2. Data Discovery

Cob Staines

2025-03-07

Table of contents

This tutorial is available as a .qmd on Github.

Motivation

- Explore what data are currently available on the database
- Identify structure of data of interest to inform access

R

Let's set up our environment to get ready to explore the database.

Load packages

```
# minimal packages for RIBBiTR DB data discovery
librarian::shelf(tidyverse, dbplyr, RPostgres, DBI, RIBBiTR-BII/ribbitrrr)
```

Establish database connection

```
# establish database connection
dbcon <- hopToDB("ribbitr")
```

```
Connecting to 'ribbitr'... Success!
```

Load database metadata

Data structure: Schemas, tables, columns and rows

The RIBBiTR database is organized into "schemas" (think of these as folders), which can contain any number of tables. Each table consists of columns ("variables") and rows ("entries").

Metadata: Data about data

We keep track of information regarding what tables, and columns exist in the database, and what information they are designed to describe, using table and column metadata. To begin our process of data discovery, let's learn what tables are present in the data by loading the table metadata.

Table Metadata

```
# load table "all_tables" from schema "public"
mdt <- tbl(dbcon, Id("public", "all_tables")) %>%
  collect()
```

Some basic database commands

Before we take a look at the metadata you just pulled, let's understand the command we just ran.

- `dplyr::tbl()` - This function is used to create a "lazy" table from a data source. To specify the source, we provide the database connection `dbcon`, as well as a pointer or "address" for the table of interest using the `Id()` function. A "lazy" table means that the data only pulled when explicitly asked for. See `collect()` below.
- `dbplyr::Id()` - This function is a pointer to pass hierarchical table identifiers (you can think of this as an address for a given table). In this case we use it to generate an pointer for the table "all_tables" in schema "public".
- `dplyr::collect()` - the `tbl()` function generates a "lazy" table, which is basically a shopping list for the data you want to pull. In order to actually pull the data from the server to your local machine (ie. "do the shopping") we need to pipe in the `collect()` function.

Also try: Run the code above without `collect()`, to see what a lazy table looks like.

Now let's take a look at the table metadata to explore what schemas and tables exist.

```
view(mdt)
```

Column metadata

Suppose our interest is in the `survey_data` schema. Let's take a closer look at the tables here by collecting metadata on table columns in this schema.

```
# load table "all_columns" from schema "public"
mdc <- tbl(dbcon, Id("public", "all_columns")) %>%
  filter(table_schema == "survey_data") %>%
  collect()
```

Notice we used the `dplyr::filter()` command on the lazy table *before* running `collect()`. This effectively revised the shopping list before going to the store, rather than bringing home the entire store and then filtering for what you want in your kitchen. Much less (computationally) expensive!

Let's check out the column metadata, and see what you can learn.

```
view(mdc)

# list the columns in our column-metadata table
colnames(mdc)
```

```
 [1] "table_schema"              "table_name"
 [3] "column_name"               "definition"
 [5] "units"                     "accuracy"
 [7] "scale"                     "format"
 [9] "reviewed"                  "natural_key"
[11] "primary_key"               "foreign_key"
[13] "unique"                    "is_nullable"
[15] "data_type"                 "character_maximum_length"
[17] "numeric_precision"         "datetime_precision"
[19] "column_default"            "ordinal_position"
[21] "pg_description"            "key_type"
[23] "fkey_ref_schema"           "fkey_ref_table"
[25] "fkey_ref_column"
```

Curious about what a certain metadata column means? There's metadata for that (metametadata?)!

```
# vew metadata on metadata columns
view(mdc %>% filter(table_name == "metadata_columns"))
```

A few columns to point out:

- definition
- units
- data_type
- natural key

(more on keys later)

Our first(?) data table

Ok, let's try to apply some of what we have learned by pulling directly from a data table. We can begin by taking a look at the visual encounter surveys (VES).

```
# create lazy table for ves (visual encounter survey) table
db_ves <- tbl(dbcon, Id("survey_data", "ves"))
```

Do these functions look familiar? Turns out, we were pulling data all along! Of course, this is a lazy table (ie. shopping list) so it doesn't look like data yet. Let's see what we can learn from it before going to the store to collect the data.

