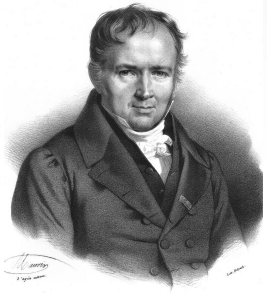
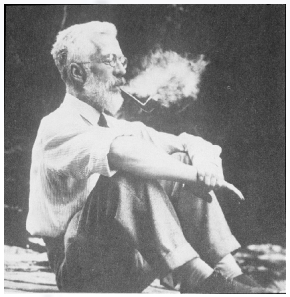
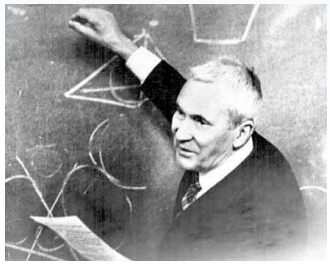
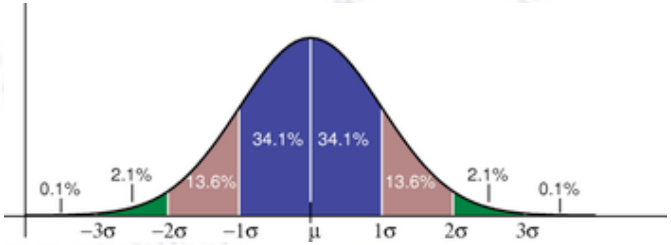
Applied Statistics

Hypothesis Testing



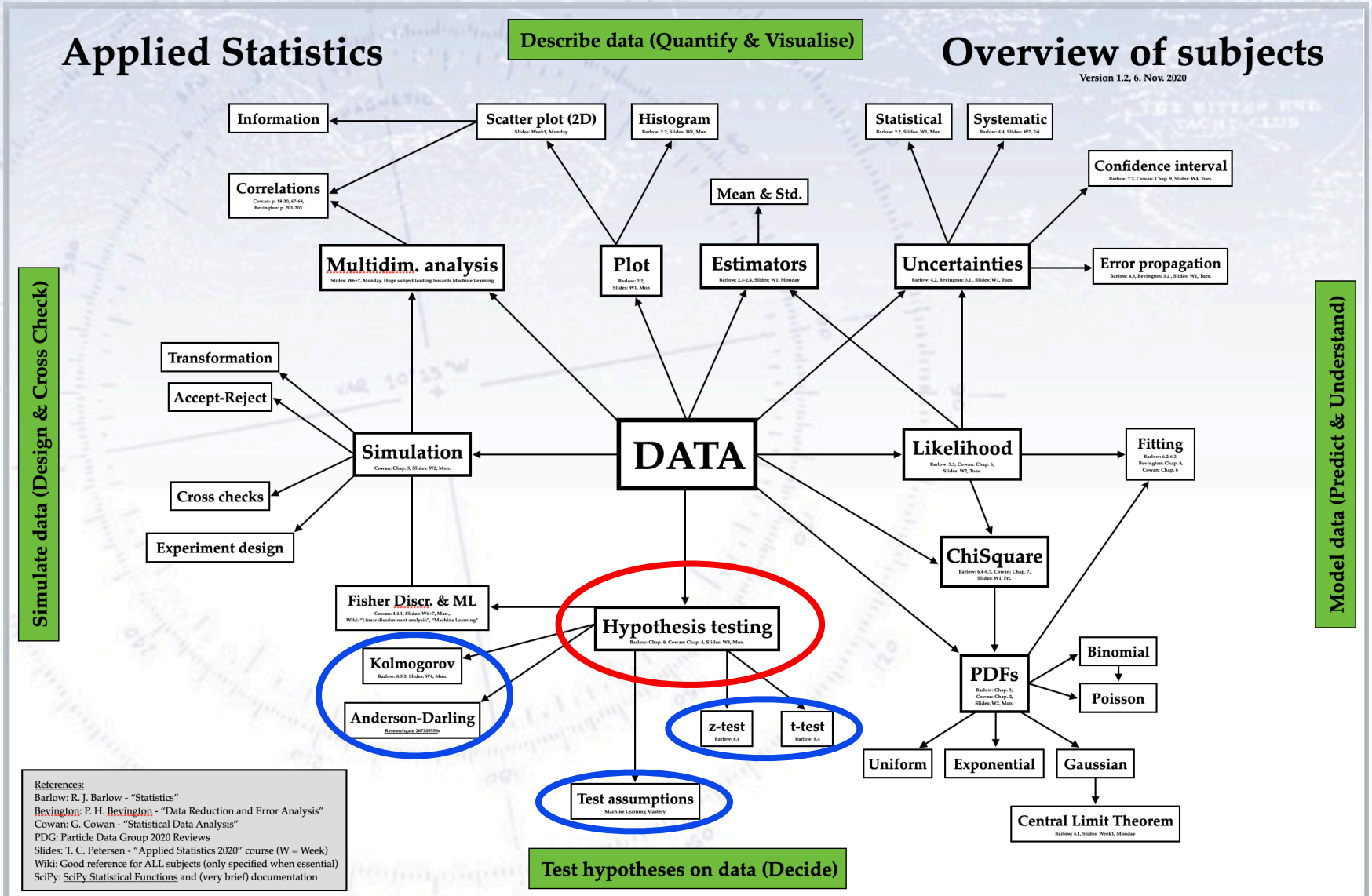





Troels C. Petersen (NBI)



"Statistics is merely a quantisation of common sense"

Hypothesis testing



Hypothesis testing

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Suppose in a beer tasting, that someone gets 9 our of 10 right.

Does that prove that the person can taste difference between beers?

Hypothesis testing

Suppose in a beer tasting, that someone gets 9 our of 10 right.

Does that prove that the person can taste difference between beers?

NO!

What we can say is that the result is **inconsistent** (at some significance level) with the hypothesis that the person chooses at random.

This leaves us with the alternative hypotheses, that the person can taste the difference or have cheated (consciously or unconsciously).

In statistics one can never prove a hypothesis directly. However, one can set up alternative hypotheses and disprove these. That is how one works in statistics…

See Barlow Chapter 8, in particular 8.2.1 (p. 146)

Hypothesis testing

Hypothesis testing is like a criminal trial. The basic "null" hypothesis is **Innocent** (called H_0) and this is the hypothesis we want to test, compared to an "alternative" hypothesis, **Guilty** (called H_1).

Innocence ("negative") is initially assumed, and this hypothesis is only rejected, if enough evidence proves otherwise, i.e. that the probability of innocence is very small ("beyond reasonable doubt").

	Truly innocent (H_0 is true)	**Truly guilty (H_1 is true)**
Acquittal (Accept H_0)	**Right decision True Negative (TN)**	**Wrong decision False Negative (FN)**
Conviction (Reject H_0)	**Wrong decision False Positive (FP)**	**Right decision True Positive (TP)**

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	Truly innocent (H_0 is true)	**Truly guilty (H_1 is true)**
Acquittal (Accept H_0)	**Right decision True Negative (TN)**	Type II error, β **Wrong decision False Negative (FN)**
Conviction (Reject H_0)	Type I error, α **Wrong decision False Positive (FP)**	**Right decision True Positive (TP)**

The rate of type I/II errors are correlated, and one can only choose one of these!

Hypothesis terminology

H_0 = Null Hypothesis:

Definition: The initial/simplest hypothesis.

Examples: Data is background, data follows simple model, particle is a pion.

H_1 = Alternative Hypothesis:

Definition: The alternative to the null hypothesis, possibly more advanced.

Examples: Data is background + signal, data does not follows simple model, particle is an electron.

α = False Positive Rate (FPR or Significance):

Definition: Probability to **reject H_0**, even if it is **true** (aka. "False Positive").

Example: Finding guilty when innocent. Concluding no signal, even if there.

Note: The signal selection efficiency = 1 - α

β = False Negative Rate (FNR or 1 - Power):

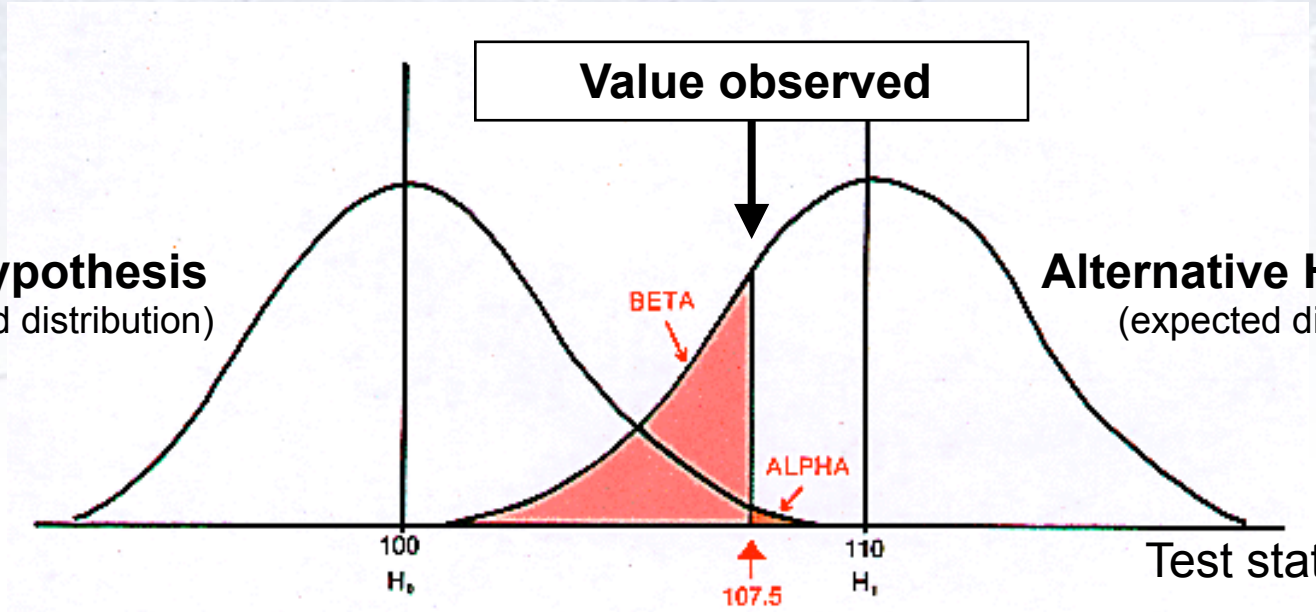
Definition: Probability to **accept H_0**, even if it is **false** (aka. "False Negative").

Example: Acquitting, when guilty. Concluding signal, even if not there.

