Exploring coefficients across models

MACHINE LEARNING IN THE TIDYVERSE

Dmitriy (Dima) Gorenshteyn
Lead Data Scientist, <Memorial Sloan Kettering Cancer Center

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>
```

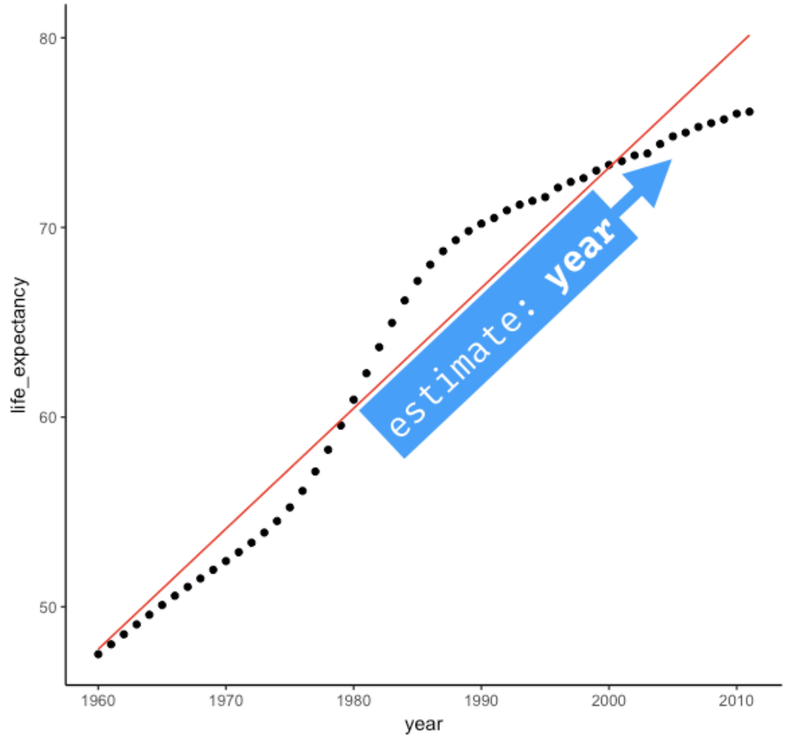
Regression coefficients

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

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
```

Let's practice!

MACHINE LEARNING IN THE TIDYVERSE

Evaluating the fit of many models

MACHINE LEARNING IN THE TIDYVERSE

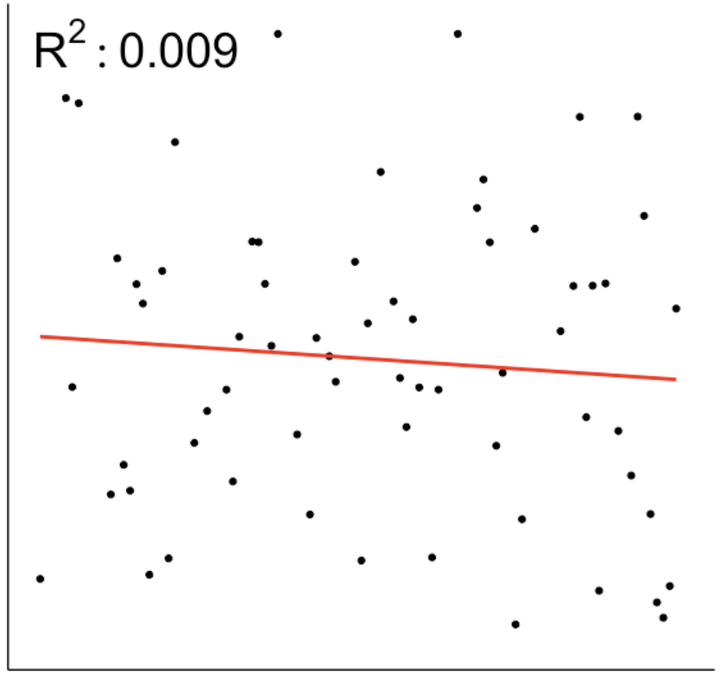
Dmitriy (Dima) Gorenshteyn
Lead Data Scientist, Memorial Sloan Kettering Cancer Center