What columns the table contains:

```
# return columns of lazy table
colnames(db_ves)
```

```
 [1] "taxon_ves"              "count_ves"              "detection_location"
 [4] "microhabitat_type"      "life_stage"             "sex"
 [7] "comments_ves"           "microhabitat_detailed" "observer_ves"
[10] "visual_animal_state"    "ves_id"                 "survey_id"
```

How many total rows a table contains:

```
# count rows
db_ves %>%
  count() %>%
  pull()
```

```
integer64
[1] 29625
```

The pull() function executes a query to return a single column or variable, synonymous with the collect() function which returns a collection of variables as a table.

We can also count rows using the `summarise()` and `n()` functions. While slightly more complicated, this will carry over into more colicated queries later.

So, how many rows after filtering for unknown species:

```
# count rows with known taxa
db_ves %>%
  filter(!is.na(taxon_ves)) %>%
  summarise(row_count = n()) %>%
  pull(row_count)
```

```
integer64
[1] 29450
```

How many rows corresponding to a each life stage:

```
# count rows by life stage
db_ves %>%
  select(life_stage) %>%
  group_by(life_stage) %>%
  summarise(row_count = n()) %>%
  arrange(desc(row_count)) %>%
  collect()
```

```
# A tibble: 9 x 2
  life_stage    row_count
  <chr>           <int64>
1 tadpole           10307
2 adult              9667
3 subadult           7186
4 <NA>               1722
5 eggmass             641
6 juvenile             78
7 egg                  16
8 metamorphosed         7
9 metamorph             1
```

Disconnect

Reinforcing best practice by disconnecting from the server.

```
dbDisconnect(dbcon)
```

Python

Let's set up our environment to get ready to explore the database.

Load packages

```python
# minimal packages for Python DB data discovery
import ibis
from ibis import _
import pandas as pd
import dbconfig
```

Establish database connection

```python
# Establish database connection
dbcon = ibis.postgres.connect(**dbconfig.ribbitr)
```

Load database metadata

Data structure: Schemas, tables, columns and rows

The RIBBiTR database is organized into "schemas" (think of these as folders), which can contain any number of tables. Each table consists of columns ("variables") and rows ("entries").

Metadata: Data about data

We keep track of information regarding what tables, and columns exist in the database, and what information they are designed to describe, using table and column metadata. To begin our process of data discovery, let's learn what tables are present in the data by loading the table metadata.

Table Metadata

```python
# load table "all_tables" from schema "public"
mdt = dbcon.table(database = "public", name = "all_tables").to_pandas()
```

Some basic database commands

Before we take a look at the metadata you just pulled, let's understand the command we just ran.

- `ibis.table()` - This function is used to create a "lazy" table from a data source. To specify the source, we modify the database connection `dbcon`. We specify the schema for the table as `public` (note ibis calls this "database"), as well as the table name `all_tables`. A "lazy" table means that the data only pulled when explicitly asked for. See `execute()` below.
- `ibis.to_pandas()` - the `table()` function generates a "lazy" table, which is basically a shopping list for the data you want to pull. In order to actually pull the data from the server to your local machine (ie. "do the shopping") we need to collect the lazy table by chaining the `to_pandas()` function.

Also try: Run the code above without `to_pandas()`, to see what an uncollected lazy table looks like.

Now let's take a look at the table metadata to explore what schemas and tables exist.

```
print(mdt)
```

```
         table_schema  ... table_description
0    microclimate_data  ...              None
1    microclimate_data  ...              None
2    microclimate_data  ...              None
3    microclimate_data  ...              None
4    microclimate_data  ...              None
5    microclimate_data  ...              None
6    microclimate_data  ...              None
7    microclimate_data  ...              None
8          survey_data  ...              None
9          survey_data  ...              None
10         survey_data  ...              None
11         survey_data  ...              None
12         survey_data  ...              None
13         survey_data  ...              None
14         survey_data  ...              None
15         survey_data  ...              None
16         survey_data  ...              None
17         survey_data  ...              None
18         survey_data  ...              None
19         survey_data  ...              None
20         survey_data  ...              None
21         survey_data  ...              None
22         survey_data  ...              None
23         survey_data  ...              None
24         survey_data  ...              None
25         survey_data  ...              None
26         survey_data  ...              None
```

```
27        survey_data  ...              None
28        survey_data  ...              None
29        survey_data  ...              None
30        survey_data  ...              None
31        survey_data  ...              None
32        survey_data  ...              None
33        survey_data  ...              None

[34 rows x 4 columns]
```

