# ML - Data Plotting and Visualization


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# Quotes

- Data, like a constellation in the night, finds its brilliance in the art of visualization, revealing the hidden stories of the universe it holds within.

# Quotes

- Data, like a constellation in the night, finds its brilliance in the art of visualization, revealing the hidden stories of the universe it holds within.
- Dimensionality reduction, where data’s symphony finds its graceful, concise melody

# Data Plots

Diagrams to Gain Insights

# Why Plot Data

| | | | | | |
|---|---|---|---|---|---|
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| 23.03 | 53.42 | 40.54 | 89.97 | | 21.85 |
| 12.07 | 93.43 | 51.93 | 49.30 | | 43.76 |
| 47.68 | 51.91 | 13.12 | 73.88 | | 60.29 |
| 86.20 | 41.28 | 66.24 | 62.15 | | 46.87 |
| 20.02 | 92.09 | 26.50 | 83.53 | | 70.99 |
| 48.38 | 46.21 | 10.85 | 29.61 | | 62.15 |
| 55.23 | 84.90 | 15.37 | 35.00 | | 83.23 |
| 65.30 | 26.56 | 5.78 | 72.59 | | 12.47 |
| 75.71 | 93.15 | 3.67 | 49.80 | ... | 43.05 |
| 69.73 | 53.77 | 82.80 | 43.59 | | 32.35 |
| 77.95 | 14.94 | 63.71 | 9.30 | | 1.31 |
| 58.90 | 42.53 | 62.74 | 99.91 | | 53.17 |
| 6.45 | 46.29 | 67.34 | 32.65 | | 23.94 |
| 32.39 | 57.39 | 10.61 | 54.07 | | 53.28 |
| 74.35 | 60.10 | 2.25 | 77.55 | | 12.05 |
| 82.87 | 17.02 | 80.73 | 29.60 | | 9.96 |
| 47.05 | 97.01 | 19.84 | 76.59 | | 45.90 |
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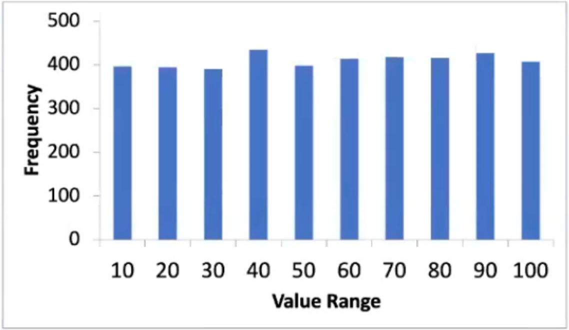

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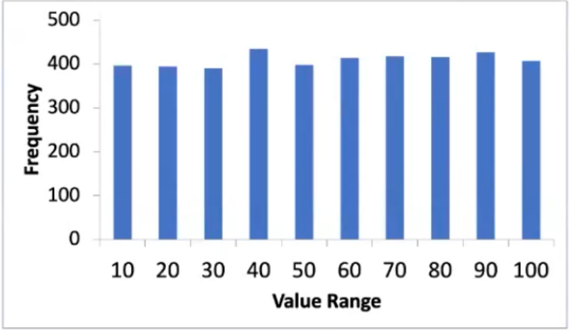


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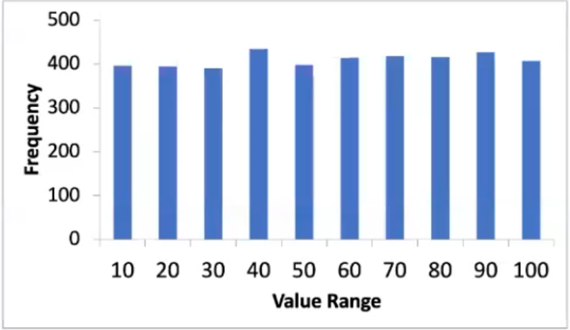
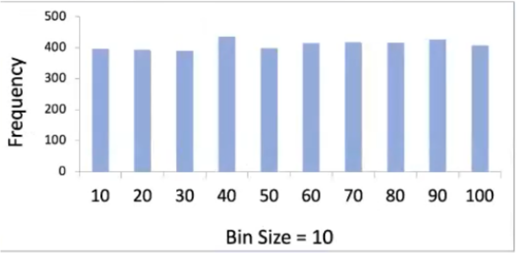



- Visualization of data provides specific insights into the nature of the data.
- Depending on the plot, we gain different insights

