Introdução a Séries Temporais

mentorama.

Conceitos fundamentais

mentorama.

Conceitos fundamentais

- AR
- MA
- ARMA
- Prophet
- Escalando Prophet
- RNN e Deep RNN

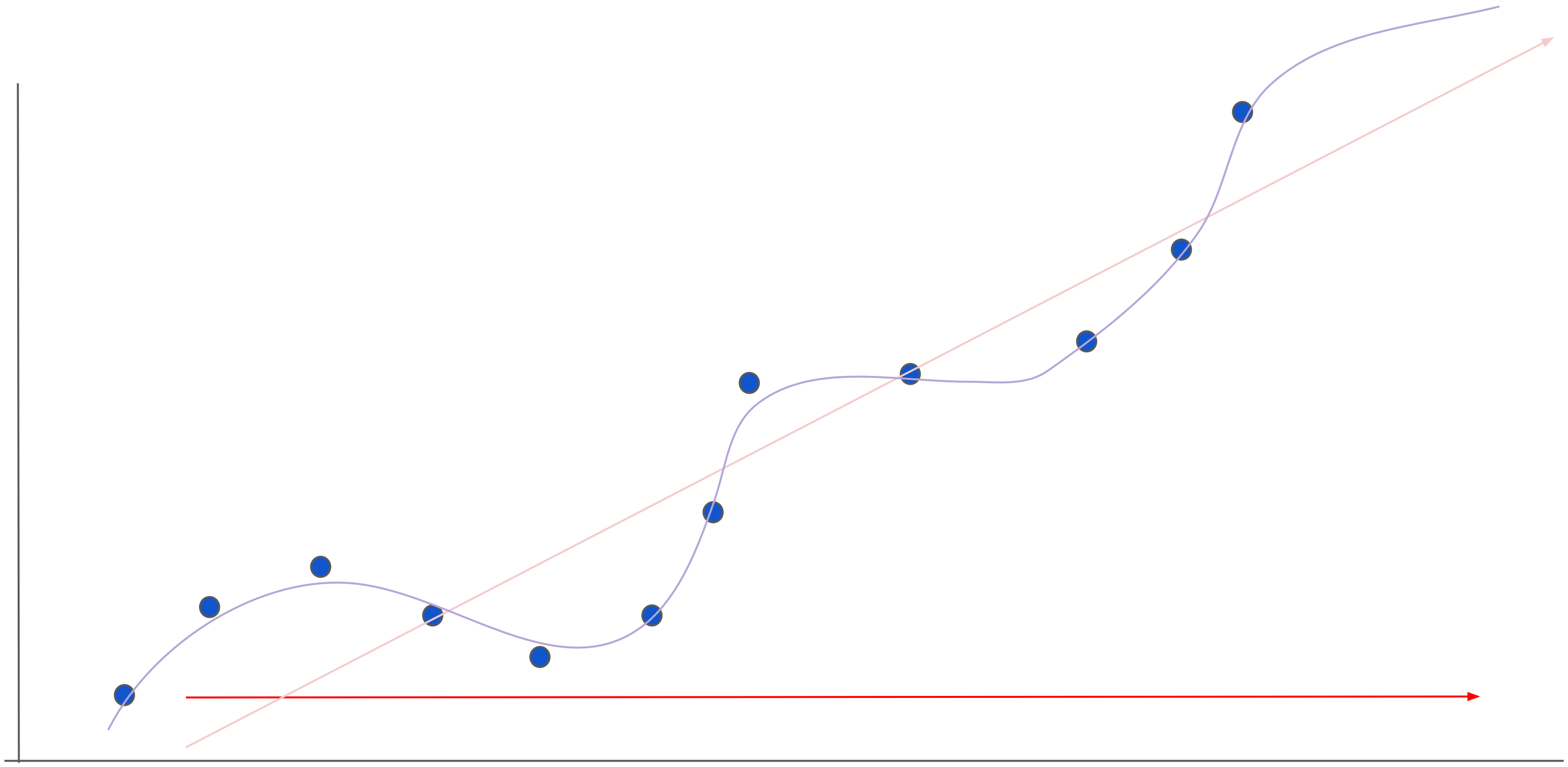
mentorama.

