SMIL

Connecting the Brain to the Body
from Molecules to Complex Social Behaviors

CHAPTER 3
BUILDING THE NOTION OF AGENCY AND SELF-DETERMINATION IN AUTISM AND BEYOND

OBJECTIVES

- Learn about agency, action ownership and basic kinesthetic reafference variability
- Learn about kinematics of complex human motions
- Learn about statistics
- Learn about the statistical properties of kinematics parameters

WHAT IS AGENCY?

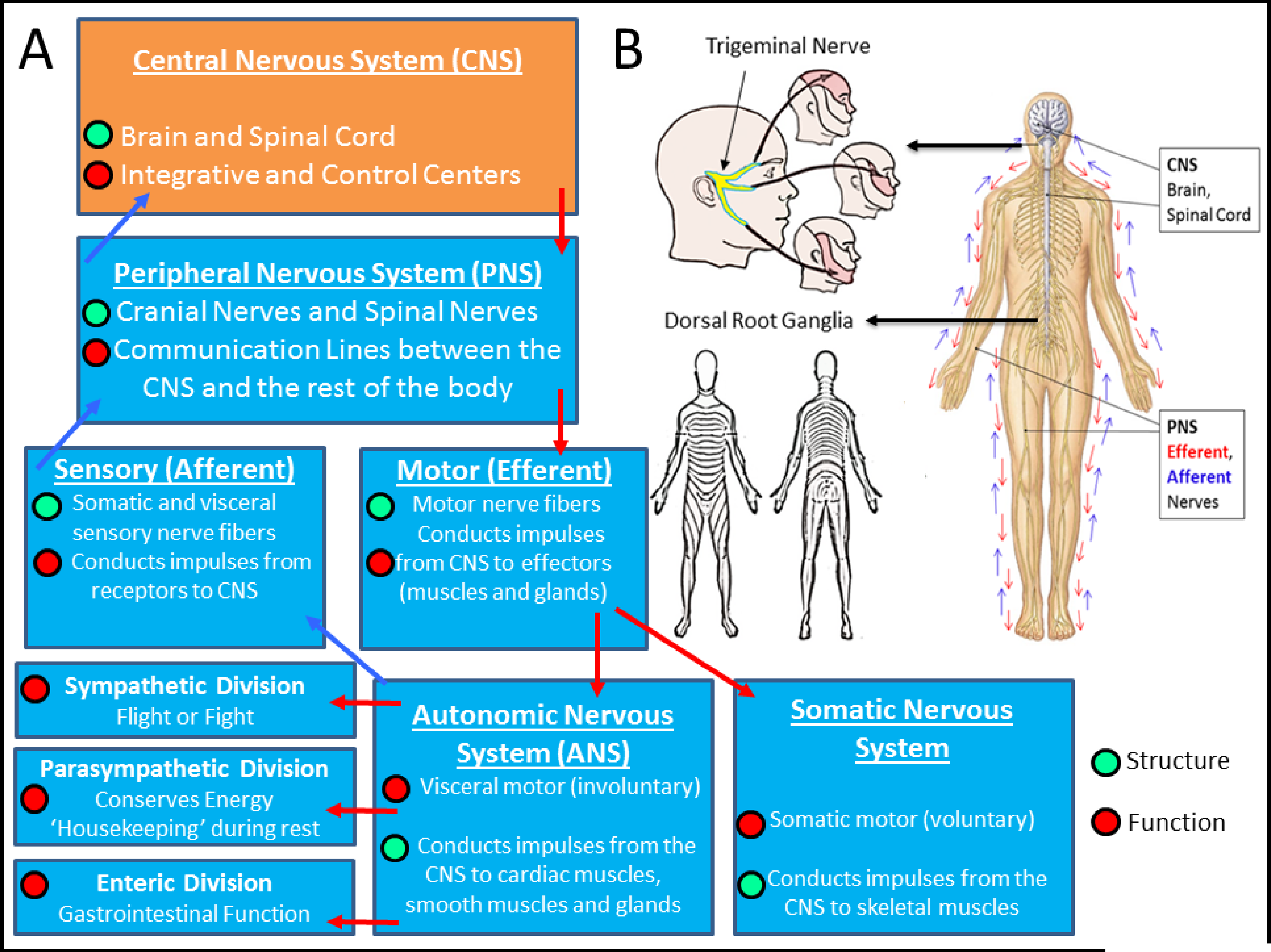
Agency (**sociology**) In social science, **agency** is the capacity of individuals to act independently and to make their own free choices. By contrast, structure is those factors of influence (such as social class, religion, gender, ethnicity, ability, customs, etc.) that determine or limit an agent and their decisions.

Agency (sociology) - Wikipedia
https://en.wikipedia.org › wiki › Agency_(sociology)

ACT INDEPENDENTLY AND

MAKE THEIR OWN FREE CHOICES

CNS AND PNS

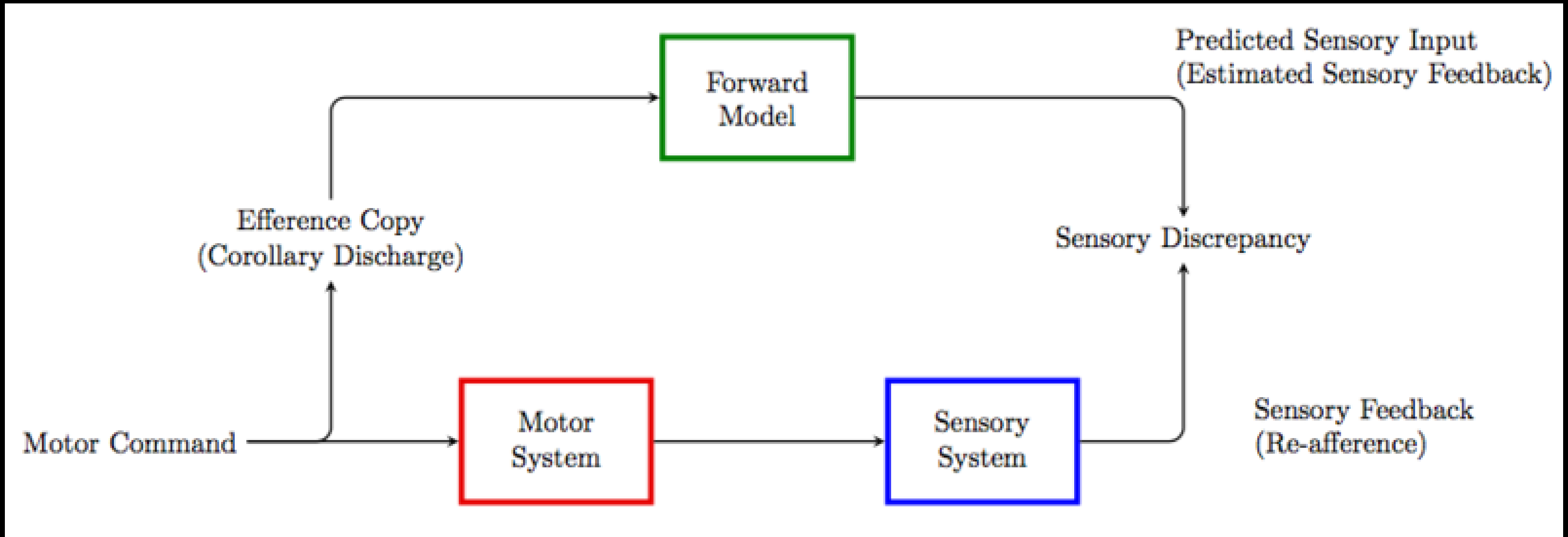


A
Central Nervous System (CNS)
Brain and Spinal Cord
Integrative and Control Centers
Peripheral Nervous System (PNS)
Cranial Nerves and Spinal Nerves
Communication Lines between the CNS and the rest of the body
Sensory (Afferent)
Somatic and visceral sensory nerve fibers
Conducts impulses from receptors to CNS
Motor (Efferent)
Motor nerve fibers
Conducts impulses from CNS to effectors (muscles and glands)
Sympathetic Division
Flight or Fight
Parasympathetic Division
Conserves Energy
'Housekeeping' during rest
Enteric Division
Gastrointestinal Function
Autonomic Nervous System (ANS)
Visceral motor (involuntary)
Conducts impulses from the CNS to cardiac muscles, smooth muscles and glands
Somatic Nervous System
Somatic motor (voluntary)
Conducts impulses from the CNS to skeletal muscles
B
Trigeminal Nerve
Dorsal Root Ganglia
CNS
Brain,
Spinal Cord
PNS
Efferent,
Afferent
Nerves
Structure
Function

IAN WATERMAN

https://www.dailymotion.com/video/x12647t

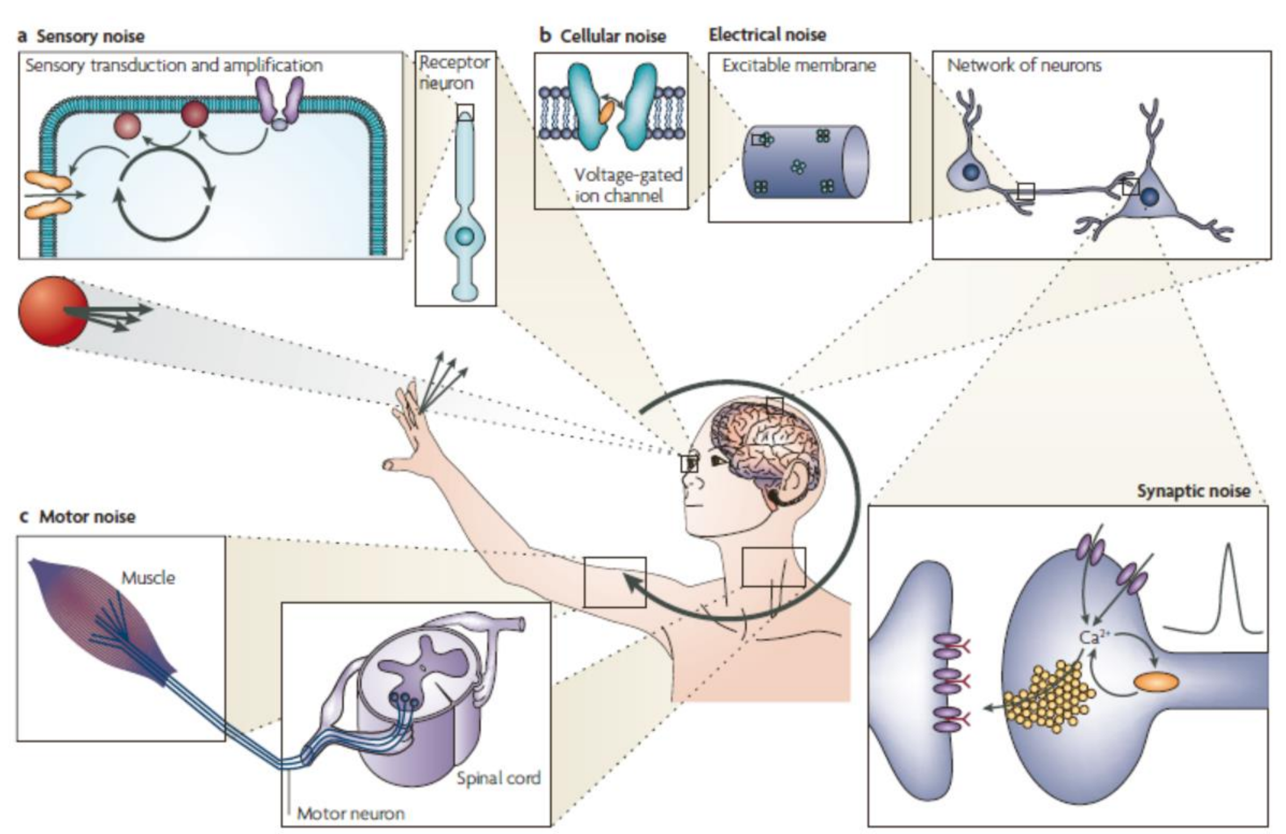
INTERNAL MODEL OF ACTION GENERATION



https://en.wikipedia.org/wiki/Internal_model_(motor_control)

Torres 2001 redefines the model to separate spatial (kinematics) from temporal (dynamics) using a geometric approach Chapter 4 Torres 2018 Elsevier

INTERNAL SENSORY-MOTOR DELAYS

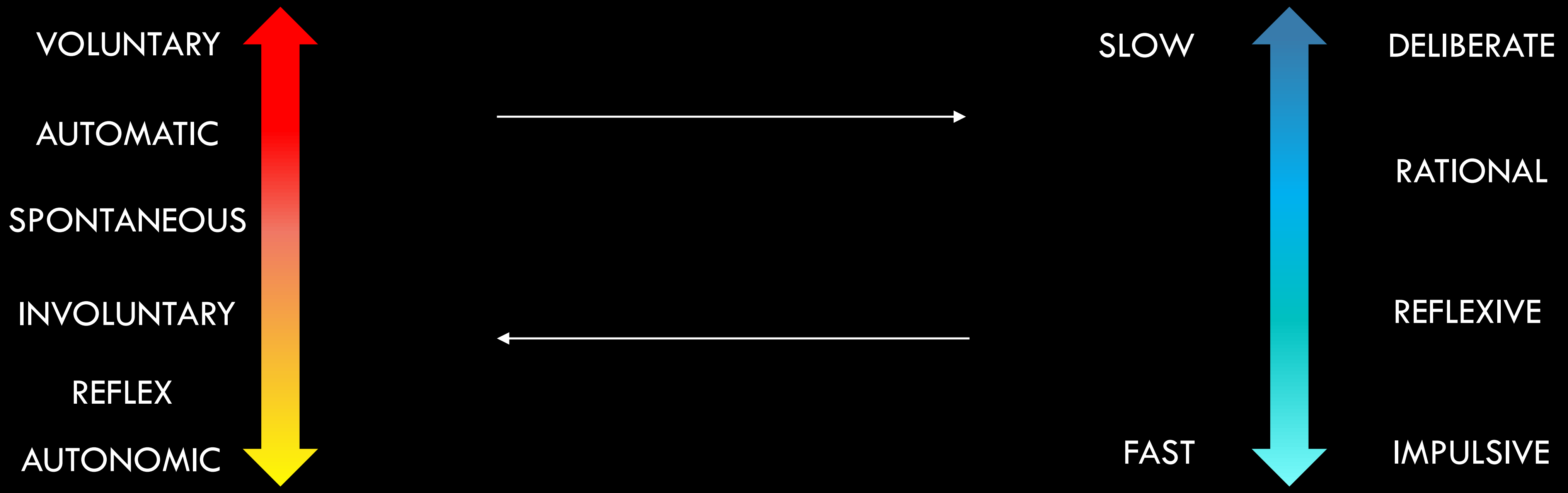


- Sensory transduction
- Sensory transmission (travel time)
- Noise in every sensory-motor transformation
- Disparate time scales (micro sec, millisec, seconds, etc)
- Goal: To experience the simultaneous perception of different sensory stimuli

HOW DO WE STUDY AGENCY?

