

Intro for Senior Design

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Agenda

- ▶ Python Basics
- ▶ Time Series Forecasting Methods
- ▶ Outlier Detection Techniques

- ▶ Python Basics
 - ▶ pytorch
 - ▶ data processing library
 - ▶ measurement

Python Basics

- ▶ pytorch
 - ▶ installation: [▶ Link](#) document: [▶ Link](#)
 - ▶ tutorial: easy start [▶ Link](#) LSTM examples [▶ Link](#) [▶ Link](#)
- ▶ data processing library
 - ▶ pandas: process data frame
 - ▶ csv: read/write csv
 - ▶ xlsread, xlswrite: read/write xls, xlsx
 - ▶ pyodbc: execute SQL query
- ▶ measurement

definition

- ▶ $MAE \equiv \frac{1}{N} \sum_{i=1}^N |\hat{y}_i - y_i| = \frac{1}{N} \sum_{i=1}^N |e_i|$
- ▶ $MAPE \equiv \frac{1}{N} \sum_{i=1}^N \left| \frac{\hat{y}_i - y_i}{y_i} \right| = \frac{1}{N} \sum_{i=1}^N \left| \frac{e_i}{y_i} \right|$
- ▶ $RMSE \equiv \sqrt{\frac{1}{N} \sum_{i=1}^N (\hat{y}_i - y_i)^2}$
- ▶ $R^2 \equiv 1 - \frac{\sum_{t=1}^T (\hat{y}_t - y_t)^2}{\sum_{t=1}^T (\mu - y_t)^2}$, where $\mu \equiv \frac{1}{T} \sum_{i=1}^T y_t$

- ▶ Time Series Forecasting Methods
 - ▶ ARIMA(p, d, q)
 - ▶ decomposition of time series
 - ▶ Linear+Nonlinear
 - ▶ freq. domain
 - ▶ Trend+Season+Holiday: Prophet (Facebook)
 - ▶ machine learning
 - ▶ XGBoost
 - ▶ LightGBM (Microsoft)
 - ▶ GPR: Gaussian process regression
 - ▶ neural networks
 - ▶ LSTM, GRU
 - ▶ WavNet
 - ▶ seq2seq
 - ▶ Self-boosted: DeepAR (Amazon)
 - ▶ attention mechanism: transformer

Time Series Forecasting Methods

- ▶ ARIMA(p, d, q)
 - ▶ wikipedia: [▶ Link](#)
 - ▶ zhihu: [▶ Link](#)
 - ▶ implementation: [▶ Link](#)
 - ▶ statsmodels: arima [▶ Link](#) acf $\Rightarrow q$, pacf $\Rightarrow p$ [▶ Link](#) [▶ Link](#)
 - ▶ example: [▶ Link](#)

definition

- ▶ $(1 - \sum_{i=1}^p \varphi_i L^i) (1 - L)^d X_t = (1 + \sum_{i=1}^q \theta_i L^i) \varepsilon_t$
- ▶ L : lag operator; φ_i : params of AR part; θ_i : params of MA part
- ▶ ε_t : error term, should be **white noise**
(independent, identically distributed variables sampled from a normal distribution with zero mean)
test ε_t white noise [▶ Link](#), test ε_t stationary [▶ Link](#)

Time Series Forecasting Methods

► decomposition of time series

- Linear+Nonlinear [▶ Link](#)

definition

- $y(t) = L(t) + N(t)$, where $L(t) \equiv \frac{1}{T} \sum_{\tau=t-T+1}^t y(\tau)$, $N(t) \equiv y(t) - L(t)$
- select $T \Rightarrow L(t)$ satisfies Gaussian distribution \Rightarrow ARIMA model $\hat{L}(t)$ to fit $L(t)$
- $\hat{L}(t), [y(t-1), \dots, y(t-q)], [N(t-1), \dots, N(t-p)] \Rightarrow$ (NN, nonlinear kernel) $\hat{y}(t)$
- freq. domain
 - FD: Fourier decomposition
 - WD: wavelet decomposition
 - EMD: empirical mode decomposition
wikipedia: [▶ Link](#) zhihu: [▶ Link](#) [▶ Link](#) implementation: [▶ Link](#)
 - VMD: variational mode decomposition
paper: [▶ Link](#) zhihu + implementation: [▶ Link](#)
- Trend+Season+Holiday: Prophet (Facebook) [▶ Link](#) [▶ Link](#) zhihu [▶ Link](#)

definition

- $y(t) = g(t) + s(t) + h(t) + \varepsilon_t$, where $g(t)$: trend, $s(t)$: season, $h(t)$: holiday

Time Series Forecasting Methods

- ▶ machine learning
 - ▶ XGBoost
 - ▶ paper: [▶ Link](#) document: [▶ Link](#)
 - ▶ zhihu: [▶ Link](#) [▶ Link](#)
 - ▶ implementation: [▶ Link](#)
 - ▶ example: [▶ Link](#) [▶ Link](#) [▶ Link](#)
 - ▶ LightGBM (Microsoft)
 - ▶ paper: [▶ Link](#) document: [▶ Link](#)
 - ▶ zhihu: [▶ Link](#)
 - ▶ example: [▶ Link](#) [▶ Link](#)
 - ▶ GPR: Gaussian process regression
 - ▶ book: [▶ Link](#) sklearn: [▶ Link](#)
 - ▶ zhihu: [▶ Link](#) [▶ Link](#) [▶ Link](#)
 - ▶ implementation [▶ Link](#)
 - ▶ example: [▶ Link](#) [▶ Link](#)

Time Series Forecasting Methods

- ▶ neural networks
 - ▶ GRU
 - ▶ wikipedia: [▶ Link](#) document: [▶ Link](#)
 - ▶ blog [▶ Link](#) implementation: [▶ Link](#)
 - ▶ WavNet (DeepMind)
 - ▶ paper: [▶ Link](#)
 - ▶ zhihu [▶ Link](#) example: [▶ Link](#) [▶ Link](#)
 - ▶ seq2seq
 - ▶ zhihu [▶ Link](#) implementation [▶ Link](#) [▶ Link](#)
 - ▶ example: [▶ Link](#)
 - ▶ attention mechanism: transformer
 - ▶ paper [▶ Link](#)
 - ▶ example [▶ Link](#)

- ▶ Outlier Detection Techniques
 - ▶ visualization: tableau
 - ▶ Z-score
 - ▶ DBSCAN
 - ▶ isolation forest
- ▶ reading



How to Identify Outliers in your Data



A Brief Overview of Outlier Detection Techniques



Four Techniques for Outlier Detection

Outlier Detection Techniques

- ▶ visualization: tableau
 - ▶ installation: [▶ Link](#)
 - ▶ tutorial: [▶ Link](#) [▶ Link](#)
- ▶ Z-score: assume Gaussian distribution

usage

- ▶ $z_i = \frac{x_i - \mu}{\sigma}$ where data x_i , $\mu \equiv \sum x_i / N$, $\sigma \equiv \sqrt{\sum (x_i - \mu)^2 / (N - 1)}$
- ▶ For abnormal value $|z_i| > z_{th}$, where z_{th} should always be 2.5, 3.0 or 3.5

- ▶ DBSCAN
 - ▶ wikipedia: [▶ Link](#)
 - ▶ sklearn: [▶ Link](#)
 - ▶ example: [▶ Link](#)
- ▶ isolation forest
 - ▶ description: [▶ Link](#) [▶ Link](#)
 - ▶ implementation: [▶ Link](#)
 - ▶ sklearn: [▶ Link](#)
 - ▶ example: [▶ Link](#)