MACHINE LEARNING IN THE TIDYVERSE

Exploring coefficients across models

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77 models

```
gap_nested <- gapminder %>%
              group_by(country) %>%
              nest()
gap_models <- gap_nested %>%
              mutate(model = map(data, ~lm(life_expectancy~year, data = .x)))
```

```
gap_models
# A tibble: 77 x 3
   country    data              model
   <fct>      <list>            <list>
 1 Algeria    <tibble [52 × 6]> <S3: lm>
 2 Argentina  <tibble [52 × 6]> <S3: lm>
 3 Australia  <tibble [52 × 6]> <S3: lm>
 4 Austria    <tibble [52 × 6]> <S3: lm>
 5 Bangladesh <tibble [52 × 6]> <S3: lm>
 6 Belgium    <tibble [52 × 6]> <S3: lm>
```

Regression coefficients

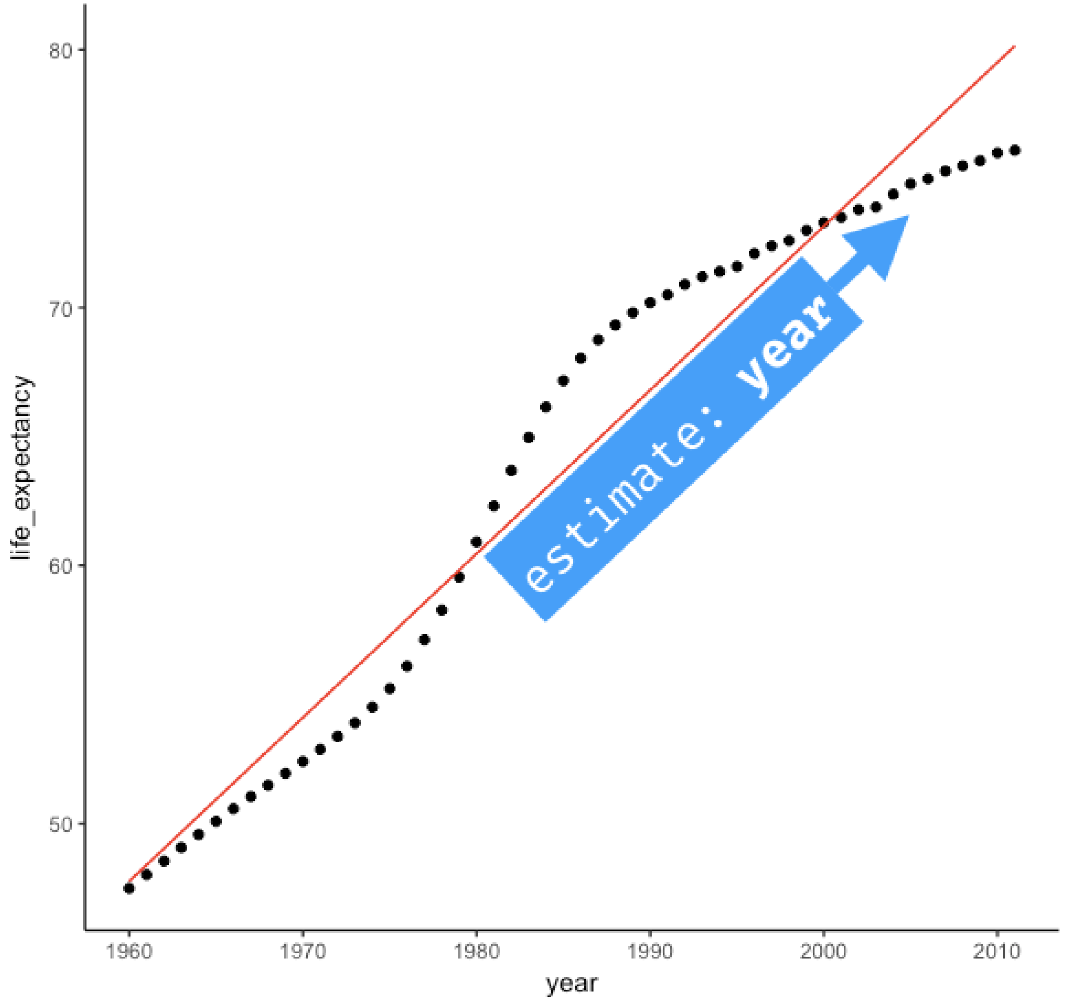
$$y = \alpha + \beta x$$

Regression coefficients

$$y = \alpha + \beta x$$

Life Expectancy	=	Term: **(intercept)**	+	Term: **year**	Year

```
tidy(gap_models$model[[1]])
         term      estimate      ...
1 (Intercept) -1196.5647772      ...
2        year     0.6348625      ...
```



