data science for (physical) scientists lla

II: physics in a probabilistic world



1 P(physics | data)2 NHRT

p-values

z-test

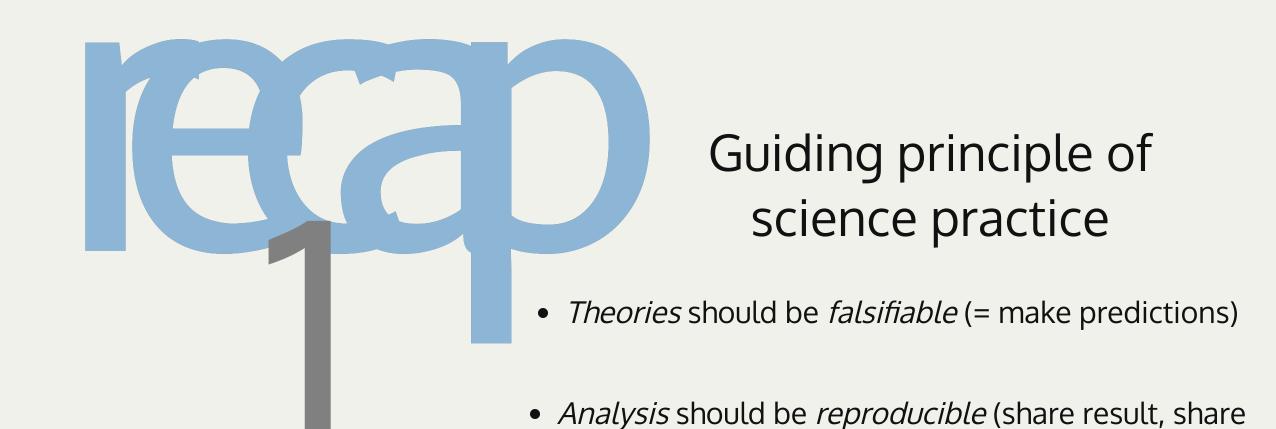
3 comparing distributions

Z, t, $\chi 2$, ks-test

KL divergence

this slide deck

http://bit.ly/dsps2019_2a



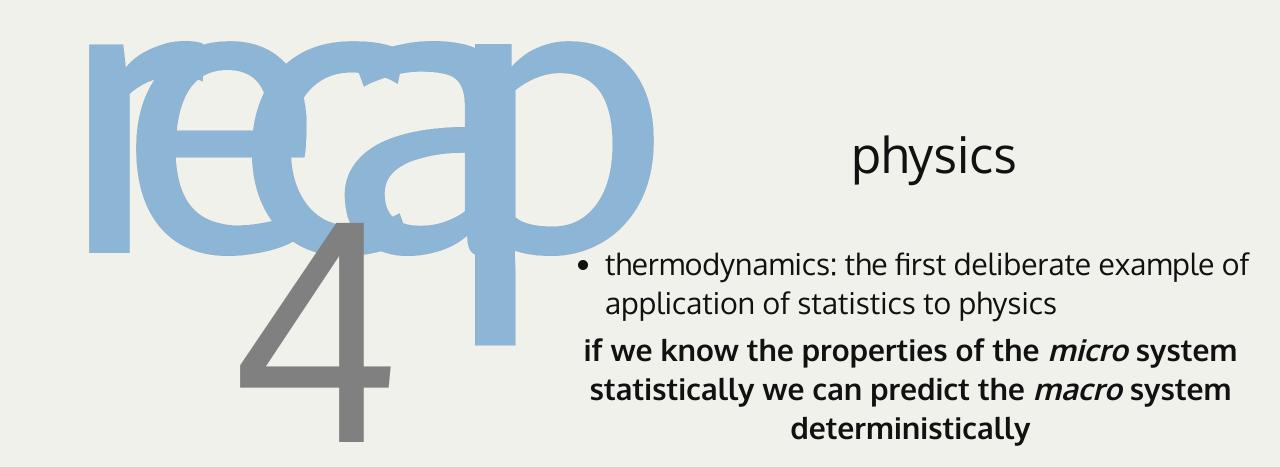
raw data, share code to get result from raw data)

probability

- Frequentist interpretation: fraction of occurrence
- *Bayesian* interpretation: degree of believe that it will happen
- Basic probability algebra rules

statistics

- links between samples (observations) and populations (general rules)
- ullet common distributions: binomial, Poisson, Gaussian, $\chi 2$
- *Descriptive statistics:* central tendency, variance, symmetry
- Central limit theorem



we summarize the proprties of a distribution

$$\mu_n = \int_{-\infty}^{\infty} (x-c)^n \, f(x) \, \mathrm{d}x.$$



we summarize the proprties of a distribution

$$\mu_n = \int_{-\infty}^{\infty} (x-c)^n f(x) dx.$$

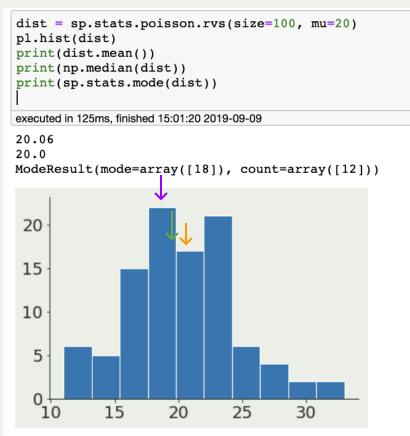
mean: n=1
$$\mu=rac{1}{N}\sum_1^N x_i$$

other measures of centeral tendency:

median: 50% of the distribution is to the left,

50% to the right

mode: most popular value in the distribution



we summarize the proprties of a distribution

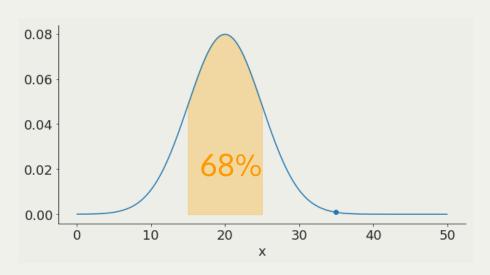
$$\mu_n = \int_{-\infty}^{\infty} (x-c)^n f(x) \, \mathrm{d}x.$$

variance: n=2
$$\operatorname{Var}(X) = \operatorname{E}\left[(X-\mu)^2\right]$$
 .

standard deviation
$$\,\sigma(X)=\mathrm{E}\left[\left(X-\mu
ight)
ight]$$
 .

