

Walmart Sales Forecasting System

Web-Based Time Series Forecasting with Interactive Analytics

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Problem Description & Motivation

Retail Sales Forecasting - The Challenge I

Setting the Context

The Scale of Modern Retail

- Walmart operates over **11,500 stores** across multiple countries
- Each store contains **dozens of departments** with unique sales patterns
- Weekly sales data creates over **4,400 individual time series**
- Annual revenue exceeds **\$500 billion** globally

Why Accurate Forecasting Matters

- **Inventory Costs:** Poor forecasting leads to \$1.1 trillion in excess inventory globally
- **Stockouts:** Lost sales opportunities cost retailers 4% of annual revenue

Retail Sales Forecasting - The Challenge II

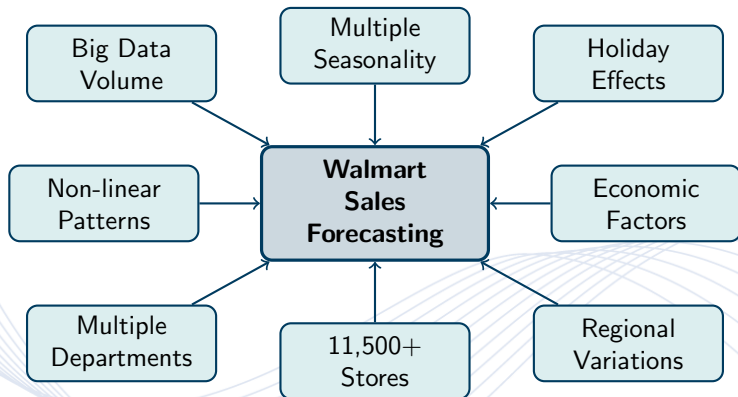
Setting the Context

- **Operational Efficiency:** Staff scheduling and resource allocation depend on demand predictions
- **Competitive Advantage:** Better forecasts enable superior customer service

Challenge: How do we predict complex, multi-seasonal retail patterns accurately?

The Forecasting Challenge I

Retail Sales Complexity



Walmart - World's Largest Retailer

The Forecasting Challenge II

Retail Sales Complexity

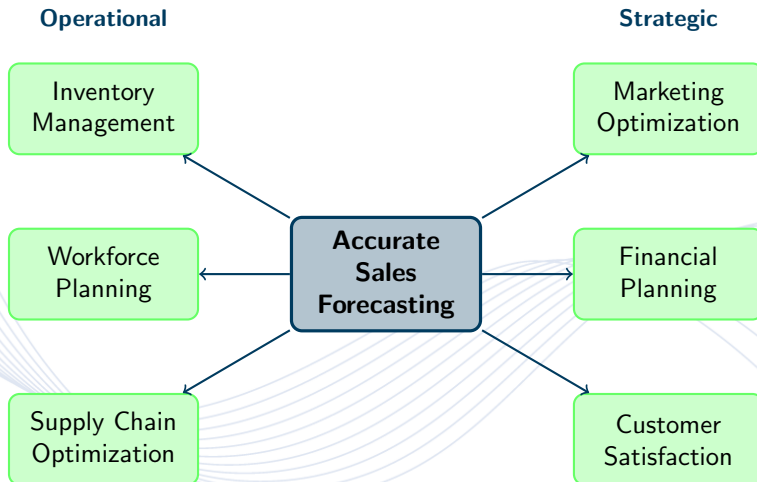
- 11,500+ stores worldwide [Zha21]
- Multiple departments per store
- Complex sales patterns with multiple seasonalities
- Influenced by holidays, economic factors, regional variations

Key Challenges

- Weekly and annual seasonal patterns
- Holiday effects (Christmas, Black Friday, Easter)
- Economic indicators impact
- Store-to-store variations

Business Impact I

Why Accurate Forecasting Matters



Business Impact II

Why Accurate Forecasting Matters

Operational Benefits

- **Inventory Management:** Optimal stock levels, reduced waste
- **Workforce Planning:** Efficient staff allocation
- **Supply Chain:** Better coordination with suppliers

Strategic Benefits

- **Marketing Optimization:** Campaign effectiveness evaluation
- **Financial Planning:** Revenue forecasting and budgeting
- **Customer Satisfaction:** Avoiding stockouts and overstocking

