



A Hands-On Guide to

Apps on Databricks

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01

Introduction to Building Apps on Databricks

Introduction to Building Apps on Databricks

As AI and analytics capabilities mature across organizations, a new challenge has emerged: delivering insights in a form people can actually use.

Data teams today have powerful tools for exploration and analysis. Notebooks support rapid iteration, dashboards enable broad visibility and models drive prediction and automation. But when business requirements shift to an interactive application that combines live data with user input — such as an AI assistant embedded in a workflow or a custom tool tailored to a specific operational process — teams often hit a wall.

Historically, building production applications meant stepping outside the data platform entirely. Moving from analysis to application meant provisioning infrastructure, configuring databases, implementing authentication, setting up deployment pipelines and navigating security reviews. Each step added cost, risk and time — without directly contributing to the business value of the application. For many organizations, this last mile challenge delayed applications for months or stopped them from ever shipping.

The problem isn't a lack of data or AI capability. It's the difficulty of delivering those capabilities as trusted, production-grade applications that others can use.

This guide is designed to help close that gap. Through practical walkthroughs, working code examples and real-world patterns, you'll learn how Databricks Apps and Lakebase work together to take an application from a working prototype to a production application without leaving the platform.



THE APPLICATION DEPLOYMENT CHALLENGE

For teams building data and AI applications today, the path from working prototype to production deployment is filled with undifferentiated heavy lifting. Whether you're a Python-fluent data engineer extending an analysis or a JavaScript developer building on lakehouse data, you encounter the same obstacles:

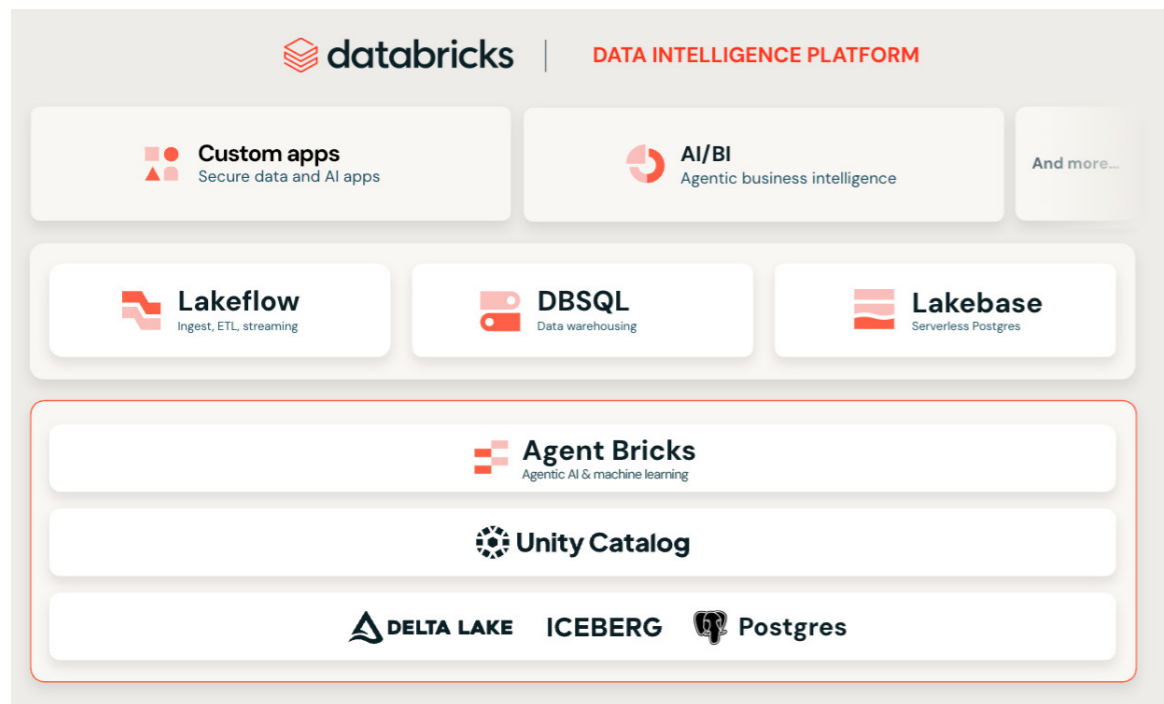
- **Infrastructure provisioning and management:** Every application needs somewhere to run. Traditionally, this means provisioning VMs or containers, configuring load balancers, setting up SSL certificates and managing scaling policies.
- **Authentication and security complexity:** Production applications require secure authentication flows, credential management and access controls. Implementing open authorization (OAuth) correctly, rotating secrets and ensuring compliance with security policies demands specialized knowledge. Getting it wrong creates vulnerabilities, and getting it right takes significant engineering effort.
- **Data synchronization and latency:** Interactive applications need fast access to data, but analytical data stores aren't optimized for the low-latency, high-concurrency access patterns that user-facing applications need. Building pipelines to move data from analytical systems to operational databases and keeping that data fresh adds another layer of complexity and potential failure points.

- **Deployment automation and environment management:** Moving code from development to staging to production requires continuous integration and continuous delivery (CI/CD) pipelines, environment configuration and careful coordination
- **Governance and compliance:** Enterprise applications must respect data access policies, maintain audit trails and enforce fine-grained permissions. Implementing governance controls in application code — separate from the governance already established in the data platform — duplicates work and creates opportunities for policy drift.

These challenges create real costs. Deployment complexity kills momentum: When you can't ship changes quickly and confidently, you slow iteration and waste time coordinating between teams. The result is that valuable capabilities remain locked inside the data platform, accessible only to some technical users rather than the broader organization.

DATABRICKS APPS AND LAKEBASE: A UNIFIED APPLICATION PLATFORM

Databricks addresses these challenges by bringing application hosting and operational databases directly into the Data Intelligence Platform. Rather than requiring separate infrastructure for applications, Databricks provides an integrated solution where apps run alongside the data and AI capabilities they depend on.



Databricks Apps provides a serverless application hosting platform for running web applications built with open source frameworks like Streamlit, Dash, Flask, FastAPI and React. Applications inherit the platform's built-in security, compliance and resource management features. There's no infrastructure to provision, no containers to manage and no scaling policies to configure. Apps automatically integrate with Unity Catalog for governance and support both service principal authentication for app-level access and on-behalf-of-user authorization for user-level permissions.

Lakebase is a fully managed PostgreSQL database deeply integrated with the lakehouse. It provides the transactional, low-latency data access that interactive applications require while automatically synchronizing data from Unity Catalog tables. With Lakebase, you can:

- Serve analytical insights to applications in real time
- Store application state and user inputs
- Maintain full atomicity, consistency, isolation and durability (ACID) transaction support

All of this is possible without building custom extract, transform, load (ETL) pipelines or managing database infrastructure.

Together, these capabilities transform what's possible:

TRADITIONAL APPROACH	MODERN DATABRICKS APPS AND LAKEBASE APPROACH
Separate hosting infrastructure	Serverless compute and zero infrastructure management
Custom authentication systems	Built-in OAuth and Unity Catalog integration
Manual data synchronization pipelines	Automated synced tables from Unity Catalog
Fragmented governance across systems	Unified governance through Unity Catalog
Complex, multi-tool deployment	Single-command deployment with Databricks Asset Bundles (DABs)

Historically, bridging OLTP and OLAP systems involved complex data engineering and bespoke integration layers. Deploying applications required separate DevOps teams, disparate CI/CD pipelines and manual security configurations. With Lakebase and Databricks Apps together, these complexities are significantly reduced. Developers can access real-time analytical data directly from the transactional layer and deploy interactive applications in minutes rather than months.

WHAT THIS GUIDE COVERS

This guide provides hands-on instruction for building production-ready data and AI applications on Databricks. Rather than focusing on isolated features, each chapter walks through a complete application pattern using working code you can adapt to your own use cases.

You'll see how to:

- Move from notebooks and prototypes to real applications
- Serve analytical data and application state through a transactional layer
- Build secure, governed applications without custom infrastructure
- Deploy and operate applications using repeatable, production-ready patterns

By the end of this guide, you should clearly understand how to build, deploy and manage intelligent applications on the Databricks Platform with confidence.

02

From Notebooks to Production Applications

From Notebooks to Production Applications

by [Pascal Vogel](#), [Evan Pandya](#) and [Christopher Pries](#)

THE CHALLENGE OF PRODUCTION DATA APPLICATIONS

Building production-ready data applications is complex. You often need separate tools to host the app, manage the database and move data between systems. Each layer adds setup, maintenance and deployment overhead.

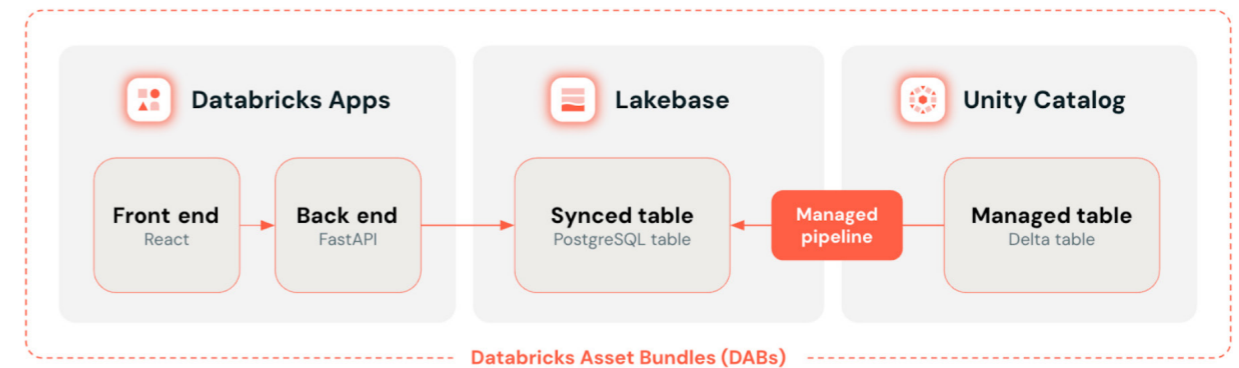
Databricks simplifies this by consolidating everything on a single platform — the [Databricks Data Intelligence Platform](#). [Databricks Apps](#) runs web applications on serverless compute. [Lakebase](#) provides a managed Postgres database that syncs with [Unity Catalog](#), giving apps fast access to governed data. And with [Databricks Asset Bundles \(DABs\)](#), you can package code, infrastructure and data pipelines together and deploy them with a single command.

This chapter shows how these three pieces work together to build and deploy a real data application, from syncing Unity Catalog data to Lakebase to running a web app on the Databricks Platform and automating deployment with DABs.

ARCHITECTURE AND HOW IT WORKS

We'll walk through a taxi trip application that demonstrates the entire pattern: a React and FastAPI application that reads from Lakebase synced tables, with automatic data updates from Unity Catalog Delta tables happening within seconds.

The following diagram provides a simplified view of the solution architecture.

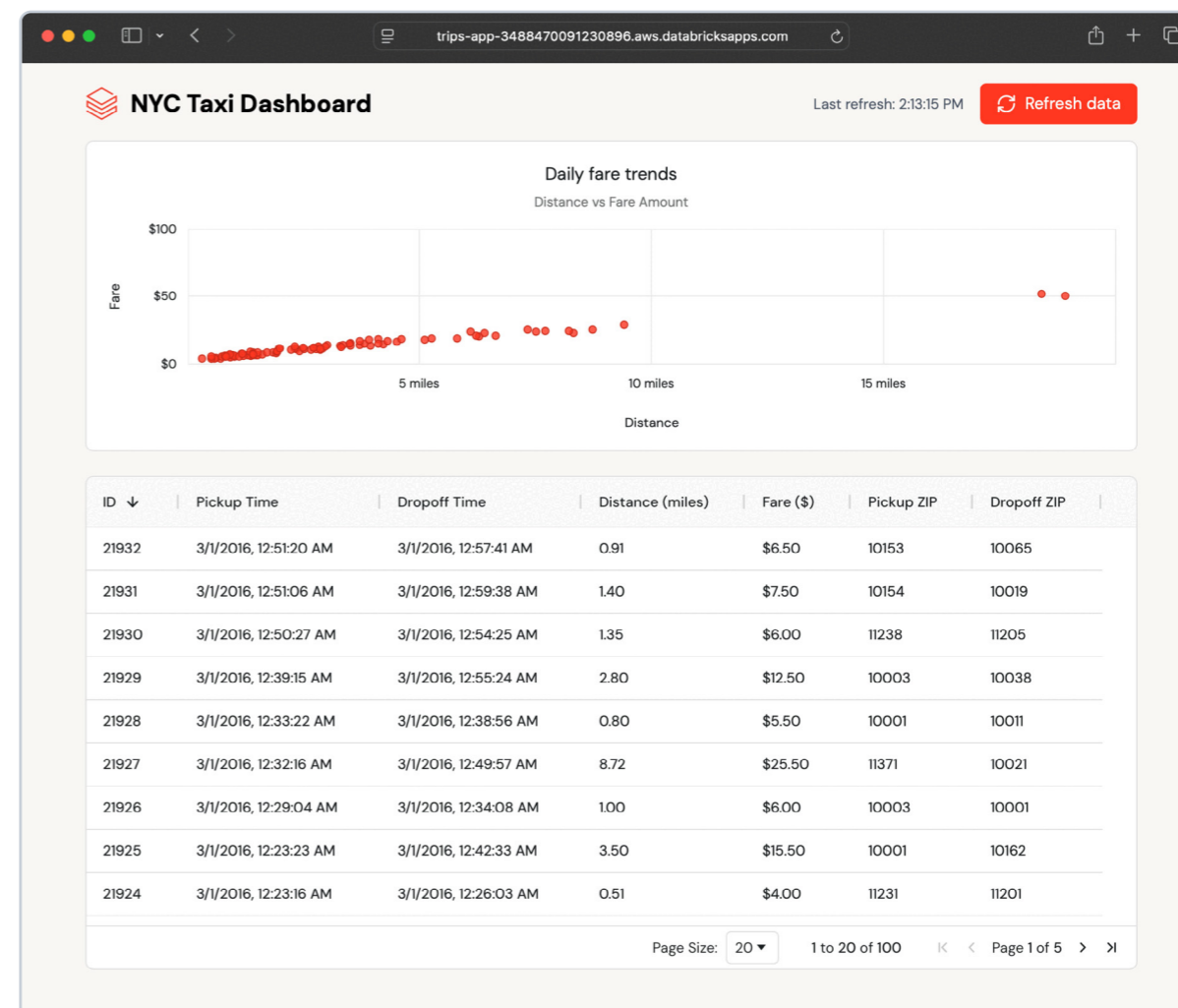


At a high level, Databricks Apps serves as the front end where users explore and visualize data. Lakebase provides the Postgres database that the app queries, keeping it close to live data from Unity Catalog with synced tables. DABs tie everything together by defining and deploying all resources — app, database and data synchronization — as one version-controlled unit.

