NYC Taxi Demand Analysis

Exploratory Data Analysis for Target Models

Dataset Information:
• Period: July 01, 2014 to January 31, 2015
• Total Records: 10,320
• Frequency: 30-minute intervals
• Total Days: 214
• Data Points per Day: 48

TARGET FORECASTING MODELS:

□ Naive Forecasting
• Baseline: Last value prediction
• Simple persistence model
• Benchmark for comparison

□ SARIMA (Seasonal ARIMA)
• Statistical time series model
• Handles trend and seasonality
• Requires stationary data

□ Random Forest
• Machine learning approach
• Feature engineering critical
• Handles non-linear patterns

□ LSTM Neural Network
• Deep learning model
• Sequence-to-sequence learning
• Captures complex dependencies

EDA FOCUS AREAS:

✓ Temporal patterns for SARIMA optimization
✓ Feature engineering for Random Forest
✓ Sequence patterns for LSTM design
✓ Data quality and preprocessing needs
✓ Seasonal decomposition analysis
✓ Stationarity testing for SARIMA

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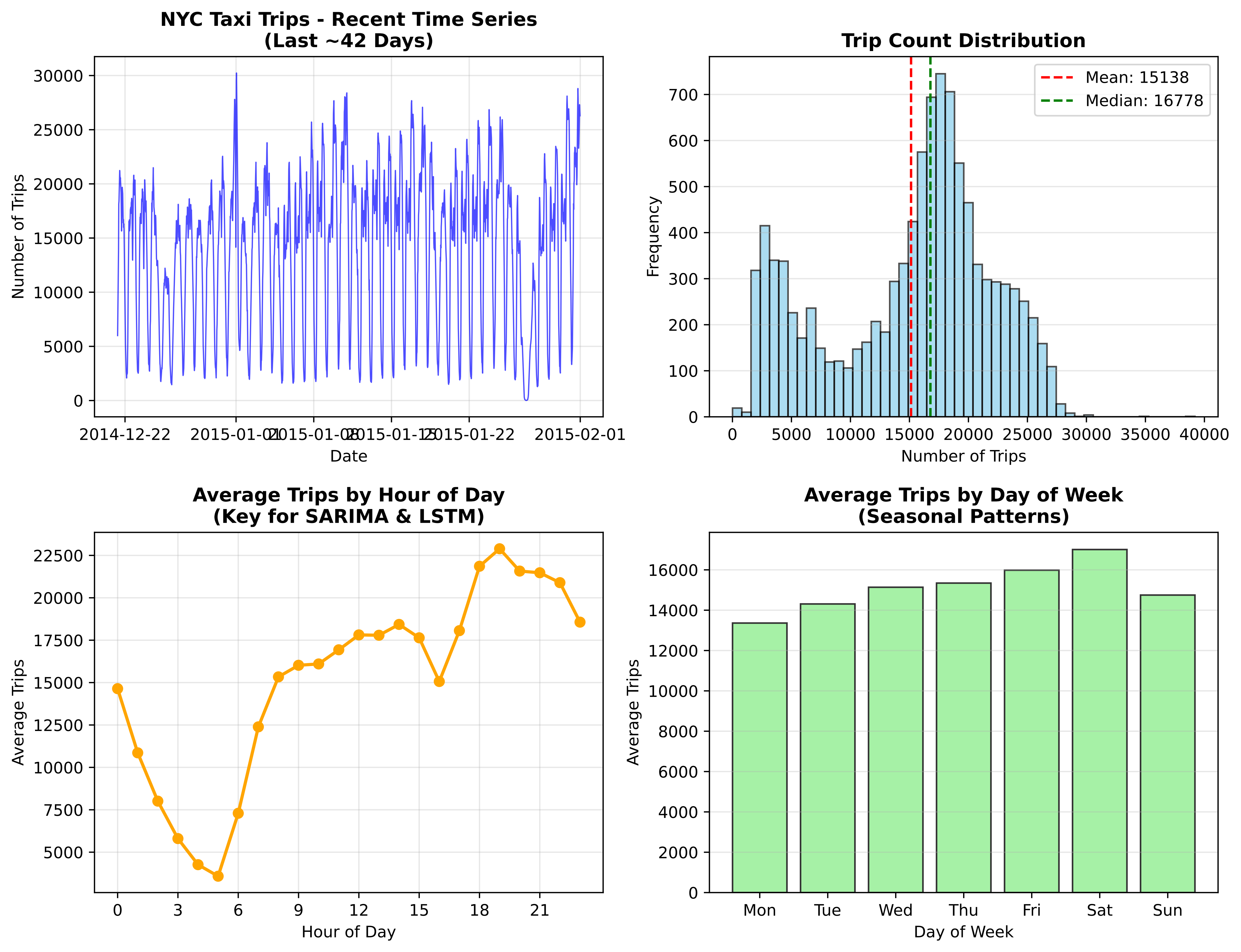
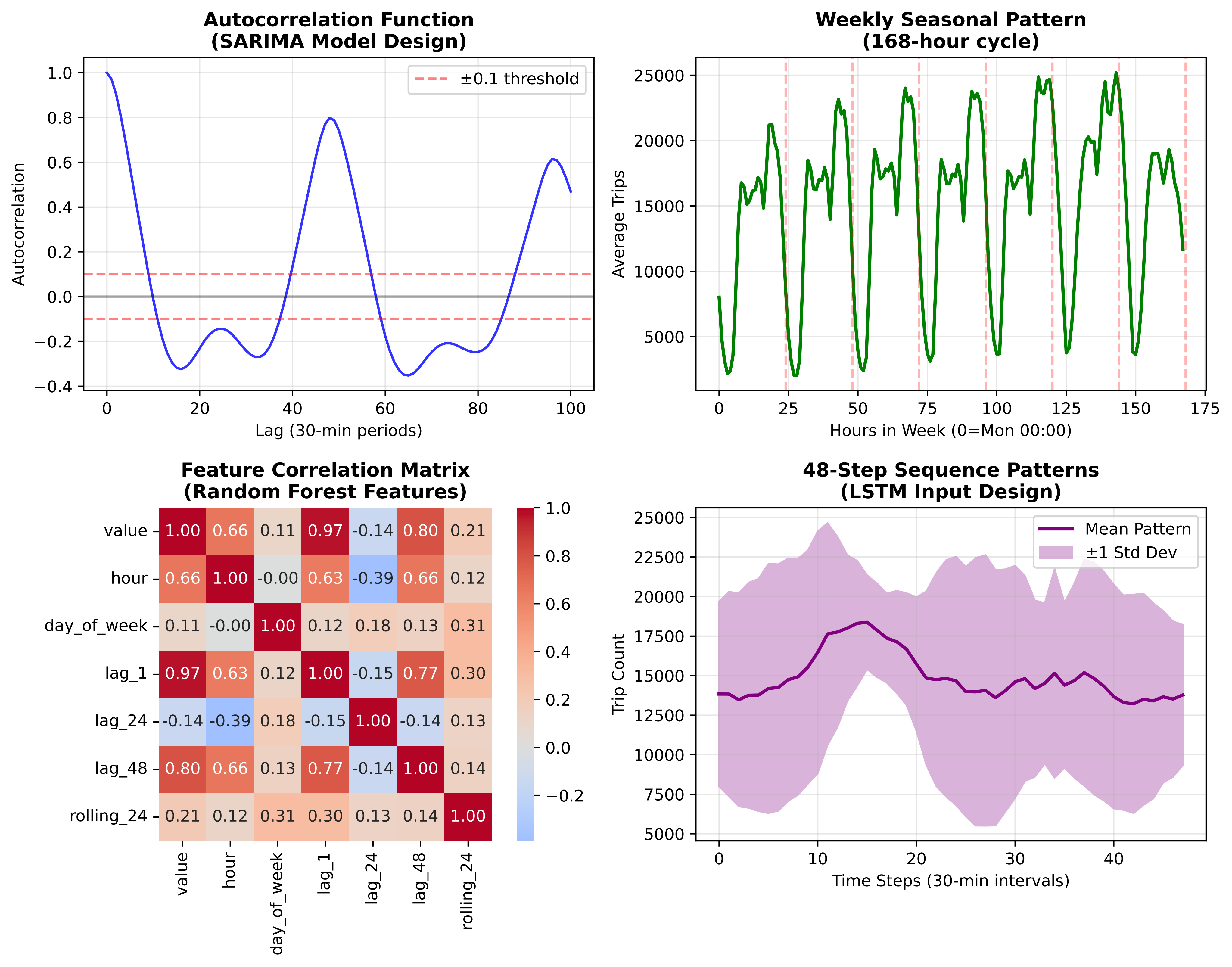
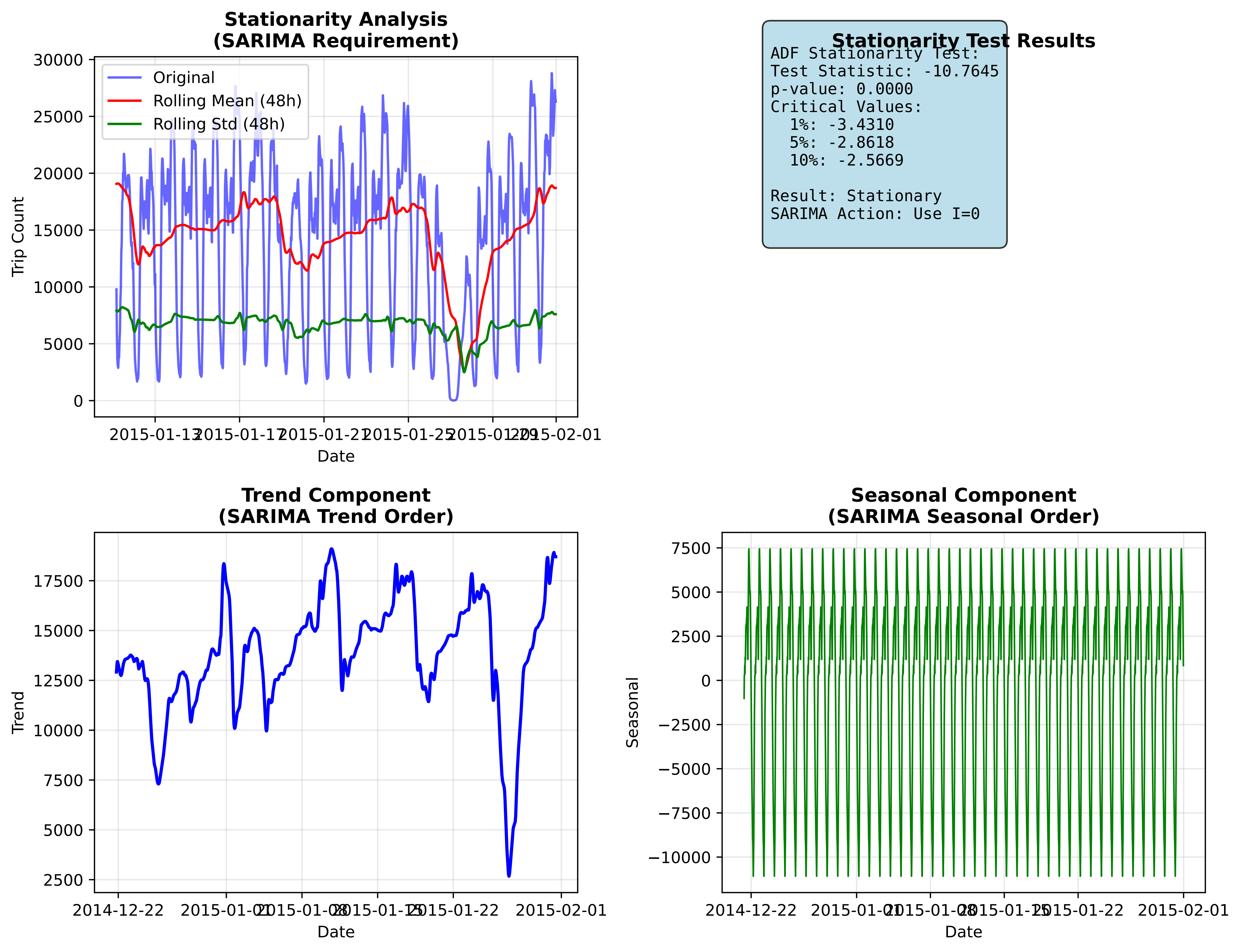
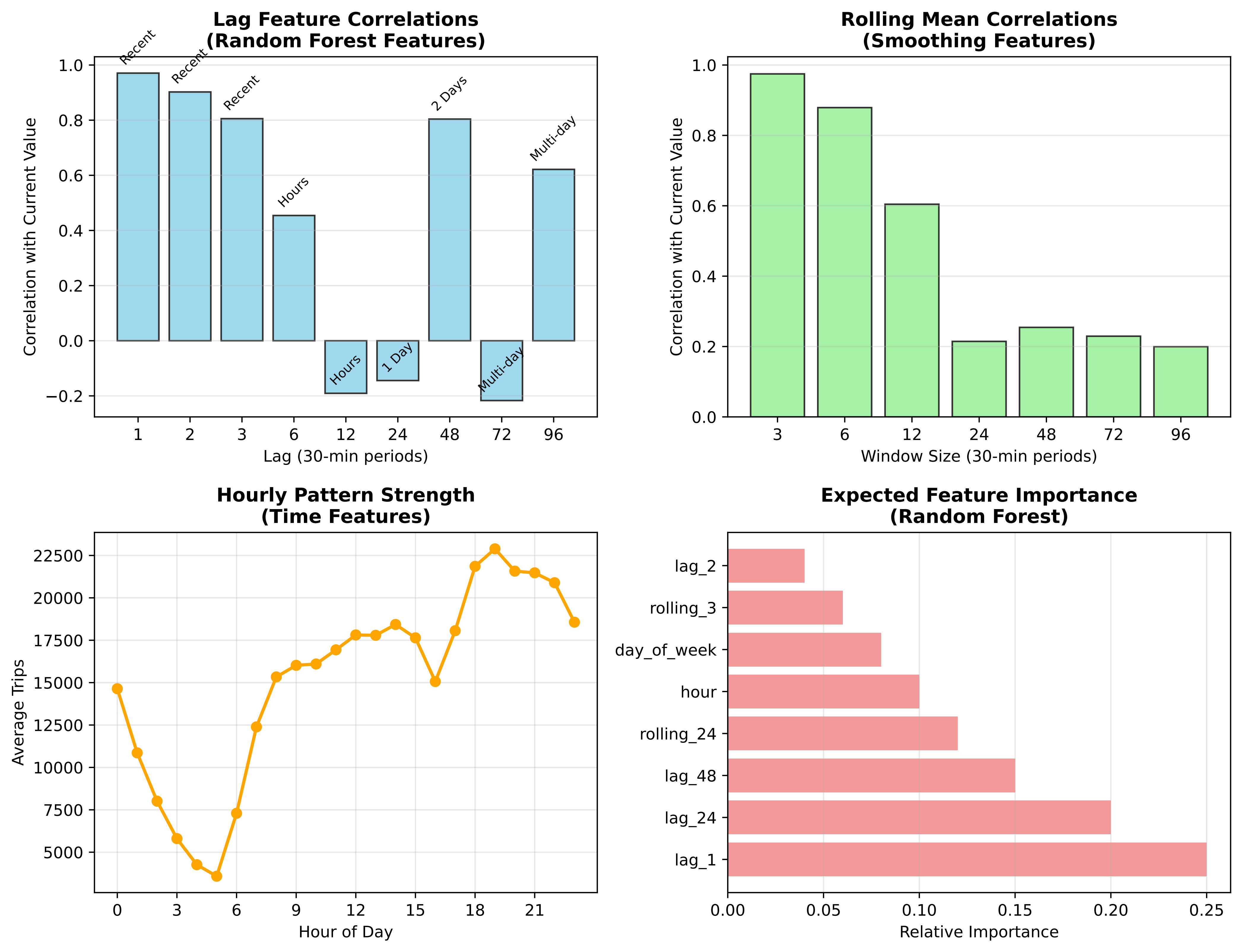

