Module_3_duckdb-key

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Learning Objectives (Module 3)

By the end of this module, you will be able to:

- **Understand** when to choose DuckDB over Arrow for analytical workloads
- **Connect** R to DuckDB databases for high-performance analytics
- **Execute** complex joins and window functions on large datasets
- **Leverage** SQL and dplyr interchangeably for data analysis
- **Optimize** analytical queries for multi-gigabyte datasets
- **Build** persistent analytical databases for reproducible research

The Mindset Shift: From Files to Database

Arrow vs. DuckDB: When to Use What?

Arrow thinking (Module 2):

```
# Great for: Reading, filtering, format conversion
open_dataset("file.parquet") |>
  filter(year == 2023) |>
  collect()
```

DuckDB thinking (Module 3):

```
# Great for: Complex analytics, joins, aggregations
#con <- dbConnect(duckdb())
#seattle_tbl <- tbl(con, "seattle_checkouts")

seattle_tbl |>
  window_rank(CheckoutYear, Checkouts) |>
  complex_join(other_table) |>
  collect()
```

Key Concept: In-Process Analytics Database

DuckDB is like having a **miniature data warehouse** running inside R:

- **In-process**: Runs directly in your R session (no separate server needed)
- **Columnar**: Optimized for analytical queries (fast aggregations)
- **SQL + dplyr**: Speaks both languages fluently
- **Persistent**: Can save your work and reuse it later

Think of it like:

- **Arrow**: "A really smart file reader"
- **DuckDB**: "A personal analytics database"

Rule of thumb:

- **Simple filtering/reading**: Use Arrow
- **Complex analytics/joins**: Use DuckDB
- **Multiple related tables**: Definitely DuckDB
- **Window functions/advanced SQL**: DuckDB shines

DuckDB Setup

Load Your Enhanced Toolkit

```r
# Enhanced package loading for database analytics
required_packages <- c("tidyverse", "arrow", "duckdb", "DBI", "dbplyr", "glue")

# Install missing packages
for (pkg in required_packages) {
  if (!requireNamespace(pkg, quietly = TRUE)) {
    install.packages(pkg)
  }
}

# Load all packages
for (pkg in required_packages) {
  library(pkg, character.only = TRUE)
}
```

```
Warning: package 'tidyverse' was built under R version 4.3.3

Warning: package 'tibble' was built under R version 4.3.3

Warning: package 'tidyr' was built under R version 4.3.3

Warning: package 'readr' was built under R version 4.3.3

Warning: package 'purrr' was built under R version 4.3.3

Warning: package 'dplyr' was built under R version 4.3.3

Warning: package 'stringr' was built under R version 4.3.3

Warning: package 'forcats' was built under R version 4.3.3

Warning: package 'lubridate' was built under R version 4.3.3

-- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
v dplyr     1.1.4     v readr     2.1.5
v forcats   1.0.0     v stringr   1.5.1
v ggplot2   3.5.2     v tibble    3.2.1
v lubridate 1.9.3     v tidyr     1.3.1
v purrr     1.0.2
```

```
-- Conflicts ------------------------------------------ tidyverse_conflicts() --
x dplyr::filter() masks stats::filter()
x dplyr::lag()    masks stats::lag()
i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to becom

Warning: package 'arrow' was built under R version 4.3.3


Attaching package: 'arrow'

The following object is masked from 'package:lubridate':

    duration

The following object is masked from 'package:utils':

    timestamp

Warning: package 'duckdb' was built under R version 4.3.3

Loading required package: DBI

Warning: package 'DBI' was built under R version 4.3.3

Warning: package 'dbplyr' was built under R version 4.3.3


Attaching package: 'dbplyr'

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

    ident, sql

Warning: package 'glue' was built under R version 4.3.3
```

Create Dataset Reference

Make sure to get your referenced .csv with `open_dataset()`. Similar to how you would use `read_csv()` but we are not reading in a file:

```r
seattle_csv <- open_dataset(
  sources = "data/seattle-library-checkouts.csv",
  col_types = schema(ISBN = string()),
  format = "csv"
)
```

Check Our Data Setup

Let's verify we have our data files from Module 2:

```r
# Check if we have our CSV file
csv_exists <- file.exists("data/seattle-library-checkouts.csv")
parquet_exists <- dir.exists("data/parquet/seattle")

glue("CSV file exists: {csv_exists}")
```

```
CSV file exists: TRUE
```

```r
glue("Parquet files exist: {parquet_exists}")
```

```
Parquet files exist: TRUE
```

```r
if (csv_exists) {
  file_size_gb <- file.size("data/seattle-library-checkouts.csv") / (1024^3)
  glue("CSV file size: {round(file_size_gb, 2)} GB")
}
```

```
CSV file size: 8.58 GB
```

Note: We already created Parquet files in Module 2, but let's review the two approaches you can use:

Method 1: Simple Parquet - This is what we created in Module 2:

```r
# Method 1: Simple Parquet (single folder, multiple files)
# Good for: Smaller datasets, simple analytics

# Save as regular Parquet files
#write_dataset(
```

```
#  seattle_csv,
#  path = "data/parquet/seattle_parquet",
#  format = "parquet"
#)
```

Method 2: Partitioned Parquet - An alternative approach for time-series data:

```
# Method 2: Partitioned Parquet (organized by year)
# Good for: Large datasets, year-based filtering
write_dataset(
  seattle_csv,
  path = "data/parquet/seattle_by_year",
  format = "parquet",
  partitioning = "CheckoutYear"  # Creates a folder for each year
)
```

Just for fun lets see compare the file sizes...

```
# Compare file sizes across all three methods

# Original CSV
csv_size_bytes <- file.size("data/seattle-library-checkouts.csv")
csv_size_gb <- csv_size_bytes / (1024^3)
glue("Original CSV size: {round(csv_size_gb, 2)} GB")
```

```
Original CSV size: 8.58 GB
```

```
# Simple parquet (from Method 1)
simple_parquet_bytes <- sum(file.size(list.files("data/parquet/seattle_parquet/",
                                                 full.names = TRUE, recursive = TRUE)))
simple_parquet_gb <- simple_parquet_bytes / (1024^3)
glue("Simple parquet size: {round(simple_parquet_gb, 2)} GB")
```

```
Simple parquet size: 4.11 GB
```

```
# Partitioned parquet (from Method 2)
partitioned_parquet_bytes <- sum(file.size(list.files("data/parquet/seattle_by_year/",
                                                      full.names = TRUE, recursive = TRUE)))
partitioned_parquet_gb <- partitioned_parquet_bytes / (1024^3)
glue("Partitioned parquet size: {round(partitioned_parquet_gb, 2)} GB")
```

```
Partitioned parquet size: 4.11 GB
```

Approach	Best For	Key Benefits	Trade-offs
Simple Parquet	General analytics, exploratory work, datasets < 5GB	→ **Simpler file structure** - easier to understand and manage → **Faster initial setup** - no need to think about partitioning → **Universal compatibility** - works with any analysis tool	→ Slower filtering by year/date → Must scan entire dataset for time-based queries
Partitioned Parquet	Time-series analysis, production pipelines, datasets > 5GB	→ **Lightning-fast date filtering** - only reads relevant year folders → **Organized structure** - easy to find specific time periods → **Scalable** - excellent performance even with massive datasets	→ More complex folder structure → Requires planning partitioning strategy → Can create many small files if over-partitioned

Connect to DuckDB: Your Personal Data Warehouse

```r
# Create a persistent DuckDB database
# (This is like opening a new Excel workbook, but for big data)
con <- dbConnect(duckdb::duckdb(), dbdir = "data/seattle.duckdb")

# Let's see what we're working with
glue("  Connected to DuckDB database at: data/seattle.duckdb")
```

```
Connected to DuckDB database at: data/seattle.duckdb
```

What just happened?

