#### CS 495: Data Visualization for Data Scientists

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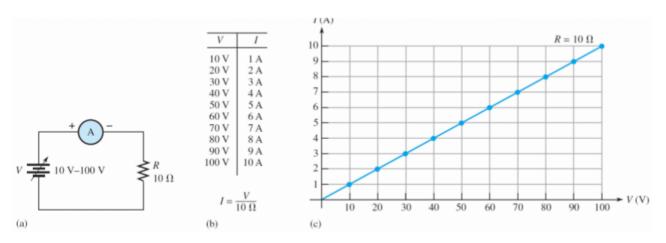
## **Prologue and Motivation**

- "A picture is worth a thousand words" (English idiom).
- Recent research suggests that:
  - "Retina communicates to brain at 10 million bits per second. 40 words per second are read at 10 sec.; call it 1000 bits/sec. which is 1/10,000" 1

 $<sup>^{1}</sup> h \texttt{ttps://www.edwardtufte.com/bboard/q-and-a-fetch-msg?msg\_id=0002NC}$ 

#### **Data Visualization for Exploration**

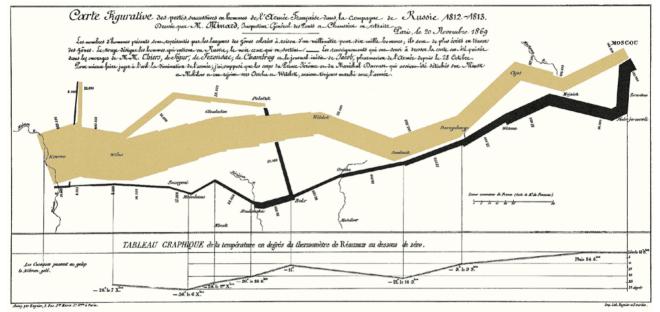
#### The discovery of the very classic Ohm's law



• Then, comes Statistics, Statistical Learning, Pattern Recognition, to formalize the observed relationship: model, regression, p-values, variance, confidence interval, etc.

#### **Data Visualization for Illustration and Presentation**

#### Invasion/retreat of French army to/from Russia:

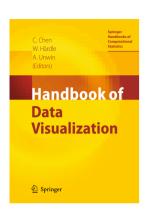


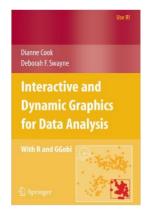
"Vivid historical content and brilliant design combine to make this one of the best statistical graphics ever" (Tufte, 2006, P. 122)

## **Course Objectives**

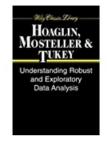
- Data Visualization:
  - for exploring, extracting secrets, and understanding
    - \* build intuition and insight.
    - \* allow you getting the feeling of the patterns, secrets, hiding in data.
    - \* understand your data before any mathematical treatment.
  - for illustration, displaying, and conveying what has been explored.
- Linking to real life problems.
- Coding and scientific computing.
- We will emphasize on the foundations than the evolving technology.
- This course is just a very interesting voyage in high dimensions and hyperspace. Please, prepare your baggage, video cam, juice, and say cheese.

## Texts, References, and Prerequisites





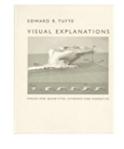




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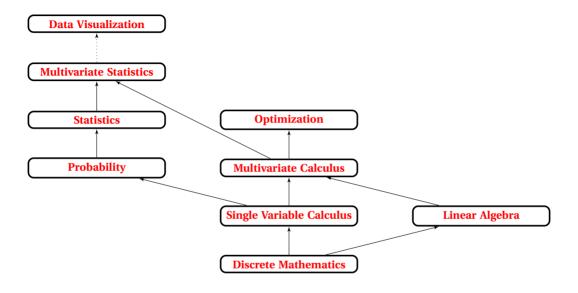


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Tufte, E. R., 2006. Beautiful evidence. Graphics Press, Cheshire, Conn



