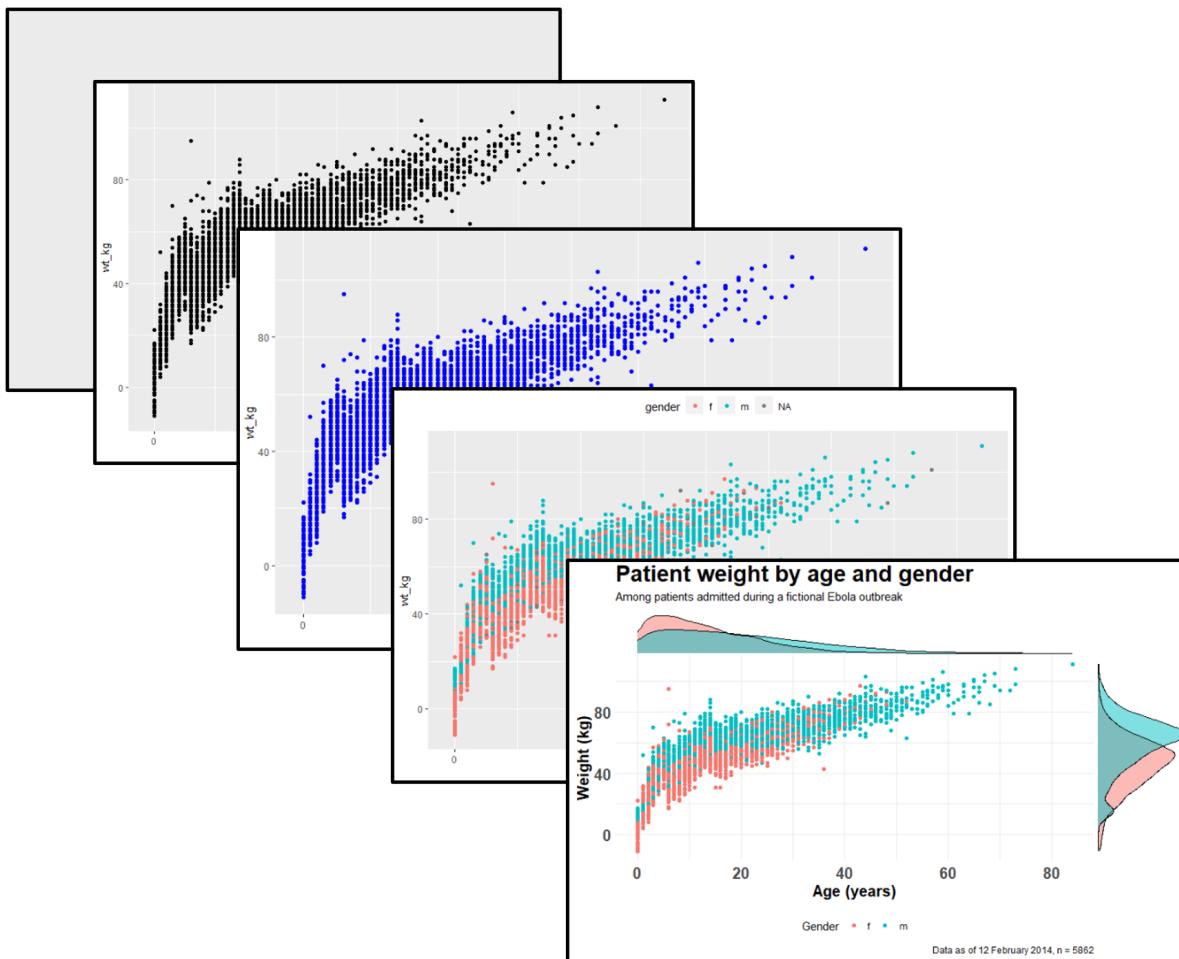


Data visualization

Extended Materials

You can find the original, extended version of these materials from chapters 30 and 31.



ggplot2 is the most popular data visualisation R package. Its `ggplot()` function is at the core of this package, and this whole approach is colloquially known as “*ggplot*” with the resulting figures sometimes affectionately called “*ggplots*”. The “*gg*” in these names reflects the “grammar of graphics” used to construct the figures. **ggplot2** benefits from a wide variety of supplementary R packages that further enhance its functionality.

The [data visualization with ggplot cheatsheet](#) from the RStudio website is a great reference to have on-hand when creating pltos. If you want inspiration for ways to creatively visualise your data, we suggest reviewing websites like the [R graph gallery](#) and [Data-to-viz](#).

Data Preparation

Import data

We import the dataset of cases from a simulated Ebola epidemic. If you want to follow along, click to download the “clean” linelist (as .rds file).

The first 50 rows of the linelist are displayed below. We will focus on the continuous variables `age`, `wt_kg` (weight in kilos), `ct_blood` (CT values), and `days_onset_hosp` (difference between onset date and hospitalisation).

	case_id	generation	date_infection	date_onset	date_hospitalisation
1	5fe599	4	2014-05-08	2014-05-13	2014-05-15
2	8689b7	4	<NA>	2014-05-13	2014-05-14
3	11f8ea	2	<NA>	2014-05-16	2014-05-18
4	b8812a	3	2014-05-04	2014-05-18	2014-05-20
5	893f25	3	2014-05-18	2014-05-21	2014-05-22
6	be99c8	3	2014-05-03	2014-05-22	2014-05-23
7	07e3e8	4	2014-05-22	2014-05-27	2014-05-29
8	369449	4	2014-05-28	2014-06-02	2014-06-03
9	f393b4	4	<NA>	2014-06-05	2014-06-06
10	1389ca	4	<NA>	2014-06-05	2014-06-07
11	2978ac	4	2014-05-30	2014-06-06	2014-06-08
12	57a565	4	2014-05-28	2014-06-13	2014-06-15
13	fc15ef	6	2014-06-14	2014-06-16	2014-06-17
14	2eaa9a	5	2014-06-07	2014-06-17	2014-06-17
15	bbfa93	6	2014-06-09	2014-06-18	2014-06-20
16	c97dd9	9	<NA>	2014-06-19	2014-06-19
17	f50e8a	10	<NA>	2014-06-22	2014-06-23
18	3a7673	8	<NA>	2014-06-23	2014-06-24
19	7f5a01	7	2014-06-23	2014-06-25	2014-06-27
20	ddddee	6	2014-06-18	2014-06-26	2014-06-28
21	99e8fa	7	2014-06-24	2014-06-28	2014-06-29
22	567136	6	<NA>	2014-07-02	2014-07-03
23	9371a9	8	<NA>	2014-07-08	2014-07-09
24	bc2adf	6	2014-07-03	2014-07-09	2014-07-09
25	403057	10	<NA>	2014-07-09	2014-07-11
26	8bd1e8	8	2014-07-10	2014-07-10	2014-07-11
27	f327be	6	2014-06-14	2014-07-12	2014-07-13
28	42e1a9	12	<NA>	2014-07-12	2014-07-14
29	90e5fe	5	2014-06-18	2014-07-13	2014-07-14
30	959170	8	2014-06-29	2014-07-13	2014-07-13
31	8ebf6e	7	2014-07-02	2014-07-14	2014-07-14

32	e56412	9	2014-07-12	2014-07-15		2014-07-17		
33	6d788e	11	2014-07-12	2014-07-16		2014-07-17		
34	a47529	5	2014-06-13	2014-07-17		2014-07-18		
35	67be4e	8	2014-07-15	2014-07-17		2014-07-19		
36	da8ecb	5	2014-06-20	2014-07-18		2014-07-20		
37	148f18	6	<NA>	2014-07-19		2014-07-20		
38	2cb9a5	11	<NA>	2014-07-22		2014-07-22		
39	f5c142	7	2014-07-20	2014-07-22		2014-07-24		
40	70a9fe	9	<NA>	2014-07-24		2014-07-26		
41	3ad520	7	2014-07-12	2014-07-24		2014-07-24		
42	062638	8	2014-07-19	2014-07-25		2014-07-27		
43	c76676	9	2014-07-18	2014-07-25		2014-07-25		
44	baacc1	12	2014-07-18	2014-07-27		2014-07-27		
45	497372	13	2014-07-27	2014-07-29		2014-07-31		
46	23e499	9	<NA>	2014-07-30		2014-08-01		
47	38cc4a	8	2014-07-19	<NA>		2014-08-03		
48	3789ee	10	2014-07-26	2014-08-01		2014-08-02		
49	c71dcd	8	2014-07-24	2014-08-02		2014-08-02		
50	6b70f0	7	<NA>	2014-08-03		2014-08-04		
	date_outcome	outcome	gender	age	age_unit	age_years	age_cat	age_cat5
1	<NA>	<NA>	m	2	years	2	0-4	0-4
2	2014-05-18	Recover	f	3	years	3	0-4	0-4
3	2014-05-30	Recover	m	56	years	56	50-69	55-59
4	<NA>	<NA>	f	18	years	18	15-19	15-19
5	2014-05-29	Recover	m	3	years	3	0-4	0-4
6	2014-05-24	Recover	f	16	years	16	15-19	15-19
7	2014-06-01	Recover	f	16	years	16	15-19	15-19
8	2014-06-07	Death	f	0	years	0	0-4	0-4
9	2014-06-18	Recover	m	61	years	61	50-69	60-64
10	2014-06-09	Death	f	27	years	27	20-29	25-29
11	2014-06-15	Death	m	12	years	12	10-14	10-14
12	<NA>	Death	m	42	years	42	30-49	40-44
13	2014-07-09	Recover	m	19	years	19	15-19	15-19
14	<NA>	Recover	f	7	years	7	5-9	5-9
15	2014-06-30	<NA>	f	7	years	7	5-9	5-9
16	2014-07-11	Recover	m	13	years	13	10-14	10-14
17	2014-07-01	<NA>	f	35	years	35	30-49	35-39
18	2014-06-25	<NA>	f	17	years	17	15-19	15-19
19	2014-07-06	Death	f	11	years	11	10-14	10-14
20	2014-07-02	Death	f	11	years	11	10-14	10-14
21	2014-07-09	Recover	m	19	years	19	15-19	15-19

22	2014-07-07	<NA>	m	54	years	54	50-69	50-54	
23	2014-07-20	<NA>	f	14	years	14	10-14	10-14	
24	<NA>	<NA>	m	28	years	28	20-29	25-29	
25	2014-07-22	Death	f	6	years	6	5-9	5-9	
26	2014-07-16	<NA>	m	3	years	3	0-4	0-4	
27	2014-07-14	Death	m	31	years	31	30-49	30-34	
28	2014-07-20	Death	f	6	years	6	5-9	5-9	
29	2014-07-16	<NA>	m	67	years	67	50-69	65-69	
30	2014-07-19	Death	f	14	years	14	10-14	10-14	
31	2014-07-27	Recover	f	10	years	10	10-14	10-14	
32	2014-07-19	Death	f	21	years	21	20-29	20-24	
33	<NA>	Recover	m	20	years	20	20-29	20-24	
34	2014-07-26	Death	m	45	years	45	30-49	45-49	
35	2014-08-14	Recover	f	1	years	1	0-4	0-4	
36	2014-08-01	<NA>	m	12	years	12	10-14	10-14	
37	2014-07-23	Death	f	3	years	3	0-4	0-4	
38	2014-08-28	Recover	f	15	years	15	15-19	15-19	
39	2014-07-28	Recover	f	20	years	20	20-29	20-24	
40	2014-07-19	Death	m	36	years	36	30-49	35-39	
41	<NA>	<NA>	f	7	years	7	5-9	5-9	
42	2014-08-03	<NA>	m	13	years	13	10-14	10-14	
43	<NA>	Death	f	14	years	14	10-14	10-14	
44	<NA>	Death	m	3	years	3	0-4	0-4	
45	<NA>	Death	m	10	years	10	10-14	10-14	
46	2014-08-06	Death	f	1	years	1	0-4	0-4	
47	2014-08-21	Recover	m	0	years	0	0-4	0-4	
48	2014-09-13	<NA>	f	20	years	20	20-29	20-24	
49	2014-08-04	Death	m	26	years	26	20-29	25-29	
50	<NA>	Death	m	14	years	14	10-14	10-14	
					hospital	lon	lat	infector	source
1					Other	-13.21574	8.468973	f547d6	other
2					Missing	-13.21523	8.451719	<NA>	<NA>
3	St. Mark's Maternity Hospital (SMMH)				-13.21291	8.464817	<NA>	<NA>	
4		Port Hospital			-13.23637	8.475476	f90f5f	other	
5		Military Hospital			-13.22286	8.460824	11f8ea	other	
6		Port Hospital			-13.22263	8.461831	aec8ec	other	
7		Missing			-13.23315	8.462729	893f25	other	
8		Missing			-13.23210	8.461444	133ee7	other	
9		Missing			-13.22255	8.461913	<NA>	<NA>	
10		Missing			-13.25722	8.472923	<NA>	<NA>	
11		Port Hospital			-13.22063	8.484016	996f3a	other	

12	Military Hospital	-13.25399	8.458371	133ee7	other					
13	Missing	-13.23851	8.477617	37a6f6	other					
14	Missing	-13.20939	8.475702	9f6884	other					
15	Other	-13.21573	8.477799	4802b1	other					
16	Port Hospital	-13.22434	8.471451	<NA>	<NA>					
17	Port Hospital	-13.23361	8.478048	<NA>	<NA>					
18	Port Hospital	-13.21422	8.485280	<NA>	<NA>					
19	Missing	-13.23397	8.469575	a75c7f	other					
20	Other	-13.25356	8.459574	8e104d	other					
21	Port Hospital	-13.22501	8.474049	ab634e	other					
22	Port Hospital	-13.21607	8.488029	<NA>	<NA>					
23	St. Mark's Maternity Hospital (SMMH)	-13.26807	8.473437	<NA>	<NA>					
24	Missing	-13.22667	8.484083	b799eb	other					
25	Other	-13.21602	8.462422	<NA>	<NA>					
26	Missing	-13.24826	8.470268	5d9e4d	other					
27	St. Mark's Maternity Hospital (SMMH)	-13.21563	8.463984	a15e13	other					
28	Military Hospital	-13.21424	8.464135	<NA>	<NA>					
29	Port Hospital	-13.26149	8.456231	ea3740	other					
30	Central Hospital	-13.24530	8.483346	beb26e	funeral					
31	Military Hospital	-13.26306	8.474940	567136	other					
32	Central Hospital	-13.23433	8.478321	894024	funeral					
33	Missing	-13.21991	8.469393	36e2e7	other					
34	Military Hospital	-13.22273	8.484806	a2086d	other					
35	Other	-13.23431	8.471212	7baf73	other					
36	Missing	-13.21878	8.484384	eb2277	funeral					
37	Missing	-13.24837	8.484662	<NA>	<NA>					
38	Port Hospital	-13.20975	8.477142	<NA>	<NA>					
39	Port Hospital	-13.26809	8.462381	d6584f	other					
40	Port Hospital	-13.25875	8.455686	<NA>	<NA>					
41	Missing	-13.26264	8.463288	312ecf	other					
42	Central Hospital	-13.26972	8.479407	52ea64	other					
43	Military Hospital	-13.22090	8.463539	cf79c	other					
44	Other	-13.23307	8.461790	d145b7	other					
45	Other	-13.26809	8.475087	174288	other					
46	Other	-13.25472	8.458258	<NA>	<NA>					
47	Missing	-13.25737	8.453257	53608c	funeral					
48	St. Mark's Maternity Hospital (SMMH)	-13.21374	8.473257	3b096b	other					
49	St. Mark's Maternity Hospital (SMMH)	-13.21760	8.479116	f5c142	other					
50	Missing	-13.24864	8.484803	<NA>	<NA>					
	wt_kg	ht_cm	ct_blood	fever	chills	cough	aches	vomit	temp	time_admission
1	27	48	22	no	no	yes	no	yes	36.8	<NA>

2	25	59	22	<NA>	<NA>	<NA>	<NA>	<NA>	36.9	09:36
3	91	238	21	<NA>	<NA>	<NA>	<NA>	<NA>	36.9	16:48
4	41	135	23	no	no	no	no	no	36.8	11:22
5	36	71	23	no	no	yes	no	yes	36.9	12:60
6	56	116	21	no	no	yes	no	yes	37.6	14:13
7	47	87	21	<NA>	<NA>	<NA>	<NA>	<NA>	37.3	14:33
8	0	11	22	no	no	yes	no	yes	37.0	09:25
9	86	226	22	no	no	yes	no	yes	36.4	11:16
10	69	174	22	no	no	yes	no	no	35.9	10:55
11	67	112	22	no	no	yes	no	yes	36.5	16:03
12	84	186	22	no	no	yes	no	no	36.9	11:14
13	68	174	22	no	no	yes	no	no	36.5	12:42
14	44	90	21	no	no	yes	no	no	37.1	11:06
15	34	91	23	no	no	yes	no	yes	36.5	09:10
16	66	152	22	no	no	yes	yes	no	37.3	08:45
17	78	214	23	no	yes	yes	no	no	37.0	<NA>
18	47	137	21	no	no	yes	no	no	38.0	15:41
19	53	117	22	<NA>	<NA>	<NA>	<NA>	<NA>	38.0	13:34
20	47	131	23	no	no	yes	no	no	36.0	18:58
21	71	150	21	no	no	yes	no	yes	37.0	12:43
22	86	241	23	no	no	yes	no	no	36.7	16:33
23	53	131	21	no	yes	yes	no	no	36.9	14:29
24	69	161	24	no	no	yes	no	no	36.5	07:18
25	38	80	23	<NA>	<NA>	<NA>	<NA>	<NA>	37.0	08:11
26	46	69	22	no	no	yes	no	no	36.5	16:32
27	68	188	24	no	no	yes	no	no	37.6	16:17
28	37	66	23	no	yes	yes	no	no	36.6	07:32
29	100	233	20	<NA>	<NA>	<NA>	<NA>	<NA>	36.6	17:45
30	56	142	24	<NA>	<NA>	<NA>	<NA>	<NA>	36.2	<NA>
31	50	110	24	no	no	yes	no	no	36.4	13:24
32	57	182	20	no	no	yes	no	yes	37.1	14:43
33	65	164	24	<NA>	<NA>	<NA>	<NA>	<NA>	37.5	02:33
34	72	214	21	no	no	yes	no	yes	37.5	11:36
35	29	26	22	no	no	yes	no	yes	37.4	17:28
36	69	157	21	<NA>	<NA>	<NA>	<NA>	<NA>	36.9	16:27
37	37	39	23	<NA>	<NA>	<NA>	<NA>	<NA>	36.4	<NA>
38	48	154	22	no	no	yes	yes	yes	37.3	20:49
39	54	133	23	no	no	yes	yes	yes	37.0	<NA>
40	71	168	23	<NA>	<NA>	<NA>	<NA>	<NA>	37.8	11:38
41	47	100	23	no	no	yes	no	yes	36.5	14:25
42	61	125	22	no	no	yes	no	yes	37.5	13:42

43	47	123	23	<NA>	<NA>	<NA>	<NA>	<NA>	36.7	21:22
44	35	67	22	no	no	yes	no	yes	37.0	13:33
45	53	134	22	no	yes	yes	no	yes	37.3	19:06
46	16	31	22	no	no	yes	no	no	36.6	17:14
47	13	36	23	no	no	yes	no	yes	36.5	20:09
48	59	125	22	no	no	yes	no	yes	36.6	<NA>
49	69	183	22	no	no	no	no	yes	37.6	10:23
50	67	169	22	<NA>	<NA>	<NA>	<NA>	<NA>	36.8	09:09
bmi days_onset_hosp										
1	117.18750				2					
2	71.81844				1					
3	16.06525				2					
4	22.49657				2					
5	71.41440				1					
6	41.61712				1					
7	62.09539				2					
8	0.00000				1					
9	16.83765				1					
10	22.79033				2					
11	53.41199				2					
12	24.28026				2					
13	22.46003				1					
14	54.32099				0					
15	41.05784				2					
16	28.56648				0					
17	17.03206				1					
18	25.04129				1					
19	38.71722				2					
20	27.38768				2					
21	31.55556				1					
22	14.80691				1					
23	30.88398				1					
24	26.61934				0					
25	59.37500				2					
26	96.61836				1					
27	19.23947				1					
28	84.94031				2					
29	18.41994				1					
30	27.77227				0					
31	41.32231				0					
32	17.20807				2					

33	24.16716	1
34	15.72190	1
35	428.99408	2
36	27.99302	2
37	243.26101	1
38	20.23950	0
39	30.52745	2
40	25.15590	2
41	47.00000	0
42	39.04000	2
43	31.06616	0
44	77.96837	0
45	29.51660	2
46	166.49324	2
47	100.30864	NA
48	37.76000	1
49	20.60378	0
50	23.45856	1

General cleaning

Some simple ways we can prepare our data to make it better for plotting can include making the contents of the data better for display - which does not necessarily equate to better for data manipulation. For example:

- Replace NA values in a character column with the character string “Unknown”
- Consider converting column to class *factor* so their values have prescribed ordinal levels
- Clean some columns so that their “data friendly” values with underscores etc are changed to normal text or title case.

Here are some examples of this in action:

```

# make display version of columns with more friendly names
linelist <- linelist %>%
  mutate(
    gender_disp = case_when(gender == "m" ~ "Male",           # m to Male
                             gender == "f" ~ "Female",        # f to Female,
                             is.na(gender) ~ "Unknown"),     # NA to Unknown

    outcome_disp = replace_na(outcome, "Unknown")             # replace NA outcome with "un"
  )

```

Pivoting longer

As a matter of data structure, for **ggplot2** we often also want to pivot our data into *longer* formats. We will learn more about pivoting later; for now it's enough to be aware that these two data formats exist.

country	1999	2000	2001	2002
Angola	800	750	925	1020
India	20100	25650	26800	27255
Mongolia	450	512	510	586

country	year	cases
Angola	1999	800
Angola	2000	750
Angola	2001	925
Angola	2002	1020
India	1999	20100
India	2000	25650
India	2001	26800
India	2002	27255
Mongolia	1999	450
Mongolia	2000	512
Mongolia	2001	510
Mongolia	2002	586

Pivot data longer

```

data %>%
  pivot_longer(
    cols = 1999:2002,
    names_to = "year",
    values_to = "cases"
  )

```

For example, say that we want to plot data that are in a “wide” format, such as for each case in the **linelist** and their symptoms. Below we create a mini-linelist called **symptoms_data** that contains only the **case_id** and symptoms columns.

```

symptoms_data <- linelist %>%
  select(c(case_id, fever, chills, cough, aches, vomit))

```

Here is how the first 50 rows of this mini-linelist look - see how they are formatted “wide” with each symptom as a column:

```
case_id  fever  chills  cough  aches  vomit
```

1	5fe599	no	no	yes	no	yes
2	8689b7	<NA>	<NA>	<NA>	<NA>	<NA>
3	11f8ea	<NA>	<NA>	<NA>	<NA>	<NA>
4	b8812a	no	no	no	no	no
5	893f25	no	no	yes	no	yes
6	be99c8	no	no	yes	no	yes
7	07e3e8	<NA>	<NA>	<NA>	<NA>	<NA>
8	369449	no	no	yes	no	yes
9	f393b4	no	no	yes	no	yes
10	1389ca	no	no	yes	no	no
11	2978ac	no	no	yes	no	yes
12	57a565	no	no	yes	no	no
13	fc15ef	no	no	yes	no	no
14	2eaa9a	no	no	yes	no	no
15	bbfa93	no	no	yes	no	yes
16	c97dd9	no	no	yes	yes	no
17	f50e8a	no	yes	yes	no	no
18	3a7673	no	no	yes	no	no
19	7f5a01	<NA>	<NA>	<NA>	<NA>	<NA>
20	ddddee	no	no	yes	no	no
21	99e8fa	no	no	yes	no	yes
22	567136	no	no	yes	no	no
23	9371a9	no	yes	yes	no	no
24	bc2adf	no	no	yes	no	no
25	403057	<NA>	<NA>	<NA>	<NA>	<NA>
26	8bd1e8	no	no	yes	no	no
27	f327be	no	no	yes	no	no
28	42e1a9	no	yes	yes	no	no
29	90e5fe	<NA>	<NA>	<NA>	<NA>	<NA>
30	959170	<NA>	<NA>	<NA>	<NA>	<NA>
31	8ebf6e	no	no	yes	no	no
32	e56412	no	no	yes	no	yes
33	6d788e	<NA>	<NA>	<NA>	<NA>	<NA>
34	a47529	no	no	yes	no	yes
35	67be4e	no	no	yes	no	yes
36	da8ecb	<NA>	<NA>	<NA>	<NA>	<NA>
37	148f18	<NA>	<NA>	<NA>	<NA>	<NA>
38	2cb9a5	no	no	yes	yes	yes
39	f5c142	no	no	yes	yes	yes
40	70a9fe	<NA>	<NA>	<NA>	<NA>	<NA>
41	3ad520	no	no	yes	no	yes

```

42 062638 no no yes no yes
43 c76676 <NA> <NA> <NA> <NA> <NA>
44 baacc1 no no yes no yes
45 497372 no yes yes no yes
46 23e499 no no yes no no
47 38cc4a no no yes no yes
48 3789ee no no yes no yes
49 c71dcd no no no no yes
50 6b70f0 <NA> <NA> <NA> <NA> <NA>

```

If we wanted to plot the number of cases with specific symptoms, we are limited by the fact that each symptom is a specific column. However, we can *pivot* the symptoms columns to a longer format like this:

```

symptoms_data_long <- symptoms_data %>%      # begin with "mini" linelist called symptoms_
  pivot_longer(
    cols = -case_id,                      # pivot all columns except case_id (all the s
    names_to = "symptom_name",            # assign name for new column that holds the s
    values_to = "symptom_is_present") %>% # assign name for new column that holds the v
  mutate(symptom_is_present = replace_na(symptom_is_present, "unknown")) # convert NA to

```

Here are the first 50 rows. Note that case has 5 rows - one for each possible symptom. The new columns `symptom_name` and `symptom_is_present` are the result of the pivot. Note that this format may not be very useful for other operations, but is useful for plotting.

```

# A tibble: 50 x 3
  case_id symptom_name symptom_is_present
  <chr>   <chr>       <chr>
1 5fe599  fever        no
2 5fe599  chills       no
3 5fe599  cough        yes
4 5fe599  aches        no
5 5fe599  vomit        yes
6 8689b7  fever        unknown
7 8689b7  chills       unknown
8 8689b7  cough        unknown
9 8689b7  aches        unknown
10 8689b7  vomit       unknown
# i 40 more rows

```

Basics of ggplot

“Grammar of graphics” - ggplot2

Plotting with **ggplot2** is based on “adding” plot layers and design elements on top of one another, with each command added to the previous ones with a plus symbol (+). The result is a multi-layer plot object that can be saved, modified, printed, exported, etc.

