

Class 18: Pertussis Mini Project

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Pertussis (aka Whooping Cough) is a deadly lung infection caused by the bacteria B. Pertussis.

The CDC tracks Pertussis cases around the US. [tinyurl.com / pertussiscdc](https://tinyurl.com/pertussiscdc)

There is interesting data to look at here, but it's not in an excel or csv file to download. We need to scrape the data using the **datapasta** package. <https://github.com/MilesMcBain/datapasta>

Q1. With the help of the R “addin” package datapasta assign the CDC pertussis case number data to a data frame called cdc and use ggplot to make a plot of cases numbers over time.

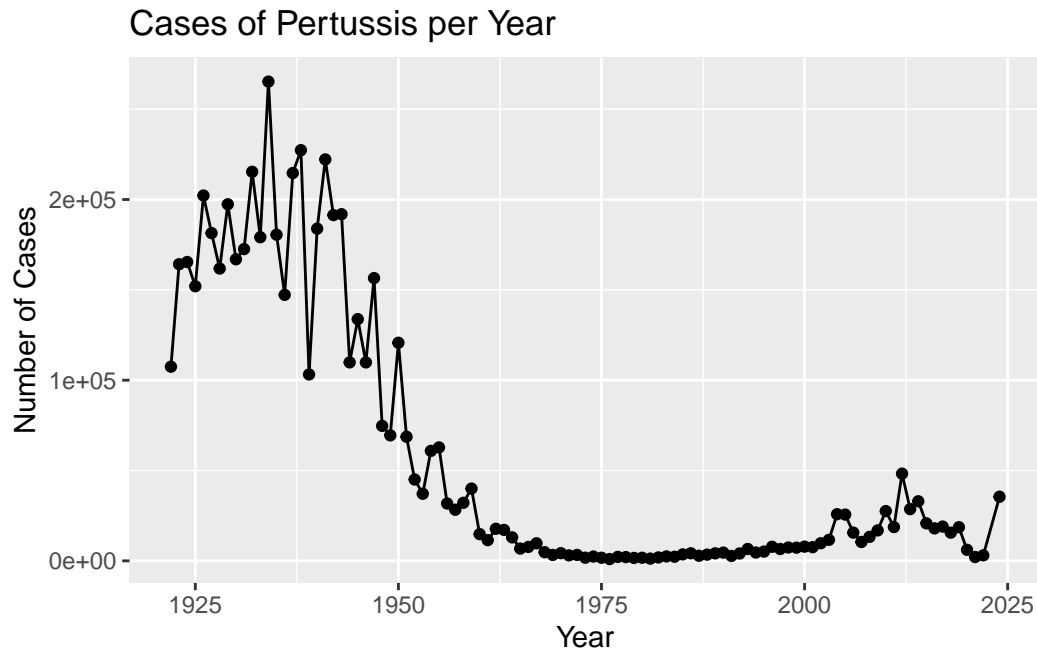
```
head(cdc)
```

```
  year  cases
1 1922 107473
2 1923 164191
3 1924 165418
4 1925 152003
5 1926 202210
6 1927 181411
```

