

Writing better SQL without writing SQL

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In this note, I use a query from Tanimura (2021) to illustrate first how one can re-write an SQL query using common table expressions (CTEs) and then how one can re-write that query again using `dbplyr`. I then do the analysis again from scratch, but using `dbplyr` expressions. I find that the SQL query contains inaccuracies, while the written-from-scratch `dbplyr` query does now. I conjecture that the “building blocks” approach to SQL facilitated by `dbplyr` may lead to more accurate of queries for many users.

In writing this note, I used the packages listed below.¹ This note was written using [Quarto](#) and compiled with [RStudio](#), an integrated development environment (IDE) for working with R. The source code for this note is available [here](#) and the latest version of this PDF is [here](#).

```
library(DBI)
library(tidyverse)
library(dbplyr)
```

1 The original query

Chapter 4 of Tanimura (2021) is entitled “cohort analysis” and uses data on US legislators to illustrate ideas related to survival analysis, including customer retention and survival analysis.

The query I focus on in this note is provided in a section on “returnship” (or repeat purchase behaviour) (Tanimura, 2021, pp. 158–163). Tanimura (2021, p. 158) provides a verbal specification of the query: “What share of [legislators] start as representatives and go on to become senators? (Some senators later become representatives, but that is much less common.) Since relatively few make this transition, we’ll cohort legislators by the century in which they first became a representative.”²

1. Execute `install.packages(c("tidyverse", "DBI", "duckdb", "dbplyr"))` within R to install all the packages you need to run the code in this note.
2. I made minor punctuation edits here.

Tanimura (2021) also discusses a filter that “excludes those [legislators] who were less than 10 years into their careers when the data was assembled” (Tanimura, 2021, p. 160). While the rationale for this filter is not made entirely clear, it is presumably to address the issue of **censoring**. Specifically, if a legislator is only five years into a career at the time of data collection, we simply do not know whether or not this legislator will become a senator in year 6 or 7 or beyond. While standard texts on **survival analysis** focus a lot of effort on dealing with statistical issues related to censoring, Tanimura (2021) does not discuss these approaches at all, presumably because addressing these would require going much more into statistics than makes sense for a book on SQL. As I discuss below (see Section 5), if my understanding of the rationale for the filter is correct, then the original query in Tanimura (2021) does not implement it correctly.

We first get the data, which requires an internet connection. I start by creating an in-memory DuckDB database.

```
db <- dbConnect(duckdb::duckdb())
```

I then read the two downloaded data files into this database.³

```
legislators <- db_get_csv(db, "legislators")
legislators_terms <- db_get_csv(db, "legislators_terms")
```

Listing 2 shows the original SQL query from Tanimura (2021, pp. 161–162).⁴ Note that the output shown in Table 1 matches the output shown in Tanimura (2021, p. 162).

Table 1: Output from original SQL query (Listing 2)

cohort	pct_5_yrs	pct_10_yrs	pct_15_yrs
18	0.0502	0.0970	0.1438
19	0.0088	0.0244	0.0409
20	0.0100	0.0348	0.0478
21	0.0400	0.0764	0.0873

2 Converting the SQL to a CTE-based query

The query shown in Listing 2 is quite complex and I will show how it can be simplified using **common-table expressions** (CTEs). According to the [documentation for PostgreSQL](#): CTEs “can be thought of as defining temporary tables that exist just for one query.” CTEs are created using the SQL keyword

3. I put the ugly details of the `db_get_csv()` function that I use here in Listing 1.

4. I edited the query slightly to reflect code style guidelines I use in later queries. I also rename the column `cohort_century` to `cohort` throughout. The value of using a more generic name will be seen in Section 4.2.

WITH. In converting to a CTE-based query, I proceed in a series of small steps to better illustrate just how such a conversion can be done.

In Listing 3, I start by cleaning that up the two identical subqueries labelled a and b. I put a as a CTE at the beginning of the query (after WITH) and refer to that in both in the place where we currently refer to a and also in place of b. All references to b are changed to references to a. If you run the query in Listing 3, you will see it produces the same results as seen in Table 1.

In Listing 4, I convert aa and bb from subqueries to CTEs. Note that there are commas after the CTEs defining a and aa, but not after bb, as it is the last CTE before the body of the query. Again, if you run the SQL, you will see that the results are unchanged.

In Listing 5, I switch to USING syntax for the join of aa and bb. My view is that USING produces more elegant SQL when it can be used and its use also facilitates the omission of the aa and bb prefixes for the variables in the final query. Noting that `age(c.term_start, a.first_term)` appears three times in the query in Listing 4. I split bb into two (part is now bbb followed by a simplified bb) so that I have a query in which `age(c.term_start, a.first_term)` appears just once.

In Listing 6, I replace the meaningless labels for the CTEs (e.g., a and bb) with more meaningful labels (e.g., cohorts and age_cuts). We also clean up ages a little (e.g., USING) and move cohort to cohorts. If you run the SQL, you will see that the results are unchanged.

In Listing 7, I also put the “main” query in a CTE. The value of doing so is that it means we can easily edit the query to debug the CTEs that are used. For example, we could put `SELECT * FROM cohorts` at the end of the query in Listing 7 to look into cohorts if we are concerned about the output we are seeing from `cohort_retention`.

