

cm014 Worksheet: The Model-Fitting Paradigm in R

```
suppressPackageStartupMessages(library(tidyverse))
library(gapminder)
library(broom)
```

So you want to fit a model to your data. How can you achieve this with R?

Topics:

1. What *is* model-fitting?
2. How do we fit a model in R?
3. How can we obtain tidy results from the model output?

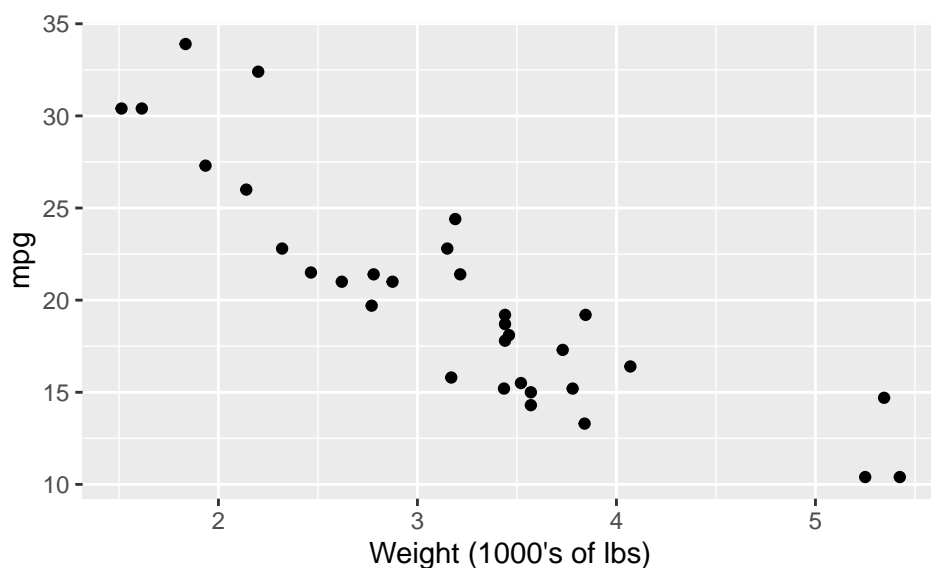
What is Model-Fitting?

When variables are not independent, then we can gain information about one variable if we know something about the other.

Examples: Use the scatterplot below:

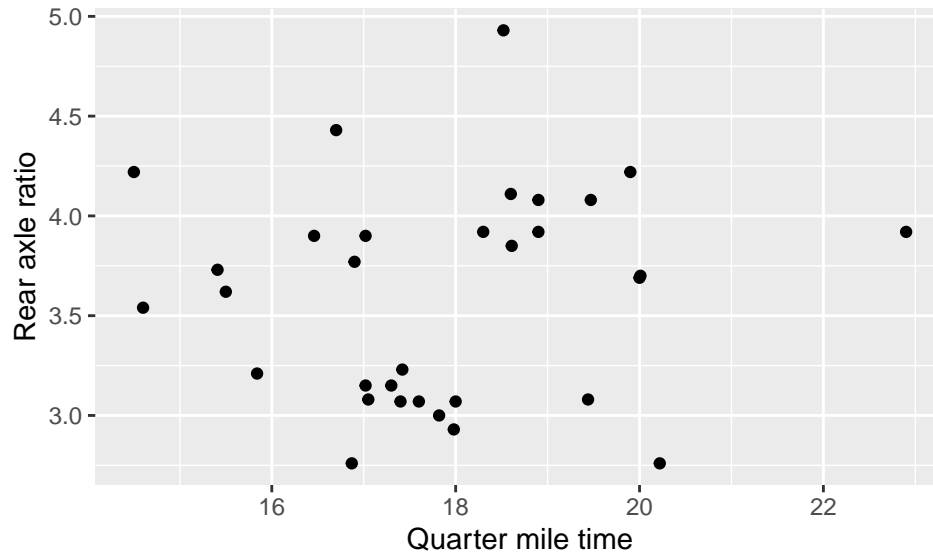
1. A car weighs 4000 lbs. What can we say about its mpg?
2. A car weighs less than 3000 lbs. What can we say about its mpg?

```
library(tidyverse)
ggplot(mtcars, aes(wt, mpg)) +
  geom_point() +
  labs(x = "Weight (1000's of lbs)")
```



Example: What can we say about rear axle ratio if we know something about quarter mile time?

```
ggplot(mtcars, aes(qsec, drat)) +
  geom_point() +
  labs(x = "Quarter mile time",
       y = "Rear axle ratio")
```



If EDA isn't enough, we can answer these questions by fitting a model: a curve that predicts Y given X. Aka, a **regression curve** or a **machine learning model**.

(There are more comprehensive models too, such as modelling entire distributions, but that's not what we're doing here)

There are typically two goals of fitting a model:

1. Make predictions.
2. Interpret variable relationships.

Fitting a model in R

Model fitting methods tend to use a common format in R:

```
method(formula, data, options)
```

They also tend to have a common output: a special *list*.

Method:

A function such as:

- Linear Regression: `lm`
- Generalized Linear Regression: `glm`
- Local regression: `loess`
- Quantile regression: `quantreg::rq`
- ...

Formula:

In R, takes the form $y \sim x_1 + x_2 + \dots + x_p$ (use column names in your data frame).