The idea behind the Grammar of Graphics it is that you can build every graph from the same 3 components: (1) a data set, (2) a coordinate system, and (3) geoms — i.e. visual marks that represent data points [source]

ggplot objects can be highly complex, but the basic order of layers will usually look like this:

1. Begin with the baseline `ggplot()` command - this “opens” the ggplot and allow subsequent functions to be added with +. Typically the dataset is also specified in this command
2. Add “geom” layers - these functions visualize the data as *geometries (shapes)*, e.g. as a bar graph, line plot, scatter plot, histogram (or a combination!). These functions all start with `geom_` as a prefix.
3. Add design elements to the plot such as axis labels, title, fonts, sizes, color schemes, legends, or axes rotation

In code this amounts to the basic template:

```
ggplot(data = <DATA>, mapping = aes(<MAPPINGS>)) + <GEOM_FUNCTION>()
```

We can further expand this template to include aspects of the visualization such as theme and labels:

```
# plot data from my_data columns as red points
ggplot(data = my_data)+                         # use the dataset "my_data"
  geom_point()+                                    # add a layer of points (dots)
  mapping = aes(x = col1, y = col2),             # "map" data column to axes
  color = "red")+
  labs()+                                         # here you add titles, axes labels, etc.
  theme()                                         # here you adjust color, font, size etc of non-d
```

We will explain each component in the sections below.

`ggplot()`

The opening command of any ggplot2 plot is `ggplot()`. This command simply creates a blank canvas upon which to add layers. It “opens” the way for further layers to be added with a `+` symbol.

Typically, the command `ggplot()` includes the `data =` argument for the plot. This sets the default dataset to be used for subsequent layers of the plot.

This command will end with a `+` after its closing parentheses. This leaves the command “open”. The `ggplot` will only execute/appear when the full command includes a final layer *without* a `+` at the end.

```
# This will create plot that is a blank canvas
ggplot(data = linelist)
```

Geoms

A blank canvas is certainly not sufficient - we need to create geometries (shapes) from our data (e.g. bar plots, histograms, scatter plots, box plots).

This is done by adding layers “geoms” to the initial `ggplot()` command. There are many `ggplot2` functions that create “geoms”. Each of these functions begins with “`geom_`”, so we will refer to them generically as `geom_XXXX()`. There are over 40 geoms in `ggplot2` and many others created by fans. View them at the [ggplot2 gallery](#). Some common geoms are listed below:

- Histograms - `geom_histogram()`
- Bar charts - `geom_bar()` or `geom_col()` (see “[Bar plot](#)” section)
- Box plots - `geom_boxplot()`
- Points (e.g. scatter plots) - `geom_point()`
- Line graphs - `geom_line()` or `geom_path()`
- Trend lines - `geom_smooth()`

In one plot you can display one or multiple geoms. Each is added to previous `ggplot2` commands with a `+`, and they are plotted sequentially such that later geoms are plotted on top of previous ones.

Mapping data to the plot

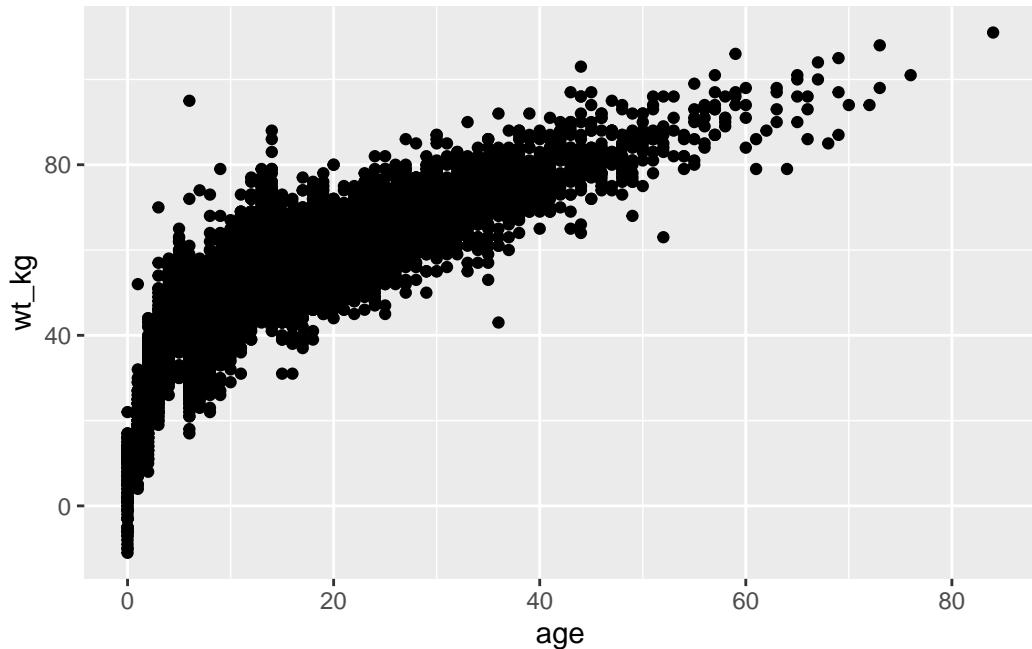
Most geom functions must be told *what to use* to create their shapes - so you must tell them how they should *map (assign) columns in your data* to components of the plot like the axes, shape colors, shape sizes, etc. For most geoms, the *essential* components that must be mapped to columns in the data are the x-axis, and (if necessary) the y-axis.

This “mapping” occurs with the `mapping = argument`. The mappings you provide to `mapping` must be wrapped in the `aes()` function, so you would write something like `mapping = aes(x = col1, y = col2)`, as shown below.

Below, in the `ggplot()` command the data are set as the case `linelist`. In the `mapping = aes()` argument the column `age` is mapped to the x-axis, and the column `wt_kg` is mapped to the y-axis.

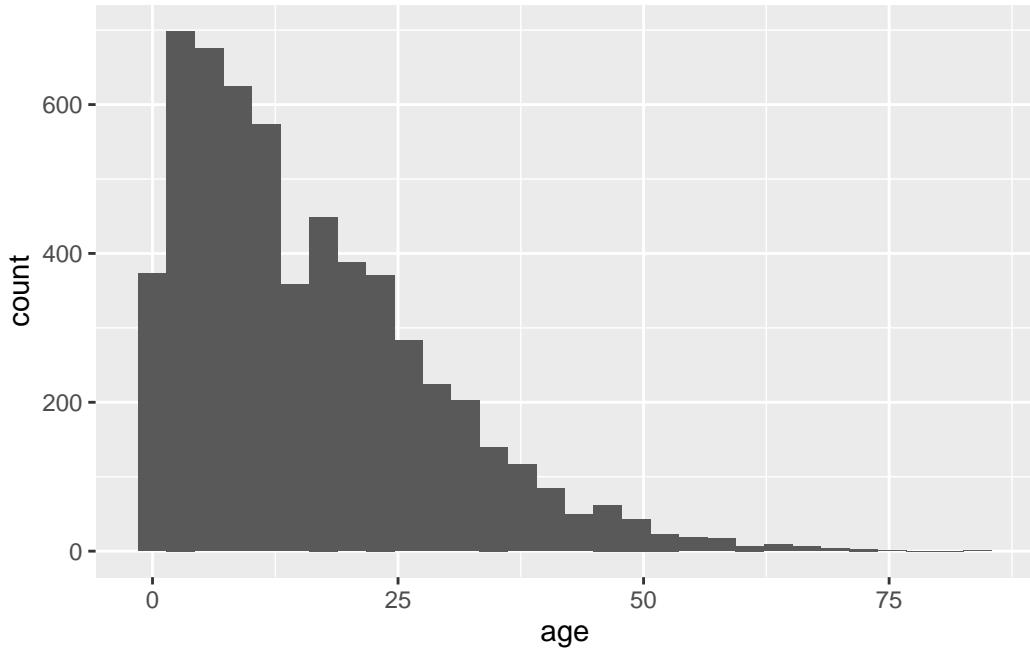
After a `+`, the plotting commands continue. A shape is created with the “geom” function `geom_point()`. This geom *inherits* the mappings from the `ggplot()` command above - it knows the axis-column assignments and proceeds to visualize those relationships as *points* on the canvas.

```
ggplot(data = linelist, mapping = aes(x = age, y = wt_kg))+
  geom_point()
```



As another example, the following commands utilize the same data, a slightly different mapping, and a different geom. The `geom_histogram()` function only requires a column mapped to the x-axis, as the counts y-axis is generated automatically.

```
ggplot(data = linelist, mapping = aes(x = age))+
  geom_histogram()
```



Plot aesthetics

In ggplot terminology a plot “aesthetic” has a specific meaning. It refers to a visual property of *plotted data*. Note that “aesthetic” here refers to the *data being plotted in geoms/shapes* - not the surrounding display such as titles, axis labels, background color, that you might associate with the word “aesthetics” in common English. In ggplot those details are called “themes” and are adjusted within a `theme()` command (see [this section](#)).

Therefore, plot object *aesthetics* can be colors, sizes, transparencies, placement, etc. *of the plotted data*. Not all geoms will have the same aesthetic options, but many can be used by most geoms. Here are some examples:

- `shape` = Display a point with `geom_point()` as a dot, star, triangle, or square...

- **fill** = The interior color (e.g. of a bar or boxplot)
- **color** = The exterior line of a bar, boxplot, etc., or the point color if using `geom_point()`
- **size** = Size (e.g. line thickness, point size)
- **alpha** = Transparency (1 = opaque, 0 = invisible)
- **binwidth** = Width of histogram bins
- **width** = Width of “bar plot” columns
- **linetype** = Line type (e.g. solid, dashed, dotted)

These plot object aesthetics can be assigned values in two ways:

- 1) Assigned a static value (e.g. `color = "blue"`) to apply across all plotted observations
- 2) Assigned to a column of the data (e.g. `color = hospital`) such that display of each observation depends on its value in that column

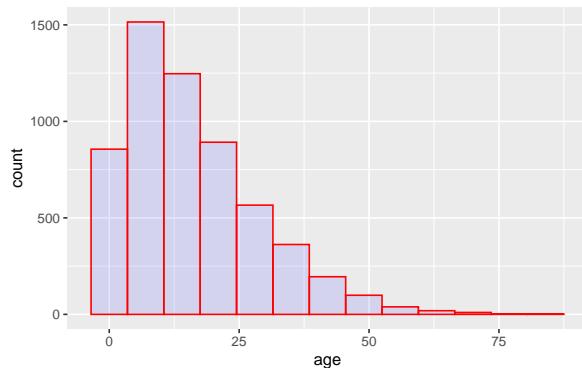
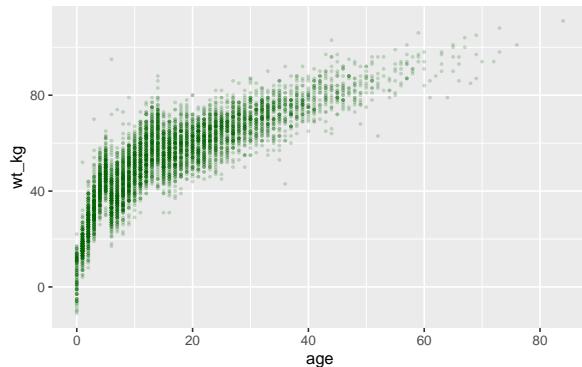
Set to a static value

If you want the plot object aesthetic to be static, that is - to be the same for every observation in the data, you write its assignment within the geom but *outside* of any `mapping = aes()` statement. These assignments could look like `size = 1` or `color = "blue"`. Here are two examples:

- In the first example, the `mapping = aes()` is in the `ggplot()` command and the axes are mapped to age and weight columns in the data. The plot aesthetics `color` =, `size` =, and `alpha` = (transparency) are assigned to static values. For clarity, this is done in the `geom_point()` function, as you may add other geoms afterward that would take different values for their plot aesthetics.
- In the second example, the histogram requires only the x-axis mapped to a column. The histogram `binwidth` =, `color` =, `fill` = (internal color), and `alpha` = are again set within the geom to static values.

```
# scatterplot
ggplot(data = linelist, mapping = aes(x = age, y = wt_kg)) + # set data and axes mapping
  geom_point(color = "darkgreen", size = 0.5, alpha = 0.2)       # set static point aest
```

```
# histogram
ggplot(data = linelist, mapping = aes(x = age))+
  geom_histogram(binwidth = 7, color = "red", fill = "blue", alpha = 0.1) # set data and axes
```



Scaled to column values

The alternative is to scale the plot object aesthetic by the values in a column. In this approach, the display of this aesthetic will depend on that observation's value in that column of the data. If the column values are continuous, the display scale (legend) for that aesthetic will be continuous. If the column values are discrete, the legend will display each value and the plotted data will appear as distinctly “grouped” (read more in the [grouping](#) section of this page).

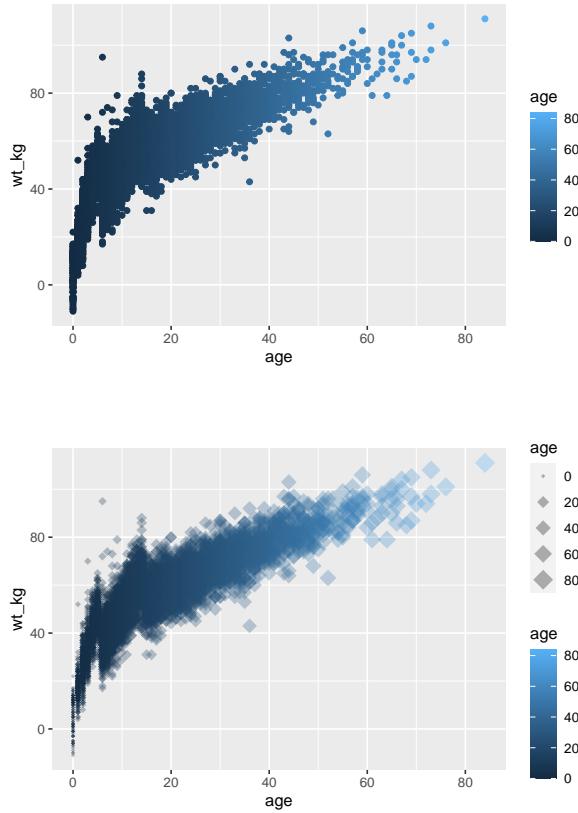
To achieve this, you map that plot aesthetic to a *column name* (not in quotes). This must be done *within a `mapping = aes()` function* (note: there are several places in the code you can make these mapping assignments, as discussed [below](#)).

Two examples are below.

- In the first example, the `color` = aesthetic (of each point) is mapped to the column `age` - and a scale has appeared in a legend! For now just note that the scale exists - we will show how to modify it in later sections.
- In the second example two new plot aesthetics are also mapped to columns (`color` = and `size` =), while the plot aesthetics `shape` = and `alpha` = are mapped to static values outside of any `mapping = aes()` function.

```
# scatterplot
ggplot(data = linelist,    # set data
        mapping = aes(      # map aesthetics to column values
            x = age,          # map x-axis to age
            y = wt_kg,         # map y-axis to weight
            color = age)
        )+      # map color to age
geom_point()           # display data as points

# scatterplot
ggplot(data = linelist,    # set data
        mapping = aes(      # map aesthetics to column values
            x = age,          # map x-axis to age
            y = wt_kg,         # map y-axis to weight
            color = age,
            size = age))+   # map size to age
geom_point(
    shape = "diamond",   # points display as diamonds
    alpha = 0.3)          # point transparency at 30%
```



i Note

Axes assignments are always assigned to columns in the data (not to static values), and this is always done within `mapping = aes()`.

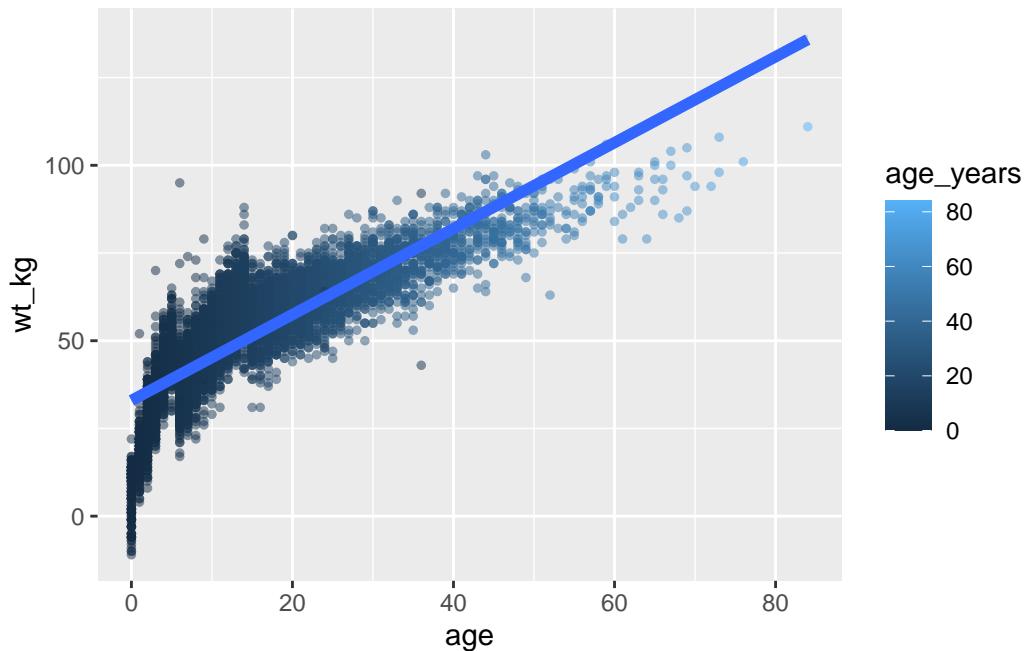
It becomes important to keep track of your plot layers and aesthetics when making more complex plots - for example plots with multiple geoms. In the example below, the `size =` aesthetic is assigned twice - once for `geom_point()` and once for `geom_smooth()` - both times as a static value.

```
ggplot(data = linelist,
       mapping = aes(                  # map aesthetics to columns
         x = age,
         y = wt_kg,
         color = age_years)
     ) +
   geom_point(                      # add points for each row of data
     size = 1,
```

```

alpha = 0.5) +
geom_smooth(
method = "lm",
size = 2)
# add a trend line
# with linear method
# size (width of line) of 2

```



Where to make mapping assignments

Aesthetic mapping within `mapping = aes()` can be written in several places in your plotting commands and can even be written more than once. This can be written in the top `ggplot()` command, and/or for each individual geom beneath. The nuances include:

- Mapping assignments made in the top `ggplot()` command will be inherited as defaults across any geom below, like how `x =` and `y =` are inherited
- Mapping assignments made within one geom apply only to that geom

Likewise, `data =` specified in the top `ggplot()` will apply by default to any geom below, but you could also specify data for each geom (but this is more difficult).

Thus, each of the following commands will create the same plot:

```

# These commands will produce the exact same plot
ggplot(data = linelist, mapping = aes(x = age))+

```

```
geom_histogram()  
  
ggplot(data = linelist)+  
  geom_histogram(mapping = aes(x = age))  
  
ggplot()+  
  geom_histogram(data = linelist, mapping = aes(x = age))
```

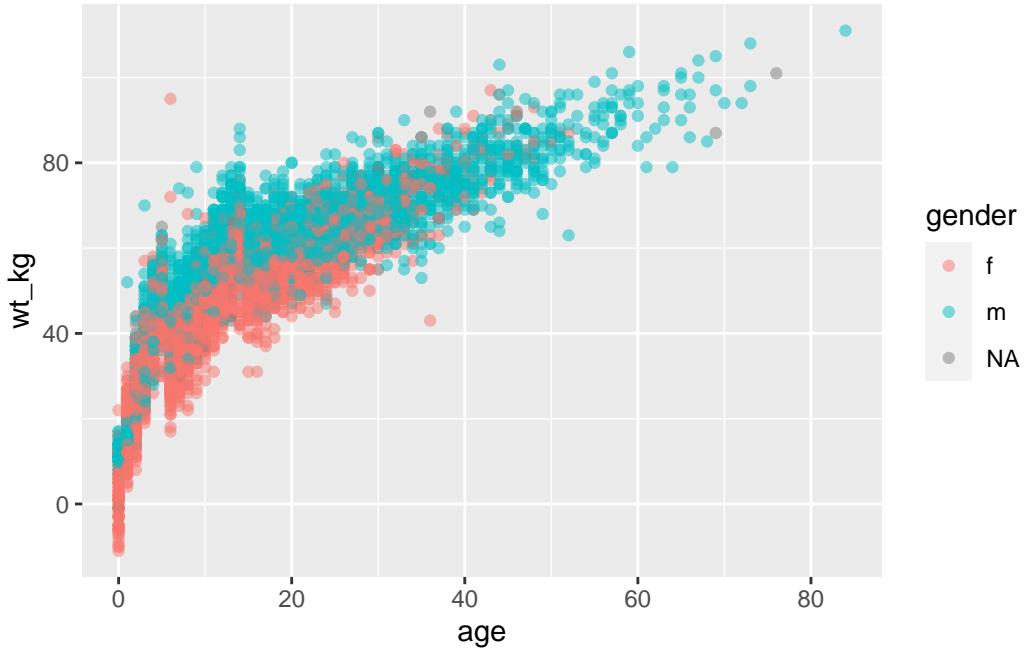
Groups

You can easily group the data and “plot by group”. In fact, you have already done this!

Assign the “grouping” column to the appropriate plot aesthetic, within a `mapping = aes()`. Above, we demonstrated this using continuous values when we assigned point `size =` to the column `age`. However this works the same way for discrete/categorical columns.

