

Data Visualisation AM10

Session 1 Visualisations

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Why not use double y-axes?

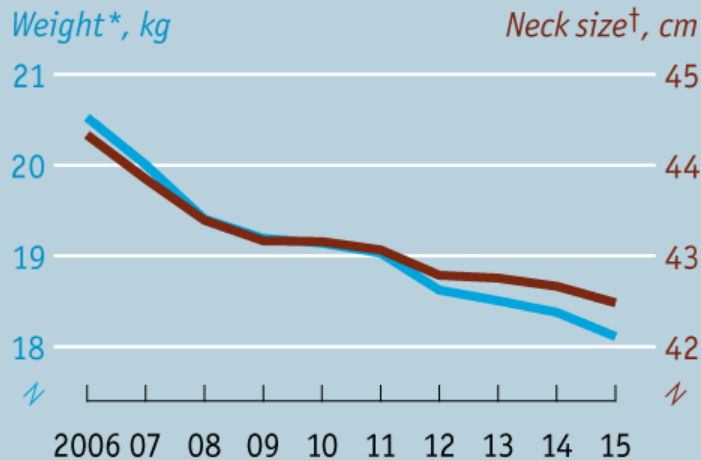
00_secondary_axis.R

If you choose where the y-axes start and stop, you can make the two trends to line up however you want!

Original

Fit as a butcher's dog

Characteristics of dogs registered with the UK's Kennel Club, average when fully grown

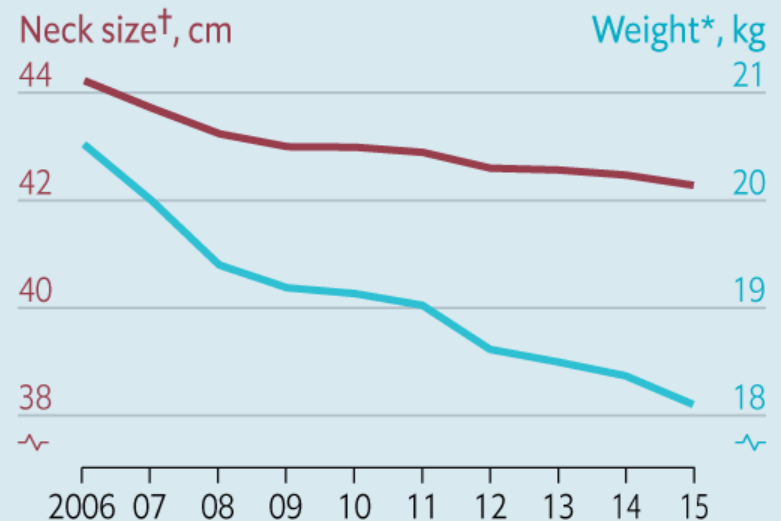


Sources: Kennel Club; *The Economist*
 *Where at least 50 are registered per year
 †Where at least 100 are registered per year

Better

Fit as a butcher's dog

Characteristics of dogs registered with the UK's Kennel Club, average when fully grown

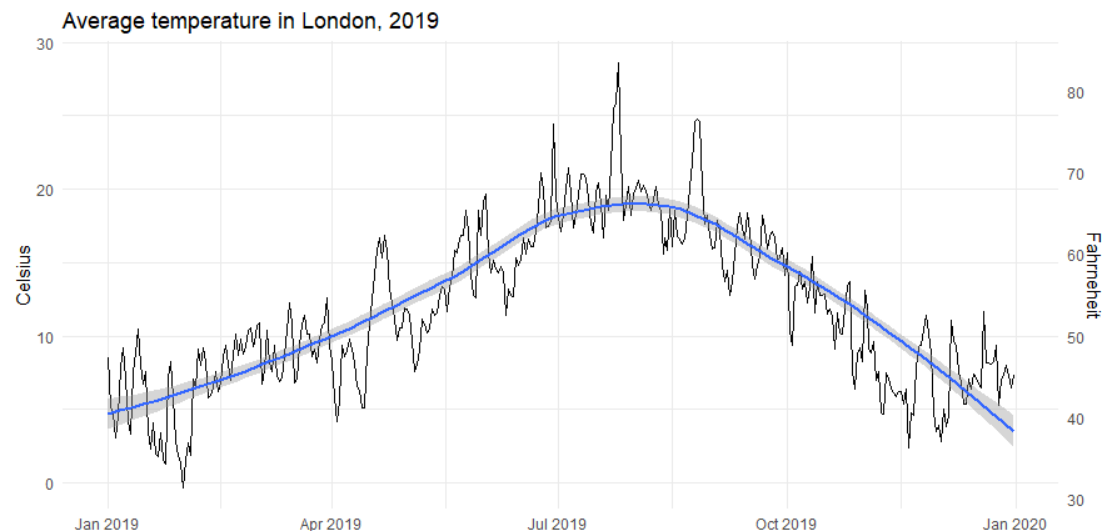


Sources: Kennel Club; *The Economist*
 *Where at least 50 are registered per year
 †Where at least 100 are registered per year

OK when both axes measure the same thing

00_secondary_axis.R

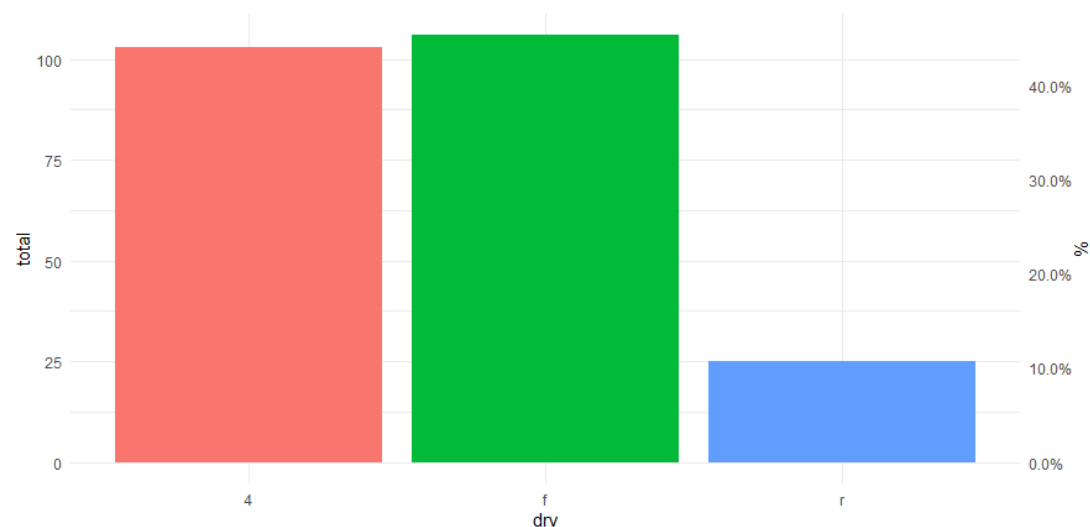
```
# from london_bikes data, that contains avg_temp
bikes %>%
  filter(year == 2019) %>%
  ggplot(aes(x = date, y = avg_temp)) +
  geom_line() +
  geom_smooth() +
  labs(
    title = "Average temperature in London, 2019",
    x = NULL,
    y = "Celsius",
    scale_y_continuous(
      sec.axis =
        sec_axis(trans = ~ (1.8 * .) + 32,
                  name = "Fahrneheit")
    ) +
  theme_minimal() +
  NULL
```



```
car_counts <- mpg %>%
  group_by(drv) %>%
  summarize(total = n())

total_cars <- sum(car_counts$total)

ggplot(car_counts,
  aes(x = drv, y = total,
      fill = drv)) +
  geom_col() +
  scale_y_continuous(
    sec.axis = sec_axis(
      trans = ~ . / total_cars,
      labels = scales::percent,
      name = "%"
    )
  ) +
  guides(fill = FALSE) +
  theme_minimal() +
  NULL
```



Assignment 1 thought piece

AM10 Reflection Paper

Why do we visualise data? What makes a great visualisation?

We visualise data because the human brain is more effective at detecting patterns, trends and outliers and making clear inferences when presented with information visually, than in almost any other way. A

Pareidolia: the tendency for incorrect perception of a stimulus as an object, pattern or meaning known to the observer, such as seeing shapes in clouds, seeing faces in inanimate objects or abstract patterns, or hearing hidden messages in music.



Assignment 1 visualisations

```
stop_and_search <- stop_and_search %>%
```

```
# Renaming a few variables which included spaces
```

```
rename(PartOfPolicingOperation = `Part of a policing operation`,
       PolicingOperation = `Policing operation`,
       AgeRange = `Age range`,
       EthnicitySelfDefined = `Self-defined ethnicity`,
       EthnicityOfficerDefined = `Officer-defined ethnicity`,
       ObjectOfSearch = `Object of search`,
       OutcomeLinkedToObjectOfSearch = `Outcome linked to object of search`,
       RemovalOfMoreThanJustOuterClothing = `Removal of more than just outer clothing`) %>%
```

janitor::clean_names()

```
mutate(
```

```
# Create a new variable for the time of day during which the stop and search took place
```

