Information Visualization Spatial, NecklaceMaps, Myriahedral *Ex: Ballotmaps*

Tamara Munzner

Department of Computer Science

University of British Columbia

Week 8, 23 Oct 2025

https://www.cs.ubc.ca/~tmm/courses/547-25

Plan for today

- mini-lecture / Q&A
 - -geographic maps
 - -paper: Necklace Maps [type: algorithm]
 - paper: Myriahedral [type: algorithm]
- small group exercises
 - Ballotmaps

Next time

- week 9 reading
 - -chap: Networks.
 - paper: Abyss-Explorer [type: design study]
 - paper: Geneaology [type: technique]
- week 10 reading
 - paper: Polaris/Tableau [type: system]
 - -paper: D3 [type: system]
 - paper: Vega-Lite [type: system]
 - -reminder: NO CLASS Nov 6

Geographic Maps

Geographic Map

poly marks with 2D shared boundaries, encode:

 position / order channels, using given spatial data

cannot use other channels to show other attributes, locked down as unavailable:

- size
- orientation
- symbol/shape

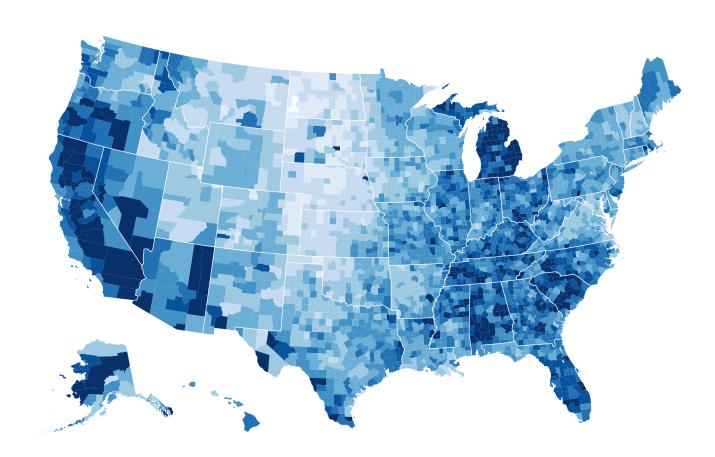


Thematic maps

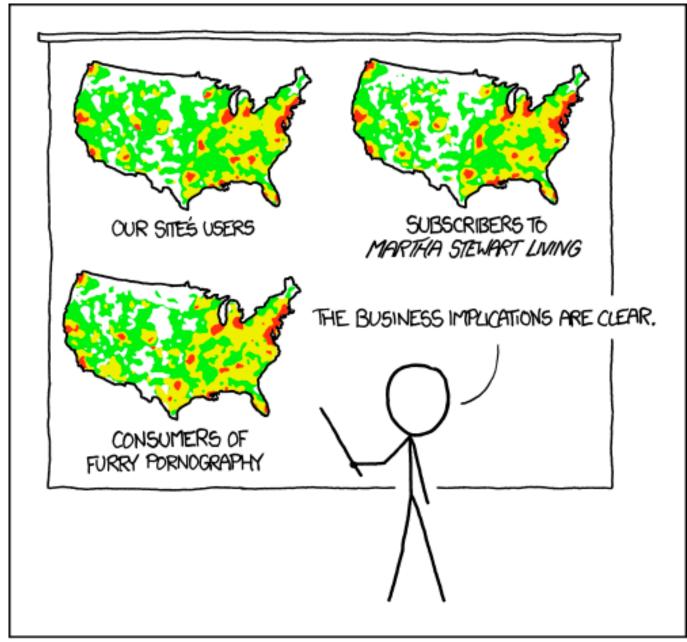
- show spatial variability of attribute ("theme")
 - -combine geographic / reference map with (simple, flat) tabular data
 - join together
 - region: shared-boundary poly marks (provinces, countries with outline shapes)
 - also could have point marks (cities, locations with 2D lat/lon coords)
 - region: categorical key attribute in table
 - use to look up value attributes
- major idioms
 - choropleth
 - -symbol maps
 - cartograms
 - dot maps

Idiom: choropleth map

- use given spatial data
 - -when central task is understanding spatial relationships
- data
 - geographic geometry
 - -table with I quant attribute per region
- encoding
 - -poly marks use given geometry for each region
 - with 2D shared boundaries
 - encode: quant attribute with color
 - this example: sequential segmented colormap
 - -encode: position/order using given spatial data
 - unavailable: size, orientation, shape/symbol
 - -only one mark type (polys)



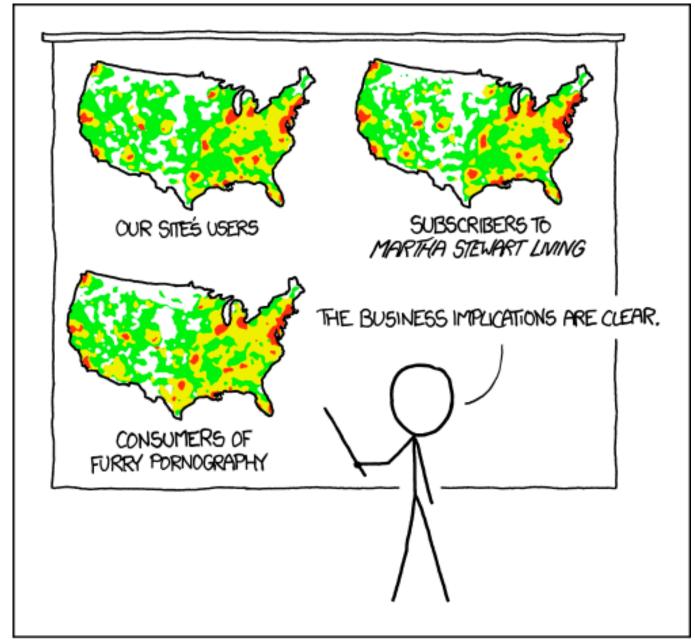
http://bl.ocks.org/mbostock/4060606



PET PEEVE #208: GEOGRAPHIC PROFILE MAPS WHICH ARE BASICALLY JUST POPULATION MAPS

[https://xkcd.com/1138]

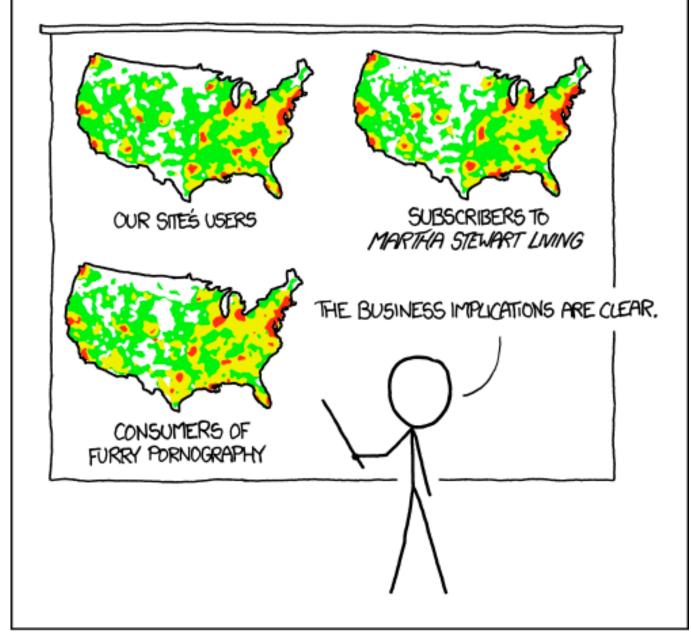
• spurious correlations: most attributes just show where people live



PET PEEVE #208: GEOGRAPHIC PROFILE MAPS WHICH ARE BASICALLY JUST POPULATION MAPS

[https://xkcd.com/1138]

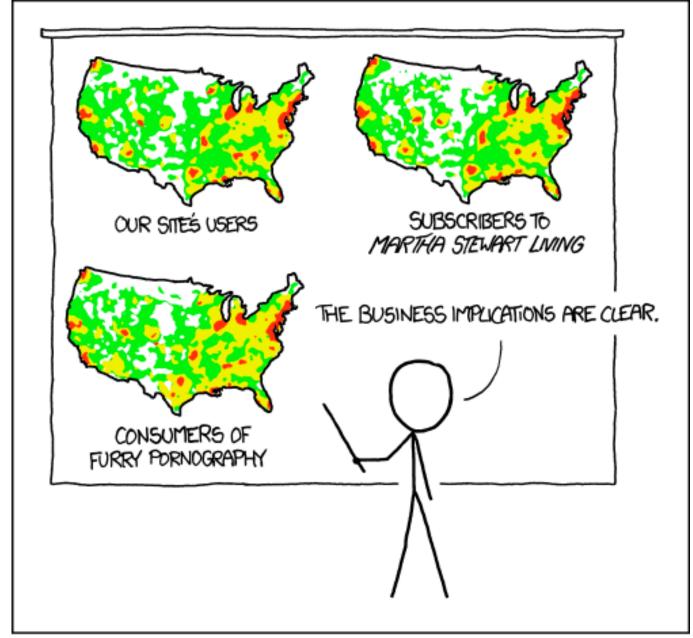
- spurious correlations: most attributes just show where people live
- consider when to normalize by population density
 - encode raw data values
 - tied to underlying population
 - but should use normalized values
 - unemployed people per 100 citizens,
 mean family income



PET PEEVE #208: GEOGRAPHIC PROFILE MAPS WHICH ARE BASICALLY JUST POPULATION MAPS

[https://xkcd.com/1138]

- spurious correlations: most attributes just show where people live
- consider when to normalize by population density
 - encode raw data values
 - tied to underlying population
 - but should use normalized values
 - unemployed people per 100 citizens,
 mean family income
- general issue
 - -absolute counts vs relative/normalized data
 - -failure to normalize is common error



PET PEEVE #208: GEOGRAPHIC PROFILE MAPS WHICH ARE BASICALLY JUST POPULATION MAPS

[https://xkcd.com/1138]

Choropleth maps: Recommendations

- can use when central task is understanding spatial relationships
- show only one attribute at a time
- normalize when appropriate
- be careful when choosing colors & bins
- best case: regions are roughly equal sized

Choropleth map: Pros & cons

pros

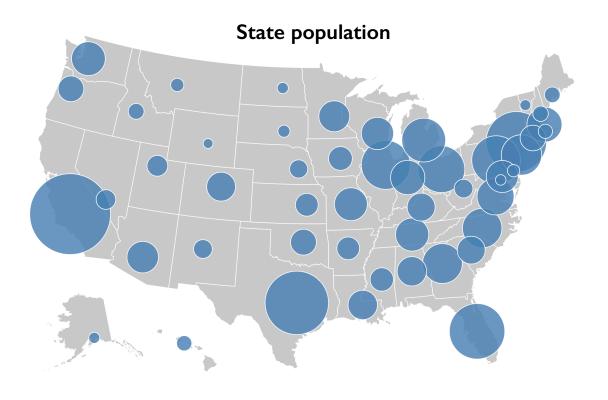
- easy to read and understand
- -well established visualization (no learning curve)
- data is often collected and aggregated by geographical regions

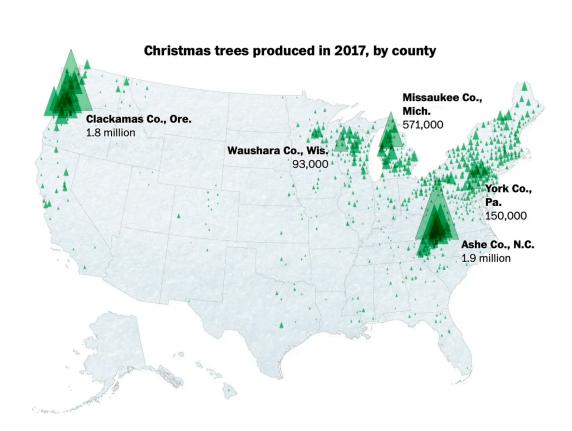
cons

- -most effective visual channel (position) used "just" for geographic location
 - reasonable if understanding spatial distribution / patterns is a central task
- -visual salience of color coding depends on region size
 - not true importance wrt attribute value
 - large regions appear more important than small ones
- -color palette choice has a huge influence on the result

