Multiple logistic regression

INTERMEDIATE REGRESSION IN R

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Bank churn dataset

has_churned	time_since_first_purchase	time_since_last_purchase
0	0.3993247	-0.5158691
1	-0.4297957	0.6780654
0	3.7383122	0.4082544
0	0.6032289	-0.6990435
...	...	...
response	*length of relationship*	*recency of activity*

[1] https://www.rdocumentation.org/packages/bayesQR/topics/Churn

glm()

```
glm(response ~ explanatory, data = dataset, family = binomial)
```

```
glm(response ~ explanatory1 + explanatory2, data = dataset, family = binomial)
```

```
glm(response ~ explanatory1 * explanatory2, data = dataset, family = binomial)
```

Prediction flow

```
explanatory_data <- expand_grid(
  explanatory1 = some_values,
  explanatory2 = some_values
)
prediction_data <- explanatory_data %>%
  mutate(
    has_churned = predict(mdl, explanatory_data, type = "response")
  )
```

The four outcomes

	actual false	actual true
predicted false	correct	false negative
predicted true	false positive	correct

[1] https://campus.datacamp.com/courses/introduction-to-regression-in-r/simple-logistic-regression?ex=10

Confusion matrix

```
actual_response <- dataset$response
predicted_response <- round(fitted(mdl))
```

```
outcomes <- table(predicted_response, actual_response)
```

```
confusion <- conf_mat(outcomes)
```

```
autoplot(confusion)
```

```
summary(confusion, event_level = "second")
```

Visualization

- Use faceting for categorical variables.
- For 2 numeric explanatory variables, use color for response.
- Give responses below `0.5` one color; responses above `0.5` another color.

```
scale_color_gradient2(midpoint = 0.5)
```

Let's practice!

The logistic distribution

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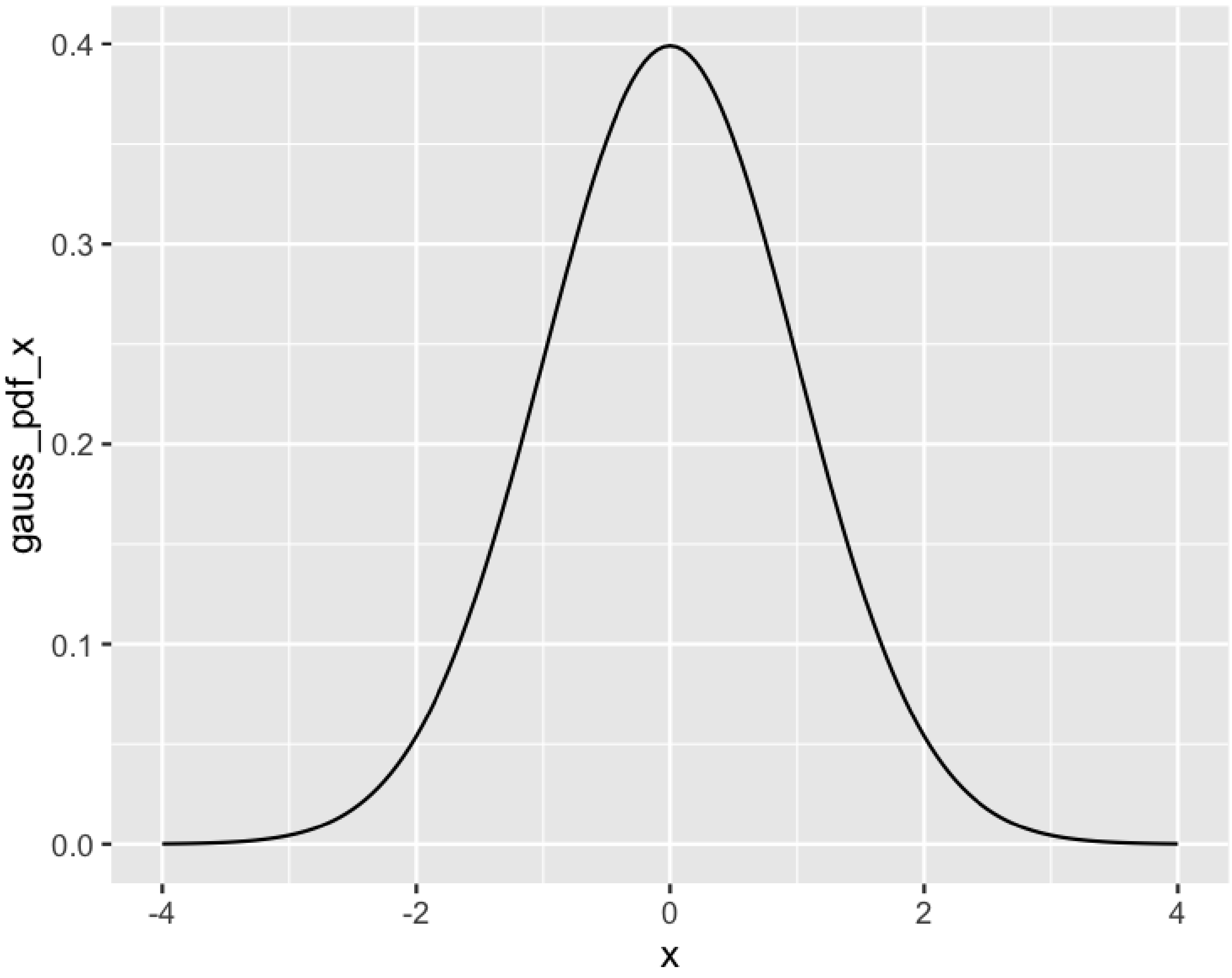
Gaussian probability density function (PDF)

```
gaussian_distn <- tibble(
  x = seq(-4, 4, 0.05),
  gauss_pdf_x = dnorm(x)
)
```

