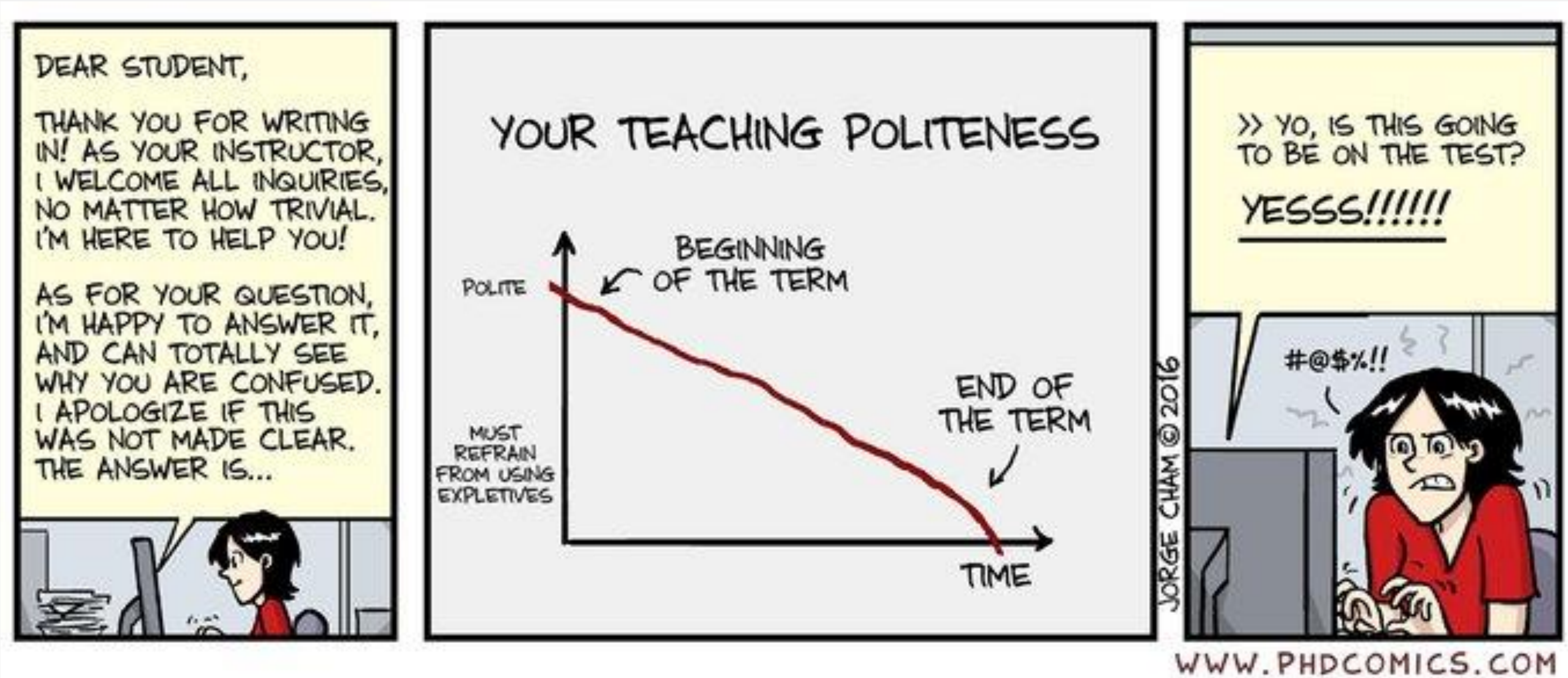
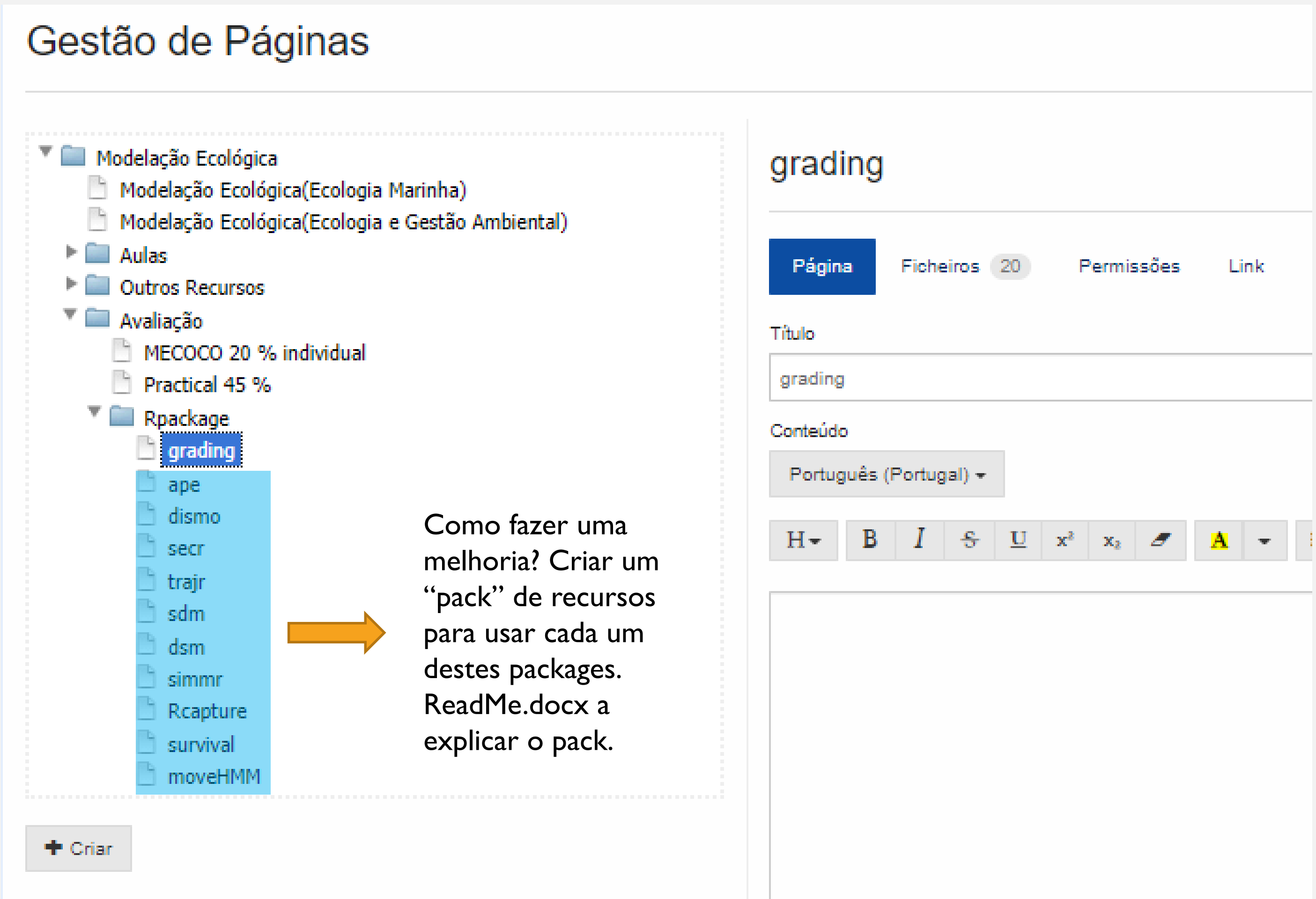
Modelação Ecológica

AULA 27

18th December 2019


DEAR STUDENT,
THANK YOU FOR WRITING IN! AS YOUR INSTRUCTOR, I WELCOME ALL INQUIRIES, NO MATTER HOW TRIVIAL. I'M HERE TO HELP YOU!
AS FOR YOUR QUESTION, I'M HAPPY TO ANSWER IT, AND CAN TOTALLY SEE WHY YOU ARE CONFUSED. I APOLOGIZE IF THIS WAS NOT MADE CLEAR. THE ANSWER IS...
YOUR TEACHING POLITENESS
POLITE
MUST REFRAIN FROM USING EXPLETIVES
BEGINNING OF THE TERM
END OF THE TERM
TIME
JORGE CHAM © 2016
>> YO, IS THIS GOING TO BE ON THE TEST?
YESSS!!!!!!
#@$%!!
WWW.PHDCOMICS.COM

R PACKAGE WORK



Como fazer uma melhoria? Criar um "pack" de recursos para usar cada um destes packages. ReadMe.docx a explicar o pack.