Let's plot the new data

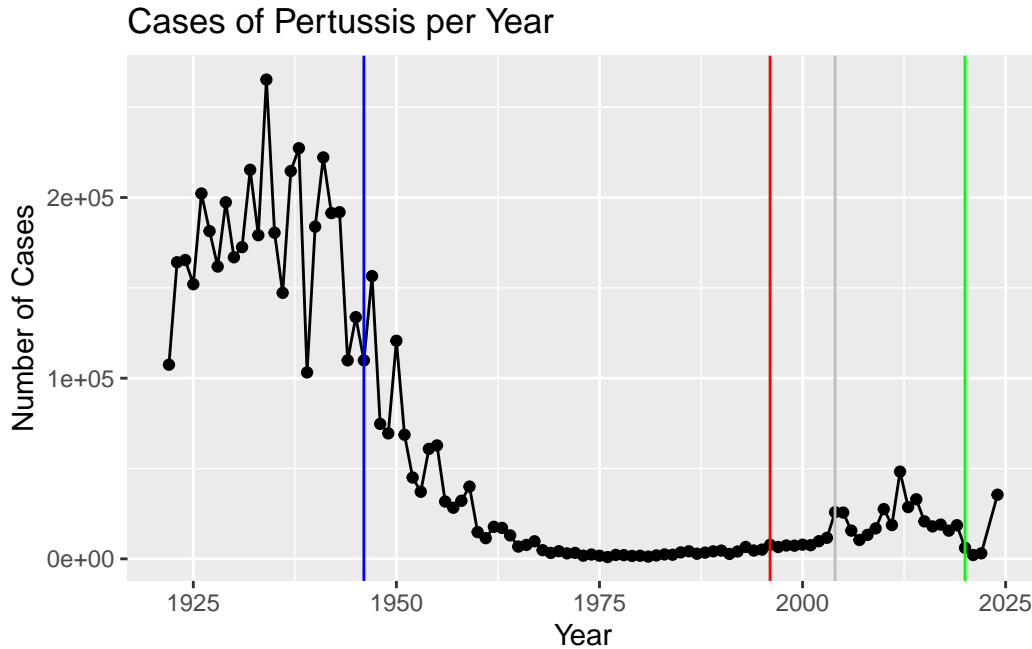
```
library(ggplot2)

ggplot(cdc, aes(year, cases))+
  geom_point() +
  geom_line() +
  ylab("Number of Cases")+
  xlab("Year")+
  ggtitle("Cases of Pertussis per Year")
```



Q2. Using the ggplot `geom_vline()` function add lines to your previous plot for the 1946 introduction of the wP vaccine and the 1996 switch to aP vaccine (see example in the hint below). What do you notice?

```
ggplot(cdc, aes(year, cases))+
  geom_point() +
  geom_line() +
  geom_vline(xintercept=1946,col="blue")+
  geom_vline(xintercept=1996,col="red")+
  geom_vline(xintercept=2004,col="gray")+
  geom_vline(xintercept=2020,col="green")+
  ylab("Number of Cases")+
  xlab("Year")+
  ggtitle("Cases of Pertussis per Year")
```



Q3. Describe what happened after the introduction of the aP vaccine? Do you have a possible explanation for the observed trend?

There were high case numbers before the first whole cell vaccine (blue line), then a rapid decline in cases following. There was a general hold of low values after the aP vaccine (red line), followed by a spike in 2004s. This could be a point where people began to mistrust vaccines and not get them as frequently or the vaccine could have been reformatted. There is a spike again following the green line after COVID19.

Infants who got the new vaccine are growing up and their immunity is waning and they need a new booster shot. It seems that something has to be different about the immune response to infection with the older wP vaccine versus the newer aP vaccine.

Computational Models of Immunity, Pertussis Booster Shot (CMI-PB)

The CMI-PB project aims to address this key question - what's different between aP and wP vaccinated individuals? This is called systems vaccinology. <https://www.cmi-pb.org/>

We can get all the data from this ongoing project via JSON API. For this we will use the **jsonlite** package.

```
library(jsonlite)

subject <- read_json ("https://www.cmi-pb.org/api/v5_1/subject", simplifyVector = TRUE)
head(subject)
```

	subject_id	infancy_vac	biological_sex	ethnicity	race
1	1	wP	Female	Not Hispanic or Latino	White
2	2	wP	Female	Not Hispanic or Latino	White
3	3	wP	Female	Unknown	White
4	4	wP	Male	Not Hispanic or Latino	Asian
5	5	wP	Male	Not Hispanic or Latino	Asian
6	6	wP	Female	Not Hispanic or Latino	White

	year_of_birth	date_of_boost	dataset
1	1986-01-01	2016-09-12	2020_dataset
2	1968-01-01	2019-01-28	2020_dataset
3	1983-01-01	2016-10-10	2020_dataset
4	1988-01-01	2016-08-29	2020_dataset
5	1991-01-01	2016-08-29	2020_dataset
6	1988-01-01	2016-10-10	2020_dataset

Q. How many individual subjects are in this dataset?

```
nrow(subject)
```

```
[1] 172
```

Q4. How many aP and wP infancy vaccinated subjects are in the dataset?

```
table(subject$infancy_vac)
```

```
aP wP
87 85
```

Q5. How many Male and Female subjects/patients are in the dataset?

```
table(subject$biological_sex)
```

```
Female  Male
112     60
```

Q6. What is the breakdown of race and biological sex (e.g. number of Asian females, White males etc...)?

```
table(subject$race, subject$biological_sex)
```

	Female	Male
American Indian/Alaska Native	0	1
Asian	32	12
Black or African American	2	3
More Than One Race	15	4
Native Hawaiian or Other Pacific Islander	1	1
Unknown or Not Reported	14	7
White	48	32

This is not representative of the US population, but it's the best we have.

