Data Cleaning Workshop:

How to Prepare your Data Prior to Analysis

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Outline for Today

- Missing Data
  - Identifying, assessing type, imputation options
- Composite Scores
  - Total scores, recoding, dummy coding
- Outliers
  - Identifying and addressing univariate and multivariate outliers
- Normality
  - Assessing and addressing (e.g., transformations, analysis specifications)
- Bivariate Linearity
  - Reading scatterplots and what to do about them
- Documentation
  - The importance of codebooks and data logs

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Missing Data

- Types
  - MCAR, MAR, MNAR
- Types of Imputation
  - Multiple, EM, regression, mean, etc.
- How to impute

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Missing Data

- More Info:
  - Rubin, Donald B. (1976). Inference and missing data. *Biometrika*, *63*(3), 581-592.
    - Free online
  - Allison, Paul D. (2001). *Missing Data*. Sage University Paper Series on Quantitative Applications in the Social Sciences, 07-136. Thousand Oaks, CA: Sage.
    - Cheap on Amazon
  - Enders, Craig K. (2010). *Applied Missing Data Analysis*. New York: Guilford Press.
    - Available in ODU library as a book and as an *e*-book

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Missing Data Types

- Conceived by Donald B. Rubin (1976)
- Missing Completely At Random (**MCAR**)
  - "Probability of missing data on Y is unrelated to the value of Y itself or to the values of other variables in the data set"
  - Missing values are completely independent from observed or unobserved data
  - Truly random skips (nothing to do with answers)
  - E.g., someone skipped salary not because their salary was particularly high or low, and not because of their race, ethnicity, gender, depressive symptoms, anxiety, etc.
  - VIOLATED if: someone skipped this question because their salary was very low, or if everyone who skipped this question was very young
  - RARE (we think)
    - People often skip for a reason

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Missing Data Types

- Missing At Random (**MAR**)
  - "Probability of missing data on Y is unrelated to the value of Y, after controlling for other variables in the analysis"
  - Missing values are completely dependent on observed values
  - You can estimate what their answer WOULD BE based on other information in the data
  - E.g., People who skipped a question about binge drinking are very high on drinking quantity and drinking frequency
  - E.g., someone skips a single item on a multi-item scale
  - VIOLATED if: people skipped a question because they are high on binge drinking, but this is not strongly related to other variables in the sample (e.g., no other drinking variables, OR not a strong correlation)
  - MUCH MORE COMMON
    - The reason people skip an item is captured somewhere else in your data

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Missing Data Types

- Analyses usually assume MCAR or MAR
  - "Ignorable" missing data
- Missing Not At Random (**MNAR**)
  - Missing values are dependent on unobserved values
  - E.g., Skipped trauma questionnaires because high on trauma (not indicated with other variables)
  - "Nonignorable" missing data
    - VERY BAD
  - Cannot perform most analyses (results would be biased)
    - Excluding everyone high in drinking, or high in trauma, or low in income, etc.
    - Everyone who is getting worse in a clinical trial drops out
  - The missing data mechanism must be modeled in your analysis
    - E.g., Heckman's (1976) two-stage estimator for regression models with selection bias on the dependent variable
    - Requires a lot of knowledge about why data are missing, sophisticated calculations, lack of software, difficulties in interpretability

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Missing Data Types

TABLE 1.2. Job Performance Ratings with MCAR, MAR, and MNAR Missing Values

	Job performance ratings			
IQ	Complete	MCAR	MAR	MNAR
78	9	—	—	9
84	13	13	—	13
84	10	—	—	10
85	8	8	—	—
87	7	7	—	—
91	7	7	7	—
92	9	9	9	9
94	9	9	9	9
94	11	11	11	11
96	7	—	7	—
99	7	7	7	—
105	10	10	10	10
105	11	11	11	11
106	15	15	15	15
108	10	10	10	10
112	10	—	10	10
113	12	12	12	12
115	14	14	14	14
118	16	16	16	16
134	12	—	12	12

Enders (2010, p. 7)

- *Y* = Job performance rating
- *X* = IQ
- Values missing for **MCAR** are truly random
- Values missing for **MAR** are related to *X*
  - Lowest IQ
- Values missing for **MNAR** are related to *Y*, even after controlling for *X*
  - Lowest job performance, even though IQ may be higher

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Missing Data Types

- How do I know what type of data I have?
  - Difficult to test. The information needed is missing!
  - Can test if missingness is related to variables in your sample
    - Little's MCAR test in SPSS, create your own *t* tests, etc.
    - If related, supports MAR (that missing values depend on observed values)
    - If unrelated, cannot determine MCAR versus MNAR
    - Best techniques for addressing missing data do not distinguish between MCAR and MAR, so test is relatively pointless
  - I recommend identifying missingness for outcome variables, and identifying potential predictors associated/correlated with them
    - Can describe your sample for readers/reviewers
    - Can include these variables in your imputation process
    - Can include these variables in your model

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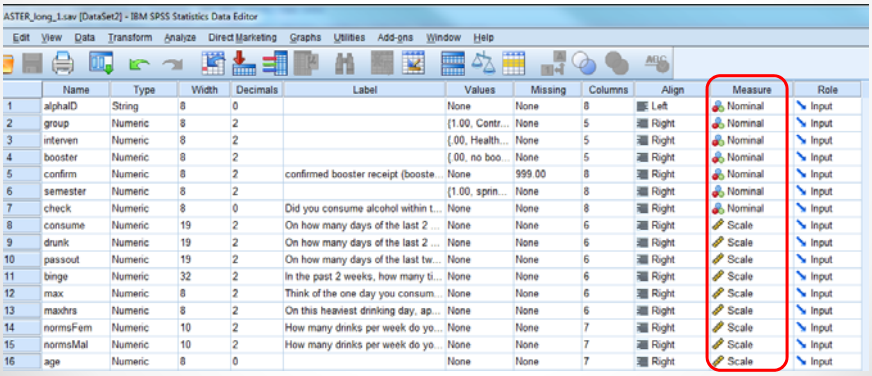
Identifying Missing Data Patterns

- Using "Missing Value Analysis" in SPSS
- Make sure "Measure" is correct in Variable View



	Name	Type	Width	Decimals	Label	Values	Missing	Columns	Align	Measure	Role
1	alphaID	String	8	0		None	None	8	Left	Nominal	Input
2	group	Numeric	8	2		{1.00, Contr...	None	5	Right	Nominal	Input
3	interven	Numeric	8	2		{.00, Health...	None	5	Right	Nominal	Input
4	booster	Numeric	8	2		{.00, no boo...	None	5	Right	Nominal	Input
5	confirm	Numeric	8	2	confirmed booster receipt (booste...	None	999.00	8	Right	Nominal	Input
6	semester	Numeric	8	2		{1.00, sprin...	None	8	Right	Nominal	Input
7	check	Numeric	8	0	Did you consume alcohol within t...	None	None	8	Right	Nominal	Input
8	consume	Numeric	19	2	On how many days of the last 2 ...	None	None	6	Right	Scale	Input
9	drunk	Numeric	19	2	On how many days of the last 2 ...	None	None	6	Right	Scale	Input
10	passout	Numeric	19	2	On how many days of the last tw...	None	None	6	Right	Scale	Input
11	binge	Numeric	32	2	In the past 2 weeks, how many ti...	None	None	6	Right	Scale	Input
12	max	Numeric	8	2	Think of the one day you consum...	None	None	6	Right	Scale	Input
13	maxhrs	Numeric	8	2	On this heaviest drinking day, ap...	None	None	6	Right	Scale	Input
14	normsFem	Numeric	10	2	How many drinks per week do yo...	None	None	7	Right	Scale	Input
15	normsMal	Numeric	10	2	How many drinks per week do yo...	None	None	7	Right	Scale	Input
16	age	Numeric	8	0		None	None	7	Right	Scale	Input

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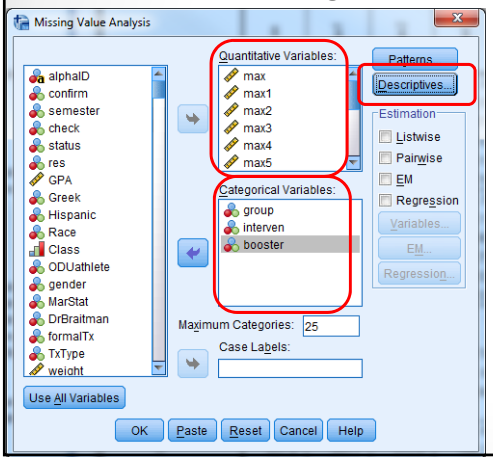
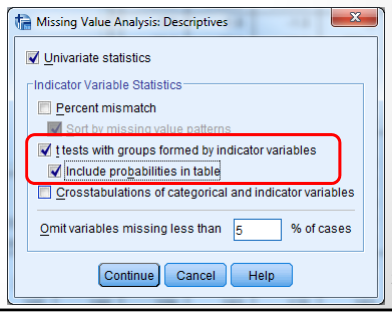
Identifying Missing Data Patterns

- Analyze > Missing Value Analysis
- Move "scale" variables into "quantitative" box, and "nominal" variables into "categorical" box.



- Select "Descriptives" button
- Request "t tests with groups formed by indicator variables"
- Include probabilities



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Identifying Missing Data Patterns

- Output will tell you how many cases are missing (*f* and %)
- Will tell you if missingness is associated with other variables

Univariate Statistics

	N	Mean	Std. Deviation	Missing Count	Missing Percent	No. of Extremes[a] Low	No. of Extremes[a] High
max	561	6.2376	4.17681	0	.0	0	17
max1	352	5.1179	4.14975	209	37.3	0	4
max2	296	5.0473	4.40852	265	47.2	0	3
max3	273	4.9158	4.98714	288	51.3	0	7
max4	222	4.8153	4.42812	339	60.4	0	6
max5	183	4.7322	4.66332	378	67.4	0	2
max6	148	4.2399	4.35791	413	73.6	0	5
consume	561	3.5811	2.34485	0	.0	0	14
drunk	560	1.7777	1.81258	1	.2	0	10
passout	561	.2299	.53341	0	.0	.	.
binge	560	2.0313	2.03181	1	.2	0	36
maxhrs	555	3.6555	2.39801	6	1.1	0	11
normsFem	560	8.6761	5.77568	1	.2	0	44
normsMal	559	13.9154	9.45788	2	.4	0	22
age	560	19.85	2.195	1	.2	0	10

a. Number of cases outside the range (Q1 - 1.5*IQR, Q3 + 1.5*IQR).

Separate Variance t Tests[a]

		max	max1	max2	max3	max4	max5	max6	consume	drunk	passout	binge
max1	t	-.1	.	1.8	.5	1.0	-1.5	-1.0	1.7	-.8	-.6	1.3
	df	453.9	.	23.2	16.5	23.7	20.6	8.6	483.8	424.8	385.7	478.8
	P(2-tail)	.947	.	.080	.594	.321	.160	.350	.094	.405	.535	.206
	# Present	352	352	278	257	203	167	139	352	351	352	351
	# Missing	209	0	18	16	19	16	9	209	209	209	209
	Mean(Present)	6.2287	5.1179	5.1259	4.9611	4.8916	4.6108	4.1259	3.7045	1.7279	.2188	2.1125
	Mean(Missing)	6.2526	.	3.8333	4.1875	4.0000	6.0000	6.0000	3.3732	1.8612	.2488	1.8947
max2	t	-.3	.6	.	-.3	-.2	-1.1	-.8	1.5	-1.0	.6	.7
	df	557.8	128.0	.	30.1	26.8	20.6	12.3	557.5	547.2	545.8	558.0
	P(2-tail)	.748	.526	.	.801	.869	.295	.457	.141	.319	.534	.457
	# Present	296	278	296	246	200	165	136	296	295	296	295
	# Missing	265	74	0	27	22	18	12	265	265	265	265
	Mean(Present)	6.1841	5.1853	5.0473	4.8862	4.8000	4.6061	4.1434	3.7179	1.7051	.2432	2.0915
	Mean(Missing)	6.2974	4.8649	.	5.1852	4.9545	5.8889	5.3333	3.4283	1.8585	.2151	1.9642
max3	t	-.9	.0	-1.1	.	-1.1	-1.6	-1.0	.2	-1.5	-.9	.8
	df	548.7	176.3	68.5	.	29.3	27.3	13.7	556.2	557.1	553.2	538.5
	P(2-tail)	.345	.972	.268	.	.300	.121	.315	.805	.141	.359	.396
	# Present	273	257	246	273	197	160	135	273	272	273	272
	# Missing	288	95	50	0	25	23	13	288	288	288	288
	Mean(Present)	6.0659	5.1226	4.9146	4.9158	4.6954	4.5063	4.1074	3.6062	1.6618	.2088	2.1066
	Mean(Missing)	6.4003	5.1053	5.7000	.	5.7600	6.3043	5.6154	3.5573	1.8872	.2500	1.9601
max4	t	-.1	.7	.3	.6	.	-.3	-1.0	1.1	-.5	.8	.5
	df	437.9	343.2	212.0	168.2	.	29.7	20.9	454.0	444.7	442.4	436.0
	P(2-tail)	.932	.496	.779	.541	.	.787	.346	.260	.644	.432	.615
	# Present	222	203	200	197	222	158	129	222	221	222	221
	# Missing	339	149	96	76	0	25	19	339	339	339	339
	Mean(Present)	6.2185	5.2438	5.0950	5.0203	4.8153	4.6899	4.0736	3.7207	1.7330	.2523	2.0860
	Mean(Missing)	6.2501	4.9463	4.9479	4.6447	.	5.0000	5.3684	3.4897	1.8068	.2153	1.9956

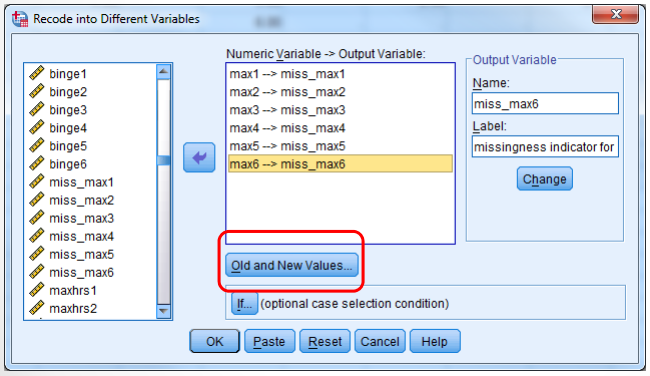
Identifying Missing Data Patterns

- Create the missingness variables yourself

	max1	miss_max1	max2	miss_max2	max3	miss_max3	max4	miss_max4	max5	miss_max5
1	.	1.00	.	1.00	.	1.00	.	1.00	.	1.00
2	2.00	.00	8.00	.00	4.00	.00	7.00	.00	9.00	.00
3	4.00	.00	4.00	.00	3.00	.00	2.00	.00	2.00	.00
4	.00	.00	.	1.00	6.00	.00	.	1.00	.	1.00
5	6.00	.00	.	1.00	4.00	.00	.00	.00	2.00	.00
6	.	1.00	.	1.00	.	1.00	.	1.00	.	1.00
7	6.00	.00	6.00	.00	.	1.00	4.00	.00	.	1.00
8	3.00	.00	6.00	.00	.	1.00	.	1.00	.	1.00
9	4.00	.00	.	1.00	5.00	.00	.00	.00	.	1.00
10	3.00	.00	2.00	.00	5.00	.00	8.00	.00	.	1.00
11	4.00	.00	.00	.00	.00	.00	.	1.00	.	1.00
12	.	1.00	.	1.00	.	1.00	.	1.00	.	1.00
13	6.00	.00	6.00	.00	5.00	.00	7.00	.00	6.00	.00
14	.	1.00	.	1.00	.	1.00	.	1.00	.	1.00
15	2.00	.00	5.00	.00	4.00	.00	3.00	.00	2.00	.00
16	1.00	.00	.	1.00	.	1.00	.	1.00	.	1.00
17	.00	.00	.	1.00	.	1.00	.	1.00	.	1.00
18	.	1.00	.	1.00	.	1.00	.	1.00	.	1.00
19	4.00	.00	3.00	.00	2.00	.00	.	1.00	.	1.00
20	6.00	.00	.	1.00	.	1.00	.	1.00	.	1.00