Table 2: Output from final translated SQL query (Listing 7)

cohort	pct_5_yrs	pct_10_yrs	pct_15_yrs
18	0.0502	0.0970	0.1438
19	0.0088	0.0244	0.0409
20	0.0100	0.0348	0.0478
21	0.0400	0.0764	0.0873

3 Translating from SQL to dbplyr

Now that I have an SQL query based on CTEs, it is *much* easier to translate from SQL to dbplyr. In effect, I can translate each CTE in turn. I start with cohorts:

```
cohorts <-
  legislators_terms |>
  filter(term_type == 'rep') |>
```

```

  summarize(first_rep_term = min(term_start, na.rm = TRUE),
            .by = id_bioguide) |>
  mutate(cohort = century(first_rep_term))

```

Note that I could have created cohort as part of the `summarize()` step using `century(min(term_start, na.rm = TRUE))`, but my view is that the code is easier to read if `min(term_start, na.rm = TRUE)` appears just once and cohort is created as a function of `first_term` in a separate `mutate()` step.

Translating `cohort_sizes` is also straightforward:

```

cohort_sizes <-
  cohorts |>
  filter(first_rep_term <= '2009-12-31') |>
  summarize(reps = n(), .by = cohort)

```

Note that `.groups = "drop"` is strictly optional in this case. Nonetheless I generally include `.groups = "drop"` in all my queries to prevent issues that can arise due to unintended grouping.⁵

Translating `ages` is not complicated:

```

ages <-
  cohorts |>
  inner_join(legislators_terms, by = "id_bioguide") |>
  filter(term_type == 'sen', term_start > first_rep_term) |>
  mutate(age = age(term_start, first_rep_term)) |>
  select(cohort, id_bioguide, age)

```

The main difference here is that `filter()` seems to go more naturally earlier in the query rather than at the end. It would make no difference if the order of the `mutate()` and `filter()` steps in the query below we flipped. However, we cannot put `filter()` at the end of the query (i.e., after `select()`) because the fields would no longer be available at that point.

In translating `age_cuts`, it is useful to note that the original SQL included both a per-row calculation (the CASE WHEN calculation) and an aggregation by cohort (the count(DISTINCT) part).⁶ To do things in a more step-by-step fashion, I put the per-row calculations in a `mutate()` call and then the aggregation in a `summarize()` call. Note that I trimmed the variable names in the `mutate()` step by using `num_` in place of `rep_and_sen_`. I also used `across()` in the `summarize()` step so that I only need to write `n_distinct()` once.

-
- 5. My view is that the choice made early in the development `dplyr` of a de facto default of `.groups = "drop_last"` is a rather unfortunate one.
 - 6. Note that `if_else(age <= years(5), id_bioguide, NA)` would be an alternative way to get the same result as `case_when(age <= years(5) ~ id_bioguide)` gives.

```

age_cuts <-
  ages |>
  mutate(num_5_yrs = case_when(age <= years(5) ~ id_bioguide),
         num_10_yrs = case_when(age <= years(10) ~ id_bioguide),
         num_15_yrs = case_when(age <= years(15) ~ id_bioguide)) |>
  summarize(across(starts_with("num_")),
            \_(x) n_distinct(x, na.rm = TRUE)),
            .by = cohort)

```

The final step of the translation is straightforward enough. I use `across()` again so that I only need to write `round(x * 1.0 / reps, 4)` once and I use `rename_with` to make it so the variables have the `pct_` prefix seen in the original query.⁷

```

cohort_sizes |>
  left_join(age_cuts, by = "cohort") |>
  mutate(across(starts_with("num_")), \_(x) round(x * 1.0 / reps, 4))) |>
  rename_with(\_(x) str_replace(x, "^num_", "pct_")) |>
  select(cohort, starts_with("pct_")) |>
  arrange(cohort) |>
  collect()

```

Table 3: Output from query translated to `dbplyr`

cohort	pct_5_yrs	pct_10_yrs	pct_15_yrs
18	0.0502	0.0970	0.1438
19	0.0088	0.0244	0.0409
20	0.0100	0.0348	0.0478
21	0.0400	0.0764	0.0873

Comparison of Table 1 and Table 3 confirms that the `dbplyr` query yields the same result as the original SQL query.

4 Building the query from scratch using `dbplyr`

Now let's do it again more or less from scratch using `dbplyr`. In this version, I will build up block by block in a way that is easier (at least for me) to reason about.

Before launching into the code, it is perhaps useful to step back and identify some key elements of the analysis.

7. An alternative would've been to use `pct_` in place of `num_` in the `age_cuts` query.

- **population:** Legislators who started as representatives before 31 December 2009.⁸
- **cohorts:** Century of the start date of the first term.
- **exposure date:** Date of the first term. Another term might be **entry date**.
- **event date:** The **event** of interest is “becoming a senator” and the date is the first date of the first term as a senator (if any). Another term might be **exit date**.

Note that cohorts here are defined based on dates, but this need not be the case in general. For example, A/B testing with websites involves cohorts based on which version of website the user is exposed to (either “A” or “B”).

Also, “exposure date” is a term that I concocted that may seem more or less natural in other contexts. For example, in a vaccine trial, the exposure date might be the date on which a series of jabs is completed. In analysis of data on life expectancies, the exposure date might be the date of birth.

I start by creating `first_terms`, a table with information about first terms for each legislator:

```
first_terms <-
  legislators_terms |>
  summarize(first_rep_term = min(case_when(term_type == 'rep' ~ term_start)),
            first_sen_term = min(case_when(term_type == 'sen' ~ term_start)),
            last_sen_term = max(case_when(term_type == 'sen' ~ term_start)),
            first_term = min(term_start),
            .by = id_bioguide) |>
  compute()
```

We are interested in legislators who “start as representatives” (`first_term == first_rep_term`) and we want to exclude those whose first term is after 31 December 2009 (`first_term <= "2009-12-31"`), our population is created by applying filters to `first_terms`:

```
cohorts_revised <-
  first_terms |>
  filter(!is.na(first_rep_term),
         first_term == first_rep_term,
         first_term <= "2009-12-31") |>
  select(id_bioguide, first_rep_term, first_sen_term) |>
  mutate(cohort = century(first_rep_term))
```

Here `first_rep_term` is the exposure date and `first_sen_term` is the event date. Note that `cohorts_revised` includes both survival data (i.e., values for exposure date and event date) and cohort data and is focused exclusively on the population of interest. In other contexts it might make sense to calculate cohorts and survival data in separate queries before merging them.⁹

We can now calculate the sizes of the cohorts that we have formed.