Data: The data frame.

Options: Specific to the method.

Exercise:

1. Fit a linear regression model to life expectancy (“Y”) from year (“X”) by filling in the formula. Notice what appears as the output.
2. On a new line, use the `unclass` function to uncover the object’s true nature: a list. Note: it might be easier to use the `names` function to see what components are included in the list.

First, create a subset of the `gapminder` dataset containing only the country of ‘France’

```
gapminder_France <- gapminder%>%
  filter(country=="France")

gapminder_France
```

```
## # A tibble: 12 x 6
##   country continent  year lifeExp      pop gdpPercap
##   <fct>    <fct>    <int>  <dbl>    <int>    <dbl>
## 1 France  Europe     1952   67.4 42459667   7030.
## 2 France  Europe     1957   68.9 44310863   8663.
## 3 France  Europe     1962   70.5 47124000  10560.
## 4 France  Europe     1967   71.6 49569000  13000.
## 5 France  Europe     1972   72.4 51732000  16107.
## 6 France  Europe     1977   73.8 53165019  18293.
## 7 France  Europe     1982   74.9 54433565  20294.
## 8 France  Europe     1987   76.3 55630100  22066.
## 9 France  Europe     1992   77.5 57374179  24704.
## 10 France Europe     1997   78.6 58623428  25890.
## 11 France Europe     2002   79.6 59925035  28926.
## 12 France Europe     2007   80.7 61083916  30470.
```

Now, using the `lm()` function we will create the linear model

```
(my_lm <- lm(lifeExp~year, data=gapminder_France))

##
## Call:
## lm(formula = lifeExp ~ year, data = gapminder_France)
##
## Coefficients:
## (Intercept)      year
##   -397.7646      0.2385
```

Does that mean that the life expectancy at “year 0” was equal to -397.7646?! We are interested in the modeling results around the modeling period which starts at year 1952. To get a meaningful “interpretable” intercept we can use the `I()` function.

```
(my_lm <- lm(lifeExp~I(year-min(year)), data=gapminder_France))
```

```
##
## Call:
## lm(formula = lifeExp ~ I(year - min(year)), data = gapminder_France)
##
## Coefficients:
##      (Intercept)  I(year - min(year))
##          67.7901          0.2385
```

Use the `unclass()` function to take a look at how the `lm()` object actually looks like.

```
unclass(my_lm)
```

```
## $coefficients
##      (Intercept) I(year - min(year))
##          67.7901282          0.2385014
##
## $residuals
##          1          2          3          4          5          6
## -0.38012821 -0.05263520  0.33485781  0.18235082 -0.18015618  0.07733683
##          7          8          9         10         11         12
## -0.05517016  0.20232284  0.12981585  0.11730886 -0.12519814 -0.25070513
##
## $effects
##      (Intercept) I(year - min(year))
##      -257.55220231          14.26030956          0.41516662
##
##          0.26479522          -0.09557618          0.16405242
##
##          0.03368103          0.29330963          0.22293823
##
##          0.21256684          -0.02780456          -0.15117596
##
## $rank
## [1] 2
##
## $fitted.values
##          1          2          3          4          5          6          7          8
## 67.79013 68.98264 70.17514 71.36765 72.56016 73.75266 74.94517 76.13768
##          9         10         11         12
## 77.33018 78.52269 79.71520 80.90771
##
## $assign
## [1] 0 1
##
## $qr
## $qr
##      (Intercept) I(year - min(year))
## 1  -3.4641016      -95.26279442
## 2   0.2886751       59.79130372
## 3   0.2886751       0.18965544
```

```

## 4      0.2886751      0.10603124
## 5      0.2886751      0.02240704
## 6      0.2886751     -0.06121716
## 7      0.2886751     -0.14484136
## 8      0.2886751     -0.22846557
## 9      0.2886751     -0.31208977
## 10     0.2886751     -0.39571397
## 11     0.2886751     -0.47933817
## 12     0.2886751     -0.56296237
## attr("assign")
## [1] 0 1
##
## $qraux
## [1] 1.288675 1.273280
##
## $pivot
## [1] 1 2
##
## $tol
## [1] 1e-07
##
## $rank
## [1] 2
##
## attr("class")
## [1] "qr"
##
## $df.residual
## [1] 10
##
## $xlevels
## named list()
##
## $call
## lm(formula = lifeExp ~ I(year - min(year)), data = gapminder_France)
##
## $terms
## lifeExp ~ I(year - min(year))
## attr("variables")
## list(lifeExp, I(year - min(year)))
## attr("factors")
##               I(year - min(year))
## lifeExp               0
## I(year - min(year))    1
## attr("term.labels")
## [1] "I(year - min(year))"
## attr("order")
## [1] 1
## attr("intercept")
## [1] 1
## attr("response")
## [1] 1
## attr(".Environment")
## <environment: R_GlobalEnv>

```

```
## attr("predvars")
## list(lifeExp, I(year - min(year)))
## attr("dataClasses")
##           lifeExp I(year - min(year))
##           "numeric"           "numeric"
##
## $model
##      lifeExp I(year - min(year))
## 1    67.410           0
## 2    68.930           5
## 3    70.510          10
## 4    71.550          15
## 5    72.380          20
## 6    73.830          25
## 7    74.890          30
## 8    76.340          35
## 9    77.460          40
## 10   78.640          45
## 11   79.590          50
## 12   80.657          55
```