Gaussian distribution:

1σ contains 68% of the distribution



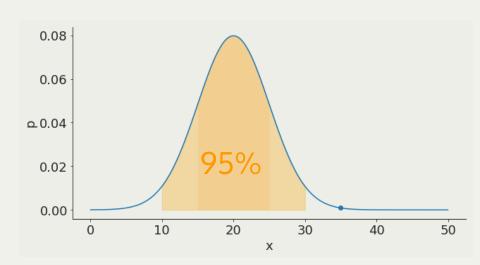
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Gaussian distribution: 2σ contains 95% of the distribution



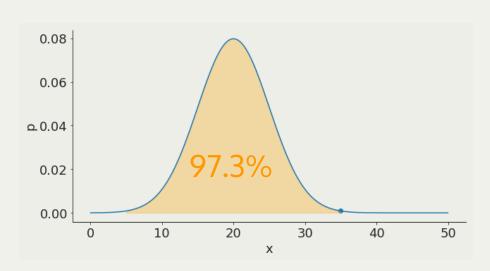
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standard deviation
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Gaussian distribution: 3σ contains 97.3% of the distribution



the scientific method in a probabilistic context

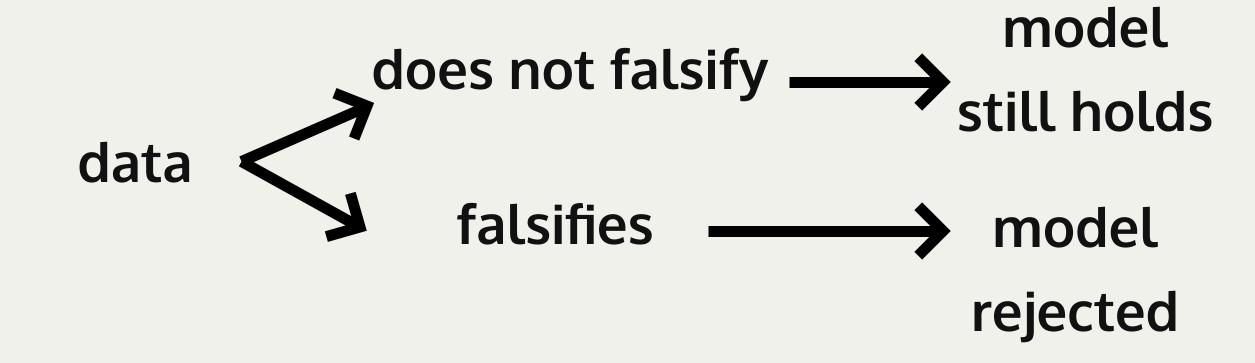
p(physics | data)

Bayesian Inference

Forward Modeling

Frequentist approach (NHRT)

p(physics | data)



model — prediction

"Under the Null Hypothesis" = if the model is true

does not falsify \longrightarrow still holds

falsifies \longrightarrow model

rejected

model

"Under the Null Hypothesis" = if the model is true

prediction

this has a high probability of happening

does not falsify \longrightarrow still hold falsifies \longrightarrow model rejected