8. Strictly speaking, it should be “on or before 31 December 2009”, but legislators never start terms on 31 December.

9. See <https://iangow.github.io/cohorts/intermezzo.html> for some discussion on this point.

```

cohort_sizes <-
  cohorts_revised |>
  summarize(reps = n(), .by = cohort)

```

Now we have our data together, we can calculate the “time to event (if any)” (`event_time`) using the SQL function `age()`. If there is no senate term for a given legislator, then `event_time` will be NA. While one approach to censoring would replaced the missing values of `first_sen_term` with the date of data collection and add an indicator variable for censoring, I follow Tanimura (2021) in just using the 2009 cutoff and ignoring any issues related to censoring.

```

cohorts_revised |>
  mutate(event_time = age(first_sen_term, first_rep_term))

```

```

# A query: ?? x 5
# Database: DuckDB 1.4.4 [igow@Darwin 25.4.0:R 4.5.2/:memory:]
  id_bioguide first_rep_term first_sen_term cohort event_time
  <chr>      <date>      <date>      <dbl> <drtm>
1 C000127    1993-01-05  2001-01-03    20  248745600 secs
2 S000770    1997-01-07  2001-01-03    20  124156800 secs
3 B001251    2004-07-21  NA            21   NA secs
4 C001068    2007-01-04  NA            21   NA secs
5 L000562    2001-10-23  NA            21   NA secs
6 M001166    2007-01-04  NA            21   NA secs
7 0000168    2009-01-06  NA            21   NA secs
8 P000197    1987-01-06  NA            20   NA secs
9 P000597    2009-01-06  NA            21   NA secs
10 S000244   1979-01-15  NA           20   NA secs
# i more rows

```

It is easy to check that `id_bioguide` is a valid key for `cohorts_revised`, which makes it easy to build up the curve of subsequent senate terms using a window function. Within each cohort we order by `event_time` and sum up the number of rows leading up to each value of `event_time`.¹⁰

Note that in our date set there will be ties in terms of `event_time`. For example, we might have exactly 6 observations with `event_time` of exactly 5 years. If we had 432 representatives with `event_time` of less than 5 years and 6 with `event_time` of exactly 5 years, we would want to step from 432 to 438 immediately upon hitting the 5-year mark. Below I accomplish using the `max()` aggregate grouped by `cohort` and `event_time`.

10. This is equivalent to `count(DISTINCT id_bioguide) OVER (PARTITION BY cohort ORDER BY event_time)`, but we do not need the `DISTINCT` here because each value of `id_bioguide` is unique in this query.

```

pct_rep_then_sen <-
  cohorts_revised |>
  mutate(event_time = age(first_sen_term, first_rep_term)) |>
  mutate(cum_ids = cumsum(1),
    .by = cohort,
    .order = event_time) |>
  mutate(cum_ids = max(cum_ids, na.rm = TRUE),
    .by = c(cohort, event_time)) |>
  inner_join(cohort_sizes, by = "cohort") |>
  mutate(pct = cum_ids / reps)

```

To produce the query analogous to that underlying Table 1, I can actually avoid the complicated CASE statements used in the original SQL. Instead, I first make a little table in R with the three cutoff values and send that to DuckDB and turn the rows into intervals using years().

```

event_time_cutoffs <-
  tibble(cutoff = c(5, 10, 15)) |>
  copy_to(db, df = _, name = "event_time_cutoffs",
    overwrite = TRUE) |>
  mutate(cutoff = years(cutoff))

```

I then use cross_join() to combine pct_rep_then_sen and event_time_cutoffs and calculate the pct values for each cutoff before using pivot_wider() to rearrange the table to match what is shown in Tanimura (2021).

```

pct_rep_then_sen |>
  cross_join(event_time_cutoffs) |>
  filter(event_time <= cutoff) |>
  summarize(pct = max(pct, na.rm = TRUE),
    .by = c(cohort, cutoff)) |>
  mutate(cutoff = year(cutoff)) |>
  pivot_wider(names_from = "cutoff",
    names_prefix = "pct_",
    values_from = "pct",
    names_sort = TRUE) |>
  arrange(cohort) |>
  collect()

```

Table 4: Output of from-scratch dbplyr query

cohort	pct_5	pct_10	pct_15
18	0.0505	0.0976	0.1448
19	0.0087	0.0244	0.0407
20	0.0101	0.0349	0.0478
21	0.0109	0.0364	0.0473

Because of the more general form of our data with this modified query, it is easy to make the plot seen in Figure 1.

```
pct_rep_then_sen |>
  mutate(event_time = (year(event_time) * 12 + month(event_time)) / 12) |>
  filter(event_time <= 15) |>
  summarize(pct = max(pct, na.rm = TRUE),
            .by = c(cohort, event_time)) |>
  mutate(cohort = as.character(cohort)) |>
  ggplot(aes(x = event_time, y = pct, group = cohort,
             colour = cohort)) +
  geom_line()
```

