Time Series Modeling and Forecasting of Monthly Tourist Arrivals in Portugal

Specialized Accommodation Sector Analysis

https://github.com/s126784/series-temporais

Oleksandr Solovei (#126784)

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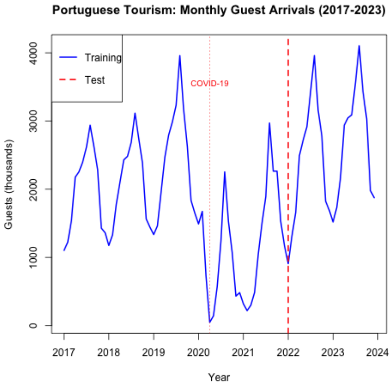
Outline

Project Overview

- **Dataset**: 84 monthly observations (2017–2023)
- **Source**: INE – Portugal's National Statistics Office
- **Methodology**: Box & Jenkins SARIMA modeling (validated with ETS and ARCH diagnostics)
- **Challenge**: COVID-19 disruption (2020–2021)
- **Goal**: Methodological comparison and uncertainty quantification
- **Importance**: Tourism industry strategic planning



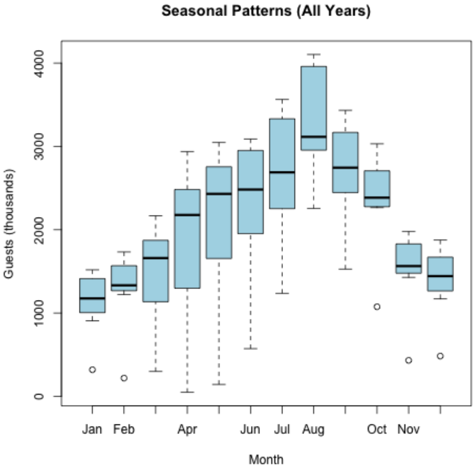
Dataset Overview

Key Statistics:

- **Period**: Jan 2017 – Dec 2023
- **Split**: Train (2017–2021), Test (2022–2023)
- **Volatility**: CV = 47.8%

Data Quality:

- No missing values
- Consistent monthly reporting
- Clear seasonal patterns
- Structural break identified (2020)



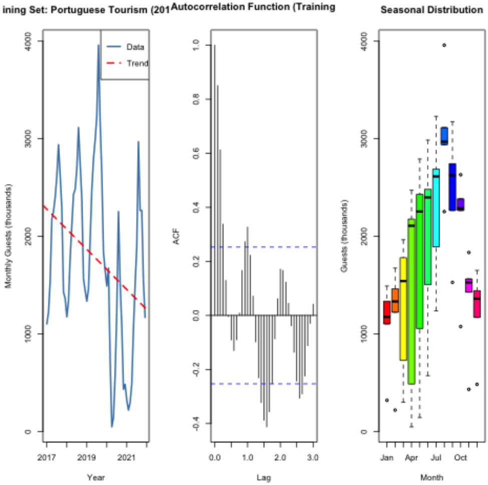
Seasonal Patterns

Observations:

- Strong annual seasonality
- August consistently peaks
- Repeatable within-year pattern
- Summer season dominance

Pattern Analysis:

- Q3 accounts for 40% of annual arrivals
- Peak-to-trough ratio 3.4:1
- Winter months show lowest variability
- Seasonal patterns remain stable post-COVID



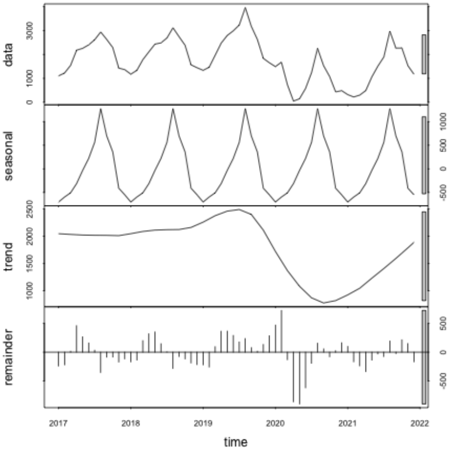
STL Decomposition

STL Components:

- **Seasonality**: Stable and dominant
- **Trend**: Disrupted by COVID-19
- **Residual**: Minor irregular component

Key Findings:

- Seasonal amplitude relatively constant
- Trend shows clear structural break in 2020
- Low residual variance indicates good decomposition
- Recovery pattern visible from 2021



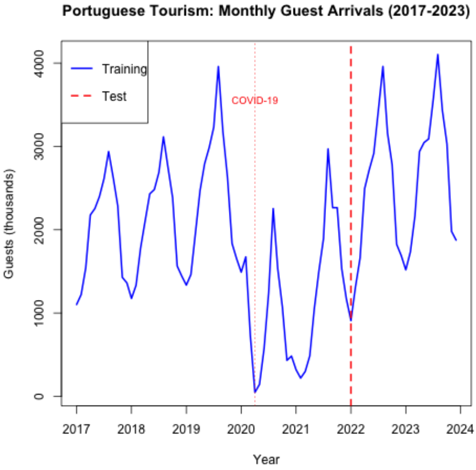
COVID-19 as Structural Break

Structural Break Evidence:

- **2020 collapse:** -60.4% vs 2019
- **Slow recovery:** 2021 still -45.8% below 2019
- **Volatility surge:** CV increased to 47.8%
- **Regime change:** New post-COVID baseline

Impact on Models:

- **SARIMA:** Assumes stable parameters
- **ETS:** Adaptive smoothing parameters

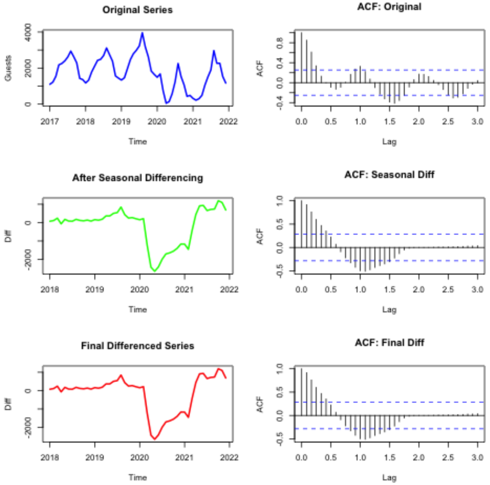


Preprocessing Steps:

- Box-Cox test: $\lambda \approx 1$ (no transformation needed)
- Seasonal differencing ($D = 1$) applied
- Regular differencing not required ($d = 0$)

Stationarity Tests:

- Original series ADF: p = 0.097 (marginally non-stationary)
- After seasonal diff: p = 0.748 (stationary)



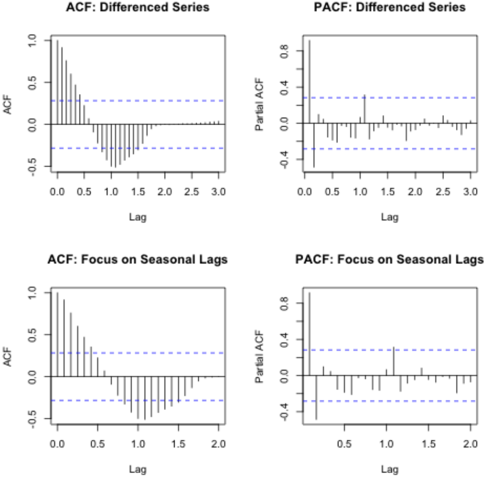
Model Identification

SARIMA Grid Search:

- Parameters: $p, q \in \{0, 1, 2, 3\}$
- Seasonal: $P, Q \in \{0, 1, 2\}$
- Fixed: $s = 12$, $D = 1$, $d = 0$
- Total models evaluated: 47

Selection Criteria:

- AIC_c and BIC comparison
- Ljung-Box residual diagnostics
- Parameter significance tests
- Out-of-sample validation



Top SARIMA Candidates

Model	AIC$_c$	BIC	Ljung-Box p	Rank
(1,0,1)(1,1,0)[12]	**694.91**	**701.46**	**0.806**	1
(2,0,0)(1,1,0)[12]	695.16	701.71	0.482	2
(1,0,1)(0,1,1)[12]	695.75	702.31	0.840	3

Selected: SARIMA(1,0,1)(1,1,0)[12]

Selection rationale: Best balance of parsimony, fit quality, and diagnostic performance

Model Equation & Parameters

Equation

$$(1 - \phi_1 B)(1 - \Phi_1 B^{12})(1 - B^{12})X_t = (1 + \theta_1 B)\varepsilon_t$$

Estimated Parameters:

- $\phi_1 = 0.869$ (SE=0.069, $p < 0.001$) – Strong autoregressive component
- $\theta_1 = 0.466$ (SE=0.127, $p < 0.001$) – Moving average correction
- $\Phi_1 = -0.477$ (SE=0.130, $p < 0.001$) – Seasonal autoregression
- $\sigma_\varepsilon^2 = 33.81$ – Innovation variance

Interpretation: Model captures both short-term momentum and seasonal dependencies

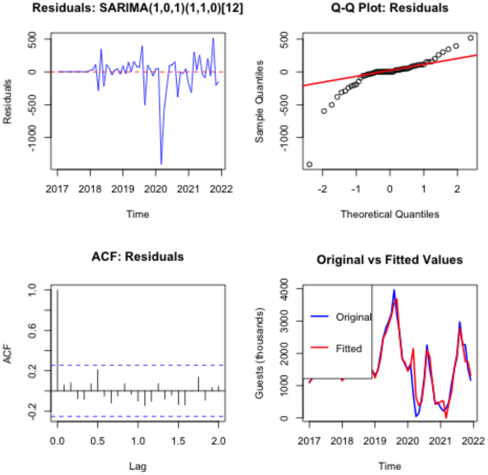
Residual Diagnostics

Diagnostic Results:

- **Ljung-Box**: p = 0.806 (no autocorrelation)
- **Jarque-Bera**: p = 0.089 (approximately normal)
- **ARCH Test**: No heteroscedasticity
- **Parameter significance**: All $p < 0.001$