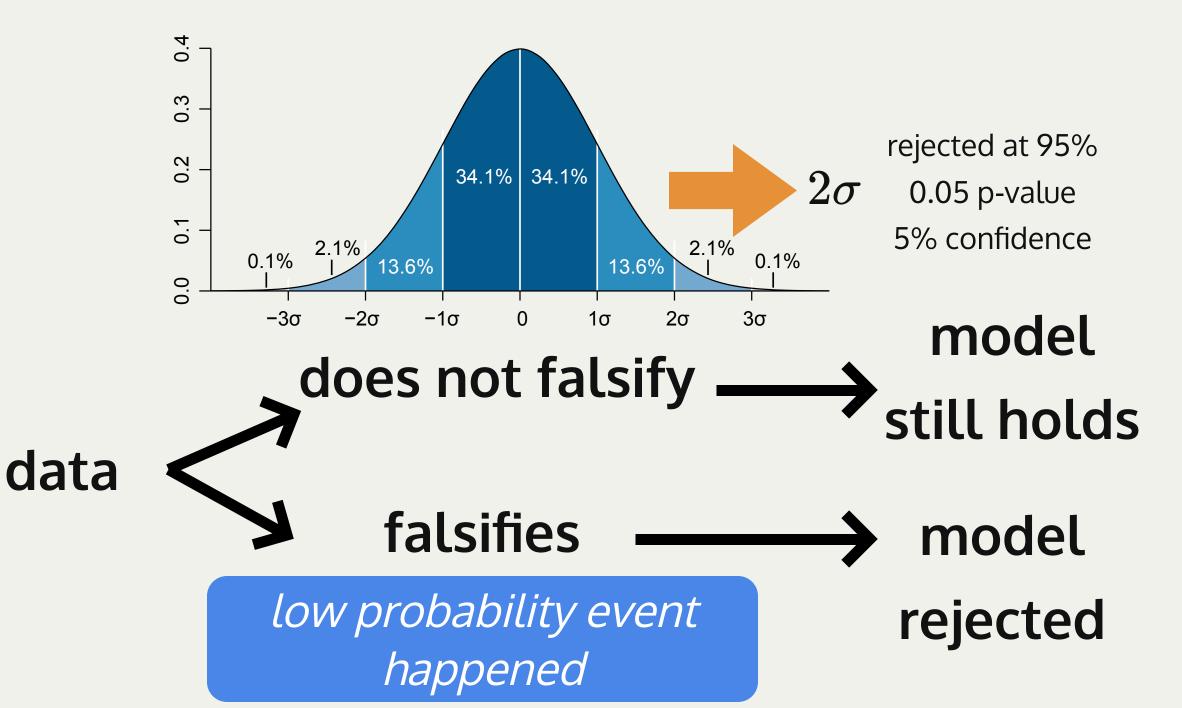
model

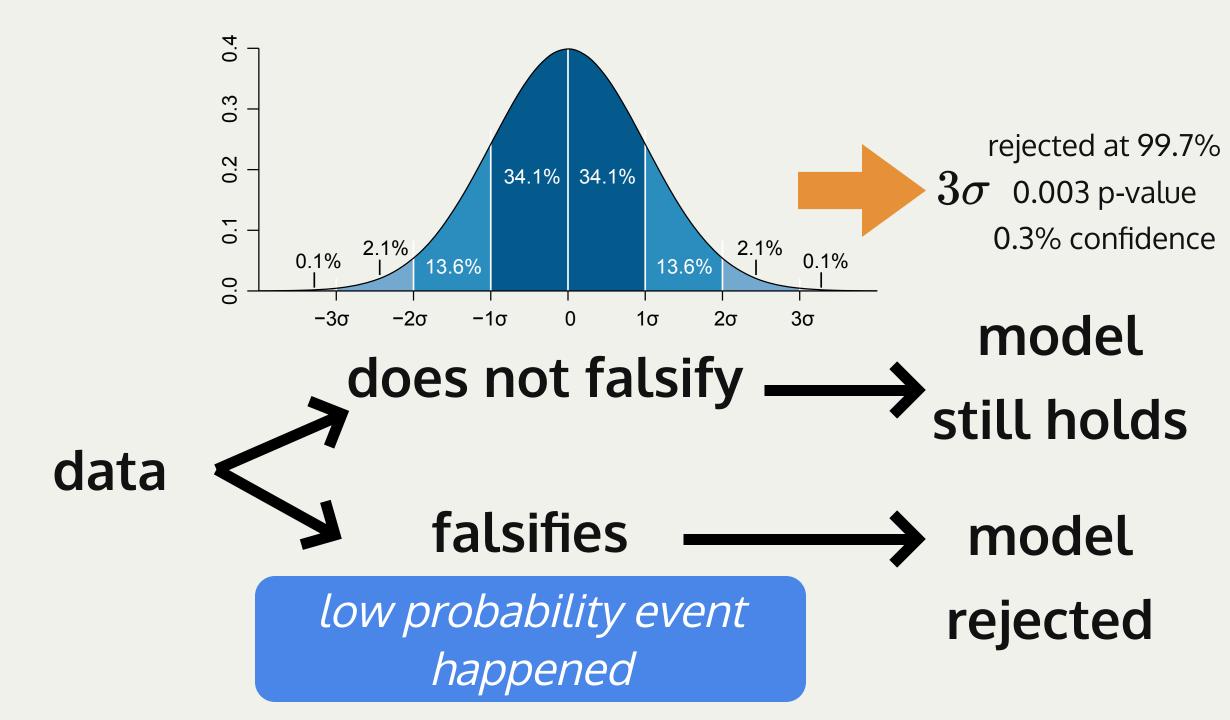
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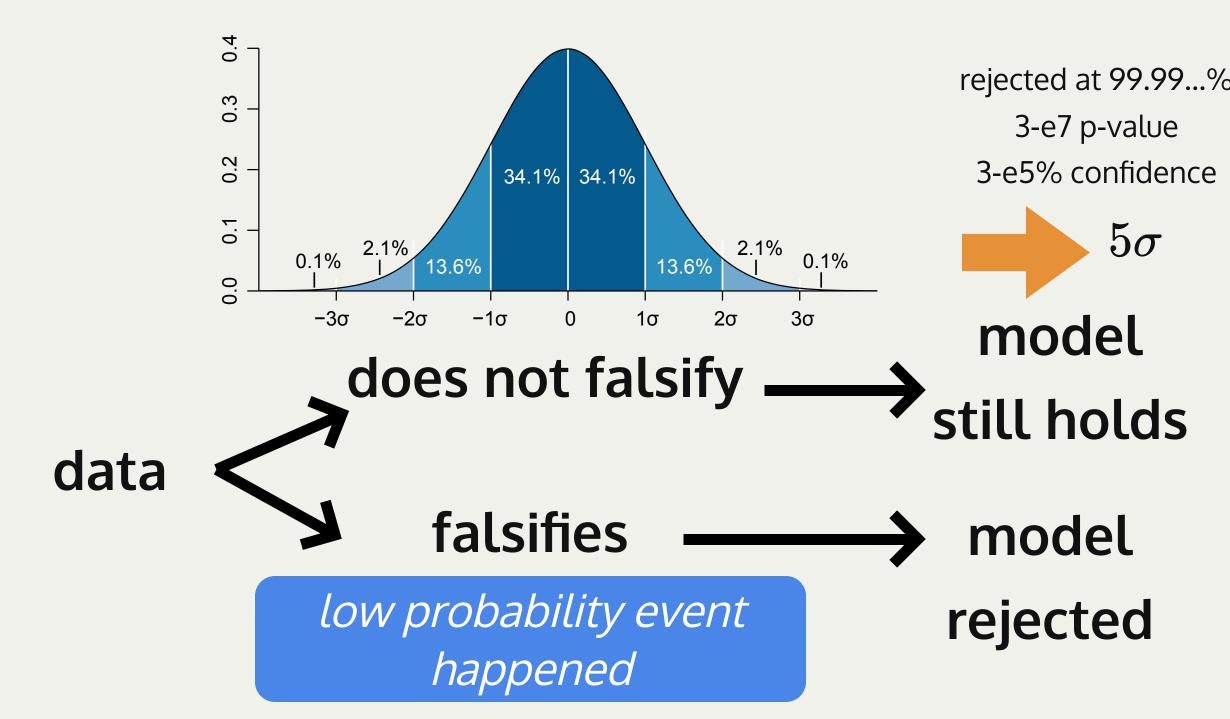
prediction

