Forecasting the Future

Lecture 5 - Management Science

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Introduction

Client Briefing: MegaMart Retail Chain

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Operations Director's Crisis:

"Last Christmas, we ran out of PlayStation 5s but had 500 unsold fitness trackers. We lost €2M in missed sales and clearance losses. How do we predict what customers will actually buy?"

Business: The Unknown Future

Question: Why can't we just order the same as last year?

- Market: New products, competition
- Seasonal Shifts: Weather, holidays, economic conditions
- Trend Changes: Changing preferences, new technologies
- Randomness: Viral TikToks, supply chain disruptions, pandemics

. . .

> ⚠ Warning
>
> Reality: Large retailers process several thousand orders per hour. Each stockout basically means lost revenue + unhappy customers.

Hidden Patterns in Data

Look at this daily sales data. What patterns do you see?

One Year of Product Sales Data

Core Concepts

Decomposing Time Series

Time series can often be decomposed:

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$$Y_t = T_t + S_t + R_t$$

. . .

Where:

- Y_t = Observed value at time t
- T_t = Trend component
- S_t = Seasonal component
- R_t = Random/Residual component

Additive vs Multiplicative Models

How do the components combine?

. . .

Additive Model

$$Y_t = T_t + S_t + R_t$$
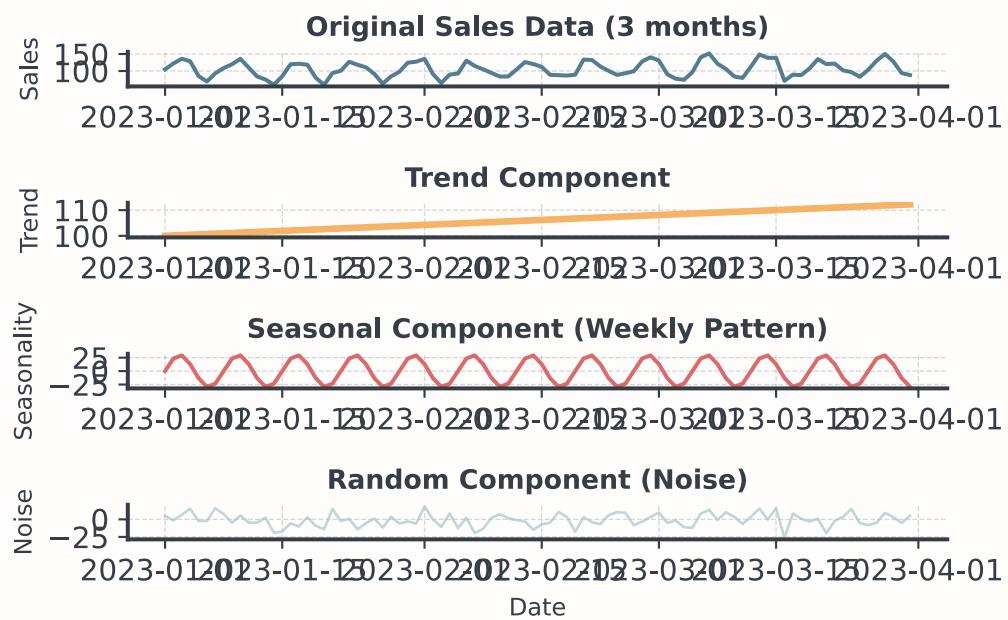
- Seasonal fluctuations are constant
- "We always sell 200 extra in December"
- Good: Stable, mature products

Multiplicative Model

$$Y_t = T_t \times S_t \times R_t$$

- Seasonal fluctuations scale with trend
- "December sales are 40% higher"
- Good: Growing businesses

