

Welcome and Introduction

SUPERVISED LEARNING IN R: REGRESSION



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What is Regression?

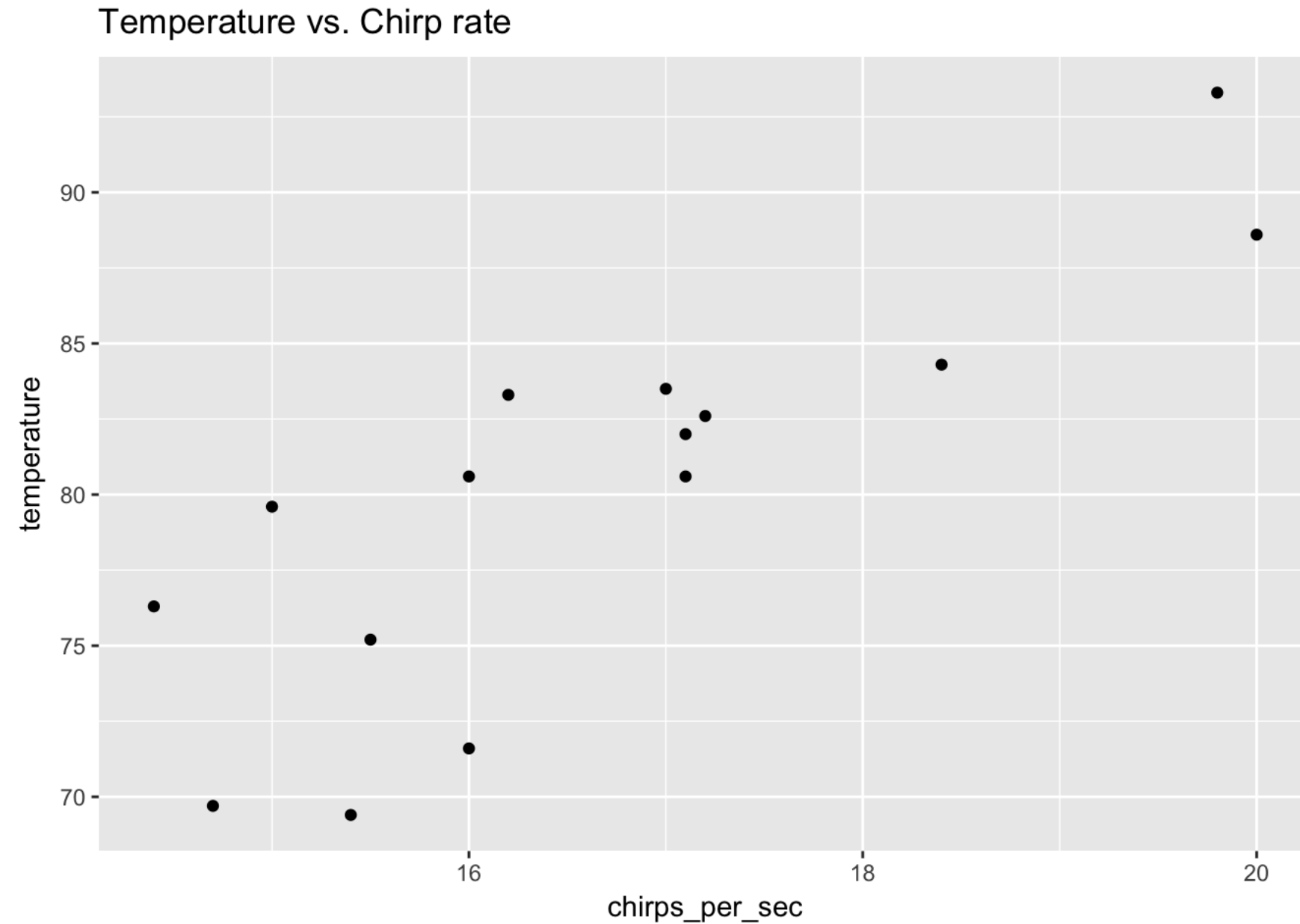
Regression: Predict a numerical outcome ("dependent variable") from a set of inputs ("independent variables").