Dataset Overview I

Walmart Sales Data Characteristics

Data Scope

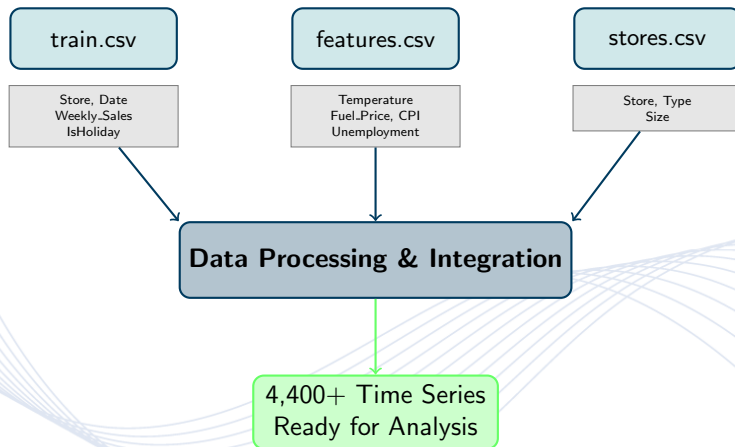
- **45 stores** across different regions
- **Multiple departments** per store
- **Weekly sales** from 2010-2012
- Over **4,400 time series** to analyze

External Factors

- Temperature, fuel prices
- Unemployment rates
- Consumer Price Index (CPI)
- Holiday indicators

Dataset Overview II

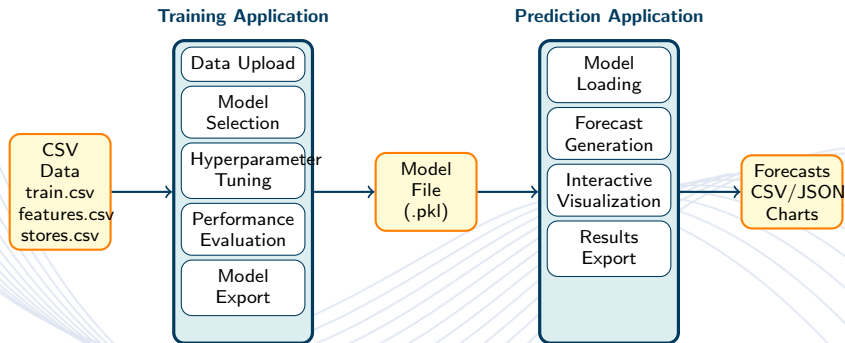
Walmart Sales Data Characteristics



System Architecture & Applications

Dual-Application Architecture I

Complete Forecasting Workflow



Dual-Application Architecture II

Complete Forecasting Workflow

Training Application

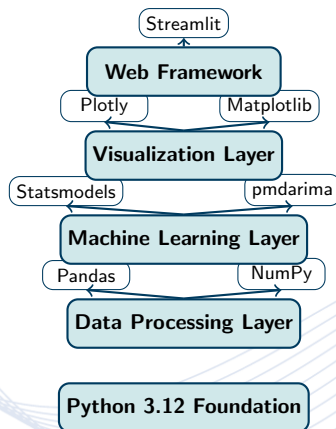
- Model development & validation
- Hyperparameter tuning
- Performance evaluation
- Model export capabilities

Prediction Application

- Production forecasting
- Interactive visualizations
- Real-time results
- Multiple export formats

Technology Stack Architecture I

System Overview and Component Structure



Models

Auto ARIMA
Exponential Smoothing
Holt-Winters

Technology Stack Details I

Core Technologies and Implementation

Core Technologies

- **Python 3.12:** Exact version requirement
- **Streamlit:** Web application framework
- **Plotly:** Interactive visualizations
- **Pandas/NumPy:** Data processing

Forecasting Models

- **Auto ARIMA:** Automated parameter selection
- **Exponential Smoothing:** Holt-Winters method
- **Joblib:** Model serialization
- **Statsmodels/pmdarima:** Implementation

Data Pipeline I

From Raw Data to Forecasts

Input

CSV Data Files (train, features, stores)