Coefficients of multiple models

```
gap_models %>%
  mutate(coef = map(model, ~tidy(.x))) %>%
  unnest(coef)
```

```
# A tibble: 154 x 6
   country    term        estimate std.error statistic  p.value
   <fct>      <chr>          <dbl>     <dbl>     <dbl>    <dbl>
 1 Algeria    (Intercept) -1197     39.9         -30.0 1.32e-33
 2 Algeria    year            0.635  0.0201       31.6 1.11e-34
 3 Argentina  (Intercept) - 372      7.91        -47.0 4.66e-43
 4 Argentina  year            0.223  0.00398      56.0 8.78e-47
 5 Australia  (Intercept) - 429      9.37        -45.8 1.71e-42
 6 Australia  year            0.254  0.00472      53.9 5.83e-46
 7 Austria    (Intercept) - 415      8.04        -51.6 5.07e-45
 8 Austria    year            0.246  0.00405      60.8 1.48e-48
```

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Let's practice!

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Evaluating the fit of many models

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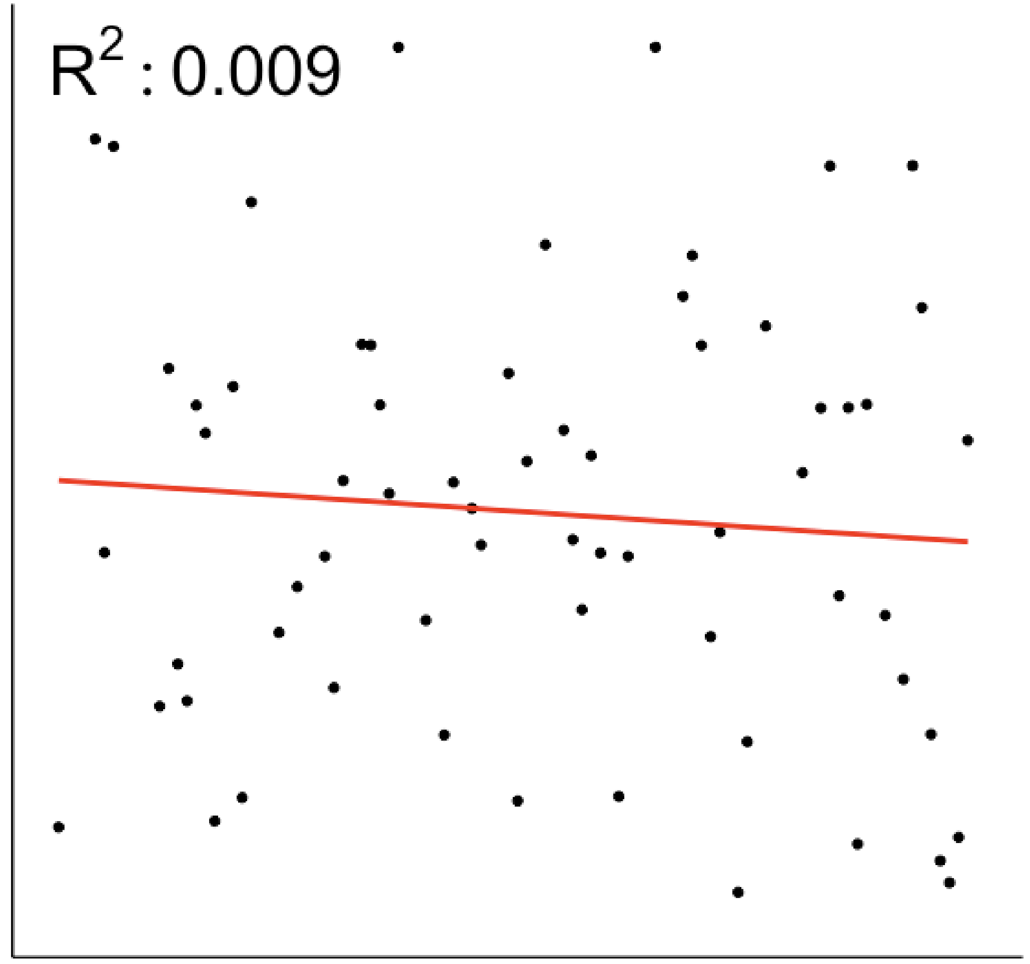
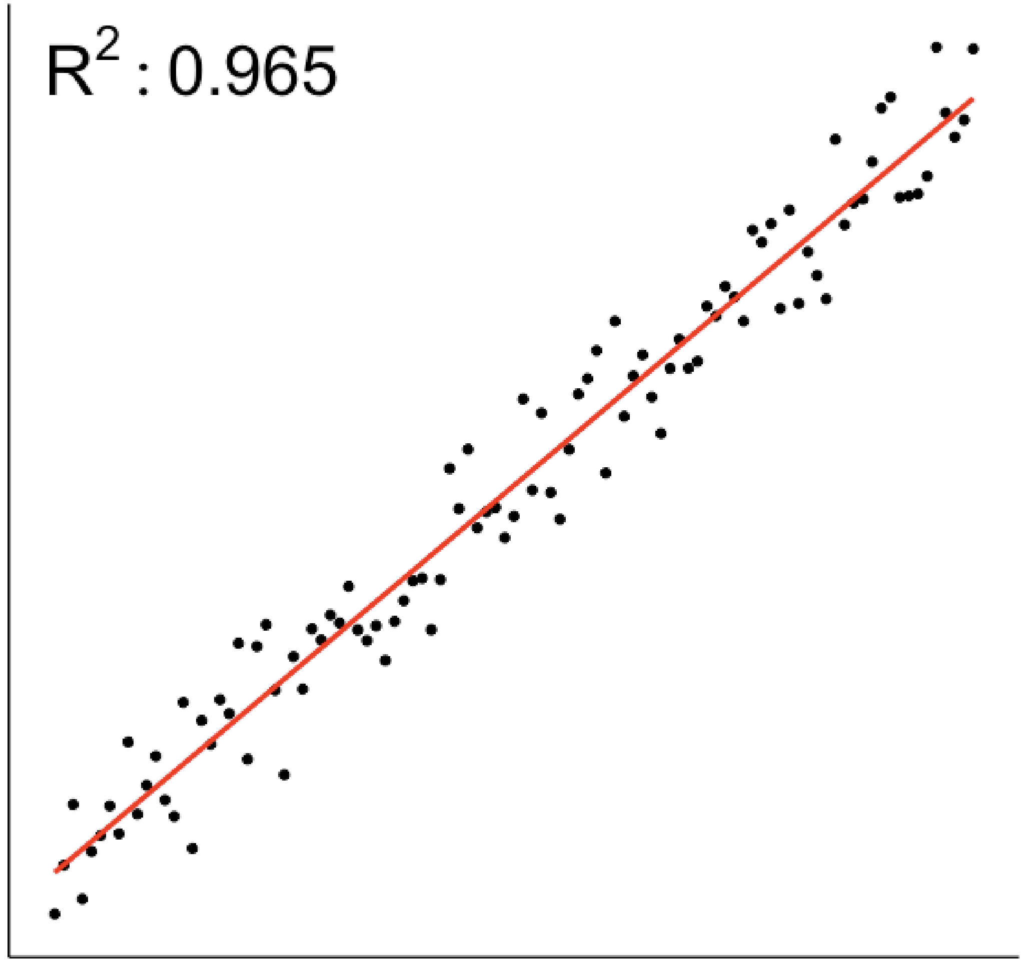
The fit of our models

$$R^2 = \frac{\%\ variation\ explained\ by\ the\ model}{\%\ total\ variation\ in\ the\ data}$$

