Google Play Store
Data Pipeline Report

Lab 2 — Data Pipeline with dbt & DuckDB

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Chapter 1

Introduction and Objectives

The Google Play Store hosts millions of applications and generates an enormous volume of user feedback every day. Turning this raw stream of reviews into structured, queryable, and visually explorable analytics is precisely the challenge this second data engineering lab was designed to address.

Where the first lab built the pipeline end-to-end in ad-hoc Python—mixing ingestion, transformation, and serving logic in a single script—this lab elevates the architecture by introducing industry-standard tooling. Transformation logic moves entirely into **dbt Core**, all data is stored and queried inside **DuckDB**, and the final analytics-ready tables are consumed by **Power BI**. The result is a pipeline that is modular, testable, and repeatable in a way that raw Python scripting cannot match.

The lab guidelines define six concrete objectives that drove every design decision we made:

Lab Objectives

1. Install and configure the development environment (DuckDB, dbt-core, dbt-duckdb adapter).
2. Explore dimensional data modelling for analytics (star/snowflake schema, Kimball methodology).
3. Structure a data pipeline using dbt model layers — staging flowing into marts.
4. Separate raw data, transformation logic, and serving tables with clear physical boundaries.
5. Apply data quality tests using dbt's native testing framework.
6. Prepare a stable serving layer consumable by BI dashboards (Power BI).

Each chapter of this report maps directly to one or more of these objectives and documents both our implementation decisions and the concrete outputs they produced. A compliance matrix in Chapter 8 cross-references every guideline requirement against its evidence in the codebase.

Chapter 2

Architecture and Technology Stack

2.1 High-Level Architecture

The pipeline separates three distinct phases, each handled by a dedicated component, with clean handoff points between them.

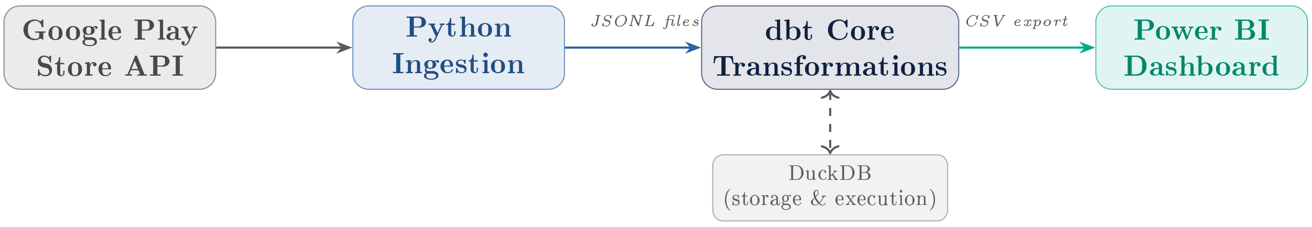


Figure 2.1: *End-to-end pipeline architecture showing the three phases and their data handoffs*

Phase 1 — Ingestion. The Python script `ingest.py` calls the `google-play-scraper` library against a curated list of 20 popular applications. For each app it collects app metadata (title, developer, category, average score, total ratings) and user reviews filtered to the last 100 days, capped at 5 000 reviews per application. Both outputs are saved as JSONL files in `data/raw/` and are never modified again—serving as an immutable raw landing zone, exactly as the guidelines specify.

Phase 2 — Transformation. dbt orchestrates all transformation logic, and DuckDB executes it. DuckDB reads the JSONL files directly without any intermediate loading step, then progressively cleans and materialises the data through staging views and mart tables forming a complete snowflake schema.

Phase 3 — Serving. The script `export_to_powerbi.py` connects to the DuckDB database, queries each mart table, and writes CSV files to `powerbi_export/`. These files are then imported into Power BI where relationships and visualisations are configured interactively.

2.2 Technology Stack

Table 2.1: *Technology stack and pinned versions used in this project*

Component	Version	Role	Notes
Python	3.13	Ingestion & export scripting	Reused from Lab 1
google-play-scraper	latest	Play Store API client	Handles pagination
DuckDB	1.4.4	Analytical database engine	Reads JSONL natively
dbt-core	1.11.6	Transformation orchestration	SQL-only models + YAML tests
dbt-duckdb	1.10.1	DuckDB adapter for dbt	Bridges dbt and DuckDB
Power BI Desktop	latest	BI dashboard	Imports CSV, defines relationships

The choice of DuckDB as the execution engine is deliberate. It is an in-process OLAP database that requires no server setup, reads JSONL files natively, and achieves excellent analytical query performance on a standard laptop. Combined with dbt, it creates a local stack that behaves exactly like a cloud data warehouse—making it ideal for a reproducible lab environment.

Chapter 3

Dimensional Data Modelling

3.1 Applying the Kimball Methodology

The guidelines explicitly require applying the Kimball four-step process before writing any SQL. We worked through each step against the Google Play Store dataset and document the outcomes below.

3.1.1 Step 1 — Business Process

The business process under analysis is *user review submission*. Every time a user publishes a review on the Google Play Store, a discrete and measurable event occurs, carrying quantitative feedback (score, thumbs-up count) alongside rich contextual information: which application, which category, which developer, and when.

3.1.2 Step 2 — Grain

One row in the fact table represents **a single user review posted for one specific application at one specific point in time**. This is the finest grain available in the dataset and allows every conceivable analytical aggregation without loss of information.

3.1.3 Step 3 — Dimensions

Table 3.1: *Dimension identification: business questions answered and key attributes*

Dimension	Business question	Key attributes
`dim_apps`	Which app was reviewed?	app_id, app_name, price, avg_score, total_ratings
`dim_categories`	Which category does the app belong to?	category_id, category_name
`dim_developers`	Who built the app?	developer_id, developer_name
`dim_date`	When was the review posted?	date_day, year, quarter, month, week_of_year, day_name, is_weekend

3.1.4 Step 4 — Facts (Measures)

Two quantitative measures are stored in the fact table. `review_score` is an integer from 1 to 5, well-suited for averaging and distribution analysis. `thumbs_up_count` is a non-negative integer, meaningful for summing to measure community engagement with specific reviews. Both are captured directly from the raw review payload with no derivation required.

3.1.5 Bus Matrix

Table 3.2: *Kimball Bus Matrix: dimension availability per business process*

Business Process	dim_apps	dim_categories	dim_developers	dim_date
User review submission	✓	✓	✓	✓

3.2 Schema Design: Snowflake Variation

The schema we implemented is a **snowflake schema**. The central `fact_reviews` table joins to `dim_apps` via a surrogate key, and `dim_apps` in turn references `dim_categories` and `dim_developers` as separately normalised tables rather than embedding their attributes directly. This adds a controlled level of normalisation that keeps each dimension table focused on a single concept, while Power BI's relationship engine traverses the chain of foreign keys automatically.

