

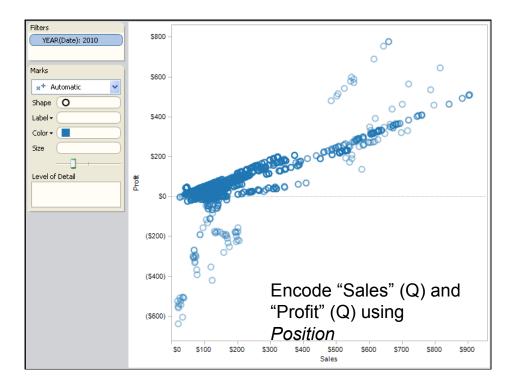
## **Example: Coffee Sales**

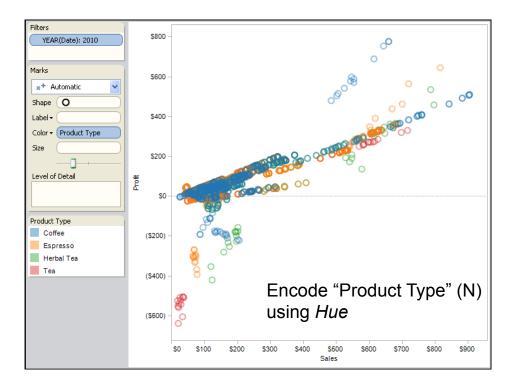
### Sales figures for a fictional coffee chain:

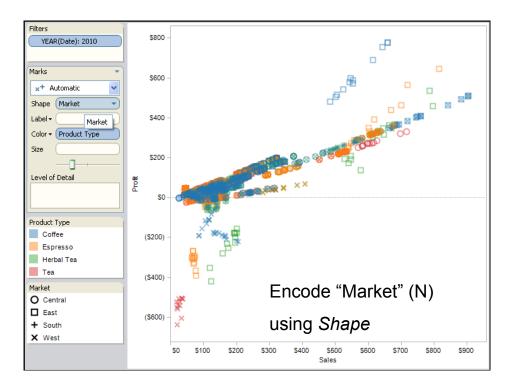
Sales	
Profit	
Marketing	
Product Type	
Market	

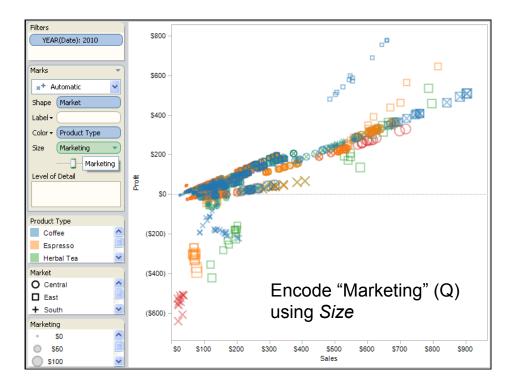
Q-Ratio Q-Ratio Q-Ratio N {Coffee, Espresso, Herbal Tea, Tea}

