SUPERVISED LEARNING IN R: REGRESSION

Welcome and Introduction

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What is Regression?

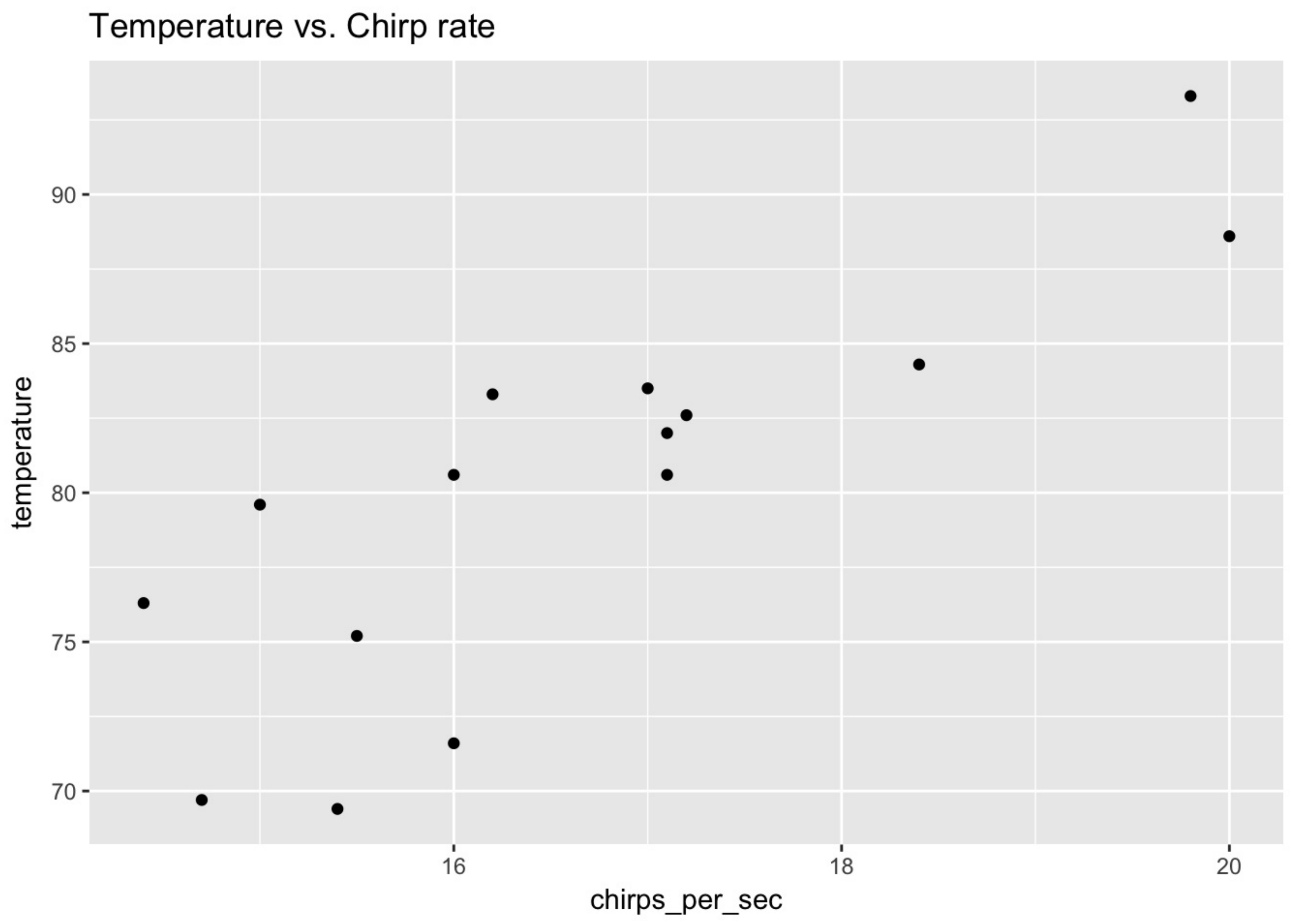
Regression: Predict a numerical outcome ("dependent variable") from a set of inputs ("independent variables").