- *Statistical Sense:* Predicting the expected value of the outcome.
- *Casual Sense:* Predicting a numerical outcome, rather than a discrete one.

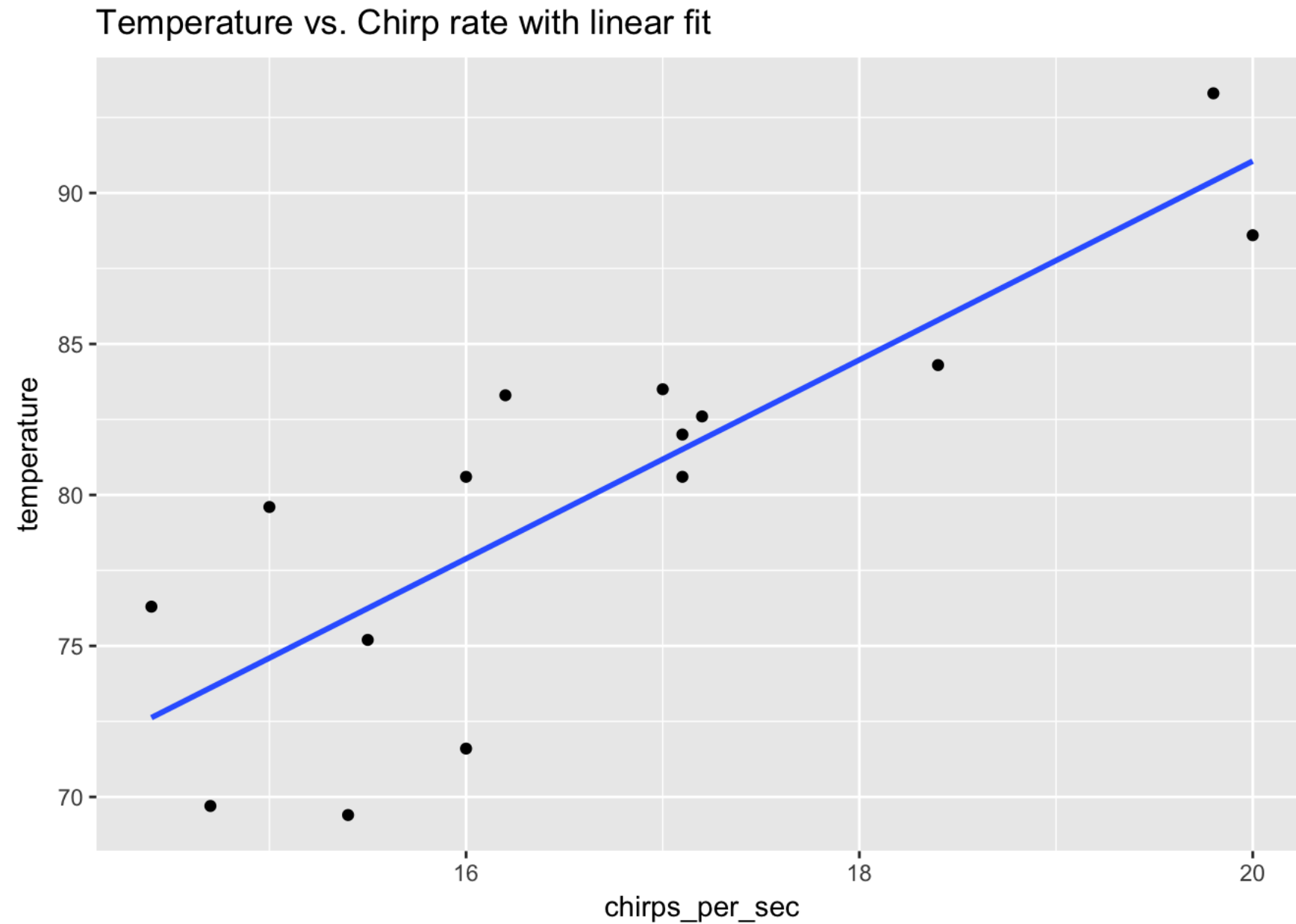
What is Regression?