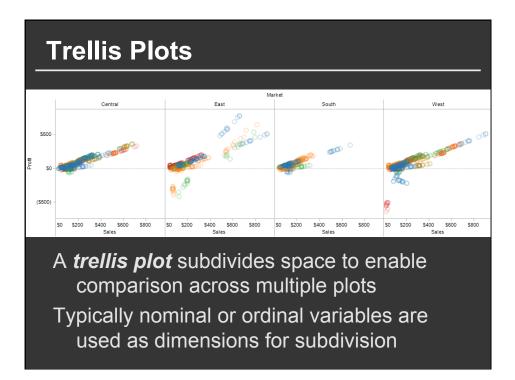
**N** {Central, East, South, West}

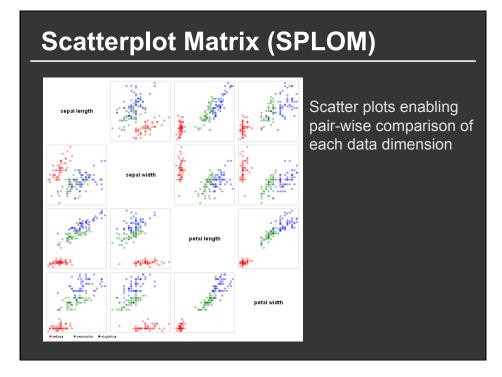


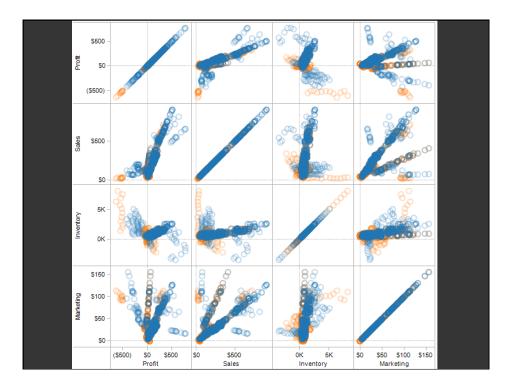


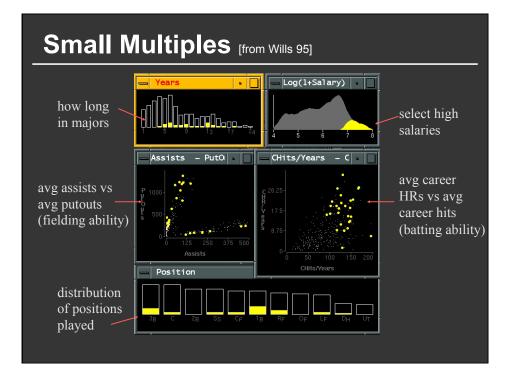




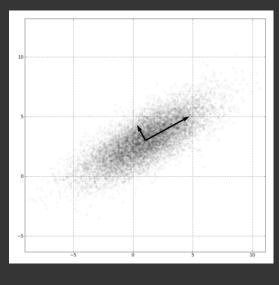




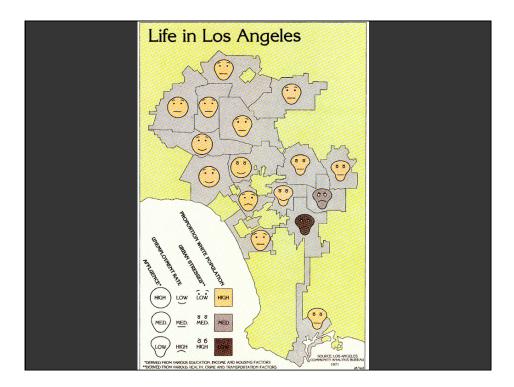




# **Principal Component Analysis**



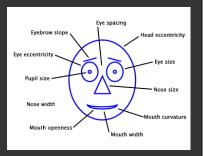
- 1. Mean-center the data
- Find ⊥ basis vectors that maximize the data variance
- 3. Plot the data using the top vectors



## **Chernoff Faces (1973)**

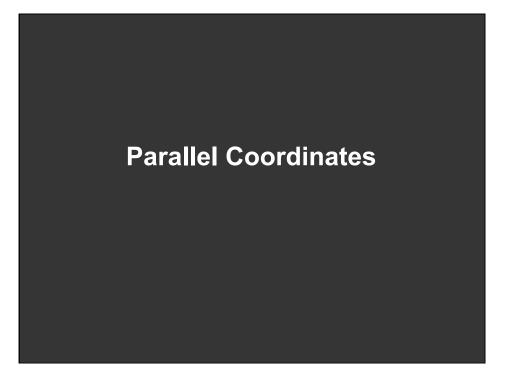
**Insight:** We have evolved a sophisticated ability to interpret facial expression

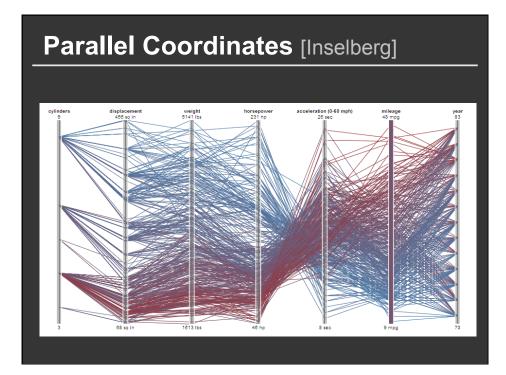
**Idea:** Map data variables to facial features



Question: Do we process facial features in an uncorrelated way? (i.e., are they *separable*?)