For example, if you want points to be displayed by gender, you would set `mapping = aes(color = gender)`. A legend automatically appears. This assignment can be made within the `mapping = aes()` in the top `ggplot()` command (and be inherited by the geom), or it could be set in a separate `mapping = aes()` within the geom. Both approaches are shown below:

```
ggplot(data = linelist,  
       mapping = aes(x = age, y = wt_kg, color = gender))+  
  geom_point(alpha = 0.5)
```



```
# This alternative code produces the same plot
ggplot(data = linelist,
       mapping = aes(x = age, y = wt_kg)) +
  geom_point(
    mapping = aes(color = gender),
    alpha = 0.5)
```

Note that depending on the geom, you will need to use different arguments to group the data. For `geom_point()` you will most likely use `color =`, `shape =` or `size =`. Whereas for `geom_bar()` you are more likely to use `fill =`. This just depends on the geom and what plot aesthetic you want to reflect the groupings.

For your information - the most basic way of grouping the data is by using only the `group =` argument within `mapping = aes()`. However, this by itself will not change the colors, fill, or shapes. Nor will it create a legend. Yet the data are grouped, so statistical displays may be affected.

Facets / Small-multiples

Facets, or “small-multiples”, are used to split one plot into a multi-panel figure, with one panel (“facet”) per group of data. The same type of plot is created multiple times, each one using a sub-group of the same dataset.

Faceting is a functionality that comes with **ggplot2**, so the legends and axes of the facet “panels” are automatically aligned. We would need to use other packages to combine completely different plots (**cowplot** and **patchwork**) into one figure.

Faceting is done with one of the following **ggplot2** functions:

1. **facet_wrap()** To show a different panel for each level of a *single* variable. One example of this could be showing a different epidemic curve for each hospital in a region. Facets are ordered alphabetically, unless the variable is a factor with other ordering defined.
 - You can invoke certain options to determine the layout of the facets, e.g. `nrow = 1` or `ncol = 1` to control the number of rows or columns that the faceted plots are arranged within.
2. **facet_grid()** This is used when you want to bring a second variable into the faceting arrangement. Here each panel of a grid shows the intersection between values in *two columns*. For example, epidemic curves for each hospital-age group combination with hospitals along the top (columns) and age groups along the sides (rows).
 - `nrow` and `ncol` are not relevant, as the subgroups are presented in a grid

Each of these functions accept a formula syntax to specify the column(s) for faceting. Both accept up to two columns, one on each side of a tilde ~.

- For **facet_wrap()** most often you will write only one column preceded by a tilde ~ like `facet_wrap(~hospital)`. However you can write two columns `facet_wrap(outcome ~ hospital)` - each unique combination will display in a separate panel, but they will not be arranged in a grid. The headings will show combined terms and these won't be specific logic to the columns vs. rows. If you are providing only one faceting variable, a period . is used as a placeholder on the other side of the formula - see the code examples.
- For **facet_grid()** you can also specify one or two columns to the formula (grid `rows ~ columns`). If you only want to specify one, you can place a period . on the other side of the tilde like `facet_grid(. ~ hospital)` or `facet_grid(hospital ~ .)`.

Facets can quickly contain an overwhelming amount of information - its good to ensure you don't have too many levels of each variable that you choose to facet by. Here are some quick examples with the malaria dataset which consists of daily case counts of malaria for facilities, by age group.

Below we import and do some quick modifications for simplicity:

```
# These data are daily counts of malaria cases, by facility-day
malaria_data <- import("data/malaria_facility_count_data.rds") %>% # import
  select(-submitted_date, -Province, -newid) # remove unne
```

The first 50 rows of the malaria data are below. Note there is a column `malaria_tot`, but also columns for counts by age group (these will be used in the second, `facet_grid()` example).

```
# A tibble: 50 x 7
  location_name data_date District `malaria_rdt_0-4` `malaria_rdt_5-14` 
  <chr>        <date>     <chr>          <int>           <int>    
1 Facility 1   2020-08-11 Spring         11            12      
2 Facility 2   2020-08-11 Bolo           11            10      
3 Facility 3   2020-08-11 Dingo          8             5      
4 Facility 4   2020-08-11 Bolo           16            16      
5 Facility 5   2020-08-11 Bolo           9             2      
6 Facility 6   2020-08-11 Dingo          3             1      
7 Facility 6   2020-08-10 Dingo          4             0      
8 Facility 5   2020-08-10 Bolo          15            14      
9 Facility 5   2020-08-09 Bolo          11            11      
10 Facility 5  2020-08-08 Bolo          19            15     
# i 40 more rows
# i 2 more variables: malaria_rdt_15 <int>, malaria_tot <int>
```

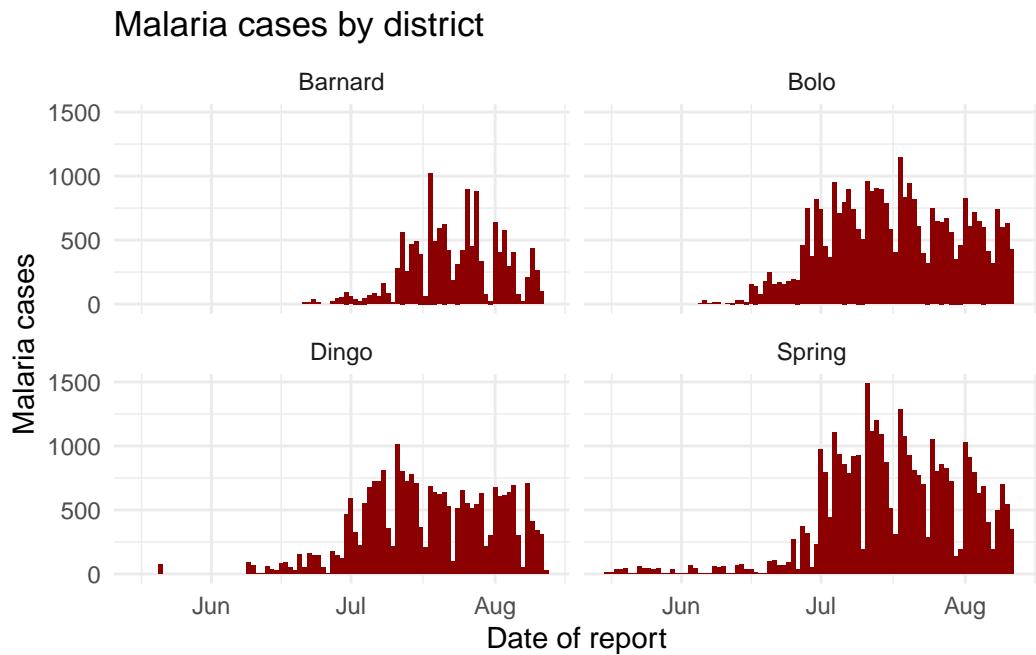
`facet_wrap()`

For the moment, let's focus on the columns `malaria_tot` and `District`. Ignore the age-specific count columns for now. We will plot epidemic curves with `geom_col()`, which produces a column for each day at the specified y-axis height given in column `malaria_tot` (the data are already daily counts, so we use `geom_col()` - see [the “Bar plot” section below](#)).

When we add the command `facet_wrap()`, we specify a tilde and then the column to facet on (`District` in this case). You can place another column on the left side of the tilde, - this will create one facet for each combination - but we recommend you do this with `facet_grid()` instead. In this use case, one facet is created for each unique value of `District`.

```
# A plot with facets by district
ggplot(malaria_data, aes(x = data_date, y = malaria_tot)) +
  geom_col(width = 1, fill = "darkred") +      # plot the count data as columns
  theme_minimal() +                            # simplify the background panels
  labs(                                         # add plot labels, title, etc.
    x = "Date of report",
```

```
y = "Malaria cases",
title = "Malaria cases by district") +
facet_wrap(~District) # the facets are created
```



facet_grid()

We can use a `facet_grid()` approach to cross two variables. Let's say we want to cross `District` and `age`. Well, we need to do some data transformations on the `age` columns to get these data into ggplot-preferred “long” format. The `age` groups all have their own columns - we want them in a single column called `age_group` and another called `num_cases`.

```
malaria_age <- malaria_data %>%
  select(-malaria_tot) %>%
  pivot_longer(
    cols = c(starts_with("malaria_rdt_")), # choose columns to pivot longer
    names_to = "age_group",                 # column names become age group
    values_to = "num_cases"                # values to a single column (num_cases)
  ) %>%
  mutate(
    age_group = str_replace(age_group, "malaria_rdt_", ""),
    age_group =forcats::fct_relevel(age_group, "5-14", after = 1))
```

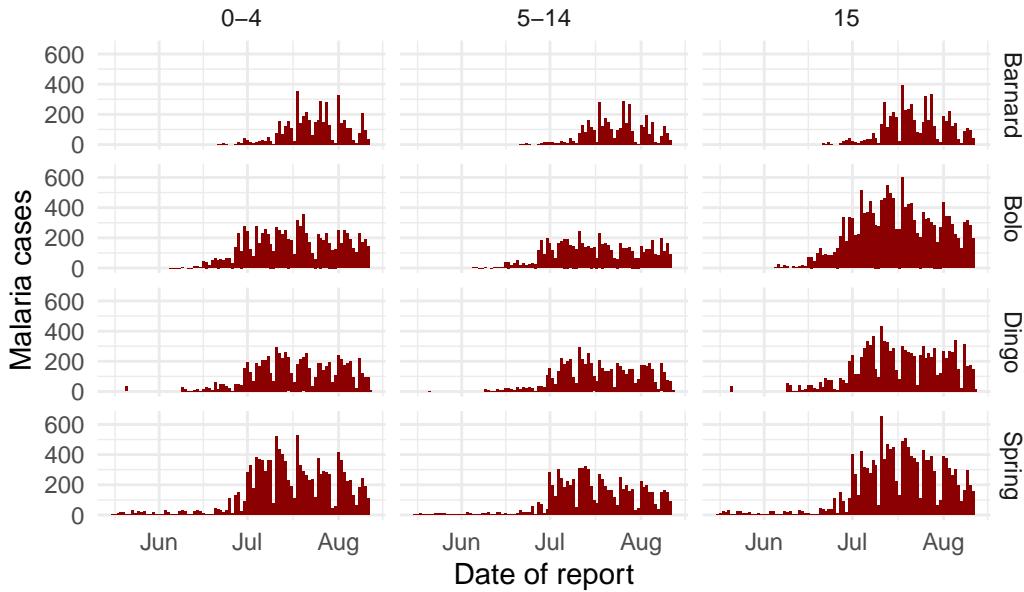
Now the first 50 rows of data look like this:

```
# A tibble: 50 x 5
  location_name data_date District age_group num_cases
  <chr>        <date>    <chr>    <fct>      <int>
1 Facility 1   2020-08-11 Spring   0-4       11
2 Facility 1   2020-08-11 Spring   5-14      12
3 Facility 1   2020-08-11 Spring   15        23
4 Facility 2   2020-08-11 Bolo     0-4       11
5 Facility 2   2020-08-11 Bolo     5-14      10
6 Facility 2   2020-08-11 Bolo     15        5
7 Facility 3   2020-08-11 Dingo   0-4       8
8 Facility 3   2020-08-11 Dingo   5-14      5
9 Facility 3   2020-08-11 Dingo   15        5
10 Facility 4  2020-08-11 Bolo    0-4      16
# i 40 more rows
```

When you pass the two variables to `facet_grid()`, easiest is to use formula notation (e.g. `x ~ y`) where x is rows and y is columns. Here is the plot, using `facet_grid()` to show the plots for each combination of the columns `age_group` and `District`.

```
ggplot(malaria_age, aes(x = data_date, y = num_cases)) +
  geom_col(fill = "darkred", width = 1) +
  theme_minimal() +
  labs(
    x = "Date of report",
    y = "Malaria cases",
    title = "Malaria cases by district and age group"
  ) +
  facet_grid(District ~ age_group)
```

Malaria cases by district and age group



Free or fixed axes

The axes scales displayed when faceting are by default the same (fixed) across all the facets. This is helpful for cross-comparison, but not always appropriate.

When using `facet_wrap()` or `facet_grid()`, we can add `scales = "free_y"` to “free” or release the y-axes of the panels to scale appropriately to their data subset. This is particularly useful if the actual counts are small for one of the subcategories and trends are otherwise hard to see. Instead of “`free_y`” we can also write “`free_x`” to do the same for the x-axis (e.g. for dates) or “`free`” for both axes. Note that in `facet_grid`, the y scales will be the same for facets in the same row, and the x scales will be the same for facets in the same column.

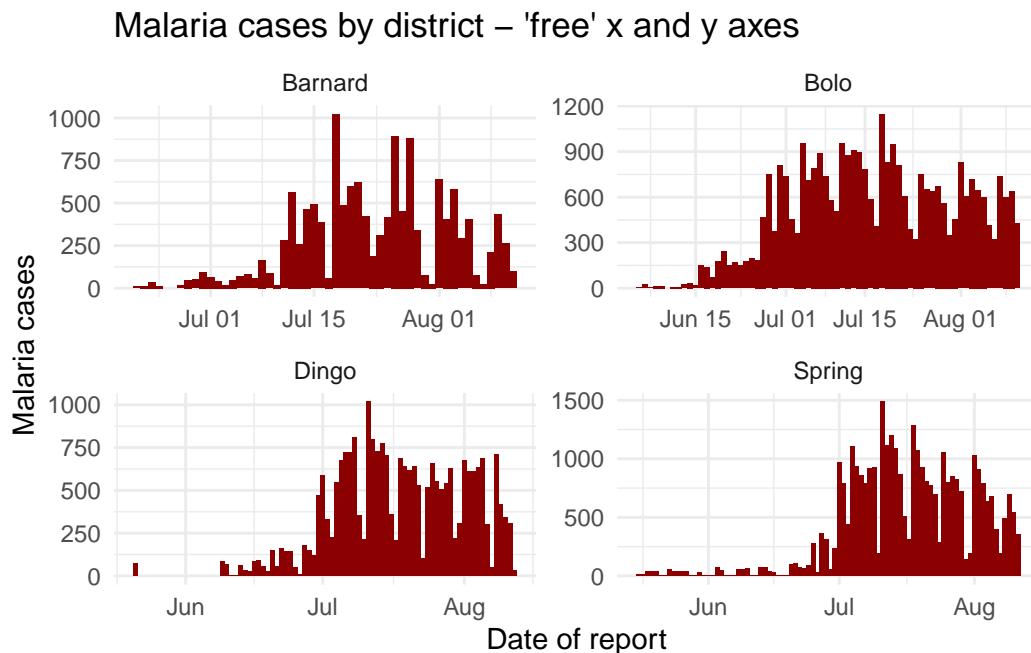
When using `facet_grid` only, we can add `space = "free_y"` or `space = "free_x"` so that the actual height or width of the facet is weighted to the values of the figure within. This only works if `scales = "free"` (y or x) is already applied.

```
# Free y-axis
ggplot(malaria_data, aes(x = data_date, y = malaria_tot)) +
  geom_col(width = 1, fill = "darkred") +          # plot the count data as columns
  theme_minimal() +                                # simplify the background panels
  labs(                                            # add plot labels, title, etc.
    x = "Date of report",
```

```

y = "Malaria cases",
title = "Malaria cases by district - 'free' x and y axes") +
facet_wrap(~District, scales = "free")           # the facets are created

```



Exporting plots

Exporting ggplots is made easy with the `ggsave()` function from **ggplot2**. It can work in two ways, either:

- Specify the name of the plot object, then the file path and name with extension
 - For example: `ggsave(my_plot, "plots/my_plot.png")`
- Run the command with only a file path, to save the last plot that was printed
 - For example: `ggsave("plots/my_plot.png")`

You can export as png, pdf, jpeg, tiff, bmp, svg, or several other file types, by specifying the file extension in the file path.

You can also specify the arguments `width =`, `height =`, and `units =` (either “in”, “cm”, or “mm”). You can also specify `dpi =` with a number for plot resolution (e.g. 300). See the function details by entering `?ggsave` or reading the [documentation online](#).

Labels

Surely you will want to add or adjust the plot's labels. These are most easily done within the `labs()` function which is added to the plot with `+` just as the geoms were.

Within `labs()` you can provide character strings to these arguments:

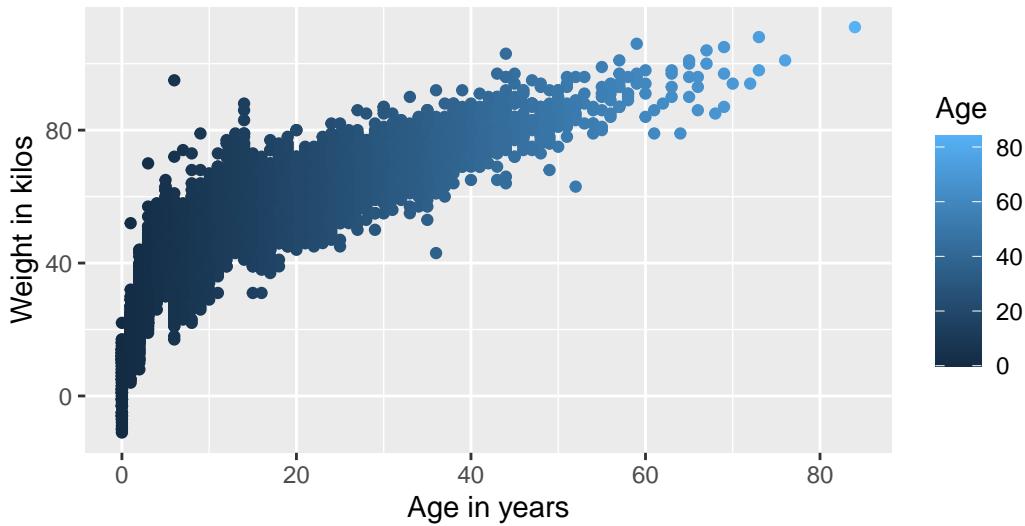
- `x` = and `y` = The x-axis and y-axis title (labels)
- `title` = The main plot title
- `subtitle` = The subtitle of the plot, in smaller text below the title
- `caption` = The caption of the plot, in bottom-right by default

Here is a plot we made earlier, but with nicer labels:

```
age_by_wt <- ggplot(  
  data = linelist,    # set data  
  mapping = aes(      # map aesthetics to column values  
    x = age,          # map x-axis to age  
    y = wt_kg,        # map y-axis to weight  
    color = age)) +  # map color to age  
  geom_point() +     # display data as points  
  labs(  
    title = "Age and weight distribution",  
    subtitle = "Fictional Ebola outbreak, 2014",  
    x = "Age in years",  
    y = "Weight in kilos",  
    color = "Age",  
    caption = stringr::str_glue("Data as of {max(linelist$date_hospitalisation, na.rm=T)}"))  
  
age_by_wt
```

Age and weight distribution

Fictional Ebola outbreak, 2014



Data as of 2015-04-30

Note how in the caption assignment we used `str_glue()` from the `stringr` package to implant dynamic R code within the string text. The caption will show the “Data as of:” date that reflects the maximum hospitalization date in the linelist.

Plot continuous data

Throughout this page, you have already seen many examples of plotting continuous data. Here we briefly consolidate these and present a few variations.

Visualisations covered here include:

- Plots for one continuous variable:
 - **Histogram**, a classic graph to present the distribution of a continuous variable.
 - **Box plot** (also called box and whisker), to show the 25th, 50th, and 75th percentiles, tail ends of the distribution, and outliers ([important limitations](#)).
 - **Jitter plot**, to show all values as points that are ‘jittered’ so they can (mostly) all be seen, even where two have the same value.
 - **Violin plot**, show the distribution of a continuous variable based on the symmetrical width of the ‘violin’.

- **Sina plot**, are a combination of jitter and violin plots, where individual points are shown but in the symmetrical shape of the distribution (via `ggforce` package).
- **Scatter plot** for two continuous variables.
- **Heat plots** for three continuous variables

Histograms

Histograms may look like bar charts, but are distinct because they measure the distribution of a *continuous* variable. There are no spaces between the “bars”, and only one column is provided to `geom_histogram()`.

Below is code for generating **histograms**, which group continuous data into ranges and display in adjacent bars of varying height. This is done using `geom_histogram()`. See the “[Bar plot](#)” section of the ggplot basics page to understand difference between `geom_histogram()`, `geom_bar()`, and `geom_col()`.

We will show the distribution of ages of cases. Within `mapping = aes()` specify which column you want to see the distribution of. You can assign this column to either the x or the y axis.

The rows will be assigned to “bins” based on their numeric age, and these bins will be graphically represented by bars. If you specify a number of bins with the `bins` = plot aesthetic, the break points are evenly spaced between the minimum and maximum values of the histogram. If `bins` = is unspecified, an appropriate number of bins will be guessed and this message displayed after the plot:

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

If you do not want to specify a number of bins to `bins` =, you could alternatively specify `binwidth` = in the units of the axis. We give a few examples showing different bins and bin widths:

```
# A) Regular histogram
ggplot(data = linelist, aes(x = age))+
  geom_histogram()+
  labs(title = "A) Default histogram (30 bins)")

# B) More bins
ggplot(data = linelist, aes(x = age))+
  geom_histogram(bins = 50)+
  labs(title = "B) Set to 50 bins")
```

```

# C) Fewer bins
ggplot(data = linelist, aes(x = age))+ # provide x variable
  geom_histogram(bins = 5)+  

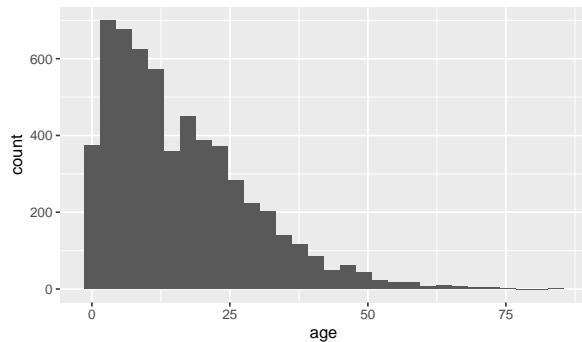
  labs(title = "C) Set to 5 bins")

# D) More bins
ggplot(data = linelist, aes(x = age))+ # provide x variable
  geom_histogram(binwidth = 1)+  

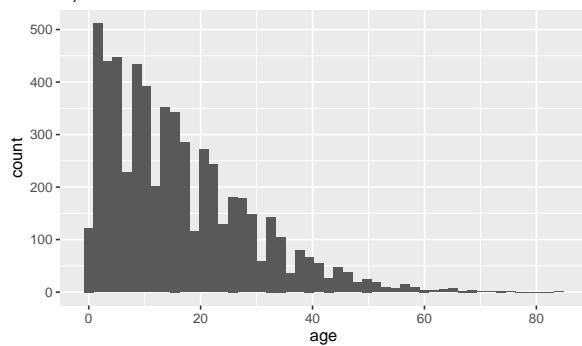
  labs(title = "D) binwidth of 1")

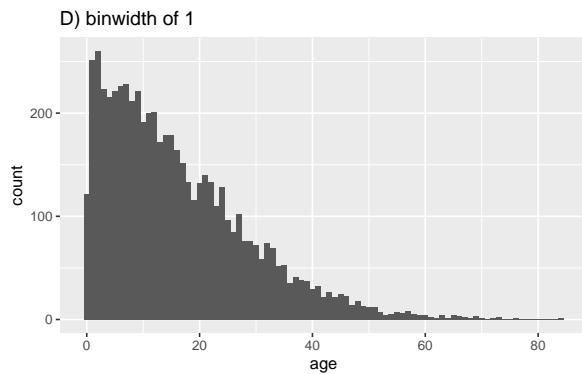
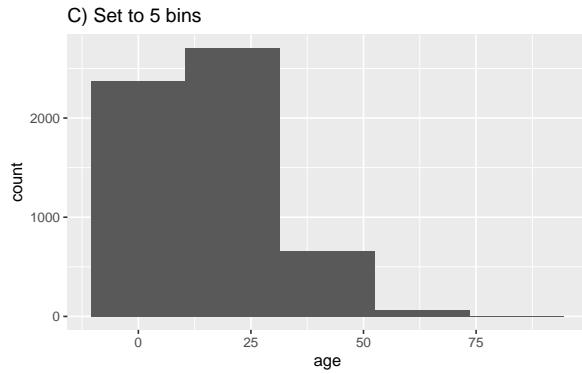
```

A) Default histogram (30 bins)



B) Set to 50 bins

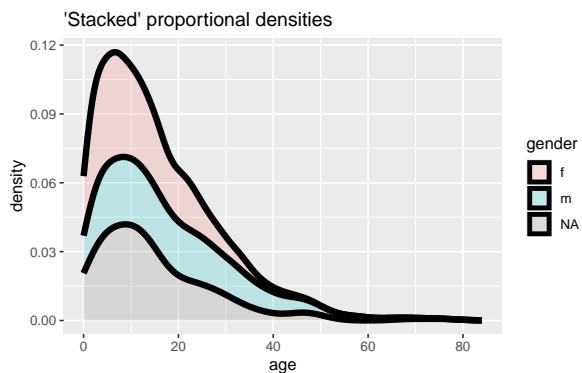
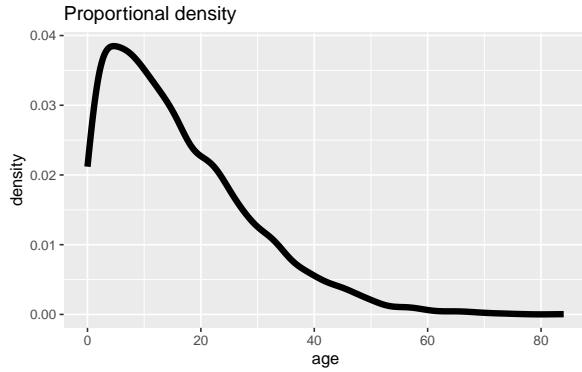




To get smoothed proportions, you can use `geom_density()`:

```
# Frequency with proportion axis, smoothed
ggplot(data = linelist, mapping = aes(x = age)) +
  geom_density(size = 2, alpha = 0.2) +
  labs(title = "Proportional density")

# Stacked frequency with proportion axis, smoothed
ggplot(data = linelist, mapping = aes(x = age, fill = gender)) +
  geom_density(size = 2, alpha = 0.2, position = "stack") +
  labs(title = "'Stacked' proportional densities")
```



To get a “stacked” histogram (of a continuous column of data), you can do one of the following:

- 1) Use `geom_histogram()` with the `fill =` argument within `aes()` and assigned to the grouping column, or
- 2) Use `geom_freqpoly()`, which is likely easier to read (you can still set `binwidth =`)
- 3) To see proportions of all values, set the `y = after_stat(density)` (use this syntax exactly - not changed for your data). Note: these proportions will show *per group*.

