### Data Visualization (CSCI 627/490)

Filtering & Aggregation

Dr. David Koop





## Composite Visualization Techniques





(d) Overloaded views.

(b) Integrated views.



(c) Superimposed views.











## What is this technique?



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[VisLink, Collins and Carpendale, 2007]









## What is this technique?



## Multiple Views



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[Munzner (ill. Maguire), 2014]





## Brushing











## Multiform & Small Multiples











## Partitioned Views

- Split dataset into groups and visualize each group
- Extremes: one item per group, one group for all items
- Can be a hierarchy
  - Order: which splits are more "related"?
  - Which attributes are used to split? usually categorical







## Partitioned Views: Trellis Matrix Alignment



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Barley Yield (bushels/acre)











# Recursive Subdivision: HiVE System











# Project Design

- Feedback:
  - Data Manipulation?
  - Questions lead, not technique!
  - Be creative! (interaction too) <u>https://xeno.graphics</u>
- Work on turning your visualization ideas into designs
- Turn in:
  - Two Design Sketches (like sheets 2-4 from 5 Sheet Design)
  - One Bad Design Sketch (like sheets 2-4: here, justify why bad)
  - Progress on Implementation
- Due Friday, Nov. 13

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### ://xeno.graphics deas into designs

### 2-4 from 5 Sheet Design) ts 2-4: here, justify why bad)





## Assignment 5

- To be released soon
- Citi Bike NYC Data
  - Trips between neighborhoods
- Covers
  - Multiple Views
  - Filtering
  - Aggregation
  - Brushing





### Overview: Reducing Items & Attributes



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# → Aggregate

### → Items







[Munzner (ill. Maguire), 2014]



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# Filtering

- Just don't show certain elements
- Item filtering: most common, eliminate marks for filtered items
- Attribute filtering:
  - attributes often mapped to different channels
  - if mapped to same channel, allows many attributes (e.g. parallel coordinates, star plots), can filter
- How to specify which elements?
  - Pre-defined rules
  - User selection







## Filter vs. Query

- Queries start with an empty set of items and **add** items
- Filters start with all items and **remove** items

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### tems and **add** items **ve** items





## Example: NYC Health Dept. Restaurant Ratings



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## Dynamic Filters

- Interaction need not be with the visualization itself
- Users interact with widgets that control which items are shown
   Sliders, Combo boxes, Text Fields
- Often tied to attribute values
- Examples:
  - All restaurants with an "A" Grade
  - All pizza places
  - All pizza places with an "A" Grade

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### ualization itself Introl which items are shown





## Scented Widgets



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![](_page_17_Picture_3.jpeg)

![](_page_17_Picture_5.jpeg)

18

## Scented Widgets

![](_page_18_Figure_1.jpeg)

![](_page_18_Figure_2.jpeg)

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on A	Name	Description	Example		
on <u>B</u> on <u>C</u>	Hue	Varies the hue of the widget (or of a visualization embedded in it)	Option A		
on <u>D</u> I rank	Saturation	Varies the saturation of the widget (or of a visualization embedded in it)	Option <u>A</u> Option <u>B</u>		
	Opacity	Varies the saturation of the widget (or of a visualization embedded in it)	Option <u>A</u> Option <u>B</u>		
	Text	Inserts one or more small text figures into the widget	(2) Option <u>A</u> (10) Option <u>B</u>		
	lcon	Inserts one or more small icons into the widget.	<ul> <li>Option<u>A</u></li> <li>Option<u>B</u></li> </ul>		
or	Bar Chart	Inserts one or more small bar chart visualizations into the widget	Option <u>A</u> Option <u>B</u>		
	Line Chart	Inserts one or more small line chart visualizations into the widget	Option <u>A</u> Option <u>B</u>		

[Willett et al., 2007]

![](_page_18_Picture_6.jpeg)

![](_page_18_Picture_8.jpeg)

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# Star Plots (aka Radar Charts)

![](_page_19_Figure_1.jpeg)

Aberlour

![](_page_19_Picture_3.jpeg)

![](_page_19_Figure_4.jpeg)

![](_page_19_Picture_5.jpeg)

![](_page_19_Figure_7.jpeg)

Auchentoshan

![](_page_19_Figure_9.jpeg)

Auchroisk

![](_page_19_Figure_11.jpeg)

![](_page_19_Picture_12.jpeg)

![](_page_19_Picture_13.jpeg)

![](_page_19_Picture_15.jpeg)

![](_page_19_Picture_16.jpeg)

![](_page_19_Picture_17.jpeg)

## Star Plot / Radar Chart

![](_page_20_Figure_1.jpeg)

- Compare variables
- Similarities/differences of items
- Locate outliers
- Considerations:
  - Order of axes
  - Too many axes cause problems

![](_page_20_Picture_10.jpeg)

![](_page_20_Picture_11.jpeg)

![](_page_20_Picture_13.jpeg)

![](_page_20_Picture_14.jpeg)

## Attribute Filtering on Star Plots

![](_page_21_Picture_1.jpeg)

(C)

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(d)

![](_page_21_Picture_5.jpeg)

![](_page_21_Picture_6.jpeg)