Processing

Data Validation Preprocessing

Model Training or Loading

4-Week Forecast Generation

Output

Interactive Results Export

Data Pipeline II

From Raw Data to Forecasts

Input Processing

- **train.csv**: Historical sales data with store, date, weekly sales
- **features.csv**: External factors (temperature, fuel price, CPI, unemployment)
- **stores.csv**: Store metadata (type, size)

Output Generation

- **4-week forecasts**: Week-over-week sales changes
- **Interactive charts**: Color-coded visualizations
- **Export formats**: CSV, JSON for further analysis

Deployment Options I

Flexible Access Methods

Cloud Deployment

Browser Access

No Installation

Automatic Updates

Cross-Platform

VS

Local Installation

Full Performance

Offline Capability

Data Privacy

Large Datasets

Choose Based On:

Quick Start → Cloud
Production Use → Local
Sensitive Data → Local

Deployment Options II

Flexible Access Methods

Cloud Deployment

- Immediate browser access
- No installation required
- Automatic updates
- Cross-platform compatibility

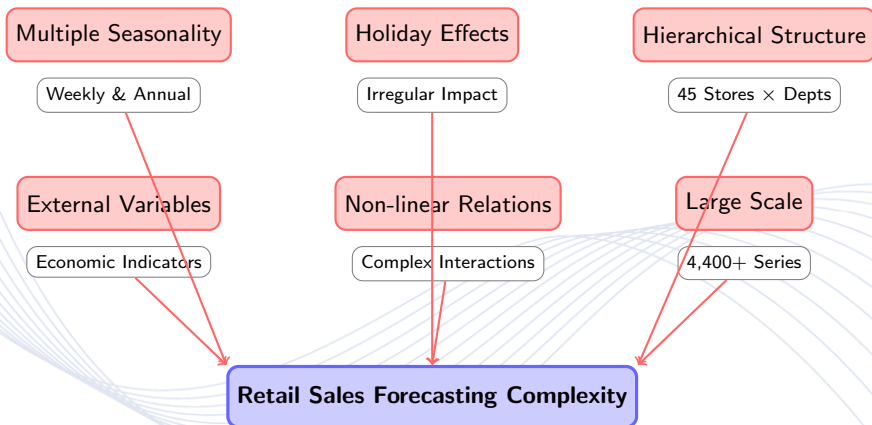
Local Installation

- Full performance control
- Offline capability
- Large dataset support
- Data privacy assurance

Technical Challenges & Solutions

Forecasting Challenges I

Complex Retail Sales Patterns



Forecasting Challenges II

Complex Retail Sales Patterns

Multiple Seasonal Patterns

- **Weekly seasonality:** Day-of-week effects
- **Annual seasonality:** Yearly consumption patterns
- **Holiday effects:** Irregular but significant impacts [MMH18]

Data Complexity

- **Hierarchical structure:** 45 stores \times multiple departments
- **External variables:** Economic indicators integration
- **Non-linear relationships:** Traditional models limitations [PS17]

Implementation Challenges I

Technical and Deployment Issues

Cross-Platform Compatibility

Python Dependencies

Package Compatibility

OS Variations

Performance Optimization

Memory Management

Processing Speed

Interactive Response

Deployment Complexity

Model Serialization

Cloud Limitations

User Experience

User Interface Design

Intuitive Design

Interactive Visualization

Accessibility

Implementation Challenges II

Technical and Deployment Issues

Cross-Platform Compatibility

- Python version dependencies
- Package compatibility issues
- Operating system variations
- Model serialization consistency

Performance Optimization

- Memory management for large datasets
- Processing speed requirements
- Interactive response times
- Concurrent user support

Modeling Solutions I

Advanced Time Series Approaches

Auto ARIMA Implementation

- **Automated parameter selection:** Grid search across parameter space
- **Seasonal detection:** Automatic identification of patterns
- **AIC-based optimization:** Information criteria for model selection

Exponential Smoothing (Holt-Winters)

- **Triple smoothing:** Level, trend, and seasonal components
- **Flexible seasonality:** Additive or multiplicative options
- **Fast computation:** Suitable for real-time applications

