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# Regression-Based Forecasting

## BSAD 8310: Business Forecasting — Lecture 2

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Spring 2026

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## From Benchmarks to Regression

Naïve models ignore information. Regression lets us use it.

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Recall the four benchmarks from Lecture 1:

Benchmark	Information used
Naïve	Last observed value only
Seasonal naïve	Same season, last year only
Historical mean	Unconditional average
Random walk + drift	Last value + average change

None of these benchmarks can use **leading indicators** — variables that move *before*  $y_t$  does.

*Examples: consumer confidence → retail sales next quarter; interest rates → housing starts.*

## Information we can exploit:

- **Leading indicators:** variables observable at  $T$  that predict  $y_{T+h}$
- **Structural relationships:** economic theory says  $x_t$  affects  $y_t$
- **Deterministic patterns:** known trend, calendar effects, holidays
- **Own-lags:** past  $y$  values predict future  $y$

- Retailer: use *ad spend*, *price*, and *calendar flags* to forecast demand
- Macro analyst: use *leading index* to forecast next quarter's GDP
- Bank: use *yield curve* to forecast loan defaults 6 months ahead

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## The Regression Model for Forecasting

OLS is not just for causal inference — it is also a forecasting tool.

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$$y_t = \mathbf{x}_t' \boldsymbol{\beta} + \varepsilon_t, \quad t = 1, \dots, T$$

- $y_t$ : scalar response (what we want to forecast)
- $\mathbf{x}_t = (1, x_{1t}, \dots, x_{kt})'$ :  $(k + 1)$ -vector of predictors (including intercept)
- $\boldsymbol{\beta} = (\beta_0, \beta_1, \dots, \beta_k)'$ : unknown coefficients
- $\varepsilon_t \sim WN(0, \sigma^2)$ : white-noise errors

**Notation reminder** (from Lecture 1):  $\varepsilon_t$  denotes the true model innovation;  $e_t = y_t - \hat{y}_{t|t-1}$  denotes the realized forecast error. These are conceptually distinct.

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Stack observations into matrices:  $\mathbf{y} = (y_1, \dots, y_T)'$ ,  $\mathbf{X} = (\mathbf{x}_1, \dots, \mathbf{x}_T)'$  ( $T \times (k + 1)$ ).

$$\hat{\boldsymbol{\beta}} = \arg \min_{\boldsymbol{\beta}} \sum_{t=1}^T (y_t - \mathbf{x}_t' \boldsymbol{\beta})^2 = (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'\mathbf{y}$$

**Gauss-Markov theorem:** Under classical assumptions,  $\hat{\boldsymbol{\beta}}$  is the **Best Linear Unbiased Estimator** (BLUE) (Hamilton 1994, Ch. 10).

**Classical assumptions for valid OLS inference:**

1.  $\mathbb{E}[\varepsilon_t \mid \mathbf{X}] = 0$  (zero conditional mean)
2.  $\mathbb{E}[\varepsilon_t^2 \mid \mathbf{X}] = \sigma^2$  (homoscedasticity)
3.  $\mathbb{E}[\varepsilon_t \varepsilon_s \mid \mathbf{X}] = 0$  for  $t \neq s$  (no autocorrelation)

**The forecasting constraint:** to use  $\mathbf{x}_{T+h}$  in the forecast  $\hat{y}_{T+h|T}$ , every element of  $\mathbf{x}_{T+h}$  must be *known* or *forecastable* at time  $T$ .

### Type 1: Deterministic

Always known at  $T$ :

- Time index:  $t, t^2$
- Seasonal dummies
- Holiday indicators
- Trend functions

### Type 2: Lagged values

Known when  $h \leq \text{lag}$ :

- $y_{t-1}, y_{t-2}$
- $x_{1,t-1}$  (lagged)
- Economic releases with delay

### Type 3: External regressors

Must be forecast first:

- GDP, CPI forecasts
- Competitor prices
- Weather forecasts
- Budget scenarios

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Given  $\hat{\beta}$  estimated on the training set  $\{1, \dots, T\}$ :

$$\hat{y}_{T+h|T} = \mathbf{x}'_{T+h} \hat{\beta}$$

Plug the *known or forecasted* predictor vector  $\mathbf{x}_{T+h}$  into the fitted model.

