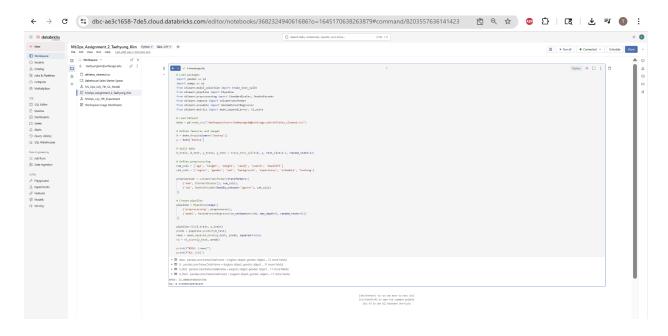
Number 2 screenshot - ML pipeline in Databricks



Number 3 screenshots - use a feature store with ML pipeline in Databricks

```
▶ ✓ 2 minutes ago (1s)
          # ===== Feature Store Setup =====
          from databricks.feature_store import FeatureStoreClient
          # Initialize Feature Store client
          fs = FeatureStoreClient()
          # Use already loaded data (from previous cell)
          print("Current data check:")
          print(f"Data shape: {data.shape}")
         print(data.head())
 Current data check:
 Data shape: (8431, 14)
region ... howlong

O South Central ... 4+ years
                                                          howlong
      Canada East ... 6-12 months
2 Central East ... 6-12 months |
3 Australia ... 1-2 years |
4 North Central ... 6-12 months |
 [5 rows x 14 columns]
      # Prepare data for Feature Store (add unique ID)
      data_with_id = data.reset_index()
data_with_id = data_with_id.rename(columns={'index': 'athlete_id'})
      spark_df = spark.createDataFrame(data_with_id)
     \label{lem:print("Feature Store data preparation completed")} print(f"Spark DataFrame size: \{spark_df.count()\} rows, \{len(spark_df.columns)\} columns") spark_df.show(5)  
  > lilli See performance (2)
 ▶ 🔳 data_with_id: pandas.core.frame.DataFrame = [athlete_id: int64, region: object ... 13 more fields]
► I spark, df: pyspark.sql.connect.dataframe.DataFrame = [athlete_id: long, region: string ... 13 more fields]

Feature Store data preparation completed
Spark DataFrame size: 8431 rows, 15 columns
| athlete_id| region|gender| age|height|weight|candj|snatch|deadlift|backsq| eat| background| experience|
e|South Central|Female|47.0| 62.0| 115.0|105.0| 75.0| 185.0| 125.0|I eat quality foo...|I have no athleti...|I began CrossFit ...|I usually only do...|
| 0|South Centralifemsale|47.0| 54.0| 143.0| 140.0| 50.0| 105.0| 50.0| 105.0| 50.0| 1 weigh and measu...|I played youth or...|I began Crossfit ...|I usually only do...|6-1
| 1 | Canada East|Female|39.0| 63.0| 140.0| 49.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0| 20.0
2 months[]
only showing top 5 rows
             # ===== Create Feature Store Table ==
              feature_table_name = "taehyungkim_athletes_features_v2"
             # ☑ 'backsq' 제외한 DataFrame 만들기
spark_df_no_label = spark_df.drop("backsq")
                    # Register table in Feature Store
                    fs.create_table(
                         mame-feature_table_name,
primary_keys=["athlete_id"],
df=spark_df no_label,
description="Athletes performance features for ML pipeline"
                    print(f"Feature Store table '{feature_table_name}' created successfully!")
                   print(f"Error creating table: {e}")
print("Table might already exist. Continuing...")
         > Illi See performance (24)
        Fig. spark_df_no_label: pyspark.sql.connect.dataframe.DataFrame = [athlete_id: long, region: string ... 12 more fields]
       2025/07/11 20:40:14 INFO databricks.ml_features_compute_client._compute_client: Setting columns ['athlete_id'] of table 'workspace.default.taehyungkim_athletes_features_v
       2' to NOT NULL.
2025/07/11 20:40:15 INFO databricks.ml_features._compute_client._compute_client: Setting Primary Keys constraint ['athlete_id'] on table 'workspace.default.taehyungkim_ath
       letes_features_v2'.
