

# Class 6: Visualising statistical and machine learning model output.

Andrew Parnell  
andrew.parnell@mu.ie



PRESS RECORD

[https://andrewcparnell.github.io/dataviz\\_course](https://andrewcparnell.github.io/dataviz_course)

## Learning outcomes

- ▶ Quick reminder on (generalised) linear models and machine learning
- ▶ Learn how to visualise output from (generalised) linear models using `ggfortify`
- ▶ Look at model performance using conditional visualisations in `condviz`
- ▶ Look at variable importance and interaction with `vivid`

## Generalised linear models (GLMs) in one slide

- ▶ In all univariate statistical models we have one variable we are trying to predict (the *response*), and multiple variables upon which to create that prediction (*features*)
- ▶ If the response is continuous and unbounded, most people use linear regression
- ▶ If the response is restricted in some way then people use a generalised linear model which models the transformed mean of the response as a linear regression

# Machine learning in one slide

- ▶ Statistical models using assume a linear relationship between the features and the response
- ▶ Machine learning models by contrast usually assume a non-linear relationship with interactions between the features
- ▶ The fitted values are usually a better fit to the data compared to those of a statistical regression model at the expense of model interpretability and uncertainty calibration
- ▶ Machine learning has its own jargon and techniques; for example models are usually compared on data that has been left out of the fitting process

## An example of a GLM fit

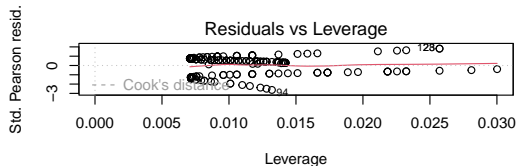
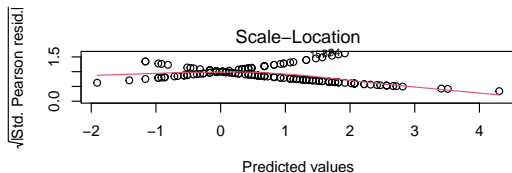
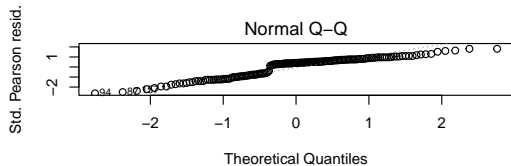
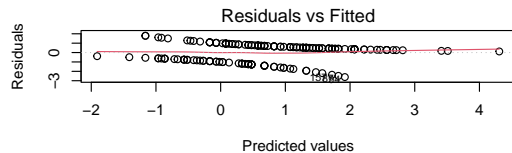
```
horseshoe <- readRDS("../data/horseshoe.rds")
model <- glm(I(satell > 0) ~ width,
             family = binomial(link = 'logit'),
             data = horseshoe)
summary(model)
```

```
##
## Call:
## glm(formula = I(satell > 0) ~ width, family = binomial(link = "logit"),
##      data = horseshoe)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.0281  -1.0458   0.5480   0.9066   1.6942
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -12.3508     2.6287  -4.698 2.62e-06 ***
## width         0.4972     0.1017   4.887 1.02e-06 ***
##
```

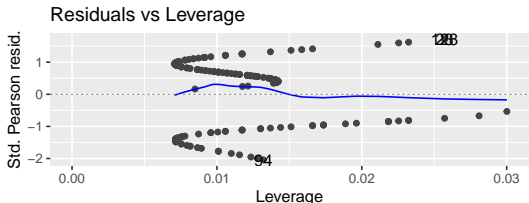
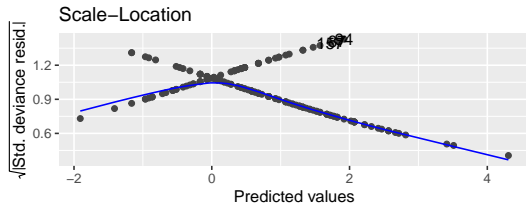
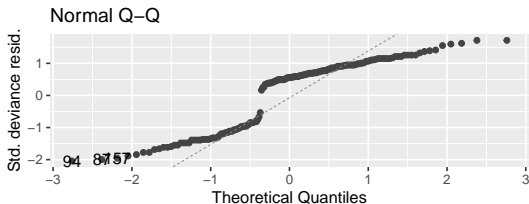
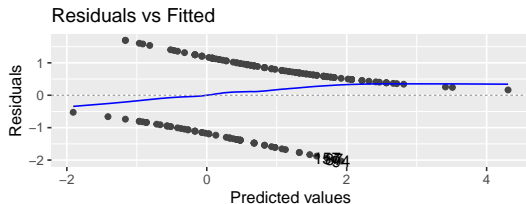
# Default glm plots

```
par(mfrow=c(2,2))  
plot(model)
```



