Visualising Vowel Space Change with GAMMs

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Introduction

Multiple recent projects at NZILBB have used Generalised Mixed Models (GAMMs) to investigate changes in vowel spaces both across multiples speakers and within single speakers.

In such projects, it is useful to visualise changes to vowel spaces over time with both static plots and animations.

This post sets out a structure for fitting models of the first and second formants of a series of vowels and for visualising them together within vowel space diagrams.

This general structure, and some specific code for visualisation, was originally developed by James Brand for Brand et al. (2021).

I'll assume the reader knows something about vowels and vowel spaces, the basics of data manipulation with `dplyr`, and setting up models in R.

Fitting Multiple Models with `purrr` and `mgcv`

Setup

We're going to fit these models with a small subset of the data from the Origins of New Zealand English (ONZE) corpus. This dataset contains first and second formant data for 100 speakers of New Zealand English (for details see supplementaries for Brand et al. 2021). The data can be found here.

For the purposes of this post any similar data set would be fine. We need:

- first and second formant data,
- a range of vowels (we'll only look at monophthongs here),
- a time variables (whether year of birth, age category, or time through recording), and
- any variables you wish to control for.

Let's load the libraries we will use and have a look at the data.

```r
#| eval: false
# Load renv environment
renv::use(lockfile = "renv.lock")
```

```r
# Load tidyverse and friends.
library(tidyverse)
```

```
Warning: package 'ggplot2' was built under R version 4.5.2
```

```
Warning: package 'tibble' was built under R version 4.5.2
```

```
Warning: package 'tidyr' was built under R version 4.5.2
```

```
Warning: package 'purrr' was built under R version 4.5.2
```

```r
library(gganimate)

# mgcv will be used for fitting gamms later and itsadug for visualisation
library(mgcv)
library(itsadug)
```

```
Warning: package 'itsadug' was built under R version 4.5.2
```

```
Warning: package 'plotfunctions' was built under R version 4.5.2
```

```r
# kable for displaying the dataset.
library(kableExtra)

vowels <- read_rds('anon_ONZE_mean_sample.rds')

vowels %>%
  head(10) %>%
  kable() %>%
  kable_styling(font_size = 11) %>%
  scroll_box(width = "100%")
```

Speaker	Vowel	F1_50	F2_50	Speech_rate	Gender	yob
CC_f_020	DRESS	622.5797	1897.986	4.9264	F	1936
CC_f_020	FLEECE	518.7458	1882.763	4.9264	F	1936
CC_f_020	GOOSE	524.0606	1944.152	4.9264	F	1936
CC_f_020	KIT	646.8214	1790.054	4.9264	F	1936
CC_f_020	LOT	735.3438	1262.969	4.9264	F	1936
CC_f_020	NURSE	534.8571	1912.714	4.9264	F	1936
CC_f_020	START	888.3929	1604.750	4.9264	F	1936
CC_f_020	STRUT	831.9661	1511.373	4.9264	F	1936
CC_f_020	THOUGHT	594.5000	1051.571	4.9264	F	1936
CC_f_020	TRAP	637.8667	1816.833	4.9264	F	1936

In this dataset each row is a vowel token, with columns:

- `F1_50` and `F2_50`: F1 and F2, taken at the midpoint measured in Hz,
- `Vowel`: Wells lexical set labels for New Zealand English monophthongs,
- `yob`: participant year of birth (our time variable),
- `Speech_rate`: the average speech rate of the participant across the recording (a control variable),
- `Speaker`: a code indicating which speaker the token comes from (sometimes useful as a random effect), and
- `Gender`: the gender of the speaker (in this case, an `M/F` binary).

In any real research project, you will need to engage in a lot of data exploration here. Do you have good data coverage? Is there evidence of outliers in the data? Does the data need to be normalised? This is the time to ask this kind of question. The answers will, of course, depend on your research questions. For this post, the only point of this data is to illustrate a method for modelling and visualising. We can skip these questions!

We will now fit separate models for the F1 and F2 of each vowel. Rather than using a big `for` loop, or fitting each model with a separate line of code, we will use the `purrr` method of *nesting* our data so that we have a row for each of the models we want to fit, fit the models, and then *unnest* to produce data which can be used to visualise our model. **We nest, we mutate, and we unnest.** This is a common pattern with `purrr`.

Before we nest, we need to slightly modify our data. Rather than having a column for our F1 data and a column for our F2 data, we want to capture there in *rows*. That is, we need our table to be *longer*. There will then be two rows for each token, one for the F1 and one for the F2.