Conceitos fundamentais

"A timeseries is a time-oriented or chronological sequence of observations on avariable of interest."

- **Time Series Analysis and Forecasting (Douglas Montgomery)**

Conceitos fundamentais



Conceitos fundamentais

$$Y_t = 1 + 0.8Y_{(t-1)} + e(1,1)$$

ruído
branco

Observado no
instante
anterior

Modelos clássicos

Modelos clássicos

- AR - Autoregressive
- MA - Moving Average
- ARMA - Autoregressive Moving Average

mentorama.

Modelos clássicos

AR(p)

Ordem do modelo

AR(1)

ruído branco

$$Y_t = \beta + \phi_1 Y_{(t-1)} + e_t$$

AR(2)

$$Y_t = \beta + \phi_1 Y_{(t-1)} + \phi_2 Y_{(t-2)} + e_t$$

AR(p)

$$Y_t = \beta + \sum_{j=1}^{p} \phi_j Y_{(t-j)} + e_t$$

mentorama.

Modelos clássicos

MA(q)

Ordem do modelo

MA(1)

$$Y_t = \beta + e_t + \theta_1 e_{(t-1)}$$

MA(2)

$$Y_t = \beta + e_t + \theta_1 e_{(t-1)} + \theta_2 e_{(t-2)}$$

MA(q)

$$Y_t = \beta + \sum_{j=1}^{q} \theta_j e_{(t-j)} + e_t$$

Modelos clássicos

ARMA(p,q)

Ordem do modelo

$$Y_t = \beta + \sum_{j=1}^{p} \phi_j Y_{(t-j)} + \sum_{j=1}^{q} \theta_j e_{(t-j)} + e_t$$

Prophet - forecasting at scale

mentorama.

Prophet - Forecasting as Scale

Prophet

- Inferência Bayesiana
- MCMC ou Otimização Bayesiana
- GAM

mentorama.

Prophet - Forecasting as Scale

"descrevemos uma abordagem prática para a previsão 'em escala' que combina modelos configuráveis com análise de desempenho do analista in the loop. Propomos um modelo de regressão com parâmetros interpretáveis que podem ser ajustados intuitivamente por analistas com conhecimento de domínio sobre as séries temporais . Descrevemos as análises de desempenho para comparar e avaliar os procedimentos de previsão e sinalizar automaticamente as previsões para revisão e ajuste manual. As ferramentas que ajudam os analistas a usar sua experiência de forma mais eficaz permitem previsões confiáveis e práticas de séries temporais de negócios. "

Prophet - Forecasting as Scale

We use a decomposable time series model (Harvey & Peters 1990) with three main model components: trend, seasonality, and holidays. They are combined in the following equation:

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t.$$

Tendência

Sazonalidade

Feriados ou eventos

Prophet - Forecasting as Scale

Tendência

Exponencial

$$g(t) = \frac{C(t)}{1 + \exp(-(k + \mathbf{a}(t)^\intercal \boldsymbol{\delta})(t - (m + \mathbf{a}(t)^\intercal \boldsymbol{\gamma})))}.$$

Linear

$$g(t) = (k + \mathbf{a}(t)^\intercal \boldsymbol{\delta})t + (m + \mathbf{a}(t)^\intercal \boldsymbol{\gamma}),$$

Prophet - Forecasting as Scale

Sazonalidade

$$s(t) = \sum_{n=1}^{N} \left(a_n \cos\left(\frac{2\pi n t}{P}\right) + b_n \sin\left(\frac{2\pi n t}{P}\right) \right)$$

mentorama.

Prophet - Forecasting as Scale

Feriados

$$Z(t) = [\mathbf{1}(t \in D_1), \ldots, \mathbf{1}(t \in D_L)]$$

$$h(t) = Z(t)\boldsymbol{\kappa}.$$

O "at scale" do Prophet

mentorama.