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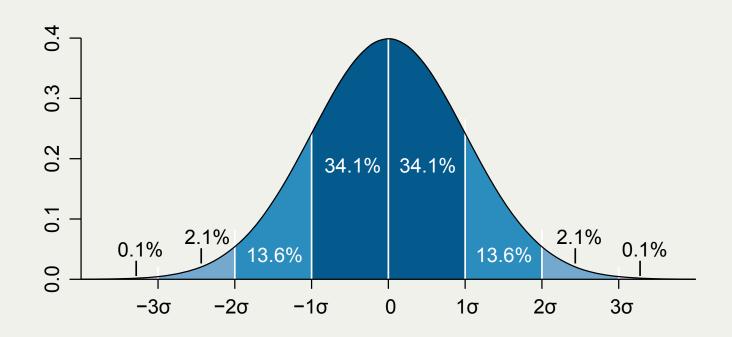






Null hyposthesis rejection testing

Null Hypothesis Rejection Testing



p(physics | data)

Null

Hypothesis

Rejection

Testing

formulate your prediction

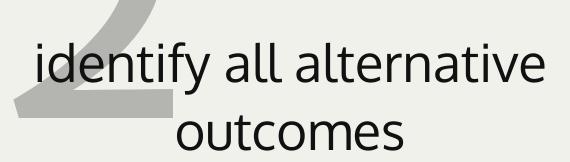
Null Hypothesis

Null

Hypothesis

Rejection

Testing



Alternative Hypothesis



Hypothesis

Rejection

Testing



$$P(A) + P(\bar{A}) = 1$$

if *all alternatives* to our model are ruled out, then our model must hold

identify all alternative outcomes

Alternative Hypothesis

But instead of verifying a theory we want to falsify one model prediction

"Under the Null Hypothesis" = if the model is true this has a low probability of happening



generally, out model about how the world works is the *Alternative* and we try to reject the non-innovative thinking as the *Null*!

But instead of verifying a theory we want to falsify one model prediction

"Under the Null Hypothesis" = if the model is true this has a low probability of happening

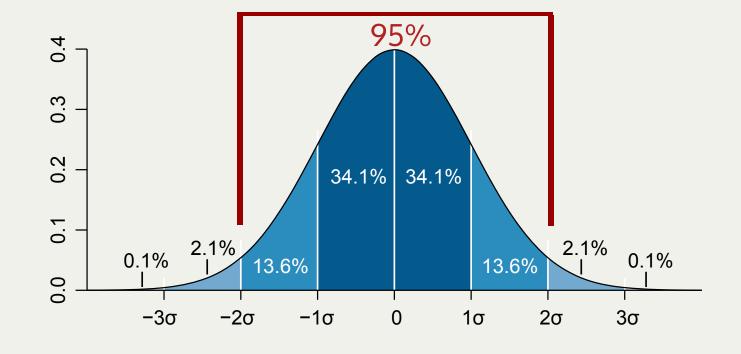


Earth is flat is Null

Earth is round is Alternative:

we reject the Null hypothesis that the Earth is flat (p=0.05)

Null Hypothesis Rejection Testing





 2σ confidence level .05 p-value

95% lpha threshold

Null
Hypothesis
Rejection
Testing

find a measurable quantity which under the Null has a known distribution

pivotal quantities

quantities that under the Null Hypotheis follow a known distribution

if a quantity follows a known distribution, once I measure its value I can what the probability of getting that value actually is! was it a likely or an unlikely draw?

