

University of Kentucky

AUTOMATED MODEL SELECTION

Animal Science

V. L. Daley National Animal Nutrition Program Modeling Commitee Postdoctoral Research Associate

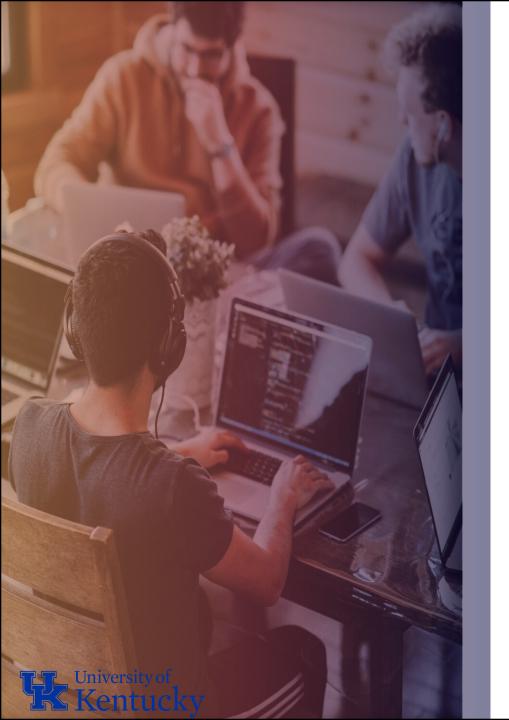


COLLEGE OF AGRICULTURE AND LIFE SCIENCES VIRGINIA TECH.

The second secon

o Multimodel inference

- Introduction
- Framework
 - ✓ Potential candidate variables
 - ✓ Global mixed model
 - ✓ Set of candidate models
 - ✓ Model selection
 - ✓ Evaluation



Multimodel Inference

Animal Science

✓ Automated "Model selection"

 Automated model selection is a procedure to select the best model from a set of candidate models.

✓ "Multimodel Inference"

- Information-theoretic approaches
- Formal inference to be based on more than one model

(Burnham and Anderson 1992, 2001, 2002, 2004)



2002.

2013...?

R.A. Fisher

Model specification, 2. Estimation of parameters,
Estimation of precision

Shannon

Mathematical theory of communication.

Kullback–Leibler (K-L information)

Distance between "full reality" and a "model" The best model loses the least information relative to other models in the set.

Hirotugu Akaike

- Model selection criterion based on K-L information
- AIC is an estimate of the K-L information.
- A set of a priori candidate models, the AIC is computed for each model
- Akaike's approach allowed model selection

Burnham and Anderson

Model Selection, biological science, candidate model, approximate model

Dairy & Animal Science

Brief History of Multimodel Inference

Model Selection and Multimodel Inference

Authors

Kenneth P Burnham David R Anderson

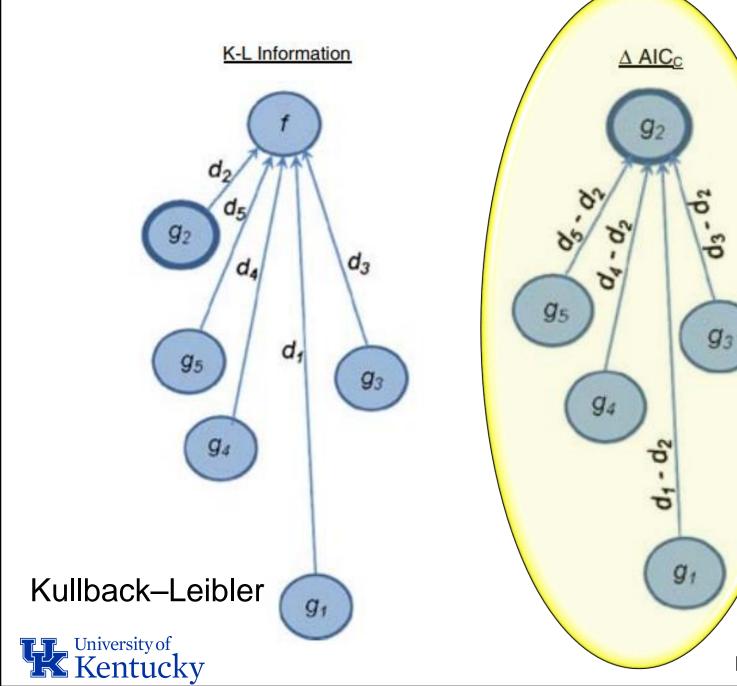


MODEL SELECTION AND MULTIMODEL INFERENCE A Practical Information-Theoretic Approach second edition kenneth P. Burnham + David B. Anderson





Multimodel Inference



Brief History of Multimodel Inference

 Δ values = the estimated distance of the various models to the best model (model g2).