Main solution components:

- **Databricks app:** Users interact with a web application built using **React**, **TypeScript**, **Vite** and **FastAPI**. The app reads data from a Unity Catalog synced table stored in a Lakebase Postgres database.
- **Unity Catalog synced table:** A read-only Postgres table that's automatically synced with a Unity Catalog table via a managed synchronization pipeline and runs on a Lakebase database instance
- **Lakebase database instance:** Manages Lakebase storage and compute and provides Postgres endpoints for the Databricks app to connect to
- **Unity Catalog table:** A Delta table containing data about taxi rides in New York City cloned from the `samples.nyctaxi.trips` [sample table available in every database workspace](#)
- **Databricks Asset Bundles (DABs):** A bundle in which all key elements of the architecture are defined in code

The example app displays recent taxi trips in table and chart format and automatically polls for new trips. It reads data from a Lakebase synced table, which mirrors a Delta table in Unity Catalog.



Because the synced table updates automatically, any change in the Unity Catalog table appears in the app within seconds — no custom ETL needed.

You can test this by inserting new data into the source Delta table and then refreshing the synced table:

SQL

```
INSERT INTO main.default.trips (id, tpep_pickup_datetime, tpep_dropoff_datetime, trip_distance, fare_amount, pickup_zip, dropoff_zip)
```

VALUES

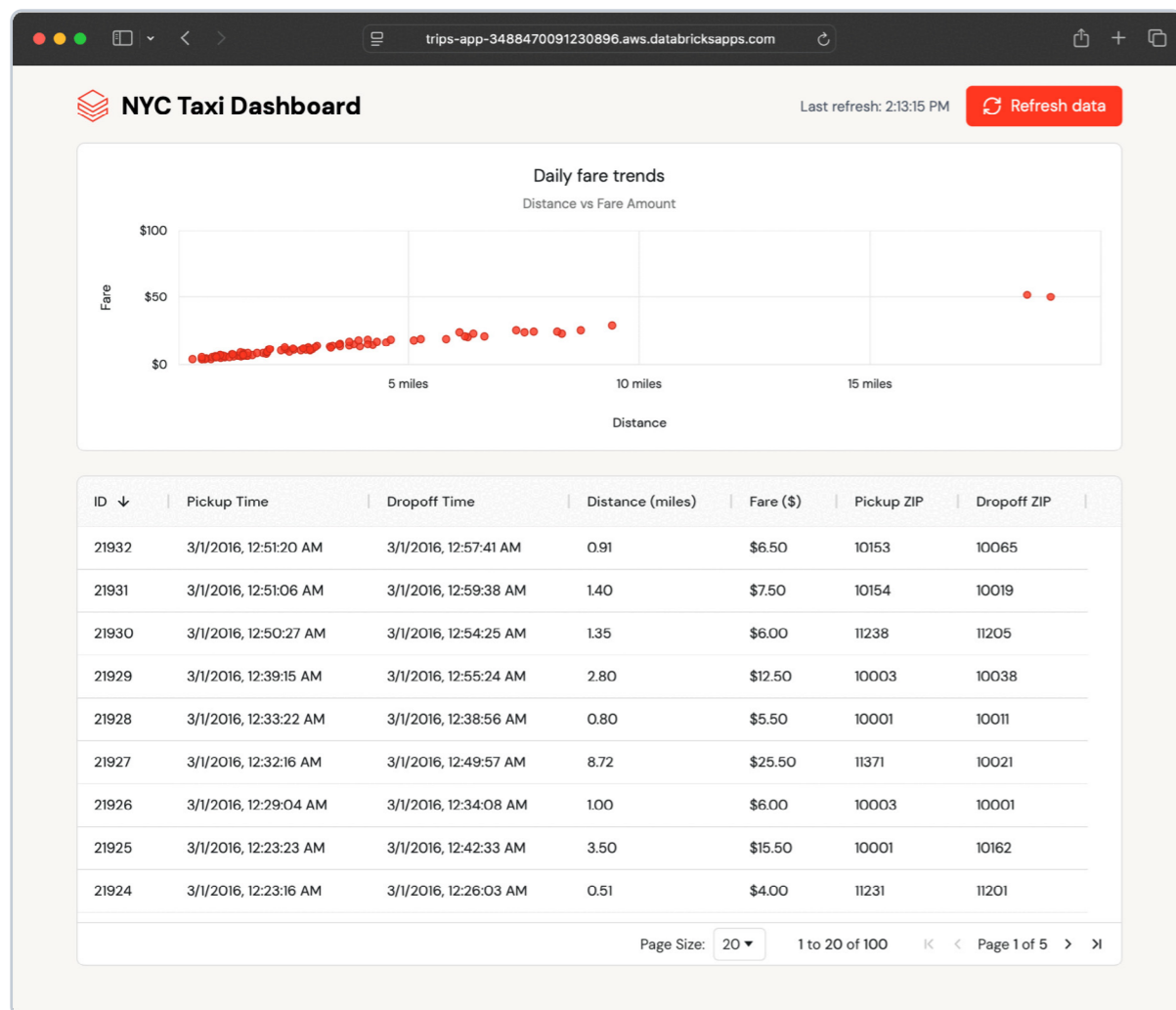
```
(21933, '2025-08-20 10:00:00', '2025-09-20 10:30:00', 5.2, 18.50, '10001', '10002'),
(21934, '2025-08-21 11:00:00', '2025-09-21 11:30:00', 6.1, 20.00, '10003', '10004'),
(21935, '2025-08-22 12:00:00', '2025-09-22 12:30:00', 7.3, 22.75, '10005', '10006')
```

Then trigger a refresh of the synced `trips_synced` table:

The screenshot shows the Databricks interface with the 'trips_synced' table selected in the Catalog Explorer. The table is a synced table from another UC table. The 'Data Ingest' section shows the pipeline id '61f3f01a-dca1-4a1d-9743-c134ccc8e9cc', update status 'Completed', last processed commit '17', and last processed timestamp 'Sep 23, 2025, 08:25 AM (8 hours ago)'. A 'Sync now' button is visible in the bottom right corner of the 'Data Ingest' section.

The managed pipeline that powers the sync creates a snapshot copy of the source Delta table and writes to the target Postgres table.

Within a few seconds, the new records appear in the dashboard. The app polls for updates and allows users to refresh on demand, demonstrating how Lakebase keeps operational data current without requiring additional engineering.



This seamless data flow happens because Lakebase synced tables handle all synchronization automatically.

ANATOMY OF THE APP

Let's examine how the various elements of the solution come together in the Databricks app.

Authentication and database connection

Each Databricks app has a unique **service principal** identity assigned on creation that it uses to interact with other Databricks resources, including Lakebase.

Lakebase supports **OAuth machine-to-machine (M2M) authentication**. An app can obtain a valid token using the **WorkspaceClient** in the **Databricks SDK for Python** along with its service principal credentials. The **WorkspaceClient** handles refreshing the short-lived OAuth token, which expires in an hour.

The app then uses this token when establishing a connection to Lakebase using the [Psycopg](#) Python Postgres adapter:

PYTHON

```
# app/database.py

[...]

def get_connection(self):
    token = self.workspace_client.config.oauth_token().access_token

    return psycopg.connect(
        host=self.postgres_host,
        port=5432,
        dbname=self.postgres_database,
        user=self.postgres_username,
        password=token,
        sslmode="require",
    )

[...]
```

The Postgres host and database name are automatically set as environment variables for the Databricks app when using the [Lakebase resource for apps](#).

The Postgres user is either the app service principal — when deployed to Databricks Apps — or the Databricks username of the user running the app locally.

RESTful FastAPI back end

The app's FastAPI back end uses this connection to query Lakebase and fetch the latest trips data from the synced table:

PYTHON

```
# app/main.py

[...]

def get_taxi_trips_data() -> List[TaxiTrip]:
    query = """
        SELECT id, tpep_pickup_datetime, tpep_dropoff_datetime,
        trip_distance,
        fare_amount, pickup_zip, dropoff_zip
        FROM {db_connection.postgres_schema}.{db_connection.postgres_table}
        ORDER BY tpep_pickup_datetime DESC
        LIMIT 100
    """

    with db_connection.get_connection() as conn:
        with conn.cursor() as cur:
            cur.execute(query)
            rows = cur.fetchall()

    return [
        TaxiTrip(
            id=row[0],
            tpep_pickup_datetime=row[1].isoformat(),
            tpep_dropoff_datetime=row[2].isoformat(),
            trip_distance=row[3],
            fare_amount=row[4],
            pickup_zip=row[5],
            dropoff_zip=row[6],
        )
        for row in rows
    ]

[...]

@app_api.get("/taxi-trips", response_model=List[TaxiTrip])
def get_taxi_trips():
    return get_taxi_trips_data()

[...]
```

In addition to serving API endpoints, FastAPI can also serve static files using the `StaticFiles` class. By bundling our React front end using Vite's build process, we can generate a set of static files that we can serve using FastAPI.

PYTHON

```
# app/main.py

from fastapi import FastAPI
from fastapi.staticfiles import StaticFiles

[...]

app = FastAPI()

app_frontend = StaticFiles(directory="frontend/dist", html=True)
app_api = FastAPI()

app.mount("/api", app_api) # Mount more specific route first,
catchall route second

app.mount("/", app_frontend)

[...]
```

React front end

The React front end calls the FastAPI endpoint to display the data:

JAVASCRIPT

```
/** app/frontend/src/taxiApi.ts */

import axios from "axios";
import type { TaxiTrip } from "./App";

const apiClient = axios.create({ baseURL: "/api" });

export const getTaxiTrips = async (): Promise<TaxiTrip[]> => {
  const response = await
  apiClient.get<TaxiTrip[]>("/taxi-trips");
  return response.data;
};
```

The example application uses ag-grid and ag-charts for visualization and automatically checks for new data every few seconds:

JAVASCRIPT

```
/** app/frontend/src/App.tsx */

const fetchData = async () => {
  try {
    setError(null);
    const data = await getTaxiTrips();
    setTaxiData(data);
    setLastRefresh(new Date());
  } catch (err) {
    setError("Failed to fetch taxi data");
    console.error("Error fetching taxi data:", err);
  }
}

useEffect(() => {
  fetchData();

  const interval = setInterval(fetchData, 3000);

  return () => clearInterval(interval);
}, []);

[...]
```



DEFINING DATABRICKS ASSET BUNDLES RESOURCES

All the Databricks resources and application code shown above can be maintained as a DAB in a single source code repository. This also means that all resources can be deployed to a Databricks workspace with a single command.

See the [GitHub repository](#) for detailed deployment instructions.

This simplifies the software development lifecycle and enables deployments via CI/CD best practices across development, staging and production environments.

The following sections explain the bundle files in more detail.