# Histogram

- Count of items in each bin



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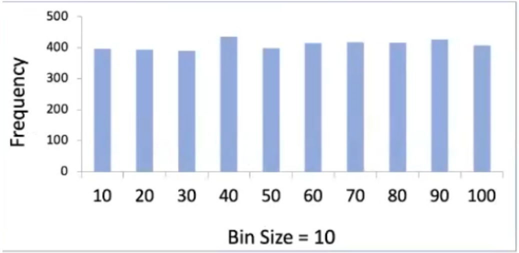
- Count of items in each bin
  - Not a bar chart of Data



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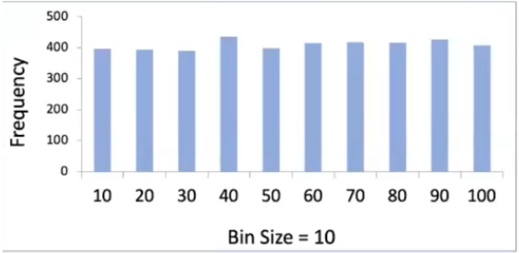

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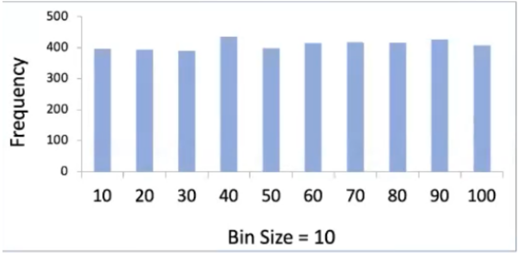

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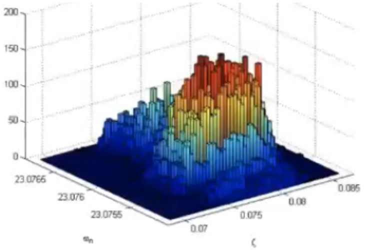
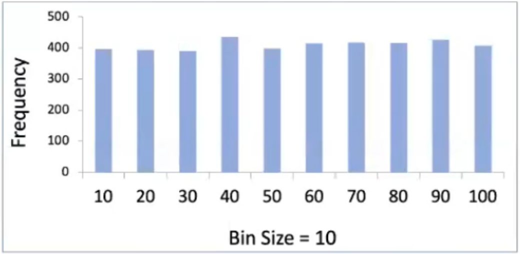
- Possible to extend to two



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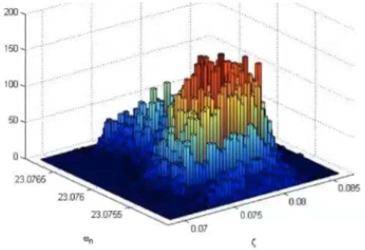