Note: The misidentification probability = β

Taking decisions

You are asked to take a decision: **Given data - how to do that best?**



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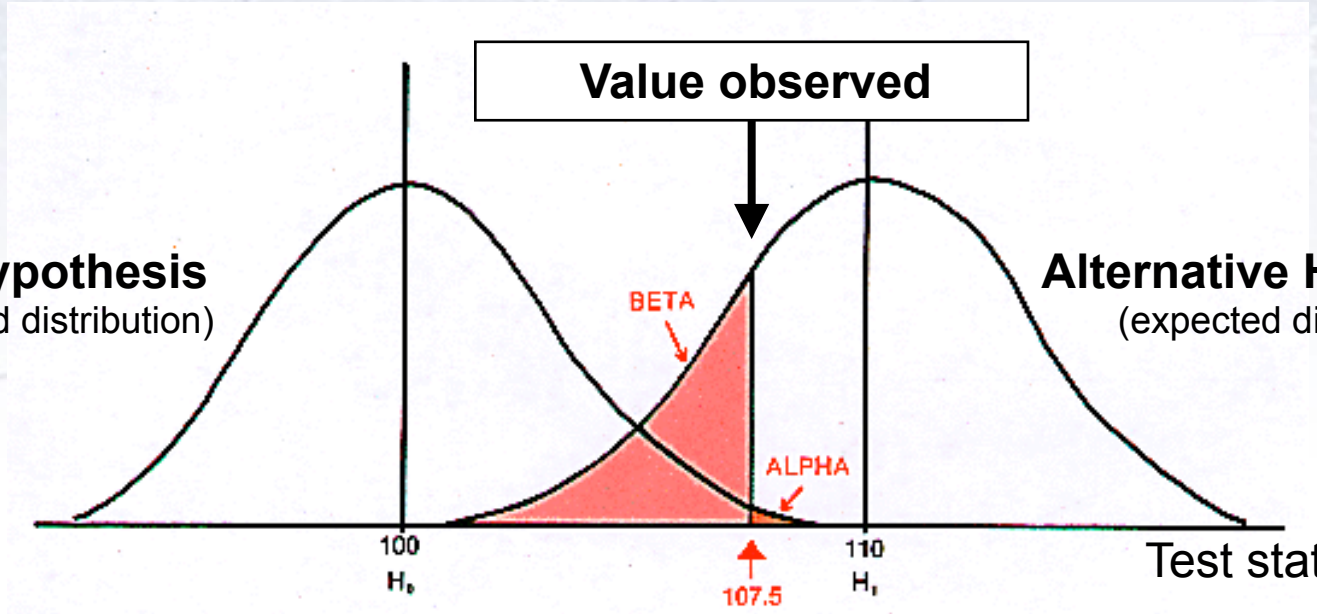
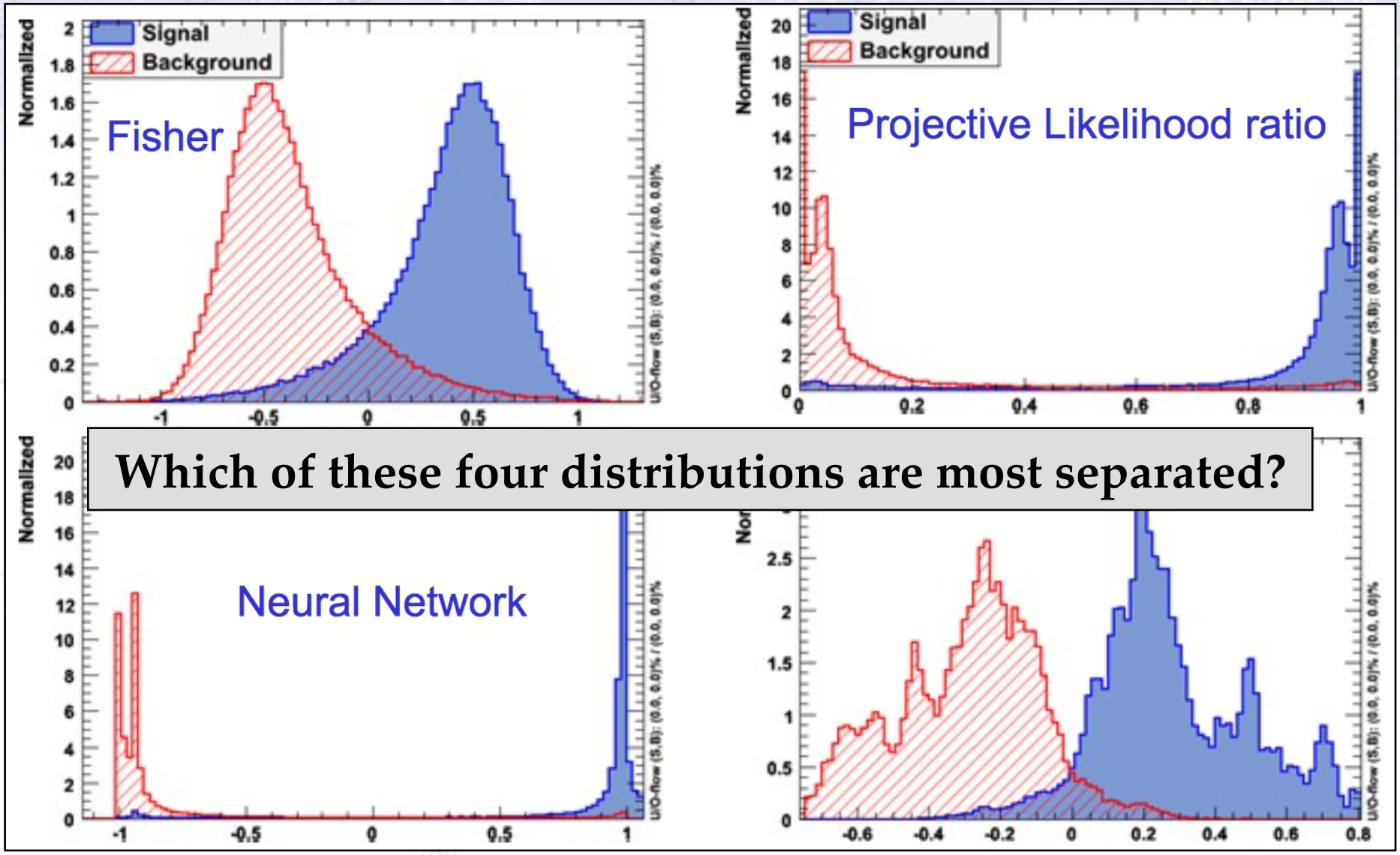
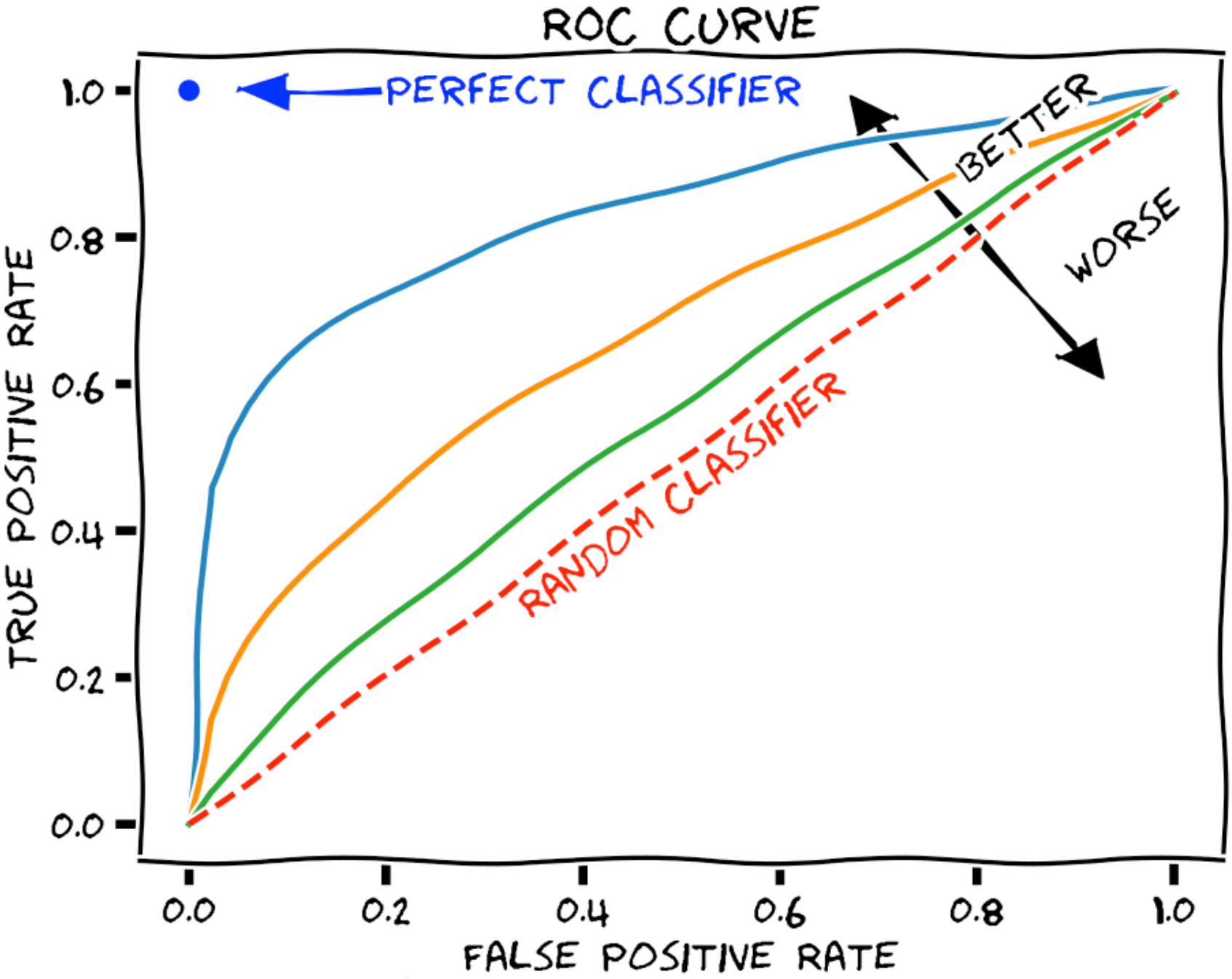


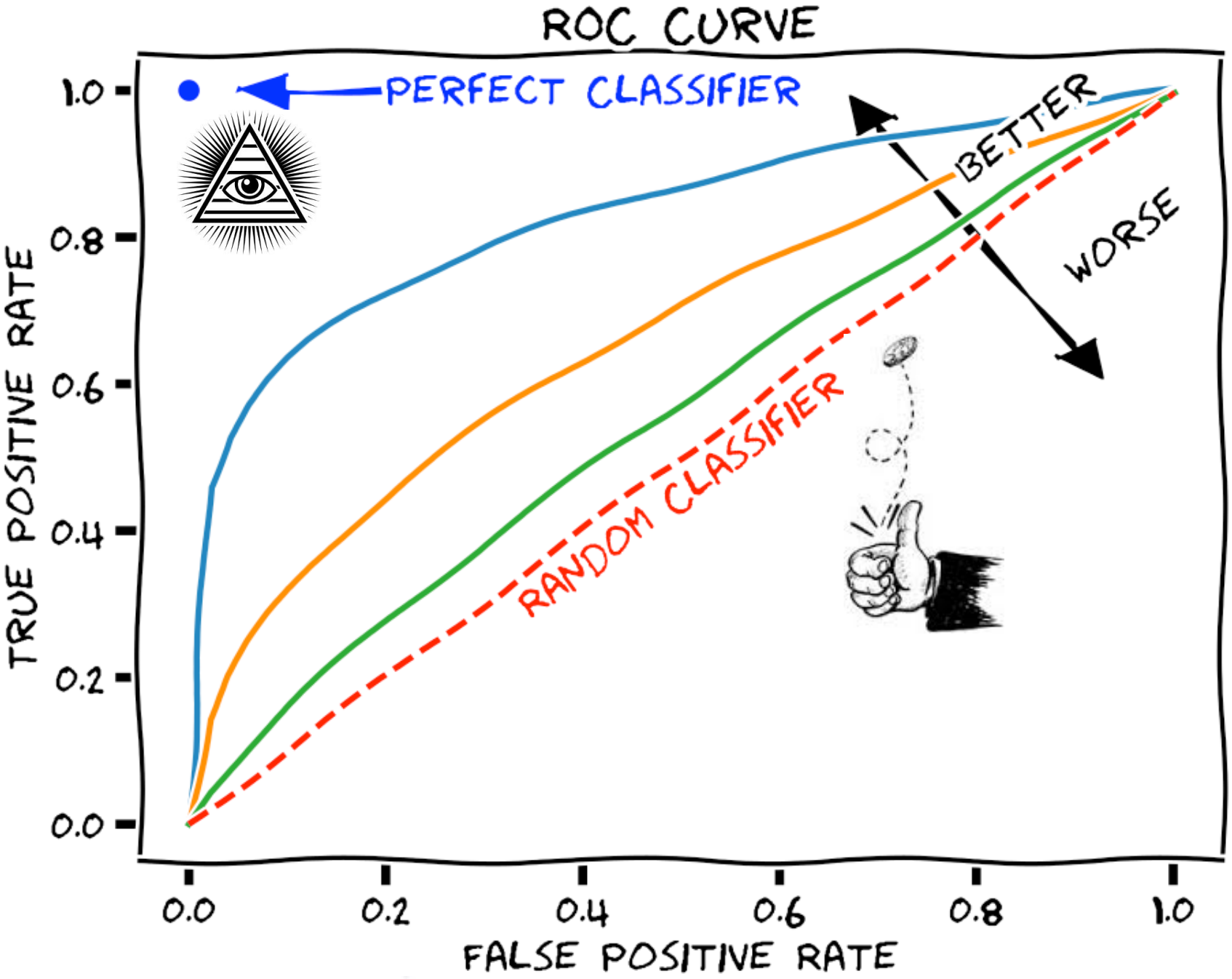
The purpose of a **test** is to yield (calculable/predictable) distributions for the **Null** and **Alternative hypotheses**, which are ***as separated from each other as possible*** (in order to minimise α and β).

Measuring separation



Which of these four distributions are most separated?


ROC CURVE
PERFECT CLASSIFIER
BETTER
WORSE
RANDOM CLASSIFIER
TRUE POSITIVE RATE
FALSE POSITIVE RATE
0.0
0.2
0.4
0.6
0.8
1.0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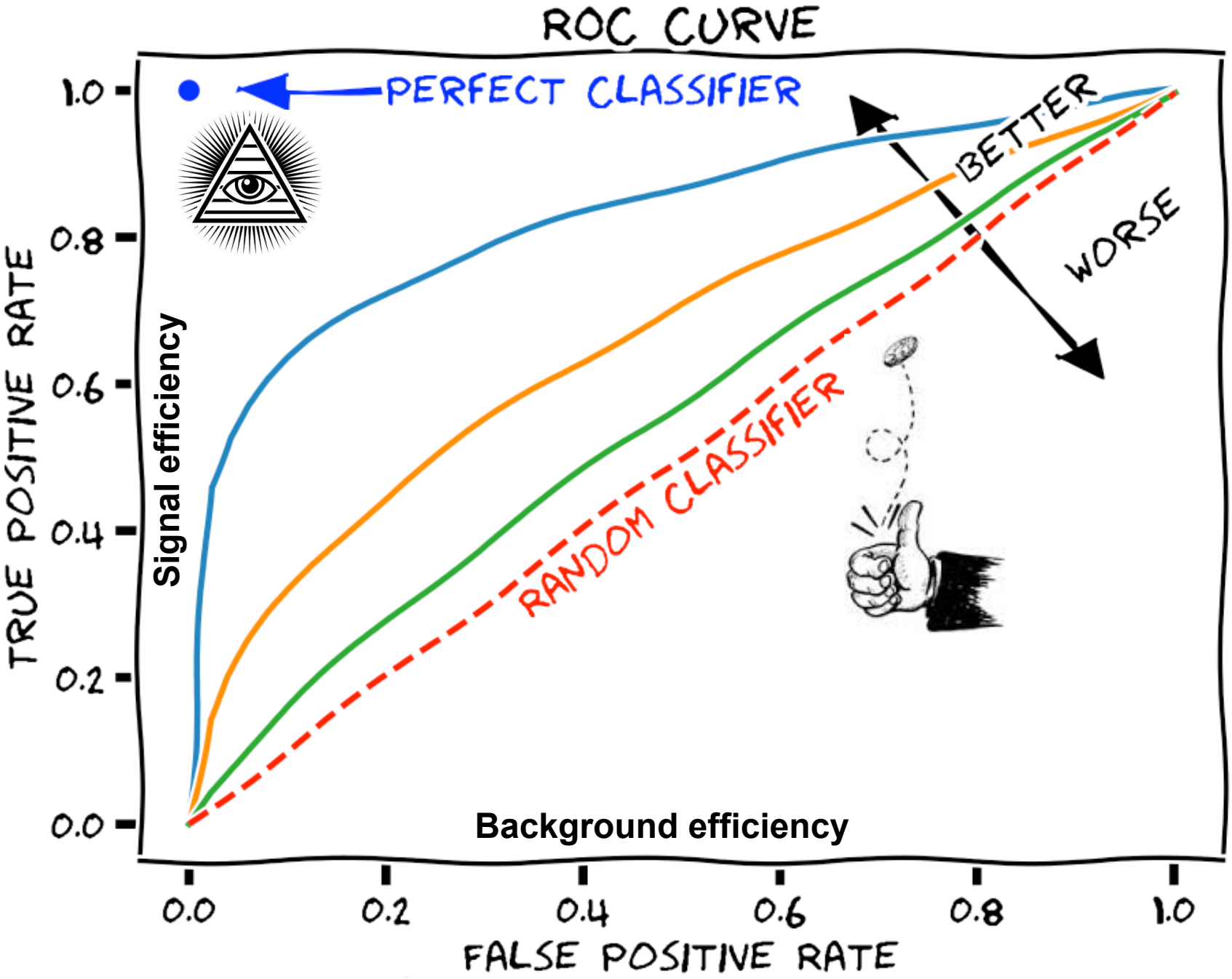
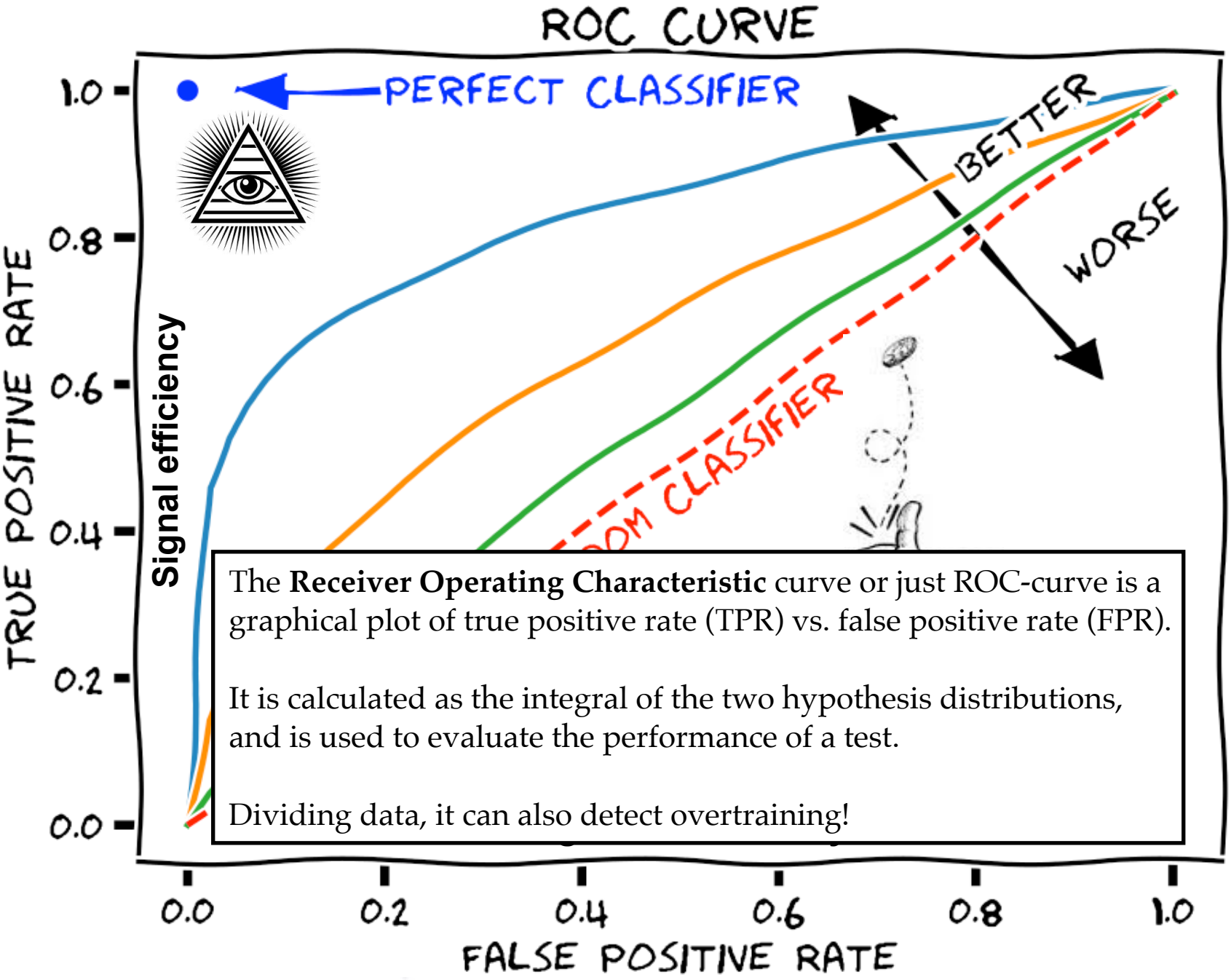

