# Challenges in High Dimensional Data Visualization

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# Outline

- » Motivation and Applications
- » Problems
- » Heidi
- » Beads
- » CROVDH
- » Related Work
- » Summary
- » Open Problems

# High Dimensional Data Visualization

» $D = \{x_1, x_2, \ldots, x_n\}$ n- points, d – dimensional

» $d > 3$

» n – large

» All real valued

» Need to

- imagine
- validate
- analyze

# Motivation

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- are within canvas
- can be accurate and/or approximate (metaphor)
- are like scatter plots
- can efficiently handle large data and higher dimensions

# Applications – Some Requirements

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» Data Sets

- Sports
- Real Estate
- Spatial-temporal
- Earthquake
- Potentially, any real valued data set

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» Useful for
  - Understanding and interpreting data
  - Clustering
  - Classification
  - Image pattern based index

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# Heidi – Visual Relationship Matrix

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**Generalization of gray scale visualization of distance matrix**

## Heidi – specific case – Nearest Neighbors

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» Construct a $n \times n$ matrix where

- Element (i,j) is a bit vector
- Bit **p** of bit vector
  - – is set to 1, if $x_j$ is in k nearest neighbor set of $x_i$,
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    - otherwise it is set to 0
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  - Length of bit vector is $2^d$-1
» Visualize bit-vectors using RGB combination of colors
» Size of matrix is $n \times n \times [(2^d - 1)$ bits mapped to RGB representation based on image type]

**So, what have you got now? – a Heidi Matrix**

# Subspaces

**Dimensions – 0, 1, 2, 3 ;**
**Number of subspaces = $2^4$ = 16;**
**sets of subspaces = $2^{15}$-1**

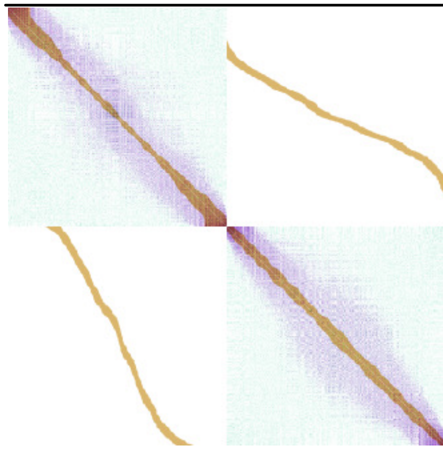
0,1,2,3

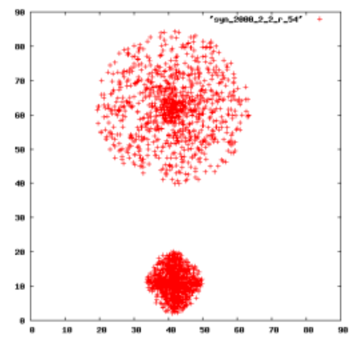
0,1,2 0,1,3 0,2,3 1,2,3

0,1 0,2 0,3 1,2 1,3 2,3

0 1 2 3

# Examples






X – brown; Y – skyblue; {X,Y} - violet

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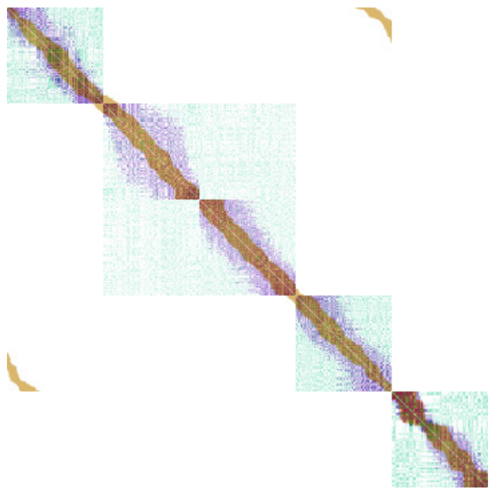

