

A lakehouse for photovoltaic and wind data: Developing with Delta Live Tables and Databricks Asset Bundles

Andreas Haselsteiner

Databricks User Group Vienna #3
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VERBUND AG & VERBUND Green Power at a glance

VERBUND AG

ca. **3,800**
employees¹

12
countries²

ca. **33**
TWh electricity³

VERBUND Green
Power GmbH

ca. **170**
employees

6
countries

ca. **2**
TWh electricity³

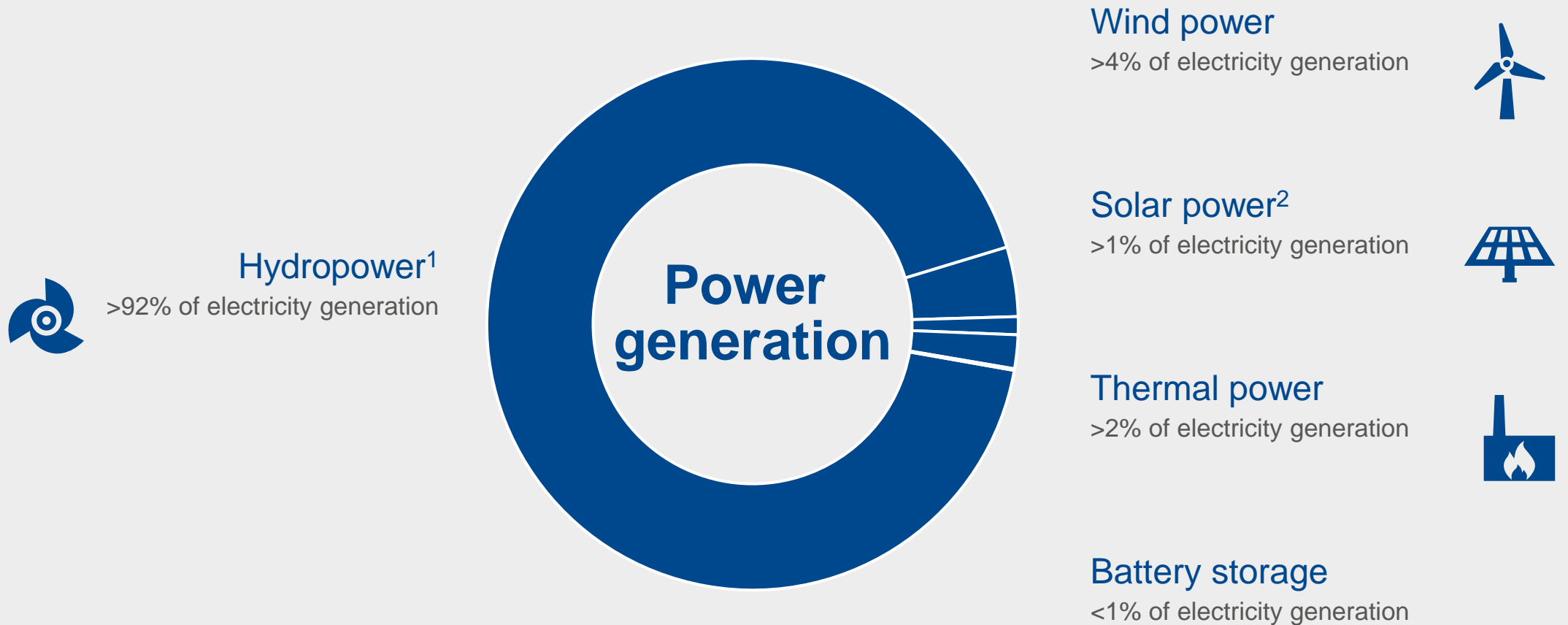


¹ Verbund AG, Integrierter Geschäftsbericht 2023, page 3, https://www.verbund.com/-/media/verbund/ueber-verbund/investor-relations/finanzpublikationen/de/2024/verbund-integrierter_geschaeftsbericht_2023_deutsch.ashx

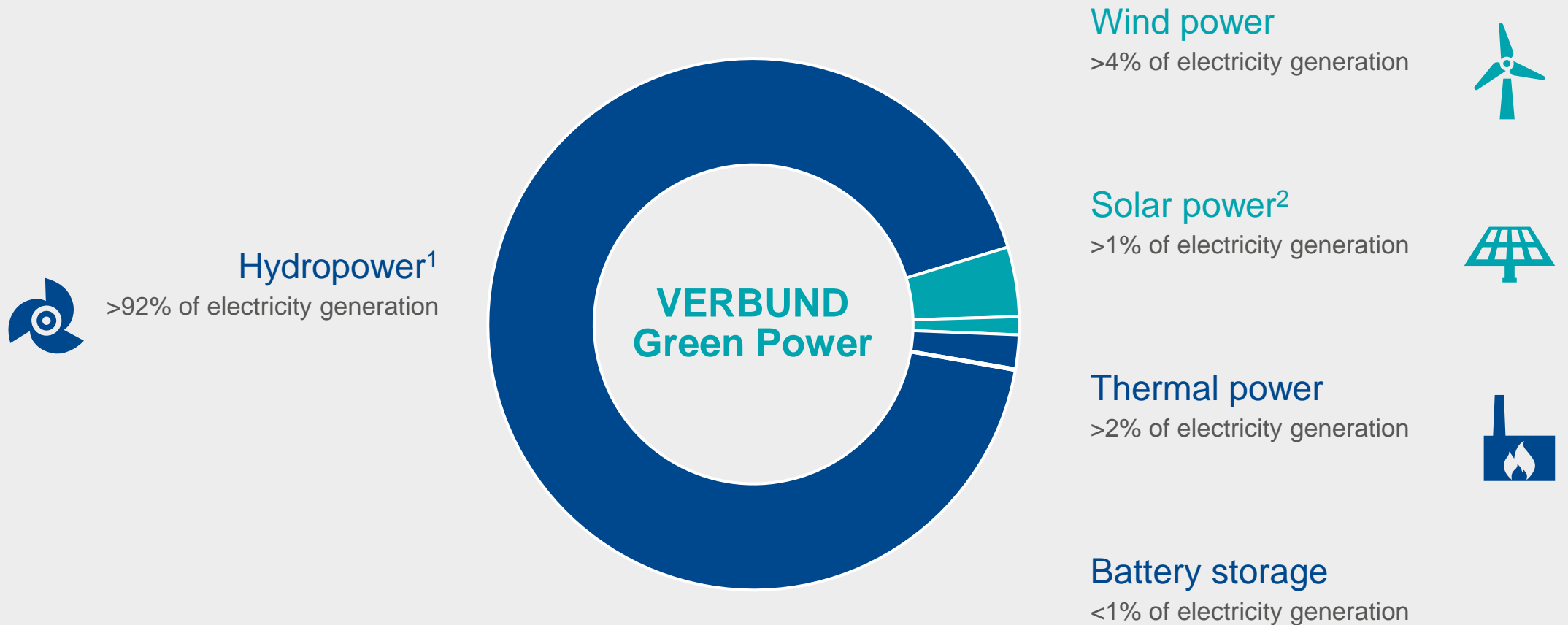
² <https://www.verbund.com/en-at/about-verbund/company>