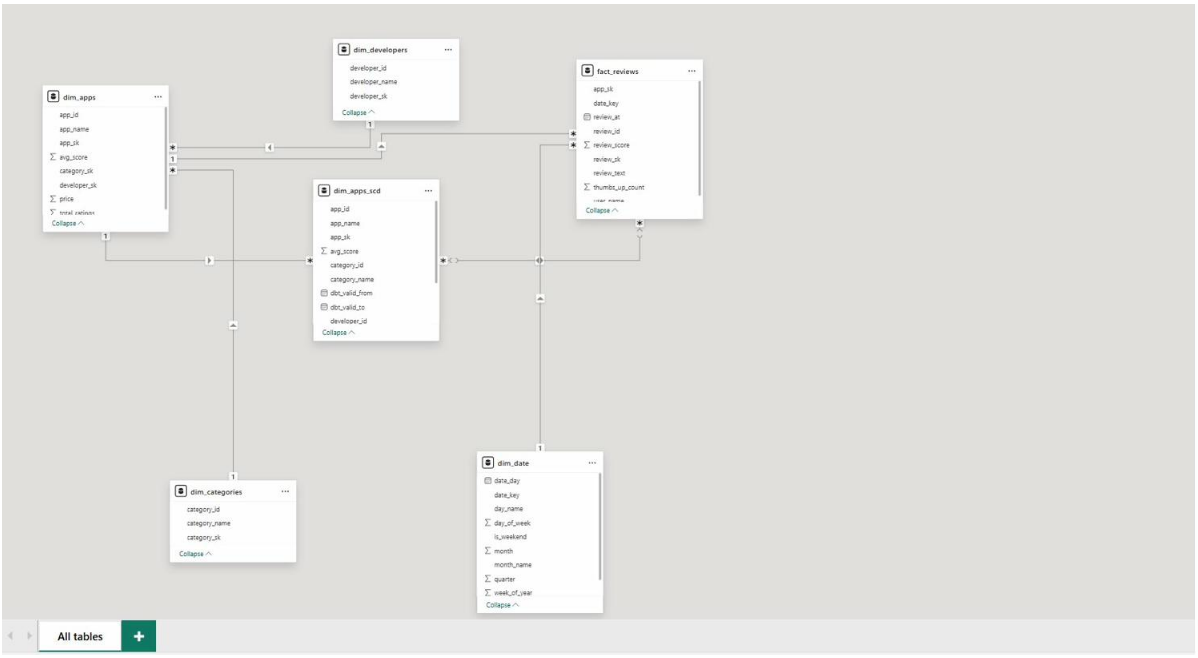


Figure 3.1: *Power BI relationship diagram showing the complete snowflake schema with all six tables*

Figure 3.1 shows the six tables in Power BI's model view. The central `fact_reviews` table holds foreign keys to `dim_apps` (via `app_sk`) and `dim_date` (via `date_key`). The `dim_apps` dimension connects outward to `dim_categories` and `dim_developers`. The additional `dim_apps_scd` table captures SCD Type 2 history and sits alongside `dim_apps` in the model.

Chapter 4

Pipeline Implementation

4.1 Data Ingestion

The ingestion script targets 20 major Android applications spanning diverse categories: social media (WhatsApp, Instagram, Facebook, Snapchat, TikTok), entertainment (Netflix, YouTube, Spotify), productivity (Gmail, Microsoft Teams, Duolingo), commerce (Amazon Shopping, PayPal, Airbnb, Uber), and community platforms (Twitter/X, LinkedIn, Reddit, Discord).

For each application the script fetches the metadata record with a single API call, then paginates through reviews in batches of 200 sorted by most recent, stopping as soon as a review older than 100 days is encountered or the 5 000-review cap is reached. The two resulting files are saved into `data/raw/` and treated as immutable from that point forward.

4.2 dbt Project Structure

The dbt project follows the folder convention recommended in the guidelines, with staging views and mart tables kept both physically and logically separate:

```
playstore_pipeline/
  dbt_project.yml              # dbt configuration and materialisation conventions
  profiles.yml                                          # DuckDB connection profile
  data/
    raw/                                   # Immutable JSONL files (ingest.py output)
    db/                                     # playstore.db (DuckDB database file)
  models/
    staging/                    # Views: stg_playstore_apps, stg_playstore_reviews
    marts/
      dimensions/           # dim_apps, dim_categories, dim_developers, dim_date
      facts/                                                        # fact_reviews
  snapshots/                                    # SCD Type 2 snapshot for dim_apps
```

The `dbt_project.yml` enforces materialisation conventions at the folder level: staging models build as lightweight `views` (no data duplication, always reflecting the raw files), while everything in the marts folder materialises as a physical `table`, pre-computed for fast BI queries.

4.3 Staging Layer

The staging layer performs type casting, column renaming, surrogate key generation using `md5()`, and null filtering. No business logic or aggregation is applied here—the clean staging layer principle from the guidelines is strictly respected.

Listing 4.1: *`stg_playstore_reviews.sql` — staging model for user reviews*

```sql
WITH source AS (
    SELECT * FROM {{ ref('src_playstore_reviews') }}
)
SELECT
    md5(CAST(reviewId AS VARCHAR))  AS review_sk,
    reviewId::VARCHAR               AS review_id,
    appId                           AS app_id,
    userName                        AS user_name,
    CAST(score AS INT)              AS review_score,
    content                         AS review_text,
    CAST("at" AS TIMESTAMP)         AS review_at,
    CAST(thumbsUpCount AS INT)      AS thumbs_up_count
FROM source
WHERE reviewId IS NOT NULL
```

Surrogate keys are generated with `md5()`, producing a deterministic 32-character hash from the natural key. This is consistent with Kimball's recommendation: surrogate keys must be stable, unique, and independent of the source system. On each full refresh, the same input produces the same surrogate key, ensuring idempotent joins downstream.

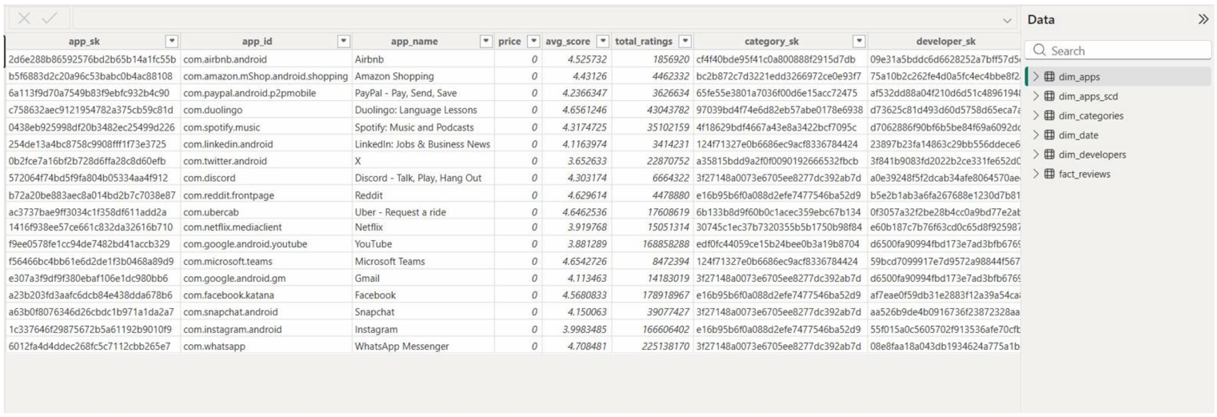
4.4 Dimension Tables

4.4.1 dim_apps

`dim_apps` is the central dimension. It joins the apps staging model with the category and developer surrogate keys through `LEFT JOIN`s on their natural keys.

