# Formulas and references

# A Tour Through the Visualization Zoo -**Summary of Graphic Types**

Time-Series Data

- Index Charts
- Stacked Graphs
- Small Multiples
- Horizon Graphs

Statistical Distributions

- Stem-and-Leaf Plots
- Q-Q Plots
- **SPLOM**
- Parallel Coordinates

Maps

- Flow Maps
- Choropleth Maps
- Graduated Symbol Maps
- Cartograms

Hierarchies

- Node-Link diagrams
- Adjacency Diagrams
- **Enclosure Diagrams**

Networks

- Force-Directed Layouts
- Arc Diagrams
- Matrix Views

## **Entropy**

If S is an arbitrary collection of examples with a binary class attribute, then:

 $Entropy(S) = -P_{c1}log_2(P_{c1}) - P_{c2}log_2(P_{c2})$ 

$$= -\frac{N_{C1}}{N} \log_2\left(\frac{N_{C1}}{N}\right) - \frac{N_{C2}}{N} \log_2\left(\frac{N_{C2}}{N}\right)$$

where C1 and C2 are the two classes.  $P_{C1}$  and  $P_{C2}$ are the probability of being in Class 1 or Class 2 respectively.  $N_{C1}$  and  $N_{C2}$  are the number of examples in each class. N is the total number of examples.

Note: 
$$log_2 x = \frac{log_{10}x}{log_{10}2} = \frac{log_{10}x}{0.301}$$

#### Information gain

The Gain(S, A) of an attribute A relative to a collection of examples, S, with v groups having  $|S_n|$ elements is:

$$Gain(S,A) = Entropy(S) - \sum_{v \in Values(A)} \frac{|S_v|}{|S|} * Entropy(S_v)$$

## Networking

Closeness Centrality:  $C_{CL}(v) = \frac{1}{\sum_{v \in V} dist(u,v)}$ 

Betweenness Centrality:  $C_B(v) = \sum_{s \neq t \neq v \in V} \frac{\sigma(s,t|v)}{\sigma(s,t)}$ ,

where (s, t) is the number of shortest paths between sand t.

(s,t|v) is the number of shortest paths between s and t passing through v

Density:  $den(g) = \frac{|E_g|}{|V_a|(|V_a|-1)/2|}$ 

where  $|E_g|$  is number of edges,  $|V_g|$  is number of

Clustering coefficient:  $clt(g) = \frac{3\tau_{\Delta}(g)}{\tau_{\Delta}(g)}$ ,

where  $3\tau_{\Delta}(g)$  is number of triangles,  $\tau 3(g)$  is number of connected triples

## Naïve Bayes'

For events  $A_1, A_2, ..., A_n$  and event C, classification probability is

$$P(C_j|A_1 \cap A_2 \dots \cap A_n) = \frac{P(C_j) \cdot P(A_1 \cap A_2 \dots \cap A_n|C_j)}{P(A_1 \cap A_2 \dots \cap A_n)}$$

For Bayesian classification, a new point is classified to  $C_i$  if  $P(C_i) * P(A_1|C_i) * P(A_1|C_i) * ... * P(A_n|C_i)$  is maximised.

Naïve Bayes assumes  $P(A \cap B) = P(A) * P(B)$  etc.

# Cosine or normalised dot product

For documents i and j with terms w

$$Sim(D_i, D_j) = \frac{\sum_{t=1}^{N} w_{it} * w_{jt}}{\sqrt{\sum_{t=1}^{N} (w_{it})^2 * \sum_{t=1}^{N} (w_{jt})^2}}$$

$$ROC$$

$$TPR = \frac{TP}{TP + FN}, \quad FPR = \frac{FP}{FP + TN}$$

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