Column metadata

Suppose our interest is in the `survey_data` schema. Let's take a closer look at the tables here by collecting metadata on table columns in this schema.

```
# load table "all_columns" from schema "public"
mdc = (
  dbcon.table(database="public", name="all_columns")
  .filter(_.table_schema == 'survey_data')
  .to_pandas()
)
```

Notice we used the `ibis.filter()` command on the lazy table *before* calling `to_pandas()`. This effectively revised the shopping list before going to the store, rather than bringing home the entire store and then filtering for what you want in your kitchen. Much less (computationally) expensive!

Let's check out the column metadata, and see what you can learn.

```
# view dataframe
print(mdc)
```

```
    table_schema        table_name  ... fkey_ref_table fkey_ref_column
0    survey_data              site  ...           None            None
1    survey_data              site  ...           None            None
2    survey_data  metadata_columns  ...           None            None
3    survey_data  metadata_columns  ...           None            None
4    survey_data  metadata_columns  ...           None            None
..           ...               ...  ...            ...             ...
414  survey_data   bd_qpcr_results  ...           None            None
415  survey_data            sample  ...           None            None
416  survey_data            sample  ...           None            None
417  survey_data   bd_qpcr_results  ...         sample       sample_id
418  survey_data   bd_qpcr_results  ...           None            None
```

```
[419 rows x 25 columns]
```

```python
# list the columns in our column-metadata table
mdc.columns
```

```
Index(['table_schema', 'table_name', 'column_name', 'definition', 'units',
       'accuracy', 'scale', 'format', 'reviewed', 'natural_key', 'primary_key',
       'foreign_key', 'unique', 'is_nullable', 'data_type',
       'character_maximum_length', 'numeric_precision', 'datetime_precision',
       'column_default', 'ordinal_position', 'pg_description', 'key_type',
       'fkey_ref_schema', 'fkey_ref_table', 'fkey_ref_column'],
      dtype='object')
```

Curious about what a certain metadata column means? There's metadata for that (metametadata?)!

```python
# view metadata on metadata columns
metameta = mdc[mdc['table_name'] == 'metadata_columns']
print(metameta)
```

```
    table_schema        table_name  ... fkey_ref_table fkey_ref_column
2    survey_data  metadata_columns  ...           None            None
3    survey_data  metadata_columns  ...           None            None
4    survey_data  metadata_columns  ...           None            None
5    survey_data  metadata_columns  ...           None            None
73   survey_data  metadata_columns  ...           None            None
238  survey_data  metadata_columns  ...           None            None
241  survey_data  metadata_columns  ...           None            None
242  survey_data  metadata_columns  ...           None            None
317  survey_data  metadata_columns  ...           None            None
318  survey_data  metadata_columns  ...           None            None
319  survey_data  metadata_columns  ...           None            None
320  survey_data  metadata_columns  ...           None            None
321  survey_data  metadata_columns  ...           None            None
322  survey_data  metadata_columns  ...           None            None
323  survey_data  metadata_columns  ...           None            None
324  survey_data  metadata_columns  ...           None            None
325  survey_data  metadata_columns  ...           None            None
326  survey_data  metadata_columns  ...           None            None
327  survey_data  metadata_columns  ...           None            None
339  survey_data  metadata_columns  ...           None            None
340  survey_data  metadata_columns  ...           None            None
```

```
341  survey_data  metadata_columns  ...           None             None
342  survey_data  metadata_columns  ...           None             None
350  survey_data  metadata_columns  ...           None             None
376  survey_data  metadata_columns  ...           None             None

[25 rows x 25 columns]
```

A few columns to point out:

- definition
- units
- data_type
- natural key

(more on keys later)

Our first(?) data table

Ok, let's try to apply some of what we have learned by pulling directly from a data table. We can begin by taking a look at the visual encounter surveys (VES).

```
# create lazy table for ves (visual encounter survey) table
db_ves = dbcon.table(database="survey_data", name="ves")
```

Do these functions look familiar? Turns out, we were pulling data all along! Of course, this is a lazy table (ie. shopping list) so it doesn't look like data yet. Let's see what we can learn from it before going to the store to collect the data.