To do this, we use the trusty `dplyr` function `pivot_longer()`:

```r
vowels <- vowels %>%
  pivot_longer(
    cols = F1_50:F2_50, # Select the columns to turn into rows.
    names_to = "Formant", # Name the column to indicate if data is F1 or F2,
    values_to = "Frequency"
  )

vowels %>%
  head(10) %>%
  kable() %>%
  kable_styling(font_size = 11) %>%
  scroll_box(width = "100%")
```

Speaker	Vowel	Speech_rate	Gender	yob	Formant	Frequency
CC_f_020	DRESS	4.9264	F	1936	F1_50	622.5797
CC_f_020	DRESS	4.9264	F	1936	F2_50	1897.9855
CC_f_020	FLEECE	4.9264	F	1936	F1_50	518.7458
CC_f_020	FLEECE	4.9264	F	1936	F2_50	1882.7627
CC_f_020	GOOSE	4.9264	F	1936	F1_50	524.0606
CC_f_020	GOOSE	4.9264	F	1936	F2_50	1944.1515
CC_f_020	KIT	4.9264	F	1936	F1_50	646.8214
CC_f_020	KIT	4.9264	F	1936	F2_50	1790.0536
CC_f_020	LOT	4.9264	F	1936	F1_50	735.3438
CC_f_020	LOT	4.9264	F	1936	F2_50	1262.9688

As the table above shows, we now have a column indicating whether a frequency value is an F1 or an F2 reading.

Nest

We now nest the data. We do this by grouping the data by the columns which identify the models we want to fit. In this case, we fit an F1 and an F2 model for each vowel. So the columns we need to identify our models are `Vowel` and `Formant`. Once we've grouped, we simply use the function `nest()`.

```r
vowels <- vowels %>%
  group_by(Vowel, Formant) %>%
  nest()

vowels
```

```
# A tibble: 20 x 3
# Groups:   Vowel, Formant [20]
   Vowel   Formant data
   <fct>   <chr>   <list>
 1 DRESS   F1_50   <tibble [100 x 5]>
 2 DRESS   F2_50   <tibble [100 x 5]>
 3 FLEECE  F1_50   <tibble [100 x 5]>
 4 FLEECE  F2_50   <tibble [100 x 5]>
 5 GOOSE   F1_50   <tibble [100 x 5]>
 6 GOOSE   F2_50   <tibble [100 x 5]>
 7 KIT     F1_50   <tibble [100 x 5]>
 8 KIT     F2_50   <tibble [100 x 5]>
 9 LOT     F1_50   <tibble [100 x 5]>
10 LOT     F2_50   <tibble [100 x 5]>
11 NURSE   F1_50   <tibble [100 x 5]>
12 NURSE   F2_50   <tibble [100 x 5]>
13 START   F1_50   <tibble [100 x 5]>
14 START   F2_50   <tibble [100 x 5]>
15 STRUT   F1_50   <tibble [100 x 5]>
16 STRUT   F2_50   <tibble [100 x 5]>
17 THOUGHT F1_50   <tibble [100 x 5]>
18 THOUGHT F2_50   <tibble [100 x 5]>
19 TRAP    F1_50   <tibble [100 x 5]>
20 TRAP    F2_50   <tibble [100 x 5]>
```

The output above shows that we now have a three column data frame (or, in tidyverse speak, a tibble), with the familiar columns `Vowel` and `Formant` and a new column `data`. The column `data` contains tibbles which live *inside* our tibble. That is, *nested* tibbles. These contain the data which we will use to model each vowel and formant separately.

Mutate (and Map)

We can perform actions on the tibbles in the `data` column by using `mutate` (just as we would modify other data in a tibble). In this case we will create a column to store our models. The basic structure will look something like this.

```
vowels <- vowels %>%
  mutate(
    model = #???
  )
```

The question marks can be filled in with the `map()` function. This enables us to apply a function to fit a model to each of our nested tibbles.

So, what will this function look like? This is not the place for a tutorial on GAMs (for which, go here). We will fit a model which predicts formant frequency from the gender of each participant, their year of birth, and their average speech rate. One way to implement this structure in `mgcv` is with the formula `Frequency ~ Gender + s(yob, by=Gender) + s(Speech_rate)`.

This structure will be the same for *all* of our nested tibbles. The only thing that will change is the data fed in to it. In this kind of case, we can use `~` to turn our model expression into a function and `.x` as a pronoun for the nested tibbles. Let's see what this look like and then explain further:

```
vowels <- vowels %>%
  mutate(
    model = map(
      data, # We are applying a function to the entries of the `data` column.
      # This is the function we are applying (introduced with a ~)
      ~ bam(
          # Here's our formula.
          Frequency ~ Gender +
            s(yob, by=Gender, k=5) +
            s(Speech_rate, k=5),
          data = .x, # Here's our pronoun.
          # Then some arguments to speed up the model fit.
          method = 'fREML',
          discrete = TRUE,
          nthreads = 2
      )
    )
  )
```

```
Warning: There were 20 warnings in `mutate()`.
The first warning was:
i In argument: `model = map(...)`.
i In group 1: `Vowel = DRESS` `Formant = "F1_50"`.
Caused by warning in `bam()`:
! openMP not available: single threaded computation only
i Run `dplyr::last_dplyr_warnings()` to see the 19 remaining warnings.
```

The function `bam` is one of the main functions for fitting GAMM models in `mgcv`. It is often used for large data sets. Our use of `~` creates a function which is applied to each of our nested tibbles. The entries in `model` are created by taking the corresponding tibble in the data column and applying the function to it. The tibble is referred to by the pronoun .x in the function. In the above, .x is used as the data fed to bam(). So, for the row of our tibble with DRESS and F1_50 in the Vowel and Formant columns, the entry for model will be a model produced from the data for DRESS and F1.

