ML Week

Introduction

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23-25 novembre 2016

About Machine Learning

The literature is overwhelmingly in English

Disclaimer: Time is short

Definition

Supervised

Unsupervised

Reinforcement

Curse of Dimensionality

Machine learning is not magic

Machine learning is mathematics

Mostly, it's these maths:

- Probability
- Statistics
- Linear algebra
- Optimisation theory
- Differential calculus

Probability

Addition rule: independent events

$$Pr(A \cup B) = Pr(A) + Pr(B)$$

Addition rule: dependent events

$$Pr(A \cup B) = Pr(A) + Pr(B) - Pr(A \cap B)$$

Multiplication rule: independent events

$$Pr(A \cap B) = Pr(A) Pr(B)$$

Multiplication rule: dependent events

$$Pr(A \cap B) = Pr(A \mid B) Pr(B)$$

Conditional probability

$$Pr(A \mid B) = \frac{Pr(A \cap B)}{Pr(B)}$$

Conditional probability

$$\cup_i A_i = A \quad \land \quad A_i \cap A_j = \emptyset \implies$$

$$P(A_1 \mid B) = \frac{\Pr(B \mid A_1) \Pr(A_1)}{\sum_{i} \Pr(B \mid A_1) \Pr(A_1) + \dots + \Pr(B \mid A_k) \Pr(A_k)}$$

Statistics

What is Statistics

- 1 Identify a question or problem.
- 2 Collect relevant data on the topic.
- 3 Analyze the data.
- 4 Form a conclusion.

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Sadly, sometimes people forget 1.

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Statistics is about making 2-4 efficient, rigorous, and meaningful.

OpenIntro Statistics, 2nd edition, D. Diez, C. Barr, M. Çetinkaya-Rundel, 2013.

(Exercise: Is this the same question as the last slide?)

- Define the question of interest
- 2 Get the data
- 3 Clean the data
- 4 Explore the data
- 6 Fit statistical models
- 6 Communicate the results
- Make your analysis reproducible

(Exercise: Is this the same question as the last slide?)

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What the public thinks.

(Exercise: Is this the same question as the last slide?)

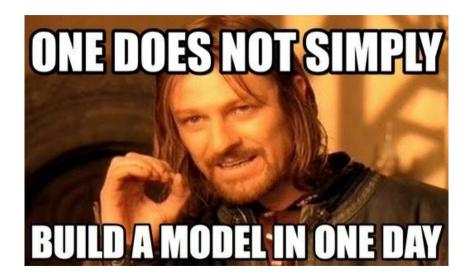
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Where we spend most of our time.

(Exercise: Is this the same question as the last slide?)

- Define the question of interest
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- 4 Explore the data
- 5 Fit statistical models
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The easiest part to forget.



Anecdote

Some properties of anecdote:

- is data
- haphazardly collected
- is generally not representative
- sometimes result of selective retention
- does not accumulate to be representative
- might be true (by chance)
- is ok to use as hypothesis, but be clear that hypothesis is anecdote

Study Types

- Observational
- Experimental

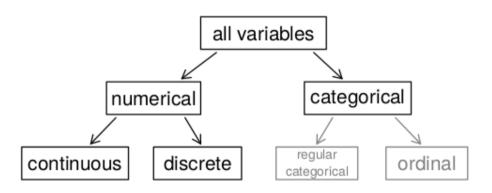
Study Types

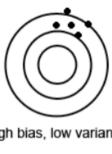
- Observational
- Experimental

What can go wrong?

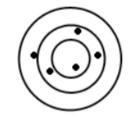
- Forgetting that association ≠ causation
- Not random
- Confounding variables

Variable types





High bias, low variance



Low bias, high variance



High bias, high variance



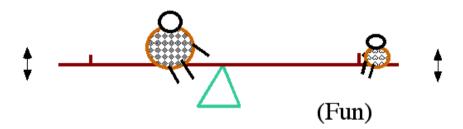
Low bias, low variance

Mean

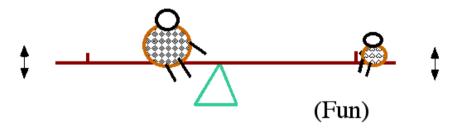
- Weighted and unweighted
- Centroid to physicists

