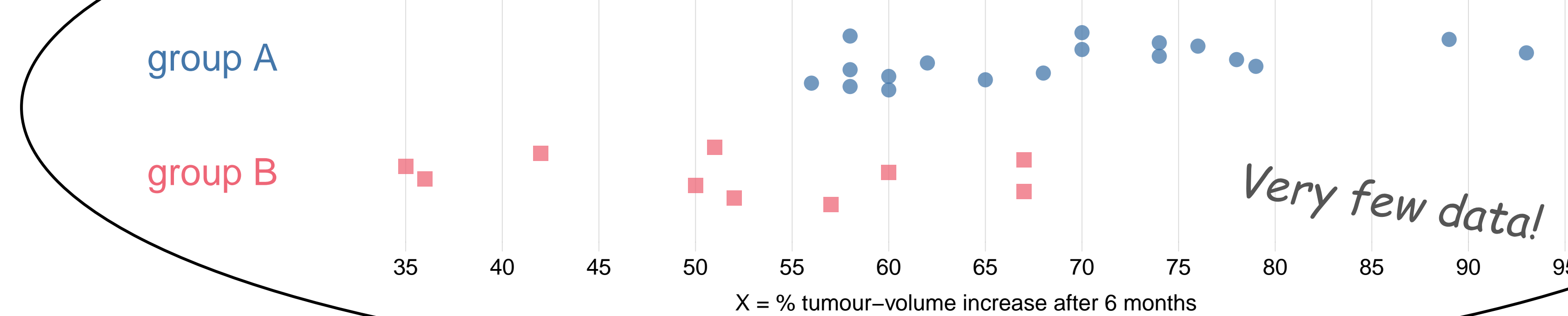


Simple example question:
do **treatment A** and **treatment B**
have different effects on tumour increase X?