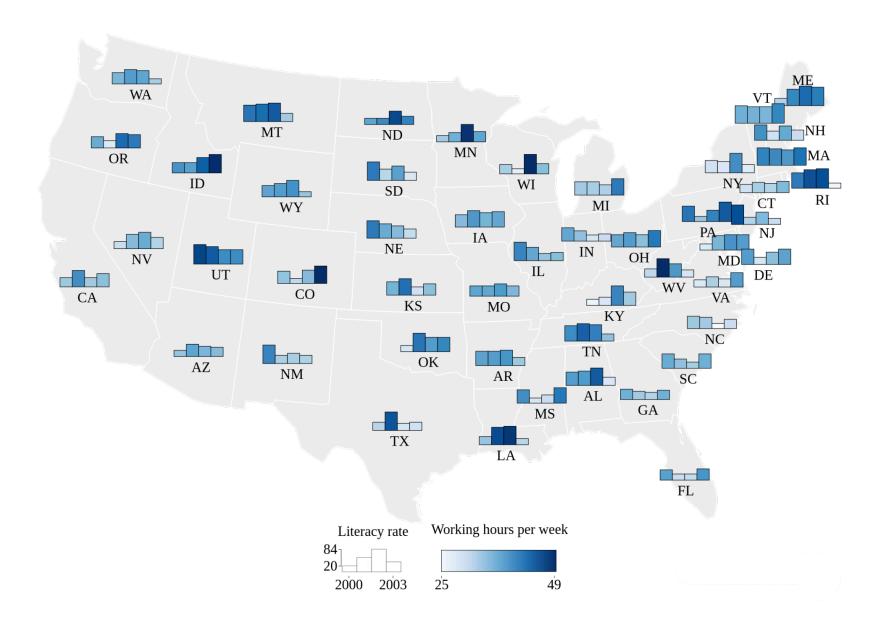
Idiom: Symbol maps

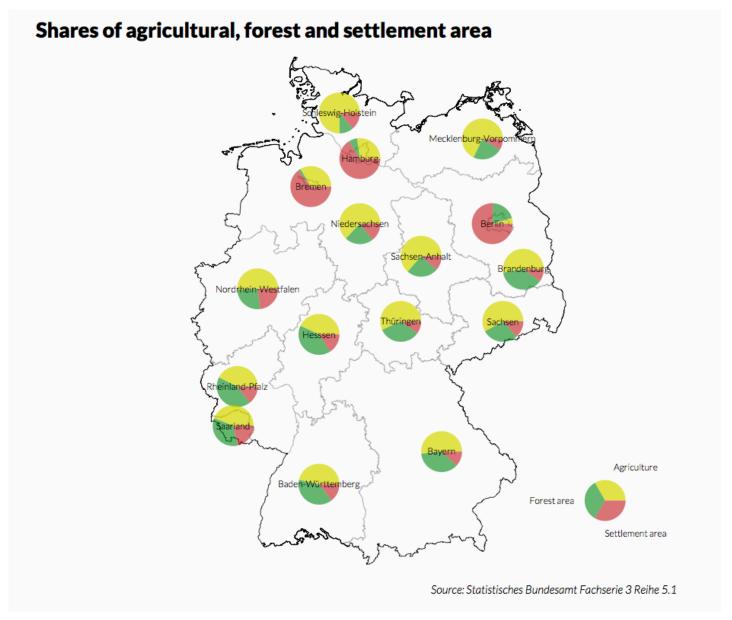
- family of idioms where symbol is used to represent aggregated data for region: point mark or glyph
 - -add second mark type: two different kinds of marks at same level, base polys & new symbols
 - keep original spatial geometry in the background
 - -one symbol per region on base map
 - -encode quant attribute with size (ID or 2D)
 - -free channels: symbol/shape, color, orientation (for asymmetric glyphs)
 - -aka proportional symbol maps, graduated symbol maps
- often a good alternative to choropleth maps





Symbol maps with glyphs





Symbol map: Pros & cons

pros

- -somewhat intuitive to read and understand
- -mitigate problems with region size vs data salience
 - marks: symbol size follows attribute value
 - glyphs: overall symbol size can be uniform (within-glyph marks follow attribute values)

cons

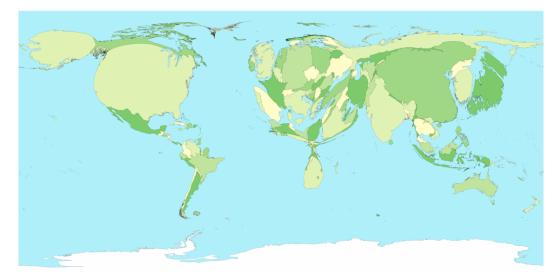
- possible occlusion / overlap
 - symbols could overlap each other
 - symbols could occlude region boundaries
- -complex glyphs may require explanation / training

Idiom: Cartograms

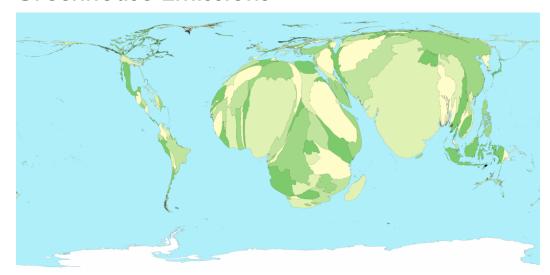
- family of idioms where change all poly marks on map simultaneously
 - only one mark type: replace old polys with new marks
 - -with shared boundaries cannot change just one mark -- but can change all at once!
 - original map polys have shared boundaries
 - -compute new set of interlocking polys, also with shared boundaries
 - preserve relative position as much as possible from old to new
- many variants exist, different constraints
 - -preserve shapes as much as possible
 - encode quant attribute with 2D size
 - regularize to uniform shape for every region
 - encode quant attribute with color
 - regularize to uniform size and shape

Idiom: Contiguous cartogram

- poly marks with 2D shared boundaries
 - aka area-proportional continuous cartogram
- derive new interlocking polys
 - based on combination of original interlocking marks and new quantitative attribute
 - encode: area (2D size) for new quant attribute
 - encode: order, maintaining relative position of polys
 - unavailable: position, orientation, shape/symbol
- algorithm to create new marks
 - input: target size (quant attribute)
 - goal: keep shape, position, orientation as close as possible to given spatial data for original polys
 - requirement: maintain constraints
 - order (relative position)
 - contiguous shared boundaries with neighbours



Greenhouse Emissions



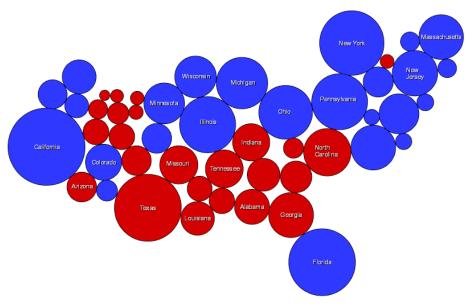
Child Mortality

D. Area-proportional continuous cartogram



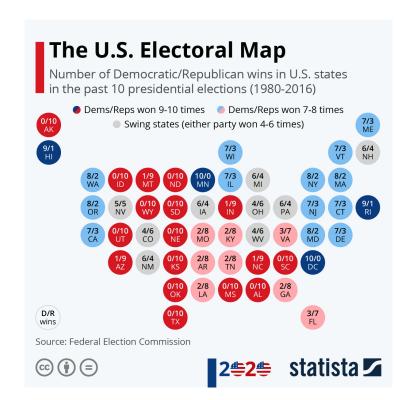
Idiom: Dorling (circle) cartogram

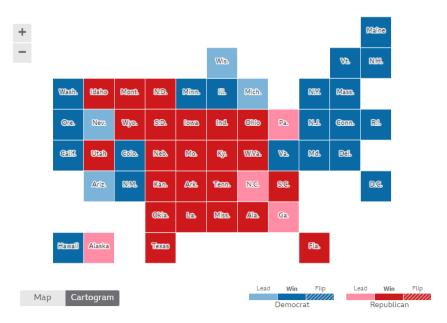
- Dorling cartogram
 - -throw away shape by regularizing to circles
 - point marks, with shared 2D boundaries
 - -encode quant attribute with 2D size
 - -encode relative locations of old polys with order
 - unavailable:
 - position: algorithm constraint to be as close as possible to original geographic locations (given spatial data)
 - orientation: meaningless since circles are symmetric
 - symbol/shape: must be circle, by definition
 - -free: color
 - -can treat as special case of circle packing, with quasi-geographic position constraints

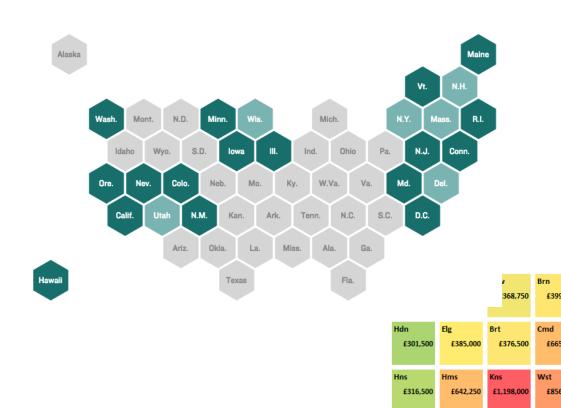


https://www.arcgis.com/apps/StorytellingTextLegend/index.html?appid=b686a7679cb747e9825dldlbb6b26046

Idiom: Equal-area (Grid) Cartogram





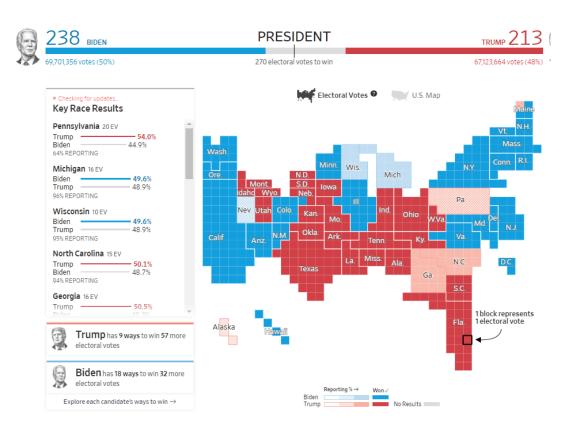


- regularize shape & size, arranged in grid
 - -derive new point marks with 2D shared boundaries
 - unavailable channels: size, shape/symbol, orientation
 - possible shapes: circles, squares, hexagons
 - unavailable: position, algorithm constraint to keep as close as possible to given spatial data
 - -encode relative location/arrangement of original polys with order
 - -encode quant attribute with color, just like with choropleth
- aka: grid map, mosaic cartogram, pseudo-Demers cartogram, geofacets, geogrid, tile grid map, tile map

