

# **DLT tutorial**

## Why `dlt`

- Basic ETL pipeline: Move data from A to B
- Most code is repetitive
- Known loading patterns
- Not many open source frameworks available
  - Airbyte: Works through UI and through YAML files, needs a dedicated server
  - Meltano: Works through CLI and YAML files, not easy to extend
  - `dlt`: Works through Python code

# Why this tutorial?

- Many tutorials exist already
- I don't like *some* things about `dlt`
- Cons
  - Explanations on **core concepts** is not consistent
  - **Code style** in examples is *not* consistent
  - API feels chaotic at times
- Pros
  - Feels like a lightweight framework that can replace a lot of boilerplate code
  - Once you get past the initial learning curve, it is easy to use

A man with a beard and mustache, wearing a grey t-shirt, stands in a workshop filled with pipes and tools. He has his hands behind his head and is looking directly at the camera with a neutral expression.

**Yeah, well you know,  
that's just like your opinion, man.**

# Roadmap

- We are starting with a simple example that loads data from a generator into a `duckdb` database
- We will use `postgres` as a target at some point, to illustrate incremental loading patterns and how to configure credentials
- We will explore different loading patterns: `replace`, `append`, `merge` with `upsert` and `scd2`
- We will explore schema definitions and data contracts
- We will explore `dlt` internals and how to debug pipelines
- We will finish with next steps and recommendations

# **Part 0: Getting started**

There **are three or four** routes to install what's needed to get started with this tutorial:

1. Install python, duckdb and use an external Postgres database from Neon (or your preferred provider)
2. If you have `docker` and `docker compose` installed, use `docker compose` to set up a local Postgres database. Install python and duckdb normally.
3. If you have `docker` and `docker compose` installed, use `devcontainers` to set up everything for you
4. Most simple: Fork this repo and use GitHub Codespaces

**Check the Getting Started part in the [guide](#) for detailed instructions on how to set up your environment**



## Simple example using duckdb

- At its most basic form, `dlt` takes in an iterable that produces dictionaries
- And treats every dictionary as a row and inserts it into a `target`

```
from uuid import uuid4
from typing import Generator
import string

def sample_data() -> Generator[dict, None, None]:
    for x in range(2):
        yield {
            "id": x,
            "name": "Mr. " + string.ascii_letters[x],
            "random_field": uuid4(),
        }
```

If we consume this generator, we get something like

```
>>> list(my_sample_data)
[{'id': 0,
 'name': 'Mr. a',
 'random_field': UUID('e9564071-54ff-4574-9726-be83e92e6240'),
 {'id': 1,
 'name': 'Mr. b',
 'random_field': UUID('8fcd6e92-ea0b-4bd3-9d61-2c248963d7e1')}]
```

`dlt` takes this generator as an argument of `dlt.pipeline` and does its thing

```
import dlt

pipeline = dlt.pipeline(
    pipeline_name="sample_pipeline",
    destination=dlt.destinations.duckdb,
    dataset_name="sample_data",
)

load_info = pipeline.run(
    sample_data,
    table_name="samples",
    write_disposition={
        "disposition": "replace",
    },
)
```

⚠️ data passed to `dlt.pipeline` is not limited to generators. We can pass a list of dictionaries. We use a generator for efficiency.

```
sample_data = [
    {"id": 0, "name": "Mr. a", "random_field": uuid4()},
    {"id": 1, "name": "Mr. b", "random_field": uuid4()},
]

load_info = pipeline.run(
    sample_data,
    table_name="samples",
    write_disposition={
        "disposition": "replace",
    },
)
```

For example, when working with dataframes,

```
import pandas as pd
def my_pandas_data_source():
    df = pd.read_csv("your_custom_data.csv")
    for _, row in df.iterrows():
        yield row.to_dict()
```

dlt works better if the generator yields dictionaries in batches, see

<https://dlthub.com/docs/reference/performance#yield-pages-instead-of-rows>

# **Part 1: A Sample pipeline using DuckDB**

1. GO TO TUTORIAL
2. EXECUTE `python dlt_tutorial/1_sample_pipeline_basic.py`
3. CHECK DUCKDB CONTENTS WITH `sample_pipeline.duckdb -c "select * from sample_data.samples;"`
4. That's it! These are the building blocks for what we'll be covering next

# What just happened?

1. We defined a `generator` that feeds from a list of dictionaries
2. This generator was consumed by a `dlt.pipeline`. It can be a plain *list of dictionaries* too!
3. `pipeline.run` was called, triggering the pipeline execution
4. `dlt` creates a `table` in a `duckdb` database, called `sample_data.samples`

Unknown to you,

1. `dlt` creates three more internal tables that persist the state of the pipeline
2. `dlt` also created a directory in `~/.dlt/pipelines/sample_pipeline`