To complicate things further, some info is stored in *another* list after applying the `summary` function:

```
summary(my_lm)
```

```
##
## Call:
## lm(formula = lifeExp ~ I(year - min(year)), data = gapminder_France)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.38013 -0.13894  0.01235  0.14295  0.33486
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    67.79013    0.11949   567.33 < 2e-16 ***
## I(year - min(year)) 0.23850    0.00368   64.81 1.86e-14 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.22 on 10 degrees of freedom
## Multiple R-squared:  0.9976, Adjusted R-squared:  0.9974
## F-statistic: 4200 on 1 and 10 DF,  p-value: 1.863e-14
```

We can use the `predict()` function to make predictions from the model (default is to use fitting/training data). Here are the predictions:

```
predict(my_lm) %>%
  head()
```

```
##           1           2           3           4           5           6
## 67.79013 68.98264 70.17514 71.36765 72.56016 73.75266
```

Or we can predict on a new dataset:

```
years1 = gapminder
predict(my_lm, years1)
```

##	1	2	3	4	5	6	7	8
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	9	10	11	12	13	14	15	16
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	17	18	19	20	21	22	23	24
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	25	26	27	28	29	30	31	32
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	33	34	35	36	37	38	39	40
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	41	42	43	44	45	46	47	48
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	49	50	51	52	53	54	55	56
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	57	58	59	60	61	62	63	64
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	65	66	67	68	69	70	71	72
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	73	74	75	76	77	78	79	80
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	81	82	83	84	85	86	87	88
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	89	90	91	92	93	94	95	96
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	97	98	99	100	101	102	103	104
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	105	106	107	108	109	110	111	112
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	113	114	115	116	117	118	119	120
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	121	122	123	124	125	126	127	128
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	129	130	131	132	133	134	135	136
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	137	138	139	140	141	142	143	144
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	145	146	147	148	149	150	151	152
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	153	154	155	156	157	158	159	160
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	161	162	163	164	165	166	167	168
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	169	170	171	172	173	174	175	176
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	177	178	179	180	181	182	183	184
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	185	186	187	188	189	190	191	192
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	193	194	195	196	197	198	199	200

##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	201	202	203	204	205	206	207	208
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	209	210	211	212	213	214	215	216
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	217	218	219	220	221	222	223	224
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	225	226	227	228	229	230	231	232
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	233	234	235	236	237	238	239	240
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	241	242	243	244	245	246	247	248
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	249	250	251	252	253	254	255	256
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	257	258	259	260	261	262	263	264
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	265	266	267	268	269	270	271	272
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	273	274	275	276	277	278	279	280
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	281	282	283	284	285	286	287	288
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	289	290	291	292	293	294	295	296
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	297	298	299	300	301	302	303	304
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	305	306	307	308	309	310	311	312
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	313	314	315	316	317	318	319	320
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	321	322	323	324	325	326	327	328
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	329	330	331	332	333	334	335	336
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	337	338	339	340	341	342	343	344
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	345	346	347	348	349	350	351	352
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	353	354	355	356	357	358	359	360
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	361	362	363	364	365	366	367	368
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	369	370	371	372	373	374	375	376
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	377	378	379	380	381	382	383	384
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	385	386	387	388	389	390	391	392
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	393	394	395	396	397	398	399	400
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	401	402	403	404	405	406	407	408
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	409	410	411	412	413	414	415	416

##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	417	418	419	420	421	422	423	424
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	425	426	427	428	429	430	431	432
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	433	434	435	436	437	438	439	440
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	441	442	443	444	445	446	447	448
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	449	450	451	452	453	454	455	456
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	457	458	459	460	461	462	463	464
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	465	466	467	468	469	470	471	472
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	473	474	475	476	477	478	479	480
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	481	482	483	484	485	486	487	488
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	489	490	491	492	493	494	495	496
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	497	498	499	500	501	502	503	504
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	505	506	507	508	509	510	511	512
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	513	514	515	516	517	518	519	520
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	521	522	523	524	525	526	527	528
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	529	530	531	532	533	534	535	536
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	537	538	539	540	541	542	543	544
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	545	546	547	548	549	550	551	552
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	553	554	555	556	557	558	559	560
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	561	562	563	564	565	566	567	568
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	569	570	571	572	573	574	575	576
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	577	578	579	580	581	582	583	584
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	585	586	587	588	589	590	591	592
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	593	594	595	596	597	598	599	600
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	601	602	603	604	605	606	607	608
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	609	610	611	612	613	614	615	616
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	617	618	619	620	621	622	623	624
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	625	626	627	628	629	630	631	632

##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	633	634	635	636	637	638	639	640
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	641	642	643	644	645	646	647	648
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	649	650	651	652	653	654	655	656
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	657	658	659	660	661	662	663	664
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	665	666	667	668	669	670	671	672
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	673	674	675	676	677	678	679	680
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	681	682	683	684	685	686	687	688
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	689	690	691	692	693	694	695	696
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	697	698	699	700	701	702	703	704
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	705	706	707	708	709	710	711	712
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	713	714	715	716	717	718	719	720
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	721	722	723	724	725	726	727	728
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	729	730	731	732	733	734	735	736
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	737	738	739	740	741	742	743	744
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	745	746	747	748	749	750	751	752
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	753	754	755	756	757	758	759	760
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
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##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	769	770	771	772	773	774	775	776
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	777	778	779	780	781	782	783	784
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	785	786	787	788	789	790	791	792
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	793	794	795	796	797	798	799	800
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	801	802	803	804	805	806	807	808
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	809	810	811	812	813	814	815	816
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	817	818	819	820	821	822	823	824
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	825	826	827	828	829	830	831	832
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	833	834	835	836	837	838	839	840
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	841	842	843	844	845	846	847	848