What columns the table contains:

```
# return columns of lazy table
db_ves.columns
```

```
['taxon_ves', 'count_ves', 'detection_location', 'microhabitat_type', 'life_stage', 'sex', '
```

How many total rows a table contains:

```
# count rows
(db_ves
 .count()
 .execute())
```

```
29625
```

The ibis.execute() function executes a query and returns the result, regardless of the format. This is synonymous with the to_pandas() function which returns query results as a pandas dataframe where possible.

How many rows after filtering for unknown species:

```
# count rows with known taxa
filtered_row_count = (
  db_ves
  .filter(_.taxon_ves.notnull())
  .count()
  .execute())

print(filtered_row_count)
```

```
29450
```

How many rows corresponding to a each life stage:

```
# count rows by life stage
life_stage_counts = (
    db_ves.group_by('life_stage')
    .aggregate(row_count=_.count())
    .order_by(_.row_count.desc())
    .to_pandas()
)

print(life_stage_counts)
```

```
     life_stage  row_count
0       tadpole      10307
1         adult       9667
2      subadult       7186
3          None       1722
4       eggmass        641
5      juvenile         78
6           egg         16
7  metamorphosed          7
8     metamorph          1
```

Disconnect

Reinforcing best practice by disconnecting from the server.

```
# close connection
dbcon.disconnect()
```

DBeaver

Double-click on the **ribbitr** connection in the "Database Navigator" panel to begin your connection. Once connected you should be able to navigae a dropdown menu to explore the connection.

Load database metadata

Data structure: Schemas, tables, columns and rows

The RIBBiTR database is organized into "schemas" (think of these as folders), which can contain any number of tables. Each table consists of columns ("variables") and rows ("entries"). You can explore this structure through the dropdown menu in the "Database Navigator" panel on the left.