Visual Decomposition

. . .
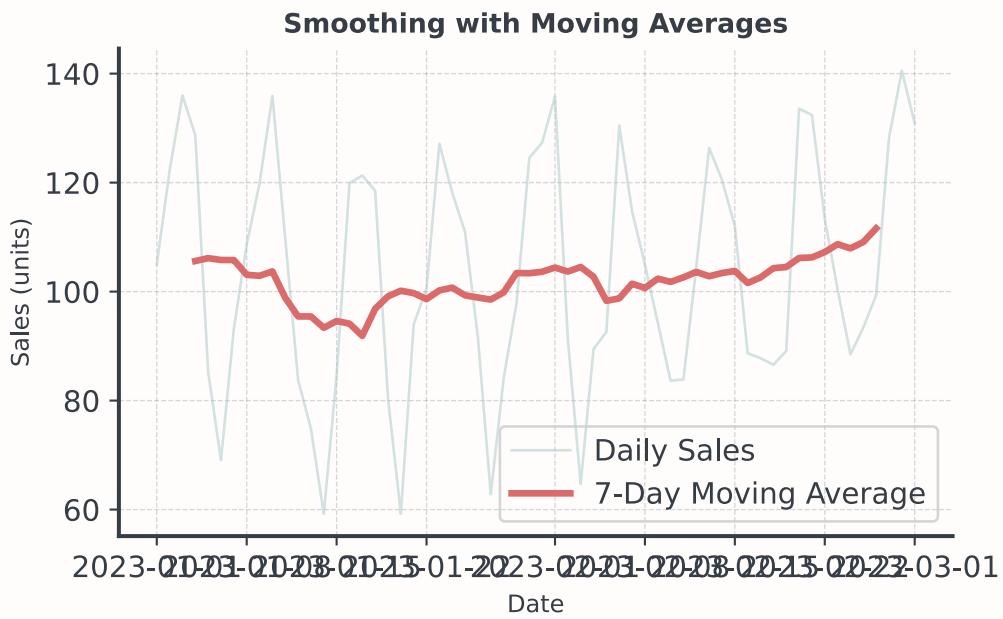
> 💡 Tip
>
> Here: Sales = Trend + Seasonality + Random Noise

Moving Average

Question: How do we separate signal from noise?

. . .

Smoothing with Moving Averages

Simple vs Weighted Averages

Which forecast would you trust more?

. . .

Simple Moving Average

- All days equally important
- We just take the average
- [14, 15, 16, 14, 15, 16, 17]
- Forecast: 15.3

Weighted Moving Average

- Recent days matter more
- Days closer are weighted more
- [0.05, 0.05, 0.1, 0.1, 0.2, 0.2, 0.3]
- Forecast: 15.9

. . .

> ! Important
>
> Recent data often predicts the future better than old data!

Exponential Smoothing Methods

Simple Exponential Smoothing

Not too simple, not too complex

. . .

$$\text{Forecast}_{t+1} = \alpha \times \text{Actual}_t + (1 - \alpha) \times \text{Forecast}_t$$

. . .

- α (alpha) = smoothing parameter (0 to 1)
- α = 0.9: Trust recent data (reactive)
- α = 0.1: Trust historical patterns (stable)
- α = 0.3: Balanced approach (common default)

. . .

> 💡 Tip
>
> Think of α like: How much do you trust the latest data point?

When Simple Smoothing Fails

Simple smoothing assumes the data is flat. What if it's not?

```
/Users/vlcek/Documents/git-teaching/Management-Science/.venv/lib/
python3.12/site-packages/pandas/util/_decorators.py:213: EstimationWarning:
Model has no free parameters to estimate. Set optimized=False to suppress
this warning
  return func(*args, **kwargs)
```

Adding Trend

Holt's Method: The Idea

Track TWO things separately: Level and Trend

1. Level (L): Where are we right now? (like simple ES)
2. Trend (b): How fast are we growing/declining per period?
3. Forecast: Combine both: Level + (Trend × periods ahead)

. . .

Why This Works:

- Simple ES only tracks level (current position)
- Holt's also tracks the slope (direction and speed)

. . .

> **i** Note
>
> Think of driving a car: Simple ES only knows your position. Holt's also knows your speed!

Holt's Method: The Math I

The formulas (simplified for intuition):

. . .

Level Equation:

$$L_t = \alpha \times Y_t + (1 - \alpha) \times (L_{t-1} + b_{t-1})$$

Trend Equation:

$$b_t = \beta \times (L_t - L_{t-1}) + (1 - \beta) \times b_{t-1}$$

Forecast Equation:

$$\hat{Y}_{t+h} = L_t + h \times b_t$$

Holt's Method: The Math II

In plain English

- Level: "Smooth current observation with previous forecast"
- Trend: "Smooth the change in level with our previous trend"
- Forecast: "Start at current, add trend for each period ahead"

. . .