This is just one example of nD "glyphs"





### **The Multidimensional Detective**

The Dataset:

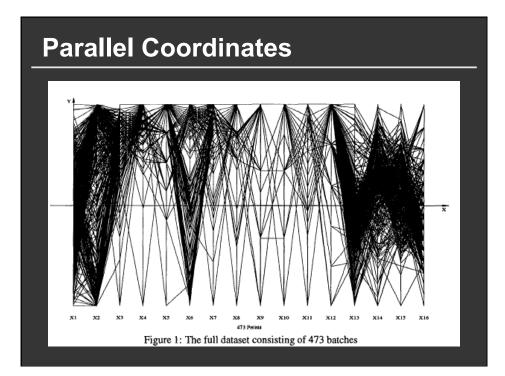
Production data for 473 batches of a VLSI chip 16 process parameters:

X1:	The yield: % of produced chips that are useful
X2:	The quality of the produced chips (speed)
X3 X12:	10 types of defects (zero defects shown at top)
X13 X16:	4 physical parameters

#### The Objective:

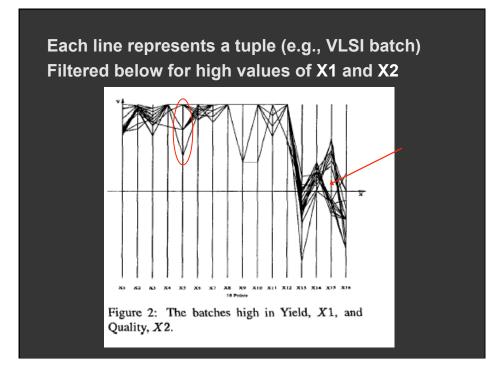
Raise the yield (X1) and maintain high quality (X2)

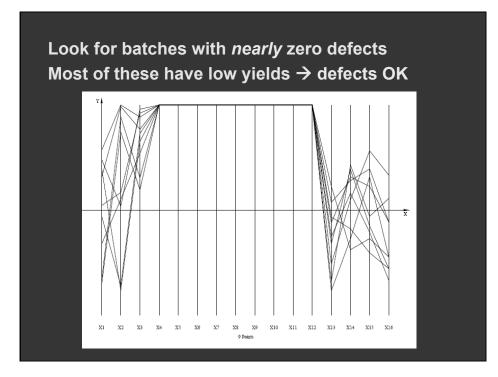
A. Inselberg, Multidimensional Detective, Proceedings of IEEE Symposium on Information Visualization (InfoVis '97), 1997

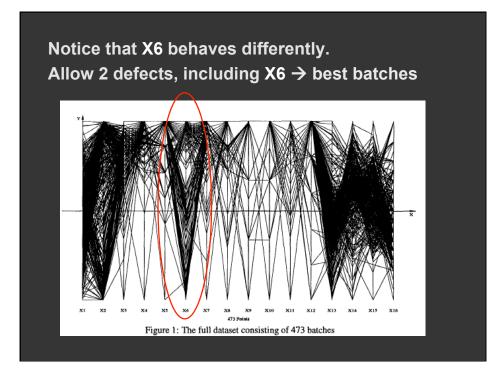


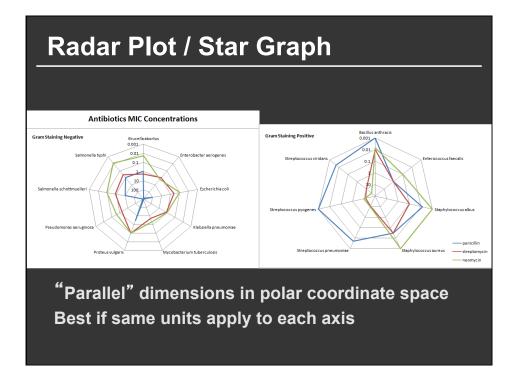
# Inselberg's Principles

- 1. Do not let the picture scare you
- 2. Understand your objectives
  - Use them to obtain visual cues
- 3. Carefully scrutinize the picture
- 4. Test your assumptions, especially the "I am really sure of's"
- 5. You can't be unlucky all the time!