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

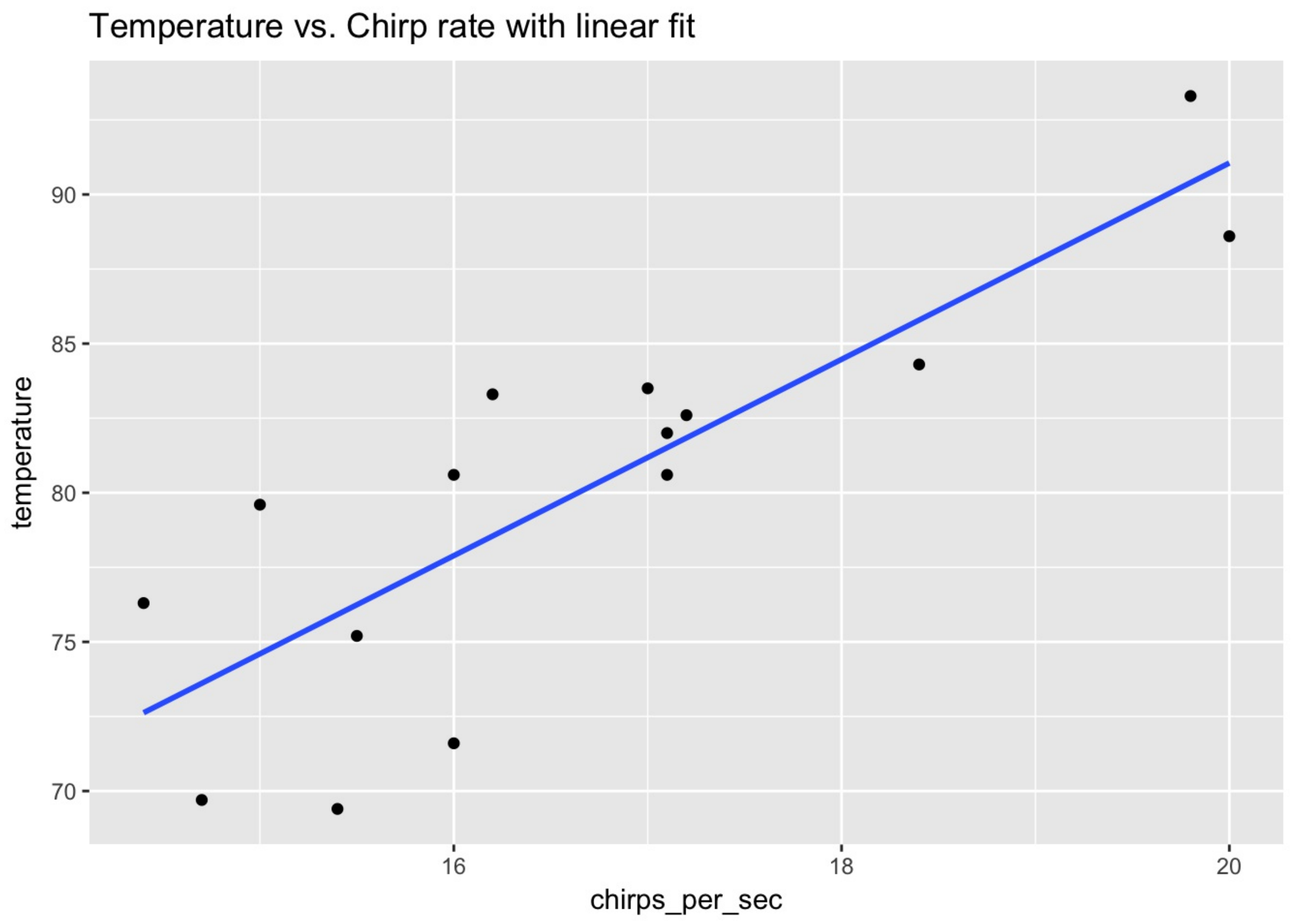
What is Regression?

