HEATMAPS FOR ECONOMIC ANALYSIS

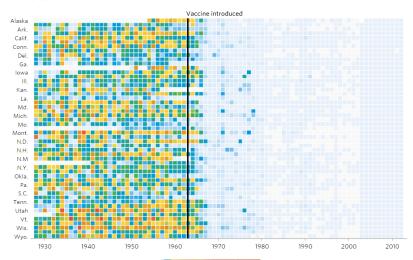
Tom Cui, Eric Zwick (DRAFT)

September 6, 2016

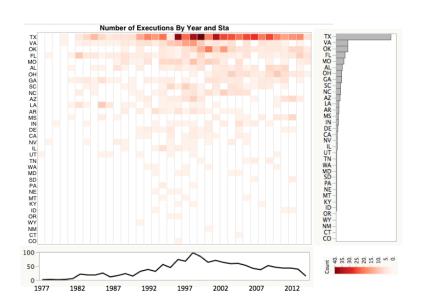
- ► A two-dimensional visualization of data using colour to represent magnitude
- Broad definition, which could be divided into
- Embedded heatmaps that overlay colour on an actual map or image (not covered here)
- Matrix heatmaps that presents a grid of values where colours differ by cell

Example: The WSJ vaccine visualization (DeBold, Friedman 2015)

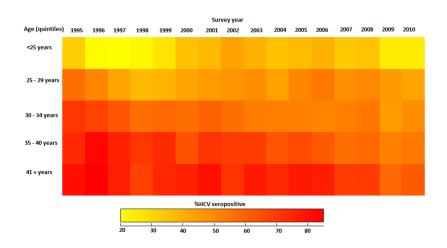
Measles



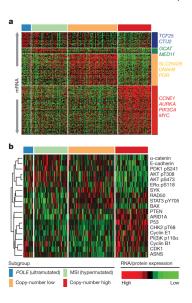
Example: Kaiser Fung's executions data



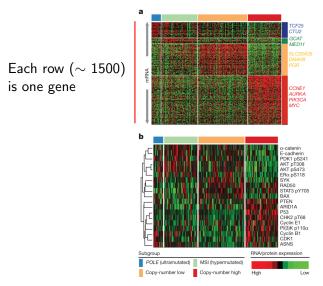
Example (Bad): A "quilt plot" of Hep C prevalence (Wand et al)



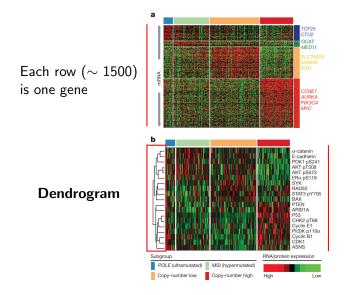
Example: Plotting gene expression data over samples (TCGN 2013)



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Each row is a protein

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 - (1) (3) use time as the X and factors as the Y, (4) uses factors for both

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 - (4) is an extreme example of this, but common in bioinformatics

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- ► The axes change the interpretation (1) (3) use time as the X and factors as the Y, (4) uses factors for both
- ► Good representation of high-dimensional data (4) is an extreme example of this, but common in bioinformatics
- Permuting axis order improves interpretation
 (2) sorts Y by total count over the sampling period, (4) uses cluster analysis (recall dendrogram)

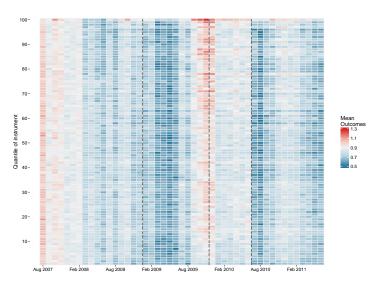
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Now consider a heatmap where time is on the X axis (**showing the policy introduction**) and where W, or a variable related to a latent W, (**showing the support of W**) is binned on the Y axis

Example: Scaled house sales in a heatmap sorted by FTHB exposure, from Berger, Turner, Zwick ()



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- ► Good representation of high-dimensional data Around 8600 ZIPs binned into 100 percentiles
- Permuting axis order improves interpretation Y axis sorted to be increasing in the instrument of W, and figure tells us the effect of W on Y is positive in a linear model

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Extensions:

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 - = Covariate balance check
- ► Time on X, individual stocks on Y, plotting market-adjusted returns
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and so on.