> **i Note**
>
> Not too complicated, right?

Step-by-Step I

Let's walk through 6 periods manually to build intuition

```python
# Sample data with clear upward trend
sales_data = np.array([100, 105, 112, 118, 124, 130])

# Parameters
alpha = 0.3  # Level smoothing
beta = 0.2   # Trend smoothing

# Initialize
level = sales_data[0]  # Start at first observation
trend = sales_data[1] - sales_data[0]  # Initial trend estimate

print(f"Period 1: Level={level:.1f}, Trend={trend:.1f}")

# Store level and trend history for visualization
level_history = [level]
trend_history = [trend]
```

```
Period 1: Level=100.0, Trend=5.0
```

Step-by-Step II

```python
# Apply Holt's method for periods 2-6
for t in range(1, len(sales_data)):
    # Update level
    prev_level = level
    level = alpha * sales_data[t] + (1 - alpha) * (prev_level + trend)

    # Update trend
    trend = beta * (level - prev_level) + (1 - beta) * trend

    # Store for visualization
    level_history.append(level)
    trend_history.append(trend)

    print(f"Period {t+1}: Sales={sales_data[t]}, Level={level:.1f},
Trend={trend:.1f}")
```

```
Period 2: Sales=105, Level=105.0, Trend=5.0
Period 3: Sales=112, Level=110.6, Trend=5.1
Period 4: Sales=118, Level=116.4, Trend=5.3
```

```
Period 5: Sales=124, Level=122.4, Trend=5.4
Period 6: Sales=130, Level=128.4, Trend=5.5
```

Step-by-Step III

```python
# Forecast next 3 periods
print(f"\nForecasts:")
forecast_values = []
for h in range(1, 4):
    forecast = level + h * trend
    forecast_values.append(forecast)
    print(f"  Period {len(sales_data)+h}: {forecast:.1f} units")
```
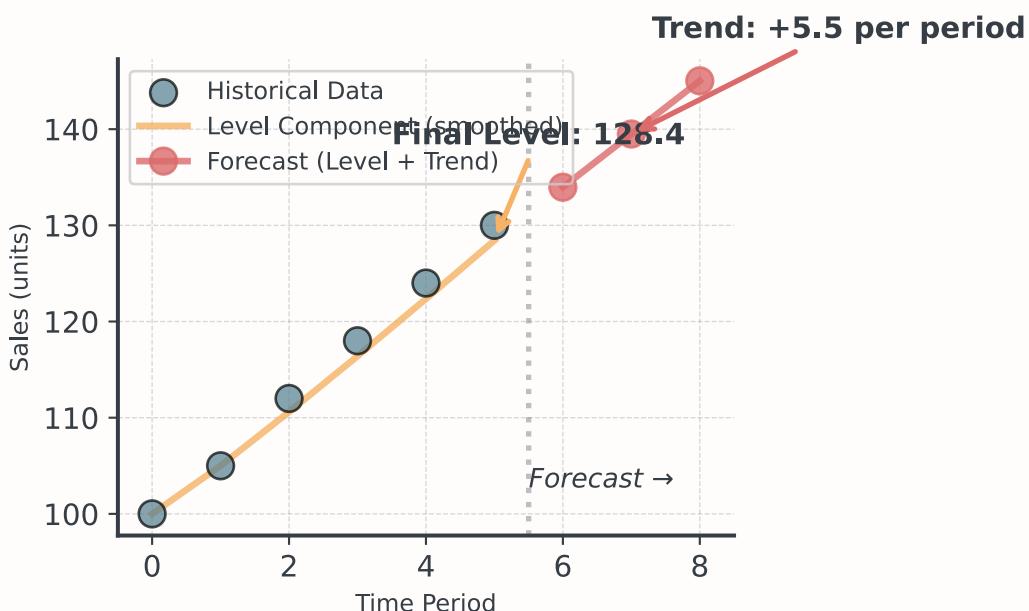
```
Forecasts:
  Period 7: 134.0 units
  Period 8: 139.5 units
  Period 9: 145.0 units
```

Holt's Method: Visual Comparison

Choosing Alpha and Beta

How do you pick the right smoothing parameters?