Movements

Decisions



Torres 2011

DIFFERENT MOVEMENT CLASSES IN NEUROMOTOR CONTROL

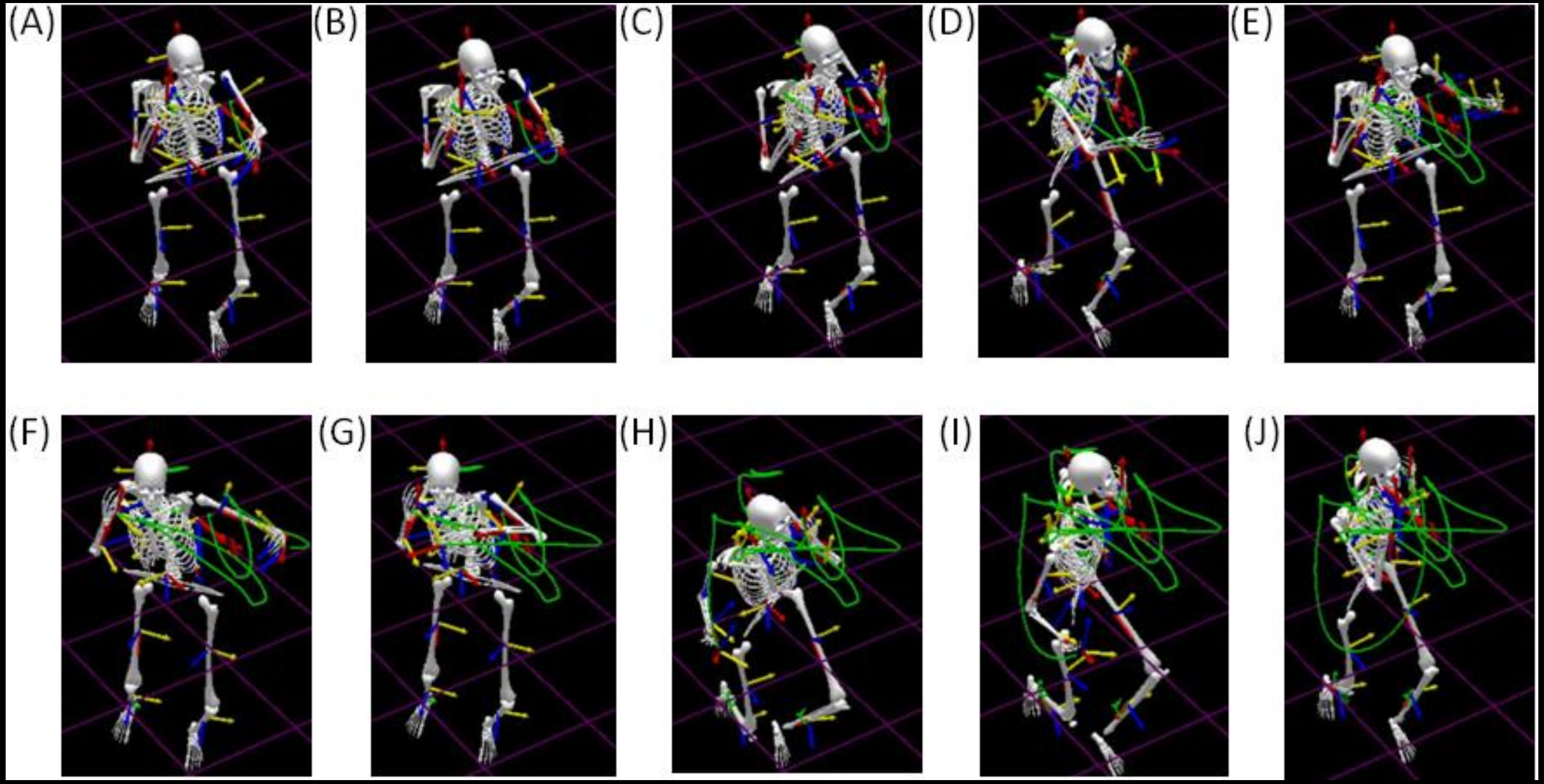
Typical Speed

Adapt to loads

Deadapt from loads

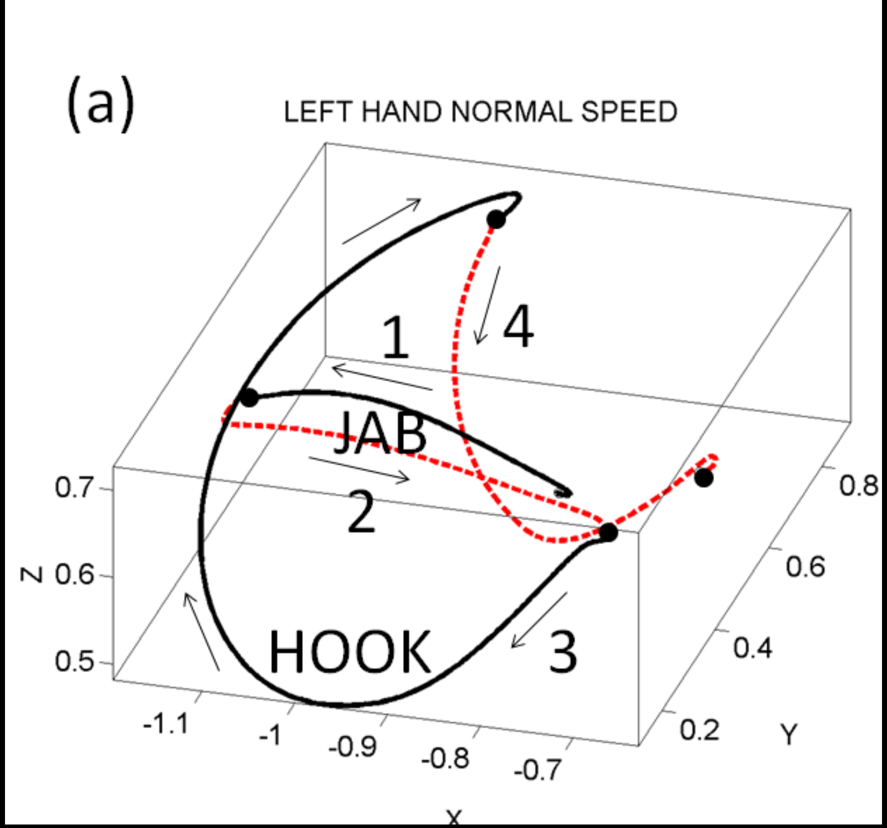
Torres 2011, Exper Brain Res

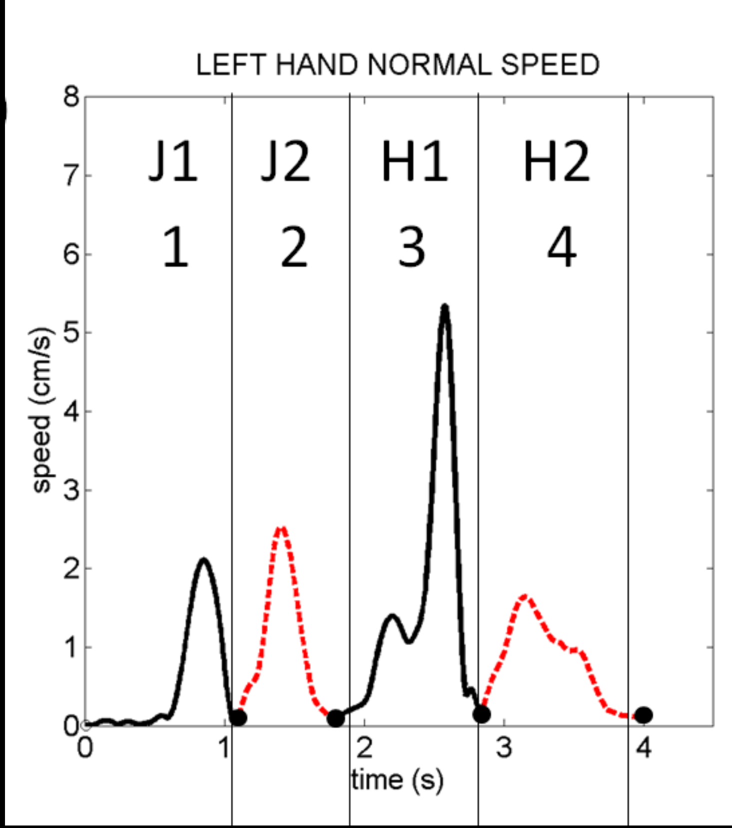
JAB-CROSS-HOOK-UPPERCUT



Torres 2011, Exper Brain Res

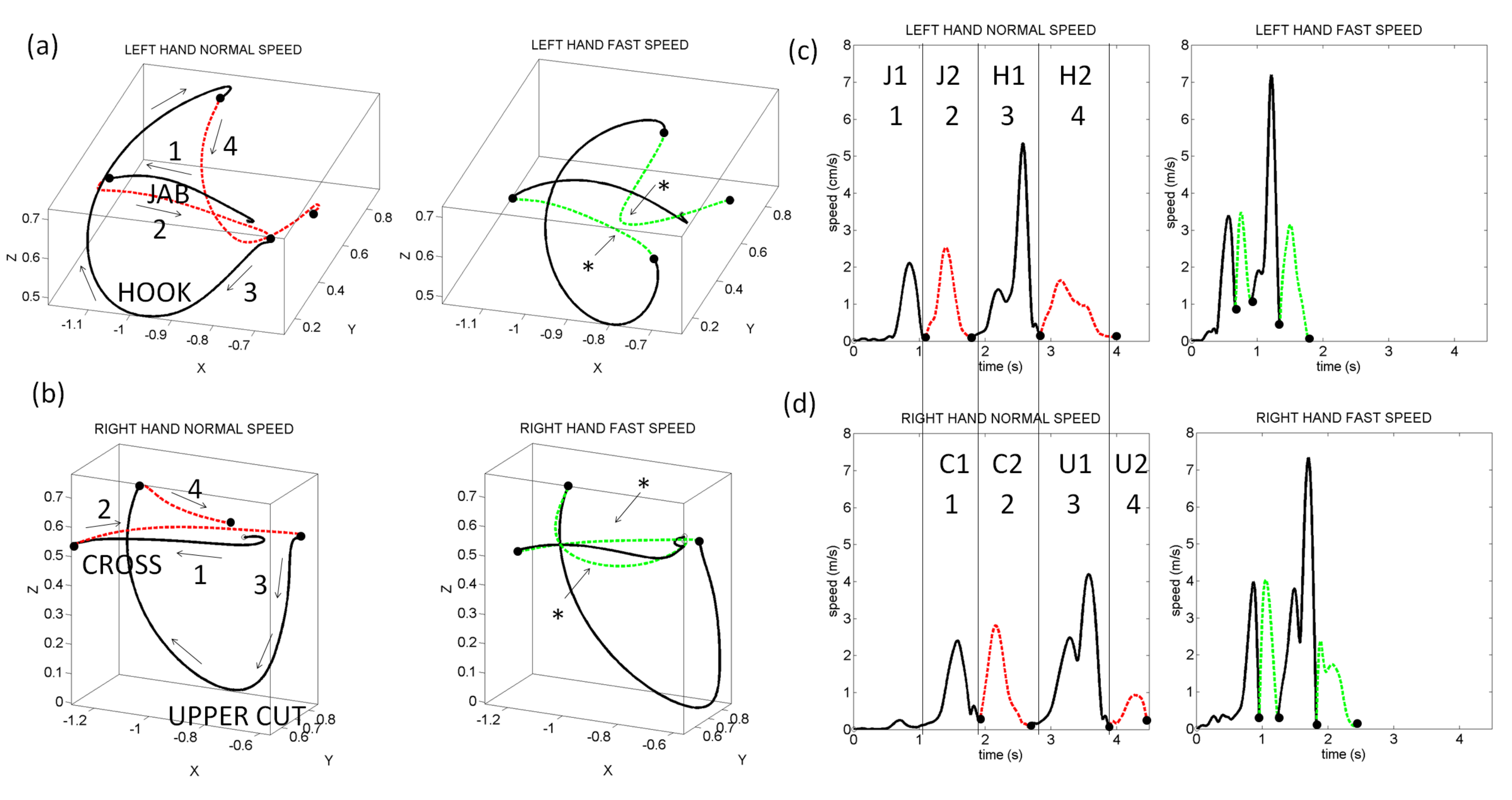
FROM POSITION TO SPEED





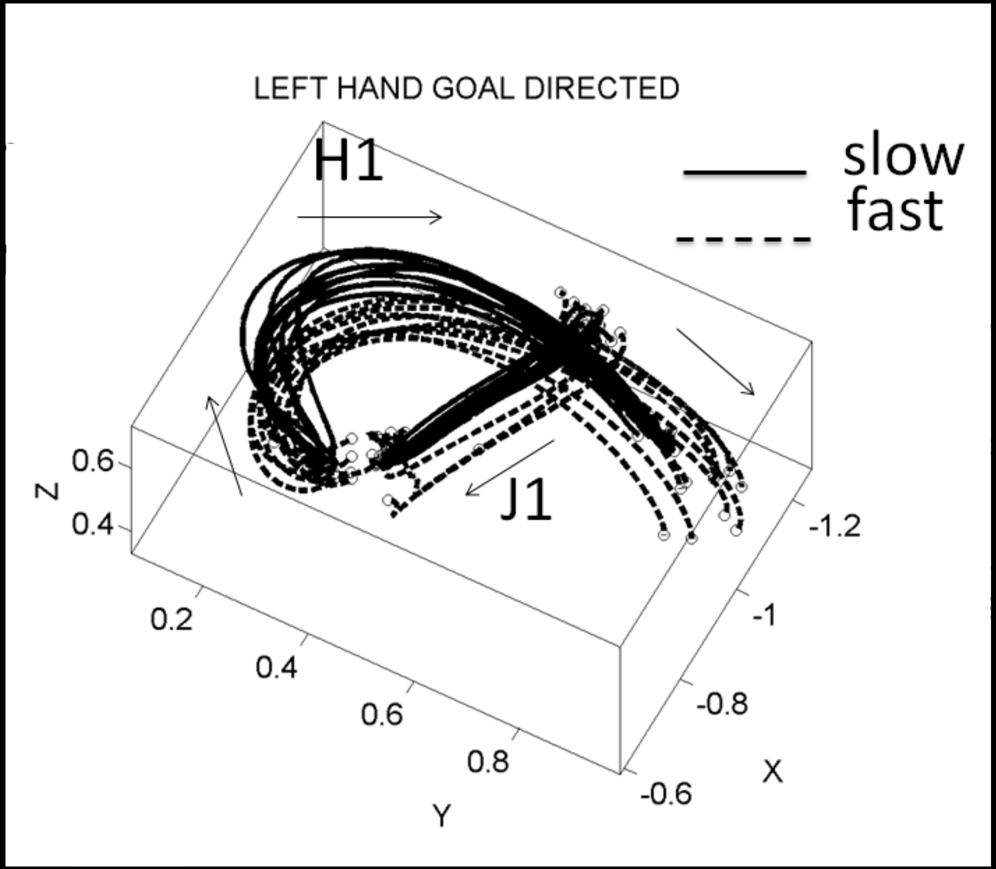
Torres 2011, Exper Brain Res

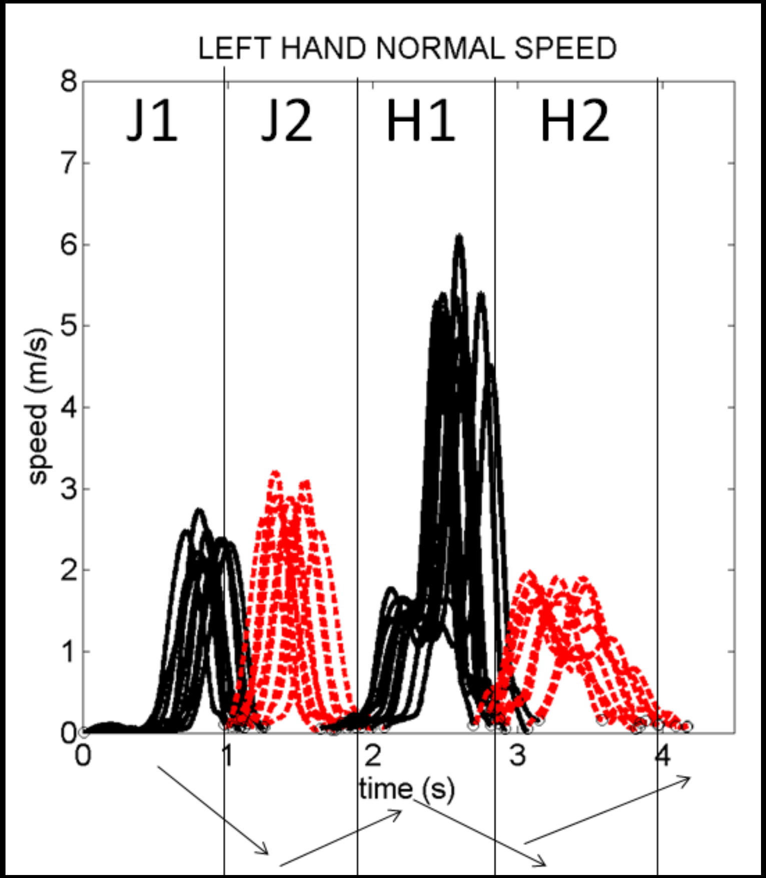
TWO MOVEMENT CLASSES: DELIBERATE VS SPONANEOUS



Torres 2011, Exper Brain Res

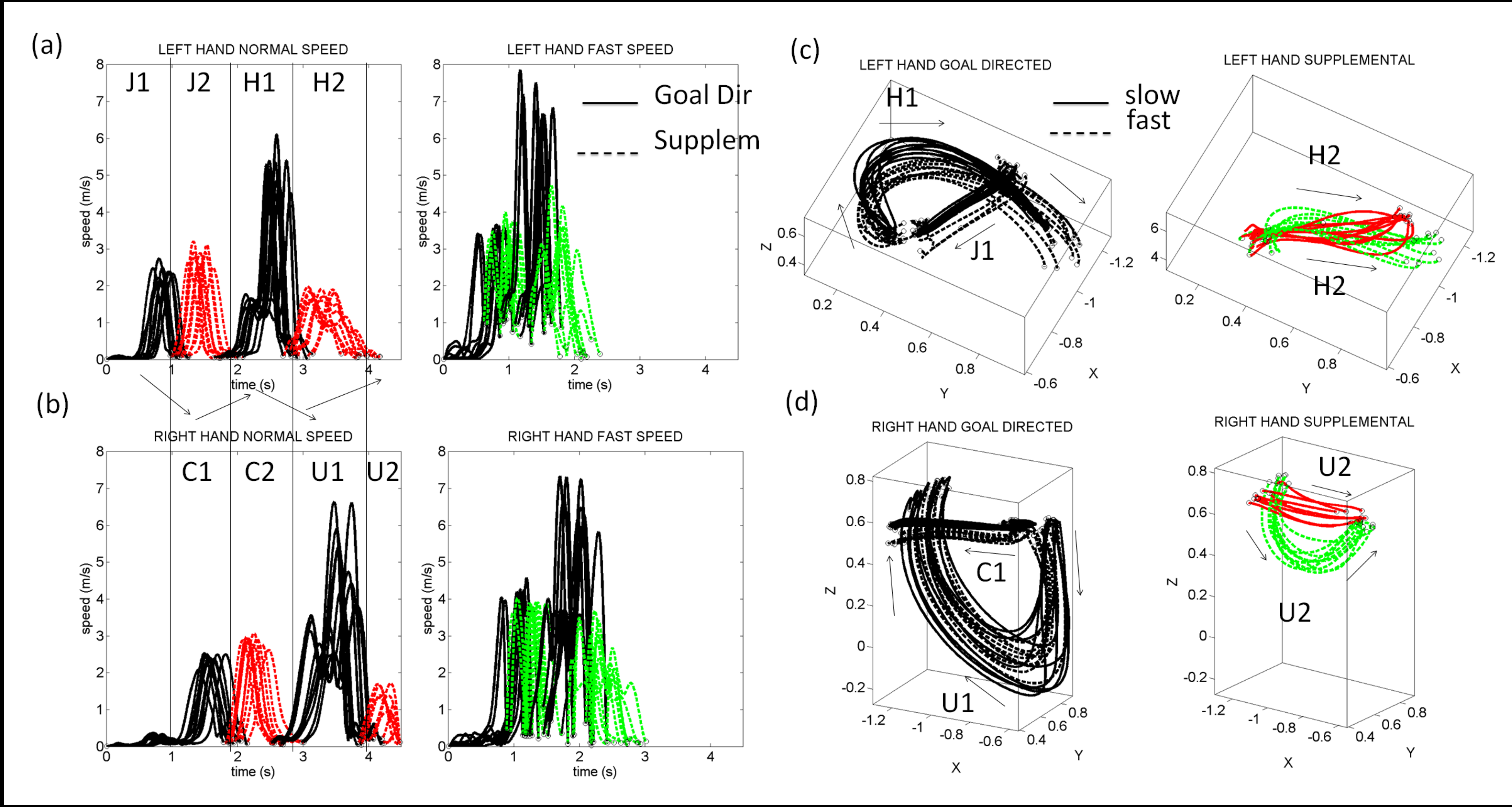
FROM POSITION TO SPEED





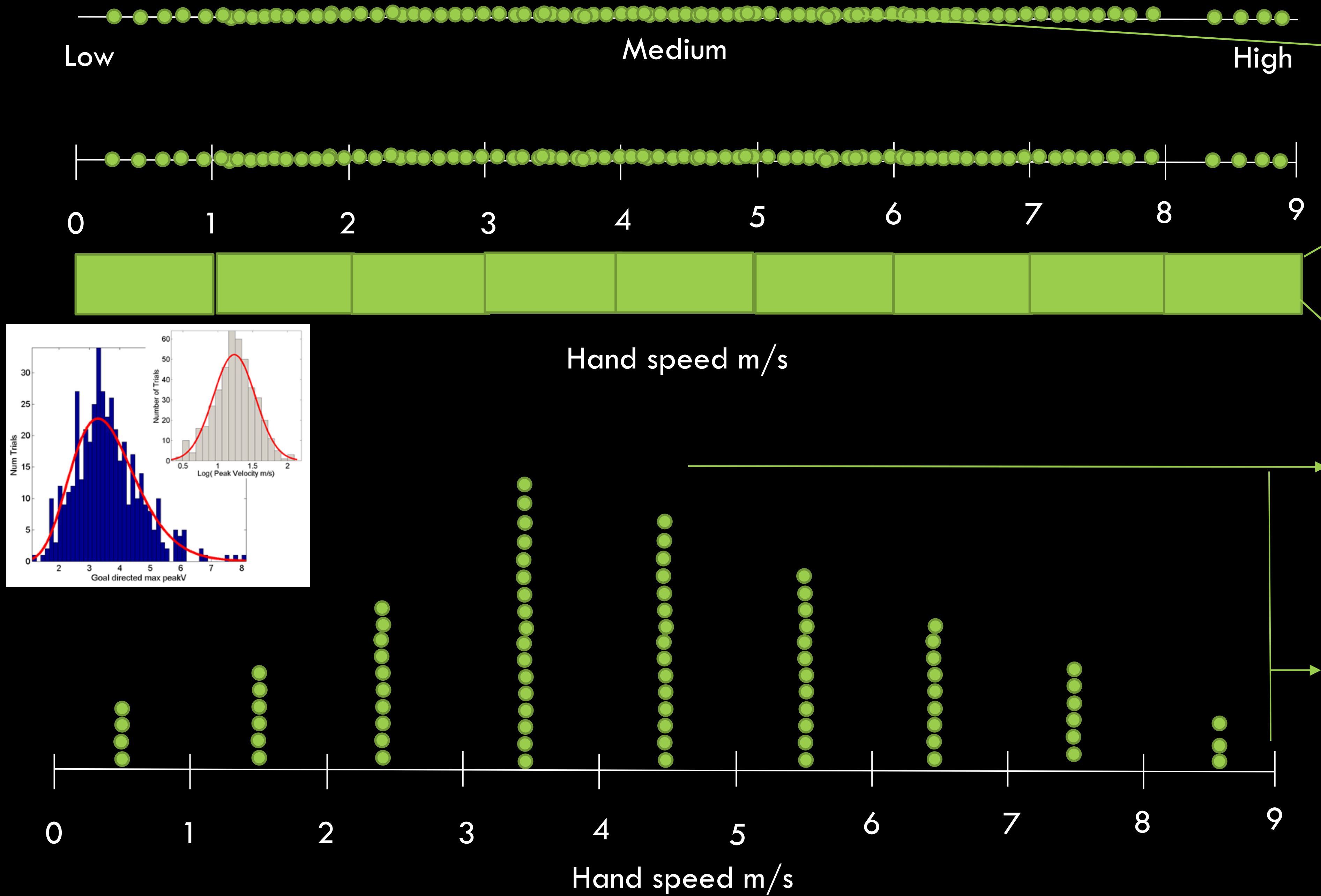
Torres 2011, Exper Brain Res