# What happens when `pipeline.run` is called?

- Extract data
  - Generates a `load package` with a unique `load_id` (`_dlt_load_id`) ([docs](#))
- Normalize
  - Infers schema from data and evolves it if needed
  - Unnest any nested structures
  - Apply schema contracts if present
- Load
  - Runs schema migrations if needed
  - Insert data according to the `write_disposition` and `write_strategy` (more on that later)
  - Updates pipeline state and internal dlt tables

## Using resources and sources

- A **resource** is an (optionally `async`) function that **yields data**. To create a resource, we add the `@dlt.resource` decorator to that function.
- A **source** is a function decorated with `@dlt.source` that returns one or more resources.
- EXECUTE `python dlt_tutorial/2_sample_pipeline_sources.py`

```
+@dlt.resource
def sample_data() -> Generator[dict, None, None]:
    for x in range(2):
        yield {
            }

+@dlt.source
+def sample_source():
+    yield sample_data
+
+
if __name__ == "__main__":
    pipeline = dlt.pipeline(
        pipeline_name="sample_pipeline",
    )

    load_info = pipeline.run(
-        sample_data,
+        sample_source(),
        table_name="samples",
        write_disposition={
            "disposition": "replace",
```

- `dlt` automatically generates configuration **specs** for functions decorated with `@dlt.source`, `@dlt.resource`, and `@dlt.destination`
- For example, **injecting configuration values**

# Injecting configuration values

```
@dlt.source
def sample_source(my_custom_parameter: str = "foo"):
    print(f"Custom parameter value: {my_custom_parameter}")
    yield sample_data
```

```
SAMPLE_PIPELINE__MY_CUSTOM_PARAMETER=bar python dlt_tutorial/2b_sample_pipeline_sources_resources_with_config.py
```

or

```
# .dlt/config.toml
[sample_pipeline]
my_custom_parameter = "bar"
```

Check the [documentation](#) for a full spec on variable precedence.

## **Part 2: Incremental pipeline with postgres**



## Current state

<b>id</b>	<b>name</b>	<b>created_at</b>	<b>updated_at</b>
1	Mr. Mario	2025-10-09 14:40:00	2025-10-09 14:50:00
2	Mr. Luigi	2025-10-08 16:15:00	2025-10-08 16:50:00

## Incoming state

<b>id</b>	<b>name</b>	<b>created_at</b>	<b>updated_at</b>
1	<b>Jumpman</b>	2025-10-09 14:40:00	<b>2025-10-10 11:50:00</b>
3	Ms. Peach	<b>2025-10-12 13:15:00</b>	<b>2025-10-13 13:50:00</b>

How should we update our table?



```
[ WITH with_query [, ...] ]
MERGE INTO [ ONLY ] target_table_name [ * ] [ [ AS ] target_alias ]
    USING data_source ON join_condition
    when_clause [...]
    [ RETURNING [ WITH ( { OLD | NEW } AS output_alias [, ...] ) ]
        { * | output_expression [ [ AS ] output_name ] } [, ...] ]
```