- *How many units will we sell?* (**Regression**)
- *Will this customer buy our product (yes/no)?* (**Classification**)
- *What price will the customer pay for our product?*
(**Regression**)

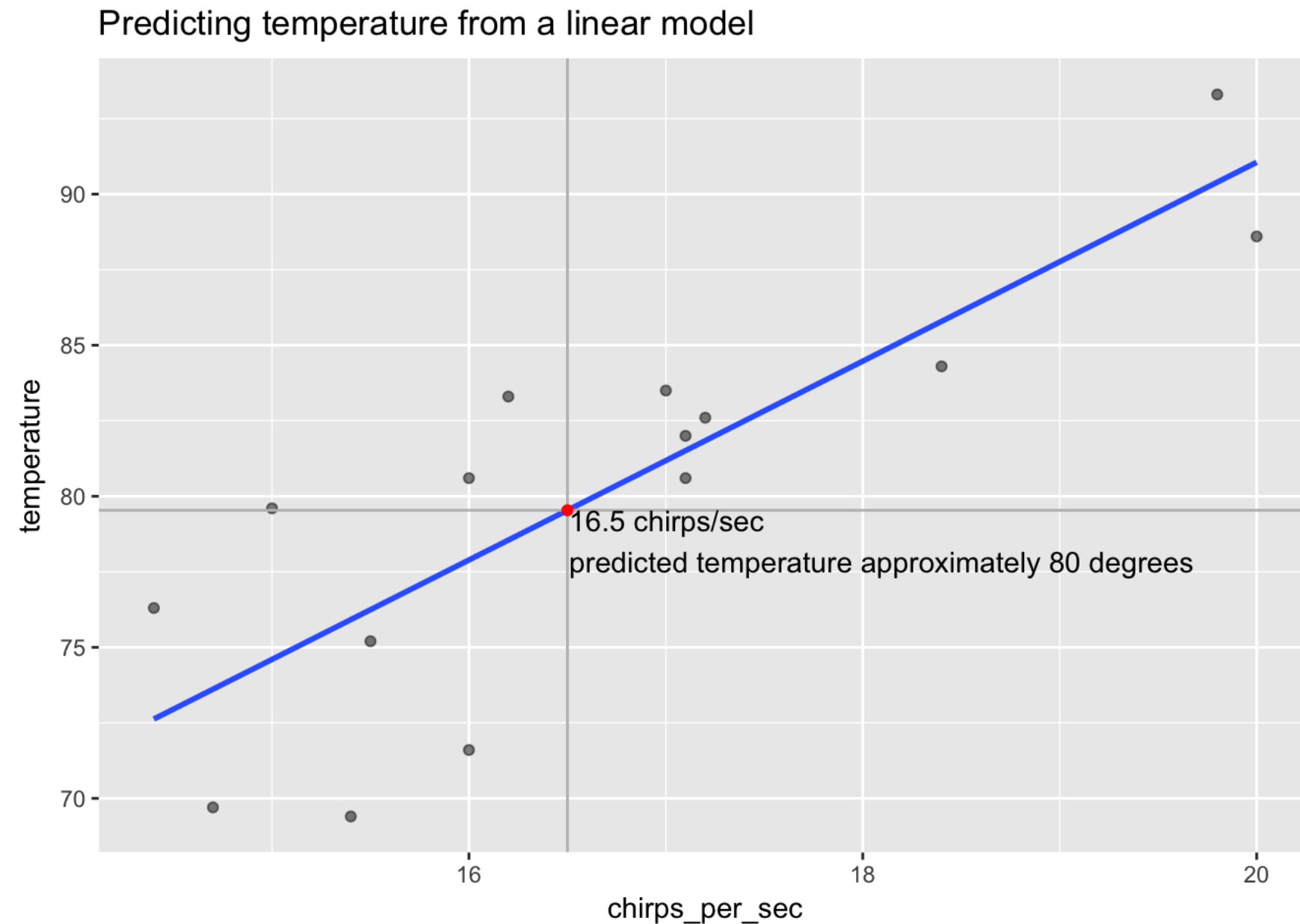
Example: Predict Temperature from Chirp Rate