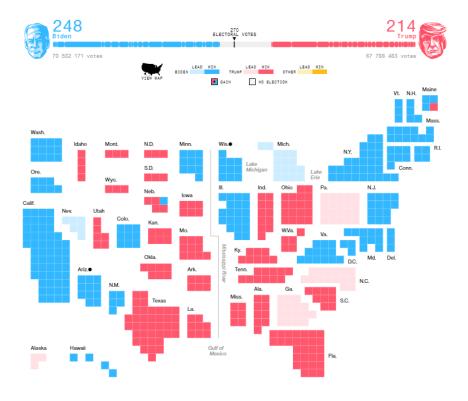
Idiom: Multi-level unit cartograms

- two levels
 - top level: poly marks (states)
 - bottom level: square point marks (units)
 - countability for votes
 - shared 2D boundaries at each level
 - F: population density thru "countable" whitespace
 - special case, still considerboundary as shared

E. Units assembled into state-like shapes



F. Units in state-like shapes spaced apart



Contiguous cartogram: Pros & cons

pros

- -can be intriguing and engaging
- -best case: strong and surprising size disparities

cons

- -require substantial familiarity with original dataset & use of memory
 - compare distorted marks to memory of original marks
 - mitigation strategies: transitions or side by side views
- -major distortion is problematic
 - may be aesthetically displeasing
 - may result in unrecognizable marks
- difficult to extract exact quantities

Non-contiguous cartogram: Pros & cons

pros

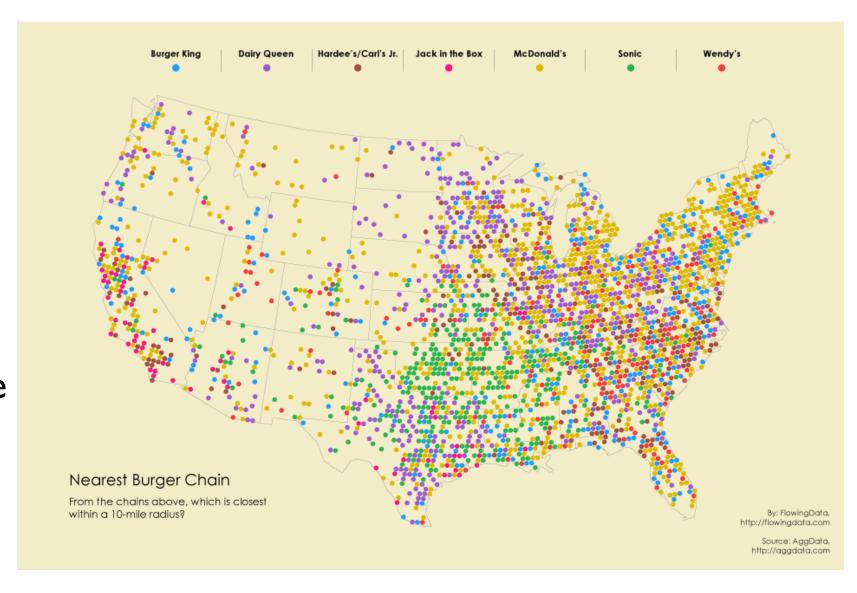
- stylized marks usually easier to understand than distorted contiguous shapes
- -can serve as good base for combining with other approaches
 - especially equal-area versions with uniform shapes
- equal-area approach can mitigate size disparities problems of cartograms

cons

- -still requires some familiarity with original dataset
- quasi-geographic positioning may need some explanation
- equal-area versions impose substantial distortions if original regions have very disparate size

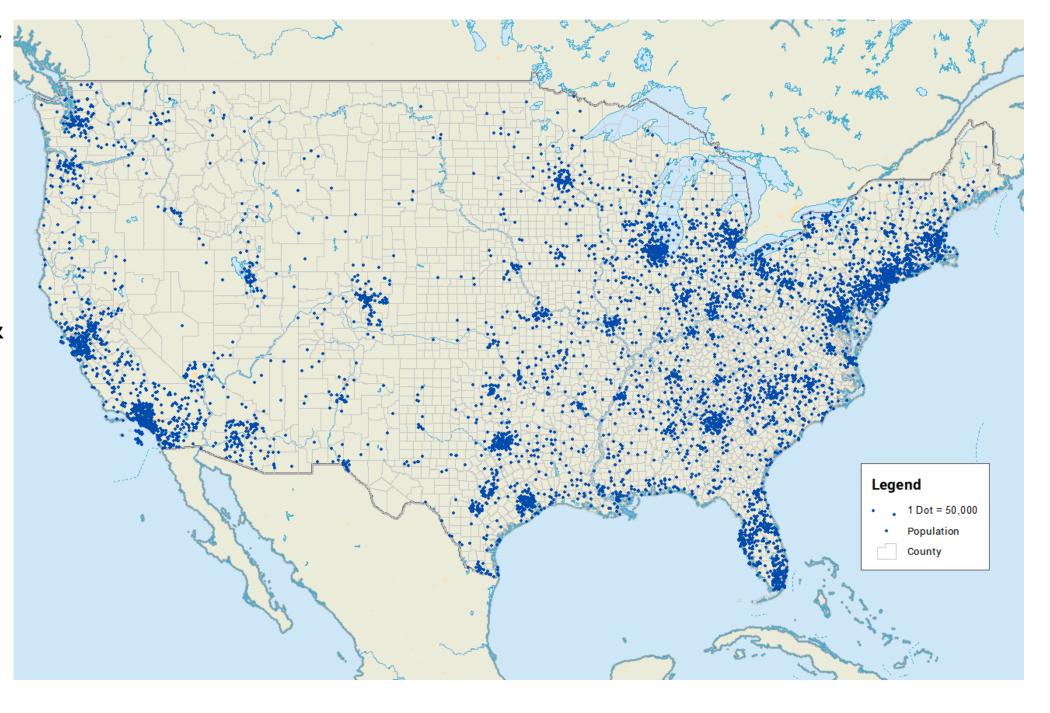
Idiom: Dot maps, one to one

- visualize actual location of item / feature / phenomenon by placing dots using 2D position channel
 - -aka dot density maps
- one point represents a specific item
 - -free channels: color, size, symbol/shape
- two mark types at same level
 - dot points and region polys
- task:
 identify detailed spatial distributions /
 patterns, clusters, outliers



Idiom: Dot density maps, many to one

- visualize distribution of a phenomenon by placing dot point marks where density within region shows quant attribute
 - one symbol representsa constant number of items, all havesame size/shape
 - unavailable channels: size & shape & orientation
 - -location random within region, **not** meaningful!
 - unavailable channel: position
 - -free channel: color
 - -aka dot distribution maps
- two mark types at same level (point, poly)
- task: show high-level spatial patterns, clusters



Dot density maps: Pros and cons

pros

- one-to-one is straightforward to understand
- -avoids choropleth non-uniform region size problems

cons

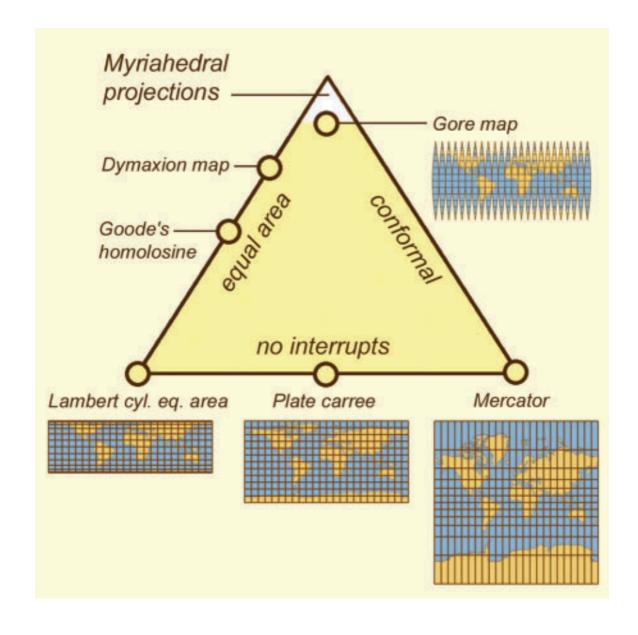
- challenge: normalization, just like choropleths
 - show population density (correlated with attribute), not effect of interest
- perceptual disadvantage:difficult to extract quantities
- performance disadvantage:rendering many dots can be slow
- many-to-one (density) may confuse if random positions assumed to be meaningful

Thematic maps combinations

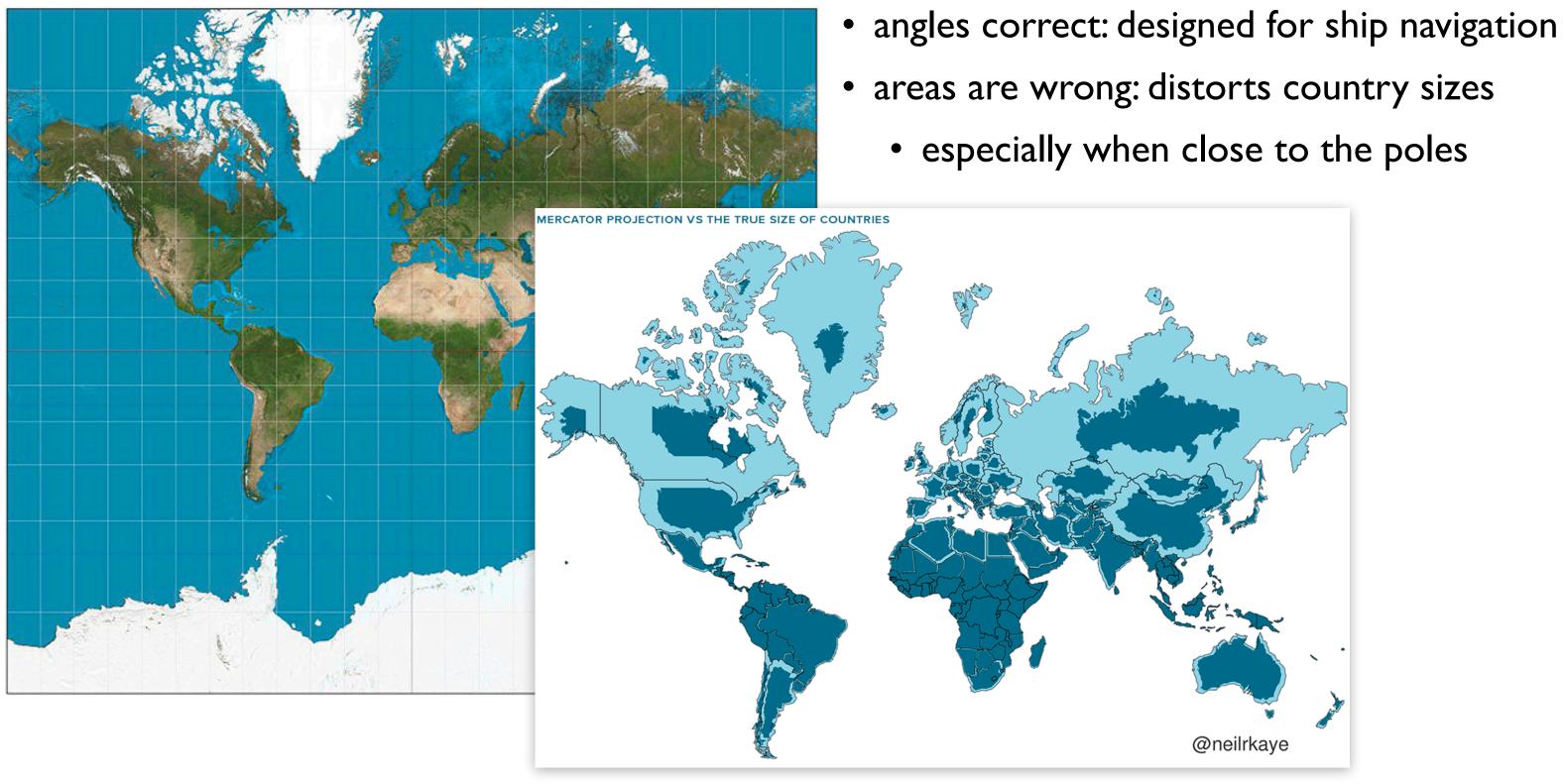
- can mostly mix and match these design elements
 - -choropleth can be combined with anything else
 - -cartograms can be used together with other approaches
 - can use choropleth color coding
 - can add symbols within those stylized regions
 - can add dots with additional geographic locations for more attributes
 - symbol maps difficult to use together with dot maps
 - ambiguity about whether point mark acting as
 - symbol (aggregate mark representing data for entire region), or
 - one-to-one dot (mark with meaningful position representing specific item of data), or
 - many-to-one dot (mark with random position representing many items of data)