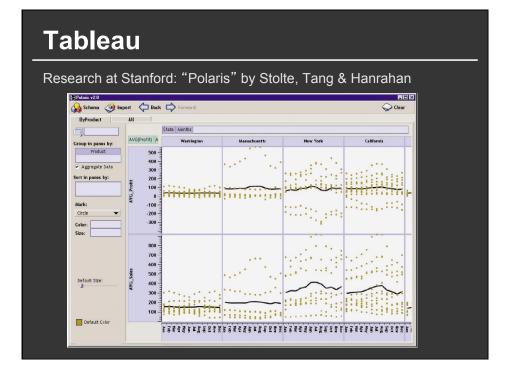


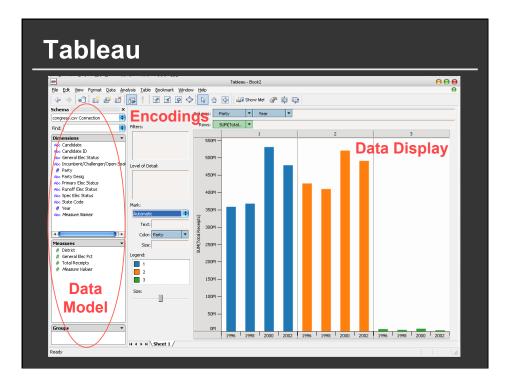












## Tableau demo

#### The dataset:

- Federal Elections Commission Receipts
- Every Congressional Candidate from 1996 to 2002
- 4 Election Cycles
- 9216 Candidacies

### **Data Set Schema**

- Year (Qi)
- Candidate Code (N)
- Candidate Name (N)
- Incumbent / Challenger / Open-Seat (N)
- Party Code (N) [1=Dem,2=Rep,3=Other]
- Party Name (N)
- Total Receipts (Qr)
- State (N)
- **District (N)**
- This is a subset of the larger data set available from the FEC, but should be sufficient for the demo

### Hypotheses?

### What might we learn from this data?

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### What might we learn from this data?

- Has spending increased over time?
- Do democrats or republicans spend more money?
- Candidates from which state spend the most money?

### **Tableau Demo**

### **Polaris/Tableau Approach**

Insight: simultaneously specify both database queries and visualization

Choose data, then visualization, not vice versa

Use smart defaults for visual encodings

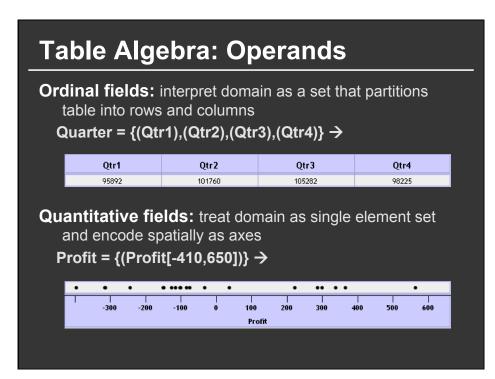
Recently: automate visualization design (ShowMe – Like APT)

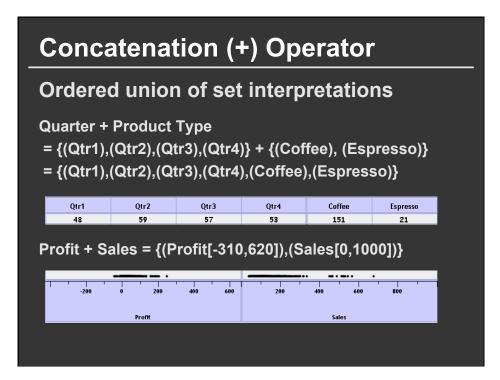
### **Specifying Table Configurations**

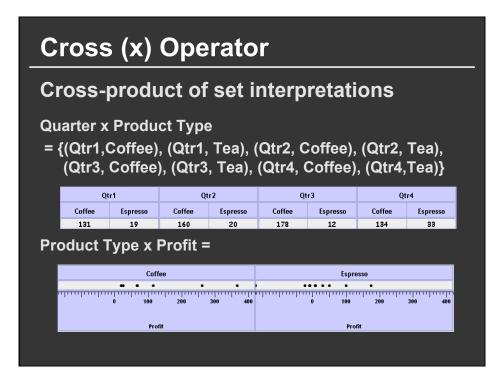
Operands are names of database fields Each operand interpreted as a set {...} Quantitative and Ordinal fields treated differently

#### Three operators:

concatenation (+) cross product (x) nest (/)







### Nest (/) Operator

**Cross-product filtered by existing records** 

**Quarter x Month** 

creates twelve entries for each quarter. i.e., (Qtr1, December)

**Quarter / Month** 

creates three entries per quarter based on tuples in database (not semantics)