Let's obtain more data from CMI-PB:

```
specimen <- read_json("http://cmi-pb.org/api/v5_1/specimen",
                      simplifyVector=TRUE)

ab_data <- read_json("http://cmi-pb.org/api/v5_1/plasma_ab_titer",
                    simplifyVector=TRUE)
```

```
head(specimen)
```

	specimen_id	subject_id	actual_day_relative_to_boost	
1	1	1	-3	
2	2	1	1	
3	3	1	3	
4	4	1	7	
5	5	1	11	
6	6	1	32	

	planned_day_relative_to_boost	specimen_type	visit
1	0	Blood	1
2	1	Blood	2
3	3	Blood	3
4	7	Blood	4
5	14	Blood	5
6	30	Blood	6

```
head(ab_data)
```

	specimen_id	isotype	is_antigen_specific	antigen	MFI	MFI_normalised
1	1	IgE	FALSE	Total	1110.21154	2.493425
2	1	IgE	FALSE	Total	2708.91616	2.493425
3	1	IgG	TRUE	PT	68.56614	3.736992
4	1	IgG	TRUE	PRN	332.12718	2.602350
5	1	IgG	TRUE	FHA	1887.12263	34.050956
6	1	IgE	TRUE	ACT	0.10000	1.000000

	unit	lower_limit_of_detection
1	UG/ML	2.096133
2	IU/ML	29.170000
3	IU/ML	0.530000
4	IU/ML	6.205949
5	IU/ML	4.679535
6	IU/ML	2.816431

I now have 3 tables of data from CMI-PB: `subject`, `specimen`, and `ab_data`. I need to join these tables so I will have all the info I need to work with.

For this we will use the `inner_join` function from the **dplyr** package.

```
library(dplyr)
```

Attaching package: 'dplyr'

The following objects are masked from 'package:stats':

`filter`, `lag`

The following objects are masked from 'package:base':

`intersect`, `setdiff`, `setequal`, `union`

```
meta <- inner_join(subject, specimen)
```

Joining with `by = join_by(subject_id)`

```
head(meta)
```

	subject_id	infancy_vac	biological_sex	ethnicity	race
1	1	wP	Female Not Hispanic or Latino	White	
2	1	wP	Female Not Hispanic or Latino	White	
3	1	wP	Female Not Hispanic or Latino	White	
4	1	wP	Female Not Hispanic or Latino	White	
5	1	wP	Female Not Hispanic or Latino	White	
6	1	wP	Female Not Hispanic or Latino	White	

	year_of_birth	date_of_boost	dataset	specimen_id
1	1986-01-01	2016-09-12	2020_dataset	1
2	1986-01-01	2016-09-12	2020_dataset	2
3	1986-01-01	2016-09-12	2020_dataset	3
4	1986-01-01	2016-09-12	2020_dataset	4
5	1986-01-01	2016-09-12	2020_dataset	5
6	1986-01-01	2016-09-12	2020_dataset	6

	actual_day_relative_to_boost	planned_day_relative_to_boost	specimen_type
1	-3	0	Blood
2	1	1	Blood
3	3	3	Blood
4	7	7	Blood
5	11	14	Blood
6	32	30	Blood

	visit
1	1
2	2
3	3
4	4
5	5
6	6

Now we can join our `ab_data` table to `metaso` we have all 3 sets of information in the same place.

```
abdata<- inner_join(meta, ab_data)
```