##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	849	850	851	852	853	854	855	856
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	857	858	859	860	861	862	863	864
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	865	866	867	868	869	870	871	872
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	873	874	875	876	877	878	879	880
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	881	882	883	884	885	886	887	888
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	889	890	891	892	893	894	895	896
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	897	898	899	900	901	902	903	904
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	905	906	907	908	909	910	911	912
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	913	914	915	916	917	918	919	920
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	921	922	923	924	925	926	927	928
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	929	930	931	932	933	934	935	936
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	937	938	939	940	941	942	943	944
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	945	946	947	948	949	950	951	952
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	953	954	955	956	957	958	959	960
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	961	962	963	964	965	966	967	968
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##	969	970	971	972	973	974	975	976
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	977	978	979	980	981	982	983	984
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	985	986	987	988	989	990	991	992
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	993	994	995	996	997	998	999	1000
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	1001	1002	1003	1004	1005	1006	1007	1008
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	1009	1010	1011	1012	1013	1014	1015	1016
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	1017	1018	1019	1020	1021	1022	1023	1024
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	1025	1026	1027	1028	1029	1030	1031	1032
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	1033	1034	1035	1036	1037	1038	1039	1040
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	1041	1042	1043	1044	1045	1046	1047	1048
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	1049	1050	1051	1052	1053	1054	1055	1056
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	1057	1058	1059	1060	1061	1062	1063	1064

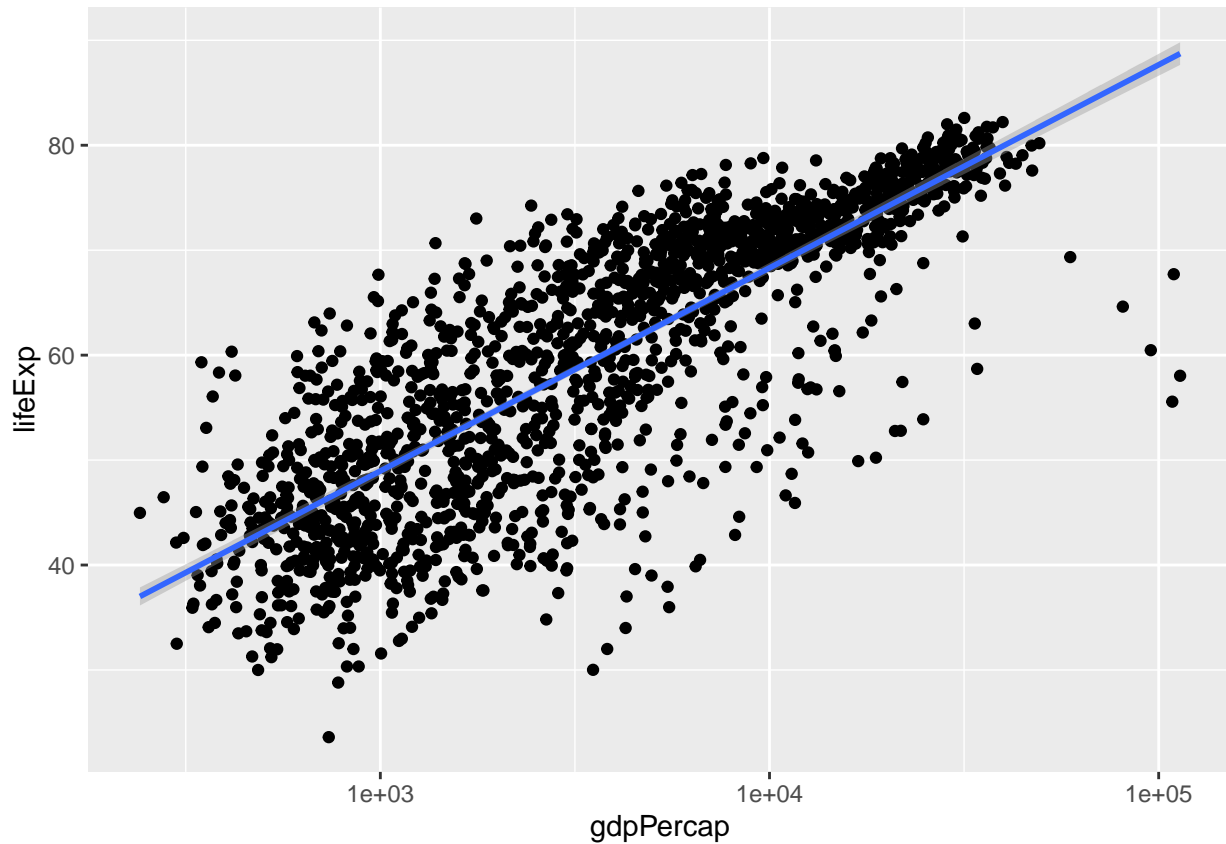
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	1065	1066	1067	1068	1069	1070	1071	1072
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	1073	1074	1075	1076	1077	1078	1079	1080
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	1081	1082	1083	1084	1085	1086	1087	1088
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	1089	1090	1091	1092	1093	1094	1095	1096
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	1097	1098	1099	1100	1101	1102	1103	1104
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	1105	1106	1107	1108	1109	1110	1111	1112
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	1113	1114	1115	1116	1117	1118	1119	1120
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##	1121	1122	1123	1124	1125	1126	1127	1128
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	1129	1130	1131	1132	1133	1134	1135	1136
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##	1137	1138	1139	1140	1141	1142	1143	1144
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	1145	1146	1147	1148	1149	1150	1151	1152
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##	1153	1154	1155	1156	1157	1158	1159	1160
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	1161	1162	1163	1164	1165	1166	1167	1168
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##	1169	1170	1171	1172	1173	1174	1175	1176
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##	1177	1178	1179	1180	1181	1182	1183	1184
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
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##	1193	1194	1195	1196	1197	1198	1199	1200
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	1201	1202	1203	1204	1205	1206	1207	1208
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	1209	1210	1211	1212	1213	1214	1215	1216
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##	1217	1218	1219	1220	1221	1222	1223	1224
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	1225	1226	1227	1228	1229	1230	1231	1232
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	1233	1234	1235	1236	1237	1238	1239	1240
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	1241	1242	1243	1244	1245	1246	1247	1248
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	1249	1250	1251	1252	1253	1254	1255	1256
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##	1257	1258	1259	1260	1261	1262	1263	1264
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	1265	1266	1267	1268	1269	1270	1271	1272
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	1273	1274	1275	1276	1277	1278	1279	1280