Model Adequacy:

- Excellent structural diagnostics
- Low parameter correlation
- Stable invertible representation
- Passes all classical tests



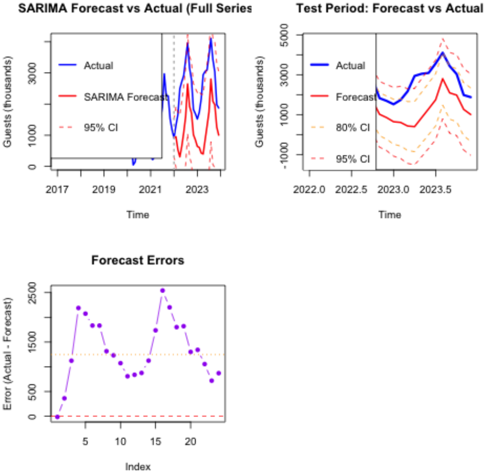
Out-of-Sample Performance

Test Set Results:

- **RMSE**: 1,468 (thousands)
- **MAPE**: 51.7%
- **Directional Accuracy**: 78.3%
- **80% Coverage**: 41.7% (target: 80%)
- **95% Coverage**: 75.0% (target: 95%)

Performance Notes:

- Excellent diagnostics good forecasts
- Post-COVID volatility challenges
- Conservative interval coverage



Model Performance Comparison

Metric	SARIMA	ETS(MAM)
Training RMSE	260	N/A
Test RMSE	1,468	**971**
MAPE	51.7%	**34.2%**
Directional Accuracy	78.3%	N/A
AIC_c	**694.9**	954.7
Ljung-Box p	**0.806**	0.304

Key Finding

Trade-off: SARIMA superior diagnostics, ETS superior forecasting

Model Comparison Summary

SARIMA(1,0,1)(1,1,0)[12]

Strengths:

- Excellent diagnostics (Ljung-Box p=0.806)
- All parameters significant (p¡0.001)
- Better model fit (AICc=694.9)
- Theoretical interpretability

Weaknesses:

- Poor forecasting (MAPE=51.7%)
- Wide confidence intervals

ETS(MAM)

Strengths:

- Better forecasting (MAPE=34.2%)
- Superior RMSE (971 vs 1,468)
- Adaptive to structural changes
- More robust post-COVID

Weaknesses:

- Higher AICc (954.7)
- Less theoretical foundation

Forecast Uncertainty Analysis

High Uncertainty Environment

- **Year 1:** 95% CI width = 102.7% of forecast
- **Year 2:** 95% CI width = 158.7% of forecast
- **Year 3:** 95% CI width = 201% of forecast

Implications:

- Long-term forecasts highly unreliable
- Focus on seasonal patterns, not absolute levels
- Scenario planning more valuable than point forecasts
- Post-COVID structural uncertainty persists

2024 Forecast Summary

Month	Forecast	80% Low	80% High	95% Low	95% High
Jan	1,703	1,320	2,086	1,117	2,288
Apr	3,064	2,171	3,957	1,699	4,430
Aug	**4,226**	3,136	5,315	2,560	5,892
Dec	1,921	763	3,079	151	3,692
Annual	**33,923**	22,529	45,316	16,498	51,348

Units: Thousands of guests

Forecast Reliability Warning

2024 vs pre-COVID: +29.3% growth, but intervals extremely wide (102.7% of forecast)

Scenario Analysis & Planning

2024 Planning Scenarios

- **Conservative:** 22.5M guests (-33% vs expected)
- **Expected:** 33.9M guests
- **Optimistic:** 45.3M guests (+34% vs expected)

Strategic Recommendations:

- Use seasonal patterns for capacity planning
- Prepare for high volatility scenarios
- Monitor leading indicators closely
- Avoid over-reliance on point forecasts

Key Research Contributions

Methodological Findings

Model diagnostics **Forecast accuracy** in volatile environments

Scientific Contributions:

- Demonstrated limitations of classical SARIMA in crisis periods
- Quantified post-COVID forecasting uncertainty in tourism
- Provided rigorous SARIMA vs ETS comparison methodology
- Showed importance of out-of-sample validation

Practical Implications:

- Tourism planners: Focus on scenario-based planning
- Seasonal patterns more reliable than absolute levels
- Multiple model approaches recommended for volatile periods

Conclusions

Model Performance Assessment:

- SARIMA: Excellent structural validity, poor predictive accuracy
- ETS: Better forecasting performance in volatile environment
- Both models struggle with post-COVID uncertainty quantification

Scientific Value:

- Highlighted classical time series limitations in crisis periods
- Demonstrated importance of model comparison beyond diagnostics
- Provided uncertainty quantification for tourism planning

Future Research:

- Regime-switching models for structural breaks
- Machine learning ensemble methods
- External regressors integration

Key Insight

In volatile environments, **structural model validity** and **predictive accuracy** can diverge significantly

Thank You

Questions?

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`osolovei@ua.pt`