ROC CURVE
PERFECT CLASSIFIER
BETTER
WORSE
RANDOM CLASSIFIER
Signal efficiency
Background efficiency
TRUE POSITIVE RATE
FALSE POSITIVE RATE
0.0
0.2
0.4
0.6
0.8
1.0

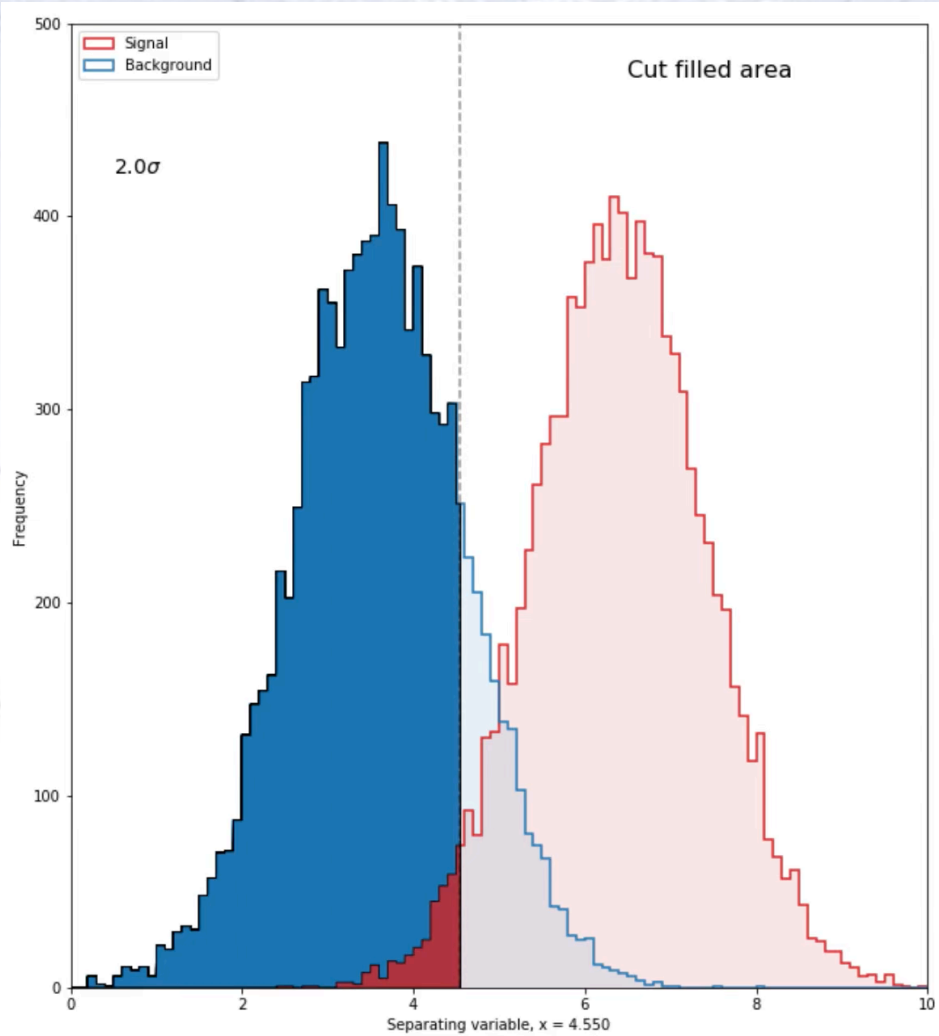


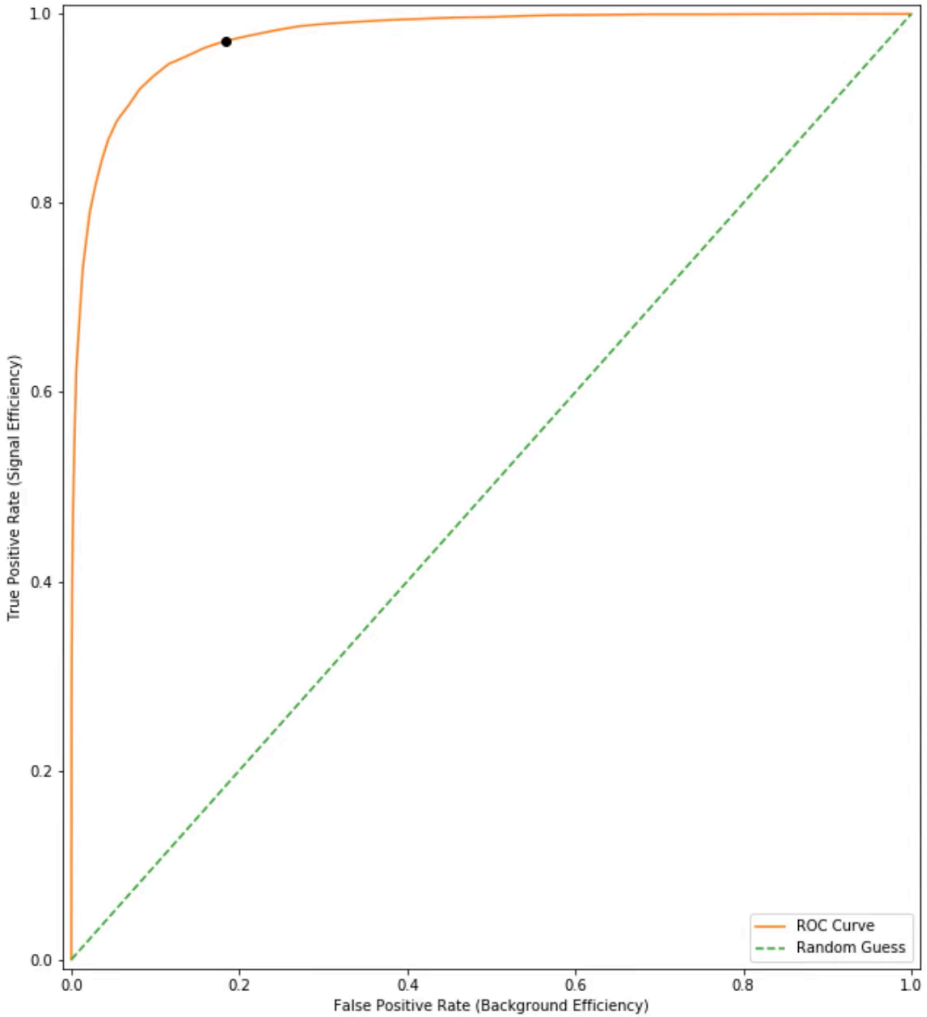
The **Receiver Operating Characteristic** curve or just ROC-curve is a graphical plot of true positive rate (TPR) vs. false positive rate (FPR).

It is calculated as the integral of the two hypothesis distributions, and is used to evaluate the performance of a test.

Dividing data, it can also detect overtraining!

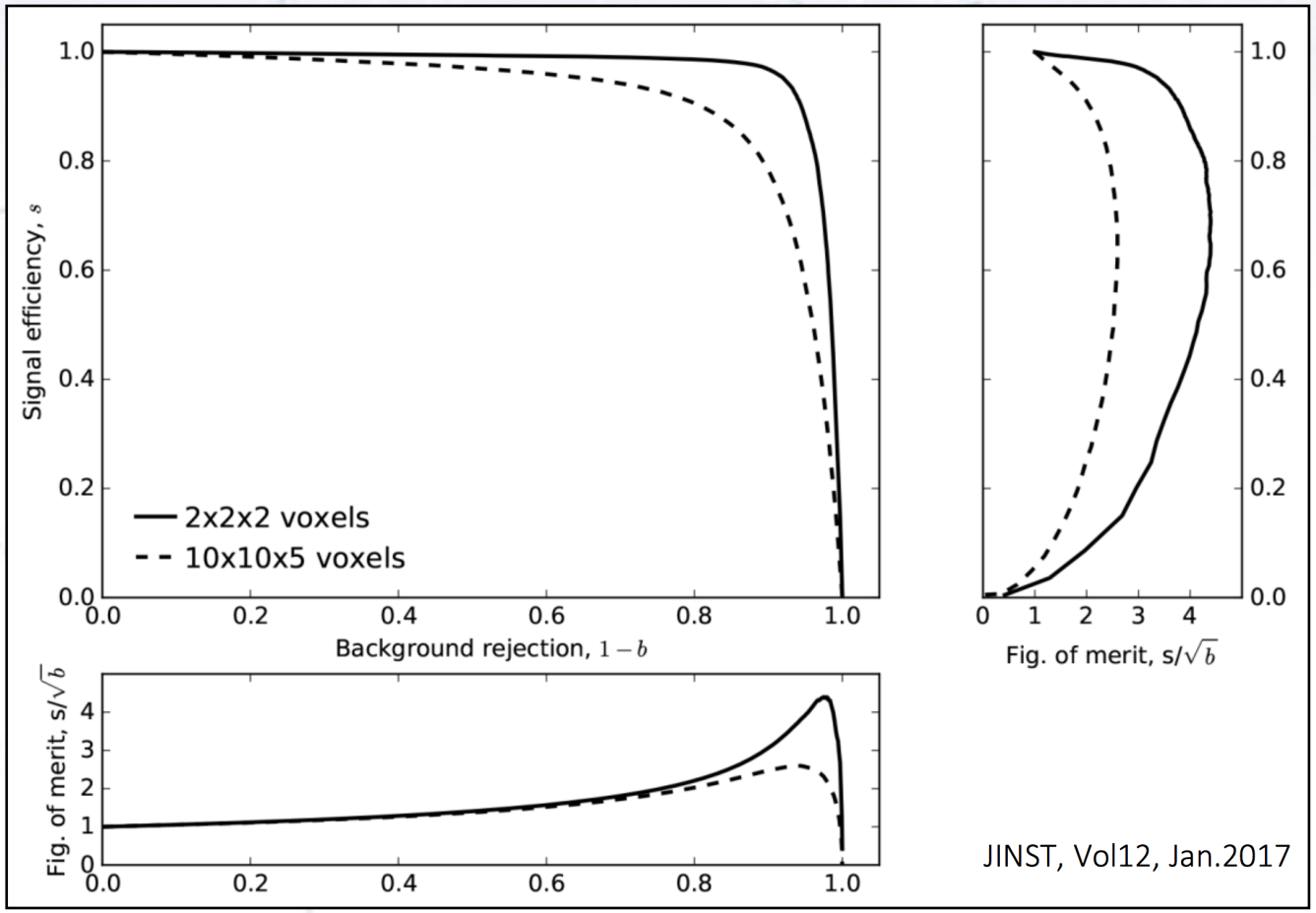
Understanding the ROC curve





Where to select?

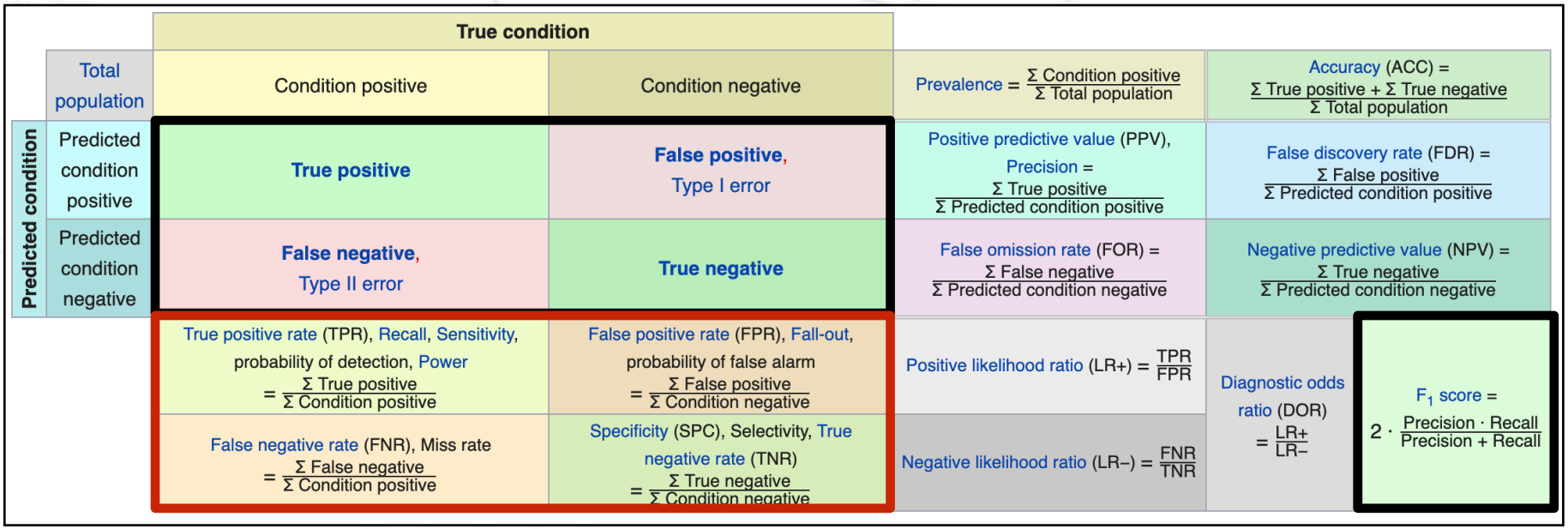
The ROC curve does **not** tell you **where** to make your selection. You have to figure that out. In searches for signal (S) in background (B), optimising S/sqrt(B) or S/sqrt(S+B) is often used.