³ Verbund AG, Integrierter Geschäftsbericht 2023, page 4, https://www.verbund.com/-/media/verbund/ueber-verbund/investor-relations/finanzpublikationen/de/2024/verbund-integrierter_geschaeftsbericht_2023_deutsch.ashx

VERBUND generates 98% from renewable energy sources



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Wind turbines and PV plants produce plenty of interesting data ...



... that need a modern lakehouse somewhere up in the clouds

For our lakehouse version 2, we use two new Databricks features

Delta Live Tables (DLTs) became generally available in 2022¹

Databricks Asset Bundles (DABs) became generally available in 2024²

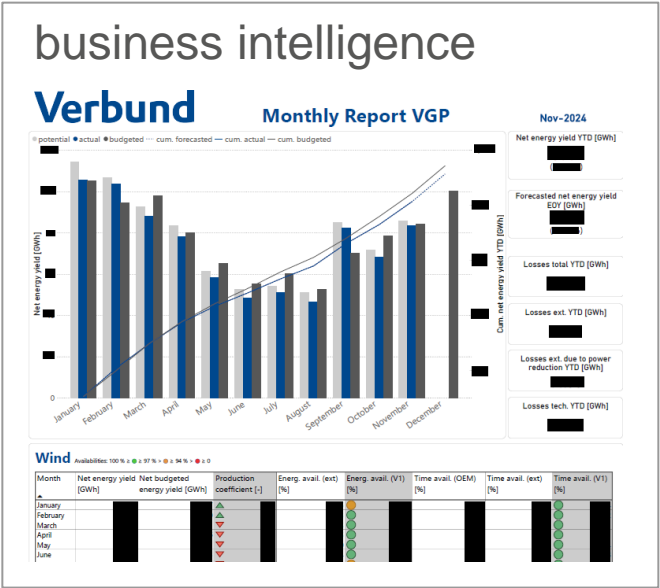
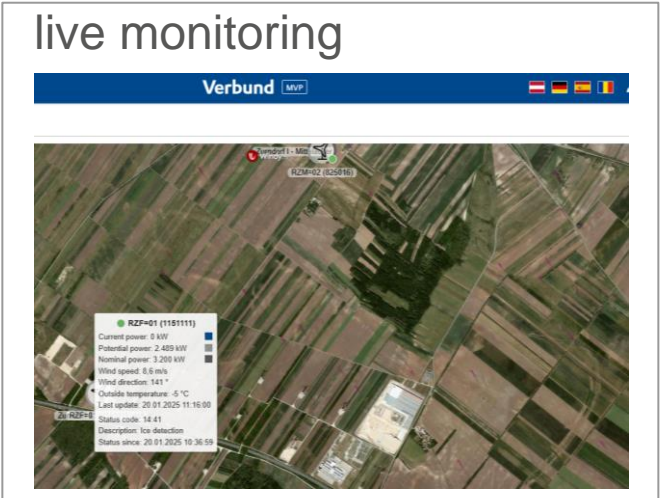
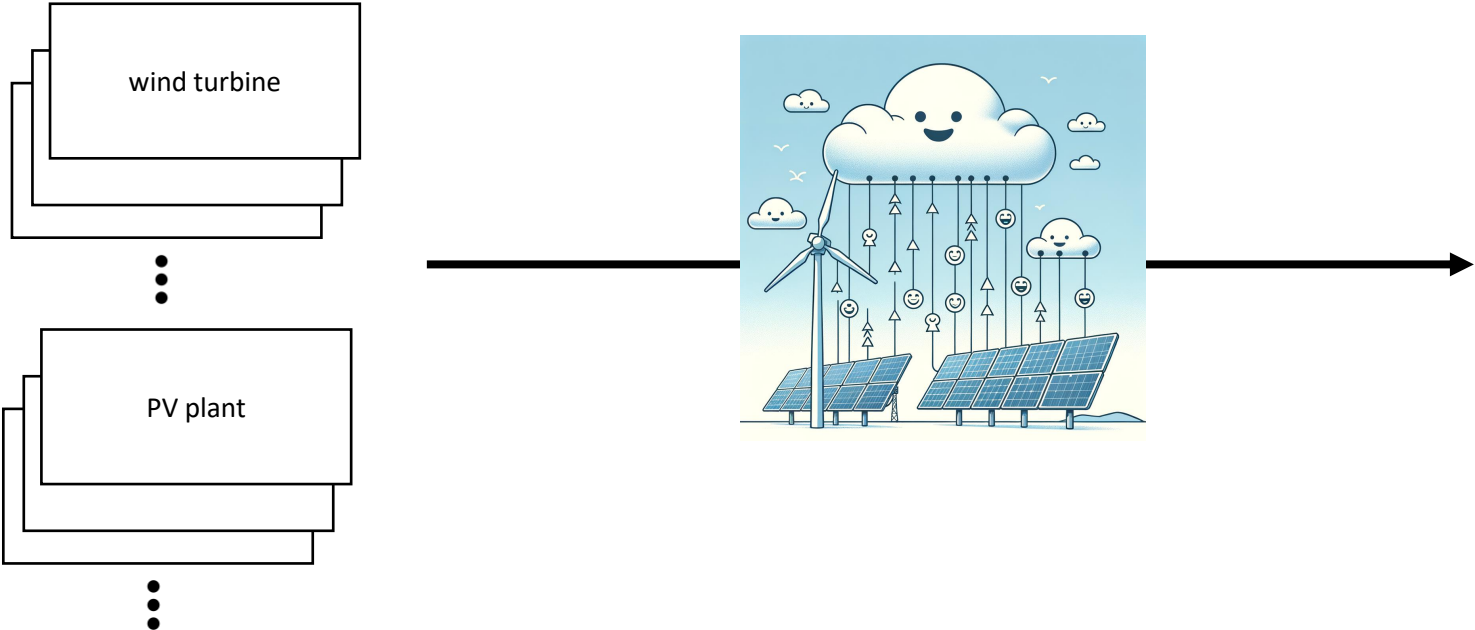
```
@dlt.table
def my_silver_table() -> DataFrame:
    return (
        dlt.read_stream("my_bronze_table").
        transform(transform_to_silver)
    )
```

```
databricks bundle deploy -t dev
```

