

#### **Logistic Regression Introduction**

Julie Deeke Statistics with Python Course Developer





#### Cartwheel Data

Random sample of 25 adults attempted cartwheels

Primary Variable of interest: Cartwheel completion



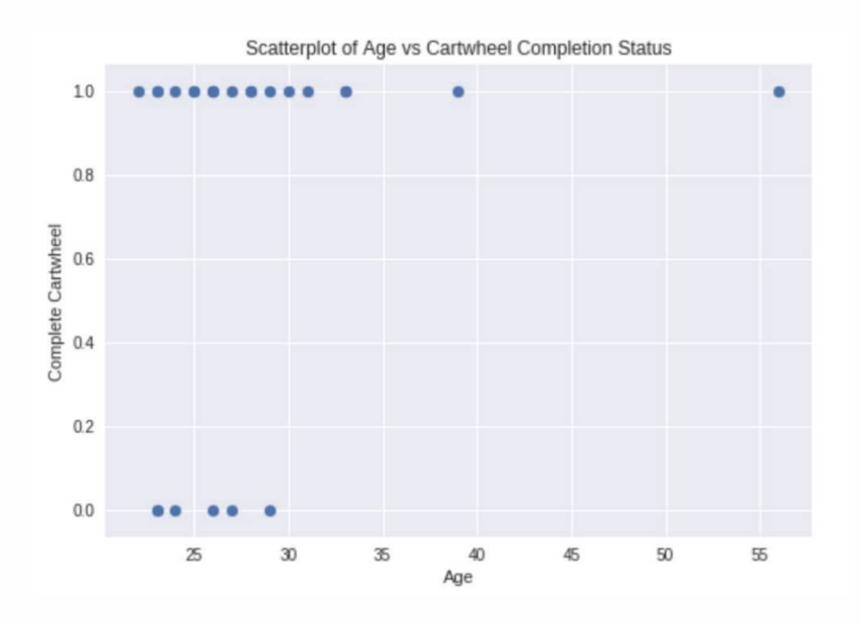


#### Research Question

Based on age, can we predict whether a cartwheel is completed?

