

Running the Statistical Gauntlet in SAS



Dr. Mark Williamson Biostatistics, Epidemiology, and Research Design Core DaCCoTA, University of North Dakota







- Soften, in an introduction to statistics, a single example is used to display a model or technique
- S This can lead to difficulty in adapting that example's particularities to your own work
- S It also fails to train your eye in reading and understanding patterns across examples
- S Here, we aim to remedy that by providing, exhaustive, back-to-back examples
- **S** Aimed at intermediate learners
- Set ready for a gauntlet, I hope it will serve you well





Assessment

Sefore continuing, please take the pre-test Pre-Test: <u>https://und.qualtrics.com/jfe/form/SV_cUqTGbRuYEDcRxA</u>

SAfter finishing, please take the post-test and survey
Post-Test: https://und.qualtrics.com/jfe/form/SV_0OqJTs8htwruJsa
Survey: https://und.qualtrics.com/jfe/form/SV_56JT2olUAQBEpxk





Overview

- **§** Today, we'll be using SAS Studio
- S Access SAS Studio via https://www.sas.com/en_us/software/studio.html
- S Access SAS code at https://med.und.edu/daccota/_files/docs/berdc_docs/model_gauntlet_sascode.txt
- S Topics Covered

≻T-tests

- 1) One-sample t-test
- 2) Two-sample t-test
- 3) Paired t-test

ANOVA

- 4) One-way ANOVA
- 5) Two-way ANOVA
- 6) Blocked/Nested ANOVA

➢ Regression

- 7) Simple Linear Regression
- 8) Multiple Linear Regression
- 9) Logistic Regression







Procedure

§ Six examples per topic

S Ignoring most assumptions condensing output for brevity

S The test statistic, p-value, and where appropriate, model fit will be outlined by color

§ Each example includes:

Research question in the form of a sentence

- Relevant statistical results from SAS
 - most values will be rounded to two decimal places
 - p-values will not be modified
- Written answer to research question
- ➢ Figure or table when appropriate
 - Some graphs will be of null results for clarity (greyscale or red)
 - Typically, only significant results are graphed

§ Get ready to run the gauntlet!







One-sample t-test



S*Tests if a variable's mean is different from a set value*

1) Is the average reater than 320	e e e e e e e e e e e e e e e e e e e	nt of White	infants)(#2) Is the average than 3200?	ge birth weigh	t of Black in	fant less		#3) Is the average than the mean w			
Mean 3411.2	DF 41857	t Value 78.92	Pr > t <.0001	-	Mean 3162.7	DF 8141	t Value -5.49	Pr > t <.0001		Mean 3162.7	DF 8141	t Value -36.54	Pr > t <.0001
Yes, birth weigh than 3200.	nt was signi	ficantly gre	ater		Yes, birth weig than 3200.	ght was signi	ficantly les	S		Yes, birth wei different than	-	ficantly	
4) Is the average layers different f		at bats for	baseball)(#5) Is the log s than 6?	salary for ba	seball play	ers less		#6) Is the avera baseball players			
Mean 390.1	DF 321	t Value -1.24	Pr > t 0.2158		Mean 5.9272	DF 262	t Value -1.33	Pr > t 0.0928	-	Mean 11.1025	DF 321	t Value	Pr > t 1.0000

No, number of at bats was not significantly different than 400.

D.9272 202 -1.00 0.0920

No, the log salary was not significantly less than 6.

No, the number of home runs was not significantly greater than 16.





Two-sample t-test

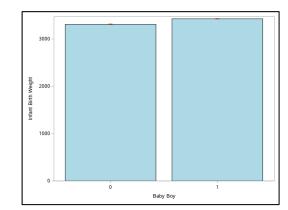


S*Tests if the mean of two different groups is different*

#1) Is the average birth weight of infants greater for boys compared to girls?

Method	Variances	DF	t Value	Pr < t
Pooled	Equal	49998	-23.15	<.0001
Satterthwaite	Unequal	49993	-23.18	<.0001
Boy	Mean	Equality of Variances		
Boy	Weall	Equality	or varian	663
0	3310.6	F Va		Pr > F

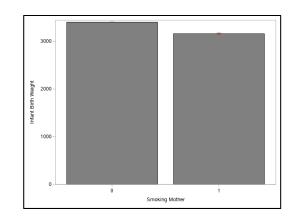
Yes, birth weight was significantly greater for boys.



#2) Is the average birth weight of infants lower for smoking vs. non-smoking mothers?

Method	Variances	DF	t Value	Pr < t
Pooled	Equal	49998	32.46	<.0001
Satterthwaite	Unequal	8474.1 31.68 <.0		<.0001
		Equality of Variances		
MomSmoke	Mean	Equality	of Variar	nces
MomSmoke 0	Mean 3402.3	Equality F Va		nces Pr > F

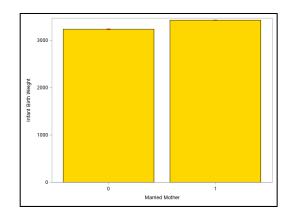
Yes, birth weight was significantly lower for smoking mothers.



#3) Is the average birth weight of infants different between married and non-married mothers?

Method	Variances	DF	t Value	Pr < t
Pooled	Equal	49998	-34.58	<.0001
Satterthwaite	Unequal	25443	-33.88	<.0001
Married	Mean	Equality	of Varia	inces
Married 0	Mean 3234.4	Equality F Va		inces Pr > F

Yes, birth weight was significantly greater for married mothers.







Two-sample t-test

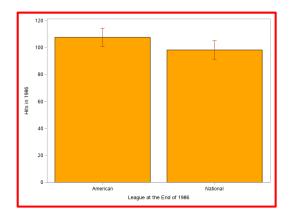


S*Tests if the mean of two different groups is different*

#4) Is the average number of hits for baseball players different across league?

Method	Variances	DF	t Value	Pr < t
Pooled	Equal	320	1.91	0.0573
Satterthwaite	Unequal	315.99	1.92	0.0559
League	Mean	Equality	of Variar	nces
League American	Mean 107.7		of Variar alue	nces Pr > F

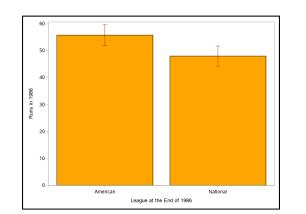
No, number of hits was not significantly different across league.