## ggfortify again

```
library(ggfortify)
autoplot(model)
```



# Options for fitting a machine learning model in R

Lots of packages for fitting machine learning models in R. Some choices:

- ▶ `caret` is the original. Hundreds of different methods. Getting a bit old fashioned
- ▶ `tidymodels` in a tidyverse style set of packages for fitting machine learning models. Links well with `ggplot2`
- ▶ `mlr3` very nice extendible package with a large number of different modelling strategies and output plots

Most of these packages use **other packages** to perform the machine learning in the background



## Once the model has been fitted...

- ▶ It is common to plot the feature importances, interactions and misclassification/error rates
- ▶ Plot individual variable performance using individual conditional expectation (ICE) curves and partial dependence plots (PDPs)
- ▶ (These can sometimes be tricky as the importance is conditional on other features)
- ▶ Once you have fitted the machine learning model there are lots of packages to compare the fit
- ▶ We will cover `tidymodels`, `mlr3`, `iml` and DALEX all briefly

## Fitting a machine learning model using tidymodels

```
library(tidymodels); library(ranger); library(palmerpenguins)

# Split the data into training and testing sets
set.seed(123)
penguins_split <- initial_split(penguins %>%
                                na.omit(),
                                prop = 0.8)
penguins_train <- training(penguins_split)
penguins_test  <- testing(penguins_split)

# Define the model specification
rf_spec <-
  rand_forest(trees = 1000) %>%
  set_engine("ranger") %>%
  set_mode("classification")
```

## tidymodels part 2

```
# Fit the model to the training data
rf_fit <- rf_spec %>% fit(species ~ .,
                          data = penguins_train)

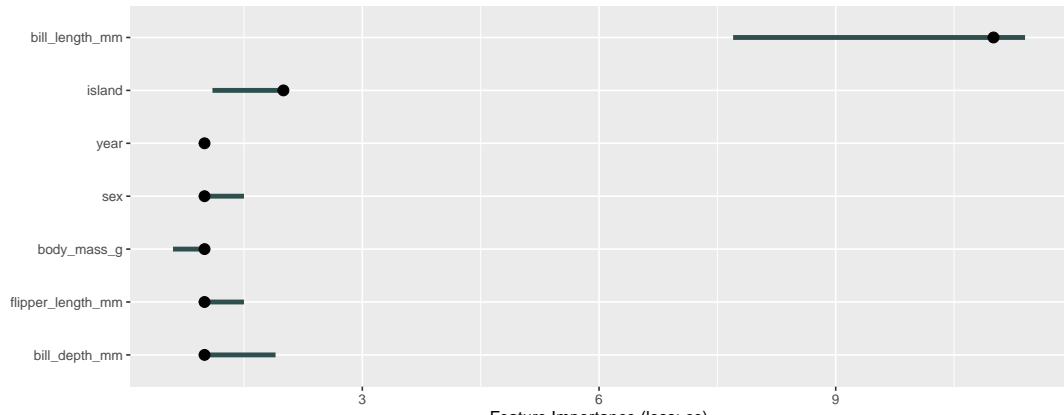
# Make predictions on the test data
rf_preds <- rf_fit %>% predict(penguins_test)

# Evaluate the model performance
rf_preds %>%
  bind_cols(penguins_test) %>%
  dplyr::select(.pred_class, species) %>%
  table
```

```
##           species
## .pred_class Adelie Chinstrap Gentoo
##   Adelie      26         0        0
##   Chinstrap    2        15        0
##   Gentoo       0         0       24
```

## iml - feature importance

```
library(iml)
predictor <- Predictor$new(rf_fit, data = penguins_test[,-1],
                           y = penguins_test[,1])
imp <- FeatureImp$new(predictor, loss = "ce") # Classification Error
plot(imp)
```



