

Discrete Data Analysis

A Friendly Guide to Visualising Categorical Data for Machine Learning Practitioners

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Introduction

Aim and Objectives

Democratise Machine Learning

Turn You On to Discrete Data

- Share tips and tricks
- Build intuition, focus on visual analytics
- By example
- Relevant to ML project life-cycle
- Simple, reproducible code
- Share simple code snippets
- Plain English
- Avoid theory and formulas where possible

Target Audience

Knowledge professionals who

- have some experience of classification on tabular data sets
- understand different data-types (continuous, nominal, ordinal, count)
- are aware of ML project life-cycle, in particular:
 - Exploratory Data Analysis
 - Classification
 - Evaluating models
- know a little stats (you know what a χ^2 test is)

You can't teach an old dog new tricks¹

About me

- BSc (Hons) Microbiology, University of Leeds
- Over 15 years database design and development through to senior management roles (mostly in higher education sector), UK and Singapore
- MSc (Distinction) Business Intelligence, Birmingham City University
- Research to PhD (in progress) in Machine Learning, Birmingham City University

¹Oh, yes you can!

$E(\text{ML project}) = ?$

1. Not fun - Getting and cleaning data, exploratory analysis, feature engineering
2. Fun! - Training Models, XVal, Param Tuning
3. Not fun - Reporting results



This might be what we want, but is it realistic?

Frequently Observed ML Projects

1. Not fun - Getting and cleaning data, exploratory analysis, feature engineering
2. Fun! - Training Models, XVal, Param Tuning
3. Not fun - Reporting results



You can teach old tricks to a new dog!

Focus on those head and tail activities:

- Developing a better EDA strategy for categorical data sets
- Exploring classification results in more detail
- Demonstrating rigorous and robust, yet visually intuitive reporting of results
- Correct handling of ordinal classification results

Theme for today:

- Stats based techniques, applied:
 - in new ways
 - to new problems

Essential Tools

- Plots and Charts
- Tables and Arrays
- χ^2 Test
- Log Odds Ratios
- Discrete Distributions

Out of Scope

No time to develop theories and proofs

Predictive and Explanatory Models

- Logistic Regression
- Cumulative Odds Models
- Loglinear Models
- Generalised Linear Models

No discussion of R software itself

Credits

Michael Friendly is a pioneer in this field and has contributed to the development of modules and libraries for SAS and R.

Code examples based on material contained in the book **Discrete Data Analysis with R: Visualization and Modeling Techniques for Categorical and Count Data** by Michael Friendly.

Shorter, valuable tutorial on these topics in the vcd vignette. Just type **vignette("vcd")** at the R console.

This **video** <https://www.youtube.com/watch?v=qfNsoc7Tf60> is a much more in depth lecture, by Michael Friendly, on topics covered in the book.

Example One: Exploring Data with Area Based Plots

Why is Exploratory Analysis so Important?

“Get to know” the data. This always pays off:

- Get rid of noise variables
- Identify most useful variables early
- Guide model selection
- Identify anomalies
- Develop intuition prior to modeling
- Develop a research question, if you don't have one

In 3D with Hair Colour, Eye Colour and Gender

592 stats students, self-categorised, University of Delaware, 1974

No	Name	Levels
1	Hair	Black, Brown, Red, Blond
2	Eye	Brown, Hazel, Green, Blue
3	Sex	Male, Female

Hard to Parse Lots of Numbers

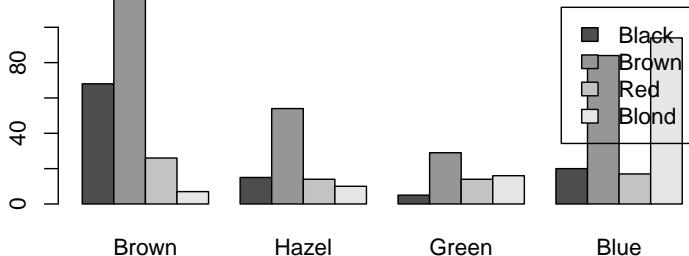
##		Hair	Black	Brown	Red	Blond
##	Sex	Eye				
##	Male	Brown	32	53	10	3
##		Hazel	10	25	7	5
##		Green	3	15	7	8
##		Blue	11	50	10	30
##	Female	Brown	36	66	16	4
##		Hazel	5	29	7	5
##		Green	2	14	7	8
##		Blue	9	34	7	64