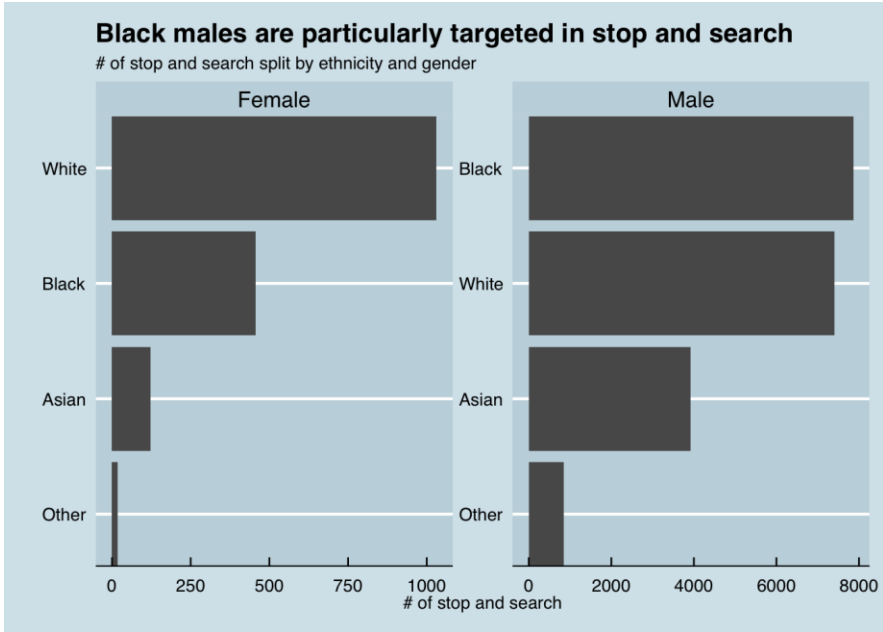
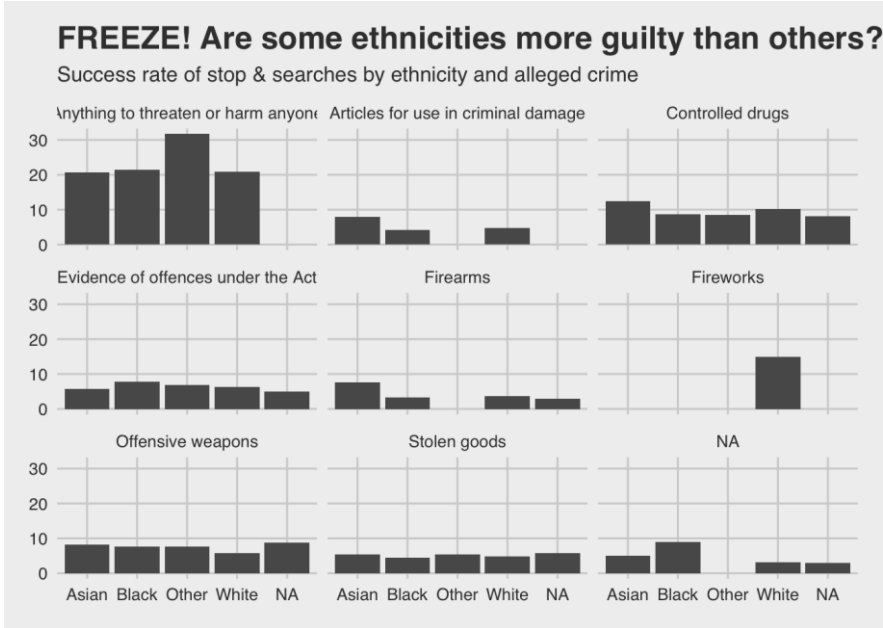
```
TimeOfDay = case_when(hour(Date) >= 23 | hour(Date) < 5 ~ "Night",
                      hour(Date) >= 17 ~ "Evening",
                      hour(Date) >= 11 ~ "Day",
                      hour(Date) >= 5 ~ "Morning"),
```

```
# Create a new variable that only stores the date without time
```

```
Day = date(Date)
) %>%
```

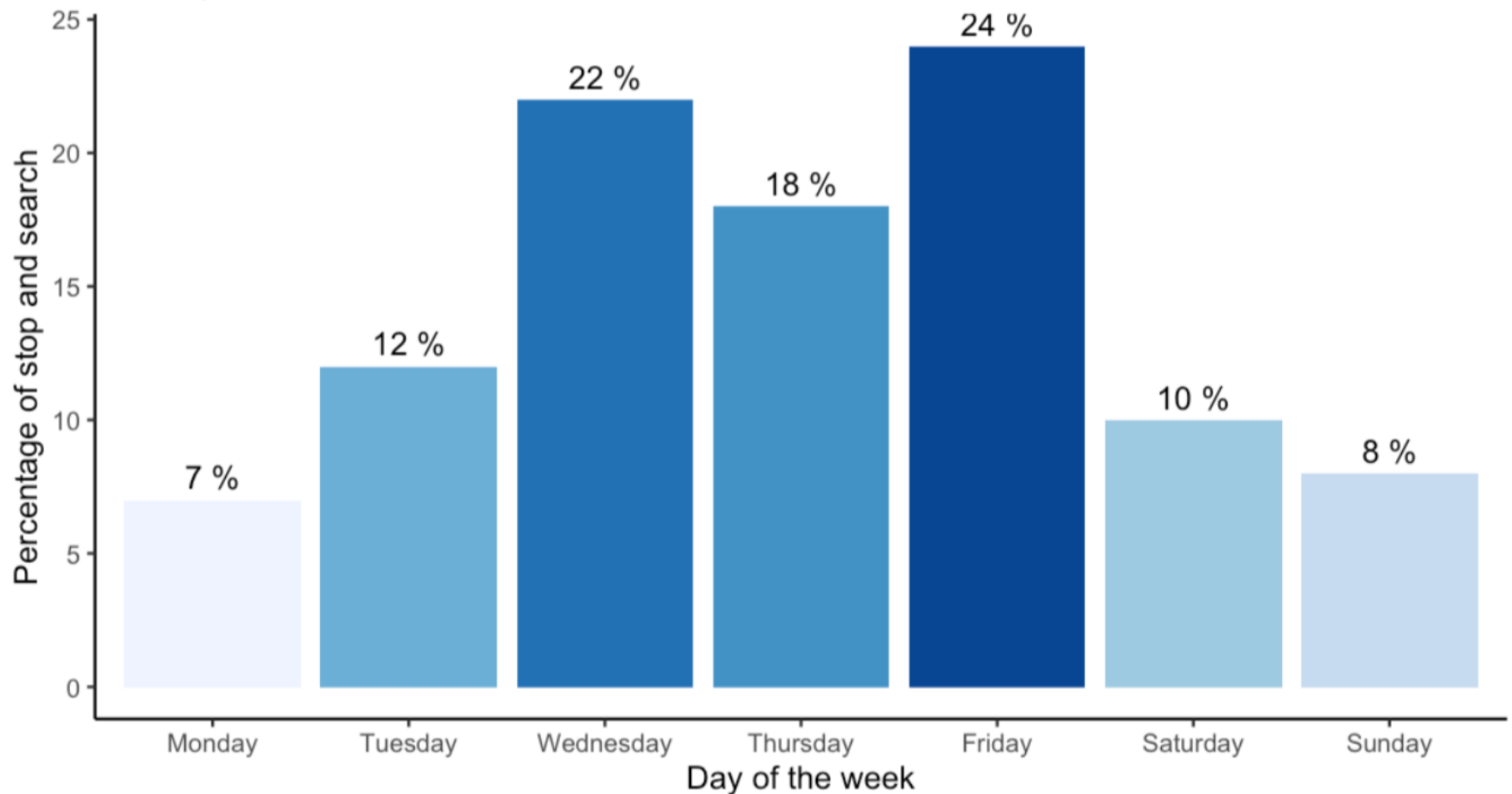
lubridate

Assignment 1 visualisations

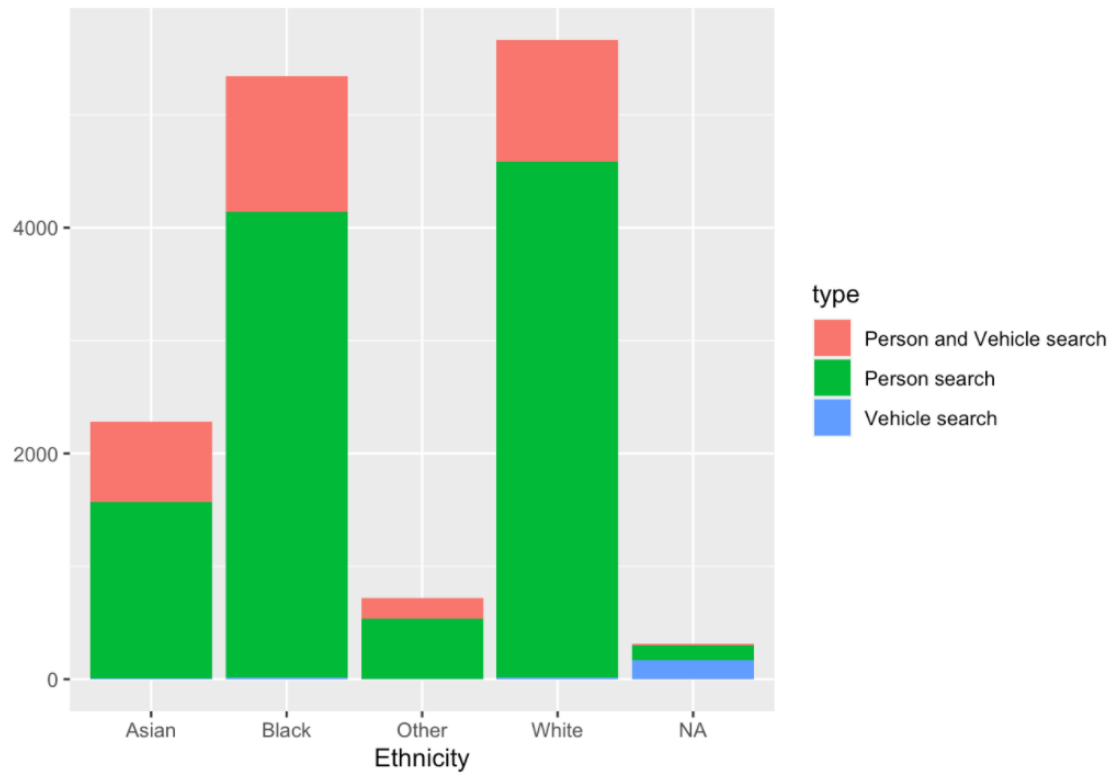


Much more activity for stop and search during the week

Distribution of stop and search on days of the week during September 2021 according to data.police.uk