FOR DIFFERENT SPEEDS, RANDOMLY PERFORMED TRIALS CONSERVE INTENDED TRAJECTORIES



Torres 2011, Exper Brain Res

BUILDING A FREQUENCY HISTOGRAM OF THE HAND SPEEDS



Measure trial by trial

Sort it into bins

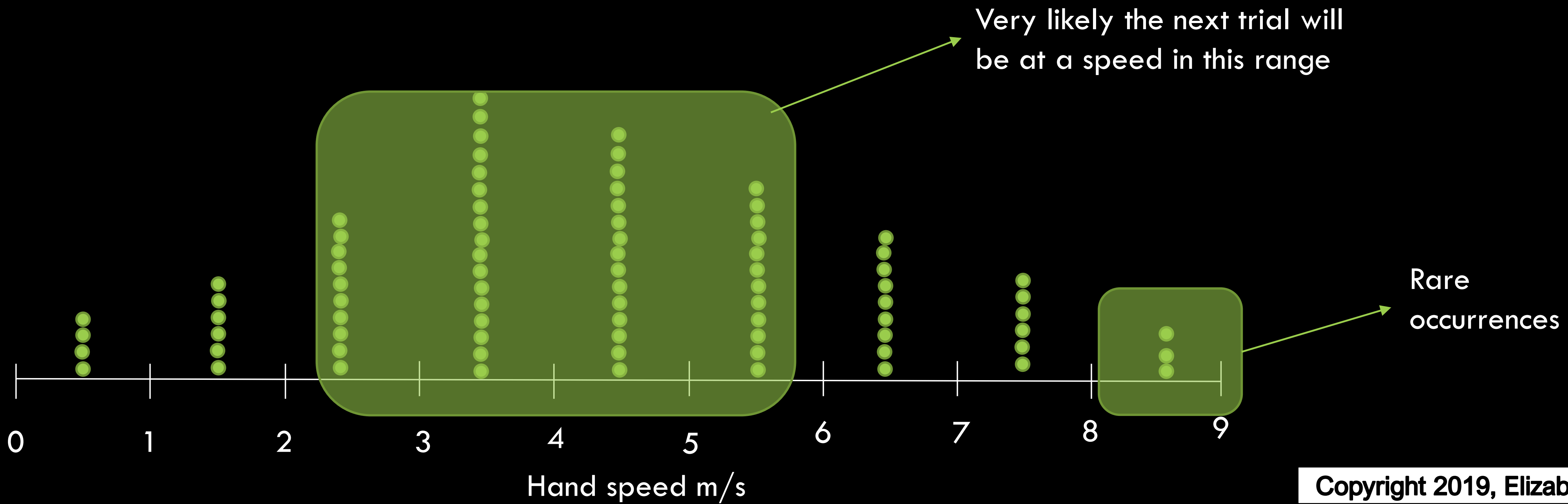
Place in the corresponding bin

Some overlap (many measurements are similar but not identical; hard to see)

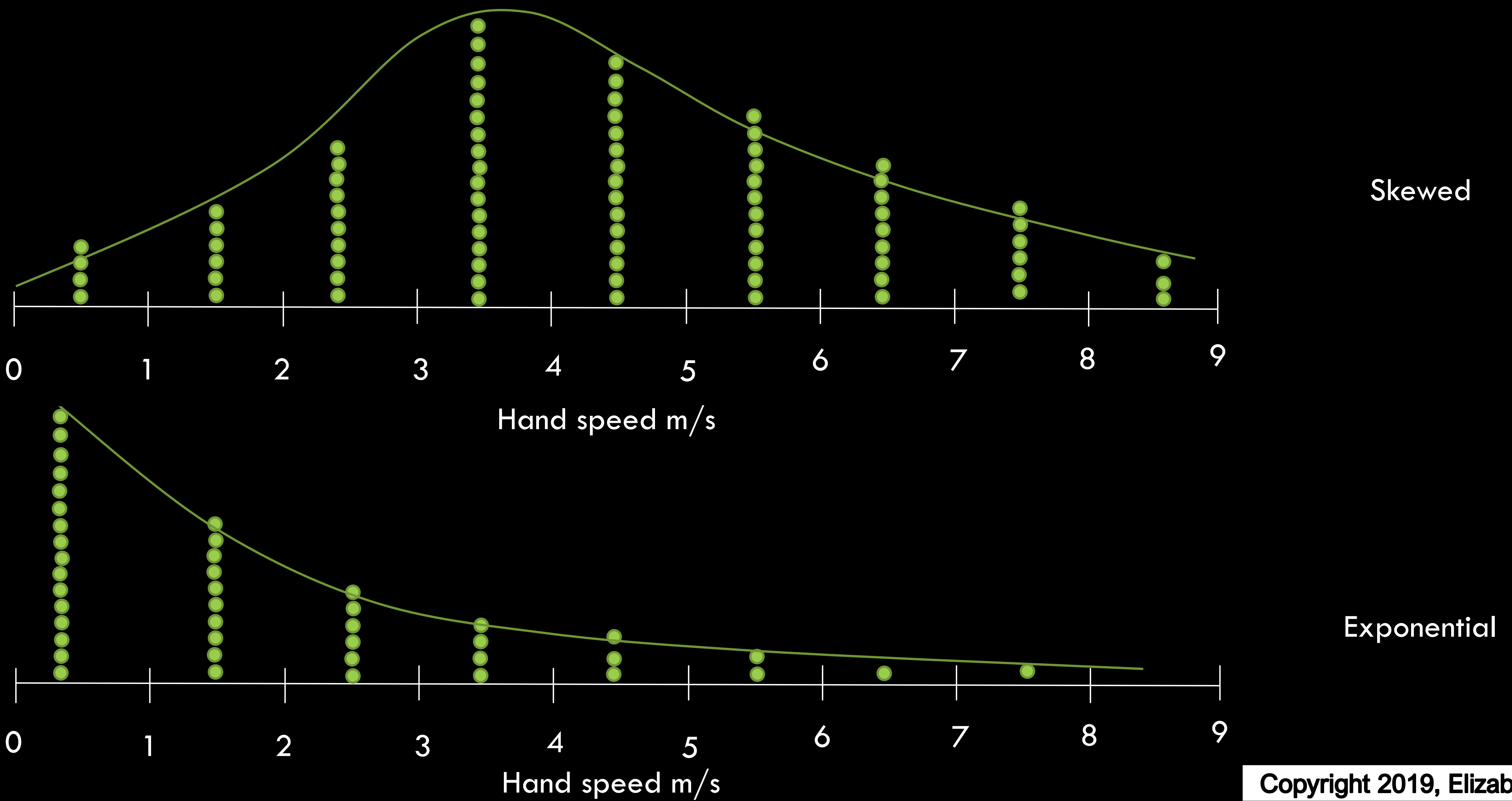
Stack up those similar ones within same bin (interval)

Count / tally their frequency per bin (interval)

HISTOGRAM OF THE SPEED DATA



HISTOGRAM OF THE SPEED DATA



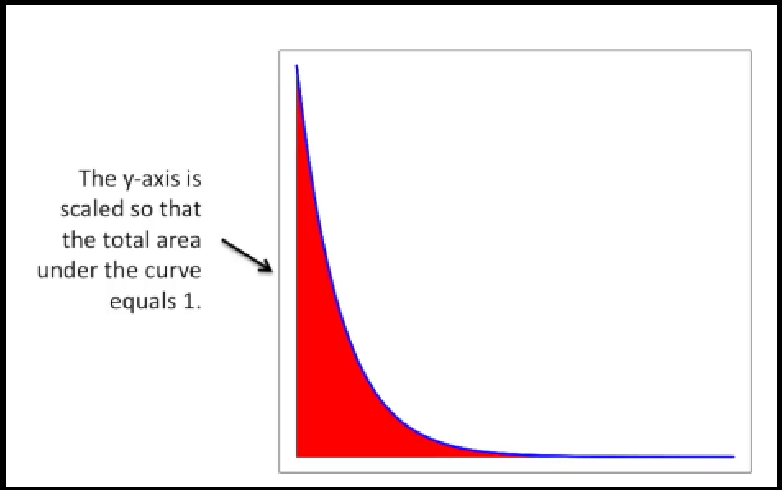
THE EXPONENTIAL DISTRIBUTION

A statistical distribution that models the times between events

e.g. how long will it be before another motion will occur in the range of 5m/s speed?