Which metric to use?

There are a ton of metrics in hypothesis testing, see below. However, those in the boxes below are the most central ones.

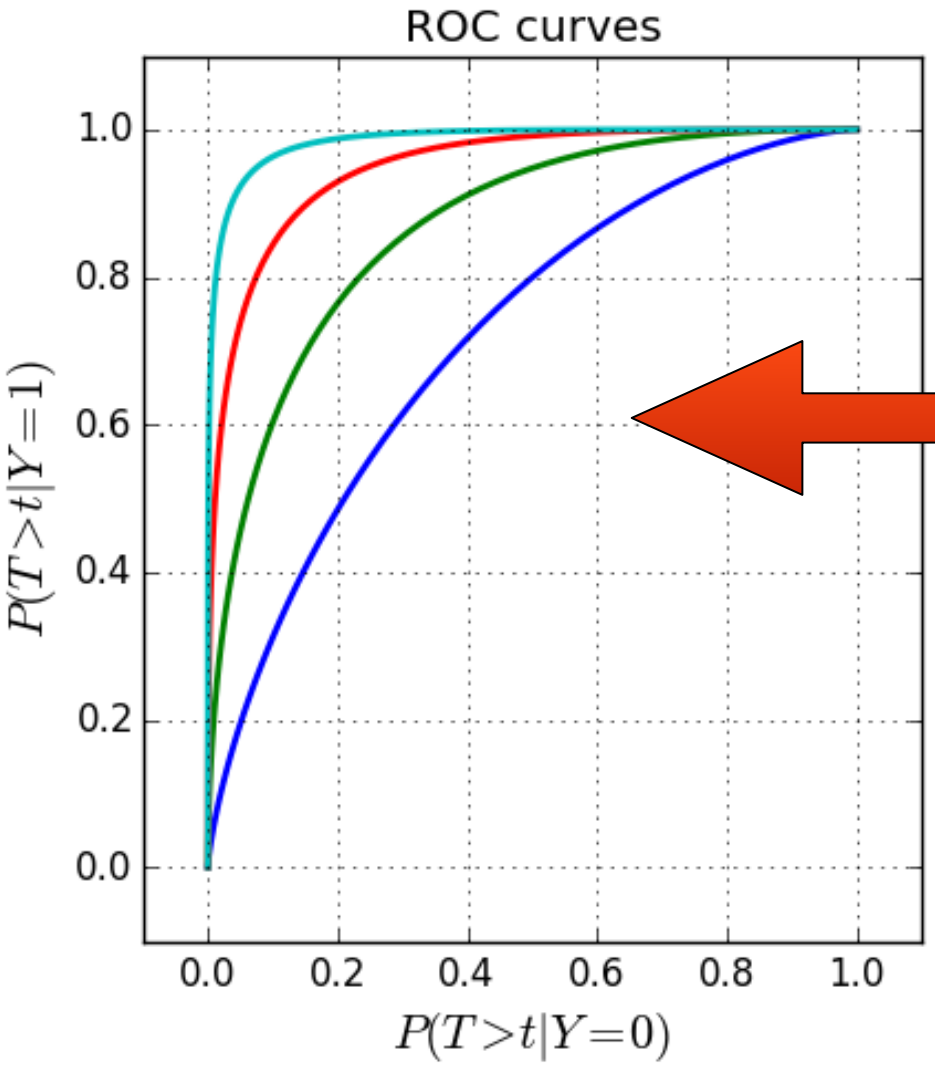
One metric - not mentioned here - is the Area Under the Curve (AUC), which is simply an integral of the ROC curve (thus 1 is perfect score). This is often used in Machine Learning to optimise performance (loss).

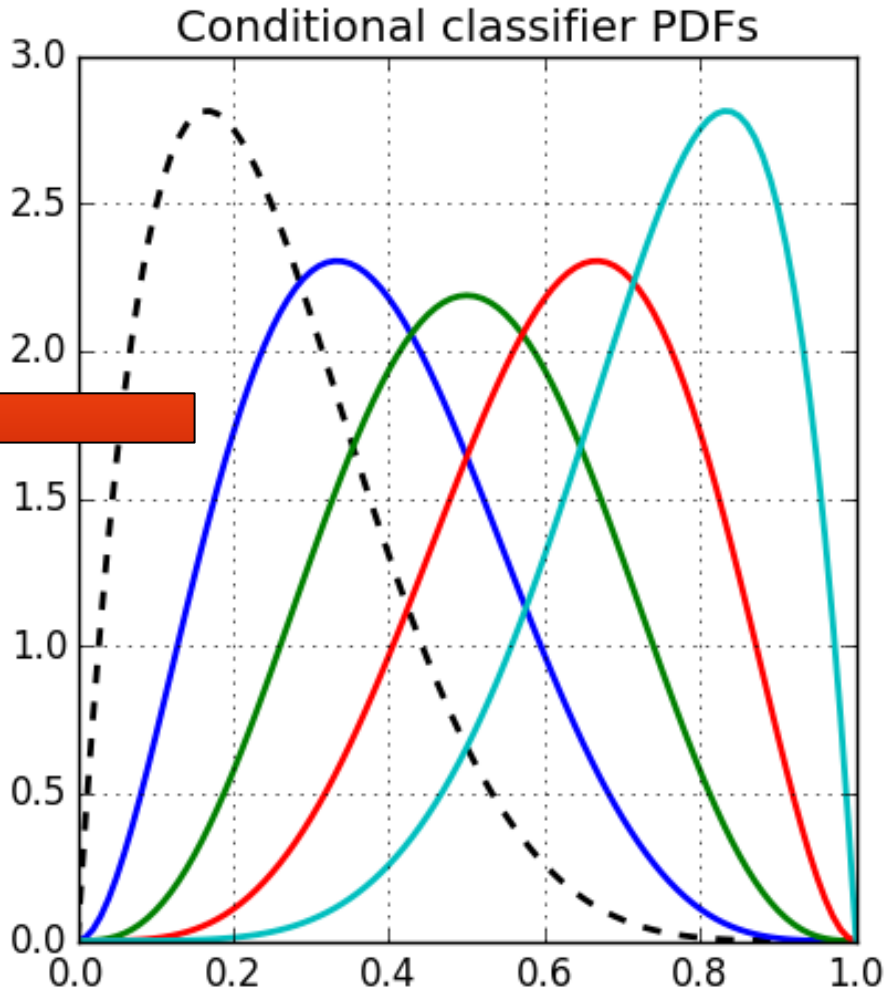


https://en.wikipedia.org/wiki/Receiver_operating_characteristic

Example of ROC curves in use

Simple case


ROC curves
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
$P(T>t|Y=1)$
$P(T>t|Y=0)$


Conditional classifier PDFs
3.0
2.5
2.0
1.5
1.0
0.5
0.0
0.0
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0.4
0.6
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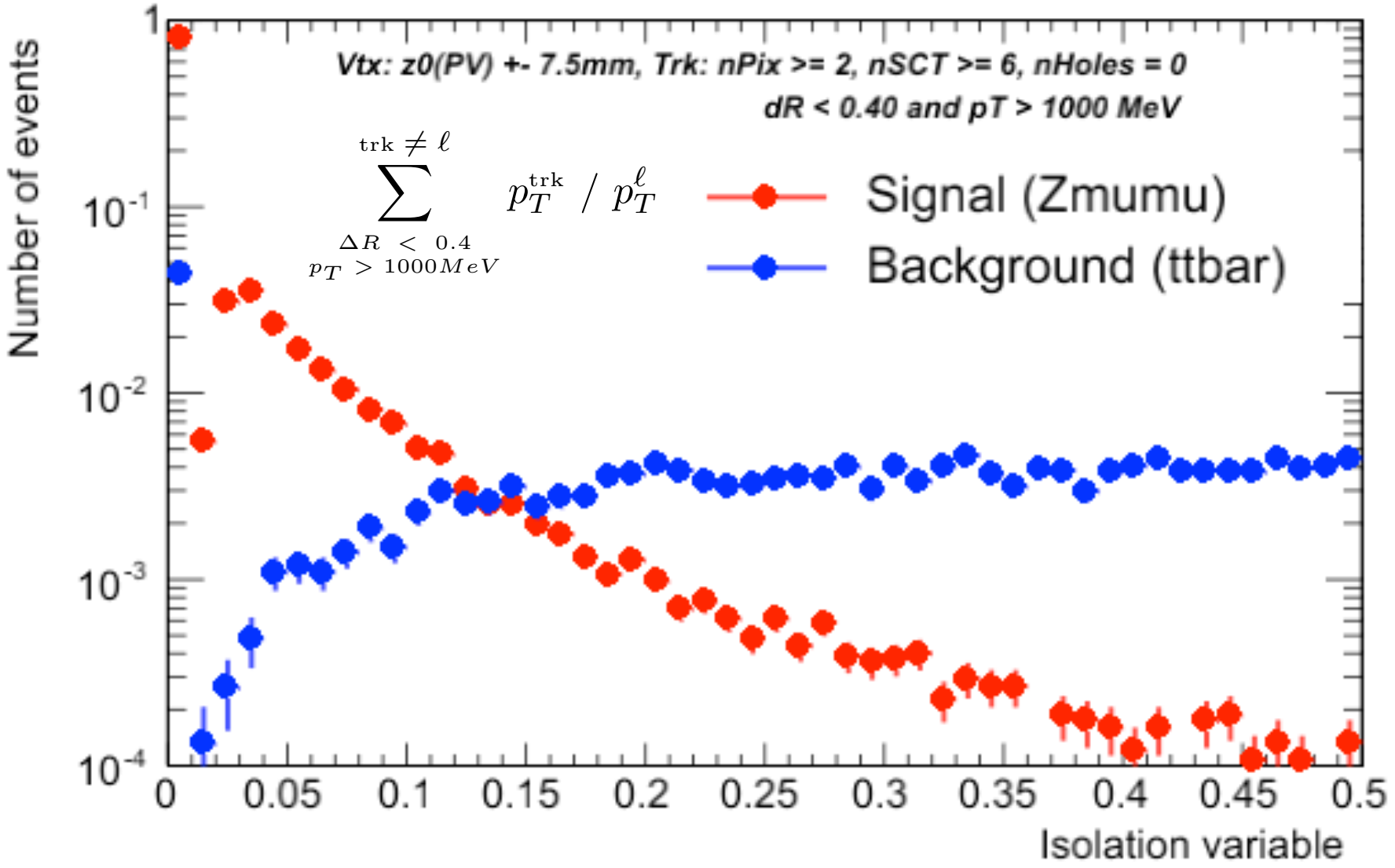
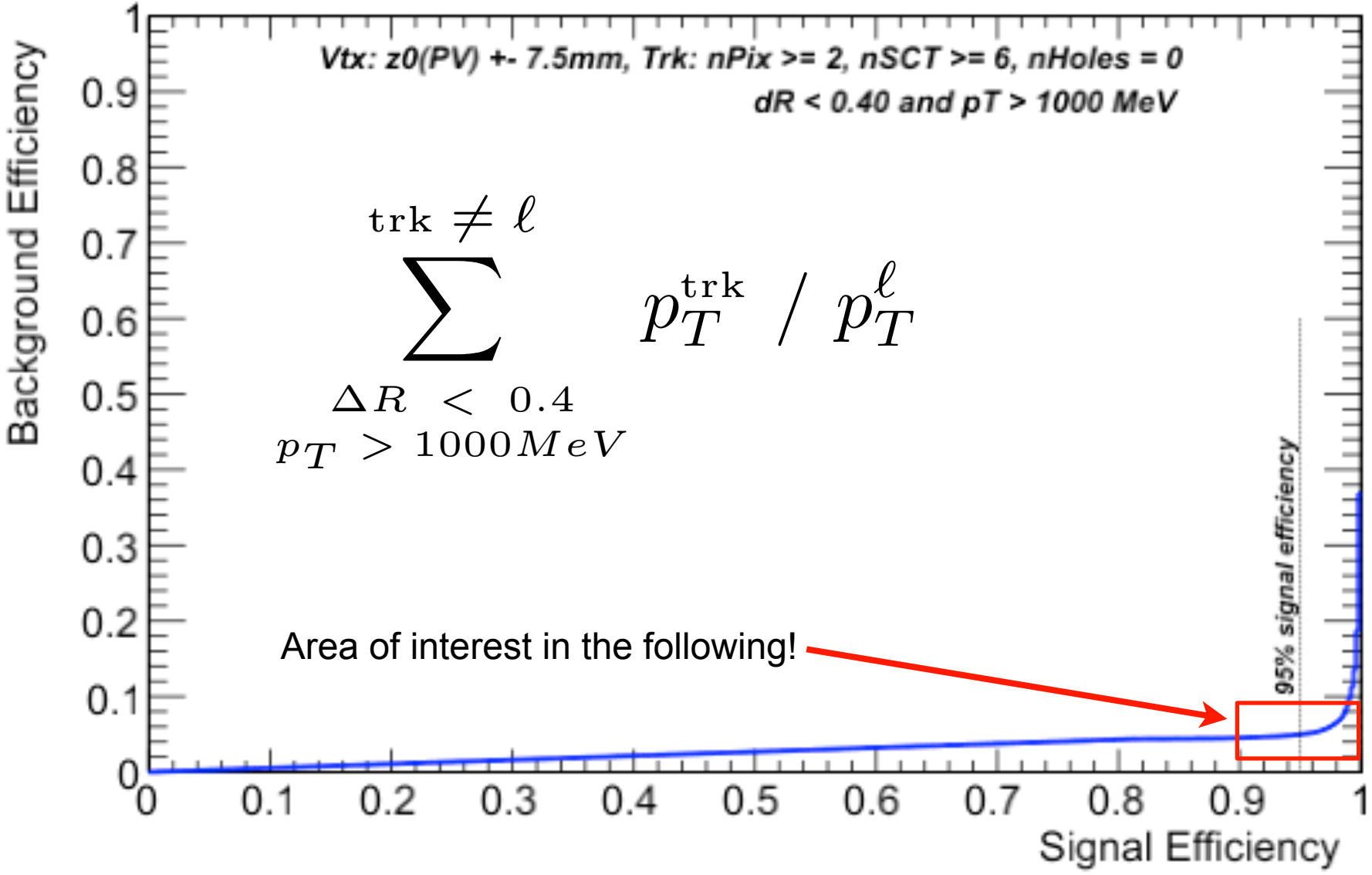
1.0