What You See Depends on the Pivot

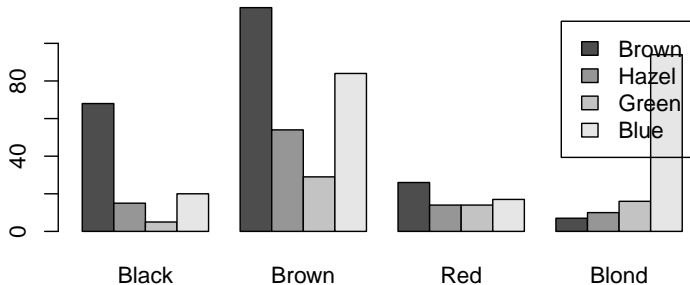
##		Sex	Male	Female
##	Hair	Eye		
##	Black	Brown	32	36
##		Hazel	10	5
##		Green	3	2
##		Blue	11	9
##	Brown	Brown	53	66
##		Hazel	25	29
##		Green	15	14
##		Blue	50	34
##	Red	Brown	10	16
##		Hazel	7	7
##		Green	7	7
##		Blue	10	7
##	Blond	Brown	3	4
##		Hazel	5	5

Naive Approach: Barplot Count in 2-D (ignoring Sex)

You're forced to favour one variable over the other. Does hair colour depend on eye colour?

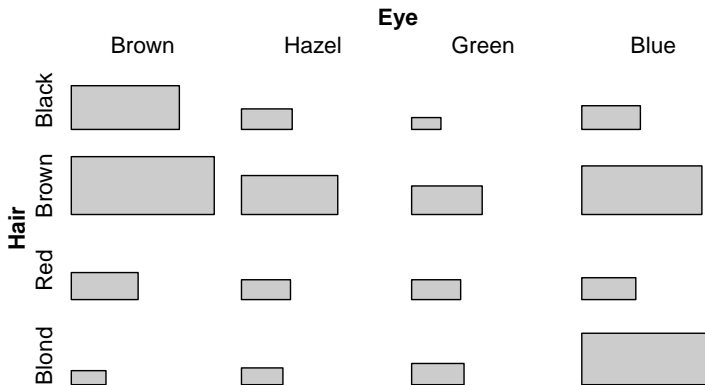


Or does eye colour depend on hair colour? Comparing between groups is tricky.



Tile Plot - Preserve Table Structure

```
# vcd package: one line of code!  
# (table haireye prepared earlier)  
tile(haireye)
```



Evidence of a Relationship

Relationship between hair colour and eye colour is evident.

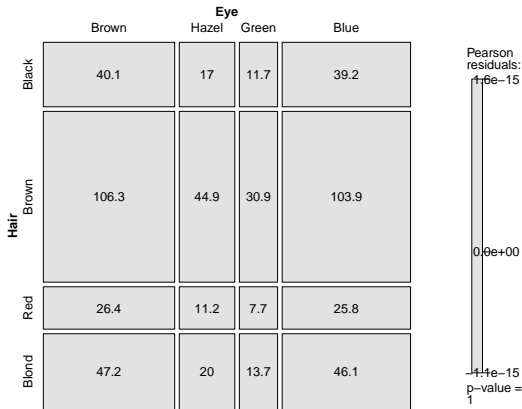
The tile plot is exploratory. We need to be rigorous.

To demonstrate pattern is real, not sampling error, we perform a χ^2 test of independence:

Check observed counts against expected counts.