Each is shown below (*note use of `color =` vs. `fill =` in each):

```
# "Stacked" histogram
ggplot(data = linelist, mapping = aes(x = age, fill = gender)) +
  geom_histogram(binwidth = 2) +
  labs(title = "'Stacked' histogram")

# Frequency
```

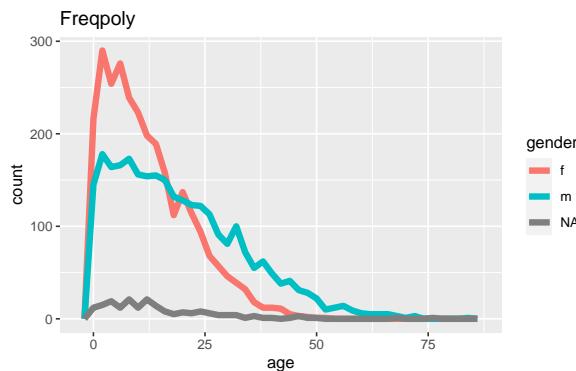
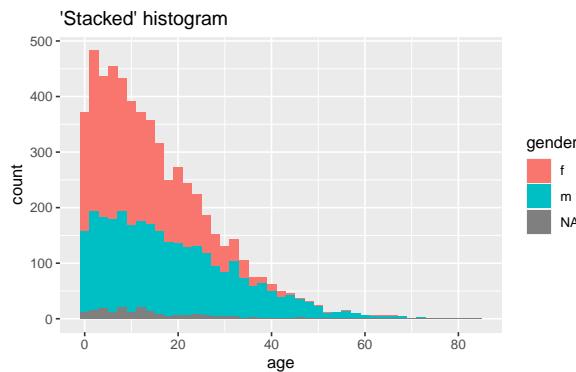
```

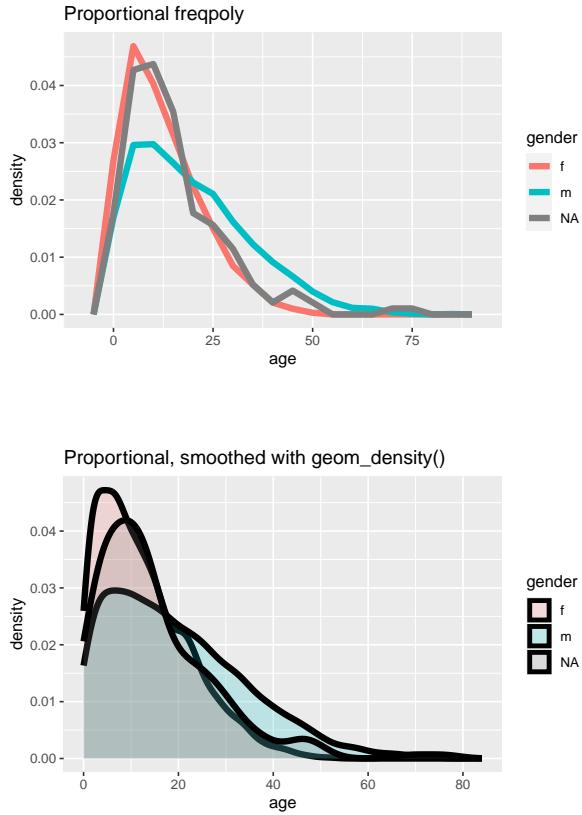
ggplot(data = linelist, mapping = aes(x = age, color = gender)) +
  geom_freqpoly(binwidth = 2, size = 2) +
  labs(title = "Freqpoly")

# Frequency with proportion axis
ggplot(data = linelist, mapping = aes(x = age, y = after_stat(density), color = gender)) +
  geom_freqpoly(binwidth = 5, size = 2) +
  labs(title = "Proportional freqpoly")

# Frequency with proportion axis, smoothed
ggplot(data = linelist, mapping = aes(x = age, y = after_stat(density), fill = gender)) +
  geom_density(size = 2, alpha = 0.2) +
  labs(title = "Proportional, smoothed with geom_density()")

```





If you want to have some fun, try `geom_density_ridges` from the `ggridges` package ([vignette here](#)).

Read more in detail about histograms at the [tidyverse page on geom_histogram\(\)](#).

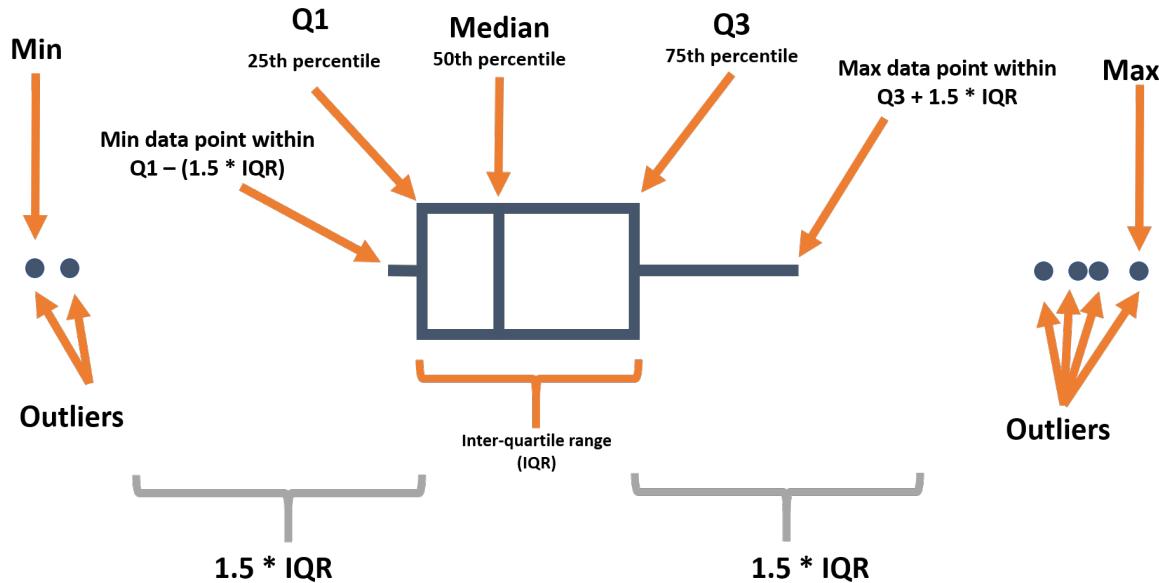
Box plots

Box plots are common, but have important limitations. They can obscure the actual distribution - e.g. a bi-modal distribution. See this [R graph gallery](#) and this [data-to-viz article](#) for more details. However, they do nicely display the inter-quartile range and outliers - so they can be overlaid on top of other types of plots that show the distribution in more detail.

Below we remind you of the various components of a boxplot:

When using `geom_boxplot()` to create a box plot, you generally map only one axis (x or y) within `aes()`. The axis specified determines if the plots are horizontal or vertical.

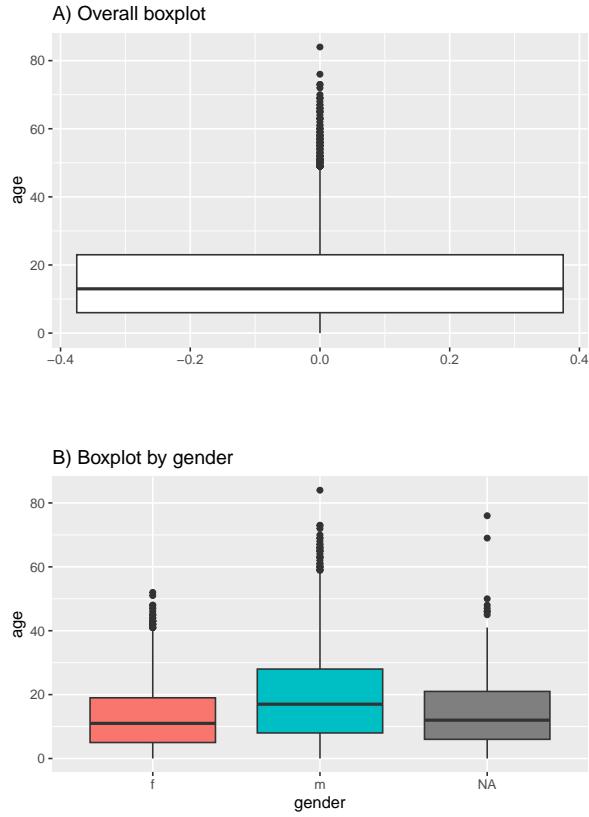
In most geoms, you create a plot per group by mapping an aesthetic like `color =` or `fill =` to a column within `aes()`. However, for box plots achieve this by assigning the grouping column to the un-assigned axis (x or y). Below is code for a boxplot of *all* age values in the dataset,



and second is code to display one box plot for each (non-missing) gender in the dataset. Note that NA (missing) values will appear as a separate box plot unless removed. In this example we also set the `fill` to the column `outcome` so each plot is a different color - but this is not necessary.

```
# A) Overall boxplot
ggplot(data = linelist) +
  geom_boxplot(mapping = aes(y = age)) +    # only y axis mapped (not x)
  labs(title = "A) Overall boxplot")

# B) Box plot by group
ggplot(data = linelist, mapping = aes(y = age, x = gender, fill = gender)) +
  geom_boxplot() +
  theme(legend.position = "none") +    # remove legend (redundant)
  labs(title = "B) Boxplot by gender")
```



Violin, jitter, and sina plots

Below is code for creating **violin plots** (`geom_violin`) and **jitter plots** (`geom_jitter`) to show distributions. You can specify that the fill or color is also determined by the data, by inserting these options within `aes()`.

```
# A) Jitter plot by group
ggplot(data = linelist %>% drop_na(outcome),
       mapping = aes(y = age,
                     x = outcome,
                     color = outcome))+ # remove missing values
# Continuous variable
# Grouping variable
# Color variable
geom_jitter()+
labs(title = "A) jitter plot by gender") # Create the violin plot

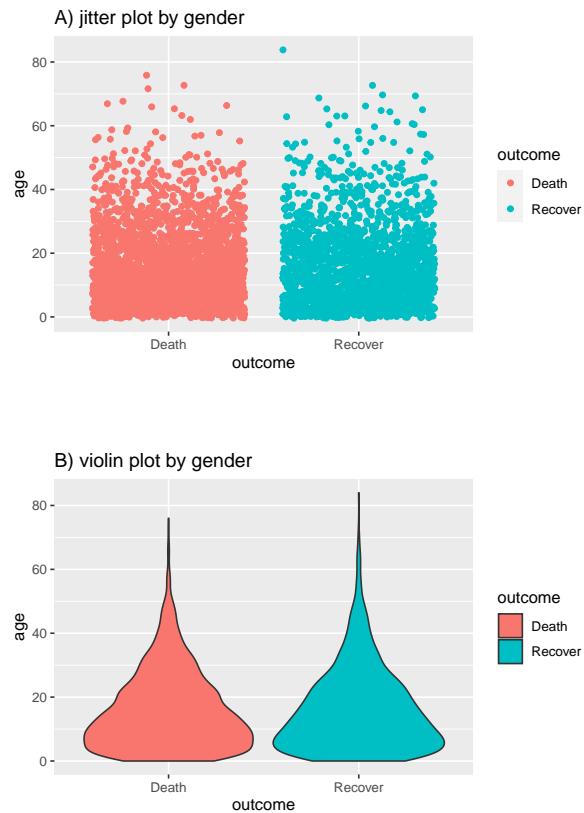
# B) Violin plot by group
```

```

ggplot(data = linelist %>% drop_na(outcome),
       mapping = aes(y = age,
                     x = outcome,
                     fill = outcome))+#
       geom_violin()+
       labs(title = "B) violin plot by gender")

```

remove missing values
Continuous variable
Grouping variable
fill variable (color)
create the violin plot



You can combine the two using the `geom_sina()` function from the `ggforce` package. The `sina` plots the jitter points in the shape of the violin plot. When overlaid on the violin plot (adjusting the transparencies) this can be easier to visually interpret.

```

# A) Sina plot by group
ggplot(
  data = linelist %>% drop_na(outcome),
  aes(y = age,           # numeric variable
      x = outcome)) +   # group variable
  geom_violin()

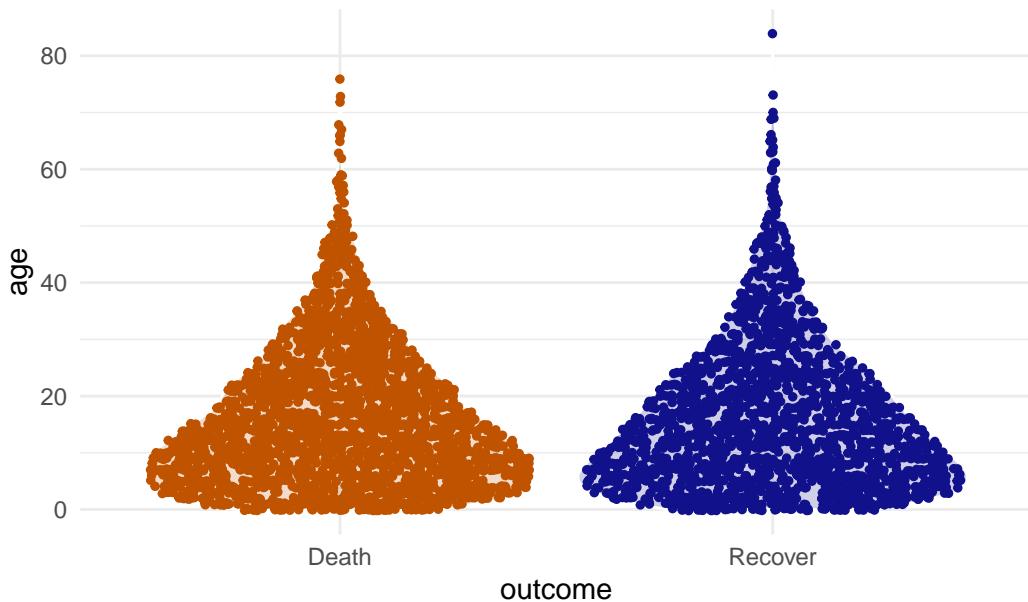
```

```

aes(fill = outcome), # fill (color of violin background)
color = "white",      # white outline
alpha = 0.2)+         # transparency
geom_sina(
  size=1,              # Change the size of the jitter
  aes(color = outcome))+ # color (color of dots)
scale_fill_manual(      # Define fill for violin background by death/recover
  values = c("Death" = "#bf5300",
             "Recover" = "#11118c")) +
scale_color_manual(      # Define colours for points by death/recover
  values = c("Death" = "#bf5300",
             "Recover" = "#11118c")) +
theme_minimal() +          # Remove the gray background
theme(legend.position = "none") +       # Remove unnecessary legend
labs(title = "B) violin and sina plot by gender, with extra formatting")

```

B) violin and sina plot by gender, with extra formatting



Two continuous variables

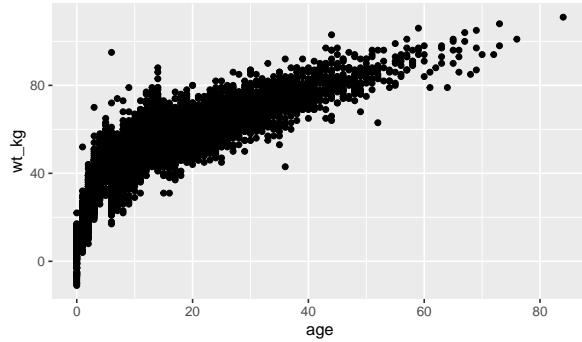
Following similar syntax, `geom_point()` will allow you to plot two continuous variables against each other in a **scatter plot**. This is useful for showing actual values rather than their distributions. A basic scatter plot of age vs weight is shown in (A). In (B) we again use

`facet_grid()` to show the relationship between two continuous variables in the linelist.

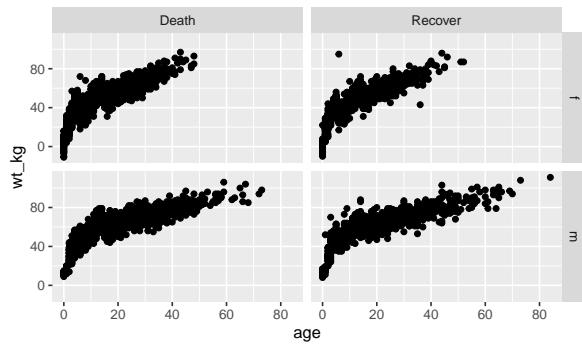
```
# Basic scatter plot of weight and age
ggplot(data = linelist,
       mapping = aes(y = wt_kg, x = age)) +
  geom_point() +
  labs(title = "A) Scatter plot of weight and age")

# Scatter plot of weight and age by gender and Ebola outcome
ggplot(data = linelist %>% drop_na(gender, outcome), # filter retains non-missing gender/outcome
       mapping = aes(y = wt_kg, x = age)) +
  geom_point() +
  labs(title = "B) Scatter plot of weight and age faceted by gender and outcome") +
  facet_grid(gender ~ outcome)
```

A) Scatter plot of weight and age



B) Scatter plot of weight and age faceted by gender and outcome



Three continuous variables

You can display three continuous variables by utilizing the `fill =` argument to create a *heat plot*. The color of each “cell” will reflect the value of the third continuous column of data. There are ways to make 3D plots in R, but for applied epidemiology these are often difficult to interpret and therefore less useful for decision-making.

Plot categorical data

Categorical data can be character values, could be logical (TRUE/FALSE), or factors.

Preparation

* Data structure

The first thing to understand about your categorical data is whether it exists as raw observations like a linelist of cases, or as a summary or aggregate data frame that holds counts or proportions. The state of your data will impact which plotting function you use:

- If your data are raw observations with one row per observation, you will likely use `geom_bar()`
- If your data are already aggregated into counts or proportions, you will likely use `geom_col()`

* Column class and value ordering

Next, examine the class of the columns you want to plot. We look at `hospital`, first with `class()` from base R, and with `tabyl()` from `janitor`.

```
# View class of hospital column - we can see it is a character
class(linelist$hospital)
```

```
[1] "character"
```

```
# Look at values and proportions within hospital column
linelist %>%
  tabyl(hospital)
```

	hospital	n	percent
Central Hospital	454	0.07710598	
Military Hospital	896	0.15217391	
Missing	1469	0.24949049	
Other	885	0.15030571	
Port Hospital	1762	0.29925272	
St. Mark's Maternity Hospital (SMMH)	422	0.07167120	

We can see the values within are characters, as they are hospital names, and by default they are ordered alphabetically. There are ‘other’ and ‘missing’ values, which we would prefer to be the last subcategories when presenting breakdowns. So we change this column into a factor and re-order it.

```
# Convert to factor and define level order so "Other" and "Missing" are last
linelist <- linelist %>%
  mutate(
    hospital = fct_relevel(hospital,
      "St. Mark's Maternity Hospital (SMMH)",
      "Port Hospital",
      "Central Hospital",
      "Military Hospital",
      "Other",
      "Missing"))

levels(linelist$hospital)

[1] "St. Mark's Maternity Hospital (SMMH)"
[2] "Port Hospital"
[3] "Central Hospital"
[4] "Military Hospital"
[5] "Other"
[6] "Missing"

geom_bar()
```

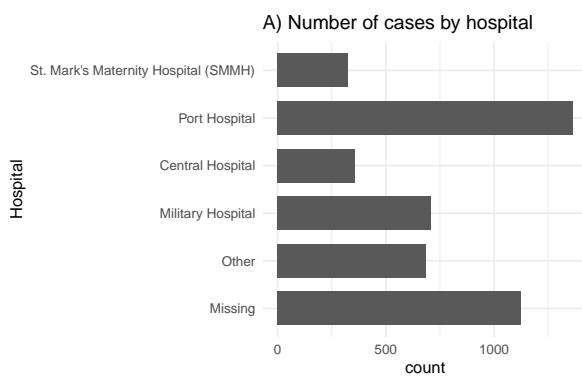
Use `geom_bar()` if you want bar height (or the height of stacked bar components) to reflect the *number of relevant rows in the data*. These bars will have gaps between them, unless the `width =` plot aesthetic is adjusted.

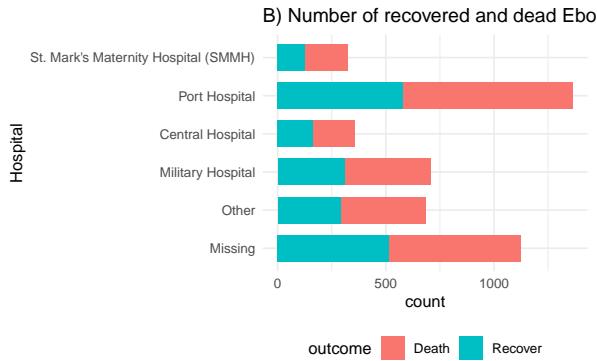
- Provide only one axis column assignment (typically x-axis). If you provide x and y, you will get `Error: stat_count() can only have an x or y aesthetic.`
- You can create stacked bars by adding a `fill = column` assignment within `mapping = aes()`
- The opposite axis will be titled “count” by default, because it represents the number of rows

Below, we have assigned outcome to the y-axis, but it could just as easily be on the x-axis. If you have longer character values, it can sometimes look better to flip the bars sideways and put the legend on the bottom. This may impact how your factor levels are ordered - in this case we reverse them with `fct_rev()` to put missing and other at the bottom.

```
# A) Outcomes in all cases
ggplot(linelist %>% drop_na(outcome)) +
  geom_bar(aes(y = fct_rev(hospital)), width = 0.7) +
  theme_minimal()+
  labs(title = "A) Number of cases by hospital",
       y = "Hospital")

# B) Outcomes in all cases by hospital
ggplot(linelist %>% drop_na(outcome)) +
  geom_bar(aes(y = fct_rev(hospital), fill = outcome), width = 0.7) +
  theme_minimal()+
  theme(legend.position = "bottom") +
  labs(title = "B) Number of recovered and dead Ebola cases, by hospital",
       y = "Hospital")
```





geom_col()

Use `geom_col()` if you want bar height (or height of stacked bar components) to reflect pre-calculated *values* that exists in the data. Often, these are summary or “aggregated” counts, or proportions.