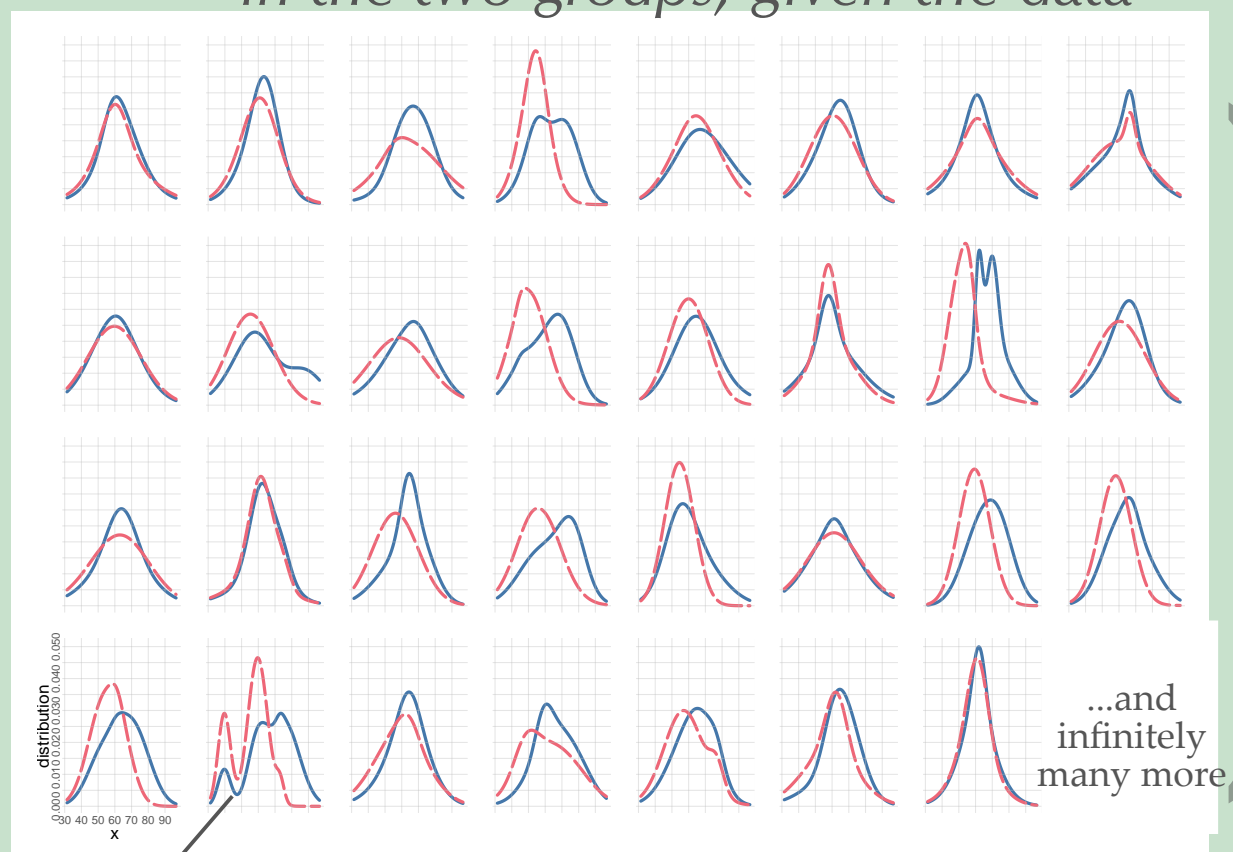


Bayesian theory

old sampling theory

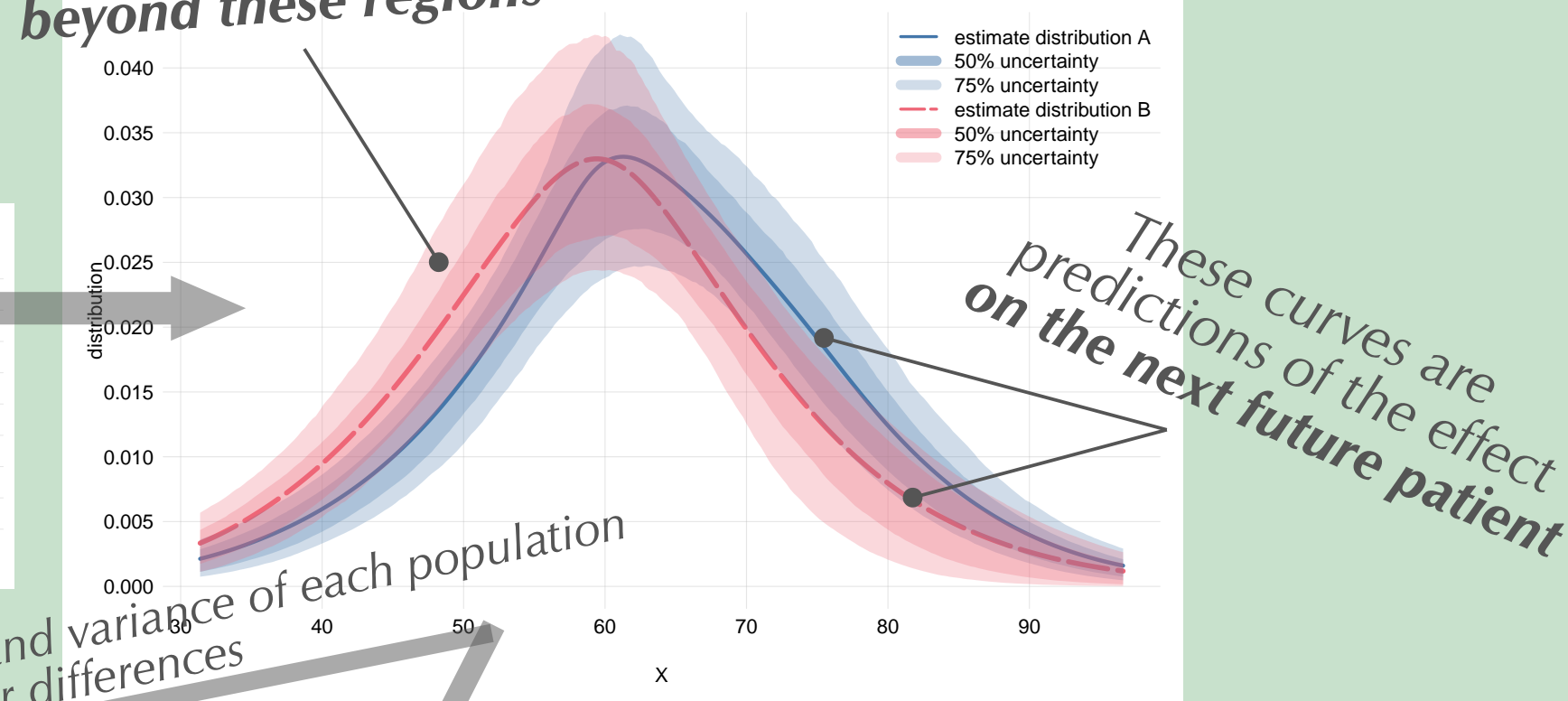
The Bayesian calculation is always the same
– no matter how many data we have
– no matter how the sample sizes were chosen
and it does not need any corrections

Bayesian probability theory considers
all likely **distributions for future patients**
in the two groups, given the data