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I	Exp	loration
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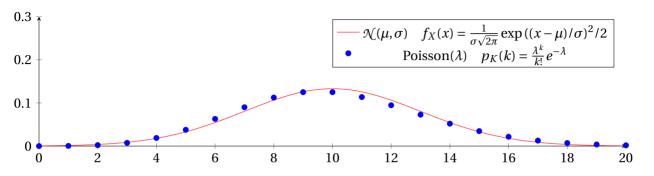
## Part I

## **Exploration**

## Chapter 1

## **Some Necessary Probability and Statistics**

#### 1.1 Samples from Discrete and Continuous Distributions



- Here,  $\mu = 10$ ,  $\sigma = 3$ ,  $\lambda = 10$  (how do you know from figure?)
- $P(X = x) = 0, P(K = k) \neq 0.$
- How samples look like?
- What about cluttering (observations overlaying each other).

#### 1.2 Cumulative Distribution Function (CDF)

$$F(x) = P(X \le x)$$

$$= \int_{-\infty}^{x} f(u) \ du = P(X < x)$$
 (cont. var.)

**Definition 1** ( $F^{-1}$ ): The  $p^{th}$  quantile is defined as, the value  $x_p$  of the r.v. that satisfies  $F(x_p) = p$ .

- If *F* is monotonically (strictly) increasing, the *p*th quantile is unique (see figure).
- $F^{-1}$  (.5) is the median.
- $F^{-1}$  (.25) and  $F^{-1}$  (.75) is the lower and upper quartile.

#### Example 2 Suppose

$$F(x) = x^{2}, 0 \le x \le 1,$$

$$x_{p}^{2} = p,$$

$$x_{p} = \sqrt{p},$$

$$x_{.5} = \sqrt{.5} = .707$$

$$x_{.25} = \sqrt{.25} = .5$$

$$x_{.75} = \sqrt{.75} = .866$$

#### 1.3 Normal Distribution

**Corollary 3** *If*  $X \sim \mathcal{N}(\mu, \sigma)$  *and*  $Z = \sim \mathcal{N}(0, 1)$  *(a standard normal), then* 

$$P(Z < z) = \int_{-\infty}^{z} f_{Z}(u) \ du = \Phi(z)$$

$$\Phi(z) = 1 - \Phi(-z)$$

$$\frac{(X - \mu)}{\sigma} \sim Z$$

$$P(X < x) = P\left(\frac{X - \mu}{\sigma} < \frac{x - \mu}{\sigma}\right) = P\left(Z < \frac{x - \mu}{\sigma}\right) = \Phi\left(\frac{x - \mu}{\sigma}\right)$$

**Example 4** [ $\sigma$  and  $\mu$ ]:

$$P(|X - \mu| < \sigma) = P(-\sigma < X - \mu < \sigma)$$

$$= P\left(-1 < \frac{X - \mu}{\sigma} < 1\right)$$

$$= P(-1 < Z < 1)$$

$$= \Phi(1) - \Phi(-1)$$

$$= .68$$

$$P(|X - \mu| < 2\sigma) = \Phi(2) - \Phi(-2)$$

$$= .9545,$$

$$P(|X - \mu| < 3\sigma) = \Phi(3) - \Phi(-3)$$

$$= .9973$$

(almost all the probability measure)

#### 1.4 Quantile Estimation, Outliers Cutoff, and Thick Tails

The ordered statistic  $x_{(p=i,d)}$  is defined by interpolation as:

$$x_{(i.d)} = x_{(i)} + d(x_{(i+1)} - x_{(i)}) = (1 - d)x_{(i)} + dx_{(i+1)} \qquad = \widehat{F}^{-1}(p)$$

$$x_{((n+1)/2)} = \begin{cases} x_{((n+1)/2)}, & n \text{ is odd.} \\ x_{(n/2+1/2)} = (1/2)(x_{(n/2)} + x_{(n/2+1)}) & n \text{ is even.} \end{cases} \qquad = \widehat{F}^{-1}(0.5)$$