Note that you can use any modelling function you like here. The general strategy of nesting and fitting models doesn't have any special connections with GAMs or mgcv. You could fit a linear model with lm or a generalised linear model using the lme4 package.

We now have GAMM models for each of these vowels. These are stored in the model column we have just created. We can check out one of these models using the itsadug plot_smooth() function as follows:

```
plot_smooth(
  vowels$model[[7]], # Pick the first entry in the model column.
  view = "yob", # The x-axis variable.
  plot_all = "Gender",
  main= paste(vowels$Vowel[[7]], vowels$Formant[[7]])
)
```

```
Summary:
    * Gender : factor; set to the value(s): F, M.
    * yob : numeric predictor; with 30 values ranging from 1864.000000 to 1981.000000.
    * Speech_rate : numeric predictor; set to the value(s): 4.5118.
    * NOTE : No random effects in the model to cancel.
```

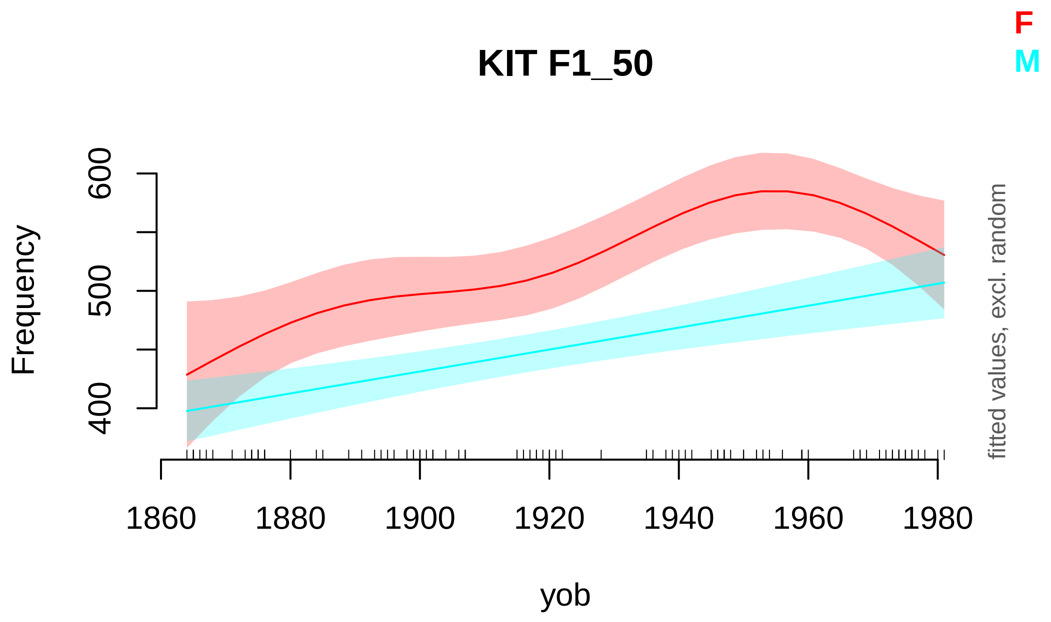


Figure 1: Smooth plot for KIT F1

Figure 1 shows a well known feature of the development of New Zealand English: the centralisation of the KIT vowel. It also indicates something to keep in mind when fitting non-linear models. The wiggles in the smooth for the female speakers might simply be over fitting our particular sample. Again, this is illustrative of a general pattern, each step of which requires criticism in practice!

For the purpose of visualisation, we want predictions from our model to plot. To do this, we map again. This time, we use the `itsadug` function `get_predictions()` instead of the `mgcv` function `bam()`, but the underlying idea is the same. The function `get_predictions()` needs us to tell it what values we want predictions for. In this case, we want predictions for the full range of years of birth in our data set (1864-1981) *and* for both genders.