2015/07/11 20:40:21 INFO databricks.ml_features__compute_client._compute_client: Created feature table 'workspace.default.taehyungkim_athletes_features_v2'.
Feature Store table 'taehyungkim_athletes_features_v2' created successfully!
```

```
Python 💠 🖸 :
    # ===== Use Feature Store with ML Pipeline =====
    from databricks.feature_store import FeatureLookup
    # Load features from Feature Store
    feature_lookups = [
      FeatureLookup(
        table_name=feature_table_name,
          lookup_key="athlete_id"
    # Create training set using Feature Store
    training_set = fs.create_training_set(
    df=spark_df.select("athlete_id", "backsq"), # target variable
       feature_lookups=feature_lookups,
      label="backsq"
  print("Feature Store integrated with ML Pipeline!")
   print("Step 3: Feature Store setup completed successfully!")
 > Illi See performance (9)
Feature Store integrated with ML Pipeline!
Step 3: Feature Store setup completed successfully!
```

Number 4 Screenshots - load data and create features with different version

```
::
      V V 04:13 PM (1s)
        # ===== Step 5: Run Experiments with ML Pipeline and Feature Store =====
         print("=== Step 5: Run experiments with ML pipeline and feature store ===")
        import mlflow
         import mlflow.sklearn
         from sklearn.model_selection import train_test_split
         from sklearn.ensemble import RandomForestRegressor
         from sklearn.preprocessing import StandardScaler, OneHotEncoder
        from sklearn.compose import ColumnTransformer
        from sklearn.pipeline import Pipeline
        from sklearn.metrics import mean_squared_error, r2_score
         # Define numerical and categorical columns (same for both versions)
         num_cols = ['age', 'height', 'weight', 'candj', 'snatch', 'deadlift']
         cat_cols = ['region', 'gender', 'eat', 'background', 'experience', 'schedule', 'howlong']
        # Experiment 1: Version 1 features + Hyperparameter Set 1
        print("\n--- Experiment 1: Feature V1 + Hyperparameter Set 1 ---")
        X_v1 = features_v1[feature_cols_v1]
         y_v1 = features_v1['backsq']
          X\_train\_v1, \ X\_test\_v1, \ y\_train\_v1, \ y\_test\_v1 = train\_test\_split(X\_v1, \ y\_v1, \ test\_size=0.2, \ random\_state=42) 
         preprocessor_v1 = ColumnTransformer(transformers=[
            ('num', StandardScaler(), num_cols),
             ('cat', OneHotEncoder(handle_unknown='ignore'), cat_cols)
         1)
         pipeline_exp1 = Pipeline(steps=[
            ('preprocessing', preprocessor_v1),
             ('model', RandomForestRegressor(n_estimators=50, max_depth=5, random_state=42))
         1)
        pipeline_exp1.fit(X_train_v1, y_train_v1)
        preds exp1 = pipeline exp1.predict(X test v1)
        rmse_exp1 = mean_squared_error(y_test_v1, preds_exp1, squared=False)
        r2_exp1 = r2_score(y_test_v1, preds_exp1)
         print(f"Experiment 1 - RMSE: {rmse_exp1:.2f}, R2: {r2_exp1:.3f}")
         print("\n 
    Experiment 1 completed!")
     ► ■ X_test_v1: pandas.core.frame.DataFrame = [age: float64, height: float64 ... 11 more fields]
     ▶ ■ X_train_v1: pandas.core.frame.DataFrame = [age: float64, height: float64 ... 11 more fields]
     ▶ ■ X_v1: pandas.core.frame.DataFrame = [age: float64, height: float64 ... 11 more fields]
    === Step 5: Run experiments with ML pipeline and feature store ===
    --- Experiment 1: Feature V1 + Hyperparameter Set 1 ---
    Experiment 1 - RMSE: 21.41, R2: 0.764
    Experiment 1 completed!
```

```
::
     ▶ ✓ ✓ 04:15 PM (25s)
          # ==== Experiment 2: Feature V1 + Hyperparameter Set 2 ==== 
print("\n--- Experiment 2: Feature V1 + Hyperparameter Set 2 ---")
           pipeline_exp2 = Pipeline(steps=[
    ('preprocessing', preprocessor_v1),
              ('model', RandomForestRegressor(n_estimators=100, max_depth=10, random_state=42))
           pipeline_exp2.fit(X_train_v1, y_train_v1)
           preds_exp2 = pipeline_exp2.predict(X_test_v1)
rmse_exp2 = mean_squared_error(y_test_v1, preds_exp2, squared=False)
           r2_exp2 = r2_score(y_test_v1, preds_exp2)
           print(f"Experiment 2 - RMSE: {rmse_exp2:.2f}, R2: {r2_exp2:.3f}")
           print("\n ☑ Experiment 2 completed!")