Joining with ``by = join_by(specimen_id)``

```
head(abdata)
```

	subject_id	infancy_vac	biological_sex	ethnicity	race
1	1	wP	Female Not Hispanic or Latino	White	
2	1	wP	Female Not Hispanic or Latino	White	
3	1	wP	Female Not Hispanic or Latino	White	
4	1	wP	Female Not Hispanic or Latino	White	
5	1	wP	Female Not Hispanic or Latino	White	
6	1	wP	Female Not Hispanic or Latino	White	

	year_of_birth	date_of_boost	dataset	specimen_id
1	1986-01-01	2016-09-12	2020_dataset	1
2	1986-01-01	2016-09-12	2020_dataset	1
3	1986-01-01	2016-09-12	2020_dataset	1
4	1986-01-01	2016-09-12	2020_dataset	1
5	1986-01-01	2016-09-12	2020_dataset	1
6	1986-01-01	2016-09-12	2020_dataset	1

	actual_day_relative_to_boost	planned_day_relative_to_boost	specimen_type
1	-3	0	Blood
2	-3	0	Blood
3	-3	0	Blood
4	-3	0	Blood
5	-3	0	Blood
6	-3	0	Blood

	visit	isotype	is_antigen_specific	antigen	MFI	MFI_normalised	unit
1	1	IgE	FALSE	Total	1110.21154	2.493425	UG/ML
2	1	IgE	FALSE	Total	2708.91616	2.493425	IU/ML
3	1	IgG	TRUE	PT	68.56614	3.736992	IU/ML
4	1	IgG	TRUE	PRN	332.12718	2.602350	IU/ML
5	1	IgG	TRUE	FHA	1887.12263	34.050956	IU/ML
6	1	IgE	TRUE	ACT	0.10000	1.000000	IU/ML

	lower_limit_of_detection
1	2.096133
2	29.170000
3	0.530000
4	6.205949
5	4.679535
6	2.816431

```
dim(abdata)
```

```
[1] 61956    20
```

Q. How many different antibody isotypes are there in this dataset?


```
length(abdata$isotype)
```

```
[1] 61956
```

```
table(abdata$isotype)
```

```
  IgE   IgG  IgG1  IgG2  IgG3  IgG4  
6698  7265 11993 12000 12000 12000
```

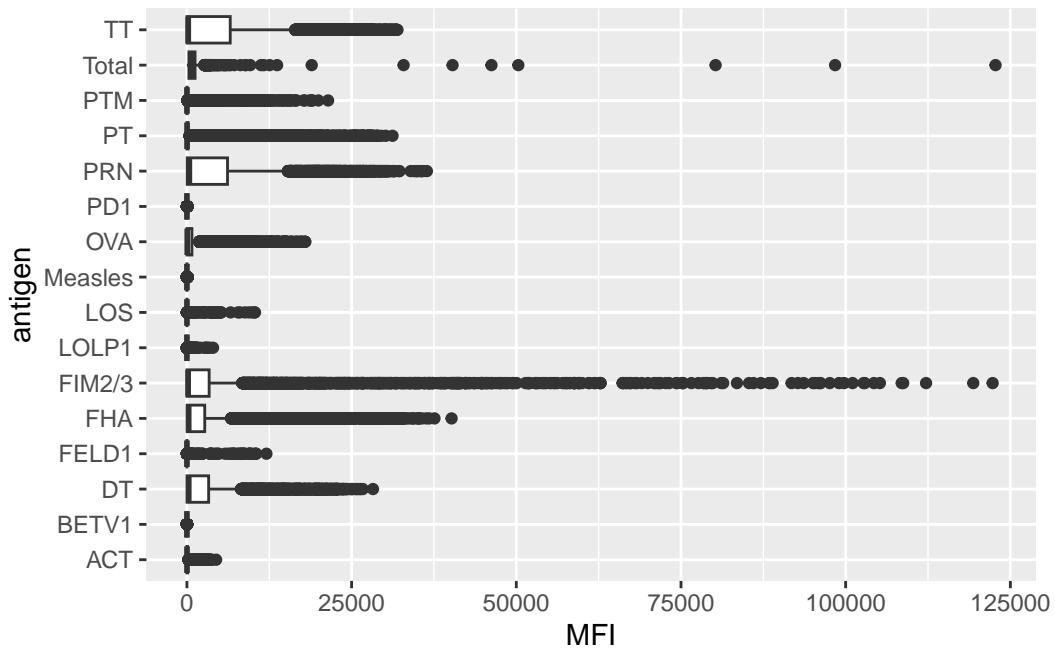
```
table(abdata$antigen)
```

```
  ACT  BETV1    DT  FELD1    FHA  FIM2/3  LOLP1    LOS Measles    OVA  
1970   1970   6318   1970   6712   6318   1970   1970   1970   6318  
  PD1    PRN    PT    PTM  Total    TT  
1970   6712   6712   1970   788    6318
```

