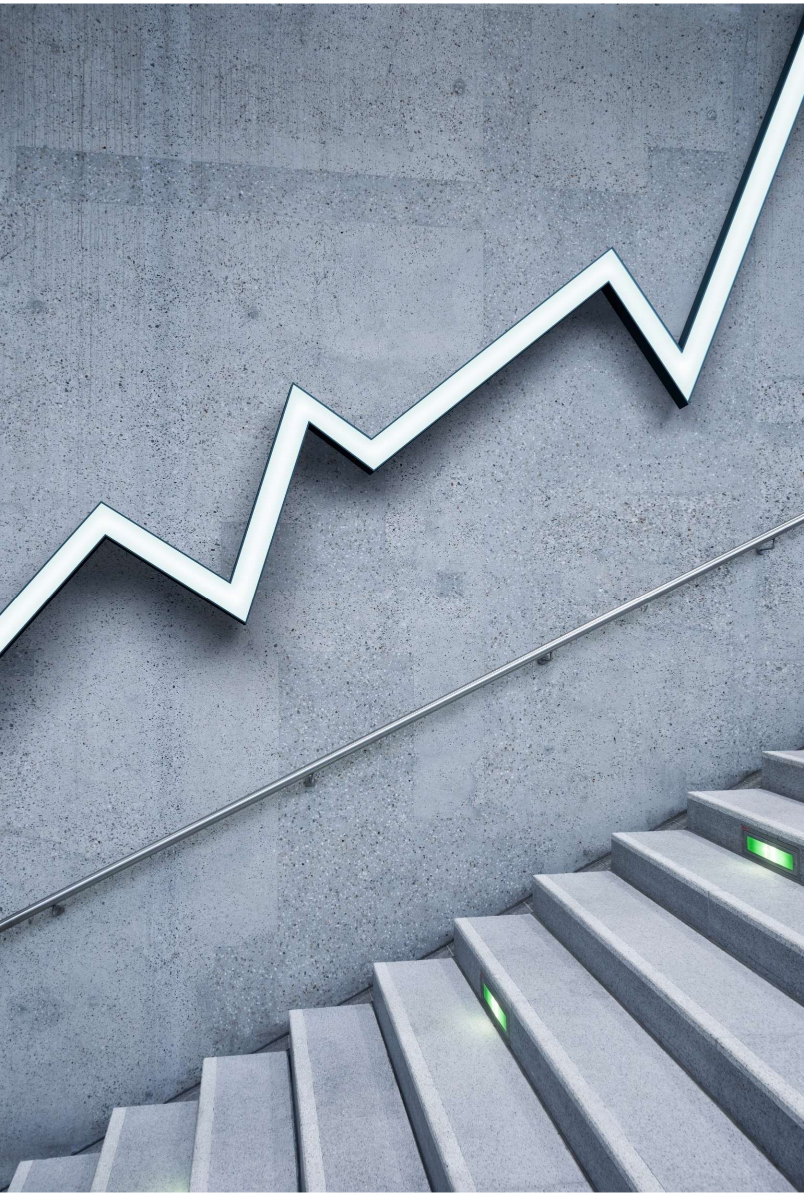

TIME SERIES ANALYSIS

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TIME SERIES ANALYSIS

A method of analyzing data points collected at consistent intervals over time, revealing patterns and trends. Time series analysis is widely used in finance, economics, healthcare, weather forecasting, and business analytics for making informed decisions.

FEATURES:

✓ **Time Dependency** – Data changes over time, making time a crucial variable.
✓ **Patterns & Trends** – Helps identify trends, seasonal effects, and long-term dependencies.
✓ **Large Data Requirement** – Ensures reliability by cutting through noise and detecting real patterns.
✓ **Forecasting** – Predicts future values based on historical trends.

TIME SERIES FORECASTING

If you have consistent historical data, you can forecast the future!”

It involves making scientific predictions based on historical time-stamped data. It requires analyzing past trends to model future outcomes and support strategic decision-making. At the time of forecasting, the future is unknown, and predictions are based on careful analysis and evidence-based priors.