The following code stores the values we want predictions for in the `to_predict` object and then creates a `prediction` column using `mutate()` and `map()`:

```
to_predict <- list(
  "yob" = seq(from=1864, to=1981, by=1), # All years
  "Gender" = c("M", "F")
)
# BTW: Get prediction will just assume the average value for any predictors not
# mentioned (in this case, Speech_rate).

vowels <- vowels %>%
  mutate(
    prediction = map(
      model, # This time we're applying the function to all the models.
      # We again introduce the function with '~', and indicate where the model
      # goes with '.x'.
      ~ get_predictions(model = .x, cond = to_predict, print.summary = FALSE)
    )
  )
```

So what does a tibble of predictions look like?

```
vowels$prediction[[1]] %>%
  head() %>%
  kable() %>%
  kable_styling() %>%
  scroll_box(width = "100%")
```

Gender	yob	Speech_rate	fit	CI
M	1864	4.4873	501.5480	27.00804
F	1864	4.4873	570.1079	36.38487
M	1865	4.4873	501.0873	26.68430
F	1865	4.4873	569.3392	35.95156
M	1866	4.4873	500.6266	26.36302
F	1866	4.4873	568.5705	35.51985

As expected, we get a predicted value for each gender in each of the years spanned by the data.

Unnest

In order to visualise the predictions of our models, we need to *unnest* this data set. We will do this in a slightly non-standard way, by making a new unnested tibble at this stage rather than modifying our original tibble again. But the same principles apply.

In this case, we need to select our identifying variables (`Vowel` and `Formant`) and the column with the data we want access to in a non-nested form (for us, `prediction`). We unnest as follows:

```r
predictions <- vowels %>%
  select(
    Vowel, Formant, prediction
  ) %>%
  unnest(prediction)

predictions %>%
  head() %>%
  kable() %>%
  kable_styling() %>%
  scroll_box(width = "100%")
```

Vowel	Formant	Gender	yob	Speech_rate	fit	CI
DRESS	F1_50	M	1864	4.4873	501.5480	27.00804
DRESS	F1_50	F	1864	4.4873	570.1079	36.38487
DRESS	F1_50	M	1865	4.4873	501.0873	26.68430
DRESS	F1_50	F	1865	4.4873	569.3392	35.95156
DRESS	F1_50	M	1866	4.4873	500.6266	26.36302
DRESS	F1_50	F	1866	4.4873	568.5705	35.51985

Our tibble now has our predicted values along with the `Vowel` and `Formant` information which identifies which model they came from.

Note that we have now thrown away our individual speaker information. This is often the case when visualising models of this sort as we are not interested in predicting the speech of this or that particular speaker in our data set. Rather, we want to say something about NZE speech *in general*.

We are now in a position to *visualise* changes in the overall NZE vowel space.

Visualise Model Predictions as a Vowel Space

We first produce a static plot using a standard `ggplot` approach and then produce an animation using `gganimate`.

We begin by defining a colour scheme (following Brand et al. (2021), again). These use html colour codes (plenty of explanations are available online).

```r
vowel_colours <- c(
  DRESS = "#9590FF",
  FLEECE = "#D89000",
  GOOSE = "#A3A500",
  KIT = "#39B600",
  LOT = "#00BF7D",
  NURSE = "#00BFC4",
  START = "#00B0F6",
  STRUT = "#F8766D",
  THOUGHT = "#E76BF3",
  TRAP = "#FF62BC"
)
```

We also need to reverse our previous use of `pivot_longer()`. Why? Well vowel spaces have F1 as the y-axis and F2 as the x-axis. This requires F1 and F2 to be distinct columns. To do this, we use `pivot_wider()`. This is made easier if we remove the columns we will not use for plotting first.

```r
predictions <- predictions %>%
  select( # Remove unneeded variables
    -Speech_rate,
    -CI
  ) %>%
  pivot_wider( # Pivot
    names_from = Formant,
    values_from = fit
  )

predictions %>%
  head() %>%
  kable() %>%
  kable_styling() %>%
  scroll_box(width = "100%")
```

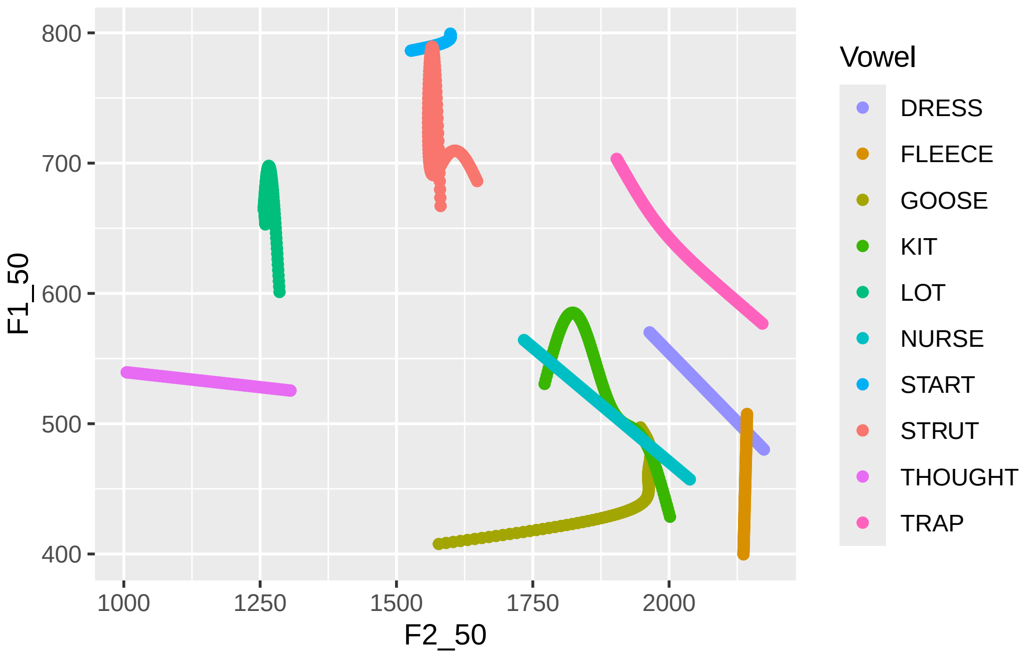
Vowel	Gender	yob	F1_50	F2_50
DRESS	M	1864	501.5480	1657.465
DRESS	F	1864	570.1079	1964.213
DRESS	M	1865	501.0873	1659.390
DRESS	F	1865	569.3392	1966.005
DRESS	M	1866	500.6266	1661.316