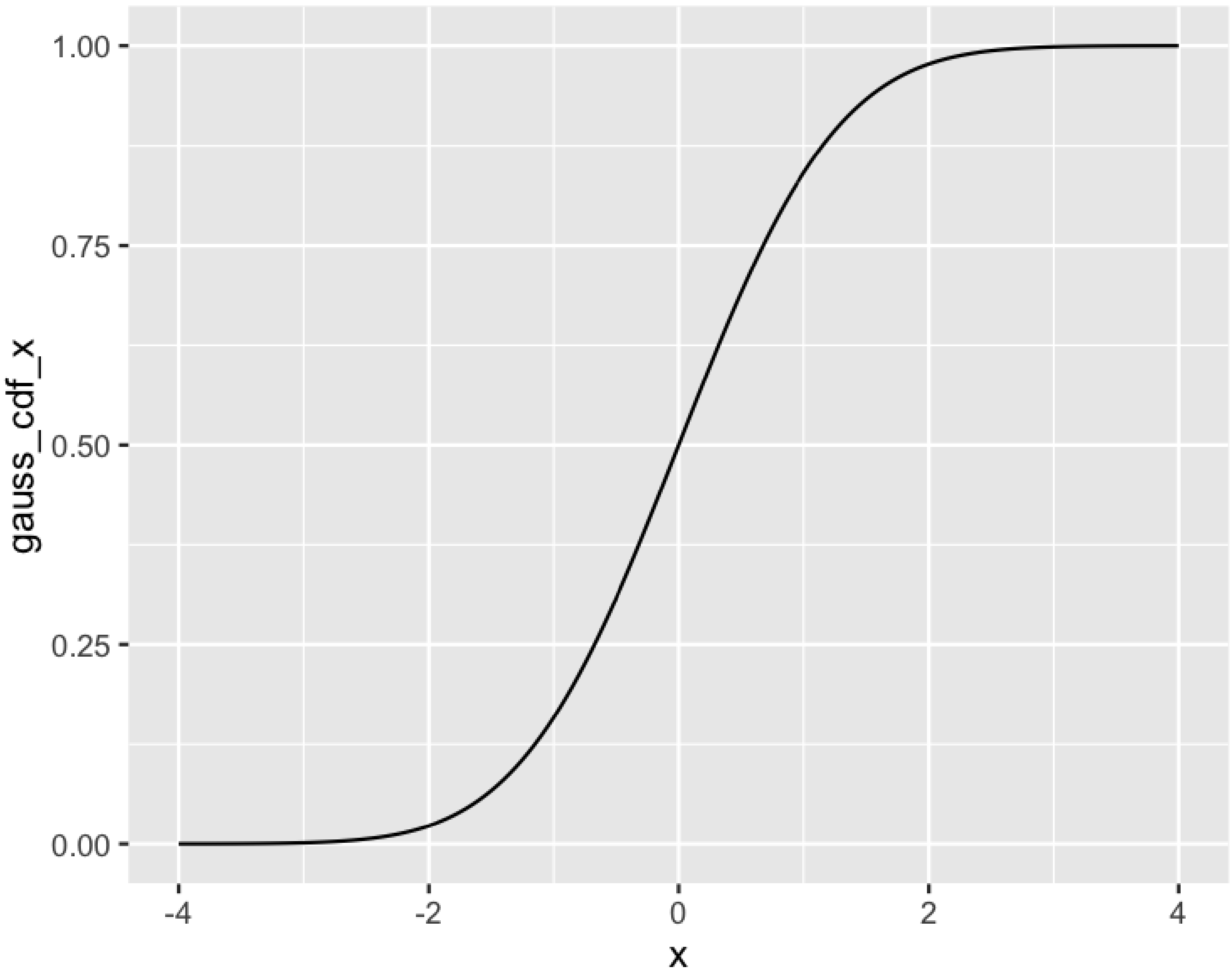
```
ggplot(gaussian_distn, aes(x, gauss_pdf_x)) +
  geom_line()
```