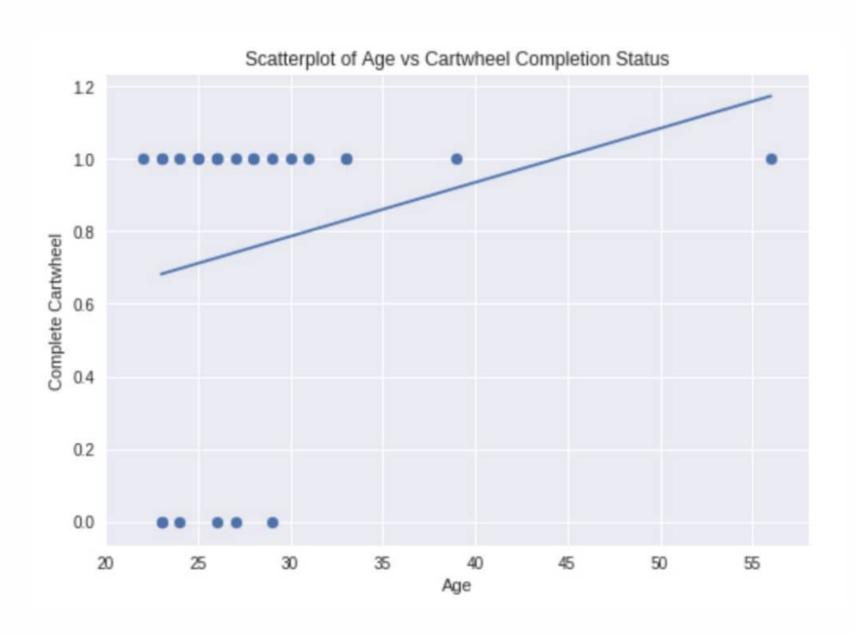


#### Let's Look at the Data



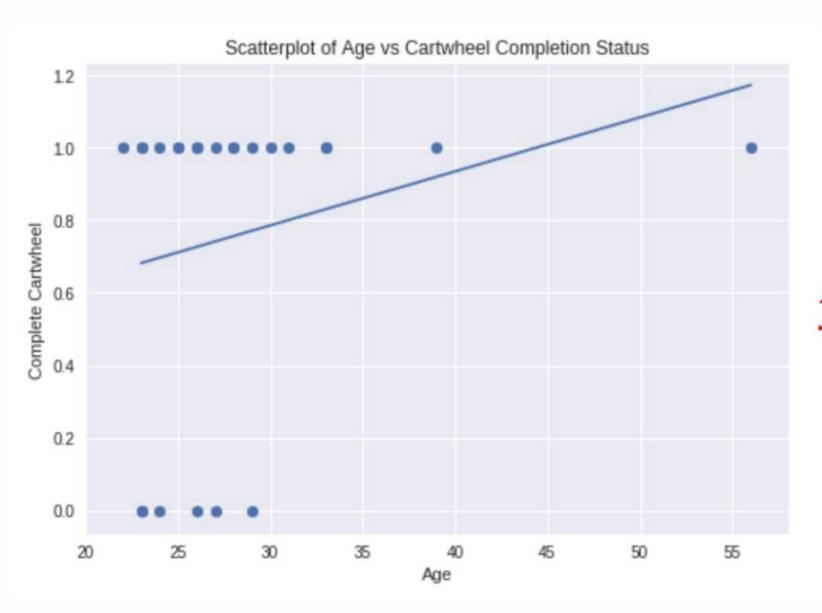


#### Linear Model





#### Linear Model



$$\hat{y} = 0.34 + 0.015$$
 age



#### Logit Transformation

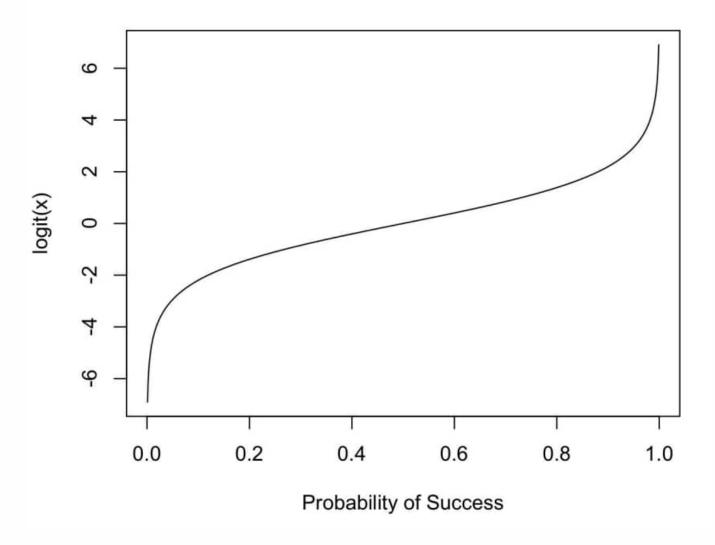
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## Logit Transformation

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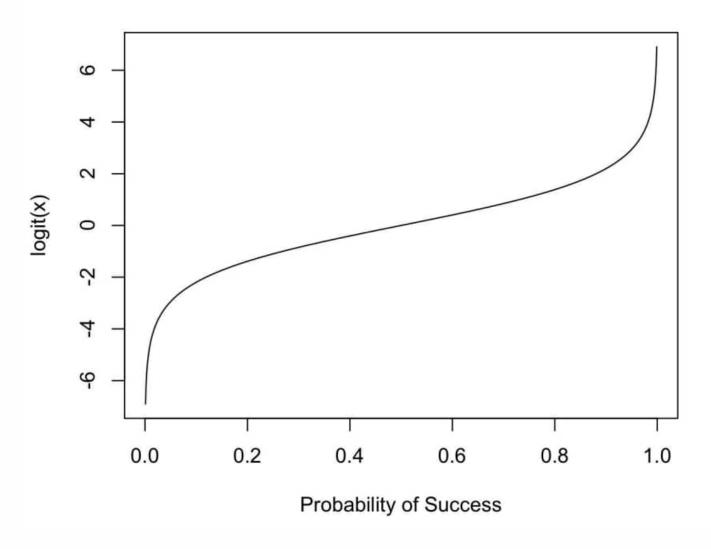




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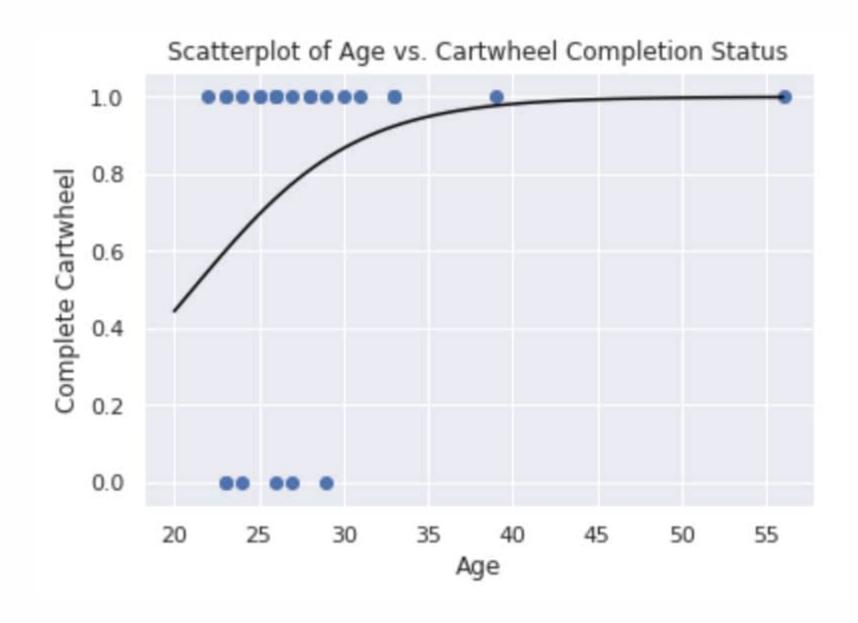
- Instead of predicting completion status, we predict a *transformed version* of the probability of a success
- Uses the logit function:  $\ln(\frac{P}{1-P})$
- logit( $\hat{y}$ ) =  $b_0 + b_1 x$