The fit of our models





Glance across your models

```
model_perf <- gap_models %>%
  mutate(coef = map(model, ~glance(.x))) %>%
  unnest(coef)
```

```
model_perf

# A tibble: 77 x 14
   country  data   model r.squared adj.r.squared sigma statistic    ...
   <fct>    <lis> <lis>      <dbl>         <dbl> <dbl>     <dbl>    ...
 1 Algeria  <tib… <S3:…      0.952         0.951 2.18       996     ...
 2 Argenti… <tib… <S3:…      0.984         0.984 0.431     3137     ...
 3 Austral… <tib… <S3:…      0.983         0.983 0.511     2905     ...
 4 Austria  <tib… <S3:…      0.987         0.986 0.438     3702     ...
 5 Banglad… <tib… <S3:…      0.949         0.947 1.83       921     ...
 6 Belgium  <tib… <S3:…      0.990         0.990 0.331     5094     ...
 # ... with 71 more rows
```

Best & worst fitting models

```
model_perf %>%
  top_n(n = 2, wt = r.squared)

# A tibble: 2 x 14
  country data  model r.squared adj.r.squared sigma statistic
  <fct>   <lis> <lis>     <dbl>         <dbl> <dbl>     <dbl>
1 Canada  <tib… <S3:…     0.995         0.995 0.231     10117
2 Italy   <tib… <S3:…     0.997         0.997 0.226     15665
```

```
> model_perf %>%
    top_n(n = 2, wt = -r.squared)

# A tibble: 2 x 14
  country data  model r.squared adj.r.squared sigma statistic
  <fct>   <lis> <lis>     <dbl>         <dbl> <dbl>     <dbl>
1 Botswa~ <tib… <S3:…   0.0136       -0.00608  5.11     0.692
2 Lesotho <tib… <S3:…   0.00296      -0.0170   5.32     0.148
```

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Visually inspect the fit of your models

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Memorial Sloan Kettering Cancer Center

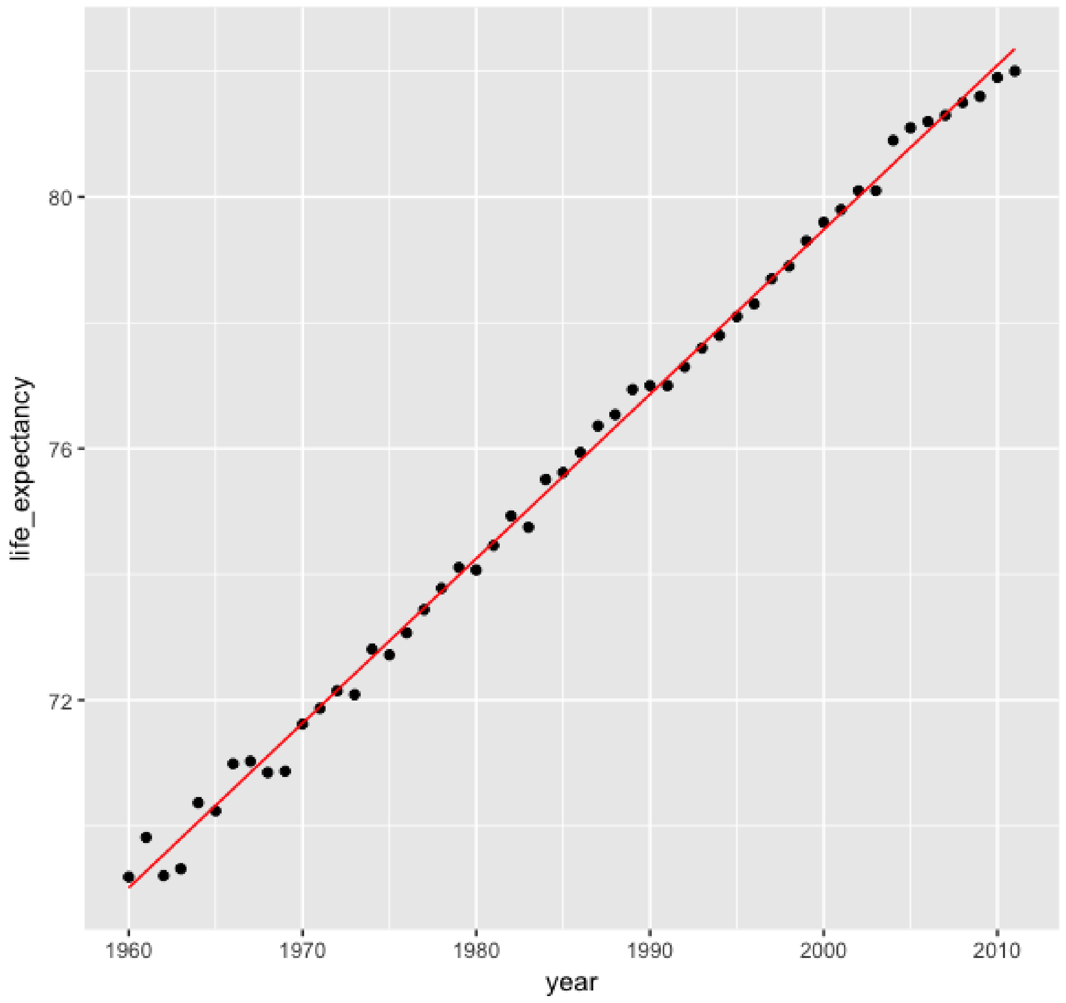
Building augmented datframes

```
augmented_models <- gap_models %>%
                    mutate(augmented = map(model, ~augment(.x))) %>%
                    unnest(augmented)
```