Gaussian cumulative distribution function (CDF)

```
gaussian_distn <- tibble(
  x = seq(-4, 4, 0.05),
  gauss_pdf_x = dnorm(x),
  gauss_cdf_x = pnorm(x)
)
```

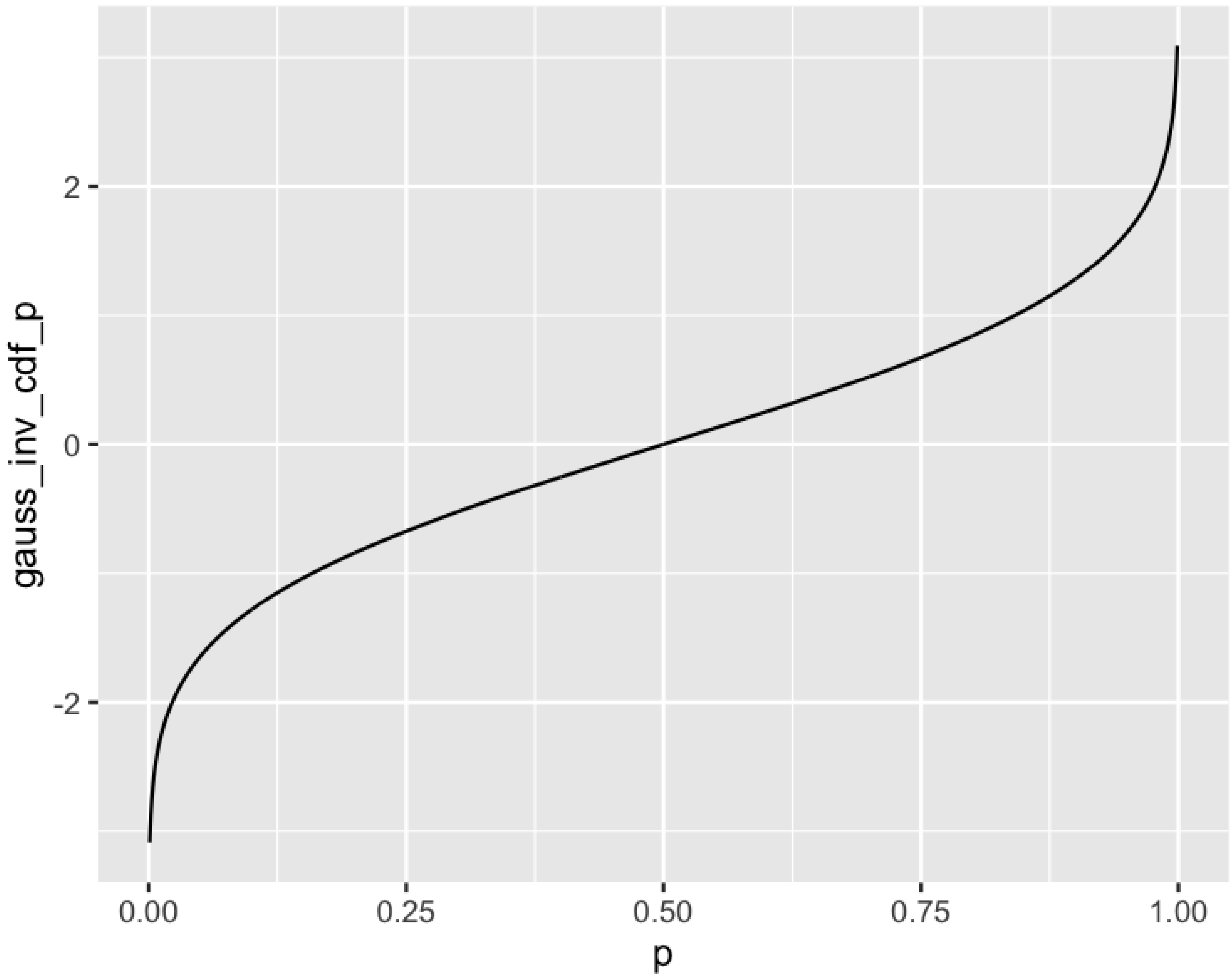
```
ggplot(gaussian_distn, aes(x, gauss_cdf_x)) +
  geom_line()
```