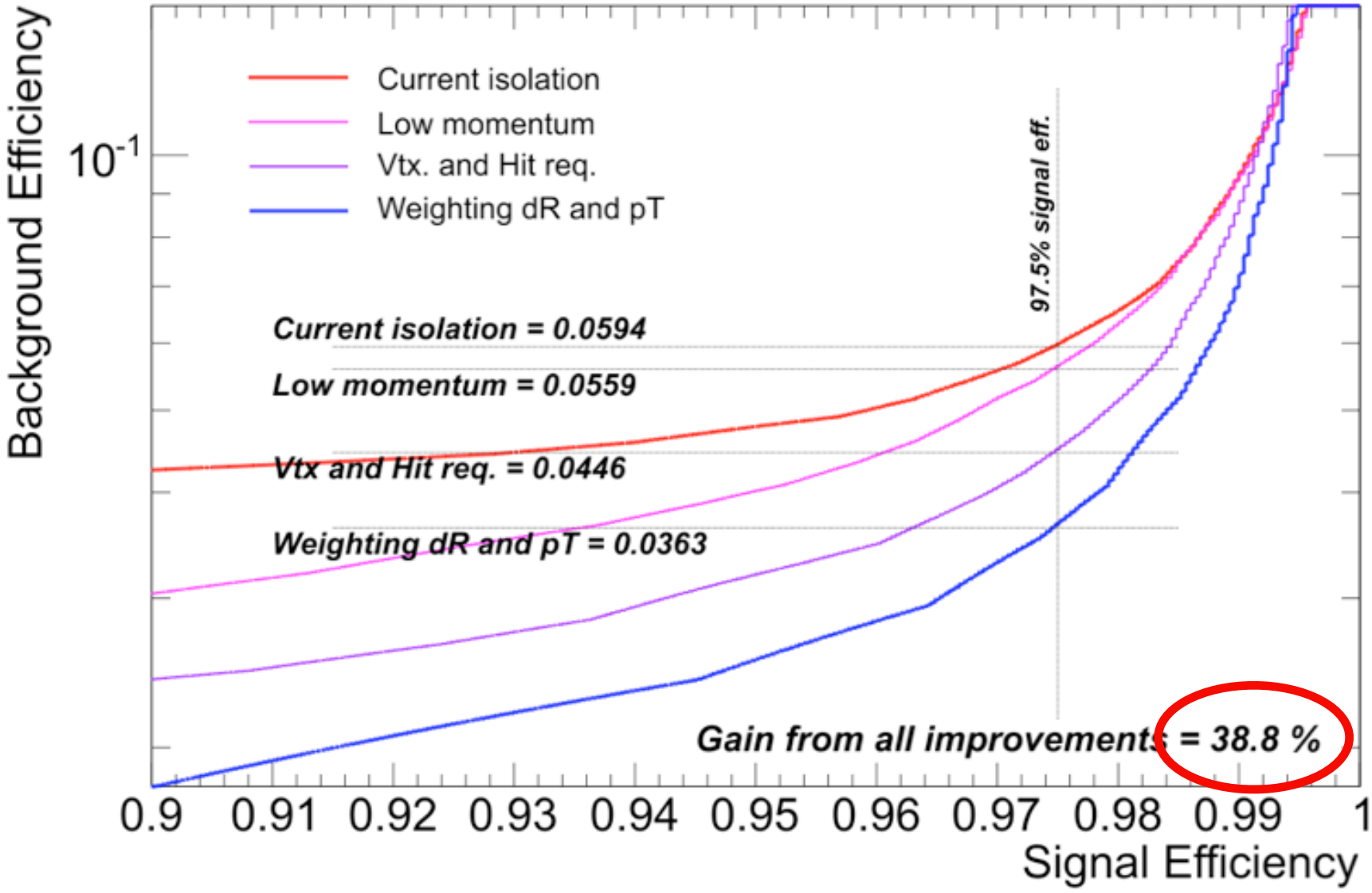
Basic steps - distributions



Basic steps - ROC curves



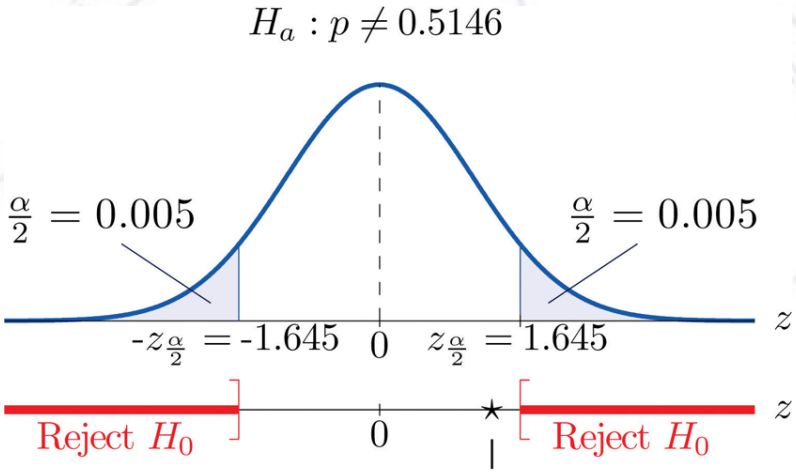
Overall improvement

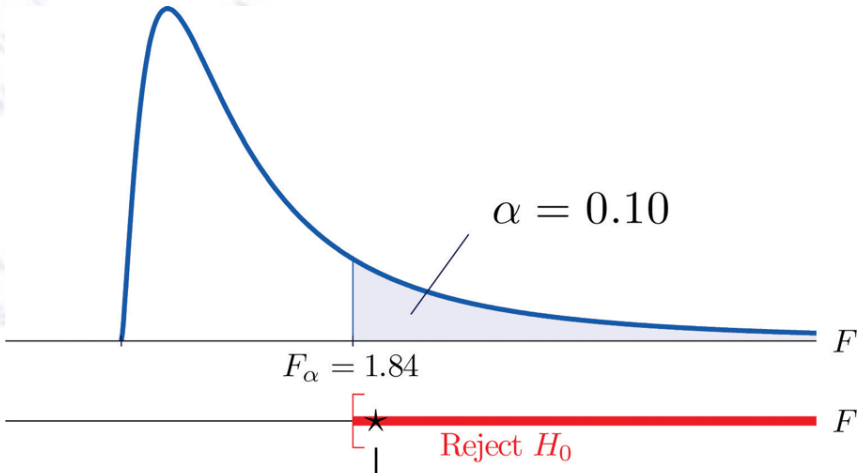


Testing procedure
&
Typical statistical tests

Testing procedure

1. Consider an **initial (null) hypothesis**, of which the truth is unknown.
2. State null and **alternative hypothesis**.
3. Consider statistical **assumptions** (independence, distributions, etc.)
4. Decide for appropriate test and state relevant **test statistic**.
5. **Derive the test statistic** distribution under null and alternative hypothesis.
   In standard cases, these are well known (Poisson, Gaussian, Student's t, etc.)
6. **Select a significance level** (α), that is a probability threshold below which null hypothesis will be rejected (typically from 5% (biology) and down (physics)).
7. Compute from (otherwise blinded) observations / data **value of test statistic *t***.
8. From *t* **calculate probability of observation** under null hypothesis (**p-value**).
9. **Reject null hypothesis** for alternative **if p-value is below significance level**.





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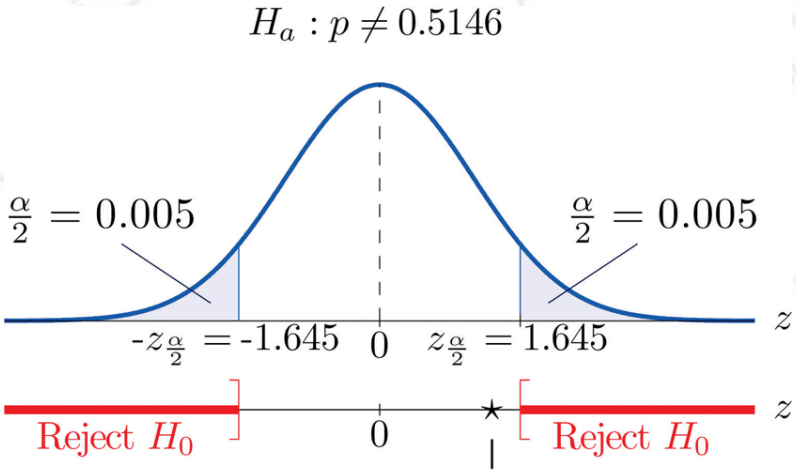
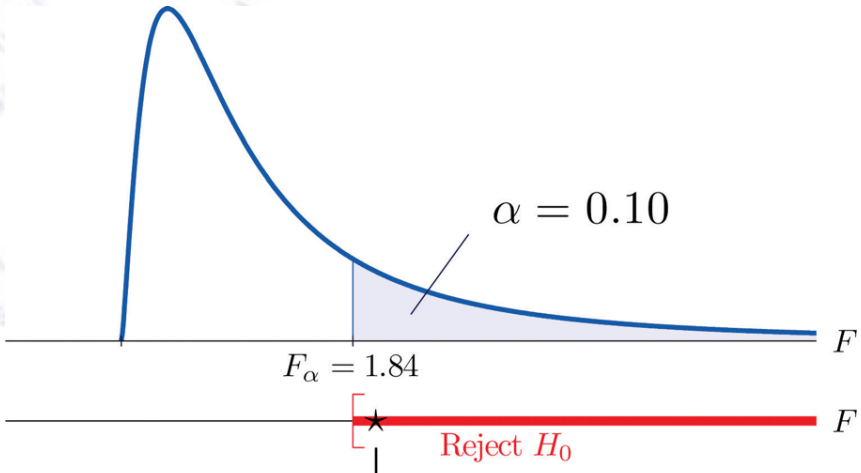
   In standa ...nt's t, etc.)
6. **Select a s** ... which null
   hypothes ... (physics)).
7. Compute ... **statistic *t***.
8. From *t* **ca** ... (**p-value**).
9. **Reject nu** ... **nce level**.

1. State hypothesis.
2. Set the criteria for a decision.
3. Compute the test statistic.
4. Make a decision.





Hypothesis testing philosophy

In hypothesis testing, you can **never prove a hypothesis**.

You can **accept** a hypothesis, but this does not exclude accepting other hypothesis.

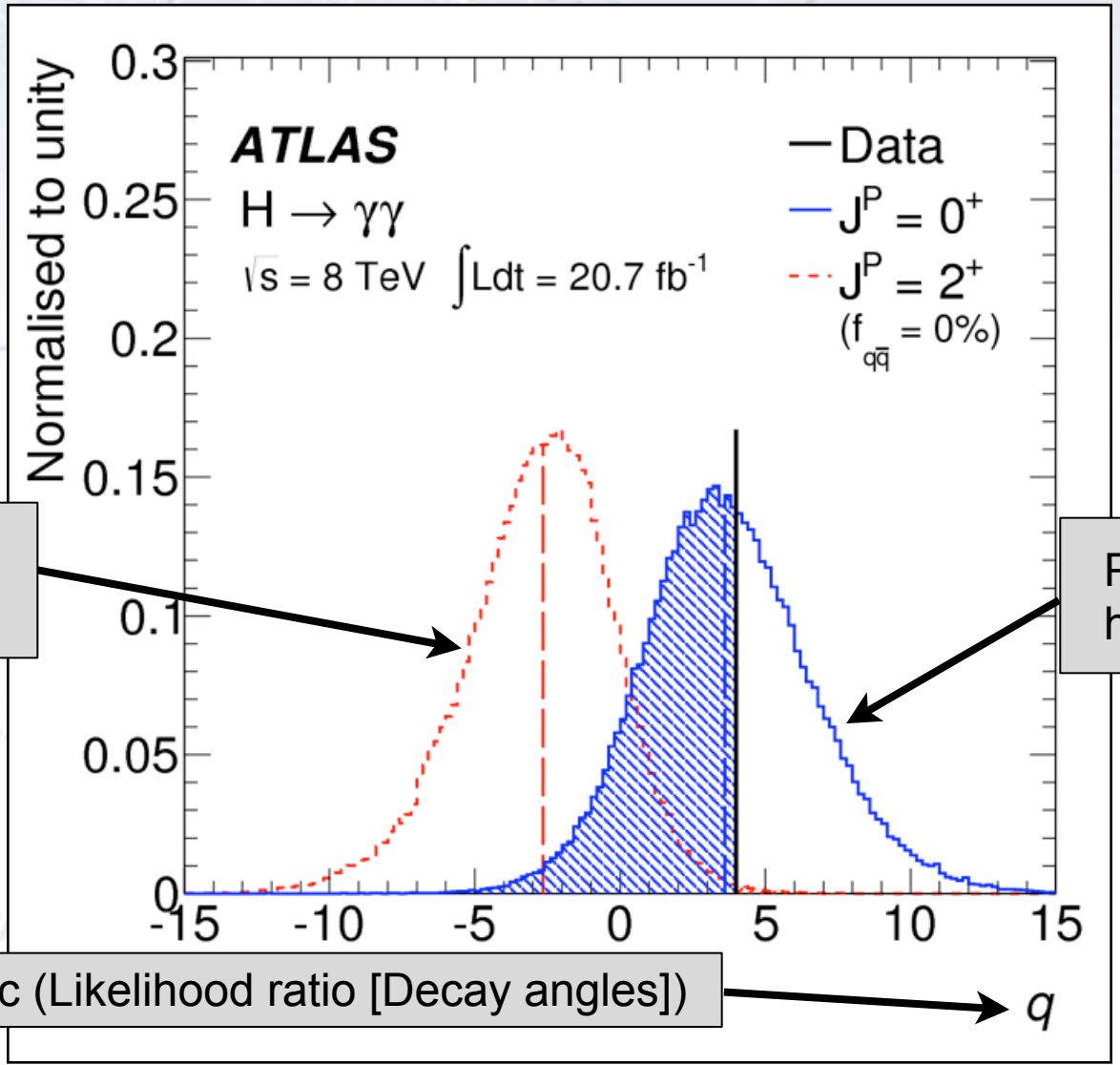
However, you can **reject** a hypothesis on the basis that it's probability of being correct (p-value) is too small.

Thus, in hypothesis testing, the line of reasoning is to state a hypothesis *opposite* of what you want to show, and then try to **reject** this hypothesis.

See Barlow 8.2.1 (p. 146)

Example of hypothesis test

The spin of the newly discovered "Higgs-like" particle (spin 0 or 2?):



PDF of spin 2 hypothesis

PDF of spin 0 hypothesis

Test statistic (Likelihood ratio [Decay angles])

Neyman-Pearson Lemma

Consider a **likelihood ratio** between the null and the alternative model:

$$D = -2 \ln \frac{\text{likelihood for null model}}{\text{likelihood for alternative model}}$$

The Neyman-Pearson lemma (loosely) states, that this is the most powerful test there is for simple hypothesis (i.e. no parameters).

In reality, the problem is that it is not always easy to write up a likelihood for complex situations!

