# Graph traversals and visual ordering: Eulerians, Hamiltonians and pairwise comparisons 

Catherine Hurley NUI Maynooth

joint work wtih Wayne Oldford (Waterloo)
catherine.hurley@nuim.ie

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## Graph traversals and visual ordering: Eulerians, Hamiltonians and pairwise comparisons <br> Outline

- Comparison of treatment groups
$\rightarrow$ A new multiple comparison display
- Visual ordering as graph traversal
$\rightarrow$ Eulerians and hamiltonians
- Parallel coordinates
$\rightarrow$ guided by scagnostics


## Comparison of treatment groups

## Vit. C treated cancer patients: Cameron and Pauling 1978

Comparisons of cancer types


- Easy to visually compare adjacent groups
- not so easy for distant groups

95\% family-wise confidence level


- Which pairs are significantly different?
- 95\% Tukey HSD comparisons


## Comparison of treatment groups



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Require 3 sequences for all pairwise comparisons.

Note there is duplication: Breast-Ovary and Bronchus-Colon are in first and third plots

## Comparison of treatment groups




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Note there is duplication: Breast-Ovary and Bronchus-Colon are in first and third plots

## Comparison of treatment groups

More compactly: Glue the sequences in the first two plots together, append an extra 'Stomach'.


## New pairwise comparison display

Pairwise comparisons of cancer types


- Rearrange boxplots so significantly different means appear on Ihs.


## New pairwise comparison display



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- Overlay 99\% (HSD) Cls $\left(\mu_{\text {left }}-\mu_{\text {right }}\right)$


## New pairwise comparison display



- Rearrange boxplots so significantly different means appear on Ihs.
- Overlay 99\% (HSD) Cls $\left(\mu_{\text {left }}-\mu_{\text {right }}\right)$
- Red arrow: significantly different comparisons
- Simple yet informative


## Improvement on..???



Hsu, Periggia (1994), Heiberger and Holland (2006)

## Graphs: nodes, edges and weights

- $n$ variables, cases, factor levels, boxplots: identify with nodes of graph
- visualisation: requires graph traversal
- All possible pairings are of interest: place an undirected edge between each pair of nodes
- Graph is complete, $K_{n}$

- Dissimilarity measure: edge weight


## Hamiltonian and Eulerian paths

Hamiltonian path gives a permutation of vertices

Eulerian path visits all edges


Hamiltonian decomposition: an eulerian tour composed of edge-distinct hamiltonian cycles


## Classical results: Euler paths- existence

- Eulerian tour (closed path) exists when every vertex is even. ie for $K_{2 m+1}$

```
- Example: K}\mp@subsup{K}{5}{
```

- Eulerian path (open) exists when two vertices are odd. Augment $K_{2 m}$ with extra edges to achieve this.


## Which eulerian?

- How many?
- $K_{7}$ : about 130 million choices
- $K_{21}$ has more than $3.4 \times 10^{184}$ discounting cyclic permutations

Online Encyclopedia of Integer Sequences (Sloane 2004)

- Prefer eulerians where low-weight edges (interesting comparisons) occur early on.
- Standard algorithm follows unused edges until all are visited. Our version (GrEul) picks low-weight edges.


## Classical results: Hamiltonian Decompositions

$K_{n}$ can be decomposed as follows:

- For $n=2 m+1$, into either
- $m$ hamiltonian cycles, or
- $m$ hamiltonian paths and an almost-one factor ©Eample:K
- For $n=2 m$ into either
- $m$ hamiltonian paths, or
- $m-1$ hamiltonian cycles and a 1-factor (or perfect matching).


## Which hamiltonian?

- Depends on question of interest.
- Sort nodes, eg by median
- Find shortest or lowest-weight path: (TSP)
- Choice of weights?
- How interesting is the comparison between treatements? or the relationship between variables?


## Which hamiltonian decomposition?

How many?

- $K_{7}: 2$ canonical forms

120 like this

and 840 like this


- $K_{11}: 45,000+$ canonical forms

Colburn (1982)
Lucas-Walecki construction: gives one canonical form Skiplw

## Hamiltonian decomposition algorithm

- for decomposition into hamiltonian cycles
- When $n$ is even $n / 2-1$ edges must be visited twice
- Lucas-Walecki construction (1892)
- Construction: $n$ even


126354

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$$
\begin{gathered}
126354 \\
231465
\end{gathered}
$$

## Hamiltonian decomposition algorithm

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black edges- visited twice
- Construction: $n$ odd

$$
\begin{array}{lllll}
7 & 1 & 2 & 6 & 5
\end{array} 4
$$

## Hamiltonian decomposition algorithm

- for weighted graphs

Goal: a decomposition where weights increase: first hamiltonian has lowest weights, 2nd has next lowest weights etc.

- Greedy algorithm:
- Start with Lucas-Walecki construction
- WHam: use TSP for first hamiltonian, using weights, vary cycle order, direction and contact point in others.
- Or:
- Or, peripatetic TSP: k-best edge-disjoint hamiltonians
- use other seriation as alternatives to TSP


## Applications

- Pairwise comparison of treatments
- Parallel coordinates
- Interaction plots
- Star glyphs of multivariate data


## Parallel coordinates

mtcars data from R: 6 variables


- Shows all pairs of variables adjacently.


## Parallel coordinates

mtcars data from R: 6 variables

Correlation guided Hamiltonian decomposition


- Shows all pairs of variables adjacently.
- WHam: use correlation to choose decomposition
- Add correlation guide.


## Parallel coordinates- more variables?

## sleep data- 10 variables, 62 species



- Eulerian has 49 edges - use GrEul to follow interesting edges first.
- Barchart shows panel scagnostics
scagnostics package, Hofmann et al.
- Lots of skinniness, skewness

Brain and body weight log transformed, colour by life expectancy Use index values of 0.7 or more.

## Parallel coordinates- more variables?

## sleep data- 10 variables, 62 species



- Zoom on first 18 panels- captures 'interesting" relationships
- Lots of skinniness, skewness


## Parallel coordinates- hamiltonian decomposition



- Hamiltonians that chase "interesting" relationships-here correlational structure
- WHam: first two (of 5) hamiltonians

Monotone (grey) + convexity (yellow)

## Categorical data

## The Donner Party- 1846-47, Sierra Nevada



- Categorical variables: spread out uniformly within bars, along axis
- Double axis
- All pairwise relationships, and p(survival $\mid x, y$ )


## Concluding remarks

- Other applications: PCP-categorical, star glyphs, interaction plots
- Wegman(1990) - LW hamiltonian path algorithm in parallel coordinate displays
- Bailey et al (2003)- Hamiltonian cycles, in DOE


## $\star \star \star \star$

- Software EulerViz R-package
- Uses TSP(Hahsler et al), scagnostics (Hofmann et al)

- Further work... better algorithms?
- other types of graphs eg bipartite?
- Next talk....


## Cars data

- Task: visually cluster cases

Default ordering of variables.
Dataset order H0


789 look similar, and to 1 ?
Other groups: 23, 56
4 on its own

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Conclusions are order denendentl

## Cars data

Eulerian order
Eulerian order



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Another hamiltonian Hamiltonian decomp, H1:H2:H3


Groups: 789,23,56,14

Less shape variation between orderings.
Conclusions are less order dependent!