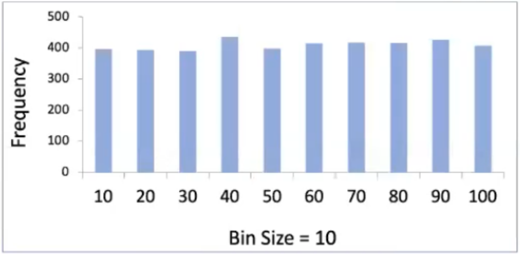


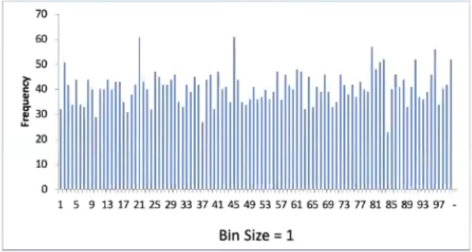

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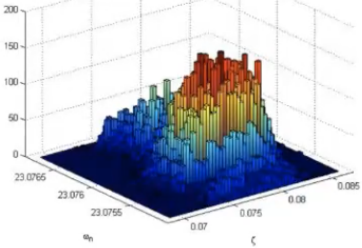
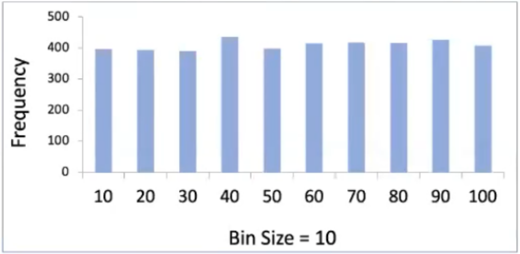
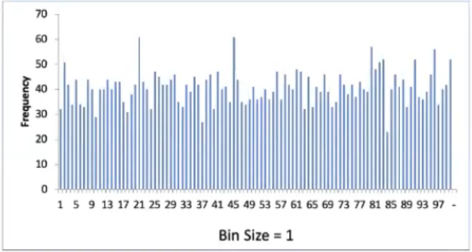
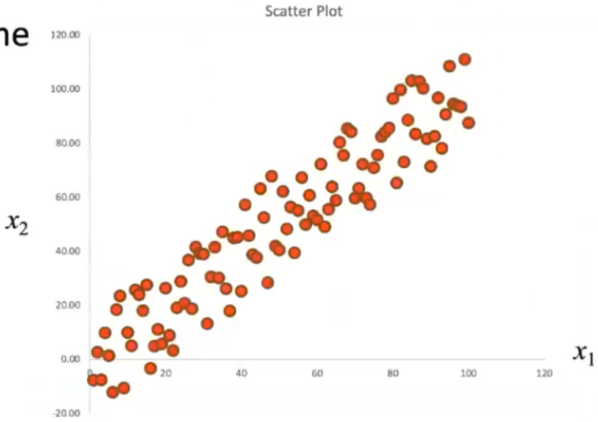


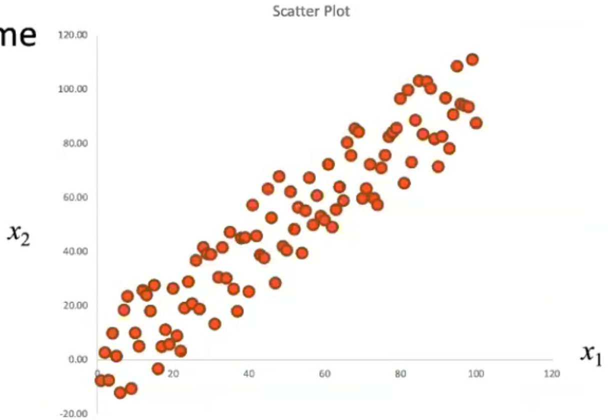
# Scatter Plot

- Plots two features at a time



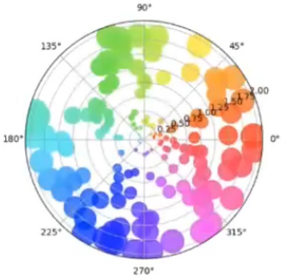
# Scatter Plot

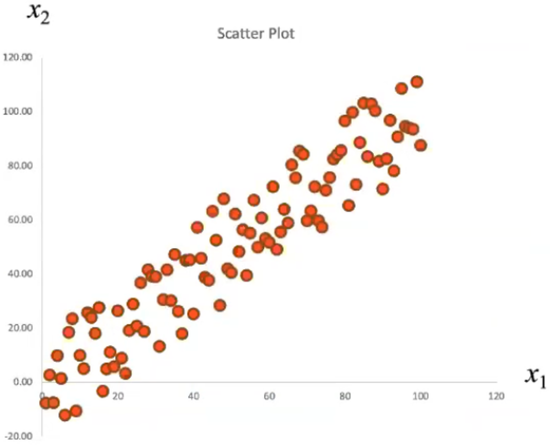
- Plots two features at a time
- Captures the correlation between the two



# Scatter Plot

- Plots two features at a time
- Captures the correlation between the two
- Other formats possible

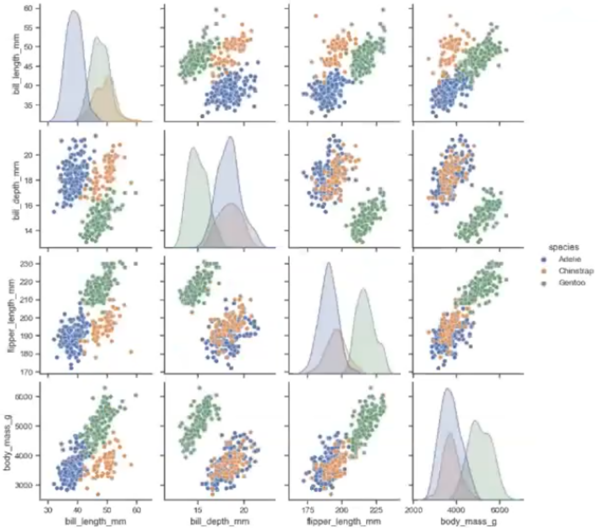



Polar Plot Courtesy: Scatterplot Documentation [matplotlib.org]

