Machine Learning

Introduction

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9, 16 décembre 2016   13 janvier, 9 mars 2017

Supervised

Unsupervised

Reinforcement

Course structure

Four days

- Friday 9 December (9h)
- Friday 16 December (9h)
- Friday 13 January (8h30)
- Thursday 9 March (8h30)

Course structure

Communication

- `https://ynov-ml.slack.com/`
- `https://github.com/ynov-ml/2016-2017`

Course structure

Tasks

- Email `jeff@purple.com` so I can invite you to slack.
- Create a github account if you don't have one. Anonymous if you must.
- Clone the course repository, add your github repository to `repositories`, send a PR.

Course structure

Good git practices

- One line summary, declarative, $<$ 60 characters
- Good comments
- Work on branches

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

events

- independent
- dependent

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

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

$$P(A_1 \mid B) = \frac{\Pr(B \mid A_1)\Pr(A_1)}{\sum_i \Pr(B \mid A_1)\Pr(A_1) + \cdots + \Pr(B \mid A_k)\Pr(A_k)}$$

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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2. Collect relevant data on the topic.
3. Analyze the data.
4. Form a conclusion.

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

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

What is data science?

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

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

What is data science?

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What the public thinks.

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Where we spend most of our time.

What is data science?

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4. Explore the data
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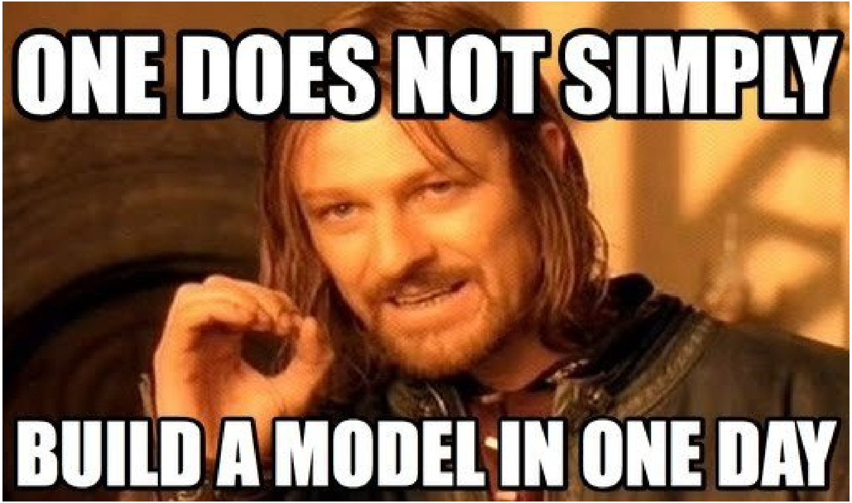
6. Communicate the results
7. Make your analysis reproducible

The easiest part to forget.

What is data science?

http://simplystatistics.org/2015/03/17/data-science-done-well-looks-easy-and-that-is-a-big-problem-for-data-scientists/

What is data science?



