SnazzieR Example Tables

```r
library(ggplot2)
library(dplyr)
library(gridExtra)
library(grid)
library(snazzieR)
library(kableExtra)
```

Imports

Iris Data Analysis

Source: Fisher, R. (1936). Iris [Dataset]. UCI Machine Learning Repository. https://doi.org/10.24432/C56C76.

```r
data(iris)
x.iris <- iris[, c("Sepal.Length", "Sepal.Width")]
y.iris <- iris[, c("Petal.Length", "Petal.Width")]
x.mat.iris <- as.matrix(x.iris)
y.mat.iris <- as.matrix(y.iris)
```

Table 1: Iris Dataset (First 6 Observations): Predictors and Responses

Sepal Length	Sepal Width	Petal Length	Petal Width
5.1	3.5	1.4	0.2
4.9	3	1.4	0.2
4.7	3.2	1.3	0.2
4.6	3.1	1.5	0.2
5	3.6	1.4	0.2
5.4	3.9	1.7	0.4
⋮	⋮	⋮	⋮

Linear Regression Analysis

```r
# Fit linear regression model
iris.lm <- lm(Petal.Length ~ Sepal.Length + Sepal.Width, data = iris)
```

```r
# Model summary table
snazzieR::model.summary.table(iris.lm, caption = "Linear Regression Model Summ
```

Table 2: **Linear Regression Model Summary**
Petal.Length = -2.525 + 1.776*Sepal.Length + -1.339*Sepal.Width

Term	Estimate	Std.Error	P.Value	Signif.	Statistic	Value
(Intercept)	-2.52476	0.56344	1e-05	:3	**MSE**	0.40958
Sepal.Length	1.77559	0.06441	0	:3	**MSE adj.**	0.41794
Sepal.Width	-1.33862	0.12236	0	:3	**df**	147.00000
					R-squared	0.86769
					R-squared adj.	0.86589

significance codes - :3 - >0.001 :) - >0.01 :/ - >0.05

Model Equation

```r
snazzieR::model.equation(iris.lm)
```

$$\text{Petal.Length} = -2.525 + 1.776(\text{Sepal.Length}) - 1.339(\text{Sepal.Width})$$

ANOVA Analysis

```r
snazzieR::ANOVA.summary.table(iris.lm, caption = "ANOVA Results")
```

Table 3: **ANOVA Results**

Term	Df	Sum.Sq	Mean.Sq	F.Value	P.Value	Signif.
Sepal.Length	1	352.86624	352.86624	844.30476	0	:3
Sepal.Width	1	50.02241	50.02241	119.68886	0	:3
Residuals	147	61.43675	0.41794			:3

significance codes - :3 - >0.001 :) - >0.01 :/ - >0.05

Eigenvalue Analysis

```r
# Prepare iris data and standardize
iris.data <- iris[, 1:4]
scaled.data <- as.data.frame(
  lapply(iris.data, function(x) {
    (x - mean(x)) / sd(x)
  })
)
correlation.matrix <- cor(scaled.data)
# Eigenvalue analysis
snazzieR::eigen.summary(correlation.matrix)
```

Table 4: Eigenvectors of Covariance Matrix

$$\begin{array}{cccc} \lambda_1 = 2.9185 & \lambda_2 = 0.914 & \lambda_3 = 0.1468 & \lambda_4 = 0.0207 \\ \begin{bmatrix} 0.52107 \\ -0.26935 \\ 0.58041 \\ 0.56486 \end{bmatrix} & \begin{bmatrix} 0.37742 \\ 0.9233 \\ 0.02449 \\ 0.06694 \end{bmatrix} & \begin{bmatrix} 0.71957 \\ -0.24438 \\ -0.14213 \\ -0.63427 \end{bmatrix} & \begin{bmatrix} -0.26129 \\ 0.12351 \\ 0.80145 \\ -0.5236 \end{bmatrix} \end{array}$$

Total Variance = 4

PLS Regression (NIPALS)

```r
NIPALS.pls.iris <- snazzieR::pls.regression(x.mat.iris, y.mat.iris, n.componen
snazzieR::pls.summary(NIPALS.pls.iris, include.scores = FALSE)
```

Table 5: X Weights (W)

Comp 1	Comp 2
-0.9046320	0.4261936
0.4261936	0.9046320

Table 6: Y Weights (C)

Comp 1	Comp 2
-0.7350032	0.5400163
-0.6780636	0.8416546

Table 7: X Loadings (P)

Comp 1	Comp 2
-11.159218	4.946903
6.224581	10.500219

Table 8: Y Loadings (Q)

Comp 1	Comp 2
-0.7350032	0.5400163
-0.6780636	0.8416546

Table 9: Regression Scalars (b)

Component	Estimate
1	15.444539
2	1.203207

Table 10: Regression Coefficients (Original Scale)

	Petal.Length	Petal.Width
Sepal.Length	1.775592	0.7232920
Sepal.Width	-1.338623	-0.4787213

Table 11: Variance Explained by Components (X)

Latent Vector	Explained Variance	Cumulative
1	54.7898%	54.7898%
2	45.2102%	100.0000%

Table 12: Variance Explained by Components (Y)

Latent Vector	Explained Variance	Cumulative
1	80.0449%	80.0449%
2	0.4858%	80.5307%