. . .

Alpha (Level Smoothing)

- High α (0.7-0.9): Responsive
  - ‣ Use: Volatile markets

- Low α (0.1-0.3): Stable
  - ‣ Use: Steady business

Beta (Trend Smoothing)

- High β (0.5-0.8): Quickly
  - ‣ Use: Dynamic growth/decline
- Low β (0.1-0.3): Stable trend
  - ‣ Use: Consistent growth

. . .

Best Practice: Let the algorithm optimize parameters automatically!

. . .

> 💡 Tip
>
> You can implement Holt's method using Python's `statsmodels` library!

When to Use

Question: When should you use Holt's method?

. . .

- Clear upward or downward trend
- No seasonal patterns

. . .

Question: When should you use NOT Holt's method?

- Data is flat (use simple ES instead)
- Strong seasonality present
- Trend direction changes frequently

Adding Seasonality

The Problem: Trend + Seasonality

What if your data has BOTH trend AND seasonality?

. . .

Holt-Winters: Three Components

Track THREE things separately: Level, Trend, AND Seasonality

1. Level (L): Current baseline demand (deseasonalized)
2. Trend (b): Growth rate per period
3. Seasonal Indices (s): Multipliers for each season

Holt-Winters Visualized

Holt-Winters Decomposes Your Data Into Three Parts

Seasonality

How does seasonality combine with the level?

. . .

Additive Model

$$Y_t = L_t + b_t + s_t$$

- Seasonal variation is constant
- "We sell +50 units every December"
- Pattern: ±constant amount

Multiplicative Model

$$Y_t = L_t \times b_t \times s_t$$

- Seasonal variation scales with level
- "December is 1.5× normal sales"
- Pattern: ×percentage change

Holt-Winters: The Math I

The formulas (don't panic - Python does this for you!)

. . .

Additive Model:

$$L_t = \alpha(Y_t - s_{t-m}) + (1 - \alpha)(L_{t-1} + b_{t-1})$$

$$b_t = \beta(L_t - L_{t-1}) + (1 - \beta)b_{t-1}$$

$$s_t = \gamma(Y_t - L_t) + (1 - \gamma)s_{t-m}$$

$$\hat{Y}_{t+h} = L_t + hb_t + s_{t+h-m}$$

Holt-Winters: The Math II

In plain English

- Level: Remove seasonality from observation, then smooth
- Trend: Same as Holt's method
- Seasonal: Update the seasonal index for this period
- Forecast: Level + trend + seasonal adjustment

. . .

Parameters:

α (level), β (trend), γ (seasonal), m (seasonal period length)

Holt-Winters: Intuition I

Understanding seasonal patterns with quarterly sales

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Quarterly Sales Pattern:

- Q1: Low season (after holidays) → Factor: 0.85
- Q2: Spring pickup → Factor: 0.95
- Q3: Summer growth → Factor: 1.05
- Q4: Holiday peak! → Factor: 1.15