However, there are many tests derived from the likelihood...

Likelihood ratio problem

While the **likelihood ratio** is in principle both simple to write up and powerful:

$$D = -2 \ln \frac{\text{likelihood for null model}}{\text{likelihood for alternative model}}$$

…it turns out that determining the exact distribution of the likelihood ratio is often very hard.
To know the two likelihoods one might use a Monte Carlo simulation, representing the distribution by an n-dimensional histogram (since our observable, x, can have n dimensions). But if we have M bins in each dimension, then we have to determine M^n numbers, which might be too much.

However, a convenient result (Wilk's Theorem) states that as the sample size approaches infinity, **the test statistic D will be χ^2-distributed with N_{dof} equal to the difference in dimensionality of the Null and the Alternative** (nested) **hypothesis**.
Alternatively, one can choose a simpler (and usually fully acceptable test)…

Common statistics tests

Common statistical tests

- **One-sample test** compares sample (e.g. mean) to known value:
  Example: Comparing sample to known constant ($\mu_{exp} = 2.91 \pm 0.01$ vs. $c = 2.99$).

$$z = \frac{\bar{x} - \mu_0}{\sigma(\bar{x})}$$

- **Two-sample test** compares two samples (e.g. means).
  Example: Comparing sample to control ($\mu_{exp} = 4.1 \pm 0.6$ vs. $\mu_{control} = 0.7 \pm 0.4$).

$$z = \frac{\bar{x_1} - \bar{x_2}}{\sqrt{\sigma(\bar{x_1})^2 + \sigma(\bar{x_2})^2}}$$

- **Paired test** compares paired member difference (to control important variables).
  Example: Testing environment influence on twins to control genetic bias ($\mu_{diff} = 0.81 \pm 0.29$ vs. 0).

- **Chi-squared test** evaluates adequacy of model compared to data.
  Example: Model fitted to (possibly binned) data, yielding p-value = Prob($\chi^2 = 45.9$, $N_{dof} = 36$) = 0.125

- **Kolmogorov-Smirnov test** compares if two distributions are compatible.
  Example: Compatibility between function and sample or between two samples, yielding p-value = 0.87

- **Wald-Wolfowitz runs test** is a binary check for independence.
- **Fisher's exact test** calculates p-value for contingency tables.
- **F-test** compares two sample variances to see, if grouping is useful.

From z- to p-value

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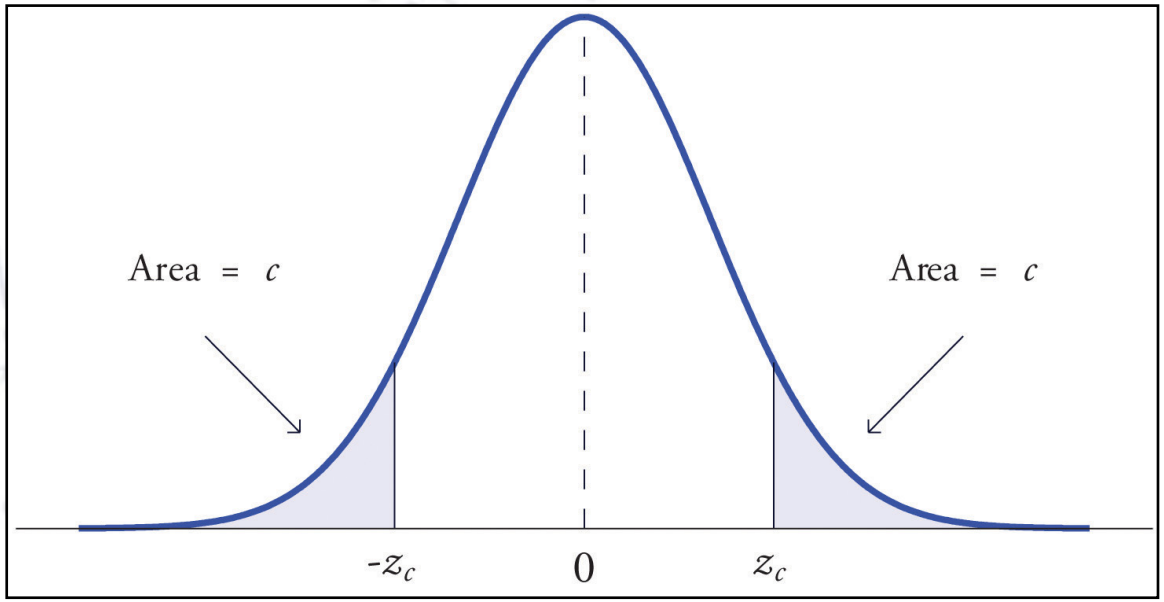
The step from z-value to p-value consists of taking the integral of a Gaussian:

You ask yourself: "What is the probability of getting this result or worse?", and find the p-value from the integral of "this result" i.e. your z-value and "out" i.e. "worse".

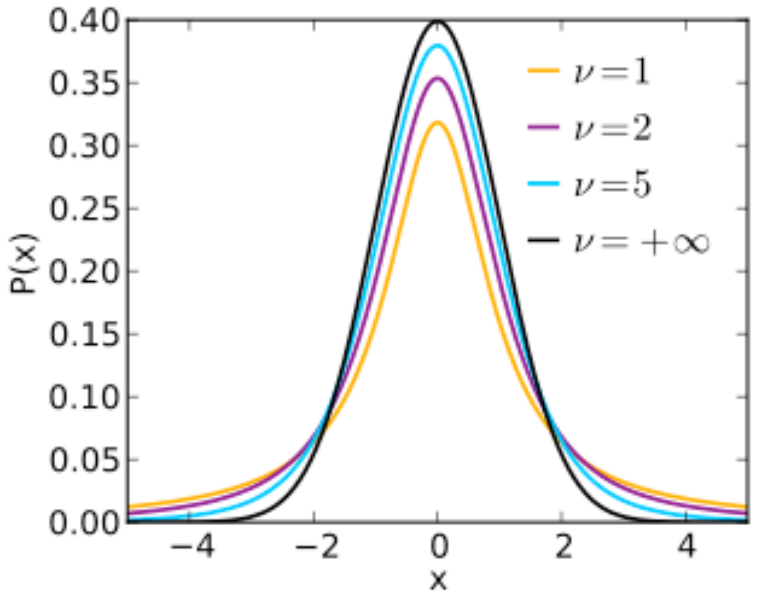


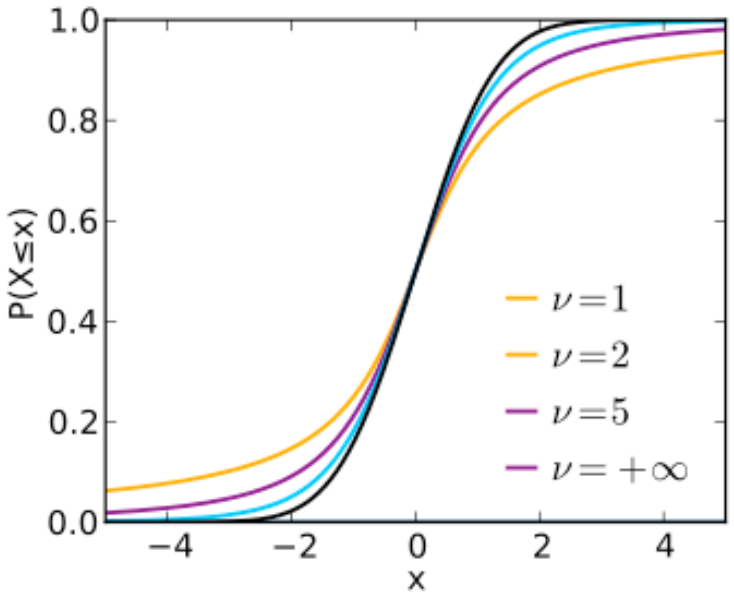
Student's t-distribution

Given only a small (n obs.) sample (still assumed Gaussian), we don't know the mean μ and width σ well - we only know estimates of them! This changes the PDF to:

$$p(x \mid \nu, \hat{\mu}, \hat{\sigma}^2) = \frac{\Gamma(\frac{\nu+1}{2})}{\Gamma(\frac{\nu}{2})\sqrt{\pi\nu\hat{\sigma}^2}} \left(1 + \frac{1}{\nu}\left(\frac{x-\hat{\mu}}{\hat{\sigma}}\right)^2\right)^{-\frac{\nu+1}{2}} \qquad \nu = N_{\mathrm{DoF}} = n - 1$$

"Discovered" by William Gosset, student's t-distribution takes into account the **lacking knowledge of the mean and variance** (as is the case for small samples).





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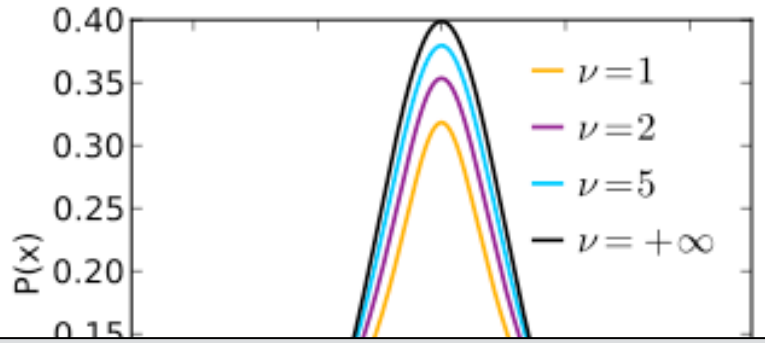

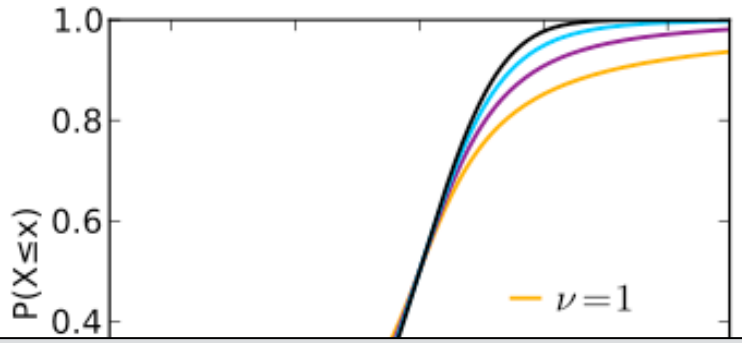

When mean and width are poorly known, estimating it from sample gives:

Gaussian: $z = \dfrac{x-\mu}{\sigma}$ **Student's:** $t = \dfrac{x-\hat{\mu}}{\hat{\sigma}}$

Simple tests (Z- or T-tests)

- **One-sample test** compares sample (e.g. mean) to known value:

  $$z = \frac{\bar{x} - \mu_0}{\sigma(\bar{x})}$$

  Example: Comparing sample to known constant ($\mu_{exp} = 2.91 \pm 0.01$ vs. $c = 3.00$).

- **Two-sample test** compares two samples (e.g. means).

  $$z = \frac{\bar{x_1} - \bar{x_2}}{\sqrt{\sigma(\bar{x_1})^2 + \sigma(\bar{x_2})^2}}$$

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  Example: Testing environment influence on twins to control genetic bias ($\mu_{diff} = 0.81 \pm 0.29$ vs. 0).

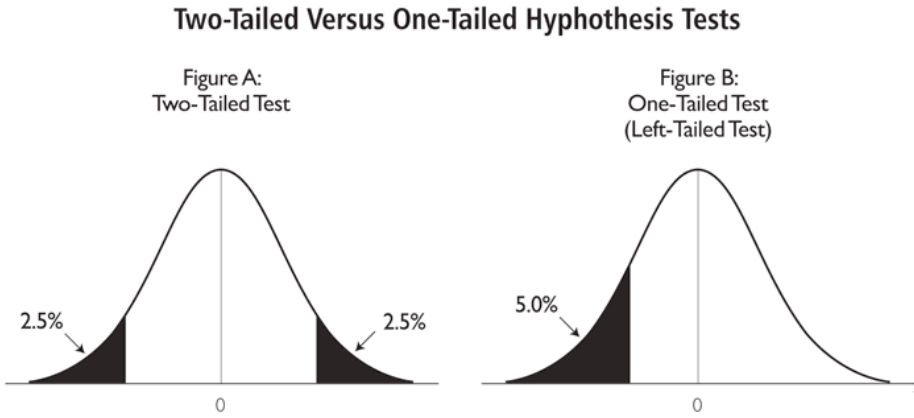
Things to consider:

- Variance known (Z-test) vs. Variance unknown (T-test).

  Rule-of-thumb: If N > 10-20 or σ known then Z-test, else T-test.

- One-sided vs. two-sided test.

  Rule-of-thumb: If you want to test for difference, then use two-sided. If you care about specific direction of difference, use one-sided.



Chi-squared test

Without any further introduction...

$$\chi^2(\bar{\theta}) = \sum_{i=1}^{N} \frac{(y_i - \lambda(x_i;\bar{\theta}))^2}{\sigma_i^2}$$

- **Chi-squared test** evaluates adequacy of model compared to data.

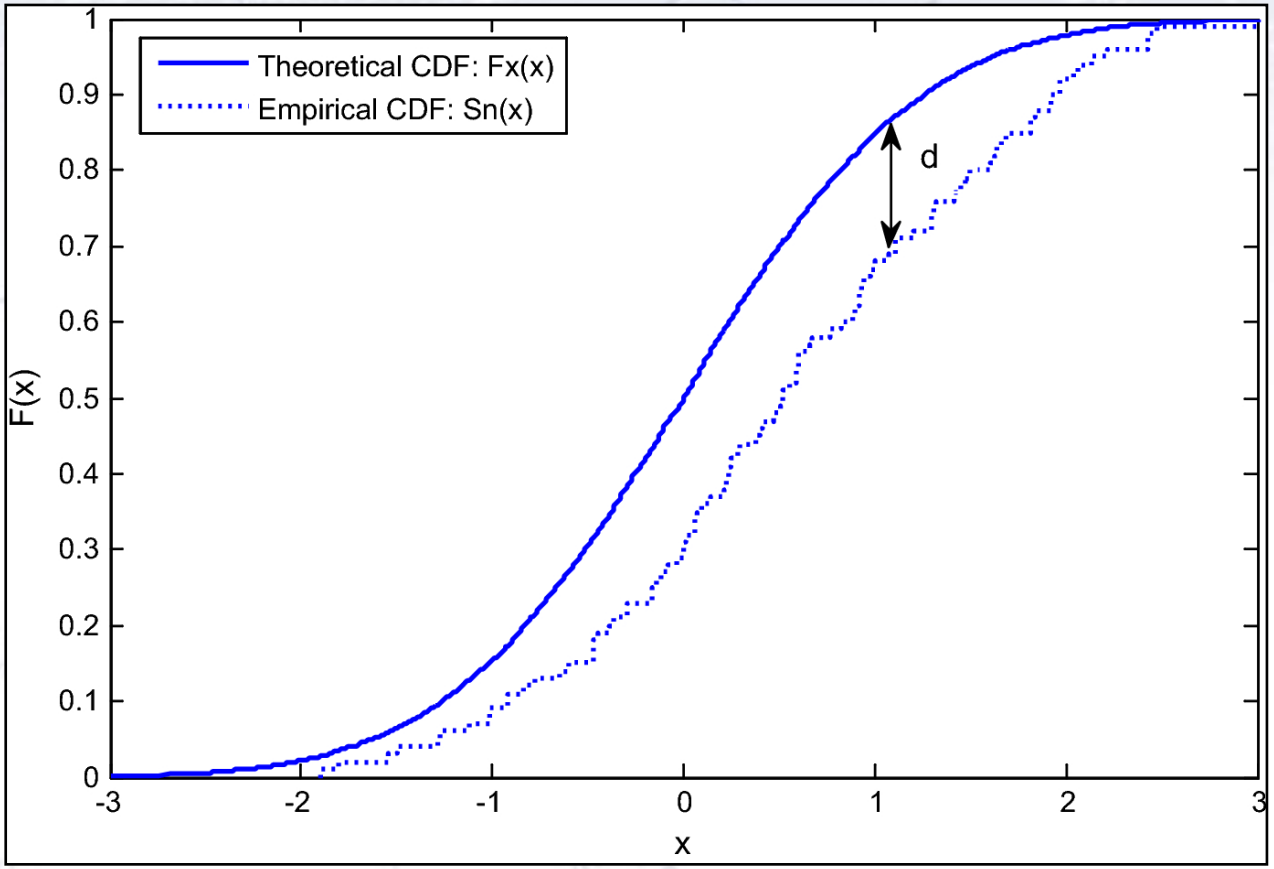
  Example: Model fitted to (possibly binned) data, yielding p-value = Prob($\chi^2 = 45.9$, $N_{dof} = 36$) = 0.125

If the p-value is small, the hypothesis is unlikely...

