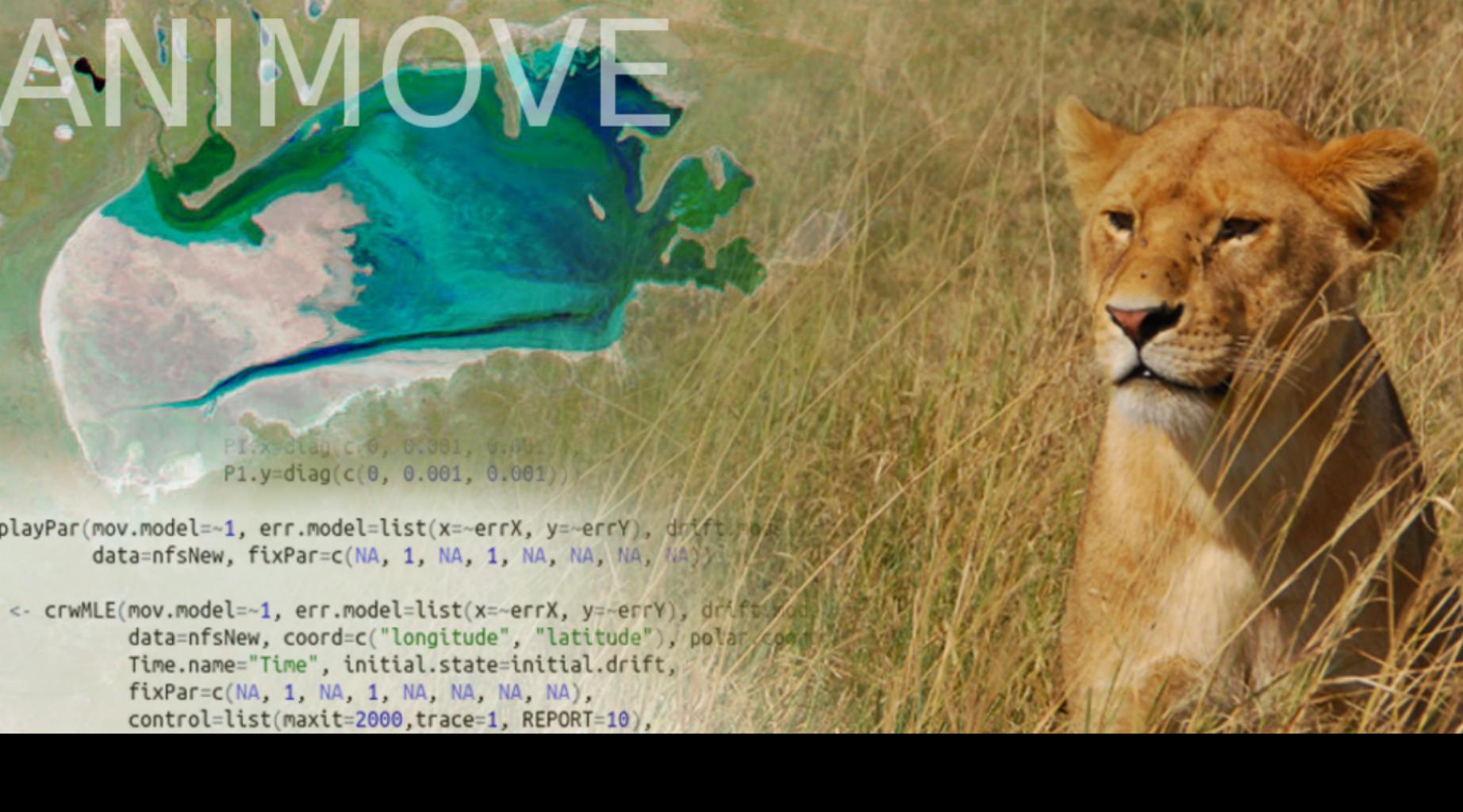


# ANIMOVE

A photograph of a lioness with a light brown coat and dark mane, looking slightly to the left. She is positioned on the right side of the image, partially obscured by tall, dry grass.

```
P1.x=diag(c(0, 0.001, 0.001))  
P1.y=diag(c(0, 0.001, 0.001))  
  
playPar(mov.model=~1, err.model=list(x=~errX, y=~errY), drift.mod=~1)  
data=nfsNew, fixPar=c(NA, 1, NA, 1, NA, NA, NA, NA))  
  
<- crwMLE(mov.model=~1, err.model=list(x=~errX, y=~errY), drift.mod=~1)  
data=nfsNew, coord=c("longitude", "latitude"), polar.coord=TRUE,  
Time.name="Time", initial.state=initial.drift,  
fixPar=c(NA, 1, NA, 1, NA, NA, NA, NA),  
control=list(maxit=2000,trace=1, REPORT=10),
```



August 2023  
Movement data in R

Trajectory centered analysis

- Information of geometry of tracks without context
- Most methods are scale sensitive and sensitive to sampling schedule
- Data should be in an equidistant projection

- **Azimuth and turning angles:**

- direction of travel, directionality of movement, and relation to speed
- recommended to exclude stationary segments from analysis

- **Net square displacement (NSD):**

- quantifies the net squared distance traveled over time compared to a point of reference (calculates distance from each location to the point of reference)
- point of reference (nest, den, colony) needed. If there is no point of reference, or animal is nomadic, use e.g. FPT

- **First passage time (FPT):**

- calculates the time it takes to cross a circle of a given radius, i.e. time the animal spends in a given area at a certain spatial scale ("draws" circle around each point and calculates how long it takes to leave the circle)
- the variance of  $\log(fpt)$  can inform about the scales at which processes are likely to be changing
- the slopes of the  $\log(\text{meanFPT}) \sim \log(\text{radii})$ , can indicate the type of movement at each scale. Flatter slopes indicate more directional movement, steeper slopes more brownian movement

- **Variance components of movement:**

- variance component of the dynamic brownian bridge movement model (dBMM)
- variance component of the dynamic bi-gaussian bridge movement model (dBGB)