                 === Experiment 3: Feature V2 + Hyperparameter Set 1 ===
           print("\n--- Experiment 3: Feature V2 + Hyperparameter Set 1 ---")
          # Add engineered features to numerical columns
num_cols_v2 = num_cols + ['bmi', 'power_ratio', 'strength_ratio', 'total_lift']
           X_v2 = features_v2[feature_cols_v2]
           y_v2 = features_v2['backsq']
           X train v2, X test v2, y train v2, y test v2 = train test split(X v2, y v2, test size=0.2, random state=42)
           preprocessor_v2 = ColumnTransformer(transformers=[
            ('num', StandardScaler(), num_cols_v2),
('cat', OneHotEncoder(handle_unknown='ignore'), cat_cols)
           pipeline_exp3 = Pipeline(steps=[
            ('preprocessing', preprocessor_v2),
('model', RandomForestRegressor(n_estimators=50, max_depth=5, random_state=42))
           pipeline_exp3.fit(X_train_v2, y_train_v2)
           preds_exp3 = pipeline_exp3.predict(X_test_v2)
           rmse_exp3 = mean_squared_error(y_test_v2, preds_exp3, squared=False)
r2_exp3 = r2_score(y_test_v2, preds_exp3)
           print(f"Experiment 3 - RMSE: {rmse_exp3:.2f}, R2: {r2_exp3:.3f}")
           print("\n ☑ Experiment 3 completed!")
                === Experiment 4: Feature V2 + Hyperparameter Set 2 ==
           print("\n--- Experiment 4: Feature V2 + Hyperparameter Set 2 ---")
            ('preprocessing', preprocessor_v2),
('model', RandomForestRegressor(n_estimators=100, max_depth=10, random_state=42))
           pipeline_exp4.fit(X_train_v2, y_train_v2)
           preds_exp4 = pipeline_exp4.predict(X_test_v2)
          rmse_exp4 = mean_squared_error(y_test_v2, preds_exp4, squared=False)
r2_exp4 = r2_score(y_test_v2, preds_exp4)
           print(f"Experiment 4 - RMSE: {rmse_exp4:.2f}, R2: {r2_exp4:.3f}")
           print("\n ☑ Experiment 4 completed!")
         print n All 4 experiments completed! Step 5 finished!"
      ▶ 📼 X_test_v2: pandas.core.frame.DataFrame = [age: float64, height: float64 ... 15 more fields]
       ➤ X_train_v2: pandas.core.frame.DataFrame = [age: float64, height: float64 ... 15 more fields]
       ► ■ X_v2: pandas.core.frame.DataFrame = [age: float64, height: float64 ... 15 more fields]
     --- Experiment 2: Feature V1 + Hyperparameter Set 2 --- 
Experiment 2 - RMSE: 20.97, R2: 0.773
      Experiment 2 completed!
```

```
--- Experiment 3: Feature V2 + Hyperparameter Set 1 --- 
Experiment 3 - RMSE: 21.25, R2: 0.767
```

--- Experiment 4: Feature V2 + Hyperparameter Set 2 ---

Experiment 4 - RMSE: 20.90, R2: 0.775

All 4 experiments completed! Step 5 finished!

Number 6 Screenshots - Compare the results of the different experiments both quantitatively (model metrics) and qualitatively (model plots).