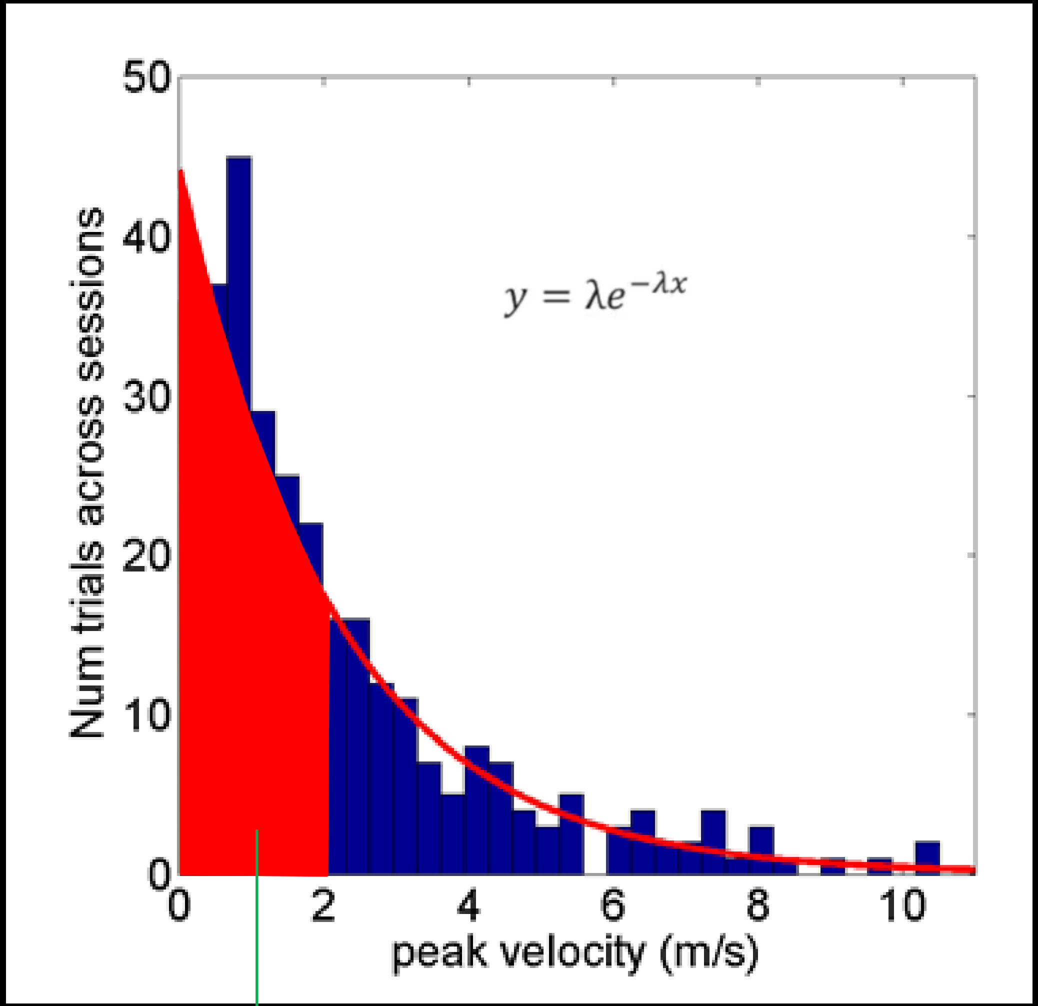
How long will it be before you get another phone call?

How long will it be before you get another text message?



Amount of time between events

THE EXPONENTIAL DISTRIBUTION

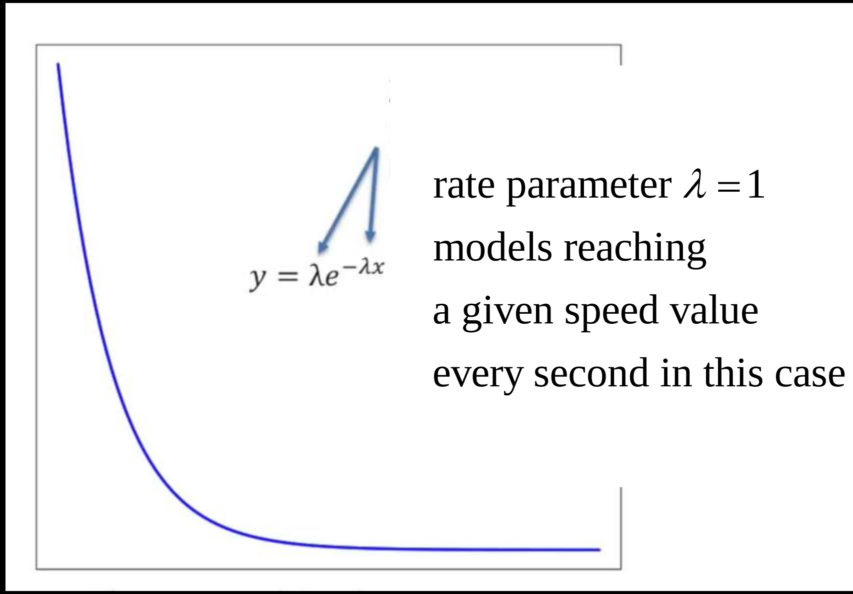


Lambda is the rate parameter; it is proportional to how quickly things happen

What is the probability of events with speed bet 0-2m/s ?
Solve for the area under the curve spanning 0<x<2m/s

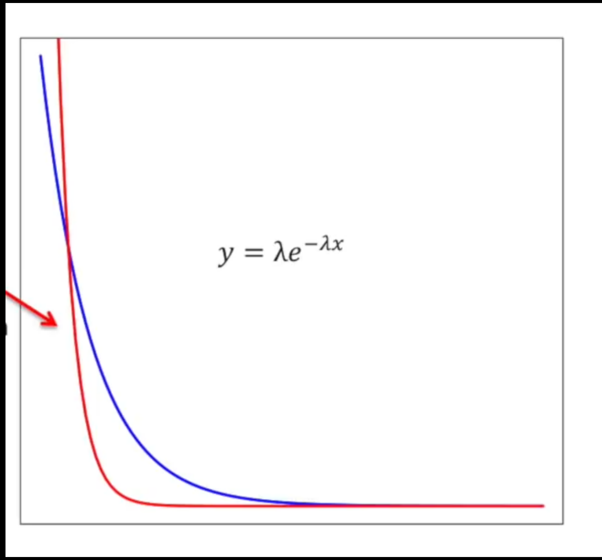
Torres 2011, Exper Brain Res

THE EXPONENTIAL DISTRIBUTION

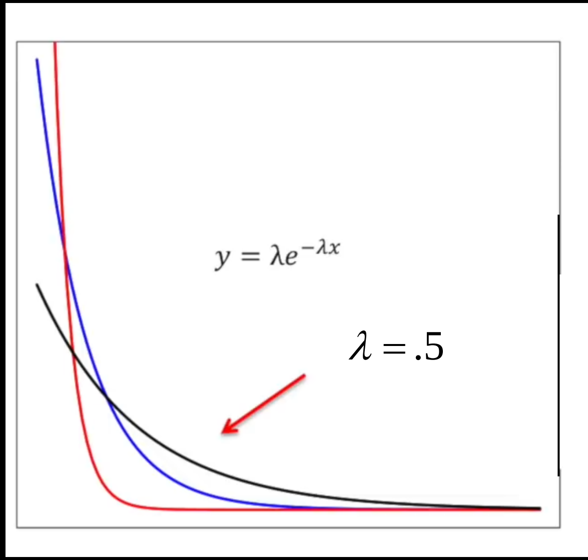


λ is proportional to how quickly things happen
Reflects the amount of time between events

$\lambda = 2$
models reaching
a given speed value
twice every second

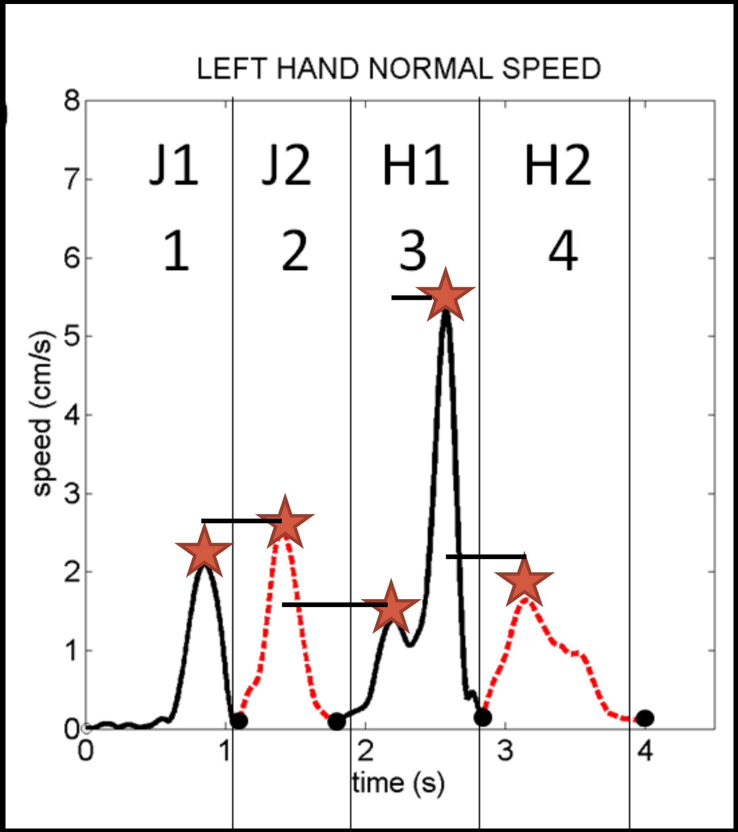


$\lambda = .5$
models reaching
a given speed value
once every 2 seconds



MLE: Given a set of measurements, find an optimal value for λ

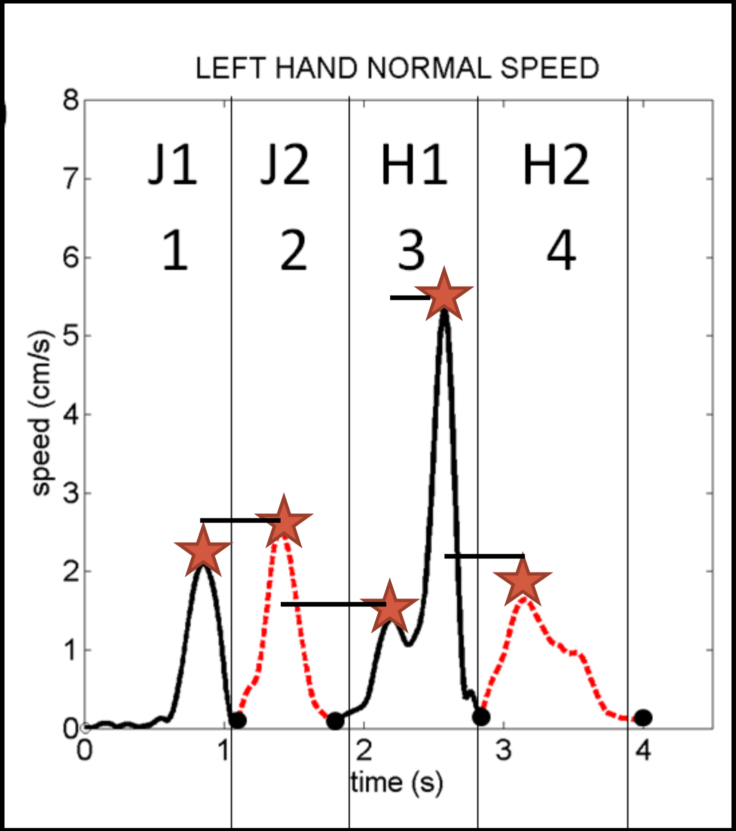
e.g. A time series of events reflecting timing between some occurrence, a text message, a heartbeat, the speed peak of a continuously sampled motion, keystrokes on a keyboard, touches on a cell phone screen, etc.



Our measurements from some sensor

$$\begin{array}{cccccc} [.6 & 1.1 & .2 & .5 & \ldots &] \\ | & | & | & | & & | \\ [x_1 & x_2 & x_3 & x_4 & \ldots & x_n] \end{array}$$

Assume that we have a λ value

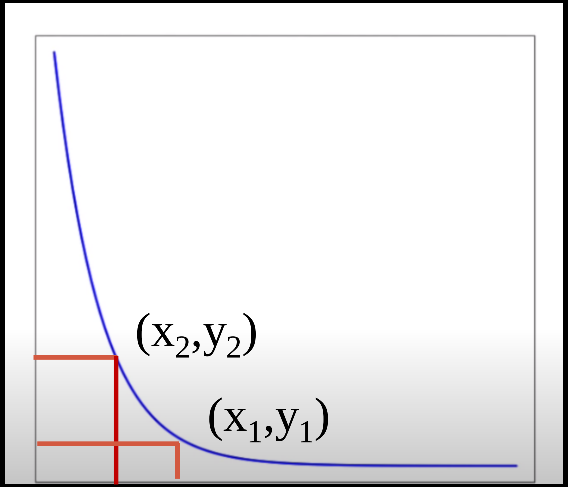


Assume that we have a λ value

We wish to know the likelihood of λ given the values

$$L(\lambda \mid x_1) = \lambda e^{-\lambda x_1} \qquad L(\lambda \mid x_2) = \lambda e^{-\lambda x_2} \quad \ldots$$

$$y_2 = \lambda e^{-\lambda x_2}$$
$$y_1 = \lambda e^{-\lambda x_1}$$



$$L(\lambda \mid x_1 \cap x_2) = L(\lambda \mid x_1) L(\lambda \mid x_2) = \lambda e^{-\lambda x_1} \lambda e^{-\lambda x_2} = \lambda^2 \left[e^{-\lambda(x_1+x_2)} \right]$$

What is the likelihood of λ given all the values in the time series?

$$L(\lambda \mid x_1 \cap x_2 \ldots \cap x_n) = L(\lambda \mid x_1) L(\lambda \mid x_2) \ldots L(\lambda \mid x_n)$$

$$= \lambda e^{-\lambda x_1} \lambda e^{-\lambda x_2} \ldots \lambda e^{-\lambda xn}$$

$$= \lambda^{n} \left[e^{-\lambda x_1} e^{-\lambda x_2} \ldots e^{-\lambda x_n} \right]$$

$$= \boxed{\lambda^{n} \left[e^{-\lambda (x_1 + x_2 + \ldots + x_n)} \right]}$$

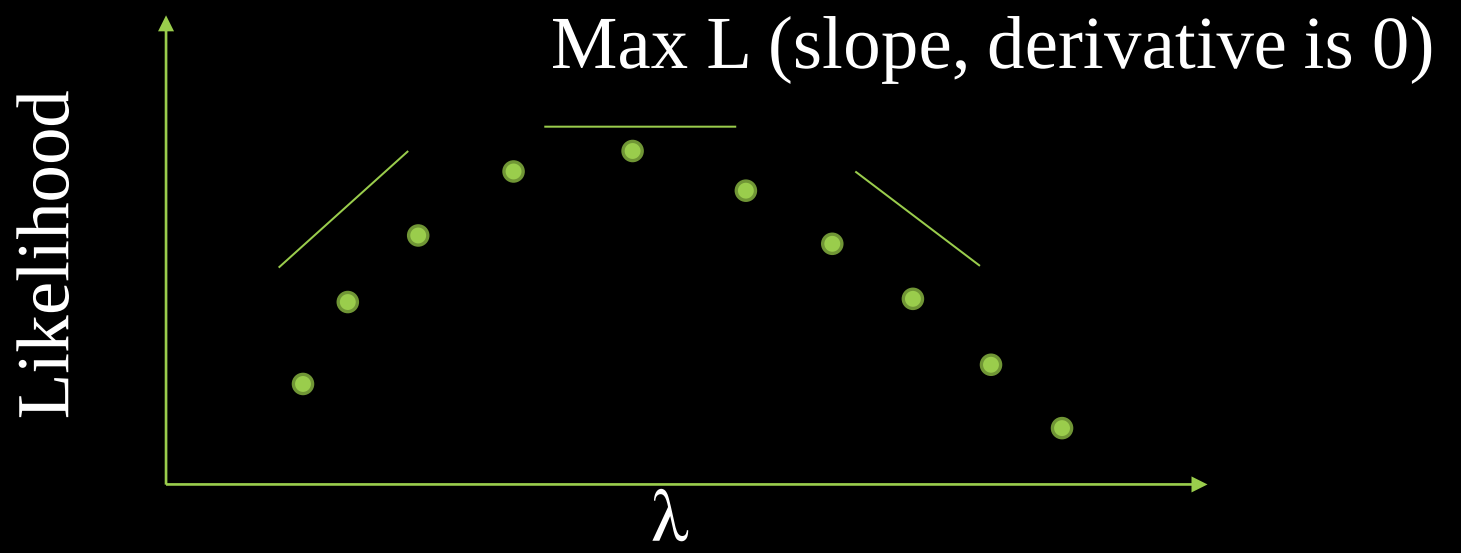
How do we determine the optimal λ in general ?