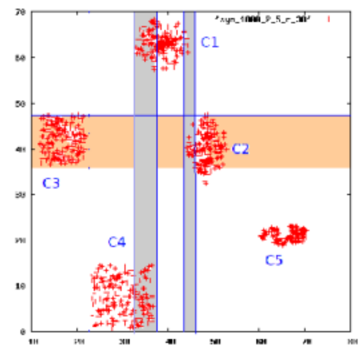


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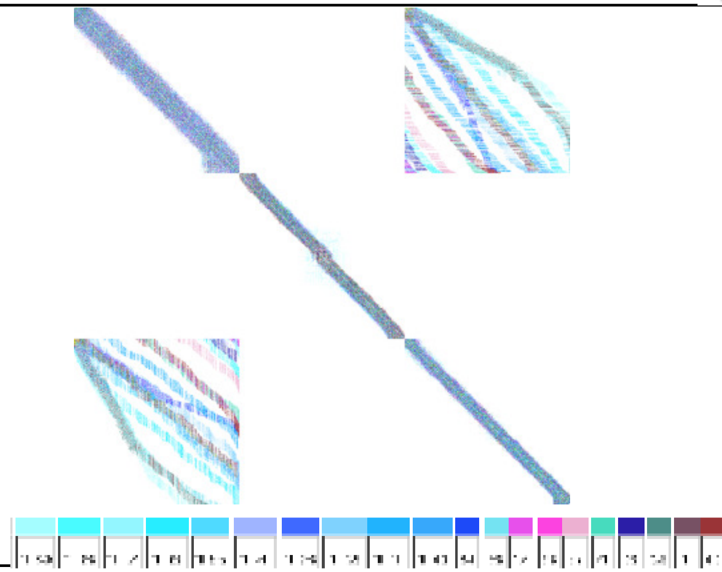
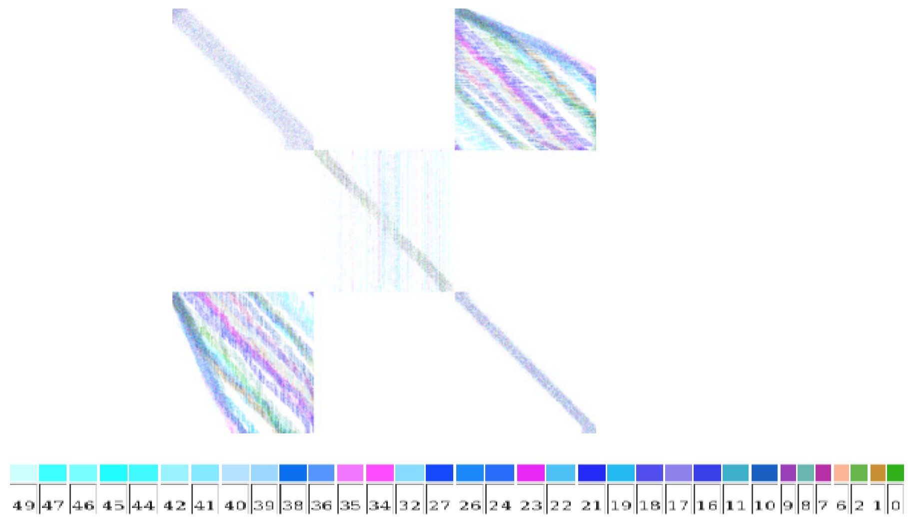
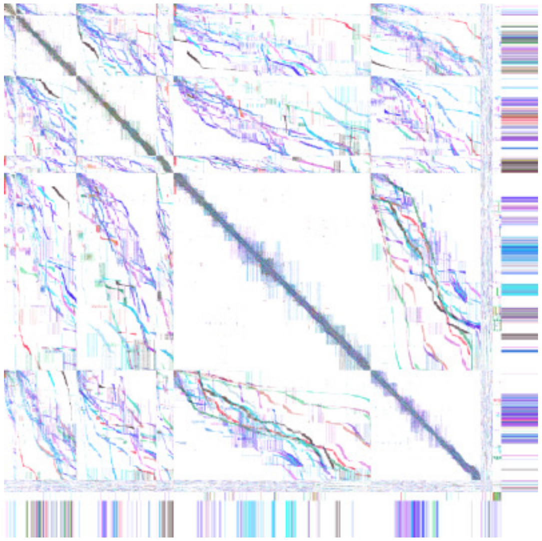
# Examples: Composite Heidi – 20d