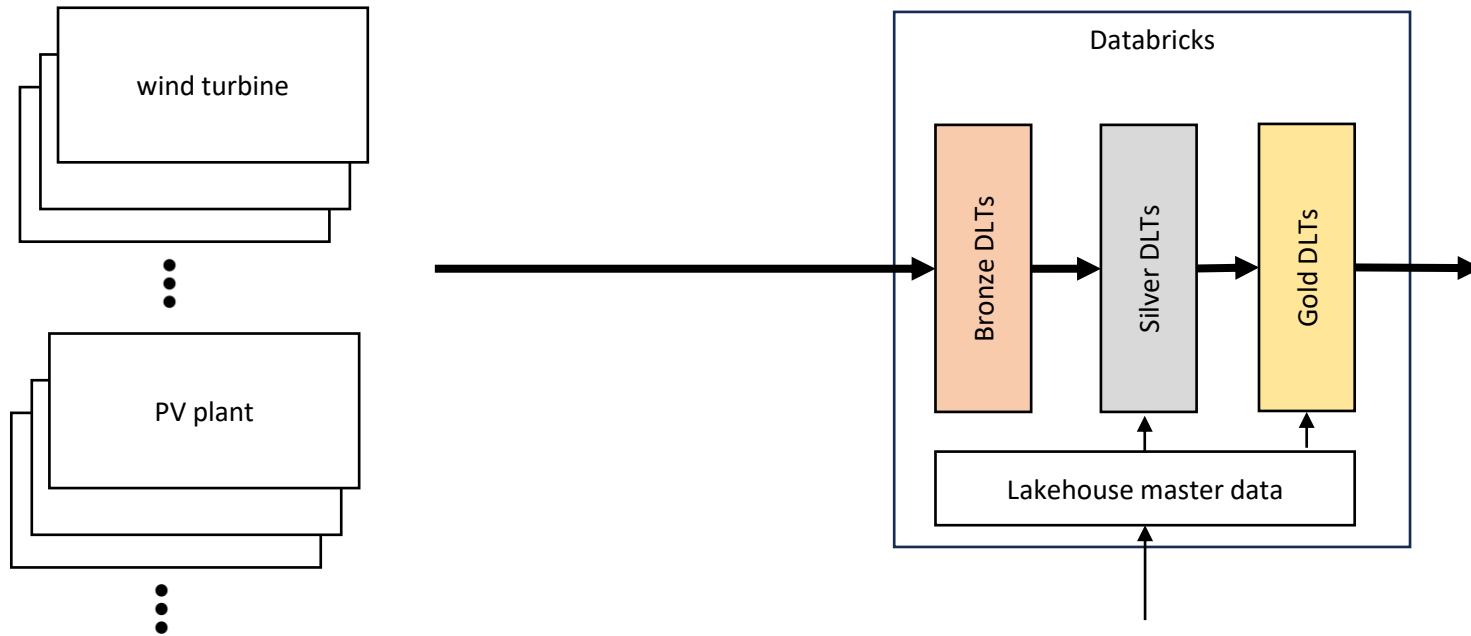
Agenda

1. Our use case: Operational plant data for live monitoring and BI reporting
2. Delta Live Tables: How we use it to stream through bronze, silver, and gold layers
3. Databricks Asset Bundles: How we use it in our development process
4. What's great and what isn't