- Created a **persistent** DuckDB database file
- Established a connection we can use throughout our session
- The database will save our work even after R shuts down

Load Our Parquet Data into DuckDB

Now we'll create a table in our database using the Parquet files we created in Module 2:

```
# This reads from the Parquet files and creates a database table
# Instead of loading all the data, we'll create a "window" to look through
# This is called a VIEW - it lets us see the data without loading it all
dbExecute(con, "
  DROP TABLE IF EXISTS seattle_checkouts;
  CREATE TABLE seattle_checkouts AS
  SELECT *
  FROM read_parquet('data/parquet/seattle_parquet/*.parquet')
")
```

```
[1] 41389465
```

```
# Verify our data loaded correctly
record_count <- dbGetQuery(con, "SELECT COUNT(*) as total FROM seattle_checkouts")
glue("  Loaded {format(record_count$total, big.mark = ',')} records into DuckDB")
```

```
  Loaded 41,389,465 records into DuckDB
```

```
# Create our dplyr reference to the table
seattle_tbl <- tbl(con, "seattle_checkouts")
```

Quick Data Exploration

```
# Basic exploration using dplyr syntax
seattle_tbl |>
  summarise(
    total_records = n(),
    earliest_year = min(CheckoutYear, na.rm = TRUE),
    latest_year = max(CheckoutYear, na.rm = TRUE),
    total_checkouts = sum(Checkouts, na.rm = TRUE)
  ) |>
  collect()
```

```
# A tibble: 1 x 4
  total_records earliest_year latest_year total_checkouts
          <dbl>         <dbl>       <dbl>           <dbl>
1      41389465          2005        2022       144487078
```

```r
# Peek at the structure
seattle_tbl |>
  head(5) |>
  collect()
```

```
# A tibble: 5 x 12
  UsageClass CheckoutType MaterialType CheckoutYear CheckoutMonth Checkouts
  <chr>      <chr>        <chr>               <dbl>         <dbl>     <dbl>
1 Physical   Horizon      BOOK                 2016             6         1
2 Physical   Horizon      BOOK                 2016             6         1
3 Digital    OverDrive    EBOOK                2016             6         1
4 Physical   Horizon      BOOK                 2016             6         1
5 Physical   Horizon      SOUNDDISC            2016             6         1
# i 6 more variables: Title <chr>, ISBN <chr>, Creator <chr>, Subjects <chr>,
#   Publisher <chr>, PublicationYear <chr>
```

What's the difference from Arrow?

With Arrow, we were always "viewing" files. With DuckDB, we've **loaded** the data into a database structure optimized for fast analytics!

Understanding SQL vs. dplyr: Two Languages, Same Ideas (10 minutes)

The Great News: You Already Know the Concepts!

This workshop is about using the dplyr that we know and love - but understanding some SQL can help you see what's happening behind the scenes. DuckDB speaks both languages fluently!

Your challenge: Create a new table called `seattle_by_year` using the partitioned files.

Do We Have to Use SQL?

Short answer: No! This workshop focuses on **dplyr** because:

- You already know dplyr syntax
- It's more intuitive and readable
- **dbplyr** automatically translates dplyr to SQL for you
- You can be productive immediately

But knowing some SQL helps because:

- You can see what dplyr is doing behind the scenes
- Some complex operations are cleaner in SQL
- You can mix both approaches when needed

Basic SQL Operations (Just for Understanding)

1. Selecting Rows (WHERE = filter())

```r
# dplyr approach (what we'll use most)
seattle_tbl |>
  filter(CheckoutYear == 2020) |>
  head() |>
  collect()
```

```
# A tibble: 6 x 12
  UsageClass CheckoutType MaterialType CheckoutYear CheckoutMonth Checkouts
  <chr>      <chr>        <chr>               <dbl>         <dbl>     <dbl>
1 Physical   Horizon      BOOK                 2020             1         2
2 Digital    OverDrive    EBOOK                2020             1        12
3 Digital    OverDrive    AUDIOBOOK            2020             5         1
4 Digital    OverDrive    EBOOK                2020             5         1
5 Digital    OverDrive    AUDIOBOOK            2020             2         4
6 Digital    OverDrive    EBOOK                2020             2         1
# i 6 more variables: Title <chr>, ISBN <chr>, Creator <chr>, Subjects <chr>,
#   Publisher <chr>, PublicationYear <chr>
```

```r
# SQL equivalent (just for comparison)
dbGetQuery(con, "
  SELECT *
  FROM seattle_checkouts
  WHERE CheckoutYear = 2020
  LIMIT 6
")
```

```
  UsageClass CheckoutType MaterialType CheckoutYear CheckoutMonth Checkouts
1   Physical      Horizon         BOOK         2020             1         2
2    Digital    OverDrive        EBOOK         2020             1        12
3    Digital    OverDrive    AUDIOBOOK         2020             5         1
```

```
4    Digital    OverDrive         EBOOK          2020              5          1
5    Digital    OverDrive     AUDIOBOOK          2020              2          4
6    Digital    OverDrive         EBOOK          2020              2          1
                                                                                   Title
1 The dolphin : two versions, 1972-1973 / Robert Lowell ; edited by Saskia Hamilton.
2                                          Dreaming of You: Gamblers Series, Book 2
3                                                 The New York Stories (Unabridged)
4                                                                         Moving On
5                                                        The Talisman (Unabridged)
6                                                                    Native Speaker
  ISBN                  Creator                      Subjects
1      Lowell, Robert, 1917-1977,                      Poetry
2                    Lisa Kleypas             Fiction, Romance
3                     John O'Hara          Fiction, Literature
4                     Anna Jacobs          Fiction, Literature
5                    Stephen King              Fiction, Horror
6                   Chang-Rae Lee Fiction, Literature, Thriller
                    Publisher PublicationYear
1    Farrar, Straus and Giroux,           2019.
2 HarperCollins Publishers Inc.            2005
3                 Books on Tape            2014
4   Severn House Publishers Ltd            2012
5 Simon & Schuster - Audiobooks            2014
6     Penguin Group (USA), Inc.            2013
```

2. Selecting Columns (SELECT = select()) #### Your Turn

```r
# dplyr approach
seattle_tbl |>
  select(Title, Creator, CheckoutYear) |>
  head() |>
  collect()
```

```
# A tibble: 6 x 3
  Title                                                     Creator CheckoutYear
  <chr>                                                     <chr>          <dbl>
1 Super rich : a guide to having it all / Russell Simmons ~ Simmon~         2016
2 Shadowheart / James Barclay.                              Barcla~         2016
3 Where I'm Reading From: The Changing World of Books       Tim Pa~         2016
4 Little spotted cat / by Alyssa Satin Capucilli ; illustr~ Capuci~         2016
5 Dog & butterfly [sound recording] / Heart.                Heart ~         2016
6 Precalculus the easy way / Larry S. Leff.                 Leff, ~         2016
```

```
# SQL equivalent
dbGetQuery(con, "
  SELECT Title, Creator, CheckoutYear
  FROM seattle_checkouts
  LIMIT 6
")
```

```
                                                                             Title
1       Super rich : a guide to having it all / Russell Simmons with Chris Morrow.
2                                                   Shadowheart / James Barclay.
3                              Where I'm Reading From: The Changing World of Books
4 Little spotted cat / by Alyssa Satin Capucilli ; illustrations by Dan Andreason.
5                                      Dog & butterfly [sound recording] / Heart.
6                                       Precalculus the easy way / Larry S. Leff.
                        Creator CheckoutYear
1               Simmons, Russell         2016
2          Barclay, James, 1965-         2016
3                      Tim Parks         2016
4 Capucilli, Alyssa Satin, 1957-         2016
5          Heart (Musical group)         2016
6              Leff, Lawrence S.         2016
```