# Examples: Composite Heidi=50d



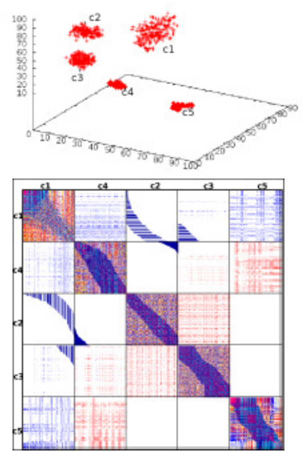
# Real-estate Property Listings

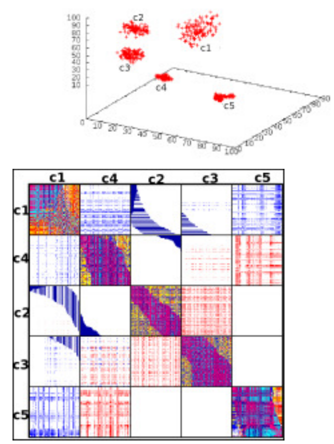


## Heidi Matrix - Issues

- » Ordering of points in a cluster
- » Size of the matrix
- » Mapping of colors to bit vectors
- » Types

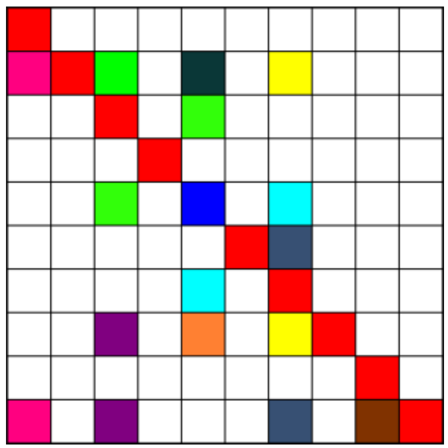
# Representative Heidi Images



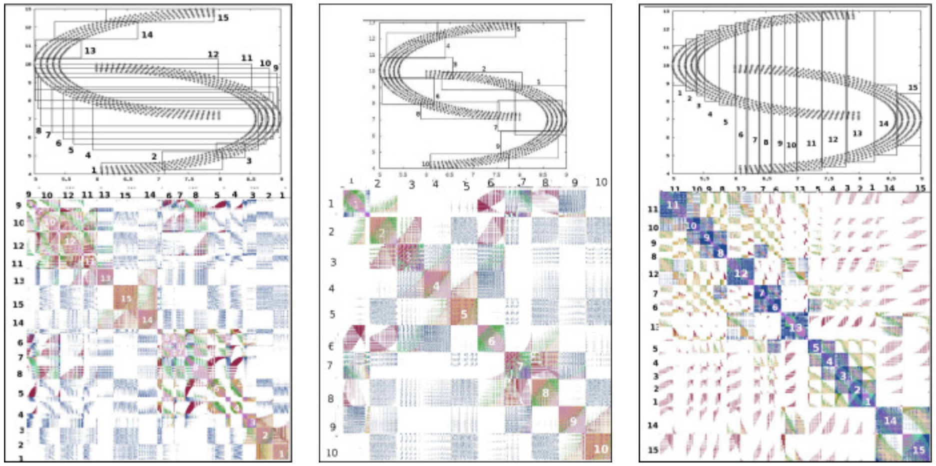

| Color | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Set of subspaces** | None | { 2 } | { 1 } | { 1 }{ 2 } | { 0 } | { 0 }{ 2 } | { 0 }{ 1 } | { 0 }{ 1 }{ 2 } |

# N= 1,00,000 and d=100, prominent subspace



| Color | Set of subspaces |
|---|---|
| | None |
| | {{ 0 }{ 1 }..{ 99 }} |
| | { 1 } |
| | {{ 0 }{ 1 }..{ 99 }} -{ 1 } |
| | {{ 0 }{ 1 }..{ 99 }} -{ 0 } |
| | { 10 } |
| | { 49 } |
| | { 65 } |
| | { 42 } |
| | { 97 } |
| | { 51 } |
| | { 16 } |
| | { 74 } |
| | { { 0 }{ 1 }..{ 99 }} - { 2 } |
| | { { 0 }{ 1 }{ 2 }..{ 99 }} - { 3 } |
| | { 9 } |
| | { 38 } |
| | { 95 } |
| | { 20 } |