The heatmapEco package

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So why another package?

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 - ▶ Stata twoway contour, hmap
 - ▶ R base, gplots, ggplot2, d3heatmap ...
 - Matlab and Python matplotlib

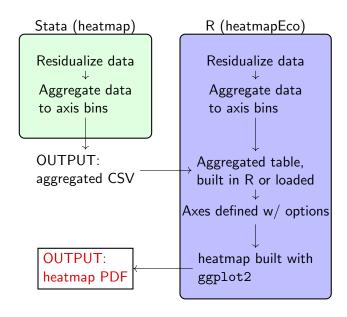
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So why another package?

- heatmapEco makes informative heatmaps easy by
 - Focusing on proper design of axes;
 - Setting relevant axis permutations;
 - ► Completing prerequisite data cleaning.

- Complicated heatmaps like TCGN's are also quite uncomplicated; they are literally a projection of some tabular data
- In other words, the data loaded in is a 373x1500 matrix. The values are then standardized, variables are clustered and given a colour
- ▶ But instead data may need to be aggregated, reshaped; axes relabelled; colour palettes adjusted to show significant results
- ► heatmapEco combines R packages to simplify these changes and adds design features of its own



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Currently output is in landscape letter format, but ultimately axis placement should be arbitrary and portrait format heatmaps possible

In R the aggregation process is inputted using a pseudo-formula

$$Y \sim CrS(X,ID,w):i(t)$$

where

- Y is the dependent variable, or the fill variable
- X is the factor independent variable or a continuous instrument to be binned
- i is the index or time axis
- ▶ t allows X to be sorted on its values at some time t, if X is time varying (use caution)
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In Stata the syntax is
heatmap Y X i [weights], id(varname) [t_sort(string)]

- Note that, in R, an anonymous function could be passed as an argument. This means the aggregation function argument grp.func can take many forms, so long as a summary function is involved
- ► E.g. take the median of a quantile-month bin. Or take the log transform of that median. Or add control flow; if data censored, first remove censored data and output log median of what remains

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- ► E.g. take the median of a quantile-month bin. Or take the log transform of that median. Or add control flow; if data censored, first remove censored data and output log median of what remains
- Stata's aggregation features are much less rich: every collapse function could be inputted into grpfunc

HEATMAPECO RESIDUALIZATION

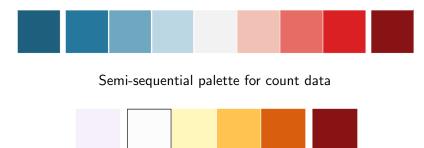
Both dependent and independent variables can be first residualized according to a model

$$Y = \beta W + D\theta + F\psi + X\gamma + \varepsilon$$

Where D, F are fixed effects and X are controls. Stata implementation uses base areg. R implementation uses plm or lfe(TODO)

COLOUR PALETTES

Standard divergent color palette

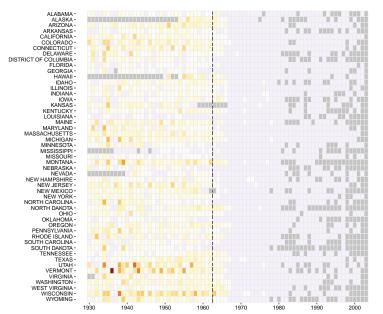


- ightharpoonup On standard palette, far two shades reserved for outlier detection: binned values above the 1.5 + IQR range are considerably darker
- Standard colors are not equally spaced: distribution below median take longer to get to dark blue hues. This is to emphasize "Ashenfelter dips"
- Count data palette is ColorBrewer YIOrBr, with high outliers and a muted hue to deemphasize data censored by 0 (by default)

heatmapEco Examples

Download data from Project Tycho. The cleaning in R:

```
library(data.table)
obj <- melt(fread("MEASLES_Incidence_1930-2003.csv"),</pre>
                    c("YEAR", "WEEK"))
obj[, value := as.numeric(value)]
Calling heatmapEco:
nasum <- function(...)</pre>
         if (all(is.na(...))) NA else sum(..., na.rm=TRUE)
heatmapEco(value ~ CrS(variable, variable): YEAR, obj,
t.fmt="\%Y", t.per="year", pol.break=c("Jan 1963"),
grp.func=nasum, count=T, factor.ax=T, outliers=T, split.x=10,
zlab="Measles Incidence (p100,000)", save="measlesRep.pdf")
```