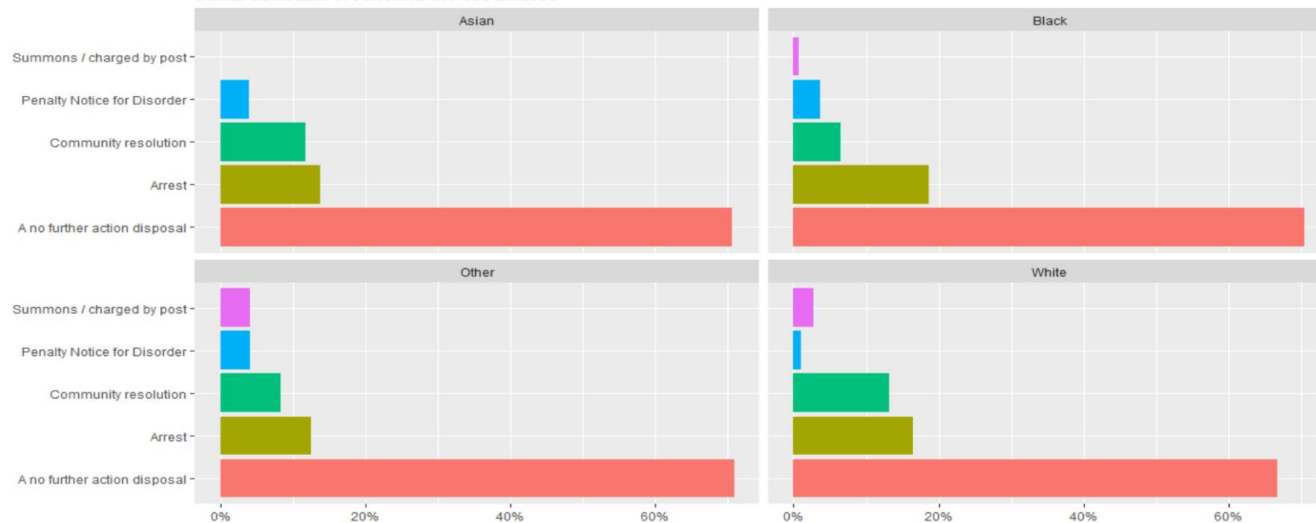


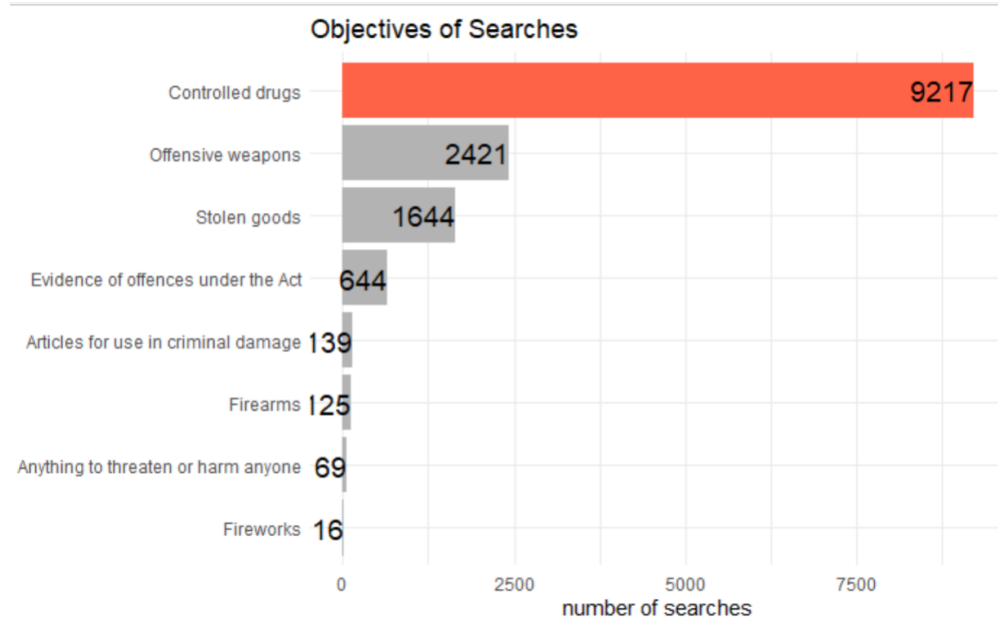
Number of Stop and Searches by Type and Ethnicity



Outcome of Stop and Search by Race

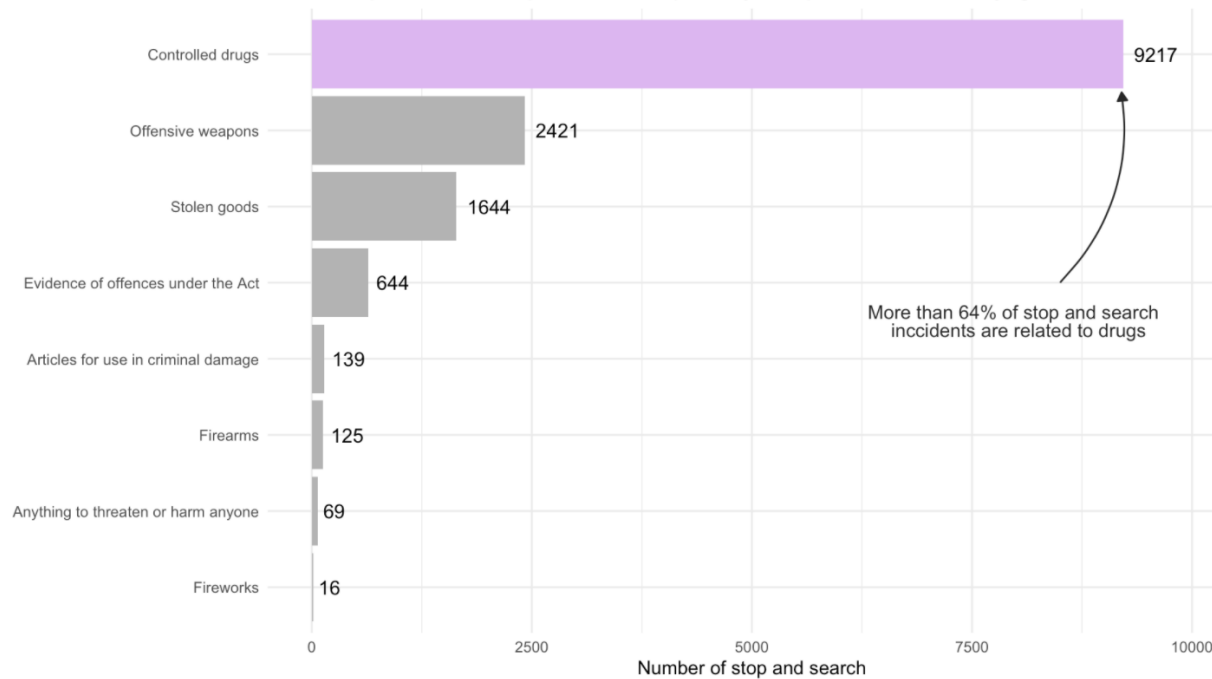
Similar distribution of outcomes across all races



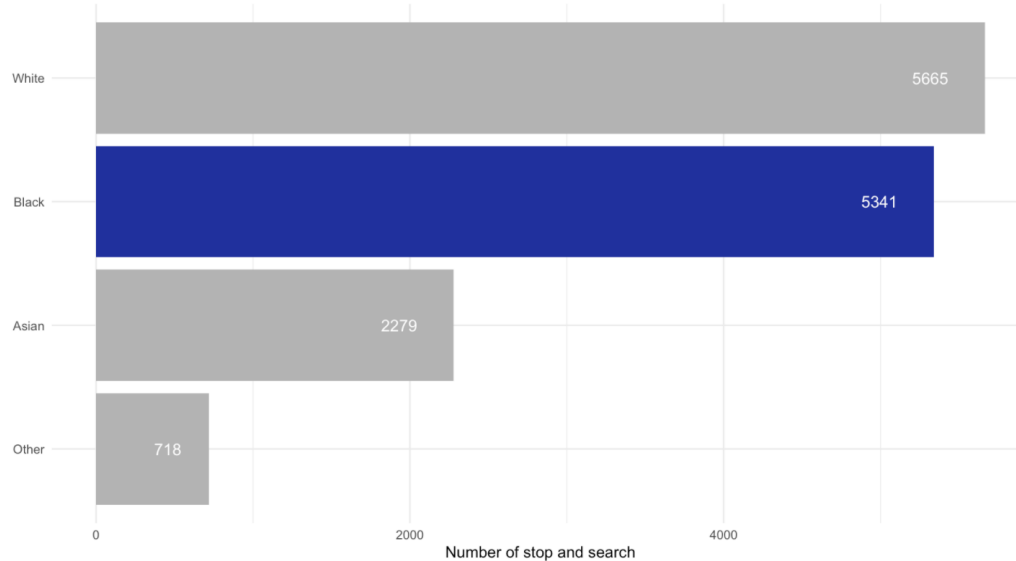


Drugs appears to be the most common reason for stop and search

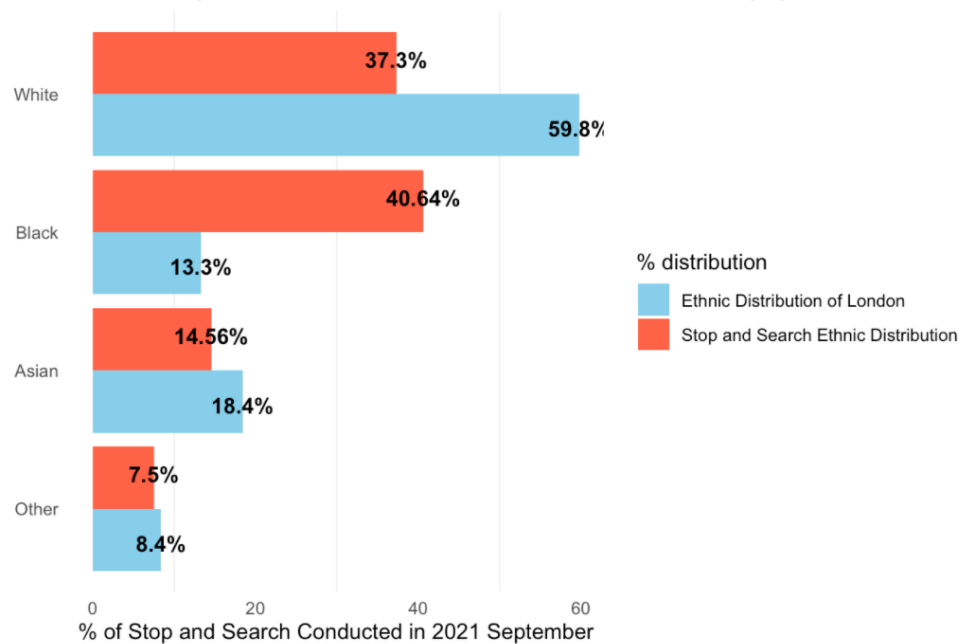
Count of stop and search in September 2019 reported by Metropolitan Police Service by age



Black people appear to be overfrequently stopped when compared to population proportion
Count of stop and search in September 2019 reported by Metropolitan Police Service by race