Predict Temperature from Chirp Rate



Predict Temperature from Chirp Rate



Regression from a Machine Learning Perspective

- *Scientific mindset*: Modeling to understand the data generation process
 - *Engineering mindset*: *Modeling to predict accurately

Machine Learning: Engineering mindset

Let's practice!

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Linear regression - the fundamental method

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Linear Regression

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots$$

- y is *linearly* related to each x_i
- Each x_i contributes *additively* to y

Linear Regression in R: lm()

```
cmodel <- lm(temperature ~ chirps_per_sec, data = cricket)
```

- formula: `temperature ~ chirps_per_sec`
- data frame: `cricket`

Formulas

```
fm1a_1 <- temperature ~ chirps_per_sec  
fm1a_2 <- blood_pressure ~ age + weight
```

- LHS: outcome
- RHS: inputs
 - use `+` for multiple inputs

```
fm1a_1 <- as.formula("temperature ~ chirps_per_sec")
```

Looking at the Model

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots$$

```
cmodel
```

```
Call:
```

```
lm(formula = temperature ~ chirps_per_sec, data = cricket)
```

```
Coefficients:
```

(Intercept)	chirps_per_sec
25.232	3.291

More Information about the Model

```
summary(cmodel)
```

```
Call:
lm(formula = fmla, data = cricket)

Residuals:
    Min       1Q   Median       3Q      Max
-6.515 -1.971  0.490  2.807  5.001

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)    25.2323    10.0601   2.508 0.026183 *
chirps_per_sec  3.2911     0.6012   5.475 0.000107 ***

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

Residual standard error: 3.829 on 13 degrees of freedom
Multiple R-squared:  0.6975, Adjusted R-squared:  0.6742
F-statistic: 29.97 on 1 and 13 DF, p-value: 0.0001067
```

More Information about the Model

```
broom::glance(cmodel)
```

```
sigr::wrapFTest(cmodel)
```

Let's practice!

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Predicting once you fit a model