Burnham et al. Behav Ecol Sociobiol (2011) 65:23–35

Automated Model Selection

AIC versus AICc

Comparing Models

- A second order bias correction for AIC
- Sample sizes are small

 $AIC = -2\log(\mathcal{L}) + 2K$

AICc = AIC + (2K(K + 1))/(n-K-1)

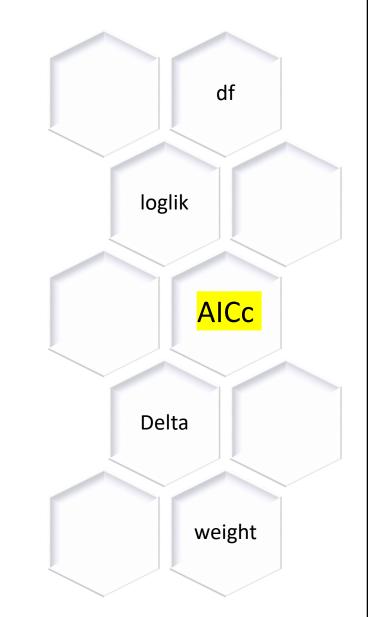
• As sample size (n) increases, AICc converges to AIC.

 \mathcal{L} = Likelihood function

- K = number of parameters in the model
- n = sample size



Small sample sizes (n/K < \approx 40)



Datasets in Multimodel Inference

1. Dataset of variables

- ✓ Representative
- \checkmark Objective of the study
- ✓ Outliers
- ✓ Biological evaluation

2. Dataset of models

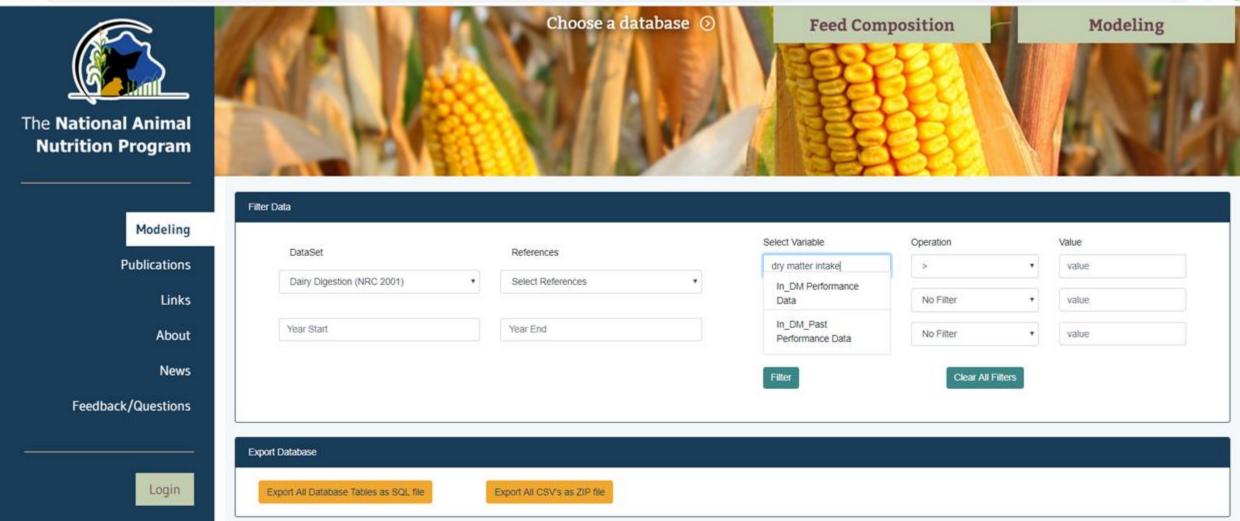
- \checkmark Assumed there is a best model (well estimated).
- ✓ Dataset for "Model selection"
- \checkmark Selection based on information criterion.
- ✓ Framework and methodology.
- \checkmark Inference based on the full set of models.
- ✓ Mathematical and philosophical background.