At Scale

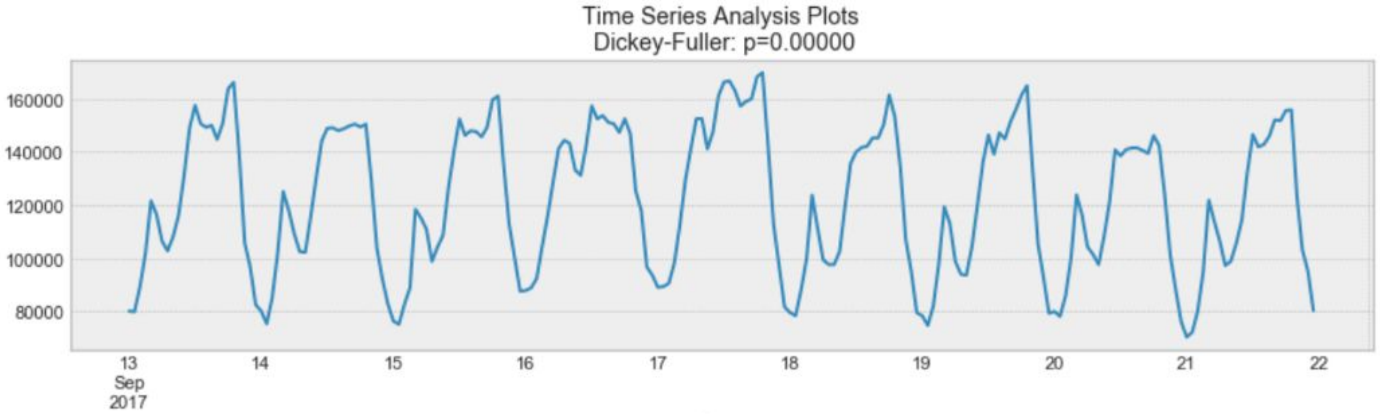
Velocidade
Sem muita supervisão
Sem muito conhecimento técnico

Complexidade X Necessidade

Tempo e dinheiro investido X retorno

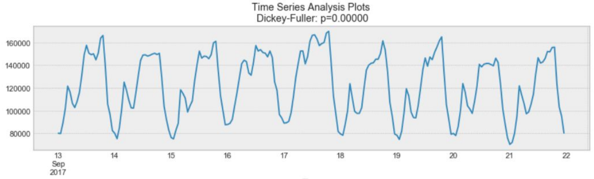
mentorama.

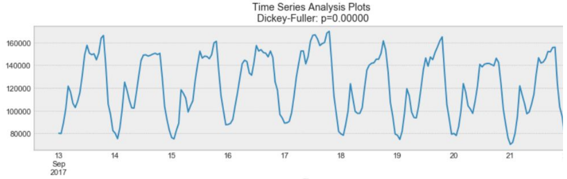
At Scale

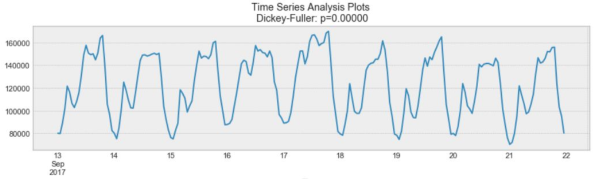


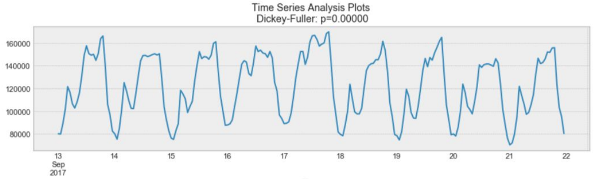
mentorama.

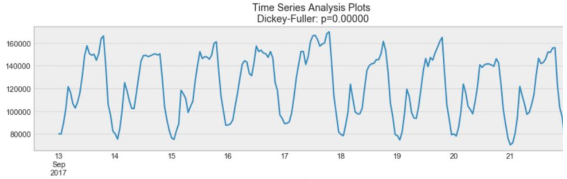
At Scale

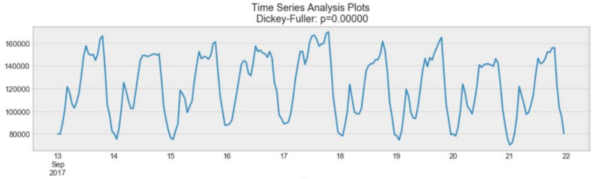

Time Series Analysis Plots
Dickey-Fuller: p=0.00000
160000
140000
120000
100000
80000
13
Sep
2017
14
15
16
17
18
19
20
21
22