Our use case: Operational plant data for live monitoring and BI reporting



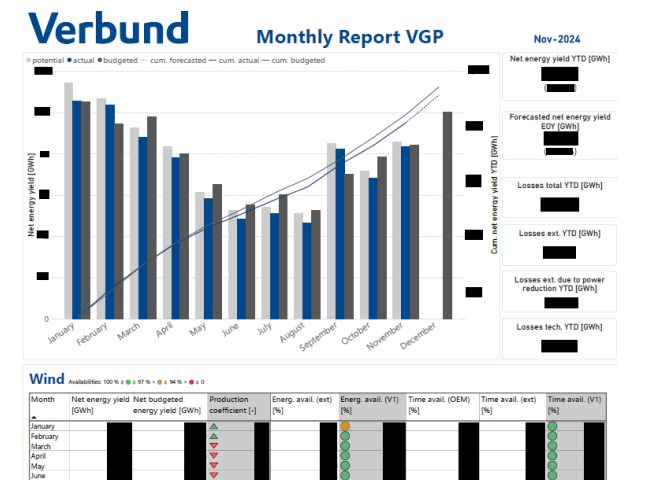
All data are streamed through Databricks



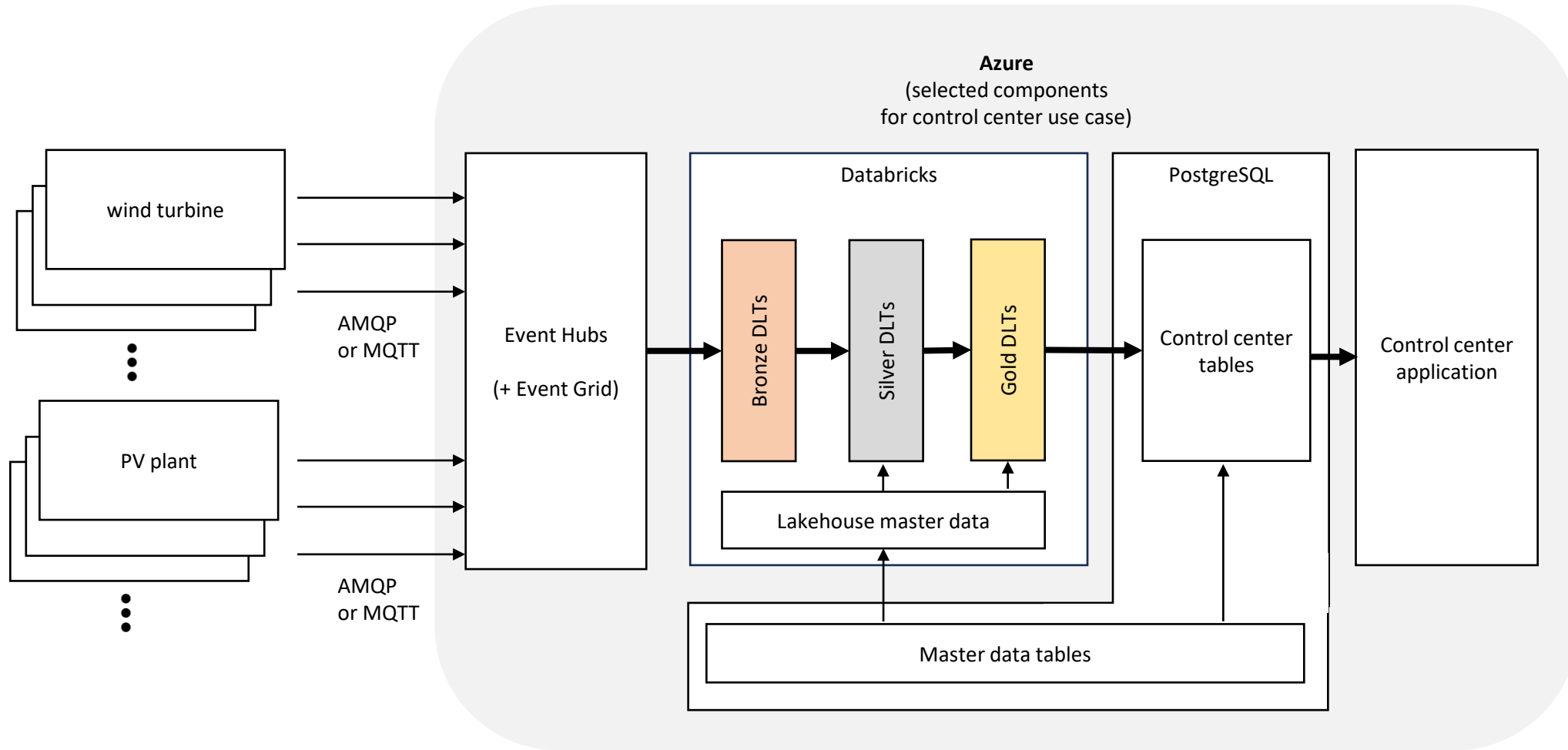
live monitoring



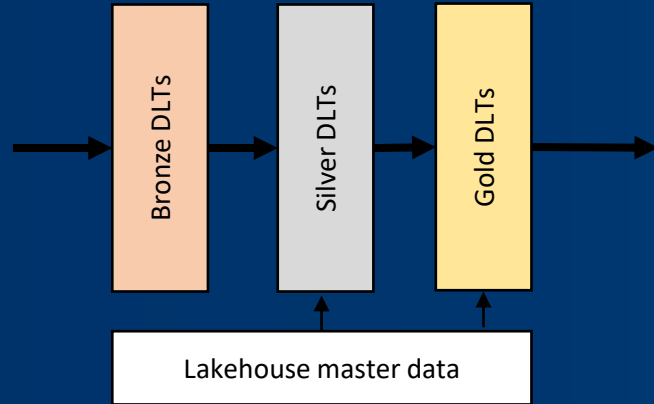
business intelligence



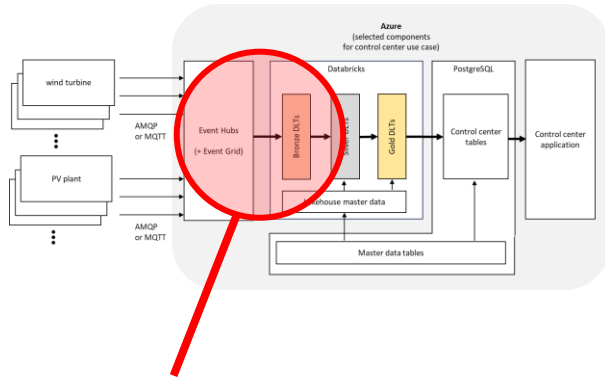
We use message protocols to send data towards the cloud and ingest these data to Databricks from Event Hubs



