





About Me

- Software Developer / ML
- Published Technical Book
- Social Entrepreneur
- International Tech Speaker
- Career Coach SkillUp with Drishti



### Why Real-Time Predictions?



### **Real-Time Predications**



Instant decisionmaking



Improved user experience



Competitive advantage



**Cost-effective solution** 



#### PostgreSQL Features



ROBUST RELATIONAL DATABASE EXTENSIBILITY WITH PROCEDURAL LANGUAGES BUILT-IN SUPPORT FOR JSON AND OTHER DATA TYPES



### PL/Python Advantages



Write PostgreSQL functions in Python



Access to Python's rich ecosystem of libraries



Seamless integration with database operations



# Implementing ML Models in PL/Python



# Implementing ML Models in PL/Python

The ability to implement ML models directly within the database using PL/Python opens new possibilities for real-time predictions and data-driven decision making.



### Serialization and Deserialization of ML Models

 Serialization is the process of converting a complex object, like a trained machine learning model, into a format that can be easily stored or transmitted.

• Deserialization is the reverse process, reconstructing the object from the serialized format.



### Database storage



Databases typically store structured data, not complex Python objects.

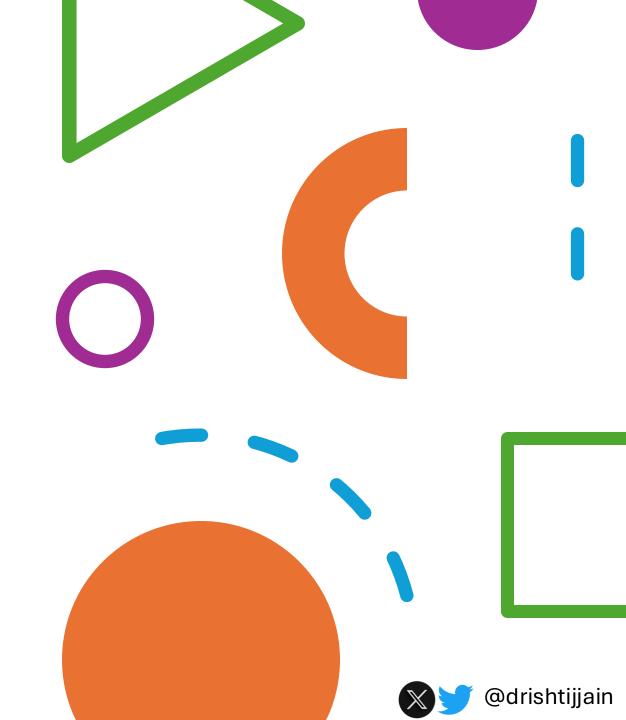


Serialization allows us to convert our ML models into a format (like binary data) that can be stored in database columns.



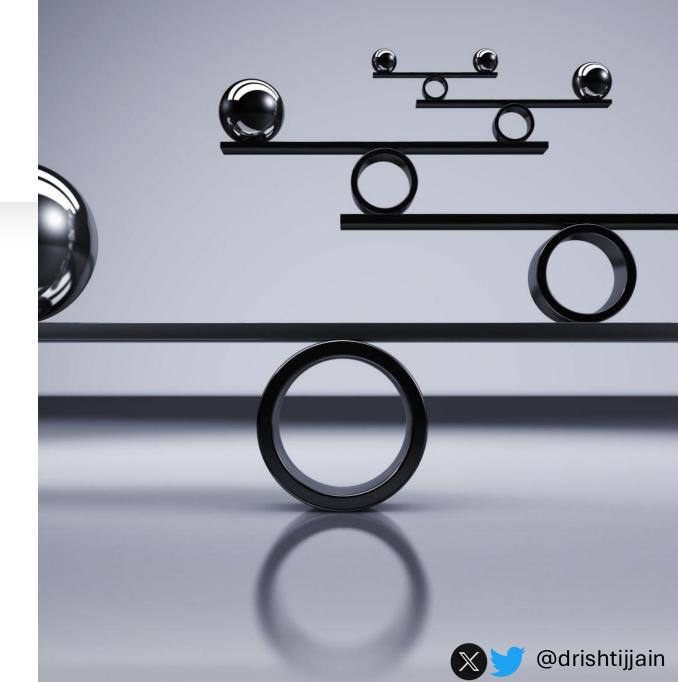
### Data transfer

When moving models between systems or from the training environment to the production database, serialization enables easy transfer of the model.