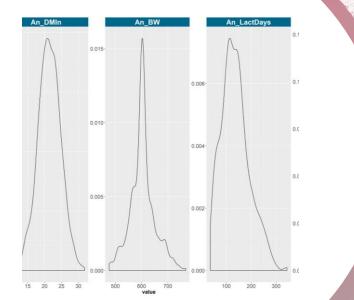
Search for Database

https://animalnutrition.org/

0

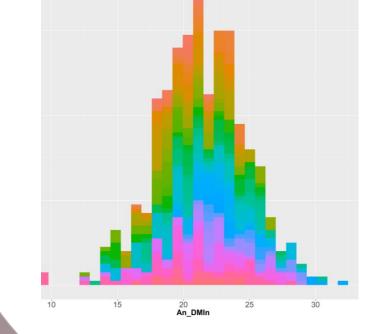
ŵ 🍩





EXAMPLE OF DATA VISUALIZATION

Biological coherence and outliers





Biological coherence and outliers

Example of a Descriptive Statistics Table

	vars	n	mean	sd	median	min	max	range
PubID*	1	645	-	-	-	1	156	155
TID	2	645	-	-	-	-	-	-
An_DMIn	3	645	21.41	3.25	21.32	12.6	30.8	18.2
An_BW	4	645	603.97	46.95	602.7	476	768	292
An_LactDays	5	645	135.79	55.58	129	42	344	302
Obs_MilkProd	6	645	32.47	6.8	32.64	16.8	53.8	37
Obs_MilkFatp	7	645	3.56	0.42	3.57	2.26	4.78	2.52
Obs_MilkPrtp	8	645	3.09	0.21	3.09	2.57	3.9	1.33
Dt_Forage	9	645	50.81	10.29	50	9.61	86.23	76.62
Dt_NDF	10	645	31.95	5.53	31.45	21.41	52.26	30.85
Dt_ForNDF	11	645	23.39	5.59	22.89	5.04	48.32	43.28