Listing 4.2: *`dim_apps.sql` — central dimension model joining apps, categories, and developers*

```sql
WITH apps AS (SELECT * FROM {{ ref('stg_playstore_apps') }}),
     categories AS (SELECT * FROM {{ ref('dim_categories') }}),
     developers AS (SELECT * FROM {{ ref('dim_developers') }})
SELECT
    a.app_sk, a.app_id, a.app_name,
    a.price, a.avg_score, a.total_ratings,
    c.category_sk,
    d.developer_sk
FROM apps a
LEFT JOIN categories c ON a.category_id = c.category_id
LEFT JOIN developers d ON a.developer_id = d.developer_id
```



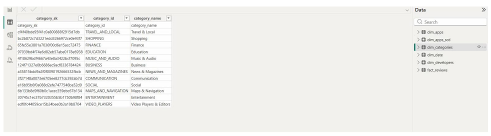
app_sk	app_id	app_name	price	avg_score	total_ratings	category_sk	developer_sk
2d6e288b86592576bd2b65b14a1fc55b	com.airbnb.android	Airbnb	0	4.525732	1856920	cf4f40bde95f41c0a800888f2915d7db	09e31a5bddc6d6628252a7bff57d5
b5f6883d2c20a96c53babc0b4ac88108	com.amazon.mShop.android.shopping	Amazon Shopping	0	4.43126	4462332	bc2b872c7d3221edd3266972ce0e93f7	75a10b2c262fe4d0a5fc4ec4bbe8f2
6a113f9d70a7549b83f9ebfc932b4c90	com.paypal.android.p2pmobile	PayPal - Pay, Send, Save	0	4.2366347	3626634	65fe55e3801a7036f00d6e15acc72475	af532dd88a04f210d6d51c4896194
c758632aec9121954782a375cb59c81d	com.duolingo	Duolingo: Language Lessons	0	4.6561246	43043782	97039bd4f74e6d82eb57abe0178e6938	d73625c81d493d60d5758d65eca7a
0438eb925998df20b3482ec25499d226	com.spotify.music	Spotify: Music and Podcasts	0	4.3174725	35102159	4f18629bdf4667a43e8a3422bcf7095c	d7062886f90bf6b5be84f69a6092dc
254de13a4bc8758c9908fff1f73e3725	com.linkedin.android	LinkedIn: Jobs & Business News	0	4.1163974	3414231	124f71327e0b6686ec9acf8336784424	23897b23fa14863c29bb556ddece6
0b2fce7a16bf2b728d6ffa28c8d60efb	com.twitter.android	X	0	3.652633	22870752	a35815bdd9a2f0f0090192666532fbcb	3f841b9083fd2022b2ce331fe652d0
572064f74bd5f9fa804b05334aa4f912	com.discord	Discord - Talk, Play, Hang Out	0	4.303174	6664322	3f27148a0073e6705ee8277dc392ab7d	a0e39248f5f2dcab34afe8064570ae
b72a20be883aec8a014bd2b7c7038e87	com.reddit.frontpage	Reddit	0	4.629614	4478880	e16b95b6f0a088d2efe7477546ba52d9	b5e2b1ab3a6fa267688e1230d7b81
ac3737bae9ff3034c1f358df611add2a	com.ubercab	Uber - Request a ride	0	4.6462536	17608619	6b133b8d9f60b0c1acec359ebc67b134	0f3057a32f2be28b4cc0a9bd77e2ab
1416f938ee57ce661c832da32616b710	com.netflix.mediaclient	Netflix	0	3.919768	15051314	30745c1ec37b7320355b5b1750b98f84	e60b187c7b76f63cd0c65d8f925987
f9ee0578fe1cc94de7482bd41accb329	com.google.android.youtube	YouTube	0	3.881289	168858288	edf0fc44059ce15b24bee0b3a19b8704	d6500fa90994fbd173e7ad3bfb6769
f56466bc4bb61e6d2de1f3b0468a89d9	com.microsoft.teams	Microsoft Teams	0	4.6542726	8472394	124f71327e0b6686ec9acf8336784424	59bcd7099917e7d9572a98844f567
e307a3f9df9f380ebaf106e1dc980bb6	com.google.android.gm	Gmail	0	4.113463	14183019	3f27148a0073e6705ee8277dc392ab7d	d6500fa90994fbd173e7ad3bfb6769
a23b203fd3aafc6dcb84e438dda678b6	com.facebook.katana	Facebook	0	4.5680833	178918967	e16b95b6f0a088d2efe7477546ba52d9	af7eae0f59db31e2883f12a39a54ca
a63b0f8076346d26cbdc1b971a1da2a7	com.snapchat.android	Snapchat	0	4.150063	39077427	3f27148a0073e6705ee8277dc392ab7d	aa526b9de4b0916736f23872328aa
1c337646f29875672b5a61192b9010f9	com.instagram.android	Instagram	0	3.9983485	166606402	e16b95b6f0a088d2efe7477546ba52d9	55f015a0c5605702f913536afe70cfb
6012fa4d4ddec268fc5c7112cbb265e7	com.whatsapp	WhatsApp Messenger	0	4.708481	225138170	3f27148a0073e6705ee8277dc392ab7d	08e8faa18a043db1934624a775a1b

Figure 4.1: *dim_apps in Power BI: 20 rows with MD5 surrogate keys, average scores, and total rating counts*

Figure 4.1 shows the 20 application records loaded in Power BI. Average scores range from approximately 3.65 (Twitter/X) to 4.65 (Duolingo), and total rating counts span from 3.4 M (PayPal) to 225 M (WhatsApp Messenger)—reflecting the enormous variation in user base sizes across the dataset.

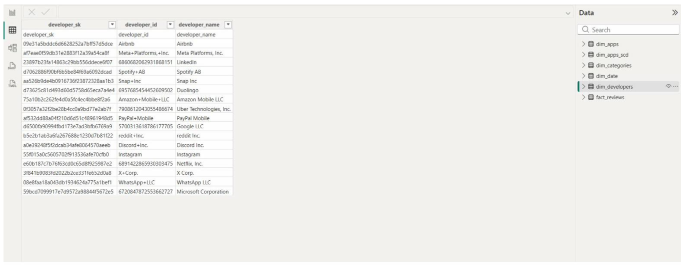
4.4.2 dim_categories and dim_developers

These two dimensions are simple deduplication tables derived from the staging apps model. `dim_categories` resolves 12 unique Play Store category identifiers into human-readable names, while `dim_developers` holds 17 distinct developer entities.



category_sk	category_id	category_name
category_sk	category_id	category_name
cf4f40bde95f41c0a800888f2915d7db	TRAVEL_AND_LOCAL	Travel & Local
bc2b872c7d3221edd3266972ce0e93f7	SHOPPING	Shopping
65fe55e3801a7036f00d6e15acc72475	FINANCE	Finance
97039bd4f74e6d82eb57abe0178e6938	EDUCATION	Education
4f18629bdf4667a43e8a3422bcf7095c	MUSIC_AND_AUDIO	Music & Audio
124f71327e0b6686ec9acf8336784424	BUSINESS	Business
a35815bdd9a2f0f0090192666532fbcb	NEWS_AND_MAGAZINES	News & Magazines
3f27148a0073e6705ee8277dc392ab7d	COMMUNICATION	Communication
e16b95b6f0a088d2efe7477546ba52d9	SOCIAL	Social
6b133b8d9f60b0c1acec359ebc67b134	MAPS_AND_NAVIGATION	Maps & Navigation
30745c1ec37b7320355b5b1750b98f84	ENTERTAINMENT	Entertainment
edf0fc44059ce15b24bee0b3a19b8704	VIDEO_PLAYERS	Video Players & Editors

