

#### **Logistic Regression Introduction**

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Statistics with Python Course Developer





#### Cartwheel Data

Random sample of 25 adults attempted cartwheels

Primary Variable of interest: Cartwheel completion



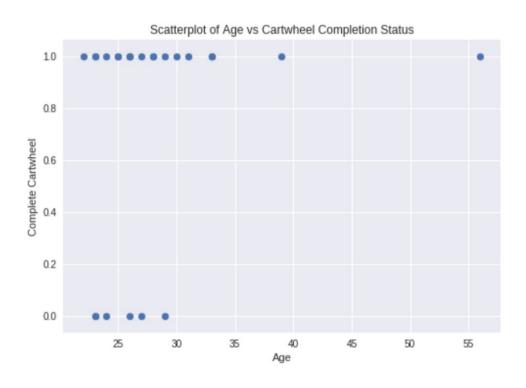


#### Research Question

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

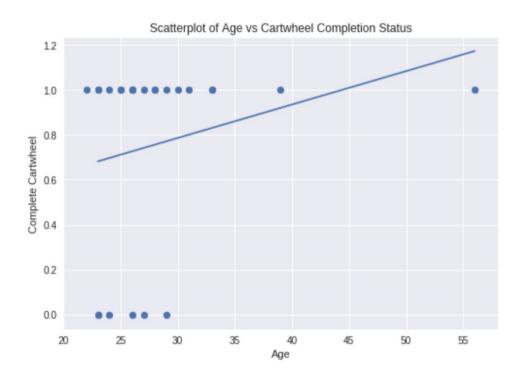


#### Let's Look at the Data



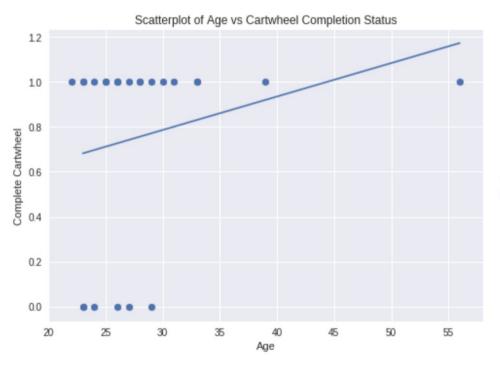


#### Linear Model





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



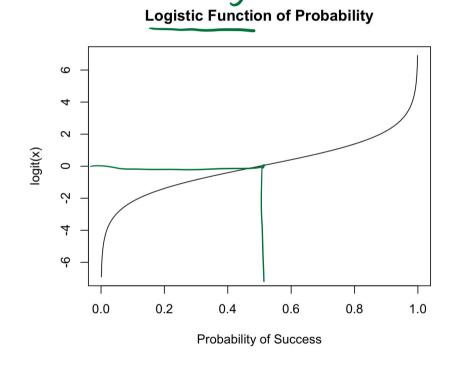
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Symmetric

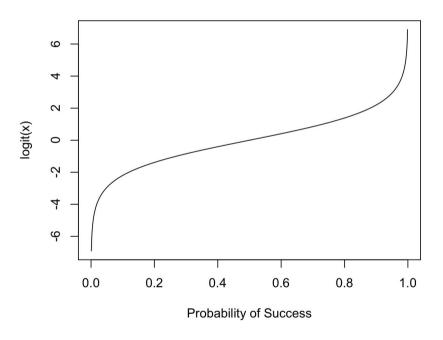


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- Uses the logit function:

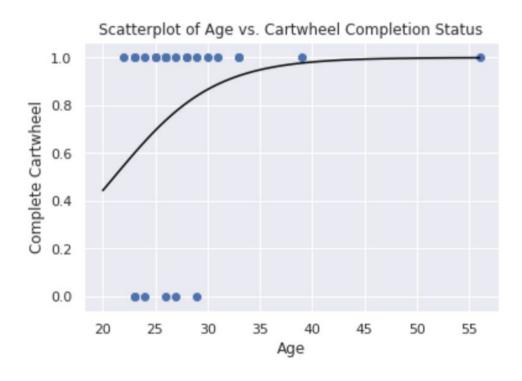
$$\begin{cases} \ln(\frac{P}{1-p}) \\ \log it(\hat{y}) = b_0 + b_1 x \end{cases}$$

#### **Logistic Function of Probability**



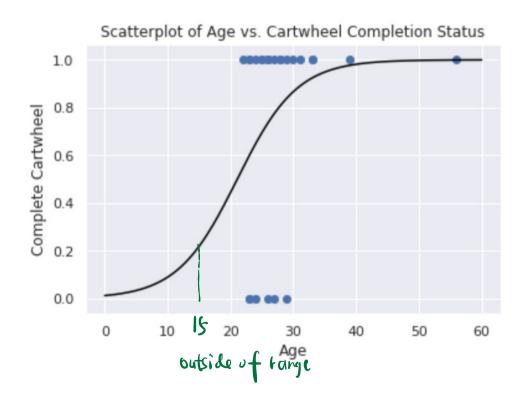


#### Logistic Regression Line





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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

Age 0.2096 0.171 1.225 0.221 -0.126 0.545



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```
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?



# Predicted Probability of Success

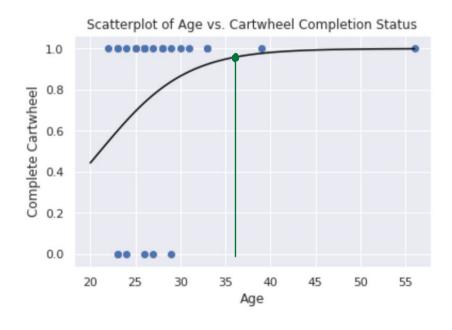
 For someone who is 36, what is their predicted log odds of a successful cartwheel using the model?

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



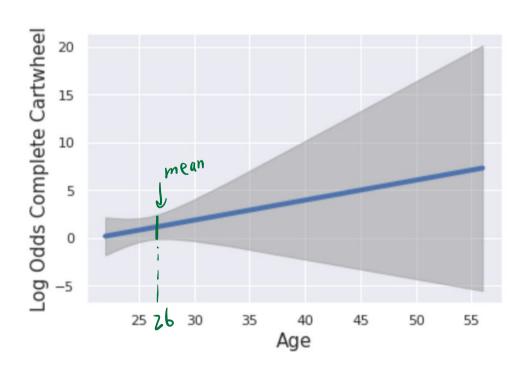
#### Predicted Probability of Success

- 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?



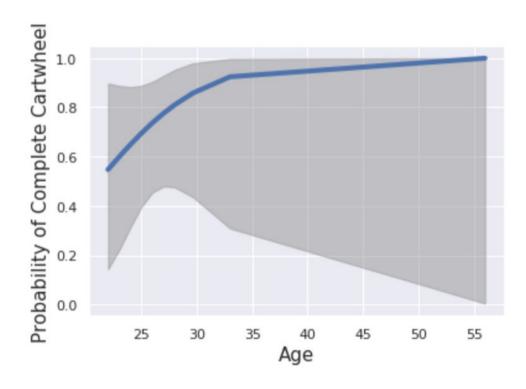


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- ~with a large enough sample size, you can identify discrepancies with residual plots
- ~y only takes two values, so residuals can be limited
- ~to create informative residual plots, it helps if x takes a wide range of values and to have additional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