##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	1281	1282	1283	1284	1285	1286	1287	1288
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	1289	1290	1291	1292	1293	1294	1295	1296
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	1297	1298	1299	1300	1301	1302	1303	1304
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##	1305	1306	1307	1308	1309	1310	1311	1312
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##	1313	1314	1315	1316	1317	1318	1319	1320
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##	1321	1322	1323	1324	1325	1326	1327	1328
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##	1329	1330	1331	1332	1333	1334	1335	1336
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##	1361	1362	1363	1364	1365	1366	1367	1368
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##	1401	1402	1403	1404	1405	1406	1407	1408
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##	1409	1410	1411	1412	1413	1414	1415	1416
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##	1417	1418	1419	1420	1421	1422	1423	1424
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##	1425	1426	1427	1428	1429	1430	1431	1432
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	1433	1434	1435	1436	1437	1438	1439	1440
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	1441	1442	1443	1444	1445	1446	1447	1448
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	1449	1450	1451	1452	1453	1454	1455	1456
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##	1513	1514	1515	1516	1517	1518	1519	1520
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##	1521	1522	1523	1524	1525	1526	1527	1528
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##	1529	1530	1531	1532	1533	1534	1535	1536
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##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	1553	1554	1555	1556	1557	1558	1559	1560
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	1561	1562	1563	1564	1565	1566	1567	1568
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	1569	1570	1571	1572	1573	1574	1575	1576
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	1577	1578	1579	1580	1581	1582	1583	1584
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	1585	1586	1587	1588	1589	1590	1591	1592
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	1593	1594	1595	1596	1597	1598	1599	1600
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	1601	1602	1603	1604	1605	1606	1607	1608
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	1609	1610	1611	1612	1613	1614	1615	1616
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	1617	1618	1619	1620	1621	1622	1623	1624
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	1625	1626	1627	1628	1629	1630	1631	1632
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	1633	1634	1635	1636	1637	1638	1639	1640
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	1641	1642	1643	1644	1645	1646	1647	1648
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	1649	1650	1651	1652	1653	1654	1655	1656
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	1657	1658	1659	1660	1661	1662	1663	1664
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	1665	1666	1667	1668	1669	1670	1671	1672
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	1673	1674	1675	1676	1677	1678	1679	1680
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771
##	1681	1682	1683	1684	1685	1686	1687	1688
##	67.79013	68.98264	70.17514	71.36765	72.56016	73.75266	74.94517	76.13768
##	1689	1690	1691	1692	1693	1694	1695	1696
##	77.33018	78.52269	79.71520	80.90771	67.79013	68.98264	70.17514	71.36765
##	1697	1698	1699	1700	1701	1702	1703	1704
##	72.56016	73.75266	74.94517	76.13768	77.33018	78.52269	79.71520	80.90771