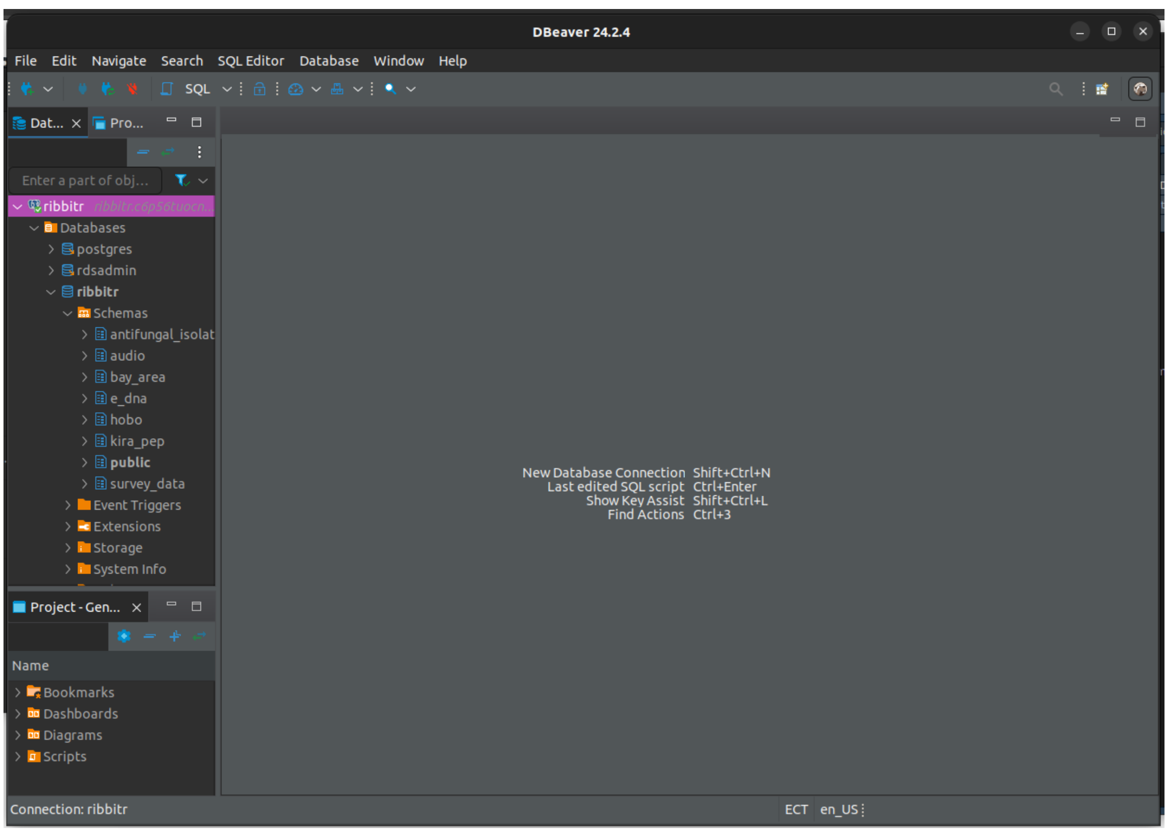


Figure 1: Navigate to `Databases -> ribbitr -> Schemas`

Metadata: Data about data

We keep track of information regarding what tables, and columns exist in the database, and what information they are designed to describe, using table and column metadata. To begin our process of data discovery, let's learn what tables are present in the data by loading the table metadata.