Bundle configuration

The databricks.yml contains the DABs bundle configuration in the form of bundle settings and included resources:

PYTHON

```
# databricks.yml

bundle:
  name: apps-lakebase-dabs

# Uploads the app/frontend/dist folder when deploying the bundle
sync:
  include:
    - app/frontend/dist

# Include app, database instance and synced table
include:
  - resources/*.yml

# Optionally override the catalog and schema for the synced table
variables:
  catalog:
    default: main
  schema:
    default: default

# Add more environments as needed
targets:
  dev:
    default: true
    mode: development
    workspace:
      host: https://company-dev.cloud.databricks.com/

  staging:
    mode: production
    workspace:
      host: https://company-stg.cloud.databricks.com/
      root_path: /Users/${workspace.current_user.userName}/.
      bundle/${bundle.name}/${bundle.target}
```

In our example, we only define a development and a staging environment. For a production use case, consider adding additional environments. See the [Databricks DAB examples repository](#) and the [DABs documentation](#) for more advanced configuration examples.

Lakebase setup and sync with Unity Catalog

To define a Lakebase instance in DABs, use the `database_instance` resource.

At a minimum, we need to define the capacity field of the instance.

Additionally, we define a `synced_database_table` resource, which sets up a managed synchronization pipeline between a Unity Catalog table and a Postgres table.

For this, define a source table via `source_table_full_name`. The source table in Unity Catalog requires a unique (composite) primary key to process updates defined in the `primary_key_columns` field.

The location of the target table in Lakebase is determined by the target database object (`logical_database_name`) and the table name (`name`).

PYTHON

```
# resources/database.yml

resources:
  database_instances:
    trips-app-instance:
      name: trips-app-instance
      capacity: CU_1
  synced_database_tables:
    trips-app-synced-table:
      # Synced table Unity Catalog object name:
      name: ${var.catalog}.${var.schema}.trips_synced
      database_instance_name: ${resources.database_instances.trips-
app-instance.name}
      # Postgres database where synced table is located:
      logical_database_name: trips-app-database
      spec:
        source_table_full_name: ${var.catalog}.${var.schema}.trips
        scheduling_policy: SNAPSHOT
        primary_key_columns:
          - id
```

A synced table is also a Unity Catalog object. In this resource definition, we place the synced table in the same catalog and schema as the source table using DABs variables defined in `databricks.yml`. You can override these defaults by [setting different variable values](#).

For our use case, we use the SNAPSHOT sync mode. Refer to the “Considerations and best practices” section of this chapter for a discussion of the available options.

Databricks Apps resource

DABs allow us to define both the Databricks Apps compute resource as an **app** resource and the application source code in one bundle. This allows us to keep both the Databricks resource definition and the source code in a single repository. In our case, the app source code, based on FastAPI and Vite, is stored in the top-level app directory of the project.

The configuration dynamically references the `database_name` and `instance_name` defined in the `database.yml` resource definition.

PYTHON

```
# resources/app.yml

resources:

  apps:

    trips-app:

      name: trips-app

      source_code_path: ../app # App source code location

      resources: # Resources that the app service principal can
        access

        - name: lakebase

          database:

            database_name: ${resources.synced_database_tables.trips-
              app-synced-table.logical_database_name}

            instance_name: ${resources.database_instances.trips-app-
              instance.name}

            permission: CAN_CONNECT_AND_CREATE
```

Database is a supported **app resource** that can be defined in DABs. By defining **the database as an app resource**, we automatically create a Postgres role to be used by the app service principal when interacting with the Lakebase instance.

CONSIDERATIONS AND BEST PRACTICES

Create modular and reusable bundles

While this example deploys to development and staging environments, DABs make it easy to define multiple environments to fit your development lifecycle. Automate deployment across these environments by setting up CI/CD pipelines with [Azure DevOps](#), [GitHub Actions](#) or other DevOps platforms.

Use DABs [substitutions and variables](#) to define environment-specific configurations. For instance, you can define different Lakebase instance capacity configurations for development and production to reduce costs. Similarly, you can define different Lakebase sync modes for your synced tables to meet environment-specific data latency requirements.

Choose Lakebase sync modes and optimize performance

Choosing the right Lakebase [sync mode](#) is key to balancing cost and data freshness.

	SNAPSHOT	TRIGGERED	CONTINUOUS
Update method	Full table replacement on each run	Initial full copy and incremental changes	Initial load and real-time streaming updates
Performance	10x more efficient than other modes	Balanced cost and performance	Higher cost – continuously running
Latency	High latency – scheduled or manual	Medium latency – on demand	Lowest latency – real time, ~15 sec
Best for	<ul style="list-style-type: none"> ▪ Infrequent changes ▪ Modifying >10% of the source table ▪ Low-urgency, high-volume updates 	<ul style="list-style-type: none"> ▪ Compromise between cost and latency ▪ Reasonably current data ▪ Controlled refresh timing 	<ul style="list-style-type: none"> ▪ Mission-critical systems ▪ Real-time data requirements ▪ No manual refresh tolerance
Limitations	<ul style="list-style-type: none"> ▪ Higher latency ▪ Full table re-creation each time 	<ul style="list-style-type: none"> ▪ Avoid running >every five minutes ▪ Requires a change data feed ▪ More expensive if run too frequently 	<ul style="list-style-type: none"> ▪ Highest cost ▪ Requires a change data feed ▪ Continuous resource consumption

Set up notifications for your managed sync pipeline to be alerted in case of failures.

To improve query performance, right-size your Lakebase database instance by choosing an appropriate [instance capacity](#). Consider creating [indexes](#) on the synced table in Postgres that match your query patterns and use the pre-installed [pg_stat_statements extension](#) to investigate query performance.

Prepare your app for production

The example application implements a polling-based approach to get the latest data from Lakebase. Depending on your requirements, you can also implement a push-based approach using [WebSockets](#) or [server-sent events](#) to use server resources more efficiently and increase the timeliness of data updates.

To scale to a larger number of app users by reducing the need for the FastAPI back end to trigger database operations, consider implementing caching, such as [fastapi-cache](#), for in-memory caching of query results.

Authentication and authorization

Use OAuth 2.0 for authorization and authentication — don't rely on [legacy personal access tokens \(PATs\)](#). During development on your local machine, use the Databricks command-line interface (CLI) to set up [OAuth U2M authentication](#) to seamlessly interact with live Databricks resources such as Lakebase.

Similarly, your deployed app [uses its associated service principal for OAuth M2M authentication and authorization](#) with other Databricks services. Alternatively, set up [user authorization for your app](#) to perform actions on Databricks resources on behalf of your app users.

See also [Best Practices for Databricks Apps](#) in the Databricks Apps documentation for additional general and security best practices.

CONCLUSION

Building production data applications shouldn't mean juggling separate tools for deployment, data synchronization and infrastructure management. Databricks Apps gives you serverless compute to run your Python and Node.js applications without managing infrastructure. Lakebase synced tables automatically deliver low-latency data from Unity Catalog Delta tables to Postgres, eliminating custom ETL pipelines. DABs tie it all together by allowing you to package your application code, infrastructure definitions and data sync configurations into a single, version-controlled bundle that deploys consistently across environments.

Deployment complexity kills momentum. When you can't ship changes quickly and confidently, you slow down iteration, introduce environment drift and waste time coordinating between teams. By treating your entire application stack as code with DABs, you:

- Enable CI/CD automation
- Ensure consistent deployments across dev, staging and production
- Allow your team to focus on building features instead of fighting deployment pipelines

This is how you move from prototype to production without the usual deployment headaches.

The complete example is available in the [GitHub repository](#) with step-by-step deployment instructions.

GET STARTED

Learn more about [Lakebase](#), [Databricks Apps](#) and [DABs](#) by viewing the Databricks documentation. For more developer resources on Databricks Apps, take a look at the [Databricks Apps Cookbook](#) and [Cookbook resource collection](#).



03

The Transactional Foundation for Intelligent Applications

The Transactional Foundation for Intelligent Applications

By [Jasper Puts](#) and [Antonio Javier Samaniego Jurado](#)

INTRODUCTION

Building internal tools or AI-powered applications the traditional way throws developers into a maze of repetitive, error-prone tasks. First, they must spin up a dedicated Postgres instance, configure networking, backups and monitoring, and then spend hours — or days — plumbing that database into the front-end framework they're using. Additionally, they must write custom authentication flows, map granular permissions and keep those security controls in sync across the UI, API layer and database. Each application component lives in a different environment, from a managed cloud service to a self-hosted VM. This forces developers to juggle disparate deployment pipelines, environment variables and credential stores. The result is a fragmented stack where a single change, such as a schema migration or a new role, ripples through multiple systems, demanding manual updates, extensive testing and constant coordination. All of this overhead distracts developers from the real value add — building the product's core features and intelligence.

With Databricks Lakebase and Databricks Apps, the entire application stack sits together, alongside the lakehouse. Lakebase is a fully managed Postgres database that offers low-latency reads and writes, integrated with the same underlying lakehouse tables that power your analytics and AI workloads.

Databricks Apps supplies a serverless runtime for the UI, along with built-in authentication, fine-grained permissions and governance controls that are automatically applied to the same data that Lakebase serves. This makes it easy to build and deploy apps that combine transactional state, analytics and AI without stitching together multiple platforms, synchronizing databases, replicating pipelines or reconciling security policies across systems.

WHY LAKEBASE AND DATABRICKS APPS

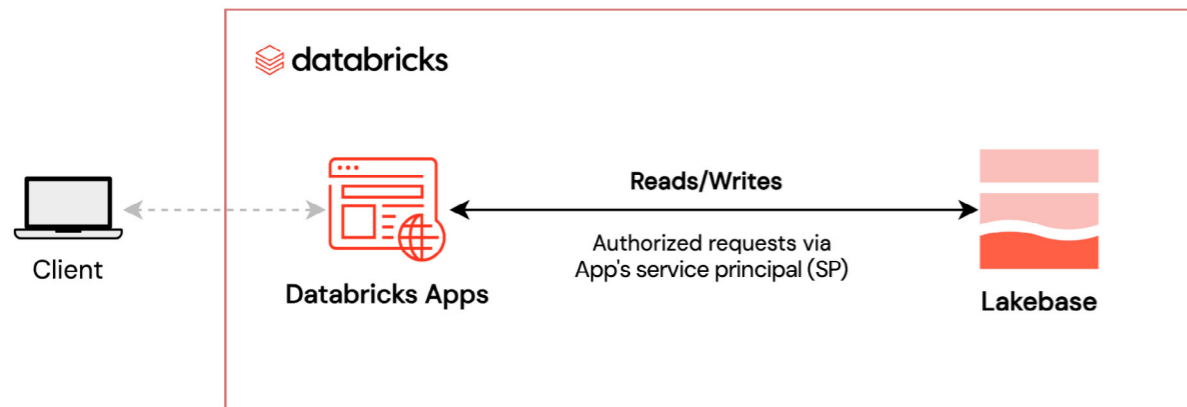
Lakebase and Databricks Apps work together to simplify full-stack development on the Databricks Platform:

- **Lakebase** provides a fully managed Postgres database with fast reads, writes and updates, plus modern features such as branching and point-in-time recovery
- **Databricks Apps** provides the serverless runtime for your application front end, with built-in identity access control and integration with Unity Catalog and other lakehouse components

By combining the two, you can build interactive tools that store and update state in Lakebase, access governed data in the lakehouse and serve everything through a secure, serverless UI — all without managing separate infrastructure. In the next example, we'll show how to build a simple holiday request approval app using this setup.

GETTING STARTED: BUILD A TRANSACTIONAL APP WITH LAKEBASE

This walkthrough demonstrates how to create a simple Databricks app that helps managers review and approve holiday requests from their team. The app is built using Databricks Apps and uses Lakebase as the back-end database to store and update the requests.



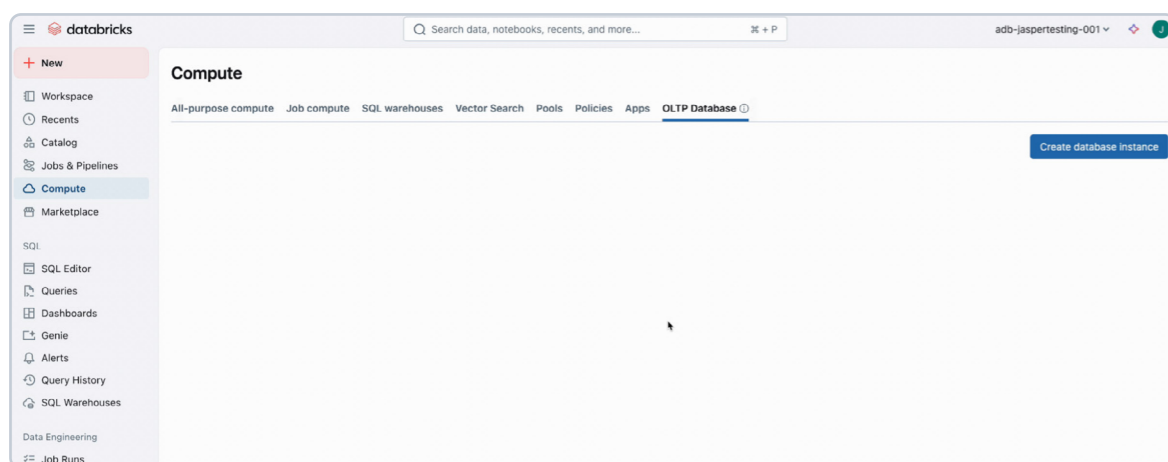
Here's what the solution covers:

- 1. Provision a Lakebase database**
Set up a serverless, Postgres OLTP database with a few clicks.
- 2. Create a Databricks app**
Build an interactive app using a Python framework — such as Streamlit or Dash — that reads from and writes to Lakebase.
- 3. Configure schema, tables and access controls**
Create the necessary tables and assign fine-grained permissions to the app using the app's client ID.
- 4. Securely connect and interact with Lakebase**
Use the Databricks SDK and SQLAlchemy to securely read from and write to Lakebase from your app code.