How do we determine the optimal λ in general ?

$$L\left(\lambda \mid x_1 \cap x_2 \ldots \cap x_n\right) = \lambda^{n}\left[e^{-\lambda\left(x_1+x_2+\ldots+x_n\right)}\right]$$

1. Take the derivative

2. Solve for λ when the derivative is 0



1. Take the derivative of the Likelihood Function wrt λ

$$\frac{d}{d\lambda}L\left(\lambda \mid x_1 \cap x_2 \ldots \cap x_n\right) = \frac{d}{d\lambda}\lambda^{\mathrm{n}}\left[e^{-\lambda\left(x_1+x_2+\ldots+x_n\right)}\right]$$

When the exp is in the term, it is easier to take the derivative of the log of the function

The derivative of a function and the derivative of the log of the function equal 0 at the same point, so they are interchangeable

$$\frac{d}{d\lambda}\log\left(\lambda^{\mathrm{n}}\left[e^{-\lambda\left(x_1+x_2+\ldots+x_n\right)}\right]\right)$$

1. Take the derivative of the Likelihood Function

$$\frac{d}{d\lambda}\log\left(\lambda^{\mathrm{n}}\left[e^{-\lambda\left(x_1+x_2+\ldots+x_n\right)}\right]\right)$$

$$\frac{d}{d\lambda}\log\left(\lambda^{\mathrm{n}}\right)+\log\left[e^{-\lambda\left(x_1+x_2+\ldots+x_n\right)}\right]$$

$$\frac{d}{d\lambda}n\log\left(\lambda\right)-\lambda\left(x_1+x_2+\ldots+x_n\right)$$

$$n\frac{1}{\lambda}-\left(x_1+x_2+\ldots+x_n\right)$$

2. Set the derivative to 0 and solve for λ

$$n\frac{1}{\lambda}-\left(x_1+x_2+\ldots+x_n\right)=0$$

$$n\frac{1}{\lambda}=\left(x_1+x_2+\ldots+x_n\right)$$

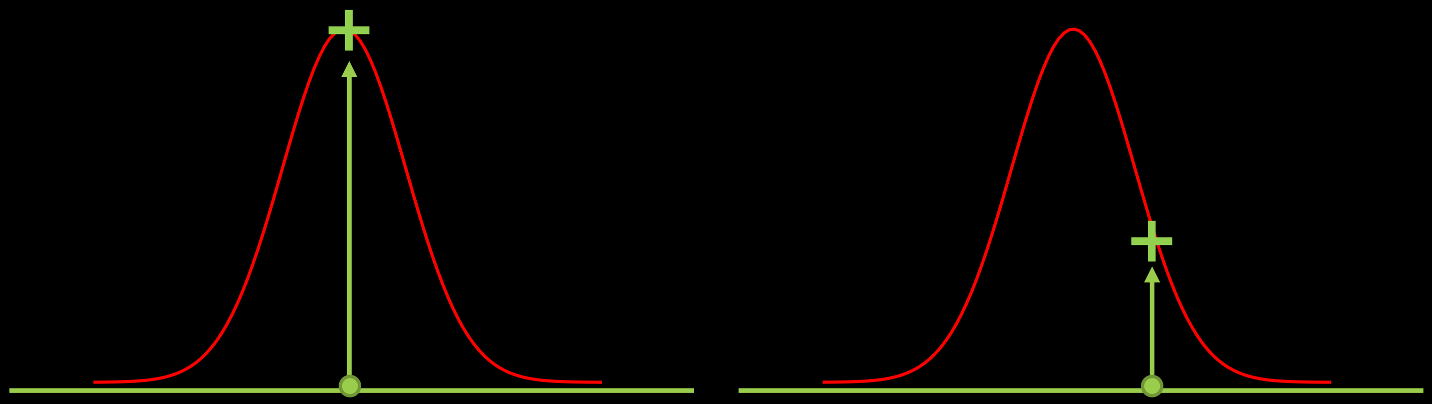
$$n=\lambda\left(x_1+x_2+\ldots+x_n\right)$$

$$\boxed{\frac{n}{\left(x_1+x_2+\ldots+x_n\right)}=\lambda}$$

Given your time series data, this is the Maximum Likelihood Estimate (MLE) for λ

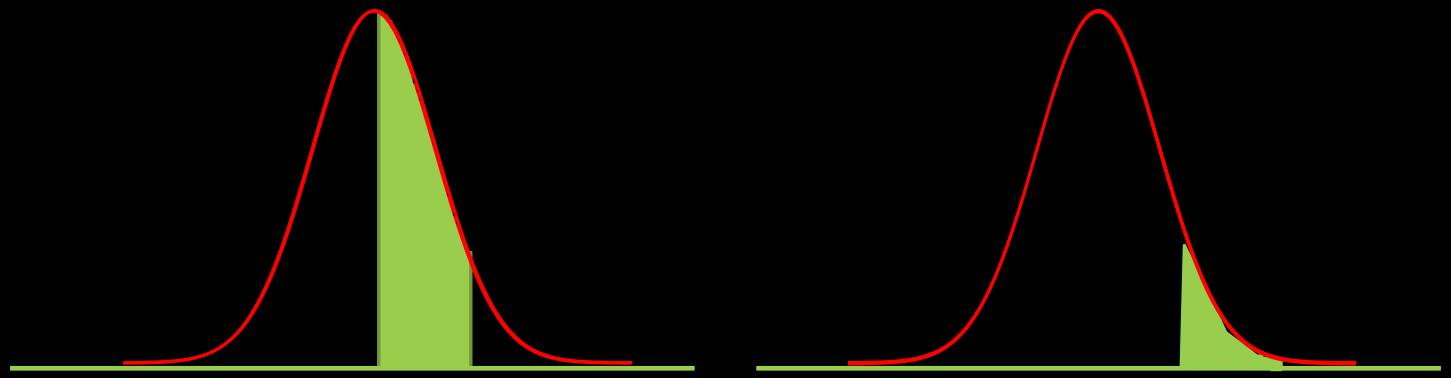
L(distribution | data)

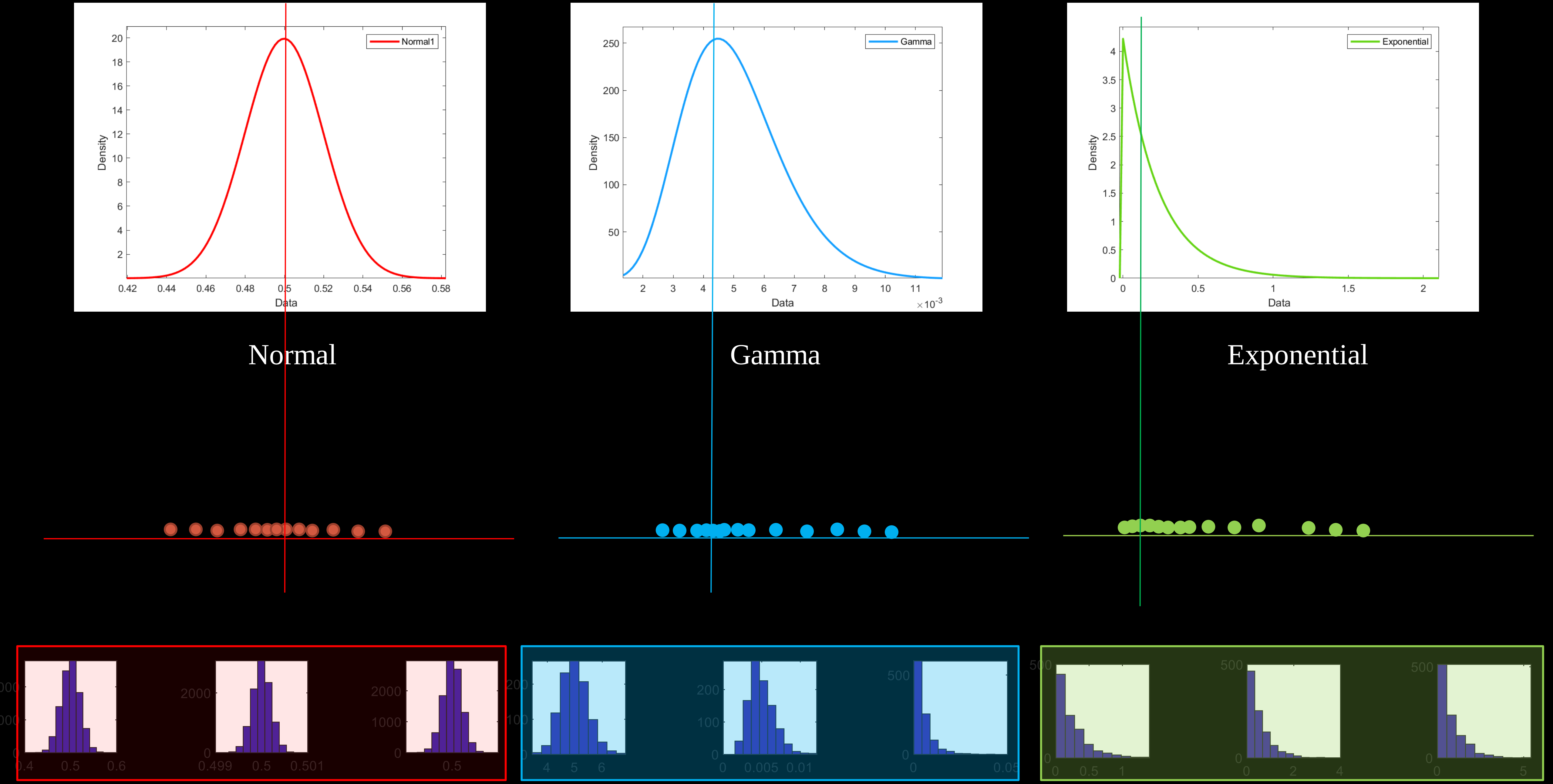
Likelihood, y-axis values for fixed data points with distributions that can be moved



Prob(data | distribution)