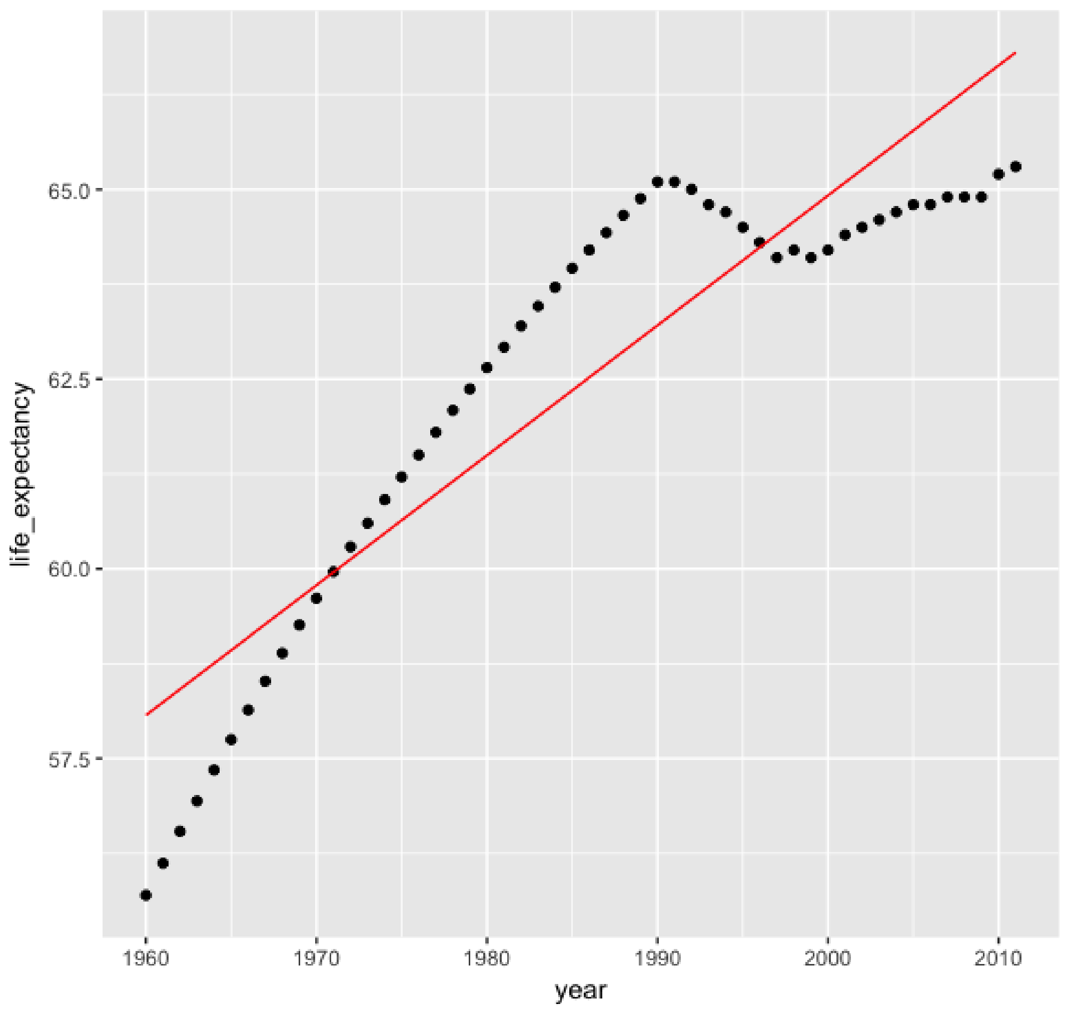
```
> augmented_models
# A tibble: 4,004 x 10
   country life_expectancy  year .fitted .se.fit .resid    .hat .sigma  ...
   <fct>             <dbl> <int>   <dbl>   <dbl>  <dbl>   <dbl>  <dbl>  ...
 1 Algeria            47.5  1960    47.8   0.595 -0.266 0.0747    2.20  ...
 2 Algeria            48.0  1961    48.4   0.578 -0.381 0.0705    2.20  ...
 3 Algeria            48.6  1962    49.0   0.561 -0.486 0.0664    2.20  ...
 4 Algeria            49.1  1963    49.7   0.544 -0.600 0.0625    2.20  ...
 5 Algeria            49.6  1964    50.3   0.527 -0.725 0.0587    2.20  ...
 6 Algeria            50.1  1965    50.9   0.511 -0.850 0.0551    2.20  ...
```

