Module 1 – Part I Welcome to the Deep forecasting course! What is Time Series Forecasting?











What is Forecasting?

Forecasting has fascinated people for thousands of years!

Tell us what the future holds, so we may know that you are gods.

Isaiah 41:23 700 BC

- Forecasting is about estimating the future, given all the information available, including historical data and knowledge of any future events that might impact the forecasts. What will happen?
- Forecasts could be short-term, medium-term or long-term.







Quantitative vs Qualitative Forecasting

Quantitative	Quantitative Forecasting	Qualitative Forecasting Qualitative	
Data	Numeric and statistical	Expert opinions, and subjective	
Accuracy	High (with good data)	Lower, but useful for intangibles	
Suitability	Measurable phenomena	subjective or hard-to-measure phenomena	
Flexibility	Rigid, Data-Driven	Flexible, Expert-Informed	
Examples	Stock prices, sales, demand for a stablished product, weather forecast	Fashion trends, demand for a new product, Election polls, Economic forecast (recession?)	

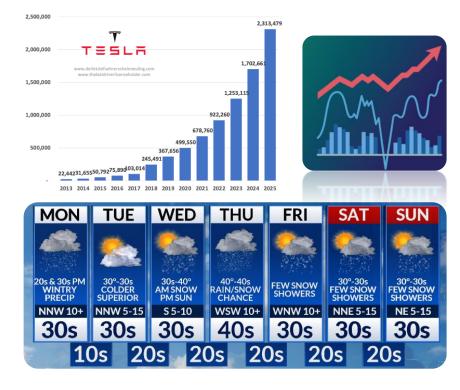






More Forecasting examples

- Which of the following examples are easier to forecast?
- 1. Time of sunset this day next month
- 2. Apple stock price in 6 months
- 3. Apple stock price tomorrow
- 4. Airline ticket demand/price next year
- 5. New car model sales in the first quarter
- 6. US presidential election 2024
- 7. Monthly rainfall in Utah next winter

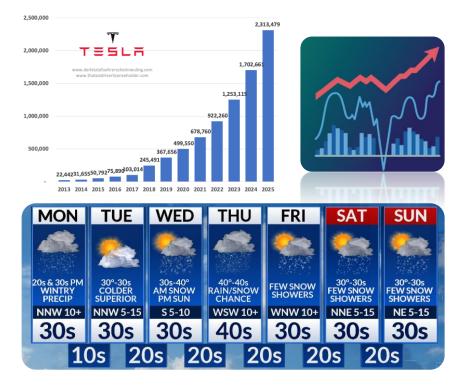






More Forecasting examples

- Which of the following examples are easier to forecast?
- 1. Time of sunset this day next month
- 2. Apple stock price in 6 months
- 3. Apple stock price tomorrow
- 4. Airline ticket demand/price next year
- 5. New car model sales in the first quarter
- 6. US presidential election 2024
- 7. Monthly rainfall in Utah next winter







What Impacts Forecastability?

- How do we say something is easier to forecast?
- Forecastability factors are:
 - Data Availability
 - How similar the future is to the past!
 - Good understanding of the underlying factors









Explanatory vs Timeseries vs Mixed models

Model	Example
Explanatory (Cross sectional) Multivariate	$P = f(\frac{P}{E}, \frac{P}{S}, size, \frac{B}{M}, GDP, CPI,, u)$
Timeseries (univariate)	$P_{t+1} = f(P_t, P_{t-1}, P_{t-2},, u)$
Mixed (dynamic regression, panel) Multivariate	$P_{t+1} = f(\frac{P_t}{E_t}, \frac{P_{t-1}}{E_{t-1}}, \dots, CPI_t, CPI_{t-1}, \dots, u_t)$

- In this course we focus on Timeseries (mostly univariate) models because:
- 1. Unknown Factors: Often, not all underlying causal factors are known or measurable.
- **2. Complex Forecasting**: It's challenging to predict the future values of multiple influencing factors simultaneously.
- **3. Predictive Focus**: Our primary goal is accurate forecasting, not necessarily understanding the cause-and-effect relationships.







Basic steps in a forecasting task

Step1: Problem definition

 Forecasting type and horizon (one-step, multi-step, multi-output forecasts), ...

Step 2: Data Collection

Time horizon, structural changes, data type, ...

Step 3: Exploratory Analysis

Trend, seasonality, outliers, ...