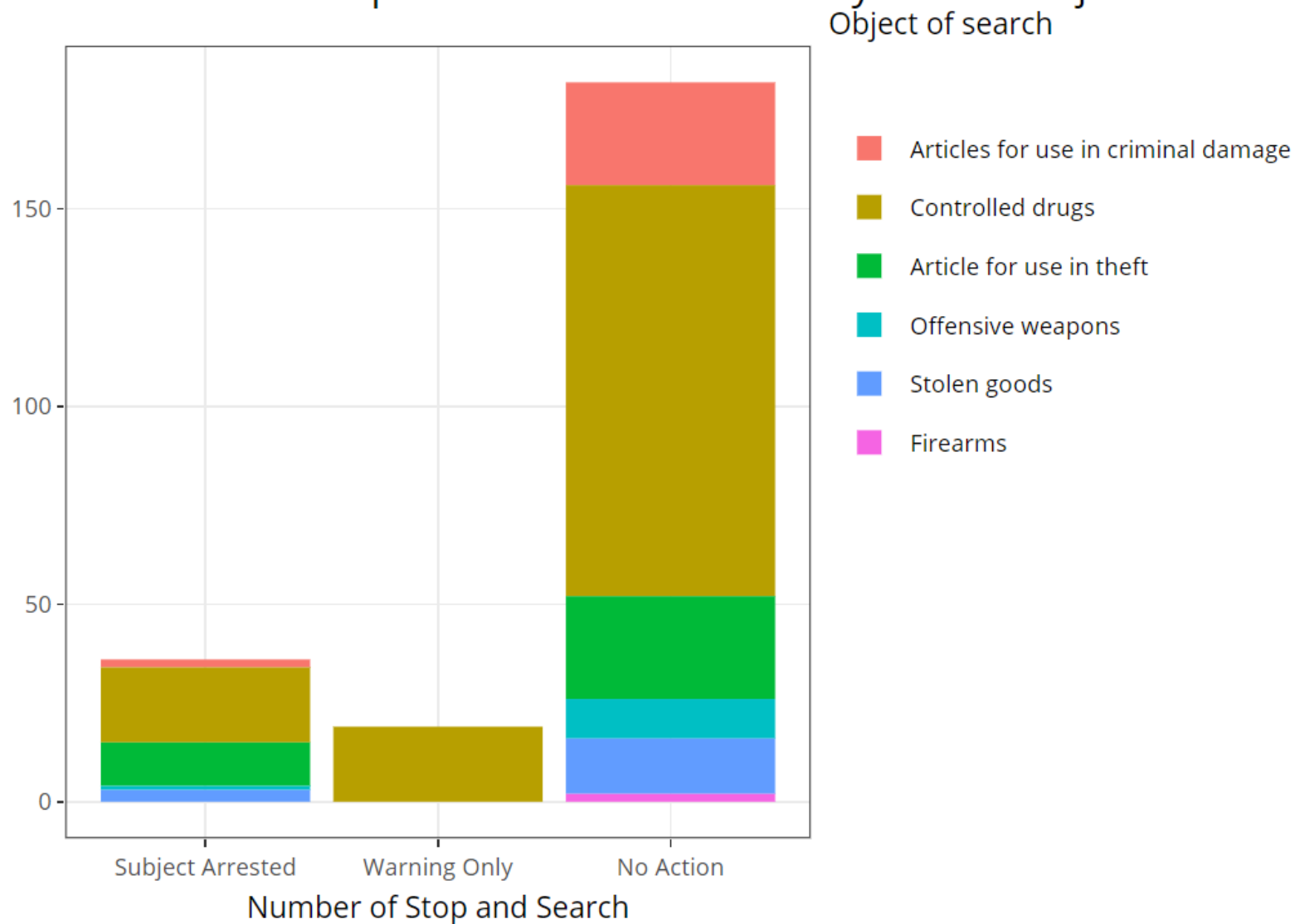


40% of Stop and Searches conducted on 13% of London's population

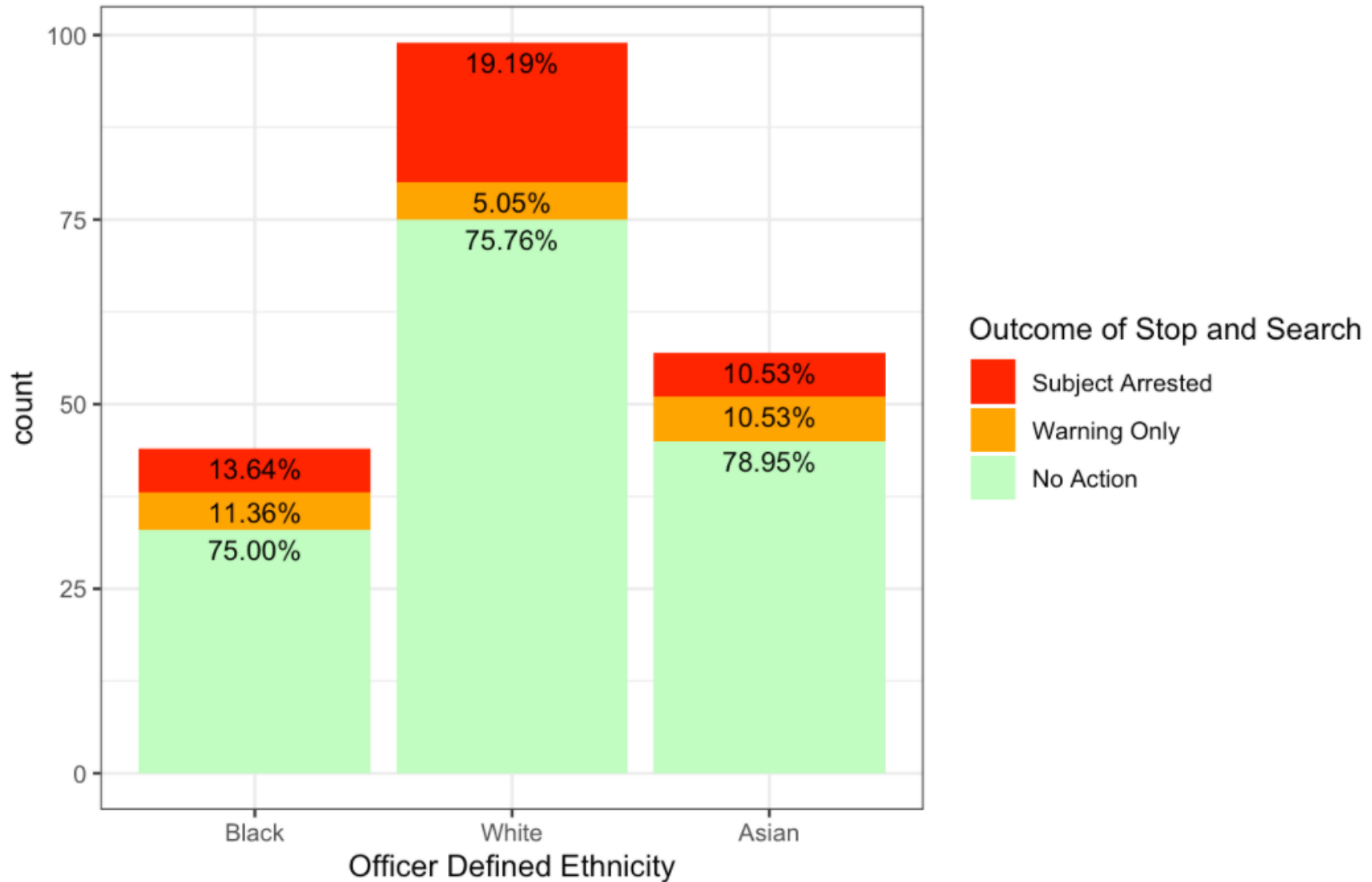


NOTE: Ethnicity Breakdown of London from Wikipedia

Outcome of Stop and Search in London by Search Object



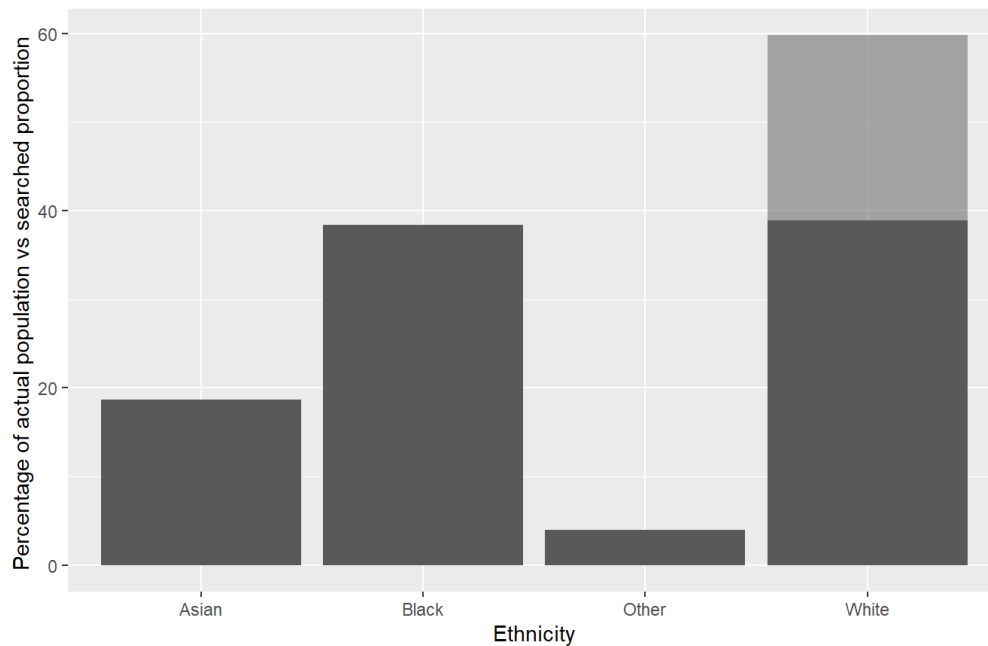
Stop and Search Outcomes by Ethnicity in September 2021 by data.police.uk



```
## ethnicity searchpercent actualper
## 1 Asian 18.69344 18.4
## 2 Black 38.39335 13.3
## 3 Other 4.00277 3.4
## 4 White 38.91043 59.8
```

```
plot4 <- ggplot(percomp, aes(ethnicity, actualper)) + geom_col(alpha=0.5) + geom_col(aes(ethnicity, searchper)) +
  labs(title = "Higher proportion of Black people are searched by the police",
    caption = "Source: https://data.police.uk/data/",
    x = "Ethnicity", y = "Percentage of actual population vs searched proportion")
plot4
```

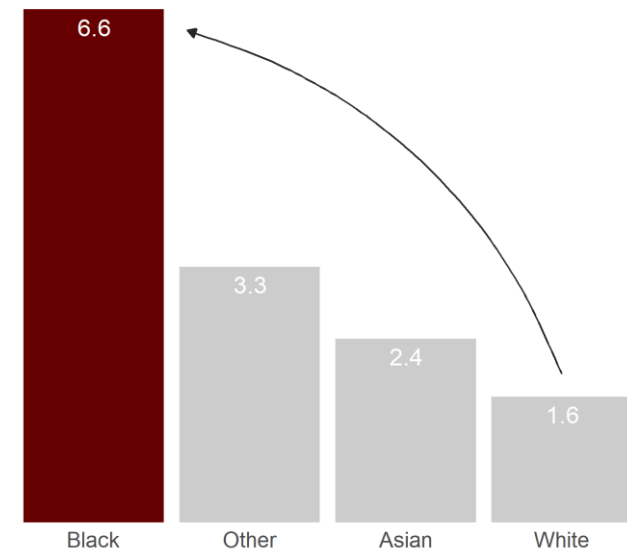
Higher proportion of Black people are searched by the police