The walkthrough is designed to get you started quickly with a minimal working example. Later, you can extend it with a more advanced configuration.

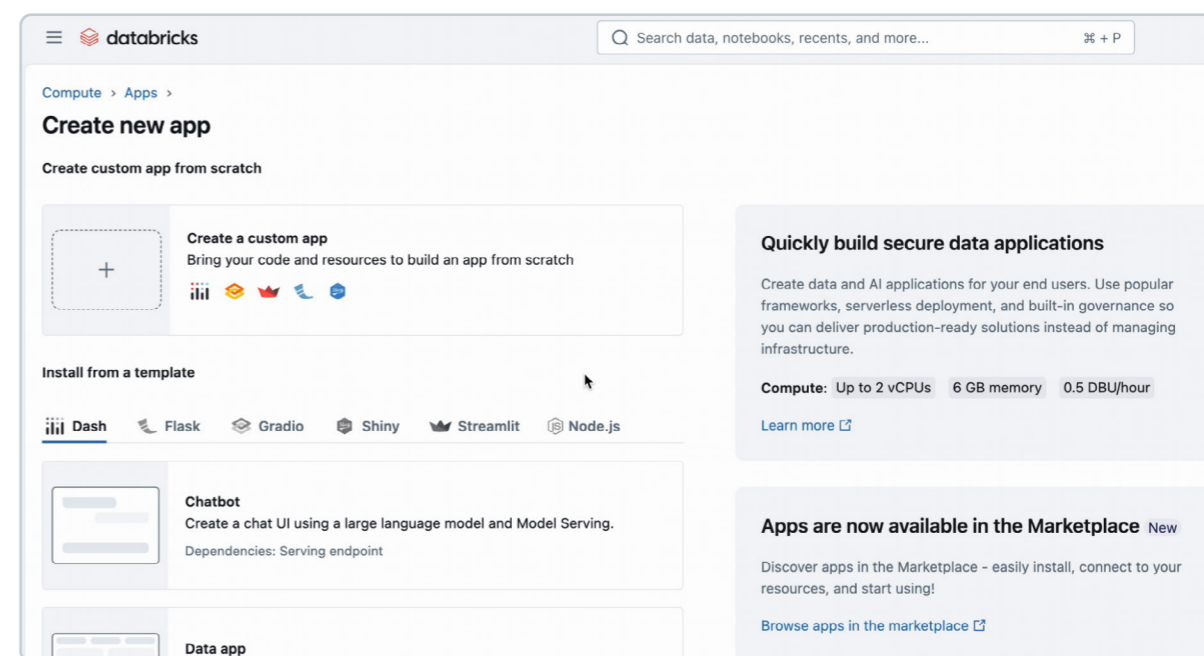
Step 1: Provision Lakebase

Before building the app, you'll need to create a Lakebase database. To do this, go to the **Compute** tab, select **OLTP Database** and provide a name and size. This provisions a serverless Lakebase instance. In this example, our database instance is called lakebase-demo-instance.



Step 2: Create a Databricks app and add database access

Now that we have a database, let's create the Databricks app that will connect to it. You can start from a blank app or choose a template — e.g., Streamlit or Flask. After naming your app, add the **database** as a resource. In this example, the pre-created databricks_postgres database is selected.



Adding the database resource automatically:

- Grants the app CONNECT and CREATE privileges
- Creates a Postgres role tied to the app's client ID

This role will later be used to grant table-level access.

Step 3: Create a schema, define a table and set permissions

With the database provisioned and the app connected, you can create the schema and define the table the app will use.

Compute > Apps >

holiday-request-manager

Overview Authorization Deployments Logs **Environment**

Environment JSON

```

1 {
2   "runtime": "Python 3.11.13; Node.js v22.16.0",
3   "env_variables": [
4     "DATABRICKS_APP_NAME=holiday-request-manager",
5     "DATABRICKS_APP_PORT=8000",
6     "DATABRICKS_APP_URL=***",
7     "DATABRICKS_CLIENT_ID=9e605e6d-a117-4079-9f32-129cb24360eb",
8     "DATABRICKS_CLIENT_SECRET=***",
9     "DATABRICKS_HOST=***",
10    "DATABRICKS_WORKSPACE_ID=***",
11    "FLASK_RUN_HOST=0.0.0.0",
12    "FLASK_RUN_PORT=8000",

```

1. Retrieve the app's client ID

From the app's **Environment** tab, copy the value of the DATABRICKS_CLIENT_ID variable. You'll need this for the GRANT statements.

2. Open the Lakebase SQL editor

Go to your Lakebase instance and click **New Query**. This opens the SQL editor with the database endpoint already selected.

The screenshot shows the Databricks interface for a Lakebase instance. The instance name is 'lakebase-demo-instance'. The Instance ID is 'bf7b38ad-52c8-48f1-b984-bf6bf3358413'. The Status is 'Available'. The PostgreSQL version is '16'. The Size (Capacity Units) is '1'. There are buttons for 'New Query', 'Edit', 'Stop', and 'Delete'.

3. Run the following SQL:

SQL

```
-- 1. Create schema

CREATE SCHEMA IF NOT EXISTS holidays;

-- 2. Create the table within the schema

CREATE TABLE IF NOT EXISTS holidays.holiday_requests (

  request_id SERIAL PRIMARY KEY,
  employee_name VARCHAR(255) NOT NULL,
  start_date DATE NOT NULL,
  end_date DATE NOT NULL,
  status VARCHAR(50) NOT NULL,
  manager_note TEXT

);

-- 3. Insert some values

INSERT INTO holidays.holiday_requests (employee_name, start_date,
end_date, status, manager_note)

VALUES
  ('Joe', '2025-08-01', '2025-08-20', 'Pending', ''),
  ('Suzy', '2025-07-22', '2025-07-25', 'Pending', ''),
  ('Charlie', '2025-08-01', '2025-08-05', 'Pending', '');

-- 4. The Lakebase resource in the App already allows connecting to
Lakebase database instance and the database.

-- Grant permissions on the required schema and table.
-- Replace the <CLIENT_ID> with the value from your App

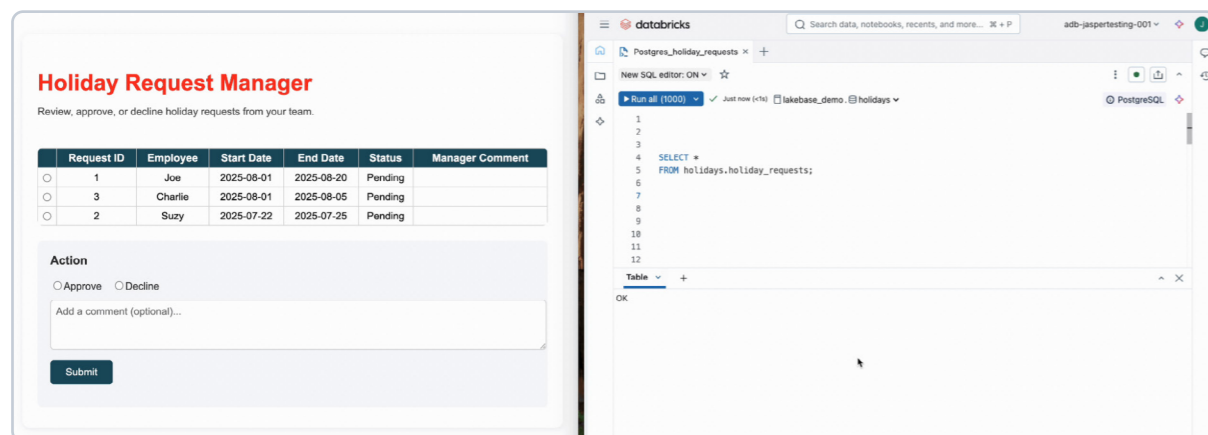
GRANT USAGE ON SCHEMA holidays TO "<CLIENT_ID>";

GRANT SELECT, INSERT, UPDATE, DELETE ON TABLE
holidays.holiday_requests TO "<CLIENT_ID>";
```

Although using the SQL editor is a quick and effective way to perform this process, managing database schemas at scale is best handled by dedicated tools that support versioning, collaboration and automation. Tools like Flyway and Liquibase allow you to track schema changes, integrate with CI/CD pipelines and ensure your database structure evolves safely alongside your application code.

Step 4: Build the app

With permissions in place, you can now build your app. In this example, the app fetches holiday requests from Lakebase and allows a manager to approve or reject them. Updates are written back to the same table.



Step 5: Connect securely to Lakebase

Use SQLAlchemy and the Databricks SDK to connect your app to Lakebase with secure, token-based authentication. When you add the Lakebase resource, PGHOST and PGUSER are exposed automatically. The SDK handles token caching.

PYTHON

```
import os
import time

import pandas as pd
from databricks.sdk import WorkspaceClient
from databricks.sdk.core import Config
from sqlalchemy import create_engine, event, text

app_config = Config()
workspace_client = WorkspaceClient()

postgres_username = app_config.client_id
postgres_host = os.getenv("PGHOST")
postgres_port = 5432
postgres_database = "lakebase_demo"

postgres_pool = create_engine(f"postgresql+psycopg://{{postgres_username}}:{{postgres_host}}:{{postgres_port}}/{{postgres_database}}")

@event.listens_for(postgres_pool, "do_connect")
def provide_token(dialect, conn_rec, cargs, cparams):
    """Provide the App's OAuth token. Caching is managed by
    WorkspaceClient"""
    cparams["password"] =
workspace_client.config.oauth_token().access_token
```

Step 6: Read and update data

The following functions read from and update the holiday request table:

PYTHON

```
def get_holiday_requests():
    """Fetch all holiday requests from the database."""
    engine = get_engine()
    df = pd.read_sql_query("SELECT * FROM holidays.holiday_
requests;", engine)
    return df

def update_request_status(request_id, status, comment):
    """Update the status and manager note for a specific holiday
request."""
    engine = get_engine()
    with engine.begin() as conn:
        conn.execute(
            text("""
                UPDATE holidays.holiday_requests
                SET status = :status, manager_note = :comment
                WHERE request_id = :request_id
                """))
        {"status": status, "comment": comment or "", "request_
id": request_id}
```

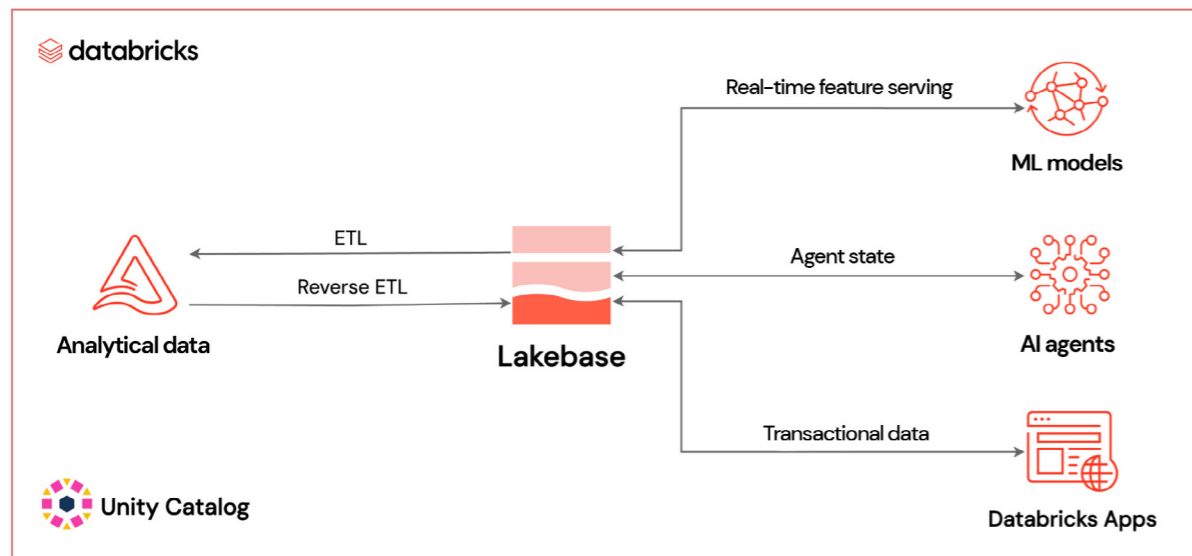
These code snippets can be used in combination with frameworks such as Streamlit, Dash and Flask to pull the data from Lakebase and visualize it in your app. To ensure all necessary dependencies are installed, add the required packages to your app's requirements.txt file. The following packages are used in the code snippets:

PLAINTEXT

```
pandas==2.3.1
databricks-sdk==0.57.0
psycopg[binary]==3.2.9
sqlalchemy==2.0.41
```

EXTENDING THE LAKEHOUSE WITH LAKEBASE

Lakebase adds transactional capabilities to the lakehouse by integrating a fully managed OLTP database directly into the platform. This reduces the need for external databases or complex pipelines when building applications that require reads and writes.