$$x_{((1+(n+1)/2)/2)} = x_{((n+3)/4)} \qquad = \widehat{F}^{-1}(0.25)$$

$$x_{(((n+1)/2+n)/2)} = x_{((3n+1)/4)} \qquad = \widehat{F}^{-1}(0.75)$$

$$W_L = Q_L - 1.5(Q_U - Q_L)$$

$$W_U = Q_U - 1.5(Q_U - Q_L)$$

$$W_U = Q_U - 1.5(Q_U - Q_L)$$

$$x_{((n+1)/2+n)/2} = x_{((3n+1)/4)} \qquad = \widehat{F}^{-1}(0.75)$$

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$$x_{((((n+1)/2+n)/2+n)/2+n} = x_{(((n+1)/2+n)/$$

(p<sup>th</sup> quantile)

(median: M)

(lower cutoff)

(upper cutoff)

(lower quartile:  $Q_L$ )

(upper quartile:  $Q_{U}$ )

 $W_U = Q_U + 1.5d_Q = \mu + 2.698\sigma$   $P(X < W_L) + P(X > W_U) = 2P(X < W_L) = 2\Phi\left(\frac{(\mu - 2.698\sigma) - \mu}{\sigma}\right) = 2\Phi(-2.698) = 0.00698$ 

 $p = F(x_p) = P(X < x_p) = \Phi\left(\frac{x_p - \mu}{\sigma}\right)$ 

 $F^{-1}(p) = x_p = \mu + (\Phi^{-1}(p))\sigma$ 

 $Q_L = F^{-1}(0.25) = \mu - 0.6745\sigma$  $Q_{II} = F^{-1}(0.75) = \mu + 0.6745\sigma$ 

 $W_L = Q_L - 1.5 d_O = \mu - 2.698 \sigma$ 

So, a sample (patch) of 1000 obs. will have almost 7 obs. outside the cutoffs.

 $d_{\rm O} = 1.349\sigma$ 

#### Definition 7 (Hoaglin et al. (2000))

**Outlier** observation with different underlying behavior as compared with the bulk of the data which deserves more investigation. The cutoffs  $W_L$  and  $W_U$  will be arbitrarily used for outlier detection. Outliers could be:

• false value due to measurement error.

Example 6 (meaning of quantile from  $X \sim \mathcal{N}(\mu, \sigma)$ ):

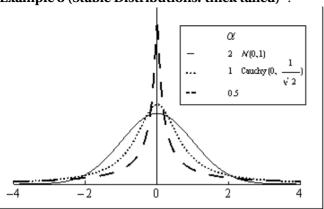
• right value due to thick tail.

when small part of the data is replaced by new numbers, possibly very different from the original ones.

**Robustness** insensitivity to departure from assumptions surrounding an underlying probabilistic model.

**Resistance** insensitivity to misbehavior in data. A resistant method produces results that change only slightly

#### **Example 8 (Stable Distributions: thick tailed)**:



$$\alpha = 2 \mathcal{N}(0,1)$$

\_

$$\alpha = 1$$
 Cauchy(0,  $1/\sqrt{2}$ )

1.5 Transformation and Log-sca	ıle
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## **Chapter 2**

## **History and Introduction**

#### 2.1 Evolution of Data Visualization

#### 2.2 Types of Variable

**Quantitative**, where some measure is given as a value; e.g., X = 1, 3, -2.5.

 $\textbf{Qualitative} \ (\text{or Categorical}), where \ \text{no measures or metrics are associated}; \text{e.g.}, \textit{X} = \textit{Diseased}, \textit{Nondiseased}.$ 