SEND ME A PACKAGE WORK README DOCUMENT

Call document "Trajr_ReadMe.docx" (adapt to your package name!)

R package – Trajr

A brief description of your work, what is the package, what can it be used for, and what you did with it.

- A descrição do package e das suas funções pode ser consultada em:

  https://cran.rapporter.net/web/packages/trajr/trajr.pdf

- O artigo utilizado para a compreensão do package trajr foi consultado em:

  https://onlinelibrary.wiley.com/doi/full/10.1111/eth.12739

- O artigo modelo utilizado teve como objetivo de estudo o mimetismo de trajetórias de himenópteros por parte de espécies da família Sesiidae. Este artigo foi consultado em:

  https://royalsocietypublishing.org/doi/full/10.1098/rsbl.2018.0152

- Os ficheiros de dados e os respetivos códigos utilizados para o trabalho podem ser consultados em:

  https://datadryad.org/stash/dataset/doi:10.5061/dryad.682dc

State explicitly the name of the file that contains the presentation slides, the report, and any other files you might have handed in

EACH STUDENT EVALUATED, INDEPENDENTLY, EACH GROUP

We can use the data to model the grades as a function of a series of characteristics:

- Sex
- Age
- Final Uni classification
- Group
- Order of presentation
- Before or after own presentation
- Others? Think !

- Write paper? Make R Package? Create an app for grading?

FEEL FREE TO CONTRIBUTE WITH YOUR IDEAS, THOUGHTS & SUGGESTIONS

THIS WILL BECOME
WHAT
YOU MAKE IT BECOME

TODAY'S MENU

- sdm: Karlis Tohters
- Filling a GEE gap
- Wrap up, take home messages and the likes
- Anything you want to work on or ask me about

FILLING A GEE GAP

WAY BACK FROM AULA 21 on GEEs

Revisit two datasets from FT7b4ME 20 11 2019.pdf in "Aula 19"

7. Find a GLM that best fits the data "Owls.txt", where you are trying to explain the begging behavior of owls offspring when the parents are absent from the nest. The variable "SiblingNegotiation" represents the number of calls produced by the chicks in the nest during a 30 second period, while "BroodSize" represents the size of the brood. More details about this data can be found in Zuur et al. 2009.

Account for variation over time in the same nest

```
> fmodelo <- formula(SiblingNegotiation~offset(LBroodSize)+FoodTreatment+ArrivalTime)
> mod1 <- geeglm(formula=fmodelo,data=owls,family = poisson,id = Nest, corstr = "ar1")
> summary(mod1)

Call:
geeglm(formula = fmodelo, family = poisson, data = owls, id = Nest,
    corstr = "ar1")

 Coefficients:
                      Estimate  Std.err  Wald Pr(>|W|)
(Intercept)            3.70322  0.66935 30.61 3.16e-08 ***
FoodTreatmentSatiated -0.56417  0.12254 21.20 4.15e-06 ***
ArrivalTime           -0.12418  0.02691 21.30 3.93e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Estimated Scale Parameters:
            Estimate Std.err
(Intercept)    6.242   0.387

Correlation: Structure = ar1  Link = identity

Estimated Correlation Parameters:
      Estimate Std.err
alpha   0.3854  0.0582
Number of clusters:   27   Maximum cluster size: 52
```

```
> sort(with(owls,tapply(BroodSize,Nest,length)))
         Forel          Sevaz       Chevroux           GDLV CorcellesFavres        Henniez
             4              4             10             10              12             13
    Gletterens     LesPlanches          Lully         Rueyes           Jeuss           Trey
            15             17             17             17              19             19
       ChEsard         Bochet        StAubin         Murist         Payerne         Franex
            20             23             23             24              25             26
         Seiry        Marnand     AutavauxTV         Lucens     Champmartin        Etrabloz
            26             27             28             29              30             34
      Yvonnand         Montet        Oleyes
            34             41            52
> length(unique(owls$Nest))
[1] 27
```

```
> mod.by.nestnight <- geeglm(formula=fmodelo,data=owls,family = poisson,id=NestNight,corstr="ar1")
> summary(mod.by.nestnight)

Call:
geeglm(formula = fmodelo, family = poisson, data = owls, id = NestNight,
    corstr = "ar1")

 Coefficients:
                      Estimate Std.err Wald Pr(>|W|)
(Intercept)              3.593   0.668 28.9  7.6e-08 ***
FoodTreatmentSatiated   -0.578   0.115 25.4  4.6e-07 ***
ArrivalTime             -0.122   0.027 20.3  6.6e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Estimated Scale Parameters:
            Estimate Std.err
(Intercept)     6.64   0.524

Correlation: Structure = ar1  Link = identity

Estimated Correlation Parameters:
      Estimate Std.err
alpha    0.517  0.0676
Number of clusters:   277   Maximum cluster size: 18
```


Aknowledgements

Alain Zuur provided some feedback about the issue where the incorrect number of groups was being considered in the analysis. Søren Højsgaard provided very useful advice about how data is dealt with within his `geepack`, which allowed to undersatnd and solve said issue.

Gestão de Páginas

- Modelação Ecológica
  - Modelação Ecológica(Ecologia Marinha)
  - Modelação Ecológica(Ecologia e Gestão Ambiental)
  - Aulas
    - Aula1 - Intorduction to Ecological Modelling, and Models
    - Aula2 - Relevant statistical concepts and Hands on Tutorial
    - Aula3 - Hands on tutorial, continued
    - Aula4 - Hands on tutorial, continued
    - Aula5 - Useful statitstical concepts
    - Aula6 - Statistical Modelling
    - Aula7 08 10 2019 - Introduction to Regression
    - Aula8 09 10 2019 - Regression, ANOVA and ANCOVA
    - Aula9 15 10 2019 - assessment, maximum likelihood and intro to
    - Aula10 16 10 2019 - more on GLMs
    - Aula11 22 10 2019 - Hands on GLMs and interactions
    - Aula12 23 10 2019 - Logistic regression, correlated variables and
    - Aula13 29 10 2019 - GLM extensions for modelling counts
    - A14 05 11 2019 HMMs by Théo Michelot
    - A15 06 11 2019 - Own work on HMMs + gamma + beta regressic
    - A16 12 11 2019 - Wrap up animal movement and GAMs
    - A17 13 11 2019 - Real life examples + hands on regression
    - A18 19 11 2019 - Mixed models
    - A19 20 11 2019 - integrating it all FT7b
    - A20 26 11 2019 - Mixed models reloaded
    - A21 27 11 2019 - Mixed models wrap up & GEEs
    - A22 03 12 2019 - hand in and present work about R package
    - A23 04 12 2019 - Wrap up GEEs
    - A24 10 12 2019 - Anything goes - combining it all
    - A25 11 12 2019 - Anything goes - working on your assigtnments
    - A26 17 12 2019 - Individual Based Models by Miguel Pais
    - A27 18 12 2019 - wrap up and everything else

A21 27 11 2019 - Mixed models wrap up & GEEs

Página | **Ficheiros 4** | Permissões | Link

Adicionar Ficheiro

#	Nome
1	The R Package geepack for Generalized Estimating Equations *v15i02.pdf*
2	A21 ME 27 11 2019.pdf
3	LookAtOwls.Rmd
4	LookAtOwls.html

```r
mod.by.nestnight <- geeglm(formula=fmodelo,data=owls,family = poisson,id=NestNight,corstr="ar1")
summary(mod.by.nestnight)
```