Source: <https://data.police.uk/data/>

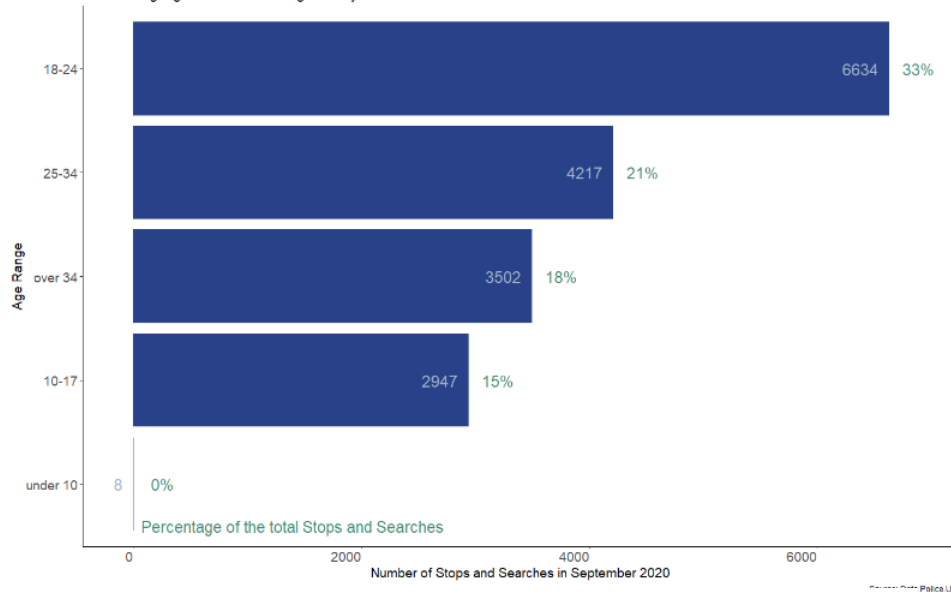
Black people in London are more than 4 times as likely to be stopped as white people

Stop and searches per 1,000 population in Sep 2020



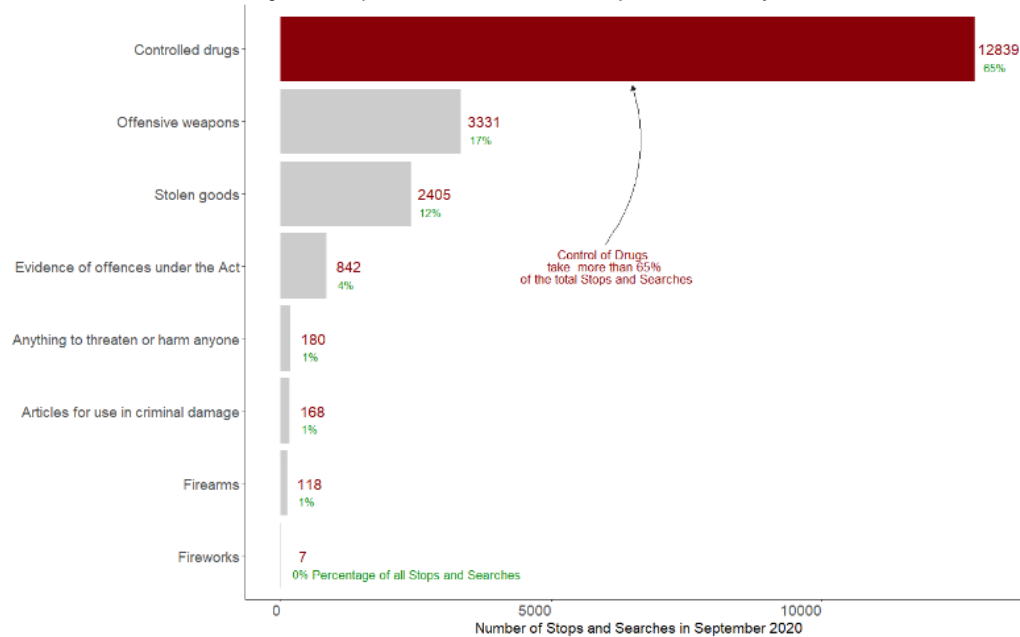
Sins of Youth pay a Price!

After leaving High School late teenagers/early adults are the most in trouble



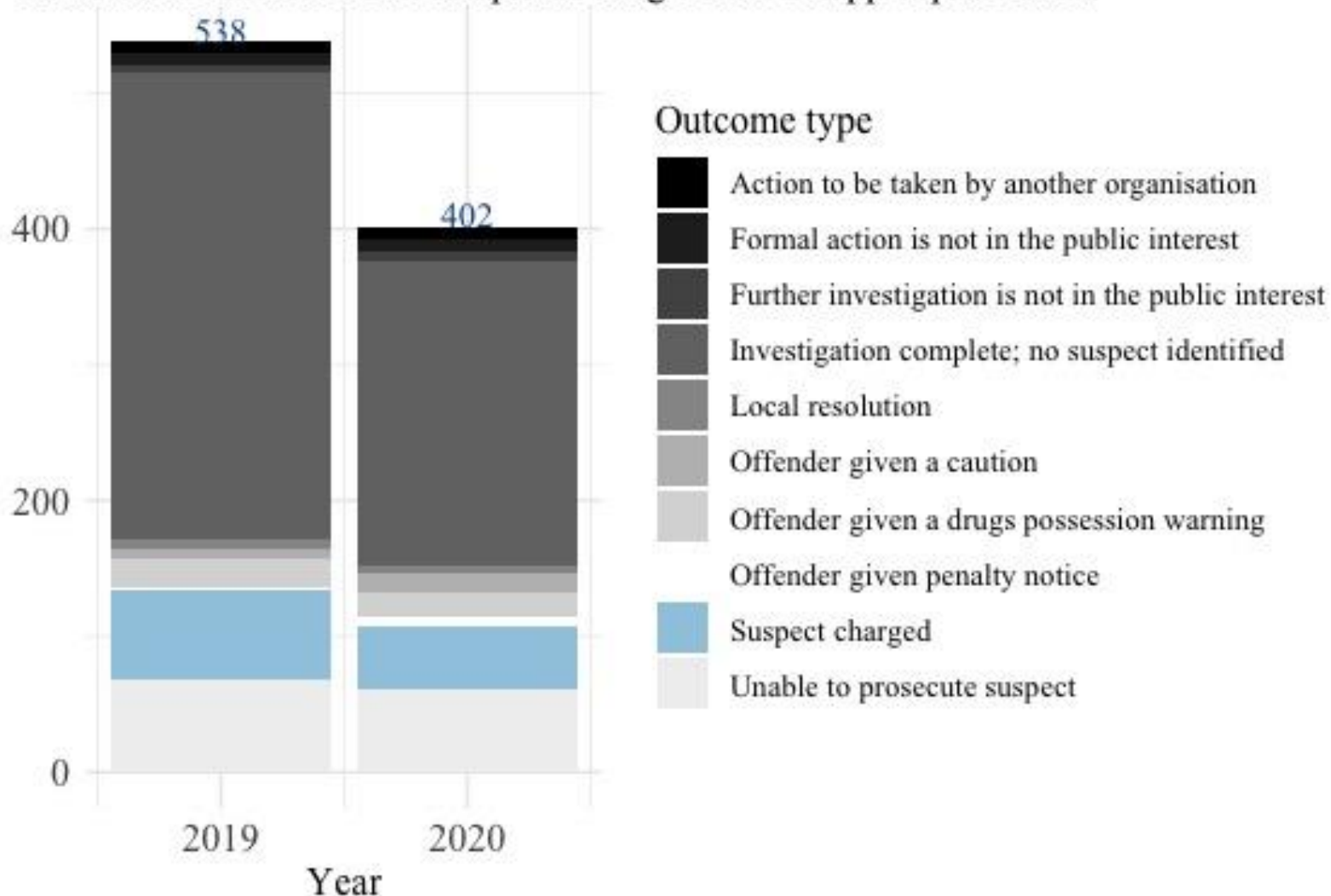
Drugs take the most attention!

Drugs related Stops and Searches are 4 times more frequent than the next Object of Search



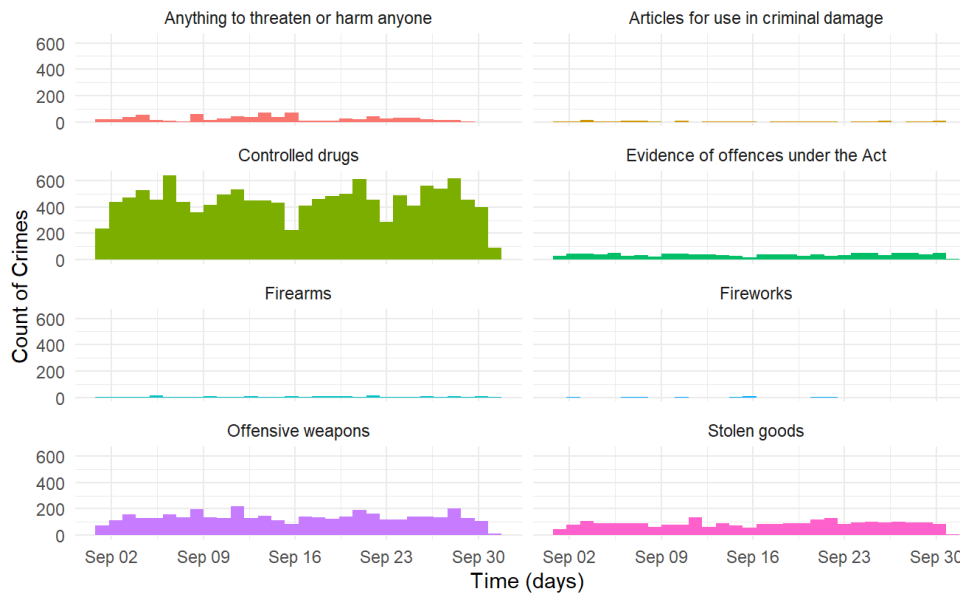
Comparison between total number of search volumes pre-covid and post-covid by outcome types

Total number searched and suspects charged have dropped post-covid



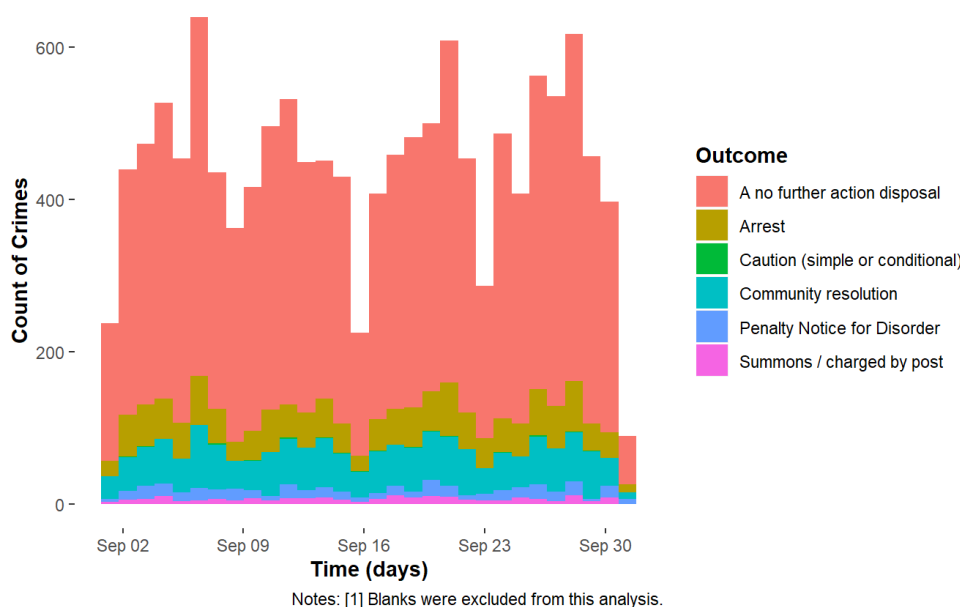
How often do certain crimes occur through November?