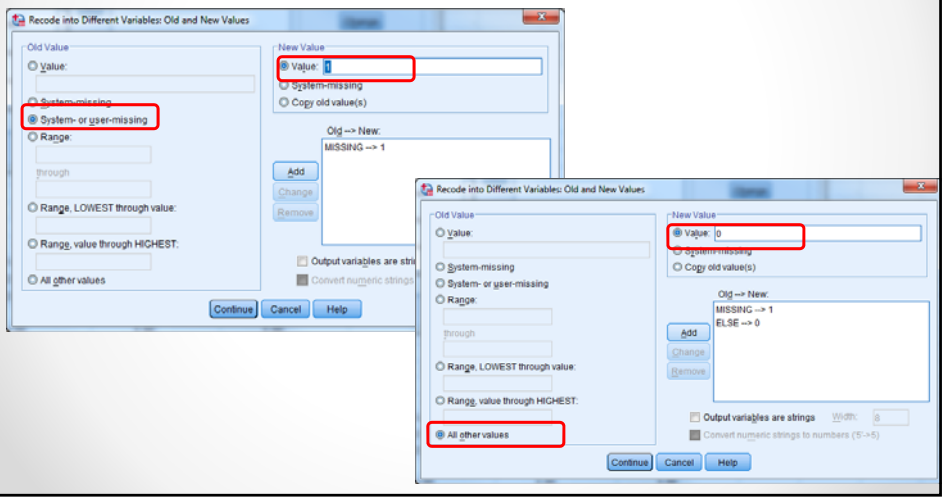
Identifying Missing Data Patterns

- Transform > Recode into Different Variables



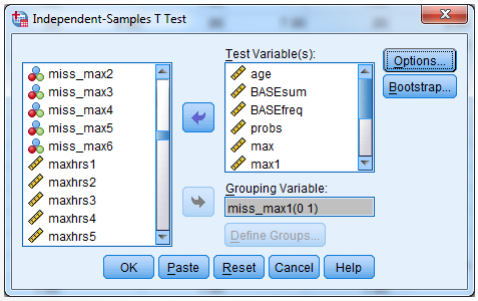
Identifying Missing Data Patterns

- Missing into 1, all else into 0



Identifying Missing Data Patterns

- Conduct t tests (or correlations, or chi-squares) to detect associations between missingness for that variable and the values of other variables in the dataset



		Levene's Test for Equality of Variances		t-test for Equality of Means					
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	
age	Equal variances assumed	2.127	.145	1.293	558	.197	.248	.192	
	Equal variances not assumed			1.351	494.102	.177	.248	.184	
Sum of drinks (both weeks)	Equal variances assumed	.315	.575	-.156	559	.876	-.23011	1.47795	
	Equal variances not assumed			-.154	418.624	.878	-.23011	1.49817	
BASE total drinking days	Equal variances assumed	.159	.690	1.172	559	.242	.24626	.21019	
	Equal variances not assumed			1.170	435.448	.243	.24626	.21043	
alcohol-related problems	Equal variances assumed	.182	.670	.765	559	.445	.40072	.52414	
	Equal variances not assumed			.755	420.400	.451	.40072	.53061	
Think of the one day you consumed the most alcohol in the past 2 weeks; How many standard drinks did you consume on that day?	Equal variances assumed	.007	.932	-.066	559	.948	-.02394	.36506	
	Equal variances not assumed			-.066	453.866	.947	-.02394	.36062	
max2: Think of the one day you consumed the most alcohol in the past 2 weeks; How many drinks?	Equal variances assumed	2.704	.101	1.206	294	.229	1.29257	1.07138	
	Equal variances not assumed			1.830	23.220	.080	1.29257	.70630	
max3: Think of the one day you consumed the most alcohol in the past 2 weeks; How many drinks?	Equal variances assumed	.051	.821	.601	271	.548	.77359	1.28652	
	Equal variances not assumed			.543	16.517	.594	.77359	1.42506	
max4: Think of the one day you consumed the	Equal variances assumed	.829	.364	.839	220	.403	.89163	1.06307	

Missing Data Patterns

- Missingness for "maximum drinks" at follow-up 1 was unrelated to age, quantity of alcohol drinks consumed, frequency of drinking, alcohol-related problems experienced, maximum drinks at baseline, maximum drinks at follow-up 2, maximum drinks at follow-up 3, etc.
- IF missingness for "maximum drinks" HAD been significantly associated with a variable, you'd want to include that variable in your model (for ML estimation), or in the variables used for imputation

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What to do about Missing Data

- Delete incomplete cases?
- Complete Case Analysis (aka Listwise Deletion)
  - Delete everyone from your sample who has missing data
  - Final sample includes only individuals with all data
- Available Case Analysis (aka Pairwise Deletion)
  - Exclude people from relevant analyses who have missing data
  - E.g., If missing on depressive symptoms, then missing from regression that examines influence of meditation on depressive symptoms
    - Present for regression that examines influence of meditation on anxiety

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Deleting/Omitting Incomplete Cases

- Reduces sample size
  - Reduces power (or ability to detect effects)
- Introduces bias (unless MCAR)
  - May be eliminating people who drink the most, or have the lowest salary, or experience the worse trauma, or are not responding to the medication, etc.
  - May lead to falsely non-significant results
    - e.g., without high-trauma individuals in sample, cannot detect association between alcohol and trauma
  - May lead to falsely significant effects
    - e.g., if people who don't get better drop out, those who remain lead to false belief the drug leads to lower depression scores
- Bad choice unless data are MCAR ☹
- What SPSS does by default if you do nothing!

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Imputation

- Impute/replace missing values (.) with best estimates
- A lot of methods exist that were once popular, but not great
  - Easy to do (easier; not computationally intensive)
- Mean imputation
  - Person mean (average of their responses for other items on that scale)
  - Item mean (average of everyone else in the sample)
  - Does not take all known information into account
  - Falsely deflates random error (makes smaller SDs and smaller SEs)
- Regression Imputation (or Conditional Mean Imputation)
  - Predicted value of Y given values of X
  - Falsely deflates random error (makes smaller SDs and smaller SEs)
- Hot Deck Imputation
  - Find someone similar in the sample, and use their value
- Last Observation Carried Forward (longitudinal only)
  - Replace missing follow-up values with the last value the participant reported
  - Assumes no change, which is typically wrong

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Outdated Imputation

- The aforementioned methods were the best available methods for decades
- Can be seen in older (and some newer) published articles
- Can be executed using older versions of SPSS, or via hand calculations
- All tend to falsely reduce your SD/SE
- Also tend to falsely increase test statistics (*t*, *F*, *r*, etc.)
- In some cases, are worse (more biased) than deletion
- Need a technique that accounts for the *uncertainty* about the value of the missing parameter

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Better Imputation

- Better methods exist that take into account the uncertainty of imputation
- Been around for decades, but becoming popular because software is starting to incorporate them more easily
- All require MAR at least (could be MCAR)
- Multiple Imputation
  - Generates multiple datasets that represent multiple imputed values possible
- Maximum Likelihood (ML) Estimation
  - Not actually imputing data, but using all available data
- Expectation Maximization (EM) Imputation
  - Iterative 2-step process

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Multiple Imputation (MI)

- Generates multiple datasets with different possible values for each missing datapoint
  - For each dataset, the observed datapoints stay the same
  - The missing values are different in each version
  - Imputed values represent a combination of the linear regression of that variable on other variables of interest, plus random error (a random draw from the residual normal distribution for that variable)
- Main analysis is conducted on all datasets, and results are combined
- Lots of decision points
  - What assumptions are there for the data (multivariate normal?)
  - How are regression coefficients generated for estimating the missing value?
  - How are error terms generated and randomly drawn?
  - How many datasets? Etc.
- Computationally difficult
  - Easy to incorporate in SPSS for a regression, mean, etc.
  - Layering MI on top of complex analyses can become overly complicated
- Gives slightly different results every time you do it
  - It was possible to specify the random "seed" so that you get the same results every time, but this removes one of the benefits of MI (introducing random error)

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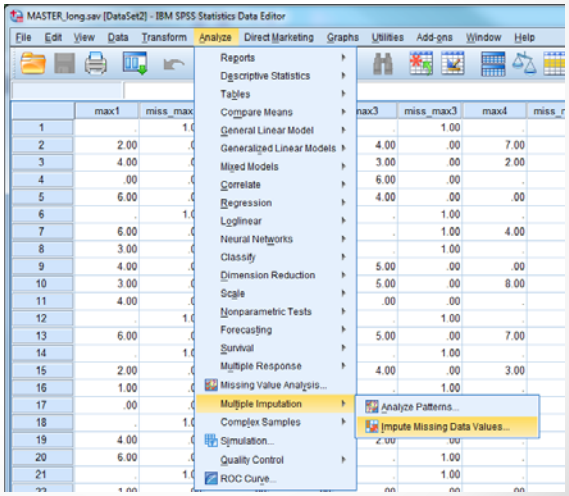
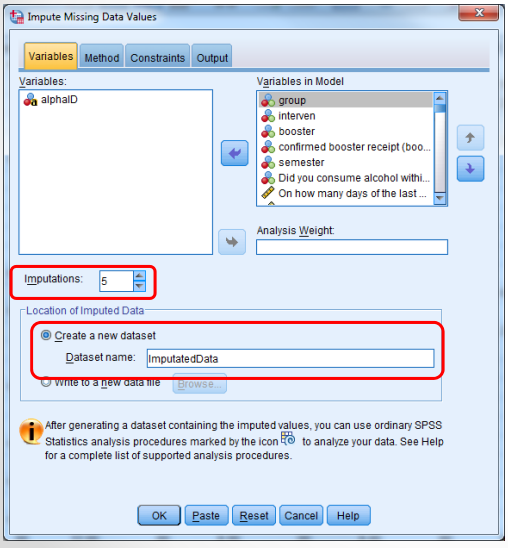
MI in SPSS

- Analyze > Multiple Imputation > Impute Missing Data Values

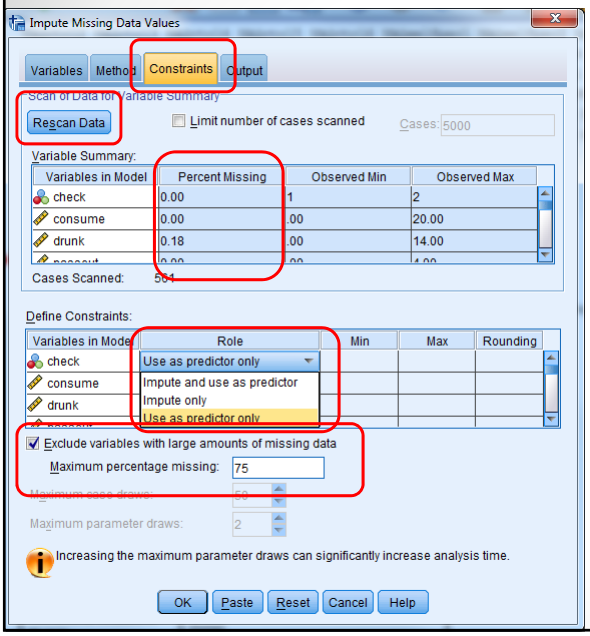


MI in SPSS



- Select all numeric variables
  - Except ID
- Choose number of datasets/imputations to generate
- Give a name to your new dataset
  - ImputedData

MI in SPSS



- Can fail if too many variables and/or too much missing data for some variables
- Might pare the dataset down to 500 variables or fewer
  - Can do the process again if you identify a different 500 variables for other analyses
- Can limit what is imputed versus what is a predictor
- Can exclude variables with too much missing data
  - If not main outcome

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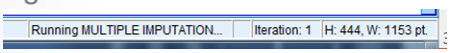
MI in SPSS

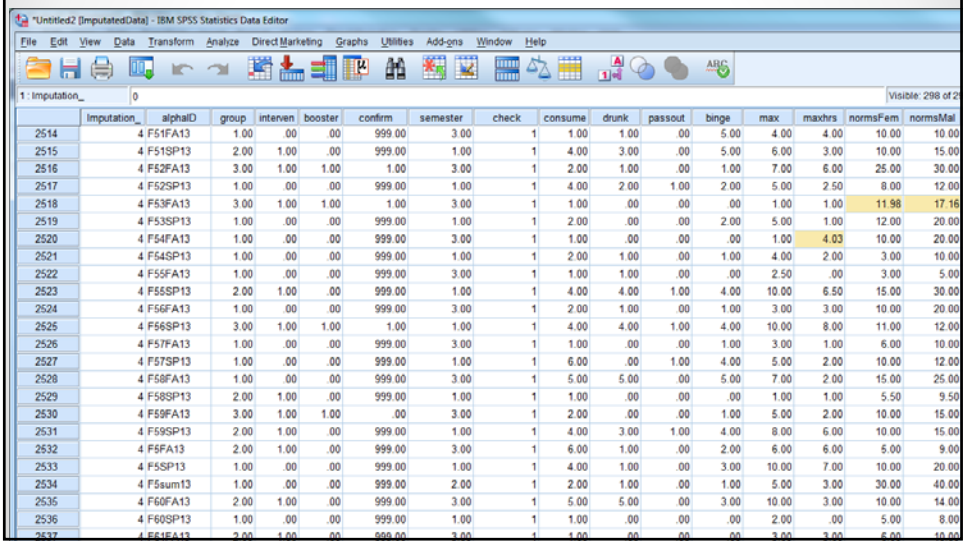
- Might take a while



- New imputed data file(s) will open in a new window
- Can scroll down to see multiple datasets
- Imputed values are highlighted