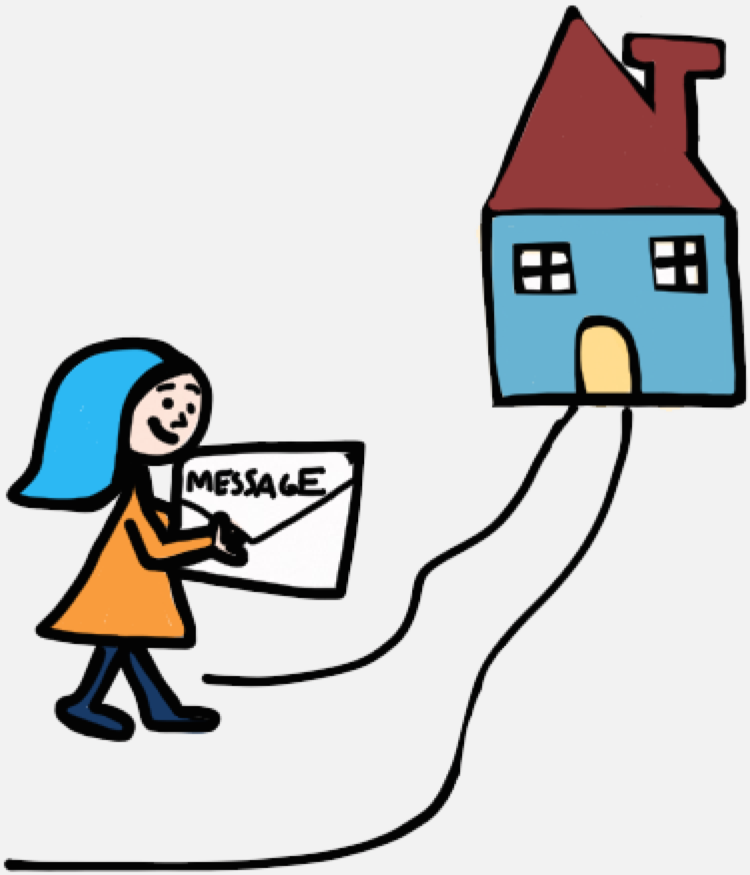
```
##
## Call:
## geeglm(formula = fmodelo, family = poisson, data = owls, id = NestNight,
##     corstr = "ar1")
##
##  Coefficients:
##                       Estimate Std.err Wald Pr(>|W|)
## (Intercept)             3.7119  0.6867 29.2  6.5e-08 ***
## FoodTreatmentSatiated  -0.5409  0.1375 15.5  8.3e-05 ***
## ArrivalTime            -0.1249  0.0272 21.2  4.2e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Estimated Scale Parameters:
##             Estimate Std.err
## (Intercept)     6.21   0.535
##
## Correlation: Structure = ar1  Link = identity
##
## Estimated Correlation Parameters:
##       Estimate Std.err
## alpha    0.382  0.0541
## Number of clusters:   54   Maximum cluster size: 28
```

Your task: where's this number coming from?

```
> sort(with(owls,tapply(BroodSize,Nest,length)))
       Forel         Sevaz      Chevroux          GDLV CorcellesFavres       Henniez
           4             4            10            10              12            13
  Gletterens    LesPlanches         Lully        Rueyes           Jeuss          Trey
          15            17            17            17              19            19
     ChEsard        Bochet       StAubin        Murist         Payerne        Franex
          20            23            23            24              25            26
       Seiry       Marnand    AutavauxTV        Lucens     Champmartin      Etrabloz
          26            27            28            29              30            34
    Yvonnand        Montet        Oleyes
          34            41            52
> length(unique(owls$Nest))
[1] 27
```

27 ×2

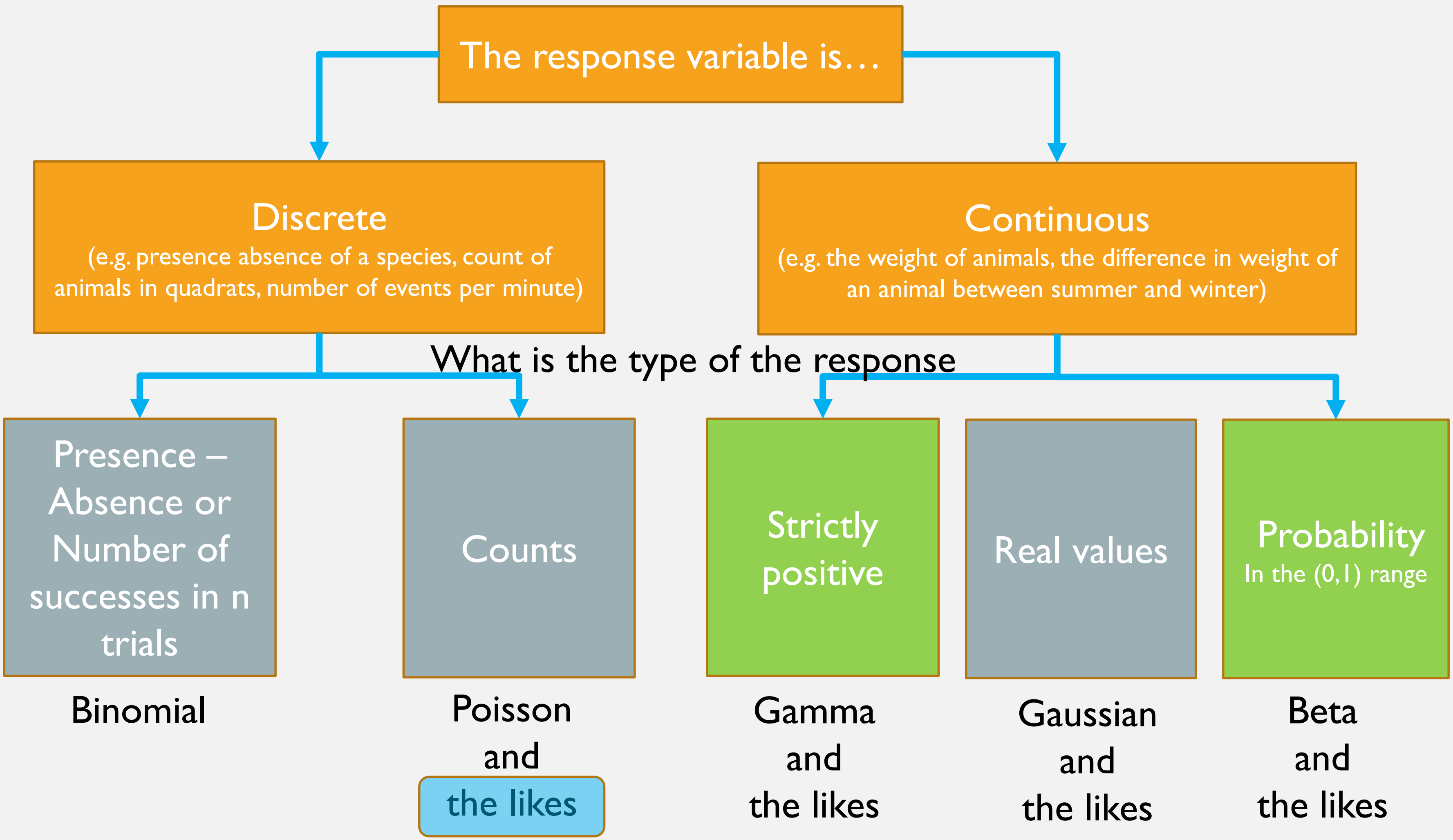
WRAP UP, TAKE HOME MESSAGES AND THE LIKES



