ANOVA(Final)

October 9, 2024

```
[1]: using Pkg
      Pkg.add("MultivariateStats")
      Pkg.add("CSV")
      Pkg.add("DataFrames")
        Resolving package versions...
       No Changes to `~/.julia/environments/v1.10/Project.toml`
       No Changes to `~/.julia/environments/v1.10/Manifest.toml`
        Resolving package versions...
       No Changes to `~/.julia/environments/v1.10/Project.toml`
       No Changes to `~/.julia/environments/v1.10/Manifest.toml`
        Resolving package versions...
       No Changes to `~/.julia/environments/v1.10/Project.toml`
       No Changes to `~/.julia/environments/v1.10/Manifest.toml`
[24]: using CSV, DataFrames, GLM
     0.1 Weight Gain
[19]: | weightgain = CSV.read("/Users/VSR/Desktop/Capstone/ANOVA/weightgain.csv", __
       →DataFrame)
[19]:
```

	source	type	weightgain
	String7	String7	Int64
1	Beef	Low	90
2	Beef	Low	76
3	Beef	Low	90
4	Beef	Low	64
5	Beef	Low	86
6	Beef	Low	51
7	Beef	Low	72
8	Beef	Low	90
9	Beef	Low	95
10	Beef	Low	78
11	Beef	High	73
12	Beef	High	102
13	Beef	High	118
14	Beef	High	104
15	Beef	High	81
16	Beef	High	107
17	Beef	High	100
18	Beef	High	87
19	Beef	High	117
20	Beef	High	111
21	Cereal	Low	107
22	Cereal	Low	95
23	Cereal	Low	97
24	Cereal	Low	80
25	Cereal	Low	98
26	Cereal	Low	74
27	Cereal	Low	74
28	Cereal	Low	67
29	Cereal	Low	89
30	Cereal	Low	58
•••			

```
4×3 DataFrame
      Row
           source
                            Mean
                    type
           String7 String7 Float64
           Beef
                    Low
                               79.2
        1
          Beef
                    High
                              100.0
          Cereal
        3
                   Low
                               83.9
           Cereal
                               85.9
                   High
     4×3 DataFrame
      Row
           source
                            SD
                    type
           String7 String7
                            Float64
        1
          Beef
                    Low
                            13.8868
        2
          Beef
                    High
                            15.1364
          Cereal
                    Low
                            15.7088
        4 Cereal
                    High
                            15.0218
[21]: using SimpleANOVA
     # Perform two-way ANOVA with SimpleANOVA
     anova_results = anova(weightgain, :weightgain, [:source, :type])
     # Display the results
     println(anova_results)
```

Analysis of Variance Results

```
Effect SS DF MS F p 2

Total 10453.5 39

type 1299.6 1 1299.6 5.81231 0.0211449 0.107388
source 220.9 1 220.9 0.987949 0.326878 -0.000301355
type × source 883.6 1 883.6 3.9518 0.0544676 0.0687235
Error 8049.4 36 223.594
```

0.2 Foster

```
[22]: # Load the foster dataset (assuming it's saved as a CSV file)
foster = CSV.read("/Users/VSR/Desktop/Capstone/ANOVA/foster.csv", DataFrame)
```

[22]:

	litgen	motgen	weight
	String1	String1	Float64
1	A	A	61.5
2	A	A	68.2
3	A	A	64.0
4	A	A	65.0
5	A	A	59.7
6	A	В	55.0
7	A	В	42.0
8	A	В	60.2
9	A	I	52.5
10	A	I	61.8
11	A	I	49.5
12	A	I	52.7
13	A	J	42.0
14	A	J	54.0
15	A	J	61.0
16	A	J	48.2
17	A	J	39.6
18	В	A	60.3
19	В	A	51.7
20	В	A	49.3
21	В	A	48.0
22	В	В	50.8
23	В	В	64.7
24	В	В	61.7
25	В	В	64.0
26	В	В	62.0
27	В	I	56.5
28	В	I	59.0
29	В	I	47.2
30	В	I	53.0
		•••	•••

```
using GLM
using GLM

# Fit the two-way ANOVA model with interaction between litgen and motgen
foster_model = fit(LinearModel, @formula(weight ~ litgen * motgen), foster)
```