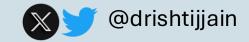


#### Persistence

Serialization allows us to save the state of a trained model, so we can load it later without retraining.



# In our PostgreSQL and PL/Python context, we're using Python's pickle module for serialization.



### Here's how it works:



After training the model, we use pickle.dumps() to serialize it into a binary format.



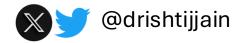
This binary data is stored in a PostgreSQL bytea column.



When we need to use the model, we retrieve the binary data and use pickle.loads() to deserialize it back into a Python object.



### Setting Up the Environment



#### Enabling PL/Python

### CREATE EXTENSION plpython3u;

 $\bigcirc \bigcirc \bigcirc$ 



#### Creating a Sample Database

#### $\bigcirc \bigcirc \bigcirc \bigcirc$

```
CREATE TABLE customer_data (
    id SERIAL PRIMARY KEY,
    age INTEGER,
    income NUMERIC,
    credit_score INTEGER,
    purchase_amount NUMERIC
);
INSERT INTO customer_data (age, income, credit_score, purchase_amount)
VALUES
    (35, 50000, 700, 1000),
    (28, 35000, 650, 500),
    (45, 80000, 750, 2000);
```



Implementing ML Models in PL/Python



### Linear Regression Model



1

### Linear regression

- Linear regression is a statistical method for modeling the relationship between a dependent variable (Y) and one or more independent variables (X)
- It assumes a linear relationship between variables
- The simplest form is simple linear regression with one independent variable:

$$Y=eta_0+eta_1X+arepsilon$$

Where:

- β\_0 is the y-intercept
- $\beta_1$  is the slope
- ε is the error term



### Linear Regression Model

#### $\bigcirc \bigcirc \bigcirc \bigcirc$

```
CREATE OR REPLACE FUNCTION train_model()
RETURNS bytea AS $$
    import pandas as pd
    from sklearn.linear_model import LinearRegression
    import pickle
```

```
# Fetch data from the database
data = plpy.execute("SELECT age, income, credit_score, purchase_amount FROM customer_data")
df = pd.DataFrame(data)
```

```
# Prepare features and target
X = df[['age', 'income', 'credit_score']]
y = df['purchase_amount']
```

```
# Train the model
model = LinearRegression()
model.fit(X, y)
```

```
# Serialize the model
return pickle.dumps(model)
```

LANGUAGE plpython3u;

\$\$



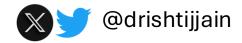
#### **Linear Regression Model**

```
-- Train and store the model
CREATE TABLE IF NOT EXISTS ml_models (
    id SERIAL PRIMARY KEY,
    model_name TEXT,
    model_data bytea
);
INSERT INTO ml_models (model_name, model_data)
```

VALUES ('purchase\_predictor', train\_model());



### **Creating a Prediction Function**



### **Prediction Function**

#### •••

```
CREATE OR REPLACE FUNCTION predict_purchase(age INTEGER, income NUMERIC, credit_score INTEGER)
RETURNS NUMERIC AS $$
    import pickle
    from sklearn.linear_model import LinearRegression
```

```
# Fetch the model
model_data = plpy.execute("SELECT model_data FROM ml_models WHERE model_name = 'purchase_predictor'")[0]['model_data']
model = pickle.loads(model_data)
```

```
# Make prediction
prediction = model.predict([[age, income, credit_score]])
return prediction[0]
```

#### \$\$

```
LANGUAGE plpython3u;
```



.00-2500759

Trade-offs in a Database Context <u>187/</u>75

.39-6.