3. Grouping and Summarizing (GROUP BY = group_by()) #### Your Turn

```
# dplyr approach (our preferred method)
seattle_tbl |>
  group_by(MaterialType) |>
  summarise(total_checkouts = sum(Checkouts)) |>
  arrange(desc(total_checkouts)) |>
  head() |>
  collect()
```

```
Warning: Missing values are always removed in SQL aggregation functions.
Use `na.rm = TRUE` to silence this warning
This warning is displayed once every 8 hours.
```

```
# A tibble: 6 x 2
  MaterialType total_checkouts
  <chr>                  <dbl>
1 BOOK                64231952
```

```
2 VIDEODISC           31389390
3 EBOOK               18918056
4 SOUNDDISC           14579739
5 AUDIOBOOK            9936233
6 VIDEOCASS            1501066
```

```r
# SQL equivalent
dbGetQuery(con, "
  SELECT MaterialType, SUM(Checkouts) as total_checkouts
  FROM seattle_checkouts
  GROUP BY MaterialType
  ORDER BY total_checkouts DESC
  LIMIT 6
")
```

```
  MaterialType total_checkouts
1         BOOK        64231952
2    VIDEODISC        31389390
3        EBOOK        18918056
4    SOUNDDISC        14579739
5    AUDIOBOOK         9936233
6    VIDEOCASS         1501066
```

The Magic: show_query() - See What dplyr Creates

The best part about **dbplyr** is you can see the SQL translation:

```r
# Write dplyr code and see the SQL it generates
seattle_tbl |>
  filter(CheckoutYear >= 2020) |>
  group_by(MaterialType) |>
  summarise(
    total_checkouts = sum(Checkouts),
    avg_checkouts = mean(Checkouts)
  ) |>
  arrange(desc(total_checkouts)) |>
  show_query()  # This shows you the SQL!
```

```
<SQL>
SELECT
  MaterialType,
```

```
  SUM(Checkouts) AS total_checkouts,
  AVG(Checkouts) AS avg_checkouts
FROM (
  SELECT seattle_checkouts.*
  FROM seattle_checkouts
  WHERE (CheckoutYear >= 2020.0)
) q01
GROUP BY MaterialType
ORDER BY total_checkouts DESC
```

Key Takeaway:

- **Use dplyr** for your analysis (it's what this workshop teaches!)
- **Use `show_query()`** when you're curious about the SQL
- **Use direct SQL** only when you need something dplyr can't do easily

Why This Matters for Big Data

Both dplyr and SQL are **pushed down** to the database:

```
# This entire pipeline runs IN the database, not in R
result <- seattle_tbl |>                    # Connect to table
  filter(CheckoutYear >= 2020) |>           # Database does the filtering
  group_by(MaterialType) |>                 # Database does the grouping
  summarise(total = sum(Checkouts)) |>      # Database does the math
  arrange(desc(total))                      # Database does the sorting
  # Only when we add collect() does data come to R!

# See the result (still in database)
result
```

```
# Source:     SQL [?? x 2]
# Database:   DuckDB v1.1.3 [jmmcclu3@Windows 10 x64:R 4.3.2/C:\Users\jmmcclu3\Documents\usel
# Ordered by: desc(total)
   MaterialType   total
   <chr>          <dbl>
 1 EBOOK        7765062
 2 BOOK         5939939
 3 AUDIOBOOK    4806033
 4 VIDEODISC    1327399
```

```
 5 SOUNDDISC     446323
 6 REGPRINT       51087
 7 MIXED          44497
 8 MUSIC           9043
 9 LARGEPRINT      5267
10 VIDEO           4449
# i more rows
```

```
# Bring it to R memory
final_result <- result |> collect()
```

The Big Idea: Whether you write dplyr or SQL, the **database does the heavy lifting**, not R!

Strategic `mutate()` Placement in Database Workflows (5 minutes)

When working with databases like DuckDB, **where** you place your `mutate()` operations can dramatically affect performance and functionality.

The Golden Rules for `mutate()` with Databases

BEFORE `collect()` (Pushed to Database)

```
# These mutate operations happen IN the database (fast!)
seattle_tbl |>
  mutate(
    #   Simple transformations - database can handle these
    checkout_decade = floor(CheckoutYear/10) * 10,
    is_recent = CheckoutYear >= 2020,
    title_length = LENGTH(Title)  # SQL function
  ) |>
  filter(is_recent == TRUE) |>  # Can filter on the new column!
  collect()
```

```
# A tibble: 6,076,919 x 15
   UsageClass CheckoutType MaterialType CheckoutYear CheckoutMonth Checkouts
   <chr>      <chr>        <chr>               <dbl>         <dbl>     <dbl>
 1 Digital    OverDrive    AUDIOBOOK            2022             9         1
 2 Digital    OverDrive    EBOOK                2022             9         2
 3 Digital    OverDrive    EBOOK                2022             9         3
 4 Digital    OverDrive    EBOOK                2022             9         1
```

```
 5 Digital    OverDrive    EBOOK                2022              9          1
 6 Digital    OverDrive    AUDIOBOOK            2022              9          1
 7 Physical   Horizon      BOOK                 2022              9          2
 8 Digital    OverDrive    AUDIOBOOK            2022              9          1
 9 Physical   Horizon      VIDEODISC            2022              9          2
10 Digital    OverDrive    AUDIOBOOK            2022              9          2
# i 6,076,909 more rows
# i 9 more variables: Title <chr>, ISBN <chr>, Creator <chr>, Subjects <chr>,
#   Publisher <chr>, PublicationYear <chr>, checkout_decade <dbl>,
#   is_recent <lgl>, title_length <dbl>
```

AFTER `collect()` (In R Memory)

```r
# These mutate operations happen in R (slower, but more flexible)
seattle_tbl |>
  collect() |>  # Brings ALL data to R first!
  mutate(
    # Complex R-specific operations
    title_words = str_count(Title, "\\w+"),
    checkout_season = case_when(
      CheckoutMonth %in% c(12,1,2) ~ "Winter",
      CheckoutMonth %in% c(3,4,5) ~ "Spring",
      # ... more complex logic
    )
  )
```

```r
#  SLOW: Bring all data to R, then transform
system.time({
  slow_result <- seattle_tbl |>
    collect() |>  # Loads millions of rows into R!
    mutate(checkout_decade = floor(CheckoutYear/10) * 10) |>
    filter(checkout_decade == 2020)
})

#  FAST: Transform in database, then collect filtered results
system.time({
  fast_result <- seattle_tbl |>
    mutate(checkout_decade = floor(CheckoutYear/10) * 10) |>
    filter(checkout_decade == 2020) |>
    collect()  # Only brings filtered results to R
})
```

When to Use Each Approach

Use `mutate()` BEFORE `collect()` when:	Use `mutate()` AFTER `collect()` when:
Simple math operations	Complex string manipulation with R functions
Date/time extraction	Custom R functions
Basic case_when logic	Advanced statistical calculations
You need to filter on the new column	Complex joins with R objects

Quick Decision Framework

Ask yourself: "Can SQL do this operation?"

- **Yes** → `mutate()` before `collect()`
- **No** → `mutate()` after `collect()`
- **Not sure** → Try before first, move after if it fails!

This strategic placement is one of the key skills that separates good big data analysts from great ones!