30

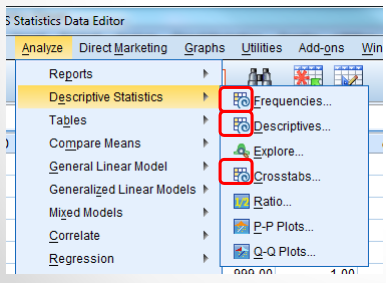
MI in SPSS

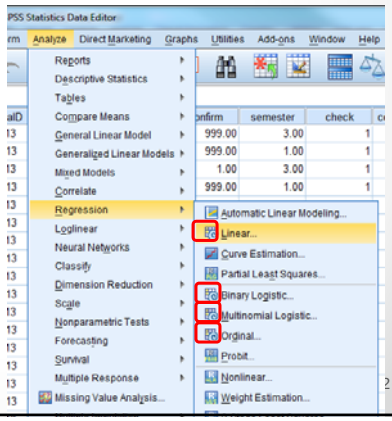


	Imputation_	alphaID	group	interven	booster	confirm	semester	check	consume	drunk	passout	binge	max	maxhrs	normsFem	normsMal
2514	4	F51FA13	1.00	.00	.00	999.00	3.00	1	1.00	1.00	.00	5.00	4.00	4.00	10.00	10.00
2515	4	F51SP13	2.00	1.00	.00	999.00	1.00	1	4.00	3.00	.00	5.00	6.00	3.00	10.00	15.00
2516	4	F52FA13	3.00	1.00	1.00	1.00	3.00	1	2.00	1.00	.00	1.00	7.00	6.00	25.00	30.00
2517	4	F52SP13	1.00	.00	.00	999.00	1.00	1	4.00	2.00	1.00	2.00	5.00	2.50	8.00	12.00
2518	4	F53FA13	3.00	1.00	1.00	1.00	3.00	1	1.00	.00	.00	.00	1.00	1.00	11.98	17.16
2519	4	F53SP13	1.00	.00	.00	999.00	1.00	1	2.00	.00	.00	2.00	5.00	1.00	12.00	20.00
2520	4	F54FA13	1.00	.00	.00	999.00	3.00	1	1.00	.00	.00	.00	1.00	4.03	10.00	20.00
2521	4	F54SP13	1.00	.00	.00	999.00	1.00	1	2.00	1.00	.00	1.00	4.00	2.00	3.00	10.00
2522	4	F55FA13	1.00	.00	.00	999.00	3.00	1	1.00	1.00	.00	.00	2.50	.00	3.00	5.00
2523	4	F55SP13	2.00	1.00	.00	999.00	1.00	1	4.00	4.00	1.00	4.00	10.00	6.50	15.00	30.00
2524	4	F56FA13	1.00	.00	.00	999.00	3.00	1	2.00	1.00	.00	1.00	3.00	3.00	10.00	20.00
2525	4	F56SP13	3.00	1.00	1.00	1.00	1.00	1	4.00	4.00	1.00	4.00	10.00	8.00	11.00	12.00
2526	4	F57FA13	1.00	.00	.00	999.00	3.00	1	1.00	.00	.00	1.00	3.00	1.00	6.00	10.00
2527	4	F57SP13	1.00	.00	.00	999.00	1.00	1	6.00	.00	1.00	4.00	5.00	2.00	10.00	12.00
2528	4	F58FA13	1.00	.00	.00	999.00	3.00	1	5.00	5.00	.00	5.00	7.00	2.00	15.00	25.00
2529	4	F58SP13	2.00	1.00	.00	999.00	1.00	1	1.00	.00	.00	.00	1.00	1.00	5.50	9.50
2530	4	F59FA13	3.00	1.00	1.00	.00	3.00	1	2.00	.00	.00	1.00	5.00	2.00	10.00	15.00
2531	4	F59SP13	2.00	1.00	.00	999.00	1.00	1	4.00	3.00	1.00	4.00	8.00	6.00	10.00	15.00
2532	4	F5FA13	2.00	1.00	.00	999.00	3.00	1	6.00	1.00	.00	2.00	6.00	6.00	5.00	9.00
2533	4	F5SP13	1.00	.00	.00	999.00	1.00	1	4.00	1.00	.00	3.00	10.00	7.00	10.00	20.00
2534	4	F5sum13	1.00	.00	.00	999.00	2.00	1	2.00	1.00	.00	1.00	5.00	3.00	30.00	40.00
2535	4	F60FA13	2.00	1.00	.00	999.00	3.00	1	5.00	5.00	.00	3.00	10.00	3.00	10.00	14.00
2536	4	F60SP13	1.00	.00	.00	999.00	1.00	1	1.00	.00	.00	.00	2.00	.00	5.00	8.00
2537	4	F61FA13	2.00	1.00	.00	999.00	3.00	1	1.00	.00	.00	.00	3.00	3.00	6.00	10.00

MI in SPSS

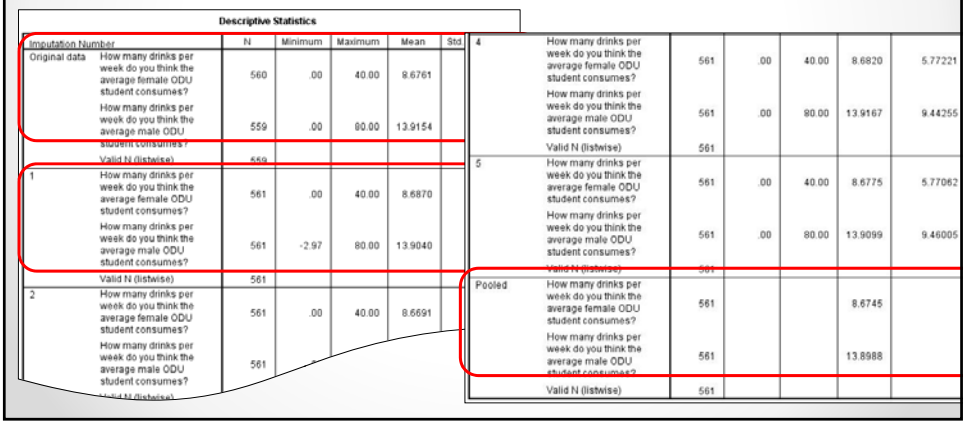
- Run your analyses from these new data
- Swirls will appear over analyses that can incorporate the multiply imputed data
- From simple (means, correlations) to complex (chi-squares, regressions)





MI in SPSS

- Will display results for: 1) original dataset, 2) each imputed dataset, and 3) **pooled results** across imputations



Descriptive Statistics

Imputation Number		N	Minimum	Maximum	Mean	Std.
Original data	How many drinks per week do you think the average female ODU student consumes?	560	.00	40.00	8.6761	
	How many drinks per week do you think the average male ODU student consumes?	559	.00	80.00	13.9154	
	Valid N (listwise)	559				
1	How many drinks per week do you think the average female ODU student consumes?	561	.00	40.00	8.6870	
	How many drinks per week do you think the average male ODU student consumes?	561	-2.97	80.00	13.9040	
	Valid N (listwise)	561				
2	How many drinks per week do you think the average female ODU student consumes?	561	.00	40.00	8.6691	
	How many drinks per week do you think the average male ODU student consumes?	561				
4	How many drinks per week do you think the average female ODU student consumes?	561	.00	40.00	8.6820	5.77221
	How many drinks per week do you think the average male ODU student consumes?	561	.00	80.00	13.9167	9.44255
	Valid N (listwise)	561				
5	How many drinks per week do you think the average female ODU student consumes?	561	.00	40.00	8.6775	5.77062
	How many drinks per week do you think the average male ODU student consumes?	561	.00	80.00	13.9099	9.46005
	Valid N (listwise)	561				
Pooled	How many drinks per week do you think the average female ODU student consumes?	561			8.6745	
	How many drinks per week do you think the average male ODU student consumes?	561			13.8988	
	Valid N (listwise)	561				

MI in Mplus

- Just generating data (from Mplus User's Guide, version 7)

```
TITLE: this is an example of multiple imputation
for a set of variables with missing values
DATA: FILE = ex11.5.dat;
VARIABLE: NAMES = x1 x2 y1-y4 v1-v50 z1-z5;
USEVARIABLES = x1 x2 y1-y4 z1-z5;
AUXILIARY = v1-v10;
MISSING = ALL (999);
DATA IMPUTATION:
IMPUTE = y1-y4 x1 (c) x2;
NDATASETS = 10;
SAVE = missimp*.dat;
ANALYSIS: TYPE = BASIC;
OUTPUT: TECH8;
```

- Variables actually to be used in imputation
- Not involved, but saved in data
- Variables w/ missing values being imputed
- Number of datasets to be generated
- Name of file to be created

MI in Mplus

- MI followed by latent growth model (not saving data)

```
DATA: FILE = ex11.5.dat;
VARIABLE: NAMES = x1 x2 y1-y4 v1-v50 z1-z5;
USEVARIABLES = x1 x2 y1-y4 z1-z5;
MISSING = ALL (999);
DATA IMPUTATION:
IMPUTE = y1-y4 x1 (c) x2;
NDATASETS = 10;
ANALYSIS: ESTIMATOR = ML;
MODEL: i s | y1@0 y2@1 y3@2 y4@3;
       i s ON x1 x2;
OUTPUT: TECH1 TECH8;OUTPUT: TECH8;
```

- Variables actually to be used in imputation
- Variables w/ missing values being imputed
- Number of datasets to be generated
- Using ML estimation for the LGM
- Analysis being conducted on imputed data

- "AUXILIARY" and "SAVE" commands not necessary because not saving data

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Maximum Likelihood (ML) Estimation

- Identifies estimates that maximize the probability of observing what has been observed
  - If beta = 0.3213, what is the probability/likelihood of the current data?
  - If beta = 0.3212, what is the probability/likelihood of the current data?
  - Yields parameter estimates with the maximum (highest) likelihood (probability) given your data
- When data are missing
  - The likelihood is computed separately for those cases with complete data on ***some*** variables and those with complete data on ***all*** variables
  - These two likelihoods are then maximized together to find the estimates
- Uses all data available (complete and incomplete)
- Want to make sure you include (or control for) any predictors that influenced missingness for your outcomes when you specify your model
- Does not require imputation
- Much less complex than MI!

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ML in Software

- SPSS
  - Default estimation is Ordinary Least Square (OLS)
  - Can switch to ML if you have the AMOS add-on
    - Must be using SEM approach or path analysis
- ML is default in Mplus for most analyses
  - Can add "ANALYSIS: ESTIMATOR= ML" to be sure
  - Will use all available data for endogenous variables
    - Variables being predicted by anything
  - Will still exclude cases with missing data on exogenous predictors
    - Variables not predicted by anything (e.g., gender, intervention status)
  - Could combine ML estimation with imputed predictors
- ML is easily available in SAS

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Expectation Maximization (EM) Imputation

- Consists of 2 steps
- *1) Expectation*: Choose values for unknown data
  - Generates means and covariance matrix based on complete data
  - Start with expected value based on regression imputation
  - What would X4 be, given what we know about X1, X2, and X3?
- *2) Maximization*: Calculate new means and covariance matrix using imputed data
  - Use the new means and covariance matrix to go back to step 1 and re-estimate missing values
- Iterative
  - Repeats until convergence (i.e., until the numbers stop changing or the changes are barely perceptible)
- Generates only ONE dataset with imputed values
  - Parameter estimates themselves are unbiased
  - Can still generate deflated SEs, so avoid as only solution, but layer on with ML

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EM Imputation in SPSS

- Can be done easily in EQS, SAS, and SPSS
- In SPSS:
- Analyze > Missing Value Analysis
- Transfer all relevant numerical variables into "Quantitative Variables"
- Transfer all relevant categorical variables into "Categorical Variables"
- Select the EM option
- Press the EM button

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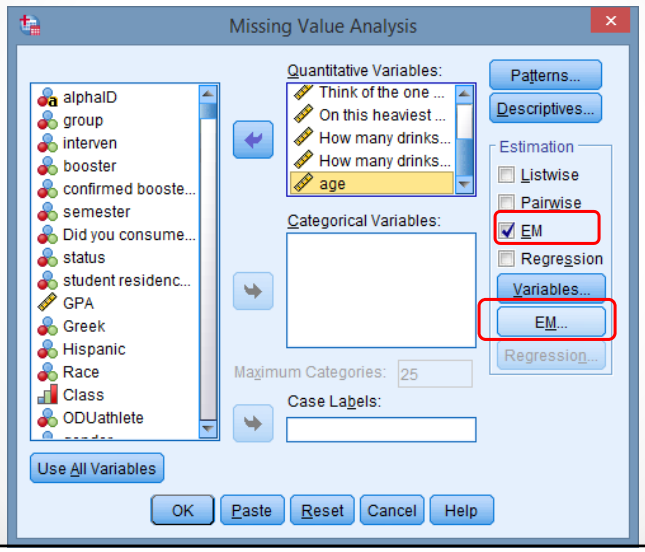
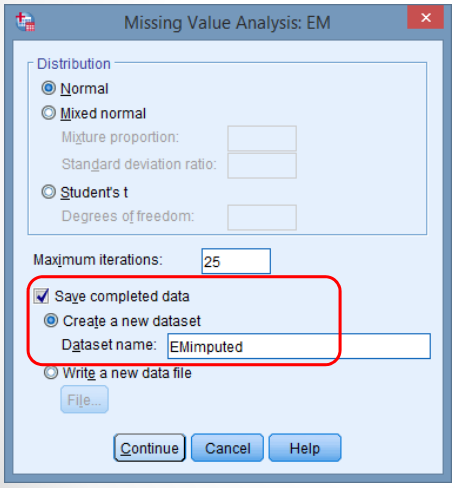
EM Imputation in SPSS



40

EM Imputation in SPSS



- Select "Save completed data"
- Choose "Create a new dataset" and name it ***OR*** "Write a new data file"
  - Press File and type a filename
- Open this new file
- Should include the observed data together with imputed data
- Conduct analyses on this file

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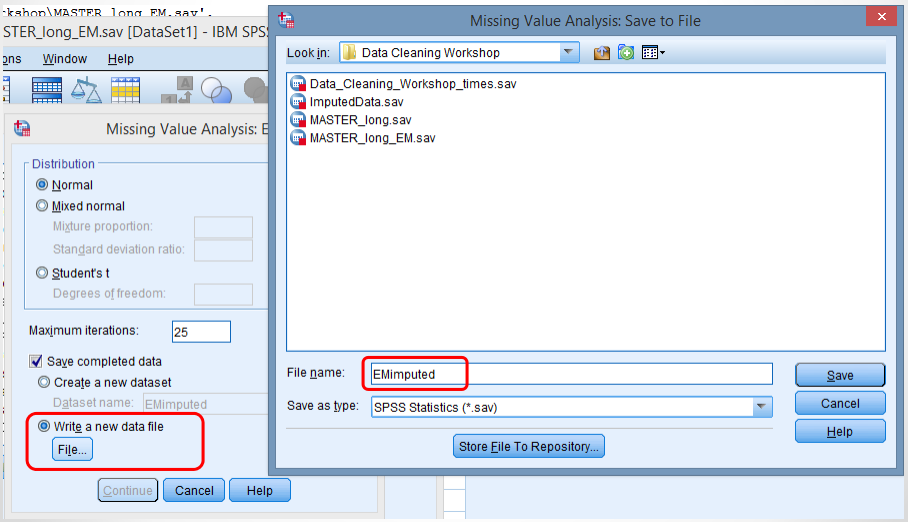
EM Imputation in SPSS