Kolmogorov-Smirnov test

- **Kolmogorov-Smirnov test** compares if two distributions are compatible.

  Example: Compatibility between function and sample or between two samples, yielding p-value = 0.87



The Kolmogorov test measures the maximal distance between the integrals of two distributions and gives a probability of being from the same distribution.

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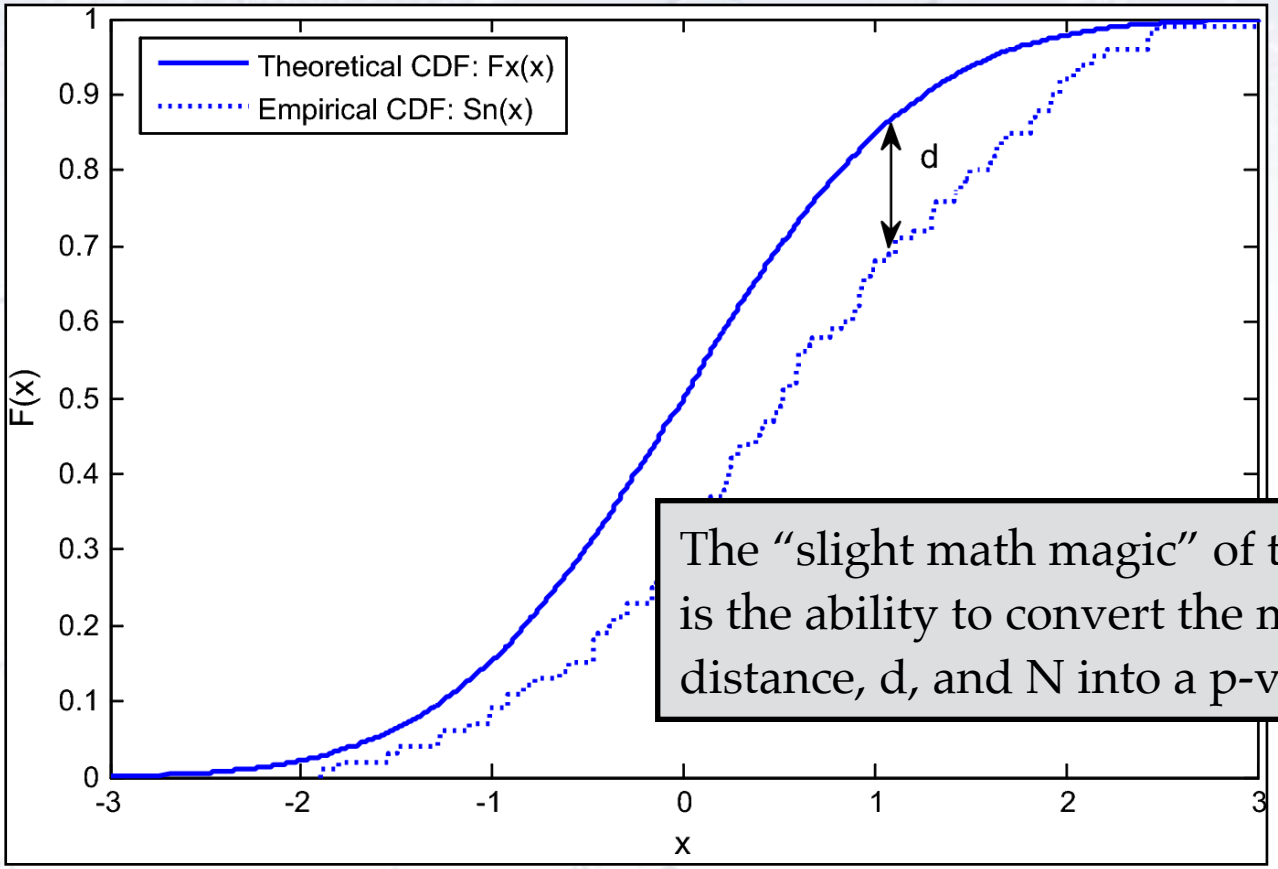

The "slight math magic" of the K-S test is the ability to convert the maximal distance, d, and N into a p-value.

The Kolmogorov test measures the maximal distance between the integrals of two distributions and gives a probability of being from the same distribution.

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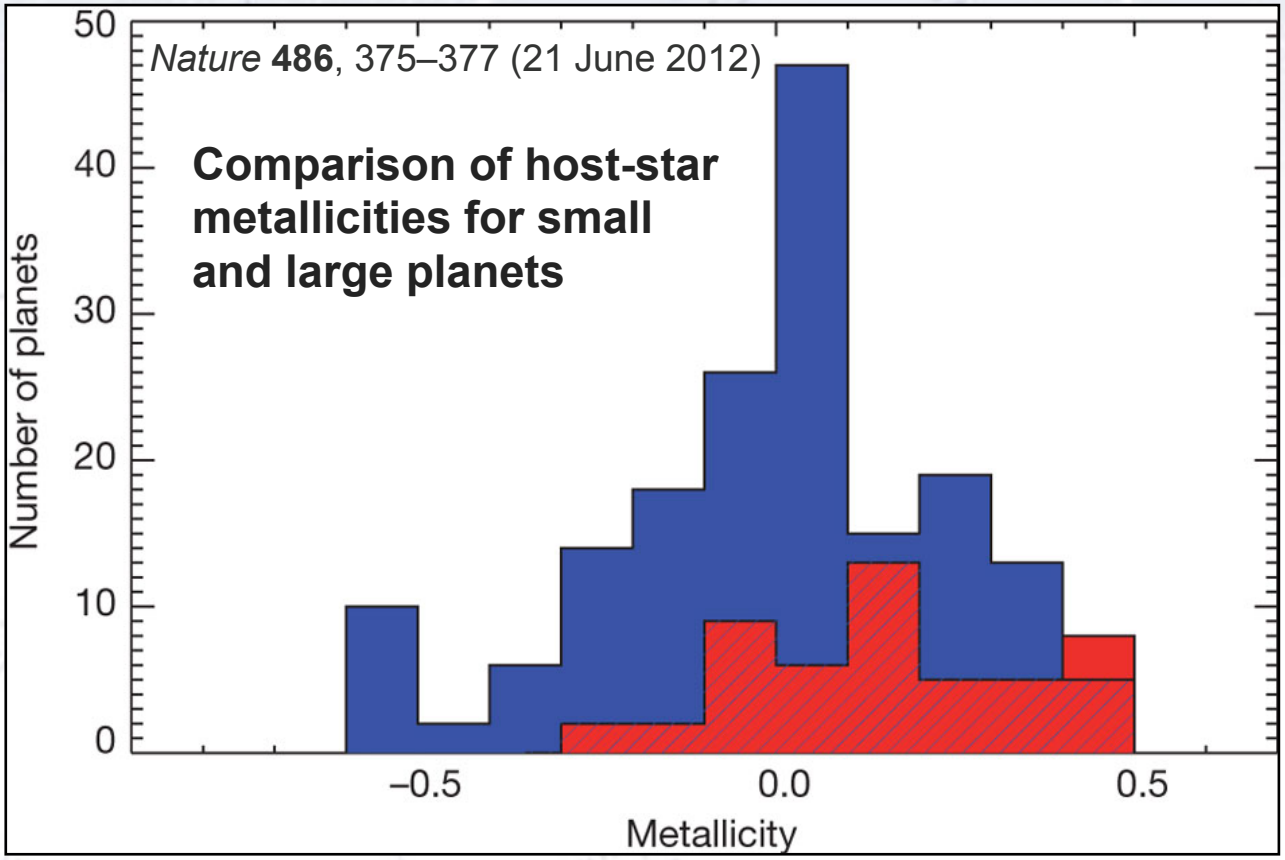

"A Kolmogorov–Smirnov test shows that the probability that the two distributions are not drawn randomly from the same parent population is greater than 99.96%; that is, the two distributions differ by more than 3.5σ". [Quote from figure caption]

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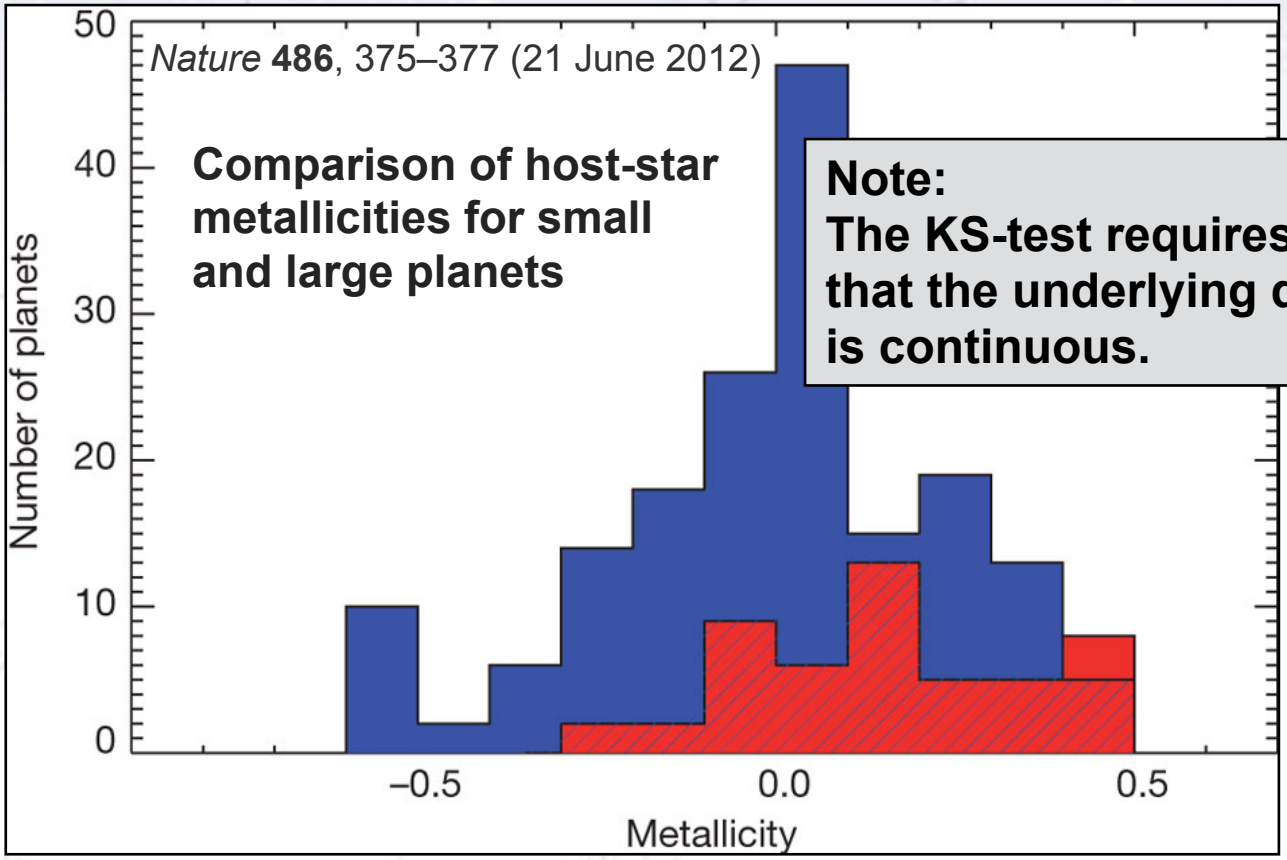
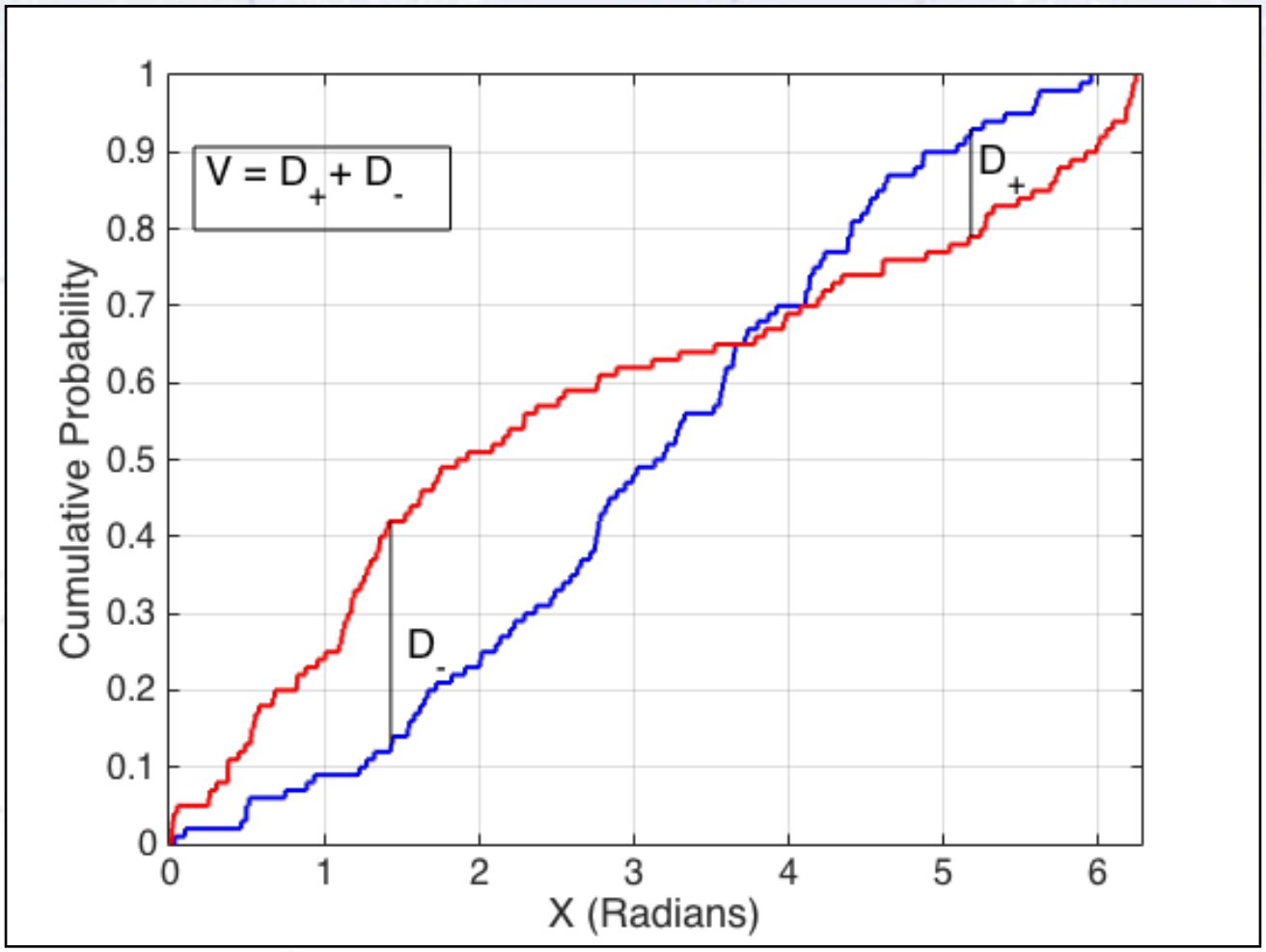


"A Kolmogorov–Smirnov test shows that the probability that the two distributions are not drawn randomly from the same parent population is greater than 99.96%; that is, the two distributions differ by more than 3.5σ". [Quote from figure caption]

Kuiper test

Is a similar test, but it is more specialised in that it is good to detect SHIFTS in distributions (as it uses the maximal signed distance in integrals).