#5) Is the average number of runs for baseball players different across league?

Method	Variances	DF	t Valu	e	Pr < t
Pooled	Equal	320	2.8	31	0.0052
Satterthwaite	Unequal	319.05	2.8	34	0.0048
League	Mean	Equality of Variances			202
Louguo	moun	Equality		iuii	663
American	55.78		alue		Pr > F

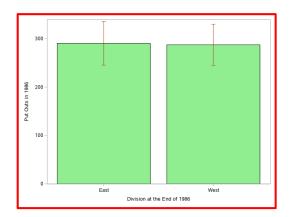
Yes, the number of runs was significantly greater in the American vs. the National League.



#6) Is the average number of outs for baseball players different across division?

Method	Variances	DF	t Valu	Ie	Pr < t
Pooled	Equal	320	0.1	0	0.9198
Satterthwaite	Unequal	317.48	0.1	0	0.9199
Division	Mean	Equality	of Var	ian	ces
Division East	Mean 290.6		of Var alue	ian	ces Pr > F

No, the number of outs was not significantly different across division.







Paired t-test



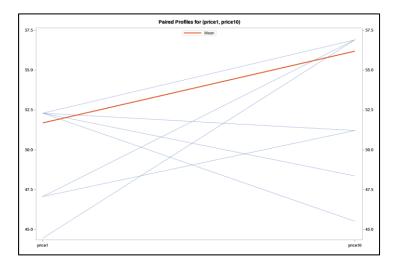
S*Tests if the means of two different paired groups are different*

#1) Is the average unit price different across time for Product 1 and 10?

 Mean
 DF
 t Value
 Pr > t

 -4.50
 1019
 -42.99
 <.0001</td>

Yes, unit price was significantly higher for Product 10.



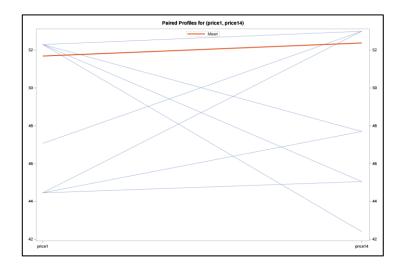
#2) Is the average unit price different across time for Product 1 and 14?

Mean		t Value	Pr > t
-0.69	1019	-7.77	<.0001

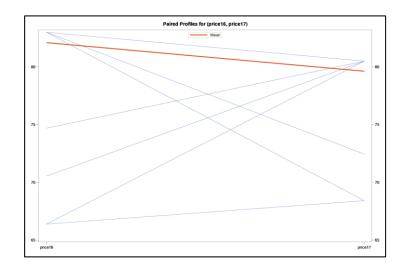
#3) Is the average unit price different across time for Product 16 and 17? Mean DF t Value Pr > t

Mean	DF	t Value	Pr > t
2.47	1019	21.57	<.0001

Yes, unit price was significantly higher for Product 14.



Yes, unit price was significantly higher for Product 16.





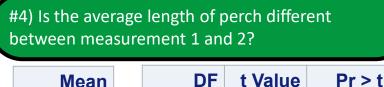


<.0001

Paired t-test



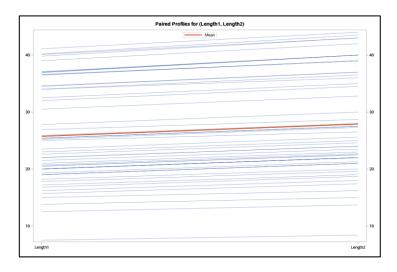
S Tests if the means of two different paired groups are different



Mean -2.16

DF	t Va
55	-31

Yes, length was significantly higher for measurement 2.



#5) Is average blo versus after a stin	a da ser a ser	e different	before
Moon	DE	t Valuo	Drst

Mean	DF	t Value	Pr > t
-1.93	11	-1.09	0.2992

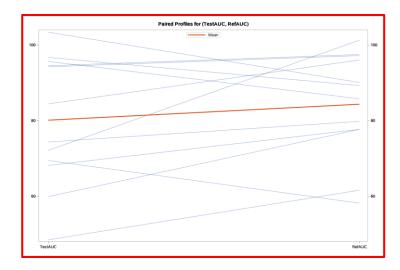
No, blood pressure was not significantly different before and after a stimulus.



concentration curve) different between a test and reference drug? t Value Pr > tMean DF 0.2834 -4.23 11 -1.13

#6) Is the average AUC (area under serum-

No, AUC was not significantly different between drugs.





Species



One-way ANOVA



S Tests if a variable's mean is different between a category with three or more groups

1) Is the pecies?	avera	age sepal	length diff	erent ac	ross iris		0 - F 119.26 Prob > F < 0001	Distribution of SepalLength			alLength Tukey Grouping for Means of Species (Alpha = 0.05) ns covered by the same bar are not significantly different. Estimate
Source Species	DF 2	Anova SS 6321.21	Mean Square 3160.61	F Value	Pr > F <.0001	spal Length (mm)	0			Virginica	65.8800
_	bal le	ngth was	significant						0	Versicolor Setosa	59.3600
							Setosa	Versicolor Iris Species	Virginica		-

<pre>#2) Is the a species?</pre>	avera	ige petal	width diffe	rent acr	oss iris	
Source	DF	Anova SS	Mean Square	F Value	Pr > F	

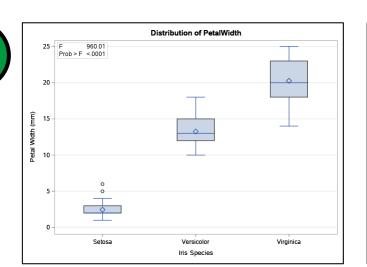
4020.67

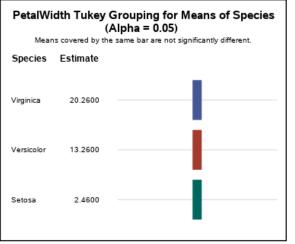
960.01

<.0001

Yes, petal width was significantly different across species.