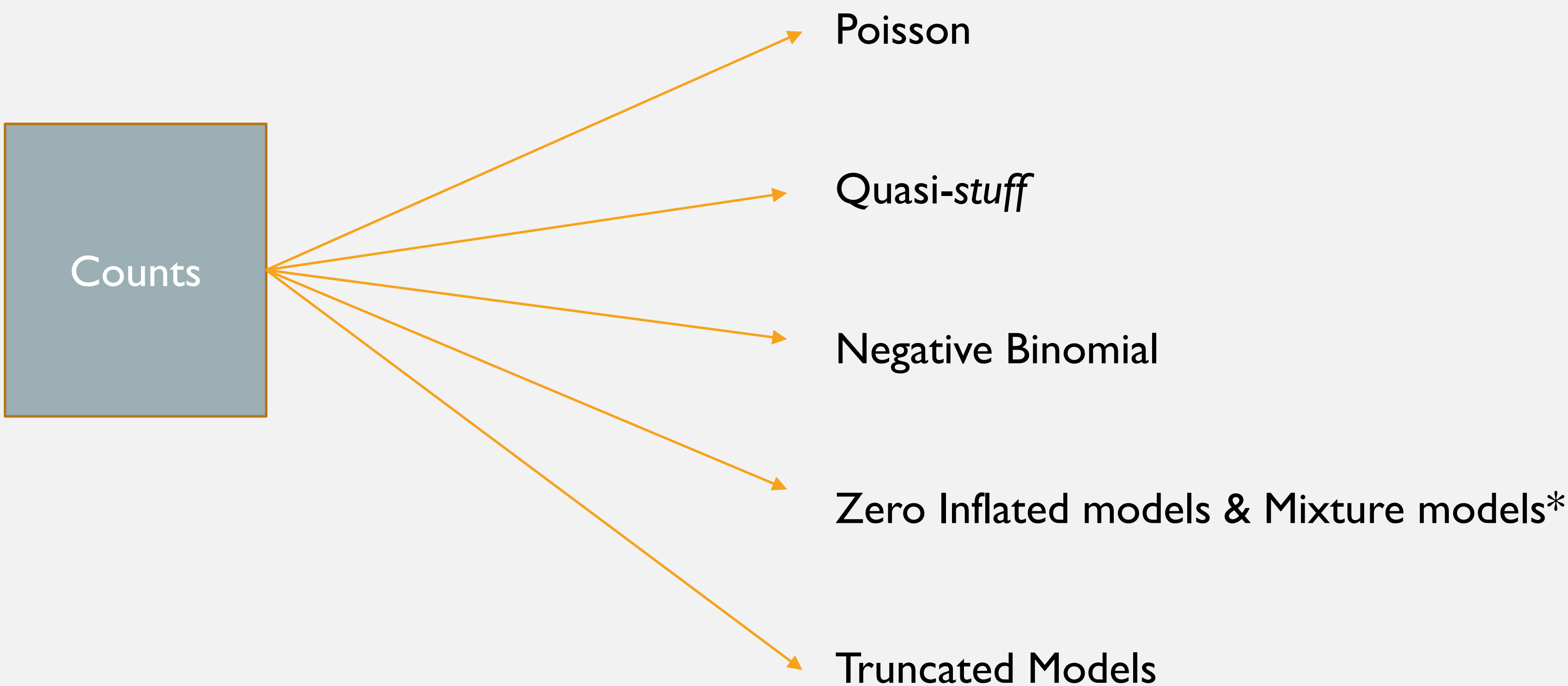
REGRESSION MODELS

- A cornerstone for statistical ecology
- The basis is the linear model (LM)
- Sometimes relationships are not linear and responses are constrained
- We can extend the LM it by using Generalized Linear Models (GLM)
  - Different distributions for the response
  - A link function (allows the relationship NOT to be linear on the response scale, but still linear on the scale of the link function)
- If the response is not linear, we can extend the GLM it with smooth additive functions, leading to a generalized additive model (GAM)

When modelling a response variable, what we want is a model that describes the data, eventually as a function of covariates.
Therefore, the first step is to decide what will be the distribution of the response variable. In other words, what to use in the `family` argument of most modelling functions in R (like `glm`, `gam`, etc.). There are a couple of big questions that need answering:



When modelling counts (very frequent biological data)

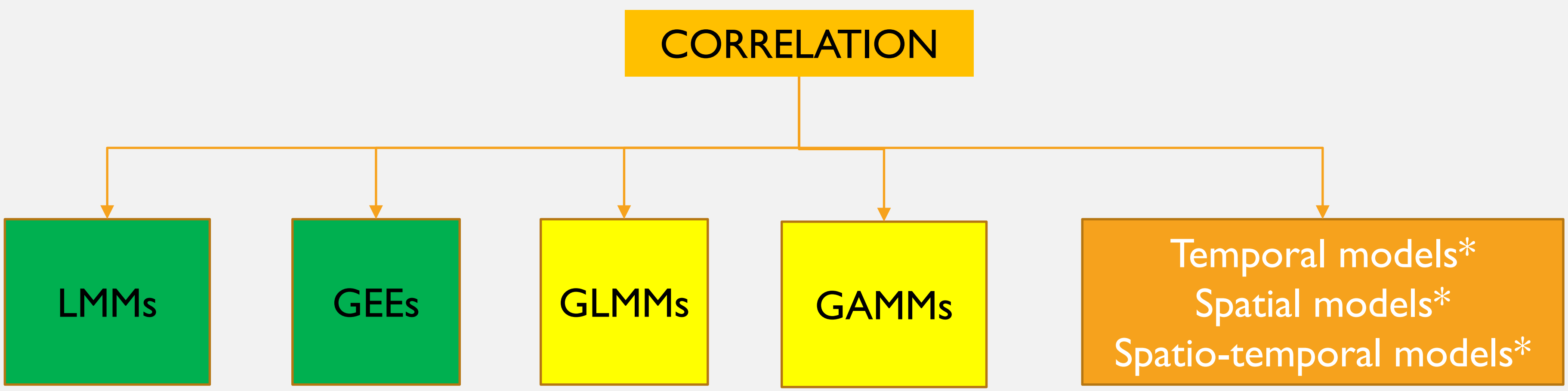


* These are available even for situations where the data are not counts!

LMs, GLMs and GAMs all share a common assumption: independent observations

Biological/Ecological data rarely is ever independent: observations are collected:

1. over space → spatial correlation
2. over time → temporal correaltion
3. within individuals units or blocks → (unstructured) correlation



* Often implemented in a Bayesian framework!

OTHER MODELS (VERY USEFUL FOR ECOLOGICAL DATA)

- Distance Sampling
- (Spatially Explicit) Capture-Recapture
- Occupancy
- Species Distribution Models
- Movement Models

Focus on the specific application

- State Space Models*
- Hidden Markov Models
- Point Process Models*
- Hierarchical Models*

Focus on the methodological aspects – hidden process models

* Often implemented in a Bayesian framework!

Ecology Letters, (2004) **7**: 509–520 doi: 10.1111/j.1461-0248.2004.00603.x

REVIEW

Bayesian inference in ecology

Aaron M. Ellison
Harvard University, Harvard Forest, PO Box 68, Petersham, MA, USA
E-mail: aellison@fas.harvard.edu

Abstract

Bayesian inference is an important statistical tool that is increasingly being used by ecologists. In a Bayesian analysis, information available before a study is conducted is summarized in a quantitative model or hypothesis: the prior probability distribution. Bayes' Theorem uses the prior probability distribution and the likelihood of the data to generate a posterior probability distribution. Posterior probability distributions are an epistemological alternative to *P*-values and provide a direct measure of the degree of belief that can be placed on models, hypotheses, or parameter estimates. Moreover, Bayesian information-theoretic methods provide robust measures of the probability of alternative models, and multiple models can be averaged into a single model that reflects uncertainty in model construction and selection. These methods are demonstrated through a simple worked example. Ecologists are using Bayesian inference in studies that range from predicting single-species population dynamics to understanding ecosystem processes. Not all ecologists, however, appreciate the philosophical underpinnings of Bayesian inference. In particular, Bayesians and frequentists differ in their definition of probability and in their treatment of model parameters as random variables or estimates of true values. These assumptions must be addressed explicitly before deciding whether or not to use Bayesian methods to analyse ecological data.

Gestão de Páginas

- Modelação Ecológica
  - Modelação Ecológica(Ecologia Marinha)
  - Modelação Ecológica(Ecologia e Gestão Ambiental)
  - Aulas
    - Aula1 - Interduction to Ecological Modelling, and Models
    - Aula2 - Relevant statistical concepts and Hands on Tutorial
    - Aula3 - Hands on tutorial, continued
    - Aula4 - Hands on tutorial, continued
    - Aula5 - Useful statitstical concepts
    - Aula6 - Statistical Modelling
    - Aula7 08 10 2019 - Introduction to Regression
    - Aula8 09 10 2019 - Regression, ANOVA and ANCOVA
    - Aula9 15 10 2019 - assessment, maximum likelihood and intro to
    - Aula10 16 10 2019 - more on GLMs
    - Aula11 22 10 2019 - Hands on GLMs and interactions
    - Aula12 23 10 2019 - Logistic regression, correlated variables and
    - Aula13 29 10 2019 - GLM extensions for modelling counts
    - A14 05 11 2019 HMMs by Théo Michelot
    - A15 06 11 2019 - Own work on HMMs + gamma + beta regressic
    - A16 12 11 2019 - Wrap up animal movement and GAMs
    - A17 13 11 2019 - Real life examples + hands on regression
    - A18 19 11 2019 - Mixed models
    - A19 20 11 2019 - integrating it all FT7b
    - A20 26 11 2019 - Mixed models reloaded
    - A21 27 11 2019 - Mixed models wrap up & GEEs
    - A22 03 12 2019 - hand in and present work about R package
    - A23 04 12 2019 - Wrap up GEEs
    - A24 10 12 2019 - Anything goes - combining it all
    - A25 11 12 2019 - Anything goes - working on your assigtnments
    - A26 17 12 2019 - Individual Based Models by Miguel Pais
    - A27 18 12 2019 - wrap up and everything else
  - Outros Recursos
    - PDFs

PDFs

Página | Ficheiros 16 | Permissões | Link

Adicionar Ficheiro

#	Nome
1	Bayesian inference in ecology *Ellison2004.pdf*
2	World Scientists' Warning of a Climate Emergency *biz088.pdf*
3	Model averaging in ecology: a review of Bayesian, information-theoretic, and tactical a *Dormann 2018.pdf*
4	Generalized additive models: Building evidence of air pollution, climate change and hu *Ravindraetal2019.pdf*
5	Significance: What does it all mean? *Sheldon-2019-Significance.pdf*
6	Publication bias: What are the challenges and can they be overcome? *jpn-37-149.pdf*
7	The R Book.pdf
8	Mixed Effects Models And Extensions In Ecology With R *Zuur_Mixed-effects-models-and-extensions-in-ecology-with-R.pdf*
9	Analyzing Ecological Data *zuur_2007.pdf*
10	A Beginner's Guide to R *Zuuretal2009useR.pdf*
11	Numerical Ecology with R *Borcardetal2001EcologyUseR.pdf*

A Bayesian view of the world?