Holt-Winters: Intuition I

How Holt-Winters Works
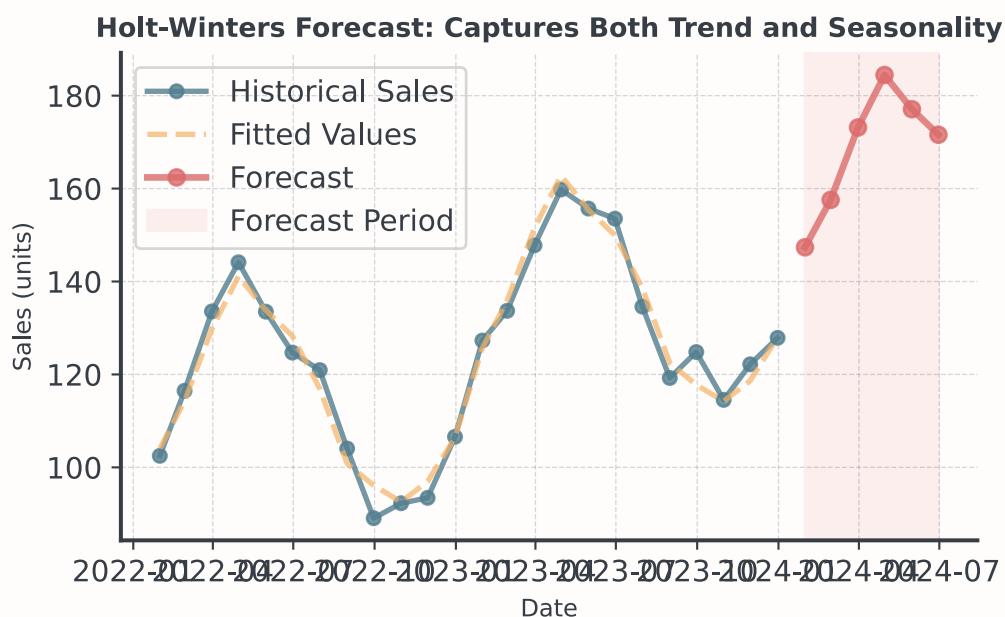
1. Deseasonalize the data (remove seasonal effect)
2. Calculate trend from deseasonalized data
3. Update seasonal indices based on actual vs. expected
4. Forecast by combining level + trend + seasonal pattern

...

> 💡 Tip
>
> Q4 is typically 35% higher than Q1 in retail! Holt-Winters captures this automatically.

Holt-Winters: Visual

Holt-Winters Forecast: Captures Both Trend and Seasonality

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> **i Note**
>
> Notice how the forecast continues the seasonal pattern while following the trend!

When to Use Holt-Winters

Question: When should you use Holt-Winters method?

. . .

- Data with trend AND seasonality
- At least 1 full seasonal cycle (2 are better!)
- Regular, repeating patterns

. . .

Question: When should you AVOID Holt-Winters method?

. . .

- Irregular or changing seasonal patterns
- Flat data with no trend
- Seasonal pattern length unknown

Method Selection & Validation

Measuring Forecast Accuracy

How wrong were we?

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Mean Absolute Error (MAE): Average size of mistakes

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|Actual_i - Forecast_i|$$

. . .

Root Mean Squared Error (RMSE): Penalizes large errors more

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Actual_i - Forecast_i\right)^2}$$

Forecast Accuracy

Easy with Python

```python
# Example: Compare two forecasting methods
actual = np.array([100, 105, 110, 108, 112])
forecast_a = np.array([98, 107, 109, 110, 111])
forecast_b = np.array([102, 103, 112, 106, 113])
```

```
mae_a = np.mean(np.abs(actual - forecast_a))
mae_b = np.mean(np.abs(actual - forecast_b))

print(f"Method A - MAE: {mae_a:.2f} units")
print(f"Method B - MAE: {mae_b:.2f} units")
print(f"\nBetter method: {'A' if mae_a < mae_b else 'B'}")
```

```
Method A - MAE: 1.60 units
Method B - MAE: 1.80 units

Better method: A
```

When to Use Which Method?

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> 💡 Tip
>
> Start simple: Try moving average first as baseline, then add complexity only if needed!

The Real Cost of Being Wrong

Not all forecast errors are equal!

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Example: Winter Coats

- Cost: €50, Selling Price: €150, Margin: €100
- Storage cost: €5/month
- Clearance markdown: 70% off

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Question: What is your intuition here?

Under and Overforecasting

Sometimes it's cheaper to overstock than to miss sales!

. . .

Underforecast by 100 units:

- Lost profit: 100 × €100
  - ‣ €10,000
- Customer disappointment
- Competitor gains market share

Overforecast by 100 units:

- Storage: 100 × €5 × 3 months
  - ‣ €1,500
- Clearance loss: 100 × €70
  - ‣ €7,000

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> !Important
>
> The "best" forecast depends on your business context.

Method Implementation

Your Python Practice Notebook

All the hands-on coding happens in the interactive tutorial!

. . .