Lakebase is natively integrated with Databricks, including data synchronization, identity authentication and network security — just like other data assets in the lakehouse. As a result, you don't need custom ETL or reverse ETL to move data between systems. For example:

- You can serve analytical features back to applications in real time using the Online Feature Store and synced tables
- You can synchronize operational data with a Delta table — e.g., for historical data analysis

These capabilities make it easier to support production-grade use cases like:

- Updating state in AI agents
- Managing real-time workflows — e.g., approvals, task routing
- Feeding live data into recommendation systems or pricing engines

Lakebase is already being used across industries for applications such as personalized recommendations, chatbot applications and workflow management tools.

SUMMARY

Lakebase provides a transactional Postgres database that works seamlessly with Databricks Apps and provides easy integration with Lakehouse data. It simplifies the development of full-stack data and AI applications by eliminating the need for external OLTP systems or manual integration steps.

If you're already using Databricks for analytics and AI, Lakebase makes it easier to add real-time interactivity to your applications. With support for low-latency transactions, built-in security and tight integration with Databricks Apps, you can go from prototype to production without leaving the platform.

In this example, we showed you how to:

- Set up a Lakebase instance and configure access
- Create a Databricks app that reads and writes to Lakebase
- Use secure, token-based authentication with minimal setup
- Build a basic app for managing holiday requests using Python and SQL

For details on usage and pricing, see the [Lakebase](#) and [Databricks Apps](#) documentation.



04

Turning Analytics Into Applications

Turning Analytics Into Applications

By [Firas Farah](#) and [Yatish Anand](#)

INTRODUCTION: ANALYTICS AND OPERATIONS ARE CONVERGING

Today's applications can't rely solely on raw events. They need curated, contextual and actionable data from the lakehouse to power personalization, automation and intelligent user experiences.

Delivering that data reliably with low latency has been a challenge, often requiring complex pipelines and custom infrastructure.

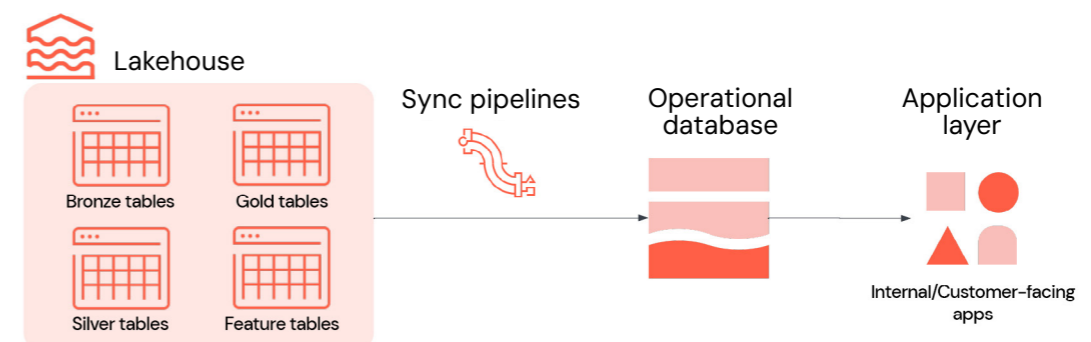
WHAT IS REVERSE ETL?

Reverse ETL syncs high-quality data from a lakehouse into the operational systems that power applications. This ensures that trusted datasets and AI-driven insights flow directly into applications that power personalization, recommendations, fraud detection and real-time decisioning.

Without reverse ETL, insights remain in the lakehouse and don't reach the applications that need them. The lakehouse is where data gets cleaned, enriched and turned into analytics, but it isn't built for low-latency app interactions or transactional workloads. That's where Lakebase comes in. It delivers trusted lakehouse data directly into the tools where it drives action.

In practice, reverse ETL typically involves four key components, all integrated into Lakebase:

- **Lakehouse:** Stores curated, high-quality data used to drive decisions, such as business-level aggregate tables (also known as Gold tables), engineered features and ML inference outputs
- **Syncing pipelines:** Move relevant data into operational stores with scheduling, freshness guarantees and monitoring
- **Operational database:** Is optimized for high concurrency, low latency and ACID transactions
- **Applications:** Serve as the final destination where insights become action, whether in customer-facing applications, internal tools, APIs or dashboards



CHALLENGES OF REVERSE ETL

Reverse ETL looks simple, but in practice, most teams run into the these challenges:

- **Brittle, custom-built ETL pipelines:** Often require streaming infrastructure, schema management, error handling and orchestration. They're brittle and resource intensive to maintain.
- **Multiple, disconnected systems:** Separate stacks for analytics and operations result in more infrastructure to manage, additional authentication layers and a higher risk of format mismatches
- **Inconsistent governance models:** Analytical and operational systems often reside in different policy domains, making it challenging to apply consistent quality controls and audit policies

These challenges create friction for both developers and the business, slowing efforts to reliably activate data and deliver intelligent, real-time applications.

LAKEBASE: INTEGRATED BY DEFAULT FOR EASY REVERSE ETL

Lakebase removes these barriers and transforms reverse ETL into a fully managed, integrated workflow. It combines a high-performance Postgres engine, deep lakehouse integration and built-in data synchronization, allowing fresh insights to flow into applications without additional infrastructure.

These capabilities of Lakebase are especially valuable for reverse ETL:

- **Deep lakehouse integration:** Syncs data from lakehouse tables to Lakebase on a snapshot, scheduled or continuous basis, without building or managing external ETL jobs. This replaces the complexity of custom pipelines, retries and monitoring with a native, managed experience.
- **Fully managed Postgres:** Built on open source Postgres, Lakebase supports ACID transactions, indexes, joins and extensions such as PostGIS and pgvector. You can connect with existing drivers and tools, such as pgAdmin or JDBC, thereby avoiding the need to learn new database technologies or maintain separate OLTP infrastructure.
- **Scalable, resilient architecture:** Lakebase separates compute and storage for independent scaling, delivering sub-10 ms query latency and thousands of QPS. Enterprise-grade features include multi-AZ high availability, point-in-time recovery and encrypted storage, which remove the scaling and resiliency challenges associated with self-managed databases.

- **Integrated security and governance:** Register Lakebase with Unity Catalog to bring operational data into your centralized governance framework, covering audit trails and permissions at the catalog level. Access via the Postgres protocol still utilizes native Postgres roles and permissions, ensuring authentic transactional security while aligning with your broader Databricks governance model.
- **Cloud-agnostic architecture:** Deploy Lakebase alongside your lakehouse in your preferred cloud environment without rearchitecting your workflows

With these capabilities in the Databricks Data Intelligence Platform, Lakebase replaces the fragmented reverse ETL setup that relies on custom pipelines, standalone OLTP systems and separate governance. It delivers an integrated, high-performance and secure service, ensuring that analytical insights flow into applications faster, with less operational effort and with governance preserved.

SAMPLE USE CASE: BUILDING AN INTELLIGENT SUPPORT PORTAL WITH LAKEBASE

As a practical example, let's walk through how to build an intelligent support portal powered by Lakebase. This interactive portal helps support teams triage incoming incidents using ML-driven insights from the lakehouse, such as predicted escalation risk and recommended actions. It does this while allowing users to assign ownership, track status and leave comments on each ticket.

Lakebase makes this possible by syncing predictions into Postgres while also storing updates from the app. This creates a support portal that combines analytics with live operations. The same approach applies to many other use cases, including personalization engines and ML-driven dashboards.

[Watch the app walkthrough.](#)

Step 1: Sync predictions from the lakehouse to Lakebase

The incident data, enriched with ML predictions, lives in a Delta table and is updated in near real time via a streaming pipeline. To power the support app, we use Lakebase reverse ETL to continuously sync this Delta table to a Postgres table.

In the UI, we select:

- **Sync mode:** Continuous for low-latency updates
- **Primary key:** incident_id

This ensures the app reflects the latest data with minimal delay.

Note: You can also create the sync pipeline programmatically using the Databricks SDK.

Create synced table

Destination
Specify where the synced table will be created

Name
dbdemos.support incidents_w_preds_st

Database instance
reverse-etl-demo

Postgres database
rev_etl

Synchronization settings
Configure how data should be synchronized from source to destination table

Primary key
incident_id X

Sync mode [sync modes explained](#)
 Snapshot Triggered Continuous

Continuous mode
Continuous keeps the table in sync with seconds of latency. However, it has a higher cost associated with it since a compute cluster is provisioned to run the continuous sync streaming pipeline.

Primary key is unique

Pipeline settings
Configure how data will be ingested and processed

Create new pipeline

Serverless budget policy
None

Step 2: Create a state table for user inputs

The support app also requires a table to store user-entered data, such as ownership, status and comments. Since this data is written from the app, it should be stored in a separate table in Lakebase — rather than the synced table.

Here's the schema:

SQL

```
CREATE TABLE support.user_updates (
  incident_id TEXT PRIMARY KEY, owner TEXT, comment TEXT, status
  TEXT
)
```

Step 3: Configure Lakebase access in Databricks Apps

Databricks Apps supports first-class integration with Lakebase. When creating your app, simply add Lakebase as an app resource and select the Lakebase instance and database. Databricks automatically provisions a corresponding Postgres role for the app's service principal, streamlining app-to-database connectivity. You can then grant this role the required database, schema and table permissions.

Compute > Apps >

Create new app

1 Name app — 2 Configure (optional)

App resources

Specify what resources the app's service principal will access on behalf of the app. [Learn more](#)

+ Add resource

Database	Permission	Resource key
reverse-etl-d... ▾	rev_etl ▾	Can conn... ▾
		database

Step 4: Deploy your app code

With your data synced and permissions in place, you can now deploy the Flask app that powers the support portal. The app connects to Lakebase via Postgres and serves a rich dashboard with charts, filters and interactivity.

CONCLUSION

Bringing analytical insights into operational applications no longer requires a complex, brittle process. With Lakebase, reverse ETL becomes a fully managed and integrated capability. It combines the performance of a Postgres engine, the reliability of a scalable architecture and the governance of the Databricks Platform. Whether you're powering an intelligent support portal or building other real-time, data-driven experiences, Lakebase reduces engineering overhead and speeds up the path from insight to action.

To learn more about how to [create synced tables](#) in Lakebase, check out our documentation and get started today.



05

Delivering Secure, Real-Time Applications on Databricks

Delivering Secure, Real-Time Applications on Databricks

By Sylvia Christin Schumacher

INTRODUCTION

Databricks Lakebase significantly enhances the ability to streamline operational databases for building intelligent applications. Databricks Apps enables the quick deployment of these data and AI apps into production, with out-of-the-box governance and auth.

As a fully managed Postgres service that integrates seamlessly with the Databricks Platform, Lakebase allows developers to work with transactional data natively — no custom ETL pipelines, connectors or middleware required. Databricks Apps takes this further by eliminating infrastructure management entirely, providing managed, serverless compute that automatically inherits your workspace's security policies and Unity Catalog permissions.

Historically, bridging OLTP and OLAP systems involved complex data engineering and bespoke integration layers, while deploying applications required separate devops and infrastructure teams, disparate CI/CD pipelines and manual security configurations. With Lakebase and Databricks Apps together, these complexities are significantly reduced. Developers can now access real-time analytical data directly from the transactional layer and deploy interactive applications in minutes rather than months, making it dramatically easier to incorporate live data into production-ready applications.

In the GenAI context, this combination is particularly powerful. Databricks Apps uniquely combines lakehouse data with interactive AI interfaces, such as Streamlit or Gradio, running directly on the Databricks Data Intelligence Platform — where your data and models already live. Transactional data from Lakebase becomes a key enabler powering real-time, context-aware applications that bring GenAI into production faster with built-in enterprise security and governance.

By surfacing this data directly in app interfaces, enterprises unlock new capabilities:

- AI assistants reference live business data while obeying easily configured access controls
- Users make data-driven decisions with up-to-date AI-driven guidance
- Retrieval augmented generation (RAG) models ground outputs in current facts
- Workflows stay aligned with evolving transactions through always-available, managed applications

This integration ensures GenAI operates with full enterprise context — exactly when and where it's needed, with the production reliability and simplified deployment that modern teams require.

In this chapter, we'll walk through how to build a secure, CI/CD-enabled **Streamlit app** and deploy it as a Databricks app that connects to Lakebase. The app enables users to explore synchronized campaign metrics from Unity Catalog in a read-only interface. This can power use cases such as business dashboards, campaign monitoring or ad hoc exploration.

