvilinear interaction model after data cleaning

Model	-2LL	Δ -2LL	p < for Δ -2LL
Intercept only	9486.68	--	--
zSES, zACH	7256.97	2229.71	.0001
zSES x zACH	7163.50	93.47	.0001
zSES ² , zACH ²	7153.59	9.92	.007
zSES ² x zACH, zSES x zACH ² , zSES ² x zACH ²	7097.97	55.62	.0001



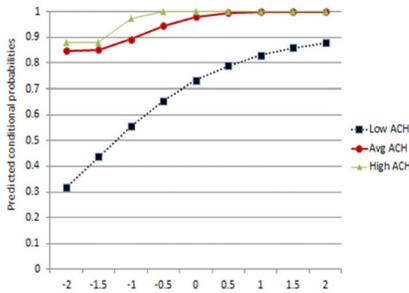
Table 15
Final step of curvilinear interaction analysis after data cleaning ZRE < 5

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
zACH	2.704	.251	115.812	1	.000	14.933	9.123	24.444
zSES	2.451	.226	117.926	1	.000	11.603	7.455	18.060
zACH by zSES	2.709	.435	38.778	1	.000	15.012	6.400	35.215
zACH2	.633	.148	18.236	1	.000	1.883	1.408	2.517
zSES2	.685	.111	37.860	1	.000	1.984	1.595	2.468
zACH by zSES2	.851	.195	19.160	1	.000	2.343	1.600	3.431
zSES by zACH2	.913	.235	15.104	1	.000	2.493	1.573	3.952
zSES2 by zACH2	.229	.108	4.539	1	.033	1.258	1.019	1.553
Constant	3.882	.121	1029.937	1	.000	48.520		

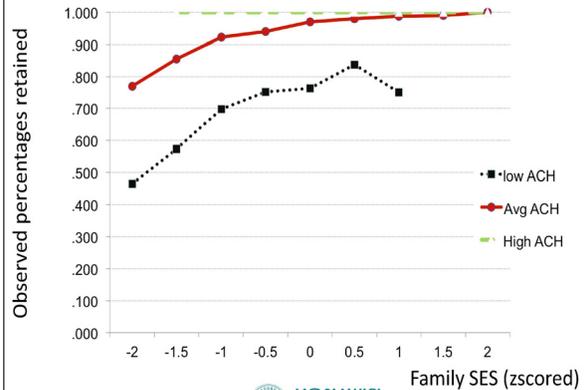
$$\text{Logit}(Y) = 3.882 + 2.704(zACH) + 2.451(zSES) + 2.709(zACH * zSES) + 0.633(zACH^2) + 0.685(zSES^2) + 0.851(zACH * zSES^2) + 0.913(zSES * zACH^2) + 0.229(zSES^2 * zACH^2)$$



Graph of curvilinear interaction



Which is a lot closer to the Observed probabilities



Composing all cross-products for a curvilinear interaction equation

	X	X ²	X ³
Dum1	X Dum1	X ² Dum1	X ³ Dum1
Dum2	X Dum2	X ² Dum2	X ³ Dum2
Dum3	X Dum3	X ² Dum3	X ³ Dum3



Using same DIFCHISQ cleaned data as above:

Model	-2LL	Δ -2LL	p < for Δ -2LL
Intercept only	8926.86	--	--
Dum1, Dum2, Dum3	8540.81	386.05	.0001
zSES, zSES ² , zSES ³	6950.01	1590.80	.0001
zSESxDUM1, zSESxDUM2, zSESxDUM3	6835.11	114.90	.0001
zSES ² xDUM1, zSES ² xDUM2, zSES ² xDUM3	6780.46	54.65	.0001
zSES ³ xDUM1, zSES ³ xDUM2, zSES ³ xDUM3	6774.65	5.81	.12

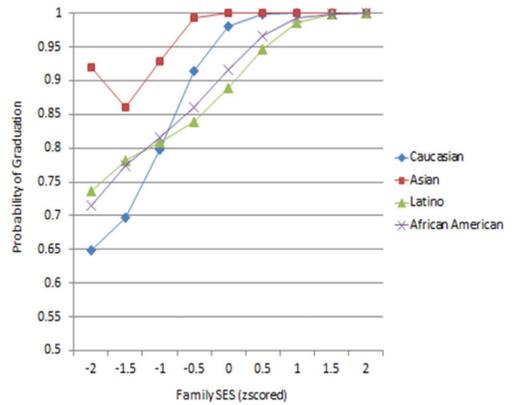


Table 18
Summary of last significant step in model

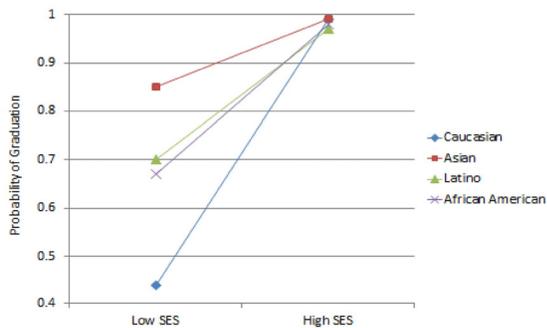
	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
dum1	4.916	2.080	5.583	1	.018	136.399	2.312	8046.207
dum2	-1.868	.161	134.484	1	.000	.154	.113	.212
dum3	-1.556	.177	76.988	1	.000	.211	.149	.299
ZSES	3.907	.250	245.122	1	.000	49.764	30.513	81.161
zses2	1.522	.190	64.447	1	.000	4.582	3.160	6.643
zses3	.202	.049	16.653	1	.000	1.223	1.110	1.348
ZSES by dum1	5.872	3.300	3.166	1	.075	355.094	.551	228788.970
ZSES by dum2	-2.730	.288	89.795	1	.000	.065	.037	.115
ZSES by dum3	-2.410	.327	54.305	1	.000	.090	.047	.170
zses2 by dum1	2.165	1.268	2.917	1	.088	8.718	.726	104.635
zses2 by dum2	-.793	.134	35.020	1	.000	.453	.348	.588
zses2 by dum3	-.738	.152	23.496	1	.000	.478	.355	.644
Constant	3.954	.111	1267.285	1	.000	52.121		



Result



Original linear interaction



Summary

- ◆ Univariate & Multivariate Analysis
- ◆ Linear & Curvilinear
- ◆ Interactions

- ◆ Curves are common if you look for them
- ◆ Curvilinear effects often more accurate models of data
- ◆ Not difficult
- ◆ Careful graphing explicates effects
- ◆ Data cleaning always important