[27]: StatsModels.TableRegressionModel{LinearModel{GLM.LmResp{Vector{Float64}}, GLM.DensePredChol{Float64}, CholeskyPivoted{Float64, Matrix{Float64}, Vector{Int64}}}, Matrix{Float64}}

weight ~ 1 + litgen + motgen + litgen & motgen

Coefficients:

95%	Coef.	Std. Error	t	Pr(> t)	Lower 95%	Upper
(Intercept) 70.3137	63.68	3.29364	19.33	<1e-22	57.0463	
litgen: B -1.4044	-11.355	4.94046	-2.30	0.0262	-21.3056	
litgen: I -5.74716	-16.58	5.37849	-3.08	0.0035	-27.4128	
litgen: J 0.620601	-9.33	4.94046	-1.89	0.0654	-19.2806	
motgen: B -0.447157	-11.28	5.37849	-2.10	0.0416	-22.1128	
motgen: I 0.395601	-9.555	4.94046	-1.93	0.0594	-19.5056	
motgen: J -5.33848	-14.72	4.65791	-3.16	0.0028	-24.1015	
litgen: B & motgen: B 34.3043	19.595	7.30317	2.68	0.0102	4.88565	
litgen: I & motgen: B 44.7959	28.5467	8.06774	3.54	0.0009	12.2974	
litgen: J & motgen: B 28.7049	13.03	7.78257	1.67	0.1010	-2.6449	
litgen: B & motgen: I 25.6129	11.155	7.17832	1.55	0.1272	-3.30289	
litgen: I & motgen: I 28.7643	14.055	7.30317	1.92	0.0606	-0.654349	
litgen: J & motgen: I 24.817	9.73833	7.48655	1.30	0.2000	-5.34035	
litgen: B & motgen: J 24.2021	8.295	7.89787	1.05	0.2992	-7.61214	
litgen: I & motgen: J 32.3733	17.0533	7.60634	2.24	0.0299	1.73338	
litgen: J & motgen: J 23.1058	9.43	6.79002	1.39	0.1717	-4.24579	

[29]: # Compute the ANOVA table
foster_anova = anova(foster_model)

```
MethodError: no method matching anova(::StatsModels.

¬TableRegressionModel{LinearModel{GLM.LmResp{Vector{Float64}}, GLM.

 □DensePredChol{Float64, CholeskyPivoted{Float64, Matrix{Float64}, __
 →Vector{Int64}}}}, Matrix{Float64}})
Closest candidates are:
  anova(::DataFrame, ::Symbol, ::Vector{Symbol}, ::Vector{FactorType};

¬factornames)
   @ SimpleANOVA ~/.julia/packages/SimpleANOVA/ljoVA/src/anova_dataframes.jl:3
  anova(::DataFrame, ::Symbol, ::Vector{Symbol}; ...)
   @ SimpleANOVA ~/.julia/packages/SimpleANOVA/ljoVA/src/anova_dataframes.jl:3
  anova(::AbstractArray{T}, ::Vector{FactorType}; factornames, hasreplicates) ∪
 ⇒where T<:Union{Number, AbstractVector{<:Number}}
   @ SimpleANOVA ~/.julia/packages/SimpleANOVA/lj0VA/src/anova.jl:98
Stacktrace:
 [1] top-level scope
   @ In[29]:2
```

[]:

[]:

0.3 WATER

```
[1]: # Load the water dataset (assuming you saved it as a CSV file)
water = CSV.read("/Users/VSR/Desktop/Capstone/ANOVA/water.csv", DataFrame)
```

[1]:

	location	town	mortality	hardness
	String7	String15	Int64	Int64
1	South	Bath	1247	105
2	North	Birkenhead	1668	17
3	South	Birmingham	1466	5
4	North	Blackburn	1800	14
5	North	Blackpool	1609	18
6	North	Bolton	1558	10
7	North	Bootle	1807	15
8	South	Bournemouth	1299	78
9	North	Bradford	1637	10
10	South	Brighton	1359	84
11	South	Bristol	1392	73
12	North	Burnley	1755	12
13	South	Cardiff	1519	21
14	South	Coventry	1307	78
15	South	Croydon	1254	96
16	North	Darlington	1491	20
17	North	Derby	1555	39
18	North	Doncaster	1428	39
19	South	East Ham	1318	122
20	South	Exeter	1260	21
21	North	Gateshead	1723	44
22	North	Grimsby	1379	94
23	North	Halifax	1742	8
24	North	Huddersfield	1574	9
25	North	Hull	1569	91
26	South	Ipswich	1096	138
27	North	Leeds	1591	16
28	South	Leicester	1402	37
29	North	Liverpool	1772	15
30	North	Manchester	1828	8
				•••

```
[3]: using MultivariateStats, LinearAlgebra, CategoricalArrays
using Statistics

# Response matrix Y (dependent variables: hardness and mortality)
Y = Matrix(water[:, [:hardness, :mortality]])

# Encode location as dummy variables
water.location = categorical(water.location)
X = hcat(ones(nrow(water)), Matrix(water[:, [:location]]))
```

```
[3]: 61×2 Matrix{Any}:
     1.0 String7("South")
```

```
1.0 String7("South")
      1.0 String7("North")
      1.0 String7("North")
      1.0 String7("North")
      1.0 String7("North")
      1.0 String7("South")
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      1.0 String7("South")
      1.0 String7("South")
      1.0 String7("South")
      1.0 String7("South")
      1.0 String7("North")
[6]: # Mean vector of Y
    Y_bar = mean(Y, dims=1)
    # Compute the total SSCP matrix
    T = (Y .- Y_bar) + (Y .- Y_bar)
    # Compute the within-group SSCP matrix
    groups = groupby(water, :location)
    W = zeros(2, 2)
    for g in groups
        Y_g = Matrix(g[:, [:hardness, :mortality]])
        Y_g_bar = mean(Y_g, dims=1)
        W += (Y_g .- Y_g_bar)' * (Y_g .- Y_g_bar)
    end
    # Between-group SSCP matrix
    B = T - W
[6]: 2×2 Matrix{Float64}:
     23122.0
                   -1.50817e5
        -1.50817e5 9.83729e5
```

1.0 String7("North")

```
[8]: using LinearAlgebra

# Ensure to use LinearAlgebra's eigvals function
eigvals_ = LinearAlgebra.eigvals

# Compute the Hotelling-Lawley trace
W_inv = inv(W)
eigvals_result = eigvals_(W_inv * B) # Use the alias eigvals_
hotelling_lawley_trace = sum(eigvals_result)

println("Hotelling-Lawley Trace: ", hotelling_lawley_trace)
```

Hotelling-Lawley Trace: 0.9002148133569229

0.4 Skulls

```
[9]: using CSV, DataFrames

# Load the skulls dataset
skulls = CSV.read("/Users/VSR/Desktop/Capstone/ANOVA/skulls.csv", DataFrame)
```

[9]:

	epoch	mb	bh	bl	$_{ m nh}$
	String7	Int64	Int64	Int64	Int64
1	c4000BC	131	138	89	49
2	c4000BC	125	131	92	48
3	c4000BC	131	132	99	50
4	c4000BC	119	132	96	44
5	c4000BC	136	143	100	54
6	c4000BC	138	137	89	56
7	c4000BC	139	130	108	48
8	c4000BC	125	136	93	48
9	c4000BC	131	134	102	51
10	c4000BC	134	134	99	51
11	c4000BC	129	138	95	50
12	c4000BC	134	121	95	53
13	c4000BC	126	129	109	51
14	c4000BC	132	136	100	50
15	c4000BC	141	140	100	51
16	c4000BC	131	134	97	54
17	c4000BC	135	137	103	50
18	c4000BC	132	133	93	53
19	c4000BC	139	136	96	50
20	c4000BC	132	131	101	49
21	c4000BC	126	133	102	51
22	c4000BC	135	135	103	47
23	c4000BC	134	124	93	53
24	c4000BC	128	134	103	50
25	c4000BC	130	130	104	49
26	c4000BC	138	135	100	55
27	c4000BC	128	132	93	53
28	c4000BC	127	129	106	48
29	c4000BC	131	136	114	54
30	c4000BC	124	138	101	46

```
[10]: using Statistics

# Response matrix Y (dependent variables: mb, bh, bl, nh)
Y = Matrix(skulls[:, [:mb, :bh, :bl, :nh]])

# Encode epoch as categorical
skulls.epoch = categorical(skulls.epoch)
X = hcat(ones(nrow(skulls)), Matrix(skulls[:, [:epoch]]))
```

[10]: 150×2 Matrix{Any}:

- 1.0 String7("c4000BC")
- 1.0 String7("c4000BC")
- 1.0 String7("c4000BC")

```
1.0 String7("c4000BC")
       1.0 String7("cAD150")
       1.0 String7("cAD150")
[11]: # Mean vector of Y
      Y_bar = mean(Y, dims=1)
      # Compute the total SSCP matrix
      T = (Y \cdot - Y_bar) \cdot * (Y \cdot - Y_bar)
      # Compute the within-group SSCP matrix
      groups = groupby(skulls, :epoch)
      W = zeros(4, 4) # There are 4 measurements: mb, bh, bl, nh
      for g in groups
          Y_g = Matrix(g[:, [:mb, :bh, :bl, :nh]])
          Y_g_bar = mean(Y_g, dims=1)
          W += (Y_g .- Y_g_bar)' * (Y_g .- Y_g_bar)
      end
      # Between-group SSCP matrix
      B = T - W
[11]: 4×4 Matrix{Float64}:
       502.827 -228.147 -626.627
                                       135.433
      -228.147 229.907
                             292.28
                                       -66.0667
      -626.627
                 292.28
                             803.293 -180.733
                 -66.0667 -180.733
                                        61.2
        135.433
```

```
[12]: using LinearAlgebra

# Compute the Hotelling-Lawley trace
W_inv = inv(W)
eigvals_ = LinearAlgebra.eigvals

# Compute the eigenvalues of W 'B
eigvals_result = eigvals_(W_inv * B)

# Hotelling-Lawley trace is the sum of the eigenvalues
hotelling_lawley_trace = sum(eigvals_result)

println("Hotelling-Lawley Trace: ", hotelling_lawley_trace)
```

Hotelling-Lawley Trace: 0.48181907888097136

```
[15]: using LinearAlgebra

# Define trace function (sum of diagonal elements)
trace(M) = sum(diag(M))

# Compute the matrix (W + B)
W_plus_B = W + B

# Invert the (W + B) matrix
W_plus_B_inv = inv(W_plus_B)

# Compute the product (W + B) ' * B
product_matrix = W_plus_B_inv * B

# Compute Pillai's trace (sum of the diagonal elements)
pillai_trace = trace(product_matrix)
println("Pillai's Trace: ", pillai_trace)
```

Pillai's Trace: 0.3533055662224513

```
[16]: using LinearAlgebra

# Compute the total SSCP matrix (W + B)
W_plus_B = W + B

# Compute the determinant of W and (W + B)
det_W = det(W)
det_W_plus_B = det(W_plus_B)

# Compute Wilks' Lambda
wilks_lambda = det_W / det_W_plus_B
```

```
println("Wilks' Lambda: ", wilks_lambda)
     Wilks' Lambda: 0.6635857985781096
[17]: using SimpleANOVA, DataFrames
     # Perform ANOVA for each dependent variable (mb, bh, bl, nh)
     # ANOVA for mb
     anova_mb = anova(skulls, :mb, [:epoch])
     # ANOVA for bh
     anova_bh = anova(skulls, :bh, [:epoch])
     # ANOVA for bl
     anova_bl = anova(skulls, :bl, [:epoch])
     # ANOVA for nh
     anova_nh = anova(skulls, :nh, [:epoch])
     # Display results
     println("ANOVA for mb:")
     println(anova_mb)
     println("\nANOVA for bh:")
     println(anova_bh)
     println("\nANOVA for bl:")
     println(anova_bl)
     println("\nANOVA for nh:")
     println(anova_nh)
     ANOVA for mb:
     Analysis of Variance Results
             SS DF MS F
     Effect
     Total 3563.89 149
      epoch 502.827 4 125.707 5.95461 0.000182632 0.116704
     Error 3061.07 145 21.1108
     ANOVA for bh:
     Analysis of Variance Results
                SS DF MS F p
     Effect
```

Total 3635.17 149
epoch 229.907 4 57.4767 2.44742 0.0489699 0.0371634
Error 3405.27 145 23.4846

ANOVA for bl:

Analysis of Variance Results

Effect	SS	DF	MS	F	p	2
Total	4309.26	149				
epoch	803.293	4	200.823	8.30566	4.63639e-6	0.163052
Error	3505.97	145	24.1791			

ANOVA for nh:

Analysis of Variance Results

Effect	SS	DF	MS	F	p	2
Total	1533.33	149				
epoch	61.2	4	15.3	1.507	0.203179	0.0133396
Error	1472.13	145	10.1526			

[]:	
Г 1.	