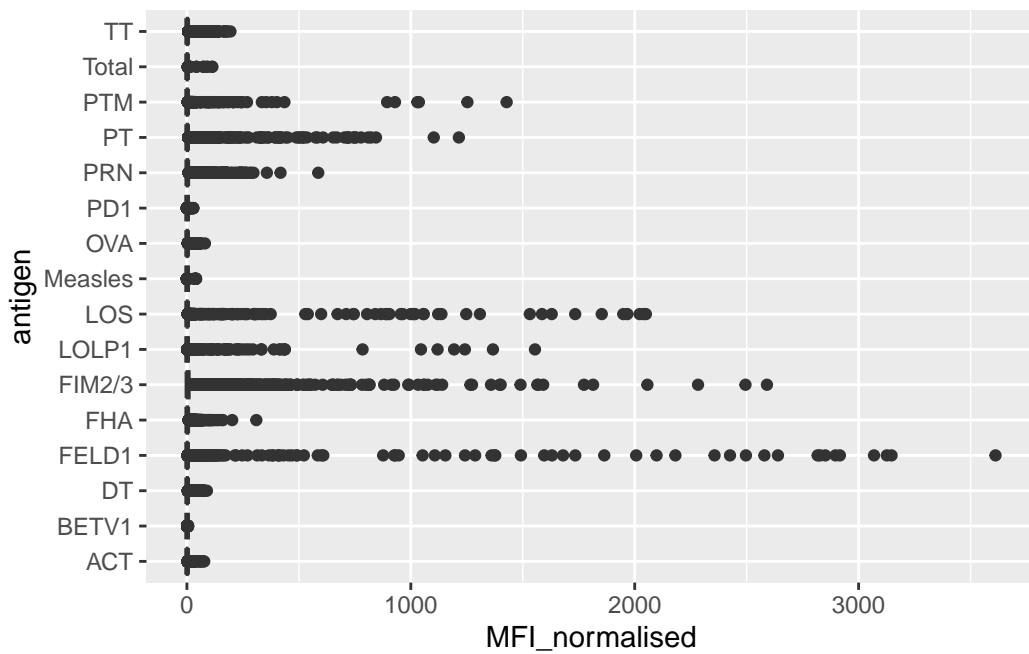
I want a plot of antigen levels across the whole dataset.

```
ggplot(abdata, aes(MFI, antigen))+  
  geom_boxplot()
```

```
Warning: Removed 1 row containing non-finite outside the scale range  
(`stat_boxplot()`).
```



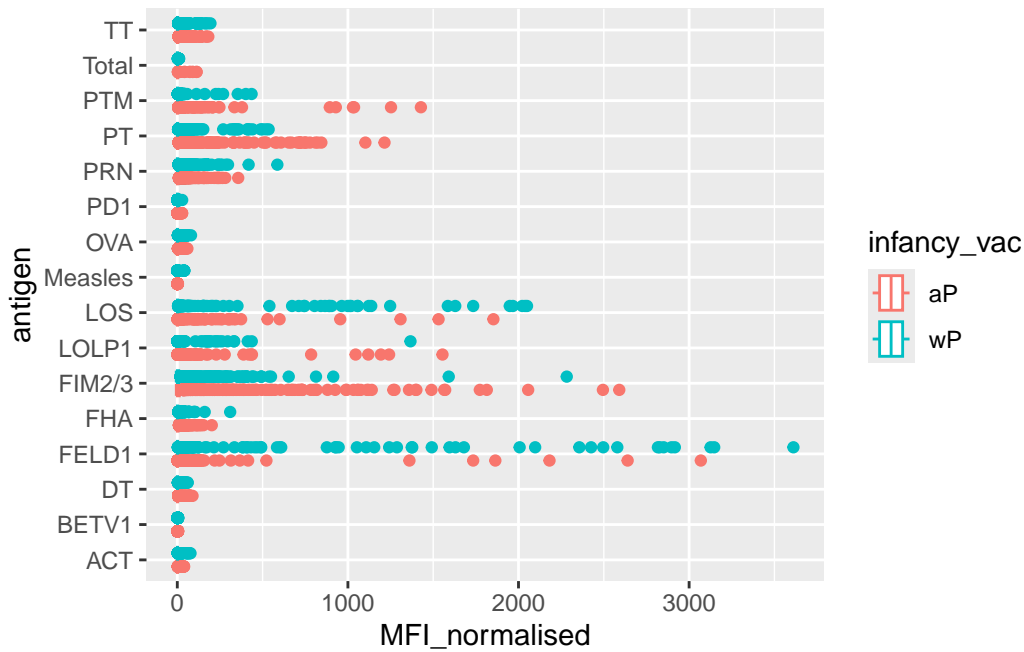
```
ggplot(abdata, aes(MFI_normalised, antigen))+
  geom_boxplot()
```