Count of crimes by the day during the month of November



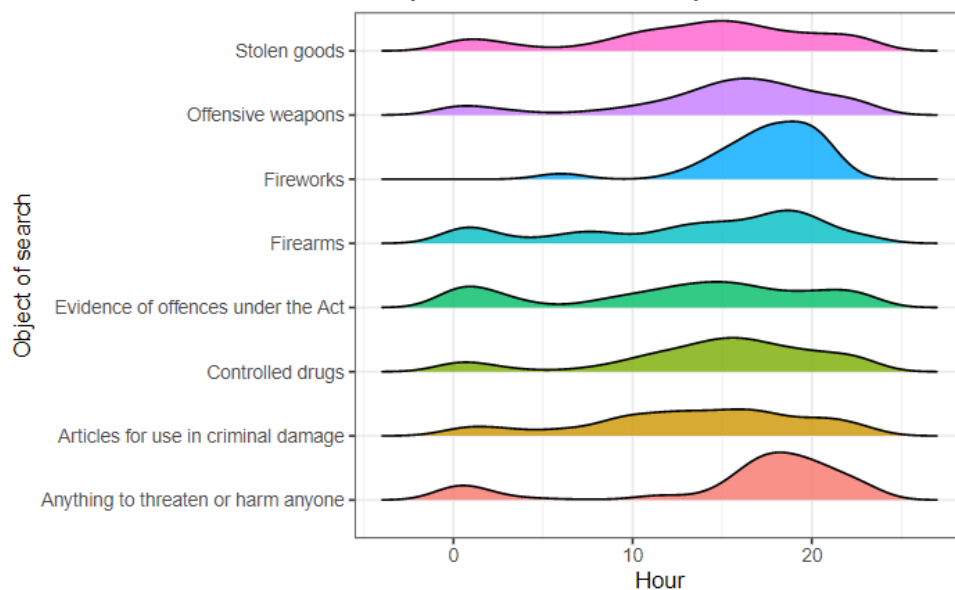
How often do Controlled Drug crimes lead to no action?

Count of controlled drug instances in November highlighted by outcome of crime

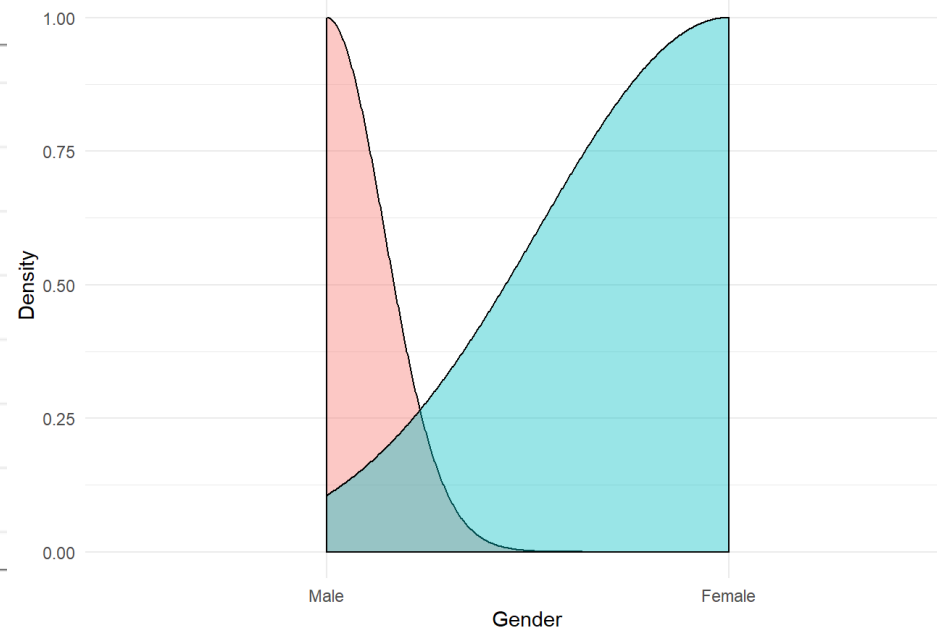


Searches concentrated around hourly peaks

Hourly distributions of different objects of search



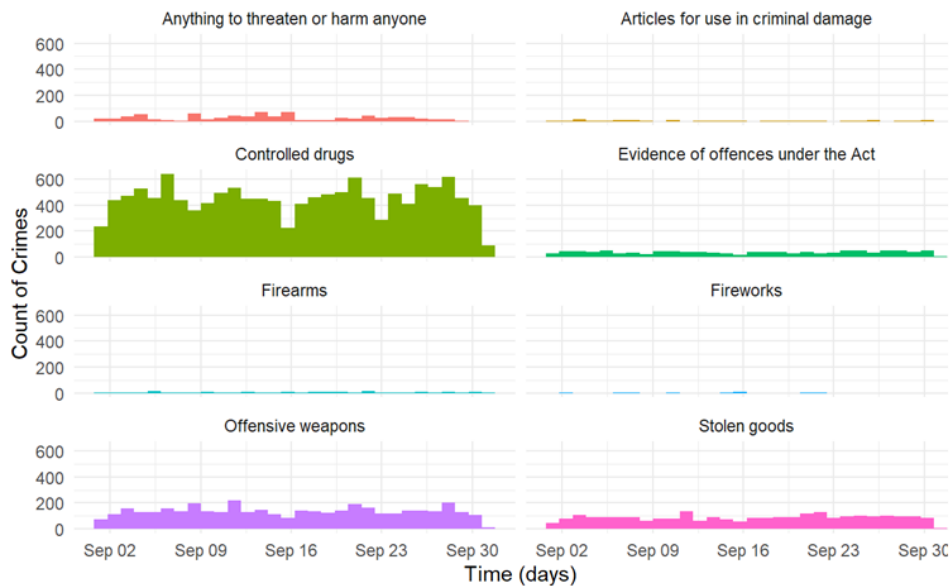
People stopped and searched according to Gender



Multiple Distributions fill with a different variable OO_multiple_distributions.R

OK, but perhaps remove empty categories? Or
scales = free

How often do certain crimes occur through November?
Count of crimes by the day during the month of November

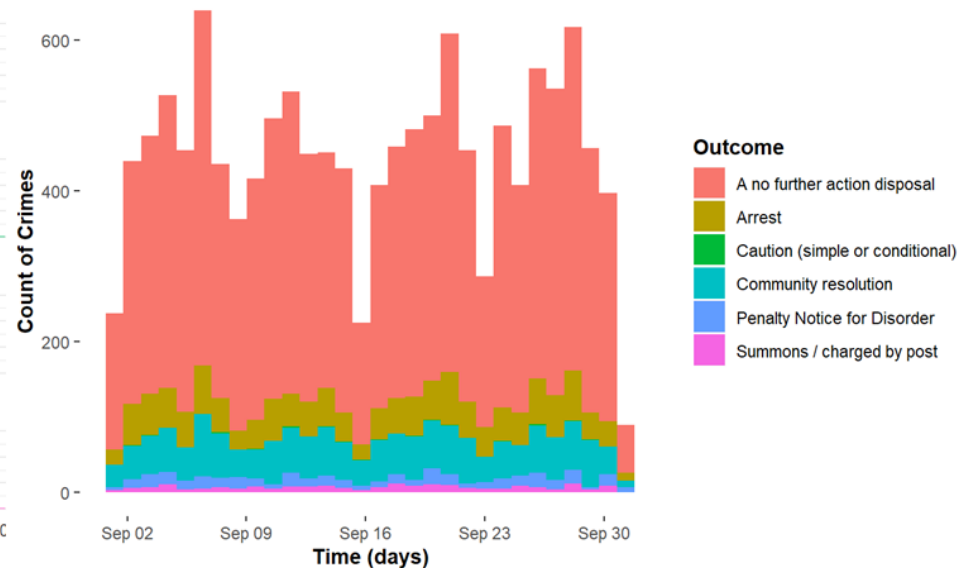


Notes: [1] Blanks were excluded from this analysis

Really hard to read

How often do Controlled Drug crimes lead to no action?

Count of controlled drug instances in November highlighted by outcome of crime



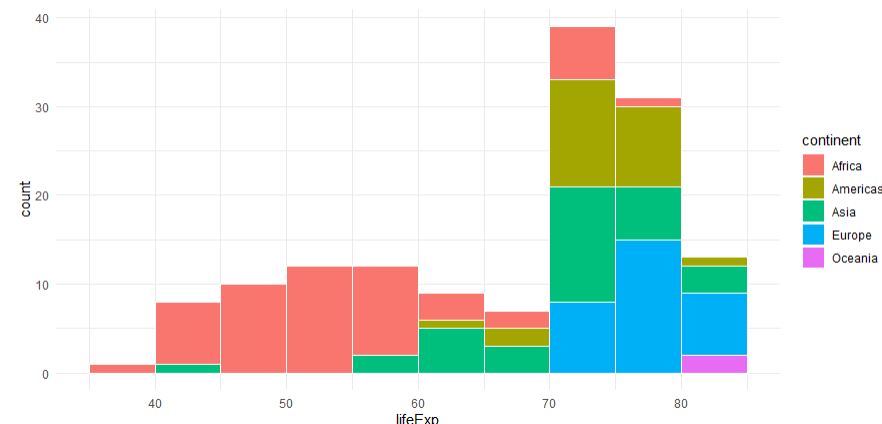
Notes: [1] Blanks were excluded from this analysis.