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

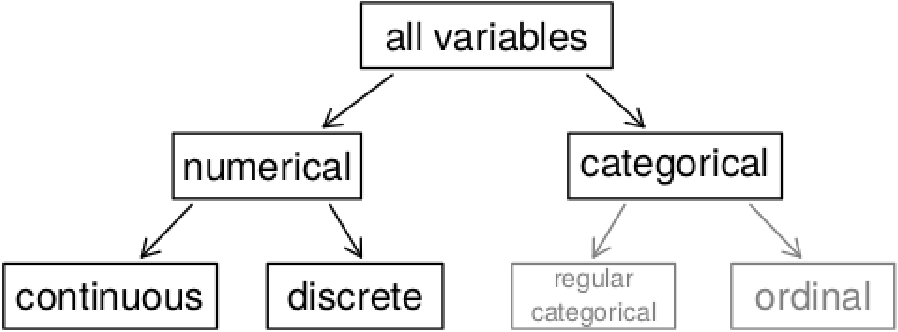
Study Types

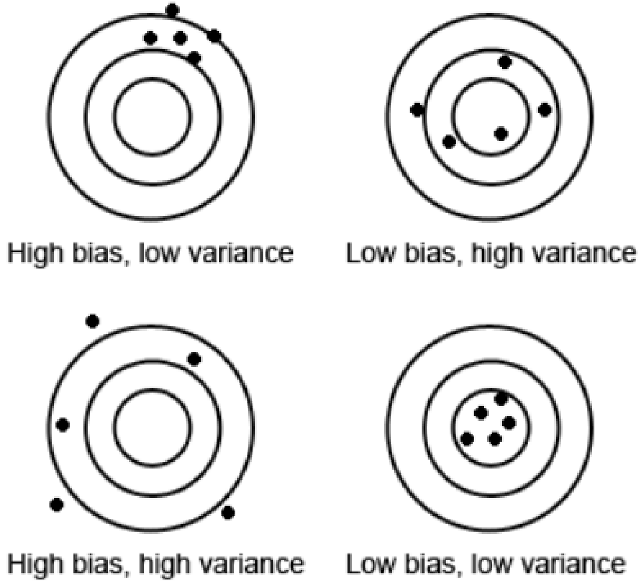
- Observational
- Experimental

What can go wrong?

- Forgetting that association $\neq$ causation
- Not random
- Confounding variables

Variable types



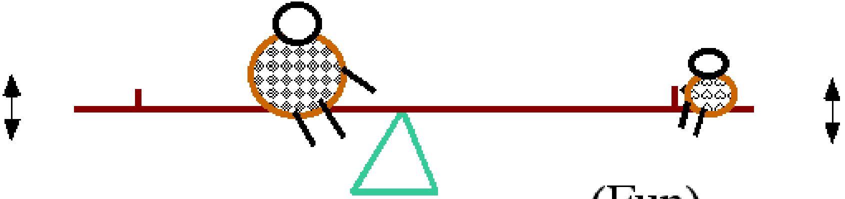

High bias, low variance
Low bias, high variance
High bias, high variance
Low bias, low variance

Mean

- Weighted and unweighted
- Centroid to physicists

Mean

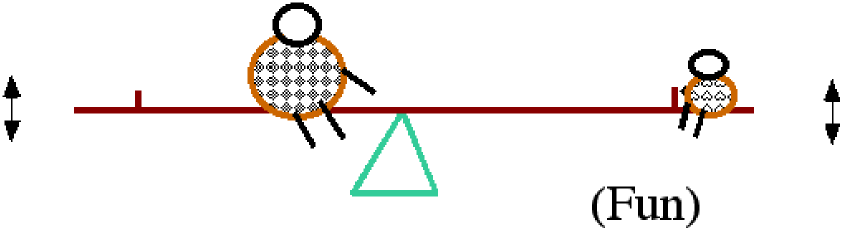
- Weighted and unweighted
- Centroid to physicists



(Fun)

Mean

- Weighted and unweighted
- Centroid to physicists



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

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

Mean

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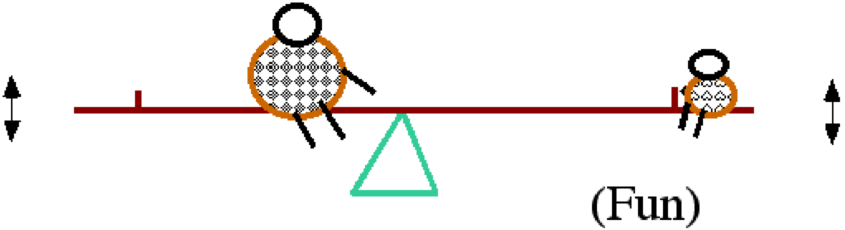