Antigens like FIM2/3, PT, FELD1 have quite a large range of values. Others, like Measles don't show much activity.

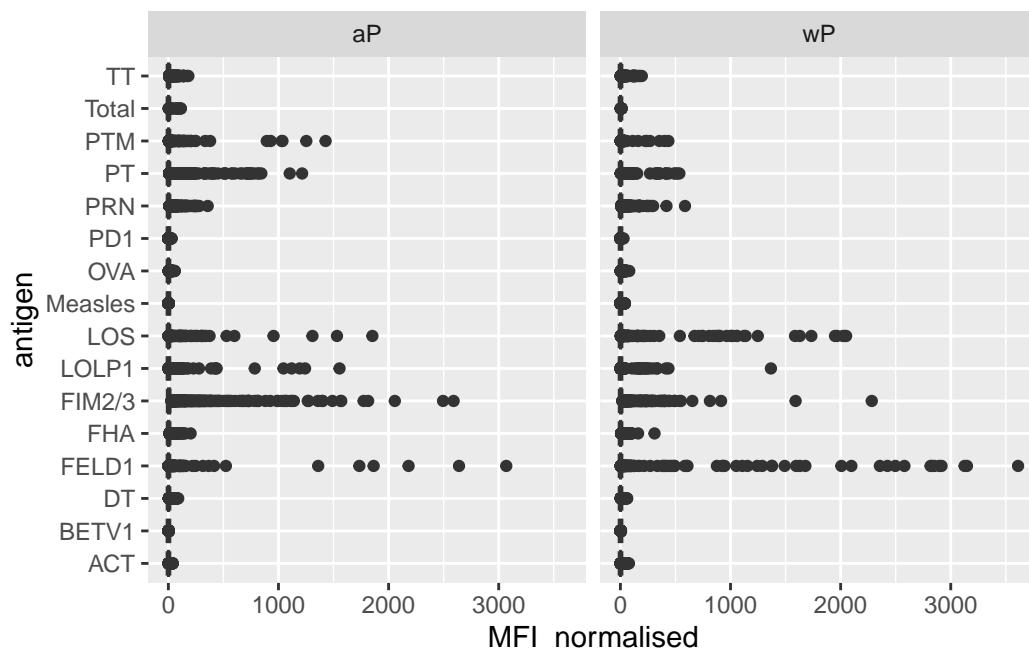
Q. Are there differences at this whole-data level between aP and wP?

```
ggplot(abdata, aes(MFI_normalised, antigen, col=infancy_vac))+
  geom_boxplot()
```



This is a lot and we're looking at every antibody type.

```
ggplot(abdata, aes(MFI_normalised, antigen))+
  geom_boxplot()+
  facet_wrap(~infancy_vac)
```



Examine just IgG levels

Isolate just isotype IgG.

```
igg <- abdata %>% filter(isotype == "IgG")
head(igg)
```

	subject_id	infancy_vac	biological_sex	ethnicity	race
1	1	wP	Female	Not Hispanic or Latino	White
2	1	wP	Female	Not Hispanic or Latino	White
3	1	wP	Female	Not Hispanic or Latino	White
4	1	wP	Female	Not Hispanic or Latino	White
5	1	wP	Female	Not Hispanic or Latino	White
6	1	wP	Female	Not Hispanic or Latino	White

	year_of_birth	date_of_boost	dataset	specimen_id
1	1986-01-01	2016-09-12	2020_dataset	1
2	1986-01-01	2016-09-12	2020_dataset	1
3	1986-01-01	2016-09-12	2020_dataset	1
4	1986-01-01	2016-09-12	2020_dataset	2
5	1986-01-01	2016-09-12	2020_dataset	2
6	1986-01-01	2016-09-12	2020_dataset	2