EM Imputation in SPSS

- The saved dataset with imputed values will only contain variables involved in the imputation
- If you excluded some variables, you'll want to merge the files
  - Use merge feature in SPSS
  - OR copy/paste variables
    - Be sure to sort both datasets by ID first so the cases match up

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Choosing Imputation Type

- Think about analysis type
- Think about software familiarity
- If easily conducted in SPSS and most familiar, might choose multiple imputation
- If SEM or HLM is required and/or comfortable with Mplus:
  - If analysis is straightforward, might choose MI
  - If analysis is complex, might choose ML estimation
    - If predictors have a lot of missing data, might layer on EM imputation for predictors
  - I personally tend to use ML estimation, and I rarely impute predictors unless it's more than a case or two being excluded

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Words of Wisdom

- "…Although some missing data methods are clearly better than others, none of them can really be described as good. The only really good solution to the missing data problem is not to have any" (Allison, 2001, *p*. 2).
- Put lots of thought and effort into recruitment and retention
  - Longitudinal
    - Strong incentives for follow-ups, Bonuses for complete data
    - Lots of reminders for longitudinal data
  - Take advantage of advanced survey features
    - Point out when people skip questions
  - Include multiple items/scales to tap into the same construct
    - Allows you to model missingness if necessary (MAR instead of MNAR)

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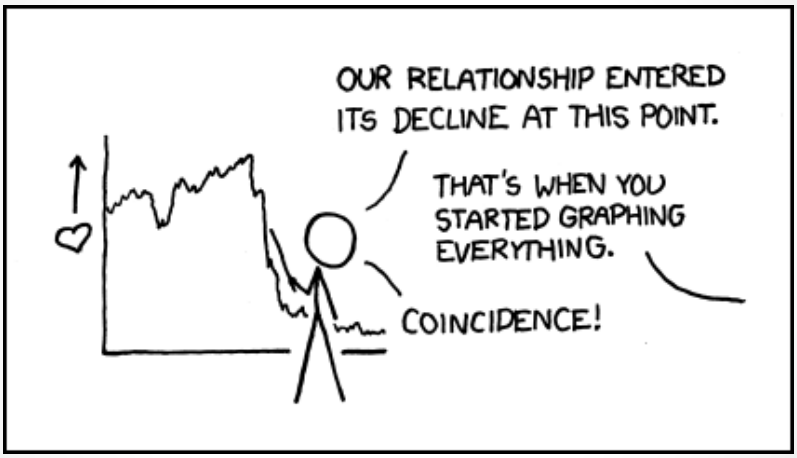

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Outline for Today

- Missing Data
  - Identifying, assessing type, imputation options
- **Composite Scores**
  - **Total scores, recoding, dummy coding**
- Outliers
  - Identifying and addressing univariate and multivariate outliers
- Normality
  - Assessing and addressing (e.g., transformations, analysis specifications)
- Bivariate Linearity
  - Reading scatterplots and what to do about them
- Documentation
  - The importance of codebooks and data logs

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Composite Scores

- Total Scores
  - E.g., Means, Sums
- Reverse scoring
  - Often select items within a scale
- Dummy Coding
  - Turning nominal variables into a series of dichotomous (0/1) variables
  - OR into one dichotomous variable
  - Race, gender, etc.
  - Only necessary for linear models (e.g., regression, SEM, HLM)
    - Not for ANOVA, chi-square

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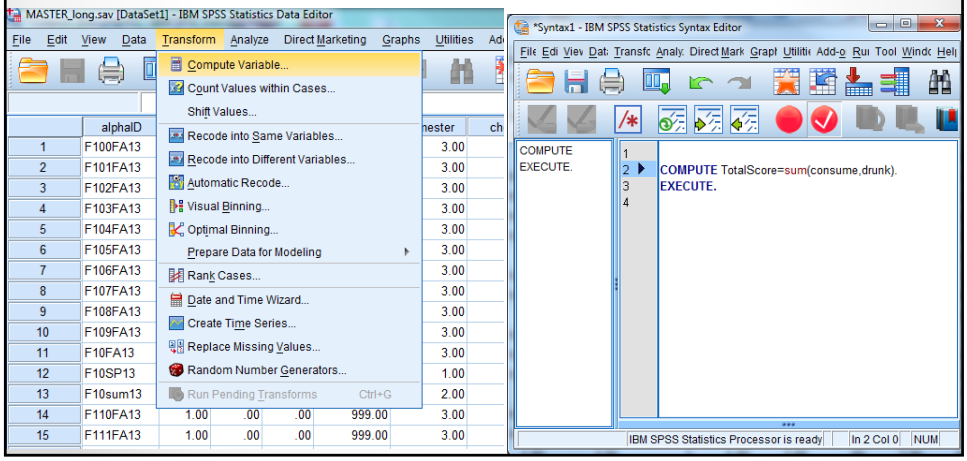
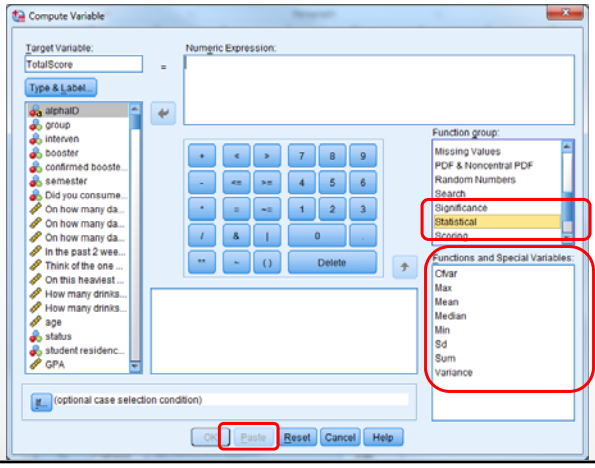
Total Scores

- Transform > Compute
- Syntax window



Total Score

- Typically sum or mean, but could be max, median, variance, etc.



50

Total Scores: Means

- *depress* = (*x*1 + *x*2 + *x*3 + *x*4 + *x*5) / 5
  - Gives average/mean when all 5 values are present
  - Gives [missing] if any values are missing
- *depress* = **MEAN**(*x*1,*x*2,*x*3,*x*4,*x*5)
  - Gives the total of all values present

- *EXAMPLE*
- *depress* = (3 + 2 + 3 + 5 + [.]) / 5 = [.]
- *depress* = MEAN(3,2,3,5,[.]) = 3.25

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Total Scores: Sums

- *depress* = *x*1 + *x*2 + *x*3 + *x*4 + *x*5
  - Gives total/sum when all 5 values are present
  - Gives [missing] if any of the values are missing
- *depress* = **SUM**(*x*1,*x*2,*x*3,*x*4,*x*5)
  - Gives the total of all values present
- *depress* = **MEAN**(*x*1,*x*2,*x*3,*x*4,*x*5)***5**
  - Gives the mean of the present values, then multiplies by number of items
  - As if that value were present, and the mean of the other values

- *EXAMPLE*
- *depress* = 3 + 2 + 3 + 5 + [.] = [.]
- *depress* = SUM(3,2,3,5,[.]) = 13
- *depress* = MEAN(3,2,3,5,[.]) = 3.25*5 = 16.25

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Total Scores

- If you'd rather exclude cases that have too much missing data, can add a digit to the command
- Digit represents the minimum number of values that must be present to execute the command
- *depress* = SUM**.3**(*x*1,*x*2,*x*3,*x*4,*x*5)
- *depress* = MEAN**.3**(*x*1,*x*2,*x*3,*x*4,*x*5)

- EXAMPLES
- *depress* = SUM.3 (3,2,3,5,[.]) = 13
- *depress* = SUM.3 (3,2,3,[.],[.]) = 8
- *depress* = SUM.3 (3,2,[.],[.],[.]) = [.]

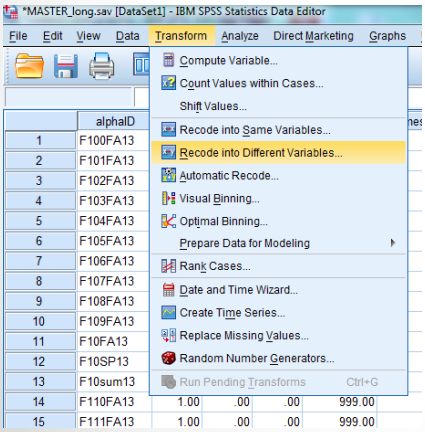
Reverse Scoring

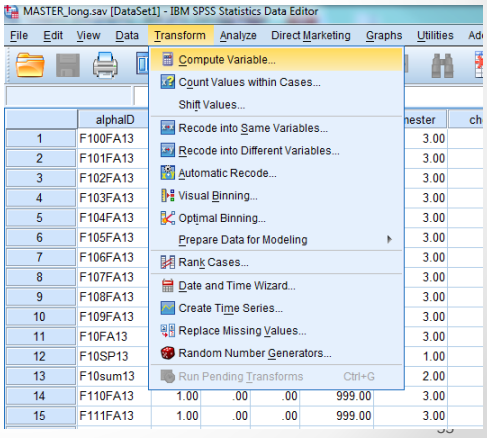
1. I was bothered by things that usually don.t bother me.
2. I did not feel like eating; my appetite was poor.
3. I felt that I could not shake off the blues even with help from my family.
4. ***I felt that I was just as good as other people.****
5. I had trouble keeping my mind on what I was doing.
6. I felt depressed.
7. I felt that everything I did was an effort.
8. ***I felt hopeful about the future.****
9. I thought my life had been a failure.
10. I felt fearful.

Source: Radloff, L.S. (1977). The CES-D scale: A self-report depression scale for research in the general population. *Applied Psychological Measurement, 1*: 385-401.
Note. First 10 items only

Reverse Scoring

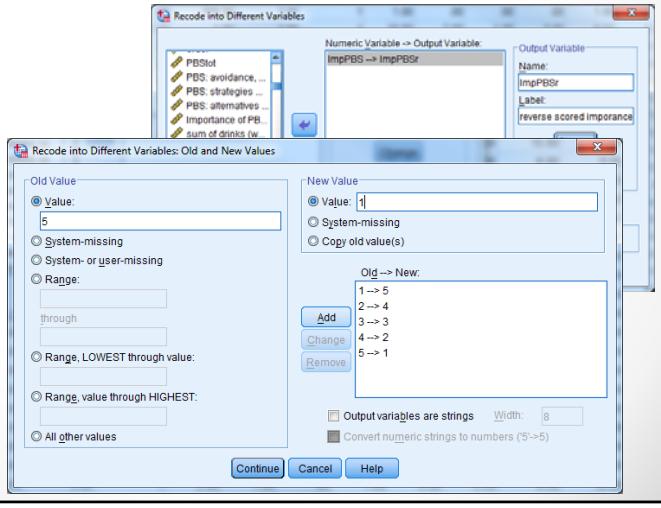
- Recode versus Compute





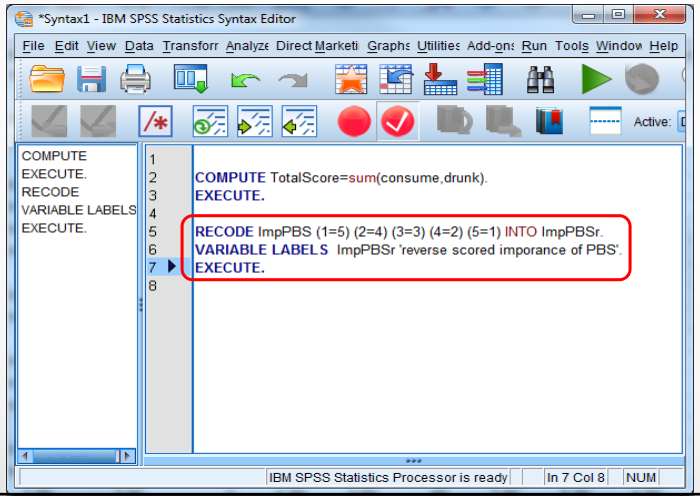
Reverse Scoring

- RECODE into Different Variables
- 1 to 5
- 2 to 4
- 3 to 3
- 4 to 2
- 1 to 5



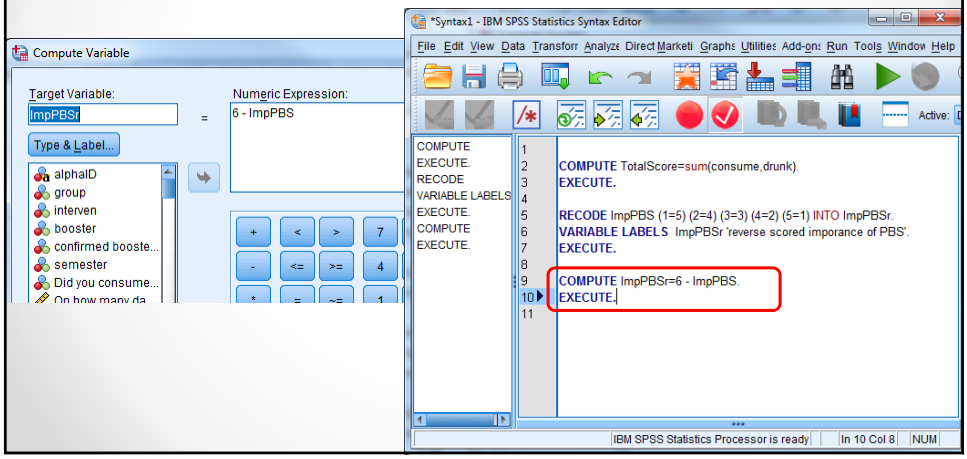
Reverse Scoring

- Recode into different variables via syntax



Reverse Scoring

- A better way!
- COMPUTE: (max+1) - value



Reverse Scoring

RECODE
(1=5) (2=4) (3=3) (4=2) (5=1)

- *1* becomes **5**
- *2* becomes **4**
- *3* becomes **3**
- *4* becomes **2**
- *5* becomes **1**

COMPUTE
= 6 - 1

- 6 – *1* = **5**
- 6 – *2* = **4**
- 6 – *3* = **3**
- 6 – *4* = **2**
- 6 – *5* = **1**

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Reverse Scoring

- COMPUTE version is faster
- Less room for human error
- Can incorporate non-whole numbers (like imputed values)
  - Imputed Value = 1.32
- Using RECODE Into Different Variables, 1.32 becomes [.] (missing again)
- Using COMPUTE, 1.32 becomes 6 – 1.32 = 4.68
  - Was between 1 and 2, now between 4 and 5
  - Successful recode

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Dummy Codes

- Turning categorical variables into a series of dichotomous (0/1) variables
  - OR into one dichotomous variable
- Only necessary for linear models (e.g., regression, SEM, HLM)
  - Not for ANOVA, chi-square
- Set of new dummy variables if you have 3+ groups and want to keep 3+ groups
- Single new dummy variable if you have 2 groups, or want to turn 3+ groups into 2 groups
- Technically more possibilities than 0/1
  - [-1/+1], [-.5/+.5], etc.
  - Only worth exploring these if want to influence the interpretation of your intercept