pivotal quantities

quantities that under the Null Hypotheis follow a known distribution

$$p(ext{pivotal quantity}|NH) \sim p(NH|D)$$

Null

Hypothesis

Rejection

Testing



prediction is unlikely

Null rejected

Alternative holds



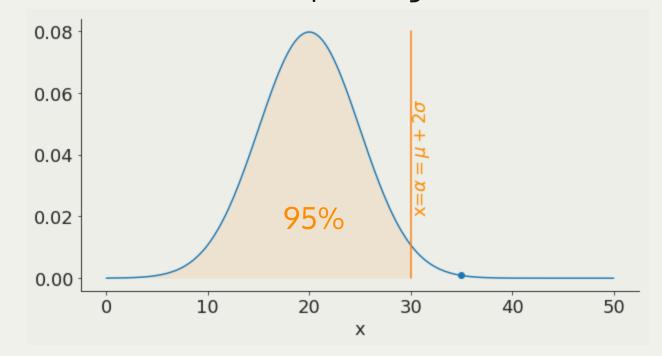
test data against alternative outcomes

Null Hypothesis Rejection Testing

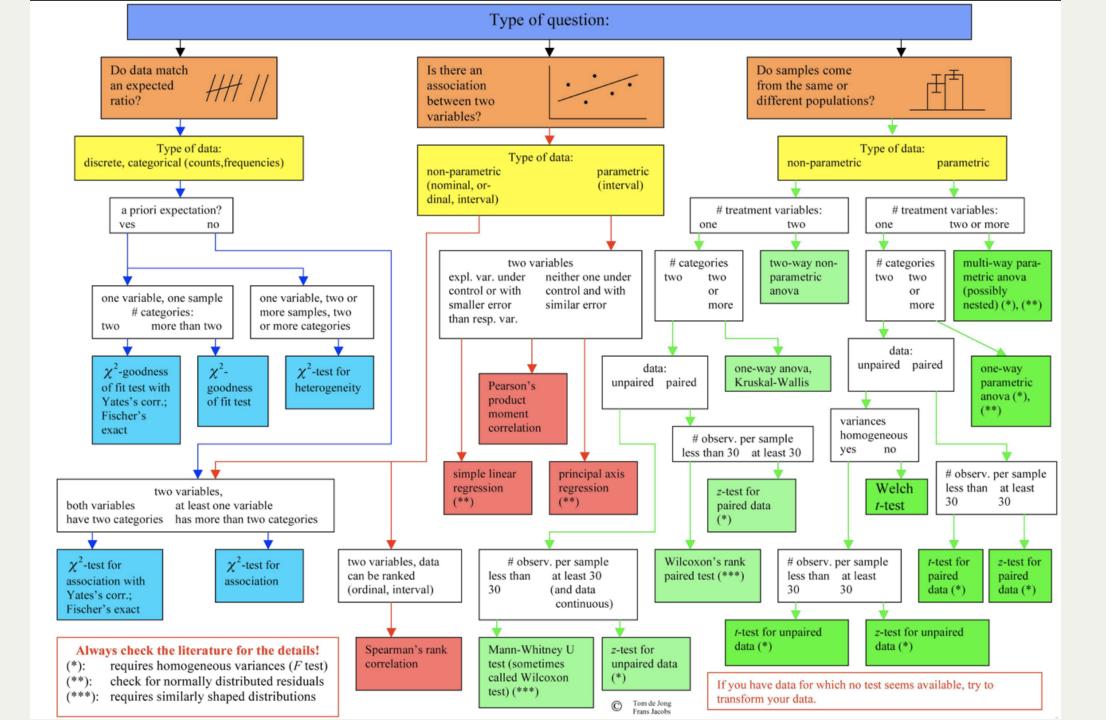
test data against alternative outcomes

what is

α is the x value corresponding to a chosen threshold



common tests and pivotal quantities



pivotal quantities

quantities that under the Null Hypotheis follow a known distribution

also called "statistics"

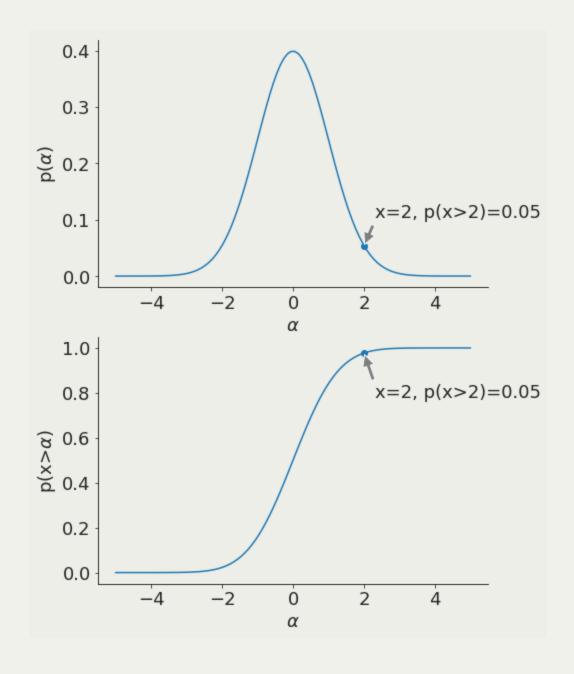
e.g.: χ^2 statistics: difference between expetation and reality squared

Z statistics: difference between means

K-S statistics: maximum distance of cumulative distributions.

Is the mean of a sample with known variance the same as that of a known population?

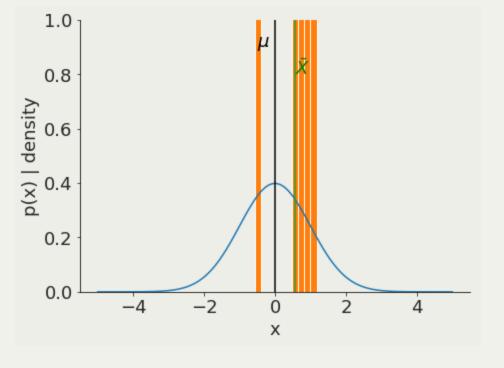
$$Z=(ar{X}-\mu 0)/s$$
 sample population sample mean wariance $Z\sim N(\mu=0,\,\sigma=1)$



Is the mean of a sample with known variance the same as that of a known population?

pivotal quantity

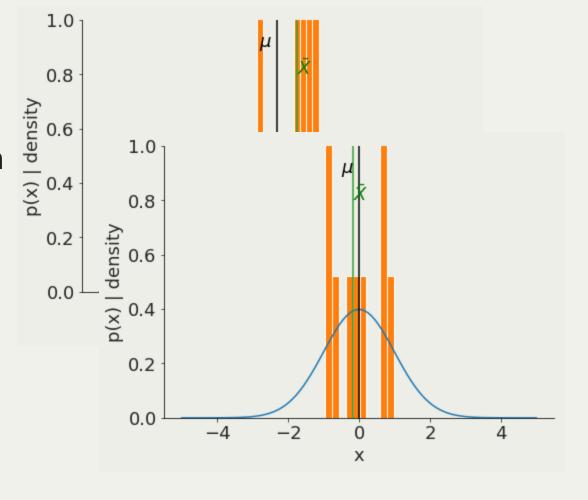
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why do we need a test? why not just measuring the means and seeing it they are the same?

