
Introduction to Forecasting

BSAD 8310: Business Forecasting — Lecture 1

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Why Forecasting Matters

Every business decision made today depends on expectations about tomorrow.

Operations & Supply Chain

- How much inventory should Walmart order for Black Friday?
- How many nurses does a hospital need next Tuesday night?
- When will this machine component fail?

Finance & Risk

- Will credit card defaults rise next quarter?
- What will the Fed Funds rate be in 6 months?
- How volatile will equity returns be tomorrow?

Marketing & Strategy

- How many units will this new product sell in year one?
- What is the customer lifetime value of this cohort?

Macro & Public Policy

- Will GDP grow by 2% or 3% next year?
- What will unemployment be in Q4?

A decision is only as good as the forecast it rests on.

- **UK NHS (2020):** Initial COVID hospitalization forecasts were off by $4\times$ — led to procurement of excess ventilators and delayed other treatments.
- **Toys R Us (2017):** systematically over-ordered inventory based on outdated demand forecasts, contributing to bankruptcy.
- **Target Canada (2015):** Inventory system forecasting errors caused shelves to be overstocked on some items and empty on others — a \$2B writedown.

Overfitting is not the only failure mode. Ignoring uncertainty (using a point forecast as if it were certain) is equally dangerous.

Fundamental challenges:

- **Uncertainty:** The future is inherently random. The best we can do is characterize the distribution of outcomes.
- **Nonlinearity:** Many economic relationships change over time or at a threshold.
- **Regime shifts:** Structural breaks (recessions, pandemics, policy changes) alter the data-generating process.
- **High dimensionality:** More potential predictors than observations (especially in the ML half of the course).

Statistical challenges:

- Serial correlation: y_t and y_{t-1} are not independent.
- Non-stationarity: the mean and variance may change over time.
- Sparse data: rare events (defaults, crises) have few observations.
- Evaluation: you can only evaluate out-of-sample.

This course: learn *when* and *why* each method works — not just how to run it.

The Forecasting Framework

A precise language for talking about prediction under uncertainty.

A **time series** is an ordered sequence of observations $\{y_1, y_2, \dots, y_T\}$ where t indexes time.

Notation:

- y_t — observed value at time t
- h — **forecast horizon** (periods ahead)
- \mathcal{F}_t — **information set** at time t (all data available up to and including time t ; may include past values of predictors and economic indicators, not only the history of y_t)
- $\hat{y}_{t+h|t}$ — forecast of y_{t+h} made at time t

Examples:

- $h = 1$: next month's sales
- $h = 12$: sales 12 months from now
- $h = 1$ vs. $h = 12$: harder problem as h increases

The subscript notation $\hat{y}_{t+h|t}$ is read “ y -hat at $t + h$ given t .”

We want a single number $\hat{y}_{t+h|t}$ to represent our best guess of y_{t+h} .

Suppose you must predict next month's retail sales. You can observe all history $\{y_1, \dots, y_t\}$.

What single number would you report to minimize your average squared miss?

Hint: think about what the mean of a distribution minimizes.

Under **squared error loss**, the optimal h -step-ahead forecast is:

$$\hat{y}_{t+h|t} = \mathbb{E}[y_{t+h} | \mathcal{F}_t]$$

the *conditional expectation* of y_{t+h} given all information at time t .

Why the conditional expectation?

- The MSE-minimizing predictor of any random variable Z is $\mathbb{E}[Z]$ — the mean.
- Conditioned on \mathcal{F}_t , that becomes $\mathbb{E}[Z | \mathcal{F}_t]$.
- Proof sketch: $\mathbb{E}[(Z - c)^2]$ is minimized at $c = \mathbb{E}[Z]$; condition on \mathcal{F}_t .

Different loss functions yield different optimal forecasts. MAE loss \Rightarrow conditional median. We will use MSE throughout unless stated otherwise.

When is MAE preferable? Hint: asymmetric costs (e.g., stockout vs. over-stocking).

The **forecast error** for a one-step-ahead forecast is:

$$e_t = y_t - \hat{y}_{t|t-1}$$

For h -step-ahead: $e_{t+h} = y_{t+h} - \hat{y}_{t+h|t}$

Properties of errors from the optimal forecast:

- $\mathbb{E}[e_t] = 0$ — unbiased (no systematic over- or under-prediction)
- $\text{Cov}(e_t, e_{t-k}) = 0$ for $k \geq 1$ — errors are uncorrelated (if forecast is truly optimal)
- Errors that are autocorrelated reveal *unexploited information*

Reserve ε_t for the true innovation (white noise) of a model. Use e_t for the realized forecast error. These are different: e_t includes parameter estimation error; ε_t does not.

Point forecast

$$\hat{y}_{t+1|t} = 42.7$$

Interval forecast

$$[38.2, 47.2]$$

Density forecast

$$p(y_{t+1} \mid \mathcal{F}_t)$$

- Single number
- Most common in practice
- Hides uncertainty

- Lower + upper bound
- 95% coverage means: 95% of such intervals contain y_{t+1}
- Calibration matters

- Full distribution
- Most informative
- Harder to produce and evaluate

This course focuses on **point** and **interval** forecasts. Density forecasting is beyond the scope of this course.