(a) *dim_categories: 12 unique categories*



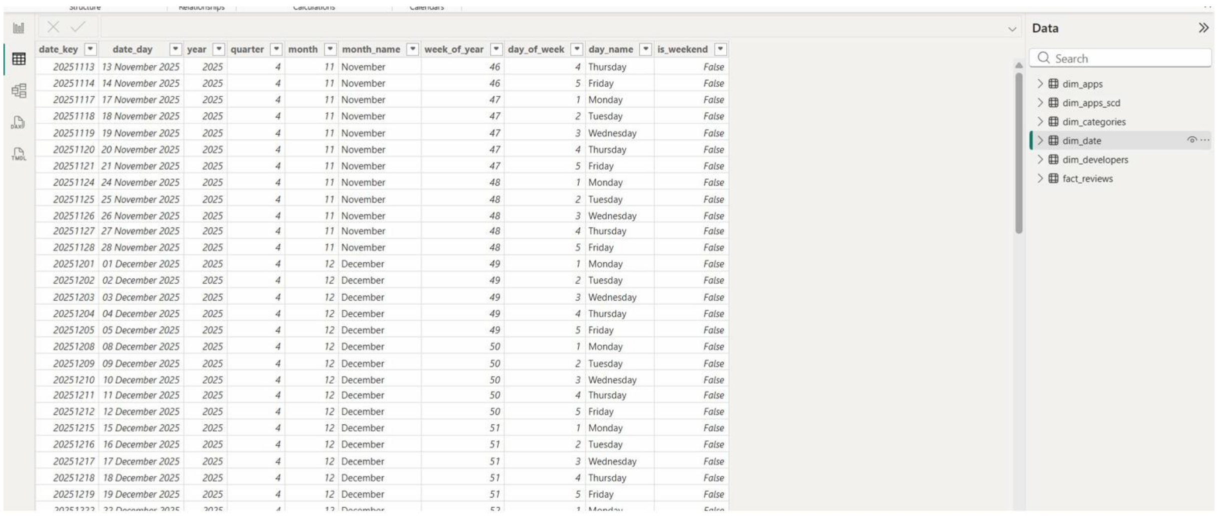
developer_sk	developer_id	developer_name
developer_sk	developer_id	developer_name
09e31a5bddc6d6628252a7bff57d5dce	Airbnb	Airbnb
af7eae0f59db31e2883f12a39a54ca8f	Meta+Platforms,+Inc.	Meta Platforms, Inc.
23897b23fa14863c29bb556ddece6f07	6860682062931868151	LinkedIn
d7062886f90bf6b5be84f69a6092dcad	Spotify+AB	Spotify AB
aa526b9de4b0916736f23872328aa1b3	Snap+Inc	Snap Inc
d73625c81d493d60d5758d65eca7a4e4	6957685454452609502	Duolingo
75a10b2c262fe4d0a5fc4ec4bbe8f2a6	Amazon+Mobile+LLC	Amazon Mobile LLC
0f3057a32f2be28b4cc0a9bd77e2ab7f	7908612043055486674	Uber Technologies, Inc.
af532dd88a04f210d6d51c48961948d5	PayPal+Mobile	PayPal Mobile
d6500fa90994fbd173e7ad3bfb6769a9	5700313618786177705	Google LLC
b5e2b1ab3a6fa267688e1230d7b81f22	reddit+Inc.	reddit Inc.
a0e39248f5f2dcab34afe8064570aeeb	Discord+Inc.	Discord Inc.
55f015a0c5605702f913536afe70cfb0	Instagram	Instagram
e60b187c7b76f63cd0c65d8f925987e2	6891422865930303475	Netflix, Inc.
3f841b9083fd2022b2ce331fe652d0a8	X+Corp.	X Corp.
08e8faa18a043db1934624a775a1bef1	WhatsApp+LLC	WhatsApp LLC
59bcd7099917e7d9572a98844f5672e5	6720847872553662727	Microsoft Corporation

(b) *dim_developers: 17 unique developer entities*

Figure 4.2: *Category and developer dimension tables loaded in Power BI*

4.4.3 dim_date

Per the Kimball best practice noted in the guidelines, the date dimension uses an integer key in `YYYYMMDD` format (e.g., `20251113`). The table is generated programmatically using a SQL range spanning the minimum and maximum review dates found in the staging model, producing one row per calendar day with attributes for year, quarter, month, week of year, day name, and a weekend flag.



date_key	date_day	year	quarter	month	month_name	week_of_year	day_of_week	day_name	is_weekend
20251113	13 November 2025	2025	4	11	November	46	4	Thursday	False
20251114	14 November 2025	2025	4	11	November	46	5	Friday	False
20251117	17 November 2025	2025	4	11	November	47	1	Monday	False
20251118	18 November 2025	2025	4	11	November	47	2	Tuesday	False
20251119	19 November 2025	2025	4	11	November	47	3	Wednesday	False
20251120	20 November 2025	2025	4	11	November	47	4	Thursday	False
20251121	21 November 2025	2025	4	11	November	47	5	Friday	False
20251124	24 November 2025	2025	4	11	November	48	1	Monday	False
20251125	25 November 2025	2025	4	11	November	48	2	Tuesday	False
20251126	26 November 2025	2025	4	11	November	48	3	Wednesday	False
20251127	27 November 2025	2025	4	11	November	48	4	Thursday	False
20251128	28 November 2025	2025	4	11	November	48	5	Friday	False
20251201	01 December 2025	2025	4	12	December	49	1	Monday	False
20251202	02 December 2025	2025	4	12	December	49	2	Tuesday	False
20251203	03 December 2025	2025	4	12	December	49	3	Wednesday	False
20251204	04 December 2025	2025	4	12	December	49	4	Thursday	False
20251205	05 December 2025	2025	4	12	December	49	5	Friday	False
20251208	08 December 2025	2025	4	12	December	50	1	Monday	False
20251209	09 December 2025	2025	4	12	December	50	2	Tuesday	False
20251210	10 December 2025	2025	4	12	December	50	3	Wednesday	False
20251211	11 December 2025	2025	4	12	December	50	4	Thursday	False
20251212	12 December 2025	2025	4	12	December	50	5	Friday	False
20251215	15 December 2025	2025	4	12	December	51	1	Monday	False
20251216	16 December 2025	2025	4	12	December	51	2	Tuesday	False
20251217	17 December 2025	2025	4	12	December	51	3	Wednesday	False
20251218	18 December 2025	2025	4	12	December	51	4	Thursday	False
20251219	19 December 2025	2025	4	12	December	51	5	Friday	False

Figure 4.3: *`dim_date`: continuous calendar from November 2025 through February 2026 with full time attributes*