1. Working with dates in Pandas
2. Implementing moving averages
3. Building forecast functions
4. Applying Holt's method
5. Using Holt-Winters
6. Measuring accuracy

. . .

> **i Note**
>
> The notebook guides you step-by-step through Bean Counter's seasonal demand forecasting challenge!

AI & Machine Learning Forecasting

The Promise of AI

Can machines predict better than classical methods?

What AI/ML brings to forecasting:

- Handle hundreds of variables simultaneously
- Detect complex non-linear patterns
- Learn from massive datasets
- Adapt automatically to changes

. . .

> **i Note**
>
> AI doesn't replace human judgment, it augments it when you have enough data!

Common AI/ML Forecasting

Overview of popular techniques

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Traditional ML:

- Random Forest: Ensemble of decision trees
- XGBoost: Gradient boosting (very popular)
- Support Vector Machines: Pattern recognition

Deep Learning:

- LSTM (Long Short-Term Memory): For sequences
- Prophet (Facebook): Automated forecasting
- Neural Networks: Complex patterns

. . .
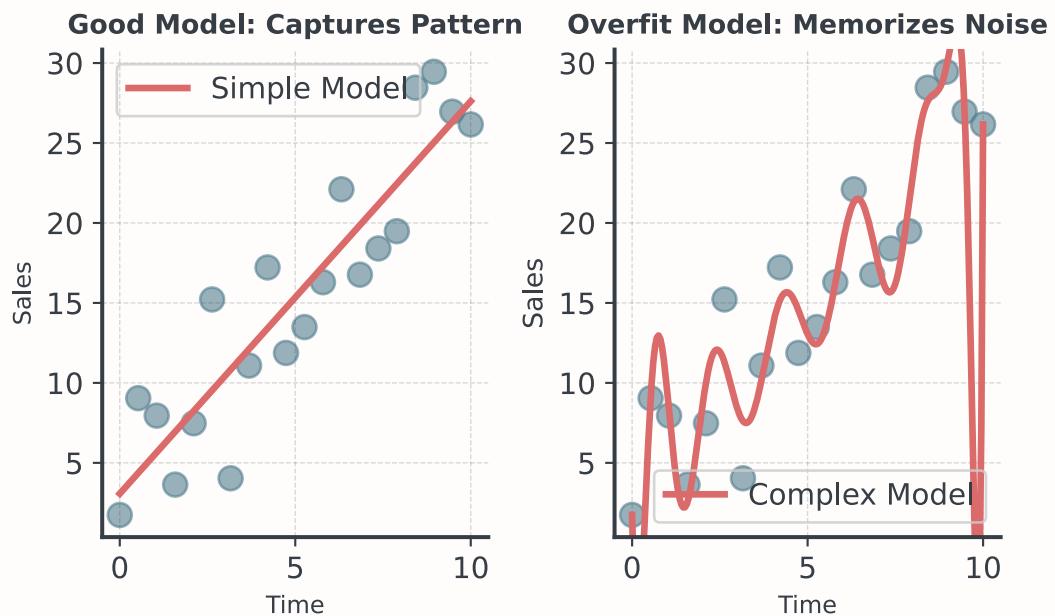
> **⚠ Warning**
>
> More complex ≠ Better! Simple methods often win in forecasting.

The Issue: Overfitting

Question: What happens when we train an AI on all our data and use it to predict… the same data?

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Good Model: Captures Pattern