Probabilities are the area under a fixed distribution

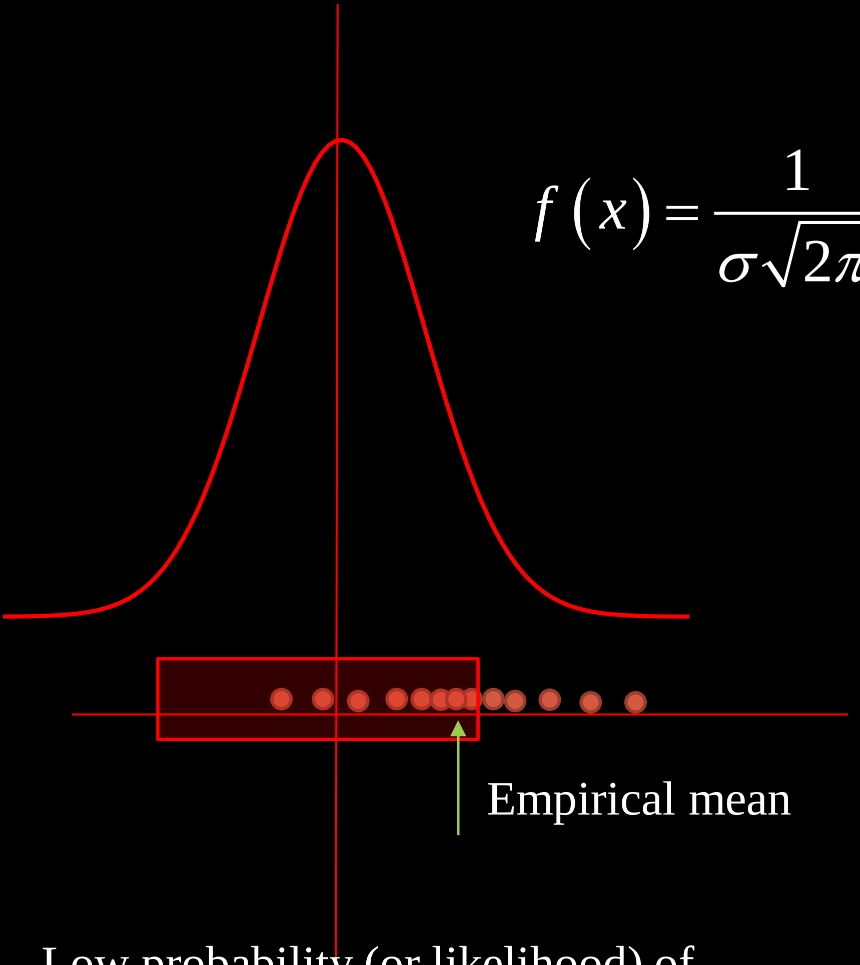




Normal1
Density
Data
Gamma
$\times 10^{-3}$
Exponential
Normal
Gamma
Exponential

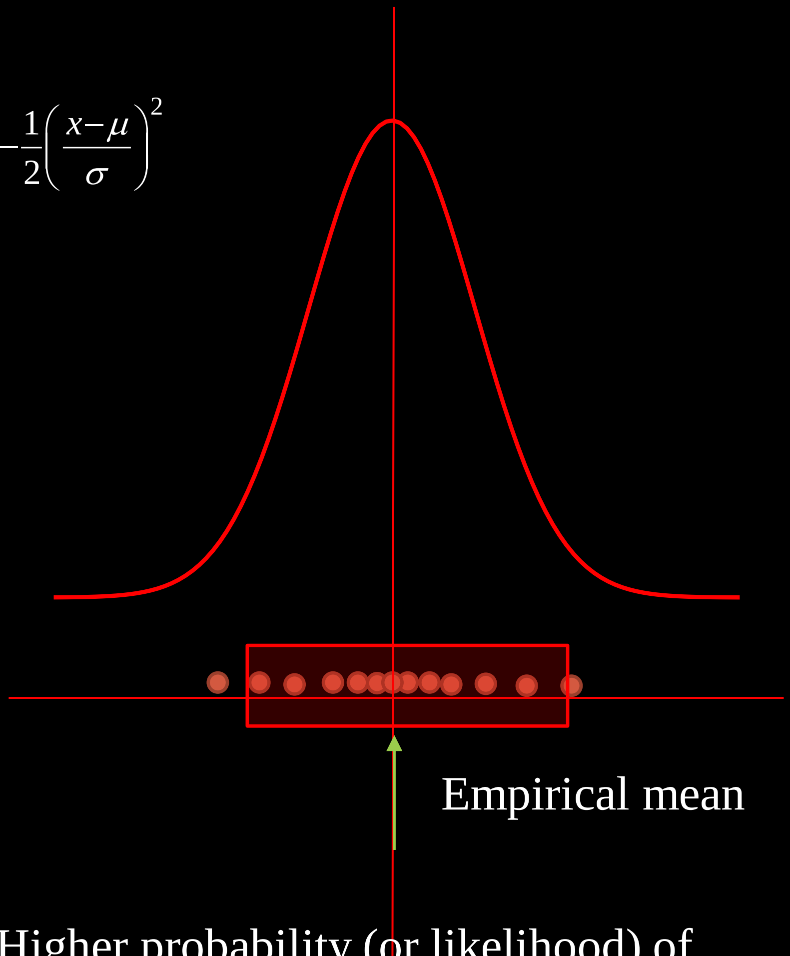
Normal Distribution
Theoretical mean

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$



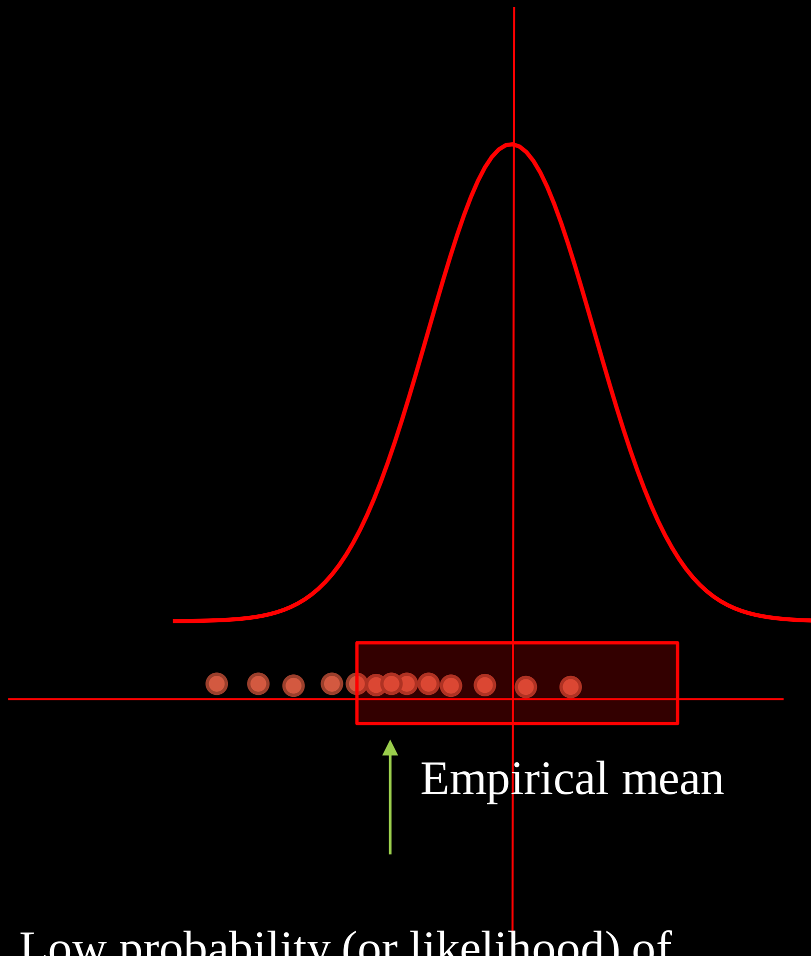
Low probability (or likelihood) of observing these values for the theoretical distribution imposed a priori

Shift Normal Distribution
Shift Theoretical mean to match the empirical data



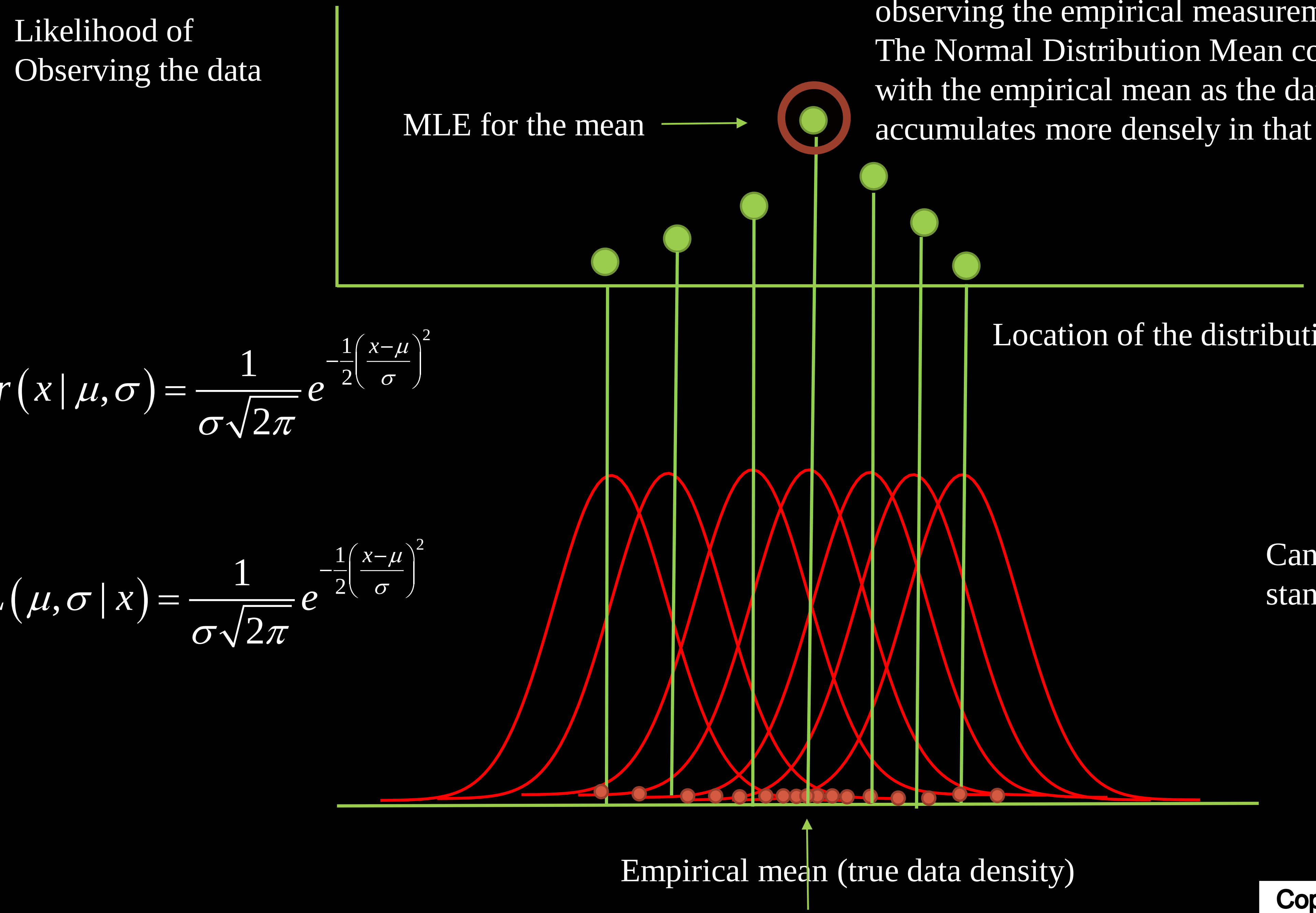
Higher probability (or likelihood) of observing these values for the theoretical distribution imposed a priori

Shift Normal Distribution over Theoretical mean does not match the empirical data



Low probability (or likelihood) of observing these values for the theoretical distribution imposed a priori

This location maximizes the likelihood of observing the empirical measurements
The Normal Distribution Mean coincides with the empirical mean as the data accumulates more densely in that area

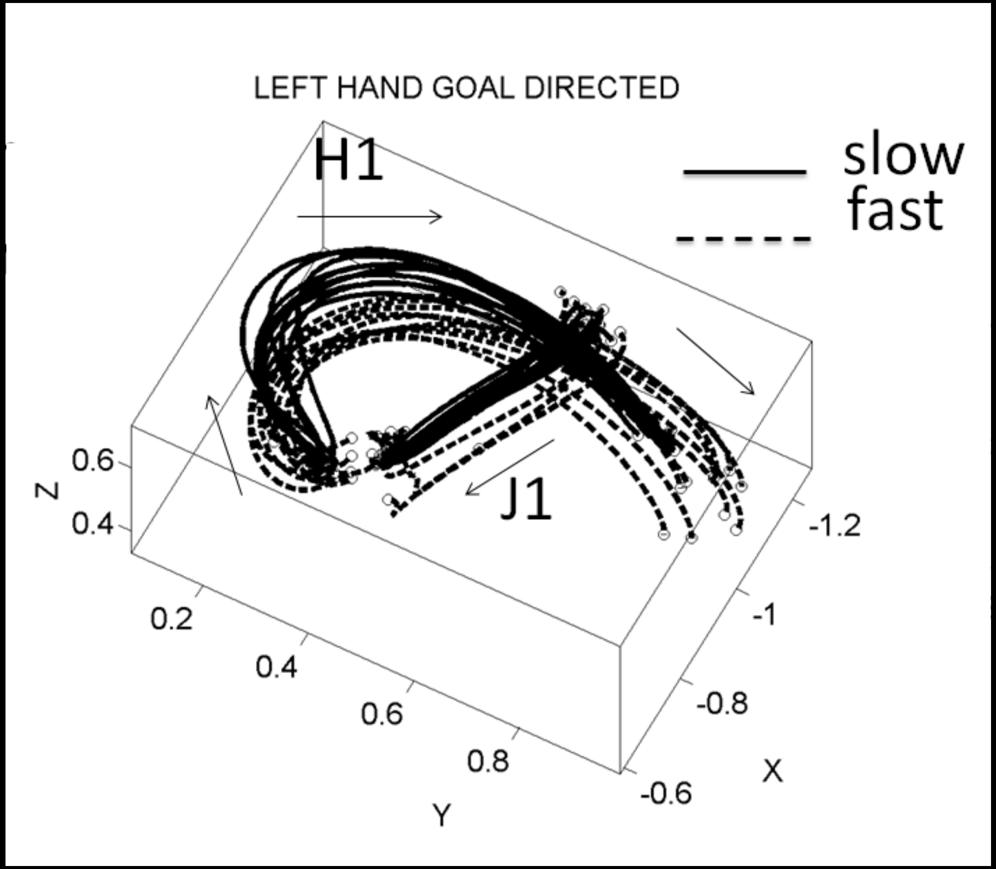


$$pr(x \mid \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

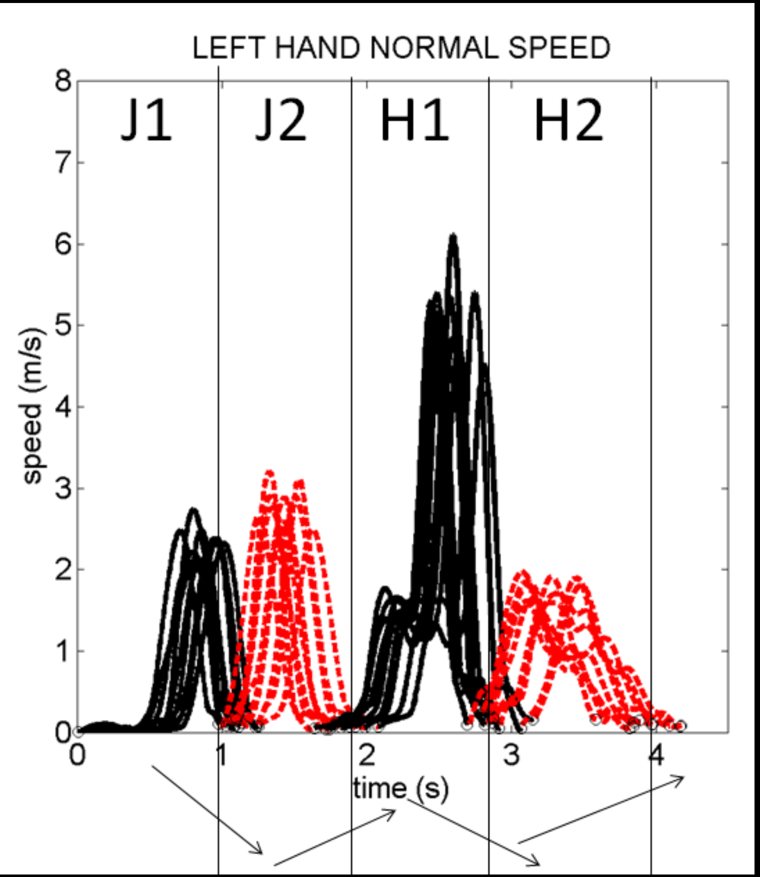
$$L(\mu, \sigma \mid x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

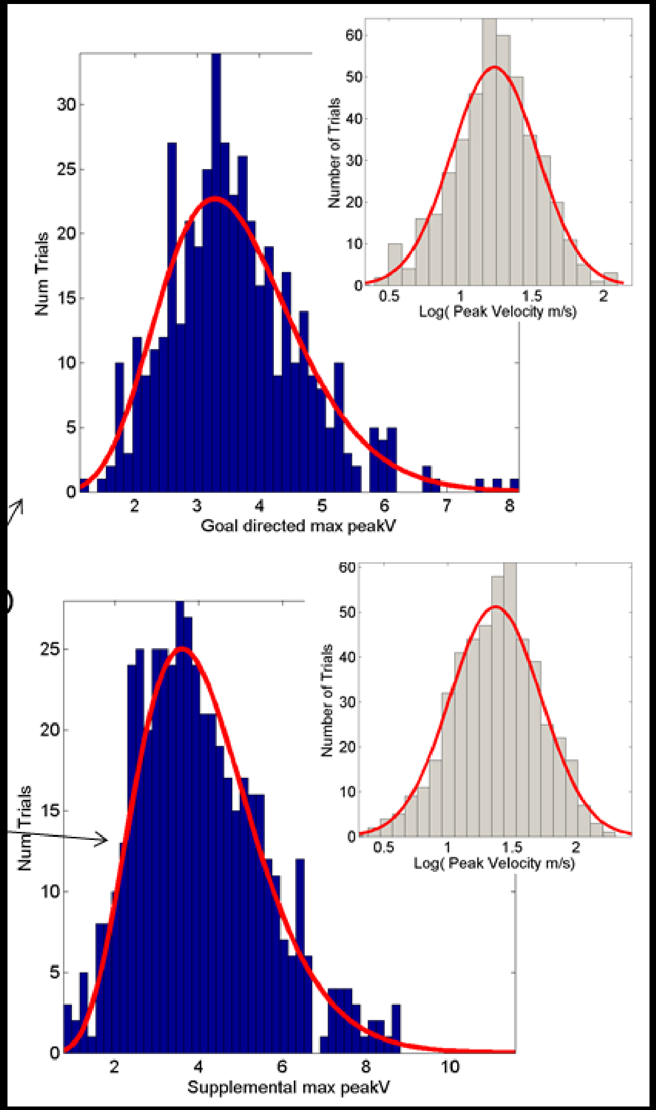
Can do the same for the standard deviation

FROM SPEED TO FREQUENCY HISTOGRAM



Intended (deliberate)





Spontaneous transition

Torres 2011, Exper Brain Res

LEAVE ONE OUT DECODING ALGORITHM

Given the speed, which type of movement does it belong to?
is it a Jab, a Cross, a Hook or an Uppercut?
is it a deliberate Jab or is it the spontaneous transitional Jab?