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Dummy Codes: Multi

- Set of new dummy variables if you have 3+ groups and want to keep 3+ groups
- For *k* groups, will create *k* – 1 variables
- Choose reference group
  - Will have value of zero for all *k* – 1 variables
  - Will be the group represented by the intercept (or the default in the path model, etc.)
  - Often the most frequent group, or "default" such as control group
- Examples:
  - Race: 6 categories into 5 dichotomous variables
  - Treatment: 3 groups into 2 dichotomous variables
  - Marital Status: 5 categories into 4 dichotomous variables

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Dummy Codes: Single

- If you have only 2 groups you want to analyze
  - Gender (male/female), treatment (control, active), Symptom (yes/no)
- Necessary if codes were [1,2], etc.
  - Common in survey software
- Choose which group is 0
  - Often most frequent group (females in SONA pool!) or default (control group, no symptom)
- Choose which group is 1
  - Other group
- Intercept represents "0" group
  - Mean for females in control group
- Variable represents how things change for "1" group
  - Change for males, change for receiving treatment, change for people who have symptom/diagnosis

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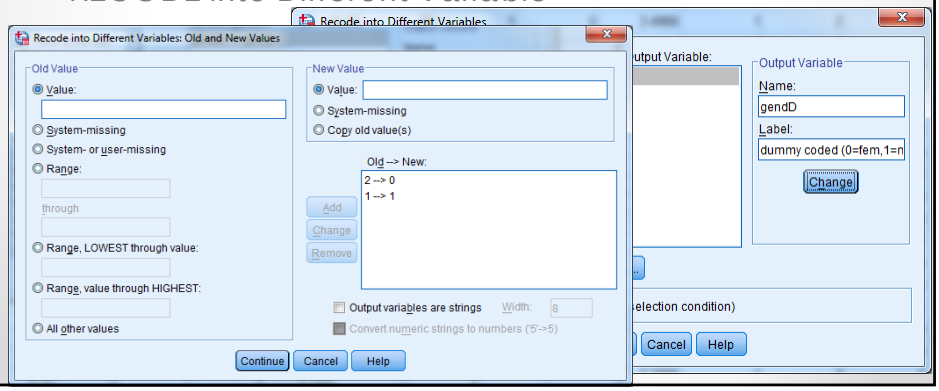
Dummy Codes: Single

- Gender example:
- Females are much more prevalent → 0
- RECODE into Different Variable

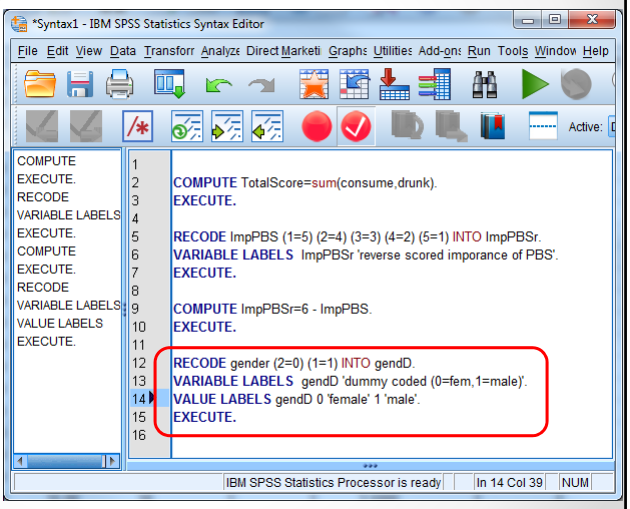
gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	183	32.6	32.6	32.6
	Female	378	67.4	67.4	100.0
	Total	561	100.0	100.0	



Dummy Codes: Gender

- Same as previous
- Added VALUE LABELS
  - "VALUE LABELS"
  - Variable name
  - Value
  - 'label'
  - Next value
  - 'label'
  - period

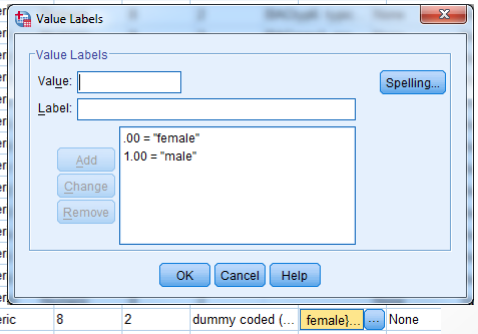


65

Dummy Codes: Gender

- Double check variable view

281	BACtyp2	Numeric	8	2	BACtyp2: typic...	None	None
282	BACtyp3	Numeric	8	2	BACtyp3: typic...	None	None
283	BACtyp4	Numeric	8	2	BACtyp4: typic...	None	None
284	BACtyp5	Numeric	8	2	BACtyp5: typic...	None	None
285	BACtyp6	Numer					
286	BACmax1	Numer					
287	BACmax2	Numer					
288	BACmax3	Numer					
289	BACmax4	Numer					
290	BACmax5	Numer					
291	BACmax6	Numer					
292	maxDrks1	Numer					
293	maxDrks2	Numer					
294	maxDrks3	Numer					
295	maxDrks4	Numer					
296	maxDrks5	Numer					
297	maxDrks6	Numer					
298	PBStotCRr	Numer					
299	gendD	Numeric	8	2	dummy coded (...	female}...	None
300							



66

Dummy Codes: Gender

- Double Check frequencies

Original →

gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	183	32.6	32.6	32.6
	Female	378	67.4	67.4	100.0
	Total	561	100.0	100.0	

Dummy →

dummy coded (0=fem,1=male)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	female	378	67.4	67.4	67.4
	male	183	32.6	32.6	100.0
	Total	561	100.0	100.0	

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Dummy Codes: Tx

- Tx example:
- Control Group ("HealthEdu") is the default → 0
- Tx group ("Alcohol 101 plus") → 1
- RECODE into Different Variable
  - RECODE interven (1=0) (2=1) INTO txD.
  - VARIABLE LABELS txD 'dummy coded tx (0=ctrl,1=alc101)'.
  - VALUE LABELS txD 0 'ctrl' 1 'alc101'.
  - EXECUTE.
- Double check in variable view and using frequencies

interven

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	HealthEdu	192	34.2	34.2	34.2
	Alcohol101plus	369	65.8	65.8	100.0
	Total	561	100.0	100.0	

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Dummy Codes: Race

- Look at frequencies and choose reference group
- White and Black are both very frequent
- Is one group the "default"?
- No, so White → 0
  - Actually, *k* = 5, so *k*-1 = 4 new dummy variables
  - White → 0,0,0,0

Race

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Other	37	6.6	6.7	6.7
	African-American or Black	209	37.3	38.0	44.7
	Asian or Pacific Islander	27	4.8	4.9	49.6
	Caucasian or White	273	48.7	49.6	99.3
	Native American	4	.7	.7	100.0
	Total	550	98.0	100.0	
Missing	System	11	2.0		
Total		561	100.0		

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Dummy Codes: Race

- *k* = 5, so *k*-1 = 4 new dummy variables
- White → 0,0,0,0
- Each non-reference group gets its own dummy variable
- raceD4 → Other =1
- raceD3 → African-American or Black =1
- raceD2 → Asian or Pacific Islander =1
- raceD1 → Native American =1

Race

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Other	37	6.6	6.7	6.7
	African-American or Black	209	37.3	38.0	44.7
	Asian or Pacific Islander	27	4.8	4.9	49.6
	Caucasian or White	273	48.7	49.6	99.3
	Native American	4	.7	.7	100.0
	Total	550	98.0	100.0	
Missing	System	11	2.0		
Total		561	100.0		

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Dummy Codes: Race

```
RECODE race (1=0) (2=0) (3=0) (4=0) (5=1) INTO raceD1.
RECODE race (1=0) (2=0) (3=1) (4=0) (5=0) INTO raceD2.
RECODE race (1=0) (2=1) (3=0) (4=0) (5=0) INTO raceD3.
RECODE race (1=1) (2=0) (3=0) (4=0) (5=0) INTO raceD4.
VARIABLE LABELS raceD1 'dummy coded race (1=other)'
  raceD2 'dummy coded race (1=Black)'
  raceD3 'dummy coded race (1=Asian/PI)'
  raceD4 'dummy coded race (1=NativeAmer)'.
VALUE LABELS raceD1  1 'other'
  raceD2  1 'American-American or Black'
  raceD3  1 'Asian or Pacific Islander'
  raceD4  1 'Native American'.
EXECUTE.
```

VARIABLE LABELS [variable name] ['label']
Period after last one ends command.

VALUE LABELS [variable name] [#] ['label']
Period after last one ends command.

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Dummy Codes: Race

ID	Race	Original	raceD1	raceD2	raceD3	raceD4
1	Asian	3	0	1	0	0
2	White	4	0	0	0	0
3	Black	2	0	0	1	0
4	Native American	5	1	0	0	0
5	White	4	0	0	0	0
6	Other	1	0	0	0	1
7	Black	2	0	0	1	0
8	Black	2	0	0	1	0
9	Other	1	0	0	0	1
10	White	4	0	0	0	0

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Dummy Codes: Race

raceD4 → Other =1
raceD3 → African-American or Black =1
raceD2 → Asian or Pacific Islander =1
raceD1 → Native American =1

ID	Race	Original	raceD1	raceD2	raceD3	raceD4
1	Asian	3	0	**1**	0	0
2	White	4	0	0	0	0
3	Black	2	0	0	**1**	0
4	Native American	5	**1**	0	0	0
5	White	4	0	0	0	0
6	Other	1	0	0	0	**1**
7	Black	2	0	0	**1**	0
8	Black	2	0	0	**1**	0
9	Other	1	0	0	0	**1**
10	White	4	0	0	0	0

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Dummy Code: Marital Status

- Most frequent group Single→0
- Other groups are VERY small (≤ 2%)
- Option 1
  - 4 variables for 5 groups
  - Three of those groups are VERY small, so those variables do not add much
- Option 2
  - 1 variable for 5 groups
  - Single (73%) versus everyone else
- Option 3
  - Meaningful groupings based on frequency AND definitions
  - Single people (72.9%) versus committed OR married (23.7 + 2.0 = 25.7%)
  - Excludes/deletes *n*=8 ("other" or divorced; 1.4%)

MarStat

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Other	7	1.2	1.2	1.2
	Single	409	72.9	72.9	74.2
	Married	11	2.0	2.0	76.1
	Divorced	1	.2	.2	76.3
	In a committed relationship	133	23.7	23.7	100.0
	Total	561	100.0	100.0	

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Dummy Code: Marital Status

- Option 1: 4 variables
  - marD1 → Other =1
  - marD2 → Married =1
  - marD3 → Divorced =1
  - marD4 → Committed =1
  - Single is 0,0,0,0

MarStat

		Frequency	Percent	Valid Percent
Valid	Other	7	1.2	1.2
	Single	409	72.9	72.9
	Married	11	2.0	2.0
	Divorced	1	.2	.2
	In a committed relationship	133	23.7	23.7
	Total	561	100.0	100.0

- Option 2: 1 variable for 5 groups
  - Single (73%) versus everyone else
  - Single → 0, everyone else → 1
- Option 3: 1 variable for meaningful groupings
  - MaritalD: 2 → 0 (single); 3 → 1, 5 → 1 (Committed or Married = 1)
  - Excludes/deletes *n*=8 ("other" or divorced)

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Recoding Blanks

- There is one last type of "missing" data that is not a true missing
- For some "check all that apply" questions, survey software will generate a variable of 1's and blanks rather than 1's and 0's
  - e.g., race, symptoms, problems, etc.
- [1,.] vs [1,0]
- Not necessary if creating totals using SUM or MEAN then deleting items
  - IS necessary if imputing item variables (blanks ARE data, not missing)
  - IS necessary if using "+" coding approach

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Recoding Blanks

x1	x2	x3	x4	x5	x6
.	2	.	.	.	.
1	.	3	4	.	.
.	.	.	.	.	6
.	2	.	4	5	.
1	2	.	.	5	.

x1	x2	x3	x4	x5	x6
0	1	0	0	0	0
1	0	1	1	0	0
0	0	0	0	0	1
0	1	0	1	1	0
1	1	0	0	1	0

- [1,.] vs [1,0]

RECODE x1 x2 x3 x4 x5 x6 (2 thru 6=1) (MISSING=0).
EXECUTE.
RECODE x1 x2 x3 x4 x5 x6 (MISSING=0).
EXECUTE

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When to Impute/Recode

- Impute then Recode?
  - Total scores can be created with all datapoints (including imputed values)
  - Recoding can be more difficult (numbers often have decimal points)
    - Particularly relevant for reverse scoring and dummy codes
  - Nominal variables are not contributing to imputation estimations, whereas they could if they were recoded first
- Recode then Impute?
  - Can include more variables in imputation analysis
    - Categorical variables are excluded, but not dummy codes
  - Total scores are already made
    - Already falsely deflated or mean value without random error

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When to Impute/Recode

- Recode then Impute then Recode
  - Dummy code and reverse score first
    - Now all variables are continuous, item-level
  - Impute
    - Now all values are unbiased (no deflated sums or reduced SE's)
  - Create composites/total scores with imputed variables
    - Means/Totals reflect unbiased estimates
      - At least, not due to bad imputation
- Recode then use ML estimation for analysis
  - If doing true SEM and using item-level analysis, then no composites are required
  - For path analyses, etc., might create composites first
  - OR can create composites in Mplus using "DEFINE", which still uses ML

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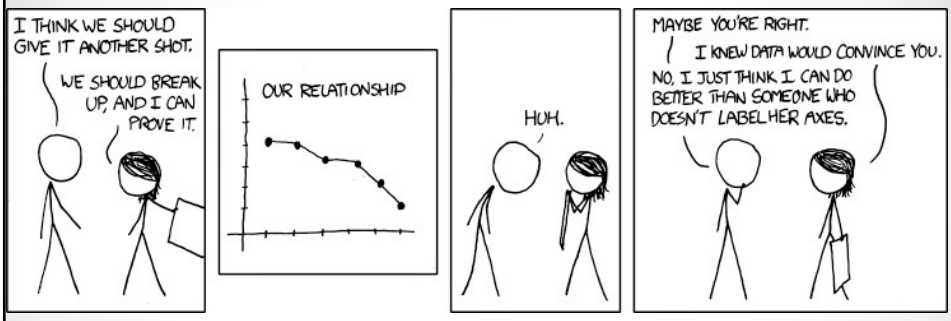

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Outline for Today

- Missing Data
  - Identifying, assessing type, imputation options
- Composite Scores
  - Total scores, recoding, dummy coding
- **Outliers**
  - **Identifying and addressing univariate and multivariate outliers**
- Normality
  - Assessing and addressing (e.g., transformations, analysis specifications)
- Bivariate Linearity
  - Reading scatterplots and what to do about them
- Documentation
  - The importance of codebooks and data logs

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Outliers

- How to identify them
- What to do about them
- Start with univariate (one variable at a time)
- Touch on multivariate

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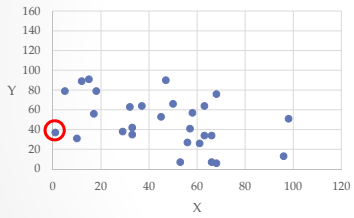
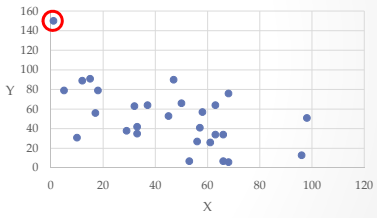
Outliers