Superpower 1: Lightning-Fast Aggregations

Let's compare the same analysis using DuckDB vs. what we might do with regular R

Why this is impressive:

- Processed millions of rows in seconds
- Calculated multiple statistics simultaneously
- All done in the database before bringing results to R

Superpower 2: Window Functions Made Easy

Window functions let you do advanced analytics like rankings, running totals, and comparisons within groups:

```
# Find the top 3 most popular titles each year
top_titles_by_year <- seattle_tbl |>
  group_by(CheckoutYear, Title) |>
  summarise(total_checkouts = sum(Checkouts), .groups = "drop") |>
  group_by(CheckoutYear) |>
  window_order(desc(total_checkouts)) |>
```

```r
  mutate(rank = row_number()) |>
  filter(rank <= 3) |>
  arrange(CheckoutYear, rank) |>
  collect()

# Display results
top_titles_by_year |>
  head(15)  # Show top 3 for first 5 years
```

```
# A tibble: 15 x 4
# Groups:   CheckoutYear [5]
   CheckoutYear Title                                      total_checkouts  rank
          <dbl> <chr>                                                <dbl> <dbl>
 1         2005 <Unknown Title>                                      34189     1
 2         2005 Greatest hits                                         1947     2
 3         2005 Uncataloged Folder or Bag--DWN                        1905     3
 4         2006 <Unknown Title>                                      52396     1
 5         2006 Greatest hits                                         3268     2
 6         2006 Flightplan [videorecording] / Touchstone ~            2564     3
 7         2007 <Unknown Title>                                      47460     1
 8         2007 Greatest hits                                         3170     2
 9         2007 Little Miss Sunshine [videorecording] / B~            2335     3
10         2008 <Unknown Title>                                      45007     1
11         2008 Michael Clayton [videorecording] / Warner~            4957     2
12         2008 No country for old men [videorecording] /~            4693     3
13         2009 <Unknown Title>                                      41854     1
14         2009 Burn after reading [videorecording] / Foc~            6152     2
15         2009 Juno [videorecording] / Fox Searchlight P~            5501     3
```

Advanced Window Functions:

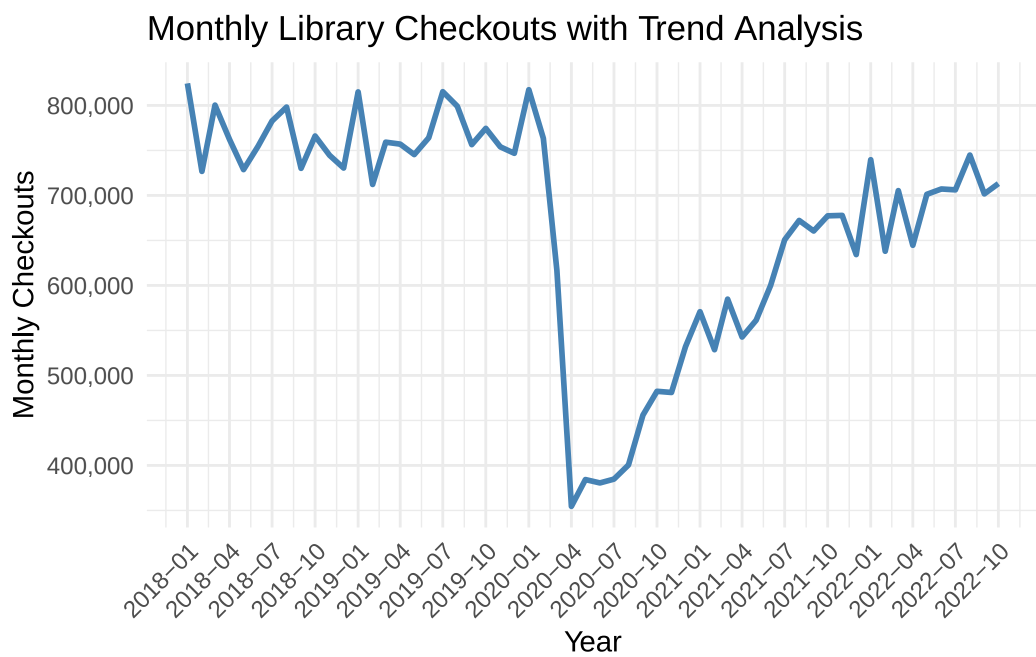
```r
# Calculate running totals and percentage changes
monthly_trends <- seattle_tbl |>
  group_by(CheckoutYear, CheckoutMonth) |>
  summarise(monthly_checkouts = sum(Checkouts), .groups = "drop") |>
  arrange(CheckoutYear, CheckoutMonth) |>
  mutate(
    # Running total throughout the dataset
    cumulative_checkouts = cumsum(monthly_checkouts),
    # Previous month's value for comparison
    prev_month = lag(monthly_checkouts),
```

```r
    # Percentage change from previous month
    pct_change = (monthly_checkouts - prev_month) / prev_month * 100
  ) |>
  collect()
```

```
Warning: ORDER BY is ignored in subqueries without LIMIT
i Do you need to move arrange() later in the pipeline or use window_order() instead?
```

```r
# Visualize the trends
monthly_trends |>
  filter(CheckoutYear >= 2018) |>
  mutate(date = as.Date(paste(CheckoutYear, CheckoutMonth, "01", sep = "-"))) |>
  ggplot(aes(x = date, y = monthly_checkouts)) +
  geom_line(color = "steelblue", size = 1) +
  scale_x_date(date_breaks = "3 months", date_labels = "%Y-%m") +
  scale_y_continuous(labels = scales::comma_format()) +
  theme_minimal() +
  labs(
    title = "Monthly Library Checkouts with Trend Analysis",
    x = "Year",
    y = "Monthly Checkouts"
  ) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```

```
Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.
i Please use `linewidth` instead.
```



Superpower 3: SQL and dplyr Interchangeability

One of DuckDB's greatest strengths is that you can use SQL and dplyr **interchangeably**:

```
# Method 1: Pure dplyr
dplyr_result <- seattle_tbl |>
  filter(CheckoutYear == 2020) |>
  group_by(MaterialType) |>
  summarise(total = sum(Checkouts)) |>
  arrange(desc(total)) |>
  collect()

#inspect
dplyr_result
```

```
# A tibble: 43 x 2
   MaterialType           total
   <chr>                  <dbl>
 1 EBOOK                2793961
 2 AUDIOBOOK            1513625
 3 BOOK                 1241999
 4 VIDEODISC             361587
```

```
 5 SOUNDDISC              116221
 6 MIXED                    9118
 7 REGPRINT                 7573
 8 VIDEO                    2430
 9 MUSIC                    2404
10 SOUNDDISC, VIDEODISC     1049
# i 33 more rows
```

```r
# Method 2: Pure SQL
sql_result <- dbGetQuery(con, "
  SELECT MaterialType, SUM(Checkouts) as total
  FROM seattle_checkouts
  WHERE CheckoutYear = 2020
  GROUP BY MaterialType
  ORDER BY total DESC
")

#inspect
sql_result
```

```
                                  MaterialType   total
1                                        EBOOK 2793961
2                                    AUDIOBOOK 1513625
3                                         BOOK 1241999
4                                    VIDEODISC  361587
5                                    SOUNDDISC  116221
6                                        MIXED    9118
7                                     REGPRINT    7573
8                                        VIDEO    2430
9                                        MUSIC    2404
10                        SOUNDDISC, VIDEODISC    1049
11                                          CR     789
12                                  LARGEPRINT     697
13                                          ER     624
14                                    SOUNDREC     499
15                               ER, VIDEODISC     244
16                                         MAP     202
17                               ER, SOUNDDISC     197
18                                       ATLAS     148
19                                      VISUAL     111
20                                 UNSPECIFIED      62
21                         REGPRINT, SOUNDDISC      30
```