**Ordered Categorical**; e.g., X = small, medium, ... The variable  $X \in \mathcal{G}$ , a set of possible values.

**Example 9** (iris **dataset**) : (150 observations, by R. A. Fisher, the father of Statistics)

Index	SepalLength	SepalWidth	PetalLength	PetalWidth	Class
1	5.1	3.5	1.4	0.2	Iris-setosa
2	4.9	3	1.4	0.2	Iris-setosa
3	4.7 3.2		1.3	0.2	Iris-setosa
4	4.6	3.1	1.5	0.2	Iris-setosa
5	5	3.6	1.4	0.2	Iris-setosa
6	5.4	3.9	1.7	0.4	Iris-setosa
7	4.6	3.4	1.4	0.3	Iris-setosa
8	5	3.4	1.5	0.2	Iris-setosa
9	4.4	2.9	1.4	0.2	Iris-setosa
10	4.9	3.1	1.5	0.1	Iris-setosa
:					
51	7	3.2	4.7	1.4	Iris-versicolo
52	6.4	3.2	4.5	1.5	Iris-versicolo
53	6.9	3.1	4.9	1.5	Iris-versicolo
54	5.5	2.3	4	1.3	Iris-versicolo
55	6.5	2.8	4.6	1.5	Iris-versicolo
56	5.7	2.8	4.5	1.3	Iris-versicolo
57	6.3	3.3	4.7	1.6	Iris-versicolo
58	4.9	2.4	3.3	1	Iris-versicolo
59	6.6	2.9	4.6	1.3	Iris-versicolo
60	5.2	2.7	3.9	1.4	Iris-versicolo
:					
101	6.3	3.3	6	2.5	Iris-virginica
102	5.8	2.7	5.1	1.9	Iris-virginica
103	7.1	3	5.9	2.1	Iris-virginica
104	6.3	2.9	5.6	1.8	Iris-virginica
105	6.5	3	5.8	2.2	Iris-virginica
106	7.6	3	6.6	2.1	Iris-virginica
107	4.9	2.5	4.5	1.7	Iris-virginica
108	7.3	2.9	6.3	1.8	Iris-virginica
109	6.7	2.5	5.8	1.8	Iris-virginica
110	7.2	3.6	6.1	2.5	Iris-virginica

- Knowing the physics of the problem helps understanding data.
- Iris is a genus of species of flowering plants with showy flowers. (In Arabic: Alsawsan).
- Iris is extensively grown as ornamental plant, medicine, drugs.





## **Chapter 3**

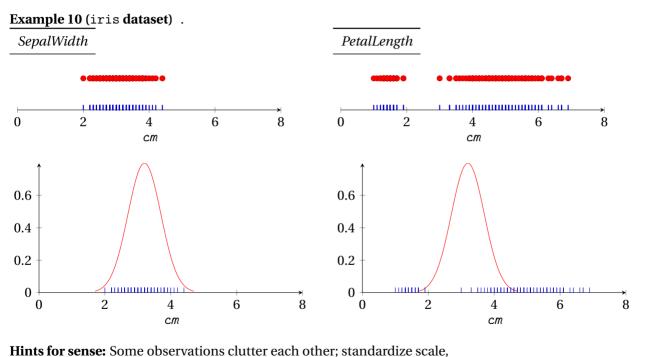
## 1-D charts

#### Per Hoaglin et al. (2000):

- How nearly symmetric the sample is?
- How spread out the numbers are?
- Whether a few values are far removed from the rest?
- Whether there are concentrations of data?
- Whether there are gaps in the data?

#### 3.1 A Quantitative Variable

#### 3.1.1 Rug Plot (the simplest ever)



@@@ use Gaussian fit (blindly before visualization) then Gaussian mixture (after visualization). Then calculate the probability of having 2<X<3 and compare to no.obs/150.

@@@ for the red normal distribution, calculate mu and sigma from data.

#### 3.1.2 Stem-and-Leaf

@@@ needs revisiting and drawing

Invented by by John W. Tukey, (who also coined the word **bi**nary digit).