![](_page_21_Picture_7.jpeg)

![](_page_21_Picture_8.jpeg)

![](_page_21_Picture_9.jpeg)

## Attribute Filtering

- How to choose which attributes should be filtered?
  - User selection?
  - Statistics: similarity measures, attributes with low variance are not as interesting when comparing items
- Can be combined with item filtering

![](_page_22_Picture_8.jpeg)

![](_page_22_Picture_10.jpeg)

![](_page_22_Picture_11.jpeg)

![](_page_22_Picture_12.jpeg)

![](_page_23_Picture_0.jpeg)

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## Aggregation

![](_page_23_Picture_3.jpeg)

![](_page_23_Picture_5.jpeg)

![](_page_23_Picture_6.jpeg)

# Aggregation

- Usually involves **derived** attributes
- Examples: mean, median, mode, min, max, count, sum
- Remember expressiveness principle: still want to avoid implying trends or similarities based on aggregation

						IV	
Х	У	Х	У	Х	У	Х	У
10.0	8.04	10.0	9.14	10.0	7.46	8.0	6.58
8.0	6.95	8.0	8.14	8.0	6.77	8.0	5.70
13.0	7.58	13.0	8.74	13.0	12.74	8.0	7.7
9.0	8.81	9.0	8.77	9.0	7.11	8.0	8.8
11.0	8.33	11.0	9.26	11.0	7.81	8.0	8.4
14.0	9.96	14.0	8.10	14.0	8.84	8.0	7.04
6.0	7.24	6.0	6.13	6.0	6.08	8.0	5.2
4.0	4.26	4.0	3.10	4.0	5.39	19.0	12.5
12.0	10.84	12.0	9.13	12.0	8.15	8.0	5.50
7.0	4.82	7.0	7.26	7.0	6.42	8.0	7.9
5.0	5.68	5.0	4.74	5.0	5.73	8.0	6.8

![](_page_24_Picture_8.jpeg)

![](_page_24_Figure_10.jpeg)

![](_page_24_Picture_11.jpeg)

![](_page_24_Picture_12.jpeg)

# ggregation

- Usually involves **derived** attributes
- Examples: mean, median, mode, min, max, count, sum
- Remember expressiveness principle: still want to avoid implying trends or similarities based on aggregation

Mean o	fx
Variance	e of x
Mean o	fy
Variance	e of y
Correlat	tion

9	
11	
7.50	
4.122	
0.816	

l		II				IV	
Х	У	Х	У	Х	У	Х	У
10.0	8.04	10.0	9.14	10.0	7.46	8.0	6.58
8.0	6.95	8.0	8.14	8.0	6.77	8.0	5.76
13.0	7.58	13.0	8.74	13.0	12.74	8.0	7.71
9.0	8.81	9.0	8.77	9.0	7.11	8.0	8.84
11.0	8.33	11.0	9.26	11.0	7.81	8.0	8.47
14.0	9.96	14.0	8.10	14.0	8.84	8.0	7.04
6.0	7.24	6.0	6.13	6.0	6.08	8.0	5.25
4.0	4.26	4.0	3.10	4.0	5.39	19.0	12.5
12.0	10.84	12.0	9.13	12.0	8.15	8.0	5.56
7.0	4.82	7.0	7.26	7.0	6.42	8.0	7.91
5.0	5.68	5.0	4.74	5.0	5.73	8.0	6.89

![](_page_25_Picture_10.jpeg)

![](_page_25_Figure_12.jpeg)

![](_page_25_Picture_13.jpeg)

![](_page_25_Picture_14.jpeg)

### Anscombe's Quartet

![](_page_26_Figure_1.jpeg)

![](_page_26_Figure_2.jpeg)

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![](_page_26_Figure_4.jpeg)

![](_page_26_Picture_5.jpeg)

![](_page_26_Picture_6.jpeg)

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![](_page_26_Picture_8.jpeg)

![](_page_26_Picture_9.jpeg)

![](_page_26_Picture_10.jpeg)

## Aggregation: Histograms

- Very similar to bar charts

- Often shown without space between (continuity)
- Choice of number of bins
  - Important!
  - Viewers may infer different trends based on the layout

![](_page_27_Picture_8.jpeg)

![](_page_27_Picture_9.jpeg)

![](_page_27_Picture_11.jpeg)

## Aggregation: Histograms

![](_page_28_Figure_1.jpeg)

![](_page_28_Figure_2.jpeg)

![](_page_28_Picture_7.jpeg)

![](_page_28_Picture_9.jpeg)

![](_page_28_Picture_10.jpeg)

## Common Distributions

![](_page_29_Figure_1.jpeg)

![](_page_29_Picture_3.jpeg)

![](_page_29_Picture_5.jpeg)

![](_page_29_Picture_6.jpeg)

![](_page_29_Picture_7.jpeg)

## Binning Scatterplots

- At some point, cannot see density
- Blobs on top of blobs
- 2D Histogram is a histogram in 2D encoded using color instead of height
- Each region is aggregated

![](_page_30_Figure_7.jpeg)

![](_page_30_Picture_8.jpeg)

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![](_page_30_Picture_10.jpeg)