- Why do we care?
  - Have a stronger influence on the data
  - Can influence results of study



r = -.426



r = -.567

- Same data, changed one value from 37 to 150

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Identifying Outliers

- Do this on the final version of your variables
  - After composites have been created
  - After imputation (if imputing)
- Standard deviations?
  - Themselves influenced by extreme values
- *SD* of [34,35,41,56,71,75] = 16.53
  - *M* = 52.0; *M* + *SD* = 52.0 + 16.53 = 68.53
  - *M* + 2 *SD*'s = 145.24 = 85.06
- *SD* of [34,35,41,56,71,150] = 40.37
  - *M* = 64.5; *M* + *SD* = 64.5 + 40.37 = 104.87
  - *M* + 2 *SD*'s = 145.24
  - *M* + 3 *SD*'s = 185.61
- So having extreme values makes it harder to detect extreme values

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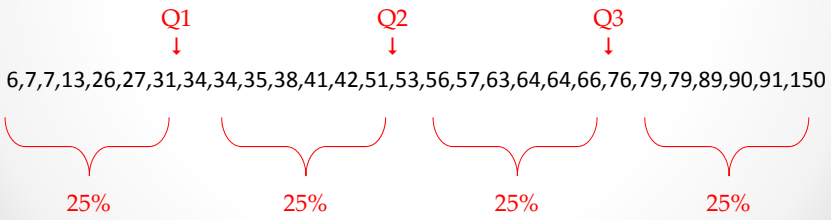
Identifying Outliers

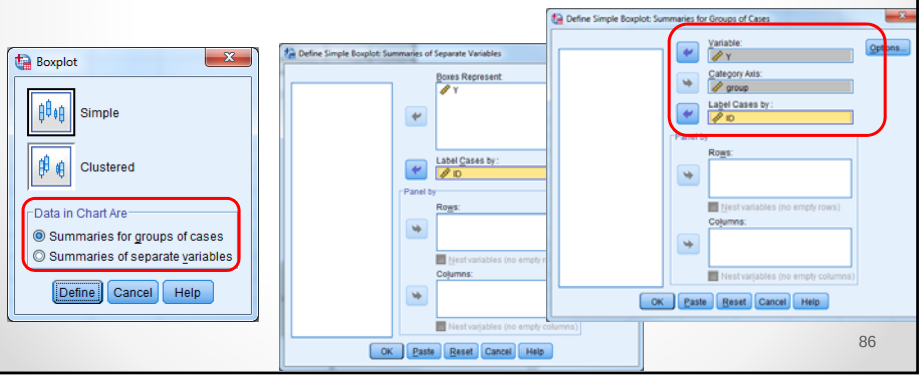
- What do you do? Boxplots!
  - Rely on Q1, Q2, Q3 (from IQR [InterQuartile Range])
  - Q2 = median
  - Q1 equals sub-median below lowest and median
  - Q3 equals sub-median below highest and median



85

Boxplots

- Graphs > Legacy Dialogs > Boxplots
- Groups? Or no groups?
  - Groups makes sense if group matters to your design, and if they are balanced
  - Can be overly sensitive if some groups have a small *n*
- Can explore more than one variable (similar scales)



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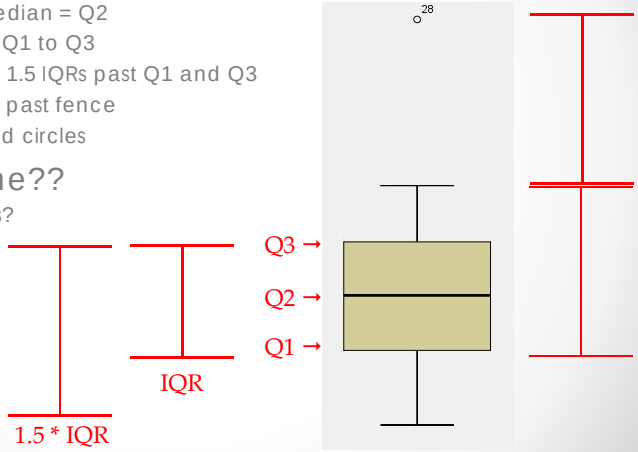
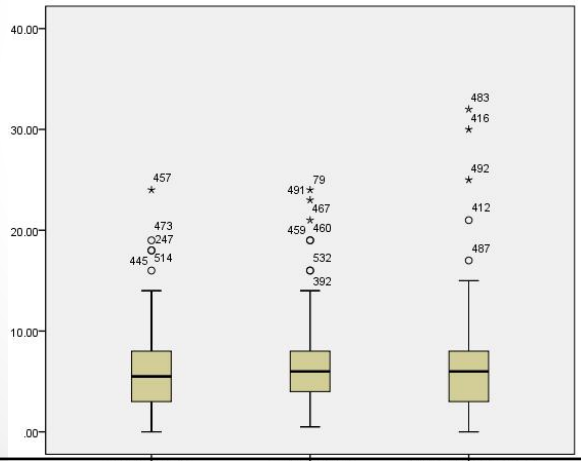
Boxplots

- Box and "whiskers" or "fence"
  - Line/middle = median = Q2
  - Box = IQR = from Q1 to Q3
  - Whiskers/fence = 1.5 IQRs past Q1 and Q3
  - Circles = 1.5 IQRs past fence
  - Asterisks = beyond circles
- What's extreme??
  - Circles? Asterisks?



Boxplots

- How many outliers do we have?
- What do we want to do with them?



Addressing Outliers

- Deletion or "Trimming"
  - Deleting values or removing entire cases deemed an outlier
- Good: Indicates noncompliance or a "bad" participant
  - Delete whole case
  - Reaction time indicates participant fell asleep (too long) or wasn't paying attention (too short)
- Bad: Just an extreme value
  - Bill Gates salary is valid/accurate
  - He is someone with average education and a very high salary
  - Deleting valid cases biases your sample

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Addressing Outliers

- Winsorize
  - Make the value less extreme
  - Find not extreme value, and go beyond it
    - Maintain rank among multiple outliers
- Examples:
- One outlier: [34,35,41,56,71,150]

  →[34,35,41,56,71,72]

- Two outliers: [34,35,41,56,71,150]

  →[34,35,41,56,57,58]

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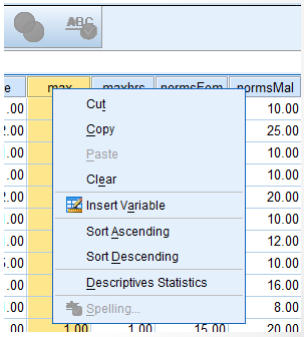
Addressing Outliers

- Winsorize in SPSS
  - No fancy syntax
- Sort cases
  - Right click on relevant variable
  - Sort ascending if looking for low outliers
  - Sort "descending" if looking for high outliers
  - Repeat for each variable
- Use discretion and common sense
  - If values are 1.2, 1.3, 1.3, 1.4
  - Don't change outliers to 2 and 3
  - Change to 1.5 and 1.6



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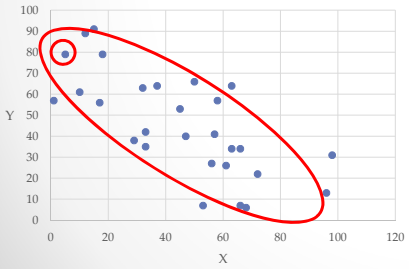
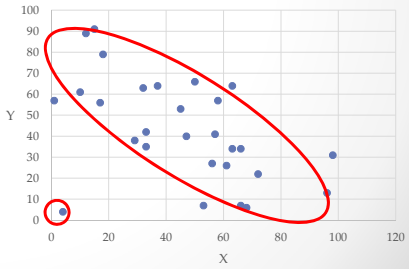
Multivariate Outliers

- Regression (linear analysis) specific
  - Requested in workshop survey; not for every analysis plan
- Value may be reasonable within its variable range
  - Not a univariate outlier
- Pattern across multiple variables indicates the combination is extreme
  - Can greatly influence analysis



r = -.710



r = -.522

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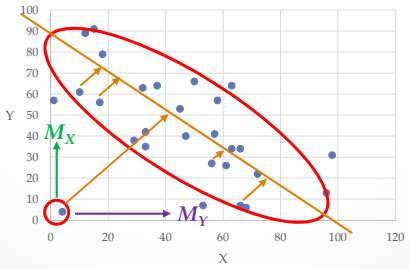
Multivariate Outliers

- Assumption of regression (and some other analyses)
- How can you examine?
  - Leverage, discrepancy, and influence
  - Rely on residuals
    - Distance from mean may not be large, but distance from predicted value may be huge
    - Especially in comparison to other deviations from predicted value



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Multivariate Outliers

- 3 approaches to asses
  - Multiple indicators for each
- Leverage
  - Distance from centroid
    - Like a multivariate mean (center of data across variables)
  - Leverage, Mahalanobis Distance
- Discrepancy
  - Distance from regression line
  - "studentized residual", "studentized deleted residual"
- Influence
  - How much a case affects the regression line
  - Product of leverage and discrepancy
  - Compare regression coefficients with and without this case
  - DFFITStandardized, Cook's D

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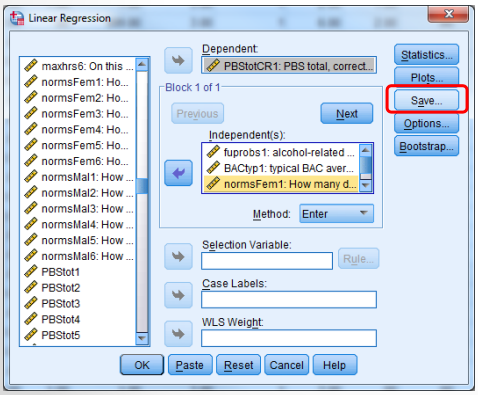
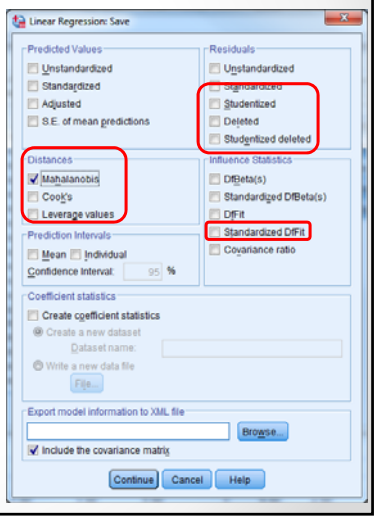
Multivariate Outliers

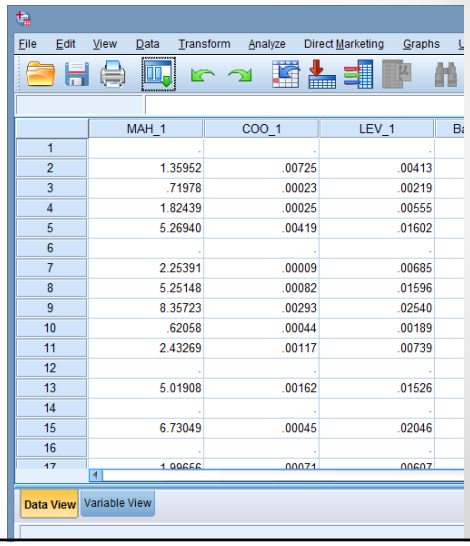
- The SPSS Regression command allows you to save the indicators for each case





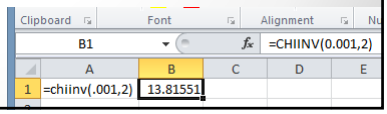
Multivariate Outliers

- Saved as new variables in the dataset
- Scroll to the end of existing variables
- Sort descending (or ascending) to view potential outliers based on cutoffs



Multivariate Outliers

- Cutoffs (excel can be helpful for critical values for distributions)
- Leverage
  - Leverage: Large samples= 2*k*/*n*, Small/medium samples: 3*k*/*n*
    - *k* represents constructs, not necessarily variables
    - Example: you are doing a regression with race and age as predictors, 200 cases
      - Even though race is 4 dummy variables, *k* is 2 (race + age), not 5 (raceD1 + raceD2 + raceD3 + raceD4 + age)
      - Cutoff = 3k/n = 3*2/200 = 0.03
  - Mahalanobis Distance: $= \chi^2_{CRIT}(k)$ [note that this is a chi-square critical value]
  - α = .001 or .01 is appropriate when assessing many assumptions
  - In excel: "=chiinv(α,*k*)"
- Discrepancy
  - "studentized residual" or "studentized deleted residual":
  - Use t_{CRIT} with a Bonferroni correction for alpha: α /*n*
  - In excel: "=tinv(α/*n*,*df*)"
- Influence
  - Standardized DFFIT: small/medium sample: >1, large sample: 2*sqrt([*k*+1]*n*)
  - Cook's D: In excel: "=finv(.5,*k*+1,*n*-*k*-1)" [not a typo… really use .5 as alpha]



Multivariate Outliers

- What do you do if you have multivariate outliers?
- Can delete cases
  - Only justified if the observations are contaminated in some way
- Model respecification (change IVs, etc.)
  - Can control for more covariates, or drop *ns* covariates
- Variable transformation
  - Any border variables for skewness or kurtosis can be re-examined (next section)
- Robust approaches
  - Other than OLS (ML estimation, weighted least squares, etc.)
- Reducing extreme scores
  - i.e., Windsorizing, but only really works for univariate outliers
- Bootstrapping
  - Can be done in SPSS, Mplus, SAS, etc.