It is a multi-functioning of the "data measure", i.e., the displaying element (here the digit) has more than one function (position and value).

Variations: e.g., adding rank left to each stem.

$$L = \left[10 \times \log_{10} n\right]$$
 very good for  $20 < n < 300$ 

#### 3.1.3 Histograms: (for more details check St 121.)

$$I_{(c)} = \begin{cases} 1 & \text{if } c \text{ is } T \\ 0 & \text{if } c \text{ is } F \end{cases}$$
 (indicator function) 
$$I_{(c)} \sim Bernoulli\left(\Pr\left(c\right)\right).$$

For data  $x_1, ..., x_n$  divide the data range T to K equal regions of equal width  $\Delta$  (so that  $K = T/\Delta$ )

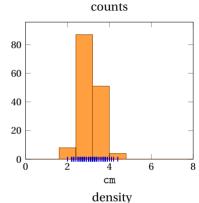
$$T_k = [t_0 + \Delta k, t_0 + \Delta (k+1)]$$
  
=  $[t_k, t_{k+1}], k = 0, ..., K-1,$ 

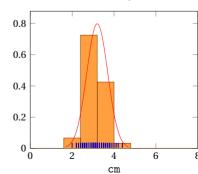
Notice: decreasing  $\Delta$  increases K.

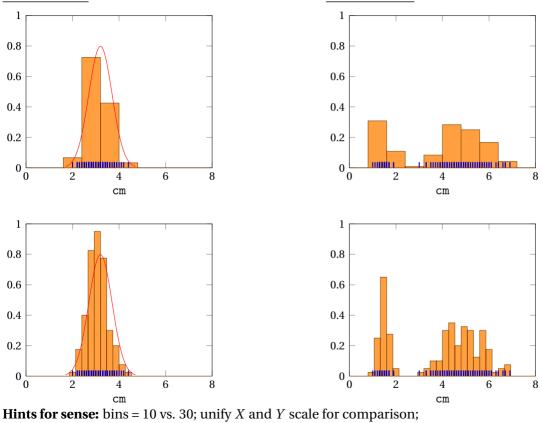
We have three versions of histogram:

$$\begin{split} N_k &= \sum_{i=1}^n I_{(X_i \in T_k)}, & \text{(counts)} \\ R_k &= \frac{N_k}{n} \xrightarrow{p} \Pr(X \in T_k) & \text{(relative counts)} \\ f_k &= \frac{N_k}{\Delta n} \xrightarrow{p} \frac{\Pr(X \in T_k)}{\Delta} \approx \frac{f_X(t_k) \Delta}{\Delta} = f_X(t_k) & \text{(density)} \end{split}$$









SepalWidth

PetalLength

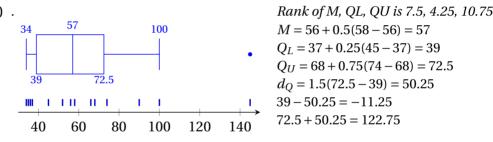
#### **3.1.4** Box Plot

back to example 11

To observe a glance: location, spread, skewness, tail length, and outlying data points.

lower whisker	lower quartile	median	upper quartile	upper whisker
$Q_L - 1.5 d_Q \le \min x_i = W_L$	$Q_L$	M	$Q_U$	$W_U = \max x_i \le Q_U + 1.5 d_Q$

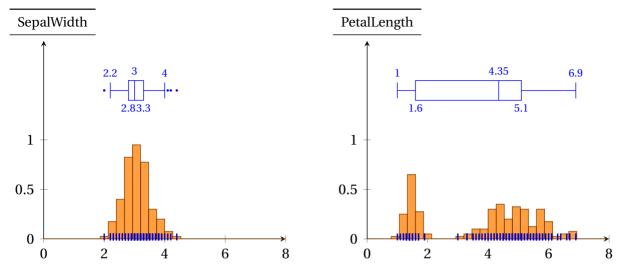
#### **Example 11 (Letter Values)** .