2 8041.33









One-way ANOVA



S Tests if a variable's mean is different between a category with three or more groups

Wagon - SUV

Wagon - Sedan

Wagon - Truck

Truck - Sports

Truck - SUV

Truck - Sedan

Truck - Wagon

 \diamond

Wagon

Truck

-5950

-933

3899

-28446

-9849

-4832

-3899

-16948

-10413

-9571

-40700

-21728

-15322

-17369

5049

8547

17369

-16191

2031

5658

9571

								Distribution of MPG_Highwa	y	Comparison	s significant at t	he 0.05 level are in	dicated by ***.	
#3) Is the car origir		age highv	way MPG d	lifferent	across	60 -	151 O		F 7.94 Prob > F 0.0004	Origin Comparison	Differer Betwo Mea	een Simultane		
						50 -	150 O 374			Asia - USA	2.2	522 0.7294	3.7750	***
		Anova	Mean	F		(Å	0	O 405		Asia - Europe	2.2	577 0.6598	3.8556	***
Source	DF	SS	Square	Value	Pr > F	u 40	0			USA - Asia	-2.2	522 -3.7750	-0.7294	***
Origin	2	506.71	253.36	7.94	0.0004	MPG (H		°		USA - Europe	0.0	055 -1.6184	1.6294	
						3 0 -	♦			Europe - Asia	-2.2	577 -3.8556	-0.6598	***
						20 -				Europe - USA	-0.0	055 -1.6294	1.6184	
			s significa	ntly				• •						
differen	nt acro	oss origin	IS.			10				Comp	arisons significant at	the 0.05 level are indicate	d by ***.	
							Asia	Europe Origin	USA	Type Comparison	Difference Between Means	Simultaneous 95% Cor	nfidence Limits	
										Sports - SUV	18597	9126	28068	***
										Sports - Sedan	23613	15958	31269	**
				المحادمة الم	ff and the			Distribution of MSRP		Sports - Wagon	24547	13144	35949	**
F4) IS the	aver	age sugg	ested retai	i price di	merent	\$200,00	10 -	٥	F 19.67 Prob > F <.0001	Sports - Truck	28446	16191	40700	**
icross ca	r type	2								SUV - Sports	-18597	-28068	-9126	*
	n type									SUV - Sedan	5017	-2023	12056	
						\$150.00	ю –			SUV - Wagon	5950	-5049	16948	
		A 10 01 / 0	Maan	-						SUV - Truck	9849	-2031	21728	
		Anova	Mean	F				O 263		Sedan - Sports	-23613	-31269	-15958	**
Source	DF	SS	Square	Value	Pr > F	8	_			Sedan - SUV	-5017	-12056	2023	
T		050555	-	40.07	1 0001	dan \$100.00	10	262 O		Sedan - Wagon	933	-8547	10413	
Туре	4	253555	63388829	19.67	<.0001		Q	0 269		Sedan - Truck	4832	-5658	15322	
		31765	41				0	õ l		Wagon - Sports	-24547	-35949	-13144	**:
		51705							0					

\$50,000

\$0

 \diamond

SUV

 \diamond

Sedan

Sports

Туре

Yes, suggested retail price was significantly different across type.





One-way ANOVA

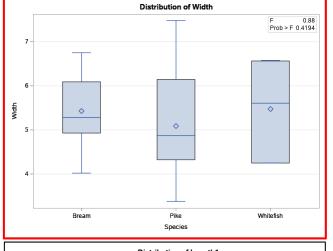


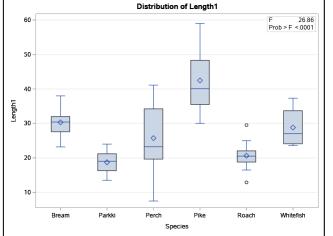
§ Tests if a variable's mean is different between a category with three or more groups

Source	DF	Anova SS	Mean Square	F Value	Pr > F
Species	2	1.46	0.73	0.88	0.4194
species.	th wa	as not diff	ferent acro	SS	

Source	DF	Anova SS	Mean Square	F Value	Pr > F
Species	5	6053.88	1210.777	26.86	<.0001
		6251	250		

Yes, length was different across species.





	Difference		I are indicated by **	
Species Comparison	Between Means	Simultaneous 95%	Confidence Limite	
Pike - Bream	12,171	6.435	17.907	***
Pike - Whitefish	13.676	4.463	22.890	***
Pike - Perch	16.741	11.368	22.090	***
Pike - Roach	21.831	15.431	28.232	***
Pike - Parkki	23.749	16.241	31.257	***
Bream - Pike	-12.171	-17.907	-6.435	***
Bream - Whitefish	1.506	-7.068	10.079	
Bream - Perch	4.570	0.389	8.751	***
Bream - Roach	9.661	4.222	15.100	***
Bream - Parkki	11.578	4.222	18.285	***
Whitefish - Pike	-13.676	-22.890	-4.463	***
Whitefish - Bream	-1.506	-10.079	7.068	
Whitefish - Perch	3.064	-5.271	11.399	
Whitefish - Roach	8.155	-0.877	17.187	
Whitefish - Parkki	10.073	0.225	19.920	***
Perch - Pike	-16.741	-22.114	-11.368	***
Perch - Bream	-4.570	-22.114	-0.389	***
Perch - Whitefish	-4.370	-0.731	-0.389	
Perch - Roach	-5.004	0.036	10.145	***
Perch - Parkki	7.008	0.609	13.408	***
Roach - Pike	-21.831	-28.232	-15.431	***
Roach - Bream	-21.631	-28.232	-13.431	***
Roach - Whitefish	-9.001	-15.100	-4.222	
Roach - Perch				***
	-5.091	-10.145	-0.036	
Roach - Parkki	1.918	-5.366	9.201	***
Parkki - Pike	-23.749	-31.257	-16.241	***
Parkki - Bream	-11.578	-18.285	-4.872	***
Parkki - Whitefish	-10.073	-19.920	-0.225	***
Parkki - Perch	-7.008	-13.408	-0.609	***
Parkki - Roach	-1.918	-9.201	5.366	