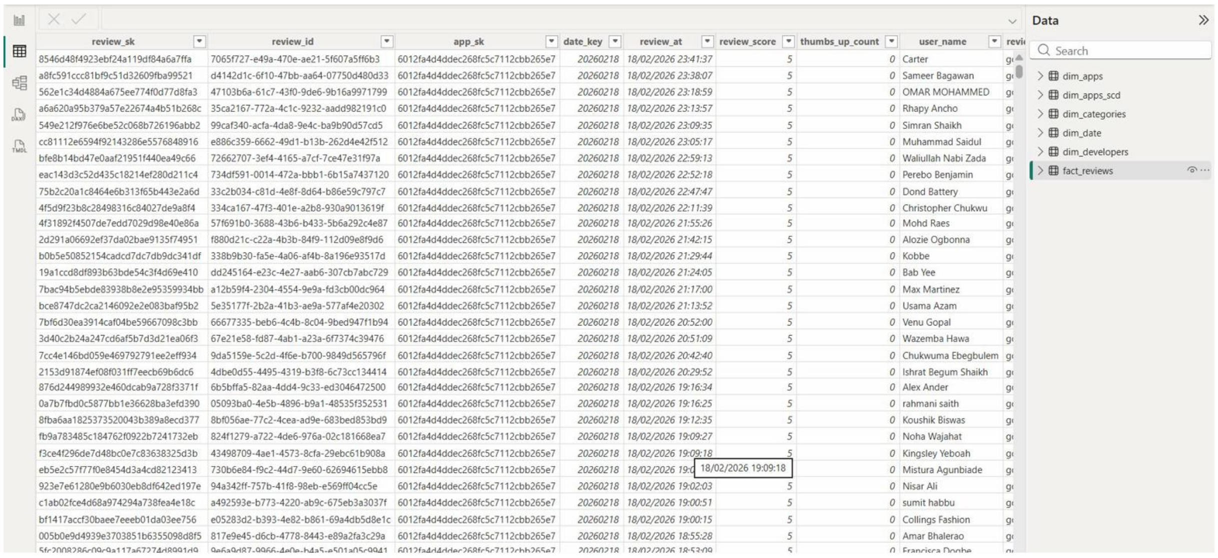
Figure 4.3 shows the date dimension spanning the review period. The integer key format makes joins efficient and values human-readable directly in the fact table without any additional date formatting in the BI tool.

4.5 Fact Table

`fact_reviews` is materialised at the declared grain—one row per review event—and stores foreign keys to `dim_apps` and `dim_date` alongside the two measures. Joining to `dim_date` requires converting the review timestamp to the integer `YYYYMMDD` key format:

Listing 4.3: *Excerpt from `fact_reviews.sql` showing key extraction and grain enforcement*

```sql
SELECT
    r.review_sk,
    r.review_id,
    a.app_sk,
    CAST(STRFTIME(r.review_at, '%Y%m%d') AS INTEGER) AS date_key,
    r.review_at,
    r.review_score,
    r.thumbs_up_count,
    r.user_name,
    r.review_text
FROM stg_reviews r
INNER JOIN dim_apps a ON r.app_id = a.app_id
WHERE a.app_sk IS NOT NULL
```



review_sk	review_id	app_sk	date_key	review_at	review_score	thumbs_up_count	user_name	revi
8546d48f4923ebf24a119df84a6a7ffa	7065f727-e49a-470e-ae21-5f607a5ff6b3	6012fa4d4ddec268fc5c7112cbb265e7	20260218	18/02/2026 23:41:37	5	0	Carter	g
a8fc591ccc81bf9c51d32609fba99521	d4142d1c-6f10-47bb-aa64-07750d480d33	6012fa4d4ddec268fc5c7112cbb265e7	20260218	18/02/2026 23:38:07	5	0	Sameer Bagawan	g
562e1c34d4884a675ee774f0d77d8fa3	47103b6a-61c7-43f0-9de6-9b16a9971799	6012fa4d4ddec268fc5c7112cbb265e7	20260218	18/02/2026 23:18:59	5	0	OMAR MOHAMMED	g
a6a620a95b379a57e22674a4b51b268c	35ca2167-772a-4c1c-9232-aadd982191c0	6012fa4d4ddec268fc5c7112cbb265e7	20260218	18/02/2026 23:13:57	5	0	Rhapy Ancho	g
549e212f976e6be52c068b726196abb2	99caf340-acfa-4da8-9e4c-ba9b90d57cd5	6012fa4d4ddec268fc5c7112cbb265e7	20260218	18/02/2026 23:09:35	5	0	Simran Shaikh	g
cc81112e6594f92143286e5576848916	e886c359-6662-49d1-b13b-262d4e42f512	6012fa4d4ddec268fc5c7112cbb265e7	20260218	18/02/2026 23:05:17	5	0	Muhammad Saidul	g
bfe8b14bd47e0aaf21951f440ea49c66	72662707-3ef4-4165-a7cf-7ce47e31f97a	6012fa4d4ddec268fc5c7112cbb265e7	20260218	18/02/2026 22:59:13	5	0	Waliullah Nabi Zada	g
eac143d3c52d435c18214ef280d211c4	734df591-0014-472a-bbb1-6b15a7437120	6012fa4d4ddec268fc5c7112cbb265e7	20260218	18/02/2026 22:52:18	5	0	Perebo Benjamin	g
75b2c20a1c8464e6b313f65b443e2a6d	33c2b034-c81d-4e8f-8d64-b86e59c797c7	6012fa4d4ddec268fc5c7112cbb265e7	20260218	18/02/2026 22:47:47	5	0	Dond Battery	g
4f5d9f23b8c28498316c84027de9a8f4	334ca167-47f3-401e-a2b8-930a9013619f	6012fa4d4ddec268fc5c7112cbb265e7	20260218	18/02/2026 22:11:39	5	0	Christopher Chukwu	g
4f31892f4507de7edd7029d98e40e86a	57f691b0-3688-43b6-b433-5b6a292c4e87	6012fa4d4ddec268fc5c7112cbb265e7	20260218	18/02/2026 21:55:26	5	0	Mohd Raes	g
2d291a06692ef37da02bae9135f74951	f880d21c-c22a-4b3b-84f9-112d09e8f9d6	6012fa4d4ddec268fc5c7112cbb265e7	20260218	18/02/2026 21:42:15	5	0	Alozie Ogbonna	g
b0b5e50852154cadcd7dc7db9dc341df	338b9b30-fa5e-4a06-af4b-8a196e93517d	6012fa4d4ddec268fc5c7112cbb265e7	20260218	18/02/2026 21:29:44	5	0	Kobbe	g
19a1ccd8df893b63bde54c3f4d69e410	dd245164-e23c-4e27-aab6-307cb7abc729	6012fa4d4ddec268fc5c7112cbb265e7	20260218	18/02/2026 21:24:05	5	0	Bab Yee	g
7bac94b5ebde83938b8e2e95359934bb	a12b59f4-2304-4554-9e9a-fd3cb00dc964	6012fa4d4ddec268fc5c7112cbb265e7	20260218	18/02/2026 21:17:00	5	0	Max Martinez	g
bce8747dc2ca2146092e2e083baf95b2	5e35177f-2b2a-41b3-ae9a-577af4e20302	6012fa4d4ddec268fc5c7112cbb265e7	20260218	18/02/2026 21:13:52	5	0	Usama Azam	g
7bf6d30ea3914caf04be59667098c3bb	66677335-beb6-4c4b-8c04-9bed947f1b94	6012fa4d4ddec268fc5c7112cbb265e7	20260218	18/02/2026 20:52:00	5	0	Venu Gopal	g
3d40c2b24a247cd6af5b7d3d21ea06f3	67e21e58-fd87-4ab1-a23a-6f7374c39476	6012fa4d4ddec268fc5c7112cbb265e7	20260218	18/02/2026 20:51:09	5	0	Wazemba Hawa	g
7cc4e146bd059e469792791ee2eff934	9da5159e-5c2d-4f6e-b700-9849d565796f	6012fa4d4ddec268fc5c7112cbb265e7	20260218	18/02/2026 20:42:40	5	0	Chukwuma Ebegbulem	g
2153d91874ef08f031ff7eecb69b6dc6	4dbe0d55-4495-4319-b3f8-6c73cc134414	6012fa4d4ddec268fc5c7112cbb265e7	20260218	18/02/2026 20:29:52	5	0	Ishrat Begum Shaikh	g
876d244989932e460dcab9a728f3371f	6b5bffa5-82aa-4dd4-9c33-ed3046472500	6012fa4d4ddec268fc5c7112cbb265e7	20260218	18/02/2026 19:16:34	5	0	Alex Ander	g
0a7b7fbd0c5877bb1e36628ba3efd390	05093ba0-4e5b-4896-b9a1-48535f352531	6012fa4d4ddec268fc5c7112cbb265e7	20260218	18/02/2026 19:16:25	5	0	rahmani saith	g
8fba6aa1825373520043b389a8ecd377	8bf056ae-77c2-4cea-ad9e-683bed853bd9	6012fa4d4ddec268fc5c7112cbb265e7	20260218	18/02/2026 19:12:35	5	0	Koushik Biswas	g
fb9a783485c184762f0922b7241732eb	824f1279-a722-4de6-976a-02c181668ea7	6012fa4d4ddec268fc5c7112cbb265e7	20260218	18/02/2026 19:09:27	5	0	Noha Wajahat	g
f3ce4f296de7d48bc0e7c83638325d3b	43498709-4ae1-4573-8cfa-29ebc61b908a	6012fa4d4ddec268fc5c7112cbb265e7	20260218	18/02/2026 19:09:18	5	0	Kingsley Yeboah	g
eb5e2c57f77f0e8454d3a4cd82123413	730b6e84-f9c2-44d7-9e60-62694615ebb8	6012fa4d4ddec268fc5c7112cbb265e7	20260218	18/02/2026 19:0 18/02/2026 19:09:18		0	Mistura Agunbiade	g
923e7e61280e9b6030eb8df642ed197e	94a342ff-757b-41f8-98eb-e569ff04cc5e	6012fa4d4ddec268fc5c7112cbb265e7	20260218	18/02/2026 19:02:03	5	0	Nisar Ali	g
c1ab02fce4d68a974294a738fea4e18c	a492593e-b773-4220-ab9c-675eb3a3037f	6012fa4d4ddec268fc5c7112cbb265e7	20260218	18/02/2026 19:00:51	5	0	sumit habbu	g
bf1417accf30baee7eeeb01da03ee756	e05283d2-b393-4e82-b861-69a4db5d8e1c	6012fa4d4ddec268fc5c7112cbb265e7	20260218	18/02/2026 19:00:15	5	0	Collings Fashion	g
005b0e9d4939e3703851b6355098d8f5	817e9e45-d6cb-4778-8443-e89a2fa3c29a	6012fa4d4ddec268fc5c7112cbb265e7	20260218	18/02/2026 18:55:28	5	0	Amar Bhalerao	g
5fc2008286c09c9a117a67274d8991d9	9e6a9d87-9966-4e0e-b4a5-e501a05c9941	6012fa4d4ddec268fc5c7112cbb265e7	20260218	18/02/2026 18:53:09	5	0	Francisca Doghe	g