# Pair Plot

- Plot each pair of features as a matrix
  - Diagonal entries are histograms (densities)
  - Off-diagonal entries are scatter plots



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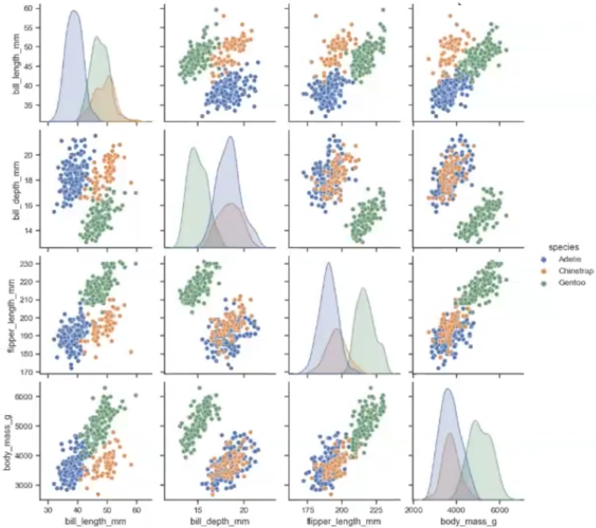
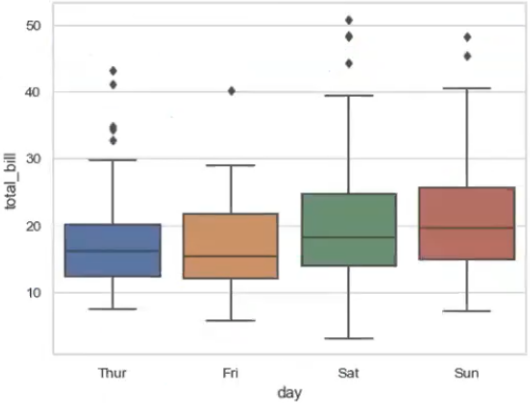
- Can use other plots at each cell.



# Box Plot

- Show median and quartiles of each feature




Plot Courtesy: Seaborn Documentation [seaborn.pydata.org]

# Box Plot

- Show median and quartiles of each feature
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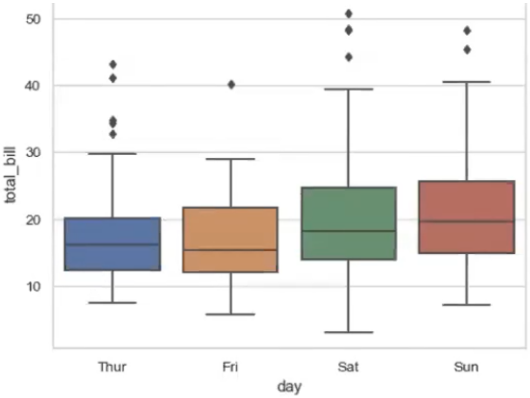


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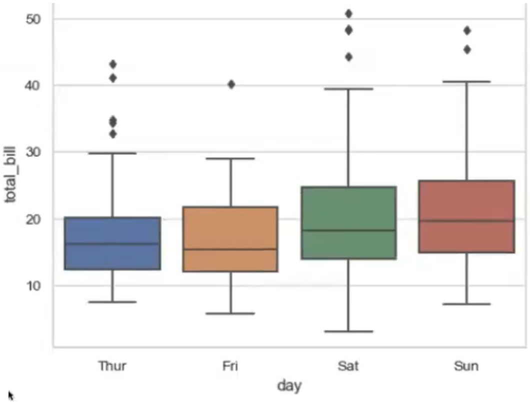


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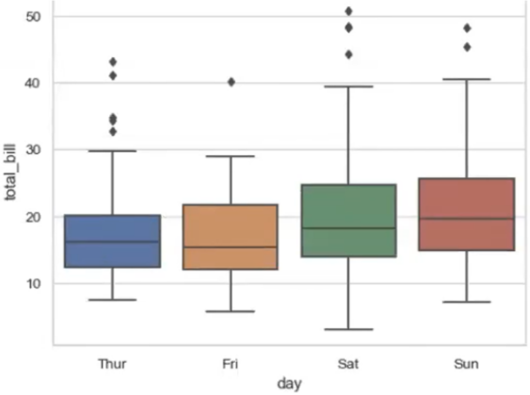