we could have defined a boxplot based on mean and variance => less resistant. Why boxplot is not defined in terms of  $W_L = \widehat{F}^{-1}(0.05)$ 

why boxplot is not defined in terms of mean and variance

for small patches  $\frac{\text{\# of obs.} n}{>} \Pr(X < W_L)$ 



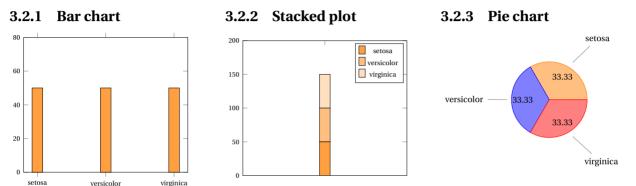
Comparison

	Rug plot	Histogram	<b>Boxplot</b>	Stem-and-leaf	
density	0 (clutter)	1	0 (region)	1	
values	1	1	0 (region)	1	
large $N$	0 (clutter)	1	1	0	
resistance	0 (outliers)	0 (outliers)	1	0 (outliers)	
discrete	0 (clutter)	1	1	1	
Clutter could be alleviated by α-channel					

Clutter could be alleviated by  $\alpha$ -channel.

#### 3.2 A Categorical Variable

Suppose we have only last column of table in Sec. 9; no numerical values. Only histogram-like charts: bar chart, stacked bar, pie chart, or any equivalent.



- Bar chart is more professional and scientific; pie chart is more for illustration.
- More details can be put on the bar chart (including boxplot for each class, etc.)
- Bar chart and Stacked plot are utilized more for several patches.

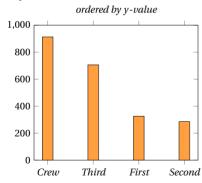
#### 3.3 An Ordered Categorical Variable

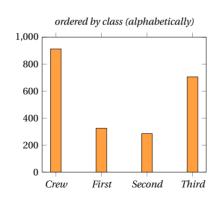
Exactly as "bar chart" with ordered *x*-axis.

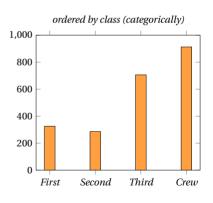
#### **Example 12 (No. of Titanic passengers and crew)** : We can consider the variable (passenger class) as:

- categorical (as previous example) and order by y-value. (sorting will provide more information for the same ink).
- ordered categorical and order it alphabetically (nonsense in this example).
- ordered categorical and order it by class rank (makes sense here).

#### Reproduced







#### Part II

## The Art of Visual Display, Presentation, and Illustration

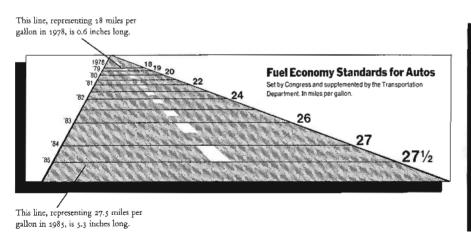
## **Chapter 4**

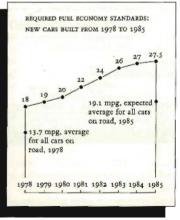
## The Visual Display of Quantitative Information (Tufte, 2001)

@@@ data ink ratio before this example, because it has a problem in this ratio as well.

**Example 13 (Lie Factor)** : (Tufte, 2001, P. 53) (The figure was published in New York Times, August 9, 1978)

- Three kinds of lies: lie, damn lie, and Statistics; also charts as well.
- Example of Statistics: Stock letters.
- Example of chart this one.
- Could have been decorated honestly like this one.





$$\textbf{\textit{Lie Factor}} = \frac{\textit{size of effect shown in graphic}}{\textit{size of effect in data}} = \frac{(5.3 - 0.6)/0.6}{(27.5 - 18)/18} = \frac{7.83}{0.53} = 14.8$$

# Part III Applications

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