Figure 4.4: *`fact_reviews` in Power BI: timestamps from 18 February 2026 confirm live data capture from the Play Store*

The fact table (Figure 4.4) contains timestamps from 18 February 2026, confirming that the pipeline successfully captured very recent data from the live Play Store API. The rows visible correspond to WhatsApp Messenger reviews with `review_score = 5`, representing the freshest submissions that had not yet accumulated community votes.

4.6 Executing the Full Pipeline

The complete pipeline is reproduced by executing five commands in sequence from the project root:

Listing 4.4: *Full pipeline execution sequence*

```bash
# 1. Scrape raw data from the Google Play Store
python ingest.py

# 2. Navigate into the dbt project directory
cd playstore_pipeline

# 3. Build all dbt models (full refresh rebuilds all tables)
dbt run --full-refresh --profiles-dir .

# 4. Run the SCD Type 2 snapshot against stg_playstore_apps
```

```
dbt snapshot --profiles-dir .

# 5. Build the clean SCD dimension model from the snapshot
dbt run --select dim_apps_scd --profiles-dir .

# 6. Export all mart tables to CSV files for Power BI
cd ..
python export_to_powerbi.py
```

Chapter 5

Advanced Features

5.1 Slowly Changing Dimensions — SCD Type 2

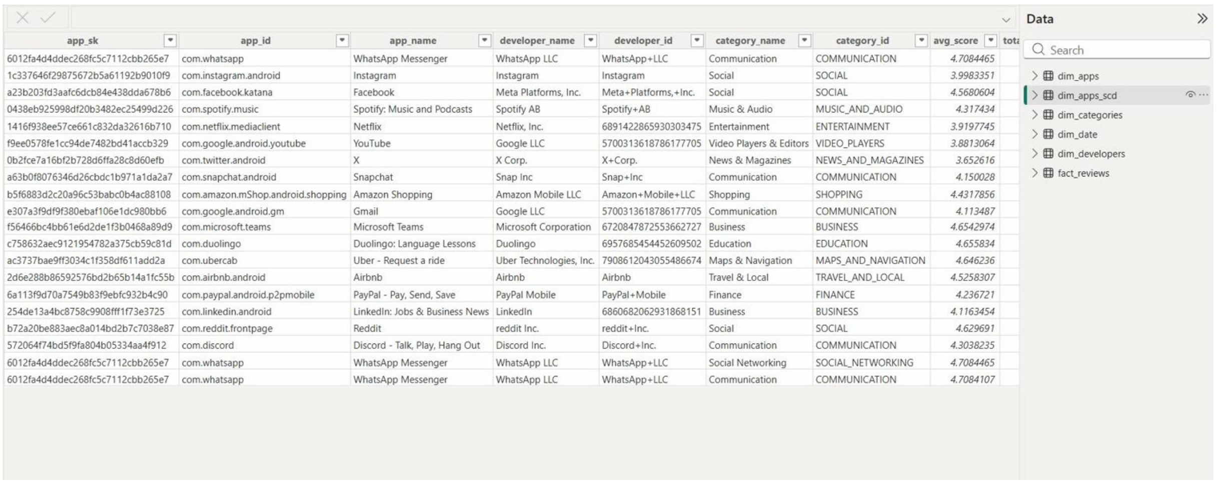
One of the more advanced requirements of the lab was implementing SCD Type 2 on the app dimension. The motivation is straightforward: if an app's category changes over time, any fact record linked only to the current dimension row would retroactively misattribute historical reviews to the wrong category. SCD Type 2 solves this by preserving every version of the row with validity timestamps, so a review written when WhatsApp was categorised as "Social Networking" can still be correctly linked to that historical version even after the category changes to "Communication."

