# Statistics for $\mathcal{H E P}$ <br> Roger Barlow <br> Mancfiester Ulniversity 

## Lecture 1: Probability

## Definition 1: Mathematical


$\mathcal{P}(\mathcal{A})$ is a number
obeying the
Kolmogorovaxioms

$$
\begin{aligned}
& P(A) \geq 0 \\
& P\left(A_{1} \vee A_{2}\right)=P\left(A_{1}\right)+P\left(A_{2}\right) \\
& \sum P\left(A_{i}\right)=1
\end{aligned}
$$

## Problem with Mathematical definition

$\mathcal{N}$ (information is conveyed by $\mathcal{P}(\mathcal{A})$

## Definition 2: Classical



The probability $\mathcal{P}(\mathcal{A})$ is a property of an object that determines how often event $\mathcal{A}$ happens.
It is given by symmetry for equally-fikely outcomes
outcomes not equally-likely are reduced to equally-likely ones Examples:
Tossing a coin:

$$
\mathcal{P}(\mathcal{H})=1 / 2
$$

Throwing two dice

$$
\mathcal{P}(8)=5 / 36
$$

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## Problems with the classical definition...

1. When are cases 'equally likely?

- If you toss two coins, are there 3 possible outcomes or 4?

Can be handled
2. How do you handle continuous variables?

Split the triangle at random:


Cannot be handled
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## Bertrand's Paradox

Ajug contains 1 glassful of water and between 1 and 2 glasses of wine
$Q:$ What is the most probable wine:water ratio?
$\mathfrak{A}$ : Betwe en 1 and $2 \rightarrow 3 / 2$
$Q:$ What is the most probable water:wine ratio?
$\mathcal{A}: \mathcal{B e t w e e n} 1 / 1$ and $1 / 2 \rightarrow 3 / 4$


$$
(3 / 2) \neq(3 / 4)^{-1}
$$

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## Definition 3: Frequentist



- Tfe probability $\mathcal{P}(\mathcal{A})$ is the limit (taken over some ensemble)
$P(A) \underset{N \rightarrow \infty}{=} N(A) / N$

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Problem (limitation) for the Frequentist definition
$\mathcal{P}(\mathcal{A})$ depends on $\mathcal{A}$ and the ensemble Eg: count 10 of a group of 30 with beards.

$$
\mathcal{P}(\text { beard })=1 / 3
$$



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## Aside: Consequences for Quantum Mechanics

- $Q \mathfrak{M}$ calculates probabilities
- Probabilities are not 'real '-they depend on the process and the ensemble


$$
\begin{aligned}
& \mathcal{P}\left(p \pi^{-}\right)=0.639 \\
& \mathcal{P}\left(n \pi^{0}\right)=0.358
\end{aligned}
$$

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## Big problem for the Frequentest definition

Cannot be applied to unique events


Is unscientific
'The statement
"It will rain tomorrow"
is probably true.'
Is quite $O K$

## But that doesn't always work

- Rain prediction in unfamiliar territory
- Euler's theorem
- Higgs discovery
- Darkmatter
- $\mathcal{L H C}$ comple tion


## Definition 4:Subjective (Baye sian)


$\mathcal{P}(\mathcal{A})$ is your degree of belief in $\mathcal{A}$;
You will accept a bet on $\mathcal{A}$ if the odds are better than

$$
1-P \text { to } P
$$

Acan be Anything: Beards, Rain, particle decays, conjectures, theories

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## Bayes Theorem

Often used for subjective probability

Conditional Probability $\mathcal{P}(\mathcal{A} \mid \mathcal{B})$ $\mathcal{P}(\mathscr{A} \not \mathcal{B})=\mathcal{P}(\mathcal{B}) \mathcal{P}(\mathcal{A} \mid \mathcal{B})$ $\mathcal{P}(\mathcal{A} \nLeftarrow \mathcal{B})=P(\mathcal{A}) P(\mathcal{B} \mid \mathcal{A})$

$$
P(A \mid B)=\frac{P(B \mid A)}{P(B)} P(A)
$$

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Example:

$$
\mathcal{W}=w h i t e ~ j a c k e t \quad \mathcal{B}=6 \text { ald }
$$

$$
\mathcal{P}(\mathcal{W} \mathcal{H} \mathcal{B})=(2 / 4) \times(1 / 2)
$$

$$
\text { or }(1 / 4) x(1 / 1)
$$

$\mathcal{P}(\mathcal{W} \mid \mathcal{B})$

$$
=\frac{1}{(2 / 4)} \chi(1 / 4)=1 / 2
$$

## Staratigisesion

Frequentest Use of Bayes Theorem
Example: Particle Identification
Particle types e, $\pi, \mu, \mathcal{K}, p$
Detector Signals: $\mathcal{D C H}, \mathcal{R I C H}, \mathcal{T} O \mathcal{F}, \mathcal{T} \mathcal{R}$

$$
P^{\prime}(e)=P(e \mid D C H)=\frac{P(D C H \mid e)}{P(D C H)} P(e)
$$

$$
P(D C H)=P(D C H \mid e) P(e)+P(D C H \mid \mu) P(\mu)+P(D C H \mid \pi) P(\pi) \ldots
$$

Then repeat for $\mathcal{P}(e \mid \mathcal{R I C H})$ using $\mathcal{P}^{\prime}(e)$ etc

## Warning $\mathcal{N}$ otic

To determine $P^{\prime}(e)$ need $\mathcal{P}(e), \mathcal{P}(\mu)$ etc

## ('a prioriprobabilities')

$I f /$ when you cut on Probability, the Purity depends on these a prior probabilities
Example: muon detectors.
$\mathrm{P}($ track $\mid \mu) \approx 0.9 \mathrm{P}(\operatorname{track} \mid \pi) \approx 0.015$
But $\mathrm{P}(\mu) \approx 0.01 \mathrm{P}(\pi) \approx 1$
Quantities like
$P(d a t a \mid \mu)$
$P($ data $\mid e)+P($ data $\mid \mu)+P($ data $\mid \pi)+P($ data $\mid K)$
Have no direct meaning -
Slide 1 sse with care!

## Bayes' Theorem and subjective probability

$P($ Theory $\mid$ Result $)=\frac{P(\text { Result } \mid \text { Theory })}{P(\text { Result })} P($ Theory $)$
Your (posterior) belief in a Theory is modified by experimental result

If $\quad \mathcal{P}$ (Result $\mid$ Theory $)=0$ belief is killed
Large $\mathcal{P}$ (Result $\mid$ Theory) increases belief, modified by generalt(Result)

Applies to successive results
Slide 16 Dependence on prior $P$ (Theory) eventually goes away

## Problem with subjective probability

It is subjective
$\operatorname{My} \mathcal{P}(\mathcal{A})$ and your $\mathcal{P}(\mathcal{A})$ may be different
Scientists are supposed to be objective

Reasons to use subjective probability:

- Desperation
- Ignorance
- Idleness


# Can Honest Ignorance justify $\mathcal{P}(\mathcal{A})=f$ fat? 

## Argument:

- you knownotfing
- every value is as believable as any other
- all possibilities equal How do you count discrete possibilities?
$S \mathbb{M}$ true or false?
SM or S US Y or light Figs or
Tectrinicolor?


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For continuous parameter (eg. $\mathcal{M}_{\text {figgs }}$ )
Take. $\mathcal{P}\left(\mathcal{M}_{\text {riggs }}\right)$ as flat Actually fils to be zero as $\int \mathcal{P}(\mathcal{M}) d \mathcal{M}=1$ but never mind... 'improper prior'

Working with $\sqrt{ } \mathfrak{M}$ or $\ln \mathcal{M}$ will give different results
Real statisticians accept this and test for robustness under different priors.

## 'Objective Prior' (geffreys)

Transform to a variable $q(\mathscr{M})$ for which the Fisher information is constant

$$
I(q)=-\left\langle\frac{\partial^{2} \ln P(x ; q)}{\partial q^{2}}\right\rangle=\text { const }
$$

For a location parameter with $\mathcal{P}(x ; \mathcal{M})=f(x+\mathcal{M})$ use $\mathcal{M}$ For scale parameter with $\mathcal{P}(x ; \mathcal{M})=\mathcal{M} f(x)$ use $\ln \mathcal{M}$ For a Poisson $\lambda$ use prior $1 / \sqrt{ } \lambda$
For a Binomial with probability $p$ use prior $1 / \sqrt{ }$ p(1-p)
This has never really caught on

Conclusion

## What is Probability?

4 ways to define it

- Mathematical
- Classical
- Frequentest
- Subjective

Each frs strong points and we ak points
None is universally applic able
Be prepared to understand and use them all.