Gaussian inverse CDF

```
gaussian_distn_inv <- tibble(
  p = seq(0.001, 0.999, 0.001),
  gauss_inv_cdf_p = qnorm(p)
)
```

```
ggplot(gaussian_distn_inv, aes(p, gauss_inv_cdf_p)) +
  geom_line()
```



Distribution function names

curve	prefix	normal	logistic	nmemonic
PDF	d	`dnorm()`	`dlogis()`	"d" for differentiate - you differentiate the CDF to get the PDF
CDF	p	`pnorm()`	`plogis()`	"p" is backwards "q" so it's the inverse of the inverse CDF
Inv. CDF	q	`qnorm()`	`qlogis()`	"q" for quantile

glm()'s family argument

```
lm(response ~ explanatory, data = dataset)


glm(response ~ explanatory, data = dataset, family = gaussian)
```

```
glm(response ~ explanatory, data = dataset, family = binomial)
```

[1] https://campus.datacamp.com/courses/introduction-to-regression-in-r/simple-logistic-regression?ex=1

gaussian()

```
str(gaussian())
```

```
List of 11
 $ family    : chr "gaussian"
 $ link      : chr "identity"
 $ linkfun   :function (mu)
 $ linkinv   :function (eta)
 $ variance  :function (mu)
 $ dev.resids:function (y, mu, wt)
 $ aic       :function (y, n, mu, wt, dev)
 $ mu.eta    :function (eta)
 $ initialize:  expression({  n <- rep.int(1, nobs)  if (is.null(etastart) && is.null(start) &&
     is.null(mustart) &&  ((family$link| __truncated__
 $ validmu   :function (mu)
 $ valideta  :function (eta)
 - attr(*, "class")= chr "family"
```

linkfun and linkinv

Link function is a transformation of the response variable

```
gaussian()$linkfun
```

```
function (mu)
mu
```

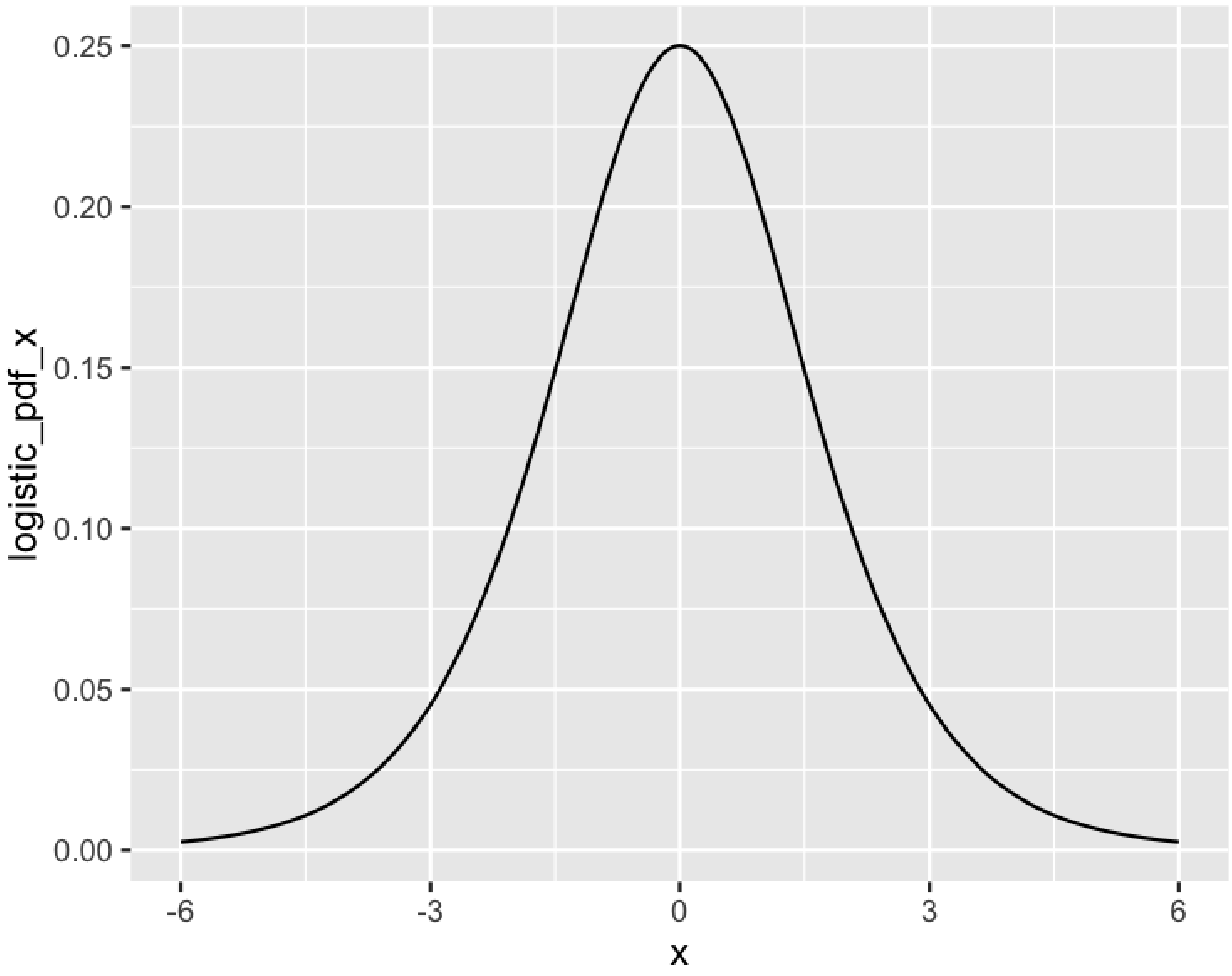
```
gaussian()$linkinv
```

```
function (eta)
eta
```