Time Series Patterns

Before fitting any model, understand the structure of the data.

Any time series can be decomposed into (additive form):

$$y_t = T_t + S_t + C_t + I_t$$

Multiplicative form: $y_t = T_t \times S_t \times C_t \times I_t$ (use when seasonal amplitude grows with level).

- T_t : **Trend** — long-run movement
(linear, quadratic, or stochastic)
- S_t : **Seasonality** — regular, calendar-driven pattern
- C_t : **Cycle** — medium-run fluctuations (business cycles)
- I_t : **Irregular** — random shocks and one-offs

- **Retail sales:** strong trend + strong seasonality
- **Quarterly GDP:** trend + cycle (weak seasonality)
- **Daily stock returns:** nearly all irregular
- **Energy demand:** trend + seasonality + cycle

Seasonal period m : the number of observations per year (or per recurring cycle).

Data frequency	Seasonal period m
Annual	1 (no seasonality)
Quarterly	4
Monthly	12
Weekly	52
Daily	7 or 365

Ignoring seasonality is a common source of large forecast errors. A non-seasonal model applied to monthly retail data will systematically under-forecast in December and over-forecast in January.

Lab 01 will visualize seasonality in US retail sales data. We will decompose the series using STL (Seasonal-Trend decomposition via LOESS).

A time series $\{y_t\}$ is **weakly stationary** if:

1. $\mathbb{E}[y_t] = \mu$ (constant mean)
2. $\text{Var}(y_t) = \sigma^2 < \infty$ (constant variance)
3. $\text{Cov}(y_t, y_{t-k}) = \gamma_k$ depends only on lag k , not on t

Why it matters:

- Most classical forecasting methods assume stationarity
- Non-stationary series produce *spurious* regressions

Rule of thumb: Visible trend or growing variance (heteroscedasticity) \Rightarrow likely non-stationary.

Full treatment: **Lecture 4** (ARIMA Models).

Is US retail sales stationary? What about daily S&P 500 returns vs. price levels?

Benchmark Models

Always beat a simple baseline before claiming success.

Before presenting any forecast model, establish what a **naive benchmark** achieves. A model that does not beat the benchmark has zero value.

Why benchmarks matter:

- Many series are hard to forecast — even “simple” models may be hard to beat.
- The M4 Competition (Makridakis et al. 2020): out of 61 methods, many sophisticated ML models failed to beat exponential smoothing.
- A benchmark defines the floor. Your goal is to clear it by a meaningful margin.

Naïve, Seasonal Naïve, Historical Mean, Random Walk with Drift. We will always compute these before evaluating any model.

$$\hat{y}_{t+h|t} = y_t \quad \text{for all } h \geq 1$$

Use the *most recent observation* as the forecast for all future periods.

Properties:

- Equivalent to a **random walk** model:
 $y_t = y_{t-1} + \varepsilon_t$
- Optimal under the random walk hypothesis
- Standard benchmark for financial prices
- Forecast does not change with h (flat forecast function)

When to use:

- ✓ Asset prices, exchange rates
- ✓ When you have very little history
- ✗ Series with strong trend or seasonality

Python: `y_hat = y_train.iloc[-1]`

$$\hat{y}_{t+h|t} = y_{t+h-12}$$

Use the *value from the same month one year ago*.

General form for arbitrary h and period m : $\hat{y}_{t+h|t} = y_{t+h-m \cdot \lceil h/m \rceil}$

Properties:

- Captures seasonality without modeling it explicitly
- Standard benchmark for monthly business data
- Automatically handles any seasonal period m

When to use:

- ✓ Retail sales, electricity demand
- ✓ Any series with clear seasonal pattern
- ✗ Non-seasonal series (use naïve instead)

Python: shift by seasonal period using
`pd.Series.shift(m)`

$$\hat{y}_{t+h|t} = \bar{y}_t = \frac{1}{t} \sum_{s=1}^t y_s \quad \text{for all } h \geq 1$$

Forecast with the *average of all past observations*.

Properties:

- Optimal under the assumption that y_t is i.i.d.
- Produces a constant, flat forecast
- Variance of forecast error decreases as t grows (more data \Rightarrow better estimate of μ)

When to use:

- ✓ Stationary series with no pattern
- ✓ Very long history, very stable series
- ✗ Any series with trend or seasonality

Python: `y_hat = y_train.mean()`

$$y_t = c + y_{t-1} + \varepsilon_t \implies \hat{y}_{t+h|t} = y_t + h\hat{c}$$

where $\hat{c} = (y_T - y_1)/(T - 1)$ is the estimated average period-to-period change.

Properties:

- Combines naïve with a linear trend component
- Forecast function: linear extrapolation from last observation
- Limiting case: as $\alpha \rightarrow 1$ and $\beta \rightarrow 1$, Holt's method approaches the random walk with drift (Lecture 3)

Which benchmark to use?

No trend, no season \rightarrow Mean
Trend, no season \rightarrow RW + Drift
Season, no trend \rightarrow Seasonal Naïve
Trend + Season \rightarrow Seasonal Naïve
Asset prices \rightarrow Naïve

Forecast Evaluation

Forecasting without evaluation is not science — it is storytelling.