DRESS	F	1866	568.5705	1967.797

Static Plot

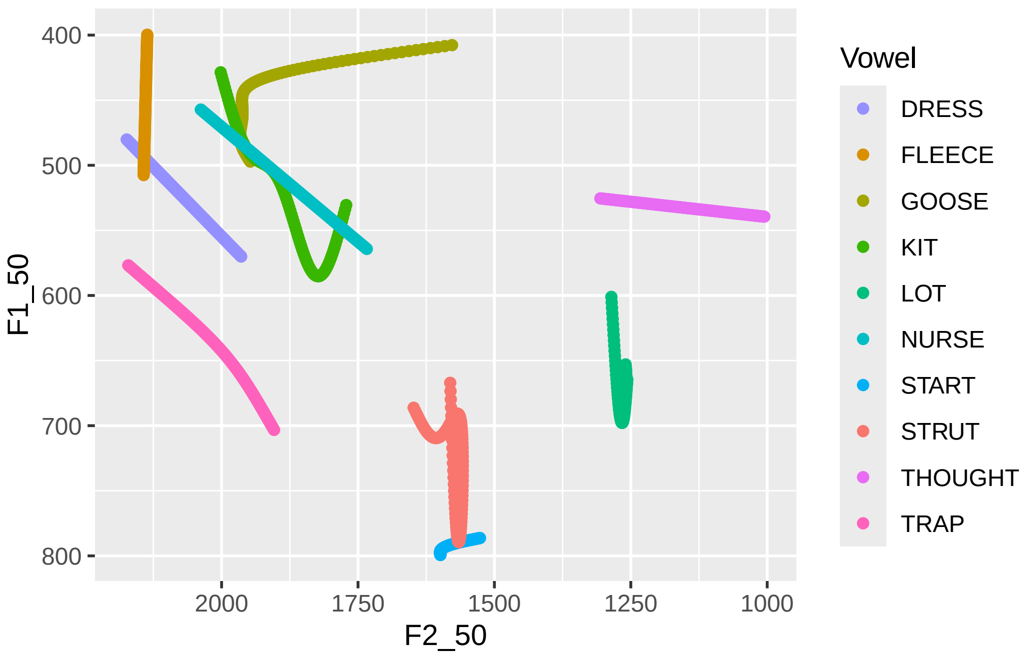
The plot we eventually produce is quite complex. Let's start with depicting the data in two-dimensions using points and only plotting the female speakers.

```r
predictions %>%
  # Filter so only female speakers are plotted.
  filter(
    Gender == "F"
  ) %>%
  ggplot(
    aes(
      x = F2_50,
      y = F1_50,
      colour = Vowel
    )
  ) +
  # Add the points
  geom_point() +
  # Change the colours for the vowels to match those defined above.
  scale_colour_manual(values = vowel_colours)
```