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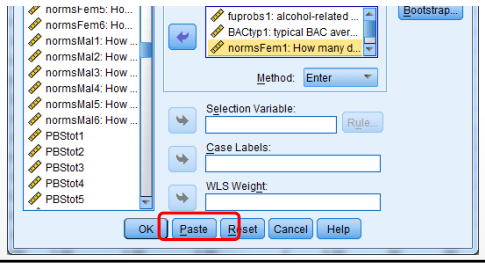
Multivariate Outliers

- Unfortunately, requesting the necessary information to detect multivariate outliers requires running the analysis
- If you have to make a change, you have to re-run the analysis after your update
- Saving your syntax is helpful
  - Use the "paste" button in ALL command windows



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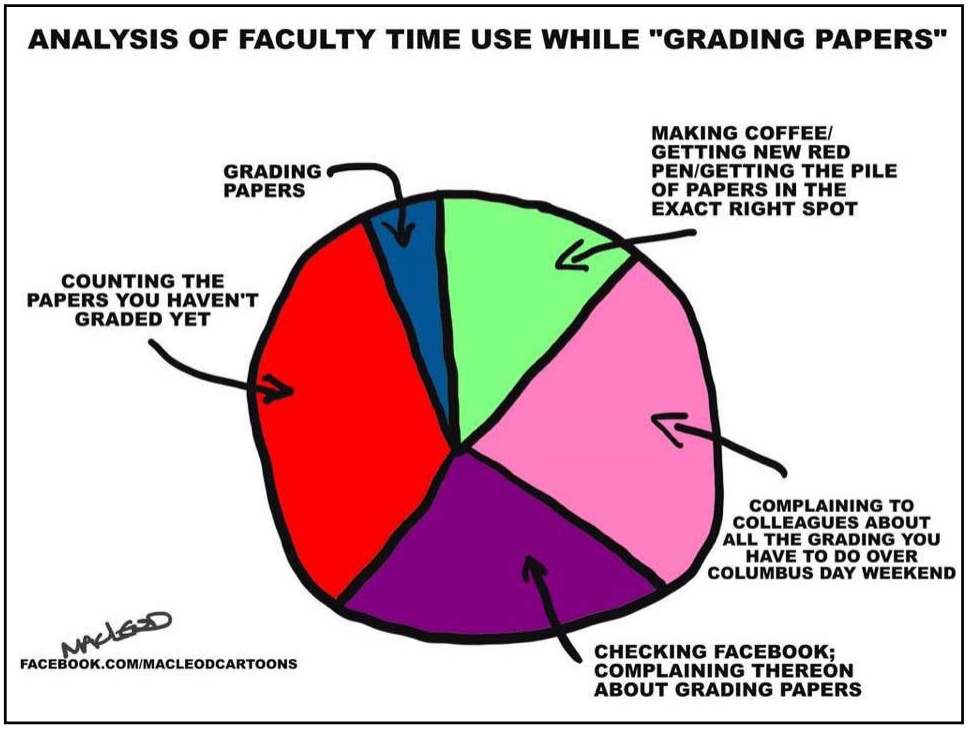

Outline for Today

- Missing Data
  - Identifying, assessing type, imputation options
- Composite Scores
  - Total scores, recoding, dummy coding
- Outliers
  - Identifying and addressing univariate and multivariate outliers
- **Normality**
  - **Assessing and addressing (e.g., transformations, analysis specifications)**
- Bivariate Linearity
  - Reading scatterplots and what to do about them
- Documentation
  - The importance of codebooks and data logs

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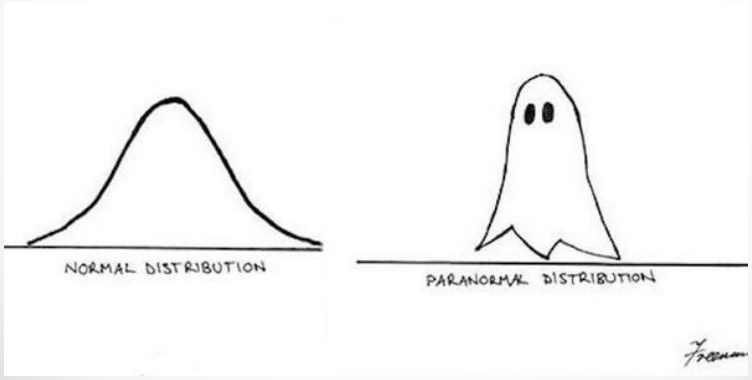
Normality

- How to assess/detect it
- What to do if you have non-normal data



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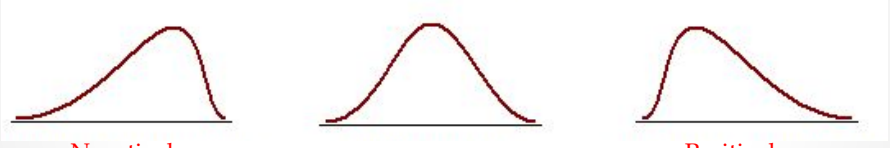
Assessing Normality

- Skewness and Kurtosis

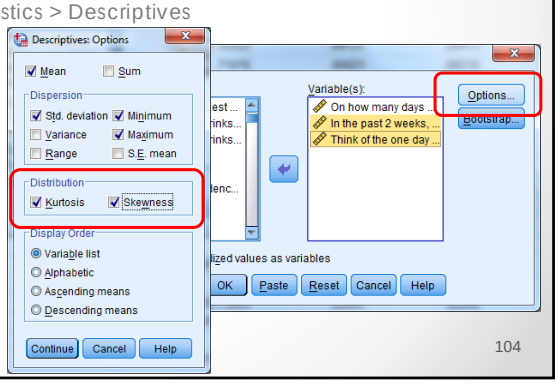


Negatively Skewed | Normal | Positively Skewed

Platykurtic | Normal | Leptokurtic

Assessing Normality

- Skewness is often more rigid for analyses than kurtosis
- Assess via requesting skewness and kurtosis for each variable
  - Analyze > Descriptive Statistics > Descriptives
- How much is too much?
  - Skewness:
    - Some say 2, some say 3
    - Use your best judgment
    - Matching skew for predictors and outcomes might be less bad
  - Kurtosis: Can be much higher (wouldn't bat an eye at 5)



Assessing Normality

- Binge frequency looks okay
  - Kurtosis is over 3, but that's not terrible
- Max drinks is surprisingly okay for skew
  - Kurtosis is a little strong
- Days passed out/sick is bad

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
On how many days of the last two weeks did you pass out or get sick from drinking alcohol?	561	.00	4.00	.2299	.53341	2.908	.103	10.771	.206
In the past 2 weeks, how many times have you consumed five or more drinks (if you are male) or four or more drinks (if you are female) on a single occasion?	560	.00	13.00	2.0313	2.03181	1.492	.103	3.121	.206
Think of the one day you consumed the most alcohol in the past 2 weeks; How many standard drinks did you consume on that day?	561	.00	32.00	6.2376	4.17681	1.854	.103	6.264	.206
Valid N (listwise)	560								

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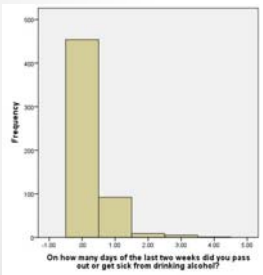
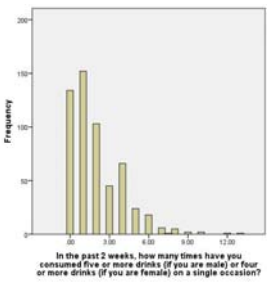
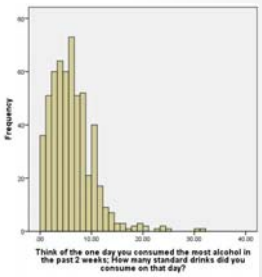
Assessing Normality

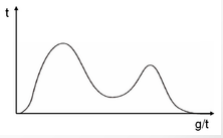
- Enough?
  - Needs to be Unimodal!
  - Check with Histograms (don't overlay normal curve)
    - Graphs > Legacy Dialogs > Historam







- Uniform (flat) is not terrible
- Don't want bi/tri/quadmodal



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Non-Normality

- What do you do if you find non-normality?
- Make sure you already addressed outliers
  - If not, winsorizing outliers may remove the problem
- Transform data
  - Particularly helpful for addressing skewness and kurtosis
    - Most transformations help both simultaneously
  - Most common solution
- Specify a different type of analysis
  - Can specify Poisson distribution
  - Logistic regression
  - Zero-inflated Poisson
  - Each type could be its own workshop or class
    - Point you in the right direction

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Non-Normality: Transformation

- Transform the offending variables to change their distribution
- Suggestions
- Positively skewed:
  - Log transform
    - Cannot log zero
    - SPSS: *NewVar* = Ln(*OldVar*)
  - Square root : *NewVar* = sqrt(*OldVar*)
- Negatively skewed:
  - Raise the power (** in SPSS)
  - $X^{1.5}$: *NewVar* = *OldVar***1.5
  - X^2 : *NewVar* = *OldVar***2
  - X^3 : *NewVar* = *OldVar***3
- Affects the interpretation of coefficients
  - To get back to raw metric, need to reverse the transformation
  - Reverse of log is exponentiation (e^X)
  - Reverse of square root is to square

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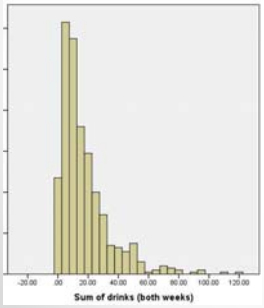
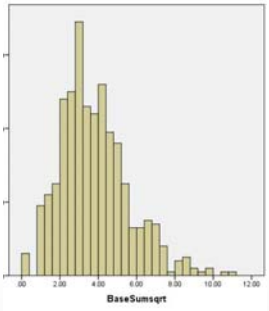
Non-Normality: Transformation

- Sum of drinks past 2 weeks: positively skewed
- Original square root log

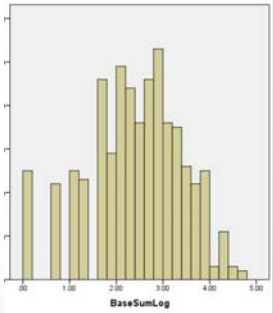
Skewness	Kurtosis
Statistic	Statistic
2.164	6.412



Skewness	Kurtosis
Statistic	Statistic
.770	.801

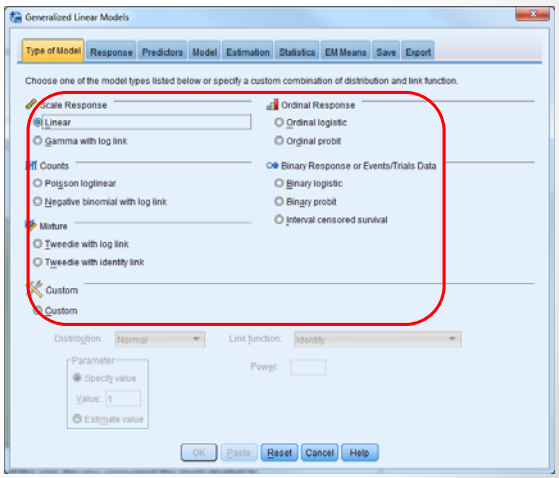


Skewness	Kurtosis
Statistic	Statistic
-.453	-.029



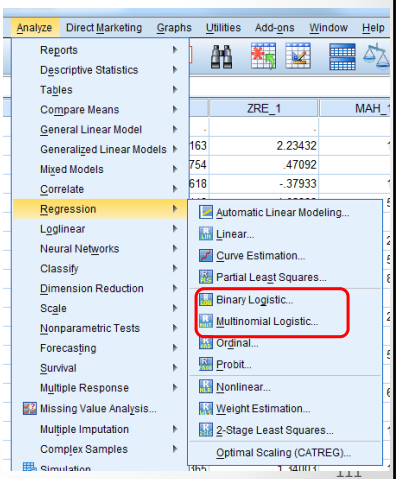
Non-Normality: Analysis

- Poisson
  - "COUNT" in Mplus
  - Button in HLM
  - Choose "Generalized Linear Model" in SPSS
    - Analyze
    - Generalized Linear Model
    - "d" is crucial
  - Choose the appropriate link function



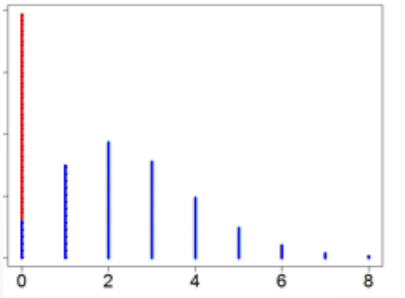
Non-Normality: Analysis

- Logistic regression
- Binary: Predict occurrence of an outcome
  - Probability of yes (compared to no)
    - Diagnosis?
    - Relapse?
    - Occurrence of violence?
  - If not naturally dichotomous, dummy code outcome variable
    - RECODE values >0 into 1
- Multinomial: Predict membership across a small number of groups
  - Probability of being medium as opposed to low, or high compared to low
  - Probability of being divorced compared to married, or single compared to married



Non-Normality: Analysis

- Zero-inflated Poisson
  - Relevant if you have a Poisson distribution, combined with a very high number of zeroes
    - Blue = Poisson; Red = zero inflation
  - Two simultaneous analyses
    - 1: probability of being a yes compared to no
    - 2: If yes, how much (Poisson/count)



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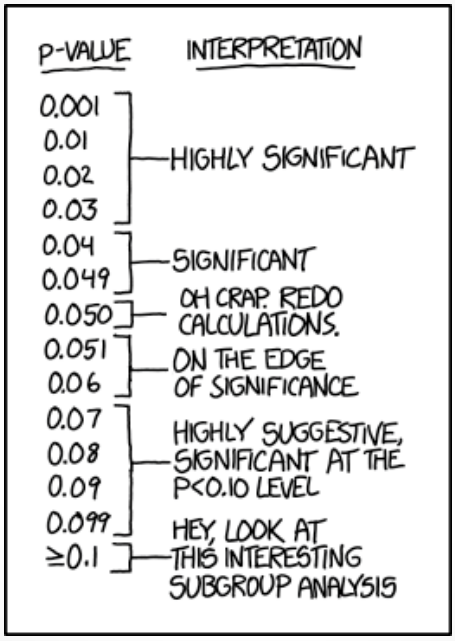

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Outline for Today

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  - Identifying and addressing univariate and multivariate outliers
- Normality
  - Assessing and addressing (e.g., transformations, analysis specifications)
- **Bivariate Linearity**
  - **Reading scatterplots and what to do about them**
- Documentation
  - The importance of codebooks and data logs

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Bivariate Linearity

- How to assess
- What to do

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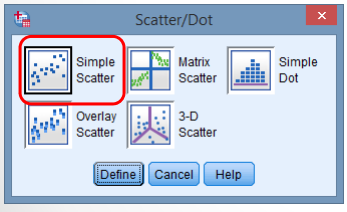
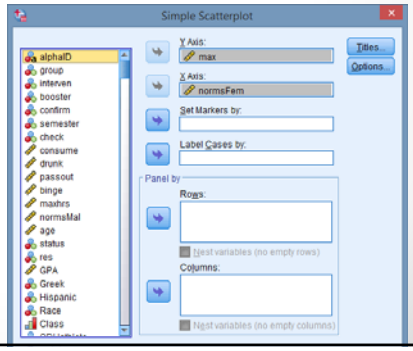
Assessing Linearity

- Another assumption of regression and other linear approaches
  - Comparing how *X* changes with *Y*
- Asses it with scatterplots!
- Graphs > Legacy Dialogs > Scatter/dog
  - Simple Scatter





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Assessing Linearity

- What's normal?
  - Line
    - Most obvious
  - Football/ellipse
    - More likely
  - True randomness
    - Pretty common among less correlated data
- What's bad?
  - Curvilinear
  - Frown or smile
  - Convex or concave

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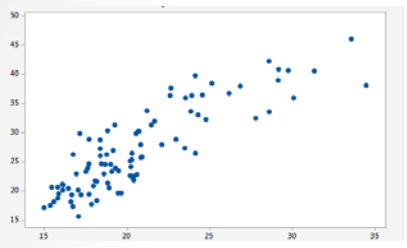
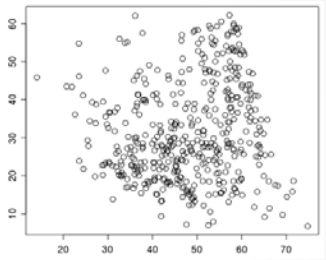
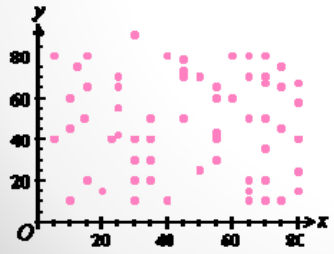
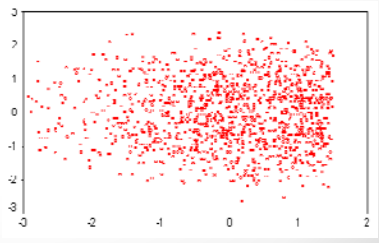
Assessing Linearity