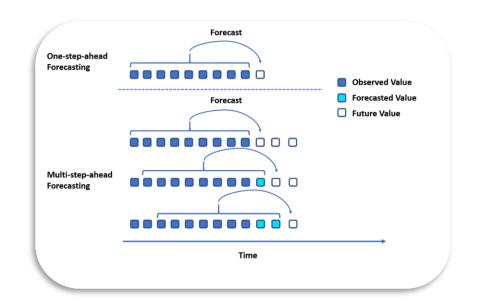
Step 4: Model Selection and Training

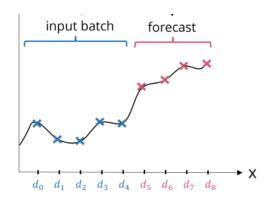
Traditional vs machine learning vs deep learning

Step 5: Model Evaluation and Comparison

MSE, RMSE, MAE, MAPE, sMAPE, ...











JON M.

UtahStateUniversity

Forecasting notation

$$\hat{y}_{t+h|t} = \boldsymbol{f}(y_t)$$

- y_t itself can be decomposed into different components (level, trend, seasonality)
- Fitted values at time t = 1 ... T, are $\hat{y}_{t|t-1}$ (h = 0)
- One-step ahead forecast at time T+1 (T last observation in train data) and h=1.
- Multi-step ahead forecast: h = 2, 3, 4, ...
 - One-output at a time
 - Multi-output at once







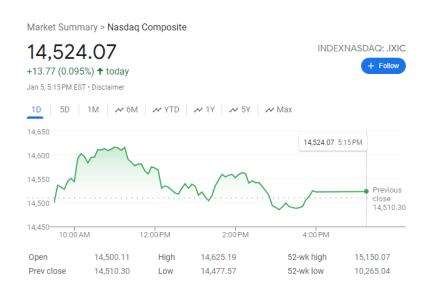
What is Time Series analysis and why it matters?



- Time series analysis is a powerful tool for understanding and predicting trends and patterns in data that are collected over time.
- Time series analysis is useful for business decision makers, as it can help them to forecast future trends and make informed decisions based on data trends and patterns.

Why?

- Time series data is everywhere! Econ, Finance, Marketing, Healthcare, Energy, Tech, ...
- Better career opportunities,
- Hedge against next recession!









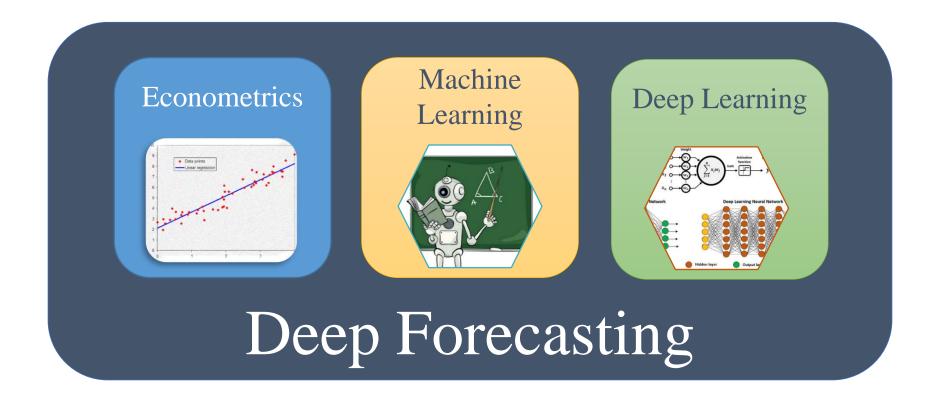
Road map!

- Module 1- Introduction to Deep Forecasting
- Module 2- Setting up Deep Forecasting Environment
- Module 3- ETS and Exponential Smoothing
- Module 4- ARIMA models
- Module 5- Machine Learning for Time series Forecasting
- Module 6- Deep Neural Networks
- Module 7- Deep Sequence Modeling (RNN, LSTM)
- Module 8- Transformers (Attention is all you need!)













Road map!

- Module 1- Introduction to Deep Forecasting
- Module 2- Setting up Deep Forecasting Environment
- Module 3- ETS and Exponential Smoothing
- Module 4- ARIMA models
- Module 5- Machine Learning for Time series Forecasting
- Module 6- Deep Neural Networks
- Module 7- Deep Sequence Modeling (RNN, LSTM)
- Module 8- Transformers (Attention is all you need!)







Predictive modeling vs forecasting: A simple example

- Quantifying air passengers!
- Let's build a model:

$$air\ passengers = \beta_0 + \beta_1 gdp + \beta_2 unemp + \beta_3 saving + \dots + u$$

- ➤ Can you **interpret** this model?
- ➤ Can you make **predictions** using your model?
- ➤ Can you make **forecasts** into the future? What are the challenges?