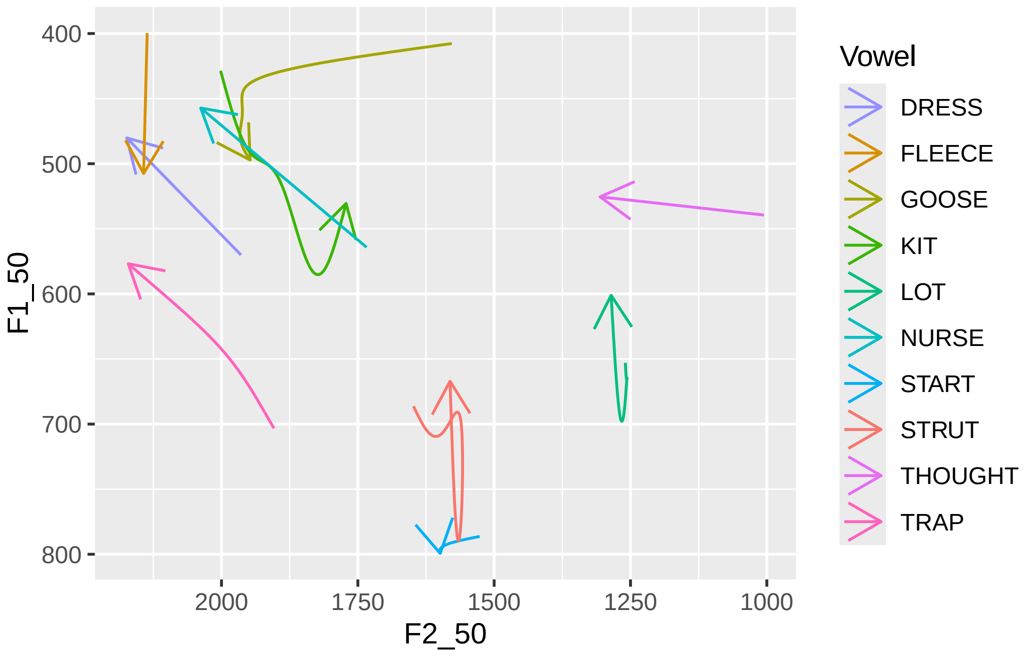
This is the wrong way around for a vowel plot. So we reverse the x and y axes.

```r
predictions %>%
  filter(
    Gender == "F"
  ) %>%
  ggplot(
    aes(
      x = F2_50,
      y = F1_50,
      colour = Vowel
    )
  ) +
  geom_point() +
  scale_x_reverse() +
  scale_y_reverse() +
  scale_colour_manual(values = vowel_colours)
```



It's also unclear which direction these changes are occurring. We need to swap out `geom_point()` for something directed. In this case, we use `geom_path()` and `arrow()`.

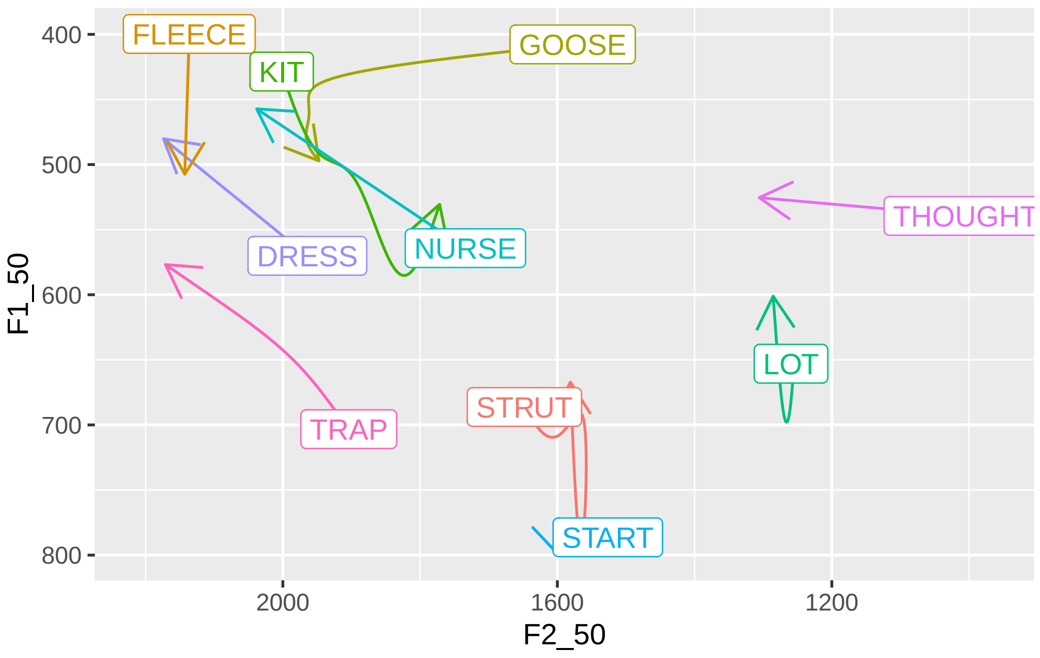
```r
predictions %>%
  filter(
    Gender == "F"
  ) %>%
  ggplot(
    aes(
      x = F2_50,
      y = F1_50,
      colour = Vowel
    )
  ) +
  geom_path(arrow = arrow(length = unit(5, "mm"))) +
  scale_x_reverse() +
  scale_y_reverse() +
  scale_colour_manual(values = vowel_colours)
```



We can add labels to the start of each arrow and remove the legend. This is found by some to be a more clear vowel plot. To do this, we have to pick out the first observation of each vowel in a new tibble. This prevents us from labelling *every* point on the line.