```
22                                       VIDEOREC      19
23                                    MUSICSNDREC      17
24                                      VIDEOCASS      17
25                               ER, NONPROJGRAPH      14
26                                      VIDEOCART      12
27                             REGPRINT, VIDEOREC      10
28                                            KIT       9
29                                      SOUNDCASS       9
30                                    NOTATEDMUSIC      8
31                            SOUNDDISC, SOUNDREC       7
32                           FLASHCARD, SOUNDDISC       6
33                                      MICROFORM       5
34                                      ER, PRINT       3
35                           SOUNDDISC, VIDEOCASS       2
36                           SOUNDCASS, SOUNDDISC       2
37                                      FLASHCARD       1
38 SOUNDCASS, SOUNDDISC, VIDEOCASS, VIDEODISC       1
39                 SOUNDCASS, SOUNDDISC, SOUNDREC       1
40                                        PICTURE       1
41                                   ER, VIDEOREC       1
42                                          PHOTO       1
43                                          GLOBE       1
```

```r
# Method 3: Mixed approach - see the SQL that dplyr generates
seattle_tbl |>
  filter(CheckoutYear == 2020) |>
  group_by(MaterialType) |>
  summarise(total = sum(Checkouts)) |>
  show_query()
```

```
<SQL>
SELECT MaterialType, SUM(Checkouts) AS total
FROM (
  SELECT seattle_checkouts.*
  FROM seattle_checkouts
  WHERE (CheckoutYear = 2020.0)
) q01
GROUP BY MaterialType
```

Real-World Analytics Pipeline (25 minutes)

Exercise 1: Multi-Table Analysis (10 minutes)

Research Question: "How have different categories of library materials (Books, Digital, Video, Audio) performed over time? Are digital formats really growing faster than physical ones?"

This is a perfect question for demonstrating **joins** - one of DuckDB's superpowers! We want to:

- Create a lookup table to categorize our materials
- Join our main data with this categorization
- Analyze trends across categories and formats
- Compare digital vs. physical growth patterns

Step 1: Create a Material Categories Lookup Table #### **Your Turn**

```
# Create a material categories lookup table using dplyr
material_categories <- seattle_tbl |>
  select(MaterialType) |>
  distinct() |>
  mutate(
    category = case_when(
      MaterialType %in% c('EBOOK', 'AUDIOBOOK') ~ 'Digital',
      MaterialType %in% c('BOOK', 'LARGEPRINT', 'REGPRINT') ~ 'Books',
      str_detect(MaterialType, 'VIDEO|DVD') ~ 'Video',
      str_detect(MaterialType, 'SOUND|CD') ~ 'Audio',
      TRUE ~ 'Other'
    ),
    format_type = case_when(
      MaterialType %in% c('EBOOK', 'AUDIOBOOK') ~ 'Digital',
      TRUE ~ 'Physical'
    )
  ) |>
  compute(name = "material_categories")

# Create our reference to the new table (it's already created above)
material_cat <- material_categories

# Look at our categories
```

```r
material_cat |>
  collect()
```

```
# A tibble: 71 x 3
   MaterialType         category format_type
   <chr>                <chr>    <chr>
 1 TELEVISION           Other    Physical
 2 SOUNDREC             Audio    Physical
 3 LARGEPRINT           Books    Physical
 4 REGPRINT, VIDEOREC   Video    Physical
 5 ER, SOUNDREC         Audio    Physical
 6 SOUNDCASS, VIDEOCASS Video    Physical
 7 ER, VIDEOCASS        Video    Physical
 8 FLASHCARD            Other    Physical
 9 EBOOK                Digital  Digital
10 MAP                  Other    Physical
# i 61 more rows
```

Step 2: Try a Complex Join (Let's See What Happens!)

Now let's join our main data with our lookup table:

```r
# Complex analysis combining our main data with categories
category_analysis <- seattle_tbl |>
  left_join(material_cat, by = "MaterialType") |>
  filter(CheckoutYear >= 2018) |>
  group_by(CheckoutYear, category, format_type) |>
  summarise(
    total_checkouts = sum(Checkouts),
    unique_titles = n_distinct(Title),
    avg_checkouts_per_title = total_checkouts / unique_titles,
    .groups = "drop"
  ) |>
  collect()

#Inspect
category_analysis
```

OHHHH NOOO!!!! You got an error. DO you know why? Read on young pawan!

Why This Happens:

- **dbplyr** translates your code to SQL
- SQL doesn't allow you to reference a column you're creating in the same SELECT statement
- The error message is actually quite helpful - it tells you exactly what to do!

The Fix: You need to split this into two steps or use a different approach because SQL can't reference `MaterialType` after you've already transformed it in the same query. You either need to:

1. **Use the original column name throughout**
2. **Split into multiple steps**
3. **Use a subquery approach with compute() between steps**

The SQL engine gets confused when you try to reference a column that's being created in the same statement - it's like trying to use a variable before you've finished declaring it!

Step 3: #### Your Turn** Fix the Code (Your Turn!)**

Update the code above so it will run. **Hint:** Move the calculation to a separate `mutate()` step.

```
# Complex analysis combining our main data with categories
category_analysis <- seattle_tbl |>
  left_join(material_cat, by = "MaterialType") |>
  filter(CheckoutYear >= 2018) |>
  group_by(CheckoutYear, category, format_type) |>
  summarise(
    total_checkouts = sum(Checkouts),
    unique_titles = n_distinct(Title),
    .groups = "drop"
  ) |>
  # Add the calculated column in a separate mutate step
  mutate(avg_checkouts_per_title = total_checkouts / unique_titles) |>
  collect()
```

The key differences are:

1. **In the `summarise()` function:**

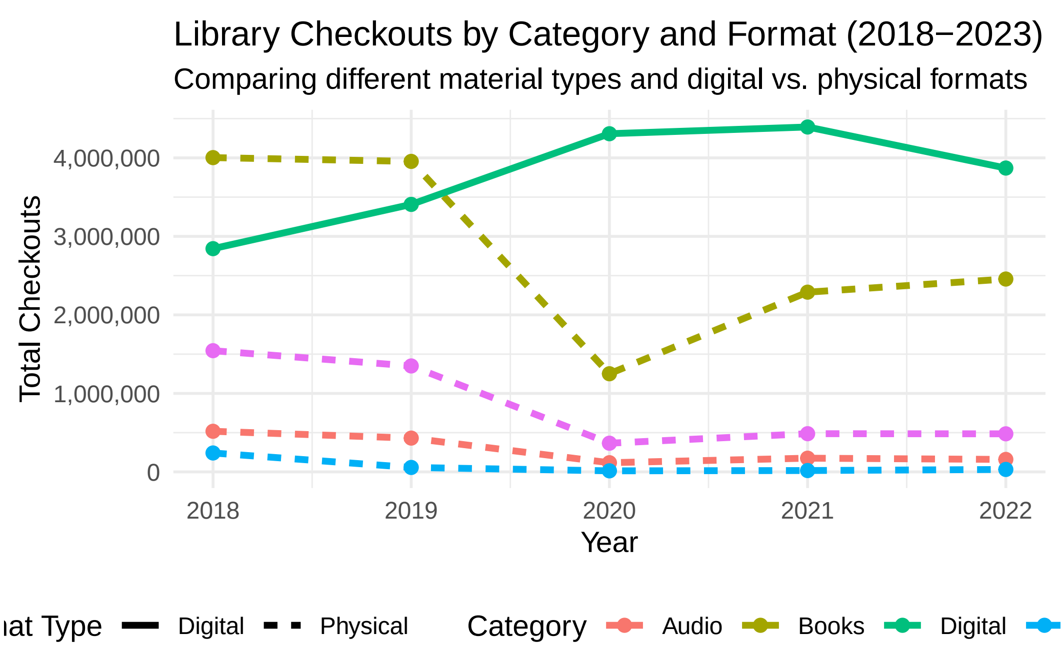
```
-    **REMOVED:** `avg_checkouts_per_title = total_checkouts / unique_titles,`  -    This li
```

2. **ADDED a separate `mutate()` step:**

-    `mutate(avg_checkouts_per_title = total_checkouts / unique_titles) |>`   -   This calcul

Step 4: Visualize the Results