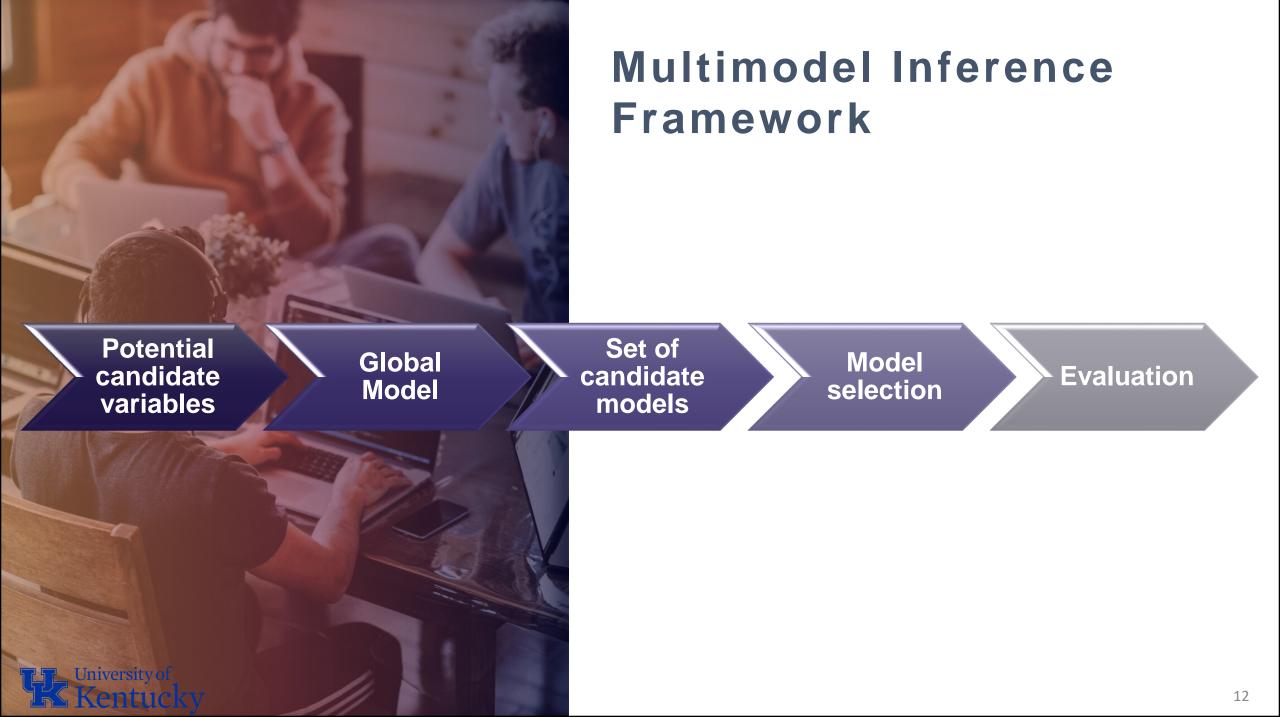
Biological coherence and outliers



MODEL DEVELOPMENT

Automated Model Selection





Automated Model Selection

1. Potential candidate variables

- ✓ Potential variables that might or might not appear in the best model
- ✓ Objective of the study
- ✓ Prior knowledge from scientific literature
- ✓ Biologically relevant variables
- ✓ Large or small
- ✓ Power of each variable
- \checkmark Association among variables



2. Global Model

- Overparameterization
- Interaction
- Large number of variables
- Fixed and random effects
- Weight



14

3. Generating a set of models

Dredge function

dredge(**global.model**, beta = c("none", "sd", "partial.sd"), evaluate = TRUE, **rank = "AICc**", fixed = NULL, m.lim = NULL, m.min, m.max, subset, trace = FALSE, varying, extra, ct.args = NULL, ...)

Pdredge: Parallel Computation

pdredge(**global.model**, cluster = NA, beta = c("none", "sd", "partial.sd"), evaluate = TRUE, **rank = "AICc"**, fixed = NULL, m.lim = NULL, m.min, m.max, subset, trace = FALSE, varying, extra, ct.args = NULL, check = FALSE, ...)





4. Set of Candidate Models

📧 RStudi	o												
File Edi	File Edit Code View Plots Session Build Debug Profile Tools Help												
•	🖸 🗸 🔯 🖌 📄 📑 📥 🕐 Go to file/function 🛛 🔚 🖌 Addins 🗸												
	Exercise #3 R script 1.R × allmods ×												
	Filter												
•	(Interce	ept) [‡] An_BW	÷	An_LactDays	Dt_FA [‡]	Dt_Forage	Dt_St 🗧 🗘	Obs_MilkProd	df 🍦	logLik 🍦	AICc 🗢	delta 🍦	weight
47	1.253	Model 1	4	0.013060979	-0.145082657	-1.454809e-02	NA	0.3108421	8	-1000.711	2017.648	0.000000	4.513738e-01
39	0.629	Model 2	3	0.011976634	-0.147986272	NA	NA	0.3166825	7	-1002.578	2019.333	1.684523	1.944226e-01
63	1.203	Model 3	7	0.013050949	-0.144719929	-1.427533e-02	0.001387305	0.3108330	9	-1000.704	2019.691	2.042979	1.625208e-01
55	0.422	Model 4	2	0.012032693	-0.145708250	NA	0.007622286	0.3160340	8	-1002.347	2020.921	3.273039	8.786280e-02