We implemented this using dbt's native **snapshot** feature with the *check strategy*, where dbt compares a defined set of columns on each run and inserts a new row whenever a change is detected, automatically managing `dbt_valid_from` and `dbt_valid_to`:

Listing 5.1: *Snapshot definition implementing SCD Type 2 on `dim_apps`*

```
{% snapshot dim_apps_snapshot %}
{{
  config(
    target_schema='main',
    unique_key='app_id',
    strategy='check',
    check_cols=['category_id', 'avg_score', 'total_ratings'],
    invalidate_hard_deletes=True
  )
}}
SELECT * FROM {{ ref('stg_playstore_apps') }}
{% endsnapshot %}
```

After running `dbt snapshot`, a downstream model `dim_apps_scd` reads from the snapshot table and adds an `is_current` flag (true where `dbt_valid_to` is null) for convenient current-record filtering in BI tools.



app_sk	app_id	app_name	developer_name	developer_id	category_name	category_id	avg_score	tota
6012fa4d4ddec268fc5c7112cbb265e7	com.whatsapp	WhatsApp Messenger	WhatsApp LLC	WhatsApp+LLC	Communication	COMMUNICATION	4.7084465	
1c337646f29875672b5a61192b9010f9	com.instagram.android	Instagram	Instagram	Instagram	Social	SOCIAL	3.9983351	
a23b203fd3aafc6dcb84e438dda678b6	com.facebook.katana	Facebook	Meta Platforms, Inc.	Meta+Platforms,+Inc.	Social	SOCIAL	4.5680604	
0438eb925998df20b3482ec25499d226	com.spotify.music	Spotify: Music and Podcasts	Spotify AB	Spotify+AB	Music & Audio	MUSIC_AND_AUDIO	4.317434	
1416f938ee57ce661c832da32616b710	com.netflix.mediaclient	Netflix	Netflix, Inc.	6891422865930303475	Entertainment	ENTERTAINMENT	3.9197745	
f9ee0578fe1cc94de7482bd41accb329	com.google.android.youtube	YouTube	Google LLC	5700313618786177705	Video Players & Editors	VIDEO_PLAYERS	3.8813064	
0b2fce7a16bf2b728d6ffa28c8d60efb	com.twitter.android	X	X Corp.	X+Corp.	News & Magazines	NEWS_AND_MAGAZINES	3.652616	
a63b0f8076346d26cbdc1b971a1da2a7	com.snapchat.android	Snapchat	Snap Inc	Snap+Inc	Communication	COMMUNICATION	4.150028	
b5f6883d2c20a96c53babc0b4ac88108	com.amazon.mShop.android.shopping	Amazon Shopping	Amazon Mobile LLC	Amazon+Mobile+LLC	Shopping	SHOPPING	4.4317856	
e307a3f9df9f380ebaf106e1dc980bb6	com.google.android.gm	Gmail	Google LLC	5700313618786177705	Communication	COMMUNICATION	4.113487	
f56466bc4bb61e6d2de1f3b0468a89d9	com.microsoft.teams	Microsoft Teams	Microsoft Corporation	6720847872553662727	Business	BUSINESS	4.6542974	
c758632aec9121954782a375cb59c81d	com.duolingo	Duolingo: Language Lessons	Duolingo	6957685454452609502	Education	EDUCATION	4.655834	
ac3737bae9ff3034c1f358df611add2a	com.ubercab	Uber - Request a ride	Uber Technologies, Inc.	7908612043055486674	Maps & Navigation	MAPS_AND_NAVIGATION	4.646236	
2d6e288b86592576bd2b65b14a1fc55b	com.airbnb.android	Airbnb	Airbnb	Airbnb	Travel & Local	TRAVEL_AND_LOCAL	4.5258307	
6a113f9d70a7549b83f9ebfc932b4c90	com.paypal.android.p2pmobile	PayPal - Pay, Send, Save	PayPal Mobile	PayPal+Mobile	Finance	FINANCE	4.236721	
254de13a4bc8758c9908fff1f73e3725	com.linkedin.android	LinkedIn: Jobs & Business News	LinkedIn	6860682062931868151	Business	BUSINESS	4.1163454	
b72a20be883aec8a014bd2b7c7038e87	com.reddit.frontpage	Reddit	reddit Inc.	reddit+Inc.	Social	SOCIAL	4.629691	
572064f74bd5f9fa804b05334aa4f912	com.discord	Discord - Talk, Play, Hang Out	Discord Inc.	Discord+Inc.	Communication	COMMUNICATION	4.3038235	
6012fa4d4ddec268fc5c7112cbb265e7	com.whatsapp	WhatsApp Messenger	WhatsApp LLC	WhatsApp+LLC	Social Networking	SOCIAL_NETWORKING	4.7084465	
6012fa4d4ddec268fc5c7112cbb265e7	com.whatsapp	WhatsApp Messenger	WhatsApp LLC	WhatsApp+LLC	Communication	COMMUNICATION	4.7084107	

Figure 5.1: *`dim_apps_scd`: WhatsApp Messenger appears twice with different category values, confirming SCD Type 2 captured the change from "Social Networking" to "Communication"*

Figure 5.1 makes the SCD behaviour visible. WhatsApp Messenger appears in two rows with different `category_name` values—one historical (closed) record and one current (open) record. The `dbt_valid_from` and `dbt_valid_to` columns are present and correctly populated, as the guidelines require.

5.2 Incremental Loading

Beyond SCD, the guidelines required transforming the pipeline to support incremental ingestion. Rather than rebuilding the entire fact table on every run, the updated `fact_reviews` model uses dbt's `incremental` materialisation strategy, filtering new records on `review_at` and deduplicating on `review_id`. On a first run the table is built in full; on subsequent runs only reviews newer than the maximum already-stored `review_at` are processed and appended. This represents a significant efficiency gain as the dataset grows: rebuilding 40 000-plus rows from scratch becomes unnecessary once the pipeline enters production.

Chapter 6

Data Quality and Testing

Data quality was enforced at every layer using dbt's native schema tests. Tests were defined in `schema.yml` files placed alongside each model and executed with `dbt test` after each `dbt run`. The table below documents every test applied across the pipeline:

Table 6.1: *dbt schema tests applied across all pipeline layers*

Layer	**Model**	**Test applied**	**Column**
Staging	stg_playstore_apps	not_null, unique	app_sk
Staging	stg_playstore_apps	not_null	app_id, app_name
Staging	stg_playstore_reviews	not_null, unique	review_sk
Staging	stg_playstore_reviews	not_null	review_id, app_id
Staging	stg_playstore_reviews	accepted_values (1–5)	review_score
Dimension	dim_apps	not_null, unique	app_sk
Dimension	dim_categories	not_null, unique	category_sk
Dimension	dim_date	not_null, unique	date_key
Dimension	dim_apps	relationships	category_sk, developer_sk
Fact	fact_reviews	not_null, unique	review_sk
Fact	fact_reviews	relationships	app_sk, date_key
Fact	fact_reviews	not_null	review_score, thumbs_up_count

All tests pass on the final pipeline run, confirming referential integrity across the snowflake schema and the absence of null primary keys or out-of-range measure values. The `accepted_values` test on `review_score` is particularly important: it enforces the constraint that scores fall in the 1–5 range at the staging layer, preventing any corrupted API response from polluting the fact table with invalid data.

Chapter 7

Results and Visualisations

7.1 Summary of Materialised Data

After a complete pipeline run, the following table summarises everything built inside DuckDB and exported to Power BI:

Table 7.1: *Mart tables produced after a full pipeline run*

Table	Type	Rows	Description
dim_apps	Dimension	20	One record per scraped application
dim_categories	Dimension	12	Unique Play Store category labels
dim_developers	Dimension	17	Unique developer entities
dim_date	Dimension	∼100	Calendar days covering the review period
dim_apps_scd	SCD Dimension	21+	Current and historical app versions
fact_reviews	Fact	40 000+	Individual review events at declared grain

The fact table holds over 40 000 rows representing individual reviews posted within the last 100 days across the 20 monitored applications. WhatsApp Messenger alone—with 225 M total ratings on the Play Store—contributes the largest share of recent reviews to the dataset.