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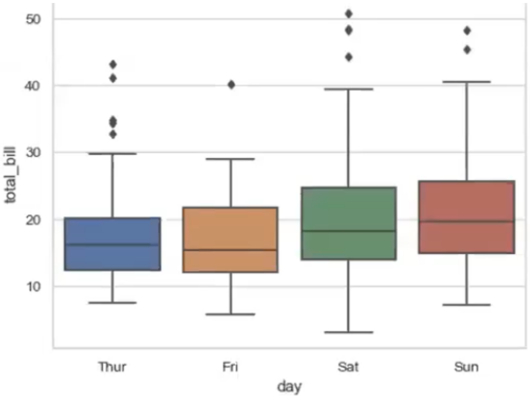
- Whiskers can represent other percentiles/data
- Simpler than histograms of each feature

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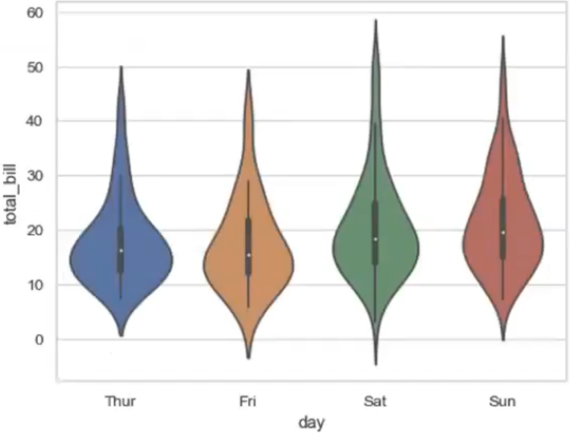
# Violin Plot

- Shows the density plot of each feature

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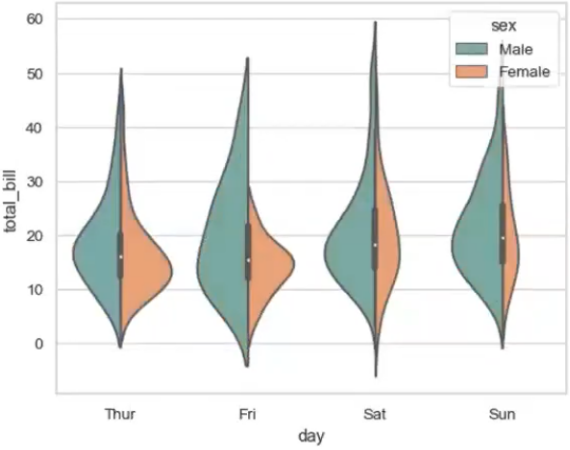


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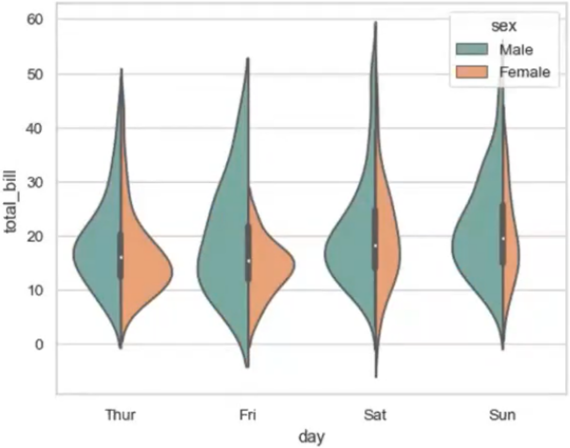


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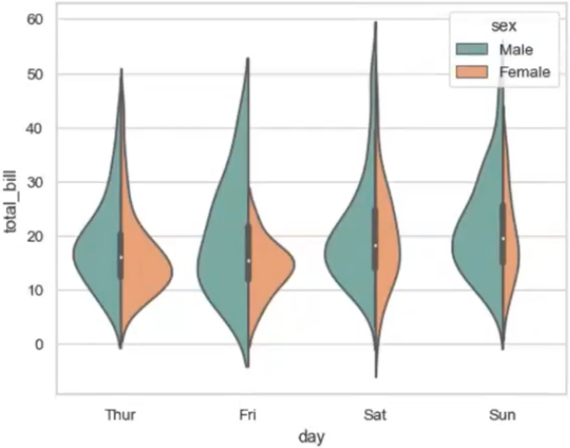