Automated Model Selection

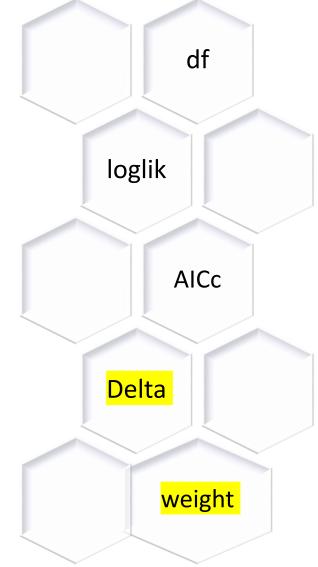
Delta

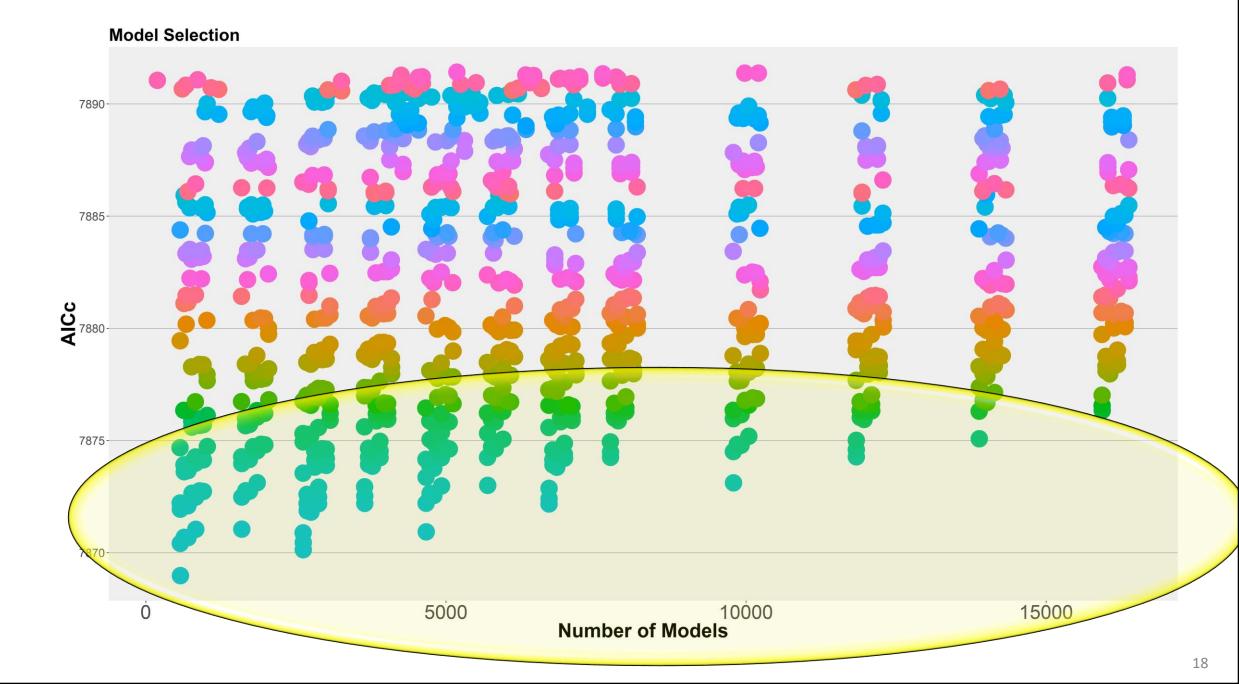
- AIC differences, relative to the smallest AIC value in the set of models.
- AICi AICmin
- These values are estimates of the expected K-L information (or distance) between the selected (best) model and the ith model.

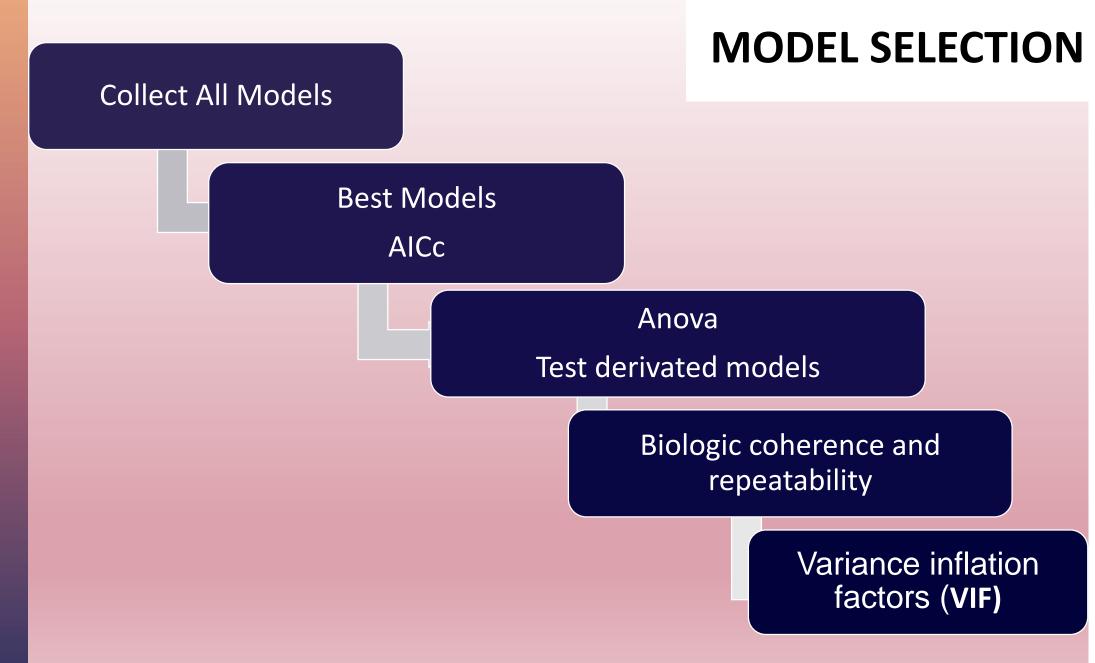
Weight

The relative likelihood of the model, given the data. These are normalized to sum to 1, are denoted by wi, and interpreted as probabilities.