Mean

- · Weighted and unweighted
- Centroid to physicists

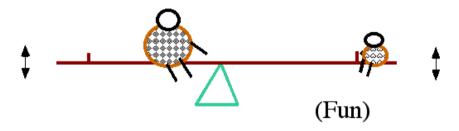


- Weighted and unweighted
- Centroid to physicists



$$\mu = E(X) = \sum w_i x_i = \mathbf{w} \cdot \mathbf{x}$$

- Weighted and unweighted
- Centroid to physicists



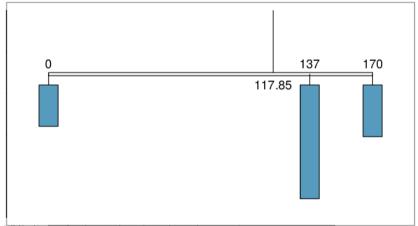
$$\mu = E(X) = \sum \Pr(X = x_i)x_i$$

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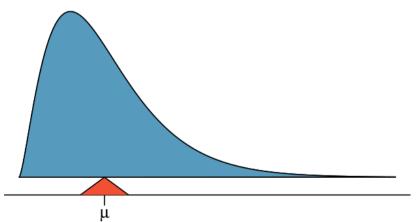
$$\mu = E(X) = \int x f(x) \, \mathrm{d}x$$

http://telescopes.stardate.org/images/research/teeter-totter/TT4.gif

- Weighted and unweighted
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Deviation is distance from mean.

Variance is mean square of deviations

Standard deviation is square root of variance

$$s^2 = \frac{(\overline{x} - x_1)^2 + \cdots (\overline{x} - x_n)^2}{n-1}$$

$$\sigma^2 = \frac{(\overline{X} - X_1)^2 + \cdots (\overline{X} - X_n)^2}{n}$$

$$Var(X) = \sigma^2 = (\overline{X} - X_1)^2 \Pr(X = X_1) + \cdots + (\overline{X} - X_n)^2 \Pr(X = X_n)$$

Given a distribution X, the

probability distribution function (pdf) (continuous) or **probability mass function (pmf)** is the probability that the variate has value *x*:

$$Pr(a \leqslant X \leqslant b)$$
or
 $Pr(X = a)$

Given a distribution X, the

cumulative probability function (cdf) is the probability that the variate is less than *x*:

$$\Pr(X \le x) = \int_{-\infty}^{x} pdf(x) dx \text{ or } \sum_{i \le x} \Pr(X = x)$$

Given a distribution X, the

percent point function (ppf) is the inverse of the cdf. Given a probability, what's x? Also called the **inverse distribution**.

Given a distribution X, the

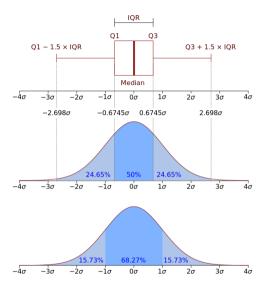
survival function (sf) is the probability that the variate takes a value greater than *x*:

$$ss(x) = Pr(X > x) = 1 - cdf(x)$$

Given a distribution X, the

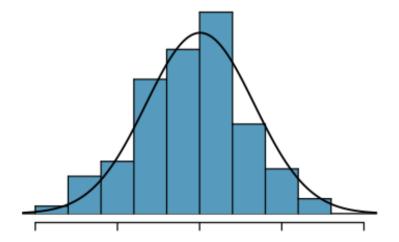
inverse survival function (isf) is the inverse of the survival function:

$$\mathsf{isf}(\alpha) = \mathsf{ppf}(\mathsf{1} - \alpha)$$



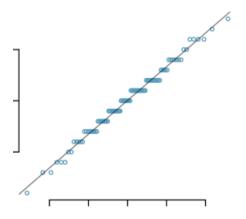
Evaluating Normal Approximations

Easy technique 1: visually compare to normal plot.



Evaluating Normal Approximations

Easy technique 2: normal probability plot.

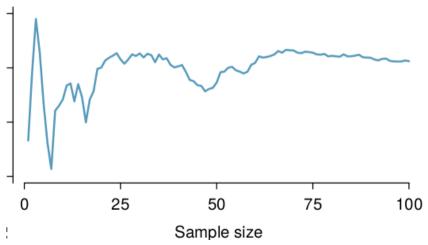


Also known as a quantile-quantile plot.

 $\overline{\mathbf{X}} \neq \mu$

Running mean. Sequence of partial sums (divided by number in sum).