Logistic PDF

```
logistic_distn <- tibble(
  x = seq(-6, 6, 0.05),
  logistic_pdf_x = dlogis(x)
)
```

```
ggplot(logistic_distn, aes(x, logistic_pdf_x)) +
  geom_line()
```



Logistic distribution

- Logistic distribution CDF is also called the *logistic function*.
- $\text{cdf}(x) = \frac{1}{(1+exp(-x))}$
- Logistic distribution inverse CDF is also called the *logit function*.
- $\text{inverse\_cdf}(p) = log(\frac{p}{(1-p)})$

Let's practice!

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How logistic regression works

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Sum of squares doesn't work

```
sum((y_pred - y_actual) ^ 2)
```

`y_actual` is always `0` or `1`.

`y_pred` is between `0` and `1`.

There is a better metric than sum of squares.

Likelihood

```
y_pred * y_actual
```

Likelihood

```
y_pred * y_actual + (1 - y_pred) * (1 - y_actual)
```

Likelihood

```
sum(y_pred * y_actual + (1 - y_pred) * (1 - y_actual))
```

When `y_actual = 1`

```
y_pred * 1 + (1 - y_pred) * (1 - 1) = y_pred
```

When `y_actual = 0`

```
y_pred * 0 + (1 - y_pred) * (1 - 0) = 1 - y_pred
```

Log-likelihood

- Computing likelihood involves adding many very small numbers, leading to numerical error.
- Log-likelihood is easier to compute.

```
log(y_pred) * y_actual + log(1 - y_pred) * (1 - y_actual)
```

Both equations give the same answer.

Negative log-likelihood

Maximizing log-likelihood is the same as minimizing negative log-likelihood.

```
-sum(log_likelihoods)
```

Logistic regression algorithm

```
calc_neg_log_likelihood <- function(coeffs) {
  intercept <- coeffs[1]
  slope <- coeffs[2]
  # More calculation!
}
```

```
optim(
  par = ???,
  fn = ???
)
```

Let's practice!

Congratulations

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You learned things

Chapter 1

- Fit/visualize/predict/assess parallel slopes

Chapter 2

- Interactions between explanatory variables
- Simpson's Paradox

Chapter 3

- Extend to many explanatory variables
- Implement linear regression algorithm

Chapter 4

- Logistic regression with multiple explanatory variables
- Logistic distribution
- Implement logistic regression algorithm

There is more to learn

- Training and testing sets
- Cross validation
- P-values and significance

Advanced regression

- Modeling with Data in the Tidyverse
- Generalized Linear Models in R
- Machine Learning with caret in R
- Bayesian Regression Modeling with rstanarm

Let's practice!