Multiple Distributions

00_multiple_distributions.R

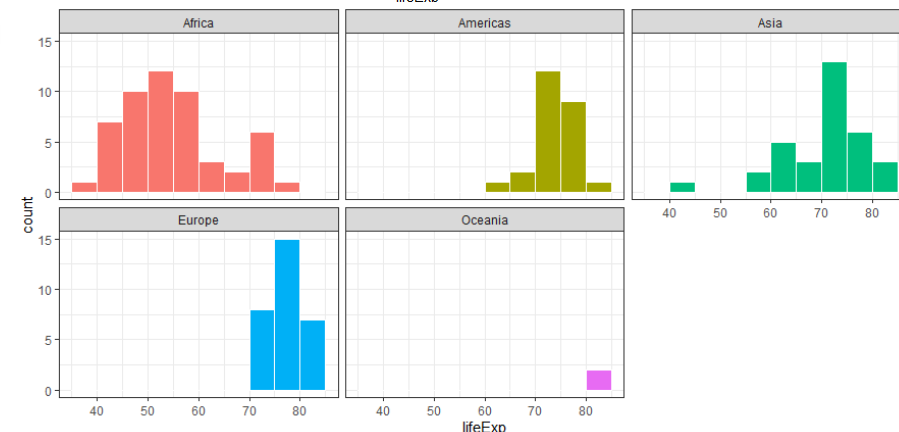
This makes it very hard to read and understand

```
ggplot(gapminder2007,
      aes(x = lifeExp,
          fill = continent)) +
  geom_histogram(binwidth = 5,
                color = "white",
                boundary = 50) +
  theme_minimal() +
  NULL
```



Facetting by continent makes it easier to read and understand

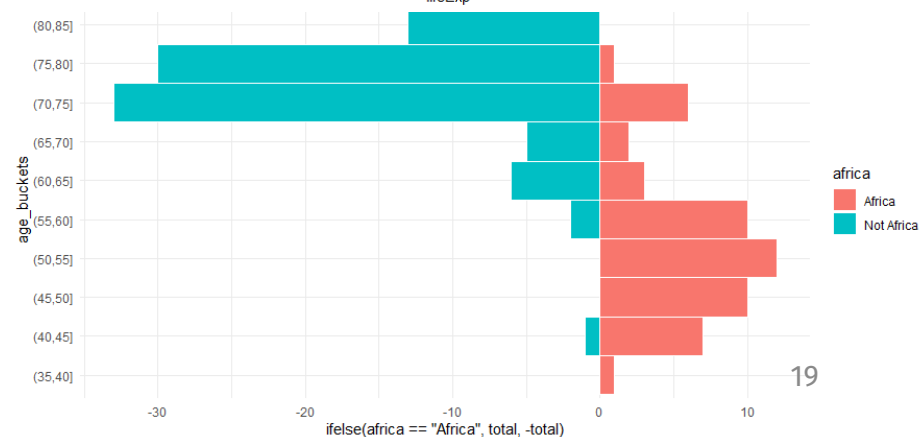
```
ggplot(gapminder2007,
      aes(x = lifeExp,
          fill = continent)) +
  geom_histogram(binwidth = 5,
                color = "white",
                boundary = 50) +
  guides(fill=FALSE) +
  theme_bw() +
  facet_wrap(~continent) +
  NULL
```



pyramid histograms

```
gapminder_intervals <- gapminder2007 %>%
  mutate(africa =
    ifelse(continent == "Africa",
           "Africa", "Not Africa")) %>%
  mutate(age_buckets =
    cut(lifeExp,
        breaks = seq(30, 90, by = 5))) %>%
  group_by(africa, age_buckets) %>%
  summarize(total = n())

ggplot(gapminder_intervals,
      aes(y = age_buckets,
          x = ifelse(africa == "Africa",
                    total, -total),
          fill = africa)) +
  geom_col(width = 1, color = "white") +
  theme_minimal() +
  NULL
```



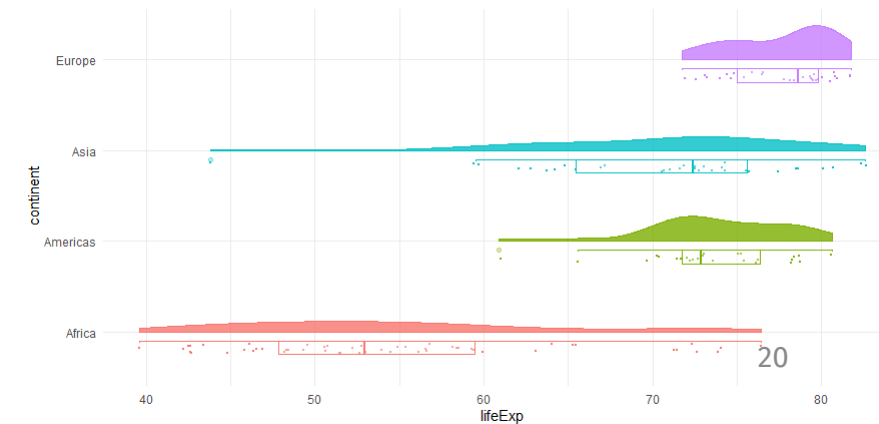
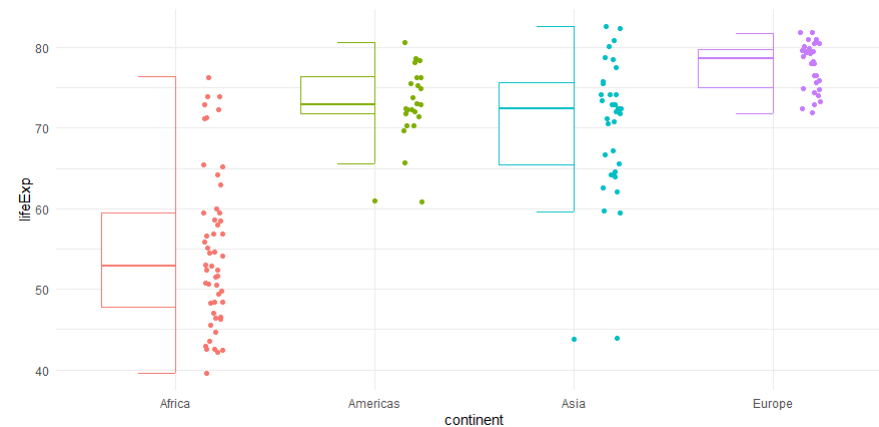
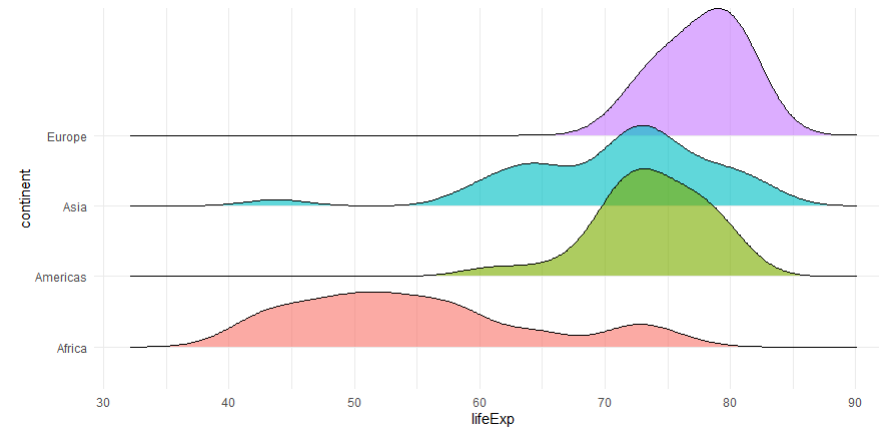
Multiple Distributions

00_multiple_distributions.R

```
# use ggribes::geom_density_ridges() for multiple density plots
ggplot(filter(gapminder2007,
  continent != "oceania"),
  aes(x = lifeExp,
    fill = continent,
    y = continent)) +
  geom_density_ridges(alpha = 5/8)+
  theme_minimal()+
  guides(fill=FALSE)+
  NULL
```

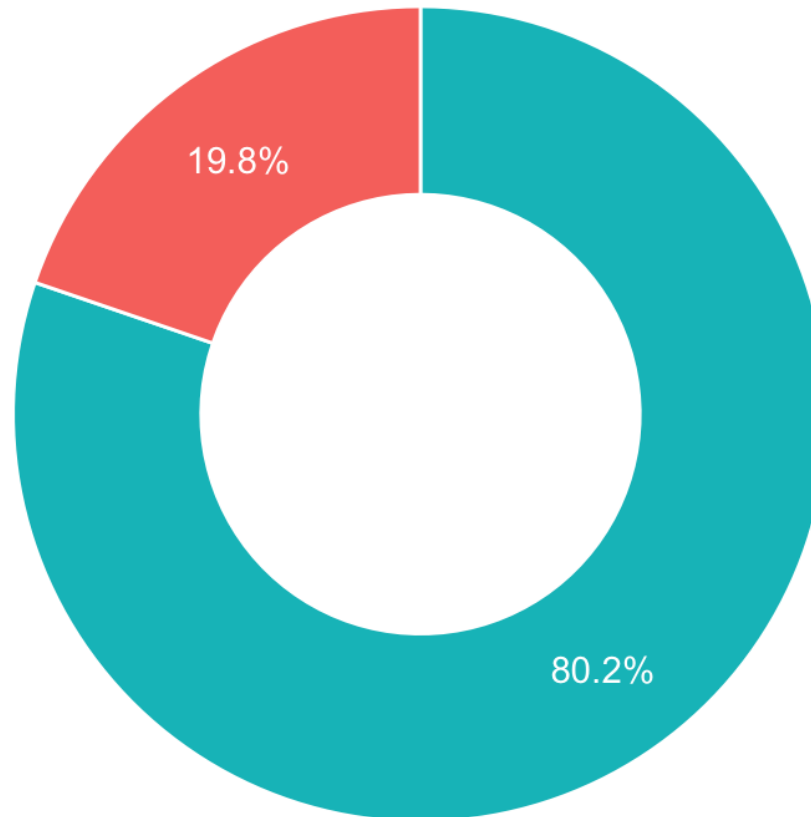
```
# use ggghalves::geom_half_boxplot(), ggghalves::geom_half_point()
ggplot(filter(gapminder2007,
  continent != "oceania"),
  aes(y = lifeExp,
    x = continent,
    colour = continent)) +
  geom_half_boxplot(side = "l") + # half boxplot to the left
  geom_half_point(side = "r")+    # points to the right
  theme_minimal()+
  guides(fill = FALSE, color = FALSE)+
  NULL
```