KEY TECHNOLOGIES

- **Streamlit:** Interactive UI framework for Python
- **SQLAlchemy:** SQL toolkit and ORM for database access
- **Databricks SDK:** Secure OAuth token management
- **Postgres (Lakebase):** Managed OLTP back end
- **DABs:** Declarative app deployment and CI/CD integration
- **GitHub:** Source control and pipeline automation

SOLUTION OVERVIEW

The process consists of two major steps:

1. Set up Lakebase

- Create a Lakebase instance (Databricks-managed Postgres)
- Sync a Unity Catalog table into the Postgres instance via **Snapshot mode**

2. Build a Databricks app

- Use **Streamlit** for the UI
- Securely connect to Lakebase using **SQLAlchemy** and **Databricks OAuth**
- Add interactive filters and views on the relational table
- Use **Databricks Asset Bundles (DABs)** and **GitHub** for version control, deployment and automation

Check out the [GitHub repository](#) for full source code and deployment instructions.

STEP-BY-STEP GUIDE

To streamline development, we recommend [setting up Cursor with Databricks Connect](#) for local testing and iterations.

1. Set up Lakebase

If you don't already have a Lakebase instance with synced tables, follow these steps:

1. Create a Lakebase instance

Follow steps 1–7 in the [Lakebase documentation](#) to create a Lakebase instance named `postgres-campaigns`.

2. Clone the GitHub repository

SHELL

```
git clone https://github.com/databricks-solutions/databricks-  
blogposts.git cd  
  
databricks-blogposts/2025-12-surfacing-lakebase-tables-in-  
databricks-apps
```

The repository contains the following files for app deployment:

- `app.py` — The main Streamlit application
- `config.yaml` — Centralized configuration for database and table parameters
- `generate_campaign_data.ipynb` — Notebook to generate campaign performance data
- `requirements.txt` — All Python dependencies, including Streamlit, SQLAlchemy and the Databricks SDK
- `databricks.yml` — Declarative deployment configuration for DABs
- `README.md` — Clear documentation for setup and usage
- `gitignore` — Local and environment-specific file exclusion to keep the repository clean

3. Create a Unity Catalog table

Open the `generate_campaign_data.ipynb` script from the cloned GitHub repository. Within the notebook widgets, provide the catalog, schema and table name, and run the script to generate synthetic campaign performance data.

4. Sync the Unity Catalog table

Use the **Synced Tables** feature to create a read-only table in Postgres that automatically synchronizes data from a Unity Catalog table. Follow the steps [here](#) to create a synced table. Sync the table to your Lakebase instance from step 1.

- Postgres database: `campaign_db`
- Table name: `campaign_metrics_synced`
- Mode: `Snapshot`

You should now have:

- A Lakebase instance: `postgres-campaigns`
- A synced relational table: `campaign_metrics_synced`

2. Deploy app

We'll now create a **Streamlit app** that connects to your Lakebase instance and surfaces the data interactively.

1. Update configuration

In your cloned GitHub repository, edit `config.yaml` with your database details. You can find the required information under the **Connection details** tab of your database.

NONE

```
postgres:
  host: "<your-managed-postgres-host>"
  port: 5432
  database: "<your-postgres-database>" # e.g."postgres-campaigns"
  username_env: "DATABRICKS_CLIENT_ID"
  password_env: "DATABRICKS_OAUTH_TOKEN"

synced_table:
  schema: "<your-schema>"
  name: "<your-synced_table>" # e.g. "campaign_metrics_synced"
```

2. Install dependencies

SHELL

```
pip install -r requirements.txt
```

3. Set Databricks environment variables

Go to **Settings > Developer > Access tokens > Manage > Generate new token** to get a new personal access token (PAT). Set environment variables as follows:

NONE

```
export DATABRICKS_TOKEN=<YOUR_DATABRICKS_PAT>

# General
export DATABRICKS_HOST="https://your-workspace.cloud.databricks.com"
export DATABRICKS_TOKEN="your_personal_access_token"
export DB_USER="<your.username@your-company.com>"
export DB_PASSWORD="your_jwt_token_here"
```

4. Configure Postgres database

To connect to your own Postgres database, update the `DB_CONFIG` section in `app.py`:

NONE

```
# Database Configuration
DB_CONFIG = {
    "host": "instance-  
<your-lakebase-id>.database.cloud.databricks.com", #
    Your Postgres host
    "port": 5432,
    "database": "your_database_name", # Database name from step 1.2
    "schema": "your_schema", # UC Schema name
    "table": "your_table_name" # Table name from step 1.2
}
```

5. Update app name

The `databricks.yml` file defines your app as a deployable resource.

Populate your app name:

NONE

```
resources:
  apps:
    <your_app_name>:
      name: <your_app_name>
      source_code_path: .
```

6. Deploy using DABs

NONE

```
databricks bundle init # Initialize DAB in your local directory
databricks bundle validate # Validate bundle config
databricks bundle deploy
apps start <your-app-name> # Start app compute
databricks apps deploy <your-app-name> --source-code-path /
Workspace/Users/<your-user>/bundle/<your-app-name>/development/files

# For future changes only run
databricks bundle deploy
```

Your bundle source code will now be available in the Databricks workspace under the following:

NONE

```
/Workspace/Users/<your-username>/bundle/lakebase-in-dbx-apps/
development
```

You can navigate to your app through **Compute > Apps > <your-app>** and open the provided link. Since your app doesn't have privileges to access your database yet, you won't be able to see your data at this point.

3. Configure app privileges for the database

1. Extract CLIENT_ID from the app

- Navigate to Compute > Apps > [<your-app>](#)
- In your app, open the **Environment** tab and copy your **DATABRICKS_CLIENT_ID** value

2. Grant privileges to the app

- Back in your Postgres instance (Compute > OLTP Database > >your-instance>), click **New Query**
- Validate that the selected compute in the editor shows Postgres compute
- Switch the database from "postgres" to your Postgres database — e.g., [postgres-campaigns](#)
- Execute the following code:

SQL

```
CREATE EXTENSION IF NOT EXISTS databricks_auth;

SELECT
pg_databricks_create_role('<DATABRICKS_CLIENT_ID>','SERVICE_PRINCIPAL');

GRANT ALL PRIVILEGES ON DATABASE "<your-postgres-database>" TO
"<DATABRICKS_CLIENT_ID>";

GRANT ALL PRIVILEGES ON SCHEMA <your-schema> TO "<DATABRICKS_
CLIENT_ID>";

GRANT ALL PRIVILEGES ON TABLE <your-schema>.<your-table> TO
"<DATABRICKS_CLIENT_ID>";
```

You can navigate back to your app through Compute > Apps > [<your-app>](#). Open the provided link and you'll see your relational table.

HIGHLIGHTS ON POSTGRES CONNECTION WITH OAUTH

Using the **Databricks SDK**, the app uses OAuth tokens to securely authenticate against the managed Postgres instance.

- Requires no manual token management
- Refreshes tokens automatically every 15 minutes
- Uses your Databricks workspace credentials

PYTHON

```
from databricks import sdk
from databricks.sdk.core import Config
from sqlalchemy import create_engine, event
import time

config = Config()
workspace_client = sdk.WorkspaceClient()

postgres_pool = create_engine(
    f"postgresql+psycopg://{config.client_id}:@<your-db-host>:5432/<your-
db-name>"
)

postgres_password = None
last_refresh = time.time()

@event.listens_for(postgres_pool, "do_connect")
def provide_token(dialect, conn_rec, cargs, cparams):
    global postgres_password, last_refresh
    if postgres_password is None or time.time() - last_refresh > 900:
        postgres_password = workspace_client.config.oauth_token().access_
token
        last_refresh = time.time()
    cparams["password"] = postgres_password
```

LESSONS LEARNED

- **Databricks OAuth** — Is seamless and production-ready for app authentication
- **Streamlit** — Offers rapid prototyping for business-facing tools
- **Databricks Asset Bundles (DABs)** — Simplify deployment and rollback — essential for CI/CD pipelines
- **Synced tables** — Make transactional data immediately accessible in Databricks Apps

TRY IT YOURSELF

Would you like to try it on your own data?

- Clone the [GitHub repository](#)
- Customize `DB_CONFIG` in `app.py`
- Customize `your-app-name` in `databricks.yml`
- Deploy using `databricks bundle deploy`

Bring operational data to life in Databricks Apps with just a few lines of code — and give your teams the insights they need, where they need them.

Create an intelligent application today. Sync your lakehouse data into Lakebase in minutes, without building a pipeline or maintaining a server.



06

How to Build AI Agents With Conversational Memory Using Lakebase

How to Build AI Agents With Conversational Memory Using Lakebase

By [Yatish Anand](#), Bo Cheng, Cathy Zdravevski, [Evan Pandya](#) and [Susan Pierce](#)

WHY CONVERSATIONAL MEMORY MATTERS

Many AI agents work well in single-turn interactions but struggle when applied to real operational workflows. In cybersecurity, investigations rarely conclude in a single step — analysts pivot from threat type to source IP, from IP to user and from user to device. These investigations often span multiple sessions and require continuity.

To be effective in production, agents need state. They must remember what has already happened and resume work with full context intact.

In this chapter, you'll build a cybersecurity AI agent on the Databricks Platform that persists conversational memory across interactions. The agent stores execution state in Lakebase using LangGraph checkpointing, allowing investigations to pause and resume seamlessly. You'll deploy the agent using the Databricks AI Agent Framework and expose it to end users as a Databricks app built using Streamlit.

USING LAKEBASE AS THE STATE LAYER FOR AGENTS

Stateful agents need a transactional database that can read and write application state with minimal latency. Lakebase provides this foundation as a fully managed, Postgres-compatible OLTP service integrated fully within the Databricks Platform. Because it's Postgres-compatible, you get the reliability and ecosystem of a proven transactional database without standing up separate infrastructure.

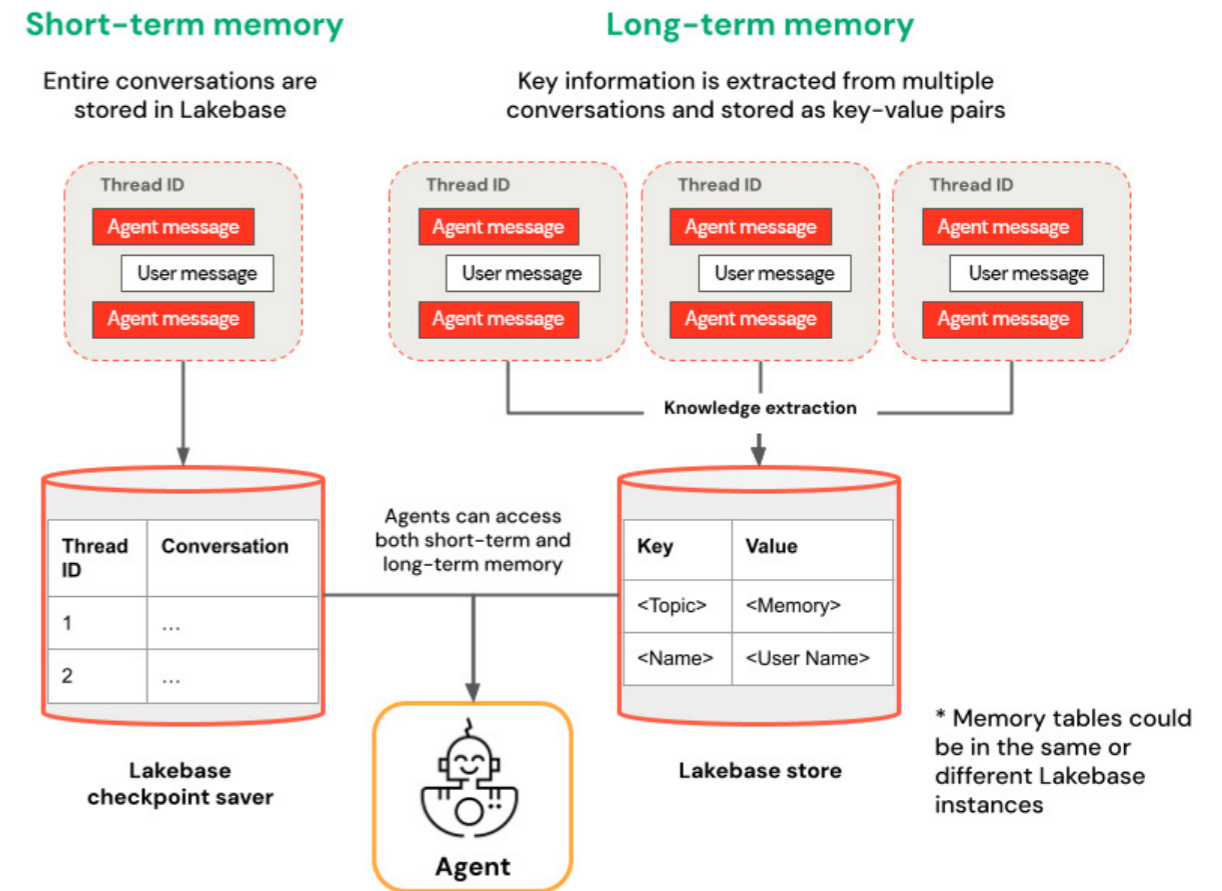
In this solution, Lakebase serves as LangGraph's checkpoint store. Each step of the agent's execution is persisted under a thread identifier, and when that thread is referenced again, the agent resumes with its full context — prior messages, tool calls and intermediate state — intact. Low-latency reads mean the agent can retrieve this context quickly, keeping conversations responsive.