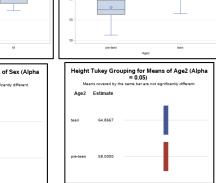


Two-way ANOVA



§ Tests if a variable's mean is different between a two categories with multiple groups each

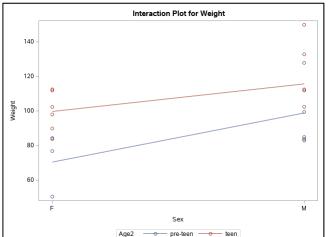
#1) Is ave for childre	<u> </u>	neight different a	across age or se	x		70 -	Interaction Plot for Height	Height	
Source	DF	Type III SS	Mean Square	F Value	Pr > F	65 -	6 0 8 0		50
Sex	1	63.2875758	63.2875758	4.83	0.0442	- 00 Heid	0		P M Sex
Age2	1	222.5603030	222.5603030	16.97	0.0009		00		Height Tukey Grouping for Means of Sex = 0.05) Means covered by the same bar are not significantly diff
Sex*Age2	1	0.0075758	0.0075758	0.00	0.9811	55 -			Sex Estimate
		significantly dinteraction betw		- · ·	ot	50 -	o F M Sex Age2 → pre-teen → teen		M 63.9100

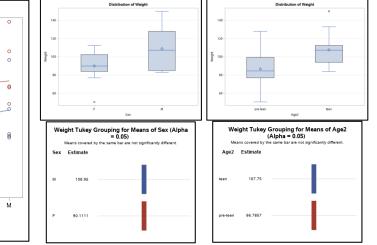


#2) Is average weight different across age or sex for children?

Source	DF	Type III SS	Mean Square	F Value	Pr > F
Sex	1	2116.001894	2116.001894	6.02	0.0269
Age2	1	2304.183712	2304.183712	6.55	0.0218
Sex*Age2	1	167.062500	167.062500	0.47	0.5013

Yes, weight was significantly different across age and sex, but not for the interaction between sex and age.









Two-way ANOVA



S Tests if a variable's mean is different between a two categories with multiple groups each

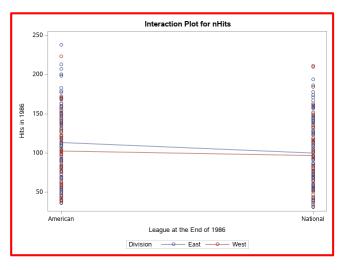
		ge number of h across league	its for baseball or division?		
Source	DF	Type III SS	Mean Square	F Value	Pr > F
League	1	7235.796171	7235.796171	3.75	0.0538
Division	1	3878.539028	3878.539028	2.01	0.1573
League* Division	1	1280.147494	1280.147494	0.66	0.4161

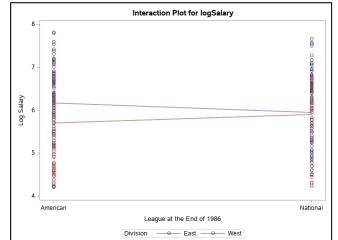
No, number of hits was not significantly different across league, division, or the interaction.

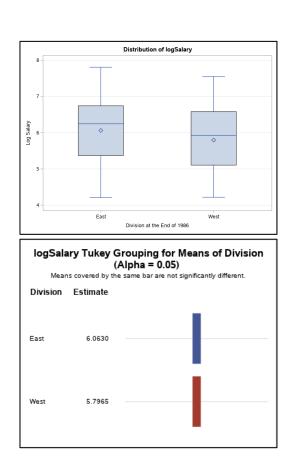
#4) Is the average log salary for baseball players different across league or division?

Source	DF	Type III SS	Mean Square	F Value	Pr > F
League	1	0.01679721	0.01679721	0.02	0.8828
Division	1	4.25477377	4.25477377	5.52	0.0196
League* Division	1	2.74858672	2.74858672	3.56	0.0602

Yes, log salary was significantly different across division, but not league or the interaction.









MomSmoke



Two-way ANOVA



S Tests if a variable's mean is different between a two categories with multiple groups each

								500	Distribution of Horsepower	Compariso	ns significant at th	ie 0.05 level arc	indicated by	***.
		ige horsepower	for cars differen	it			Interaction Plot for Horsepower	1 400		Origin Comparison	Difference Between Means	Simultaneou Confidence		
across orig	gin oi	drive train?				500	0 0 0 0	Jawo 300		Europe - USA	39.071	21.308	56.834	***
							0	Horsep		Europe - Asia	61.192	43.713	78.671	***
Source	DF	Type III SS	Mean Square	F Value	Pr > F	400	0 - 0	200		USA - Europe USA - Asia	-39.071 22.121	-56.834 5.463	-21.308 38.778	***
Origin	2	98610.3193	49305.1597	12.91	<.0001	ver		100		Asia - Europe	-61.192	-78.671	-43.713	***
		90010.3193	49505.1597			300 size			Asia Europe USA Origin	Asia - USA	-22.121	-38.778	-5.463	***
DriveTrain	2	323276.2312	161638.1156	42.32	<.0001	Ϋ́			Distribution of Horsepower	Compariso	ns significant at th	e 0.05 level arc	indicated by	***
Origin* DriveTrain	4	9396.6601	2349.1650	0.62	0.6520	200		500 400	8 0 0	DriveTrain Comparison	Difference Between	e 1 Simultan	eous 95% nce Limits	
Vec heree							0	Jaw 00 300		Rear - All	27.475	5 6.938	48.012	***
-		er was significar		ross origin	1		Asia Europe USA Origin	Horse		Rear - Front	77.232	2 60.333	94.131	***
and drive	chair	i, but not the in	teraction.				DriveTrain — All — Front — Rear	200		All - Rear	-27.475		-6.938	***
								100		All - Front	49.757		67.734	***
									All Fiont Rear	Front - Rear			-60.333	***
#6) Is infa	nt hir	th weight differe	ent across		Г			_	DriveTrain	Front - All	-49.757	-67.734	-31.780	***
	educa	Type III SS	oking status?	F Value	Pr > F	3000 -								

MomEdLevel 42006795.9 14002265.3 3 **MomSmoke** 143245320.3 143245320.3 459.85 1 MomEdLevel* 3 3360388.6 1120129.5

Yes, birth weight is different across maternal education level, smoking status, and the interation.