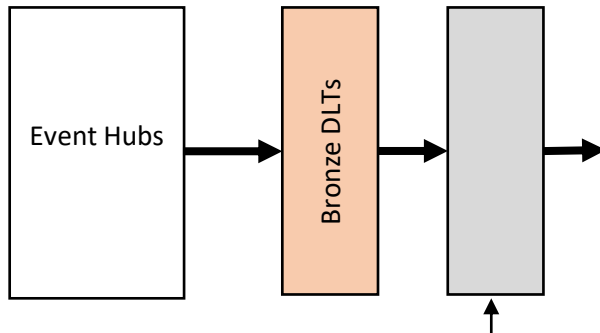
Delta Live Tables



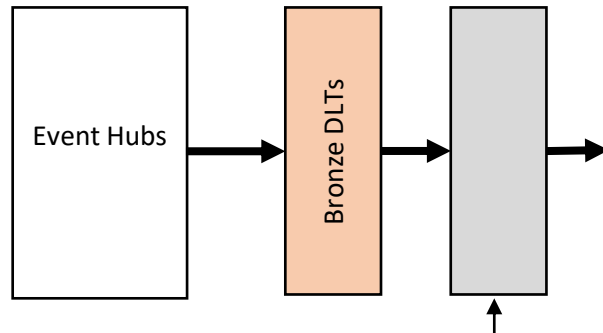
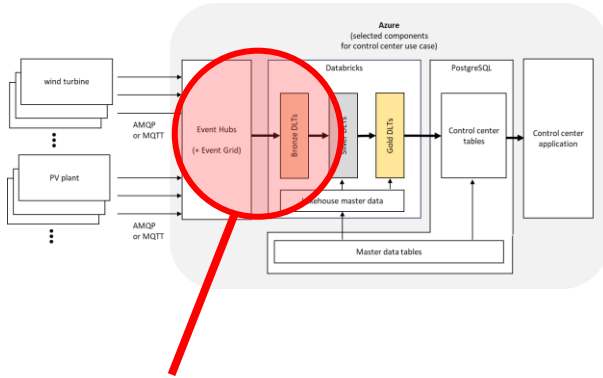
DLT makes ingesting messages into a table straight-forward



```
@dlt.table
def my_bronze_table() -> DataFrame:
    return (
        spark.readStream.format("kafka")
            .options(**kafka_options) # Contains Event Hub name and credentials
            .load()
            .transform(parse_message)
    )
```



DLT makes ingesting messages into a table straight-forward



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    )
```

```
def parse_message(df: DataFrame) -> DataFrame:
    return df.selectExpr(
        "cast(timestamp as timestamp) as _eh_enqueued_ts",
        "current_timestamp() as _inserted_at_ts",
        "cast(value as string) as payload", # Actual message
    )
```

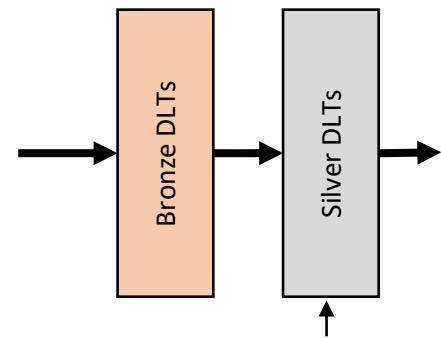
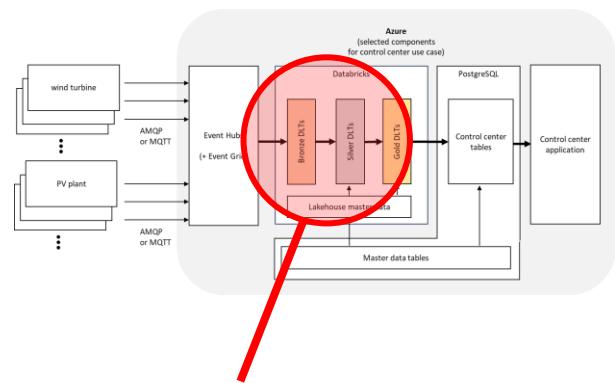
Our bronze table holds raw JSON messages

my_bronze_table

_eh_enqueued_ts ¹	_inserted_at_ts	payload
2025-01-22T17:40:12.371+00:00	2025-01-22T17:40:14.422+00:00	{ "turbine_id": "RG15", "measurement_ts": "2025-01-22T17:40:11.371894Z", "data": { "WTUR.W": 67000, "WMET.HorWdSpd": 4.3, "WMET.HorWdDir": 134.5, ... } }
2025-01-22T17:40:42.560+00:00	2025-01-22T17:40:44.119+00:00	{ "turbine_id": "RG15", "measurement_ts": "2025-01-22T17:40:41.050264Z", "data": { "WTUR.W": 67000, "WMET.HorWdSpd": 4.4, "WMET.HorWdDir": 137.1, ... } }

¹ Some people like to add an underscore prefix to technical columns: <https://towardsdatascience.com/best-practices-for-technical-columns-in-database-design-f3fce9357426>

Append-only operations like extracting and casting JSON values work well

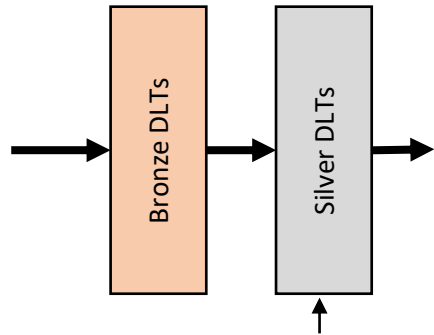
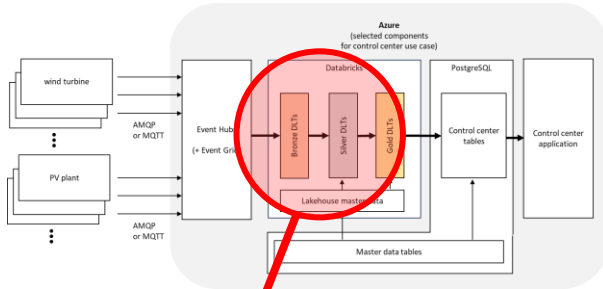


