(starting with 15 Jan 2021 morning section discussion document camera notes)

STAT 206
19 Jan 21
Lecture

① Take-home test 1 published to you later today or tomorrow, "due" about 10-14 days later

Quiz 2 target tomorrow night

DD makeup office hour today 1.25–2.55p 1-time-only

read: Gelman et al. ch 2 (opt. Jaynes ch. 2)

practical significance & statistical significance

when comparing $\underline{\underline{2}}$ or more quantitative summaries (e.g., $\underline{\underline{\bar{y}_C}}^{(0.9)}$ & $\underline{\underline{\bar{y}_T}}^{(0.7)}$ in IHGA case study)

practical significance addresses the question: is the difference large enough to matter in a real-world sense?

if so, difference is practically significant (practsig) (large in practical terms) this involves value judgments: best source for such judgments: domain/subject matter expert(s) in your data science team

$\boxed{\text{tricks:}}$ instead of looking at (e.g.) $|\bar{y}_C - \bar{y}_T| = 0.9 - 0.7 = 0.2$ (absolute comparison) hosp./2 yrs $\rightarrow$ 0.1 hosp./yr $\rightarrow$ non-insti (policy)

trick 1 $\boxed{\text{aggregate}}$ this over {all elderly people in Denmark} = P (2) the result is large cost savings for Danish health care system

(benefit only) (if cost low) (need to trade off costs & benefits)

(R) also : better for elderly people

trick (2) (relative comparison)

$$\frac{\bar{y}_T - \bar{y}_c}{\bar{y}_c} \doteq -20\% \doteq -0.2$$

(really) 20% improvement in medicine is big

would like rule of the form

if relative improvement $\geq c\%$ then practsig

no such universal rule exists; it's problem-specific

statistical significance (~~statsig~~)

$\hat{\theta}$ differs from 0 by an amount that's

statsig $\leftrightarrow$ the ⊕ is $\boxed{\text{so small}}$ that →

how small is small enough?

(p. 6)

statistical inference : generalizing outward (backwards) from (the sample) your data to the broadest-possible population

pop. P

all non-inst. elderly in Denmark in early 1980s under

hosp. Y

$\boxed{C}$

sample

the observed eld. people

hosp. Y

$\boxed{C}$ like-at-random

131 prob.

stat. inf. 206

representative (like-at-random)

$N = ?$ (big)

0
0
2
1
⋮

$n_C = 285$

mean $\bar{y}_C = 0.9$

mean $\mu_C = ?$

$$\hat{\theta} = \frac{\bar{y}_T - \bar{y}_C}{\bar{y}_C} = -0.2$$

ditto $\boxed{T}$

$$\boxed{\theta} \doteq \frac{\mu_T - \mu_C}{\mu_C}$$

$\mu_C = ?$

statistical inference : drawing conclusions about θ

mean $\bar{y}_T = 0.7$

mean $\mu_T = ?$

mathematics: study of structures & patterns, & relationships among them

devil's advocate (DA) (bullshit detector)

we think IHGA works $\hat{\theta} = -0.2$	DA says: no, $\theta = 0$ IHGA doesn't work

if $\theta = 0$, you could get $\hat{\theta} = -0.2$ just by unlucky random sampling

$$\hat{\theta} = -0.2 \pm \boxed{}$$

if small enough, DA is probably wrong

(go to p③ bottom)

"unlucky random sampling is a highly unlikely explanation
(this is an inferential conclusion)

R.A. Fisher
stat ✓
genetics ✓
eugenics X

saying IHGA works when it really doesn't
(bad & worse)
(false positive)

saying IHGA doesn't work when it really does
(false negative)
(bad but less bad)

Fisher's false ⊕ cutoff not strict enough ← replicability crisis

only 30-60% of major studies actually replication

good data science conclusions are replicable

7 core statistical data science activities

nickname: 7 pillars of wisdom in statistical data science

math:

if A (assumptions)

then C (consequences) (conclusions)

simple version of Bayes's Thm

IF

you can ~~[illegible]~~ uniquely

specify $p(\theta|B)$,

$p(D|\theta B)$, $(\mathcal{A}|B), U(a, \theta|B))$,

then Bayes's Thm & its corollaries

specify ~~give~~ the unique optimal

information processing algorithm

statistical data science: building

prob. models for data-generating process (Bayes strength) & using Bayes as our optimal algorithm : stat. DS have model uncertainty but no algorithm uncertainty

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pure machine learning (ML) DS : specify task*, find algorithm that does task well

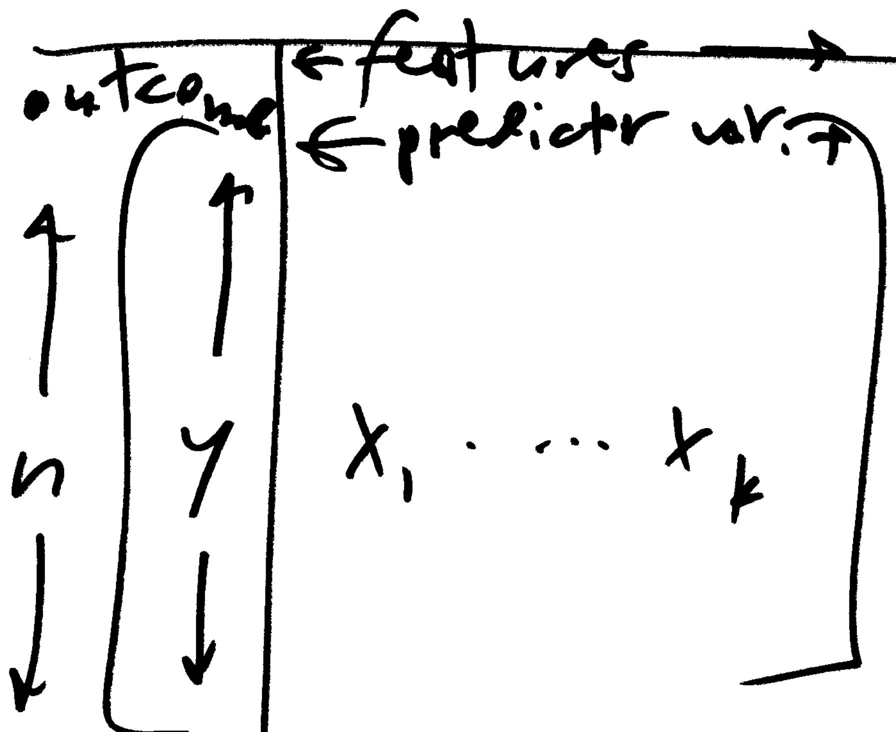
predict y from $x_1, \ldots, x_k$

MLDS has algorithm uncertainty but no model uncertainty (no model)

ML weakness

[both stat & ML have both strengths & weaknesses (like: frequentist & Bayesian in prob.)

⊛



1 row for each subject (instance)

$\boxed{\text{Big Data:}}$ $n = 10^9$, $k = 10^6$

Bayes weakness
ML strength