NYC Taxi Trips - Recent Time Series
(Last ~42 Days)
Number of Trips
30000
25000
20000
15000
10000
5000
0
2014-12-22
2015-01-01
2015-01-08
2015-01-15
2015-01-22
2015-02-01
Date
Trip Count Distribution
Mean: 15138
Median: 16778
Frequency
700
600
500
400
300
200
100
0
0
5000
10000
15000
20000
25000
30000
35000
40000
Number of Trips
Average Trips by Hour of Day
(Key for SARIMA & LSTM)
Average Trips
22500
20000
17500
15000
12500
10000
7500
5000
0
3
6
9
12
15
18
21
Hour of Day
Average Trips by Day of Week
(Seasonal Patterns)
Average Trips
16000
14000
12000
10000
8000
6000
4000
2000
0
Mon
Tue
Wed
Thu
Fri
Sat
Sun
Day of Week

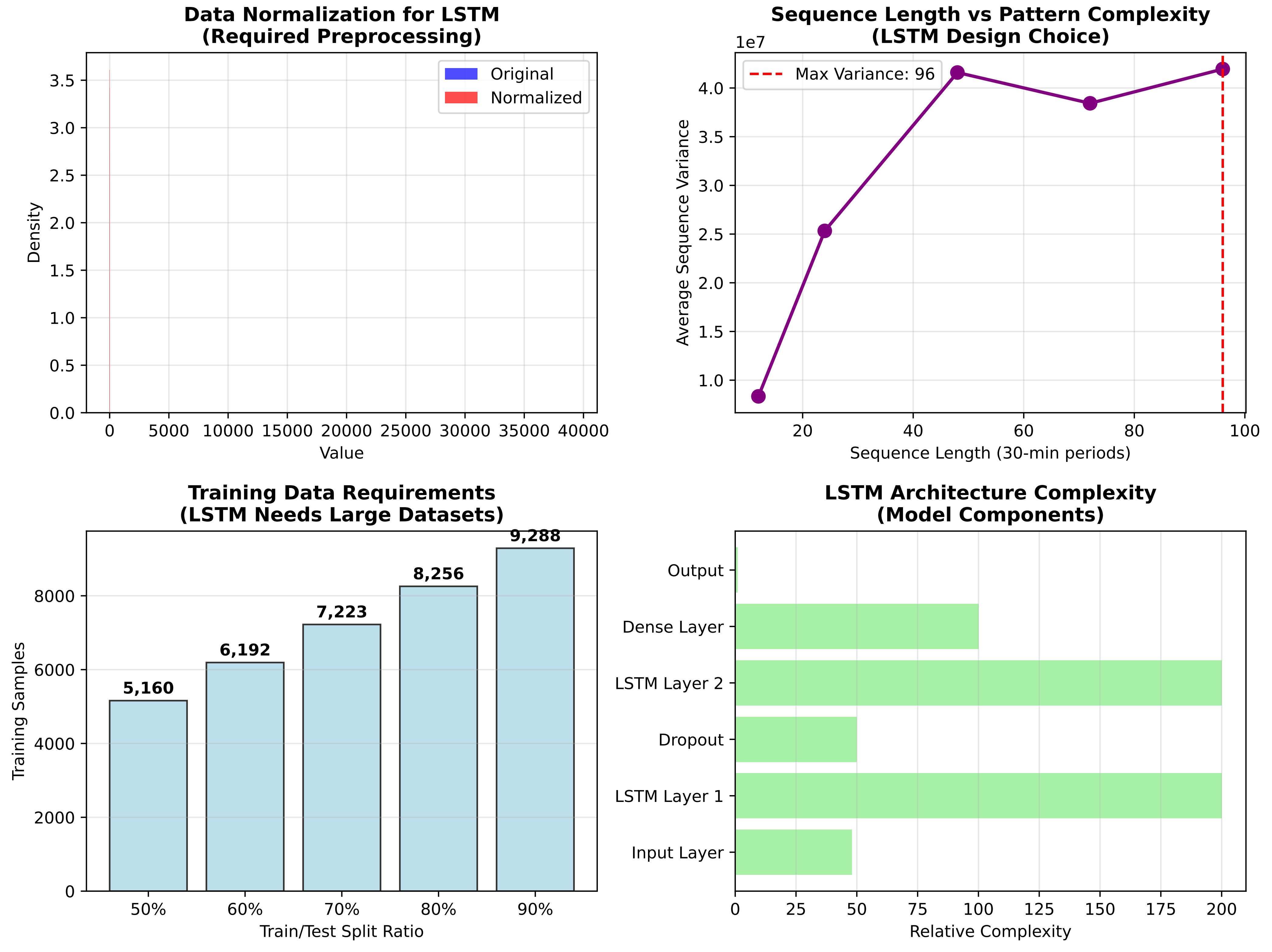

Autocorrelation Function
(SARIMA Model Design)
±0.1 threshold
Autocorrelation
Lag (30-min periods)
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
0
20
40
60
80
100
Weekly Seasonal Pattern
(168-hour cycle)
Average Trips
Hours in Week (0=Mon 00:00)
25000
20000
15000
10000
5000
0
25
50
75
100
125
150
175
Feature Correlation Matrix
(Random Forest Features)
value 1.00 0.66 0.11 0.97 -0.14 0.80 0.21
hour 0.66 1.00 -0.00 0.63 -0.39 0.66 0.12
day_of_week 0.11 -0.00 1.00 0.12 0.18 0.13 0.31
lag_1 0.97 0.63 0.12 1.00 -0.15 0.77 0.30
lag_24 -0.14 -0.39 0.18 -0.15 1.00 -0.14 0.13
lag_48 0.80 0.66 0.13 0.77 -0.14 1.00 0.14
rolling_24 0.21 0.12 0.31 0.30 0.13 0.14 1.00
value
hour
day_of_week
lag_1
lag_24
lag_48
rolling_24
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
48-Step Sequence Patterns
(LSTM Input Design)
Mean Pattern
±1 Std Dev