$$\mu = E(X) = \sum \Pr(X = x_i) x_i$$

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

Mean

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

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Mean

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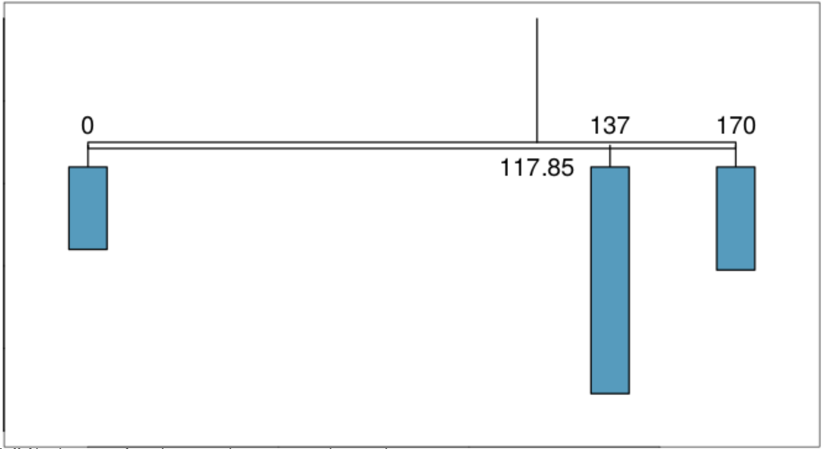

Mean

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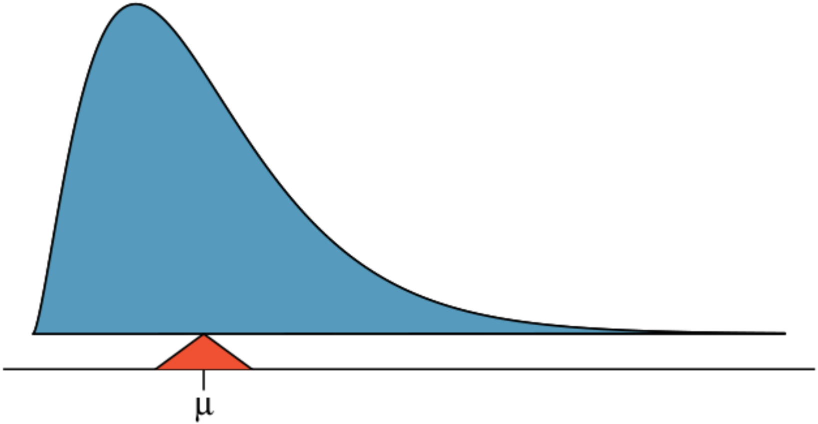


Population statistics

Deviation is distance from mean.

Population statistics

Variance is mean square of deviations

Population statistics

Standard deviation is square root of variance

Population statistics

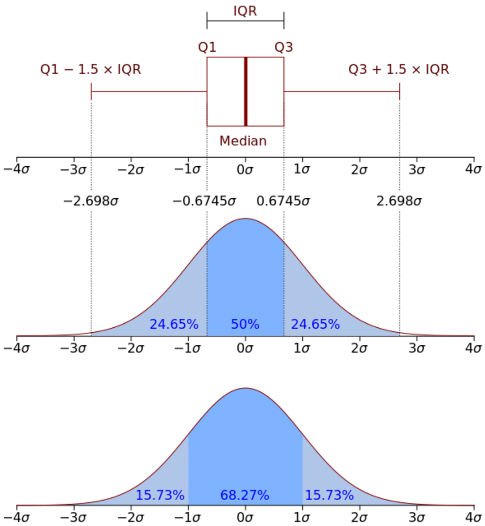
$$s^2 = \frac{(\overline{x} - x_1)^2 + \cdots (\overline{x} - x_n)^2}{n - 1}$$

Population statistics

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

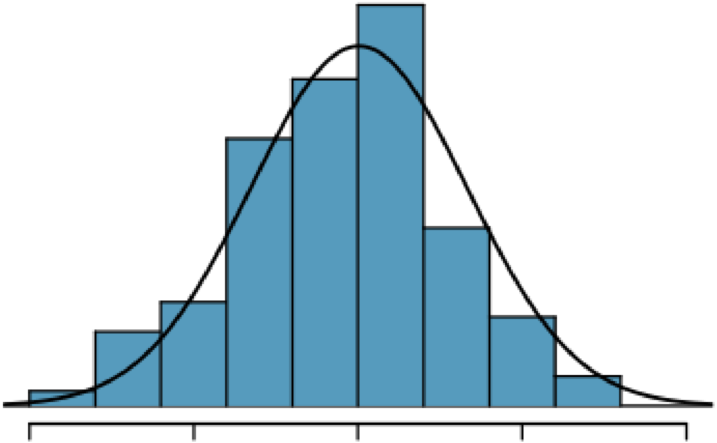
Population statistics

$$\mathrm{Var}(X) = \sigma^2 = (\overline{x} - x_1)^2 \Pr(X = x_1) + \cdots (\overline{x} - x_n)^2 \Pr(X = x_n)$$