Model for Italy $R^2 : 0.99$

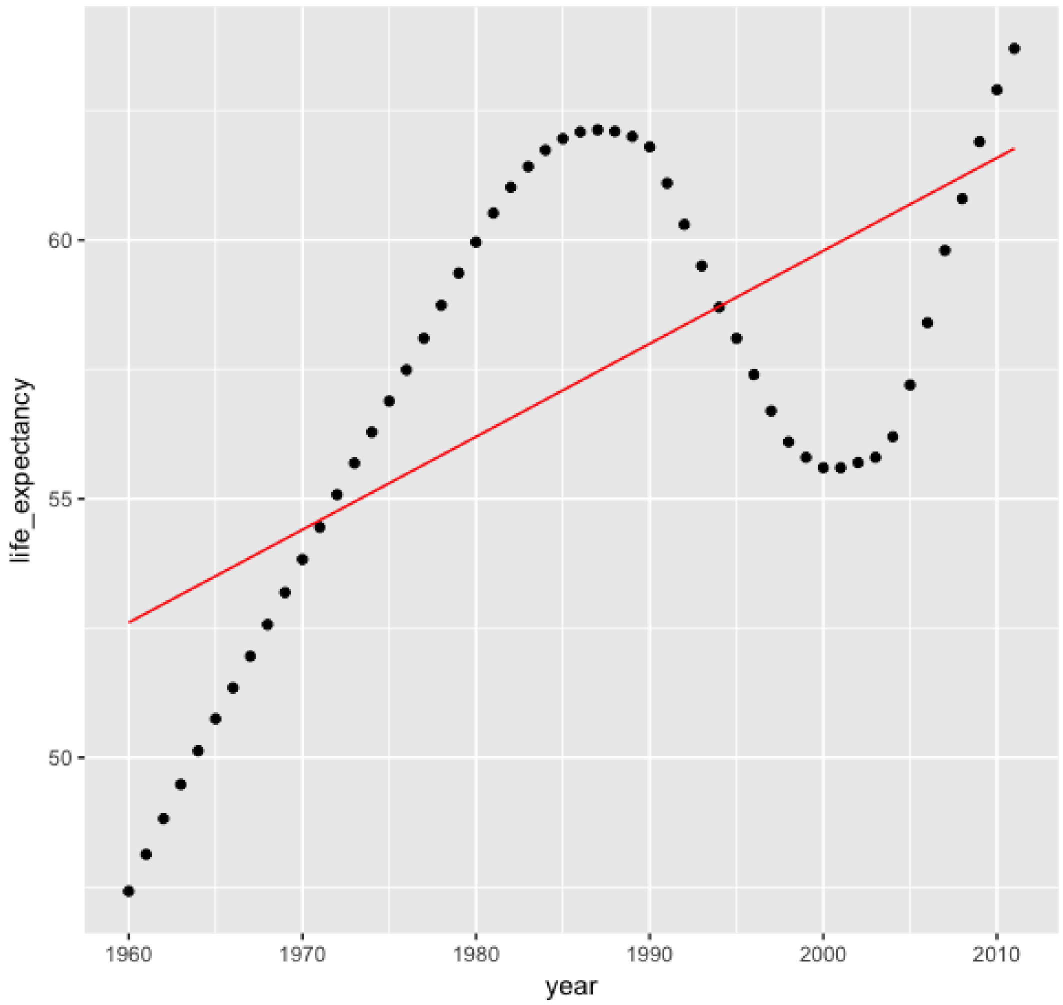
```
augmented_model %>% filter(country == "Italy") %>%
  ggplot(aes(x = year, y = life_expectancy)) +
  geom_point() +
  geom_line(aes(y = .fitted), color = "red")
```