60.61

18742.51-4.9

@drishtijjain

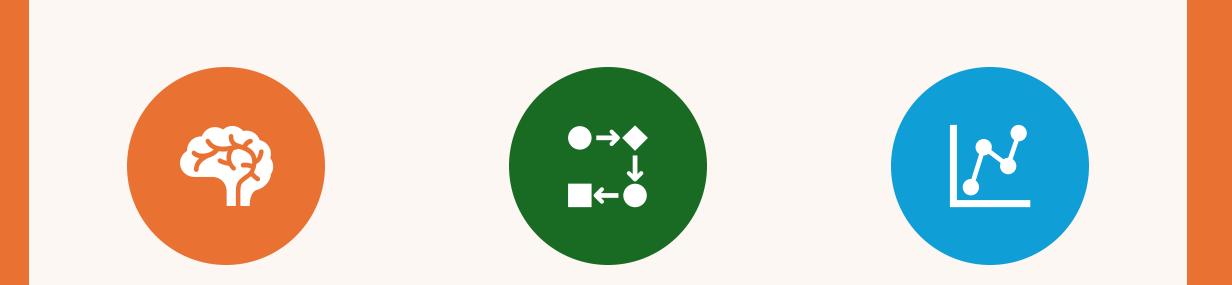
18754.73

18747.50

8737

18752

### Model Complexity vs. Prediction Speed



MORE COMPLEX MODELS (LIKE DEEP NEURAL NETWORKS) MAY PROVIDE HIGHER ACCURACY BUT SLOWER PREDICTION TIMES. SIMPLER MODELS (LIKE LINEAR REGRESSION OR SMALL DECISION TREES) OFFER FASTER PREDICTIONS BUT MAY SACRIFICE SOME ACCURACY. IN A DATABASE CONTEXT WHERE REAL-TIME PREDICTIONS ARE OFTEN NEEDED, YOU MAY NEED TO BALANCE ACCURACY WITH SPEED.

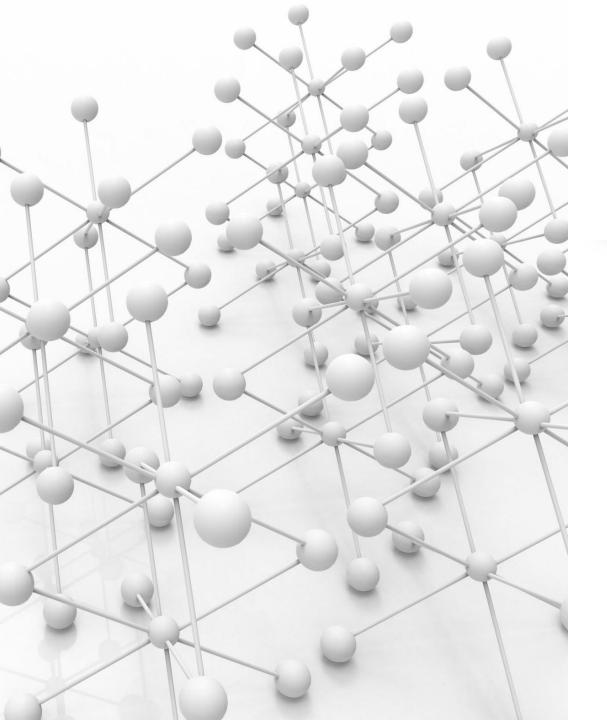


### Memory Usage:

- 1. More complex models require more memory, which could impact database performance.
- 2. Consider the scalability of your solution as the number of concurrent predictions increases.







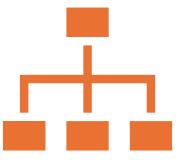
### Interpretability

In many business contexts, being able to explain predictions is crucial.

While a complex neural network might provide high accuracy, a simpler model like a decision tree might be preferred for its interpretability.



