

WSP modelling

Lizzie Jones

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Quantitative analysis/modelling

Quantitative data analysis: Descriptive and statistical - to understand variation in respondent's awareness, knowledge and attitudes towards white storks and their reintroduction.

Methods plan

- GLM approach + model selection and averaging
 - Anderson, D. and Burnham, K., 2004. Model selection and multi-model inference. Second. NY: Springer-Verlag, 63(2020), p.10.
 - Burnham, K.P., Anderson, D.R. and Huyvaert, K.P., 2011. AIC model selection and multimodel inference in behavioral ecology: some background, observations, and comparisons. Behavioral ecology and sociobiology, 65(1), pp.23-35.
- PCA/Clustering?

Exploring the response variable

Response variable = Attitudes to WS reintroduction (Composite score)

```
str(final_data$OverallAttitudeScore) # check it's a numeric column
```

```
##   num [1:3531] NA NA NA 4.93 4.64 4.86 4.57 4.86 3.29 3.93 ...
```

```
final_data %>%  
  group_by(SurveyType) %>%  
  summarise(sum(!is.na(OverallAttitudeScore))) ## Counting NON-NA values per  
survey type
```

```
## # A tibble: 2 x 2  
##   SurveyType `sum(!is.na(OverallAttitudeScore))`  
##   <fct>                                <int>  
## 1 NatRep                                743  
## 2 Proactive                            1749
```

Possible predictor variables

Factor variables

- Age (collapse further?)
- Gender (female / male)

- Urban / suburban / rural
- Highest education (collapse – e.g. degree; below degree)
- Occupation (use? If so, would need to collapse! unemployed; retired; potentially pool responses except for those who answered “environment, nature & wildlife”)
- Visited Knepp (yes / no)
- Time spent in nature
- Member of conservation/environmental organisation (quite a few people listed RSPB)
- Awareness
- Heard of white stork before taking this survey?
- Heard of white stork project / reintroduction effort?

```
# Select all possible predictor vars
model_data <- final_data %>%
  dplyr::select(UniqueID_all, OverallAttitudeScore, SiteProximity, SurveyType,
    Age_short, Gender, Area_type, Education_short, Occupation_short,
    Q27_Knepp_visit, Q18_exp_nature, Q1_aware_stork, Q9_heard, KnowledgeScore,
    Q22....Are.you.a.member.of.any.environmental..wildlife.or.conservatio
n.organisations.,
    NCI, ProCoBS, BirdInterestScore, EnvConcern.score)
nrow(model_data)
```

```
## [1] 3531
```

```
model_clean <- model_data[!is.na(model_data$OverallAttitudeScore), ]
nrow(model_clean) ## Dropped ~1100 rows due to NA in AttitudeScore
```

```
## [1] 2492
```

```
# Select numeric variables
model_clean1 <- model_clean %>%
  drop_na()
nrow(model_clean1)
```

```
## [1] 2483
```