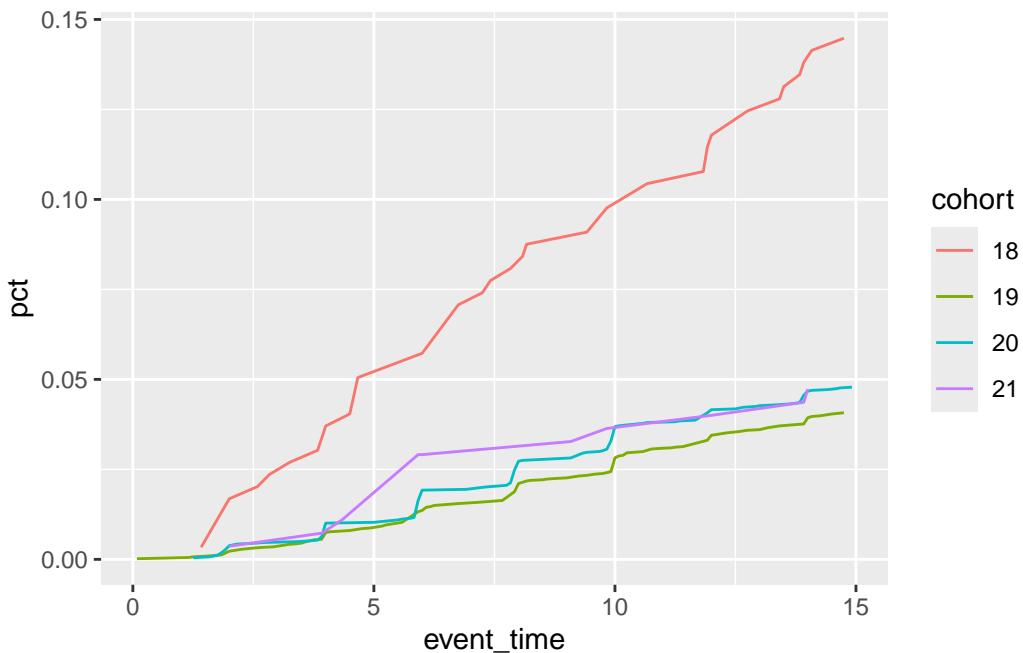


Figure 1: Representatives becoming senators over time by century

Note that it would be easy to translate our `dbplyr` code—arguably a more precise solution than the original SQL query—back into SQL (probably using CTEs) if that were desired.¹¹

4.1 Reproducing Figure 4-12 of Tanimura (2021)

Finally, I reproduce Figure 4-12 of Tanimura (2021, p. 163). This plot requires changes to the cohorts, to the cutoffs (now 10 and 20 years), and (it seems) to the population. From visual inspection of Figure 4-12 of Tanimura (2021), it seems that we now require a representative's first term to have begun before 2000.

Note that the query underlying Figure 4-12 of Tanimura (2021) is not provided in the book. Nor is the code for generating the plot itself. Because Tanimura (2021) only include SQL code, readers are on their own when it comes to code for generating the plots; this is an additional weakness of focusing on SQL code.

The first step I take is to make a new version of `pct_rep_then_sen` with `cohort` now based on decades and with the stricter filter on `first_rep_term`. Note that I simply overwrite whatever value for `cohort` was already in `cohorts_revised`. I also embed the calculation of `reps` (the number of members of each cohort) in the same pipeline as the other calculations.

```
pct_rep_then_sen <-  
  cohorts_revised |>  
  filter(first_rep_term <= "1999-12-31") |>  
  mutate(cohort = decade(first_rep_term),  
         event_time = age(first_sen_term, first_rep_term)) |>  
  mutate(reps = n(), .by = cohort) |>  
  mutate(cum_ids = cumsum(1), .by = cohort, .order = event_time) |>  
  mutate(cum_ids = max(cum_ids, na.rm = TRUE),  
         .by = c(cohort, event_time)) |>  
  mutate(pct = cum_ids / reps)
```

I replace `event_time_cutoffs` with the new values (10 and 20 years):

```
event_time_cutoffs <-  
  tibble(cutoff = c(10, 20)) |>  
  copy_to(db, df = _, name = "event_time_cutoffs",  
          overwrite = TRUE) |>  
  mutate(cutoff = years(cutoff))
```

Making the plot is now quite straightforward and the results of the following code can be seen in Figure 2:

11. I explain why I think it is a more precise solution in Section 5.

```

pct_rep_then_sen |>
  cross_join(event_time_cutoffs) |>
  filter(event_time <= cutoff) |>
  summarize(pct = max(pct, na.rm = TRUE),
            .by = c(cohort, cutoff)) |>
  mutate(cutoff = as.character(year(cutoff))) |>
  ggplot(aes(x = cohort, y = pct, color = cutoff, group = cutoff)) +
  geom_line()

```



Figure 2: Share of representatives who become senators by decade

4.2 Making a function

Creating the code underlying Figure 4-12 of Tanimura (2021) likely involved a lot of copy-pasting and editing (e.g., to create new CASE statements for the new cutoffs and new WHERE clauses) even before moving the code (or data) to Python or Tableau to make the plot. The code above suggests that we might accomplish variants on the plot more programmatically and I pursue this idea in this section.

One benefit of doing this is that I can show how putting the survival data into a canonical structure can make it easier to run variants based on different populations and cohort definitions.