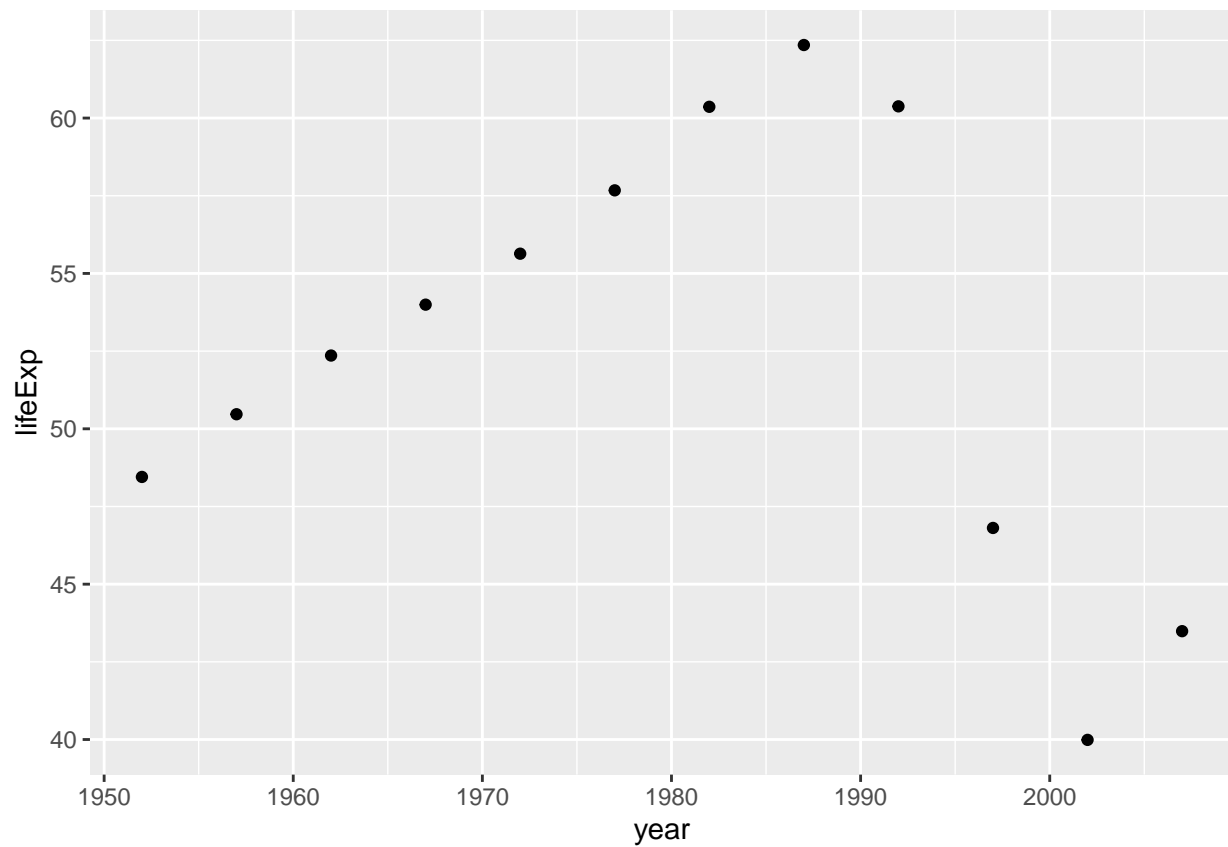
We can plot models (with one predictor/ X variable) using `ggplot2` through the `geom_smooth()` layer. Specifying `method="lm"` gives us the linear regression fit (but only visually!):

```
ggplot(gapminder, aes(gdpPercap, lifeExp)) +  
  geom_point() +  
  geom_smooth(method="lm") +  
  scale_x_log10()
```



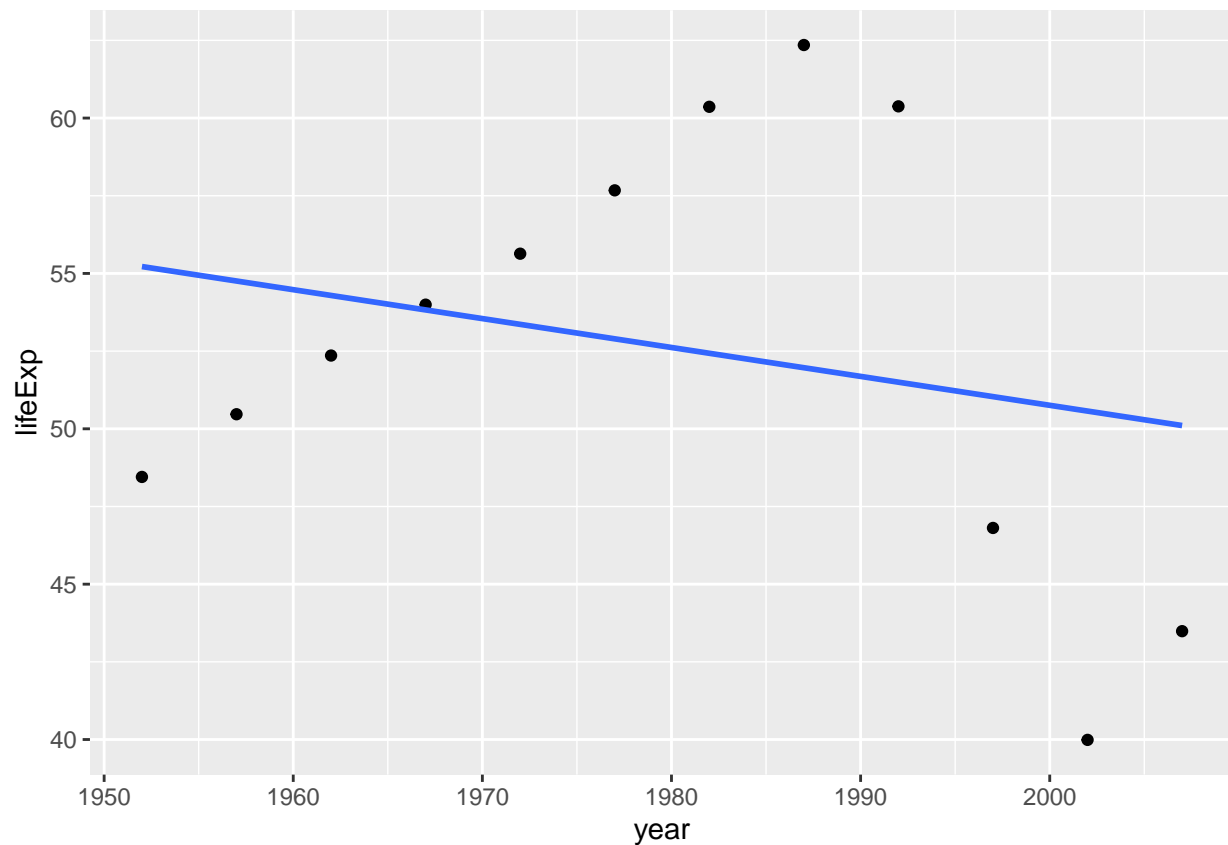
Lets consider another country “Zimbabwe”, which has a unique behavior in the `lifeExp` and `year` relationship.

```
gapminder_Zimbabwe <- gapminder%>%  
  filter(country=="Zimbabwe")  
gapminder_Zimbabwe %>% ggplot(aes(year, lifeExp)) + geom_point()
```