```
@dlt.table
def my_silver_table() -> DataFrame:
    return dlt.read_stream("my_bronze_table").transform(transform_bronze_to_silver)
```

my_bronze_table

_eh_enqueued_ts	_inserted_at_ts	payload
		{ "turbine_id": "RG15", "measurement_ts": "2025-01-22T17:40:11.371894Z", "data": { "WTUR.W": 67000, "WMET.HorWdSpd": 4.3, "WMET.HorWdDir": 134.5, ... } }

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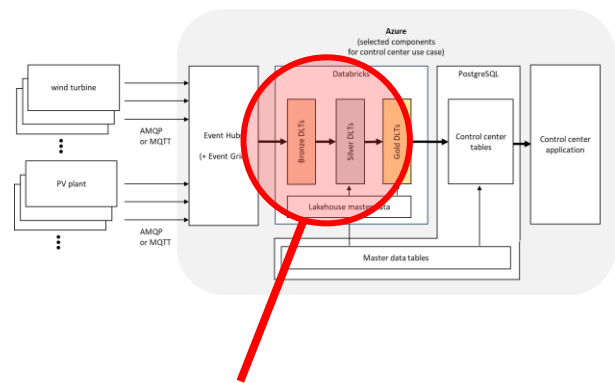
```
from pyspark.sql import functions as F

def transform_bronze_to_silver(df: DataFrame) -> DataFrame:
    """Transforms the DataFrame to [turbine_id, measurement_ts, wind_speed_ms]"""

    expression_for_id = F.get_json_object("payload", "$['turbine_id']").alias(
        "turbine_id"
    )
    expression_for_timestamp = (
        F.get_json_object("payload", "$['measurement_ts']")
        .cast(TimestampType())
        .alias("measurement_ts")
    )
    expression_for_wind_speed = (
        F.get_json_object("payload", "$['data']['WMET.HorWdSpd']")
        .cast(DoubleType())
        .alias("wind_speed_ms")
    )

    return df.select(
        expression_for_id, expression_for_timestamp, expression_for_wind_speed
    )
```

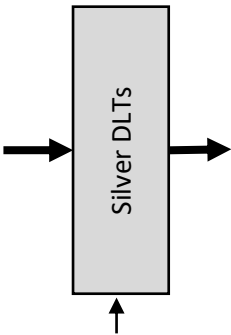

Append-only operations like extracting and casting JSON values work well



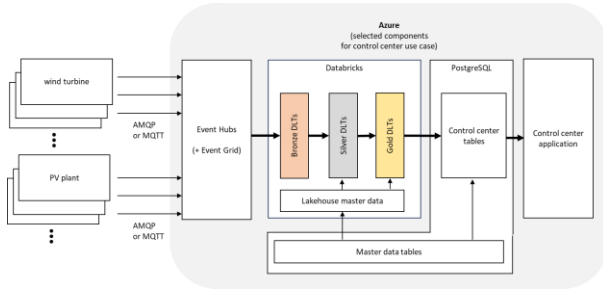
```
@dlt.table
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```

my_silver_table

turbine_id	measurement_ts	wind_speed_ms
RG15	2025-01-22T17:40:11.371894+00:00	4.3
RG15	2025-01-22T17:40:41.050264+00:00	4.4



Removing, updating, and aggregating rows can be tricky and slow



```
@dlt.table
def my_output_table() -> DataFrame:
    return dlt.read_stream("my_input_table").transform(remove_duplicated_rows)
```

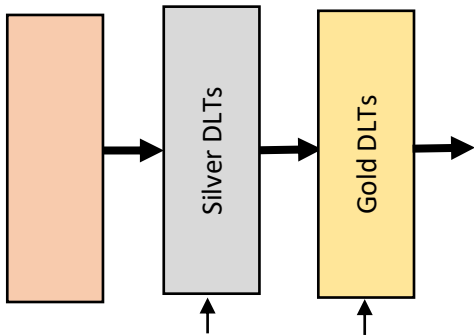
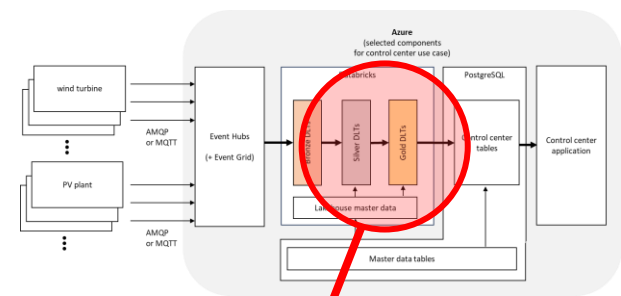
```
def remove_duplicated_rows(df: DataFrame) -> DataFrame:
    df = df.withWatermark("_inserted_at_ts", "5 seconds")
    df_deduped = df.dropDuplicatesWithinWatermark(
        ["turbine_id", "measurement_ts", "wind_speed_ms"]
    )
    return df_deduped
```