Common statistical tests

- **One-sample test** compares sample (e.g. mean) to known value: $z = \frac{\bar{x} - \mu_0}{\sigma}\sqrt{n}$

  Example: Comparing sample to known constant ($\mu_{exp} = 2.91 \pm 0.01$ vs. $\mu_0 = 3.00$).

- **Two-sample test** compares two samples (e.g. means): $z = \frac{(\bar{x}_1 - \bar{x}_2) - d_0}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}}$

  Example: Comparing sample to control ($\mu_{exp} = 4.1 \pm 0.6$ vs. $\mu_{ctrl} = 3.7 \pm 0.4$).

- **Paired test** compares paired member difference (to control important variables).

  Example: Testing environment influence on twins to control genetic bias ($\mu_{exp} = 0.81 \pm 0.29$ vs. 0).

- **Chi-squared test** evaluates adequacy of model compared to data.

  Example: Model fitted to (possibly binned) data, yielding p-value = Prob($\chi^2 = 45.9$, $N_{dof} = 36$) = 0.125

- **Kolmogorov-Smirnov test** compares if two distributions are compatible.

  Example: Compatibility between function and sample or between two samples, yielding p-value = 0.87

These tests you should know by heart!
Those below are for general education,
and you should just know about them
(and the last one is not curriculum).

- **Wald-Wolfowitz runs test** is a binary check for independence.
- **Fisher's exact test** calculates p-value for contingency tables.
- **F-test** compares two sample variances to see, if grouping is useful.

Which test to use?

In principle all statistical tests can be used on every problem, but they are not all equally powerful, and some might also be biased (low stat.) or otherwise unfit. Finally, they may not all be equally easy to implement!

One figure of merit could be the **Power of a Test***, defined as $(1 - \beta)$, complement of the false negative rate, β.

This is thus the test's probability of correctly rejecting the null hypothesis.

Example:
This is a powerful test: Thus, since the result is negative, we can confidently say that the null hypothesis is not rejected (e.g. the patient does not have the condition).

In medical science, it is typically important to have a powerful test (i.e. low β), while in criminal science it is a low type I error rate (i.e. low α), convicting innocents.
In the end, choosing a test comes down to **experience, importance of power, ease of use**, and even standards in the field of research in question.

* Power of a test is often termed sensitivity in biostatistics.

Wald-Wolfowitz runs test

Barlow, 8.3.2, page 153

A different test to the Chi2 (and in fact a bit orthogonal!) is the Wald-Wolfowitz runs test.

It measures the number of "runs", defined as sequences of same outcome (only two types).

Example:

++++−−−+++−−+++++−−−−

If random, the mean and variance is known:

$$\mu = \frac{2\,N_+\,N_-}{N} + 1$$

$$\sigma^2 = \frac{2\,N_+\,N_-\,(2\,N_+\,N_- - N)}{N^2\,(N-1)} = \frac{(\mu-1)(\mu-2)}{N-1}.$$

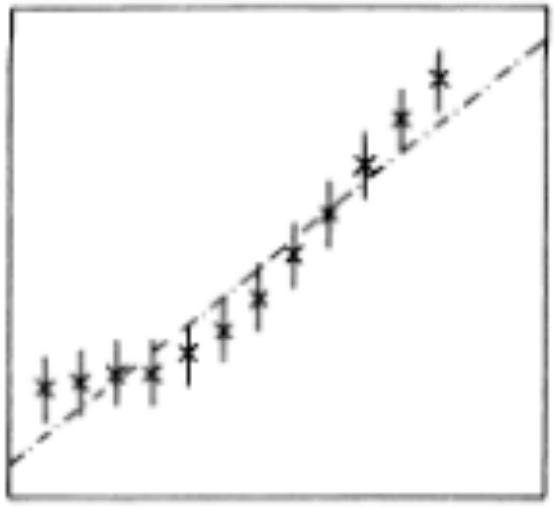


Fig. 8.3. A straight line through twelve data points.

N = 12, N_+ = 6, N_- = 6
μ = 7, σ = 1.76
(7-3)/1.65 = 2.4 σ (~1%)

Note: The WW runs test requires N > 10-15 for the output to be approx. Gaussian!

Fisher's exact test

When considering a **contingency table** (like below), one can calculate the probability for the entries to be uncorrelated. This is **Fisher's exact test**.

	Row 1	Row 2	Row Sum
Column 1	A	B	A+B
Column 2	C	D	C+D
Column Sum	A+C	B+D	N

$$p = \frac{\binom{A+C}{A}\binom{B+D}{B}}{\binom{N}{A+B}} = \frac{(A+B)!\,(C+D)!\,(A+C)!\,(B+D)!}{A!\,B!\,C!\,D!\,N!}$$

Simple way to test categorial data (Note: Barnard's test is "possibly" stronger).

Fisher's exact test - example

Consider data on patients taking a certain medicin or not and result of this. The data can be found in the below table:

	Got well	Remained ill
Medicin	9	3
No Medicin	1	11

Is there a correlation between medicin and getting well?

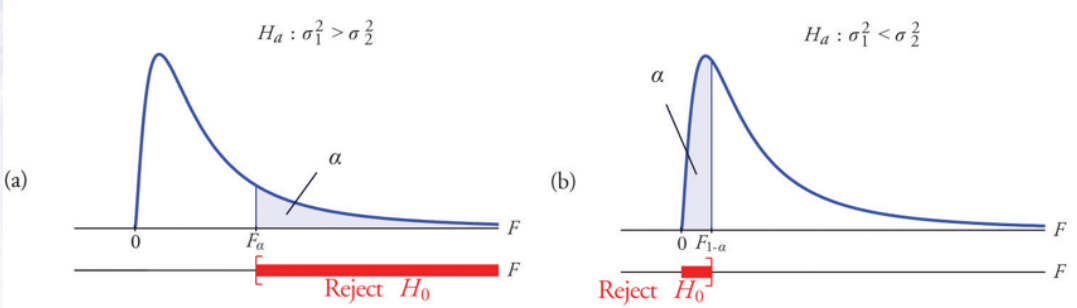
The Chi-square test is not optimal, as there are (several) entries, that are very low (< 5), but Fisher's exact test gives the answer:

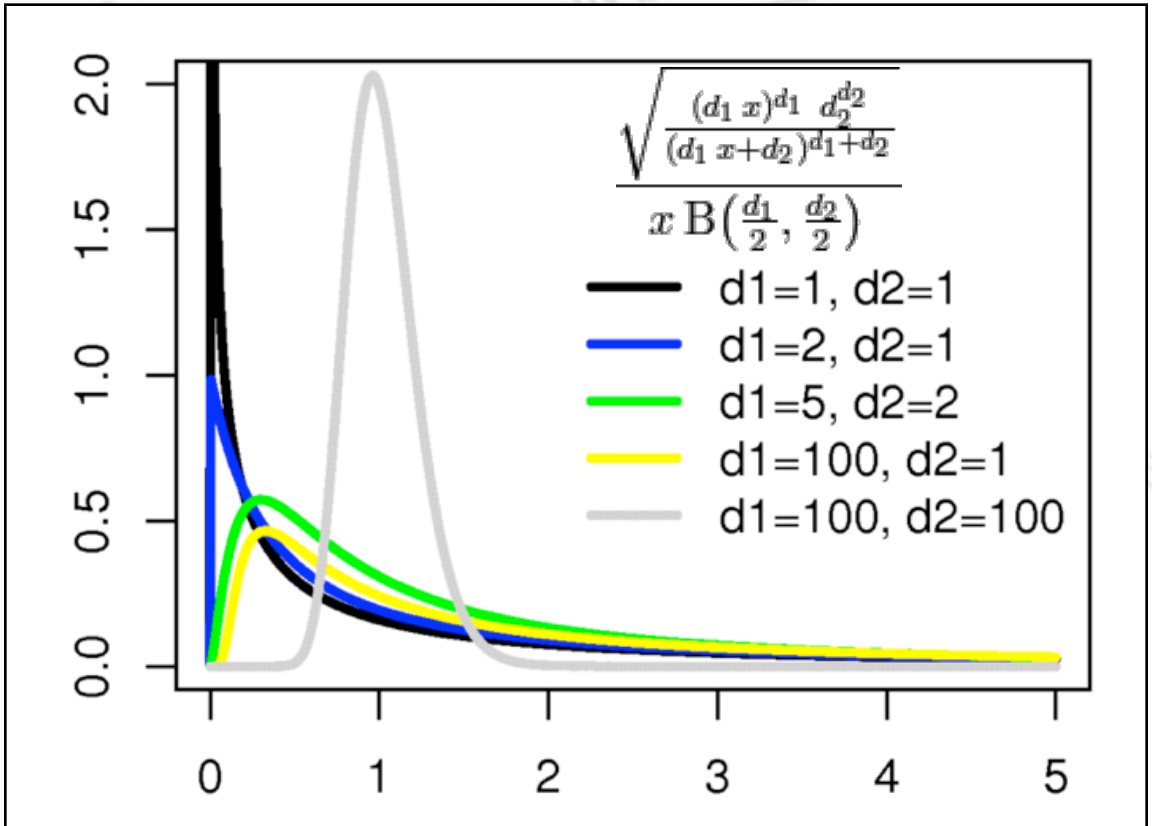
$$p = \begin{pmatrix} 10 \\ 1 \end{pmatrix} \begin{pmatrix} 14 \\ 11 \end{pmatrix} / \begin{pmatrix} 24 \\ 12 \end{pmatrix} = \frac{10!\ 14!\ 12!\ 12!}{1!\ 9!\ 11!\ 3!\ 24!} \simeq 0.00135$$

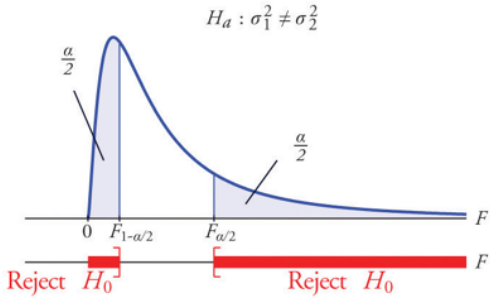
F-test

To test for differences between variances in two samples, one uses the F-test:

$$F = \frac{S_X^2}{S_Y^2}$$







Note that this is a two-sided test. One is generally testing, if the two variances are the same.

Anderson-Darling Test

A "simple" and powerful test between cumulative data F_n and distribution F is defined as:

$$n \int_{-\infty}^{\infty} (F_n(x) - F(x))^2 \; w(x) \; dF(x)$$

Here, n is the number of elements in the sample and w(x) is a weighting function.

Choosing w(x) = F(x) (1-F(x)) yields the Anderson-Darling test statistic:

$$A^2 = n \int_{-\infty}^{\infty} \frac{(F_n(x) - F(x))^2}{F(x)(1 - F(x))} \; dF(x)$$

which has more emphasis on the tails than the above (w(x) = 1, i.e. Cramer-von Mises) test statistic. An alternative is Shapiro-Wilks test, see here for comparison.

The test is implemented in the Python Statistics package (stats), with tests for the Gaussian, Exponential, Logistic & Gumbel distributions.

What value to decide at?

How many sigmas?

The number of sigmas (or p-value) required to make a claim should perhaps vary, according to the target of the data analysis.

Louis Lyons has below given his take on it (aimed at particle physics searches).

Search	Degree of surprise	Impact	LEE	Systematics	Number of σ
Higgs search	Medium	Very high	Mass	Medium	5
Single top	No	Low	No	No	3
SUSY	Yes	Very high	Very large	Yes	7
B_s oscillations	Medium/low	Medium	Δm	No	4
Neutrino oscillations	Medium	High	$sin^2(2\theta), \Delta m^2$	No	4
$B_s \to \mu\mu$	No	Low/Medium	No	Medium	3
Pentaquark	Yes	High/very high	M, decay mode	Medium	7
$(g-2)_\mu$ anomaly	Yes	High	No	Yes	4
H spin $\neq 0$	Yes	High	No	Medium	5
4^{th} generation q, l, ν	Yes	High	M, mode	No	6
$v_\nu > c$	Enormous	Enormous	No	Yes	>8
Dark matter (direct)	Medium	High	Medium	Yes	5
Dark energy	Yes	Very high	Strength	Yes	5
Grav waves	No	High	Enormous	Yes	7

From: "Discovering the Significance of 5 sigma", ArXiv: 1310.1284

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$(g-2)_\mu$ anomaly	Yes	High	No	Yes	4
H spin $\neq 0$	Yes	High	No	Medium	5
4^{th} generation q, l, ν	Yes	High	M, mode	No	6
$v_\nu > c$	Enormous	Enormous	No	Yes	>8
Dark matter (direct)	Medium	High	Medium	Yes	5
Dark energy	Yes	Very high	Strength	Yes	5
Grav waves	No	High	Enormous	Yes	7

The more extraordinary the claim, the more extraordinary the evidence needed!

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