Let's try fitting a linear model to this relationship

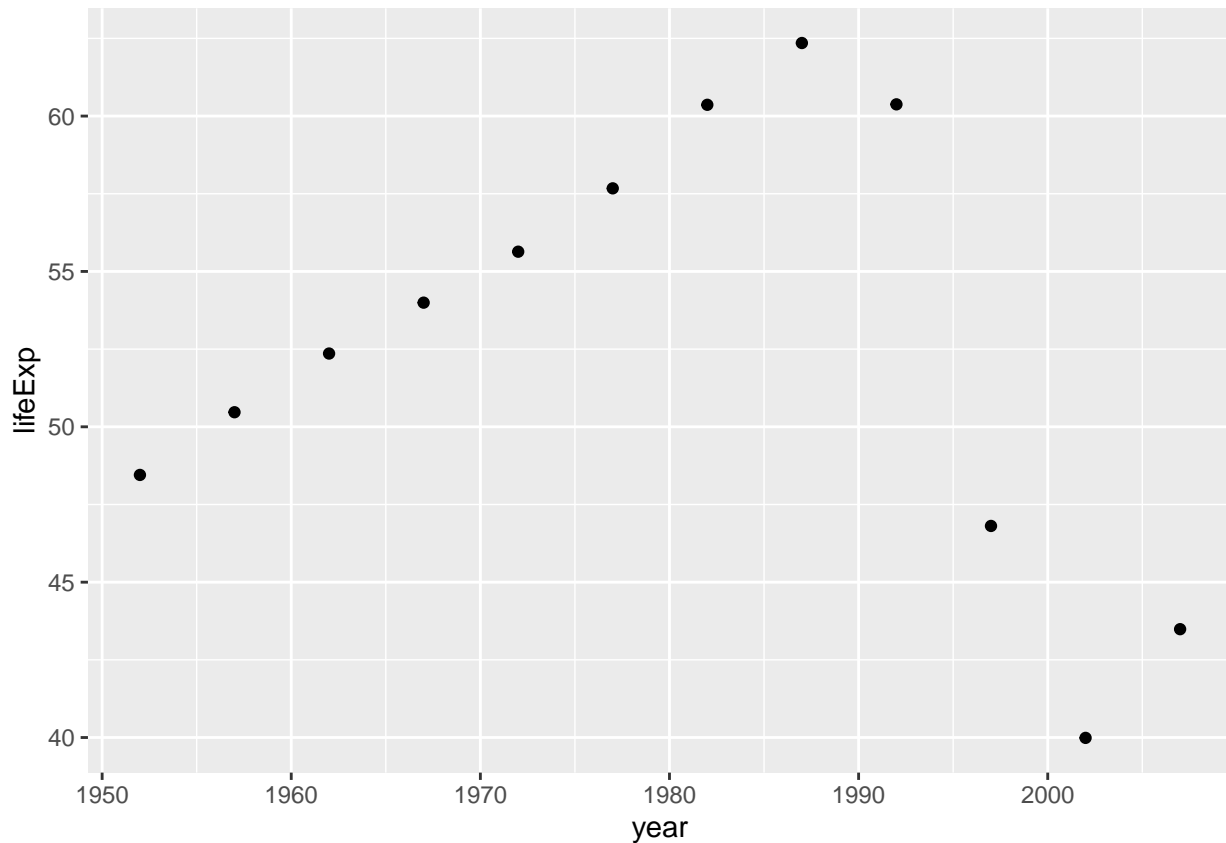
```
ggplot(gapminder_Zimbabwe, aes(year, lifeExp)) + geom_point() + geom_smooth(method = "lm", se = F)
```