Mosaic Plot - Expected Counts

Expected frequencies



H_0 : No Association Between Hair and Eye

```
##  
## Pearson's Chi-squared test  
##  
## data:  haireye  
## X-squared = 138.29, df = 9, p-value < 2.2e-16
```

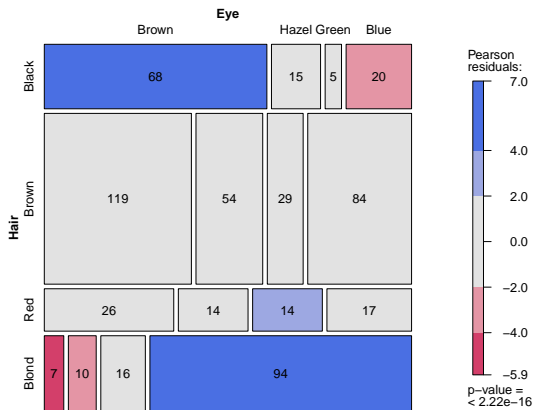
Rejected, obviously. There clearly is a relationship.

χ^2 test gives no details. How to describe it?

χ^2 residuals contain a lot of information!

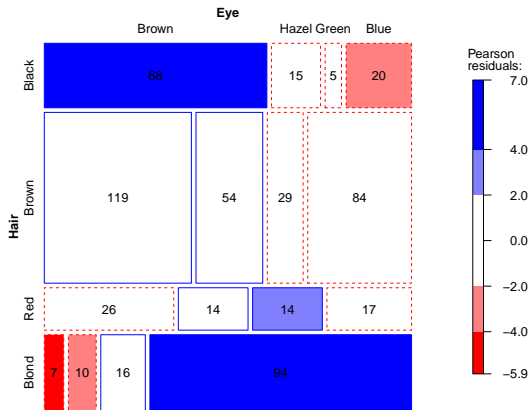
Mosaic Plot - Observed Counts

Actual frequencies

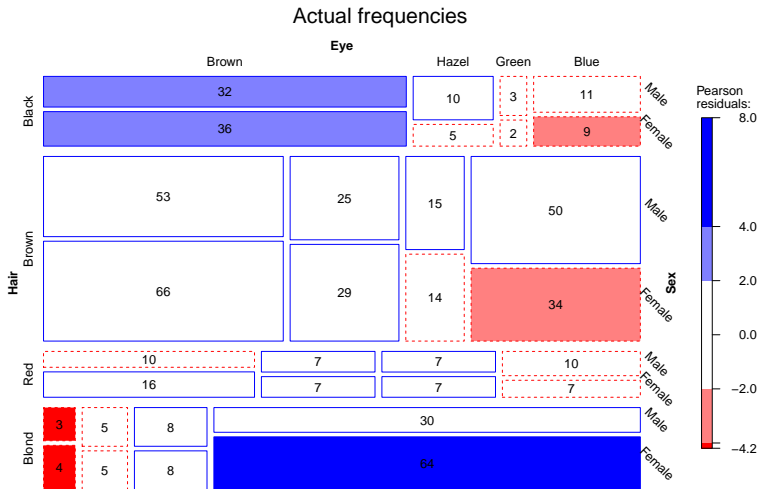


Mosaic Plot - Friendly Colour Scheme

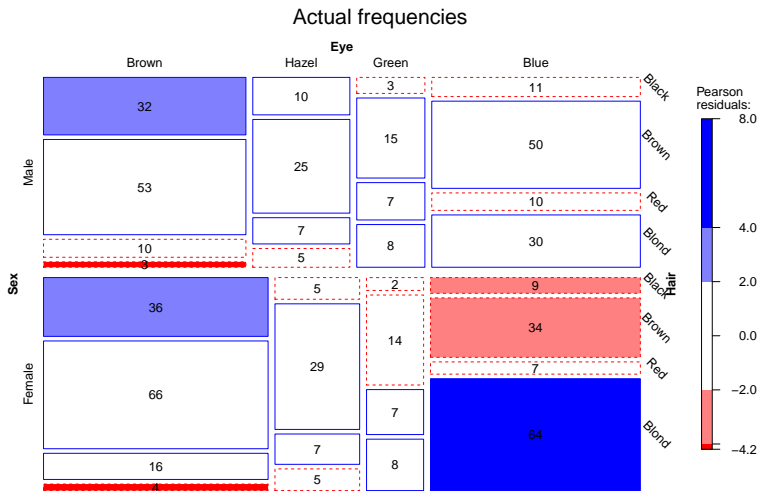
Actual frequencies



Previous + Sex Feature: Now in 3D

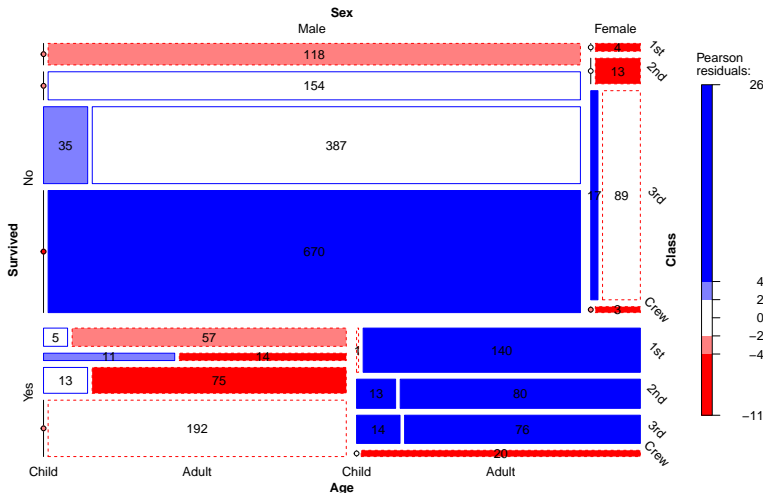