### Important nuances:

- $\hat{\beta}$  is estimated only on training data — never on the test set
- If  $\mathbf{x}_{T+h}$  contains forecasted values, forecast uncertainty propagates (widens intervals)
- For  $h > 1$  with lagged- $y$  predictors, use *recursive substitution* (see Section 5)

*In Lab 02,  $\mathbf{x}_{T+h}$  will contain only deterministic terms (trend index + seasonal dummies), so  $\mathbf{x}_{T+h}$  is always known exactly.*

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## Trend and Seasonality as Regressors

Deterministic components require no forecasting: their values are always known at the forecast origin.

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The simplest structural model for a series with an upward or downward drift:

$$y_t = \beta_0 + \beta_1 t + \varepsilon_t, \quad t = 1, 2, \dots, T$$

**Forecast:**  $\hat{y}_{T+h|T} = \hat{\beta}_0 + \hat{\beta}_1(T+h)$  — always known.

**When appropriate:**

- Steady linear growth or decline
- No pronounced seasonality
- Relatively stable variance

Linear trend extrapolates indefinitely. Long-horizon forecasts assume growth continues forever — verify this is substantively reasonable.

*US retail sales grow by roughly 3% per year. Should you use linear or log-linear trend? What feature of the data would help you decide?*

Define  $D_{j,t} = 1$  if observation  $t$  is in season  $j$ , else 0.

$$y_t = \beta_0 + \sum_{j=2}^m \gamma_j D_{j,t} + \varepsilon_t$$

Include  $m - 1$  dummies; drop one season as the **base category**.

### Interpretation:

- $\beta_0$ : mean level in the base season (e.g., January)
- $\gamma_j$ : seasonal deviation from the base in season  $j$
- $\hat{y}_{T+h|T} = \hat{\beta}_0 + \hat{\gamma}_{s(T+h)}$

**Dummy trap:** Including all  $m$  dummies creates exact multicollinearity with the intercept. Always drop one season.

$$y_t = \underbrace{\beta_0 + \beta_1 t}_{\text{trend}} + \underbrace{\sum_{j=2}^m \gamma_j D_{j,t}}_{\text{seasonal}} + \varepsilon_t$$

**Forecast:**  $\hat{y}_{T+h|T} = \hat{\beta}_0 + \hat{\beta}_1(T+h) + \hat{\gamma}_{s(T+h)}$  (always known)

Monthly retail sales exhibit both components:

- Upward trend (growing economy and population)
- Strong December spike, January dip (Lab 02 quantifies both)

## Polynomial trend:

$$y_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \varepsilon_t$$

Still OLS — just add  $t^2$  as another predictor column.

## Log-linear trend (when variance grows with level):

$$\ln y_t = \beta_0 + \beta_1 t + \varepsilon_t \quad \Leftrightarrow \quad y_t = e^{\beta_0} e^{\beta_1 t} e^{\varepsilon_t}$$

Forecasts:  $\hat{y}_{T+h|T} = \exp(\hat{\beta}_0 + \hat{\beta}_1(T+h) + \frac{1}{2}\hat{\sigma}^2)$  (bias correction)

**Rule of thumb:** If the series grows at a roughly *constant percentage rate* (e.g., 3% per year), use log-linear trend. If it grows by a *constant dollar amount*, use linear trend.

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## Prediction Intervals

A point forecast without uncertainty bounds is an incomplete forecast.

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$$\hat{y}_{T+h|T} \pm t_{0.025, T-k-1} \cdot \hat{\sigma}_e \sqrt{\underbrace{1}_{\text{irreducible error}} + \underbrace{\mathbf{x}'_{T+h}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{x}_{T+h}}_{\text{estimation uncertainty}}}$$

where  $\hat{\sigma}_e^2 = \frac{1}{T-k-1} \sum_{t=1}^T e_t^2$  is the estimated residual variance.