![](_page_30_Picture_11.jpeg)

![](_page_30_Picture_12.jpeg)

# Binning

- Hexagonal bins are more circular
- Distance to the edge is not as variable
- More efficient aggregation around the center of the bin

![](_page_31_Figure_4.jpeg)

![](_page_31_Figure_7.jpeg)

![](_page_31_Picture_8.jpeg)

![](_page_31_Picture_10.jpeg)

![](_page_31_Picture_11.jpeg)

## Spatial Aggregation

![](_page_32_Figure_1.jpeg)

![](_page_32_Figure_2.jpeg)

![](_page_32_Figure_4.jpeg)

[Penn State, GEOG 486]

![](_page_32_Picture_8.jpeg)

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# Modifiable Areal Unit Problem

- of aggregation you get
- Similar to bins in histograms
- Gerrymandering

![](_page_33_Figure_4.jpeg)

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[Wonkblog, Washington Post, Adapted from S. Nass]

![](_page_33_Picture_9.jpeg)

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![](_page_33_Picture_11.jpeg)

![](_page_33_Picture_12.jpeg)

![](_page_33_Picture_13.jpeg)

![](_page_33_Picture_14.jpeg)

## Drawing Different Maps: Compactness

### borders

specifically the 2018 midterms – based on historical patterns since 2006

![](_page_34_Figure_3.jpeg)

![](_page_34_Picture_5.jpeg)

![](_page_34_Picture_6.jpeg)

![](_page_34_Picture_8.jpeg)

![](_page_34_Picture_9.jpeg)

![](_page_34_Picture_10.jpeg)

## Drawing Different Maps

![](_page_35_Figure_1.jpeg)

![](_page_35_Picture_3.jpeg)

![](_page_35_Picture_4.jpeg)

![](_page_35_Picture_6.jpeg)

![](_page_35_Picture_7.jpeg)

![](_page_35_Picture_8.jpeg)

## Boxplots

- Show **distribution**
- Single value (e.g. mean, max, min, quartiles) doesn't convey everything
- Created by John Tukey
- Show spread and skew of data
- Best for **unimodal** data
- Variations like vase plot for multimodal data
- Aggregation here involves many different marks

![](_page_36_Figure_9.jpeg)

![](_page_36_Picture_10.jpeg)

![](_page_36_Picture_11.jpeg)

![](_page_36_Picture_12.jpeg)

## Aggregation: Boxplots

![](_page_37_Figure_1.jpeg)

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![](_page_37_Picture_3.jpeg)

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![](_page_37_Picture_6.jpeg)

![](_page_37_Picture_7.jpeg)

## Four Distributions, Same Boxplot...

![](_page_38_Figure_1.jpeg)

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![](_page_38_Picture_4.jpeg)

![](_page_38_Picture_5.jpeg)

![](_page_38_Picture_6.jpeg)

## Hierarchical Parallel Coordinates

![](_page_39_Figure_1.jpeg)

![](_page_39_Picture_3.jpeg)

![](_page_39_Picture_5.jpeg)

![](_page_39_Picture_6.jpeg)

![](_page_39_Picture_7.jpeg)

### K-Means

![](_page_40_Picture_1.jpeg)

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### <u>Run</u>

![](_page_40_Picture_4.jpeg)

![](_page_40_Picture_5.jpeg)

![](_page_40_Picture_7.jpeg)

### K-Means Issues

![](_page_41_Figure_1.jpeg)

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![](_page_41_Figure_3.jpeg)

Number of Clusters

![](_page_41_Picture_5.jpeg)

![](_page_41_Picture_7.jpeg)

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## Dimensionality Reduction

- individual attribute
- Example: Understanding the language in a collection of books
  - Count the occurrence of each non-common word in each book
  - (e.g. "western")
  - Don't want to have to manually determine such rules
- techniques

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• Attribute Aggregation: Use fewer attributes (dimensions) to represent items • Combine attributes in a way that is more instructive than examining each

- Huge set of features (attributes), want to represent each with an aggregate feature (e.g. high use of "cowboy", lower use of "city") that allows clustering

Techniques: Principle Component Analysis, Multidimensional Scaling family of

![](_page_42_Picture_15.jpeg)

![](_page_42_Picture_17.jpeg)

![](_page_42_Picture_18.jpeg)

![](_page_42_Picture_19.jpeg)

## Principle Component Analysis (PCA)

original data space

![](_page_43_Figure_2.jpeg)

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![](_page_43_Figure_4.jpeg)

PC 1

![](_page_43_Picture_6.jpeg)

![](_page_43_Picture_7.jpeg)

![](_page_43_Picture_8.jpeg)

![](_page_43_Picture_9.jpeg)

![](_page_43_Picture_10.jpeg)

![](_page_43_Picture_11.jpeg)

### PCA

![](_page_44_Figure_1.jpeg)

[Principle Component Analysis Explained, Explained Visually, V. Powell & L. Lehe, 2015]

![](_page_44_Figure_4.jpeg)

![](_page_44_Picture_5.jpeg)

![](_page_44_Picture_7.jpeg)

![](_page_44_Picture_8.jpeg)