



THE UNIVERSITY OF TEXAS AT AUSTIN  
McCOMBS SCHOOL OF BUSINESS

# Logistic Regression 1

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**Lecture 22**

**STA 371G**

## Near, far, wherever you are....

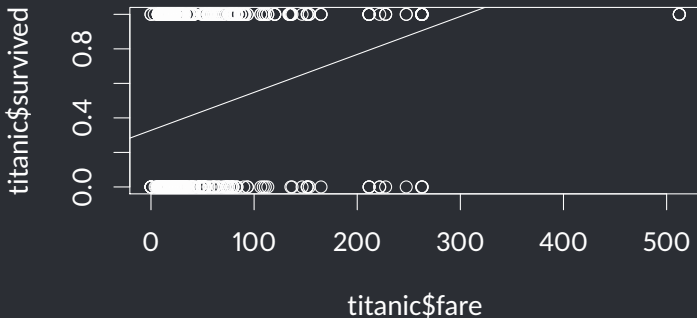
- How much did the ticket price affect whether someone survived the Titanic?
- We have a data set of 1045 passengers on the Titanic; 427 survived
  - **fare**: the amount of money paid for the ticket
  - **survived**: a dummy variable indicating whether the passenger survived (1) or not (0)

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- We have a data set of 1045 passengers on the Titanic; 427 survived
  - **fare**: the amount of money paid for the ticket
  - **survived**: a dummy variable indicating whether the passenger survived (1) or not (0)
- What is unusual about this data set?

## What goes wrong with linear regression?

```
plot(titanic$fare, titanic$survived)
model <- lm(survived ~ fare, data=titanic)
abline(model)
```



## The idea behind logistic regression

- Instead of predicting whether someone survives, let's predict the *probability* that they survive
- Let's fit a curve that is always between 0 and 1

# Odds

- When something has “even (1/1) odds,” the probability of success is  $1/2$
- When something has “2/1 odds,” the probability of success is  $2/3$
- When something has “3/2 odds,” the probability of success is  $3/5$
- In general, the odds of something happening are  $p/(1 - p)$



## The logistic regression model

Logistic regression models the **log odds** of success  $p$  as a linear function of  $X$ :

$$\log \left( \frac{p}{1-p} \right) = \beta_0 + \beta_1 X + \epsilon$$

This fits an S-shaped curve to the data (we'll see what it looks like later).

Let's try it

```
model <- glm(survived ~ fare, data=titanic,  
             family=binomial)  
summary(model)
```



## How to interpret the curve?

The regression output tells us that our prediction is

$$\log \left( \frac{P(\text{survival})}{1 - P(\text{survival})} \right) = -0.794 + 0.012 \cdot \text{fare}.$$



## How to interpret the curve?

The regression output tells us that our prediction is

$$\log \left( \frac{P(\text{survival})}{1 - P(\text{survival})} \right) = -0.794 + 0.012 \cdot \text{fare}.$$

Let's solve for  $P(\text{survival})$ :

$$\widehat{P(\text{survival})} = \frac{e^{-0.794 + 0.012 \cdot \text{fare}}}{1 + e^{-0.794 + 0.012 \cdot \text{fare}}}$$



## Making predictions

We can use `predict` to automate the process of plugging into the equation:

```
predict(model, data.frame(fare=50), type="response")
```

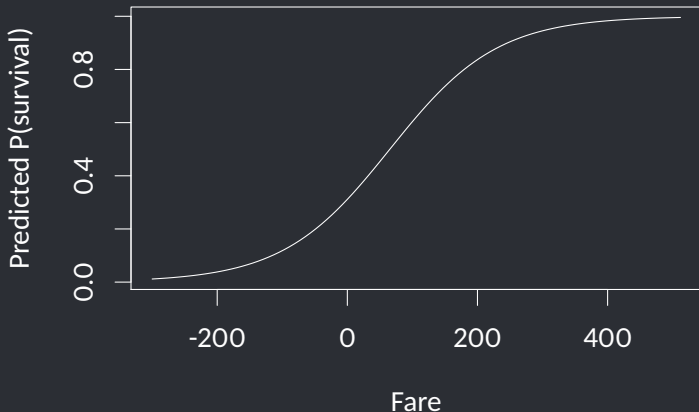
1

0.453

$$\frac{e^{-0.794+0.012 \cdot 50}}{1 + e^{-0.794+0.012 \cdot 50}} = 0.453$$

## How to interpret the curve?

$$P(\widehat{\text{survival}}) = \frac{e^{-0.794+0.012 \cdot \text{fare}}}{1 + e^{-0.794+0.012 \cdot \text{fare}}}$$