What You See Depends on the Pivot

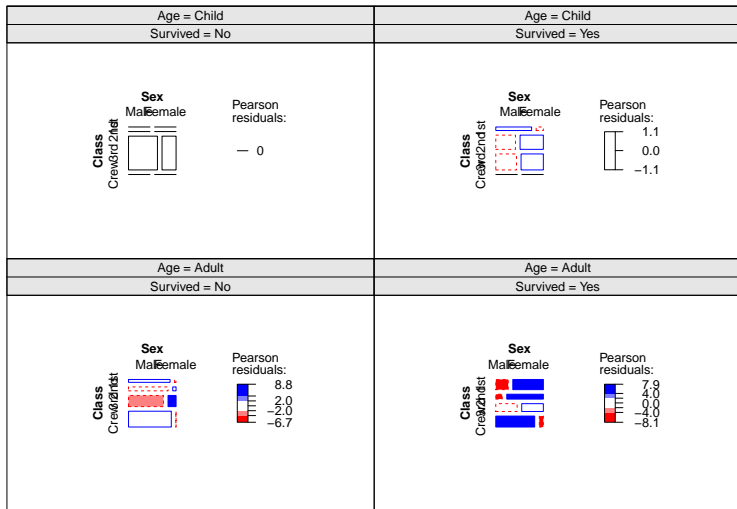


Mosaic Plot in 4D - Who Survived the Titanic?

Who Died and Who Survived the Titanic?



Mosaic in n-D - Faceting



Mosaic - Summary

The final plot didn't render nicely on these slides. Screen real-estate at run time was used more efficiently.

Important points:

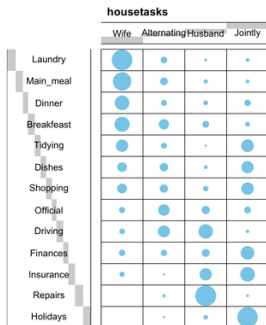
- Mosaic plots; area \propto cell count
- Fill colour by size of deviance residual
- Option for outline colour by deviance residual sign
- Scales well to 4-D
- At least a further 2-D can elevate up to facet
- Allows visual exploration of n-way interactions

Example Two: Clustering and Dimension Reduction with Correspondence Analysis

What is Correspondence Analysis?