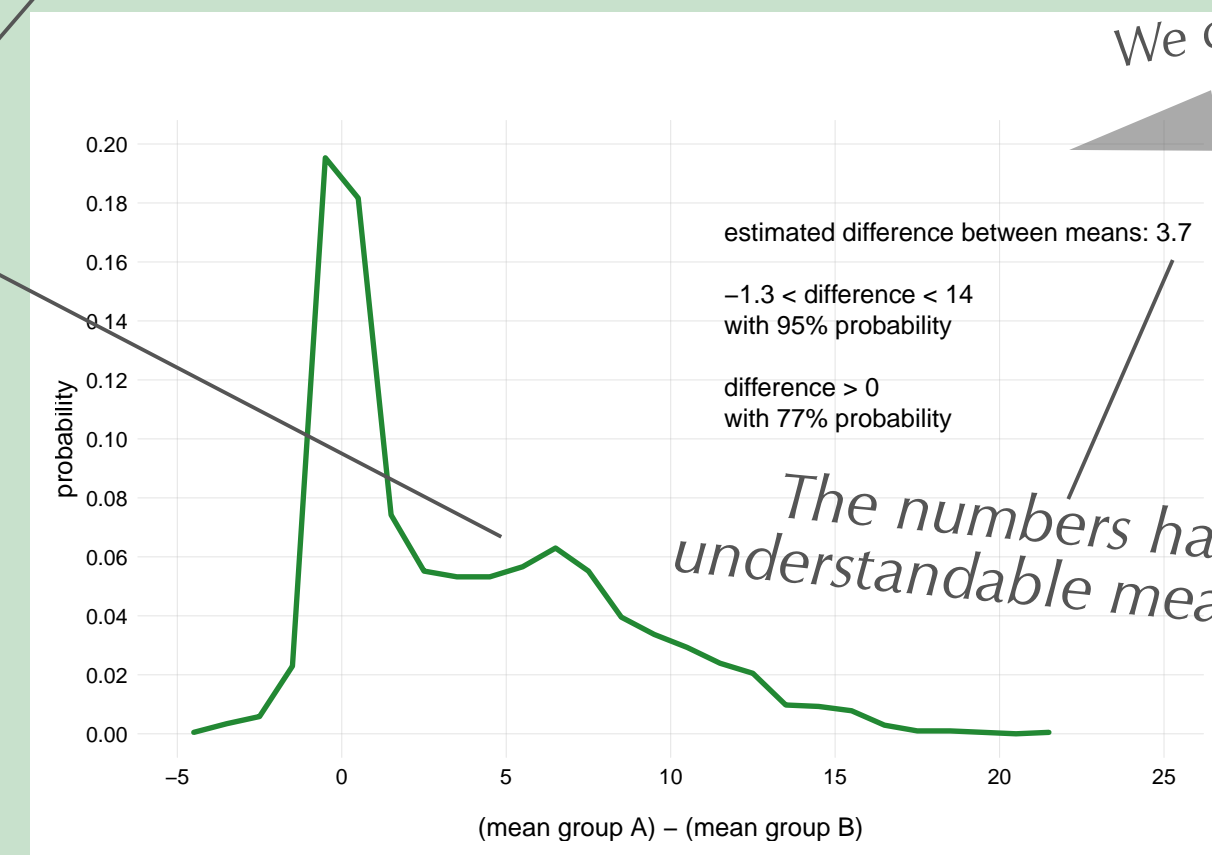
all possible distributions
are combined

Estimates of full distributions
and uncertainty of estimates.
New data **cannot modify our predictions**
beyond these regions