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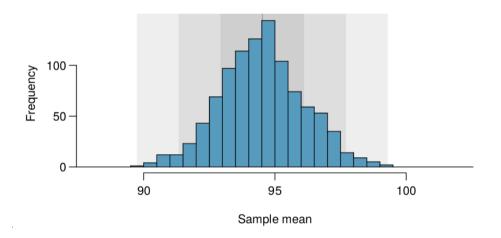
Sampling variation. Change of \overline{x} from one sample to the next.

Running mean. Sequence of partial sums (divided by number in sum).

Sampling variation. Change of \overline{x} from one sample to the next.

Sampling distribution. The distribution of possible point samples of a fixed size from a given population.

Sampling distribution



Confidence intervals

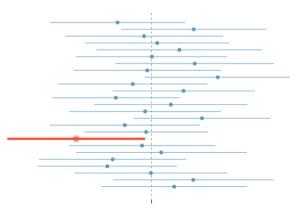
Sample n points, choose an interval around the sample mean.

A 95% confidence interval means if we sample repeatedly, about 95% of the samples will contain the population mean.

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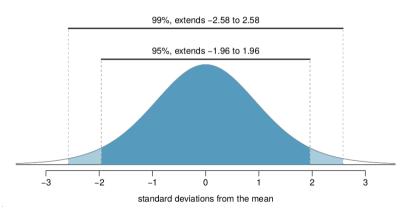
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Linear Algebra

$$v = \begin{pmatrix} v_1 \\ v_2 \\ \vdots \\ v_n \end{pmatrix} \in \mathbb{R}^n$$

$$A = \begin{bmatrix} a_{1,1} & a_{1,2} & a_{1,3} \\ a_{2,1} & a_{2,2} & a_{2,3} \\ a_{3,1} & a_{3,2} & a_{3,3} \end{bmatrix} = \begin{pmatrix} a_{1,1} & a_{1,2} & a_{1,3} \\ a_{2,1} & a_{2,2} & a_{2,3} \\ a_{3,1} & a_{3,2} & a_{3,3} \end{pmatrix}$$
$$= \begin{cases} a_{1,1} & a_{1,2} & a_{1,3} \\ a_{2,1} & a_{2,2} & a_{2,3} \\ a_{3,1} & a_{3,2} & a_{3,3} \end{cases} \in \mathbb{R}^{n \times n}$$

$$u+v=\begin{pmatrix} u_1+v_1\\u_2+v_2\\\vdots\\u_n+v_n\end{pmatrix}$$

$$\alpha \mathbf{V} = \begin{pmatrix} \alpha \mathbf{V}_1 \\ \alpha \mathbf{V}_2 \\ \vdots \\ \alpha \mathbf{V}_n \end{pmatrix} \qquad (\alpha \in \mathbb{R})$$

$$\parallel v \parallel = \sqrt{v_1^2 + \cdots + v_n^2}$$

$$u \cdot v = u_1 \cdot v_1 + \dots + u_n \cdot v_n$$

= $\| u \| \| v \| \cos \theta$

$$C = A + B \iff c_{ij} = a_{ij} + b_{ij}$$
 $C = AB \iff c_{ij} = \sum_{k} a_{ik} b_{kj}$ $A = B^T \iff a_{ij} = b_{ji}$

 $AA^{-1} = A^{-1}A = \text{diag}(1)$

$$Ax = y$$
 $f = T_A : \mathbb{R}^n \to \mathbb{R}^n$

$$x = A^{-1}Ax = A^{-1}y$$
 $f^{-1} = T_{A^{-1}} : \mathbb{R}^n \to \mathbb{R}^n$

B is a basis for *V* iff any of these conditions are met:

- B is a minimal generating set of V
- B is a maximal set of linearly independent vectors
- Every vector $v \in V$ can be expressed in a unique way as a sum of $b_i \in B$

(The conditions are equivalent.)

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Bases are not unique.

Eigenvectors, eigenvalues:

$$Av = \lambda v$$

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$$Av = \lambda 1v \iff (A - \lambda 1)v = 0$$

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Some matrices are diagonalisable. Then

$$A = Q \wedge Q^{-1}$$
 with $\Lambda = \begin{bmatrix} \lambda_1 & \cdots & 0 \\ \vdots & \ddots & 0 \\ 0 & 0 & \lambda_n \end{bmatrix}$

and
$$Q = \begin{bmatrix} | & & | \\ v_1 & \cdots & v_n \\ | & & | \end{bmatrix}$$

Questions?

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