First, I put the essence of the code in the following function with the only real edits being that I use more generic names for the tables and fields and put the cutoffs to be used in a variable `cutoffs`.

```

make_plot <- function(cohorts, survival_data, cutoffs = c(10, 20)) {
  plot_data <-
    survival_data |>
    mutate(event_time = age(event_date, entry_date)) |>
    inner_join(cohorts, by = "id") |>
    mutate(reps = n(), .by = cohort) |>
    mutate(cum_ids = cumsum(1), .by = cohort, .order = event_time) |>
    mutate(cum_ids = max(cum_ids, na.rm = TRUE),
          .by = c(cohort, event_time)) |>
    mutate(pct = cum_ids / reps)

  event_time_cutoffs <-
    tibble(cutoff = cutoffs) |>
    copy_to(db, df = _, name = "event_time_cutoffs",
            overwrite = TRUE) |>
    mutate(cutoff = years(cutoff))

  plot_data |>
    cross_join(event_time_cutoffs) |>
    filter(event_time <= cutoff) |>
    summarize(pct = max(pct, na.rm = TRUE),
              .by = c(cohort, cutoff)) |>
    mutate(cutoff = as.character(year(cutoff))) |>
    ggplot(aes(x = cohort, y = pct, color = cutoff, group = cutoff)) +
    geom_line()
}

}

```

I next construct `survival_data` in a canonical form with `id`, `entry_date`, and `event_date` as the fields.

```

survival_data <-
  first_terms |>
  filter(!is.na(first_rep_term),
         first_term == first_rep_term) |>
  rename(id = id_bioguide,
         entry_date = first_rep_term,
         event_date = first_sen_term) |>
  select(id, entry_date, event_date)

```

Now I can easily reproduce Figure 2 using the following code with the results being seen in Figure 3:

```

survival_data |>
  filter(entry_date <= "1999-12-31") |>
  mutate(cohort = decade(entry_date)) |>
  select(id, cohort) |>
  make_plot(survival_data = survival_data,
            cutoffs = c(10, 20))

```



Figure 3: Share of representatives who become senators by decade (encore)

And with a few lines of code, I can make a plot version of Table 4, which can be seen in Figure 4:

```

survival_data |>
  filter(entry_date <= "2009-12-31") |>
  mutate(cohort = century(entry_date)) |>
  select(id, cohort) |>
  make_plot(survival_data = survival_data,
            cutoffs = c(5, 10, 15))

```

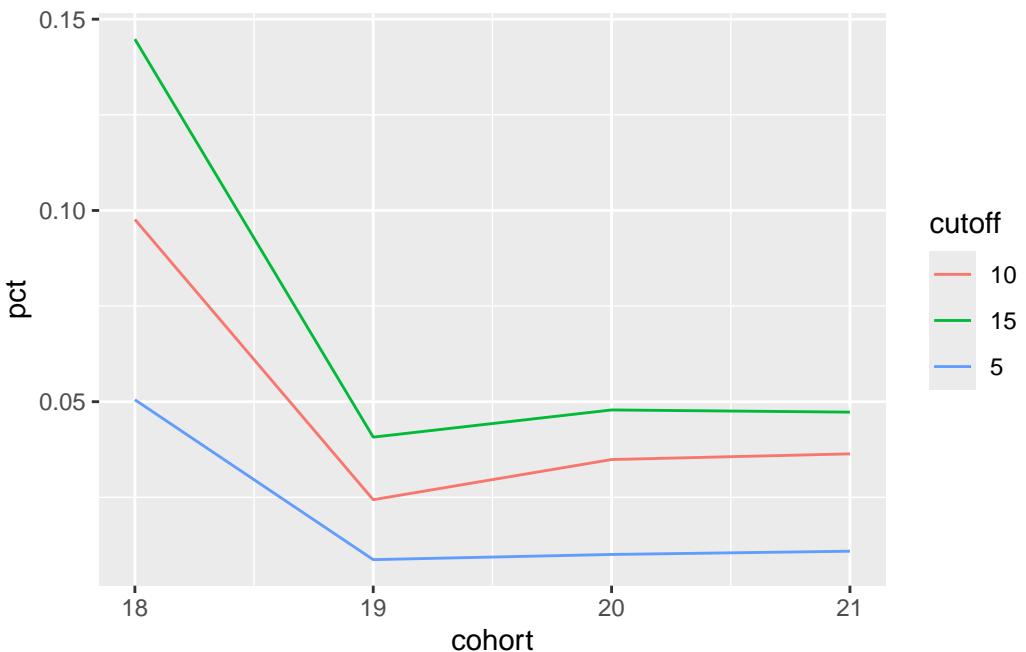


Figure 4: Share of representatives who become senators by century

5 Reconciling differences in output

A careful reader might have noticed differences between the numbers in Table 3 and those in Table 4 and wonder why these differences exist. These differences seem particularly pronounced for the representatives from the 21st century cohort, which seems consistent with the explanations I provide below.

I would argue that the numbers in Table 4 better address the original question from Tanimura (2021, p. 158): “What share of [legislators] start as representatives and go on to become senators? (Some senators later become representatives, but that is much less common.) Since relatively few make this transition, we’ll cohort legislators by the century in which they first became a representative.”¹² My query is also more consistent in applying “`WHERE first_term <= '2009-12-31'` [which] excludes those [legislators] who were less than 10 years into their careers when the data was assembled” (Tanimura, 2021, p. 160).