R-bloggers

R news and tutorials contributed by hundreds of R bloggers

Home | About | RSS | add your blog! | Learn R | R jobs | Contact us

WELCOME!

Follow @rbloggers 78K f

Here you will find daily **news and tutorials about R**, contributed by hundreds of bloggers.
There are many ways to **follow us** -
By e-mail:

Your e-mail here

Subscribe

On Facebook:

Bayesian models in R

May 1, 2019

By Francisco Lima

[This article was first published on poissonisfish, and kindly contributed to R-bloggers]. (You can report issue about the content on this page here)

Want to share your content on R-bloggers? click here if you have a blog, or here if you don't.

Share | Tweet

Greater Ani (*Crotophaga major*) is a cuckoo species whose females occasionally lay eggs in conspecific nests, a form of parasitism recently explored [source]

If there was something that always frustrated me was not fully understanding Bayesian inference. Sometime last year, I came across an article about a TensorFlow-supported R package for Bayesian analysis, called `greta`. Back then, I searched for `greta` tutorials and stumbled on this blog post that praised a textbook called *Statistical Rethinking: A Bayesian Course with Examples in R and Stan* by Richard McElreath. I had found a solution to my lingering frustration so I bought a copy straight away.

SEARCH R-BLOGGERS

Search..

Go

MOST VISITED ARTICLES OF THE WEEK

1. How to write the first for loop in R
2. 5 Ways to Subset a Data Frame in R
3. Learning Linux - the wrong way - day 2
4. R – Sorting a data frame by the contents of a column
5. Date Formats in R
6. Logistic Regression in R: A Classification Technique to Predict Credit Card Default
7. Installing R packages
8. How to perform a Logistic Regression in R
9. How to install packages on R + screenshots

SPONSORS

R Training and

https://www.r-bloggers.com/bayesian-models-in-r-2/

Bayes approach to GLM

R-bloggers
R news and tutorials contributed by hundreds of R bloggers

Home | About | RSS | add your blog! | Learn R | R jobs | Contact us

WELCOME!

Follow @rbloggers 78K f

Here you will find daily **news and tutorials about R**, contributed by hundreds of bloggers.
There are many ways to **follow us** -
By e-mail:

Your e-mail here
Subscribe
51586 readers
BY FEEDBURNER

On Facebook:

R blog…
77 mil gostos

Gostar da Página

18 amigos gostam disto

Poisson regression fitted by glm(), maximum likelihood, and MCMC

October 29, 2013

By petrkeil

Tweet | Share

[This article was first published on Are you cereal? » R, and kindly contributed to R-bloggers]. (You can report issue about the content on this page here)

Want to share your content on R-bloggers? click here if you have a blog, or here if you don't.

Share | Tweet

The goal of this post is to demonstrate how a simple statistical model (Poisson log-linear regression) can be fitted using three different approaches. I want to demonstrate that both frequentists and Bayesians use the same models, and that it is the fitting procedure and the inference that differs. This is also for those who understand the likelihood methods and do not have a clue about MCMC, and vice versa. I use an ecological dataset for the demonstration.

The complete code of this post is available here on GitHub

SEARCH R-BLOGGERS

Search.. Go

MOST VISITED ARTICLES OF THE WEEK

1. 5 Ways to Subset a Data Frame in R
2. How to write the first for loop in R
3. R – Sorting a data frame by the contents of a column
4. Date Formats in R
5. How to perform a Logistic Regression in R
6. Installing R packages
7. Sept 2019: "Top 40" New R Packages
8. Using apply, sapply, lapply in R
9. R Tutorial Series: Simple Linear Regression

SPONSORS

https://www.r-bloggers.com/poisson-regression-fitted-by-glm-maximum-likelihood-and-mcmc/

Inferences are not only based on the data. We know things about our process even before collecting the data. Why not use that to help our inferences?

We do that via a prior distribution…

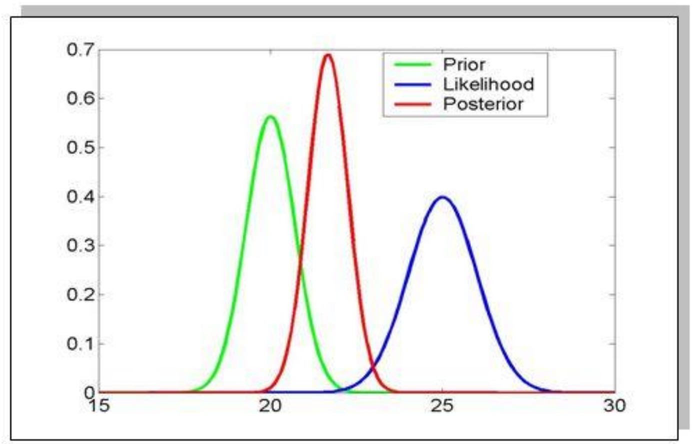
Inferences are then based on a posterior distribution

Bayesian statistics

new data $\boxed{p(y \mid \theta)}$ prior knowledge $\boxed{p(\theta)}$

$$\boxed{p(\theta \mid y) \propto p(y \mid \theta)\, p(\theta)}$$

posterior $\propto$ likelihood • prior



Bayes theorem allows one to formally incorporate prior knowledge into computing statistical probabilities.

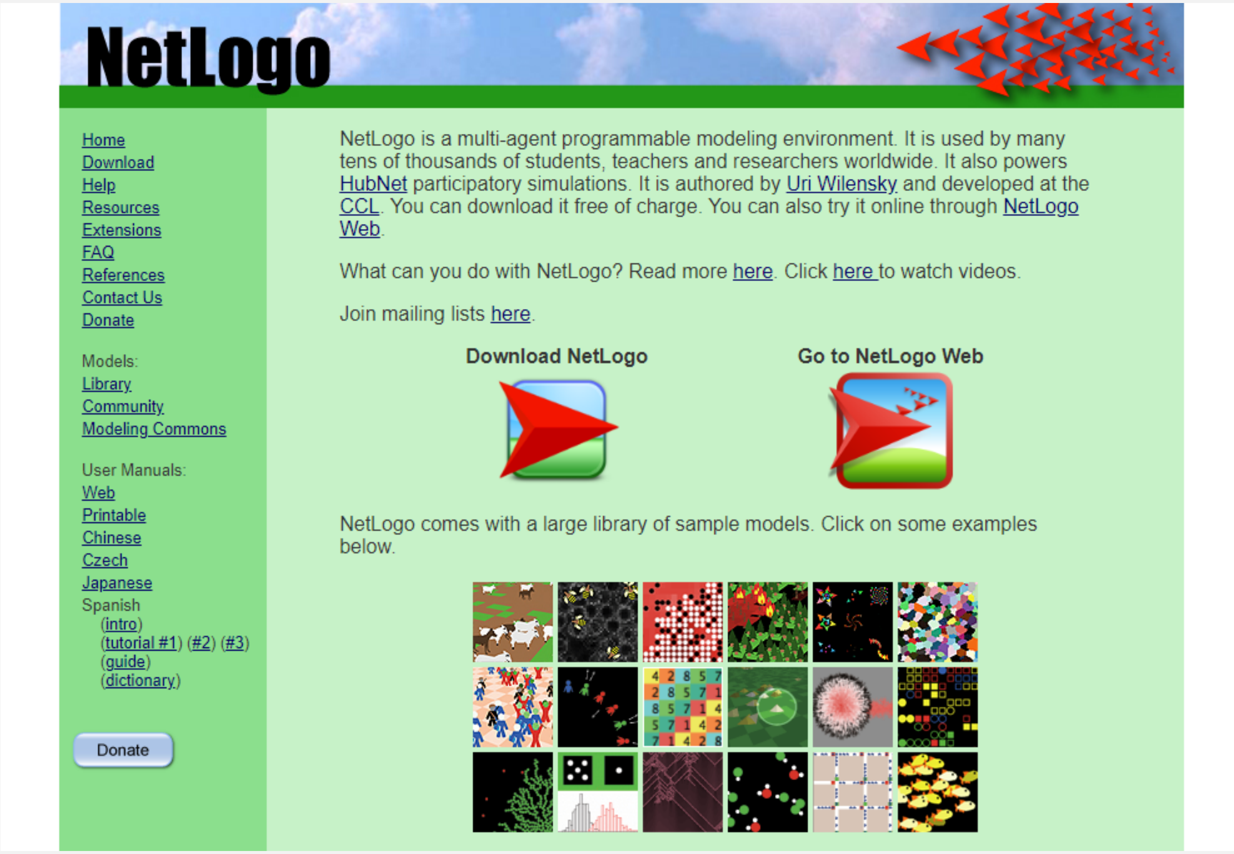
Priors can be of different sorts: empirical, principled or shrinkage priors.