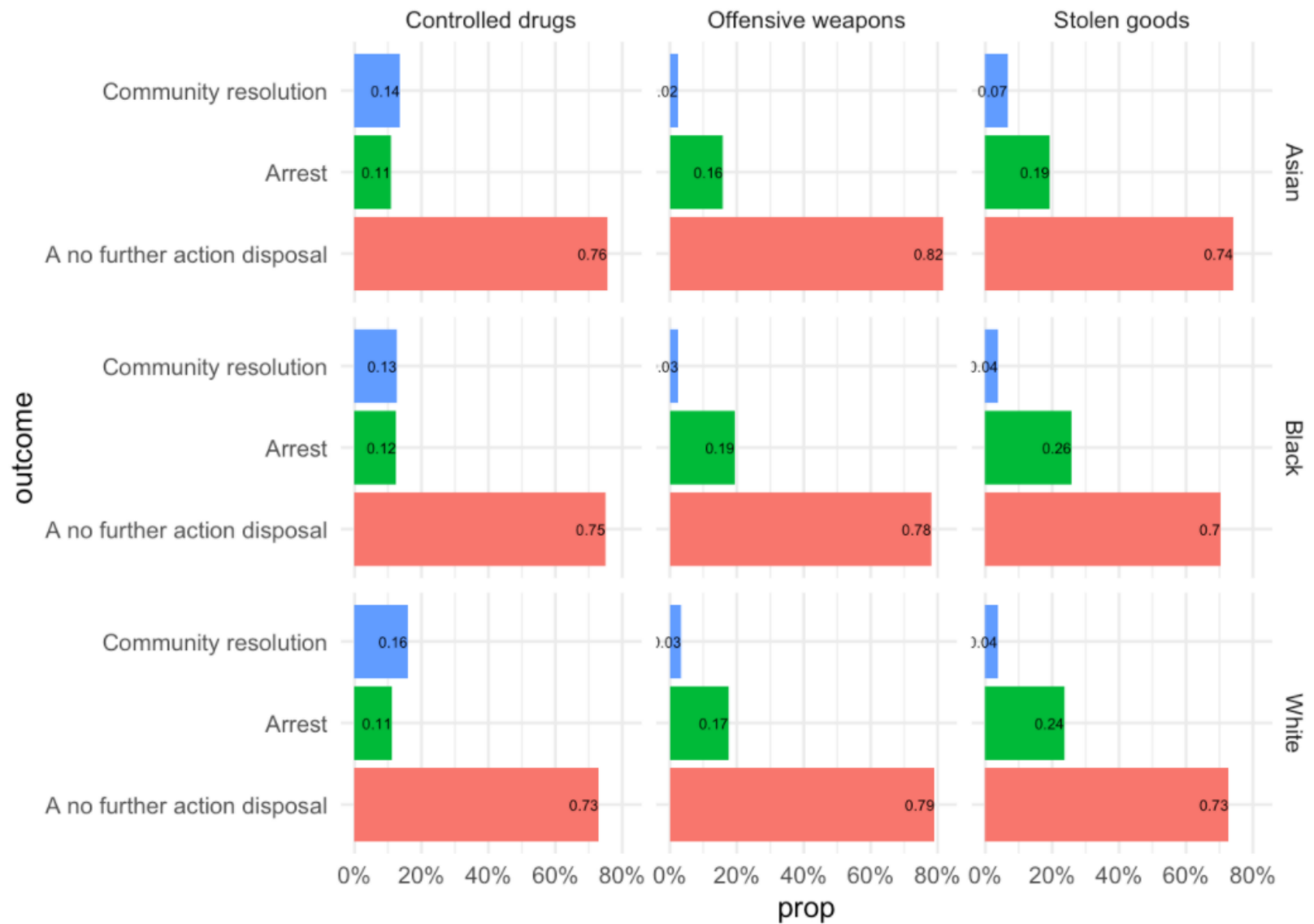
```
# Raincloud plots
ggplot(filter(gapminder2007,
  continent != "oceania"),
  aes(y = lifeExp,
    x = continent,
    colour = continent)) +
  geom_half_point(side = "l", size = 0.3) +
  geom_half_boxplot(side = "l", width = 0.5,
    alpha = 0.3, nudge = 0.1) +
  geom_half_violin(aes(fill = continent),
    alpha = 0.8,
    side = "r") +
  guides(fill = FALSE, color = FALSE) +
  coord_flip()+
  theme_minimal()+
  NULL
```



How judgemental are the police when they decide your race?

Our analysis showed that almost one-fifth of police stops result in incorrect racial profiling

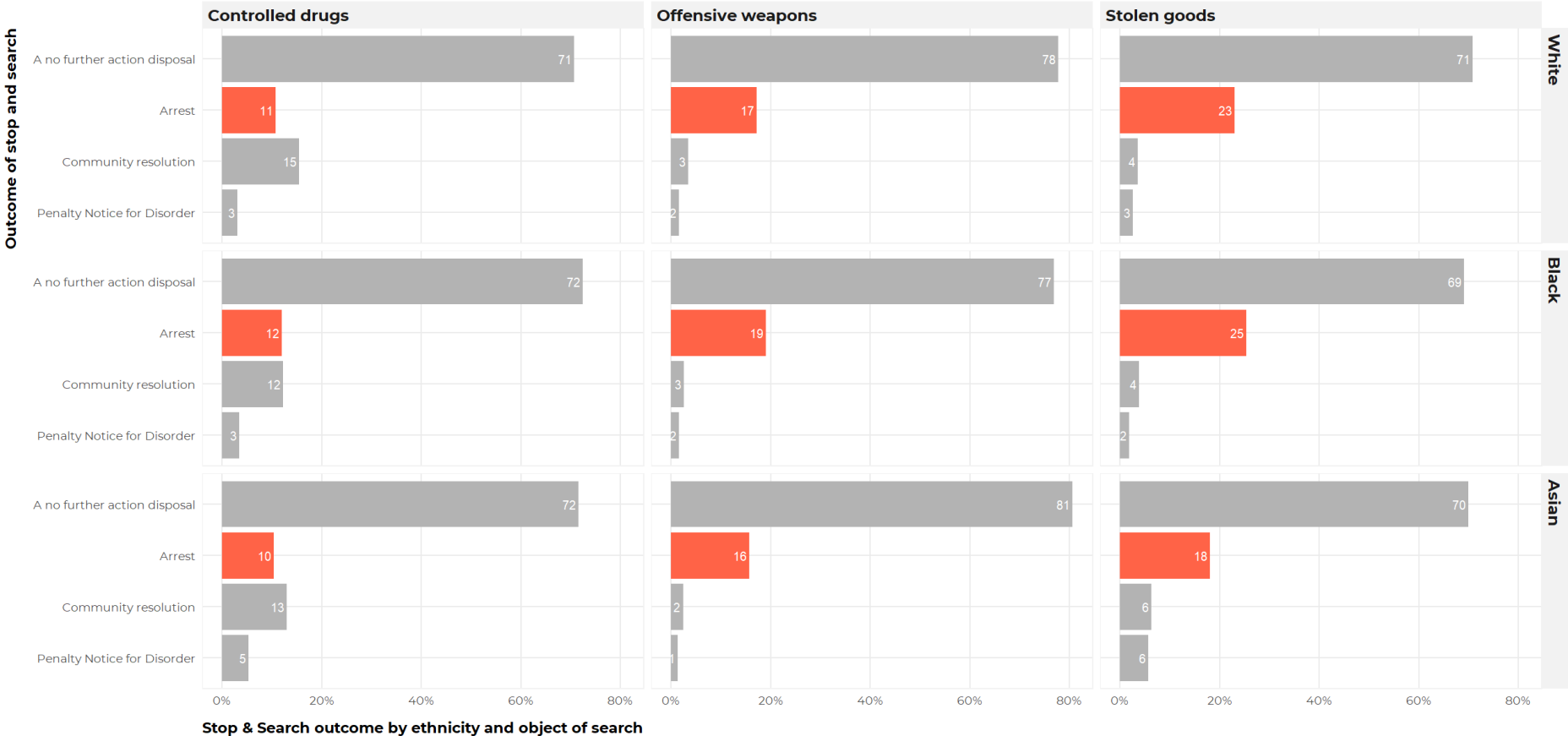




Blacks consistently have a higher % of arrests

Sep 2021

Outcome of stop and search



Source: Metropolitan Police

Estimates of relative survival rates, by cancer site

	% survival rates and their standard errors							
	5 year		10 year		15 year		20 year	
Prostate	98.8	0.4	95.2	0.9	87.1	1.7	81.1	3.0
Thyroid	96.0	0.8	95.8	1.2	94.0	1.6	95.4	2.1
Testis	94.7	1.1	94.0	1.3	91.1	1.8	88.2	2.3
Melanomas	89.0	0.8	86.7	1.1	83.5	1.5	82.8	1.9
Breast	86.4	0.4	78.3	0.6	71.3	0.7	65.0	1.0
Hodgkin's disease	85.1	1.7	79.8	2.0	73.8	2.4	67.1	2.8
Corpus uteri, uterus	84.3	1.0	83.2	1.3	80.8	1.7	79.2	2.0
Urinary, bladder	82.1	1.0	76.2	1.4	70.3	1.9	67.9	2.4
Cervix, uteri	70.5	1.6	64.1	1.8	62.8	2.1	60.0	2.4
Larynx	68.8	2.1	56.7	2.5	45.8	2.8	37.8	3.1
Rectum	62.6	1.2	55.2	1.4	51.8	1.8	49.2	2.3
Kidney, renal pelvis	61.8	1.3	54.4	1.6	49.8	2.0	47.3	2.6
Colon	61.7	0.8	55.4	1.0	53.9	1.2	52.3	1.6
Non-Hodgkin's	57.8	1.0	46.3	1.2	38.3	1.4	34.3	1.7
Oral cavity, pharynx	56.7	1.3	44.2	1.4	37.5	1.6	33.0	1.8
Ovary	55.0	1.3	49.3	1.6	49.9	1.9	49.6	2.4
Leukemia	42.5	1.2	32.4	1.3	29.7	1.5	26.2	1.7
Brain, nervous system	32.0	1.4	29.2	1.5	27.6	1.6	26.1	1.9
Multiple myeloma	29.5	1.6	12.7	1.5	7.0	1.3	4.8	1.5
Stomach	23.8	1.3	19.4	1.4	19.0	1.7	14.9	1.9
Lung and bronchus	15.0	0.4	10.6	0.4	8.1	0.4	6.5	0.4
Esophagus	14.2	1.4	7.9	1.3	7.7	1.6	5.4	2.0
Liver, bile duct	7.5	1.1	5.8	1.2	6.3	1.5	7.6	2.0
Pancreas	4.0	0.5	3.0	1.5	2.7	0.6	2.7	0.8