It turns out that some representatives that were correctly excluded in producing Table 4 were incorrectly included in the original analysis underlying Table 3. I compile the “problem cases” in a single data frame `problem_cases`:

12. I made minor punctuation edits here.

Table 5: Problematic cases: Senators first, later senators again

id_bioguide	first_sen_term	first_rep_term	last_sen_term
C000482	1806-01-01	1811-11-04	1849-12-03
J000137	1818-01-01	1833-12-02	1844-01-01
M000519	1826-01-01	1833-12-02	1837-09-04

```
problem_cases <-
  first_terms |>
  semi_join(cohorts, by = "id_bioguide") |>
  anti_join(cohorts_revised, by = "id_bioguide") |>
  filter(!is.na(first_sen_term) & !is.na(first_rep_term)) |>
  mutate(rep_to_sen = last_sen_term > first_rep_term,
        sen_to_rep = first_sen_term < first_rep_term ,
        too_late = first_rep_term > '2009-12-31')
```

The first set of problem cases comprises those legislators who were senators *before* they were representatives. These legislators should have been excluded on the basis that they do not meet the “start as representatives” criterion. Note that this set can be viewed as comprising two subsets. The first subset are those legislators who started as senators, then became representatives, then became senators again. These observations will affect both the numerators and the denominators of the proportions shown in Table 3. Cases from this first subset—shown in Table 5—are identified using the following code:

```
problem_cases |>
  filter(sen_to_rep, rep_to_sen) |>
  arrange(first_rep_term) |>
  select(id_bioguide, first_sen_term, first_rep_term, last_sen_term)
```

The second subset are those legislators who started as senators, then became representatives, but did *not* become senators again after serving as a representative. These observations will not affect the numerators of the proportions shown in Table 3, but will affect the denominators. Some cases from this second subset—shown in Table 6—are identified using the following code:

```
problem_cases |>
  filter(sen_to_rep, !rep_to_sen) |>
  select(id_bioguide, first_sen_term, last_sen_term, first_rep_term) |>
  collect(n = 10)
```

The second set of problem cases are representatives whose terms began after ‘2009-12-31’. The original SQL query imposed this requirement in calculating cohort_sizes, but not in constructing the

Table 6: Problematic cases: Senators first, not later senators again (10 cases)

id_bioguide	first_sen_term	last_sen_term	first_rep_term
C000325	1813-05-24	1825-12-05	1853-12-05
L000240	1953-07-10	1953-07-10	1957-01-03
R000125	1806-11-25	1807-10-26	1817-12-01
K000069	1868-01-01	1877-10-15	1883-12-03
W000012	1915-12-06	1921-04-11	1933-03-09
W000768	1801-12-07	1801-12-07	1809-05-22
P000354	1798-12-06	1799-12-02	1819-12-06
R000063	1851-02-01	1851-02-01	1851-03-04
N000050	1861-07-04	1861-07-04	1873-12-01
C000703	1842-01-01	1842-01-01	1849-12-03

cohorts themselves. Thus, while the SQL in Listing 2 does exclude these cases from the denominator, these legislators are included in the numerator if they go on to serve as senators. These cases are shown in Table 7. In contrast I was consistent in application of the `first_rep_term <= '2009-12-31'` criterion throughout. These observations will not affect the denominators of the proportions shown in Table 3, but will affect the numerators. The members of this set of problem cases—shown in Table 7—are identified using the following code:

```
problem_cases |>
  filter(too_late) |>
  select(id_bioguide, first_rep_term, first_sen_term, last_sen_term)
```

It is easy to show that these issues explain the differences between Table 3 and Table 4. To do so, I need to recapitulate some steps from the analysis above, starting with a revised version of `ages` in which I `anti_join()` the `problem_cases` data frame.

```
ages <- 
  cohorts |>
  anti_join(problem_cases, by = "id_bioguide") |>
  inner_join(legislators_terms, by = "id_bioguide") |>
  filter(term_type == 'sen', term_start > first_rep_term) |>
  mutate(age = age(term_start, first_rep_term)) |>
  select(cohort, id_bioguide, age)
```

We then pass this revised `ages` to create a new version of `age_cuts`.

Table 7: Problematic cases: Too late

id_bioguide	first_rep_term	first_sen_term	last_sen_term
D000618	2013-01-03	2015-01-06	2015-01-06
M001197	2015-01-06	2019-01-03	2019-01-03
C001096	2013-01-03	2019-01-03	2019-01-03
Y000064	2011-01-05	2017-01-03	2017-01-03
G000562	2011-01-05	2015-01-06	2015-01-06
S001191	2013-01-03	2019-01-03	2019-01-03
D000622	2013-01-03	2017-01-03	2017-01-03
L000575	2011-01-05	2015-01-06	2017-01-03
S001184	2011-01-05	2013-01-03	2017-01-03
C001095	2013-01-03	2015-01-06	2015-01-06
R000608	2017-01-03	2019-01-03	2019-01-03

```
age_cuts <-
  ages |>
  mutate(num_5_yrs = if_else(age <= years(5), id_bioguide, NA),
         num_10_yrs = if_else(age <= years(10), id_bioguide, NA),
         num_15_yrs = if_else(age <= years(15), id_bioguide, NA)) |>
  summarize(across(starts_with("num_")),
            \((x) n_distinct(x, na.rm = TRUE)),
            .by = cohort)
```

Finally, I `left_join()` this revised `age_cuts` to produce Table 8. We now see that the output lines up with that in Table 4, confirming that the observations in `problem_cases` are the source of the differences between Table 4 and Table 3.

```
cohort_sizes |>
  left_join(age_cuts, by = "cohort") |>
  mutate(across(starts_with("num_"), \((x) round(x * 1.0 / reps, 4))) |>
    rename_with(\((x) str_replace(x, "^num_", "pct_"))) |>
    select(cohort, starts_with("pct_")) |>
    arrange(cohort) |>
    collect()
```

Table 8: Output from query translated to `dbplyr` omitting problem cases

cohort	pct_5_yrs	pct_10_yrs	pct_15_yrs
18	0.0505	0.0976	0.1448
19	0.0087	0.0244	0.0407
20	0.0101	0.0349	0.0478
21	0.0109	0.0364	0.0473

Listing 1 Utility functions

```
download_data <- function(filename, data_dir = "data") {  
  if (!dir.exists(data_dir)) dir.create(data_dir)  
  
  url <- paste0("https://raw.githubusercontent.com/cathytanimura/",  
                "sql_book/master/Chapter%204%3A%20Cohorts/")  
  
  local_filename <- file.path(data_dir, paste0(filename, ".csv"))  
  if (!file.exists(local_filename)) {  
    download.file(url = paste0(url, filename, ".csv"), destfile = local_filename)  
  }  
}  
  
db_read_csv <- function(db, table, data_dir = "data") {  
  csv_file <- file.path(data_dir, paste0(table, ".csv"))  
  tbl(db, paste0("read_csv_auto('", csv_file, "')")) |>  
  compute(name = table)  
}  
  
db_get_csv <- function(db, table, data_dir = "data") {  
  download_data(table, data_dir = data_dir)  
  db_read_csv(db, table, data_dir = data_dir)  
}
```

References

Tanimura, C., 2021. [SQL for data analysis](#). O'Reilly Media.