The "posterior" probability of the parameters given the data is an optimal combination of prior knowledge and new data, weighted by their relative precision.

Agent Based Models!

Simulating reality allows us to gain insight

Comparing simulated reality with observed data allows you to make inferences about the processes that might have generated the data



Approximate Bayesian Computation

A process that formally can link Agent Based Models and the Bayesian Paradigm, useful for when we want to make formal inferences but we can't specify a likelihood, yet we can simulate the process that generated the data


OPEN ACCESS Freely available online

PLOS | COMPUTATIONAL BIOLOGY

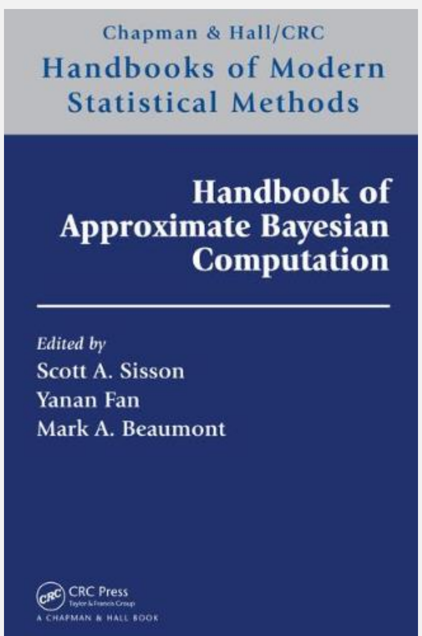
Topic Page

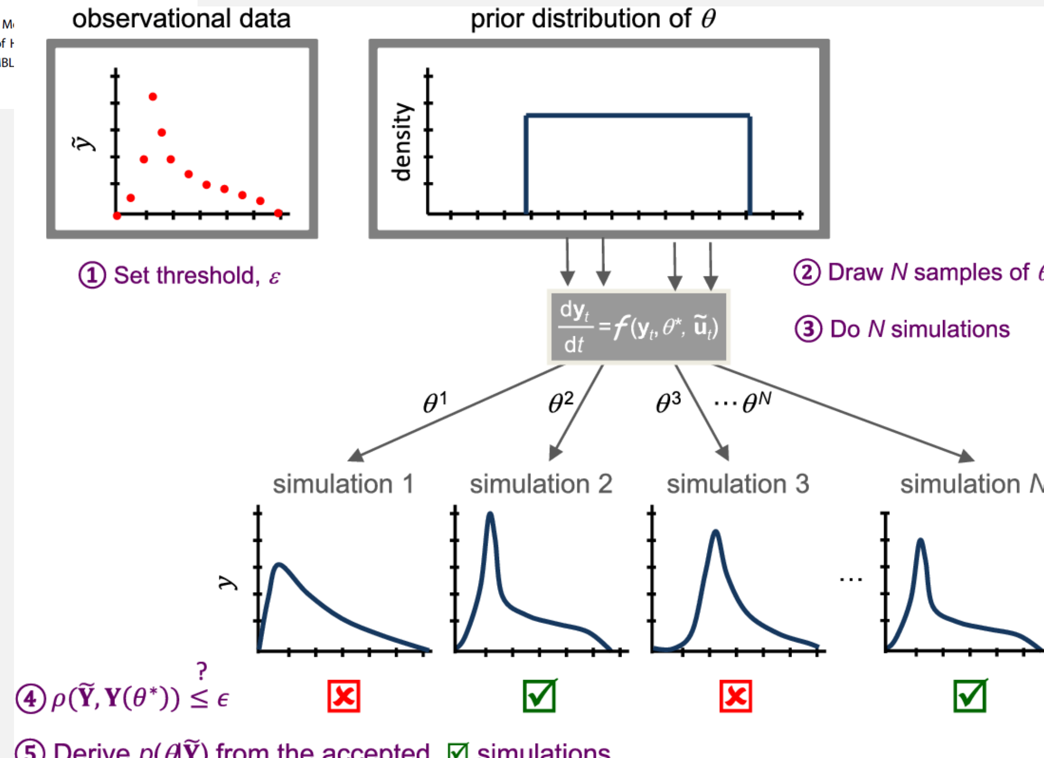
Approximate Bayesian Computation

Mikael Sunnåker[1,2*], Alberto Giovanni Busetto[2,3¶], Elina Numminen[4¶], Jukka Corander[4], Matthieu Foll[2,5], Christophe Dessimoz[3,6,7*]

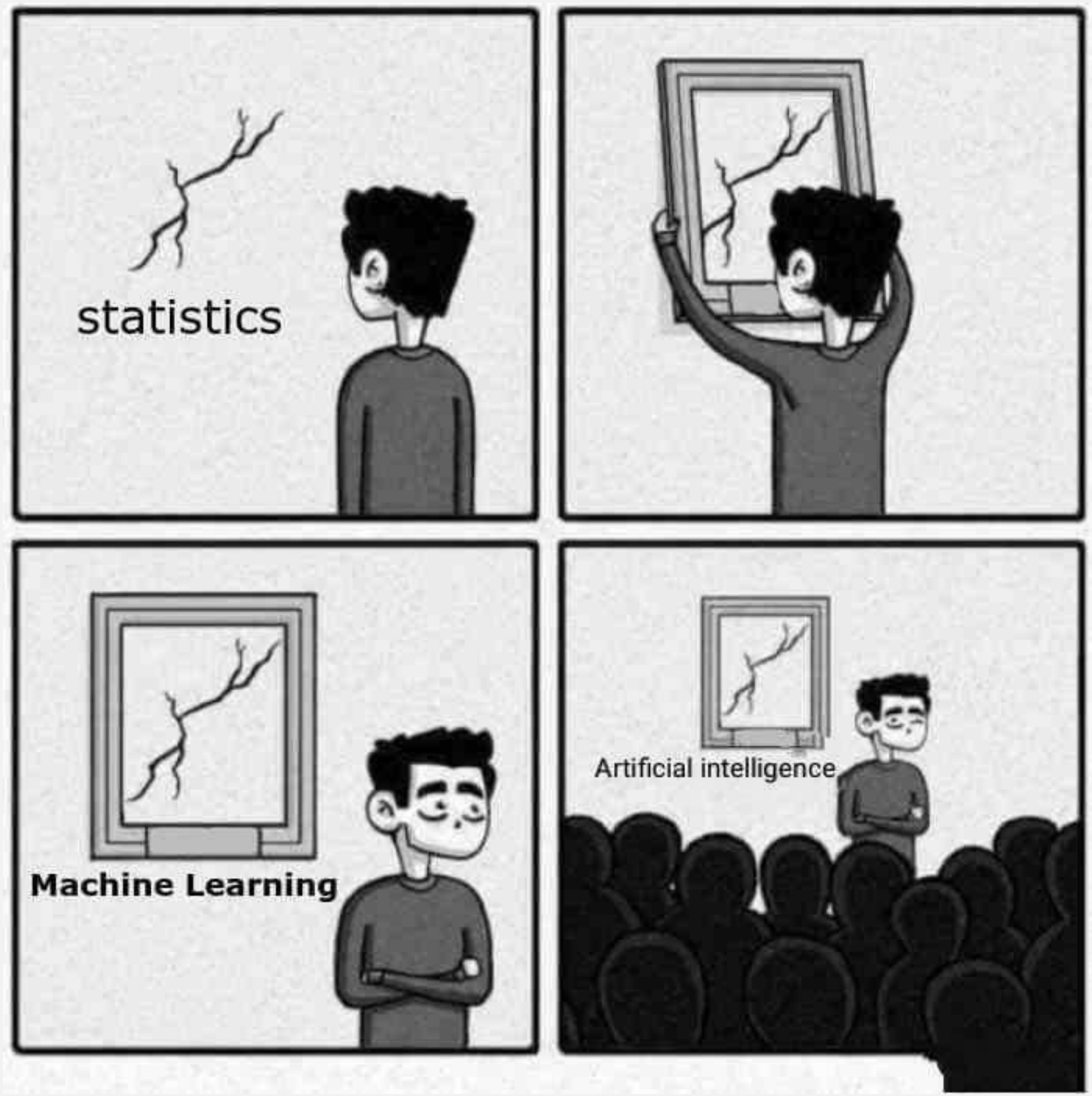
1 Department of Biosystems Science and Engineering, ETH Zurich, Zurich, Switzerland, 2 Competence Center for Systems Physiology and M Switzerland, 3 Department of Computer Science, ETH Zurich, Zurich, Switzerland, 4 Department of Mathematics and Statistics, University of H 5 CMPG Institute of Ecology and Evolution, University of Bern, Bern, Switzerland, 6 Swiss Institute of Bioinformatics, Zurich, Switzerland, 7 EMBL Institute, Cambridge, United Kingdom