## Two sources of uncertainty in the PI:

- **Irreducible:** future shock  $\varepsilon_{T+h}$  has variance  $\sigma^2$  (the “1” under the square root)
- **Estimation:**  $\hat{\beta} \neq \beta$  (the  $(X'X)^{-1}$  term; shrinks as  $T \rightarrow \infty$ )

*PIs widen for predictions far from the center of the training data — including long-horizon forecasts where  $t = T + h$  is far from  $\bar{t}$ .*

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The standard PI formula assumes:

1.  $\varepsilon_t \stackrel{iid}{\sim} \mathcal{N}(0, \sigma^2)$  (normality + homoscedasticity)
2. No autocorrelation:  $\text{Cov}(\varepsilon_t, \varepsilon_s) = 0$
3. No model misspecification
4. Predictors  $\mathbf{x}_{T+h}$  known exactly

Violation of any assumption **invalidates** the nominal coverage. Always check: residual histogram, ACF of residuals, Breusch-Pagan test for heteroscedasticity. (Lecture 6 covers formal tests.)

**Empirical rule of thumb:** If ACF of residuals shows spikes at short lags (1–4), the PI is too narrow. Residual autocorrelation is exploitable information — switch to an AR or ARIMA model.

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## Autoregressive Models

The past values of a series often predict its future. AR models formalize this idea.

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An **autoregressive model of order 1** is just OLS regression with one lag of  $y$  as the predictor:

$$y_t = \phi_0 + \phi_1 y_{t-1} + \varepsilon_t, \quad \varepsilon_t \stackrel{iid}{\sim} (0, \sigma^2) \text{ (normality not required for OLS)}$$

**Stationarity condition:**  $|\phi_1| < 1$ . If  $\phi_1 = 1$ , the model is a *random walk* (non-stationary, covered in Lecture 4).

**One-step forecast:**

$$\hat{y}_{T+1|T} = \hat{\phi}_0 + \hat{\phi}_1 y_T$$

**Two-step forecast (recursive):**

$$\hat{y}_{T+2|T} = \hat{\phi}_0 + \hat{\phi}_1 \hat{y}_{T+1|T}$$

As  $h \rightarrow \infty$ , multi-step AR(1) forecasts converge to the unconditional mean  $\mu = \phi_0 / (1 - \phi_1)$  when  $|\phi_1| < 1$ .

$$y_t = \phi_0 + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + \varepsilon_t = \phi_0 + \sum_{i=1}^p \phi_i y_{t-i} + \varepsilon_t$$

**Lag order selection:** choose  $p$  to minimize an information criterion.

$$\text{AIC} = -2\hat{\ell} + 2(p + 2)$$

$$\text{BIC} = -2\hat{\ell} + (p + 2) \ln T$$

$\hat{\ell}$ : maximized log-likelihood.  $p + 2$  parameters:  $p$

AR coefs + intercept +  $\sigma^2$ .

*BIC selects  $p = 2$  but the residual ACF shows a significant spike at lag 12. What should you do?*

AIC tends to select more lags (asymptotically inconsistent: does not recover the true order with probability 1). BIC penalizes more and is consistent. **Use BIC** for forecasting in most business applications (Box et al. 2015, Ch. 5).

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For an  $AR(p)$  model,  $h$ -step-ahead forecasts use the **recursive substitution** method:

$$\hat{y}_{T+h|T} = \hat{\phi}_0 + \sum_{i=1}^p \hat{\phi}_i \hat{y}_{T+h-i|T}$$

where  $\hat{y}_{T+j|T} = y_{T+j}$  for  $j \leq 0$  (observed values).

$$\hat{y}_{T+1|T} = \hat{\phi}_0 + \hat{\phi}_1 y_T + \hat{\phi}_2 y_{T-1}$$

$$\hat{y}_{T+2|T} = \hat{\phi}_0 + \hat{\phi}_1 \hat{y}_{T+1|T} + \hat{\phi}_2 y_T$$

$$\hat{y}_{T+3|T} = \hat{\phi}_0 + \hat{\phi}_1 \hat{y}_{T+2|T} + \hat{\phi}_2 \hat{y}_{T+1|T}$$