Map projections

- mathematical functions that map curved 3D surface geometry of Earth to flat 2D maps
- all projections of sphere on plane necessarily distort surface in some way
 - imagine flattening orange peel onto table
 - something must give
 - cannot have all 3 correct: area, angles, contiguity

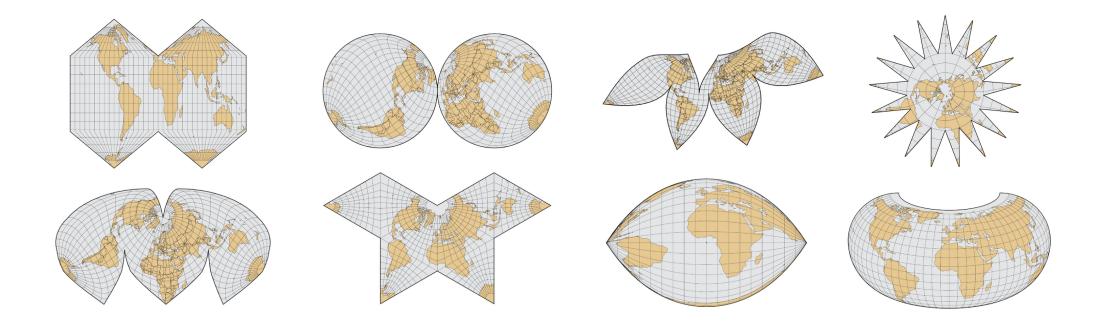


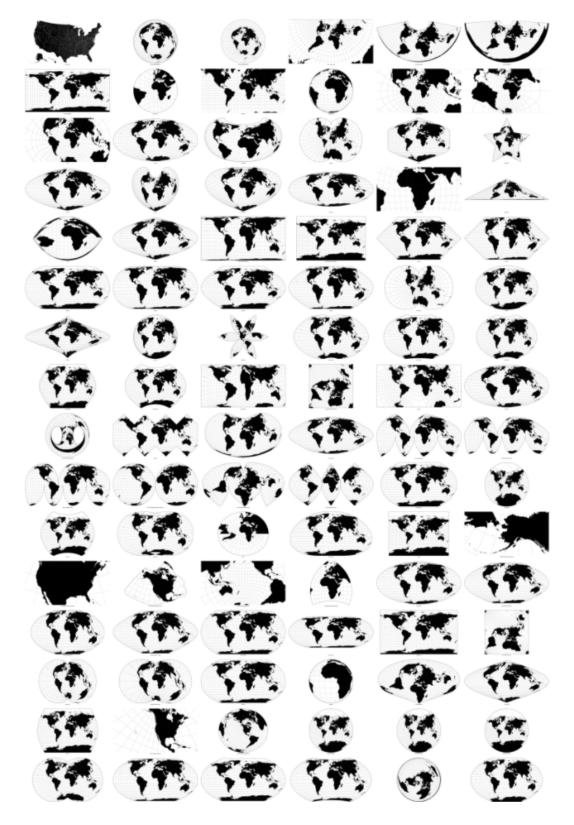
Mercator Projection



Map Projections

- many, many, many projections proposed
- interactive: jasondavies.com/maps/



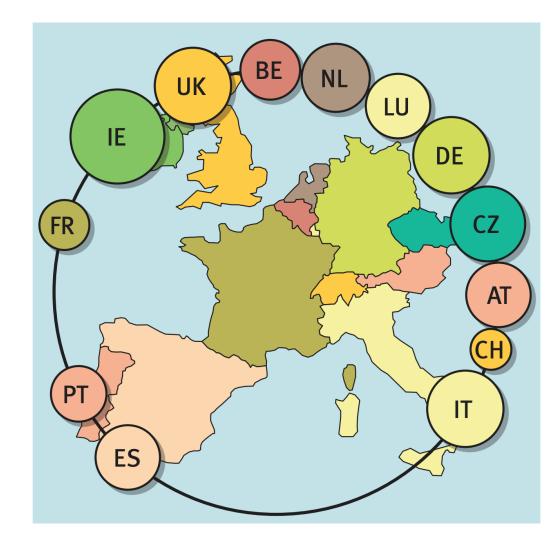


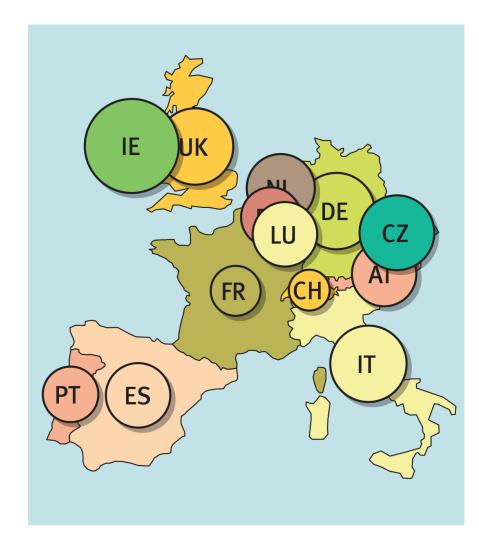
[Every Map Projection](https://bl.ocks.org/mbostock/ 29cddc0006f8b98eff12e60dd08f59a7) 30

Paper: Necklace Maps

Idiom: Necklace maps

- symbol map variant
 - place symbols algorithmically outside, not inside, region
 - -goal: address clutter problem
 - -map 2D data to ID domain
- strengths
 - -addresses clutter problem
 - -can be hierarchical
- limitations
 - weaker association between symbol and region





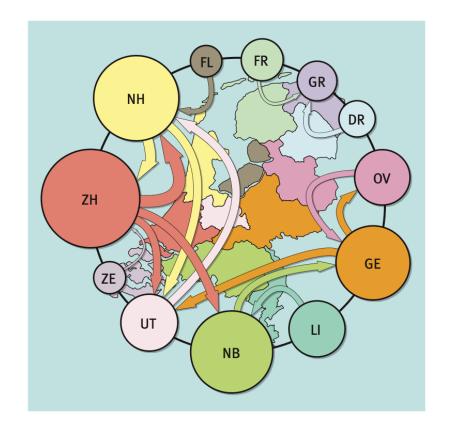
Necklace maps

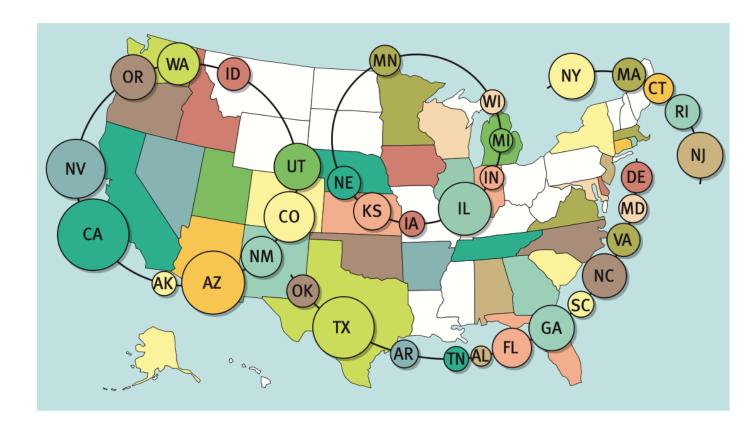
- algorithm: multiple variants provided in many cases
 - -compute feasible intervals
 - optimize symbol sizes
 - optimize symbol placements
- quality criteria: some tradeoffs
 - -symbol position wrt associated region
 - -maximal symbol size
 - disjoint symbols
 - -suitable order of symbols along line

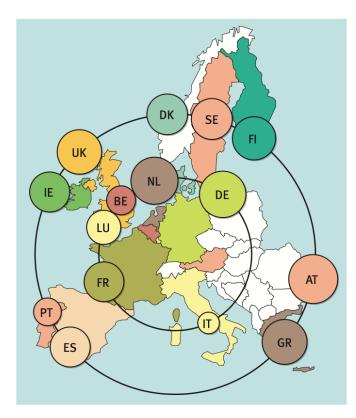
Necklace map extensions / variations

- multiple necklaces
 - nested
 - disjoint

• flows







[Fig 9, 10, 11. Necklace Maps. Bettina Speckmann and Kevin Verbeek.TVCG (16)6:881-889, 2010.]

Scope

- contribution: propose technique and propose algorithm
 - -some explanation / analysis of what it's good for
- evaluation
 - qualitative analysis/discussion of result images
 - high-level performance discussion

Paper: Myriahedral

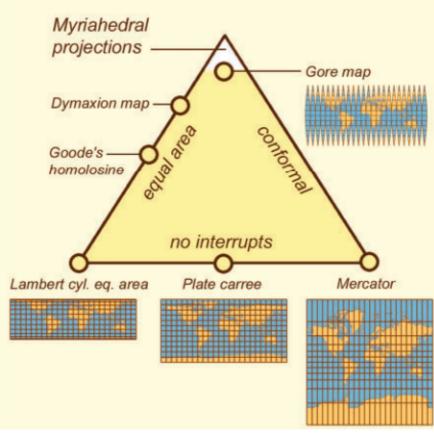
Myriahedral projections

- algorithmic framework for many possible projections
 - -including unusual ones
- later re-implementation from Belmonte: https://philogb.github.io/page/myriahedral/

[Unfolding the Earth: Myriahedral Projections. Jarke J. van Wijk. The Cartographic Journal, 45(1):32-42, 2008.]

Myriahedral projections

- project from 2D sphere surface to 2D plane
 - -can only fully preserve 2 out of 3
 - angles: conformal
 - area: equal area
 - contiguity: no interruptions



https://www.win.tue.nl/~vanwijk/myriahedral/

Tissot's Indicatrix

https://www.jasondavies.com/maps/tissot/

Break 3-3:10

Breakouts

PosAcross

• To what extent does the position in the ballot affect the number of votes received by a candidate, overall? Is there variation across political party?

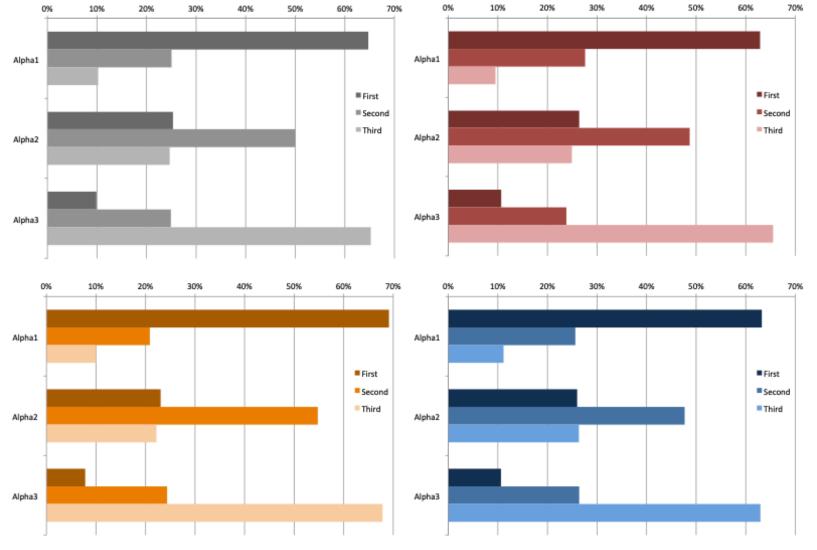


Fig. 5. Alpha position and vote order for, all candidates (gray); Labour candidates (red); Conservative (blue) and Liberal Democrat (orange). If no name order bias existed, all bars would be about the same length.