In FENIX





Statistics, Pattern Recognition, Machine Learning, Neural Networks, Deep Learning, Artificial Intelligence, and the likes…



Received: 17 April 2019 | Accepted: 25 June 2019
DOI: 10.1111/2041-210X.13256

Check for updates

REVIEW

Methods in Ecology and Evolution BRITISH ECOLOGICAL SOCIETY

Applications for deep learning in ecology

In FENIX

Sylvain Christin[1] | Éric Hervet[2] | Nicolas Lecomte[1]

[1]Canada Research Chair in Polar and Boreal Ecology, Department of Biology, University of Moncton, Moncton, NB, Canada
[2]Department of Computer Science, University of Moncton, Moncton, NB, Canada

Correspondence
Nicolas Lecomte
Email: nicolas.lecomte@umoncton.ca

Funding information

Abstract

1. A lot of hype has recently been generated around deep learning, a novel group of artificial intelligence approaches able to break accuracy records in pattern recognition. Over the course of just a few years, deep learning has revolutionized several research fields such as bioinformatics and medicine with its flexibility and ability to process large and complex datasets. As ecological datasets are becoming larger and more complex, we believe these methods can be useful to ecologists as well.

Ecological Informatics 4 (2009) 206–214

ELSEVIER

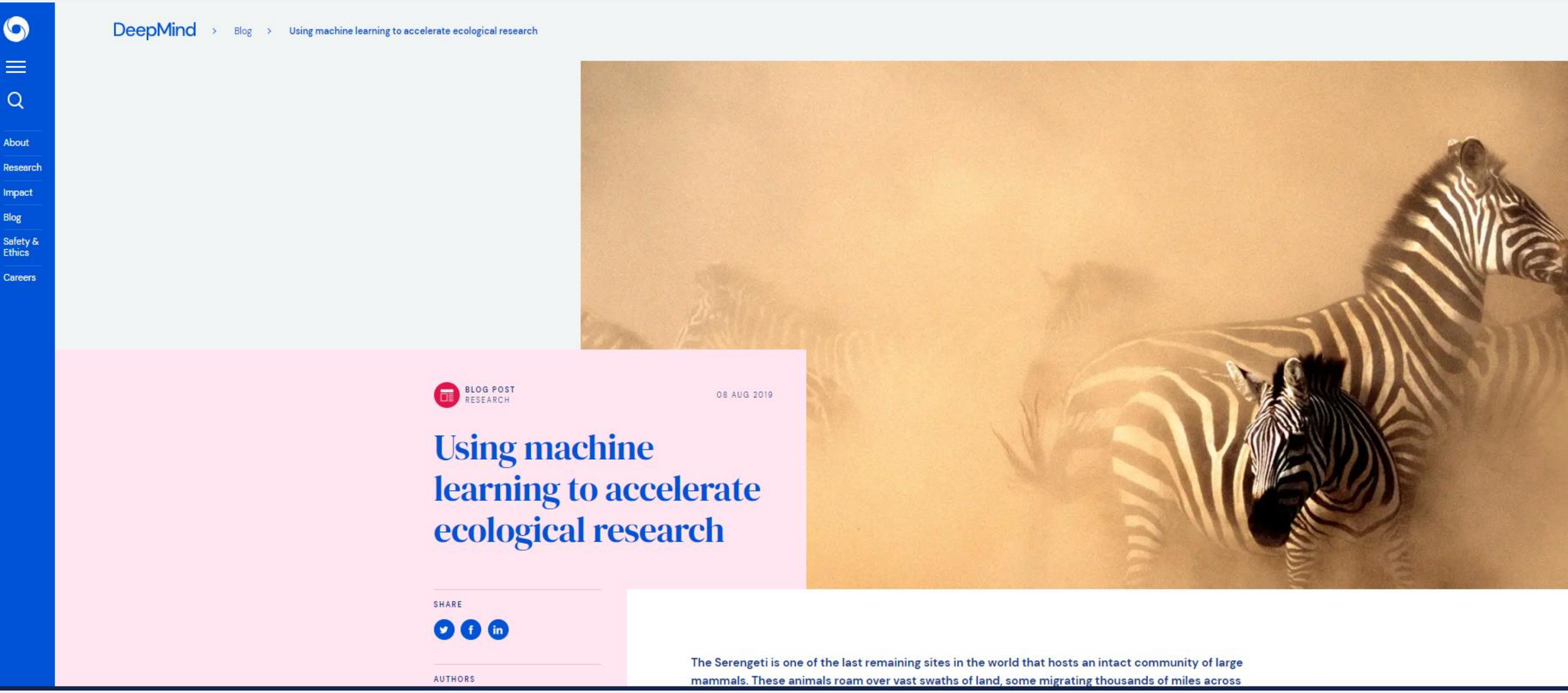
Contents lists available at ScienceDirect

Ecological Informatics

journal homepage: www.elsevier.com/locate/ecolinf

Automated classification of bird and amphibian calls using machine learning: A comparison of methods

Miguel A. Acevedo [a,*], Carlos J. Corrada-Bravo [c], Héctor Corrada-Bravo [b], Luis J. Villanueva-Rivera [d], T. Mitchell Aide [a]



https://deepmind.com/blog/article/using-machine-learning-to-accelerate-ecological-research

SAMPLE(ECOLOGY)

RANDOM THOUGHTS ON ECOLOGY, BIODIVERSITY, AND SCIENCE IN GENERAL

A PRACTICAL GUIDE TO MACHINE LEARNING IN ECOLOGY

February 6, 2015

Recently, I was exploring techniques to interpolate some missing environmental data, and stumbled across something called 'random forest' analysis. Random what now? I did a little digging and came across the massive and insanely complicated field of machine learning. I couldn't find a concise guide to machine learning techniques, or when I might want to use one or the other, so I thought I would cobble together a brief guide on my own. Below is a rough stab at explaining and exploring different machine learning techniques, from CARTs to GBMs, using R.