# Application – index visualization



R-tree, R-tree quadratic splitting, R*-tree

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- Need to determine shape and size of the cluster
- Partition points into subsets of points
- Each subset forms a bead
- Beads are mapped to well-specified shapes

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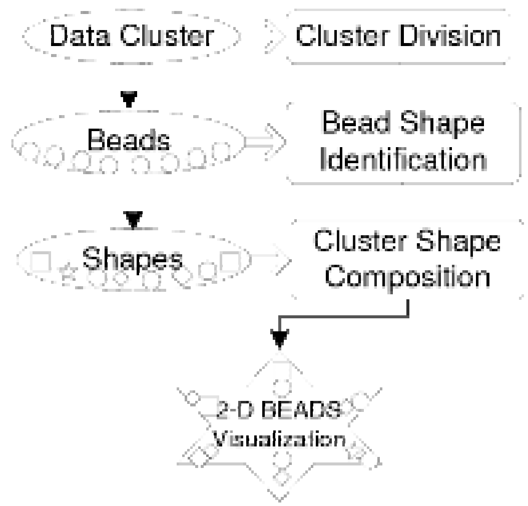
» Partition points into subsets of points

» Each subset forms a bead

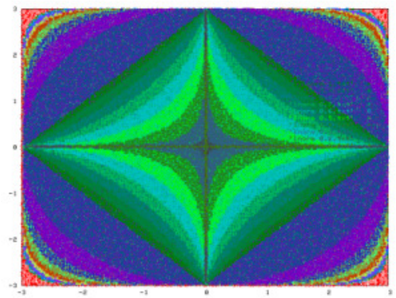
» Beads are mapped to well-specified 2-d shapes

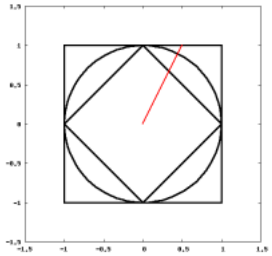
» Beads are placed in canvas to visually represent shape and size of cluster – **a necklace**

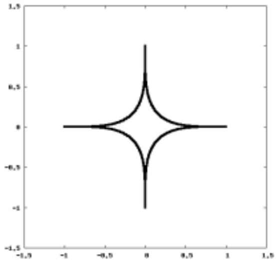
# Beads - Approach



# Basis for Beads





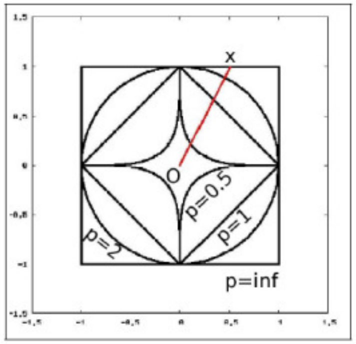


# Beads – shape and size

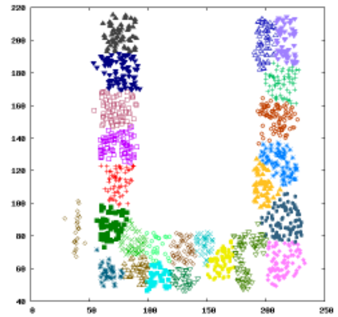
- P = set of distinct *p* values for $L_p$ norm
- Aim: Identify '*p*' and radius '$r_p$' that covers the bead tightly
- *Two approaches*

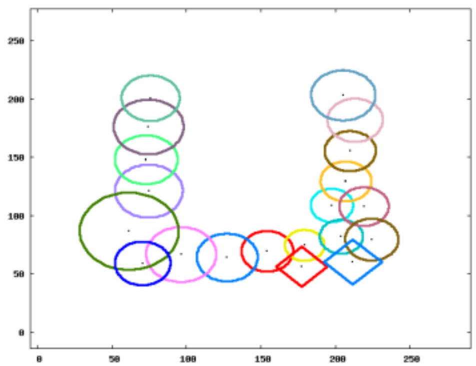
1. *Iterate from p by considering distances between centroid and furthest point using $L_p$, select the p which has the smallest distance.*
2. *Find the sum of distances among all pairs of points using $L_p$, and select the p that has smallest sum of distances*

- *The selected p gives the shape.*
- *The size is given by the diameter using the $L_p$*