Predictor correlation matrix

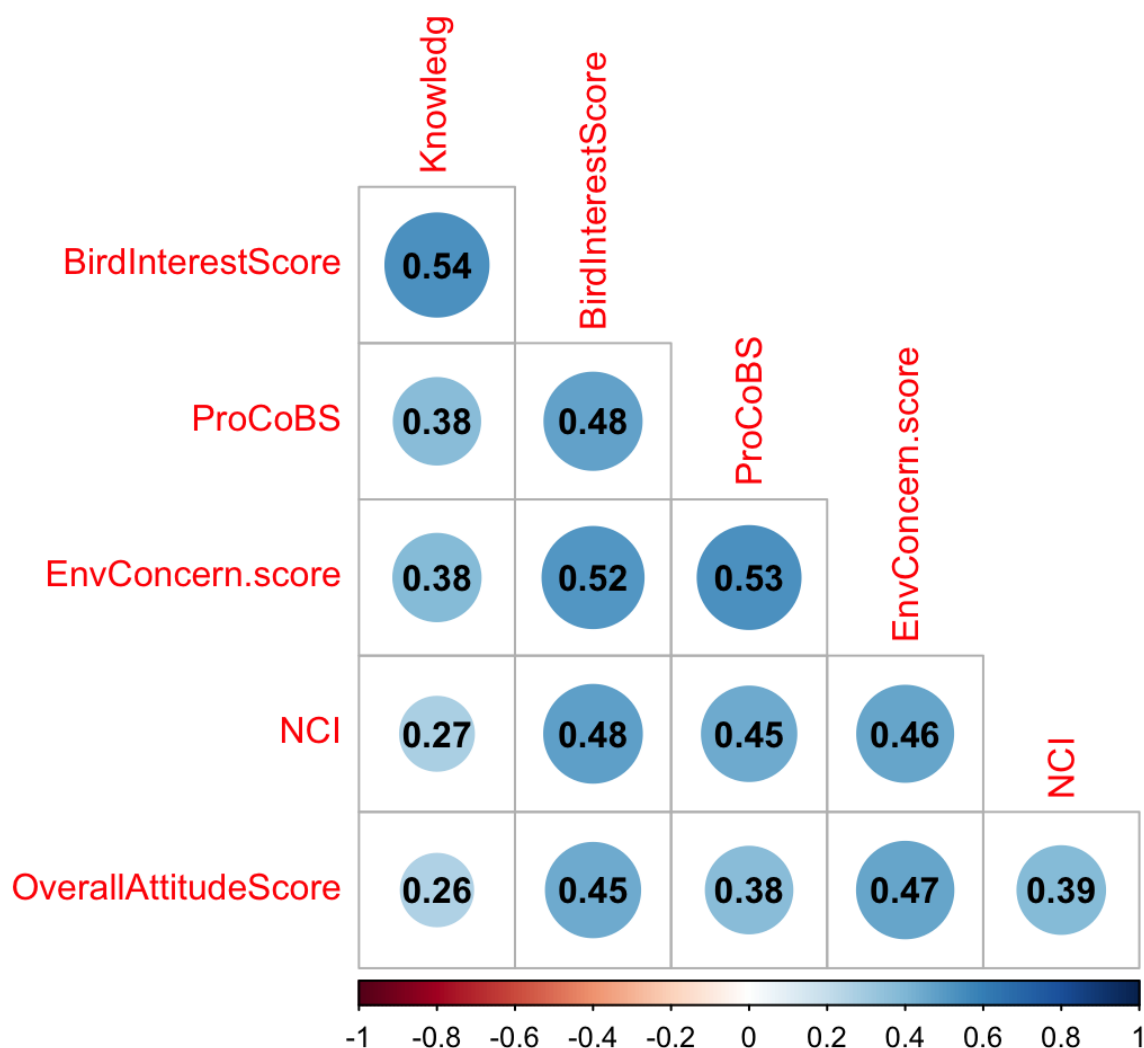
Numeric variables

- Contact and connection with nature; general environmental attitudes and behaviour
- Nature Connection Index (composite score)
- Environmental concern (composite score)
- General attitude towards birds (composite score)

```
# Select numeric variables
model_numeric <- model_clean1 %>%
  dplyr::select_if(., is.numeric) %>%
  dplyr::select(., -UniqueID_all) %>%
  drop_na()
nrow(model_numeric)
```

```
## [1] 2483
```

```
# Create correlation matrix
model.cor = cor(model_numeric, method = c("spearman"))
res1 <- cor.mtest(model_numeric, conf.level = .95)
corrplot::corrplot(model.cor, p.mat = res1$p, method = "circle", type = "lower",
  insig='blank',
  addCoef.col = 'black', order = "AOE", diag=FALSE)
```



```
### All variables moderately correlated but non significant
```

Global model

We now generate the global model. Remember, this is a saturated model with all of the fixed effects and their interesting interactions. There are no random effects in this model so we use a linear model.

```
head(model_clean, 20)
```