Trip Count
Time Steps (30-min intervals)
25000
22500
20000
17500
15000
12500
10000
7500
5000
0
10
20
30
40



Stationarity Analysis
(SARIMA Requirement)
Original
Rolling Mean (48h)
Rolling Std (48h)
Trip Count
Date
30000
25000
20000
15000
10000
5000
0
2015-01-13
2015-01-17
2015-01-21
2015-01-25
2015-01-29
2015-02-01
Stationarity Test Results
ADF Stationarity Test:
Test Statistic: -10.7645
p-value: 0.0000
Critical Values:
1%: -3.4310
5%: -2.8618
10%: -2.5669
Result: Stationary
SARIMA Action: Use I=0
Trend Component
(SARIMA Trend Order)
Trend
Date
17500
15000
12500
10000
7500
5000
2500
2014-12-22
2015-01-01
2015-01-08
2015-01-15
2015-01-22
2015-02-01
Seasonal Component
(SARIMA Seasonal Order)
Seasonal
Date
7500
5000
2500
0
−2500
−5000
−7500
−10000
2014-12-22
2015-01-01
2015-01-08
2015-01-15
2015-01-22
2015-02-01



Lag Feature Correlations
(Random Forest Features)
Correlation with Current Value
Lag (30-min periods)
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
1
2
3
6
12
24
48
72
96
Recent
Recent
Recent
Hours
Hours
1 Day
2 Days
Multi-day
Multi-day
Rolling Mean Correlations
(Smoothing Features)
Correlation with Current Value
Window Size (30-min periods)
1.0
0.8
0.6
0.4
0.2
0.0
3
6
12
24
48
72
96
Hourly Pattern Strength
(Time Features)
Average Trips
Hour of Day
22500
20000
17500
15000
12500
10000
7500
5000
0
3
6
9
12
15
18
21
Expected Feature Importance
(Random Forest)
Relative Importance
lag_2
rolling_3
day_of_week
hour
rolling_24
lag_48
lag_24
lag_1
0.00
0.05
0.10
0.15
0.20
0.25