## Interpreting the coefficients

Our prediction equation is:

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Let's start with some basic, but not particularly useful, interpretations:

- When fare = 0, we predict that the log odds will be  $-0.794$



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Let's start with some basic, but not particularly useful, interpretations:

- When fare = 0, we predict that the log odds will be  $-0.794$ , so the probability of survival is predicted to be 31%.
- When fare increases by £1, we predict that the log odds will increase by 0.012.



## Interpreting the coefficients

Let's rewrite the prediction equation as:

$$\text{Predicted odds of survival} = e^{-0.794 + 0.012 \cdot \text{fare}}$$

Increasing the fare by £1 will *multiply* the odds by  $e^{0.012} = 1.012$ ; i.e., increase the odds by 1.2%.



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Increasing the fare by £1 will *multiply* the odds by  $e^{0.012} = 1.012$ ; i.e., increase the odds by 1.2%.

Increasing the fare by £10 will *multiply* the odds by  $e^{10 \cdot 0.012} = 1.129$ ; i.e., increase the odds by 12.9%.

## Testing the null hypothesis

As in regular linear regression, the overall null hypothesis is that  $\beta_1 = 0$ ; we can test this by using the  $p$ -value for that variable on the output.

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Since  $p$  is very small, we can reject the null hypothesis that  $\beta_1 = 0$ ; i.e., there is a statistically significant relationship between fare and survival.

## How good is our model?

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- Unfortunately, the typical  $R^2$  metric isn't available for logistic regression.
- However, there are many “pseudo- $R^2$ ” metrics that indicate model fit.

## Take 1: How many cases did we accurately predict?

We could use our model to make a prediction of survival (or not), based on the probability. Suppose we say that our prediction is:

$$\text{Prediction} = \begin{cases} \text{survival,} & \text{if } P(\widehat{\text{survival}}) \geq 0.5, \\ \text{tragedy,} & \text{if } P(\widehat{\text{survival}}) < 0.5. \end{cases}$$

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Now we can compute the fraction of people whose survival we correctly predicted:

```
predicted.survival <- (predict(model, type='response') >= 0.5)
actual.survival <- (titanic$survived == 1)
sum(predicted.survival == actual.survival) / nrow(titanic)

[1] 0.644
```

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64.4% sounds pretty good—what should we compare it against?



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```
1 - sum(actual.survival) / nrow(titanic)
```

```
[1] 0.591
```

## Take 2: McFadden's pseudo- $R^2$

To get a metric on the usual 0-1 scale (like regular  $R^2$ ), McFadden's pseudo- $R^2$  can be used (this is what is described in the reading):

$$\text{pseudo-}R^2 = 1 - \frac{\text{residual deviance}}{\text{null deviance}} = 1 - \frac{1339.941}{1413.571} = 0.052$$

```
Call:
glm(formula = survived ~ fare, family = binomial, data = titanic)
```

```
Deviance Residuals:
```

Min	1Q	Median	3Q	Max
-2.231	-0.928	-0.898	1.335	1.528

```
Coefficients:
```

	Estimate	Std. Error	z value	Pr(> z )
(Intercept)	-0.7941	0.0844	-9.41	< 2e-16 ***
fare	0.0121	0.0017	7.13	9.9e-13 ***

```
---
```

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

```
(Dispersion parameter for binomial family taken to be 1)
```

```
Null deviance: 1413.6  on 1044  degrees of freedom
Residual deviance: 1339.9  on 1043  degrees of freedom
AIC: 1344
```

```
Number of Fisher Scoring iterations: 4
```



## What else can we use logistic regression for?

- **Finance:** Predicting which customers are most likely to default on a loan
- **Advertising:** Predicting when a customer will respond positively to an advertising campaign
- **Marketing:** Predicting when a customer will purchase a product or sign up for a service