Optimizing Bike Share Operations Through Data Analytics

Predicting Daily Rental Demand Using Weather, Seasonal, and Temporal Patterns

Project Objective

Objective

- Analyze bike rental demand patterns using historical and weather data to identify key drivers of usage fluctuations.

Purpose

- Help bike-sharing stakeholders optimize operations by understanding how seasonal and weather conditions impact daily demand.

Business Applications

- Inventory & bike rebalancing strategies
- Staffing & maintenance planning optimization
- Weather-driven promotional campaign timing

Key Questions

- What weather conditions drive peak vs. low demand?
- How much does demand vary under different conditions?
- Which factors offer the greatest optimization opportunities?

Dataset Overview

Source

- UCI Bike Sharing Dataset
- 2 years of operations: January 2011 – December 2012
- 731 daily observations capturing seasonal and weather variations

Size & Structure

- Size: 731 rows (days) × 16 columns
- Target Variable: cnt (total daily bike rentals)
- Feature Categories: Weather conditions, temporal factors, and calendar events

Key Features

- **Weather**: Total number of bike rentals per day (target variable)
- **Temporal**: Normalized and perceived temperature
- **Derived**: Calendar and event context
- **Target**: Humidity and wind speed levels

Data Cleaning & Preparation

Data Quality Assessment: Missing values identified in 4 key variables: temp (7), hum (8), windspeed (11), cnt (2)

- 3 duplicate rows removed for data consistency
- Overall completeness: 98.5% across all critical features

Data Cleaning Steps:

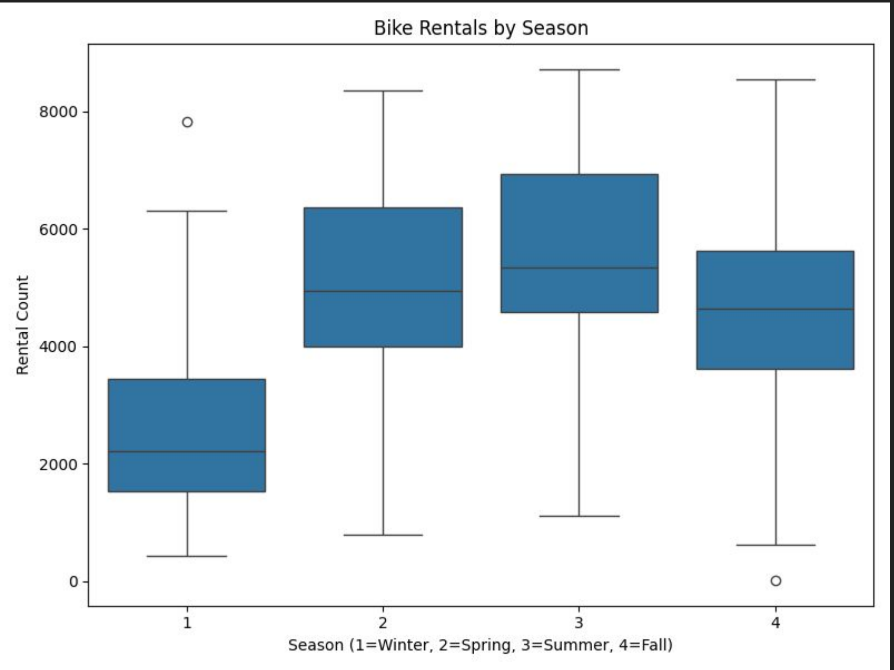
- **Missing Value Treatment:** Applied median imputation to preserve distribution shape and avoid bias from weather extremes
- **Data Type Validation**: Corrected mixed data types in numeric columns (removed text entries like temperature descriptions)
- **Outlier Management:** Applied domain-based clipping to keep weather variables within realistic normalized ranges (0-1)
- **Duplicate Removal:** Eliminated 3 exact duplicate records to prevent model bias