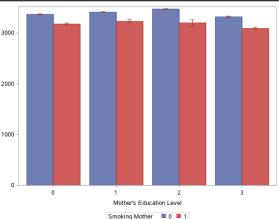
44.95

3.60

<.0001

<.0001

0.0129







Blocked/Nested ANOVA



S Tests if a variable's mean is different across categories while accounting for blocking/nesting

#1) Are average responses different across school and instructor, where instructor is nested in school?

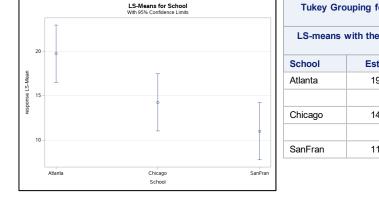
Type III Tests of Fixed Effects						
Effect	Num DF	Den DF	F Value	Pr > F		
School	2	6	11.18	0.0095		
Instructor(School)	3	6	27.02	0.0007		

Yes, responses were significantly different for both school and instructor.

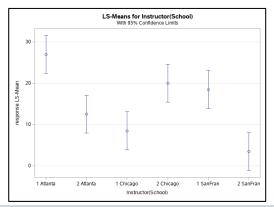
#2) Is average log revenue for airlines different across flight type, where flight type is nested in flight source?

Type III Tests of Fixed Effects						
Effect	Num DF	Den DF	F Value	Pr > F		
SOURCE	3	8	2.70	0.1161		

No, log revenue was not different across flight source.

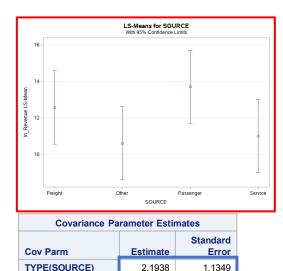


I S moons		=0.05)	not significantly
Lo-means		rent.	not significanti
School	Estimate		
Atlanta	19.7500		A
			А
Chicago	14.2500	В	А
		В	
SanFran	11.0000	В	



Tukey Grouping for Instructor(School) Least Squares Means (Alpha=0.05)

	LS-means with	the same letter	are not s	ignificantly diff	erent.
School	Instructor	Estimate			
Atlanta	1	27.0000		A	
				A	
Chicago	2	20.0000	В	A	
			В	A	
SanFran	1	18.5000	В	A	С
			В		С
Atlanta	2	12.5000	В	D	С
				D	С
Chicago	1	8.5000		D	С
				D	
SanFran	2	3.5000		D	



0.4410

0.08120

Residual





Blocked/Nested ANOVA

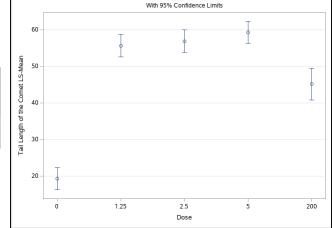


S Tests if a variable's mean is different across categories while accounting for blocking/nesting

plants, w	iverage calciu vhere sample							- 4	.0	LS-Means for Plant With 95% Confidence Limits	T	Tukey Gr	ouping for Plaı (Alpha	nt Least Squares =0.05)	Means
plants?					Covariance	Parameter Esti			Т		•	LS-n	neans with the significantl	same letter are no y different.	ot
	Type III Te	ests of Fixe	d Effects		Cov Parm	Estimate	Standard Error	3	.5	T		Plant	Estimate		
Effect	Num DF	Den DF	F Value	Pr > F	Leaf(Plant)	0.1611	0.08220	S-Meal	.0			4	3.7433	A	
					Sample(Plant*Leaf	0.000951	0.002717	in LS						A	
Plant	3	8	7.67	0.0097	Residual	0.005703		C C	.5 -			1	3.1750	B A	
										¢.				B A	
Vec calc		voro cigni	ficantly dif	forest				2	.0 -			3	2.9517	B A	
-	ium levels v	were signi	incantiy di	lierent				1	5	Ţ				В	
across p	lants.								1	2 3	4	2	2.1783	В	
										Plant		Tukov-Kra	mer Grouping	for Dose Least Sc	wares Me
#4) 10 204		NA dama	to differen	tacross						LS-Means for Dose With 95% Confidence Limits		Tukey-Kla		bha=0.05)	
	erage cell D se, when co							61	0	T T		LS-mear		ne letter are not si fferent.	gnificant
		Ŭ						Mean 21	0	ţ l –	т		ylhydrazine oride Dose Lev	vel Estima	ate
		ests of Fixe	d Effocts		Covariance	Parameter Esti		et LS-			φ	5		59.24	16 A
					Cov Parm	Estimate	Standard Error	U 44	0						A
Effect	Num DF	Den DF	F Value	Pr > F	Rat	13.9414	4.3715	h of th				2.5		56.84	405 A
Dose	4	4023	112.53	<.0001	Residual	83.5834	1.8636	engt	0						A

Yes, cell damage was different across drug dose.

Covariance Parameter Estimates					
Cov Parm	Estimate	Standard Error			
Rat	13.9414	4.3715			
Residual	83.5834	1.8636			



	2.9517	в		А	
		В			
	2.1783	В			
ey-Kram	er Grouping	for Dose	Leas	t Square	es Means
		oha=0.05)		· ·	
S-means	s with the san di	ne letter a fferent.	are n	ot signif	icantly
)imethvl	hydrazine				
	ride Dose Lev	/el	E	stimate	
			Ę	59.2416	А
					А
			Ę	56.8405	А
					А
			Ę	55.6127	А
			2	15.1176	В

19.3232 C

1.25

200

0





Blocked/Nested ANOVA



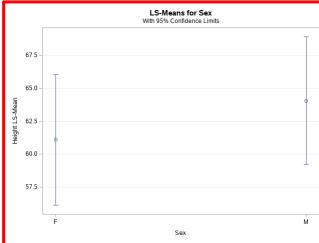
§ Tests if a variable's mean is different across categories while accounting for blocking/nesting

#5) Is average height different across sex in children when controlling for age?