This approach enables real conversational memory without introducing a separate database or managing additional operational complexity. Agent logic, tools, memory and deployment all live on the same platform where your data and AI workloads already run.

MEMORY PATTERNS FOR AI AGENTS

This chapter focuses on short-term memory implemented through thread-level checkpointing. Each conversation is associated with a unique thread identifier, and the agent’s state is saved incrementally as the workflow progresses. This allows investigations to be resumed at any point without losing context.

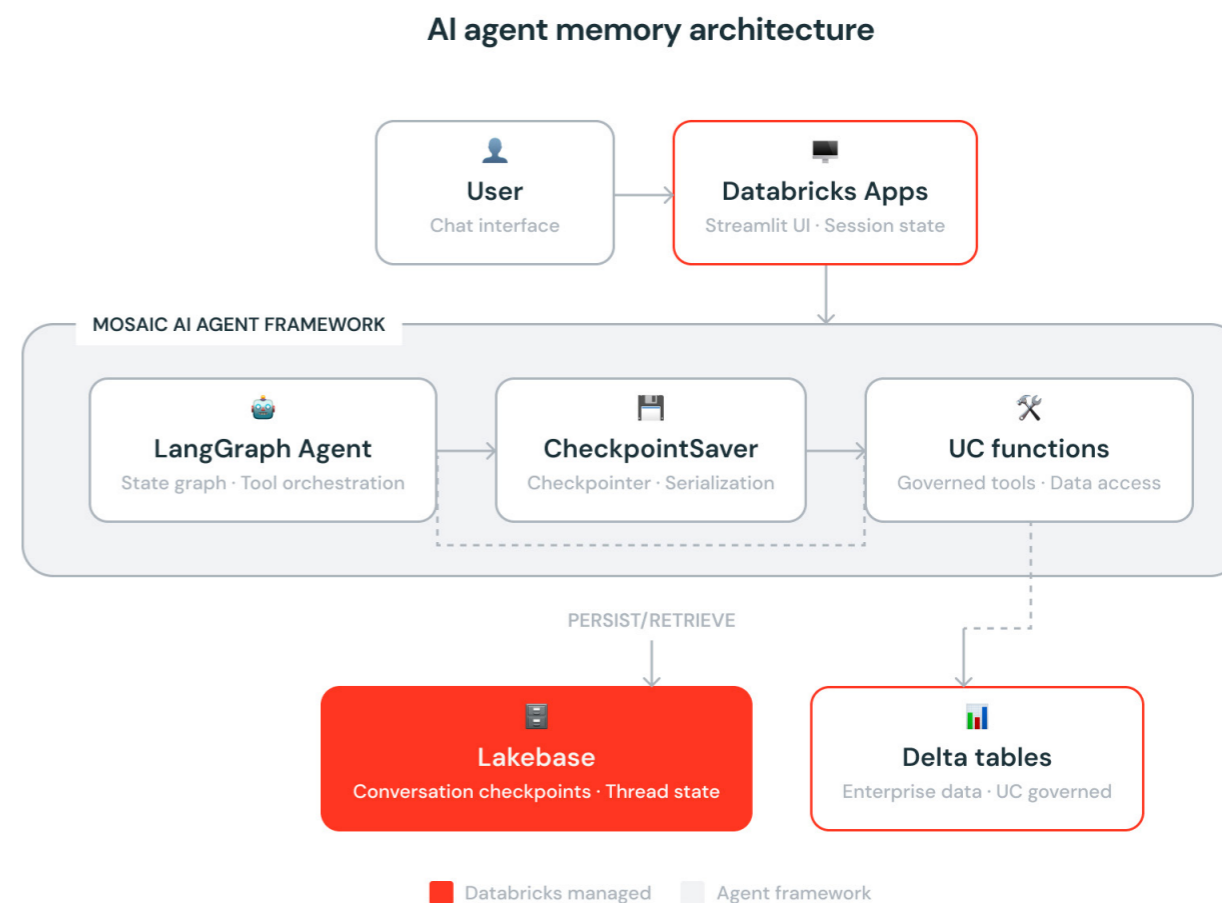
Lakebase also supports longer-lived memory patterns that persist information across threads and users. These patterns enable agents to accumulate knowledge over time but introduce additional design considerations around scope, retention and governance. For long-term memory that persists user preferences or accumulated findings across sessions, see the long-term memory section in the [Databricks documentation](#).



ARCHITECTURE OVERVIEW

The solution consists of the following components:

- A chat model served on Databricks that performs reasoning
- Unity Catalog functions that expose governed security data as tools
- LangGraph orchestration to manage control flow and tool invocation
- Lakebase Provisioned as a transactional checkpointer for agent state
- Databricks AI Agent Framework for packaging and deployment
- A Streamlit-based Databricks app for end user interaction



Together, these components form a production-ready, stateful agent architecture that runs entirely on the Databricks Platform.

IMPLEMENTATION GUIDE

Prerequisites

This guide assumes familiarity with building AI applications on the Databricks Platform and focuses on agent architecture rather than environment bootstrapping.

Before you begin, ensure you have:

- A Databricks workspace with access to serverless compute
- Permissions to create Unity Catalog functions
- Permissions to create a Lakebase-provisioned instance
- Access to Databricks Model Serving and Databricks Apps

You'll use the following libraries in this demo. Run the setup on Databricks serverless compute in a notebook, then follow along step by step. The GitHub repository with the full working solution can be found [here](#).

PYTHON

```
databricks-connect
databricks-agents
databricks-langchain
unitycatalog-langchain[databricks]
psycopg[binary,pool]
langgraph-checkpoint-postgres==2.0.21
langgraph==0.3.4
langchain
mlflow
uv
```

Step 1: Add governed security context with Unity Catalog functions

Agents depend on trusted context to make decisions. In cybersecurity workflows, this context often resides in structured event and identity tables. Unity Catalog functions provide a secure mechanism to expose this data to agents as callable tools.

In this example, you create two SQL functions:

- `get_cyber_threat_info` retrieves the most recent threat event for a given threat type
- `get_user_info` retrieves user details associated with a source IP address

These functions are authored in Databricks SQL (DBSQL) and governed by Unity Catalog, ensuring consistent access control, auditing and lineage.

SQL

```
-- Create a SQL function that returns the cyber threat info given a threat
type
CREATE OR REPLACE FUNCTION catalog.schema.get_cyber_threat_info(
  threat_type STRING COMMENT 'input cyber threat type'
)
RETURNS STRING
COMMENT 'Returns latest threat_id, event_timestamp, source_ip, protocol,
detection_tool given a threat_type'
```

```
RETURN
SELECT
  CONCAT(
    'Threat ID: ',
    threat_id,
    ', ',
    'Timestamp: ',
    event_timestamp,
    ', ',
    'Source IP: ',
    source_ip,
    ', ',
    'Protocol: ',
    protocol,
    ', ',
    'Detection Tool: ',
    detection_tool
  )
FROM
  catalog.schema.cyber_threat_detection
WHERE
  threat_type = threat_type
ORDER BY
  event_timestamp DESC
LIMIT 1;
```

```

-- Create a SQL function that returns the user info given a source ip address
CREATE OR REPLACE FUNCTION catalog.schema.get_user_info(
  source_ip STRING COMMENT 'input ip address'
)
RETURNS STRING
COMMENT 'Returns latest user_name, department, email, ip_address,
location given a source_ip address'
RETURN
SELECT
  CONCAT(
    'Username: ',
    user_name,
    ' ',
    'Department: ',
    department,
    ' ',
    'Email: ',
    email,
    ' ',
    'IP Address: ',
    ip_address,
    ' ',
    'Location: ',
    location
  )

```

```

FROM
  catalog.schema.user_info
WHERE
  ip_address = source_ip
LIMIT 1;

```

Once you create the functions, you should see them in your designated catalog and schema, under the **Functions** tab.

The screenshot shows the Databricks Catalog Explorer interface. The breadcrumb path is 'Catalog Explorer > bo_cheng_dnb_demos > agents'. The function name is 'get_cyber_threat_info'. There are tabs for 'Overview' and 'Permissions'. The 'Description' section states: 'Returns latest threat_id, event_timestamp, source_ip, protocol, detection_tool given a threat_type'. The 'About this function' section shows the owner as 'Bohao Cheng' and the language as 'SQL'. The 'Definition' section displays the following SQL code:

```

1 (SELECT
2   CONCAT(
3     'Threat ID: ',
4     threat_id,
5     ', ',
6     'Timestamp: ',
7     event_timestamp,
8     ', ',
9     'Source IP: ',
10    source_ip,
11    ', ',
12    'Protocol: ',
13    protocol,
14    ', ',
15    'Detection Tool: ',

```

Below the definition is the 'Function metadata' table:

Parameter	Value
Parameters	threat_type: STRING COMMENT input cyber threat type
Type	SCALAR
Return type	STRING
Language	SQL

Step 2: Create a Lakebase instance for checkpointings

To persist agent state, create a Lakebase instance that serves as a LangGraph checkpoint. Rather than managing an external Postgres database, Lakebase provides a managed transactional service that integrates directly with Databricks security and identity.

Each execution step of the agent is written to Lakebase. Because Lakebase is optimized for low-latency transactional workloads, these writes add minimal overhead to the agent's response time. By associating checkpoints with a thread identifier, the agent can reliably resume conversations across sessions without sacrificing the responsiveness users expect.

This implementation uses the [langgraph-checkpoint-postgres](#) integration so LangGraph can persist agent state directly into Lakebase using standard Postgres semantics.

You can create the Lakebase instance using the [Databricks SDK for Python](#) or manage it declaratively with [Databricks Asset Bundles](#) (DABs), depending on how you standardize infrastructure.

In addition, by creating the database catalog, you can now query your checkpoint history using DBSQL.

Compute > Lakebase Postgres >

bo-test-lakebase-3

Configuration Connection details Catalogs Metrics Permissions

Name	bo-test-lakebase-3
Instance ID	cd00746e-b544-45c8-9f08-5062a0858c7d
Status	Available
PostgreSQL version	16
Serverless usage policy	None
Size (Capacity Units)	1

Advanced settings

Run all Just now (5s) main default New SQL editor: ON feature/bo-che... Edit Query Visual 00vsdb M Schedule Share Save

```

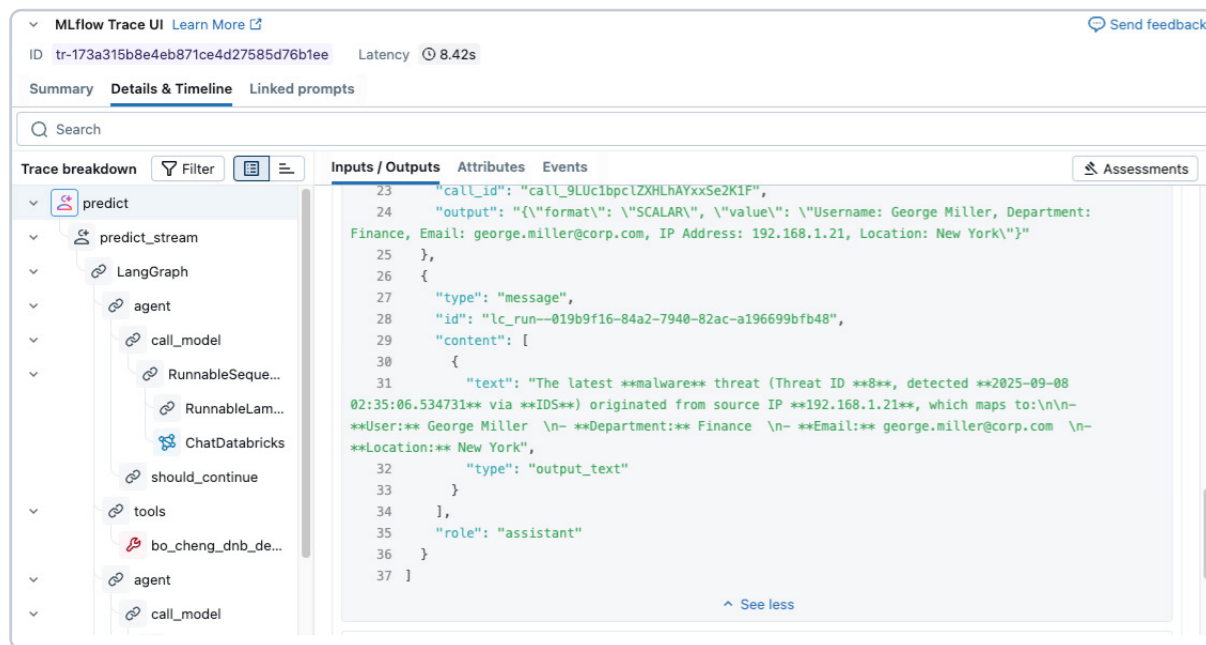
1 SELECT
2   thread_id,
3   metadata,
4   checkpoint,
5   checkpoint_id parent_checkpoint_id,
6   checkpoint_ns,
7   type
8 FROM
9   'bo-test-lakebase-catalog'.public.checkpoints;

```

Add parameter

Table	thread_id	metadata	checkpoint
1	522eba5f-4b99-48d6-941b-015f6b9727ab	{"step": -1, "source": "input", "parents": {}}	> {"v": 4, "id": "1f0ecc86-f16d-69ff-bfff-6d023ea8805a", "ts": "2026-01-08T19:30:06.454822+00:00", "pendi
2	522eba5f-4b99-48d6-941b-015f6b9727ab	{"step": 0, "source": "loop", "parents": {}}	> {"v": 4, "id": "1f0ecc86-f172-6e6c-8000-38367559b803", "ts": "2026-01-08T19:30:06.456980+00:00", "pendi
3	522eba5f-4b99-48d6-941b-015f6b9727ab	{"step": 1, "source": "loop", "parents": {}}	> {"v": 4, "id": "1f0ecc87-0b4e-68b6-8001-7f3aab8bf825", "ts": "2026-01-08T19:30:07.700371+00:00", "pendi
4	522eba5f-4b99-48d6-941b-015f6b9727ab	{"step": 2, "source": "loop", "parents": {}}	> {"v": 4, "id": "1f0ecc87-22ea-64ce-8002-5c9939feb76a", "ts": "2026-01-08T19:30:10.175901+00:00", "pendi
5	522eba5f-4b99-48d6-941b-015f6b9727ab	{"step": 3, "source": "loop", "parents": {}}	> {"v": 4, "id": "1f0ecc87-2b3a-6f26-8003-f70b4346f8a6", "ts": "2026-01-08T19:30:11.047789+00:00", "pendi

Step 3: Orchestrate with LangGraph and trace with MLflow



Databricks integrates directly with the LangGraph orchestration framework.