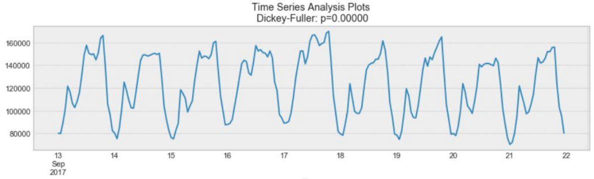

Time Series Analysis Plots
Dickey-Fuller: p=0.00000
160000
140000
120000
100000
80000
13
Sep
2017
14
15
16
17
18
19
20
21

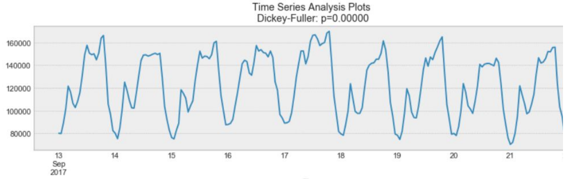

Time Series Analysis Plots
Dickey-Fuller: p=0.00000
160000
140000
120000
100000
80000
13
Sep
2017
14
15
16
17
18
19
20
21
22

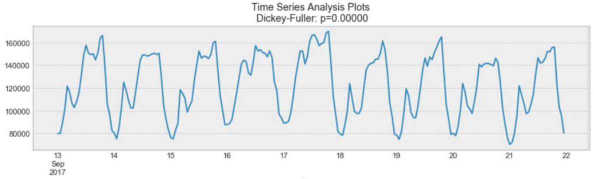

Time Series Analysis Plots
Dickey-Fuller: p=0.00000
160000
140000
120000
100000
80000
13
Sep
2017
14
15
16
17
18
19
20
21
22

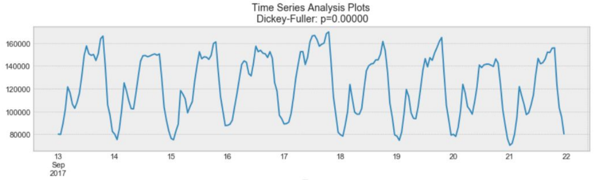

Time Series Analysis Plots
Dickey-Fuller: p=0.00000
160000
140000
120000
100000
80000
13
Sep
2017
14
15
16
17
18
19
20
21

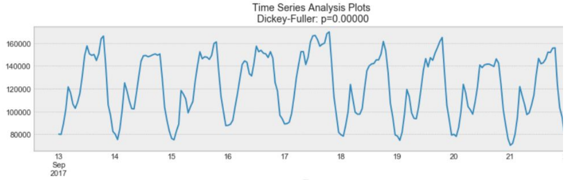

Time Series Analysis Plots
Dickey-Fuller: p=0.00000
160000
140000
120000
100000
80000
13
Sep
2017
14
15
16
17
18
19
20
21
22

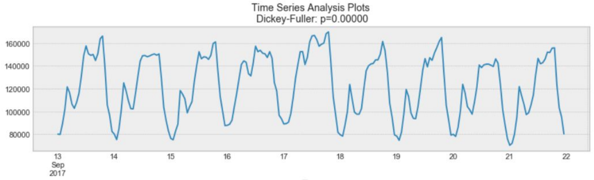

Time Series Analysis Plots
Dickey-Fuller: p=0.00000
160000
140000
120000
100000
80000
13
Sep
2017
14
15
16
17
18
19
20
21
22


Time Series Analysis Plots
Dickey-Fuller: p=0.00000
160000
140000
120000
100000
80000
13
Sep
2017
14
15
16
17
18
19
20
21


Time Series Analysis Plots
Dickey-Fuller: p=0.00000
160000
140000
120000
100000
80000
13
Sep
2017
14
15
16
17
18
19
20
21
22


Time Series Analysis Plots
Dickey-Fuller: p=0.00000
160000
140000
120000
100000
80000
13
Sep
2017
14
15
16
17
18
19
20
21
22


Time Series Analysis Plots
Dickey-Fuller: p=0.00000
160000
140000
120000
100000
80000
13
Sep
2017
14
15
16
17
18
19
20
21


Time Series Analysis Plots
Dickey-Fuller: p=0.00000
160000
140000
120000
100000
80000
13
Sep
2017
14
15
16
17
18
19
20
21
22

RNN e Deep RNN

mentorama.