Type III Tests of Fixed Effects						
Effect	Num DF	Den DF	F Value	Pr > F		
Sex	1	12	4.22	0.0624		

No, height was not significantly different across sex, even when controlling for age.

Covariance Parameter Estimates					
Cov Parm	Estimate	Standard Error			
Age	23.7445	18.8052			
Residual	9.2149	3.8705			

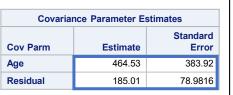


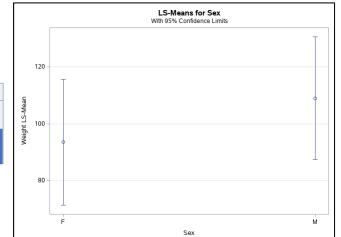
Tukey-Kramer Grouping for Sex Least Squares Means (Alpha=0.05)						
LS-means with the same letter are not significantly different.						
Sex	Estimate					
Μ	64.0582	A				
		A				
F	61.0993	A				

#6) Is average weight different across sex in children when controlling for age?

Type III Tests of Fixed Effects							
Effect	Num DF	Den DF	F Value	Pr > F			
Sex	1	12	5.74	0.0338			

Yes, weight was significantly different across sex when controlling for age.





	Grouping for Sex Means (Alpha=0.05				
LS-means with the same letter are not significantly different.					
Sex	Estimate				
Μ	108.98	А			
F	93.5252	В			





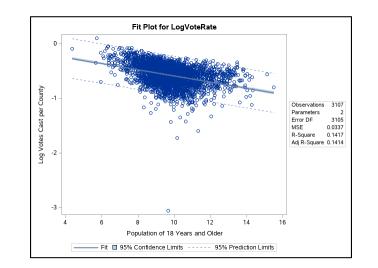
Simple Linear Regression



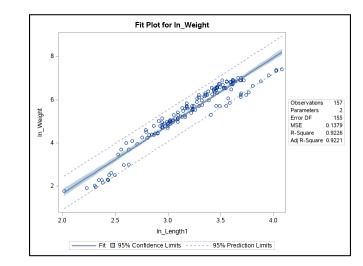
S Tests if there is a relationship between a numerical response variable and one numerical predictor variable

#1) Can the log number of votes be predicted by population in US counties?			icted by	#2) Can log fish?						ridth for	
Variable	Parameter Estimate	t Value	Pr > t	Variable	Parameter Estimate	t Value	Pr > t	Variable	Parameter Estimate	t Value	Pr > t
Intercept	-0.025	-1.04	0.3003	Intercept	-4.63	-19.67	<.0001	Intercept	1.54	23.23	<.0001
Рор	-0.056	-22.64	<.0001	Ln_length1	3.15	42.97	<.0001	Ln_width	2.77	61.38	<.0001

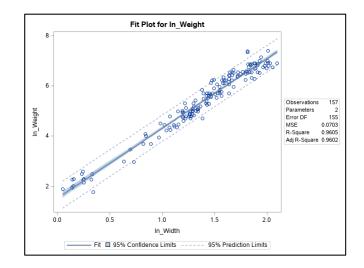
Yes, there was a significant negative relationship. As population increased, log voting rate decreased.



Yes, there was a significant positive relationship. As log length increased, log weight increased.



Yes, there was a significant positive relationship. As log width increased, log weight increased.







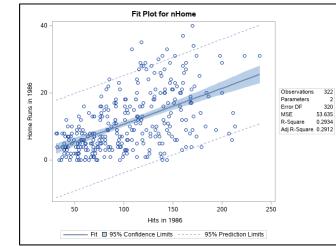
Simple Linear Regression



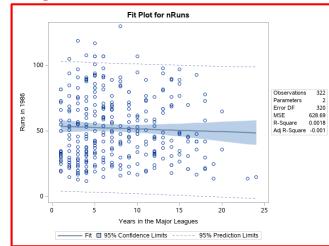
S Tests if there is a relationship between a numerical response variable and one numerical predictor variable

#4) Can the number of home runs be predicted by #6) Can log salary be predicted by the number of #5) Can the number of runs be predicted by the number of years in the major leagues for baseball players? the number of hits for baseball players? runs for baseball players? Variable **Parameter Estimate** t Value Pr > |t| Variable **Parameter Estimate** t Value **Pr > |t|** Variable **Parameter Estimate** t Value Pr > |t| 53.87 20.92 <.0001 5.017 <.0001 Intercept 0.076 0.07 0.9424 Intercept Intercept 42.35 11.53 -0.22 -0.76 0.4454 0.016 8.43 <.0001 nHits 0.107 <.0001 **YrMajor** nRuns

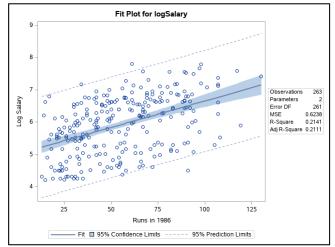
Yes, there was a significant positive relationship. As the number of hits increased, the number of home runs increased.



No, there was no significant relationship between the number of runs and the number of years in the major leagues.



Yes, there was a significant positive relationship. As the number of runs increased, log salary increased.







Multiple Linear Regression



S Tests if there is a relationship between a numerical response variable and multiple numerical predictor variables

#1) Can the log number of votes be predicted by population, education, and housing in US counties?

Yes, there was a significant negative relationship with population, and significant positive relationships with education and houses. The log number of votes increased as population decreased, education increased, and houses increased.

#2) Can the log number of votes be predicted by population, education, housing, and all interactions in US counties?

Yes, there was a significant relationship for all variables and several interactions.