If you're following along, select the LangGraph option. LangGraph provides the control plane for agent behavior — when to call the model, when to call tools and how to persist state between turns. In this implementation, you bind Unity Catalog tools to the chat model and use a Lakebase-backed checkpointer to save and restore thread-level state.

Before deployment, validate behavior with [MLflow Tracing](#). Tracing makes it easier to audit inputs, outputs, tool calls and intermediate steps, which is essential for debugging and for understanding agent behavior in production.

Step 4: Deploy the agent with the Databricks AI Agent Framework

Once validated, the agent is packaged and deployed using the Databricks AI Agent Framework. This simplifies registration, versioning and serving while preserving authentication passthrough to governed resources.

When logging the agent with MLflow, explicitly declare dependent resources, including model serving endpoints, Unity Catalog functions and the Lakebase instance. This ensures the deployment has clear visibility into the assets it relies on. The following code shows only the relevant parts of the predict and predict_stream functions, which demonstrate the databricks_langchain short-term memory CheckpointSaver, which integrates with Lakebase. Feel free to check our [GitHub repository](#) for the full model code.

PYTHON

```

def predict(self, request: ResponsesAgentRequest) ->
ResponsesAgentResponse:
    outputs = [
        event.item
        for event in self.predict_stream(request)
        if event.type == "response.output_item.done"
    ]
    return ResponsesAgentResponse(
        output=outputs, custom_outputs=request.custom_inputs
    )

def predict_stream(
    self, request: ResponsesAgentRequest
) -> Generator[ResponsesAgentStreamEvent, None, None]:
    thread_id = self._get_or_create_thread_id(request)
    ci = dict(request.custom_inputs or {})
    ci["thread_id"] = thread_id
    request.custom_inputs = ci

# Convert incoming Responses messages to ChatCompletions format
# LangChain will automatically convert from ChatCompletions to
LangChain format
    cc_msgs = self.prep_msgs_for_cc_llm([i.model_dump() for i in request.
input])
    langchain_msgs = cc_msgs
    checkpoint_config = {"configurable": {"thread_id": thread_id}}

```

```

with
CheckpointSaver(instance_name=LAKEBASE_INSTANCE_NAME) as
checkpointer:
    graph = self._create_graph(checkpointer)

    for event in graph.stream(
        {"messages": langchain_msgs},
        checkpoint_config,
        stream_mode=["updates", "messages"],
    ):
        if event[0] == "updates":
            for node_data in event[1].values():
                if len(node_data.get("messages", [])) > 0:
                    yield from output_to_responses_items_stream(
                        node_data["messages"]
                    )
        elif event[0] == "messages":
            try:
                chunk = event[1][0]
                if isinstance(chunk, AIMessageChunk) and chunk.content:
                    yield ResponsesAgentStreamEvent(
                        **self.create_text_delta(
                            delta=chunk.content, item_id=chunk.id
                        ),
                    )
            except Exception as exc:
                logger.error("Error streaming chunk: %s", exc)

```

Subsequently, you must log and register your agent using the [models from code](#) approach in MLflow.

PYTHON

```
# Determine Databricks resources to specify for automatic auth
passthrough at deployment time
import mlflow
    databricks_langchain import VectorSearchRetrieverTool
from mlflow.models.resources import (
    DatabricksFunction,
    DatabricksServingEndpoint,
    DatabricksLakebase,
    DatabricksVectorSearchIndex,
) # we are adding DatabricksLakebase resource type
from mlflow.models.auth_policy import AuthPolicy, SystemAuthPolicy,
UserAuthPolicy
from unitycatalog.ai.langchain.toolkit import UnityCatalogTool
from agent import LLM_ENDPOINT_NAME, LAKEBASE_INSTANCE_NAME,
tools
from pkg_resources import get_distribution

# TODO: Manually include additional underlying resources if needed and
update values for endpoint/lakebase
resources = [
    DatabricksServingEndpoint(endpoint_name=LLM_ENDPOINT_NAME),
    DatabricksLakebase(database_instance_name=LAKEBASE_INSTANCE_
NAME),
]
```

```
for tool in tools:
    if isinstance(tool, VectorSearchRetrieverTool):
        resources.extend(tool.resources)
    elif isinstance(tool, UnityCatalogTool)

resources.append(DatabricksFunction(function_name=tool.uc_function_
name))

# System policy: resources accessed with system credentials
system_policy = SystemAuthPolicy(resources=resources)

# User policy: API scopes for OBO access
api_scopes = [
    "sql.statement-execution",
    "mcp.genie",
    "mcp.external",
    "catalog.connections",
    "mcp.vectorsearch",
    "vectorsearch.vector-search-indexes",
    "iam.current-user:read",
    "sql.warehouses",
    "dashboards.genie",
    "serving.serving-endpoints",
    "iam.access-control:read",
    "apps.apps",
    "mcp.functions",
    "vectorsearch.vector-search-endpoints",
]
```

```

user_policy = UserAuthPolicy(api_scopes=api_scopes)

input_example = {
    "input": [{"role": "user", "content": "What is an LLM agent?"}],
    "custom_inputs": {"thread_id": "example-thread-123"},
}

with mlflow.start_run():
    logged_agent_info = mlflow.pyfunc.log_model(
        name="agent",
        python_model="agent.py",
        input_example=input_example,
        pip_requirements=[
            f"databricks-langchain[memory]=={get_distribution('databricks-
langchain[memory]').version}",
        ],
        resources=resources,
    )

```

After the model is logged, you can use the catalog to view versions, artifacts and even get an overview of lineage showing relevant Unity Catalog objects.

Catalog Explorer > bo_cheng_dnb_demos > agents > memory_agent >

memory_agent version 37 Copy this version

Overview **Lineage** Artifacts Traces

Filter lineage All assets Up and Downstream Last year See lineage graph

Name	Direction	Type	Last activity
agents_bo_cheng_dnb_demos-agents-memory_agent	↓ Downstream	Serving endpoint	4 days ago
memory_agent_9_payload bo_cheng_dnb_demos.agents	↓ Downstream	Table	4 days ago
memory_agent_8_payload bo_cheng_dnb_demos.agents	↓ Downstream	Table	4 days ago
get_cyber_threat_info bo_cheng_dnb_demos.agents	↑ Upstream	Function	4 days ago
get_user_info bo_cheng_dnb_demos.agents	↑ Upstream	Function	4 days ago
02-lakebase-langgraph-checkpointer-agent	↑ Upstream	Notebook	4 days ago

< Previous Next >

Finally, you can use a simple `agents.deploy()` function call to create the model serving endpoint and instantiate the Review App for SME evaluation. Here, you log any necessary environment variables that your agent needs for authentication, such as a service principal client id and client secret designated for authentication to the Lakebase-provisioned instance.

PYTHON

```
from databricks import agents

agents.deploy(
    UC_MODEL_NAME,
    uc_registered_model_info.version,
    environment_vars={
        "DATABRICKS_HOST": "{{secrets/dbdemos/DATABRICKS_HOST}}",
        "DATABRICKS_CLIENT_ID": "{{secrets/dbdemos/DATABRICKS_CLIENT_ID}}",
        "DATABRICKS_CLIENT_SECRET": "{{secrets/dbdemos/DATABRICKS_CLIENT_SECRET}}",
    },
    tags={"endpointSource": "playground"},
)
```

After deployment, the agent can be tested using the AI Playground or Review App before being exposed to end users. The Review App is a built-in chat UI to vibe-check your AI app before integrating with your front-end Databricks app.

The screenshot displays the Databricks AI Playground interface. At the top, it says "Playground" with a "Provide feedback" link. Below that, there's a header for the agent: "agents_bo_cheng_dnb_demos-agents-memory_agent" and a "Get code" button. The main area is a chat window. On the left, under "You", the user asks: "Who was just mentioned in the previous context?". On the right, the AI agent responds: "George Miller was just mentioned in the previous context. He's the user from the Finance department in New York who was identified in connection with the latest malware threat (originating from IP address 192.168.1.21)". Below the response, it shows "5.13s to generate" and a "View Trace" link. At the bottom of the chat area, there are "Suggested questions" and a "Preview" button. To the left of the chat, there's a "custom_inputs" section with a toggle set to "On" and a text area containing a JSON string: {"thread_id": "4"}. Below that, there's an "AI judge" section with a toggle set to "Off" and a "Preview" button, with a note: "Get assessments from the LLM judges in Mosaic AI Agent Evaluation."

Now you can integrate the model serving endpoint with a Databricks app — the most secure way to build AI apps on the Databricks Platform — with out-of-the-box support for Python frameworks like Streamlit, Gradio, Plotly Dash, Shiny and Flask. For this cybersecurity analyst agent, we're using Streamlit.

Databricks Apps offers two authentication modes: app authorization (using a provided service principal) or user authorization (on-behalf-of-user, where the app acts with the identity of the logged-in user). Either way, you use the MLflow deployments client to interact with your agent's model serving endpoint.

The key to conversational memory is the `thread_id` — a unique identifier that ties a conversation's checkpoints together in Lakebase. In your Streamlit app, users can enter an existing `thread_id` in the sidebar to resume a previous conversation exactly where they left off. In the next figure, the `thread_id` is 4, so if the user closes the app and later returns with that same identifier, the agent picks up with full context of the prior conversation.

If no `thread_id` is provided, the app generates a new one for the session, starting a fresh conversation. This is a simple implementation to demonstrate how short-term memory works. In production, your app would typically handle `thread_id` persistence automatically, associating each user with their conversation threads so they don't have to track identifiers manually.



CONCLUSION

Stateful memory is essential for production AI agents. In domains like cybersecurity, investigations span multiple turns and sessions and agents must retain context to be effective.

In this guide, you built a stateful cybersecurity agent on Databricks using Lakebase as a transactional memory layer for LangGraph checkpointing. Unity Catalog functions provide governed access to data, MLflow enables tracing and lifecycle management and the Databricks AI Agent Framework simplifies deployment. Together, these components deliver an end-to-end agent architecture that runs entirely on the Databricks Platform.

This pattern applies broadly to any multistep workflow that requires continuity. With Lakebase, you can add conversational memory to agents without external databases, keeping state, governance and deployment unified in a single platform.

RESOURCES

- [Documentation](#)
- [Example notebooks](#)
- [GitHub repository](#)



Build Intelligent Apps on the Databricks Platform

With Databricks Apps and Lakebase, the entire application stack sits together, alongside the lakehouse. By combining the two, you can build interactive tools that store and update state in Lakebase, access governed data in the lakehouse and serve everything through a secure, serverless UI — all without managing separate infrastructure. This makes it easier to build and deploy apps that combine transactional state, analytics and AI.

[Try Databricks free](#)[Watch a demo](#)

Documentation

[Read Databricks Apps documentation](#)[Read Lakebase documentation](#)

About Databricks

Databricks is the data and AI company. More than 20,000 organizations worldwide — including adidas, AT&T, Bayer, Block, Mastercard, Rivian, Unilever and over 60% of the Fortune 500 — rely on Databricks to build and scale data and AI apps, analytics and agents. Headquartered in San Francisco with 30+ offices around the globe, Databricks offers a unified Data Intelligence Platform that includes Agent Bricks, Lakeflow, Lakehouse, Lakebase and Unity Catalog. To learn more, follow Databricks on [LinkedIn](#), [X](#), [YouTube](#) and [Instagram](#).

