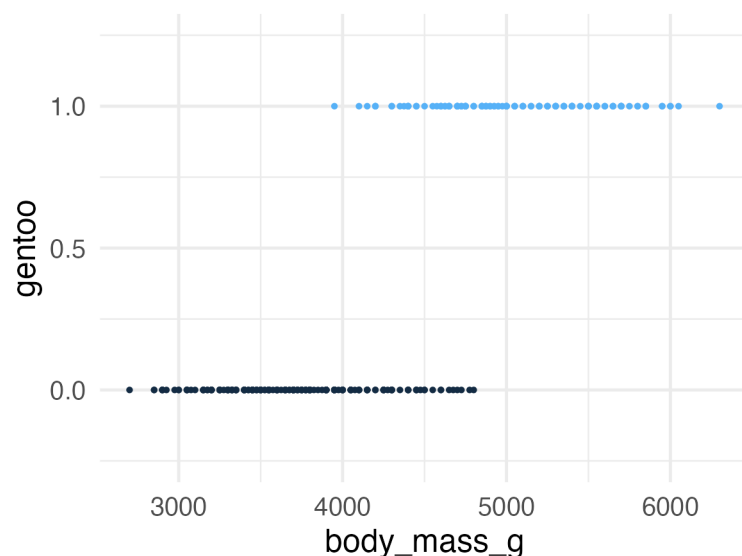


# 18: INTRO TO GENERALIZED LINEAR MODELS

Prof Amanda Luby

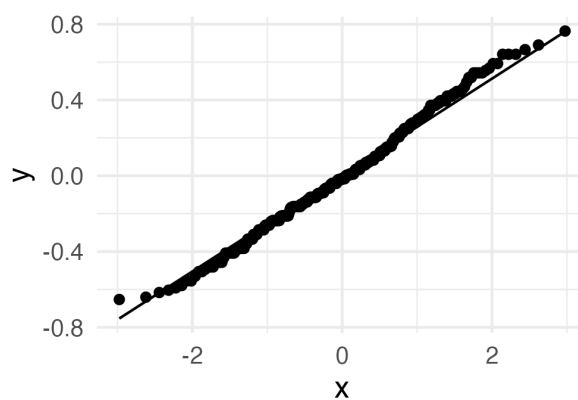
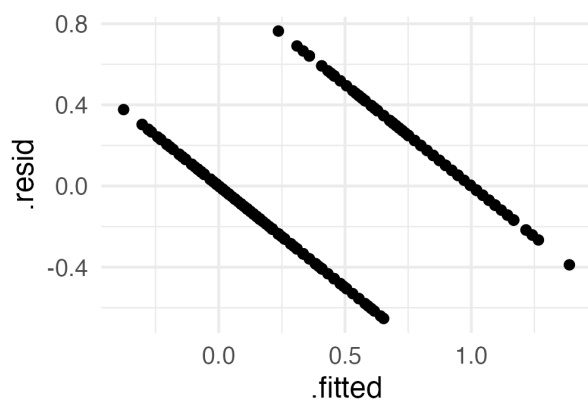
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Let's start with our dear old penguins friends. The full dataset contains information about three different species of penguins. Rather than understanding the relationship between `body_mass` and `flipper_length`, we might instead be interested in how `body_mass` is related to species. In this case, we'll treat species as either `Gentoo` or `Not Gentoo`



On first glance, it looks like we could go ahead and fit a linear regression model for this problem:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	-1.7006	0.0799	-21.2771	0
body_mass_g	0.0005	0.0000	26.2408	0



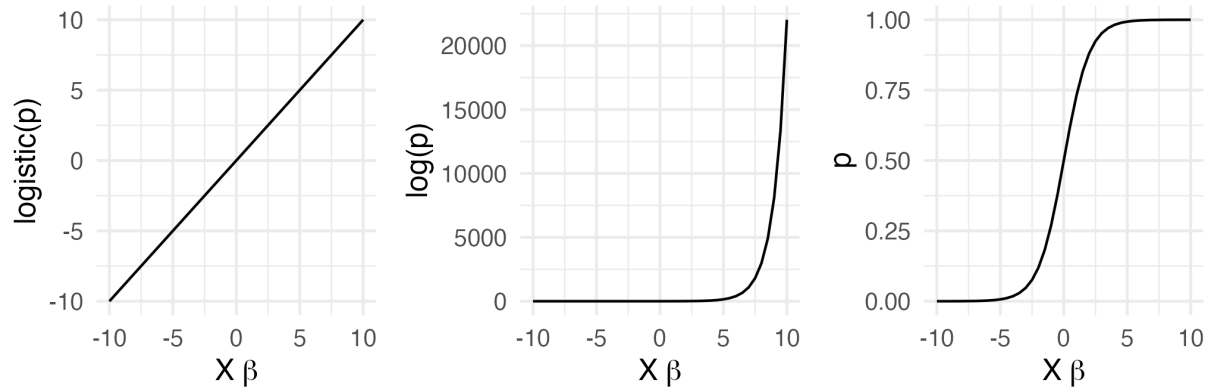
Let's list some reasons why this approach is not ideal:

What distribution does `gentoo` have? A better approach would be to start there.

## 1 Logistic Regression

**Logistic Regression Model**

Solving for  $p$ , this gives:



## 1.1 Maximum Likelihood Estimation

Now that we have the structure of the model, we have to think about how to estimate the  $\beta$ 's. Recall that the likelihood function for a  $n$  Bernoulli random variables is:

$$l(p) = \sum y_i \ln p + (1 - y_i) \ln(1 - p)$$

But, since we now have an  $X$  variable,  $p = p(x_i)$

**Sampling distribution of logistic regression coefficients**

```
gentoo_mod = glm(gentoo ~ body_mass_g,
                 data = penguins,
                 family = "binomial")
summary(gentoo_mod)
```

Call:

```
glm(formula = gentoo ~ body_mass_g, family = "binomial", data = penguins)
```

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-2.842e+01	3.609e+00	-7.873	3.46e-15	***
body_mass_g	6.371e-03	8.131e-04	7.835	4.69e-15	***

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Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 446.80 on 341 degrees of freedom  
 Residual deviance: 117.85 on 340 degrees of freedom  
 (2 observations deleted due to missingness)  
 AIC: 121.85

Number of Fisher Scoring iterations: 7

## 1.2 Interpretation of coefficients

## 2 Generalized Linear Models

We've now seen two different settings for regression. If  $X$  is a vector of predictors and  $Y \in \mathbb{R}$ , we have assumed a linear model:

and if  $Y \in \{0, 1\}$ , we assumed a logistic model:

In both settings, we are assuming that a transformation of the conditional expectation is a linear function of  $X$ :