```
# Visualize the category trends
category_analysis |>
  ggplot(aes(x = CheckoutYear, y = total_checkouts,
              color = category, linetype = format_type)) +
  geom_line(size = 1.2) +
  geom_point(size = 2) +
  theme_minimal() +
  labs(
    title = "Library Checkouts by Category and Format (2018-2023)",
    subtitle = "Comparing different material types and digital vs. physical formats",
    x = "Year",
    y = "Total Checkouts",
    color = "Category",
    linetype = "Format Type"
  ) +
  scale_y_continuous(labels = scales::comma) +
  theme(legend.position = "bottom")
```



Step 5: Answer Our Research Question

Turn and Talk (3 minutes):

- What trends do you see in digital vs. physical checkouts?
- Which categories seem most affected by recent changes?
- How might the library use this information for collection development?

Key Learning Points:

- **LEFT JOIN** kept all our checkout records and added category information
- **Two-step calculations** avoid SQL reference errors
- **Complex analysis** becomes manageable when broken into clear steps
- **Real insights** emerge from combining multiple data perspectives

What is a JOIN? (Think of it like dating apps!)

Imagine you have two lists:

- **List A**: People's names and their favorite books
- **List B**: Book titles and their authors

A **JOIN** is like playing matchmaker - you connect the two lists based on something they have in common (the book title)!

Join Type	Dating App Analogy	What it does
INNER JOIN	"Only show matches where both people liked each other"	Only keep records that exist in BOTH tables
LEFT JOIN	"Show all people from List A, even if no book match"	Keep ALL records from left table, add info from right when available
RIGHT JOIN	"Show all books, even if no person likes them"	Keep ALL records from right table (less common)
FULL JOIN	"Show everyone and everything"	Keep ALL records from both tables

Exercise 2: Understanding Joins with our data and duckdb (10 minutes)

Research Question: "Do books with complete author information get checked out more often than books with missing author details?"

This is a great question for learning joins! We want to:

- Compare checkout patterns for books with vs. without author information
- Combine information from multiple "tables" (views of our data)
- Use joins to connect book metadata with checkout statistics

Step 1: Create Book Information Table #### Your Turn

```
# Create books_info with author status
books_info <- seattle_tbl |>
  select(Title, Creator, MaterialType) |>
  filter(MaterialType == "BOOK") |>
  distinct() |>
  mutate(
    has_author = case_when(
      is.na(Creator) | Creator == "" ~ "Missing Author",
      TRUE ~ "Has Author"
    )
  )
```

Your Turn - Inspect what we have**

```
# Check what we have
books_info |>
  head() |>
  collect()
```

```
# A tibble: 6 x 4
  Title                                            Creator MaterialType has_author
  <chr>                                            <chr>   <chr>        <chr>
1 Mountain top mystery / Gertrude Chandler Warn~ Warner~ BOOK         Has Author
2 American lion : Andrew Jackson in the White H~ Meacha~ BOOK         Has Author
3 Wherever you are : my love will find you / Na~ Tillma~ BOOK         Has Author
4 Tricky journeys. #2, Tricky Rabbit tales / Ch~ Schwei~ BOOK         Has Author
5 The mouse on the moon.                           Wibber~ BOOK         Has Author
6 Night Knight / Owen Davey.                       Davey,~ BOOK         Has Author
```

Step 2: Create Checkout Statistics Table

```
# Create checkout_stats
checkout_stats <- seattle_tbl |>
  filter(MaterialType == "BOOK") |>
  group_by(Title) |>
  summarise(
    total_checkouts = sum(Checkouts),
    .groups = "drop"
  )
```

Your Turn - Inspect what we have**

```
# Inspect
checkout_stats |>
  head() |>
  collect()
```

```
# A tibble: 6 x 2
  Title                                                         total_checkouts
  <chr>                                                                   <dbl>
1 Bed of lies : a Chesterton scandal novel / Shelly Ellis.                   27
2 Legends of the Tour / Jan Cleijne.                                         28
3 Robert Jordan's The wheel of time. The eye of the world. Volu~              90
4 Meiguo, zhen de he ni xiang de bu yi yang / Wang Houhou, zhu.              61
5 Smoke jumpers / by R.A. Montgomery ; illustrated by Laurence ~            354
6 The low-FODMAP diet cookbook : 150 simple, flavorful, gut-fri~            376
```

Step 3: INNER JOIN - Books in Both Tables #### **Your Turn**

```
# INNER JOIN - only books that exist in BOTH tables
books_with_checkouts <- books_info |>
  inner_join(checkout_stats, by = "Title") |>
  collect()

# Inspect
books_with_checkouts |>
  head()
```

```
# A tibble: 6 x 5
```

```
  Title                           Creator MaterialType has_author total_checkouts
  <chr>                           <chr>   <chr>        <chr>                <dbl>
1 Arcadia / Lauren Groff.         Groff,~ BOOK         Has Author            1183
2 Craft-a-day : 365 simple hand~ Goldsc~ BOOK         Has Author             366
3 Tian xiang / Wang Anyi, zhu.    Wang, ~ BOOK         Has Author              66
4 Merle's door : lessons from a~ Keraso~ BOOK         Has Author             591
5 Dreaming of the bones / Debor~ Crombi~ BOOK         Has Author              83
6 Summer of the wolves / by Pol~ Carlso~ BOOK         Has Author             204
```

Step 4: Answer Our Research Question

```
# Compare books with vs without author information
author_impact <- books_with_checkouts |>
  group_by(has_author) |>
  summarise(
    book_count = n(),
    avg_checkouts = mean(total_checkouts),
    median_checkouts = median(total_checkouts)
  )

#inspect
author_impact
```

```
# A tibble: 2 x 4
  has_author     book_count avg_checkouts median_checkouts
  <chr>               <int>         <dbl>            <dbl>
1 Has Author         516558         104.                31
2 Missing Author     301065          44.2               11
```

Step 5: Visualize the Results #### Your Turn