	Stepwise Selection Summary					Parameter Estimates							
Step 0	Effect Entered Intercept	Effect Removed	Number Effects In	AICC -6951.7424	Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > t		
Ŭ	intercept		1	-0331.7424	Intercept	Intercept	1	0.68664	0.02358	29.12	<.0001		
1	Рор		2	-7424.3175	Рор	Population of 18 Years and Older	1	-0.92521	0.01938	-47.74	<.0001		
2	Edu		3	-8672.4932	Edu	Population with 12th Grade and Higher	1	0.44113	0.01155	38.21	<.0001		
3	Houses		4	-9201.1182*	Houses	Number of Owned Housing Units	1	0.43312	0.01802	24.04	<.0001		

	Stepwise Selection Summary								
Step	Effect Entered	Effect Removed	Number Effects In	AICC					
0	Intercept		1	-6951.7424					
1	Рор		2	-7424.3175					
2	Edu*Houses		3	-8801.8095					
3	Pop*Edu*Houses		4	-9368.6768					
4	Houses		5	-9400.4895					
5	Pop*Houses		6	-9503.4026					
6	Pop*Edu		7	-9526.6255					
7		Edu*Houses	6	-9528.2158	-				
8	Edu		7	-9552.5803					
9	Edu*Houses		8	-9563.3115*					

Parameter	Estimate	Standard Error	t Value	Pr > t
Intercept	2.486964421	0.33037095	7.53	<.0001
Рор	-0.920060663	0.11198424	-8.22	<.0001
Edu	-0.647090478	0.10383141	-6.23	<.0001
Pop*Edu	0.080618456	0.01054684	7.64	<.0001
Houses	1.079449517	0.08153133	13.24	<.0001
Pop*Houses	-0.087593996	0.01041664	-8.41	<.0001
Edu*Houses	0.042278596	0.01184683	3.57	0.0004
Pop*Edu*Houses	-0.000872167	0.00036969	-2.36	0.0184

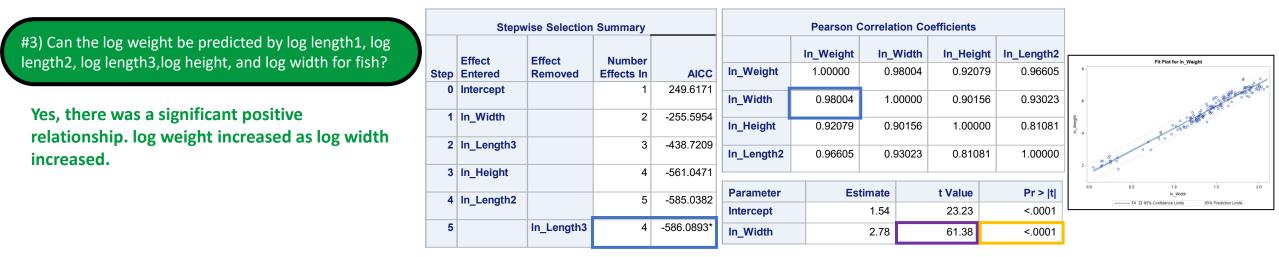




Multiple Linear Regression



S Tests if there is a relationship between a numerical response variable and multiple numerical predictor variables



#4) Can log salary be predicted by the number of hits, home runs, and runs for baseball players?

Yes, there was a significant positive relationship. Log salary increased as the number of hits and home runs increased.

Pearson Correlation Coefficients							Standard			
	logSalary	nHits	nHome	nRuns	Parameter	Estimate	Error	t Value	Pr > t	
logSalary	1.00000	0.49233	0.37124	0.46268	Intercept	4.834927492	0.12687258	38.11	<.0001	
nHits	0.49233	1.00000	0.54165	0.91167	nHits	0.008294892	0.00126440	6.56	<.0001	
nHome	0.37124	0.54165	1.00000	0.63965	nHome	0.015799126	0.00630231	2.51	0.0128	
nRuns	0.46268	0.91167	0.63965	1.00000						





Multiple Linear Regression



S Tests if there is a relationship between a numerical response variable and multiple numerical predictor variables

#5) Can log salary be predicted by the number of hits, home runs, outs, assists, and years in the major league?

Yes, there were significant relationships. Log salary increased as the number of hits and years in the major leagues increased.

	Pearson Correlation Coefficients							Estimate	t Value	Pr > t
	logSalary	nHits	nHome	nOuts	nAssts	YrMajor	Intercept	4.053421841	35.87	<.0001
logSalary	1.00000	0.49233	0.37124	0.22448	0.04997	0.56436	nHits	0.009264021	8.20	<.0001
nHits	0.49233	1.00000	0.54165	0.32743	0.32131	-0.00803				
nHome	0.37124	0.54165	1.00000	0.27319	-0.11134	0.09768	nHome	0.004112093	0.78	0.4363
nOuts	0.22448	0.32743	0.27319	1.00000	-0.02520	-0.00995	nOuts	0.000261019	1.89	0.0598
nAssts	0.04997	0.32131	-0.11134	-0.02520	1.00000	-0.09730	nAssts	-0.000237545	-0.82	0.4108
YrMajor	0.56436	-0.00803	0.09768	-0.00995	-0.09730	1.00000	YrMajor	0.103663918	13.55	<.0001

#6) Can log salary be predicted by the number of at bats, hits, runs, home runs, walks, outs, assists, and years in the major league?

Yes, there were significant relationships. Log salary increased as the number of hits, walks, and years in the major leagues increased.

	Stepwise Selection Summary								
Step	Effect Entered	Effect Removed	Number Effects In	AICC					
0	Intercept		1	204.2699					
1	YrMajor		2	105.4641					
2	nHits		3	-8.3967					
3	nBB		4	-18.8356					
4	nOuts		5	-19.7284					
5	nAtBat		6	-20.6135*					
	Deereen	Correlation C	aofficiente						

	Pearson Correlation Coefficients										
	logSalary	nAtBat	nHits	nBB	nOuts	YrMajor					
logSalary	1.00000	0.46183	0.49233	0.46920	0.22448	0.56436					
nAtBat	0.46183	1.00000	0.96447	0.63578	0.34395	-0.00848					
nHits	0.49233	0.96447	1.00000	0.60620	0.32743	-0.00803					
nBB	0.46920	0.63578	0.60620	1.00000	0.30121	0.10870					
nOuts	0.22448	0.34395	0.32743	0.30121	1.00000	-0.00995					
YrMajor	0.56436	-0.00848	-0.00803	0.10870	-0.00995	1.00000					

Parameter	Estimate	t Value	Pr > t
Intercept	3.997650575	35.92	<.0001
nHits	0.007609097	7.56	<.0001
nBB	0.006798852	3.30	0.0011
nOuts	0.000231664	1.72	0.0872
YrMajor	0.101189024	13.44	<.0001





Logistic Regression

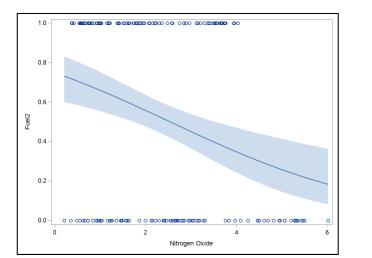


S Tests if there is a relationship between a binary response variable and one or more predictor variables

#1) Can fuel status (1=ethanol, 0=non-ethanol) be
predicted by nitrogen oxide emission?