Provide column assignments for *both* axes to `geom_col()`. Typically your x-axis column is discrete and your y-axis column is numeric.

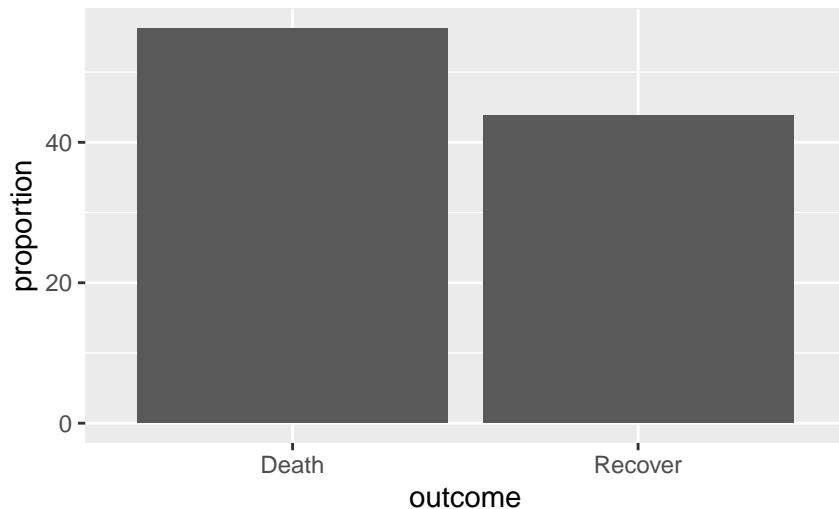
Let’s say we have this dataset `outcomes`:

```
# A tibble: 2 x 3
  outcome     n proportion
  <chr>   <int>     <dbl>
1 Death      1022      56.2
2 Recover    796       43.8
```

Below is code using `geom_col` for creating simple bar charts to show the distribution of Ebola patient outcomes. With `geom_col`, both x and y need to be specified. Here x is the categorical variable along the x axis, and y is the generated proportions column `proportion`.

```
# Outcomes in all cases
ggplot(outcomes) +
  geom_col(aes(x=outcome, y = proportion)) +
  labs(subtitle = "Number of recovered and dead Ebola cases")
```

Number of recovered and dead Ebola cases



To show breakdowns by hospital, we would need our table to contain more information, and to be in “long” format. We create this table with the frequencies of the combined categories `outcome` and `hospital`.

```

outcomes2 <- linelist %>%
  drop_na(outcome) %>%
  count(hospital, outcome) %>% # get counts by hospital and outcome
  group_by(hospital) %>%       # Group so proportions are out of hospital total
  mutate(proportion = n/sum(n)*100) # calculate proportions of hospital total

head(outcomes2) # Preview data

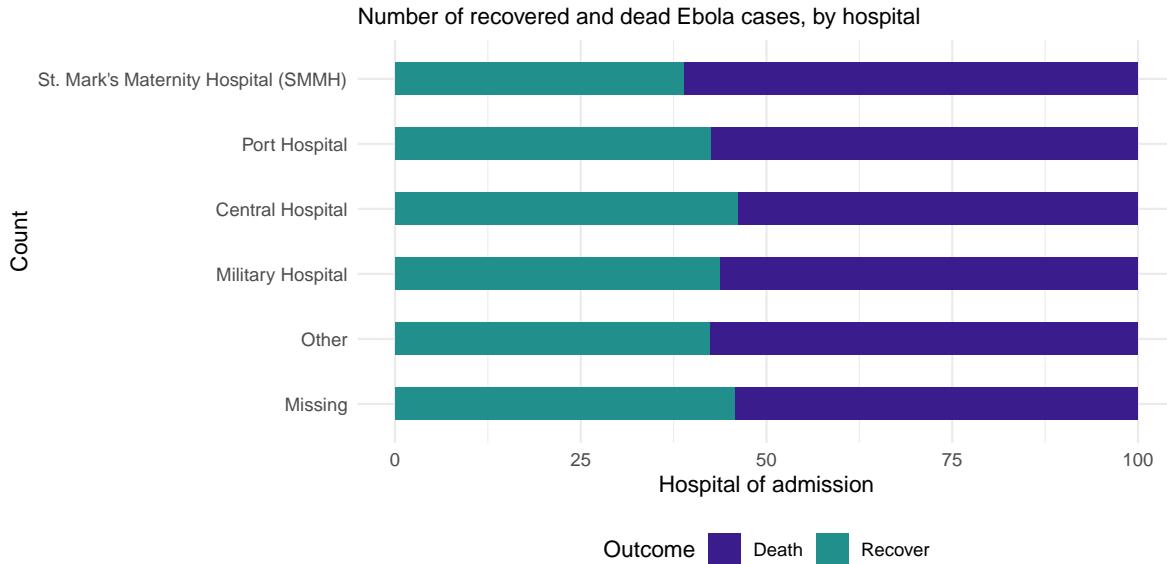
# A tibble: 6 x 4
# Groups:   hospital [3]
  hospital          outcome     n proportion
  <fct>            <chr>    <int>     <dbl>
1 St. Mark's Maternity Hospital (SMMH) Death     199     61.2
2 St. Mark's Maternity Hospital (SMMH) Recover   126     38.8
3 Port Hospital           Death     785     57.6
4 Port Hospital           Recover   579     42.4
5 Central Hospital         Death     193     53.9
6 Central Hospital         Recover   165     46.1

```

We then create the ggplot with some added formatting:

- **Axis flip:** Swapped the axis around with `coord_flip()` so that we can read the hospital names.
- **Columns side-by-side:** Added a `position = "dodge"` argument so that the bars for death and recover are presented side by side rather than stacked. Note stacked bars are the default.
- **Column width:** Specified ‘width’, so the columns are half as thin as the full possible width.
- **Column order:** Reversed the order of the categories on the y axis so that ‘Other’ and ‘Missing’ are at the bottom, with `scale_x_discrete(limits=rev)`. Note that we used that rather than `scale_y_discrete` because hospital is stated in the `x` argument of `aes()`, even if visually it is on the y axis. We do this because Ggplot seems to present categories backwards unless we tell it not to.
- **Other details:** Labels/titles and colours added within `labs` and `scale_fill_color` respectively.

```
# Outcomes in all cases by hospital
ggplot(outcomes2) +
  geom_col(
    mapping = aes(
      x = proportion,                      # show pre-calculated proportion values
      y = fct_rev(hospital),              # reverse level order so missing/other at bottom
      fill = outcome),                   # stacked by outcome
      width = 0.5)+                      # thinner bars (out of 1)
    theme_minimal() +                   # Minimal theme
    theme(legend.position = "bottom") +
    labs(subtitle = "Number of recovered and dead Ebola cases, by hospital",
         fill = "Outcome",               # legend title
         y = "Count",                  # y axis title
         x = "Hospital of admission") + # x axis title
    scale_fill_manual(                 # adding colors manually
      values = c("Death"= "#3B1c8C",
                 "Recover" = "#21908D" ))
```



Note that the proportions are binary, so we may prefer to drop ‘recover’ and just show the proportion who died. This is just for illustration purposes.

If using `geom_col()` with dates data (e.g. an epicurve from aggregated data) - you will want to adjust the `width =` argument to remove the “gap” lines between the bars. If using daily data set `width = 1`. If weekly, `width = 7`. Months are not possible because each month has a different number of days.

Themes

One of the best parts of **ggplot2** is the amount of control you have over the plot - you can define anything! As mentioned above, the design of the plot that is *not* related to the data shapes/geometries are adjusted within the `theme()` function. For example, the plot background color, presence/absence of gridlines, and the font/size/color/alignment of text (titles, subtitles, captions, axis text...). These adjustments can be done in one of two ways:

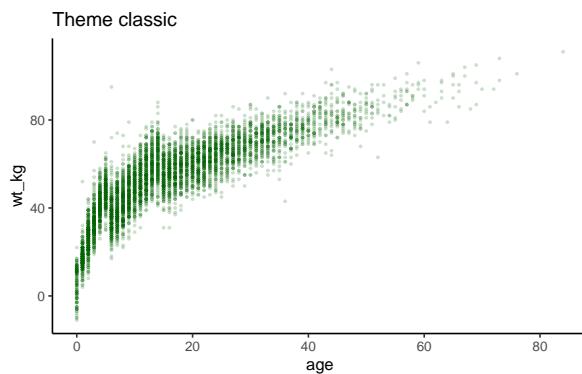
- Add a `complete theme` `theme_()` function to make sweeping adjustments - these include `theme_classic()`, `theme_minimal()`, `theme_dark()`, `theme_light()` `theme_grey()`, `theme_bw()` among others
- Adjust each tiny aspect of the plot individually within `theme()`

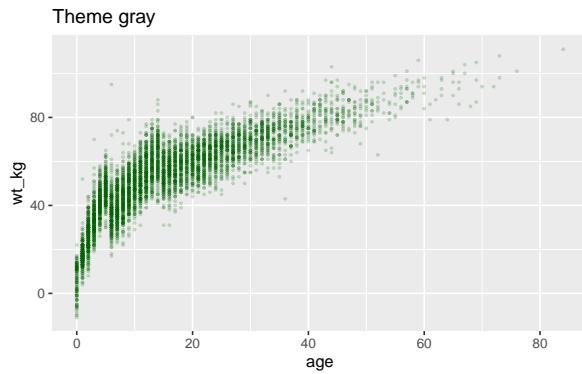
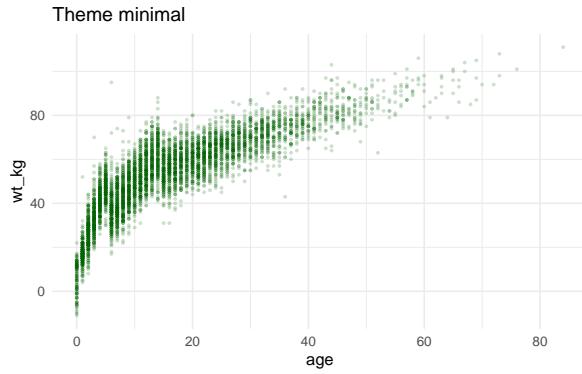
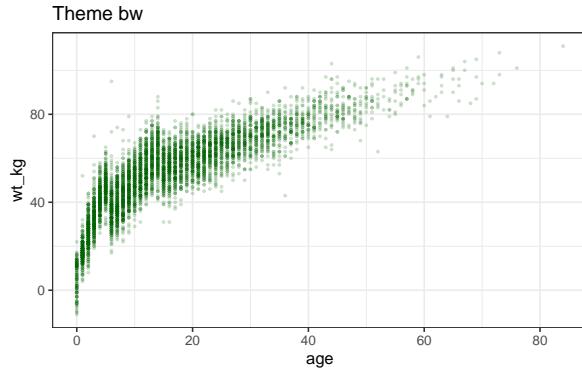
Complete themes

As they are quite straight-forward, we will demonstrate the complete theme functions below and will not describe them further here. Note that any micro-adjustments with `theme()` should be made *after* use of a complete theme.

Write them with empty parentheses.

```
ggplot(data = linelist, mapping = aes(x = age, y = wt_kg))+  
  geom_point(color = "darkgreen", size = 0.5, alpha = 0.2)+  
  labs(title = "Theme classic")+  
  theme_classic()  
  
ggplot(data = linelist, mapping = aes(x = age, y = wt_kg))+  
  geom_point(color = "darkgreen", size = 0.5, alpha = 0.2)+  
  labs(title = "Theme bw")+  
  theme_bw()  
  
ggplot(data = linelist, mapping = aes(x = age, y = wt_kg))+  
  geom_point(color = "darkgreen", size = 0.5, alpha = 0.2)+  
  labs(title = "Theme minimal")+  
  theme_minimal()  
  
ggplot(data = linelist, mapping = aes(x = age, y = wt_kg))+  
  geom_point(color = "darkgreen", size = 0.5, alpha = 0.2)+  
  labs(title = "Theme gray")+  
  theme_gray()
```





Modify theme

The `theme()` function can take a large number of arguments, each of which edits a very specific aspect of the plot. There is no way we could cover all of the arguments, but we will describe the general pattern for them and show you how to find the argument name that you need. The basic syntax is this:

1. Within `theme()` write the argument name for the plot element you want to edit, like
`plot.title =`
2. Provide an `element_()` function to the argument
- Most often, use `element_text()`, but others include `element_rect()` for canvas background colors, or `element_blank()` to remove plot elements
4. Within the `element_()` function, write argument assignments to make the fine adjustments you desire

So, that description was quite abstract, so here are some examples.

The below plot looks quite silly, but it serves to show you a variety of the ways you can adjust your plot.

- We begin with the plot `age_by_wt` defined just above and add `theme_classic()`
- For finer adjustments we add `theme()` and include one argument for each plot element to adjust

It can be nice to organize the arguments in logical sections. To describe just some of those used below:

- `legend.position` = is unique in that it accepts simple values like “bottom”, “top”, “left”, and “right”. But generally, text-related arguments require that you place the details *within* `element_text()`.
- Title size with `element_text(size = 30)`
- The caption horizontal alignment with `element_text(hjust = 0)` (from right to left)
- The subtitle is italicized with `element_text(face = "italic")`

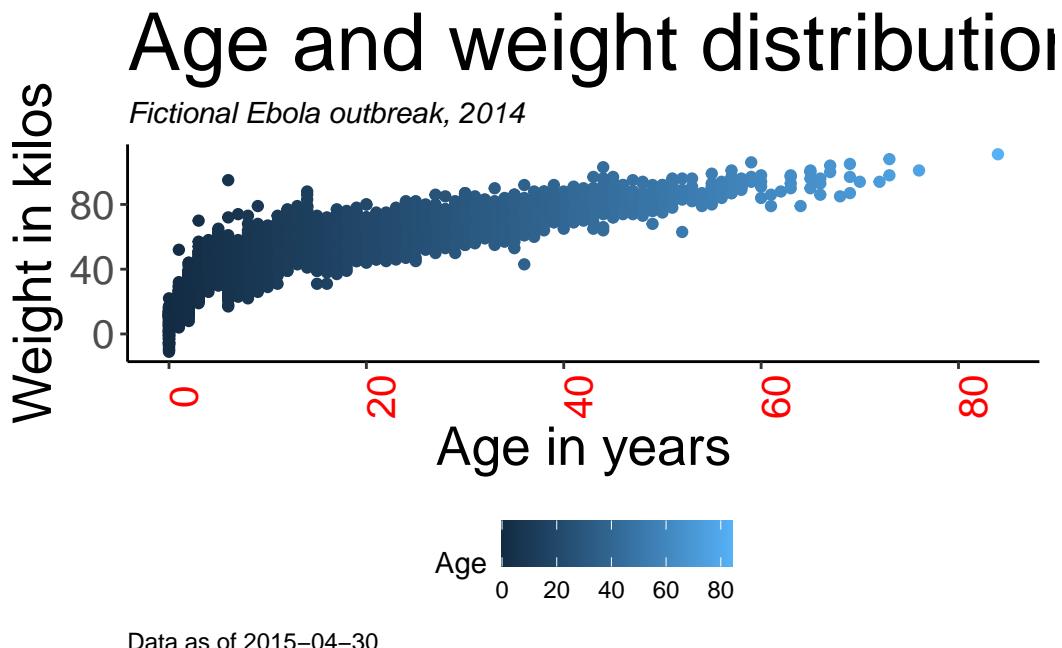
```
age_by_wt +
  theme_classic() +                                     # pre-defined theme adjustments
  theme(
    legend.position = "bottom",                         # move legend to bottom
    plot.title = element_text(size = 30),                # size of title to 30
    plot.caption = element_text(hjust = 0),               # left-align caption
    plot.subtitle = element_text(face = "italic"),        # italicize subtitle
```

```

axis.text.x = element_text(color = "red", size = 15, angle = 90), # adjusts only x-axis
axis.text.y = element_text(size = 15), # adjusts only y-axis text

axis.title = element_text(size = 20) # adjusts both axes titles
)

```



Here are some especially common `theme()` arguments. You will recognize some patterns, such as appending `.x` or `.y` to apply the change only to one axis.

theme() argument	What it adjusts
<code>plot.title = element_text()</code>	The title
<code>plot.subtitle = element_text()</code>	The subtitle
<code>plot.caption = element_text()</code>	The caption (family, face, color, size, angle, vjust, hjust...)
<code>axis.title = element_text()</code>	Axis titles (both x and y) (size, face, angle, color...)
<code>axis.title.x = element_text()</code>	Axis title x-axis only (use <code>.y</code> for y-axis only)
<code>axis.text = element_text()</code>	Axis text (both x and y)
<code>axis.text.x = element_text()</code>	Axis text x-axis only (use <code>.y</code> for y-axis only)
<code>axis.ticks = element_blank()</code>	Remove axis ticks

theme() argument	What it adjusts
<code>axis.line = element_line()</code>	Axis lines (colour, size, linetype: solid, dashed, dotted etc)
<code>strip.text = element_text()</code>	Facet strip text (colour, face, size, angle...)
<code>strip.background = element_rect()</code>	facet strip (fill, colour, size...)

But there are so many theme arguments! How could I remember them all? Do not worry - it is impossible to remember them all. Luckily there are a few tools to help you:

The **tidyverse** documentation on [modifying theme](#), which has a complete list.

💡 Tip

Run `theme_get()` from **ggplot2** to print a list of all 90+ `theme()` arguments to the console.

💡 Tip

If you ever want to remove an element of a plot, you can also do it through `theme()`. Just pass `element_blank()` to an argument to have it disappear completely. For legends, set `legend.position = "none"`.

Scales for color, fill, axes, etc.

In **ggplot2**, when aesthetics of plotted data (e.g. size, color, shape, fill, plot axis) are mapped to columns in the data, the exact display can be adjusted with the corresponding “scale” command. In this section we explain some common scale adjustments.

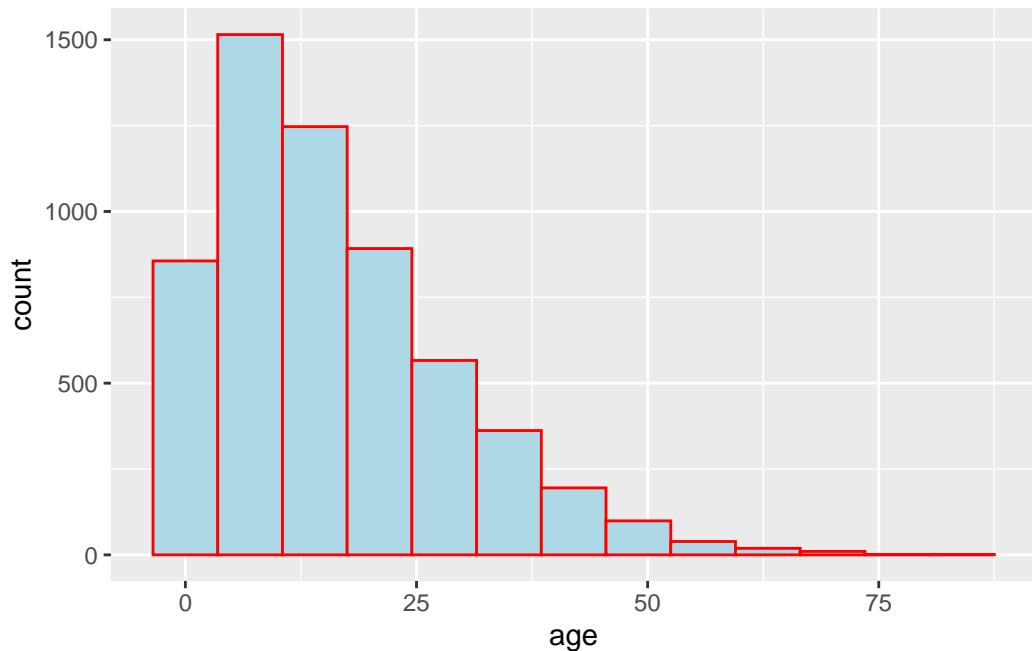
Color schemes

One thing that can initially be difficult to understand with **ggplot2** is control of color schemes. Note that this section discusses the color of *plot objects* (geoms/shapes) such as points, bars, lines, tiles, etc.

To control “color” of *plot objects* you will be adjusting either the `color =` aesthetic (the *exterior* color) or the `fill =` aesthetic (the *interior* color). One exception to this pattern is `geom_point()`, where you really only get to control `color =`, which controls the color of the point (interior and exterior).

When setting colour or fill you can use colour names recognized by R like "red" (see [complete list](#) or enter `?colors`), or a specific hex colour such as "#ff0505".

```
# histogram -
ggplot(data = linelist, mapping = aes(x = age))+
  geom_histogram(binwidth = 7, color = "red", fill = "lightblue") # set data and axes
```



Aesthetics such as `fill =` and `color =` can be defined either *outside* of a `mapping = aes()` statement or *inside* of one. If *outside* the `aes()`, the assigned value should be static (e.g. `color = "blue"`) and will apply for *all* data plotted by the geom. If *inside*, the aesthetic should be mapped to a column, like `color = hospital`, and the expression will vary by the value for that row in the data. A few examples:

```
# Static color for points and for line
ggplot(data = linelist, mapping = aes(x = age, y = wt_kg))+
  geom_point(color = "purple")+
  geom_vline(xintercept = 50, color = "orange")+
  labs(title = "Static color for points and line")

# Color mapped to continuous column
ggplot(data = linelist, mapping = aes(x = age, y = wt_kg))+
```

```

geom_point(mapping = aes(color = temp))+  

  labs(title = "Color mapped to continuous column")

# Color mapped to discrete column  

ggplot(data = linelist, mapping = aes(x = age, y = wt_kg))+  

  geom_point(mapping = aes(color = gender))+  

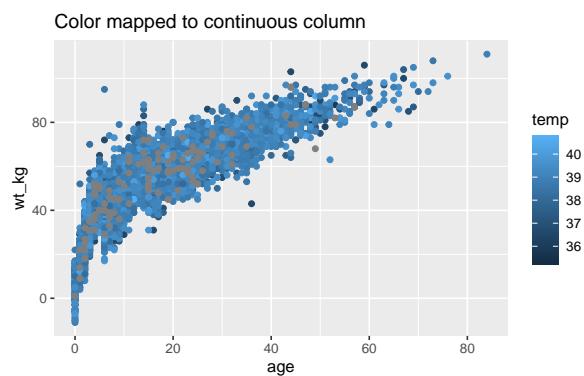
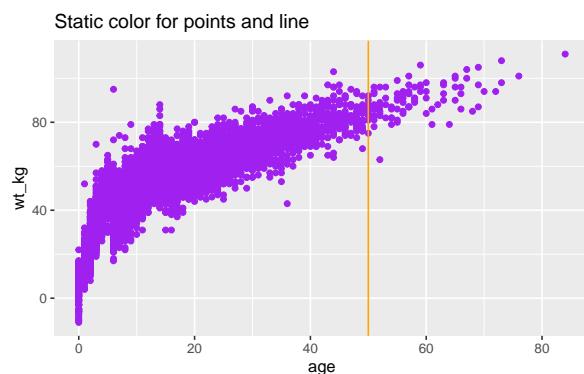
  labs(title = "Color mapped to discrete column")

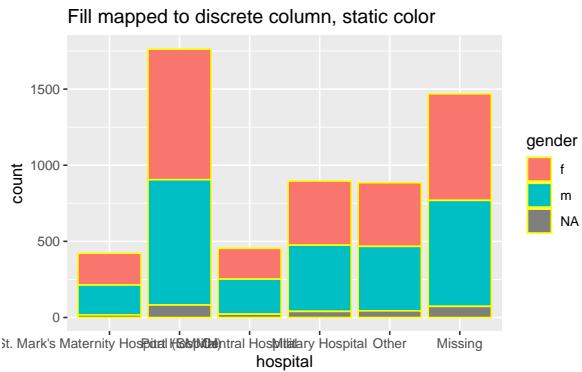
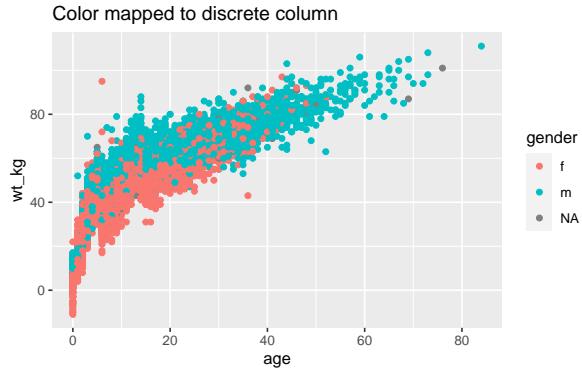
# bar plot, fill to discrete column, color to static value  

ggplot(data = linelist, mapping = aes(x = hospital))+  

  geom_bar(mapping = aes(fill = gender), color = "yellow")+
  labs(title = "Fill mapped to discrete column, static color")

```





Scales

Once you map a column to a plot aesthetic (e.g. `x =`, `y =`, `fill =`, `color =`...), your plot will gain a scale/legend. See above how the scale can be continuous, discrete, date, etc. values depending on the class of the assigned column. If you have multiple aesthetics mapped to columns, your plot will have multiple scales.