- *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



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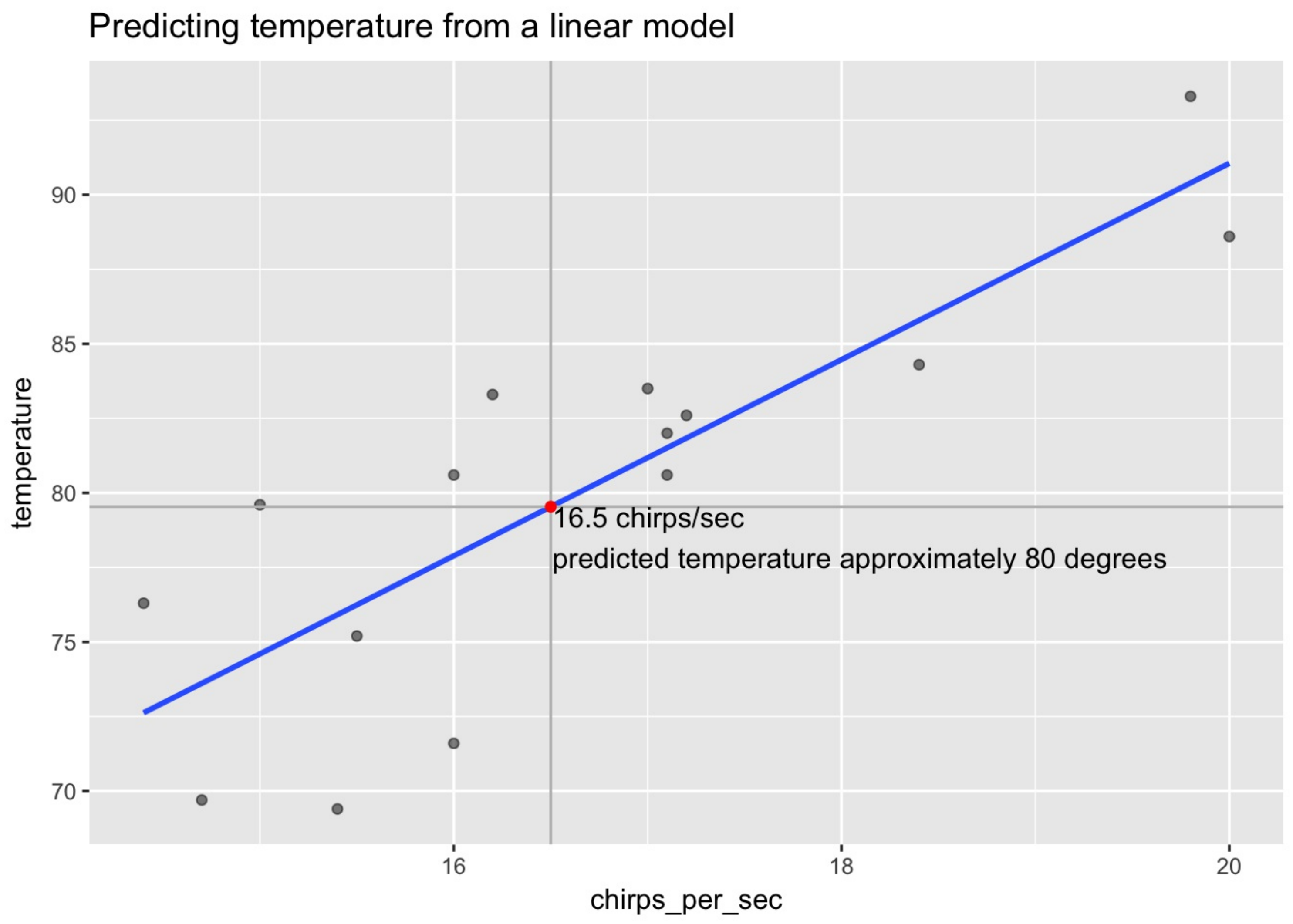

Regression from a Machine Learning Perspective

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

Machine Learning: Engineering mindset

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Let's practice!