### **Training and Updating**





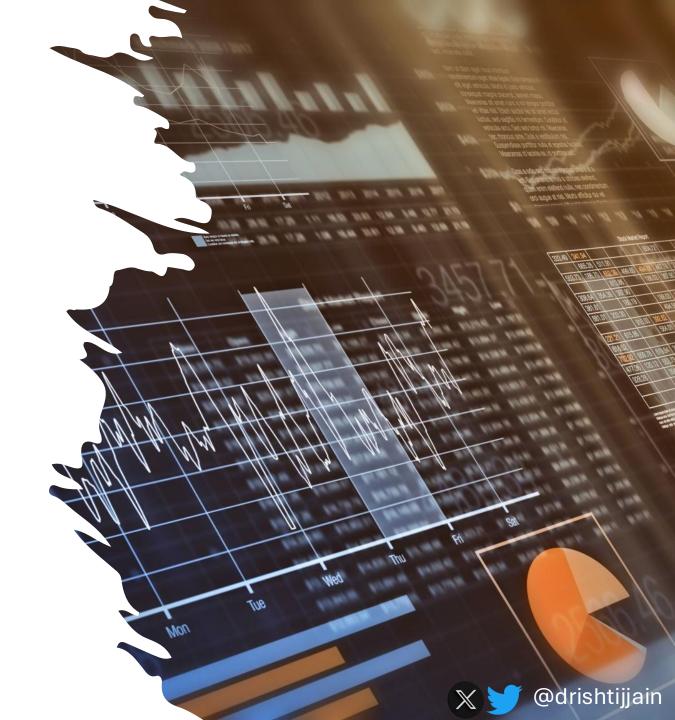
Consider how often the model needs to be retrained or updated.

More frequent updates might favor simpler models that can be quickly retrained within the database.



### Data Volume and Velocity

If you're dealing with highvolume, high-velocity data, you might need to opt for models that can handle streaming data effectively.



### Regulatory Compliance

In some industries, regulatory requirements might limit the types of models you can use, favoring more interpretable models.

risht

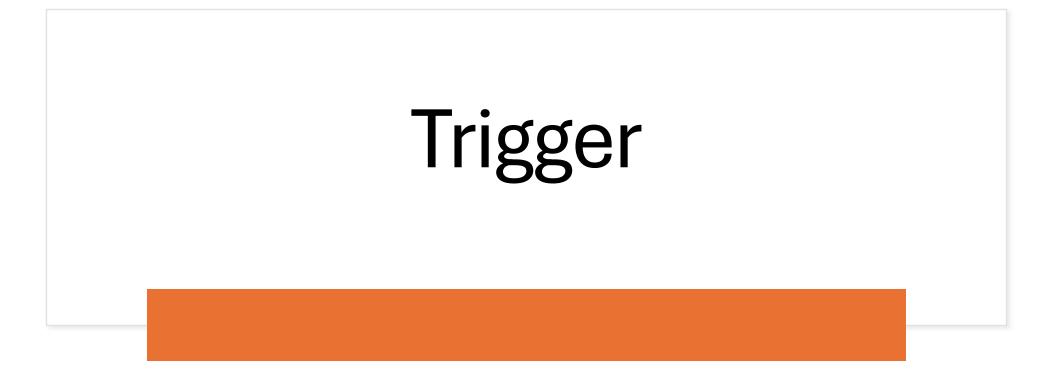
### Real-Time Prediction Pipeline



### **Integrating Predictions into Queries**

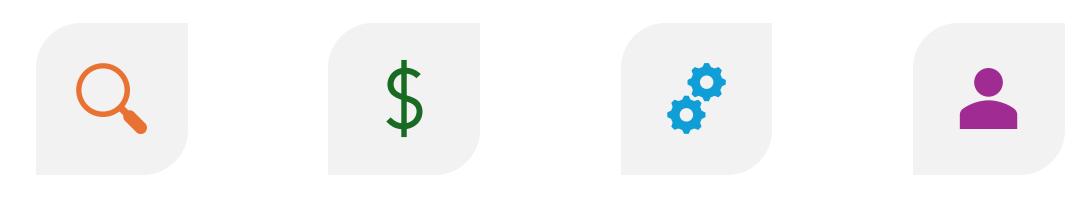
$\bigcirc \bigcirc \bigcirc$
<pre>SELECT     id,     age,     income,     credit_score,     predict_purchase(age, income, credit_score) AS predicted_purchase FROM customer_data;</pre>