*Forecast uncertainty compounds with horizon: each substitution propagates estimation error from earlier steps.*

## How do we know if the AR order is adequate?

### Residual ACF check:

- Compute residuals  $e_t = y_t - \hat{y}_{t|t-1}$
- Plot autocorrelation function (ACF) of residuals
- All spikes should fall inside the 95% bands:  $\pm 1.96/\sqrt{T}$
- Significant spike at lag  $k \Rightarrow$  add lag  $k$  to the model

Residual autocorrelation signals information the model has not yet captured. A model with autocorrelated residuals is **suboptimal** and its prediction intervals are **invalid**. Full treatment: Lecture 4 (ARIMA).

*Lab 02 plots the residual ACF for the  $AR(p)$  model and checks whether any spikes suggest a higher order is needed.*

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## Pitfalls

Regression in time series requires extra care. Three failure modes to avoid.

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Granger and Newbold (1974): Regressing two *independent* random-walk series  $y_t$  and  $x_t$  yields  $R^2 \approx 0.7$  and apparently significant  $t$ -statistics — despite no true relationship between them.

### Why this happens:

- Both  $y_t$  and  $x_t$  are  $I(1)$  (non-stationary; require one difference to become stationary): their levels share a stochastic trend
- The usual  $t$ -distribution critical values are *invalid* under non-stationarity

**Diagnostic heuristic:**  $R^2 > DW$  statistic suggests spurious regression (Granger and Newbold 1974).

**Fix:** Difference the series ( $\Delta y_t, \Delta x_t$ ) before regressing. Or test for cointegration (Lecture 5).

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**More predictors  $\Rightarrow$  better in-sample fit, but often worse out-of-sample forecast.**

**What happens:**

- OLS fits noise along with signal
- High  $R^2$  in-sample; large errors out-of-sample
- Worse with small  $T$ , large  $k$
- Many lags: AR(20) on monthly data likely overfits

**Rule of thumb:** Keep  $k \ll T$ . A common bound:  $k \leq T/10$ .

A 12-month history and 11 seasonal dummies + intercept = 12 parameters. You are fitting the data, not the underlying pattern.

Regularization (LASSO, Ridge) addresses this formally in Lecture 8.

**Critical constraint:** To forecast  $y_{T+h}$  using a regressor  $x_{T+h}$ , you must know (or forecast)  $x_{T+h}$  at time  $T$ . Using data that won't be available at the forecast origin is **data leakage**.

**Valid predictors for  $y_{T+1}$ :**

- ✓  $y_T, y_{T-1}, \dots$  (lagged  $y$ )
- ✓  $x_{T-1}$  (lagged leading indicator)
- ✓ Seasonal dummy at  $T + 1$
- ✓ Weather forecast for  $T + 1$

**Invalid predictors for  $y_{T+1}$ :**

- ✗  $x_{T+1}$  (contemporaneous, unknown)
- ✗  $y_{T+1}$  (the target itself)
- ✗ Future CPI or GDP
- ✗ Any variable with publication lag  $< h$

Regression extends benchmarks by incorporating **predictors**: deterministic trends, seasonal dummies, lagged values, and leading indicators.




The OLS forecast is  $\hat{y}_{T+h|T} = \mathbf{x}'_{T+h} \hat{\beta}$ , but  $\mathbf{x}_{T+h}$  must be **known or forecastable** at time  $T$ .

Prediction intervals have two components: irreducible error ( $\sigma^2$ ) and estimation uncertainty ( $(X'X)^{-1}$  term). Valid only under no autocorrelation and homoscedasticity.

AR( $p$ ) is OLS with lagged  $y$ . Use **BIC** to select  $p$ . Multi-step forecasts use recursive substitution.

Three pitfalls: **spurious regression** (I(1) levels), **overfitting** (too many predictors), and the **regressor availability problem** (data leakage).

*Next: Exponential Smoothing (Lecture 3) — adaptive weighting without requiring explicit predictor specification.*

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