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Linear regression - the fundamental method

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Linear Regression

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

- 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

```
fmla <- temperature ~ chirps_per_sec
fmla <- blood_pressure ~ age + weight
```

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

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

Looking at the Model

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

```
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

broom::glance(cmodel)

sigr::wrapFTest(cmodel)
```

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Predicting once you fit a model

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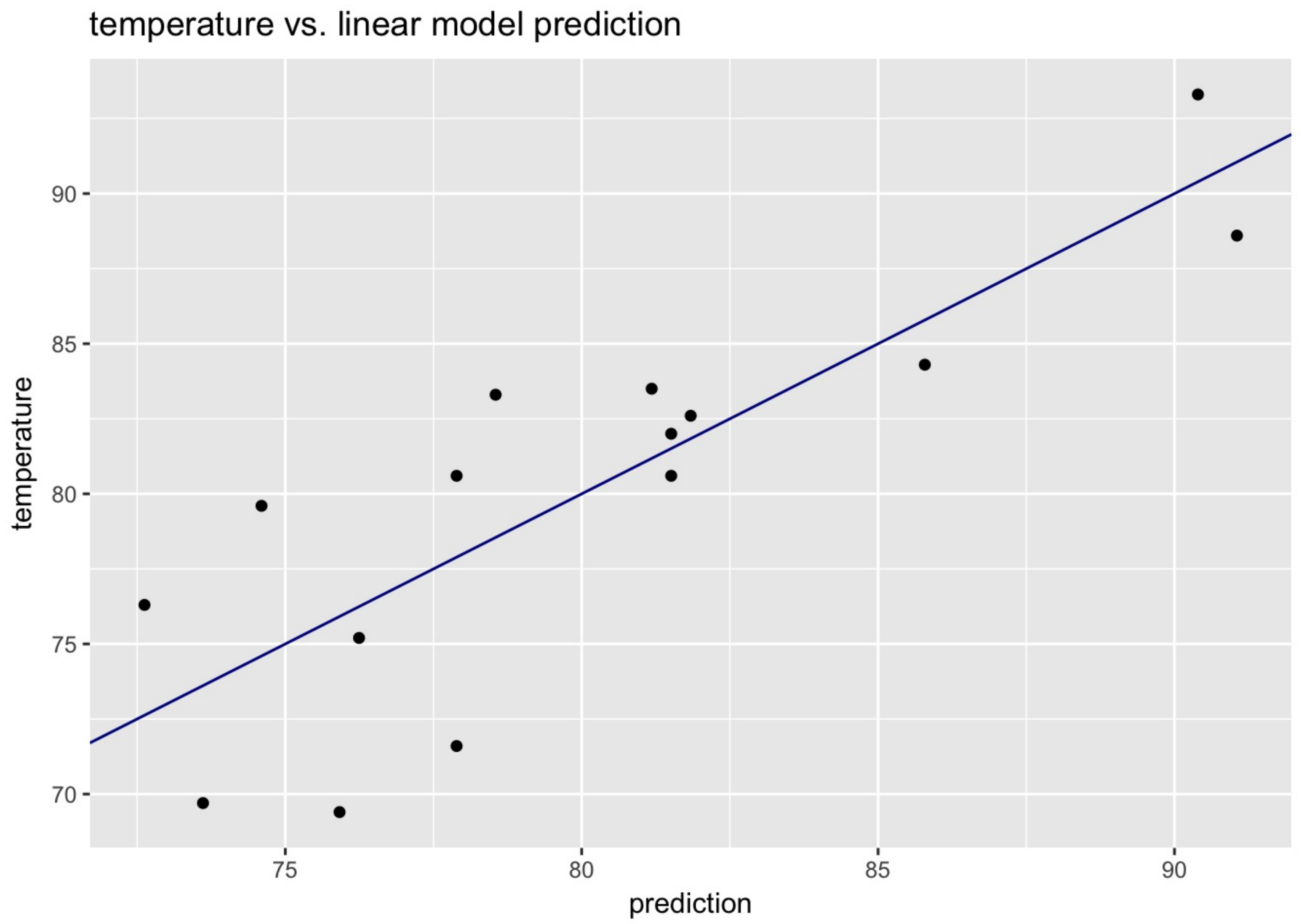
Predicting From the Training Data