```
# Create a simple comparison
author_impact |>
  ggplot(aes(x = has_author, y = avg_checkouts, fill = has_author)) +
  geom_col() +
  theme_minimal() +
  labs(
    title = "Do Books with Author Info Get Checked Out More?",
    x = "Author Information",
    y = "Average Checkouts"
  ) +
  scale_fill_manual(values = c("Missing Author" = "#d73027", "Has Author" = "#1a9850"))
```

Choose Your DuckDB Adventure (15 minutes)

Work in pairs, or by yourself to tackle these real-world analytical challenges or take a brain break:

Beginner Challenge: Popular Authors Analysis

Your Turn

Goal: Analyze the trend from physical to digital library materials over time.

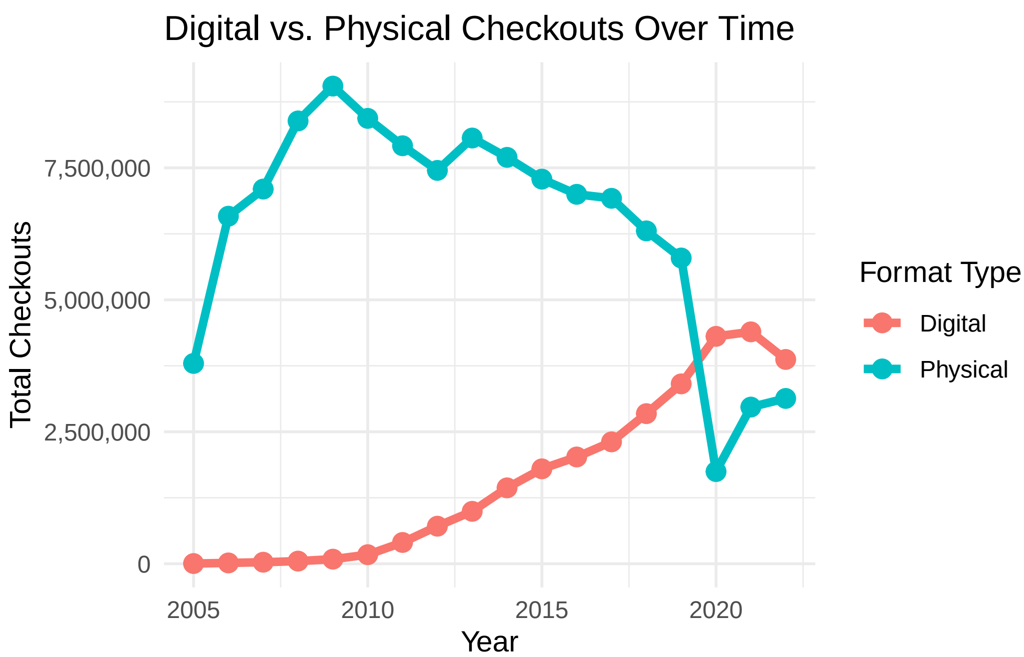
Your mission:

1. Create a list of digital material types
2. Use `case_when()` to classify materials as "Digital" or "Physical"
3. Group by CheckoutYear and format_type
4. Calculate total checkouts per year for each format
5. Create two visualizations: trend lines and percentage breakdown

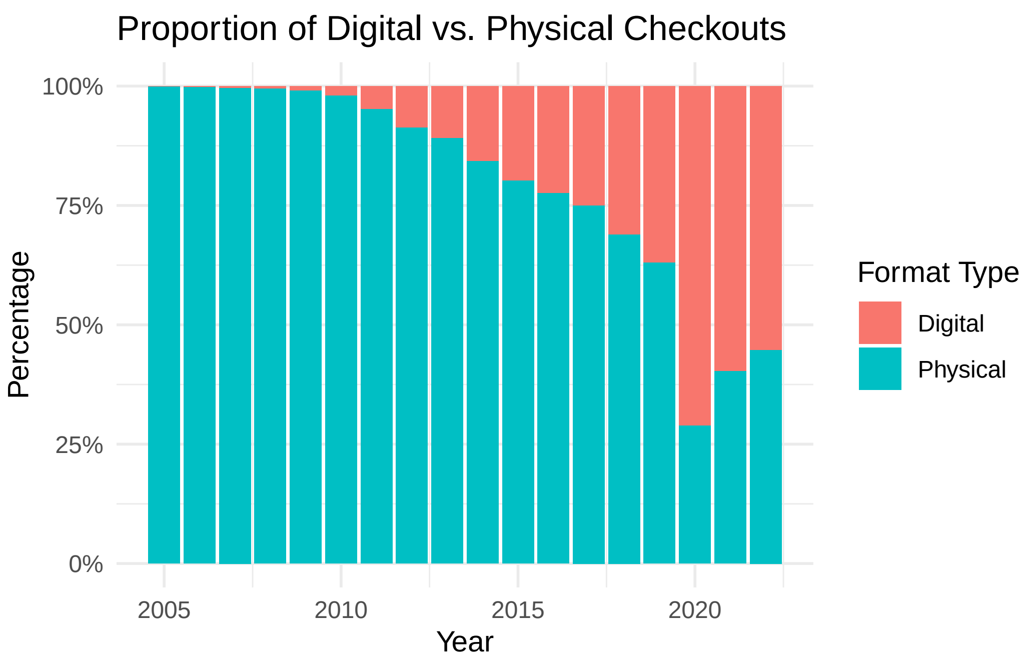
Helpful hints for beginners:

- Use `%in%` to check if MaterialType is in your digital_materials list
- Use `case_when()` with `TRUE ~ "Physical"` as the default case
- Remember to use `.groups = "drop"` in your summarise
- Don't forget to `collect()` before creating visualizations!
- Use `geom_line()` for trends and `geom_col()` for percentages

```r
# Classify materials as digital or physical
digital_materials <- c("EBOOK", "AUDIOBOOK", "DOWNLOAD", "ELECTRONIC RESOURCE")

material_trends <- seattle_tbl |>
  mutate(
    format_type = case_when(
      MaterialType %in% digital_materials ~ "Digital",
      TRUE ~ "Physical"
    )
  ) |>
  group_by(CheckoutYear, format_type) |>
  summarise(total_checkouts = sum(Checkouts, na.rm = TRUE), .groups = "drop") |>
  collect()

# Visualize the trends
ggplot(material_trends, aes(x = CheckoutYear, y = total_checkouts,
                            color = format_type, group = format_type)) +
  geom_line(linewidth = 1.5) +
  geom_point(size = 3) +
  theme_minimal() +
  labs(title = "Digital vs. Physical Checkouts Over Time",
       x = "Year", y = "Total Checkouts", color = "Format Type") +
  scale_y_continuous(labels = scales::comma)
```




```
# percentage of digital vs physical for each year
format_percentages <- material_trends |>
  group_by(CheckoutYear) |>
  mutate(percentage = total_checkouts / sum(total_checkouts) * 100) |>
  arrange(CheckoutYear, format_type)

# Visualize the changing percentages
ggplot(format_percentages, aes(x = CheckoutYear, y = percentage,
                               fill = format_type)) +
  geom_col() +
  theme_minimal() +
  labs(title = "Proportion of Digital vs. Physical Checkouts",
       x = "Year", y = "Percentage", fill = "Format Type") +
  scale_y_continuous(labels = function(x) paste0(x, "%"))
```



Intermediate Challenge: Popular Authors Analysis

Your Turn

Goal: Find the most popular authors by checkout volume and diversity.

Your mission:

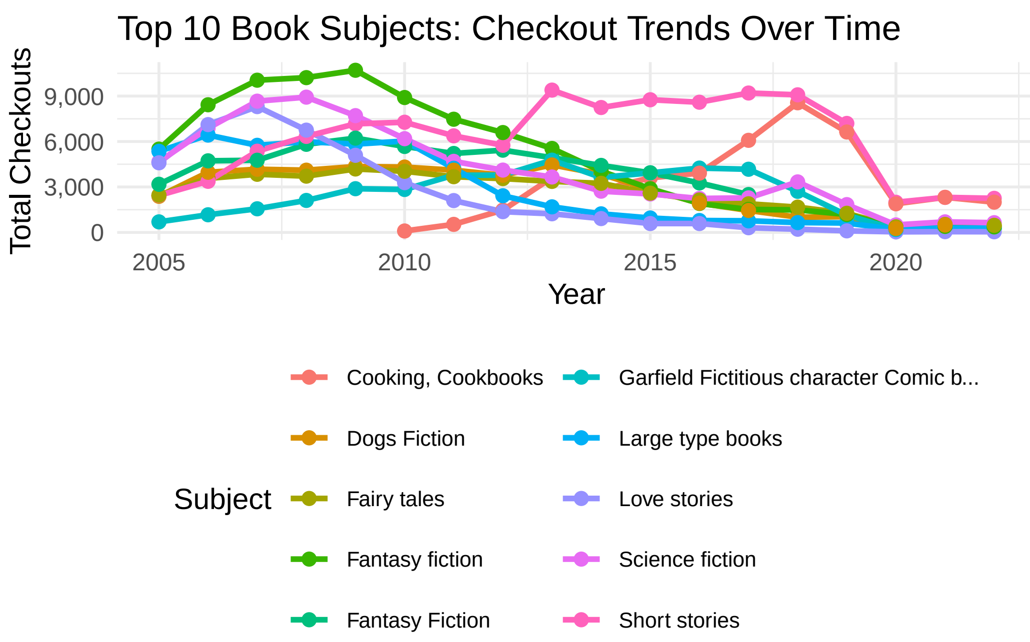
1. Filter to books only and remove missing author information
2. Group by Creator (author)
3. Calculate total checkouts, unique titles, and average checkouts per title
4. Filter to authors with at least 5 different titles
5. Rank by total checkouts and create a horizontal bar chart

Helpful hints for intermediate:

- Use `filter(!is.na(Creator) & Creator != "")` to remove missing authors
- Remember the mutate-after-summarise pattern for calculated columns
- Use `n_distinct(Title)` to count unique titles per author
- Use `coord_flip()` to make horizontal bars

- Use `reorder(Creator, total_checkouts)` to sort bars by value