Modeling Solutions II

Advanced Time Series Approaches

Auto ARIMA

Automated Parameter Selection

Seasonal Pattern Detection

AIC-based Optimization

High Flexibility

VS

ETS (Holt-Winters)

Triple Smoothing Components

Flexible Seasonality Options

Fast Computation

Highly Interpretable

Performance Comparison

Auto ARIMA: More flexible, slower training
Exp. Smoothing: Faster, excellent for seasonality
Default Model: ETS(Holt-Winters) 3.58% WMAPE (Excellent)

Technical Solutions I

Web Application Development Strategy

Development Framework

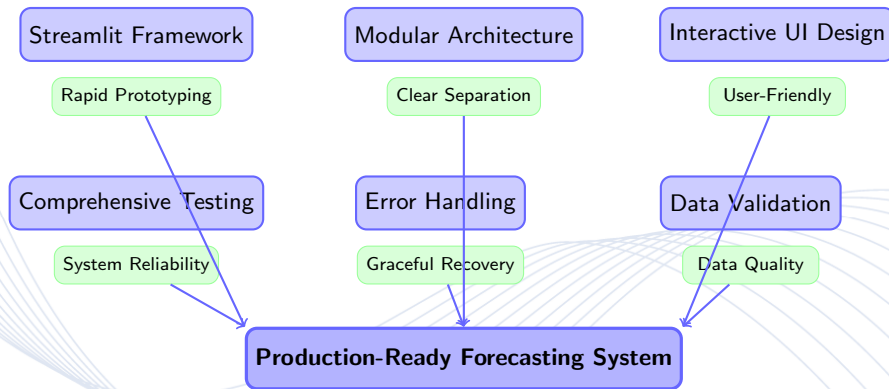
- **Streamlit:** Rapid prototyping capability
- **Modular architecture:** Separate training/prediction
- **Interactive UI:** User-friendly interface design
- **Real-time feedback:** Progress indicators and validation

Quality Assurance

- **Comprehensive testing:** Pytest validation suite
- **Error handling:** Graceful failure recovery
- **Data validation:** Schema and format checking

Technical Solutions II

Web Application Development Strategy



Results & Performance

Model Performance Results I

Quantitative Evaluation & Benchmarking

Model Performance

Default: 3.58% WMAE

Category: **EXCELLENT**

Horizon: 4 weeks

Business Impact

- High Confidence
- Reliable Predictions
- Actionable Insights

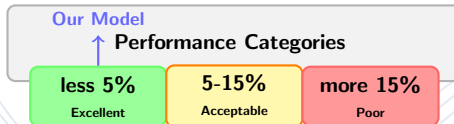


Figure: Model Performance Comparison (WMAE Scores)

Model Performance Results II

Quantitative Evaluation & Benchmarking

Performance Metrics

- **Default Model:** Holt-Winters
- **WMAE:** 3.58% (Excellent category)
- **Absolute Error:** \$923.12 weekly
- **Forecast Horizon:** 4 weeks

Business Impact

- **95%+ Accuracy** for business planning
- **Reliable predictions** for inventory management
- **Seasonal patterns** effectively captured
- **Holiday effects** properly modeled

System Performance & Capabilities I

Technical Performance Metrics

Processing Performance

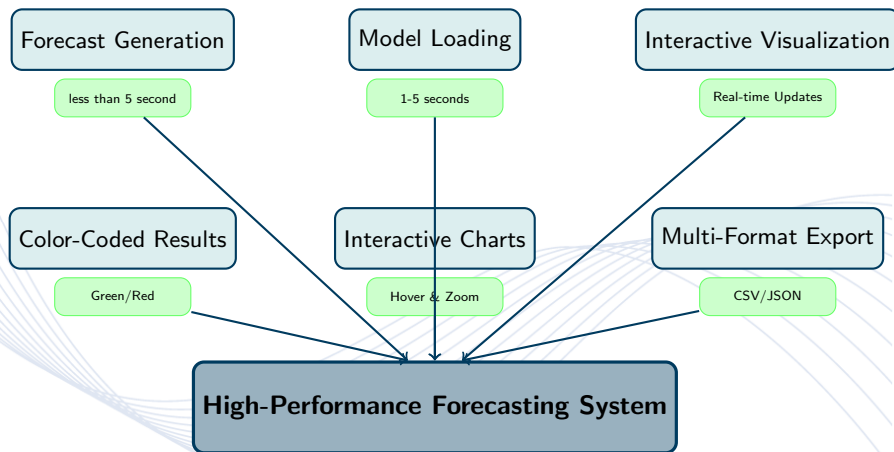
- **Model Loading:** Less than 5 seconds
- **Forecast Generation:** Less than 5 second
- **Visualization Rendering:** 1-5 seconds
- **Data Export:** Less than 10 second