Listing 2 Original SQL from Tanimura (2021)

```
SELECT aa.cohort,
    round(bb.rep_and_sen_5_yrs * 1.0 / aa.reps, 4) AS pct_5_yrs,
    round(bb.rep_and_sen_10_yrs * 1.0 / aa.reps, 4) AS pct_10_yrs,
    round(bb.rep_and_sen_15_yrs * 1.0 / aa.reps, 4) AS pct_15_yrs
FROM
(
    SELECT date_part('century', a.first_term) AS cohort,
        count(id_bioguide) AS reps
    FROM
    (
        SELECT id_bioguide, min(term_start) AS first_term
        FROM legislators_terms
        WHERE term_type = 'rep'
        GROUP BY 1
    ) a
    WHERE first_term <= '2009-12-31'
    GROUP BY 1
) aa
LEFT JOIN
(
    SELECT date_part('century', b.first_term) AS cohort,
        count(DISTINCT CASE WHEN age(c.term_start, b.first_term) <=
            INTERVAL '5 years'
            THEN b.id_bioguide END) AS rep_and_sen_5_yrs,
        count(DISTINCT CASE WHEN age(c.term_start, b.first_term) <=
            INTERVAL '10 years'
            THEN b.id_bioguide END) AS rep_and_sen_10_yrs,
        count(DISTINCT CASE WHEN age(c.term_start, b.first_term) <=
            INTERVAL '15 years'
            THEN b.id_bioguide END) AS rep_and_sen_15_yrs
    FROM
    (
        SELECT id_bioguide, min(term_start) AS first_term
        FROM legislators_terms
        WHERE term_type = 'rep'
        GROUP BY 1
    ) b
    JOIN legislators_terms c
    ON b.id_bioguide = c.id_bioguide AND c.term_type = 'sen'
        AND c.term_start > b.first_term
    GROUP BY 1
) bb ON aa.cohort = bb.cohort
ORDER BY 1;
```

Listing 3 SQL with our first CTE

```
WITH a AS (
    SELECT id_bioguide, min(term_start) AS first_term
    FROM legislators_terms
    WHERE term_type = 'rep'
    GROUP BY 1)

SELECT aa.cohort,
    round(bb.rep_and_sen_5_yrs * 1.0 / aa.reps, 4) AS pct_5_yrs,
    round(bb.rep_and_sen_10_yrs * 1.0 / aa.reps, 4) AS pct_10_yrs,
    round(bb.rep_and_sen_15_yrs * 1.0 / aa.reps, 4) AS pct_15_yrs
FROM
(
    SELECT date_part('century', a.first_term) AS cohort,
        count(id_bioguide) AS reps
    FROM a
    WHERE first_term <= '2009-12-31'
    GROUP BY 1
) aa
LEFT JOIN
(
    SELECT date_part('century', a.first_term) AS cohort,
        count(DISTINCT CASE WHEN age(c.term_start, a.first_term) <=
            INTERVAL '5 years'
            THEN a.id_bioguide END) AS rep_and_sen_5_yrs,
        count(DISTINCT CASE WHEN age(c.term_start, a.first_term) <=
            INTERVAL '10 years'
            THEN a.id_bioguide END) AS rep_and_sen_10_yrs,
        count(DISTINCT CASE WHEN age(c.term_start, a.first_term) <=
            INTERVAL '15 years'
            THEN a.id_bioguide END) AS rep_and_sen_15_yrs
    FROM a
    JOIN legislators_terms c ON a.id_bioguide = c.id_bioguide
    AND c.term_type = 'sen' AND c.term_start > a.first_term
    GROUP BY 1
) bb ON aa.cohort = bb.cohort
ORDER BY 1;
```

Listing 4 SQL with CTEs for aa and bb

```
WITH a AS (
    SELECT id_bioguide, min(term_start) AS first_term
    FROM legislators_terms
    WHERE term_type = 'rep'
    GROUP BY 1),

aa AS (
    SELECT date_part('century',a.first_term) AS cohort,
        count(id_bioguide) AS reps
    FROM a
    WHERE first_term <= '2009-12-31'
    GROUP BY 1),

bb AS (
    SELECT date_part('century', a.first_term) AS cohort,
        count(DISTINCT CASE WHEN age(c.term_start, a.first_term) <=
            INTERVAL '5 years'
            THEN a.id_bioguide END) AS rep_and_sen_5_yrs,
        count(DISTINCT CASE WHEN age(c.term_start, a.first_term) <=
            INTERVAL '10 years'
            THEN a.id_bioguide END) AS rep_and_sen_10_yrs,
        count(DISTINCT CASE WHEN age(c.term_start, a.first_term) <=
            INTERVAL '15 years'
            THEN a.id_bioguide END) AS rep_and_sen_15_yrs
    FROM a
    JOIN legislators_terms c ON a.id_bioguide = c.id_bioguide
        AND c.term_type = 'sen' AND c.term_start > a.first_term
    GROUP BY 1)

SELECT aa.cohort,
    round(bb.rep_and_sen_5_yrs * 1.0 / aa.reps, 4) AS pct_5_yrs,
    round(bb.rep_and_sen_10_yrs * 1.0 / aa.reps, 4) AS pct_10_yrs,
    round(bb.rep_and_sen_15_yrs * 1.0 / aa.reps, 4) AS pct_15_yrs
FROM aa
LEFT JOIN bb ON aa.cohort = bb.cohort
ORDER BY 1;
```