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

- predict() by default returns training data predictions

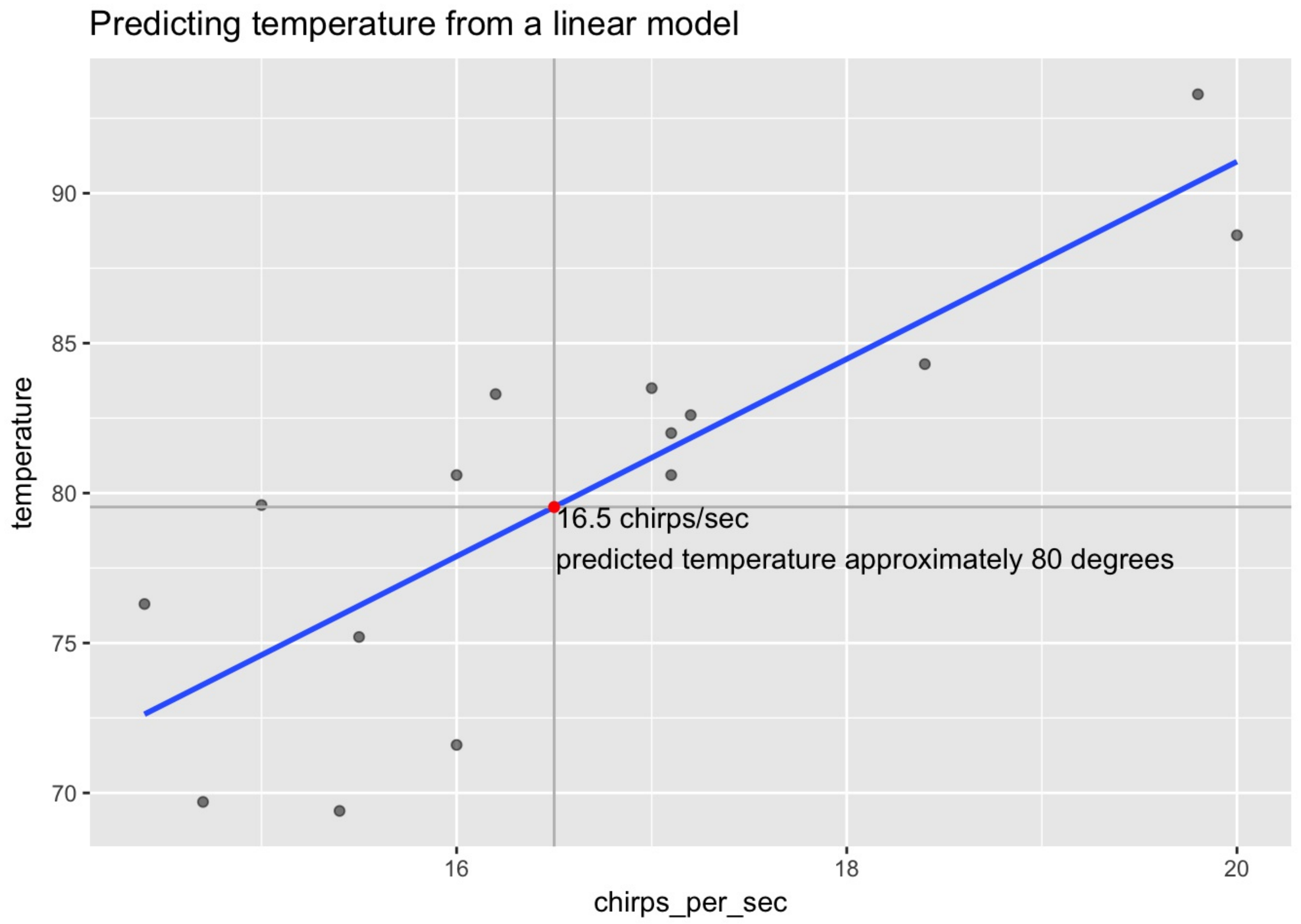
Looking at the Predictions

```
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
```



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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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  - **Interpretable**

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## 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.

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- Coefficients might change sign

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Collinearity

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- Coefficients might change sign
- High collinearity:
  - Coefficients (or standard errors) look too large
  - Model may be unstable

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Coming Next

- Evaluating a regression model
- Properly training a model