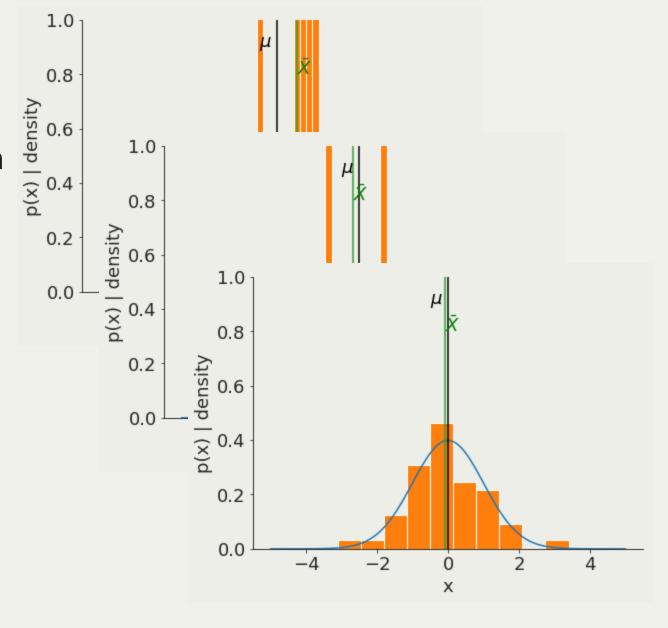
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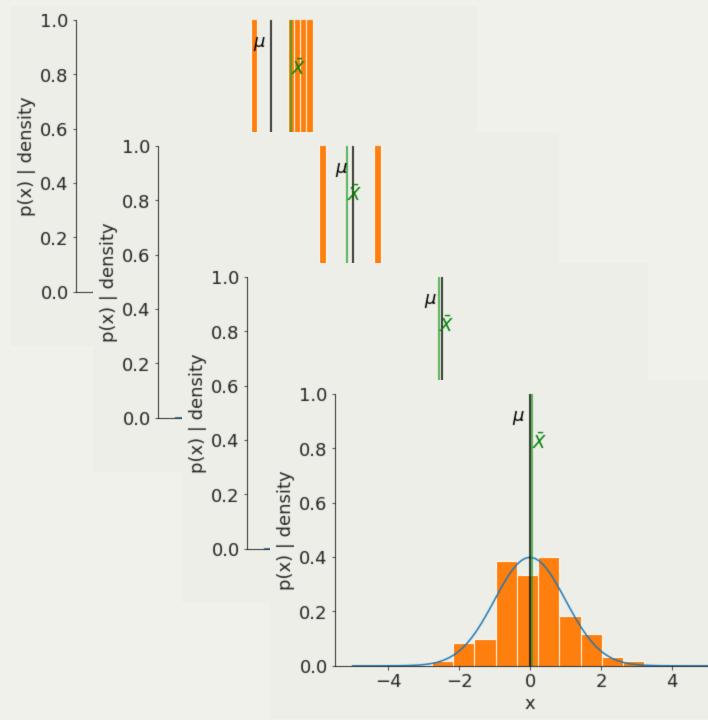
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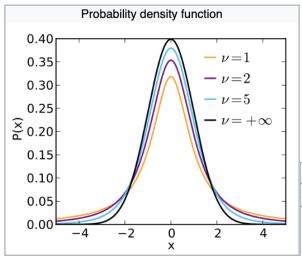
t- test

Are the means of 2 samples significantly different?

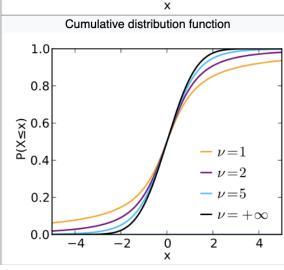
pivotal quantity

 $t=rac{ar{X}_1-ar{X}_2}{\sqrt{rac{s_1^2}{n_1}+rac{s_2^2}{n_2}}} \stackrel{ ext{ size of }}{\stackrel{ ext{sample}}{ ext{sample}}}$

Student's t







Parameters	u>0 degrees of freedom (real)
Support	$x\in (-\infty,\infty)$
PDF	$rac{\Gamma\left(rac{ u+1}{2} ight)}{\sqrt{ u\pi}\Gamma\left(rac{ u}{2} ight)}\left(1+rac{x^2}{ u} ight)^{-rac{ u+1}{2}}$
CDF	$rac{1}{2} + x\Gamma\left(rac{ u+1}{2} ight) imes$
	$\frac{{}_2F_1\left(\frac{1}{2},\frac{\nu+1}{2};\frac{3}{2};-\frac{x^2}{\nu}\right)}{\sqrt{\pi\nu}\Gamma\!\left(\frac{\nu}{2}\right)}$
	where ₂ F ₁ is the hypergeometric function
Mean	0 for $ u>1$, otherwise undefined
Median	0
Mode	0
Variance	$rac{ u}{ u-2}$ for $ u>2$, $ infty$ for $1< u\leq 2$,
	otherwise undefined

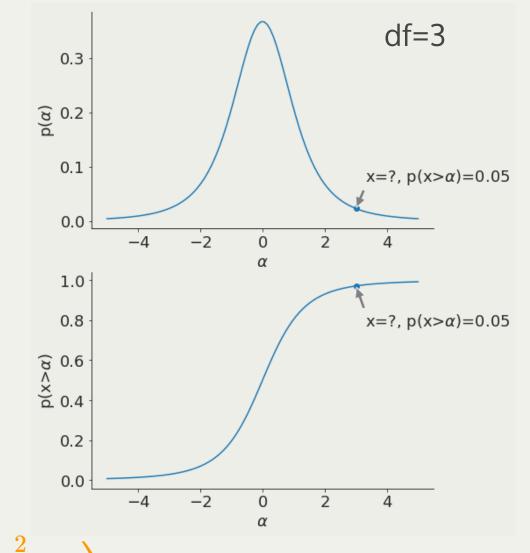
$$t \sim ext{Student's } t \left(ext{df} = rac{\left(rac{s_1^2}{n_1} + rac{s_2^2}{n_2}
ight)}{rac{\left(s_1^2/n_1
ight)^2}{n_1 - 1} + rac{\left(s_2^2/n_2
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ight.$$

t- test

Are the means of 2 samples significantly different?

pivotal quantity

 $ar{X}_1 - ar{X}_2$ estimator $\sqrt{rac{s_1^2}{n_1} + rac{s_2^2}{n_2}}$ size of sample