Model for Fiji $R^2 : 0.82$



Model for Kenya $R^2 : 0.42$



MACHINE LEARNING IN THE TIDYVERSE

Let's practice!

MACHINE LEARNING IN THE TIDYVERSE

Improve the fit of your models

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Multiple Linear Regression model

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

Life Expectancy	=	Term: **(intercept)**	+	Term: **year**	Year	+	Term: **population**	Population	+	Term: **...**	...

Available Features: year, population, infant_mortality, fertility, gdpPercap

Using all features

Simple Linear Model: **life_expectancy ~ year**

```
gap_models <- gap_nested %>%
  mutate(model = map(data, ~lm(formula = life_expectancy ~ year, data = .x)))
```

Multiple Linear Model: **life_expectancy ~ year + population + ...**

Multiple Linear Model: **life_expectancy ~ .**

```
gap_fullmodels <- gap_nested %>%
  mutate(model = map(data, ~lm(formula = life_expectancy ~ ., data = .x)))
```

Using broom with Multiple Linear Regression models

```
tidy(gap_fullmodels$model[[1]])
              term      estimate    std.error  statistic      p.value
1      (Intercept) -1.830195e+03 1.502271e+02 -12.182848 5.325478e-16
2             year  9.814091e-01 7.800580e-02  12.581232 1.693870e-16
3 infant_mortality -1.603504e-01 4.021732e-03 -39.870986 2.525847e-37
4        fertility -2.600935e-01 1.648652e-01  -1.577614 1.215074e-01
5       population -1.611437e-06 1.704374e-07  -9.454716 2.347590e-12
6        gdpPercap -1.797662e-03 4.878209e-04  -3.685086 6.008755e-04
```

```
augment(gap_fullmodels$model[[1]])
   life_expectancy year infant_mortality fertility population ...   .fitted
1            47.50 1960            148.2      7.65   11124892 ...  47.45394
2            48.02 1961            148.1      7.65   11404859 ...  48.35078
3            48.55 1962            148.2      7.65   11690152 ...  49.26449
...            ...  ...              ...       ...        ... ...  ...
```

```
glance(gap_fullmodels$model[[1]])
  r.squared adj.r.squared     sigma statistic      p.value df    logLik ...
1 0.9990732     0.9989724 0.3160595  9917.133 1.562325e-68  6 -10.70225 ...
```

Adjusted R^2

```
glance(gap_fullmodels$model[[1]])

  r.squared adj.r.squared     sigma statistic      p.value df    logLik ...
1 0.9990732     0.9989724 0.3160595  9917.133 1.562325e-68  6 -10.70225 ...
```

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