##	UniqueID_all	OverallAttitudeScore	SiteProximity	SurveyType	Age_short	Gen
## 4	4	4.93	Not local	Proactive	18-44	M
## 5	5	4.64	Not local	Proactive	18-44	Fem
## 6	6	4.86	Local	Proactive	18-44	Fem
## 7	7	4.57	Not local	Proactive	45-64	Fem
## 8	8	4.86	Not local	Proactive	18-44	M
## 9	9	3.29	Not local	Proactive	45-64	M
## 10	10	3.93	Not local	Proactive	45-64	M
## 11	11	4.71	Not local	Proactive	18-44	Fem
## 12	12	4.36	Not local	Proactive	18-44	M
## 13	13	3.79	Not local	Proactive	18-44	M
## 14	14	4.71	Not local	Proactive	45-64	M
## 17	17	3.86	Not local	Proactive	18-44	Fem
## 18	18	4.29	Not local	Proactive	45-64	Fem
## 19	19	3.93	Not local	Proactive	65+	M
## 20	20	4.29	Not local	Proactive	18-44	Fem
## 21	21	4.64	Not local	Proactive	18-44	M
## 22	22	4.86	Not local	Proactive	18-44	M
## 23	23	4.57	Not local	Proactive	18-44	Fem
## 24	24	3.86	Not local	Proactive	18-44	Fem
## 26	26	4.00	Not local	Proactive	65+	M
##	Area_type	Education_short	Occupation_short	Q27_Knepp_visit		
## 4	Urban	University graduate	Environment/Nature	Yes		
## 5	Rural	University graduate	Environment/Nature	Yes		
## 6	Sub-urban	University graduate	Non-environmental	No		
## 7	Rural	High school/College	Student	No		
## 8	Urban	University graduate	Non-environmental	No		
## 9	Rural	University graduate	Prefer not to say	No		
## 10	Sub-urban	High school/College	Non-environmental	No		
## 11	Urban	University graduate	Non-environmental	Yes		

## 12	Sub-urban University graduate	Environment/Nature	No
## 13	Rural University graduate	Non-environmental	No
## 14	Sub-urban High school/College	Unemployed/Retired	No
## 17	Sub-urban University graduate	Education	No
## 18	Rural University graduate	Non-environmental	Yes
## 19	Sub-urban High school/College	Unemployed/Retired	No
## 20	Urban University graduate	Environment/Nature	No
## 21	Urban High school/College	Non-environmental	No
## 22	Sub-urban University graduate	Non-environmental	No
## 23	Urban University graduate	Student	No
## 24	Sub-urban University graduate	Other	No
## 26	Urban University graduate	Unemployed/Retired	Yes
##	Q18_exp_nature	Q1_aware_stork	Q9_heard KnowledgeScore
## 4	Every day, 7 days	Yes	Yes 6.1
## 5	Every day, 7 days	Yes	Yes 5.6
## 6	Every day, 7 days	Yes	Yes 3.0
## 7	3-4 days	Yes	Yes 2.7
## 8	1-2 days	Yes	Yes 2.0
## 9	Every day, 7 days	Yes	Yes 6.8
## 10	5-6 days	Yes	Yes 5.7
## 11	1-2 days	Yes	Yes 4.9
## 12	Every day, 7 days	Yes	Yes 5.6
## 13	Every day, 7 days	Yes	Yes 3.5
## 14	Every day, 7 days	Yes	No 4.0
## 17	3-4 days	Yes	Yes 3.5
## 18	3-4 days	Yes	Yes 3.1
## 19	1-2 days	Yes	No 2.4
## 20	5-6 days	Yes	Yes 4.5
## 21	3-4 days	Yes	Yes 3.6
## 22	Every day, 7 days	Yes	Yes 4.5
## 23	3-4 days	Yes	Yes 5.2
## 24	Every day, 7 days	Yes	Yes 2.4
## 26	5-6 days	Yes	Yes 7.0
##	Q22....Are.you.a.member.of.any.environmental..wildlife.or.conservatio.o rganisations.		
## 4	Yes		
## 5	Yes		
## 6	Yes		
## 7	No		
## 8	No		
## 9	Yes		
## 10	Yes		
## 11	No		