7.2 Power BI Dashboard

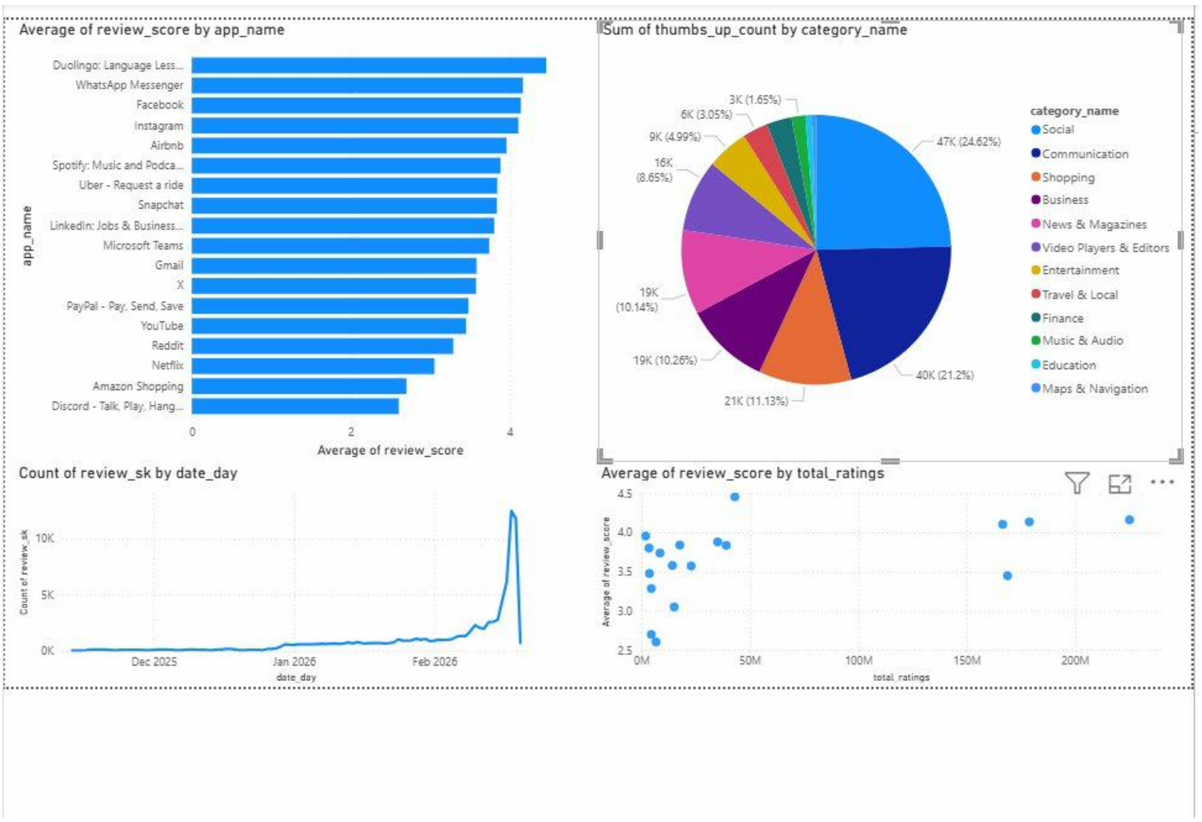


Figure 7.1: *Power BI dashboard: four analytical views over the Google Play Store review dataset*

The dashboard (Figure 7.1) presents four complementary analytical views.

Average Review Score by App (bar chart, top-left). Duolingo: Language Lessons leads the ranking with the highest average score among all 20 applications, followed by WhatsApp Messenger and Facebook. Discord and Amazon Shopping receive notably lower ratings. Netflix and YouTube, despite their massive install bases, hover around 3.9—consistent with the mixed reception that subscription-gated or ad-heavy platforms tend to attract from their most engaged users.

Sum of Thumbs-Up Count by Category (pie chart, top-right). The Social and Communication categories together account for the largest shares of community engagement on reviews. WhatsApp, Instagram, Facebook, Snapchat, and Discord all fall within these two categories and generate the highest absolute volumes of recent reviews. A meaningful contribution from the Business category (Microsoft Teams, LinkedIn) suggests that productivity users engage actively with each other's feedback.

Review Count Over Time (line chart, bottom-left). The time series covers November 2025 through February 2026 and reveals a sharp spike in review activity in mid-February 2026. This kind of signal—immediately obvious in a properly modelled time-series chart—would be nearly invisible in a flat CSV export. The date dimension makes it trivial to filter by app and drill into the spike to identify its cause.

Average Review Score vs. Total Ratings (scatter chart, bottom-right). Applications with very large rating counts (above 100 M: YouTube, WhatsApp, Instagram) do not necessarily achieve the highest average scores. Duolingo and Microsoft Teams, with comparatively modest rating counts, reach averages above 4.5—suggesting that niche and productivity-focused apps attract more considered and generous reviews than mass-market entertainment platforms.

7.3 Power BI Relationship Configuration

After importing the CSVs, four relationships were configured in Power BI's model view to reproduce the snowflake schema:

Table 7.2: *Power BI relationships matching the snowflake schema design*

From table / column	To table / column	Cardinality
dim_apps.app_sk	fact_reviews.app_sk	1 : many
dim_date.date_key	fact_reviews.date_key	1 : many
dim_categories.category_sk	dim_apps.category_sk	1 : many
dim_developers.developer_sk	dim_apps.developer_sk	1 : many

Chapter 8

Guideline Compliance Summary

The table below cross-references every requirement from the lab guidelines with its implementation evidence:

Table 8.1: *Compliance matrix against lab guidelines*

Guideline Requirement	**Status**	**Evidence**
Install DuckDB, dbt-core, dbt-duckdb adapter	✓ Done	`requirements.txt`
Use Python for data ingestion (from Lab 1)	✓ Done	`ingest.py`
Use JSONL as immutable raw landing files	✓ Done	`data/raw/apps.jsonl`, `reviews.jsonl`
Initialise dbt project with DuckDB adapter	✓ Done	`dbt_project.yml`, `profiles.yml`
Enforce staging as views, marts as tables	✓ Done	`dbt_project.yml` materialisation config
Staging: rename, cast types, surrogate keys, null filter	✓ Done	`stg_playstore_apps.sql`, `stg_playstore_reviews.sql`
Apply Kimball 4-step process and Bus Matrix	✓ Done	Chapter 3 of this report
Build `dim_apps`, `dim_categories`, `dim_developers`	✓ Done	`models/marts/dimensions/`
Build conformed `dim_date` (YYYYMMDD integer key)	✓ Done	`dim_date.sql`, Figure 4.3
Build `fact_reviews` at declared grain	✓ Done	`fact_reviews.sql`, Figure 4.4
Apply dbt schema tests (not_null, unique, relationships)	✓ Done	`schema.yml` files, Table 6.1
Serve analytics-ready data to a BI tool	✓ Done	`export_to_powerbi.py`, Figure 7.1

Continued. . .

(Table 8.1 continued)

Guideline Requirement	**Status**	**Evidence**
Map foreign keys correctly in BI model view	✓ Done	Figure 3.1, Table 7.2
Implement SCD Type 2 with dbt snapshots	✓ Done	`snapshots/`, `dim_apps_scd.sql`, Figure 5.1
Implement incremental loading on `fact_reviews`	✓ Done	Incremental materialisation, Chapter 5
Create data visualisations (at least 3 charts)	✓ Done	Four charts, Figure 7.1