- Votes: 0-N
- Position Overall: I-9
- Party: I-3 (Lab, LibDem, Cons)
- derived: Position_Within: I-3

[Fig 5. BallotMaps: Detecting name bias in alphabetically ordered ballot papers. Wood, Badawood, Dykes, and Slingsby. IEEE TVCG (Proc. InfoVis) 17(12):2384-2391, 2011.]

If no name order bias existed, all bars would be same length; but systematic structure visible!

AcrossDistrib

• Does the ballot-position influence vary geographically in different boroughs?

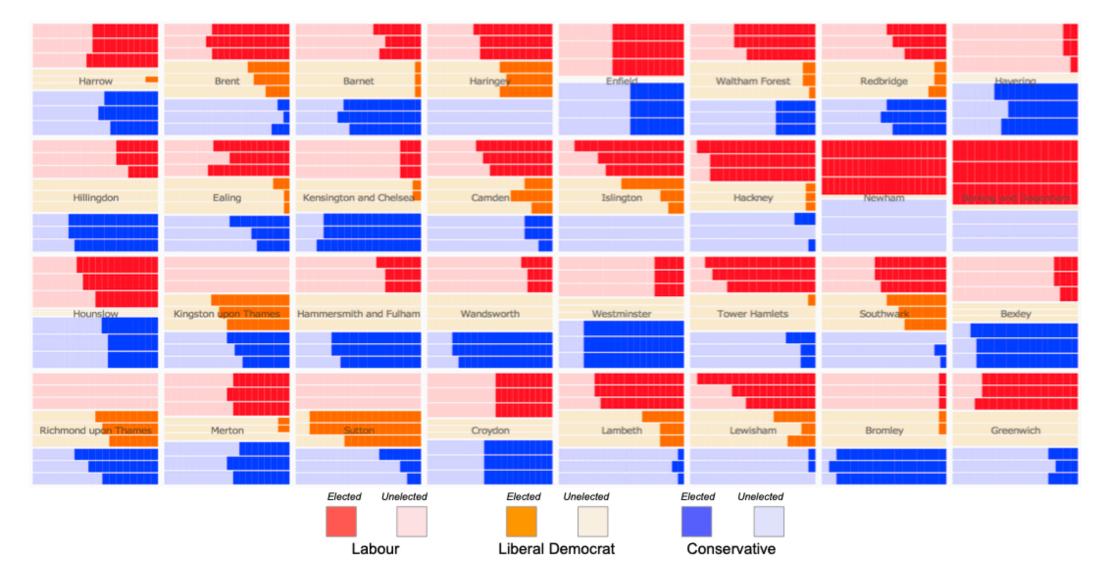


Fig. 1. BallotMap showing electoral success (or otherwise) of each candidate for the three main parties in wards (small rectangles) in each London borough (grid squares) in the 2010 local government elections. Vertical ordering of candidates within each borough is by ballot paper position within party (top row first, middle row second, bottom row third). Main parties with three candidates in a ward are shown. If no ballot ordering bias existed there would be no systematic structure to bar lengths. This ballotMap shows that more candidates get elected who are listed first within their party than do candidates who are second or third.

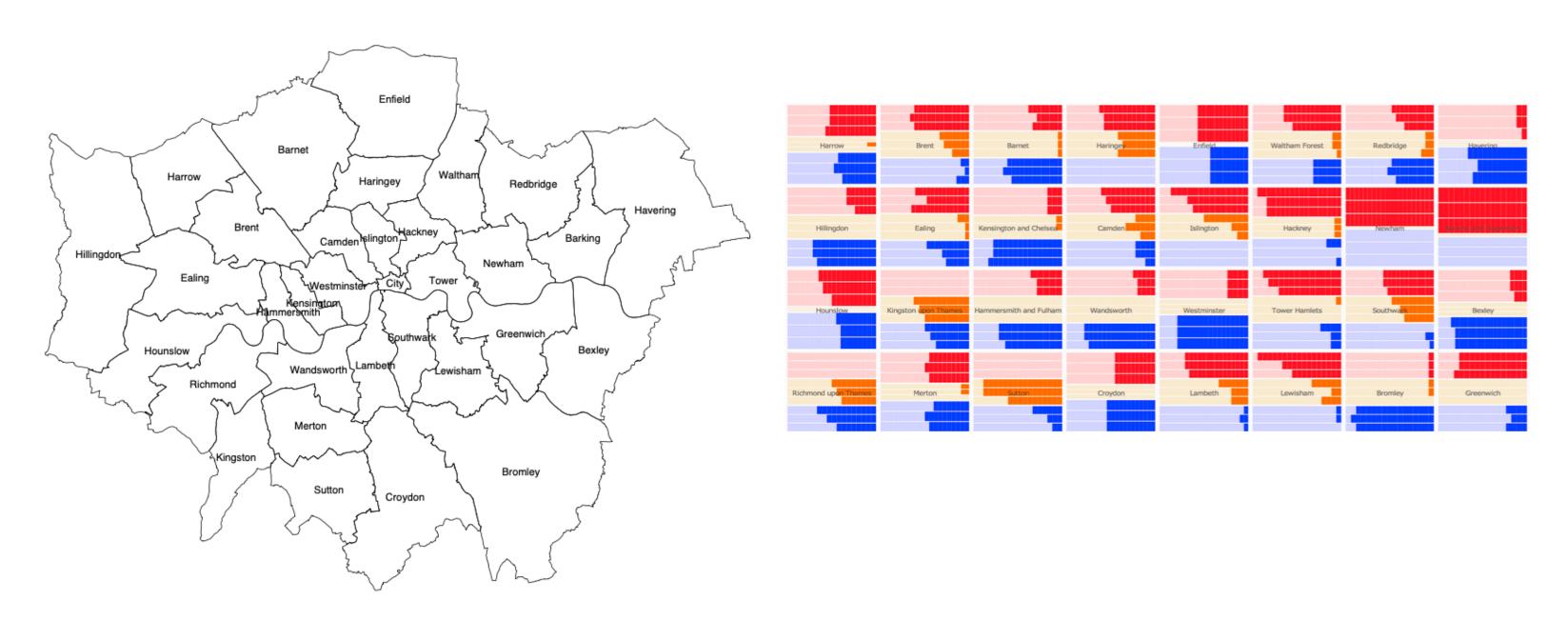
Borough: count of 32

[Fig 1. BallotMaps: Detecting name bias in alphabetically ordered ballot papers. Wood, Badawood, Dykes, and Slingsby. IEEE TVCG (Proc. InfoVis) 17(12):2384-2391, 2011.]

If no name order bias existed, all bars would be same length; but systematic structure visible!

Best of both worlds: quasi-geographic positioning

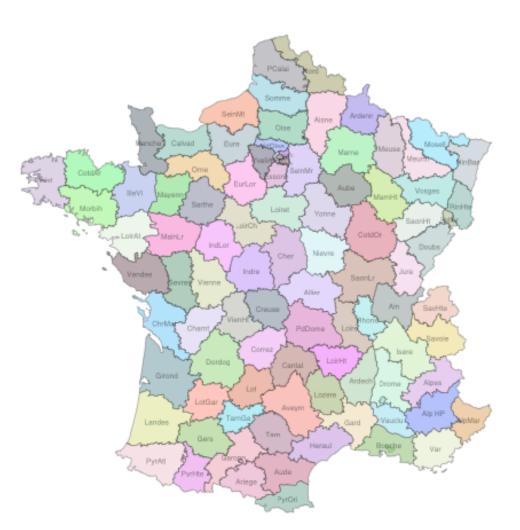
- choropleth: size issues
- tabular: lose geographic position information



Spatially ordered treemaps

quasi-geographic positions

Spatially ordered treemaps. Wood and Dykes. IEEETVCG (Proc. InfoVis) 14(6):1348-1355, 2008.







Across Distrib, Take 2

Does it vary in different wards? Does it depend on party affiliation?

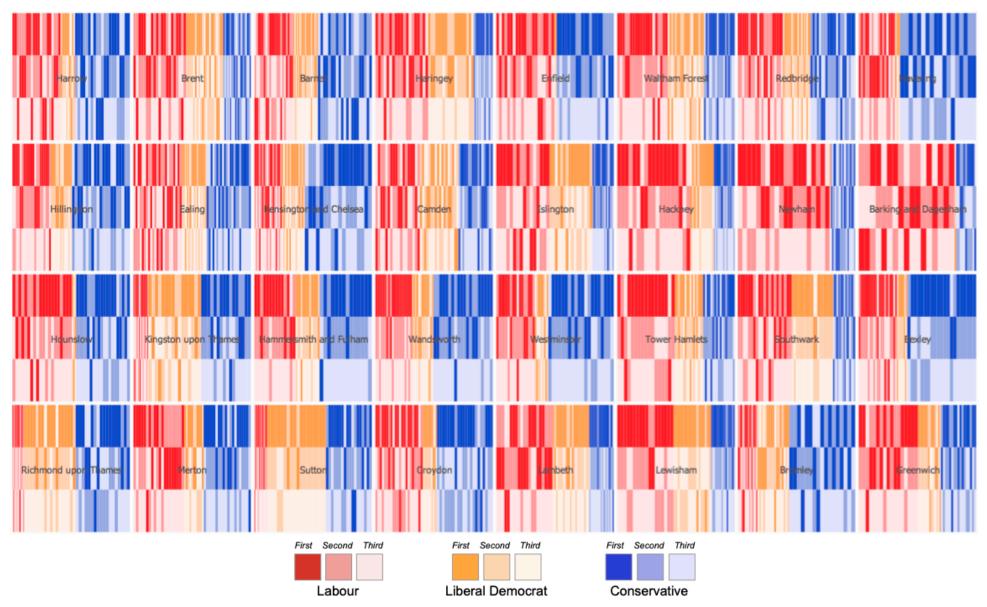


Fig. 4. Alpha position within party (vertical position) and voting rank within party for the three main parties in each ward (vertical bars) in each borough (grid squares). If no name order bias existed, dark and light cells would be randomly distributed in the top, middle and bottom thirds of each borough. Actual voting data show that darker cells (indicating a candidate most votes within their party) are more common in the upper third (listed first on the ballot paper within their party) and lighter cells (least votes within party) are more common in the lower third (listed third within their on the ballot paper).