12
Yes
13
Yes
14
Yes
17
Yes
18
Yes
19
No
20
Yes
21
Yes
22
Yes
23
No
24
Yes
26
Yes

##	NCI	ProCoBS	BirdInterestScore	EnvConcern.score
## 4	43	19	17	10
## 5	100	23	19	10
## 6	59	17	17	10
## 7	59	16	17	10
## 8	59	18	19	10
## 9	100	28	20	10
## 10	45	22	15	10
## 11	40	20	16	10
## 12	100	24	20	10
## 13	53	16	18	8
## 14	49	18	20	10
## 17	75	18	18	10
## 18	59	16	15	10
## 19	55	18	16	8
## 20	59	24	19	10
## 21	62	21	20	10
## 22	100	20	17	10
## 23	34	15	16	10
## 24	34	21	16	10
## 26	83	24	20	10

```
# Create saturated model (potentially SurveyType or locality as a random effect?)
global_model <- glm(OverallAttitudeScore ~ SiteProximity + SurveyType +
  Age_short + Gender + Area_type + Education_short + Occupation_short +
  Q27_Knepp_visit + Q18_exp_nature + Q1_aware_stork + Q9_heard + KnowledgeScore +
  Q22....Are.you.a.member.of.any.environmental..wildlife.or.conservations.organisations. +
  NCI + ProCoBS + BirdInterestScore + EnvConcern.score, data = model_clean1)
summary(global_model)
```



```
##
## Call:
## glm(formula = OverallAttitudeScore ~ SiteProximity + SurveyType +
##      Age_short + Gender + Area_type + Education_short + Occupation_short +
##      Q27_Knepp_visit + Q18_exp_nature + Q1_aware_stork + Q9_heard +
##      KnowledgeScore + Q22....Are.you.a.member.of.any.environmental..wildlif
e.or.conserva
tion.organisations. +
##      NCI + ProCoBS + BirdInterestScore + EnvConcern.score, data = model_clea
n1)
##
## Deviance Residuals:
##      Min        1Q      Median        3Q        Max
## -2.98646  -0.24504   0.08231   0.34999   1.37574
##
## Coefficients:
##
Estimate
## (Intercept)
1.9250392
## SiteProximityNot local
0.0309636
## SurveyTypeProactive
0.1413150
## Age_short45-64
-0.0195080
## Age_short65+
0.0050121
## Age_shortN/A
-0.2888474
## GenderMale
-0.0736924
## GenderN/A
-0.1402716
## Area_typeSub-urban
-0.0123917
## Area_typeUrban
-0.0462044
## Education_shortNo formal quals.
-0.0305604
## Education_shortOther
-0.2211145
## Education_shortUniversity graduate
-0.0140019
## Occupation_shortEnvironment/Nature
-0.2498903
## Occupation_shortNon-environmental
-0.0172591
## Occupation_shortOther
-0.0212587
## Occupation_shortPrefer not to say
-0.1263891
```

```
## Occupation_shortStudent
-0.0808504
## Occupation_shortUnemployed/Retired
-0.0419222
## Q27_Knepp_visitYes
0.0110452
## Q18_exp_nature3-4 days
-0.0273542
## Q18_exp_nature5-6 days
-0.0166776
## Q18_exp_natureEvery day, 7 days
-0.0497188
## Q18_exp_natureNone
0.0038165
## Q1_aware_storkYes
0.1490855
## Q9_heardNot sure
-0.0849757
## Q9_heardYes
0.0140659
## KnowledgeScore
-0.0231093
## Q22....Are.you.a.member.of.any.environmental..wildlife.or.conserva.orga
nisations.Yes -0.0666779
## NCI
0.0020069
## ProCoBS
0.0085734
## BirdInterestScore
0.0459183
## EnvConcern.score
0.1316478
##
Std. Error
## (Intercept)
0.1048284
## SiteProximityNot local
0.0290671
## SurveyTypeProactive
0.0368516
## Age_short45-64
0.0260297
## Age_short65+
0.0370880
## Age_shortN/A
0.1980219
## GenderMale
0.0226040
## GenderN/A
0.1260233
## Area_typeSub-urban
```

0.0258798
Area_typeUrban
0.0310454
Education_shortNo formal quals.
0.0801647
Education_shortOther
0.0793529
Education_shortUniversity graduate
0.0245173
Occupation_shortEnvironment/Nature
0.0469196
Occupation_shortNon-environmental
0.0386381
Occupation_shortOther
0.0508600
Occupation_shortPrefer not to say
0.0803485
Occupation_shortStudent
0.0708754
Occupation_shortUnemployed/Retired
0.0439091
Q27_Knepp_visitYes
0.0286365
Q18_exp_nature3-4 days
0.0305464
Q18_exp_nature5-6 days
0.0334786
Q18_exp_natureEvery day, 7 days
0.0333505
Q18_exp_natureNone
0.0540408
Q1_aware_storkYes
0.0355500
Q9_heardNot sure
0.0581903
Q9_heardYes
0.0312539
KnowledgeScore
0.0085784
Q22....Are.you.a.member.of.any.environmental..wildlife.or.conservations.organisations.Yes 0.0275251
NCI
0.0005082
ProCoBS
0.0025724
BirdInterestScore
0.0052108
EnvConcern.score
0.0110773