How informative is the trial by trial variability in our data set?

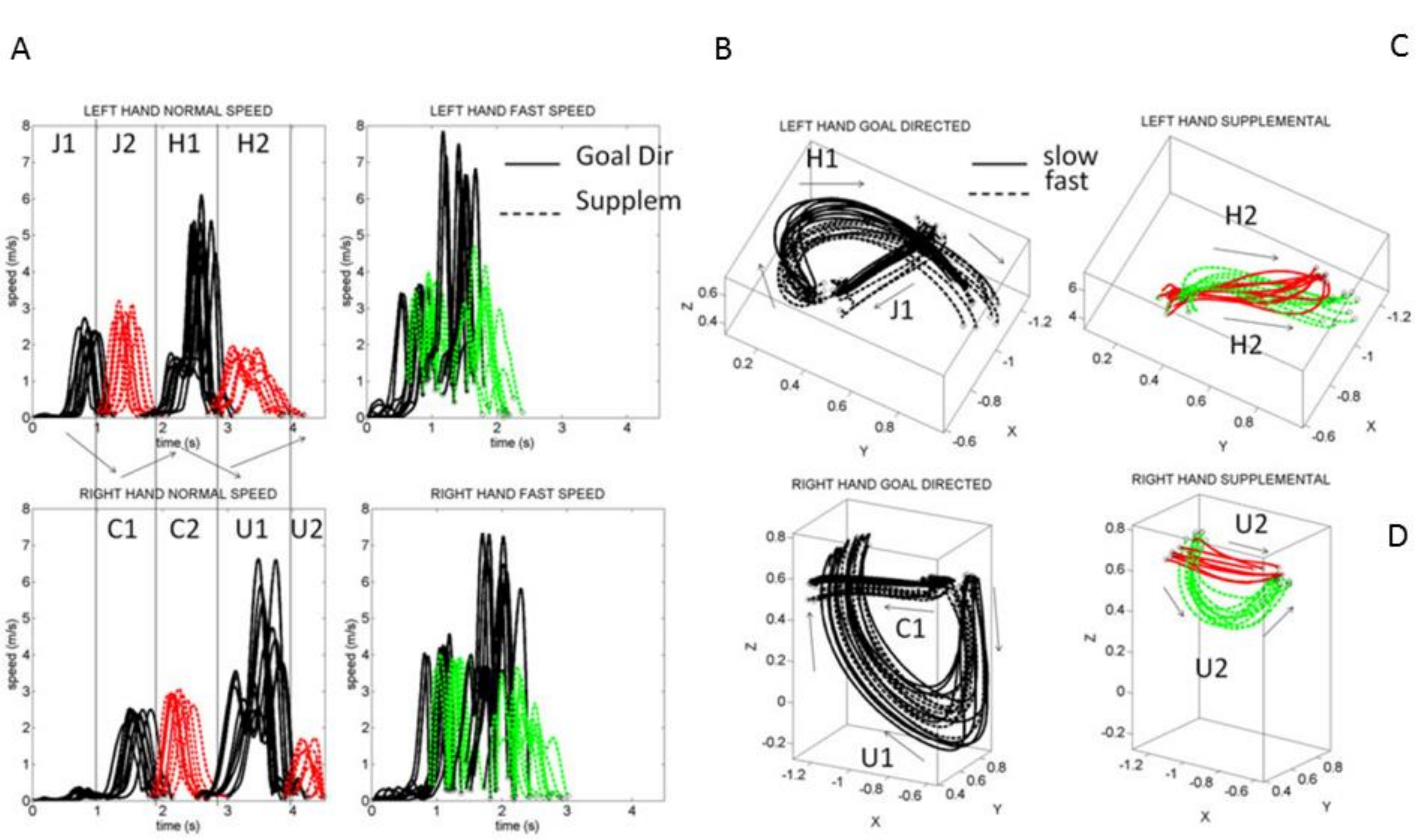
An expert, 9 novices from college age and one autistic adolescent

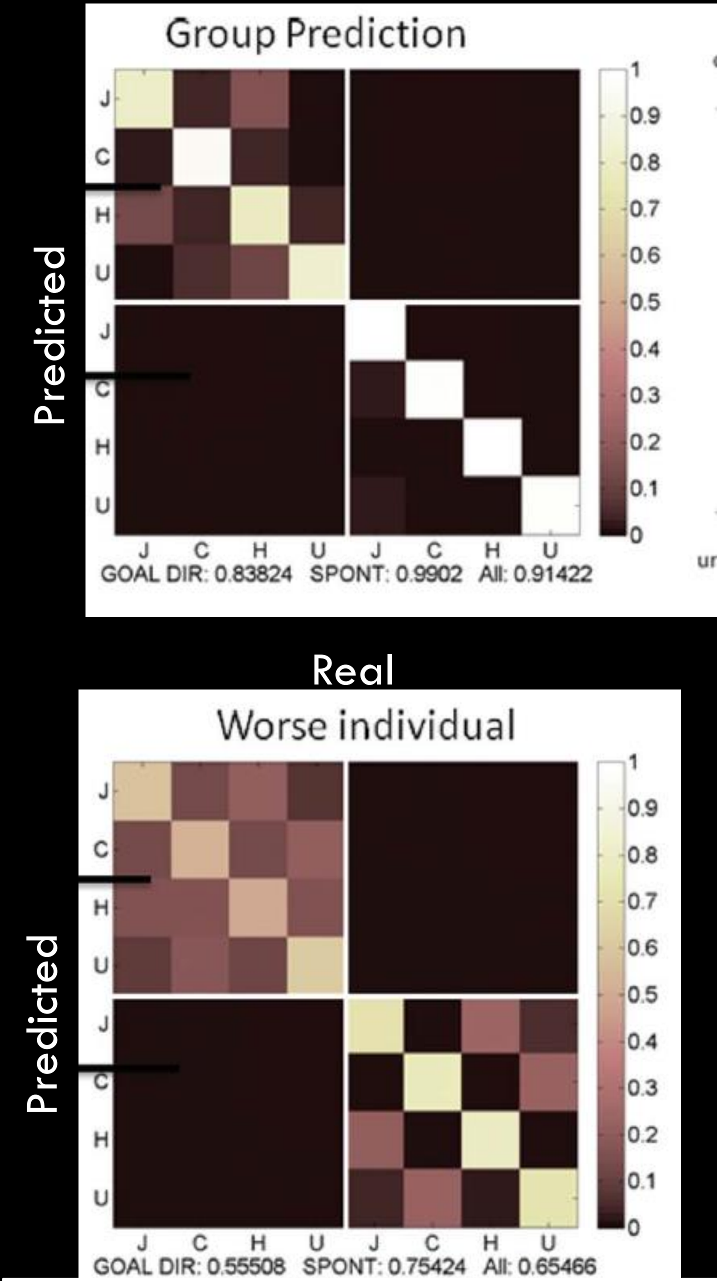
We divide the set of all trials into the “training set” and the “testing set”
Every iteration, we “show” the training set to the algorithm but leave out the trial that we want to test

Then we measure the prediction error

Torres 2011, Exper Brain Res

MOMENT BY MOMENT MOTOR VARIABILITY NEVER CONFUSES DELIBERATE VS CONSEQUENTIAL SEGMENTS





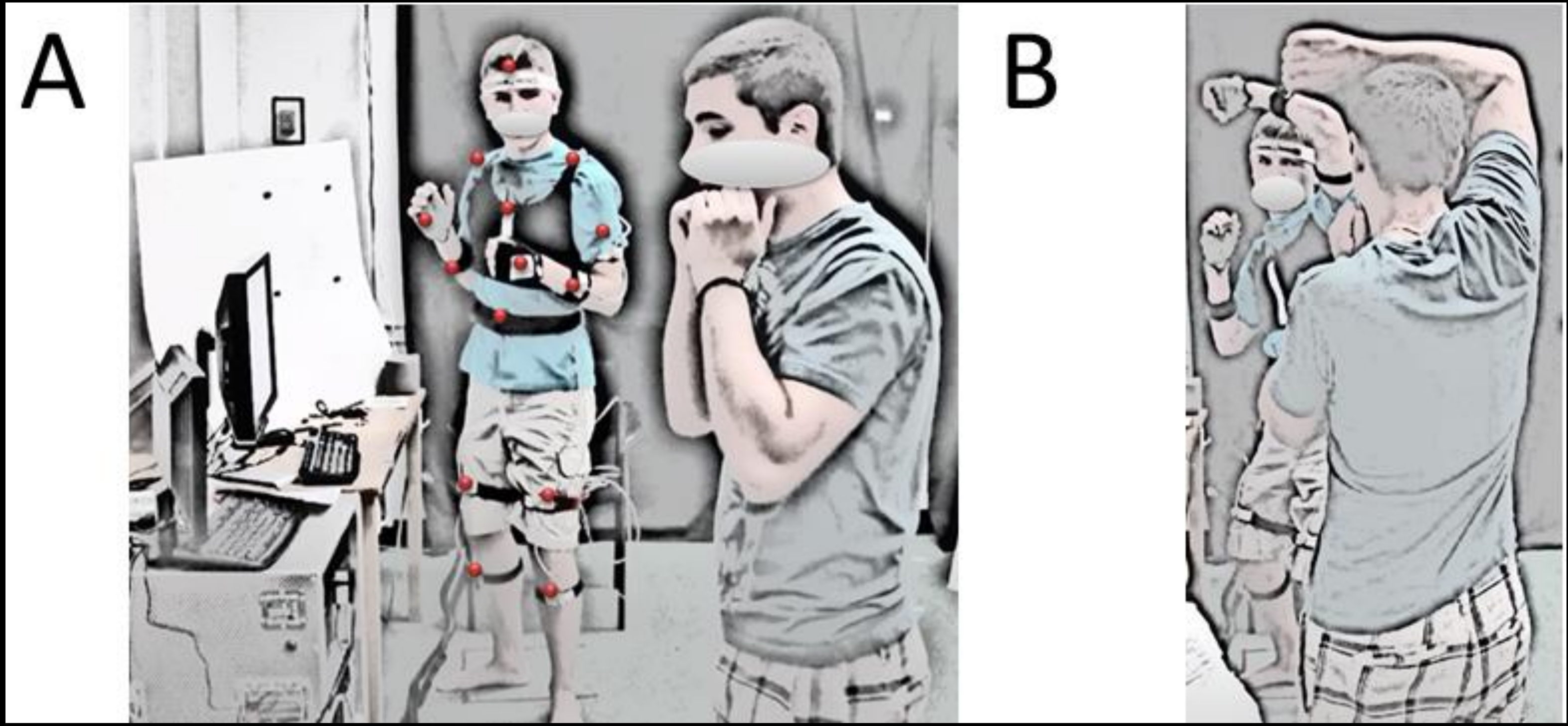
Torres 2011, Exper Brain Res

SERENDIPITOUS DISCOVERY

https://www.youtube.com/watch?v=ji1yNa0mDJ0

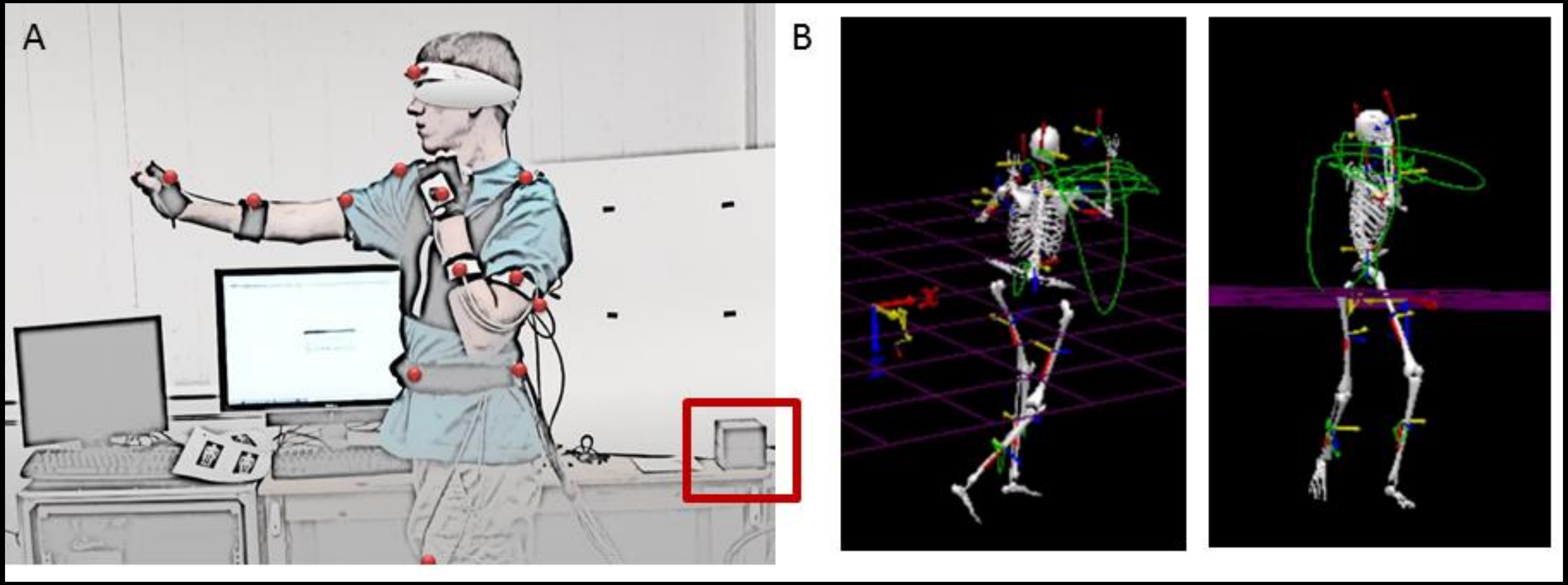
Torres 2011, Exper Brain Res

THE DISCOVERY OF EXPONENTIAL DISTRIBUTION IN HUMAN MOTIONS (AUTISM)



Torres EB, 2011 Neurocase

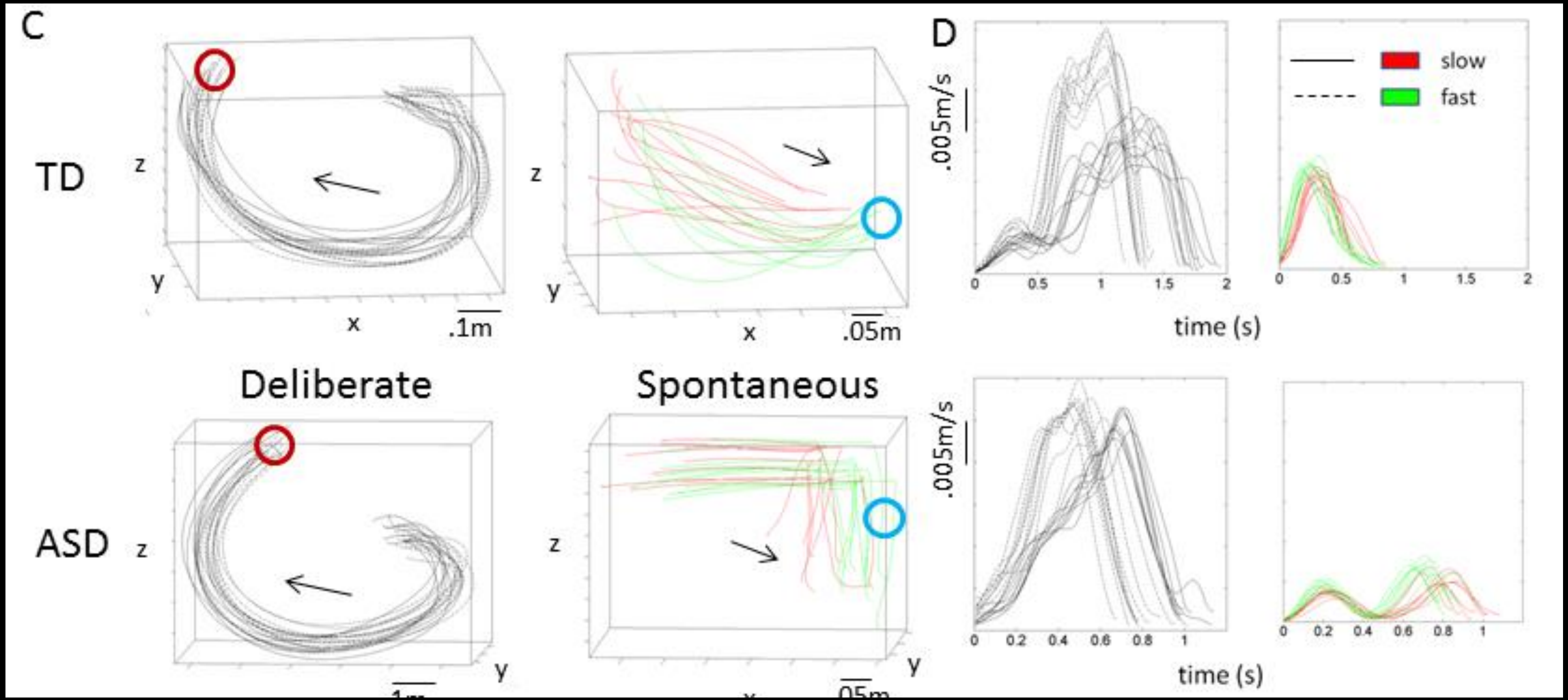
LARGER DIFFERENCES IN SIGNATURES BETWEEN DELIBERATE AND SPONTANEOUS MOTIONS IN ASD