```
₩ ✓ ✓ 04:42 PM (<1s)
              print("=== Step 6: Compare Results of Different Experiments ===")
               import matplotlib.pyplot as plt
               # ===== Re-define experiment results ====
# From previous experiments (based on the output we saw)
rmse_exp1 = 21.41 # Feature V1 + HP Set 1
r2_exp1 = 0.764
                rmse_exp2 = 20.97  # Feature V1 + HP Set 2
r2_exp2 = 0.773
                rmse_exp3 = 21.25  # Feature V2 + HP Set 1 r2_exp3 = 0.767
               rmse_exp4 = 20.90  # Feature V2 + HP Set 2
r2_exp4 = 0.775
                print("--- Quantitative Comparison (Model Metrics) ---")
              # Create results summary
results_df = pd.DataFrame({
    'Experiment': ['Exp 1: V1+HP1', 'Exp 2: V1+HP2', 'Exp 3: V2+HP1', 'Exp 4: V2+HP2'],
    'Feature_Version': ['V1', 'V1', 'V2', 'V2'],
    'Hyperparameters': ['n_est=50, depth=5', 'n_est=100, depth=10', 'n_est=50, depth=5', 'n_est=100, depth=10'],
    'NOSE': [rmsc_exp1, rmsc_exp2, rmsc_exp3, rmsc_exp4],
    'Tall'_if_are_version_depth=10', rmsc_exp3, rmsc_exp4],
                      'R2': [r2_exp1, r2_exp2, r2_exp3, r2_exp4]
               print("\nExperiment Results Summary:")
print(results_df.to_string(index=False))
              # Find best experiment
best_rmse_idx = results_df['RMSE'].idxmin()
best_r2_idx = results_df['R2'].idxmax()
               print(f"\nBest RMSE: {results_df.loc[best_rmse_idx, 'Experiment']} (RMSE: {results_df.loc[best_rmse_idx, 'RMSE']:.2f})")
print(f"Best R2: {results_df.loc[best_r2_idx, 'Experiment']} (R2: {results_df.loc[best_r2_idx, 'R2']:.3f})")
            print("\n ☑ Quantitative comparison completed!")
         ▶ ■ results df: pandas.core.frame.DataFrame = [Experiment: object, Feature Version: object ... 3 more fields]
         === Step 6: Compare Results of Different Experiments ===
--- Quantitative Comparison (Model Metrics) ---
         Experiment Results Summary:
       Experiment Results Summary:

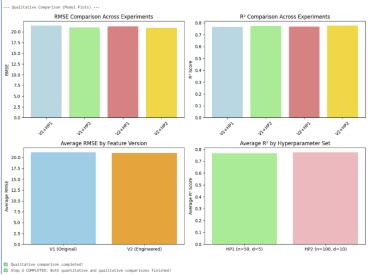
Experiment Feature_Version Hyperparameters RMSE R2

Exp 1: V1+HP1 V1 n_est+50, depth=5 21.41 0.764

Exp 2: V1+HP2 V1 n_est+50, depth=10 20.97 0.773

Exp 3: V2+HP1 V2 n_est+50, depth=5 21.55 0.76

Exp 4: V2+HP2 V2 n_est+100, depth=10 20.90 0.775
        Best RMSE: Exp 4: V2+HP2 (RMSE: 20.90)
Best R2: Exp 4: V2+HP2 (R2: 0.775)
       Quantitative comparison completed!
```



Number 7 Screenshots -

```
=== Step 7: Compare Carbon Emissions for Different Experiments =====
print("--- Step 7: Compare Carbon Emissions for Different Experiments ---")
# Carbon emissions estimation for different experiments
print("\n--- Carbon Emissions Analysis ---")
# Estimate carbon emissions based on:
# 1. Training time (number of estimators x complexity)
# 2. Model complexity (max_depth)
# 3. Feature processing overhead
def estimate_carbon_emissions(n_estimators, max_depth, n_features, base_emission=0.01):
      Estimate carbon emissions in kg CO2 equivalent
      Based on computational complexity and training time
 "Base emission per model training complexity_factor = (n_estimators " max_depth " n_features) / 1000 total_emission = base_emission " complexity_factor return total_emission
experiments carbon = []
# Experiment 1: V1 (13 features) + HP1 (n=50, depth=5)
carbon_exp1 = estimate_carbon_emissions(50, 5, 13)
experiments_carbon.append(('Exp 1: V1+HP1', carbon_exp1))
# Experiment 2: V1 (13 features) + HP2 (n=100, depth=10)
carbon_exp2 = estimate_carbon_emissions(100, 10, 13)