```
# Step 1: Filter to books only
books_only <- seattle_tbl |>
  filter(MaterialType == "BOOK")

# Step 2: Group by Subjects column and CheckoutYear
# Step 3: Calculate total checkouts per subject per year
subject_analysis <- books_only |>
  filter(!is.na(Subjects) & Subjects != "") |>  # Remove missing subjects
  group_by(Subjects, CheckoutYear) |>
  summarise(total_checkouts = sum(Checkouts), .groups = "drop") |>
  collect()

# Step 4: Find the top 10 subjects by total checkouts
top_subjects <- subject_analysis |>
  group_by(Subjects) |>
  summarise(total_all_years = sum(total_checkouts)) |>
  arrange(desc(total_all_years)) |>
  head(10) |>
  pull(Subjects)

# Filter to just the top 10 subjects for cleaner visualization
top_subject_trends <- subject_analysis |>
  filter(Subjects %in% top_subjects) |>
  mutate(Subjects = str_trunc(Subjects, 40))  # Shorten long subject names

# Step 5: Create a visualization showing trends over time
top_subject_trends |>
  ggplot(aes(x = CheckoutYear, y = total_checkouts, color = Subjects)) +
  geom_line(linewidth = 1) +
  geom_point(size = 2) +
  theme_minimal() +
  labs(
    title = "Top 10 Book Subjects: Checkout Trends Over Time",
    x = "Year",
    y = "Total Checkouts",
    color = "Subject"
  ) +
  scale_y_continuous(labels = scales::comma) +
  theme(legend.position = "bottom", legend.text = element_text(size = 8)) +
  guides(color = guide_legend(ncol = 2))
```




```r
# Bonus: Summary table of top subjects
top_subjects_summary <- subject_analysis |>
  filter(Subjects %in% top_subjects) |>
  group_by(Subjects) |>
  summarise(
    total_checkouts = sum(total_checkouts),
    years_active = n_distinct(CheckoutYear),
    avg_yearly = round(mean(total_checkouts)),
    peak_year = CheckoutYear[which.max(total_checkouts)],
    peak_checkouts = max(total_checkouts)
  ) |>
  arrange(desc(total_checkouts))

top_subjects_summary
```

```
# A tibble: 10 x 6
   Subjects     total_checkouts years_active avg_yearly peak_year peak_checkouts
   <chr>                  <dbl>        <int>      <dbl>     <dbl>          <dbl>
 1 Short stori~          111096           18     111096      2015         111096
 2 Fantasy fic~           87516           18      87516      2006          87516
 3 Science fic~           72277           18      72277      2020          72277
 4 Fantasy Fic~           60078           13      60078      2017          60078
```

```
 5 Large type ~            49486            18      49486      2022            49486
 6 Dogs Fiction            48917            18      48917      2019            48917
 7 Fairy tales             46545            18      46545      2017            46545
 8 Garfield Fi~            44044            18      44044      2011            44044
 9 Cooking, Co~            43511            13      43511      2018            43511
10 Love stories            42690            18      42690      2007            42690
```

Cleanup: Closing Your Database Connection

Always remember to close your database connections when you're done:

```
# Close the DuckDB connection
dbDisconnect(con, shutdown = TRUE)

# Verify it's closed
glue("  DuckDB connection closed successfully")
```

Connection Best Practices:

```
# Method 1: Explicit cleanup (recommended for scripts)
con <- dbConnect(duckdb(), "data/seattle.duckdb")

# ... do your analysis ...
dbDisconnect(con, shutdown = TRUE)

# Method 2:
Automatic cleanup with on.exit() (good for functions)

analyze_library_data <- function()
  {con <- dbConnect(duckdb(), "data/seattle.duckdb")
  on.exit(dbDisconnect(con, shutdown = TRUE))  # Always runs, even if error

# Your analysis code here
result <- tbl(con, "seattle_checkouts") |>
  summarise(total = sum(Checkouts)) |>
    collect()


return(result)
# Connection closes automatically when function exits }
```

```
# Method 3: Check for existing connections

if (exists("con") && !is.null(con)) {dbDisconnect(con, shutdown = TRUE)}
```

Why close connections?

- **Free memory**: Releases database resources
- **Prevent errors**: Avoids "connection already exists" issues
- **Good practice**: Professional database hygiene
- **File locks**: Allows other processes to access the database file

The `shutdown = TRUE` parameter:

- Completely shuts down the DuckDB instance
- Required for persistent databases (those saved to files)
- Ensures the database file is properly closed

Key Takeaways from Module 3

What You've Accomplished Today

Congratulations! You've just:

- Connected R to a high-performance analytical database
- Executed complex joins and aggregations on millions of rows

```
Used window functions for advanced time-series analysis
```

- Leveraged both SQL and dplyr syntax interchangeably
- Built persistent databases for reproducible analytics
- Optimized queries for maximum performance

Essential DuckDB Patterns to Remember

1. **The Connection Pattern**:

```
con <- dbConnect(duckdb(), "database.duckdb")  # Create persistent DB seattle_tbl <- tbl(con
```

2. **The SQL-dplyr Bridge Pattern**:

```
# See what dplyr generates
query |>
  show_query()

# Use SQL directly when needed
  dbGetQuery(con, "SELECT ...")

# Mix both approaches
  tbl(con, "table") |>
    filter(...) |>
    show_query()
```

3. **The Window Function Pattern**:

```
data |>
  group_by(category) |>
  window_order(date) |>
  mutate(rank = row_number(),
         cumulative = cumsum(value),
         pct_change = (value - lag(value)) / lag(value))
```

When to Choose Each Tool

Task	Arrow	DuckDB
Reading large files	Best	Good
Simple filtering	Fast	Fast
Complex joins	Limited	Excellent

Task	Arrow	DuckDB
Window functions	No	Excellent
SQL queries	No	Native
Persistent storage	No	Yes
Memory efficiency	Excellent	Good

Coming Up: Advanced Applications

Now you have the complete toolkit:

- **dplyr**: Intuitive data manipulation grammar
- **Arrow**: Efficient large file processing
- **DuckDB**: Database-powered analytics

In real projects, you'll often use all three:

1. **Arrow** to efficiently read your data
2. **DuckDB** for complex analytics and joins
3. **dplyr** as your consistent interface to both

Quick Self-Assessment

I feel confident that I can:

- Connect R to DuckDB databases
- Choose between Arrow and DuckDB for different tasks
- Use window functions for advanced analytics
- Build reproducible analytical pipelines

I'd like more practice with:

- SQL queries
- Window function syntax
- Performance optimization
- Multi-table joins
- Mixed SQL/dplyr workflows

Ready to apply these tools to your own data? You now have professional-grade capabilities for analyzing datasets of any size!

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