Overfit Model: Memorizes Noise
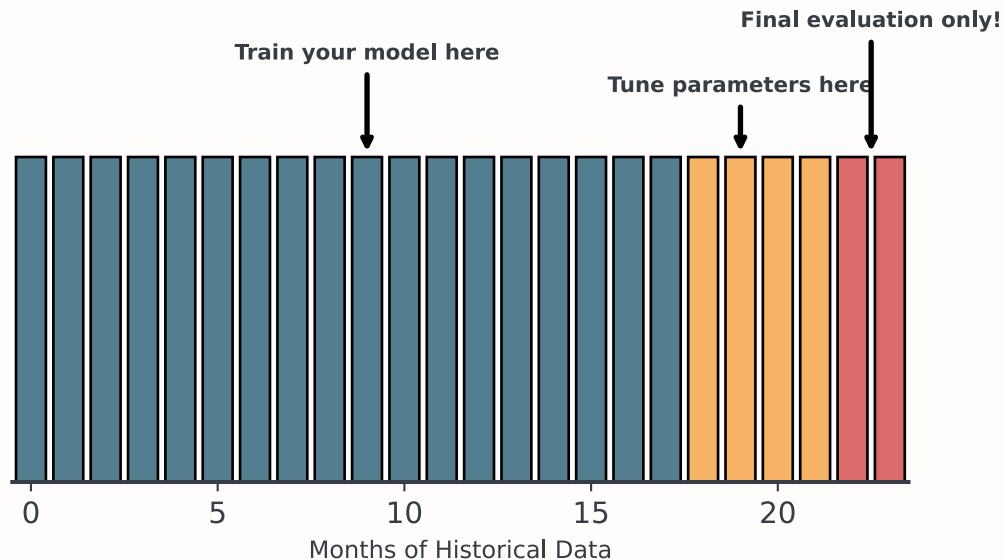
Training vs Test Data

Never judge a complex model on the data it learned from!

The Split: Never Mix Training and Test Data

- Training Data: Where the model learns patterns (70-80%)
- Validation Data: Where you tune hyperparameters (10-15%)

- Test Data: The "future", only once for final evaluation (10-15%)

Data Leakage: The Silent Problem

When future information sneaks into your training data

. . .

1. Target leakage
   - Wrong: Including "total_sales" when predicting "monthly_sales"
   - Right: Only use information available at prediction time
2. Temporal leakage
   - Wrong: Random split for time series (mixes past and future)
   - Right: Always split chronologically

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> **!** Important
>
> Data leakage can make a terrible model look amazing… until it fails in production!

Time Series Cross-Validation

Time Series Cross-Validation: Always Respect Time Order!

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> **i** Note
>
> Unlike regular cross-validation, we NEVER use future data to predict the past!

When to Use AI/ML Forecasting I

Use AI when you have:

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- Sufficient historical data (2+ years)
- Rich feature data (weather, promotions, events)
- Non-linear patterns
- Resources for training/maintenance

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Examples:

- Large retailers (Amazon, Walmart)
- Demand forecasting with many variables

When to Use AI/ML Forecasting II

Don't use AI when you have:

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- Limited historical data
- High noise, low signal
- Need explainable forecasts
- Limited expertise

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Examples:

- New products (no history)
- Regulatory environments

Advanced Topics
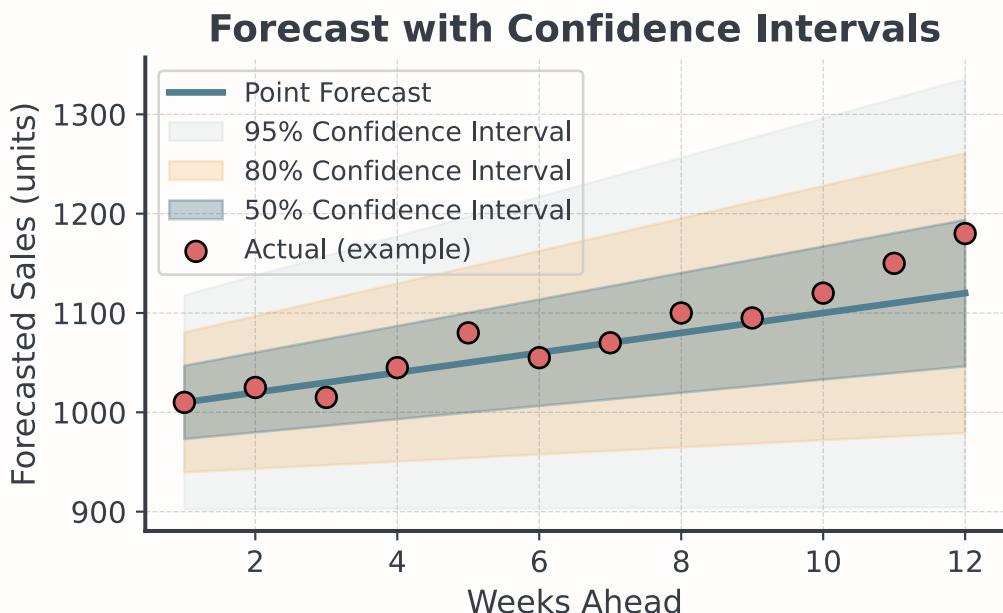
Forecast Horizons

How far into the future can we predict?