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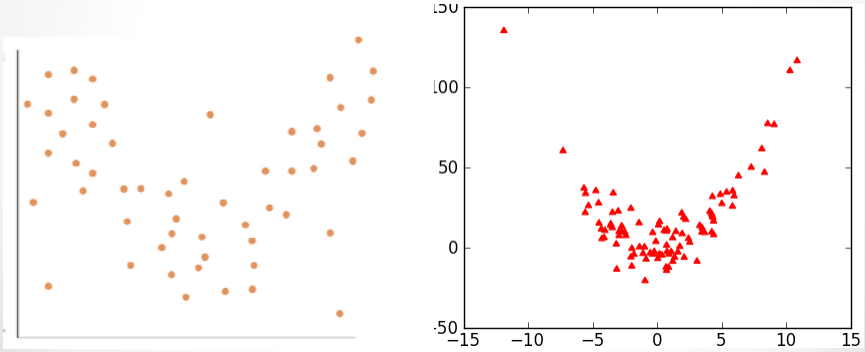
Assessing Linearity



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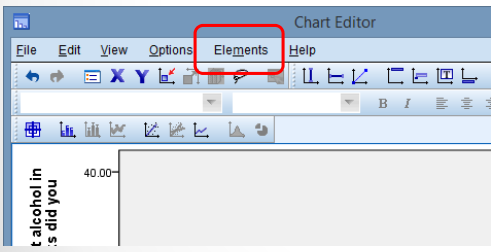
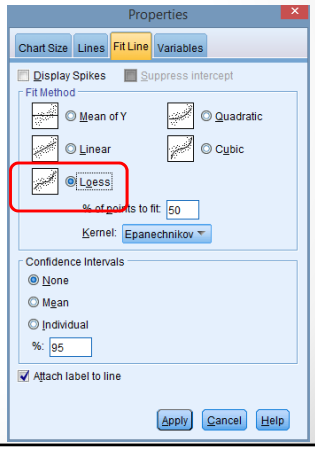
Assessing Linearity

- Having trouble? Use Lowess (Loess) lines!
- Double-click the Scatterplot to Activate it
- Elements > Fit Line at Total





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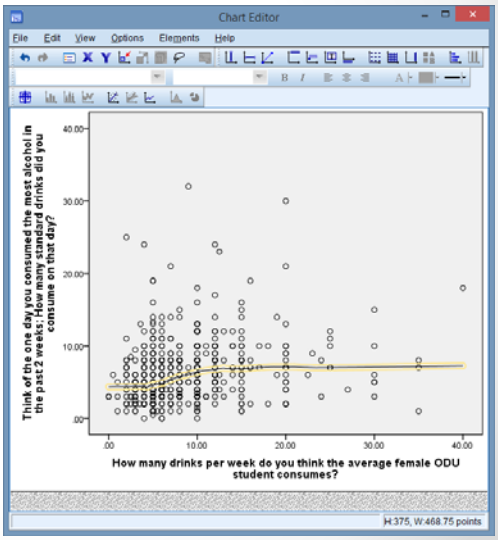
Assessing Linearity

- A curvy Loess line indicates a problem
- Mild bumps are okay
- Be on the lookout for smile or frown
- U = bad
- ∩ = bad



Addressing Nonlinearity

- What if your data are curvilinear?
- Split your data
  - For younger… for older…
- Transformations might help
  - Not for extreme curvilinearity
- Include polynomial predictors (regression)
  - X^2, X^3
  - Linear AND quadratic relationships

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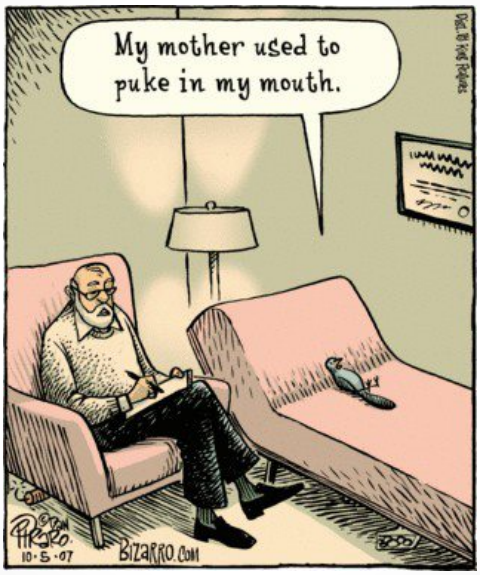

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Documenting Your Activities

- Codebooks
- Datalogs
- Syntax for composites and recoding
  - This may happen multiple times
- Save multiple versions of dataset
  - Data.sav
  - Data_dummy.sav
  - Data_dummy_imputed.sav
  - Data_dum_imp_composites.sav
  - Data_dum_imp_com_nooutliers.sav
  - Data_dum_imp_com_noout_small.sav
  - Data_dum_imp_com_noout_small_999.sav
  - Mplus.sav
- If lots of versions, can keep a version document

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Documenting Your Activities

- Why?
- Committee members
  - Request edits
  - Readers may want more info
  - Want to ensure you're a skilled scientist/researcher
- Journal Reviewers/Editors
  - "How many outliers?"
- Collaborators

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Codebooks

- For each item:
  - Variable names (short SPSS version)
  - Longer description of variable, if appropriate
  - Response scale
  - Any comments
- For each scale:
  - Citations
  - Coding schemes
  - If adjustments are appropriate
- If longitudinal
  - Timeframe for each construct
  - At which time points each construct was assessed
    - Baseline only versus follow-ups only versus all

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Codebook Example

Construct (These are all in all three waves.)	Corresponding Name in SPSS	Items	# of items	Responses	Scale	Citation
Rumination	rum_ Q706	rum1 (...deserve this) rum2 (...react this way) rum3 (...wishing gone better) rum4 (... problems others don't) rum5 (...handle things better)	5	(1-4): Almost never Sometimes Often Almost always	Response Styles Questionnaire – Brooding subscale	Treynor, Gonzalez, & Nolen Hoeksema, 2003
Suppression	sup Q706	supp1 (kept emotion to self) supp2 (controlled emotions / not express)	2	(1-4): Almost never Sometimes Often Almost always	**Two items from "Emotion Regulation Questionnaire; ERQ" (usually *strongly disagree* to *strongly agree*)**	**Gross & John, 2003**
Psychological Distress	psyd Q711	psyd1 - Distressed psyd2 - Upset psyd3 - Shame psyd4 - Nervous psyd5 - Afraid	5	Very slightly/ not at all A little Moderately Quite a bit Extremely	PANAS	Mackinnon, Jorm, Christensen, Korten, Jacomb, & Rodgers, 1999
Physical Aggression (Trait)	pha Q716	pha1 (hit another) pha2 (came to blows) pha3 (threatened)	3	1 = Very unlike me 2 3 4 5 = Very like me	Aggression (modified from Buss Perry [BP-AQ])	Bryant & Smith, 2001
Verbal Aggression (Trait)	va_sum Q716	va1 (often disagreeing) va2 (arguments) va3 (argumentative)	3	1 = Very unlike me 2 3 4 5 = Very like me	Aggression (modified from Buss Perry [BP-AQ])	Bryant & Smith, 2001

Codebook Example

Name in SPSS	Variable Label	Value Labels	Name in Mplus
alphaID			NOT IN MPLUS
numID			numID
group		1=Control (HlthEdu) 2=Intervention-Only 3=Intervention-plus-booster	group
interven		0=HealthEdu 1=Alcohol 101 Plus	interven
booster		0=no booster sent 1=booster sent	booster
confirm	confirmed booster receipt (booster group only)	0 = no 1 = yes	confirm
semester		1=spring 2013 2=summer 2013 3=fall 2013	semester
check	Did you consume alcohol within the previous two weeks?	0=no 1=yes	check
consume	On how many days of the last 2 weeks did you consume alcohol?		consume
drunk	On how many days of the last 2 weeks did you drink to the point of		drunk

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Codebook example

- Includes scale instructions for participants

Since arriving back at ODU for the Fall 2009 semester, when you socialized with others, how often did you: **Protective Behavioral Strategies (Griffin/Novik, 2013)**			
pbs1	Alternate non-alcoholic beverages and alcoholic beverages?	1 = "Never" 2 = "Rarely" 3 = "Sometimes" 4 = "Usually" 5 = "Always"	
pbs2	Determine, in advance, not to exceed a set number of drinks?	Same as above	
pbs3	Eat before and/or during drinking?	Same as above	
pbs4	Have a friend let you know when you'd had enough?	Same as above	
pbs5	Keep track of how many drinks you were having?	Same as above	
pbs6	Pace your drinks to 1 or fewer per hour?	Same as above	
pbs7	Avoid drinking games?	Same as above	
pbs8	Stop drinking at least 1-2 hours before going home?	Same as above	
pbs9	Limit money spent on alcohol?	Same as above	
pbs10	Only drink in safe environments?	Same as above	
pbs11	Make your own drinks?	Same as above	
pbs12	Avoid hard liquor or spirits?	Same as above	
pbs13	Refuse a drink from a stranger?	Same as above	

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Codebook Example

- Longitudinal information

Daily: ("@" represents indicator for day of the week, M, T, W, R, F, Sa, Su)

drink@, home@, bar@, rest@, party@, other@, alone@, friend@, fam@, Oplace@, drinks@, pbsplan@, pbsdo@, pbsall@,

Note that "drink" is yes/no, but "drinks" is plural

Weekly:

datesall, dates, COMP_DT, weight, anx, dep, Motives (socm, amxm, depm, enhm, confm), expectancies (socexp, trexp, lcexp, sexexp, dbiexp, aggexp, negexp), weekfreq, weekquan, rapiwk, Dthdm, pbsplan, pbsdo, pbsall

Person-level:

SONA, count, freq30, drunk30, sick30, drinkage, binge30, heavyday, heavytime, height, Impulsivity (Premed, Urgency, Senseek, Persev), QuanTDW, QuanHDW, Drinking Context (dcsout, dcscope, dcssex), RAPI, semester-PBS (PBSpSEM, PBSdSEM, PBSaSEM),

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Datalogs

- Date can be helpful, but not required
- ACTIVITIES are required, with specific details
  - What you did
  - Why you did it
- Missing data
  - What percentage for data? Each variable?
  - How did you address it?
- Outliers
  - How many for each variable?
  - Old and new values?
- Recoding
  - What dummy codes did you create? Why?
  - What composites scores did you create? Means or sums or something else?
    - Did you remember to reverse score??
- Did you check linearity? Normality?
  - Confirmed for which variables?
  - What adjustments were made for which variables (if any)?

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Datalog Example

Deleted 39 cases that had no follow-ups (within the 1 to 5 weeks post).

Version 9: BraitmanLindenData_weekly_8c

Deleted birthdate and height.

Changed all names to 8 characters or less.

Windsorized 5 quantity outliers (31 to 25 for typical week at baseline, 42 to 28 for two people week quantity at baseline, 34 to 25 for quant follow-up 2, and 22 to 18 for quant follow-up 5). Even though there were a handful of outliers for the rapi (11), we only windsorized one extreme value from follow-up 2 (changed 11 to 8) because the scores were generally not that extreme and could have ranged up to 23.

Dummy coded gender, race, greek status, residence, marital status. Based categories on group differences on drinking quantity across timepoints. Of final two categories, largest group was coded as 0. Was not necessary to recode class standing because not predictive of drinking quantity.

CODING:

RECODE gender (1=1) (MISSING=999) (ELSE=0) INTO gendD.
VARIABLE LABELS gendD 'dummy-coded gender (male = 1; female = 0)'.

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Datalog Example

November 25, 2015

Went back and added MaxDrks (number of drinks on highest of 14 days) to both baseline composite files, follow-up files, and merged files.

Looked for outliers:

Construct	Baseline	FU1 (2 weeks)	FU2 (4 weeks)	FU3 (6 weeks)	FU4 (3 months)	FU5 (6 months)	FU6 (9 months)
normsFem	4	5	4	7	6	1	3
normsMal	7	7	7	7	7	4	1
PBStot	0	0	0	0	0	0	0
PBSavoid	0	0	0	0	0	0	0
PBSswd	0	0	0	0	0	0	0
PBSalt	0	0	0	0	0	0	0
ImpPBS	11	5	0	5	2	0	0
ImpPBSm	11	4	0	5	2	5	3
w1sum	4	2	5	7	3	2	3
w2sum	4	3	5	7	3	2	6
BASEsum	5	3	4	7	4	0	4
w1freq	0	Did not change	0	0	0	0	0

Datalog Example

- Noted exactly what changes were made

And made the following changes:

normsFem baseline: changed 35 to 31 (n=3), changed 40 to 32

normsMal baseline: changed 50 to 46 (n=3), 55 to 47, 60 to 48, 70 to 49, and 80 to 50

ImpPBS: changed 11 to 14, 9 to 13 (n=2), 8 to 12, 5 to 11 (n=7)

ImpPBSm: changed 10 to 11, 9 to 10, 8 to 9, 5 to 8 (n=8)

w1sum: changed 50 to 42, 51 to 43, 63 to 44, and 96 to 45

w2sum: changed 50 to 47, 55 to 48, 57 to 49, and 59 to 50

BASEsum: changed 90 to 81, 95 to 82, 96 to 83, 110 to 84, 118 to 85

PBSavoid (baseline): changed 77 to 76 (n=4)

YAQrisk: changed 7 to 6

PBSavdCR: 43 to 39, 48 to 39.5, 49 to 40, 66 to 40.5 (n=2), 67 to 41, 70 to 41.5, 74 to 42 (n=3)

Datalog Example

Exploring if missing data matter:

Missingness (none versus any follow-ups) was not related to normsF, normsM, age, importance of PBS in general, importance of PBS to me, quantity, frequency, problems, typical BAC, maxBAC, max drinks, PBS: alternatives, PBS selective avoidance (CR), PBS strategies while drinking (CR), PBS total (CR).

It was also not related to condition, student status, student residence, Greek status, race, Hispanic ethnicity, year in school, marital status, or past formal treatment. It WAS related to sex and athlete status, where female participants were more likely to complete follow-up assessments, and student athletes were less likely to complete follow-up assessments.

Variable	*t*	*df*	*p*
Norms: Female	-0.04	558	.967
Norms: Male	0.05	557	.962
Age	-1.11	558	.266
Importance of PBS (general)	-1.09	559	.276
Importance of PBS (me)	-1.56	266.767	.120
Quantity	0.39	559	.697
Frequency	-1.29	559	.198
Problems	-1.49	559	.138
Typical BAC	1.34	559	.182
Max BAC	0.64	559	.520
Max Drinks	0.61	559	.539
PBS: alterantives	-0.37	559	.709
PBS: avoid (CR)	0.00	553	.997
PBS: swd (CR)	-0.82	553	.411

Thank you! Questions?

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