

AE6

Brandon Leslie

1). Generate 50 X values between 0 and 5.

```
set.seed(88)  
  
ex1 <- tibble(x = runif(50, 0, 5))
```

2). Generate 50 y values where $Y = -(X - 0.4)^2(X - 5.5) + 2 + \epsilon$ where ϵ is random normal with $\mu = 0, \sigma = 2.8$. There is no special significance to this form other than it gives a nice looking plot with a vaguely recognizable cubic shape.

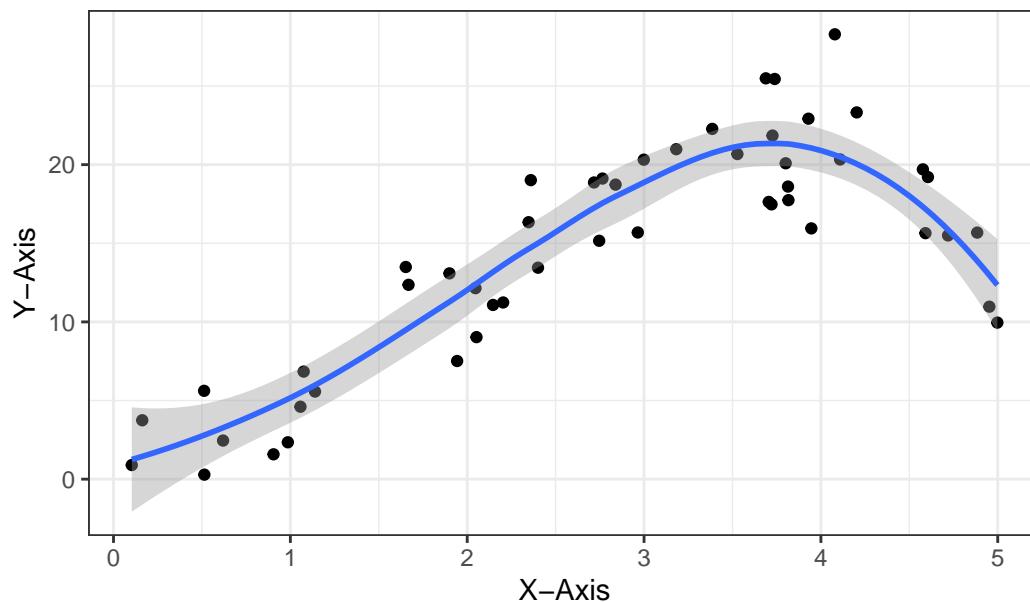
```
ex1 <- ex1 %>%  
  mutate(y = -(x - 0.4)^2 * (x - 5.5) + 2 + rnorm(50, 0, 2.8))
```

3). Plot a scatterplot of the data, and use `geom_smooth()` to plot a smoothed curve for polynomials of various degree.

```
ex1 %>% ggplot(aes(x = x, y = y)) +  
  geom_point() +  
  geom_smooth() + labs(  
    x = "X-Axis",  
    y = "Y-Axis",  
    title = "Smoothed Curve for Polynomials of Various Degree"
```

```
) +  
theme_bw()
```

Smoothed Curve for Polynomials of Various Degree



4). Split the data into Train and Test sets, with 70/30 split.

```
set.seed(88)  
  
Splitting <- sample(1:nrow(ex1), size = 0.70 * nrow(ex1))  
  
Test <- ex1[-Splitting, ]  
Train <- ex1[Splitting, ]
```

5). Fit polynomial regression models of degree 1, 2, 3, 5, 10, 20 on the training set, predict both training and Test sets, and find rmse and r-squared values.

```

rec <- recipe(y ~ x, data = Train) %>%
  step_poly(x, degree = 4)
rec %>% prep() %>% bake(Train) %>% head()

# A tibble: 6 x 5
#>   y     x_poly_1 x_poly_2 x_poly_3 x_poly_4
#>   <dbl>    <dbl>    <dbl>    <dbl>    <dbl>
#> 1 23.3     0.199    0.145   -0.00588  -0.151
#> 2 19.1      0.0150   -0.167   -0.0508    0.171
#> 3 20.3      0.187    0.112   -0.0462   -0.157
#> 4 25.4      0.140   -0.00107  -0.141    -0.0957
#> 5 12.4     -0.126   -0.126     0.207   -0.0668
#> 6  5.62    -0.274    0.178   -0.00116  -0.176

rec <- recipe(y ~ x, data = Train) %>%
  step_poly(x, degree = 15)
flow <- workflow() %>%
  add_recipe(rec) %>%
  add_model(linear_reg())

flow_fit <- flow %>% fit(data = Train)

pred_train <- predict(flow_fit, new_data = Train)
pred_test <- predict(flow_fit, new_data = Test)

results_train <- bind_cols(pred_train, Train %>% select(y))
results_test <- bind_cols(pred_test, Test %>% select(y))

metrics <- metric_set(yardstick::rsq, yardstick::rmse)

print("Train Metrics")

```

[1] "Train Metrics"

```
results_train %>% metrics(truth = y, .pred)
```

```

# A tibble: 2 x 3
#>   .metric .estimator .estimate
#>   <chr>    <chr>        <dbl>
#> 1 rsq      standard     0.929
#> 2 rmse     standard     1.91

```

```

print("Test Metrics")

[1] "Test Metrics"

results_test %>% metrics(truth = y, .pred)

# A tibble: 2 x 3
  .metric .estimator .estimate
  <chr>   <chr>        <dbl>
1 rsq     standard     0.0403
2 rmse    standard     338.

```

6). Now repeat the above but use cross validation with k = 5 folds

```

rec <- recipe(y ~ x, data = Train) %>%
  step_poly(x, degree = 15)

folds <- vfold_cv(Train, v = 5)

flow <- workflow() %>%
  add_recipe(rec) %>%
  add_model(linear_reg())

results <- fit_resamples(flow, resamples = folds, metrics = metric_set
                        (yardstick::rsq, yardstick::rmse))

collect_metrics(results)

# A tibble: 2 x 6
  .metric .estimator     mean     n std_err .config
  <chr>   <chr>      <dbl> <int>   <dbl> <chr>
1 rmse    standard     1400.     5 1122. Preprocessor1_Model1
2 rsq     standard     0.362     5    0.156 Preprocessor1_Model1

```