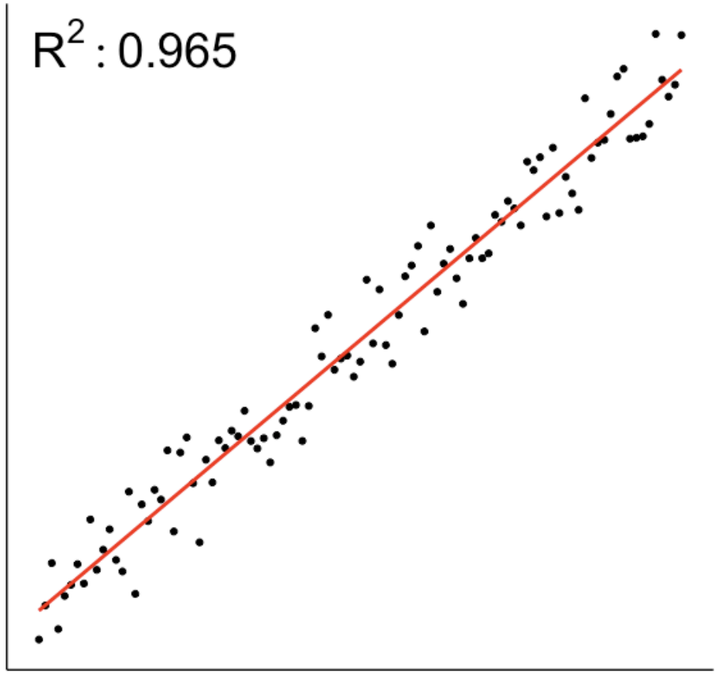
datacamp

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    ...
 # ... with 72 more rows
```

```
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
```

Let's practice!

MACHINE LEARNING IN THE TIDYVERSE

Visually inspect the fit of your models

MACHINE LEARNING IN THE TIDYVERSE

Dmitriy (Dima) Gorenshteyn
Lead Data Scientist, Memorial Sloan Kettering Cancer Center

datacamp

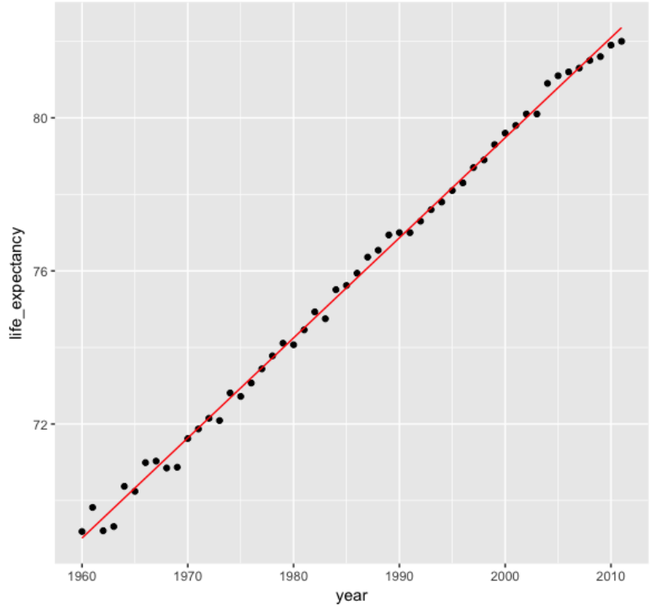
Building augmented datframes

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

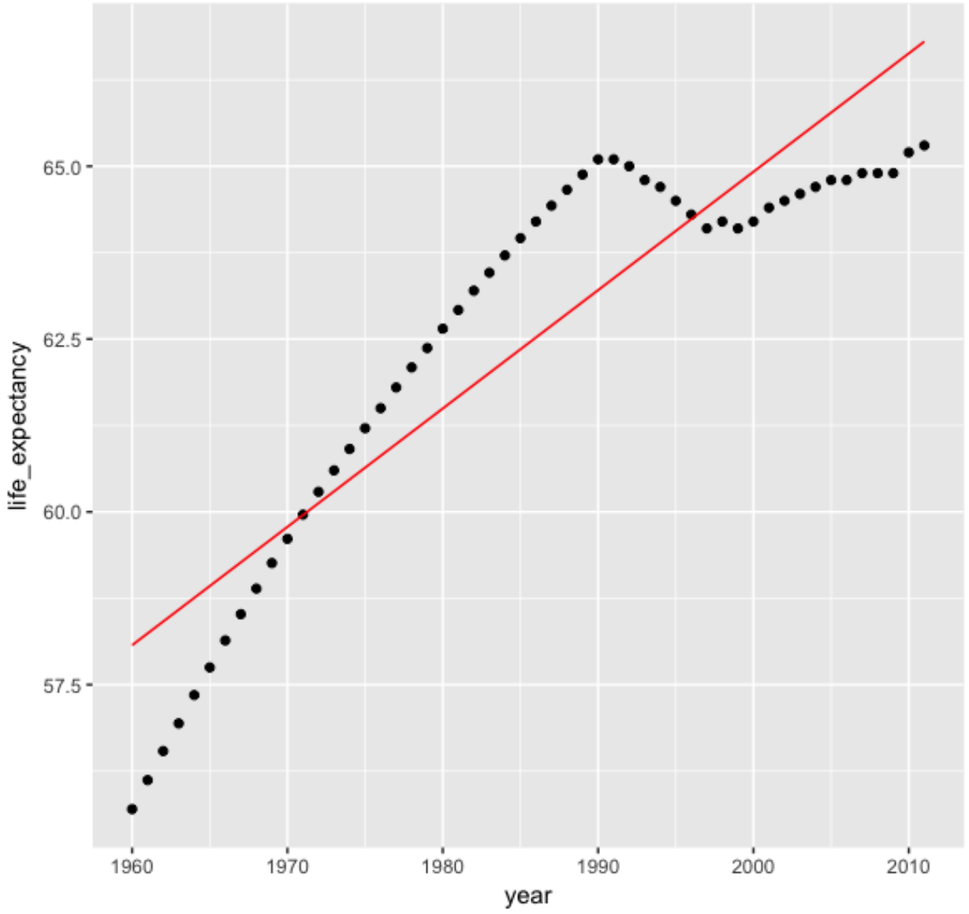
```
# A tibble: 4,004 x 10
   country life_expectancy  year .fitted .se.fit .resid   .hat .sigma
   <fct>              <dbl> <int>   <dbl>   <dbl>  <dbl>  <dbl>  <dbl>
 1 Algeria             47.5  1960    47.8   0.595 -0.266 0.0747   2.20
 2 Algeria             48.0  1961    48.4   0.578 -0.381 0.0705   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