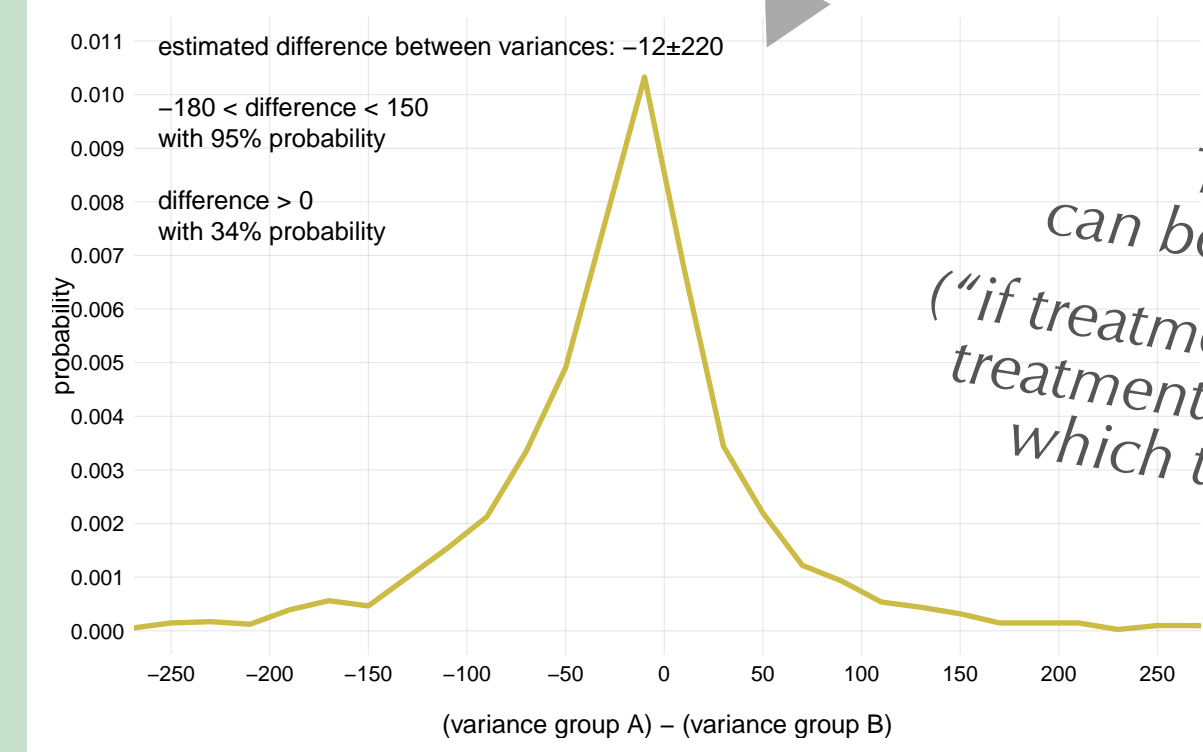


We can estimate the mean and variance
of each population
and their differences

No assumptions
of gaussianity



The numbers have
understandable meanings



These detailed probabilities
can be used in a **cost/benefit analysis**
("if treatment A costs \$ and gives Y% benefit,
treatment B costs \$\$ and gives Z% benefit,
which treatment should we choose?")



“ Assuming that the two full populations:

- are gaussian and independent
- have identical variances (F -test, $p = 0.44$)

and that the sample sizes were decided
before running the experiment, then:

The hypothesis that the population means are equal
has a p -value 0.00043 (two-tail t -test: +4.0).

The sample mean difference of X is 17.6
The 95% confidence interval is [8.6, 26.7] ”

What does the number “0.00043” really mean?

This does **not** mean that $8.6 < X < 26.7$ with 95% probability!
It means that this technique to construct the interval
contains the true value in 95% of all imaginary datasets.
But what's the best interval that contains X for **our** dataset?

It's actually more probable
that the variances are **different**:
non-gaussianity leads to unreliable F -test

This p -value is wrong
If the sample sizes 18 & 10
were decided not in advance
but by some other rule

“ Assuming that the two full-population distributions are smooth, we predict:

- The distributions of **future treatment outcomes** will be as in the plots, within the uncertainties shown
- Future patients under treatment A will have on average $X=63$, and $59 < X < 69$ with 95% probability
- Future patients under treatment B will have on average $X=59$, and $52 < X < 66$ with 95% probability
- The difference between the mean X of the treatments will be within -1.3 and 14 with 95% probability
- Average X under treatment A will be **larger** than under treatment B with 77% probability
- Variance of X under treatment A will be **smaller** than under treatment B with 66% probability ”

Compare the two analyses

The predictions of Bayesian theory are:

- detailed
- quantitative
- easy to understand

(eg, “fraction $x\%$ of population will have effect y ”)

The statements of sampling theory are:

- vague
- obscure or misleading
- heavily dependent on tacit assumptions

*This was just a simple example. Bayesian theory deals in the same way
with multiple hypotheses, variates, and correlation questions*



“Looks great, but
there's very little
friendly software
for doing this!”

True! That's why we are preparing
a user-friendly software to do Bayesian analysis
on (non-imaging) medical data

The maths will be taken care of under the hood
The software will suggest meaningful questions to be asked (in line with ASA's statement)
Works with continuous and categorical variables
– allows predictions about their correlations and relevance
No assumptions of gaussianity, linearity or other assumptions typical of sampling theory
No need for corrections of any kind

*We're already using a prototype version
for drug-discovery research*

*Please get in touch if you want to test it
and help us making a great software!*