t value

```
## (Intercept)
18.364
## SiteProximityNot local
1.065
## SurveyTypeProactive
3.835
## Age_short45-64
-0.749
## Age_short65+
0.135
## Age_shortN/A
-1.459
## GenderMale
-3.260
## GenderN/A
-1.113
## Area_typeSub-urban
-0.479
## Area_typeUrban
-1.488
## Education_shortNo formal quals.
-0.381
## Education_shortOther
-2.786
## Education_shortUniversity graduate
-0.571
## Occupation_shortEnvironment/Nature
-5.326
## Occupation_shortNon-environmental
-0.447
## Occupation_shortOther
-0.418
## Occupation_shortPrefer not to say
-1.573
## Occupation_shortStudent
-1.141
## Occupation_shortUnemployed/Retired
-0.955
## Q27_Knepp_visitYes
0.386
## Q18_exp_nature3-4 days
-0.895
## Q18_exp_nature5-6 days
-0.498
## Q18_exp_natureEvery day, 7 days
-1.491
## Q18_exp_natureNone
0.071
## Q1_aware_storkYes
4.194
## Q9_heardNot sure
```

```
-1.460
## Q9_heardYes
0.450
## KnowledgeScore
-2.694
## Q22....Are.you.a.member.of.any.environmental..wildlife.or.conserva
n
tions.Yes -2.422
## NCI
3.949
## ProCoBS
3.333
## BirdInterestScore
8.812
## EnvConcern.score
11.884
##
Pr(>|t|)
## (Intercept)
< 2e-16
## SiteProximityNot local
0.286871
## SurveyTypeProactive
0.000129
## Age_short45-64
0.453658
## Age_short65+
0.892513
## Age_shortN/A
0.144786
## GenderMale
0.001129
## GenderN/A
0.265791
## Area_typeSub-urban
0.632110
## Area_typeUrban
0.136805
## Education_shortNo formal quals.
0.703073
## Education_shortOther
0.005370
## Education_shortUniversity graduate
0.567983
## Occupation_shortEnvironment/Nature
1.10e-07
## Occupation_shortNon-environmental
0.655142
## Occupation_shortOther
0.675995
## Occupation_shortPrefer not to say
0.115845
```

```

## Occupation_shortStudent
0.254090
## Occupation_shortUnemployed/Retired
0.339798
## Q27_Knepp_visitYes
0.699750
## Q18_exp_nature3-4 days
0.370610
## Q18_exp_nature5-6 days
0.618417
## Q18_exp_natureEvery day, 7 days
0.136143
## Q18_exp_natureNone
0.943703
## Q1_aware_storkYes
2.84e-05
## Q9_heardNot sure
0.144334
## Q9_heardYes
0.652712
## KnowledgeScore
0.007111
## Q22....Are.you.a.member.of.any.environmental..wildlife.or.conserva.orga
nisations.Yes 0.015489
## NCI
8.07e-05
## ProCoBS
0.000872
## BirdInterestScore
< 2e-16
## EnvConcern.score
< 2e-16
##
## (Intercept)
***
## SiteProximityNot local
## SurveyTypeProactive
***
## Age_short45-64
## Age_short65+
## Age_shortN/A
## GenderMale
**
## GenderN/A
## Area_typeSub-urban
## Area_typeUrban
## Education_shortNo formal quals.
## Education_shortOther
**
## Education_shortUniversity graduate
## Occupation_shortEnvironment/Nature