## Another example - using mlr3

```
library(mlr3)
library(mlr3learners)

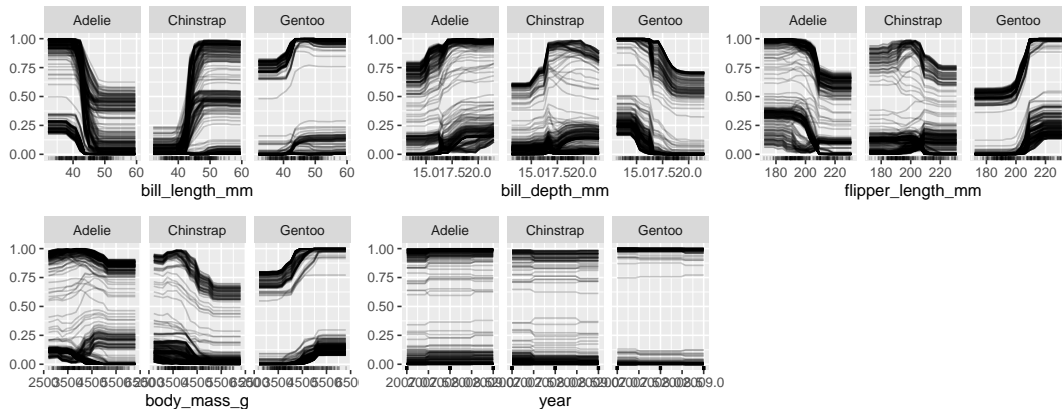
# Create a task
penguins2 = na.omit(penguins)
task_peng = as_task_classif(penguins2, target = "species")

learner = lrn("classif.ranger")
learner$predict_type = "prob"
learner$train(task_peng)

x = penguins2 %>% dplyr::select(island:year)
model = Predictor$new(learner, data = x, y = penguins2$species)
```

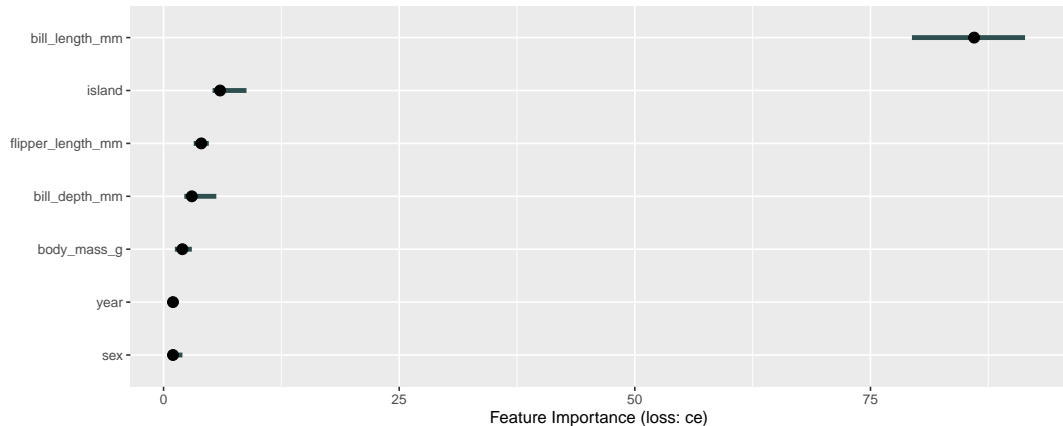
## Feature effects: ICE and PDPs

```
num_features = c("bill_length_mm", "bill_depth_mm", "flipper_length_mm", "l  
effect = FeatureEffects$new(model, method = 'ice')  
plot(effect, features = num_features)
```



## Feature importance

```
effect = FeatureImp$new(model, loss = "ce")  
effect$plot(features = num_features)
```



## DALEX

```
library(DALEX)
library(DALEXtra)
ranger_exp = explain_mlr3(learner,
  data      = penguins2,
  y         = penguins2$species,
  label     = "Ranger RF",
  colorize  = FALSE)
```

```
## Preparation of a new explainer is initiated
```

```
## -> model label      : Ranger RF
## -> data              : 333 rows 8 cols
## -> data              : tibble converted into a data.frame
## -> target variable   : 333 values
## -> predict function  : yhat.LearnerClassif will be used ( default
## -> predicted values  : No value for predict function target column.
## -> model_info        : package mlr3 , ver. 0.14.1 , task multiclass
## -> predicted values  : predict function returns multiple columns: 3
```



# Instance level explanations

```
penguin1 = penguins2[1, ]  
ile_ranger = predict_parts(ranger_exp,  
    new_observation = penguin1)  
plot(ile_ranger)
```

## Break Down profile

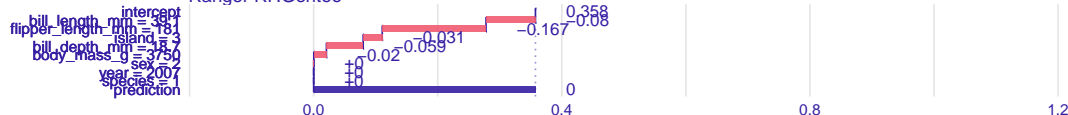
Ranger RF.Adelie



Ranger RF.Chinstrap



Ranger RF.Gentoo



## Exercise

# Summary

- ▶ So many choices for machine learning approaches and
- ▶ `tidymodels` and `mlr3` seem to be best supported for fitting lots of machine learning models
- ▶ DALEX has wealth of useful plots you can use to understand your model