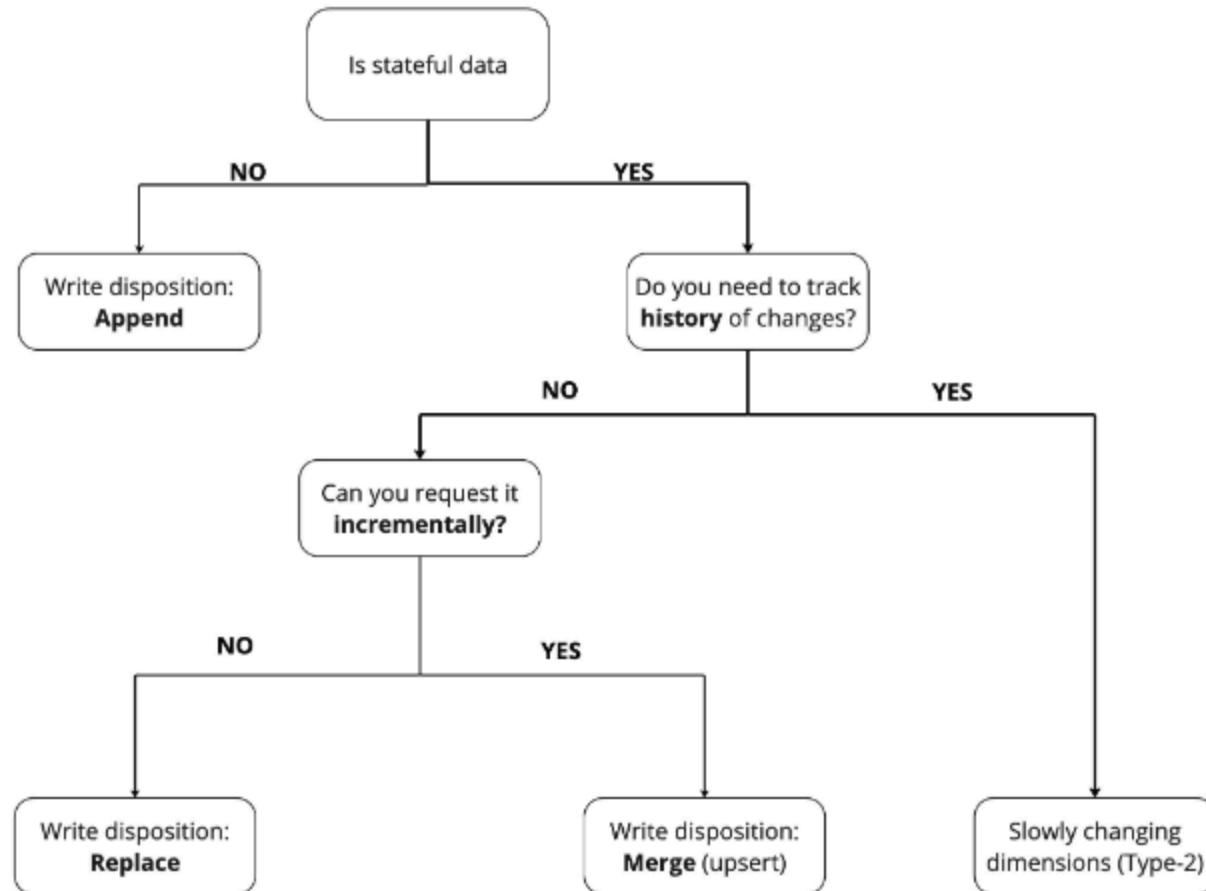
## Write dispositions

1. Write disposition = "replace": Replace the table entirely
2. Write disposition = "append": Load rows incrementally, regardless of their values
3. Write disposition = "merge": Insert only rows that are relevant to the update, e.g.  
that *match* data in target according to some **strategy** and some **key** that allows for identifying matching rows.

## **For the "merge" disposition**

1. "delete-insert"
2. "upsert"
3. "scd2"

dlt summarizes every use case with the following diagram:



# Setting up postgres

## Configuring credentials Defining TOML files

```
mkdir .dlt
touch .dlt/config.toml
touch .dlt/secrets.toml
```

Update these files as

```
# .dlt/secrets.toml
+[sample_pipeline.destination.postgres.credentials]
+host = "localhost"
+port = 5555
+username = "postgres"
+password = "test"
+database = "postgres"
```

or

```
# .dlt/config.toml
sample_pipeline_postgres.destination.postgres.credentials = 'postgresql://postgres:test@localhost:5555/postgres'
```

# Using the "replace" disposition

```
@dlt.resource(
    write_disposition={
        "disposition": "replace",
    },
)
...
    pipeline = dlt.pipeline(
-        pipeline_name="sample_pipeline",
+        pipeline_name="sample_pipeline_postgres",
-        destination=dlt.destinations.duckdb,
+        destination=dlt.destinations.postgres,
        dataset_name="sample_data",
    )
```

```
python dlt_tutorial/3_sample_pipeline_postgres_config.py
```

## Using the "append" disposition

```
+     primary_key="id",
-     write_disposition=
+         "disposition": "replace",
+         "disposition": "append",
},
```

```
python dlt_tutorial/4_sample_pipeline_append.py --refresh
```

Run it again to see how data is appended

```
python dlt_tutorial/4_sample_pipeline_append.py
```

## Using "merge" and "upsert"

```
@dlt.resource(  
+   primary_key="id",  
+   write_disposition={  
-     "disposition": "append",  
+     "disposition": "merge",  
+     "strategy": "upsert",  
},
```

```
python dlt_tutorial/5_sample_pipeline_merge_upsert.py --refresh
```

Run it again to see how data is merged

```
python dlt_tutorial/5_sample_pipeline_merge_upsert.py
```

Run it again with new incoming data to see how data is merged

```
USE_NEW_DATA=1 python dlt_tutorial/5_sample_pipeline_merge_upsert.py --refresh
```

## Using scd2

```
+     primary_key="id",
      write_disposition=
+         "disposition": "merge",
-         "strategy": "upsert",
+         "strategy": "scd2",
      },
```

```
python dlt_tutorial/6_sample_pipeline_merge_scd2.py --refresh
```

Run it again to see how data is merged

```
python dlt_tutorial/6_sample_pipeline_merge_scd2.py
```

Run it again with new incoming data to see how data is merged

```
USE_NEW_DATA=1 python dlt_tutorial/6_sample_pipeline_merge_scd2.py
```

# **Data schema validation**



- The schema describes the **structure** of normalized data
- `dlt` generates schemas from the data during the normalization process.
- Users can affect this standard behavior by providing **hints**
- `dlt` associates a schema with a **source** and a table schema with a **resource**.