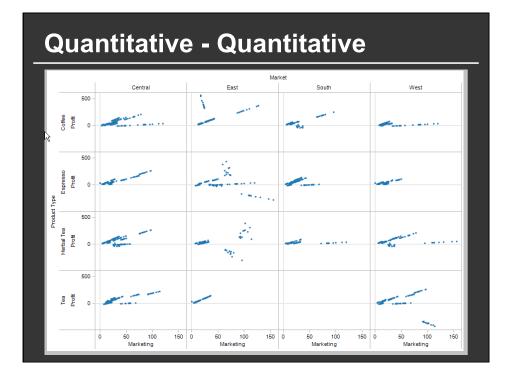
### Polaris/Tableau Table Algebra

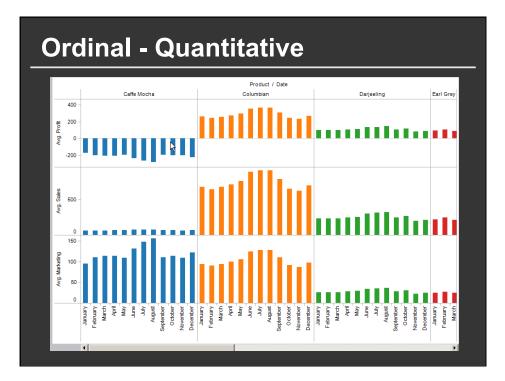
The operators (+, x, /) and operands (O, Q) provide an *algebra* for tabular visualization.

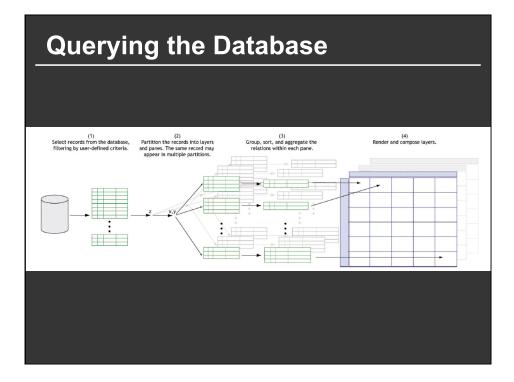
Algebraic statements are then mapped to: Visualizations - trellis plot partitions, visual encodings Queries - selection, projection, group-by aggregation

In Tableau, users make statements via drag-and-drop Note that this specifies operands NOT operators! Operators are inferred by data type (O, Q)

Ordinal - Ordinal					
State	Product Type Coffee Espresso Herbal Tea			-	
	Coffee		Herbal Lea	Tea	
Colorado	•	•	•	•	
Connecticut	•	•	•	•	
Florida	•		•	•	
Illinois	•		•	•	
lowa	•	•	•		
Louisiana	•	•	•		
Massachusetts	•	•	•	•	
Missouri	•	•	•	•	
Nevada	•	•			
New Hampshire	•	•	•	•	
New Mexico	•	•	•		
New York	٠	•	•	•	
Ohio	•	•	•	•	
Oklahoma	•	•	•		
Oregon	٠	٠	•	•	
Texas	٠	•	•		
Utah	•	•	•	•	
Washington	٠	•	•	•	
Wisconsin	٠	•	•	•	







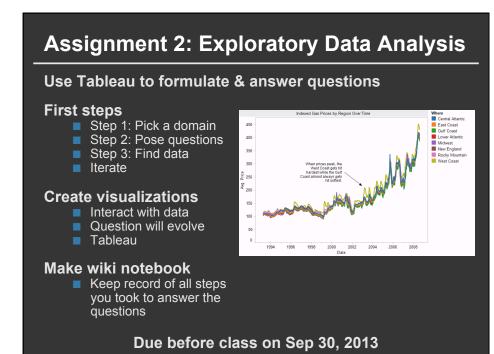
### Summary

### **Visualizing Multiple Dimensions**

- Start by visualizing individual dimensions
- Avoid "over-encoding"
- Use space and small multiples intelligently
- Use interaction to generate *relevant* views

There is rarely a single visualization that answers all questions. Instead, the ability to generate appropriate visualizations quickly is key.

### Announcements





### Mackinlay's ranking of encodings

ORDINAL

#### QUANTITATIVE

Position Length Angle Slope Area (Size) Volume Density (Val) Color Sat Color Hue Texture Connection Containment Shape Position Density (Val) Color Sat Color Hue Texture Connection Containment Length Angle Slope Area (Size) Volume Shape NOMINAL

Position Color Hue Texture Connection Containment Density (Val) Color Sat Shape Length Angle Slope Area Volume

### Topics

Signal Detection Magnitude Estimation Pre-Attentive Visual Processing Using Multiple Visual Encodings Gestalt Grouping Change Blindness