IQR
Q1
Q3
Q1 − 1.5 × IQR
Q3 + 1.5 × IQR
Median
−4σ −3σ −2σ −1σ 0σ 1σ 2σ 3σ 4σ
−2.698σ
−0.6745σ
0.6745σ
2.698σ
24.65%
50%
24.65%
−4σ −3σ −2σ −1σ 0σ 1σ 2σ 3σ 4σ
15.73%
68.27%
15.73%
−4σ −3σ −2σ −1σ 0σ 1σ 2σ 3σ 4σ

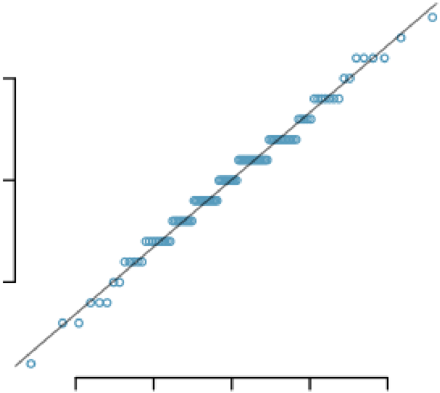
Evaluating Normal Approximations

Easy technique 1: visually compare to normal plot.



Evaluating Normal Approximations

Easy technique 2: normal probability plot.



Also known as a quantile-quantile plot.

$$\overline{x} \neq \mu$$

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

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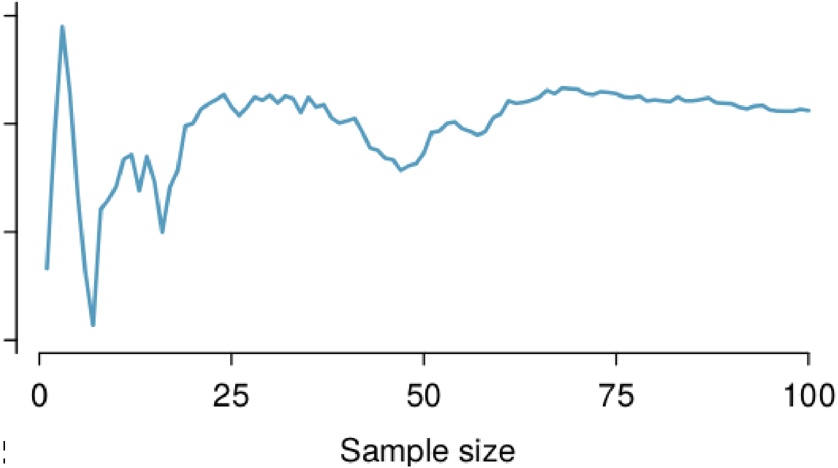


Running mean. Sequence of partial sums (divided by number in sum).