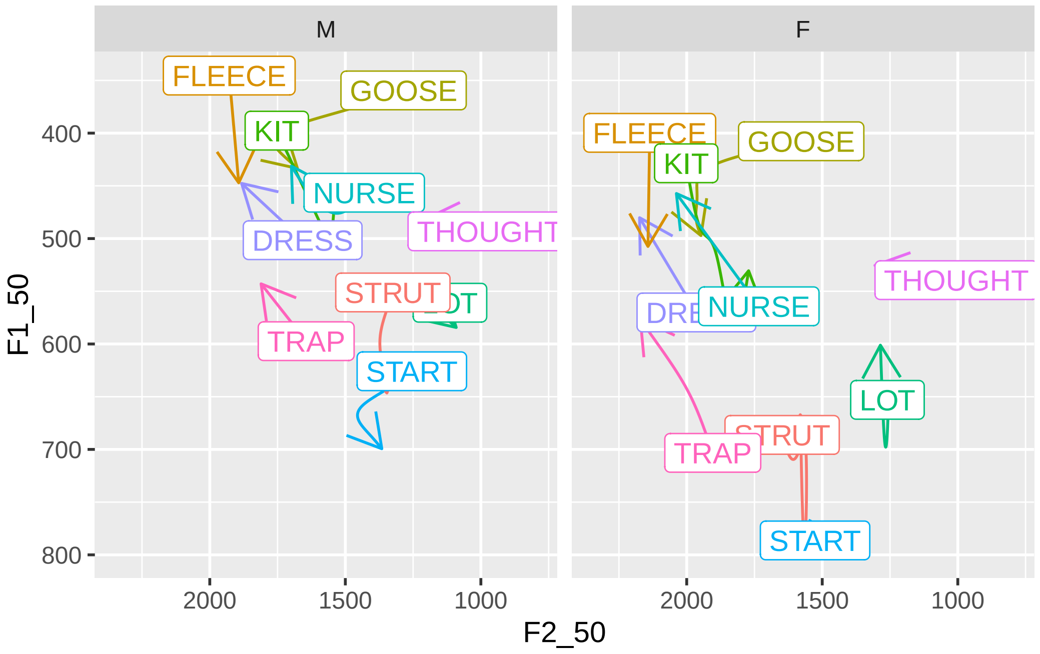
```
first_obs <- predictions %>%
  group_by(Vowel, Gender) %>%
  slice(which.min(yob))

predictions %>%
  filter(
    Gender == "F"
  ) %>%
  ggplot(
    aes(
      x = F2_50,
      y = F1_50,
      colour = Vowel,
      label = Vowel # Add label to the aesthetics.
    )
  ) +
  geom_path(
    arrow = arrow(length = unit(5, "mm")),
    show.legend = FALSE # Remove legend
  ) +
  geom_label(
    # Note filtering as we are only dealing with female speakers now.
    data = first_obs %>% filter(Gender == "F"),
    show.legend = FALSE # Again remove legend.
  ) +
  # Often need to use 'expansion' here to fit in 'THOUGHT'
  scale_x_reverse(expand = expansion(add = 100)) +
  scale_y_reverse() +
  scale_colour_manual(values = vowel_colours)
```



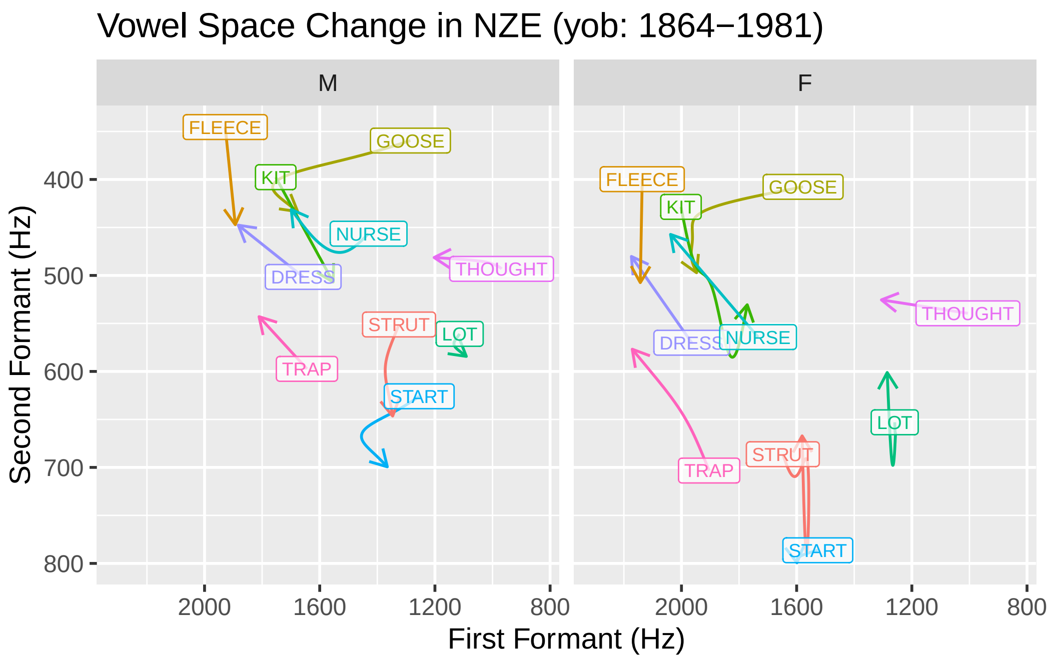
We can use the faceting functions to plot both male and female data. We use the `facet_grid()` function. **NB**: this requires us to remove the `filter()` functions from the above.

```
predictions %>%
  ggplot(
    aes(
      x = F2_50,
      y = F1_50,
      colour = Vowel,
      label = Vowel
    )
  ) +
  geom_path(
    arrow = arrow(length = unit(5, "mm")),
    show.legend = FALSE
  ) +
  geom_label(
    data = first_obs,
    show.legend = FALSE
  ) +
  scale_x_reverse(expand = expansion(add = 250)) +
  scale_y_reverse() +
  scale_colour_manual(values = vowel_colours) +
  facet_grid(
    cols = vars(Gender)
  )
```