experiments_carbon.append(('Exp 2: V1+HP2', carbon_exp2))
 # Experiment 3: V2 (17 features) + HP1 (n=50, depth=5)
carbon_exp3 = estimate_carbon_emissions(50, 5, 17)
experiments_carbon.append(('Exp 3: V2+HP1', carbon_exp3))
# Experiment 4: V2 (17 features) + HP2 (n=100, depth=10)
carbon_exp4 = estimate_carbon_emissions(100, 10, 17)
experiments_carbon.append(('Exp 4: V2+HP2', carbon_exp4))
# Create carbon emissions summary
# Create carbon emissions summary
carbon,df = pto.DataFrame(f

"Experiment': [exp[0] for exp in experiments_carbon],

"Carbon_Emissions_tg_CO2': [exp[1] for exp in experiments_carbon],

"NRSE': [mse_expl, rmse_exp2, rmse_exp3, rmse_exp4],

"R2': [r2_exp1, r2_exp2, r2_exp3, r2_exp4]
 # Calculate efficiency metrics
print("\nEfficiency Analysis:")
print("COZ per RZ Improvement and COZ per RMSE reduction:")
efficiency, summary = carbon_eff(['Experiment', 'COZ_per_RZ_Improvement', 'COZ_per_RMSE_reduction']].round(4)
print(efficiency_summary.to_string(index=False))
# Find most efficient experiment
most_efficient_idx = carbon_df['CO2_per_R2_improvement'].idomin()
print(f"wlost_carbon_dfficient_Experiment: (carbon_df.loc[most_efficient_idx, 'Experiment'])")
print(f"Carbon Efficiency Score: (carbon_df.loc[most_efficient_idx, 'CO2_per_R2_improvement']:.4f) kg CO2 per R2 point")
```

```
print("\nCarbon Emissions Summary:")
    print(carbon_df.to_string(index=False))
    # Calculate efficiency metrics
    carbon_df['CO2_per_R2_improvement'] = carbon_df['Carbon_Emissions_kg_CO2'] / carbon_df['R2']
    carbon_df['CO2_per_RMSE_reduction'] = carbon_df['Carbon_Emissions_kg_CO2'] / (25 - carbon_df['RMSE']) # Baseline RMSE=25
    print("\nEfficiency Analysis:")
    print("CO2 per R2 improvement and CO2 per RMSE reduction:")
    efficiency\_summary = carbon\_df[['Experiment', 'CO2\_per\_R2\_improvement', 'CO2\_per\_RMSE\_reduction']].round(4)
    print(efficiency_summary.to_string(index=False))
    # Find most efficient experiment
    most_efficient_idx = carbon_df['CO2_per_R2_improvement'].idxmin()
    print(f"\nMost Carbon-Efficient Experiment: {carbon_df.loc[most_efficient_idx, 'Experiment']}")
    print(f"Carbon Efficiency Score: {carbon_df.loc[most_efficient_idx, 'CO2_per_R2_improvement']: 4f} kg CO2 per R2 point")
   print("\n ✓ Step 7 COMPLETED: Carbon emissions comparison finished!")
 • 🔳 carbon_df: pandas.core.frame.DataFrame = [Experiment: object, Carbon_Emissions_kg_CO2: float64 ... 4 more fields]
→ ■ efficiency_summary: pandas.core.frame.DataFrame = [Experiment: object, CO2_per_R2_improvement: float64 ... 1 more field]
--- Carbon Emissions Analysis ---
  Experiment Carbon_Emissions_kg_CO2 RMSE R2
                   0.0325 21.41 0.773
0.1300 20.97 0.773
0.0425 21.25 0.767
0.1700 20.90 0.775
Exp 1: V1+HP1
Exp 2: V1+HP2
Exp 3: V2+HP1
Exp 4: V2+HP2
Efficiency Analysis:
CO2 per R2 improvement and CO2 per RMSE reduction:
  Experiment CO2_per_R2_improvement CO2_per_RMSE_reduction
                    0.0425
Exp 1: V1+HP1
                                             0.0091
0.0323
Exp 2: V1+HP2
Exp 3: V2+HP1
Exp 4: V2+HP2
                              0.0554
                                                       0.0113
                             0.2194
                                                       0.0415
Most Carbon-Efficient Experiment: Exp 1: V1+HP1
Carbon Efficiency Score: 0.0425 kg CO2 per R2 point
☑ Step 7 COMPLETED: Carbon emissions comparison finished!
```