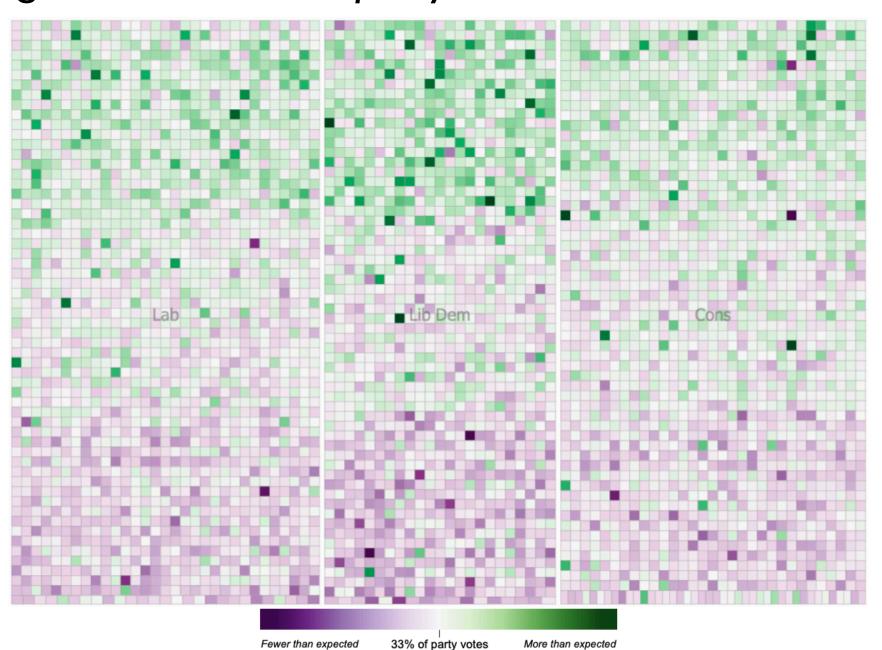
Ward: count of 614

[Fig 4. BallotMaps: Detecting name bias in alphabetically ordered ballot papers. Wood, Badawood, Dykes, and Slingsby. IEEE TVCG (Proc. InfoVis) 17(12):2384-2391, 2011.]

If no name order bias existed, dark/light random distribution; but systematic structure visible!

PosWithin

• To what extent does the position in the ballot influence the number of votes a candidate gets **within** their party?



- Signed_Chi: -I to I
- Residual: I to I

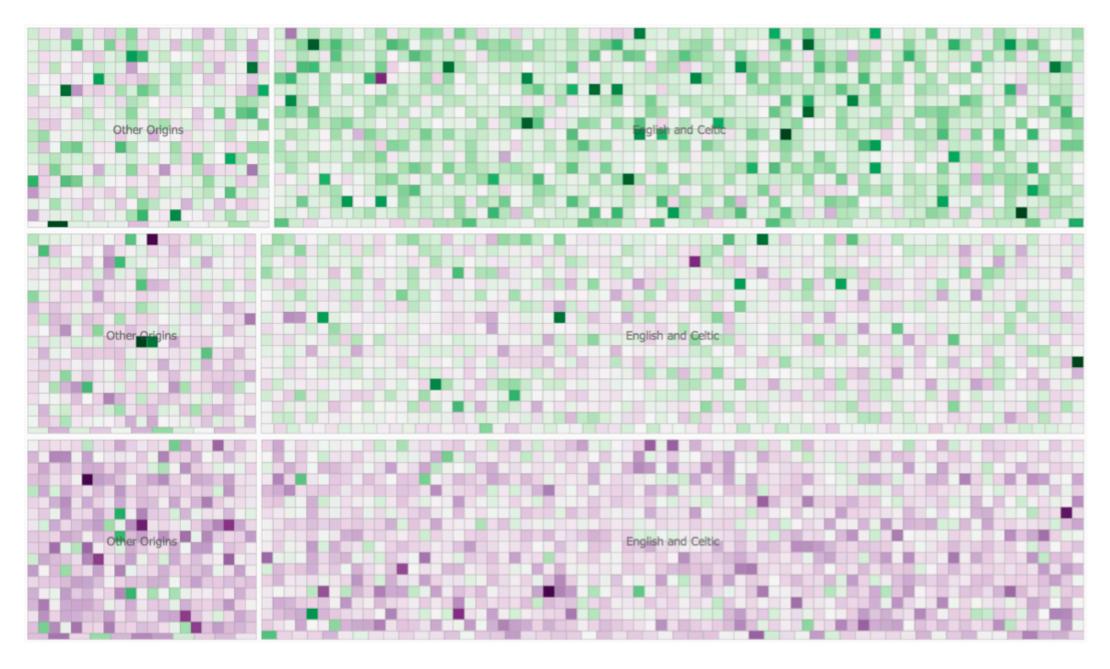
[Fig 6. BallotMaps: Detecting name bias in alphabetically ordered ballot papers. Wood, Badawood, Dykes, and Slingsby. IEEE TVCG (Proc. InfoVis) 17(12):2384-2391, 2011.]

If no name order bias existed, green/purple random distribution; but systematic structure visible!

Fig. 6. Signed chi values for each candidate arranged by party (left to right) and ballot position within party (top to bottom, row by row). The top third represents candidates ordered first in their party, then ordered by absolute position on the ballot paper; the middle third represents candidate ordered second within their party etc. If no name order bias existed, purple and green cells would be randomly distributed within the ballotMap.

NameEthnicity

To what extent does the perceived ethnicity of candidate's name matter?



Name: English or Celtic vs Other Origins

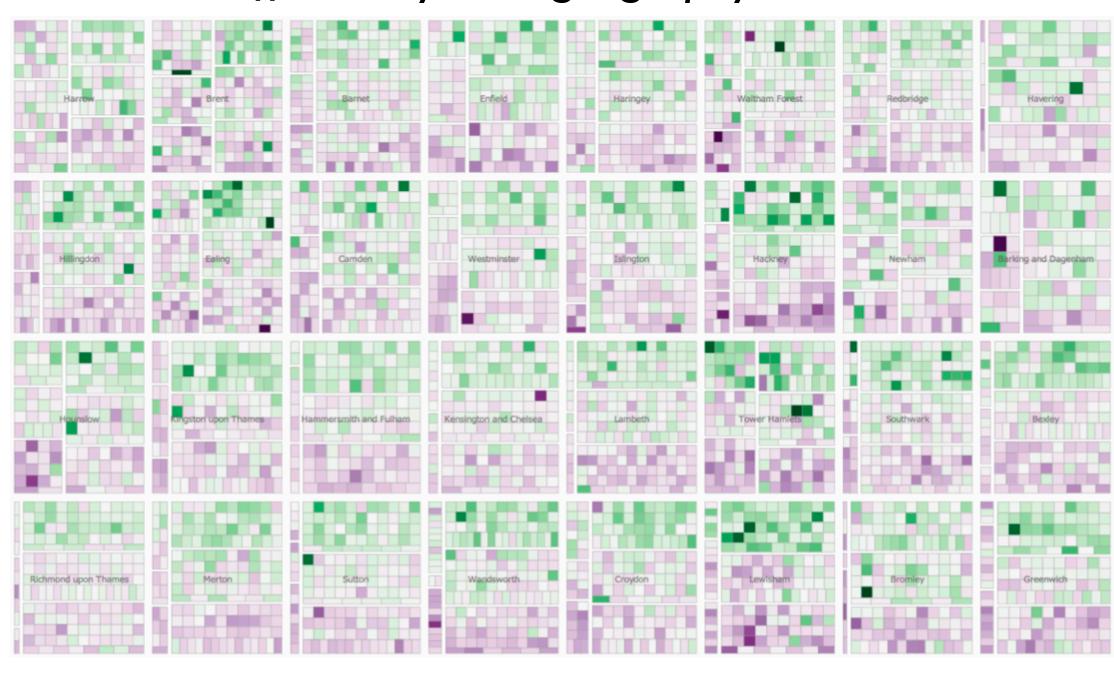
[Fig 7. BallotMaps: Detecting name bias in alphabetically ordered ballot papers. Wood, Badawood, Dykes, and Slingsby. IEEE TVCG (Proc. InfoVis) 17(12):2384-2391, 2011.]

Name order bias differs w/ perceived ethnicity: green/purple structure more visible on right than left!

Fig. 7. Signed chi values for candidates arranged by binary classification of name origin and ballot position within party (top to bottom, row by row). The top third represents candidates ordered first in their party, then ordered by absolute position on the ballot paper; the middle third represents candidate ordered second within their party etc. Name order bias (tendency for green cells in the upper third and purple in the lower third) is stronger for 'English or Celtic' names than for other names where candidates listed first are not so likely to get more votes than expected.

NameEthnicity

Does this effect vary with geography?



[Fig 8. BallotMaps: Detecting name bias in alphabetically ordered ballot papers. Wood, Badawood, Dykes, and Slingsby. IEEE TVCG (Proc. InfoVis) 17(12):2384-2391, 2011.]

Yes. Varies by both borough & perceived ethnicity

Fig. 8. Signed chi values for each candidate in each borough arranged by binary classification of name origin ('other name origins' left, 'English or Celtic' right) and ballot position within party (top to bottom). The degree of name order bias is indicated by the strength of separation of green (more votes than expected) and purple (fewer votes than expected) cells. This varies by borough and by ethnic origin of candidate names.

Key principles

- deriving data
- normalization
- information density
- ordering/position

Ballotmaps: Design study paper

BallotMaps: Detecting Name Bias in Alphabetically Ordered Ballot Papers

Jo Wood, Member, IEEE, Donia Badawood, Jason Dykes, and Aidan Slingsby Member, IEEE

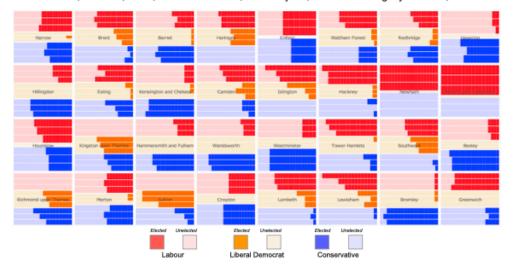


Fig. 1. BallotMap showing electoral success (or otherwise) of each candidate for the three main parties in wards (small rectangles) in each London borough (grid squares) in the 2010 local government elections. Vertical ordering of candidates within each borough is by ballot paper position within party (top row first, middle row second, bottom row third). Main parties with three candidates in a ward are shown. If no ballot ordering bias existed there would be no systematic structure to bar lengths. This ballotMap shows that more candidates get elected who are listed first within their party than do candidates who are second or third.

Abstract—The relationship between candidates' position on a ballot paper and vote rank is explored in the case of 5000 candidates for the UK 2010 local government elections in the Greater London area. This design study uses hierarchical spatially arranged graphics to represent two locations that affect candidates at very different scales: the geographical areas for which they seek election and the spatial location of their names on the ballot paper. This approach allows the effect of position bias to be assessed; that is, the degree to which the position of a candidate's name on the ballot paper influences the number of votes received by the candidate, and whether this varies geographically. Results show that position bias was significant enough to influence rank order of candidates, and in the case of many marginal electoral wards, to influence who was elected to government. Position bias was observed most strongly for Liberal Democrat candidates but present for all major political parties. Visual analysis of classification of candidate names by ethnicity suggests that this too had an effect on votes received by candidates, in some cases overcoming alphabetic name bias. The results found contradict some earlier research suggesting that alphabetic name bias was not sufficiently significant to affect electoral outcome and add new evidence for the geographic and ethnicity influences on voting behaviour. The visual approach proposed here can be applied to a wider range of electoral data and the patterns identified and hypotheses derived from them could have significant implications for the design of ballot papers and the conduct of fair elections.

Index Terms-Voting, election, bias, democracy, governance, treemaps, geovisualization, hierarchy, governance.

that the order in which candidate names appear on a ballot paper may,

 Jo Wood (jwo@city.ac.uk), Donia Badawood (Donia.Badawood.1@city.ac.uk), Jason Dykes (j.dykes@city.ac.uk), and Aidan Slingsby (sbbb717@city.ac.uk) are at the giCentre (http://gicentre.org/) in the School of Informatics, City University London.

Manuscript received 31 March 2011; accepted 1 August 2011; posted online 23 October 2011; mailed on 14 October 2011.

For information on obtaining reprints of this article, please send email to: tvcg@computer.org.

There has long been a suspicion from candidates standing for election in part, influence the number of votes received (e.g. [18]). Despite a number of studies investigating the degree of this effect [24, 1, 13, 5, 20, 19], evidence appears inconclusive and sometimes contradictory. This paper considers how information visualization may be designed and applied to investigating the degree to which some form of name bias may exist in influencing votes received by candidates.