In short, `dlt` will **infer** the schema but we can force it to explicit types

1. Using a `dict` specification
2. Using a `Pydantic` model

# Using a dict

```
@dlt.resource(  
    name="sample_data",  
    primary_key="id",  
    write_disposition="replace",  
    +   columns={  
    +       "id": {"data_type": "bigint"},  
    +       "name": {"data_type": "text"},  
    +       "uuid": {"data_type": "text"},  
    +       "created_at": {"data_type": "timestamp"},  
    +       "updated_at": {"data_type": "timestamp"},  
    +   },
```

# Using a Pydantic model

```
+class SampleDataModel(BaseModel):
+    id: int
+    name: str
+    uuid: UUID
+    created_at: dt.datetime
+    updated_at: dt.datetime
+    metadata: SampleDataMetadataModel

@dlt.resource(
    name="sample_data",
    primary_key="id",
    write_disposition="replace",
+    columns=SampleDataModel,
```

## Data contracts

`dlt` handles changes in tables, columns and data types by default. You can set its behaviour explicitly by passing values to the `schema_contract` argument of the `dlt.resource` decorator, such as:

```
@dlt.resource(  
    schema_contract={  
        "tables": "evolve",  
        "columns": "freeze",  
        "data_type": "freeze",  
    })  
def my_resource():  
    ...
```

## **Other tricks and recommendations**



- Pass `PROGRESS=log|tqdm|enlighten` python `script.py` to change the progress bar style ([source](#))
- Stick to one `pipeline.run` per script.
- Use `dlt` for ELT, not for ETL. Transform data as close to the source as possible.
- Send the output of `pipeline.run` to another call to `pipeline.run` to persist execution logs to the same target
- Pass `dev_mode=True` to `dlt.pipeline` for fast iteration ([source](#))
- Separate dev/prod environments using `pipelines_dir` ([source](#))
- `dlt` supports parallel execution through `concurrent.futures` ([source](#))
- Send errors to sentry by setting `runtime.sentry_dsn="https://<...>"` in `config.toml` ([source](#))

## Nested fields

`dlt` is able to serialize from *nested* tables, and it will generate tables for each nested structure (see [docs](#)). For example:

```
data = [
  {
    "id": 1,
    "name": "Alice",
    "pets": [
      {"id": 1, "name": "Fluffy", "type": "cat"},
      {"id": 2, "name": "Spot", "type": "dog"},
    ],
  },
  {"id": 2, "name": "Bob", "pets": [{"id": 3, "name": "Fido", "type": "dog"}]},
]
```

Running a pipeline with `dataset_name='mydata'` and `table_name='users'` Will produce

`mydata.users`

<code>id</code>	<code>name</code>	<code>_dlt_id</code>	<code>_dlt_load_id</code>
1	Alice	wX3f5vn801W16A	1234562350.98417
2	Bob	rX8ybgTeEmAmmA	1234562350.98417

`mydata.users__pets`

<code>id</code>	<code>name</code>	<code>type</code>	<code>_dlt_id</code>	<code>_dlt_parent_id</code>	<code>_dlt_list_idx</code>
1	Fluffy	cat	w1n0PEDzuP3grw	wX3f5vn801W16A	0
2	Spot	dog	9uxh36VU9lqKpw	wX3f5vn801W16A	1
3	Fido	dog	pe3FVtCwz8VuNA	rX8ybgTeEmAmmA	0

**What's next?**



You should now be able to build basic pipelines using `dlt`. Here are some suggestions on what to explore next:

## **Ask the community and the `dlthub` bot on Slack**

If you have questions or need help, you can join the [DLT Slack community](#) and ask your questions there. The community is very active and helpful.

# Using the CLI

`dlt` provides a CLI tool to manage pipelines, and a UI to navigate data visually. See more in the [docs](#)

```
dlt pipeline --list # shows existing pipelines  
dlt pipeline <pipeline_name> show # shows pipeline details using streamlit  
dlt pipeline <pipeline_name> show --dashboard # shows pipeline dashboard using marimo
```

You can query data and inspect the pipeline states, from a streamlit interface!

## Using `dlt init`

`dlt` provides a CLI tool to bootstrap a project

```
dlt init rest_api duckdb
```

This will generate the code shown before and dependencies needed.

1. `rest_api_pipeline.py`
2. `.dlt/` and TOML files
3. `requirements.txt`

You can try this with any other source and/or destination!

```
dlt init rest_api postgres
```

⚠ Beware that the code generated can be at times overwhelming! Check the generated code before running it.

I did not open with this because it makes things complicated right away.

## **Explore more advanced tutorials and courses**

See <https://dlthub.com/docs/tutorial/education> for more



That's all folks! Thank you :)