There are still a few shortcomings here. We have overlap of the labels, which are now a little large. We attempt to fix this, while also adding a call to `labs()` to properly label the plot.

```
predictions %>%
  ggplot(
    aes(
      x = F2_50,
      y = F1_50,
      colour = Vowel,
      label = Vowel
    )
  ) +
  geom_path(
    arrow = arrow(length = unit(2.5, "mm")), # Make arrows smaller
    show.legend = FALSE
  ) +
  geom_label(
    data = first_obs,
    show.legend = FALSE,
    size = 2.5, # Make labels smaller...
    alpha = 0.7 # ...and slightly transparent.
  ) +
  scale_x_reverse(expand = expansion(add = 200)) + # less expanasion needed.
  scale_y_reverse() +
  scale_colour_manual(values = vowel_colours) +
  facet_grid(
    cols = vars(Gender)
  ) +
  labs(
    title = "Vowel Space Change in NZE (yob: 1864-1981)",
    x = "First Formant (Hz)",
    y = "Second Formant (Hz)"
  )
```



This figure is a good starting point for the kind of smaller adjustments needed to produce a good vowel space visualisation. In your own cases, a lot will depend on the specifics of the models and how much change is being depicted. In this case, it would be nice to make some of these lines a little less messy. Some of the problems here, for instance, the messy lines for START and STRUT in the male speakers, suggest that our models might be behaving a strangely. This is not a problem for this illustration, but some model criticism would be required in a real research project!

Animation

One problem with the static plot is that we can't see variation in the rate of change (if any exists). Nor can we figure out, for any point on the line (apart from the start and end) which year it represents. This can be fixed with the `gganimate` package.

We use the `gganimate` function `transition_reveal()` at the end of our plot with `yob` as the variable we animate with. Our `geom_label()`, the text with the vowel name, will be the main item we animate. The labels will move around the vowel space over time. We change our `geom_path()` so that it has no arrows and simply traces where the label of the vowel moves.

We add a caption to our `labs()` in which we reference the `gganimate` variable `frames_along`. This allows us to show what year it is. Finally, a call to `theme()` lets us make this caption larger.

```r
predictions %>%
  ggplot(
    aes(
      x = F2_50,
      y = F1_50,
      colour = Vowel,
      label = Vowel
    )
  ) +
  geom_path(show.legend = FALSE) +
  # NB: our labels just use the predictions dataframe now, so no need for the
  # 'data = ' line.
  geom_label(
    show.legend = FALSE,
    size = 2.5,
    alpha = 0.7
  ) +
  scale_x_reverse(expand = expansion(add = 200)) +
  scale_y_reverse() +
  scale_colour_manual(values = vowel_colours) +
  facet_grid(
    cols = vars(Gender)
  ) +
  labs(
    title = "Vowel Space Change in NZE (yob: 1864-1981)",
    x = "First Formant (Hz)",
    y = "Second Formant (Hz)",
    caption = 'Year of Birth: {round(frame_along, 0)}'
  ) +
  theme(
    plot.caption = element_text(size = 14, hjust = 0)
  ) +
  transition_reveal(along = yob)
```

So there is it: a general structure for fitting models to visualise changes in vowel formants over time, and for plotting them within vowel space diagrams.

As I've noted multiple times above, the details will matter at every step in a real research project. Data quality assessment before modelling, sensible model structures, evaluation of model quality, and careful consideration of exactly what needs to be visualised are all necessary.

Brand, James & Hay, Jen & Clark, Lynn & Watson, Kevin & Sóskuthy, Márton. 2021. Systematic co-variation of monophthongs across speakers of New Zealand English. *Journal of Phonetics*. 88. 101096. Retrieved from https://www.sciencedirect.com/science/article/pii/S0095447021000711