MODEL EVALUATION

- ✓ Variance inflation factors
- ✓ Concordance correlation coefficient
- ✓ Root mean square error
- ✓ Cross Evaluation

MODEL EVALUATION

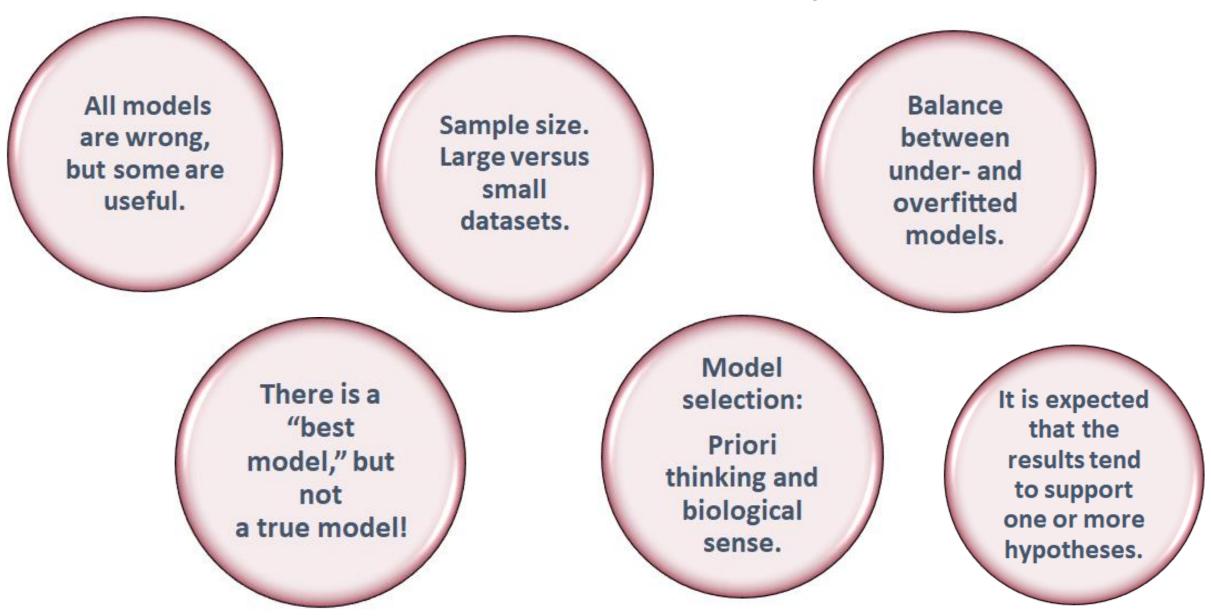
Biological coherence

Testing on the training data

Repeated crossevaluation

FABRIKAM

Multimodel Inference – Key Points



TAKEAWAYS







PREVIOUS KNOWLEDGE IS REQUIRED USEFUL FOR LARGE DATASETS

SELECT THE BEST MODELS BASED ON BOTH BIOLOGICAL SENSE AND INFERENCE ADOPTED





VERIFY THE CONSISTENCY OF ESTIMATED PARAMETERS ACROSS CANDIDATE SET OF MODELS

CROSS EVALUATION



University of Kentucky

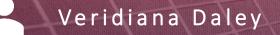
THANK YOU



National Animal Nutrition Program Leveraging Resources, Linking Researchers



COLLEGE OF AGRICULTURE AND LIFE SCIENCES VIRGINIA TECH...





United States Department of Agriculture National Institute of Food and Agriculture



veridi7@vt.du

https://www.linkedin.com/in/Veridiana L. Daley

HANDS-ON LESSONS



Practice

Development of empirical models to predict the dry matter intake of dairy cows



1- CLEAN THE DATASET AND PLOT THE VARIABLES.

2- DEVELOP A SET OF CANDIDATE MODELS.

4- SELECT THE BEST 4 MODELS BASED ON THE AIC_C

5- IF TIME ALLOWS, EVALUATE THE BEST 4 MODELS



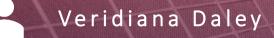
University of Kentucky

THANK YOU





National Animal Nutrition Program Leveraging Resources, Linking Researchers





veridi7@vt.du



United States Department of Agriculture National Institute of Food and Agriculture

https://www.linkedin.com/in/Veridiana L. Daley