RNN e Deep RNN

Feed-Forward

car

motorcycle

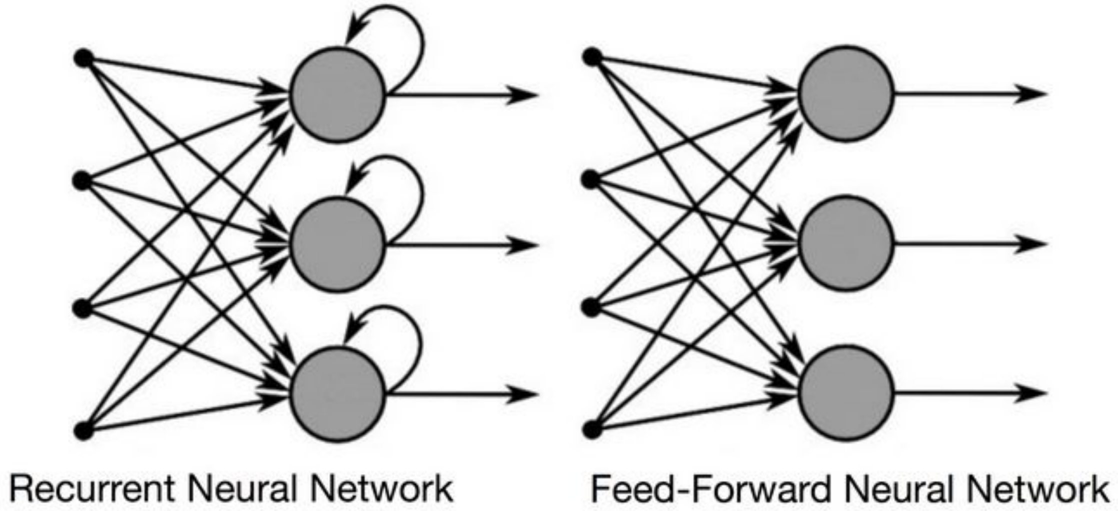
mentorama.

RNN e Deep RNN

RNN

mentorama.

RNN e Deep RNN



RNN e Deep RNN

Recurrent Neural Network

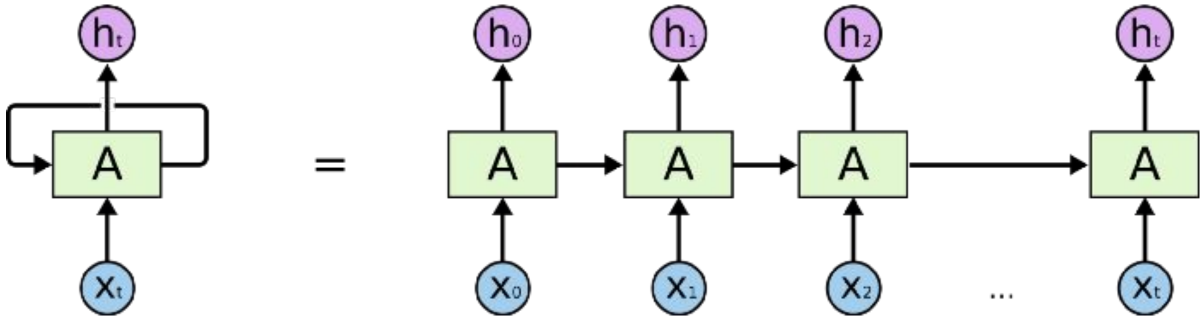
Exemplo:

$$h_t = \sigma_h(W_h x_t + U_h h_{(t-1)} + b_h)$$

$$y_t = \sigma_y(W_y h_t + b_y)$$

mentorama.

RNN e Deep RNN



mentorama.