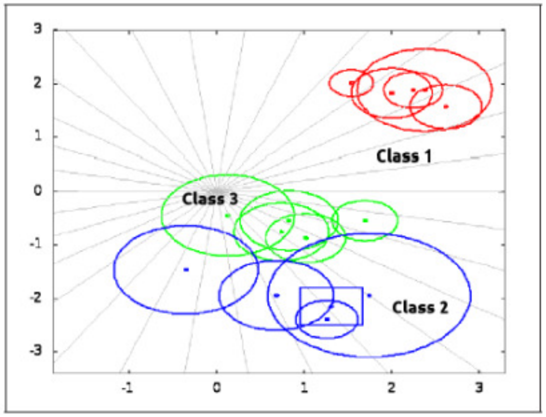


# Examples

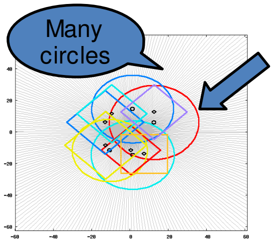




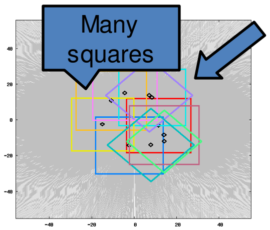
# Example – Iris Data Set



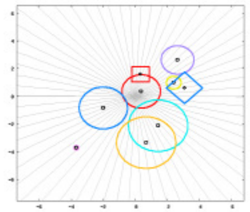
# More results




**10-D Hyper-sphere**




**10-D Hyper-cube**



**5-D NBA Player Data**

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» Divide regions of 2-d space as concentric circles

» Give region colors based on relative density

» Can also show actual points

# Uniform 100,000 [0,1] points dimensions increasing

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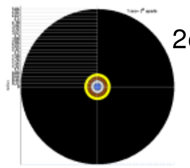
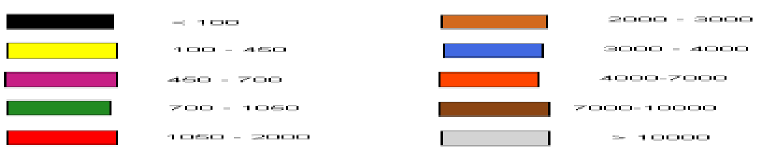


2d



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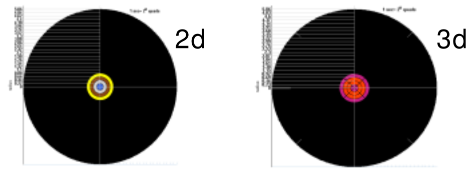


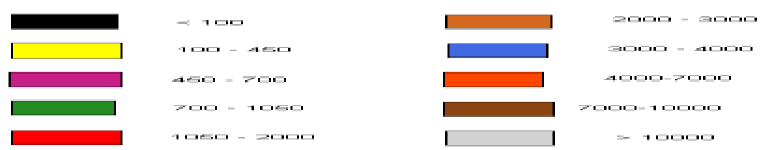

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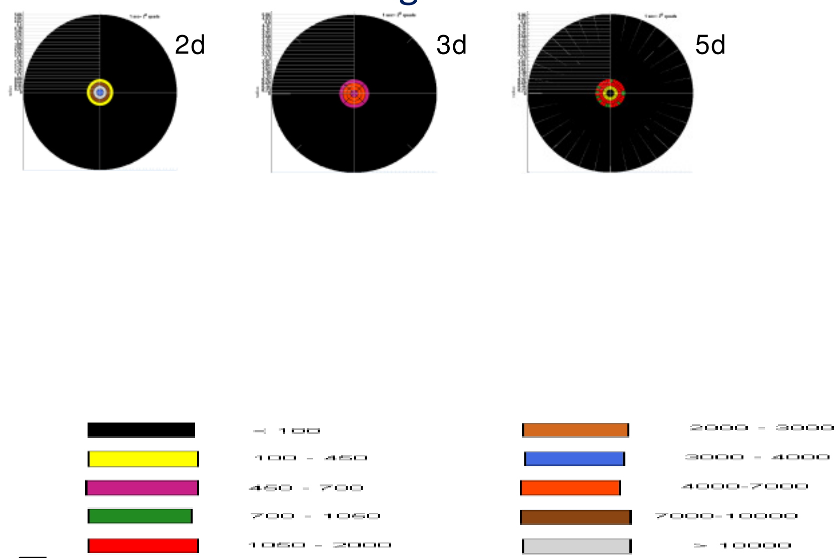