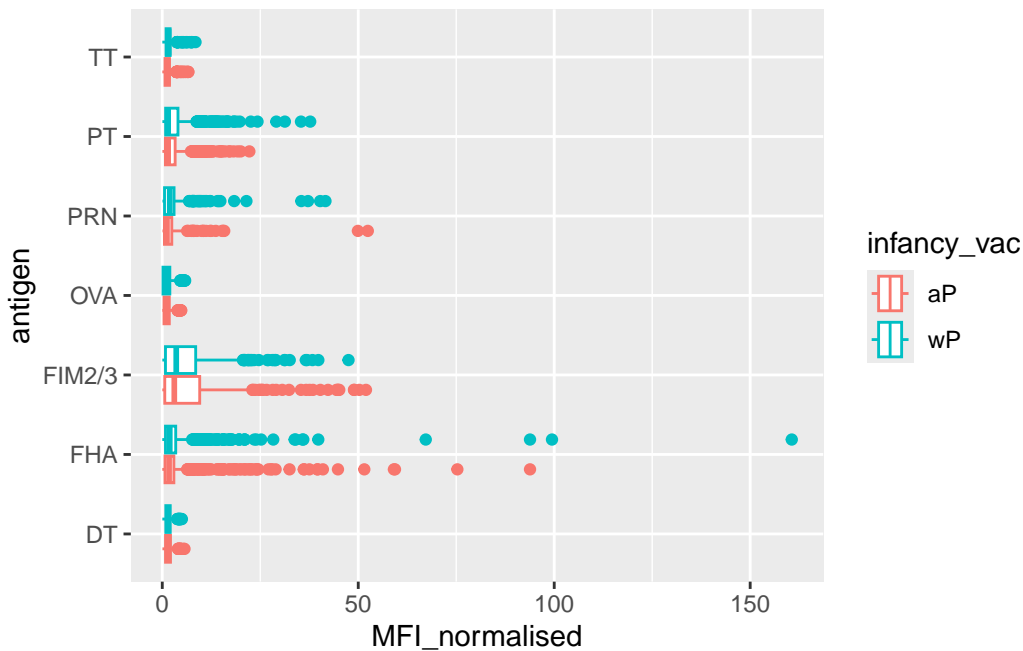
	actual_day_relative_to_boost	planned_day_relative_to_boost	specimen_type
1			
2			
3			
4			
5			
6			

1			-3			0	Blood
2			-3			0	Blood
3			-3			0	Blood
4			1			1	Blood
5			1			1	Blood
6			1			1	Blood

	visit	isotype	is_antigen_specific	antigen	MFI	MFI_normalised	unit
1	1	IgG	TRUE	PT	68.56614	3.736992	IU/ML
2	1	IgG	TRUE	PRN	332.12718	2.602350	IU/ML
3	1	IgG	TRUE	FHA	1887.12263	34.050956	IU/ML
4	2	IgG	TRUE	PT	41.38442	2.255534	IU/ML
5	2	IgG	TRUE	PRN	174.89761	1.370393	IU/ML
6	2	IgG	TRUE	FHA	246.00957	4.438960	IU/ML

	lower_limit_of_detection
1	0.530000
2	6.205949
3	4.679535
4	0.530000
5	6.205949
6	4.679535

```
ggplot(igg, aes(MFI_normalised, antigen, col=infancy_vac))+
  geom_boxplot()
```



This is still too muddy, across all time points before and after vaccination. Let's dig into a more specific point, time course of IgG isotype PT antigen levels across aP and wP individuals. First we filtered to include the 2021 dataset, then filtered to look at IgG and PT data only. We plotted this data and colored by infancy_vac, with a setup of wP vs aP.

```
abdata.21 <- abdata %>% filter(dataset == "2021_dataset")

abdata.21 %>%
  filter(isotype == "IgG", antigen == "PT") %>%

  ggplot() +
    aes(x=planned_day_relative_to_boost,
        y=MFI_normalised,
        col=infancy_vac,
        group=subject_id) +
    geom_point() +
    geom_line() +
    geom_vline(xintercept=0, linetype="dashed") +
    geom_vline(xintercept=14, linetype="dashed") +
    labs(title="2021 dataset IgG PT",
         subtitle = "Dashed lines indicate day 0 (pre-boost) and 14 (apparent peak levels)")
```