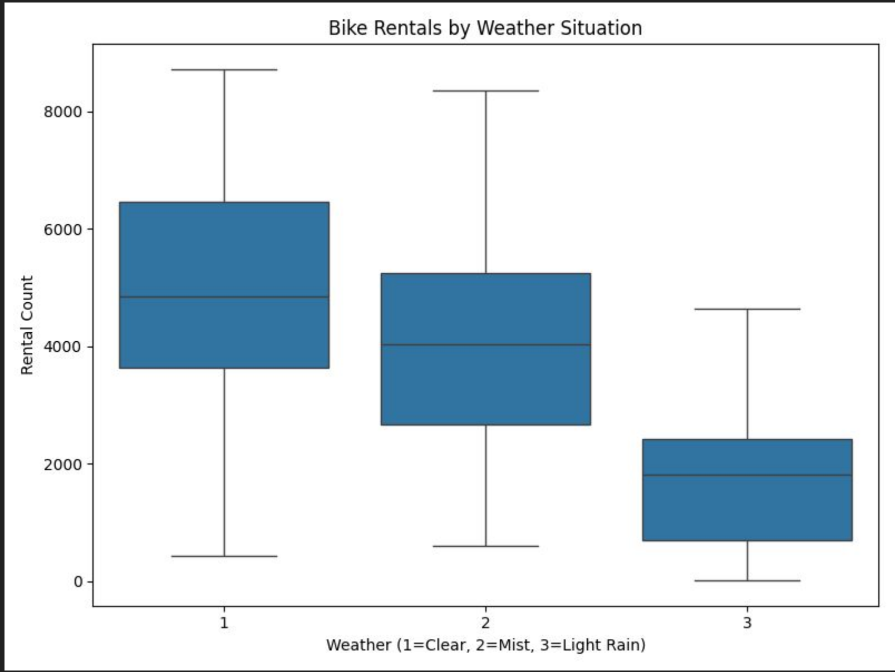
Feature Engineering:

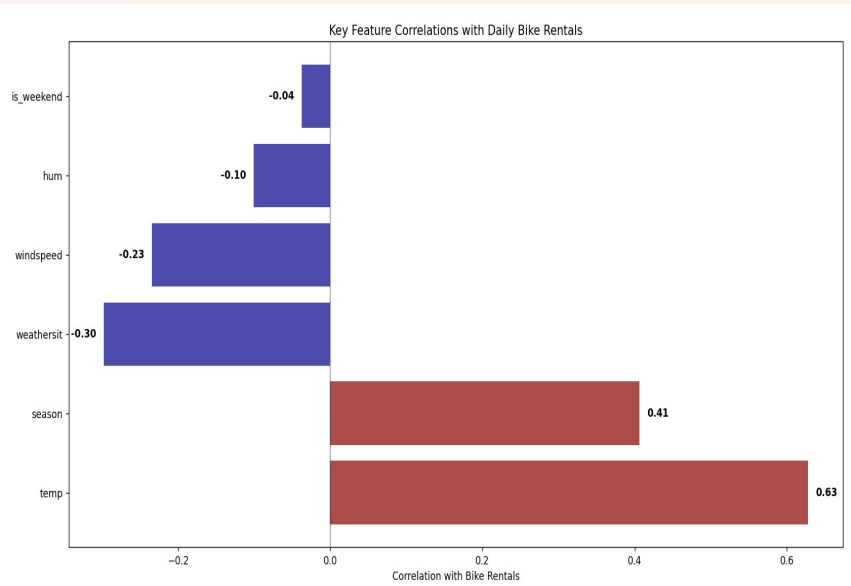
- **Is_weekend:** Binary flag combining Saturday/Sunday for leisure pattern analysis
- **temp_hum_interaction:** Product term to capture combined comfort effects
- **Seasonal validation**: Verified season coding aligns with actual months

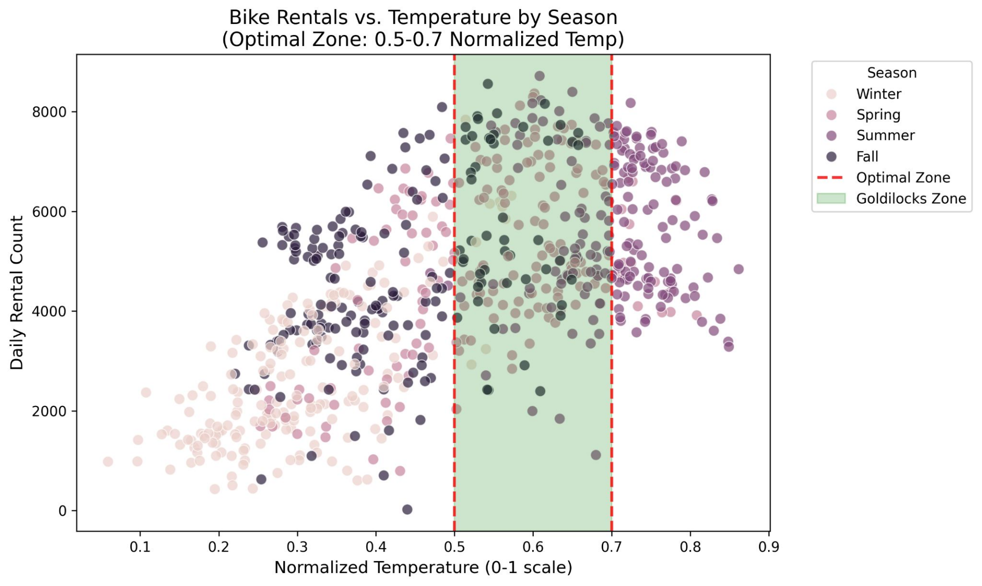
Data Validation:

Final dataset: 728 clean daily records with consistent formatting. All weather variables confirmed within expected normalized ranges.