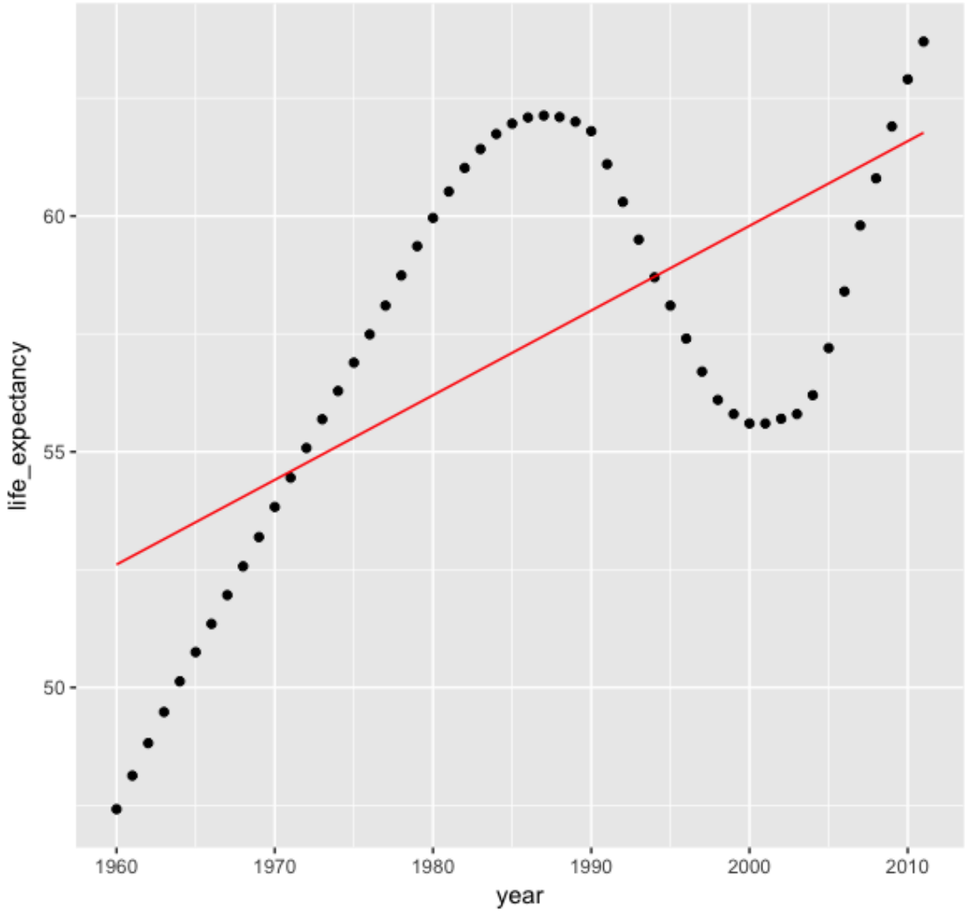
```
augmented_model %>% filter(country == "Italy") %>%
  ggplot(aes(x = year, y = life_expectancy)) +
  geom_point() +
  geom_line(aes(y = .fitted), color = "red")
```



Model for Fiji R^2 : 0.82



Model for Kenya R^2 : 0.42



Let's practice!

MACHINE LEARNING IN THE TIDYVERSE

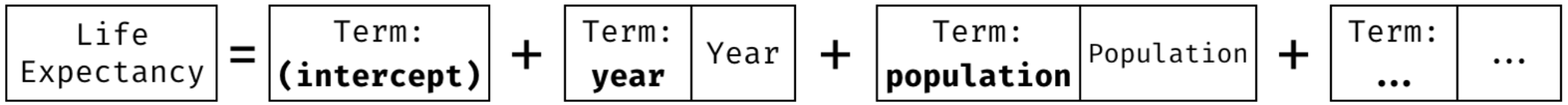
Improve the fit of your models

MACHINE LEARNING IN THE TIDYVERSE

Dmitriy (Dima) Gorenshteyn
Lead Data Scientist, Memorial Sloan Kettering Cancer Center

Multiple Linear Regression model

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



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)))
```

```
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
```

```
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 ...
```

Let's practice!

MACHINE LEARNING IN THE TIDYVERSE