A simple example (cont'd)

Focusing on Forecasting for one country:

$$air\ passengers_{\mathbf{t}} = \beta_0 + \beta_1 g dp_{\mathbf{t}} + \beta_2 unemp_{\mathbf{t}} + \beta_3 saving_{\mathbf{t}} + \dots + u_{\mathbf{t}}$$

This explanatory model is contemporaneous (static). How can we make it a dynamic forecasting model?

$$air\ passengers_{t+1} = \beta_0 + \beta_1 gdp_t + \beta_2 unemp_t + \beta_3 saving_t + \dots + u_t$$

Assumption: everything is reflected in passengers' number already! So, why not →

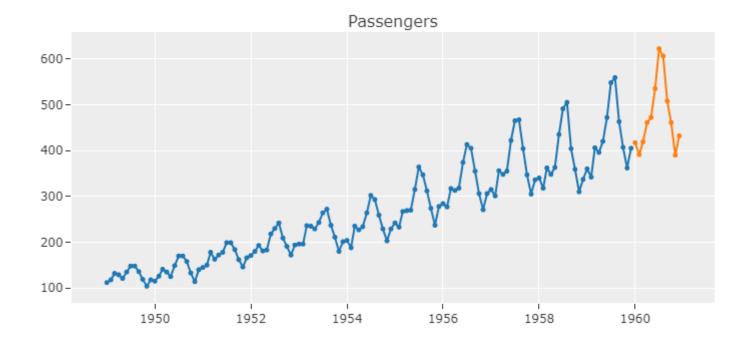
$$passengers_{t+1} = f(passengers_t, passengers_{t-1}, ...)$$





A simple example (cont'd)

$$passengers_{t+1} = f(passengers_{t}, passengers_{t-1}, ...)$$



Goal: Identify existing patterns in data to project future patterns!







Predictive modeling vs forecasting?

$$passengers = \beta_0 + \beta_1 gdp + \beta_2 unemp + \beta_3 saving + \dots + u$$

Aspect	Predictive Modeling	Forecasting
Definition	Creating models to analyze data and predict an outcome.	Making informed predictions about future events based on past data.
Focus	Any point in time (past, present, future)	Primarily focused on future outcomes.
Type of Analysis	Can include clustering, classification, and regression.	Typically involves time series analysis and trend estimation.
Variables	Multivariate	Typically, univariate

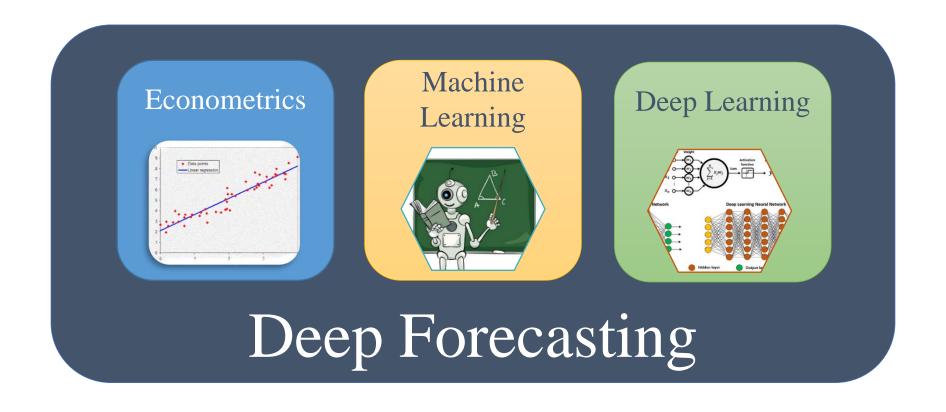
- Forecasting is a subset of predictive modeling.
- We can use econometrics, ML or DL for predictive modeling.







What is our approach to time series forecasting?



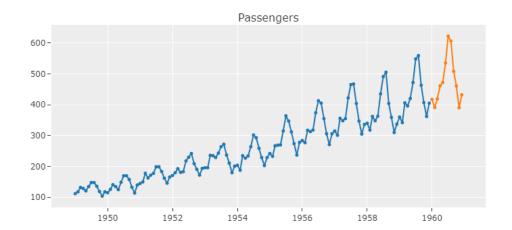






Why do we need ML/DL?

$$passengers_{t+1} = f(passengers_t, passengers_{t-1}, ...)$$



- How do we identify the functional form of f()?
- How about this:

$$passengers_{t+1} = c + \phi_1 passengers_t + \phi_2 passengers_{t-1} + ... + \epsilon_t$$

- What if we are looking for **more complex** relationships?
- Or a **non-parametric** approach?