Type III Tests of Fixed Effects								
Effect	F Value	Pr > F						
NOx	12.87	0.0004						
Pearson Chi-Squ	are / DF 1.00							

Yes, there was a significant negative relationship. As nitrogen oxide emission increased, the probability of being ethanol decreased.

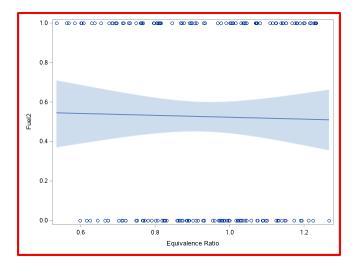


#2) Can fuel status (1=ethanol, 0=non-ethanol) be predicted by Equivalence Ratio?

Type III Tests of Fixed Effects								
Effect	F Value	Pr >						
EqRatio	0.05	0.81724						

Pearson Chi-Square / DF 1.0

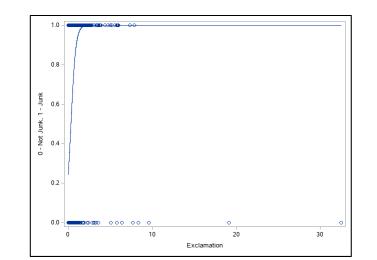
No, there was no significant relationship.



#3) Can Junk mail status (1=junk, 2=non-junk) be predicted by the frequency of exclamation marks?

Type III Tests of Fixed Effects								
Effect	F Value Pr >							
Exclamation		578.85		<.0001				
Pearson Chi-Squ	are / DF	1.540	E10					

Yes, there was a significant positive relationship. As the frequency of exclamations increased, the probability of being junk mail increased. However, the model had poor fit.







Logistic Regression



S Tests if there is a relationship between a binary response variable and one or more predictor variables

#4) Can Junk mail status (1=junk, 2=non-junk) be predicted by the frequency several words and symbols?

Type III Tests of Fixed Effects				
Effect	F	- Value	Pr > F	
Address		0.57	0.4493	
Receive		49.28	<.0001	
Report		0.20	0.6516	
Free		148.03	<.0001	
Credit		33.31	<.0001	
Money	61.55		<.0001	
Exclamation	160.40		<.0001	
Dollar	278.37		<.0001	
Pearson Chi-Square / DF		8.0357	7E8	

Yes, there were significant relationships. As the frequency of the words 'receive', 'free', 'credit', 'money', and the symbols '!', and '\$' increased, the probability of being junk mail increased. However, the model had poor fit.

#5) Can death status (1=dead, 0=censored) be predicted by risk category for post- bone marrow transplant leukemia patients?

Type III Tests of Fixed Effects				
Effect	F Value	Pr > F		
Group	4.31	0.0154		
Pearson Chi Square / DE 102				

Pearson Chi-Square / DF 1.02

Parameter Estimates					
Effect	Disease Group	Estimate	t Value	Pr > t	
Group	AML-High Risk	0.5895	1.22	0.2246	
Group	AML-Low Risk	-0.6874	-1.59	0.1148	
Group	ALL	0			

Odds Ratio Estimates				
Disease Group	Disease Group	Estimate	95% Confidence Limits	
AML-High Risk	ALL	1.803	0.693	4.688
AML-Low Risk	ALL	0.503	0.214	1.184

No, the AML-High Risk group was more likely to have died than ALL, while the AML-Low Risk was less likely, but the Odds Ratios were not significant. #6) Can car type (1=sedan, 0=other) be predicted by origin, drive train, or cylinders?

Type III Tests of Fixed Effects				
Effect	F Value Pr > F			
Origin		3.37		0.0353
DriveTrain		28.58		<.0001
Cylinders		0.71		0.6450
Pearson Chi-Square / DF		1	.01	

L.				
Odds Ratio Estimates				
Comparison	Estimate	95% Confidence Limits		
Origin				
Asia vs. USA	0.898	0.518	1.558	
Europe vs. USA	1.905	1.052	3.451	
DriveTrain				
All vs. Front	0.096	0.051	0.178	
Rear vs. Front	0.249	0.139	0.446	

Yes, origin and drive train predicted car type, while cylinders did not. European cars were more likely to be sedans vs. US cars. All- and Rear-wheel-drive cars were less likely to be sedans vs. Front-wheel drive cars.





Acknowledgements

References

SAS-code:

https://med.und.edu/daccota/_files/docs/berdc_docs/model_gauntlet_sascode.txt

Title image:

<u>https://commons.wikimedia.org/wiki/File:Spiessgasse_Frundsberger_Kriegsbuch_Jost_Ammann_1525.JPG</u>

Selected Examples:

- <u>https://support.sas.com/documentation/cdl/en/statug/63033/HTML/default/viewer.htm#statug_ttest_sect011.htm</u>
- <u>https://support.sas.com/documentation/cdl/en/statug/63033/HTML/default/viewer.htm#statug_ttest_sect013.htm</u>
- https://online.stat.psu.edu/stat502/lesson/4/4.2/4.2.1
- <u>https://support.sas.com/documentation/onlinedoc/stat/132/nested.pdf</u>

<u>DaCCoTA</u>

The DaCCoTA is supported by the National Institute of General Medical Sciences of the National Institutes of Health under Award Number U54GM128729. For projects that use the Biostatistics, Epidemiology, and Research Design Core in any way, including this presentation, please acknowledge us for publications. *"Research reported in this publication was supported by DaCCoTA (the National Institute of General Medical Sciences of the National Institutes of Health under Award Number U54GM128729)"*.