> The overall aims of the work are twofold: to identify the degree to which the position of candidate name affects numbers of votes received; and to develop a data visualization design appropriate for exploring the spatial and non-spatial influences over candidate votes. Addressing these aims is important because conducting fair and neutral elections is an essential part of the democratic process. The aims

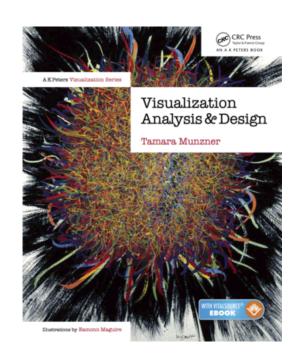
BallotMaps: Detecting name bias in alphabetically ordered ballot papers.

Wood, Badawood, Dykes, and Slingsby. IEEE TVCG (Proc. InfoVis) 17(12):2384-2391, 2011.

http://openaccess.city.ac.uk/436/1/wood_ballotmaps_2011.pdf

Q&A / Backup Slides

Visualization Analysis & Design



Spatial Data (Ch 9)

Tamara Munzner

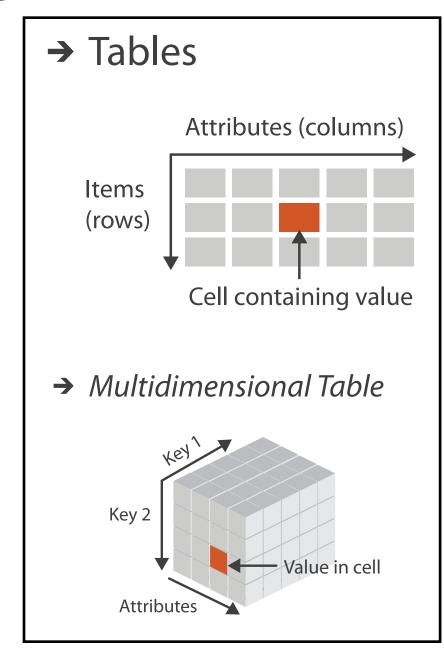
Department of Computer Science

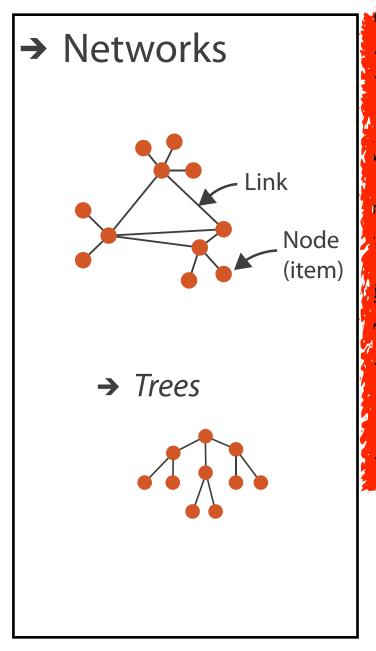
University of British Columbia

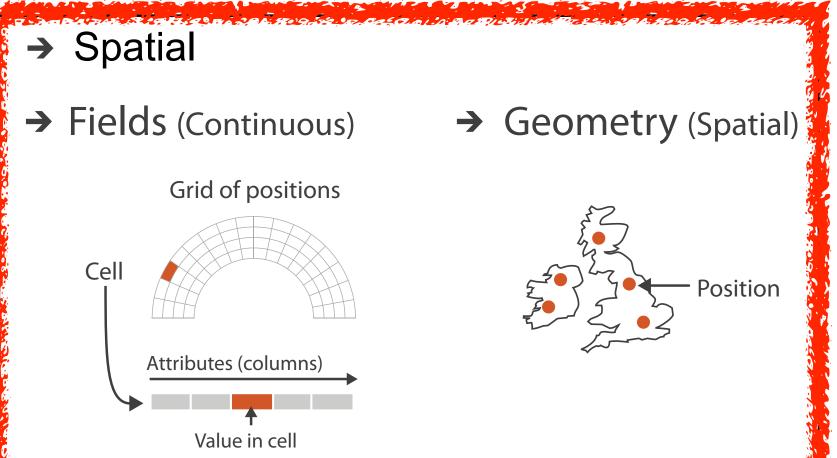
@tamaramunzner

Focus on Spatial

Dataset Types







How?

Encode

aprinis diasisen salarabe analas

→ Arrange

→ Express

→ Separate





→ Order







→ Use



What?
Why?
How?

the second of the second section of the second seco

Map

from categorical and ordered attributes

→ Color



→ Size, Angle, Curvature, ...



→ Shape



→ Motion

Direction, Rate, Frequency, ...



Manipulate

Facet

Reduce

→ Change



Juxtapose



→ Filter



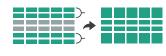
→ Select



→ Partition



Aggregate



→ Navigate



→ Superimpose



→ Embed



How?

Encode



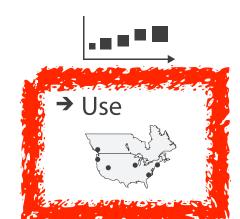
→ Express



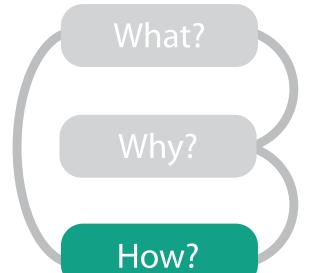


→ Order









→ Map

from categorical and ordered attributes

→ Color



→ Size, Angle, Curvature, ...



→ Shape



→ Motion

Direction, Rate, Frequency, ...



Manipulate

Facet

Reduce

→ Change



Juxtapose



→ Filter



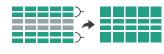
→ Select



→ Partition



Aggregate



→ Navigate



→ Superimpose



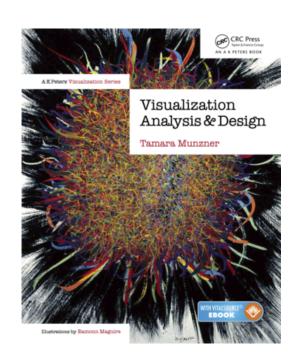
→ Embed



Spatial data

- use given spatial position
- when?
 - dataset contains spatial attributes and they have primary importance
 - central tasks revolve around understanding spatial relationships
- examples
 - -geographical/cartographic data
 - sensor/simulation data

Visualization Analysis & Design



Spatial Data (Ch 9) II

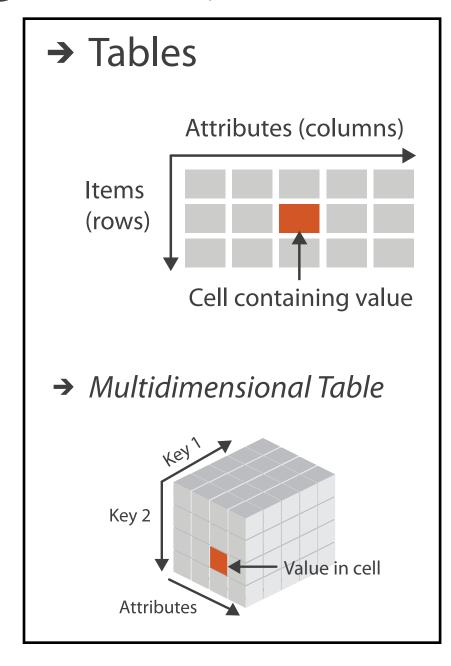
Tamara Munzner

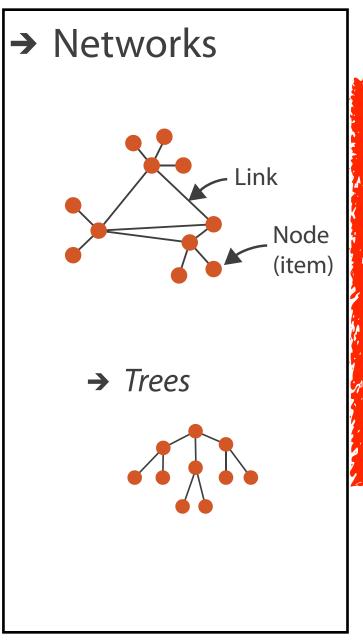
Department of Computer Science University of British Columbia

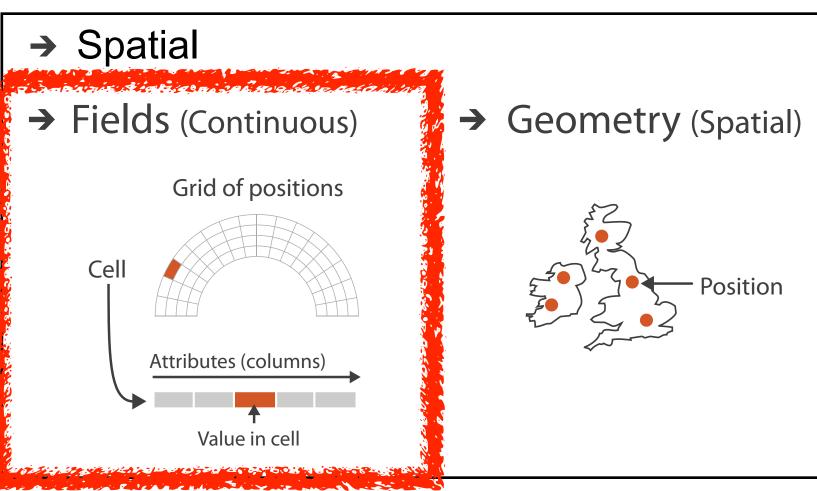
@tamaramunzner

Focus on Spatial

Dataset Types



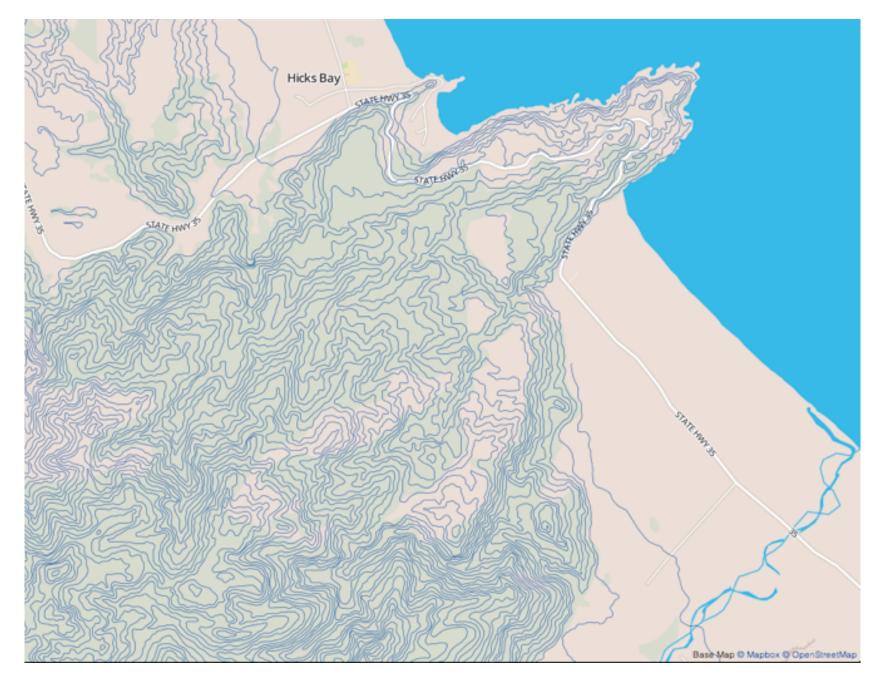




Spatial Fields

Idiom: topographic map

- data
 - geographic geometry
 - -scalar spatial field
 - I quant attribute per grid cell
- derived data
 - isoline geometry
 - isocontours computed for specific levels of scalar values
- task
 - understanding terrain shape
 - densely lined regions = steep
- pros
 - -use only 2D position, avoid 3D challenges
 - color channel available for other attributes
- cons
 - significant clutter from additional lines