You can control the scales with the appropriate `scales_()` function. The scale functions of `ggplot()` have 3 parts that are written like this: `scale_AESTHETIC_METHOD()`.

- 1) The first part, `scale_()`, is fixed.
- 2) The second part, the AESTHETIC, should be the aesthetic that you want to adjust the scale for (`_fill_`, `_shape_`, `_color_`, `_size_`, `_alpha_`...) - the options here also include `_x_` and `_y_`.
- 3) The third part, the METHOD, will be either `_discrete()`, `_continuous()`, `_date()`, `_gradient()`, or `_manual()` depending on the class of the column and *how* you want to control it. There are others, but these are the most-often used.

Be sure that you use the correct function for the scale! Otherwise your scale command will not appear to change anything. If you have multiple scales, you may use multiple scale functions to adjust them! For example:

Scale arguments

Each kind of scale has its own arguments, though there is some overlap. Query the function like `?scale_color_discrete` in the R console to see the function argument documentation.

For continuous scales, use `breaks =` to provide a sequence of values with `seq()` (take `to =`, `from =`, and `by =` as shown in the example below. Set `expand = c(0,0)` to eliminate padding space around the axes (this can be used on any `_x_` or `_y_` scale).

For discrete scales, you can adjust the order of level appearance with `breaks =`, and how the values display with the `labels =` argument. Provide a character vector to each of those (see example below). You can also drop NA easily by setting `na.translate = FALSE`.

Manual adjustments

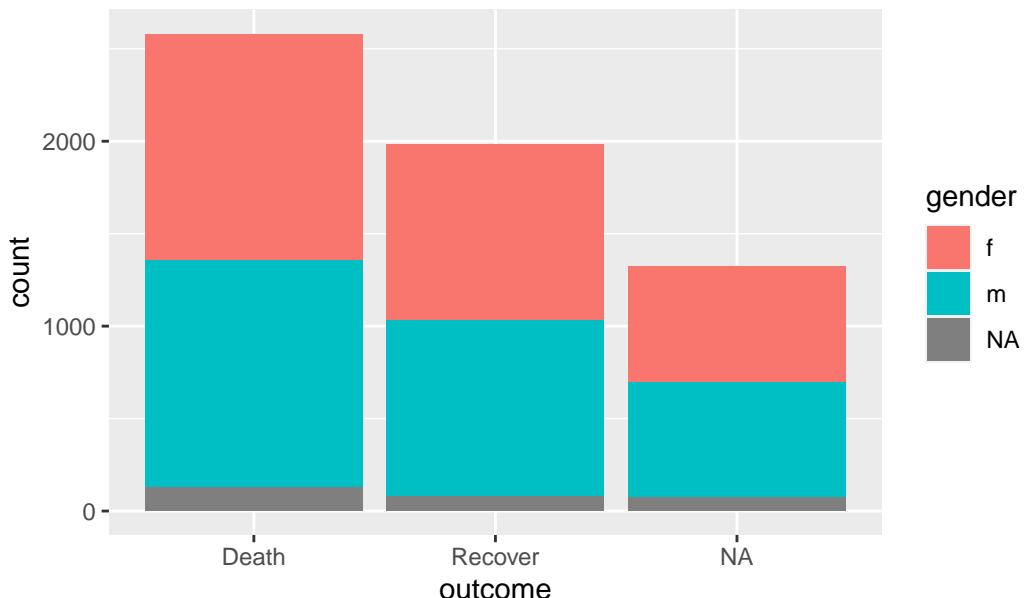
One of the most useful tricks is using “manual” scaling functions to explicitly assign colors as you desire. These are functions with the syntax `scale_xxx_manual()` (e.g. `scale_colour_manual()` or `scale_fill_manual()`). Each of the below arguments are demonstrated in the code example below.

- Assign colors to data values with the `values =` argument
- Specify a color for NA with `na.value =`
- Change how the values are *written* in the legend with the `labels =` argument
- Change the legend title with `name =`

Below, we create a bar plot and show how it appears by default, and then with three scales adjusted - the continuous y-axis scale, the discrete x-axis scale, and manual adjustment of the fill (interior bar color).

```
# BASELINE - no scale adjustment
ggplot(data = linelist) +
  geom_bar(mapping = aes(x = outcome, fill = gender)) +
  labs(title = "Baseline - no scale adjustments")
```

Baseline – no scale adjustments



```
# SCALES ADJUSTED
ggplot(data = linelist)+

  geom_bar(mapping = aes(x = outcome, fill = gender), color = "black")+

  theme_minimal()+                                # simplify background

  scale_y_continuous(                            # continuous scale for y-axis (counts)
    expand = c(0,0),                           # no padding
    breaks = seq(from = 0,                      # show all factor levels (even if not in data)
                 to = 3000,
                 by = 500))+

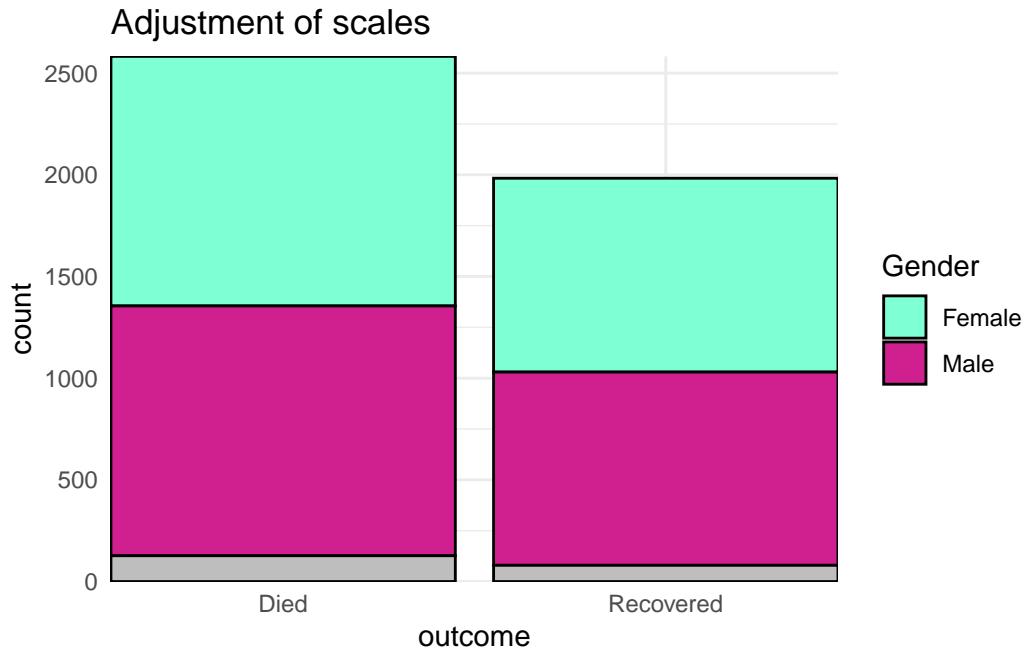
  scale_x_discrete(                            # discrete scale for x-axis (gender)
    expand = c(0,0),                           # no padding
    drop = FALSE,                             # remove NA outcomes from plot
    na.translate = FALSE,                      # remove NA outcomes from plot
    labels = c("Died", "Recovered"))+        # Change display of values

  scale_fill_manual(                          # Manually specify fill (bar interior color)
    values = c("m" = "violetred",            # reference values in data to assign colors
              "f" = "red",
              "NA" = "darkgrey"))
```

```

        "f" = "aquamarine"),
labels = c("m" = "Male",           # re-label the legend (use "=" assignment to avoid m
         "f" = "Female",
         "Missing"),
name = "Gender",                  # title of legend
na.value = "grey"                 # assign a color for missing values
) +
labs(title = "Adjustment of scales") # Adjust the title of the fill legend

```



Continuous axes scales

When data are mapping to the plot axes, these too can be adjusted with scales commands. A common example is adjusting the display of an axis (e.g. y-axis) that is mapped to a column with continuous data.

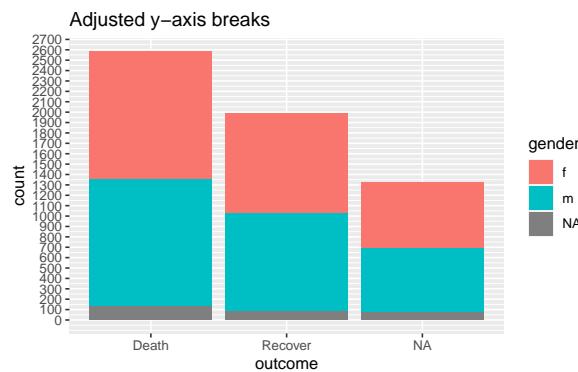
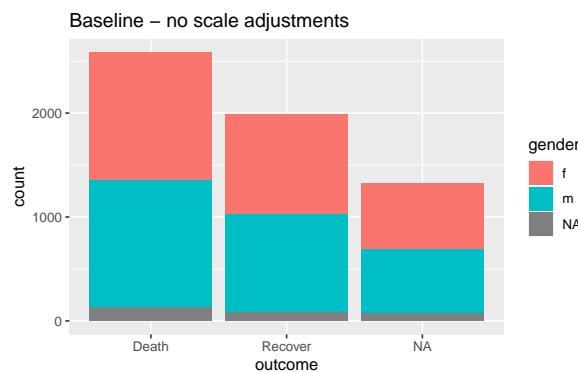
We may want to adjust the breaks or display of the values in the ggplot using `scale_y_continuous()`. As noted above, use the argument `breaks =` to provide a sequence of values that will serve as “breaks” along the scale. These are the values at which numbers will display. To this argument, you can provide a `c()` vector containing the desired break values, or you can provide a regular sequence of numbers using the `base` R function `seq()`. This `seq()` function accepts `to =`, `from =`, and `by =`.

```

# BASELINE - no scale adjustment
ggplot(data = linelist) +
  geom_bar(mapping = aes(x = outcome, fill = gender)) +
  labs(title = "Baseline - no scale adjustments")

#
ggplot(data = linelist) +
  geom_bar(mapping = aes(x = outcome, fill = gender)) +
  scale_y_continuous(
    breaks = seq(
      from = 0,
      to = 3000,
      by = 100)
  ) +
  labs(title = "Adjusted y-axis breaks")

```



- * Display percents

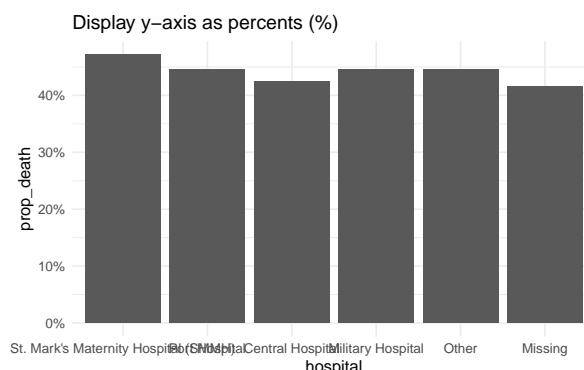
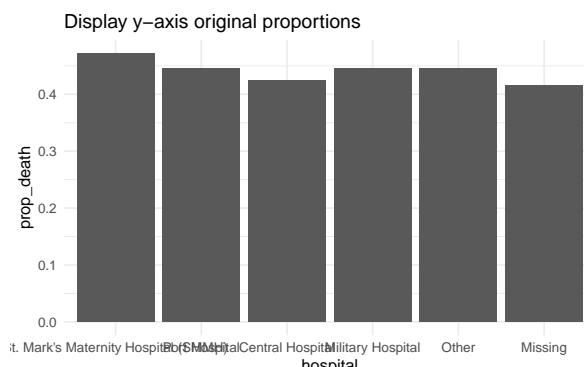
If your original data values are proportions, you can easily display them as percents with “%” by providing `labels = scales::percent` in your `scales` command, as shown below.

While an alternative would be to convert the values to character and add a “%” character to the end, this approach will cause complications because your data will no longer be continuous numeric values.

```
# Original y-axis proportions
#####
linelist %>%
  group_by(hospital) %>%
  summarise(
    n = n(),
    deaths = sum(outcome == "Death", na.rm=T),
    prop_death = deaths/n) %>%
  ggplot(
    mapping = aes(
      x = hospital,
      y = prop_death))+
  geom_col()+
  theme_minimal()+
  labs(title = "Display y-axis original proportions")

# Display y-axis proportions as percents
#####
linelist %>%
  group_by(hospital) %>%
  summarise(
    n = n(),
    deaths = sum(outcome == "Death", na.rm=T),
    prop_death = deaths/n) %>%
  ggplot(
    mapping = aes(
      x = hospital,
      y = prop_death))+
  geom_col()+
  theme_minimal()+
  labs(title = "Display y-axis as percents (%)")+
  scale_y_continuous(
    labels = scales::percent) # display proportions as percents
```

)



* Log scale

To transform a continuous axis to log scale, add `trans = "log2"` to the scale command. For purposes of example, we create a data frame of regions with their respective `preparedness_index` and cumulative cases values.

```
plot_data <- data.frame(
  region = c("A", "B", "C", "D", "E", "F", "G", "H", "I"),
  preparedness_index = c(8.8, 7.5, 3.4, 3.6, 2.1, 7.9, 7.0, 5.6, 1.0),
  cases_cumulative = c(15, 45, 80, 20, 21, 7, 51, 30, 1442)
)

plot_data
```



```
region preparedness_index cases_cumulative
```

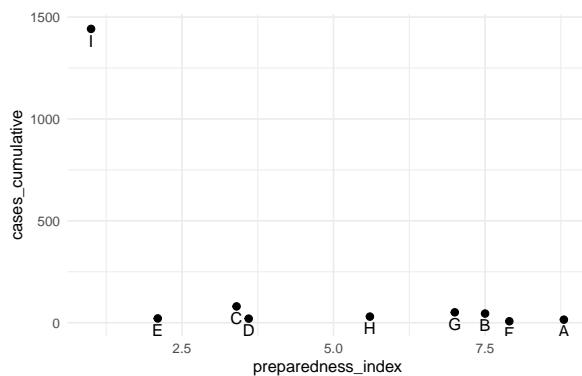
1	A	8.8	15
2	B	7.5	45
3	C	3.4	80
4	D	3.6	20
5	E	2.1	21
6	F	7.9	7
7	G	7.0	51
8	H	5.6	30
9	I	1.0	1442

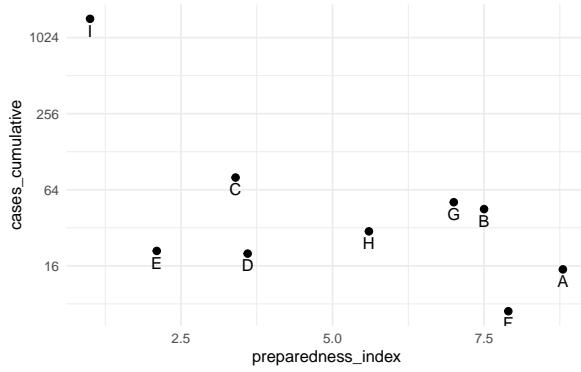
The cumulative cases for region “I” are dramatically greater than all the other regions. In circumstances like this, you may elect to display the y-axis using a log scale so the reader can see differences between the regions with fewer cumulative cases.

```
# Original y-axis
preparedness_plot <- ggplot(data = plot_data,
  mapping = aes(
    x = preparedness_index,
    y = cases_cumulative))+ 
  geom_point(size = 2)+           # points for each region
  geom_text(
    mapping = aes(label = region),
    vjust = 1.5)+                 # add text labels
  theme_minimal()

preparedness_plot                  # print original plot

# print with y-axis transformed
preparedness_plot+                # begin with plot saved above
  scale_y_continuous(trans = "log2") # add transformation for y-axis
```





Gradient scales

Fill gradient scales can involve additional nuance. The defaults are usually quite pleasing, but you may want to adjust the values, cutoffs, etc.

To demonstrate how to adjust a continuous color scale, we'll use a data set that contains the ages of cases and of sources in a contact tracing case.

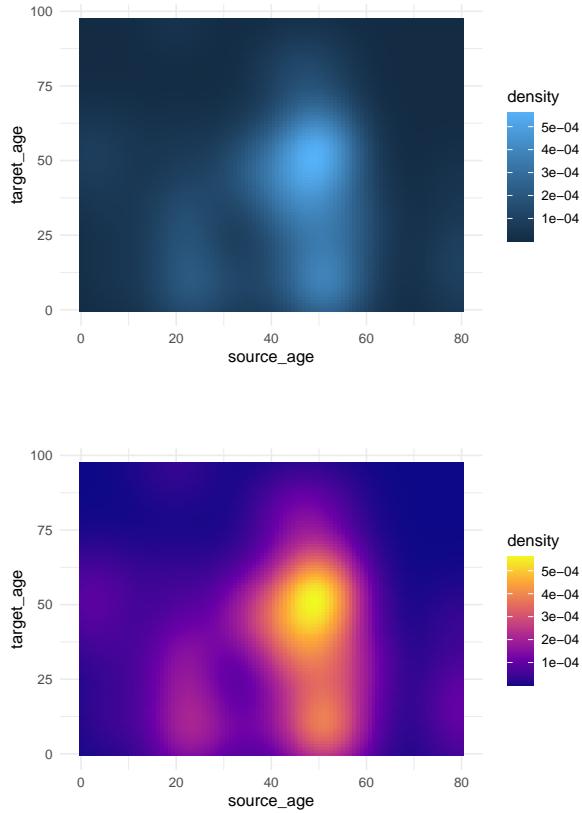
```
case_source_relationships <- rio::import("data/godata/relationships_clean.rds") %>%
  select(source_age, target_age)
```

Below, we produce a “raster” heat tile density plot. Note how the `fill` scale is *continuous*.

```
trans_matrix <- ggplot(
  data = case_source_relationships,
  mapping = aes(x = source_age, y = target_age)) +
  stat_density2d(
    geom = "raster",
    mapping = aes(fill = after_stat(density)),
    contour = FALSE) +
  theme_minimal()
```

Now we show some variations on the fill scale:

```
trans_matrix
trans_matrix + scale_fill_viridis_c(option = "plasma")
```



Now we show some examples of actually adjusting the break points of the scale:

- `scale_fill_gradient()` accepts two colors (high/low)
- `scale_fill_gradientn()` accepts a vector of any length of colors to `values =` (intermediate values will be interpolated)
- Use `scales::rescale()` to adjust how colors are positioned along the gradient; it rescales your vector of positions to be between 0 and 1.

```
trans_matrix +
  scale_fill_gradient(      # 2-sided gradient scale
    low = "aquamarine",    # low value
    high = "purple",       # high value
    na.value = "grey",     # value for NA
    name = "Density")+
  labs(title = "Manually specify high/low colors")
```

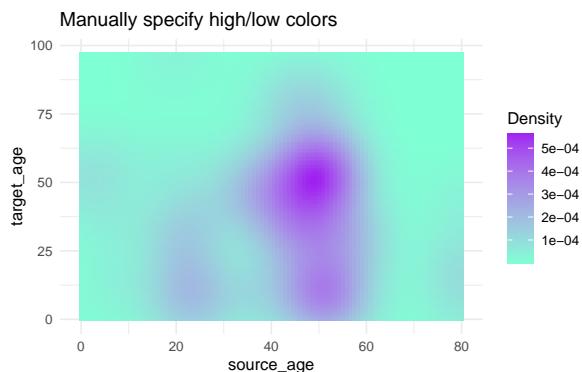
```

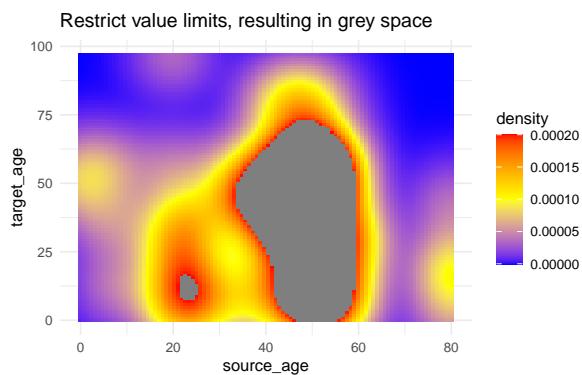
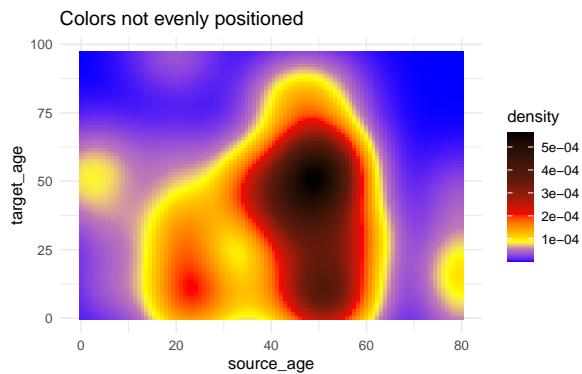
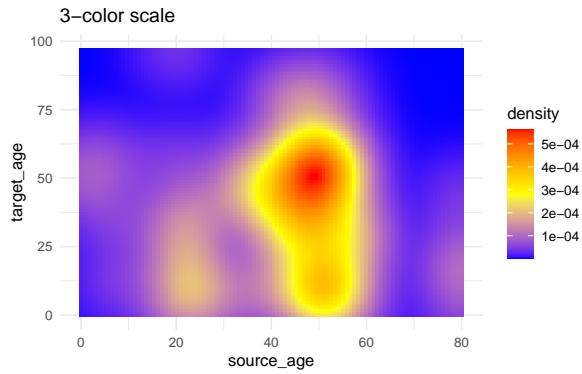
# 3+ colors to scale
trans_matrix +
  scale_fill_gradientn(    # 3-color scale (low/mid/high)
    colors = c("blue", "yellow","red") # provide colors in vector
  )+
  labs(title = "3-color scale")

# Use of rescale() to adjust placement of colors along scale
trans_matrix +
  scale_fill_gradientn(    # provide any number of colors
    colors = c("blue", "yellow","red", "black"),
    values = scales::rescale(c(0, 0.05, 0.07, 0.10, 0.15, 0.20, 0.3, 0.5)) # positions for
  )+
  labs(title = "Colors not evenly positioned")

# use of limits to cut-off values that get fill color
trans_matrix +
  scale_fill_gradientn(
    colors = c("blue", "yellow","red"),
    limits = c(0, 0.0002))+ 
  labs(title = "Restrict value limits, resulting in grey space")

```





Palettes

- * Colorbrewer and Viridis

More generally, if you want predefined palettes, you can use the `scale_xxx_brewer` or `scale_xxx_viridis_y` functions.

The ‘brewer’ functions can draw from colorbrewer.org palettes.

The ‘viridis’ functions draw from viridis (colourblind friendly!) palettes, which “provide colour maps that are perceptually uniform in both colour and black-and-white. They are also designed to be perceived by viewers with common forms of colour blindness.” (read more [here](#) and [here](#)). Define if the palette is discrete, continuous, or binned by specifying this at the end of the function (e.g. discrete is `scale_xxx_viridis_d`).