```

```

***
## Occupation_shortNon-environmental
## Occupation_shortOther
## Occupation_shortPrefer not to say
## Occupation_shortStudent
## Occupation_shortUnemployed/Retired
## Q27_Knepp_visitYes
## Q18_exp_nature3-4 days
## Q18_exp_nature5-6 days
## Q18_exp_natureEvery day, 7 days
## Q18_exp_natureNone
## Q1_aware_storkYes
***
## Q9_heardNot sure
## Q9_heardYes
## KnowledgeScore
**
## Q22....Are.you.a.member.of.any.environmental..wildlife.or.conserva
nisations.Yes *
## NCI
***
## ProCoBS
***
## BirdInterestScore
***
## EnvConcern.score
***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.2767955)
##
##      Null deviance: 1006.63  on 2482  degrees of freedom
## Residual deviance:  678.15  on 2450  degrees of freedom
## AIC: 3891.9
##
## Number of Fisher Scoring iterations: 2

```

Model selection

Caveats to model selection

Depends on the models included in the candidate set. You can't identify a model as being the "best" fit to the data if you didn't include the model to begin with! The parameter estimates and predictions arising from the "best" model or set of best models should be biologically meaningful. Need to decide whether to use model selection or common inferential statistics (e.g. based on P-values). Techniques that rely on both approaches are possible (e.g. backward variable selection followed by averaging of top models), such as the example provided above.

```
# #### MODEL SELECTION USING MUMIN PACKAGE
# options(na.action = na.fail)
# # Check assumptions of lmm model (using cur_lmm2)
# vif(global_model)
# # plot_model(full_trend_dev)
# attitude_dredge <- dredge(global_model)
# summary(get.models(attitude_dredge, 1)[[1]])
# plot(attitude_dredge, labAsExpr = TRUE)
#
# #### Use a all-subsets model subsetting approach find a confidence set of models, recalculating weights each time:
# attitude_del <- subset(attitude_dredge, delta <= 2, recalc.weights = TRUE) #
# delta(AIC) cutoff
# attitude_del
```

Model averaging

But how much evidence do we actually have that this is the best model? We have over XXX models so it's unlikely that only one model explains the data. From the dredge output we can see there is little difference in the AIC and weights of the first few models. Is there really much of a difference between two models who's AIC differ by only 0.14 points? How do we decide which model(s) to interpret? Statisticians have thought about this problem and it turns out that models with delta AIC (or other criterion) less than 2 are considered to be just as good as the top model and thus we shouldn't just discount them. Alternatively, we could use the weights: if a model has weight greater or equal to 95% then it is likely to be the top model. Otherwise we can generate a "credibility" set consisting of all models whose cumulative sum of AIC weights is 0.95. In any case, the point is that we have no good reason to exclude models other than the top one when the next models after it are likely to be just as good. To get around this, we can perform what's called model averaging (AKA multi-model inference), which allows us to average the parameter estimates across multiple models and avoids the issue of model uncertainty. Let's do this below by averaging all models with a delta AIC <= 2.

Key references

- Harrison XA, Donaldson L, Correa-Cano ME, Evans J, Fisher DN, Goodwin CED, Robinson BS, Hodgson DJ, Inger R. 2018. A brief introduction to mixed effects modelling and multi-model inference in ecology. PeerJ 6:e4794 <https://doi.org/10.7717/peerj.4794> (<https://doi.org/10.7717/peerj.4794>)


```

### Model averaging the top XXX models according to the delta AIC value
# attitude_aves <- model.avg(get.models(attitude_del, subset = delta < 2))
# summary(attitude_aves)
# sjPlot::plot_model(attitude_aves, type = "est",
#                     show.values = TRUE, value.offset = .3, title = "Model averaged results") # + ylim(-.05, 0.05)
# ggplot2::ggsave(filename = "Attitude_averaging_table.png", width = 9, height = 15, dpi = 300)
#
# # Print coefficients in table
# attitude_confint <- as.table(round(confint(attitude_aves), 3))
# attitude_ave <- round(summary(attitude_aves)$coefmat.subset, 3)
# stargazer(attitude_ave, digits=3, title="Model averaged results", type = "html", out="Attitude_averages_table.doc")
#
# # Create tab_df table of model averaged estimates
# attitude_ave1 <- tibble::rownames_to_column(as.data.frame(attitude_ave), "Predictor")
# sjPlot::tab_df(attitude_ave1, title = "Model averaged results", alternate.rows = TRUE, digits=3, use.viewer = TRUE)

```