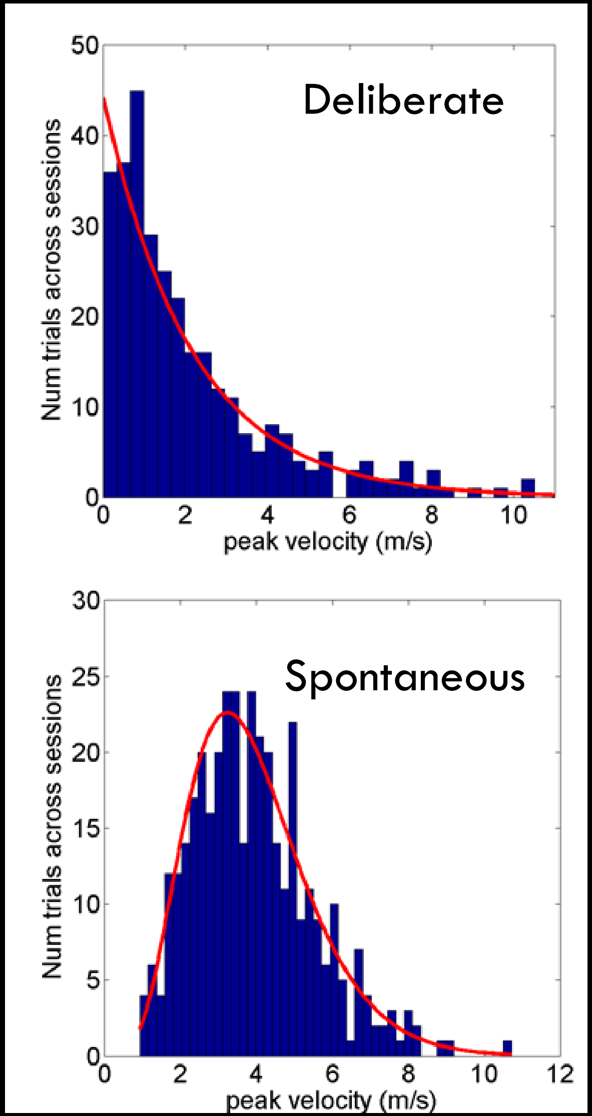


Torres EB, 2011 Neurocase

https://www.youtube.com/watch?v=ji1yNa0mDJ0

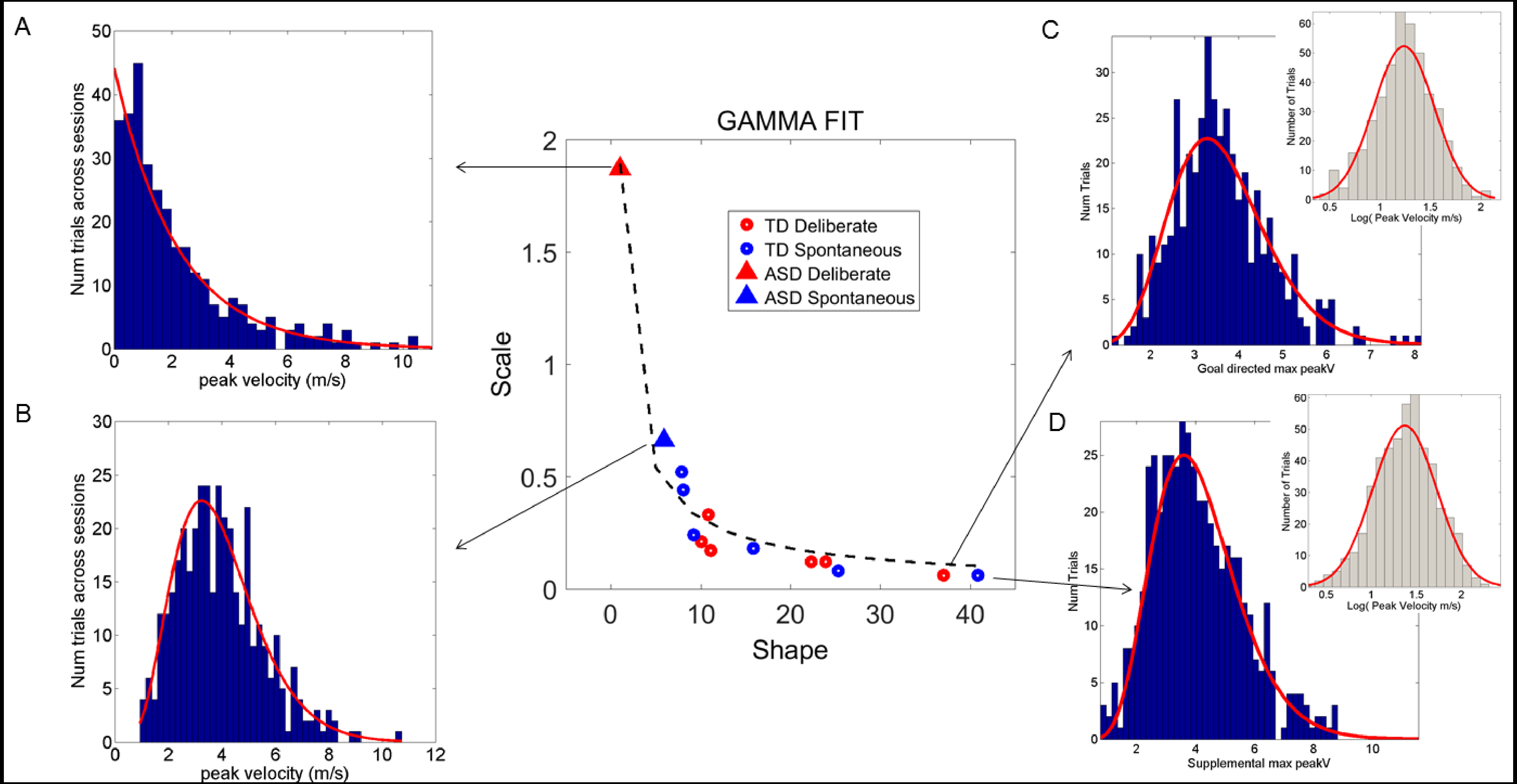
FROM SPEED TO FREQUENCY HISTOGRAM





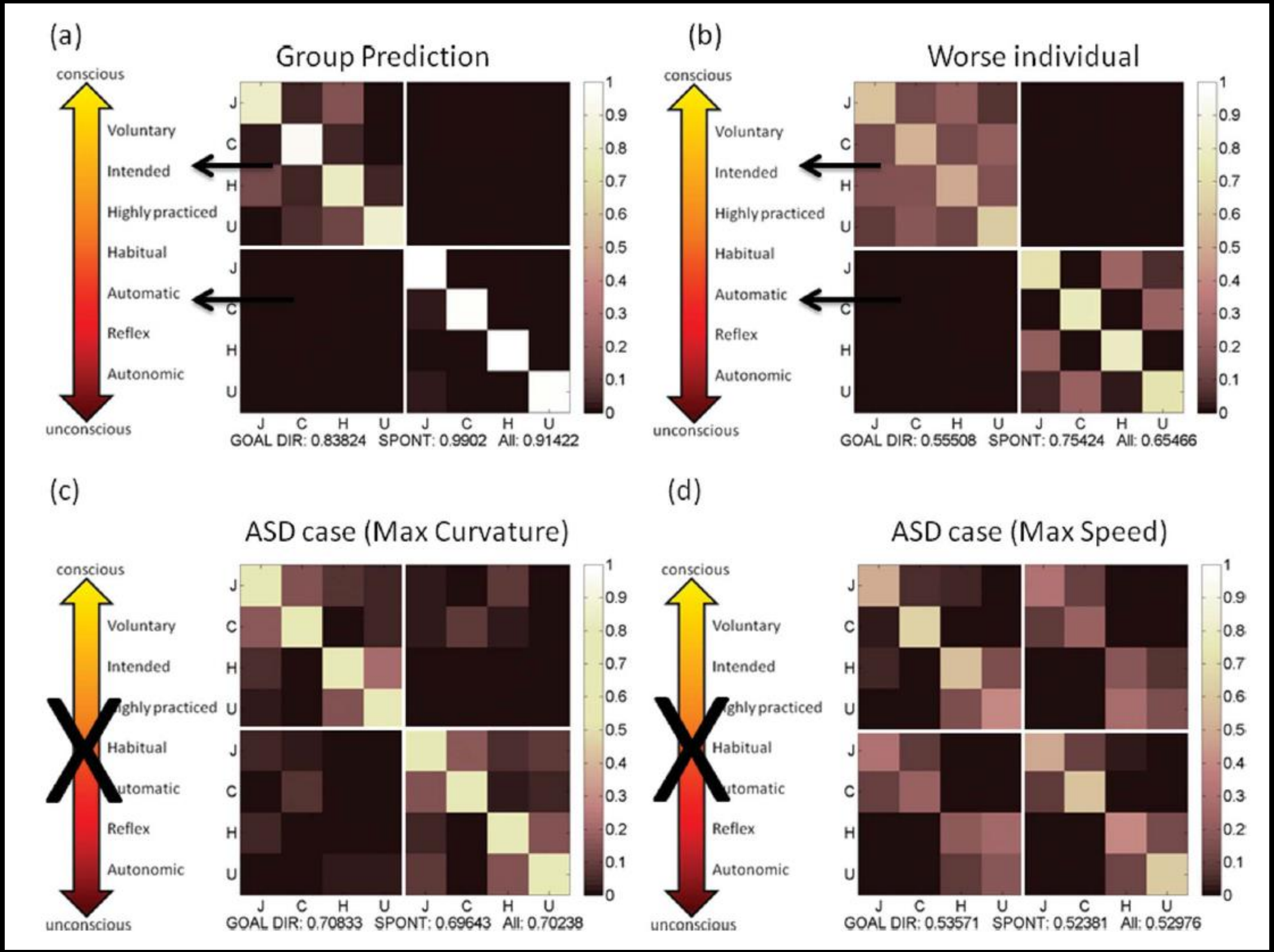
Torres EB, 2011 Neurocase

DELIBERATE AUTISTIC MOTION SPEED DISTRIBUTES EXPONENTIALLY



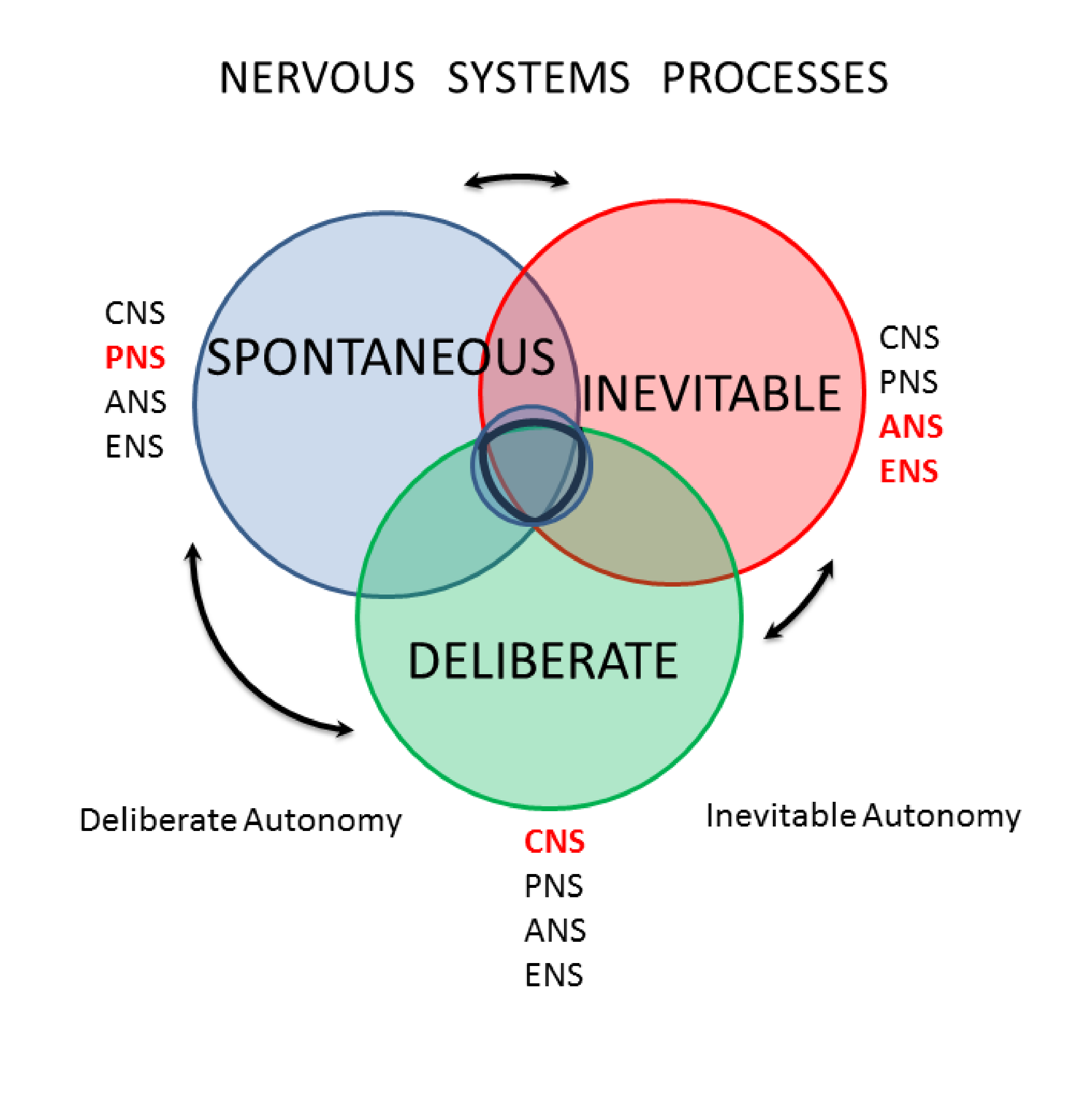
Torres 2011, Exper Brain Res

DECODING FAILS FOR THE ASD MOTOR VARIABILITY



Torres 2011, Exper Brain Res

NEXT CLASS: CHARACTERIZING INTENT THROUGH DIFFERENT TYPES OF PROCESSES



Elsevier 2018; Torres EB