Data Normalization for LSTM
(Required Preprocessing)
Original
Normalized
Density
Value
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
0
5000
10000
15000
20000
25000
30000
35000
40000
Sequence Length vs Pattern Complexity
(LSTM Design Choice)
1e7
Max Variance: 96
Average Sequence Variance
Sequence Length (30-min periods)
1.0
1.5
2.0
2.5
3.0
3.5
4.0
20
40
60
80
100
Training Data Requirements
(LSTM Needs Large Datasets)
5,160
6,192
7,223
8,256
9,288
Training Samples
Train/Test Split Ratio
0
2000
4000
6000
8000
50%
60%
70%
80%
90%
LSTM Architecture Complexity
(Model Components)
Output
Dense Layer
LSTM Layer 2
Dropout
LSTM Layer 1
Input Layer
Relative Complexity
0
25
50
75
100
125
150
175
200

Model-Specific Data Insights & Recommendations

DATA CHARACTERISTICS SUMMARY:

Total Data Points: 10,320
Average Trips: 15138 ± 6939
Range: 8 to 39197
Coefficient of Variation: 0.458
Missing Data Rate: 0.000%
Seasonal Strength: 0.378

MODEL-SPECIFIC RECOMMENDATIONS:

□ NAIVE FORECASTING:
Strengths:
• Excellent baseline with minimal computation
• Robust to data quality issues
• Fast execution for real-time applications

Considerations:
• Will perform poorly in volatile periods
• Coefficient of variation 0.458 suggests moderate volatility
• Best used as benchmark for other models

Data Requirements: □ Minimal - just last observation

□ SARIMA MODELING:
Strengths:
• Strong seasonal patterns detected (strength: 0.378)
• Suitable for 48-period seasonal cycle (24-hour days)
• Statistical foundation with interpretable parameters

Considerations:
• May need differencing for stationarity
• Requires parameter tuning (p,d,q)(P,D,Q,s)
• Sensitive to outliers and structural breaks

Data Requirements: □ Good - 10,320 points sufficient
Recommended Configuration: SARIMA(1,1,1)(1,1,1,48)

□ RANDOM FOREST:
Strengths:
• Can handle non-linear patterns
• Robust to outliers and missing data
• Feature importance interpretability
• Good with engineered features

Considerations:
• Requires extensive feature engineering
• May overfit with too many features
• Computationally more intensive

Data Requirements: □ Excellent - 10,320 points ideal
Feature Strategy:
• Lag features: 1, 2, 3, 24, 48 periods
• Rolling means: 3, 12, 24 period windows
• Time features: hour, day_of_week, month
• Seasonal features: sin/cos transformations

□ LSTM NEURAL NETWORK:
Strengths:
• Captures complex temporal dependencies
• Excellent for sequence-to-sequence learning
• Can model non-linear relationships
• Handles multiple input features naturally

Considerations:
• Requires significant computational resources
• Needs careful hyperparameter tuning
• Data normalization critical
• Risk of overfitting with small datasets

Data Requirements: □ Good - 10,320 points adequate
Architecture Recommendations:
• Sequence Length: 48 periods (24 hours)
• Hidden Units: 50-100 per layer
• Layers: 2 LSTM layers with dropout
• Batch Size: 32-64
• Epochs: 50-100 with early stopping

PREPROCESSING RECOMMENDATIONS:

For All Models:
• Data quality: 100.0% complete □
• Outlier detection and handling
• Consistent time intervals validation

For SARIMA:
• Stationarity testing and differencing
• Seasonal decomposition analysis
• Parameter selection via AIC/BIC

For Random Forest:
• Feature scaling (optional)
• Lag feature creation
• Rolling statistics computation
• Categorical encoding for time features

For LSTM:
• MinMax normalization to [0,1] range □ Critical
• Sequence windowing (48 time steps)
• Train/validation/test split: 70/15/15
• Early stopping to prevent overfitting

EXPECTED PERFORMANCE RANKING:
Based on data characteristics and model capabilities:

1. LSTM (Best) - Complex patterns, sufficient data
2. Random Forest - Good with features
3. SARIMA - Strong seasonality
4. Naive (Baseline) - Simple persistence

SUCCESS FACTORS:
• Strong daily/weekly seasonality favors SARIMA and LSTM
• Large dataset size supports complex models
• Moderate volatility suggests all models viable
• Clear temporal patterns support sequence models

Analysis completed: September 15, 2025 at 12:25 PM