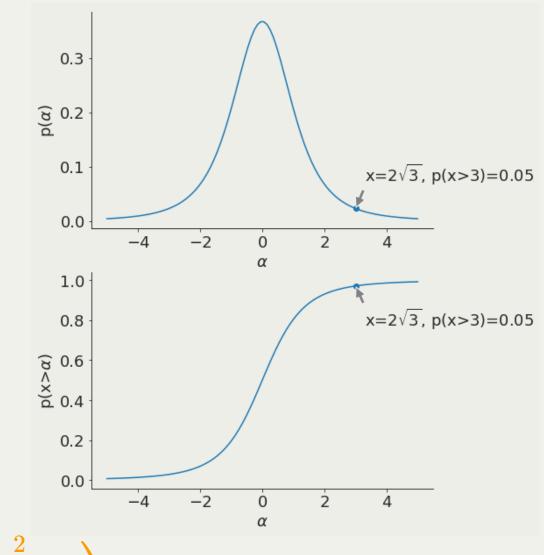
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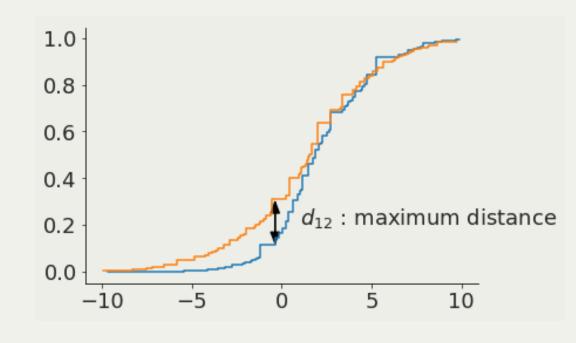
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ight)^2}{n_2 - 1}}$$

K-S test

Kolmogorof-Smirnoff:

do two samples come from the same parent distribution?

$$d_{12} \equiv max_x \, |C_1(x) - C_2(x)|$$
 \downarrow \downarrow \downarrow Cumulative distribution 1 distribution 2



$$P(d>observed) \ = 2\sum_{j=1}^{\infty} (-1)^{j-1} e^{-2j^2x^2} \sqrt{rac{N_1N_2}{N_1+N_2}} D$$

K-S test

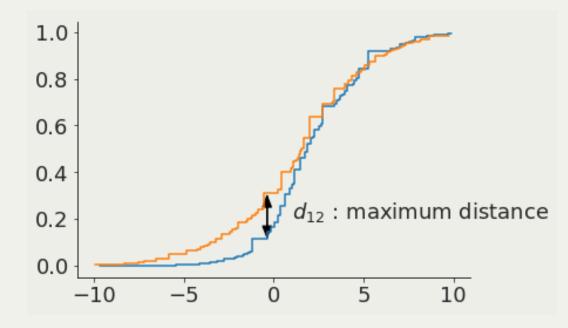
Kolmogorof-Smirnoff:

do two samples come from the same parent distribution?

pivotal quantity

$$d_{12} \equiv max_x \left| C_1(x) - C_2(x)
ight|$$
 \downarrow
Cumulative Cumulative

distribution 1



$$P(d > observed) =$$

sp.stats.ks_2samp(x, y)

distribution 2

executed in 7ms, finished 14:45:10 2019-09-09

Ks_2sampResult(statistic=0.4, pvalue=0.3128526760169558)

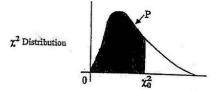
x2 test

are the data what is expected from the model (if likelihood is Gaussian... we'll see this later) - ther are a few $\chi 2$ tests. The one here is the "Pearson's $\chi 2$ tests"

pivotal quantity

$$\chi^2 \equiv \sum_i \frac{(f(x_i) - y_i)^2}{\sigma_i^2}$$
model observation uncertainty

$$\chi^2 \sim \chi^2 (df = n-1)$$
 number of observation



The table below gives the value x_0^2 for which $P[x^2 < x_0^2] = P$ for a given number of degrees of freedom and a given value of P.

Degrees of Freedom	Values of P									
	0.005	0.010	0.025	0.050	0.100	0.900	0.950	0.975	0.990	0.995
1			0.001	0.004	0.016	2.706	3.841	5.024	6.635	7.879
2	0.01	0.020	0.051	0.103	0.211	4.605	5.991	7.378	9.210	10.597
3	0.072	0.115	0.216	0.352	0.584	6.251	7.815	9.348	11.345	12.838
4	0.207	0 297	0.484	0.711	1.064	7.779	9.488	11.143	13.277	14.860
5	0.412	0.554	0.831	1.145	1.610	9.236	11.070	12.833	15.086	16.750
6	0.676	0.872	1.237	1.635	2.204	10.645	12.592	14.449	16.812	18.548
7	0.989	1.239	1.690	2.167	2.833	12.017	14.067	16.013	18.475	20.278
8	1.344	1.646	2.180	2.733	3.490	13.362	15.507	17.535	20.090	21.955
9	1 735	2.088	2.700	3.325	4.168	14.684	16.919	19.023	21.666	23.589
10	2.156	2.558	3.247	3.940	4.865	15.987	18.307	20.483	23.209	25.188
11	2.603	3.053	3.816	4 575	5.578	17.275	19.675	21.920	24,725	26.757
12	3.074	3.571	4.404	5.226	6.304	18.549	21.026	23.337	26.217	28.300
13	3.565	4.107	5.009	5.892	7.042	19.812	22.362	24.736	27.688	29.819
14	4.075	4.660	5.629	6.571	7.790	21.064	23.685	26.119	29.141	31.319
15	4.601	5.229	6.262	7.261	8.547	22.307	24.996	27.488	30.578	32.801
16	5.142	5.812	6.908	7 962	9.312	23.542	26.296	28.845	32.000	34.267
17	5.697	6.408	7.564	8.672	10.085	24.769	27.587	30.191	33.409	35.718
18	6.265	7.015	8.231	9.390	10.865	25.989	28 869	31.526	34.805	37.156
19	6.844	7.633	8.907	10.117	11.651	27.204	30.144	32.852	36.191	38.582
20	7.434	8.260	9.591	10.851	12.443	28.412	31.410	34.170	37.566	39.997

x2 test

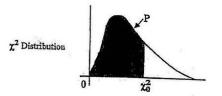
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pivotal quantity