The Forecast Accuracy Degradation Curve

Confidence Intervals

A forecast without confidence intervals is incomplete!

Forecast with Confidence Intervals

Forecast Combination

Why choose one method when you can combine several?

...

```
# Example: Combining multiple forecasts
ma_forecast = 120       # Moving average prediction
```

```
exp_forecast = 125      # Exponential smoothing prediction
seasonal_forecast = 135 # Seasonal model prediction

# Simple average (equal weights)
simple_combo = (ma_forecast + exp_forecast + seasonal_forecast) / 3
print(f"Simple combination: {simple_combo:.0f} units")

# Weighted average (based on historical accuracy)
weights = [0.3, 0.5, 0.2]  # Exp smoothing was most accurate historically
weighted_combo = (ma_forecast * weights[0] +
                  exp_forecast * weights[1] +
                  seasonal_forecast * weights[2])
print(f"Weighted combination: {weighted_combo:.0f} units")
```

```
Simple combination: 127 units
Weighted combination: 126 units
```

Lead Times and Safety Stock

...

> !Important
>
> Long lead times = Forecasting further out = Less accuracy = More safety stock!

Safety Stock Calculation

How much buffer do you need?

...

```python
# Safety stock formula
import scipy.stats as stats

avg_weekly_demand = 300; std_weekly_demand = 40; lead_time_weeks = 3
service_level = 0.95  # Want 95% availability

# Z-score for 95% service level
z_score = stats.norm.ppf(service_level)

# Safety stock calculation
safety_stock = z_score * std_weekly_demand * np.sqrt(lead_time_weeks)
reorder_point = (avg_weekly_demand * lead_time_weeks) + safety_stock

print(f"Average demand during lead time: {avg_weekly_demand *
lead_time_weeks} units")
print(f"Safety stock needed: {safety_stock:.0f} units")
print(f"Reorder point: {reorder_point:.0f} units")
```

```
Average demand during lead time: 900 units
Safety stock needed: 114 units
Reorder point: 1014 units
```

Today's Tasks

Today

Hour 2: This Lecture

- Patterns & decomposition
- Simple ES, Holt's, Holt-Winters
- Method selection
- Practical pandas

Hour 3: Notebook

- Bean Counter CEO
- Daily and weekly aggregation
- Implement methods
- Compare accuracy

Hour 4: Competition

- MegaMart challenge
- 3 real products
- 4-week forecast
- €10K per error unit!

The Competition Challenge

"The Christmas Predictor"

...

1. Analyze 2 years of weekly sales for 3 products
2. Identify patterns (trend, seasonality, volatility)
3. Forecast 4 December weeks for each product
4. Minimize Mean Absolute Error across all 12 predictions

Key Takeaways

Remember This!

The Rules of Forecasting

1. Always plot first - Your eyes catch patterns algorithms miss
2. Start simple - Complexity is not your friend
3. Recent matters more - Weight recent data higher
4. Match method to pattern - Trend? Seasonality? Match!
5. Validate on holdout - Never test on training data
6. Add confidence intervals - Uncertainty is information
7. Consider business context - Cost of errors matters

Final Thought

Forecasting is both art and science

. . .

The Science:

- Statistical methods
- AI based forecasting
- Error metrics (MAE, RMSE)
- Confidence intervals
- Systematic validation

The Art:

- Choosing the right method
- Balancing complexity vs simplicity
- Interpreting context
- Communicating uncertainty

. . .

> **!Important**
>
> Make better decisions, not perfect predictions!

Break!

Take 20 minutes, then we start the practice notebook

Next up: You'll become Bean Counter's forecasting expert, preparing for seasonal demand!

Then: The MegaMart Christmas Challenge!

Bibliography