Now we will try to fit a second degree polynomial and see what would that look like.

```
ggplot(gapminder_Zimbabwe, aes(year, lifeExp)) +
  geom_point() +
  geom_smooth(method = "lm", se = F, formula = lifeExp ~ poly(year, 2))
```

```
## Warning: Computation failed in `stat_smooth()`:
## object 'lifeExp' not found
```



```
lm_linear <- lm(data = gapminder, formula = lifeExp ~ year)
lm_poly <- lm(data = gapminder, formula = lifeExp ~ poly(year, 2))
```

anova lets you compare between different models.

```
anova(lm_linear, lm_poly)
```

```
## Analysis of Variance Table
##
## Model 1: lifeExp ~ year
## Model 2: lifeExp ~ poly(year, 2)
##   Res.Df    RSS Df Sum of Sq    F Pr(>F)
## 1    1702 230229
## 2    1701 228793  1    1436.2 10.678 0.001106 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Regression with categorical variables

```
(lm_cat <- lm(gdpPercap ~ I(year - 1952) + continent, data = gapminder))
```

```
##
## Call:
```

```
## lm(formula = gdpPercap ~ I(year - 1952) + continent, data = gapminder)
##
## Coefficients:
##      (Intercept)      I(year - 1952) continentAmericas
##      -1375.3          129.8          4942.4
## continentAsia      continentEurope      continentOceania
##      5708.4          12275.7          16427.9
```

How did R know that continent was a categorical variable?

```
class(gapminder$continent)
```

```
## [1] "factor"
```

```
levels(gapminder$continent)
```

```
## [1] "Africa" "Americas" "Asia" "Europe" "Oceania"
```

```
contrasts(gapminder$continent)
```

```
##      Americas Asia Europe Oceania
## Africa      0    0     0      0
## Americas    1    0     0      0
## Asia        0    1     0      0
## Europe      0    0     1      0
## Oceania     0    0     0      1
```

How can we change the reference level?

```
gapminder$continent <- relevel(gapminder$continent, ref = "Oceania")
```

Let's build a new model

```
lm_cat2 <- lm(gdpPercap ~ I(year - 1952) + continent, data = gapminder)
lm_cat2
```

```
##
## Call:
## lm(formula = gdpPercap ~ I(year - 1952) + continent, data = gapminder)
##
## Coefficients:
##      (Intercept)      I(year - 1952) continentAfrica
##      15052.5          129.8          -16427.9
## continentAmericas      continentAsia      continentEurope
##      -11485.5          -10719.5          -4152.1
```

Broom

Let's make it easier to extract info, using the **broom** package. There are three crown functions in this package, all of which input a fitted model, and outputs a tidy data frame.

1. **tidy**: extract statistical summaries about each component of the model.
 - Useful for *interpretation* task.
2. **augment**: add columns to the original data frame, giving information corresponding to each row.
 - Useful for *prediction* task.
3. **glance**: extract statistical summaries about the model as a whole (1-row tibble).
 - Useful for checking goodness of fit.

Exercise: apply all three functions to our fitted model, `my_lm`. What do you see?

```
tidy(my_lm) #This gives us a 'tidy' table with the different values from our regression model.
```

```
## # A tibble: 2 x 5
##   term                estimate std.error statistic  p.value
##   <chr>                <dbl>    <dbl>    <dbl>    <dbl>
## 1 (Intercept)          67.8      0.119     567.  7.12e-24
## 2 I(year - min(year))   0.239    0.00368     64.8 1.86e-14
```

```
augment(my_lm) #Augment gives us additional variables such as residuals. It also gives us observation-l
```

```
## # A tibble: 12 x 9
##   lifeExp I.year...min.ye~ .fitted .se.fit .resid .hat .sigma .cooksd
##   <dbl>    <I<int>>    <dbl>  <dbl>  <dbl>  <dbl>  <dbl>  <dbl>
## 1  67.4          0  67.8  0.119 -0.380  0.295  0.176  0.885
## 2  68.9          5  69.0  0.104 -0.0526  0.225  0.231  0.0107
## 3  70.5         10  70.2  0.0905  0.335  0.169  0.197  0.283
## 4  71.6         15  71.4  0.0784  0.182  0.127  0.223  0.0572
## 5  72.4         20  72.6  0.0693 -0.180  0.0991  0.223  0.0409
## 6  73.8         25  73.8  0.0642  0.0773  0.0851  0.230  0.00628
## 7  74.9         30  74.9  0.0642 -0.0552  0.0851  0.231  0.00319
## 8  76.3         35  76.1  0.0693  0.202  0.0991  0.221  0.0516
## 9  77.5         40  77.3  0.0784  0.130  0.127  0.227  0.0290
## 10 78.6         45  78.5  0.0905  0.117  0.169  0.228  0.0348
## 11 79.6         50  79.7  0.104 -0.125  0.225  0.227  0.0606
## 12 80.7         55  80.9  0.119 -0.251  0.295  0.210  0.385
## # ... with 1 more variable: .std.resid <dbl>
```

```
glance(my_lm) #glance gives us a concise one-row summary of the model including AIC and BIC.
```

```
## # A tibble: 1 x 11
##   r.squared adj.r.squared sigma statistic p.value    df logLik  AIC  BIC
##   <dbl>    <dbl> <dbl>    <dbl>    <dbl> <int>  <dbl> <dbl> <dbl>
## 1  0.998      0.997 0.220    4200. 1.86e-14     2   2.23  1.53  2.99
## # ... with 2 more variables: deviance <dbl>, df.residual <int>
```