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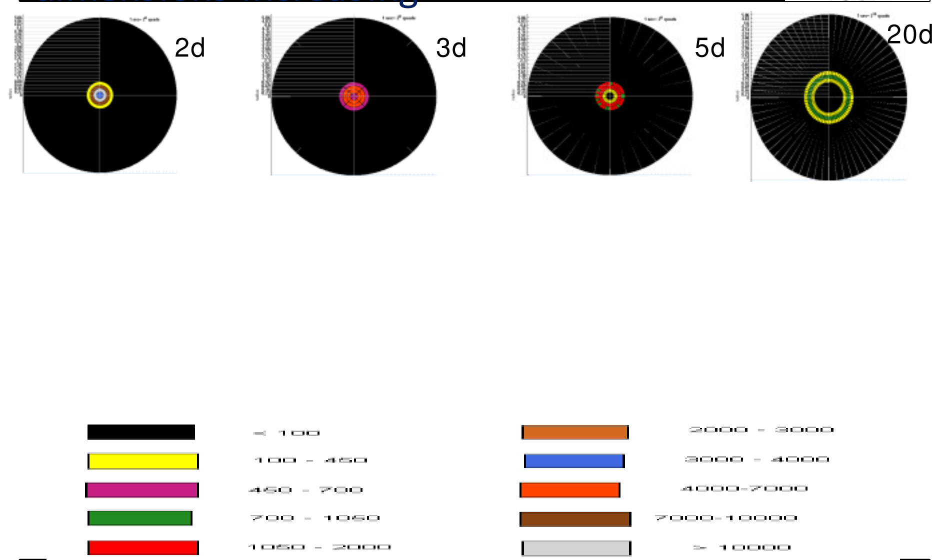

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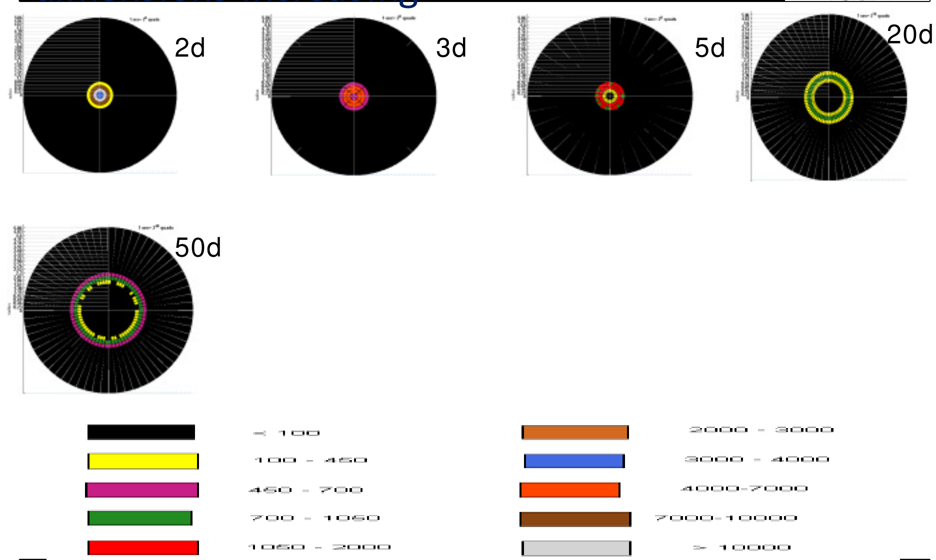