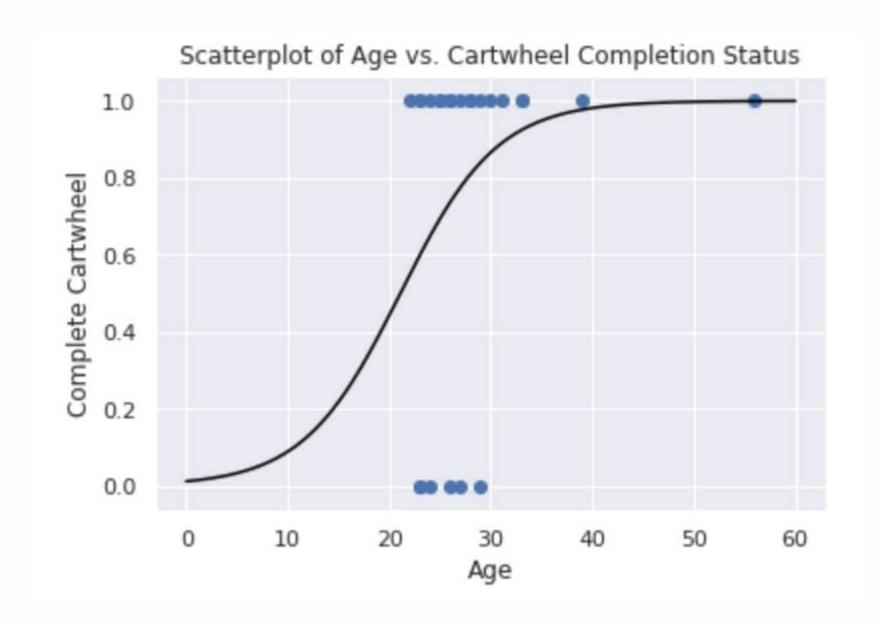


#### Logistic Regression Line





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# Extrapolation IVQ

Would you feel comfortable using this model to estimate the probability that a teenager who is 15 can complete a cartwheel?



Generalized Linear Model Regression Results

Dep. Variable: CompleteGroup No. Observations: 25

Model: GLM Df Residuals: 23

Model Family: Binomial Df Model: 1

Link Function: logit Scale: 1.0

coef std err z P>|z| [0.025 0.975]

Intercept -4.4213 4.429 -0.998 0.318 -13.101 4.259



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 coef
 std err
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 P>lzl
 [0.025
 0.975]

 Intercept -4.4213
 4.429
 -0.998
 0.318
 -13.101
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 Age
 0.2096
 0.171
 1.225
 0.221
 -0.126
 0.545



 $logit(\hat{y}) = -4.42 + 0.2096$  age

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#### **Slope interpretation:**

For each increase in age by I year, the log odds of a successful cartwheel increases by about 0.2096, on average.

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 $logit(\hat{y}) = -4.42 + 0.2096$  age

**Slope interpretation:** For each year increase in age, the odds of a successful cartwheel increases by about 1.23 (e<sup>0.2096</sup>) times that of the younger age, on average.

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#### Predicted Probability of Success

 For someone who is 36, what is their predicted log odds of a successful cartwheel using the model?



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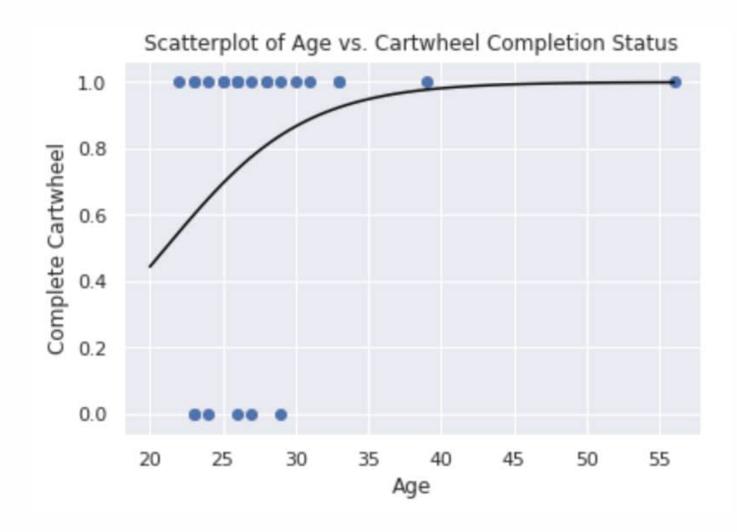
 For someone who is 36, what is their predicted log odds of a successful cartwheel using the model?

```
logit(\hat{y}) = -4.42 + 0.2096 age
= -4.42 + 0.2096 (36)
= 3.13
```