Search …

- LATEST TWEETS -

@LiesbethTip @ModEviPol @stats_o @RLadiesEdinb @edinb_r @RladiesNijmegen @AcademicChatter @JKRWard Check out… twitter.com/i/web/status/1… 16 hours ago

@ModEviPol @stats_o @LiesbethTip @RLadiesEdinb @edinb_r @RladiesNijmegen @AcademicChatter @JKRWard What kind of ass… twitter.com/i/web/status/1… 1 day ago

RT @JohnFBruno: Im at AIMS, about to give a talk "The Protection Paradox and Climate Resilience within Marine Reserves" Slides are here: h… 2 days ago

https://jonlefcheck.net/2015/02/06/a-practical-guide-to-machine-learning-in-ecology/

XXIV CONGRESSO
SOCIEDADE PORTUGUESA DE ESTATÍSTICA

CURRENT TRENDS IN ECOLOGICAL STATISTICS ARE DETACHED FROM ECOLOGISTS' STATISTICAL TEACHING

"…Ainda ensinamos estatística como há 20 anos atrás…" – Maria do Rosário Oliveira, 2019

TIAGO A. MARQUES

CREEM
Centre for Research into Ecological and Environmental Modelling

University of St Andrews

CEAUL
Centro de Estatística e Aplicações Universidade de Lisboa

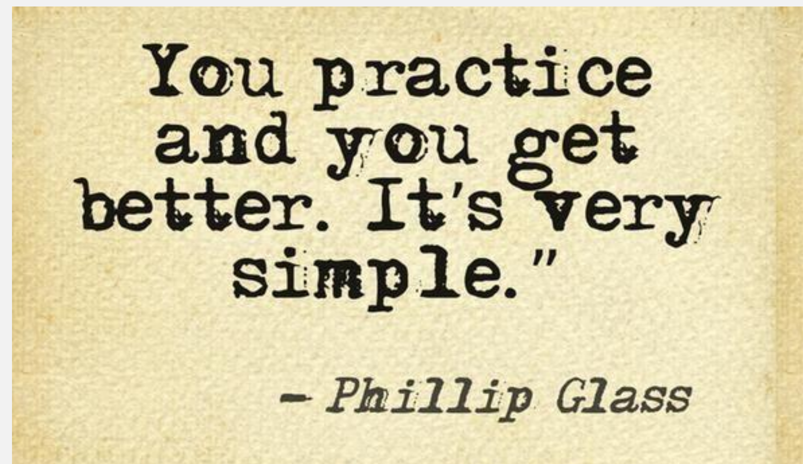
Ciências ULisboa | Biologia Animal

9TH NOVEMBER 2019

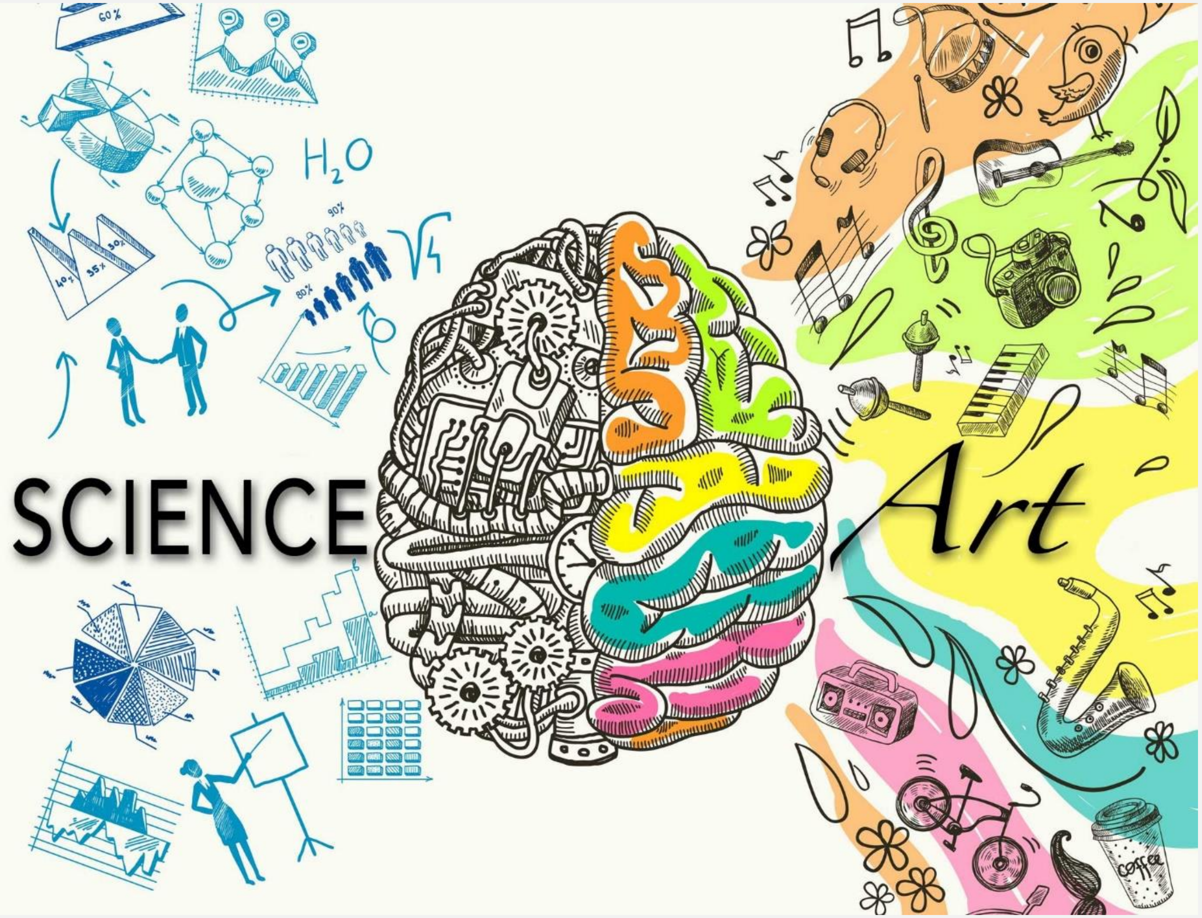
SO WHAT SHOULD WE AIM TO TEACH BIOLOGY STUDENTS? (SOME RANDOM THOUGHTS)

- Data: collection, processing, management
- **Think before acting**
- Randomness, variability, confounding
- **Uncertainty is a good thing**
- Models are not truth
- Decisions under uncertainty lead to errors
- R programing, dynamic reports and reproducible research
- Data visualization (if you can’t plot it… is it real?)
- Regression models: GLMs, GAMs, GLMMs, GAMMs
- Bayesian paradigm
- The limitations of statistics

It can take a lifetime to master modelling, but you do get better by practicing



Modelling can be as much of a science as an art ☺



Some of the most amazing ecological statisticians that I know started as biologists…

Google Scholar

James Nichols

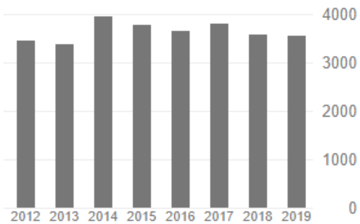
FOLLOW

Senior Scientist Emeritus, Patuxent Wildlife Research Center, USGS
Verified email at usgs.gov
population ecology   conservation biology   wildlife management   biostatistics

TITLE	CITED BY	YEAR
Estimating site occupancy rates when detection probabilities are less than one DI MacKenzie, JD Nichols, GB Lachman, S Droege, J Andrew Royle, ... Ecology 83 (8), 2248-2255	3497	2002
Occupancy estimation and modeling: inferring patterns and dynamics of species occurrence JDN D.I. Mackenzie Elsevier	3349 *	2006
Analysis and management of animal populations BK Williams, JD Nichols, MJ Conroy Academic Press	3268	2002
Statistical inference for capture-recapture experiments KH Pollock, JD Nichols, C Brownie, JE Hines Wildlife monographs, 3-97	2280	1990
Dispersal J Clobert, E Danchin, AA Dhondt, J Nichols	1477	2001
Estimating site occupancy, colonization, and local extinction when a species is detected imperfectly DI MacKenzie, JD Nichols, JE Hines, MG Knutson, AB Franklin Ecology 84 (8), 2200-2207	1421	2003
Estimation of tiger densities in India using photographic captures and recaptures KU Karanth, JD Nichols Ecology 79 (8), 2852-2862	1329	1998
Monitoring of biological diversity in space and time NG Yoccoz, JD Nichols, T Boulinier Trends in ecology & evolution 16 (8), 446-453	1321	2001

Cited by   VIEW ALL

	All	Since 2014
Citations	54884	22369
h-index	103	67
i10-index	346	233



Do you dare to go to the dark side and become one?


That's all Folks!

If you are looking at
this slide,
I have pressed click
one time too many
☺
!