Listing 5 SQL with bbb

```
WITH a AS (
    SELECT id_bioguide, min(term_start) AS first_term
    FROM legislators_terms
    WHERE term_type = 'rep'
    GROUP BY 1),

aa AS (
    SELECT date_part('century', first_term) AS cohort,
        count(id_bioguide) AS reps
    FROM a
    WHERE first_term <= '2009-12-31'
    GROUP BY 1),

bbb AS (
    SELECT date_part('century', a.first_term) AS cohort,
        a.id_bioguide,
        age(c.term_start, a.first_term) AS age
    FROM a
    JOIN legislators_terms c
    ON a.id_bioguide = c.id_bioguide
    AND c.term_type = 'sen' AND c.term_start > a.first_term),

bb AS (
    SELECT cohort,
        count(DISTINCT CASE WHEN age <= INTERVAL '5 years'
            THEN id_bioguide END) AS rep_and_sen_5_yrs,
        count(DISTINCT CASE WHEN age <= INTERVAL '10 years'
            THEN id_bioguide END) AS rep_and_sen_10_yrs,
        count(DISTINCT CASE WHEN age <= INTERVAL '15 years'
            THEN id_bioguide END) AS rep_and_sen_15_yrs
    FROM bbb
    GROUP BY 1)

SELECT cohort as cohort,
    round(rep_and_sen_5_yrs * 1.0 / reps, 4) AS pct_5_yrs,
    round(rep_and_sen_10_yrs * 1.0 / reps, 4) AS pct_10_yrs,
    round(rep_and_sen_15_yrs * 1.0 / reps, 4) AS pct_15_yrs
FROM aa
LEFT JOIN bb
USING (cohort)
ORDER BY 1;
```

Listing 6 SQL with meaningful labels

```
WITH cohorts AS (
    SELECT id_bioguide, min(term_start) AS first_term,
        date_part('century', min(term_start)) AS cohort,
    FROM legislators_terms
    WHERE term_type = 'rep'
    GROUP BY 1),

cohort_sizes AS (
    SELECT cohort, count(id_bioguide) AS reps
    FROM cohorts
    WHERE first_term <= '2009-12-31'
    GROUP BY 1),

ages AS (
    SELECT cohort, id_bioguide,
        age(term_start, first_term) AS age
    FROM cohorts
    JOIN legislators_terms
    USING (id_bioguide)
    WHERE term_type = 'sen' AND term_start > first_term),

age_cuts AS (
    SELECT cohort,
        count(DISTINCT CASE WHEN age <= INTERVAL '5 years'
            THEN id_bioguide END) AS rep_and_sen_5_yrs,
        count(DISTINCT CASE WHEN age <= INTERVAL '10 years'
            THEN id_bioguide END) AS rep_and_sen_10_yrs,
        count(DISTINCT CASE WHEN age <= INTERVAL '15 years'
            THEN id_bioguide END) AS rep_and_sen_15_yrs
    FROM ages
    GROUP BY 1)

SELECT cohort,
    round(rep_and_sen_5_yrs * 1.0 / reps, 4) AS pct_5_yrs,
    round(rep_and_sen_10_yrs * 1.0 / reps, 4) AS pct_10_yrs,
    round(rep_and_sen_15_yrs * 1.0 / reps, 4) AS pct_15_yrs
FROM cohort_sizes
LEFT JOIN age_cuts
USING (cohort)
ORDER BY 1;
```

Listing 7 SQL with main query in CTE

```
WITH cohorts AS (
    SELECT id_bioguide, min(term_start) AS first_term,
        date_part('century', min(term_start)) AS cohort,
    FROM legislators_terms
    WHERE term_type = 'rep'
    GROUP BY 1),

cohort_sizes AS (
    SELECT cohort, count(id_bioguide) AS reps
    FROM cohorts
    WHERE first_term <= '2009-12-31'
    GROUP BY 1),

ages AS (
    SELECT cohort, id_bioguide, age(term_start, first_term) AS age
    FROM cohorts
    JOIN legislators_terms
    USING (id_bioguide)
    WHERE term_type = 'sen' AND term_start > first_term),

age_cuts AS (
    SELECT cohort,
        count(DISTINCT CASE WHEN age <= INTERVAL '5 years'
            THEN id_bioguide END) AS rep_and_sen_5_yrs,
        count(DISTINCT CASE WHEN age <= INTERVAL '10 years'
            THEN id_bioguide END) AS rep_and_sen_10_yrs,
        count(DISTINCT CASE WHEN age <= INTERVAL '15 years'
            THEN id_bioguide end) AS rep_and_sen_15_yrs
    FROM ages
    GROUP BY 1),

cohort_retention AS (
    SELECT cohort,
        round(rep_and_sen_5_yrs * 1.0 / reps, 4) AS pct_5_yrs,
        round(rep_and_sen_10_yrs * 1.0 / reps, 4) AS pct_10_yrs,
        round(rep_and_sen_15_yrs * 1.0 / reps, 4) AS pct_15_yrs
    FROM cohort_sizes
    LEFT JOIN age_cuts
    USING (cohort))

SELECT *
FROM cohort_retention
ORDER BY cohort;
```