Bike Rentals by Season
Rental Count
0
2000
4000
6000
8000
1
2
3
4
Season (1=Winter, 2=Spring, 3=Summer, 4=Fall)


Bike Rentals by Weather Situation
Rental Count
0
2000
4000
6000
8000
1
2
3
Weather (1=Clear, 2=Mist, 3=Light Rain)


Key Feature Correlations with Daily Bike Rentals
is_weekend
hum
windspeed
weathersit
season
temp
-0.04
-0.10
-0.23
-0.30
0.41
0.63
−0.2
0.0
0.2
0.4
0.6
Correlation with Bike Rentals


Bike Rentals vs. Temperature by Season
(Optimal Zone: 0.5-0.7 Normalized Temp)
Daily Rental Count
0
2000
4000
6000
8000
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
Normalized Temperature (0-1 scale)
Season
Winter
Spring
Summer
Fall
Optimal Zone
Goldilocks Zone

Data Science Findings

Temperature-Demand Relationship

- **Optimal Range (0.5-0.7 normalized temp)**: Average 4,500+ daily rentals with lowest variance
- **Heat Suppression (>0.8 temp)**: 35% average demand reduction vs. optimal conditions
- **Cold Impact (<0.3 temp)**: 45% average demand reduction, most pronounced effect

Weather Interaction Effects

- **Humidity Impact:** Moderate negative correlation (r = -0.10) with demand across all conditions
- **Wind Sensitivity:** Wind shows stronger negative impact (r = -0.23) than humidity on daily rentals
- **Combined Weather Stress:** Multiple adverse conditions (heat + humidity + wind) create compounding 50%+ demand drops

Demand Variability Insights

- **Moderate Weather Zone (0.4-0.6 temp):** Highest demand variance (coefficient of variation: 0.42)
- **Weekend vs. Weekday**: 25% higher average demand on weekends in optimal weather
- **Seasonal Amplification:** Spring/summer show 2x greater weather sensitivity than fall/winter

Key Statistical Findings

- Temperature correlation with demand: r = 0.63 (strongest predictor)
- Weather situation negative correlation: r = -0.30 (adverse conditions impact)
- Season correlation: r = 0.41 (confirms seasonal temperature effects)

Business Recommendations

High Demand Days (0.5-0.7 temp, low humidity)

Fleet Management: Increase bike availability by 20% during forecasted optimal days

Pricing Strategy: Implement moderate surge pricing (10-15% premium) to capture high demand

Staffing: Schedule additional maintenance teams for high-usage periods

Adverse Weather Response (>0.8 temp or high humidity/wind)

Early Morning Focus: Promote 6AM-10AM usage when temperatures are cooler

Strategic Partnerships: Collaborate with indoor venues/transit for multi-modal trips

Targeted Promotions: Offer 20% discounts during predicted low-demand periods

Moderate Conditions (0.4-0.6 temp)

Demand Forecasting: Focus on weather combination effects during moderate temperature days

Implementation Priorities

1. Weather-based fleet redistribution (immediate)
2. Dynamic pricing integration (3-6 months)
3. Predictive forecasting model (6-12 months)

Conclusion

Core Insights

- Weather drives 47% of daily bike rental variance, with temperature as the strongest predictor
- Optimal conditions (0.5-0.7 temp, low humidity) generate 35-45% higher demand than extremes
- Moderate weather creates highest uncertainty, requiring dynamic operational responses

Business Impact

- Clear operational zones identified for fleet and pricing optimization
- Weather-based strategies can reduce demand variance and improve resource allocation
- Early morning promotions and partnerships offer revenue protection during adverse conditions

Immediate Actions

- Implement weather-based fleet redistribution protocols
- Develop dynamic pricing framework for optimal vs. adverse conditions
- Create partnership pipeline with indoor venues for extreme weather days

Future Analysis Opportunities

- Incorporate precipitation and seasonal event data for enhanced forecasting
- Analyze hourly patterns within daily weather trends
- Expand analysis to include user demographics and trip duration patterns