It is advised that you test your plot in this [color blindness simulator](#). If you have a red/green color scheme, try a “hot-cold” (red-blue) scheme instead as described [here](#)

Here is an example of using various color schemes.

```
symp_plot <- linelist %>%
  select(c(case_id, fever, chills, cough, aches, vomit)) %>%
  pivot_longer(
    cols = -case_id,
    names_to = "symptom_name",
    values_to = "symptom_is_present") %>%
  mutate(
    symptom_is_present = replace_na(symptom_is_present, "unknown")) %>%
  ggplot(
    mapping = aes(x = symptom_name, fill = symptom_is_present))+
  geom_bar(position = "fill", col = "black") +
  theme_classic() +
  theme(legend.position = "bottom")+
  labs(
    x = "Symptom",
    y = "Symptom status (proportion)"
  )

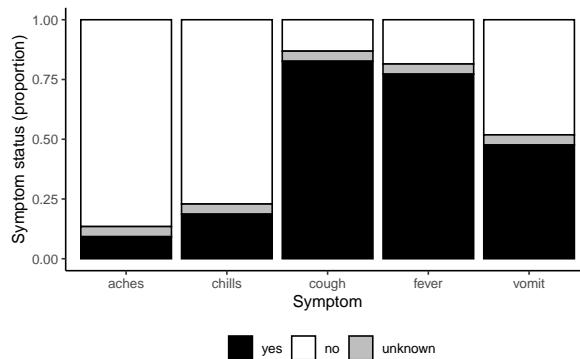
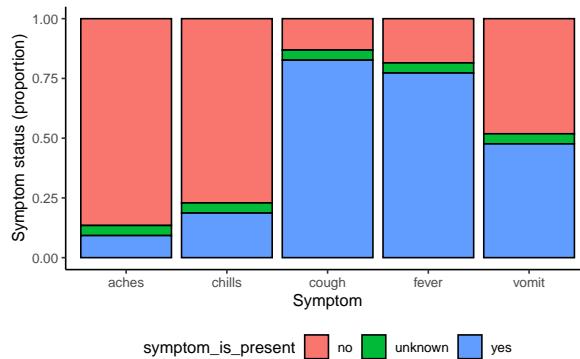
symp_plot # print with default colors

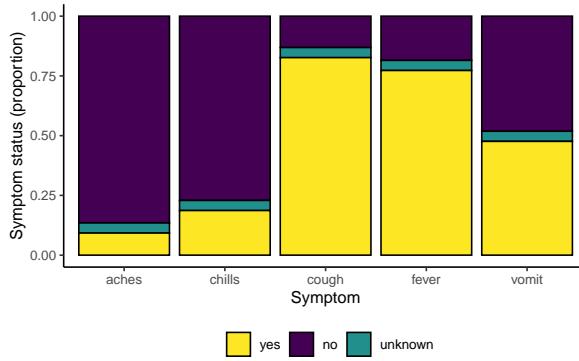
#####
# print with manually-specified colors
symp_plot +
  scale_fill_manual(
    values = c("yes" = "black",           # explicitly define colours
              "no" = "white",
              "unknown" = "grey"),
    breaks = c("yes", "no", "unknown"), # order the factors correctly
    name = "")                         # set legend to no title
```

```

)
#####
# print with viridis discrete colors
symp_plot +
  scale_fill_viridis_d(
    breaks = c("yes", "no", "unknown"),
    name = ""
)

```





Change order of discrete variables

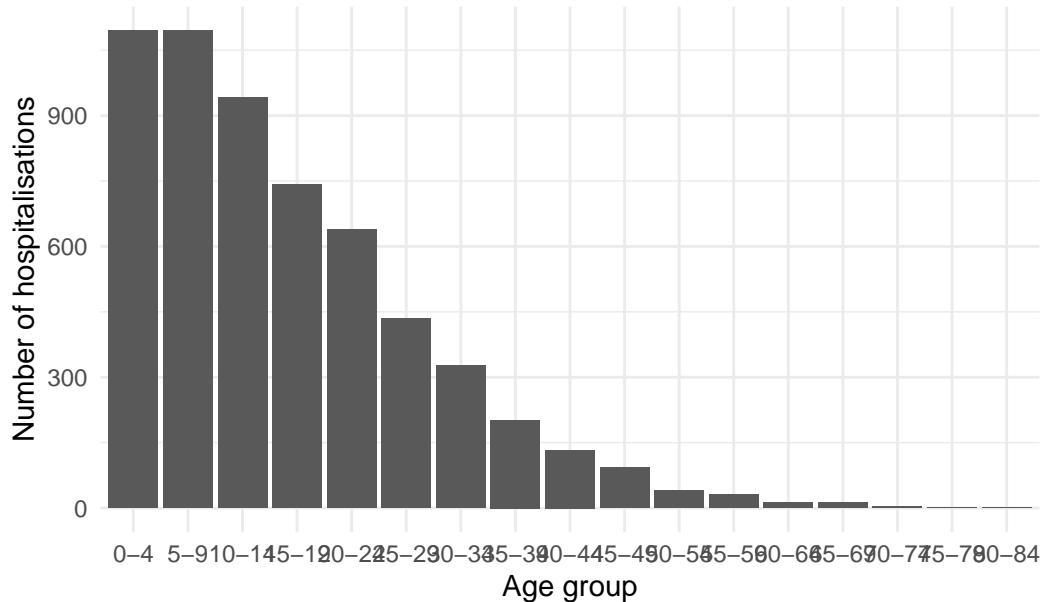
Changing the order that discrete variables appear in is often difficult to understand for people who are new to `ggplot2` graphs. It's easy to understand how to do this however once you understand how `ggplot2` handles discrete variables under the hood. Generally speaking, if a discrete variable is used, it is automatically converted to a `factor` type - which orders factors by alphabetical order by default. To handle this, you simply have to reorder the factor levels to reflect the order you would like them to appear in the chart. For more detailed information on how to reorder `factor` objects, see the factor section of the guide.

We can look at a common example using age groups - by default the 5-9 age group will be placed in the middle of the age groups (given alphanumeric order), but we can move it behind the 0-4 age group of the chart by releveling the factors.

```
ggplot(
  data = linelist %>% drop_na(age_cat5),                                # remove rows where age_c
  mapping = aes(x = fct_relevel(age_cat5, "5-9", after = 1))) + # relevel factor

  geom_bar() +
  labs(x = "Age group", y = "Number of hospitalisations",
       title = "Total hospitalisations by age group") +
  theme_minimal()
```

Total hospitalisations by age group



Advanced ggplot (optional)

These are a collection of less common plot types, ggplot2 extensions, and advanced examples of some of the things you can do visualizing data in R.

Contour lines

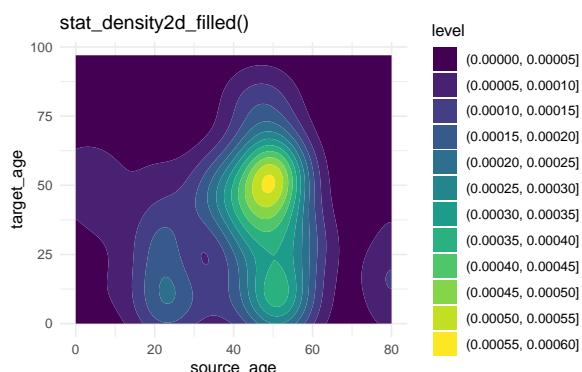
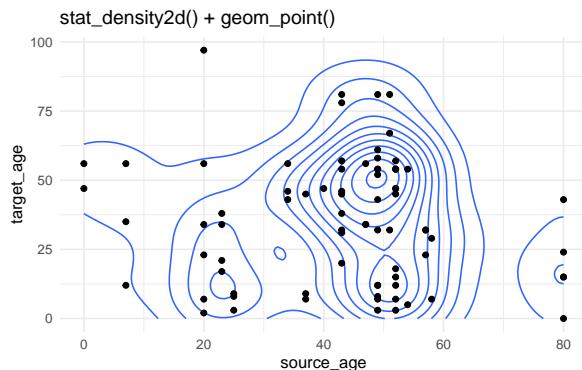
Contour plots are helpful when you have many points that might cover each other ("overplotting"). The case-source data used above are again plotted, but more simply using `stat_density2d()` and `stat_density2d_filled()` to produce discrete contour levels - like a topographical map. Read more about the statistics [here](#).

```
case_source_relationships %>%
  ggplot(aes(x = source_age, y = target_age)) +
  stat_density2d() +
  geom_point() +
  theme_minimal() +
  labs(title = "stat_density2d() + geom_point()")
```



```
case_source_relationships %>%
```

```
ggplot(aes(x = source_age, y = target_age))+
  stat_density2d_filled()+
  theme_minimal()+
  labs(title = "stat_density2d_filled()")
```



Marginal distributions

To show the distributions on the edges of a `geom_point()` scatterplot, you can use the `ggExtra` package and its function `ggMarginal()`. Save your original ggplot as an object, then pass it to `ggMarginal()` as shown below. Here are the key arguments:

- You must specify the `type =` as either “histogram”, “density” “boxplot”, “violin”, or “densigram”.
- By default, marginal plots will appear for both axes. You can set `margins =` to “x” or “y” if you only want one.

- Other optional arguments include `fill` = (bar color), `color` = (line color), `size` = (plot size relative to margin size, so larger number makes the marginal plot smaller).
- You can provide other axis-specific arguments to `xparams` = and `yparams` =. For example, to have different histogram bin sizes, as shown below.

You can have the marginal plots reflect groups (columns that have been assigned to `color` = in your `ggplot()` mapped aesthetics). If this is the case, set the `ggMarginal()` argument `groupColour` = or `groupFill` = to TRUE, as shown below.

Read more at [this vignette](#), in the [R Graph Gallery](#) or the function R documentation `?ggMarginal`.

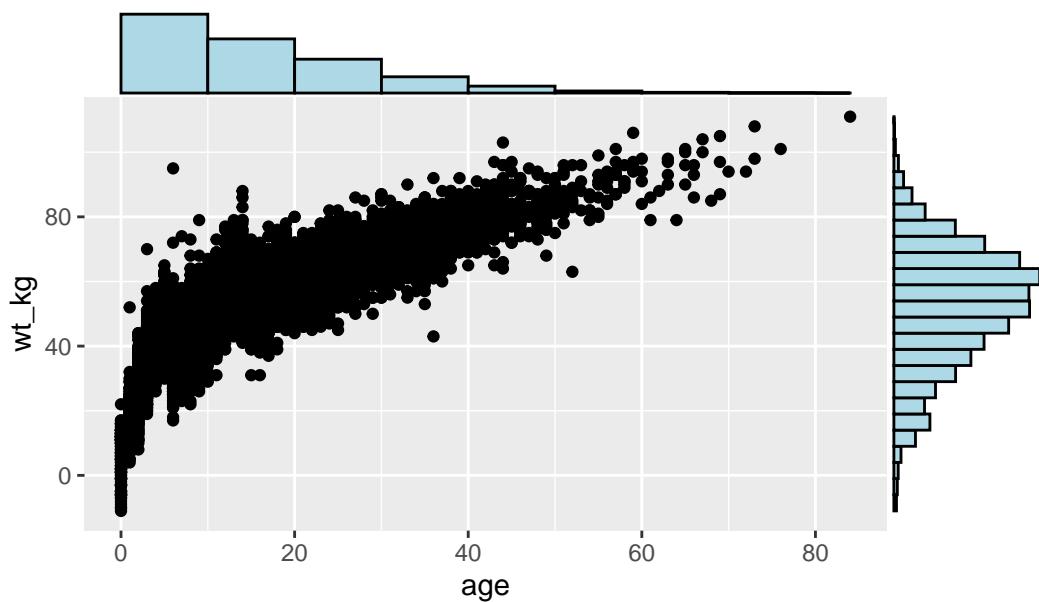
```
# Install/load ggExtra
pacman::p_load(ggExtra)

# Basic scatter plot of weight and age
scatter_plot <- ggplot(data = linelist) +
  geom_point(mapping = aes(y = wt_kg, x = age)) +
  labs(title = "Scatter plot of weight and age")
```

To add marginal histograms use `type` = "histogram". You can optionally set `groupFill` = TRUE to get stacked histograms.

```
# with histograms
ggMarginal(
  scatter_plot,                      # add marginal histograms
  type = "histogram",                # specify histograms
  fill = "lightblue",                 # bar fill
  xparams = list(binwidth = 10),       # other parameters for x-axis marginal
  yparams = list(binwidth = 5))        # other parameters for y-axis marginal
```

Scatter plot of weight and age

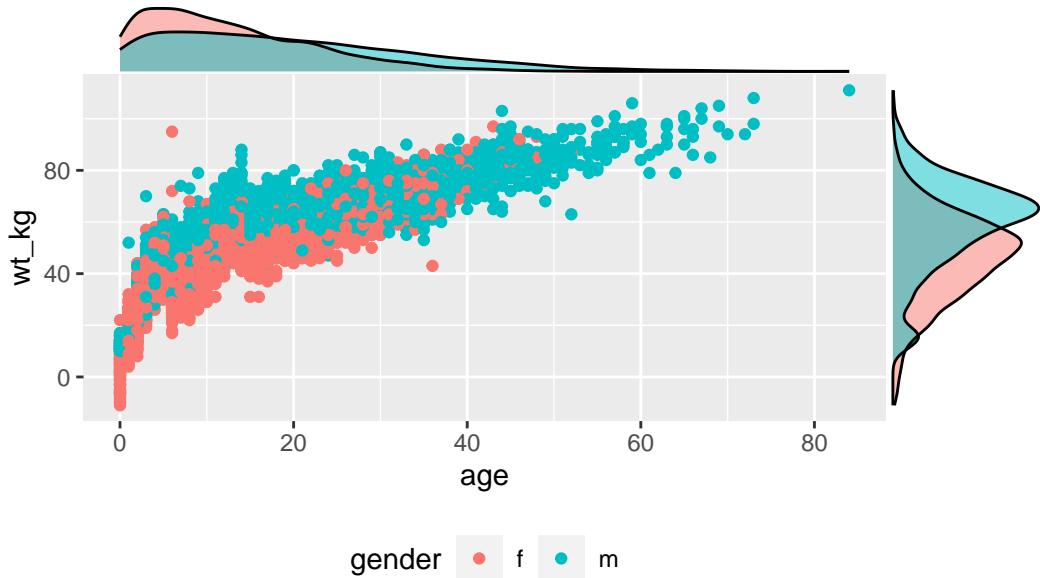


Marginal density plot with grouped/colored values:

```
# Scatter plot, colored by outcome
# Outcome column is assigned as color in ggplot. groupFill in ggMarginal set to TRUE
scatter_plot_color <- ggplot(data = linelist %>% drop_na(gender)) +
  geom_point(mapping = aes(y = wt_kg, x = age, color = gender)) +
  labs(title = "Scatter plot of weight and age") +
  theme(legend.position = "bottom")

ggMarginal(scatter_plot_color, type = "density", groupFill = TRUE)
```

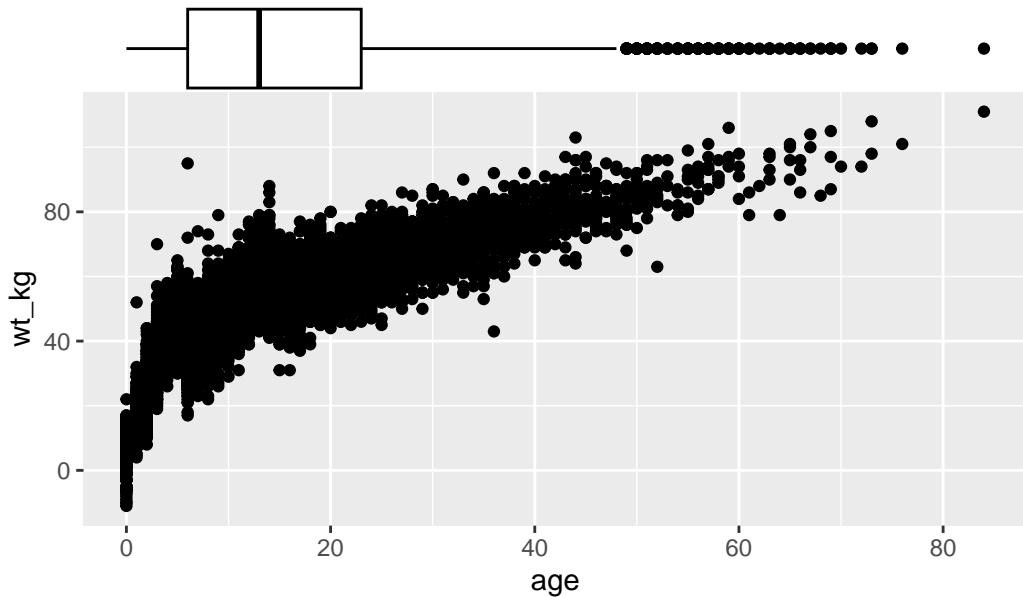
Scatter plot of weight and age



Set the `size` = argument to adjust the relative size of the marginal plot. Smaller number makes a larger marginal plot. You also set `color` =. Below are is a marginal boxplot, with demonstration of the `margins` = argument so it appears on only one axis:

```
# with boxplot
ggMarginal(
  scatter_plot,
  margins = "x",      # only show x-axis marginal plot
  type = "boxplot")
```

Scatter plot of weight and age



Smart Labeling

In **ggplot2**, it is also possible to add text to plots. However, this comes with the notable limitation where text labels often clash with data points in a plot, making them look messy or hard to read. There is no ideal way to deal with this in the base package, but there is a **ggplot2** add-on, known as **ggrepel** that makes dealing with this very simple!

The **ggrepel** package provides two new functions, `geom_label_repel()` and `geom_text_repel()`, which replace `geom_label()` and `geom_text()`. Simply use these functions instead of the base functions to produce neat labels. Within the function, map the aesthetics `aes()` as always, but include the argument `label =` to which you provide a column name containing the values you want to display (e.g. patient id, or name, etc.). You can make more complex labels by combining columns and newlines (`\n`) within `str_glue()` as shown below.

A few tips:

- Use `min.segment.length = 0` to always draw line segments, or `min.segment.length = Inf` to never draw them
- Use `size =` outside of `aes()` to set text size

- Use `force =` to change the degree of repulsion between labels and their respective points (default is 1)
- Include `fill =` within `aes()` to have label colored by value
 - A letter “a” may appear in the legend - add `guides(fill = guide_legend(override.aes = aes(color = NA)))`+ to remove it

See this is very in-depth [tutorial](#) for more.

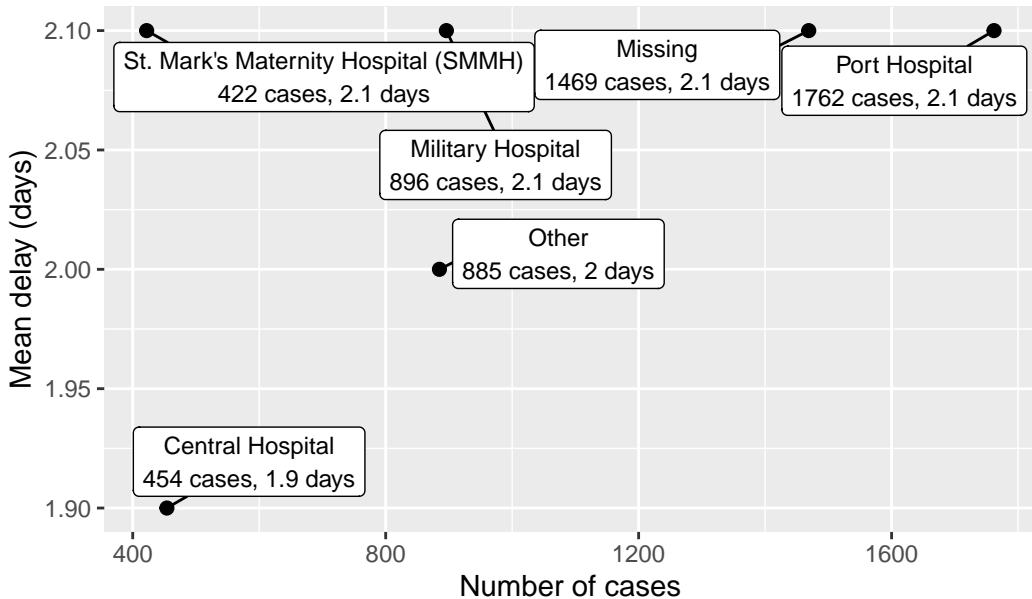
```

pacman::p_load(ggrepel)

linelist %>%
  group_by(hospital) %>%
  summarise(
    n_cases = n(),
    delay_mean = round(mean(days_onset_hosp, na.rm=T),1),
  ) %>%
  ggplot(mapping = aes(x = n_cases, y = delay_mean))+
  geom_point(size = 2)+                                # start with linelist
  geom_label_repel(                                     # group by hospital
    mapping = aes(                                     # create new dataset with summa
      label = stringr::str_glue(                      # number of cases per hospita
        "{hospital}\n{n_cases} cases, {delay_mean} days")# mean delay per hospital
    ),                                                 # send data frame to ggplot
    size = 3,                                         # add points
    min.segment.length = 0)+                           # add point labels
  labs(                                               # how label displays
    title = "Mean delay to admission, by hospital",
    x = "Number of cases",
    y = "Mean delay (days)")                         # text size in labels
  # show all line segments
  # add axes labels

```

Mean delay to admission, by hospital



You can label only a subset of the data points - by using standard `ggplot()` syntax to provide different `data` = for each `geom` layer of the plot. Below, All cases are plotted, but only a few are labeled.

```
ggplot()+
  # All points in grey
  geom_point(
    data = linelist,
    mapping = aes(x = ht_cm, y = wt_kg),
    color = "grey",
    alpha = 0.5) +                                     # all data provided to this layer

  # Few points in black
  geom_point(
    data = linelist %>% filter(days_onset_hosp > 15),  # filtered data provided to this layer
    mapping = aes(x = ht_cm, y = wt_kg),
    alpha = 1) +                                         # default black and not transparent

  # point labels for few points
  geom_label_repel(
    data = linelist %>% filter(days_onset_hosp > 15),  # filter the data for the labels
    mapping = aes(
```

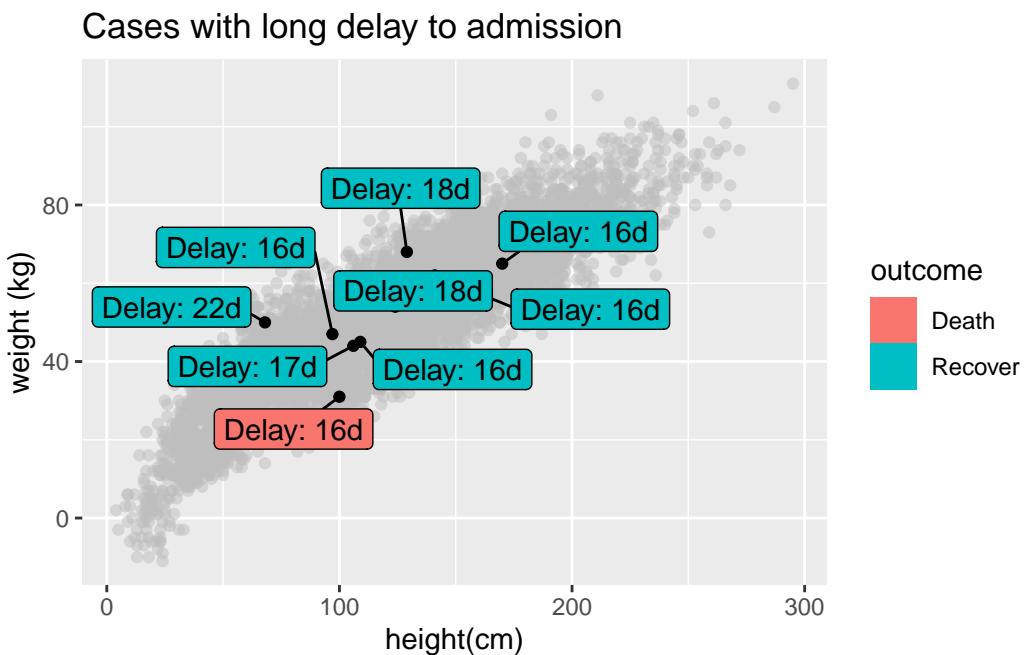
```

x = ht_cm,
y = wt_kg,
fill = outcome,                                     # label color by outcome
label = stringr::str_glue("Delay: {days_onset_hosp}d"), # label created with str_glue
min.segment.length = 0) +                           # show line segments for all

# remove letter "a" from inside legend boxes
guides(fill = guide_legend(override.aes = aes(color = NA)))+

# axis labels
labs(
  title = "Cases with long delay to admission",
  y = "weight (kg)",
  x = "height(cm)")

```



Highlighting

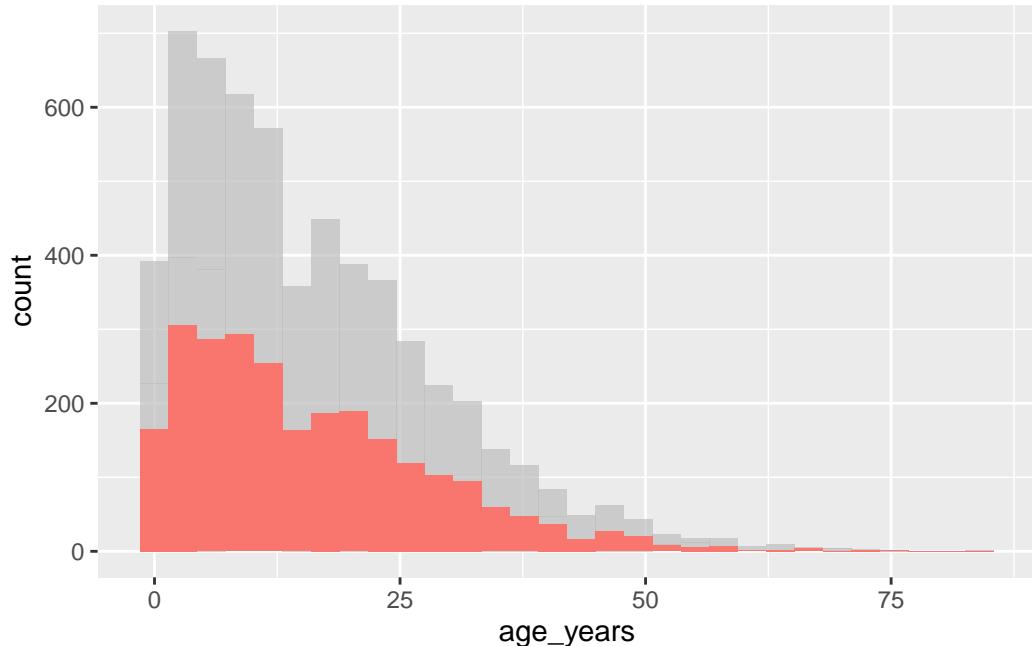
Highlighting specific elements in a chart is a useful way to draw attention to a specific instance of a variable while also providing information on the dispersion of the full dataset. While this is not easily done in base **ggplot2**, there is an external package that can help to do this known as **gghighlight**. This is easy to use within the ggplot syntax.