Think of CA as somewhere between correlation analysis and PCA for continuous data.

Features and categories that change together, move together. Cells with the largest values have the strongest influence.



Audience Viewing Data

Audience viewing data from Nielsen Media Research for the week starting November 6, 1995

It is a 3-D array cross-tabulating the viewing figures for three networks, between 8-11pm, Monday to Friday. The features and their levels are as follows:

No	Name	Levels
1	Day	Monday, Tuesday, Wednesday, Thursday, Friday
2	Time	8, 9, 10
3	Network	ABC, CBS, NBC

CA - A Cinch

```
# multiple CA - one line of code!
```

```
TV3.mca <- mjca(TV3)
```

```
# Flatten to 2-D by stacking time and day
```

```
TV3s <- as.matrix(structable(Network~Time+Day  
                             , TV3))
```

```
# simple CA - one line of code!
```

```
TV3s.ca <- ca(TV3s)
```

Other Considerations

Constructing a plot needs a little bit more work (not shown).

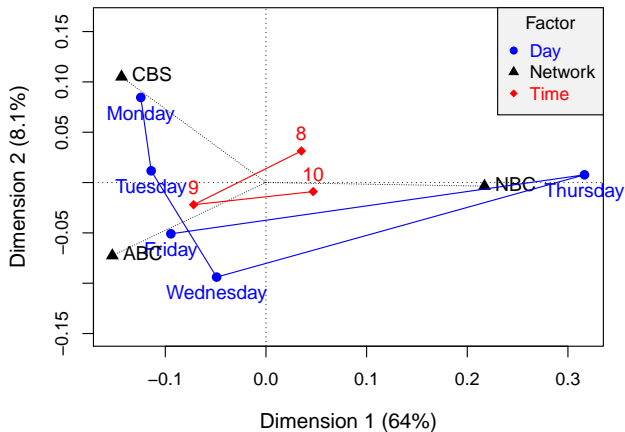
Really, just a little and all base R graphics.

When you've done it once, it's easy to customise for your needs.

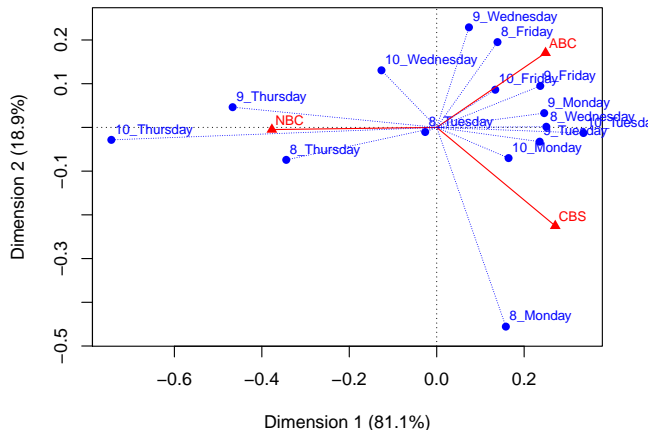
Multiple and Joint CA examines relationships among all features at once and can be used for dimension reduction.

Simple CA only supports 2D data to start with. However, smart use of pivots can actually reveal more information because there are more free points. It will take a bit of trial and error.

Multiple Correspondence Analysis Plot



Simple Correspondence Analysis Plot



Correspondence Analysis - Summary

- CA is a very powerful technique based on matrix decomposition
- Offers additional perspective for exploring data
- Complex, non-parametric relationships are easily visualised can be explored
- Useful for reducing dimensions
- Converting categorical dimensions to continuous, while preserving information
- Sort data by CA dimension rather than natural ordering:
[*Monday, Tuesday, Wednesday, Thursday, Friday*] \nRightarrow [1,2,3,4,5]