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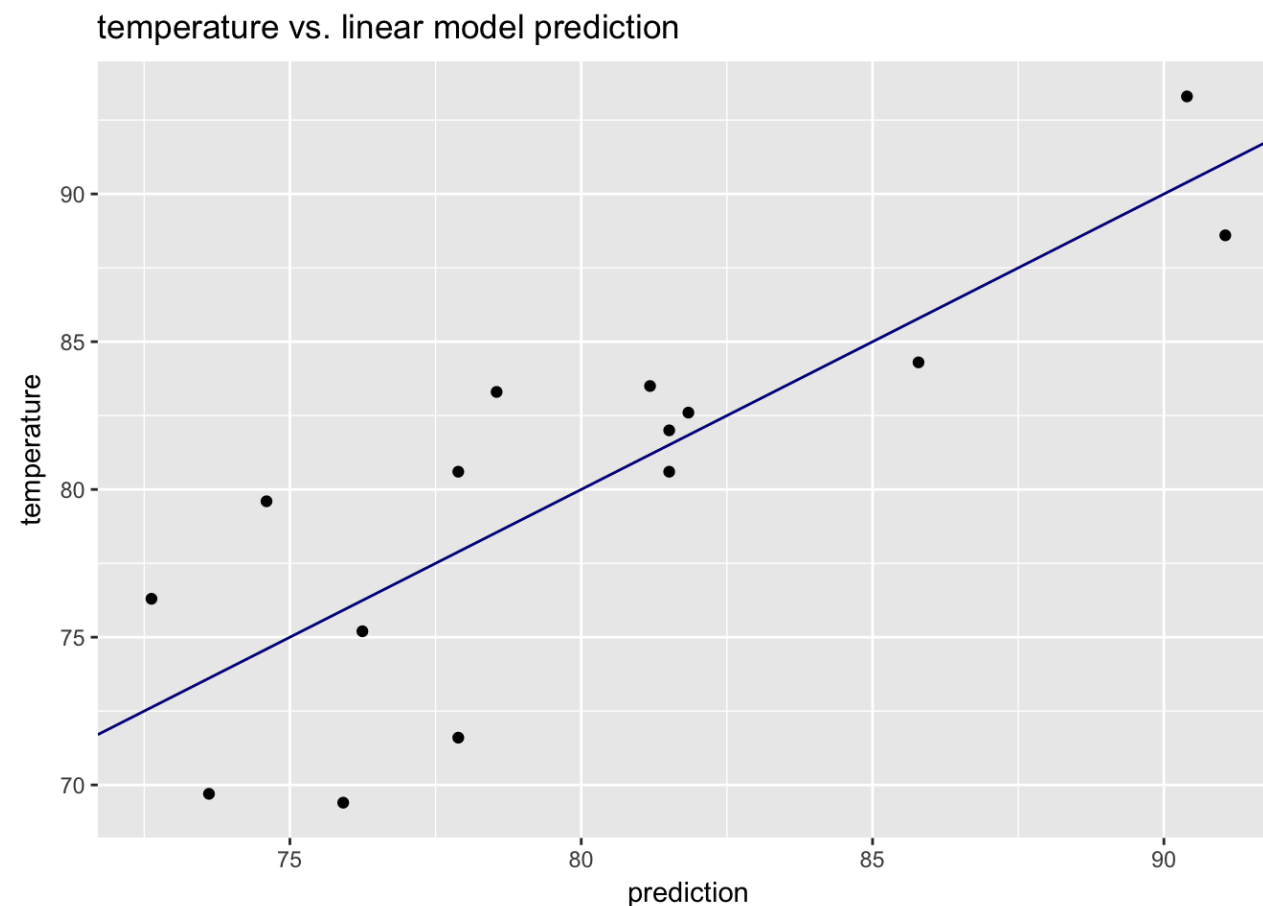
Predicting From the Training Data

```
cricket$prediction <- predict(cmodel)
```