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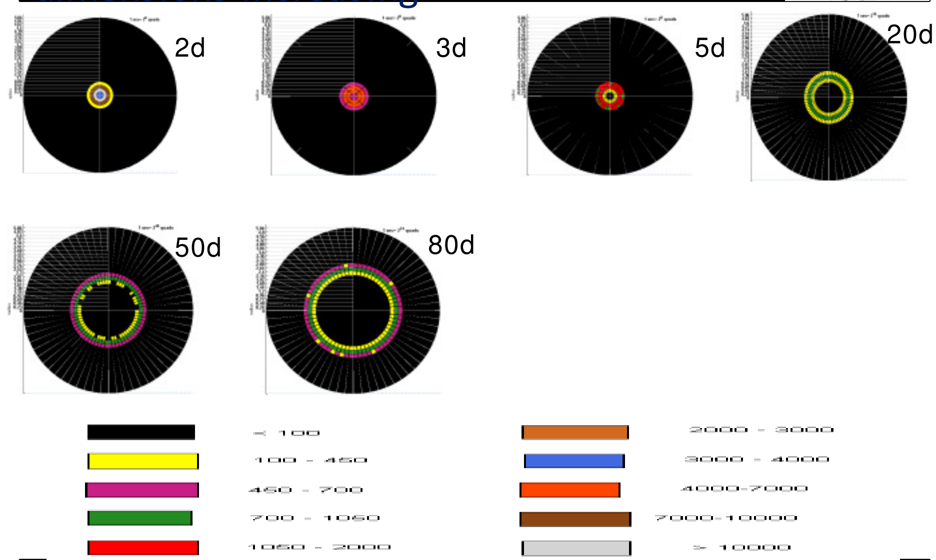

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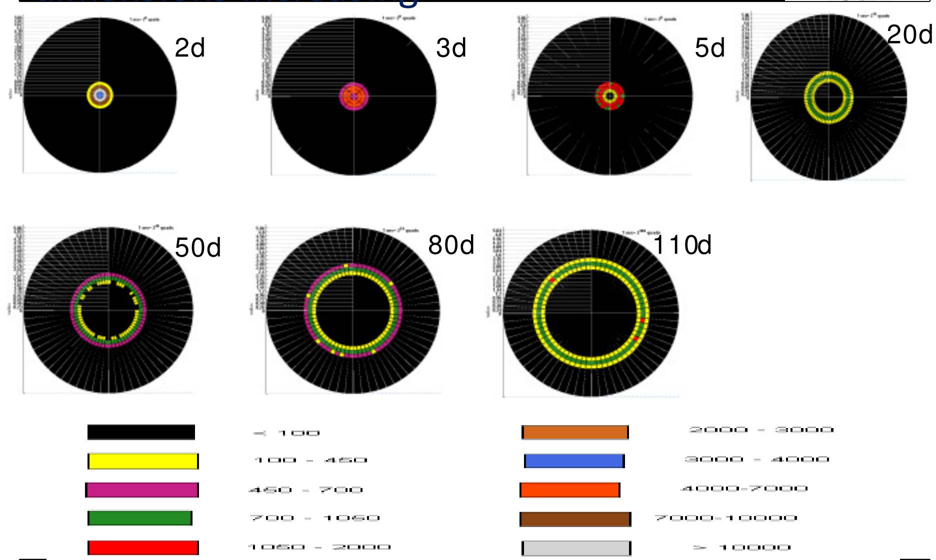