Real-World Applications

- Finance – Stock market predictions, risk assessment
- Retail – Sales forecasting, demand planning
- Healthcare – Disease outbreaks, hospital resource planning
- Weather & Climate – Storm predictions, temperature trends
- Business & Economics – Revenue forecasting, market trends

Why Time Series Analysis?

"Enables businesses to make data-driven decisions with confidence!"

- ✓ **For Understanding Trends:**
  - Helps identify patterns and systemic changes over time.
  - Uses visualizations to explore seasonality and cyclic behaviors.
- ✓ **For Forecasting & Predictive Analytics**
  - Predicts future trends based on historical data.
  - Essential for decision-making in dynamic environments.
- ✓ **Examples in action:**
  - Quarterly sales
  - Stock prices
  - Rainfall measurements
  - Temperature readings
  - Automated stock trading
  - Industry forecasts
  - Interest rates

Models of Time Series Analysis

Classification
Categorizes data based on patterns.

Curve Fitting
Models relationships by fitting curves to data.

Descriptive Analysis
Identifies trends, cycles, and seasonality.

Explanative Analysis
Examines cause-and-effect relationships.

Exploratory Analysis
Visualizes key characteristics of data.

Forecasting
Predicts future values using historical data.

Intervention Analysis
Assesses impact of events on data.

Segmentation
Divides data to highlight key patterns.

Classification of Time Series Data

1. Based on Data Characteristics

- **Univariate:** Single variable recorded over time *(e.g., stock price, daily temperature)*
- **Multivariate:** Multiple related variables recorded together *(e.g., temperature, humidity, wind speed)*

2. Based on Stationarity

- **Stationary:** Constant mean & variance over time *(e.g., white noise)*
- **Non-Stationary:** Changes in mean, variance, or trends *(e.g., economic growth trends)*

3. Based on Patterns & Trends

- **Trend-Based:** Increasing or decreasing behavior *(e.g., population growth)*
- **Seasonal:** Repeating patterns at fixed intervals *(e.g., electricity demand in summer/ winter)*
- **Cyclical:** Long-term fluctuations without a fixed period *(e.g., business cycles)*
- **Irregular (Random):** No apparent pattern, highly unpredictable *(e.g., stock market crashes)*

Core Principles of Time Series Analysis

1. Decomposition

A time series consists of four components:

- **Trend (T(t))**: Long-term movement (e.g., increasing sales).
- **Seasonality (S(t))**: Regular patterns (e.g., summer ice cream sales).
- **Cyclic (C(t))**: Economic or business cycles (irregular but long-term).
- **Random Noise (e_t)**: Unexplained variations.

2. Stationarity & Differencing

- A stationary series has a constant mean & variance over time.
- Differencing helps stabilize trends & make data stationary.

3. Autocorrelation & Lag Analysis

- **Autocorrelation**: Relationship between current & past values.
- **ACF & PACF**: Identify dependencies to build models.

4. Forecasting Models

- **Statistical**: ARIMA, Exponential Smoothing, Prophet
- **Machine Learning**: Random Forest, XGBoost, LSTMs, Transformers

Time Series technologies

Prophet (by Facebook/Meta)

Neural ODE (Ordinary Differential Equations for time series modeling)

Prophet (Meta's Forecasting Model)

What is Prophet?

- *A time series forecasting tool developed by Meta (formerly Facebook)*
- *Designed for business applications with minimal data preparation*

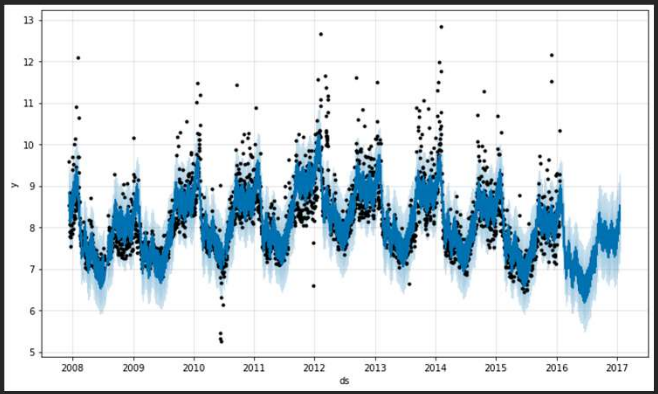
Core Components:

- ***Trend:*** *Piecewise linear regression captures non-linear changes*
- ***Seasonality:*** *Fourier series models daily, weekly, and yearly patterns*
- ***Holiday Effects:*** *Integrates custom events (holidays) for one-off impacts*

Key Features:

- *Automatic handling of missing data and outliers*
- *Bayesian framework via Stan for generating forecasts with confidence intervals*

Advantages and Limitations



Advantages

- ***Ease of Use:*** *Requires minimal tuning and data preprocessing*
- ***Interpretability:*** *Decomposes forecasts into trend, seasonality, and holidays*
- ***Robustness:*** *Effective even with messy data and strong seasonal effects*
- ***Automation:*** *Automatically detects trend changepoints*

Limitations

- ***Limited Flexibility:*** *Best suited for additive models; may not capture complex interactions*
- ***Data Format Requirements:*** *Needs data in a specific format*
- ***Primarily Univariate:*** *Optimized for forecasting a single variable (though regressors can be added)*

Ideal Use Cases

- *Time series with clear seasonal patterns and known holiday effects*
- *Scenarios requiring quick, interpretable forecasts without deep statistical expertise*

Neural ODEs

Neural Ordinary Differential Equations (Neural ODEs)

- Neural ODEs replace discrete layers of traditional neural networks with a continuous dynamic system defined by an ODE (Ordinary Differential Equation).
- Instead of sequential layers, an ODE solver is used to compute the transformation of inputs over a continuous "depth."

Key Components:

- **Continuous Depth**: Network depth is treated as a continuous variable.
- **ODE Solver**: Computes outputs by solving the differential equation.
- **Derivative Function**: Defined by a neural network to determine data evolution.
- **Adjoint Sensitivity Method**: Enables efficient backpropagation for training.

When to Use Neural ODEs?

Best Applications:

- **Continuous-Time Data:** Ideal for **time-series analysis, physics simulations, and dynamic systems.**
- **Irregular Time Series:** Handles **unevenly sampled data** better than RNNs.
- **Memory Efficiency:** Uses less memory compared to deep neural networks.
- **Physical Systems:** Easily integrates **known physics laws** into ML models.

Advantages:

- **Memory-Efficient:** No need to store activations for multiple layers.
- **Adaptive Computation:** Solvers adjust computational effort dynamically.
- **Handles Continuous-Time Models:** Naturally supports **continuous dynamics.**

Challenges:

- **Computationally Expensive:** Solving ODEs can be slow.
- **Training Complexity:** Harder to optimize compared to traditional networks.
- **Solver Dependence:** Performance varies based on the chosen ODE solver.
- **Potential Instability:** Some ODEs may lead to **unstable training.**

COMPARISON OF PROPHET AND NEURAL ODEs

Feature	Prophet 🕰	Neural ODEs 🔄
Purpose	Time-series forecasting with seasonality & holidays.	Modeling continuous-time dynamics & irregular data.
Model Type	Additive regression model.	Neural network-based differential equations.
Data Type	Univariate time-series with seasonal patterns.	Continuous-time & irregular time-series data.
Approach	Decomposes trend, seasonality, and holidays.	Learns rate of change via a neural network.
Interpretability	Highly interpretable, clear components.	Less interpretable, requires analysis of ODEs.
Computational Cost	Efficient, low cost.	Computationally expensive due to ODE solving.
Handling Irregular Data	Handles missing values, but best for regular data.	Naturally handles irregular time series.
Use Case	Business forecasting (sales, demand, etc.).	Modeling physical & dynamic systems.
Seasonality & Trends	Excels in modeling both.	Can model but not the primary focus.

TIME SERIES ANALYSIS & CRYPTOCURRENCY

How They Correlate

Data Characteristics:

- Crypto prices are inherently time-series, fluctuating over time.
- Exhibits **high volatility** & **non-stationarity** (changing statistical properties).
- Influenced by **news, social media sentiment, regulations, and technology**.

Preprocessing for Analysis:

- **Stationarity:** Apply techniques like **differencing** to stabilize trends.
- **Normalization/Scaling:** Improves model performance.
- **Feature Engineering:** Create **moving averages, volatility indicators**, etc., for better predictions.

THANK YOU