} watermarking required

my_output_table

turbine_id	measurement_ts	wind_speed_ms
RG15	2025-01-22T17:40:11.371894+00:00	4.3
RG15	2025-01-22T17:40:11.371894+00:00	4.3
RG15	2025-01-22T17:40:41.050264+00:00	4.4

Removing, **updating**, and aggregating rows can be tricky and slow




```
dlt.create_streaming_table(
    name="latest_wind_speed_by_turbine",
)
dlt.apply_changes(
    target="latest_wind_speed_by_turbine",
    source="my_silver_table",
    keys=["turbine_id"],
    sequence_by=F.col("measurement_ts"),
    stored_as_scd_type=1,
)
```


latest_wind_speed_by_turbine

turbine_id	measurement_ts	wind_speed_ms
RG15	2025-01-22T17:40:11.371894+00:00	4.3
	2025-01-22T17:40:41.050264+00:00	4.4

Delta Live Tables



Impressively
simple for some
streaming use
cases



Tricky for some
transformations

What are Databricks Asset Bundles?

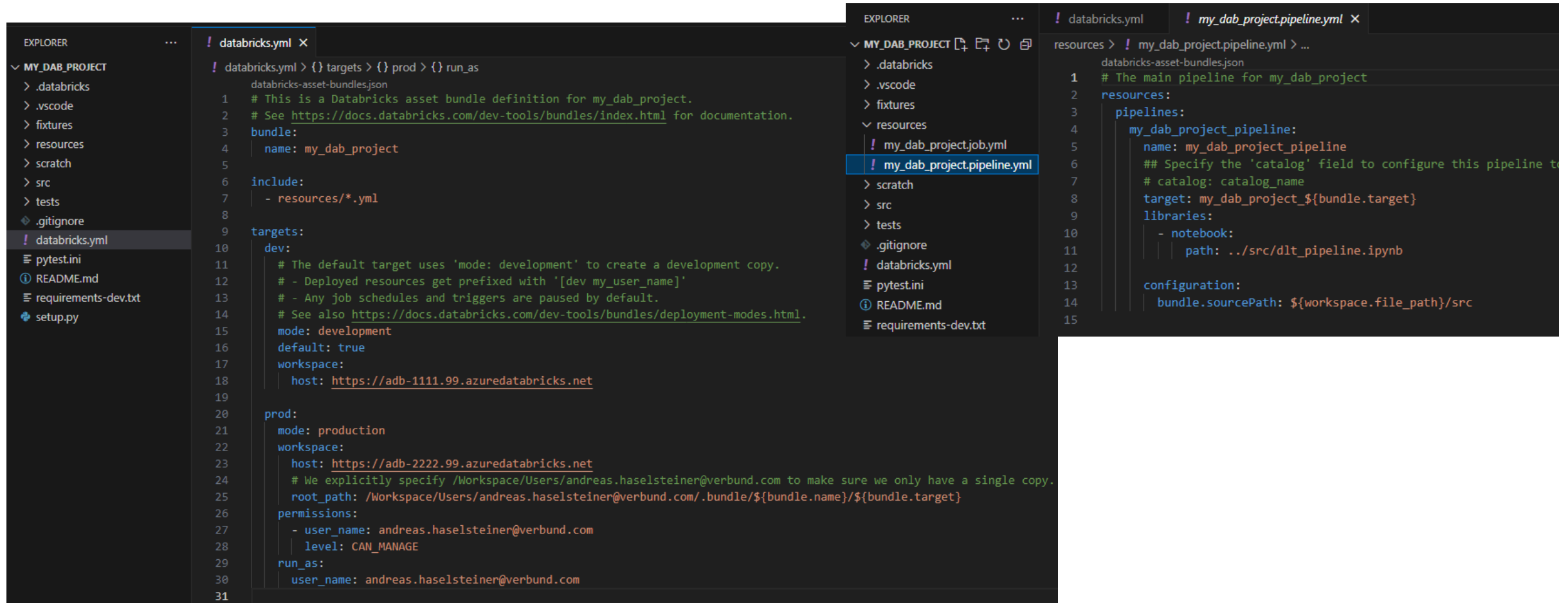
„Databricks Asset Bundles (DABs) are a tool to facilitate the adoption of software engineering best practices, including source control, code review, testing, and continuous integration and delivery (CI/CD)”¹

Sounds good.. When should I use Databricks Asset Bundles?