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 model observation uncertainty

$$rac{\chi^2}{n-1} \sim \chi^2(df=1)$$

number of observation



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Null

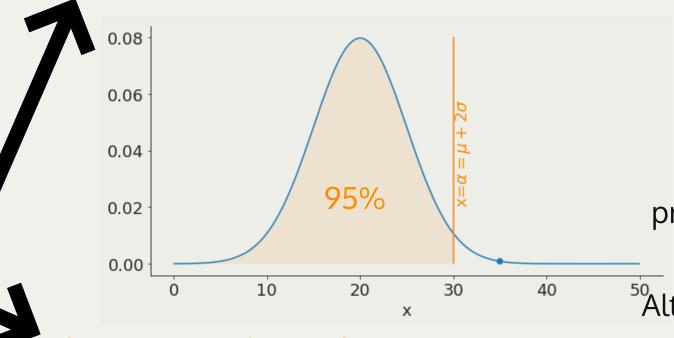
Hypothesis

Rejection

Testing



prediction is unlikely Null rejected Alternative holds





prediction is likely Null holds

Alternative rejected

test data against *alternative* outcomes



Null

Hypothesis

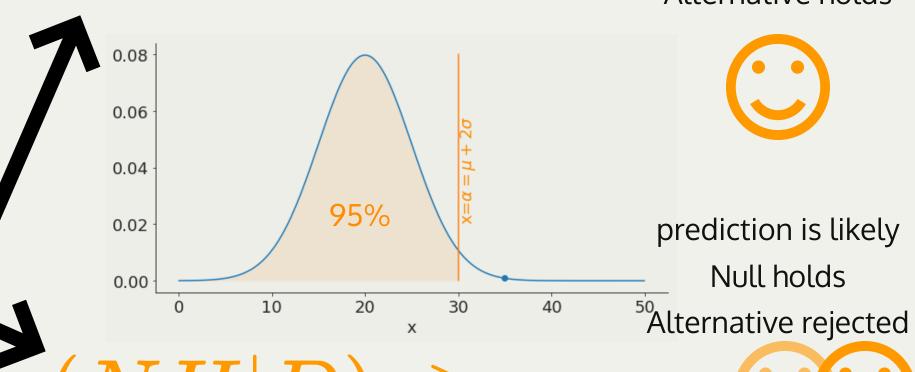
Rejection

Testing



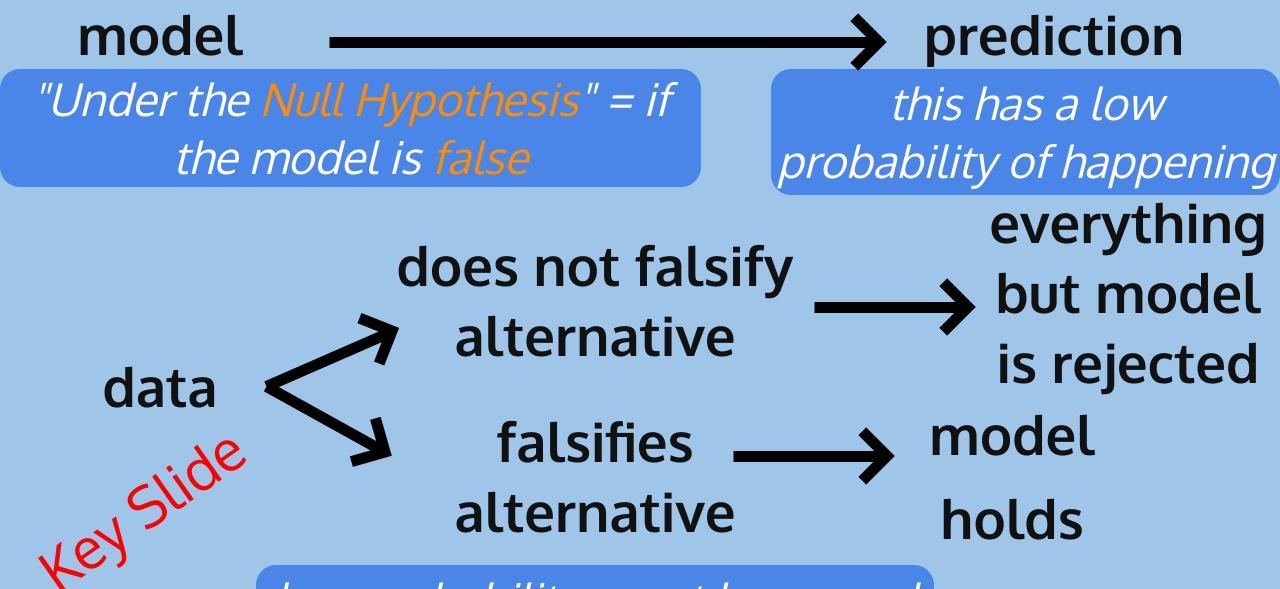
prediction is unlikely Null rejected Alternative holds

Null holds



test data against *alternative* outcomes

formulate the Null as the comprehensive opposite of your theory



low probability event happened

descriptive statistics

null hypothesis rejection testing setup

key anapts

pivotal quantities

Z, t, $\chi 2$, K-S tests

 HW1: earthquakes and KS test (https://arxiv.org/pdf/0910.0055.pdf)

•



Sarah Boslaugh, Dr. Paul Andrew Watters, 2008

Statistics in a Nutshell (Chapters 3,4,5)

https://books.google.com/books/about/Statistics_i n_a_Nutshell.html?id=ZnhgO65Pyl4C

David M. Lane et al.

Introduction to Statistics (XVIII)

http://onlinestatbook.com/Online_Statistics_Education.epub http://onlinestatbook.com/2/index.html