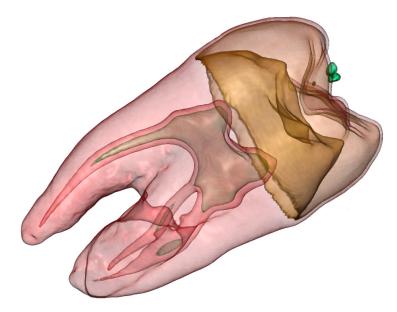
Land Information New Zealand Data Service

Idioms: isosurfaces, direct volume rendering

- data
 - -scalar spatial field (3D volume)
 - I quant attribute per grid cell
- task
 - shape understanding, spatial relationships

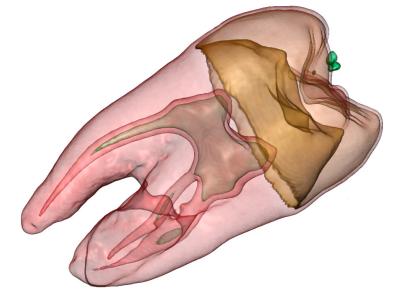
Idioms: isosurfaces, direct volume rendering

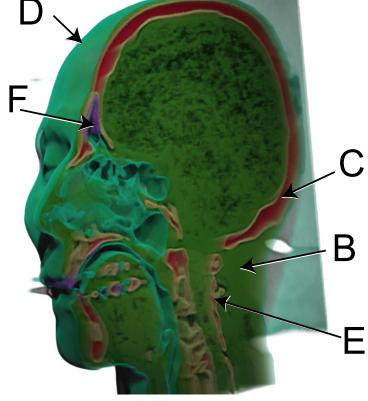
- data
 - -scalar spatial field (3D volume)
 - I quant attribute per grid cell
- task
 - -shape understanding, spatial relationships
- isosurface
 - derived data: isocontours computed for specific levels of scalar values



Idioms: isosurfaces, direct volume rendering

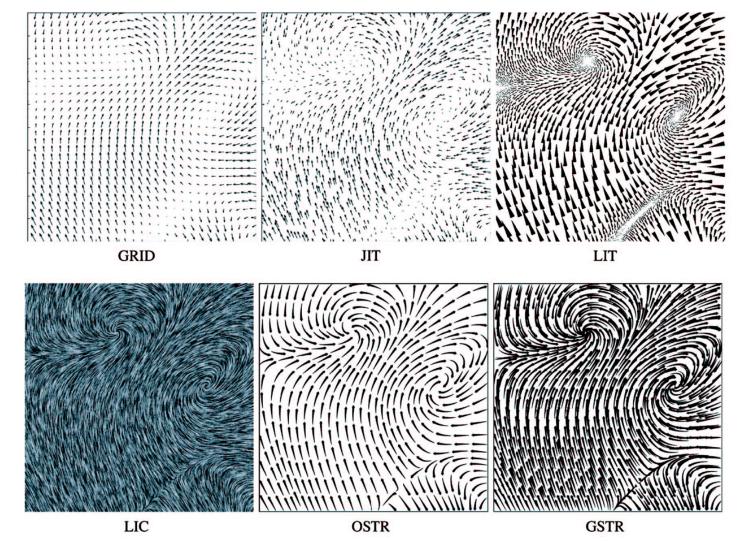
- data
 - -scalar spatial field (3D volume)
 - I quant attribute per grid cell
- task
 - -shape understanding, spatial relationships
- isosurface
 - derived data: isocontours computed for specific levels of scalar values
- direct volume rendering
 - -transfer function maps scalar values to color, opacity
 - no derived geometry



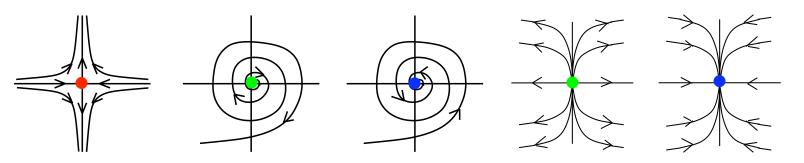


Vector and tensor fields

- data
 - -multiple attribs per cell (vector: 2)
- idiom families
 - -flow glyphs
 - purely local
 - geometric flow
 - derived data from tracing particle trajectories
 - sparse set of seed points
 - texture flow
 - derived data, dense seeds
 - -feature flow
 - global computation to detect features



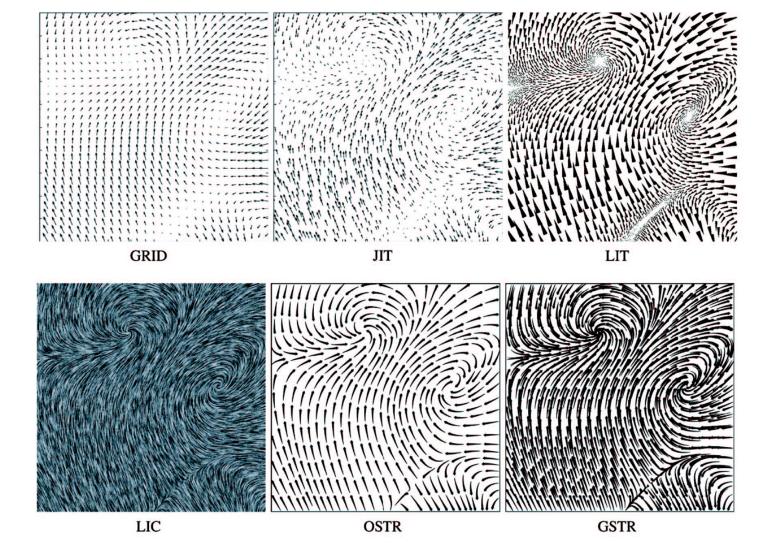
[Comparing 2D vector field visualization methods: A user study. Laidlaw et al. IEEE Trans. Visualization and Computer Graphics (TVCG) 11:1 (2005), 59–70.]



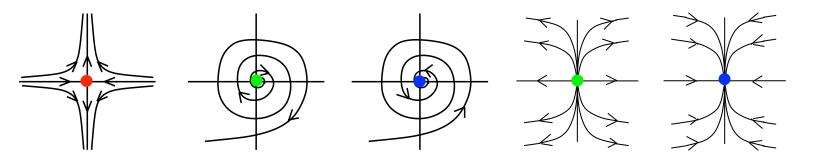
[Topology tracking for the visualization of time-dependent two-dimensional flows. Tricoche, Wischgoll, Scheuermann, and Hagen. Computers & Graphics 26:2 (2002), 249–257.]

Vector fields

- empirical study tasks
 - finding critical points, identifying their types
 - identifying what type of critical point is at a specific location
 - predicting where a particle starting at a specified point will end up (advection)



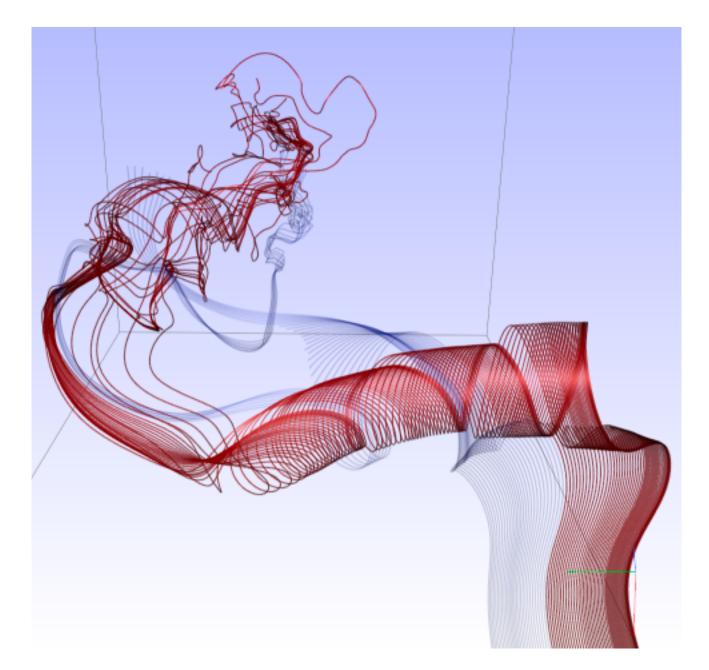
[Comparing 2D vector field visualization methods: A user study. Laidlaw et al. IEEE Trans. Visualization and Computer Graphics (TVCG) 11:1 (2005), 59–70.]



[Topology tracking for the visualization of time-dependent two-dimensional flows. Tricoche, Wischgoll, Scheuermann, and Hagen. Computers & Graphics 26:2 (2002), 249–257.]

Idiom: similarity-clustered streamlines

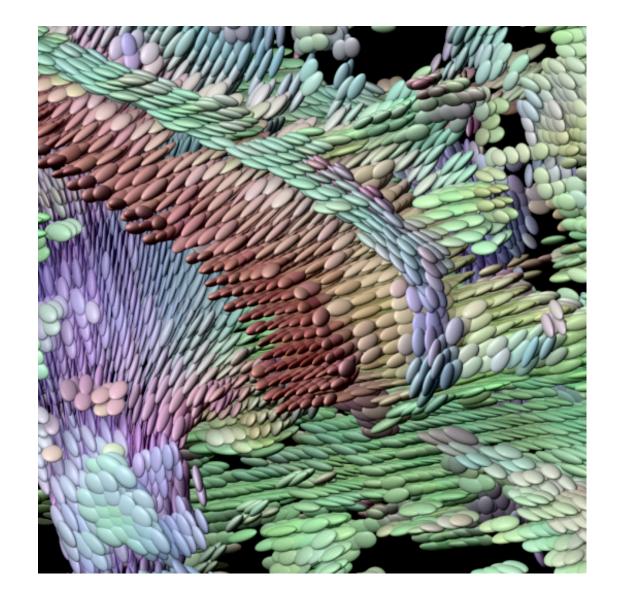
- data
 - -3D vector field
- derived data (from field)
 - streamlines: trajectory particle will follow
- derived data (per streamline)
 - curvature, torsion, tortuosity
 - signature: complex weighted combination
 - compute cluster hierarchy across all signatures
 - encode: color and opacity by cluster
- tasks
 - find features, query shape
- scalability
 - millions of samples, hundreds of streamlines



[Similarity Measures for Enhancing Interactive Streamline Seeding. McLoughlin,. Jones, Laramee, Malki, Masters, and. Hansen. IEEE Trans. Visualization and Computer Graphics 19:8 (2013), 1342–1353.]

Idiom: Ellipsoid Tensor Glyphs

- data
 - tensor field: multiple attributes at each cell (entire matrix)
 - stress, conductivity, curvature, diffusivity...
 - derived data:
 - shape (eigenvalues)
 - orientation (eigenvectors)
- visual encoding
 - -glyph: 3D ellipsoid

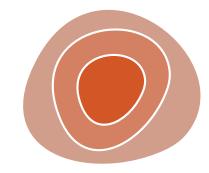


Arrange spatial data

- Use Given
 - → Geometry
 - → Geographic



- → Spatial Fields
 - → Scalar Fields (one value per cell)
 - → Isocontours
 - → Direct Volume Rendering



- → Vector and Tensor Fields (many values per cell)
 - → Flow Glyphs (local)
 - → Geometric (sparse seeds)
 - → Textures (dense seeds)
 - → Features (globally derived)