Table Metadata

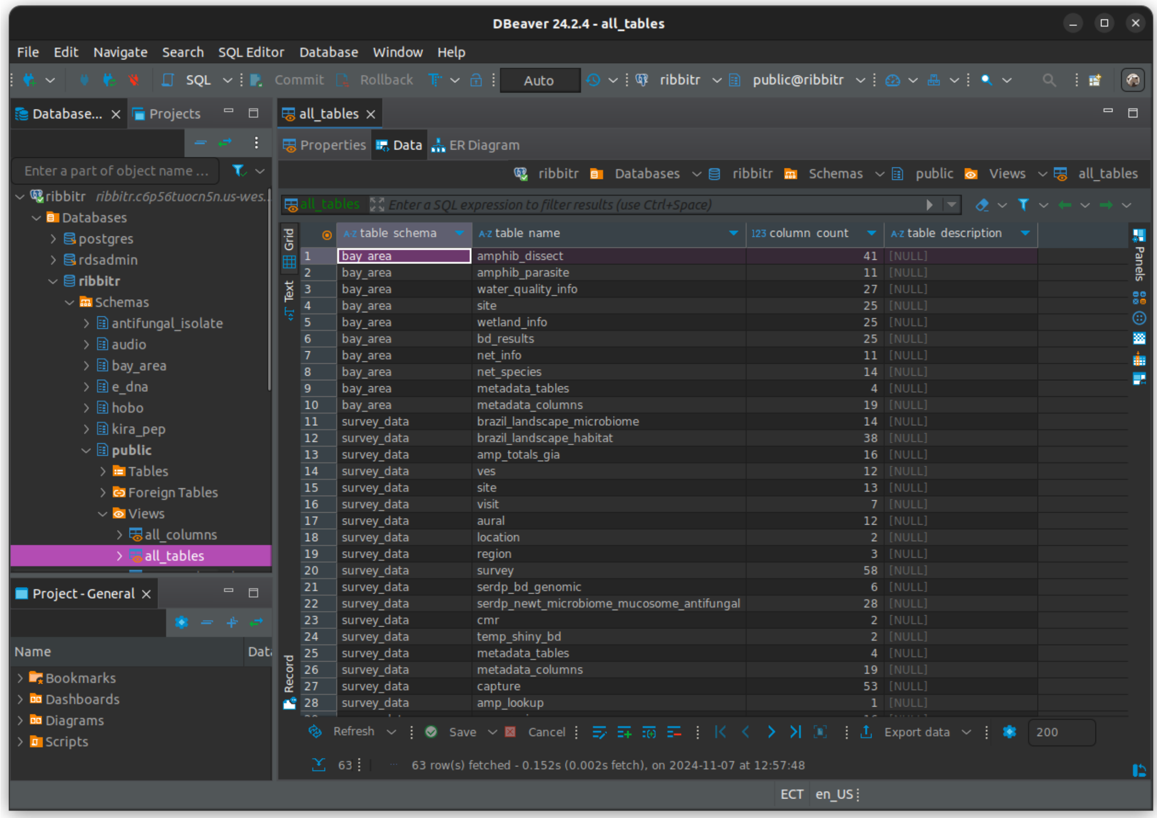
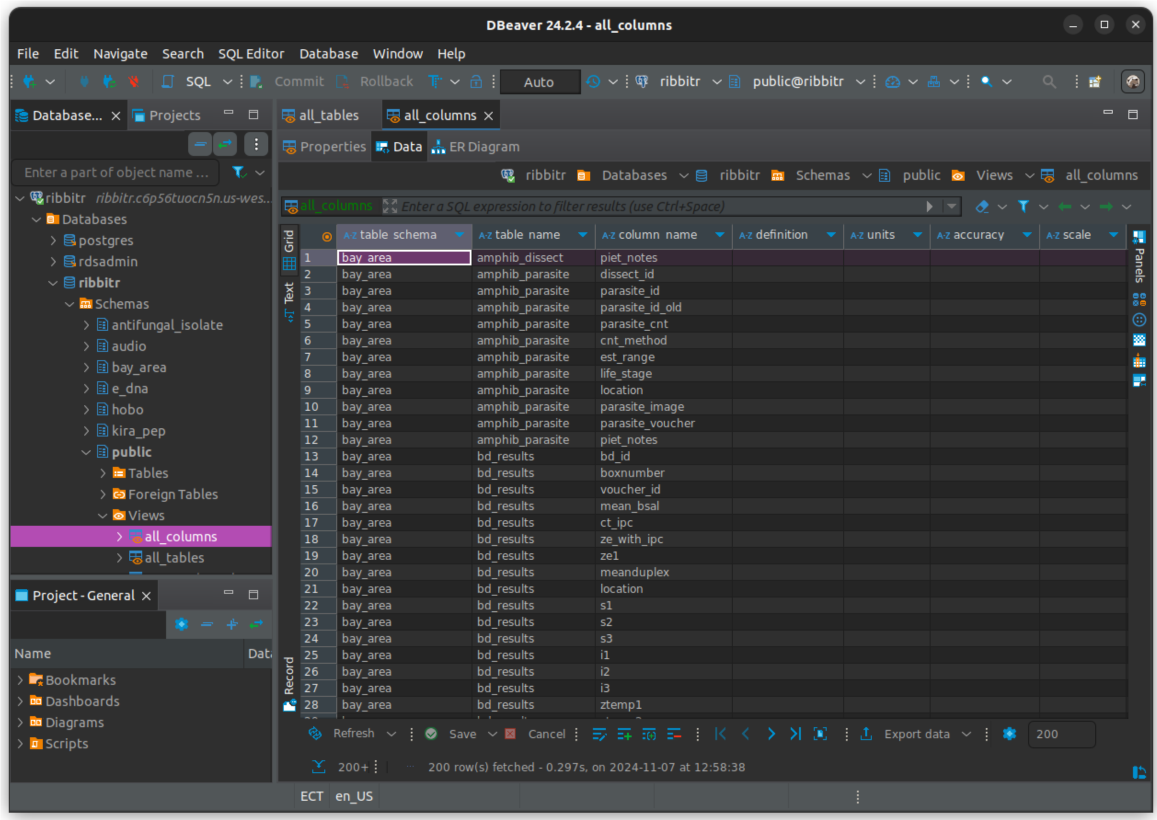