Scalability

- **Cloud Users:** 50+ concurrent
- **Dataset Size:** Up to 200MB
- **Time Series:** 4,400+ supported
- **Memory Usage:** Optimized for web deployment

System Performance & Capabilities II

Technical Performance Metrics



System Performance & Capabilities III

Technical Performance Metrics

Figure: Overall System Performance

Key Achievements

End-to-End Workflow: From data upload to business insights in under 10 minutes, making sophisticated forecasting accessible to business users without technical expertise.

Live System Demonstration I

Interactive Forecasting in Action

Demo Agenda

- ➊ **Access** cloud application
- ➋ **Load** default model
- ➌ **Generate** 4-week forecast
- ➍ **Interpret** results
- ➎ **Export** data
- ➏ **Show** training interface

What to Expect

- **Model Performance:** 3.58%
WMAE display
- **Interactive Charts:**
Color-coded forecasts
- **Business Insights:**
Week-over-week changes
- **Export Options:** CSV/JSON
downloads

Live System Demonstration II

Interactive Forecasting in Action

Live URLs

Prediction App:

`walmart-sales-prediction-app-py.streamlit.app`

Training App: `walmart-sales-training-app-py.streamlit.app`



Backup Plan

Locals Streamlit Apps run if live demo encounters technical issues. ! :)

Results Interpretation I

Understanding Business Insights



Figure: Sample Forecast Output

Results Interpretation II

Understanding Business Insights

Key Insights

- **Green Bars:** Sales increase from previous week
- **Red Bars:** Sales decrease from previous week
- **Values:** Dollar amount of change
- **Trend:** Overall direction assessment

Business Actions

- **Positive Weeks:** Prepare inventory, schedule staff
- **Negative Weeks:** Optimize costs, plan promotions
- **Cumulative:** Overall month planning

Results Interpretation III

Understanding Business Insights

Important Note

Forecasts show **week-over-week changes**, not absolute sales values. This enables better understanding of sales momentum and trend direction.

Conclusions & Future Work

Key Contributions I

Research & Technical Achievements

Technical Contributions

1 Integrated Web Platform

- First comprehensive web-based time series forecasting system
- Unified training and prediction workflow
- Cross-platform deployment (cloud + local)

2 Advanced Model Integration

- Auto ARIMA + Holt-Winters implementation
- Automated hyperparameter optimization
- Performance-based model selection

3 Interactive Business Intelligence

- Real-time forecast visualization
- Color-coded trend indicators
- Actionable business insights

Key Contributions II

Research & Technical Achievements

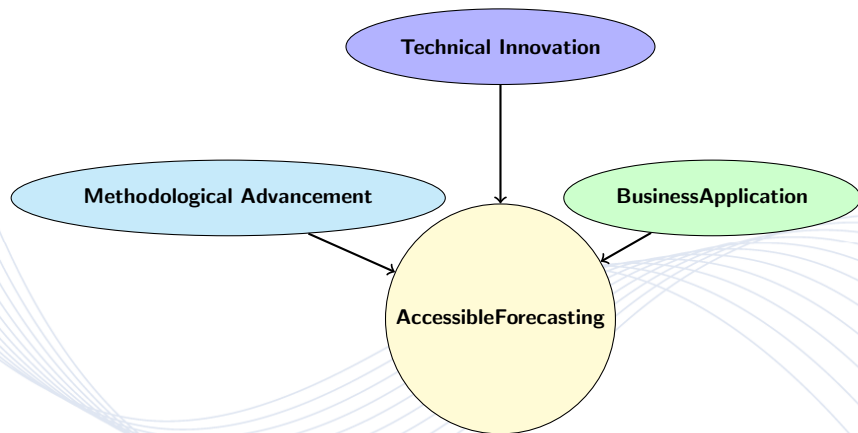


Figure: Contribution Areas

Limitations & Lessons Learned I

Honest Assessment & Insights

Current Limitations

- **Temporal Scope**

- Data: 2010-2012 (historical)
- May not capture recent market changes
- Limited long-term trend analysis