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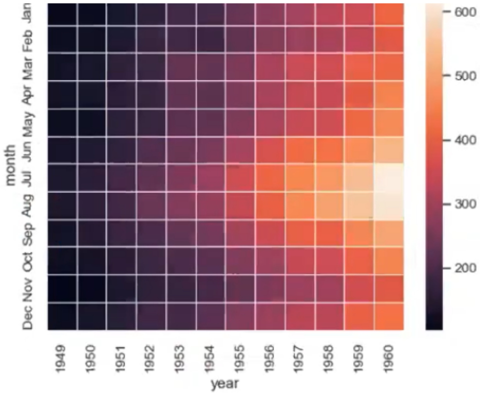
# Heat Map

- A color-coded representation of 2D data
- Can be raw data, 2D histogram or any other function of 2 variables

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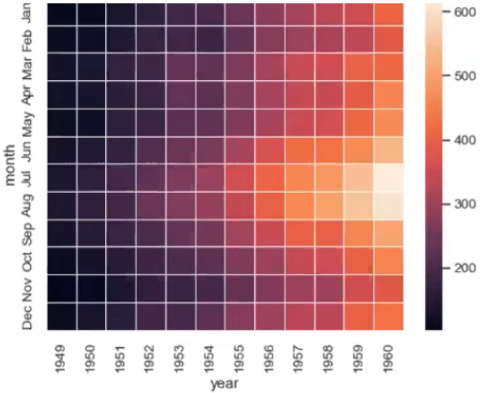


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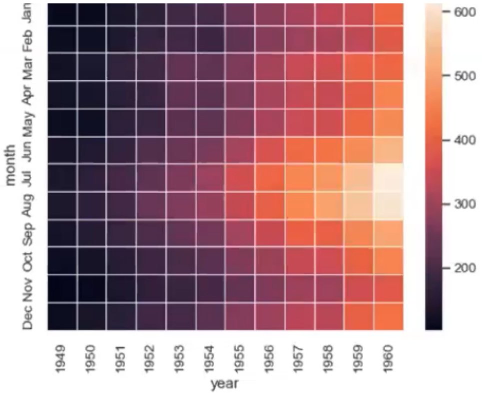
- We will learn other metrics in future that may be visualized as a heat map

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# Dimensionality Reduction

Representing data using fewer features

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$$\begin{bmatrix} z_1 \\ z_2 \end{bmatrix} = \begin{bmatrix} 1.2 & -0.4 & 2.1 & 0.3 \\ -2 & 1.1 & 0.1 & 5.8 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}$$

# Feature Selection: Forward Selection

***Algorithm:***

$z \leftarrow$ null vector; $x$ is the original feature vector

**for** each new feature to be added to $z$:

  **find** $x_i$ that gives highest accuracy when added to $z$

  **if** adding $x_i$ to $z$ improves accuracy:

    move $x_i$ to $z$

  **else**

    **break**

# Feature Selection: Backward Elimination

***Algorithm:***

$z \leftarrow x$

**for** each new feature to be removed from $z$:

    **find** $z_i$ that gives highest accuracy when removed from $z$

    **if** removing $z_i$ improves accuracy:

        remove $z_i$ from $z$

    **else**

        **break**

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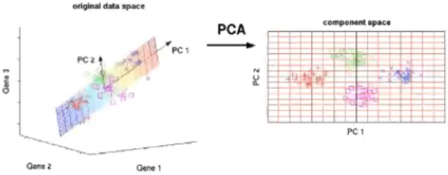
- Identify the best subset $z$ of $x$ that gives the highest accuracy for a given length of $z$
- Identify the smallest subset, $z$ of $x$, that gives a given accuracy or more
- We will learn specific algorithms that can do such selections
- The final subset may be written as a binary matrix

$$\begin{bmatrix} z_1 \\ z_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}$$

# Feature Extraction

- Goal: Identify a matrix $W$, such that $z = Wx$.