	table schema	table name	column count	table description
1	bay_area	amphib_dissect	41	[NULL]
2	bay_area	amphib_parasite	11	[NULL]
3	bay_area	water_quality_info	27	[NULL]
4	bay_area	site	25	[NULL]
5	bay_area	wetland_info	25	[NULL]
6	bay_area	bd_results	25	[NULL]
7	bay_area	net_info	11	[NULL]
8	bay_area	net_species	14	[NULL]
9	bay_area	metadata_tables	4	[NULL]
10	bay_area	metadata_columns	19	[NULL]
11	survey_data	brazil_landscape_microbiome	14	[NULL]
12	survey_data	brazil_landscape_habitat	38	[NULL]
13	survey_data	amp_totals_gia	16	[NULL]
14	survey_data	ves	12	[NULL]
15	survey_data	site	13	[NULL]
16	survey_data	visit	7	[NULL]
17	survey_data	aural	12	[NULL]
18	survey_data	location	2	[NULL]
19	survey_data	region	3	[NULL]
20	survey_data	survey	58	[NULL]
21	survey_data	serdp_bd_genomic	6	[NULL]
22	survey_data	serdp_newt_microbiome_mucosome_antifungal	28	[NULL]
23	survey_data	cmr	2	[NULL]
24	survey_data	temp_shiny_bd	2	[NULL]
25	survey_data	metadata_tables	4	[NULL]
26	survey_data	metadata_columns	19	[NULL]
27	survey_data	capture	53	[NULL]
28	survey_data	amp_lookup	1	[NULL]

See what you can learn about the tables in the database form the table metadata.

Column metadata

Suppose our interest is in the `survey_data` schema. Let's take a closer look at the tables here by collecting metadata on table columns in this schema.



Click on the dropdown arrow next to `table_schema`, click on `Order by table_schema ASC`. Repeat for the `table_name` and `column_name` columns.

Scroll down until you see rows with `table_schema` = `survey_data`. Explore a table of interest t see what you can learn.

Curious about what a certain metadata column means? There's metadata for that (metametadata?)! Scroll down to `table_name` = `metadata_columns` to learn what the different columns in the current table mean.

A few columns to point out:

- definition
- units
- data_type
- natural key

(more on keys later)