Given T out-of-sample observations $\{y_{T+1}, \dots, y_{T+H}\}$ and forecasts $\{\hat{y}_{T+1|T}, \dots, \hat{y}_{T+H|T}\}$:

Scale-dependent metrics:

$$\text{MSE} = \frac{1}{H} \sum_{h=1}^H e_{T+h}^2$$

$$\text{RMSE} = \sqrt{\text{MSE}}$$

$$\text{MAE} = \frac{1}{H} \sum_{h=1}^H |e_{T+h}|$$

RMSE and MAE are in the same units as y_t .
Use to compare models on the *same* series.

Scale-free metric:

$$\text{MAPE} = \frac{1}{H} \sum_{h=1}^H \left| \frac{e_{T+h}}{y_{T+h}} \right| \times 100\%$$

MAPE: cross-series comparison; undefined at $y_{T+h} = 0$; asymmetric.

RMSE vs. MAE: RMSE penalizes large errors more heavily. If large errors are very costly, prefer RMSE.

Never evaluate a forecast model on the data used to fit it. In-sample fit measures how well the model reproduces past observations, not how well it can predict the future.

Correct time series train/test split:

- Use observations $1, \dots, T$ to estimate the model
- Evaluate on $T + 1, \dots, T + H$ (held-out future observations)
- *Never randomly shuffle observations — time order must be preserved*

Common mistake: Using sklearn's KFold on time series data. This randomly assigns observations to folds, allowing future data to "train" the model. Always use TimeSeriesSplit. Full treatment in **Lecture 7**.



- Model estimated on $\{y_1, \dots, y_T\}$
- Forecasts $\{\hat{y}_{T+1|T}, \dots, \hat{y}_{T+H|T}\}$ evaluated against realized values
- Typical test set size: **10–20%** of the series, or a fixed future window

Walk-forward (rolling-origin) evaluation: Lecture 6.

Hyndman and Koehler (2006) propose the **Mean Absolute Scaled Error**:

$$\text{MASE} = \frac{\text{MAE}}{\frac{1}{T-m} \sum_{t=m+1}^T |y_t - y_{t-m}|}$$

- Denominator: in-sample MAE of the seasonal naïve forecast
- $\text{MASE} < 1$: model beats seasonal naïve
- $\text{MASE} > 1$: model is *worse* than the seasonal naïve benchmark
- Works when $y_t = 0$ (unlike MAPE)
- Symmetric — positive and negative errors treated equally

MASE is the standard metric in the M-competitions (Makridakis et al. 2020). We will use it in Lecture 6 for model comparison.

Course Roadmap

What we will cover, and how it fits together.

Part I: Classical Econometric Forecasting

1. **Introduction** ← today
2. Regression-Based Forecasting
3. Exponential Smoothing (ETS)
4. ARIMA Models
5. Multivariate Methods (VAR, ARIMAX)
6. Forecast Evaluation & Combination

Focus: theory + properties + principled model selection.

Part II: Predictive Analytics & Machine Learning

7. ML Introduction & Cross-Validation
8. Regularization (LASSO, Ridge, Elastic Net)
9. Tree-Based Methods (RF, XGBoost)
10. Neural Networks & LSTM
11. Feature Engineering
12. Capstone & Applications

Focus: scalability, data-driven model selection, real-world pipelines.

Python throughout:

- statsmodels — ARIMA, ETS, VAR, statistical tests
- scikit-learn — ML models, cross-validation, pipelines
- pandas — data manipulation
- matplotlib — visualization
- numpy — numerical computing

Lab format: Jupyter notebooks. Each lab implements the methods from the preceding lecture.

What you will be able to do:

- ✓ Select and justify a forecasting method for a business problem
- ✓ Implement ARIMA, ETS, LASSO, and RF models in Python
- ✓ Evaluate and compare models rigorously
- ✓ Communicate forecast uncertainty to stakeholders
- ✓ Avoid the most common forecasting mistakes

Forecasting underpins every forward-looking business decision. Bad forecasts have measurable, costly consequences.

The optimal point forecast (under squared loss) is the **conditional expectation**:
 $\hat{y}_{t+h|t} = \mathbb{E}[y_{t+h} | \mathcal{F}_t]$.

Always establish **benchmark performance** first. A model that does not beat naïve is not useful.

Evaluate out-of-sample only. Never shuffle time series; always use `TimeSeriesSplit`.

Metric choice matters: RMSE penalizes large errors; MAPE allows cross-series comparison; MASE benchmarks against naïve.

Next: *Regression-Based Forecasting — when and how do predictor variables improve on these benchmarks?*

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- Hyndman, Rob J. and Anne B. Koehler (2006). "Another Look at Measures of Forecast Accuracy". In: *International Journal of Forecasting* 22.4, pp. 679–688.
 - Makridakis, Spyros, Evangelos Spiliotis, and Vassilios Assimakopoulos (2020). "The M4 Competition: 100,000 Time Series and 61 Forecasting Methods". In: *International Journal of Forecasting* 36.1, pp. 54–74.