The **gghighlight** package uses the **gghighlight()** function to achieve this effect. To use this function, supply a logical statement to the function - this can have quite flexible outcomes, but here we'll show an example of the age distribution of cases in our linelist, highlighting them by outcome.

```
# load gghighlight
library(gghighlight)

# replace NA values with unknown in the outcome variable
linelist <- linelist %>%
  mutate(outcome = replace_na(outcome, "Unknown"))

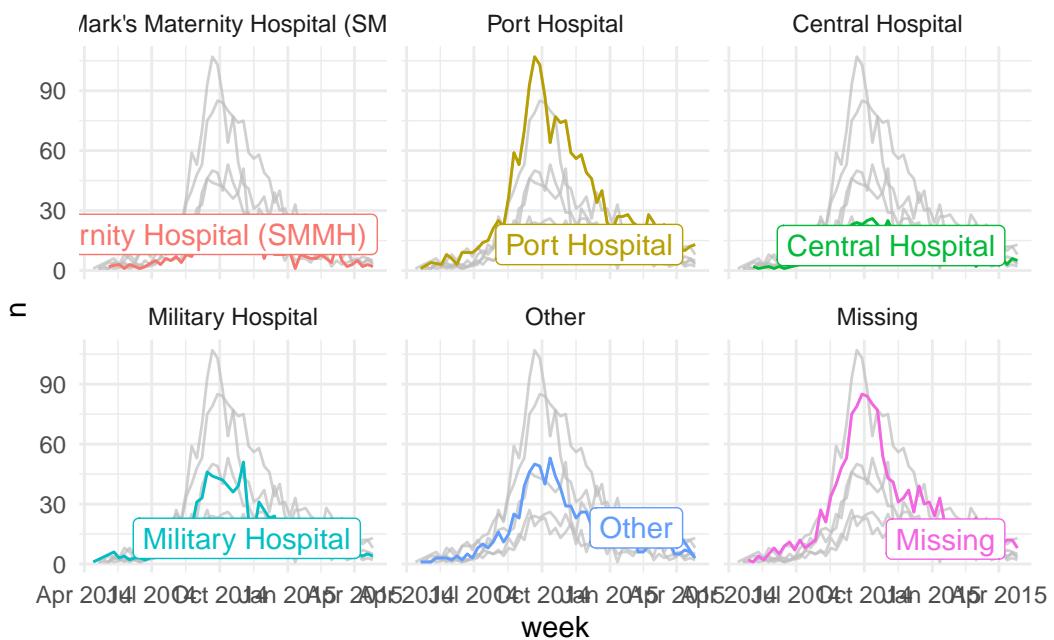
# produce a histogram of all cases by age
ggplot(
  data = linelist,
  mapping = aes(x = age_years, fill = outcome)) +
  geom_histogram() +
  gghighlight::gghighlight(outcome == "Death")      # highlight instances where the patient
```



This also works well with faceting functions - it allows the user to produce facet plots with the background data highlighted that doesn't apply to the facet! Below we count cases by week and plot the epidemic curves by hospital (**color =** and **facet_wrap()** set to **hospital**

column).

```
# produce a histogram of all cases by age
linelist %>%
  count(week = lubridate::floor_date(date_hospitalisation, "week"),
    hospital) %>%
  ggplot()+
  geom_line(aes(x = week, y = n, color = hospital))+
  theme_minimal()+
  gghighlight::gghighlight() +
  facet_wrap(~hospital) # highlight instances where the patient
# make facets by outcome
```



Plotting multiple datasets

Note that properly aligning axes to plot from multiple datasets in the same plot can be difficult. Consider one of the following strategies:

- Merge the data prior to plotting, and convert to “long” format with a column reflecting the dataset
- Use **cowplot** or a similar package to combine two plots (see below)

Combine plots

Two packages that are very useful for combining plots are **cowplot** and **patchwork**. In this page we will mostly focus on **cowplot**, with occassional use of **patchwork**.

Here is the online [introduction to cowplot](#). You can read the more extensive documentation for each function online [here](#). We will cover a few of the most common use cases and functions below.

The **cowplot** package works in tandem with **ggplot2** - essentially, you use it to arrange and combine ggplots and their legends into compound figures. It can also accept **base** R graphics.

```
pacman::p_load(  
  tidyverse,      # data manipulation and visualisation  
  cowplot,        # combine plots  
  patchwork       # combine plots  
)
```

While faceting is a convenient approach to plotting, sometimes its not possible to get the results you want from its relatively restrictive approach. Here, you may choose to combine plots by sticking them together into a larger plot. There are three well known packages that are great for this - **cowplot**, **gridExtra**, and **patchwork**. However, these packages largely do the same things, so we'll focus on **cowplot** for this section.

```
* plot_grid()
```

The **cowplot** package has a fairly wide range of functions, but the easiest use of it can be achieved through the use of **plot_grid()**. This is effectively a way to arrange predefined plots in a grid formation. We can work through another example with the malaria dataset - here we can plot the total cases by district, and also show the epidemic curve over time.

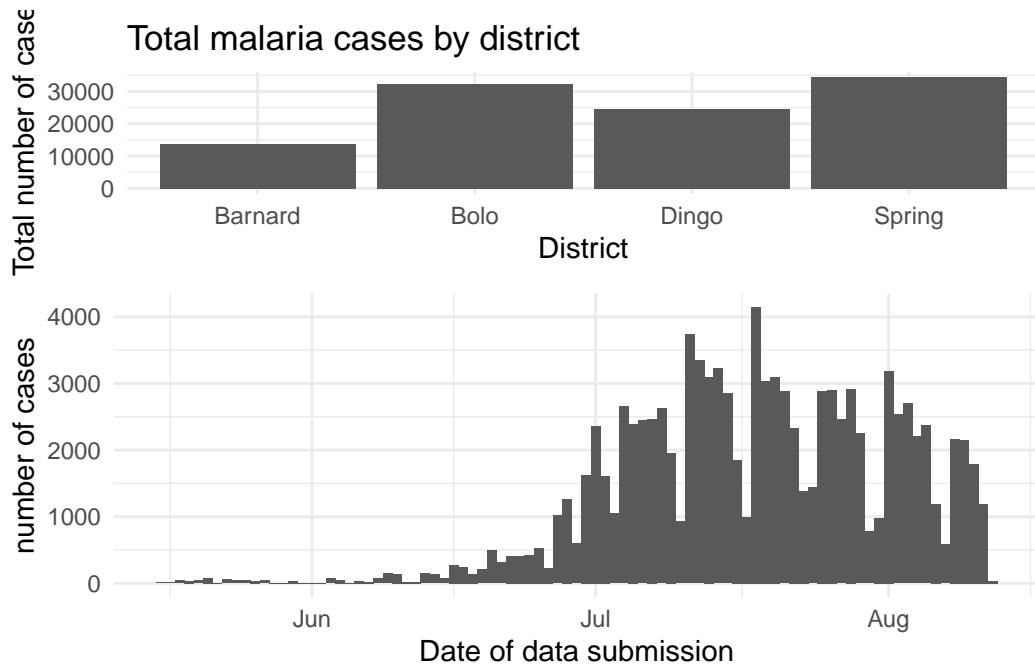
```
malaria_data <- rio::import("data/malaria_facility_count_data.rds")  
  
# bar chart of total cases by district  
p1 <- ggplot(malaria_data, aes(x = District, y = malaria_tot)) +  
  geom_bar(stat = "identity") +  
  labs(  
    x = "District",  
    y = "Total number of cases",  
    title = "Total malaria cases by district"  
) +  
  theme_minimal()
```

```

# epidemic curve over time
p2 <- ggplot(malaria_data, aes(x = data_date, y = malaria_tot)) +
  geom_col(width = 1) +
  labs(
    x = "Date of data submission",
    y = "number of cases"
  ) +
  theme_minimal()

cowplot::plot_grid(p1, p2,
  # 1 column and two rows - stacked on top of each other
  ncol = 1,
  nrow = 2,
  # top plot is 2/3 as tall as second
  rel_heights = c(2, 3))

```



- * Combine legends

If your plots have the same legend, combining them is relatively straight-forward. Simple use the **cowplot** approach above to combine the plots, but remove the legend from one of them (de-duplicate).

If your plots have different legends, you must use an alternative approach:

- 1) Create and save your plots *without legends* using `theme(legend.position = "none")`
- 2) Extract the legends from each plot using `get_legend()` as shown below - *but extract legends from the plots modified to actually show the legend*
- 3) Combine the legends into a legends panel
- 4) Combine the plots and legends panel

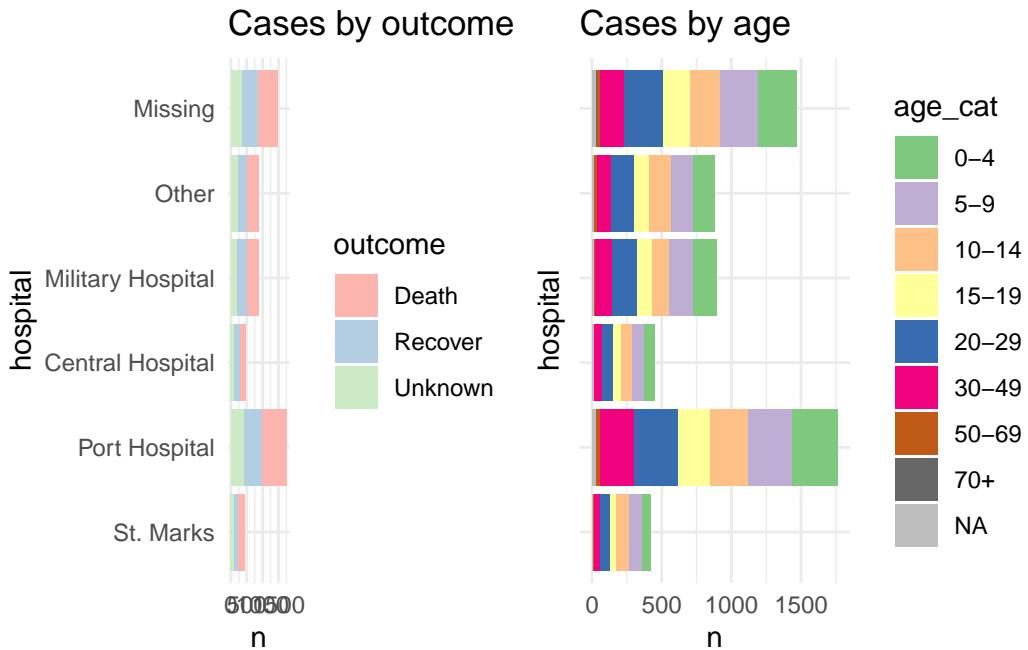
For demonstration we show the two plots separately, and then arranged in a grid with their own legends showing (ugly and inefficient use of space):

```
p1 <- linelist %>%
  mutate(hospital = recode(hospital, "St. Mark's Maternity Hospital (SMMH)" = "St. Marks"))
  count(hospital, outcome) %>%
  ggplot()+
  geom_col(mapping = aes(x = hospital, y = n, fill = outcome))+
  scale_fill_brewer(type = "qual", palette = 4, na.value = "grey")+
  coord_flip()+
  theme_minimal()+
  labs(title = "Cases by outcome")

p2 <- linelist %>%
  mutate(hospital = recode(hospital, "St. Mark's Maternity Hospital (SMMH)" = "St. Marks"))
  count(hospital, age_cat) %>%
  ggplot()+
  geom_col(mapping = aes(x = hospital, y = n, fill = age_cat))+
  scale_fill_brewer(type = "qual", palette = 1, na.value = "grey")+
  coord_flip()+
  theme_minimal()+
  theme(axis.text.y = element_blank())+
  labs(title = "Cases by age")
```

Here is how the two plots look when combined using `plot_grid()` without combining their legends:

```
cowplot::plot_grid(p1, p2, rel_widths = c(0.3))
```



And now we show how to combine the legends. Essentially what we do is to define each plot *without* its legend (`theme(legend.position = "none")`), and then we define each plot's legend *separately*, using the `get_legend()` function from `cowplot`. When we extract the legend from the saved plot, we need to add + the legend back in, including specifying the placement ("right") and smaller adjustments for alignment of the legends and their titles. Then, we combine the legends together vertically, and then combine the two plots with the newly-combined legends. Voila!

```
# Define plot 1 without legend
p1 <- linelist %>%
  mutate(hospital = recode(hospital, "St. Mark's Maternity Hospital (SMMH)" = "St. Marks")) +
  count(hospital, outcome) %>%
  ggplot() +
  geom_col(mapping = aes(x = hospital, y = n, fill = outcome)) +
  scale_fill_brewer(type = "qual", palette = 4, na.value = "grey") +
  coord_flip() +
  theme_minimal() +
  theme(legend.position = "none") +
  labs(title = "Cases by outcome")

# Define plot 2 without legend
p2 <- linelist %>%
  mutate(hospital = recode(hospital, "St. Mark's Maternity Hospital (SMMH)" = "St. Marks")) +
  count(hospital, age_cat) %>%
  ggplot() +
  geom_col(mapping = aes(x = hospital, y = n, fill = age_cat)) +
  scale_fill_brewer(type = "qual", palette = 8, na.value = "grey") +
  coord_flip() +
  theme_minimal() +
  theme(legend.position = "none") +
  labs(title = "Cases by age")
```

```

p2 <- linelist %>%
  mutate(hospital = recode(hospital, "St. Mark's Maternity Hospital (SMMH)" = "St. Marks"))
  count(hospital, age_cat) %>%
  ggplot()+
  geom_col(mapping = aes(x = hospital, y = n, fill = age_cat))+
  scale_fill_brewer(type = "qual", palette = 1, na.value = "grey")+
  coord_flip()+
  theme_minimal()+
  theme(
    legend.position = "none",
    axis.text.y = element_blank(),
    axis.title.y = element_blank()
  )+
  labs(title = "Cases by age")

# extract legend from p1 (from p1 + legend)
leg_p1 <- cowplot::get_legend(p1 +
                                theme(legend.position = "right",           # extract vertical
                                      legend.justification = c(0,0.5))+ # so legends align
                                      labs(fill = "Outcome"))          # title of legend)

# extract legend from p2 (from p2 + legend)
leg_p2 <- cowplot::get_legend(p2 +
                                theme(legend.position = "right",           # extract vertical
                                      legend.justification = c(0,0.5))+ # so legends align
                                      labs(fill = "Age Category"))        # title of legend)

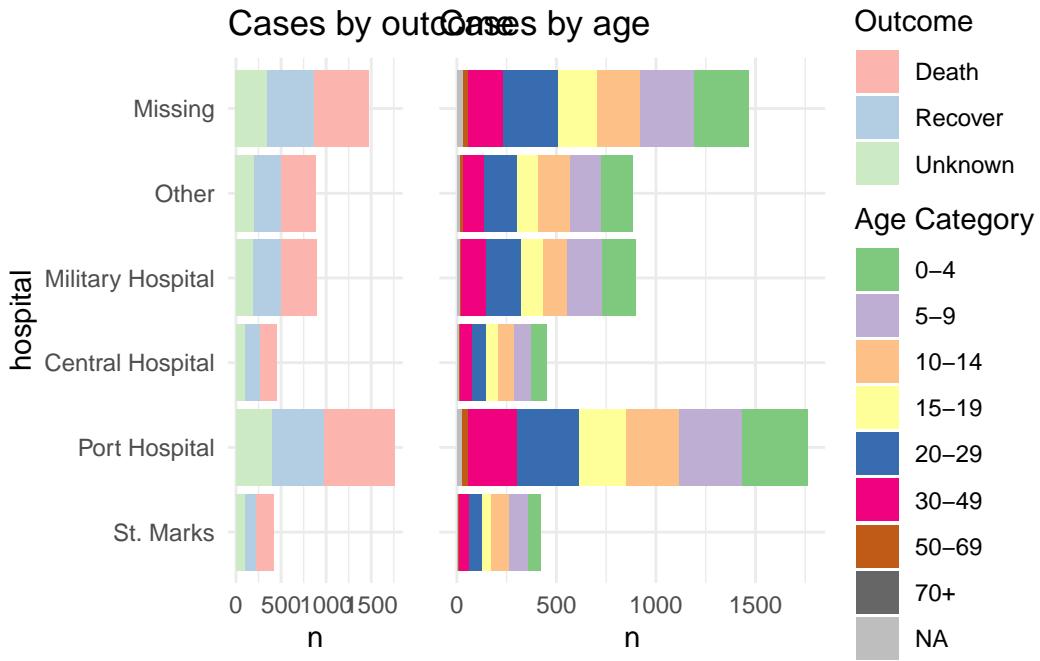
# create a blank plot for legend alignment
#blank_p <- patchwork::plot_spacer() + theme_void()

# create legends panel, can be one on top of the other (or use spacer commented above)
legends <- cowplot::plot_grid(leg_p1, leg_p2, nrow = 2, rel_heights = c(.3, .7))

# combine two plots and the combined legends panel
combined <- cowplot::plot_grid(p1, p2, legends, ncol = 3, rel_widths = c(.4, .4, .2))

combined # print

```



This solution was learned from [this post](#) with a minor fix to align legends from [this post](#).

TIP: Fun note - the “cow” in **cowplot** comes from the creator’s name - Claus O. Wilke.

* Inset plots

You can inset one plot in another using **cowplot**. Here are things to be aware of:

- Define the main plot with `theme_half_open()` from **cowplot**; it may be best to have the legend either on top or bottom
- Define the inset plot. Best is to have a plot where you do not need a legend. You can remove plot theme elements with `element_blank()` as shown below.
- Combine them by applying `ggdraw()` to the main plot, then adding `draw_plot()` on the inset plot and specifying the coordinates (x and y of lower left corner), height and width as proportion of the whole main plot.

```
# Define main plot
main_plot <- ggplot(data = linelist)+  
  geom_histogram(aes(x = date_onset, fill = hospital))+  
  scale_fill_brewer(type = "qual", palette = 1, na.value = "grey") +  
  theme_half_open()
```

```

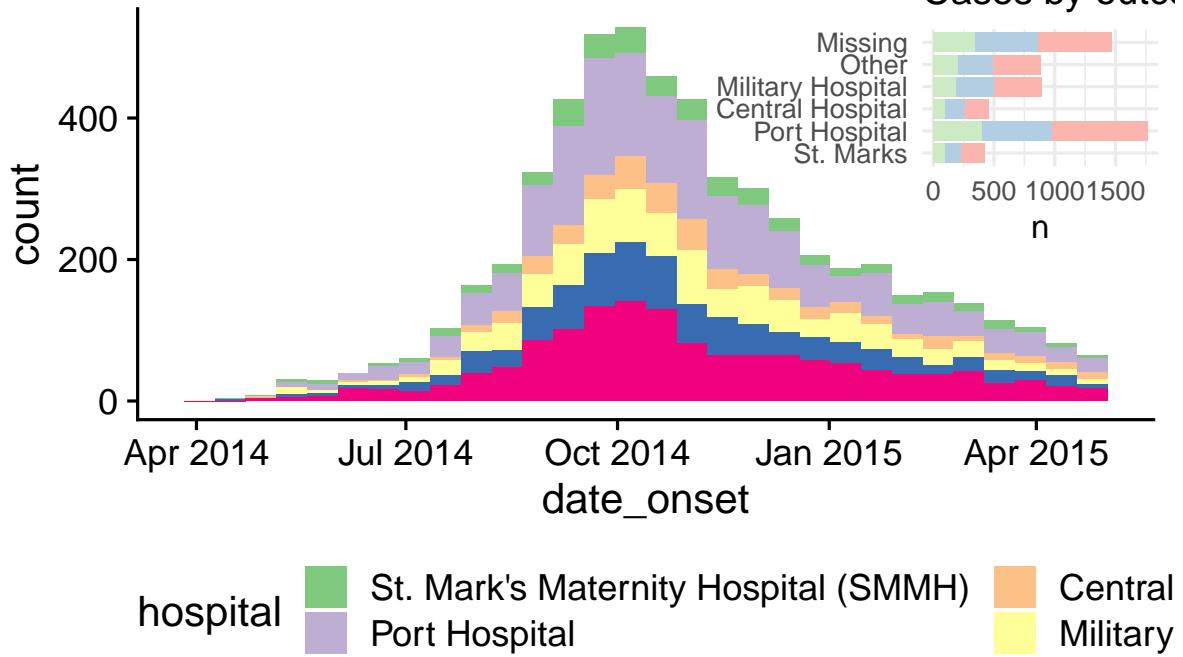
theme(legend.position = "bottom")+
  labs(title = "Epidemic curve and outcomes by hospital")

# Define inset plot
inset_plot <- linelist %>%
  mutate(hospital = recode(hospital, "St. Mark's Maternity Hospital (SMMH)" = "St. Marks"))
  count(hospital, outcome) %>%
  ggplot()+
    geom_col(mapping = aes(x = hospital, y = n, fill = outcome))+
    scale_fill_brewer(type = "qual", palette = 4, na.value = "grey")+
    coord_flip()+
    theme_minimal()+
    theme(legend.position = "none",
          axis.title.y = element_blank())+
    labs(title = "Cases by outcome")

# Combine main with inset
cowplot::ggdraw(main_plot)+
  draw_plot(inset_plot,
            x = .6, y = .55,      #x = .07, y = .65,
            width = .4, height = .4)

```

Epidemic curve and outcomes by hospital



This technique is explained more in these two vignettes:

[Wilke lab](#)

[draw_plot\(\) documentation](#)