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

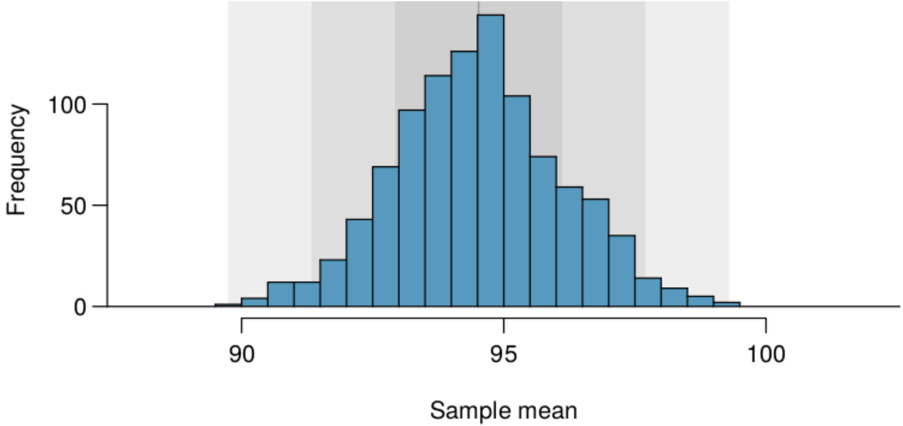
Inference Concepts

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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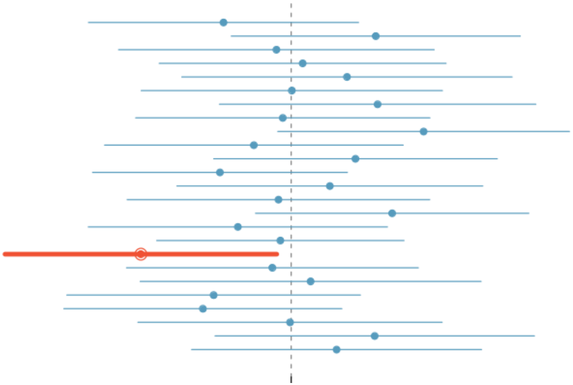
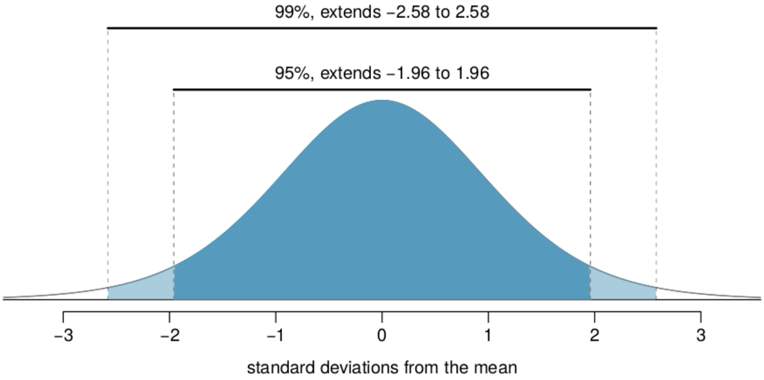


Confidence intervals

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.



Linear Algebra

Linear algebra: basics

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

Linear algebra: basics

$$A = \begin{bmatrix} a_{1,1} & a_{1,2} & a_{1,3} \\ a_{2,1} & a_{2,2} & a_{2,3} \\ a_{3,1} & a_{3,2} & a_{3,3} \end{bmatrix} = \begin{pmatrix} a_{1,1} & a_{1,2} & a_{1,3} \\ a_{2,1} & a_{2,2} & a_{2,3} \\ a_{3,1} & a_{3,2} & a_{3,3} \end{pmatrix}$$

$$= \begin{Bmatrix} a_{1,1} & a_{1,2} & a_{1,3} \\ a_{2,1} & a_{2,2} & a_{2,3} \\ a_{3,1} & a_{3,2} & a_{3,3} \end{Bmatrix} \in \mathbb{R}^{n \times n}$$

Linear algebra: basics

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

Linear algebra: basics

$$\alpha v = \begin{pmatrix} \alpha v_1 \\ \alpha v_2 \\ \vdots \\ \alpha v_n \end{pmatrix} \qquad (\alpha \in \mathbb{R})$$

Linear algebra: basics

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

Linear algebra: basics

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

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

Linear algebra: basics

$$C = A + B \iff c_{ij} = a_{ij} + b_{ij}$$

$$C = AB \iff c_{ij} = \sum_k a_{ik} b_{kj}$$

$$A = B^T \iff a_{ij} = b_{ji}$$

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

Linear algebra: transformations

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

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

Linear algebra: transformations

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.)

Linear algebra: transformations

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Bases are not unique.

Linear algebra: transformations

Eigenvectors, eigenvalues:

$$Av = \lambda v$$

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$$Av = \lambda v$$

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

Linear algebra: transformations

Eigenvectors, eigenvalues:

$$Av = \lambda v$$

Some matrices are diagonalisable. Then

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

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

video time

Questions?