Courtesy: "PCA in Neuroscience", [math.waterloo.ca]

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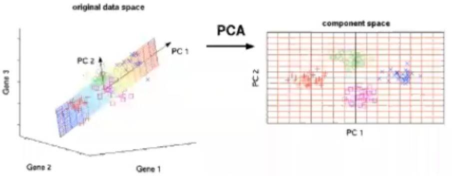


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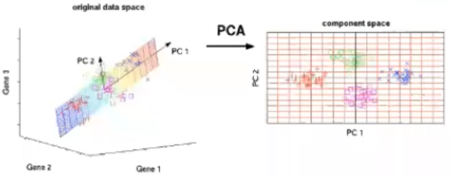


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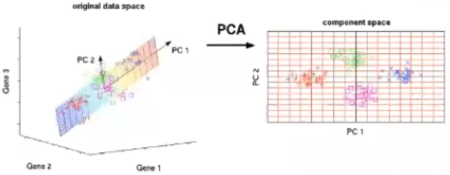


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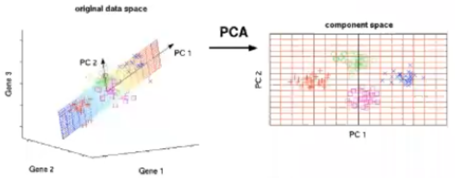


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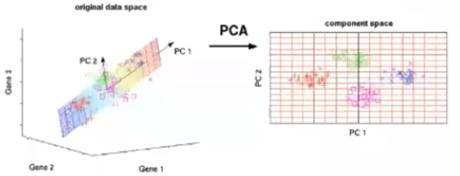


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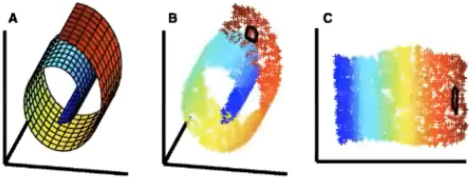
- The above model is linear.
  Non-linear methods exists as well
  - $z = f_w(x)$



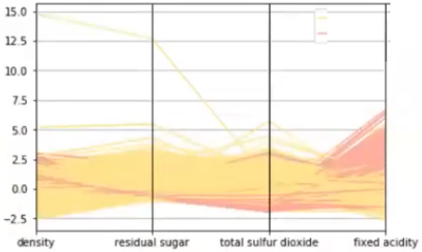

Courtesy: “DR by LLE”, by Roweis and Saul

# High Dimensional Data Visualisation

Direct Methods and Dimensionality Reduction

# Direct Visualisation

- Parallel Co-ordinates
  - Each vertical line is a dimension
  - A data item is connected by line segments
  - Large number of samples clutters the visualization



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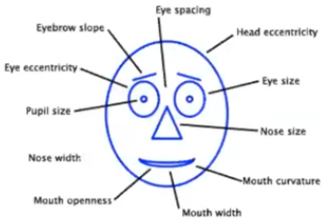

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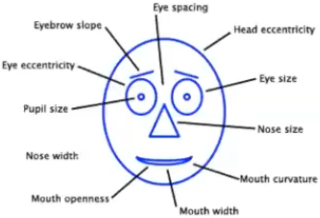


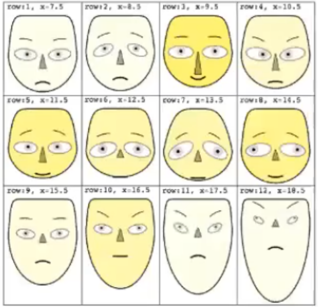

# Other Methods for Direct Visualisation

- A few approaches have been proposed to improve upon Chernoff Faces
- Empathic Visualization
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Image: The Empathic Visualization Algo: Chernoff Faces Revisited
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  - Improve visual similarity of similar vectors
- Metaphoric 3D glyphs
  - Use metaphors other than faces (say Trees)

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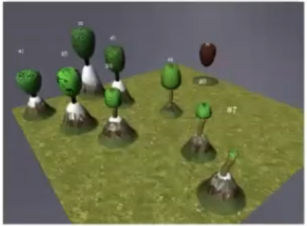

Image: "Beyond Chernoff faces: Multivariate visualization with metaphoric 3D glyphs", Marco Lardelli

# Challenges in HD Visualisation

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    - e.g., In Chernoff faces, emotions are not ordinal in eyebrow slant


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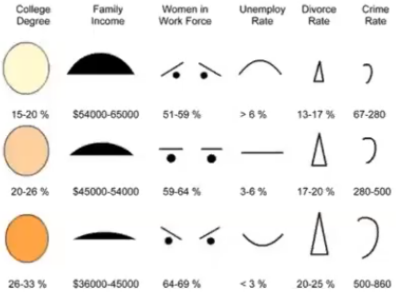


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