Schema sructure

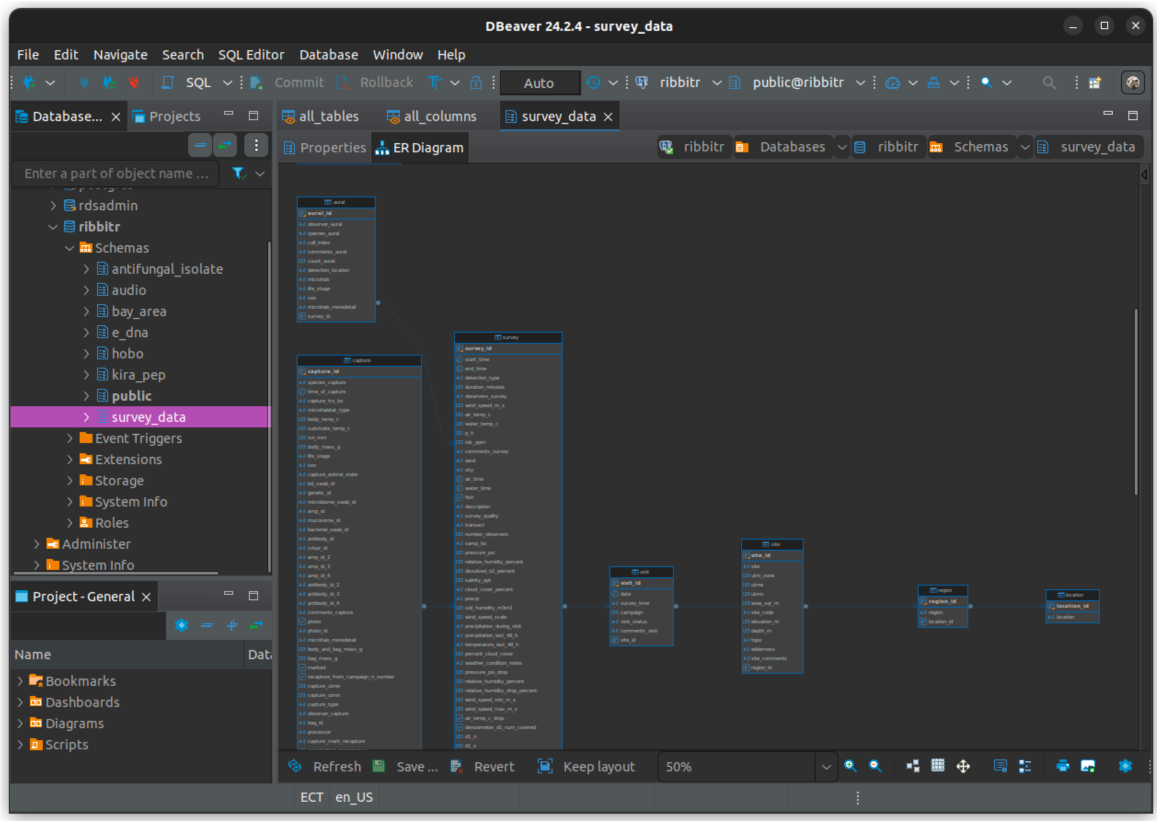
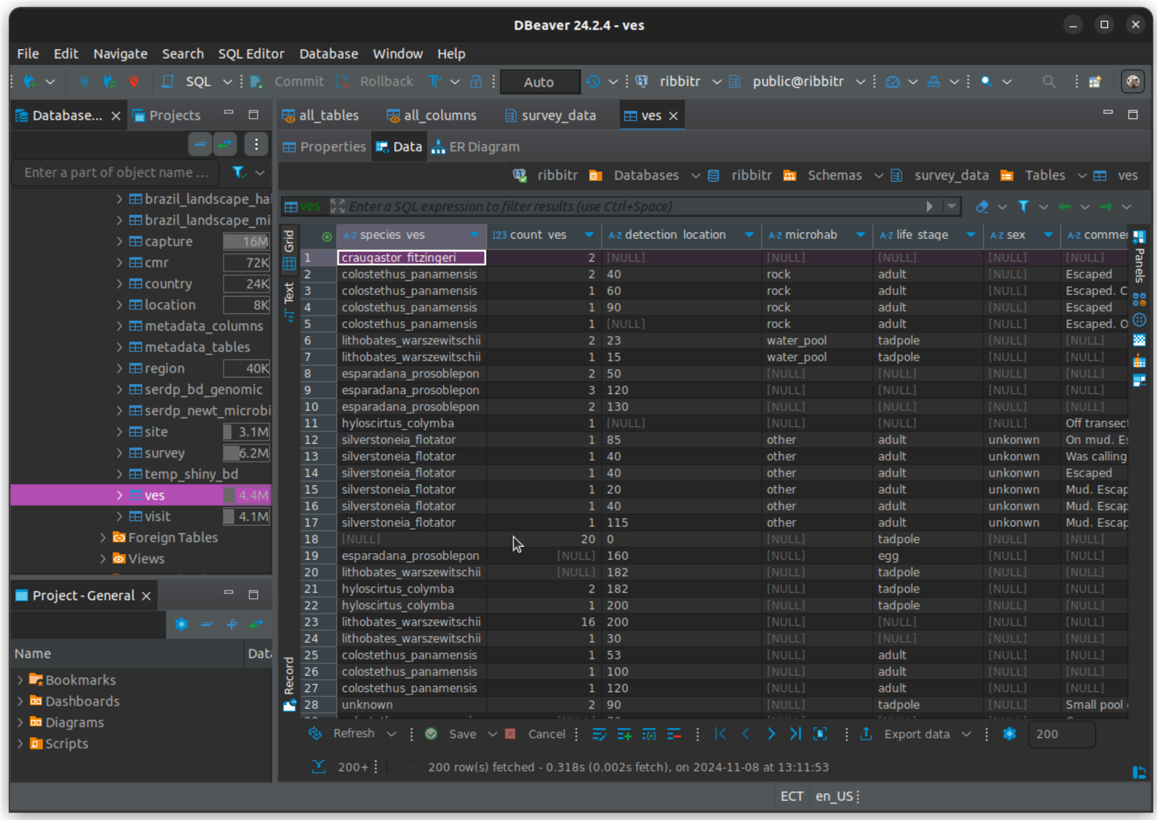


Figure 2: Navigate to `Databases` -> `ribbitr` -> `Schemas` -> `survey_data`. Right-click and select `View Schema`. Select the `ER Diagram` tab.

This shows a diagram of the different tables within the `surevy_data` schema, as well as their columns and any relationships between tables. This is a useful visual reference for later, when we begin joining tables.

Our first data table

To begin looking at data, let's navigate to the visual encounter surveys (VES).



This is your first look at field data within the database! From here you can explore organizing the data by columns, as well as exporting the table to a .csv.

<- 1. Connection Setup | 3. Data Pulling ->