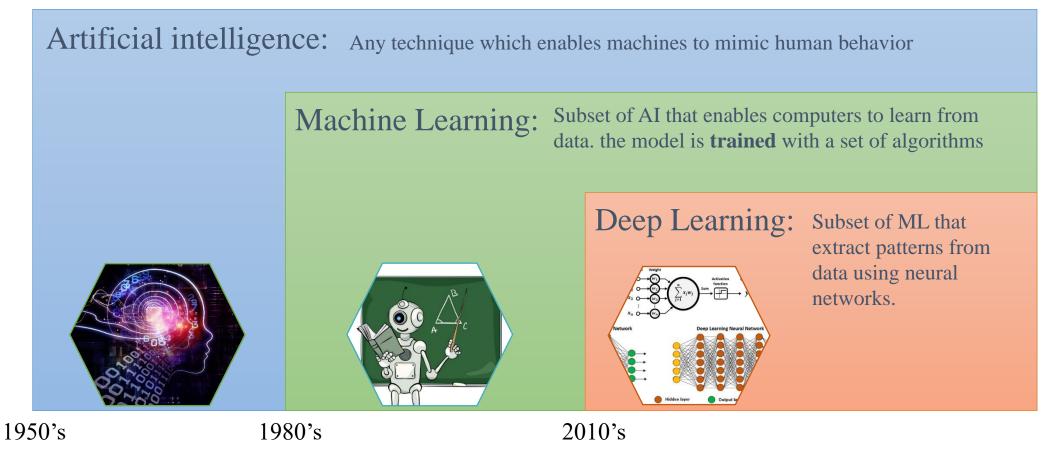




JON M.

UtahStateUniversity

Artificial intelligence vs Machine learning vs Deep learning

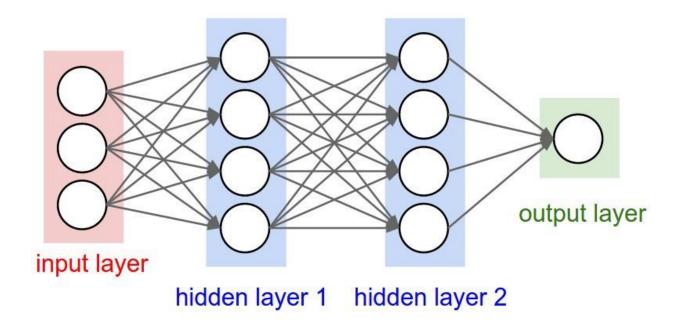






What is Deep Learning?

- Deep learning is a type of machine learning that uses multiple layers of neurons to process data
- The goal of deep learning is to build a model that can automatically learn complex patterns from the data and make accurate predictions or decisions









Contrasting Econometrics, ML and DL for forecasting!

Aspect	Econometric Models	Machine Learning (ML)	Deep Learning (DL)
Feature Engineering	Requires explicit modeling of seasonality and trend	Captures complex patterns with less need for manual engineering	Often automates feature engineering
Model Complexity	Lower ; focuses on data generation process	Moderate ; can handle non-linear interactions	High ; suited for complex and high-dimensional data
Interpretability	High; offers interpretable parameters and statistical tests	Moderate; provides feature importance but less interpretable than econometric models	Low; considered a 'black box' approach
Core Models	ARIMA, Exponential Smoothing (ETS)	Random Forest, Gradient Boosting	RNNs, LSTMs, CNNs







Contrasting Econometrics, ML and DL for forecasting!

Aspect	Econometric Models	Machine Learning (ML)	Deep Learning (DL)
Computational Intensity	Generally lower	Varies; dependent on model complexity and data size	High; requires significant computational resources
Data Suitability	Works well when the underlying process is well understood	Effective for structured datasets with complex relationships	Ideal for large datasets, including unstructured data
Core Models	ARIMA, Exponential Smoothing (ETS)	Random Forest, SVM, Gradient Boosting	RNNs, LSTMs, CNNs







Road map!

- ✓ Module 1- Introduction to Deep Forecasting
- Module 2- Setting up Deep Forecasting Environment
- Module 3- ETS and Exponential Smoothing
- Module 4- ARIMA models
- Module 5- Machine Learning for Time series Forecasting
- Module 6- Deep Neural Networks
- Module 7- Deep Sequence Modeling (RNN, LSTM)
- Module 8- Transformers (Attention is all you need!)