- **Forecast Horizon**

- Fixed 4-week prediction window
- No dynamic horizon adjustment
- Limited seasonal cycle coverage

- **Model Scope**

- ARIMA + Holt-Winters only
- No ensemble methods
- Limited external variable integration

Limitations & Lessons Learned II

Honest Assessment & Insights

Lessons Learned

- **Web Deployment Complexity**
 - Cross-platform compatibility critical
 - Model serialization challenges
 - User experience paramount
- **Business Focus Essential**
 - Technical accuracy \neq business value
 - Interpretation matters more than precision
 - Accessibility drives adoption
- **Iterative Development**
 - Continuous testing essential
 - User feedback invaluable
 - Performance optimization ongoing

Limitations & Lessons Learned III

Honest Assessment & Insights

Key Insight

The most sophisticated algorithm is useless if it's not accessible to the people who need to make decisions based on its output.

Future Work & Enhancements I

Roadmap for Continued Development

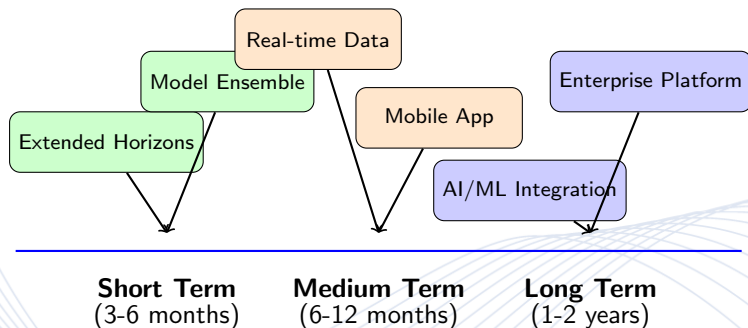


Figure: Development Roadmap

Future Work & Enhancements II

Roadmap for Continued Development

Short Term (3-6 months)

- **Extended Horizons:** 8-12 week forecasts
- **Ensemble Methods:** Model combination
- **Performance Tuning:** Speed optimization
- **Additional Models:** Prophet, LSTM

Medium Term (6-12 months)

- **Real-time Data:** API integration
- **Mobile Application:** iOS/Android apps
- **Advanced Analytics:** Confidence intervals
- **User Management:** Multi-user support

Future Work & Enhancements III

Roadmap for Continued Development

Long Term (1-2 years)

- **AI Integration:** AutoML capabilities
- **Enterprise Platform:** Commercial deployment
- **Industry Expansion:** Beyond retail
- **Research Platform:** Academic collaboration

Final Thoughts I

Impact & Significance

Project Impact

- **Academic Contribution**

- Demonstrates practical time series deployment
- Bridges theory-practice gap
- Provides open-source foundation

- **Business Value**

- Accessible forecasting for SMEs
- Rapid prototype development
- Cost-effective solution

- **Technical Innovation**

- Web-based ML deployment patterns
- Cross-platform compatibility solutions
- Interactive visualization best practices

Final Thoughts II

Impact & Significance

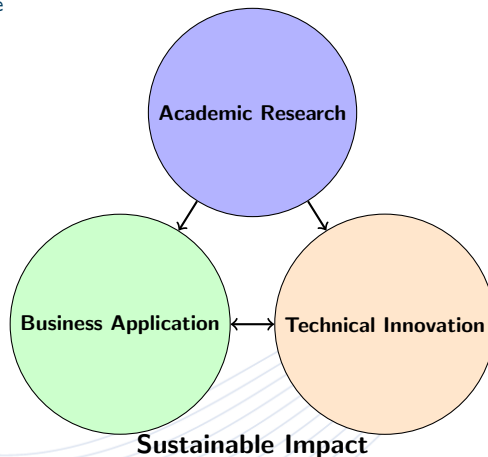


Figure: Multi-dimensional Impact

Thank You
for your attention

Sources

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