- `predict()` by default returns training data predictions

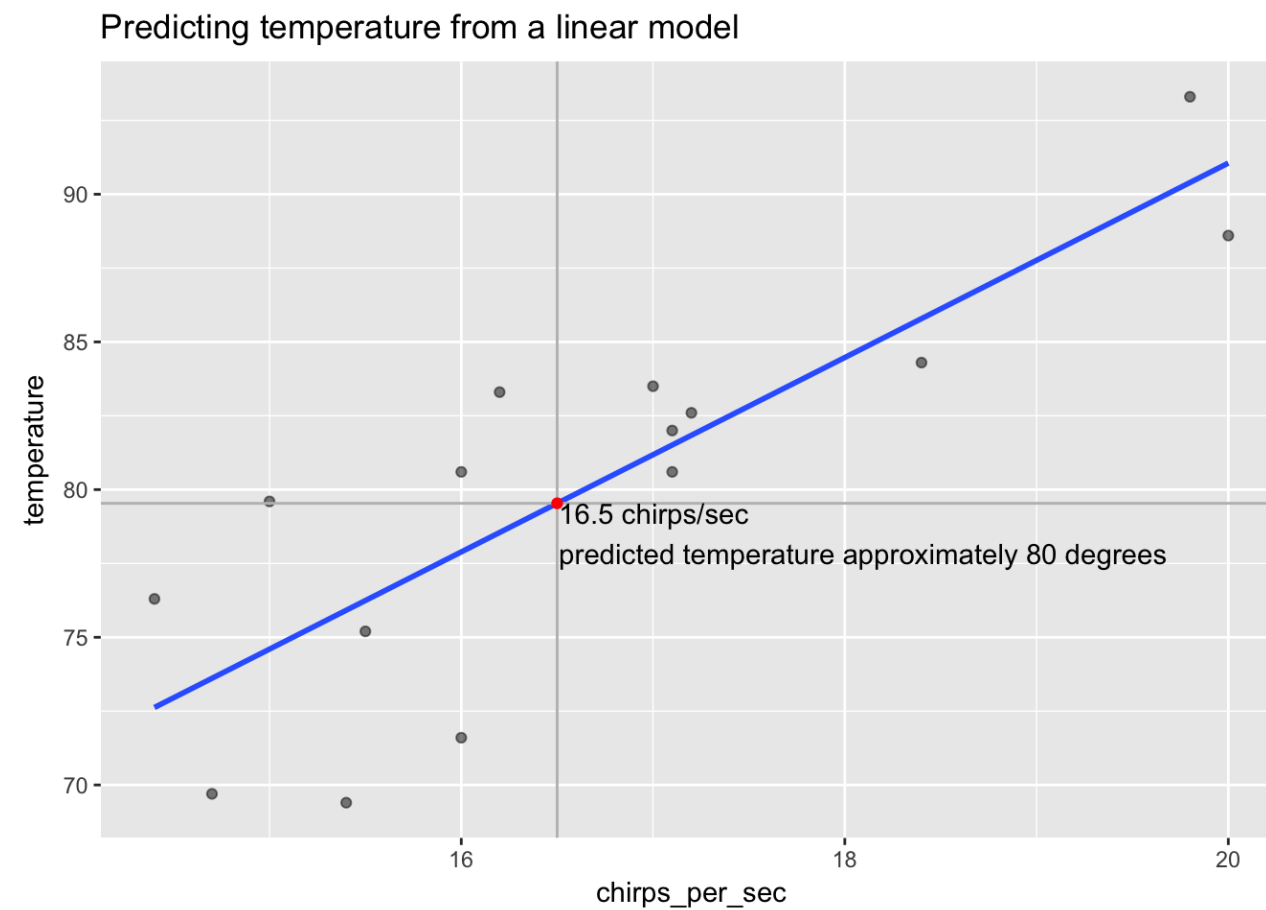
Looking at the Predictions

```
ggplot(cricket, aes(x = prediction, y = temperature)) +  
+   geom_point() +  
+   geom_abline(color = "darkblue") +  
+   ggtitle("temperature vs. linear model prediction")
```



Predicting on New Data

```
newchirps <- data.frame(chirps_per_sec = 16.5)
newchirps$prediction <- predict(cmodel, newdata = newchirps)
newchirps
  chirps_per_sec    pred
1         16.5 79.53537
```



Let's practice!

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Wrapping up linear regression

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Pros and Cons of Linear Regression

- Pros
 - Easy to fit and to apply
 - Concise
 - Less prone to overfitting

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 - Easy to fit and to apply
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 - **Interpretable**

Call:

```
lm(formula = blood_pressure ~ age + weight, data = bloodpressure)
```

Coefficients:

(Intercept)	age	weight
30.9941	0.8614	0.3349

Pros and Cons of Linear Regression

- Pros
 - Easy to fit and to apply
 - Concise
 - Less prone to overfitting
 - Interpretable
- Cons
 - Can only express linear and additive relationships

Collinearity

- **Collinearity** -- when input variables are partially correlated.

Call:

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Collinearity

- **Collinearity** -- when variables are partially correlated.
- Coefficients might change sign

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Collinearity

- **Collinearity** -- when variables are partially correlated.
- Coefficients might change sign
- High collinearity:
 - Coefficients (or standard errors) look too large
 - Model may be unstable

Call:

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```

Coefficients:

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Coming Next

- Evaluating a regression model
- Properly training a model

Let's practice!

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