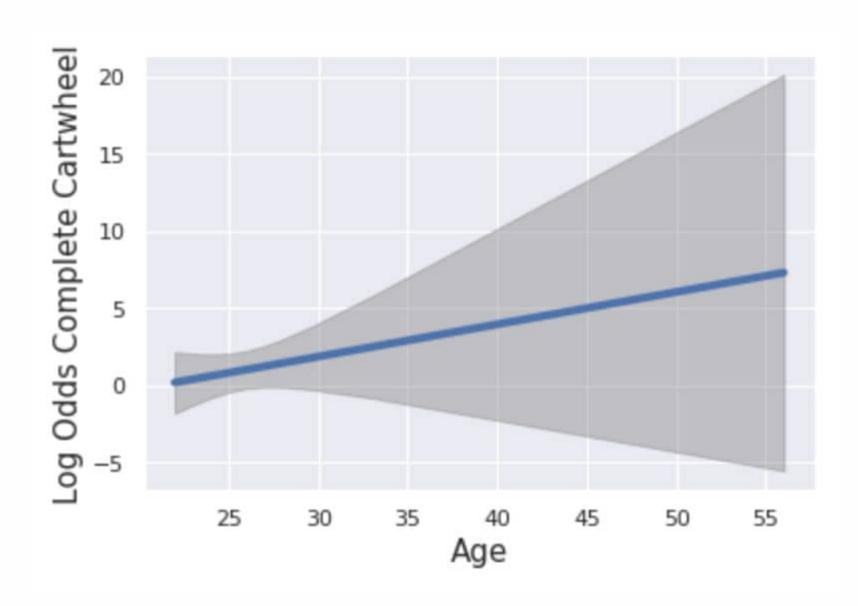
## Predicted Probability of Success

- For someone who is 36, what is their predicted log odds of a successful cartwheel using the model?
- Using the graph on the right, estimate what the probability of success might be?



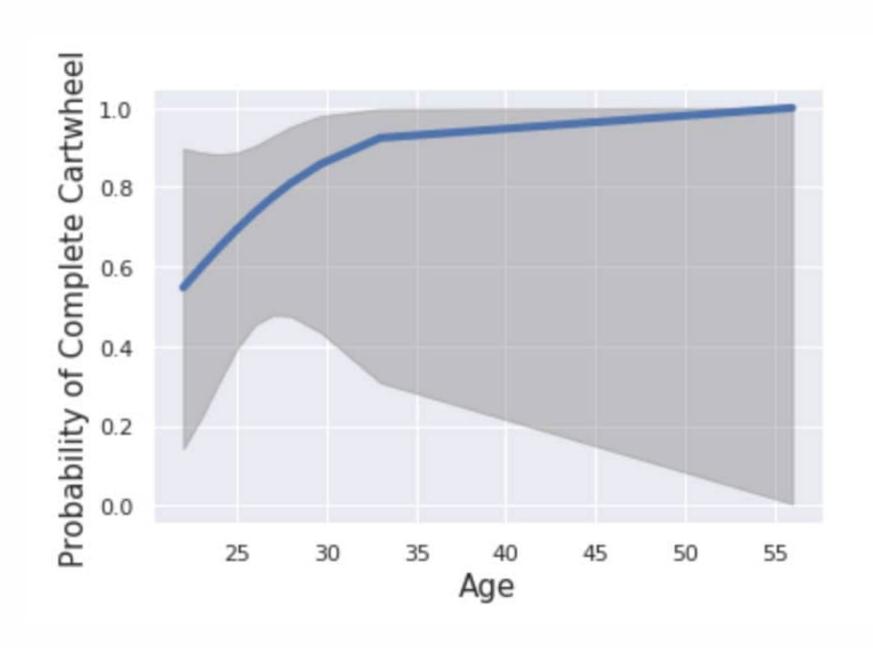


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- ~with a large enough sample size, you can identify discrepancies with residual plots
- ~y only takes two values, so residuals can be limited
- ~to create informative residual plots, it helps if x takes a wide range of values and to have additional covariates