0

- ▶ heatmapEco(value ~ CrS(variable,variable):YEAR,obj, Inputs formula for aggregation and dataset
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Line by line:

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Overall: 9 lines of code w/ data.table

- ▶ 9 lines fewer than base w/ heatmap.2
- ▶ **25 lines fewer** than pure ggplot2

Let's call the program from Stata this time

```
heatmap y3_trim fthomebuyers_filingunits_2000 mdate ///
        [aw=totalhsales_base], n(100) id(zip) tperiod(yearmon) ///
        splity(10) polbreak(Jan 2009, Dec 2009, Jul 2010) ///
        save(BTZRep.pdf)
```

▶ Default group function is mean, but the quantiles are weighted

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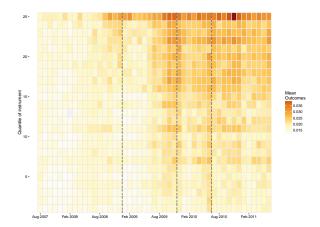
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- Each column is a month, labelled appropriately
- polbreak() interprets time strings and adds policy lines accordingly
- splity(n) divides y-axis labels into n even intervals

Another perspective: check the standard errors on the mean estimates over a coarser partition

```
heatmap y3_trim fthomebuyers_filingunits_2000 mdate ///
        [aw=totalhsales_base], n(25) id(zip) tperiod(yearmon) ///
        grpfunc(sem) splity(5) count out ///
        polbreak(Jan 2009, Dec 2009, Jul 2010) save(BTZRep_se.pdf)
```



Conclusions

WHEN NOT TO USE HEATMAPS

- Heatmaps are not a panacea: there is a tradeoff between
 - ► The additional information they effectively display;
 - ► The information lost in using colours to represent change instead of geometric shapes
- It is also unclear how heatmaps can display uncertainty of estimates: distribution of estimates, e.g.?
- ▶ A good argument for a package that simplifies heatmap creation — the less time spent making a visualization, the less likely one gets overattached to one when a better solution exists

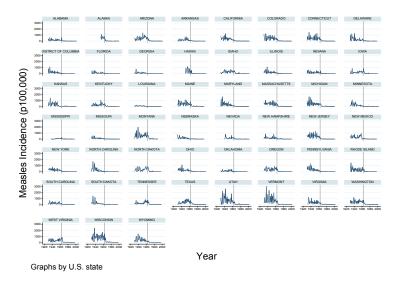
WHEN NOT TO USE HEATMAPS

A good heuristic (define Z as the variable plotted with colour):

- Plotting quantiles on the Y axis: Is your graph confounded if you plotted Z against X in overlapping line graphs split by Y?
- ▶ Plotting a factor variable on the Y axis: Is your graph confounded if you plotted Z against X in a small multiples plot split by Y?

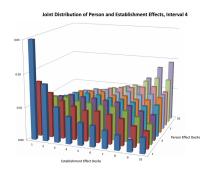
When not to use heatmaps

Example: Measles vaccine revisited



When not to use heatmaps

Example: visualizing positive assortative matching



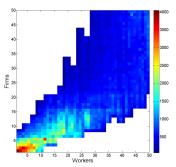


Figure 6: Estimated Match Density.

(L: Card, Heining & Kline (2012); R: Hagedorn, Law & Manovskii (2016)) 2016 How would the interpretation change if the visualization was instead overlaying many marginals over each other? Small multiples of marginals?

FUTURE UPDATES

- Syntax revisions
- ► Complementary side plots (histograms, time series, diffs...)
- ▶ Both axes can belong in one of four types
- ▶ Port the heatmap palette for utilisation in base R heatmap f'n
- ▶ ???

REFERENCES

Thanks!