### Triggers for automating predictions



FRAUD DETECTION IN FINANCIAL TRANSACTIONS REAL-TIME PRICING IN E-COMMERCE PREDICTIVE MAINTENANCE IN INDUSTRIAL SETTINGS PERSONALIZED CONTENT RECOMMENDATIONS



### Triggers for automating predictions

Challenges:

- Database Performance
- Scalability concerns
- Keeping models up-to-date



#### $\bigcirc \bigcirc \bigcirc$

### Creating a Trigger for Real-Time Predictions

- We can automate the prediction process using PostgreSQL triggers
- This trigger will automatically calculate and store a prediction when new data is inserted



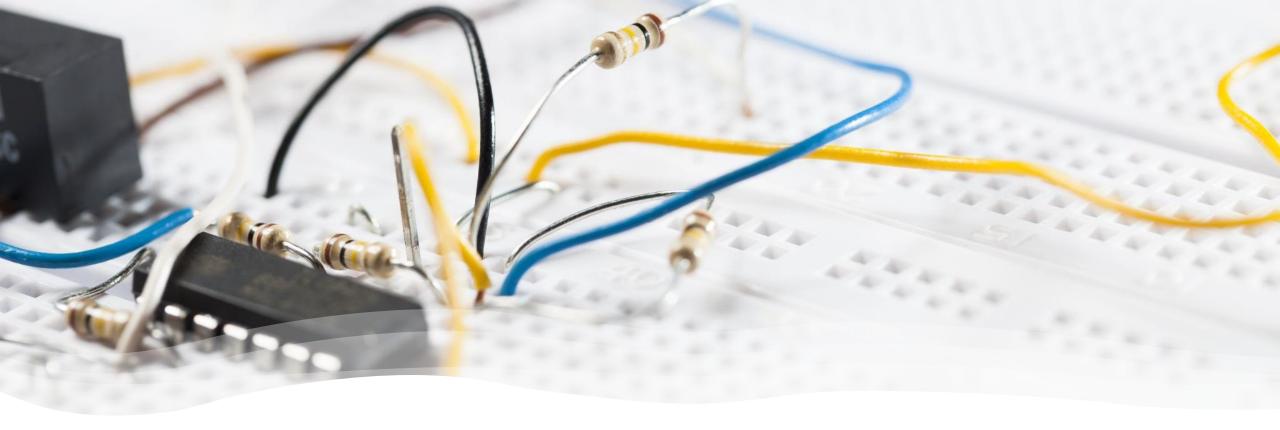
#### Inserting New Data and Getting Real-Time Predictions

#### $\bigcirc \bigcirc \bigcirc \bigcirc$

INSERT INTO customer\_data (age, income, credit\_score)
VALUES (30, 60000, 720);

SELECT \* FROM customer\_data ORDER BY id DESC LIMIT 1;





#### Retrain the Model with all available data (NEW + Exisitng)



#### Updating the Model

# O O O -- Update the model with new data UPDATE ml\_models SET model\_data = train\_model() WHERE model\_name = 'purchase\_predictor';





#### **Best Practices**



#### **Best Practices**





#### Takeaways







PostgreSQL with PL/Python enables powerful real-time predictions

Seamless integration of ML models into database operations

Potential for enhanced decisionmaking and user experiences







### **THANK YOU!**





in linkedin.com/in/jaindrishti/



M medium.com/@drishtijjain



@geekyearthian