“Use them when you want to manage complex projects where multiple contributors and automation are essential, and continuous integration and deployment (CI/CD) are a requirement”¹

Show me the thing

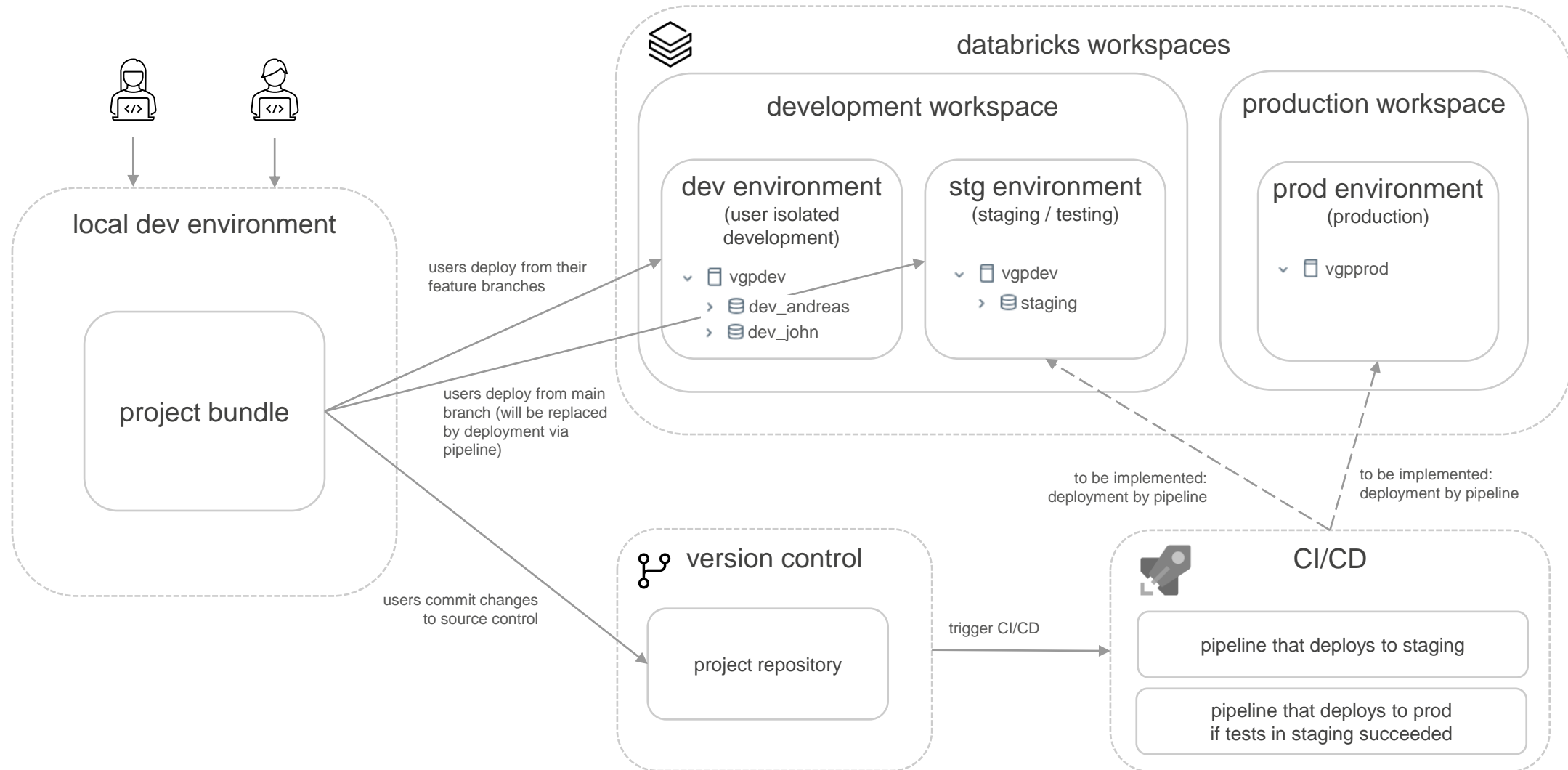
databricks bundle init



```
! databricks.yml > {} targets > {} prod > {} run_as
databricks-asset-bundles.json
1 # This is a Databricks asset bundle definition for my_dab_project.
2 # See https://docs.databricks.com/dev-tools/bundles/index.html for documentation.
3 bundle:
4   name: my_dab_project
5
6 include:
7   - resources/*.yaml
8
9 targets:
10  dev:
11    # The default target uses 'mode: development' to create a development copy.
12    # - Deployed resources get prefixed with '[dev_my_user_name]'
13    # - Any job schedules and triggers are paused by default.
14    # See also https://docs.databricks.com/dev-tools/bundles/deployment-modes.html.
15    mode: development
16    default: true
17    workspace:
18      host: https://adb-1111.99.azuredatabricks.net
19
20  prod:
21    mode: production
22    workspace:
23      host: https://adb-2222.99.azuredatabricks.net
24    # We explicitly specify /Workspace/Users/andreas.haselsteiner@verbund.com to make sure we only have a single copy.
25    root_path: /Workspace/Users/andreas.haselsteiner@verbund.com/.bundle/${bundle.name}/${bundle.target}
26    permissions:
27      - user_name: andreas.haselsteiner@verbund.com
28        level: CAN_MANAGE
29    run_as:
30      user_name: andreas.haselsteiner@verbund.com
31
```

```
resources > ! my_dab_project.pipeline.yml > ...
databricks-asset-bundles.json
1 # The main pipeline for my_dab_project
2 resources:
3   pipelines:
4     my_dab_project_pipeline:
5       name: my_dab_project_pipeline
6       ## Specify the 'catalog' field to configure this pipeline to
7       # catalog: catalog_name
8       target: my_dab_project_${bundle.target}
9       libraries:
10        - notebook:
11          path: ../src/dlt_pipeline.ipynb
12
13 configuration:
14   bundle.sourcePath: ${workspace.file_path}/src
15
```

Our development process with Databricks Asset Bundles



Delta Live Tables & Asset Bundles: What's great and what isn't

Delta Live Tables

- + Reading a streaming source is straightforward
- + Append-only transformations over multiple tables
- Things that are straightforward in batch like removing, updating, and aggregating records can be tricky

Delta Live Tables & Asset Bundles: What's great and what isn't

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- + Reading a streaming source is straightforward
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Databricks Asset Bundles

- + The best thing since sliced bread
- ?

V Thank you!

andreas.haselsteiner@verbund.com