Variance estimation is based on a leave-one-out method where from 3 consecutive locations the 2nd one is omitted. Based on the timestamp of the 2nd location, a location is estimated on a straight line between location 1 and 3. The distance between the actual and the estimated location represents the amount of variance.

Estimated variances of the movement process can change over a trajectory.

- \* **variance of dBMM:** changes in speed and/or deviation from straight line
- \* **variances of dBGB:** parallel (changes in speed) and orthogonal (deviation from the straight line)

Very useful to test methods and be able to interpret results

- **bi-variate normal random distribution around a mean of 0:** uncorrelated and unbiased random walk, movement in any direction is equally likely (brownian motion)
- **uniform random distribution:** same probability to do all types of movement, it's unrealistic
- **multivariate normal distribution:** can maintain the variance/covariance structure of e.g. speed and turning angle from a real animal (i.e. more realistic).
- **correlated random walk:** considered to be a more natural movement process, as empirical tracks show some degree of consistency in direction
- **randomized track:** randomized order of segments connect start and end point. Maintains distribution of step length and heading. Breaks up the auto-correlation in speed, heading and turning angle. Represents the alternative routs the animal could have taken

The correlation structure can inform about the underlying processes in the movement and changes in these processes.

Auto-correlation is calculated and quantified based on correlation of values of e.g. speed, dependent on the distance in the sequence of appearance (lag), between any two observations

Fundamental assumption: lag represents equal distances in time (regular sampling). But most trajectories have gaps and shifts.

Two solutions:

- reduce data to largest gap in time. Problem: dropping data removes auto-correlation and affects speed and turning angle
- interpolate positions in gappy sections. Problem: underestimating speed, variance in azimuth and turning angle. Interpolation has to be used with care!