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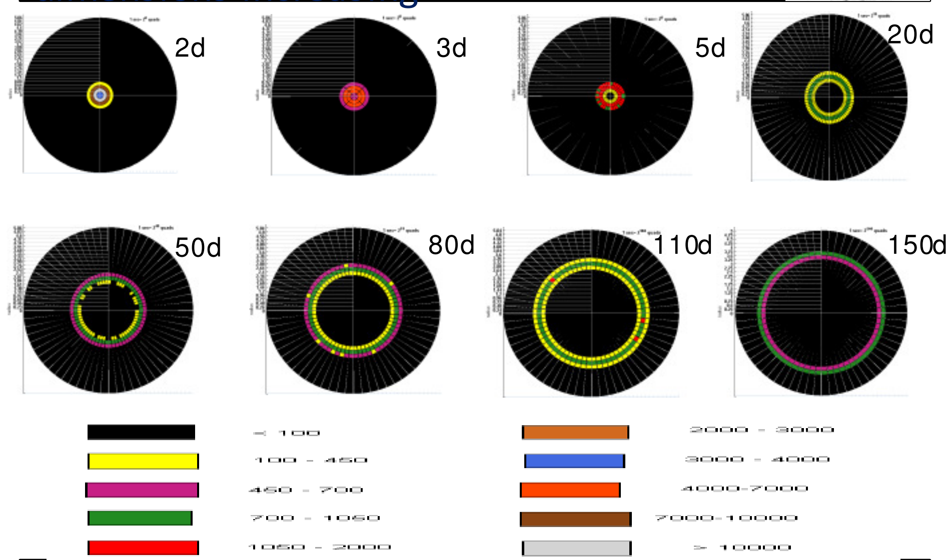
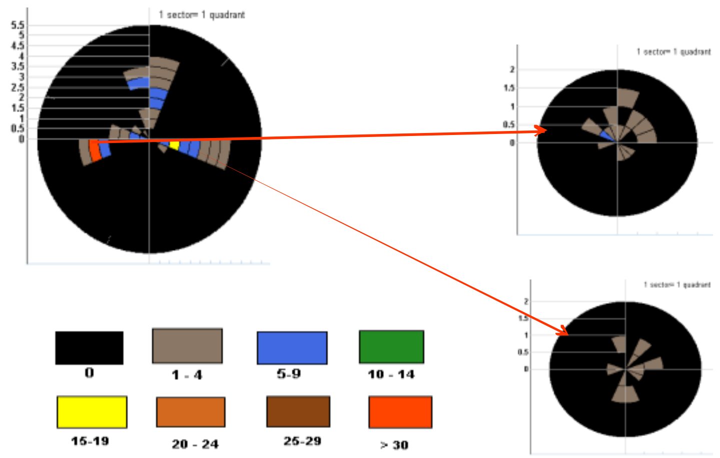


## CROVDH Visualization of IRIS data set



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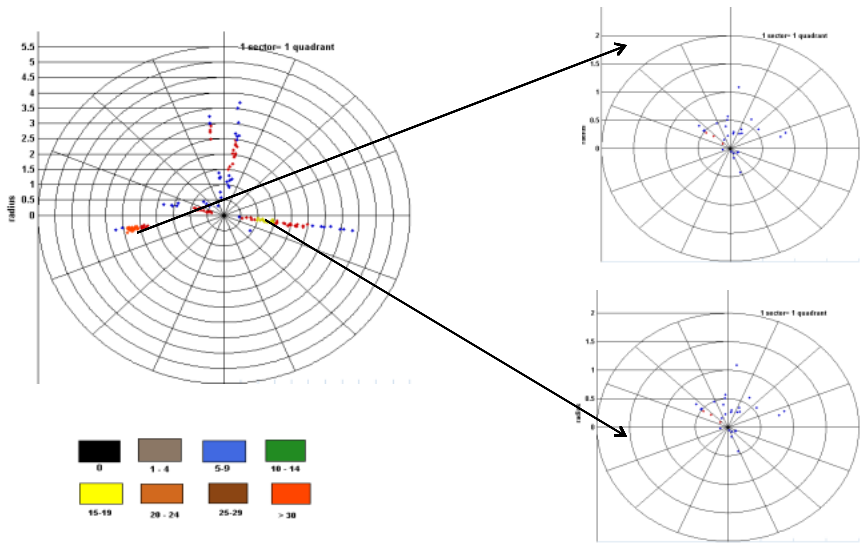

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# Related Work

» Parallel Coordinates [Inselberg 1985]

» VISA provides subspace overlap [Assent et al 2007]

» Best fit spheres or ellipsoids at high dimensions [Fitzgibbon, et al 1999, Calafiore 2002]

» Illustrative parallel coordinates [McDonnell & Muellller 2008]

» All 2-d subspaces scatter plots

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# Summary

» Subspace overlaps in high dimensions - Heidi

» Applications of Heidi

» Shape and Structure of clusters – Beads

» High Dimensional Scatter Plots - CROVDH

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# Open Problems

» Ordering of points in Heidi
» Tight fit of shapes – composition of shapes – extending to 3d shapes
» Exploration with navigation in Beads and Heidi
» Explorative analysis and analytics from CROVDH
» Time and space efficiency
» Integrated visualization tool kit for $R^d$ data

## Take away!

» Subtle work

» Fun with visualization

» Vast open areas to work in

» Dashboards for visual analytics

» Domain specific vertical solutions

» Deep mathematical problems – shape fitting – multiple loss-less visuals